



Article

Potential of Using Night-Time Light to Proxy Social Indicators for Sustainable Development

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Abstract: Satellite-observed night-time light (NTL) data provide a measure of the lighting brightness seen from space at different times and spatial and temporal resolutions, thus offering opportunities to explore them in many applications at different spatial locations (global, regional, local). However, most applications to date have been at relatively large spatial scales, despite the need to measure indicators at a local level. This paper sets out an analysis of the potential of NTL data for populating indicators at more local (neighbourhood, street) scales. We first reviewed the overall potential of NTL data for social indicators at different spatial scales by using a systematic search of the literature and applying the Maturity Matrix Framework (MMF). We also explored a case study (Durango State, Mexico) using Visible Infrared Imaging Radiometer Suite (VIIRS) imageries, other geospatial data, and the social gap index (SGI) to identify social gaps at the local scale. The literature review showed that NTL can play a role in supporting 49 out of 192 sustainable development goal (SDG) indicators having a focus on social issues, but most of these have been explored at the global or country scales. In the case study, we found that low radiance is indeed associated with higher SGI levels (i.e., more social deprivation) and vice versa. However, more research is needed from other contexts to support a link between NTL radiance levels and social indicators at local scales.

Keywords: sustainable development goals; social indicators; night-time light; local scale



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1. Introduction

Night-time light (NTL) data have increasingly become useful as a means for assessing various indicators important in sustainable development, and a summary of the characteristics of existing satellite sources of NTL data is provided in Table 1. The era of NTL imagery began when Croft [1] observed faint emission sources, such as city lights, auroras, and gas flares, from night-time photographs taken by the Defence Meteorological Satellite Program's Operational Linescan System (DMSP/OLS), which was originally designed to monitor cloud top temperatures in the early 1970s. In 1992, the National Oceanic and Atmospheric Administration/National Geophysical Data Center (NOAA/NGDC) developed an open access digital archive. DMSP/OLS collected night-time images for 20 years (1992–2013) at a coarse spatial resolution between 1 and 2.7 km over swaths of 3000 km and covered the entire planet every 24 h. These images have been processed into four datasets: daily and monthly datasets, cloud-free coverage, a composite of night-time stable light, and average visible data [2]. These products can be openly accessed from three different sources [3–5] and have resulted in many applications [6].

The Visible Infrared Imaging Radiometer Suite (VIIRS) sensor on board the Suomi NPP was launched in October 2011 and features a panchromatic sensor for measuring night-time lights through the Day and Night Band (DNB) sensor. The VIIRS/DNB brought significant improvements over the DMSP/OLS sensor through its higher spatial resolution

of 742 m, free access to daily images, and improved radiometrically calibrated products; thus, blooming effects have been largely mitigated [7]. From April 2012 until the present, NPP-VIIRS/DNB global, monthly and annual composites have been available and freely accessible [3–5] along with other products such as VIIRS night fire, VIIRS gas flaring, VIIRS boat detection, and Standard Black Marbles [4].

Astronaut photography has been taken from various NASA missions, including the Space Shuttle missions and the International Space Station (ISS). The database of these photos is extensive, includes both daytime and night-time photos, and is freely accessible via the Gateway of Astronaut Photography of the Earth [8]. However, one of the main problems of astronaut photography is the motion blur produced by the orbital movement of the ISS [9]. To overcome this issue, in 2012, ESA mounted aboard the space station a special tripod called Nightpod. The mechanism incorporated into the camera allowed it to capture the Earth at night in greater detail [10].

The Luojia 1-01 (LJ1-01) satellite was built by Wuhan University and launched in June 2018, providing night-time images at 130 m resolution due to its onboard complementary high-sensitivity planar array metal oxide semiconductor [11]. The LJ1-01 is the world's first professional night-time satellite with a swath width of 250 km and covers China and Southeast Asia, North America and a good part of Europe's surface every 15 days, and its data are freely available for research purposes [12]. These night-time images play a critical role in achieving more accurate results in detecting distinct energy-releasing objects, such as urban impervious surfaces [13], population density and human activities [14]. Further, researchers have found it feasible to detect urban expansion through the combination of LJ1-01 data and other imagery data [15].

Table 1. Satellite and Sensor capabilities in capturing NTL.

Satellite/Sensors	Spatial Resolution	Temporal Resolution	Overpass Time	Coverage	Data Availability	Products	Product Source
DMSP/OLS	1–2.7 km (depending on the product) and 30 arc-seconds	Every 24 h	20:00–22:00	65°S to 75°N	1992–2013	Cloud-free coverage; composite of night-time stable light; average visible data	[3] [4] [5]
VIIRS/DNB	742 m (one pixel) and 15 arc-seconds	Every 24 h	01:30 (+/– 1 h depending on the latitude)	65°S to 75°N	April 2012–present	NTL annual and monthly composites; VIIRS night fire; VIIRS gas flaring; VIIRS boat detection; standard Black Marble.	[3] [4] [5]
CubeSat (AeroCube-4 and 5) *	500 m and 124 m	Inconsistent	12–4 a.m.	Different areas across the planet	2014 and 2015 (both experimental)	High spatial resolution imagery	[16]
International Space Station (ISS)	5–200 m	Occasionally	11 p.m.	Varies	2003–present (occasionally)	Photos of Earth during the night	[8] [17]
LJ1-01	130 m	15 days	10:30 p.m.	China, Southeast Asia, Europe, South and North America, and eastern Australia.	June 2018–March 2019	High spatial resolution imagery	[12]
EROS-B *	0.7 m	3 days (30° off-nadir) 6 days (15° off-nadir)	Varies (equatorial crossing time—12:20 a.m.)	Depends on the season and sun’s position	June 2013–present	VHR of night-time imagery with panchromatic band	[18]
JL1-3B and JL1-07/08 *	<1 m	At least once per day	Around 10 p.m.	Images are acquired on request.	2018–present 2019–present	VHR of night-time imagery with panchromatic band and improved multispectral (red, green, and blue) bands.	[19]

* Commercial satellite imagery.

The first commercial satellites to acquire data at night at 0.7 m spatial resolution were the EROS-B satellites, and the data have become publicly available since 2013 via ImageSat International [20]. Jilin-1 (JL1)-3B, the first commercial satellite to offer multispectral night-time light images at 0.92 m spatial resolution, launched in 2017, and was followed by the JL1-07/08 satellite launched in 2018. Both have a panchromatic band, and the latter brought improvements to the multispectral bands (i.e., blue, green, red, red edge, and near-infrared) [19]. Likewise, a variety of CubeSats have been launched in recent years, including the CubeSat Multispectral Observing System (CUMULOS), as well as the multispectral AeroCube 4 and 5, both experimental, offering medium spatial resolution and inconsistent coverage [16].

Various studies have indicated that NTL data have a high correlation with indicators that have commonly been used in sustainable development and are at the heart of the Sustainable Development Goals (SDGs) initiative mediated by the United Nations. The SDGs have an associated set of targets and indicators, and the intention is for all countries to meet these targets by 2030. The SDG indicators span environmental, economic, and social concerns [21], but while there has been much progress in the use of Earth Observation (EO) to monitor environment issues such as land degradation and deforestation, less progress has been made with economic and social indicators. Included in the latter, for example, would be indicators of employment, poverty and exclusion, life expectancy and welfare, living conditions and human resources [22–25]. NTL data have been used to assess indicators such as GDP per capita (a proxy for income) [26–29], electrification rates and access to electrification in rural areas [30], population density [31–33] and global population [34], urbanisation dynamics [35], socioeconomic activities [36–38], quality of life [39], regional inequality [40], poverty [41,42], fishing activities [43,44], human rights [45], incidence of cancer [46–48] and political conflicts and wars [49]. Moreover, poverty estimation was initially assessed through NTL at the global scale because of the strong correlation between economic activity and light intensity [50]. Elvidge et al. (2009) [41] developed the first global poverty map, and Wang et al. (2012) [50] estimated poverty at the county level using night-time light images. In addition, Sutton et al. (1997) [51] correlated DMSP night-time satellite data with population density and found that saturated pixels of DMSP imagery can predict population size.

Most of the published studies to date have been based on relatively large spatial scale assessments (i.e., country and regions), and few studies have explored the potential of night-time light data for social indicators at more local scales such as neighbourhoods within a city. However, the identification of areas of poverty and weak infrastructure and services at the local scale is critical for strategic policy interventions, especially for regions with sparse statistical data. Using satellite imagery and geospatial data means, at least in theory, such socioeconomic evaluations could be performed with great efficiency and relative cost-efficiency when compared with more traditional approaches to data collection. However, the potential for use of NTL data at such local scales has received relatively little attention to date. The research reported in this paper aimed to address this important gap in knowledge, and the approach taken was first to review the potential of night-time satellite data for social indicators (within the SDG framework and others) at all scales and spatial resolutions. This review did not focus on all of the literature in this field, as this has been covered previously, including a detailed review published in this journal [6,52], but rather on those works that suggest a potential to use NTL data to specifically support social indicators within the SDG framework [53], as well as revealing gaps in the literature where future research should be directed and explored. As part of this analysis, the potential of using data from NTL imagery for populating SDG social indicators (listed in Tables S1–S3) was assessed using the Matrix Maturity Framework (MMF) [54], representing the first time that this has been done with such data. Secondly, to illustrate the challenges involved in such work, the paper presents a case study of the use of VIIRS, very high resolution (VHR) daytime imagery and Google Street View (GSV) imagery coupled with the social gap index (SGI) at a local scale in Santiago Papasquiaro in Durango State, Mexico.

2. Materials and Methods

2.1. Literature Acquisition and Evaluation of All NTL Satellites for Social Indicators

An outline of the approach taken with the analysis of the literature is provided as Figure 1. The literature was first sourced via Google Scholar using the search terms “night-time” + “sensors” + “satellite” + “data” + “datasets”. To address research themes, a more granular search was implemented using a specific name of the satellite or sensor along with the terms “night-time” and “main application” (acquired from the first step). The final search was conducted by using the name of a research theme (which emerged from previous steps) and the satellite/sensor that was not found in the previous step to ensure that no themes had been missed. For example, in the first search, “human and economic” application might have been generated, while in the second step when combining the satellite/sensor name, e.g., “DMSP” + “night-time” + “human and economic” resulted in the “Poverty evaluation” research theme; thus, later we queried the research theme with all other NTL satellite names e.g., “EROS-B” + “Poverty evaluation”. Likewise, we included information about the scalability of the approach reviewed (spatial resolution and spatial location) so that for each publication cited, we added one of the following abbreviations: L—local (small town, rural, or neighbouring level), C—City, CT—Country, R—Regional, G—Global.

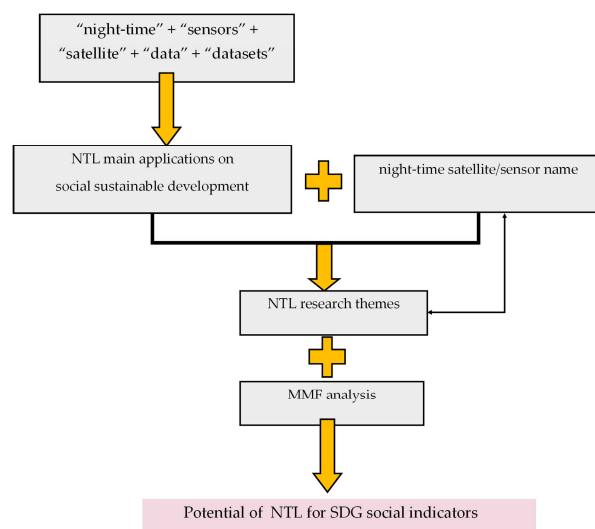


Figure 1. Flowchart of the NTL satellites for social indicators analysis.

The final step of the analysis of the literature was based on the latest version of the Maturity Matrix Framework (MMF) developed by Andries et al. (2018) [54]. MMF is an analytical framework designed to assess the potential of EO to populate SDG indicators. MMF is based on six premises (uncertainty assessment (A), directness (B), completeness (C), requirement for non-EO information (D), practicability (E), and cost-effectiveness analysis (F)), where each premise has five scored components (from 1 to 5), that generate an aggregated assessment score, referred to as the Maturity Matrix Score (MMS). MMS is calculated as follows: $MMS = (Premise A + Premise B + Premise C + Premise D + Premise E + Premise F) / 6$, and was applied to the reviewed papers and their approaches linked to the relevant indicators, aiming to understand the potential utility of EO data to populate SDG indicators. Examples of the application of MMF and conclusions that can be reached are provided in [54]. However, here it was applied more specifically for NTL data and SDG social indicators (listed in Tables S1–S3). Indicators with MMS values between 1 and 2 (colour coded as red) had weak support from satellite data; indicators with MMS values between 2 and 4 (amber) had partial support; and indicators with MMS values between 4 and 5 (green) had strong support. The resulting MMS scores were tabulated.

2.2. Case Study

2.2.1. Study Area and Data Sources

Santiago Papasquiaro (SP) is a city located in the municipality of SP, one of 39 municipalities of Durango State, Mexico (Figure 2). In Mexico, the administrative hierarchy is State (e.g., Durango), municipality (e.g., Santiago Papasquiaro) and locality (e.g., Santiago Papasquiaro, El Aguajito, etc.). According to the 2020 census, the population of SP city was 30,063, and that of the municipality was 48,549 [55]. The SP municipality comprises 416 localities, 22 of which were included in this study, and represents an area of relatively high social deprivation, although this can vary significantly between localities. CONEVAL (acronym in Spanish for Consejo Nacional de Evaluación de la Política de Desarrollo Social—National Council for the Evaluation of Social Development Policy) calculated the social gap index (SGI) (Índice de Rezago Social) for states, municipalities, and localities across Mexico in 2000, 2005, 2010 and 2020 across 32 states, 2469 municipalities and 108,149 localities, according to the methodology described in [56]. The SGI is a weighted measurement that comprises a range of social deprivation indicators covering education, access to health services, basic services in the dwelling, and assets in people's households (Table S4) [56]. It allows a regional ordering from the highest to the lowest degree of social lag, and it is categorised into five levels from “very low” to “very high”, the latter corresponding to the highest levels of deprivation. The SGI is not a multidimensional index of poverty, as it does not incorporate income, social security, and food indicators, but instead, the index attempts to capture social features. Having information on social indicators disaggregated to the municipal level enables decision-making in matters of social policy, especially to analyse inequality of social coverage in the national territory [56].

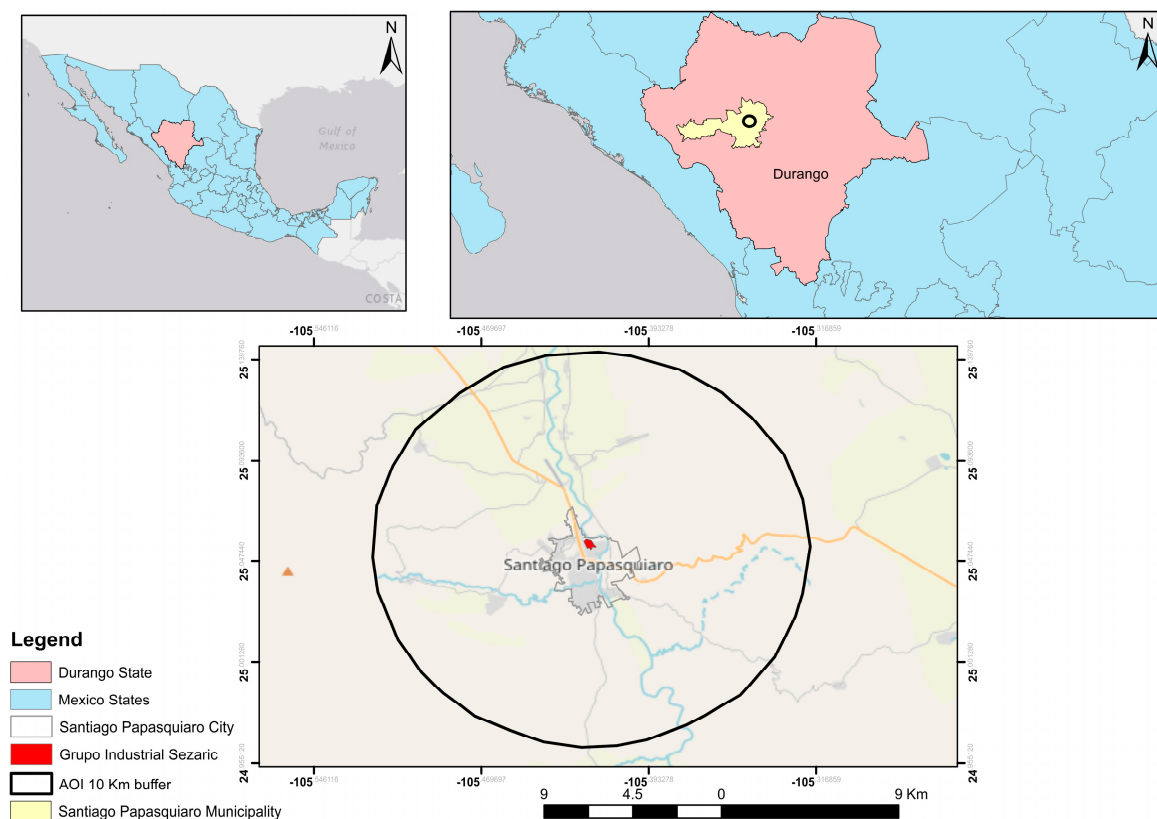


Figure 2. Study area map, part of Santiago Papasquiaro city.

In terms of NTL data sources, we used VIIRS from 2014 and 2021 monthly composites imagery, via Google Earth Engine (GEE) [57], Very high resolution (VHR) daytime satellite data (obtained from Google Earth Pro—GEP), Google Street View (GSV) and existing values

of the SGI. Table 2 presents all datasets used to address the aim of the case study. The VHR images for the study area were extracted from Google Earth Pro (GEP) and manipulated in ArcGIS 10.8. With the assistance of GSV, a tool integrated into the GEP, it was possible to validate road extraction and discriminate between paved and unpaved roads only in those available areas across Santiago Papasquiaro (Figure S1). The blue lines in Figures S1.1 and S1.2 represent the roads available on GSV, and the “yellow man” pegman offers the user the possibility to navigate virtually up and down the road along the existing blue line, with a complete 360° view of the street level (Figure S1.4). An additional function is provided by the photo sphere, which allowed observation of some of the unpaved areas for which GSV is not available (Figure S1.3).

Table 2. Data sources and description.

Data	Data Acquisition	Data Product	Resolution	Source
Night-time satellite imagery	2014 and 2021 VIIRS	Average of radiance	~750 m	[3–5]
Very high resolution (VHR) satellite data from Google Earth Pro	2012 Maxar Technologies (e.g., WorldView, GeoEye)	Road extraction via object-based classification	Vary (0.35 m and 1 m)	[58]
Google Street View (GSV)	N/A Google	Streets view and 360° loops for validating the road type	N/A	[58]
Social deprivation gap index	2010 CONEVAL	5 levels (very low, low, medium, high, very high)	N/A	[56]

2.2.2. Data Analysis of VIIRS

Geemap, a Python package for interactive mapping with GEE [59], was used to process monthly VIIRS-DNB composites for 2014 and 2021. The night-time data were filtered for ephemeral lights (fires, aurora, fishing boats, etc.), and had background (non-light) areas set to zero. The procedure for removing these lights is described by Elvidge et al. (2017) [7]. First, the annual composite for the area of interest (AOI) was calculated, based on the monthly VIIRS-DNB for both years, reducing the image collection by using the average function. In GEE, VIIRS-DNB Image Collection can be found as follows: `viirs2014 = ee.ImageCollection("NOAA/VIIRS/DNB/MONTHLY_V1/VCMSLCFG").filterDate("1 January 2014", "31 December 2014").select('avg_rad')`; `viirs2021 = ee.ImageCollection("NOAA/VIIRS/DNB/MONTHLY_V1/VCMSLCFG").filterDate("1 January 2021", "31 December 2021").select('avg_rad')`.

After these monthly composite average radiances were obtained, background light that the VIIRS instrument is sensitive to could influence interpretation (example shown in Figure 3). The removal of the background light is particularly important when these data are used at local scales and/or small areas, and a common approach is to standardize the data to be “zero-centred” (i.e., have a mean of zero) and have unit variance. Therefore, Equation (1) was used to subtract the mean of the entire image from each pixel’s value and then divide that by the standard deviation of the entire image. In order to obtain the mean and standard deviation of the image, the *reduceRegion* functions (*reducer = ee.Reducer.mean()* and *reducer = ee.Reducer.stdDev()*) were used (as described by GEE [60]) and illustrated in Figure 3.

$$X' = (X - \mu) / \sigma \quad (1)$$

where X' is the “noise removed” image (Figure 3)

X is the annual composite (Figure 3),

μ = mean of the X image,

σ = standard deviation of X image.

Further, the average radiance values were classified as follows: no lights (≤ 0), low ($>1-2$), medium ($2-5$), and high (>5) for both years 2014 and 2021.

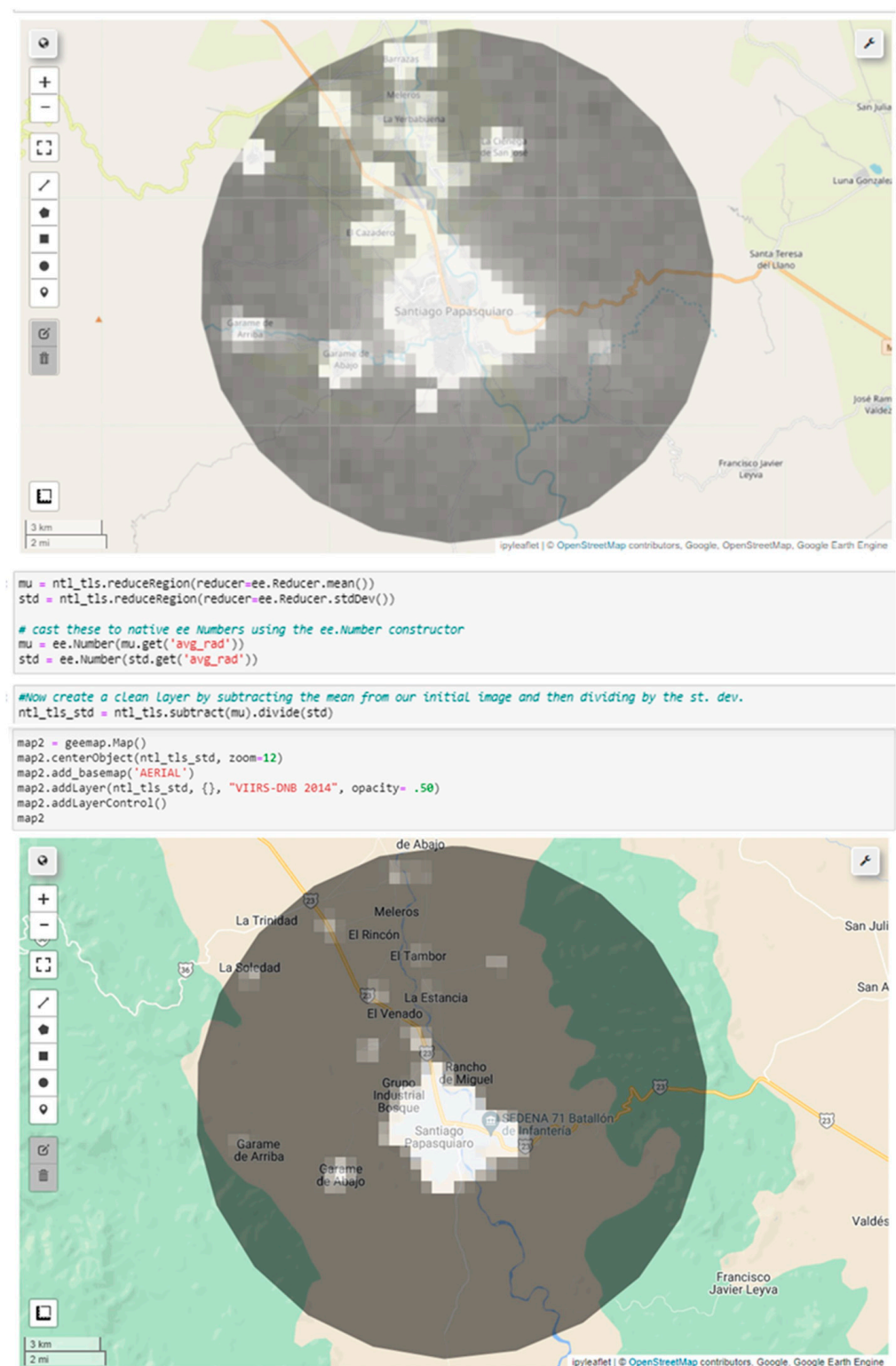


Figure 3. The impact of background noise removal.

2.2.3. Analysis of Variance on the Radiance Data

A three-way analysis of variance (ANOVA) via SPSSTM was used to explore a potential relationship between log-transformed radiance and the SGI using the following factors:

1. SGI: 0 = SGI values less than 0 (i.e., negative values); 1 = SGI values equal to and greater than zero (i.e., positive values) (Table S5)

2. Year codes: 0 for the SGI from 2010 (radiance values from 2014) and 1 for SGI from 2020 (radiance values from 2021)
3. Location codes: Each of the 24 locations was given a categorical code from 1 to 24.

No interaction terms were included in the model.

The data were first tested to ensure they had a normal distribution, and Levene's test was used to achieve this. Levene's test can be based on any measure of location but typically involves the use of the sample mean [47], median [48] and trimmed mean [48]. Levene's test (based on median) was used in this study, and the results are presented below:

Levene statistic for the two SGI groups: 1.35 ($p = 0.252$)

Levene statistic for the two-year groups: 0.00 ($p = 0.999$)

Neither test was statistically significant, thereby suggesting that ANOVA could be applied to these data.

2.2.4. Analysis of Automatic Road Extraction

To provide a degree of "ground-truthing" of the NTL data, it was assumed that in the AOI the major sources of night-time lights would be roads and buildings. It was thus necessary to explore how the NTL data matched with known infrastructure that could generate NTL. To acquire satellite images from Google Earth Pro (GEP), the grid overlay function was used to divide the area of interest into several grids (Figure S2), and JPEG images of each square grid were captured with a size of 145 m². A complete image of each grid was then reconstructed by mosaicking the JPEG images and georeferencing them [61] using ArcGIS 10.8 (ESRI, Redlands, CA, USA).

Having a complete image for our AOI allowed the extraction of the roads by using image segmentation (images were segmented based on their spectral, spatial, and/or texture characteristics) [62]. Image segmentation can be performed in different ways and processed by software such as ArcGIS and ENVI, which allow quick automation to identify roads and other types of surfaces.

To classify the imagery in this study, we first used the Feature Extraction with Rule-based Classification tool in ENVI software (described in [63]), which has been used previously in the literature [64–66]. The main steps are presented in Figure 4. First, ENVI created and displayed a segmentation image in the Layer Manager. The object/segment was represented by a group of pixels with similar spectral, spatial and texture attributes, in which our image was split into many segments. Each segment was assigned the mean spectral values of all of the pixels that belonged within a segment. For each segment, ENVI computed various spatial, spectral, and texture attributes. Merge level was the option used to aggregate all of the small segments in order to avoid over-segmentation and to improve the delineation of feature boundaries. This is a non-parametric technique and is independent of the assumption that the data are normally distributed [67]. In the next step, we built several rules to define and extract two types of asphalt classes, unpaved and paved roads. Therefore, we first defined as spectral min and max for paved roads the pixel values between 85 to 175, and then for unpaved roads, the pixel values from 50 to 85. The selection of pixel values was helped by inspecting different areas using the Attribute Histogram dialogue. To distinguish and extract the two types of roads from parking lots, house roofs or any other rectangular surface, we used the Major Length rule and Texture Mean rule, thus obtaining two individual rasters. Once the extracted paved and unpaved roads were obtained, the paved roads were further classified into two classes, <10 m and >10 m. In the final step, we convert each raster in vector (polyline) as paved and unpaved, respectively, using the Export Classification Vectors tool, which comes with the information on the width of the road. The level of correctness of the results for the paved/unpaved roads classification was visually evaluated by using GSV roads and sphere availability (Figure S1).

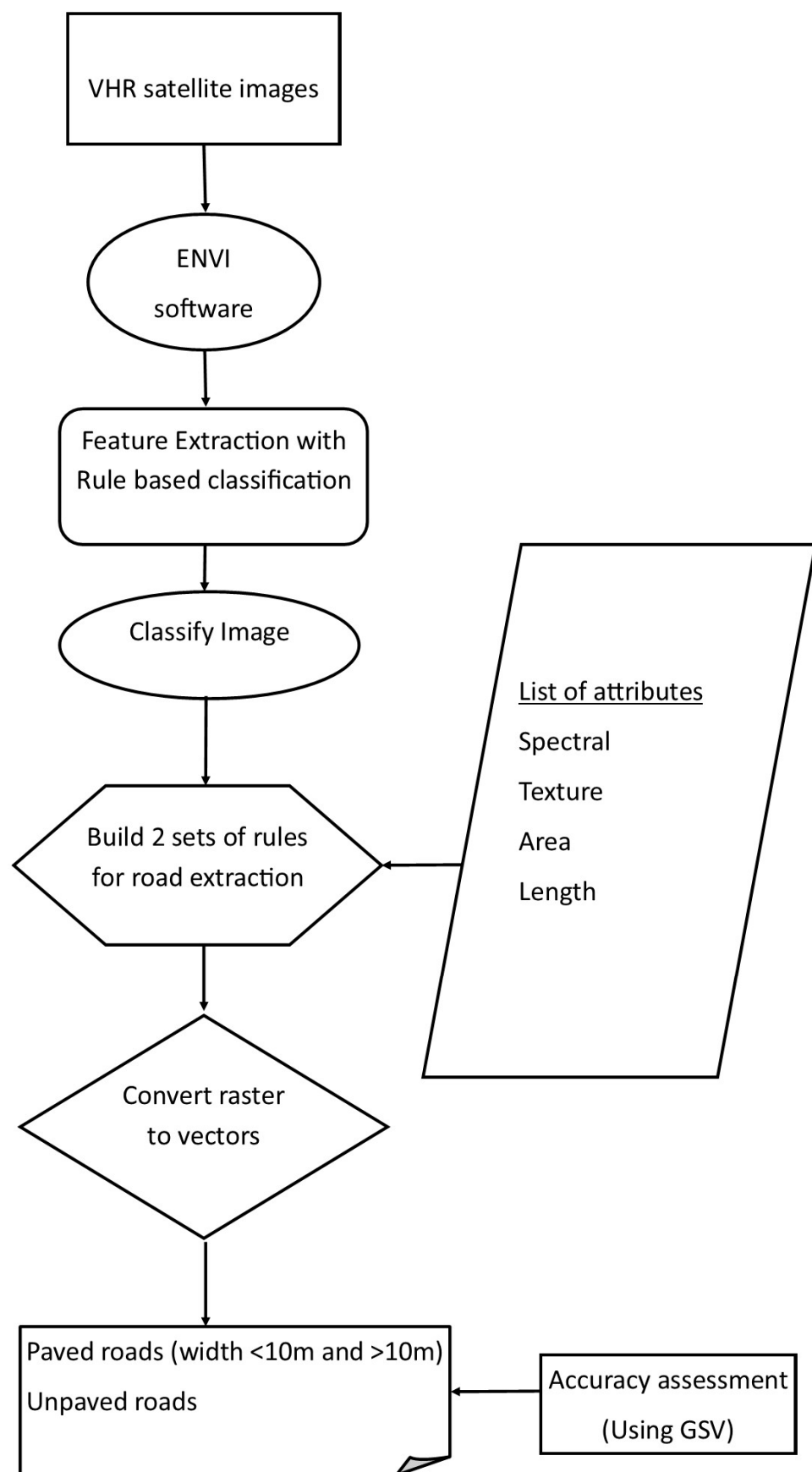


Figure 4. Road extraction workflow.

3. Results

3.1. Analysis of Published Studies on the Use of NTL Data for Social Indicators

Table 3 presents an overview of the NTL datasets collected from various sensors and platforms that have been explored for a wide range of applications and research themes, where the abbreviation next to the paper reviewed indicates the approach's spatial location. The columns in Table 3 have been arranged from the lowest (coarse) resolutions to the highest (as the arrow pointed). Most peer-reviewed articles have been based on the use of free open-access NTL satellites/sensors (DMSP and VIIRS) to explore a wide range of social applications and research themes. Table 3 also suggests a trade-off between spatial and location resolutions, where coarse resolutions have higher applicability on the large scale (global, regional, and country) and vice versa. For instance, using DMSP data could detect only the cores of towns with a minimum area of 4.5 km². On the other hand, VIIRS and LJ1-01 images could detect most town and city levels and some village levels, with the minimum area of 0.3 km² and 0.1 km², respectively [68], with applications for poverty evaluation [69,70], energy supply [71,72], prediction of GDP and income [14,38], urbanisation [73,74], population distribution and density [14,32], marine activities [75,76], assessment of flood risk and wildfire [77,78], and understanding religious and cultural festivals [79]. LJ1-01 NTL data do allow for some limited applications at a local level [14,80–82], but the satellite's coverage is limited, only some parts of the planet are covered (Figure 5), and there is no availability of monthly or annual composites, unlike DMSP and VIIRS data. Higher spatial resolution night-time imagery from commercial satellites (e.g., EROS-B, and JL1-03) has shown great potential for investigating spatial patterns and measuring light pollution [83], freight traffic [20], urban functional zones [84], urbanisation [85] and road quality [86], including at the local level, such as neighbourhoods and streets [20,87]. However, to date, the commercial NTL data available from these sources have been underused.

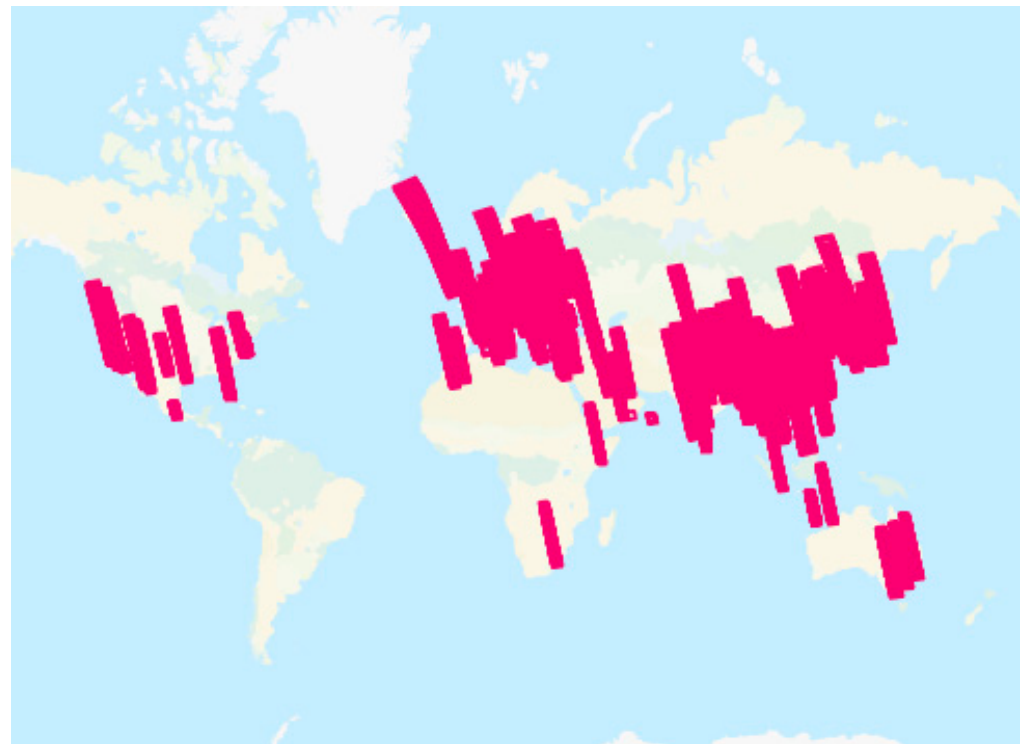


Figure 5. LJ1-01 data coverage since 2018. Source: [12].

Table 3. Applications of night-time satellites by spatial resolution and location. G—Global; R—Regional, CT—Country; C—City; L—Local.

Main Application	Research Themes	Spatial Resolution						
		1–2.7 km	742 m	124–500 m	5–200 m	130 m	0.7 m	<0.7 m
		DMSP	VIIRS	CubeSat	ISS	LJ1-01	EROS-B	JL1-3B & JL1-07/08
Human and economic aspects	Poverty evaluation	[88] (R)	[69] (CT)	—	[70] (C)	[89] (L)	—	[87] (L)
	Inequality	[90] (G)	[91] (CT)	—	—	—	—	—
	Education inequality	[92] (CT)	—	—	—	—	—	—
	Energy supply/energy consumption	[93] (R)	[71] (CT)	—	—	[72] (R)	—	[94] (L)
	Rural electrification coverage	[95] (L)	[71] (CT)	—	—	—	—	—
	Renewable energy	[96] (G)	[97] (L)	—	—	—	—	—
Socioeconomic features	Urban economic development (e.g., GDP, income, unemployment rates)	[36] (CT)	[38] (L)	—	—	[14] (C)	—	—
	Rural economic development (e.g., GDP, income, unemployment rates)	[37] (L)	[98] (L)	—	—	[14] (C)	—	—
	Housing vacancy	—	—	—	—	[80] (C)	—	[99] (L)
	“Ghost” cities	[100] (C)	—	—	—	[81] (L)	—	—
	Freight traffic and road density	[101] (CT)	[102] (CT)	—	[103] (C)	[82] (C)	[20] (L)	[86] (C)
	Road lighting	[104] (L)	[105] (C)	—	[106] (C)	—	[86] (C)	[87] (L)
	Copper/steel stock	[107] (G)	[108] (G)	—	—	—	—	—

Table 3. Cont.

Main Application	Research Themes	Spatial Resolution						
		1–2.7 km	742 m	124–500 m	5–200 m	130 m	0.7 m	<0.7 m
		DMSP	VIIRS	CubeSat	ISS	LJ1-01	EROS-B	JL1-3B & JL1-07/08
Urbanisation	Long-term urbanisation	[109] (CT)	—	—	—	[14] (C)	—	—
	Urban functional zones	[110] (C)	[111] (C)	—	[112] (L)	[113] (L)	—	[84] (L)
	Scaling city expansion	[114] (C)	[115] (R)	—	[116] (C)	[15] (C)	—	—
	Impervious surface area detection/distribution	[117] (R)	[118] (R)	—	[119] (C)	[13] (C)	—	[120] (C)
	Urban settlement	[121] (R)	[122] (R)	—	[70] (C)	[72] (R)	[85] (L)	[123] (L)
	Rural settlement	[35] (L)	[124] (R)	—	—	[68] (R)	—	—
	Urban surface temperature	[125] (C)	[126] (R)	—	[127] (C)	[128] (C)	—	—
	Urban impacts on habitat/soil	[129] (CT)	[130] (R)	—	—	—	—	—
	Dynamics of urban agglomeration	[131] (C)	[73] (R)	—	—	[74] (R)	—	—
	War/political tensions	[132] (C)	[133] (C)	—	—	—	—	—
Conflicts and disasters	Governmental favouritism	[134] (G)	[135] (G)	—	—	—	—	—
	People's displacement due to disasters/wars (refugees)	[136] (CT)	[137] (CT)	—	—	—	—	—
	Population distribution	[138] (C)	[139] (R)	—	[112] (L)	[140] (C)	—	—
Demographic and socioeconomic information	Population migration	[141] (R)	[142] (L)	—	—	—	—	—
	Population density	[31] (CT)	[32] (C)	—	[33] (C)	[14] (C)	—	—
	“Ambient population”	[143] (C)	[144] (C)	—	—	—	—	—

Table 3. Cont.

Main Application	Research Themes	Spatial Resolution						
		1–2.7 km	742 m	124–500 m	5–200 m	130 m	0.7 m	<0.7 m
		DMSP	VIIRS	CubeSat	ISS	LJ1-01	EROS-B	JL1-3B & JL1-07/08
Environmental	Gas flares and biomass burning	[145] (G)	[146] (G)	[147] (C)	—	—	—	—
	Land use types	—	—	—	—	[87] (L)	—	[148] (L)
	Net primary productivity	[149] (C)	—	—	—	—	—	—
	Water footprint	[150] (G)	—	—	—	—	—	—
	Aerosol properties	[151] (R)	[152] (G)	—	—	—	—	—
	Virtual water	[153] (R)	—	—	—	—	—	—
	Ecosystem services	[154] (R)	[155] (R)	—	—	—	—	—
	Bioluminescence in the sea	[156] (R)	[157] (R)	—	—	—	—	—
	Air quality	[158] (G)	[159] (C)	—	—	[160] (R)	—	—
	Light pollution and its effect on biodiversity and conservation	[161] (G)	[162] (G)	—	[163] (L)	—	[83] (C)	[164] (C)
Marine activities	Lightning flashes	[165] (G)	[166] (G)	[147] (C)	[167] (G)	—	—	—
	Nocturnal fishing vessel detection	[168] (G)	[75] (R)	[147] (C)	—	[76] (R)	—	—
Disaster and natural hazards	Earthquake destruction	[169] (CT)	[170] (CT)	—	—	—	—	—
	Natural disasters	[171] (R)	[172] (C)	—	—	—	—	—
	Flood risk	[173] (CT)	[77] (C)	—	—	[78] (C)	—	—
	Wildfire	[174] (R)	[175] (R)	—	—	[176] (R)	—	—

Table 3. Cont.

Main Application	Research Themes	Spatial Resolution						
		1–2.7 km	742 m	124–500 m	5–200 m	130 m	0.7 m	<0.7 m
		DMSP	VIIRS	CubeSat	ISS	LJ1-01	EROS-B	JL1-3B & JL1-07/08
Human health	Breast cancer	[177] (CT)	[48] (C)	—	[47] (C)	—	—	—
	Prostate cancer	[178] (G)	—	—	[47] (C)	—	—	—
	COVID-19 outbreak	[179] (R)	—	—	—	—	—	—
	Circadian rhythms, sleep disruptions	[180] (CT)	[181] (CT)	—	—	—	—	—
	Obesity/body mass	[180] (CT)	—	—	[182] (C)	—	—	—
	Birth mortality	[183] (L)	[183] (L)	—	—	—	—	—
Other applications with social nuances	Religious/cultural festivals	[184] (CT)	[185] (CT)	—	—	[79] (C)	—	[123] (L)
	Human lifestyle during COVID-19 lockdown	—	[186] (CT)	—	—	—	—	—
	Tourism/recreational opportunities	[187] (C)	[188] (C)	—	—	—	—	—
	Public space lighting preferences	—	—	—	—	—	—	[189] (L)
	Forced labour	—	[190] (R)	—	—	—	—	—
	Voting rights	[191] (G)	—	—	—	—	—	—
	Human trafficking	[192] (CT)	—	—	—	—	—	—
Total articles reviewed		G = 12	G = 7	G = 0	G = 1	G = 0	G = 0	G = 0
		R = 12	R = 12	R = 0	R = 0	R = 8	R = 0	R = 0
		CT = 14	CT = 10	CT = 0	CT = 0	CT = 0	CT = 0	CT = 0
		C = 10	C = 20	C = 3	C = 11	C = 12	C = 2	C = 3
		L = 5	L = 5	L = 0	L = 3	L = 3	L = 2	L = 9
		Total = 53	Total = 54	Total = 3	Total = 15	Total = 23	Total = 4	Total = 12

It should be noted that VHR NTL imagery is not necessarily useful for all applications, and actually, Anderson et al. (2010) [33] and Katz and Levin (2016) [83] have shown that medium and low resolutions would correlate better for assessing urbanisation, population density and light pollution. Elvidge et al. (2007) [193] have suggested that a sensor with a medium spatial resolution of 50–100 m would be sufficient to explore urban and rural areas.

In rural areas, the prediction of poverty using NTL was shown to be more uncertain than in more densely populated areas [37,194]. As NTL disperses over large areas (known as the “blooming effect”), these data alone provide meaningful interpretation typically only at the city level, as demographic and wealth variations are far more granular within urban neighbourhoods. Thus, to target disadvantaged areas and groups, especially in rural areas, satellite-based poverty estimation models must provide more detailed estimates than just NTL. Lately, several studies have investigated multiple types of satellite imagery, including multispectral and night-time imagery [42], by extracting the land cover and use [195] and assessing road and roof materials [196], all acting as proxies when correlating with traditional data (e.g., census, income, GDP, etc) for representing poverty, socioeconomic condition and household wealth [197].

Table 4 presents the results of applying the MMF to the potential of NTL data for populating social indicators. The analysis suggests that a total of 49 of the SDG indicators could be supported by NTL (and other datasets), albeit to varying degrees. The results are represented by the MMS values from 1 to 5 in traffic light colours, green, amber and red. The grey colour was assigned to those SDG indicators that lack any NTL contribution in the literature reviewed. Of these 49, 21 in red had MMS values between 1 and 2, meaning that NTL could provide weak support, 27 amber indicators had MMS values between 2 and 4, indicating that NTL data could partially and indirectly contribute to populating the indicator, and 1 green indicator had MMS values between 4 and 5, indicating strong and direct support from EO data. Some example applications are for SDG indicators 4.4.1, 11.7.1 and 7.1.1, and the following paragraphs provide some more detailed context.

SDG indicator 4.4.1 (Proportion of youth and adults with information and communications technology (ICT) skills, by type of skill) is considered a social indicator, as it measures the proportion of the population that has equal learning opportunities to develop ICT skills [198]. For countries and years where no data from household surveys are available, proxy measurements can be conducted by assessing the electricity consumption rate and electricity access. Many studies have shown that there is a strong relationship between electricity access and ICT skills [199,200], as many developing countries have unreliable and fluctuating local power supplies and internet, which hinder the ability to use a computer or to connect to local data centres. Where traditional data about electricity coverage and access are missing, NTL data have been explored to estimate the electricity consumption [93], electrification rate [71,95] and power outages [39,144]. However, on balance, this indicator may have weak support from NTL (MMS = 1.88, red), but there is potential that can be developed further.

SDG indicator 11.7.1 (Average share of the built-up area of cities that is open space for public use for all, by sex, age and persons with disabilities) can be supported partially by Liu et al. (2018) [201]’s research (MMF 2.33, amber), as they developed a global urban land product that predicts urban land by the Normalized Urban Areas Composite Index (NUACI). The index, implemented through the GEE platform, uses Landsat imagery and DMSP-OLS night-time lights as datasets. Three indexes (the Normalized Difference Water Index, Normalized Difference Vegetation Index, and Normalized Difference Built-up Index) were extracted from Landsat imagery to calculate the NUACI. In addition, a binary mask was obtained by segmenting DMSP-OLS into urban and non-urban by applying a specific threshold. Based on these data, the NUACI was calculated, obtaining a raster showing the percentage of impervious surface area per pixel. The final Global Urban Land dataset was obtained after applying region-specific segmentation thresholds to the NUACI images showing the degree of imperviousness. However, even though the approach is straightforward to measure only a part of the 11.7.1 indicator (the part that focuses on

spatial analysis to delimit the built-up area of the city), this cannot offer information on population characteristics or green area functionality (e.g., public parks or gardens, playing fields, golf courses, allotments, etc.), and further exploration is required.

SDG indicator 7.1.1 measures the extent of the population with access to electricity, by urban and rural (%), where the World Bank is currently the data custodian collecting household surveys, such as the Demographic and Health Surveys, Living Standards Measurement Surveys, Multi-Indicator Cluster Surveys, and the World Health Survey. When these surveys were missing or too expensive to collect, NTL proved to have a high potential to estimate where the electricity exists or is missing [71,72,93–97]. Therefore, observations of NTL have been widely used to map human presence and the availability of electricity at global and regional scales. There are fewer examples of the use of this method at the sub-national level, especially when measuring the energy access of rural areas located inside forests, as these are more difficult to detect using NTL imagery. In this case, survey data and the use of daytime optical satellites and more advanced techniques based on SAR data can be used [202]. Moreover, when assessing SDG 7.1.1 under MMF 2.0 and supported by Falchetta et al. [203]’s work, we obtained a high MMS score (4.18, green), which meant that NTL could directly measure the electricity coverage. Falchetta et al. found wide inequality in electrification quality, especially in developing countries, which actually is not reflected in traditional statistics. For instance, with the same density of people with access to electricity, Nepalese households emit less light than Ugandan households, which emit less than Zambian households. This finding may be explained by a variety of socioeconomic variables, including consumption patterns, a decline in outdoor activities, energy-saving technologies, the absence of streetlights, and other infrastructural and building-specific factors.

Table 4. Analysis of SDG social indicators against Maturity Matrix Score (MMS) and categorisation into research topics.

Main Application	Research Themes	Social SDG Indicator	MMS 2.0 Score	Reference Assessed
Human and economic aspects	Poverty evaluation	1.1.1.; 1.2.1.	3.33	[42]
		1.2.2.	1.66	[88]
		1.3.1.	1.83	[204]
	Inequality	10.2.1	2	[90]
	Education inequality	4.1.2.; 4.a.1.	1.66	[92]
		4.4.1.	1.83	[71]
	Energy supply/energy consumption	7.1.1.	4.18	[203]
		7.3.1.	1.83	[203]
	Rural electrification cover	7.1.1.	4.18	[95]
		7.3.1.	1.83	[95]
	Renewable energy	12.a.1; 7.b.1.	2.33	[97]
		7.1.2.	1.66	[96]
		7.2.1.	2.33	[96]
Socioeconomic features	Urban economic development (e.g., GDP, income, unemployment rates)	8.5.2.	2.33	[205]
		8.3.1.	1.83	[206]
	Rural economic development (e.g., GDP, income, unemployment rates)	8.5.2.	2.33	[205]
		8.3.1.	1.83	[206]
	Housing vacancy	n/a		
	“Ghost” cities	n/a		
	Freight traffic and road density	9.1.2.	2.33	[101]
	Road lighting	16.1.4.	2.33	[207]
Urbanisation	Copper/steel stock	n/a		n/a
	Long-term urbanisation	11.3.1.	2.33	[208]
	Urban functional zone	11.1.1.	2.33	[209]
	Scaling city expansion	n/a		
	Impervious surface area detection/distribution	11.7.1.	2.33	[201]
	Urban settlement	11.3.1.	2.33	[208]
	Rural settlement	11.3.1.	2.33	[208]
		9.1.1.	3	[124]
	Urban surface temperature	n/a		n/a
	Urban impacts on habitat/soil	n/a		n/a
	Dynamics of urban agglomeration	n/a		n/a

Table 4. Cont.

Main Application	Research Themes	Social SDG Indicator	MMS 2.0 Score	Reference Assessed
Conflicts and disasters	War/political tensions	16.1.1.; 16.1.2.	1.83	[133]
	Governmental favouritism	16.5.1.;16.5.2	1.83	[134]
	People's displacement due to disasters/wars (refugees)	10.7.4.	2.33	[137]
Demographic and socioeconomic information	Population distribution	n/a		n/a
	Population migration	n/a		n/a
	Population density	n/a		n/a
	"Ambient population"	n/a		n/a
Environmental	Gas flares and biomass burning	n/a		n/a
	Land use types	n/a		n/a
	Net primary productivity	n/a		n/a
	Water footprint	n/a		n/a
	Aerosol properties	n/a		n/a
	Virtual water	n/a		n/a
	Ecosystem services	n/a		n/a
	Bioluminescence in the sea	n/a		n/a
	Air quality	11.6.2	2.88	[159]
		3.9.1.	1.66	[159]
	Light pollution and its effect on biodiversity and conservation	n/a		n/a
	Lightning flashes	n/a		n/a
Marine activities	Nocturnal fishing vessel detection	14.6.1.	3	[76]
		14.7.1.	1.83	[76]
Disaster and natural hazards	Earthquake destruction	1.5.1.; 11.5.1;13.1.1.	2.88	[170]
		1.5.2.; 11.5.2.	3.66	[170]
	Natural disasters	1.5.1.; 11.5.1;13.1.1.	2.33	[169]
		1.5.2.; 11.5.2.		
	Flood risk	1.5.1.; 11.5.1;13.1.1.	2.88	[77]
		1.5.2.; 11.5.2.	3.66	[77]
	Wildfire	1.5.1.; 11.5.1;13.1.1.	1.66	[176]
		1.5.2.; 11.5.2.	3.66	[176]

Table 4. Cont.

Main Application	Research Themes	Social SDG Indicator	MMS 2.0 Score	Reference Assessed
Human health	Birth mortality	3.1.1.; 3.2.1; 3.2.2.	3.18	[183]
	Prostate cancer	n/a		n/a
	COVID-19 outbreak	n/a		n/a
	Circadian rhythms, sleep disruptions	n/a		n/a
	Breast cancer	n/a		n/a
	Obesity/body mass	3.4.1.	1.83	[180]
Other applications with social nuances	Religious/cultural festivals	n/a		n/a
	Human lifestyle during COVID-19 lockdown	n/a		n/a
	Tourism/recreational opportunities	8.9.1.; 11.4.1	1.88	[188]
	Public space lighting preferences	n/a		n/a
	Forced labour	2.3.1; 8.7.1.; 8.8.2.; 10.4.1.	1.66	[190]
	Voting rights	10.6.1.; 16.8.1.	2.66	[191]
	Human trafficking	16.2.2.	2	[192]
Total		Number of indicators 49 indicators out of 192	1, 27, 21, 143	

Indicators colour coded in red, amber and green represents weak, partial and strong respectively from NTL data.

3.2. Case study: Durango, Mexico

Figures 6 and 7 illustrate the NTL brightness average radiance classified into four groups: no lights (≤ 0), low (0.1–2), medium (2–5) and high light (>5). Figure 6 shows the total population in Santiago Papasquiro (SP) and the 25 localities within the 10 km AOI, overlayed by the average radiance. All localities, except SP city, had low average radiance in both 2014 and 2021. In addition, the average radiance values in SP city slightly increased from 2014 to 2021, but the areas around it remained relatively unlit or unchanged, indicating limited development. In Figure 7, the SGI levels are shown from 2010 and 2020 over the NTL's brightness in 2014 and 2021, respectively, revealing that most of the deprived localities (medium, high, and very high values of SGI) were unlit or had low radiance values.

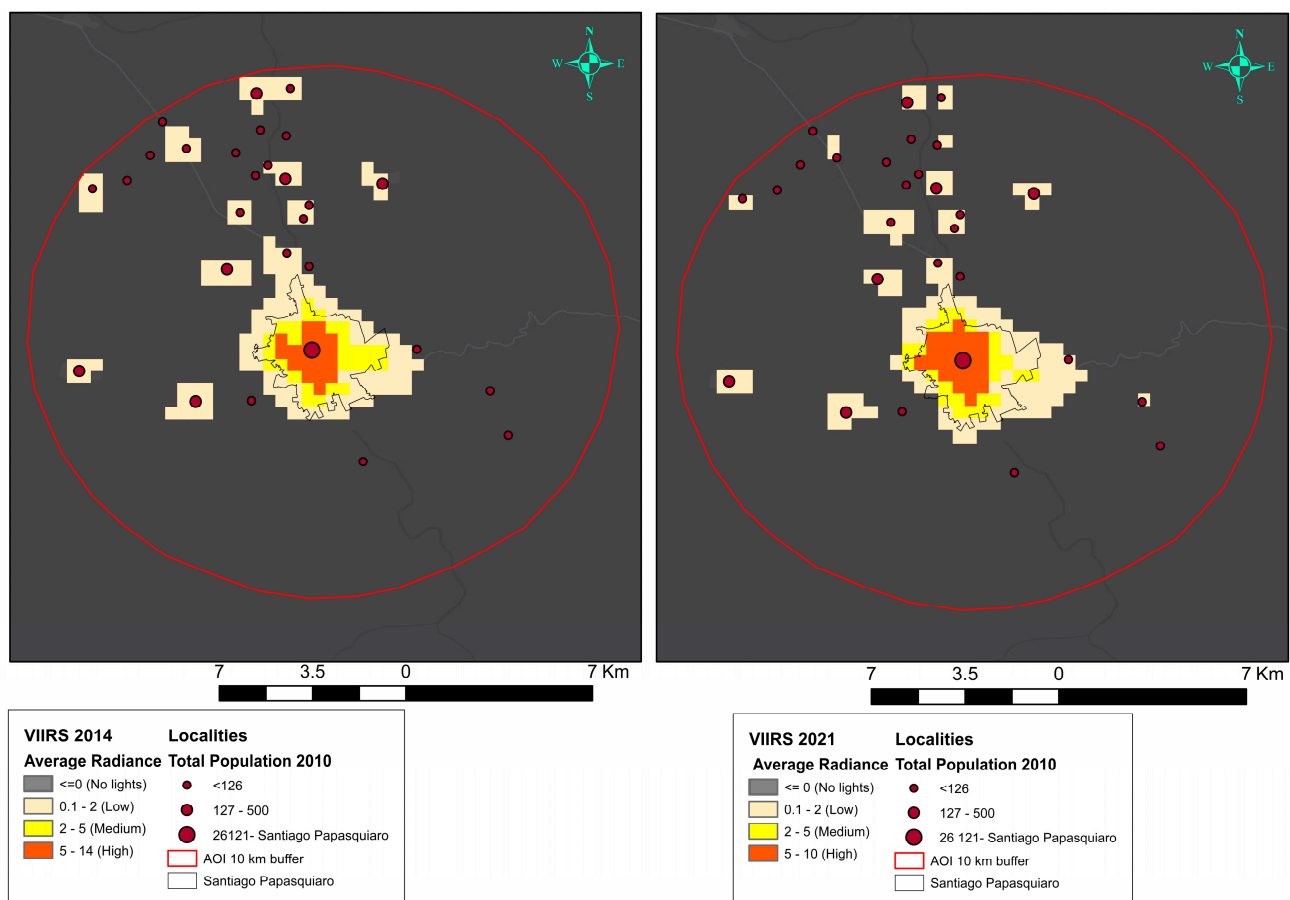


Figure 6. Average radiance brightness and total population in 2014 and 2021.

For the names of localities represented by the annotations (numbers 1 to 24), please see Table S5.

Table S5 contains information about the SGI and its scaling, and the average radiance taken from the point location of each locality across the AOI. Figure 7 shows that some of the localities with very low or low SGI (i.e., those doing well), such as localities numbered 3, 4, 5, 8, 9, 12 and 18 (Table S5), had a degree of light, whereas localities with very high, high, and medium SGI values (i.e., those not doing well), such as localities 1, 2, 11, 13, 14, 21 (Table S5), had no lights at all (unlit area). The radiance and SGI data from Table S5 are shown plotted below in Figure 8. Table 5 presents the descriptive statistics of the average radiance analysed under the SGI dummies (0 and 1) and SGI years. From the mean values in Table 5, low SGI (0) was represented by higher average radiance, indicating that localities with lower social deprivation had higher radiance, whereas the localities with low average radiance had high social deprivation (1).

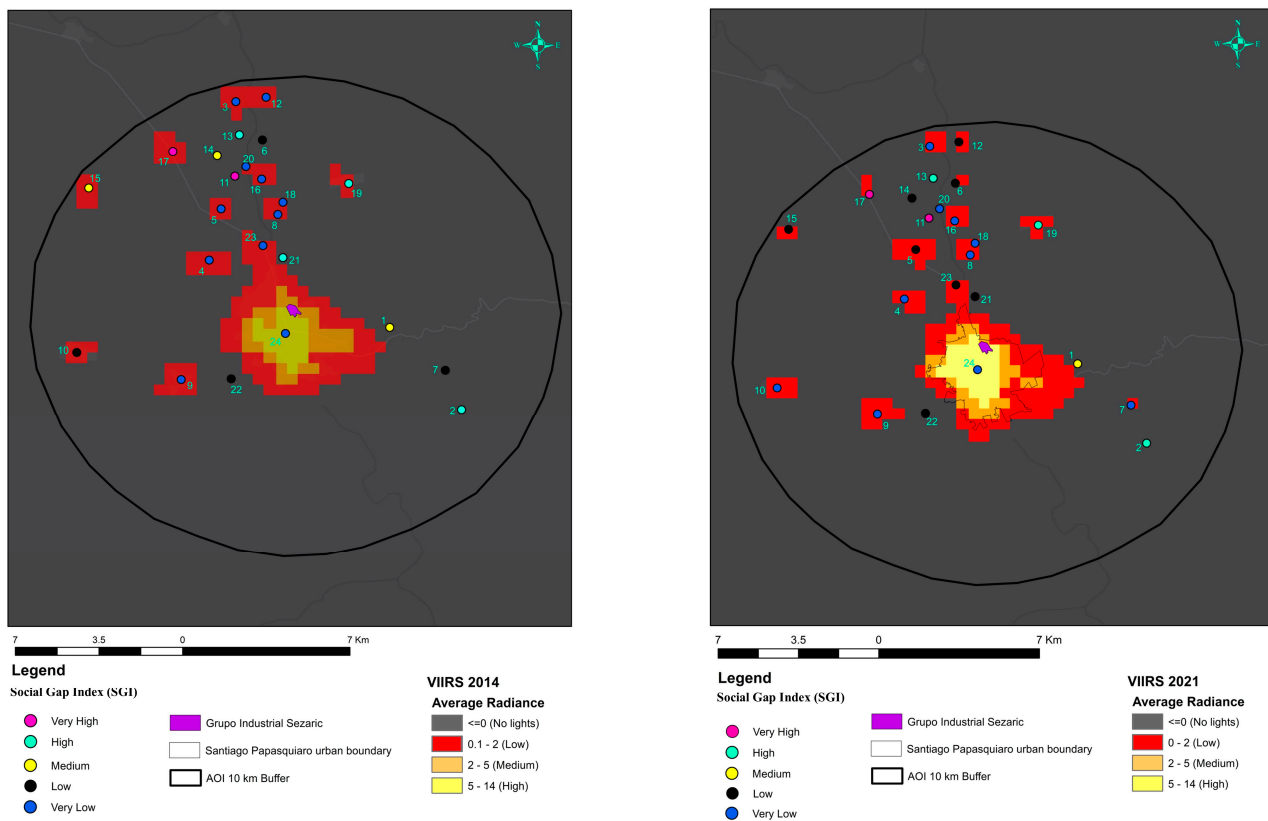


Figure 7. VIIRS average radiance in 2014 and 2021 and SGI from 2010 and 2020.

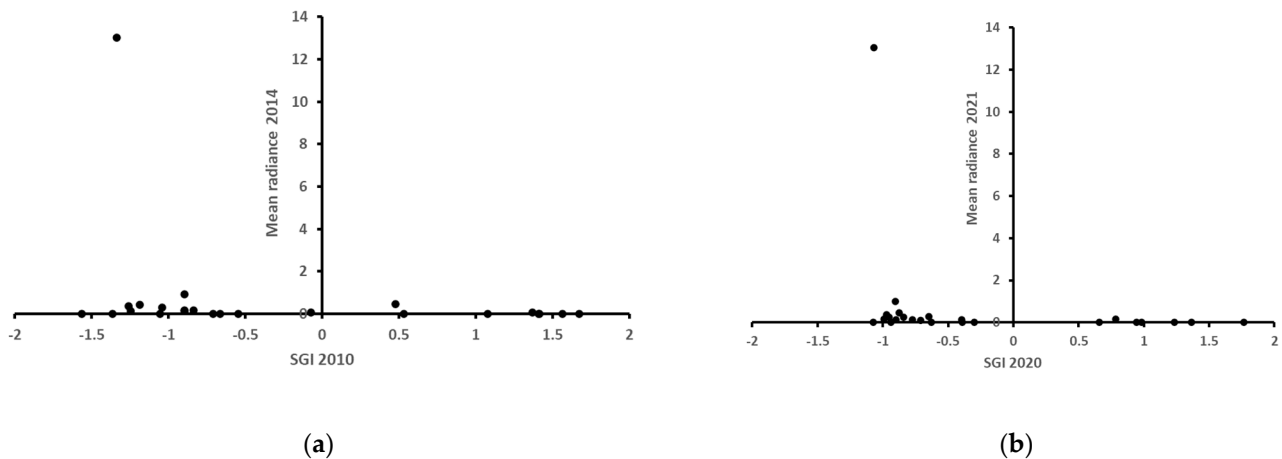


Figure 8. Average radiance plotted against SGI for the 24 locations in Table S5. (a) Radiance for 2014 and SGI for 2010 and (b) radiance for 2021 and SGI for 2020.

The results of an ANOVA (general linear model approach) applied to the radiance data listed in Table S5 are shown in Table 6. The results suggest that location was statistically significant ($p < 0.001$) as was SGI ($p < 0.05$). Year was not statistically significant, suggesting that radiance in these places had not changed significantly between 2014 and 2021 (also illustrated in Figure 8). The statistical significance for location is perhaps not surprising, as places clearly do differ in their levels of radiance. More interesting is that these results also suggest that low values of the SGI (representing low levels of social deprivation) are equated with higher radiance, while high values of the SGI (higher levels of social deprivation) equate to lower radiance.

Table 5. Descriptive statistics of radiance in relation to SGI categories.

Categories (a) Social Gap Index	Count	Mean Radiance	Median Radiance	Standard Error of Radiance
0 (Low SGI)	32	0.998	0.131	0.560
1 (High SGI)	16	0.046	0	0.029
(b) Year				
0 (SGI year 2010; radiance year 2014)	24	0.677	0.030	0.539
1 (SGI year 2020; radiance year 2021)	24	0.685	0.104	0.539

Pearson correlation of SDGI and log radiance (where $Z = \text{LN}(X + 1)$) = -0.309 (df = 46); p -Value = 0.032.

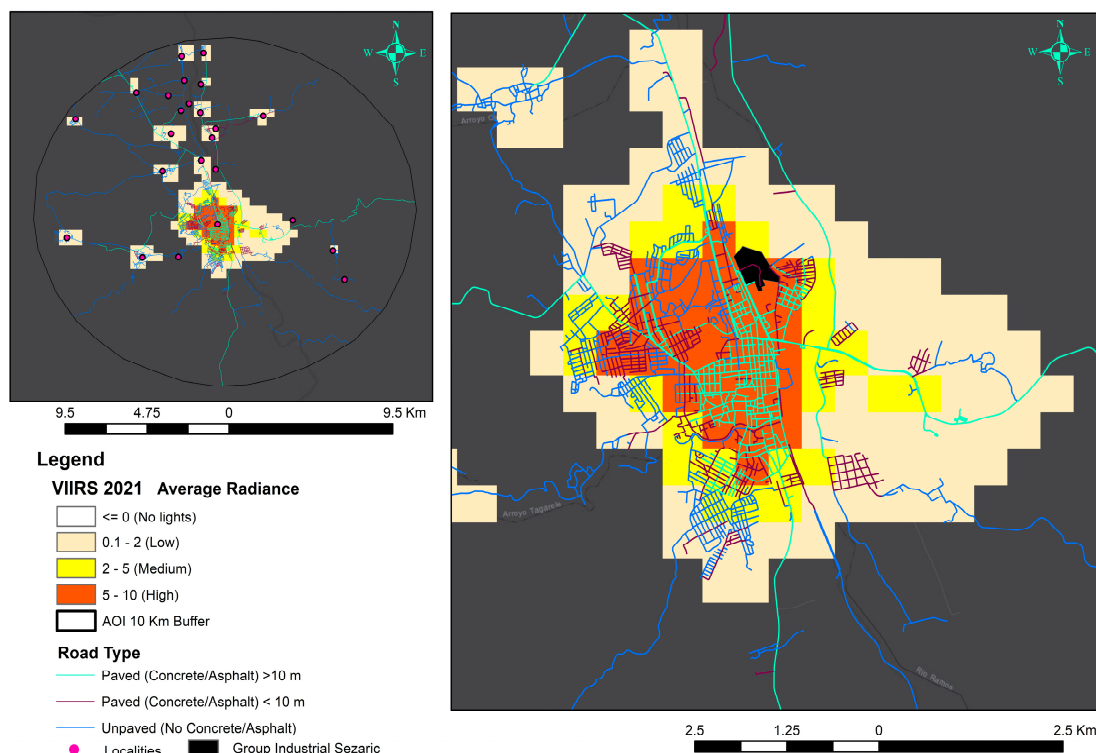
Table 6. Results of an ANOVA applied to the log-transformed radiance data in Table S5.

Source	DF	Seq SS	Adjusted SS	Adjusted MS	F
Location (24 codes)	23	13.39846	12.60764	0.54816	178.91 ***
Year (2 year codes)	1	0.00067	0.00032	0.00032	0.1 ns
Social Gap Index (2 SDGI codes)	1	0.02169	0.02169	0.02169	7.08 *
Error	22	0.06741	0.06741	0.00306	
Total	47	13.48823			

Adjusted $R^2 = 98.93\%$. Note: Radiance data transformed as $Z = \text{LN}(X + 1)$; ns = not statistically significant ($p > 0.05$); * $p < 0.05$; *** $p < 0.001$.

Road Quality and Night-Time Satellite Radiance

Figure 9 illustrates the state of roads as paved (concrete/asphalt) (with widths $<$ and $>$ 10 m) and unpaved (no concrete/asphalt) and the night-time average radiance in 2021 classified as described in the methodology section. Except for the paved roads within SP city, only a few paved roads connected the wider localities with the city. Most unpaved roads outside SP city were in localities that also had low or no light, indicating that the localities were underdeveloped. At the SP city level, most unpaved roads were located on the periphery, where night-time radiance was of low or zero intensity.

**Figure 9.** Roads' states and VIIRS 2021 average radiance.

4. Discussion

The results of the MMF analysis set out in this paper suggest that NTL data have been widely used in a variety of sustainable development applications and have the potential to populate 49 out of 192 SDG social indicators that are linked to the quality of life, poverty, inequality, education, electrification access, urbanisation, political tensions, armed conflicts, corruption, fishing activities, disasters, human health, human lifestyle, etc., but to date, these have mostly been at large (country and regional) scales, despite the need to measure indicators at the local scale [210]. MMF was chosen for this analysis, as it is the first strongly consolidated framework designed to bridge the field of EO with the SDG indicator framework. It is well known that, in general, frameworks facilitate the use of systematic reviews that are widely used in social studies and also in designing best practices that can be applied in the field of EO. In addition, the results of the MMF assessment can provide untried opportunities for applying EO sourced data, including NTL for SDG. Moreover, the results of such assessment reveal the potential for involving the wide range of current and emerging EO products in indicator monitoring to deliver real support to countries and NSOs, also having an impact on improving the information flow to inform SDG-related decision-making, and to promulgate partnerships between NSOs and geospatial experts. In particular, the MMF allows people to review possible new approaches and new EO-based ways of supporting the SDG indicators. It provides guidance to review novel approaches, and it potentially gives the broader community a reproducible way of evaluating such approaches before introducing them into operational practice.

Higher-resolution NTL data do have the potential for use at smaller, more local scales, and some examples have been published, but there are challenges and limitations involved in this. Therefore, the Durango case study illustrated that it is possible to use NTL data derived from VIIRS (2014 and 2021 monthly composite imagery) to detect differences between the 24 locations in the AOI, but more encouraging than this was the statistical association (using ANOVA) between log-transformed NTL radiances and SGI. Low values of the SGI (areas that are better off) equated with higher radiance, while high values of the SGI (areas that are worse off) equated with lower radiance. The GSV used as a tool for ground truthing is not new in the literature [211], and the results do suggest differences in the quality of the roads and street-lighting, although there are also likely to be differences in the size and lighting of residences. However, it is important to acknowledge that the coverage of GSV imagery can be limited, especially for more remote areas, and updates to GSV imagery are irregular. In addition, SGI is an index with many components that are designed to assess social deprivation without taking into consideration income (often proxied as GDP/capita). Many studies in the literature estimate poverty at different levels, including county [69], but their approaches are typically based on measures of income rather than more diverse measures of deprivation. However, as a further study, point of interest (POI) data can be used for social and economic analysis at the local scale coupled with NTL, and this approach has been taken for assessing recreation resources [187] and public space lighting [188].

In this case study, it was possible to compare good-quality datasets collected via traditional methods (surveys, etc.) with the NTL data, but more studies of this type are needed to provide greater confidence. Nonetheless, while the use of NTL data for assessing factors such as social deprivation at local scales is in its infancy, it does have advantages, as collecting data via traditional surveys has limitations in terms of the time needed and cost [212]. Collecting such data via surveys can also be a security and—following the COVID pandemic—health concern for those involved.

Commercial satellite imagery is often underutilized due to price misconceptions, and there is still a lack of research on the relative costs and benefits of using satellite imagery versus traditional methods. For example, the use of NTL data at a small scale could help guide more local development initiatives, and an example is provided in the AOI by a community electrification project being planned by the Sezaric sawmill located in SP. The Sezaric sawmill manufactures wooden furniture for export as well as plywood and

pinewood boards. The sawmill sources its energy only from secondary wood material that remains from their production process, and that cannot be converted into other commercial products, thus applying the principles of biomass cascading. Sezaric is considered one of the best examples of a social enterprise in Durango, since it promotes sustainable forestry and creates income and jobs locally [40]. According to Lopez [213], inter-community forest associations (FA) in Durango have played a crucial role in helping communities solve regional problems such as improving the road infrastructure, preventing and combating forest fires, and improving market access and political representation. Surplus electricity from the mill's bioenergy generation system and potential upscaling of the capacity of the mill's installed power generation system could provide a positive socioeconomic impact to the surrounding localities by improving electricity access or providing affordable energy. However, as the sawmill has only a limited capacity for power generation, it is important for the project to target the areas in its immediate surroundings that have the highest levels of social deprivation. This is a common situation in such projects, and there may only be limited funds available to identify potential areas for prioritization.

In comparison with collecting traditional data, the NPP-VIIRS night-time light composite data have been shown in this study to be an effective and efficient data source for examining social deprivation at local scales, at least for more urban contexts. However, the proposed approach still has some limitations: (1) SGI is not available for all localities, as many of those are situated at altitudes above 2000 m, and this can be seen from the lack of road access. (2) While the case study results are encouraging, it does need to be acknowledged that the spatial resolution of VIIRS data allow for only a coarse assessment, and care does need to be taken with interpretation. Further research should be focused on exploring the finer resolution. (3) SGI data equate to a point in space (geographical coordinates) and not to a polygon covering the entire locality, whereas the average radiance derived from VIIRS across AOI has different values at every ~500 m. Our ability to correlate these two variables was hampered by this, but also by the small number of localities within the AOI of the 10 km buffer. Whatever the explanation, it would appear that the use of VIIRS data can help identify priority areas that need to be reached with development initiatives such as that potentially offered by the Sezaric bioenergy plant.

The results of a wide analysis of the literature and the Durango case study suggest that NTL data could be used when evaluating the opportunities and potential benefits for energy infrastructure developments and livelihood enhancement. Such data and approaches can also play a valuable role in the measurement of some of the indicators of SDG 7 (e.g., Indicator 7.1.2: Proportion of population with primary reliance on clean fuels and technology, Indicator 7.2.1: Renewable energy share in the total final energy consumption, Indicator 7.b.1: Installed renewable energy-generating capacity in developing countries (in watts per capita)) and by contributing to the achievement of SDG 1 (No Poverty). Hence, in terms of policy recommendations, the approach set out here can help with planning interventions such as the use of bioenergy, for example from forestry waste, for supporting people living in disadvantaged areas. Likewise, identifying bioenergy benefits and weaknesses in a policy design will enable local solutions that address social deprivation. The approach also can be used in supporting the production and integration of bioenergy into the grid and its usefulness in meeting SDG 7 and SDG 1, including waste management and rural development.

In the context of practicability at the community level, our study could be combined with a participatory approach to further analyse and reflect on the information generated. The information is useful for documenting local realities and can be used to inform policy and practice. In addition, identifying social gaps at the local scale might aim for the empowerment of communities, especially in municipalities with more social deprivation. Finally, and more specifically in terms of interventions designed to explore the use of bioenergy, outcomes for disadvantaged local areas where the potential additional renewable electricity energy is produced by a sawmill are applicable not only for stakeholders of the Durango municipality, the fourth largest community in the state in terms of population

but also for Durango state, which is amongst the top five producers of forest products nationwide, in addition to having the first forest reserve in the country.

5. Conclusions

This paper presented a literature evaluation of NTL data for social applications, first by using a systematic search and then applying MMF to the available literature that could populate the SDG indicators with social nuances, mostly at broad scales. We obtained 58 research themes by reviewing 164 peer-reviewed articles, and these were connected with 49 SDG indicators where NTL data can offer support to varying extents. Likewise, we used SGI, VIIRS and other datasets to explore disadvantaged local areas where the potential additional renewable electricity energy produced by a sawmill could be efficiently and fairly distributed in the context of achieving SDG 7.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs15051209/s1>, Figure S1: Google Street View (GSV) and different types of roads in Santiago Papasquiaro city, (1) view in Google Earth Pro with GSV availability, (2) Sphere availability on Google Maps, (3) unpaved roads with < 10 m width, (4) paved roads with > 10 m width; Figure S2: Google Earth Pro grid over the AOI; Figure S3. Different types of roads, (A) paved with > 10 m width, (B) paved roads with < 10 m width, and (C) unpaved roads with width < 10 m; Table S1: Social indicators SDG indicators; Table S2: Socio-economic SDG indicators; Table S3: Socio-environmental SDG indicators; Table S4: Indicators used to calculate the Social Gap Index (SGI) in 2010 and 2020; Table S5: SGI and average radiance in the localities across the AOI. Refs. [53,56] are cited in supplementary.

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