

Leveraging SDGSAT-1 data for exploring the interactions of nighttime lights and human settlement structure at high spatial resolution

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Abstract

Nighttime light (NTL) Earth observation data represent an invaluable resource for measuring population distribution, disaster impact, economic activity, and socio-economic inequalities from space. Traditional NTL data sources are spatially coarse, impeding detailed analyses of nighttime lights. Novel, high-resolution NTL data from the SDGSAT-1 satellite capture NTL variations at fine spatial detail of 10 to 40 m and open new research avenues. Herein, we demonstrate the potential of jointly assessing annual SDGSAT-1 composites and human settlement data from the Global Human Settlement Layer (GHSL) and other data, characterizing the built environment, human population distribution, and the rural-urban continuum. For a study area in Northern Italy, we illustrate that such data integration generates new insights on the interactions of nighttime lights and settlement-related characteristics at unprecedented detail. For example, we find that NTL emissions tend to be highest in old parts of settlements (<1975) and lowest in very recently developed land. The brightness of non-residential areas at night approximately doubles, on average, compared to residential built-up areas. Similarly, main roads in urban settings tend to be twice as bright as residential built-up areas, while this difference largely disappears towards rural settlements. Moreover, ~80% of urban population resides in areas characterized by luminous, stationary NTL, while this population share drops to ~15% in very rural areas. Looking at infrastructure-related land use, we find that airports emit the highest levels of stationary and non-stationary NTL in our study area. These results illustrate the potential of SDGSAT-1 data for settlement analysis and population modelling.

1. Introduction

Remotely sensed measurements of nighttime light (NTL) reflectance have been widely used for mapping human settlements (Li and Zhou, 2017; Hu et al., 2020) population (Lloyd et al., 2019; Wang et al., 2020), and for characterizing inequality (Kuffer et al., 2018) or economic activity (Ghosh et al., 2010; Mellander et al., 2015; Pérez-Sindín et al., 2021). Therefore, observations from space-borne sensors such as the Defense Meteorological Satellite Program (DMSP) Operational Line-Scan System (OLS) or the Visible Infrared Imaging Radiometer Suite (VIIRS) satellites (with ground sampling distances ranging from 15 to 30 arcseconds) have long been the state-of-the-art data source (Zheng et al., 2023). In 2021, the SDGSAT-1 satellite has been launched by the Chinese Academy of Sciences. SDGSAT-1 has been designed specifically to support the UN 2030 Agenda for Sustainable Development (Liu et al., 2024) and carries three sensors, including a thermal infrared spectrometer, a multispectral daytime imager, and the “Glimmer imager for urbanization” (SDGSAT-1 GIU) that enables the acquisition and analysis of nighttime light reflectance at high resolution, i.e., ground sampling distances of 40m for RGB (Red-Green-Blue) data, and 10m for panchromatic data. This represents a major advancement in large-scale NTL mapping. SDGSAT-1 GIU data enables for example the detailed delineation of settlements (Li et al., 2023) and improved extraction of built-up areas (Yan et al., 2025), the delineation of intra-urban main roads (Wu et al., 2024), as well as the estimation of inner-urban anthropogenic heat fluxes (Guo et al. 2023a) and the assessment of disaster impact (Yu et al., 2023) and illumination types (Lv et al., 2024; Yin et al., 2024). However, the large-scale analysis of SDGSAT-1 NTL data requires robust and performant image compositing methods, reducing the effects of cloud cover,

moonlight, snow cover, band misalignment and sensor artefacts to leverage the full potential of SDGSAT-1 NTL data. In previous work, Pesaresi et al. (2026a) introduced a robust and low-cost compositing method based on the ranking of structural image features that has been applied to SDGSAT-1 NTL data. This compositing method does not require cloud masking or atmospheric correction models and enables the creation of SDGSAT-1 NTL composites at scale for both RGB and panchromatic channels at 40 m and 10 m resolution, respectively. Such compositing techniques are crucial to provide high-resolution SDGSAT-1 NTL data as annual composites in an analysis-ready format, automatically and at scale.

The main contribution of this article is the demonstration of the potential of such high-resolution, analysis-ready SDGSAT-1 NTL RGB composites by integrating them with multivariate human settlement data from the Global Human Settlement Layer (GHSL) (Pesaresi et al., 2024) and other datasets. We illustrate how such an integrated assessment enables the generation of knowledge about nighttime light variability across space and over time at unprecedented levels of detail. Specifically, we assess the correlation of NTL brightness across the rural-urban continuum, across settlement construction epochs, for different land uses (residential vs. non-residential built-up areas, major roads, infrastructure-related land use types), and showcase how the color tones of nighttime lights and their changes over time can be assessed visually-analytically. Our results reveal the interactions between nighttime lights and human settlement characteristics at high resolution, demonstrating the usefulness of such data and representing a promising step towards large-scale employment of SDGSAT-1 NTL data for population and settlement modelling at scale, and to deepen our understanding of human settlement characteristics.

2. Data and methods

2.1 Study area and data

The area under study is the Po Plain in Northern Italy and adjacent regions near the Alps and the Adriatic region, covering parts of France, Switzerland, Austria, Slovenia and Croatia (Figure 1). This region is characterized by diverse settlement types from urban to rural places, various geographic regions (mountainous, plains, coastal) and comprising both highly and sparsely populated areas (Pesaresi et al., 2026a). For this study area, we used SDGSAT-1 composites that have been produced using the compositing method proposed in Pesaresi et al. (2026a), based on a total of 317 SDGSAT-1 scenes acquired in 2022 and 2023. These data include annual composites and a composite across the two years, as well as a separation between total and stationary NTL sources and a classification based on cross-tabulation of NTL luminosity, stationarity, and built-up areas (GHS-NTL taxonomy) (Pesaresi et al., 2026a). All data are openly available at 40-m spatial resolution (Pesaresi et al., 2026b; see Figure 1 for examples of the 2-year composite data). Besides the SDGSAT-1 NTL data, we used settlement-related datasets from the Copernicus Exposure Mapping Component (EMC), specifically built-up area estimates at 10 m resolution obtained from Sentinel-2 multispectral data of 2022 (Figure 2b),

non-residential built-up area estimates (Figure 2c) and a greenness index (i.e., Normalized Difference Vegetation Index, NDVI; Figure 2d) (Kemper et al., 2025). Moreover, we used gridded resident population estimates at 100 m resolution from the GHS-POP R2023A dataset (Pesaresi et al. 2024; Figure 2e), the Degree of Urbanization rural-urban continuum model (Dijkstra et al., 2021) at 1 km resolution from the year 2020 (Pesaresi et al. 2024; Figure 2f), as well as gridded settlement age estimates (i.e., median building construction epoch estimates from 1975 to 2020, obtained from the GHS-AGE dataset; Uhl et al., 2025; Figure 2g) and gridded building volume estimates per 100-m grid cell from the GHS-BUILT-V R2023 dataset (Pesaresi et al. 2024; Figure 2h), all at 100 m resolution. These datasets have been produced from the integration of Sentinel-2, historical Landsat multispectral data, and population census data (Pesaresi et al. 2024). Furthermore, we used the LUISA landuse / landcover (LULC) dataset for Europe 2018. LUISA ("Land Use-based Integrated Sustainability Assessment"; Figure 2i) is based on the integration of various data sources such as Corine Land Cover, OpenStreetMap, and others and provides LULC data using the CLC classification scheme at high thematic depth (i.e., 44 classes), and at a refined spatial resolution of 50 m (Pigaiani and Batista e Silva, 2021). We also used OpenStreetMap road network data, constraining the full road network to primary and

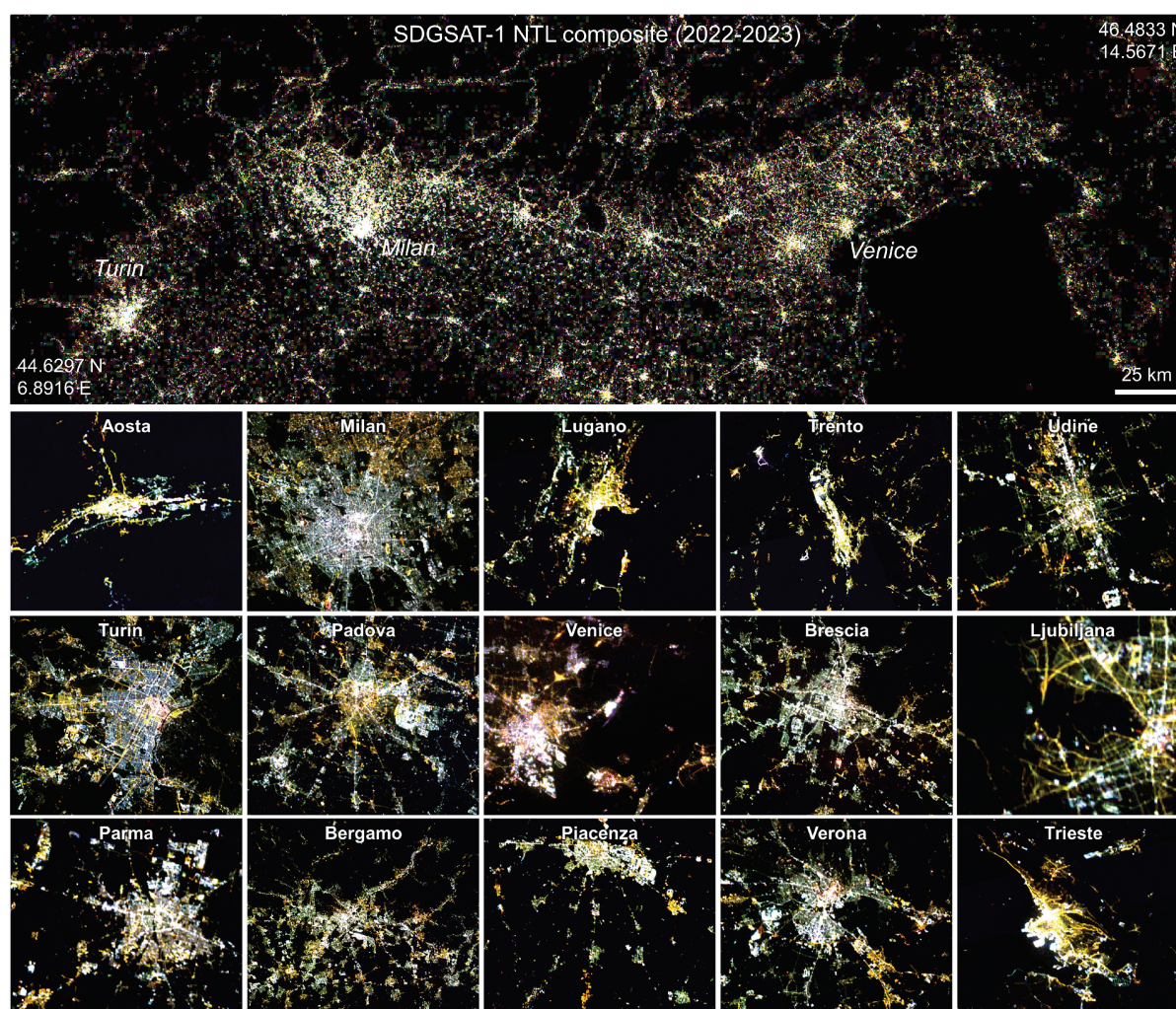


Figure 1. SDGSAT-1 input RGB data composite. Upper part: SDGSAT-1 nighttime light data composite (40-m resolution) from 2022-2023 over the Po Plain study area and adjacent regions. Lower part: data shown for 15 cities in the study area in Northern Italy and adjacent regions. Map scale varies across cities. RGB data rescaled for visualization purposes.

secondary roads (Figure 2j), and the GHS-NTL taxonomy accompanying the SDGSAT-1 composite for the Po Plain study area (Pesaresi et al. 2026b; Figure 2k). We also used alternative gridded population counts from WorldPop to compare to the GHS-POP estimates. Finally, vector delineations of major cities, as defined by the Urban Centre Database (UCDB R2024A; Melchiorri et al., 2025) in our study area were used to extract city-level NTL change statistics. All datasets used herein are publicly available (see "Data availability" statement).

2.2 Data integration and processing

All gridded input data were resampled to the grid of the SDGSAT-1 NTL composite (i.e., 40-m grid spacing in World Mollweide Equal Area projection; ESRI:54009), using area-weighted sum resampling for count and density data, and majority resampling for categorical data. Geospatial vector data (i.e., OSM road network, UCDB urban center geometries) were rasterized to the same grid. Subsequently, all data layers were converted into tabular form by reading the grid cell values into a large alphanumerical table. This multi-variate data stack, where each row represents a 40-m grid cell, holds for each cell the NTL RGB values for 2022, 2023, and 2022-2023 composites, for both stationary and total NTL signals, the GHS-NTL taxonomy classes, the built-up area, volume, greenness, population, settlement age class, degree of urbanization class codes, as well as the LUISA LULC class code, a binary road vs. non-road attribute, and the UCDB urban center code. This data

structure allows for joint statistical assessment of the relationship between NTL RGB reflectance (and derived luminance or hue measures) and settlement-related characteristics at unprecedented spatial detail and thematic depth.

2.3 NTL data processing and RGB color reduction

From the RGB data of total and non-stationary NTL components of the composites 2022, 2023, and 2022-2023, we calculated the NTL luminance for each year and component as

$$L = 0.3 \times R + 0.59 \times G + 0.11 \times B \quad (1)$$

as a measure of NTL brightness (Handschuh et al., 2010; Figure 2l). NTL brightness is measured in digital numbers (DNs). Note that these digital numbers are encoded as 16-bit integers, exceeding the maximum of 255 commonly used in RGB imagery. We used k-means color quantization to reduce the number of NTL colors for $k=10$, $k=25$, and $k=100$ (Celebi, 2011) to assess NTL color tones and their variation across space and time. This k-means clustering can be applied to the overall composite (2022-2023) or to the annual composites of 2022 and 2023, separately or jointly across both epochs, to assess changes between the two years.

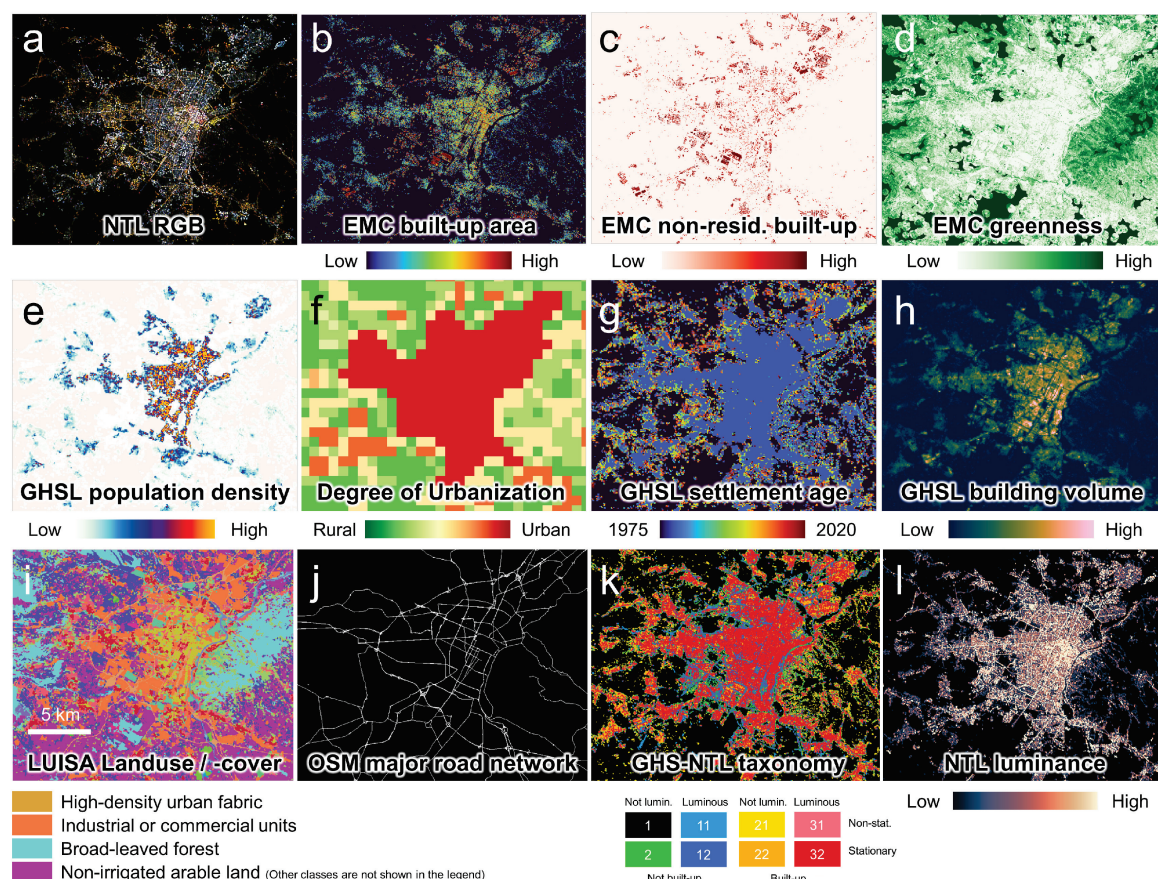


Figure 2. Input datasets used in this study: (a) SDGSAT-1 NTL RGB composite for 2022-2023, (b) GHS-EMC-BUILT-S built-up surface data, (c) GHS-EMC-BUILT-S-NRES non-residential built-up areas, (d) greenness (NDVI) layer from GHS-EMC-BUILT-GREENNESS, all for 2022 (e) GHS-POP gridded residential population estimates 2020, (f) Degree of Urbanisation settlement model for 2020, (g) GHS-AGE estimates of the age of the built stock in 2020, and (h) GHS-BUILT-V building volume in 2020, (i) LUISA LULC data 2018, (j) OSM major roads, (k) GHS-NTL taxonomy, (l) SDGSAT-1 NTL luminance. Data show the larger Turin area.

2.4 Exploratory data analysis

Herein, we conducted exploratory data analyses that quantify and characterize the relationship between NTL and settlement-related variables. We employed analytical methods (e.g., correlation analysis, cross-tabulation, histogramming), and visual methods such as box-and-whisker plots and Sankey diagrams to obtain our results. In Section 3, we present the results of this multi-variate exploratory assessment, demonstrating the potential of the integration of SDGSAT-1 NTL data with other data sources to conduct large-scale, multi-variate human settlement analysis.

3. Results and discussion

3.1 Correlation of NTL luminance with settlement-related characteristics

We look at correlations of NTL luminance and settlement-related variables (Table 1) and find strongest positive correlations with building volume (Spearman = 0.503), and strongest negative correlation with greenness (Spearman = -0.368). The more an area is built-up and the taller the buildings, the higher the NTL luminance. The more vegetation, the darker the NTL signals are. While this is expected, it is notable that we generally observe higher magnitudes of correlation for Spearman than for Pearson, indicating a strong rank-based covariation, but a weaker linear relationship between luminance and these settlement variables. Correlation with population density is high for WorldPop 2022 (Spearman = 0.479) and lower for GHS-POP 2020 (Spearman = 0.335), but as expected, positive in both cases. This difference can be explained with the fact that WorldPop already uses DMSP-OLS/VIIRS NTL data as spatial covariate in its population disaggregation model (Lloyd et al., 2019), unlike GHS-POP, and could also be an effect of the temporal gap between GHS-POP (2020) and the NTL data (2022-2023). How stable are these associations between NTL luminance and settlement variables across different settlement domains? We test this by stratifying the correlation analysis to grid cells contained in strata of the Degree of Urbanization (Figure 3a), observing higher levels of

association from rural towards urban areas, likely due to the higher levels of small-scale variability of NTL and settlement variables in dense urban areas. An exception is observed for correlation to population across rural classes with correlation peaking for rural clusters, representing settlements of 500 to 5,000 inhabitants that are surrounded by (mostly unlit, and thus more contrasting) low-density or uninhabited settlements. Across settlement age classes, correlation between NTL luminance and settlement variables are very stable (Figure 3b), indicating that the association of these variables is not affected by different construction epochs and land development phases.

Settlement variable	Correlation	
	Pearson	Spearman
Building height 2018	0.316	0.478
Building volume 2020	0.318	0.528
Built-up surface 2022	0.133	0.154
Population 2020 (GHS-POP)	0.147	0.344
Population 2022 (WorldPop)	0.258	0.498
Greenness 2022 (NDVI)	-0.298	-0.386

Table 1. Correlations of NTL luminance (2022-2023) with settlement-related variables calculated at 40m spatial resolution (see Figure 4a for a corresponding boxplot of building volume, the highest-correlated settlement variable).

3.2 Relationship of NTL luminance with settlement age and the rural-urban continuum

For the settlement variable with the highest positive correlation (i.e., building volume), we show the NTL luminance distribution within quintile classes, indicating a steady increase in NTL luminance across building volume classes, on average (Figure 4a). While building volume per grid cell is expected to increase from rural to urban areas, we test this hypothesis explicitly using the seven rural-urban classes of the Degree of Urbanization (Figure 4b): we observe steadily increasing average luminance from the most rural towards the most urban class, while values in rural clusters (light green) and peri-urban areas (beige) are very similar. Analyzing NTL luminance across settlement age classes, we find highest luminance levels in old

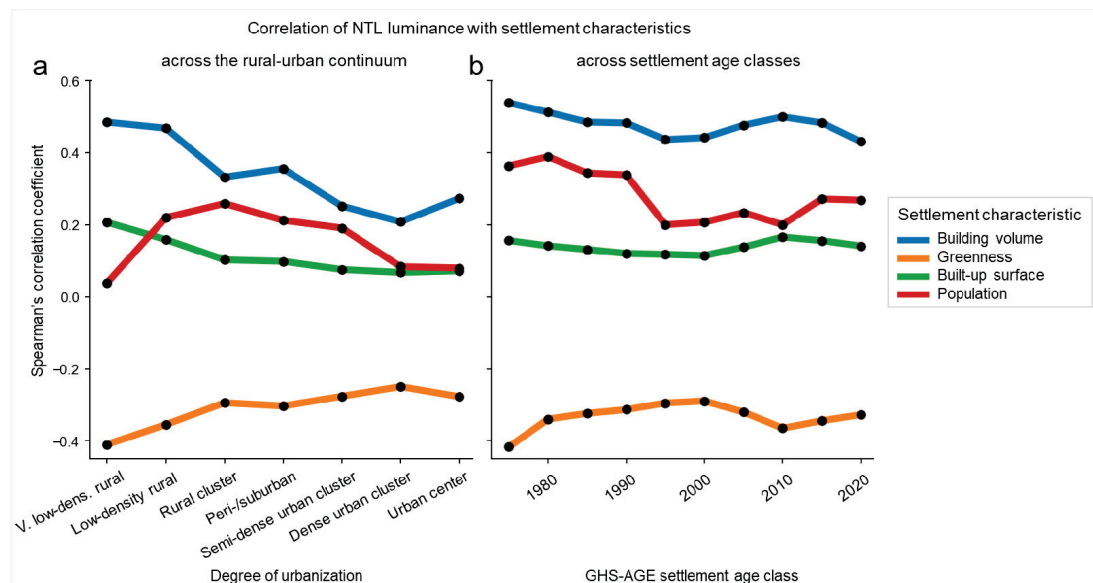


Figure 3. Correlation of NTL luminance with settlement variables (a) across the rural-urban continuum using the Degree of Urbanization methodology, and (b) across settlement age classes from the GHS-AGE dataset. Data shown for the Po Plain (Italy) study area. Building volume is measured by GHS-BUILT-V R2023A epoch 2020, while greenness and built-up surface are derived from EMC-BUILT R2025A (epoch 2022), and population estimates are used from GHS-POP R2023A epoch 2020.

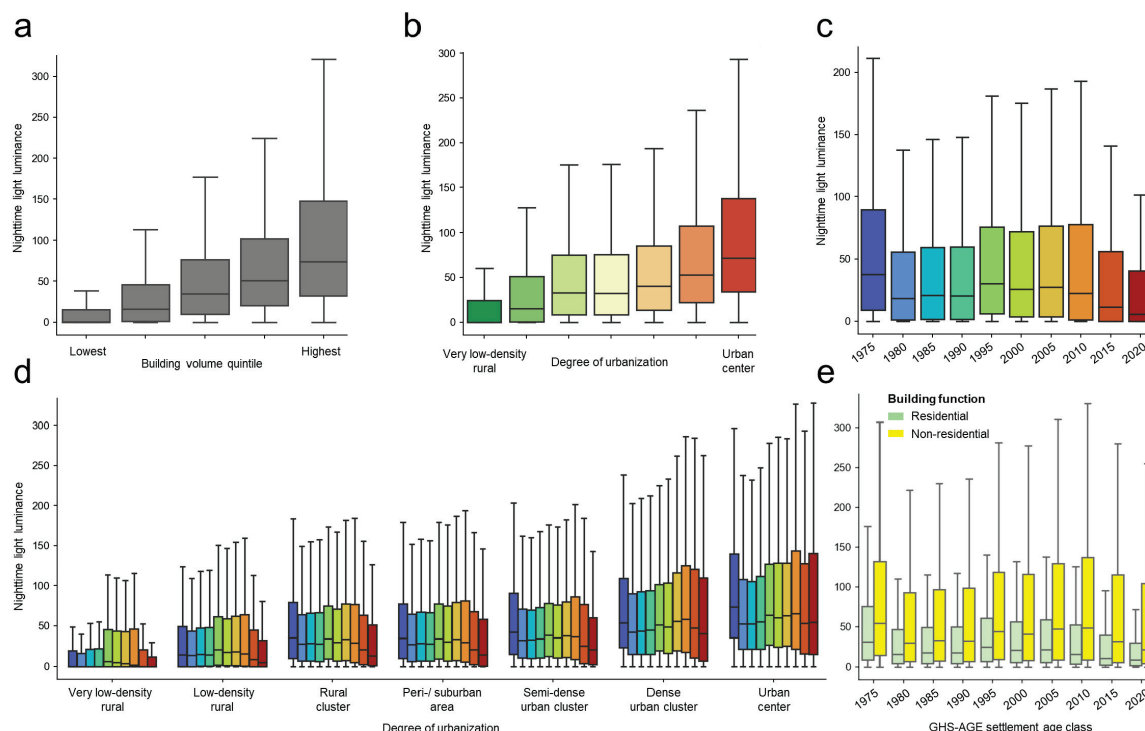


Figure 4. Trends of SDGSAT-1 NTL luminance across different settlement variables. (a) NTL luminance within quintiles of building volume, (b) for Degree of Urbanization rural-urban classes, (c) for settlement age classes, (d) for settlement age classes within each rural-urban class, and (e) NTL luminance by settlement age class, separately for predominantly residential and non-residential areas. Boxplots represent the distributions of 40m×40m grid cells. Data shown for the Po Plain (Italy) study area.

neighborhoods (<1975), and low luminance in recently (>2010) built-up neighborhoods. This observation could be an effect of a decreasing density gradient from old, typically dense to more dispersed, recently built-up areas. We also find that areas predominantly built between 1995 and 2010 tend to be slightly more lit up than areas built between 1980 and 1990 (Figure 4c) – such trends could indicate that a brighter streetlamp technology was used in specific epochs. However, this needs further, more localized investigation. This trend across settlement age classes also holds largely across the rural-urban continuum, except for extremely rural areas, where oldest settlements are among the “darkest” (Figure 4d). Furthermore, we tested if this trend holds across residential and non-residential built-up areas (Figure 4e). As can be seen, the higher luminance values for settlements built-up between 1995-2010 are largely attributed to non-residential built-up areas (including large commercial and industrial buildings), while the NTL luminance of the residential component steadily decreases since 1995.

3.3 Stationary and non-stationary nighttime lights and their relationship to building function

This finding suggests considerable disparities between the NTL emitted by residential and non-residential areas, which is also shown in Figure 5a – the average NTL luminance attributed to non-residential areas exceeds those of residential built-up areas by around 25 digital numbers (DNs) in each class of the Degree of Urbanization, exhibiting an interesting, largely systematic offset between residential and non-residential NTL brightness across the rural-urban continuum. Moreover, NTL luminance can be further dissected into luminance attributed to stationary and non-stationary light sources, using a frequency-based approach (see Pesaresi et al., 2026 for details). As shown in Figure 5b, the stationary NTL component is brighter, on

average, than the non-stationary component, within both residential and non-residential strata and within rural-urban classes. Stationary NTL is consistently higher in non-residential areas than in residential areas, while the brightness of non-stationary NTL sources does not differ much between residential and non-residential areas (Figure 5b). Our analytical framework also allows for measuring NTL “luminance density” – i.e., total luminance, measured as the sum of the DN_s per km² – a metric that quantifies whether bright objects may be spatially clustered (high density) or spread-out (low density). We show trajectories of luminance density for stationary, non-stationary, residential and non-residential classes across the rural-urban continuum (Figure 5c, d), and across settlement age classes (Figure 5e, f). These visualizations show several interesting trends: First, we observe increasing luminance density from rural to urban strata (Figure 5c), for both residential and, as expected at higher magnitude for the non-residential areas, but exhibiting a steeper increase towards urban areas for residential than for non-residential built-up areas, in particular in rural classes. The effect of clustered vs. distributed NTL luminance becomes evident for the local maxima of NTL luminance density in residential areas for rural clusters (i.e., settlements of 500 to 5,000 inhabitants) that then drops to typically lower-density peri- and suburban areas, while luminance density in non-residential built-up increases steadily. This anomaly indicates exceptionally bright or clustered NTL signals in these settlements, attributed to residential but not non-residential areas, and deserves further investigation. Conversely, non-stationary luminance density shows an opposite trend (Figure 5d), indicating punctual, bright non-stationary signals in rural areas (e.g. ski slopes, football fields), but low-density non-stationary NTL signals in urban areas, e.g., major roads, large parking lots, etc.). NTL luminance density across settlement age classes (Figure 5e) largely confirms the previously observed trends (Figure 4e): NTL emissions in non-residential built-up

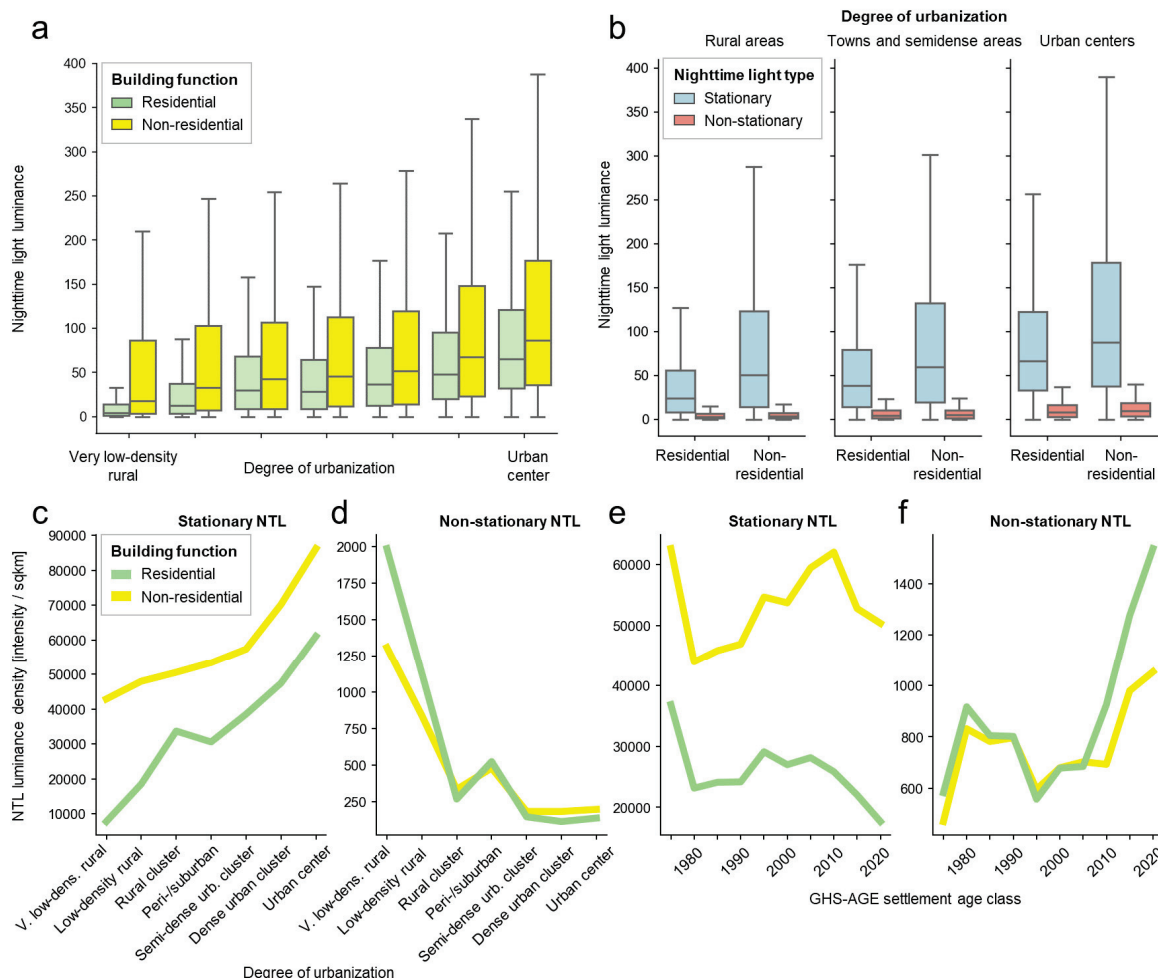


Figure 5. Nighttime light luminance by building function and signal stationarity. (a) NTL luminance across rural-urban classes, separately for residential and non-residential areas, (b) Luminance of stationary and non-stationary NTL sources within residential and non-residential areas, for rural-urban classes (Level-1 3-class Degree of Urbanization classification). Boxplots represent the distributions of 40m×40m grid cells. The bottom row shows NTL luminance densities (i.e., total luminance per km²) across the rural-urban continuum for (c) stationary and (d) non-stationary NTL sources; Also shown are luminance density trends across settlement age classes for (e) stationary and (f) non-stationary NTL sources. Densities calculated across total class area. Boxplots represent the distributions of 40m×40m grid cells. Data shown for the Po Plain (Italy) study area.

areas built around 2010 are either more spatially clustered, or considerably brighter than those of other epochs. Interestingly, non-stationary NTL luminance density in recent epochs is higher in residential than in non-residential built-up areas (Figure 5f) – this could be attributed to the generally lower illumination levels of recently built-up areas (cf. Figure 4c), where non-stationary NTL sources may be more dominant.

3.4 Nighttime light emission variations between built-up areas and roads

The high-resolution NTL data and our analytical framework enable the separate analysis of nighttime lights emitted by buildings and by roads, using the OSM-derived, rasterized major road network as analysis mask. The results are shown in Figure 6. Road-related NTL are on average, considerably brighter than NTL associated with residential (Figure 6a) and non-residential (Figure 6d) built-up areas, in particular in urban centers and other rather urban settings, in line with findings from China (Liu et al., 2024). However, towards rural areas, road- and building-related NTL appear to have similar brightness levels, on average, and in the case of non-residential built-up areas, building-related NTL brightness even exceeds

that of roads in peri-urban and more rural classes (Figure 6d) – likely an effect of less street illumination in non-residential than in residential areas, paired with highly lit non-residential built-up areas (e.g., commercially / industrially used areas), and this difference appears to increase in rural areas. These observations are similar for the total NTL (Figure 6a, d) and the stationary NTL component (Figure 6b, e), but differ drastically for non-stationary NTL (Figure 6c, f): most of the non-stationary NTL is attributed to roads, not to buildings, and this disparity is most nuanced in dense urban settings (i.e., urban centers) where bright non-stationary NTL sources are predominantly associated with roads, likely caused by traffic-related irregular events such as urban highway congestions or moving objects (i.e., cars) in general.

3.5 Nighttime light emissions across infrastructure-related land use classes

While we observe strong differences between NTL brightness of roads, residential and non-residential built-up areas, we can further disentangle infrastructure-related NTL emissions using the infrastructure-related LUISA LULC classes that we integrated with the other data used herein. From all LULC

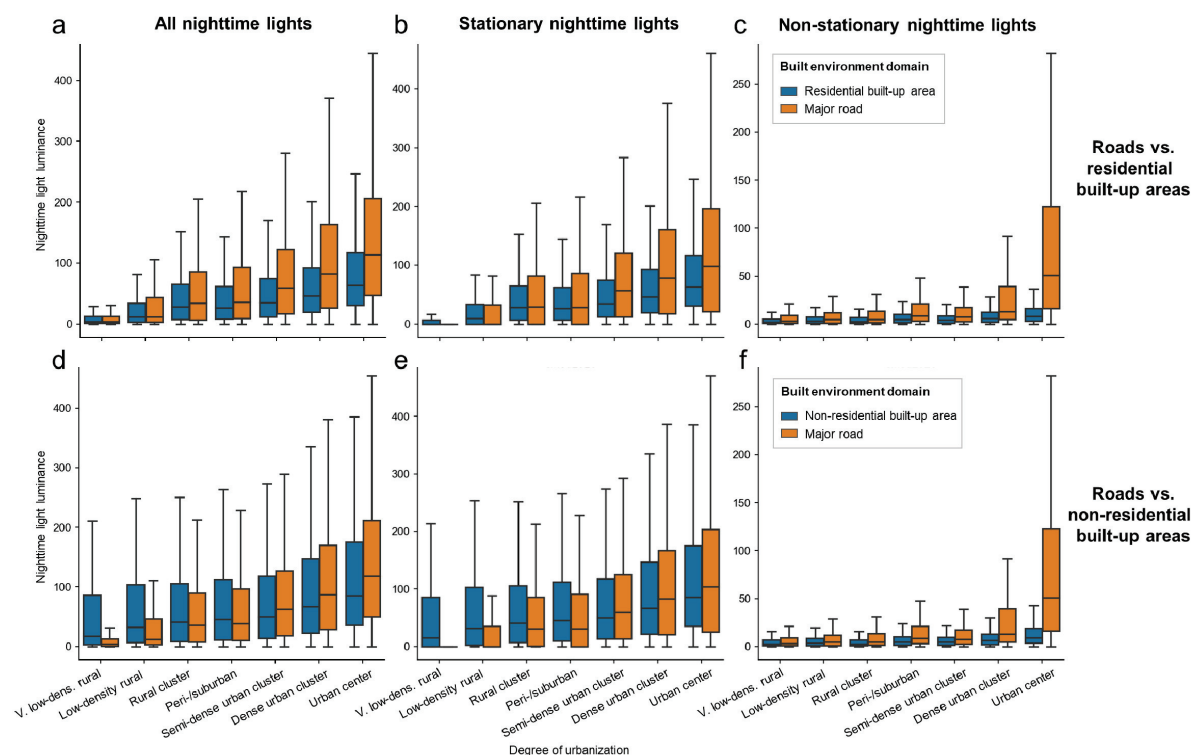


Figure 6. Assessing nighttime emitted lights of roads versus built-up areas. Top row: SDGSAT-1 luminance from (a) all sources, (b) stationary sources, and (c) non-stationary NTL sources, respectively, separately for road areas and for residential built-up areas. Bottom row: SDGSAT-1 luminance from (d) all sources, (e) stationary sources, and (f) non-stationary NTL sources, respectively, separately for road areas and for non-residential built-up areas. Boxplots represent the distributions of 40m×40m grid cells, data shown for the Po Plain (Italy) study area.

classes, we identified 17 infrastructure-related classes. For the grid cells associated with each LULC class, we visualized the NTL luminance distributions separately for non-stationary and stationary NTL sources (Figure 7). As can be seen, grid cells related to airport terminals exhibit highest levels of both stationary and non-stationary NTL luminance, followed by large train stations, high-density urban fabric and ports. Conversely, airport areas (including airfields) emit low levels of NTL luminance. Notably, ports are also associated with elevated levels of non-stationary NTL luminance, likely related to

irregular nocturnal (un)loading and shipping activities. At the other end of the distribution, we observe that mining and dump sites, as well as vegetation-related infrastructure (sport and leisure green, urban vegetation, green urban areas) exhibit low levels of NTL luminance. The color-coding used in Figure 7 represents the RGB cluster to which each LULC class contributes most, derived from the k-means color quantization carried out in the preprocessing step ($k=25$), as described in Section 2.3. While these colors may not represent the natural color tones as seen from space, but rather an aggregated,

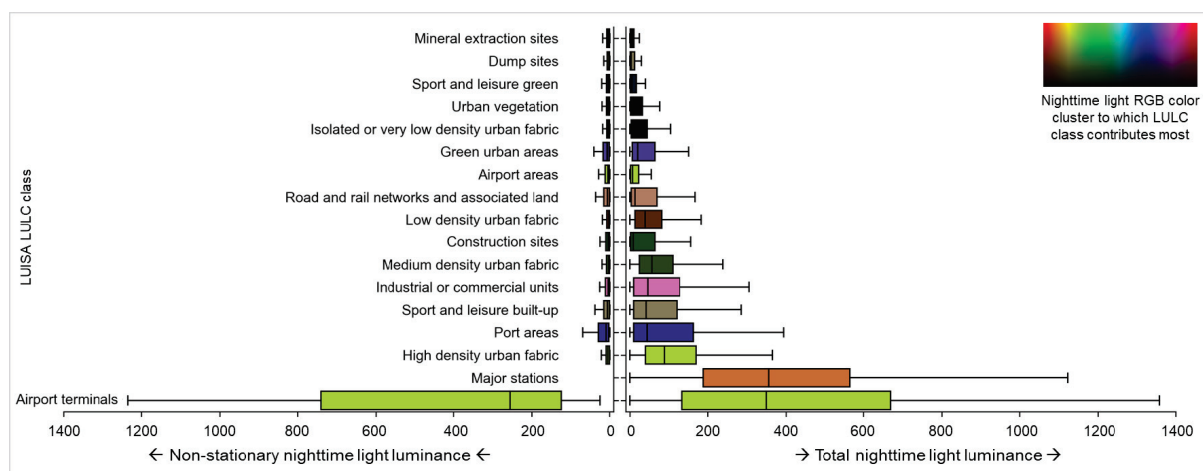


Figure 7. Non-stationary (left) and total (right) SDGSAT-1 NTL luminance distributions within infrastructure- and settlement-related land use / land cover classes from the LUISA basemap dataset. The colors of each bar correspond to the nighttime light RGB color of the cluster centroid associated with the color cluster to which each LULC class contributes most, after reducing NTL image colors to $k=25$ using RGB k-means color reduction applied to the 2022-2023 NTL composite. Data shown for the Po Plain (Italy) study area. Classes are sorted by the mean stationary luminance, increasingly from top to bottom.

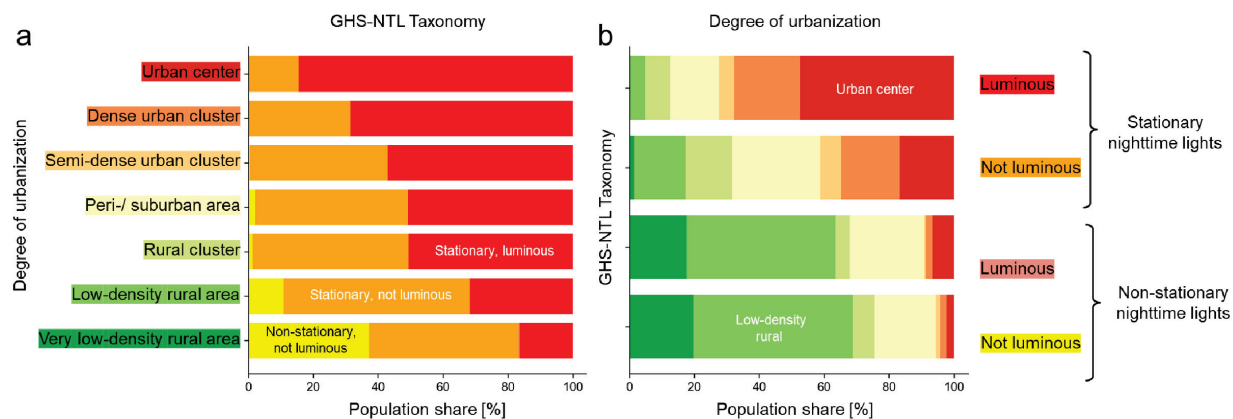


Figure 8. Stratified population shares residing in discrete global human settlement nighttime light (GHS-NTL) classes. (a) population share per Degree of Urbanization class within GHS-NTL classes, and (b) population share per GHS-NTL class within Degree of Urbanization classes. Data shown for the Po Plain (Italy) study area.

symbolic color representing the location in the RGB color space where the clusters tend to be predominantly located. The green tone of airport terminals vs. brown tone of major stations may indicate differences in illumination technology used (e.g., white lights at airports, vs yellow lights at and around major train stations in Northern Italy).

3.6 Human population across nighttime light classes

Until here, we have largely looked at nighttime lights related to the physical component of settlements. However, our data also enable us to analyze the relationship of resident population with nighttime lights. While we observe generally a positive association of population density and nighttime light luminance (Table 1), the high resolution of SDGSAT-1 data and the separation of stationary vs. non-stationary NTL components allows for further disaggregation. We use the classes of the GHS-NTL taxonomy (Figure 2k) and report the population shares cross-tabulated by Degree of Urbanization rural-urban classes (Figure 8): We note that the share of population residing in areas emitting stationary, luminous NTL is highest in urban centers (~80%) and decreases gradually to the most rural class, where only ~15% of the population reside in areas emitting stationary, luminous NTL, and over 80% reside in areas of non-luminous NTL. Almost 40% of the population in very-low density rural areas even resides in areas classified as “non-stationary + non-luminous” where stationary NTL sources are extremely sparse and of low intensity that they are superimposed by non-stationary signals (Figure 8a). Visualizing the data the other way round (Figure 8b), we observe that the peri-/suburban population is almost evenly represented (i.e., ~20%) across all GHS-NTL classes, indicating that these areas are characterised by high levels of variability of the predominant NTL type. Such cross-tabulations can be particularly useful for measuring inequalities, especially when applied to diverse geographic contexts.

3.7 Visual-analytical strategies for NTL color tone change analysis

Finally, the high spatial resolution of SDGSAT-1 and its ability to provide RGB rather than only panchromatic imagery allows for assessing the color tones of nighttime lights and their changes over time. As described in Section 2.3, we performed color reduction using k-means based color quantization. This k-means clustering can be done in various ways – A) for the RGB values of the joint 2022–2023 composite, and B) for the RGB

values of the 2022 composite and of the 2023 composite. The former produces a reduced image of the NTL “averaged” across a two-year period of presumably higher stability, while the RGB color clusters for an individual year are expected to be more prone to atmospheric noise and other disturbance effects. The color clusters produced with the method A (using $k=100$ to preserve the “natural” image colors) can then be stratified by a settlement variable (e.g., settlement age) and visualized using circular histograms, per stratum, as shown in Figure 9a, for all infrastructure or built-up related grid cells within the urban centre of Verona, Italy, using the LULC information from LUISA, the built-up area from GHSL, and the city delineation from the UCDB. Notably, around 30% of the urban center area appears very dark in all strata, likely representing poorly lit built-up areas. The red tone for brighter grid cells indicates brighter areas but may not represent their “true” color tones, as previous work has shown higher sensitivity of the red color channel than the blue and green channel of the SDGSAT-1 sensor (Pesaresi et al. 2026a). Importantly, a small portion of yellow NTL appears in the 1980–1990 stratum, possibly indicating that yellow streetlamps were predominantly used in areas mainly developed during that period. The 2000–2010 stratum has the highest proportion of bright cells, likely representing non-residential areas such as commercial or industrial areas, as observed previously (cf. Figure 5e). The method B, consisting of *joint* k-means color reduction based on RGB values from the 2022 and 2023 annual composites together, enables measuring cluster transitions between the two years. These transitions can be visualized at the city-level using Sankey diagrams (Figure 9b, c). In the specific case of changes between 2022 and 2023 for the cities of Verona and Turin, we observe dominant changes between different brown color tones. These transitions need to be interpreted with caution, as annual composites are likely to be less stable than the 2-year SDGSAT-1 composite, and the transitions may be affected by remaining noise in the NTL composites. Transitions from darker brown towards brighter brown tones may indicate newly developed land, or installation of streetlamps, or possibly changes in streetlamp technology, while changes from brighter towards darker color tones seem less plausible in the case of Northern Italian cities and are likely related to data noise. However, it is important to note that while these concrete examples are of limited usefulness due to the limited observational window, such visual-analytical tools can be highly useful instruments to detect and quantify changes in NTL luminance playing out at larger magnitudes in the case of disasters or war scenarios.

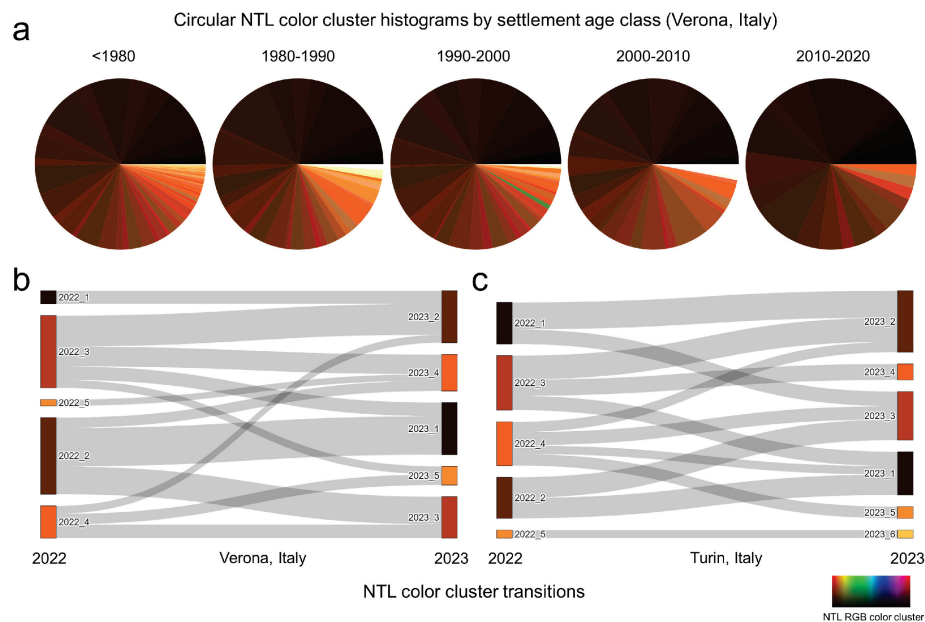


Figure 9. Examples of visual-analytical methods to assess nighttime light color tone changes over time. Upper row: (a) Circular histograms of NTL colors within the urban center of Verona (Italy) within settlement age classes from GHS-AGE, after applying RGB color reduction using k-means ($k=100$). Bottom row: Sankey diagrams visualizing the 12 most dominant changes in NTL color tones from 2022 to 2023 over the urban centers of (b) Verona and (c) Turin (Italy) after applying k-means RGB color reduction ($k=10$). Node colors in the Sankey diagrams represent the RGB value of the cluster centroids.

4. Conclusions

Herein, we demonstrated the potential of SDGSAT-1 nighttime light data, mapping the Earth at night at unprecedented spatial detail (i.e., 10 to 40m) and in RGB color. When combined with effective image compositing methods, the resulting NTL composites can be integrated with settlement-related variables as demonstrated herein. We showcased how the joint assessment of multivariate, high-resolution, settlement-related data and SDGSAT-1 NTL luminance and color information reveals novel insights of the interactions between nocturnal light emissions and settlement age, density, land use and population across the rural-urban continuum, at unprecedented spatial detail, opening new analytical avenues for settlement-related research and beyond. In the context of disaster risk management, infrastructure damage resulting in the absence of electricity can be quantified using the visual-analytical methods showcased in Section 3.7. The same methods can be employed to monitor changes in streetlamp technology at local to regional scales, supporting urban planning and data-driven policy making. The integrated assessment of population and the GHS-NTL nighttime light taxonomy (Pesaresi et al. 2026a) as shown in Section 3.6 provides a simple, yet useful instrument to assess inequality that often manifests in variations of nighttime light emissions (Kuffer et al., 2018). The fine spatial detail of SDGSAT-1, in combination with road network data (see Section 3.4) enables novel analytical strategies to monitor street illumination, crucial to tackle safety issues in both urban and rural contexts. Moreover, the identified correlations and their variations or stability across settlement age strata and rural-urban classes provide useful information for high-resolution population modelling, for example to improve NTL-based population disaggregation methods. In future work, we will extend this analysis by expanding our study area to diverse geographic settings, including areas in the Global South, facilitated by the global or at least continent-level scope of all data used in this study. We will test further measures of NTL

luminance and spectral indices (e.g., Guo et al., 2023b), and plan to further assess the relationship between NTL color tones and settlement characteristics, analyse NTL per-capita measures at fine spatial grain, and link data to socio-economic data. Furthermore, high-resolution SDGSAT-1 data can be used to downscale and sharpen coarse, historical VIIRS nighttime light data. Concluding, this work greatly illustrates the potential of high-resolution nighttime light data, and demonstrates the benefits of data integration, providing novel insights on geographic, demographic and societal phenomena, based on non-commercial data sources, aligned with global efforts¹ to gain in-depth understanding of human settlements and to transform Earth observation data into actionable intelligence, fostering evidence-based decision making and policy support in the context of sustainable development, urban resilience and beyond.

Data availability

This study is exclusively based on free and open data sources. The SDGSAT-1 nighttime light composite (including stationary and non-stationary NTL sources) and the GHS-NTL taxonomy for the Po Plain study area are available at <https://doi.org/10.2905/JRC.G2DATVR>. The code underlying the data compositing method is available at <https://code.europa.eu/jrc-ghsl/maxifico>. GHS-AGE data are available at <https://doi.org/10.2905/JRC.YCNTMNG>. All other datasets from the Global Human Settlement Layer and the Copernicus Exposure Mapping dataset are openly available at <https://human-settlement.emergency.copernicus.eu/>. The LUISA basemap LULC dataset is available at <https://doi.org/10.2905/JRC.NBGPQJ8>.

¹ Group on Earth Observations (GEO) 'Human Planet' and 'Earth Intelligence' initiatives; <https://earthobservations.org/>

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