Coloring panchromatic nighttime satellite images: Elastic maps vs. kernel smoothing and multivariate regression approach

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Abstract: Artificial light-at-night (ALAN), emitted from residential, industrial, and commercial areas and visible from space, marks human presence on Earth. Since the launch of the Suomi National Polar Partnership satellite with the Visible Infrared Imaging Radiometer Suite Day/Night Band (VIIRS/DNB) instrument in late 2011, global nighttime satellite images have considerably improved in terms of spatial resolution, quantization, saturation, and light detection limits. However, VIIRS/DNB images remain panchromatic, reporting aggregated light emissions in the
500-900μm range. Although multispectral satellite images, reporting light emissions for different parts of the light spectrum, are also available, such images are, at present, either commercial or free, but sporadic. In this paper, we use different machine learning techniques, ranging from standard (linear and kernel) regressions to a more advanced non-linear elastic map approach, to transform panchromatic VIIRS/DBN images into RGB. To validate the proposed approach, we analyze nighttime satellite images available for eight urban areas worldwide – Atlanta, Beijing, Haifa, Khabarovsk, London, Naples, Nashville, and Tianjing. The analysis links RGB values, obtained from International Space Station (ISS) photographs, to panchromatic ALAN intensities, obtained from VIIRS/DBN images and combined with pixel-wise difference measures and several readily available (or easy-to-calculate) proxies for land use types. During the analysis, each dataset is used for model training, while the rest of the datasets are used for model validation. We compare the models' performance using several performance measures – Pearson correlation, weighted mean squared errors (WMSE), contrast similarity between the original and model-estimated RGB data, and consistency of the performance measures for training and testing sets. As the analysis shows, the RGB images, generated using panchromatic VIIRS/DBN data, are not only visually similar to the original RGB images, available from ISS, but also demonstrate a high degree of correspondence with the latter. Yet, estimates, based on linear and non-linear kernel regressions, appear to provide better correlations and lower WMSEs, while RGB images, generated using the elastic map approach, appear to provide better contrast similarity and better consistency of predictions. As we conclude, the proposed method demonstrates its utility in enhancing the spectral resolution of panchromatic nighttime satellite imagery and can thus be used for obtaining seamless RGB coverages using panchromatic VIIRS/DBN data.
Keywords: Artificial Light-at-Night (ALAN); Day-Night Band of the Visible Infrared Imaging Radiometer Suite (VIIRS/DNB); International Space Station (ISS); panchromatic and RGB images; elastic map approach; multiple linear regression; non-linear kernel regression; validation.

1. Introduction

Artificial Light-at-Night (ALAN), emitted from streetlights, residential areas, places of entertainment, industrial zones, and captured by satellites' nighttime sensors, has been used in previous studies for remote identification of different Earth phenomena: stellar visibility (Cinzano et al., 2000; Falchi et al., 2019, 2016); ecosystem events (Bennie et al., 2015; Hu et al., 2018); estimating urban development and population concentrations (Amaral et al., 2006; Anderson et al., 2010; Elvidge et al., 1997; Hopkins et al., 2018; Sutton et al., 2001; Zhuo et al., 2009); assessing the economic performance of countries and regions (Doll et al., 2000; Ebener et al., 2005; Ghosh et al., 2010; Henderson et al., 2012; Mellander et al., 2015; Wu et al., 2018); and in health geography research (Kloog et al., 2010, 2009; Rybnikova et al., 2016).

Compared to traditional techniques, which national statistical offices use to monitor the concentrations of human activities (such as, e.g., monitoring the level of urbanization, production density, etc.), using ALAN as a remote sensing tool has several advantages (see (Levin et al., 2020) for a recent review). First and foremost, satellite-generated ALAN data are available seamlessly all over the world, providing researchers and decision-makers with an opportunity to generate data even for countries and regions with extremely poor reporting behavior. Second, ALAN data are mutually comparable for different geographic regions, which minimizes the problem of comparability between socio-economic activity estimates, potentially originating from differences in national reporting procedures. Third, data on remotely sensed ALAN intensities are now available worldwide on a daily basis (Román et al., 2018), which enables researchers and official
bodies to obtain prompt estimates of ongoing changes in the geographic spread of different human activities and their temporal dynamics. The latter is especially important for socioeconomic activities, for which estimates, based on traditional techniques, are unavailable with a desired frequency or time-consuming to generate.

Several sources of global nighttime imagery exist today. Between 1992 and 2013, nighttime satellite imagery was provided by the U.S. Defense Meteorological Satellite Program (DMSP/OLS) on an annual basis, with the spatial resolution of about 2.7 km per pixel (Elvidge et al., 2013). From April 2012 on, nighttime images, generated by the Day-Night Band of the Visible Infrared Imaging Radiometer Suite (VIIRS/DNB) instrument of the Suomi National Polar Partnership (SNPP) satellite, have become available. The satellite in question moves through a sun-synchronous polar orbit at the altitude of about 824 km, and captures ALAN emissions at about 1:30 am local time (Elvidge et al., 2013). The VIIRS/DNB program routinely provides panchromatic global imagery in the 500-900 nm range at about 742 m per pixel spatial resolution, on annual and monthly bases. From the first quarter of 2019 on, ALAN data are available daily from the NASA Black Marble night-time lights product suite, or VNP46 (Román et al., 2018), the Distributed Active Archive Center (“LP DAAC - Homepage,” n.d.).

In comparison to DMSP/OLS images, VIIRS/DNB data have a better spatial resolution and lower light detection limits (2E-11 Watts/cm²/sr vs. 5E-10 Watts/cm²/sr in US-DMSP), which is especially important for analyzing dimly lit areas. VIIRS/DNB data also do not exhibit bright light saturation (Elvidge et al., 2013), which is essential for the analysis of brightly lit areas, such as major cities and their environs.

However, despite the above-mentioned improvements in the ALAN image quality and resolution, the main drawback of global ALAN data, available today, is that they remain panchromatic,
reporting the *summarized* intensity of light in the 500-900 nm diapason (Elvidge et al., 2013). This limitation makes it difficult to use such data to differentiate *between* specific economic activities, which are characterized by varying spectral signatures (Rybnikova and Portnov, 2018), because they use light sources of different spectral properties, to fit their resources and needs (Veitch et al., 2008). Panchromatic ALAN data also do *not* make it possible to investigate health effects, associated with ALAN exposures to different sub-spectra, such as e.g., hormone-dependent cancers, known to be strongly related to ALAN exposure in the short-wavelength (blue) light spectra (Cajochen et al., 2005; Czeisler, 2013).

In addition, the 500-900nm sensitivity diapason, reported by global VIIRS/DNB images, omits some important intervals of the visible light spectrum. In particular, it omits the emission peaks of the incandescent and quartz halogen lamps that are at about 1000 nm, and a large share of ALAN emissions from the Light Emitting Diodes (LED), which occur in the 450-460 nm range (Elvidge et al., 2010). This means that the reported *summarized ALAN intensities* are essentially *biased*, and this bias, potentially introduced by local lighting standards and/or cultural preferences, is *not random* but may vary systematically across different geographical areas, depending e.g., on the level of propagation of specific light sources, such as LEDs, which light emission are outside the captured ALAN range. In this respect, the ongoing rapid propagation of LEDs is of particular concern, as it might gradually diminish the capability of presently available global ALAN images to serve as a reliable proxy for monitoring the human footprint, and may thus impede research progress on estimating various side effects of light pollution.

RGB nighttime imagery of better spectral resolution, provided by the habitable International Space Station (ISS) (“Search Photos,” n.d.), is also available. However, the use of ISS data for a global analysis is problematic. The matter is that these night-time images are photographs, captured
sporadically by varying cameras, which need to be geo-referenced and calibrated, to produce a continuous image from a mosaic of fragmented local pictures, taken by different cameras and different astronauts (see Cities at Night project (“Cities at night – mapping the world at night,” n.d.). In addition, the ISS images in question are not available on a regular basis.

Considering these limitations of the globally available polychromatic ALAN data, the present study aims to verify a possibility that spectral resolution of global panchromatic VIIRS/DBN nighttime imagery can be enhanced, by transforming such panchromatic data into RGB images. To achieve this goal, we test different machine learning techniques to build and cross-validate the models associating light intensities of red, green, or blue sub-spectra with panchromatic ALAN data, pixel-wise neighborhood difference measures and several land-use proxies. As the study demonstrates, using multivariate regression tools and the elastic map approach, originating from the manifold learning field, helps to produce reasonably accurate RGB estimates from panchromatic data. The importance of this result is that it may help to generate more informative and freely available remote proxies for a human presence on Earth.

The rest of the paper is organized as follows. We start by outlining our study design and describe the datasets used for model training and validation. Next, we itemize criteria used for model validation, report the obtained results, and discuss controversial issues raised by the analysis and limitations that should be addressed in future studies.

2. Methods

2.1 Research hypothesis and study design

According to (Hale et al., 2013), each type of land use is characterized by a certain combination of different luminaires. As a result, different land uses differ in terms of both aggregated light flux
and the primary emission peak diapason (Rybnikova and Portnov, 2017)). In addition, some types of light emission are *spatially localized* (such as e.g., blue-light emissions from commercial and industrial hubs), while other light emissions are more geographically uniform, such as e.g., long-wavelength light emissions from homogeneous low-density residential areas. Therefore, we *hypothesize that information on different ALAN sub-spectra (red, green, and blue) can be extracted from a combination of panchromatic ALAN data, pixel-wide neighborhood differences, and built-up area characteristics.*

To test this hypothesis, we link the intensity of each ALAN sub-spectra (Red-Green-Blue) with the intensity of panchromatic ALAN, pixel-wise neighborhood ALAN difference measures and characteristics of built-up areas available for several major metropolitan areas worldwide (see Section 2.2).

The former group of pixel-wise neighborhood controls includes differences between the panchromatic ALAN intensity in a given pixel and either average or the most extreme ALAN intensity in its neighborhood. The potential importance of such differences is expected to be due to the fact that *substantial* differences in neighboring ALAN intensities may occur, if, for instance, a brightly lit commercial facility, often characterized by blue luminaries, stands out against nearby dimly lit areas or if such a facility is separated from its surrounding by a dimly-lit buffer zone. In contrast, similar light emissions in the pixel's neighborhood may result from the pixel's location in a homogenously lit residential area, where long wavelength luminaries (such as incandescent or vapor lamps) are often used. Concurrently, the above-mentioned built-up area characteristics include the percent of built-up area and its spatial homogeneity, considering that each type of land use has its spatial configuration and land cover (Herold et al., 2003).
We examine three types of machine learning models. The first one is the elastic map approach, originating from the manifold learning field, and two standard methods, represented by multiple linear and non-linear kernel regressions (see Subsection 2.4). Using these three methods, the models are first estimated for training sets and then are validated against testing sets (see Subsection 2.4). In each case, the models’ performance is assessed by mutually comparing the model-estimated and original RGB data. To this purpose, different similarity measures are used – Pearson’s correlation coefficients, weighted mean squared error (WMSE), and contrast similarity. In addition, we control for the consistency of these measures by comparing the results obtained for training and testing datasets (see Subsection 2.5).

2.2 Data sources

For each metropolitan area under analysis, we built a dataset that included three separate images of the RGB sub-spectra (red, green and blue), a panchromatic image of ALAN intensity, a layer of neighborhood differences, calculated for the panchromatic ALAN layer, and a land-use layer (see Subsection 2.1).

As a source of RGB ALAN data, we use local night-time images provided by the International Space Station (ISS) and available from the Astronaut Photography Search Photo service (‘‘Search Photos,’’ n.d.). Concurrently, panchromatic ALAN images were obtained from the VIIRS/DNB image database, maintained by the Earth Observation Group site (‘‘Earth Observation Group,’’ n.d.), while land-use characteristics of built-up area were computed from the global raster layer of human built-up area and settlement extent (HBASE) database available at the NASA Socioeconomic Data and Application Centre site (‘‘HBASE Dataset From Landsat,’’ n.d.).

It should be noted that ISS images report ALAN levels in digital numbers, which are camera-specific (‘‘How Digital Cameras Work,’’ n.d.). Therefore, to ensure the comparability of RGB
levels, reported for different localities, we selected from the ISS database only images taken by the same – a Nikon D4 Electronic Still – camera. In addition, to enable the comparability of ISS images with panchromatic ALAN images, we selected the ISS images taken at the time close to the VIIRS/DNB image acquisition, that is, at about 01:30 a.m., local time.

The selected images were georeferenced to the World Street Basemap, available in the ArcGIS v.10.x software (“About ArcGIS | Mapping & Analytics Platform,” n.d.) and clipped to the extent of the corresponding urban area. Next, the ISS images were paired with corresponding monthly VIIRS/DNB composites, and clipped to the extent of the corresponding RGB image. In particular, the following pairs of images were used:

- For the Atlanta region, the USA, the ISS image (ID ISS047-E-26897, taken on March 29, 2016), was matched with the VIIRS/DNB image taken in March 2016 Tile 1 (75N/180W) composite;

- For the Beijing region, China, the ISS image (ID ISS047-E-11998, taken on March 20, 2016), was matched with the VIIRS/DNB image taken in March 2016 Tile 3 (75N/060E) composite;

- For the Haifa region, Israel, the ISS image (ID ISS045-E-148262, taken on November 29, 2015), was matched with the VIIRS/DNB image taken in November 2015 Tile 2 (75N/060W) composite;

- For the Khabarovsk region, Russia, the ISS image (ID ISS047-E-12012, taken on March 20, 2016), was matched with the VIIRS/DNB image taken in March 2016 Tile 3 (75N/060EW) composite;
• For the London region, the UK, the ISS image (ID ISS045-E-32242, taken on September 27, 2015), was matched with the VIIRS/DNB image taken in September 2015 Tile 2 (75N/060W) composite;

• For the Naples region, Italy, the ISS image (ID ISS050-E-37024, taken on January 30, 2017), was matched with the VIIRS/DNB image taken in January 2017 Tile 2 (75N/060W) composite;

• For the Nashville region, the USA, the ISS image (ID ISS045-E-162944, taken on December 6, 2015), was matched with the VIIRS/DNB image taken in December 2015 Tile 1 (75N/180W) composite;

• Lastly, for the Tianjing region, China, the ISS image (ID ISS047-E-12004, taken on March 20, 2016) was matched with the VIIRS/DNB image taken in March 2016 Tile 3 (75N/060E) composite.

Figure 1 reports examples of images used for the Greater Haifa metropolitan area in Israel. [Images for other areas under analysis are not reported here, for brevity's sake, and can be obtained from the authors upon request].
Figure 1: Input information for the Greater Haifa metropolitan area: (a) an ~10-meter resolution RGB image with the range of values of 0-255 DN for each band; (b) an ~750-meter resolution panchromatic image with the values in the 1-293 nanoWatts/cm²/sr range, and (c) an ~30-meter resolution HBASE image with the values in the 0-100 % range.

2.3 Image processing

The data for the analysis were processed in several stages. First, we reduced the high-resolution of ISS RGB images (~10 meters per pixel), to match the resolution of corresponding VIIRS/DNB images (~750 meters per pixel) and then converted the resized images into point layers, using the Raster-to-Point conversion tool in ArcGIS v.10.x software. Next, to each point in the layer (i.e., reference points), we assigned the corresponding values of the red, green, and blue light sub-spectra from the corresponding ISS RGB image. The task was performed using the Extract MultiValues to Points tool in ArcGIS v.10.x software. Next, after VIIRS/DNB images were converted into points, each point was assigned with the following information: 1) panchromatic ALAN flux; 2) average difference between ALAN intensity in the point and ALAN intensities in its eight neighboring pixels, and 3) maximum difference between the ALAN intensity in a given pixel and ALAN values in eight neighboring pixels in the pixel's immediate neighborhood. Lastly,
after the HBASE image was converted into points, its pixel averages and standard deviations (SDs) were calculated and assigned to the reference points as well.

During data processing, all the points located outside the study area (for instance, points falling into water bodies) or classified as outliers in each dataset (see Outliers Analysis Box in Supplementary Materials section) were excluded from the analysis. Table S1 reports the number of observations for each geographic site, and other relevant information, while descriptive statistics for research variables are reported in Table S2 in the Supplementary Materials (SM) section.

2.4 Modelling

To estimate models linking ALAN intensities of red, green and blue sub-spectra with the set of explanatory variables (see Subsection 2.1), we used, as previously mentioned, three alternative modeling approaches: the elastic map approach, originating from the manifold learning field (Gorban and Zinovyev, 2010), and two standard supervised multivariate modeling methods, that is, ordinary multiple linear regression and non-linear kernel regression (see inter alia (Hastie et al., 2017)).

All three approaches belong to the field of supervised machine learning, as they model the relations between variables based on some training data and use the revealed relationships to make predictions for others – that is, testing – data. This generates a so-called bias-variance dilemma (Luxburg and Schölkopf, 2011). The better a model fits the training data, the worse it is expected to fit the test data. As a result, while linear regression's performance may be relatively poor for the training dataset, it may generate reasonably good predictions for test datasets. By contrast, non-linear kernel regression might fit training data perfectly but may fare poorly, when applied to new datasets. In this context, elastic maps with varying bending regimes can be viewed as an approach for optimizing such a bias-variance trade-off.
Each of the aforementioned models was first estimated separately for the red, green, blue light intensities for each of the eight metropolitan areas covered by analysis – i.e., Atlanta, Beijing, Haifa, Khabarovsk, London, Naples, Nashville, and Tianjing (see Subsection 2.2). Each estimated model was next applied to the other metropolitan areas, to validate its performance. In the subsections below, we describe, in brief, each modeling approach used in the analysis.

2.4.1 Elastic map approach

Elastic map approach implies constructing a non-linear principal manifold approximation, represented by nodes, edges (connecting pairs of nodes) and ribs (connecting triples of nodes), by minimizing the squared distances from the dataset points to the nodes, while penalizing for stretching of the edges and bending of the ribs (Gorban and Zinovyev, 2010). Elastic map, eventually presented by multidimensional surface, built of piece-wise linear simplex fragments, might be considered as a non-linear 1D, 2D, or 3D screen, on which the multidimensional data point vectors are projected. It is built, on the one hand, to fit the data, and, on the other hand, not to be too stretched and too bent.

The general algorithm of the elastic map follows the standard splitting approach. Elastic map is initialized as a regular net, characterized by nodes, edges, connecting two closest nodes, and ribs, connecting two adjacent continuing edges. This net is embedded into a space of multidimensional data, and the node embedments are optimized to achieve the smooth and regular data approximation. The optimization is done in iterations, similarly to the k-means clustering algorithm. At the first step of each iteration, the data point cloud is partitioned accordingly to the closest elastic net’s node embedment. At the second step, the total energy of the net ($U$) is minimized, and the node embedment is updated. After this, a new iteration starts, and this process continues till a maximum number of iterations is achieved or the changes in the node positions in
the multidimensional data space become sufficiently small at each iteration. For detailed formal methodology description, see (Gorban and Zinovyev, 2001) and (“ElMap/Elastic maps.docx at master · Mirkes/ElMap · GitHub,” n.d.)).

The energy of the elastic map is represented by the following three components: summarized energy of nodes \( (U^V) \), calculated as the averaged squared distance between the node and the corresponding subset of data points closest to it; summarized energy of edges \( (U^E) \), which is the analog to the energy of elastic stretching and is proportional – via a certain penalty – to the sum of squared distances between edge-connected nodes; and summarized energy of ribs \( (U^R) \), which might be considered as the analog to the of elastic deformation of the net and is calculated as proportional – via a certain penalty – to the sum of squared distances between the utmost and center nodes of the ribs. Figuratively, the described energies are depicted in Fig.2: Each node is connected by elastic bonds to the closest data points and simultaneously to the adjacent nodes.

It is important to note that, unlike standard supervised methods, such as linear or kernel regression models, elastic map is, by its nature, a non-supervised manifold learning method which does not treat any variable as dependent one; it is designed to explain – under pre-defined penalties for stretching and bending – total variance of the data. However, similarly to Principal Component Analysis (see, for example, (Grung and Manne, 1998)), the elastic map data approximations can be used for predicting the values of some of the variables (e.g., those which are considered to be dependent) through imputing them. The imputing approach,
in this case, consists in fitting the elastic map using the part of the dataset containing no missing values and then projecting the data vectors containing a missing value for the dependent variable. The imputed (or, predicted) value is the value of the variable in the point of its projection onto the elastic map.

By construction, elastic map, represented by a sufficient number of nodes, and given the low penalties for stretching of edges and bending of ribs, would fit input data perfectly. Theoretically, when the number of elastic map nodes approaches the number of points in the input dataset, and under zero penalties, the fraction of the total unexplained variance of input point cloud by corresponding elastic map would equal to zero. At that, this elastic map’s ability to generalize to another dataset or predict one of its variables levels is expected to be low.

The present elastic map analysis was conducted in MATLAB software (“GitHub - Elastic map,” n.d.). We utilized a two-dimensional net with a rectangular grid with nodes, which were brought into actual data subspace spanned by the first three principal components. Due to the outlier analysis performed, we settled the stretching penalty at a zero level. To prevent overfitting, the number of nodes was also fixed at a level of 144 (12x12), which is about 5-50 times smaller than the number of points of input datasets. We experimented with the bending coefficient only. In the attempt to optimize bias-variance trade-off, we tested elastic maps built under nine varying bending penalties. (Fig. S2 in Supplementary Materials section, reporting corresponding models for blue light association with the set of predictors for Haifa dataset, gives an idea of how these maps look like. As one can see from the figure, representing the general tendency for either red, green or blue lights containing datasets, map smoothness gradually grows with an increasing penalty for bending, while the level of a fraction of total variance (that is, a fraction of variance by all six variables in the dataset) unexplained (FVU) by smoother map further decreases).
2.4.2 Multiple linear regression

The general idea behind the multiple least-squares linear regression is fitting the observations (each represented by a point in $N$-dimensional space with $(N-1)$ number of predictors and one dependent variable) by a linear relationship, represented by an $(N-1)$-dimensional linear surface, or hyperplane, by minimizing the sum of squared errors between the actual and estimated over this hyperplane levels of the dependent variable. In the current analysis, for each geographic site dataset, the following multiple ordinary least squares (OLS) regression model was estimated:

$$CL_{ij} = b_0 + \sum_k (b_k \times P_{kl}) + \varepsilon_i,$$

(1)

where $CL_i$ = observation $i$ of ALAN intensity in color band $j$ (either red, green or blue sub-spectra); $b_0$ = model intercept; $b_k$ = regression coefficient for the $k^{th}$ predictor; $P$ = vector of model predictors, represented by pixel-specific panchromatic ALAN intensity, reported by VIIRS/DNB (i); the difference between the pixel-specific panchromatic ALAN intensity and average panchromatic ALAN intensities of eight neighboring pixels (ii); the maximum difference between the panchromatic ALAN flux from a pixel and panchromatic ALAN fluxes from eight neighboring pixels (iii); average percent and standard deviation of land coverage, calculated from HBASE, and $\varepsilon$ = random error term.

The multiple regression analysis of the factors associated with RGB ALAN intensities was performed in the IBM SPSSv.25 software (“SPSS Software | IBM,” n.d.).

2.4.3 Non-linear kernel regression

Non-linear kernel regression is a non-parametric technique, fitting the observations into a hypersurface. The method uses a sliding window, with a dataset being divided into smaller subsets. Within each data subset, each data point is treated as a ‘focal point’, and its value along the
dependent variable axis is re-estimated from a hyperplane (or hypersurface), built to minimize the errors, weighted for the distance to the focal point along independent variables axes and for the difference between estimated and actual levels of the dependent variable (Wand and Jones, n.d.).

Under this estimation technique, many parameters are a matter of choice. First, the size of the sliding window may vary from several points to significant amounts of the whole dataset, providing correspondingly less or more flat hypersurface. Second, the modelled association between a dependent variable and its predictors might be either linear, parabolic, exponential, etc. Third, the errors between estimated and actual levels might be either minimized or not allowed to exceed a certain value. Fourth, the ‘weights’ function might vary, implying paying more or less attention for more distant data points. Finally, the number of iterations on re-estimating dependent variable actual levels might also be increased, so the resulting hypersurface would be flatter.

In the present analysis, we used a standard realization of the Gaussian kernel regression built-in MATLAB software under the chosen automatic option for the kernel regression parameters optimization (“Fit Gaussian kernel regression model using random feature expansion - MATLAB fitrkernel,” n.d.). The latter implies the optimization of the kernel regression parameters by using five-fold cross-validation based on mean squared errors.

2.5 Criteria for the models’ comparison

To compare models estimated using the above-discussed statistical techniques, we used the following indicators:

(i) Pearson correlation coefficients were calculated to determine the strength of association between the actual and predicted levels of RGB sub-spectra. This metric assesses the model's
ability to produce RGB estimates, which— in their relative tendency — correspond well with the actually observed RGB levels;

(ii) Weighted mean squared errors (WMSE) between the actual and predicted levels of ALAN emissions in the red, green, and blue sub-spectra. This metric is calculated as mean squared difference between the model-estimated and actually observed RGB levels, divided by the actually observed value; the metric helps to assess differences between the estimated and actual RGB levels on an absolute scale;

(iii) Contrast similarity index between the original and model-predicted RGB images. This measure generates a pairwise comparison of local standard deviations of the signals from the original and model-generated images (Wang et al., 2004). In our analysis, this indicator was used to compare the spatial patterns of differences between light intensities of a variety of restored RGB images and corresponding RGB originals. The calculations of the index were performed in MATLAB software using its structural similarity computing module (“Structural similarity (SSIM) index for measuring image quality - MATLAB ssim,” n.d.), while setting the exponents of two other terms, that is, luminance and structural terms, to zero.

(iv) Consistency of the estimated obtained using the aforementioned metrics— Pearson correlation, WMSE, and the contrast similarity index,— was estimated as the geometric mean of the ratio between the average value and standard deviations of a given measure, assessed for the training and testing sets, respectively. The consistency was considered a measure of universality of the modeling approach.
3. Results

3.1 General comparison of the models' performance

Figs. 3-10 report results of the analysis, in which different models are estimated for one metropolitan area (Haifa) and then applied to seven other metropolitan areas under analysis. In particular, Figures 3-10 report the original ISS RGB image, resized to the spatial resolution of the corresponding panchromatic VIIRS/DNB image, and, next to it, RGB images generated from panchromatic ALAN VIIRS/DNB images and HBASE maps. The figures also report several assessment criteria – Person correlation, WMSE, and contrast similarity. Although we performed similar assessments for all other metropolitan areas, by applying the models estimated for one of them to all the "counterpart" geographical areas, in the following discussion, we report only general statistics of such assessments (see Figure 11 and Table 1), while the RGB images generated thereby are not reported in the following discussion, for brevity's sake, and can be obtained from the authors upon request.

As Figures 3-10 show, the model-generated RGB maps are, in all cases, visually similar to the original ISS RGB data. In addition, the models’ performance measures show a close correspondence between original and model-generated RGB images, with Pearson correlation coefficients, both for training and testing sets, ranging between 0.719 and 0.910, WMSE varying from 0.067 to 4.223 and contrast similarity ranging from 0.931 to 0.983 (for corresponding statistics for other case studies covered by the analysis, see Tables S3-S10 in the SM section).

Figure 11, which mutually compares the performance of linear regressions, kernel regressions, and elastic maps built under different bending penalties, for training and testing sets, also shows that models-generated RGB estimates demonstrate a high degree of correspondence with the original
ISS RGB data. In particular, as Figure 11 shows, Pearson correlation coefficients exceed in all cases, for both testing and training sets, 0.62, WMSE are smaller than 2.03, and contrast similarity is greater than 0.91 (91%), indicating a high level of correspondence with the original ISS data.

As Figure 11 further shows, in terms of Pearson correlation coefficients and WMSE, kernel regressions perform somewhat better for training sets (with \( r = 0.80-0.89 \) and \( \text{WMSE} = 0.10-0.26 \) vs. \( r = 0.77-0.87 \) and \( \text{WMSE} = 0.14-0.37 \) for linear regressions and \( r = 0.69-0.85 \) and \( \text{WMSE} = 0.12-0.59 \) for elastic map models). However, for testing sets, in terms of Pearson correlations, linear regression outperforms other modeling methods (\( r = 0.75-0.85 \) vs. \( r = 0.68-0.85 \) for kernel regressions and \( r = 0.62-0.82 \) for elastic map models). Concurrently, in terms of WMSE, linear regressions also perform better for the blue light band (\( \text{WMSE} = 0.81 \) vs. \( \text{WMSE} = 0.91 \) for kernel regressions and \( \text{WMSE} = 0.97-1.17 \) for elastic map models), while kernel regressions perform better for the red and green light sub-spectra (\( \text{WMSE} = 1.18-1.12 \), in compare to \( \text{WMSE} = 1.44-1.70 \) for linear regressions and \( \text{WMSE} = 1.17-2.03 \) for elastic map models). Yet, in terms of contrast similarity (\( C_{\text{sim}} \)), elastic map models demonstrate better performance, for both training and testing sets (\( C_{\text{sim}} = 0.930-0.979 \) vs. \( C_{\text{sim}} = 0.913-0.966 \) for linear regressions and \( C_{\text{sim}} = 0.922-0.973 \) for kernel regressions). Notably, for both training and testing datasets, elastic map performance generally improves initially in line with increasing smoothness, but then levels off (see Figs. 11 (a),(c),(d), and (f)), thus indicating diminishing benefits of over-smoothing.

Table 1 reports consistency assessment of the models’ performance across training and testing sets. As the table shows, in most cases, elastic map models outperform both linear and kernel regressions, except for Pearson’s correlation coefficients’ consistency, assessed for green light datasets, for which linear regression outperforms other methods (\( r = 0.979 \) vs. \( r = 0.976 \) for elastic map models and \( r = 0.804 \) for kernel regressions).
Table 1: Mutual comparison of linear, kernel and elastic map models in terms of estimate consistency for training and testing datasets

| Model type            | Model performance measure |             | WMSE |              | Contrast similarity |
|-----------------------|---------------------------|-------------|------|--------------|---------------------|
|                       |                           | Pearson correlation coefficient | WMSE |              |                     |
|                       |                           | R  | G  | B  | R  | G  | B  | RGB |
| Linear regression     |                           | 0.938 | 0.979 | 0.880 | 0.124 | 0.147 | 0.096 | 0.541 |
| Kernel regression     |                           | 0.680 | 0.804 | 0.572 | 0.135 | 0.148 | 0.059 | 0.514 |
| Elastic map model     | 1a 0.970 1b 0.975 1c 0.257 1d 0.108 1d | 0.970 | 0.976 | 0.975 | 0.371 | 0.257 | 0.108 | 0.598 |

Note: The results of the best-performing model are reported with: 1a $\alpha=0.0001$; 1b $\alpha=0.05$; 1c $\alpha=0.00001$; 1d $\alpha=0.001$. The grey cell backgrounds mark the best-performed model for specific measures.
$R = 0.86$; $WMSE = 0.56$

$R = 0.89$; $WMSE = 0.37$

$R = 0.85$; $WMSE = 0.09$

$C_{\text{sim}} = 0.96$

$R = 0.88$; $WMSE = 0.39$

$R = 0.91$; $WMSE = 0.25$

$R = 0.87$; $WMSE = 0.07$

$C_{\text{sim}} = 0.98$
**Fig. 3:** RGB images of *Haifa metropolitan area (Israel)*: ISS-provided, resampled to the spatial resolution of VIIRS imagery (the first row), and generated from the estimates produced by linear multiple regressions (the second row), non-linear kernel regressions (the third row), and elastic map models (the fourth row), run upon *Haifa datasets*.

*Notes:* Output generated by elastic maps, built under 0.05 bending penalty, is reported. $R$ and $WMSE$ denote correspondingly for Pearson’s correlation and weighted mean squared error of the red, green, and blue lights’ estimates, $C_{sim}$ – for contrast similarity between restored and original RGB images. White points in the city area correspond to outliers.
$R = 0.81; \text{WMSE} = 15.57$

$R = 0.80; \text{WMSE} = 9.62$

$R = 0.73; \text{WMSE} = 1.80$

$C_{\text{sim}} = 0.93$

$R = 0.81; \text{WMSE} = 10.64$

$R = 0.78; \text{WMSE} = 9.11$

$R = 0.69; \text{WMSE} = 2.53$

$C_{\text{sim}} = 0.95$
Fig. 4: RGB images of the Atlanta metropolitan area (the US): ISS-provided, resampled to the spatial resolution of VIIRS imagery (the first row), and generated from the estimates produced by linear multiple regressions (the second row), non-linear kernel regressions (the third row), and elastic map models (the fourth row), run upon Haifa datasets.

Notes: Output generated by elastic maps, built under 0.05 bending penalty, is reported. R and WMSE denote correspondingly for Pearson’s correlation and weighted mean squared error of the red, green, and blue lights’ estimates, C_sim – for contrast similarity between restored and original RGB images. White points in the city area correspond to outliers.
$R = 0.79; \quad WMSE = 3.31$

$R = 0.85; \quad WMSE = 3.60$

$R = 0.78; \quad WMSE = 2.58$

$C_{sim} = 0.94$

$R = 0.85; \quad WMSE = 1.81$

$R = 0.85; \quad WMSE = 3.89$

$R = 0.74; \quad WMSE = 3.77$

$C_{sim} = 0.95$
Fig. 5: RGB image of the Beijing metropolitan area (China): ISS-provided, resampled to the spatial resolution of VIIRS imagery (the first row), and generated from the estimates produced by linear multiple regressions (the second row), non-linear kernel regressions (the third row), and elastic map models (the fourth row), run upon Haifa datasets.

Notes: Output generated by elastic maps, built under 0.05 bending penalty, is reported. $R$ and $WMSE$ denote correspondingly for Pearson’s correlation and weighted mean squared error of the red, green, and blue lights’ estimates, $C_{sim}$ – for contrast similarity between restored and original RGB images. White points in the city area correspond to outliers.
\[ R = 0.80; \ WMSE = 3.48 \]
\[ R = 0.86; \ WMSE = 2.52 \]
\[ R = 0.73; \ WMSE = 4.02 \]
\[ C_{\text{sim}} = 0.82 \]

\[ R = 0.85; \ WMSE = 2.10 \]
\[ R = 0.87; \ WMSE = 2.20 \]
\[ R = 0.75; \ WMSE = 3.81 \]
\[ C_{\text{sim}} = 0.86 \]
Fig. 6: RGB images of *Khabarovsk (Russia)*: ISS-provided, resampled to the spatial resolution of VIIRS imagery (the first row), and generated from the estimates produced by linear multiple regressions (the second row), non-linear kernel regressions (the third row), and elastic map models (the fourth row), run upon *Haifa datasets*.

Notes: Output generated by elastic maps, built under 0.05 bending penalty, is reported. *R* and *WMSE* denote correspondingly for Pearson’s correlation and weighted mean squared error of the red, green, and blue lights’ estimates, *C_sim* – for contrast similarity between restored and original RGB images. White points in the city area correspond to outliers.
$R = 0.83; WMSE = 2.00$

$R = 0.85; WMSE = 1.06$

$R = 0.77; WMSE = 0.23$

$C_{sim} = 0.98$
Fig. 7: RGB images of the London metropolitan area (the UK): ISS-provided, resampled to the spatial resolution of VIIRS imagery (the first row), and generated from the estimates produced by linear multiple regressions (the second row), non-linear kernel regressions (the third row), and elastic map models (the fourth row), run upon Haifa datasets.

Notes: Output generated by elastic maps, built under 0.05 bending penalty, is reported. $R$ and WMSE denote correspondingly for Pearson’s correlation and weighted mean squared error of the red, green, and blue lights’ estimates, $C_{sim}$ – for contrast similarity between restored and original RGB images. White points in the city area correspond to outliers.
**Fig. 8:** RGB images of the *Naples metropolitan area* (Italy): ISS-provided, resampled to the spatial resolution of VIIRS imagery (the first row), and generated from the estimates produced by linear multiple regressions (the second row), non-linear kernel regressions (the third row), and elastic map models (the fourth row), run upon *Haifa datasets*.

*Notes:* Output generated by elastic maps, built under 0.05 bending penalty, is reported. *R* and *WMSE* denote correspondingly for Pearson’s correlation and weighted mean squared error of the red, green, and blue lights’ estimates, *C_sim* – for contrast similarity between restored and original RGB images. White points in the city area correspond to outliers.
$R = 0.84; \text{WMSE} = 2.35$

$R = 0.86; \text{WMSE} = 1.24$

$R = 0.80; \text{WMSE} = 0.24$

$C_{sim} = 0.97$

$R = 0.87; \text{WMSE} = 1.20$

$R = 0.88; \text{WMSE} = 1.08$

$R = 0.77; \text{WMSE} = 0.37$

$C_{sim} = 0.98$
Fig. 9: RGB images of the Nashville metropolitan area (the US): ISS-provided, resampled to the spatial resolution of VIIRS imagery (the first row), and generated from the estimates produced by linear multiple regressions (the second row), non-linear kernel regressions (the third row), and elastic map models (the fourth row), run upon Haifa datasets.

Notes: Output generated by elastic maps, built under 0.05 bending penalty, is reported. \( R \) and \( WMSE \) denote correspondingly for Pearson’s correlation and weighted mean squared error of the red, green, and blue lights’ estimates, \( C_{sim} \) – for contrast similarity between restored and original RGB images. White points in the city area correspond to outliers.
\[ R = 0.82; \text{WMSE} = 2.57 \]

\[ R = 0.87; \text{WMSE} = 2.54 \]

\[ R = 0.69; \text{WMSE} = 2.67 \]

\[ C_{\text{sim}} = 0.93 \]

\[ R = 0.87; \text{WMSE} = 1.15 \]

\[ R = 0.85; \text{WMSE} = 3.43 \]

\[ R = 0.68; \text{WMSE} = 4.27 \]

\[ C_{\text{sim}} = 0.95 \]
Fig.10: RGB images of the Tianjing metropolitan area (China): ISS-provided, resampled to the spatial resolution of VIIRS imagery (the first row), and generated from the estimates produced by linear multiple regressions (the second row), non-linear kernel regressions (the third row), and elastic map models (the fourth row), run upon Haifa datasets.

Notes: Output generated by elastic maps, built under 0.05 bending penalty, is reported. $R$ and WMSE denote correspondingly for Pearson’s correlation and weighted mean squared error of the red, green, and blue lights’ estimates, $C_{sim}$ – for contrast similarity between restored and original RGB images. White points in the city area correspond to outliers.
Figure 11: Mutual comparison of linear, kernel and elastic map models for the training (top row) and testing (bottom row) data sets, in terms of averaged Pearson correlation coefficients ((a) & (d)), WMSE ((b) & (e)), and contrast similarity ((c) & (f))
3.2 Factors affecting light flux in different RGB bands

As hypothesized in Section 2.1, different types of land-use tend to emit nighttime lights, different in terms of light intensity and spectra. This fact potentially enables a successful extraction of RGB information from panchromatic ALAN images. To verify this hypothesis, we ran multiple regression models, linking the set of predictors, described in Section 2.1, with light intensities in different spectra – either red, green, or blue. We estimated the models for all eight study-datasets together, to identify a general trend.

Table 2 reports the results of this analysis and generally confirms the above hypothesis. In particular, as the models’ pairwise comparison shows, differences between regression coefficients estimated for different RGB models are statistically significant for all the variables under analysis (P<0.01). The table also indicates that, in line with our initial research hypothesis, different RGB intensities are associated with different strength with different features in the panchromatic image and different land-use attributes.

In particular, as Table 2 shows, the panchromatic ALAN intensities contributes more to the Red and Green light emissions than to the Blue ones (M1: B=0.98, t=171.61; P<0.01 vs. M2: B=0.81, t=197.63; P<0.01 vs. M3: B=0.49, t=158.12; P<0.01). In addition, Blue spectrum intensities appear to be strongly and negatively associated with the average percent of built-up area (M3: B=-0.01, t=-4.90; P<0.01), while, in contrast, ALAN emissions in the Red and Green sub-spectra exhibit positive associations with land use percent (M1: B=0.15, t=32.77; P<0.01 and M2: B=0.05, t=16.68; P<0.01).

Furthermore, ALAN – Mean Diff. appears to be significantly and negatively associated with ALAN emissions in the Red and Green spectra, while its association with the Blue spectrum emissions is much weaker (M1: B=-0.67, t=-20.99; P<0.01 vs. M2: B=-0.39, t=-16.80; P<0.01 vs.
M3: \( B = -0.07, \ t = -3.80; \ P < 0.01 \). In addition, the ALAN – Max Diff. variable is positively and highly significantly associated with the Red and Green sub-spectra, while this variable is insignificant in the model, estimated for the Blue sub-spectrum (M1: \( B = 0.24, \ t = 26.78; \ P < 0.01 \) vs. M2: \( B = 0.13, \ t = 20.32; \ P < 0.01 \) vs. M3: \( B = 0.01, \ t = 1.41; \ P > 0.1 \).  

3.3 Factor contribution test

Since neither kernel regression nor elastic map models provide explicit estimates of the explanatory variables' coefficients, which multiple regression analysis enables (see Table 2), we implemented a different strategy, for a cross-model comparison. In particular, we estimated the relative contribution of individual factors, by removing each variable, once at a time, from the augmented model, while tracking changes in the strength of correlation between the observed and model-estimated RGB data. Figure 12 features the results of this test. As Figure 13 shows, the factor ranking appears to be similar in all types of the model, with ALAN intensity contributing most to \( \Delta r \) (\( \Delta r = 0.197 - 0.251 \) for linear regressions vs. \( \Delta r = 0.131 - 0.159 \) for kernel regressions vs. \( \Delta r = 0.180 - 0.203 \) for elastic map models), while HBASE-based predictors come second (\( \Delta r < 0.006 \) for linear regressions vs. \( \Delta r < 0.009 \) for kernel regressions vs. \( \Delta r < 0.126 \) for elastic map models), and inter-pixel differences emerge third (\( \Delta r < 0.010 \) for all model types).
Table 2: The association between ALAN intensities in different RGB bands and predictors from the VIIRS and HBASE datasets (Study area – all geographical sites together (N. of pixels/obs. = 33,846); method – ordinary least square regression (OLS); dependent variables – ALAN intensities in different parts of the RGB spectra) and significance of differences in the regression coefficients

| Predictors     | Models | Models’ comparison |
|----------------|--------|-------------------|
|                |        | M1 vs. M2 | M1 vs. M3 | M2 vs. M3 |
|                |        | ∆B  | SE    | Sig.  | ∆B  | SE    | Sig.  | ∆B  | SE    | Sig.  |
| (Constant)     | 3.34   | (8.93)*** | 2.09 | (7.77)*** | 5.49 | (27.35)*** | -   | -    | -    | -    | -    |
| ALAN           | 0.98   | (171.61)*** | 0.81 | (197.63)*** | 0.49 | (158.12)*** | 1.90 | 0.17  | 0.003 | 0.00E0 | 0.50 | 0.005 | 0.00E0 | 0.33 | 0.003 | 0.00E0 |
| ALAN – Mean Diff. | -0.67 | (-20.99)*** | -0.39 | (-16.80)*** | -0.07 | (-3.80)*** | 4.02 | -0.28 | 0.015 | 4.98E-75 | -    | 0.61  | 0.030 | 6.27E-92 | -0.32 | 0.016 | 2.64E-93 |
| ALAN – Max Diff. | 0.24   | (26.78)*** | 0.13 | (20.32)*** | 0.01 | (1.41)   | 3.31 | 0.11  | 0.004 | 7.06E-138 | 0.23 | 0.008 | 8.79E-171 | 0.12 | 0.004 | 3.39E-175 |
| HBASE – mean   | 0.15   | (32.77)*** | 0.05 | (16.68)*** | -0.01 | (-4.90)*** | 1.49 | 0.09  | 0.002 | 0.00E0 | 0.16 | 0.004 | 0.00E0 | 0.07 | 0.002 | 3.313E-194 |
| HBASE – SD     | -0.32  | (-24.24)*** | -0.13 | (-13.71)*** | -0.01 | (-1.06)   | 1.15 | -0.19 | 0.006 | 1.67E-191 | -    | 0.31  | 6.55E-142 | -0.12 | 0.006 | 3.64E-80 |
| \(R^2\)        | 0.67   | 0.70    | 0.57    |        |        |        |        |        |        |        |        |        |        |        |        |        |

Notes: B = unstandardized regression coefficients; \(t\) = \(t\)-statistics; \(VIF\) = variance of inflation; *, ** and *** indicate correspondingly 0.1, 0.05 and 0.01 significance levels.
Figure 13: Changes in the models’ performance ($\Delta r$), attributed to the exclusion of particular variables from the set of predictors, estimated separately for different model types (Study dataset: all metropolitan areas under analysis; N. of pixels/obs. = 33,846); the models are estimated separately for the Red (a), Green (b), and Blue (c) spectra)
4. Summary, discussion and conclusions

The present analysis tests the possibility of generating RGB information from panchromatic ALAN images, combined with freely available, or, easy-to-compute, land-use proxies. As we hypothesized from the outset of the analysis, since different land-use types emit night-time light of different intensity and spectrum, it might be possible to extract RGB information from panchromatic ALAN-images, coupled with built-up-area-based predictors.

To verify this possibility, we used ISS nighttime RGB images available for eight major metropolitan areas worldwide – Atlanta, Beijing, Haifa, Khabarovsk, London, Naples, Nashville, and Tianjing. In the analysis, three different modeling approaches were used and their performance mutually compared – multiple linear regressions, non-linear kernel regressions, and elastic map models. During the analysis, the dataset for each geographical site was used, once at a time, as a training set, while other datasets were used as testing sets. To assess the models’ performance, we used four different measures of correspondence between the observed and model-estimated RGB data: Pearson correlation, WMSE, contrast similarity, and consistency of the models’ performance for training and testing sets. In addition, we analyzed how different predictors influence the explained variance of Red, Green, and Blue ALAN emissions in different model types.

The analysis supports our research hypothesis about the feasibility of extracting RGB information from panchromatic ALAN images coupled with built-up-area-based predictors. Thus, as the study reveals, different RGB intensities appear to be associated with varying strength with different features of panchromatic ALAN images. In particular, as the multiple regression analysis shows, the association between panchromatic ALAN intensities appears to be stronger for Red and Green sub-spectra in comparison to the Blue sub-spectrum. This difference may be explained by a smaller overlapping diapason of the relative spectral sensitivities of the Blue channel (in comparison to
the Red and Green diapasons) of the DSLR cameras, used by ISS astronauts and that of the VIIRS/DNB sensor (see Fig. S1).

The regression coefficients for the mean and max ALAN-diff. indices also emerged with different strengths in different RGB models, being stronger for the Red and Green bands than for the Blue band. To understand these differences, we should keep in mind that ALAN-diff. can be negative for mean-difference, and positive for ALAN-max differences only if the following conditions are met simultaneously: (i) a pixel is, on the average, dimmer than the adjacent pixels, but is (ii) brighter than, at least, one of the neighboring pixels. Such a situation might happen if a pixel in question is located at the edge of a lit area. As a result, it may not stand out against its surroundings. Since Red and Green lights are more associated with moderately lit residential areas (unlike industrial and commercial facilities often lit by Blue light), we assume the mentioned effect is more pronounced in the Red and Green light models.

In addition, the built-up percent emerged positive in the Red and Green lights models, and negative in the Blue light model. Built-up area SD also emerged negative, being weaker in the Blue-light model than in the Red and Green light models. This phenomenon may also be attributed to the fact that Red and Green lights are more associated with densely and homogenously built residential areas, while Blue lights are more common in industrial and commercial areas, which are characterized by more sparse and heterogeneous built-up patterns. Kernel-based and elastic maps models generally confirm these associations.

Another important finding of the study is that different model types appear to differ in performance, when used to convert panchromatic ALAN images into RGB. In particular, as the study revealed, non-linear kernel regression models generally perform well in terms of Pearson correlation and WMSE for training sets, while multiple linear regressions outperform, in most
cases, other methods for testing sets. As we suggest, this difference is due to the flexibility of kernel regressions, which helps to fit the training data more precisely, while linear regressions fare better in capturing trends. Concurrently, elastic map models emerged, in most cases, as best-performing in terms of the contrast similarity index, accounting for local differences between RGB light intensities in the model-estimated and original images, both for training and testing sets. Given medium bending penalties, elastic map models also show better performance, compared to less and more bent counterparts, thus indicating diminishing benefits of under- and over-smoothing. It is also important to note that in terms of the consistency of model performance upon training and testing sets, elastic map models, built under predominantly medium bending penalty, fared better than other models.

To the best of our knowledge, this study is the first attempt to extract RGB information from panchromatic imagery, which determines its novelty. The importance of this result is due to the possibility of obtaining seamless RGB data coverage from panchromatic ALAN images, which are widely available today at various temporal frequencies. In its turn, generating RGB information from freely available or easy-to-compute information from panchromatic nighttime imagery and built-up area data might contribute to research advances in different fields, enabling more accurate analysis of various human economic activities and by opening more opportunities for ecological research. In particular, the panchromatic-to-RGB image conversion may also enable studies of different health effects, associated with ALAN exposures to different sub-spectra, such e.g., breast and prostate cancers. The conversion in question may also help to correct a bias in the light pollution estimates, obtained from panchromatic VIIRS/DNB ALAN imagery by widening their spectrum sensitivity diapason.
Several study limitations of the study are yet to be mentioned. *First and foremost*, VIIRS/DNB reports panchromatic ALAN intensities in physical units (nanoWatts/cm²/sr), while ISS-provided imagery reports raw data in digital numbers (DN), and, therefore, a direct comparison between the two might be problematic. However, since we do not mutually compare red, green, and blue light levels, but only compare each of them separately with panchromatic ALAN intensities, this consideration is less critical, and should not affect the results of our analysis substantially. Furthermore, as conversion of DNs into physical quantities should conform linear (or near-linear) transformation, our results are unlikely to be distorted by such a potential conversion. *Second*, our analysis revealed some peculiar cases which demonstrate relatively poor low applicability of our models to some test datasets. One example is the application of the models estimated for Haifa and Naples to Atlanta, for which high WMSE levels of red and green light levels for testing sets were reported (see e.g., Tables S5 and S8 in the SM section). This suggests that the proposed approach should be further refined. In particular, as we suggest, in future studies, other combinations of predictors can be tested, and outlier analysis can be improved, by using alternative procedures for data normalization, and experimenting with elastic maps’ pre-defined parameters. As we expect, these procedures will make it possible to obtain more robust results and thus to improve generic and area-specific algorithms used for predicting polychromatic ALAN intensities.

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Supplementary Materials Section

Box 1: Outliers Analysis Procedure

Outliers analysis was performed separately for each geographic site dataset. Proceeding from each variable distribution, we defined a cut-off point separating 99% of data. An observation was considered to be an outlier if either:

(i) It was beyond the cut-off point at the scale of at least one of the ‘predictors’ while being within the ‘normal’ interval at the scale of each of dependent\(^1\) variables;

(ii) It was beyond the cut-off point at the scale of at least one of the dependent variables while being ‘normal’ at the scale of each independent variable;

(iii) It was beyond opposite cut-off points (that is, upper/lower or lower/upper) at the scale of predictor and dependent variable under their positive bivariate association;

(iv) It was beyond same-range cut-off points (that is, upper/upper or lower/lower) at the scale of predictor and dependent variable under their negative bivariate association.

Thus, the percentage of excluded outlying observations varied from 2.92% for the Atlanta dataset to 3.90% for the Beijing dataset (see Table S1).

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\(^1\) We should emphasize that here and hereinafter the notes ‘dependent variable’, as well as ‘independent variable’ (or ‘predictor’), when applied to elastic map approach, are used figuratively. Elastic map is set of points, connected via edges and ribs, aimed at approximating points dataset in N-dimensional coordinate system, where N is number of input variables, no matter which of them is implied to be dependent variable.
**Figure S1:** Relative response of VIIRS/DNB sensor and Nikon D3 DSLR camera from the ISS

(Source: built from data obtained upon request from A. Sánchez de Miguel)
Figure S2: Examples of elastic maps (depicted by red network) built for the Haifa's blue light containing dataset (marked by blue dots) using varying bending regimes (see text for explanations): (a) 0.00001; (b) 0.0001; (c) 0.001; (d) 0.01; (e) 0.05; (f) 0.1; (g) 0.3; (h) 0.5, and (i) 1

Notes: The first three principal components (PC1, PC2, and PC3) are used as coordinates for the elastic maps' visualization. Fraction of total (by all six coordinates of the parameter space) variance unexplained (FVU) by elastic maps built under varying bending regimes are reported.
Table S1: Datasets representation: Number of observations and numbers of contributing points from middle-resolution HBASE layer and high-resolution RGB layer to each observation

| Dataset     | N. of observations (incl. N. of outliers in brackets) | Average N. of contributing points from HBASE image | Average N. of contributing points from RGB image |
|-------------|-----------------------------------------------------|--------------------------------------------------|-------------------------------------------------|
| Atlanta     | 5589 (163)                                          | 239.2                                            | 1663                                            |
| Beijing     | 6588 (257)                                          | 239.1                                            | 2080                                            |
| Haifa       | 685 (24)                                            | 239.0                                            | 3677                                            |
| Khabarovsk  | 3550 (133)                                          | 239.1                                            | 1433                                            |
| London      | 5148 (152)                                          | 239.1                                            | 1810                                            |
| Naples      | 1539 (55)                                           | 238.8                                            | 1472                                            |
| Nashville   | 5852 (172)                                          | 239.1                                            | 1576                                            |
| Tianjing    | 6044 (193)                                          | 239.1                                            | 1158                                            |
| Total       | 34995 (1149)                                        | 239.1                                            | 1669                                            |
Table S2: Descriptive statistics of research variables

| Variable | Minimum | Maximum | Mean |
|----------|---------|---------|------|
| **All datasets (n=33,846)** | | | |
| Red ALAN level, dn | 2.493 | 237.283 | 37.484 |
| Green ALAN level, dn | 1.779 | 198.602 | 26.843 |
| Blue ALAN level, dn | 2.522 | 180.178 | 17.860 |
| Panchromatic ALAN level, nanowatts/cm2/sr | 0.360 | 361.520 | 27.568 |
| Panchromatic ALAN (mean difference), nanowatts/cm2/sr | -37.499 | 174.290 | -0.025 |
| Panchromatic ALAN (max difference), nanowatts/cm2/sr | -152.750 | 268.780 | -3.737 |
| HBASE (mean), % | 0.000 | 100.000 | 76.272 |
| HBASE (standard deviation) | 0.000 | 43.991 | 9.788 |
| **Atlanta dataset (n=5,426)** | | | |
| Red ALAN level, dn | 2.949 | 201.203 | 25.235 |
| Green ALAN level, dn | 2.388 | 167.117 | 21.345 |
| Blue ALAN level, dn | 4.166 | 136.365 | 17.243 |
| Panchromatic ALAN level, nanowatts/cm2/sr | 2.640 | 357.470 | 32.261 |
| Panchromatic ALAN (mean difference), nanowatts/cm2/sr | -33.824 | 174.290 | -0.031 |
| Panchromatic ALAN (max difference), nanowatts/cm2/sr | -129.640 | 268.780 | -7.327 |
| HBASE (mean), % | 38.642 | 100.000 | 83.334 |
| HBASE (standard deviation) | 0.000 | 25.222 | 11.063 |
| **Beijing dataset (n=6,331)** | | | |
| Red ALAN level, dn | 2.493 | 184.672 | 41.140 |
| Green ALAN level, dn | 1.779 | 151.764 | 24.322 |
| Blue ALAN level, dn | 2.522 | 100.429 | 12.913 |
| Panchromatic ALAN level, nanowatts/cm2/sr | 1.160 | 115.870 | 25.876 |
| Panchromatic ALAN (mean difference), nanowatts/cm2/sr | -8.977 | 45.115 | -0.079 |
| Panchromatic ALAN (max difference), nanowatts/cm2/sr | -42.250 | 78.790 | -1.691 |
| HBASE (mean), % | 8.892 | 100.000 | 89.846 |
|                                | Haifa dataset (n=661) | Khabarovsk dataset (n=3,417) | London dataset (n=4,996) | Naples dataset (n=1,484) |
|--------------------------------|-----------------------|-------------------------------|--------------------------|--------------------------|
| HBASE (standard deviation)     | 0.000                 | 29.064                        | 4.946                    | 0.000                    |
| Red ALAN level, dn             | 5.686                 | 237.283                       | 73.389                   | 3.802                    |
| Green ALAN level, dn           | 5.686                 | 198.602                       | 58.030                   | 2.217                    |
| Blue ALAN level, dn            | 15.249                | 157.615                       | 40.651                   | 2.935                    |
| Panchromatic ALAN level, nanowatts/cm2/sr | 2.380               | 288.840                       | 55.450                   | 0.360                    |
| Panchromatic ALAN (mean difference), nanowatts/cm2/sr | -37.499           | 101.203                       | 0.216                    | -14.268                  |
| Panchromatic ALAN (max difference), nanowatts/cm2/sr | -152.750         | 179.620                       | -10.234                  | -60.490                  |
| HBASE (mean), %                | 14.633                | 99.904                        | 64.053                   | 0.000                    |
| HBASE (standard deviation)     | 0.000                 | 34.345                        | 12.504                   | 0.000                    |
|                                |                       |                               |                          |                          |
|                        |     |        |        |
|------------------------|-----|--------|--------|
| Red ALAN level, dn     | 8.900 | 197.201 | 80.248 |
| Green ALAN level, dn   | 6.587 | 191.646 | 63.354 |
| Blue ALAN level, dn    | 11.251 | 169.717 | 36.273 |
| Panchromatic ALAN level, nanowatts/cm2/sr | 4.800 | 159.820 | 46.287 |
| Panchromatic ALAN (mean difference), nanowatts/cm2/sr | -18.786 | 49.996 | 0.290 |
| Panchromatic ALAN (max difference), nanowatts/cm2/sr | -70.390 | 107.510 | -1.815 |
| HBASE (mean), %        | 5.979 | 100.000 | 84.457 |
| HBASE (standard deviation) | 0.000 | 33.648 | 12.047 |

Nashville dataset (n=5,680)
|                        |     |        |        |
|------------------------|-----|--------|--------|
| Red ALAN level, dn     | 4.784 | 210.018 | 31.819 |
| Green ALAN level, dn   | 4.287 | 189.544 | 24.478 |
| Blue ALAN level, dn    | 7.985 | 168.177 | 20.051 |
| Panchromatic ALAN level, nanowatts/cm2/sr | 0.630 | 361.520 | 21.483 |
| Panchromatic ALAN (mean difference), nanowatts/cm2/sr | -20.979 | 152.166 | 0.007 |
| Panchromatic ALAN (max difference), nanowatts/cm2/sr | -117.960 | 218.170 | -4.782 |
| HBASE (mean), %        | 1.688 | 100.000 | 71.797 |
| HBASE (standard deviation) | 0.000 | 30.919 | 9.019 |

Tianjing dataset (n=5,851)
|                        |     |        |        |
|------------------------|-----|--------|--------|
| Red ALAN level, dn     | 3.446 | 228.292 | 36.674 |
| Green ALAN level, dn   | 2.433 | 132.322 | 21.654 |
| Blue ALAN level, dn    | 2.998 | 52.529 | 10.245 |
| Panchromatic ALAN level, nanowatts/cm2/sr | 1.300 | 215.670 | 20.605 |
| Panchromatic ALAN (mean difference), nanowatts/cm2/sr | -11.671 | 79.840 | -0.005 |
| Panchromatic ALAN (max difference), nanowatts/cm2/sr | -55.160 | 147.140 | -2.373 |
| HBASE (mean), %        | 3.388 | 100.000 | 72.228 |
| HBASE (standard deviation) | 0.000 | 39.663 | 13.770 |

58
Table S3: Comparison of Linear, Kernel and Elastic map models performance upon training (Atlanta dataset) and testing sets

| Approach                  | Quality indicator |           | WMSE | Contrast similarity |
|---------------------------|-------------------|-----------|------|---------------------|
|                           |                   | Correlation |      |                     |
|                           |                   | Red light data | Green light data | Blue light data | Red light data | Green light data | Blue light data | RGB image    |
| Training set (Atlanta dataset) |                   | 0.819 | 0.803 | 0.749 | 0.808 | 0.888 | 0.294 | 0.910 |
| Linear regression         |                   | 0.811 | 0.788 | 0.725 | 0.875 | 0.919 | 0.243 | 0.952 |
| Kernel regression         |                   | 0.824 | 0.813 | 0.748 | 0.650 | 0.713 | 0.209 | 0.924 |
| Elastic map models ¹      |                   | 0.860 | 0.870 | 0.758 | 0.348 | 0.322 | 0.242 | 0.793 |
|                           |                   | 0.858 | 0.870 | 0.751 | 0.307 | 0.250 | 0.215 | 0.800 |
|                           |                   | 0.843 | 0.847 | 0.733 | 0.230 | 0.247 | 0.296 | 0.856 |
| Testing sets (Beijing, Haifa, Khabarovsk, London, Naples, Nashville, Tianjing datasets)² | | 0.860 | 0.870 | 0.758 | 0.348 | 0.322 | 0.242 | 0.793 |
| Linear regression         |                   | 0.858 | 0.870 | 0.751 | 0.307 | 0.250 | 0.215 | 0.800 |
| Kernel regression         |                   | 0.843 | 0.847 | 0.733 | 0.230 | 0.247 | 0.296 | 0.856 |
| Elastic map models        |                   | 0.860 | 0.870 | 0.758 | 0.348 | 0.322 | 0.242 | 0.793 |

Notes: ¹ For elastic map approach, the results of the best-performing model are reported; ² Averaged – across seven testing sets – levels are reported.
**Table S4:** Comparison of Linear, Kernel and Elastic map models performance upon training (Beijing dataset) and testing sets

| Approach                  | Quality indicator | Correlation | WMSE | Contrast similarity |
|---------------------------|-------------------|-------------|------|---------------------|
|                           |                   | Red light data | Green light data | Blue light data | Red light data | Green light data | Blue light data | RGB image     |
| **Training set (Beijing dataset)** |                   |              |      |                     |
| Linear regression         |                   | 0.879        | 0.885 | 0.784              | 0.220          | 0.196          | 0.109          | 0.985          |
| Kernel regression         |                   | 0.888        | 0.889 | 0.789              | 0.163          | 0.149          | 0.081          | 0.988          |
| Elastic map models ¹      |                   | 0.857        | 0.858 | 0.759              | 0.257          | 0.215          | 0.121          | 0.990          |
| **Testing sets (Atlanta, Haifa, Khabarovsk, London, Naples, Nashville, Tianjing datasets) ²** |               |              |      |                     |
| Linear regression         |                   | 0.848        | 0.856 | 0.755              | 1.149          | 0.582          | 0.246          | 0.963          |
| Kernel regression         |                   | 0.795        | 0.837 | 0.714              | 0.740          | 0.393          | 0.255          | 0.959          |
| Elastic map models        |                   | 0.812        | 0.808 | 0.671              | 0.865          | 0.524          | 0.273          | 0.961          |

**Notes:** ¹ For elastic map approach, the results of the best-performing model are reported; ² Averaged – across seven testing sets – levels are reported.
Table S5: Comparison of Linear, Kernel and Elastic map models performance upon training (Haifa dataset) and testing sets

| Approach                  | Quality indicator |             |             |             |             |             |             |
|---------------------------|-------------------|-------------|-------------|-------------|-------------|-------------|-------------|
|                           |                   | Correlation | WMSE        | Contrast similarity |
|                           |                   | Red light data | Green light data | Blue light data | Red light data | Green light data | Blue light data | RGB image |
| Training set (Haifa dataset) |                   |             |             |             |             |             |             |             |
| Linear regression         |                   | 0.861       | 0.887       | 0.845       | 0.558       | 0.370       | 0.091       | 0.964      |
| Kernel regression         |                   | 0.879       | 0.910       | 0.871       | 0.388       | 0.252       | 0.067       | 0.978      |
| Elastic map models ¹      |                   | 0.872       | 0.895       | 0.833       | 0.236       | 0.200       | 0.074       | 0.983      |
| Testing sets (Atlanta, Beijing, Khabarovsk, London, Naples, Nashville, Tianjing datasets) ² | |             |             |             |             |             |             |             |
| Linear regression         |                   | 0.820       | 0.847       | 0.730       | 4.223       | 2.979       | 1.669       | 0.931      |
| Kernel regression         |                   | 0.851       | 0.848       | 0.719       | 2.628       | 2.992       | 2.166       | 0.949      |
| Elastic map models        |                   | 0.826       | 0.840       | 0.721       | 1.852       | 2.281       | 2.004       | 0.952      |

Notes: ¹ For elastic map approach, the results of the best-performing model are reported; ² Averaged – across seven testing sets – levels are reported.
Table S6: Comparison of Linear, Kernel and Elastic map models performance upon training (Khabarovsk dataset) and testing sets

| Approach                      | Quality indicator | Correlation | WMSE | Contrast similarity |
|-------------------------------|-------------------|-------------|------|---------------------|
|                               |                   | Red light data | Green light data | Blue light data | Red light data | Green light data | Blue light data | RGB image |
| **Training set (Khabarovsk dataset)** |
| Linear regression             |                   | 0.879        | 0.882 | 0.788              | 0.223       | 0.230       | 0.093       | 0.978     |
| Kernel regression             |                   | 0.883        | 0.897 | 0.812              | 0.151       | 0.150       | 0.074       | 0.974     |
| Elastic map models \(^1\)    |                   | 0.881        | 0.887 | 0.804              | 0.198       | 0.214       | 0.086       | 0.986     |
| **Testing sets (Atlanta, Beijing, Haifa, London, Naples, Nashville, Tianjing datasets)** \(^2\)  |
| Linear regression             |                   | 0.846        | 0.858 | 0.758              | 0.400       | 0.338       | 0.226       | 0.858     |
| Kernel regression             |                   | 0.848        | 0.831 | 0.732              | 0.359       | 0.316       | 0.235       | 0.870     |
| Elastic map models            |                   | 0.812        | 0.828 | 0.710              | 0.424       | 0.409       | 0.245       | 0.901     |

Notes: \(^1\) For elastic map approach, the results of the best-performing model are reported; \(^2\) Averaged – across seven testing sets – levels are reported.
Table S7: Comparison of Linear, Kernel and Elastic map models performance upon training (London dataset) and testing sets

| Approach                  | Quality indicator |          |          |          |          |          |          |
|---------------------------|-------------------|----------|----------|----------|----------|----------|----------|
|                           |                   | Correlation | WMSE     | Contrast similarity |
|                           |                   | Red light data | Green light data | Blue light data | Red light data | Green light data | Blue light data | RGB image |
| **Training set (London dataset)** |                   |           |           |           |           |           |           |          |
| Linear regression         |                   | 0.857     | 0.862    | 0.778    | 0.336    | 0.279     | 0.169     | 0.956     |
| Kernel regression         |                   | 0.874     | 0.869    | 0.815    | 0.210    | 0.196     | 0.108     | 0.967     |
| Elastic map models ¹      |                   | 0.841     | 0.841    | 0.768    | 0.305    | 0.252     | 0.109     | 0.979     |
| **Testing sets (Atlanta, Beijing, Haifa, Khabarovsk, Naples, Nashville, Tianjing datasets) ²** | |           |           |           |           |           |           |          |
| Linear regression         |                   | 0.853     | 0.863    | 0.756    | 1.155    | 1.050     | 0.649     | 0.938     |
| Kernel regression         |                   | 0.826     | 0.860    | 0.678    | 0.575    | 0.623     | 0.761     | 0.935     |
| Elastic map models        |                   | 0.822     | 0.822    | 0.680    | 0.844    | 0.955     | 0.877     | 0.949     |

Notes: ¹ For elastic map approach, the results of the best-performing model are reported; ² Averaged – across seven testing sets – levels are reported.
**Table S8**: Comparison of Linear, Kernel and Elastic map models performance upon training (**Naples dataset**) and testing sets

| Approach                        | Quality indicator | Correlation | WMSE  | Contrast similarity |
|--------------------------------|-------------------|-------------|-------|---------------------|
|                                 |                   | Red light data | Green light data | Blue light data | Red light data | Green light data | Blue light data | RGB image |
| **Training set (Naples dataset)** |                   |              |       |                     |
| Linear regression               |                   | 0.866        | 0.874 | 0.687               | 0.211          | 0.257          | 0.126          | 0.985     |
| Kernel regression               |                   | 0.895        | 0.898 | 0.741               | 0.120          | 0.146          | 0.099          | 0.992     |
| Elastic map models¹             |                   | 0.875        | 0.872 | 0.646               | 0.112          | 0.129          | 0.091          | 0.992     |
| **Testing sets (Atlanta, Beijing, Haifa, Khabarovsk, London, Nashville, Tianjing datasets)**² |                   |              |       |                     |
| Linear regression               |                   | 0.825        | 0.824 | 0.704               | 3.740          | 4.588          | 2.391          | 0.937     |
| Kernel regression               |                   | 0.821        | 0.803 | 0.567               | 2.705          | 2.950          | 2.616          | 0.950     |
| Elastic map models              |                   | 0.822        | 0.818 | 0.728               | 2.620          | 2.716          | 2.261          | 0.953     |

Notes: ¹ For elastic map approach, the results of the best-performing model are reported; ² Averaged – across seven testing sets – levels are reported.
Table S9: Comparison of Linear, Kernel and Elastic map models performance upon training (Nashville dataset) and testing sets

| Approach                  | Quality indicator |          |          |          |          |          |          |
|---------------------------|-------------------|----------|----------|----------|----------|----------|----------|
|                           |                   | Correlation | WMSE     | Contrast similarity |
|                           | Red light data    | Green light data | Blue light data | Red light data | Green light data | Blue light data | RGB image |
| **Training set (Nashville dataset)** |                   |                         |                         |                         |                         |                         |          |
| Linear regression         |                   | 0.868     | 0.876    | 0.831    | 0.458    | 0.344    | 0.087    | 0.971    |
| Kernel regression         |                   | 0.900     | 0.900    | 0.833    | 0.246    | 0.224    | 0.073    | 0.982    |
| Elastic map models ¹      |                   | 0.878     | 0.883    | 0.821    | 0.288    | 0.242    | 0.069    | 0.983    |
| **Testing sets (Atlanta, Beijing, Haifa, Khabarovsk, London, Naples, Tianjing datasets) ²** | | | | | | | | |
| Linear regression         |                   | 0.836     | 0.851    | 0.748    | 0.995    | 0.949    | 0.872    | 0.921    |
| Kernel regression         |                   | 0.856     | 0.866    | 0.746    | 0.778    | 0.838    | 0.774    | 0.946    |
| Elastic map models        |                   | 0.816     | 0.826    | 0.717    | 0.839    | 0.886    | 0.789    | 0.951    |

Notes: ¹ For elastic map approach, the results of the best-performing model are reported; ² Averaged – across seven testing sets – levels are reported.
Table S10: Comparison of Linear, Kernel and Elastic map models performance upon training (Tianjing dataset) and testing sets

| Approach               | Quality indicator |                | WMSE       |                | Contrast similarity |
|------------------------|-------------------|----------------|------------|----------------|---------------------|
|                        |                   | Correlation    |            |                |                     |
|                        |                   | Red light data | Green light data | Blue light data | Red light data | Green light data | Blue light data | RGB image     |
| Training set (Tianjing dataset) |                   |                |            |                |                     |
| Linear regression      | 0.905             | 0.899          | 0.729      | 0.173          | 0.198              | 0.134              | 0.978          |
| Kernel regression      | 0.911             | 0.903          | 0.768      | 0.153          | 0.155              | 0.073              | 0.981          |
| Elastic map models ¹   | 0.878             | 0.871          | 0.726      | 0.358          | 0.399              | 0.128              | 0.987          |
| Testing sets (Atlanta, Beijing, Haifa, Khabarovsk, London, Naples, Nashville datasets) ² | |                |            |                |                     |                   |
| Linear regression      | 0.847             | 0.857          | 0.751      | 1.624          | 0.726              | 0.206              | 0.967          |
| Kernel regression      | 0.860             | 0.863          | 0.529      | 1.322          | 0.567              | 0.243              | 0.968          |
| Elastic map models     | 0.821             | 0.825          | 0.679      | 1.269          | 0.670              | 0.222              | 0.966          |

Notes: ¹ For elastic map approach, the results of the best-performing model are reported; ² Averaged – across seven testing sets – levels are reported.