Estimating the relationship between touristic activities and night light emissions

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**ABSTRACT**

The spatio-temporal dynamics of urban development can effectively be considered as a stepping stone for urban planning, decision-making and resource use and conservation. Consecutive satellite observations of night anthropogenic lighting and their profound study have provided beneficial estimators of both demographic and socio-economic dynamics. In the light of the above, the main aim of this paper is to examine the seasonal changes in night-time satellite images, and their correlation with the touristic activity in European Union (EU) countries. This study is conducted using 2012 and 2013 earth observation (night light imagery from Defence Meteorological Satellite Program (DMSP; yearly basis) and visible infrared imaging radiometer suite (VIIRS; seasonal basis) satellite programmes) and statistical data associated with the touristic activity (total nights spent) on a country level (NUTS 0). These data were processed using both remote sensing techniques, geographic information system (GIS) and statistical analyses (linear regression and geographically weighted regression (GWR)). The research results show that the night-time light emissions are highly correlated with the touristic activity and that the GWR proved to be an effective tool for the investigation of this relationship. However, a number of additional parameters should be further considered before determining the ability and the accuracy of the nightlight imagery in the assessment of the touristic activity.

**Introduction**

The depiction of human settlements and activities on a global scale, and the estimation of its dynamics, is a challenging process. Although the characteristics of urban areas can be derived from high-resolution satellite images, the creation of global maps on an annual basis – and even more on a seasonal basis, is not feasible taking into account both data collection and analysis.

The acquisition of socio-economic information in various spatial scales and in an accurate and standardized way is a challenge for in-depth policy analysis and decision-making. National and local authorities as well as the relevant European Union (EU) instruments (Directorates-General (DGs), European Economic Area (EEA), etc) require constant monitoring of the socio-economic development across EU, analysis of the influence factors and forecasting of the future trends. To this end, the developments in information technology and particularly in the domain of geographic information and earth observation systems provide a valuable asset towards the acquisition of comparable data for decision-making across EU.

Night-time images provide a continuous, relatively accurate, affordable and direct way to identify human activities and their spatial characteristics (Qingling, Levin, Chalkias, & Letu, 2015). Various studies have been published, highlighting the applicability of Defence Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) in monitoring spatial variations and temporal changes in an annual basis since 1992 (Chalkias, Petrakis, Psiloglou, & Lianou, 2005; Cinzano, Falchi, & Elvidge, 2001; Doll 2000, 2008; Elvidge et al., 2007, 2010, 2014, 2015, 2017; Ghosh et al., 2010; Huang 2014; Imhoff 1997; Letu, Hara, Tana, & Nishio, 2010; Lu 2008; Rayner, Raupach, Paget, Peylin, & Koffi, 2010; Small 2005; Sutton, 1997; Sutton, 2001). However, its coarse spatial (2.7 km) and radiometric resolutions (6-bit quantization) in combination with the lack of onboard calibration, the over-glow around urban areas, the saturation in the urban core and the poor geolocation, puts barriers in its applicability in certain research areas and/or in the accuracy of the results (Elvidge et al., 2017).

The Suomi National Polar-orbiting Partnership (S-NPP) satellite’s visible infrared imaging radiometer suite (VIIRS) day/night band (DNB) sensor retains important capabilities in the context of detecting and characterizing anthropogenic light sources. The availability of monthly radiometrically calibrated VIIRS DNB composites with higher spatial resolution (750 m) and digitization range (14 bit) over DMSP/OLS generates better results regarding the detection of temporal changes and trends in various phenomena (Miller et al., 2013).
One of the most important economic activities in EU that also falls under the scope of this paper is tourism. Tourism has a wide-ranging impact on economic growth, employment and social development, and it is considered as one of the key countermeasures in the fight against economic decline and unemployment (UNWTO, 2017). Any appraisal of its competitiveness requires a good knowledge of the volume of tourism, its characteristics, the profile of the tourist and tourism expenditure and the benefits for the European economies. Due to its importance, EU has developed an individual policy aiming others to maintain the Europe's positions as a leading tourist destination and to maximize the industry's contribution to growth and employment (EC, 2018). Various communications have been adopted by the Commission in the last decade. For instance, the communication on “A renewed EU tourism policy: towards a stronger partnership for European tourism” (European Commission (EC), 2006; COM (2006) 134 final) pursued to address the challenges that will shape the future of the tourism sector in EU to develop more sustainable and environmentally friendly tourism practices. The latter was followed by a set of actions in relation to the sustainable management of destinations, the integration of sustainability concerns by businesses and the awareness of sustainability issues among tourists (“agenda for a sustainable and competitive European tourism” (EC, 2006; COM (2007) 621 final)). In 2010, EC adopted a communication titled “Europe, the world’s No 1 tourist destination – a new political framework for tourism in Europe” (EC, 2006; COM (2010) 352 final) defining a new framework for actions to increase the competitiveness of tourism and its capacity for sustainable growth.

In addition, the Commission has developed a dedicated portal called Virtual Tourism Observatory (EC, 2018a) for collecting information and conducting analysis on performance and trends in the sector. The portal provides data visualizations as maps, tables or graphs regarding (i) the tourist demand in terms of change in arrivals accommodation establishments, (ii) changes in the employment of the status, (iii) net occupancy rate of rooms by month, (iv) distribution of nights spent at tourist accommodation establishments, (v) arrivals and expenditure of tourists from non-EU countries to the EU28 and (vi) nights spent at tourist accommodation establishments by region. The above-mentioned analysis is based mainly on data provided from Eurostat.

Tourism can be considered as the activity of visitors to travel to a destination outside their usual environment, for less than a year. Eurostat divides tourism statistics in those relating to capacity and occupancy of collective tourist accommodation and in those relating to tourism demand. In most EU Member States, the former information is collected via surveys filled in by accommodation establishments, while the latter are mainly collected via traveller surveys at border crossings or through household surveys (Eurostat, 2017). It must be highlighted that these acquisition mechanisms involve a great deal of cost and effort and that certain countries lack such information. Thus, at the moment, there is not a streamlined modelling framework to support the calculation of tourism statistics in EU countries and regions.

Our objective is to examine the seasonal changes in the brightness of night-time satellite images, as well as their correlation with socio-economic activities in EU countries. More specifically, the focus lies in the analysis of touristic activities and the investigation of the suitability of the above-mentioned earth observation products as a proxy variable for this domain. Moreover, the proposed analysis will contribute to the study of the seasonality of touristic activities as well as the investigation/reveal of possible arisen seasonal patterns (e.g. differences between summer and winter periods).

Acknowledging the need for easily applicable, efficient and low-cost collection of socio-economic data, international organizations such as the “World Bank” (WB), the “European Investment Bank” (EIB) and the Organization for Economic Co-operation and Development (OECD) identify the importance of the use of night-time lights images to measure and evaluate economic development (Mukim et al., 2013).

**Data and study area**

**Data**

The main sources of data for this study are the night lights as recorded by the VIIRS DNB sensor and the night lights as recorded by the DMSP-OLS sensor, which is the predecessor of VIIRS. A comparative analysis of their main characteristics is given in Table 1.

The substantial improvements of VIIRS images over the DMSP can be outlined to their higher level of quantization, their rigorous calibration and the existences of additional spectral bands useful for cloud, ocean and combustion source characterizations (Elvidge, Zhizhin, Baugh, & Hsu, 2015), while their limitations can be referred to the shorter time series and to the fact that a substantial number of images are affected by stray light.

In the context of this paper, DMSP night light images were obtained through the National Oceanic and Atmospheric Administration website. The two selected images (for years 2012 and 2013, respectively) concern the average visible, stable lights and
Table 1. Comparative analysis of the main characteristics of VIIRS and OLS sensor.

| Variable                      | DMSP-OLS                                      | SNPP-VIIRS                                   |
|-------------------------------|-----------------------------------------------|----------------------------------------------|
| Differences                   | From 1992 to 2018                             | From 2012-Present                            |
| Time series availability      | Sun-synchronous-polar-850-km altitude, 98.8° inclination, 102 min | Sun-synchronous-polar-827-km altitude, 98.7° inclination, 102 min |
| Orbit                         | Sun-synchronous-polar                        | Sun-synchronous-polar                        |
| Swath                         | 3000 km                                       | 3000 km                                      |
| Low-light imaging bandpass    | Panchromatic 0.5–0.9 µm                       | Panchromatic 0.5–0.9 µm                      |
| Night-time overpass           | −19:30                                        | −01:30                                       |
| Builder/operator              | US Air Force                                  | NASA-NOAA Joint Polar Satellite System (JPSS) |
| Ground footprint              | 5 km x 5 km at nadir                          | 742 m x 742 m                                |
| Spatial resolution            | 2.7 km                                        | 750 m                                        |
| Additional spectral bands     | Two spectral bands (visible and thermal infrared (TIR); 10 µm) | 21 additional bands spanning (11 at night/21 at day) 0.4–13 µm |
| Quantization                  | 6 bit                                         | 14 bit                                       |
| Saturation                    | Common in urban cores                         | No saturation                                |
| Calibration                   | None for low-light imaging band               | On-board solar diffuser used to calibrate daytime DNB data. Calibration is extended also to low-light imaging mode |

Cloud-free coverages. The pixel value has 6-bit radiometric quantification levels, with a range between 0 (no light) and 63 (Wei, Hongxing, Wei, Bailang, & Chunliang, 2014). The stable light image composites were produced by making a further cleaning up of the ephemeral light sources (e.g. fires, fishing boats, etc). Their characteristics refer to cloud-free composites, 30-arc second grids (approximately 1 km), −180° to 180° longitude and −65° to 75° latitude.

The 24 monthly images (covering the period from January 2012 to December 2013), of version 1 of the night-time VIIRS DNB, cloud-free composites and Tile 2 (75N/180W TO 0N/60W/) covering almost the entire Europe, were accessed through the same source. The images are produced in 15-arc second geographic grids. Each tile is actually a set of images containing average radiance values and numbers of available observations. DNB monthly composites are available in two different configurations: The first excludes any data affected by stray light (denoted as “vcm”), while the second includes these data if the radiance values have undergone the stray-light correction procedure (denoted as “vcmsl”). Due to the reduced quality of the “vcmsl” version, the first configuration was used in order to achieve better results in our seasonal monitoring application.

Statistical information used for this study was acquired by The Eurostat Dissemination Database, which provides official statistics for the EU. We made use of the available variable regarding the “Nights spent at tourist accommodation establishments by residents/non-residents (tin00171)” – Total nights spent,” in NUTS 0 level (country level), on a monthly basis, for the years 2012 and 2013, respectively (Eurostat, 2018). Taking also into account that nights are used to assess the flows of visitors (OECD, 2018), we consider that “total-nights spent” value can be used as a reliable index of “touristic activity” at a national scale (Papatheodorou & Arvanitis, 2014). It must be also taken into consideration that the statistical data are also affected by tax evasion (establishments which do not declare the real number of stays) and by current accommodation trends (such as Airbnb, couch-surfing), which do not make their data publicly available (Stathakis & Baltas, 2017).

Study area

Europe is selected as a study area for this analysis. According to EC (Eurostat, 2013), Europe is considered as a prominent tourist destination and world’s most visited region, holding approximately a 49% share of the global tourist arrivals in 2016 (UNWTO, 2017). Given also the fact that tourism, except for its operation as an engine of economic prosperity, is considered as a significant source of employment –especially in the Mediterranean region (EC, 2001) – and its rapid growth during the last 15 years (Stevenson, Aiery, & Miller, 2008), its study through the use of satellite products and its consideration as a proxy variable can provide policymakers and tourism industry with a comparative advantage in the way of defining new sustainable strategies.

Applied method

In this study, a two-step methodology is applied, for examining the seasonal changes in night images and their correlation with the touristic activity. The first step comprises a sequence of image-processing analyses of DMSP and VIIRS images, respectively, leading to the extraction of the sum of lights (SOL) index. The second step is related to the statistical analysis, using the linear and the geographically weighted regression (GWR). The aforementioned steps are thoroughly described in the following sections.

1The alphabetical part of the code stands for tourism industry, and it refers to the dataset identification code, which was used for this study (Eurostat, 2018).
Image processing

We started by projecting the images to the Lambert azimuthal equal-area (ETRS89-LAEA Europe; EPSG: 3035) system. DMSP images were then calibrated using a second-order polynomial regression model (1), and the intercalibration model coefficients (Table 2) of each image have been calculated by Galimberti (2017):

\[ \text{Image}_{\text{calibrated}} = C_0 \ast \text{Image}^2 + C_1 \ast \text{Image} + C_2 \] (1)

In order to avoid both the blooming effect and the light saturation problem, the digital number (DN) values of the calibrated images were based on the 6-bit (0–63) quantization. Thus, zero value pixels and pixels with a significant lower value (DN < 6) were discarded, and blooming effect was removed, and brightest pixels (DN = 63) were removed, and saturation problem was resolved. Given this, the threshold for the lowest value has been set to zero and for the highest to 63, for each of the two calibrated images.

For VIIRS, a mean algorithm is used to remove the abnormal lights (outliers) that may be associated with fires and gas flares. The maximum DN value of the five biggest EU28 cities (London (UK13), Berlin (DE30), Rome (ITI4), Paris (FR10) and Madrid (ES30)) was calculated and assigned as the threshold value, based on which the outliers will be removed (Tables 3 and 4). For pixels exceeding this threshold value, the mean algorithm is used, calculating the new value based on the surrounding pixel values in a 5 × 5 block area. However, the outliers of the image are not removed via this single application of the algorithm while they correspond to a quite small fraction of the whole image. While an option could be to set these pixels as not a number (NaN), it is preferred to iterate the algorithm multiple times (until the complete removal of the abnormal values) due to the fact that these pixels are located in the centre of large cities and it would be "un-natural” to have blank spots. Finally, the negative values of the images have been set up to 0.

Following this preliminary correction, two approaches are basically applied in the literature, in order to remove the background noise in DNB monthly composite data. The first one is referred as the noise masking method (NMM) and involves the removal of the background noise via a mask generated by DMSP/OLS stable lights that is applied to DNB composite data (Shi et al., 2014a, 2014b; Jing, Shao, Cao, Fu, & Yan, 2016; Li, Huimin, Xiaoling, & Chang, 2013). The DNB data are resampled to the same resolution as DMSP (30 arc seconds). Then, the pixels of DMSP stable lights with a positive value (DN > 0) are extracted in order to generate a mask. The pixels of the DNB data that fall outside the mask are set as NaN, while the pixel value is kept the same for pixels inside the mask (Jing et al., 2016). Following a similar approach, Li et al. (2013) multiplied the mask of DMSP/OLS data with the VIIRS image in order to derive noise-free VIIRS data.

The basic drawback of this method is the fact that relies on the DMSP stable lights to generate the mask. The lack of on-board calibration in combination with the saturation in areas of intense brightness and the blooming effect may lead to inaccurate results. In addition, the mask will exclude some low-light emission sources such as small towns and road features that the DNB product is sensitive enough to pick up.

Thus, Jing et al. (2016) introduced the optimal threshold method to remove background noise. This method relies on the use of an object function to determine the optimal threshold. Given the fact that DMSP/OLS studies have already proved the close relationship between the light intensity and the type of land use/cover, the latter attempt to use the

| Table 2. Intercalibration model coefficients. |
|-----------------------------------------------|
| Image  | C2 | C1 | C0 | R²  |
| F182012 | 1.6511 | 0.3815 | 0.0078 | 0.954 |
| F182013 | 1.5803 | 0.4479 | 0.0064 | 0.957 |

| Table 3. Maximum DN values for VIIRS monthly composites for 2012. |
|---------------------------------------------------------------|
| NUTS 2 areas | Apr | May | June | July | Aug | Sept | Oct | Nov | Dec |
|-----------------|-----|-----|------|------|-----|------|-----|-----|-----|
| UKI3            | 0   | 0   | 0    | 0    | 0   | 195.27 | 314.35 | 186.96 | 314.27 |
| DE30            | 0   | 0   | 0    | 0    | 0   | 250.75 | 109  | 768.23 | 123.29 |
| ES30            | 218.12 | 0   | 0    | 0    | 0   | 172.08 | 20.67 | 307.42 | 313.19 |
| ITI4            | 181.39 | 0   | 0    | 0    | 0   | 703.9 | 186.57 | 195.72 | 265.72 |
| FR10            | 0   | 0   | 0    | 0    | 0   | 264.44 | 202.49 | 223.72 | 265.72 |

| Table 4. Maximum DN values for VIIRS monthly composites for 2013. |
|---------------------------------------------------------------|
| NUTS 2 areas | Jan | Feb | Mar | Apr | May | June | July | Aug | Sept | Oct | Nov | Dec |
|-----------------|-----|-----|-----|-----|-----|------|------|-----|------|-----|-----|-----|
| UKI3            | 92.78 | 258.46 | 245.98 | 161.43 | 0   | 0    | 0    | 121.10 | 143.31 | 313.62 | 202.35 |
| DE30            | 39.31 | 96.08 | 160.02 | 0    | 0    | 0    | 0    | 145.17 | 74.07 | 126.06 | 130.06 |
| ES30            | 176.70 | 240.93 | 193.93 | 212.76 | 0   | 0    | 0    | 187.36 | 314.35 | 202.35 | 208.22 |
| ITI4            | 182.02 | 226.16 | 147.18 | 199.56 | 0   | 0    | 0    | 228.36 | 203.14 | 515.55 | 250.28 |
| FR10            | 259.88 | 321.85 | 225.55 | 230.82 | 0   | 0    | 0    | 250.28 | 250.28 | 250.28 | 250.28 |
correlation between light area and built-up area as the object function.

In the context of this analysis, the background noise will be removed via the well-established correlation of night light emissions with the population. The radiance values ranging from 0 to $1 \times 10^{-9}$ W/cm$^2$ sr and with pace of 0.1 are used as potential threshold values. Then, the SOL for each region is calculated for each of the selected threshold values. The correlation coefficient is calculated between the population of January 2013 and the EU countries. The threshold value with the highest $R^2$ is used to remove background noise. In our case, pixels with value smaller than 1 nW/cm$^2$ sr are removed from the monthly composites.

As mentioned before, a number of VIIRS monthly composites face the problem of being affected by stray light. As a consequence, composites of April, May, June, July, August and September contain pixels with no data, because of the solar illumination which affects the northern regions in summer (Zhao, 2017). Computational techniques were applied so as to forecast the no-data values in the images of the above-mentioned months.

In the context of this analysis, linear regression and exponential smoothing have been used and evaluated towards their applicability in calculating the missing values in the VIIRS imagery. The linear regression method is used to investigate the potential relationship between a variable of interest (often called the response variable, but there are many other names in use) and a set of one or more variables (known as the independent variables or some other term).

Forecasts are obtained via the use of a simple linear model (2) as follows:

$$Y = \beta_0 + \beta_1 x$$ (2)

where $x$ is the value of the predictor for which we require a forecast (i.e. pixels with known values) and $y$ is the value of the corresponding forecast (pixels with missing values).

When this calculation is done using an observed value of $x$ from the data, we call the resulting value of $y$ a "fitted value." This is not a genuine forecast as the actual value of $y$ for that predictor value was used in estimating the model, and so the value of $y$ is affected by the true value of $y$. When the value of $x$ is a new value (i.e. not part of the data that were used to estimate the model), the resulting value of $y$ is a genuine forecast (Hyndman & Athanasopoulos, 2013).

The second method implies the use exponential smoothing. Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In other words, the more recent the observation, the higher the associated weight. This framework generates reliable forecasts quickly and for a wide spectrum of time series which is a great advantage and of major importance to applications in industry. The simplest of the exponentially smoothing methods is naturally called "simple exponential smoothing" (SES). (In some books, it is called "single exponential smoothing.") This method is suitable for forecasting data with no trend or seasonal pattern (Hyndman et al., 2014). In the context of this study, the Holt–Winters exponential smoothing function was utilized.

Original monthly VIIRS DNB composites of January, February and March were stacked sequentially and then each pixel had three time series DN values applied. The following exponential smoothing (Equation (3)) described by Holt (2004) is used in the context of this analysis:

$$S_t = ax_t + (1-a)S_{t-1} (0 < a < 1)$$ (3)

where $x$ denotes an observation value (i.e. the radiance of a pixel in an original monthly VIIRS DNB image), $S$ represents a smoothed (or predicted) value, $t$ denotes a period (i.e. a month in this study) and $a$ is the smoothing factor. The above-mentioned equation demonstrates that in exponential smoothing, a new smoothed (or predicted) value $S_t$ is affected by a current observation value $x_t$ and the last period smoothed value $S_{t-1}$. Old observation values have an exponentially declined effect on the predicted value depending on period $t$. The value of $a$ determines the smoothing effect. Large values of $a$ (i.e. close to 1) contribute to a small smoothing effect, while smaller values of $a$ (i.e. close to 0) indicate that the prediction is influenced considerably by both current and the previous observations.

Usually, a region’s economic level and population in 1 month are closer to its adjacent months than in later/earlier months. For instance, night-time lights in April should be closer to the brightness levels of March than the ones in February or January.

Since in the original April image, only a portion of pixels suffer from no data values, a patched image for April was produced by combining the original and the estimated April image. The patched April image was added into the stacked images of January, February and March resulting in each pixel having four time series radiance values. The same process was repeated for the images of May and June. Following the same approach, the original images of December, November and October were sequentially stacked to produce a patched image of September. The patched image of September was added into the stacked images of December, November and October so as to produce a patched image of August. Similarly, the image of July was calculated.
To support the evaluation of the Holt–Winters forecasting method, the image of April 2013 is calculated for the Municipality of Athens, as also performed in the linear regression. A visual comparison between the forecasted images from exponential smoothing and linear regression and the original image can be achieved in Figure 1.

It seems that the linear regression method provides results closer to the original image of April than the one of exponential smoothing. However, in order to obtain more accurate results, the Pearson correlation is calculated for each of the forecasted images with the original image (Table 5). In particular, a set of 100 random points was created in which values of cells from the three images were stored, for the defined locations. The linear regression appears higher values of $R^2$ (0.9142) in comparison with the Holt–Winter’s exponential smoothing. Thus, the linear regression method is used for the calculation of no-data values in the monthly composites.

For the calculation of the final images, the linear regression method has been applied. Thus, forecasted and patched images for April, May, June, July, August and September were produced for the preprocessed monthly composites. The new produced monthly composites were resampled to the cell size (436 × 436) of the existing raster images. The new produced composites were constituted both from the new forecasted pixel values and the existing ones – where available – using raster mosaic techniques.

The last step of this process was the calculation of the SOL index (both for DMSP and VIIRS images) within the zones of European countries (NUTS 0 level). SOL was calculated per country, both on a yearly basis and on a semester (6-month) basis for the years 2012 and 2013, respectively.

**Statistical analysis**

Exploring the possibility of using night light imagery as a proxy for monitoring touristic activities demands the implementation of regression models that will establish the relationship between SOL index and the variables under investigation. Regression analyses attempt to show the degree to which one or more variables can potentially cause positive or negative

![Figure 1](image)

**Figure 1.** Visual comparison of the forecasted images from exponential smoothing and linear regression with the original image (in DN values).

**Table 5.** Evaluation of the exponential smoothing and linear regression models – calculation of Pearson correlation.

| Variables          | M042016_Original | M042016_Exponential Smoothing | M042016_Linear Regression |
|--------------------|------------------|------------------------------|--------------------------|
| M042016_Original   | 1.00             | 0.89                         | 0.91                     |
| M042016_Exponential Smoothing | 0.89             | 1.00                         | 0.96                     |
| M042016_Linear Regression | 0.91             | 0.96                         | 1.00                     |
change in another variable (Murak, 2013). The commonly used linear model (4) is adopted (Darlington & Hayes, 2017):

\[ Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_kX_k + e \] (4)

where \( Y \) is the dependent variable that we are trying to predict or understand (in our case the total nights spent), \( X \) is the independent variable of the model (the SOL index), \( b_0 \) is the regression constant (also called Y intercept), \( b \) are the regression coefficients or simply the regression weight that determines how much the equation uses values on that variable to produce an estimate of \( Y \) and \( e \) is the random error (residuals) that indicates the unexplained portion of the dependent variable.

Since the derivation of the regression equation is based on minimizing the sum of the squared residuals, this method is called ordinary least squares regression or just OLS regression. In OLS regression, the distribution’s spread is measured via the standard deviation, while the correlation between \( X \) and \( Y \) is calculated via the Pearson correlation coefficient. The Pearson correlation coefficient (5), or simply the correlation, between \( X \) and \( Y \) is defined as the covariance of \( X \) and \( Y \) divided by their standard deviations.

\[ r_{xy} = \frac{Cov (X,Y)}{S_X S_Y} \] (5)

To further examine the spatial heterogeneity and the variance of the residuals, a local model, namely a GWR model, with adaptive spatial kernels has been employed. The GWR is the first alternative approach to overcome the lack of spatial stability (Fotheringham & Charlton, 1998). It is a variation of single or multiple linear regression. Its difference lies in the fact that the observations are weighted by their geographic location. This is in superscale as a direct result in the analysis of classical regression while in the GWR in local scale (Fotheringham, Brunsdon, & Charlton, 2002; Milaka, 2010). The formula of the GWR is as follows:

\[ Y_i = \beta_0 i + \sum_j \beta_{ij} \rho_i j + e_i \] (6)

where \( \rho_i \) is the geographic location of observation \( i \). A fundamental idea of GWR is the calculation of the parameters \( \beta_{ij} (\rho_i) \) for each variable \( j \) and for each spatial unit \( i \) (summed \( \beta_{ij} \)) (Fotheringham et al., 2002). The Akaike Information Criterion (AIC) method is used to calculate the bandwidth. The input features (dependent and explanatory variables) are the same with those specified in the OLS models.

**Results**

A cross-sectional (linear) regression analysis has been applied for defining the correlation between the SOL of DMSP images and the variable of “total nights spent in a place” on an annual basis (for 2012 and 2013, respectively). The calculated Pearson correlation (0.94 for 2012 and 0.93 for 2013) indicates the positive correlation of the examined variables and implies that a liner equation describes the relationship between the examined variables.

The \( R \) value (coefficient of correlation) represents the simple correlation and is 0.943 (for 2012) and 0.939 (for 2013), which indicates a very high degree of correlation between the examined variables. The \( R^2 \) (coefficient of determination) indicates the percentage of variability of SOL interpreted by the model. Possible values range from 0 to 1. Values closer to 1 indicate that the model has a better predictive character. In our case, this percentage is 89% (for 2012) and 88% (for 2013), which is very high too. Results from the statistical analysis using IBM SPSS, indicate that the regression model predicts the depended variable, significantly well (\( p = 0.0000, p < 0.0005 \)), and there is a positive correlation between the two variables (\( b_1 = 130 \) for 2012 and \( b_1 = 124 \) for 2013). A schematic presentation of the linear regression model using the OLS (Figures 2 and 3), indicates also the absence of a specific structure (e.g. grouping) in overestimations (areas depicted in the shades of red colour) and in underestimations (areas depicted in the shades of blue colour), thus the satisfactory performance of the model is depicted.

For further examination of the spatial relationships and exploration of potential geographical heterogeneous, Morani’s \( I \) index has been calculated. When the index gets values higher than 0, then the set of observations shows a grouped spatial pattern, while for less than 0, a scattered pattern is presented. Given the \( z \)-score of 1.5274 (for April–September 2012), there is a less than 10% likelihood that this clustered pattern could be the result of random chance. Also, the \( z \)-score of 1.8931 (for October–March 2012) indicates that there is a less than 10% likelihood that this clustered pattern could be the result of random chance. However, for October–March 2013 although the given \( z \)-score of 1.5274 reflects a pattern which
Figure 2. Ordinary least squares for SOL 2012 (predictor variable) and total nights spent (response variable) – (residuals) using DMSP.

Figure 3. Ordinary least squares for SOL 2013 (predictor variable) and total nights spent (response variable) – (residuals) using DMSP.
does not appear to be significantly different from random, the $R^2$ (68%) indicates not quite high degree of correlation between the examined variables.

**Interpretation of results**

Individual results of local $R^2$, which indicate how well (values close to 1.0) the local regression model fits observed $y$ values (values close to 0.0 indicate that the local model is performing poorly), are presented in Table 7.

Following the execution of GWR, higher values of the local coefficient of determination $R^2$ are depicted in the southern countries of Europe for both the summer and winter periods; this indicates that the method performs better in Southern Europe rather than in Northern Europe. These values are systematically higher for the summer period analysis indicating stronger correlation during the summer period, while relatively lower values of local $R^2$ are observed in north Europe (Figure 4–7).

The diagnostic statistics, which are derived from ArcGIS and IBM SPSS, provide a good indication of the existence of possible goodness of fit of the model. Any spatial dependences which were presented in the residuals in the global model have been removed with the geographical weighting in the local model (Moran’s $I$ index). The local $R^2$ takes slightly higher values, and this is a good token of improvement in the model performance. Also, by comparing the global model’s AICc value with the local model’s AICc value, it is evident that in three of the four cases, the lower values in the local model depict a strong evidence of an improvement in the fit of the model to the data, namely a better performance for the local model. This improvement can also be statistically supported and verified by the calculated Moran’s $I$ index in the local model, which shows lower variances and higher probabilities of random distribution (p-values and z-scores).

The relationship between nights spent in a place and DMSP generated SOL is positive, suggesting areas with higher SOL are related to touristic activities, in terms of nights spent in these areas. The global model of VIIRS appears to follow this positive correlation between the examined variables. Besides, the local regression model shows that this relationship is stronger in Southern Europe during the summer, where there is a peak in touristic activity. From the above, it seems that the association between touristic activities and night-time emissions, although evident, is not homogeneous in both spatial and temporal terms.

Seasonality of touristic activity can be captured by seasonal night light images. Further to this, results also show that the nights spent in a place have better correlation with SOL during the summer period (April–September), in comparison with the winter period (January–March and October–December), where the correlation is lower (<80%) but still in high level.

**Conclusions**

In this study, we investigate the seasonal changes in the brightness of night-time satellite images, as well as their correlation with the touristic activity in EU countries. Using a linear regression model, DMSP examination on a yearly basis showed a strong positive relationship between the variables under investigation. VIIRS global examination showed that the positive relationship still exists on a semester (6-month) basis, but the level of correlation is different between the winter and summer periods. The local model (GWR) in VIIRS produced better results in terms of goodness of fit of the model and residuals independency than the global model (OLS). Also, from the local regression analysis, it can be assumed that the model works better for the South Europe.

**Recommendation and future research**

It is worth mentioning that in future researches, possible use of complete data series of light emission (without forecasted images), as well as the simultaneous investigation of other variables (such as population and/or gross domestic product (GDP) or energy

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**Table 6. OLS statistical results for VIIRS 2012 and 2013.**

| Indexes | Summer period 2012 | Summer period 2013 | Winter period 2012 | Winter period 2013 |
|---------|--------------------|--------------------|--------------------|--------------------|
| $R^2$   | 0.82               | 0.72               | 0.65               | 0.68               |
| Pearson | 0.90               | 0.87               | 0.83               | 0.87               |
| Moran’s $I$ | 0.129808          | 0.107529          | 0.064978           | 0.045629           |
| z-score | 3.076078           | 2.662905           | 1.893164           | 1.527449           |
| p-value | 0.002097           | 0.007747           | 0.058386           | 0.126649           |
| AICc    | 1030.53            | 1038.11            | 1000.44            | 1003.37            |

**Table 7. GWR statistical results for VIIRS 2012 and 2013.**

| Indexes | Summer period 2012 | Summer period 2013 | Winter period 2012 | Winter period 2013 |
|---------|--------------------|--------------------|--------------------|--------------------|
| $R^2$   | 0.32–0.92          | 0.31–0.95          | 0.30–0.88          | 0.29–0.86          |
| Moran’s $I$ | 0.051305         | 0.029315           | 0.013380           | -0.004890          |
| z-score | 1.610853           | 1.198801           | 0.930152           | 0.574600           |
| p-value | 0.107212           | 0.230605           | 0.352292           | 0.565562           |
| AICc    | 1497.048           | 1023.79            | 997.57             | 1001.17            |
Figure 4. Mapping of local $R^2$ for summer (April–September) period 2012, using VIIRS SOL 2012 predictor variable and total nights spent response variable.

Figure 5. Mapping of local $R^2$ for summer (April–September) period 2013, using VIIRS SOL 2013 predictor variable and total nights spent response variable.
Figure 6. Mapping of local $R^2$ for winter (January–March and October–December) period 2012, using VIIRS SOL 2012 predictor variable and total nights spent response variable.

Figure 7. Mapping of local $R^2$ for winter (January–March and October–December) period 2013, using VIIRS SOL 2013 predictor variable and total nights spent response variable.
consumption), could interpret better the relationship between the examined variables and could give better results in the assessment of the model. Besides considering also that the examined socio-economic variable (total nights spent) has a strong relationship with the space, a further investigation of its correlation with the SOL index is highly recommended, by taking into account categories of areas around Europe (geographical heterogeneity), for example, North and South Europe, large cities (inland) and coastal zones, and/or examining the level of their correlation in other spatial classification (e.g. NUTS 1 or NUTS 2). Thus, a stratified more detailed spatially analysis could provide more reliable results.

In addition, the existence of other parameters that affect the recording of night light emission sources (such as albedo, land cover, etc) (Liang et al., 2005) should also be investigated, in order to determine and specify the ability and the accuracy of the night light imaginary in the assessment of the touristic activity.

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No potential conflict of interest was reported by the authors.

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