Analysis of Spatiotemporal Patterns of Changes in Brightness of Nighttime Lights (NTL) in the Former USSR Territory

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***Abstract*—The distribution of brightness of nighttime lights (NTL) at the Earth’s surface in the visible band of the electromagnetic spectrum is a new forward-looking data source for socio-economic studies. Visual and statistical analysis of this distribution in time and space requires new mathematical and geo-informational methods of cooperative processing of many raster images and vector data (geographical maps) together with socio-economic analytics. The current research develops new means of the spatiotemporal analysis, reveals basic problems of applied monitoring, and outlines forward-looking approaches to their solution.**

Keywords - remote sensing, nighttime lights, data mining, big data, spatio-temporal analysis, socio-economic applications.

I. SPATIOTEMPORAL PATTERNS OF NTL DYNAMICS

Basic data for the applied analysis of changes in Nighttime Lights (NTL) in the visible spectrum are received in the form of a continuous sequence of images from two constellations of American low-Earth-orbit heliosynchronous meteorological satellites DMSP and JPSS with a 1 km spatial resolution ([1], [2]). Monthly maps of the mean brightness of cloudless and moonless NTL created on the basis of VIIRS/DNB data were used for the analysis of statistics of changes in urban NTL.

Figure 1 demonstrates an example of a monthly brightness distribution map of Moscow in the DNB channel. Yellow color corresponds to pixels with higher brightness, blue – to pixels with lower brightness.

In order to create the map, the data range was compressed with the use of a logarithmic function. The obtained image was laid over a map in the Google Earth application. The map contains several distinct large objects: the Kremlin and city center are much brighter even after a logarithmic compression; blue color corresponds to large forest parks; major highways are clearly visible. Nevertheless, it is clearly seen that the borders of districts with high and low brightness are blurred. It is associated with the spatial resolution of images and the fact that detection coordinates (the center of a pixel in which the light source is reflected) differ from the coordinates of the source itself, so in the course of several flyovers one and the same light source corresponds to a “cloud” of detections with different coordinates.

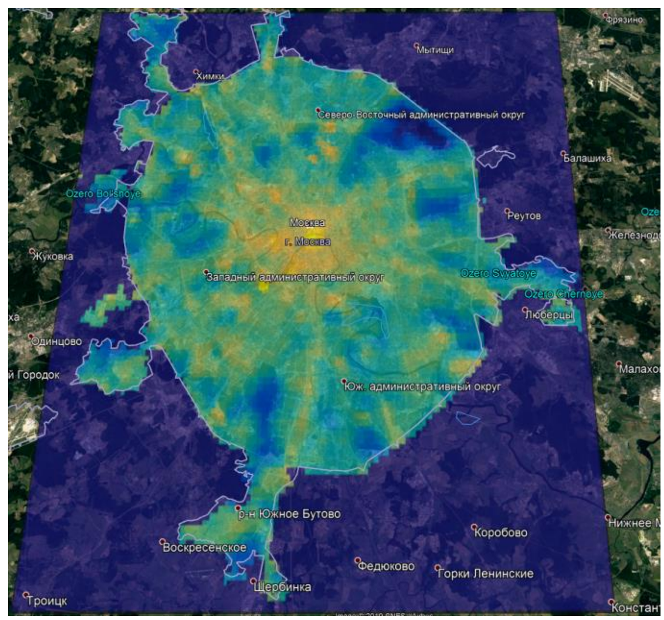

Figure 1. Brightness distribution maps of Moscow in the VIIRS / DNB spectrum channel.

Figure 2 demonstrates an example of a time sequence of the mean brightness value of pixels obtained in Moscow, that was formed starting from January 2017 till July 2019. The graph is characterized by the absence of indications in several summer months because of sunlight contamination in the satellite images and an abnormal increase in brightness during winter months because of snow [3]. Manual exclusion of abnormal indications can ensure more precise results but has two significant drawbacks:

1) Subjectivity of the analysis. Different specialists can keep different months and consequently obtain different trends. It is hard to answer which trend is the right one and which is not;

2) Labor intensity. If it is necessary to analyze several hundreds of cities, manual exclusion of indications will require large labor inputs.

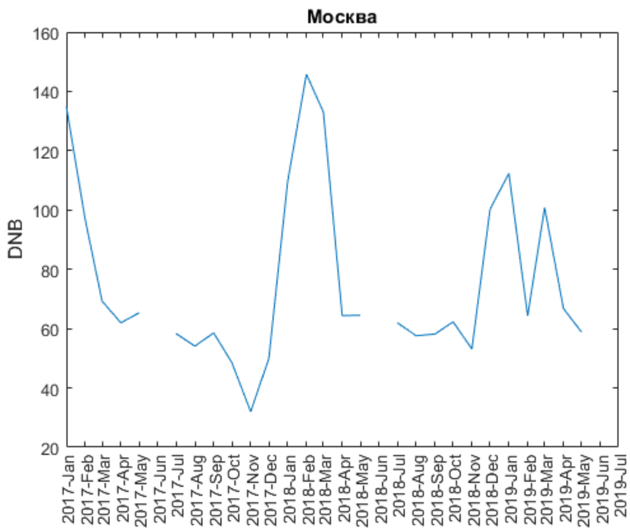

Figure 2. Time sequence with monthly intervals formed by averaging brightness indications of all pixels in the DNB channel that correspond to Moscow.

II. OUTLIER REMOVAL IN NTL DYNAMICS

We have automated the outlier removal with the help of the RANSAC algorithm [4]. The algorithm includes two basic steps: generation of a hypothesis and its testing. In the generation step, a random subset is chosen from the whole sample of data. It is supposed that the chosen subset does not contain any abnormalities. Optimal model parameters are selected for the chosen subset. The class of the model is defined beforehand. For example, if it is a linear model of the form $ax + by + c = 0$, it is necessary to evaluate the coefficients a, b and c.

In the testing step, all points of the input sample are tested for abnormality. The process of testing depends on the examiner. For example, in the case of a linear model, it can be fulfilled on the basis of the distance between the point and the line of the examined model: if it is larger than a given parameter, then the point is considered abnormal.

Once all points are tested for belonging to the model, the overall number of abnormal points is estimated. If at this iteration the number of abnormalities is the smallest one among all previous iterations, the result is saved as an intermediate one. If the number of iterations has not reached the limit (indicated by the examiner), a new iteration begins; otherwise, the intermediate result returns.

Thus, while using RANSAC, it is necessary to define a set of parameters including:

- Model on the basis of which the data will be evaluated;
- Metric for the separation of points in the corresponding models and abnormalities;
- Number of iterations sufficient for the construction of a consistent model.

In this case, we selected a linear model and used the distance between the point and the line as an abnormality filtration metric defined by the following formula:

$$TH = 9 \times \frac{STD}{STD\_M}, \quad (1)$$

where *TH* stands for the admission threshold, *STD* defines the root mean square deviation of the time sequence of the mean brightness indications of the examined city, and *STD_M* is the root mean square deviation of the time sequence of the mean brightness indications of Moscow.

The result of the RANSAC algorithm application for Moscow are demonstrated in figure 3. Indications belonging to the model are marked by green points and the red line shows the linear trend.

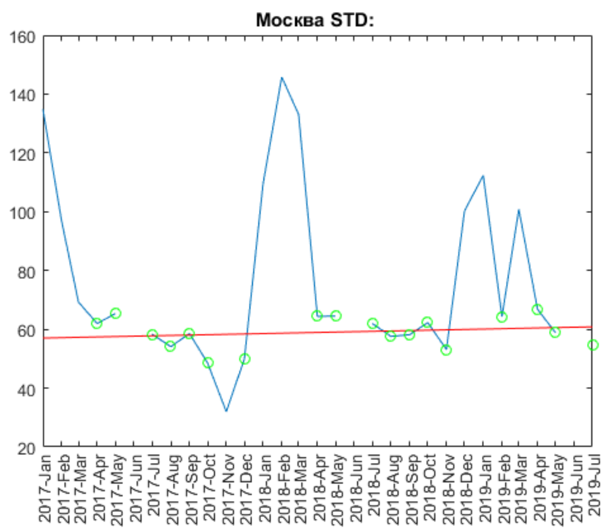

Figure 3. Results of the RANSAC algorithm application for Moscow (excluding Novomoskovsky Administrative Okrug, Troitsky Administrative Okrug, and Zelenogradsky Administrative Okrug).

Figure 3 demonstrates that the algorithm excluded those points that corresponded to the increase in urban brightness in winter. However, apart from brightness increase, the observations from November 2017 were also excluded due to a downturn in the signal level, possibly due to the low cloud free coverage. The reason for such a significant downfall requires further examination but whatever it is, the question arises as to whether such months should be excluded from the calculations.

In this case, a long time period is examined and the linear trend is consequently defined, so it is implied that the analysis is long-term and the changes are gradual. In this regard, it seems logical to exclude both upward and downward abnormalities in the signal level.

III. Statistical analysis of NTL Dynamics

A detailed analysis of changes in NTL over time can be carried out with the help of time sequences that are obtained by summing up and averaging the light sources' brightness in a limited region over a short period of time.

Mean brightness of the Nighttime Lights (MNL) indicates the mean level of artificial lighting in the examined area. For integral quantization values of the brightness of the DMSP / OLS sensor it is defined by the formula:

$$MNL_{OLS} = \frac{\sum_{i=0}^{63} C_i DN_i}{\sum_{i=0}^{63} C_i}, \qquad (2)$$

where DN_i is the i-th level of brightness ($i = 0–2^6$) in a DMSP/OLS image, C_i stands for the number of pixels that correspond to the given brightness color within the examined region.

Figure 4 demonstrates a time sequence of indexes of the annual mean radiance MNL_{OLS} in the vicinity of the city of Grozny for the period from 1992 to 2013. DN_i images from different satellites F10 — F18 were compared with the use of cross-calibration according to the method [5]. The graph demonstrates downfalls in the brightness of the nighttime radiance during the First and the Second Chechen Wars and a stable positive trend in the postwar reconstruction period.

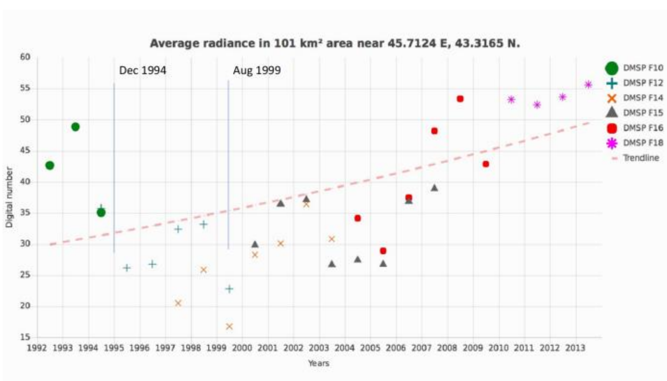

Figure 4. Time sequence of indexes of annual mean radiance MNL_{OLS} in the vicinity of the city of Grozny, the Chechen Republic for the entire period of digital registration of nighttime images from the DMSP satellites from 1992 to 2013.

To compare the time series of the NTL brightness in different regions, we use an index calculated on the map of NTL in an equal area projection (Area Corrected Total Nighttime Lights, ACTNL). ACTNL is used to compare the total brightness of night lights in regions located at different latitudes.

We need to adjust the pixel area because the NTL are mapped on the grid with a regular 15 arcsec step in latitude and longitude. The choice of step is determined by the spatial resolution of the DNB channel of the VIIRS sensor, equal to 750 × 750 m, which is about 20 arcsec at the equator [1]. A grid cell area of a fixed angular step will change with latitude when moving from angular to metric coordinates according to the law of cosine (decrease from the equator to the poles). Therefore, to correctly compare the total brightness of regions with equal area, but located at different latitudes, you have to introduce the trigonometric correction::

$$ACTNL_{DNB} = \sum_{i \in R} \cos\left(\varphi_i\right) DNB_i, \qquad (3)$$

where φ_i defines the latitude at which the pixel with the index i is located within the region R on the map that is constructed in the latitude-longitude projection.

We illustrate the potential of using the $ACTNL_{DNB}$ index for the analysis of regional socio-economic dynamics with changes in the total brightness of night lights from 2012 to 2018 in three cities of Ukraine: Kiev, Donetsk and Lugansk. Due to the possible straylight in the DNB sensor at these latitudes in summer, the analysis was carried out only for the mean brightness of lights calculated for the months when no-straylight, cloud free, and low moon satellite images were available for each city.

The vector boundaries of cities within which the monthly $ACTNL_{DNB}$ index was calculated are shown in Figure 5. It also shows the time series of indices and their mean values for the period before and after the outbreak of armed conflict in eastern Ukraine in May 2014, in the zone of which Donetsk and Lugansk did fall, but Kiev did not. The results of the analysis are summarized in table 1.

We use Student's t-test to estimate the significance of changes in the mean values of the $ACTNL_{DNB}$ index before and after the outbreak of armed conflict in the Donbass. The null hypothesis assumes that the mean values for the monthly $ACTNL_{DNB}$ indices in the periods of time before and after the start of the conflict are equal. In other words, that the total brightness of the city lights has not changed. As follows from table 1, the null hypothesis is confirmed only for Kiev: despite a small negative trend, the average brightness before and after May 2014 can be considered unchanged. We get a different result for the total brightness of the lights in Donetsk and Lugansk. Here, with a confidence of 99.999%, a stepwise decrease in brightness is observed right after the outbreak of the military conflict in proportions of 0.6 and 0.47, respectively, to the pre-war level.

TABLE I. Mean values of the $ACTNL_{DNB}$ index and leaps in the mean values before/after May 2014

City	Mean $ACTNL_{DNB}$ before May 2014, nW	Mean $ACTNL_{DNB}$ after May 2014, nW	Ratio of $ACTNL_{DNB}$ before and after	Significant difference	Level of statistical significance, %
Kiev	10442	9432	0,90	No	29
Donetsk	4629	2779	0,60	Yes	99,9999
Luhansk	959	448	0,47	Yes	99,9999

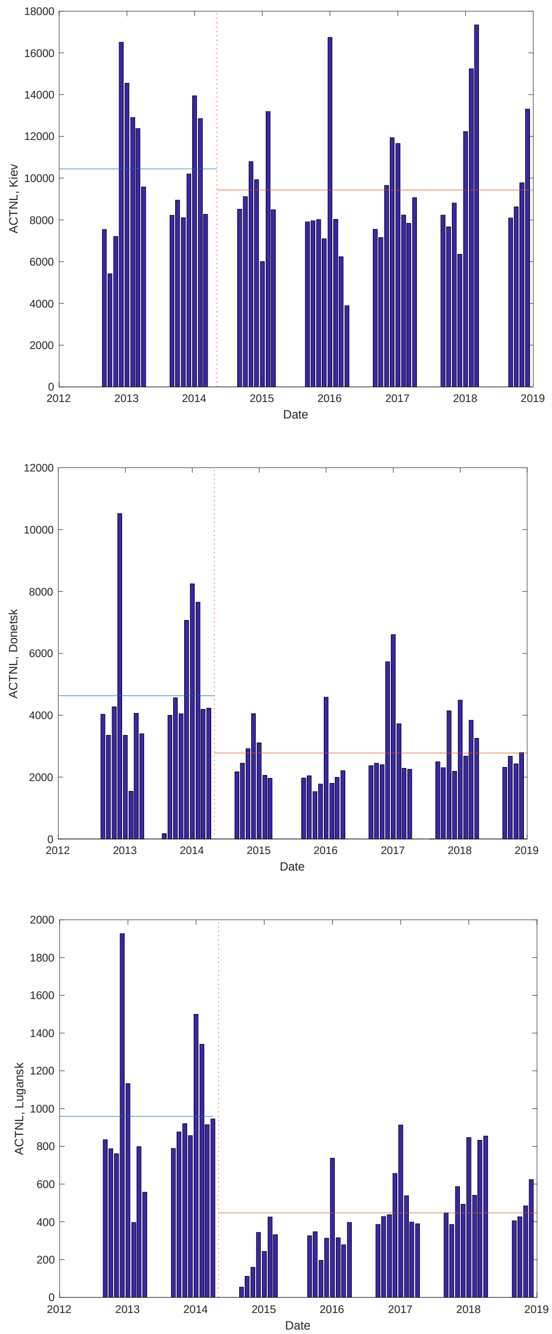

Figure 5. Study of the monthly $ACTNL_{DNB}$ indices for Kiev (top), Donetsk (middle) and Lugansk (bottom) from 2012 to 2018. Summer months with interference from straylight in the VIIRS sensor are excluded.

Changes in the total brightness of nighttime lights are consistent with regional macroeconomic changes due to conflict. Macroeconomic estimates were obtained by German scientists Julia Bluszcz and Marica Valente in their work “The War in Europe: Economic Costs of the Ukrainian Conflict” [6], which used the “potential opportunities” approach to assess the impact of armed conflict in Ukraine on the GDP.

The proposed approach is based on their Synthetic Control Method (SCM) developed in 2003 and refined in 2010. The authors assess the impact of armed conflict on GDP by determining the difference in the values of GDP before and after the war, extrapolated to years after the war. For this, a control group of countries not involved in the armed conflict is taken, and all parameters of the country under study (in this case, Ukraine) before the conflict are expressed through the parameters of these countries. It is further assumed that this ratio of parameters between Ukraine and the control group would have to be maintained in subsequent years if it were not for the armed conflict, and all changes in the found ratio were caused solely by military operations.

Results from the counterfactual estimation by the synthetic control method indicate that the Donbass war led to a considerable decline of Ukraine’s economy. Namely, authors estimate that, due to this war, the country’s per capita GDP decreased by 15.1% (1438.90$) on average over the period 2013-2017. Statistical significance of the causal estimates was estimated by multiple placebo tests, and robustness was checked by leave-one-out estimations, and confoundedness analyses. In particular, the 2009 gas disputes with Russia and the financial crisis in the same year may lead to overestimated causal effects. As a consequence, the estimated lower-bound of Ukraine’s per capita GDP foregone due to the war amounts to 12.7%. Additionally, authors show that the conflict affected the Donbass more severely than the other Ukrainian regions. Over the period 2013-2016, the per capita GRP of the Donbass provinces of Donetsk and Luhansk is found to be, on average, 43% (4630$) lower compared to its synthetic counterpart not affected by the military conflict.

Conclusion

The current research presents new methods of visualization of changes in NTL brightness at the Earth’s surface underpinned by economic, sociologic, and political factors. A quantitative analysis of time sequences of the integral NTL brightness over a limited area in Russia is aggravated by interseasonal changes in albedo because of snow (see [3]). The current research provides a new method of distinguishing interseasonal abnormalities on the basis of the RANSAC algorithm. After the separation of abnormalities in NTL brightness associated with the regional climate, it is possible to apply pattern recognition for time sequences in the form of stepwise changes and trends associated with different socio-economic and political phenomena. This research presents the results of such analysis for Eastern Ukrainian cities affected by the military conflict since spring 2014.

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