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### **Mapping GDP and PPPs at Sub-national Level through Earth Observation in Eastern Europe and CIS Countries**

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# **Mapping GDP and PPPs at sub-national level through earth observation in Eastern Europe and CIS countries**

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## **Abstract**

Following the line of research originated from Henderson et al. (2012), this paper focuses on how ‘observations from the above’, in the form of night-lights satellite data, might contribute in mapping at very fine geographical level (ideally, one square km), two core macroeconomic indicators used extensively in the Sustainable Development Goals monitoring and reporting framework: Gross Domestic Product, GDP, and Purchasing Power Parities, PPPs. The analyses are carried out on a panel of 17 Eastern Europe and CIS countries for the period 2000-2013 and use indicators constructed from satellite images in the form of night lights, as processed by the US Department of Defense, and its Defense Meteorological Satellite Program’s Operational Linescan System. Estimations of GDP in current US dollars and PPP terms are carried out at both national and sub-national level, testing for the existence of a modifiable areal unit problem, and comparing results with the official available information. Maps for GDP and PPP at the sub-national levels are obtained as a final product of the research.

## **1. Introduction**

The adoption of the Sustainable Development Goals in September 2015 by the United Nations General Assembly is calling National Statistics Offices (NSOs) worldwide to underpin a data revolution, as they are asked to extend both the scope and disaggregation of the data traditionally produced, and measure new economic, social and environmental phenomena, leaving none behind.

There is a growing consensus in the digital era that Big Data, particularly satellite images captured from the above, might strengthen the capacity of traditional data sources and official statistics to help in monitoring sustainable well-being, thus facing the increasing request for more spatially disaggregated data.

Following the line of research originated from the paper by Henderson et al. (2012), this paper focuses on how ‘observations from the above’, in the form of night-lights satellite data, might contribute in mapping at very fine geographical level (ideally, one square km), two core macroeconomic indicators used extensively in the SDG monitoring and reporting framework: GDP and PPPs.

Nowadays, the use of night-light as proxy of GDP has become a standard in empirical economics (see, e.g., Donaldson and Storeygard (2016)). The obvious advantage in using

night-lights is that they generally show a good correlation with GDP, they are available for free and for a long time span, and they are objectively measured.

This research uses extensively the set of information coming from satellite images, as processed by the US Department of Defense, and its Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS). Scientists at the National Geophysical Data Center (NGDC) process these raw data and distribute the final set to the public, thus making freely available 34 annual products from six satellites spanning 22 years, from 1992 to 2013. However, given the proximity of the first data available for satellites with the dissolution of the Soviet Union and the length of the transition period in the economies of the region, the sample analysed in this paper goes from 2000 to 2013.

The stable night lights are those used in this research to proxy GDP in nominal and PPP terms for 17 CIS and Eastern Europe countries: Azerbaijan, Armenia, Belarus, Bulgaria, Czechia, Hungary, Kazakhstan, Kyrgyzstan, Poland, Republic of Moldova, Romania, Russian Federation, Slovakia, Tajikistan, Turkmenistan, Ukraine and Uzbekistan.

Henderson et al. (2012) were the first to use night-lights in a complete statistics and econometric framework to estimate, in a panel of world time series, real economic growth. Following their examples, the relation between lights and GDP at sub-national administrative levels have been deeply investigated for North Korea, Kenya, Rwanda, Sweden, Nigeria, India and China.

More recently, while some papers have confirmed the ideas underlying the lights-to-GDP hypothesis at the country level (see, e.g., Elvidge et al. (2014)), the approach used by Henderson et al. (2012) have been criticized due to the implicit assumption of stable elasticity made in obtaining sub and/or supra-national estimates (Bickenbach et al. (2016), Addison and Stewart (2015)), which is hardly met under common situations where a modifiable area unit problem (MAUP) exists. Particularly, it has been stressed that the elasticity of GDP-to-lights should be statistically significant and positive, as well as temporally and spatially stable.

For CIS and Eastern Europe countries, the literature on lights and GDP is practically non-existent, the only indirect reference being a global exercise carried out by Elvidge et al. (2014) on the correlation (in levels) between GDP, night-lights and population at national level during 1992-2012. Furthermore, to the best of our knowledge, no study has been so far carried out on the direct or indirect relation between lights and PPPs.

Our paper innovates with respect to the preceding literature in at least three respects. First, it analyses in a systematic way the relationship between DMSP-OLS night-lights and GDP in CIS and Eastern Europe countries at the finer extent possible, looking at conditions under which lights can be used to obtain estimates of GDP and PPPs at detailed geographical level.

Second, the research uses both a time and spatial approach in the analysis, particularly through the use of balanced panel regressions models, and tests the conditions of spatially and time stability of GDP-to-light elasticity.

Third, use is made of the available national and sub-national data produced by NSOs of the region. After testing for the existence of temporally and spatially stable elasticity of GDP both in real and PPP terms with respect to lights, the estimated coefficients are used to map economic activity and parities at very fine geographical level, thus offering two sets of information that are mostly needed for SDGs monitoring and reporting.

We are fully aware that the estimations provided in this paper cannot replace primary statistics produce by NSOs of the region. However, we hope these estimates will be of some use for policy makers and researchers for their policy intervention, analyses and discussion, and contribute in partially answering the increasing demand for more spatially disaggregated macroeconomic data to further advance the sustainable development agenda.

The scheme of the paper is as follows. The next section describes the main characteristics of the DMSP system and the satellite information obtained in terms of night lights. Section 3 details on the indices considered in empirical analyses, the transformation carried out on night lights information and the population data used. Section 4 follows with the results of the empirical applications. The last Section of the paper summarizes main results and concludes.

## **2. Night-lights Data from Satellite Images**

Earth observation have been used in many respects to shed light on specific aspects of human development, such as economic output, population, urbanization, land, water and natural resources use, weather conditions and climate change, and pollution monitoring.

In parallel, there has been a growing use of night-lights, one of the most important by-products of satellite remote sensing, as proxy for measuring economic, social and environmental phenomena.

This paper makes an extensive use of the set of information coming from satellite images, as processed by the US Department of Defense, and its Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS), see Croft (1979) and Doll (2008) on technical aspects of the programme and, for a survey on use of such images, Huang et al. (2014).

A characteristic of DMSP-OLS data that has attracted most attention of researcher in the last years is their availability at a very fine geographical level (1 square km), thus making it possible to estimate through them a number of statistics at sub-national level, particularly those related to the level and growth of economic activity, thus providing an answer to chronicle lack of official statistics at the level of disaggregation requested within the framework of the sustainable development agenda.

The Defence Meteorological Satellite Program (DMSP) is a Department of Defence program of the US Air Force Space and Missile Systems Center, which started to capture imagery in the early 1970s through the Operational Linescan System (OLS) sensor. One of the primary objectives of the OLS sensors was to collect worldwide cloud cover observations twice per day.

In 1992 the National Oceanic and Atmospheric Administration (NOAA) was established and it processed and archived the DMSP nighttime light satellite imagery for 22 years. The DMSP programme has been repeatedly upgraded over time, with the latest series in its Version 4 spanning data for the years 1992-2013 and actually publicly available from NOAA from its website (<http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html>). Satellites from DMSP-OLS measure light emissions in the evening hours between 8:30 and 10:00 pm local time around the globe every day.

The OLS sensor has two broadband sensors, in the visible/near-infrared (VNIR, 0.4 – 1.1 $\mu$ m) and thermal infrared (10.5 – 12.6 $\mu$ m) wavebands. The OLS is an oscillating scan radiometer with a broad field of view (~ 3,000 km swath) and captures images at a

nominal resolution of 0.56 km, which is smoothed on-board into 5x5 pixel blocks to 2.8 km.

Scientists at the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC) process these raw data and distribute the final data to the public, following an undertaking of monumental difficulty. Original data are from the centre half of the 3000 km wide OLS swaths.

NGDC recently reprocessing of the DMSP time series have produced 34 annual products from six individual sensors on satellites, called F, spanning 22 years: F10 (1992-1994), F12 (1994-1999), F14 (1997-2003), F15 (2000-2008), F16 (2004-2009), and F18 (2010-2013). This is referred to as the v.4 DMSP stable lights time series, the ones used here for GDP and PPP analysis.

Lights in the centre half have better geo-location, are smaller, and have more consistent radiometry. In processing the raw data, a number of filters are applied before releasing final results. Sunlit data are excluded based on the solar elevation angle. Glare is also excluded based on solar elevation angle. Moonlit data are omitted based on a calculation of lunar luminance (Croft 1979, Elvidge 2013).

The recorded daily data are pre-processed, by removing observations of cloudy days and sources of lights which are not man-made, such as auroral lights or forest fires.

Data from all orbits of a given satellite in a given year are then averaged over all valid nights to produce a satellite-year dataset. These are the datasets that are distributed to the public. As a result, each satellite-year dataset reports annual light intensities for every pixel around the globe at a resolution of 30 by 30 arc seconds (approximately 0.86 square km at the equator) between 65 degrees S and 75 degrees N latitude.

Data are released in three different versions: raw, stable lights and the calibrated versions. The stable lights version removes ephemeral events such as fires and background noise. The calibrated version is currently available only for 2006 and has the advantage of not being saturated (top-coded).

Our analyses are based on the stable lights version. Data made available to the public by the NOAA have been geo-referenced at national and regional levels by digital number (DN) using the administrative areas and boundaries (level 0 and 1, respectively) provided in the form of shape-files by GADM, Version 3.6, available at <https://www.gadm.org>. A geolocation algorithm was used to map the data onto the 1km grid developed for the NASA-USGS Global 1km AVHRR project (Eidenshink and Faundeen, 1994), that limit error in geolocation in the project process.

The light intensity values of the stable lights product are recorded in a fixed range of digital numbers (DN) from 0 (missing or completely dark) to 63 (bright). Sensor saturation implies that the satellites are not able to capture a light intensity higher than 63 DN. A small fraction of pixels, generally in rich and dense city areas, have DN values equal to 63.

The saturation and blooming issues in DMSP/OLS NTL images are the main limiting factors in their use. Imagery from the DMSP-OLS satellite has a tendency to overestimate NTL imagery, an effect generally referred to as "blooming" in the literature. Blooming occurs when cells producing NTL cause lit pixels to extend beyond the source's true illuminated area. This phenomenon can be acute in OLS imagery and it is more pervasive over water and snow areas, as these reflect close lights more than dark ground. Blooming should be of particular concern when examining coastal metropolises,

since changes in brightness tend to be bigger in area than associated land cover changes (Small and Elvidge, 2013). Typically, blooming is proportional to the SOL emitted by a light source, such as an urban area.

Sensor settings vary over time across satellites and with the age of a satellite, so that comparisons of raw DN over years can be problematic. This explains why satellites, in the very last years, are replaced by new ones, accompanying them for their last few years of life. That happened for all satellites but the last, F16, substituted by the last orbiting F18 without an overlapping period. A map of night lights for Europe, including Eastern Europe and CIS countries, is represented in Figure 1 below.



**Figure 1** Plot of night lights of Europe (including Eastern Europe and CIS countries)

There are several studies aimed at radiance calibration of DN over time across satellites (e.g., Li and Zhou 2017, and the literature cited therein). Their goal is to make data comparable across time, creating a consistent time series of satellite observation that eliminates abrupt jumps in the series, when passing from observations of one satellite to another. DMSP light data collected in different years (and satellites) may have variations in gain settings, sensor degradation, and change in atmospheric condition.

We did not perform such calibration on the original data, but we control for such issues, whenever appropriate, by using panel regression estimations with fixed effects for time and satellites. Such estimations are able to take into considerations the differences in the capacity of satellites to identify lights intensity due to obsolescence.

For years with two satellite observations, the arithmetic average of the two outcomes is considered in the empirical applications.

The DN is not exactly proportional to the physical amount of light received (called true radiance) for several reasons. The first is sensor saturation, which is analogous to top-coding. Further, the scaling factor (“gain”) applied to the sensor in converting it into a digital number varies for reasons that are not explained, possibly to allow Air Force analysts to get clearer information on cloud cover.

Unfortunately, the level of gain applied to the sensor is not recorded in the data. The DMSP night-time lights provide the longest continuous time series of global urban remote sensing products, now spanning 22 years. The flagship product is the stable lights, an annual cloud-free composite of average digital brightness value for the detected lights, filtered to remove ephemeral lights and background noise.

The follow on to DMSP for global low-light imaging of the earth at night is the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB), flown jointly by the same NASA-NOAA Suomi National Polar Partnership launched in 2011. These data are available for a shorter time period (data are indeed available on a monthly basis only from 2012 onwards, annually only for 2015-2016), but they are of greater precision than DMSP images and made available to public in a very timely way, after some few days from the end of each month. They offer substantial improvements in spatial resolution, radiometric calibration and usable dynamic range when compared to the DMSP low light imaging data.

VIIRS DNB key improvements over DMSP-OLS data include a vast reduction in the pixel footprint (15 arc-second, about 500 m), uniform ground instantaneous field of view from nadir to edge of scan, lower detection limits, wider dynamic range, finer quantization, in-flight calibration and no saturation (Elvidge et al. 2013). Prior to averaging, the DNB data is filtered to exclude data impacted by stray light, lightning, lunar illumination, and cloud-cover. Cloud-cover is determined using the VIIRS Cloud Mask product.

### 3. GDP, PPPs and Explanatory Variables

The data on GDP are obtained from the World Bank, World Development Indicators database, which contains data by country on different measures of national accounts. Those used in this paper include current local currency unit data, current US dollars data, and data in PPPs (current international US dollars). PPPs time series can be obtained implicitly by dividing current data in local currency by the corresponding data expressed in PPP, in current international US dollars.

An alternative indicator often used as proxy for GDP is electricity consumption. We consider here an electric power consumption (kWh per capita) indicator obtained from the World Development Indicators database.

Night lights data have been used to derive a number of indicators for our empirical analyses, as follows. Let us indicate with  $V_j$  the  $DN$  value, ranging from 0.51 to 63, and with  $N_j$  the number of pixels with a  $DN$  value equal to  $V_j$ . The sum ( $SL$ ), mean ( $ML$ ), and standard deviation ( $SDL$ ) of lights are defined as:

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<sup>1</sup> Non-integer values may occur in years where two satellites are available (the final image value  $DN$  is equal to the average of the two values captured by the satellites orbiting during the same calendar year).

$$SL_i = \sum_{j=1}^K V_j \times N_j \quad ML_i = \frac{SL_i}{\sum_{j=1}^K N_j} \quad SDL_i = \sqrt{\frac{1}{\sum_{j=1}^K N_j} \sum_{j=1}^K (V_j - ML_i)^2 N_j} \quad i = 1, 2, \dots, 17$$

where K may range from 63 (one satellite) to 126 (two satellites).

Among the indicators constructed using night lights information, we considered a Gini night-light index. The index measures the extent to which the distribution of light intensities (in terms of DN) among pixels (the Lorenz curve of the traditional Gini index), deviates from a perfectly equal distribution. The Gini index measures the area between the Lorenz curve and this hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. Thus, a Gini index of 0 represents perfect equality, while an index of 1 implies perfect inequality.

The data set used in analyses includes also population data, which are extracted from the World Bank national and sub-national population total estimates of the de facto mid-year population at national and first level administrative division.

We construct the Gini coefficient using only information from nightlight as per the formulas below, where it is assumed that the  $V_j$ 's represent values of lights, and the  $N_j$ 's the pixels pertaining to those values.

The Gini index (Gini 1914) is defined as follows:

$$GN_i = \frac{\sum_{l=1}^{K_i} \sum_{j=1}^{K_i} |V_l - V_j| N_l N_j}{2 \cdot K_i \cdot \sum_{l=1}^{K_i} N_l} \quad i = 1, 2, \dots, 20; \quad K_i = \sum_{j=1}^K N_{i,j}$$

As an alternative to the Gini, we also consider as concentration measure the Bonferroni inequality index (Bonferroni 1930), which is based on the comparison of the partial means and the general mean of the light distribution:

$$BF_i = \frac{1}{K-1} \sum_{j=1}^{K-1} \frac{(ML_i - ML_j)}{ML_i} = 1 - \frac{1}{K-1} \sum_{j=1}^{K-1} \frac{ML_j}{ML_i} \quad ; \quad ML_j = \frac{1}{K} \sum_{j=1}^K V_j$$

Compared to the Gini, the Bonferroni index has a number of advantages, see e. g. Tarsitano (1989), most notably it is more sensitive at the lower tail of the income (light) distribution, where indeed night lights are concentrated in our sample: this is a common feature of most countries around the world, see Henderson et al. (2012). The Gini and Bonferroni indices are defined over the interval [0,1], with lower and upper limits reached in case of perfectly equal and concentrated distributions of lights in the extremes of the definition interval. The indices are supposed to have positive correlation with GDP measures, and  $BF \geq GN$ .



Other less used measures of concentration considered in this paper are the Mean Log Deviation, *MLD*, and the first, second and third quartiles of the lights distribution, as well as the inter-quartile difference, *IQD*, which have straightforward definitions.

We also follow other authors in considering, as possible explanatory variables, indices aimed at measuring the extent of urbanization in the countries analysed. In this respect, it is quite common to use a threshold of  $DN = 7$  or  $DN = 10$ , e. g. Imhoff et al. (1997), as the values to discriminate between urban and non-urban areas. The first index, the Urban Light Index, *ULI*, has been proposed by Yi et al. (2014):

$$ULI_i = 100 \times \sum_{j=7 \text{ or } 10}^{max V_j} \frac{V_j}{max(V_j)} \times \frac{c_j}{\sum c}$$

where  $c_j$  and  $\sum c$  are the count of  $DN$  and the number of lit pixels, respectively. Here,  $\frac{V_j}{max(V_j)}$  indicates the brightness, which reflects the light intensity of each area, while  $\frac{c_j}{\sum c}$  reflects the weight of  $DN$ .

Finally, as an alternative indicator of urbanization, we consider in our analyses the Night Light Index, *NLI*, and its two subcomponents, the Mean Light Intensity Index, *MLII*, characterizing light intensity, and the Light Area Index, *LAI*, characterizing the light spatial distribution of each area. This is an index originally proposed by Yang et al. (2009), and it is supposed to accommodate for three main factors affecting the degree of urbanization: urban population, industrial structure, and build-up area distribution. The index and the components are defined as follows:

$$NLI_i \equiv MLII \times LAI = \frac{\sum_{j=1}^K (V_j \times N_j)}{63 \times \sum_{j=1}^K N_j} \times \frac{\sum_{j=1}^K N_j}{\sum_{j=1}^{K+1} N_j}$$

In computing the *LAI* index, the sum of pixels at the denominator includes also those with  $DN = 0$ . *MLII* is the ratio of the actual lights compared to its maximum value (the value obtainable if all pixel were saturated): it represents a measure for light intensity. *LAI* is the percentage of lit pixels over total area (lit and unlit) of the country.

A sense of our data-set is provided by the statistics for GDP and some derived night-lights indicators for the 17 Eastern Europe and CIS countries considered, as reported in Table 1.

In ‘Stan’ countries, a high fraction of pixels, generally above 90%, is unlit. This is a characteristic in common with Russia, where the unlit area is a 92.5% of the entire territory. The lit area is predominant in most Eastern Europe countries, notably Czechia (5.0%), Poland (17.3%), Slovakia (28.5%), Hungary (36.8%), Bulgaria (46.0%) and Romania (47.0%). Czechia, Poland and Slovakia show a relatively high degree of urbanization and, in general, percentages of lit pixels - in the frequencies over 10  $DN$  - larger than 35%. Top-coded areas are virtually non-existent in Kazakhstan, Moldova, Kyrgyzstan and Tajikistan. With the exception of Moldova, these countries show the lowest levels of population densities in the whole region.

Overall, higher values of mean lights tend to be associated with higher variability among frequencies. Higher mean values of  $DN$  are found in richer realities having top GDP per capita values in terms of PPPs, Czechia, Poland, Slovakia, Hungary and Russia, showing a clearly positive correlation between lights and GDP, which seems at odds with Martinez (2019) findings of a negative relation between GDP and night-time lights. In this respect, electricity consumption growth rates data seem less correlated with GDP changes than satellite information on light average growths, and give misleading indications over the whole period i.e. in Azerbaijan, Moldova, Tajikistan and Uzbekistan.

Among the poorest and relatively sparsely populated countries of CIS, like Kyrgyzstan and Tajikistan, a great percentage of pixels are unlit, the average intensity of lights is low (below 8.0), the degree of urbanization shows the minimum values in the region, and top-coded areas are practically absent.

While richer countries tend to have higher average digital numbers, geography and population density also play strong roles. The mean  $DN$  reaches its peak in richer realities, notably Eastern Europe countries, which show the highest levels of GDP indicators among the countries in the sample. For these two countries, the indicators in Table 1 display a quite similar pattern: low percentages of unlit area, relatively strong urbanization levels and higher values of light concentration, average percentage of top-coded areas, and relatively high population density.

#### TABLE 1 HERE

Cross-section and panel comparisons usually perform better among countries with similar culture in terms of use of lights (i.e. energy-saving policies), geographical characteristics, population density, and top-coding magnitude.

As clearly evidenced from the descriptive analyses above and the indications emerging from Table 1, this is not completely the case in our sample of countries, which however show, in their distinct trajectories and patterns, especially those of Eastern Europe and CIS countries, some sub-regional commonalities and trends.

In the empirical part of this work, we will also explore whether changes in dispersion measures (like the Gini and the Bonferroni indices, the inter-quintile as well as the standard deviation of lights), the degree of urbanization, the fraction of unlit and top-coded area, contribute additionally in modelling and forecasting GDP growth and PPPs measures and map them at sub-national levels.

## 4. Model and Empirical Results

The analytical approach used here is similar to the one proposed in Henderson et al. (2012), who in their pioneering work used a panel model with country and year effects to predict GDP at the international level through night lights, and where country effects controlled for factors like lighting technology and investment in outdoor lighting, whereas year effects monitored differences in light sensitivity across the satellites and changes in global external conditions, like technology and economic conditions.

In our applications, we estimate a panel model where the dependent variable,  $y_{i,t}$ , represents GDP, and the  $x_{i,t}$  are the explanatory variables, defined through different night-lights metrics, population and energy consumption data.

The measures of GDP considered are those that permit, based on model fitted data, to estimate PPP measures, which are not directly supposed to be in relation with measures of night lights. These are GDP in current US dollars and in PPP.

Concretely, the various steps followed in the analyses are as follows:

- (a) Identification of the best performing series in each group of night-light-based indicators (standard measures, dispersion indices, measures of urbanization, other series, including population and energy consumption) using pooling regressions;
- (b) Estimation of panel data models for both GDP in current US dollars and PPP (current international US dollars) with national data for the 17 countries;
- (c) Conversion of the estimated values of the model for GDP in current US dollar to local currency;
- (d) Derivation of implicit PPP estimates from the two models and comparison with World Bank PPP time series estimates;
- (e) Application of the coefficients obtained with the estimation of the national model for GDP in current US dollars to sub-national night-lights indicators available at NUTS 1 level;
- (f) Comparison of the data estimated in step (e) with the official regional available data published by countries to verify the existence of a MAU problem; and
- (g) Use of the estimated coefficient to obtain further space disaggregation of the interest series, namely GDP and PPP.

Let us analyse, step by step, how the procedure above was carried out for our data-set. Preliminary analyses on our two GDP series,  $y_{i,t}$ , suggest that - based on Pesaran (2007) CIPS tests -, the panel should be estimated in first differences. The preliminary analyses made using pooled regressions on the rate of growth against standard measures of lights (sum and mean in log terms, and the corresponding per-capita values), dispersion measures (the Gini and the Bonferroni indices, the mean log deviation, the inter-quintile difference as well as the standard deviation of lights), different measures of urbanization (the night light intensity index,  $NLI$ , and its two components, the urban light index,  $ULI$ , with lower threshold at 7 or 10  $DN$ ), population density, as well as energy consumption, shows that the series performing better are the sum of light per-capita, the ratio of standard deviation to mean of lights, the Gini concentration index, and the urban light index, with  $DN = 10$ . Given the upwards trend characterizing lights and GDP data, both series are expressed in log-difference in our panels, while other series, for their bounded characteristic, are considered in level form.

A flavour of our data-set, composed by 221 observations when expressed in growth rates, is provided in the conditioning plots reported in Figures 2 and 3. Bars at top indicates the corresponding graphs (by years) from left to right, starting from the bottom. Further insights on the heterogeneity across years and countries are provided in Figure 4, where it emerges a certain degree of country and time-heterogeneity along the reference period.

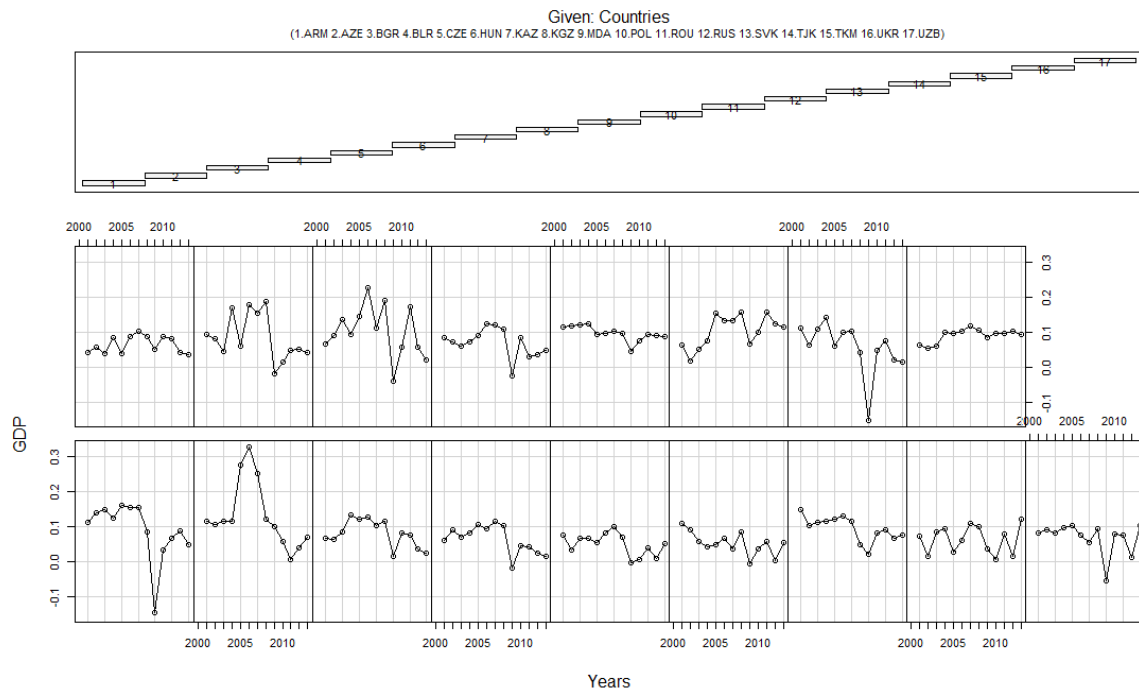


Figure 2 Conditioning plots of GDP in PPP (current international US dollars), by years, 2001-2013

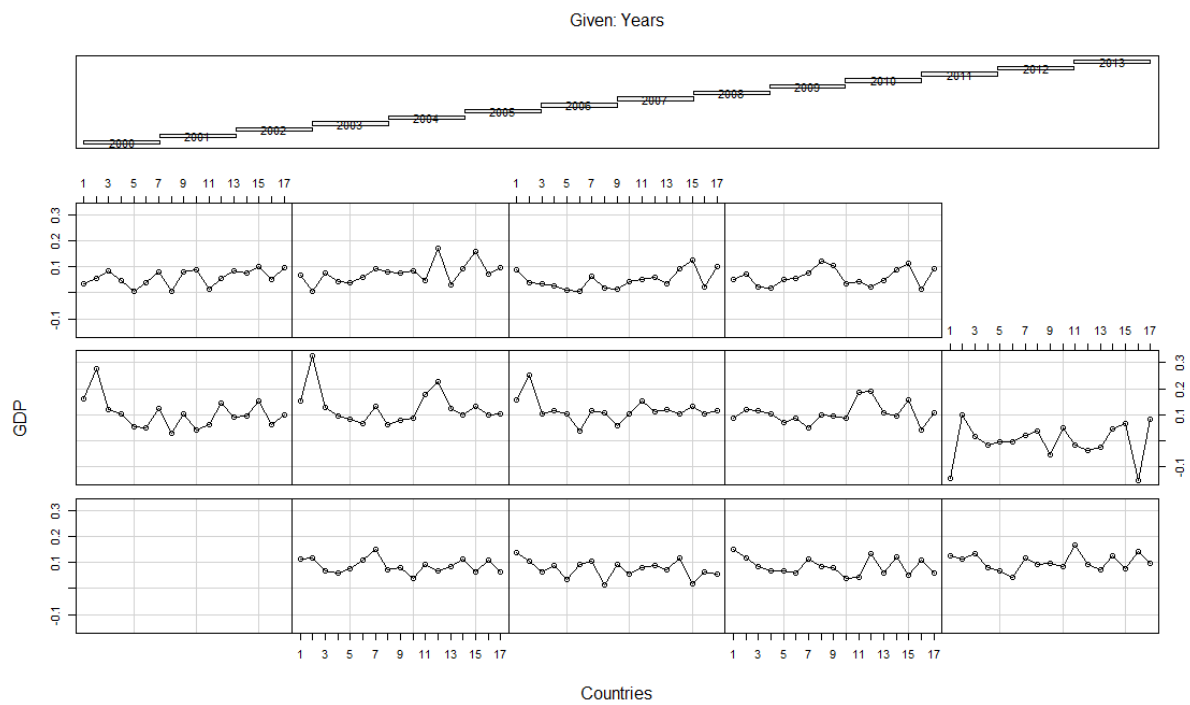


Figure 3 Conditioning plots of GDP in PPP (current international US dollars), by country, 2001-2013

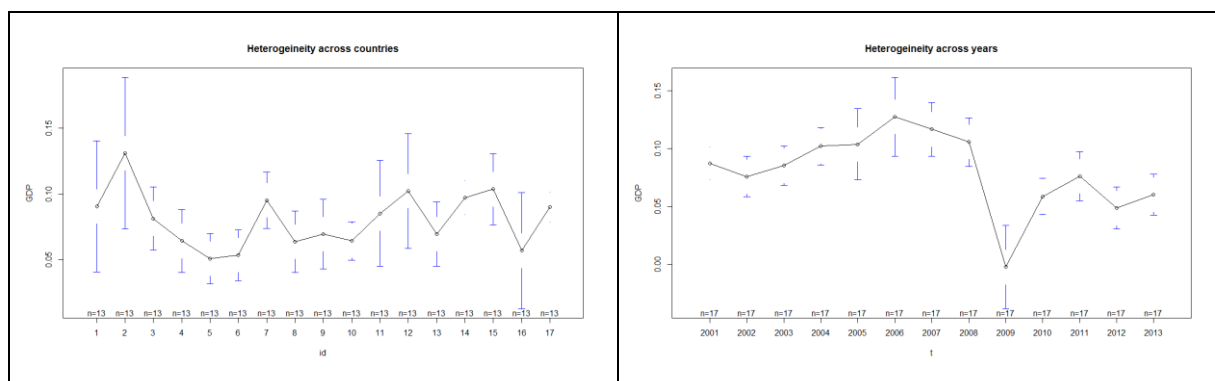


Figure 4 Heterogeneity across years and countries of GDP in PPP (current international US dollars), 2001-2013

The results obtained from the estimations of pooled linear regression, random and fixed effects models, reported in Table 2, show a strong significance of the exogenous variables identified above for both GDP series.

The Hausman tests statistics of 6.827 and 7.160 respectively for GDP in PPP (current international US dollars) and GDP at current US dollars, with their associated p-values of 0.145 and 0.128, lead to accept the null of random effects against a fixed effects model, while Breusch-Pagan Lagrange Multiplier tests for random effects uniformly reject the null that variances across entities are zero in all models considered.

TABLE 2 HERE

After conversion of the estimated values of the model for GDP in current US dollar to local currency using official exchange rates available in the World Bank data-base, implicit PPP estimates are obtained from the two models using the coefficients reported in Table 2, and comparisons are made with World Bank PPP time series estimates, after reporting estimates of growth rates to level variables for the two measures of GDP. The correlation of the two series with official PPPs is strong, equal over the whole 2000-2013 sample and for all data obtained for the 17 countries, to 0.981. Similar results are obtained for GDP measures used in the analyses.

When the estimated coefficients are applied to subnational lights indicators at the level-1 administrative official boundaries, and the results compared with the available data on GDP at current US dollars, the correlation between the official and estimated level data show values close to those obtained for PPPs (step (f) of our procedure), thus making it feasible to proceed to step (g). Mapping of GDP and PPP data are not reported here, but will be included, in the form of summary choropleth maps, in an extended and completed version of this paper.

## 5. Conclusions

Spatially disaggregated maps of GDP and PPP, especially if updated on an annual basis or at higher frequency, would be extremely beneficial for tracking the effectiveness of policy efforts in specific areas or, for example, evaluating the consequences of natural

disasters, conflicts or other general policy purposes. Satellite images in the form of night lights could help in better understanding those economic phenomena and their space-temporal dynamics.

The sub-national analyses carried out in this paper had a twofold objective. First, to examine the feasibility of applying the country level approach to the sub-national level on a country-by-country basis, and second to explore the opportunity of using global/regional models for countries where sub-national data on GDP are either missing or deemed to be unreliable. Furthermore, attempts to estimate sub-national PPPs data, although important to identify space price dynamics and measuring, amongst others, poverty lines at sub-national level, so far have provided quite unsatisfactory results, whilst the way to obtain information through traditional approaches is practically unfeasible for costs reasons.

The analyses and outcomes of this research rest on the assumption that coefficients describing GDP at the national level continue being of use at the finer disaggregated geographical level.

MAUP is a well-known problem in geography and spatial analysis. However, there is scarce research on MAUP's impact in studies that make extensive use of satellite images, particularly those obtained from DMSP images, see e. g. Chen and Nordhaus (2019). Indeed, the majority of literature on socio-economic spatial disaggregation through night lights rests on the assumption of negligible MAUP. This is indeed a line for future research on the GDP-PPP-nighttime images relation, possibly with use of sensitivity analysis.

While the OLS is remarkable for its detection of dim lighting over a long time span, the quality of its mapping products could be improved in a number of ways. The main shortcomings of the OLS data include the following, in part resolved by the introduction of the new VIIRS products: (a) granular spatial resolution; (b) lack of on-board calibration; (c) limited dynamic range; (d) signal saturation in urban populated centres; (e) limited data recording and download capabilities; and (f) lack of multiple spectral bands for discriminating lighting types. The use of VIIRS data could clearly improve on the results presented in this paper, permitting estimations and updating of maps at higher frequencies, but longer time series of data would be necessary to obtain sufficient information for use in a panel framework.

The research could also expand by analysing images captured by other non-US satellites. European data on earth observations are another incredible source of statistics information, with Copernicus being perhaps the most ambitious earth observation programme to date. This initiative, headed by the European Commission in partnership with the European Space Agency, is actually providing accurate, timely and easily accessible information.

The information provided by this incredible source of information for Sustainable Development Goals monitoring and reporting is in its preliminary phase, but there is an enormous amount of information awaiting for investigation to help shape the future of our planet for the benefit of all, leaving none behind.

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**Table 1** Main statistics of night lights and GDP, averages over the available years, 2000-2013

| Statistics                                                       | Armenia | Azerbaijan | Bulgaria | Belarus | Czechia | Hungary | Kazakhstan | Kyrgyzstan | Moldova |
|------------------------------------------------------------------|---------|------------|----------|---------|---------|---------|------------|------------|---------|
| % Area unlit ( $DN = 0$ )                                        | 78.4%   | 70.2%      | 46.0%    | 70.8%   | 5.0%    | 36.8%   | 95.0%      | 91.7%      | 57.5%   |
| % Urban area<br>( $10 \leq DN \leq 63$ ) *                       | 22.3%   | 18.3%      | 14.5%    | 19.9%   | 43.6%   | 28.9%   | 20.3%      | 19.5%      | 9.8%    |
| ‰ Top-coded area<br>( $DN = 63$ ) *                              | 0.95‰   | 0.46‰      | 0.42‰    | 0.49‰   | 1.36‰   | 1.27‰   | 0.11‰      | 0.04‰      | 0.02‰   |
| Mean ( $DN$ )                                                    | 8.79    | 8.00       | 6.97     | 8.19    | 12.47   | 10.21   | 8.54       | 7.81       | 5.92    |
| St. Dev. ( $DN$ )                                                | 9.73    | 9.26       | 7.13     | 8.80    | 10.23   | 9.94    | 10.03      | 7.68       | 6.16    |
| Second quartile ( $DN$ )                                         | 5.6     | 5.0        | 4.9      | 5.6     | 8.9     | 6.6     | 5.2        | 5.3        | 4.5     |
| Gini ( $DN$ )                                                    | 0.436   | 0.446      | 0.382    | 0.429   | 0.378   | 0.419   | 0.470      | 0.393      | 0.363   |
| Bonferroni ( $DN$ )                                              | 0.521   | 0.523      | 0.462    | 0.507   | 0.473   | 0.507   | 0.546      | 0.477      | 0.431   |
| Population density<br>(population/pixel)                         | 65.3    | 65.7       | 54.6     | 18.8    | 73.0    | 63.3    | 3.3        | 17.1       | 61.9    |
| GDP per capita, PPP<br>(constant 2011<br>international \$)       | 5 730   | 11 057     | 12 791   | 13 136  | 26 147  | 21 740  | 17 071     | 2 555      | 4 145   |
| % growth rate, GDP<br>(constant 2010 US\$)                       | 7.3     | 11.7       | 6.3      | 3.7     | 2.4     | 1.7     | 7.8        | 4.4        | 5.0     |
| % growth rate, Mean<br>Lights ( $DN$ )                           | 4.0     | 3.9        | 3.9      | 3.9     | 0.8     | 2.9     | 3.2        | 2.9        | 3.5     |
| % growth rate, Electric<br>power consumption<br>(kWh per capita) | 3.1     | 0.2        | 1.5      | 1.8     | 0.7     | 1.3     | 4.1        | 0.8        | -1.5    |

Statistics are calculated averaging data over the period 2000-2013

Rates of growth are calculated with the compound interest formula over the period 2013-2000

\* Percentages calculated on total lit area

**Table 1 (continue)** Main statistics of night lights and GDP, averages over the available years, 2000-2013

| Statistics                                                       | Poland | Romania | Russia | Slovakia | Tajikistan | Turkmenistan | Ukraine | Uzbekistan |
|------------------------------------------------------------------|--------|---------|--------|----------|------------|--------------|---------|------------|
| % Area unlit ( $DN = 0$ )                                        | 17.3%  | 47.0%   | 92.5%  | 28.5%    | 89.9%      | 91.9%        | 58.4%   | 82.7%      |
| % Urban area ( $10 \leq DN \leq 63$ ) <sup>*</sup>               | 36.2%  | 16.7%   | 25.7%  | 35.2%    | 17.0%      | 24.6%        | 15.0%   | 29.2%      |
| ‰ Top-coded area ( $DN = 63$ ) <sup>*</sup>                      | 1.64‰  | 0.44‰   | 0.19‰  | 0.37‰    | 0.00‰      | 0.18‰        | 0.18‰   | 0.38‰      |
| Mean ( $DN$ )                                                    | 11.36  | 7.58    | 9.75   | 10.66    | 7.29       | 9.16         | 7.08    | 9.66       |
| St. Dev. ( $DN$ )                                                | 10.19  | 7.77    | 10.65  | 9.04     | 7.04       | 10.32        | 7.61    | 9.72       |
| Second quartile                                                  | 7.9    | 5.6     | 5.9    | 7.7      | 5.2        | 5.3          | 4.8     | 6.4        |
| Gini ( $DN$ )                                                    | 0.401  | 0.385   | 0.461  | 0.380    | 0.379      | 0.473        | 0.406   | 0.430      |
| Bonferroni ( $DN$ )                                              | 0.496  | 0.467   | 0.549  | 0.474    | 0.462      | 0.562        | 0.483   | 0.525      |
| Population density<br>(population/pixel)                         | 64.6   | 52.8    | 3.5    | 62.3     | 33.3       | 6.6          | 44.1    | 38.8       |
| GDP per capita, PPP<br>(constant 2011<br>international \$)       | 18 931 | 15 469  | 20 498 | 21 725   | 1 839      | 8 133        | 7 261   | 3 546      |
| % growth rate, GDP,<br>(constant 2010 US\$)                      | 3.6    | 3.8     | 4.5    | 4.2      | 8.0        | 8.7          | 3.7     | 7.2        |
| % growth rate, Mean<br>Lights ( $DN$ )                           | 3.1    | 3.5     | 3.1    | 1.6      | 2.9        | 3.9          | 3.4     | 1.9        |
| % growth rate, Electric<br>power consumption (kWh<br>per capita) | 1.5    | 1.8     | 1.8    | 0.4      | -1.9       | 3.2          | 2.0     | -0.6       |

Statistics are calculated averaging data over the period 2000-2013

Rates of growth are calculated with the compound interest formula over the period 2013-2000

<sup>\*</sup> Percentages calculated on total lit area

**Table 2** Main results of the pooled regressions and panel fixed and random effect models, 2001-2013

|                      | <i>GDP</i> , PPP (current international \$) |                       |                       | <i>GDP</i> (current US\$) |                       |                       |
|----------------------|---------------------------------------------|-----------------------|-----------------------|---------------------------|-----------------------|-----------------------|
|                      | Pooled                                      | Fixed Effect          | Random Effect         | Pooled                    | Fixed Effect          | Random Effect         |
| Constant             | -0.1167**<br>(0.0421)                       | -                     | -0.1834**<br>(0.0574) | -0.2395*<br>(0.0954)      | -                     | -0.3065**<br>(0.1158) |
| <i>ln(SL/POP)</i>    | 0.0542***<br>(0.0158)                       | 0.0565***<br>(0.0149) | 0.0548***<br>(0.0150) | 0.1652***<br>(0.0360)     | 0.1668***<br>(0.0348) | 0.1646***<br>(0.0349) |
| <i>SDL/ML</i>        | 0.1722***<br>(0.0376)                       | 0.1579***<br>(0.0360) | 0.1684***<br>(0.0359) | 0.6659***<br>(0.0851)     | 0.6162***<br>(0.0839) | 0.6533***<br>(0.0833) |
| <i>GN</i>            | 0.3375***<br>(0.0694)                       | 0.3273***<br>(0.0713) | 0.3312***<br>(0.0695) | 0.9406***<br>(0.1572)     | 1.0367***<br>(0.1661) | 0.9797***<br>(0.1590) |
| <i>ULI (DN ≥ 10)</i> | 0.0017<br>(0.0015)                          | 0.0088**<br>(0.0027)  | 0.0038<br>(0.0019)*   | -0.0003<br>(0.0035)       | 0.0122<br>(0.0063)    | 0.0013<br>(0.0040)    |
| Nr. of obs.          | 221                                         | 221                   | 221                   | 221                       | 221                   | 221                   |
| $R^2$                | 0.297                                       | 0.324                 | 0.303                 | 0.425                     | 0.460                 | 0.434                 |
| <i>F</i>             | 22.855***                                   | 24.012***             | 23.474***             | 39.946***                 | 42.529***             | 41.496***             |

$R^2$  not corrected. \*\*\*  $p < .001$ ; \*\*  $p < .01$ ; \*  $p < .05$ . Country (excluding the pooled models) and time dummies are included in the estimated models.