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Detecting spatial pattern of inequalities from remote sensing

Towards mapping of deprived communities and poverty

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Abstract

Spatial inequalities across the globe are not easy to detect and satellite data have shown to be of use in this task. Earth Observation (EO) data combined with other information sources can provide complementary information to those derived from traditional methods. This research shows patterns of inequalities emerging by combining global night lights measured from Earth Observation, population density and built-up in 2015. The focus of the paper is to describe the spatial patterns that emerge by combing the three variables.

This work focuses on processing EO data to derive information products, and in combining built-up- and population density with night-time lights emission. The built-up surface was derived entirely from remote sensing archives using artificial intelligence and pattern recognition techniques. The built-up was combined with population census data to derive population density. Also the night-time lights emission data were available from EO satellite sensors. The three layers are subsequently combined as three colour compositions based on the three primary colours (i.e. red, green and blue) to display the "**spatial human settlement pattern"** maps. These **GHSL nightlights** provide insights in inequalities_across the globe. Many patterns seem to be associated with countries income. Typically, high income countries are very well lit at night, low income countries are poorly lit at night. All larger cities of the world are lit at night, those in low-income countries are often less well lit than cites in high-income countries. There are also important differences in nightlights emission in conflict areas, or along borders of countries. This report provides a selected number of patterns that are described at the regional, national and local scale. However, in depth analysis would be required to assess more precisely that relation between wealth access to energy and countries GDP, for example.

This work also addresses regional inequality in GHSL nightlights in Slovakia. The country was selected to address the deprivation of the Roma minority community. The work aims to relate the information from the GHSL nightlights with that collected from field survey and census information conducted at the national level. Socio-economic data available at subnational level was correlated with nightlight. The analysis shows that despite the potential of GHSL nightlights in identifying deprived areas, the measurement scale of satellite derived nightlights at 375 x 375 m to 750 x 750 m pixel size is too coarse to capture the inequalities of deprived communities that occur at finer scale. In addition, in the European context, the gradient of inequality is not strong enough to produce strong evidence. Although there is a specific pattern of GHSL nightlights in settlements with high Roma presence, this cannot be used to identify such areas among the others.

This work is part of the exploratory data analysis conducted within the GHSL team. The exploratory analysis will be followed by more quantitative assessments that will be available in future work.

1 Introduction

Earth Observation (EO) satellites have changed the way we perceive and understand Planet Earth. The synoptic view of satellite allows us to better measure continental and global processes as well as spatial patterns that traditional survey based methods cannot easily reveal. The EO satellite missions focusing on land have measured physical properties of the land surface as well as the use of the land in different forms. This includes generic land cover and land use, (Gong et al., 2013) or more thematic maps such as forest cover maps (Hansen et al., 2013), surface water (Pekel et al., 2016), and human settlements and their dynamics (Melchiorri et al., 2018; Martino Pesaresi et al., 2016). Nightlights recorded by satellites (Elvidge et al., 2017) can now be used to complement the information provided by global built-up areas and population density used to address societal activities (Ehrlich et al., 2018).

The demand for providing global scale information on societal activity in settlements have prompted researchers and scientists to combine socio-economic data from field surveys and population census with EO data or satellite derived products. That demand originates from the scientific community striving to understand the human impact on the planet as well as the impact of the earth system on human society. That demand also comes from the need to monitor the post-2015 framework agreements. This work contributes to the discussion on the development of SDG indicators in particular for SDG 1 (end poverty in all its forms everywhere) and SDG 7 (ensure access to affordable, reliable, sustainable and modern energy for all). Access to electricity is a crucial factor for achieving the SDG Goals (The World Bank, 2017), and it is one of the indicators of well-being and development. Nightlights are considered to be included in the development of socio-economic indicators (Proville et al., 2017). The scientific literature has attempted to correlate nightlight with a variety of socio-economic variables including population density (Sutton et al., 2001), Gross Domestic Product (GDP) (Sutton et al., 2007), the relation with other socio-economic variables (Nordhaus, 2006), the quantification of CO_2 emission (Ou et al., 2015), and poverty at global scale (Elvidge et al., 2009; Jean et al., 2016). Scientists discussed also the limitation of using nightlights to estimate socio-economic variable such as GDP (Wu et al., 2013).

Spatial inequalities in income, health, education, and poverty present significant economic and political challenges for the governments of many, mostly developing countries (Kim, 2008). In other words, spatial inequality is a dimension of overall inequality, but it has added significance when spatial and regional divisions align with political and ethnic tensions to undermine social and political stability. For the purpose this report we define spatial inequality as inequality in economic and social indicators of wellbeing across geographical units within an area or a country (Kanbur and Venables, 2005).

Despite the evidence of spatial inequalities in many forms in various countries in Asia, Europe, Africa and Latin America (Kanbur and Venables, 2005), there is little systematic evidence on the extent of spatial inequality globally as well as within countries. This report proposes a new approach to combine EO data to detect spatial inequalities.

The spatial inequalities are addressed by combining the variables of resident population, the presence of built-up areas and nightlights emissions. The characteristics of the input data used in this study may allow developing potential applications with frequent updates for nowcasting or projection of spatially-explicit indicators reporting about deprivation, poverty, and the resilience of human communities. There might as well be potential to measure the impact of by major crises and disasters at a local level.

In this study on the *spatial patterns of inequalities,* we test the possibility to use global, open available spatial data for the objective identification of major inequalities of human living conditions in the spatially-explicit domain. In particular, in this study three basic components of the human settlements are merged using spatially-explicit gridded data

input at a resolution of 1000x1000 meters and 250x250 meters: the amount of resident population, the amount (surface share) of built-up areas, and the amount of nightlight emissions for each considered spatial unit of the Earth's landmass. The combination of these information layers are observed and statistically significant data clusters are determined in the spatial domain. Accordingly, they are projected in the spatial domain in order to study their correlation with the presence of specific human development patterns and the human exposure to major crises and disasters.

This document it is subdivided in three parts. The first part succinctly describes the spatial data layers used in this research and the method used to integrate them. The second part showcases the proposed method applied at the global scenario. The third part explores the potential of the proposed method in a specific sub-national scenario, aiming to assess the presence of ethnic minorities and their spatial segregation.

2 Methods

This section describes the input data used by the study, and the method used to integrate them in order to assess the *spatial patterns of inequalities.*

2.1 Data

In this study we integrate three basic spatial information layers reporting about the human presence on Earth, and that are available in the open scientific domain: they are i) the amount of resident population, ii) the amount of built-up surface share and iii) the amount of night light emissions. For the purpose of the study, they have been considered at the nominal year of 2015.

The first two information layers quantify the amount of resident population and the amount of built-up area per surface units that have been extracted from the data generated by the JRC Global Human Settlement Layer (GHSL). The GHS-POP and GHS-BUILT are open products used in this report and briefly introduced here.

The third information layer used in this study reports about the amount of night light emissions (NLE) per unit surface. These data are generated by the Earth Observations Group (EOG) at National Oceanic and Atmospheric Administration (NOAA)/National Geophysical Data Center (NGDC). They are the measure of the average radiance yearly composite using data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB), that are filtered from the radiance generated by natural phenomena such as moonlight and aurora.

2.1.1 Global Human Settlement Built-up layer (GHS-BUILT)

The Global Human Settlement Built-up layer (GHS-BUILT) used in this study was produced by processing global records of satellite imagery collected by the Landsat-8 optical satellite platform for the years 2014, 2015 (Pesaresi, 2016) and the Sentinel-1 radar satellite platform for the years 2016 and2017 (Corbane et al., 2017). These satellite sensors produce imagery at spatial resolution of 30 m (multispectral), 15 m (panchromatic), and 10 m for the Sentinel-1. The GHS-BUILT data used in this study were produced at 30x30 spatial resolution, using a fully automated supervised classification method based on Symbolic Machine Learning (M. Pesaresi et al., 2016).
For use in in this research, the data are also aggregated at spatial resolution of 250x250 meters and 1000x1000 meters, using the average (surface share) operator, in Mollweide projection (EPSG 54009).

2.1.2 Global Human Settlement Population Density (GHS-POP)

The Global Human Settlement Population Density (GHS-POP) used in this work is produced from a combination of built-up area (GHS-BUILT) and population data available at administrative boundaries from the Gridded Population of the World (GPW) project (Center For International Earth Science Information Network-CIESIN-Columbia University, 2017). The GPW project assembles a global population database from a number of data providers that combines spatially explicit administrative boundary and corresponding population estimates for use in population disaggregation (Balk et al., 2006). The GPW global population database (version 4.10), available as administrative boundaries, is disaggregated spatially in this research based on the 250 m x 250 m GHSL built-up spatial grid in Mollweide projection (EPSG 54009). The built-up spatial grid is used to “anchor people to the ground”. This is based on a probability that is modified by combining the built-up information with population suitability (Freire et al., 2015). The year of reference of the GHS-POP data used for this study it is 2015.

2.1.3 Night Light Emission

The Night Light Emission (NLE) data recorded by satellite platforms have been used in a number of application areas (Elvidge et al., 2007) (Elvidge et al., 2017).

The NLE layer selected for the purpose of this report is the Version 1 VIIRS (Visible Infrared Imaging Radiometer Suite) DNB (Day/Night Band) Night-time Lights Composites suite[1] produced by the Earth Observations Group (EOG) at NOAA/NCEI. These grids span the globe from 75N latitude to 65S and have a resolution of 15 arc-second in WGS84 geographic coordinates (EPSG 4326), which corresponds to roughly 500 m at the equator. The following analysis uses the "vcm-orm-ntl" (VIIRS Cloud Mask - Outlier Removed - Night-time Lights) layer showing the cloud-free average radiance emitted, expressed as nano-watt per steradian per square centimetre (nW cm^{-2} sr^{-1}) with outlier removal process to filter out fires and other ephemeral lights. The year of reference for these data is 2015.

2.2 Data processing

The GHS_POP, GHS_BUILT, and NLE variables were prepared for the processing by projecting all of them to the same global geographic projection. We used the equal-area, pseudocylindrical map projection known as the "Mollweide" projection (EPSG 54009).

After the spatial harmonization phase of the data, the main data processing steps applied in the study are summarized below:

$$standardization \rightarrow sequence\ encoding \rightarrow clustering\ \ or\ visualization$$

In the standardization phase, a linear rescaling approach was chosen using a statistical parametric method as detailed below. Be x the spatial information under processing GHS_POP, NLE , and

(1) $x' = \log_{10} x$

the log transform of x , and be

(2) $x'' = \frac{(x' - c_{min})}{(c_{max} - c_{min})}$

the linear rescaling of (1), bounded in the $[0..1]$ interval.

We estimate the $c_{max} = \mu_{x'_d} + 2\sigma_{x'_d}$ and $c_{min} = \mu_{x'_d} - 2\sigma_{x'_d}$, with $\mu_{x'_d}$ being the average of x' in the spatial domain d, and $\sigma_{x'_d}$ being the standard deviation of x' in the same spatial domain d.

For the GHS_BUILT variable a similar approach was taken without passing through the log transform, instead equation (2) was directly applied to the original data.

The spatial domain d used in this study corresponds to the universe used as reference for estimating the statistical standardization parameters.

In the global showcase, the domain d was corresponding to the *whole global inhabited surfaces*, formalized as the union of all the 1x1km^2 spatial samples in the Earth landmass, where more than 50 resident persons was estimated by the GHS_POP source, or $d \in \{x : x_{GHS\_POP} > 50\}$. In the national showcase, a similar approach was taken, but

[1] https://www.ngdc.noaa.gov/eog/viirs/download_dnb_composites.html#NTL_2015

bounding the universe by the intersection with the domain of the national boundaries taken in to consideration.

The clustering was performed by assuming an additive colour mixing model and associating the standardized GHS_POP, GHS_BUILT, and NLE variables to the Red, Green, Blue colour components, in that order. The RGB colour space can be used directly for data visualization purposes, or used as input for a data reduction transform such as the Minimum Variance Quantization implemented in MATLAB[2] and used in the study.

The resulting combination and the spatial arrangements of GHS_POP, GHS_BUILT, and NLE variables define the colour patterns displayed in Figure 1. This is also the legend for the interpretation to the figures in the following chapters.

The three primary colours red green and blue are respectively associated to population built-up and night lights. The secondary colours are the combination of two primary colours; yellow originates by combining red and green; magenta from red and blue; and cyan from blue and green. In Figure 1 the primary colours and secondary colours are displayed as the vertices in a colour cube space as 1, 3 and 5 for blue, red and green respectively. The secondary colours as vertices labelled 2, 4 and 6 for magenta, yellow and cyan respectively. The three sides of the cube display each combination of two variables with at least one of the 6 colours saturated (maximum intensity). The inner of the cube represent all possible combination of the three primary variables at different intensity of colour.

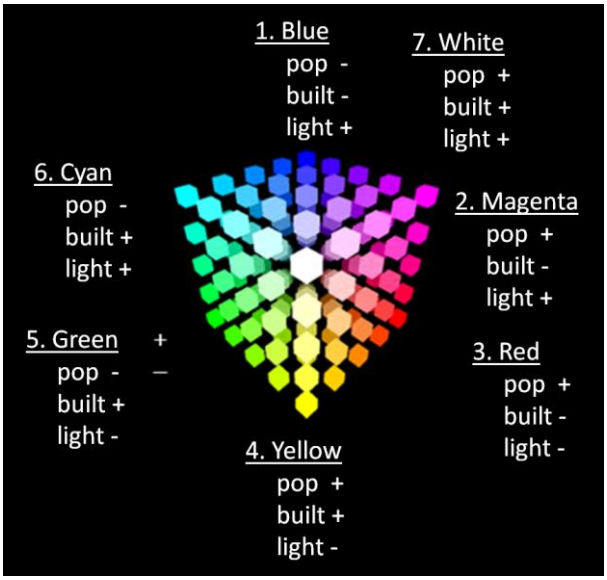

Figure 1. Night-lit settlement map colour legend based on the colour cube (see appendix B)

For this research, the colours and combination of colours are associated to one or more combinations of night-lit settlements patterns. In fact, there is not unique association between the colours and the pattern or process. The association of colours with one or more given night-lit spatial patterns is summarized in Table 1. The table also provides when possible, examples of association of colours and the night-lit spatial patterns occurring throughout the text.

[2] https://www.mathworks.com/help/matlab/ref/rgb2ind.html

Table 1. The table provides example of the association of colours and colour combinations with the three variables used in this colour composition.

Code	Colours	Combination of colours	Typical settlement patterns corresponding to that combination of colours
1	Blue	Light only	Large industrial installation Security infrastructure (fences, walls) Oil and gas extraction sites Illuminated road infrastructure
2	Magenta (Red and Blue)	Population and light No built-up	Deprived areas, historic urban civilization Scarce settlement infrastructure Densely inhabited Increased electrification
3	Green	Built up only No lights No population	Second homes Abandoned villages Over-built rural areas
4	Yellow (Red and Green)	Population and built-up No Lights	Poor lit cities, deprived areas (many cities of the developing world) Historic urban civilization Diffuse settlement infrastructure Scarce public illumination Densely in-habited (China, Bangladesh, Pakistan)
5	Red	Population only	Deprived areas or large and dense slums Dense population, no public illumination War-affected areas (Yemen, Syria) Disasters-affected areas (part of Africa, C. America and Caribbean's)
6	Cyan (Blue and Green)	Built-up and Lights No population	Affluent cities, suburbs Large built-up soil use Large public illumination Sparse population
7	White	Population, Built-up and Lights	Well lit cities – Most large cities of the world High density of people, high density of buildings, large night light emissions

3 Global patterns of spatial inequality

Maps of global night-time lights are often used to represent the human presence on the planet Earth. However, this representation excludes the communities that are deprived from access to electricity – and hence street illumination. In this representation Africa, for example, is almost invisible, except for the Nile region in Egypt and the Gauteng province in South Africa.

Figure 2. Global night-time lights map for the year 2015.

The combination of night-time lights with population and built-up densities takes this into account and highlights exactly this omission. The spatial inequality that we aim to illustrate is a dimension of overall inequality, but it adds significance when spatial and regional divisions align with political and ethnic tensions to undermine social and political stability (Kanbur and Venables, 2005). This chapter presents examples of spatial pattern of inequality based on the joint analysis of built-up and population density with night-time lights emissions. The results of the global patterns of spatial inequality are presented as three-colour combination depicting night-lit spatial pattern for different scales. The section includes the global and continental overview, urban-rural patterns, conflict areas, divides along country borders or within countries and even between cities. All figures are displayed aiming to highlight the spatial patterns generated by different proportion of population, built-up and, nightlights. The captions and the text aim to qualitatively address and explain the patterns in a qualitative and comparative way.

The colours in each figure result from the prevalence of one variable over the other two. In this initial discussion, we do not address the absolute values of each variable; this is beyond of the scope of this document. The aim is to analyse the three variables relatively to each other and to list and describe the resulting patterns across the globe. The colour that is generated from the combination of the three variables results from the prevalence of the corresponding variable over the other two. For example, the red spatial pattern is generated when population – that is coded in red - prevails over built-up and nightlight. Similarly, the colour blue is generated when nightlights dominates over population and built-up.

3.1 Global overview and continental patterns

In contrast to the black marble map that uses only the night-time light, the new approach shows a much more differentiated picture of the globe (Figure 3). The dominant blue features– that were nightlights dominate over the other variables– occurs in the energy producing countries including those of the Gulf states as well as high income countries of North America, Europe, Australia, New Zeeland, South Korean, Japan and Taiwan. It is also present in Southern Africa and the Southern part of South America. The figure shows lack of lights in Sub-Saharan Africa with exception for South Africa, rural as well as central China. The low lit and high population human settlement patterns – visible as red colour- are typically of low income countries and are found abundantly in Sub-Saharan Africa. The high built-up and population and no lights – visible as green –is typical of high income countries. Mid-income and emerging economies display intermediate night lit patterns that are addressed in the following sections. The patterns are explored at finer cartographic scale and visualized in the following figures.

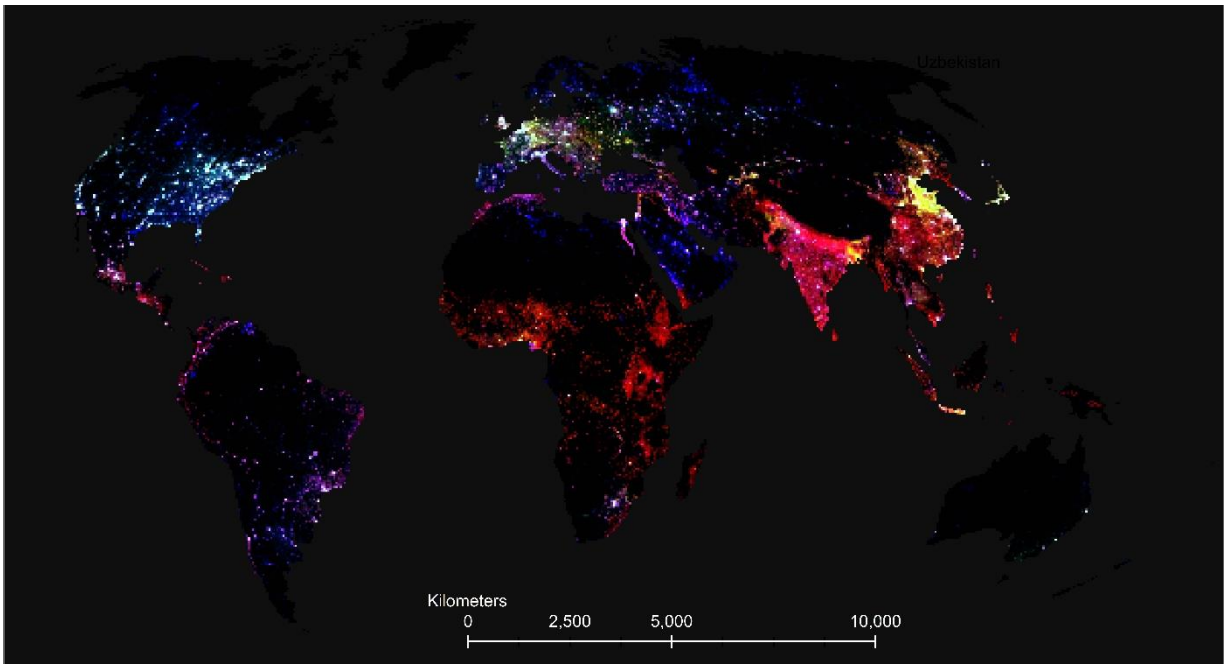

Figure 3: Global patterns of inequality detected by combining global population density, built-up density and night light emission for 2015.

This section shows five spatial settlement patterns at continental scale. The figures aim to provide insight in the inequalities of the three variables within continents, between continents at the city level.

Figure 4 shows the relative diverse settlement spatial patterns in Central and Southern Europe. Overall, Europe is well lit including the peripheries. However, there are large variations between metropolitan areas, peripheries and in the rural areas. Southern Europe is well lit in both urban and rural areas. This is in contrast with less well lit central European countries that in turn show also significant differences that can be noticed along country borders. For example, Belgium is differently lit than the Netherlands that in turn is different from Germany. In fact, this is the possibly the effect of different spatial patterns originating from different planning traditions and different energy use/- saving policies that are implemented in each country. The spatial patterns in Germany differ from that in the former Eastern Germany and from Poland. Often within a country night light emission may vary. For example, Western/Atlantic France shows a larger percentage of not lit built-up when compared to the rest of the country.

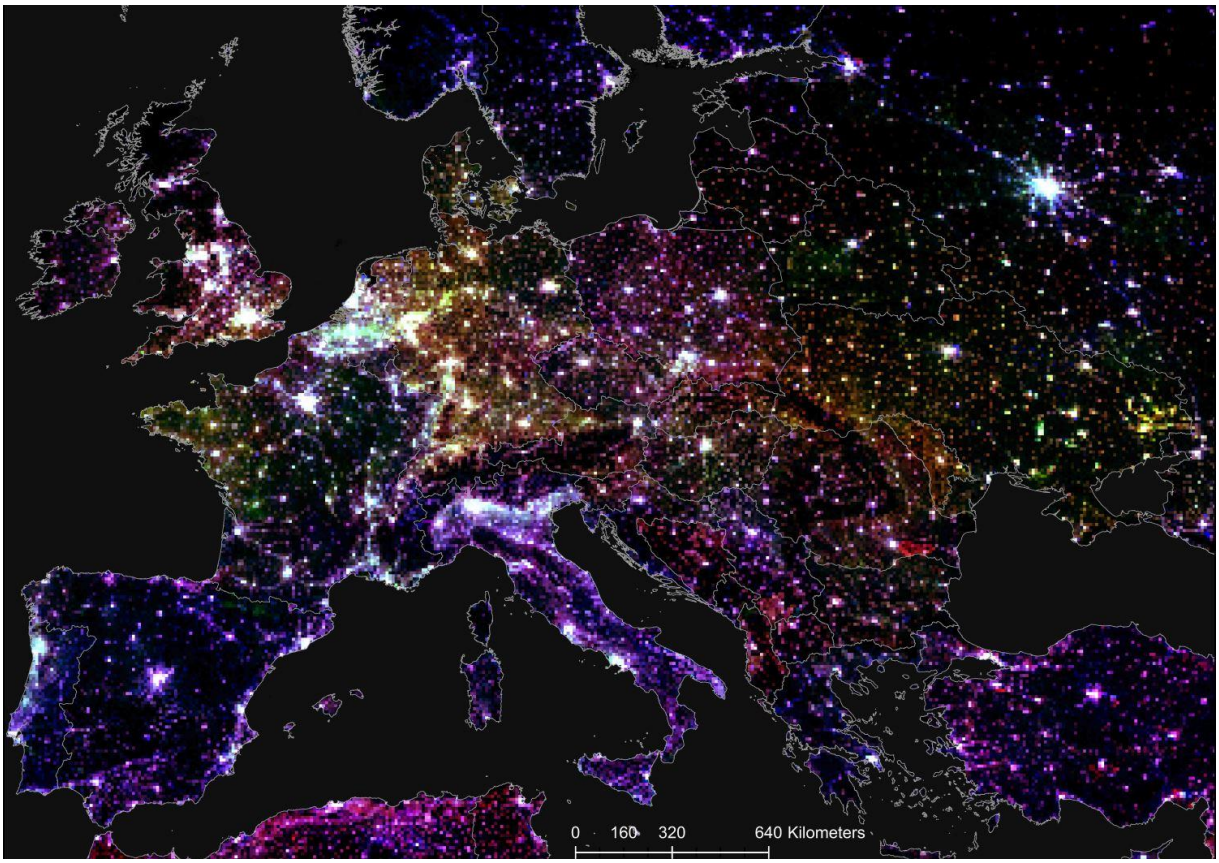

Figure 4 Europe shows a rather divers settlement spatial patterns, and some seem to coincide with administrative boundaries, but spatial patterns diverge also within countries.

North America, more specifically the United States of America, (Figure 5) shows more homogeneous settlement spatial patterns, when compared to that of Europe (Figure 4). North America is characterized by high concentration of nightlight in all larger and smaller cities and rural areas and a regular spacing and hierarchy of cities. The patterns are the result of a more regular topography and a more recent urbanization process (300 years). Peripheries of the Eastern States and Southern states seem to be more populated than those in central plains of North America. The pattern in the United States is in strong contrast with those of Central America except for the larger metropolitan including Mexico City.

Relevant is the difference of Mexico with high night lit area in northern Mexico and less lit areas in the rural countries. Similarly, Central America shows diverse patterns with El Salvador, Nicaragua and Guatemala lit only in the larger urban centres.

Haiti, Dominican and Puerto Rico, for this dataset of 2015 show large differences in nightlights Haiti that is almost deprived of nightlights except for the capital. The Dominican Republic is relatively well lit but less than Puerto Rico.

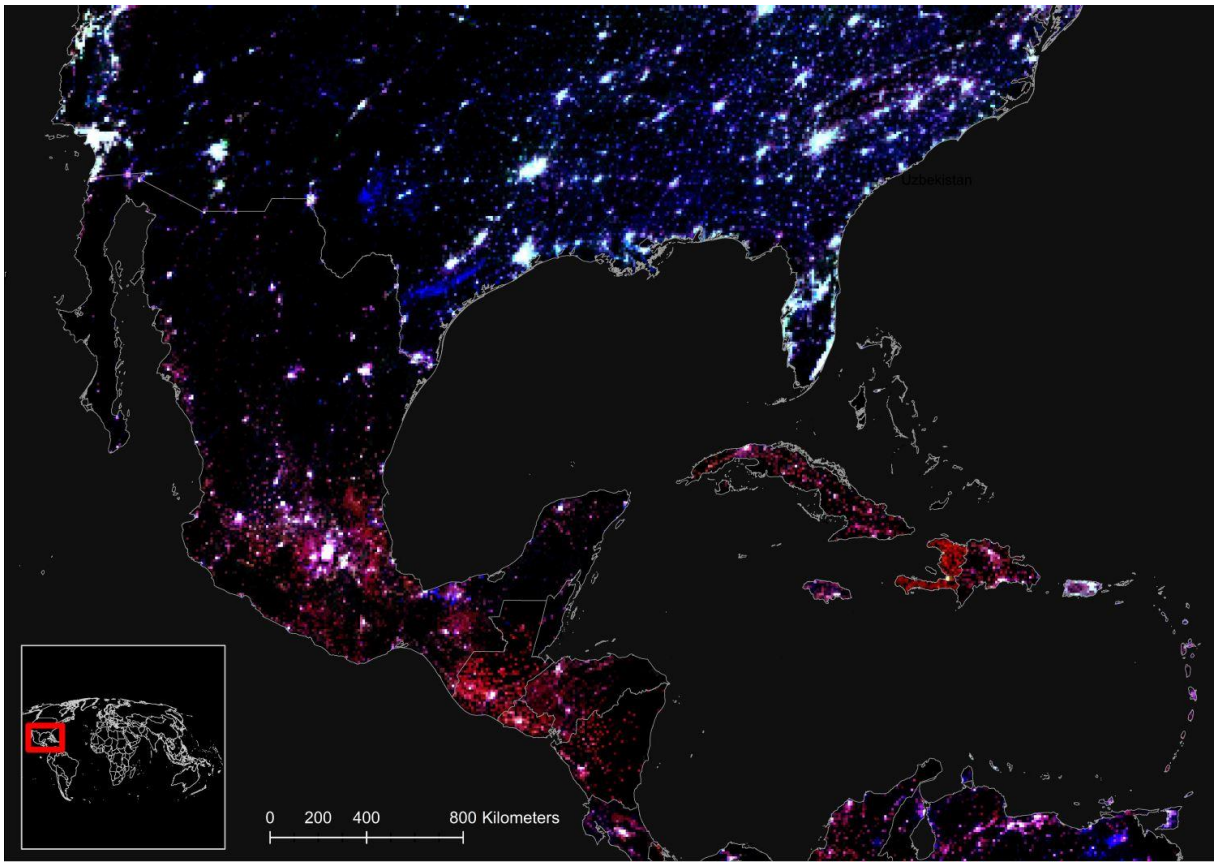

Figure 5 North America shows relativey well lit urban centers and rural ares, smaller urban areas and rural centres.

Figure 6 focuses on Northern/Central part of Africa and the Middle East. The image shows the big divide in lit areas between the oil producing Middle-East countries and large part of Africa. The first very well lit also along transport corridors, the latter not lit also in high density populated areas. In fact, night lights dominate over the population density and built-up area even if it is relatively low except for largest urban centres. The magenta colour shows the relatively low density of built up in the peripheries when compared to the city centres. Within the Arab peninsula Yemen – already in conflict in 2015 – stands out as the only almost completely light deprived country of the Arabian Peninsula.

Northern Africa is dominated by the well-lit populated Nile river delta. The image shows Cairo as one of the best lit cities in the continent. In addition Libya oil producing (Western part).

West and East Africa are the least lit regions globally. In fact, the electrification process is underway and still needs to be completed. Most rural areas are still deprived of nightlights. Most large cities are lit, but West Africa cities as are less lit than average (Yellow colour). The coloured human settlement spatial patterns are typical of emerging economies.

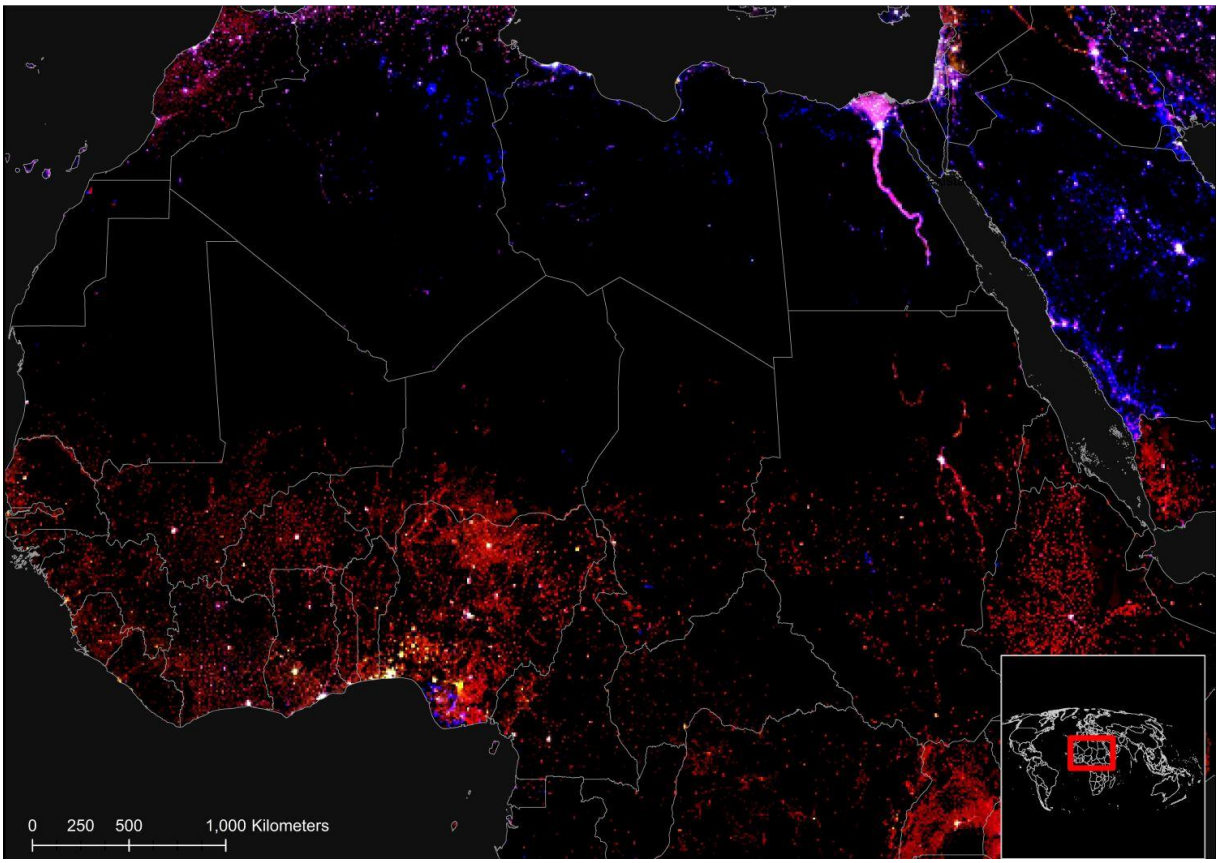

Figure 6 Africa and middle-east shows a variety of settlment spatial patters. From the well lit energy producing countries to deprived rural aras and conflict countries (Yemen) and the densly populate ancient civilization country.

Figure 7 focuses on South-east Asia including India, China and Japan. The Indian subcontinent shows Pakistan and Bangladesh very densely populated with low nightlight. The foothills of the Himalayas are also not lit. In comparison, India has a higher degree of nightlights especially South of New Delhi and around larger centres. India is more lit than Bangladesh and Pakistan and Nepal. India shows different patterns of nightlights with some regions including New Delhi more lit than others, in particular Eastern Indian states.

China, displays an even more complex pattern. The Sichuan regions in Southern Central China shows rural areas not lit, while the coastal plains in the east show high concentration of both built up and population and relatively low light emissions. All larger settlements on the other hand are very well lit, with the larger megacities including Shanghai are very well lit. The coastal plains of Eastern China show densely populated spatial patterns with high built-up and relatively little nightlights except for the bigger centres. The Shenzhen industrial areas stands out for being extremely well it despite the fragmented urban fabric, on which it is built.

Both Taiwan and South Korea stand out for nightlights similar to those of the highest income countries. The Far East centred on the Korean peninsula show the variety of night lit-spatial patterns, from the poorly lit North Korea, the well-lit South Korea and Japan.

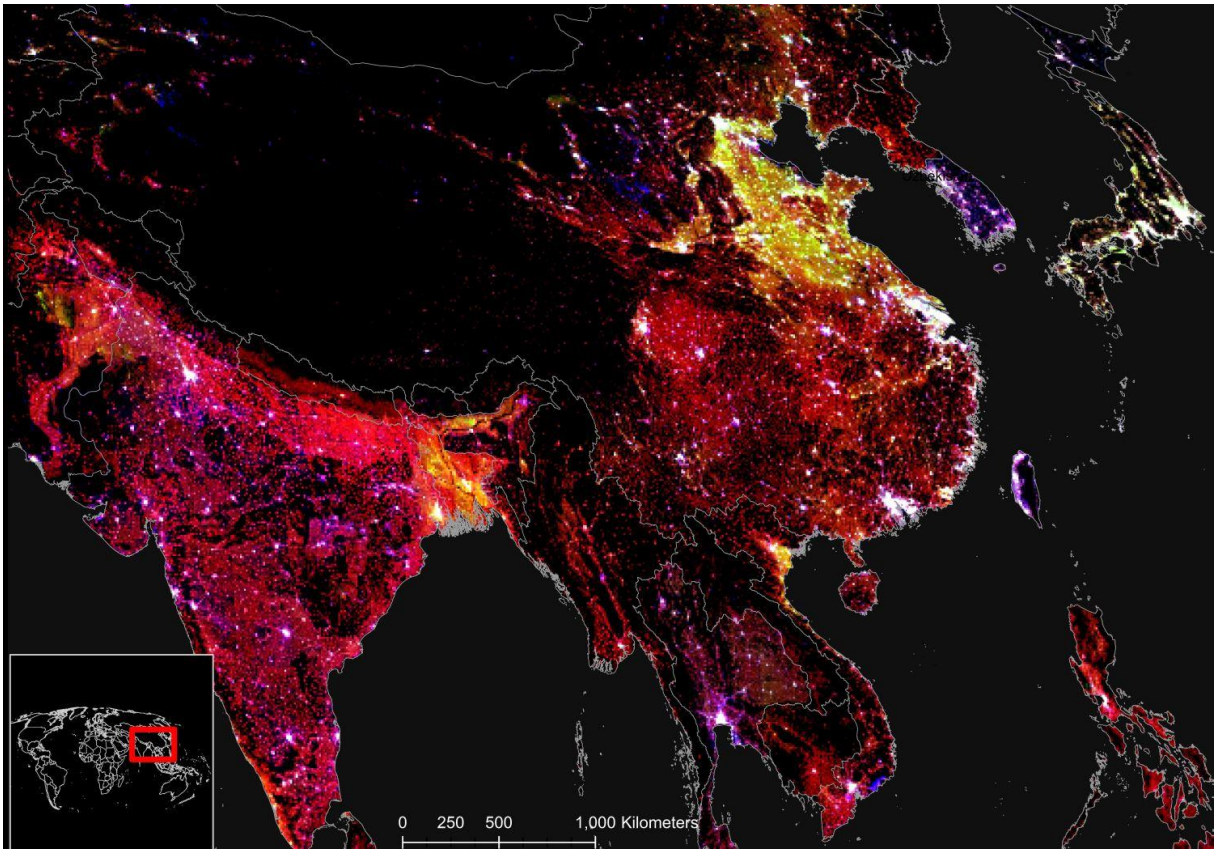

Figure 7 Asia spatial patterns. India is better lit than Bangladesh and Pakistan and Nepal. India shows different patterns of nightlights with some regions including New Delhi more lit than others, Eastern Indian states. The Far East centred on the Korean peninsula show the variety of night lit-spatial patterns, from the poorly lit North Korea, the well-lit South.

South East Asia (Figure 8) strikes for its mix of high and low densities settlments as well as high and low intensity lighting. The dominant features are the large metropolitan areas and capitals, Bangkok, Ho-Chi Min city, Kulalumpur, Singapore, Jakarta, that all are well lit. The surrounding areas show diferent patterns. Bangkok periphery is typical high density and relatively low lit. While the Tourist areas South East of Bangkok stand out as well lit. West of Ho-Chi Min city the tourist resort as an area that has low poulation and igh lights.

There are also striking devidies between the Oil producing country of Malesia and Bruenei show high light patterns when compared to that of the other neighbouring countries, and countries in the areas that are typicaly not lit.

Indonesia shows also different patterns within the countries. First, the main island – Java - shows very high concentraiton of population and built-up when compared to the other islands of Indonesia (i.e. Sumatra). Philippines show the patterns of the low income countries with non lit rural poulation areas as the main night lit spatial patterns. The island of Borneo is the last inhabitated except for the margins.

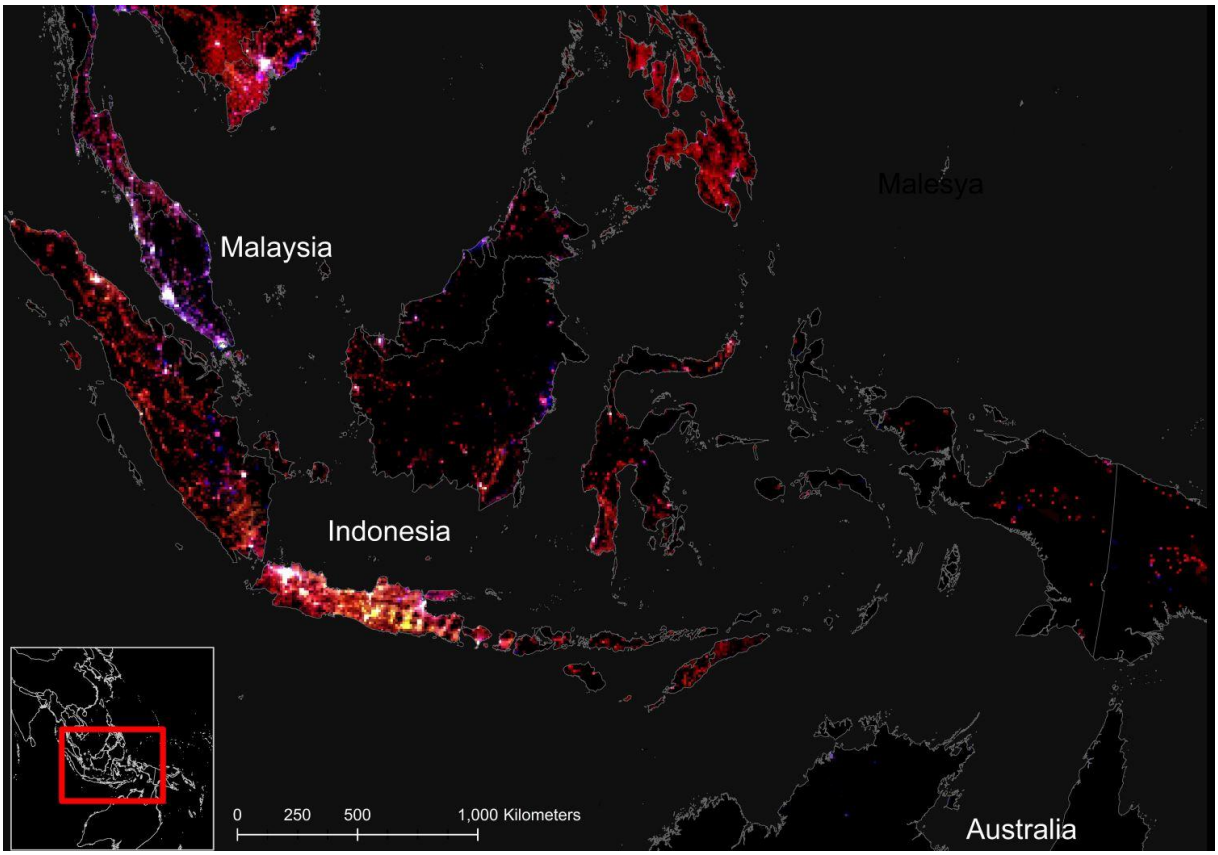

Figure 8: South-East Asia shows a dominance of low lit/heavily populationed lit spatial patterns over a small part of well lit spatial patterns that is due to oil producing countries.

South America spatial patterns are typical of new colonization of land, with a regular spacing of settlments (Figure 9). The Andean region shows the settlments along topographically favourable areas. The settelments are well lit mostly in large cities only.

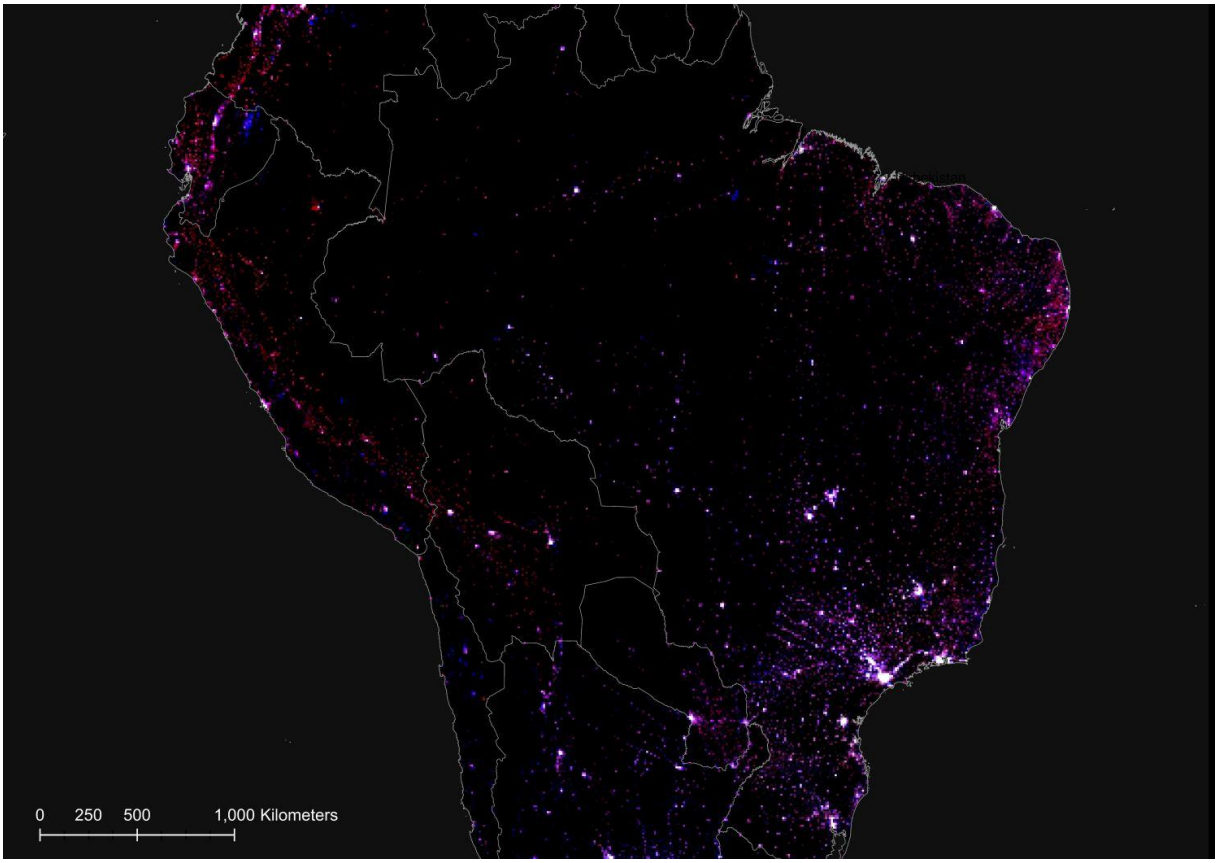

Figure 9 Continental South America spatial patterns

3.2 Inequality creating sharp contrast between neighbouring countries

The previous section has highlighted the strong regional differences in the combined analysis of population, built-up and night-time lights emission. This section will focus on divides between countries. The divide is mostly noticeable in countries with different income and/or political regimes. The best-known example is contrast between North and South Korea. The North Korean and South Korea nightlight divide runs along the two countries border (Figure 10). South Korea is well lit, similarly to other high income countries, while North Korea mostly not lit except for the largest cities. In North Korea, even largest cities display similar lighting patterns visible in West Africa. Japan shows high light use and characteristic patterns of low population, high built up in the peripheries of the major centres. Japan as for a number of high-income countries also shows a high degree of built-up in rural areas and peripheries of large cities as a high land per capita ratio.

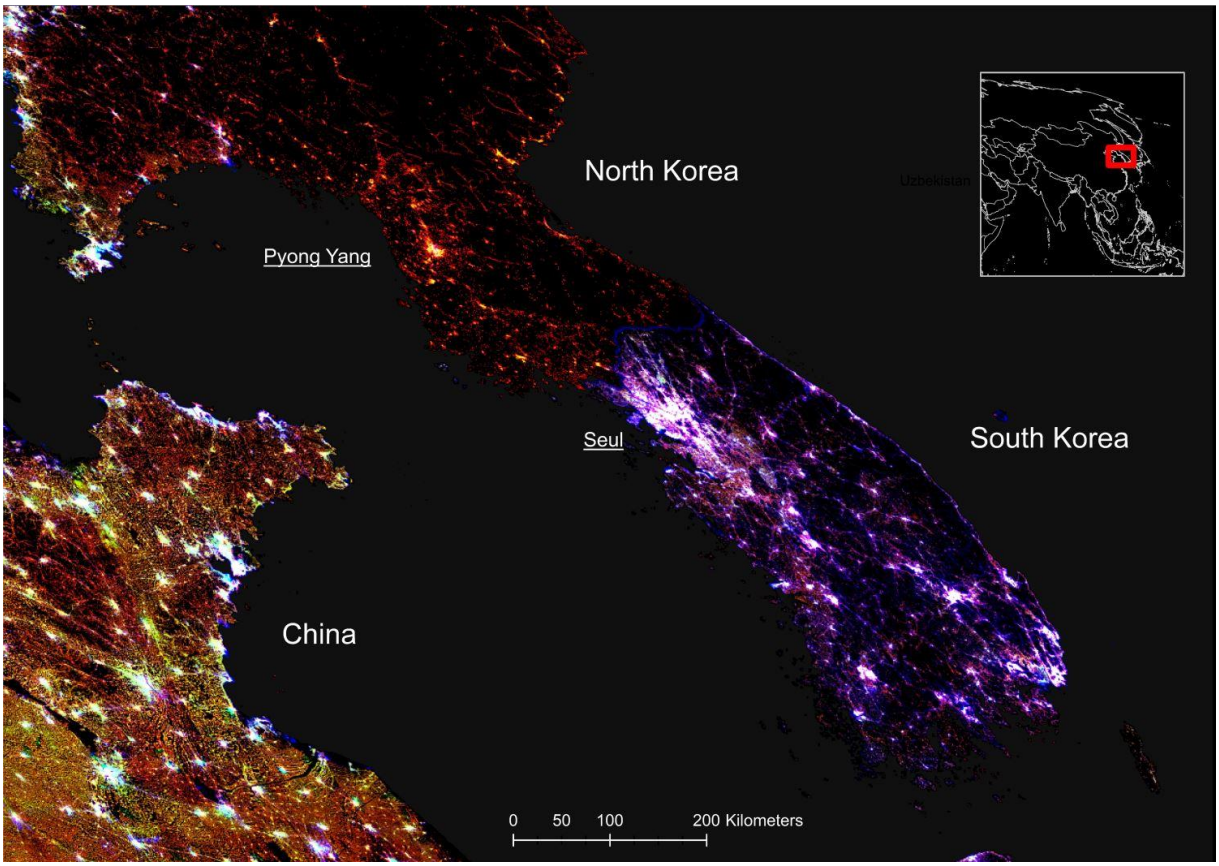

Figure 10. South and North Korea show different night-lit spatial patterns. South Korea well illuminated and North Korea very poorly night-lit.

Figure 11 shows there countries, Haiti, Dominican Republic, and Puerto Rico. The latter exhibits an US American style of strong illumination throughout the country. The map depicts the situation of the year 2015. After the hurricane Maria hit the country, the situation changes dramatically leaving large part of the country in the dark[3]. The Dominican Republic shows a mix of well-lit urban areas and towns with some rural areas without night-time illumination. In strong contrast, the entire country of Haiti is without night-time light illumination, except the capital, Port au Prince. However, also here the level of illumination is much lower compared to the other capitals.

The Amur Darya is feeding the Aral lake in Central Asia. The riverbanks are characterised by intense irrigation agriculture. The border between Turkmenistan and Uzbekistan cuts through the area (Figure 12). In the combined population built-up and night-time light map this border is clearly visible. The gas- and oil-rich Turkmenistan, one of the world's fastest growing economies, invested in infrastructure that illuminates all of the country. In Uzbekistan only the main city of the area, Urgench, is illuminated to some extent.

Figure 13 shows Malaysia and Indonesia (Sumatra); the former an oil producing countries clearly lit and the latter poorly lit except for the main cities.

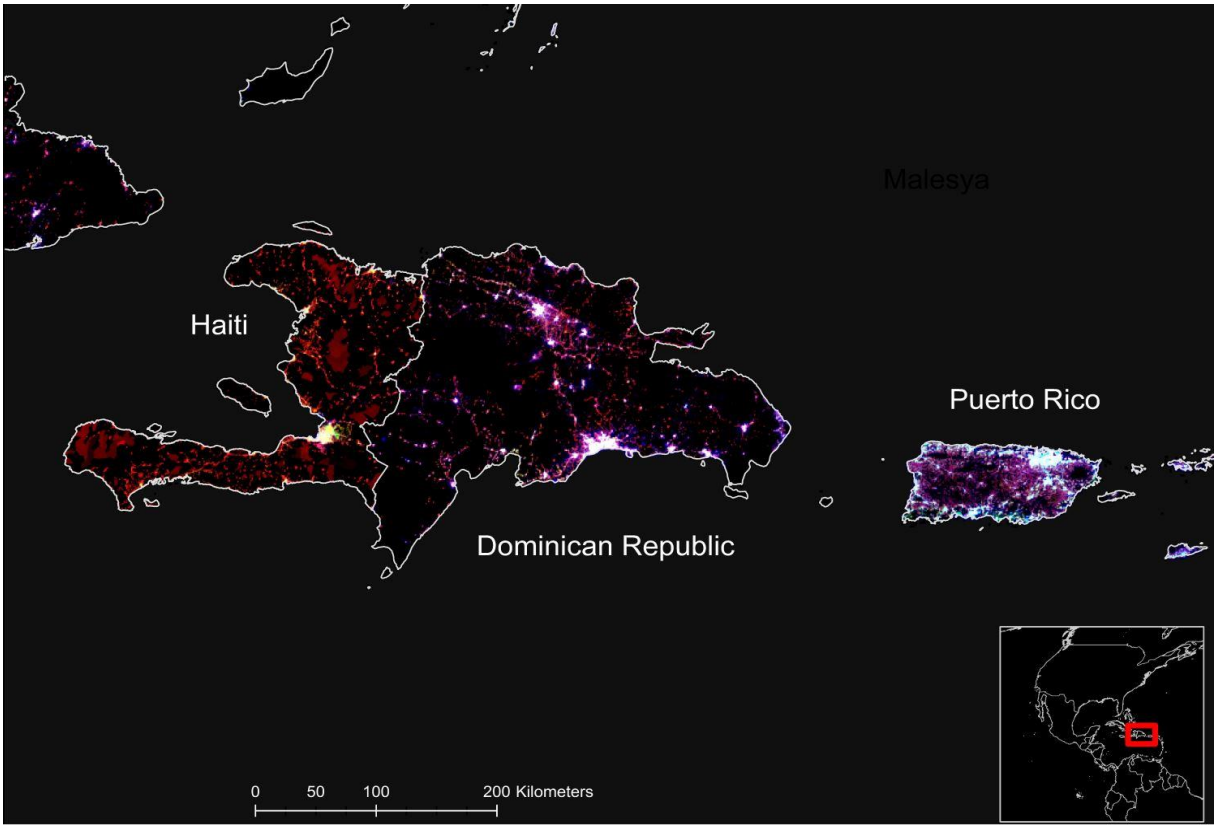

Figure 11. Puerto Rico, Dominican Republic and Haiti – neighbours with a decreasing degree of night-time illumination.

[3] https://earthobservatory.nasa.gov/images/91044/pinpointing-where-the-lights-went-out-in-puerto-rico

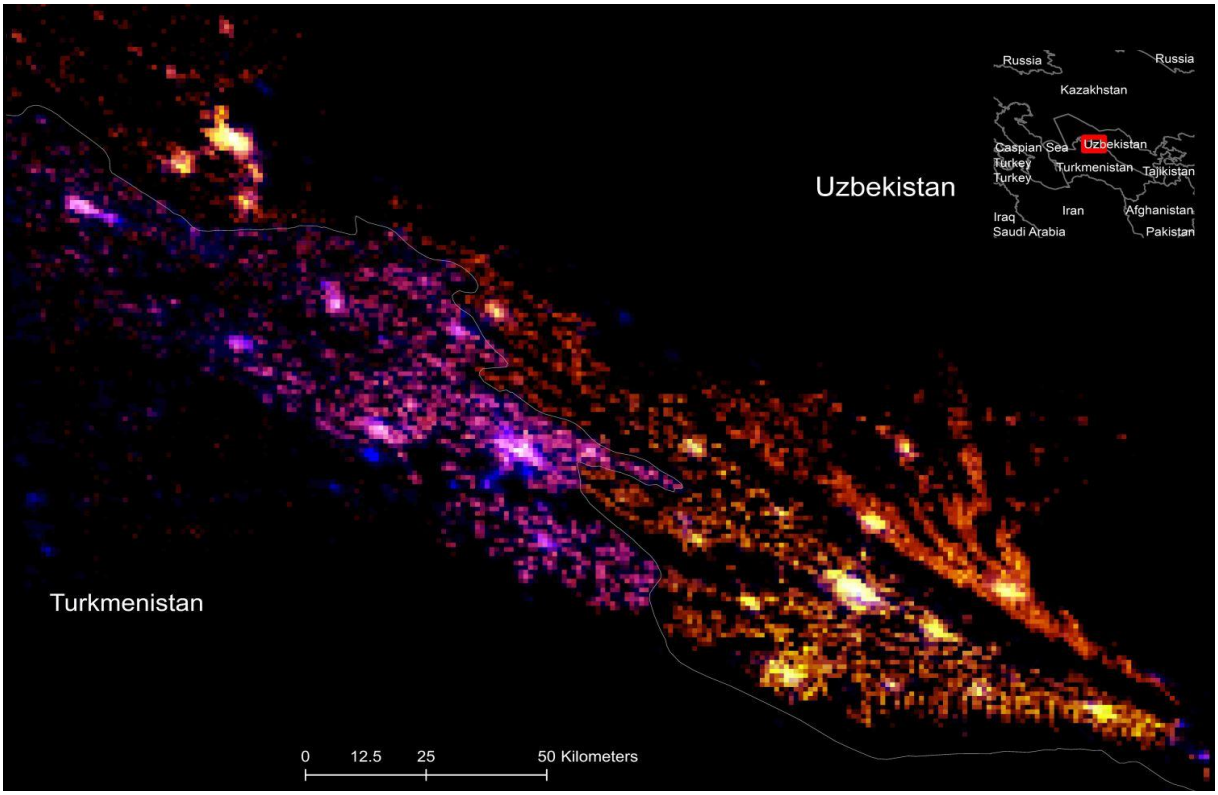

Figure 12. Divides between Turkmenistan (Dashoguz) that shows lights in the city, while Uzbekistan (Urgench, Khiva) show no lights but rather population and built up (yellow and red).

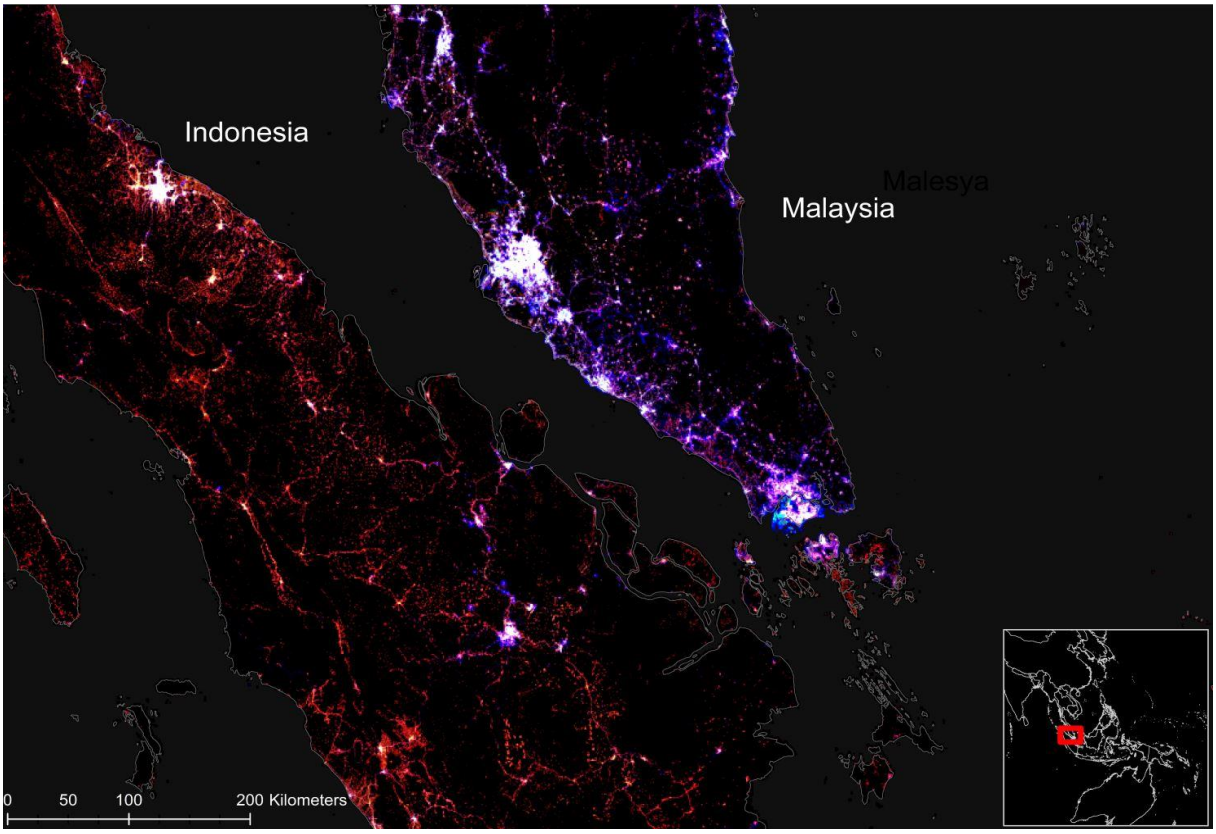

Figure 13. Indonesia displays the patterns of emerging economies with well-lit urban centres and few lights in rural areas. Malaysia shows high intensity nightlights with similar spatial arrangements of settlements.

3.3 Inequality along the urban-rural gradient

In many countries the living standards and economic opportunities in rural areas lag far behind those of urban areas (e.g. Sahn, 2003). Such trends are also be reflected by the built-up, population, night-time light nexus. This section shows a set of urban-rural spatial patterns from different continents. Figure 14 shows a area in the Unites States of America with the city of Chicago in the East. The map illustrates a classical example of US settlements pattern with a number of larger settlements and in between small cities and towns of often in evenly spaced distances along a linear road network. All settlements are evenly illuminated.

A similar pattern of colonization of land can be observed in Argentina (Figure 15). From the capital Buenos Aires a number of settlements are aligned along linear road networks. However, many of the settlements in Argentina – including the capital are surrounded a halo of magenta tones indicating the presence of population and light with low amounts of built-up. Such settings are typically for poorly constructed areas that nevertheless have access to night-time illumination.

The example of central Western Europe with Germany, France and the Benelux countries (Figure 16) shows a distinctively different pattern settlement pattern that grew over centuries. There is a strong variation between and within the countries. At the centre of the map is the Rhine-Ruhr area with a number of major cities between Cologne and Dortmund. While the large cities show the expected white colours, many settlements in West Germany are characterised by yellowish colours, which represent more people and built-up compared to the night-time light emission. The reduced night-time light emission is probably caused by measures to reduce 'light pollution'. In the territory of the former German Democratic Republic, these tones are less prominent; they almost allow identifying the former border. Belgium, in particular the Flemish part, and also parts of the Netherlands are very bright also due to the partial illumination of highways.

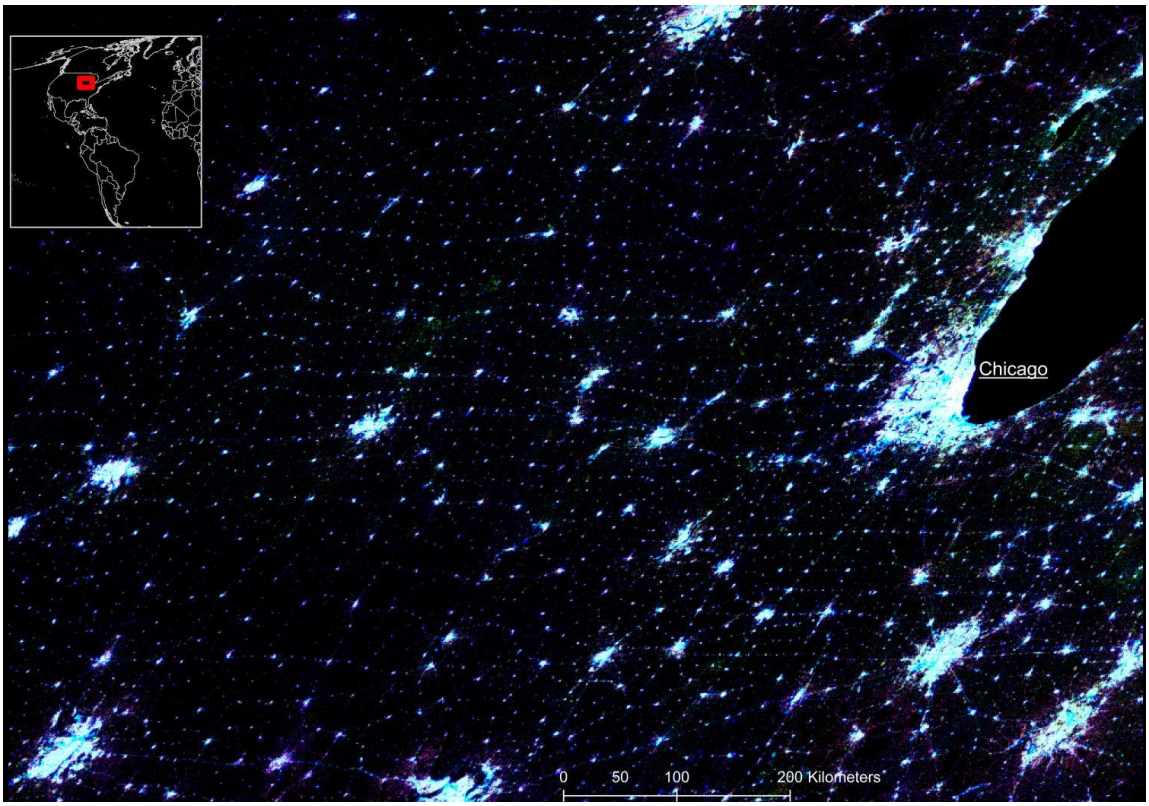

Figure 14 Urban rural spatial patterns in North America

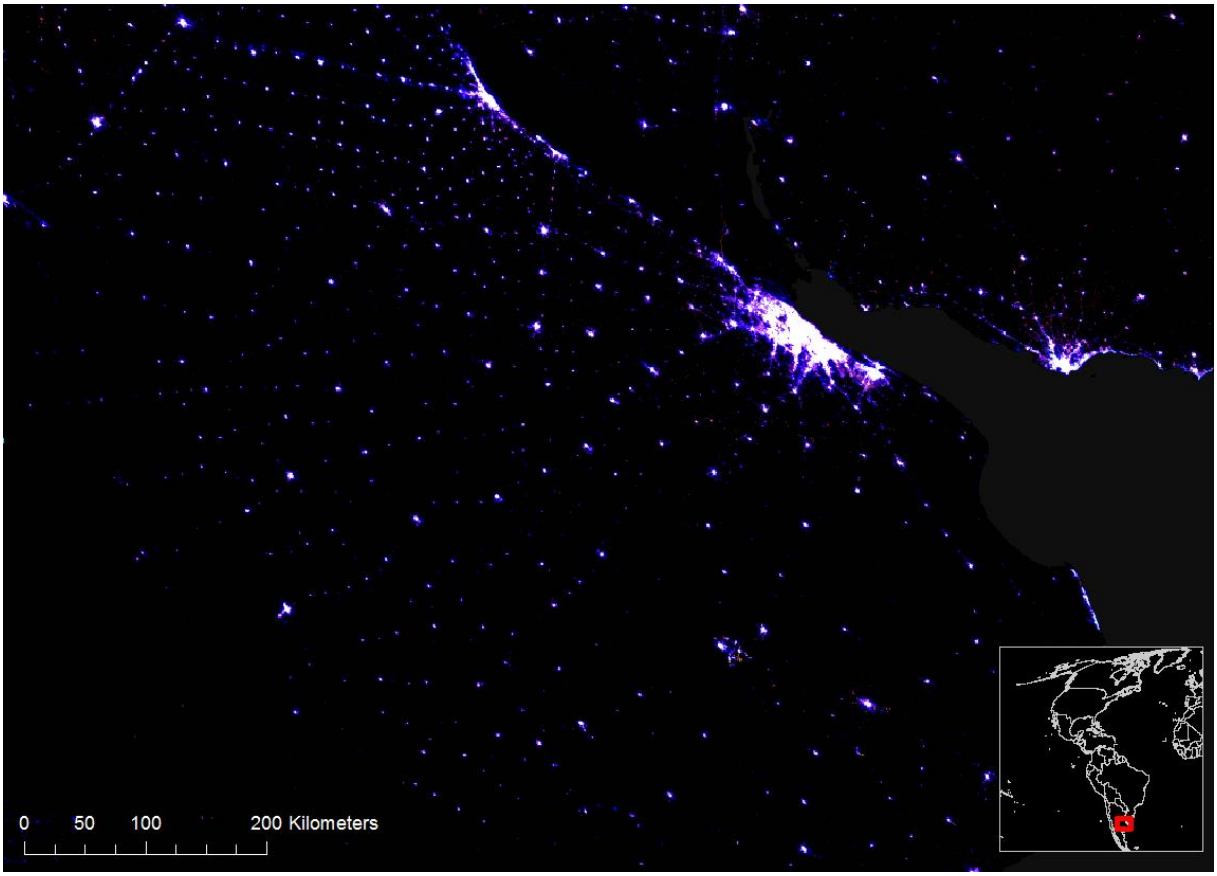

Figure 15 Urban rural spatial patterns in Argentina centered on the city of Buenos Aires

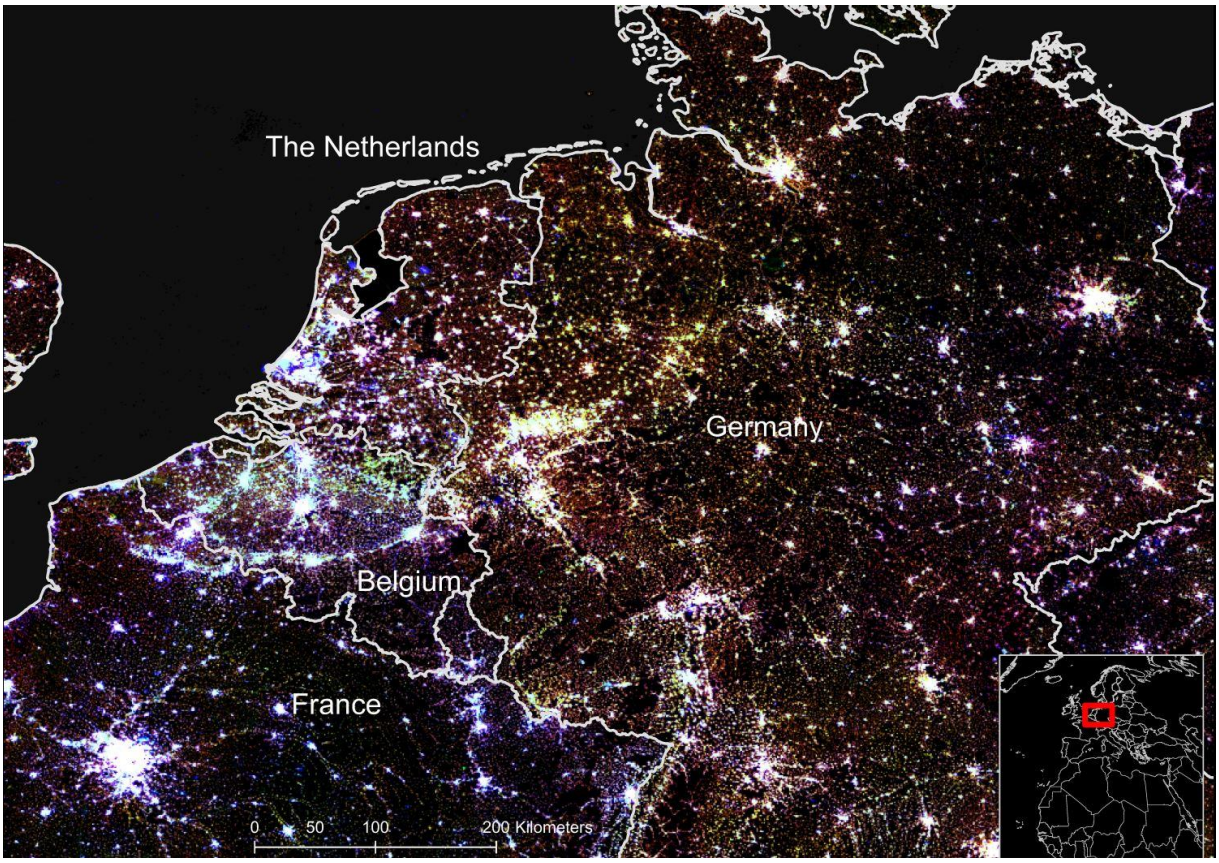

Figure 16 Urban rural spatial patterns in Central Europe with high diversity among European countries.

The gradient between well-lit urban areas and dark rural settlements is very pronounced in Central America. Figure 17 illustrates this for Guatemala, El Salvador, Honduras and Nicaragua. The capitals and other major urban centres are displayed in white with magenta tones in the surroundings. Most of the rural settlements are deprived from night-time illumination are therefore represented in red.

An even more pronounced gradient exists in the Great Lakes Region in Eastern Africa (Figure 18). Only the capitals Nairobi (Kenya), Kampala (Uganda), Kigali (Ruanda), and Bujumbura (Burundi) are well lit. The often densely populated rural areas are mostly dark. There is also a significant difference in the illumination intensity between Nairobi and the other capitals.

Figure 19 shows the Niger River Delta between Lagos (Nigeria) in the West and Doula (Cameroon) in the East. Both major cities exhibit the expected features of large well-lit metropolitan areas. The secondary cities and rural areas are represented by yellow-reddish colours representing diffuse settlement infrastructure with little or no public illumination. There is however a number of blue dots, which map the oil extraction sites in the delta. They can be seen as an allegory of inequality. The oil revenues generated by the oil extraction a largely disconnected from the local population.

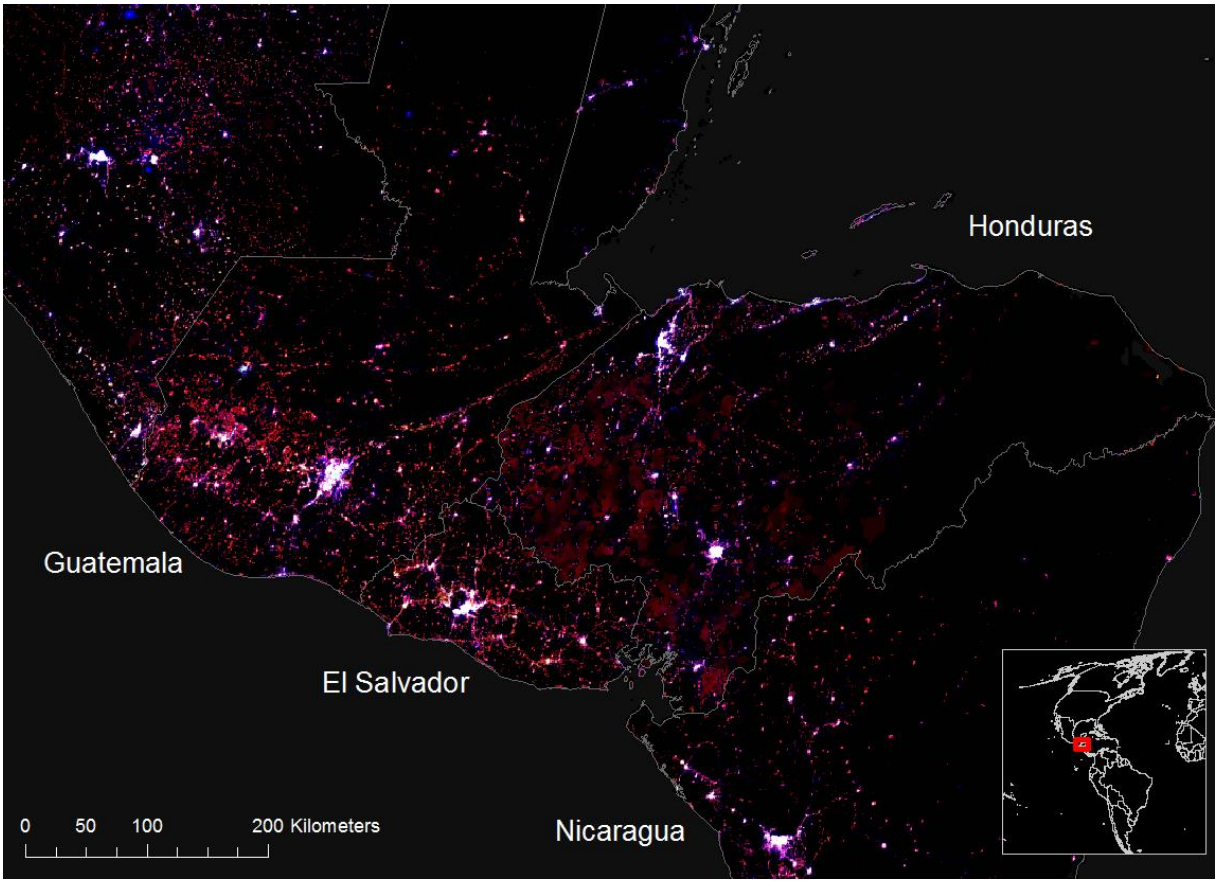

Figure 17 Urban rural spatial patterns in Central America with metropolitan aras well lit

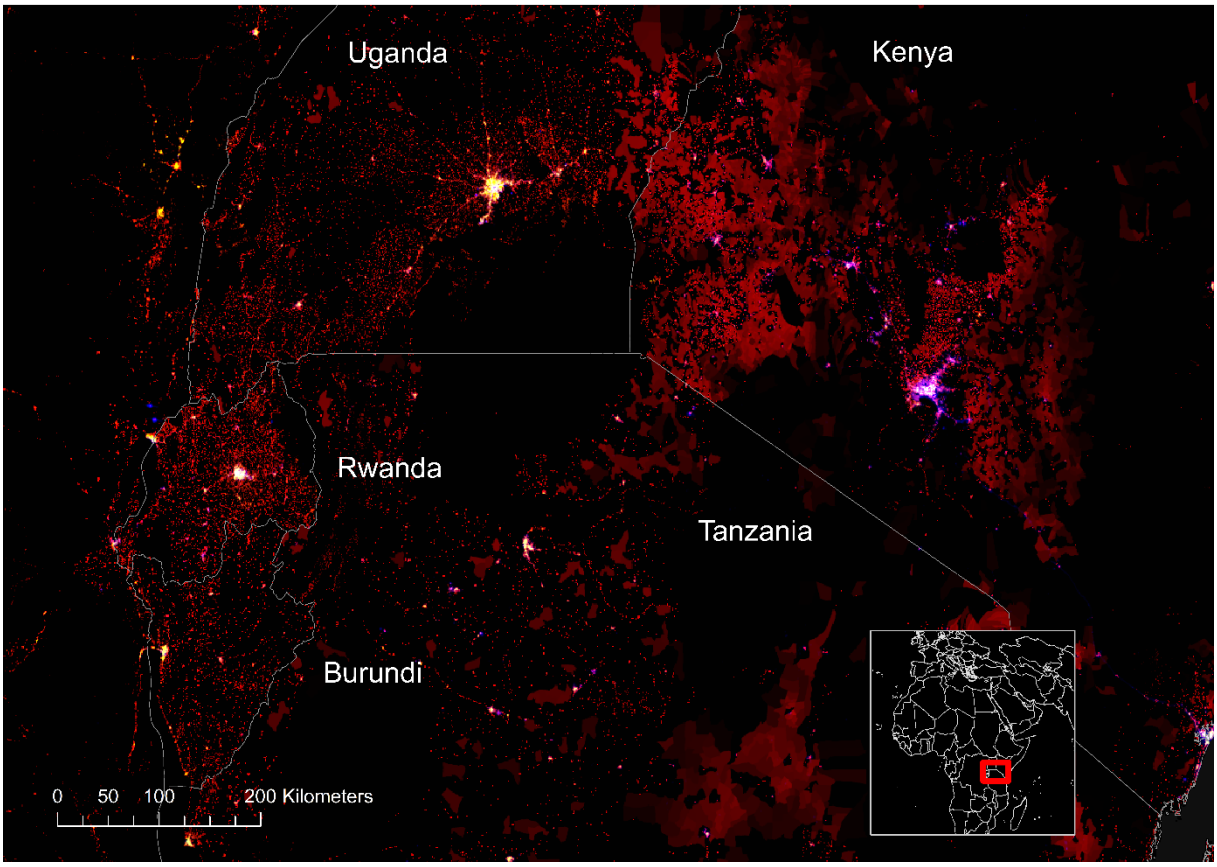

Figure 18 Urban rural spatial patterns in the Great Lakes region of Africa with Nairobi Kampala, Kigali and Bujumbura standing out among the rural areas.

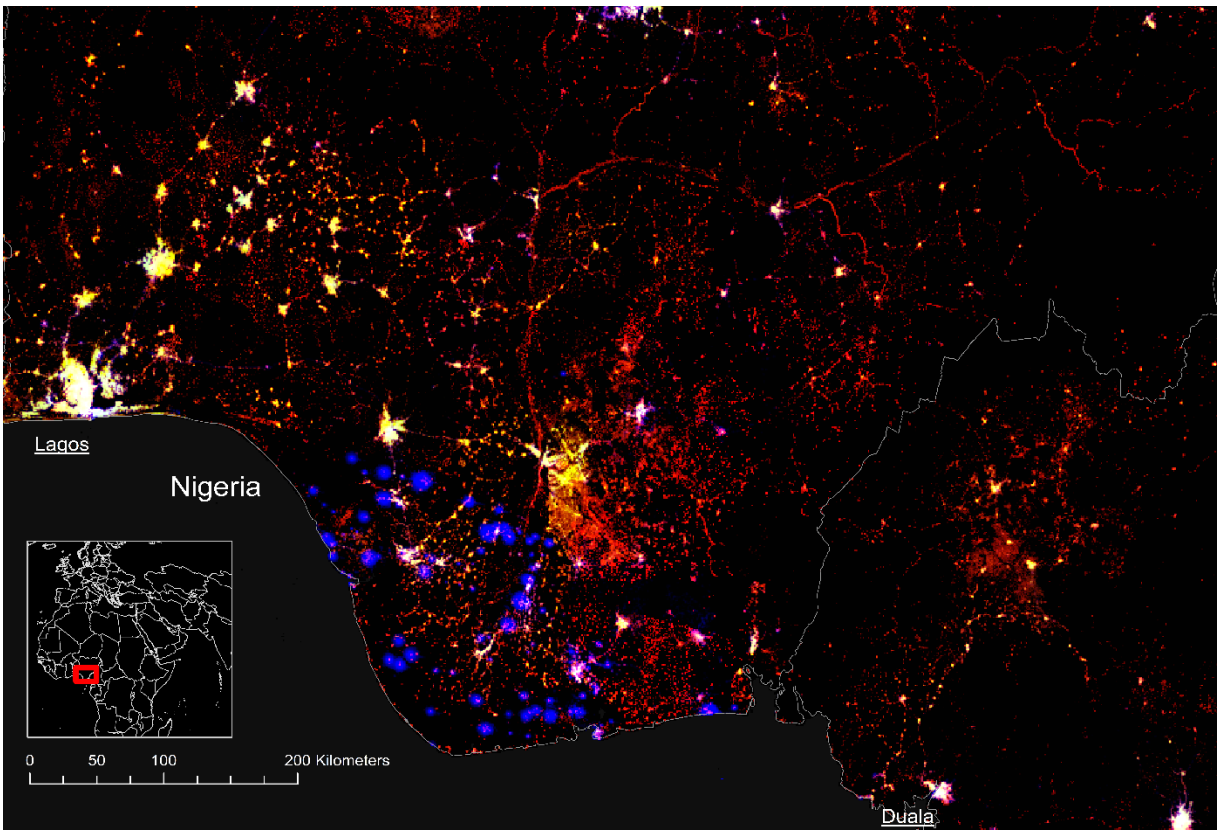

Figure 19 Well-lit oil extraction sites in the midst of highly populated settlements deprived of nightlights.

The urban rural gradient pattern in Central China is also very distinct (Figure 20). There is a strong inequality between the larger urban centres and the rural areas. Chengdu, Chongqing, and Wuhan (from East to West) are the main metropolitan areas in the subset. However, also many smaller cities are well illuminated. Within the rural areas, there is a strong change in the settlement pattern between the lowlands of the Hubei and Henan provinces in the East and the hillier and mountainous areas of the Western part of the map section including Sichuan. The latter are characterised by reddish tones representing high population densities in sparsely built-up areas without illumination along the valleys. The plains appear in yellow-orange tones indicative for high population densities in diffuse settlement pattern limited or no public illumination.

Similar pattern can be observed in the Indian Sub-continent. The map (Figure 21) shows urban rural spatial pattern in the bordering area of West Bengal (India) and Bangladesh. The image shows also the two major metropolitan areas of the city of Kolkata and Dhaka. There is a high density of very close spaced villages in the rural areas. The metropolitan areas are well lit, while the countryside shows patterns of low nightlights. There is also a gradual change in the increase if the nightlight intensity towards the West.

Figure 22 looks at the border area of Pakistan and India. The Hindus Valley and the Punjab region are characterised by dense population largely deprived from night-time illumination with few, well-lit urban areas. Very interesting to note is the blue line, which represents the border installations even in the largely uninhabited Thar desert.

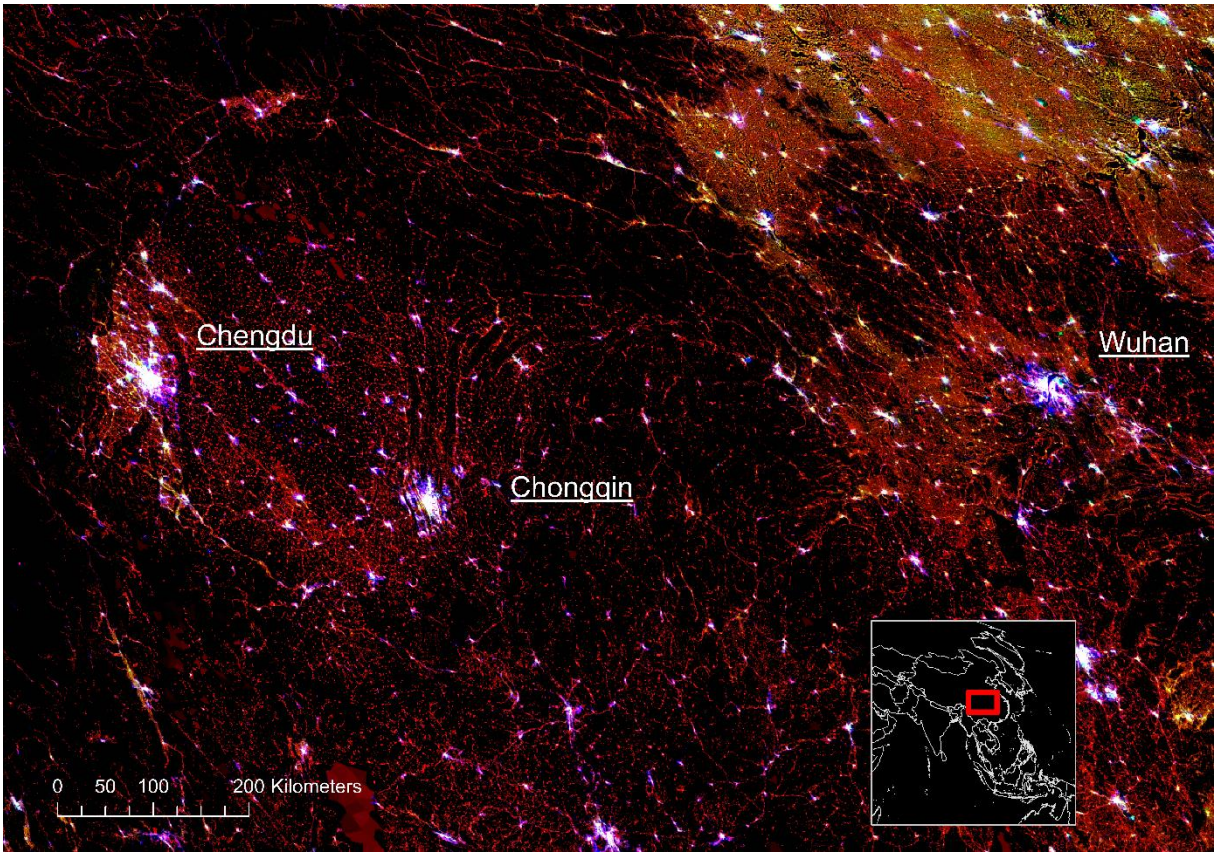

Figure 20 Urban rural spatial patterns in central China between the city of Chengdu, Chongqing and Wuhan.

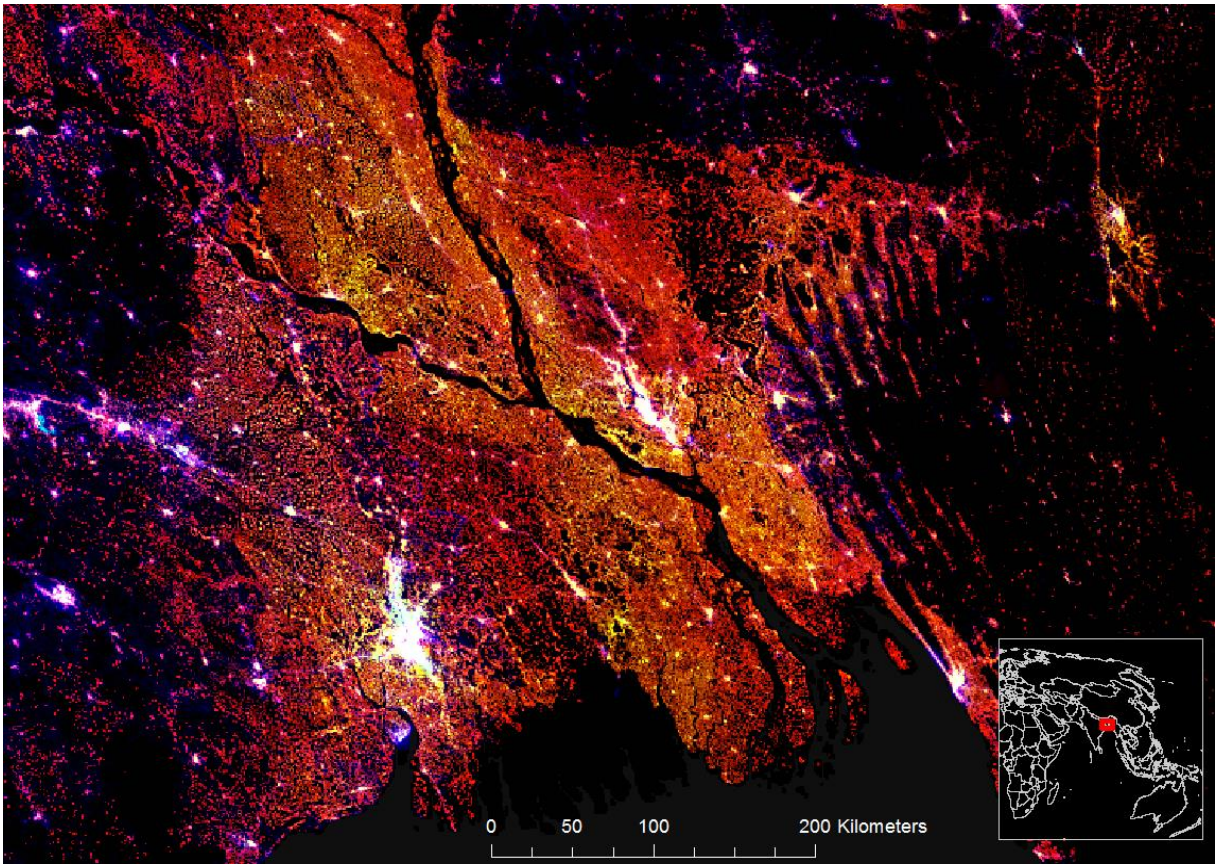

Figure 21 Urban rural spatial pattern in the Indian sub-continent around the metropolitan cities of Calcutta and Dhaka.

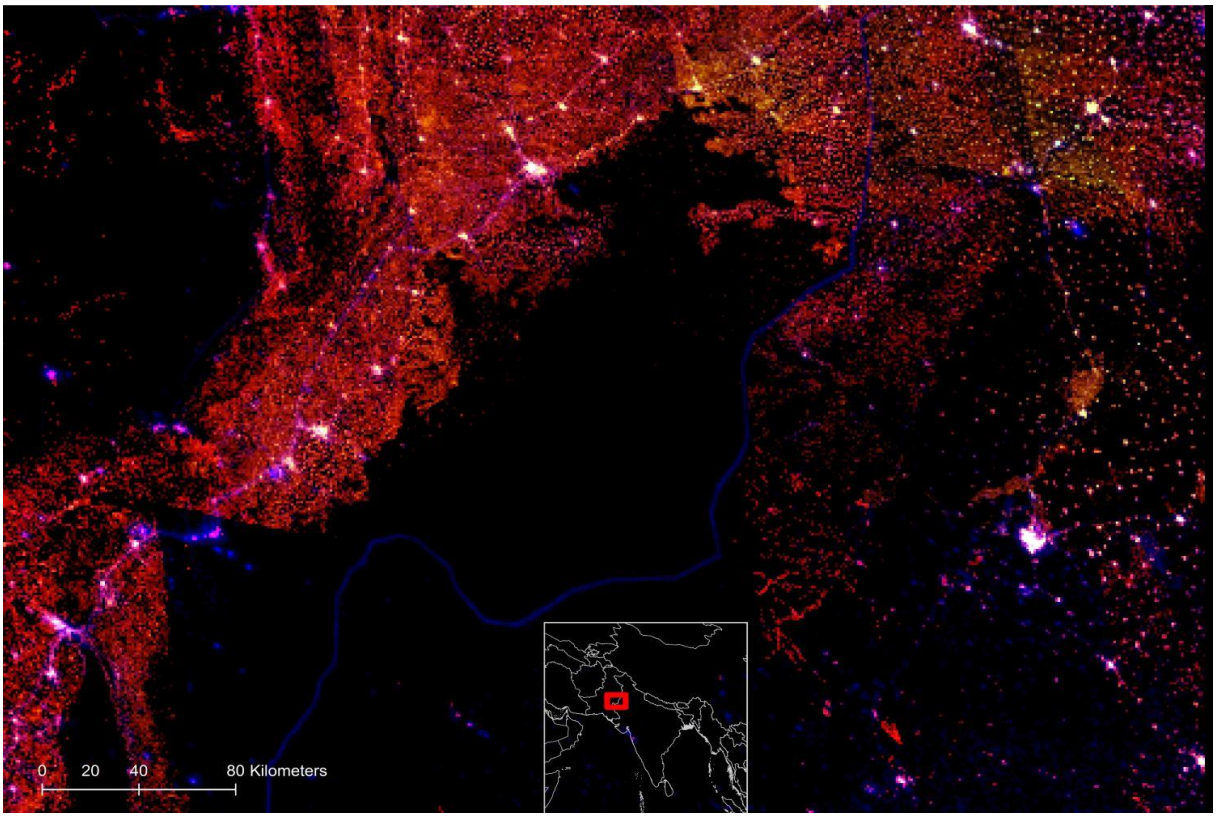

Figure 22 Night illuminated security fence on the Pakistan Indian Border (in dark blue).

3.4 Inequality in and between cities

Narrowing down further from the urban rural gradient described in the previous section there are also strong gradients between neighbouring cities and even within a city.

Figure 23 shows the central part Poland with Warsaw in the middle. The circled cities show a repetition in patterns of light deprivation in cities. A number of medium sized cities in Poland show centre town very well lit and the surrounding peripheries not lit at all. The patters stand out over the rural areas that are more dispersed and not lit or over that of larger cities that are all very well lit. The image shows also the hierarchy of cities within Poland.
Apart from this, the example illustrates also the divide between the EU and many of its Eastern neighbours. The border between Poland and Belarus is visible as difference in spatial illumination patterns. Belarus shows lower population densities for similar amount of built up, a pattern that is consistent and in striking contrast with that of Poland that shows relatively higher population densities.

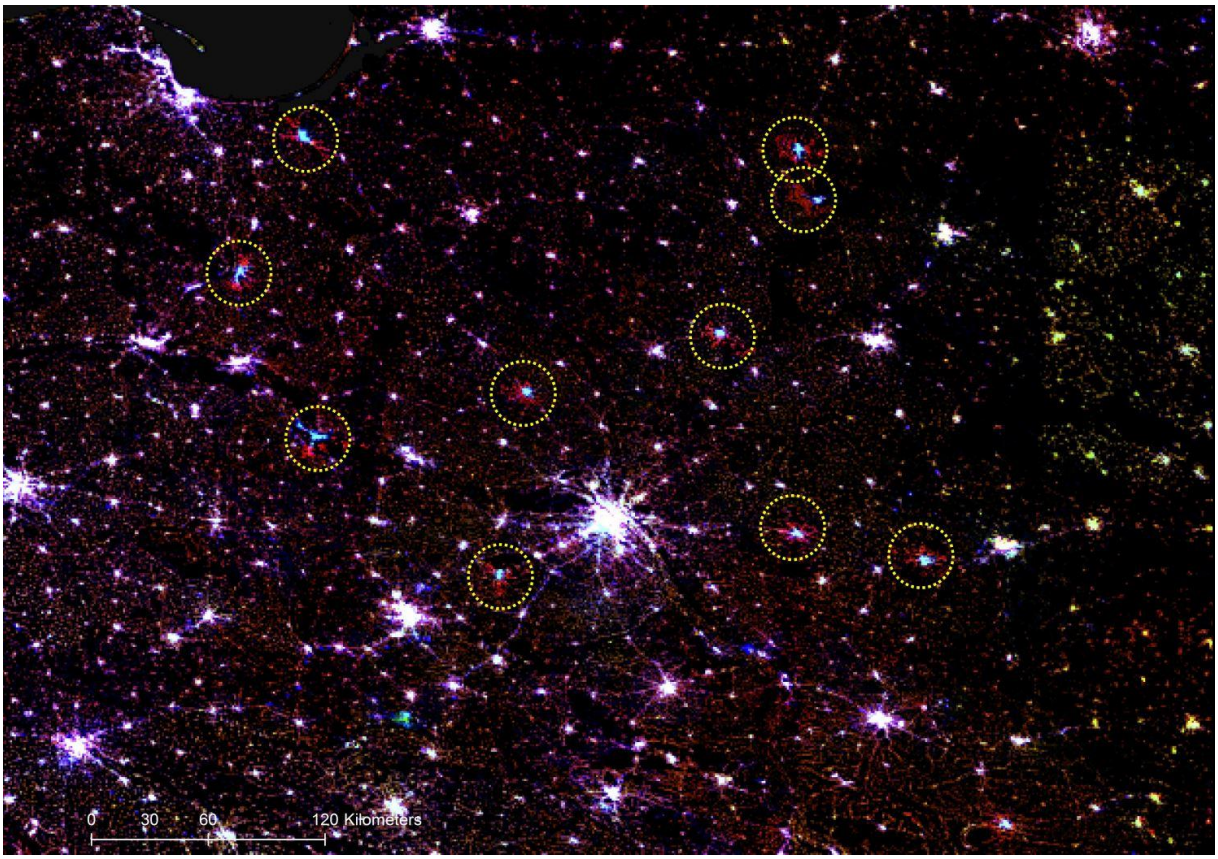

Figure 23 Central Europe light deprived city peripheries and divide along the European Union out border.

Abuja is the capital city of Nigeria located in the centre of the country. It is a planned city and was built mainly in the 1980s replacing the country's most populous city of Lagos as the capital. While the city centre with the governmental buildings and the central business district is well panned and maintained, the space for residential areas for low income employees was limited. These new dwellers settled in existing surrounding towns that developed fast as result of urban sprawl from Abuja. Settlements like Karu to the east of Abuja, are some of the fastest growing urban areas in the world. Most of the growth occurs in a spontaneous, unplanned manner, which is resulting in large informal settlements deprived from access to services such as night-time illumination as shown by the yellowish tones (Figure 24).

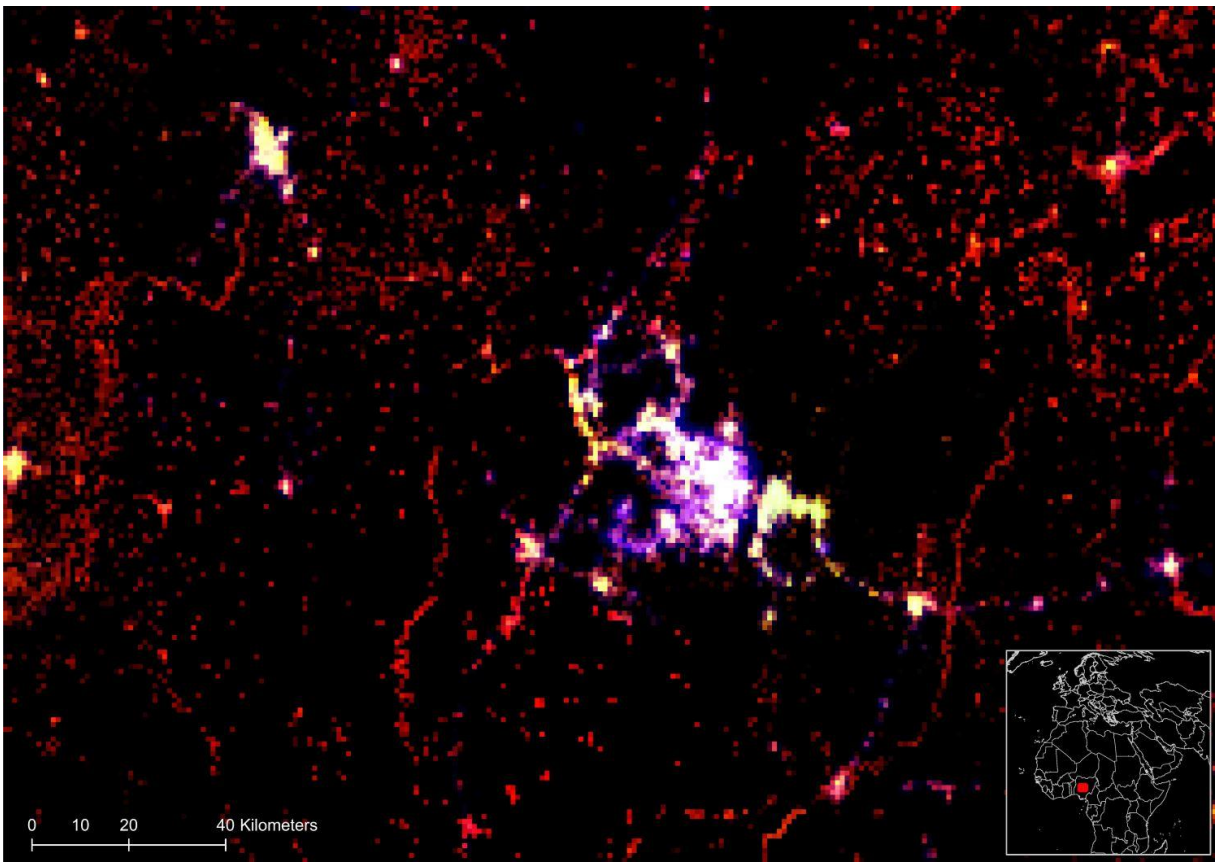

Figure 24. Abuja (Nigeria) has a well-lit centre, but it is surrounded by peripheries with high population density in poor living conditions. Abuja also exhibits a strong urban rural gradient.

The Gauteng province is South Africa's industrial and commercial centre. Figure 25 shows the large metropolitan area of Johannesburg that is connected with the city of Tshwane/Pretoria in the North. The area exhibits a number of spatial patterns typical of complex modern economies and rapidly expanding cities. Large part of the centre of the metropolitan area of is well lit including the townships of the former apartheid regime, like Soweto, Tembisa or Mamoledi. However, the peripheries show a number of informal settlements with a high concentration of population and some light but low built-up density. The latter is probably caused by an underestimation of the built-up area due to the sensor resolution of Landsat that does not capture the informal settlements.

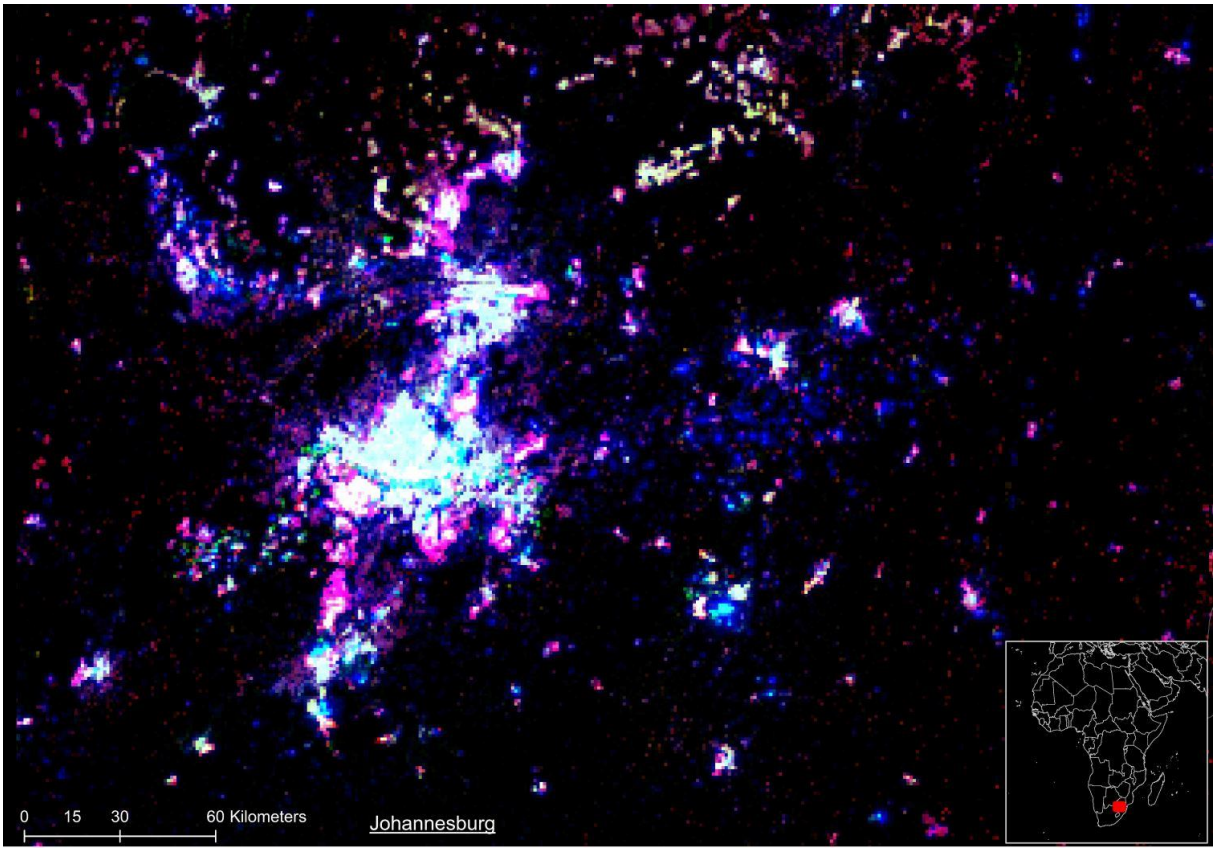

Figure 25 The patterns of Johannesburg allow to locate the commercial/industrial areas (cyan) with lower income housing that account for little built-up in that is typical of the periphery (Magenta).

3.5 Conflict areas

Apart from long-term development pattern illustrated in the previous sections, the combination of people, built-up and night-time illumination reveals also the impact of fast-onset events, like disasters or conflicts. Night-time satellite data was, for example, used in synergy with electric utility infrastructure, and ambient population to improve power outage detections in urban areas (Cole et al., 2017).

In conflict areas, electricity is the first service that is shut down is as it is most vulnerable to disruption. In fact, nightlights have been used to detect conflict areas and conflict severity (Jiang et al., 2017)(Li et al., 2017) as well as for the estimation of affected population (Corbane et al., 2016). Figure 26 shows the area of the Middle East centred on Syria. The country can be identified from the combination of low lights, high population and built up densities, which is reflected in yellow colours. These colours separate it from the surrounding countries, except for the Western part of Iraq that was also affected by the conflict. Tones that are closer to write include areas with both population and night lights, while areas that only display cyan colour show lit areas with low population. It is important to note that the population for Syria available in this research is part of global datasets, which is based on the latest pre-conflict census figures. The conflict in Syria has generated movement of people within the cities, within the country as well as outside of the country that is not reflected in the datasets shown below.

Conflict cities are typically deprived of nightlights. Figure 27 is an enlargement of figure 26 with focus on the city of Aleppo completely deprived of nightlights in 2015. Figure 28 shows the city of Damascus with two distinct lit settlement patterns. The western part of the city is lit while the eastern part is not lit. In 2015 the government controlled are west of the city has continuous electricity supply that was not available in the he rebel held area.

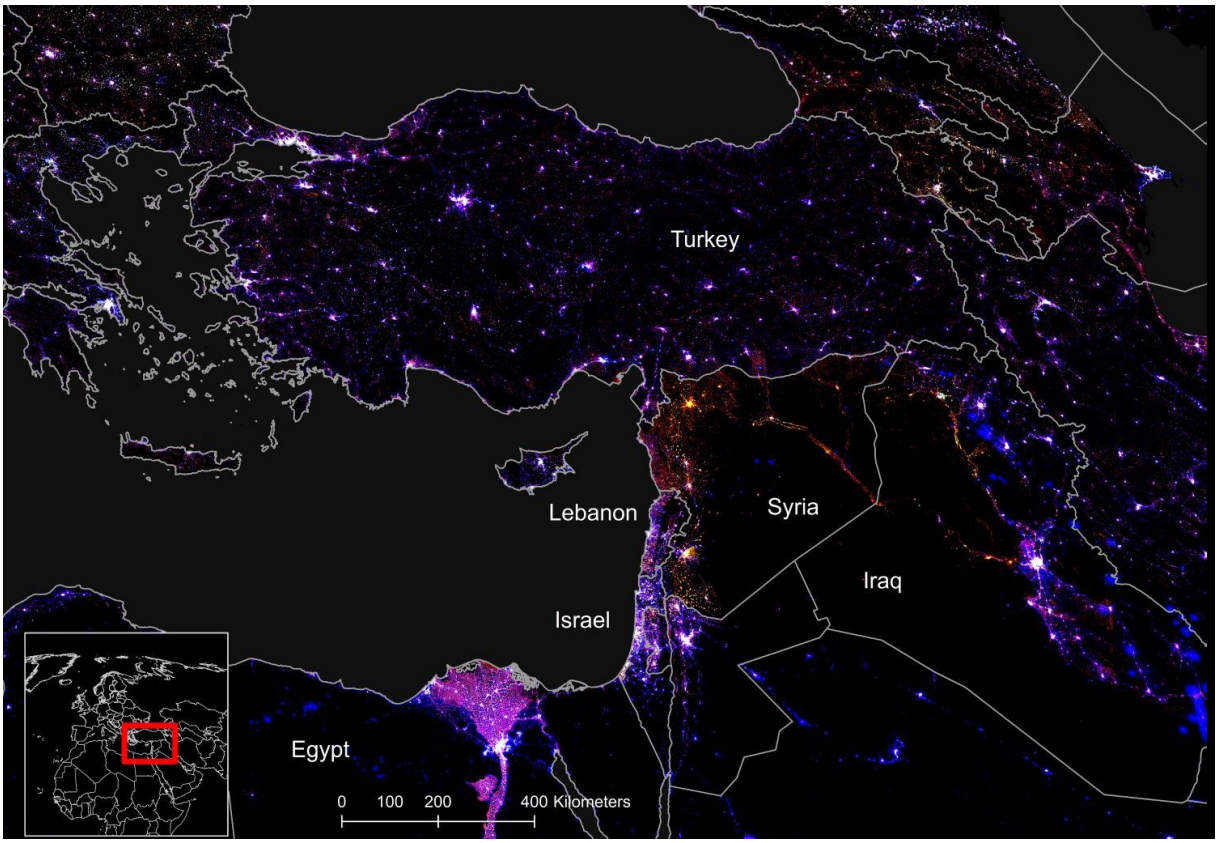

Figure 26 The image shows the middle east centered on Syria in 2015. The yellow color (poplation and built-up no lights) show the entire countrly largely deprived of nightlights. That in contrast to the well lit neighbouring countries(blue colors and magenta).

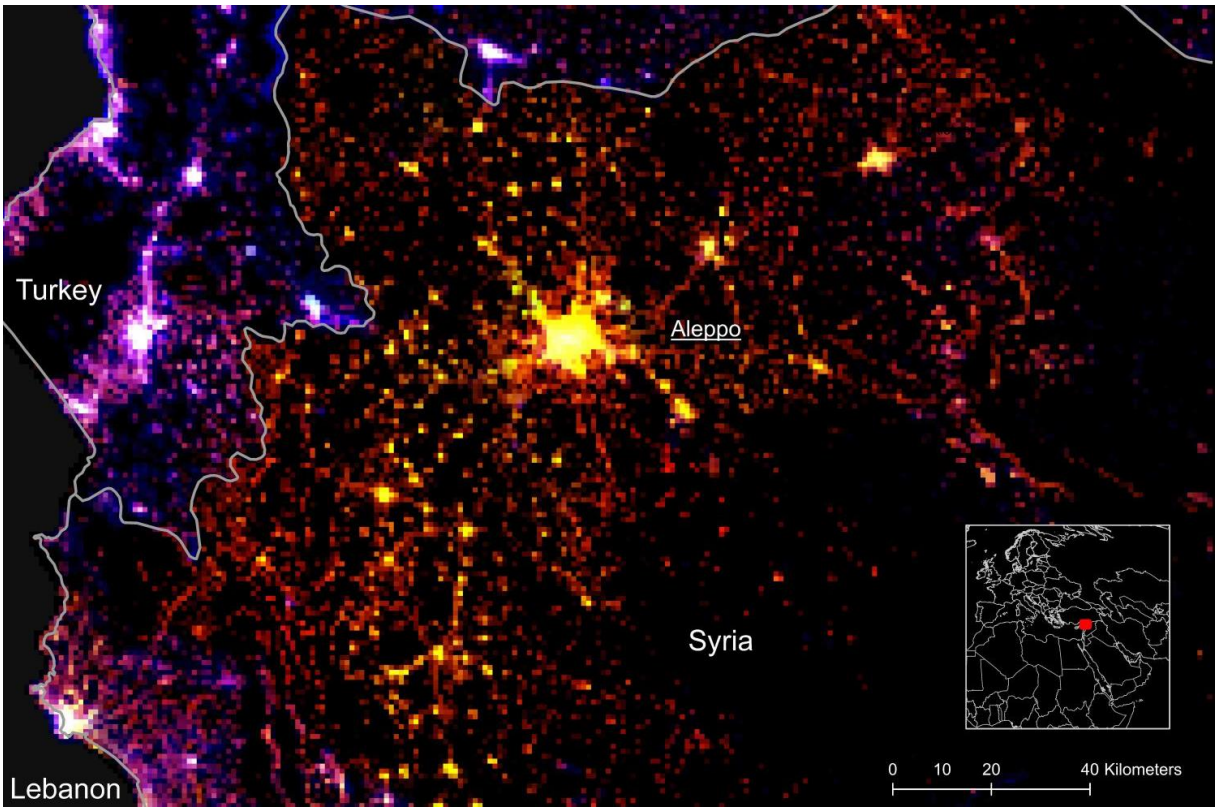

Figure 27 Night-lit settlement patterns for Aleppo and surrounding rural areas in 2015. The city and the surrounding settlements are deprived of nightlights. The population is that from pre-conflict sources.

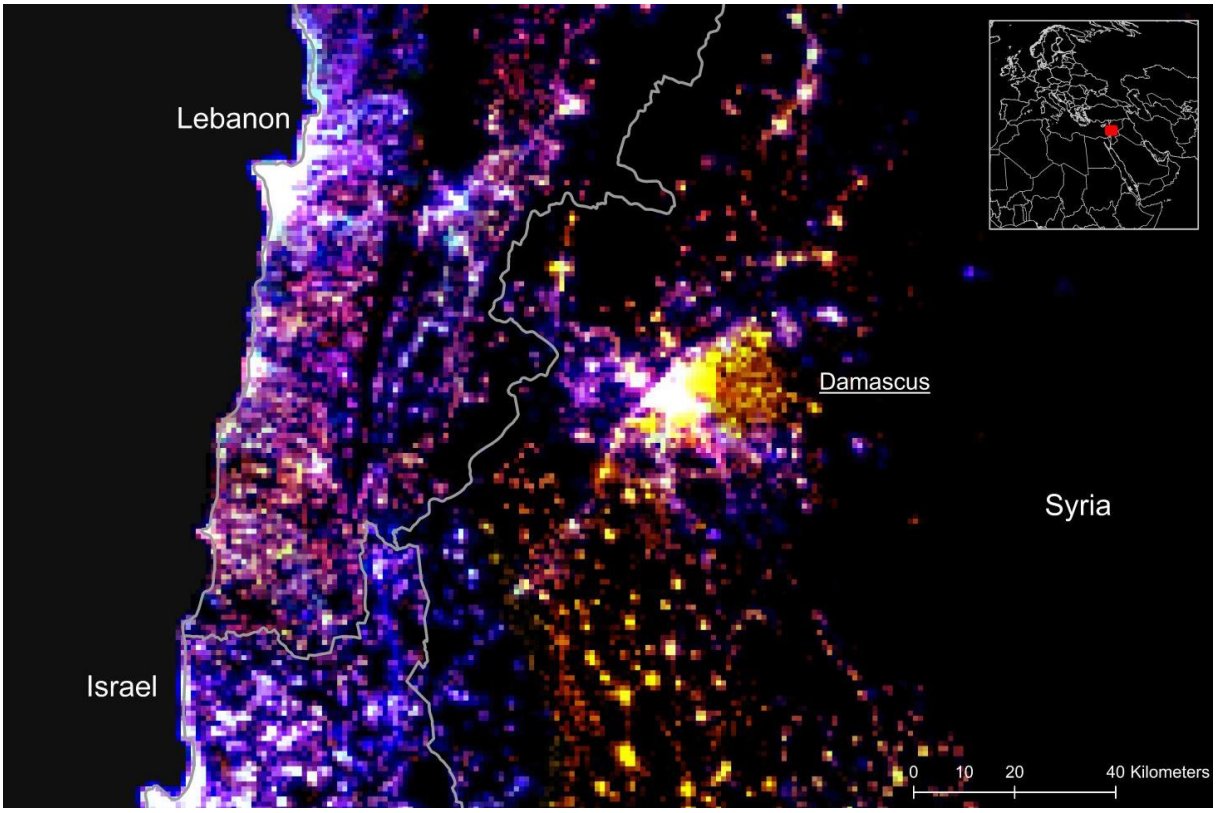

Figure 28 Damascus in 2015 at the centre of the image. The Western part of the city controlled by government forces is well lit

4 Local pattern of inequality – the case of Roma in Slovakia

4.1 Introduction

The previous chapter has provided examples of inequality at regional, national and city level through the joint analysis of population and built-up density with night-time lights emission intensity. This section addresses the use of nightlights to assess deprived communities in Slovakia. The focus is on the less affluent segment of Roma communities.

Roma (also known as Gypsies, Tsigane and Sinti) presence in Europe is documented since the 12th century and it represents the largest ethnic minority (Kosa et al., 2011). Roma are subject to racial prejudice due to their nomadic lifestyle and distinct culture with consequent social exclusion, segregation, and racial discrimination (Filčák, 2012; Pop and Vincze, 2016). As a result of centuries of discrimination, Roma communities live on the fringe of society in often severely deprived conditions (Kosa et al., 2011). The health inequalities and barriers in accessing health services derived from such living conditions are the main subject of recent health studies (Boruzs et al., 2018; Čvorović and James, 2018; Drazilova et al., 2018; HEPA-META team et al., 2013; Parekh and Rose, 2011). Some studies are also focused on mapping the spatial extent of Roma settlements in Slovakia and Hungary (Brunn et al., 2018; Kosa et al., 2011), where Roma presence is considerably higher than in other countries, but also in Serbia and Slovenia (Komac, 2015; Vuksanović-Macura, 2012). Such mapping studies use traditional approaches that rely on field measures and questionnaire to update cadastral maps and national census information.

Our work aims to combine the socio-economic data available at municipality level (national census data and information of presence of Roma settlements) with nightlights, and built-up area. The aim is to test whether nightlight spatial patterns correlate with socio-economic data, or whether deprived areas are characterised by specific patterns of night-time illumination that allow identifying deprived areas using EO data.

We focused on Slovakia, a country with a very high relative presence of Roma, for which the national census provides data at the municipal level on presence of Roma and the Register of Territorial Units (RPJ) specifies Roma settlements at the Basic residential unit level (ZSJ). Roma communities are scattered throughout Slovakia. Roma families settle mostly in three different types of communities: first, the integration of communities in cities, second, in villages within other ethnic groups and, third, occasionally in segregated areas outside the villages.

4.2 Methods

The official 2011 Slovak census[4] reports information aggregated at the municipality level (LAU2). The attributes that were used in this research include:

- the share of people using Roma as primary language at home (RLH);
- the share of people using Roma as native language (RNH);
- the share of people with self-reported Roma ethnicity (RER).

The Register of Territorial Units[5] provides characteristics of all Basic residential units (ZSJ) in Slovakia. We selected among all ZSJ the units labelled as "Roma settlement" or "Roma village". Each spatial unit is characterized by its population abundance. Such units, hereafter called Roma settlement units (RSU), are used as reference for the Roma settlements characteristics in Slovakia. The selected RSU are not a comprehensive dataset of Slovak Roma settlements.

Comparing the population of each RSU and the estimated Roma population at LAU2 level, obtained using the three available shares (RLH, RNH and RER), revealed that "Roma as

[4] https://census2011.statistics.sk/
[5] http://nipi.sazp.sk/ArcGIS/rest/services/stat/rzsj_hranice/MapServer

primary language at home" indicator (RLH) was the most relevant to account for Roma population in each LAU2 polygon. Therefore, this indicator and the estimation of Roma population at LAU2 level based on the primary language spoken at home were used in the following analysis.

Using the data presented in section 2.1, (GHS-BUILT; GHS-POP and VIIRS nightlights) at 250m resolution, we characterized each LAU2 and each RSU with the sum, mean and standard deviation of built-up surface, population and nightlight intensity. Then, we performed a pairwise correlation analysis (both Pearson linear correlation and Spearman rank correlation) of all data sets.

A dedicated GHSL night-time layer has been generated for Slovakia. The same procedure applied at global level, has been repeated using only the Slovak extent and 250 m resolution (i.e. calculation of mean values and standard deviation within Slovak area ranges) for the purpose of the analysis at the country level to capture the variance and typical patterns within this area. The RGB combination has been also classified in 16 groups, each embracing similar RGB values, to simplify the quantitative pattern analysis within RSU. The 16 classes are alphabetically labelled from "a" to "p".

The "fingerprint" of RSU is calculated as the frequency of polygons showing the presence of a particular RGB class. The same procedure is applied to all LAU2 polygons and to subsets of LAU2 constrained by minimum levels of Roma population share (from 5% to 70%).

To analyse whether the presence of Roma is characterized by the presence of the fingerprint RGB classes, we inspected the prevalence of the first 2, 3, 4 and 5 modes of the RSU fingerprint in all the histograms at different level of Roma population share. The prevalence is calculated as the number of polygons in the modal RGB classes over the total number of polygons analysed.

To study whether such modal classes identify the presence of Roma, we set up a binary classification model labelling each LAU2 according to the prevalence of the modal RGB classes. We study the sensitivity (true positives over all labelled positives) and the specificity (true negative over all labelled negatives) of such a model varying the threshold of the prevalence to return a positive value and the share of Roma population to be identified.

4.3 Results

Figure 29, shows the scatter plots of all variables used in the correlation analysis conducted at LAU2 level. The selected variables are:

- Total census population (*Total Pop*);
- Estimated Roma population using the share of people speaking Roma as primary language at home (*RLH Pop*);
- Share of people speaking Roma as primary language at home (*Share RLH Pop*);
- Roma population in RSU (*Roma Pop*);
- Total nightlight emitted (*Total NL*);
- Standard deviation of nightlight emitted (*STD NL*);
- Average built-up area (*Avg BU*).

No significant correlation between Roma presence indicators and nightlights or built-up area has been found. This result indicates that there is no relationship or interdependence between the presence of Roma and the single information (nightlights or built-up surface) alone.

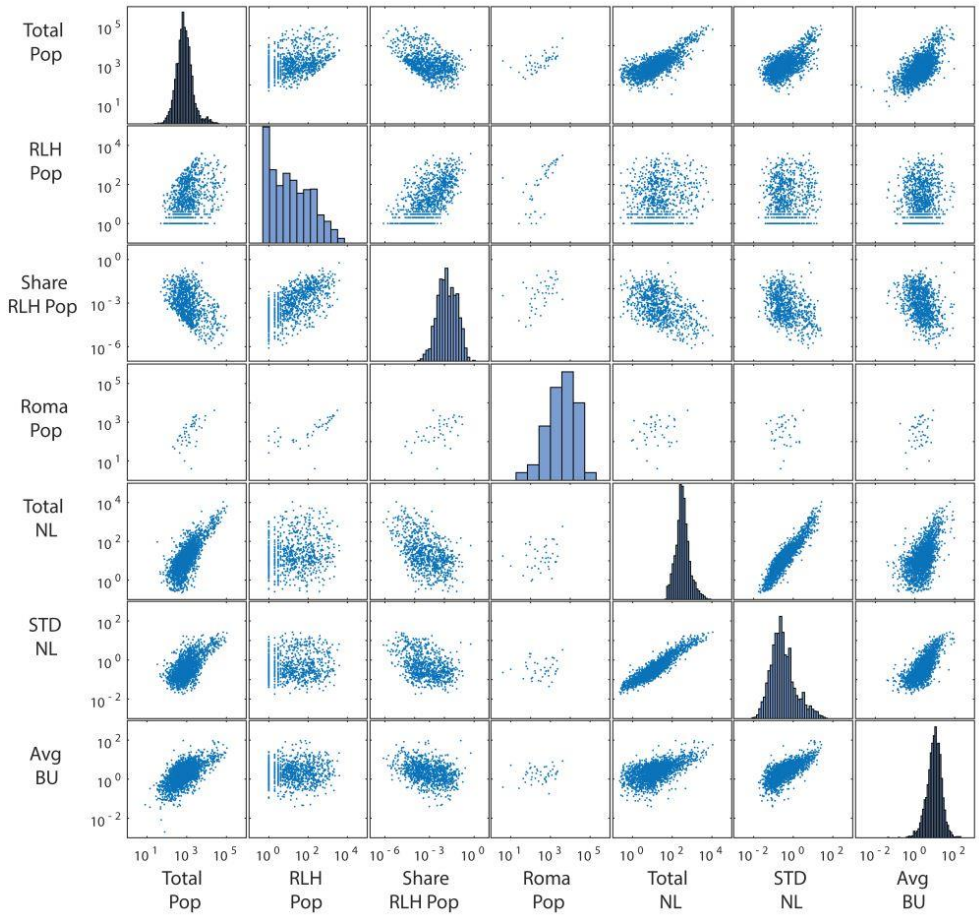

Figure 29: Scatter plots used in the correlation analysis. Axis are in logarithmic scale. No significant correlation found among Roma presence indicators (RLH Pop; Share RLH Pop; Roma Pop) and nightlights or built-up area.

A second analysis aims to identify regular patterns in the GHSL night-time layer for Roma settlements and municipalities with high presence of Roma (>10% of total population). If such characteristics exist, they could be used to develop a model to identify Roma settlements with high Roma presence.

For this purpose, a dedicated night-time lights emission layer at 250m has been generated focusing only on Slovakia (Figure 30).

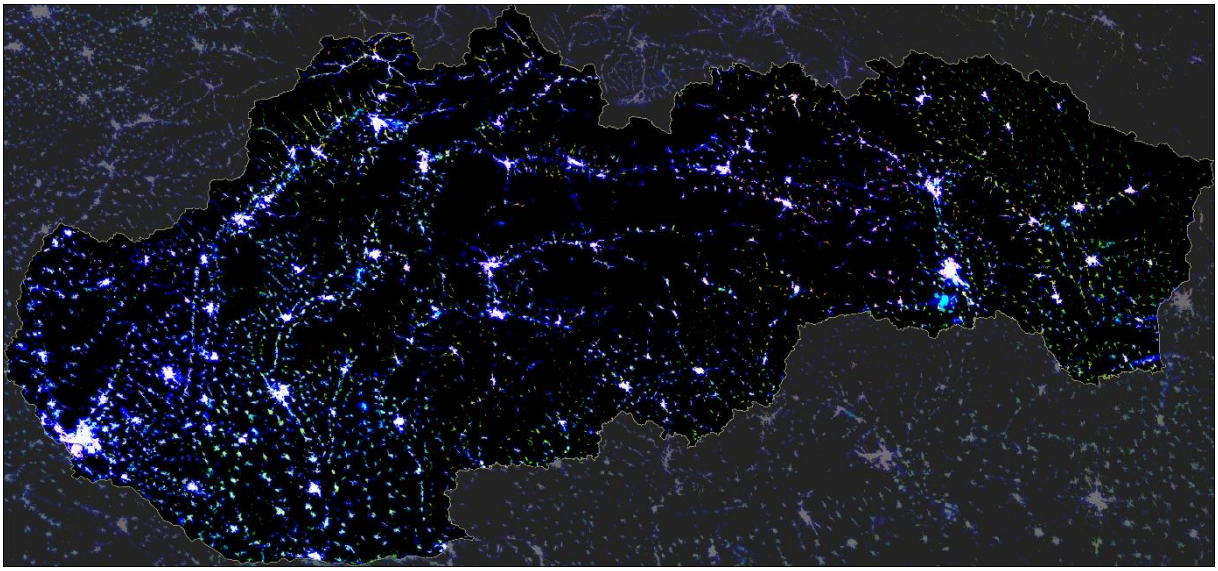

Figure 30: Slovak patterns of inequality detected by combining Slovak population density, built-up and nightlights for 2015 clipped from global layers.

Figure 31 shows the distribution of polygon frequencies for each RGB class of the Slovak GHSL night-time lights layer. These frequencies are obtained analysing all polygons together (Figure 31a), all polygons with less than 5% of Roma people (Figure 31b), all polygons with more than 40% and 70% of Roma people (Figure 31c-d) and for all RSU (the "Roma settlement fingerprint", Figure 31e). Inspecting the prevalence of the top 4 modal classes of the "Roma settlement fingerprint" within each distribution, there is a relationship between this prevalence and the share of Roma population in a LAU2 (Figure 31f). The more the Roma increase their relative abundance in the municipality the more the 4 modal RGB classes are present in the Slovak GHSL night-time layer.

The interpretation of this results is that there is a typical characterization of areas with high presence of Roma that is within the RGB ranges classified by *"g"*, *"j"*, *"a"* and *"b"* groups. Such classes have an average low population density and night-time light emitted with variable built-up surface values.

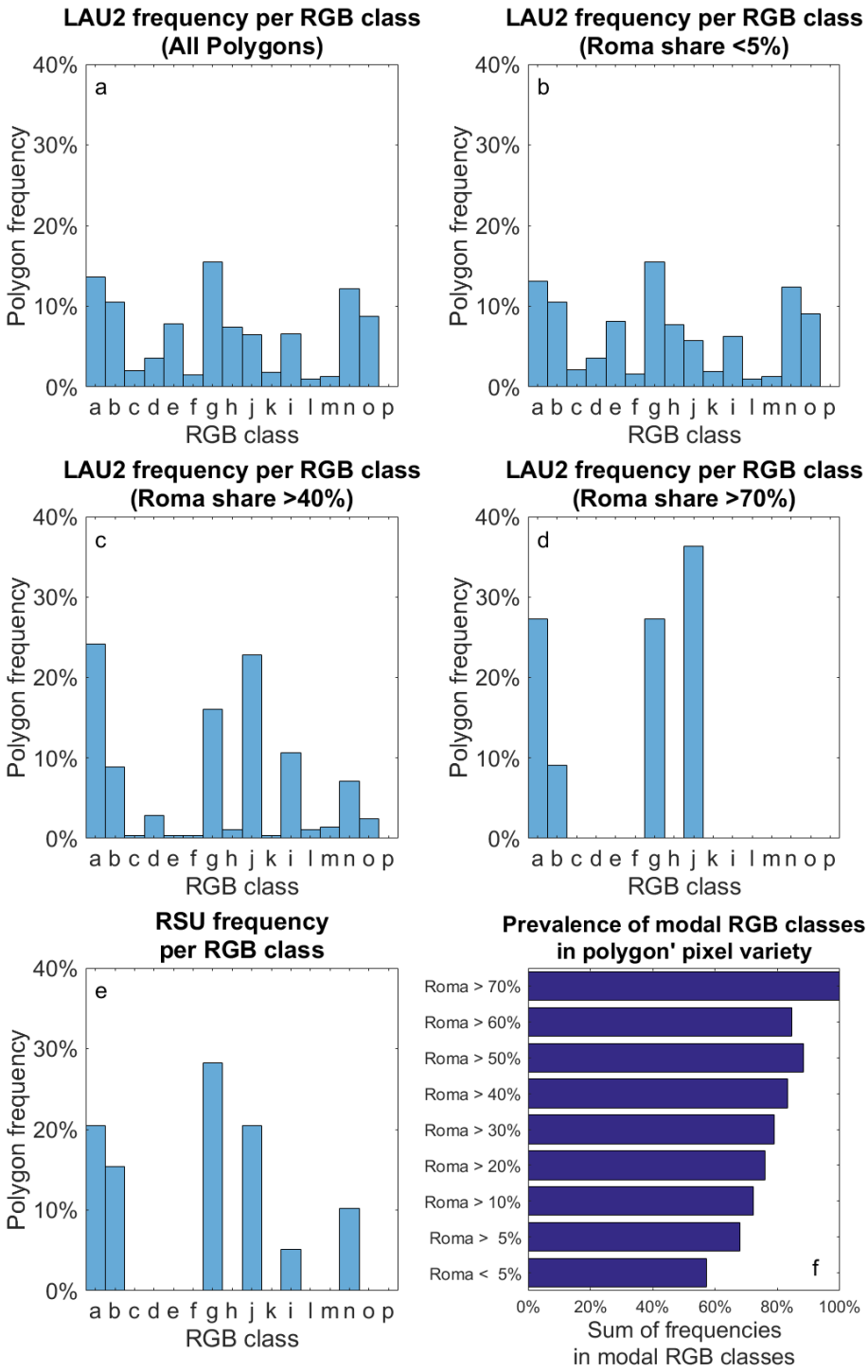

Figure 31. Polygon frequency for each RGB classes. a) polygons are all LAU2; b) polygons are all LAU2 with less than 5% of Roma population; c) polygons are all LAU2 with more than 40% of Roma population; d) polygons are all LAU2 with more than 70% of Roma population; e) polygons are the Roma settlements units (RSU). f) represents the prevalence of the 4 modal RGB classes in the LAU2 Polygon frequency at different minimum share of Roma population.

Based on the above findings we can conclude that there are Roma where we have such characteristics. However, is this characterization enough to determine the presence of Roma?" or "do we find Roma where we have such characteristics?". To answer such questions we tested a binary classification model. Figure 32 shows the sensitivity and specificity performances of the model varying the prevalence threshold to classify a LAU2 unit as positive. Each line represents a different target according to the relative abundance of Roma population.

The model has very poor performance in detecting and identifying LAU2 units with presence of Roma. The best model can only identify 25% of the LAU2 with presence of Roma, wrongly labelling 20% of LAU2 without Roma. Obviously, the model performance increases as the target to be positively classified increases the share of Roma population, reaching a sensitivity of 85% and a specificity of 80% for classification of LAU2 with Roma presence above 60%. On the other hand, the sample municipality showing such shares is highly reduced as only 1% of LAU2 with Roma presence have a share higher than 60%. This percentage is around 11%, when the model targets the Roma share above 20% with sensitivity and specificity both below 75%.

Based on the above findings, it is not possible to identify settlements with Roma presence using only the RGB features of the Slovak GHSL night-time layer, as these characteristics are present in all municipal areas of Slovakia and do not characterize only Roma settlements. Moreover, only very high prevalence of such characteristics usually identifies areas with very high share of Roma population (above 40%) that represent a small fraction of the LAU2 with Roma population in Slovakia and very rare, if not absent, in other countries.

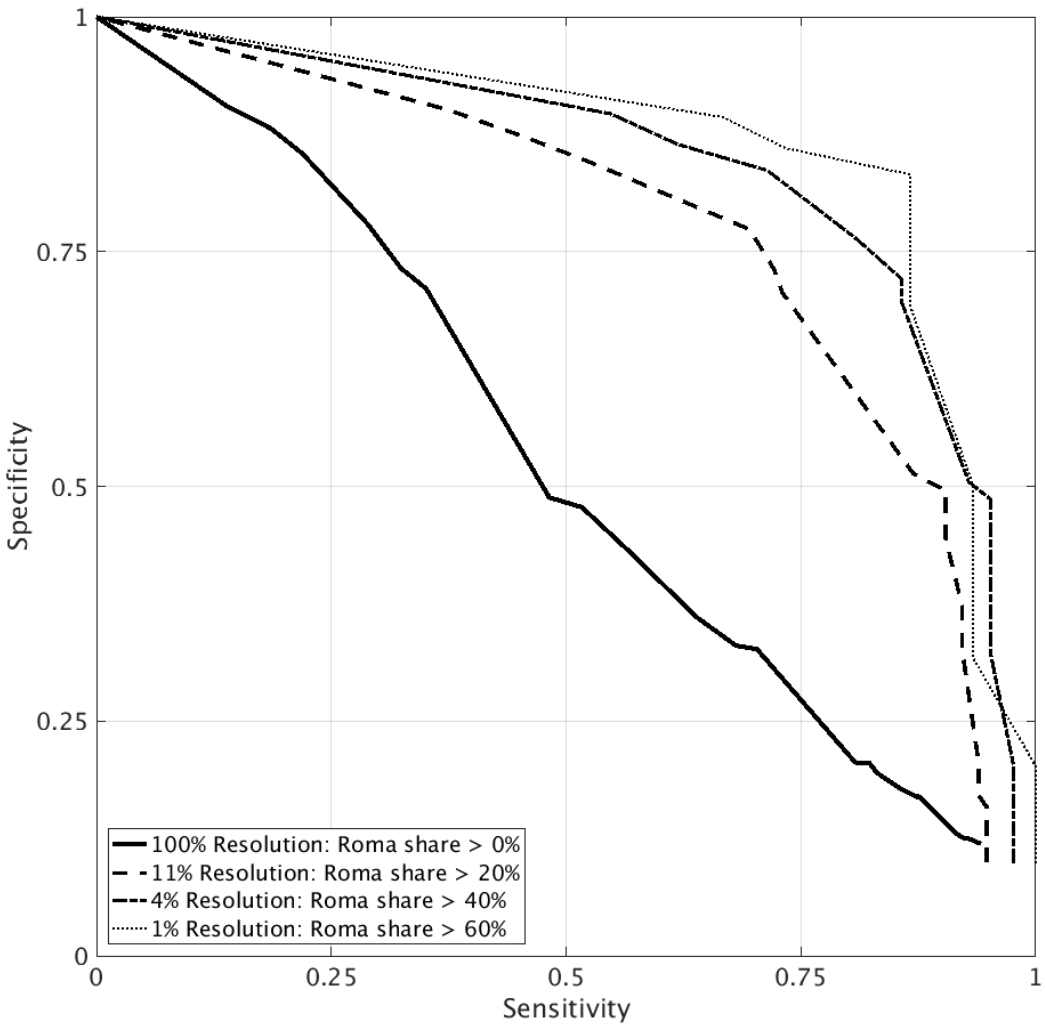

Figure 32. Sensitivity and Specificity of the classification models for Roma presence. Each line represents a target share of Roma population to be classified as positive varying the model parameter (the prevalence of RGB modal classes). The resolution is the fraction of LAU2 showing the target Roma share among all LAU2 with Roma presence.

5 Conclusions

This report analyses the potential to address inequalities based on a combination of EO derived information layers and population densities at regional, national and local scale. The first part is descriptive and provides a global overview, the second is local and more quantitative. The global part allowed identifying settlement spatial patterns that are often clearly related to energy use or energy access, especially in low-income countries, and other times in energy use policies. In fact, high-income countries show quite diverse patterns, in particular in Europe. In addition, there is a large variability of spatial pattern within countries like India, China or France. The coloured human settlement patterns may have a diverse range of patterns.

The resolution of the data is adequate for addressing some global patterns of inequality. At the continental level, the coloured spatial patterns correlate in large part to countries income. The high income and energy producing countries stand out as opposed to the lower income countries. Mid-income countries display more diverse night-lit spatial patterns relating to access to energy, geography, and historical urbanization processes.

The 1x1 km spatial patterns show processes also at the local scale. Most notable are the inequalities across borders in countries with very different income (i.e. North and South Korea) and that originating from conflict (i.e. Damascus). However, the 1 x 1 km datasets probably averages out features that could be identified with data at finer resolution.

In Europe and most notably with Slovakia, the datasets may be too coarse to extract socio-economic information at the local level. In fact, it is anticipated that finer scale data may provide insights in local patterns and processes that in these datasets are not visible.

The report has illustrated that the novel combination of built-up and population density together with night-time lights provides an added value compared to previous attempts to use only night-time lights for the characterisation and identification of settlements. However, more work is needed to turn this into a stable indicator for possible nowcasting and quantification of inequalities.

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