Centre of Excellence
for Science and Innovation Studies

CESIS Electronic Working Paper Series

Paper No. 315

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June, 2013

The Royal Institute of technology
Centre of Excellence for Science and Innovation Studies (CESIS)
http://www.cesis.se

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Abstract:

Research has suggested that night-time light (NTL) can be used as a proxy for a number of variables, including urbanization, density, and economic growth. But, just how close is the relationship between NTL and economic activity? This paper uses a combination of correlation analysis and geographically weighted regressions in order to examine the relationship between the two. We use fine-grained geo-coded micro-data for Swedish establishments and individuals, and match it with both radiance and saturated light emissions. We find that the correlation between NTL and economic activity is strong enough to make it a relatively good proxy for population and establishment density, but the correlation is weaker in relation to wages. In general, we find a stronger relation between light and density values, than with light and total values. We also find a closer connection between radiance light and economic activity, than with saturated light. Further, we find the link between light and economic activity, especially estimated by wages, to be slightly overestimated in large urban areas, and underestimated in rural areas.

Keywords: Light-Emission, Economic Activity, Proxy

JEL: O18, R10

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1. Introduction

Homo sapiens is now an urban species with over half the world's population living in urban areas, including many millions in informal settlements (Angel et al. 2011). Urbanization is a hallmark of the 21st century, characterized by massive demographic shifts and an unprecedented rapid expansion of urban areas and the built environment (Seto et al. 2011). Our planet has indeed become a "planet of cities" (Angel 2012).[5] The pressing challenges of sustainability, adaptation to climate change, economic recovery and poverty reduction are in effect, all urban challenges. Studying urban dynamics at a truly global scale is therefore an urgent research task, but also one which is hampered by the absence of comprehensive, consistently-defined, and reliably collected data on urban economic output, population size and physical presence. This lamentable empirical situation is not surprising given the inherent difficulties in collecting socio-economic and demographic data at the sub-national level. The urban databases with an international scope which do exist—such Moody's Analytics' "Global Metro Areas", the OECD's Metropolitan Database and the Brookings Institution's Global MetroMonitor—leave much of the developing world uncovered and are constructed mainly by imputation from national-level relationships to assign values to variables meant to capture urban characteristics.

It is difficult to imagine how a scientific understanding of urbanization can be developed without global data on the processes and consequences of urbanization. Even the simple, yet analytically essential, exercise of comparing urban economic performance across regions and nations is currently impaired by the absence of data on urban GDP. In the midst of this empirical sterility, one type of data has recently come to be seen (pardon the pun) by urbanists as providing the means to overcome the scarcity of global urban information: the

[5] Throughout the text we use the terms "cities", "urban areas", and "metropolitan areas" interchangeably, avoiding the unnecessary controversy of defining them and relying on the readers' sense of what differentiates urban from non-urban population agglomerations.

Nighttime light (NTL) data from the U.S. Air Force's Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS). A hallmark of contemporary urban settlements, and of urban activity in general, is the artificial illumination of buildings, transportation infrastructure (such as roads, airplane runways and railway lines), parking lots, and other components of the built environment. Succinctly stated, wherever humans agglomerate, there will be artificial light. The DMSP satellites, in low sun-synchronous polar orbits, generate a global night time and day time coverage of the Earth every 24 hours with the main purpose of monitoring the distribution of clouds and assessing navigation conditions. The U.S. Department of Commerce's NOAA National Geophysical Data Center (NGDC) takes the data from the DMSP satellites and, after extensive manipulation, puts it through several algorithms to produce an annual database of night-time lights emissions. A digital archive of the data is available starting with the year 1992.[6]

While the brightness and spatial extent of anthropogenic visible near-infrared emissions (i.e., night-time lights) obviously depend on a variety of socioeconomic and cultural factors (Elvidge et al. 2009), and although many non-urban phenomena generate night-time light—including agricultural fields, fishing vessels, natural gas flares, and natural and human-made fires— these data have been extensively used by researchers as a measure of urbanization. Specifically, NTL data has been deployed to identify the real extent of urban agglomerations and to estimate urban population size (Elvidge et al. 1997a,b; Imhoff 1997; Elvidge et al. 1999; Small et al. 2011) as well as population density (Sutton et al. 1997, 2001, 2003; Zhuo et al. 2009). These data have also been used to track the pace of urbanization (Zhang and Seto 2011), and measure electricity use, energy consumption and greenhouse gas emissions (Elvidge et al. 1997a; Doll et al 2000; Letu et al 2010; Townsend and Bruce 2010). More ambitiously NTL data has been used as a proxy indicator of national, regional and

[6] For data documentation and download, go to: http://www.ngdc.noaa.gov/dmsp/dmsp.html.

urban Gross Domestic Product (Elvidge et al. 1997a; Sutton et al. 2007; Florida et al. 2008, Florida et al. 2010; Chen and Nordhaus 2011; Henderson et al. 2011).

The strong empirical link between urban habitation and the generation of artificial light seems straightforwardly, even self-evidently, robust. And to the extent that the principal source of energy used for generating artificial light is electricity, so is the use of NTL data as a proxy measure for urban electricity consumption—this can even be stretched so that night-time light emissions are used as an indicator of overall energy use. The connection between the generation of artificial light and economic activity, however, seems to us to require more exploration than has been proffered so far. While NTL data can capture the emissions from lampposts at a factory's parking lot, the satellites cannot detect light use inside a cavernous production plant, whether mostly empty or running at full capacity. Nor can the satellite's sensors pick up the light emitted from offices in buildings, or distinguish between buildings with offices staffed by high-valued software developers and one crowded with textile workers. Size of population is surely a major determinant of economic output so to the extent that NTL data is used to estimate regional or urban populations it is also indirectly capturing economic activity. But how close is the relationship between NTL emissions and economic activity? What is needed is a fine-grained examination, both at the level of economic units and spatial resolution, of the association between economic activity and the generation of artificial light. This will allow us to gauge just how sensitive an empirical probe night time lights really are. We take it as a given that night-time light data is a proxy measure for human agglomerations—the question is just how good of a proxy is it for economic activity?

Here we examine the link between economic activity and NTL emissions by taking advantage of the fine grained spatial resolution at which NTL data is available and combining it with economic data from Sweden that is also available at an incredibly detailed spatial resolution. Statistics Sweden (the Swedish government agency responsible for producing official statistics) has collected geo-coded data for all individuals and establishments (a single physical location at which business is conducted and/or services are provided.) on a yearly basis since 1985. The data is provided for square grids whose size of one square kilometer or one-sixteenth a square kilometer depends on the degree of urbanization. By matching NTL data with the Swedish data we can examine just how close the correlation is between specific levels of economic activity and specific levels of NTL emissions. Our a priori assumption is that these variables are correlated but the research questions address how closely correlated they are, and whether information about the relationship between NTL emission and economic activity is clearly differentiated from that contained in the relationship between NTL emissions and population size.

The detail and spatial resolution of the Swedish socio-economic data makes it a very valuable analytical resource, but how relevant or applicable are insights gleaned from such data? Sweden is, after all, a fairly small country population-wise with slightly less than ten million inhabitants— whose large land area (almost 70% that of France and 25% larger than that of Germany) yields a low population density (roughly equal to that of the United States but 11 times smaller than that of Germany). Sweden's historical peculiarities and its relative isolation from many of the social cross-currents that have shaped modern Europe, as well as its long-standing commitment to social-democratic egalitarianism must also be considered. Is Sweden just too different from other developed economies for Swedish findings to be useful? In many ways, however, Sweden is typical of the "advanced" European economies. Sweden has been a member of the European Union for almost two decades, and many of the country's policies and regulations have been brought into alignment with the EU's framework. The country's economy is heavily oriented toward foreign trade, with privately owned firms generating the vast majority of economic output and the high-technology engineering sector accounting for about 50% of total output and exports (CIA 2013). Sweden's GDP per capita

(41,000 in Purchasing Power Parity 2012 dollars) ranks above that of Germany and South Korea, and slightly below that of the United States. What about Sweden's energy consumption? Based on data provided by the Department of Energy's Energy Information Administration, Sweden's energy use is fairly typical of an advanced industrial economy (controlling for its Northern location and its use of energy for heating purpose). The energy intensity per capita (for the time period 2005-2009) in Sweden averaged 245, which could be compared with the US (328), Germany (328), South Korea (199), or Brazil (62). For energy use measured in 2005 purchasing power adjusted in dollars, Sweden measures 7,065, while the US has a value of 7,625, Germany 5,503, and South Korea 9,959. We have, in other words, no reason to believe that Sweden should be over or under-consuming in terms of energy. We therefore believe that examining the micro-level relationship between economic activity and the generation of night-time light data in Sweden will provide insights applicable to other wealthy, highly developed, technologically advanced, and export-oriented market economies.

The discussion is organized as follows. The next section describes the night-time lights emission data and the Swedish data, as well as the matching and merger of these two variables. The results are presented in section three, with a conclusion in section four. Anticipating our main results, we find that night-time light emissions are a better proxy for population density than for total population, and that the radiance light is slightly more closely related to people and establishments than the saturated light. We also find that the relation between light and economic activity (especially in terms of wages) is underestimated in rural areas and small and medium sized cities, while it is overestimated in the largest regions. The relatively weak relationship between night-time light and economic activity suggests that light is a restricted proxy for economic activity. At the same time, the relatively strong relation to population density suggests that it is a good proxy for understanding urbanization across regions around the world.

2. Data Sets and Variables

2.1 Night-Time Lights Data

We used Nighttime Lights Data made available by the U.S. National Oceanographic and Atmospheric Administration (NOAA). The observations on which the data is assembled are made by the Operational Linescan System (OLS) flown on the Defense Meteorological Satellite Program (DMSP) satellites. An excellent detailed description of the satellite instrumentation, and the data collection and processing methods is provided by Elvidge, et al. (2007). Here we restrict ourselves to a providing a brief summary. The DMSP program is designed to capture information about global weather and weather systems. It needs to provide up to the minute information 24 hours a day. Cloud cover and weather systems can be identified and analyzed visually at any point during the daytime. However, clouds are difficult to spot at night. To that end, the satellites (there are two of them) have onboard sensors designed to detect moonlight (and even starlight) that is reflected off of clouds. Of course, when the night is clear, no clouds get in the way, and the instrument detects the light emanating from the surface of the Earth. That light, as previously, mentioned can be from several sources but is primarily the result of electricity-powered illumination.

Unfortunately for our analytic purposes the satellite OLS instruments are operated at high gain settings in the visible light band for the specific purpose of cloud detection. ("Gain" is a measurement unit for how much light per unit of area is detected by a light intensifier instrument of the sort used by the DMSP satellites.) There is an implicit tradeoff:

while the satellites' instrumentation can detect dim lighting present at the Earth's surface— emanating from small settlements or gas flares— the recorded data are saturated in the bright cores of urban centers. In effect, the intensity of light is not measured past a certain threshold value: the light emitted at the center and much of the surrounding area of say New York, Mumbai, or Tokyo is quantified to be at the same level as that emitted in their peripheries. Saturation occurs in almost all cities of any size across the globe. Letu et al. (2012) discuss the saturation problem in depth and present one possible method of addressing it. In 2006 permission was granted by the DMSP to readjust the calibration on the instrument for selected periods of time so that human-generated night-time light emissions (NTL data) could be detected and not suffer from the saturation problem. The process by which the 2006 "radiance" NTL data, as it is known in the remote sensing research community, was constructed is discussed in Ziskin et al. (2010).[7] To date the radiance data provides the most accurate record of night-time light emissions from human settlements but, to emphasize, it is available for only one time period (in contrast to the "standard" NTL data electronic records which are available yearly starting in 1992) .

NTL data is provided in 30 arc-second grids through geo-referenced TIFF images and covers most of the world. The grid essentially puts down squares on a globe. But since it is a (rough) sphere and not a cube, the grid creates what essentially looks like squares at/near the equator, but as the measurements move towards the poles, the "squares" become narrower toward the poles. This effect increases the closer you are to either the North or South Poles. The data provided does not include the polar extremes because of both measurement and projection issues.

We employ two different datasets in our analysis: "Global Radiance Calibrated Nighttime Lights" based on satellite readings collected in 2006 (referred to as "Radiance

[7] Radiance data, and associated documentation, is available at www.ngdc.noaa.gov/dmsp/download_radcal.html.

Light" in this discussion), and the standard "Average Lights x Pct" (which we refer to "Saturated Light") also based on satellite readings from the year 2006.[8] The pixel (light) gain values range from 0 to 63 for the Saturated Light, while the radiance data contains light values that range from 0 to 846 for Sweden (and higher in other parts of the world).

2.2 Swedish Data

The empirical and analytical novelty of the work reported on here results from the use of geo-coded population and establishment counts for Sweden, and its spatial matching with light-emissions data. The Swedish data is compiled by Statistics Sweden and covers all individuals and all establishments in the country. Since each individual and establishment use a unique identification number in relation to tax authorities, governmental bodies, etc. data collected from these different Swedish authorities can be combined into one unified dataset by Statistics Sweden. When the data is made public, all observations are anonymized. This data is referred to as MONA data and can be accessed only from Sweden, under the law of Personal Data Act. Statistics Sweden offers access to researchers via secure access to the special retrieval system Microdata Online Access (MONA).

The geo-coded socio-economic data is divided into square grids; the size of these squares depends on whether the specific territory is classified as urban or rural. Urban squares have an area of 250 by 250 meters, while the rural squares have a size of 1,000 by 1,000 meters (1 square kilometer). To our knowledge, no other country provides data on both total population and establishments at such a fine-grained spatial resolution, and it is this

[8] We also used two other NTL datasets, the "Average Visible" and "Stable Lights, & Cloud Free Coverage" for the year 2006 (www.ngdc.noaa.gov/dmsp/downloadV4composites.html). This data performed very similarly to the Average Light x Pct light data in the analysis, but was somewhat weaker in the relation to industry and people activity, and we therefore excluded this version of the light data from the analysis. Additional information about this light data analysis is available from the authors upon request.

resolution that makes the data suitable for matching with the light-emission data. Statistics Sweden categorizes each place as urban or rural based on population density. In order to be defined as urban, the place should have at least 200 inhabitants, and the distance between the houses cannot be more than 200 meters. There are a number of exceptions allowed from the 200 meters rule, e.g., if the area is disconnected by sports arenas, cemeteries, parks, roads or parking lots. In the 2010 count of the Swedish population, approximately 85 percent of the total population was living in urban areas. Whether a square is urban or rural is defined by the neighborhood level of "urbanity," rather than the regional or metropolitan definition. This implies that a metropolitan region can have both urban and rural squares, depending on the level of urbanity in each specific square. In the present discussion we utilize two kinds of definitions: count data and density data. In the case of density, we calculate this measure based on the size of the actual square.

We have access to data on the squares where all Swedish individuals reside (in other words, a geo-coding of the total population) as well as the square where they work (provided they have a job), which means that we can take both day- and nighttime activities into account. We use data on the number of individuals and their total wage income, as well as the density of the two. Wage income is in this context defined as night-time (take-home) wages (in other words, the income individuals bring home to where they live). The constructed variables are based on where individuals reside, in other words, the nighttime population and their wage income. We also use data on counts of establishments so as to measure economic activity in each of the squares. We think that number of establishments—physical locations which presumably use artificial lighting—is a fairly straightforward way to connect economic activity with the generation of NTL data. Information is available, on a per square basis, on the number of establishments, the number of employees in these establishments, and the total wage bill paid by the establishments (in other words, where the incomes are earned). In addition to counts we calculated density measures (dividing by land area) which, from a population perspective, reflect their daytime activities. Since the population is distributed across a larger geographical area than the establishments, the population dataset covers 188,986 squares while the establishment data covers 115,496 squares. All values in the analysis are for the year 2006 so that we can compare results using the standard and radiance NTL data.

2.3. Matching the NTL and Socio-Economic Data

To compare the light data with the Statistics Sweden demographic data we generated a grid based on coordinates provided by Statistics Sweden with their demographic data, as described in the section above. The light data was then summarized to this grid to allow for analysis. Using ESRI's ArcGIS software we created a grid of squares based on the lower left coordinates provided by Statistics Sweden. Separate grids were generated for both industry and population data, resulting in two grids overall (the coordinates provided were based on the data available). The *squares* making up each grid are 250m x 250m in urban areas and 1,000m x 1,000m in rural areas (defined by Statistics Sweden).

The methodology used to aggregate the light data to the squares depended on the size of the square (urban vs. rural) because of how they compared to the size of the cells in the light grid. The TIFF raster image was converted to integer format to obtain the light (pixel) values and complete these calculations. Note that we did not clip the image to the Sweden boundary until after these calculations because that would have resulted in no data for areas that should have a light value. To calculate the light values for the rural squares we used the "Zonal Statistics as Table" tool in ArcGIS. This tool is used to summarize raster values within a polygon (the rural squares). We used the mean statistic and so the raster value generated for each rural square was the average light value from all the cells that intersected a square. The zonal statistics as table tool was less effective for the urban squares due to their small size. Because most of the urban squares only covered part of a single cell (with some exceptions) we used the "Extract Values to points" tool. This tool generates a light value for the centroid of each square by taking the value of the cell that the point is on. Once light values for each square were generated, we joined this data back to the Statistics Sweden demographic data to complete the analysis.

2.4. Variables

The following are the variables geo-coded for Sweden and used in the analysis. (Summary statistics are presented in Table 1.)

Population: This is the total employed population in each square. This is the night-time population value. We also use an employed population density value, which is equal to the total population per square kilometer in each square

Wage Incomes: This is the total wage sum in each square. This value is counted based on the square where the person earning this income lives, in other words, night-time wage income value. We also use wage income density, based on the wage income of the night time population, per square kilometer.

Establishments: This is the total number of establishments in each square. We also employ an establishment density value, which is equal to the total number of establishments per square kilometer.

Employees: We use the total number of employees in each square, as well as the employee density values. This is equivalent to the daytime, employed population.

Wage Sums: This is the wage sums paid by the establishments in each square, which to a certain degree would be related to the aggregated productivity of the establishments in each square. Also in this case, we employ both count data as well as a density measure.

(**Table 1 about here**)

Table 1: Data Descriptives

Variable	N	Min	Max	Mean	Std. Deviation
Light*					
Radiance	188,986	.00	846.00	50.03	91.81
Saturated	188,986	.00	63.00	17.16	19.96
Population					
Total Population	188,986	1	1,696	23.30	52.12
Population Density	188,986	1	27,136	310.50	844.44
Wage Incomes (SEK)	188,986	0	4,481,690	55,293	131,138
Wage Income Density (SEK)	188,986	0	71,707,040	750,219	2,118,500
Light**					
Radiance	115,496	.00	846.00	75.31	114.25
Saturated	115,496	.00	63.00	23.35	22.01
Establishments					
No of Establishments	115,496	1	451	3.94	10.14
No of Employees	115,496	0	14,577	32.79	167.02
Wage Sums (SEK)	115,496	0	48,882,297	82,350	547,740
Establishment Density	115,496	1	7,216	50.94	163.91
Employee Density	115,496	0	233,232	483.47	2,611.53
Wage Sum Density (SEK)	115,496	0	782,116,752	1,239,033	85,72,241

*Descriptives for light emissions for the squares with people (N=188,986). **Descriptives for light emissions for the squares with establishments (N=115,496).

As can be seen in Table 1, we divide the dataset based on either employed population or establishments. Since the employed population is distributed across a larger geographical area, we have more squares for this data set (188,986). In order to have information about a square, at least one person needs to be living in that place. The average number of employed population in each square is 23.3, and the average population density per square is 310. As for wage incomes, the average total wage income per square is 55,293 SEK and the average wage income density is 750,219 (SEK per km^2). For the establishment data, the average number of establishments in each square is 3.94 and the average number of employees per square is 32.79. The wage sums paid by these establishments are on average 82,350 SEK, and the density is 1,239,033 SEK per km^2. In each square, we find on average 33 employees, and the employment density is on average 51 employees per km^2.

3. Empirical Results

3.1. Correlation Analysis

We now turn to the empirical analysis where we connect the light-emission data with the population and establishment data across the squares. We begin with a basic correlation analysis so as to identify bivariate relations between light-intensity and the activity in the same geographical places. We employ both Radiance light as well as Saturated Light in the correlations, to be able to examine possible differences. The results are presented in Table 2.

(**Table 2 about here**)

Table 2: Correlation Analysis

Variables	**Radiance**		**Saturated Light**	
	Totals	**Density**	**Totals**	**Density**
People				
No. of People	.597**	.763**	.530**	.725**
Wage Incomes	.524**	.700**	.475**	.666**
Establishment				
No. of Est.	.490**	.757**	.399**	.719**
No. of Emp.	.475**	.679**	.410**	.636**
Wage Sums	.456**	.542**	.424**	.512**

**indicates significance at the 1 percent level.

To start with, the correlation between radiance and saturated light is approximately 0.915. The correlation between people and light is slightly stronger when we use the radiance light-emissions instead of the saturated light. However, the overall structure is very similar, with the strongest correlations between density and light. The correlation between light and the number of people is 0.597 (for radiance) vs. 0.530 (for saturated light), which could be compared with the correlation between light and people density (0.763 vs. 0.725). The correlation between light and wage income is also stronger for the density of wages (0.700 vs. 0.666) compared to total wage income correlations (0.524 vs. 0.475). In other words, we find light to be a better estimation of population than wage incomes. Also, light seems to be capturing density better than the actual number of people or the total amount of wage incomes.

For the establishment correlations, we find similar correlation structures between light and the establishment variables, regardless of whether we use the radiance or saturated light data. However, we find slightly stronger relations between these variables and the radiance light data, compared to the saturated light correlation coefficients. In general, the density variables are again slightly stronger than the count variables which indicates that dense economic activity produces more light than the number of establishments or number of employees. We find the strongest correlations between light emissions and establishment density (0.757 or 0.719 depending on if we use radiance or saturated light). The same correlations for the actual number of establishments are 0.490 vs. 0.399. Also employment density is more strongly related to light emissions than the number of employees (0.679 vs. 0.636 to be compared to 0.475 vs. 0.410). While light has been used as a measure of productivity, out of the three industry variables, light-emissions seem to be the least related to wage sums paid by the companies in each square. The correlation with wage density is equal to 0.542 vs. 0.512 while the correlation with total wage sums is 0.456 vs. 0.424.

3.2. Regression Analysis

Since we would expect that light, as well as people and establishment activities, would spill over across squares of such a small size as the ones we employ here, we now continue to a regression analysis where we're able to take such effects into account. We ran Geographically Weighted Regressions (GWR), which we then compared with OLS regressions. While the single OLS regression result add very little compared to the bivariate correlation analysis, we use it as a baseline for comparison reasons when we run the geographically weighted regressions, and we also use them to generate Moran's I values. GWR is a technique which allows us to examine possible spatial non-stationarity, by the use of distance-weighted sub-samples of the data. This implies that we can produce locally linear regression estimates for every point in space, in other words, we generate a beta value for every observation. The methodology makes it possible to compare the unstandardized beta coefficients from the OLS estimation (the global estimate) with the locally produced GWR unstandardized beta coefficients, to see if those are significantly above or below our "globally" estimated unstandardized beta coefficient. In other words, the GWR estimation produces information about parameter variation over space.[9] The difference between GWR and spatial autocorrelation techniques is that the latter identify spatial dependence through the residual, while GWR addresses spatial non-stationarity directly through the estimated parameters. In a GWR we assume the regression model to be:

$$y_i = \beta_0(i) + \beta_1(i)x_{1i} + \beta_2(i)x_{2i} + \ldots + \beta_n(i)x_{ni} + \varepsilon_i \quad (1)$$

with the estimator

$$\beta'(i) = \left(\mathbf{X}^T\mathbf{W}(i)\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{W}(i)\mathbf{Y}. \quad (2)$$

[9] For more detailed information about GWR estimations, see e.g. Brunsdon et al. (2002).

Where W(i) is a weight specific matrix to location i, so that observations near to i are given greater weight than distant observations.

However, in our empirical analysis below, all estimations will be in single regressions due to the strong multicollinearity between the independent variables. The aim is still to examine if we find any strong geographic interdependencies between the squares, in other words, to compare the OLS generated β-values with the GWR generated ones. All GWR has been produced using Arc Map software. Given that the radiance emissions generated somewhat stronger correlation coefficients, we will use the radiance light-emission (instead of the saturated light data) as dependent variable in all regressions below. All regressions are run in a log-log functional form.

(**Table 3 about here**)

In all regressions, the GWR generated AIC value is below the equivalent value from the OLS regression, indicating that we improved the model and results by allowing variations across space. Moran's I values generated from the OLS regression also suggested that spatial autocorrelation was present at the 1 percent level, using 100, 200 and 400 neighbors. (We had to restrict our tests to 400 neighbors, since that was the maximum number of neighbors in some cases, given that we geographically do not cover all space in Sweden, but only places with individuals or establishments.) For the GWR estimations we used an adaptive version, which identify the optimal adaptive number of neighbors. The results suggest that the spatial relation is relatively local still. The number of neighbors is below 100 in all cases except the total wage incomes, wage income density, and wage sum density regressions. Given that the squares are of a relatively small size, the actual distance across which we experience spatial relations is quite small. Out of the variables we employ in our estimations, wage density (both people and establishment based) experience the largest spatial effect in the estimations of the unstandardized beta coefficients.

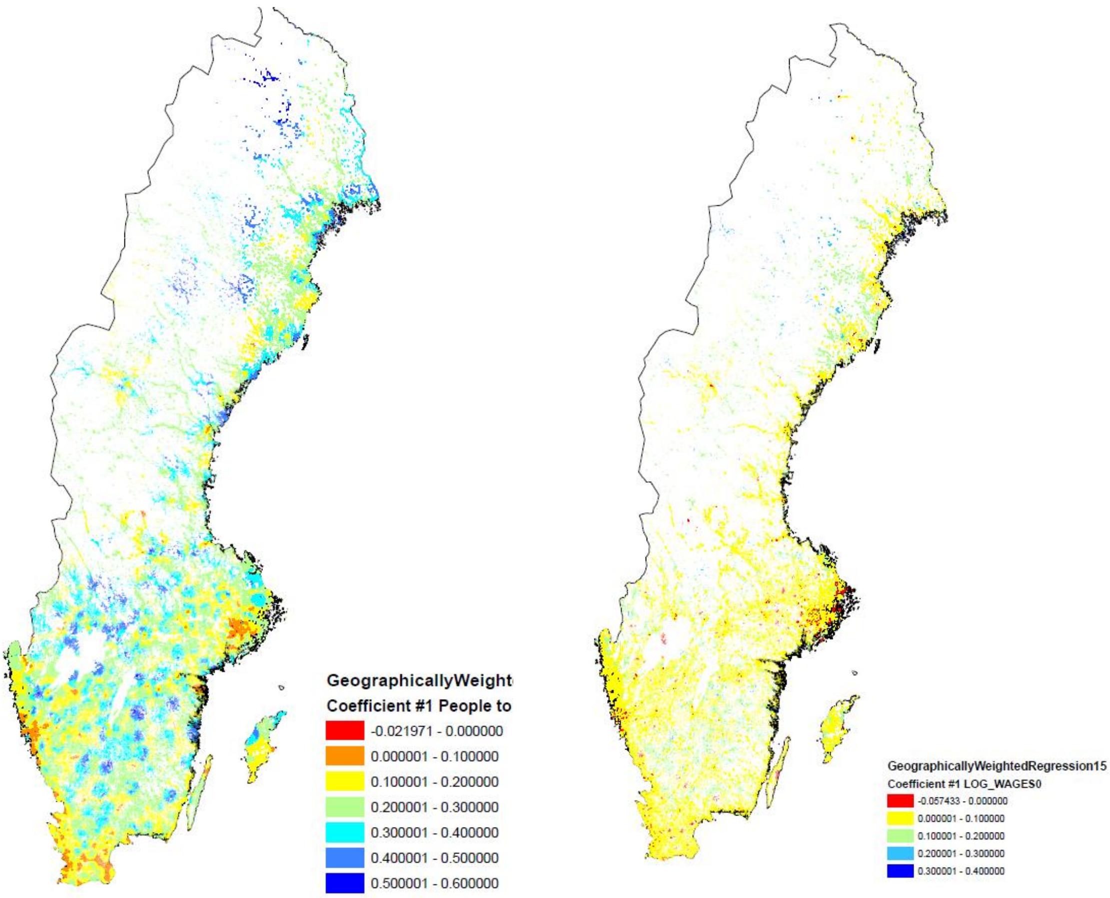
The variables with the lowest explanatory value, with the most neighbors and with the smallest difference between the OLS and GWR AIC values are people wages, both total wages as well as wage density. These results are also in line with the earlier correlation analysis (see Table 3) where industry wage and industry wage density had among the weakest correlation coefficients.

Table 3: OLS and GWR Regression Results (Dependent Variable: Radiance)

	Min	Lower quartile	Mean	Global (OLS)	Upper quartile	Max	Neighbors	R2	OLS AICc	GWR AICc	Residual Squares	No of Observations
People												
Total Population	-0.616	0.009	0.101	0.724	0.147	1.522	62	0.356	649,648.9	198,778	26,167.99	115,496
Population Density	-0.366	0.055	0.172	0.544	0.261	0.963	116	0.582	568,130.7	239,680	35,784.33	115,496
Total Wage Incomes	-0.075	0.090	0.170	0.424	0.226	0.908	407	0.275	672,166.9	459,727.3	122,551.2	115,496
Wage Income Density	-0.022	0.165	0.231	0.400	0.294	0.599	639	0.490	605,692.4	453,967.4	120,111.8	115,496
Establishments												
No of Establishments	-2.685	-0.010	0.088	0.944	0.115	3.649	30	0.240	417,341.5	98,928.66	10,370.47	188,986
Establishment Density	-0.612	0.032	0.171	0.692	0.257	1.814	62	0.573	350,702.4	115,807	15,311.45	188,986
No of Employees	-0.695	-0.002	0.045	0.420	0.060	1.684	38	0.226	419,521	113,875.5	13,074.59	188,986
Employment Density	-0.241	0.014	0.091	0.417	0.136	1.168	69	0.461	377,607.3	141,256.6	19,401.43	188,986
Total Wage Sums	-0.270	0.001	0.031	0.176	0.045	0.495	87	0.208	422,154.3	185,909.5	29,480.34	188,986
Wage Sum Density	-0.057	0.010	0.040	0.171	0.059	0.398	112	0.294	408,902.2	198,244.6	33,932.07	188,986

All regressions are in log-log format.

If we examine the generated beta coefficients from our analysis, we can see that the OLS generated global coefficient seems to be an over-estimation for most squares. In all cases, the GWR generated estimates are below the global one up to the upper quartile. In order to examine if there are any clustering effects for those residuals, we produced a map based on each GWR regression. Figure 1 illustrates the GWR estimations for people vs. establishment wage density, which we will use to illustrate spatial differences[10].



People Wage Density Establishment Wage Density

Figure 1: Geographically Weighted Regression Coefficients for Wage Density

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[10] All additional maps are attached in the appendix. However, they suggest that there are little spatial clustering effects in those cases.

Figure 1 clearly illustrates the difference in clustering effects for the individually estimated beta-coefficients from the geographically weighted regressions. While the value of the beta coefficients are more or less equally distributed across the squares in the establishment wage density regression (map to the right),we notice a minor over-valuation in the bigger regions, such as Stockholm and Gothenburg, which are marked out in red. When we turn to the results for the geographically weighted regression where people wage density explains light (the map to the left), we see how the individually estimated beta-coefficients from the regression have a very different, and more clustered pattern. The regions with beta coefficients closest to the globally estimated one (based on the OLS regression) are the larger cities of Stockholm, Gothenburg and Malmö, indicated by the orange areas in the map. In the darker blue and turquoise areas, the globally estimated beta-coefficient is an underestimation. These are basically sparsely populated areas or small city regions.

When we examined the maps from all other equations, we found patterns very similar to the establishment wage density regression map, with very little clustering for the individually estimated beta coefficients. We found bigger cities to somewhat over-estimate the beta value while the rest of the country (medium sized and smaller cities, as well as sparsely populated areas) tend to underestimate the beta values.

4. Discussion

We have examined the relationship between night-time light (NTL) emissions and several variables capturing economic activity. While much research has focused on the use of night-time light as a proxy variable for urbanization and growth, the question of what exactly artificial light emissions are capturing has been left largely unexamined. By matching NTL data to the fine-grained, geo-coded micro data for Sweden, we have been able to assess just how closely NTL data tracks the presence and activities of wage earners and establishments.

Our results suggest that night-time light is best used as a proxy for population and establishment density, and can thereby indirectly act as a measure of urbanization. However, NTL is relatively weakly related to economic activity as measured by total wages, which in theory are closely related to productivity. With correlations of approximately 0.5, we conclude that NTL emissions are a weak proxy for economic activity. We examined radiance (non-saturated) light, as well as saturated light, and found that radiance light had a somewhat closer connection to economic activity when compared to saturated light. Further, we found that NTL captures density better than total count values, and that the correlation coefficients in general increased to approximately 0.7, when we compared to people and establishment density. This suggests that night-time light may be a better proxy for the degree of urbanization, as captured by density, than total population, total number of establishments, or total production or consumption in terms of wages.

The results obtained from estimating geographically weighted regressions also suggest that there is spatial dependence in the estimations of economic activity using night-time light, and that these estimated values depend on the results of the neighbor squares. The relationship between night-time light and economic activity, both in terms of people and establishments, varies across regions, primarily based on regional size. This connection tends to be overestimated, especially for wages, in bigger urban regions, while it is underestimated in small and medium sized regions as well as in rural areas.

There is a pressing need to measure and compare socio-economic activities at a truly global scale. Night time lights data has come to be seen, mostly with good reason, as a very good indicator of urban expansion and distinctly urban activities. Whether NTL is adequate as a proxy measure for economic activity--- say, to estimate GDP for urban areas---is far from clear however. The saturation problem is definitely more severe than many of the proponents of using NTL to derive GDP-like measures let on, and even sophisticated augmentations of NTL data, such as that by Zhang et al. (2013), leave the problem mainly unresolved. After all, there is only so much that can be done to correct for an instrument with limited sensibility. The recent availability of unsaturated data measured by an instrument designed to capture light emissions---data collected by the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument aboard the Suomi National Polar-orbiting Partnership satellite---holds great promise, but how much of an improvement it represents over standard NTL data remains to be assessed.

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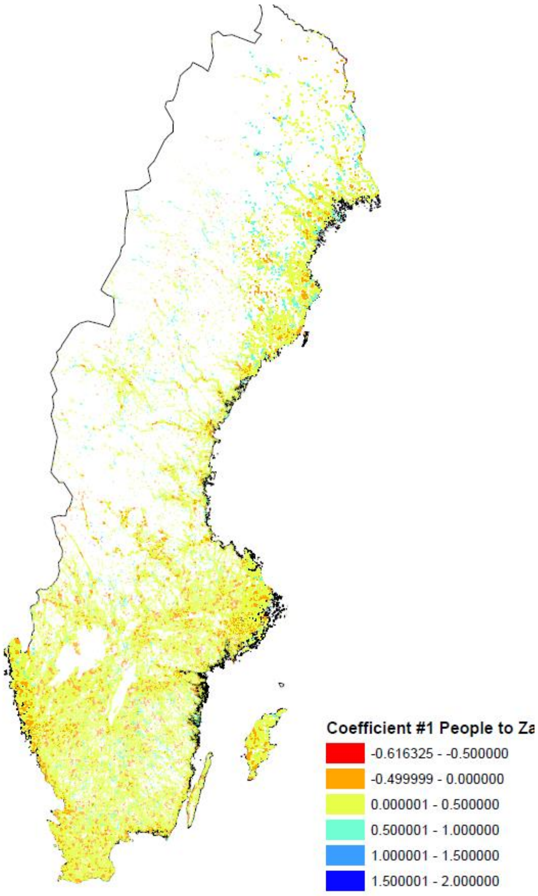
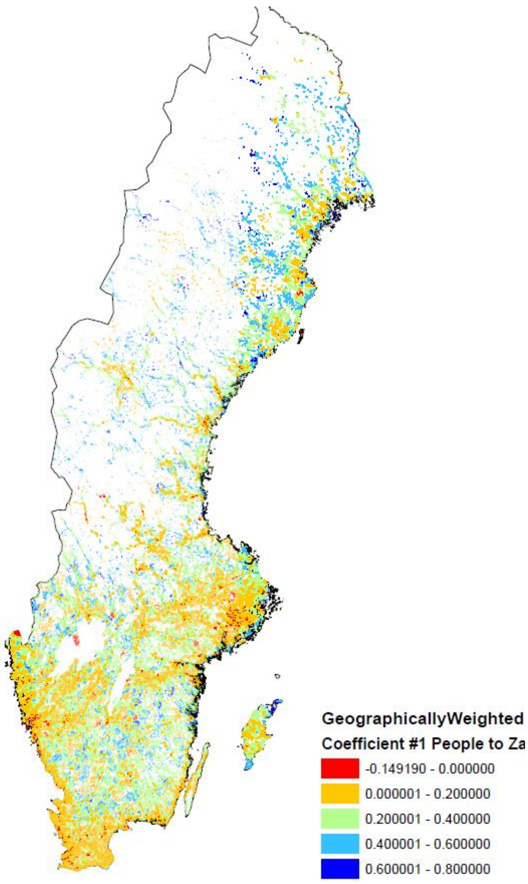
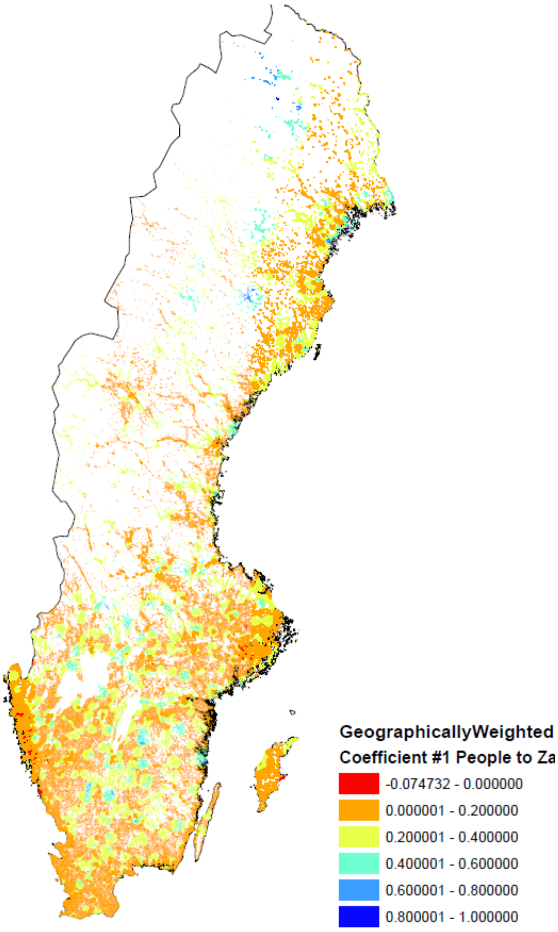
APPENDIX: GWR MAPS

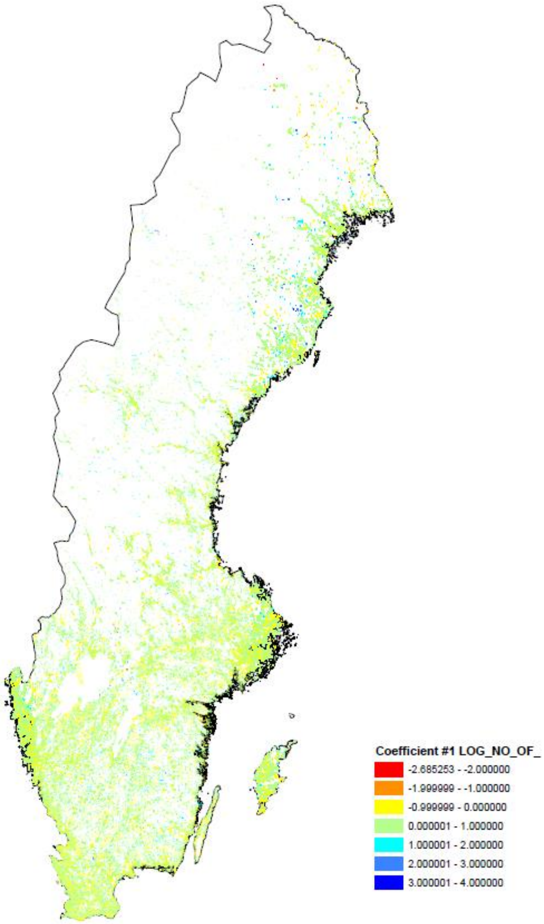


People - Total Population



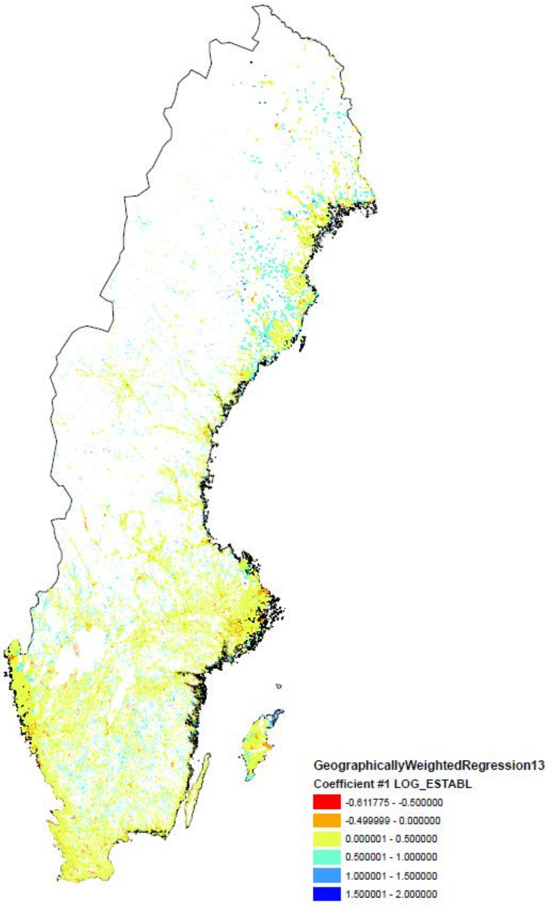
People - Population Density



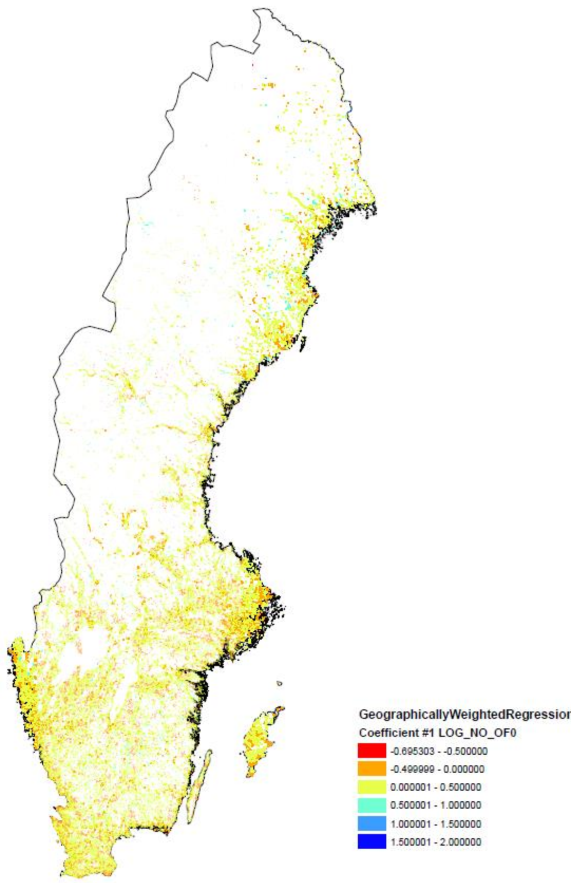


People – Total Wage Incomes

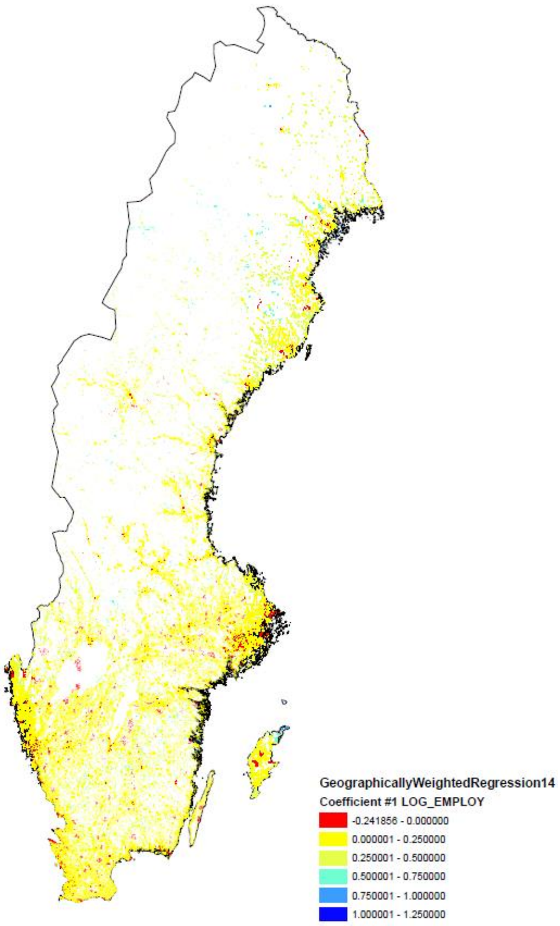
Establishment – Number of Establishments



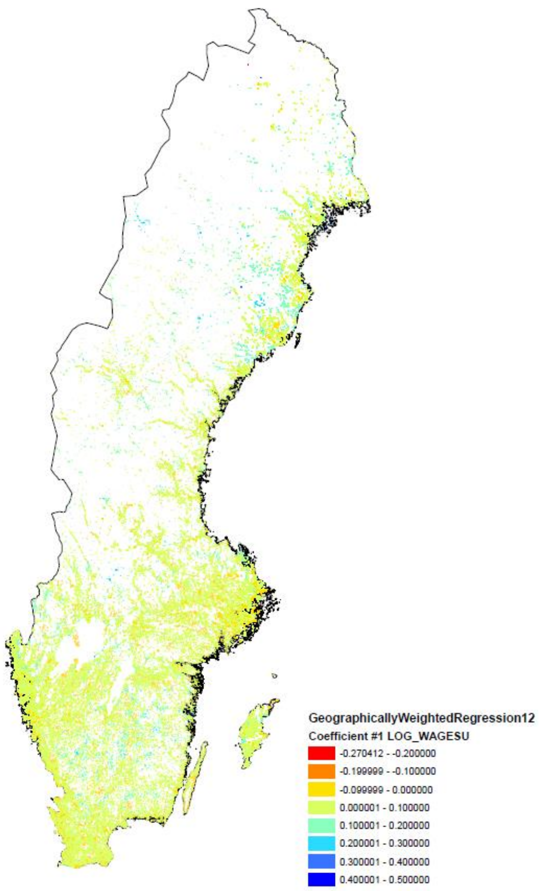
Establishment –Establishments Density



Establishment – Number of Employees



Establishment – Employment Density



Establishment – Total Wage Sums