Census from Heaven: An Estimate of Global Electricity Demand "if Everyone Lived Like in OECD"

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ABSTRACT

How much electricity does the world really need? Economic theory suggests that electricity demand depends on a number of factors such as per capita income, economic output, supply and cost of electricity. However, formal electricity demand models based on Gross Domestic Product (GDP), population growth and efficiency improvement assumptions may not capture the appropriate variables for responses at high geographical resolution level and, as a result, may be quite wrong about the prospective electricity need.

This study proposed a method and then implemented it for the question of whether luminosity (measures of nighttime lights visible from space) could be used to improve estimates of electricity prospective demand in non-OECD countries at the high geographical resolution. Further, we investigated whether luminosity may serve as a proxy for electricity consumption. Luminosity data has an advantage over other proxies as night lights data are available over time and all space, but data on electricity consumption are unavailable for many lower income countries and generally are unavailable for most countries at sub-national levels. To the extent that luminosity is a good proxy for electricity consumption, we evaluated how much electricity the world would likely demand "if everyone lived like in OECD countries".

Keywords: Nighttime light, luminosity, DMSP/OLS, population density

1. INTRODUCTION AND BACKGROUND

It is an unrealistic attempt to imagine global economic development without electricity use. However, a quarter of global population lives without access to electricity and most of them live in rural villages and urban ghettos in developing nations. These people continue to suffer a multitude impacts that are harmful to their welfare. Access to affordable modern energy carriers is a necessary step toward alleviating poverty and enabling the expansion of local economies.

How much electricity does the world really need? Economic theory suggests that electricity demand is based on a number of factors such as per capita income, economic output, population, supply and cost of electricity. GDP is a crucial indicator in many socio-economic studies and an important reference for political decision making. However, GDP is imperfectly measured all over the world (Feige & Urban, 2008). Many developing countries have only rudimentary economic statistics and the poor data quality has obstructed attempts to estimate economic growth, poverty, health and environmental quality in these countries (Nordhaus and Chen, 2010). The lack of good sub-regional data has been even more discouraging for researchers working at the subnational level.

The wide distribution of global population has made it difficult to collect and synthesize consistent data on the human socio-economic conditions at the high-resolution levels (the levels that are higher than national and sub-national units). In addition, many developing countries have no reliable censuses of population. Thus, formal electricity demand models may not capture the

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appropriate variables for responses at the high geographical resolution, and, as a result, may be quite wrong about prospective electricity demand. Therefore one of the most important issues in social, economic and environmental research has been how to improve the quality of socioeconomic data in developing countries (Nordhaus and Chen, 2010; Nordhaus and Chen, 2014).

Our aim in this study is to explore the advantages offered by spatial resolution global nighttime light images in order to estimate the luminosity gap between the OECD nations and the rest of the world and use it as a proxy for electricity consumption gap between developed countries and other nations. The distinct advantage of nighttime lights is that they are a unique dataset related to human activities that is available for most of the globe at a very high resolution and it may provide useful information on economic activity for regions with poor-quality data systems or no data. We hypothesized that nighttime lights can serve as an indicator for demographic and economic activity properties, and perform as a tool for evaluating intraregional differences in energy infrastructure and urban patterns. Our analysis is an attempt to estimate prospective electricity consumption that is required for economic catch-up of developing nations.

The rest of this paper is organized as follows. Section 2 gives a brief literature review on luminosity in social and economic studies. In section 3 we introduce the data and methodology that we used for our analysis. In section 4 we present discussion and conclusions.

2. LUMINOSITY IN SOCIAL AND ECONOMIC STUDIES

The luminosity data in the literature were gathered by the US Department of Defense satellites that were started in the mid-1960s. In December 1972, the data were declassified and became publicly available and known as the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) data. Despite obvious complications, many studies have used luminosity in social and economic research for more than a decade.

Nighttime light intensity is affected by multiple factors, such as population density, economic activity, infrastructure, etc. Luminosity data are employed as social and economic indicators to study regional and sub-regional socioeconomic systems. For example, nighttime light data were used to map the distribution of economic activity (Elvidge et al. 1997, Doll et al. 2000, Ebener et al. 2005; Ghosh et al.2010), poverty levels (Elvidge et al.2009; Wang,W. et al 2012), electrification rates (Elvidge et al. 2010; Doll, C., Pachauri, S., 2010), resource consumption (Sutton et al. 2009; Elvidge et al. 1997), density of constructed surfaces (Elvidge et al. 2007), the copper and steel stocks (Takahashi et al. 2009, Hattori et al. 2013).

One of the first publications on nighttime lights analysis was a study that indicated the positive correlation between luminosity and population, electric power consumption, and economic activity (see Elivdge et al., 1997). Elivdge et al. have undertaken a series of tests to support conclusion that luminosity data could be a proxy for economic statistics. Several studies have proven that the amount of luminosity in an area has a positive correlation with its GDP. Doll et al. tested the relationship between country-level GDP at Purchasing Power Parity (GDP PPP) and total lit area using the data between October 1994 and March 1995. By considering the lit area of a city, Doll et al. got the R^2 of the regression model of 0.85 (see Doll et al., 2000). Ghosh et al. analysed GDP and sum of lights globally and at the sub-national level for China, India, Mexico, and the U.S. in 2006 and obtained the R^2 of 0.73 (see Ghosh et al., (2010).

In one of the first economic studies that applied luminosity data, Doll et al. used the 1996–1997 radiance calibrated product and sub-national GDP data (see Doll et al. 2006). Each European country was tested for correlation of night-time radiance data and regional economic productivity data at sub-national levels. The US states were compared to the regions defined by the US Census Bureau. Strong positive correlations between total radiance and sub-national GDP were observed for all the countries examined at the finest level of observation with a very strong relationship (R^2 value of 0.98) between the nighttime lights of these countries and their nominal GDP. Sutton et al. further confirmed these results (see Sutton et al. 2007). Using the stable light product for the year 2000 of the U.S., India, China and Turkey, Sutton et al. found a log-linear relationship between the night light and the nominal GDP (with an R^2 value of 0.74). Similar studies were conducted for China (see Zhao, et al., 2010), India (see Bhandari & Roychowdhury, 2011) and Mexico (see Ghosh, et al., 2009). All mentioned above studies used one-year record only.

More recently, Chen & Nordhaus (2011), Kulkarni et al. (2011) and Nordhaus & Chen (2014) linked the time evolution of luminosity to economic activity and used all available nighttime lights annual data. Nordhaus and Chen concluded that light can be used as a proxy for nominal GDP, but this approach adds value to the official statistics for countries only with poor reporting standards and low data quality (see Chen & Nordhaus, 2011, Nordhaus & Chen, 2014). Henderson et al. furthermore confirmed this statement for GDP growth (see Henderson et al., 2012).

Persistent nighttime light is a clear indicator of the presence of human activities and settlements. An early effort to assess the population densities with luminosity data was done by Sutton (see Sutton, 1997). Sutton compared data from the 1990 U.S. census with a binary image containing only the saturated pixels and found that these images could only explain 22-25% of the variation in the population density of the urban areas in the U.S. In a later study, Sutton, et al. estimated the global human population for the year 1997 as 6.3 billion people compared to 5.9 billion, which was the generally accepted estimate this year (see Sutton, et al., 2001). Similar studies were done at the national levels, e.g. for China (see Lo, 2001; Ma, T. et al., 2012) and Brazil (see Amaral, et al., 2005). Thus, luminosity may not be a perfect proxy to measure population; however, in combination with other sources, it can substantially add value.

Moreover, Elvidge, et al. constructed a global Poverty Index using luminosity data through dividing population numbers by the average light intensity (Elvidge, et al., 2009). Elvidge, et al. developed an approach using national poverty levels reported by the World Development Indicators (WDI) in 2006. The resulting estimate for the number of people living in poverty (live with an income below $2 a day) was 2.2 billion, or consistent with the 2.6 billion estimated by the World Bank in 2006.

A further application of luminosity data is maps and estimations of urban boundaries. Imhoff, et al. presented a study for urban areas in the U.S and Henderson, et al. for three distinct cities: Lhasa, San Francisco and Beijing (see Imhoff, et al.,1997; Henderson, et al., 2003). Other studies on the level of urbanization estimations can be found in Small et al. (2005) and Elvidge, et al. (see Small et al., 2005; Elvidge, et al., 2007). Another obvious application of the night light data is energy consumption estimates. In an early study, Elvidge et al. showed a very strong relationship between the lighted area and the energy consumption at a country level (see Elvidge et al. 1997). Further similar studies were conducted at the national level for Brazil (Amaral, et al., 2005), India (Kiran Chand, et al., 2009), and Japan (Letu, et al., 2010).

A review of the literature reveals that up to date the majority of existing socioeconomic studies use only a single one-year nighttime light dataset and do not examine time evolutionary processes. One of the reasons is the complexity of data handling and inter-calibration between the different satellite sensors and possible errors (see Pestalozzi et al., 2013, Chen and Nordhaus, 2010).

The present study examines luminosity (measures of nighttime lights visible from space), population and electricity consumption for 2010. We compared population density, luminosity at the 1° latitude × 1° longitude grid-cell resolution level, and electricity consumption at the country level. In the next section, we provide detailed information on data that we developed for our study.

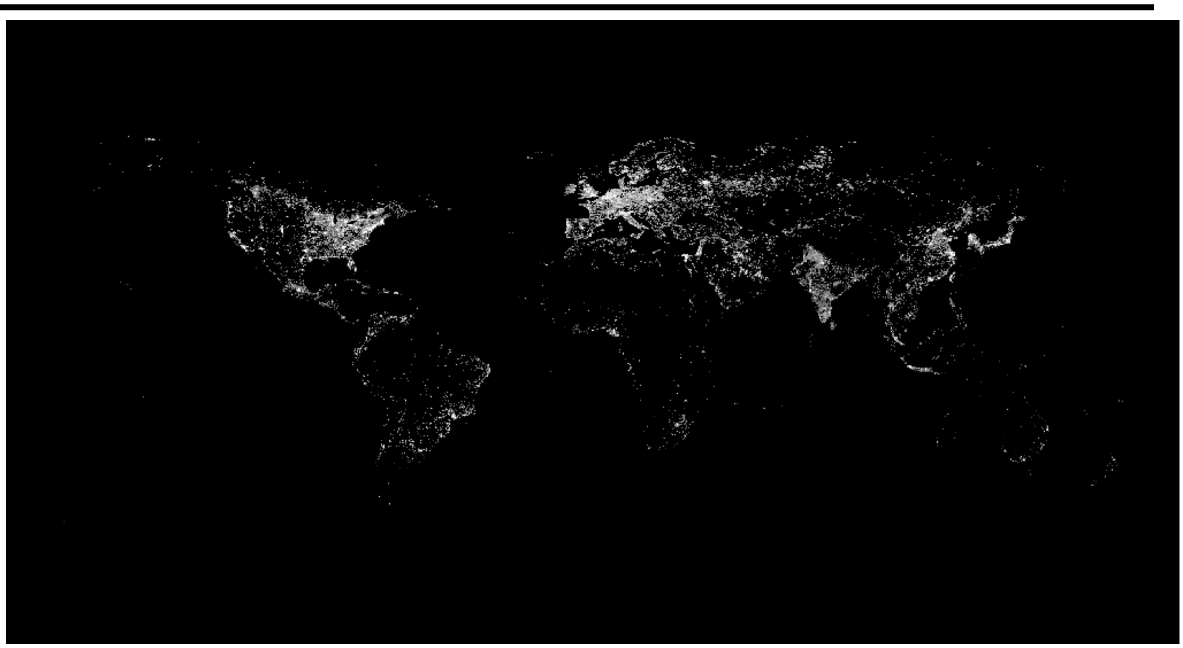
3. DATA AND METHODOLOGY

3.1 Data Sources

There are two primary data sources for this study: the Defence Meteorological Satellite Program (DMSP)'s nighttime lights and the gridded population data. The majority of studies to date use the coarse spatial resolution datasets from the DMSP and data on luminosity at night are collected by the DMSP-OLS satellite program, maintained, and processed by the National Oceanic and Atmospheric Administration (NOAA), (see NOAA, 2014). Satellites orbit the Earth fourteen times a day with a nigttime overpass between 20:30 and 21:30 with sending images of every location spanning -180 to 180 degrees longitude and -65 to 75 degrees latitude at a resolution of 30 arc-seconds (approximately 1 square km at the equator). The images are processed to remove cloud cover, snow and ephemeral lights (such as forest fires) to produce the final product publically available (see Figure 1). The nighttime lights data are available for 1992-2012. We used only 2010 data because of lack of reliable electricity consumption and population data behind 2010 for non-OECD countries at the time of writing.

Figure 1 illustrates clear differences in the quantity of lighting around the world. Populations in the OECD countries generally have a surplus of lighting, yielding the white areas on Figure 1. Areas with high population count and modest lighting levels show up as grey (some parts of India and China). The black color on Figure 1 indicates areas where no lighting was detected by the DMSP sensor.

Figure 1. 2010 Nighttime Lights Composite



Data Source: NOAA (2014)

There are few global gridded population products currently available. The U.S. Department of Energy Landscan data are compatible with the DMSP nightime lights as both datasets are created with the same 30 arc second grid resolution (see Bhaduri et al. 2002 and

Landscan, 2014). In addition, Landscan provides the most up-to date, gridded worldwide population data. The population values are the result of a model that allocates census counts at sub-national level to each cell of a 30 arc-second grid according to likelihood coefficients. These coefficients are based on proximity to roads, slope, land cover, nighttime lights, etc. The database is updated annually by incorporating new spatial data and remotely sensed imagery.

Another database was created by Center for International Earth Science Information Network (CIESIN) at Columbia University. CIESIN developed Gridded Population of the World (GPW) database that consists of population estimates for 1990, 1995, 2000 and 2005 at a resolution of 2.5 arc-minute. The following indicators are available in the GWP database: population counts (raw counts), population densities (per square km), land area (actual area net of ice and water), and population-weighted mean administrative unit area. These data are accessible in GIS-compatible data formats at the global, continent, and country levels. CIESIN used a proportional allocation gridding algorithm, utilizing more than 300,000 national and sub-national administrative units to assign population values to grid cells (see CIESIN, 2014).

Besides, United Nations Environment Programme (UNEP) created Global Resource Information Database (UNEP/GRID) that includes population spatial data with resolution of 2.5 arc-minute and consistent with GPW datasets (see UNEP/GRID, 2014). The database is largely a compilation of existing data sources. There are several datasets for different regions and different years. However, global population distribution data are available only for 1990, so the data are not practical for our study.

Yale University developed Geographically based Economic data set (GEcon) that is devoted to creating geophysically based data on economic activity at the global level (see GEcon, 2011). The main effort of this research was to create data on gross cell product (GCP), but in addition to GCP data, the authors merged the economic data with other important demographic and geophysical data such as climate, physical attributes, location indicators, population, and luminosity. The data set is publicly available at a 1-degree longitude by 1-degree latitude resolution at a global scale (see GEcon, 2011).

After consideration of all publically available sources we used GEcon database. The reasons are, first, the database's resolution level of 1° x 1° grid cells is convenient for data analysis and modeling exercises; second, population data are largely based on peer reviewed GPW datasets and, third, the database includes RIG (Rate in Grid) coefficient. RIG is a proportion of grid cell in country and land and it is an important element for population and luminosity densities estimations.

To start with, we calibrated the NOAA's luminosity data. Each pixel (1 square km at the equator) in the luminosity data set is assigned to a digital number (DN) representing its luminosity and the DNs are integers ranging from 0 to 63. These data can be converted to radiance by the equation: Radiance = $(DN)^{3/2} * 10^{-10}$ Watts/cm2/sr/um (see Chen and Nordhaus, 2010). We aggregated (upscaled) the NOAA's luminosity data up to 1° x 1° grid cells to match GEcon data. For upscaling we used the ESRI's ArcGIS 10.1 software. We took each pixel's DN and then summed these radiances over all pixels in the grid cell (each grid cell includes 120 x 120 pixels). After upscaling luminosity data we merged them with GEcon dataset.

At the next step, we aggregated luminosity data by country using RIG coefficient and combined these data with electric power consumption data from the World Development Indicators (WDI) database (see WB, 2013). The reported indicators include output from power plants, but exclude small generators unconnected to the power grid. The World Bank has been compiling and reporting on electricity consumption data since 1965 in a WDI series and they are consistent with International Energy Agency (IEA) statistics for non-OECD and OECD countries. The IEA used the best available data from several different official national sources. For the member countries of the Economic Commission for Europe of the United Nations

(UNECE), the data are based on information provided by the national administrations through annual questionnaires. The electricity consumption data for all other countries are based on national energy statistics from varied sources, converted and adjusted to fit the IEA format and methodology.

3.2 Methodology

Under economic theory, GDP per capita represents economic welfare, but, in some cases, other indicators may better reflect the level of economic development: per capita electricity consumption, for instance, is considered as one of the most relevant alternatives (Joyeux and Ripple, 2007). The hypothesis on convergence in electricity per capita consumption could be an analog of the hypothesis on convergence in economics when the economies with low GDP per capita will tend to grow at faster per capita rates than richer economies.[1] There are many examples of countries which have converged with developed countries which validate the convergence theory (for example, the East Asian Tigers rapidly converged with developed economies). Maza and Villaverde find that a process of electricity consumption convergence has taken place and that the reduction of disparities is related to the rapid economic changes experienced by some developing countries and the energy conservation policies implemented by most developed countries (see, Maza and Villaverde, 2008).

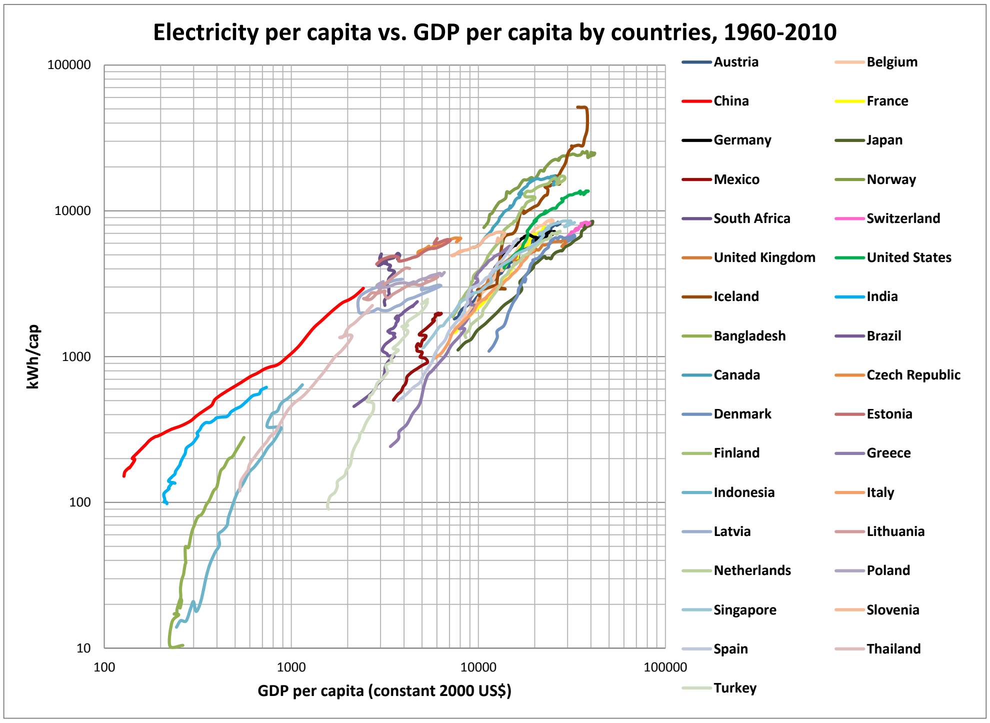
Figure 2 shows electricity per capita consumption versus GDP per capita in 1960-2010 in logarithmic scale. Electricity consumption per capita varies significantly over time and across the countries, and, generally, countries with lower per capita income are associated with lower electricity per capita consumption. Figure 2 illustrates electricity use convergence: diversity of electricity consumption is higher with lower GDP per capita, diversity decreases with increases in income. How much electricity will non-OECD countries be likely to demand in the future under the growth paths of economic catch-up? This is a very important question as electricity shortage is a limiting factor to economic growth, so answering this question help to estimate electricity demand of non-OECD nations in order to reach the higher level of socio-economic development.

Economic theory suggests that electricity demand is based on a number of factors such as per capita income, economic output, the supply and cost of electricity. Population, economic variables, energy and electricity consumption data are available at low resolution level, but there is a scarcity of data at high resolution level. Even if some data are available at high resolution level, such data are collected through variations of methods, surveys and time frames, so it is hard to integrate them into a global assessment. Formal models based on the assumption of GDP, population growth and efficiency improvement may not capture the appropriate variables for responses at the high geographical resolution and as a result, may be quite wrong about the level of possible electricity demand.

However, recently, satellite derived nighttime lights have been used to study global economic and demographic differences between countries and the majority of studies to date have used the coarse spatial resolution datasets of the DMSP. Chen and Nordhaus (see Chen and Nordhaus, 2010) find that luminosity is likely to add value as a proxy for GDP for countries with the poorest statistical systems.

[1] The idea of convergence in economics is the hypothesis that poorer economies' per capita incomes will tend to grow at faster rates than richer economies and as a result, all economies should eventually converge in terms of per capita income. Some economists criticize the theory, stating that endogenous factors, such as government policy, are much more influential in economic growth than exogenous factors.

Figure 2. Electricity per capita versus GDP per capita by Countries, 1960-2010



Data Source: WDI (2014)

We estimated prospective global electricity demand in non-OECD countries using luminosity, population and electricity consumption data. First, we estimated luminosity gap between the OECD countries and the rest of the world using regression equation of the presence of satellite detected nighttime lighting and population density at the 1° latitude × 1° longitude grid-cell resolution level. Figure 3 is a scatter plot of log luminosity density and log population density ("log" always refers to natural logarithms) for all grid cells associated with OECD countries for 2010 (n = 2,559) (see Appendix A, equation [1]).

The regression equation of luminosity density as a function of population density for OECD countries shows a significant elasticity of 0.81 and R^2 of 0.79 (see Appendix B for parameters and statistics). We used the coefficient estimates from the OECD regression equation to estimate prospective luminosity in non-OECD countries "if Everyone Lived Like in OECD" (see Appendix A, equation [2] and Figure 4). Subtractions of observed luminosity data from estimations for non-OECD countries provided the estimated luminosity gap between OECD and the rest of the world (Appendix A, equation [3]).

In Figure 4 unlit areas are black, and lights appear with intensity increasing from dark-gray to white. Light intensity in the OECD areas is the DMSP-OLS 2010 data and lights in non-OECD areas reflect luminocity gap. In most regions, the higher concentration of lights in coastal areas mirrors the higher population densities. The comparison of lights in Europe and India reveals huge differences in population density.

Figure 3. Luminosity Density versus Population Density in OECD Countries, 2010

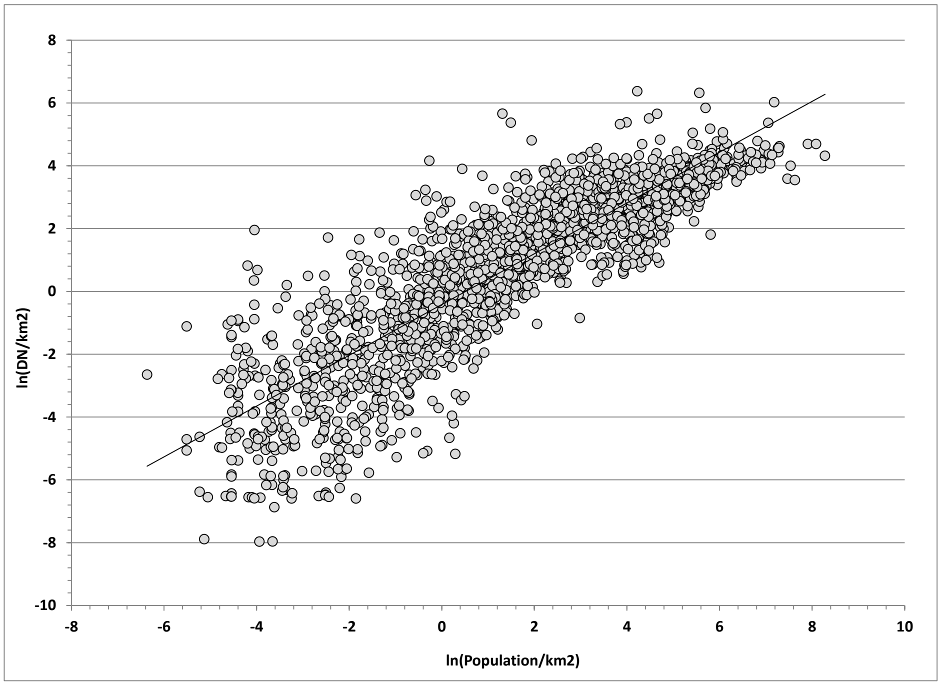
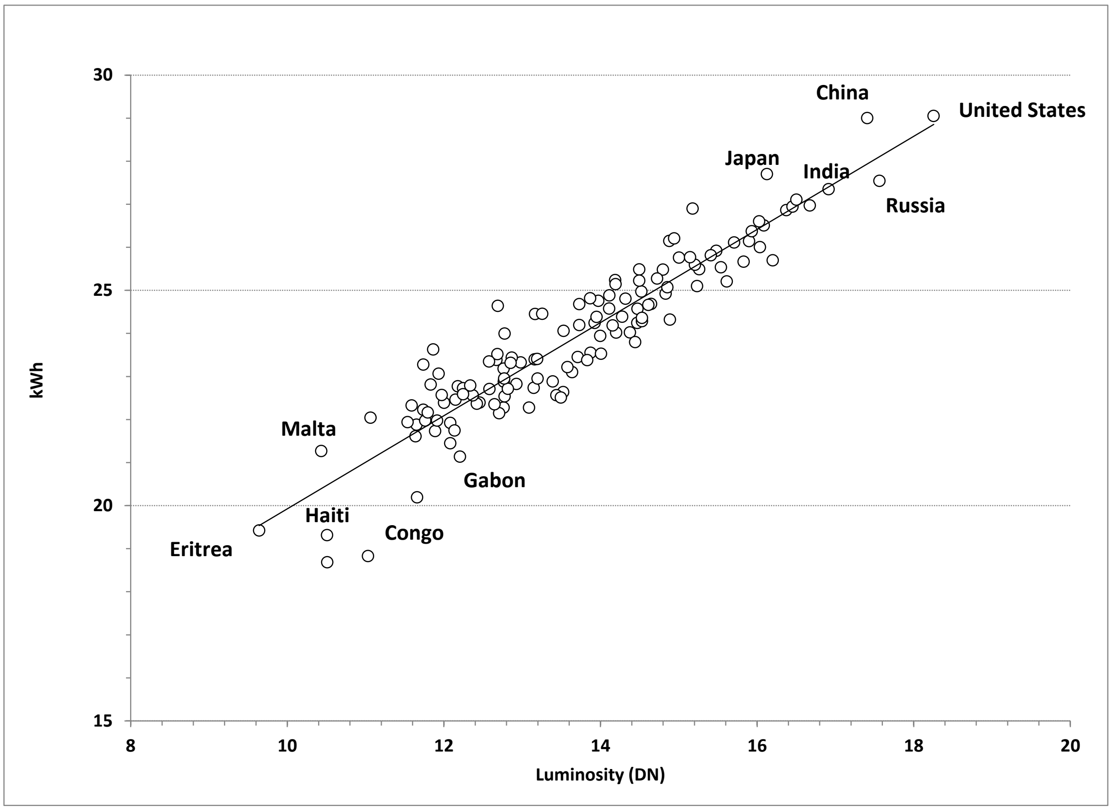


Figure 4. Nighttime Lights Composite "if Everyone Lived Like in OECD"

Nighttime lights provide an appealing innovative instrument to measure economic activity and Chen & Nordhaus concluded that luminosity data may be a useful supplement to current economic indicators in countries and regions with very poor quality or missing data (see Chen and Nordhaus, 2010). We employed luminosity as a proxy for electricity consumption estimates. The reason is that much light observable from space is from electric illumination. Lighting is normally the primary application of electricity in households (especially in developing countries), so electricity is primarily used for lighting and small appliances, rather than cooking, and represents an insignificant share of total household consumption in energy terms.

Luminosity data has an advantage over other proxies as night lights data are available over time and all space, but data on electricity consumption is unavailable for many lower income countries and is generally unavailable for most countries at sub-national levels. We used all available cells from merging the GEcon data and DMSP-OLS data and aggregated luminosities for all grid cells in a country to obtain that country's total luminosity (see Appendix A, equation [4]). We estimate a regression of log electricity consumption as a function of log of luminosity by country and got a highly significant elasticity of 1.08, and a R^2 of 0.87 (see regression statistics in Appendix B). As is seen in Figure 5, countries such as Japan and China consume more electricity relative to their sum of nighttime lights value; on the other hand, Russia consumes less electricity relative to its sum of lights. This relationship provided a moderately strong R^2 value of 0.87.

Figure 5. Electricity Consumption vs. Luminosity by Country, 2010



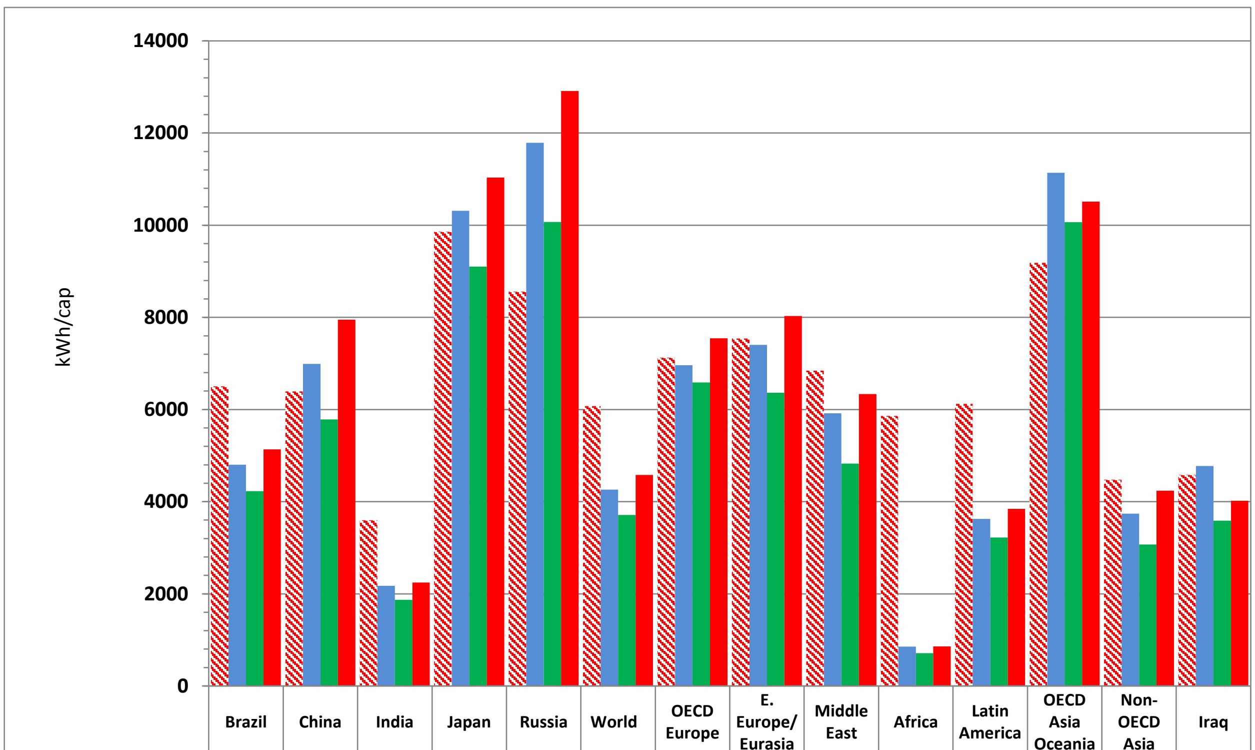
We applied the regression equation to estimate prospective electricity demand in non-OECD countries (see Appendix A, equations [4]-[7]) and received estimations of electricity demand "if everyone lived like in OECD countries" at 1° x 1° grid cells resolution and by countries (see Appendix A, equations [8]). Our approach allows to estimate electricity demand in the areas with low population density and without luminosity indication. Nordhaus & Chen noted that almost one-third of grid-cells with positive population and output were recorded with zero lights (see Nordhaus and Chen, 2014). While these grid-cells contain only a small fraction of economic output and population, it is a large part of the land area of the globe and using our approach it is possible to assess prospective electricity consumption in these areas.

4. DISCUSSION AND CONCLUSIONS

The future of energy production, transportation, and consumption is subject to numerous uncertainties. These uncertainties include, but are not limited to, future energy prices, economic growth, demographic changes, technological advances, and government policies. Various energy system scenarios have been developed at the national and regional levels. Thus, there are numerous electricity demand projections based on per capita income, economic growth, population, supply etc. However, there are no estimates on how much electricity the world actually needs to benefit from the same level of electricity consumption as the OECD countries today.

We projected prospective electricity demand using luminosity data and estimate the prospective luminosity worldwide is 1.48 times higher than luminosity observations in 2010. To the extent that luminosity is a good proxy for GDP and electricity consumption, we evaluated how much electricity the world would likely demand if everyone lived like in OECD countries. The results show that prospective global electricity consumption is 2.4 times higher than observation in 2010. At the per capita level, the average prospective global electricity consumption is 7,224 kWh/cap or about the same as in Germany today -- a significant increase from the current level of about 2,500 kWh/cap (see Appendix C for electricity consumption projections details).

Figure 6. Electricity Generation per capita in 2035 (IEA, 2013) and Prospective Electricity Demand per capita based on Luminosity Data



	Brazil	China	India	Japan	Russia	World	OECD Europe	E. Europe/ Eurasia	Middle East	Africa	Latin America	OECD Asia Oceania	Non-OECD Asia	Iraq
Prospective Demand	6501	6393	3599	9857	8555	6074	7123	7542	6841	5861	6123	9184	4476	4578
NPS	4801	6991	2174	10314	11791	4262	6963	7404	5916	853	3626	11138	3740	4776
450	4230	5785	1870	9102	10070	3712	6587	6364	4828	711	3222	10064	3073	3586
CPS	5133	7948	2246	11034	12915	4580	7545	8031	6337	860	3846	10512	4237	4017

According to the IEA the global electricity consumption in 2010 was 21,408 TWh and by 2035 it is projected to increase by 86% in the Current Policy Scenario (CPS), by 51% in the 450

Scenario (450), and by 73% in the New Policy Scenario (NPS) (see IEA, 2013). Electricity per capita consumption growth is 19%-50% by 2035, and it is projected that almost 280 million people will get connected to the electricity by 2030 in NPS scenario (IEA, 2012).

The IEA estimated the global electrification rate at 80.5% with 1.32 billion people living without electricity. Thus, according to the NPS scenario, almost one billion people will live without electricity access by 2030 (see IEA, 2012). Both theoretical and most empirical studies have demonstrated a causal relationship between per capita electricity consumption and per capita GDP globally. Though the empirical results are varied and sometimes conflicting (see, for example, Maza, Villaverde, 2008), the conclusions derived from most of these studies show that the causality is running from energy and electricity consumption to GDP (see Ozturk and Acaravcia,2010; Chontanawat et al., 2008). Thus, electricity is a limiting factor to economic growth and, therefore, lack of electricity supply or shocks/interruptions of supply will have a negative impact on economic growth.[2]

On the other hand, in 1990-2008, almost two billion people received access to electricity globally (see GEA, 2012) and global electricity consumption in 2008 was 1.7 times higher than in 1990. This provides a basis to believe that electrifying the remaining 1.3 billion people without electricity is feasible. However, if universal access to electricity is achievable by 2030 (see GEA 2012), the challenge to increase electricity usage up to the OECD level is tremendous and the results presented in this paper show the magnitude of the challenge for developing countries in electricity convergence.

This study proposed a method and then implemented it for the question of whether nighttime luminosity measures could be used to improve estimates of electricity prospective demand at the high resolution level. The future analysis will be particularly aimed at countries and sub-national regions with low-quality data systems.

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[2] The literature distinguishes four categories of this relationship: no causality at all, causality from electricity consumption to GDP growth, causality from GDP growth to electricity consumption, and bi-directional causality between the two. The empirical results on this issue are varied and sometimes conflicting (see, for example, Maza, Villaverde, 2008), however, the conclusions derived from most of these studies show that the causality is running from electricity consumption to GDP (see Acaravcia, Ozturk, 2010; Chontanawat et al., 2008).

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Appendix A. Regression Equations

$$\ln(l_i) = \alpha_{OECD} \cdot \ln(p_i) + \beta_{OECD} \quad [1]$$

Where l_i is luminosity density and p_i is population density in grid cell i,
$i \in$ OECD countries

$$l'_j = e^{\alpha_{OECD} \cdot \ln(pj) + \beta_{OECD}} \quad [2]$$

Where l'_j is luminosity density and p_j is population density in grid cell j,
$j \in$ non-OECD countries

$$\delta(l_j) = l'_j - l_j = e^{\alpha_{OECD} \cdot \ln(pj) + \beta_{OECD}} - l_j \quad [3]$$

$\delta(l_j)$ is luminosity density "gap" in grid cell j,
$j \in$ non-OECD countries

$$L_n = \sum_{k \in N} l_k, \quad [4]$$

L_n is luminosity in country n; l_k is luminosity in grid cell k; $k \in$ country n*'s* grid cells set N

$$\ln(E_n) = a \cdot \ln(L_n) + b \quad [5]$$

$$E_n = \sum_{k \in N} e'_k \ ; \ L_n = \sum_{k \in N} l_k \quad [6]$$

E_n is electricity consumption in country n and e'_k is electricity consumption in grid cell k

$$\delta(e_{nk}) = a \cdot \ln\left((e^{\alpha_{OECD} \cdot \ln(p_{nk}) + \beta_{OECD}} - l_k) * S_{nk} \right) + b \quad [7]$$

$\delta(e_{nk})$ is electricity consumption "gap" in grid cell k, country n, $n \in$ non-OECD countries; Snk is the land area of country n in grid k

$$E_n^* = E_n + \sum_k \delta(e'_k) \quad [8]$$

Appendix B. Regressions Statistics

B1. Regression Statistics for Luminosity Density as a Function of Population Density (Linear-Log Model, OECD Countries, 2010)

Regression Statistics	
Multiple R	0.89
R Square	0.79
Adjusted R Square	0.79
Standard Error	1.17
Observations	2559

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	12971	12971	9504	0.00
Residual	2557	3490	1		
Total	2558	16460			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.42	0.03	-14.65	0.00	-0.47	-0.36	-0.47	-0.36
X Variable 1	0.81	0.01	97.49	0.00	0.79	0.83	0.79	0.83

B2. Regression Statistics for Electricity Consumption as a Function of Luminosity in natural logarithms (Linear-Log Model, by Country, 2010)

Regression Statistics	
Multiple R	0.93
R Square	0.86
Adjusted R Square	0.86
Standard Error	0.31
Observations	130

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	76	76	812	0.00
Residual	128	12	0		
Total	129	88			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	4.11	0.22	18.56	0.00	3.67	4.55	3.67	4.55
X Variable 1	1.05	0.04	28.50	0.00	0.98	1.13	0.98	1.13

Appendix C. Prospective Electricity Consumption Projections by Countries

	2010 Electric power consumption (kWh per capita)	2010 Electric power consumption (TWh)	Electricity Deficit based on Luminosity Deficit Regression (TWh)	Total Prospective Electricity Demand (TWh)	Prospective Electricity Demand per capita , kWh/cap
Albania	1770	5.7	11	16	5052
Algeria	1026	36.4	121	157	4433
Angola	248	4.7	126	130	6830
Argentina	2904	117.4	145	263	6503
Armenia	1606	5.0	10	15	4961
Azerbaijan	1603	14.5	37	51	5672
Bangladesh	279	41.5	332	373	2511
Belarus	3564	33.8	22	56	5862
Belgium	8387	91.4	0	91	8387
Benin	17	0.2	43	44	4930
Bolivia	616	6.1	64	70	7090
Bosnia&Herzegovina	3110	11.7	14	26	6918
Botswana	1586	3.2	12	16	7771
Brunei	8759	3.5	0	3	8759
Bulgaria	4476	33.7	34	68	8965
Cambodia	146	2.1	75	77	5420
Cameroon	271	5.3	124	130	6615
Chile	3297	56.4	70	126	7380
Colombia	1012	46.9	218	265	5732
Congo	145	0.6	27	28	6813
Costa Rica	1855	8.6	17	26	5511
Cote d'Ivoire	210	4.1	112	116	5891
Croatia	3813	16.8	4	21	4739
Cuba	1299	14.6	51	65	5788
Cyprus	4675	5.2	1	6	5439
Czech Republic	6321	66.5	0	67	6334
Democratic Republic of Cc	95	6.3	486	492	7459
Dominican Republic	1442	14.3	42	56	5623
Ecuador	1055	15.3	65	81	5575
Egypt	1608	130.4	147	277	3417
El Salvador	855	5.3	18	23	3761
Eritrea	52	0.3	34	34	6446
Ethiopia	54	4.5	476	480	5790
Gabon	1004	1.5	6	8	5025
Georgia	1743	7.8	26	34	7557
Ghana	298	7.3	132	139	5708
Guatemala	567	8.2	60	68	4712
Haiti	24	0.2	32	32	3243
Honduras	671	5.1	40	45	5925
Indonesia	641	153.8	815	969	4039
Iran	2652	196.2	245	441	5967
Iraq	1183	37.9	109	147	4578
Israel	6856	52.3	8	61	7958
Jamaica	1222	3.3	7	11	3937
Jordan	2226	13.5	12	26	4283
Kazakhstan	4728	77.2	60	138	8431
Kenya	156	6.3	198	204	5034
Latvia	3026	6.8	3	10	4549
Lebanon	3569	15.1	6	21	4886
Libya	4270	27.1	14	41	6407
Lithuania	3271	10.8	3	14	4180
Macedonia	3591	7.4	6	13	6530
Malaysia	4117	116.9	95	212	7456
Malta	4151	1.7	0	2	4151
Mexico	1990	225.8	400	626	5518
Moldova	1049	3.7	0	4	1189
Mongolia	1530	4.2	9	13	4808
Morocco	781	25.0	143	168	5257
Mozambique	444	10.4	178	188	8049
Myanmar	131	6.3	302	309	6437
Namibia	1479	3.4	11	14	6198
Nepal	93	2.8	160	162	5421
Nicaragua	473	2.7	34	36	6302
Nigeria	136	21.6	655	676	4269
North Korea	749	18.2	96	114	4687
Oman	5933	16.5	2	19	6709
Pakistan	457	79.3	574	653	3763
Panama	1832	6.4	17	24	6728
Paraguay	1134	7.3	34	41	6361
Peru	1106	32.1	163	195	6718
Philippines	643	59.9	310	370	3971
Portugal	4929	52.4	3	55	5188
Romania	2392	51.3	75	127	5901
Senegal	195	2.4	68	71	5684
Serbia and Montenegro	4359	31.8	24	56	7690
Sri Lanka	449	9.3	64	74	3561
Sudan	141	4.7	292	297	8834
Syria	1905	39.0	75	114	5580
Tanzania	78	3.5	312	315	7033
Thailand	2243	155.1	258	413	5981
Togo	22	0.1	36	36	5993
Trinidad and Tobago	5894	7.9	1	9	6370
Tunisia	1350	14.2	35	49	4655
Ukraine	3550	162.8	181	343	7488
Uruguay	2763	9.3	20	29	8708
Uzbekistan	1648	47.1	94	141	4942
Venezuela	3287	94.8	100	195	6768
Vietnam	1035	89.9	298	388	4467
Yemen	249	6.0	105	111	4622
Zambia	623	8.1	97	105	8153