

Article

## Creating a Global Grid of Distributed Fossil Fuel CO<sub>2</sub> Emissions from Nighttime Satellite Imagery

Tilottama Ghosh <sup>1\*</sup>, Christopher D. Elvidge <sup>2</sup>, Paul C. Sutton <sup>3</sup>, Kimberly E. Baugh <sup>1</sup>, Daniel Ziskin <sup>1</sup>, and Benjamin T. Tuttle <sup>1</sup>

<sup>1</sup> Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, CO 80309, USA; E-Mails: tilottama.ghosh@noaa.gov (T.G.); kim.baugh@noaa.gov (K.E.B.); daniel.ziskin@noaa.gov (D.Z.); ben.tuttle@noaa.gov (B.T.T.);

<sup>2</sup> Earth Observation Group, Solar and Terrestrial Physics Division, NOAA National Geophysical Data Center, 325 Broadway, Boulder, CO 80305, USA; E-Mail: chris.elvidge@noaa.gov

<sup>3</sup> Department of Geography, University of Denver, Denver, CO 80208, USA; E-Mail: paul.sutton@du.edu

\* Author to whom correspondence should be addressed; Email: tilottama.ghosh@noaa.gov; Tel.: +1-303-497-6385; Fax: +1-303-497-6513

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**Abstract:** The potential use of satellite observed nighttime lights for estimating carbon-dioxide (CO<sub>2</sub>) emissions has been demonstrated in several previous studies. However, the procedures for a moderate resolution (1 km<sup>2</sup> grid cells) global map of fossil fuel CO<sub>2</sub> emissions based on nighttime lights are still in the developmental phase. We report on the development of a method for mapping distributed (excluding electric power utilities) fossil fuel CO<sub>2</sub> emissions at 30 arc-seconds or approximately 1 km<sup>2</sup> resolution using nighttime lights data collected by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS). A regression model, Model 1, was initially developed based on carbon emissions from five sectors of the Vulcan data produced by the Purdue University and a nighttime satellite image of the U.S. The coefficient derived through Model 1 was applied to the global nighttime image but it resulted in underestimation of CO<sub>2</sub> emissions for most of the world's countries, and the states of the U.S. Thus, a second model, Model 2 was developed by allocating the distributed CO<sub>2</sub> emissions (excluding emissions from utilities) using a combination of DMSP-OLS nighttime image and population count data from the U.S. Department of Energy's (DOE) LandScan grid. The CO<sub>2</sub> emissions were distributed in

proportion to the brightness of the DMSP nighttime lights in areas where lighting was detected. In areas with no DMSP detected lighting, the CO<sub>2</sub> emissions were distributed based on population count, with the assumption that people who live in these areas emit half as much CO<sub>2</sub> as people who live in the areas with DMSP detected lighting. The results indicate that the relationship between satellite observed nighttime lights and CO<sub>2</sub> emissions is complex, with differences between sectors and variations in lighting practices between countries. As a result it is not possible to make independent estimates of CO<sub>2</sub> emissions with currently available coarse resolution panchromatic satellite observed nighttime lights.

**Keywords:** CO<sub>2</sub> grid, Nighttime satellite image, LandScan population grid

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## 1. Introduction

Since the beginning of the Industrial Revolution, the world's population has continued to increase, adding each subsequent billion in a span of fewer years than ever before. The world hit the 4 billion mark in 1974, 5 billion just 13 years later, in 1987, and passed the 6 billion milestone 12 years later in 1999 [1]. The world population is likely to reach 7 billion in the latter half of 2011, again in a span of 12 years [2]. Population growth has led to land use change through intensification of agriculture, and improved contemporaneous increases in average standards of living have substantially increased energy use [1]. Changing land use and increased fossil fuel combustion for meeting the growing energy demand are the primary causes for augmented carbon dioxide (CO<sub>2</sub>) concentration in the atmosphere [3]. The anthropogenic contribution in global warming is indisputable and is evident in the rising global and ocean temperatures, extensive melting of snow and ice, and rise in the global average sea level [3]. The need for quantification of anthropogenic fossil fuel CO<sub>2</sub> emissions in the atmosphere at finer spatial and temporal resolutions has been felt by the scientific and policymaking communities since the last decade [4]. From the policy-making perspective it is necessary to construct emission inventories in order to monitor and agree upon emission reduction targets [5]. Spatial distribution of emissions is also an important input to "atmospheric-inversion" methods, which combine CO<sub>2</sub> concentration measurements with transport and process models to estimate land and ocean CO<sub>2</sub> sources and sinks [6-9]. Anthropogenic CO<sub>2</sub> emissions disrupt the equilibrium of the carbon cycle and makes it all the more important to monitor the spatial distribution of CO<sub>2</sub> emissions.

Most of the existing inventory on the spatial distribution of CO<sub>2</sub> emissions is available on a national basis. The U.S. Department of Energy's Carbon Dioxide Information Analysis Center (CDIAC) and the International Energy Agency (IEA) provide a global database of CO<sub>2</sub> emissions for countries. The national geographic distribution of CO<sub>2</sub> emissions has been disaggregated to finer resolutions (1° grid resolution) using population density grids as proxy measures [10-13]. Although the population density grid provides a reasonably good proximate measure of CO<sub>2</sub> emissions at a spatial resolution of 1°, it is not capable of providing satisfactory maps depicting geographic distribution of CO<sub>2</sub> emissions at a resolution finer than this. This is because the population density grids do not depict transportation links and emissions from power stations. Moreover, the census data on which these

population density grids are based are collected at specific spatial units and disaggregating these data to the source regions is problematic [13].

From a satellite remote sensing perspective, it is possible to measure the CO<sub>2</sub> concentration in the atmosphere at coarse spatial resolution using high spectral resolution infrared interferometer data. Examples of such systems include the Japanese Greenhouse Gas Observing Satellite (GOSAT) and NASA's planned Orbiting Carbon Observatory (OCO). With data from these systems the CO<sub>2</sub> signal from major urban centers are diffused and spatially offset from the sources due to the coarse spatial resolution, atmospheric transport, mixing, and retention of CO<sub>2</sub> in the atmosphere. Thus it is difficult to discern increases or decreases in CO<sub>2</sub> emissions from specific cities or towns from systems such as GOSAT by themselves. Application of inversion methods to detect changes in fossil fuel carbon emissions would require surface maps of fossil fuel CO<sub>2</sub> emissions. There are databases that list the locations and estimated emissions for electric power utilities (e.g. Carbon Monitoring for Action "CARMA"). This leaves the spatial distribution of non-point sources (from vehicles, homes and businesses) as a major gap in the mapping of fossil fuel CO<sub>2</sub> emissions that would enable inversion modeling changes in emissions based on GOSAT or OCO style data.

The Defense Meteorological Satellite Program's Operation Linescan System (DMSP-OLS) satellite-observed nightlight data acts as a suitable proximate measure for mapping the distribution of CO<sub>2</sub> emissions at a finer spatial resolution. Elvidge et al. [14] was the first to identify the correlation between lit area of lights and CO<sub>2</sub> emissions. Doll et al. [15] built upon this relationship and created the first global grid of CO<sub>2</sub> emissions at 1° x 1° resolution. A 6-month 1-kilometer stable light composite acquired between October 1994 and March 1995 was used in this study. Country level relationships between lit area and CO<sub>2</sub> emissions were used to create global maps of these parameters. This map was then compared to CDIAC's CO<sub>2</sub> emissions map. Comparison with CDIAC's CO<sub>2</sub> emissions map showed that the emissions map created from the nighttime lights resulted in an underestimation of CO<sub>2</sub> emissions for most countries. However, the nighttime lights image did a superior job in mapping the spatial distribution of the emissions [16]. Under- and over-estimation of CO<sub>2</sub> emissions predicted from the nighttime image is expected because countries usually have more or less emissions than what is predicted from the nighttime lights, as the lights and CO<sub>2</sub> emissions do not always have a direct linear relationship. This was observed in the case of many of the former Soviet Republics by Doll et al. [15]. The authors noted that many of the former Soviet Republics appeared to have more emissions than what was predicted from the nighttime lights [16].

Other recent efforts at developing a fine resolution CO<sub>2</sub> emissions map is the one by Rayner et al. [17]. They developed a "model-data synthesis" approach called the "Fossil Fuel Data Assimilation System" (FFDAS). Using two main datasets – the gridded population data and satellite observed nighttime lights they produced global fossil fuel CO<sub>2</sub> emission fields based on the Kaya identity. Realizing the saturation of the nighttime lights as a major problem in areas of high light intensity, they developed a 'global correction factor' which was used to correct the saturation errors in the nighttime lights image. Then, these 'corrected' spatial data were used to create the fine resolution CO<sub>2</sub> emissions map.

Oda and Maksyutov [13] have developed a global high resolution annual CO<sub>2</sub> emission inventory for the years 1980-2007, named Open-source Data Inventory of Anthropogenic CO<sub>2</sub> emission

(ODIAC) to inform the observational data collected by satellites such as the Japanese Greenhouse gas Observing SATellite (GOSAT), especially for CO<sub>2</sub> emissions regional flux inversions study. They estimated national emissions using global energy consumption statistics. Emissions from power plants were estimated separately using the Carbon Monitoring for Action (CARMA) database. The CARMA CO<sub>2</sub> emissions were directly mapped on power plant locations using the coordinate information, and the residual emissions (total emissions minus power generation emission) were distributed using the nighttime lights image as a proxy. Since the nighttime image is available in 30 arc-second grid (approximately 1 km), the CO<sub>2</sub> emission map was also mapped at a resolution of 1 km<sup>2</sup>. In order to correct for the saturation of lights in the city centers in the stable light images, Oda and Maksyutov [13] obtained radiance values from the 1996-97 radiance-calibrated nighttime image, and using a conversion equation converted the digital number (DN) values between 0-254 for all the stable light images of the years 1980-2007 to radiance values. Oda and Maksyutov [13] determined the spatial distribution of emissions based on a linear correlation between nightlights and CO<sub>2</sub> emissions, and also assumed it to be uniform over different countries, though in actuality the relationship maybe strongly country-dependent. They have discussed these drawbacks in their paper.

Gurney et al. [18] at Purdue University have created a Vulcan U.S. fossil fuel CO<sub>2</sub> emissions inventory at spatial scales of 10 km and 0.1 degree and at an hourly time scale for the year 2002. The Vulcan dataset was developed based on fine scale reported inventory by individual source economic sectors, and is perhaps the best available carbon emissions inventory available for the U.S. at such a fine spatial and temporal resolution. The Vulcan dataset will be discussed in greater details in a later section.

In this paper, we have built upon the previous efforts at creating a global CO<sub>2</sub> emissions grid from the nighttime satellite image and population grid and have tried to address some of the drawbacks of the previous studies. Two separate models were built, Model 1 and Model 2. Model 1 was developed based solely on the statistical correlation between the nighttime lights and selected Vulcan sectors. The coefficient derived from Model 1 was applied to the nighttime lights of the world to estimate global CO<sub>2</sub> emissions. Since the Vulcan emissions data for the U.S. is the best available fine resolution data for any country of the world, it was hypothesized that the coefficients derived through Model 1 when applied to the global nighttime image would provide fairly accurate estimations of CO<sub>2</sub> emissions for other countries as well. However, when the aggregated CO<sub>2</sub> emission estimates for the countries and states of the U.S. (hereafter, will be referred to as administrative units) were compared to the official non-utility CO<sub>2</sub> emission values, they were seen to have been underestimated for most of the administrative units. This led to the development of Model 2, which allocates CO<sub>2</sub> emissions using a combination of DMSP nighttime lights and DOE Landscan population count data. Model 2 was developed by distributing the official non-utility CO<sub>2</sub> emission values into two parts – emission from areas with DMSP detected lighting and emission from the dark areas of the world. It was assumed that the per-capita CO<sub>2</sub> emissions from the dark areas of the world were one-half of the per-capita emissions from the lit areas. The estimates of CO<sub>2</sub> emission derived from aggregation of the grid cell values of Model 2 provided much better estimates of the official CO<sub>2</sub> emission values.

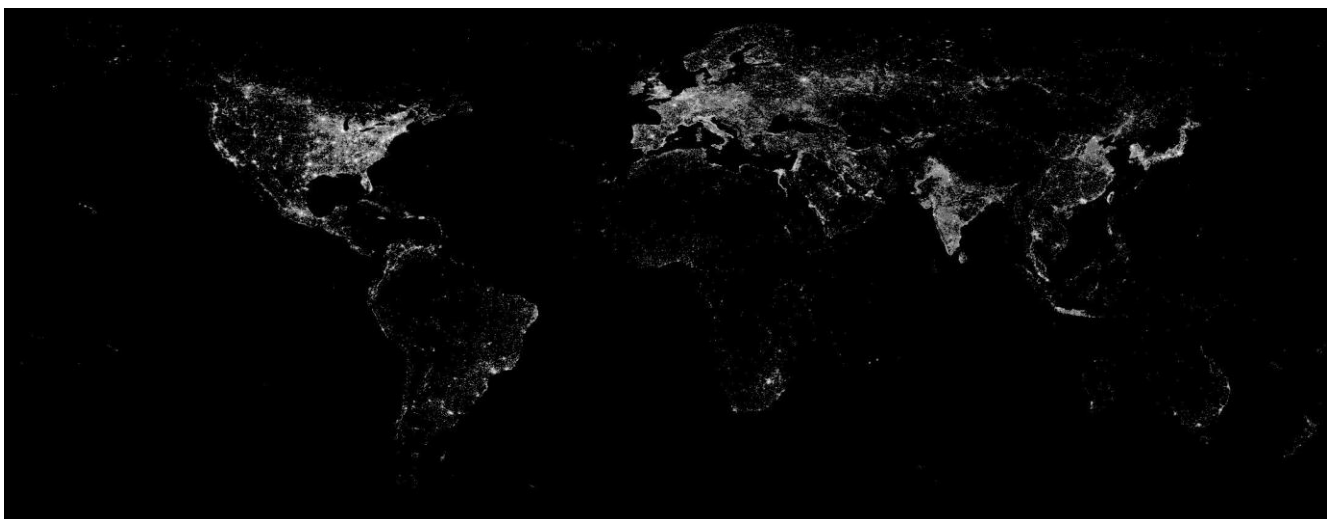
## 2. Data Sources

### 2.1. Nighttime lights imagery

In Model 1, the DMSP-OLS nighttime image of 2000 was used to calculate the light intensity values for all the lit areas of the U.S. corresponding to the surface grid extent of the Vulcan dataset. For Model 2, the DMSP-OLS nighttime image was used to compute the sum of light intensity values of all the administrative units, demarcate the population in the lit and dark areas of the world, and to distribute the estimated CO<sub>2</sub> emissions from the lit areas. A merged stable lights and radiance-calibrated image of 2000 was used in this study (Figure 1). The National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration (NOAA) has been archiving and processing Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) nighttime lights data since 1994. The stable lights data of 2000 were composited from hundreds of cloud-free orbits for the year 2000, with the ephemeral light sources, such as fires and lightning removed [19]. The stable lights data suffer from saturation of light intensity values in the brightly lit city centers. The radiance-calibrated images, on the other hand, are produced by combining images collected at different gain settings (high, medium, and low), and thus can help to deal with the problem of saturation of city centers and also provide a much better view of the internal structure of cities [20]. Merging the stable lights and radiance-calibrated image of 2000 therefore makes it possible to include the best features of both types of nighttime lights dataset. For this study, the bright lights produced by gas flaring activities were masked out. The gas flares have very high light intensity values and it was believed that their inclusion in the global CO<sub>2</sub> emissions estimation model from nighttime lights might give erroneous coefficient values. However, Elvidge et al. [21] have delineated global gas flares from nighttime light images for the years 1994 through 2008, and gas flaring activities also contribute to global carbon emission. Thus, separate coefficients will have to be developed for estimating carbon emissions from gas flaring activities in a future endeavor.

The spatial resolution of the smoothed nighttime lights data is 2.7 km. However, the images are geolocated to 30 arc-second grids, which is approximately 1 km<sup>2</sup> at the equator. The latitudinal extent of the image is from 75°N to 65°S and the longitudinal extent is from 180°W to 180°E.

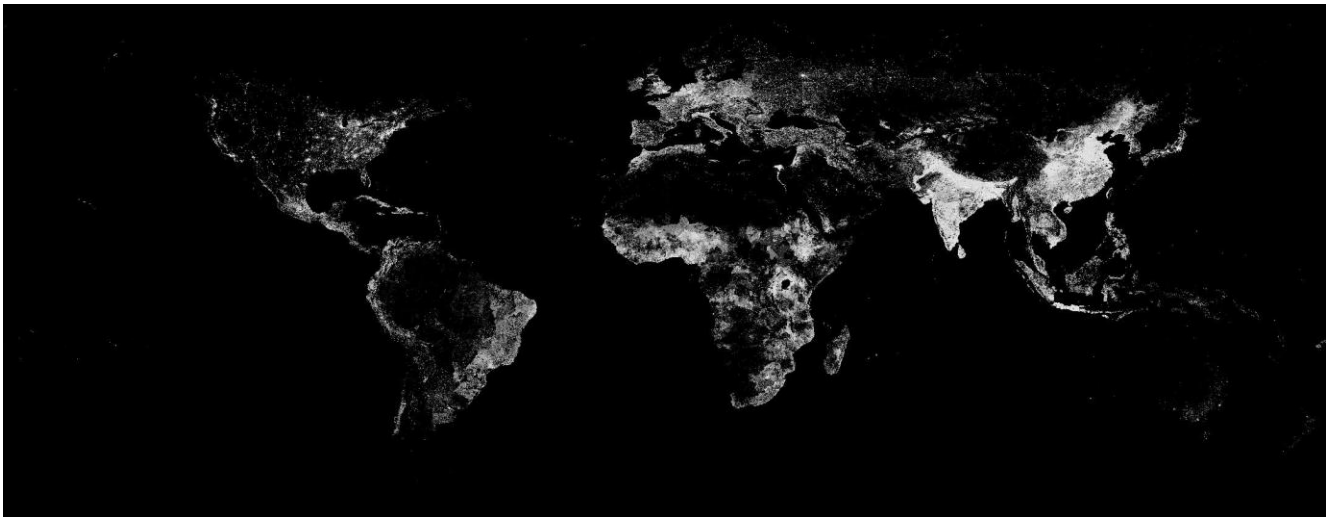
**Figure 1.** Merged stable lights and radiance-calibrated DMSP-OLS nighttime image of 2000.



## 2.2. LandScan population grid

The LandScan population grid of 2000 was used in Model 2 to derive the total population in the lit and dark areas of the administrative units and also to distribute the estimated CO<sub>2</sub> emission values in the dark areas of the world where there are settlements but no lights (Figure 2). The LandScan population dataset is a progressive series of spatially disaggregated global population count datasets that is produced by the Department of Energy at Oak Ridge National Laboratory. The LandScan model uses spatial data and image analysis techniques, in conjunction with a multi-variable dasymetric modeling approach, to allocate sub-national level census counts to each grid cell based on proximity to roads, slope, land cover, and other information within an administrative boundary. The cells represent ambient population counts in integer values. Ambient population takes into account the movement of people for work or travel and not only where people sleep. The dataset has a spatial resolution of 30 arc-seconds [22]. In order to match the geographic extent of the nighttime image, the LandScan population grid was cropped to 75°N (originally extends to 84°N) and the southern latitudinal extent was cropped to 65°S (originally extends to 90°S).

**Figure 2.** LandScan population grid of 2000.

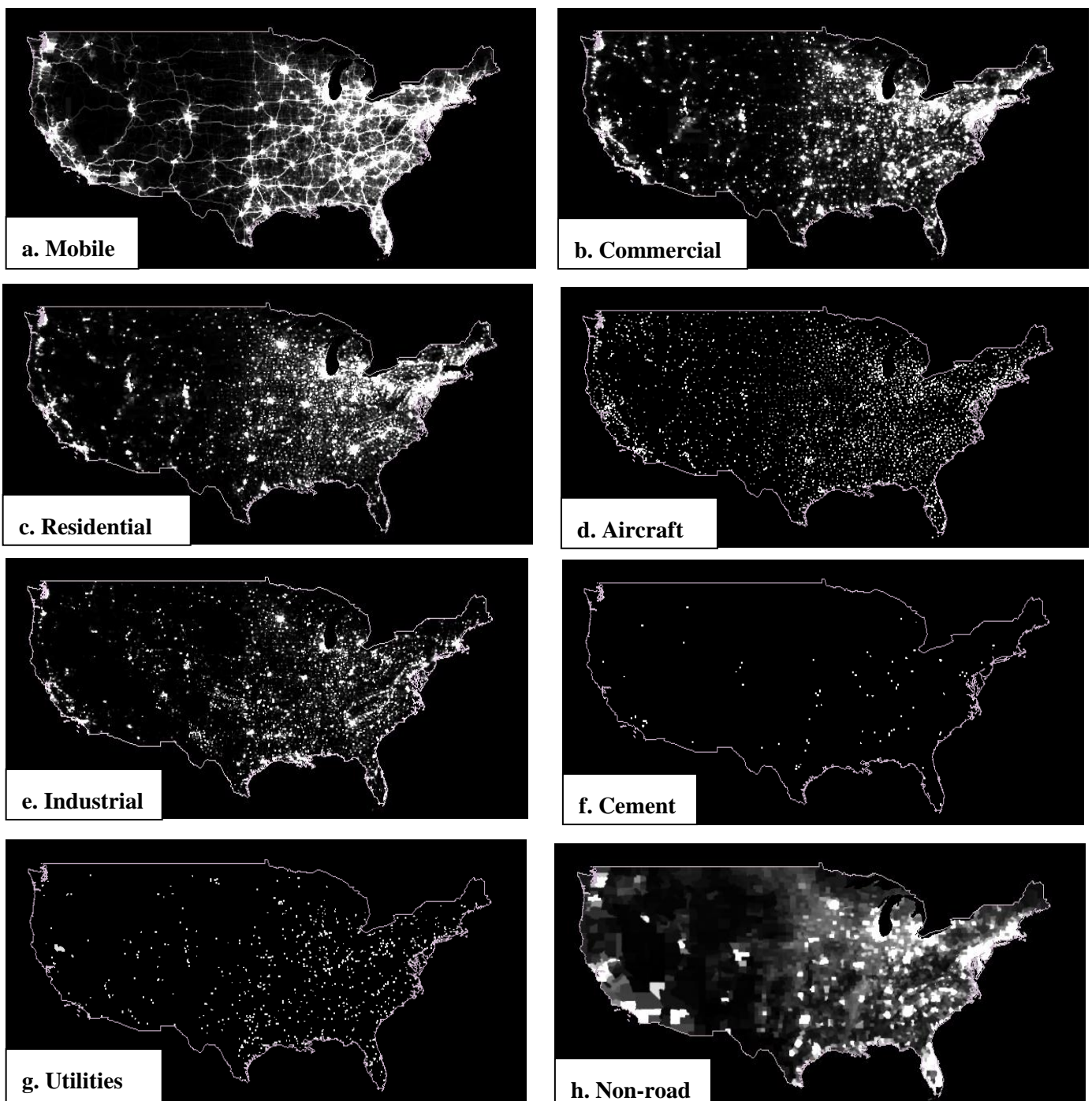


## 2.3. Vulcan data

The Vulcan fossil fuel carbon emission inventory provides a unique spatial depiction of the carbon emissions for key functional sectors. The currently available Vulcan dataset is for the year 2002. It was produced at Purdue University along with other collaborators at Colorado State University and Lawrence Berkeley National Laboratory [18] and was based primarily on emission inventories. The data cover the continental U.S. at a spatial resolution of 0.1° x 0.1°, reporting carbon emissions in units of tonnes of carbon /hour/ gridcell. The longitudinal direction has 650 gridcells, and the latitudinal direction has 280 gridcells and the time dimension has 8,760 timesteps. Inputs include

carbon emission inventory data from the Environmental Protection Agency (EPA), National Emission Inventory (NEI) and other data on mobile sources, power plants, and U.S. census data. All emitting locations are geocoded to latitude, longitude, and postal address. Emissions from fixed locations are divided among residential, commercial, industrial, utilities and cement production sectors. The transport sector contains three separate components: on road or mobile sector emissions (mobile transport using designated roadways), non-road emissions (e.g. boats, trains, all terrain vehicles (ATVs), and emissions associated with air travel (airports and airborne craft)) (Figures 3a-h).

**Figures 3 (a-h).** Vulcan sectoral carbon emissions data, 2002



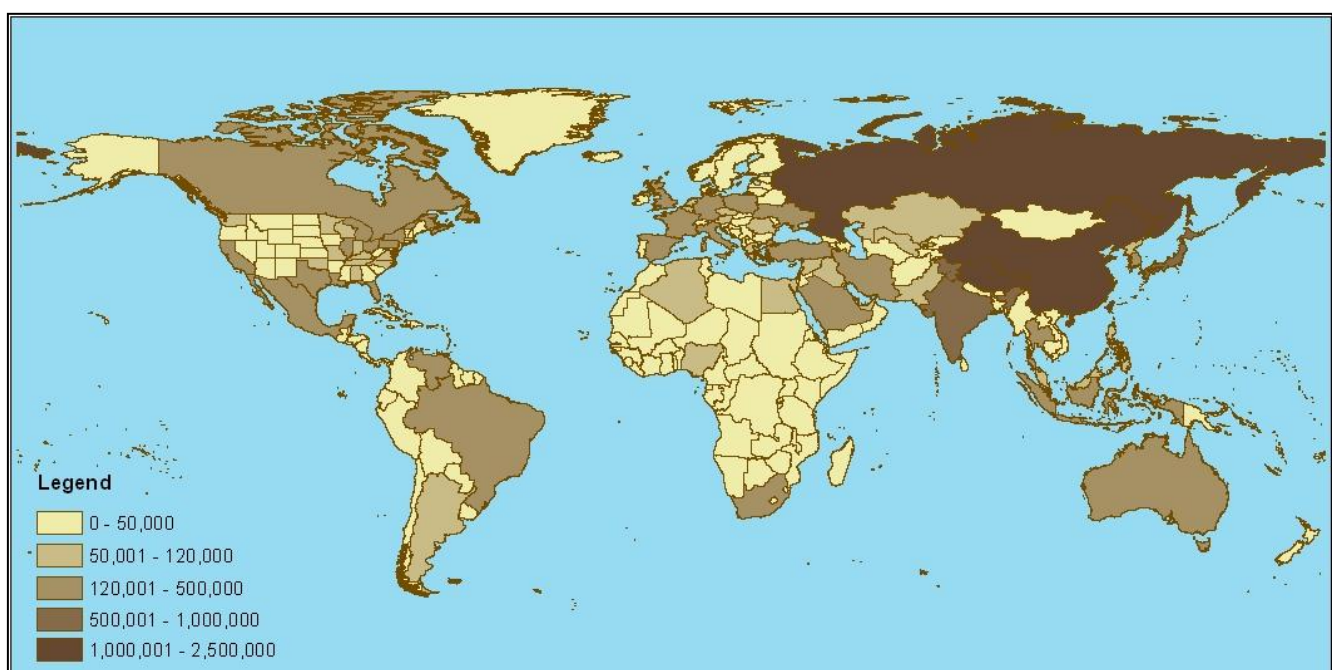
#### 2.4. Official carbon-dioxide (CO<sub>2</sub>) emissions data – countries of the world and states of the U.S.

Official total CO<sub>2</sub> emissions data, for the year 2000, for all the countries of the world were retrieved from United Nations Millennium Indicators website [23] although the primary data source is the Carbon Dioxide Information Analysis Center (CDIAC). CDIAC housed in the Department of Energy's (DOE) Oak Ridge National Laboratory is the primary source of climate change data. CO<sub>2</sub> emissions data in thousand metric tonnes for 206 countries were procured from CDIAC's data repository. Data on CO<sub>2</sub> emissions for only two countries, Liechtenstein and Monaco, were taken from United Nations Framework Convention on Climate Change (UNFCCC) as emission values for these two countries were not available from CDIAC's data repository [23].

The total CO<sub>2</sub> emissions data for the states of the U.S. were available from the U.S. Environmental Protection Agency's (EPA) website. The EPA provides state CO<sub>2</sub> emission inventories from fossil fuel combustion, by end-use sector (commercial, industrial, residential, transportation, and electric power), in million metric tonnes of carbon dioxide from 1990 through 2007 [24]. We used the data of 2000 for our analysis.

The official CO<sub>2</sub> emissions with the electric power plant emissions subtracted from them were used to compare the estimated CO<sub>2</sub> emissions derived through multiplying the nighttime lights grid with the coefficient derived through Model 1, and in Model 2 the non-utility CO<sub>2</sub> emissions were distributed using the nighttime lights grid and the LandScan population grid. The estimated CO<sub>2</sub> emissions data derived through Model 2 were also compared to the non-utility official CO<sub>2</sub> emissions data (Figure 4).

**Figure 4.** Official non-utility CO<sub>2</sub> emissions data in thousand tonnes, 2000





### 2.5. Carbon-dioxide (CO<sub>2</sub>) emissions data from electric power plants - countries of the world and states of the U.S.

The nighttime lights satellite images can account for the distribution of the CO<sub>2</sub> emissions but cannot fully articulate intense emission from major point sources, such as power plants [13]. Therefore, power plant CO<sub>2</sub> emissions data were subtracted from official total CO<sub>2</sub> emissions data for all administrative units. Power plant emissions data for all countries of the world were obtained from the Carbon Monitoring for Action (CARMA) [25], which is a huge database including information on the carbon emissions of over 50,000 power plants and 4,000 power companies worldwide. The data for all the available countries were downloaded. The data were in ‘short’ or ‘U.S. tons’, and were converted to metric tonnes by multiplying the values with the conversion factor of 0.90718474.

CO<sub>2</sub> emissions from electric power plants for the states of the U.S. which were derived from EPA are the point source emissions. These emission values were subtracted from the total CO<sub>2</sub> emissions (sum of commercial, industrial, residential, transportation) for the states of the U.S.

## 3. Methods and Results

The estimated CO<sub>2</sub> emissions grid of the world which was created from the DMSP-OLS nighttime lights image and the LandScan population grid were developed through experimentation with two models. Model 1, based solely on the correlation between the nighttime lights and the Vulcan dataset did not give satisfactory results, and so Model 2 was developed. The two models are discussed separately.

### 3.1 Model 1

Visual comparison of the Vulcan sector images indicates that several of the sectors are correlated to nighttime lights. This includes the residential, commercial, industrial, mobile, and aircraft sectors. To investigate this further we used a stepwise linear regression to determine the best combination of Vulcan sectors for estimating the brightness of the DMSP nighttime lights. The basis of this development is that the DMSP sensor measures lighting across multiple sectors, with lights detected in residential areas, along streets and road, in commercial centers, at airports and in industrial areas. To develop this model we first aggregated the nighttime lights to match the spatial resolution of the Vulcan data. A stepwise regression using the JMP statistical software indicated that the carbon emissions from the five sectors - mobile, commercial, residential, industrial, and aircraft sectors, which together account for about 57% of total carbon emissions in the continental U.S., provide the highest coefficient of determination ( $R^2 = 0.67$ ) when regressed against the nighttime lights of the U.S. The other three sectors – utilities, non-road, and cement sector make only a slight contribution in increasing the  $R^2$  in the stepwise regression (Table 1). Because of the low correlation of the three sectors – utilities, non-road, and cement, with the nighttime lights of the U.S., they were excluded from the analysis. The five sectors which together provide the highest  $R^2$  with the lights of the U.S. were added

up (Figures 5 a-b) and a regression model (Model 1) was developed to derive the coefficient, which was applied on a global basis.

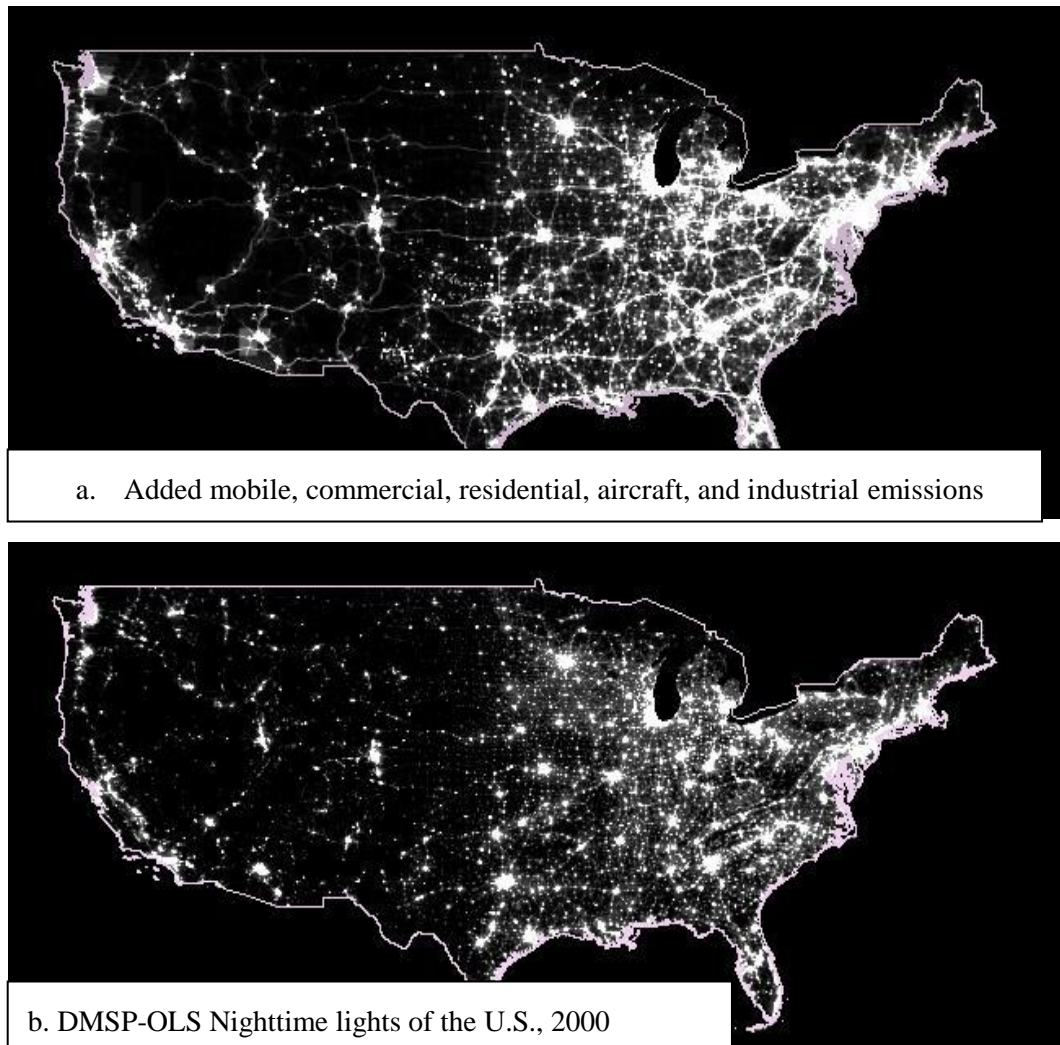
In reviewing the scattergram and regression line for Model 1 we found that the regression line was not passing through the dense core of data points that extend out from the origin. We attribute this to the inclusion of small numbers of outliers which were skewing the regression. Based on the scattergram, we removed outliers including all carbon emissions above 1,000,000 tonnes were excluded, only nighttime lights value below  $30 \mu\text{W}/\text{cm}^2/\text{sr}$  were included, and only non-zero values of carbon emissions and nighttime light values were taken into consideration. The regression Model 1 provided an  $R^2$  of 0.55. For this regression model the intercept was taken as zero implying that carbon emissions are zero when the light intensity value is zero (Figure 6).

The coefficient derived through Model 1 ( $\beta_{\text{US}}$ ) was multiplied with the nighttime lights image of continental U.S., to derive the modeled carbon emissions grid of the U.S. Then in order to analyze the outliers for each of the five sectors, excess  $\text{CO}_2$  emissions were calculated by subtracting the modeled emissions from each of the five individual sectors. Examination of these difference images indicated that the model was systematically underestimating the  $\text{CO}_2$  emissions in several of the sectors. To develop a metric for this underestimation we divided the computed excess of each of the sectors by the total carbon emissions of each of the sectors to calculate a percentage underestimation. The underestimation was highest for the mobile and industrial sectors (Table 1).

**Table 1. Coefficient of determination derived from the stepwise regression, percentage contribution of each sector to the total carbon emissions, and the underestimation percentages of each of the five Model 1 sectors**

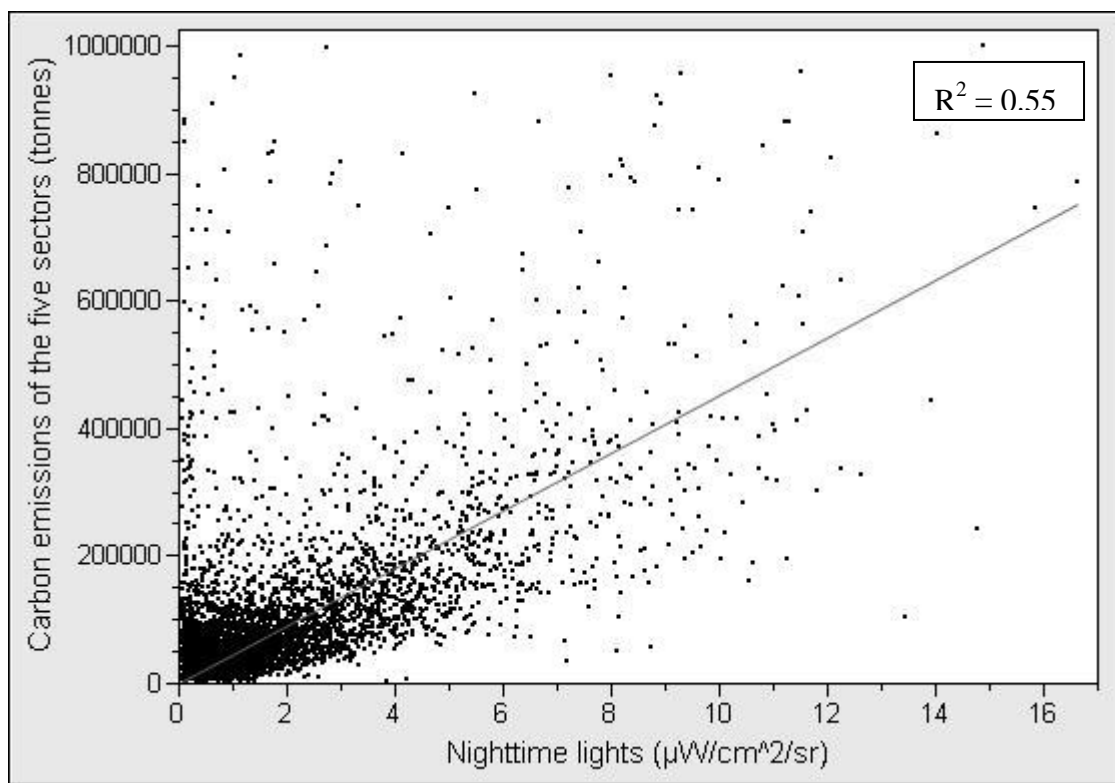
<b>Vulcan sectoral carbon emission</b>	<b><math>R^2</math></b>	<b>% contribution of each sector to the total carbon emissions</b>	<b>% Underestimation</b>
Mobile	0.6433	27.94	20.43
Non-road	0.3724	3.14	
Residential	0.3628	6.36	2.62
Commercial	0.3116	4.12	7.38
Aircraft	0.1398	1.19	6.25
Industrial	0.0555	17.56	37.24
Utilities	0.0130	38.81	
Cement	0.0011	0.87	
Aircraft+Mobile+Residential+Commercial+Industrial	0.6708	57.17	

**Figure 5.** (a) Vulcan mobile, commercial, residential, aircraft, and industrial sectors added together; (b) DMSP-OLS Nighttime lights of the U.S., 2000.



The coefficient derived through Model 1 ( $\beta_{\text{IUS}}$ ) was also multiplied with the light intensity value of each pixel ( $L_p$ ) in the global nighttime lights grid and the value of 3.67 (ratio of the molecular weight of CO<sub>2</sub> (44) to the atomic weight of carbon (12) =  $44/12 = 3.67$ , as the Vulcan data is provided in terms of the mass of carbon atom) to get the estimated CO<sub>2</sub> emission values for each 1 km<sup>2</sup> pixel in the nighttime lights grid (CO<sub>2p</sub>') (Equation 1). The estimated CO<sub>2</sub> emissions were then aggregated to the administrative units, CO<sub>2i</sub>', where 'i' corresponds to each administrative unit.

**Figure 6.** Model 1 - The regression model of the nighttime lights of the U.S. and the Vulcan carbon emissions data of the five sectors (mobile, commercial, residential, aircraft, and industrial sectors) combined.



$$\text{CO}_{2p}' = \beta_{1US} * L_p, \quad (1)$$

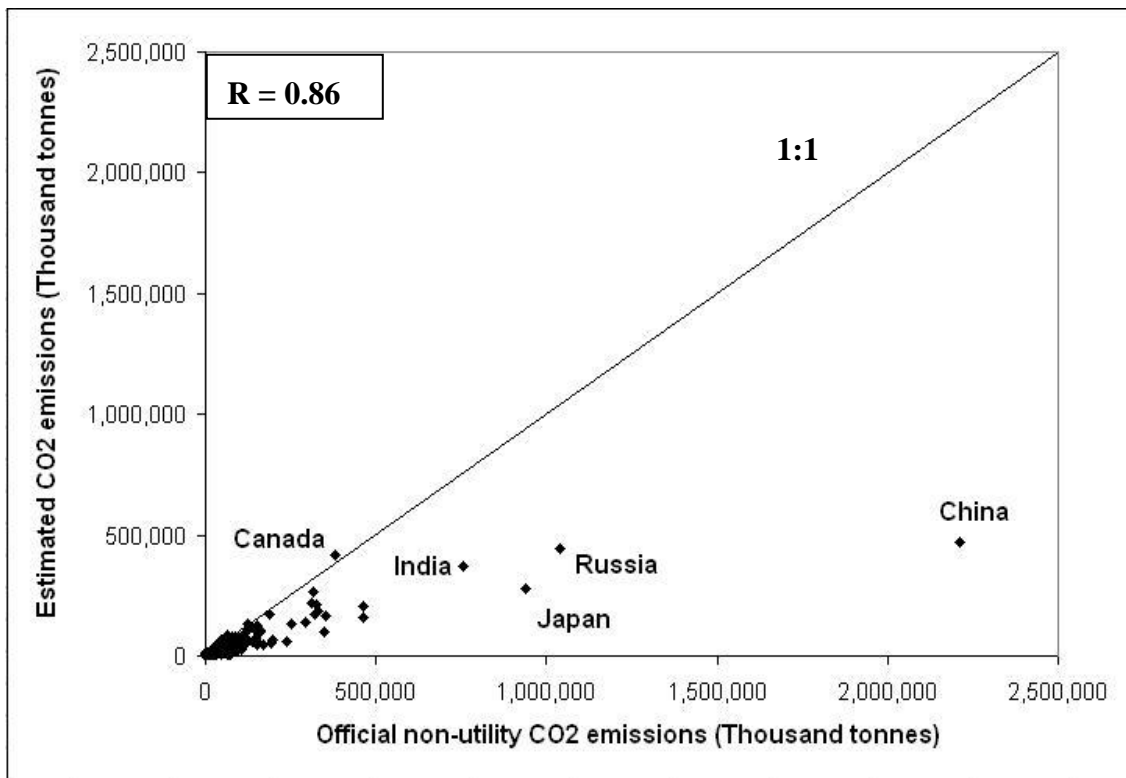
where,  $\text{CO}_{2p}'$  = Estimated  $\text{CO}_2$  emission for each pixel  $p$

$L_p$  = Light intensity value for each pixel  $p$  in the nighttime lights image

$\beta_{1US}$  = slope coefficient derived through Model 1 (Value of  $\beta_{1US} = 45169$ )

The  $\text{CO}_2$  emissions from electric power utilities reported by CARMA and EPA were subtracted from the official  $\text{CO}_2$  emission values obtained from CDIAC and UNFCC. Plotting the aggregated estimated  $\text{CO}_2$  emissions of the administrative units ( $\text{CO}_{2i}'$ ) against the non-utility reported  $\text{CO}_2$  emission values ( $\text{CO}_{2i}$ ), provided a correlation coefficient of 0.86. However, the  $\text{CO}_2$  emissions were underestimated for most of the administrative units, except for a few (Figure 7).

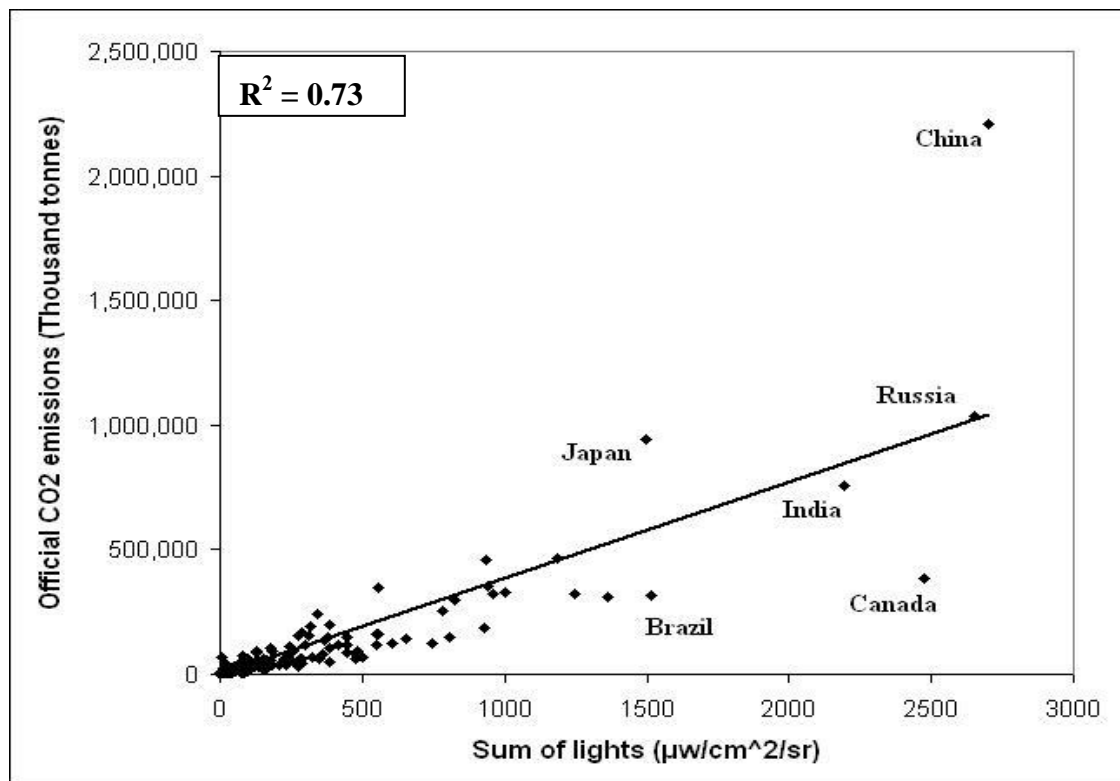
**Figure 7.** Official non-utility CO<sub>2</sub> emission values versus modeled (Model 1) CO<sub>2</sub> emission values for the countries of the world and the states of the U.S.



### 3.2 Model 2

A single coefficient derived from the U.S. Model 1 resulted in underestimation of CO<sub>2</sub> emissions for most of the countries and even most states in the U.S. We attribute this to variations in CO<sub>2</sub> emissions that are independent of the quantity of light emitted to the sky and variations in lighting use patterns between countries. Similar results were alluded to in previous studies [13, 15]. Moreover, regressing the sum of lights against the official CO<sub>2</sub> emission values (Figure 8) show that countries such as Canada are brighter compared to their CO<sub>2</sub> emission values, whereas, countries such as China have higher CO<sub>2</sub> emission than what is estimated from the nighttime light intensity values.

**Figure 8.** Regression relationship between sum of lights and official non-utility CO<sub>2</sub> emissions for all countries and states of the U.S.



Furthermore, although the nighttime lights can identify the locations for the CO<sub>2</sub> emissions from the lit areas of the world, there are more than 1.6 billion people living in areas with no DMSP light detections [26].

As a result of these considerations, we began the development of a Model 2, which performs a spatial allocation of the reported CO<sub>2</sub> emissions (minus the emissions from electric power utilities) based on nighttime lights and population count. An attempt was made to use lights and population count together; however this regression yielded a negative slope for population and negative CO<sub>2</sub> emissions for many grid cells. To resolve this problem we developed a model which estimated CO<sub>2</sub> emissions in lit areas based on the DMSP nighttime lights and the CO<sub>2</sub> emissions in areas without DMSP lights based on population count. We proceeded with the assumption that people living in areas with no detected DMSP lighting have half the CO<sub>2</sub> emissions as people living in the lit areas of an individual country.

At first a mask of the lit areas of the world was created from the nighttime lights grid. This mask was overlaid on the LandScan population grid and the sum of population of the lit areas of each administrative unit was extracted (SOP<sub>Li</sub>). Similarly, a mask of the dark areas of the world was created from the nighttime image and was overlaid on the population grid to extract sum of population of the dark areas of each administrative unit (SOP<sub>Di</sub>). The non-utility official CO<sub>2</sub> emissions of the

administrative units ( $CO_{2i}$ ) were distributed between the dark and lit areas based on the following equation (Equation 2).

$$\begin{aligned} CO_{2i} &= CO_{2Li} + CO_{2Di} & (2) \\ CO_{2i} &= (SOP_{Li} * x_i) + (SOP_{Di} * x_i/2) \\ x_i &= CO_{2i}/(SOP_{Li} + SOP_{Di}/2) \end{aligned}$$

Through Equation 2 the value of the variable 'x<sub>i</sub>' for each administrative unit was derived. The variable x<sub>i</sub> was then multiplied with the sum of population in lit areas for each administrative unit i (SOP<sub>Li</sub>) and half of the variable x<sub>i</sub>, that is, x<sub>i</sub>/2, was multiplied with the sum of population in the dark areas for each administrative unit i (SOP<sub>Di</sub>). This provided the total CO<sub>2</sub> emissions from the lit areas (CO<sub>2Li</sub>) and total CO<sub>2</sub> emissions from the dark areas (CO<sub>2Di</sub>), respectively, for each administrative unit. (Equations 3 and 4).

$$CO_{2Li} = SOP_{Li} * x_i \quad (3)$$

$$CO_{2Di} = SOP_{Di} * (x_i/2) \quad (4)$$

The CO<sub>2</sub> emissions from the lit areas (CO<sub>2Li</sub>) were then divided by the sum of lights (in radiance units) for each administrative unit (SOL<sub>Li</sub>). This yielded the CO<sub>2</sub> emissions per radiance unit for each administrative unit. Conversely, CO<sub>2</sub> emissions from the dark areas (CO<sub>2Di</sub>) were divided by sum of population in the dark areas (SOP<sub>Di</sub>) to get CO<sub>2</sub> emissions per person for the dark areas for each administrative unit. Finally, in order to distribute the CO<sub>2</sub> emissions from the lit areas (and to create the grid of CO<sub>2</sub> emissions from lit areas, CO<sub>2Lp</sub>'), each of the lit pixels of the nighttime lights grid (L<sub>p</sub>) was multiplied by the CO<sub>2</sub> emissions per radiance unit for each administrative unit, and to distribute the CO<sub>2</sub> emissions from the dark areas (and to create the grid of CO<sub>2</sub> emissions from dark areas, CO<sub>2Dp</sub>') the population count in each pixel of the dark areas of the population grid (P<sub>Dp</sub>) were multiplied by the CO<sub>2</sub> emissions per person for the dark areas for each administrative unit (Equations 5 and 6).

$$CO_{2Lp}' = (CO_{2Li}/SOL_{Li}) * L_p \quad (5)$$

$$CO_{2Dp}' = (CO_{2Di}/SOP_{Di}) * P_{Dp} \quad (6)$$

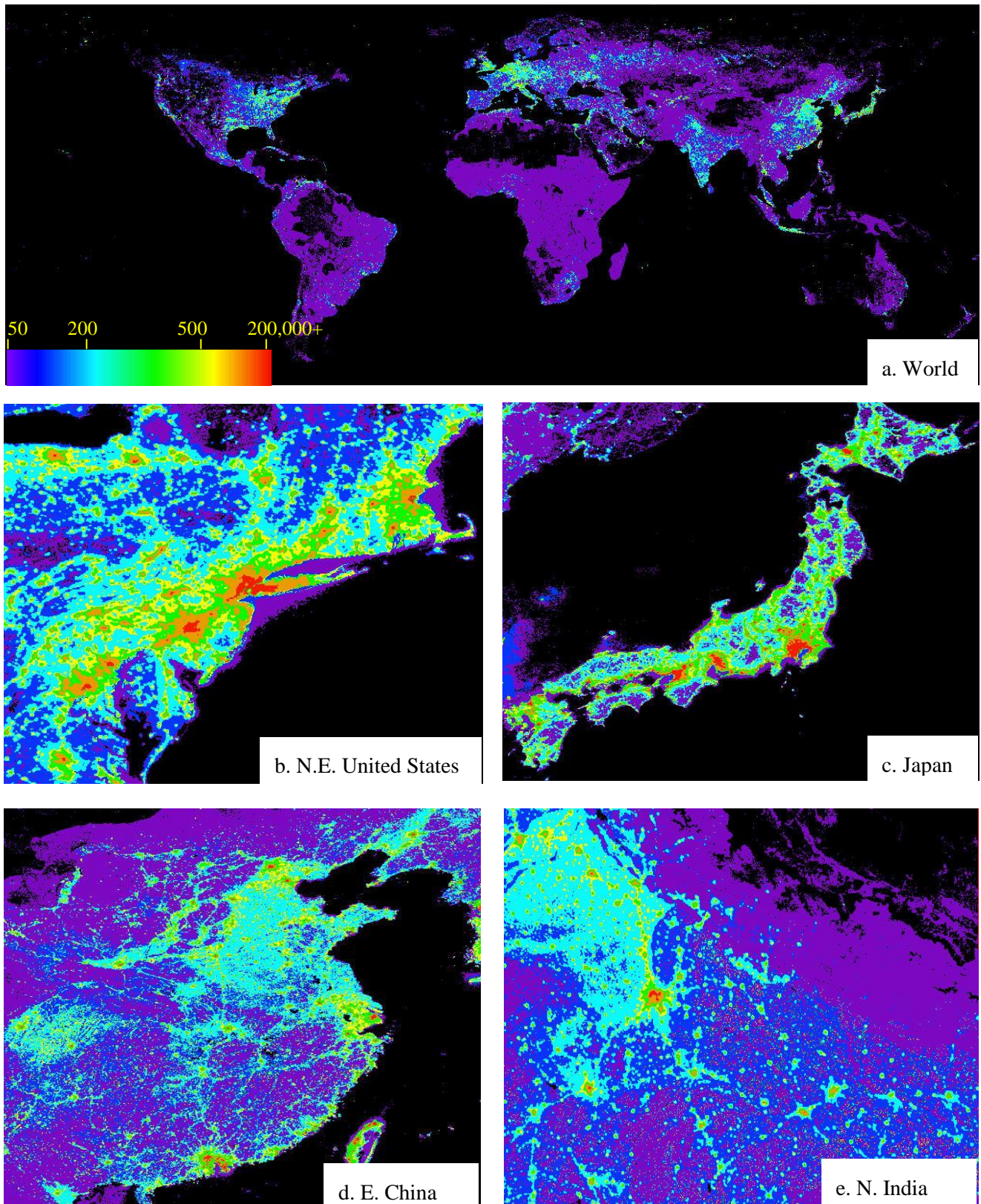
These two separate CO<sub>2</sub> emissions grid from the lit areas and the dark areas of the world (CO<sub>2Lp</sub>' and CO<sub>2Dp</sub>') were added up to create the final estimated CO<sub>2</sub> emissions grid (CO<sub>2p</sub>') (Equation 7, Figure 9a).

$$CO_{2p}' = CO_{2Lp}' + CO_{2Dp}' \quad (7)$$

The disaggregated CO<sub>2</sub> emissions map represents values in tonnes assigned to 1 km<sup>2</sup> pixels, or CO<sub>2</sub> emissions in tonnes/km<sup>2</sup>/year. In the disaggregated map the ocean pixels have a value of 0. Also, pixels in the inaccessible areas of the world, such as the high mountainous areas and deserts, with no population or nighttime lights also have a value of 0. The major cities and urban areas of the world have CO<sub>2</sub> emissions greater than 500 tonnes/ km<sup>2</sup>/year. Areas of the world which have population but

no lights have CO<sub>2</sub> emissions less than 50 tonnes/km<sup>2</sup>/year. Figure 9(a) shows the CO<sub>2</sub> emissions grid of the world, and Figures 9(b), (c), (d), and (e) show CO<sub>2</sub> emissions of North-eastern United States, Japan, Eastern China, and Northern India, respectively.

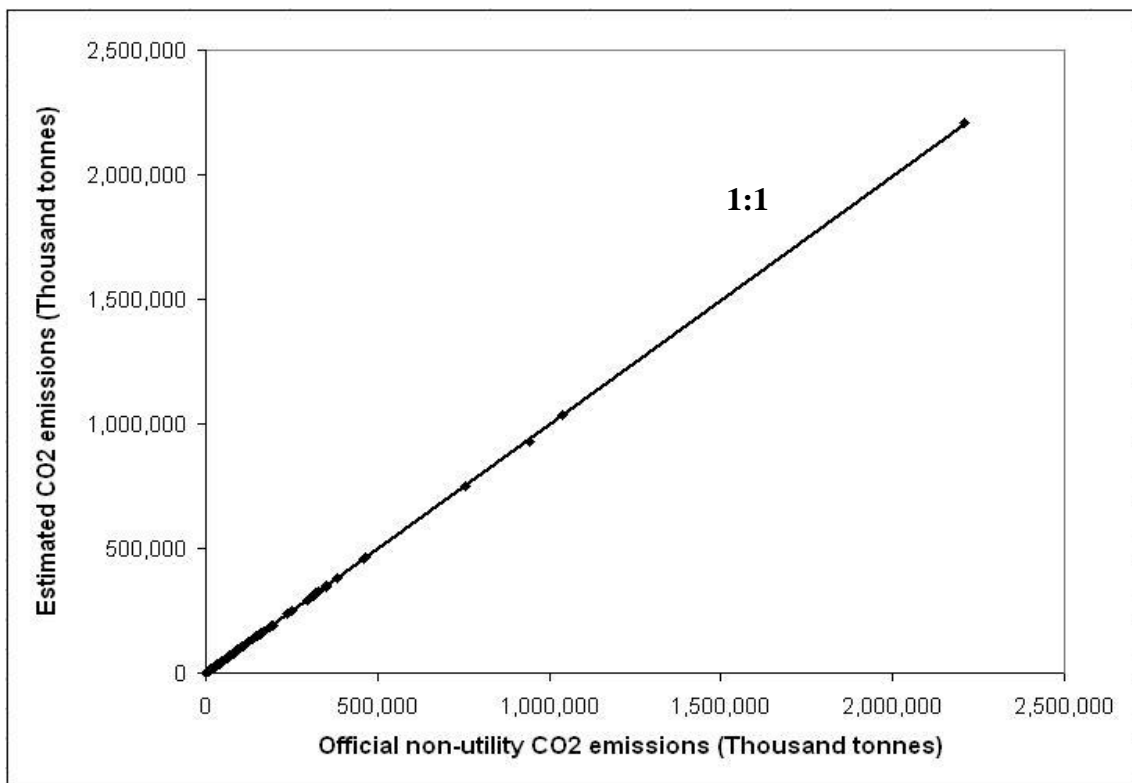
**Figure 9 (a-e).** Estimated CO<sub>2</sub> emissions grid in tonnes/km<sup>2</sup>/year





We have validated the disaggregated map of CO<sub>2</sub> emissions, showing emissions in each pixel (CO<sub>2p</sub>) by aggregating it to the level of the administrative units (CO<sub>2i</sub>) and comparing it to the official non-utility CO<sub>2</sub> emission values (CO<sub>2i</sub>). The graph of the estimated CO<sub>2</sub> emissions plotted against the official CO<sub>2</sub> emission values shows how close the estimated values are to the official values (Figure 10).

**Figure 10.** Official non-utility CO<sub>2</sub> emission values versus modeled (Model 2) CO<sub>2</sub> emission values for the countries of the world and the states of the U.S.



## 5. Discussion and Conclusion

Two separate models were built for creating a disaggregated map of global non-utility CO<sub>2</sub> emissions. The first model was based on a regression relationship between the nighttime lights of the U.S. and the combined carbon emissions of the five sectors (residential, commercial, aircraft, industrial, and mobile sector) of the Vulcan data. The slope coefficient derived through this

relationship (CO<sub>2</sub> emissions per radiance) was multiplied with the global nighttime lights radiance data and this provided the estimated CO<sub>2</sub> emissions grid. However, when this estimated CO<sub>2</sub> emissions grid was aggregated to the level of the administrative units it was seen that CO<sub>2</sub> emissions were underestimated for almost all administrative units. Thus, it was realized that a single coefficient derived through a regression relationship developed for the U.S would not enable accurate estimations of CO<sub>2</sub> emissions for all administrative units. Based on the Vulcan data we found the underestimation to be highest (Table 1) in the industrial and mobile (streets, roads and highways) sectors. We attribute this underestimation in part to the inability of a single coefficient to adequately represent the differences that exist between carbon emissions across multiple sectors. For instance, on a per square kilometer basis the CO<sub>2</sub> emissions from residential areas is undoubtedly lower than the emissions from a heavily trafficked highway of an industrial facility. Another aspect of the underestimation is that Model 1 assumes that the use of lighting in each country is comparable to the U.S. The vast underestimation of CO<sub>2</sub> emissions in China under Model 1 suggests that China uses far less lighting per person than the U.S. Previous studies [19, 26] have indicated that there are variations in lighting types, lighting fixtures, and lighting preferences that affect the brightness of satellite observed nighttime lights. In order to address these drawbacks Model 2 was developed.

To address these shortcomings with the available data sources we developed Model 2, which uses nighttime lights grid and the LandScan population grid to model the spatial distribution of reported CO<sub>2</sub> emissions (minus those associated with electric power utilities). The use of LandScan population grid in estimating CO<sub>2</sub> emissions proved to be advantageous because population count can serve as a proxy for estimating CO<sub>2</sub> emissions in areas in the world which have no satellite detected lighting. Furthermore, since in the LandScan population model, sub-national level census accounts are allocated to each grid cell based on proximity to roads, slope, and land cover; transportation links are depicted in greater details in the LandScan population grid. Thus, inclusion of the LandScan population grid in the model for estimating CO<sub>2</sub> emissions ensured the estimation of emissions from the transport linkages. These road linkages contributed to the outlier percentages from the Vulcan mobile sector emissions when the modeled carbon emissions grid of the U.S was created from its nighttime lights. Model 2 was developed with the assumption that per capita CO<sub>2</sub> emissions from the dark areas of the world were one-half of the per capita emission in the lit areas. On the basis of this assumption, the total non-utility official CO<sub>2</sub> emissions were distributed into the lit and the dark areas of the world using the nighttime lights image and the LandScan population grid. In Model 2 the total CO<sub>2</sub> emissions are constrained to match the reported values minus the component associated with electric power utilities.

It is important to note that DMSP nighttime lights indicate the spatial distribution for the majority of CO<sub>2</sub> emissions but that they cannot articulate the variability that exists between sectors. If the CO<sub>2</sub> estimation coefficient is tuned to work well for residential and commercial sectors, the emissions for industrial and mobile will be underestimated. With higher spatial resolution and multispectral nighttime lights it would be possible to distinguish the lighting from residential, commercial/industrial, and transportation sectors [27, 28]. While such a Nightsat sensor has not been built, the prospects for making improved CO<sub>2</sub> emission grids with such data are clear. It may even be possible to estimate the CO<sub>2</sub> emissions from electric power utilities with Nightsat data. Electric power utility emissions accounts for 40% of all carbon emissions in the United States and about one-quarter of global

emissions [25]. Thus, by excluding the utility emissions, the CO<sub>2</sub> emissions grid created from the nighttime lights image and population grid actually maps the distribution of about 75% of all distributed CO<sub>2</sub> emissions.

The method developed here is not an independent method for estimating CO<sub>2</sub> as official CO<sub>2</sub> emission values were used to set the coefficients for the spatial allocation performed in each administrative unit. However, it is an easy and quick method for estimating and mapping CO<sub>2</sub> emissions at a fine spatial resolution. Moreover, the availability of radiance-calibrated nighttime lights image has made it possible to map variability in distribution of CO<sub>2</sub> emissions into bright urban cores, where previous nighttime lights products contained saturated data values. The NGDC at NOAA is currently producing a radiance-calibrated time series for the years 1996-97, 1999, 2000, 2003, 2004, and 2010. The method developed in this paper could be used to create disaggregate maps of CO<sub>2</sub> emissions for all of these years. However, it should be noted that the lack of on-board calibration for the DMSP nighttime visible band complicates the direct comparison of the data values across the time series.

The greatest advantage of creating a disaggregated map of CO<sub>2</sub> emissions is that it can be aggregated to different environmental, physical, and socio-economic units of analysis and can be easily integrated with other physical and environmental data available in gridded format. Such a fine resolution disaggregated map of CO<sub>2</sub> emissions would also aid in CO<sub>2</sub> emissions regional flux inversions studies. These model outputs can also inform the monitoring of the progress of countries as they move towards achieving emission reduction targets.

Although not an entirely flawless method, the second model developed in this paper provides a simple, useful, and inexpensive technique to create a fine resolution CO<sub>2</sub> grid of the entire planet. Our future endeavors will include testing this methodology for estimating CO<sub>2</sub> emissions for other years and also to include the CO<sub>2</sub> emissions from gas flaring [21].

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