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Spatial distribution of building energy use in the United States through satellite imagery of the earth at night

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ABSTRACT

Despite the importance of geospatial analysis of energy use in buildings, the data available for such exercises is limited. A potential solution is to use geospatial information, such as that obtained from satellites, to disaggregate building energy use data to a more useful scale. Many researchers have used satellite imagery to estimate the extent of human activities, including building energy use and population distribution. Much of the reported work has been carried out in rapidly developing countries such as India and China where urban development is dynamic and not always easy to measure. In countries with less rapid urbanization, such as the United States, there is still value in using satellite imagery to estimate building energy use for the purposes of identifying energy efficiency opportunities and planning electricity transmission. This study evaluates nighttime light imagery obtained from the VIIRS instrument aboard the SUOMI NPP satellite as a predictor of building energy use intensity within states, counties, and cities in the United States. It is found that nighttime lights can explain upwards of 90% of the variability in energy consumption in the United States, depending on conditions and geospatial scale. The results of this research are used to generate electricity and fuel consumption maps of the United States with a resolution of less than 200 square meters. The methodologies undertaken in this study can be replicated globally to create more opportunities for geospatial energy analysis without the hurdles often associated with disaggregated building energy use data collection.

1. Introduction

The latest IPCC report suggests that global annual greenhouse gas (GHG) emissions must decrease 40–70% by 2050 and be entirely neutralized by 2100 to keep global temperatures from increasing more than 2 °C and to avoid the worst consequences of climate change. Globally, buildings are responsible for a third of all energy consumption and greenhouse gas (GHG) emissions [1]. In the United States, buildings are responsible for 40% of energy consumption and GHG emissions [2]. In order to meet the IPCC's goals, energy use and emissions from the building sector must be reduced substantially.

Understanding where and how buildings consume energy is important for identifying opportunities for energy use reductions developing efficient electricity distribution networks, where in the US for example, buildings consume 70% of electricity [3]. Despite the importance of geospatial analysis of energy use in buildings, the data available for such exercises is limited. Building energy use data at the state level is obtainable from the Energy Information Administration in the US [4]; however, building energy use data at finer scales is difficult to find because it is held by many different parties and often access is restricted due to privacy concerns. Methods for obtaining or estimating building energy use at finer scales utilize bottom-up or top-down approaches.

Bottom-up approaches focus on energy consumed in individual buildings and often employ statistical and deterministic energy models that account for physical building characteristics [5]. These approaches require large samples of energy use data and building information in order to calibrate the models. National surveys of building energy use, such as CBECS [6] and RECS [7], are a useful resource for bottom-up approaches to modeling building energy use, but extending the model beyond the sample buildings requires detailed information about the entire building stock, which is not usually available. Utility and energy supply companies have information on customer-specific building energy use derived from either utility bills or meter data; however, this information is not readily available to third parties due to privacy concerns. In fact, several US states have laws that protect customer privacy and limit what information utilities can share with third parties [8,9,10].

Top-down modeling of energy consumption generally consists of establishing relationships between energy consumption at a coarser

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scale with variables that impact energy consumption, such as population, GDP, or satellite imagery. Top-down approaches typically face fewer privacy-related regulatory hurdles because the requisite data are at such a high level that they do not reveal specific customer information. These methods also do not rely on specific building energy consumption for model calibration. Top-down allocation of energy consumption can be achieved with census data, economic data, or property tax assessment records [11,12]. However, these methods are limited in their applicability at small scales and replicability across geographies. Census data may not achieve accurate high-resolution disaggregation as the location of domiciles does not capture commercial and industrial energy use that occurs in city centers or areas with few permanent residents. Economic data is often not available at small scales. Property tax assessment records reside in different databases held by multiple organizations, necessitating coordination between multiple parties especially across larger geographic regions.

Unlike the aforementioned methods, satellite imagery of the earth at night, which shows the extent and intensity of human activity, provides a scalable and replicable dataset for top-down geospatial disaggregation of energy consumption. Additionally, this imagery-based data is useful for mapping and quantifying the light pollution associated with anthropogenic light sources and investigating the impacts of this pollution on human health [13,14,15]. Nighttime light imagery is available from both the DMSP and VIIRS satellites, which travel in sun-synchronous orbits and measure the radiance of the earth during both the daytime and nighttime pass. The measurements taken during the nighttime pass include non-anthropogenic sources of light such as lightning, fires, and reflected moonlight. The Earth Observation Group at the NOAA National Geophysical Data Center processes the raw data, removing many sources of non-anthropogenic lights, including cloud-cover and ephemeral lights, and generates images showing mainly the lights from human sources.

Annual composite stable-lights imagery from the DMSP satellite is available from 1992 to 2013. Beginning in 2012, imagery from the Visible Infrared Imaging Radiometer Suite Day Night Band (VIIRS DNB) scanning radiometer aboard the Suomi National Polar-Orbiting Partnership (NPP) satellite was made available. The VIIRS imagery offers many benefits over the DMSP imagery. The VIIRS DNB has a constant spatial resolution of $742\,m \times 742\,m$ [16,17] compared to DMSP-OLS which has a ground footprint of $5\,km \times 5\,km$ [18]. VIIRS imagery is projected to a 15 arcsecond grid compared to a 30 arcsecond grid for the DMSP-OLS imagery. The upper end of the dynamic range for the DMSP-OLS imagery is $10^{-8}\,W\,cm^{-2}{\cdot}sr^{-1}$ [19], and the sensor often saturated when measuring densely lit urban cores. Conversely, the VIIRS DNB has a larger dynamic range of $3 \times 10^{-9}\,W\,cm^{-2}{\cdot}sr^{-1}$ to $0.02\,W\,cm^{-2}{\cdot}sr^{-1}$, although the instrument has been found to actually outperform this range with a low end of $5 \times 10^{-11}\,W\,cm^{-2}{\cdot}sr^{-1}$ [16], and does not saturate. An onboard solar diffuser is used to calibrate the VIIRS DNB measurements so that radiance can be reported in units of $W{\cdot}cm^{-2}{\cdot}sr^{-1}$ whereas the DMSP-OLS measurement were taken only as a digital number from 0 to 63 that required post-processing to calibrate to an actual radiance value. The VIIRS DNB instrument collects panchromatic radiometric data in the range of 0.5–0.9 µm.

Because the VIIRS-DNB imagery is relatively new, most of the literature using nighttime lights as a measure of socio-economic activity has considered imagery from the DMSP-OLS. A significant portion of the reported research was focused on correcting for the shortcomings of the DMSP-OLS imagery, such as developing methods to overcome the low-resolution [20], post-processing calibration [21,22], and correcting for over-saturated pixels in city centers [23]. While the VIIRS-DNB imagery does not have many of these shortcomings, the images can still benefit from processing to deal with over glow and seasonal variations in radiance [20,24].

Nighttime lights has been used to measure urban extent [20,25], population [22,26], economic output [19,24], and energy use [25,10,27,19]. These studies found a strong relationship between nighttime lights and socio-economic indicators at multiple scales. Although, some studies found that the relationship is not as strong at smaller scales [10,20] and in areas with specific activities, such as mining, which increasenighttime lights without a commensurate increase in socio-economic indicators like population [25].

In the study summarized in this paper, the suitability of nighttime lights as an indicator of electricity and stationary fuel consumption, including natural gas and heating oil, is evaluated at three geospatial scales and compared against other available socio-economic datasets. The potential for disaggregating energy data with nighttime light satellite imagery is also explored. The general methodology is first outlined. Then, applications of the nighttime lights to predict site and source building energy uses for states, counties, and cities within the contiguous US are described and select results are discussed.

2. Methodology description

2.1. Overview

The images used for this study were monthly VIIRS DNB composite from 2012 through 2016 and an annual composite of 2015 ("VIIRS Cloud Mask - Outlier Removed - Nighttime Lights") which was processed by NOAA, as described by Baugh et al. and Elvidge et al., to remove outliers and to set background non-lights to zero [28,29]. Nighttime light measurements were compared to building energy use at the state-level and city-level in the contiguous United States and at the county-level in California. Building energy use was evaluated using four different scopes: electricity, stationary fuel, site energy, and source energy. Site energy is the energy consumed at the point of use, e.g. electricity consumed by a building. Source energy is the total upstream energy consumed to provide a unit of site energy, e.g. the coal consumed in a powerplant to generate the electricity used by the building. Source energy was calculated using EPA Portfolio Manager coefficients of 3.14 for electricity and 1.05 for natural gas [30]. Additionally, other potential predictors of building energy use including GDP, population, latitude, land area, elevation, cooling degree days (CDD), and heating degree days (HDD) were evaluated for their potential to predict electricity and stationary fuel use.

2.2. Total night lights (TNL)

Total night lights (TNL) is a common approach for quantifying the nighttime lights in a region [31,19], this is also sometimes referred to as "sum of lights" [32,33]. In this paper, the convention "total night lights" or TNL is used. VIIRS DNB images were analyzed using the WGS 84 projection system and the TNL for each region was calculated using an area-weighted sum of all radiance measurements within a polygon defining the region (see equation (1)).

$$TNL = \sum_{k=1}^{K} L_k * \frac{A_k}{A_R} \tag{1}$$

In Eq. (1), L_k is the radiance measured by the scanner in nW/cm^2-sr, A_k is the area of pixel, and A_R is the reference area of a 15 arc-second pixel at the equator ($463\,m \times 463\,m$). This definition of TNL is consistent with other research [23], and does not require making assumptions about surface conditions (e.g. Lambertian) that would be necessary to calculate photometric properties such as radiant intensity or exitance. Most of the satellite images were not filtered or modified before use. While some researchers have patched and smoothed the data from VIIRS-DNB, and set a minimum threshold of 9 nW/cm^2-sr, these processes provided only marginal improvements to the regression analysis and were not undertaken for this analysis [24]. Additionally, setting a threshold of 9 nW/cm^2-sr would remove valid anthropogenic light sources from the image, for example the San Mateo Bridge was found to have an average radiance of $\sim$4 nW/cm^2-sr by Ref. [16].