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Detection of Rural Electrification in Africa using DMSP-OLS Night Lights Imagery

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We report on the first systematic ground-based validation of DMSP-OLS night lights imagery to detect rural electrification in the developing world. Drawing upon a unique survey of villages in Senegal and Mali, this study compares nighttime light output from the U.S. Air Force Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) against ground-based survey data on electricity use in 232 electrified villages and additional administrative data on 899 unelectrified villages. The analysis reveals that electrified villages are consistently brighter than unelectrified villages across annual composites, monthly composites, and a time series of nightly imagery. Electrified villages appear brighter because of the presence of streetlights and brighter villages tend to have more streetlights. By contrast, the correlation with household electricity use and access is low. Villages with more streetlights are brighter than those with fewer streetlights. We further demonstrate that a detection algorithm using data on nighttime light output and the geographic location of settlements can accurately classify electrified villages. This research highlights the potential to use night lights imagery for the planning and monitoring of ongoing efforts to connect the 1.4 billion people who lack electricity around the world.

Keywords: nighttime lights; electrification; DMSP; validation

1. Introduction

Satellite imagery of nighttime lights provide a unique perspective on the distribution and location of the world's electrified settlements. Earlier studies have reported on the ability of the U.S. Air Force Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) to detect bright lights from cities, fires, gas flares, and heavily lit fishing boats (Croft 1978, Elvidge et al. 1997b). Several studies have now shown that nighttime light output strongly correlates with electricity generating capacity and economic activity at the regional and national levels (Elvidge et al. 1997b, De Souza Filho 2004, Doll et al. 2006, Sutton et al. 2007, Kiran Chand et al. 2009, Ghosh et al. 2010, Henderson et al. 2012). To date, most studies have been conducted either in

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the industrialized world or in urban environments (Elvidge et al. 1997a, Imhoff et al. 1997, Small et al. 2005, Sutton et al. 2010, Small et al. 2011) where nighttime light output is generally high and consistent over time. However, there is little systematic knowledge about the properties of DMSP-OLS in detecting electrification in rural settings in the developing world. This is a significant gap since these are areas in which ground-based data collection is most sparse and difficult to collect. Moreover, the vast majority of the 1.4 billion people who lack access to electricity are assumed to be concentrated in rural areas (International Energy Agency 2012), though their precise distribution is not well known in many countries (for a related approach, see Elvidge et al. 2010 and Min 2012). This research provides the first systematic evaluation of DMSP-OLS nighttime imagery to detect rural electrification in the developing world where electricity use is characterized by low power loads, small numbers of dispersed users, limited infrastructure, and erratic service provision.

This study presents results from a systematic comparison of ground-based survey data collected in May and June 2011 across 202 electrified villages in Senegal and 30 electrified villages in Mali. Additional administrative data were also collected for 800 unelectrified villages in Senegal and 99 more in Mali. Senegal is located on the western coast of Africa with a population of 13 million citizens and a per capita income estimated to be \$1,070. Its household electrification rate in 2008 was 42%, with 75% in urban areas and 18% in rural areas (Sarr 2011). Neighboring Senegal to the east, Mali is home to about 15 million people spread across a vast territory nearly twice the size of France. Its per capita income is \$610 and the rural electrification rate in 2009 is estimated at 13%, up from 1% in 2006 (Agalassou 2011). The study therefore provides data in low income settings with limited rural access to electricity, typical conditions in much of the developing world. By comparing ground-based data against annual and monthly nighttime satellite imagery composites and a time series of nightly imagery, we evaluate the reliability of satellite imagery in detecting access to electricity across a diverse range of rural settings.

The analysis reveals that electrified villages are consistently brighter than unelectrified villages across various nighttime image products. The survey results show that electrified villages appear brighter because of the presence of streetlights but that the correlation of light output with household electricity use and access is low. Villages with more streetlights are brighter than those with fewer streetlights. We further demonstrate that a detection algorithm using data on nighttime light output and the geographic location of settlements can accurately classify electrified villages. Overall, while acknowledging some limitations, the findings support the viability of monitoring electrification projects from satellite imagery.

Section 2 of this paper describes the DMSP-OLS sensor and data processing that creates imagery of the earth at night. Section 3 summarizes our research methodology, in which we conducted parallel data collection by ground teams and by satellite across hundreds of villages. Section 4 describes our key results before concluding.

2. Description of DMSP-OLS Nighttime Satellite Imagery

Since the 1970s, satellites from the U.S. Air Force Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) have flown in polar orbit capturing high-resolution images of the entire earth every day and night. From an altitude of 830 km above the earth, these images reveal concentrations of outdoor lights, fires, and gas flares at a fine resolution of 0.56 km. On-board averaging of 5 by 5 blocks of fine data produces "smoothed" data with a nominal spatial resolution of 2.7 km. Technically, the low-light sensing capabilities of the OLS permit the detection of radiances down to 10^{-9} W/cm²/sr/µm (Elvidge et al. 2007).

The subset of nighttime imagery captured in the late evening hours provide an unusually rich perspective on human activity, as it reveals the use of electricity for outdoor lighting. To date, the most widely analyzed data products are a series of annual composite images, currently available from 1992 to 2010 (Elvidge et al. 1997a, Imhoff et al. 1997, Elvidge et al. 2001). These are created by overlaying all images captured between 20:00 and 21:30 local time during a calendar year, dropping images where lights are shrouded by cloud cover or overpowered by the aurora or solar glare, and removing ephemeral lights like fires and other visual noise.¹ The time stable annual composites generated by NGDC's image processing algorithms are useful for many purposes. However, the screening process to remove pixels with ephemeral light output may be a constraint on efforts to detect electricity provision in rural areas of the developing world where electricity access is known to be subject to erratic power outages and planned load shedding.

Figure 1 shows an annual composite image of stable night lights in Africa for 2009. The brightness of each pixel is encoded with a digital number on a relative 6-bit scale from 0 to 63. These are relative values and are affected by the gain settings on the image capture device. The gain levels are set automatically on-board the satellite and are not recorded in the data stream. As a result, variations in pixel brightness values over a series of nightly images can result from changes in gain settings as well as changes in light-generating activities on the ground.

Some prior research has documented that the DMSP sensors can capture concentrated light output from very small areas. For example, individual large fishing boats used for squid-fishing are visible off the Japanese coast. These boats, weighing between 60 and 100 tons, can be equipped with as many as 50 incandescent lamps with an average power of 3,500 watts per lamp in order to attract squids in the dark. A single well-lit boat can be seen in DMSP imagery (Croft 1978). Other research has found that lights from U.S. towns with populations as low as 130 can be seen in the DMSP imagery (Elvidge et al. 2001).

In the developing world, however, little research exists to document whether night-time satellite imagery can reliably detect electrification. While cities and large towns are easy to detect because of the overall intensity and concentration of outdoor lighting, it is not known whether satellite imagery can reliably detect electricity availability and use in smaller village settings.

The challenge is complicated by the satellite's technical limitations which do not enable it to detect light output if it is below the threshold of detection. Especially in the developing world, rural electrification is characterized by low power loads distributed across small numbers of users, and often dispersed widely across space. An electrified village might not be detectable simply because it does not generate enough light output at night to be detectable by the sensor. But it is also complicated by the realities of rural electrification in much of the developing world. Electrified villages may or may not have outdoor street lighting, and when they do, streetlights are often dim using low wattage designs.

¹ The geographic extent of usable DMSP data is -65 to +65 latitude. This results in missing data for portions of the world within the Arctic and Antarctic circles. These regions are estimated to be home to only about 0.0005% of the global population.

[FIGURE 1 ABOUT HERE]

Classifying a village as electrified or not is rarely straightforward. In the developing world, villages vary widely in the intensity, concentration, and levels of electricity use. In India, for example, villages were once considered "electrified" so long as there was any use of electricity, including a single electrified pumpset or irrigation system. Thus it was possible for a village to be classified as electrified even without a single lightbulb working in any given home. That definition changed in 2005 and now requires at least 10% of households to be connected and the provision of electricity to public places like schools and the village administrative office. One result of the change in definitions was a substantial drop in the official number of electrified villages in India.²

Assuming a consistent definition, conventional statistics imply that once a village is electrified, it stays electrified. Yet the benefits of electricity depend on whether power is flowing through the lines. Power outages are common across much of the developing world, especially in rural areas. In 2007, power outages occurred every other day in the Democratic Republic of Congo, 50 days a year in Senegal, and 20 days a year in Mali.³ Even within the same country, the frequency and length of outages can vary substantially (see Min 2012 for a study of India). In some cases, load shedding follows predictable schedules in order to manage excess demand. Unplanned outages can also occur during spikes in demand or as a result of short circuits and equipment failures.

As people adapt and incorporate electricity into their daily lives, the effects of power outages can feel harsh. As one respondent in a recently electrified village lamented, "Now when there is a blackout, the village seems even darker than before!" The severity of power outages means that even in electrified areas, those who can afford it continue to rely on private diesel generators, car batteries, and other solutions to meet their energy needs (Eberhard et al. 2011, p. 7).

Accurately tracking access to electricity in rural areas is thus a challenging enterprise. Typically, that task falls to rural electrification agencies and national regulators with limited resources. Given the high cost and logistical difficulty of regularly sending teams to dispersed villages, satellite imagery may provide a powerful and cost-effective tool to monitor power availability.

Figure 2 illustrates the ability of satellite imagery to detect rural electrification from space. The top image shows ASER's electrification plan for Rao, a village of 2000 people located 20 km from Saint Louis in Senegal.⁴ The location of 71 outdoor streetlights are highlighted by large red markers. The lower image shows annual average nighttime light output from Rao, observed by satellite in 2009. Overall, light output corresponds well with the roughly southwest to northeast axis of the village. By contrast, the same region observed by satellite in 1997 shows no nighttime light output from Rao.

[FIGURE 2 ABOUT HERE]

² Government of India Ministry of Power. 2005. RGGVY brochure http://recindia.gov.in/download/rggvy_brochure.pdf>.

³ World Bank Enterprise Survey Database 2008. Cited in Anton Eberhard et al. 2011. *Africa's Power Infrastructure*. World Bank: Washington, DC.

⁴ Rao was electrified by SENELEC around 2000, prior to the creation of ASER. The map was created in 2007 to support a grid extension project in Rao.

While suggestive, Rao is only a single example. How reliably and consistently can nighttime satellite imagery detect other electrified villages? Can a village with fewer streetlights be detected? What if the village is electrified but has no streetlights? Are annual average imagery the best way to detect electrified villages? Or can they be distinguished even in a single nightly image capture? The following sections describe the strategy for evaluating these questions and present our key findings.

3. Methodology

The goal of the project was to evaluate the reliability of DMSP-OLS imagery in detecting the availability and use of electricity in rural areas in the developing world. Our primary study zone was Senegal and Mali. To study the relationship between electricity use at the village-level against light output captured by satellite, we collected survey data collected in May and June 2011 against a range of nighttime satellite imagery products, including images captured on the same day that surveys were administered. Our study provides the first comprehensive comparison of nighttime lights satellite imagery against ground measurements of village electrification in the developing world. The project was implemented in close partnership with the Agence Sénégalaise d'Electrification Rurale (ASER) and the Agence Malienne pour le Développement de l'Energie Domestique et l'Electrification Rurale (AMADER).

3.1 Survey of Electrified Villages in Senegal and Mali

In both Senegal and Mali, we fielded survey teams to collect ground-based data on the use of electricity across a large number of villages. In Senegal, the survey was administered by ASER staff from June 1 to June 10, 2011, covering over 360 villages. About 25 surveyors were deployed in teams across Senegal. In Mali, the survey was administered from May 21 to May 28, 2011 across 30 villages by staff from MFC Nyetaa.

The sampled villages were chosen to be representative of the range of conditions that characterize electrified villages in the respective countries. We did not administer surveys in unelectrified villages. Since the primary goal was to collect data on the range of electricity use in villages and not necessarily to identify national patterns, we did not pursue the goal of drawing a nationally representative sample of villages. Instead, we used a two-stage selection design. The first step divided the country into regions. Then within each region, villages were selected largely via convenience sampling. Given time and process constraints, villages were selected so as to be relatively accessible by automobile or motorcycle.

In each village, a pair of surveyors interviewed a knowledgeable village leader using a standardized survey form. A copy of the survey questionnaire can be found in the Appendix. In Senegal, the survey respondent was usually the village chief. In Mali, the respondent was usually the local AMADER operator. The survey took about 30-45 minutes to administer.

The surveys collected information about the use of electricity in each village. Questions asked when the village was electrified, how many homes have access to electricity, how many streetlights are in the village, how many hours of power are available, the frequency of power outages, and opinions about the quality of electricity service. In addition, background information about population size and local economic conditions were also collected. In each village, the geographic coordinates of the village center and the brightest outdoor evening location were recorded using handheld GPS coordinates.

To enable broader statistical analysis, we also collected some administrative data on the location and characteristics of unelectrified villages in Senegal and Mali. Due to time and budget constraints, these villages were not surveyed on the ground. As a result, we rely on their estimates of village locations, which were collected in various ways, including comparisons against paper maps. As a result, the geographic coordinates of unelectrified villages may not be as precise as those of the surveyed villages. We include these unelectrified villages in some of the analysis below. In the discussion below, we call the group of surveyed electrified villages our "treatment group" and this set of unelectrified villages the "control group."

To enable comparison against nighttime imagery, we needed to know the location of all villages. In Senegal, our surveyors mapped the precise location of 202 electrified villages. Surveyors used handheld GPS units to record the location of the brightest part of the village at night, as identified by the respondent. Coordinates were recorded in WGS 1984 UTM Zone 28N meter coordinates. We used ArcGIS 10 to reproject the locations into the WGS 1984 latitude/longitude geographic coordinate system.

For unelectrified villages, ASER provided administrative records of the locations of about 7000 unelectrified villages. Because this file had been created at some earlier period, we discovered that some of these villages appeared on other more recent lists of electrified villages. To avoid using misclassified villages, we further limited the list of unelectrified villages to those at least 5 km away from an electrified village. From this set, we selected a random sample of 800 villages to create a "control" group of unelectrified villages.

In Mali, surveyors used GPS units to record the latitude and longitude coordinates of all 30 surveyed villages. To create a control group, we drew randomly from a list of unelectrified villages provided by AMADER. Limiting the selection to villages at least 10 km away from the nearest electrified village, the control group comprises 99 unelectrified villages. Figures 3 and 4 show the location of all surveyed villages, as well as unelectrified villages in the control groups, for both Senegal and Mali.

[FIGURE 3 ABOUT HERE]

[FIGURE 4 ABOUT HERE]

3.2 Analysis of Nighttime Satellite Imagery

We acquired a range of nighttime satellite imagery covering all of Senegal and Mali. The images come from the following products developed and archived by NOAA's National Geophysical Data Center:

- 2009 DMSP F16 annual composite of stable lights (single image)
- 2009 DMSP F16 annual composite of average lights (single image)
- April 2011 DMSP F18 monthly composite of average lights (single image)
- May 2011 DMSP F18 monthly composite of average lights (single image)
- April 18 June 15, 2011 DMSP F18 nightly visible lights (142 image orbits)

From each image, we used information on the geographic coordinates of village locations to extract the encoded brightness level from each set of nighttime satellite

imagery. The satellite imagery is encoded at 30 arc-second resolution, resulting in pixels that are about 1 square kilometer in size. We extracted the brightness value of the pixel in which the village coordinates lie. However, since villages are typically larger than a single square kilometer and to ensure robustness of our results, we also estimated local brightness values using bilinear interpolation of all adjacent pixels. In general, results were very similar using both methods.

Figures 5-7 below show sample images from the annual, monthly, and nightly imagery for Senegal and Mali. The images reveal very different views of the region at night, influenced by the timeframe over which data are collected and the outcomes of image processing algorithms.

[FIGURE 5 ABOUT HERE]

The stable lights annual composite in Figure 5 provides the clearest view of how access to electricity varies across the two countries. Lights from large cities and towns are sharply distinguished against swaths of darkness in the countryside. The stable lights image is the product of sophisticated image processing designed to identify the presence of persistent lighting over a calendar year (Baugh et al. 2010).

By contrast, average visible band imagery, which do not screen out ephemeral lighting, reveal thousands of more points of light scattered across the countryside. These patterns are clearly visible in the monthly composites in Figure 6. Many of these spots reflect the burning of agricultural fires, a common feature of crop management in this region. At first glance, the brightness and density of these events make it difficult to discern patterns of rural electrification. Indeed, a hot burning field is much brighter than the few dozen streetlights found in a typical electrified village. However, crop fires have two key features that reduce the challenge of working with average visible band imagery. First, deliberately set crop fires tend to be brief, unlikely to last more than a few days. These events can thus be screened out with additional imagery and other data. Second, because the fires occur on croplands, they are less likely to affect brightness values recorded at the geographic center of villages. This highlights the importance of having accurate geographic coordinates.

[FIGURE 6 ABOUT HERE]

The two sample nightly images shown in Figure 7 look quite different, even though they were taken just two days apart. Cloud cover on April 18 shrouds much of the region around the Senegal-Mali border. By contrast, atmospheric conditions appear much clearer on April 20, revealing many more lit areas. Variations in weather, moon illumination, and sensor noise all limit the inferences that can be drawn from any single nightly image. We acquired two months of nightly images to support our analysis. For each village, we linked the brightness values from each image product to the responses we collected on electricity use. Our analysis enables us to compare the relative utility of the various image products in supporting different applications to monitoring rural electrification.

[FIGURE 7 ABOUT HERE]

4. Results

We constructed a village-level dataset made up of responses from the ground surveys and brightness levels measured by satellite. Table 1 provides key summary statistics of all villages surveyed during the study. For these same villages, Table 2 summarizes light output values recorded from different sets of nighttime satellite imagery. In general, we found relatively high correlations across all image products, as shown in Table 3. While the correlations are all high, there are differences. For example, the April and May monthly composites have a .89 correlation coefficient suggesting that brightness levels measured in April and May 2011 differ in at least some cases.

[TABLE 1 ABOUT HERE]

[TABLE 2 ABOUT HERE]

[TABLE 3 ABOUT HERE]

Based upon analysis of all the data collected during our study, we conclude that electrified villages can be reliably and consistently identified from space using nighttime satellite imagery provided there is sufficient intensity of electricity use and that image data are acquired over a sufficient timeframe.

Our analysis reveals that the timeframe of data collection is also important. In general, when brightness levels are measured over more nights, the reliability of those measurements increases. All else equal, more nights of data, enable greater separation of true "signal" from "noise." By contrast a single nightly image can be challenging to analyze. Under optimal conditions, a single nightly image can clearly reveal higher light output from cities compared to the countryside. But to detect a small village with low levels of electricity use, such an image is insufficient. In many cases, a single image cannot be used to distinguish electrical light output from other artifacts.

However, annual composite imagery, the most commonly available and analyzed data source also has weaknesses. Since annual composites average over such a long time period, they provide little ability to discern periods of blackouts, power outages, or changes in infrastructure and customer access. Moreover, annual composite imagery is produced with a significant time lag and thus data are usually lacking for the most recent year.

4.1 Comparing Brightness Levels of Electrified and Unelectrified Villages

We compared the average light output captured in a range of nighttime satellite imagery for all electrified and unelectrified villages in the study sample. Nighttime satellite imagery is available that captures annual, monthly, and nightly timeframes. In essentially all cases, electrified villages appeared consistently brighter than nonelectrified villages.

Table 4 summarizes the key results. In Senegal, the 202 electrified villages are consistently brighter than the 800 unelectrified villages in our study. For example, in the April 2011 monthly composite image, electrified villages have an average brightness of 5.23 compared with 4.15 for unelectrified villages. The difference in means is statistically significant, as it is in all cases in the table.

Overall, the brightness values observed here approach the lower bounds of sensitivity of the satellite sensors. By contrast, small cities like Segou, Mali (pop. 131,000) and Louga, Senegal (pop. 83,000) have brightness values in the 30s. At the

high end, light output at the centers of Dakar and Bamako are above 60, including some fully saturated pixels recorded at 63 that are above the range of the sensor. Our findings suggest, however, that even at these low levels, the light signatures of electrified villages are consistently brighter than those of unelectrified settlements.

We observed the lowest average brightness levels from the stable lights annual composite image. Visual comparison reveals that the algorithm used to generate the stable lights imagery often masks areas of low-level illumination (see Figure 8 for an example of the process applied to the region around Kaolack, Senegal). While this is useful for many purposes, our findings suggest that stable light composite imagery may be less useful for detection and evaluation of rural electrification where light levels are low and subject to power outages.

[FIGURE 8 ABOUT HERE]

The difference in brightness levels between electrified and unelectrified villages is generally smallest when comparing nightly imagery. We suspect that the smaller differences (and the negative finding for Mali in one case) may be because raw nightly imagery were not processed to exclude observations with cloud coverage. Moonlit clouds and other atmospheric disturbances can result in higher visible band values and are not screened out in the raw nightly imagery. By contrast, the annual and monthly composites include observations captured only on cloud-free nights.

[TABLE 4 ABOUT HERE]

4.2 Tracking Brightness Over Time

We also tracked brightness levels over time using annual imagery. Using the annual imagery from 1992-2009, we analyzed temporal trends in light output to see whether villages get brighter after they are electrified. Survey respondents were asked when their village was first electrified. Knowing the year of electrification, we can compare average brightness levels in the years prior to electrification to those afterwards. Analyzing data for each village over time, we observe that villages are indeed brighter in years after they have been electrified.

In Senegal, for the 141 surveyed villages that were electrified between 1992 and 2009, we observe an average increase of about 0.5 points. To account for other explanations unrelated to electrification that might have led to this observed increase, we also analyzed the trends using fixed effects regressions, as shown in Table 5.

[TABLE 5 ABOUT HERE]

The regressions use village-years as the unit of analysis. The variable *Electrified Village* is coded one for all years following the year of electrification. The coefficient thus provides the increase in brightness a village experienced following electrification. By adding fixed effects for all villages, the models account for all village-specific factors that are invariant over time, like geography or socioeconomic conditions. The results of Model 1 confirm the observational findings of a 0.5 increase in brightness following observation. The addition of satellite fixed effects helps control for potential idiosyncrasies across the five satellites used to capture data across the two-decade time frame of analysis. Model 2 shows this reduces the expected increase to just under 0.4 points.

From other analysis, we observe that increase in light output are most directly linked to the installation of substantial numbers of streetlights (see discussion below). Focusing only on villages which installed 40 or more streetlights upon electrification, we observe an even greater increase in brightness. Model 3 shows an expected increase of over 0.9 points, or slightly lower when we control for satellite effects in Model 4.

Figure 9 plots average brightness levels for Senegal villages with more than 40 streetlights, with year of electrification marked in red. In years where more than one satellite sensor captured data, two points are drawn. Overall an upward trend is visible in the years following electrification. However, in many cases the increase appears slow, perhaps because it can take time before all streetlights are installed after the official commencement of service.

[FIGURE 9 ABOUT HERE]

4.3 Light Output and Streetlights

The findings above found that electrified villages appear brighter than unelectrified villages in satellite imagery. We sought to identify what specific characteristics of electricity use lead to the increase in brightness. Our analysis focused on Senegal, where we were able to collect data across a wider range of villages.

[TABLE 6 ABOUT HERE]

Our surveys collected data on different metrics of electricity use at the community level. We conducted multivariate regressions of the Senegal data to compare the relationship between these metrics and nighttime light output. The number of streetlights in a village was the single most important and robust predictor of brightness. Overall, we observe a one-point increase in average nighttime light output for every additional 20-60 streetlights present in a village, depending on which imagery is used. Analyzing the regressions results using monthly imagery in Table 6, between 21 and 24 streetlights were associated with a one-point increase in output.⁵ To detect an increase in light output in the raw nightly imagery, a higher number of streetlights is required. Interpreting the coefficients in Table 7 indicates that between 48 and 58 streetlights are required for a one-point increase in average light output. Results of regressions using the annual composite imagery are in the Statistical Appendix (the results are similar).

While the adoption of streetlights might vary around the world, they are installed consistently in electrified villages in Senegal. Officials at ASER confirmed that street lights were part of all village electrification plans and that they were highly valued by villagers. Typically, streetlights are equipped with 70W low-pressure sodium lamps. More recently, some villages have been equipped with 20W compact fluorescent (CFL) tubes. In Mali, streetlights are also installed with every new village electrification project, typically using 25W-36W CFL bulbs.

The luminous efficacy, or light output per watt varies, depending on the bulb technology. Low-pressure sodium bulbs are regarded to be the most energy-efficient outdoor lighting technology, typically emitting between 60-150 lumens per watt.

⁵ The coefficient describes the impact of a one unit increase of the explanatory variable on the outcome. Thus in Model 1, the addition of one streetlight is predicted to increase light output by 0.0423 points. A one-point increase in light output thus requires 1/0.0423=24 streetlights.

However, they have poor color rendition, casting a yellowish light. By contrast, CFL bulbs typically output 50-70 lumens per watt.⁶ All else equal, this implies that about five 25W or three 36W CFL bulbs are needed to generate the same light output as one 70W LPS bulb. As a result, consideration of the bulb technology must be made when considering the relationship between the number of streetlights and light output detectable by satellite.

[TABLE 7 ABOUT HERE]

Other measures of electricity use like the number of electrified compounds, the number of years since electrification, low availability of power, and subjective opinions of dissatisfaction with the quality of service are all insignificant. and do not appear to be systematically related to light output.

One conclusion from this analysis is that electrified villages with fewer than 20 streetlights are unlikely to be detectable in most nighttime satellite imagery. This can be seen in the scatterplot in Figure 10 that compares monthly average light output against the number of streetlights for all 180 villages in Senegal for which we were able to collect data. While the overall pattern is noisy, the upward pattern suggests that villages with more streetlights are brighter.

[FIGURE 10 ABOUT HERE]

4.4 Identifying Anomalies Using Time Series Data

By comparing the light output from a village over time against national trends, it may be possible to detect anomalies in electricity service provision. For example, Figure 11 shows light output from the village of Palmeao, Senegal across the full sequence of nightly images. The dashed line shows the average light output for all surveyed electrified villages. While both lines generally move in the same direction, there are several nights where light output from Palmeao appears unusually low. While we have not verified this, we speculate that several of these cases were a result of power outages in Palmeao. Additional figures in the appendix show the nightly light output trends for all surveyed villages.

[FIGURE 11 ABOUT HERE]

A simple algorithm that identifies pixels that are brighter than the average pixel performs well in correctly detecting electrified villages. Several different tests were assessed. Even a simple diagnostic test evaluating whether a pixel was brighter than average performs well in positively detecting electrified villages. The test is strongest when using the full series of nightly data: 71% of electrified villages are correctly detected (with a 42% false positive rate). The test also performs well with annual average lights data: 61% of electrified villages are correctly detected (with a 36% false positive rate). The test performs worst with monthly average lights data, detecting only 50% of electrified villages.

There is a tradeoff between test sensitivity and specificity. A test that is more sensitive in detecting electrified villages is likely to also be less specific and will

⁶ US Department of Energy Office of Energy Efficiency and Renewable Energy. http://www.energysavers.gov/your_home/lighting_daylighting/index.cfm/mytopic=12030

misclassify many unelectrified villages. But a test that is very good at preventing erroneous classifications of unelectrified villages is likely to be less good at detecting electrified villages. Thus selection of the test parameters and data set to be used should be guided by the specific goals of the application.

In practice, we usually have more data on villages. When we add more relevant data, like population size and geographic region of the country, we can strengthen the analytical value of the models by identifying "underperformers" and "overperformers" in the provision of electricity service. In other words, we can identify villages that seem to generate too little light given what we know about its characteristics.

Consider a simple model that predicts whether a village is electrified based upon how much light it emits, its population, and the region of the country in which it is located. From that model, we can calculate the predicted probability of electrification and then compare it to what we already know about the actual electrification status of the village. We can use this comparison to identify villages that are not well classified by the model. If we focus on the most extreme under-performers, we can identify villages that might be having problems in delivering adequate service.

The regression results, shown in Table 8, use only village data on average monthly light output, population, and region of the country. The models are intentionally lean to mimic the reality that data is scarce for most rural villages. To the extent that other data are available (such as proximity to the power grid, local economic conditions, etc.), they could be added to augment the predictive power of the model.

[TABLE 8 ABOUT HERE]

Using Model 3, we calculate predicted probabilities of being electrified for all villages based on actual observed data values, including monthly average light output. Figure 12 plots the predicted probabilities for all villages in the sample, with green dots denoting villages known to be electrified and red dots denoting villages that are unelectrified. The concentration of green dots at high probability values and red dots at low probability values shows that most villages are correctly classified by the model. However, some electrified villages have very low predicted probabilities, inviting additional investigation.

[FIGURE 12 ABOUT HERE]

For example, Taiba Nianguene is an electrified village whose characteristics lead the model to predict only a 7% likelihood of electrification. Closer examination of this case reveals low average light output of 3.3 in April 2011 despite 35 streetlights for its 450 residents. Why does Taiba Nianguene appear so dim, despite a relatively high concentration of streetlights? One possibility is the limited availability of power supply. Our survey data confirm this, noting that power is usually available for only 6-12 hours per day in the village.

Relying on satellite-derived data will not substitute for the information that can be gathered by a human monitor investigating whether the power is on or not, whether there are problems with infrastructure. Yet by using such data and statistical models as illustrated here, it may be possible to identify anomalies quickly and efficiently, thus providing guidance on how to focus limited and more costly human resources.

5. Conclusion

This paper systematically evaluates the accuracy and reliability of using DMSP-OLS nighttime light output to detect rural electrification in the developing world. Compared with traditional ground-based data collection efforts that are expensive to replicate over time and prone to variations in measurement and data quality, satellite imagery have the virtue of being collected every single night over every corner of the globe using an objective and automated process. Moreover, all images are digitized and stored on a nightly basis. This data archive, extending back over twenty years, enables both analysis and visualization of progress in service extension over time and identification of areas that remain underserved.

Based on a comparison of nighttime lights imagery against data collected on the ground in villages across Senegal and Mali, we find consistent evidence that satellite imagery can reliably detect electrified villages. Electrified villages appear brighter because of the presence of streetlights and brighter villages tend to have more streetlights. By contrast, the correlation with household electricity use and access is low. Villages with more streetlights are brighter than those with fewer streetlights. We further demonstrate that a detection algorithm using data on nighttime light output and the geographic location of settlements can accurately classify electrified villages.

Satellite imagery of nighttime lights provides a unique ability to detect access to electrification, especially in rural settings in the developing world where access is most limited and also most difficult to monitor on the ground. In addition to the historical archive of DMSP-OLS imagery that spans the last two decades, newer nighttime data has been collected since 2011 from the Soumi National Polar-orbiting Partnership (SNPP) Visible Infrared Imaging Radiometer Suite (VIIRS). Nighttime light data from VIIRS have multiple advantages over earlier sources, including higher spatial resolution, greatly improved dynamic range, and full radiometric calibration (Baugh et al. 2013). These valuable tools can strengthen the capacity of governments, development agencies, and other entities as they identify inequities in electricity access and opportunities for both grid and off-grid improvements in electricity provision.

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Tables

| Table 1. Brightness of surveyed elements | ctrified villages act | coss nighttime imag | gery. |
|--|-----------------------|---------------------|---------|
| Ser | negal (n=202 villag | ges) | |
| | Average | Minimum | Maximum |
| Population | 2,145 | 40 | 19,000 |
| Concessions | 249 | 4 | 5,000 |
| Concessions electrified | 138 | 3 | 4,000 |
| Concession electrification rate | 56% | 4% | 100% |
| Number of streetlights | 23 | 1 | 120 |
| | | | |
| I | Mali (n=30 villages | 3) | |
| | Average | Minimum | Maximum |
| Population | 9,110 | 459 | 36,700 |
| Concessions | 943 | 60 | 7,149 |
| Concessions electrified | 304 | 35 | 1,426 |
| Concession electrification rate | 50% | 7% | 96% |
| Number of streetlights | 60 | 10 | 179 |

Note: Concessions are household compounds, comprised of a group of clustered dwellings often surrounded by a wall or fence.

| Table 2. | Brightness | of surveye | ed electrified | villages | across nighttime | imagery. |
|----------|------------|------------|----------------|----------|------------------|----------|
| | | | | 8 | | |

| Se | $n = \alpha = 1 (n = 202)$ | villages) | | | |
|---|----------------------------|-----------|------------|---------|---------|
| | nogai (II–202 | villages) | | | |
| | Mean | Median | Standard | Minimum | Maximum |
| | | | Deviation | | |
| Annual Composites+ | | | | | |
| 2009 Annual composite (average visible) | 4.04 | 4 | 1.3 | 3 | 9 |
| 2009 Annual composite (stable lights) | 1.39 | 0 | 2.52 | 0 | 9 |
| Monthly Compositor | | | | | |
| A pril 2011 monthly composites (| 5 4 6 | 4.00 | 5 20 | 2.44 | 51 (|
| April 2011 monthly composite (average | 5.46 | 4.22 | 5.39 | 2.44 | 51.6 |
| May 2011 monthly composite (average | 5 1 2 | 4 1 1 | 4.2 | 1.92 | 40.3 |
| visible) | 5.12 | 4.11 | 4.2 | 1.65 | 49.5 |
| , | | | | | |
| Nightly Imagery+++ | | | | | |
| April 18 – June 15, 2011 (59 nights, | 5.75 | 5 | 3.02 | 0 | 32 |
| excluding outliers) | | | | | |
| | | | | | |
| | | | | | |
| | | | | | |
| | Mali (n=30 vi | illages) | | | |
| | Maar | Madia | Cton Joy 1 | Minimum | Manimu |
| | Mean | Median | Standard | Minimum | Maximum |
| | | | Deviation | | |

| | wiean | Median | Deviation | MIIIIIIIIIII | Maximum |
|---|-------|--------|-----------|--------------|---------|
| Annual Composites+ | | | | | |
| 2009 Annual composite (average visible) | 3.93 | 4 | 0.86 | 3 | 6 |
| 2009 Annual composite (stable lights) | 0.5 | 0 | 1.5 | 0 | 5 |
| Monthly Composites++ | | | | | |
| April 2011 monthly composite (average visible) | 3.86 | 3.85 | 1.32 | 1 | 6.75 |
| May 2011 monthly composite (average visible) | 3.66 | 3.76 | 0.85 | 2.25 | 5.8 |
| Nightly Imagery +++ April 18 – June 15, 2011 (59 nights | 5 | 5 | 19 | 2 | 11 |
| excluding outliers) | 5 | 5 | 1.7 | 2 | 11 |

Notes:

⁺Annual imagery is from the F16 DMSP satellite, using the most recent year available.

⁺⁺Monthly imagery is from the F18 satellite. The composites are average visible band values calculated over all cloud-free coverages.

over all cloud-free coverages. ⁺⁺⁺ Nightly imagery is from the F18 satellite, dropping outliers, defined as those observations with brightness levels more than one standard deviation from the mean for each village.4/18 - 6/

| | 2 | Senegal (n=20 |)2 villages) | | |
|--------------------|--------------------|--------------------|--------------|----------|------------|
| | Nightly Imagery | Monthly Composites | | Annual C | composites |
| | 18 April – | April 2011 | May 2011 | 2009 | 2009 |
| | 15 June | | | Average | Stable |
| | 2011 | | | Visible | Lights |
| Nightly Imagery | 1.0000 | | | | |
| April 2011 | 0.9336 | 1.0000 | | | |
| May 2011 | 0.9295 | 0.8913 | 1.0000 | | |
| 2009 Avg. visible | 0.8881 | 0.7790 | 0.8815 | 1.0000 | |
| 2009 Stable lights | 0.8765 | 0.7755 | 0.8376 | 0.9083 | 1.0000 |

Table 3. Correlations of brightness values across different nighttime imagery products.

Table 4. Comparing brightness of electrified and unelectrified villages across nighttime imagery.

| | Senegal | | | |
|--|------------------------------------|--------------------------------------|---------------------|-----------------|
| | Electrified Villages (n=202) | Unelectrified Villages (n=800) | Difference of means | t- statistic |
| Annual Composites ⁺ | | | | |
| 2009 annual composite (average visible) | 4.04 | 3.56 | 0.48 | 5.71 |
| 2009 annual composite (stable lights) | 1.39 | 0.03 | 1.36 | 14.36 |
| Monthly Composites ⁺⁺ | 5.00 | | 1.00 | 5.01 |
| April 2011 monthly composite (average visible) | 5.23 | 4.15 | 1.08 | 5.81 |
| May 2011 monthly composite (average visible) | 4.9 | 4.23 | 0.67 | 3.51 |
| Nightly Imagery ⁺⁺⁺ | | | | |
| April 18 – June 15, 2011 (59 nights, all evening orbits) | 7.42 | 6.69 | 0.73 | 11.43 |
| April 18 – June 15, 2011 (59 nights, excluding outliers) | 5.75 | 5.16 | 0.59 | 21.58 |

| | Mali | | | |
|--|-----------------------------------|-------------------------------------|---------------------|-----------------|
| | Electrified Villages (n=30) | Unelectrified Villages (n=99) | Difference of means | t- statistic |
| Annual Composites ⁺ | . , | . , , | | |
| 2009 annual composite (average visible) | 3.93 | 3.18 | 0.75 | 4.24 |
| 2009 annual composite (stable lights) | 0.5 | 0 | 0.5 | 3.4 |
| Monthly Composites ⁺⁺ | | | | |
| April 2011 monthly composite (average visible) | 3.86 | 3.53 | 0.33 | 1.21 |
| May 2011 monthly composite (average visible) | 3.66 | 3.33 | 0.33 | 1.52 |
| Nightly Imagery ⁺⁺⁺ | | | | |
| April 18 – June 15, 2011 (59 nights, all evening orbits) | 5.69 | 6.01 | -0.32 | -2.45 |
| April 18 – June 15, 2011 (59 nights, excluding outliers) | 4.99 | 4.97 | 0.02 | 0.34 |

Notes:

⁺Annual imagery is from the F16 DMSP satellite, using the most recent year available.

⁺⁺Monthly imagery is from the F18 satellite. The composites are average visible band values calculated over all cloud-free coverages.

⁺⁺⁺ Nightly imagery is from the F18 satellite. We compute average brightness in two ways. First, averaging the visible band values across all evening orbits (which may include nights with cloud cover or other disturbances). Second. we drop outliers. defined as those observations with brightness levels more

| | (1) | (2) | (3) | (4) |
|-----------------------------|----------|----------|------------------|------------------|
| Outcome is average | All | All | | |
| annual visible | surveyed | surveyed | Villages with | Villages with |
| brightness | villages | villages | 40+ streetlights | 40+ streetlights |
| Village has been | | | | |
| electrified | 0.521** | 0.357** | 0.944** | 0.663** |
| | (0.0440) | (0.0524) | (0.107) | (0.123) |
| Village fixed effects | Yes | Yes | Yes | Yes |
| Satellite fixed effects | No | Yes | No | Yes |
| Constant | 2.383** | 3.174** | 6.206** | 6.149** |
| | (0.166) | (0.115) | (0.277) | (0.281) |
| Observations | 1 371 | 1 371 | 061 | 961 |
| Dusci variolis Descuared | 4,371 | 4,371 | 0 596 | 0.620 |
| N-Squateu | 0.433 | 0.303 | 0.390 | 0.029 |

Table 5. Explaining light output in electrified villages. Fixed effects regressions of village brightness before and after electrification.

Robust standard errors in parentheses

** p<0.01, * p<0.05, + p<0.1

Note: Observations are village-years for surveyed villages in Senegal, 1992-2009.

| | (1) | (2) | (3) | (4) | (5) |
|-----------------------------------|----------|------------|------------|------------|------------|
| | | | | | |
| Streetlights | 0.0423* | 0.0426* | 0.0442* | 0.0436* | 0.0467* |
| | (0.0166) | (0.0190) | (0.0182) | (0.0175) | (0.0193) |
| Compounds electrified | | -2.33e-05 | 2.23e-05 | -2.79e-06 | 0.000288 |
| | | (0.000344) | (0.000353) | (0.000420) | (0.000420) |
| Years electrified | | | -0.0259 | -0.0238 | -0.0289 |
| | | | (0.0276) | (0.0271) | (0.0273) |
| <6 hours power/day | | | | 0.339 | 0.400 |
| | | | | (0.644) | (0.653) |
| Not satisified with power service | | | | 0.574 | 0.788 |
| | | | | (0.516) | (0.527) |
| Population (logged) | | | | | -0.0938 |
| | | | | | (0.334) |
| Latitude | | | | | 0.508 + |
| | | | | | (0.277) |
| Longitude | | | | | -0.371 |
| | | | | | (0.235) |
| Constant | 3.982** | 4.000** | 4.167** | 3.939** | -8.821 |
| | (0.329) | (0.353) | (0.424) | (0.492) | (8.230) |
| Observations | 360 | 340 | 322 | 322 | 312 |
| R-squared | 0.046 | 0.045 | 0.046 | 0.054 | 0.070 |

Table 6. Determinants of light output in electrified villages. Senegal monthly average lights imagery, April and May 2011. 2 composites per village.

Robust standard errors in parentheses, clustered on village.

** p<0.01, * p<0.05, + p<0.1

| | (1) | (2) | (3) | (4) | (5) |
|-----------------------------------|-----------|------------|------------|------------|------------|
| | | | | | |
| Streetlights | 0.0172 + | 0.0182 + | 0.0184 + | 0.0181 + | 0.0207 + |
| | (0.00900) | (0.0102) | (0.0102) | (0.0104) | (0.0115) |
| Compounds electrified | | -0.000220 | -0.000207 | -0.000128 | 0.000126 |
| | | (0.000152) | (0.000151) | (0.000186) | (0.000169) |
| Years electrified | | | -0.00890 | -0.00795 | -0.0121 |
| | | | (0.0135) | (0.0141) | (0.0139) |
| <6 hours power/day | | | | -0.301 | -0.123 |
| | | | | (0.281) | (0.288) |
| Not satisified with power service | | | | 0.141 | 0.315 |
| | | | | (0.235) | (0.232) |
| Population (logged) | | | | | -0.0799 |
| | | | | | (0.179) |
| Latitude | | | | | 0.508** |
| | | | | | (0.138) |
| Longitude | | | | | -0.285** |
| | | | | | (0.106) |
| Thermal infrared band (clouds) | | | | | -0.0154** |
| | | | | | (0.00125) |
| Constant | 5.296** | 5.306** | 5.371** | 5.391** | -2.910 |
| | (0.178) | (0.191) | (0.216) | (0.261) | (3.808) |
| | 10.460 | 0.001 | 0.262 | 0.262 | 0.072 |
| Observations | 10,460 | 9,881 | 9,363 | 9,363 | 9,073 |
| R-squared | 0.010 | 0.010 | 0.010 | 0.011 | 0.052 |

Table 7. Determinants of light output in electrified villages. Senegal nightly imagery, April 18 – June 15, 2011. Up to 59 nights per village; outliers excluded.

Robust standard errors in parentheses, clustered on village.

** p<0.01, * p<0.05, + p<0.1

| Outcome is Village Electrified or Not | (1) | (2) | (3) |
|---|----------|----------|----------|
| | | 0.4454 | |
| Average Light Output (monthly data) | 0.125** | 0.117* | 0.253** |
| | (0.0239) | (0.0514) | (0.0669) |
| Population (logged) | | 2.502** | 2.710** |
| | | (0.198) | (0.304) |
| Region fixed effects | No | No | Yes |
| Constant | -1.939** | -17.68** | -20.44** |
| | (0.134) | (1.271) | (2.034) |
| Observations | 2,004 | 1,968 | 1,504 |
| Standard errors clustered on village in | | | |
| naranthasas | | | |

Table 8. Detecting anomalies with statistical models. Logit regressions to predict electrification status.

Figures



Figure 1. Africa at night. 2009 Stable Lights Annual Composite, DMSP F16 satellite. Source: NOAA's National Geophysical Data Center.



Figure 2. Seeing electrification projects from space: (a) electrification plan for village of Rao, Senegal and (b) satellite imagery of night lights, village of Rao, Senegal. Sources: (a) Agence Sénégalaise d'Electrification Rurale and (b) NOAA's National Geophysical Data Center.



Figure 3. Location of villages in study, Senegal. Surveyed electrified villages in green (n=202). Control group of unelectrified villages in red (n=800). Background image shows 2009 stable lights annual composite from the F16 satellite. Source: Village data from Agence Sénégalaise d'Electrification Rurale. Imagery from NOAA's National Geophysical Data Center.



Figure 4. Location of villages in study, Mali. Surveyed electrified villages in green (n=30). Control group of unelectrified villages in red (n=99). Background image shows 2009 stable lights annual composite from the F16 satellite. Source: Village data from AMADER. Imagery from NOAA's National Geophysical Data Center.



Figure 5. Annual night-time satellite imagery: (a) 2009 stable lights annual composite and (b) 2009 average visible band annual composite. Source: NOAA's National Geophysical Data Center.



Figure 6. Monthly night-time satellite imagery: (a) April 2011 average visible band monthly composite and (b) May 2011 average visible band monthly composite. Source: NOAA's National Geophysical Data Center.



Figure 7. Nightly night-time satellite imagery: (a) April 18, 2011, 21:13 UTM orbit start time and (b) April 20, 2011, 20:49 UTM orbit start time. Source: NOAA's National Geophysical Data Center.



Figure 8. Comparing annual composite imagery, Kaolack, Senegal: (a) stable lights 2009 and (b) average visible 2009. Surveyed electrified villages in green, unelectrified villages in red. Source: NOAA's National Geophysical Data Center.



Figure 9. Brightness of villages before and after electrification, 1992-2009. Surveyed villages in Senegal with more than 40 streetlights in 2011. Red dots indicate year of electrification according to administrative records.



Figure 10. Light output and streetlights in Senegal. Dots are village-month observations for 180 villages from April and May 2011.







Figure 12. Detecting anomalies using a statistical model. Comparing predicted electrification status against actual status. Predicted probabilities based on Table 8, Model 3.