

Automating Electricity Access Prediction with Satellite Imagery



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Introduction & Overview

Energy access is correlated with improvements in the wellbeing, economic prosperity, and gender equality of a region. Particularly, it is linked to an increase in the number of students enrolled in school, time students spend studying, business hours, agricultural productivity and labor supply, and a reduction of the poverty rate (Khandker, et al., 2012).

Despite these benefits, an estimated 1.2 billion people do not have electricity access, and more have too unreliable electricity to achieve the aforementioned welfare gains (World Energy Outlook, 2017).

This study aims to fill current data gaps on global energy access assessment through producing high resolution geographic energy access metrics. We seek to overcome data unavailability and inaccuracies in existing data by creating a method for continuously monitoring electricity access over time, and to produce higher resolution estimates of electricity access data at the village-level.

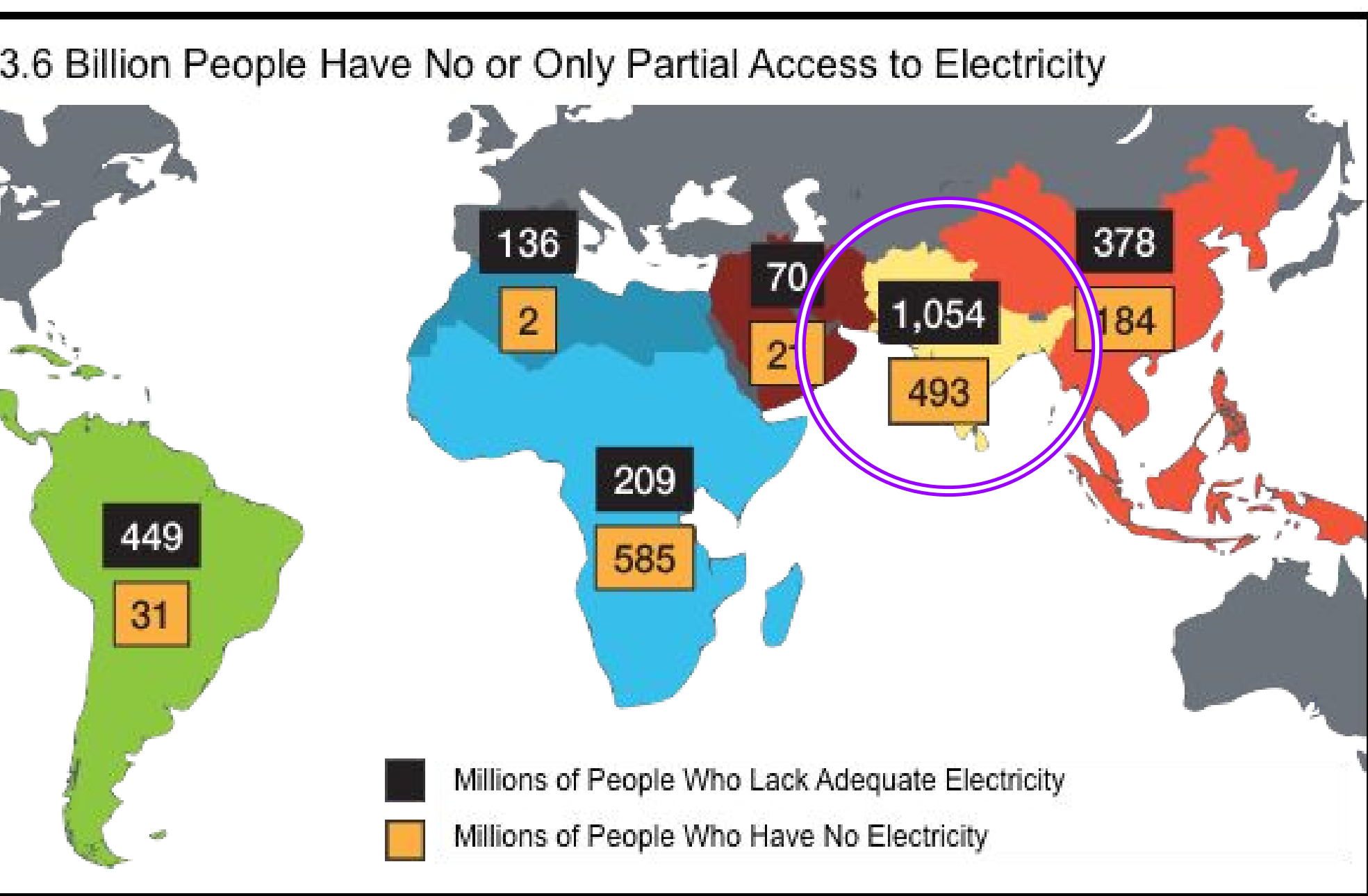


Figure 1: Global population with access to no or inadequate electricity
Source: International Energy Agency World Energy Outlook 2011 and The World Bank World Development Indicators 2011

The goal of this preliminary study is to produce a functional machine learning infrastructure that uses VIIRS Lights at Night data to predict electrification rates at the village level in Bihar, India, building on previous work exploring the relationship between lights at night and electrification (Shi et al., 2014; Min et al., 2013; Min & Gaba, 2014).

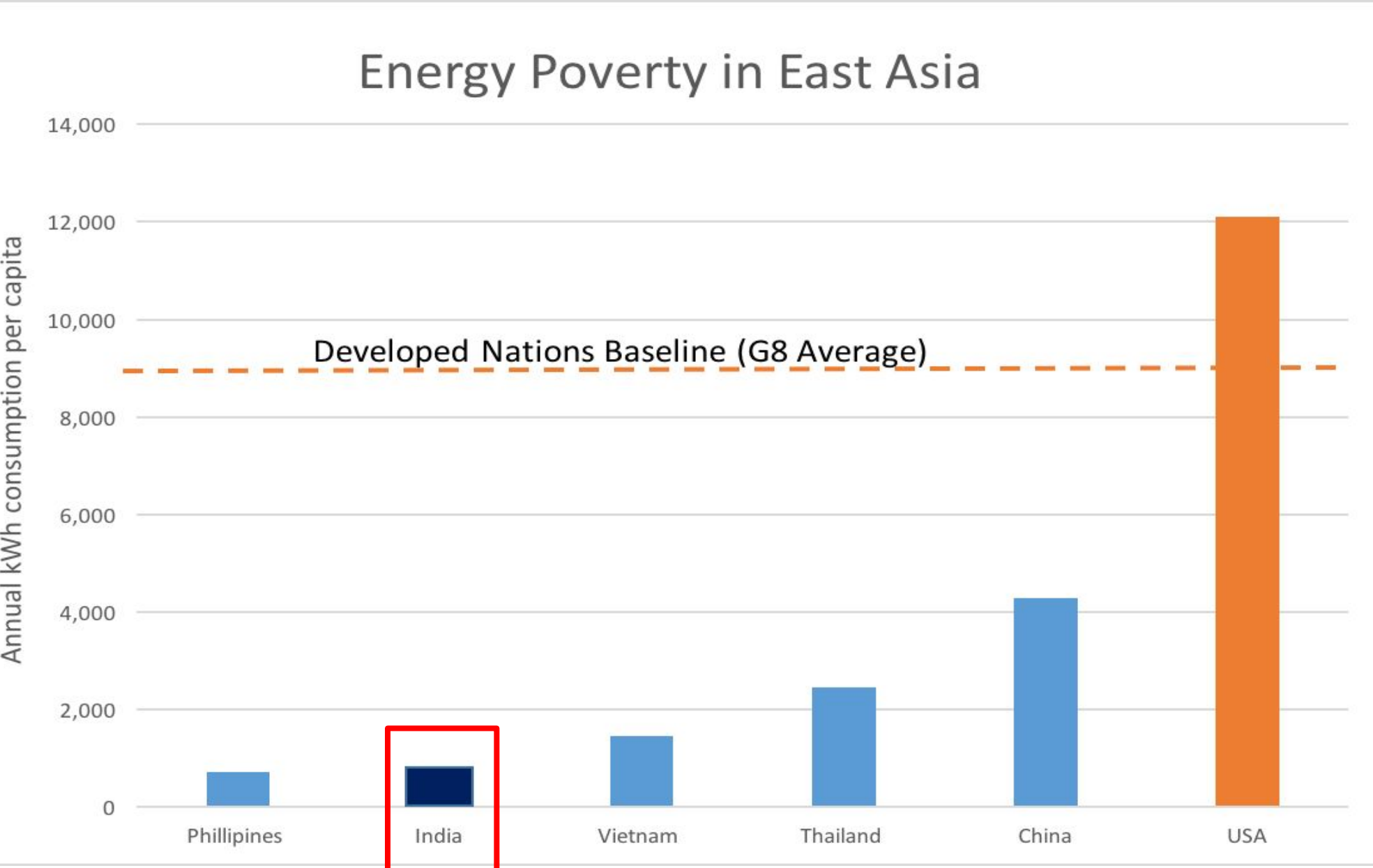


Figure 2: Energy poverty in East Asia India relative to developed nations and the G8 average.
Source: CIA World Factbook, 2016

Process Summary

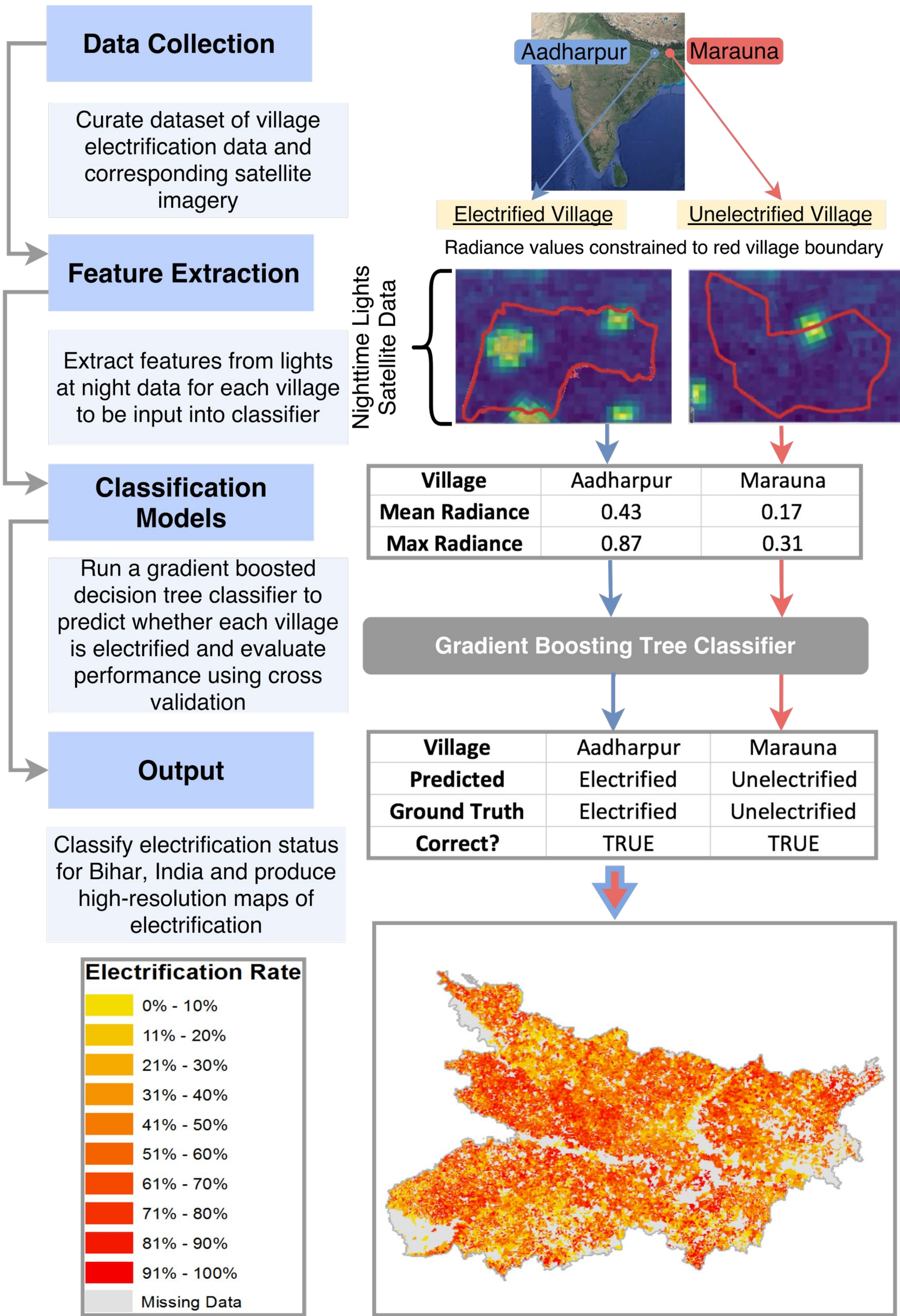


Figure 3: Process of data collection, feature extraction, village electrification classification and output validation.

Our team classified VIIRS data from 16, 389 villages in Bihar as either electrified or unelectrified based on ground truth data from the Indian government's Garv dataset. Here we assume that an electrified village is one where at least 10% of households are electrified (Min and Gaba, 2014). We extracted the lights at night data within each village boundary and for each village calculated the mean, max, and sum radiance values as well as the 10th, 25th, 50th, 75th, and 90th radiance percentiles. We used these values as features to train our classifier to predict the electrification status of each village. We used a gradient boosted decision tree classifier and cross validated with testing data.

Results

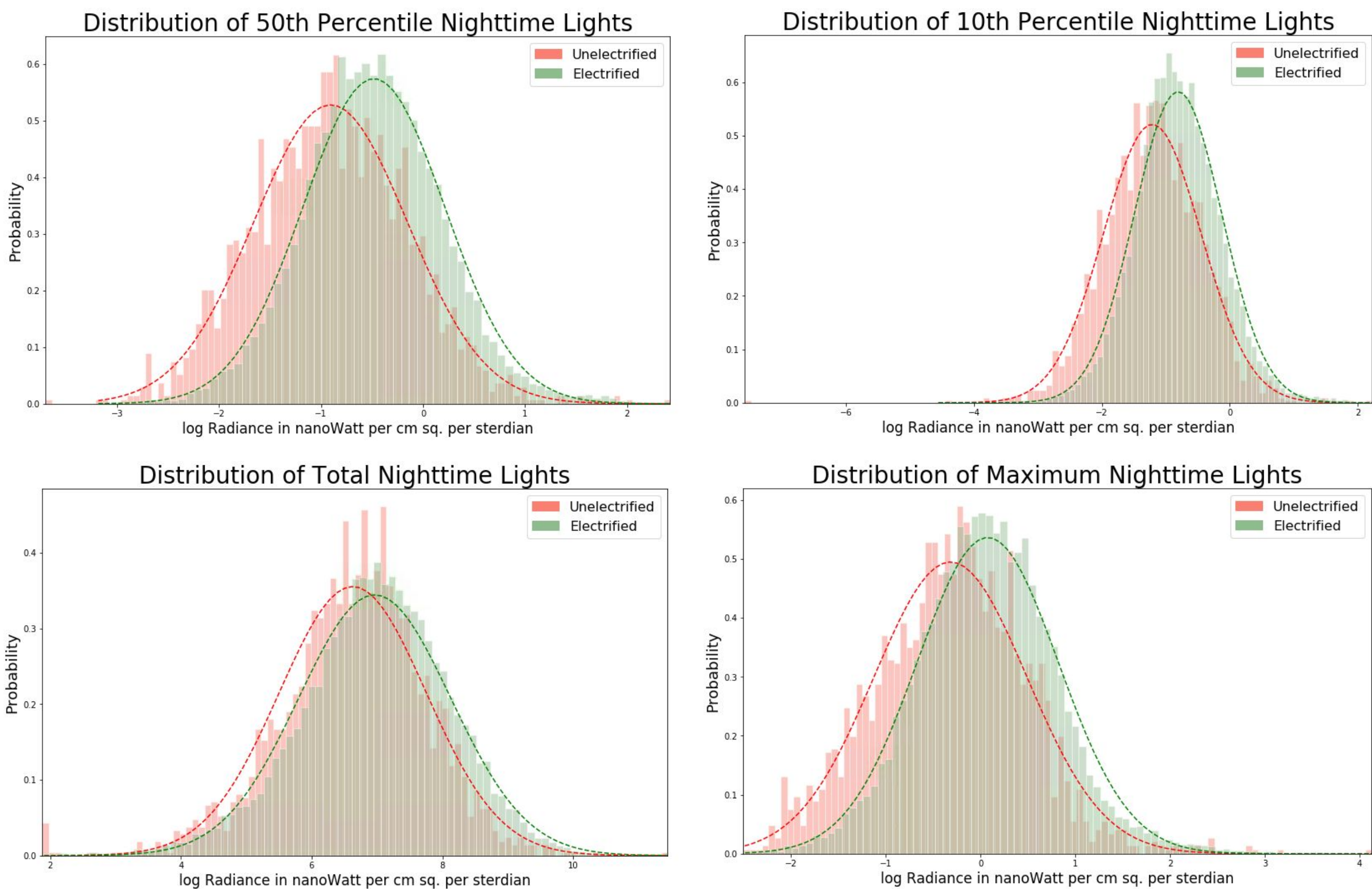


Figure 4: Distribution of top four features of importance separated by Electrified and Unelectrified classes.

We demonstrate the performance of our classifier using Receiver Operating Characteristic (ROC) curves in Figure 5. Since smaller villages may not always have sufficient light visible at night to register on the VIIRS instrument (Min and Gaba 2014), we also explore the discriminative abilities of our classifier limited to villages with at least 100 or 400 households, also demonstrating better performance in classifying the electrification rate of larger villages than smaller villages.

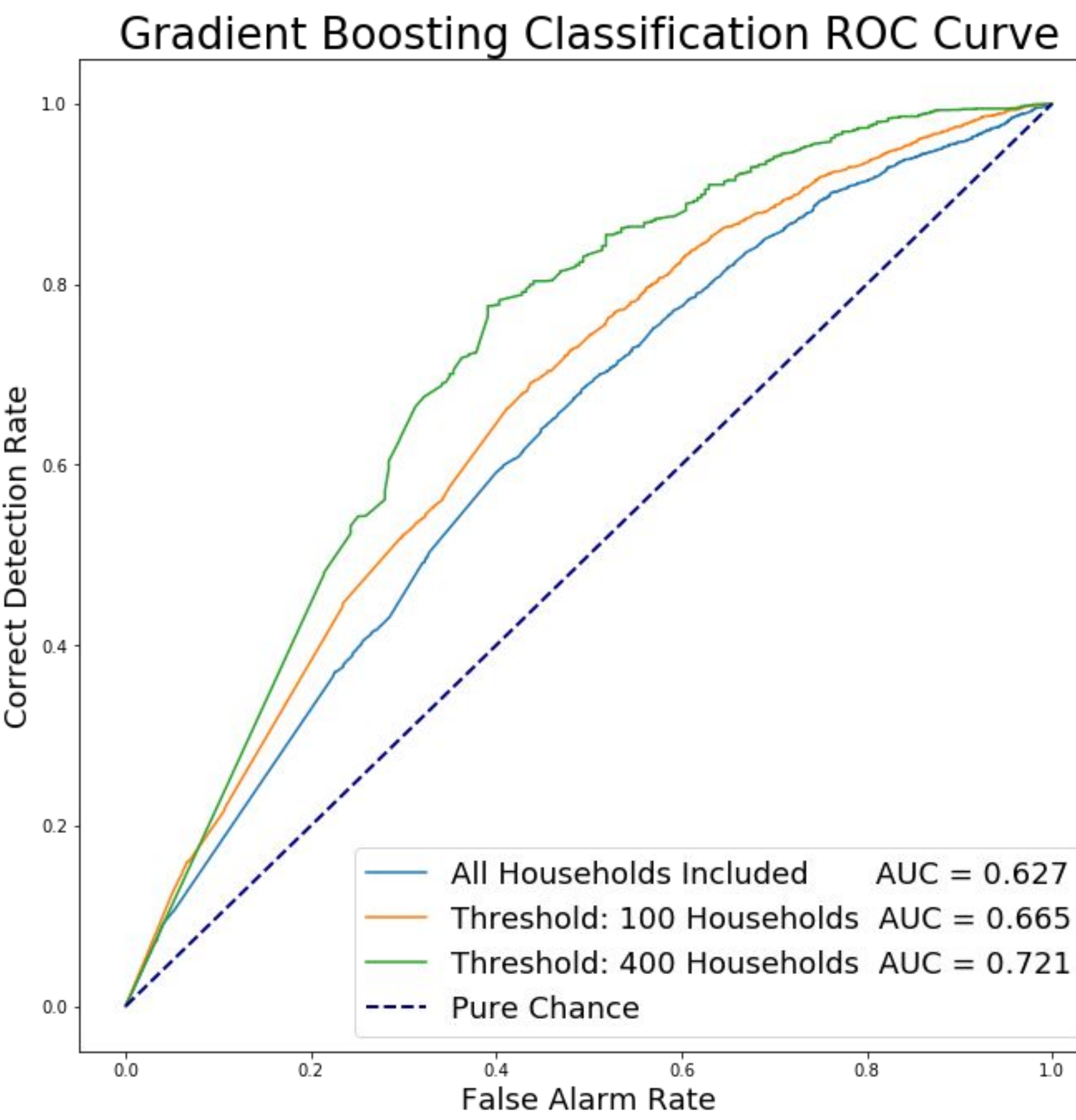


Figure 5: ROC Curve demonstrating results of energy access projections separated by three models, each by selecting a minimum number of households threshold.

Conclusion & Future Steps

This study confirms that lights at night data can be used to estimate village electrification status and quantified the cross-validated performance of our classifier. We also found that villages with larger populations were more accurately classified than villages with smaller populations, since the difference between larger electrified villages and unelectrified villages is much more visible in the lights at night imagery data. In the future, additional features extracted from satellite imagery will be added to explore potential classification performance improvements using information such as vegetation and rainfall data for identifying electrified irrigation, built environment detection (buildings and roads), and other energy access indicators.

Sources

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