Automating Electricity Access Prediction Using Satellite Imagery

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Introduction & Overview

An estimated 1.2 billion people around the world do not have electricity access, and far more have unreliable electricity access (World Energy Outlook, 2017). Energy access is correlated with improvements in health, economic prosperity, and gender equality outcomes. Particularly, access to electricity is linked to an increase in student enrollment in schools, time students spend studying, available business hours, agricultural productivity and labor supply, and a reduction of the poverty rate (Khandker et al., 2012). We present a technique to determine regional electricity access from satellite imagery to aid electrification efforts.

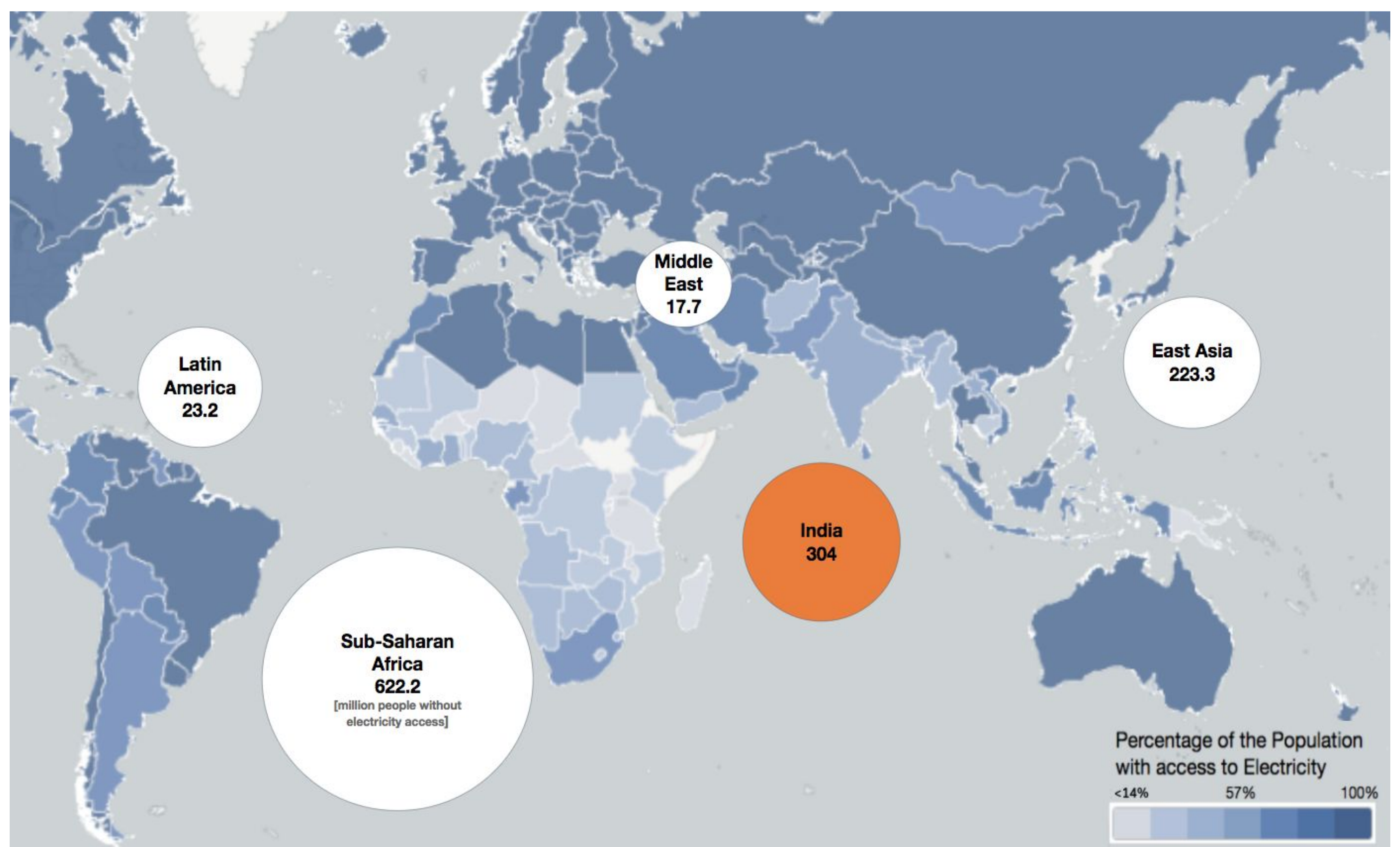

Figure 1: Global electricity access broken down into percentage of population and number of people in the millions without access to electricity (Lindeman 2015; Brixey-Williams, 2015).

This project aims to fill a data gap by producing high resolution estimates of electrification rates through a case study in the Indian states Bihar and Uttar Pradesh. India has over 300 million people without access to electricity (Figure 1) and there were ground truth data available for Bihar to enable our analysis. Currently, however, electricity access estimates in India are generally available at a district level, which is still highly aggregated (Figure 2). The algorithm we developed through this work is able to classify electrification status at the village level, which is an order of magnitude improvement in spatial resolution.

Using the electrification data from Bihar, we developed a process for automating the classification of satellite imagery data from a region as electrified or unelectrified (Figure 3). We curated a dataset of satellite imagery from Bihar, India, and extracted features that from those data related to electricity access.

Araria District, Bihar

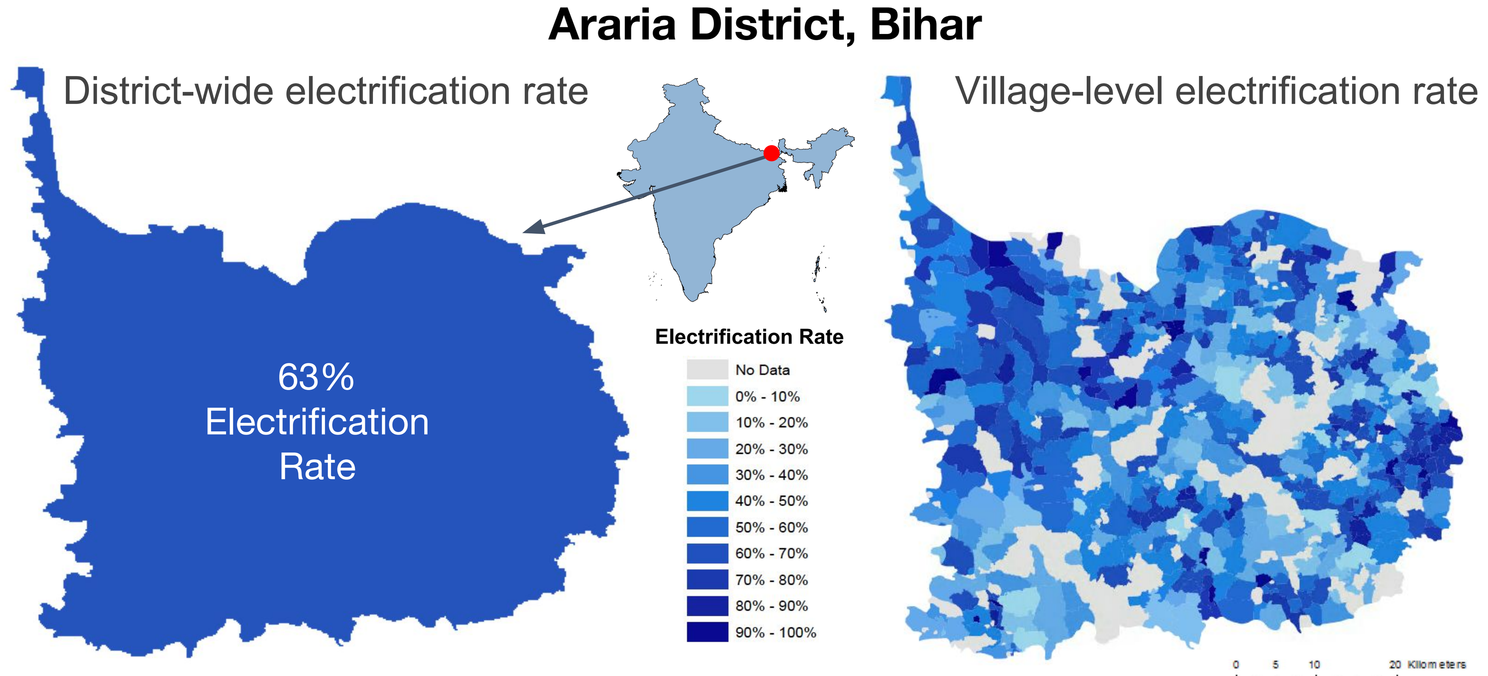

Figure 2. District level electrification data compared to higher granularity village level electrification data (Government of India Ministry of Power, 2018)

Process Summary

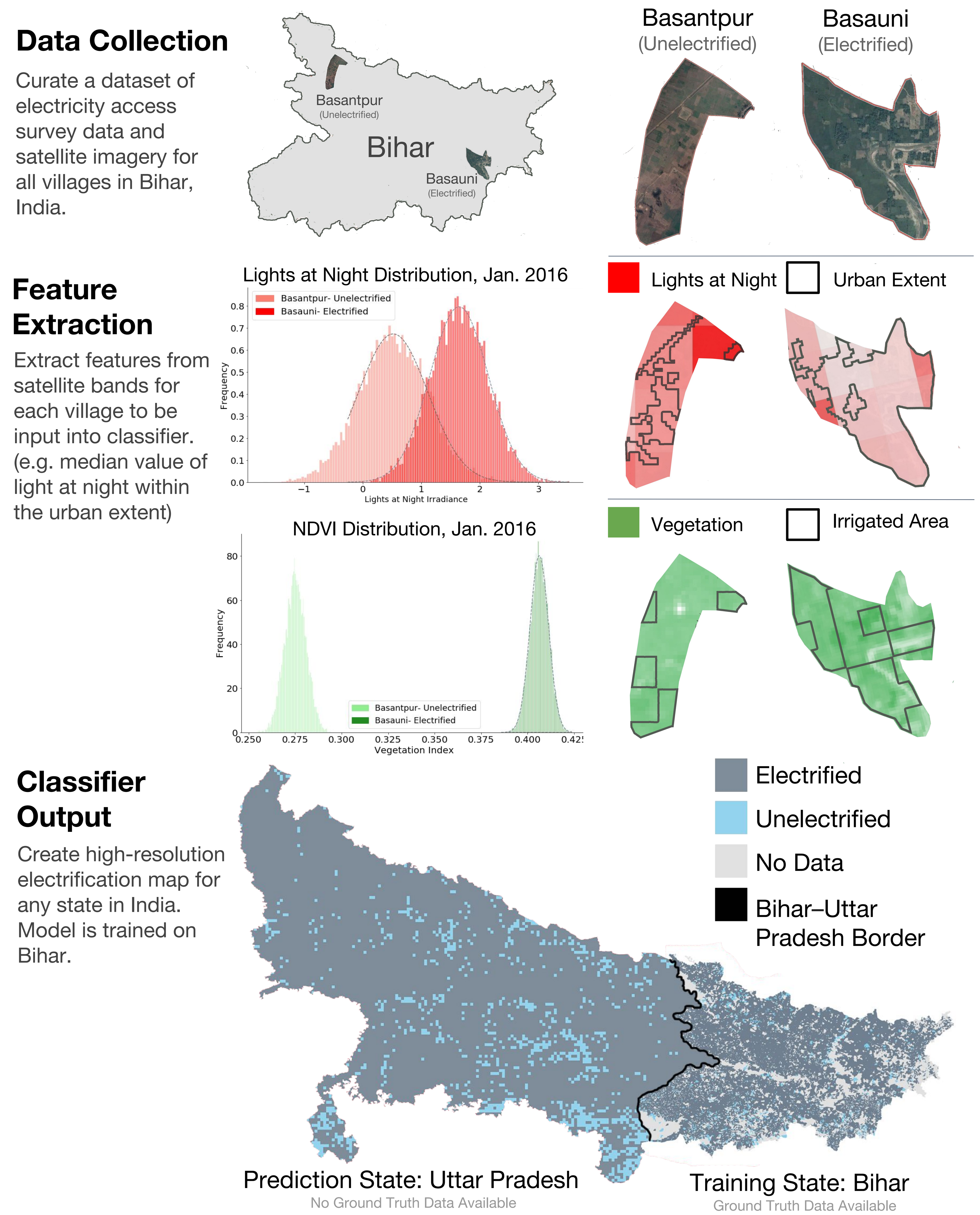

Figure 3. Process of data collection, feature extraction, village electrification classification and output validation.

The features our team extracted features include: Lights at night (VIIRS: Visible Infrared Imaging Radiometer Suite) data, population density, measures of possible agricultural activity including NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index), known irrigation activity, and Human Built-up and Settlement Extent (HBASE) index. We used data on urban extent and irrigated regions to focus our feature extraction on those areas within each village. We trained a gradient boosted decision tree classifier using these features to predict whether 16,389 individual villages in Bihar were either electrified or un-electrified based on ground truth data from the Indian government's GARV dataset. Our cross-validated results demonstrated through Receiver Operating Characteristic (ROC) performance curves show an area under the curve of 0.693, 0.73, and 0.799 respectively (higher is better). We then used this algorithm to predict electrification of villages in a neighboring state Uttar Pradesh. Our resulting accuracy is promising in its performance and our model can be scaled to identify electricity access in different parts of the world.

Results

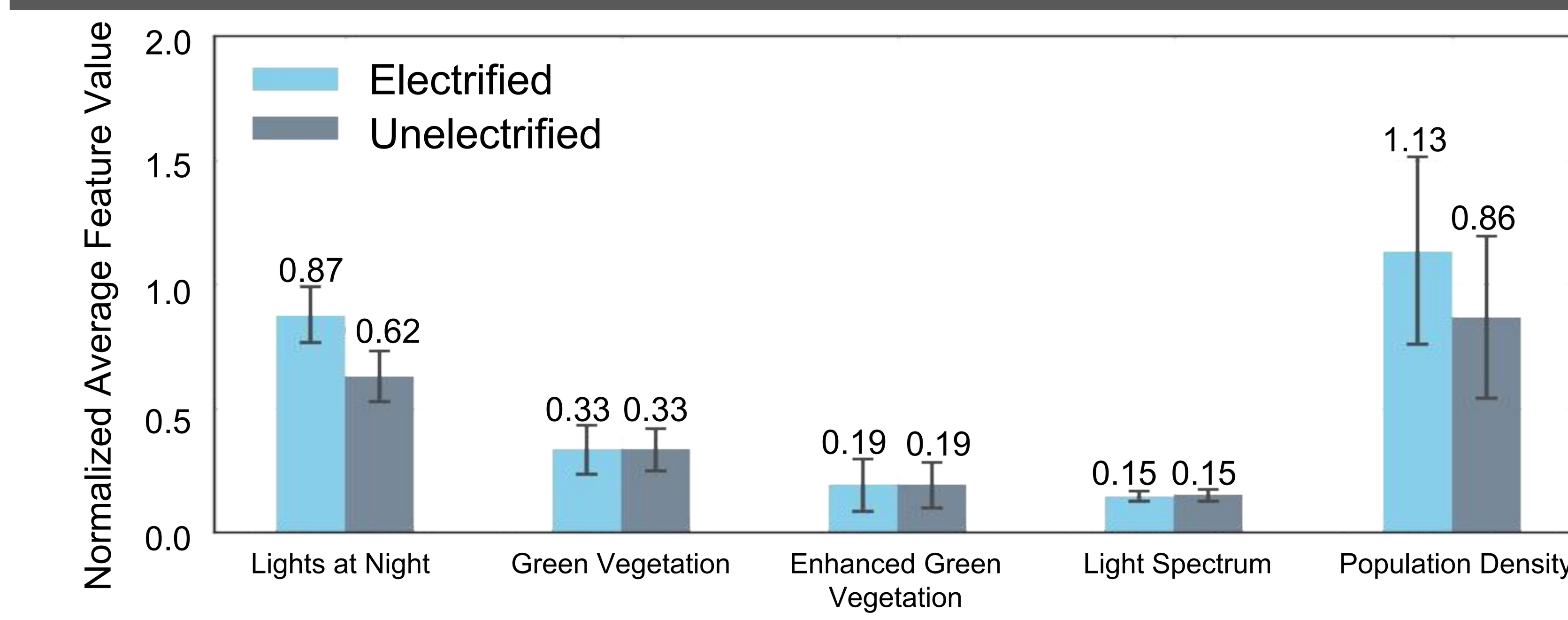

Figure 4. Mean of the five most important features for classification of electrified vs unelectrified villages

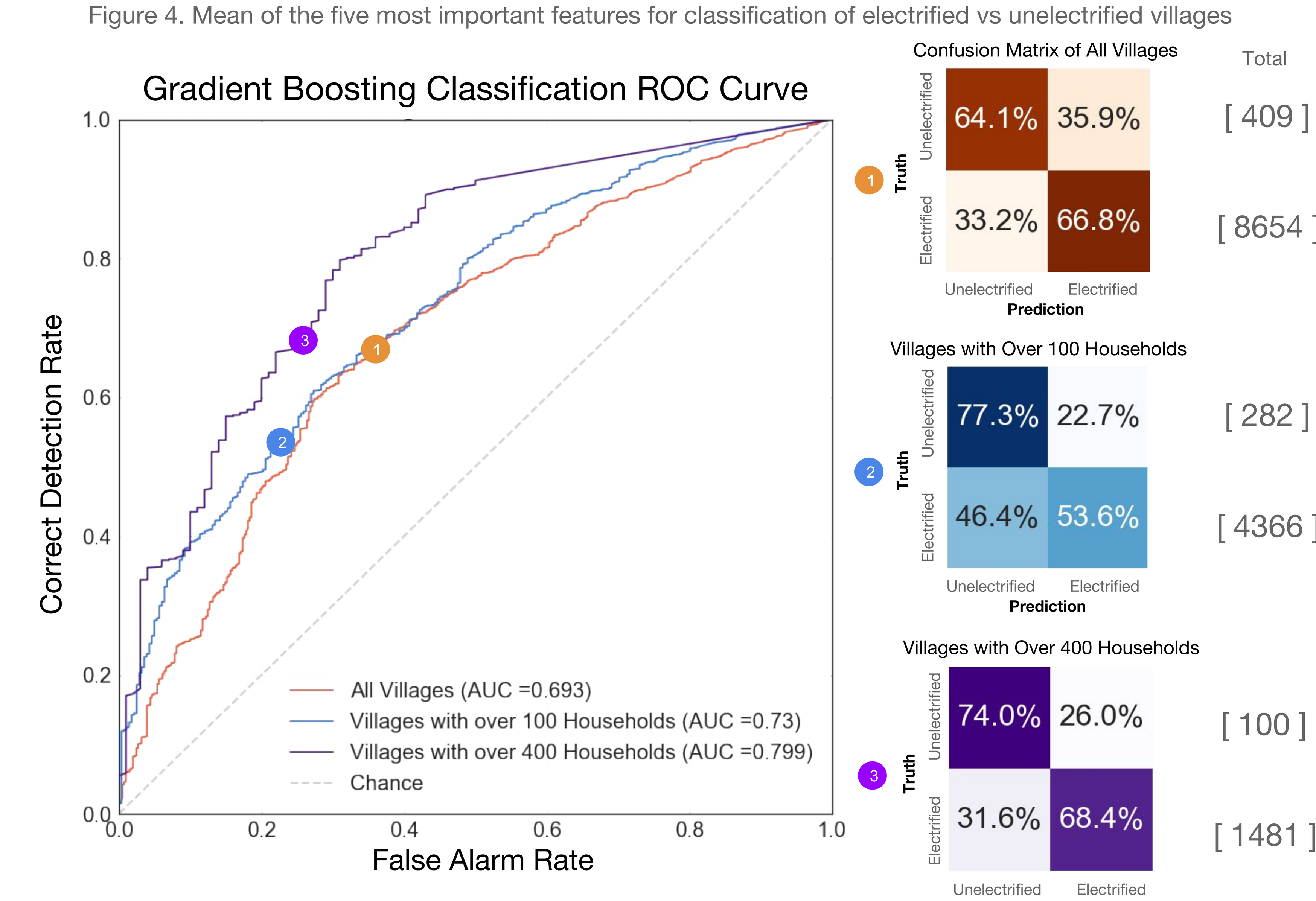

Figure 5. ROC Curve demonstrating results of energy access projections separated by three models, one with all villages included, and two others including only those villages with at least 100 or 400 households, respectively, since villages with more households potentially present stronger visible signals in the satellite imagery. The confusion matrices to the right show the performance at three specific points along the ROC curves to the left.

Conclusions & Future Work

Our results present evidence that it may be feasible to automate electricity access assessment using satellite imagery. This approach provides higher resolution data than existing data sources and can be used to produce estimates in regions of India (or other countries) which have not been surveyed down to the village level to determine electrification status. In the future, our village level data could be combined with geospatial electricity grid data to identify the economically and environmentally optimal pathways to electrification for rural villages via grid extension, microgrid development, or off-grid systems such as solar photovoltaics. Additionally, we will explore the use of other advanced computer vision techniques such as convolutional neural networks to improve prediction accuracy to enable even wider application of these methods in other countries.

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