Automating Electricity Access Prediction with Satellite Imagery

Fangge Deng, Shamikh Hossain, Prithvir Jhaveri, Ashley Meuser, Harshvardhan Sanghi, Joe Squillace, Anuj Thakkar, Brian Wong, Xiaolan You
Faculty Advisors: Dr. Kyle Bradbury (Energy Initiative), Dr. Leslie Collins (Pratt), Dr. T. Robert Fetter (Nicholas Institute), Dr. Marc Jeuland (Sanford), Dr. Timothy Johnson (Nicholas)

Duke University | Bass Connections

Duke Energy Initiative

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.

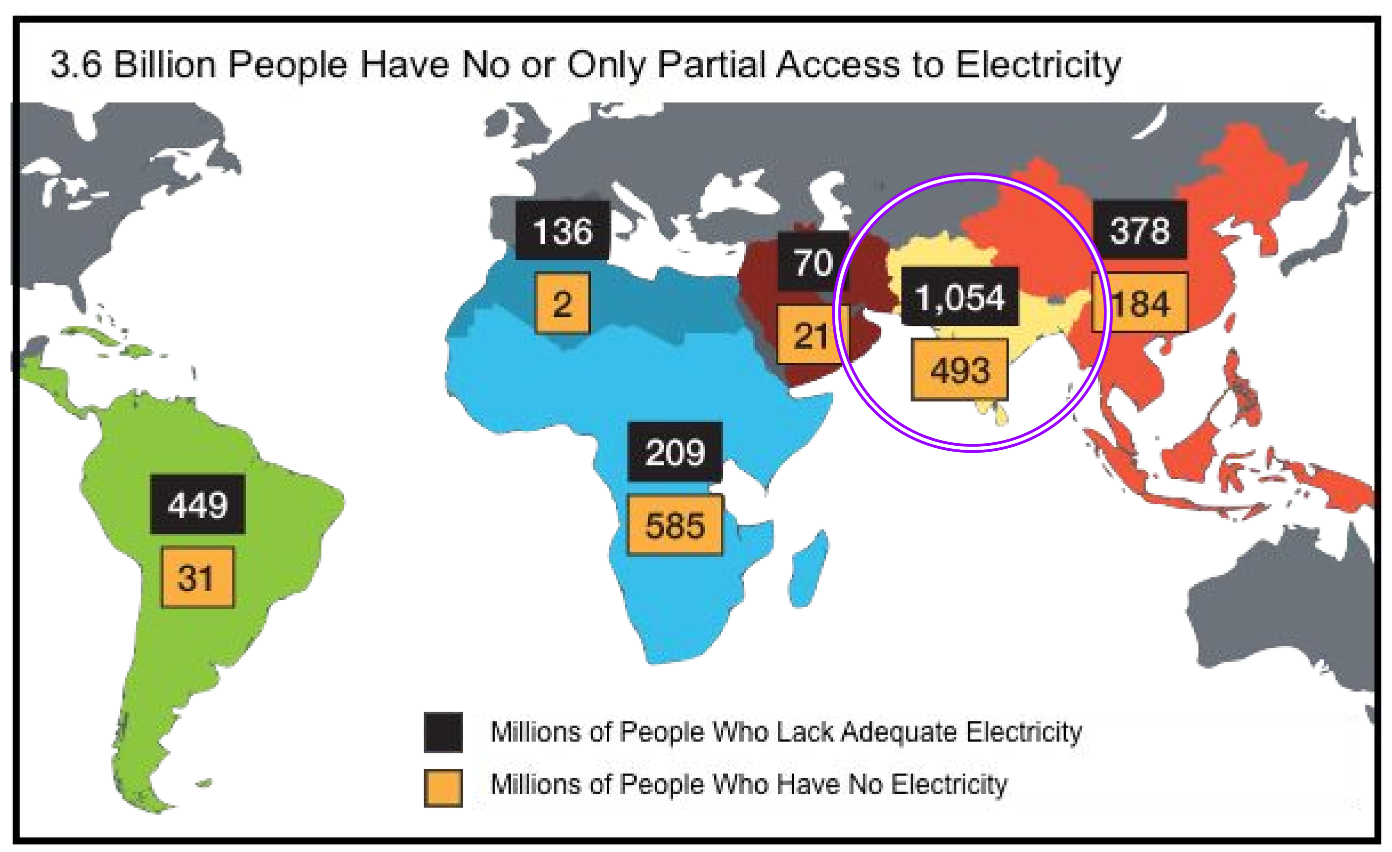


Figure 1: Global population with access to no or inadequate electricity

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).

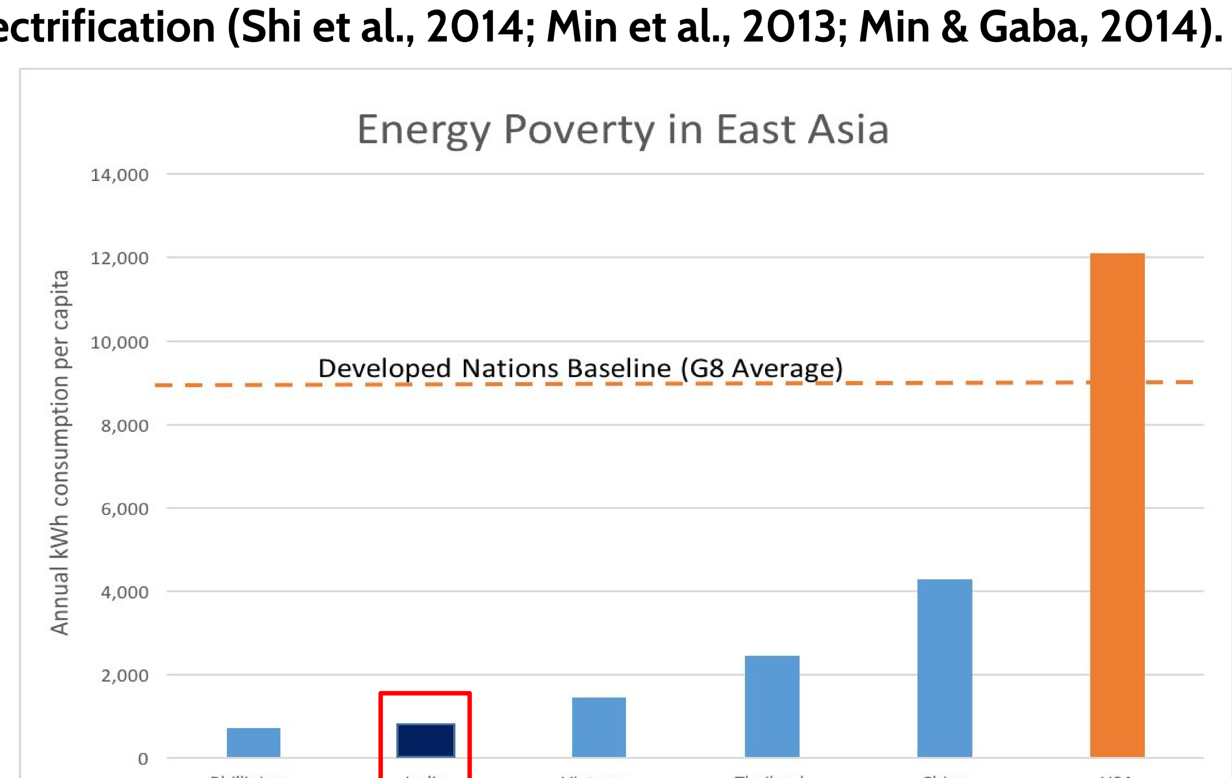


Figure 2. Energy poverty in East Asia India relative to developed nations and the G8 average.

Source: CIA World Factbook, 2016

Process Summary

Data Collection

Curate dataset of village electrification data and corresponding satellite imagery

Feature Extraction

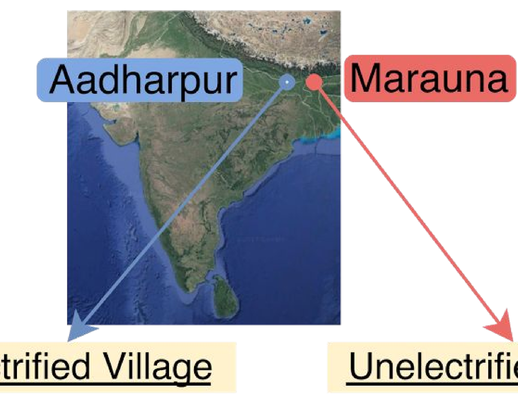
Extract features from lights at night data for each village to be input into classifier

Classification Models

Run a gradient boosted decision tree classifier to predict whether each village is electrified and evaluate performance using cross validation

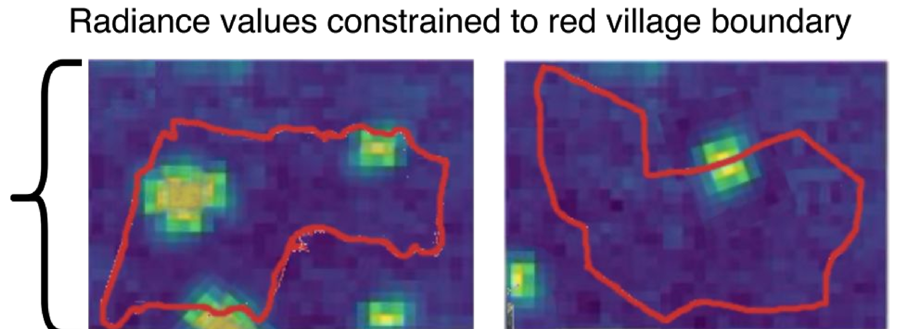
Output

Classify electrification status for Bihar, India and produce high-resolution maps of electrification



Radiance values constrained to red village boundary

Nighttime Lights Satellite Data



Village	Aadharpur	Marauna
Mean Radiance	0.43	0.17
Max Radiance	0.87	0.31

Gradient Boosting Tree Classifier

Village	Aadharpur	Marauna
Predicted	Electrified	Unelectrified
Ground Truth	Electrified	Unelectrified
Correct?	TRUE	TRUE

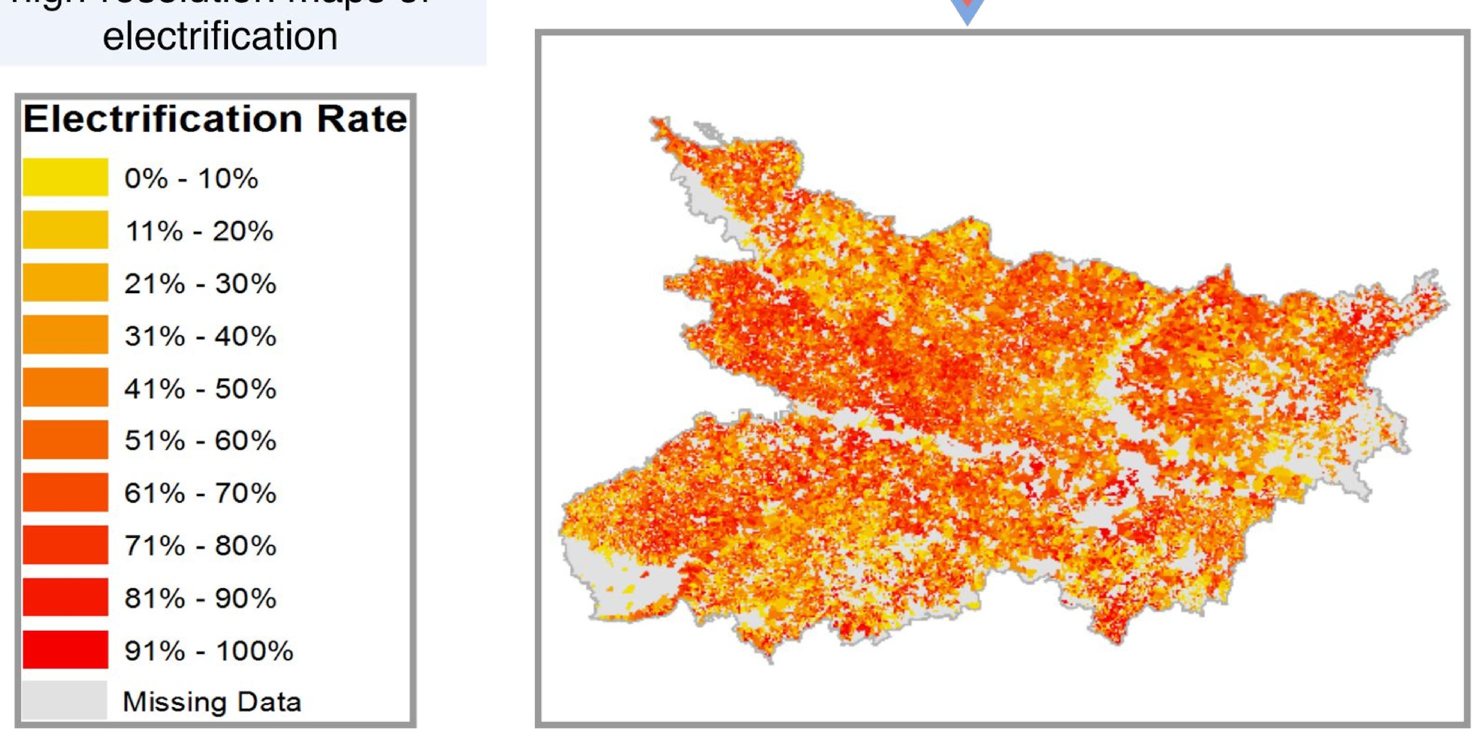


Figure 3. Process of data collection, feature extraction, village electrification classification and output validation.

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

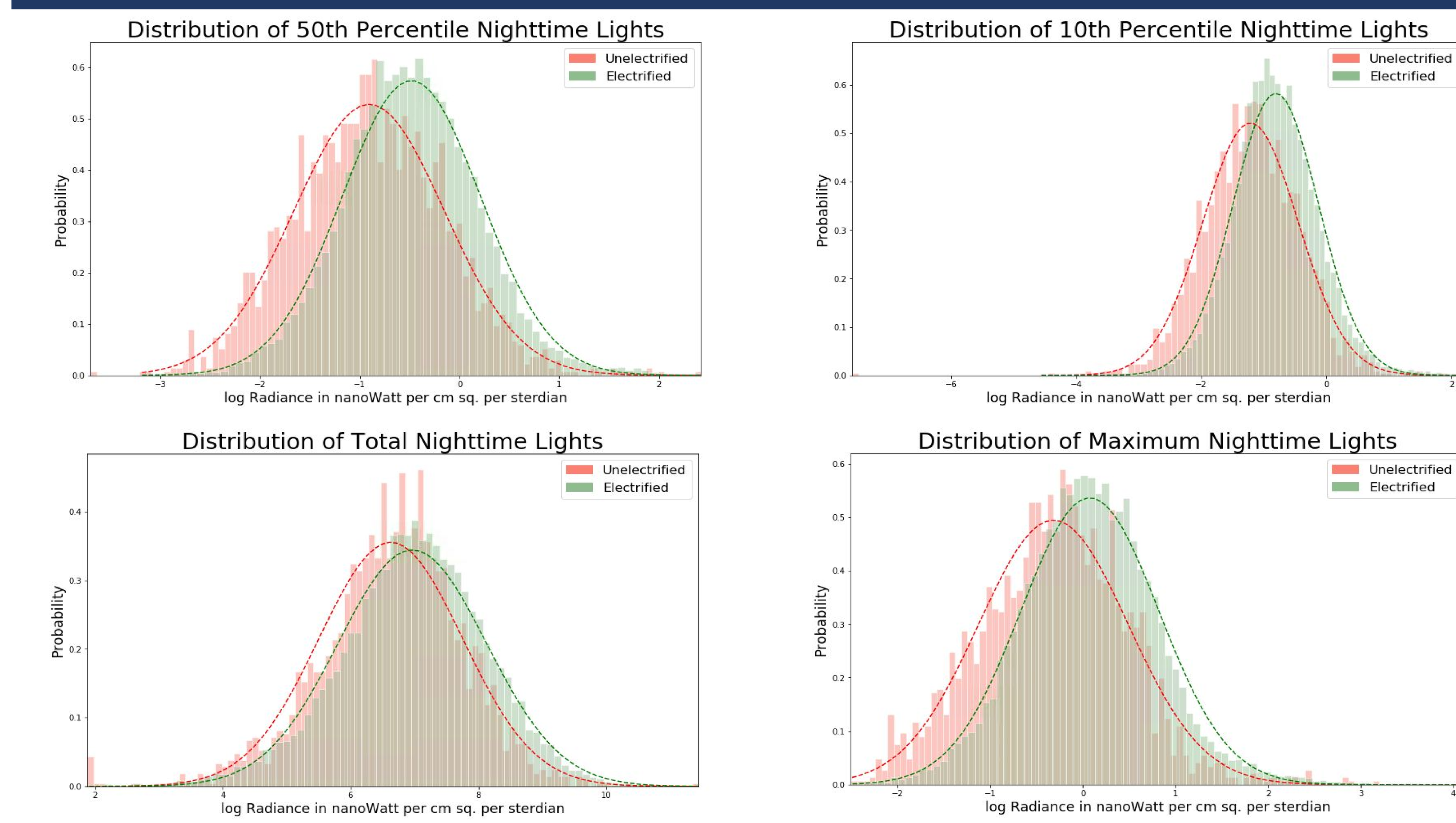


Figure 4. Distribution of top four features of importance separated by Electrified and Unelectrified classes.

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.

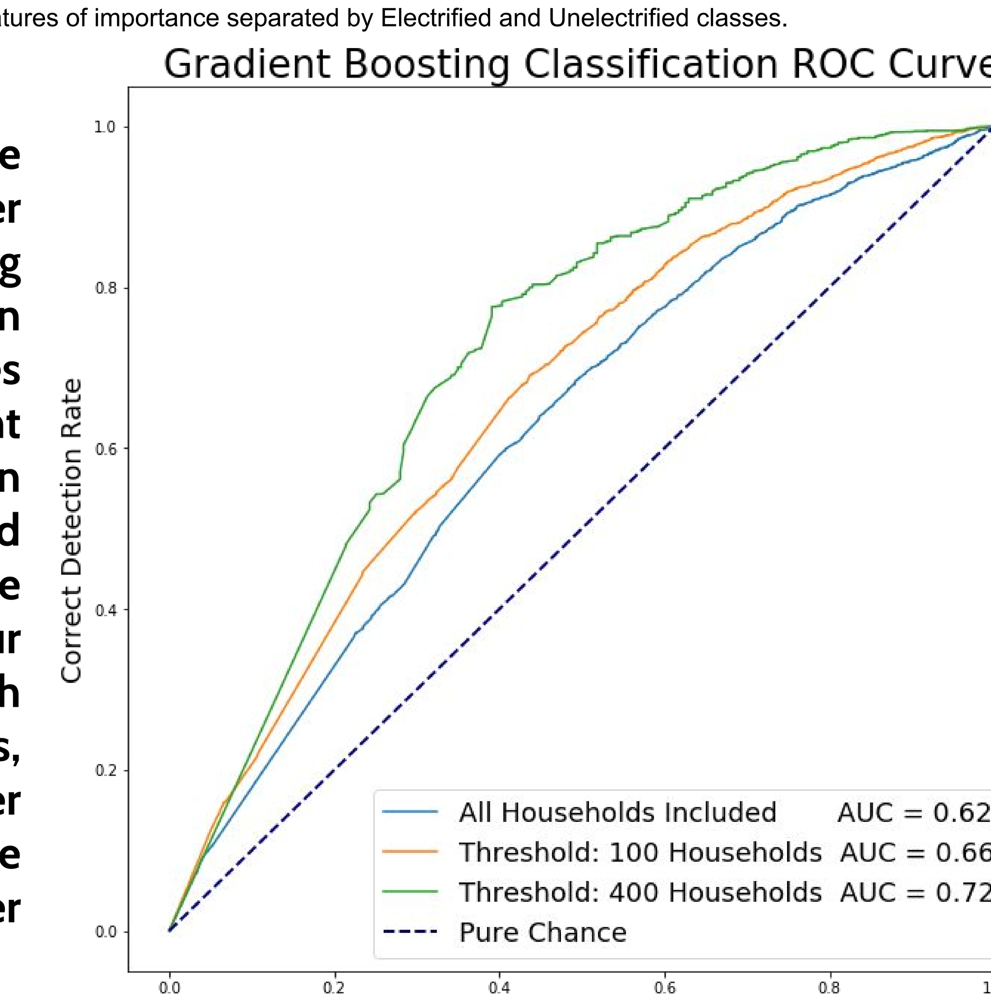


Figure 5. ROC Curve demonstrating results of energy access projections separated by three models, each by selecting a minimum number of households threshold.

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

International Energy Agency (2011), World Energy Outlook 2011, OECD Publishing, Paris. http://dx.doi.org/10.1787/weo-2011-en

Khandker, S.R., Samad, H.A., Ali, R., & Barnes, D.F. (2012). Who Benefits Most from Rural Electrification? Evidence in India. *Policy Research Working Papers*. doi:10.1596/1813-9450-6095

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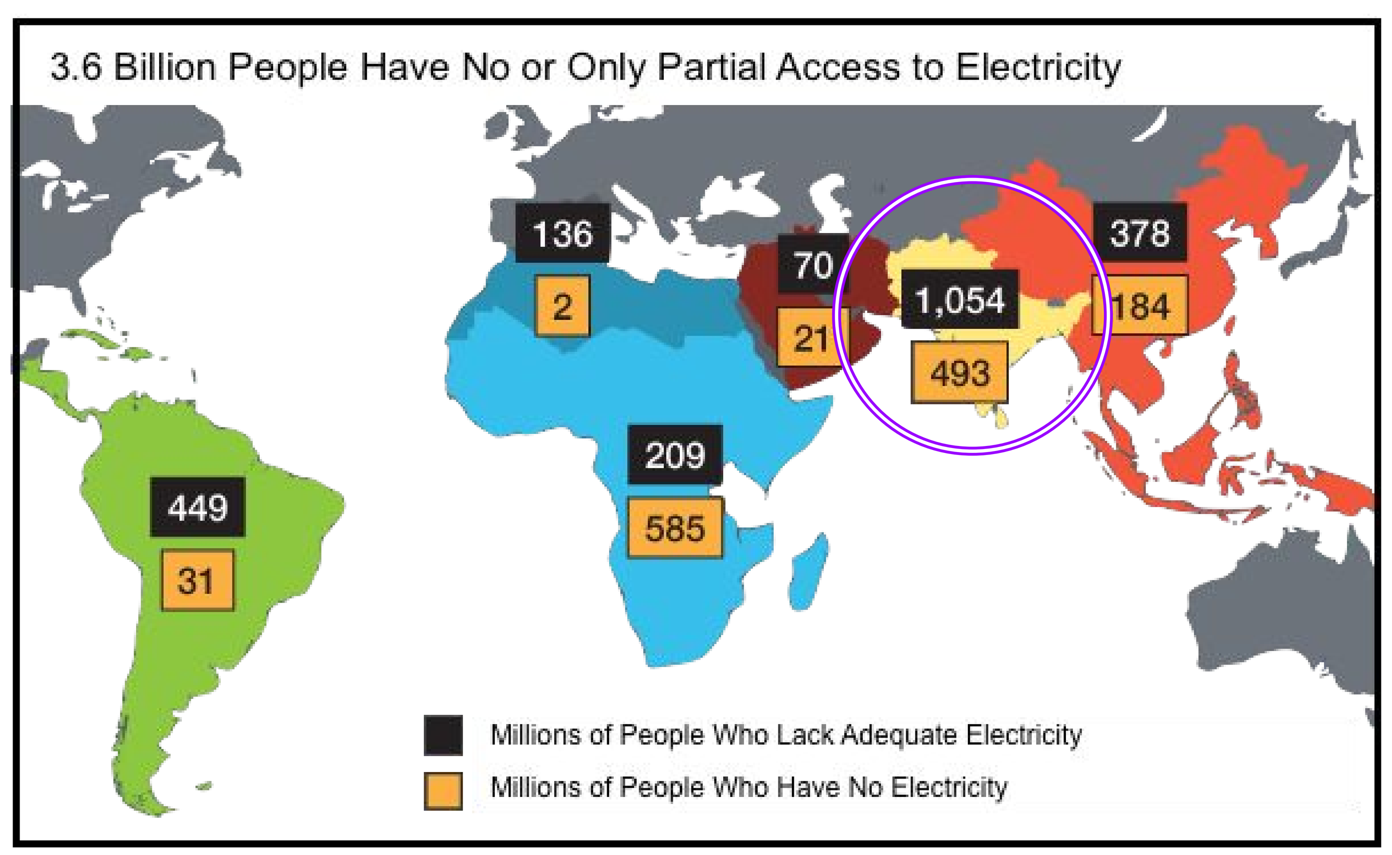

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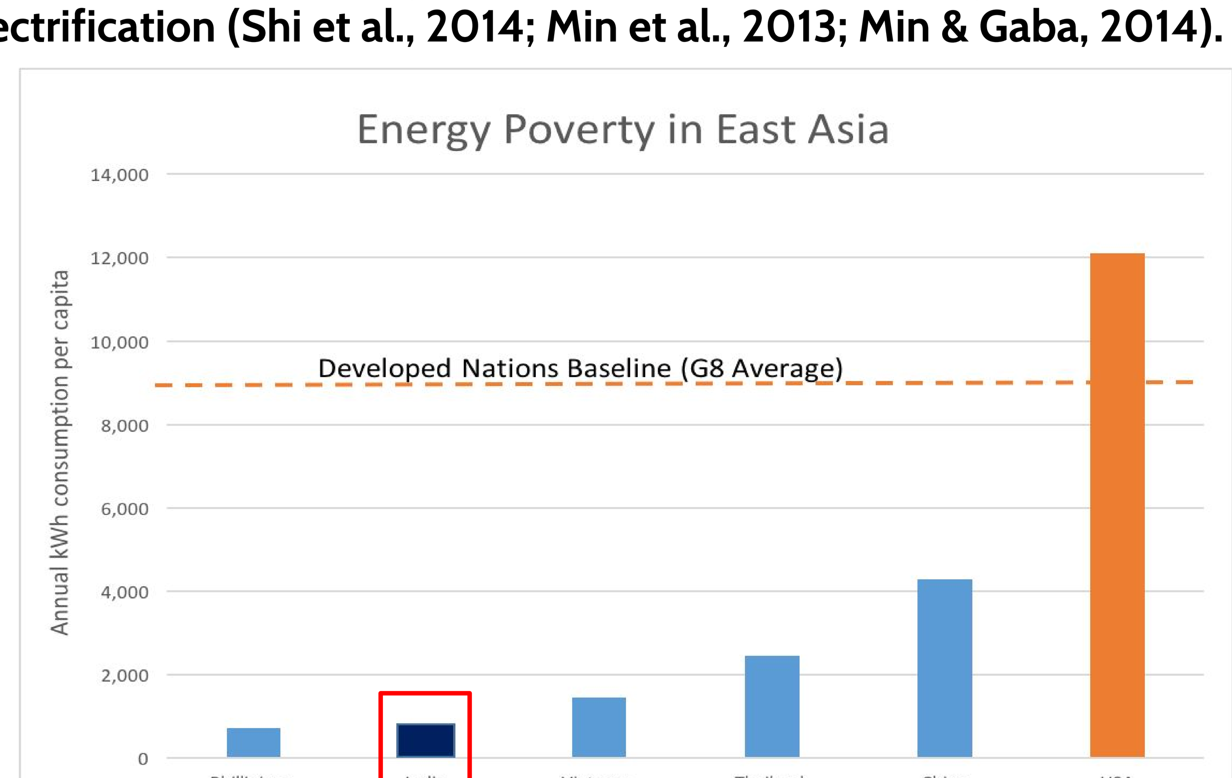

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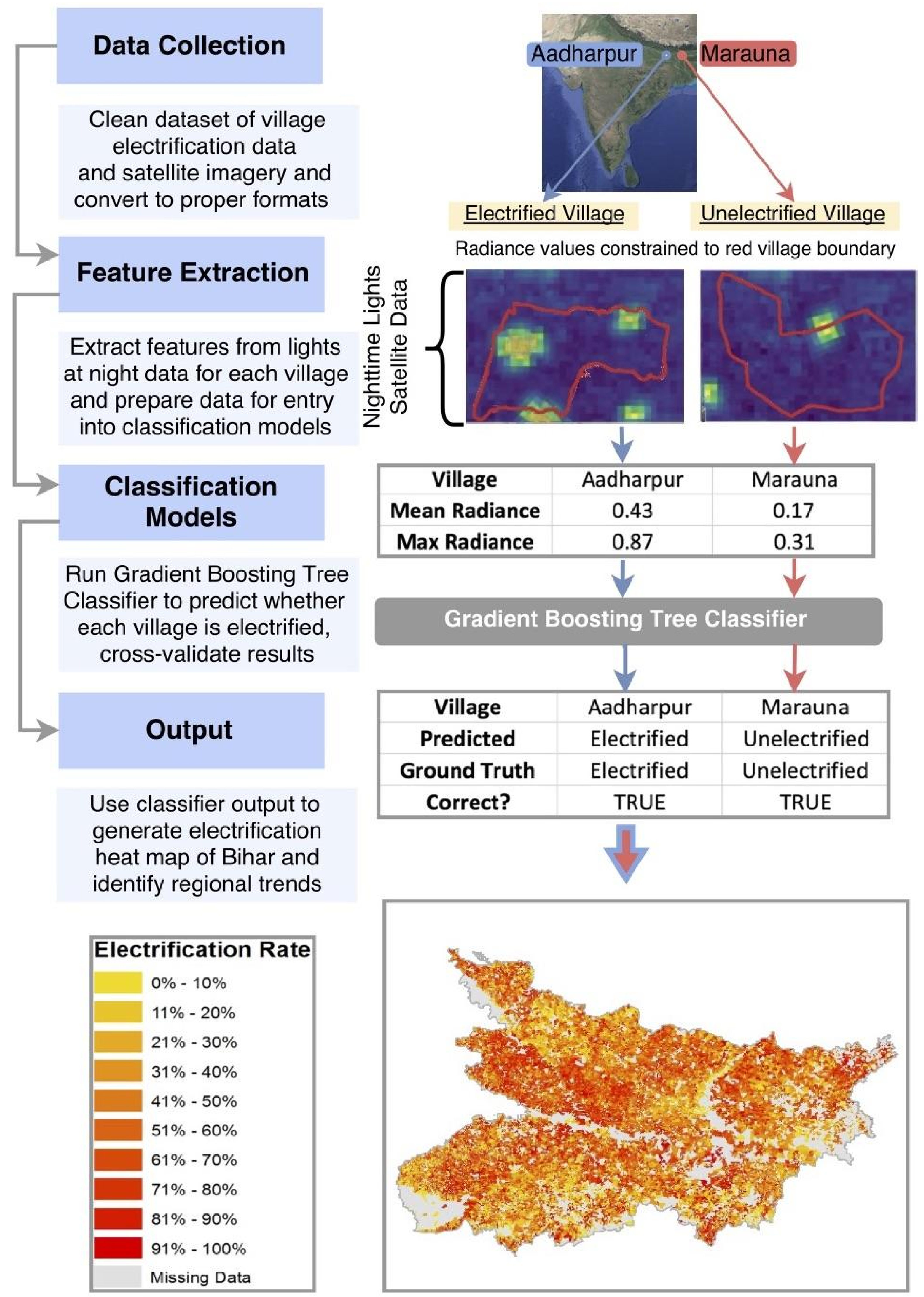

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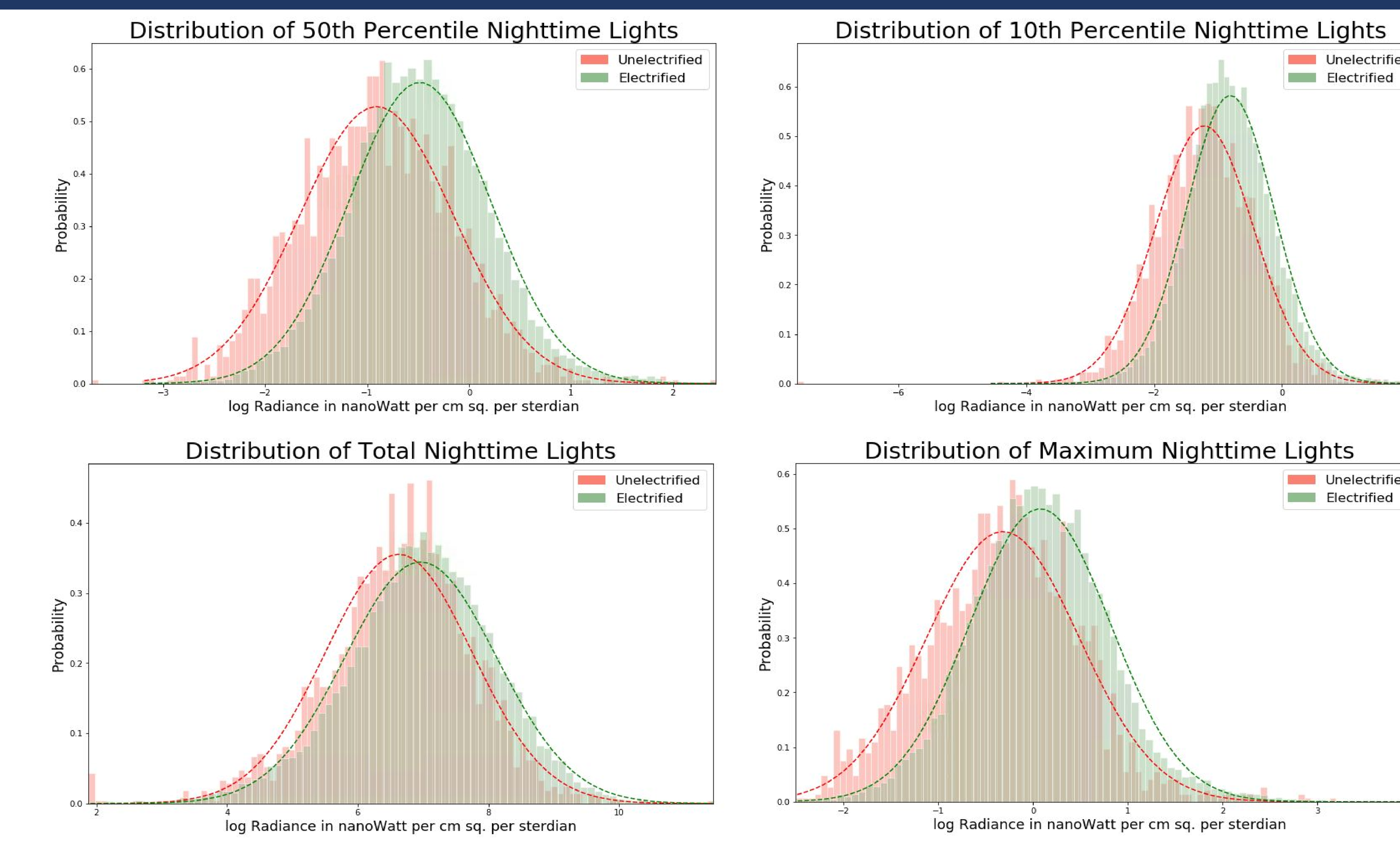

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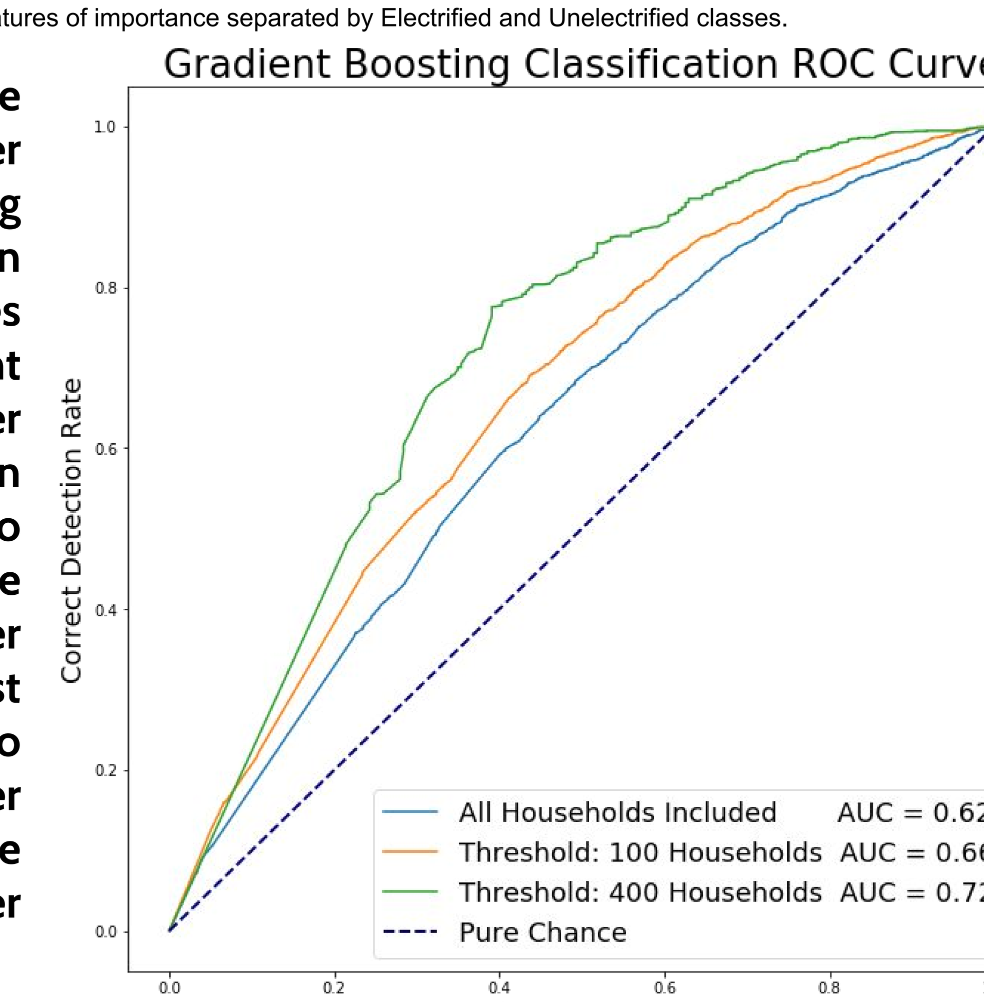

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Despite these benefits, an estimated 1.2 billion people do not have electricity access, and even more have either too unreliable or insufficient supply to reap the aforementioned welfare gains (World Energy Outlook, 2017).

This study aims to fill current data gaps on global energy access, particular in resolving finer-scale geographic access metrics. The study aims to overcome inaccurate or biased data, to provide a method for continuously measuring progress in electricity access over time, and to get more refined electricity access data on a village-to-village basis.

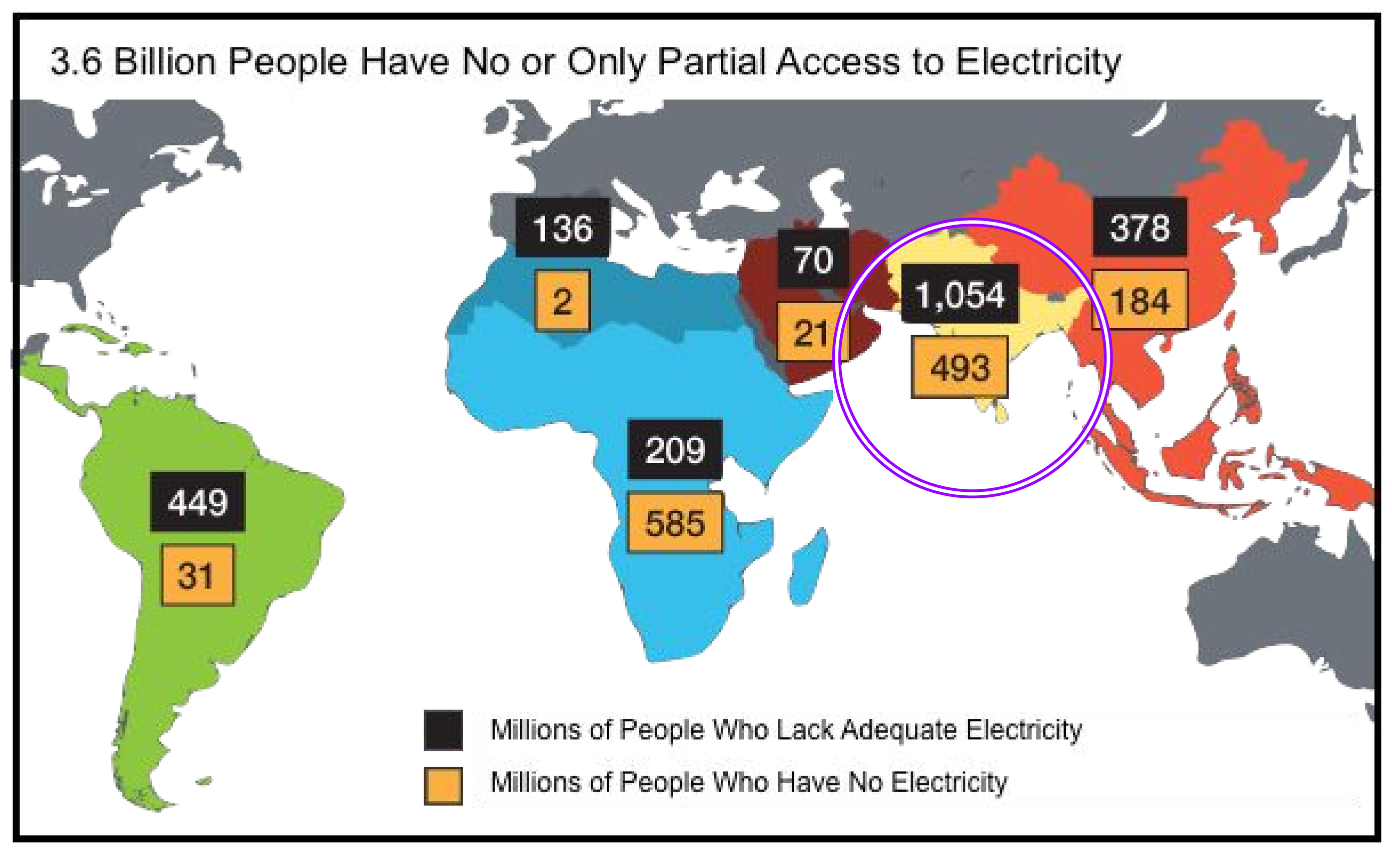
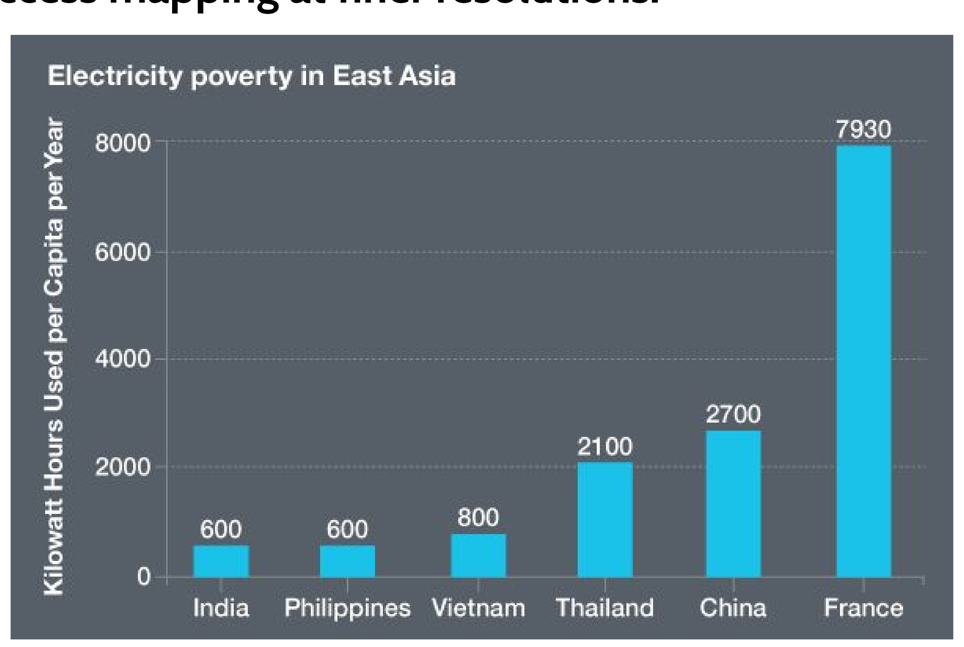


Figure 1: Global population with access to no or inadequate electricity

The primary deliverable of this preliminary study is to produce a functional collaborative machine learning infrastructure with VIIRS Lights at Night data capable of predicting electrification rates at the village level in Bihar, India. In doing so, the study aims to advance energy access mapping at finer resolutions.



Sources

- Energy access database. (n.d.). Retrieved October 03, 2017, from http://www.worldenergyoutlook.org/resources/energydevelopment/energyaccessdatabase/.
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Process Summary

Input Data | Extracted/Output Data

Data Collection

Download dataset of village household electrification data in Bihar and satellite imagery, convert to proper formats.

Satellite Data

Village	% Electrified
Aadharpur	22.80%
Marauna	UNKNOWN
...	...

Indian Government Electrification Data

Feature Extraction

Extract features from lights at night data for each village and prepare data for entry into classification models.

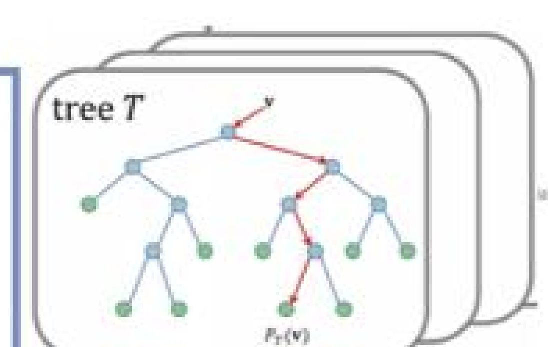
Lights at Night

Village	Mean	Max	...
Aadharpur	0.40	0.86	...
Marauna	0.32	0.71	...
...	...	...	...

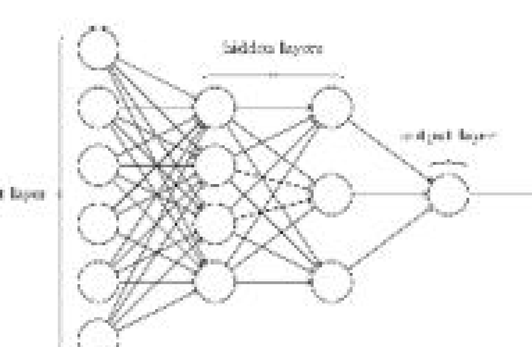
Radiance values

Classification Models

Run Random Forest and MLP binary classification models to estimate electricity access from lights at night values.



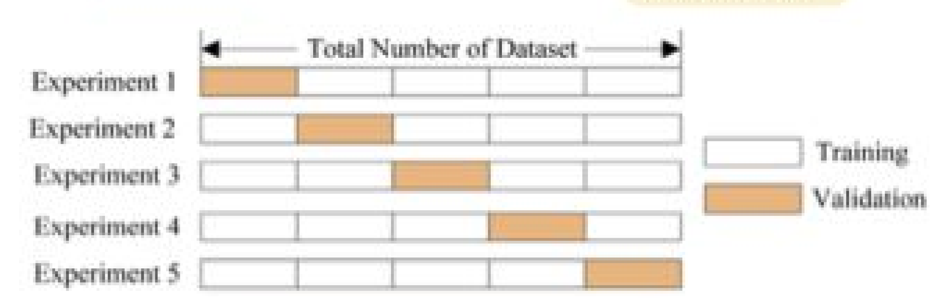
Random Forest



Multilayer Perceptron

Validation

Use cross validation to test classifiers and evaluate performance using ROC curve.



K-folds cross validation

Output

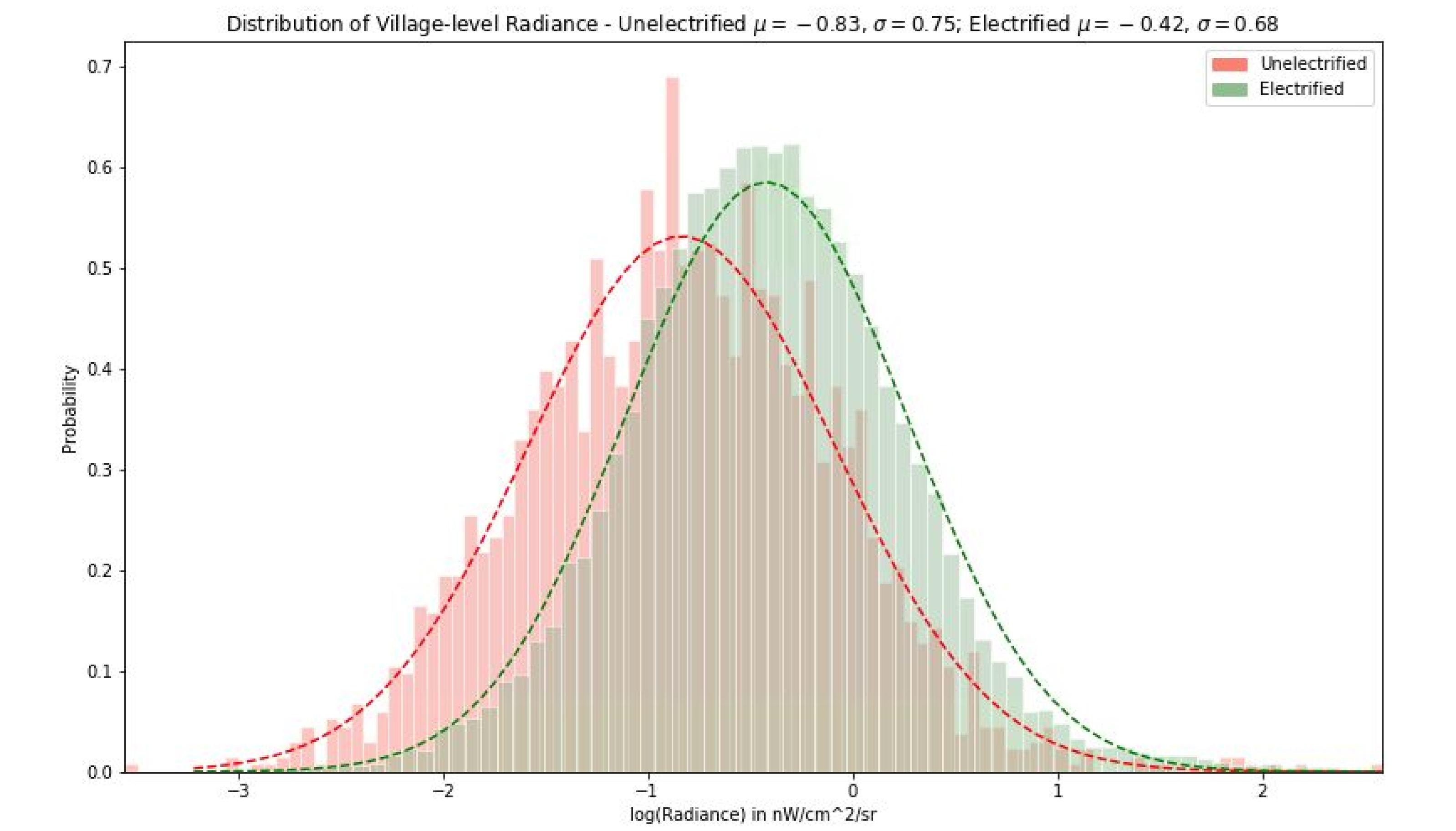
Data Processing

Operations were performed on VIIRs band arrays that corresponded to villages in Bihar. Each array was first masked to include only pixels that corresponded to the specific village. From these arrays the mean and max radiance values and the 10%, 25%, 50%, 75%, and 90% radiance percentiles were calculated.

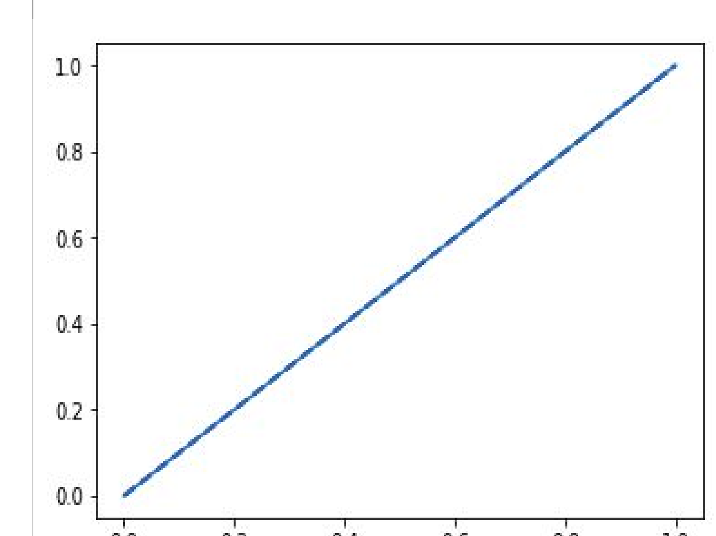
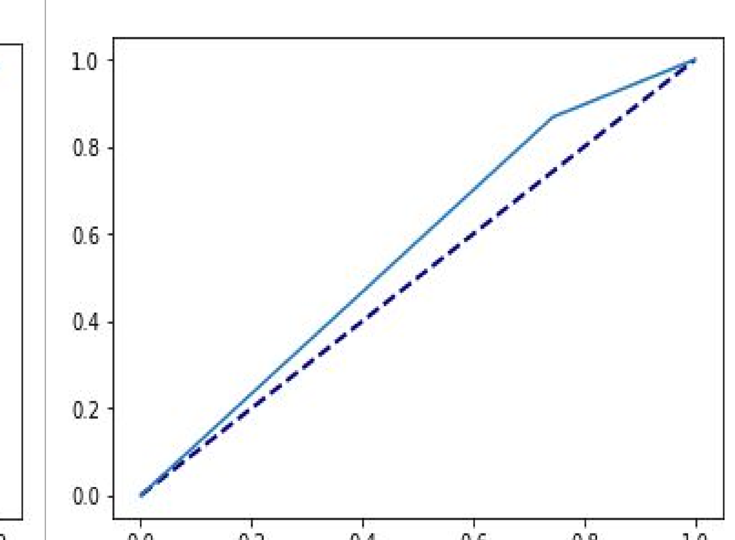
Our team consolidated the following software infrastructure for adding new features:

1. load_features.py to add new features for each village
2. viirs_feature_extraction.ipynb to merge with other village data and produce cleaned data ready for experimentation with different modeling techniques.

Machine Learning Model



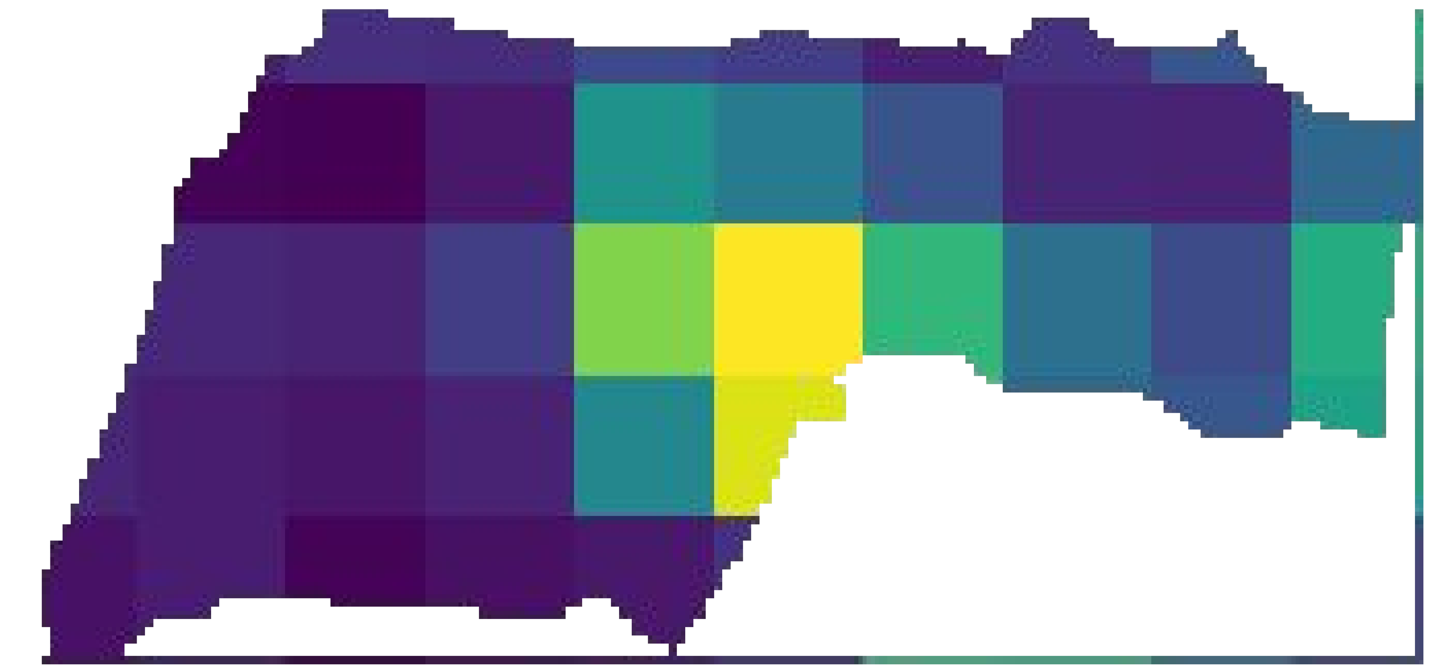
Machine learning classifiers were run to classify the village data into two categories: un-electrified and electrified, ere represented with labels 1 and 2. The first classifier assumed less than 10% as not electrified, the second classifier assumed less than 50% as not electrified. These thresholds were chosen based on visual analysis of data clustering. The results of our classifiers are shown below in the form of Receiver operating characteristic (ROC) curves.

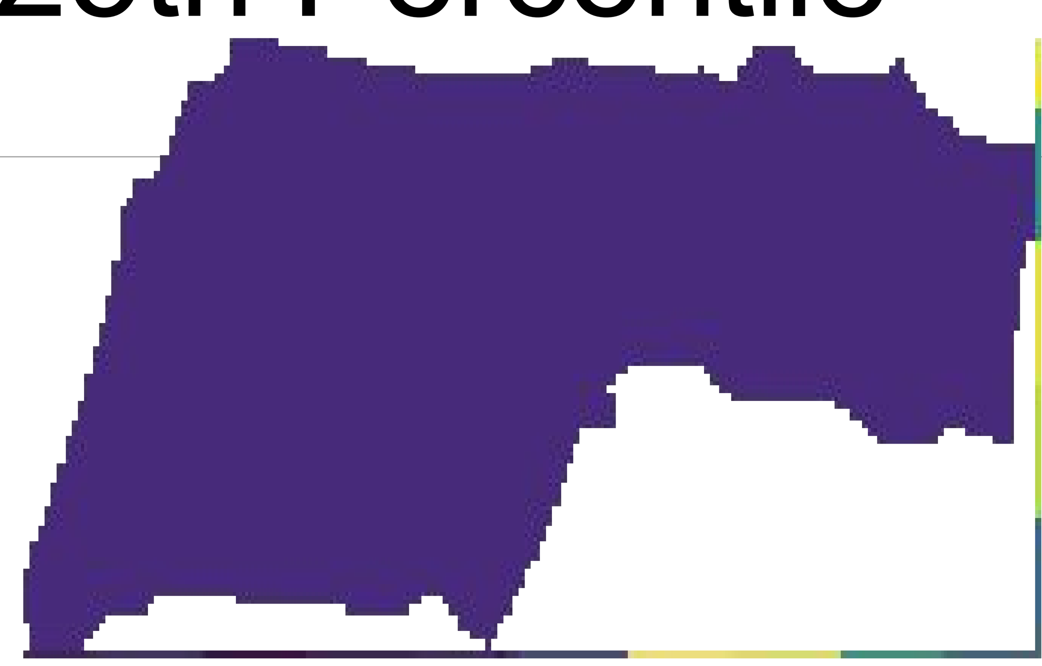
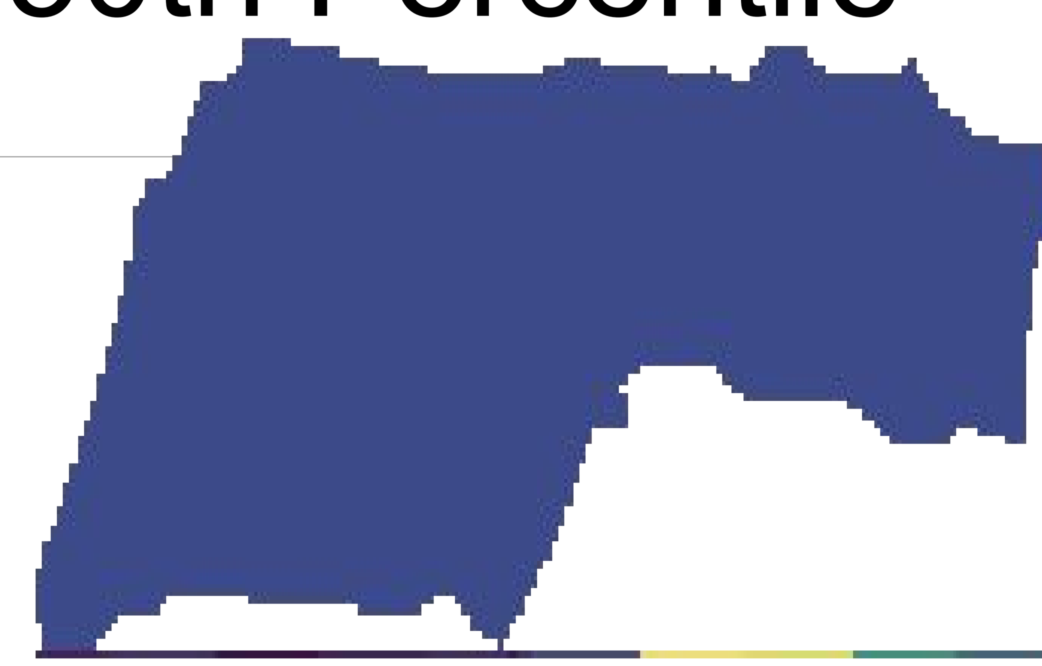
Classifier	Neural Network MLP 10%	50%
Accuracy	91.75%	53.83%
Area under ROC	0.50	0.5624
ROC curve		

Conclusion & Future Steps

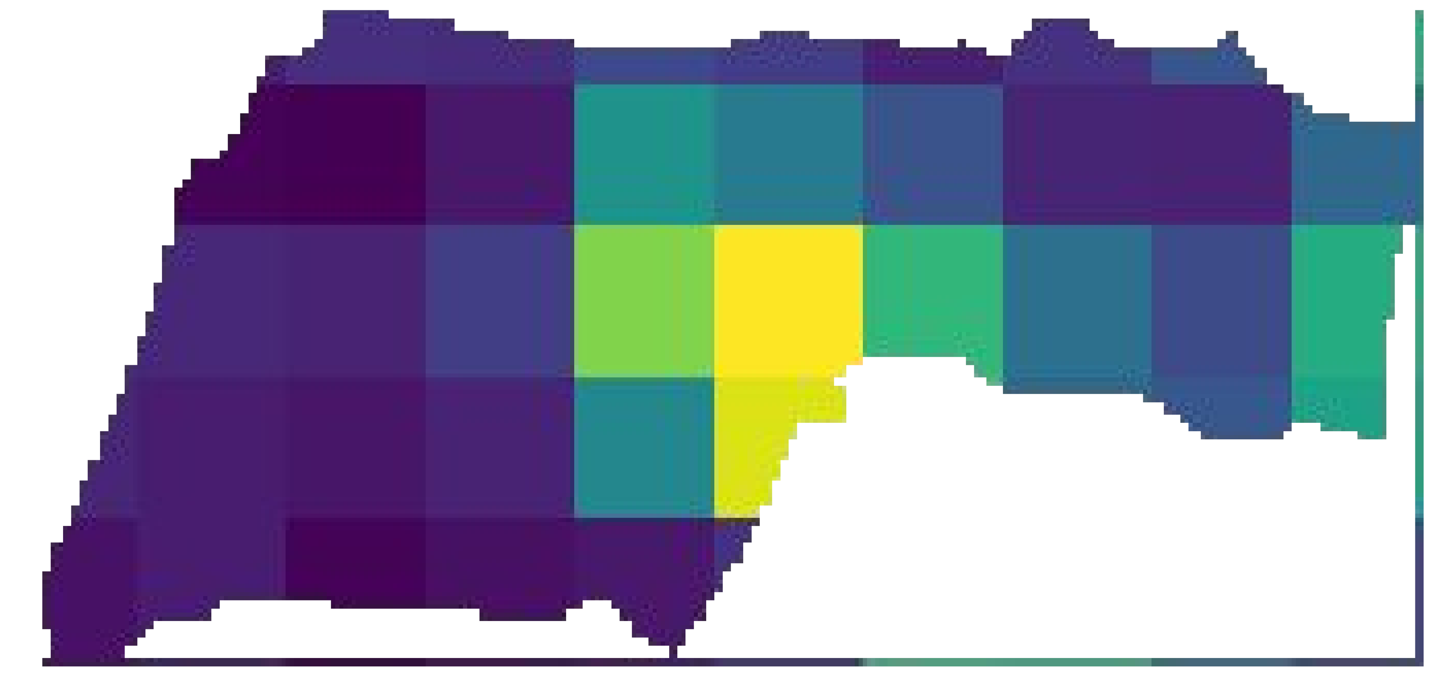
This exploratory study demonstrated that the data are nonlinear, and thus a nonlinear classifier will be more successful in differentiating between village electrification rates. It also yielded Python scripts that are flexible to new feature extraction and testing for quicker iterations of modeling in the future. These features may include other objects detected from the VIIRS imagery, such as buildings or other features of the built environment. However, tests are limited by the size of the village imagery dataset, so future tests must continue to limit the number of features that are tested. Once more features are extracted, a CNN may prove effective at determining village electrification rates.

Feature Extraction

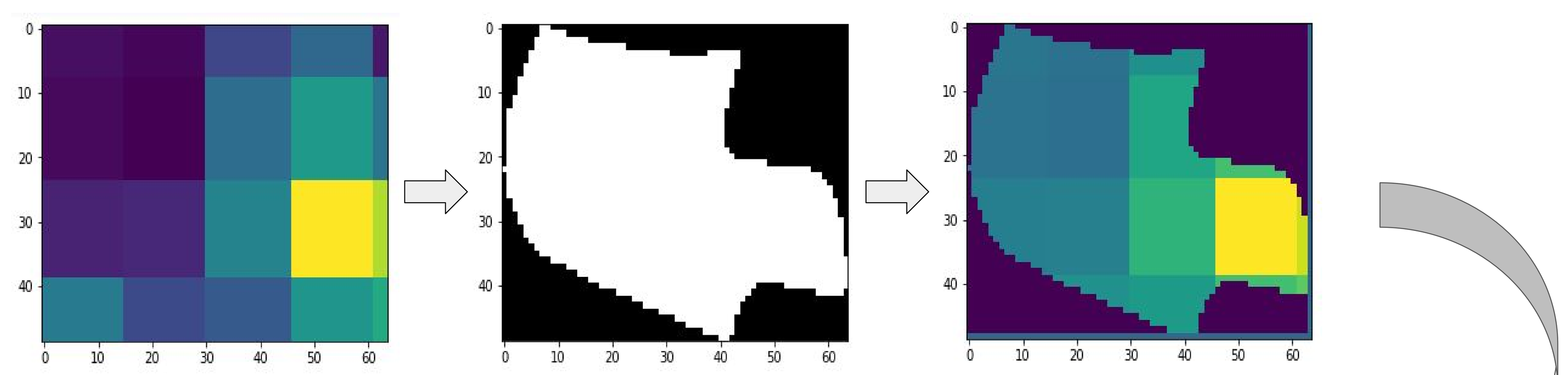


Mean 	Max 	Total Night Lights 	10th Percentile 
25th Percentile 	50th Percentile 	75th Percentile 	90th Percentile 

Feature Extraction



10th Percentile	25th Percentile	50th Percentile	Mean	75th Percentile	90th Percentile	Max	Total Night Lights
0.27	0.32	0.43	0.56	0.76	0.99	2.24	2283.31



Census 2011 ID	Village Name	District Name	State Name	Number of Households	Number of Electrified Households	Percentage Electrified	Mean	Max	Standard Deviation	TNL	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile
215989	Kalapani	Pashchim Ch	Bihar	445	42	9.43820225	0.339502	0.523828	0.0733962	920.051	0.265501	0.267205	0.324645	0.401243	0.464612
215991	Tharhi	Pashchim Ch	Bihar	339	214	63.1268437	0.475338	3.98845	0.512065	20174.8	0.172867	0.199608	0.260938	0.533222	1.10447
215992	Pipra	Pashchim Ch	Bihar	107	59	55.1401869	1.01376	1.8018	0.448887	2263.73	0.425144	0.568891	0.872517	1.22083	1.67852
215993	Kotaraha	Pashchim Ch	Bihar	128	64	50	0.561286	2.24641	0.341734	2283.31	0.274397	0.325906	0.424527	0.76102	0.990788
215995	Lachhmipur	Pashchim Ch	Bihar	615	449	73.0081301	0.40072	1.23223	0.182626	1599.68	0.281324	0.298837	0.339738	0.385788	0.590184