

Automating Electricity Access Prediction using Satellite Imagery

Duke University Energy Data Analytics Lab

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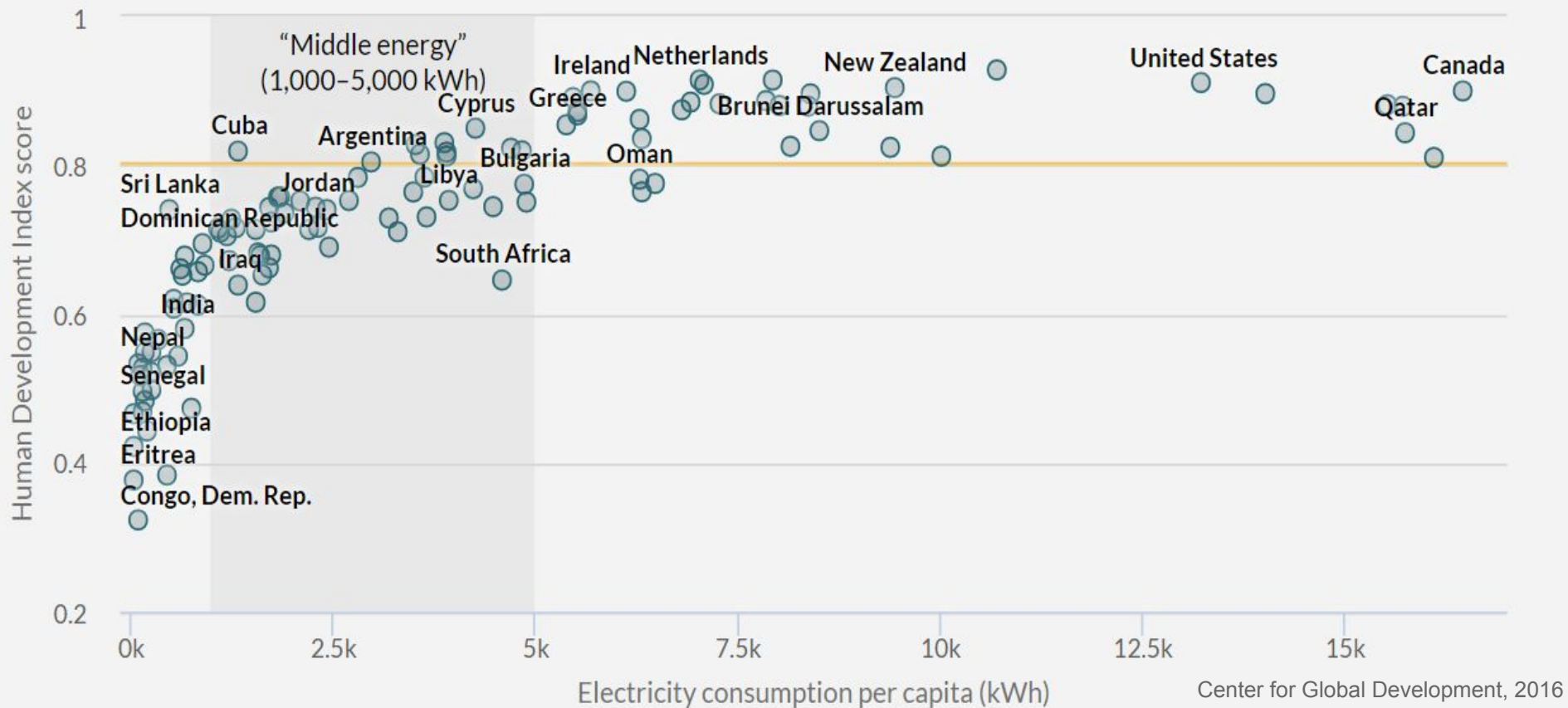


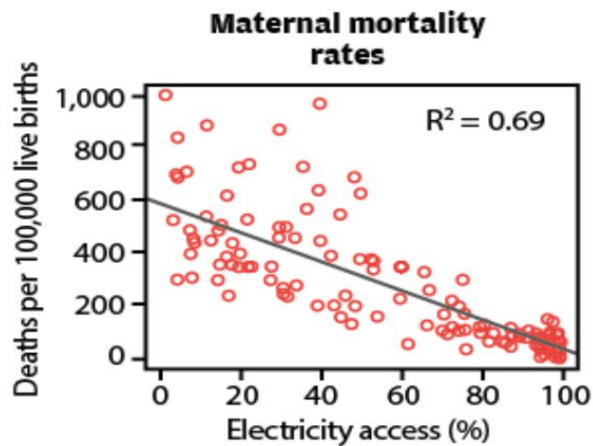
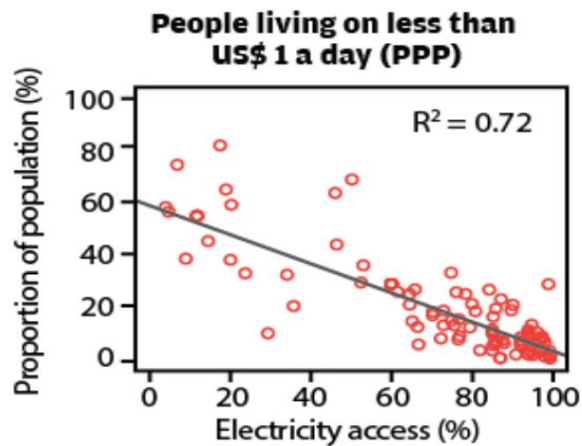
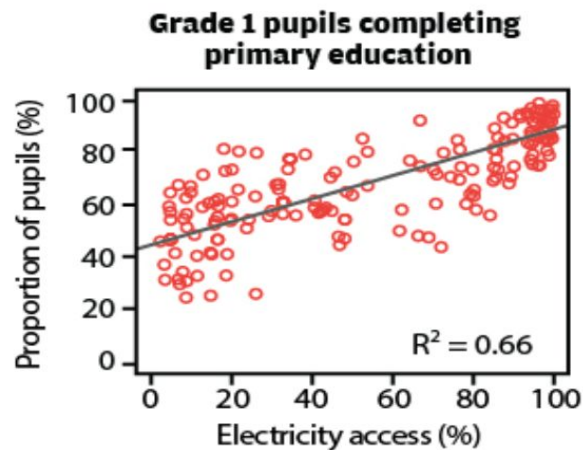
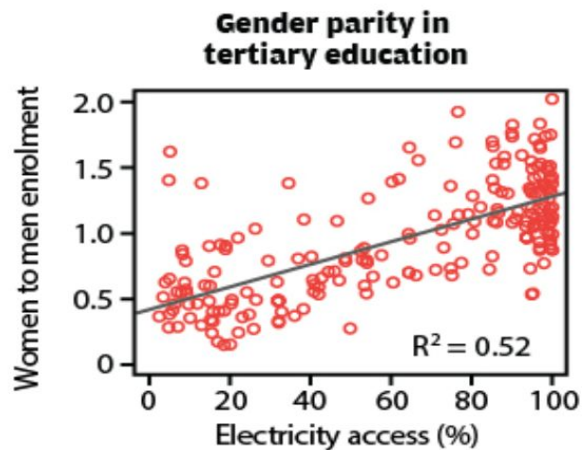


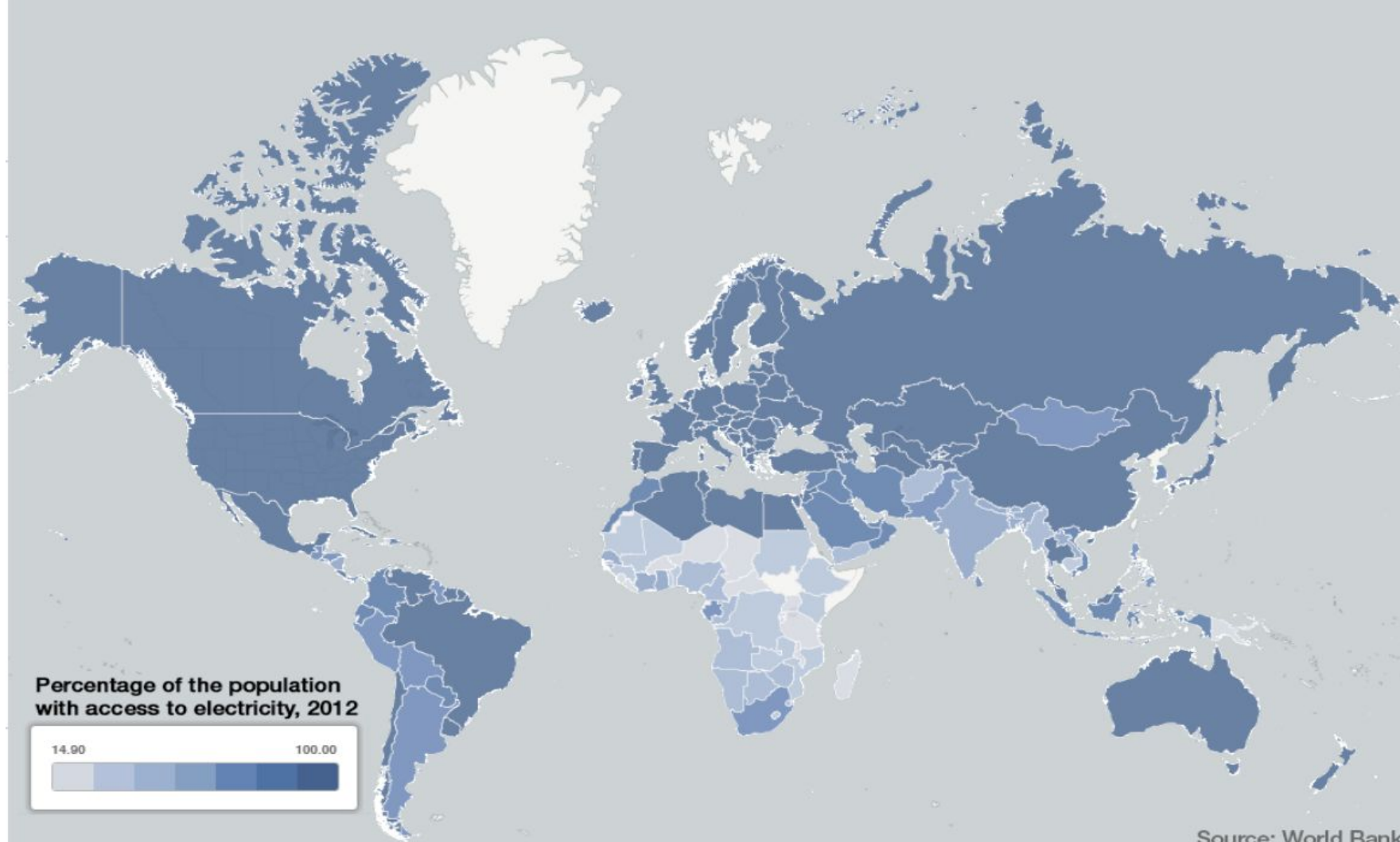
Presentation Roadmap

- 1. The Importance of Electricity**
- 2. The Problem in Developing Countries**
- 3. Our Team's Goal & Approach**
- 4. Results**
- 5. Future Work**

Higher electricity consumption is correlated with higher development and human welfare indicators







Source: World Bank



Why a data & satellite image based approach?

Data Needed

- Continuous
- High resolution
- Cheap
- Reliable
- Automatic
- Complete coverage

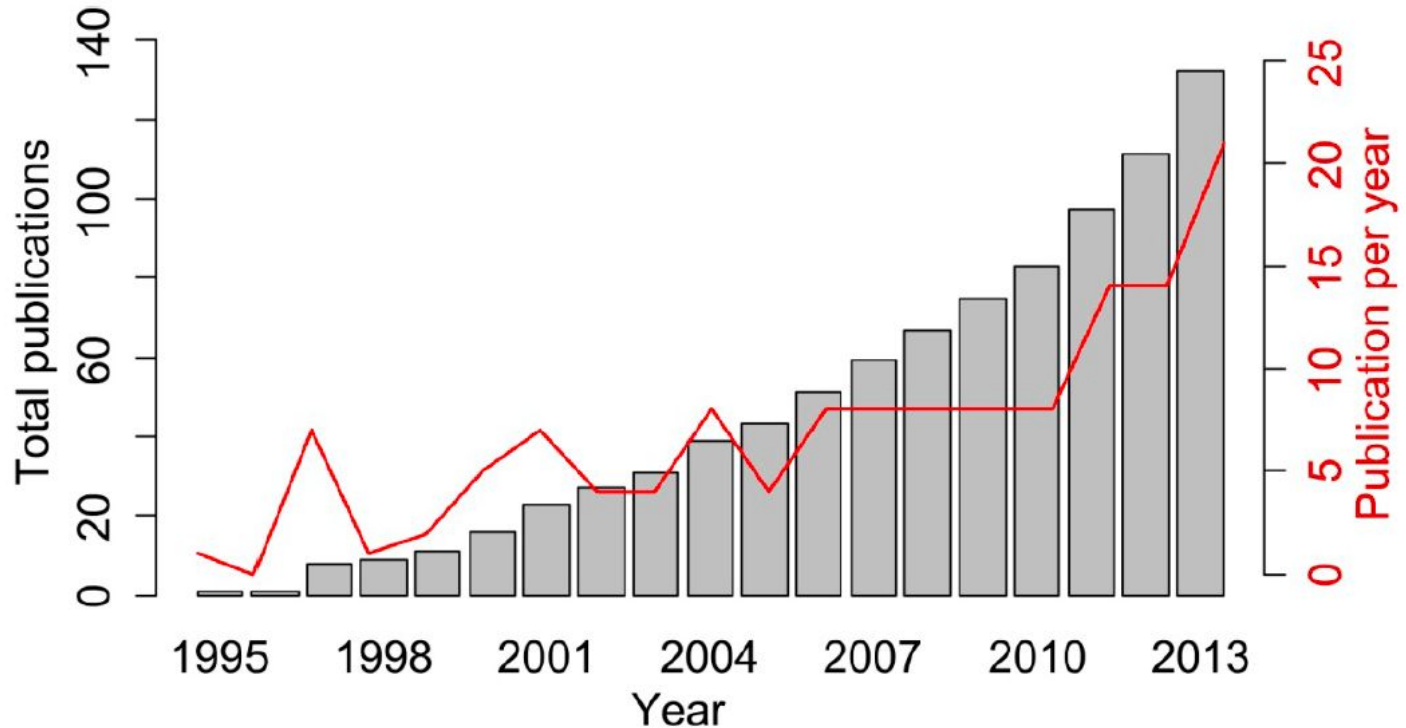
Issues

- Sporadic
- Low granularity
- Expensive
- Inaccurate
- Based on manual surveys
- Little data for remote regions

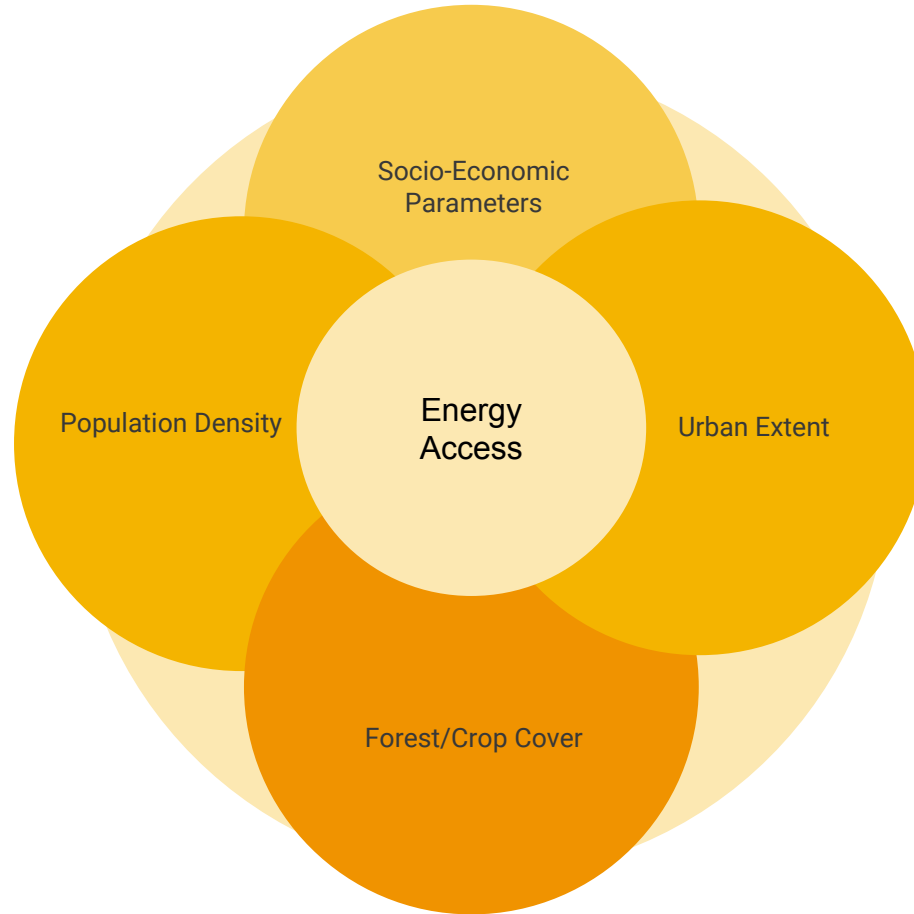
Solution

- Visit time - 12 hours
- High resolution images
- Satellite images widely available
- No bias, 100% accurate
- ML based approach
- Total coverage

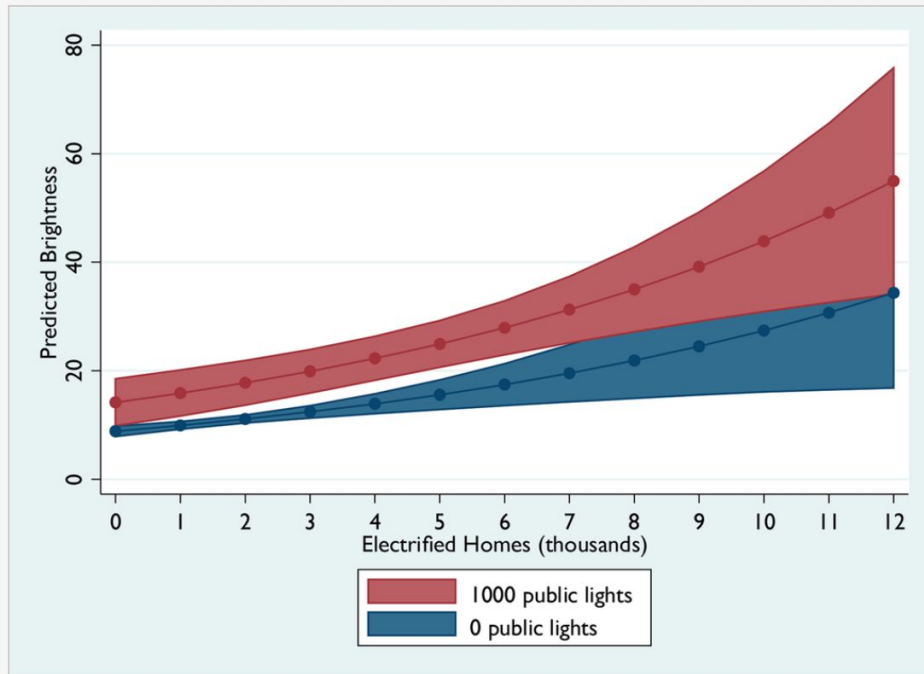
Nighttime Lights Expanding Literature



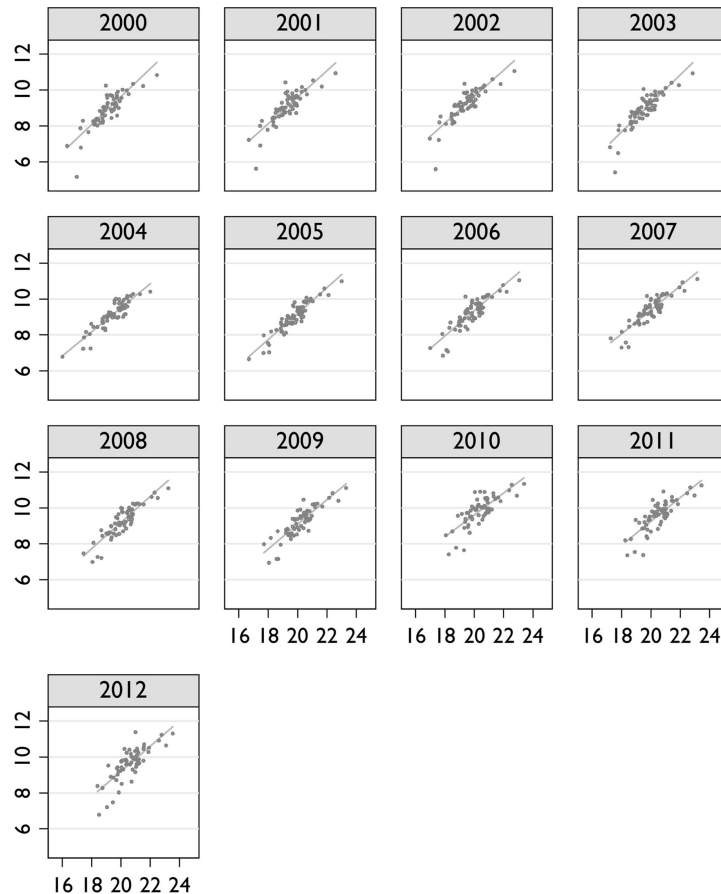
Nighttime Lights Data Uses



Literature Review

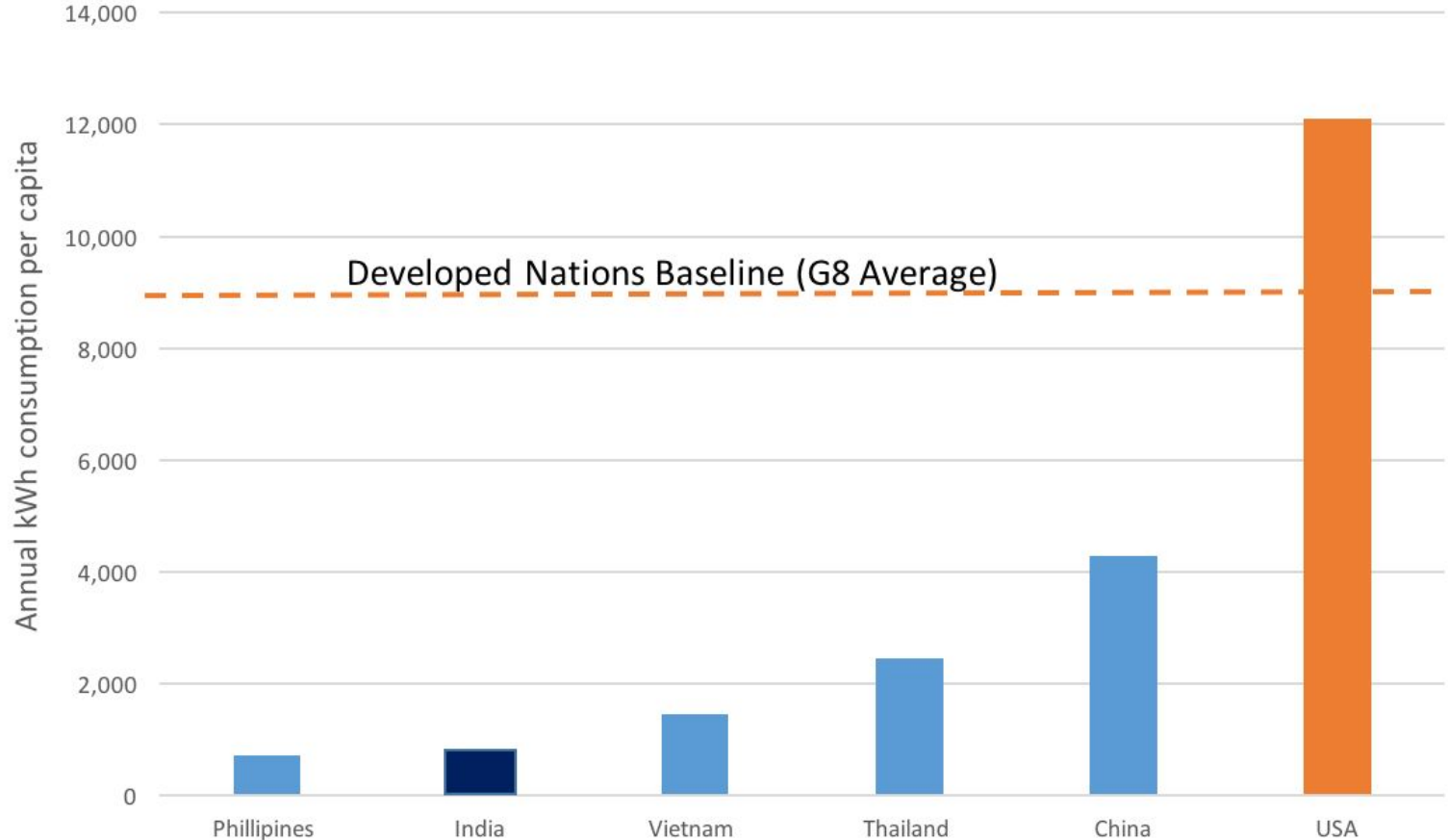


Sum of light output, DMSP-OLS



Total electricity consumption (kWh), EVN
Log scales
Min et. al 2014

Energy Poverty in East Asia



Why India? Why Bihar?

- Large Electricity Access Problem
- Narendra Modi's \$2.5 Billion Power Plan to bring 100% electricity access
- GARV data- useful baseline

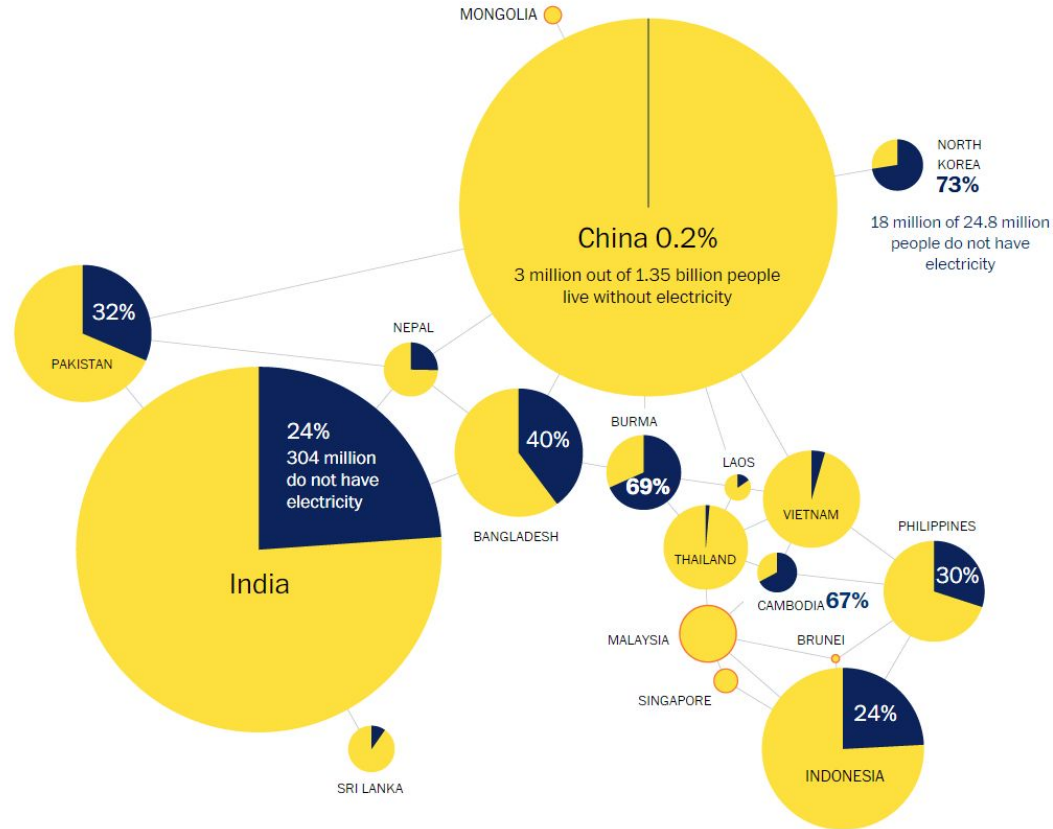
ASIA



Nearly 2 out of 10 people do not have access to electricity

622 million

of 3.6 billion people do not have electricity



*Source: Washington Post. Source does not define electricity access



GARV Data

Census 2011	Village Name	District Name	State Name	Number of Households	Number of Electrified Households
215990	Bhaisalotan	Pashchim Champaran	Bihar	-9	-9
215989	Kalapani	Pashchim Champaran	Bihar	445	42
215991	Tharhi	Pashchim Champaran	Bihar	339	214
216180	Naurangia	Pashchim Champaran	Bihar	-9	-9
216179	Gardi	Pashchim Champaran	Bihar	-9	-9

Valuable for:

- Calculating Percentage Electrification for Lights at Night Villages
- Ground Truth Data; Useful for Training and Validation

Living in the Dark: 240 Million Indians Have No Electricity

50 million rural homes without power despite idle generation.

Power To The People: India Plans To Electrify 40 Million Households By 2018



In 2 years, BJP govt electrified 13523 villages; only 8% were completely electrified

Fateh Nagla, Uttar Pradesh- less than 10% electrification



The Goal



Build an automated, scalable mechanism for predicting electrification using aerial imagery

What can we do with this?

- Identify target areas currently deprived of electricity with ease
- In long term: Assist researchers, policymakers in placement of energy expansion efforts (pre grid-expansion)
- Longer term: Evaluate success and effectiveness of energy expansion efforts, hold accountable (post grid-expansion)



Source: Descartes Labs, Forbes

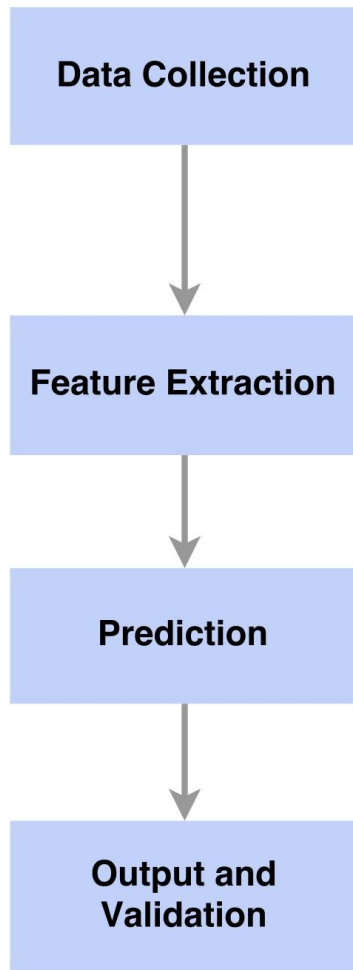


Our Approach

Find a method to determine village-level electricity access in Bihar

Create machine learning model that predicts if a village is electrified and refine this model

Use lights at night data as input and Indian Government Electricity Access Data to train machine learning model



Village	Aadharpur
Mean Radiance	0.43
Max Radiance	0.87

Machine Learning Model

Village	Aadharpur
Predicted	Electrified
Ground Truth	Electrified
Correct?	TRUE

What are lights at night data?

Lights at night is a band of satellite imagery that shows the lights of a region that are visible at night

Indicates built-environment features such as buildings and houses, roads, and other infrastructure

Used for predicting electricity access because it intuitively is indicative of electricity access

Image Processing



Lights at night



Village boundaries



Combined data

0.27

0.32

0.43

0.56

0.76

0.99

2.24

2283.31



10th
Percentile



25th
Percentile



50th
Percentile



Mean



75th
Percentile



90th
Percentile



Max

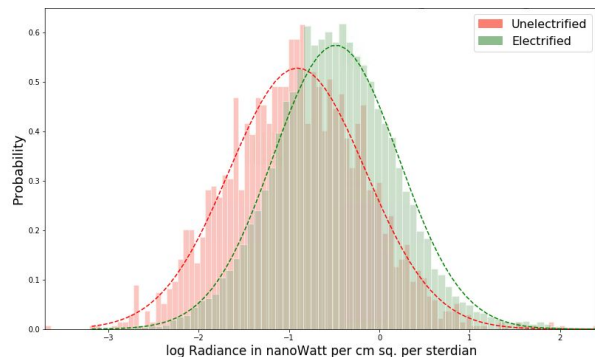


Total Night Lights

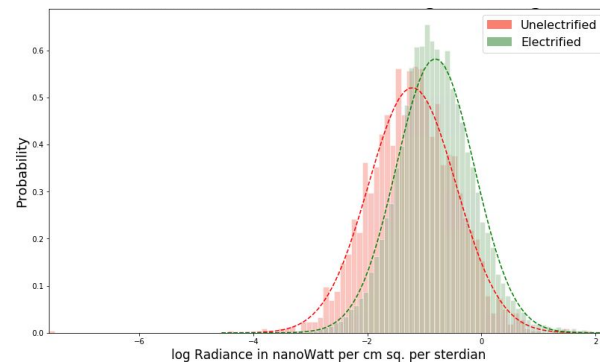
Data Distribution

Max, mean, 10th Percentile, 25th Percentile, Median, 75th Percentile, 90th Percentile of radiance per pixel

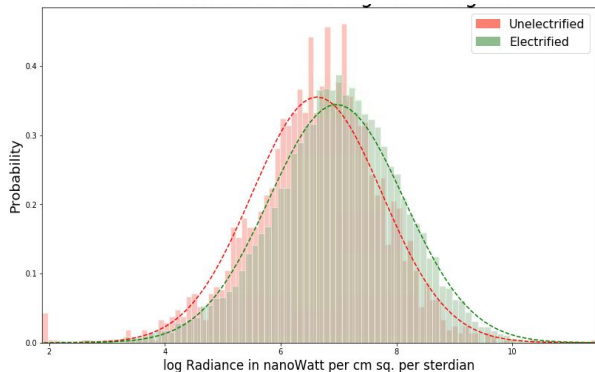
50th Percentile



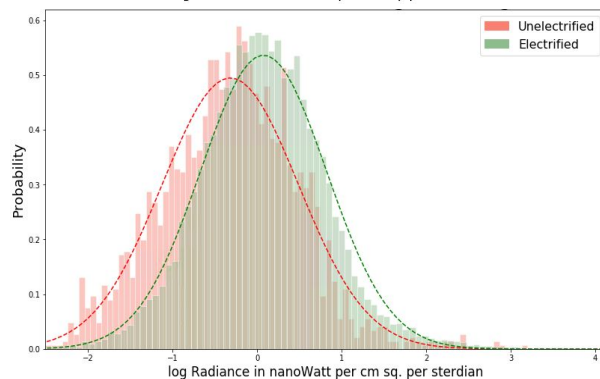
10th Percentile



Total Night Lights



Max



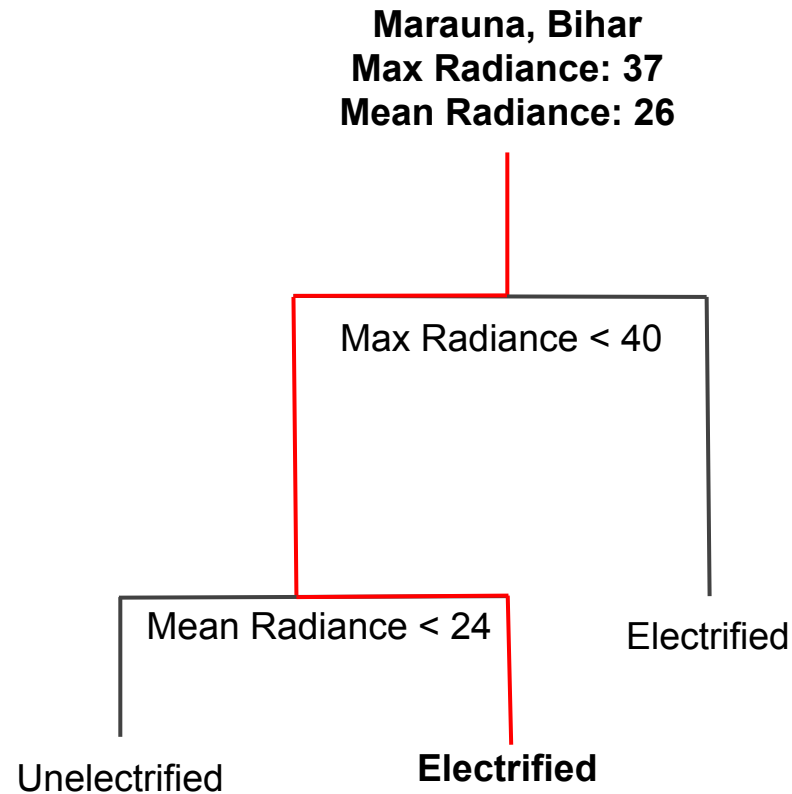


Classification Model

Gradient Boosting Tree Binary Classification Model was selected

Model uses many decision trees to classify villages based on the entire feature space

Decision trees use values of different predictors (such as mean radiance and max radiance) to intelligently group similar villages



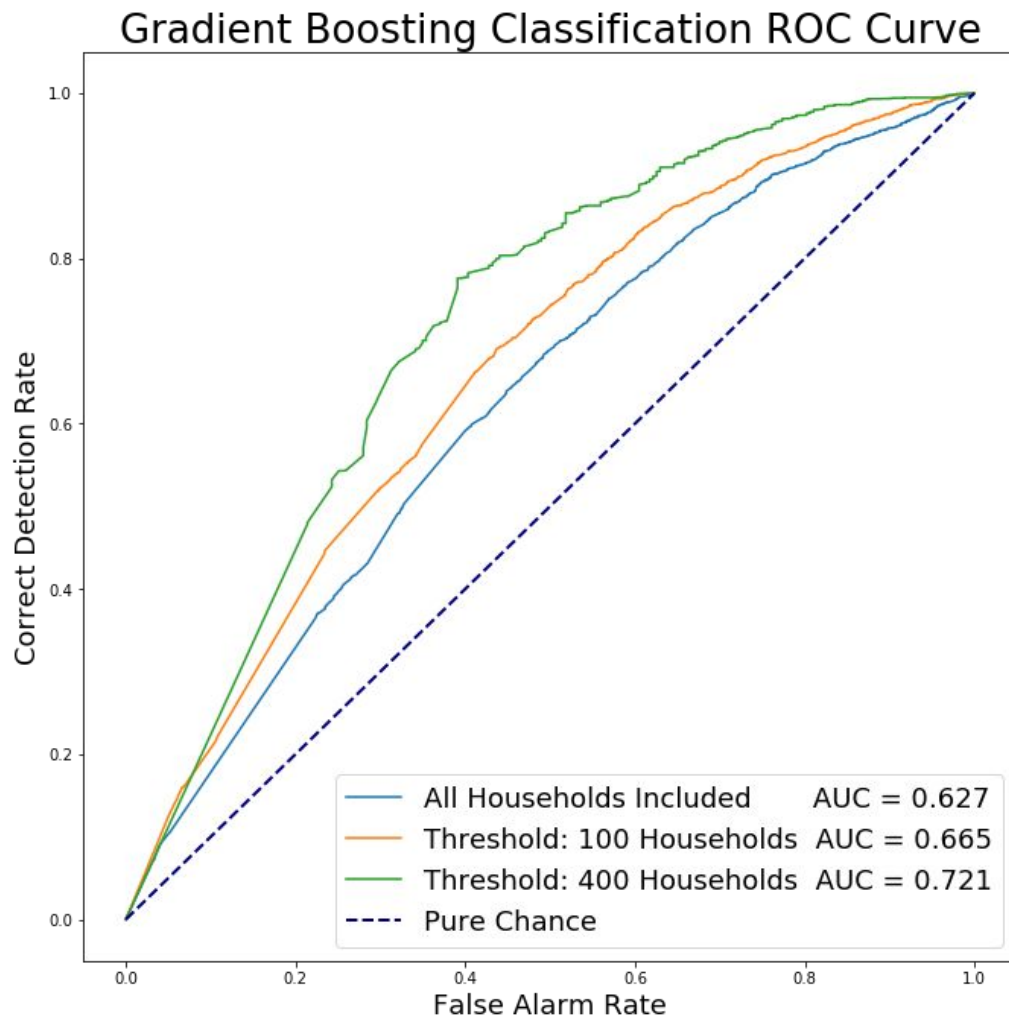


Results & Analysis

Improved results by increasing minimum # households

AUC = 0.627 unfiltered

AUC = 0.721 with threshold of 400 households



Future Work

- Increase dimensionality of model
 - Identify predictive features
 - Improve model accuracy
- Train a neural network
- Extend the model to predict electricity outside of Bihar

Bands

- 1: Coastal aerosol
(0.43 - 0.45 μm)
- 2: Blue
(0.45 - 0.51 μm)
- 3: Green
(0.53 - 0.59 μm)
- 4: Red
(0.64 - 0.67 μm)
- 5: Near Infrared
(0.85 - 0.88 μm)
- 6: Short-wave Infrared 1
(1.57 - 1.65 μm)
- 7: Short-wave infrared 2
(2.11 - 2.29 μm)
- 8: Panchromatic (30-meter)
(0.50 - 0.68 μm)
- 9: Cirrus (1.36 - 1.38 μm)
- 10: Thermal Infrared 1
(10.60 - 11.19 μm)
- 11: Thermal Infrared 2
(11.50 - 12.51 μm)
- 12-23: NDVI
Jan-Dec 2016
- 24-35: green index
Jan-Dec 2016
- 36-47: rainfall data
Jan-Dec 2016
- 48: Nighttime lights



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Questions?





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