Probabilistic Modeling for Power Outages and Adoption of Renewables for Enhancing Power Infrastructure Resilience to Extreme Events

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Doctoral Dissertation Defense
07/09/2025

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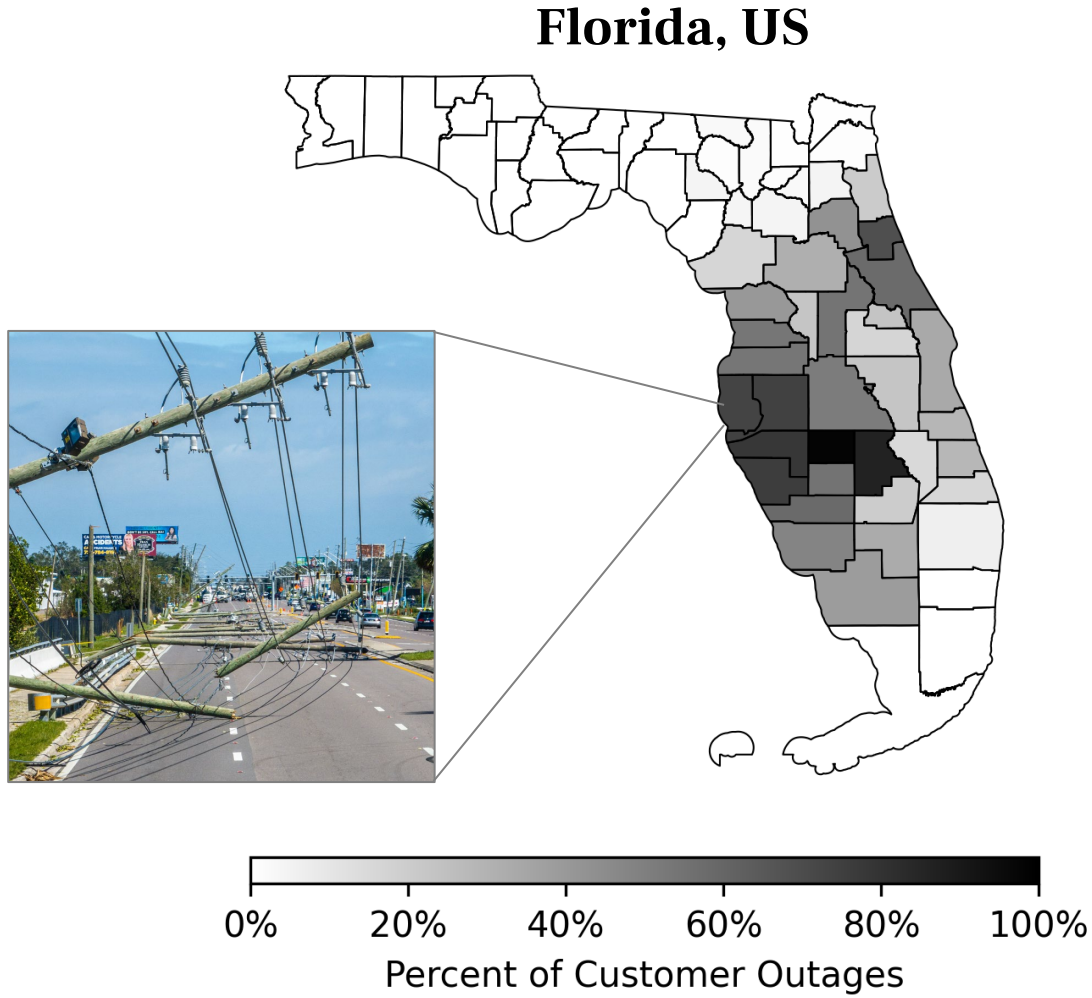
Power Systems are extremely vulnerable to disasters

Hurricane Milton, 10th October 2024

- 3.4 M customers without power at peak electricity loss.
- Systems is centralized and power lines are vulnerable.

More recent blackout events

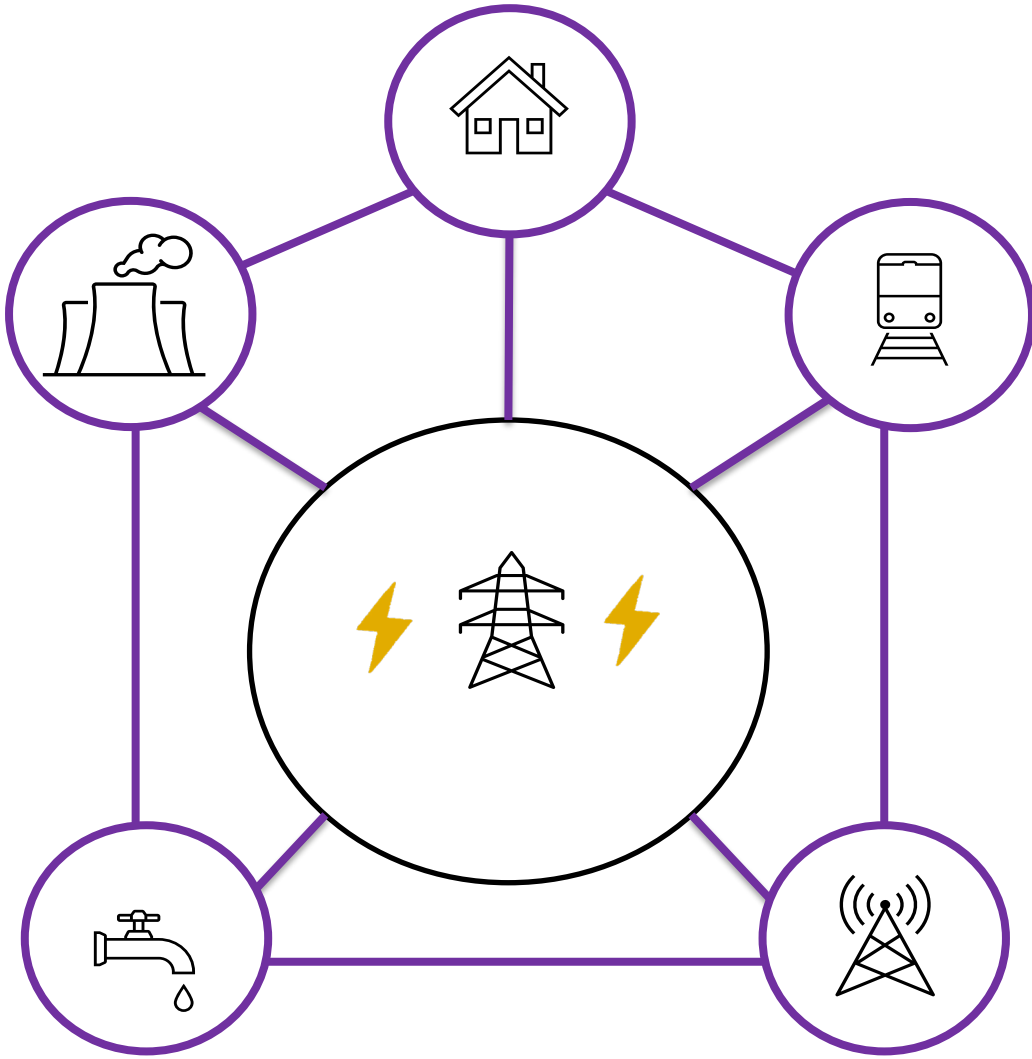
- Hurricane Helene (2024) – 4.7 M
- Hurricane Beryl (2024) – 2.2 M



Source: Florida Public Service Commission; Duke Energy @ Twitter

Power Systems as Critical Infrastructure

- Study **power network resilience** because of interdependencies of critical infrastructure(**e.g., transport, water, hospitals)**.
- Increase situational awareness and decision making for timely interventions.
- Study the interactions of natural disasters with critical infrastructure.
- Understand the power grid resilience across regions.



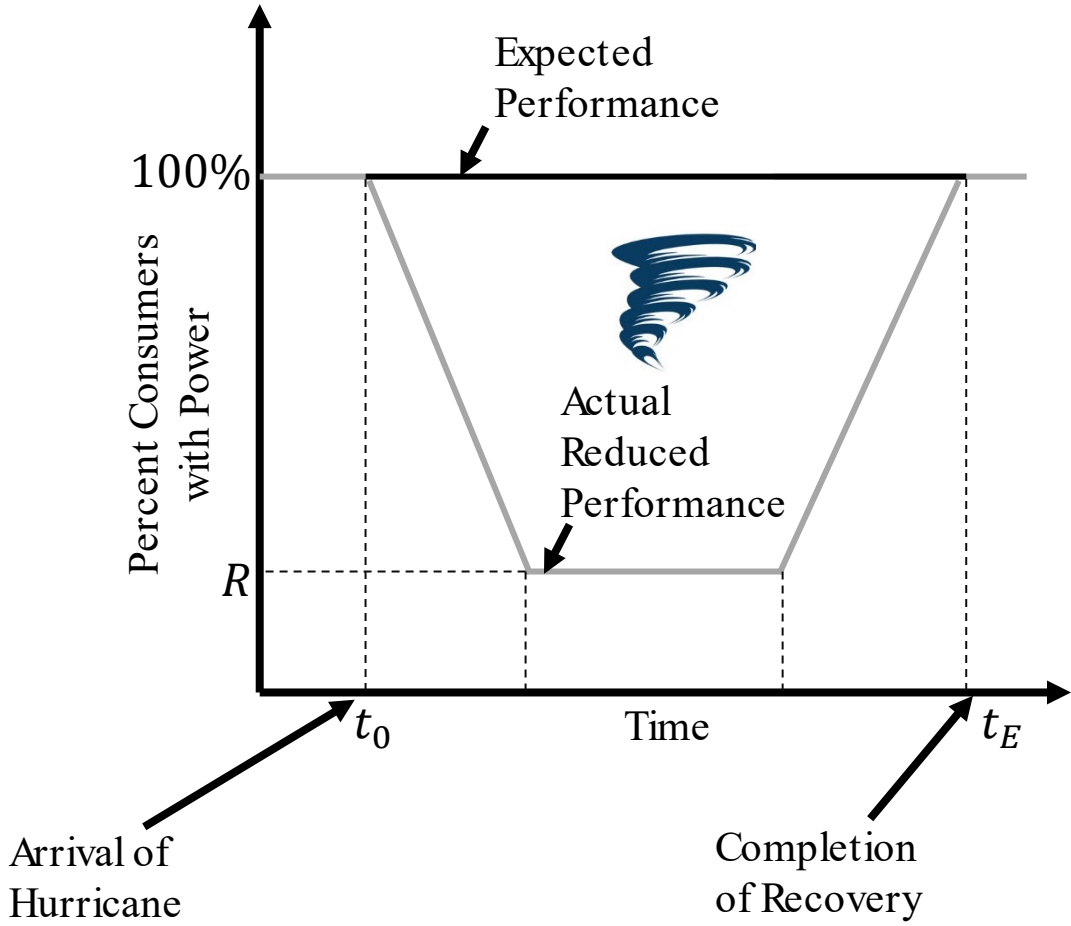
Resilience of Power Grid

Resilience

- Resilient power system should withstand changing conditions and recover rapidly

Resilience Dimensions:

- **Rapidity** – speed of response and repair crews' deployment
- **Robustness** – ability to withstand stress without failure
- **Redundancy** – alternate source of energy and pathways
- **Resourcefulness** – energy backup, crew availability

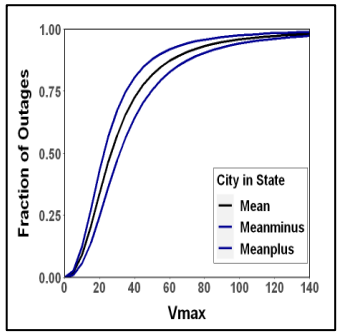


National Academies of Sciences, Engineering, and Medicine (2017); Ouyang et al. (2014)

Can we model and assess the power outage risk and resilience during hurricanes?

Dissertation Overview

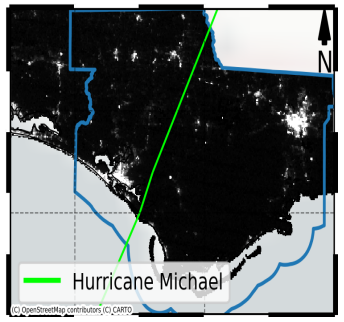
Risk Assessment of Existing Power Systems and the Potential of Renewable Energy



0 1 . Predictive Outage Model



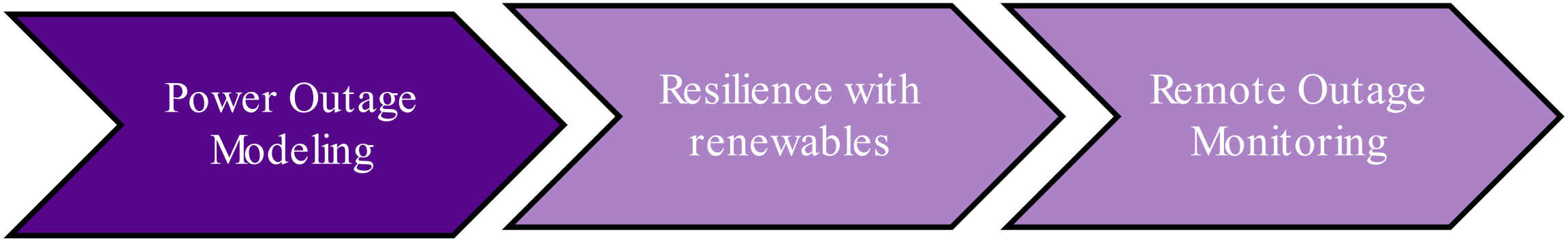
0 2 . Distributed Energy Resources



0 3 . Outage Observations from Satellite

Objectives

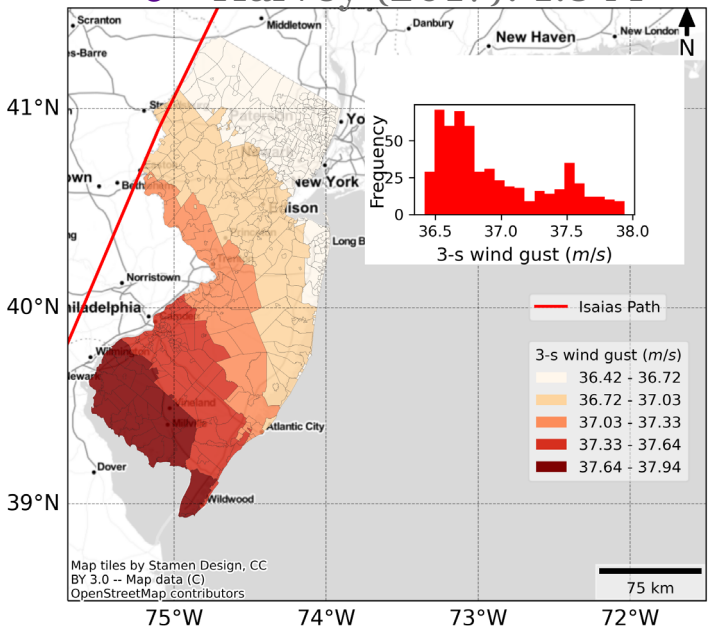
- Developing an outage **model that better captures the mechanistic behavior of power systems** and improves prediction accuracy.
- Assessing the **feasibility of energy communities** with renewables for enhancing resilience during hurricane emergencies.
- Developing the **physics-based relationship between power outages and nightlights** to enable a consistent, globally scalable outage detection approach.


Power Outage Modeling
Resilience with renewables
Remote Outage Monitoring

Background

Data (~2,300 cities)

- Ida (2021): 1.2 M
- Isaias (2020): 3.8 M
- Michael (2018): 1.6 M
- Harvey (2017): 1.3 M



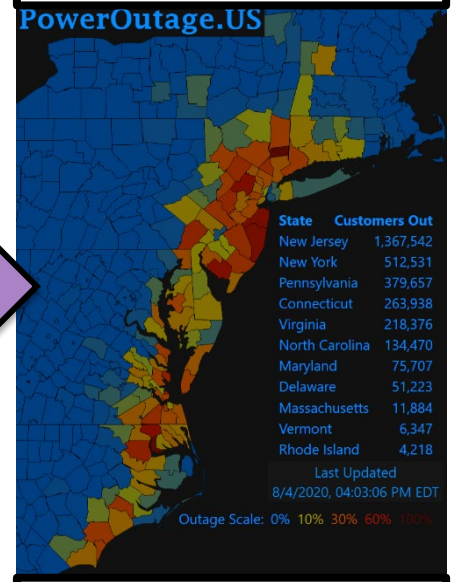
Inputs

- Hurricane Winds
- Precipitation
- Soil Moisture
- System Variables
- Population Density
- Land Cover
- Root Zone Depth
- Treed Area
- Elevation

Probabilistic Models

(Power Outage Data for Historical Hurricanes)

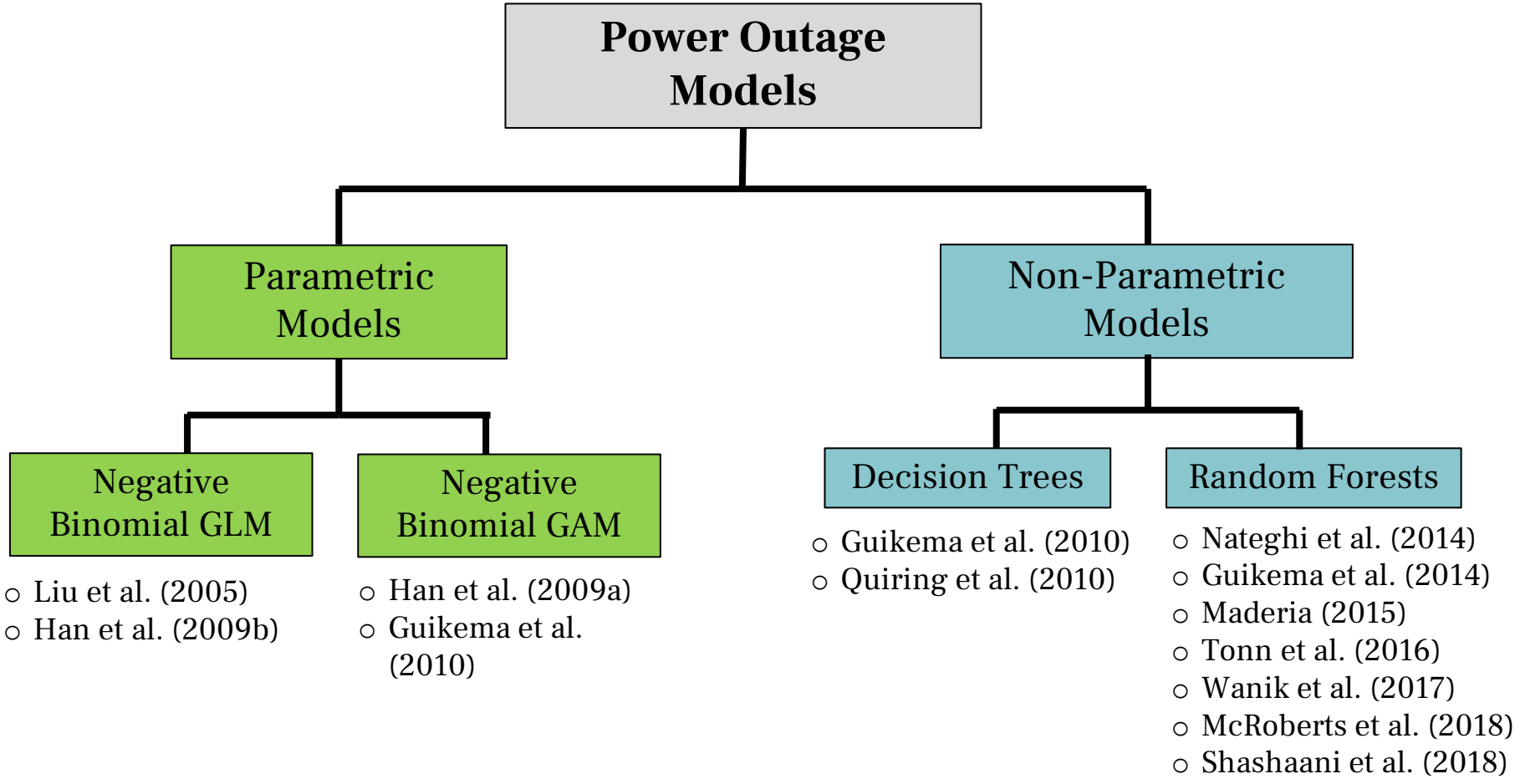
Power Outage Modeling



Preparedness and Crew Deployment

Arora & Ceferino, Nat. Haz. Earth Sys. Sci. 23, 1665-1683 (2023)

Literature: Existing Power Outage Models

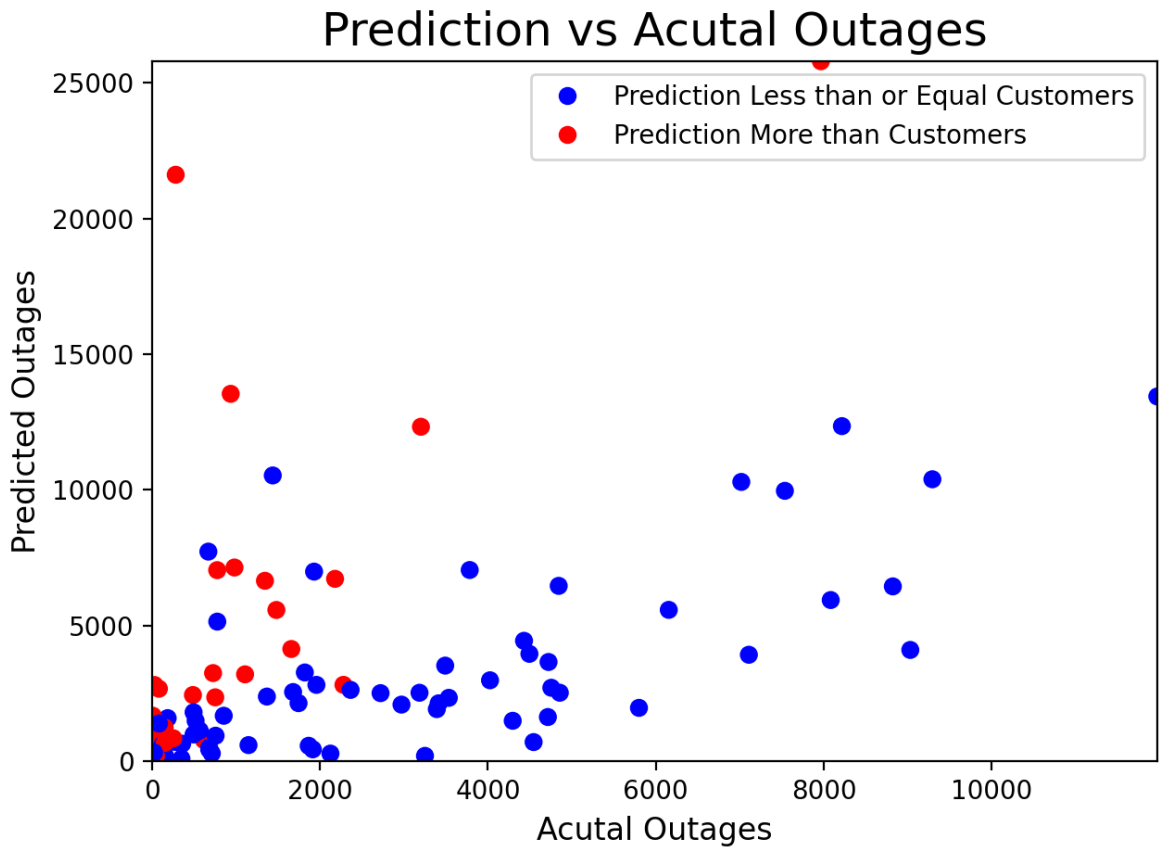


Arora & Ceferino, Nat. Haz. Earth Sys. Sci. 23, 1665-1683 (2023)
Arora & Ceferino, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng. 10 (2), 04024027 (2024)

Limitations I: Outage Overpredictions

Negative-Binomial regressions do not have an upper bound

- In some counties (in red), predictions where above the number of customers
- This limitation can be addressed by imposing a cap on the predictions (or changing the model)

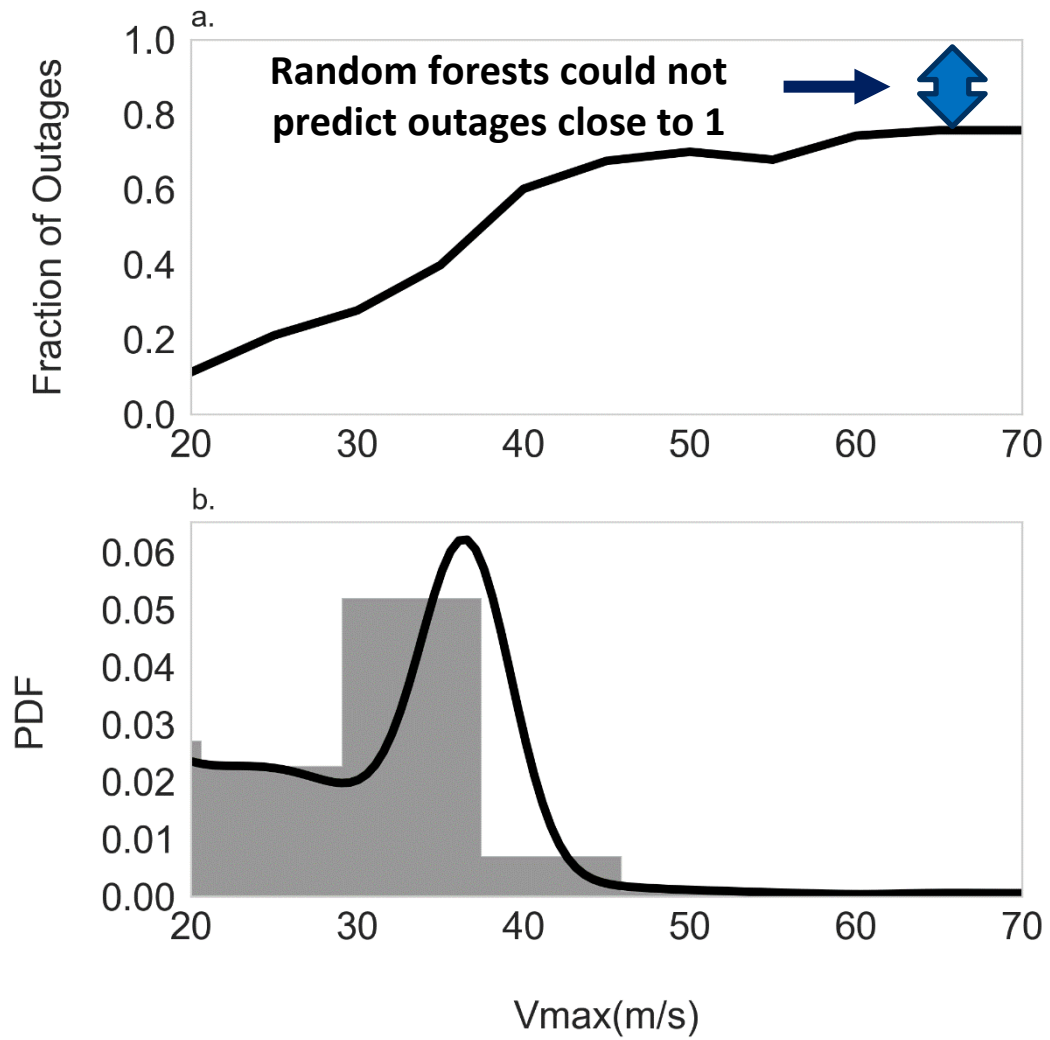


Arora & Ceferino, Nat. Haz. Earth Sys. Sci. 23, 1665-1683 (2023)

Limitation II: Non-parametric models extrapolate poorly

Non-parametric models could not reproduce high outage ratios

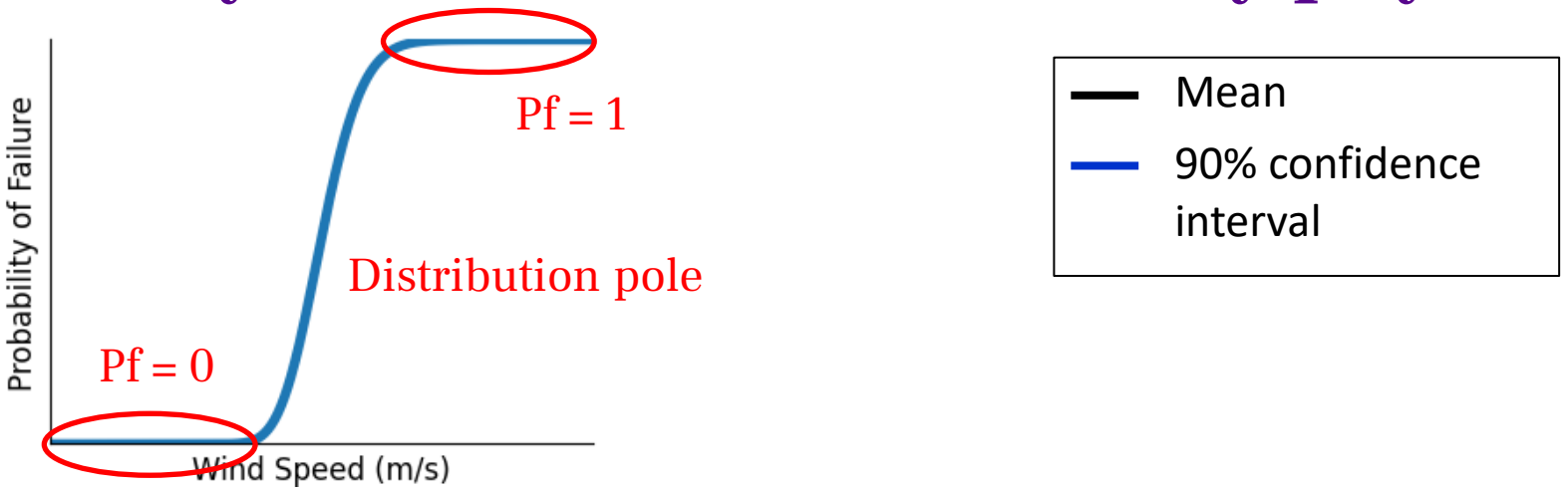
- Random forest models can reproduce non-linear effects within the training range
- But, they are not suitable for extrapolation. Thus, they struggle in many disaster applications with scarce data



Arora & Ceferino, Nat. Haz. Earth Sys. Sci. 23, 1665-1683 (2023)

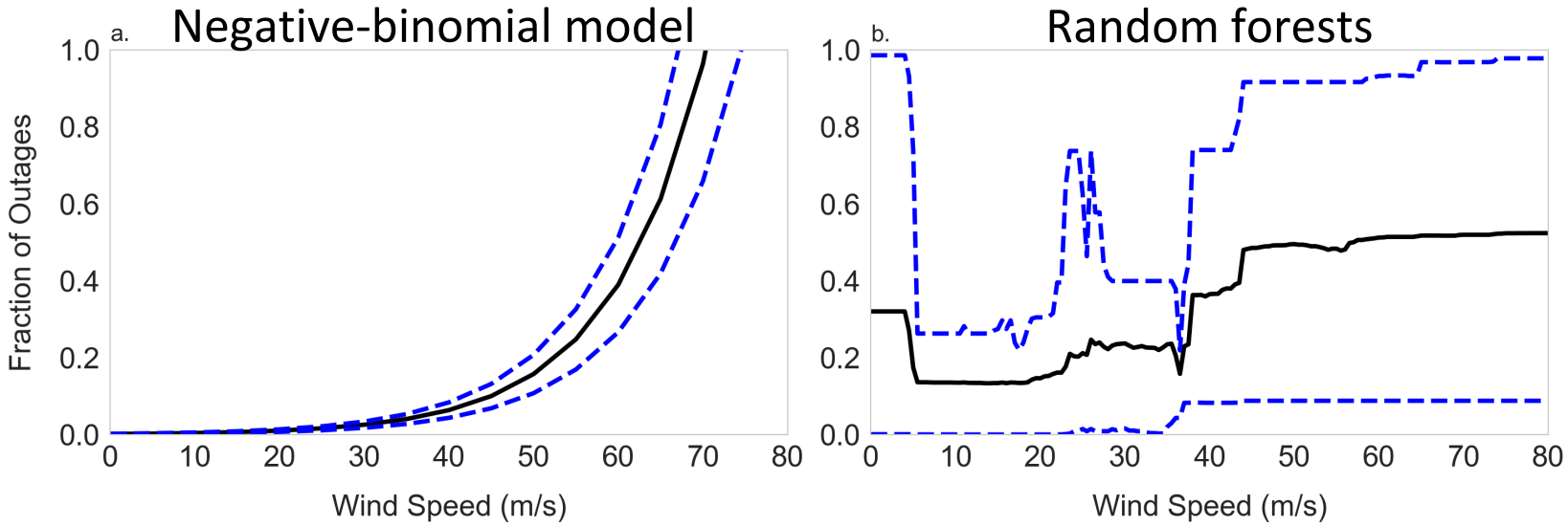
Limitations III: Uncertainty is not well constrained by physics

Hypothesis: uncertainty must be small at high and low winds



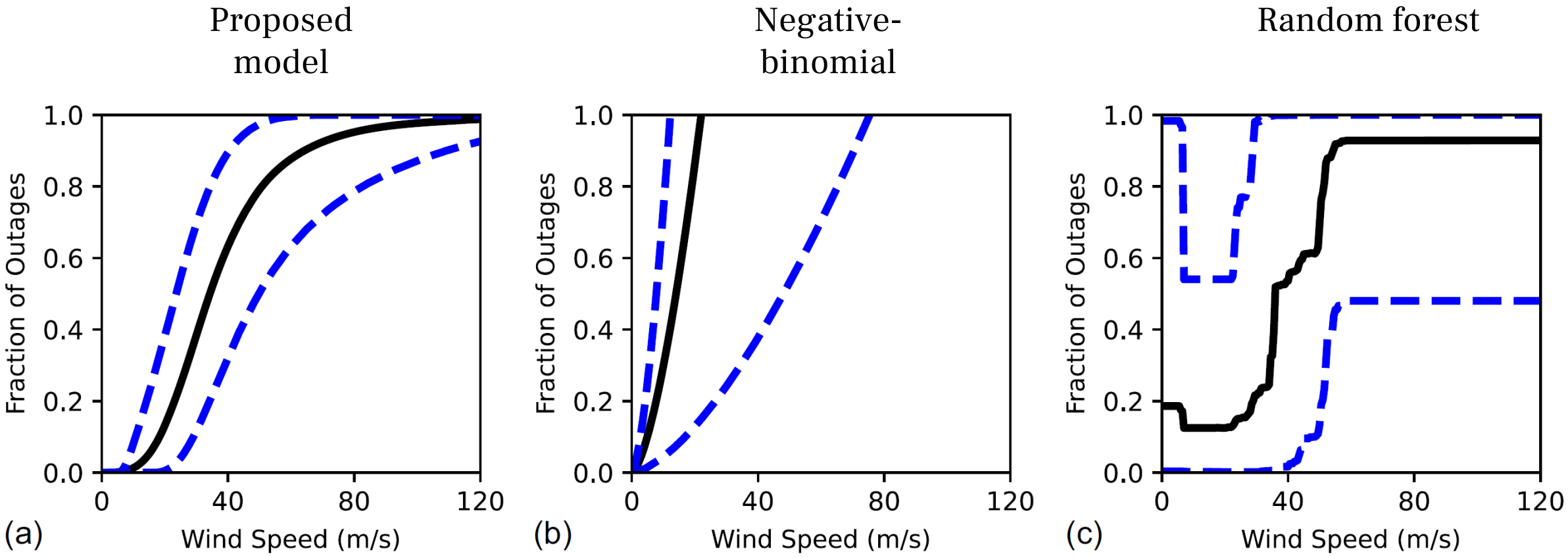
However:

- Negative binomial has increasing variances (due to formulation)
- Random forest cannot calibrate well uncertainty due to lack of data



Arora & Ceferino, Nat. Haz. Earth Sys. Sci. 23, 1665-1683 (2023)

Quasi-binomial power outage model to address these limitations



Arora & Ceferino, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng. 10 (2), 04024027 (2024)

Quasi-binomial Power Outage Model

- Appropriate when response variable is in proportion and distributed from zero to one.
- Fraction of consumers without power (y) in a city can be modeled as quasi-binomial

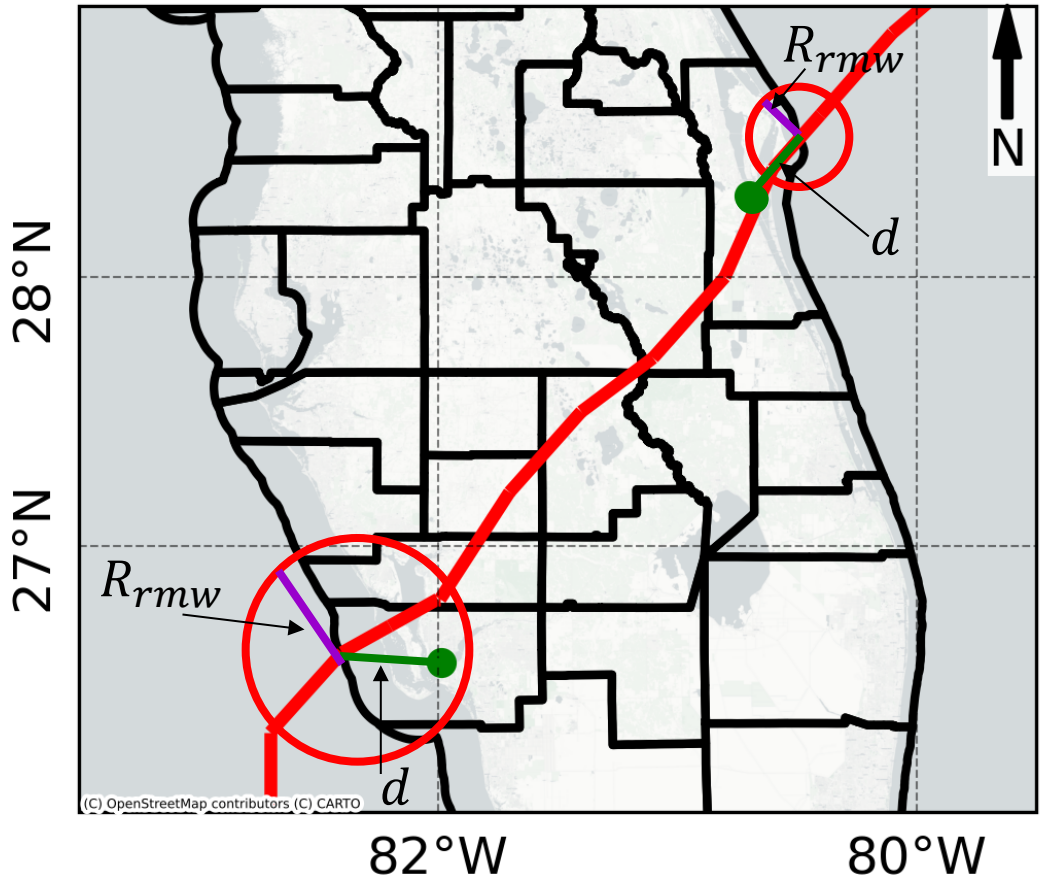
Link between Fraction of Consumers without power and Inputs:

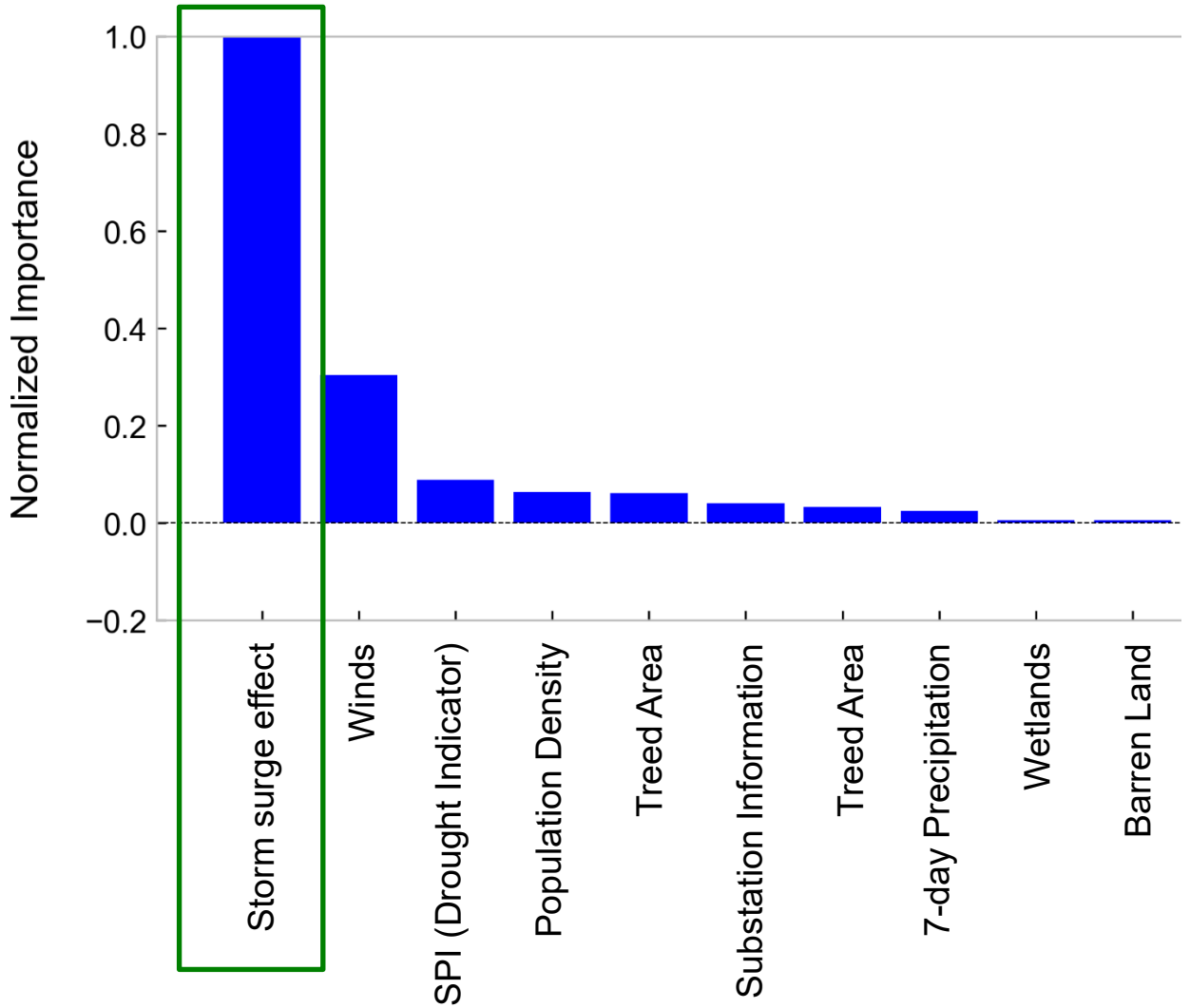
$$\log\left(\frac{\mu}{1-\mu}\right) = \alpha + \sum_{i}^{p} f_i(X_i)\,;$$

$$E[y] = \mu;\ \mathrm{Var}[y] = \phi(1-\mu)\mu$$

Compound Damage from Storm Surges

Storm Surge Effect: $\frac{d}{R_{rmw}}$





Arora & Ceferino, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng. 10 (2), 04024027 (2024)

Overcoming Limitations with Quasi-binomial Power Outage Model

Bounded predictions

- Maximum possible outages are equal to number of consumers

Hazard to Risk Propagation

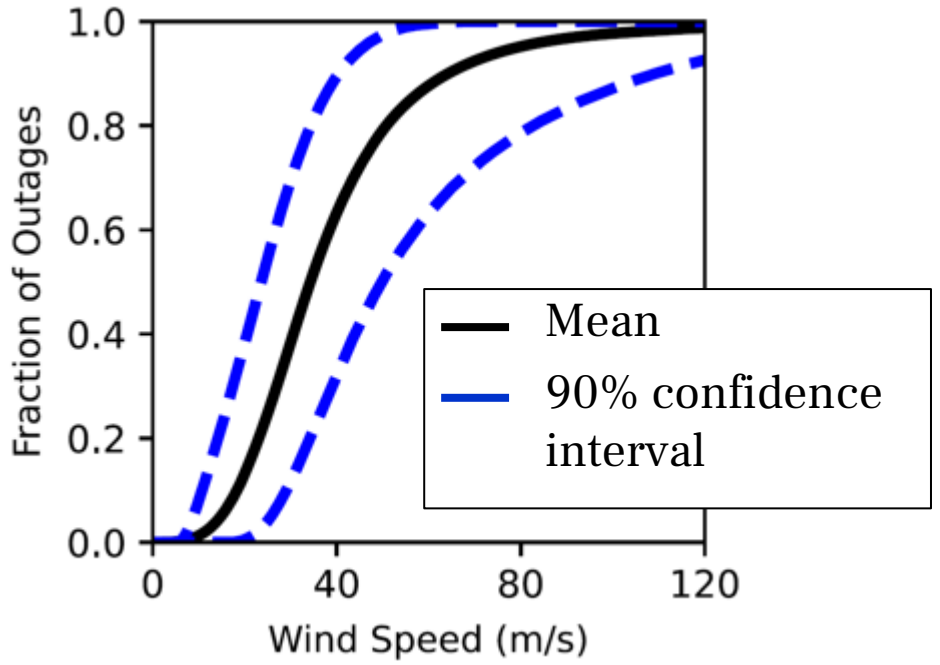
- Increase in outages with increase in wind speed

Uncertainty Quantification

- Close to no damage at low and high damage at high wind speeds

Damage from storm surge

- Storm surge along coastal cities can exacerbate the damage to power systems; include storm surge indicator

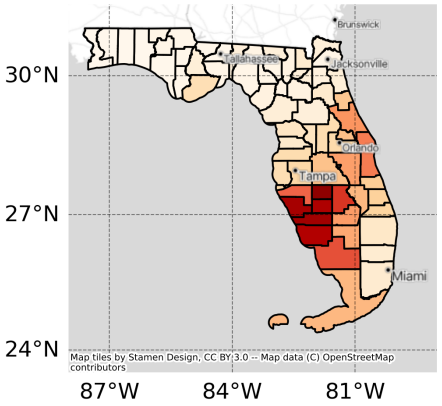


Variation of outages with wind speed

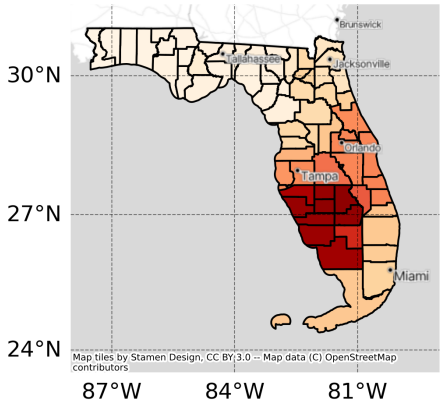
Arora & Ceferino, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng. 10 (2), 04024027 (2024)

Test on Hurricane Ian (2022): 3.1 M outages

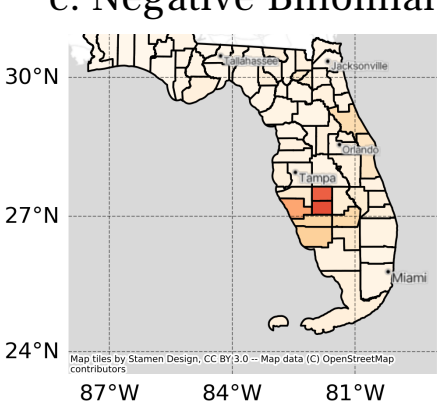
a. Quasi-Binomial



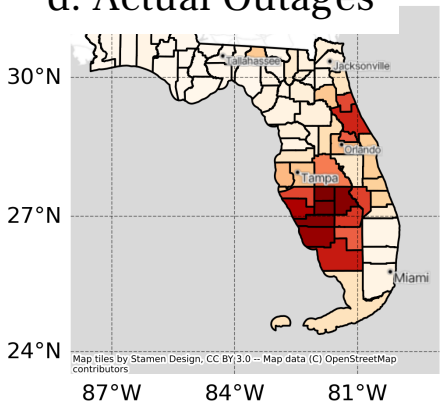
b. Random Forest



c. Negative Binomial



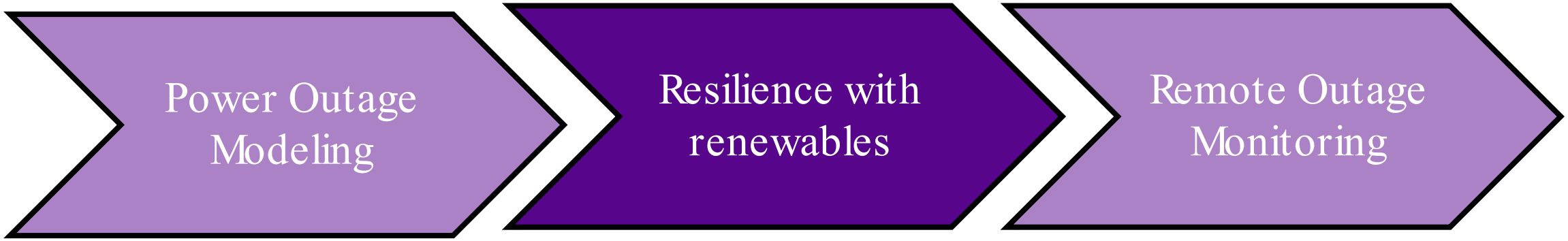
d. Actual Outages





Fraction of customers without power

Regression Model	Total Outages	Error on Total Outages
Quasi-Binomial	2,886,413	7.04%
Random Forest	4,649,134	49.72%
Negative Binomial	735,768	76.30%
Actual Outages	3,105,294	


Power Outage Modeling
Resilience with renewables
Remote Outage Monitoring

Distributed Energy Resources (DERs) can enhance the resilience of vulnerable power systems

DERs' features for resilience:

- **Decentralization**: energy avoids old and vulnerable power lines
- **Recent example**: Hurricane Ian (2022) caused 2.7 million outages in Florida, USA. However, Babcock Ranch community continued to have the power supply for 2000 households from solar energy

Goals:

- Quantify the resilience value of solar panels
- Evaluate solar generation during a hurricane emergency



Patel *et. al.* (2021)

Solar Panels' Structural Vulnerabilities

Solar panel vulnerability

- Structural performance in the Caribbean after Hurricane Irma and Maria in 2017 and Dorian in 2019
- **46 rooftop** installations and **14 ground-mounted** installations
- Common failures: clip and racking failures; rooftop attachment failures



Rooftop panels



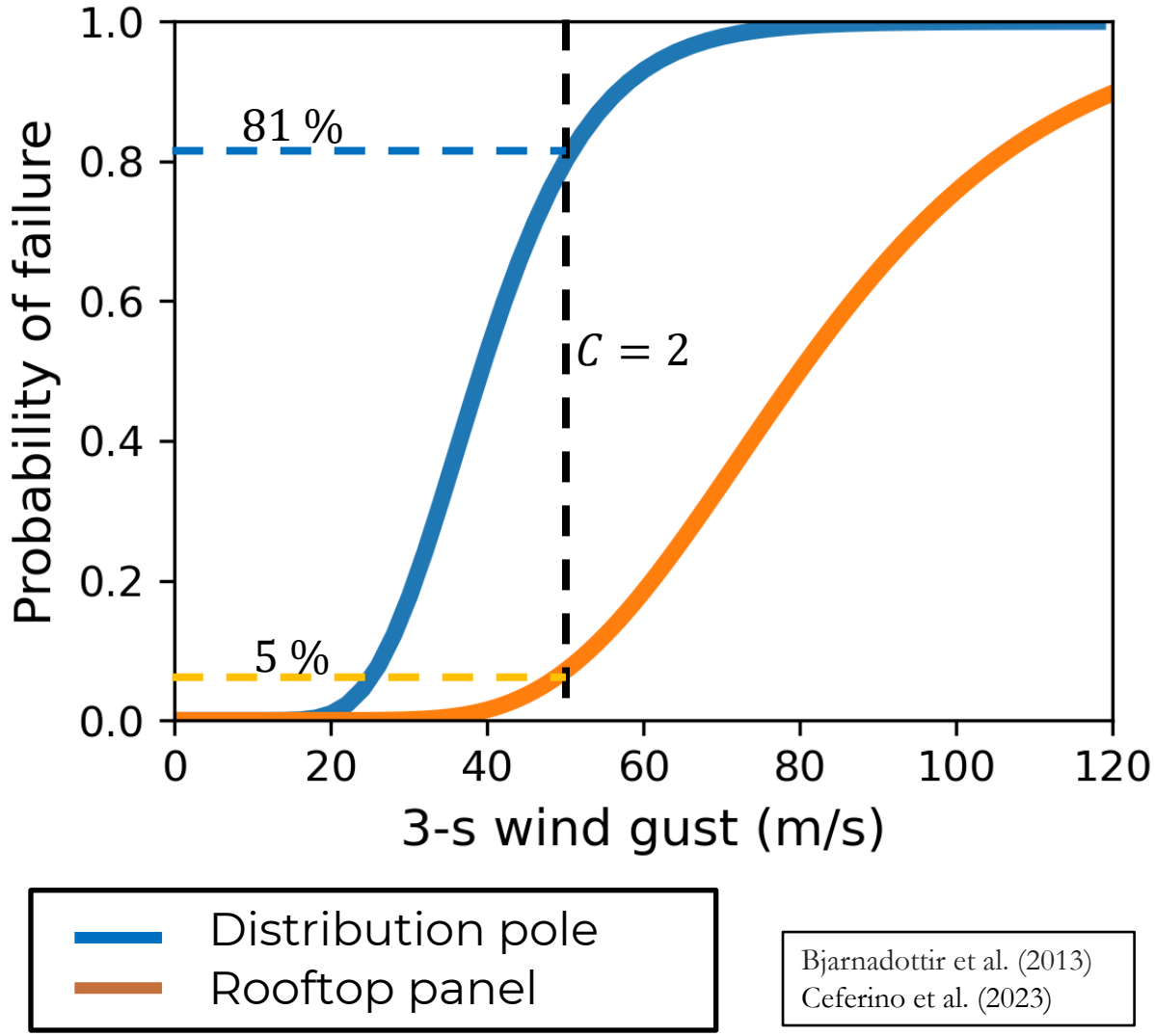
Ground-mounted panels

Source: "Solar Under the Storm" by Rocky Mountain Institute

Solar Panels' Structural Vulnerabilities

Solar panel vulnerability

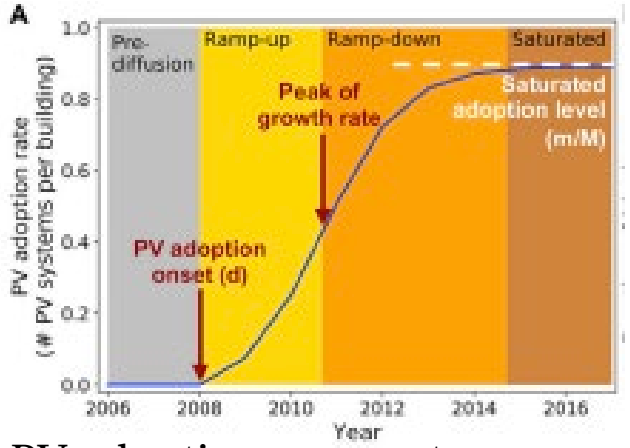
- Structural performance in the Caribbean after Hurricane Irma and Maria in 2017 and Dorian in 2019
- **46 rooftop** installations and **14 ground-mounted** installations
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Bjarnadottir et al. (2013)
Ceferino et al. (2023)

Literature: Assumptions and Limitations of previous studies

- Adoption of solar by individual households



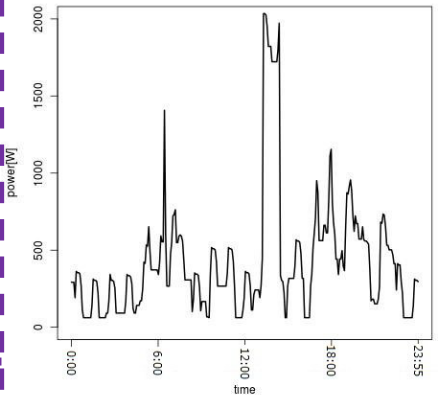
PV adoption may not even reach 100% (Wang et. al. (2022))

- No damage to panels



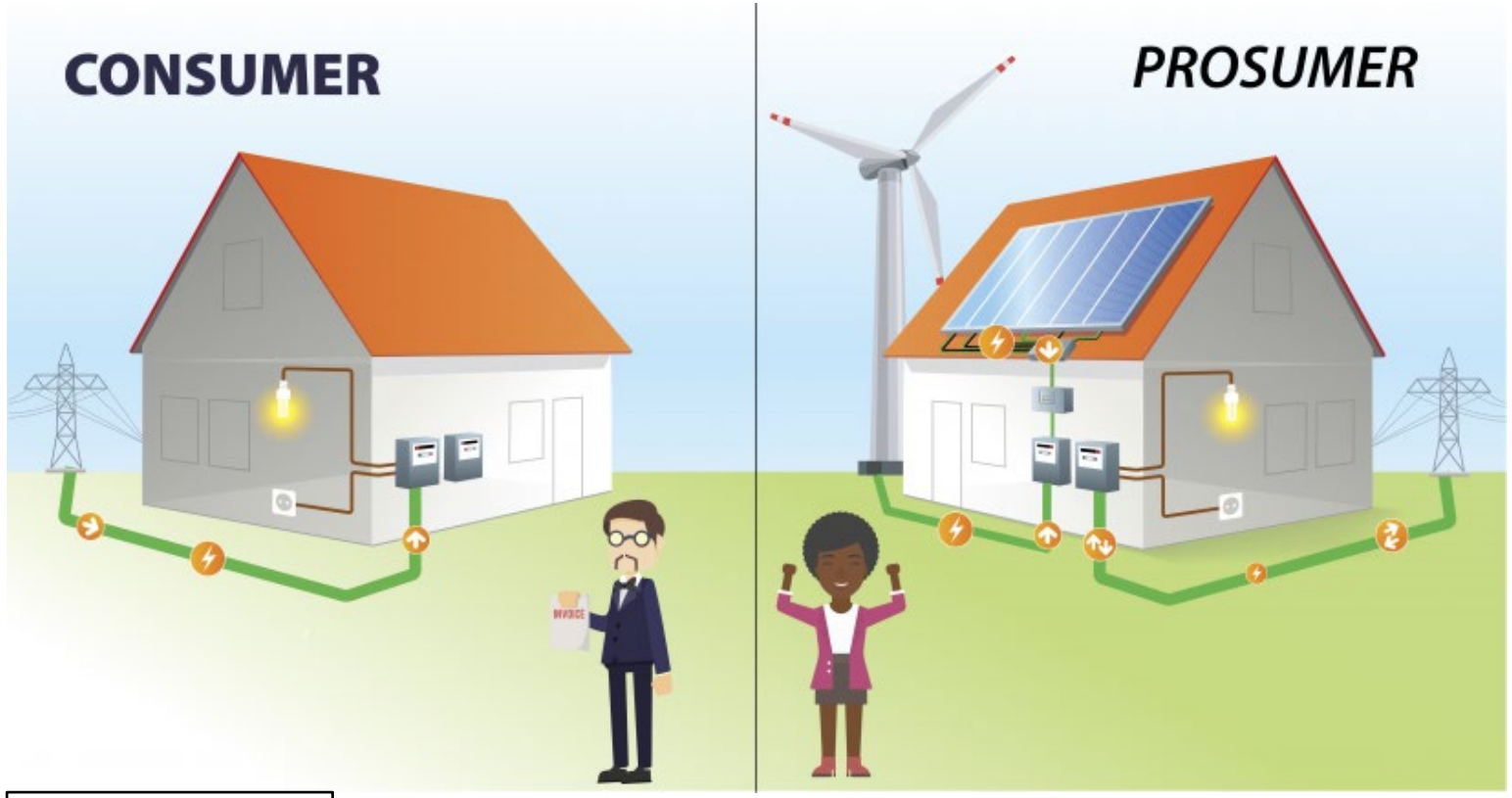
Panel damage post Hurricane Ian (2022)

- Constant power loading



Variable load profile (Shen et. al. (2011))

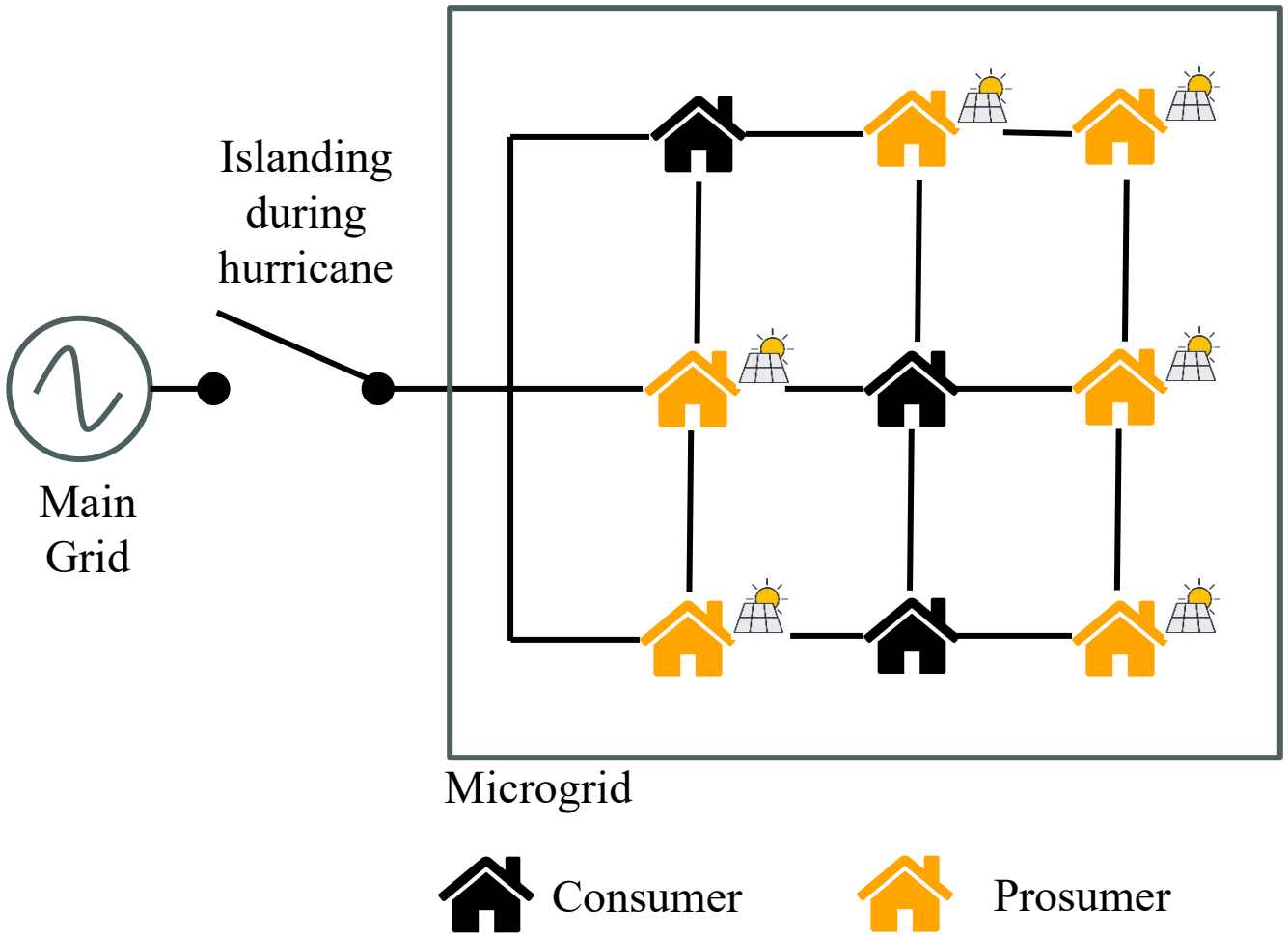
Background: Energy Communities (Microgrids)



Source: Energy.gov

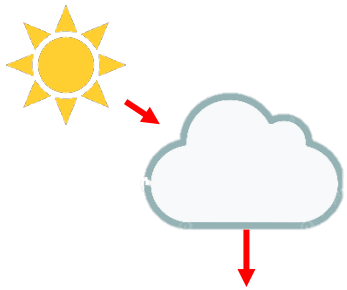
- Instead of selling electricity back to grid: **net metering, sell electricity locally**
- **Local selling price ≤ net metering rate**
- Example: Brooklyn Microgrid
- In most cases current electricity distributor is still important

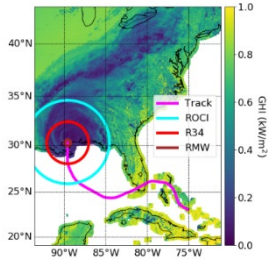
Can we depend on solar power to sustain power outages?



Modeling Framework

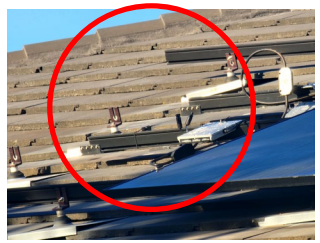






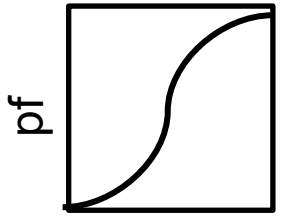
Solar Irradiance

Hurricane Hazard



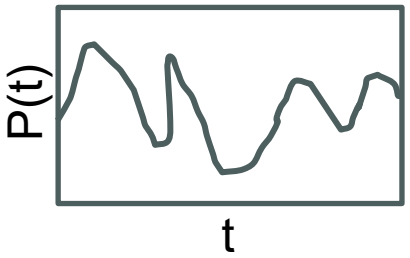
Generated Power

Panel Failure



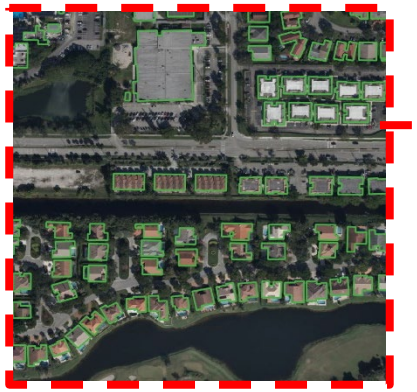


Grid's Failure

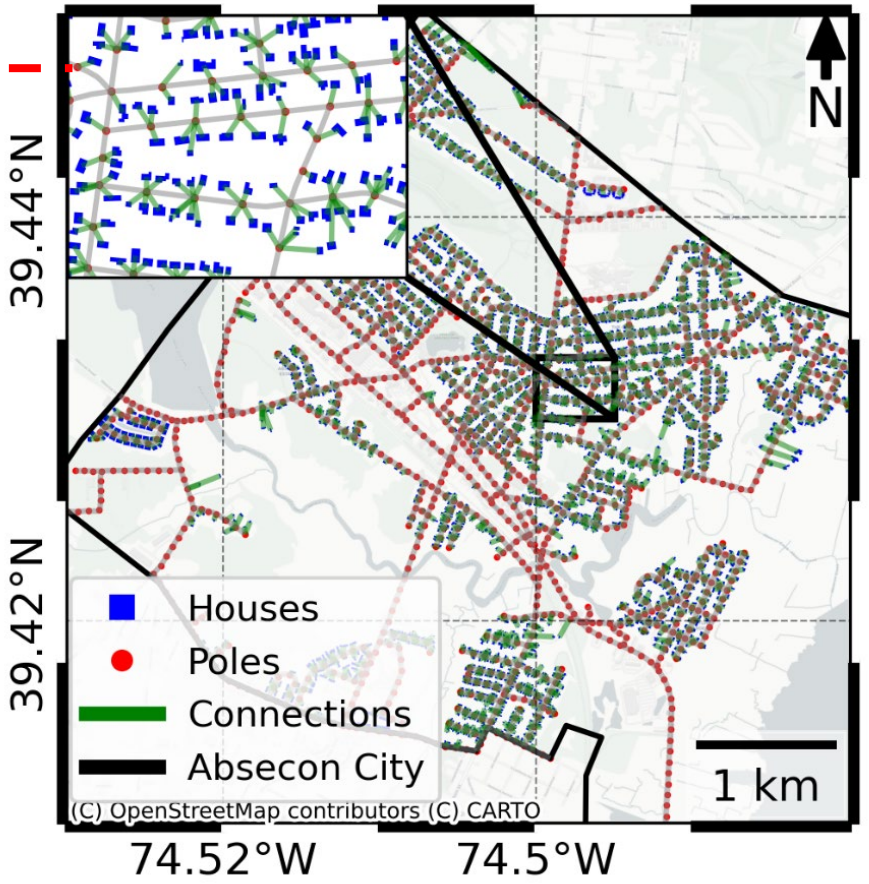


Synthetic High-Fidelity Outage Risk Model for Energy Sharing

- Grid data is not open source: security concerns.
- **Solution: Synthetic Grid** (Zhai *et al.*, 2021).
- **Open-Source Data:** roads, parcels, building footprints, limited pole location from open street maps, and consumption data from NREL based on construction year and built area.
- Calibrate grid recovery for historical outages: **fragility of poles and recovery time.**
- Simulation for energy during grid islanding for 2,640 households.

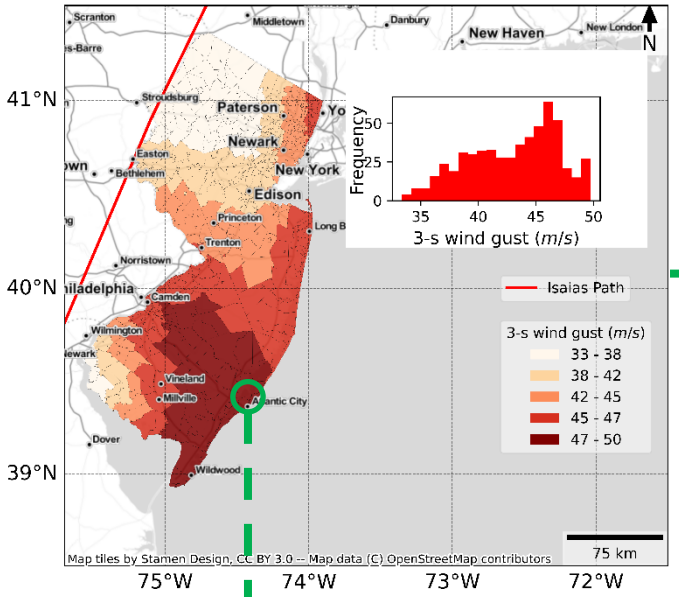


Synthetic Network: Absecon City, NJ



Calibration for Historical Outage During Hurricane Isaias (2020)

Hurricane Winds: obtained from tropical cyclone model based on hurricane track from IBTRACS

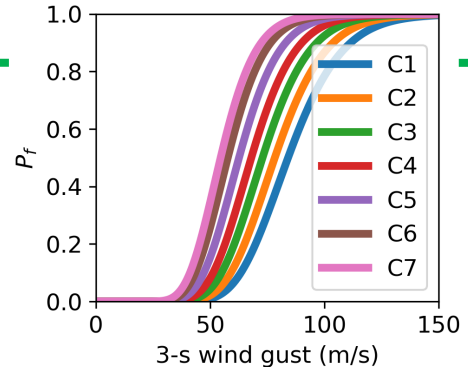


Failure of Poles

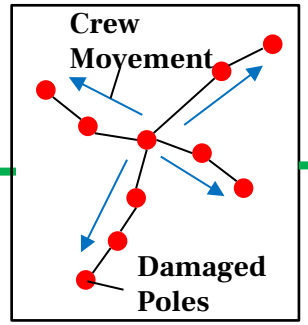


$$p_f = \phi\left(\frac{\ln\left(w/\bar{w}\right)}{\beta}\right)$$

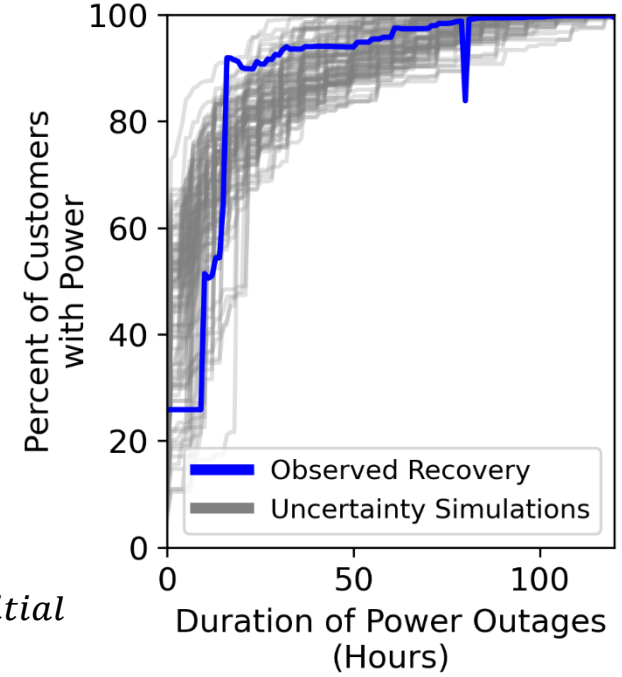
ϕ: *standard normal*
w: *observed* $3-s$ *wind gust*
$\bar{w}$ *and* β: *median and dispersion*



Recovery

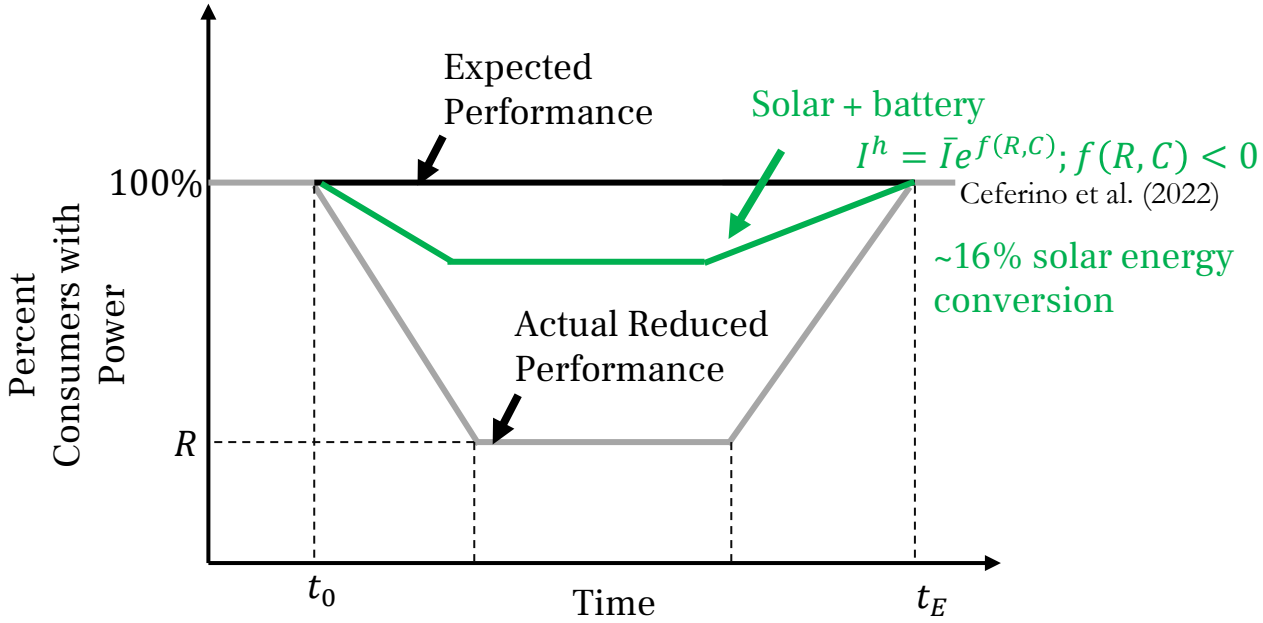


$$t \sim d \cdot t_{repair} + t_{initial}$$



Update Network: disconnect the network at failed poles (**nodes in networkx**) – **record all the previous connections**

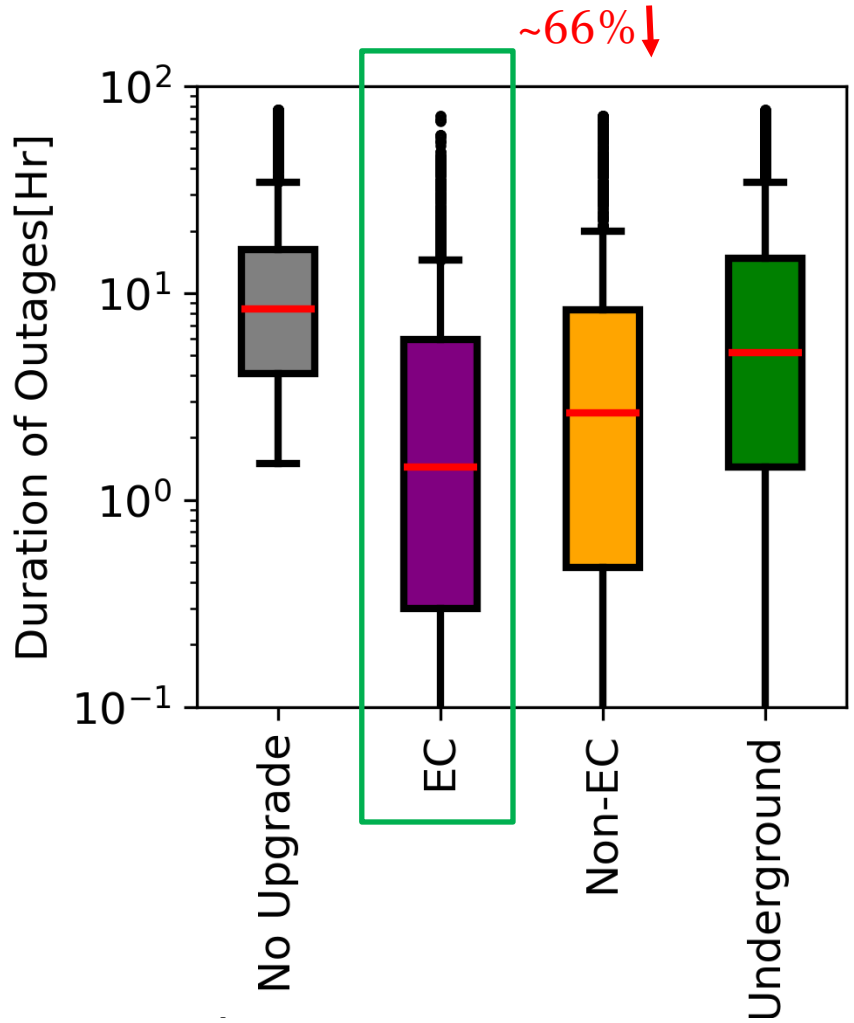
Feasibility of Energy Communities for Resilience during Hurricanes



Grid Configurations:

- **No upgrade:** no grid hardening measure.
- **EC: energy sharing** with 50 % of houses have solar panels in a **cluster of ~ 10 homes.**
- **Non-EC: no energy sharing** with 50 % of houses have solar panels.
- **UG:** undergrounding poles with budget similar to solar panel adoption.

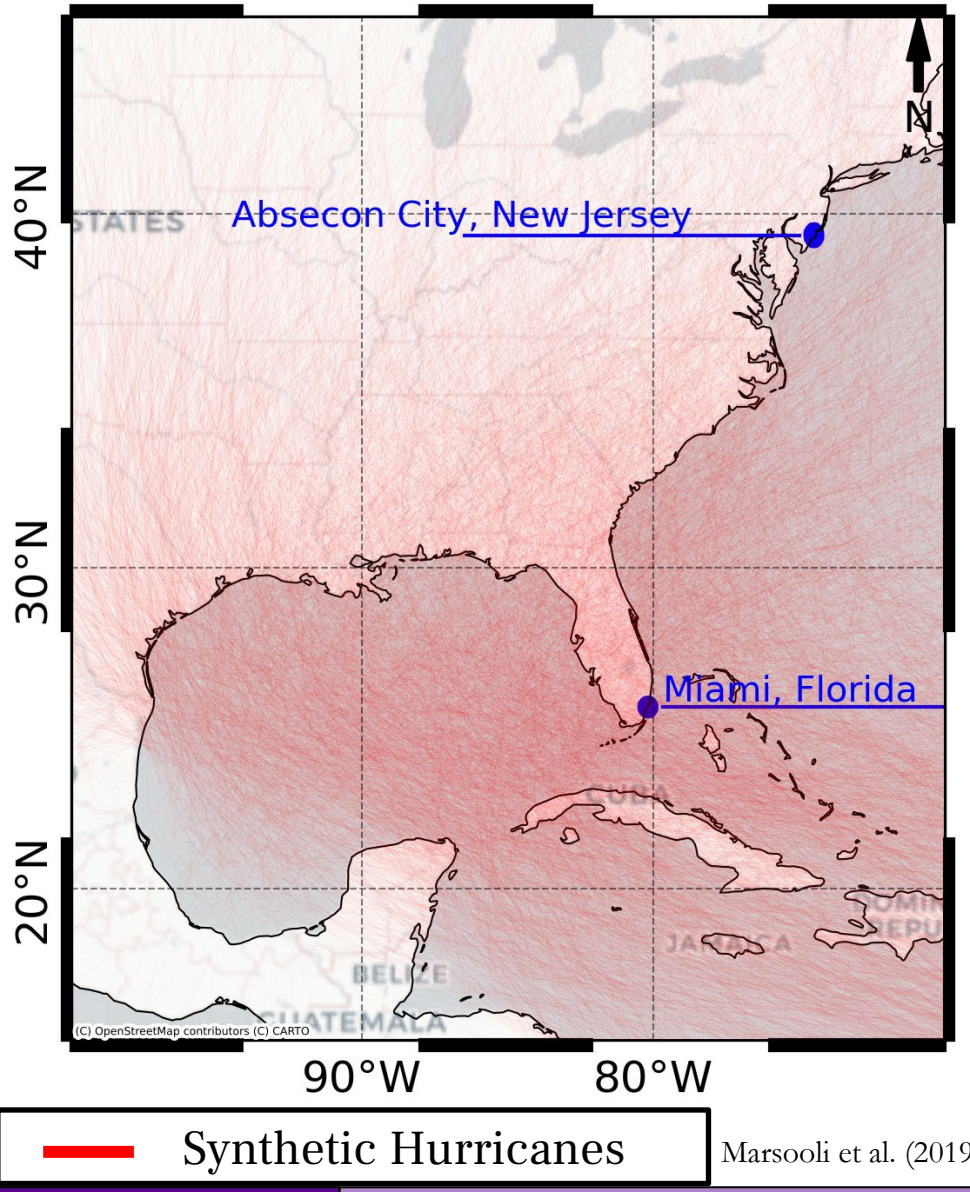
Hurricane Isaias (2020) Scenario



Arora & Ceferino, Preprint (2024)

Assessing Feasibility in Stronger Wind Regions

- Hurricane Isaias was a Category “1” Storm.
- US is exposed to more stronger hurricanes, e.g., 2024 Category “5” Hurricane Beryl with 165 mph winds.
- **Miami experiences ~38% greater 100-year return period winds than Absecon City.**
- Feasibility of energy communities in Absecon City and Miami with **5,018 landfalling NA synthetic Hurricanes**.
- **Monte Carlo Simulation for 1,485 years** of simulation with 3.38 landfalling hurricanes per year

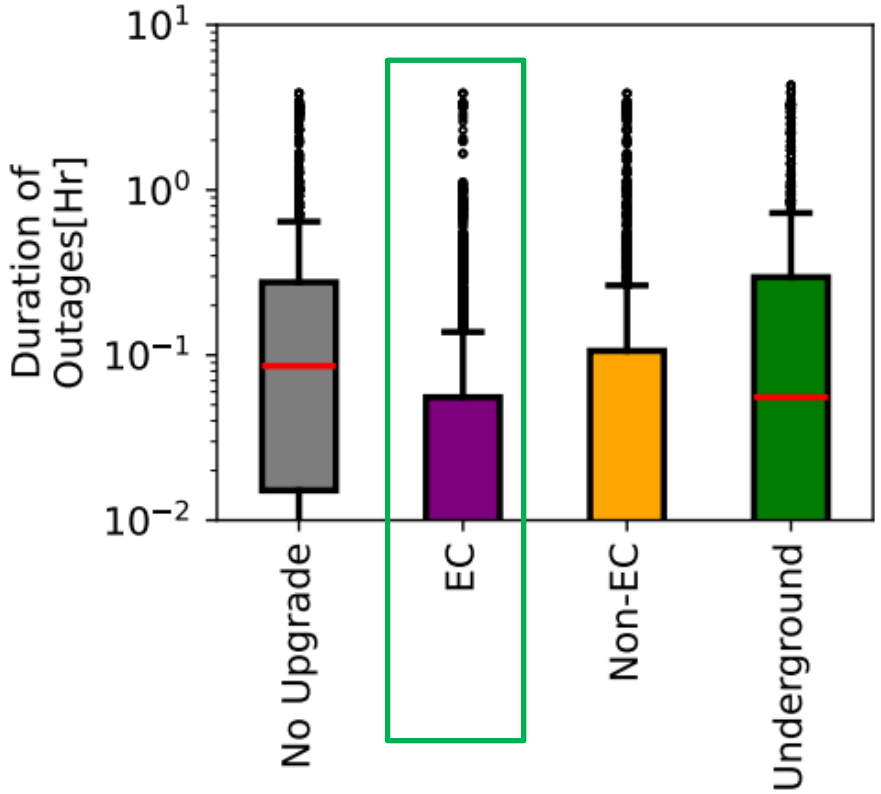


Marsooli et al. (2019),

Outage Durations to Future Hurricanes

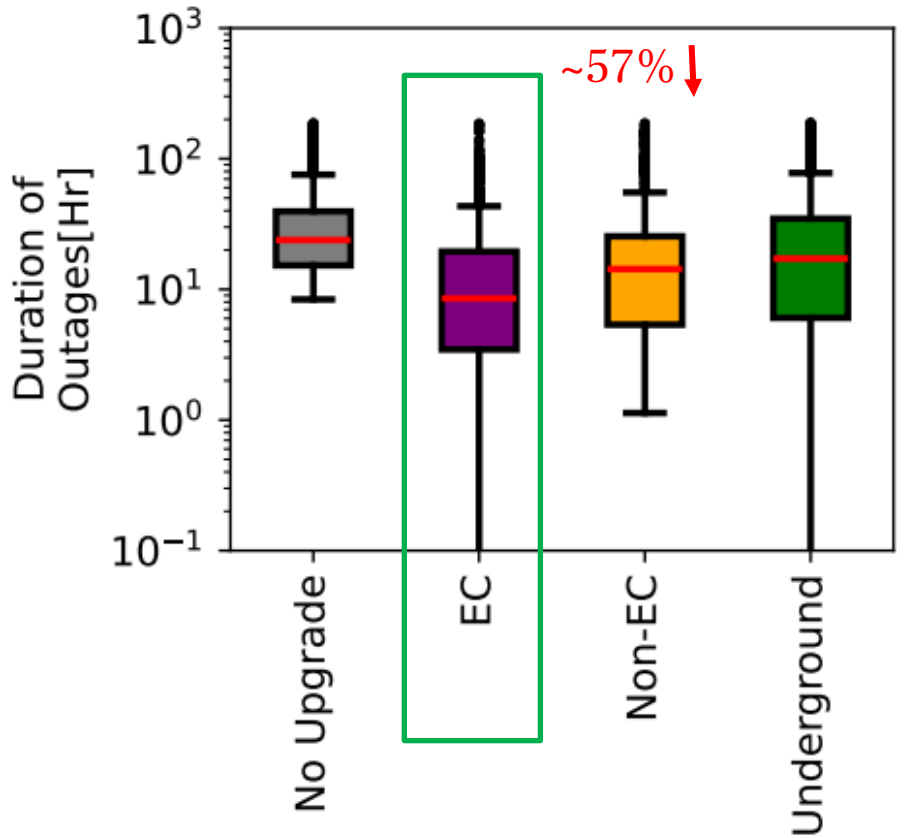
Time period: 25 years

Absecon



Minimal gains in Absecon

Miami

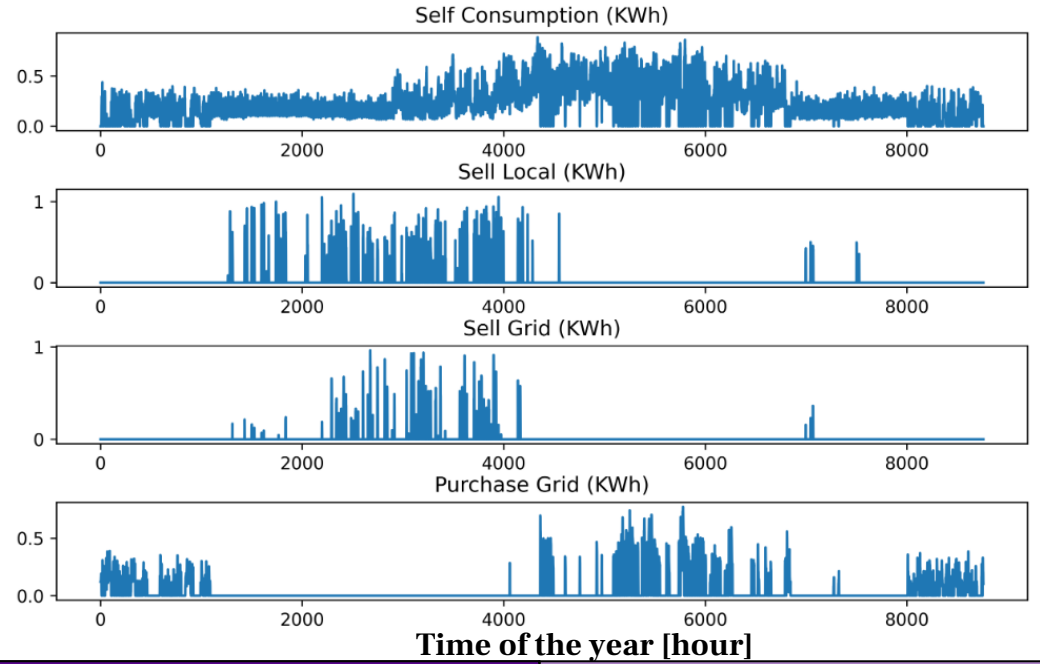


Net Present Value (NPV)

$$NPV = -I_o - \Sigma_{i=1}^{25} \frac{O_c}{(1+r)^i} + \Sigma_{i=1}^{25} \frac{S}{(1+r)^i} + \Sigma_{i=1}^{25} \frac{C}{(1+r)^i}$$

- I_o **(initial investment): cost of panels, batteries, and invertors**
- O_c **(operations cost): annual maintenance and damages from hurricane winds**
- S **(savings): reduced bill, benefits from exporting electricity, state incentives ($90/MWh)**
- C **(cost of avoided outages): reduced cost of arranging alternate source of energy (diesel generators)**

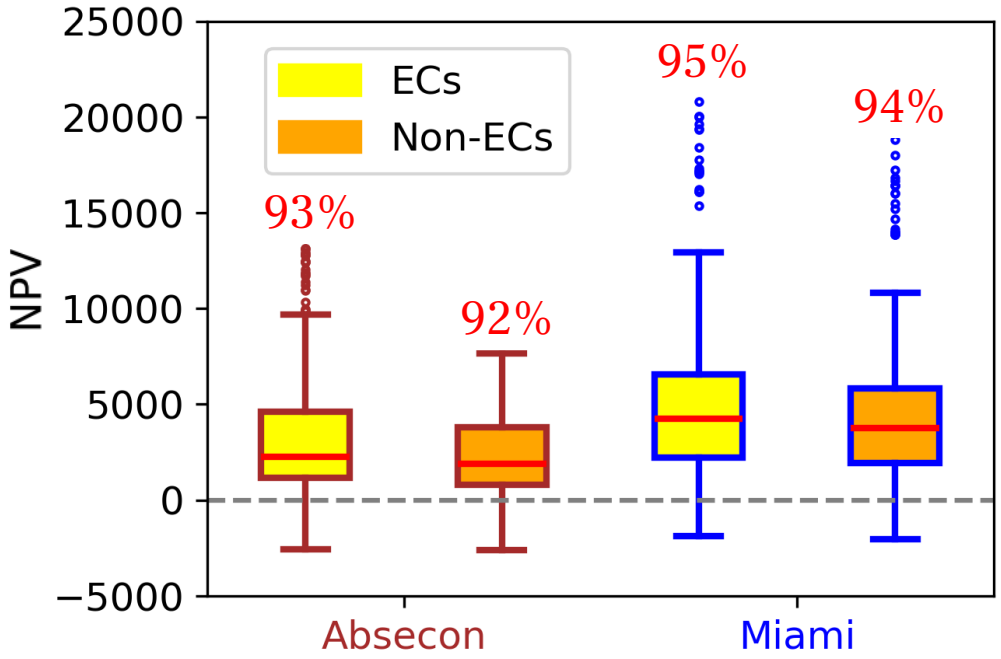
Hourly simulation for solar generation, consumption, grid export and grid import.



Financial Viability

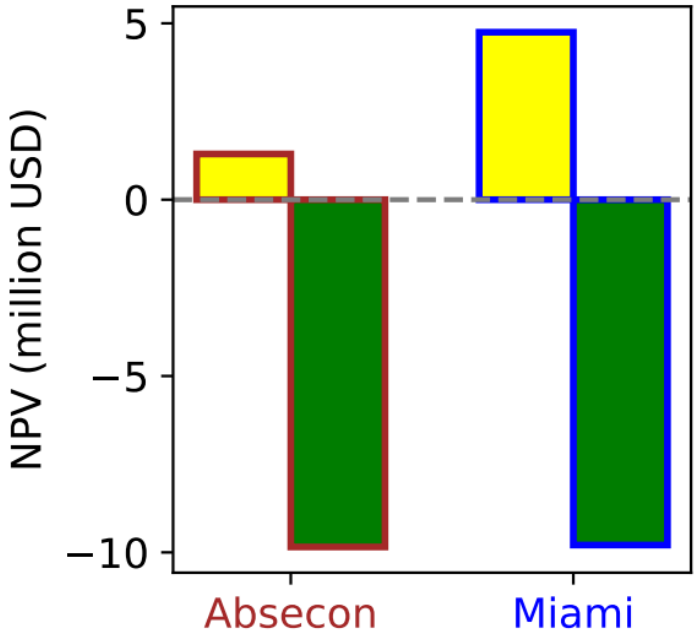
Net present value for individual prosumers:

Total prosumers = 1,254
Profitable Prosumer: NPV> 0



- 25 % higher solar irradiance, smaller solar panels can produce more energy
- Prosumers in ECs receive more benefit with higher export tariffs to local neighbors

Net present value for entire community:



- Undergrounding costs transferred to consumers through increased tariffs, only benefit is avoided outage cost.

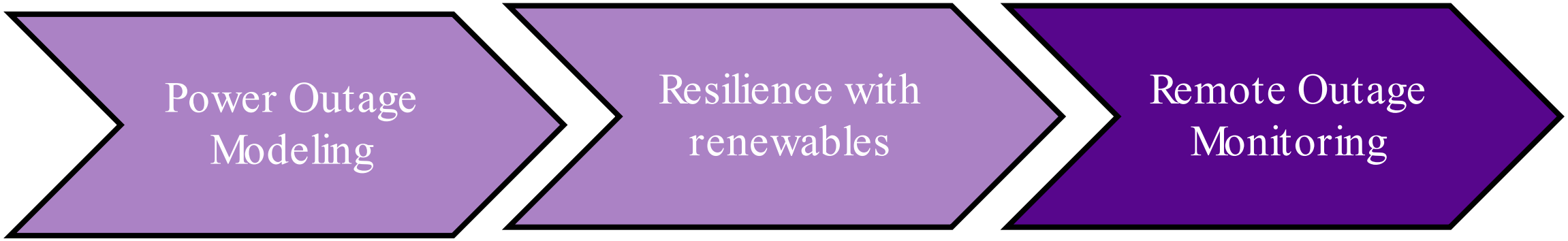
Additional Results

- **Reduction in Solar Investment Tax Credit from 30% to 22% can lower profitable prosumers** in energy communities from 93% to 79% in Absecon and from 95% to 86% in Miami.

- **State incentives like New Jersey's Successor Solar Incentive Program** offering $90/MWh for 15 years can offset up to 34% of investment cost in Absecon and 52% in Miami.

- Cost of avoided outages is estimated based on the expense of not installing a diesel generator, but **traditional questionnaires may undervalue the true cost of avoided outages.**

- In Miami, average damage accounts for 21% of investment cost and can be avoided by using **resilient bolts (Solar Under the Storm Report) that add only 5% to installation cost.**


Power Outage Modeling
Resilience with renewables
Remote Outage Monitoring

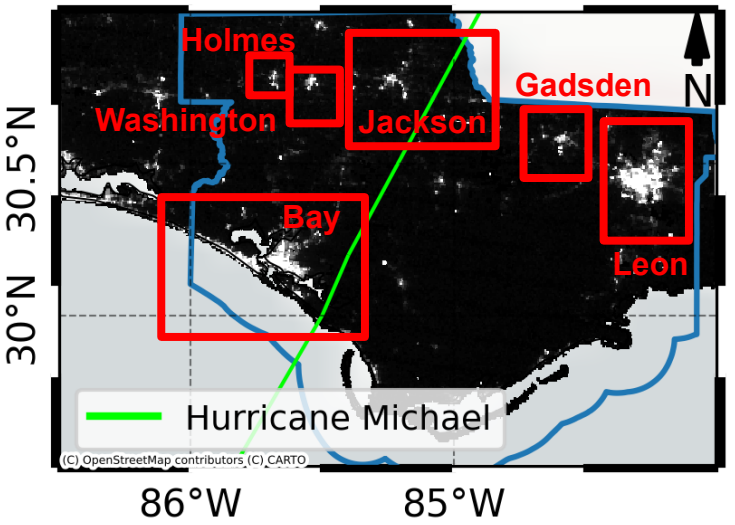
Background

- Many regions do not have automatic reporting systems after large events.
- Outage data is often restricted or unavailable publicly available due to security concerns.

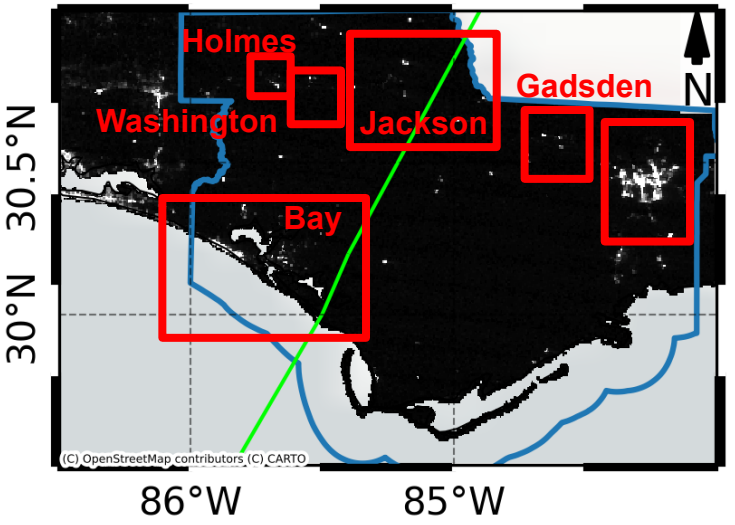
NASA's Nighttime Light Data:

- Daily Nighttime Lights available through Visible Infrared Imaging Radiometer Suite (VIIRS) at 500m spatial resolution.
- Power loss can be detected through loss in nightlights.

Pre-Hurricane Michael (10-06-2018)



Post-Hurricane Michael (10-12-2018)

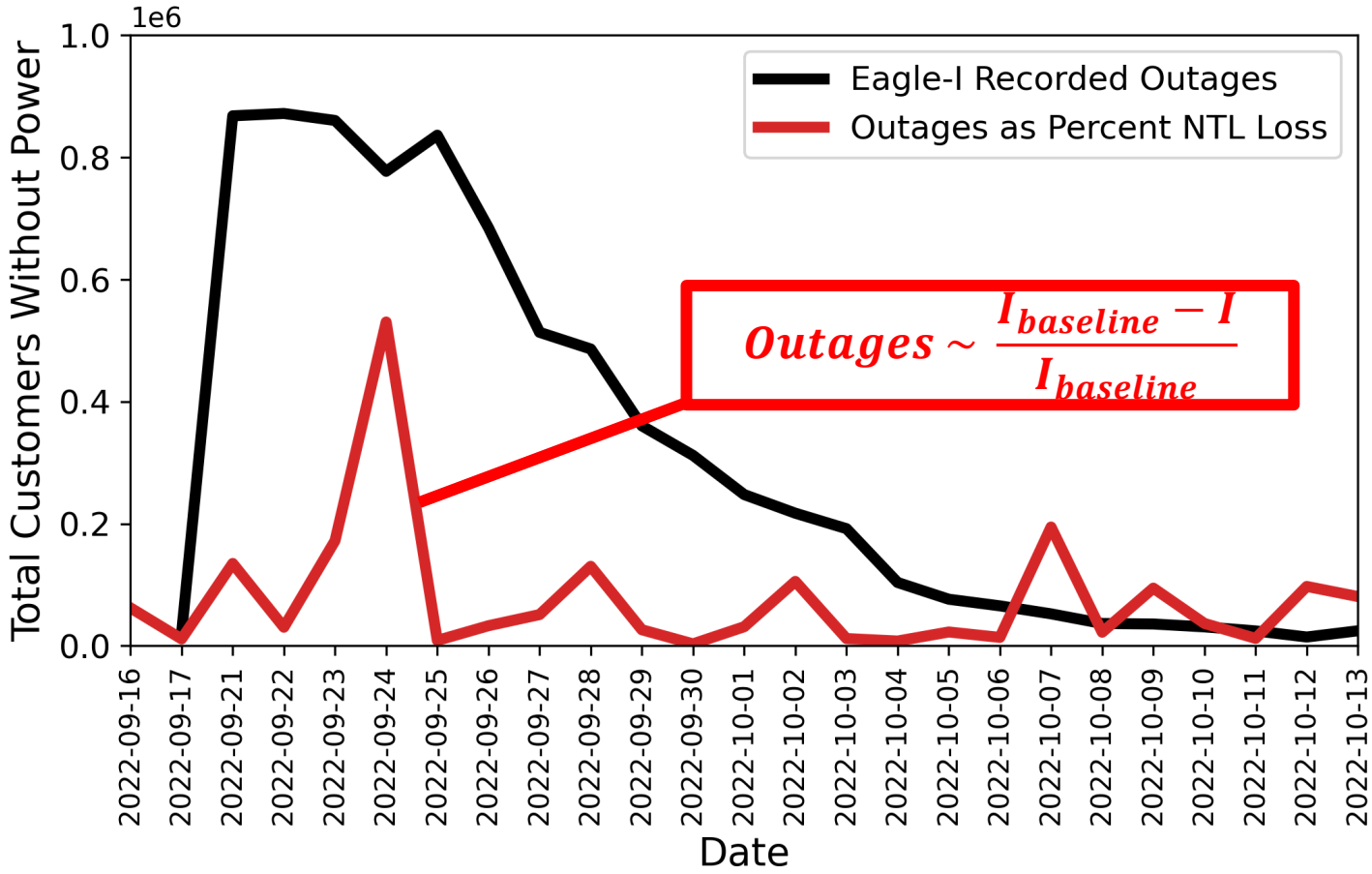


Nightlights over Puerto Rico, Hurricane Fiona

Previous Work Using Nightlights

- **Montoya-Rincon et al. (2018)**
  Used nightlight reduction as a proxy for power outages to study recovery after disasters.

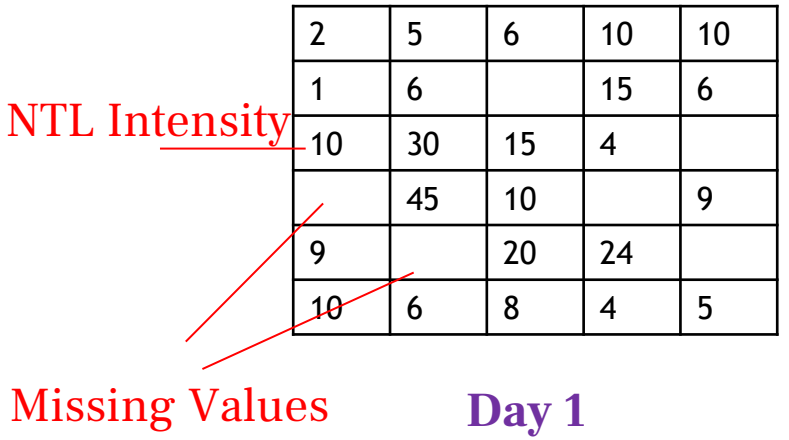
- **Cole et al. (2017)**
  Used nightlights to detect outage patterns but did not estimate the number of customers affected.



Goal: Understand the physics between power outages and nightlights loss and develop models to predict power outages at a daily temporal scale.

Normalized Total Nightlights Intensity

- Daily satellite coverage over a region could be limited by clouds or poor retrieval by satellite sensors.
- Nightlights grows with covered building footprint coverage.



2	5	6	10	10
1	6		15	6
10	30	15	4	
	45	10		9
9		20	24	
10	6	8	4	5

Day 1

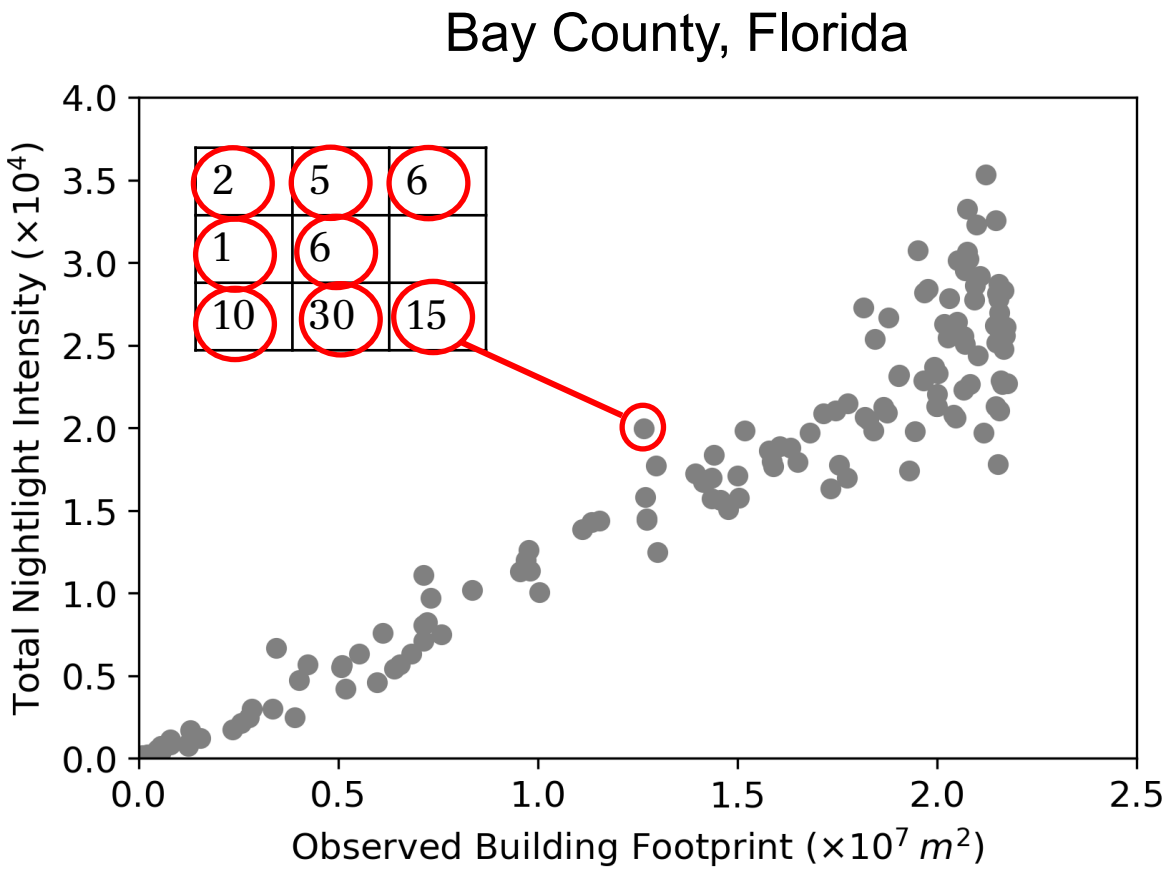
		6	10	
1	6		15	6
	30	15	4	
3		10		9
		20	24	
	6	8	4	5

Day 2

Normalized Total Nightlights Intensity

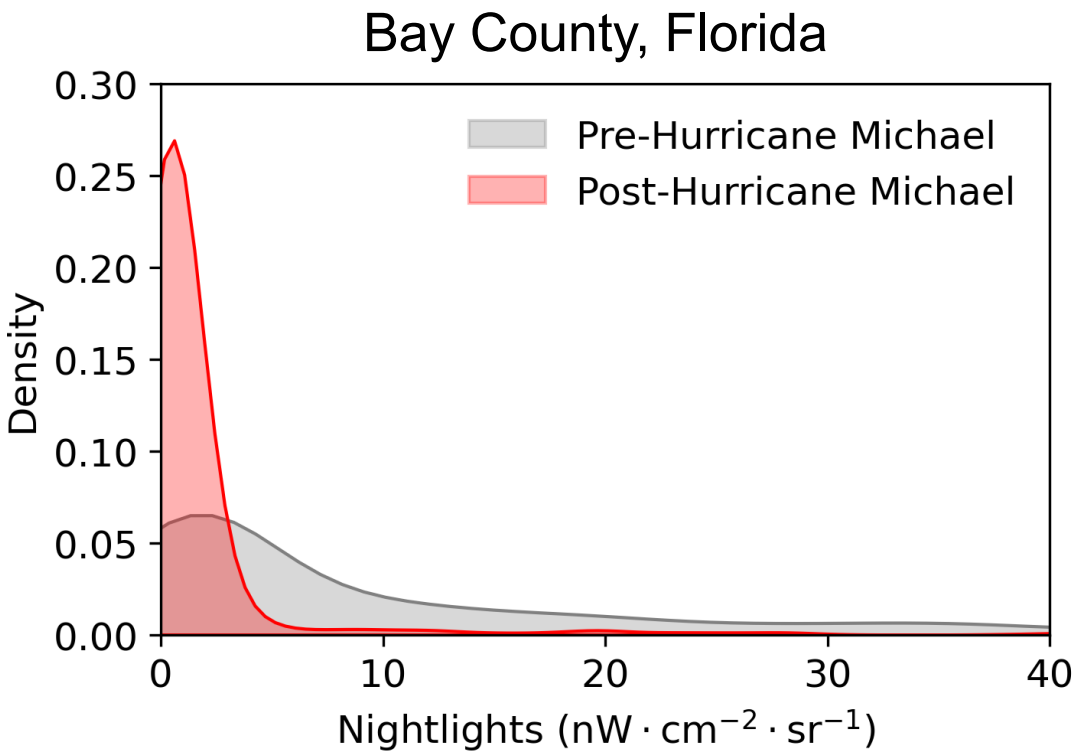
- Daily satellite coverage over a region could be limited by clouds or poor retrieval by satellite sensors.
- Nightlights grows with covered building footprint coverage.
- **Normalized Intensity:**

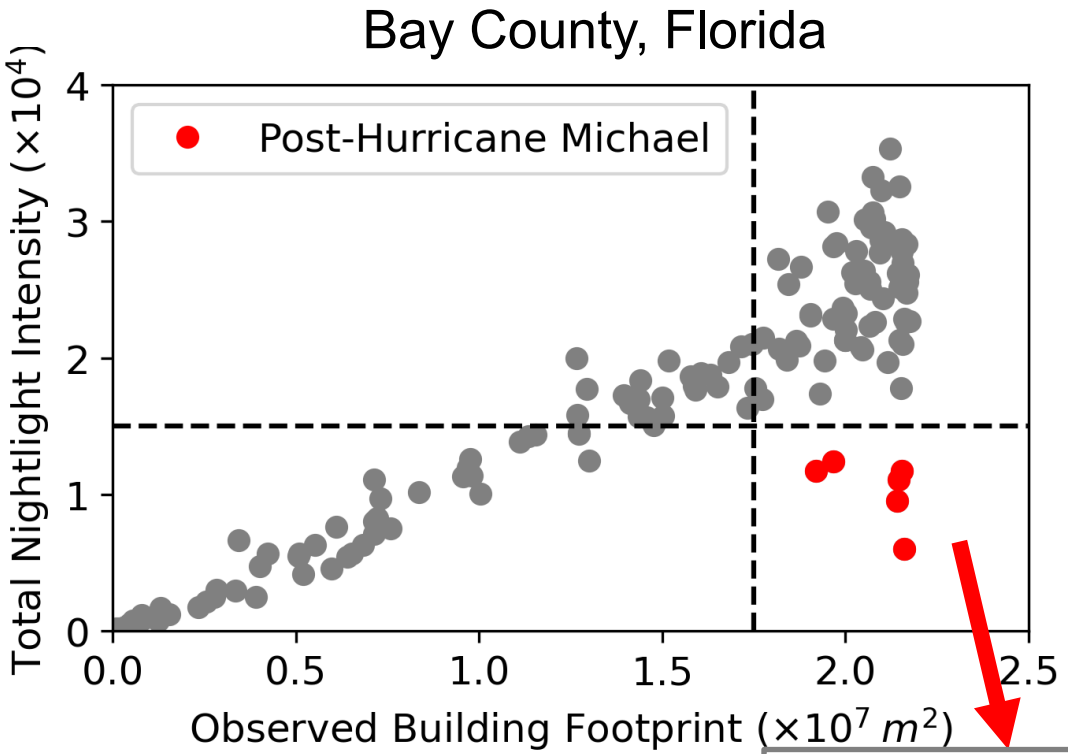
$$I = \frac{\sum L_i}{\sum A_i}$$



where L_i is intensity of each pixel and A_i is footprint covered in each pixel.

Change in Nightlights Distribution

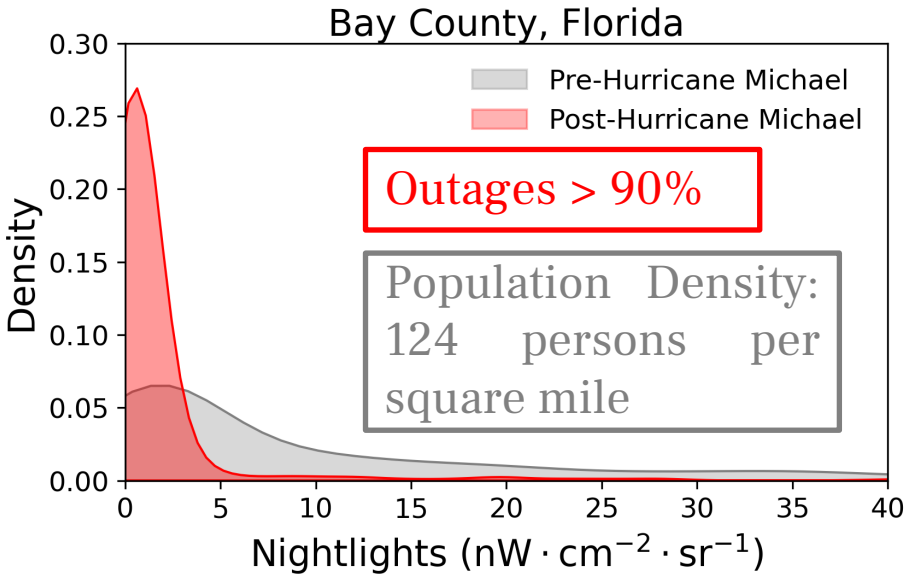


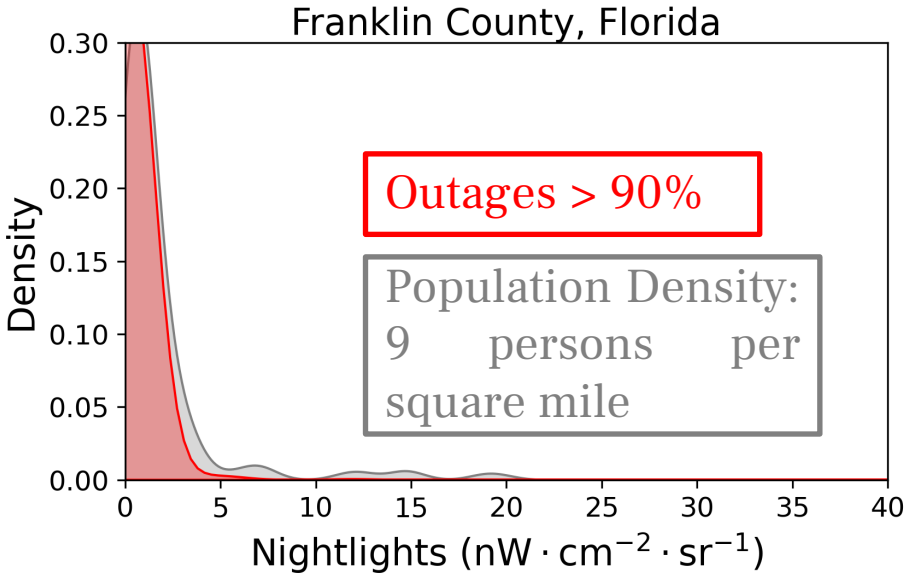


Drop in nightlights after Hurricane Michael, 12 Oct. to 17 Oct. 2018

Change in Nightlights Distribution

- Naturally low nightlight emissions in less populus areas make changes less detectable.
- Focused analysis on counties with **at least 25 persons per square mile** to ensure meaningful signals.
- Days are considered only when satellite captures cover at least one-third of pixels and one-third of footprints in a county.



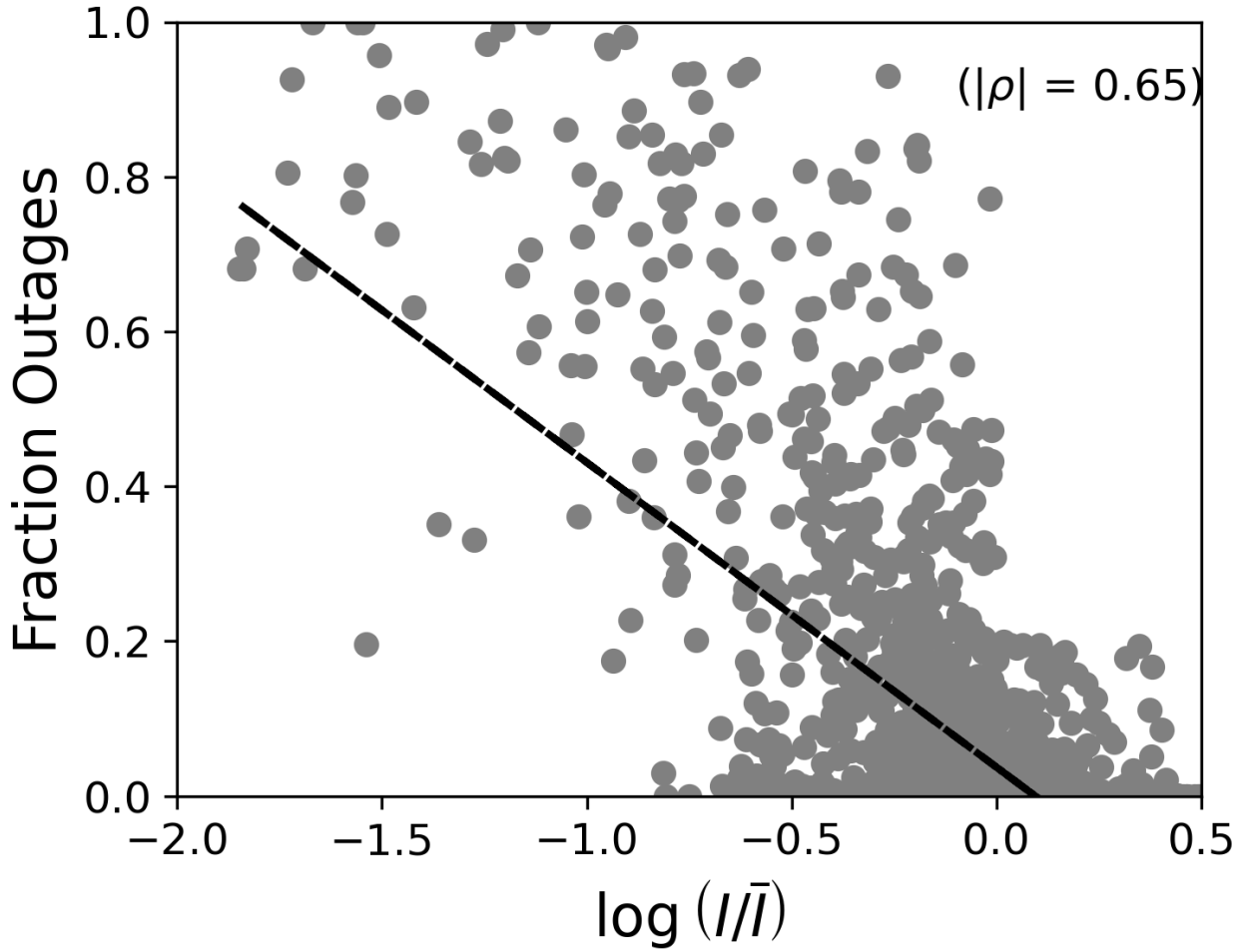


Developing Physics for Nightlights and Outages

- Beer's law for transmission of lights through a medium.
- Previously application: percent fraction of nightlight transmission through vegetation (**Román et al., 2018**).
- Based on Beer's Law, nightlights decay exponentially with fraction of outages.

$$\frac{I}{\bar{I}} \propto \exp(-f_O)$$

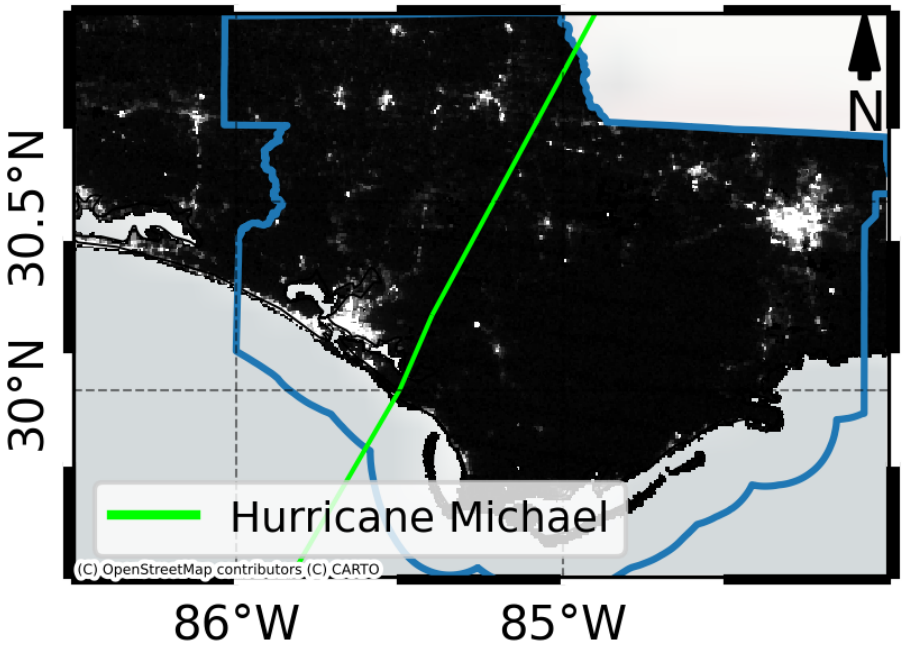
where I is the normalized intensity for day of observation, $\bar{I}$ is the mean of previous 30 observations, and f_O is the fraction of customers without power



Power Outage Predictors

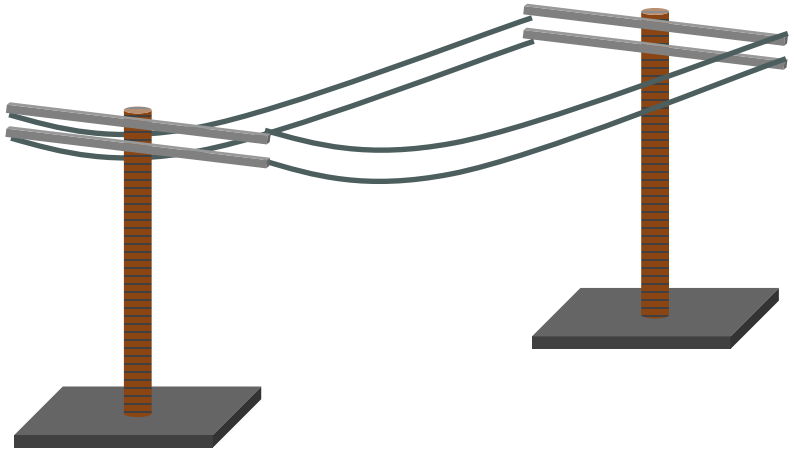
Nightlight Variables:

- δ– nightlights reduction ($\log(I/\bar{I})$)
- L_M - Pre-disaster Mean nightlights
- f_p - Ratio of footprint in imagery
- M - Moon Fraction



Power Systems Proxy:

- ρ_{bldg} - building density



Outage Prediction in Two Stages through Nightlights

Power Outage Data from Oak Ridge National Lab EAGLE-I (Brelsford et al. 2024)

- Averaged from 6pm to 4am local time

Major Events:

- Irma (2017)
- Michael (2018)
- Ida (2021)
- Ian (2022)

Data Points:

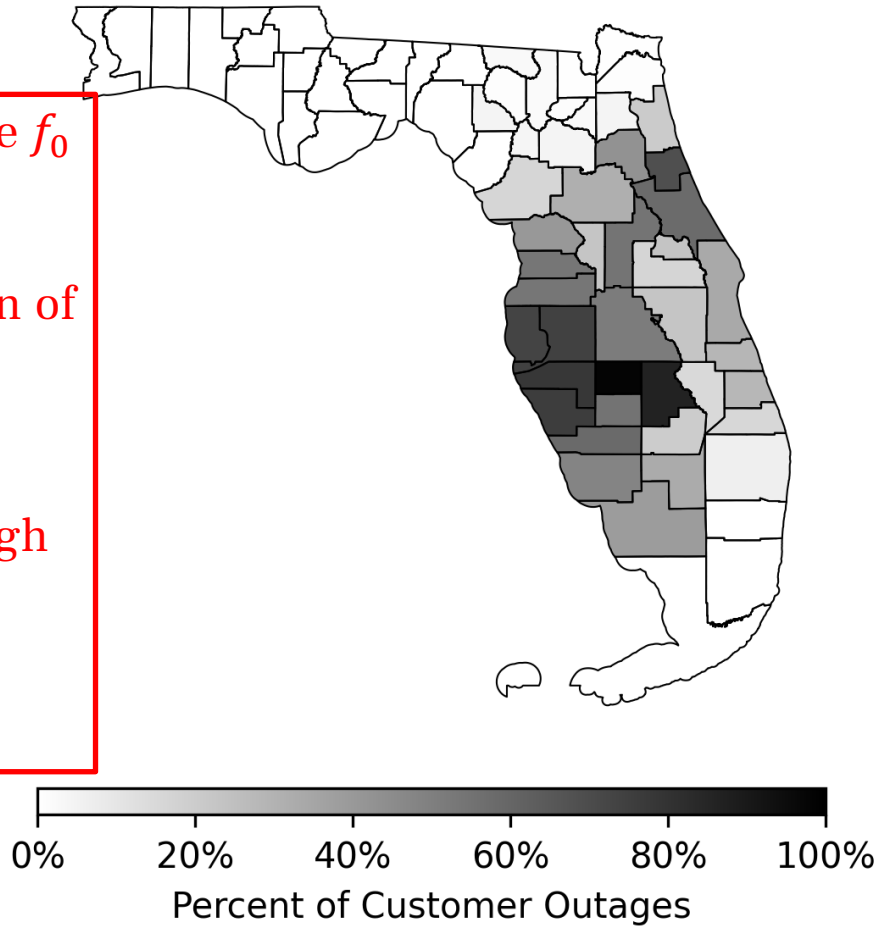
- Training: 1936
- Validation: 764

Only ~18% of data points have $f_0 > 0.05$

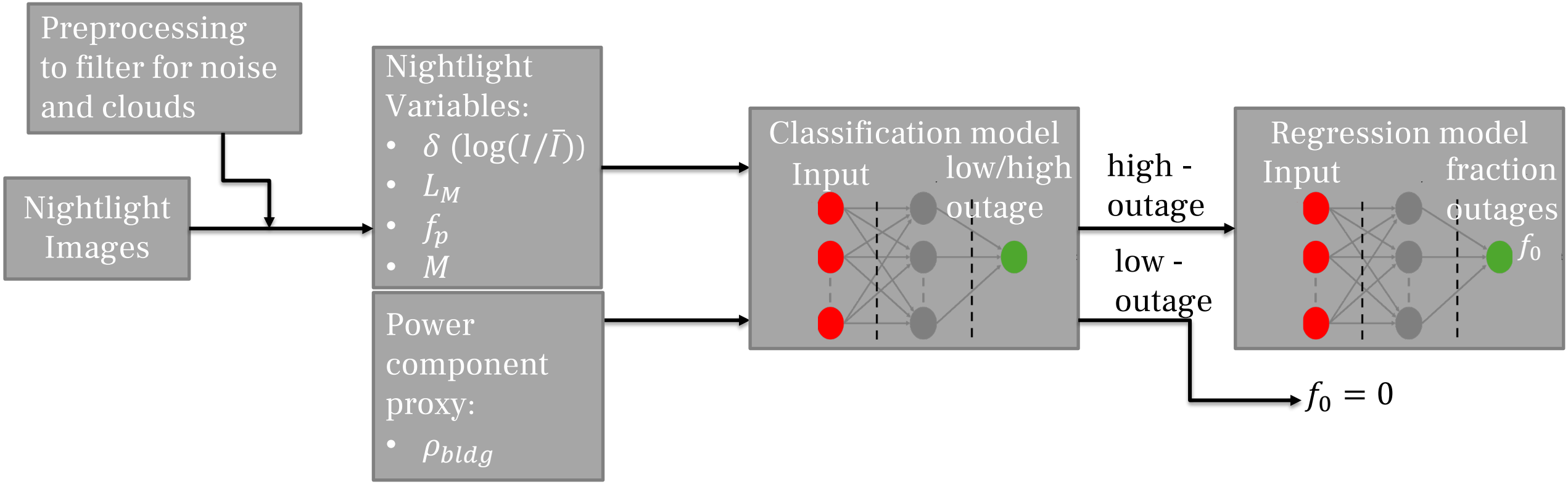
Could lead to underestimation of high outages

Approach:

1. Predict low ($f_0 < 0.05$) and high ($f_0 > 0.05$) outages
2. Predict f_0 for high outage events



Outage Prediction in Two Stages through Nightlights



Classification and Regression Models

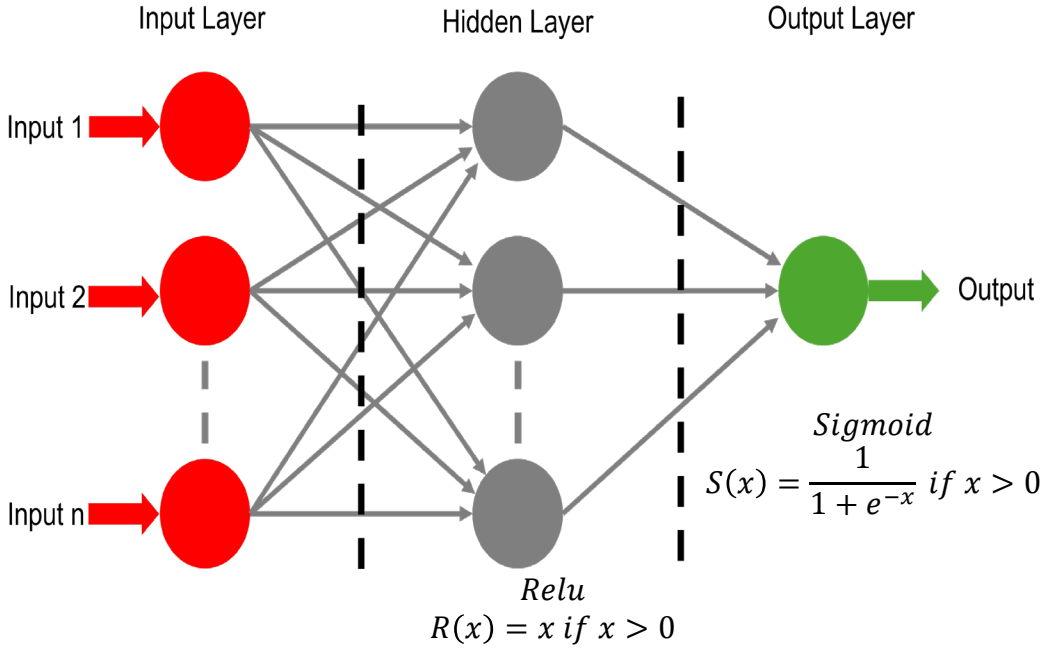
Choice 1: Artificial Neural Networks (ANN)

- ANN for classification and regression tasks can capture non-linear interactions.
- Structure: 5 Inputs, 1 Hidden Layer with 8 neurons, 1 output
- **Classification Loss (cross-entropy):**

$$L_c = -\frac{1}{N}\Sigma(y_i log(S(x_i)) + (1-y_i)\log(1-S(x_i))]$$

- **Regression (Huber) Loss:**

$$L_H = \frac{1}{N}\Sigma \begin{cases} \frac{1}{2}(y_i - S(x_i))^2, & for\ |y_i - S(x_i)| \le \delta \\ \delta\left(|y_i - S(x_i)| - \frac{1}{2}\delta\right), & otherwise \end{cases}$$



Classification and Regression Models

Choice 2: Logistic Regression and Linear Regression

- Easy to interpret and can be adaptable widely
- **Classification:**

$$P_f = \begin{cases} 1 \; if \; \dfrac{1}{1 + exp(-(a_1 log\left(\frac{I}{\bar{I}}\right) + b_1 L_M + c_1 f_p + d_1 M + e_1 \rho_{bldg} + f_1))} > 0.5 \\ 0 \; otherwise \end{cases}$$

$$L_c = \frac{1}{N}\sum\left(y_i log\left(S(x_i)\right) + (1 - y_i)\log\left(1 - S(x_i)\right)\right] + \lambda\left|\left|w_i\right|\right|^2$$

L2 regularization

- **Regression:**

$$g(f_O) = \; a_2 log\left(\frac{I}{\bar{I}}\right) + b_2 L_M + c_2 f_p + d_2 M + e_2 \rho_{bldg} + f_2$$

$g(f_O) = log\left(\frac{f_O}{1-f_O}\right)$ - logit transform to bound output from 0 to 1

$$L_R = \frac{1}{N}\sum\left(g(f_O) - g(f_O)\right)^2 + \lambda\left|\left|w_i\right|\right|^2$$

L2 regularization

Performance on Validation Data Points

Classification:

~18 % data points are high outages, randomly resample low outage points as same as high outages

Model	Validation Accuracy	Recall (High Outage)
ANN	83%	79% (118 out of 148)
Logistic Regression	76%	72% (106 out of 148)

On average high outage events of value ~0.2 are misclassified as low outages

Regression:

Model	Validation MAE
ANN	0.13
Linear Regression	0.14

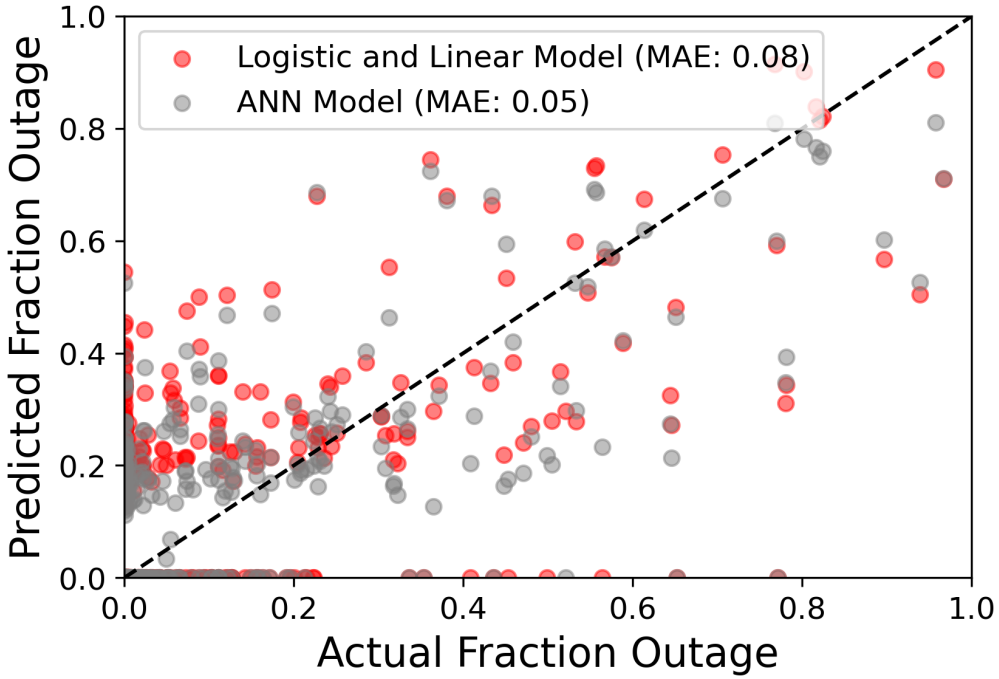
Combined Model Performance

- Logistic and Linear Model gives comparable performance to ANN model.
- Easier representation

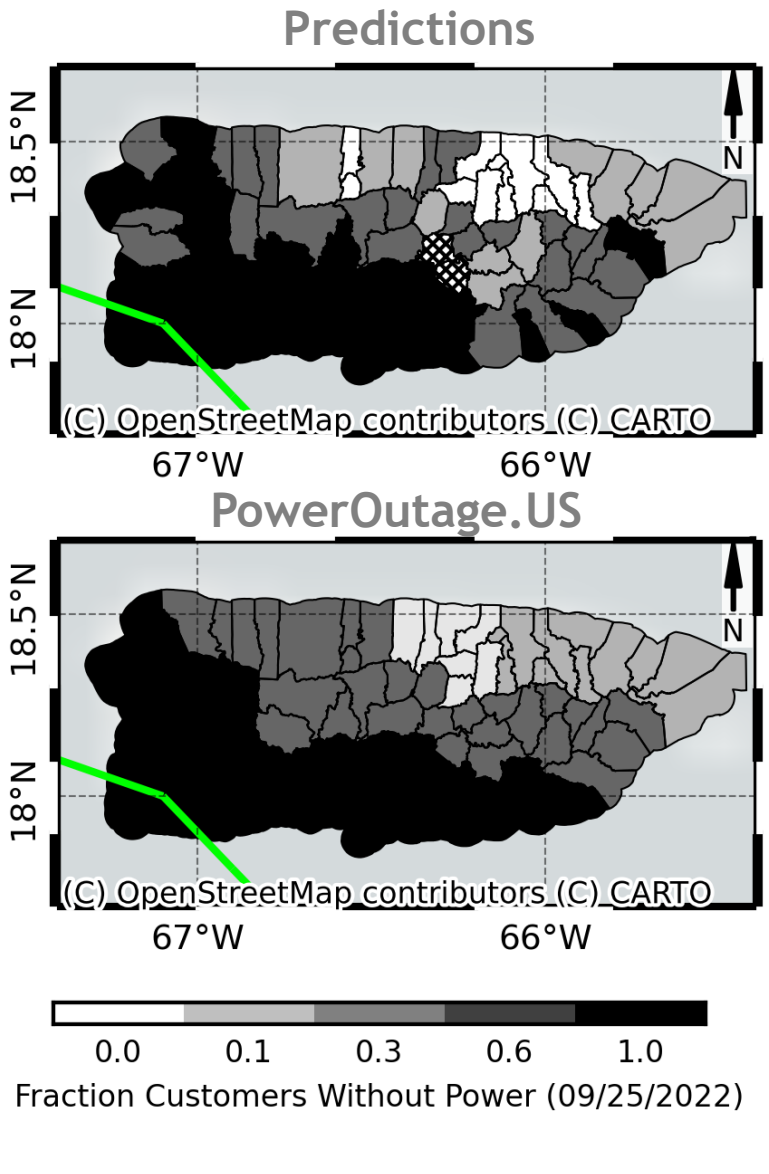
$$\text{Logistic: } P_f = \begin{cases} 1 \; if \; \frac{1}{1+exp(-(a_1 log\left(\frac{I}{\bar{I}}\right)+b_1 L_M+c_1 f_p+d_1 M+e_1 \rho_{bldg}+f_1))} > 0.5 \\ 0 \; otherwise \end{cases}$$

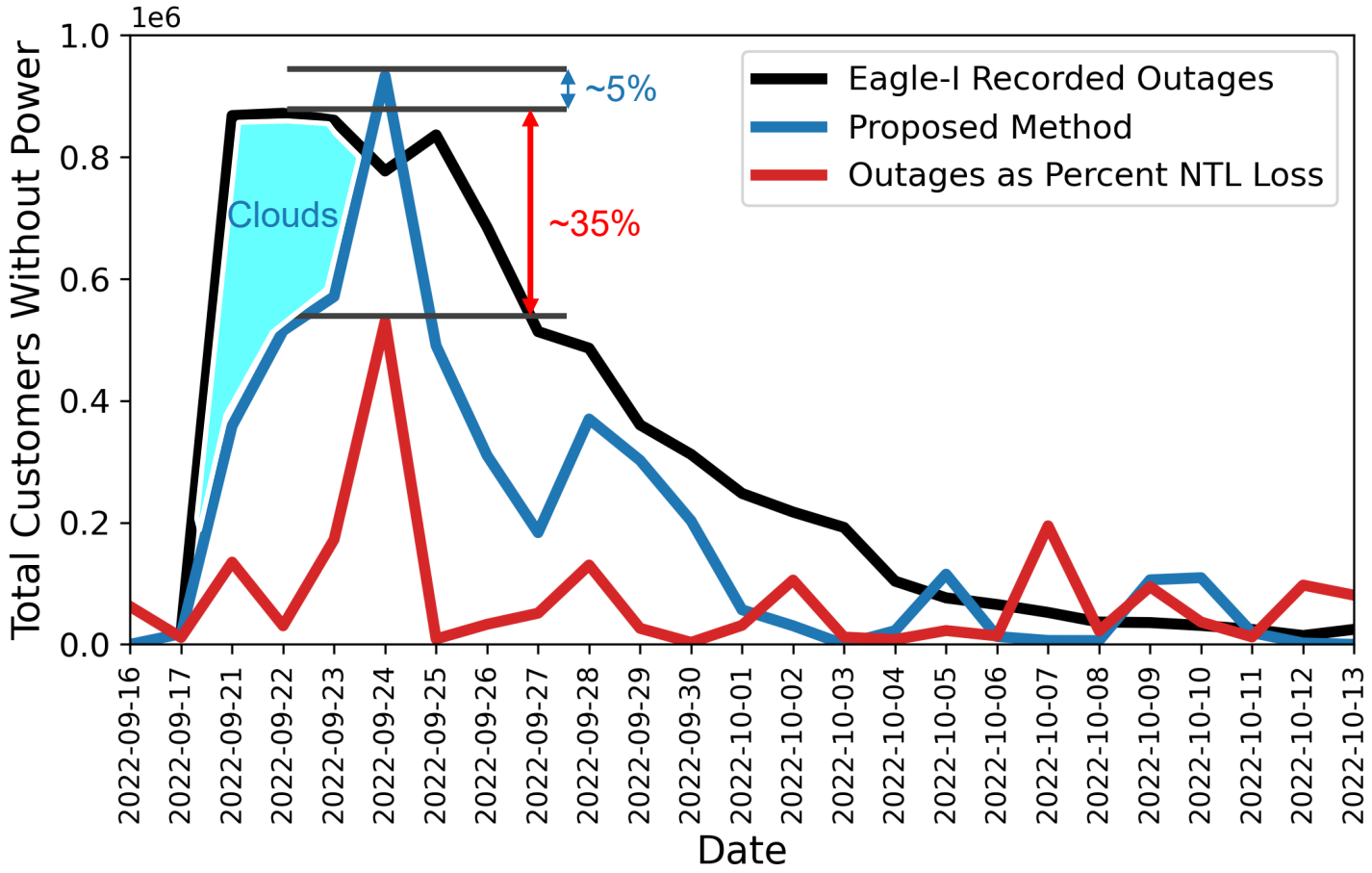
$$\text{Linear: } g(f_O) = a_2 log\left(\frac{I}{\bar{I}}\right) + b_2 L_M + c_2 f_p + d_2 M + e_2 \rho_{bldg} + f_2$$

- Use of combined model to track outages across different regions.



Hurricane Fiona

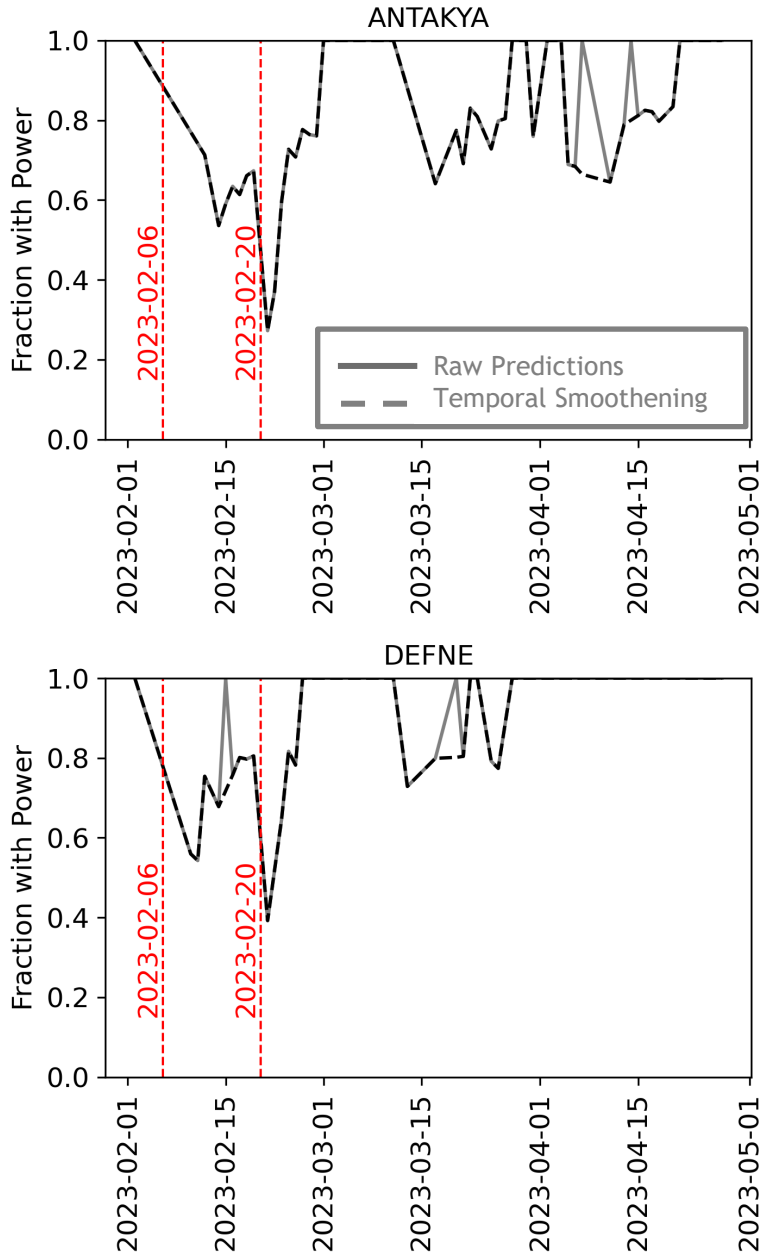






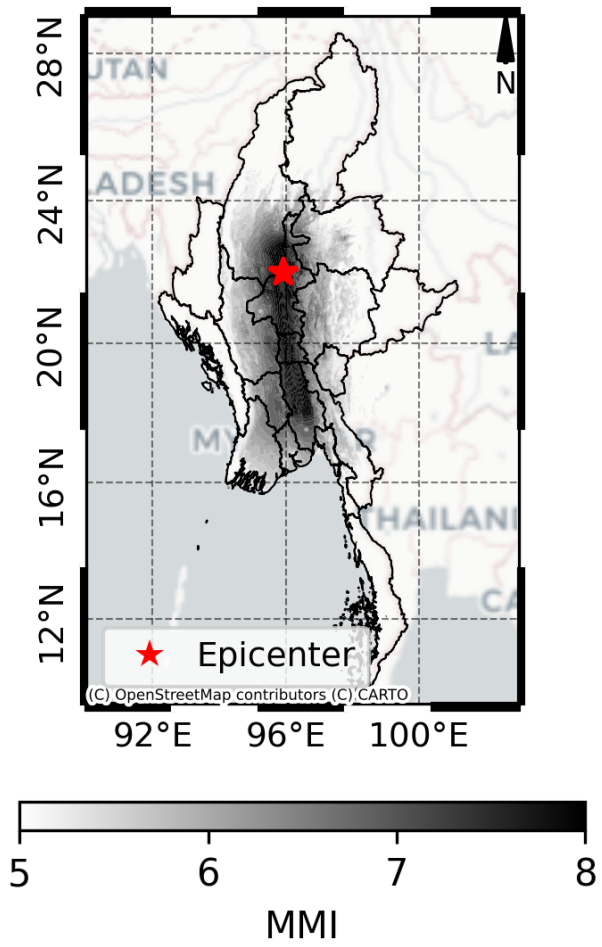
Turkey Earthquake

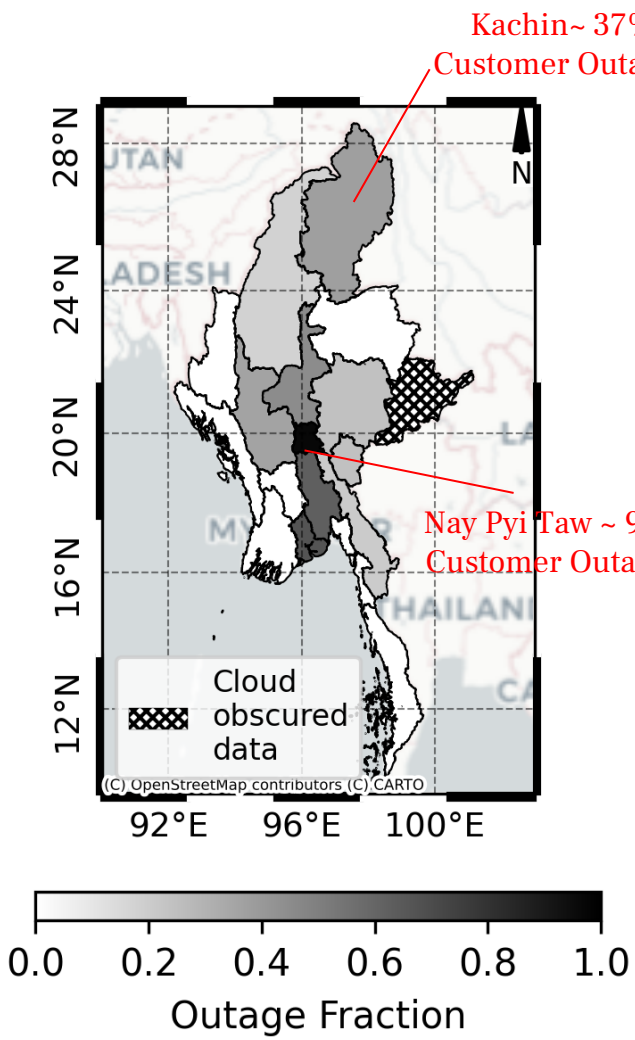
- On February 6, 2023, Turkey was hit by mainshock of 7.8 magnitude and aftershock of 7.5 magnitude.
- On February 20, 2023, another major earthquake of 6.4 magnitude hits Hatay Province.
- Antakya and Defne were worst hit districts with 50% of the buildings heavily damaged **(Sakarya et al. 2024).**



Myanmar Earthquake

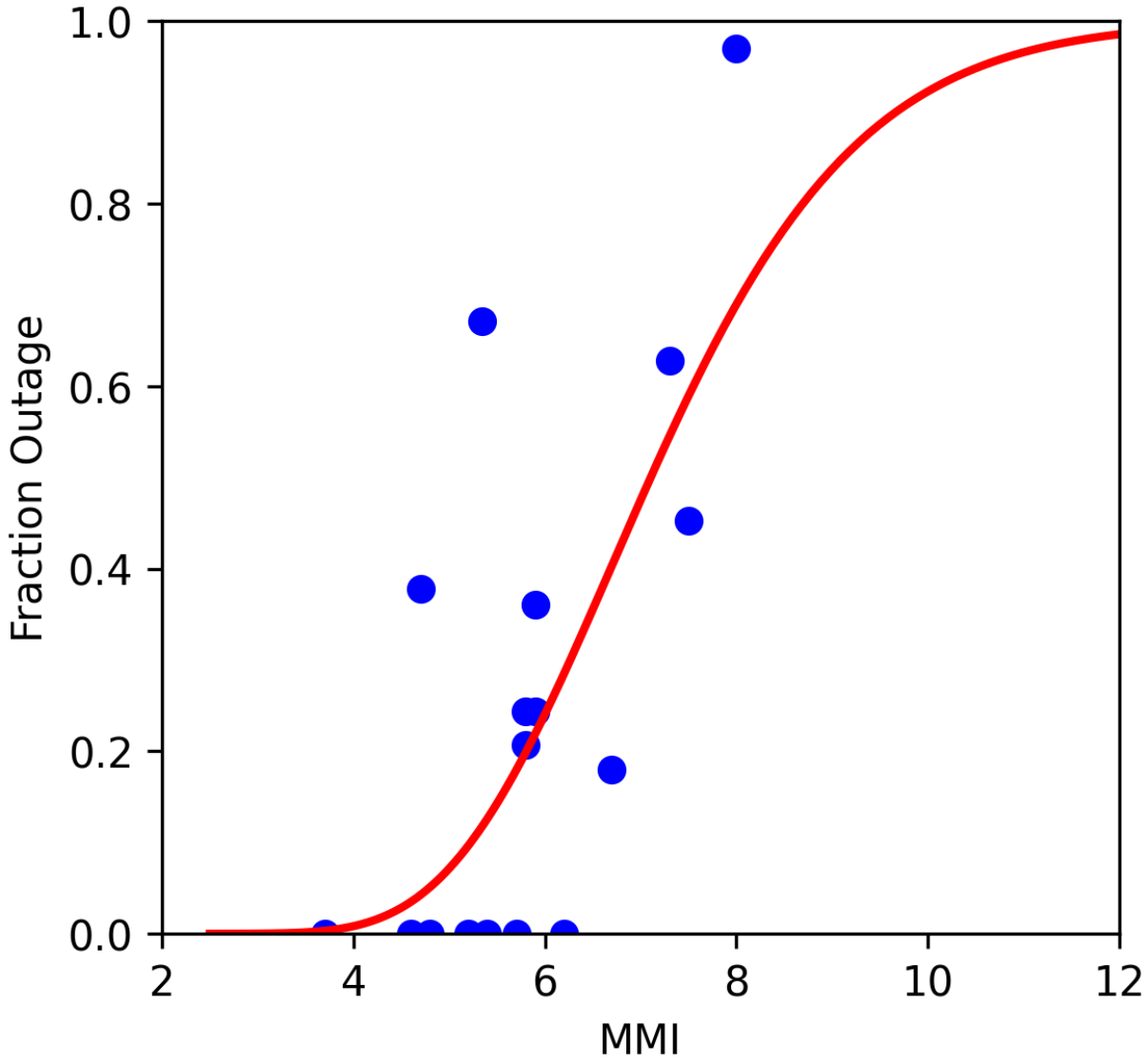
- On March 25, 2025, Myanmar was hit by an earthquake of 7.9 magnitude at 12:05 pm.
- Power was not restored until next morning (powerchina.cn).
- MMI and outages show a significant correlation ($|\rho|$) of 0.65.





Hazard Intensity and Outages

- Satellite observations could be utilized to develop damage functions.
- Lays a foundation for study grid resilience under future hazards.
- Rapid assessment of outages after a natural disaster.



Conclusions

Power outage models

- Developments required to account for uncertainty quantification in power outage models.
- A novel quasi-binomial power outage model is proposed and tested for outages during Hurricane Ian.

Resilience with renewables

- A validated high-fidelity outage risk model of power network is presented to study energy communities.
- ECs gain the highest resilience to hurricane emergencies compared to other strategies like undergrounding.
- Prosumers in ECs can be more profitable with more savings and incentives.

Remote Outage Monitoring

- Nightlights can inform about the outages in aftermath of disasters.
- A novel framework based on Beer's Law was presented to predict the power outages.
- Mapping power outages provides a potential to understand grid resilience to extreme events.

Future Directions

- Integration of higher resolution power systems data such as underground and overhead into power outage models to better quantify power outages.
- Integration of tree data to determine the additional damage from trees into the high-fidelity power outage risk model.
- Determination of grid synchronization and validation of power flow through existing power grid during disasters.
- Better understand the cost of avoided outages that might further motivate households to adopt solar panels.

Contributions

Power Outage Modeling

- Arora, P. & Ceferino, L.: **Probabilistic and machine learning methods for uncertainty quantification in power outage prediction due to extreme events**, Nat. Hazards Earth Syst. Sci., 23, 1665–1683
- Arora, P. & Ceferino, L.: **A Quasi-Binomial Regression Model for Hurricane-Induced Power Outages during Early Warning**, ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 10 (2).
- Arora, P. & Ceferino, L. (2023). **A Performance-Based Probabilistic Framework to Model Risk to Power Systems from Hurricanes**. In 14th International Conference on Applications of Statistics and Probability in Civil Engineering. Dublin, Ireland.

Resilience with Renewables

- Arora, P. & Ceferino, L. (2024). **The Feasibility of Energy Communities for Hurricane Resilience [Preprint]**
- Arora, P. & Ceferino, L. (2023). **Could rooftop solar panels and storage have enhanced the electricity resilience during Hurricane Isaias (2020)?** In 14th International Conference on Applications of Statistics and Probability in Civil Engineering. Dublin, Ireland.

Remote Outage Monitoring

- Arora, P., Ceferino, L. & Dobler, G. (2025). **A Novel Framework for Detecting Disaster-Induced Power Outages Globally via Satellite Observations and Physics-guided AI [Upcoming]**

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- Dr. Semiha Ergan
- Dr. Chen Feng
- Dr. Gregory Dobler

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Thank you