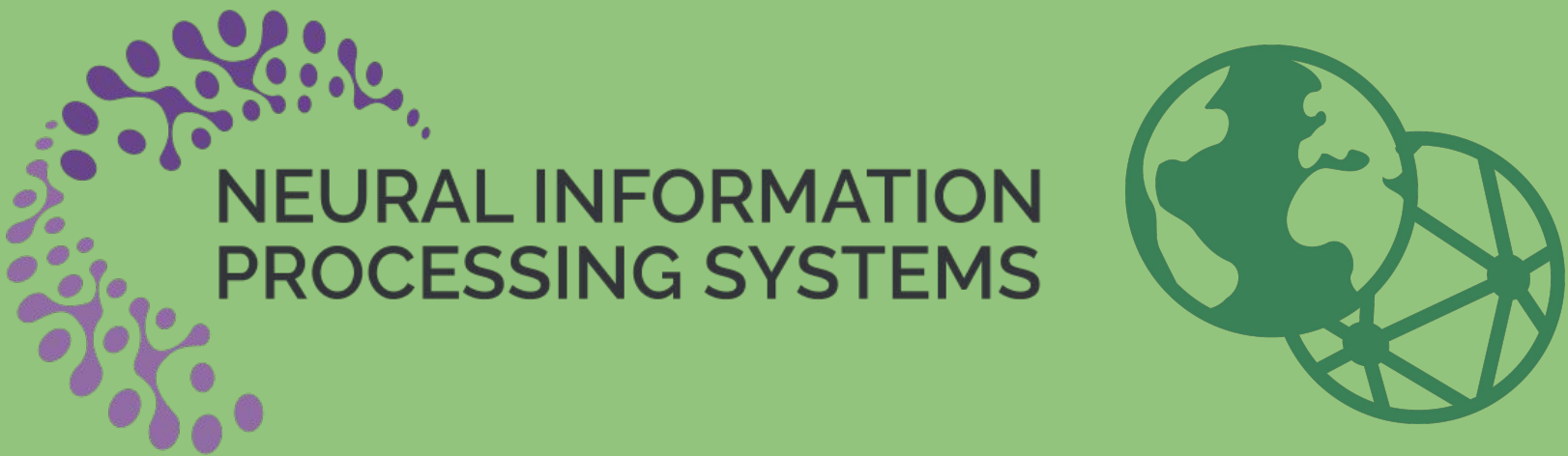


Prioritization Learning for Equitable Residential Decarbonization Investments

NeurIPS 2025: Tackling Climate Change with Machine Learning Workshop

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Introduction

The Need For Residential Decarbonization

- Residential and commercial buildings account for 31% of U.S. greenhouse gas emissions. [1]
- California Climate Investments (CCI) defines priority populations as those most vulnerable to energy poverty and climate change. [2]
- Prioritizing low-income home decarbonization reduces national energy costs and the average energy burden. [3]
- California Energy Commission (CEC) and others enacted affordable programs via the Federal Inflation Reduction Act [4] motivated by the 2021 Building Decarbonization Assessment. [5]

Fixing the Prioritization Problem

- Manually selecting homes to direct affordable retrofit options is too slow and inefficient to meet the pace required.
- Limited funding and affordability programs must be used efficiently and effectively.
- Machine learning techniques can accelerate the solutions to the building decarbonization problems like never before.

Proposed Research

- Develop a prioritization tool to identify and rank homes for retrofits based on their potential for emissions reduction, electricity savings, cost savings, and energy burden relief.

Methods: Two Layer Model

Data Source

- National Renewable Energy Laboratory ResStock Dataset 25.1, filtered for San Mateo County, October 2025 [6]

First Layer: Four Score Component Models

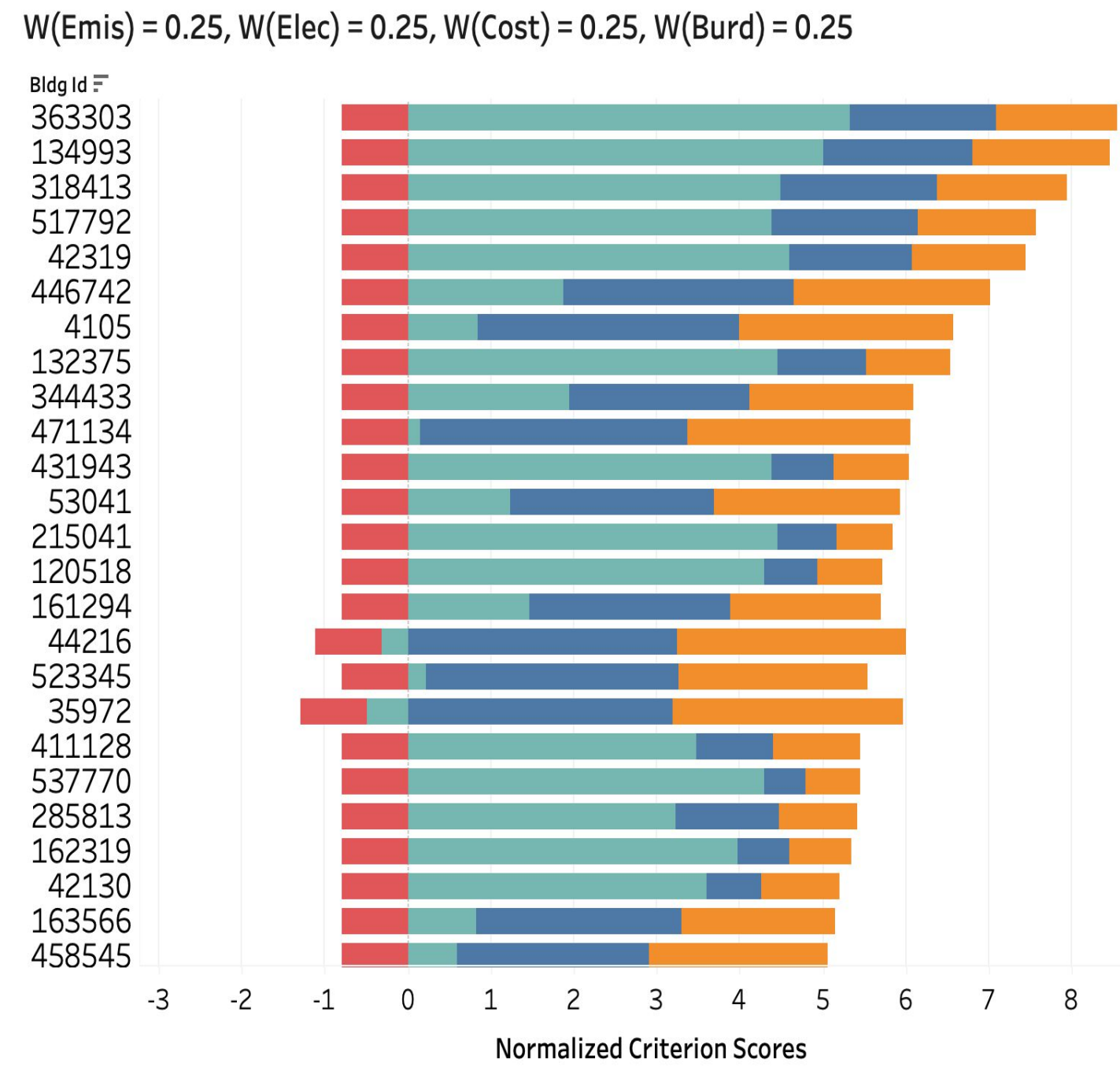
- (1) Emission Reduction (2) Bill Savings (3) Electricity Savings (4) Energy Burden Reduction
- Input features shared across all four, including income, house size, utility rates
- Median imputation to replace NaN values with median values
- Histogram-based Gradient Boosting Regressor with L2 Regularization
- Each model outputs a score per building, and ranks the homes correspondingly

Second Layer: Combining into a Policy-Weighted Aggregate Score

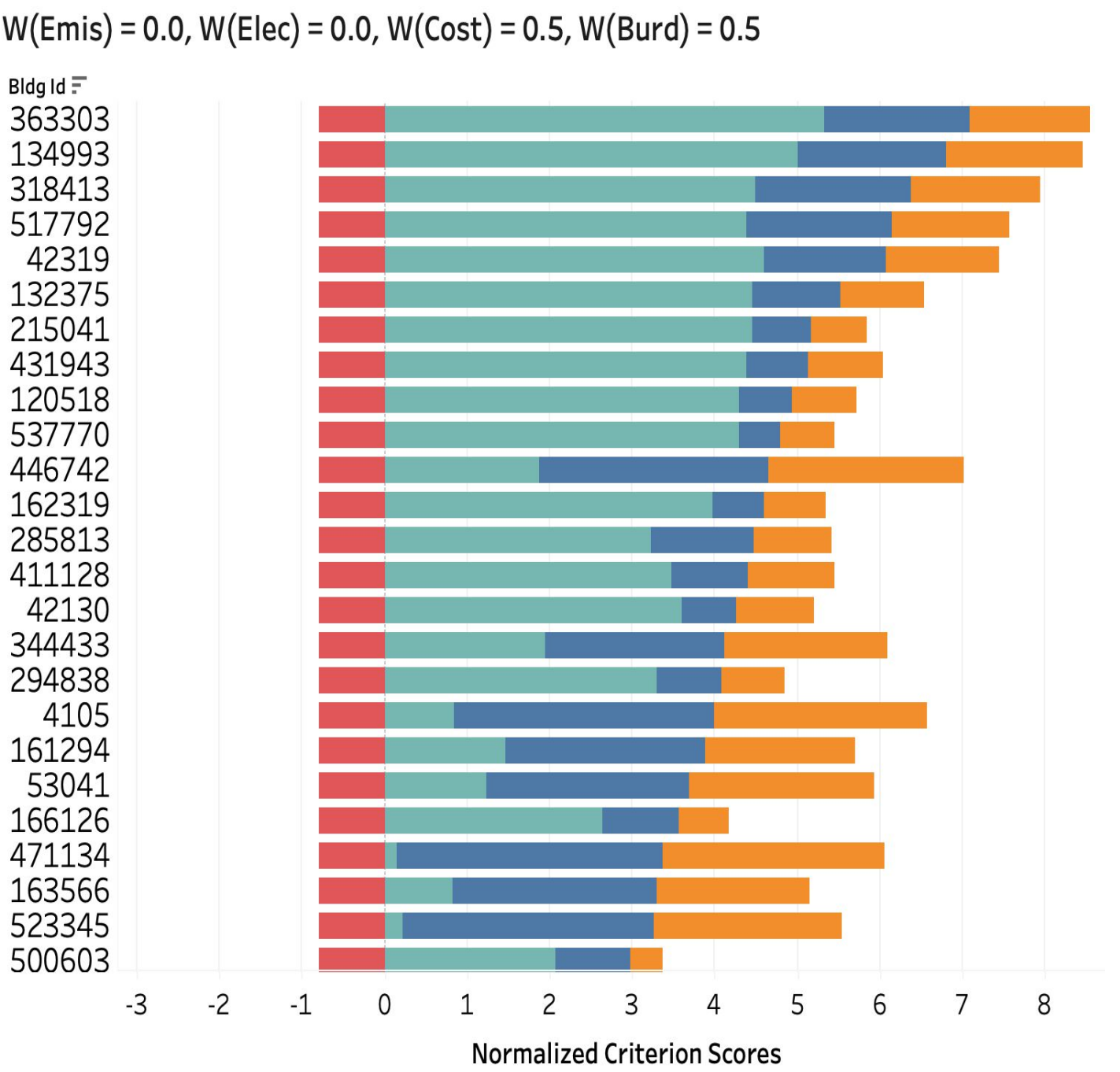
- Four criterion scores are z-score normalized, then combined
- Total = B1[emission reduction] + B2[bill savings] + B3[electricity savings] + B4[energy burden reduction]
- B1 - B4 are weights are user-chosen for policy and community goals
- Produces an aggregate priority score to rank buildings
- Trade-off analysis between factor weight scenarios
- User input boosts explainability and decision-making control

Findings

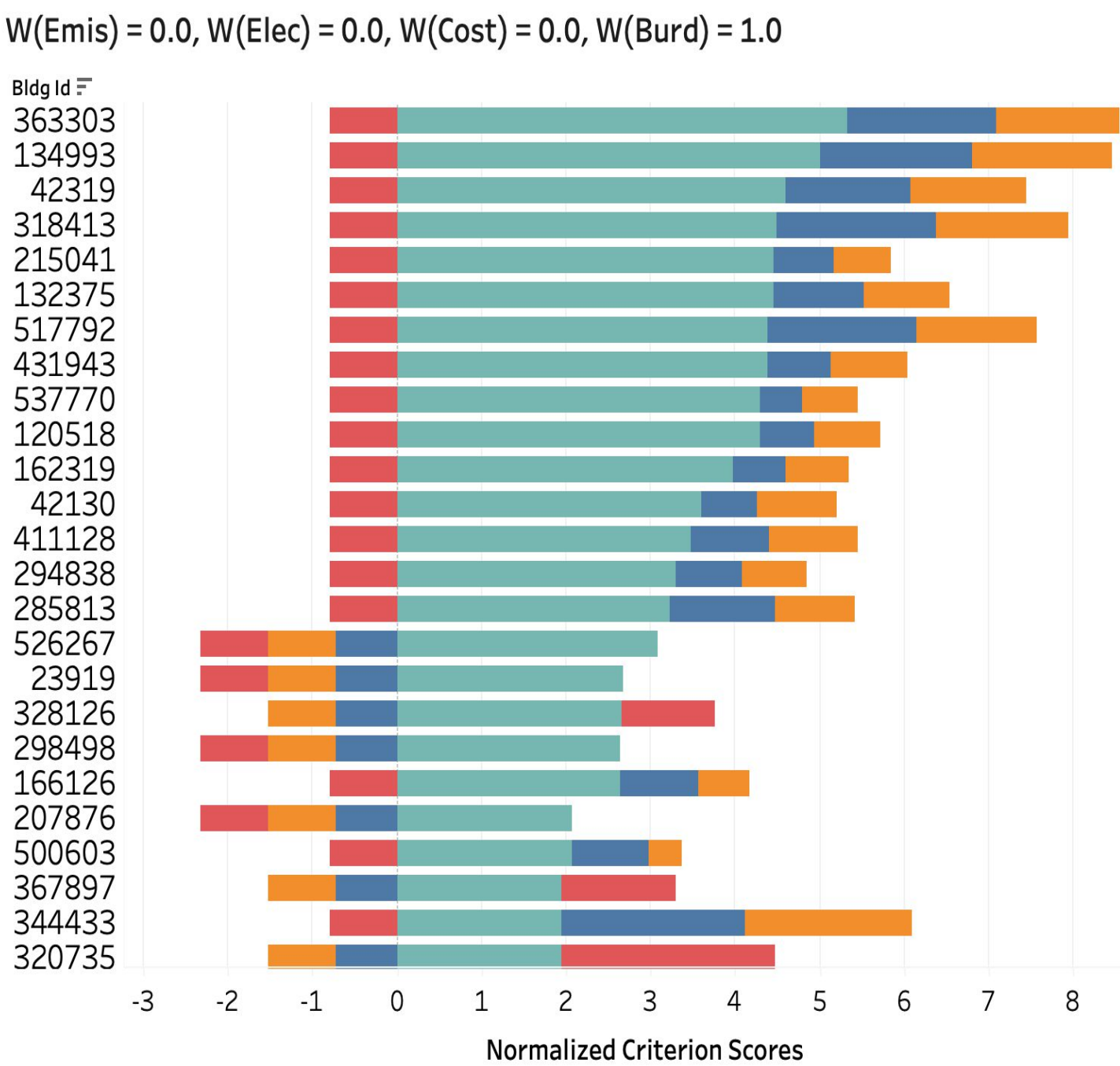
Equal Weight Scenario



Burden and Cost-Heavy Scenario



Burden-Only Scenario



- Emissions Reduction
- Electricity Energy Savings
- Cost Savings
- Energy Burden Reduction

Performance

Component Models:

- Emissions Reduction: $R^2 = 0.737308$ RMSE = 0.501736
- Electricity Usage Reduction: $R^2 = 0.812021$ RMSE = 0.453819
- Cost Savings Regression: $R^2 = 0.715062$ RMSE = 0.550245
- Burden Reduction Regression: $R^2 = 0.523284$ RMSE = 0.664795

Top 200 dwellings by each model versus actual top 200 in the criterion category:

- Precision for Emissions Reduction = 0.810
- Precision for Electricity Savings = 0.960
- Precision for Cost Savings = 0.905
- Precision for Energy Burden Reduction = 0.865

Intended Outcomes

- The optimized ranking of households demonstrates which would most benefit from energy upgrades.
- Data-driven planning with machine learning allows communities to prioritize energy upgrades more strategically and with greater impact.
- If this model helps achieve electrification of 75% of U.S. homes by 2050, American households could save \$96 billion in utility bills Without prioritizing low- and moderate-income households, the same level of electrification would instead cost \$88 billion. [7]

Top 20 Ranked, Emission Score

bldg_id	Prediction Score	Emissions Reduction (kg)
325522	3.129280	2436.625637
60490	3.017451	2435.446297
92916	2.607981	2113.323139
123395	2.574732	2445.216676
430807	2.476378	2501.988297
196756	2.326338	2469.143674
320735	2.320930	1930.058214
291264	2.217868	1801.700645
231374	2.057622	2025.503120
314670	2.022480	1528.043832
471559	2.018063	1446.968732
21540	2.011092	1723.455961
194297	2.002189	1251.429597
526221	1.964030	1590.830088
166735	1.928463	1618.567262
227771	1.887070	1835.461525
32674	1.867135	1212.239217
98554	1.862389	1620.145763
276565	1.853878	1810.119319
510222	1.846552	1541.352232

Next Steps

- Consider combining with CCI priority population spatial data [8], smart meter data from the CEC [9], and other sources by local relevance.
- Develop, test on multiple regions, and reiterate model design.
- Consult with utility engineers, policymakers, authors of related publications, academic researchers, and environmental justice advocacy groups to improve the model and discuss implementation of findings.

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Acknowledgements

- Dr. Holmes Hummel, Stanford University, Civil/Env. Engineering
- Prathamesh Pawar, Climate Change AI conference mentor, Amazon
- Dash Beavers, Stanford University, for qualitative preliminary research