



NeurIPS 2025: Climate Change AI Proposals Track

Prioritization Learning for Equitable Residential Decarbonization Investments



NEURAL INFORMATION
PROCESSING SYSTEMS

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The Need For Residential Decarbonization

- ▶ Residential and commercial buildings account for 31% of GHG emissions (US) [1]
 - ▶ California Climate Investments (CCI) defines *priority populations* as the communities 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 have enacted affordable programs via the Federal Inflation Reduction Act (IRA) [4] motivated by the 2021 Building Decarbonization Assessment [5]
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Fixing the Prioritization Problem

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

Related Work

- ▶ People's Energy Analytics identifies at-risk utility customers for missing bill payments [6]
- ▶ Rewiring America provides tools to assess upgrade options to replace fossil fuel-based appliances with electric alternatives [7]
- ▶ MyHeat California uses thermal imaging and machine learning to identify heat loss and leakage [8]
- ▶ Google's Environmental Insights Explorer (EIE) uses satellite data to measure, analyze, and reduce emissions using data and modeling [9]
- ▶ *The missing piece: a prioritization tool that helps policymakers identify and rank homes for retrofits based on their potential for emissions reduction, electricity savings, cost savings, and energy burden relief.*

Proposal

DATA: Leverage open-source National Renewable Energy Laboratory (NREL) ResStock residential upgrade analysis [10] to learn patterns from post-retrofit results



MODEL: Develop a prioritization algorithm to enumerate the homes with the greatest predicted benefit (emissions reduction, energy savings, cost savings, and energy burden reduction); Prototype from San Mateo County, CA



APPLY: Policy and Decision-Making

- User input on weights for the four optimized outputs: emissions reductions, energy savings, cost savings, and energy burden reduction
- Direct policy design and optimize financing

Methodology: First Layer

Machine Learning for Component Scores

- ▶ 4 Independent 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
- ▶ Learning rate 0.05, Max. tree depth 8, Max. it. 300, L2 Regularization = 0.1
- ▶ Each model outputs a score per building, and ranks the homes correspondingly

Methodology: Second Layer

Component scores into a policy-weighted aggregate score

- ▶ Four criterion scores are z-score normalized from the first layer
- ▶ $\text{Total} = B1[\text{energy burden}] + B2[\text{emission reduction}] + B3[\text{cost savings}] + B4[\text{electricity savings}]$
 - ▶ B1, B2, B3, and B4 are weights assigned by the user based on policy intentions and community partner values
- ▶ Produces an aggregate priority score
- ▶ Buildings can be ranked according to the score
- ▶ Trade-off analysis between factor weight scenarios provides technical assistance on choosing optimal weight combinations
- ▶ Adding user input boosts explainability and decision-making control

Anticipated Results and Impact

- ▶ The result of the two-layer model produces an optimized ranking of households, demonstrating 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 equitable electrification of 75% of U.S. homes by 2050, American households would save \$96 billion in utility bills between 2024 and 2050. Without prioritizing low- and moderate-income households, the same level of electrification would instead cost \$88 billion. [11]

Preliminary Results: San Mateo County

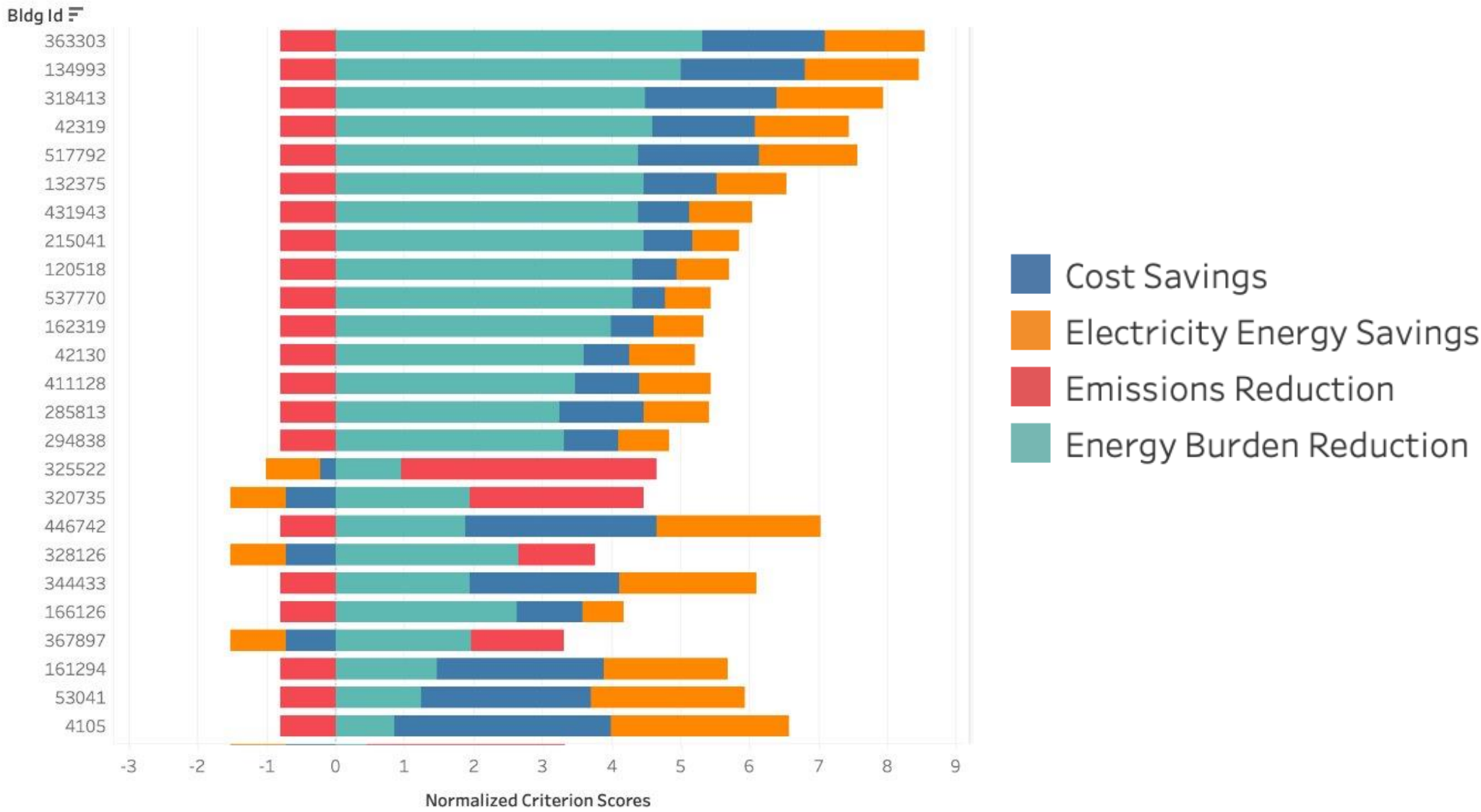
- ▶ San Mateo County data from the California ResStock dataset, October 2025
- ▶ Input Includes (but not limited to):
 - ▶ "in.utility_bill_electricity_marginal_rates"
 - ▶ "in.water_heater_efficiency"
 - ▶ "in.income"
 - ▶ "in.geometry_building_type_height"
 - ▶ "in.cec_climate_zone"
 - ▶ "in.usage_level"
 - ▶ "in.sqft..ft2"
- ▶ Output:
 - ▶ "out.emissions_reduction.total.aer_mid_case_avg..co2e_kg", Scenario total emissions reduction
 - ▶ "out.electricity.net.energy_savings..kwh", Total net electricity savings.
 - ▶ "out.utility_bills.total_bill_savings..usd", Savings on the scenario annual total charges.
 - ▶ "out.energy_burden_savings..percentage", Reduction on the percentage of income spent on energy.

Emissions Component Model: Segment of Results for Top Predictions

bldg_id	Predicted Emissions Reduction	Actual 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

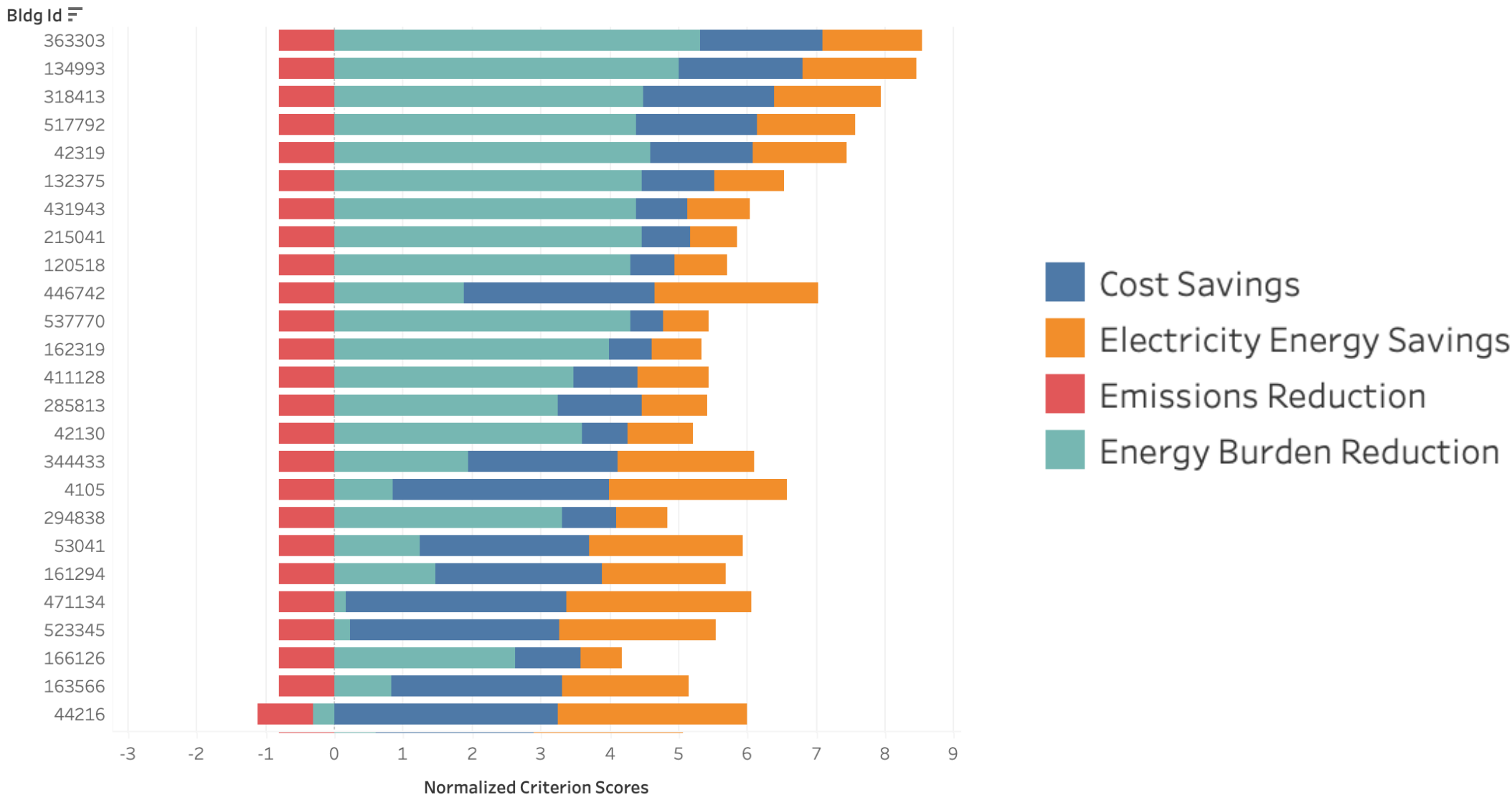
Sample Weight Scenario: Emission and Burden Heavy

$W(\text{Emis}) = 0.3, W(\text{Elec}) = 0.2, W(\text{Cost}) = 0.1, W(\text{Burd}) = 0.4$



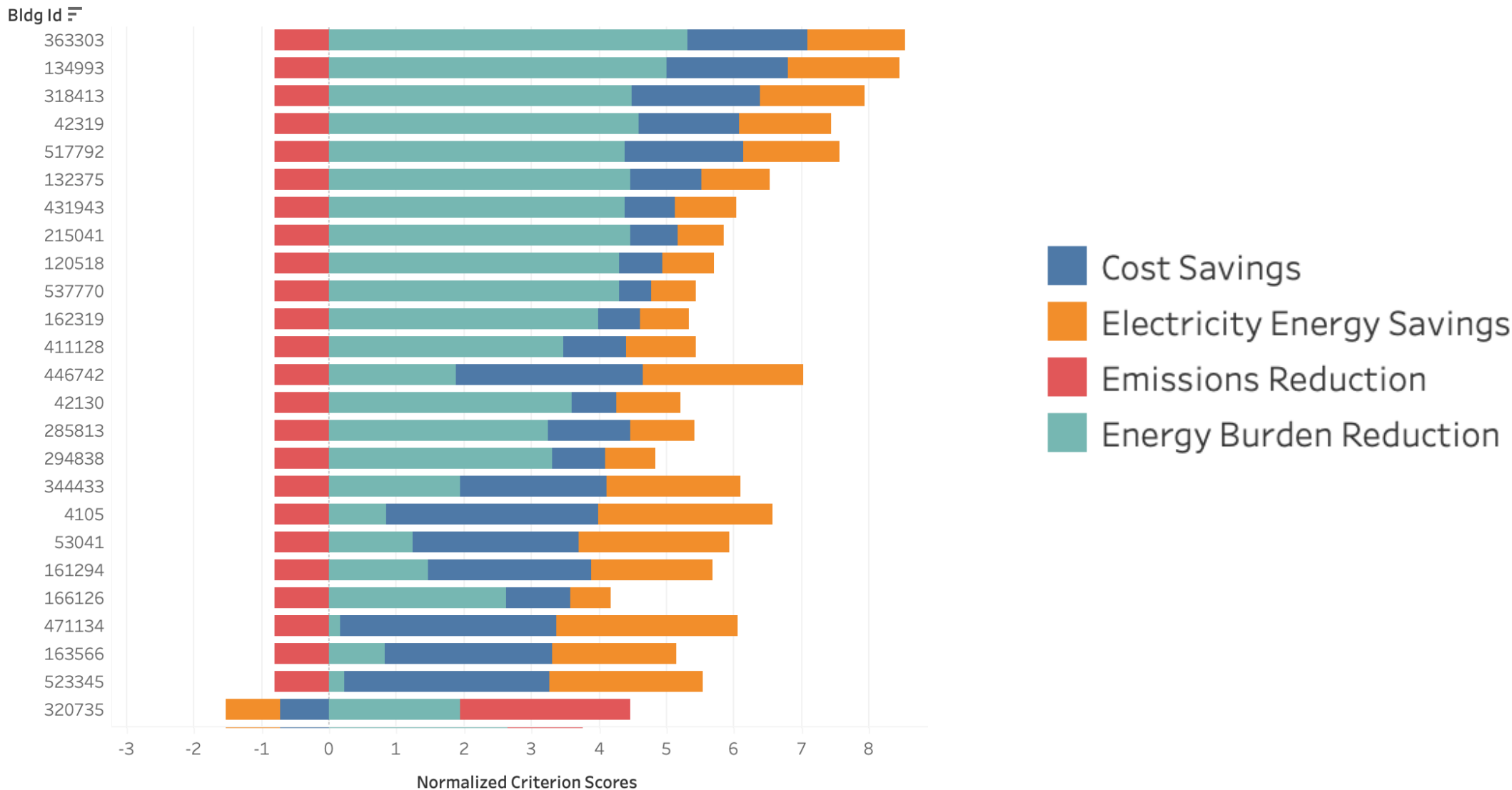
Sample Weight Scenario: Cost and Burden Heavy

$W(\text{Emis}) = 0.1, W(\text{Elec}) = 0.2, W(\text{Cost}) = 0.3, W(\text{Burd}) = 0.4$



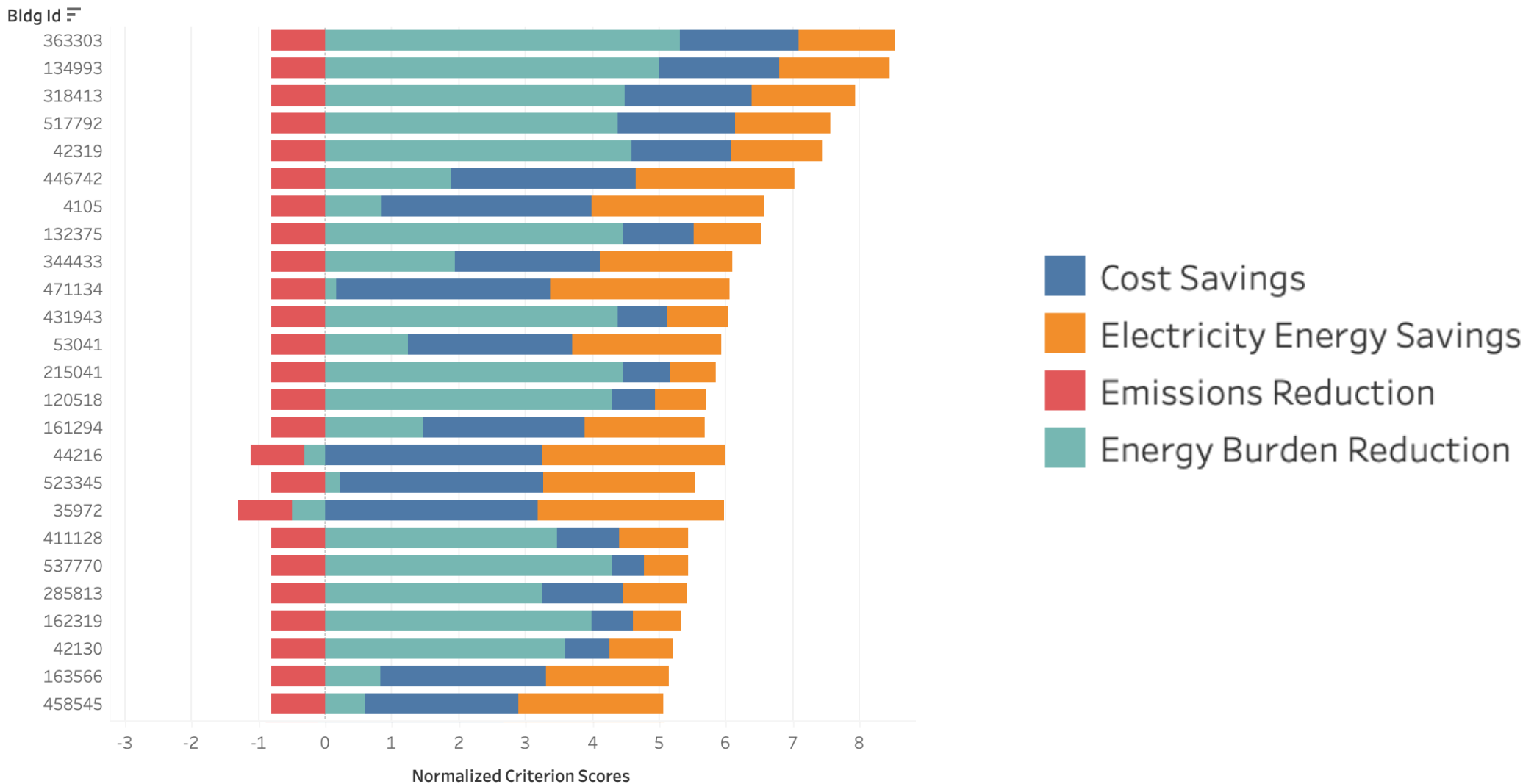
Sample Weight Scenario: Even with Burden Emphasis

$W(\text{Emis}) = 0.2$, $W(\text{Elec}) = 0.2$, $W(\text{Cost}) = 0.2$, $W(\text{Burd}) = 0.4$



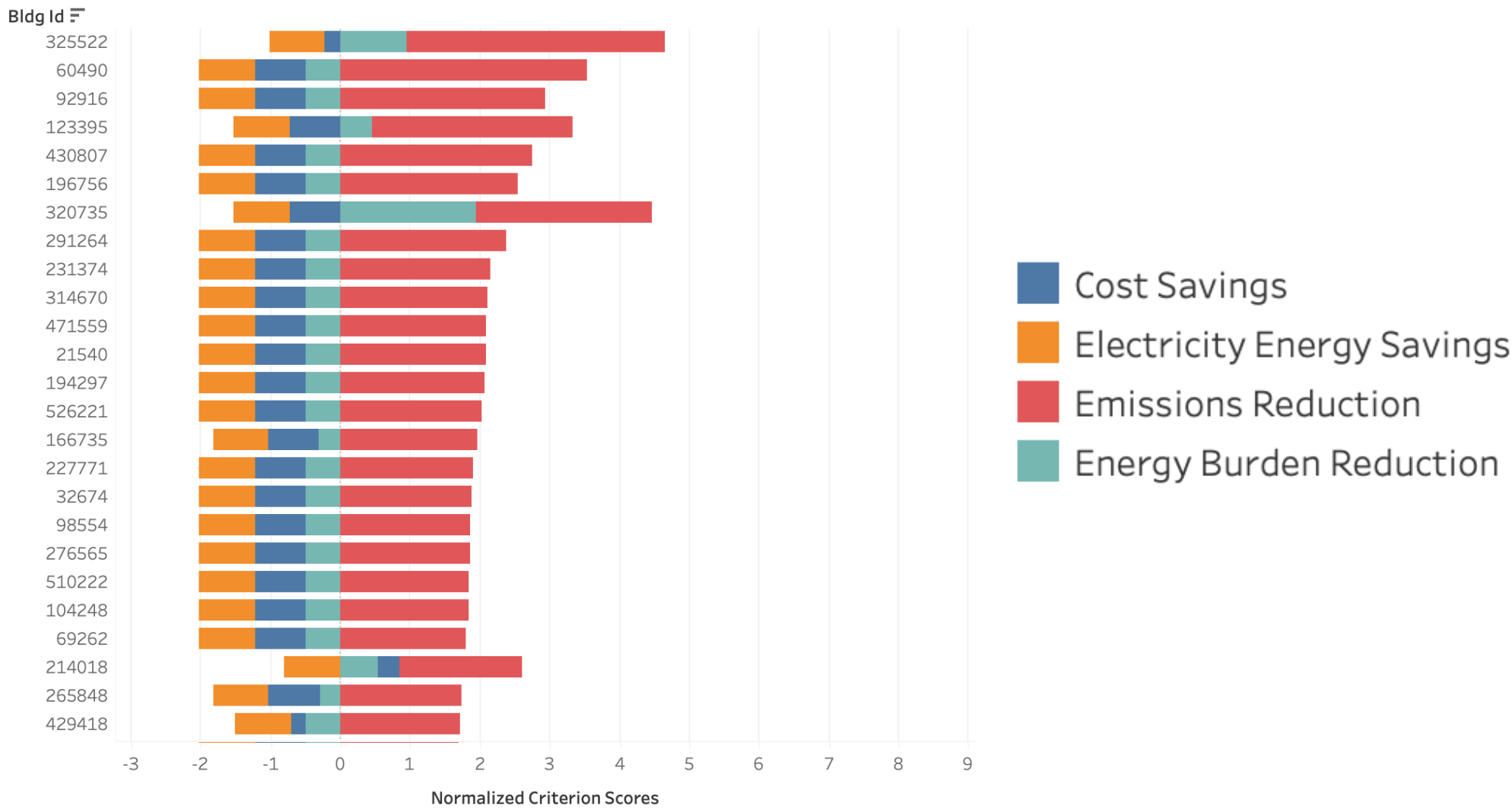
Sample Weight Scenario: Equal Weights

$W(\text{Emis}) = 0.25, W(\text{Elec}) = 0.25, W(\text{Cost}) = 0.25, W(\text{Burd}) = 0.25$



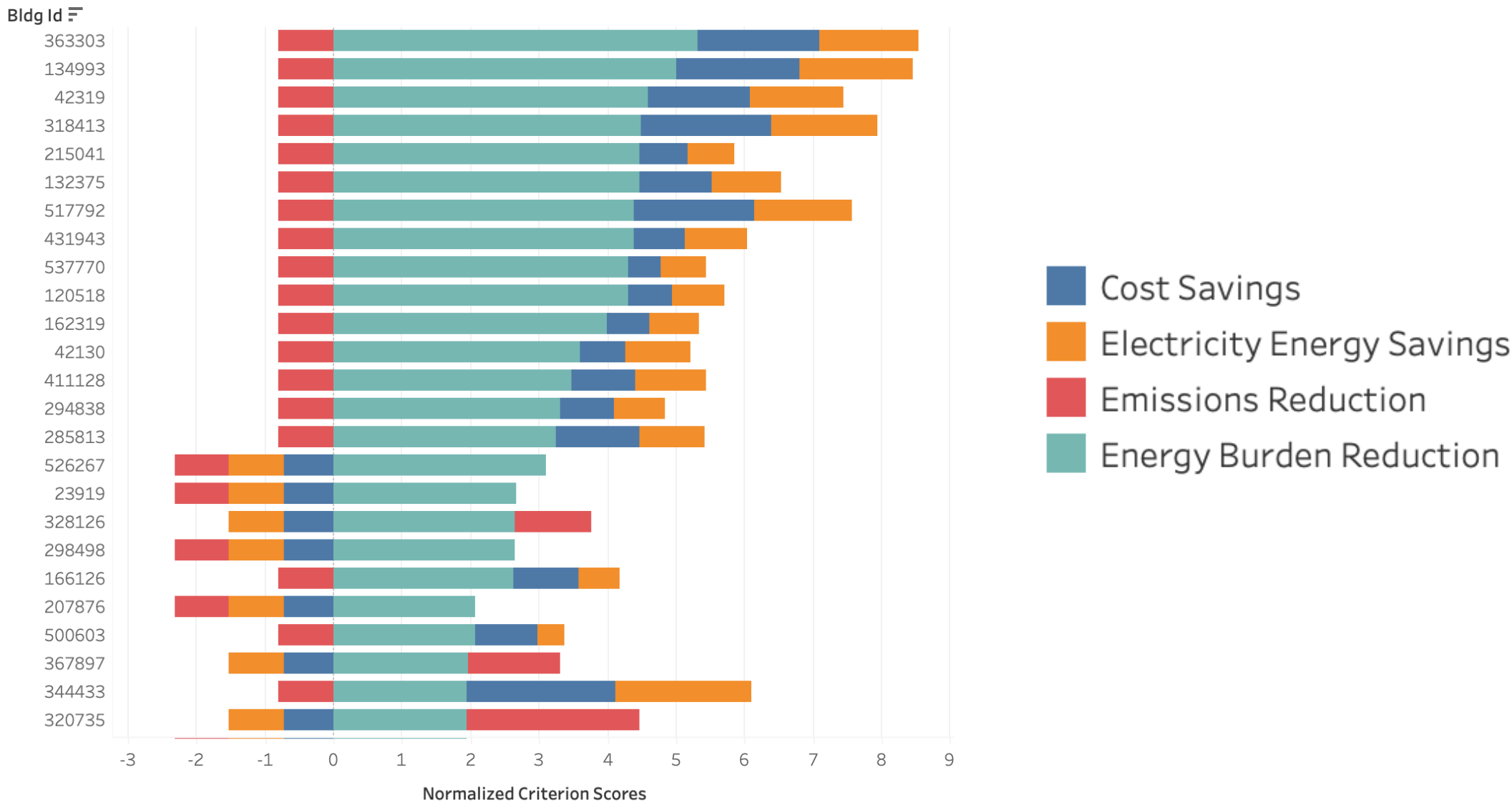
Sample Weight Scenario: Emissions Only

$W(\text{Emis}) = 1.0, W(\text{Elec}) = 0.0, W(\text{Cost}) = 0.0, W(\text{Burd}) = 0.0$



Sample Weight Scenario: Burden Only

$W(\text{Emis}) = 0.0$, $W(\text{Elec}) = 0.0$, $W(\text{Cost}) = 0.0$, $W(\text{Burd}) = 1.0$



Validation and Performance

To validate the results, a segment of the training data was set aside for testing

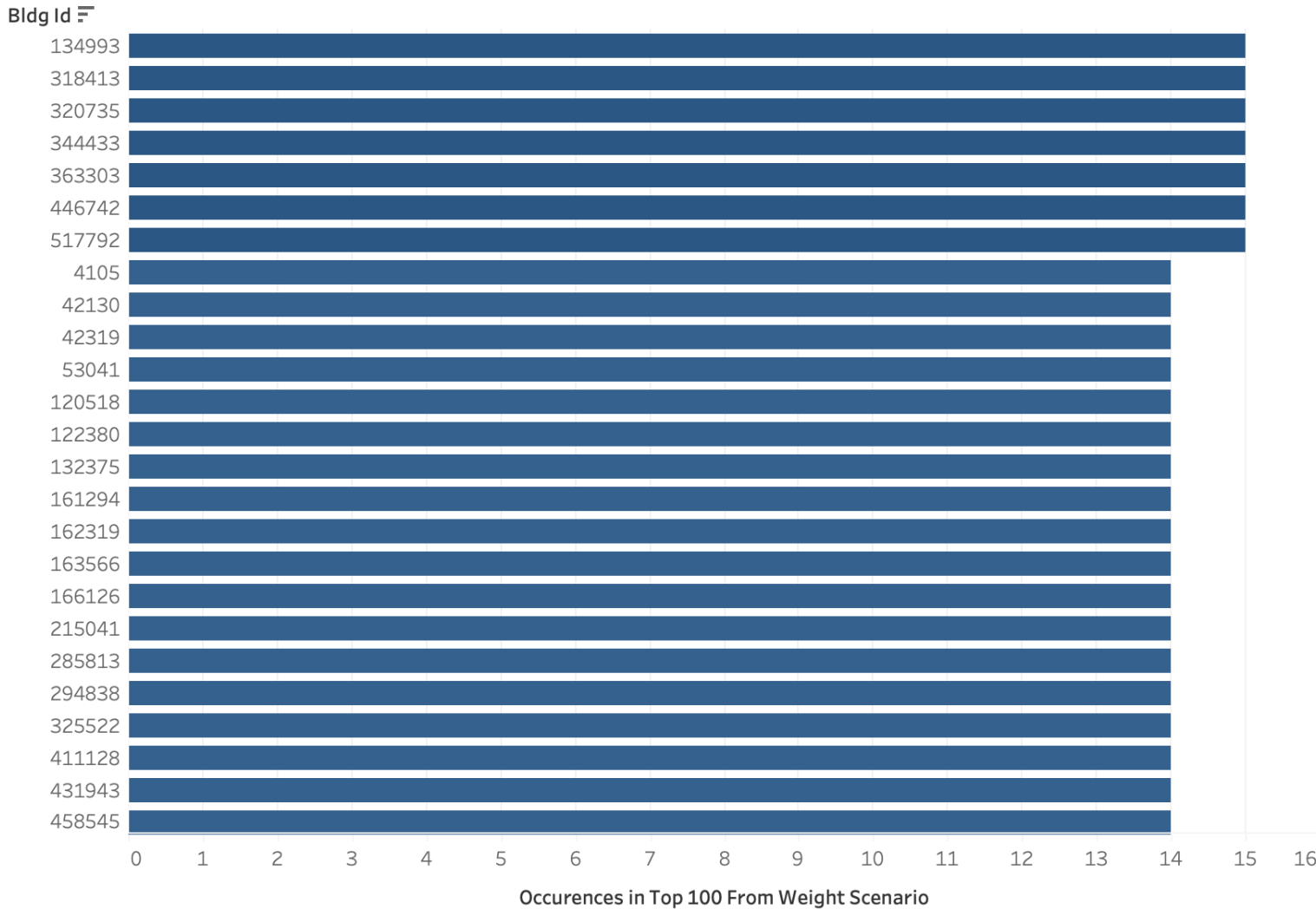
Component Performance:

- ▶ (1) Emissions Reduction: $R^2 = 0.737308$ RMSE = 0.501736
- ▶ (2) Electricity Usage Reduction: $R^2 = 0.812021$ RMSE = 0.453819
- ▶ (3) Cost Savings Regression: $R^2 = 0.715062$ RMSE = 0.550245
- ▶ (4) Burden Reduction Regression: $R^2 = 0.523284$ RMSE = 0.664795
 - ▶ Variance in customer income levels; not all energy-burdened

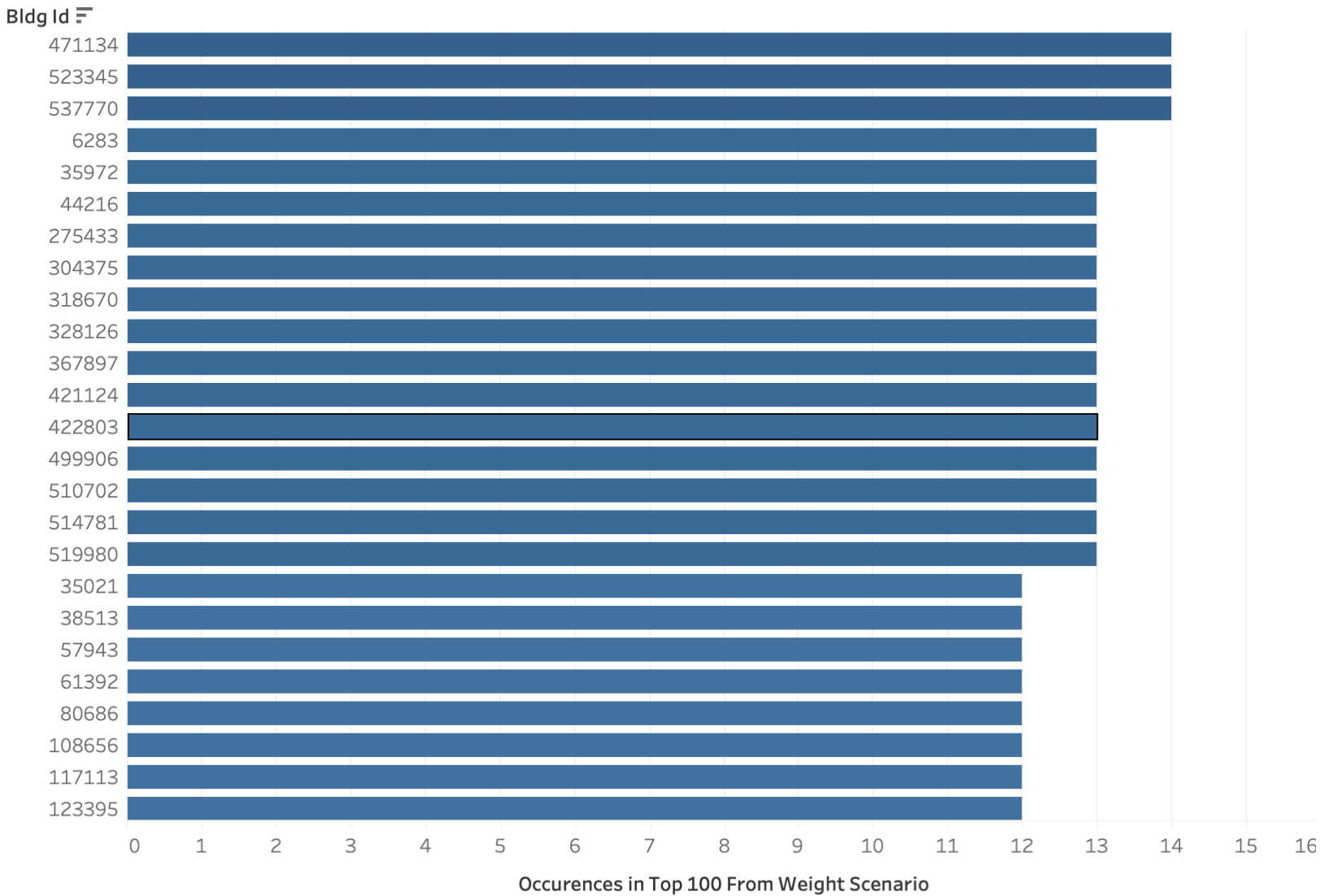
Top 200 dwellings by each model v. actual top 200 in the criterion category

- ▶ 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

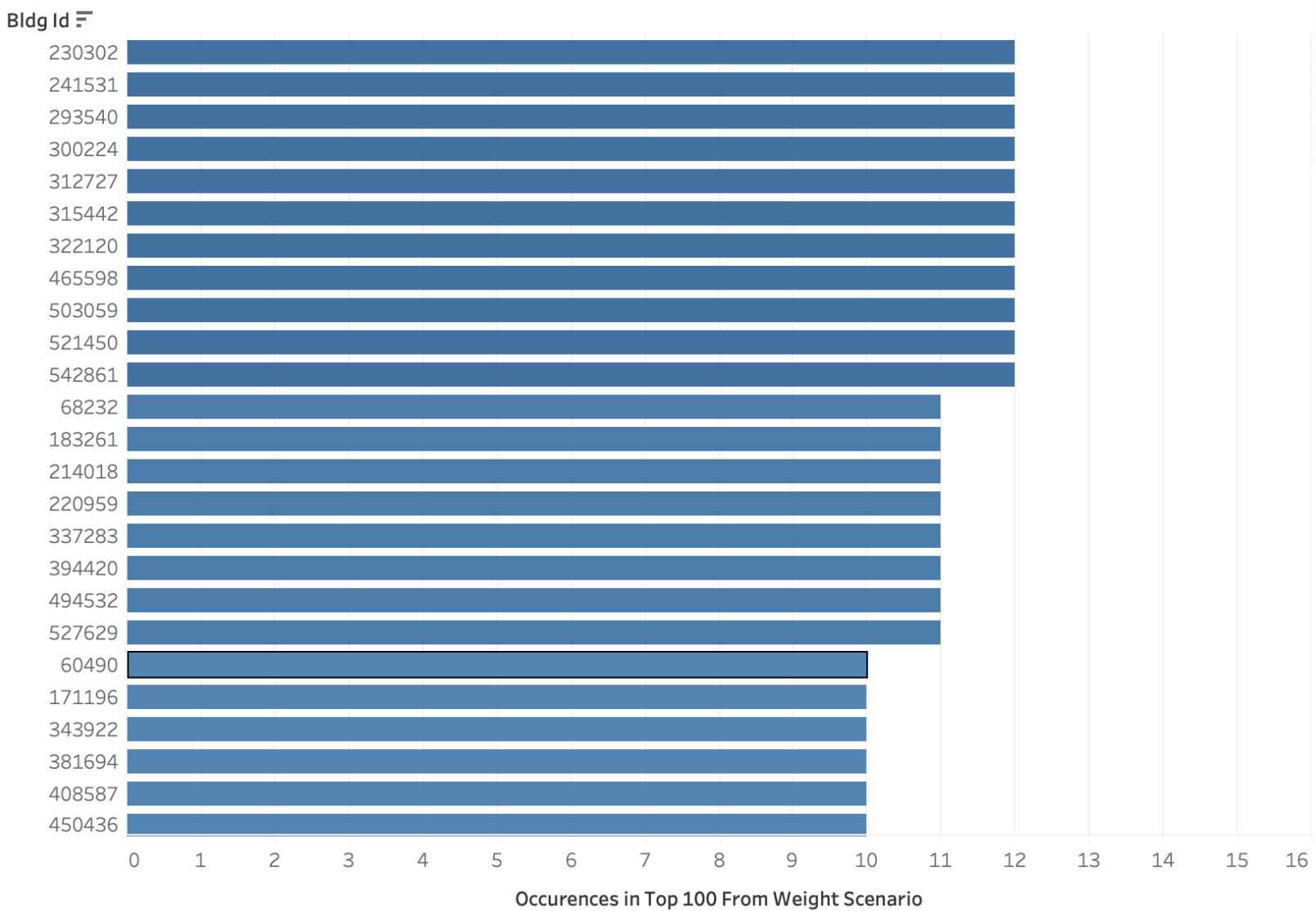
Buildings in San Mateo Country Occurences in Top 100 Across Weight Scenarios



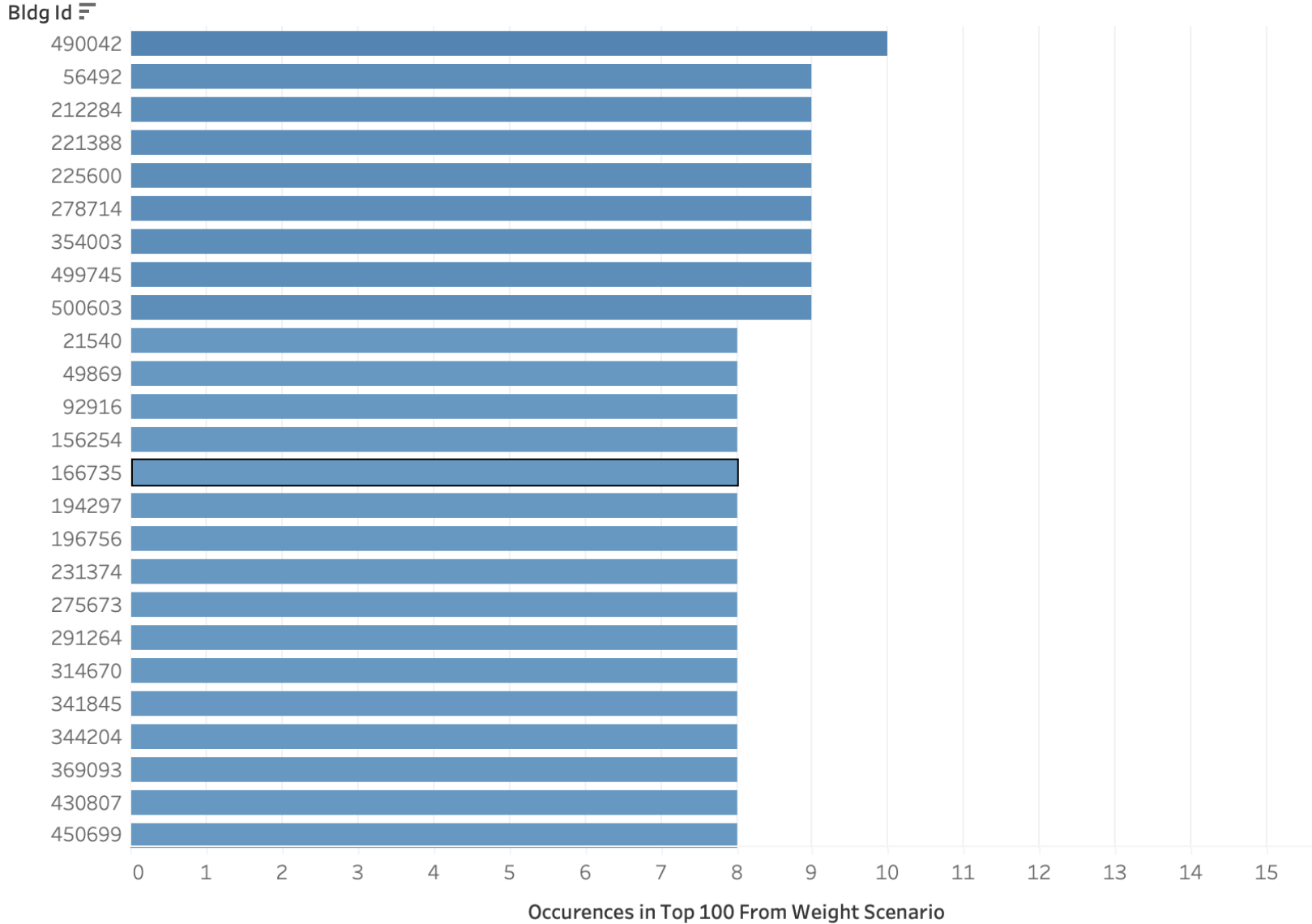
Buildings in San Mateo Country Occurences in Top 100 Across Weight Scenarios



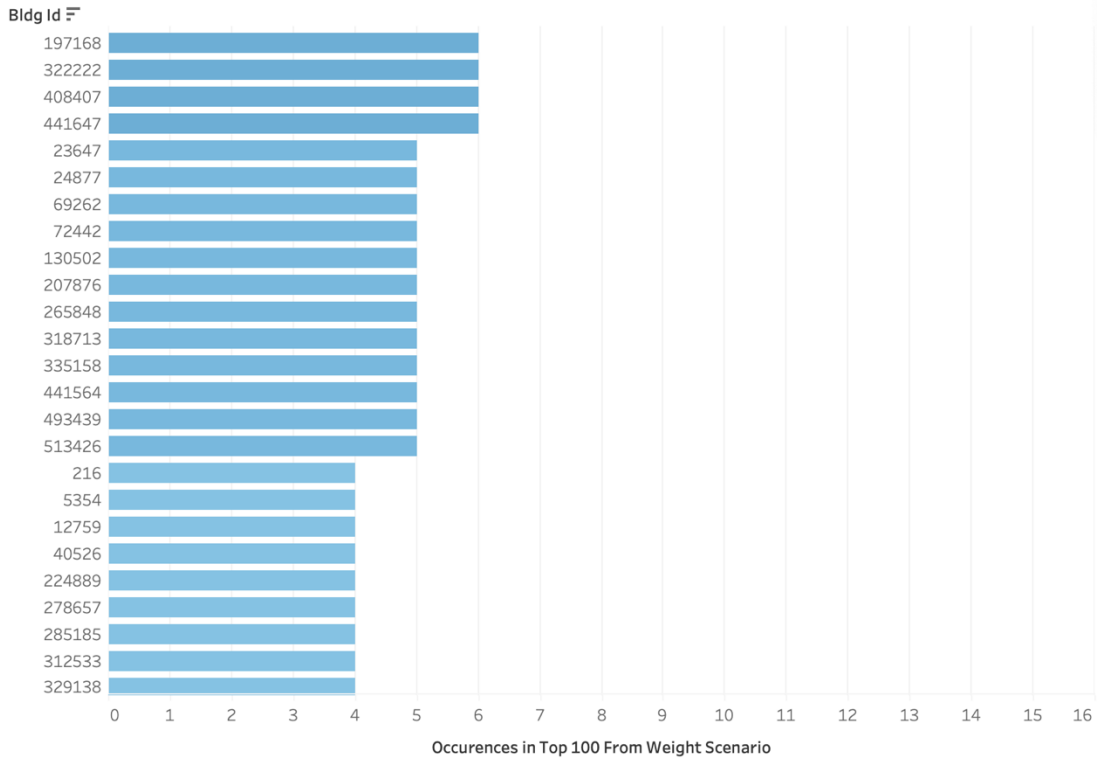
Buildings in San Mateo County Occurences in Top 100 Across Weight Scenarios



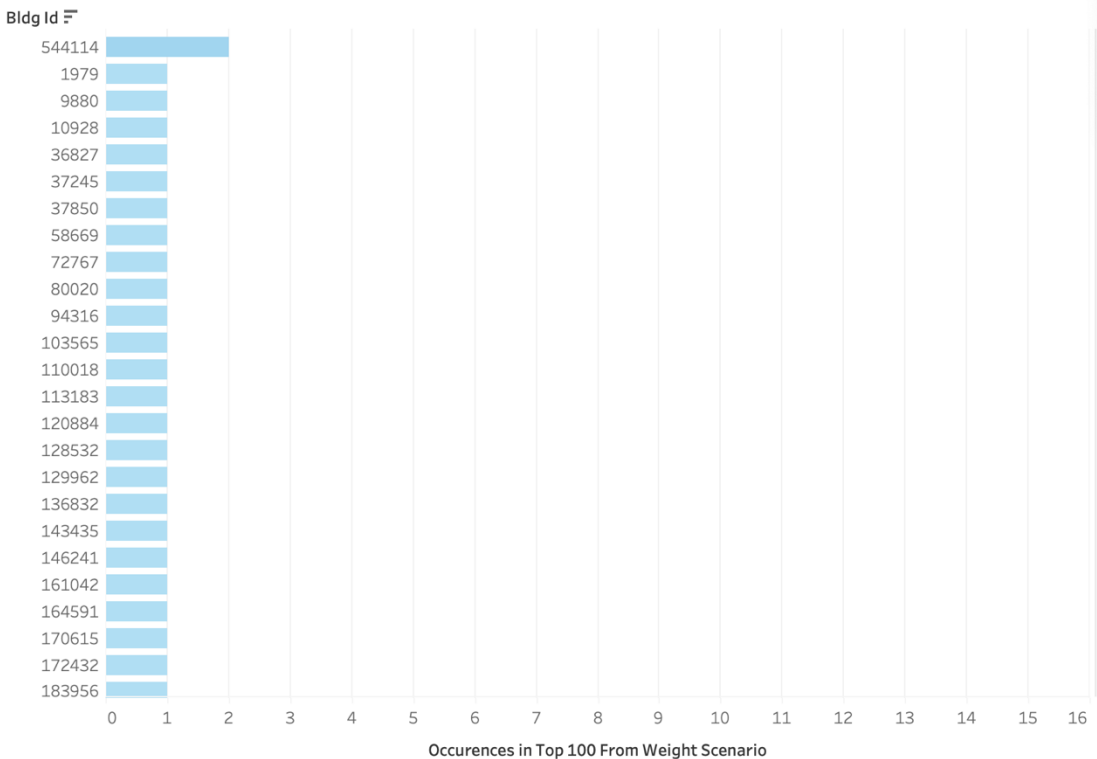
Buildings in San Mateo Country Occurences in Top 100 Across Weight Scenarios



Buildings in San Mateo Country Occurences in Top 100 Across Weight Scenarios



Buildings in San Mateo Country Occurences in Top 100 Across Weight Scenarios



Overcoming Potential Limitations

- ▶ Model minimization of the equity piece: reducing energy burden of BIPOC and low-income households must remain a top priority
- ▶ Biased data: homes chosen for upgrades were not the most optimal
- ▶ Shifting utility rates and policy incentives
- ▶ Steps after identification: financing forward

Next Steps

- ▶ Consider: Combine with CCI priority population spatial data [12], smart meter data from the CEC [13], and other sources by local relevance
- ▶ Test on multiple regions
- ▶ Develop, test, and reiterate model design
- ▶ Consult with utility engineers, policymakers, authors of related publications, academic researchers, and environmental justice advocacy groups



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