End-use Load Profiles for the U.S. Building Stock

Technical Advisory Group Meeting #9
January 28, 2021

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Logistics

- We are recording the webinar.
- Because of the large number of participants on the phone, please keep yourself muted during presentations.
- Please use the chat box to send us clarifying questions during presentations. You can chat or unmute yourself to ask a question during our designated discussion time.

Agenda

- Welcome back! (5 minutes)
  - Project overview, timeline, deliverables and resources
- Update on ComStock calibration: Commercial AMI Classification and discussion (40 minutes)
- Update on ResStock calibration: Residential Calibration on Region 3 and discussion (40 minutes)
- Next steps/wrap up (5 minutes)

Links to the slides are also in the chat box.

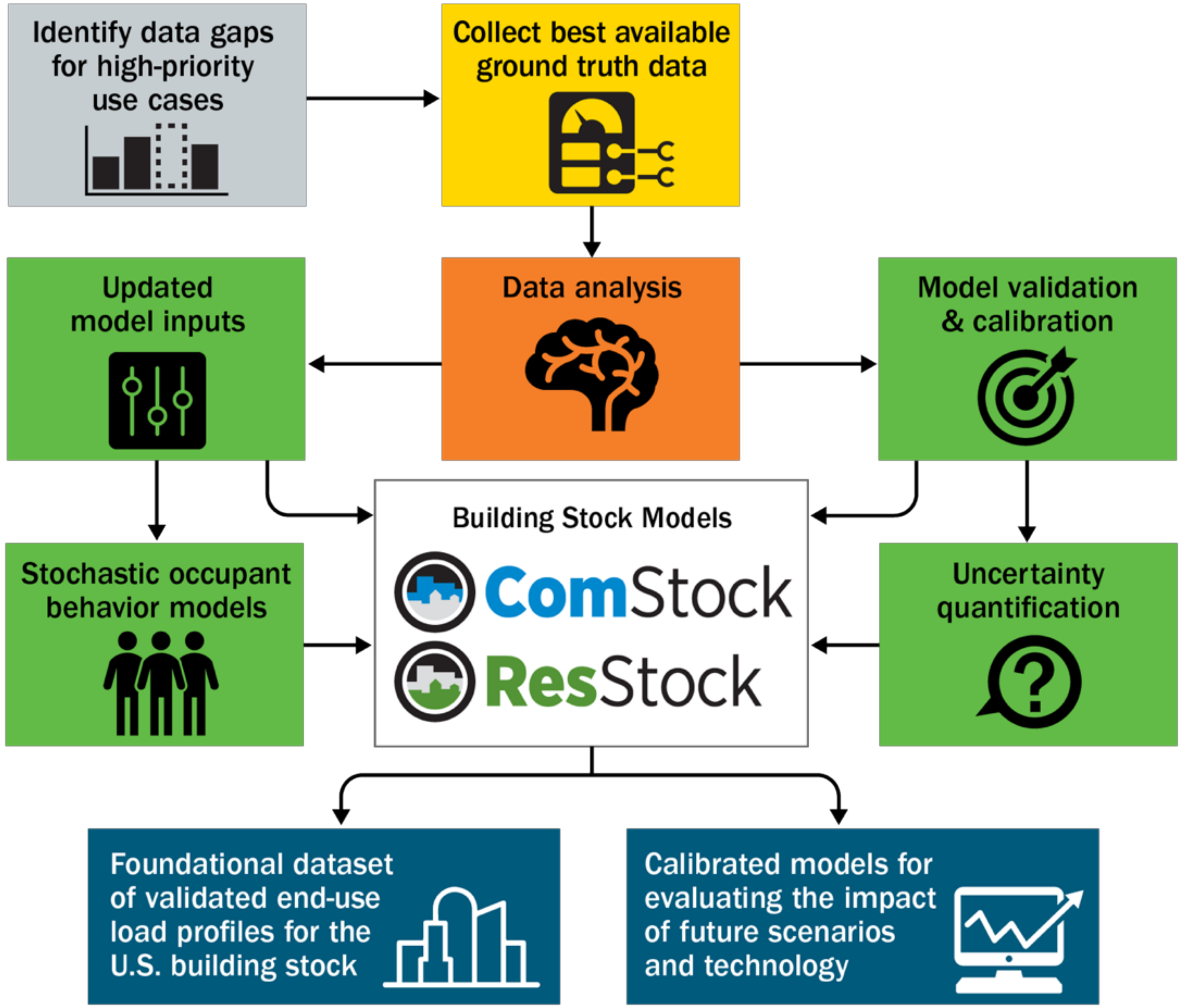
Project Overview

Hybrid approach combines best-available ground-truth data—

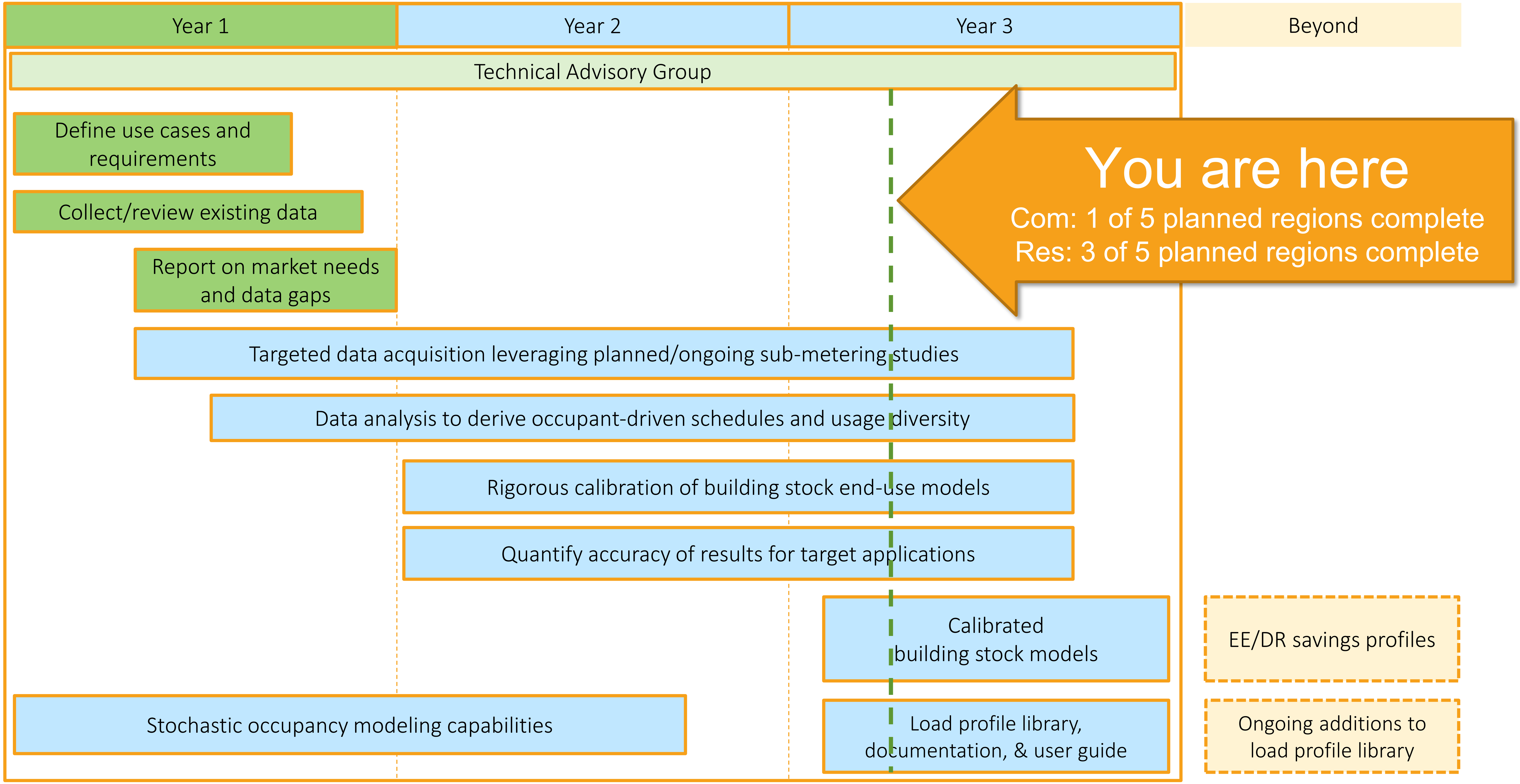
- submetering studies,
- whole-building interval meter data, and
- other emerging data sources

—with the reach, cost-effectiveness, and granularity of physics-based and data-driven building stock modeling capabilities

The novel approach delivers a nationally-comprehensive dataset at a fraction of the historical cost.



Project Timeline



Summary of FY21 Final Products for End-Use Load Profiles

Published by 9/30/2021*

Public Datasets
- VizStock Web Interface
- Pre-aggregated Load Profiles
- Raw Individual Building Load Profiles
- Raw Individual Building Models

Dataset Access Instructions
The project website will provide instructions on how to access and download the various dataset formats

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Completed by 9/30/2021*

Webinar
Conduct public outreach webinar to TAG and other stakeholders to present project outcomes

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Drafts to DOE & TAG by 9/30/2021*

Final reports published by 12/31/2021*

EERE or NREL report
End-Use Load Profiles for the U.S. Building Stock: <u>Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification</u>
- Content: Detailed description of model improvements made for calibration; detailed explanation of validation and uncertainty of results
- Audience: Dataset and model users interested in technical details
- NREL lead; LBNL and ANL co-authors

EERE or LBNL report
End-Use Load Profiles for the U.S. Building Stock: <u>Applications and Opportunities</u>
- Content: Example applications and opportunities for using the dataset
  Audience: General users of datasets
- LBNL lead; NREL co-authors

* Dates may change

Resources

Publications

- Li et al. Characterizing Patterns and Variability of Building Electric Load Profiles in Time and Frequency Domain (forthcoming)
- Bianchi et al. 2020. Modeling occupancy-driven building loads for large and diversified building stocks through the use of parametric schedules
- Parker et al. 2020. Framework for Extracting and Characterizing Load Profile Variability Based on a Comparative Study of Different Wavelet Functions
- Present et al. 2020. Putting our Industry's Data to Work: A Case Study of Large Scale Data Aggregation
- Northeast Energy Efificency Partnership (NEEP). 2020. Sharing Load Profile Data: Best Practices and Examples
- Frick et al. 2019. End-Use Load Profiles for the U.S. Building Stock: Market Needs, Use Cases, and Data Gaps
- N. Frick. 2019. End Use Load Profile Inventory
- E.Present and E. Wilson. 2019. End use load profiles for the U.S. Building Stock

Presentations and Slides

- Technical Advisory Group slides
  - LBNL and NREL site
- E. Wilson. 2020. EFX webinar
- E. Wilson. 2019. E Source interview
- E. Wilson. 2019. Peer Review presentation
- E. Present. 2019. NEEP presentation.

Software

- OpenStudio Occupant Variability Gem and Non Routine Variability Gem (more info at IBPSA newsletter)

Data

- First year of 15-min NEEA HEMS data available: https://neea.org/data/end-use-load-research/energy-metering-study-data

Commercial AMI Classification

Chris CaraDonna
Peter DeWitt
Amy LeBar
January 28, 2021

Recap & Motivation from Commercial Calibration Region 1

Building Classification

- Classification of AMI is critical for commercial building stock model calibration
  - Area and building type

- CoStar classifies based on real-estate needs
  - Some are clear: offices, outpatient, standalone retail
  - Some are ambiguous: strip malls, warehouses

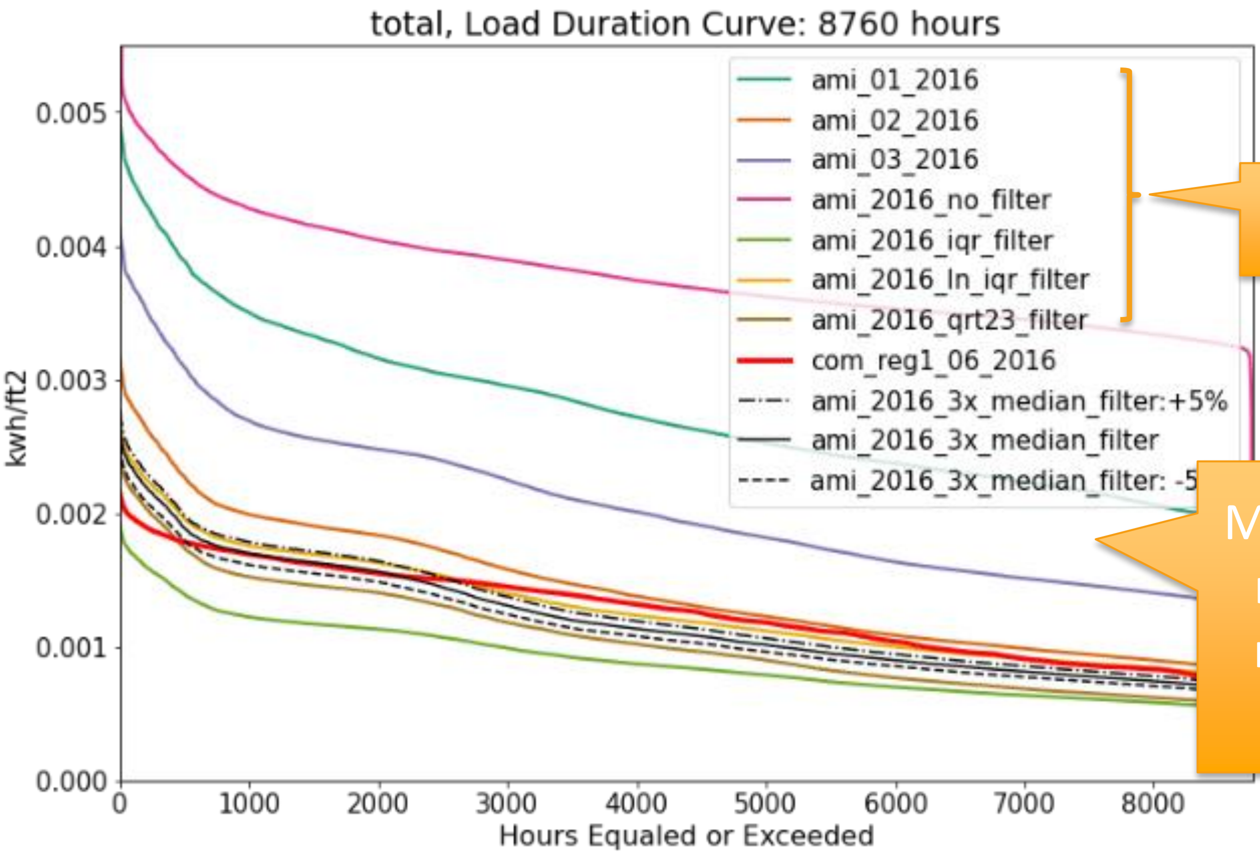
- We care that the classifications also match from an energy standpoint
  - Otherwise, we are comparing modeled apples to AMI oranges

Investigated “Outliers” with Google Maps

- strip_mall (23 outliers)
  - 9 are convenience store/gas stations
  - 11 are restaurants (or primarily restaurants)
- warehouse (18 outliers)
  - 13 are manufacturing
  - 2 are autobody shops
- small_office (13 outliers)
  - 2 are manufacturing
  - 1 is a nursery/greenhouse
  - 1 is a multifamily condo w/ maybe office space on first floor?
  - The rest are just normal-looking offices
- retail (5 outliers)
  - 3 are nursery/greenhouses
- outpatient (4 outliers)
  - All appear to legitimately be outpatient... perhaps some specialties use much more energy?
- quick_service_restaurant (1 outlier)
  - Drive-through where service is not tied to floor area

Conclusion: Most “outliers” were actually misclassified buildings, not truly “outliers” of the target building type

Impact of Misclassification & Outliers



Identification methods

Misclassification & outliers: more impactful than any model changes we did in Region 1!

Misclassification Detection Study

Introducing a New Team Member

- Peter DeWitt, Ph.D.
  - Joint Appointee between NREL and the University of Colorado Anschutz Medical Campus
  - Ph.D. Biostatistics
    - University of Colorado Anschutz Medical Campus
  - M.S. Statistics
    - Colorado State University
  - B.S. and M.S. Mathematics & Computer Science
    - Colorado School of Mines
  - Primary Role:
    - Inform study design and assessment from a statistician's point of view

Xcel Energy Test Dataset

Xcel Energy has provided our project with **monthly energy billing data** for over 500,000 meters.

The scale of this dataset is ideal for testing outlier removal methods based on annual electric EUI (kWh/sf/yr), building area, and total electric usage, which can then be translated to our AMI dataset processing workflow.

For the context of this work, outliers could be defined as buildings that have inaccurate metadata (area and/or building type), or unrealistically high/low energy values.

Building Classification & Outliers

Goals:

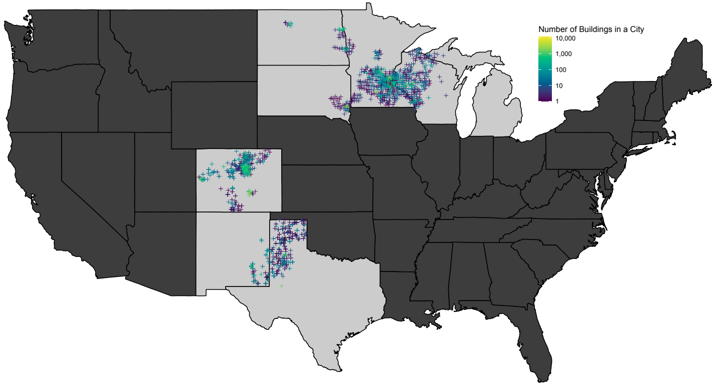
1. Determine effective method for detecting/removing misclassified buildings based on energy consumption and building area
2. Retain a reasonable distribution of energy consumption, footprint, and energy use intensity

Approach:

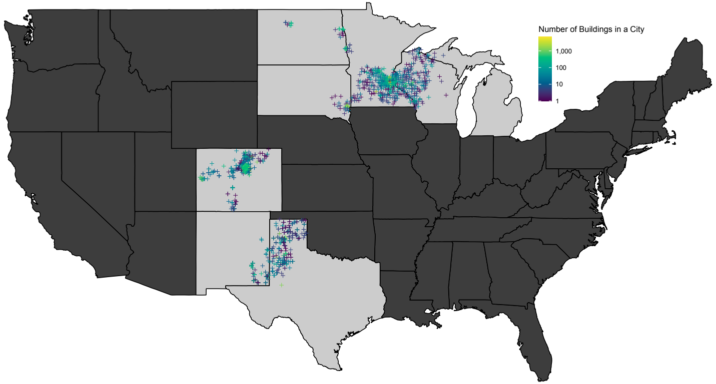
1. Initial dataset of **~517k** monthly meters from Xcel Energy
   - Covers **8** states
   - ~**211k** have CoStar matches (for building type & area metadata)
2. Sample the population, manually classify samples
3. Test different misclassification/outlier detection approaches
   - Only testing simple, non-timeseries-based approaches

Data Set Before/After Culling

Before: 8 States, 89k Buildings



After: 8 States, 57k Buildings



Premise: 1 Xcel location

Meter: 1 Xcel energy reading; can have multiple per premise

Building: 1+ Xcel meters/premises matched with 1+ CoStar entries

- 1 building with 1 meter
- 1 building with several meters
- 2 buildings of the same type on the same parcel with several meters

Data Culling

Started with ~89k buildings

Number removed	Reason
805	Missing information about DOE building type
25	Remove billing credits (not actually energy consumption data)
11,224	Remove Xcel gas-only (keep buildings where Xcel provides electricity)
4	Restrict to billing from 2017-Dec-01 through 2019-Jan-01
6,376	Restrict to buildings with all meters observed for the full 2018 calendar year
311	Remove Zero energy use
72	Remove buildings with footprint < 100 sf
13,296	Remove buildings where not all premise ids have complete billing data

Ended with ~57k buildings

Misclassification and Outlier Detection

- Apply a filter to identify misclassified data, i.e., wrong building type.

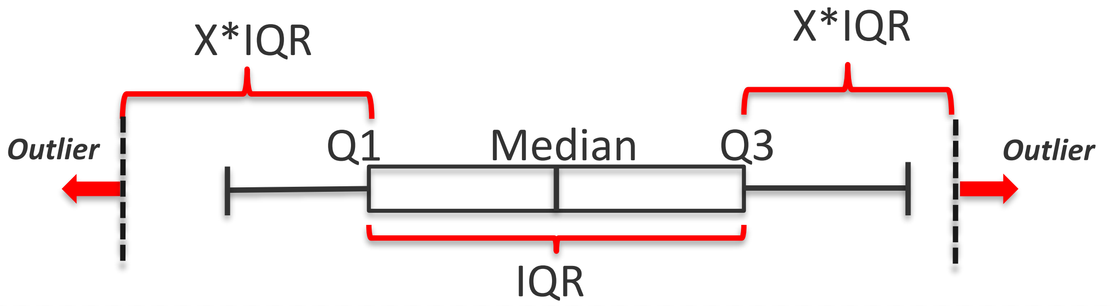
- Methods are based on
  - Extremes of EUI (kWh / sqft / year) or
  - Extremes of 2D density of consumption (kWh / year) and footprint (sqft)

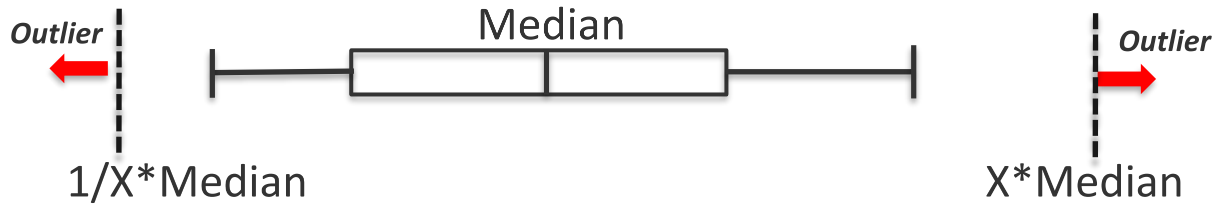
- Extreme values could indicate:
  - Misclassified building, e.g., small office is really a hospital
  - Uncharacteristic building, e.g., small office with a bitcoin mining setup

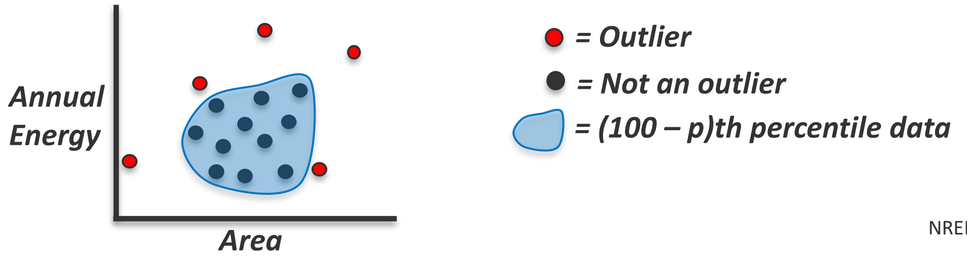
Misclassification and Outlier Detection Methods Tested

Outlier removal occurs per CoStar building type

Method	Dimension(s)
Boxplot	• EUI • $\log_{10}$ EUI
Multiple of the Median	• EUI • $\log_{10}$EUI
Kernel Density (KD)	2D: kWh/year by square footage (both on $\log_{10}$ scale)







Misclassification and Outlier Detection Methods Tested

Method	Dimension(s)	Outlier Test	Pros	Cons
Boxplot	• EUI • $\log_{10}$ EUI	$< Q_1 - xIQR$ $> Q_3 + xIQR$ $x \in \{1.5, 3\}$	• Common • Easy to implement	• Will not exclude low EUI if $Q_1 - xIQR < 0$
Multiple of the Median	• EUI • $\log_{10}$EUI	$< \frac{1}{x}\tilde{m}$ or $> x\tilde{m}$ where $\tilde{m}$ is the median $x \in \{3, 4, 5\}$	• Easy to implement • Can exclude low and high values	• Does not account for spread in the data • Sensitive to magnitude of the median
Kernel Density (KD)	2D: kWh/year by square footage (both on $\log_{10}$ scale)	Based on percentile estimates; omit the lowest p^{th} percentile	• Can id extremes in consumption and square footage even when EUI is "reasonable"	• Implementation for AMI is to be determined • May exclude "good data"

Verification and Evaluation of Methods

- Sampled ~300 buildings for human verification from lower 10th percentile of kernel densities
  - Focus on buildings which were uncharacteristic of others with the same label

		Truth	
		Misclassified	Correctly Classified
Method	Mis-classified	True Positive (TP)	False Positive (FP)
	Correctly Classified	False Negative (FN)	True Negative (TN)

- Sensitivity = TP / (TP + FN)
- Specificity = TN / (TN + FP)

- **High Sensitivity**
  - identify and remove misclassified data at the expense of omitting correctly classified data
- **High Specificity**
  - retain a lot of correctly classified data at the expense of retaining misclassified data

- Sensitivity and Specificity are inversely related
- Selection of preferable methods is subjective

Manual Verification Procedure

1. Search the address in Google Maps
2. Check for building type match using exterior signage or business name
   - Can you make any reasonable argument that it is properly classified?
3. Check for building area match using Google measure tool (accounting for multiple stories)
   - Report as misclassified if error > 50%
4. Report building classification as accurate or inaccurate
   - **If both** building type and area are **correct**, the building is listed as “Verified Accurate”
   - **If at least one** of building type or area is **incorrect**, the building is listed as “Verified Inaccurate”
   - If the building is not available on Google Maps, the building is listed as “Not Verifiable”

Human verification error is possible when identifying building type and measuring area.

Verification Results

- 309 sites were verified – these sites are weighted towards the tails and are not representative
- Building Area Classification Results
  - Unverifiable: 27 (9%)
  - Correctly Classified: 248 (80%-all sites; 88%-removing unverifiable)
  - Incorrectly Classified: 33 (11%- all sites; 12%-removing unverifiable)
- CoStar Building Type Classification Results
  - Unverifiable: 31 (10%)
  - Correct: 211 (68%-all sites; 76%-removing unverifiable)
  - Incorrect: 67 (22%- all sites; 24%-removing unverifiable)
- Combined Classification Results (both building area and building type were correctly classified)
  - Unverifiable: 36 (12%)
  - Correct: 186 (60%-all sites; 68%-removing unverifiable)
  - Incorrect: 87 (11%- all sites; 12%-removing unverifiable)

Examples of Misclassified Buildings

- Provided Data Set
  - CoStar: OFFICE
- Human
  - RETAIL_AUTO DEALERSHIP

Examples of Misclassified Buildings

- Provided Data Set
    - CoStar: INDUSTRIAL_TRUCK TERMINAL
- Human
    - OFFICE_SERVICE

Examples of Misclassified Buildings

- Provided Data Set:
  - CoStar: Flex Light Distribution
- Human:
  - Small Office

Examples of Misclassified Buildings

- Provided Data Set
  - CoStar: INDUSTRIAL_WAREHOUSE
- Human
  - Flea Market

kWh/sf/year value < 0.5 – ComStock does not attempt to model buildings of this type of irregularity

Examples of Misclassified Buildings

- Provided Data Set
  - CoStar: FLEX
- Human
  - Camper/trailer retailer

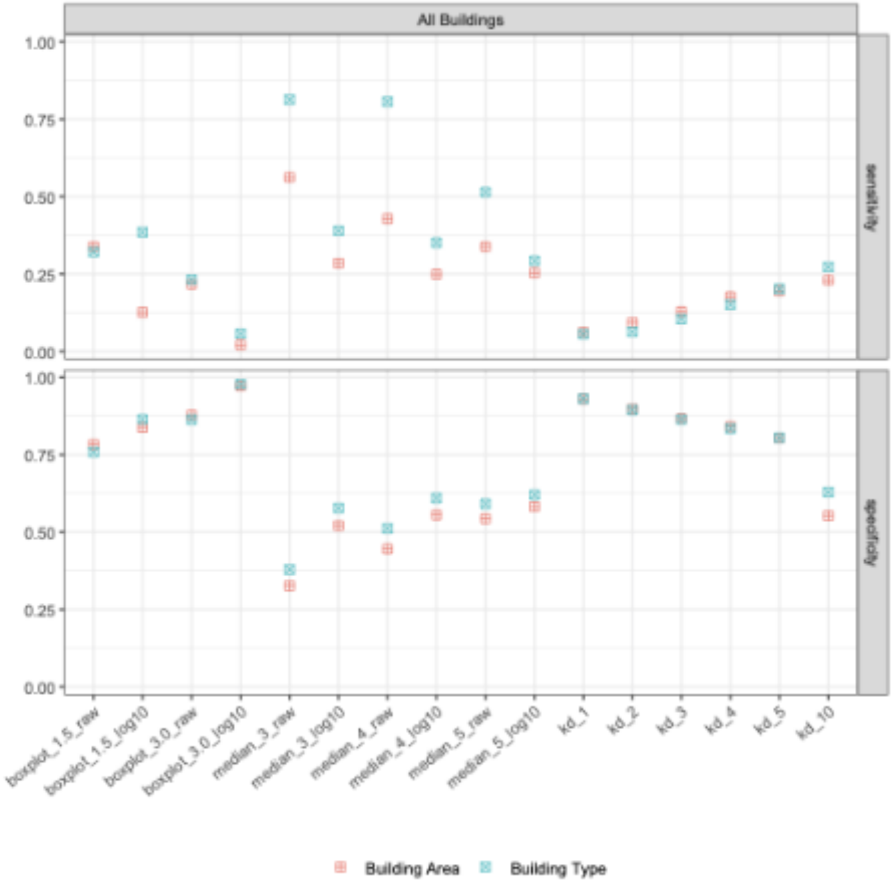
kWh/sf/year value < 0.1 – ComStock does not attempt to model buildings of this type of irregularity

Examples of Misclassified Buildings

- Provided Data Set
  - CoStar: INDUSTRIAL_WAREHOUSE
- Human
  - Church maintenance equipment storage

kWh/sf/year value < 0.2 – ComStock does not attempt to model buildings of this type of irregularity

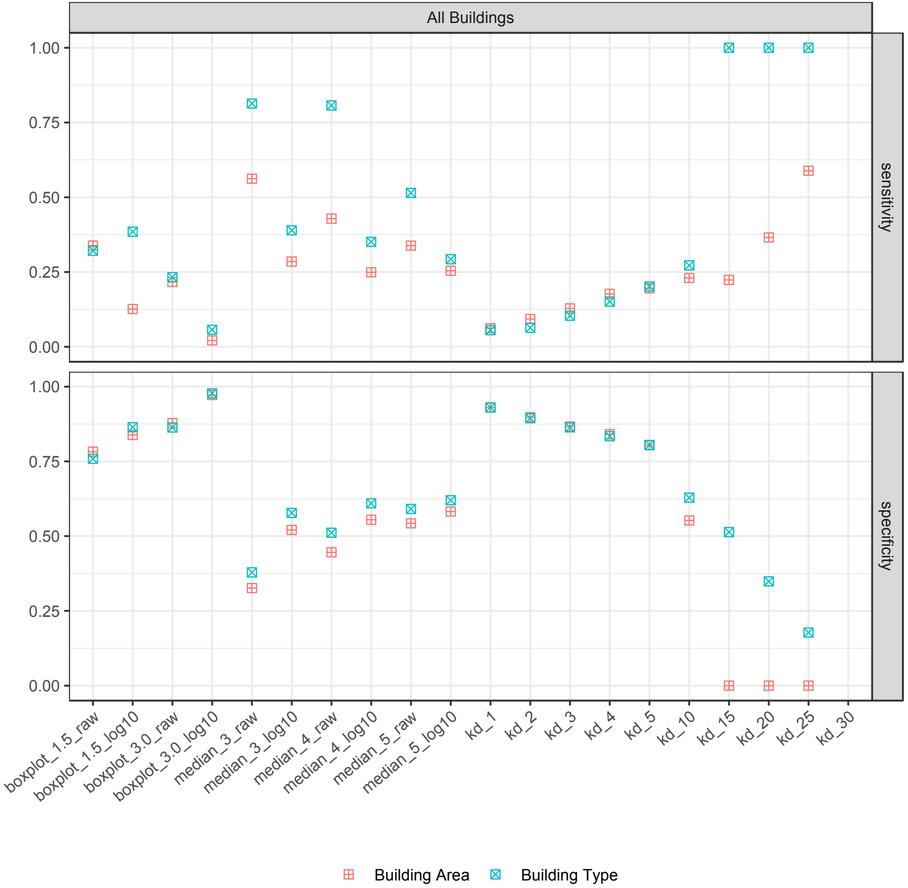
Sensitivity and Specificity



If **sensitivity** (identifying misclassified data) was priority, then the 3X Median or a higher-percentile Kernel Density method would be of interest.

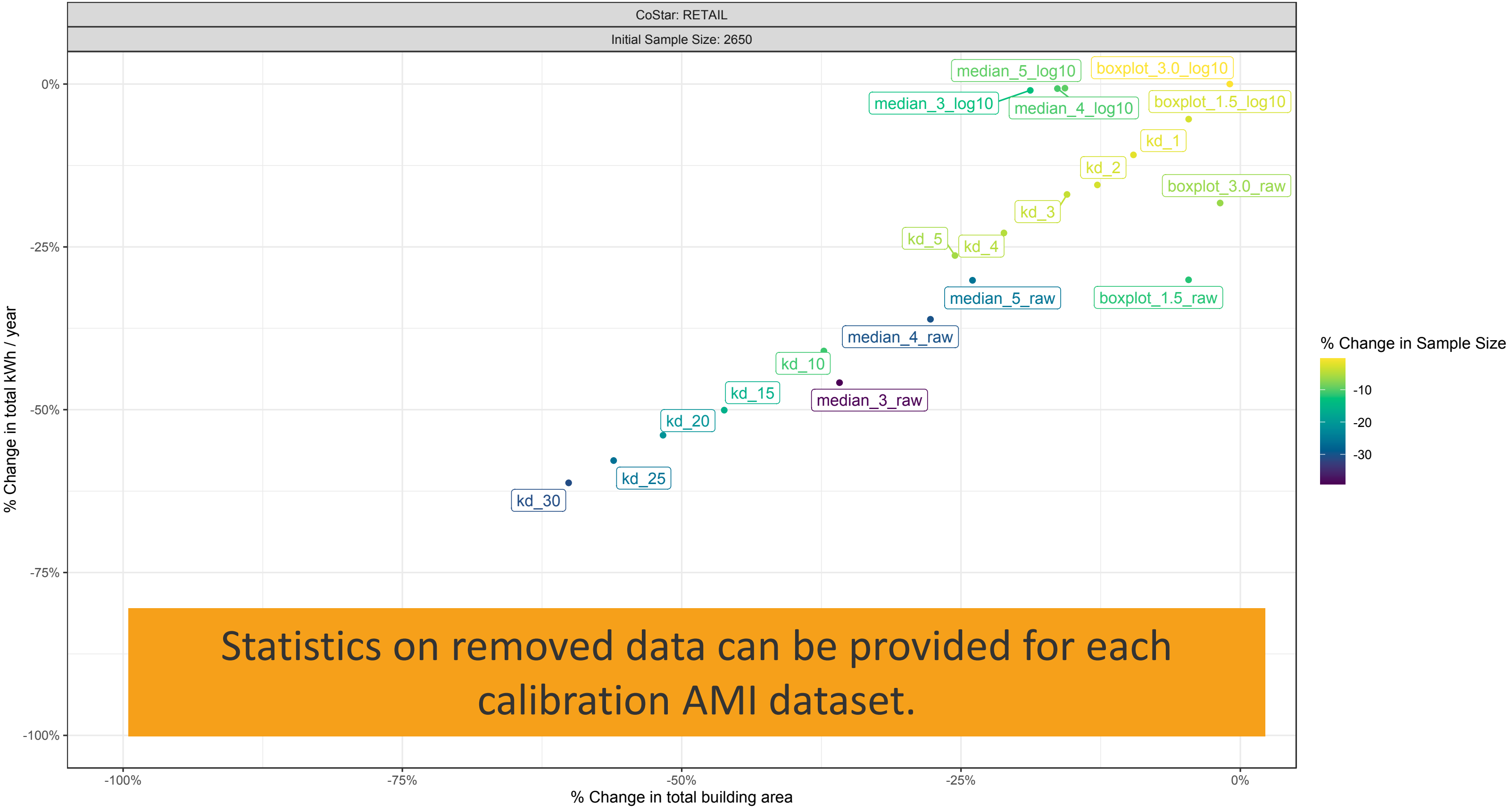
If **specificity** (maintaining properly classified data) was priority, then the Boxplot methods or a lower-percentile Kernel Density method would be of interest.

Sensitivity and Specificity



- Verification bias accounted for via methods of Begg and Greenes (1983)
- Estimates for kernel density (KD) percentiles greater than 10 are the least reliable
  - Initial sampling did not account for interest in percentiles > 10
  - Expanding the method set includes buildings which were not considered to be at risk of being an outlier
  - Could extend the verification set so useful estimates of for KD with p > 10 can be made

Example: Outlier Removal Methods on CoStar Small Retail



Statistics on removed data can be provided for each calibration AMI dataset.

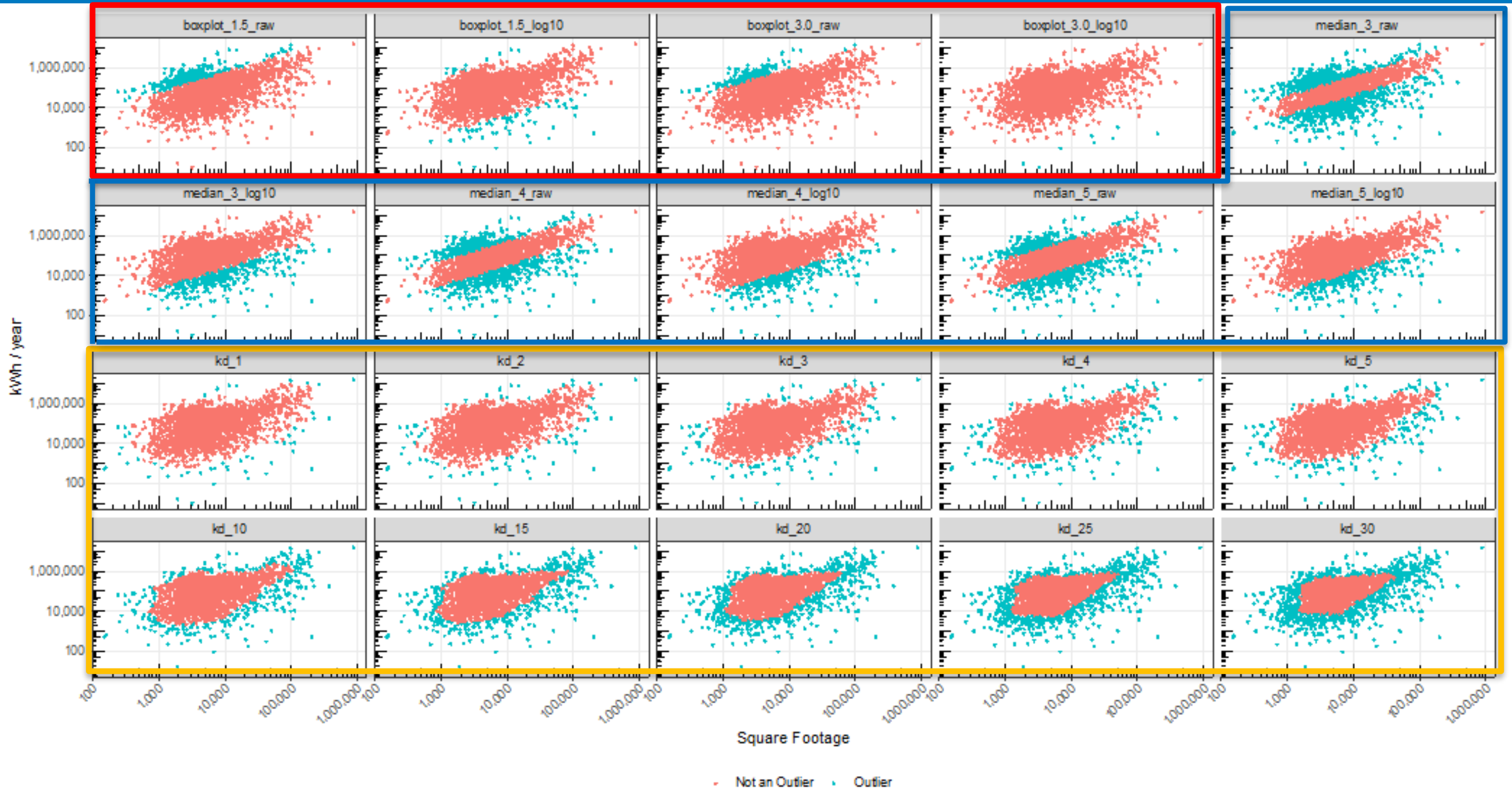
Notes on Reported Units and Scales

All reported energy values are for **electricity only**, and therefore exclude any potential gas heating or equipment. EUI values may seem lower than typical due to this exclusion.

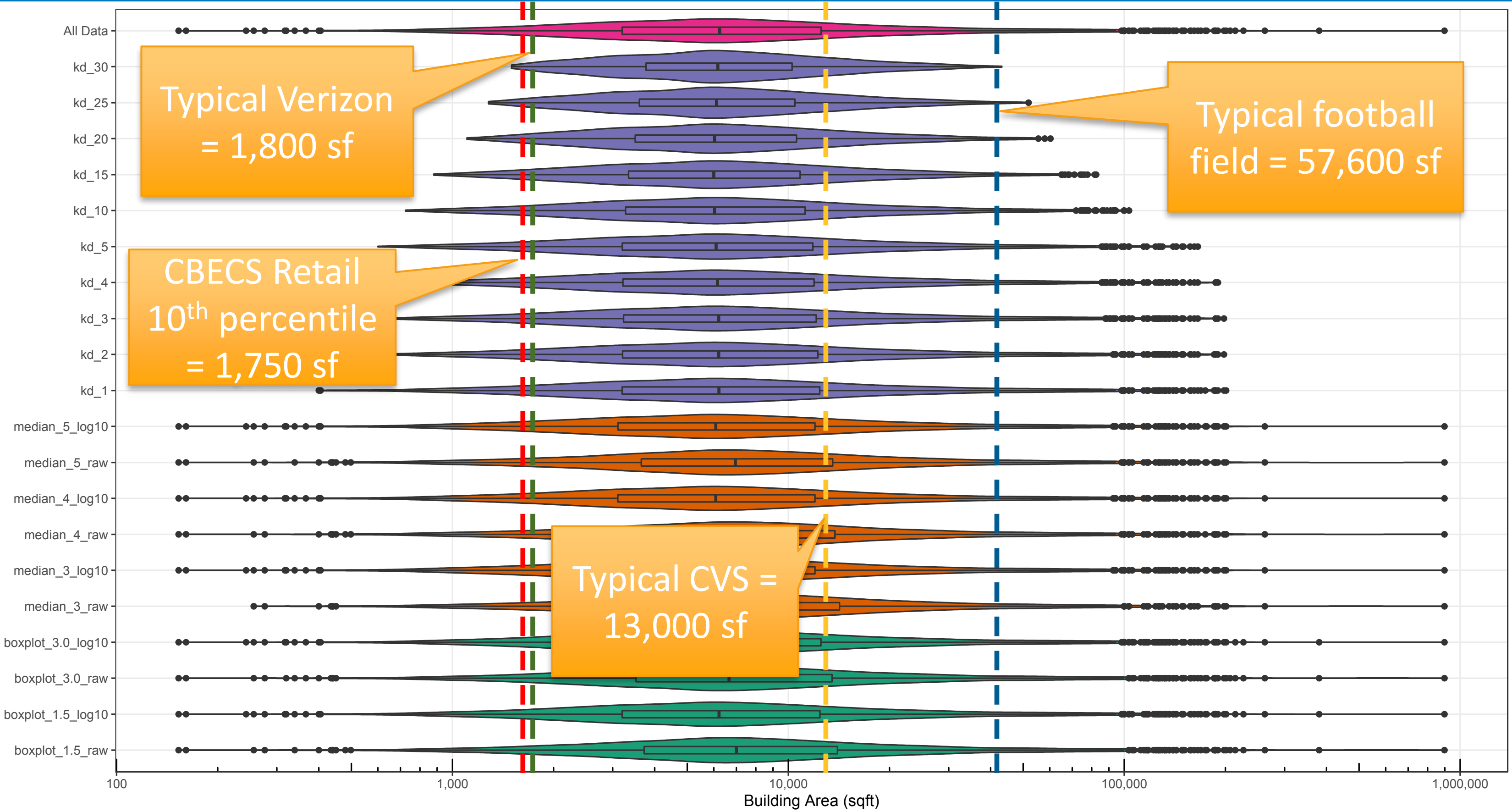
All EUI values are reported in **kWh/sf/year**, not kBtu/sf/year. Multiply the reported values by ~3.41 if kBtu/sf/year is a more familiar metric to you.

Log scales are used on several plots – keep this in mind when assessing behavior at increased values.

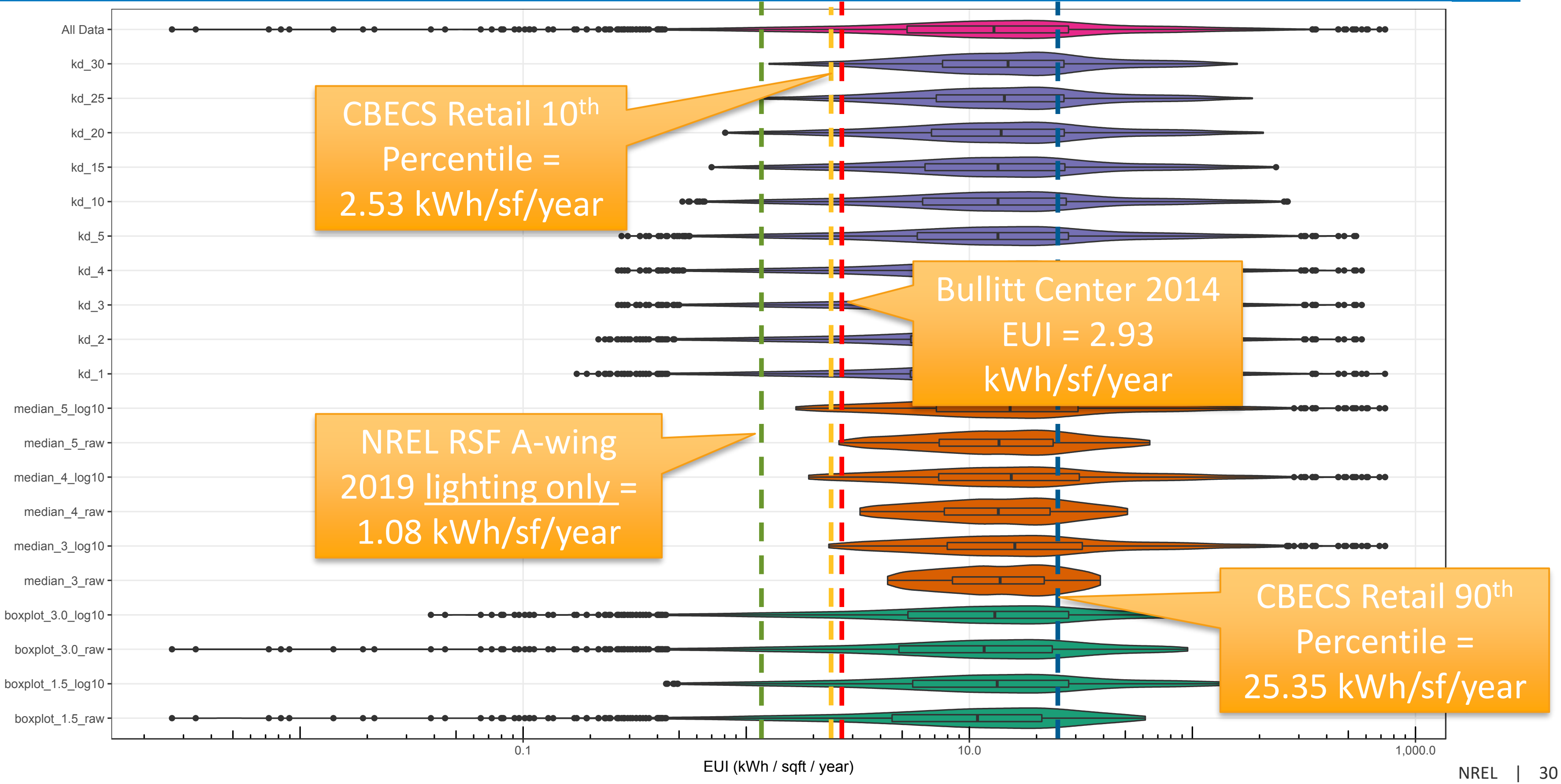
Example: Outlier Removal Methods on CoStar Small Retail



Example: Outlier Removal Methods on CoStar Small Retail



Example: Outlier Removal Methods on CoStar Small Retail



What We Do and Don’t Model

- We ***do not*** currently model buildings that are unconditioned or not adequality lit in accordance with commercial building standards (i.e., an unconditioned “warehouse” barn with minimal lighting)
  - All ComStock models include an HVAC system and regularly-used lighting
- We ***do not*** currently model buildings that experience irregular occupancy, including:
  - Buildings that are up for lease or sale with no active tenants
  - Buildings that experience unoccupancy due to renovations
  - Buildings that typically experience abnormally low, sporadic usage (e.g., a restaurant that only serves on Sundays, flea market, etc.)
- We **do** model buildings with varying occupied start and end times
- We **do** model buildings with typical low-occupancy periods (e.g., summer setbacks in schools)
- We **do** model buildings with varying schedules (e.g., lighting and plug loads) and operation behavior
- We **do** model buildings with varying HVAC system types, lighting power densities, vintages, insulation values, window properties, size, aspect ratio, etc.

Selecting Method(s)

- There is no clear statistical "winner", as the most appropriate option is highly subjective to the application.

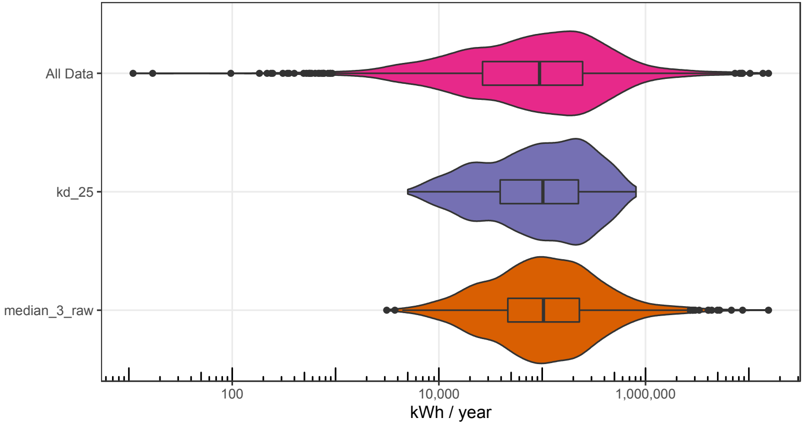
- The main goals of the EULP project are to calibrate our stock models to:
  1. realistic measured building energy data with reasonable and achievable energy behavior that we can represent with ComStock.
  2. datasets that cover the variety of occupied and operational buildings in the stock.

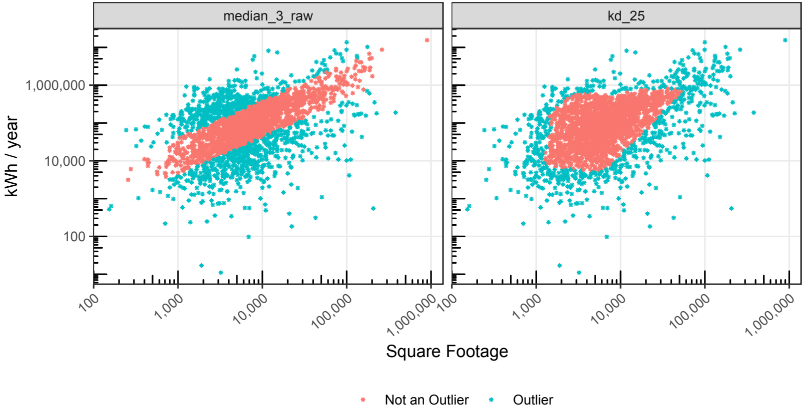
- The **gold standard** approach would be to manually verify every data point in every AMI dataset for calibration, but this is **unrealistic** due to both time and insufficient metadata.

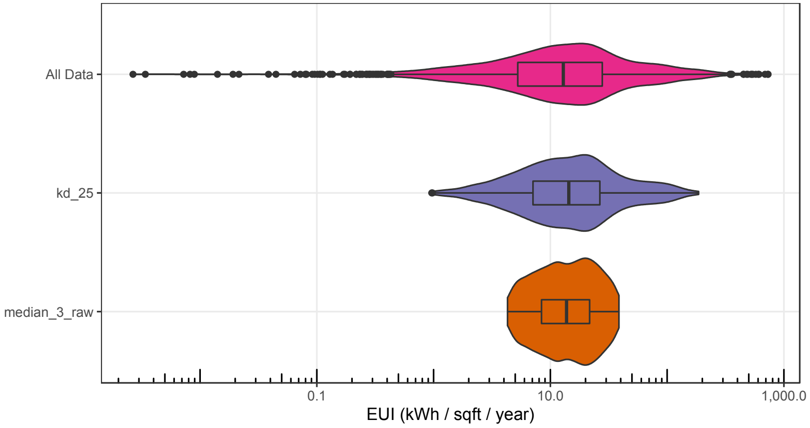
- Must find a ***balance*** between keeping data that provides a ***useful and representative variety***, while being sure to maximize the removal of ***misclassified and unrealistic*** data that could skew calibration.

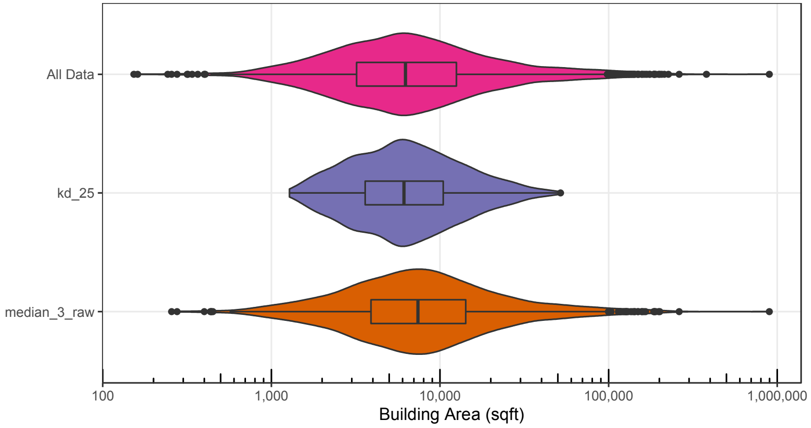
- **Median 3X outlier** and **Kernel Density 25%** methods were chosen for further investigation by the project team as they appear to best meet the intent of the project goals.

Focus on Two Methods: CoStar Small Retail

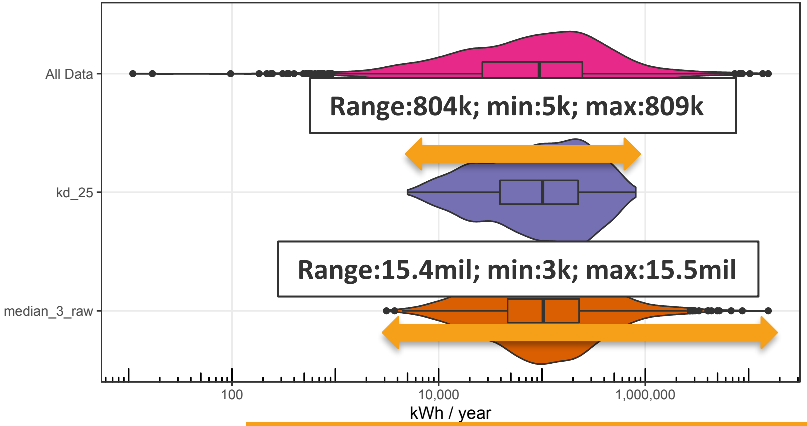


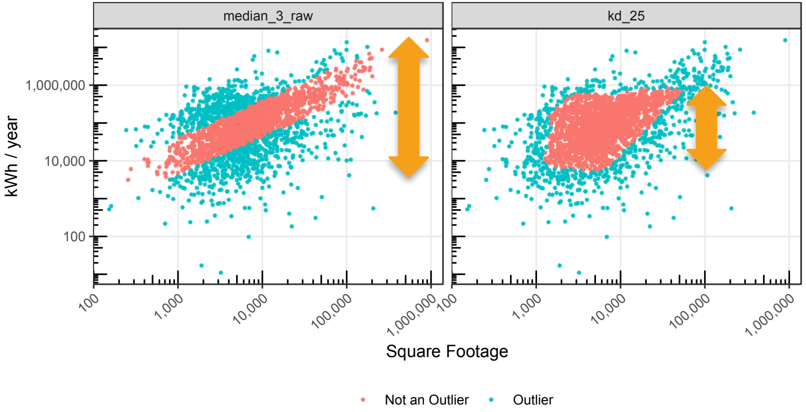




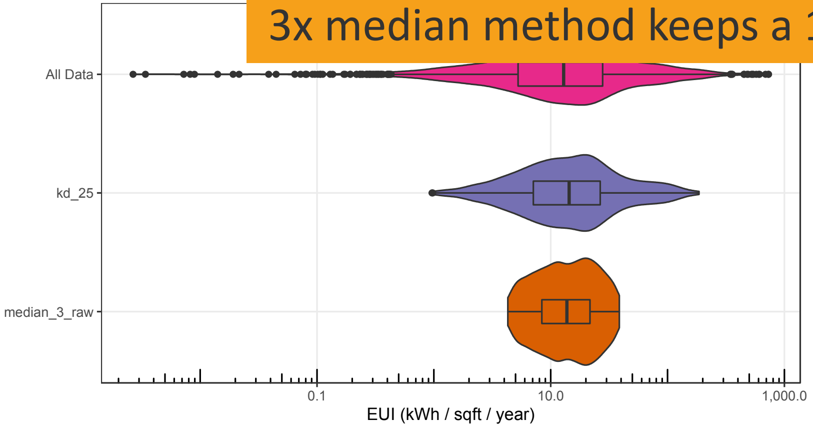


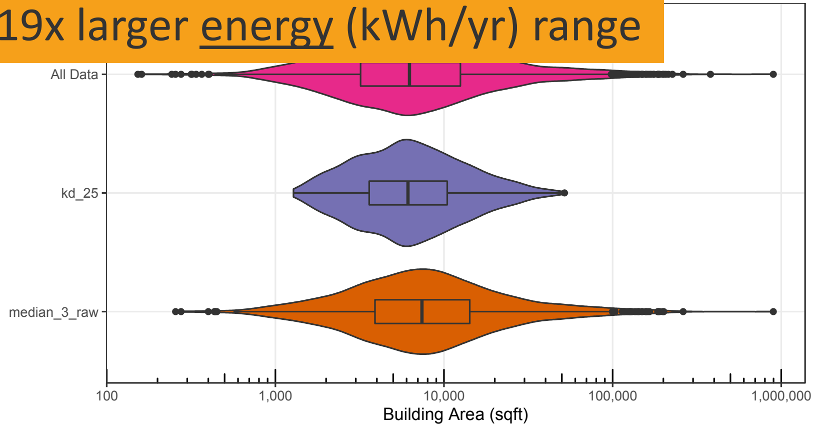
Focus on Two Methods: CoStar Small Retail



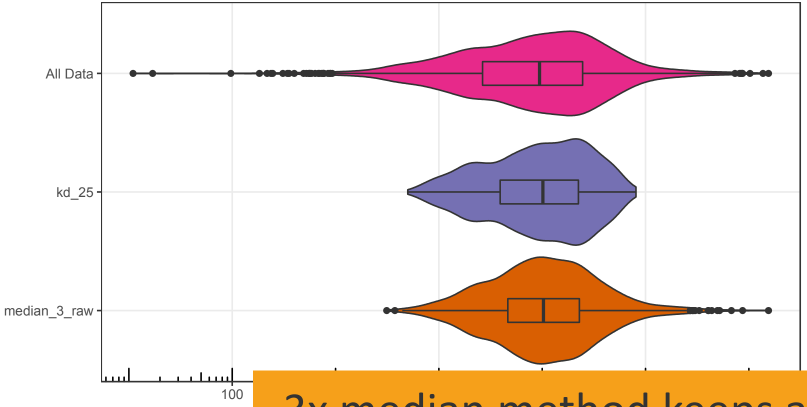


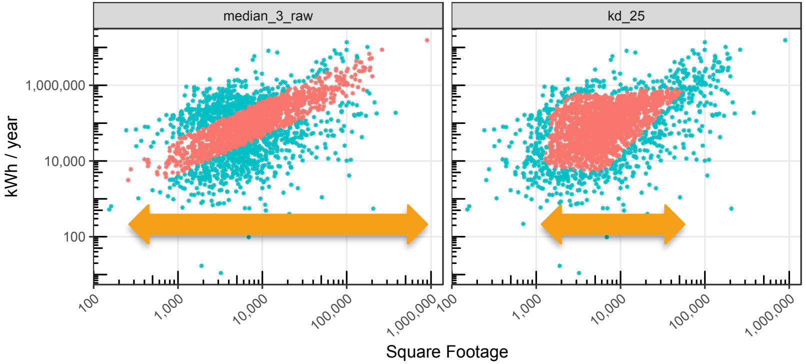
3x median method keeps a 19x larger <u>energy</u> (kWh/yr) range



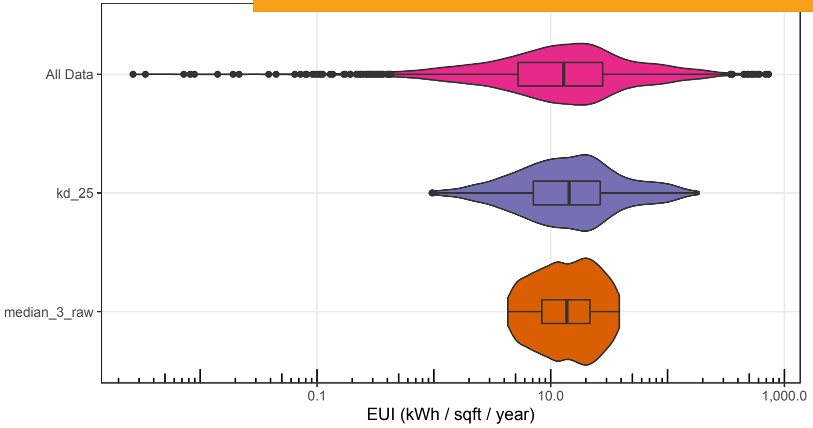


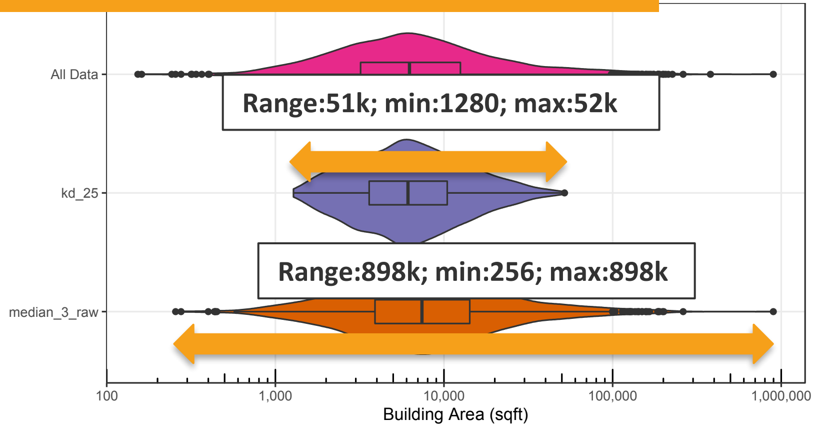
Focus on Two Methods: CoStar Small Retail





3x median method keeps a 18x larger <u>square footage</u> range

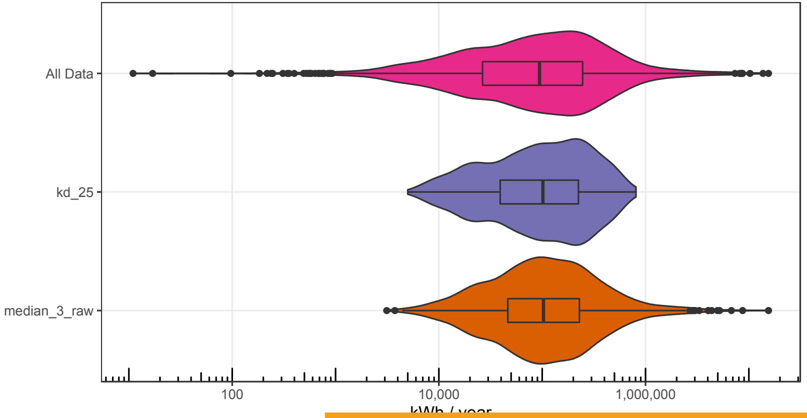


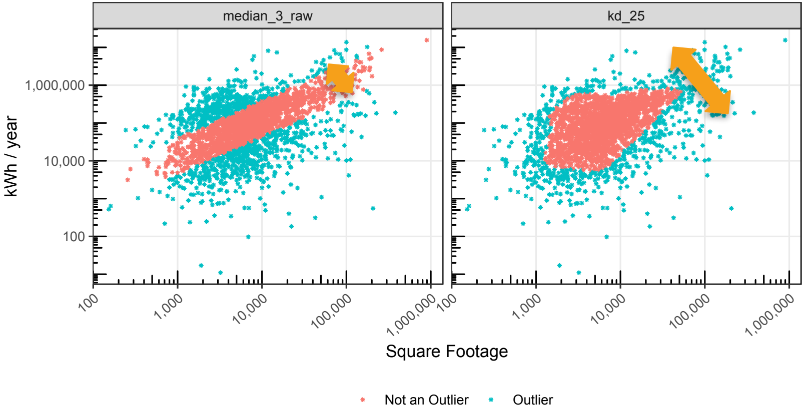


Range:51k; min:1280; max:52k

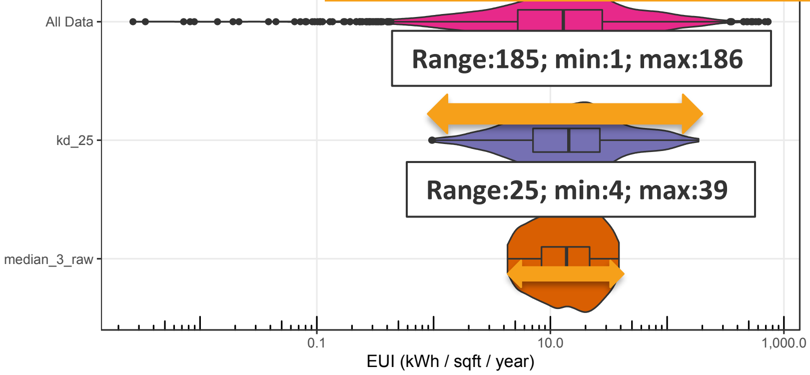
Range:898k; min:256; max:898k

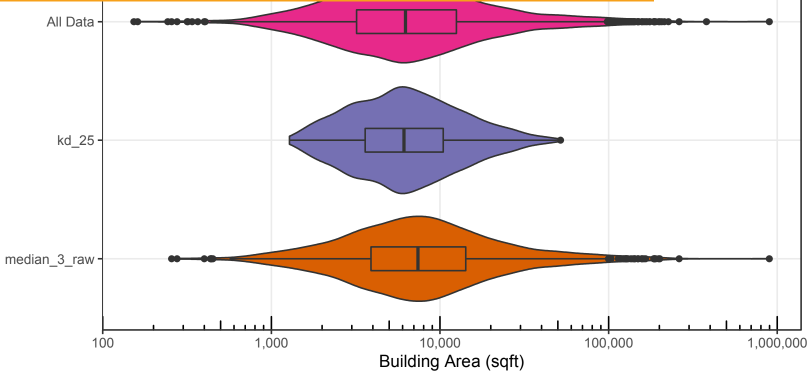
Focus on Two Methods: CoStar Small Retail





KD 25% method keeps a 5x larger EUI (kWh/sf/yr) range





Focus on Two Methods: Summary

3x Median:

- Tends to maintain a larger range of building area and energy usage as this method filters by EUI only. This can leave uncommonly large or small buildings in the dataset.
- Usually results in a narrower range of EUIs as it filters specifically along this axis.

KD 25%:

- Tends to maintain a smaller range of building area and energy usage as this method removes outliers on both axis, resulting in an inclusion boundary that hugs the mass. This can remove buildings with uncommonly small and large area and energy usage relative to the dataset.
- Usually results in a wider range of EUIs as it does not filter specifically along this axis.

Next Steps:

- Test both outlier removal methods on AMI dataset to understand performance and stability on a calibration-region dataset, where dataset size is smaller.
- Determine if minimum and maximum EUI and square footage values would be appropriate in conjunction with either or both methods.

Key Takeaways

1. Confirmed finding from Region 1 using a multi-state dataset
   - Many buildings are misclassified
   - These must be removed before using data for calibration to avoid bad comparison

2. Evaluated 20 different approaches
   - No statistical "winner"
   - But several methods are reasonable given the project goals

3. Classification is a hard, even with manual human verification

4. Key factors moving forward are to be **clear** and **transparent** about the outlier removal methods being used when processing AMI datasets for calibration
   - Communicate the outlier detection method used
   - Report percentages of data being removed (square footage and energy) for each AMI dataset

Commercial AMI Classification

Poll Question

Commercial AMI Classification Poll Question 1

1. Based on the approaches presented today, which of the following are you more concerned about having a negative effect on commercial calibration efforts?

    a. Misclassified buildings and bad data will remain in the calibration data set

    b. Valid data will be removed from the calibration data set

Questions?

Appendix

Summary Statistics For CoStar: SMALL RETAIL

	EUI (kWh/sf/yr)			Building Area			kWh / year		
	Min	Median	Max	Min	Median	Max	Min	Median	Max
All Data	0.002	12.9	730.7	153	6,243.5	897,644	10.9	94,230	15,496,659
Median 3	4.300	13.7	38.7	256	7,400.0	897,644	3,128.4	103,027	15,496,659
KD25	0.964	14.3	185.7	1,280	6,111.0	51,874	4,996.5	101,731	809,403

3x Median:

- EUI – min value of 4.3 EUI seems reasonable; max value of 38.7 EUI seems reasonable.
- Building Area – max value of 900k sf seems uncommon but reasonable. Method does not filter specifically along area axis, which allows for a greater range.
- kWh/year - Method does not filter specifically along kWh/yr axis, which allows for a greater range.

KD 25%:

- EUI – min value of 0.964 EUI is very low; max value of 185.7 EUI seems high. Yields larger EUI range.
- Building Area – yields large decrease in maximum value, resulting in a decreased building area range.
- kWh/year – yields large decrease in maximum value, resulting in a decreased energy range.

Summary Statistics For DOE: Warehouse

	EUI (kWh/sf/yr)			Building Area			kWh / year		
	Min	Median	Max	Min	Median	Max	Min	Median	Max
All Data	<0.01	4.36	1,318.4	300	11,000	794,253	1.9	47,267.04	67,324,000
Median 3	1.45	4.49	13.0	347	10,597	794,253	1,093.2	48,043.86	6,946,160
KD25	0.71	4.51	24.6	1,614	10,050	102,425	3,402.1	47,046.98	683,925

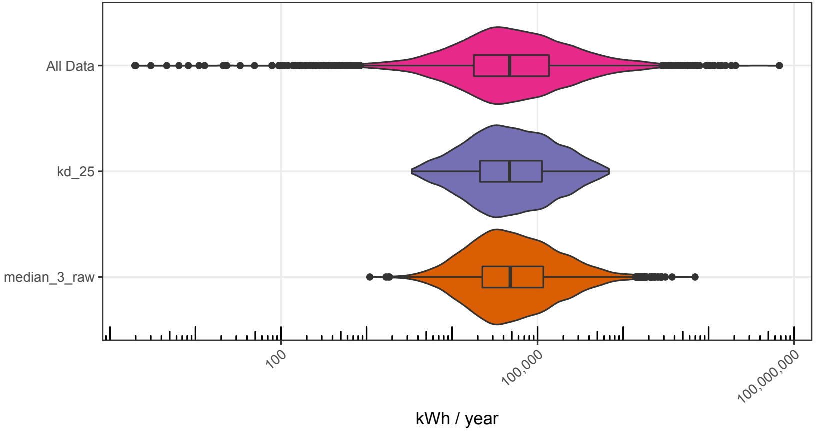
3x Median:

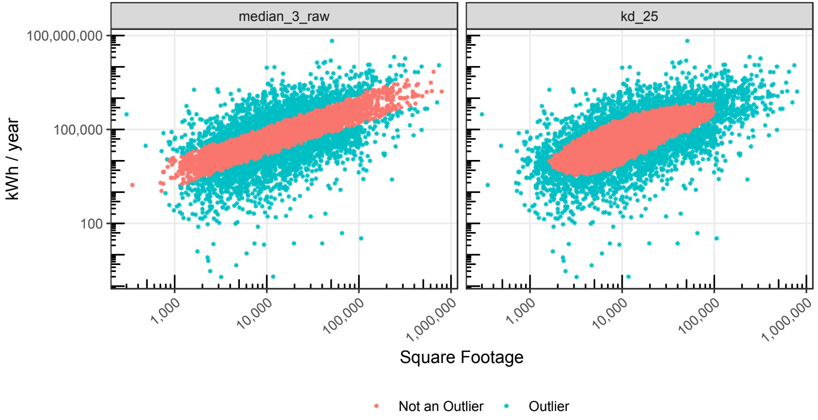
- EUI – min value of 1.45 electric EUI seems low but reasonable for a low-occupancy storage warehouse
- Building Area – min value of 347 sf seems low for a warehouse, but max value of 794k sf seems reasonable.
- kWh/year - Method does not filter specifically along kWh/yr axis, which allows for a greater range.

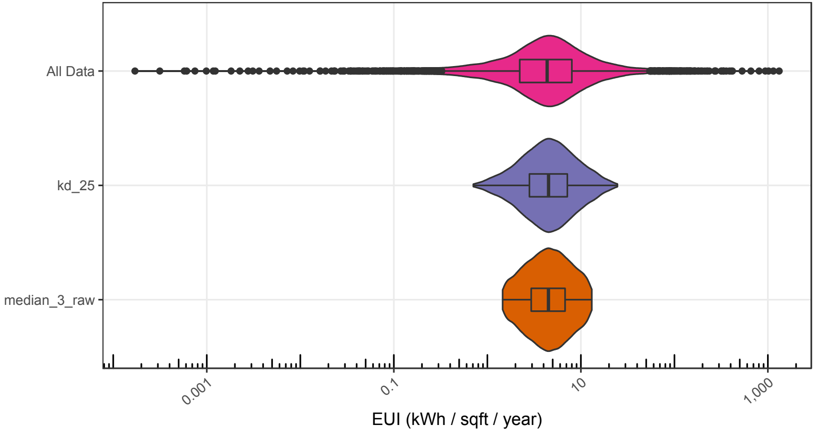
KD 25%:

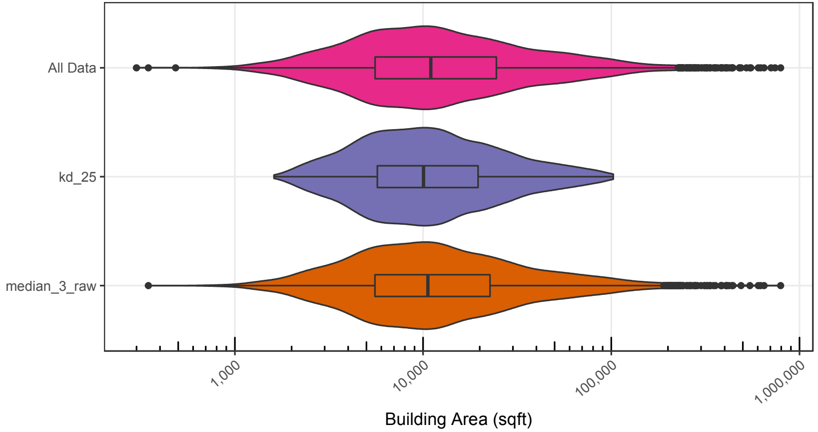
- EUI – min value of 0.71 EUI seems very low; max value of 24.6 EUI seems reasonable. Method yields larger EUI range.
- Building Area – minimum value seems reasonable, but maximum value seems low.
- kWh/year – yields large decrease in maximum value, resulting in a decreased energy range.

Focus on Two Methods: DOE Warehouse (n = 8,671)









Examples of Misclassified Building Types

- Provided Data Set:
    - DOE: small office
    - CoStar: Office
- Human:
    - Office Medical

- This is a potential issue – the data set might be correct, “support services” suggest that there are few, or no medical procedures done here.
- What is the difference between a “Office” and “Office Medical”

Examples of Misclassified Building Types

- Provided Data Set:
  - DOE: outpatient
  - CoStar: Health Care, Rehabilitation Center
- Human:
  - Specialty Religious Facility

- Facility was associated with a church, but upon further investigation it was determined that the facility is a rehabilitation center and was correctly classified in CoStar.

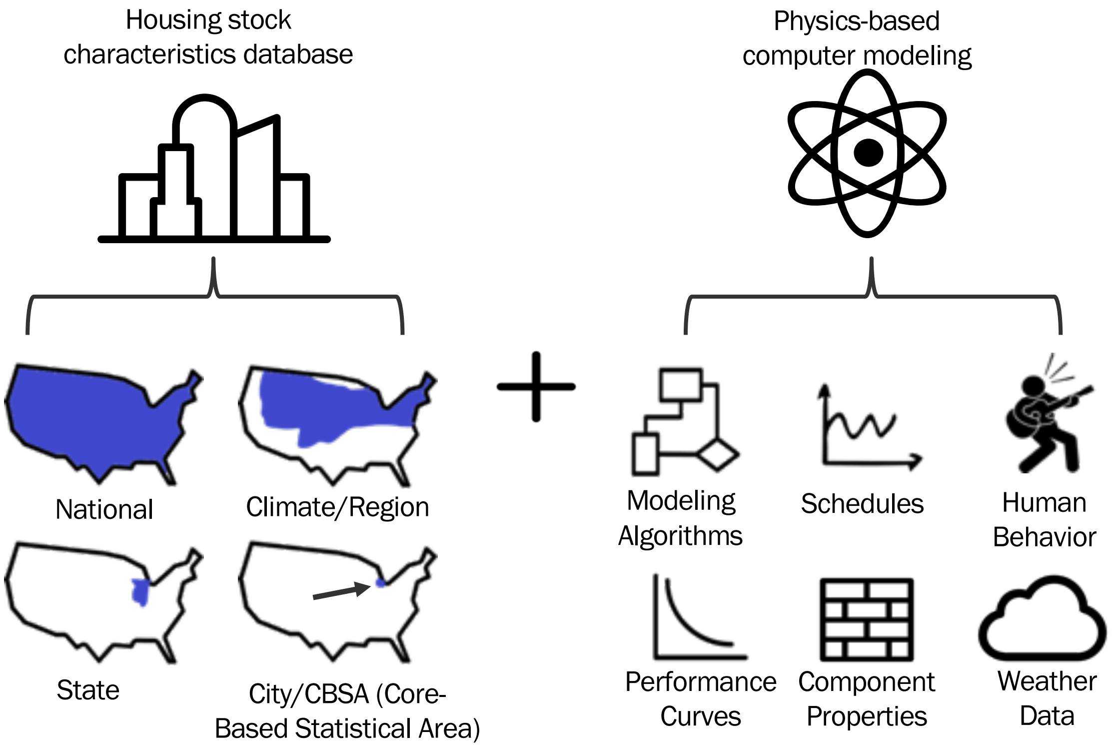
Residential Region 3 Calibration

Anthony D. Fontanini, Ph.D.
Eric Wilson
Technical Advisory Group
January 28, 2021

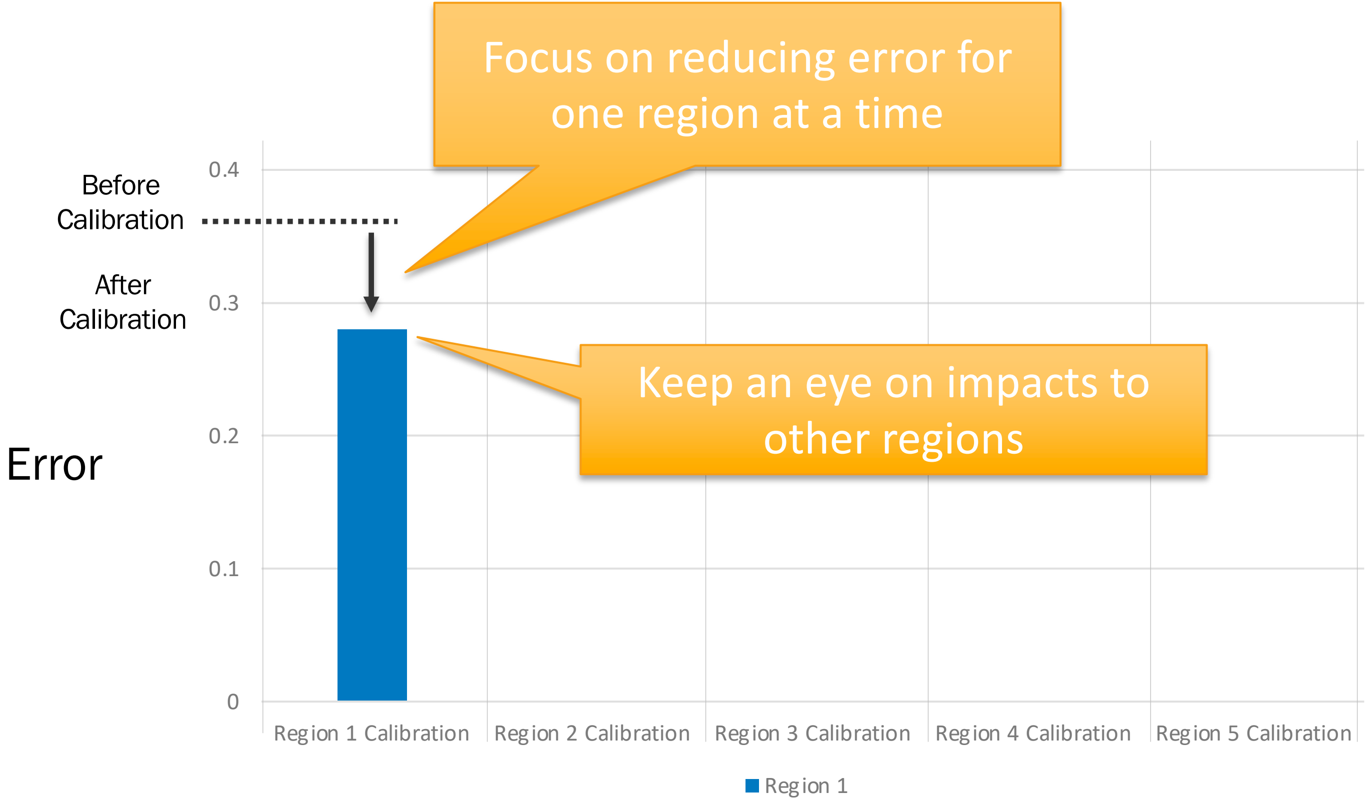
Calibration Strategy

Model Architecture

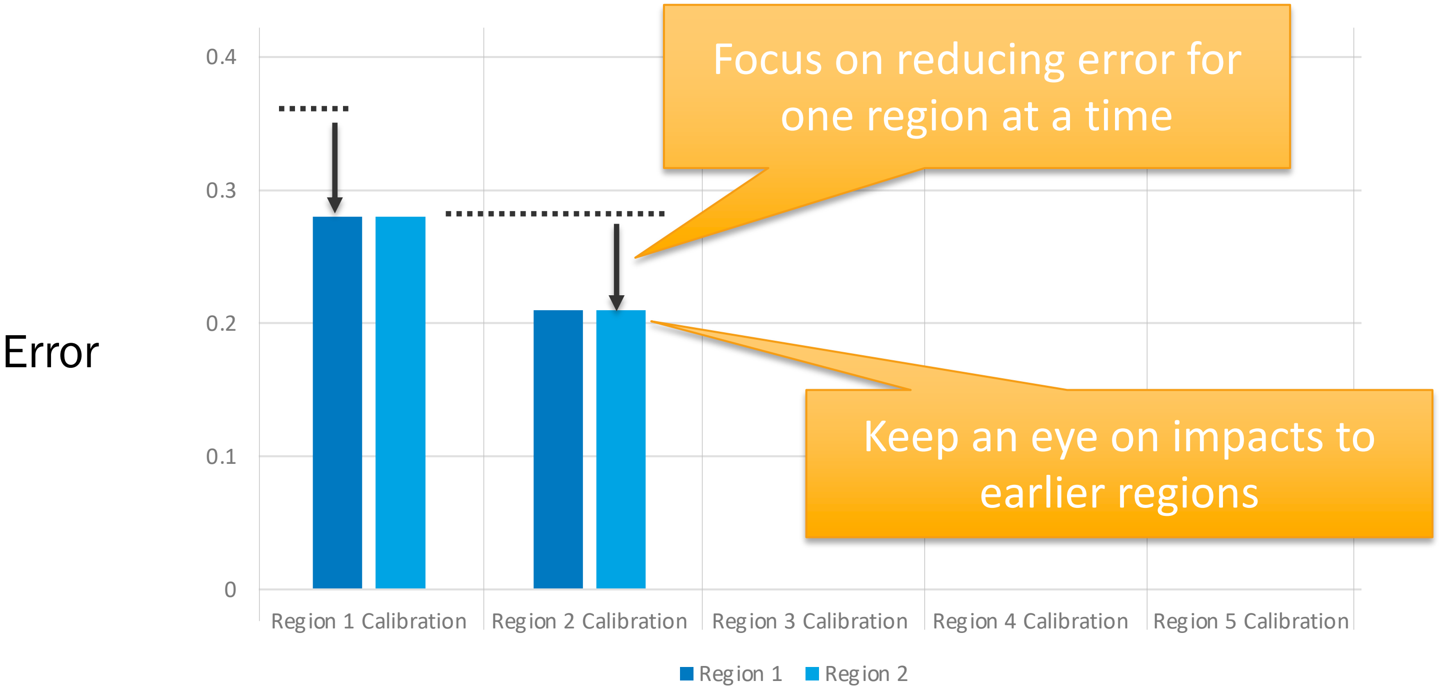
ResStock



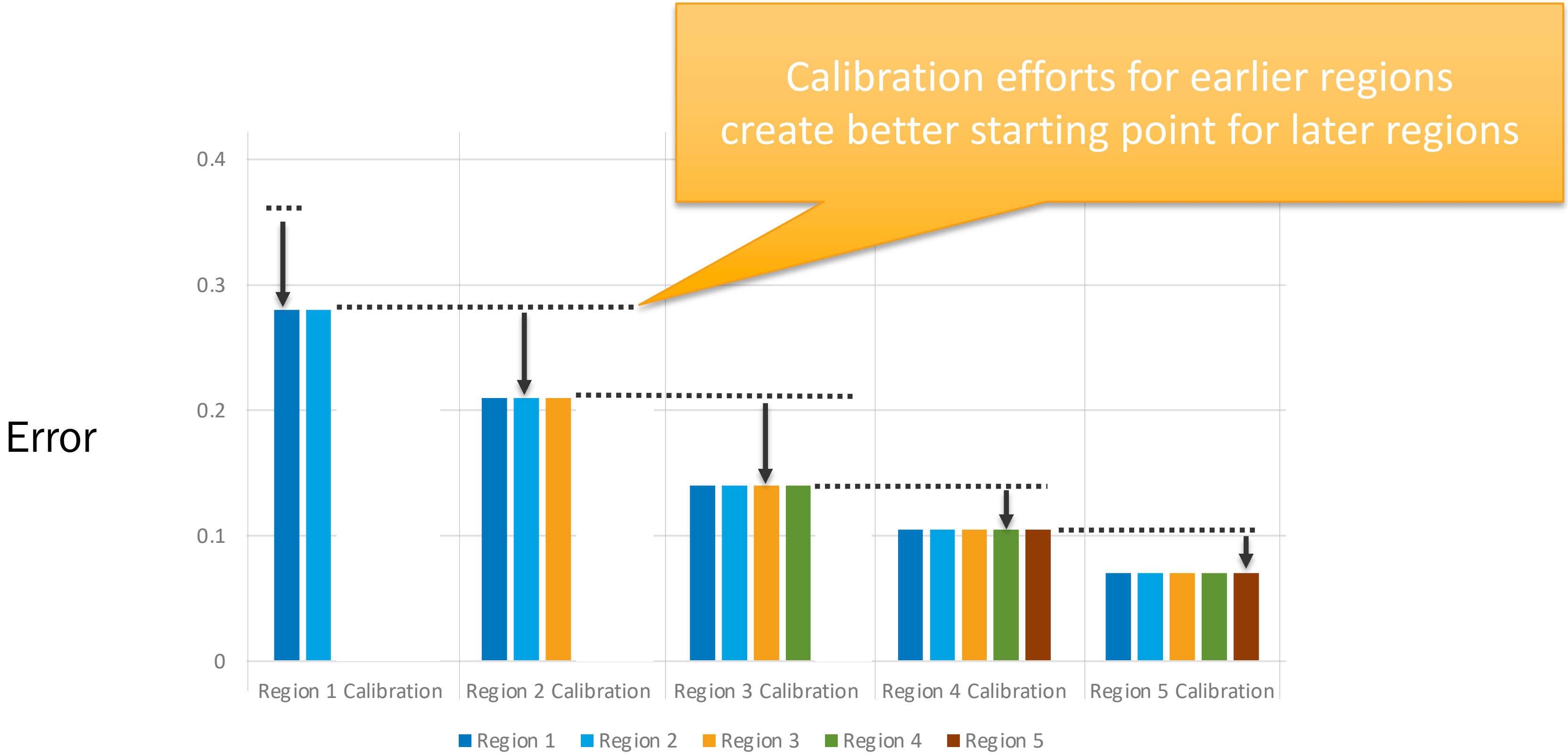
Calibration Process for One Region



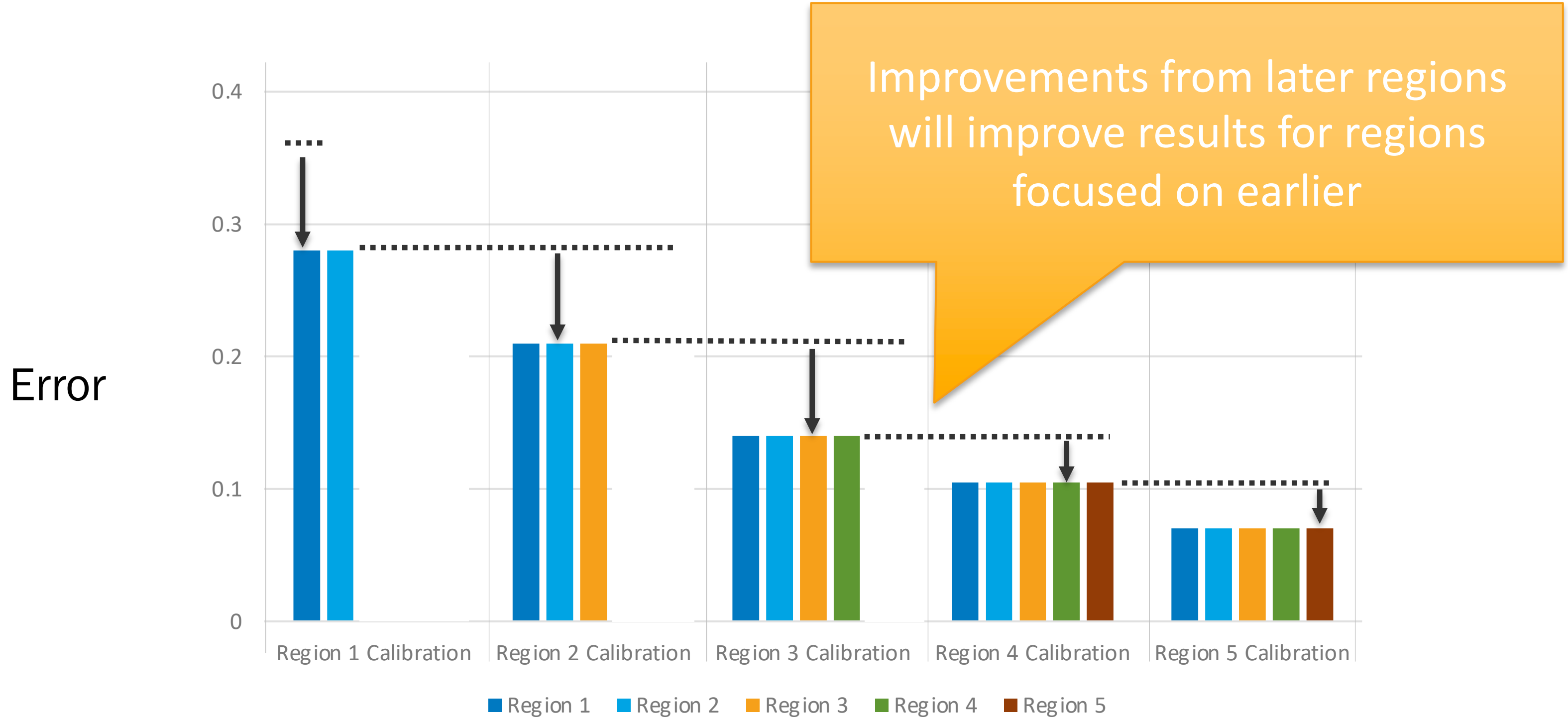
Calibration Process Over Time



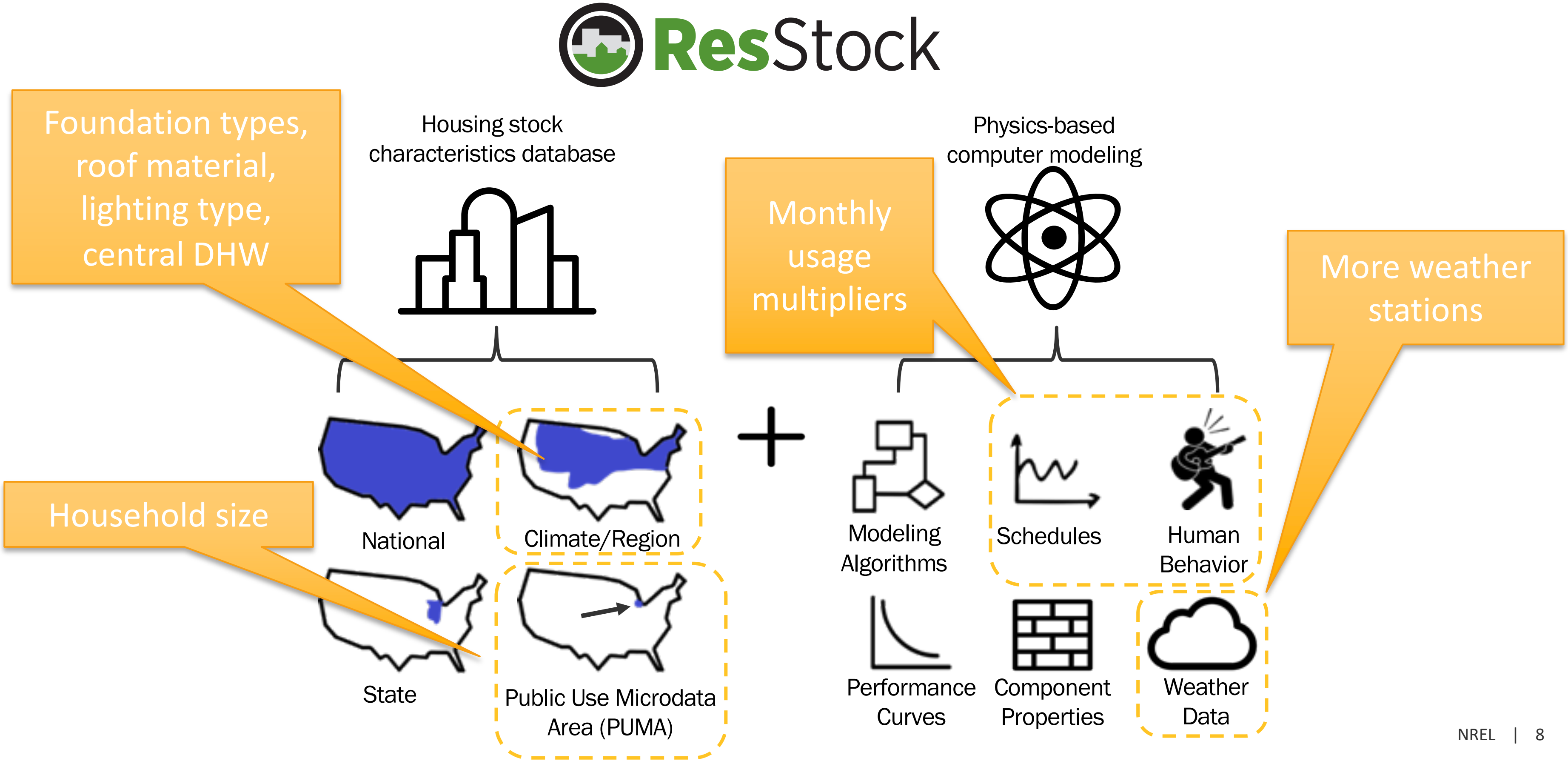
Calibration Process Over Time



Calibration Process Over Time

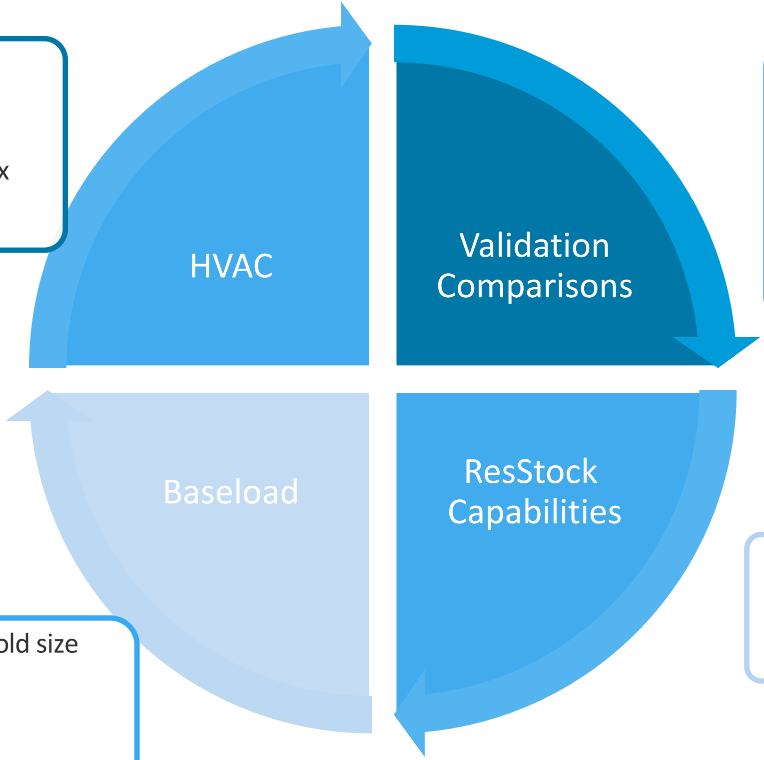


Region 3 Focus: Nationally-Relevant Updates



Region 3 Calibration Strategy

- Roof material distributions
- Update foundation type distributions
- Cooling type IECC dependency fix
- Cooling load/sizing bugfix

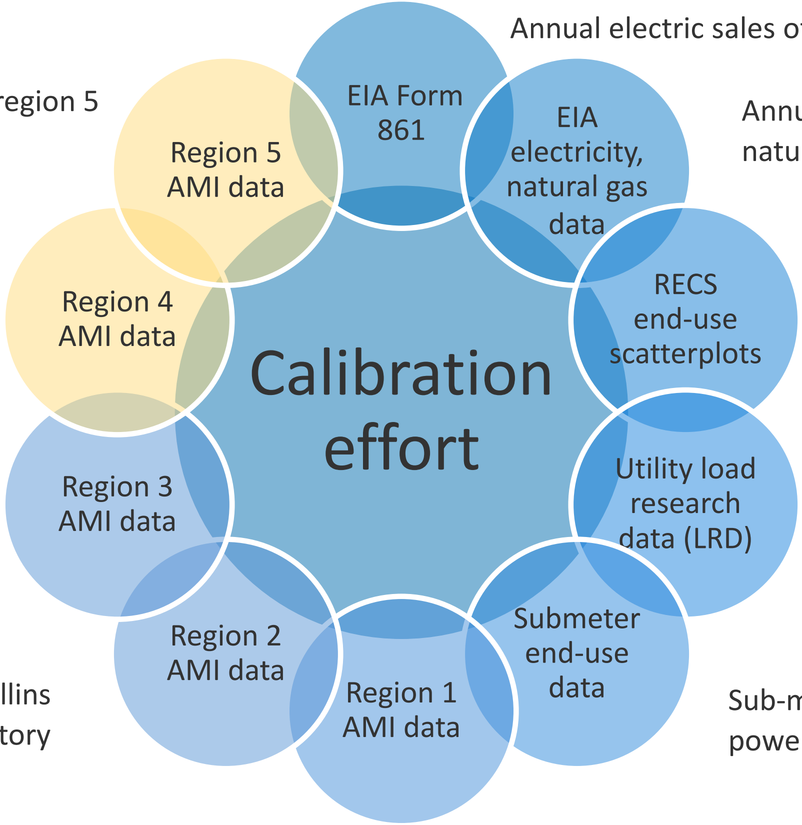


- 2019 end-use data from 73 homes from ongoing NEEA HEMS
- Monthly EIA electricity sales by state for residential sector
- Monthly EIA natural gas sales by state for residential sector
- Aggregates of AMI data from Seattle City Light

- More weather data locations
- Faster multifamily modeling

- More geographic resolution in household size
- Monthly appliance usage multipliers
- Regional variation in lighting efficiency
- Regional variation in plug load usage
- Add Multifamily Central DHW differentiation
- Water heater fuel type and efficiency dependencies

Residential Calibration Dimensions



Annual electric sales of all utilities in U.S.

Annual and monthly electricity and natural gas consumption by state, sector

Annual end-use loads of occupied dwelling units

- Building type
- Climate zone
- Fuel (electricity, natural gas, propane, fuel oil)

Load duration curves and seasonal load shapes of >20 utilities around U.S.

Sub-metered end-use load data power levels and load shapes

Advanced metering infrastructure (AMI) data from ComEd service territory (IL)

AMI data from Fort Collins municipal service territory (CO)

Aggregates of AMI data from Seattle City Light, WA

AMI data from future region 4

AMI data from future region 5

Residential Calibration Dimensions

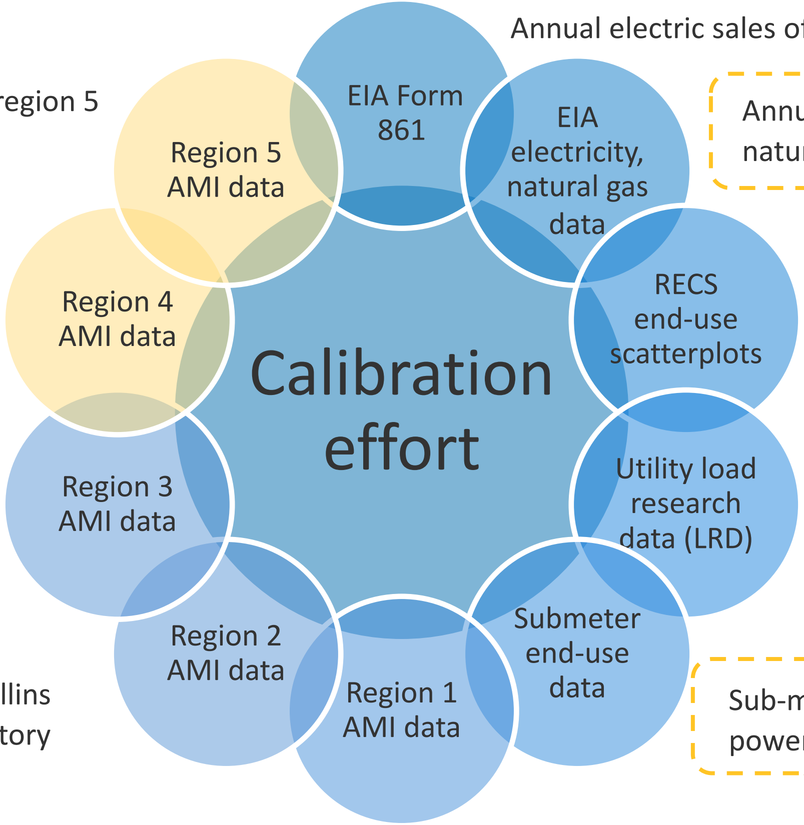
New: monthly electric and gas comparisons

Annual electric sales of all utilities in U.S.

Annual and monthly electricity and natural gas consumption by state, sector

AMI data from future region 5

AMI data from future region 4



Annual end-use loads of occupied dwelling units

- Building type
- Climate zone
- Fuel (electricity, natural gas, propane, fuel oil)

AMI data (aggregated by building type) from Seattle City Light, WA

New

Load duration curves and seasonal load shapes of >20 utilities around U.S.

AMI data from Fort Collins municipal service territory (CO)

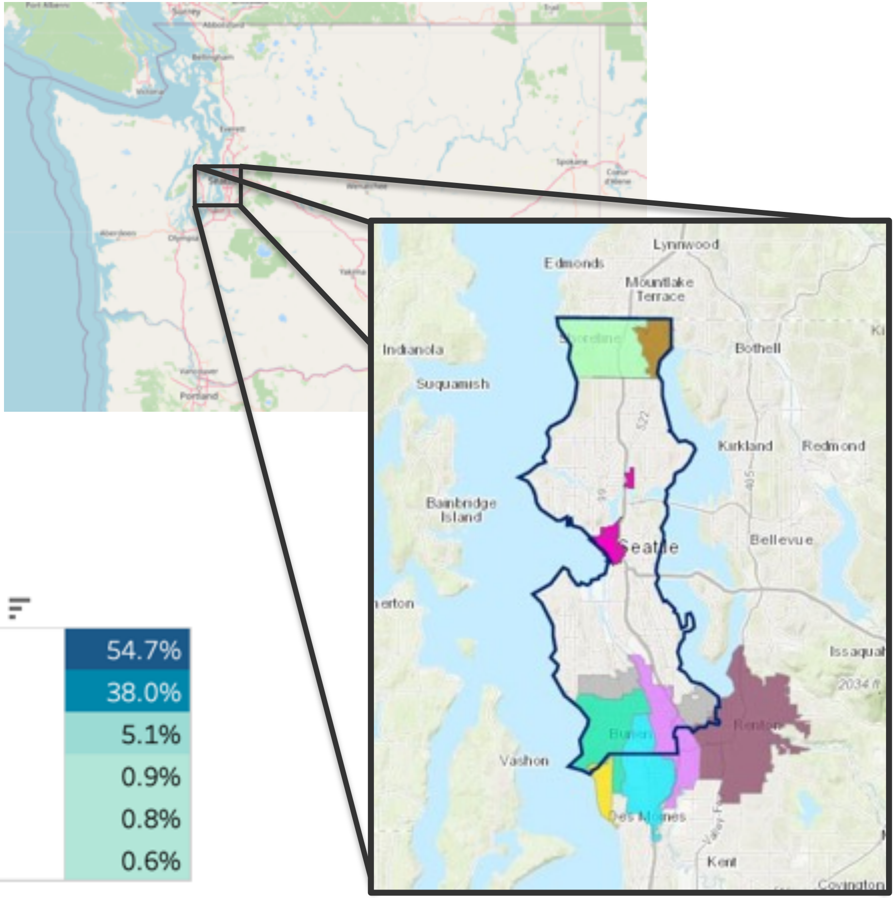
Sub-metered end-use load data power levels and load shapes

New: NEEA HEMS 73 homes

Advanced metering infrastructure (AMI) data from ComEd service territory (IL)

Region 3 – Seattle, WA

- Seattle, WA (pop. ~745k) plus parts of adjacent suburbs
- Municipal utility
- Primarily used AMI data from 2019 (8% sample; aggregated by building type)
- Compared to previous regions:
  - Higher % multifamily
  - Higher % electric heating



chars.geometry_building..	
Single-Family Detached	46.7%
Multi-Family with 5+ Units	41.4%
Multi-Family with 2 - 4 Units	6.2%
Single-Family Attached	4.7%
Mobile Home	0.9%

chars.heating_fuel	
Electricity	54.7%
Natural Gas	38.0%
Fuel Oil	5.1%
None	0.9%
Other Fuel	0.8%
Propane	0.6%

List of updates

<u>New validation comparisons</u>

- 2019 end-use data from 73 homes from ongoing NEEA HEMS
- Monthly EIA electricity sales by state for residential sector
- Monthly EIA natural gas sales by state for residential sector
- Aggregates of AMI data sample from Seattle City Light

<u>New capabilities</u>

- More weather data locations
- Faster multifamily modeling

<u>Baseload updates</u>

- More geographic resolution in households size → Usage of DHW, appliances, and plug loads
- Monthly appliance usage multipliers
- Regional variation in lighting efficiency
- Regional variation in plug load usage
- Add Multifamily Central DHW differentiation
- Water heater fuel type and efficiency dependencies

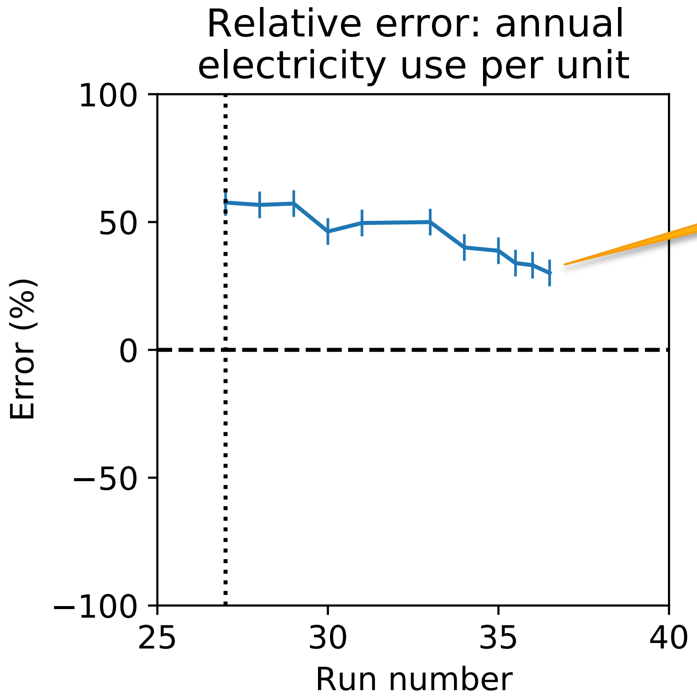
<u>HVAC updates</u>

- Roof material distributions
- Update foundation type distributions
- Cooling type IECC dependency fix
- Cooling load/sizing bugfix

Where did we end up?

Calibration improvements and load shape status

Seattle City Light, WA: Annual Error

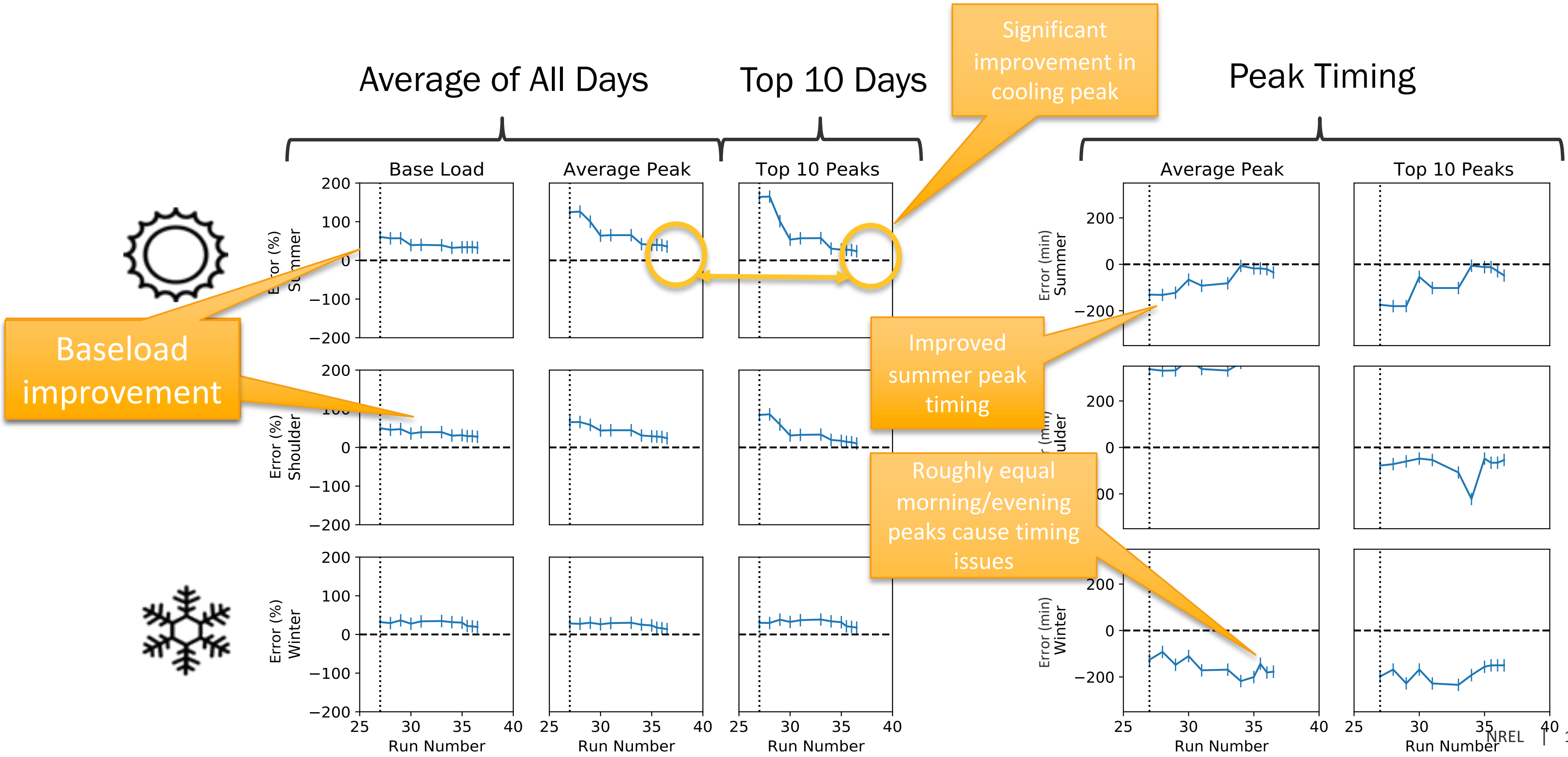


High on annual usage per unit

Reasons

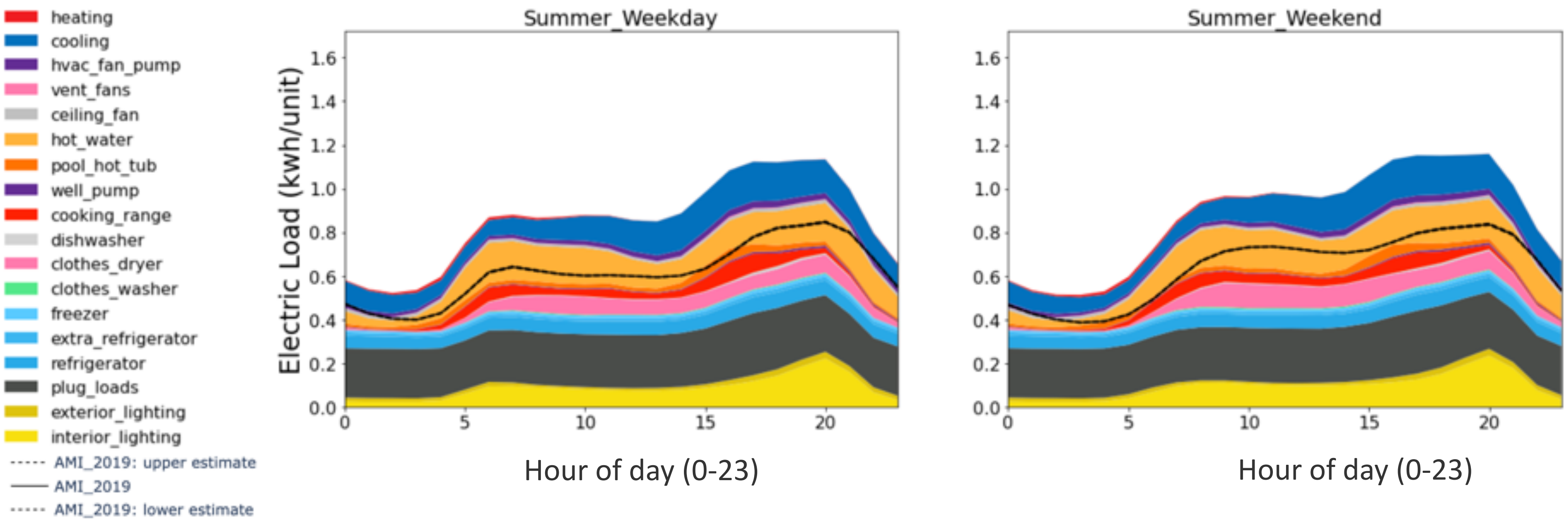
- Single-Family Detached load too high
- Electric heating load too high

Seattle City Light, WA: Total Error Metrics



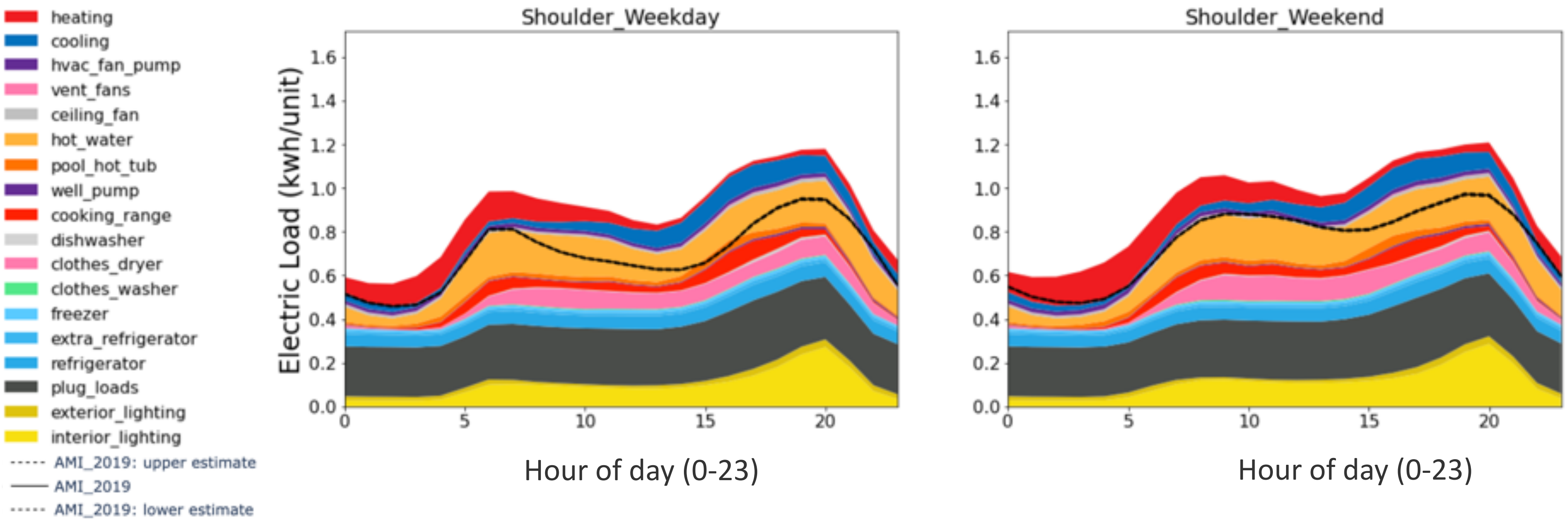
Seasonal end-use loads by day type

Seattle City Light service territory, WA



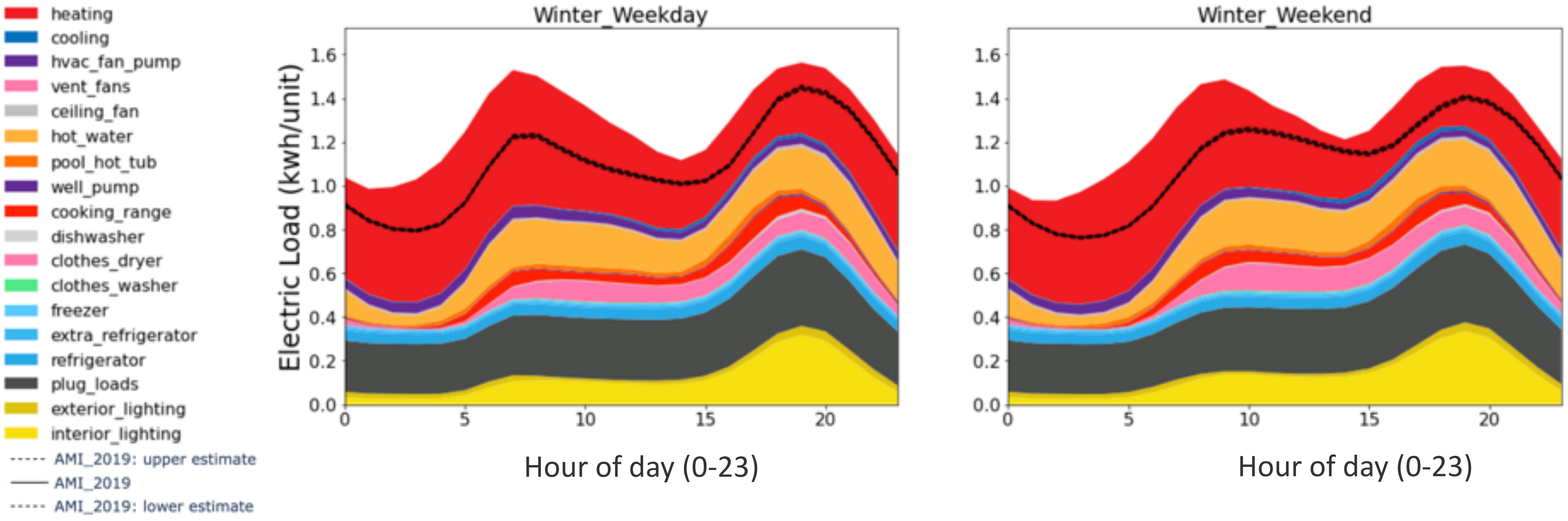
Seasonal end-use loads by day type

Seattle City Light service territory, WA



Seasonal end-use loads by day type

Seattle City Light service territory, WA

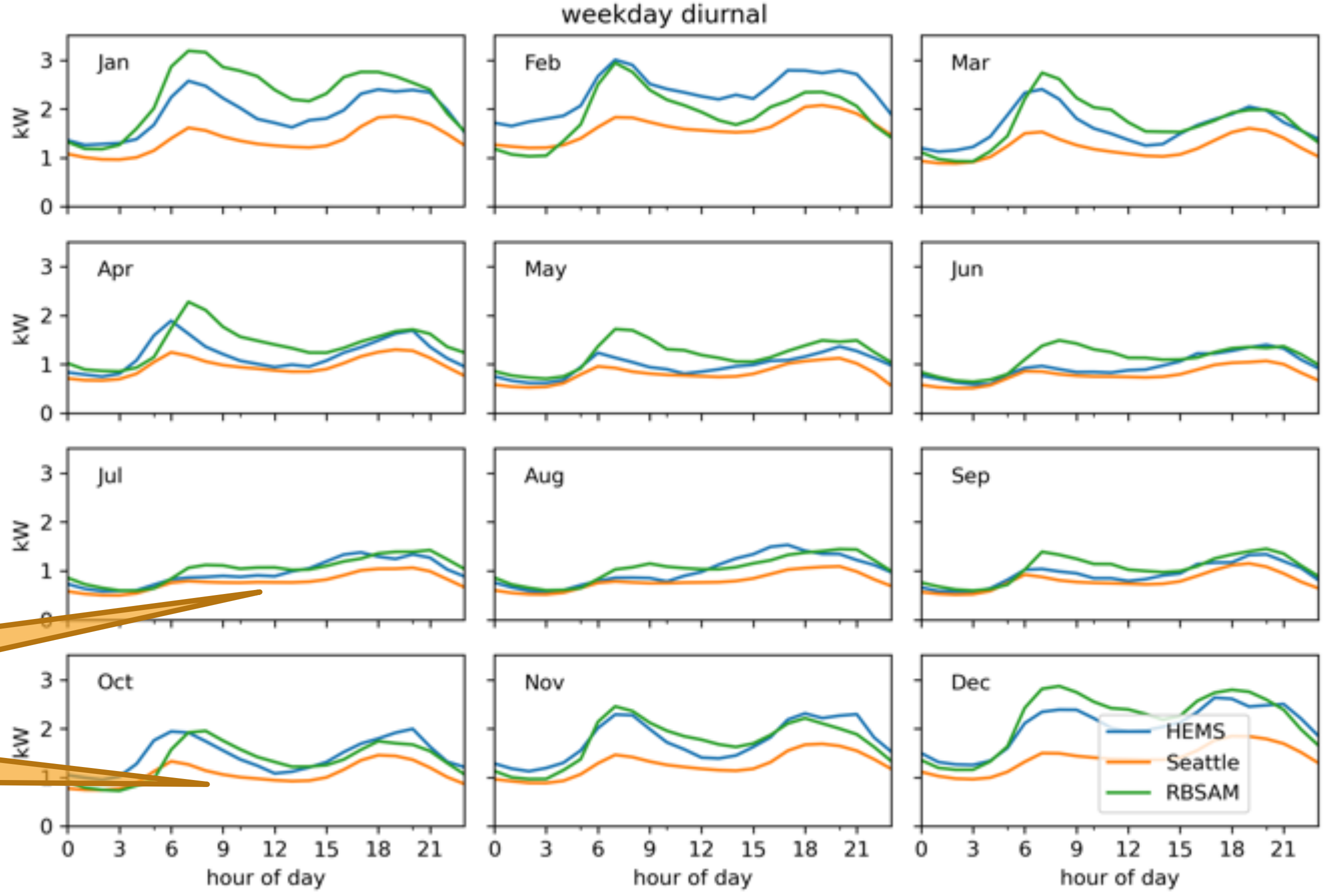


New validation comparisons

NEEA Home Energy Metering Study (HEMS) Comparisons

Monthly kW per home profiles

- Seattle 2019 AMI,
  - 8% sample
  - Aggregate for single-family only
- HEMS (2019),
  - filtered to west of Cascades (BPA H1C1; N=36)
  - Single-family only
- RBSAM (2012-2013)
  - filtered to west of Cascades (BPA H1C1; N=57)
  - Single-family only



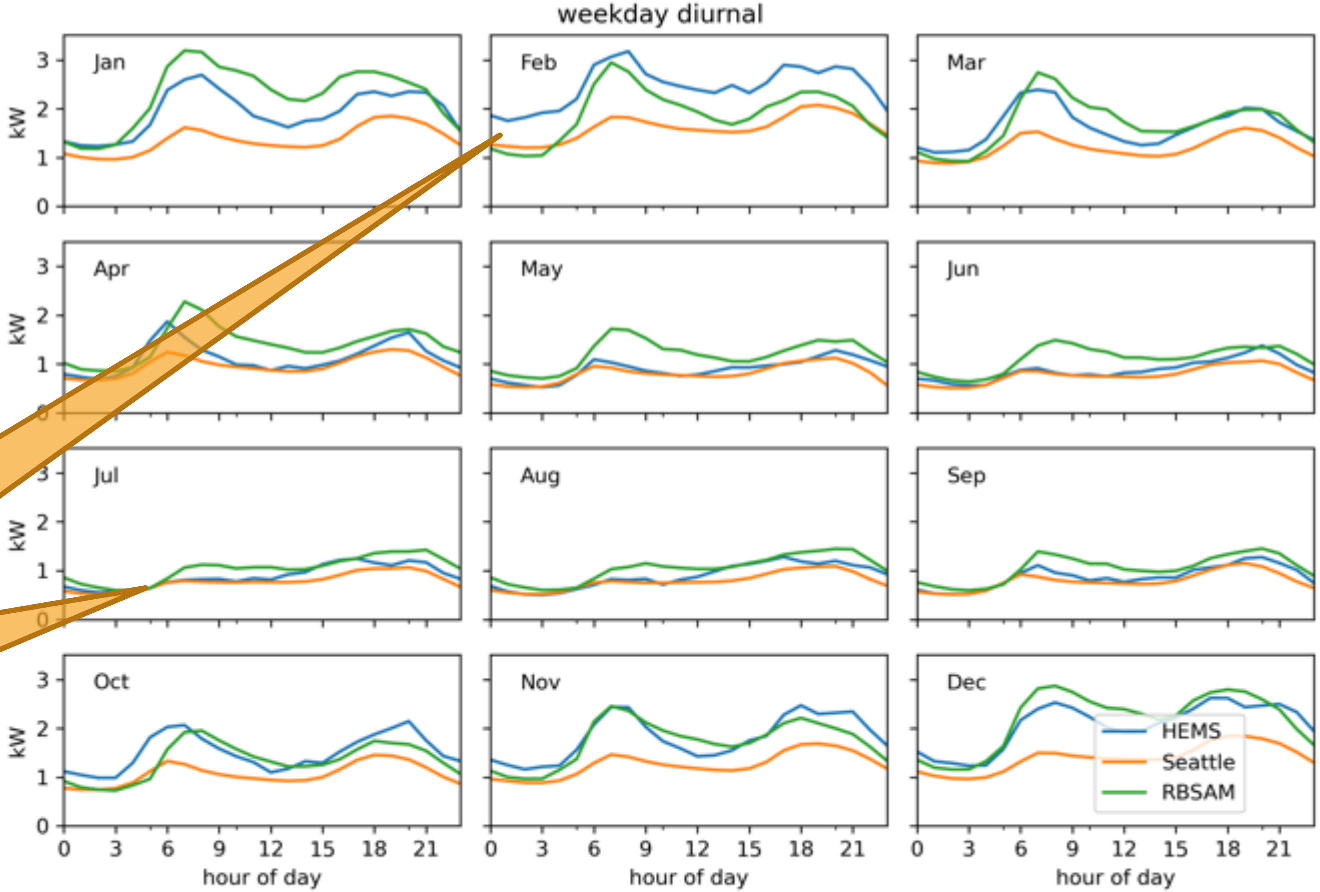
AMI is lower on cooling

AMI is much lower on heating

NEEA Home Energy Metering Study (HEMS) Comparisons

Monthly kW per home profiles

- Seattle 2019 AMI,
  - 8% sample
  - Aggregate for single-family only
- HEMS (2019),
  - **filtered to WA**, west of Cascades (BPA H1C1; **N=24**)
  - Single-family only
- RBSAM (2012-2013)
  - filtered to west of Cascades (BPA H1C1; N=57)
  - Single-family only



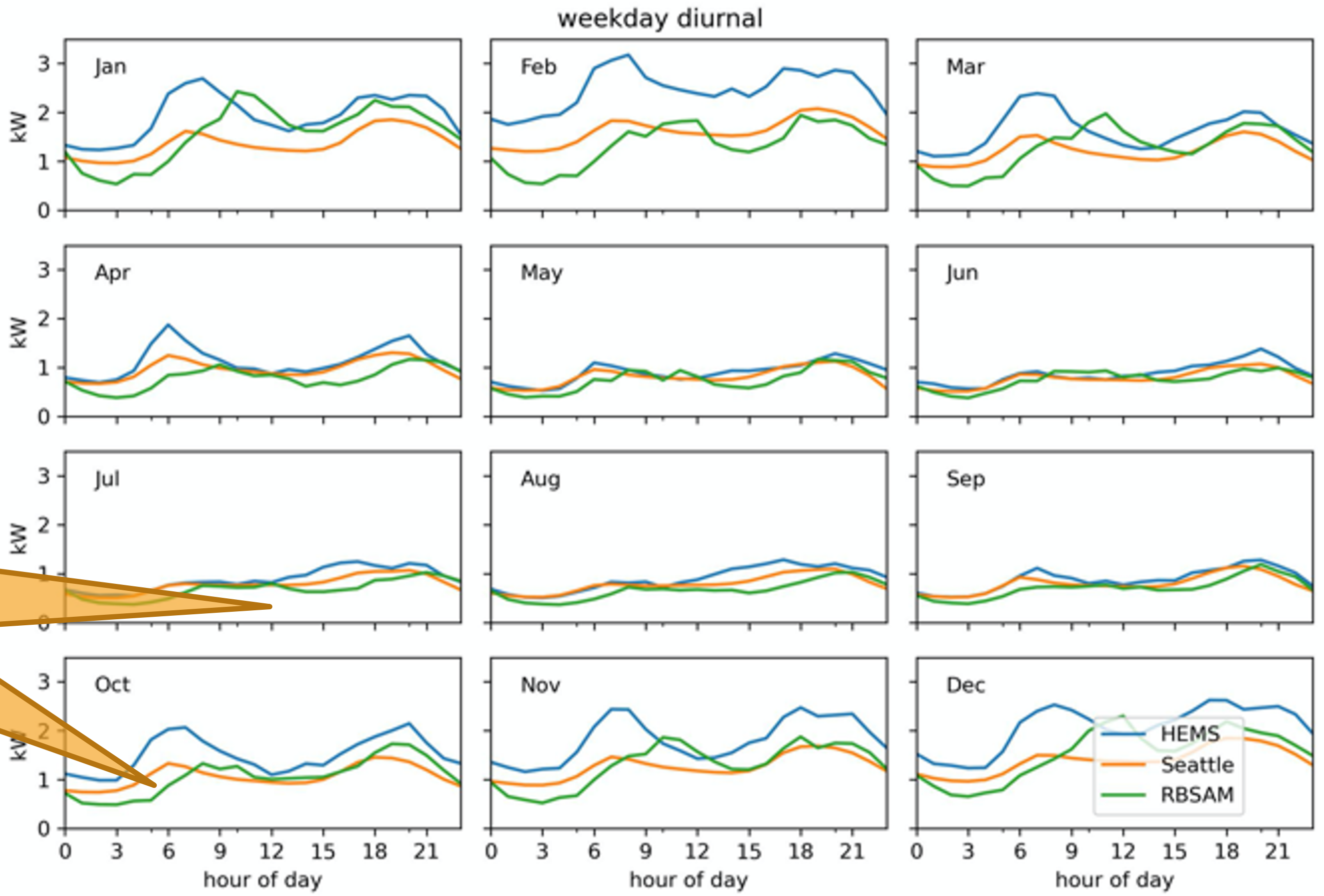
Filtering HEMS to WA (and not OR) west of the Cascades **reduces cooling slightly and increases heating slightly**

NEEA Home Energy Metering Study (HEMS) Comparisons

Monthly kW per home profiles

- Seattle 2019 AMI,
  - 8% sample
  - Aggregate for single-family only
- HEMS (2019),
  - filtered to WA, west of Cascades (BPA H1C1; N=24)
  - Single-family only
- RBSAM (2012-2013)
  - **Seattle city limits (N=12)**
  - Single-family only

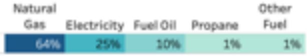
Filtering RBSAM to Seattle reduces cooling and heating, improving match to AMI, but sample size is low and weather is 2012-2013



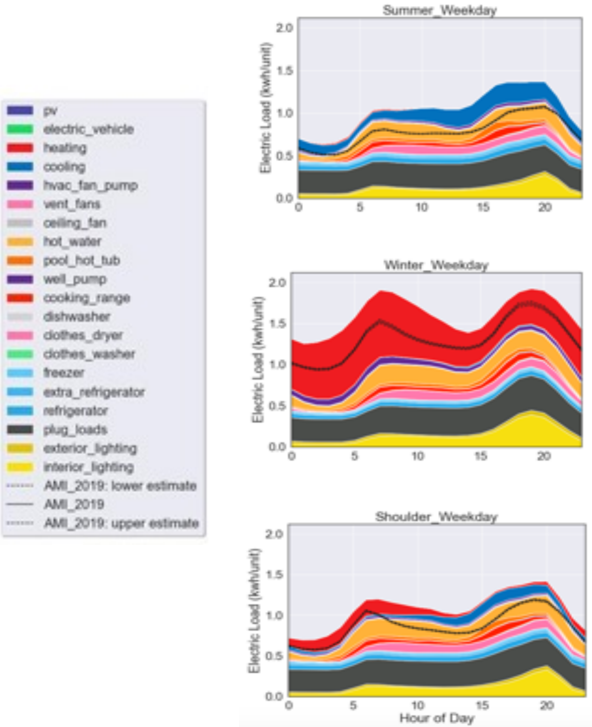
ResStock vs. HEMS vs. RBSAM
End Use Comparison (Single-Family Only)

ResStock, AMI for Seattle

2019



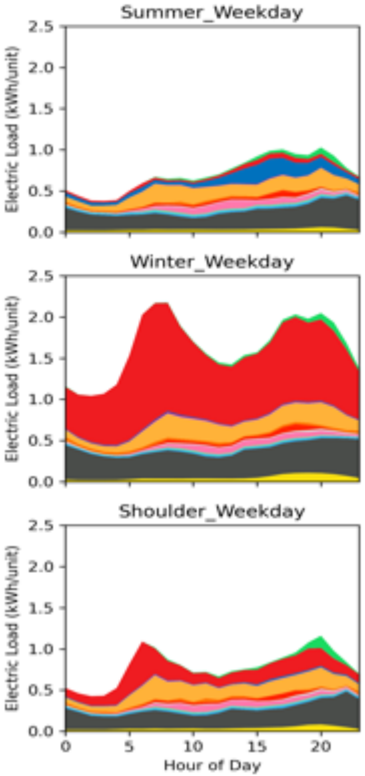
res_seattle_36_01_01_2019



HEMS for WA, west of Cascades (N=24)

2019

N=20 elec. (83%) (14 heat pumps)
N=4 gas heat



Plug loads and lighting are not separately metered in HEMS (except for a few circuits)

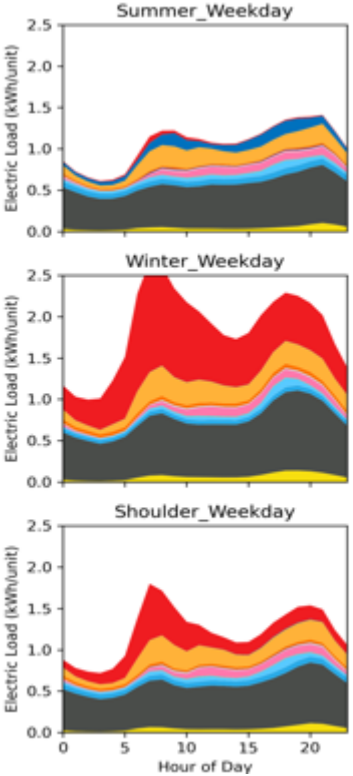
Misc. electric space heaters categorized as *heating* in HEMS and *plug loads* in RBSAM and ResStock

Heat pumps in shoulder months assumed to be in heating mode but may actually include cooling

RBSAM, west of Cascades (N=57)

2012-13
(different weather)

N=27 elec. (47%) (18 heat pumps)
N=30 gas heat (53%)



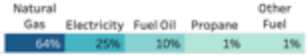
Plug loads and lighting are not separately metered in RBSAM (except for a few circuits)

Heat pumps in shoulder months assumed to be in heating mode but may actually include cooling

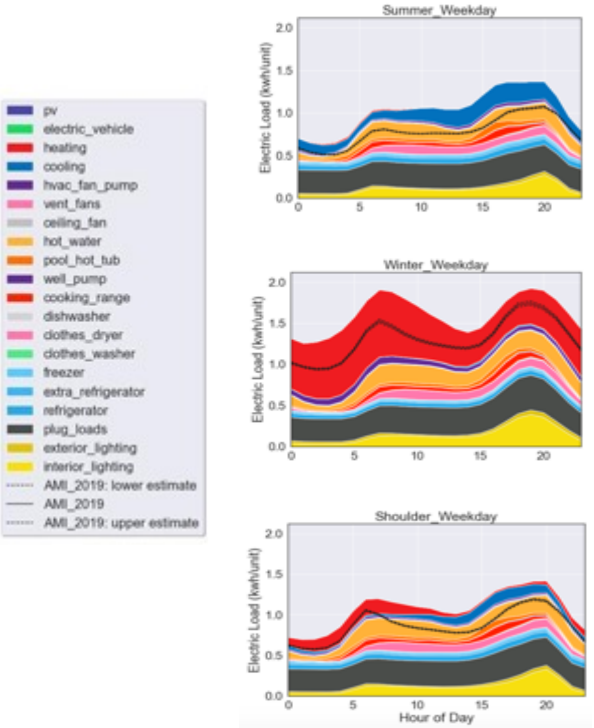
ResStock vs. HEMS vs. RBSAM
End Use Comparison (Single-Family Only)

ResStock, AMI for Seattle

2019



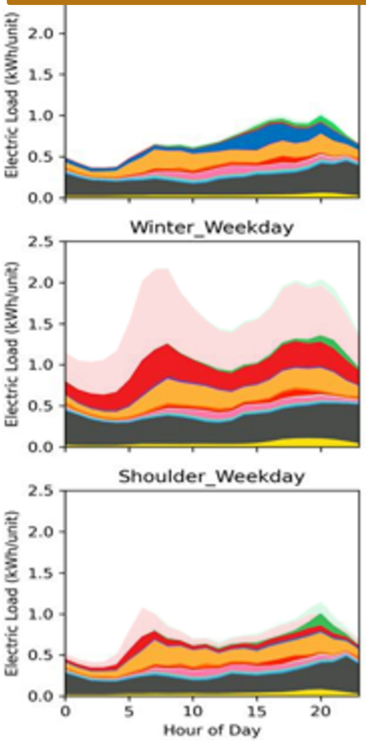
res_seattle_36_01_01_2019



HEMS for WA, west of Cascades (N=24)

Corrected to 25% elec. heat (70% of samples are heat pumps vs. 25-35% in the stock)

ps)



Plug loads and lighting are not separately metered in HEMS (except for a few circuits)

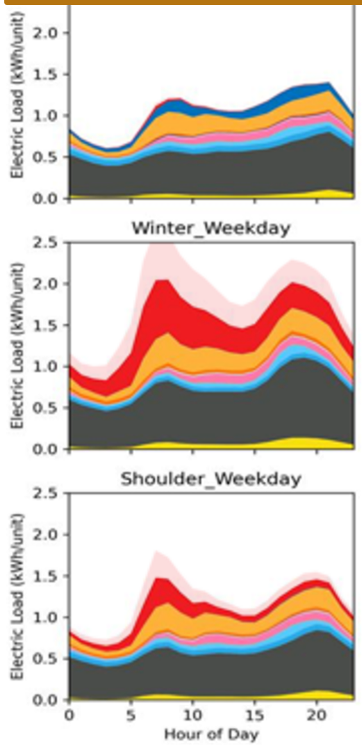
Heat pumps in shoulder months assumed to be in heating mode

RBSAM, west of Cascades (N=57)

Corrected to 25% elec. heat (67% of samples are heat pumps vs. 25-35% in the stock)

(18 heat pumps)

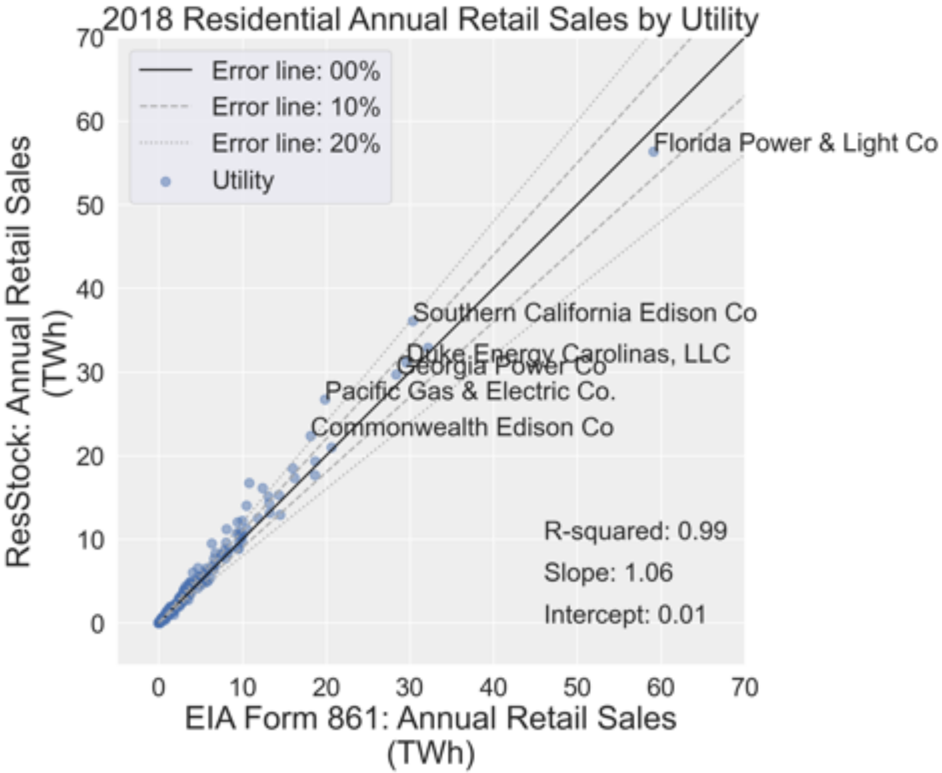
%)

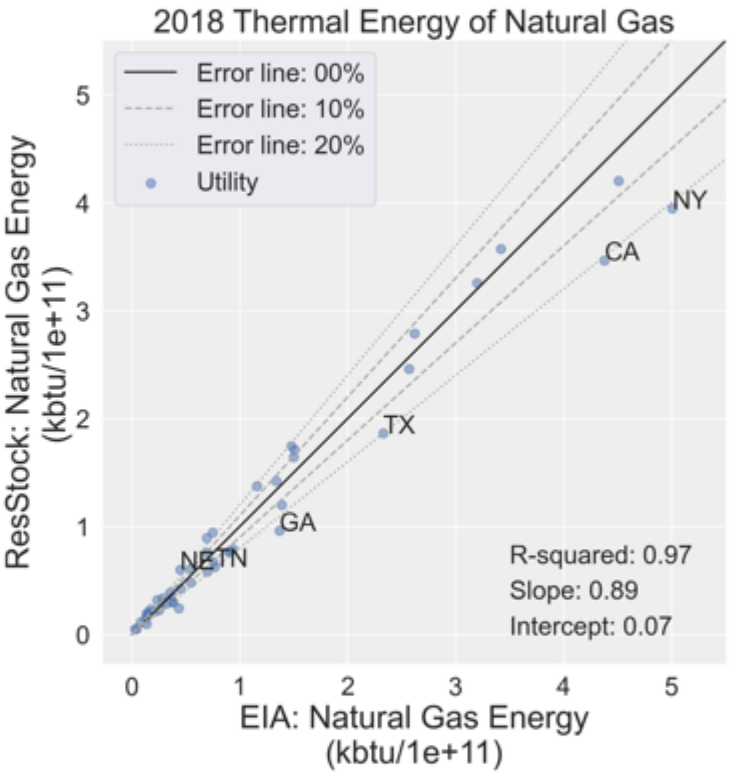


Plug loads and lighting are not separately metered in RBSAM (except for a few circuits)

Monthly EIA electricity sales by state, sector

Region 1 and 2 calibration regions included comparison to annual EIA sales data:



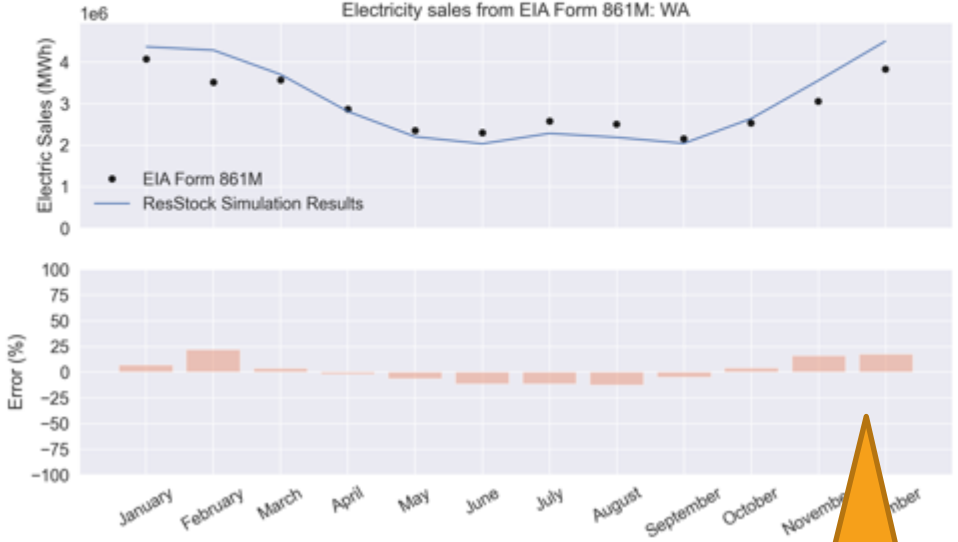


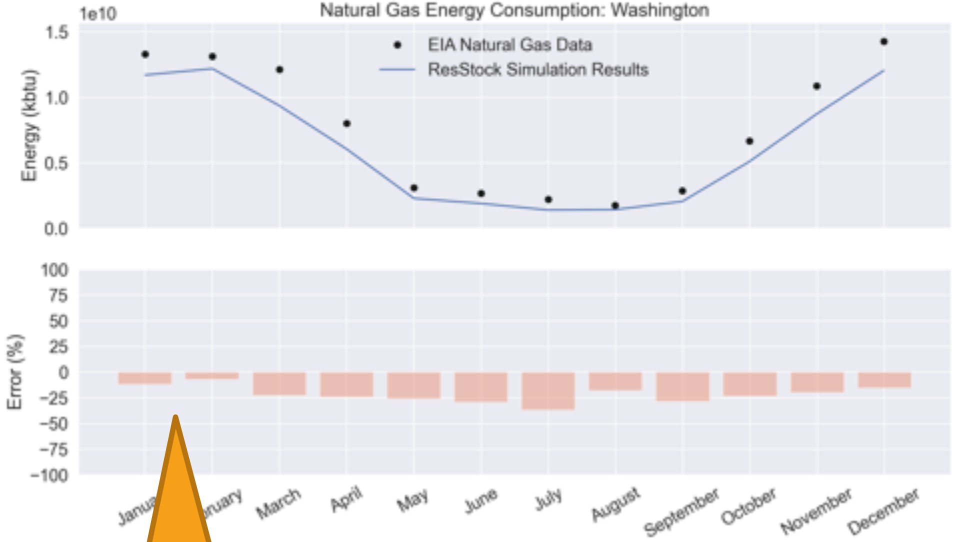
res_national_36_01_01_2018

Monthly EIA electricity, gas sales by state, sector

We now compare monthly residential sector electricity and gas sales for every state

Washington (Region 3)





Overpredicting electric heating

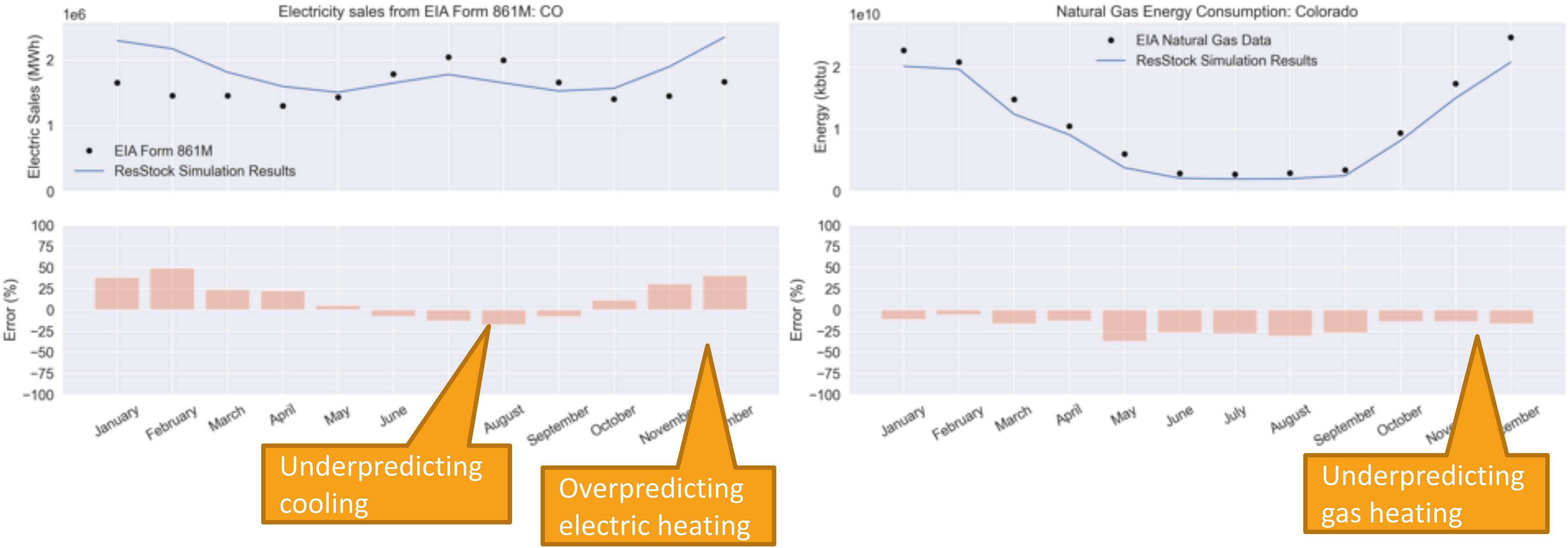
Underpredicting gas heating

res_national_36_01_01_2018

Monthly EIA electricity, gas sales by state, sector

We now compare monthly residential sector electricity and gas sales for every state

Colorado (Region 2)

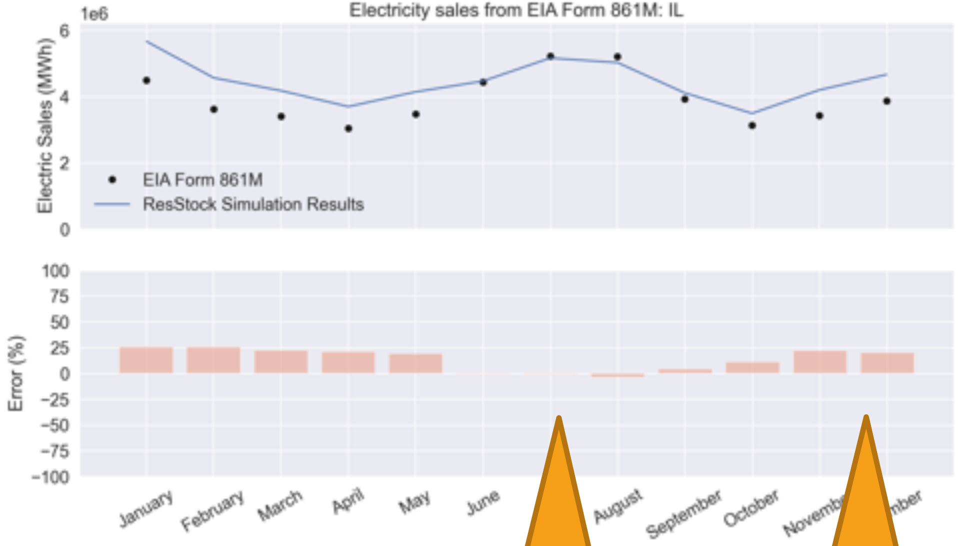


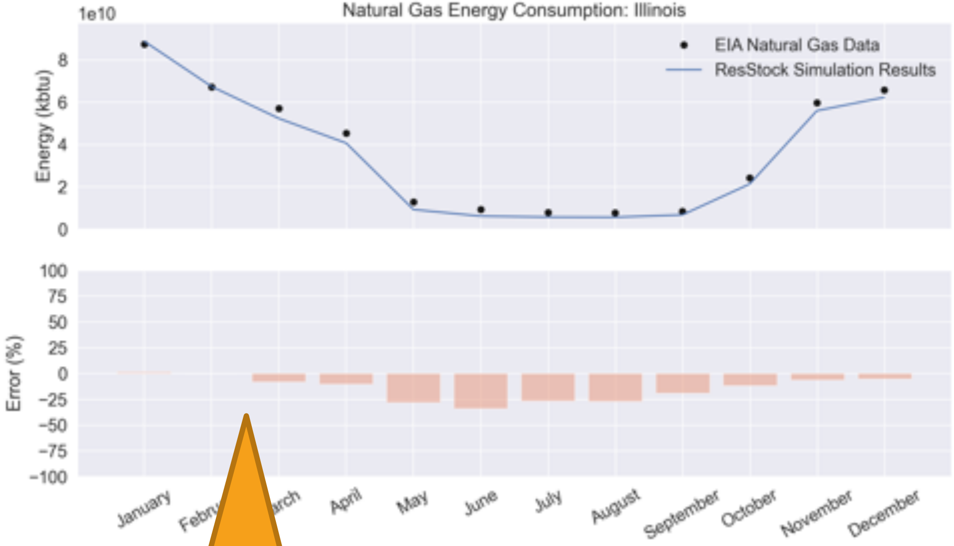
res_national_36_01_01_2018

Monthly EIA electricity, gas sales by state, sector

We now compare monthly residential sector electricity and gas sales for every state

Illinois (Region 1)





Cooling looks good

Overpredicting electric heating

Gas consumption looks good

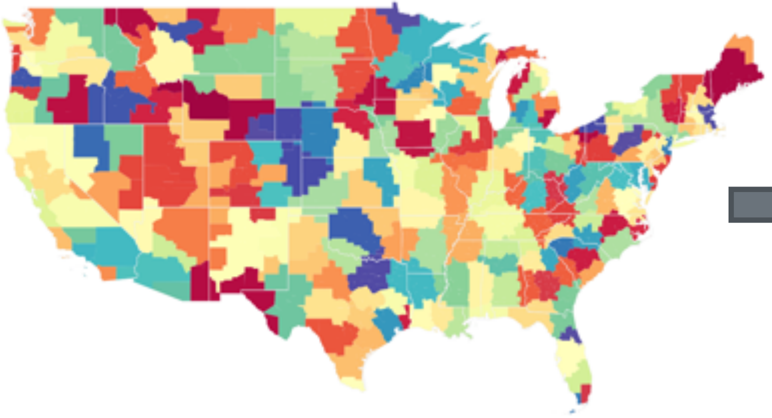
res_national_36_01_01_2018

Added Capabilities

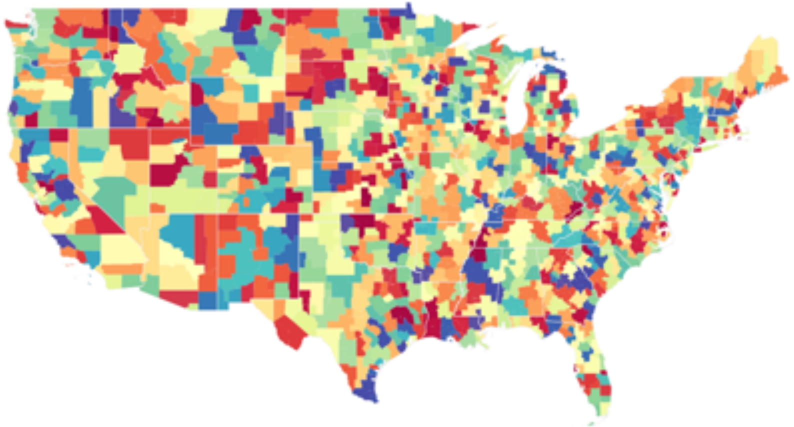
Update: More weather data locations

- Increased number of weather station data regions from 215 to 941
- Weather data regions are the same for ResStock and ComStock
- Increases resolution in weather events (e.g., cold fronts rolling across grid) and sunrise/sunset times, which should increase weather response diversity in aggregate load profiles

Before: 215 weather data regions

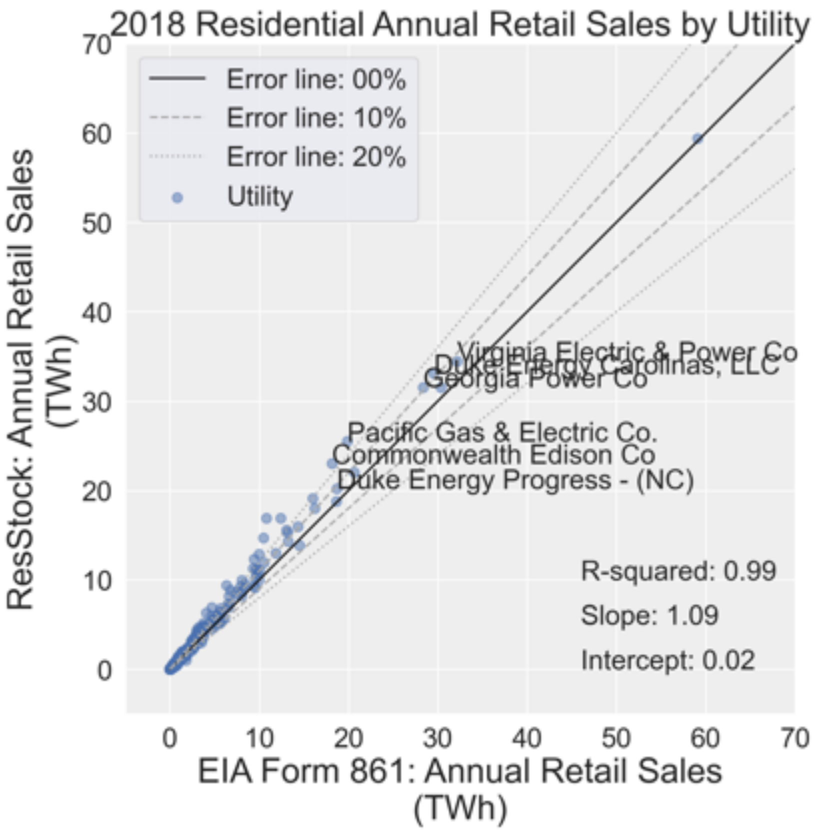


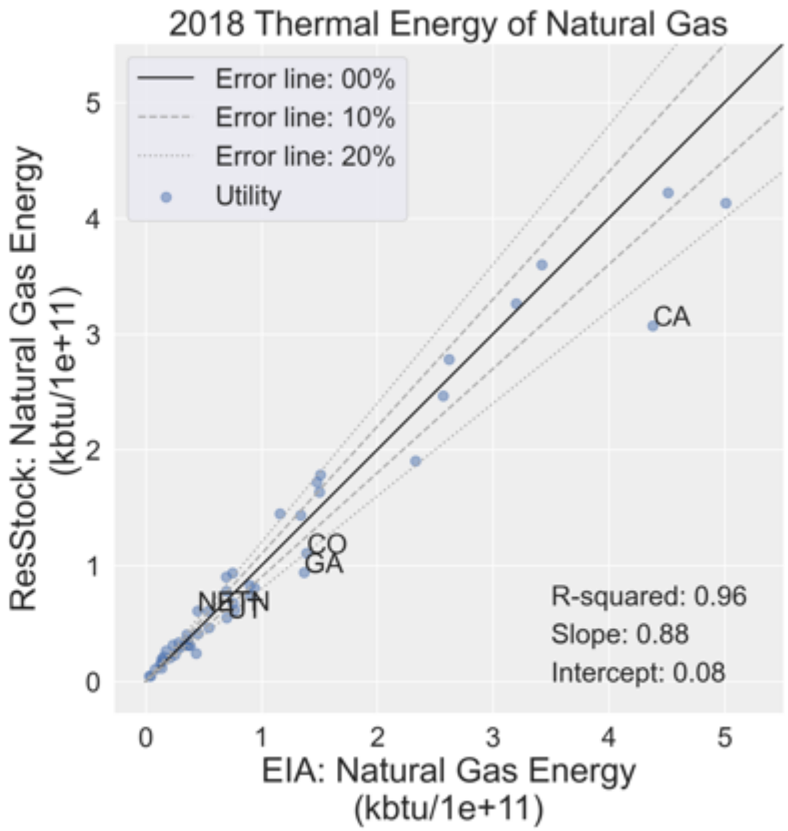
After: 941 weather data regions



Impact: More weather data locations

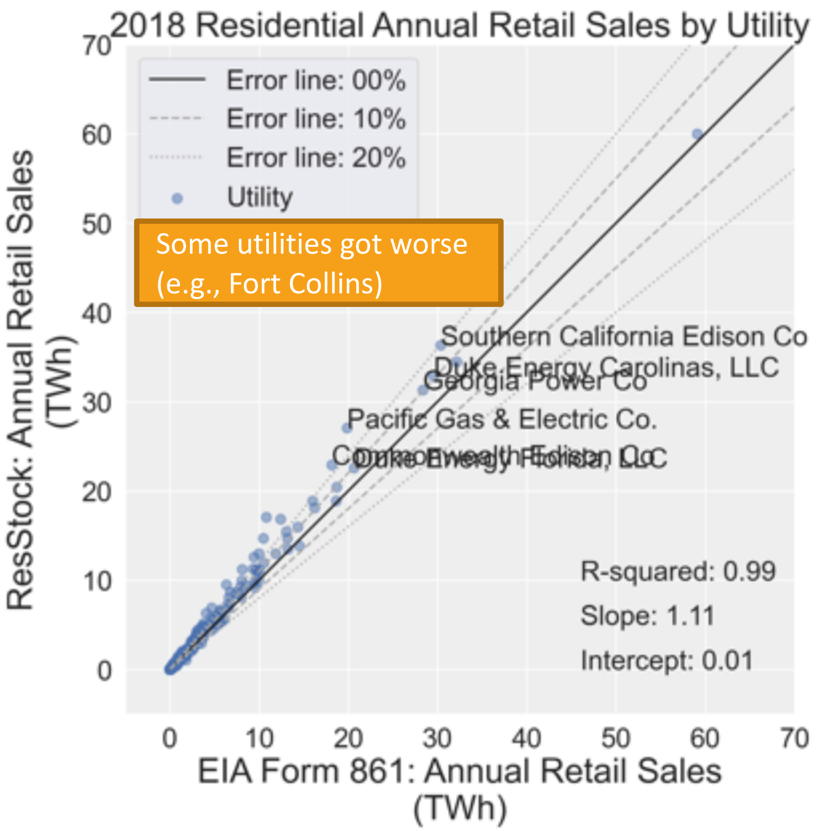
Before: 215 weather data regions

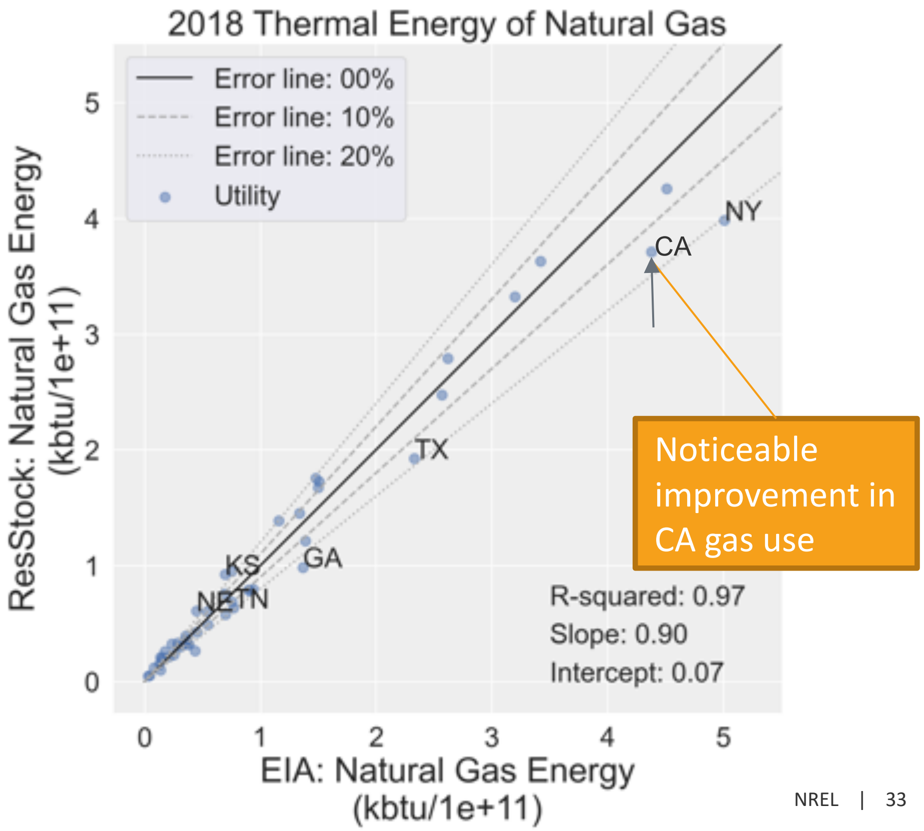




Impact: More weather data locations

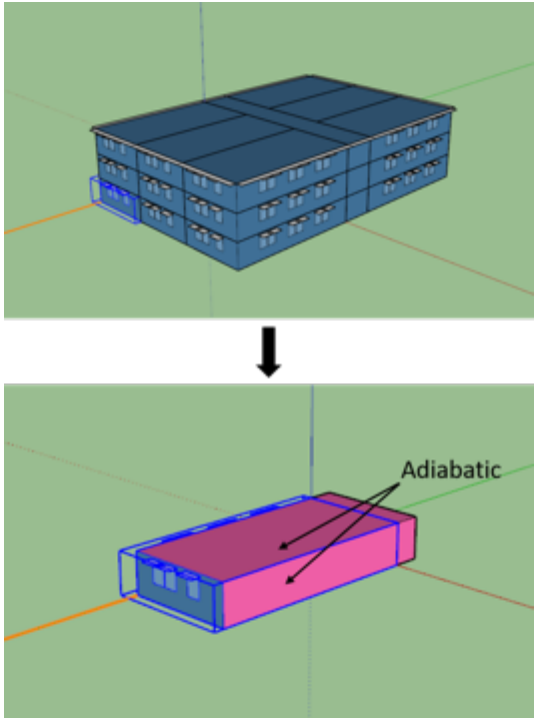
After: 941 weather data regions





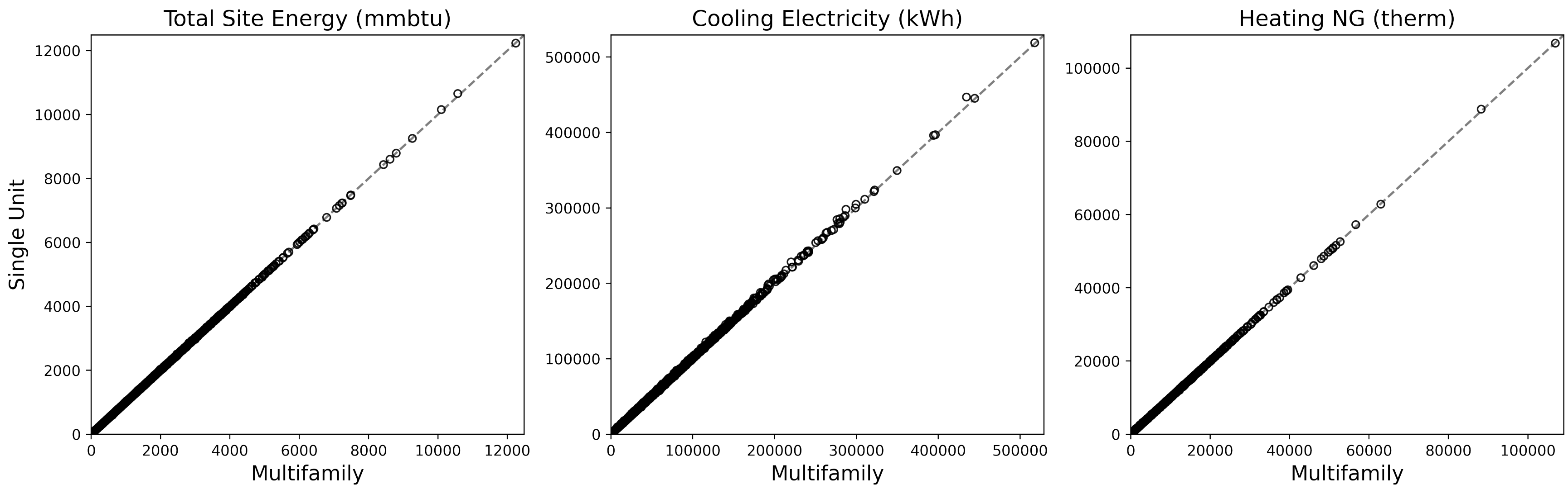
Update: Faster Multifamily Modeling

- ResStock data sources are primarily defined in terms of dwelling units (and not multifamily buildings)
- Previous approach:
  - Model an entire multifamily building for each sampled dwelling unit
- New approach:
  - Model only a dwelling unit for each sampled dwelling unit
  - Shared walls are modeled as adiabatic
- Benefits:
  - Speed improvements: HPC usage reduced by about 80%
  - Aligns with HPXML and associated workflows (Home Energy Score, WAP, ERI)
- Drawbacks:
  - Some heat flows not captured
    - Heat transfer between shared walls
    - Minor shading differences
    - 0.20% effect across total energy, 2.46% effect for worst test building
  - Cannot explicitly model central HVAC systems serving multiple units; using ANSI/RESNET/ICC 301-2019 approach instead



Testing: Faster Multifamily Modeling

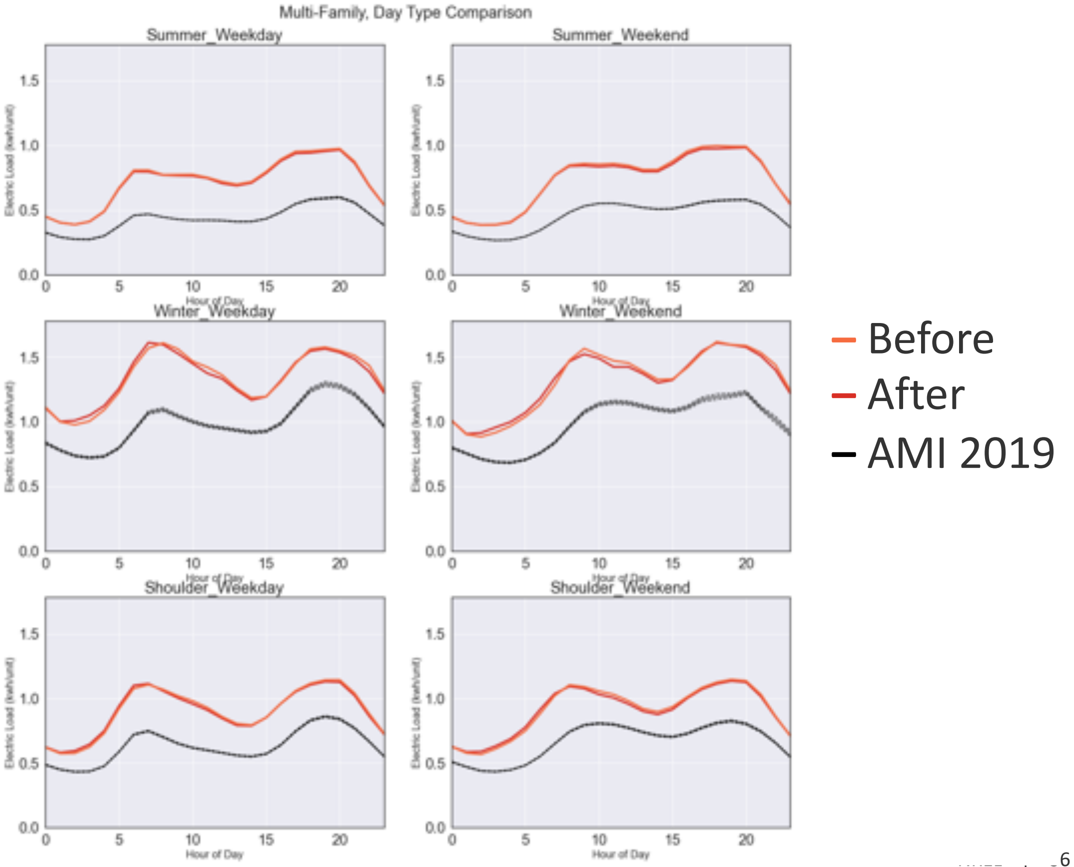
Test results for 10,000 MF buildings



Median Total Site Energy Difference	0.11%
Maximum Total Site Energy Difference	3.80%

Impact: Faster Multifamily Modeling

Negligible change to multifamily in Seattle, which is expected



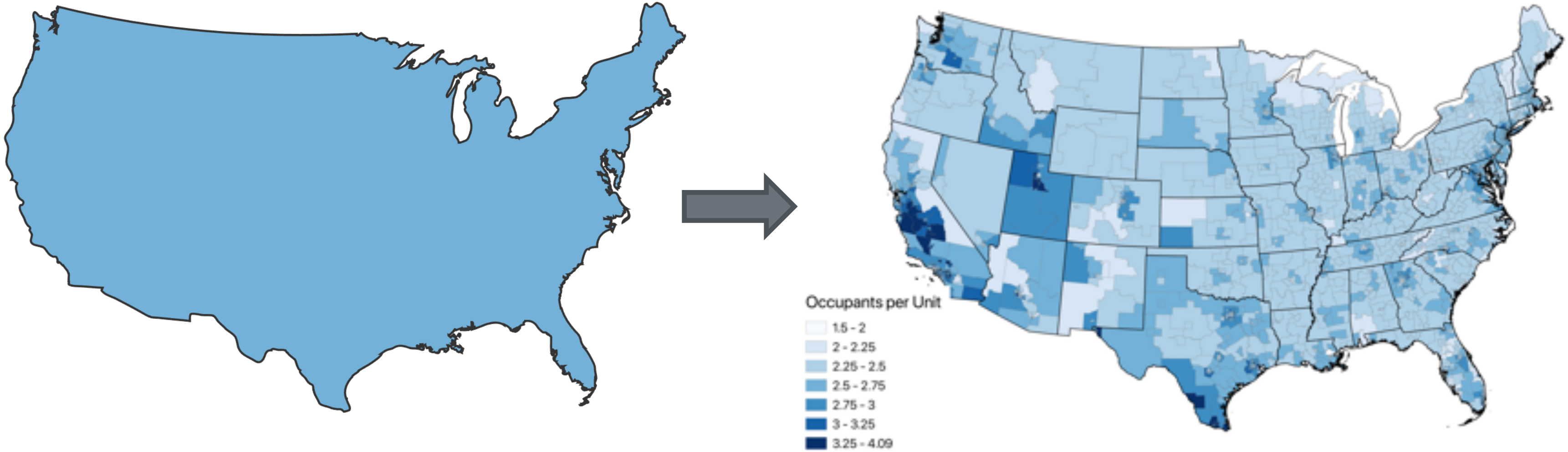
This change leveraged work from another project; it was motivated by runtime improvements and not by an observed error.

Baseload Updates

Update: More granular household sizes

Before: Number of occupants depends on building type and number of bedrooms
After: Number of occupants depends on building type and number of bedrooms **and PUMS region (N=2,335)**

- Number of occupants affects usage of domestic hot water, appliances, and plug loads
- Switch from RECS 2015 to PUMS 2017 allows PUMA level spatial granularity in the distributions and leverages more than 6 million samples.

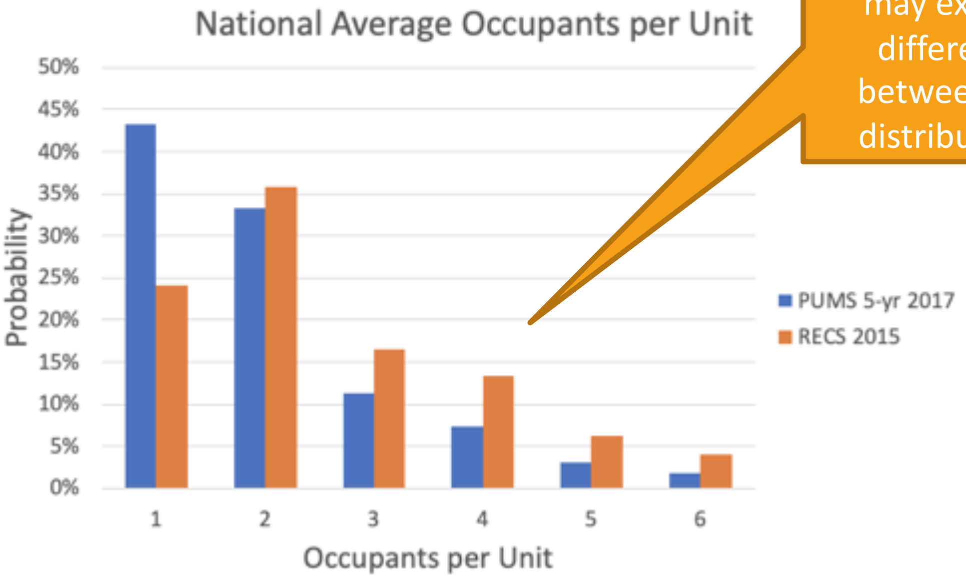


Update: More granular household sizes

Before: Number of occupants depends on building type and number of bedrooms
After: Number of occupants depends on building type and number of bedrooms **and PUMS region (N=2,335)**

- Number of occupants affects usage of domestic hot water, appliances, and plug loads
- Switch from RECS 2015 to PUMS 2017 allows PUMA level spatial granularity in the distributions and leverages more than 6 million samples.

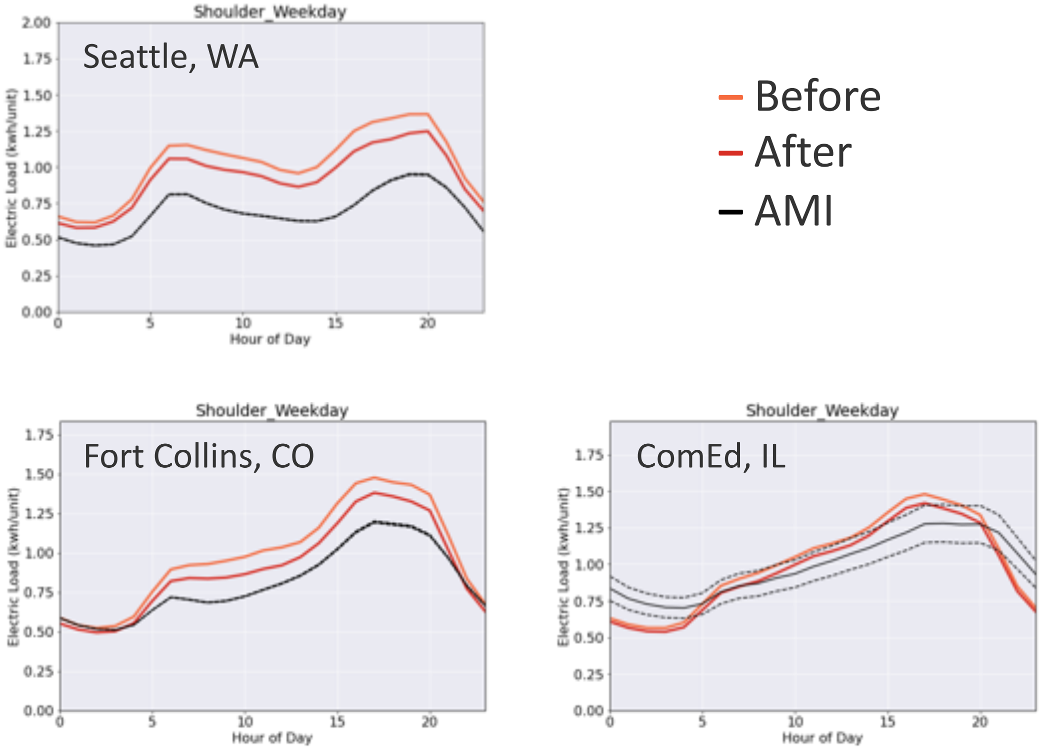
PUMS shows fewer occupants on average, so baseload is reduced nationally



Smaller sample size in RECS 2015 may explain difference between the distributions

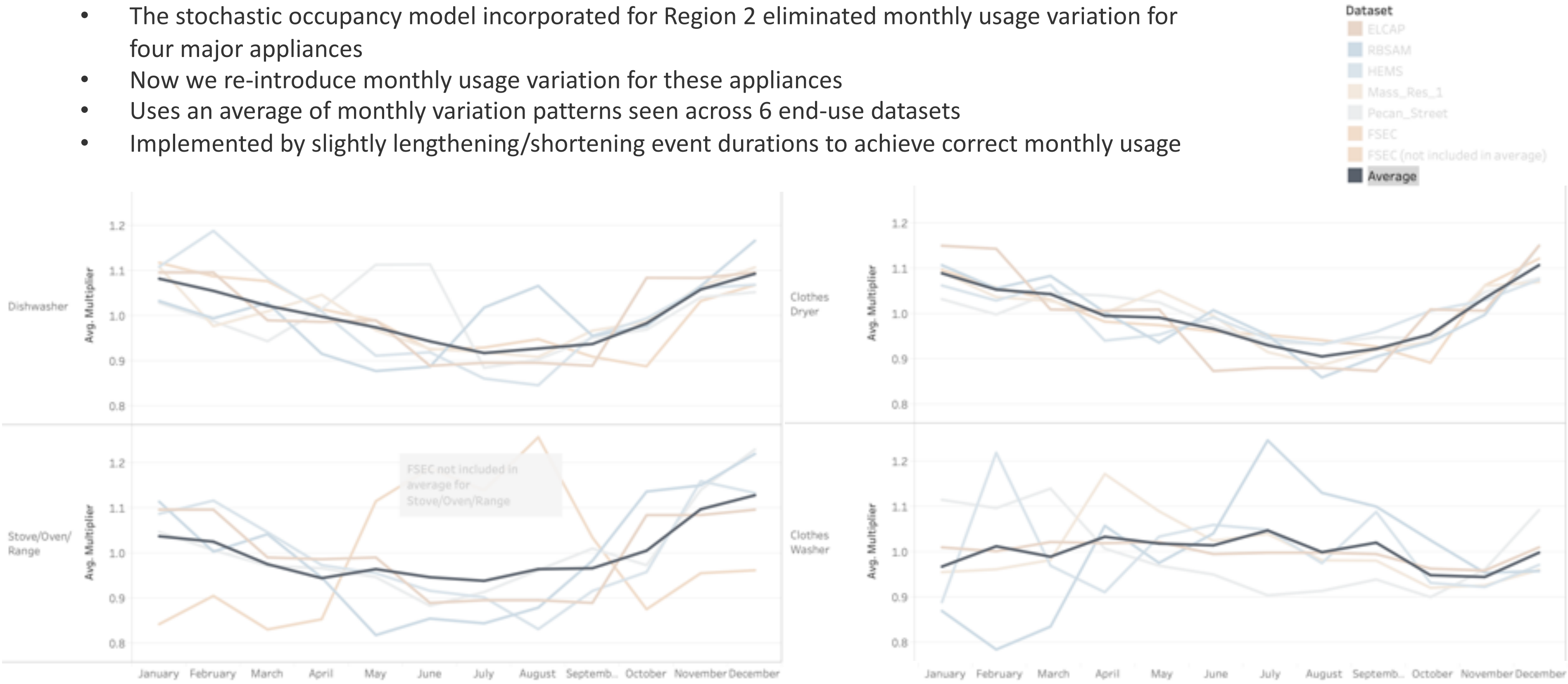
Impact: More granular household sizes

Modeling fewer occupants per household reduces baseload



Update: Monthly appliance usage multipliers

- The stochastic occupancy model incorporated for Region 2 eliminated monthly usage variation for four major appliances
- Now we re-introduce monthly usage variation for these appliances
- Uses an average of monthly variation patterns seen across 6 end-use datasets
- Implemented by slightly lengthening/shortening event durations to achieve correct monthly usage



Update: Regional variation in lighting efficiency

Before: Lighting technology saturation is a national average distribution
After: Lighting technology saturation depends on building type and Census Division (N=10)

Before:

Option=100% Incandescent	Option= 100% CFL	Option= 100% LED
52%	41%	7%

Update: Regional variation in lighting efficiency

Before: Lighting technology saturation is a national average distribution
After: Lighting technology saturation depends on building type and RECS Census Division (N=10)

Before:

Option=100% Incandescent	Option= 100% CFL	Option= 100% LED
52%	41%	7%

After:

Dependency=Census Division RECS	Dependency=Geometry Building Type RECS	Option=100% Incandescent	Option=100% CFL	Option=100% LED
East North Central	Single-Family Detached	44%	46%	10%
East South Central	Single-Family Detached	49%	44%	7%
Middle Atlantic	Single-Family Detached	43%	44%	13%
Mountain North	Single-Family Detached	36%	51%	14%
Mountain South	Single-Family Detached	38%	52%	10%
New England	Single-Family Detached	41%	44%	15%
Pacific	Single-Family Detached	34%	50%	16%
South Atlantic	Single-Family Detached	48%	43%	9%
West North Central	Single-Family Detached	48%	41%	11%
West South Central	Single-Family Detached	46%	46%	8%

Dependency=Census Division RECS	Dependency=Geometry Building Type RECS	Option=100% Incandescent	Option=100% CFL	Option=100% LED
Pacific	Mobile Home	34%	50%	16%
Pacific	Multi-Family with 2 - 4 Units	39%	54%	8%
Pacific	Multi-Family with 5+ Units	39%	54%	8%
Pacific	Single-Family Attached	39%	50%	11%
Pacific	Single-Family Detached	34%	50%	16%

Update: Regional variation in lighting efficiency

Before: Lighting technology saturation is a national average distribution
After: Lighting technology saturation depends on building type and RECS Census Division (N=10)

Pacific region has most efficient lighting

Before:

Option=100% Incandescent	Option= 100% CFL	Option= 100% LED
52%	41%	7%

After:

Dependency=Census Division RECS	Dependency=Geometry Building Type RECS	Option=100% Incandescent	Option=100% CFL	Option=100% LED
East North Central	Single-Family Detached	44%	46%	10%
East South Central	Single-Family Detached	49%	44%	7%
Middle Atlantic	Single-Family Detached	43%	44%	13%
Mountain North	Single-Family Detached	36%	51%	14%
Mountain South	Single-Family Detached	38%	52%	10%
New England	Single-Family Detached	41%	44%	15%
Pacific	Single-Family Detached	34%	50%	16%
South Atlantic	Single-Family Detached	48%	43%	9%
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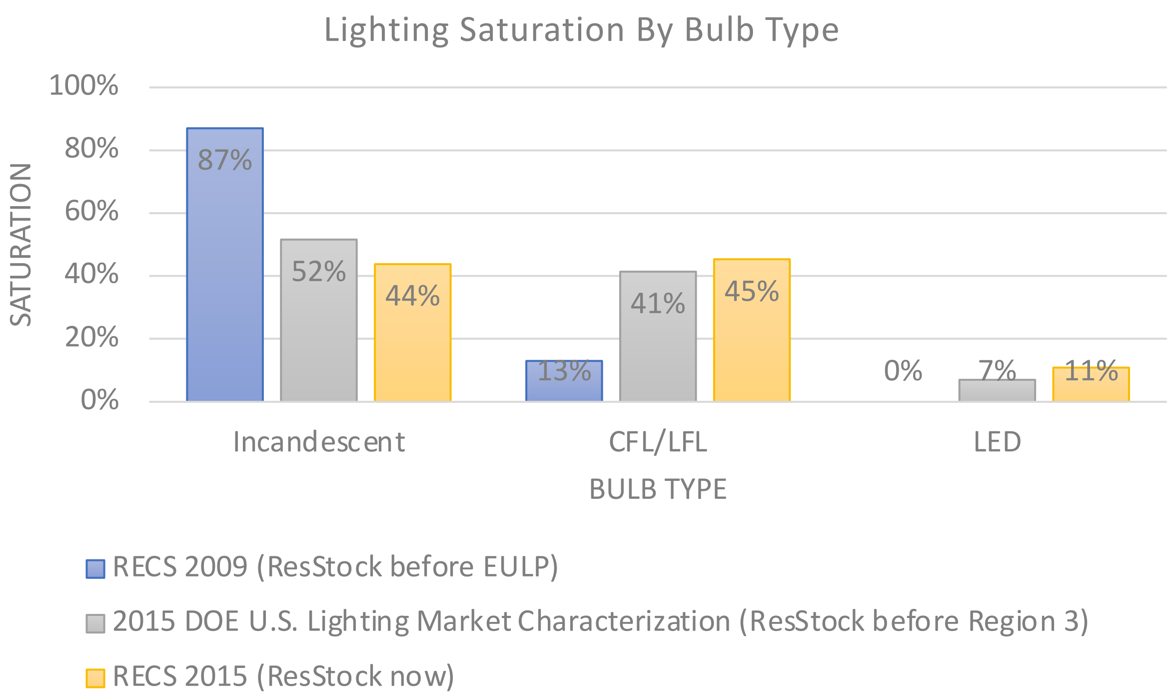
Dependency=Census Division RECS	Dependency=Geometry Building Type RECS	Option=100% Incandescent	Option=100% CFL	Option=100% LED
Pacific	Mobile Home	34%	50%	16%
Pacific	Multi-Family with 2 - 4 Units	39%	54%	8%
Pacific	Multi-Family with 5+ Units	39%	54%	8%
Pacific	Single-Family Attached	39%	50%	11%
Pacific	Single-Family Detached	34%	50%	16%

Single-family has more efficient lighting than multifamily

Update: Regional variation in lighting efficiency

Before: Lighting technology saturation is a national average distribution
After: Lighting technology saturation depends on building type and RECS Census Division (N=10)

Comparison of national average lighting saturation to previous ResStock data sources →



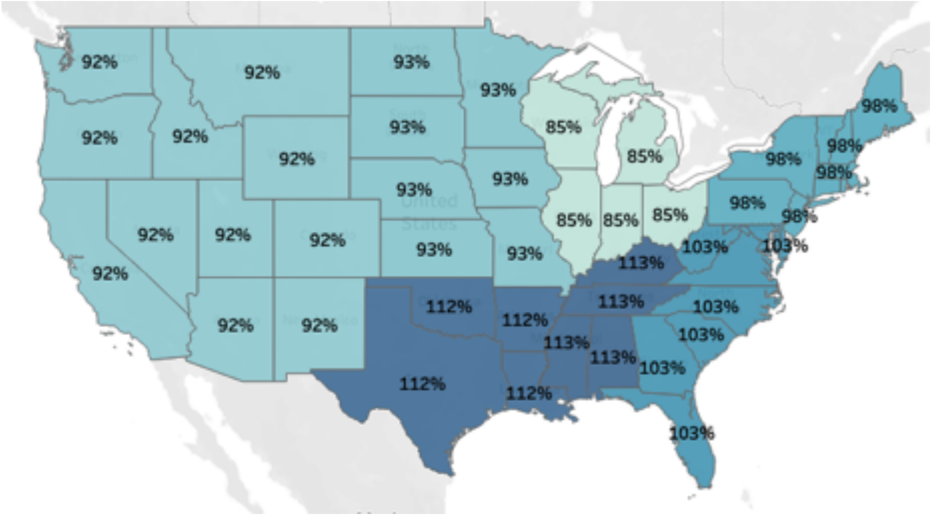
Update: Regional variation in plug load usage

Captures regional variation in plug loads that isn’t captured elsewhere (e.g., humidifiers, dehumidifiers, fans)

Misc. plug load kWh reported in RECS 2015 microdata relative to misc. plug load kWh calculated using regression equations derived from RECS 2015 →

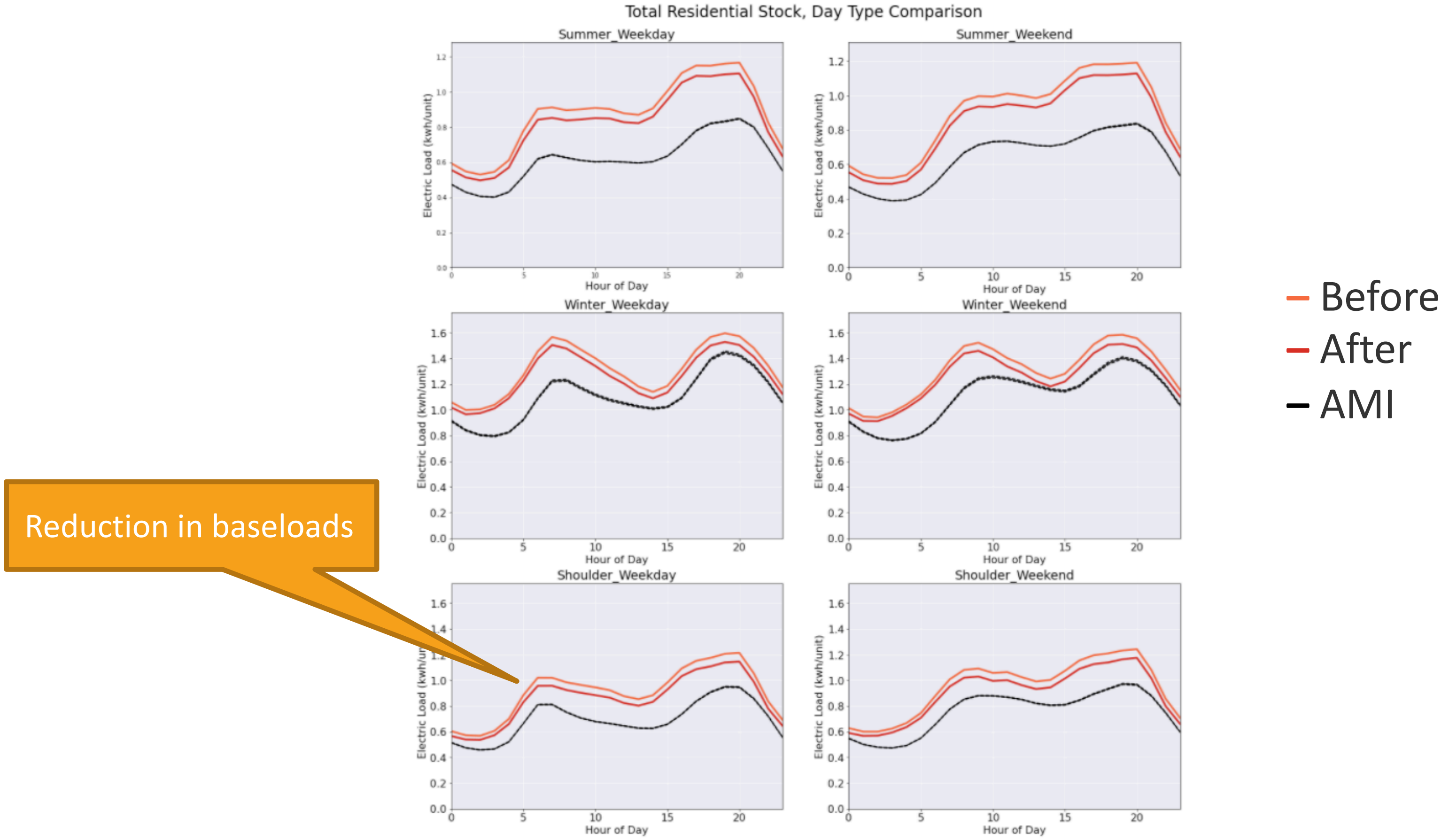
$$MELS_{SFD} = \alpha(1146.95 + 296.94\, n_{occupants} + 0.30 ffa)$$
$$MELS_{SFA} = \alpha(1395.84 + 136.53 n_{occupants} + 0.16 ffa)$$
$$MELS_{MF} = \alpha(875.22 + 184.11 n_{occupants} + 0.38 ffa)$$

$n_{occupants}$: Number of occupants
ffa: Finished floor area
α: Plug load regional and building type multiplier
SFD: Single-Family Detached
SFA: Single-Family Attached
MF: Multi-Family



** MELS are defined by the following fields in RECS 2015: televisions, microwaves, humidifiers, and other devices not elsewhere classified

Impact: Base load updates (lighting, appliances, plug loads)



Update: Water heater dependencies

Before: Water heating **fuel type** and **efficiency** depends on space heating fuel type and custom region (N=10)

After: Water heating **fuel type** depends on space heating fuel type, custom region (N=10), and building type
Water heating **efficiency** depends on water heater fuel type and custom region (N=10)

Water Heater Fuel

Allows other data sources to be integrated

Dependency=Geometry Building Type RECS	Dependency= Heating Fuel	Dependency= Location Region	Option= Electricity	Option=Fuel Oil	Option=Gas	Option= Other Fuel	Option= Propane
Mobile Home	Electricity	CR06	90%	0%	4%	0%	5%
Multi-Family with 2 - 4 Units	Electricity	CR06	93%	0%	7%	0%	0%
Multi-Family with 5+ Units	Electricity	CR06	93%	0%	7%	0%	0%
Single-Family Attached	Electricity	CR06	87%	0%	13%	0%	0%
Single-Family Detached	Electricity	CR06	90%	0%	4%	0%	5%
Mobile Home	Natural Gas	CR06	25%	0%	75%	0%	0%
Multi-Family with 2 - 4 Units	Natural Gas	CR06	0%	0%	100%	0%	0%
Multi-Family with 5+ Units	Natural Gas	CR06	0%	0%	100%	0%	0%
Single-Family Attached	Natural Gas	CR06	13%	0%	87%	0%	0%
Single-Family Detached	Natural Gas	CR06	25%	0%	75%	0%	0%

Water Heater Efficiency

Dependency= Location Region	Dependency= Water Heater Fuel	Option=Electric Heat Pump, 80 gal	Option=Electric Premium	Option=Electric Standard	Option=Electric Tankless	Option=Oil Indirect	Option=Oil Premium	Option=Oil Standard	Option=Gas Premium	Option=Gas Standard	Option=Gas Tankless	Option=Other Fuel	Option=Propane Premium	Option=Propane Standard	Option=Propane Tankless
CR06	Electricity	3%	17%	79%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
CR06	Fuel Oil	0%	0%	0%	0%	9%	15%	76%	0%	0%	0%	0%	0%	0%	0%
CR06	Gas	0%	0%	0%	0%	0%	0%	0%	17%	83%	0%	0%	0%	0%	0%
CR06	Other Fuel	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%
CR06	Propane	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	19%	81%	0%

Update: Higher efficiency water heaters

Before: Tank vs. Tankless from RECS; all tanks are "Standard Efficiency"

After: RECS water heater blanket field is used as a proxy for premium storage tank water heaters
Heat pump water heaters are added in (3% of electric stock in WA, OR per RBSA II; 0.5% elsewhere per Butzbaugh et al.)

Water Heater Fuel

Dependency=Geometry Building Type RECS	Dependency= Heating Fuel	Dependency= Location Region	Option= Electricity	Option=Fuel Oil	Option=Gas	Option= Other Fuel	Option= Propane
Mobile Home	Electricity	CR06	90%	0%	4%	0%	5%
Multi-Family with 2 - 4 Units	Electricity	CR06	93%	0%	7%	0%	0%
Multi-Family with 5+ Units	Electricity	CR06	93%	0%	7%	0%	0%
Single-Family Attached	Electricity	CR06	87%	0%	13%	0%	0%
Single-Family Detached	Electricity	CR06	90%	0%	4%	0%	5%
Mobile Home	Natural Gas	CR06	25%	0%	75%	0%	0%
Multi-Family with 2 - 4 Units	Natural Gas	CR06	0%	0%	100%	0%	0%
Multi-Family with 5+ Units	Natural Gas	CR06	0%	0%	100%	0%	0%
Single-Family Attached	Natural Gas	CR06	13%	0%	87%	0%	0%
Single-Family Detached	Natural Gas	CR06	25%	0%	75%	0%	0%

Now model higher efficiency tank models

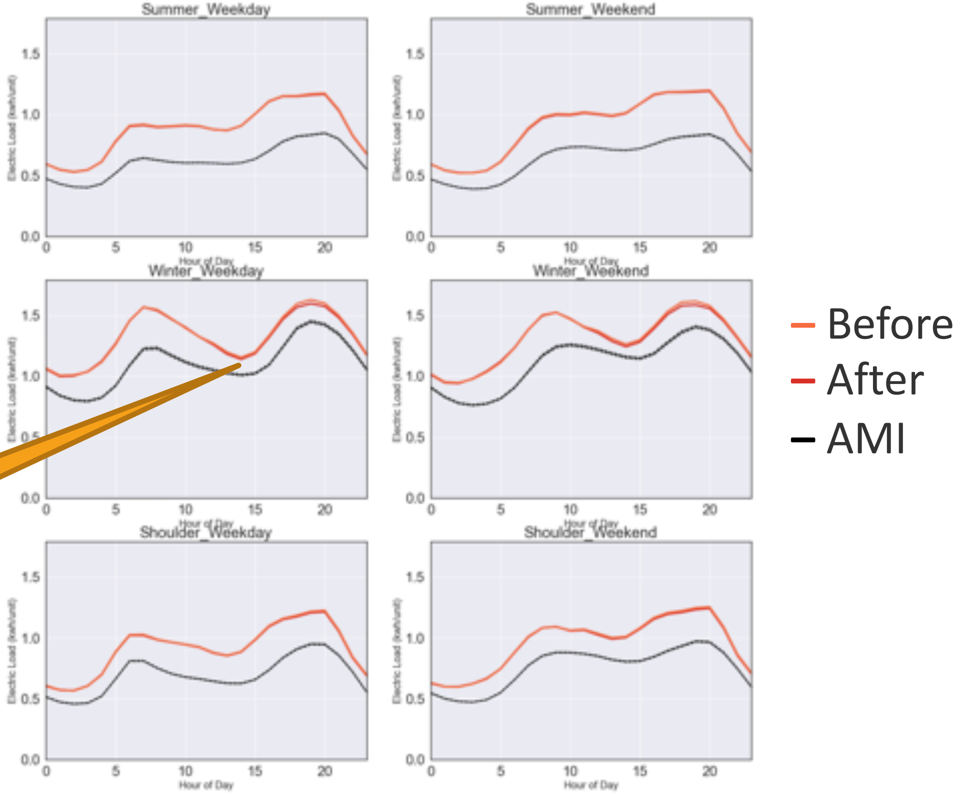
Now model Heat pump water heaters

Water Heater Efficiency

Dependency= Location Region	Dependency= Water Heater Fuel	Option=Electric Heat Pump, 80 gal	Option=Electric Premium	Option=Electric Standard	Option=Electric Tankless	Option=Oil Indirect	Option=Oil Premium	Option=Oil Standard	Option=Gas Premium	Option=Gas Standard	Option=Gas Tankless	Option=Other Fuel	Option=Propane Premium	Option=Propane Standard	Option=Propane Tankless
CR06	Electricity	3%	17%	79%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
CR06	Fuel Oil	0%	0%	0%	0%	9%	15%	76%	0%	0%	0%	0%	0%	0%	0%
CR06	Gas	0%	0%	0%	0%	0%	0%	0%	17%	83%	0%	0%	0%	0%	0%
CR06	Other Fuel	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%
CR06	Propane	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	19%	81%	0%

Impact: Water heater dependencies, Higher efficiency water heaters

Seattle, WA



Efficiency improvements are minimal

HVAC Updates

Update: Roof material distributions

Before: the EULP project

100% medium asphalt shingles

This change leveraged work from another project; it was not motivated by an observed error.

After: Calibration region 2

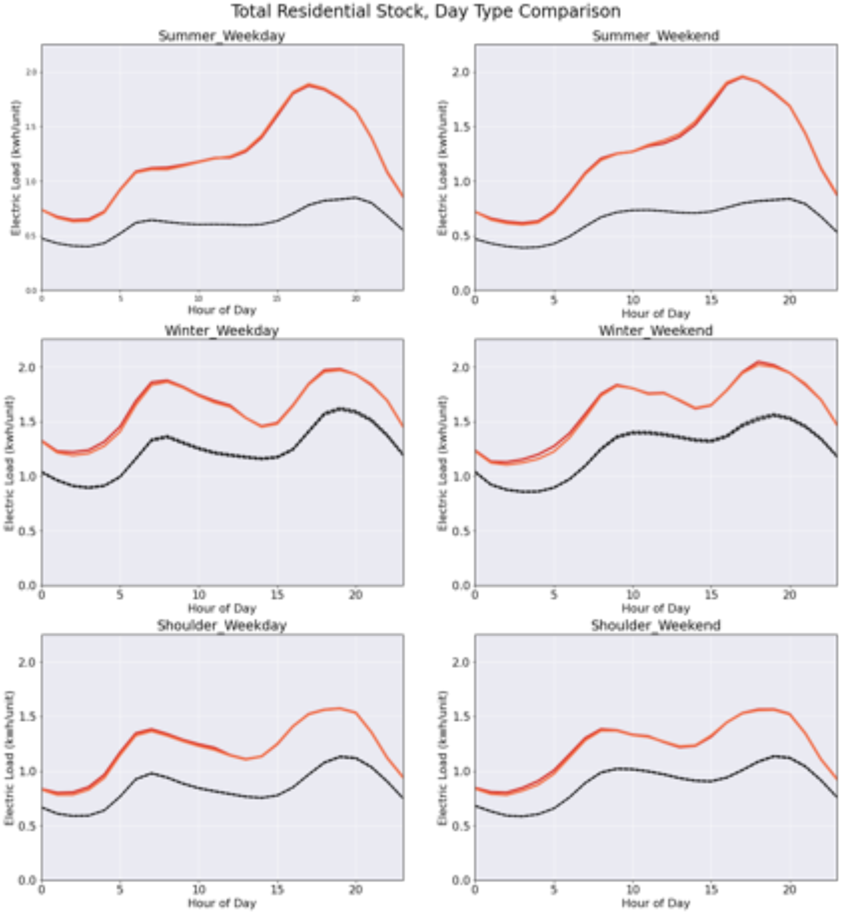
Distribution based on RECS

For example:

Dependency= Geometry Building Type RECS	Dependency= Location Region	Option= None	Option= Asphalt, Medium	Option= Composition Shingles	Option= Metal, Dark	Option= Slate	Option= Tile, Clay or Ceramic	Option= Tile, Concrete	Option= Wood Shingles
Mobile Home	CR06 (WA, OR)	0%	0%	49%	45%	0%	0%	0%	7%
Single-Family Attached	CR06 (WA, OR)	0%	9%	74%	0%	4%	0%	0%	12%
Single-Family Detached	CR06 (WA, OR)	0%	5%	84%	4%	0%	1%	0%	6%

Impact: Roof material distributions

Negligible change
(as was expected)



– Before
– After
– AMI

Update: Cooling type IECC dependency

The HVAC organization restructure completed during Region 2 accidentally removed a dependency on location

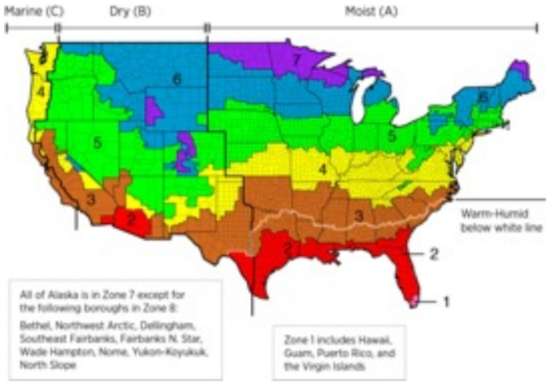
Cooling type (central AC, room AC, heat pump, none) depends on:

<u>Before:</u>

- building type,
- vintage,
- heating type (ducts or not, heat pump or not)

<u>After:</u>

- building type,
- vintage,
- heating type (ducts or not, heat pump or not),
- **IECC Climate Zone**



Slicing RECS 2009 four ways requires careful binning of responses to ensure sufficient samples for all combinations:

- Due to low sample sizes for some Heating Types, Heating Type data for Non-Ducted Heating and None is grouped.
- Due to low sample sizes for some Building Types, Building Type data are grouped into: 1) Single-Family Detached and Single-Family Attached, and 2) Multifamily 2-4 units and Multifamily 5+ units, and 3) Mobile Homes.
- Due to low sample sizes for some Vintages, Vintage ACS (20-year bins) is used instead of the typical 10-year bins used for RECS data.

Other assumptions:

- If a sample has both Central AC and Room AC, we assume it has Central AC only
- If a sample indicates using a heat pump for AC but does not indicate using a heat pump for heating, then we either assign it a heat pump for heating (if electric heating was indicated), or we assign it Central AC (if non-electric heating was indicated).

Update: HVAC Cooling Load/Sizing Fix

The stochastic occupancy feature added during Region 2 accidentally increased the magnitude of internal gains used for the design cooling load calculation for air conditioner sizing.

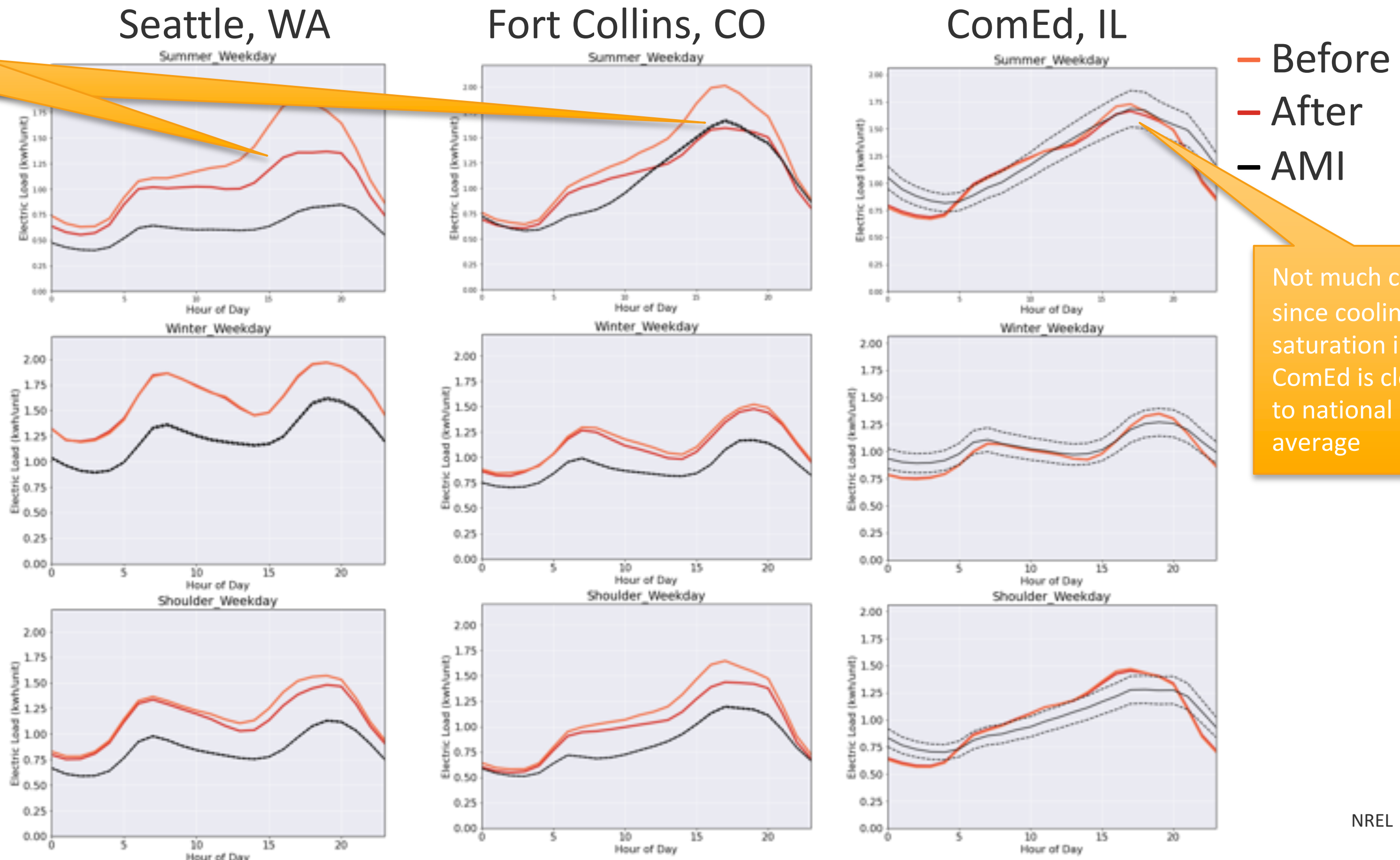
This did not significantly affect annual energy use, only peak demand (~1% of hours).

After this discovery, we implemented automated before/after checks on heating/cooling capacities and other output variables such as unmet hours for heating/cooling setpoints.

Impact: Cooling type IECC dependency, Cooling Load/Sizing Fix

Major improvement in cooling

** Also includes fix to air conditioner sizing bug introduced in Region 2 calibration (primarily affect peak days)*



Not much change since cooling saturation in ComEd is closer to national average

Update: Foundation type distributions

Before:

Depends on state (1988 source)

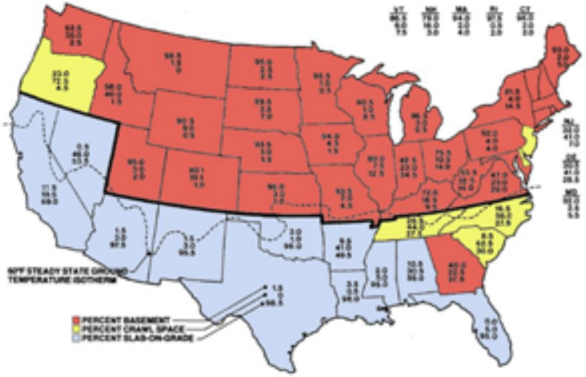


Figure 3. Share of residential foundations by state (Labs, et al., 1988)[1]

From *Building Foundation Design Handbook*, ORNL/Sub-86-72143/1, Oak Ridge National Laboratory/US Dept. of Energy.

After:

Depends on IECC Climate Zone, building type, and vintage

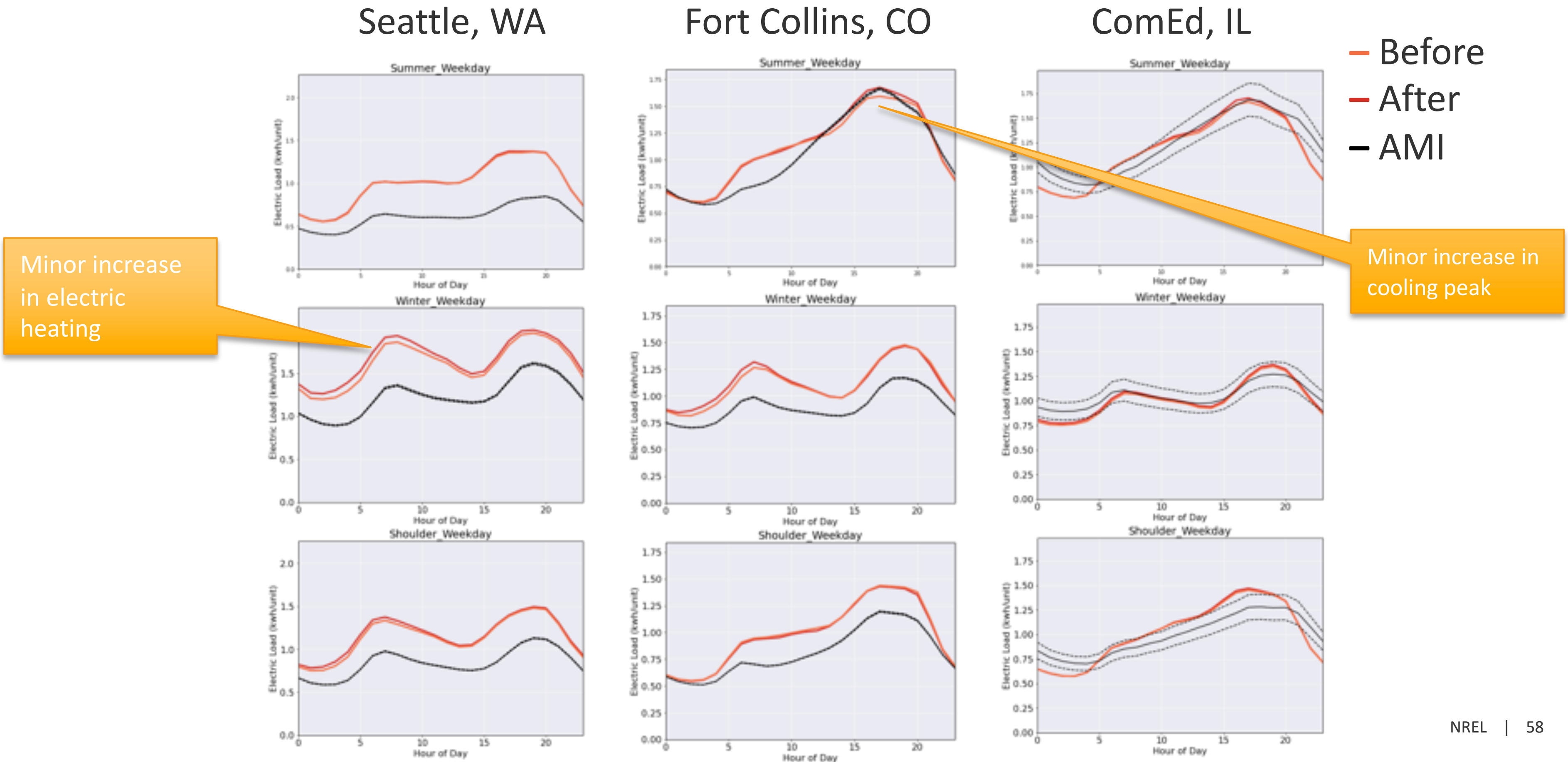
For example:

Dependency= ASHRAE IECC Climate Zone 2004	Dependency=Geometry Building Type RECS	Dependency=Vintage ACS	Option= Crawl	Option= Heated Bsmt	Option= Pier and Beam	Option= Slab	Option= Unheated Bsmt
4C	Single-Family Detached	<1940	55%	15%	0%	17%	13%
4C	Single-Family Detached	1940-59	39%	30%	0%	29%	2%
4C	Single-Family Detached	1960-79	55%	6%	10%	28%	0%
4C	Single-Family Detached	1980-99	68%	2%	3%	25%	2%
4C	Single-Family Detached	2000-09	64%	3%	9%	25%	0%
4C	Single-Family Detached	2010s	64%	3%	9%	25%	0%

Assumptions:

- All mobile homes have Pier and Beam foundations.
- Multi-family buildings cannot have Pier and Beam and Heated Basements
- Single-family attached buildings cannot have Pier and Beam foundations

Impact: Foundation type distributions



Alternate Comparisons

Multifamily Building-Level Meters

The overprediction of electric heating in multifamily buildings led us to investigate whether building-level meters for centrally metered HVAC and domestic hot water (DHW) are included in the Seattle residential AMI data.

For Seattle:

- Individual units typically have a residential rate code
- Common areas and central metering are typically given a commercial rate code

We can remove central system HVAC and DHW from ResStock results for Seattle to see how this affects the comparison (see next slide).

- Uses data from RECS (entire U.S.) and RBSA (Pacific Northwest) on the prevalence of central HVAC and DHW

We have inquiries out to Fort Collins and EIA to better understand how much this affects other dataset comparisons.

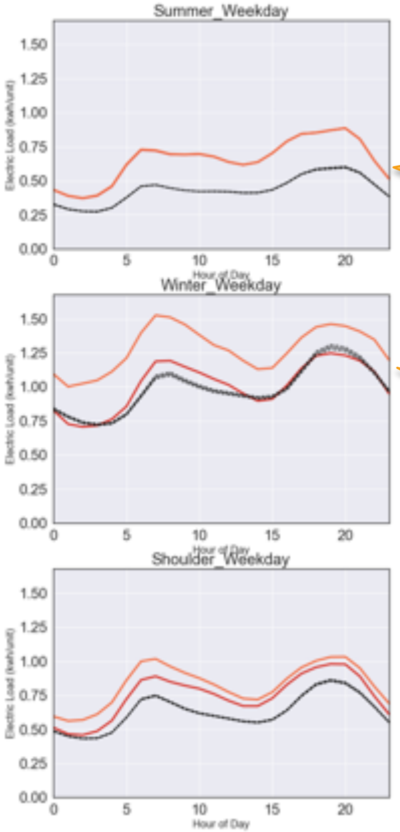
- In ComEd, common meters are classified as residential
- This effect may show up in Region 4 Hot Humid, which has higher electric heat fractions.

(Photo by Dennis Schroeder / NREL #48963)

Alternate Comparisons

With and without central heating/cooling

Seattle, WA – Multifamily Units



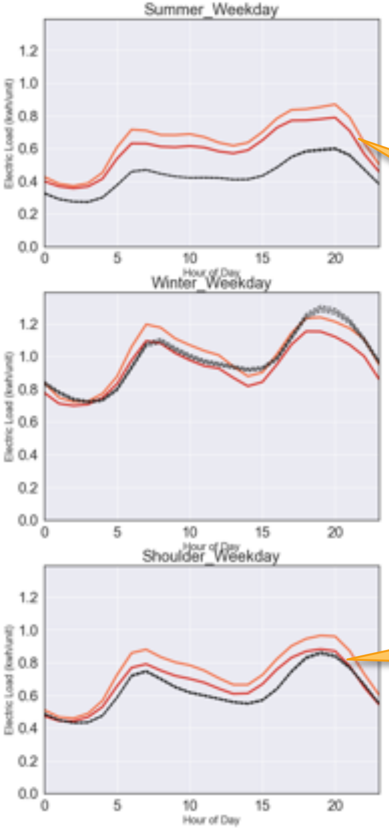
– **With** central heating/cooling
– **Without** central heating/cooling
– **AMI**

No significant difference because there is little to no central cooling

Significant improvement in winter load match

With and without DHW

Seattle, WA – Multifamily Units



Without central heating/cooling
– **With** central DHW
– **Without** central DHW
– **AMI**

Improvement in summer load match

Improvement in shoulder load match

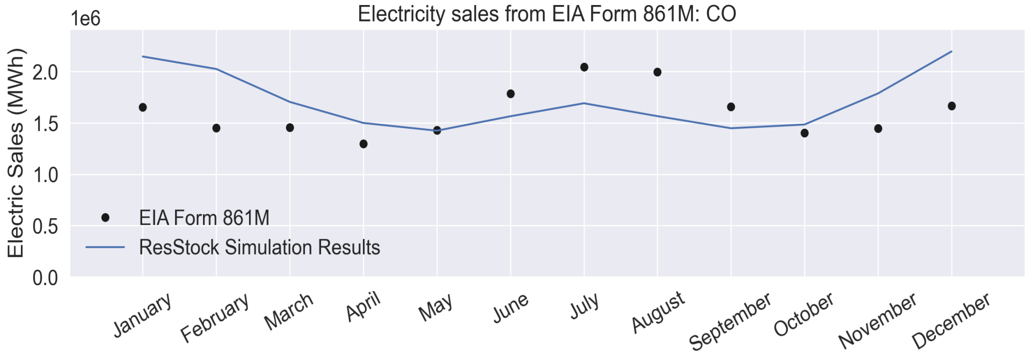
ResStock Correction Model

Motivation for a correction model

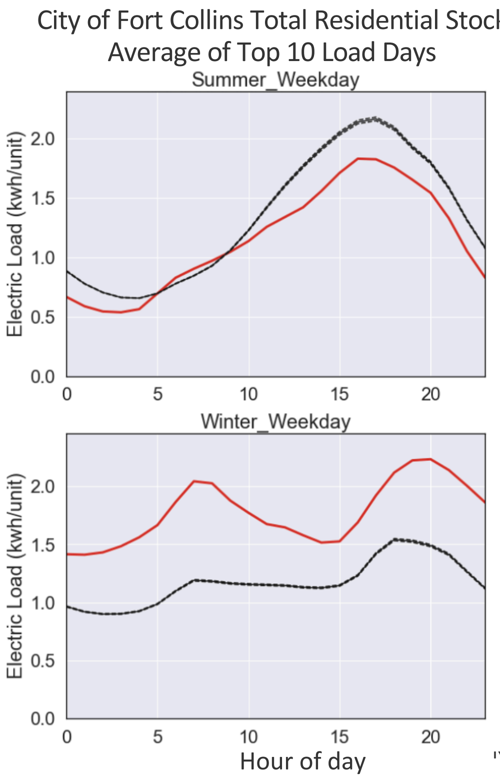
- Cannot model everything
  - Ex: Cooling setpoints are lower in summer than shoulder
  - Ex: Mean radiant temperature causes setpoints to change during heat waves
- Best available data does not accurately capture all aspects in building stock
  - Ex: RECS does not capture monthly changes in setpoints
  - Ex: Best available data could over or underpredicts appliance saturations, age/efficiency, setpoints, etc.

Example: model discrepancies across timescales

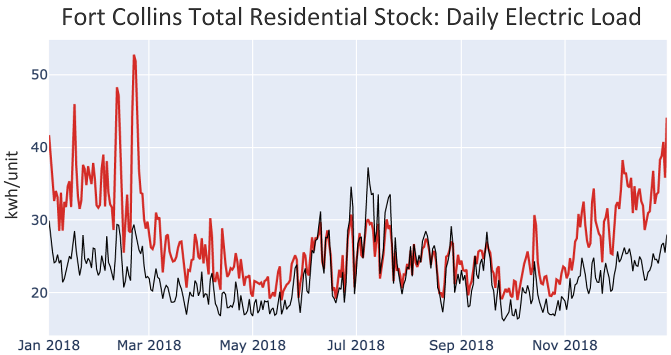
Monthly



Hourly



Daily



Consistent under-prediction of cooling and over-prediction of heating across timescales and data sources

ResStock
AMI Data

Example approaches

Goal is to correct bulk errors but not overfit

Correction to EIA state and monthly data

1. Adjust all end-uses
2. Adjust only HVAC loads
3. …

Suggests that discrepancies are combination of baseload and HVAC loads

Suggests that discrepancies are mostly HVAC loads

Approach will evolve until calibration is finished

- Example extension: County and daily factors based on HDD/CDD

Example model formulation

Planning on using multiplicative factors

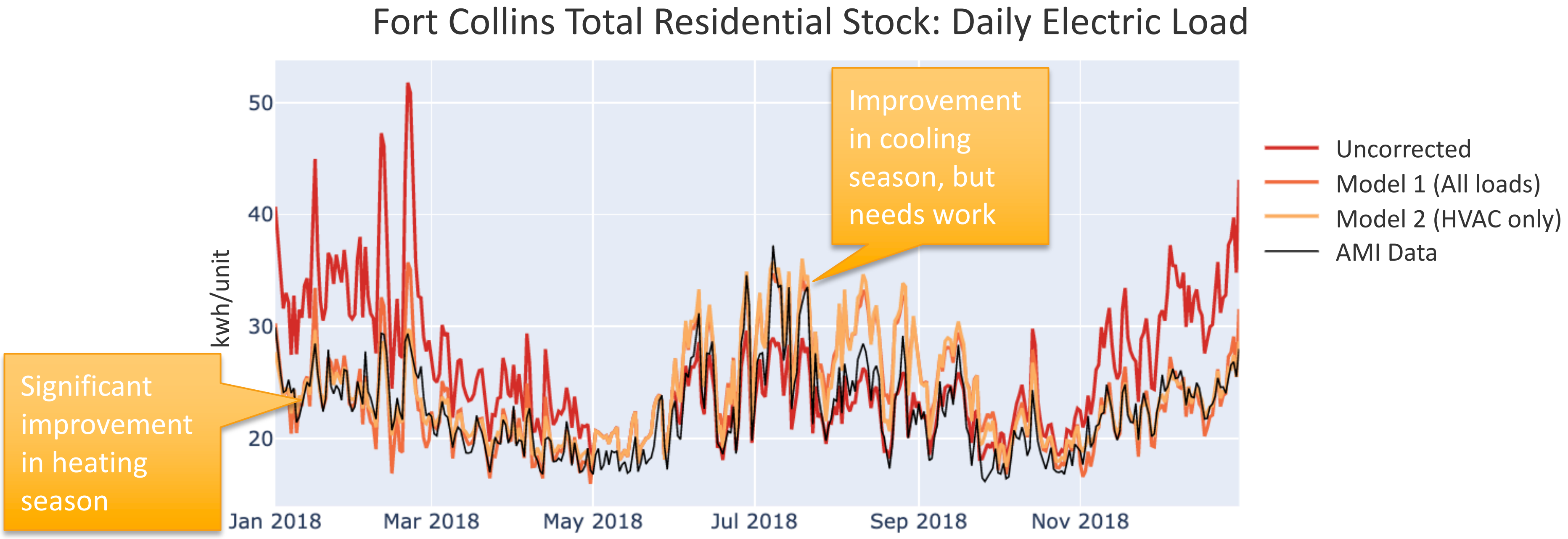
- If use state and month factors, then calculate 588 (49x12) factors
- Model 1: all end-uses
- Model 2: only HVAC end-uses

Do not model Alaska and Hawaii, but do model DC

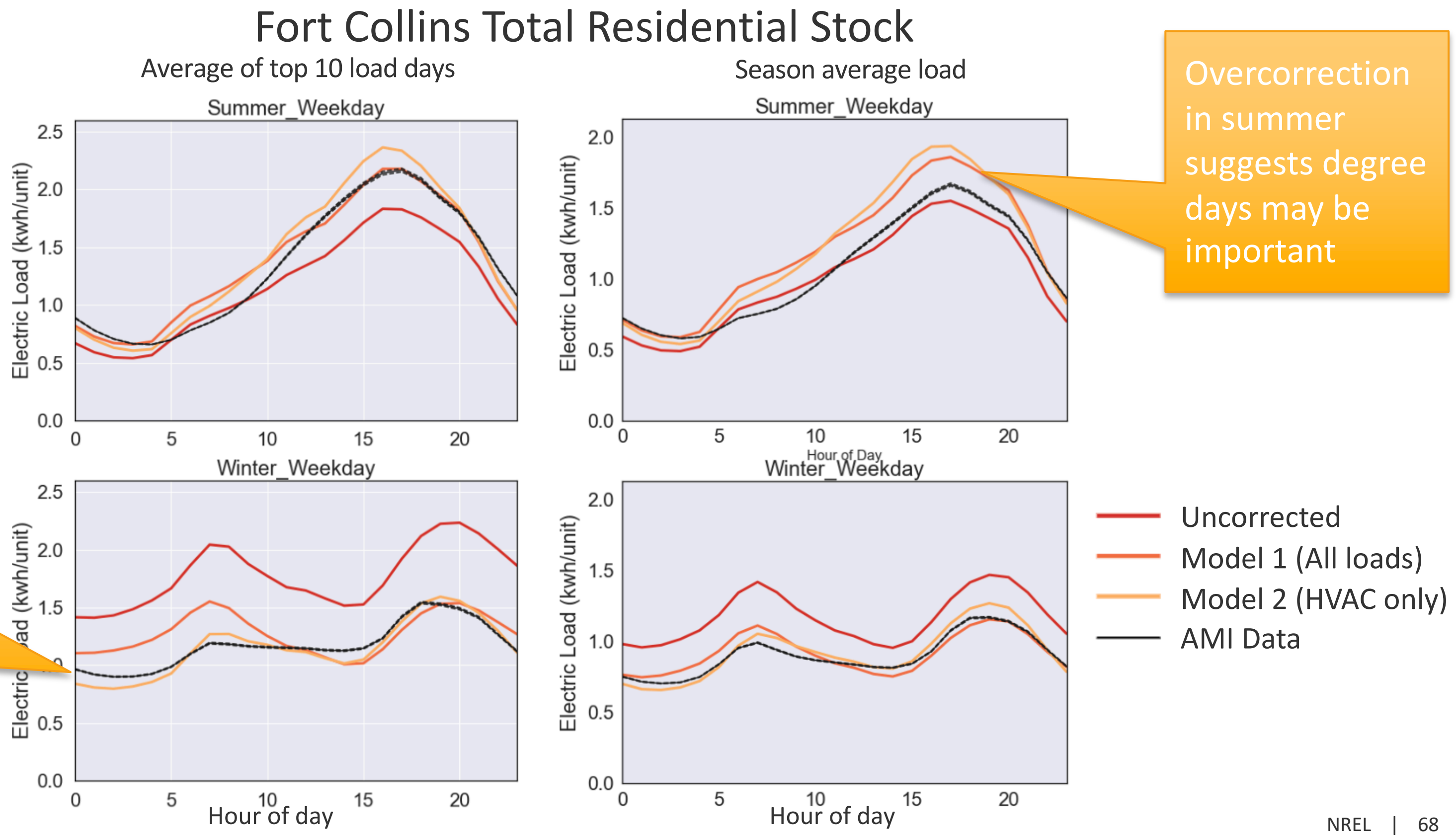
$$\overbrace{\tilde{e}_{sm}(t)}^{\text{Corrected end-use energy}} = \underbrace{\alpha_{sm}}_{\text{State and month correction factor}} \overbrace{e_{sm}(t)}^{\text{Simulated end-use energy}}$$

$$s \in \{AL, AZ, AR, \dots, WI, WY\}$$
$$m \in \{Jan, \dots, Dec\}$$

Example impacts of the potential correction models



Example impacts of the potential correction models



Overcorrection in summer suggests degree days may be important

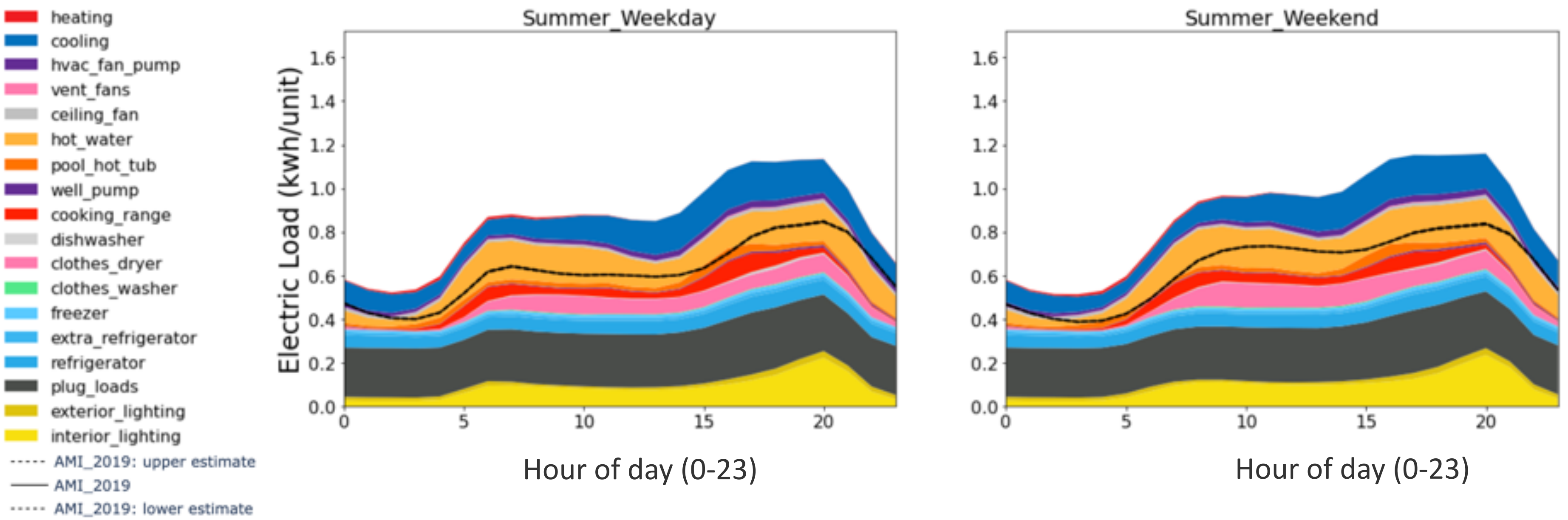
Model 2 slightly better load shape suggests errors are HVAC related

Residential stock end-use summary

Seattle, WA

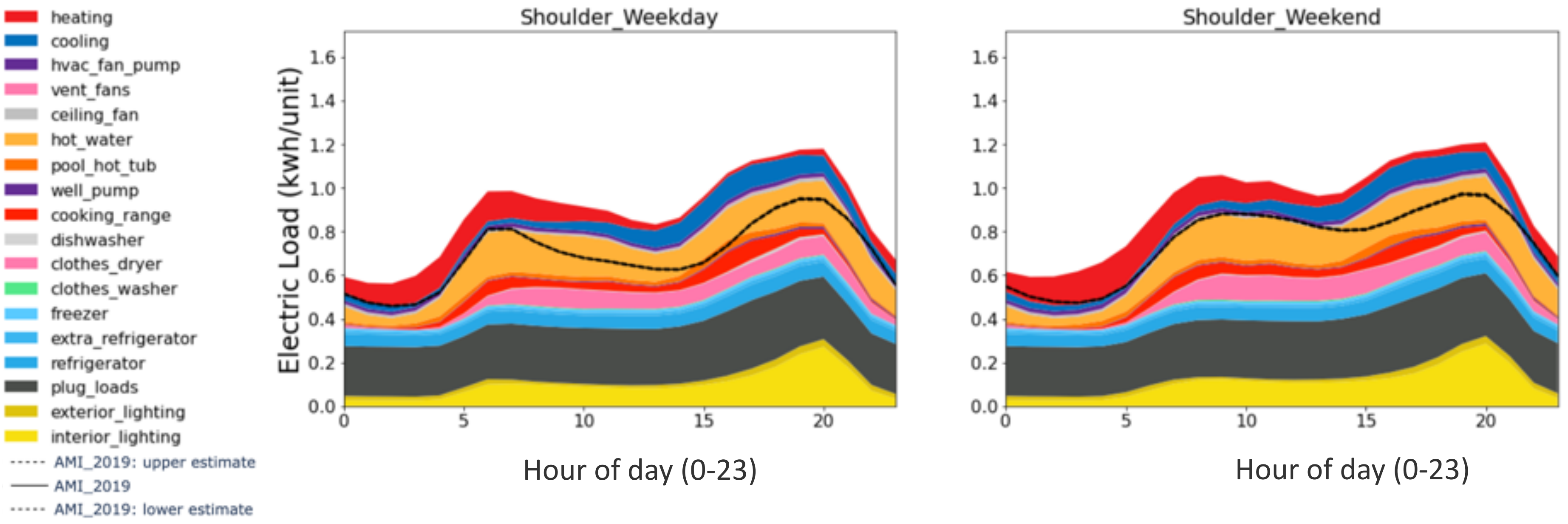
Seasonal end-use loads by day type

Seattle City Light service territory, WA



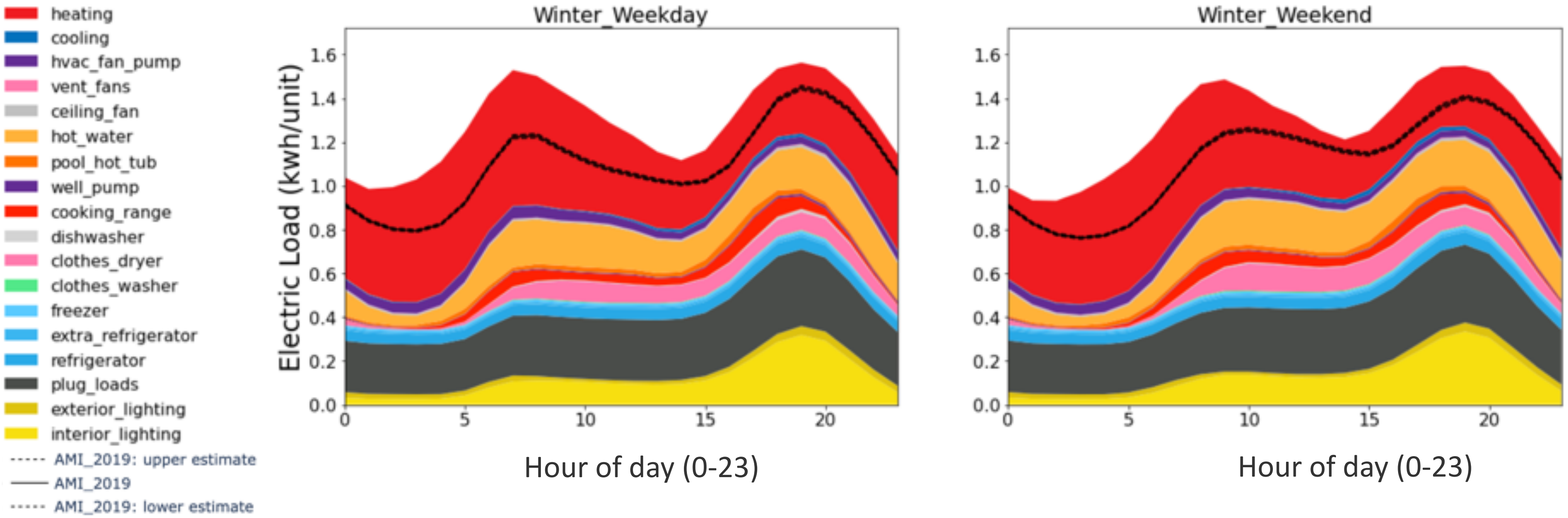
Seasonal end-use loads by day type

Seattle City Light service territory, WA



Seasonal end-use loads by day type

Seattle City Light service territory, WA

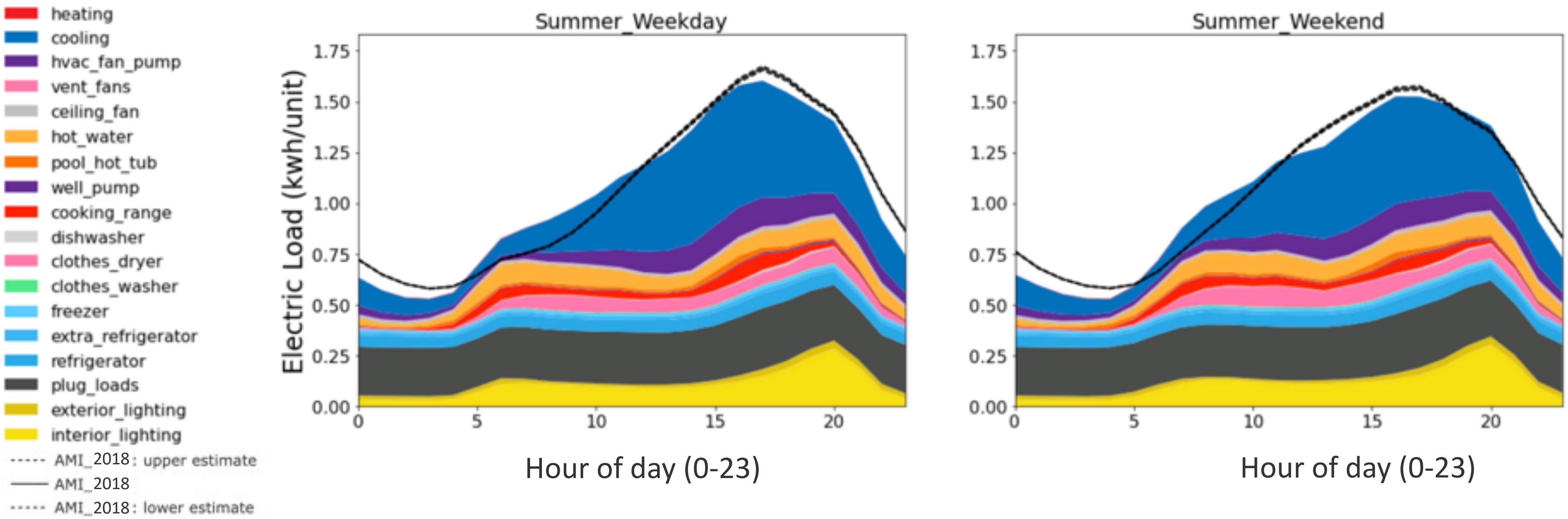


Residential stock end-use summary

Fort Collins municipal utility, CO

Seasonal end-use loads by day type

Fort Collins municipal utility, CO



Seasonal end-use loads by day type

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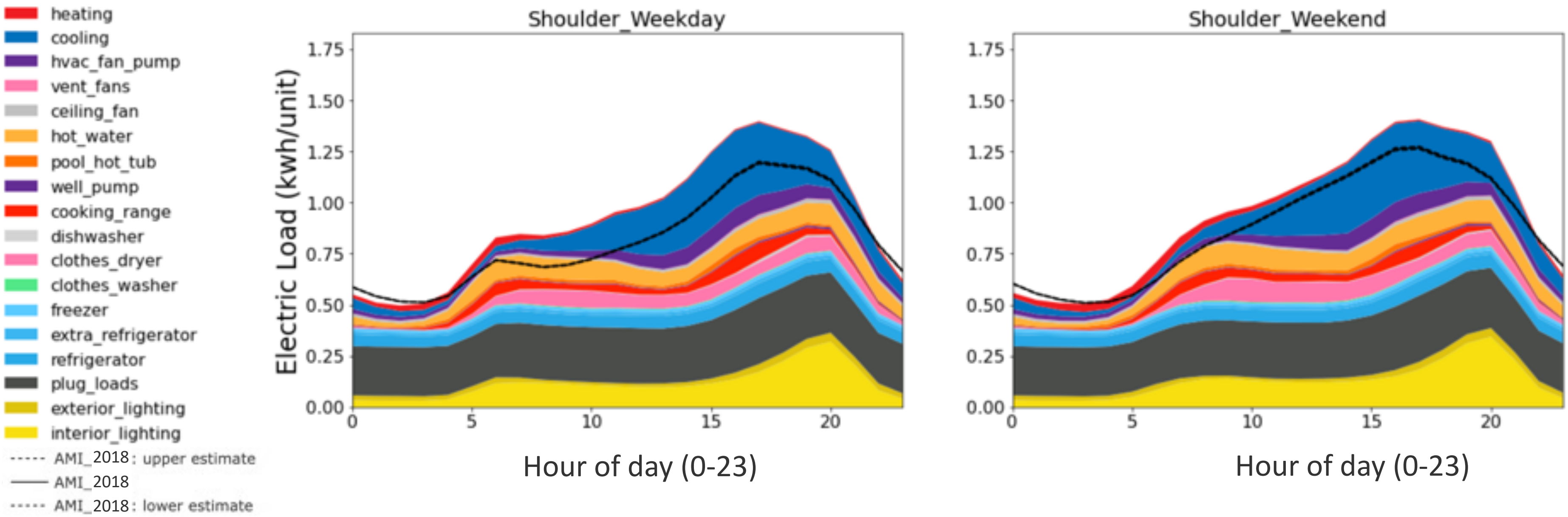

Seasonal end-use loads by day type

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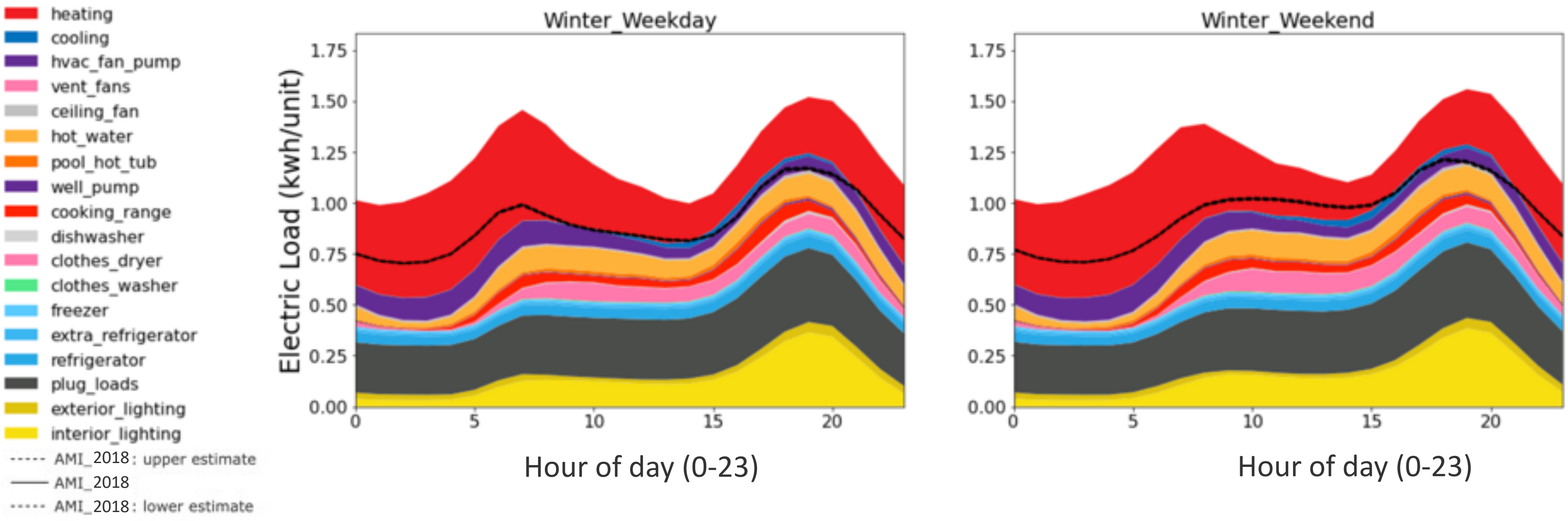
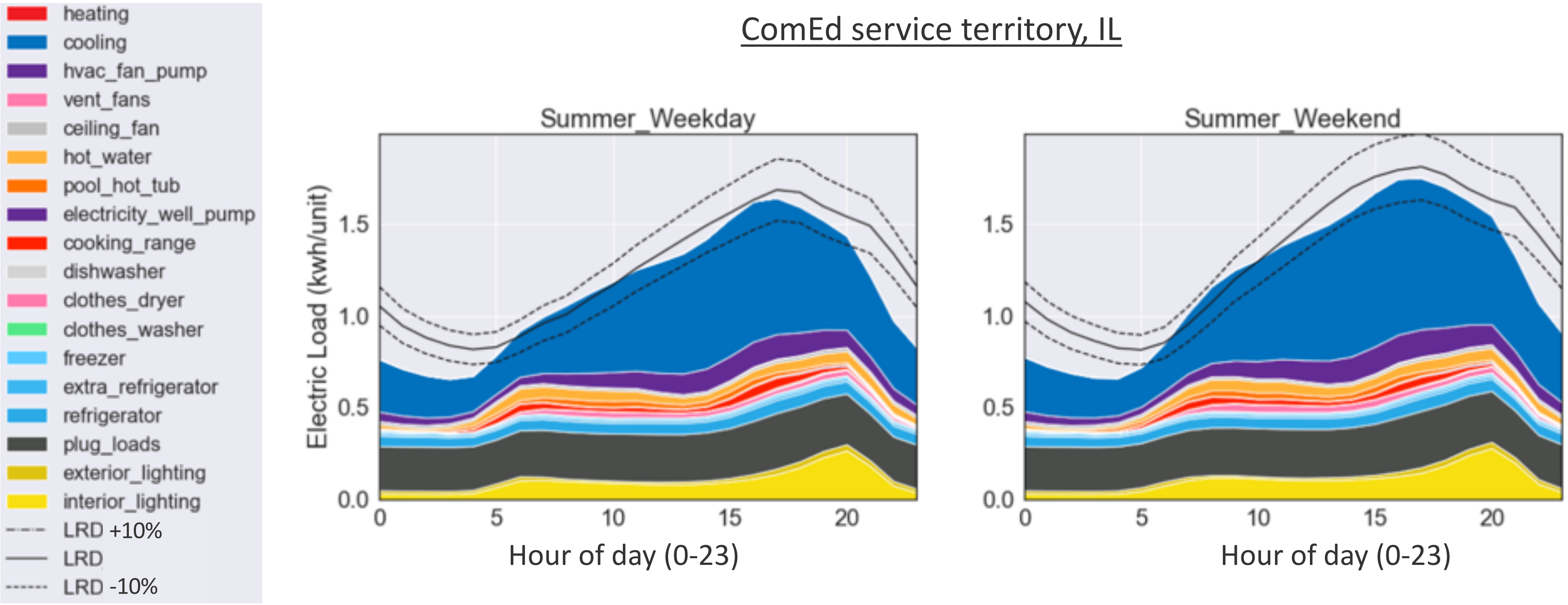


Residential stock end-use summary

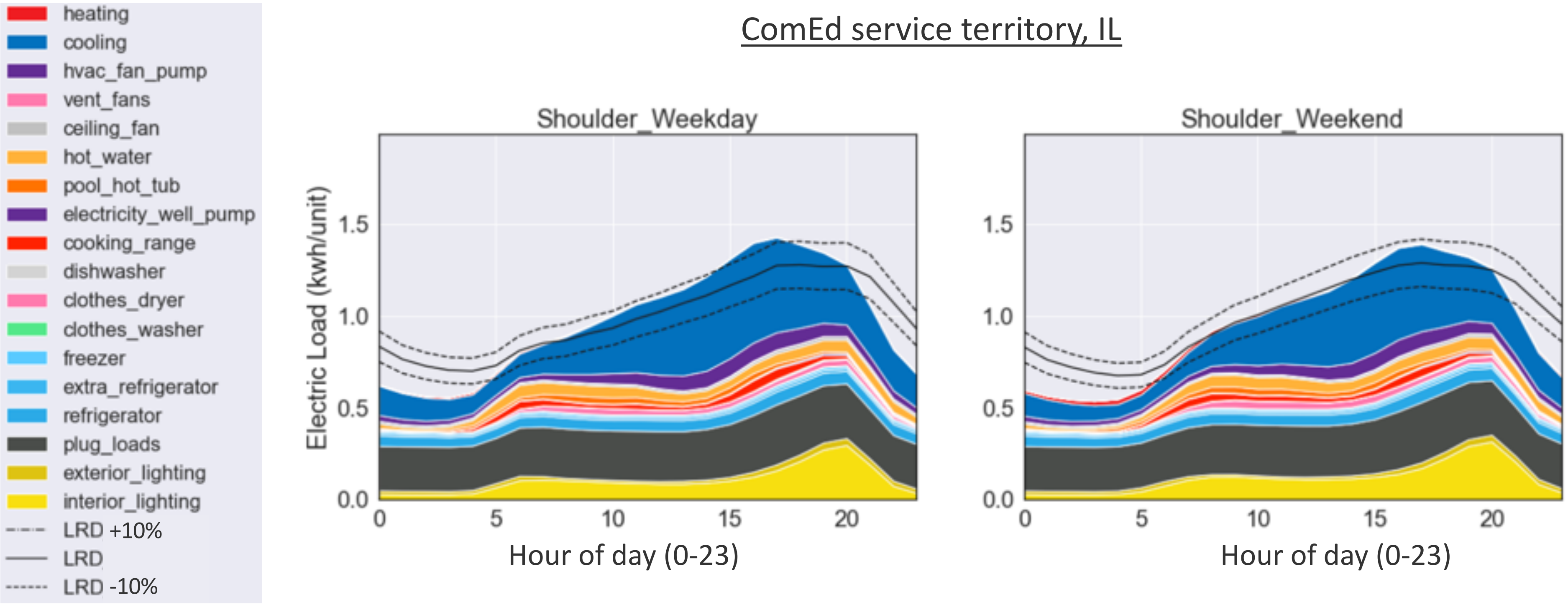
ComEd service territory, IL

Seasonal end-use loads by day type

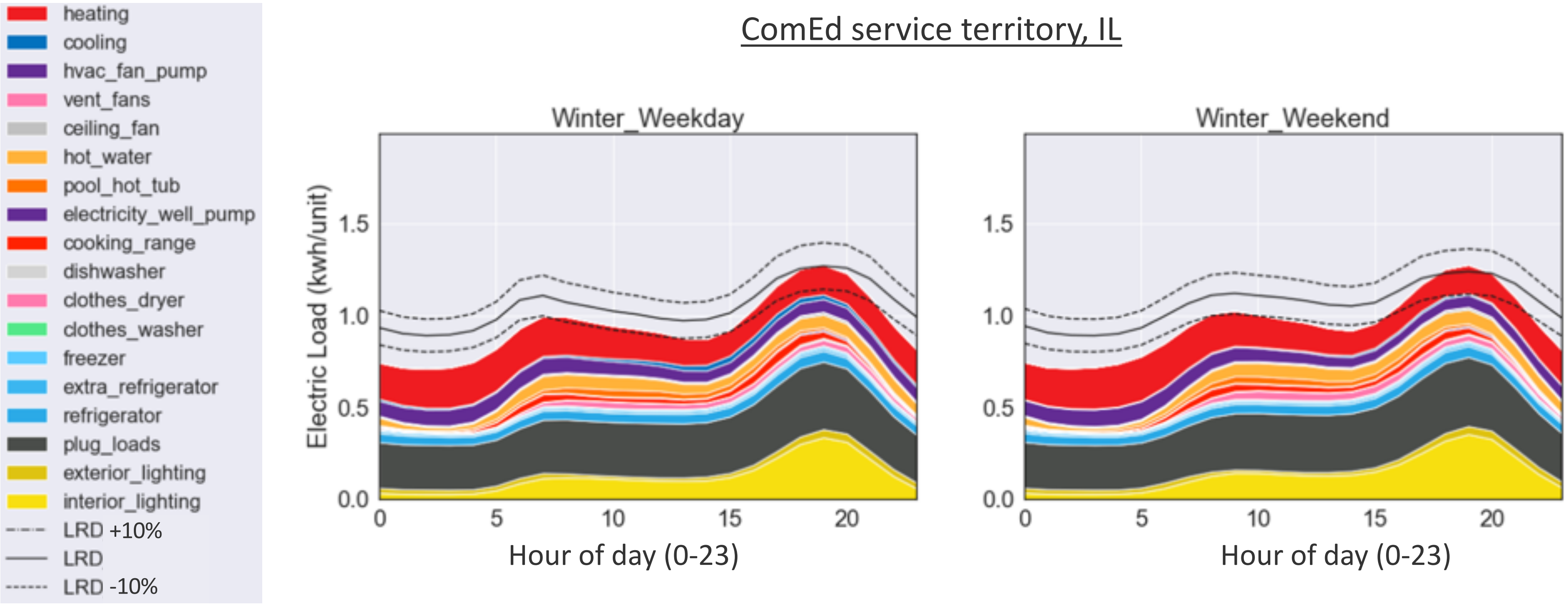
ComEd service territory, IL



Seasonal end-use loads by day type

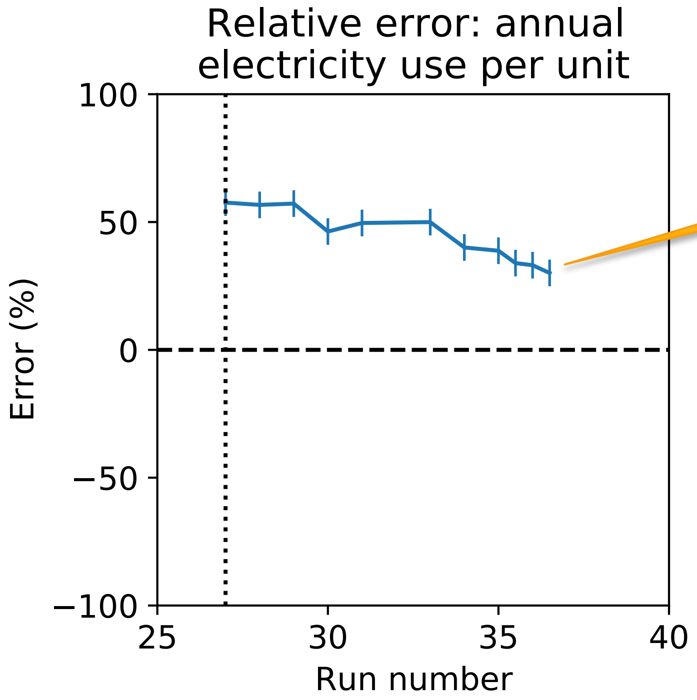


Seasonal end-use loads by day type



Tracking Quantities of Interest

Seattle City Light, WA: Annual Error

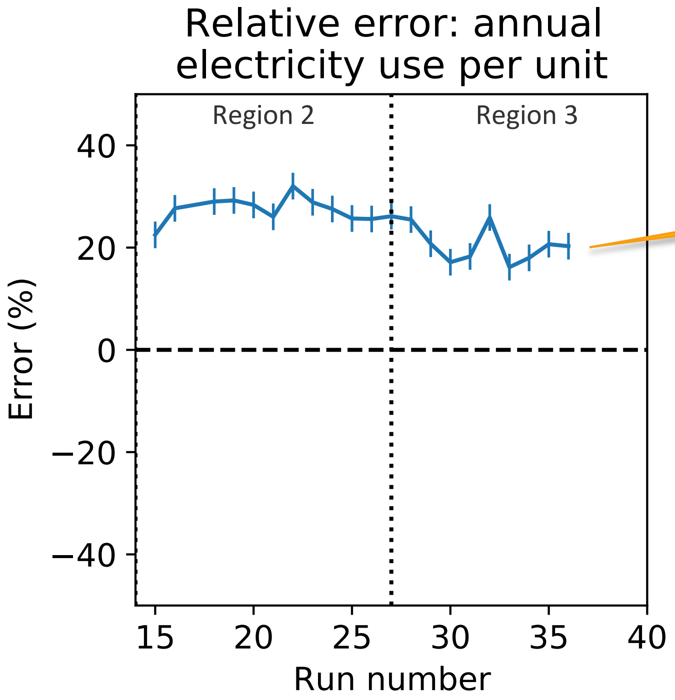


High on annual usage per unit

Reasons

- Single-Family Detached load too high
- Electric heating load too high

Fort Collins, CO: Annual Error

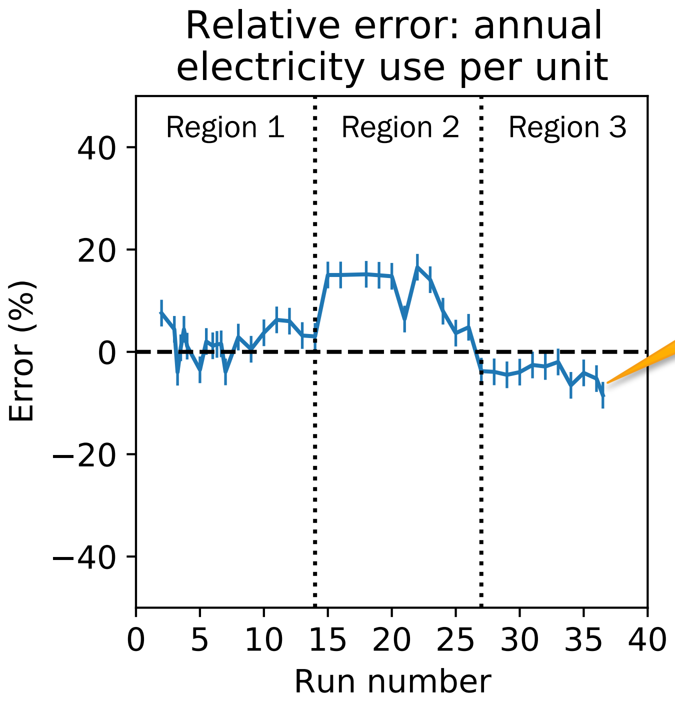


High on annual usage per unit

Reasons

- Heating energy too high

ComEd, IL: Annual Error

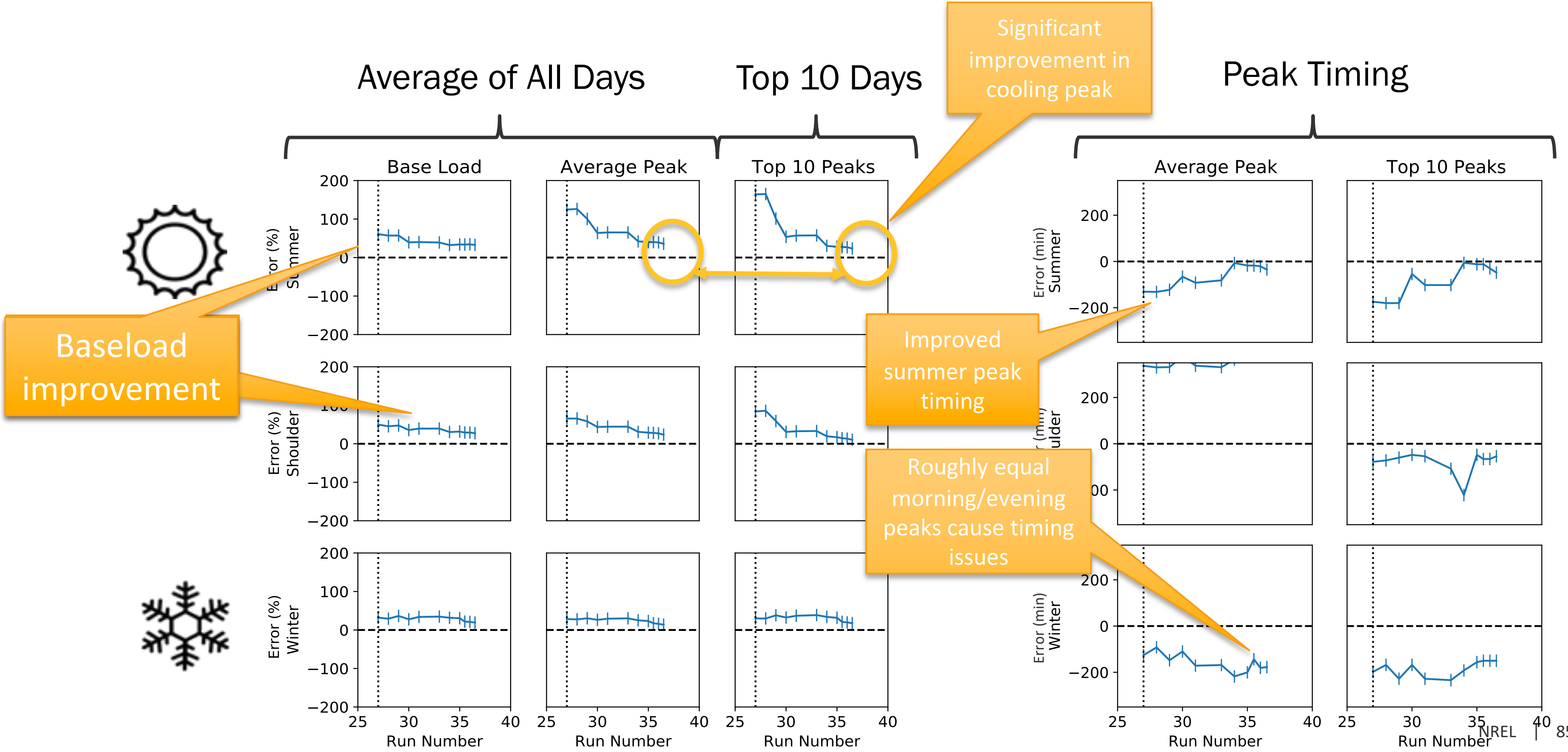


Only slightly low after corrections

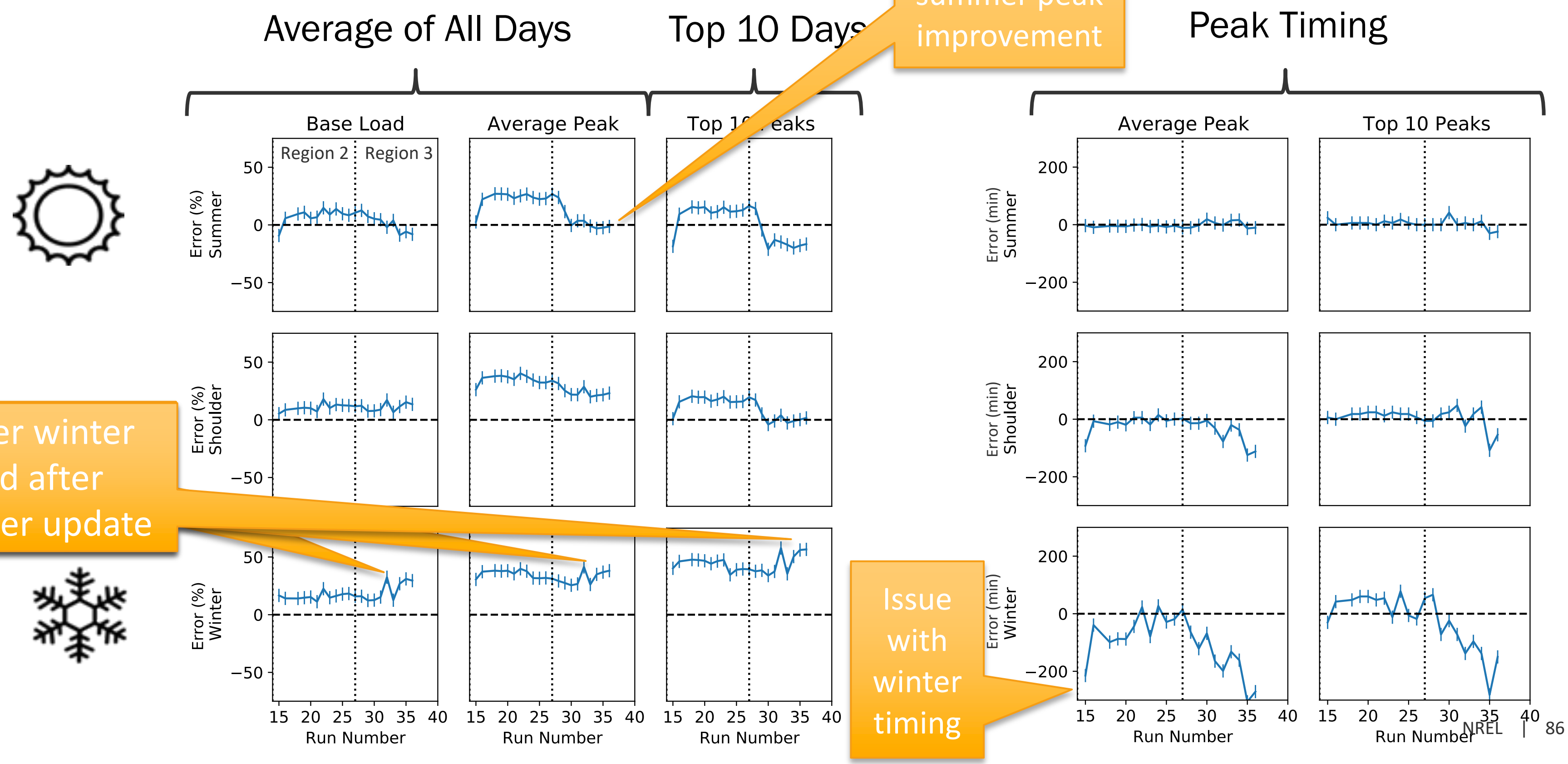
Reasons

- Baseload is low in early morning

Seattle City Light, WA: Total Error Metrics



Fort Collins, CO: Total Error Metrics

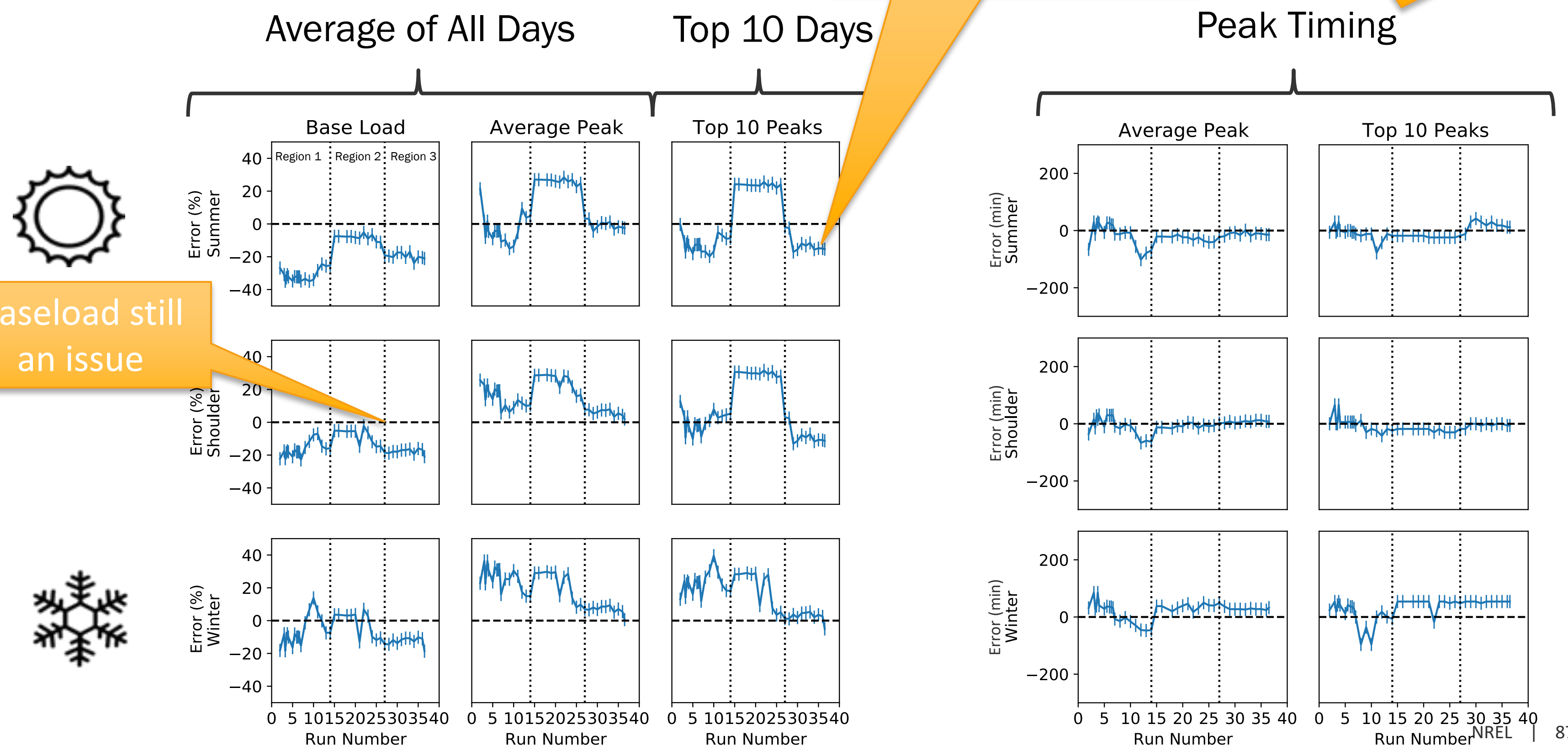


ComEd, IL: Total Error Metrics

Timing of peak heating relatively accurate

Low on top peaks in summer

Baseload still an issue

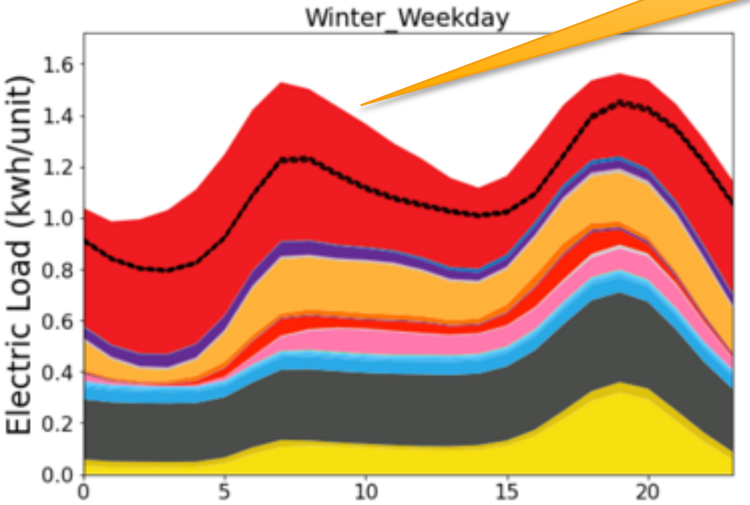


Areas for Improvement

Next Region: Likely Areas for Improvement

Too much electric heating

Seattle, WA

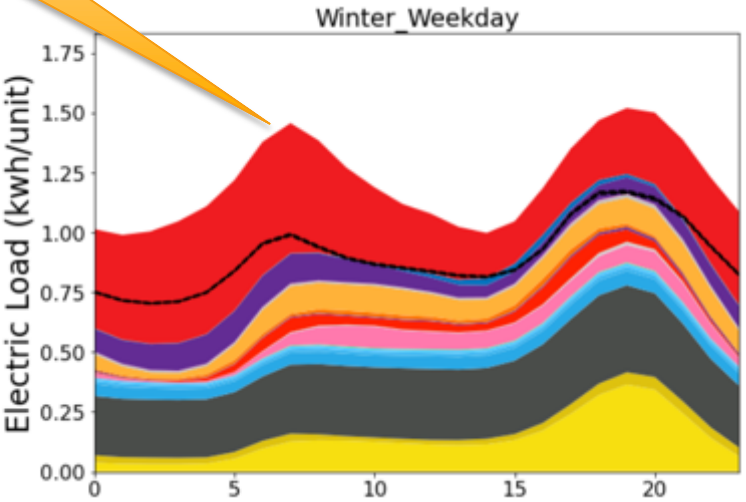


Hour of day (0-23)

→ Incorporate partial home heating with electric baseboard

→ Update vacant unit setpoint assumptions

Fort Collins, CO



Hour of day (0-23)

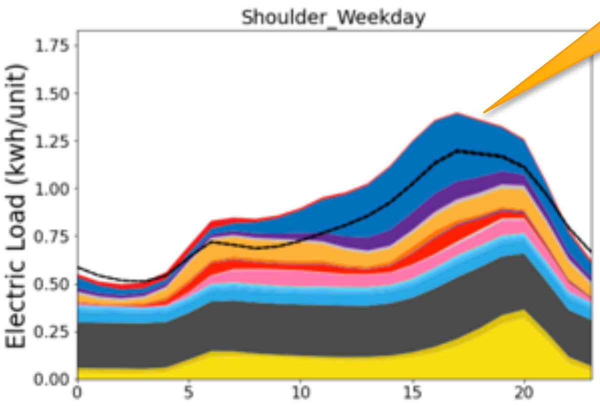
Next Region: Likely Areas for Improvement

Two regions provides additional insight into areas for improvement

Overpredicting cooling in Fort Collins, especially in the shoulder season

Overpredicting cooling in ComEd in May, though not in remainder of summer

Fort Collins, CO

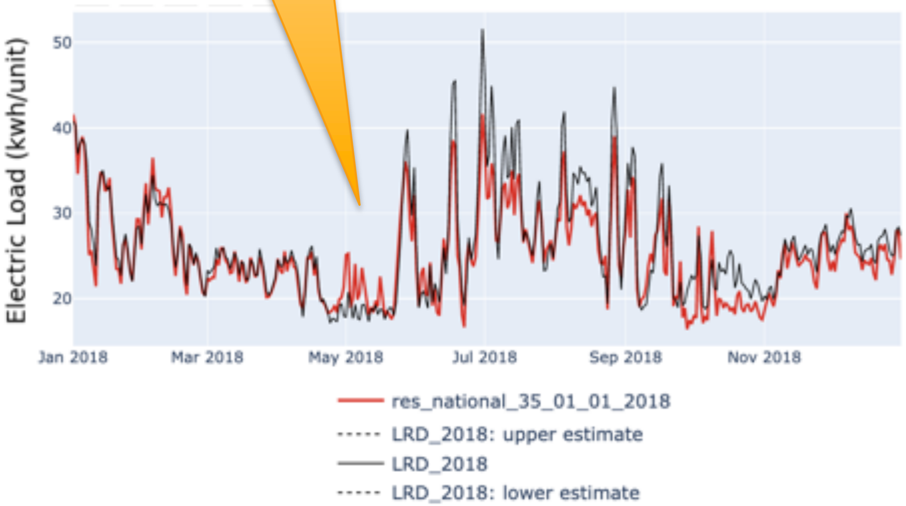


Hour of day (0-23)

→ Incorporate more seasonal usage of AC

ComEd, IL

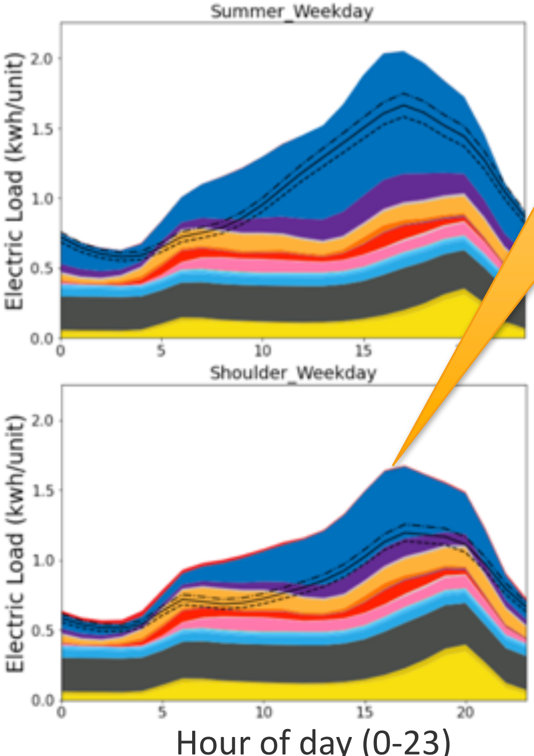
Daily electric load



Next Region: Likely Areas for Improvement

Two regions provides additional insight into areas for improvement

Fort Collins, CO

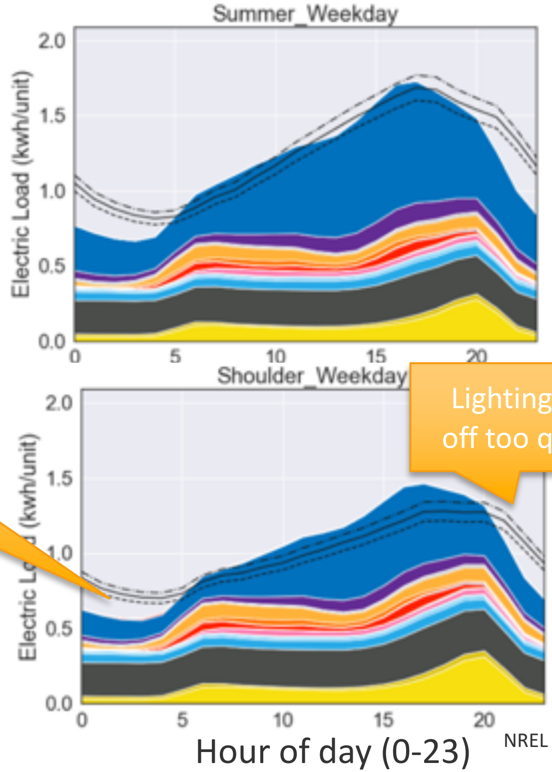


Fort Collins still shows too much cooling, especially in the shoulder season

→ Incorporate more seasonal usage of AC

ComEd peak magnitude is good, but still too low at night

ComEd, IL



Lighting drops off too quickly?

Conclusions (1)

- Ran 10 iterations of ResStock incorporating 12 discrete changes
  - Saw general improvements in QOI metrics
  - Most of the improvements made will carry over to the entire U.S.
- Increased number of weather stations
  - Weather data regions are the same for ResStock and ComStock
  - Increases resolution in weather events
- Integrated single-unit modeling capability
  - Reduces computational cost for running ResStock
- New/Updated visualizations
  - EIA monthly state electric and natural gas sales
  - NEEA Home Energy Metering Study (HEMS) Comparisons

Conclusions (2)

- Summary of changes
  - Reduced baseload by adding geographic resolution to household size
  - Increases resolution in weather events by increasing number of weather stations
  - Added regional and building type variation in lighting and plug loads
  - Included monthly variation of baseloads with the stochastic occupant-driven load model
  - Added multifamily central DHW differentiation
  - Model higher efficiency tank and heat pump water heaters
  - More granular roof materials and updated foundation type distributions
- Priority areas for improvement for next region
  - Electric Heating
  - Regional behavior time shifts
  - Heating/cooling correction model
- Will be moving on to Regional Dataset 4 (Horry and EPB), but continue tracking metrics for the first three region datasets

Residential Calibration
Poll Questions

Residential Calibration Poll Question 1

1. Are we addressing the calibration issues you hoped we would address?

    a. Yes

    b. Some (please explain in chat)

    c. No (please explain in chat)

Residential Calibration Poll Question 2

2. If the residential EULP calibration stopped today, would our results be more useful than existing load profile sources (e.g., Hourly Load Profiles for TMY3 Locations on OpenEI.org)?

    a. Yes, for **all** of my desired use cases
    b. Yes, for **most** of my desired use cases (please explain in chat)
    c. Yes, for **some** of my desired use cases (please explain in chat)
    d. No, for **none** of my desired use cases (please explain in chat)

Residential Calibration Poll Question 3

3. If we have multiple regional data set options for the final residential region, which should we prioritize?

   a. Using a data set from a **new climate or geographic region**
   b. Using a **large dataset**, even if it is from a climate and geographic region that has already been covered
   c. Other (enter in chat)

Wrap-up

Next steps

- Next technical advisory group meeting via webinar in April/May 2021.
- Region 4 residential calibration (Hot-Humid/Southeast)
- Region 2 commercial calibration (Seattle, Portland)
- Begin working on our final year reports

https://www.nrel.gov/buildings/end-use-load-profiles.html

Poll Question #5

Since we were unable to meet in person this year, we missed the opportunity for longer dialogue.

If you have any ideas/critiques/concerns you think would be helpful to talk through on a smaller call, please indicate “yes” and we will reach out.

- Yes
- No