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

Technical Advisory Group Meeting #11

September 21, 2021

NREL/PR-5500-82385

Natalie Mims Frick, LBNL

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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.
- We will send links to the slides after the webinar.

Today's agenda

	Mountain Time
Welcome	10:00 - 10:10
Commercial calibration update	10:10 - 10:35
Residential calibration update	10:35 - 11:00
Discussion	11:00 – 11:25
Next steps	11:25 – 11:30

PUBLIC WEBINAR ANNOUCING LOAD PROFILES!
OCTOBER 28, 2021, 10-11:30 MT

Register here

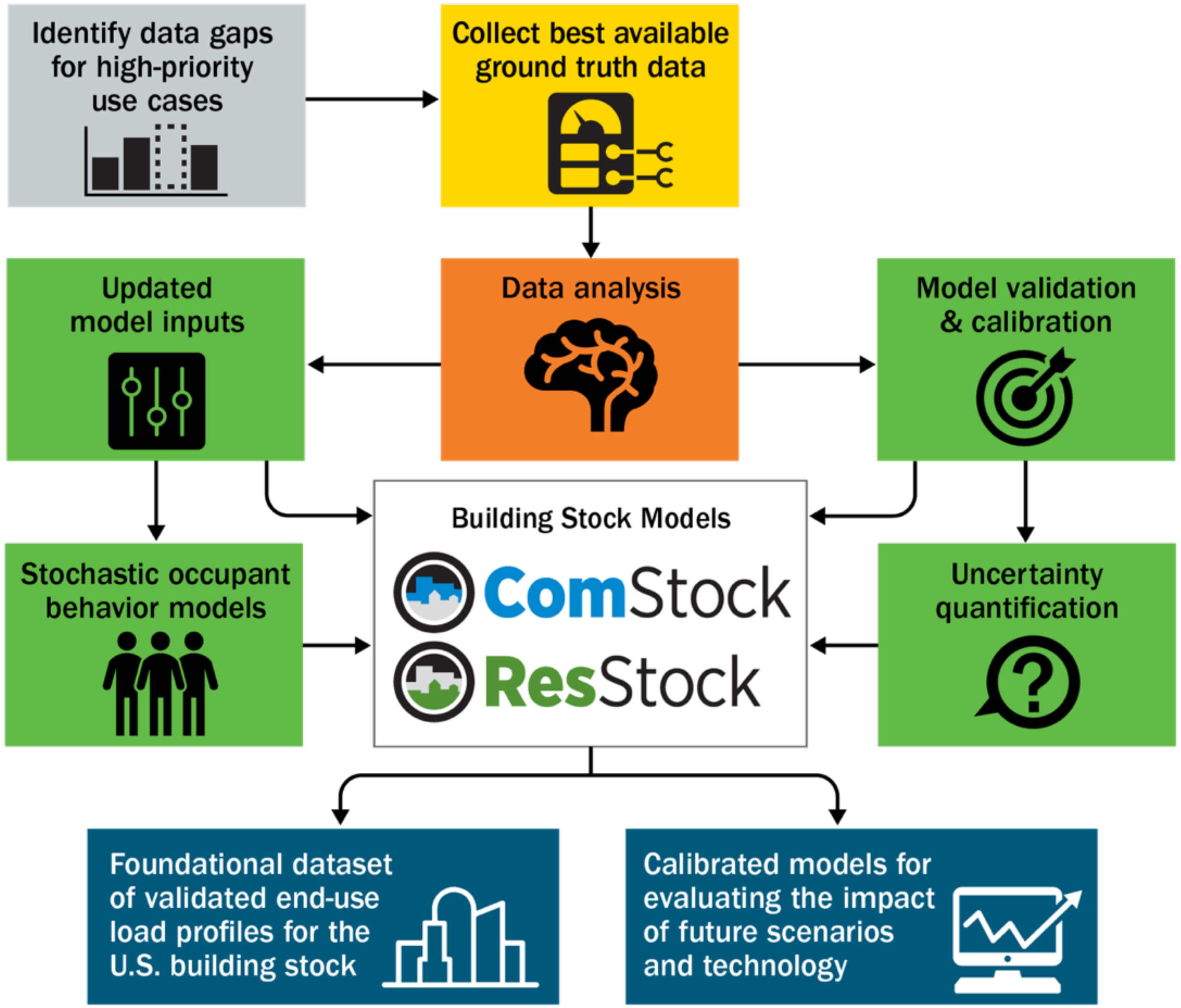
Project Overview

Hybrid approach combines best-available ground-truth data—

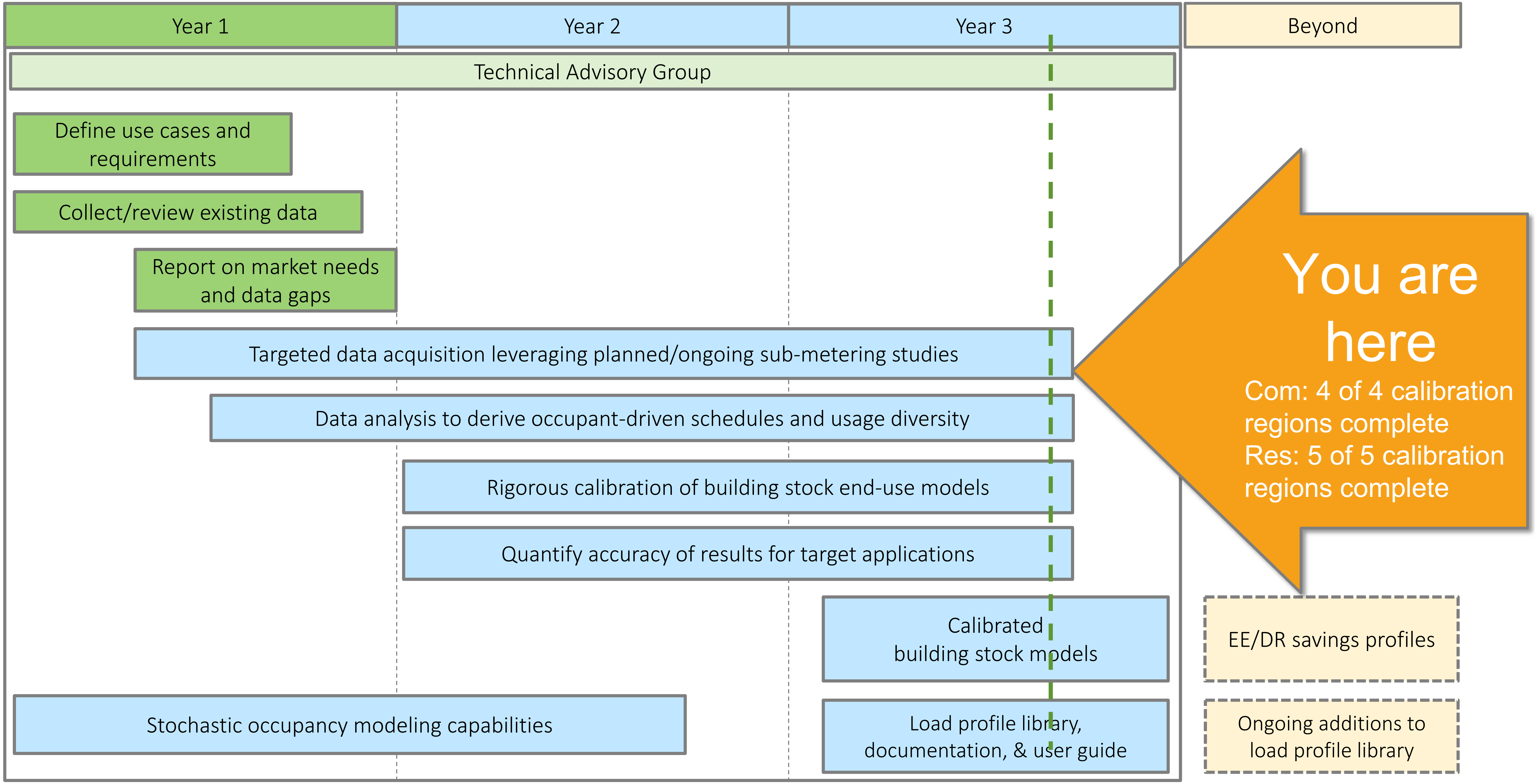
- submetering studies,
- whole-building interval meter data, and
- other emerging data sources

—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 10/30/2021

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 10/30/2021

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

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Draft to DOE & TAG by 10/30/2021

Final report published by 12/31/2021

EERE or NREL report
End-Use Load Profiles for the U.S. Building Stock: Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification
- 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

Draft to DOE & TAG by 11/30/2021

Final report published by 1/31/2022

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

Publications and software

Publications

- Eric Zhang, L., Platthotam, S., Reyna, J., Merket, N., Sayers, K., Yang, X., Reynolds, M., Parker, A., Wilson, E., Fontanini, A., Roberts, D., & Muehleisen, R. (2021). *High-Resolution Hourly Surrogate Modeling Framework for Physics-Based Large-Scale Building Stock Modeling. Sustainable Cities and Society*, 103292. https://doi.org/10.1016/j.scs.2021.103292
- Van Hove, M., Fennell, P., Weinberg, L., Bennett, G., Delghust, M., Forthuber, S., Jakob, Mata, E., Nageli, C., Reyna, J., & Catenazzi, G. (2021). Challenges and Lessons Learned in Applying Sensitivity Analysis to Building Stock Energy Models. I17th IBPSA International Conference and Exhibition, Building Simulation 2021.
- Han Li, Zhe Wang, Tianzhen Hong, Andrew Parker, Monica Neukomm. 2021. "Characterizing patterns and variability of building electric load profiles in time and frequency domains." Applied Energy.
- Carlo Bianchi, Liang Zhang, David Goldwasser, Andrew Parker, Henry Horsey. 2020. "Modeling occupancy-driven building loads for large and diversified building stocks through the use of parametric schedules." Applied Energy.
- Andrew Parker, Kevin James, Dongming Peng, Mahmoud A. Alahmad. 2021. "Framework for Extracting and Characterizing Load Profile Variability Based on a Comparative Study of Different Wavelet Functions." IEEE Access 8: 217483-217498.
- Elaina Present, Chris CaraDonna, Eric Wilson, Natalie Frick, Janghyun Kim, Rajendra Adhikari, Anna C. McCreery, Elizabeth Titus. 2020. Putting Our Industry's Data to Work: A Case Study of Large-Scale Data Aggregation: Preprint. Golden, CO: National Renewable Energy Laboratory.
- Natalie Mims Frick, Eric Wilson, Janet Reyna, Andrew Parker, Elaina Present, Janghyun Kim, Tianzhen Hong, Han Li, Tom Eckman. 2019. *End-Use Load Profiles for the U.S. Building Stock: Market Needs, Use Cases, and Data Gaps*. Berkeley, CA: Lawrence Berkeley National Laboratory.
- Natalie Mims Frick. 2019. "End Use Load Profile Inventory." September.
- Elaina Present, Eric Wilson. 2019. "End Use Load Profiles for the U.S. Building Stock."

Software

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

Presentations

- Technical Advisory Group (TAG) presentations (2019-2021) - Berkeley Lab and National Renewable Energy Lab websites.
- A. Fontanini. July 2021. International Building Performance Simulation Association (IBPSA)-USA Research Committee. *End-Use Load Profiles for the U.S. Building Stock: Residential Stock Model Calibration and Validation*.
- E. Present and N. Frick. June 2021. *CEE Summer Conference - Using Load Shapes to Capture Modern Energy Use and Find Opportunities for Efficiency Breakout Session*. End-Use Load Profiles for the U.S. Building Stock. E. Present. May 2021. Intranational Energy Program Evaluation Conference (IEPEC) Webinar Series – A New Look at Load Profiles. *End-Use Load Profiles for the U.S. Building Stock*.
- A. Parker. May 2021. Efficiency Exchange 2021 Conference. *Northwest End Use Load Research: How three Organizations are Using the Data.*
- E. Wilson. August 2020. Efficiency Exchange Webinar. *Valuing Capacity Savings*.
- E. Wilson. December 2019. E Source interview. *Exploring business customer nuances.*
- E. Present. October 2019. Northeast Energy Efficiency Partnerships (NEEP) webinar. *Introducing End-Use Load Profiles for the U.S. and the Northeast.*
- E. Wilson. May 2019. Building Technologies Office Peer Review. *End-Use Load Profiles for the U.S. Building Stock*.

Upcoming presentations

Upcoming presentations

- Public webinar announcing the final report and data (also TAG meeting #12). October 2021. Register here.
- American Council for an Energy Efficient Economy (ACEEE) 2021 Energy Efficiency as a Resource Conference. October 2021.
- The Centre for Energy Advancement through Technological Innovation (CEATI) International Demand Side Management Program member presentation in November/December 2021.
- 2022 National Home Performance Conference and Trade Show. April 2022.

Help us promote the webinar and data access!

- Will your organization share our webinar announcement with their contacts?
- Will you promote the webinar on your Twitter or LinkedIn account?
- Is your organization interested in a webinar to learn more about accessing or using the data?
- Are you aware of an upcoming conference where we can share information about the load profiles?

Chat *Yes* during today's webinar or mail Natalie after the presentation if you are able to help!

nfrick@lbl.gov

Commercial calibration update

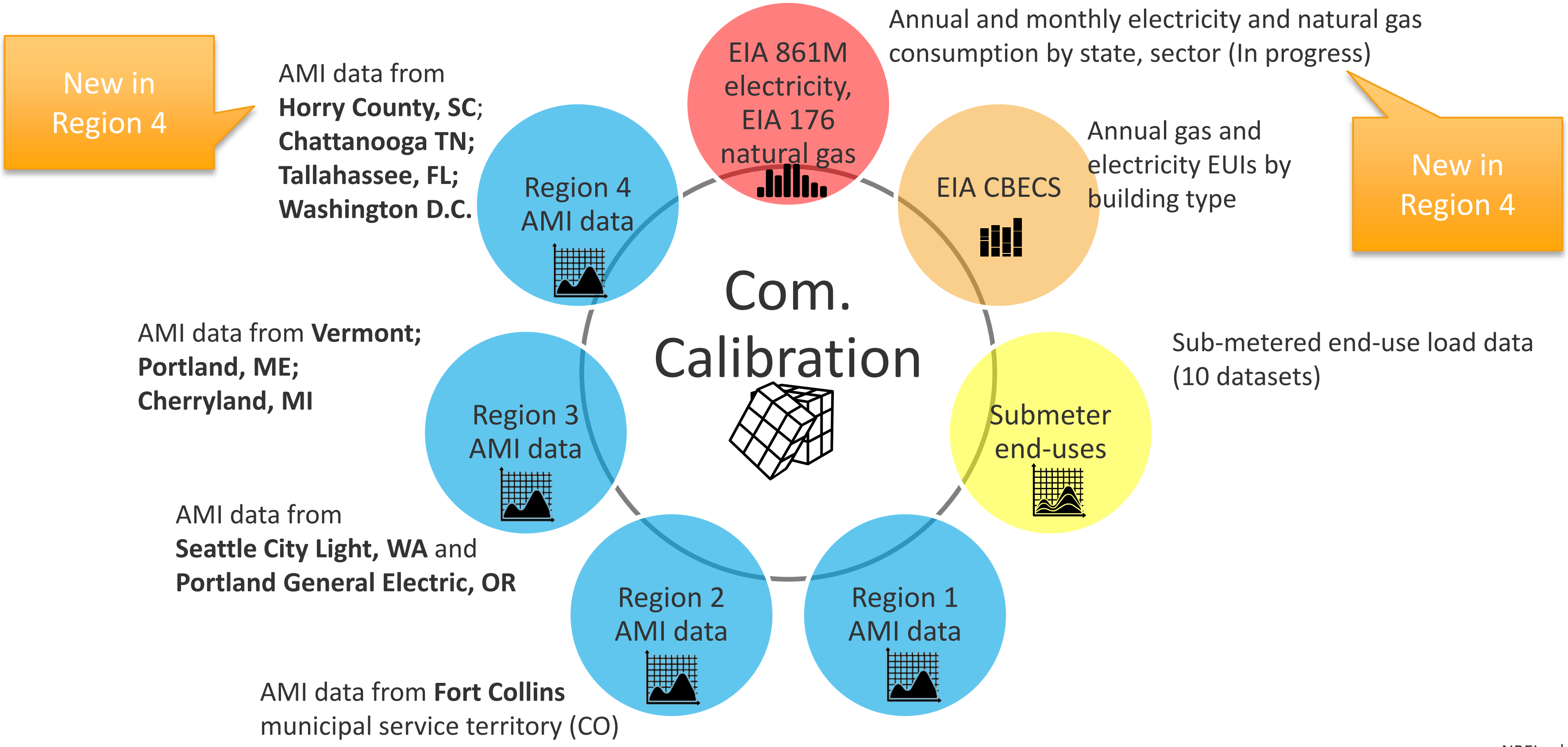
Next steps

- Register for our final webinar on October 28
- Reports will be sent to the TAG for review. We will provide at least 10 business days for review and comment.
  - *End-Use Load Profiles for the U.S. Building Stock: Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification*, mid-October to mid-November
  - *End-Use Load Profiles for the U.S. Building Stock: Applications and Opportunities*, early December – mid January
- Contact Natalie if you or your organization are interested in helping us publicize our webinar, data access or would like a separate webinar to learn about the data.

Commercial Calibration Update Region 4

Andrew Parker
Matthew Dahlhausen
September 21, 2021

Commercial Calibration Dimensions



Commercial AMI Data Challenges

- ✓ Misclassification of buildings (outlier removal technique, see previous TAG presentation)
- ✓ Partially-occupied buildings (outlier removal)
- ✓ Knowingly/unknowingly missing large fraction of meters for a building (outlier removal)
- ✓ Missing some timesteps for some meters (method described in Region 2 slides)
- ✓ Knowingly missing a small fraction of the meters for a building

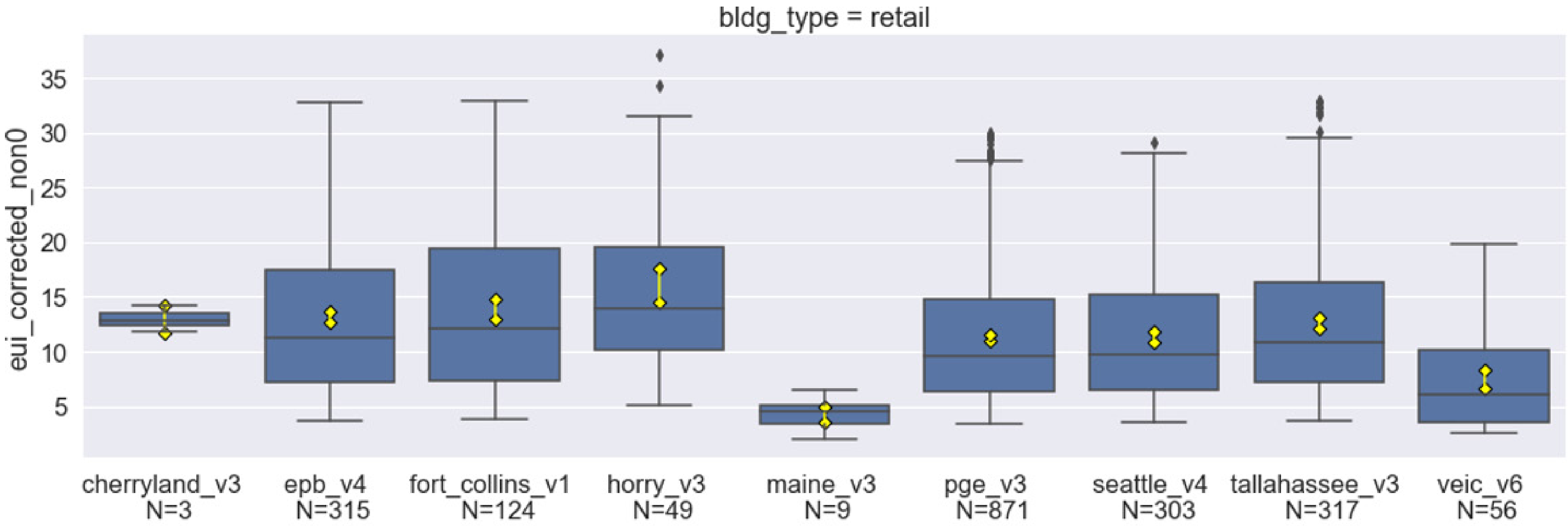
- ✗ Unknowingly missing a small fraction of meters for a building
  - EUI likely within 3x median, load shape still reasonable… undetectable error?
- ✗ For utilities, fundamental unit of reporting is a meter, not buildings or sqft
- ✗ Building type classification based on real-estate data is imprecise

Evaluating AMI Trustworthiness

- Some AMI looked “suspicious” based on judgment
- Wanted an objective way to evaluate
- Approaches:
    1. Compared AMI between regions (once we had AMI)
    2. Compared EUI distributions to CBECS using K-S test

- Allowed us to identify and address issues in Tallahassee and EPB

Evaluating AMI – Comparing Regions



1. Blue histogram represents distribution of 3x median-filtered AMI
2. Yellow represents 80% confidence interval around the mean
3. N= number of samples in AMI

Evaluating AMI – Comparing to CBECS

K-S Test Matrix **Target metric = distance** **AMI filter = LowEnd+3xMed** **CBECS weight = False**	Small Office	Medium Office	Large Office	Strip Mall	Retail	Warehouse	Full Service Restaurant	Quick Service Restaurant	Small Hotel	Large Hotel	Outpatient
region 1: Fort Collins, CO	Distance = 0.13 AMI = 313 CBECS = 46	Distance = 0.2 AMI = 23 CBECS = 12	Low Sample AMI = 4 CBECS = 18	Distance = 0.4 AMI = 156 CBECS = 21	Distance = 0.26 AMI = 126 CBECS = 23	Distance = 0.43 AMI = 112 CBECS = 47	Distance = 0.42 AMI = 61 CBECS = 17	Low Sample AMI = 26 CBECS = 6	Low Sample AMI = 5 CBECS = 7	Low Sample AMI = 8 CBECS = 13	Distance = 0.52 AMI = 78 CBECS = 30
region 2a: Seattle, WA	Distance = 0.28 AMI = 480 CBECS = 95	Distance = 0.42 AMI = 64 CBECS = 60	Distance = 0.19 AMI = 105 CBECS = 43	Distance = 0.63 AMI = 561 CBECS = 52	Distance = 0.21 AMI = 304 CBECS = 57	Distance = 0.25 AMI = 410 CBECS = 163	Distance = 0.2 AMI = 107 CBECS = 40	Distance = 0.21 AMI = 26 CBECS = 18	Distance = 0.33 AMI = 19 CBECS = 13	Distance = 0.33 AMI = 25 CBECS = 26	Distance = 0.46 AMI = 105 CBECS = 46
region 2b: Portland, OR	Distance = 0.12 AMI = 250 CBECS = 95	Distance = 0.4 AMI = 10 CBECS = 60		Distance = 0.66 AMI = 889 CBECS = 52	Distance = 0.22 AMI = 926 CBECS = 57	Distance = 0.29 AMI = 1938 CBECS = 163	Distance = 0.2 AMI = 308 CBECS = 40	Distance = 0.27 AMI = 123 CBECS = 18	Distance = 0.33 AMI = 54 CBECS = 13	Distance = 0.32 AMI = 79 CBECS = 26	Distance = 0.29 AMI = 456 CBECS = 46
region 3a: Portland, ME	Distance = 0.31 AMI = 15 CBECS = 26	Distance = 0.21 AMI = 24 CBECS = 15	Low Sample AMI = 9 CBECS = 11	Distance = 0.39 AMI = 32 CBECS = 13	Low Sample AMI = 9 CBECS = 14	Distance = 0.36 AMI = 12 CBECS = 23	Low Sample AMI = 8 CBECS = 12				
region 3b: State of Vermont	Distance = 0.25 AMI = 261 CBECS = 26	Distance = 0.28 AMI = 58 CBECS = 15	Low Sample AMI = 3 CBECS = 11	Distance = 0.68 AMI = 151 CBECS = 13	Distance = 0.3 AMI = 56 CBECS = 14	Distance = 0.26 AMI = 158 CBECS = 23	Distance = 0.51 AMI = 32 CBECS = 12	Low Sample AMI = 16 CBECS = 3	Low Sample AMI = 2 CBECS = 1	Low Sample AMI = 107 CBECS = 3	Distance = 0.49 AMI = 35 CBECS = 12
region 3c: Cherryland, MI	Distance = 0.12 AMI = 17 CBECS = 72			Distance = 1.0 AMI = 11 CBECS = 32	Low Sample AMI = 3 CBECS = 52	Distance = 0.25 AMI = 63 CBECS = 78	Low Sample AMI = 3 CBECS = 32		Low Sample AMI = 3 CBECS = 2		Low Sample AMI = 1 CBECS = 46
region 4b: Chattanooga, TN	Distance = 0.12 AMI = 552 CBECS = 38	Distance = 0.55 AMI = 120 CBECS = 12	Low Sample AMI = 33 CBECS = 6	Distance = 0.56 AMI = 437 CBECS = 15	Distance = 0.26 AMI = 323 CBECS = 18	Distance = 0.23 AMI = 490 CBECS = 31	Distance = 0.42 AMI = 86 CBECS = 18	Distance = 0.41 AMI = 108 CBECS = 11	Low Sample AMI = 20 CBECS = 4	Low Sample AMI = 75 CBECS = 9	Distance = 0.46 AMI = 155 CBECS = 14
region 4c: Tallahassee, FL	Distance = 0.36 AMI = 918 CBECS = 126	Distance = 0.37 AMI = 214 CBECS = 45	Distance = 0.32 AMI = 24 CBECS = 84	Distance = 0.44 AMI = 173 CBECS = 89	Distance = 0.15 AMI = 322 CBECS = 59	Distance = 0.21 AMI = 346 CBECS = 148	Distance = 0.27 AMI = 123 CBECS = 42	Distance = 0.14 AMI = 95 CBECS = 28	Distance = 0.52 AMI = 25 CBECS = 14	Distance = 0.41 AMI = 33 CBECS = 38	Distance = 0.38 AMI = 155 CBECS = 44
region 4d: Horry County, SC	Distance = 0.28 AMI = 71 CBECS = 126	Low Sample AMI = 2 CBECS = 45		Distance = 0.5 AMI = 41 CBECS = 89	Distance = 0.25 AMI = 49 CBECS = 59	Distance = 0.24 AMI = 43 CBECS = 148	Low Sample AMI = 8 CBECS = 42	Low Sample AMI = 6 CBECS = 28	Low Sample AMI = 2 CBECS = 14		Low Sample AMI = 7 CBECS = 44

Color Legend

Strongest Agreement Between AMI & CBECS → Weakest Agreement Between AMI & CBECS	Not enough CBECS or AMI to Test Agreement (N < 10)	No AMI

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Comparing to the Truth

Evaluating Sources of Truth Data

Source	Pros	Cons
AMI	• Recent (2018, 2019) • Geographically specific • Includes load shape	• Availability & count varies by building type • “Unknown missing meter” error • Building type classification from real-estate data
CBECS	• Covers every building type • Geographically diffuse • Building classification known	• From 2012 • Only annual data
EIA	• Recent (through 2020) • Monthly • Available by state	• No disaggregation by building type • Utility (mis)classification of commercial vs. industrial

No single “best” data set

Comparing to Multiple Sources of Truth Data

Show comparisons to all datasets – draw conclusions from the whole picture

AMI (2018, 2019)

- Distributions of EUIs by building & region, including 80% confidence interval
- Load shape & magnitude by building type & region, including 80% confidence interval
- Load shape (normalized) by building type & region
- NOT regional total load shape – weighting AMI introduces too many questions

CBECS (2012)

- Distributions of EUIs by building type & census division
- Annual totals by building type & census division

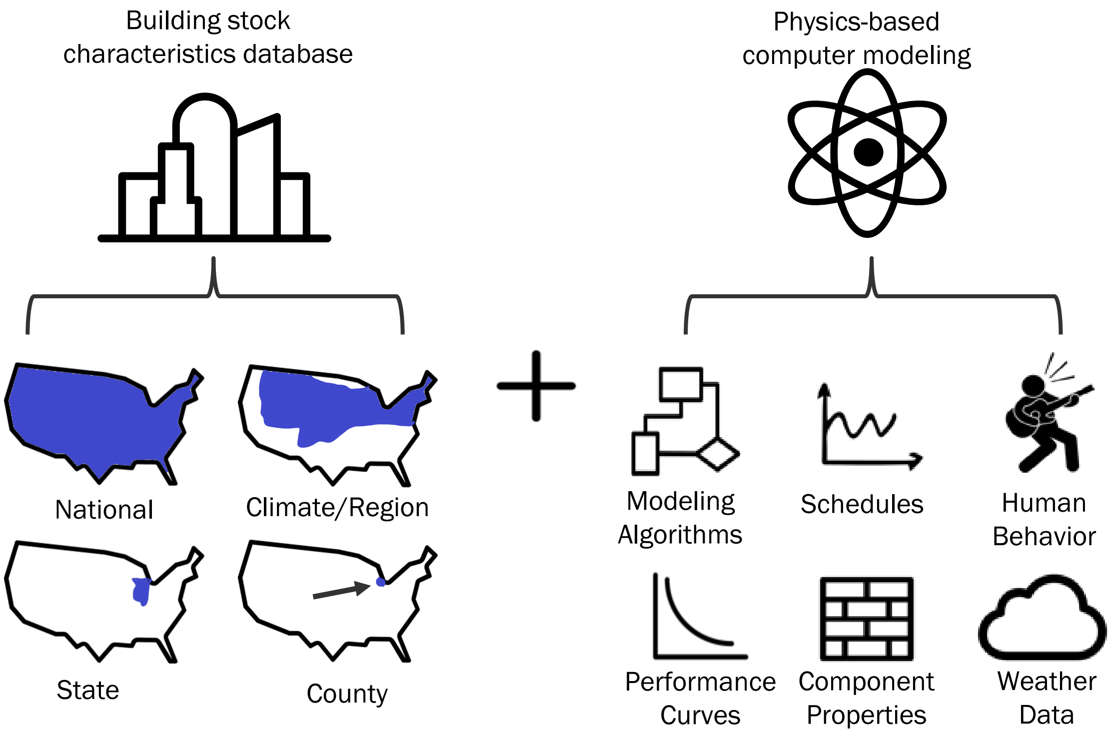
EIA (2018)

- Monthly totals by census division
- Annual totals by census division
- Annual totals by state

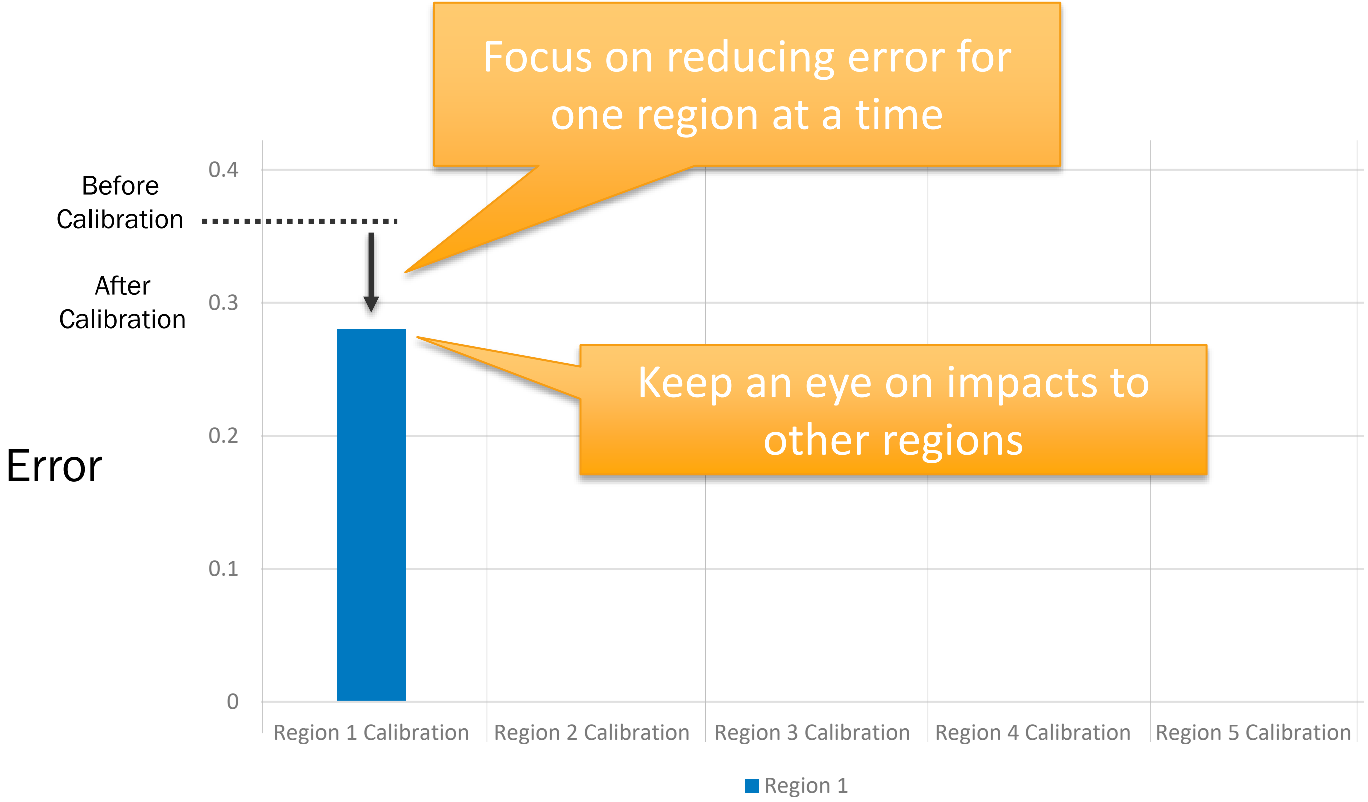
Calibration Strategy

Model Architecture

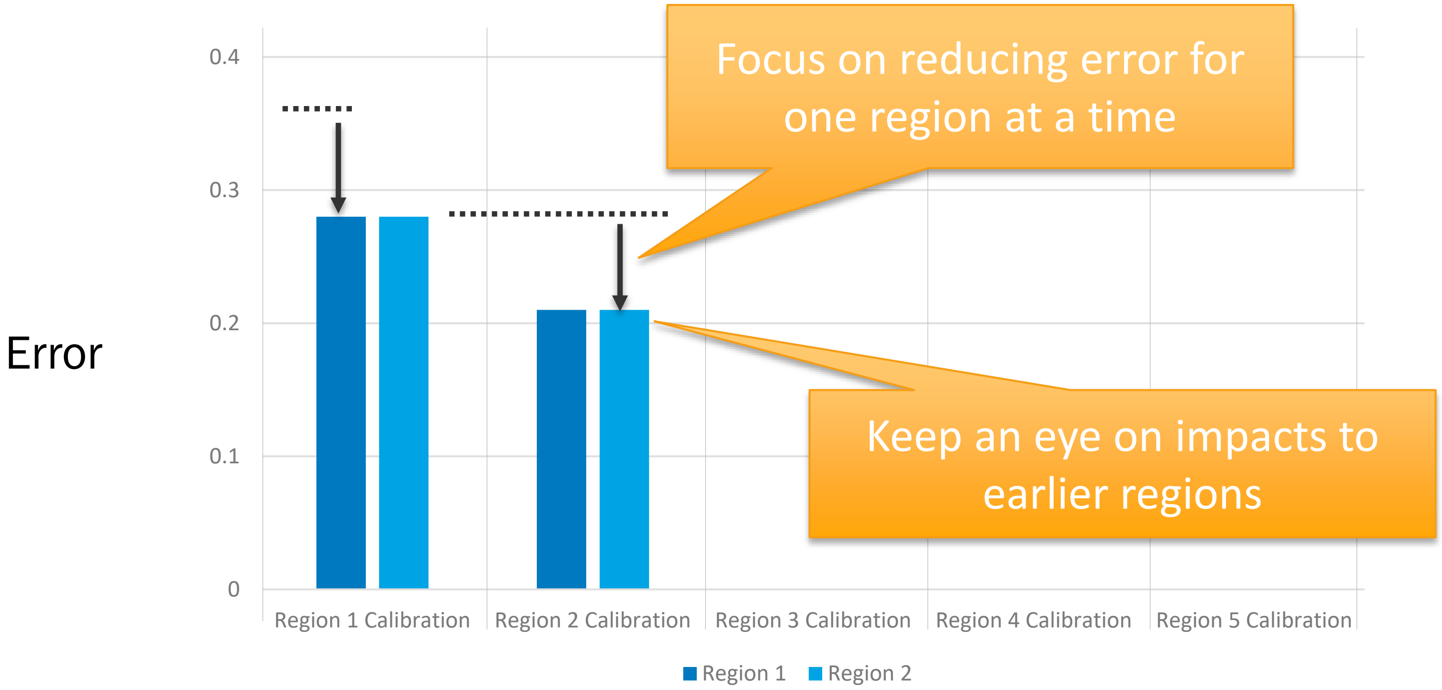
ComStock



Calibration Process for One Region



Calibration Process Over Time



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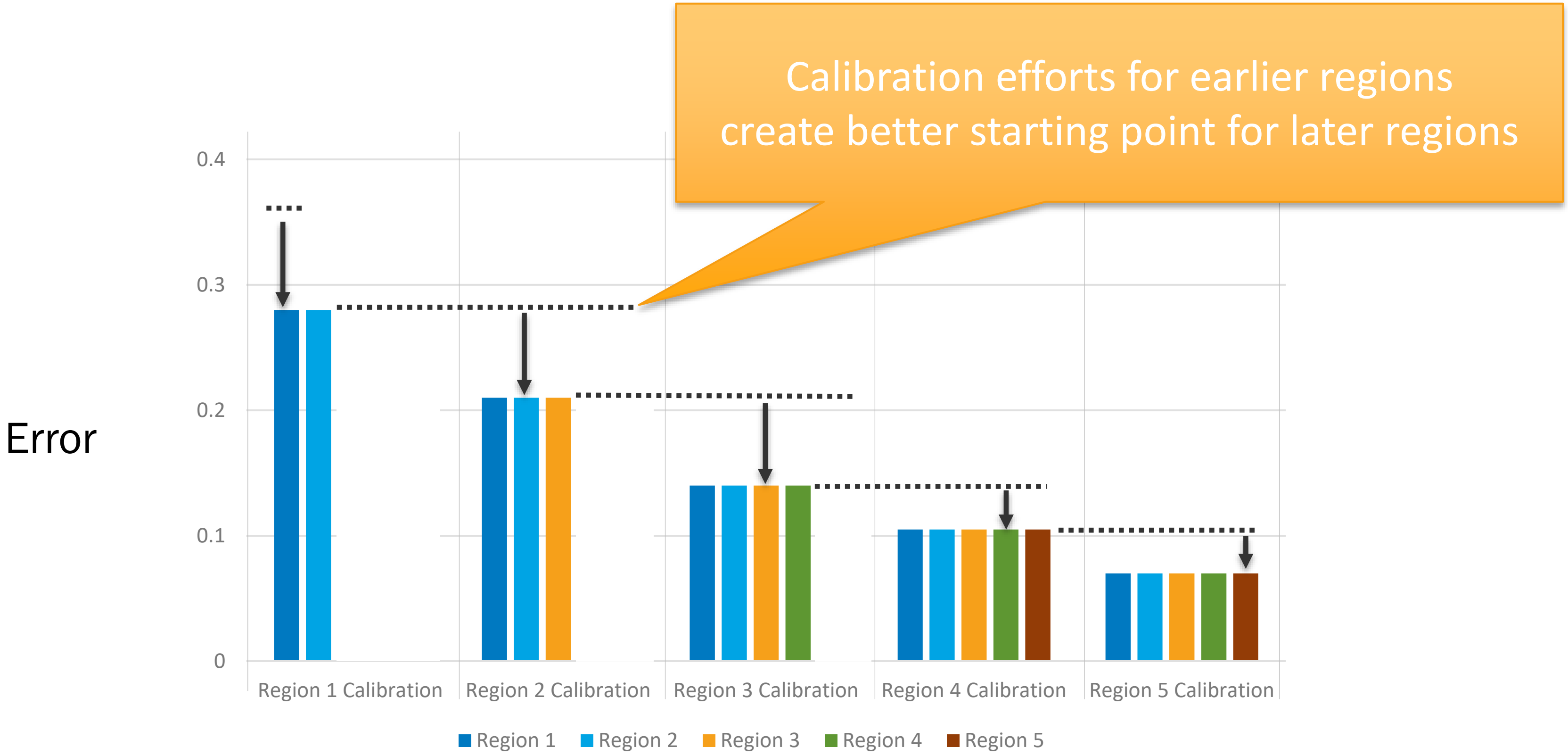
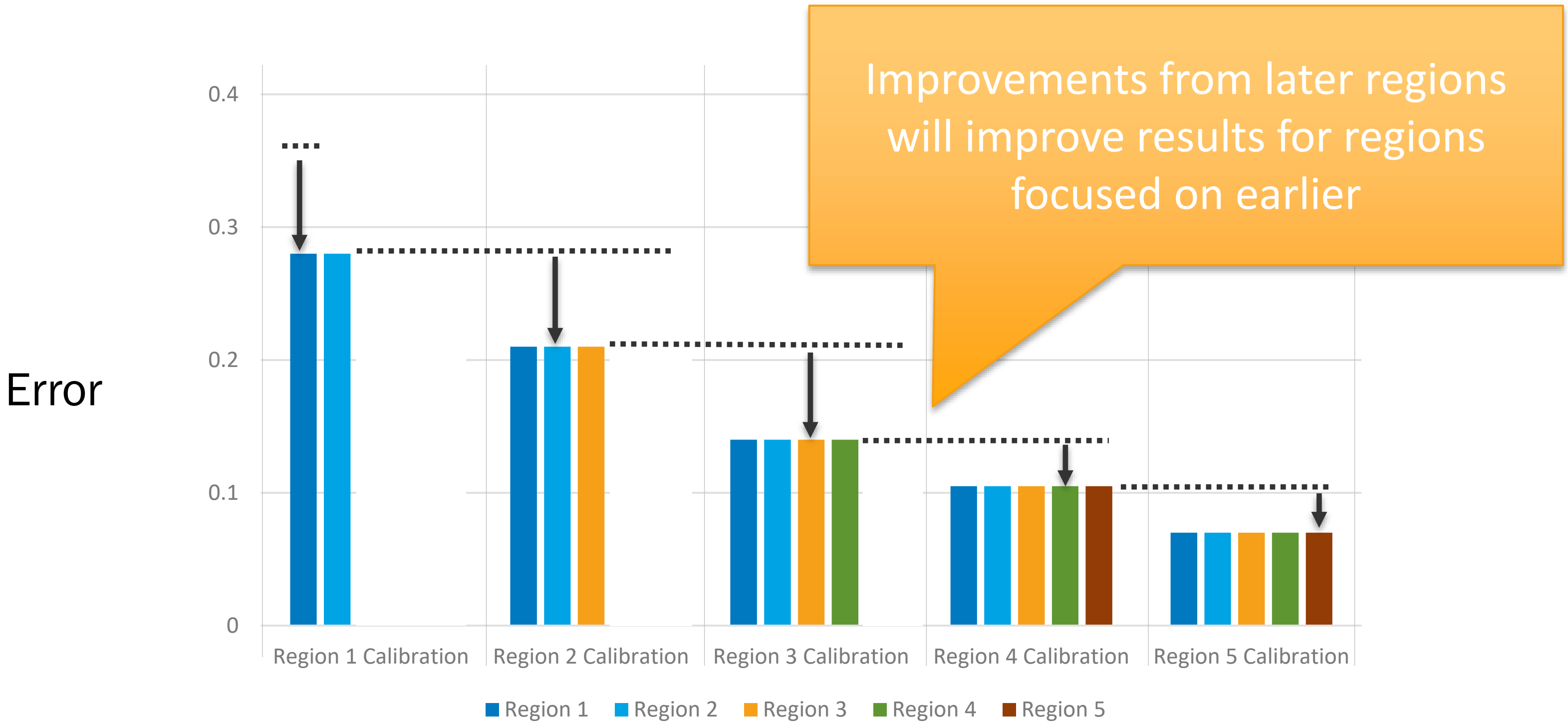
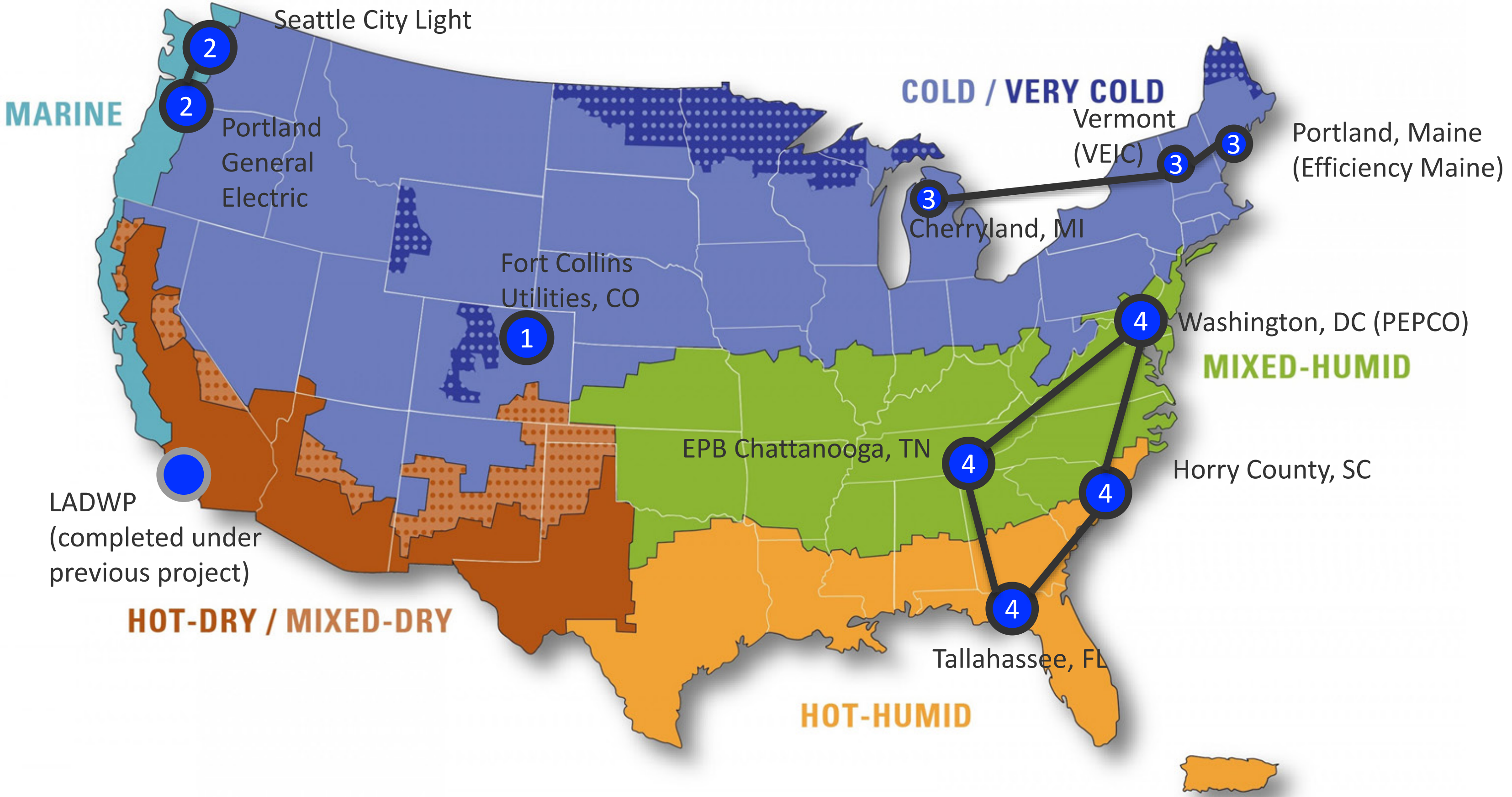


Calibration Process Over Time

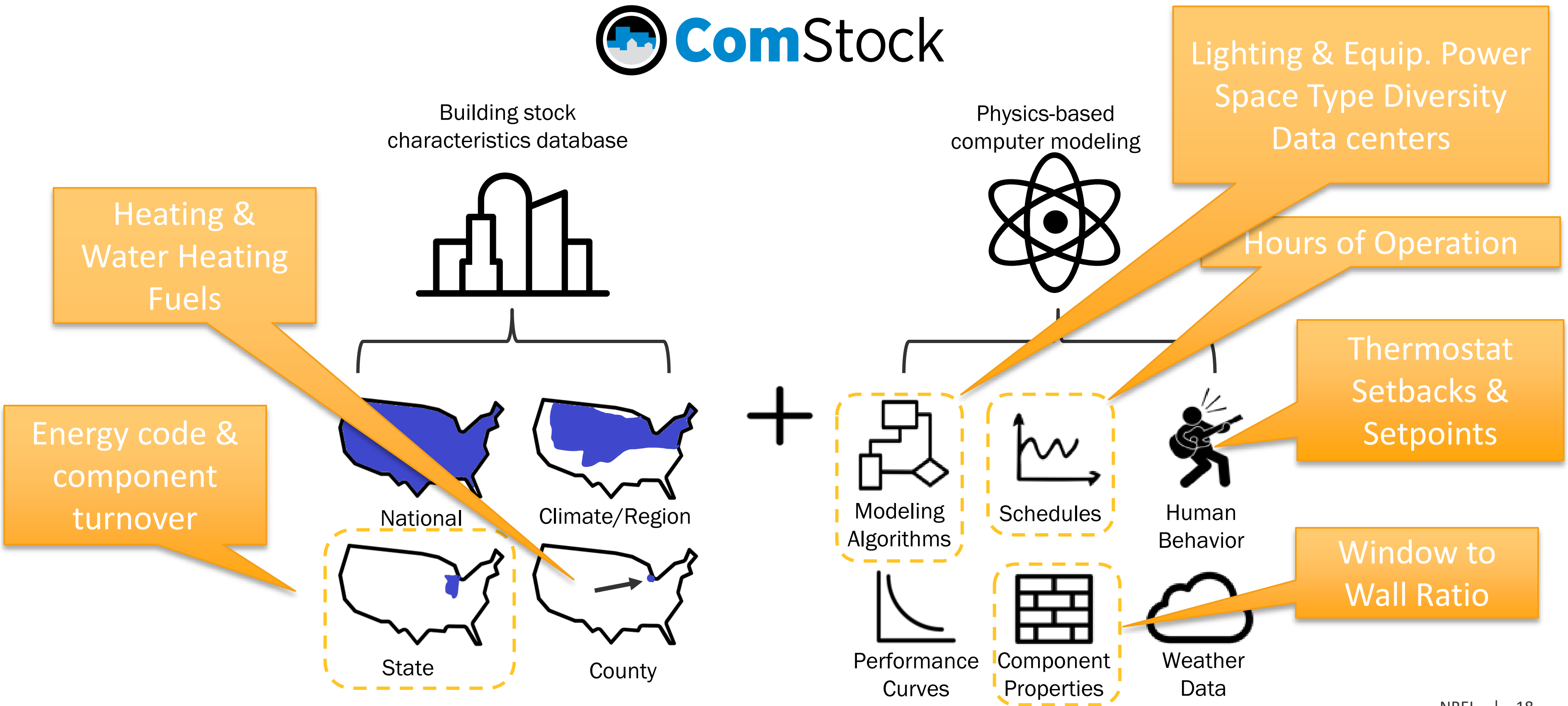


Summary of Commercial AMI Calibration Regions



Background colors are DOE Building America Climate Regions

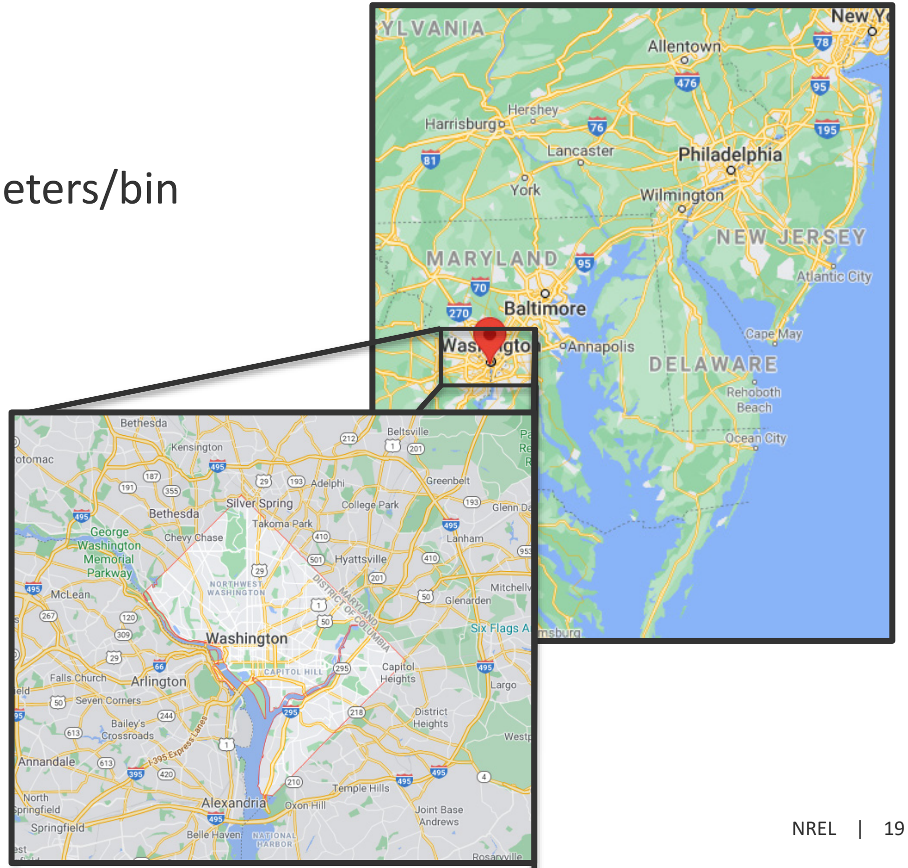
Region 3 Focus: Code, Schedules, HVAC Operation



Region 4a – Washington DC

- Data from PEPCO
- Investor-owned Utility
- AMI data from 2019
- Data grouped for anonymization, 5+ meters/bin

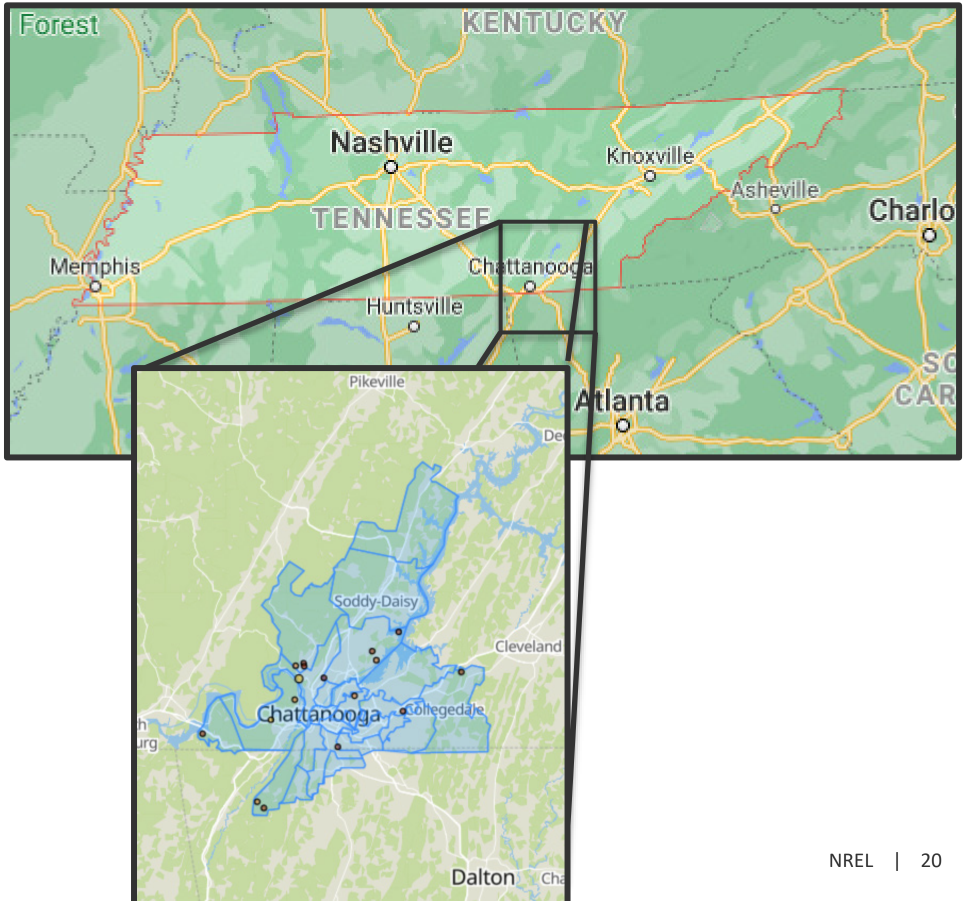
building_type	count
full_service_restaurant	114
hospital	17
large_hotel	77
large_office	615
medium_office	345
outpatient	43
primary_school	43
quick_service_restaurant	11
retail	248
small_office	551
strip_mall	2635
warehouse	240



Region 4b – Chattanooga, TN

- Data from EPB
- Municipal Utility
- Serves ~170k customers
- AMI data from 2019

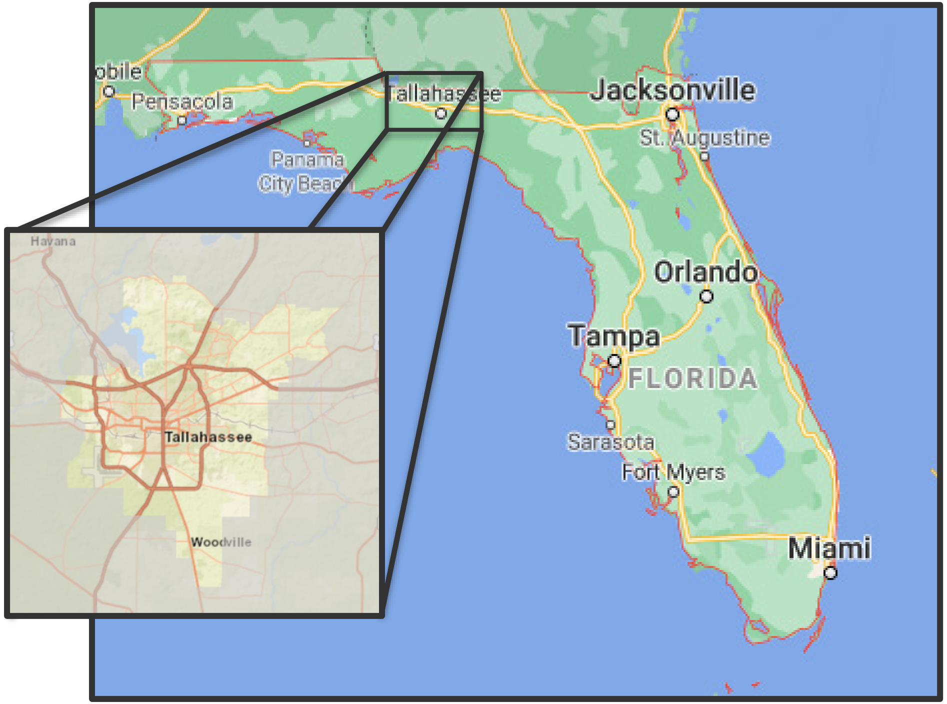
building_type	count
full_service_restaurant	141
hospital	5
large_hotel	83
large_office	35
medium_office	146
outpatient	200
primary_school	33
quick_service_restaurant	130
retail	481
small_hotel	24
small_office	733
strip_mall	652
warehouse	742



Region 4c – Tallahassee, FL

- City of Tallahassee Utilities
- Electric, Gas, Water
- Serves ~122,000 customers
- Municipal utility
- AMI data from 2019

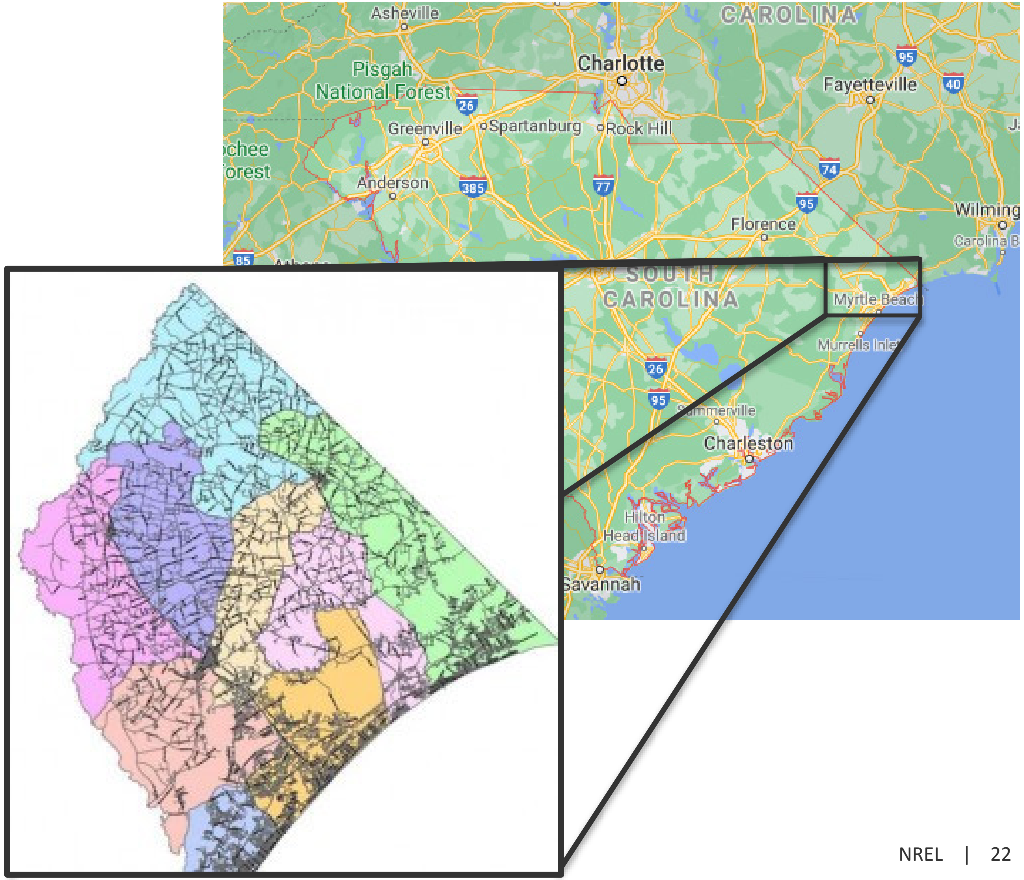
building_type	count
full_service_restaurant	153
hospital	3
large_hotel	36
large_office	29
medium_office	249
outpatient	181
primary_school	61
quick_service_restaurant	104
retail	437
small_hotel	28
small_office	1074
strip_mall	249
warehouse	444



Region 4d – Horry County, SC

- Horry Electric Cooperative
- Co-op Utility
- Serves ~70,000 customers
- Municipal utility
- AMI data from 2019

building_type	count
full_service_restaurant	15
large_hotel	1
medium_office	2
outpatient	8
primary_school	4
quick_service_restaurant	7
retail	61
small_hotel	3
small_office	95
strip_mall	52
warehouse	61



List of updates

New validation comparisons
- AMI data from Horry County, Chattanooga, Tallahassee, Washington D.C.
- EIA Forms 861M (electricity) and 176 (natural gas)

New capabilities
- Adjusting space type ratios within building types
- Changing energy code adoption and stock turnover to reflect history and improved lifespans

Baseload updates
- Lighting update
- Added data centers to offices
- Added restaurants to strip malls
- Office equipment power densities
- Updated hours of operation distributions
- WWR update

HVAC updates
- Used residential spatial distribution of heating fuels to refine commercial distribution
- Updated relationship between space heating and service water heating fuels
- Added variability to thermostat setpoints and absence/presence of setbacks

New Capabilities

Update: Energy Code Adoption and Turnover

Task	Affected Building Type	Considerations
Change energy code adoption to be based on the historic adoption by state.	All	• Each state has a different history of energy code adoption, and many states lag significantly behind the latest current model energy codes • Not all building systems fail at the exact moment they reach the end of their typical lifespans • Combine these factors together to model the change in the building stock over time, based on construction year of buildings and the lifespans of systems within that building (lighting, HVAC, windows, walls, etc.)
Change building subsystem replacement to be based on lifetime distributions.		

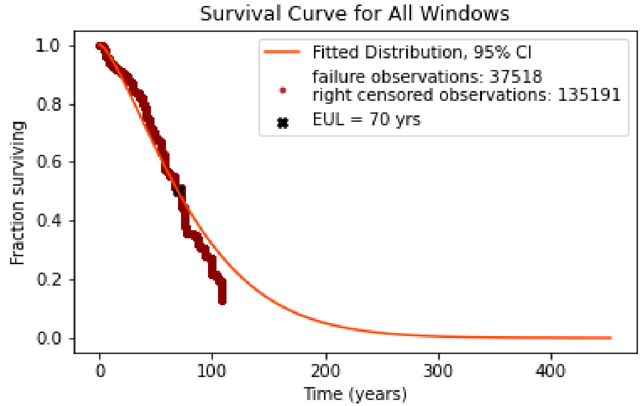
Update: Energy Code Adoption and Turnover

Methodology

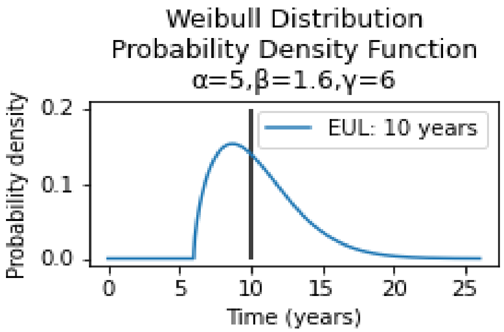
1. Determined energy code adoption history from DOE codes program sources. Included mechanism to incorporate code compliance levels by major building system.
2. Determined effective useful life and lifespan probabilities for each major building system windows) based on previous work (interior lighting, interior equipment, exterior lighting, service water heating, HVAC, roof, and walls) or new calculations (windows).
3. Created a series of TSV files describing the distributions, and revised Sobol sampling approach to work with increased dimensionality.

Analysis of window lifespan distribution

(Raw data from CBSA in Pacific NW)



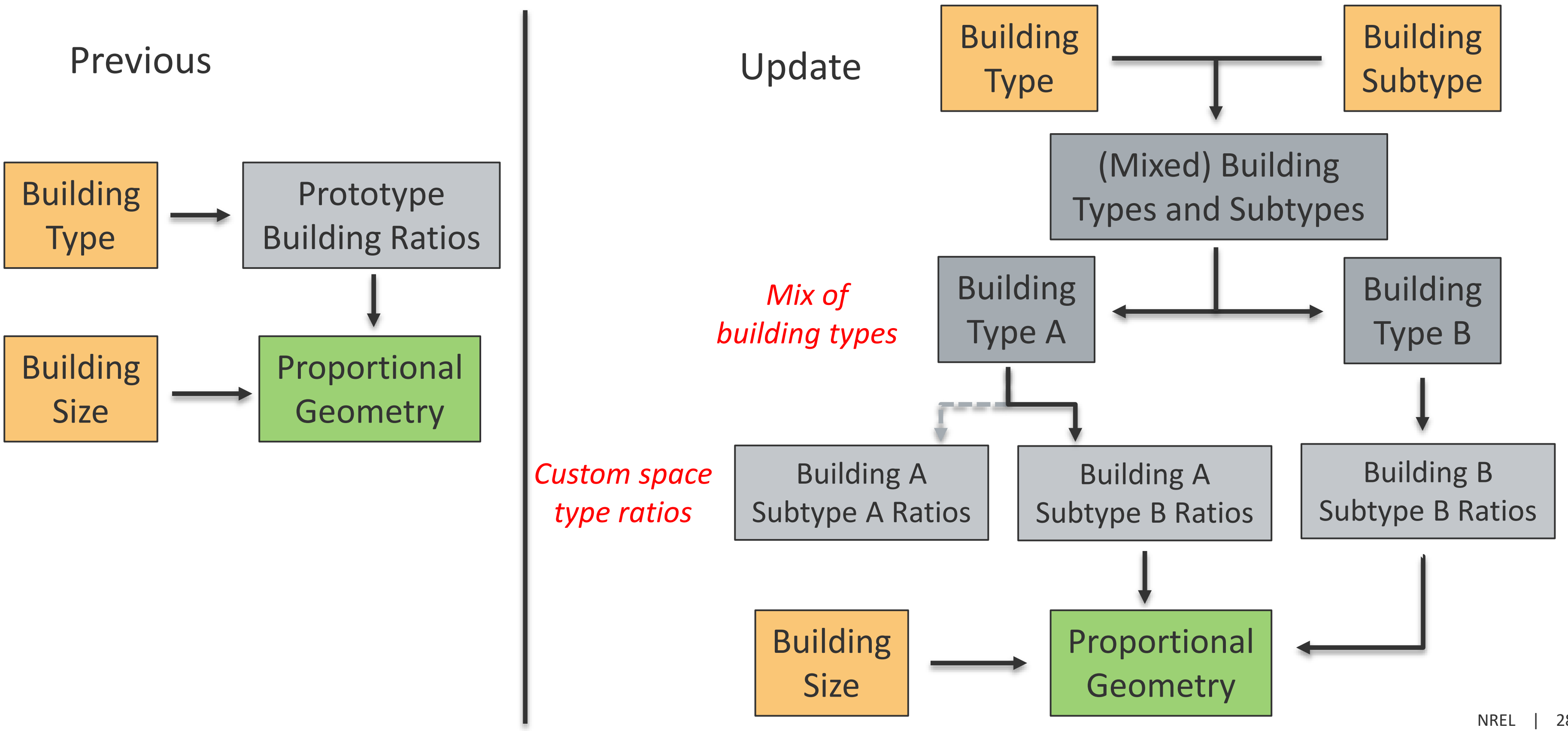
Lifespan distribution for interior lighting



Capability: Enable Diversity of Space Types in Buildings

Task	Affected Building Type	Considerations
Edit workflow to allow a mix of building types and different ratios of space types within a building type	Large Office, Medium Office, Strip Mall, Warehouse	• From the prototype building space type ratios, large offices have data centers and medium office do not. Many but not all large offices and medium offices contain data centers. • Strip malls contain not-retail uses, especially restaurants with higher EUIs. • There are variety of warehouses ranging from infrequently used storage warehouses to nearly full industrial or distribution center use cases.

Capability: Enable Diversity of Space Types in Buildings



Impact: Enable Diversity of Space Types in Buildings

Impact discussed in separate updates below:

- Added data centers to offices
- Added restaurants to strip malls

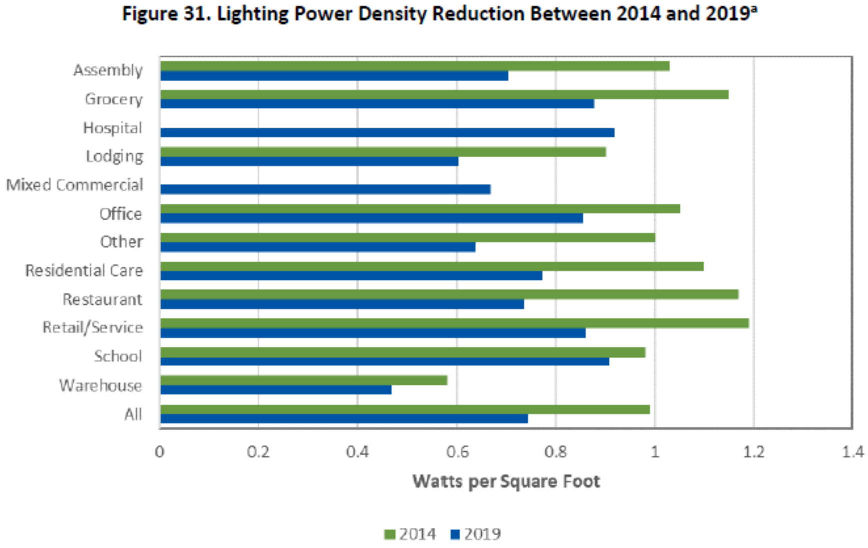
Baseload Updates

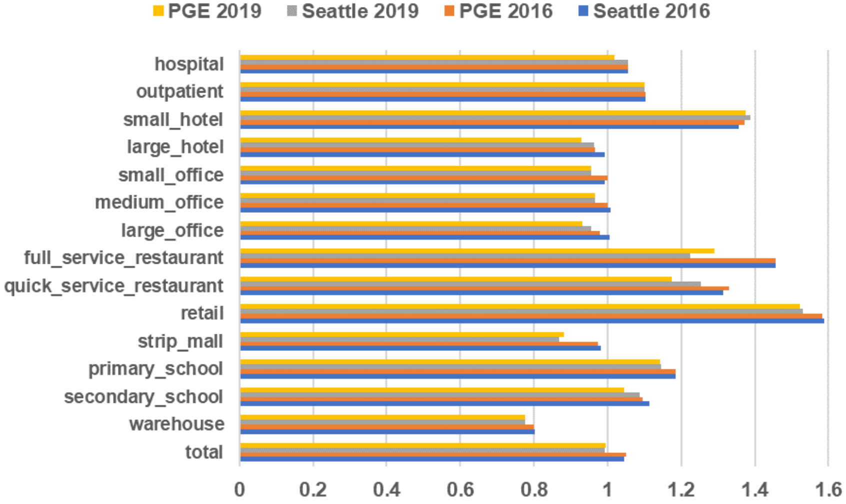
Update: Revised Interior Lighting Power Density

Task	Affected Building Type	Considerations
Review and update interior lighting power density assumptions, particularly in retail buildings	All	Typical lighting equipment is more efficient than prescriptive code minimum for several reasons: • Prescriptive code in most jurisdictions is older than the most recent 90.1 version • Most buildings use less than the lighting allowance • Lighting retrofits are frequent; lighting systems are replaced faster than other building systems • Ample availability of more efficient lighting technology • Incentive programs typically target commercial lighting <u>Before</u> • Interior lighting power density based on corresponding 90.1 prescriptive minimum at time of retrofit • Lighting alone comprised most of load shown by the AMI data in some building types, particularly retail <u>After</u> • Compared lighting power density to *NEEA Commercial Building Stock Assessment 2019* and *DOE U.S. Lighting Market Characterization 2015* • The average lighting power density most closely aligns with the 90.1-2019 prescriptive minimum

Update: Revised Interior Lighting Power Density

CBSA lighting (NEEA Commercial Building Stock Assessment 2019)





An initial comparison against CBSA data shows ComStock overestimating lighting power density substantially (20-30%), especially in retail buildings

Update: Revised Interior Lighting Power Density

Methodology

1. Compare average lighting power density by building type and vintage, particularly retail and strip mall

2. Select the vintage that is representative of typical stock lighting power density, ~0.7 watts/ft2 in **2019**

Commercial Sector Lighting Electricity Use by Commercial Buildings in 2015					
	Average Lamps per 1,000 ft^2	Installed Wattage (W/ft^2)	Electricity Use per Building (kWh/yr)	Intensity ($kWh/yr/ft^2$)	Intensity Rank
Education	38	1.4	117,100	3.7	3
Food sales	29	1.1	48,900	6.9	1
Food service	24	0.7	15,700	3.3	6
Health care - Inpatient	18	0.5	471,200	2.0	11
Health care - Outpatient	19	0.6	22,700	1.9	12
Lodging	26	0.6	138,000	3.7	2
Offices (Non-medical)	19	0.6	27,900	1.8	13
Other	24	0.8	44,900	2.8	8
Public assembly	21	0.8	40,400	2.6	9
Public order and safety	17	0.7	60,500	3.5	4
Religious worship	30	1.0	19,500	1.8	14
Retail - Mall & Non-Mall	20	0.8	59,700	3.2	7
Services	33	1.3	25,300	3.4	5
Warehouse and storage	20	0.8	37,200	2.3	10

Table 4-21 U.S. Lighting Market Characterization **2015**

Building Type	Average LPD (W/ft^2)
full_service_restaurant	**1.76**
ComStock 90.1-2007	1.95
ComStock 90.1-2010	0.96
ComStock DOE Ref 1980-2004	2.37
hospital	**1.56**
ComStock 90.1-2007	1.06
ComStock DOE Ref 1980-2004	2.07
large_hotel	**1.11**
ComStock 90.1-2007	1.00
ComStock 90.1-2010	0.98
ComStock DOE Ref 1980-2004	1.71
large_office	**1.13**
ComStock 90.1-2007	1.05
ComStock 90.1-2010	0.95
ComStock DOE Ref 1980-2004	1.58
medium_office	**1.11**
ComStock 90.1-2007	1.05
ComStock 90.1-2010	0.95
ComStock DOE Ref 1980-2004	1.65
outpatient	**1.22**
ComStock 90.1-2007	1.11
ComStock 90.1-2010	1.09
ComStock DOE Ref 1980-2004	1.55
primary_school	**1.30**
ComStock 90.1-2007	1.23
ComStock 90.1-2010	1.10
ComStock DOE Ref 1980-2004	1.71
quick_service_restaurant	**1.41**
ComStock 90.1-2007	1.65
ComStock 90.1-2010	0.94
ComStock DOE Ref 1980-2004	1.49
retail	**1.89**
ComStock 90.1-2007	1.63
ComStock 90.1-2010	1.58
ComStock DOE Ref 1980-2004	3.16
secondary_school	**1.22**
ComStock 90.1-2007	1.17
ComStock 90.1-2010	1.02
ComStock DOE Ref 1980-2004	1.49
small_hotel	**1.41**
ComStock 90.1-2007	1.35
ComStock 90.1-2010	1.40
ComStock DOE Ref 1980-2004	1.51
small_office	**1.18**
ComStock 90.1-2007	1.05
ComStock 90.1-2010	0.95
ComStock DOE Ref 1980-2004	1.90
strip_mall	**1.48**
ComStock 90.1-2007	0.96
ComStock 90.1-2010	0.83
ComStock DOE Ref 1980-2004	3.75
warehouse	**0.77**
ComStock 90.1-2007	0.85
ComStock 90.1-2010	0.74
ComStock DOE Ref 1980-2004	0.65
(blank)	-
Building-Weighted Average	1.24
Area-Weighted Average	1.12

run 19

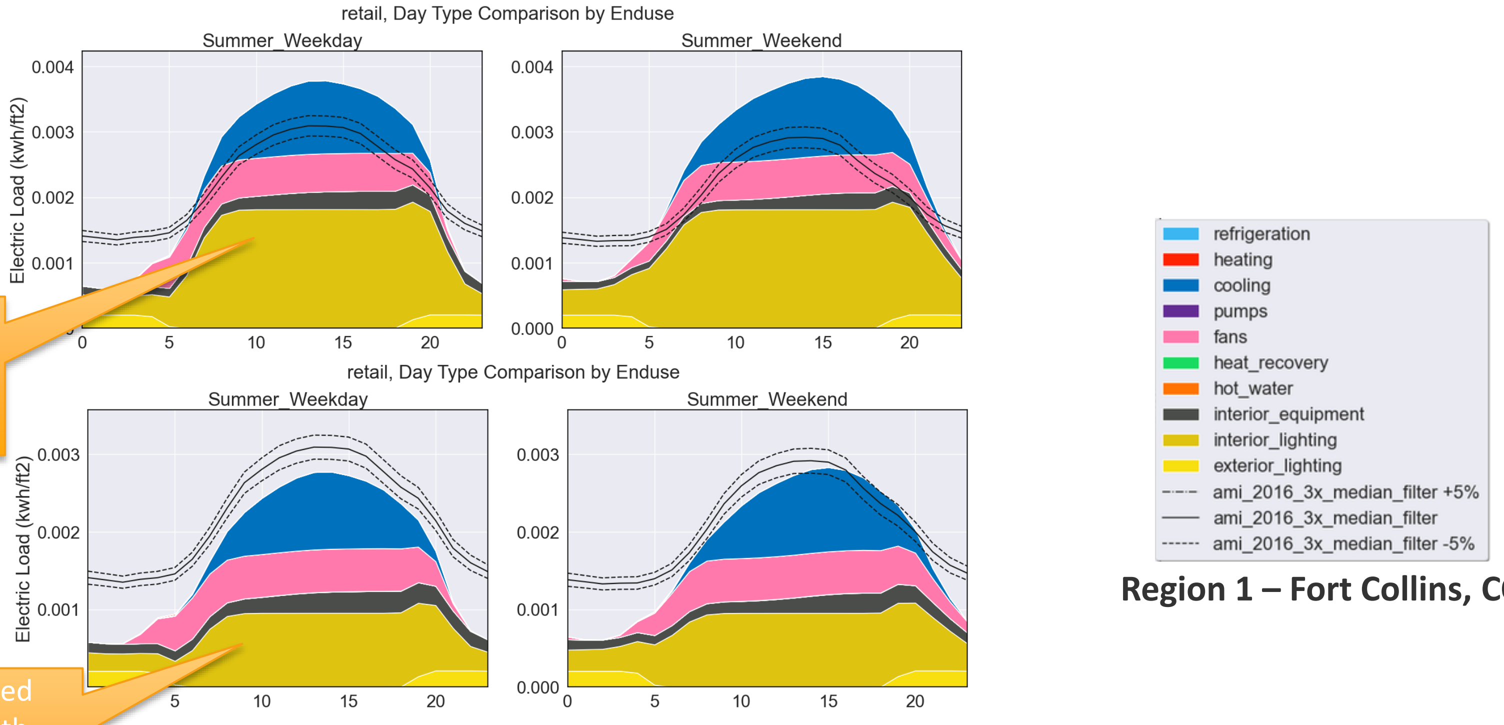
Building Type	Average LPD (w/ft^2)
full_service_restaurant	**0.77**
ComStock 90.1-2019	0.77
hospital	**0.98**
ComStock 90.1-2019	0.98
large_hotel	**0.44**
ComStock 90.1-2019	0.44
large_office	**0.67**
ComStock 90.1-2019	0.67
medium_office	**0.67**
ComStock 90.1-2019	0.67
outpatient	**0.87**
ComStock 90.1-2019	0.87
primary_school	**0.69**
ComStock 90.1-2019	0.69
quick_service_restaurant	**0.85**
ComStock 90.1-2019	0.85
retail	**0.98**
ComStock 90.1-2019	0.98
secondary_school	**0.71**
ComStock 90.1-2019	0.71
small_hotel	**0.71**
ComStock 90.1-2019	0.71
small_office	**0.67**
ComStock 90.1-2019	0.67
strip_mall	**0.80**
ComStock 90.1-2019	0.80
warehouse	**0.45**
ComStock 90.1-2019	0.45
(blank)	-
Building-Weighted Average	0.69
Area-Weighted Average	0.64

run 20

Update: Revised Interior Lighting Power Density

Before

After



lighting is a majority of load profile

lighting decreased substantially with lighting power density update

Region 1 – Fort Collins, CO

Retail

Update: Revised Office EPD

Task	Affected Building Type	Considerations
Reviewing office equipment power densities (EPD) and making appropriate updates	small, medium, and large offices	<u>Before</u>: • Previous EPD update based on end-use data was based on biased (and small) building samples. • Thus, not representing generic/typical office buildings. <u>After</u>: • Reviewed data sources (both in-hand and public) and determined that the current EPDs were too low for offices. • While data sources were pointing towards higher EPDs, representativeness of the data sources was not good enough to generate new EPDs from them. • Thus, EPDs for offices were reverted back to the DOE prototype building models' EPD definitions.

Update: Revised Office EPD

Data Source	Description	SQFT	Including data center?	Operational EPD [W/sqft] Weekday avg = 1.343	Operational EPD [W/sqft] Weekend avg = 1.005
Source 1	-	360000	y	0.320	0.180
Source 2	standard med, land records	4544	n	1.990	0.910
	standard large, logistics	13688	n	1.030	0.850
	standard small, election office	1550	n	1.710	1.310
	omputer intensive, regulatory agenc	13072	n	1.100	0.420
	nputer intensive, investment analyt	13688	n	2.740	2.160
Source 3	single gov tenant	18818	n	0.520	0.520
	single gov tenant	138000	n	0.160	0.160
	single gov tenant with data center	18755	y	0.340	0.340
	single gov tenant with data center	220000	y	0.770	0.770
Source 4	EPA office, LEED Gold	420000	n	0.000	0.000
Source 5	Office Building_3758	972	-	9.624	7.673
	Office Building_1432	934	-	1.929	1.764
	Office Building_1573	20000	-	0.033	0.022
	Office Building_1435	3175	-	0.477	0.399
	Office Building_1452	10000	-	0.459	0.291
	Office Building_1933	7278	-	0.842	0.494
	Office Building_1704	3000	-	2.031	1.593
	Office Building_1956	2000	-	2.517	2.695
	Office Building_2078	17000	-	0.509	0.125
	Office Building_7055	11487	-	0.150	0.100
	Office Building_3920	15000	-	0.616	0.568
	Office Building_7249	156053	-	0.294	0.104
	Office Building_5823	4000	-	0.126	0.073
	Office Building_5431	5000	-	1.014	0.580
	Office Building_7168	3000	-	7.118	4.439
	Office Building_5424	3000	-	0.736	0.596
	Office Building_5448	5400	-	0.661	0.466
	Office Building_6157	31741	-	0.235	0.210
	Office Building_5644	1000	-	2.551	2.147
	Office Building_7877	8000	-	0.397	0.316
	Office Building_8549	329649	-	0.278	0.105
	Office Building_1571	1000	-	0.846	1.094
	Office Building_934	4500	-	0.791	0.753
	Office Building_870	1900	-	1.299	0.147
	Office Building_917	7011	-	0.002	0.002

ComStock	Large office	-	y	1.300	1.000
	Medium office	-	n	0.500	0.200
	Small office	-	n	0.500	0.200

Methodology

1. Five different data sources were gathered and processed to understand operational EPDs in real office buildings.
2. EPDs from these data sources were compared against each other and against the EPDs being used in ComStock office models.
3. While the gathered EPDs still include variability and uncertainty in reality, the average EPD was generally higher than ComStock EPDs.
4. While it was clear that ComStock is currently simulating plug loads lower than what it can be expected, EPDs gathered from the data sources were still not good enough as a replacement.
5. Decision was made to adopt EPDs defined previously in the DOE prototype building models again.

Update: Revised Office EPD

Before

After

plug load too low

plug load increased with EPD updates

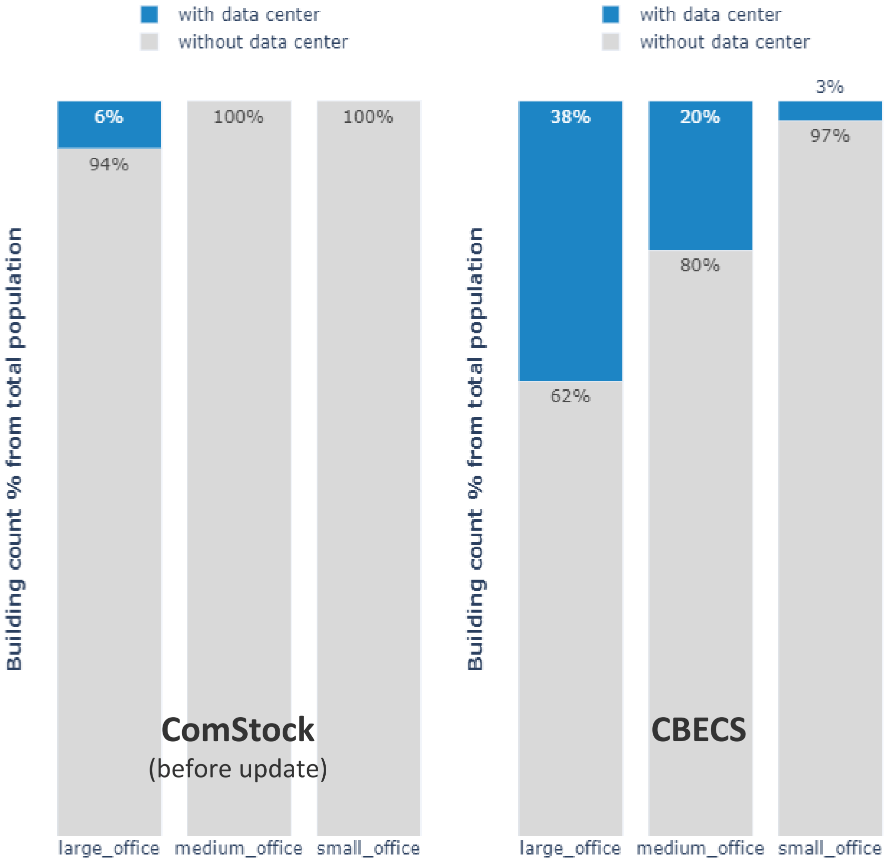
Region 1 – Fort Collins, CO

Small Office

Update: Data Center in Offices

Task	Affected Building Type	Considerations
Reflecting data centers in office models close to reality	medium and large offices	Before: • Data centers were only applied in newer and large office models • Previous calibration results consistently showed lower electricity predictions for office buildings After: • Reviewed survey data in CBECS to understand the population of office buildings that include (or don’t include) data centers • Made updates on medium/large office models in ComStock to include the same portion (derived from CBECS) of data centers in medium/large office model population

Update: Data Center in Offices



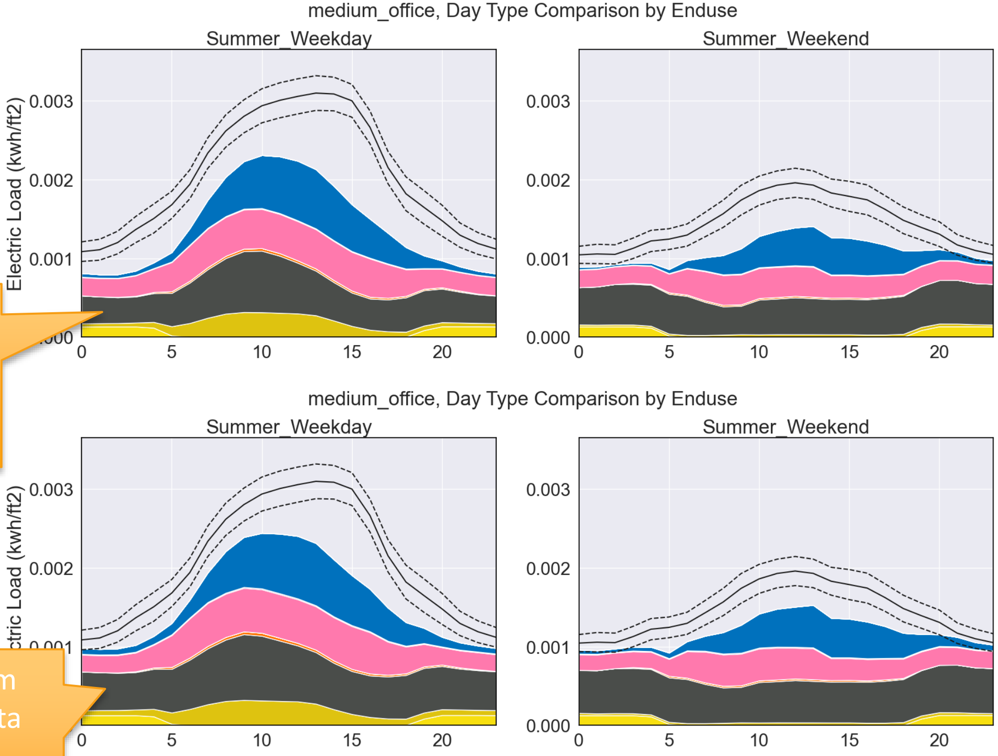
<u>Methodology</u>

1. Calculated the portion of data centers in office buildings (in terms of both sqft and count) from CBECS.
2. Decided to add data centers in medium and large offices (data center portion for small offices is very small).
3. Updated TSV file which defines sub-space types (in this case for data center) by adding ratio of data centers in medium and large office models.

Impact: Data Center in Offices

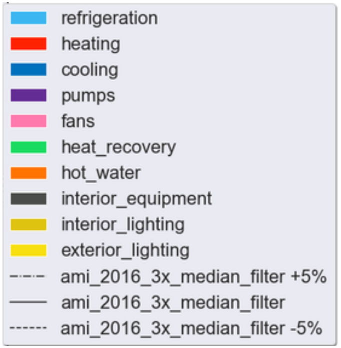
Before

After



data center is not included in any medium offices

20% of all medium offices include data center → slight increase in interior equipment load



Region 1 – Fort Collins, CO

Small Office

Update: Window Wall Ratio

Task	Affected Building Type	Considerations
Updating Window-Wall Ratio based on Guidehouse's NFRC Commercial Fenestration Market Study (2020)	All	Before: • WWR based off prototype buildings, and is therefore the same for all buildings of the same type After: • WWR is a distribution for each combination of building type, floor area, and vintage

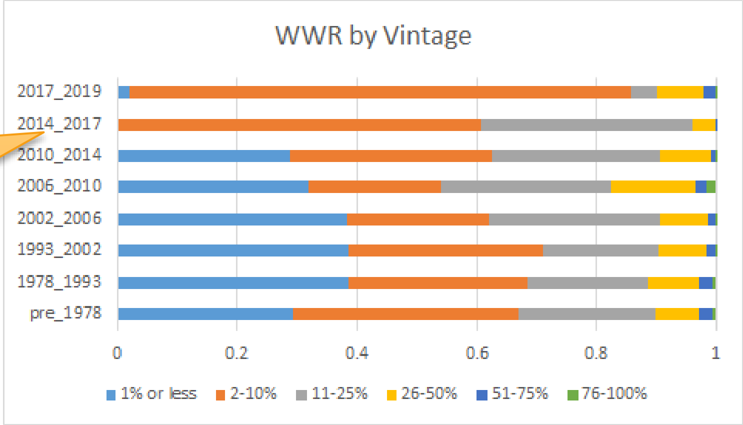
Update: Window Wall Ratio

Data sources used in Guidehouse NFRC Commercial Fenestration Market Study

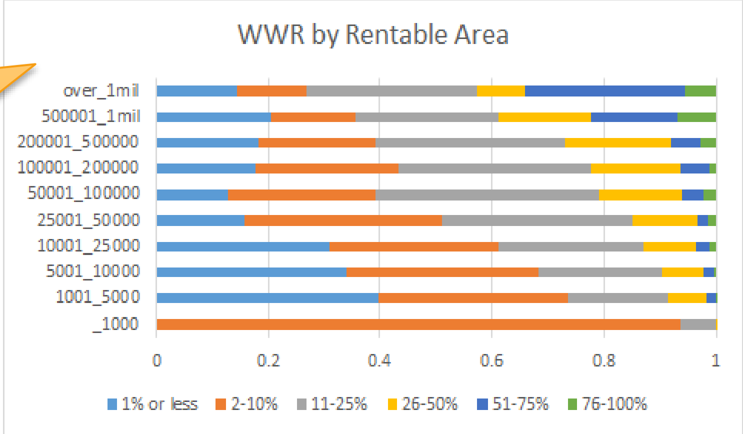
Source	Data Collection Year	Building Samples	Regions
Guidehouse Survey	2020	800	National
NEEA CBSA	2014, 2018	1996	WA, OR, MT, ID
DOE Code Study	2016-2019	104	FL, IA, IL NE
CAEUS	2006	5862	California
EIA CBECS	2012	6721	National
EIA RECS	2015	858	National (Multifamily)
Programs	2020	30	TX, CO, WA
Other	2019	6	WA, TN
AAMA	2017	Summary Level	National (Sales)
Manufacturer Data	2019	3000+	National (Sales)
Guidehouse Market Size Estimates	2020	Summary Level	National

Note: Data was weighted based on several factors including coverage, completeness, and fidelity

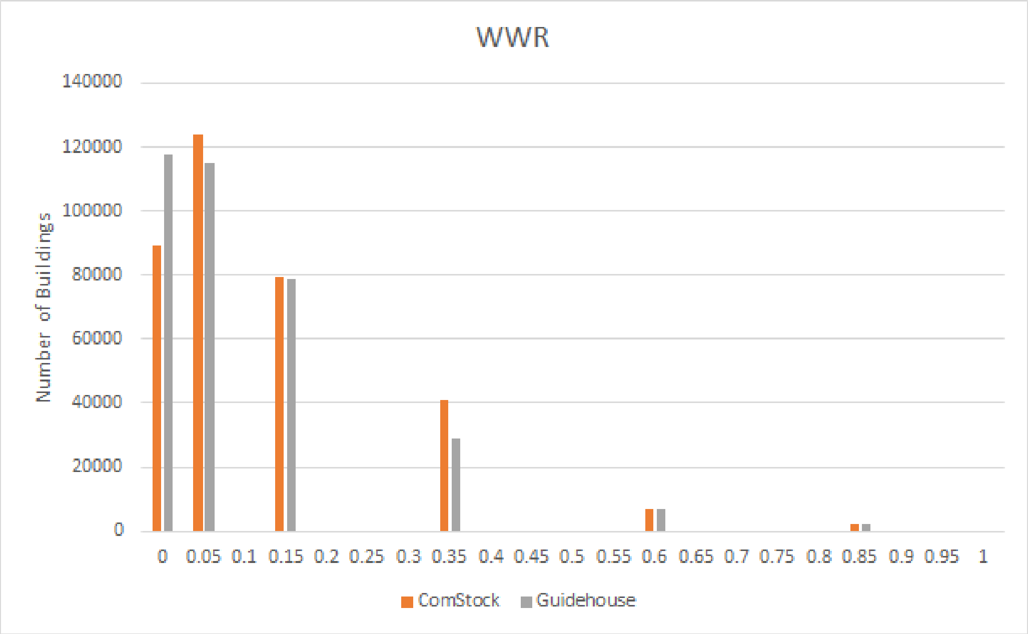
Around 2014, we see a noticeable change in the WWR distribution



We see an obvious trend in WWR based on building floor area. Larger buildings --> more windows



Update: Window Wall Ratio



The final distributions do not appear to change the stock much, but the key difference is having a *distribution* of WWR for each combination of building type/vintage/floor area. This adds more variability within building types.

Note: The distinct bins shown above are a result of the way WWR is binned in the CBECS Show Card: 0-1% --> 0.0, 2-10% --> 0.06, 11-25% --> 0.18, 26-50% --> 0.38, 51-75% --> 0.63, 76-100% --> 0.88

Update: Add Restaurants to Strip Malls

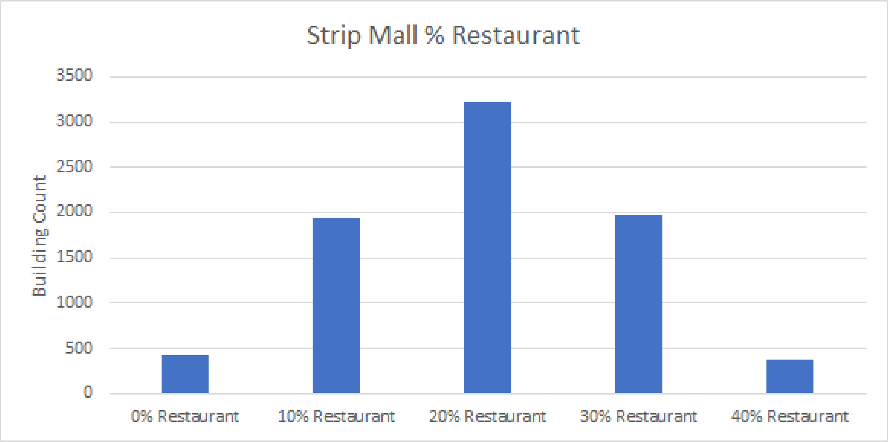
Task	Affected Building Type	Considerations
Adding restaurant space type to strip malls	Strip malls	Before: • Strip mall models consisted solely of retail space types, resulting in low internal loads and low variability After: • Strip mall models contain a distribution of 0-40% restaurant space types based on surveying of strip malls in Denver area by NREL team

Update: Add Restaurants to Strip Malls

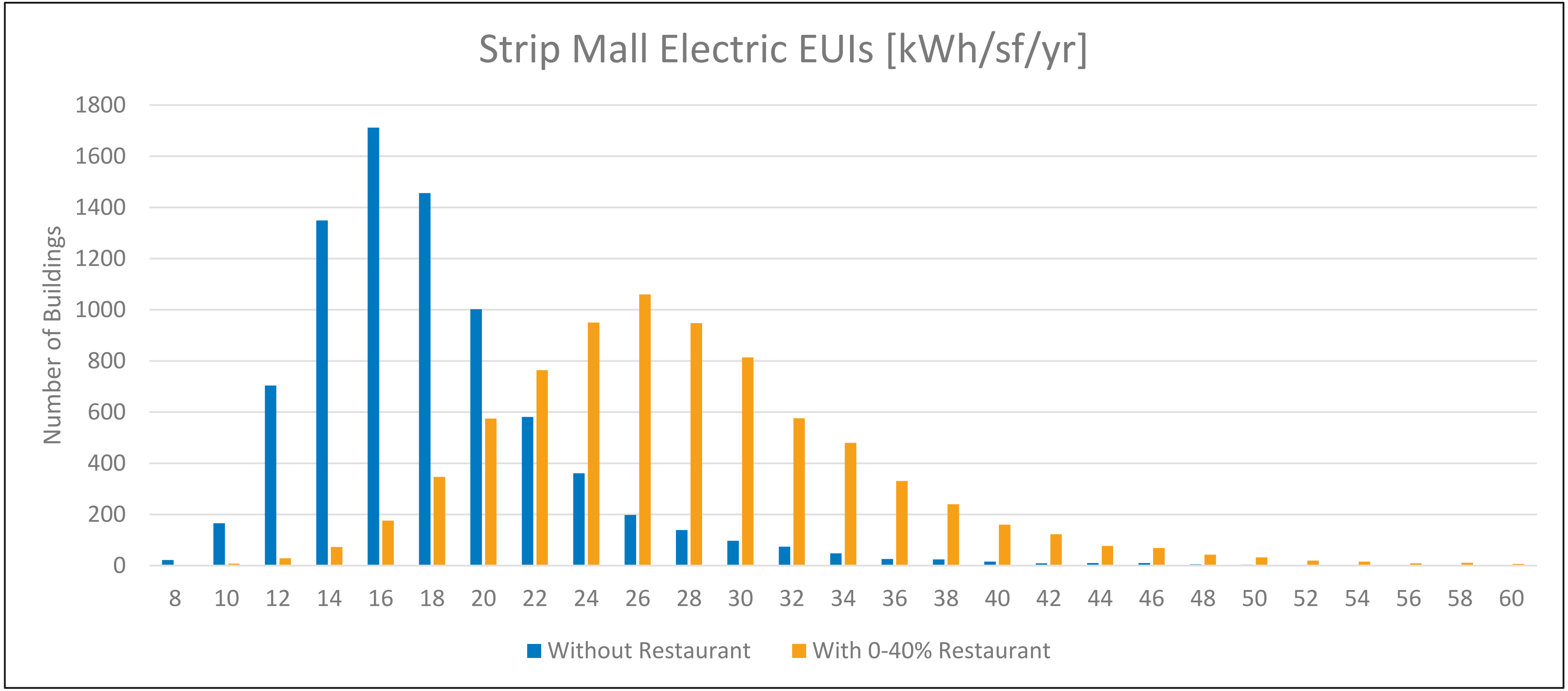
NREL Strip Mall Surveying

Number of Restaurants	Total Number of Businesses	% Restaurant in Strip Malls
40	189	Mean: 21% Median: 20% Minimun: 5% Maximum: 50%

New Strip Mall Restaurant Distribution



Update: Add Restaurants to Strip Malls

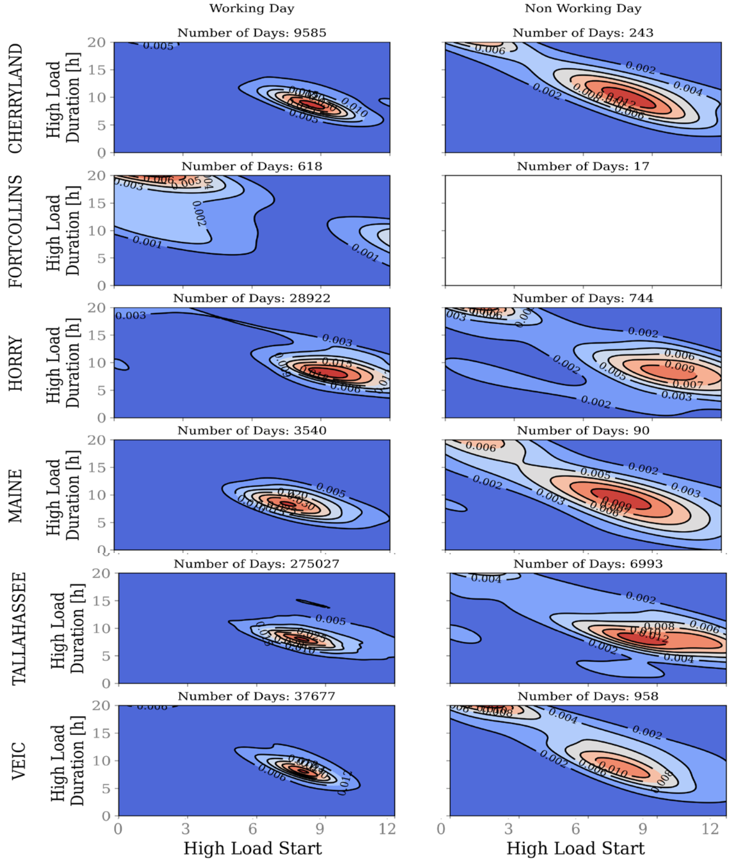


Update: Hours of Operation Update

Task	Affected Building Type	Considerations
Update hours of operation schedules	All	Originally, distributions of hours of operation were based on a single AMI dataset with a limited number of samples covering a subset of building types. Additionally, the start time were constrained to the highest-probability 4-hr rolling windows for each building type. AMI from 6 utilities around the country was analyzed and combined to create distributions of start time and duration for weekends and weekdays for all building types in ComStock.

Impact: Hours of Operation Update

Small Office - High Load Duration



Methodology

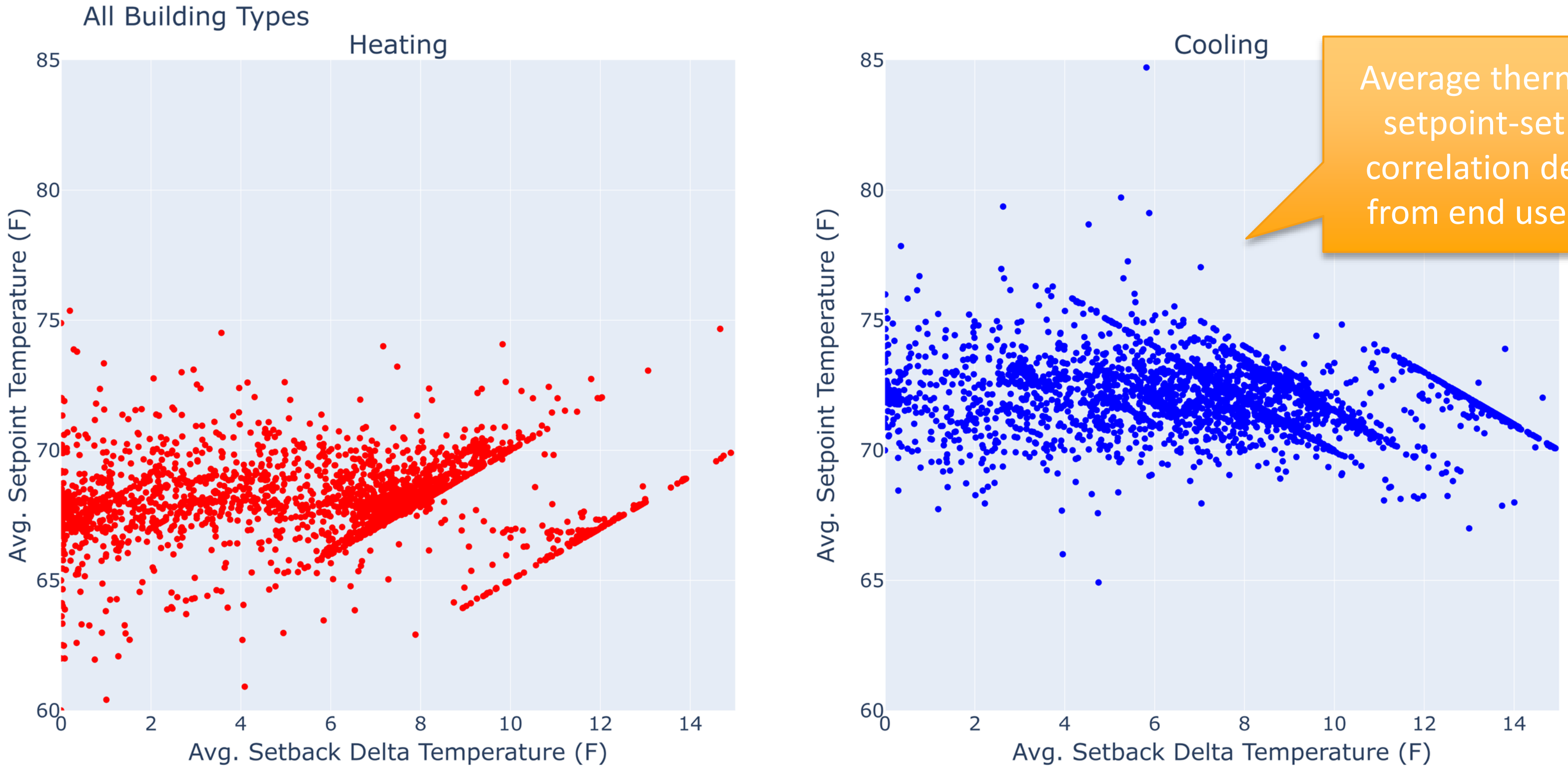
1. Extract high load start time and duration from each day's AMI data using previously-described techniques.
2. Compare distributions of these characteristics for each building type, keeping in mind that some building types in some datasets had a low number of samples.
3. Overall, distributions were broadly similar across utilities, especially considering sample sizes.
4. Create a combined national distribution of start time and duration for each building type by combining data from all AMI datasets.

HVAC Updates

Update: Thermostat Setpoint Variability

Task	Affected Building Type	Methods
Add variability to thermostat setpoints and setbacks.	All building types excluding hotels and hospitals.	Previously, thermostat schedules were set in models by building type; each building type had a single set of profiles. These schedules were derived from averaging metered profiles across several data sources. This method lacked variability in thermostat setpoints and setbacks between individual buildings as would be seen in the commercial building stock. The new method, informed by the same metered data sets as well as CBECS, creates distributions of thermostat setpoints and setbacks to capture the variety seen in the commercial building stock.

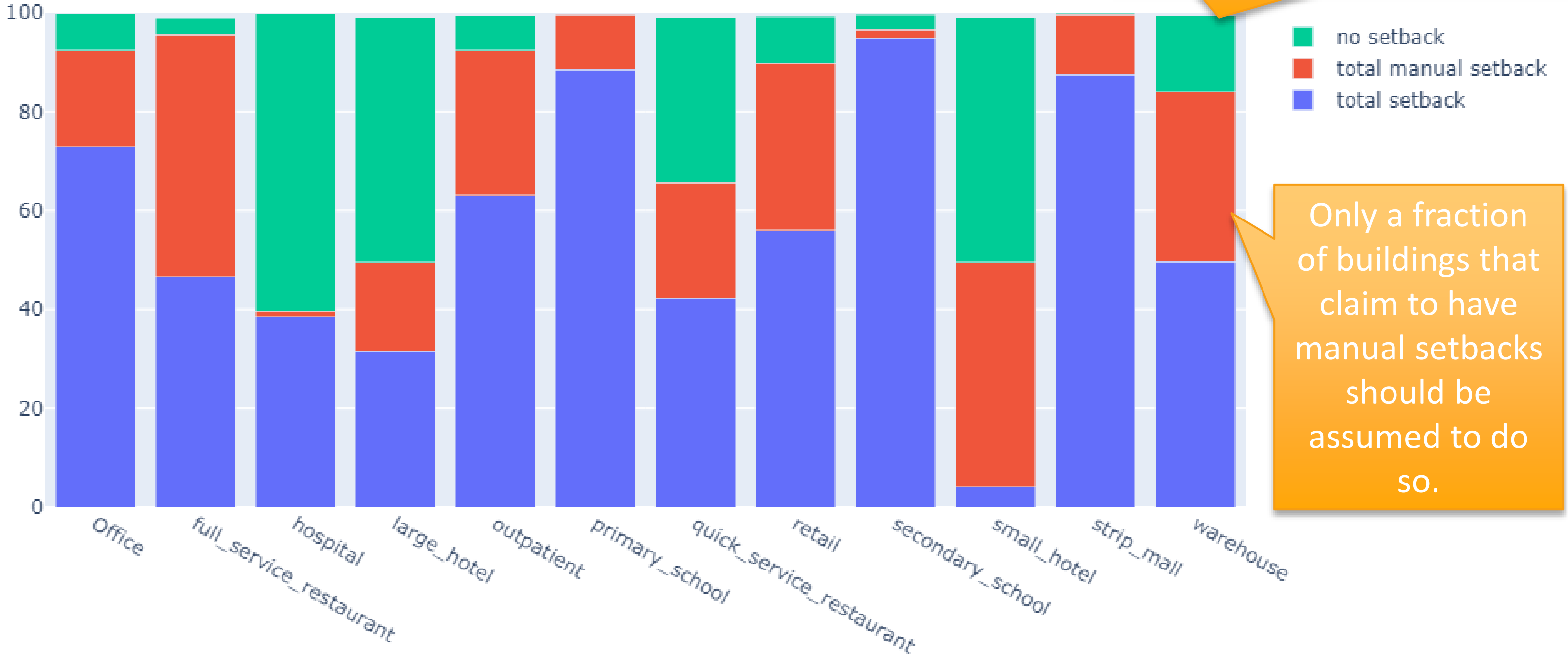
Update: Thermostat Setpoint Variability



Average thermostat setpoint-setback correlation derived from end use data.

Update: Thermostat Setpoint Variability

Some building types have large percentages of buildings with no thermostat setbacks.



Only a fraction of buildings that claim to have manual setbacks should be assumed to do so.

Variation in the presence of thermostat setbacks exists between building types and within a given building type.

Update: Thermostat Setpoint Variability

Creating setpoint and setback distributions per building type

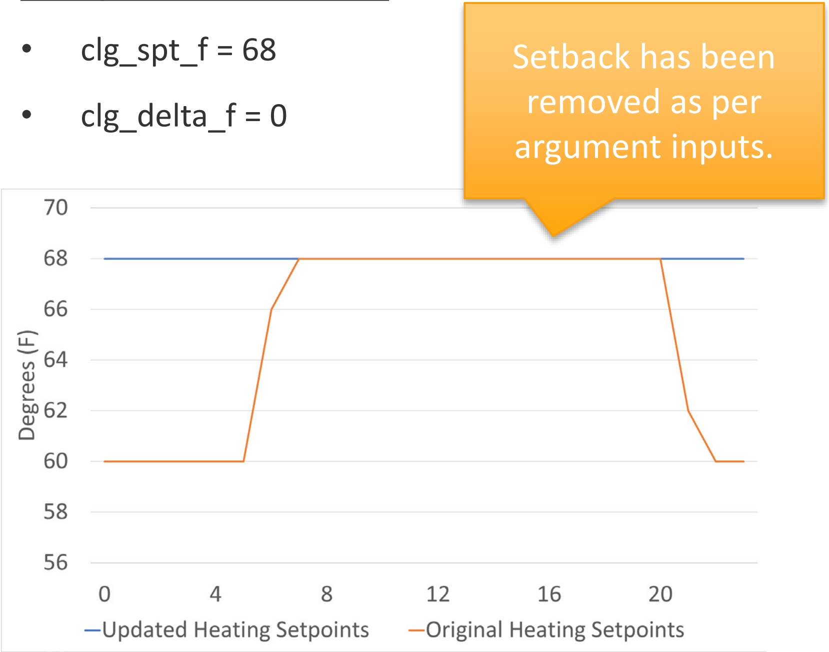
- Thermostat data was used to create setpoint and setback distributions:
    - **clg_spt_f:** occupied cooling setpoints
    - **clg_delta_f:** unoccupied cooling setback difference from occupied cooling setpoint
    - **htg_spt_f:** occupied heating setpoints
    - **htg_delta_f:** unoccupied heating setback difference from occupied heating setpoint

Measure implementation

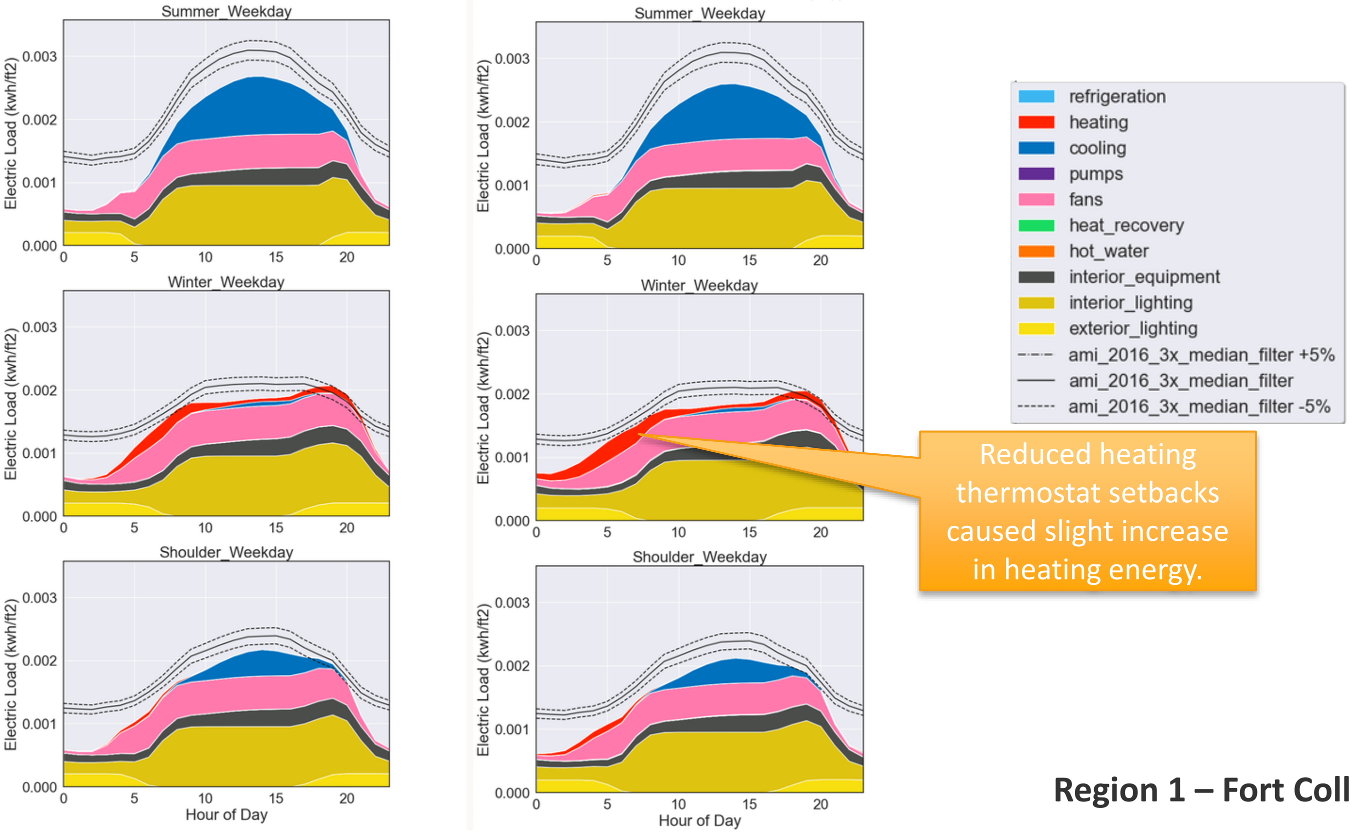
- The measure sets the thermostat setpoints and setbacks per the sampling distributions in the models
- The four measure arguments determined from the distributions will modify the schedules in the model to use the specified setpoints and setbacks.

Example measure results:

- clg_spt_f = 68
- clg_delta_f = 0



Update: Thermostat Setpoint Variability



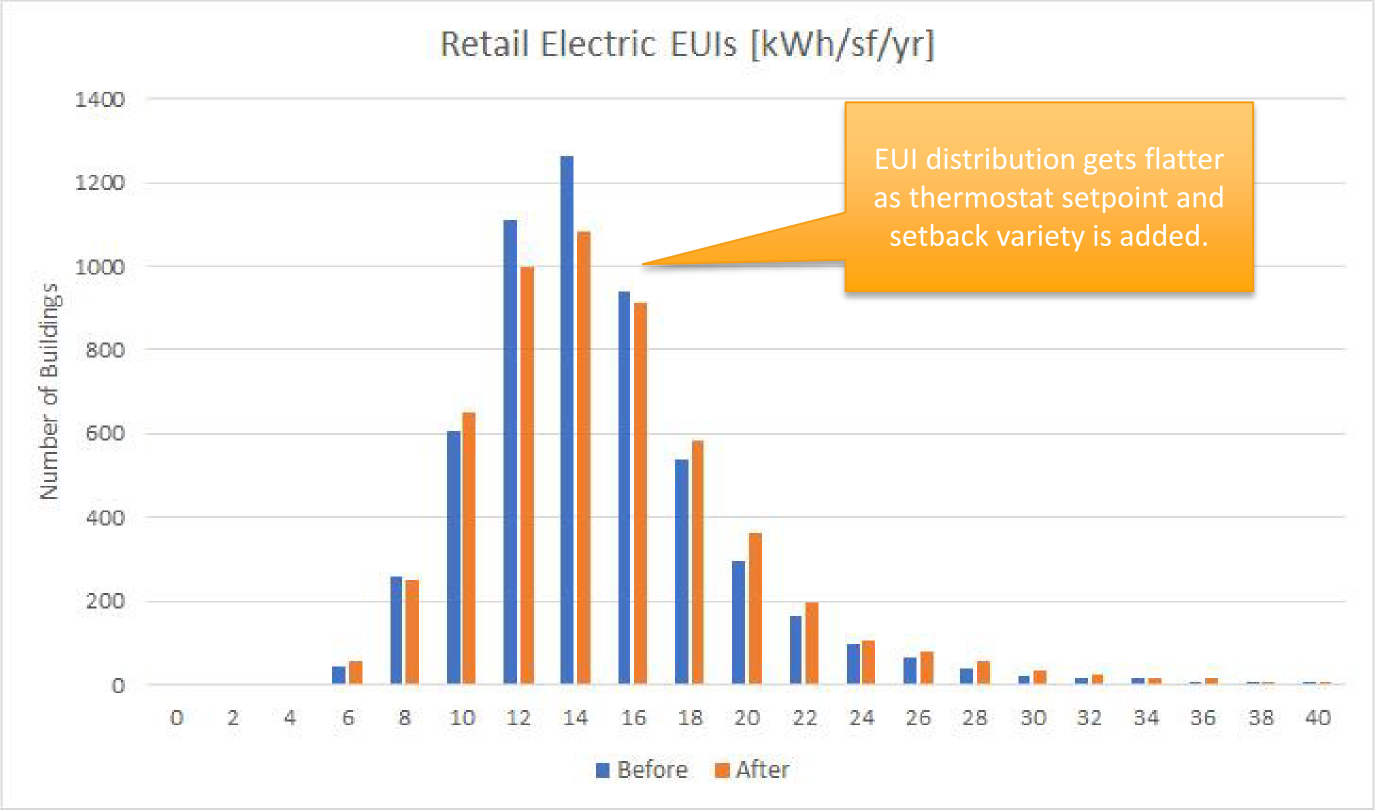
Before

Retail

After

Region 1 – Fort Collins, CO

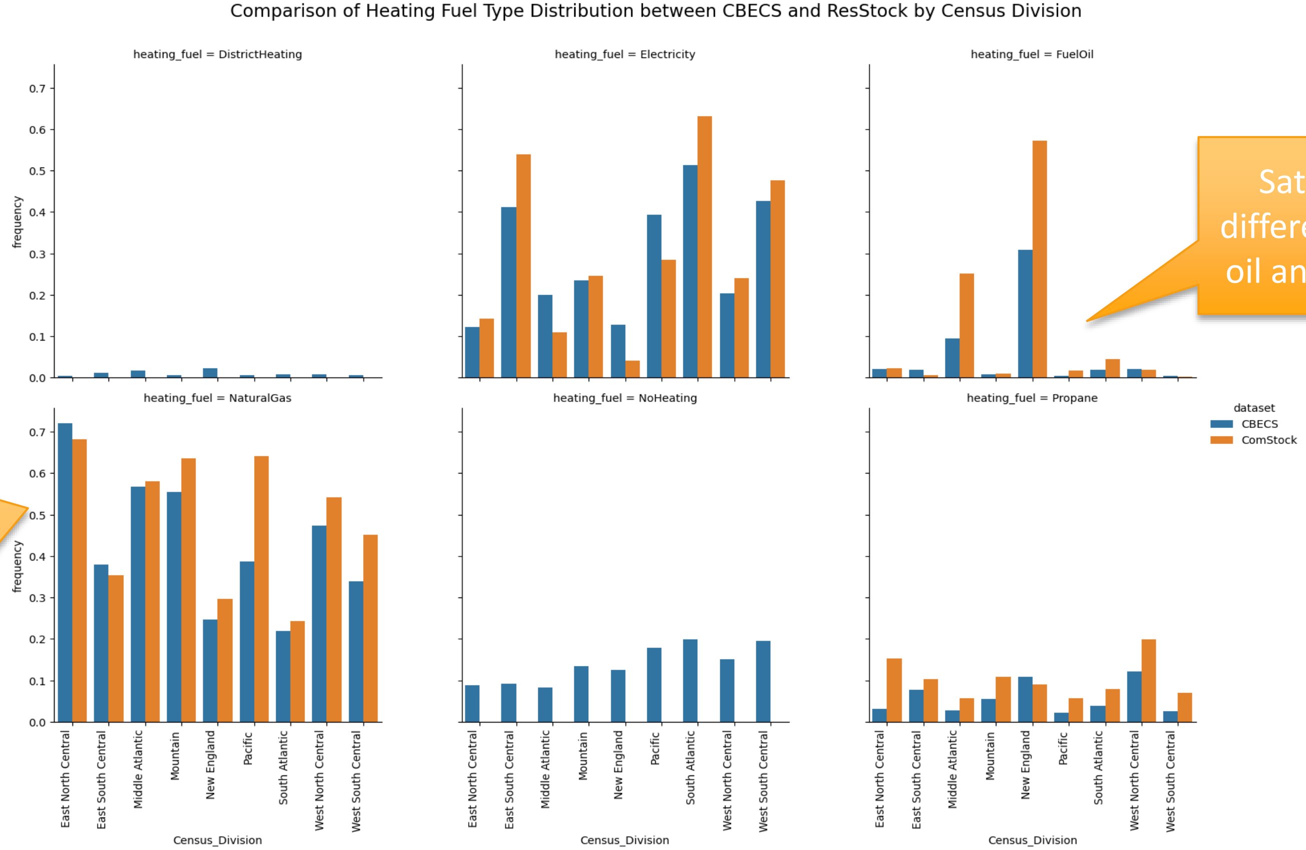
Update: Thermostat Setpoint Variability



Update: Spatial Distribution of Heating Fuels

Task	Affected Building Type	Methods
Update granularity of geographic distribution of heating fuels.	All buildings.	Previously, heating fuel distribution was derived from the distribution of HVAC systems, which was pulled from CBECS at the census division granularity. This led to uniform distributions of heating fuels across all counties in each census division. An analysis of residential heating fuel distributions showed a diversity across counties, with both intra-regional and urban/rural differences. Similarly granular heating fuel data did not exist for commercial buildings, so census-division level totals from CBECS for census division were apportioned using residential heating fuel distributions by county to create more granular distributions for commercial.

Update: Spatial Distribution of Heating Fuels



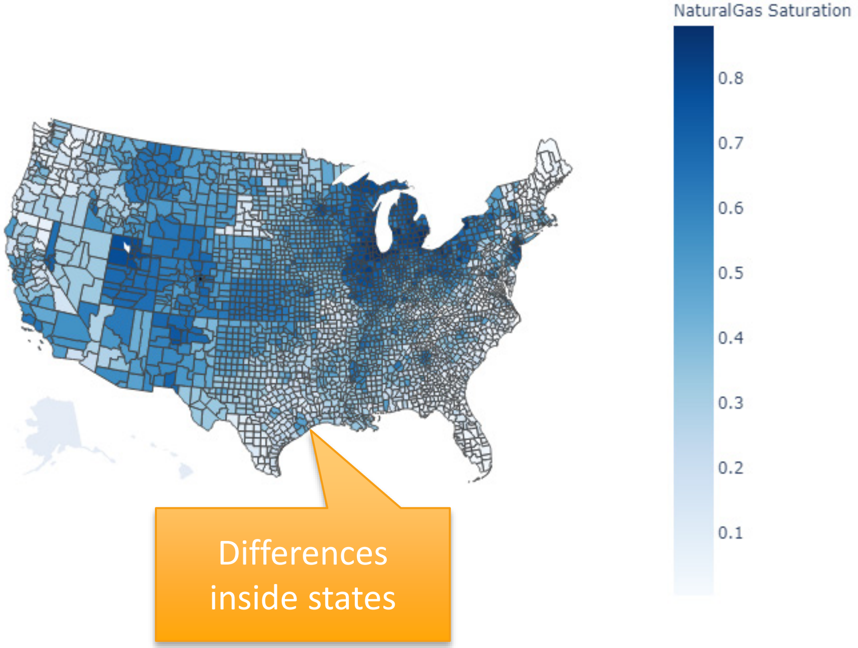
Saturations different for fuel oil and propane

Saturation of Res heating fuels broadly similar by census division for electricity and natural gas

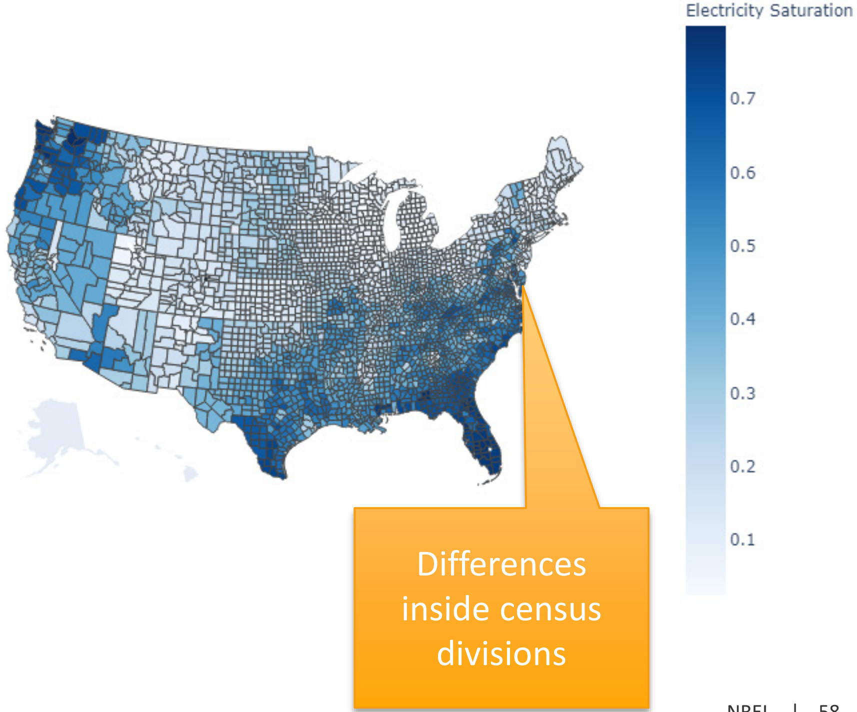
Update: Spatial Distribution of Heating Fuels

Aggregates match CBECS by census division, geographic granularity scaled to residential data within census divisions

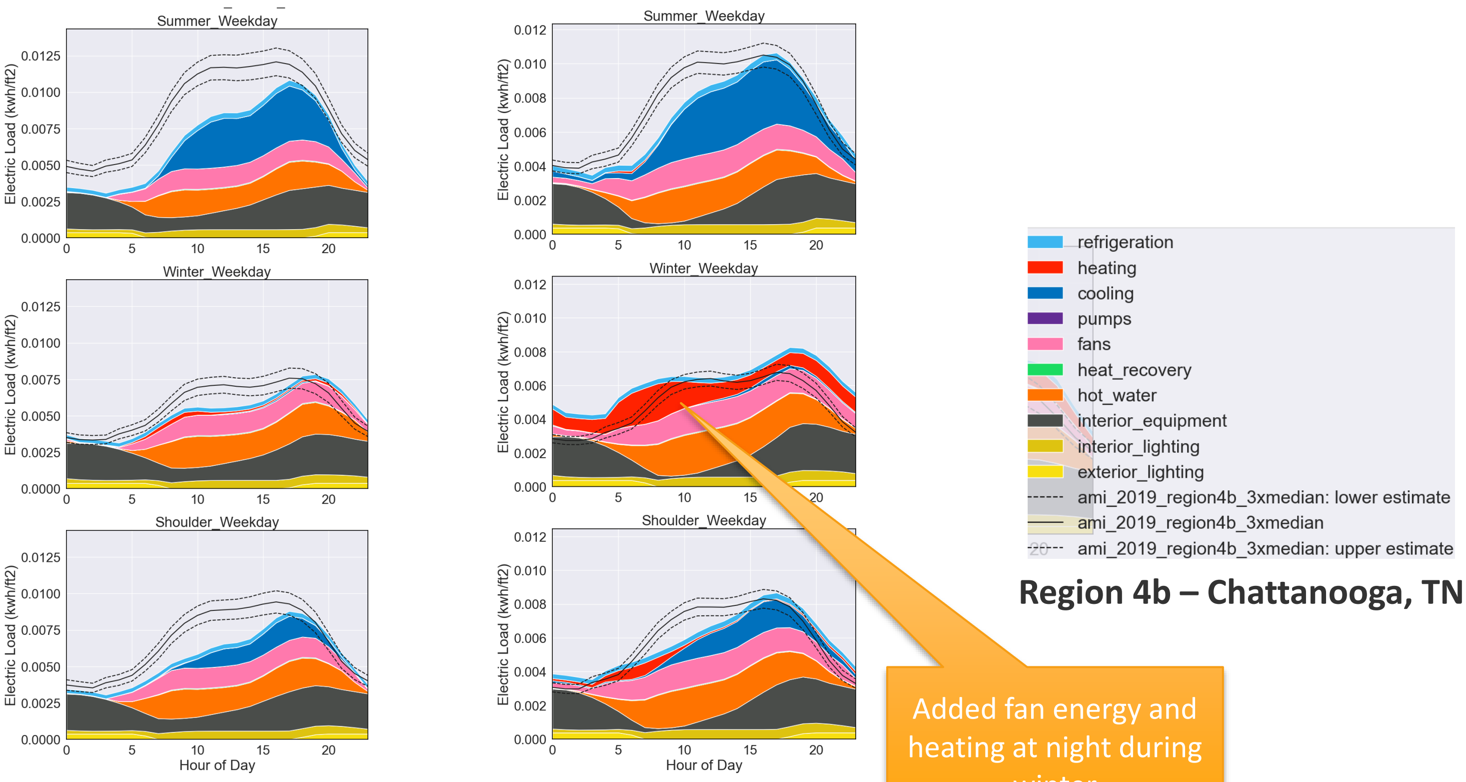
NaturalGas Heating Fuel by County



Electricity Heating Fuel by County



Impact: Spatial Distribution of Heating Fuels



Region 4b – Chattanooga, TN

Added fan energy and heating at night during winter

Before

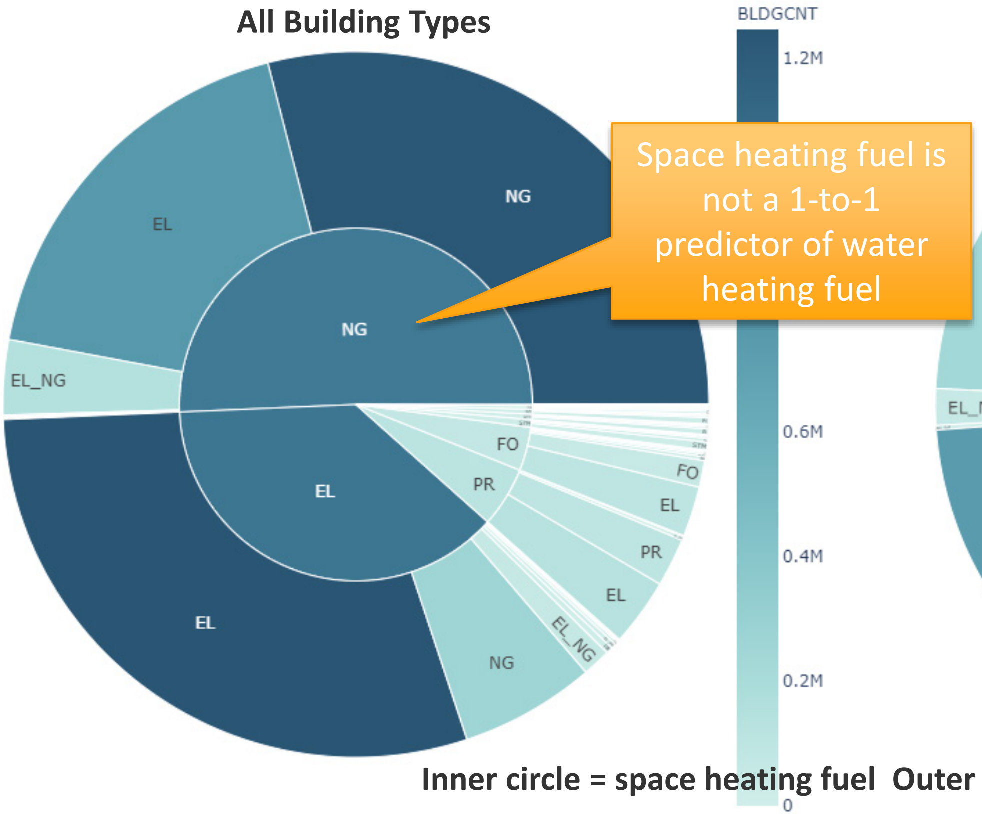
After

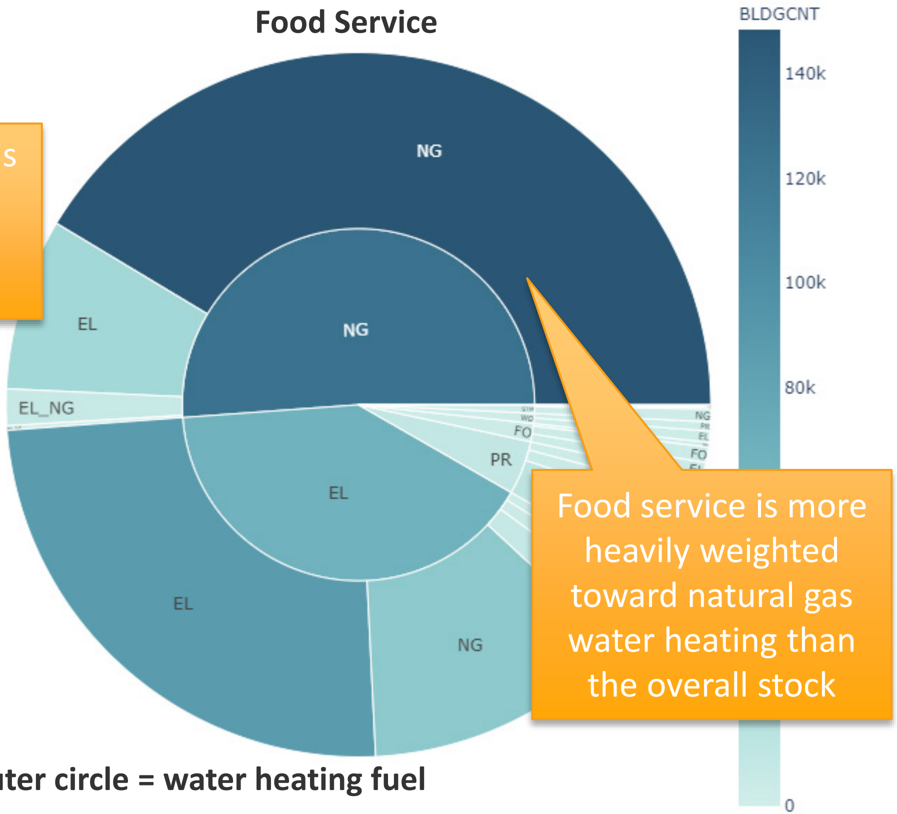
Full Service Restaurant

Update: Service Water Heating Fuels

Task	Affected Building Type	Methods
Update relationship between heating and service water heating fuels.	All buildings.	Previously, water heating fuel type was inferred directly from heating fuel type. An analysis of CBECS showed that for many buildings, this was not a good assumption. Probabilities of service water heating fuel as a function of each space heating fuel and building type were generated from the CBECS data.

Update: Service Water Heating Fuels

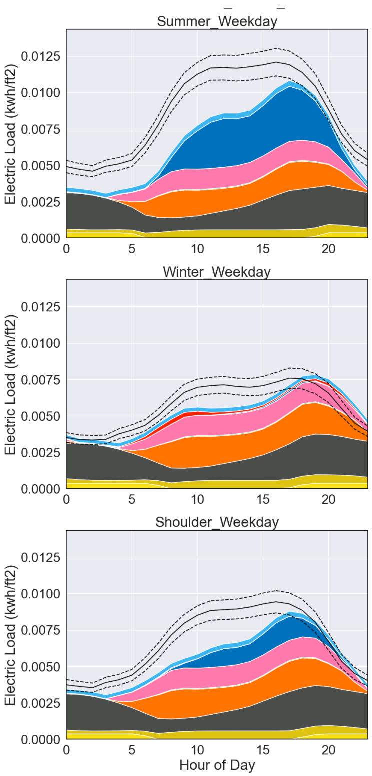




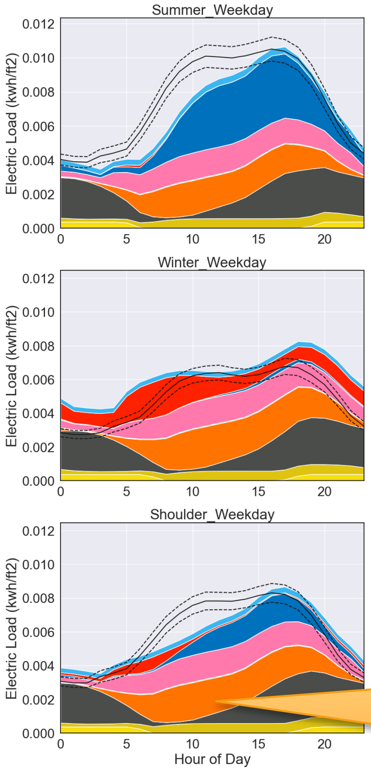
Inner circle = space heating fuel Outer circle = water heating fuel

NG = Natural Gas, EL = Electricity, PR = Propane, FO = Fuel Oil

Update: Service Water Heating Fuels



Before



After

Full Service Restaurant

Region 4b – Chattanooga, TN

Added electric water heating energy

Total Commercial Stock Status - AMI

Regional Total AMI Comparisons

- In the AMI datasets, the relative fraction of each building type does not represent the fraction that exists in the full population.
  - Biases in metadata availability for certain building types
  - For some utilities, we only got data for a fraction of the population
- Need to weight AMI for each building type in order to combine
  - Currently using nationwide weighting factors based on CBECS
- Total AMI has uncertainty because of necessity of weighting

Conclusion:

- **Limitations in AMI data make regional totals unreliable**
- **Therefore, don’t report them**

Total Commercial Stock Status - CBECS

CBECS Comparison

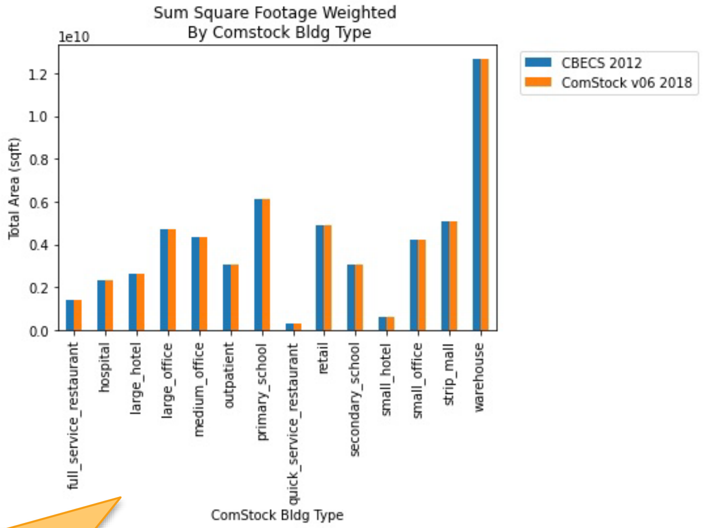
- CBECS 2012 is latest microdata available, while ComStock is modeling 2018
  - We decreased lighting end use from 2012 to 2018 (LEDs)
- CBECS 2018 consumption data not available until 2022 (per EIA manager)

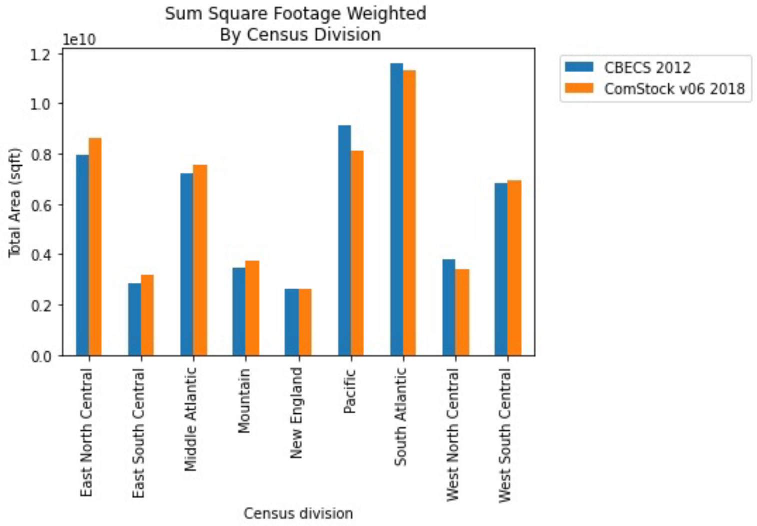
CBECS comparisons in this deck do not include all ComStock calibration changes described – awaiting full final national run results.

CBECS Comparison – Floor Area

ComStock results are scaled to match floor area in CBECS by building type

- Scaling factors are calculated on a national basis

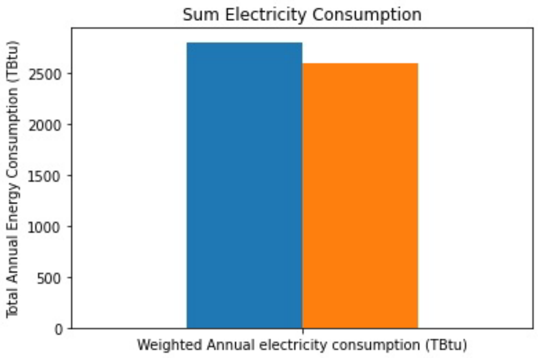


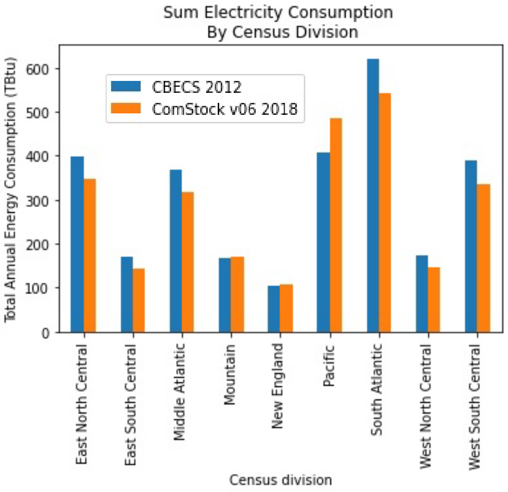


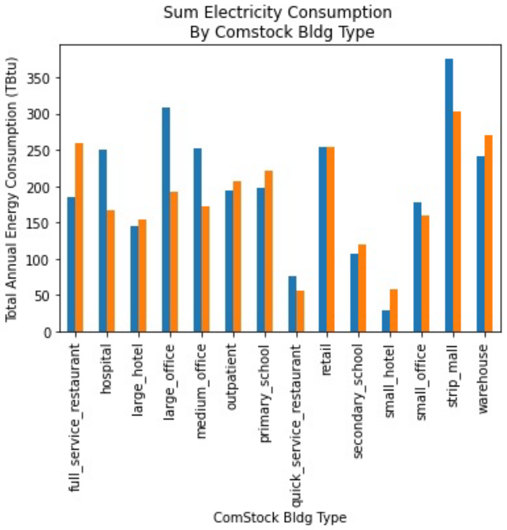
Same areas because ComStock scaled by floor area per building type nationally

CBECS Comparison - Electricity

- Nationally and by census division, ComStock is under-predicting electricity
- Compensating errors:
  - Many building types slightly over-estimated
  - Offices should be improved by data center and EPD changes

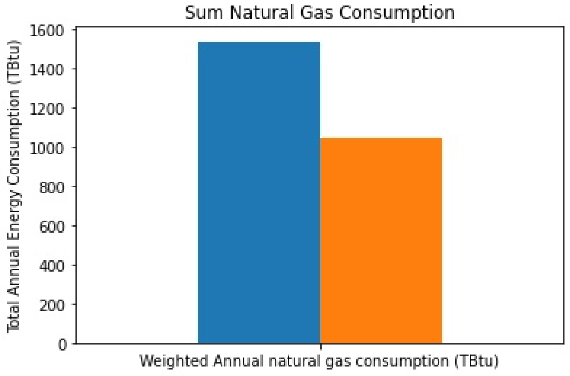


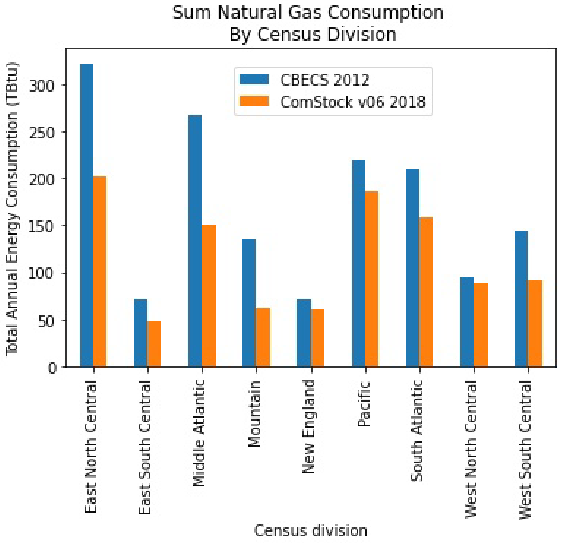


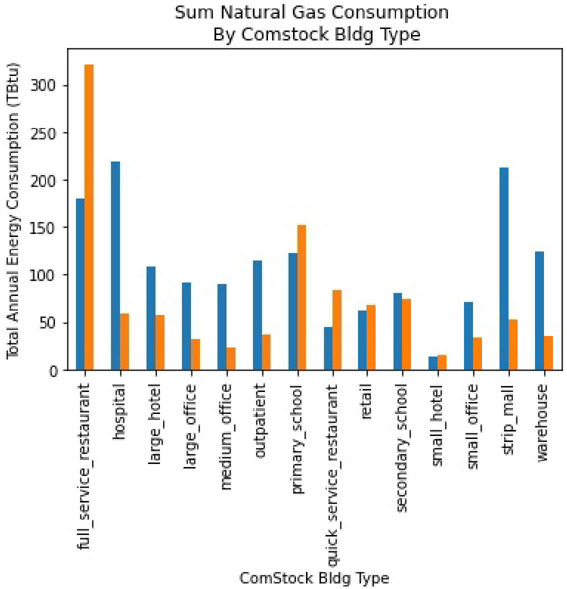


CBECS Comparison – Natural Gas

- Not the focus of EULP, but important for future electrification analysis
- Nationally and by census division, ComStock is under-predicting gas
- Most building types significantly underestimated
- Full-service restaurants significantly overestimated
- Heating/water heating fuel changes may improve in final run







Total Commercial Stock Status - EIA

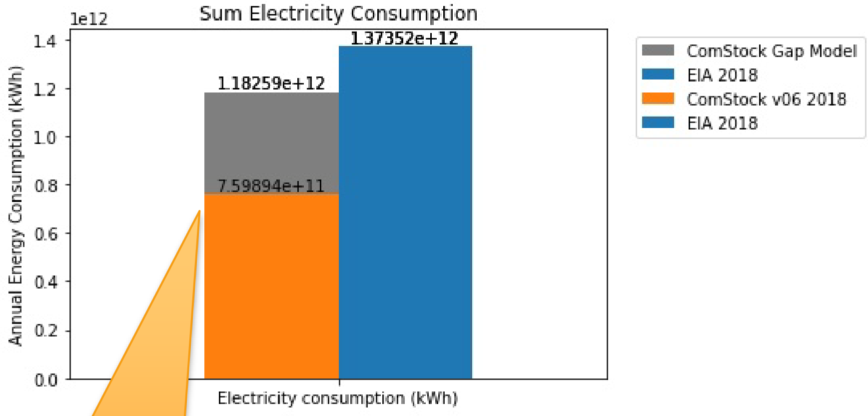
EIA Comparison

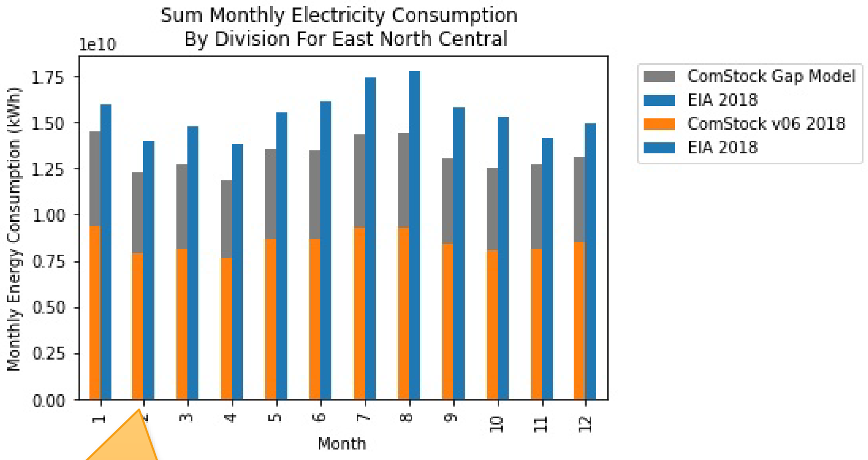
- EIA Forms 861 M (Electricity) and 176 (Natural Gas) reported by utilities
- Data available from 2018 to match ComStock run (latest CBECS was 2012)
- ~30% difference between CBECS and EIA 176 “commercial” natural gas in 2012
  - Per EIA, likely due to discrepancies in classifying commercial vs. industrial load
  - Difference in electricity consumption is less dramatic
  - Highlights the difficulty in defining “the truth” for commercial calibration

EIA comparisons in this deck do not include all ComStock calibration changes described – awaiting full final national run results.

EIA Comparison – Electricity

ComStock Gap Model represents buildings not modeled in ComStock – from CBECS



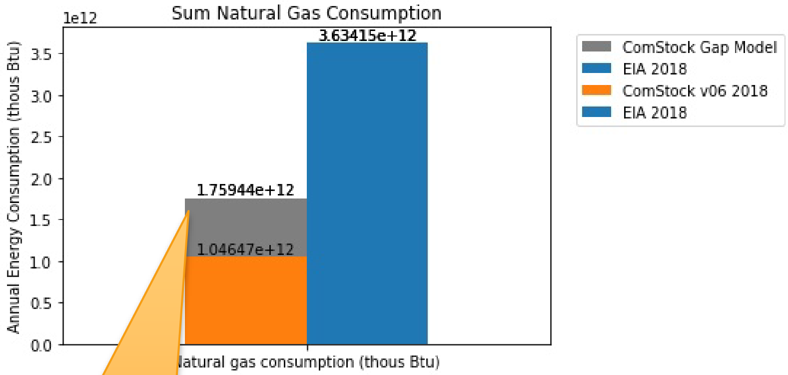


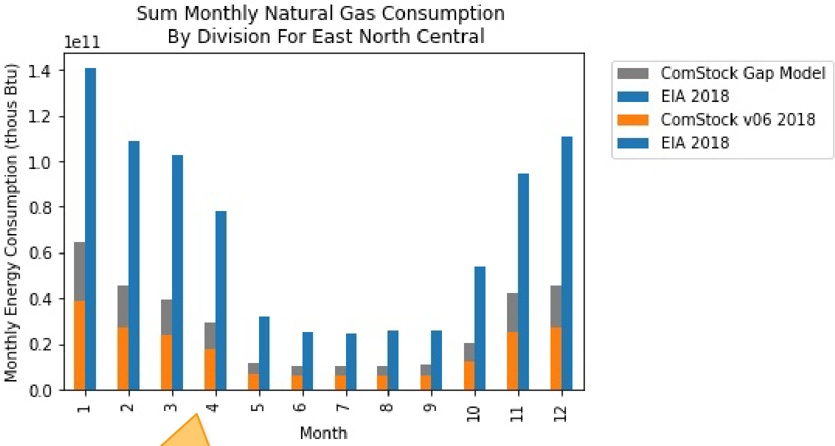
ComStock is probably a little low; matches takeaway from CBECS comparison

ComStock monthly patterns generally match EIA data (example census division data)

EIA Comparison – Natural Gas

ComStock Gap Model represents buildings not modeled in ComStock – from CBECS
Natural gas was not focus of EULP, but important for electrification analyses



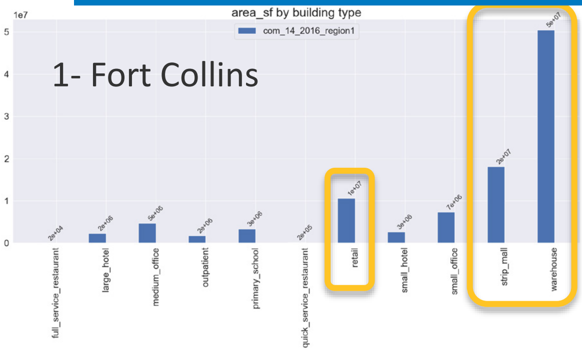


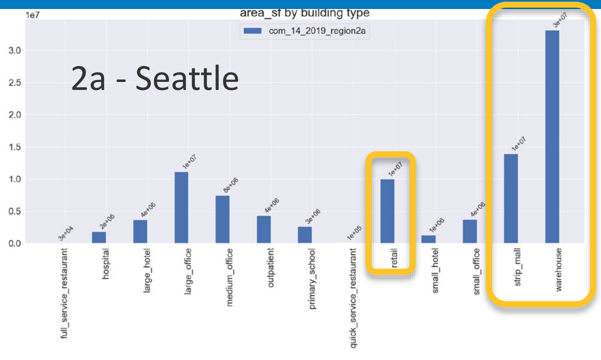
ComStock is likely very low on natural gas; matches takeaway from CBECS

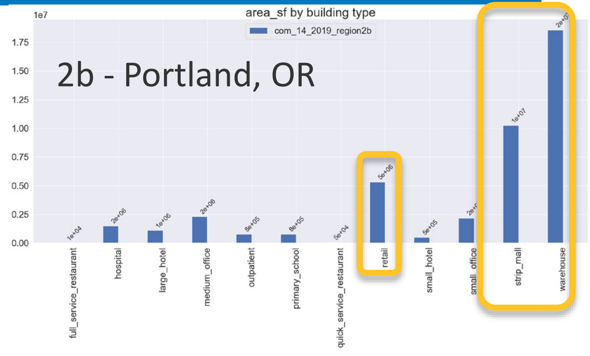
Monthly pattern of error shows some issues with baseload (water heating, cooking) but bigger issue is with weather-responsive (heating)

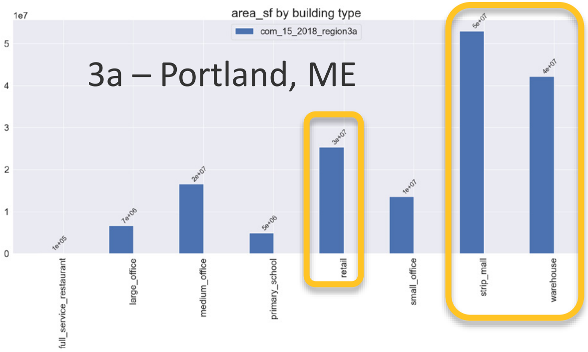
Building Type Focus

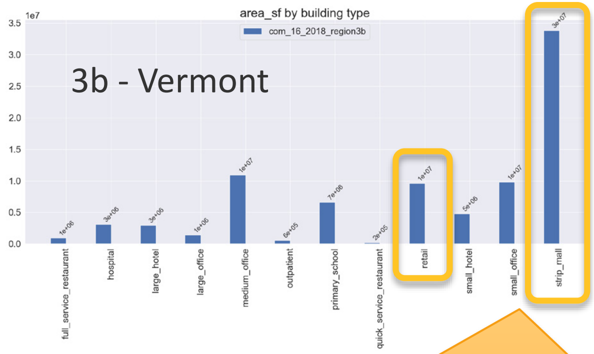
Dominant Building Types by Area

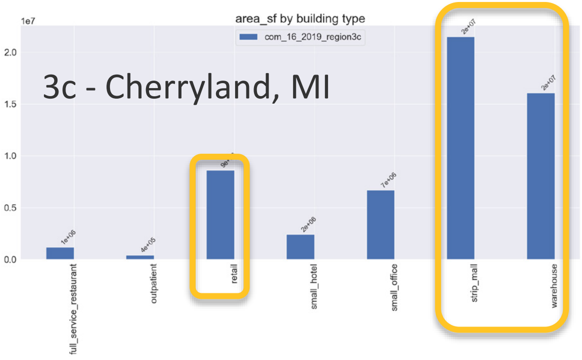










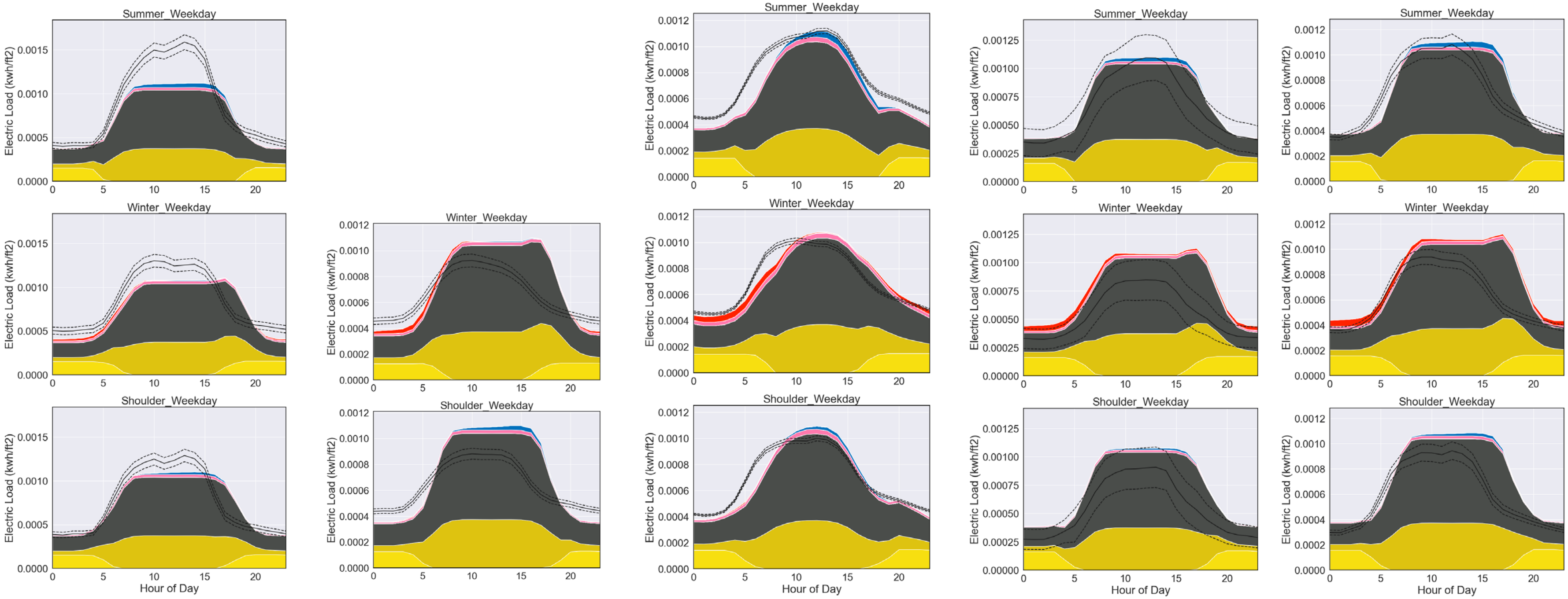


Warehouse, Strip Mall + Retail generally dominate building area for all datasets

Warehouse

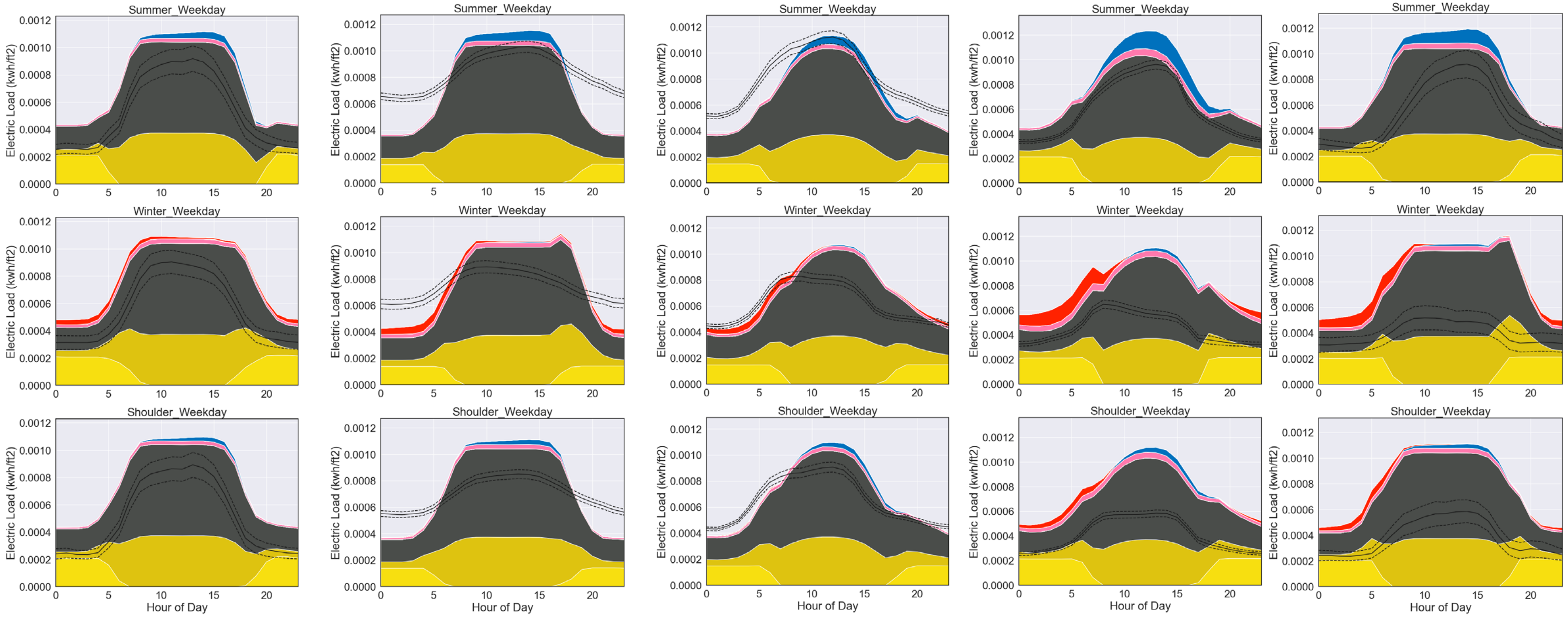
Warehouse - AMI

1- Fort Collins | 2a - Seattle | 2b - Portland, OR | 3a – Portland, ME | 3b - Vermont

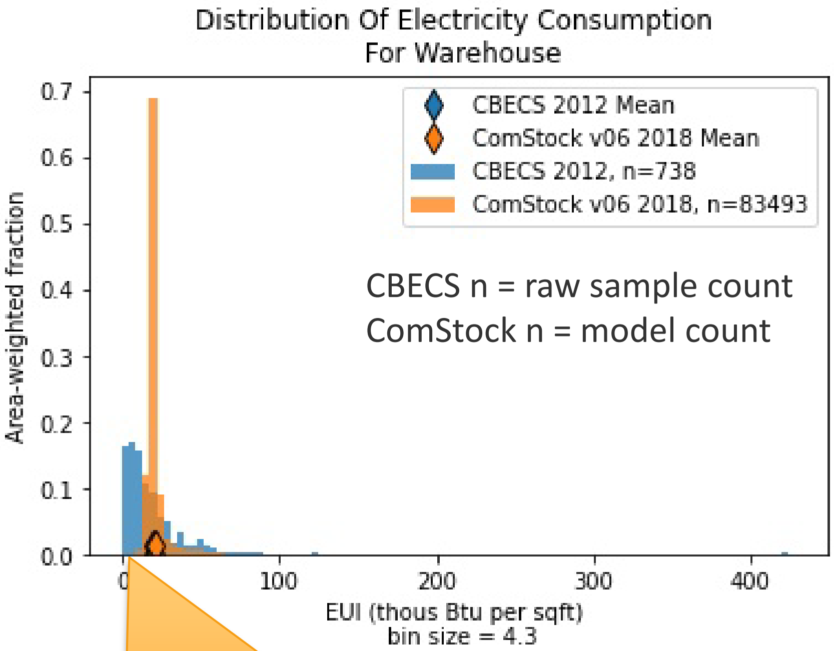


Warehouse - AMI

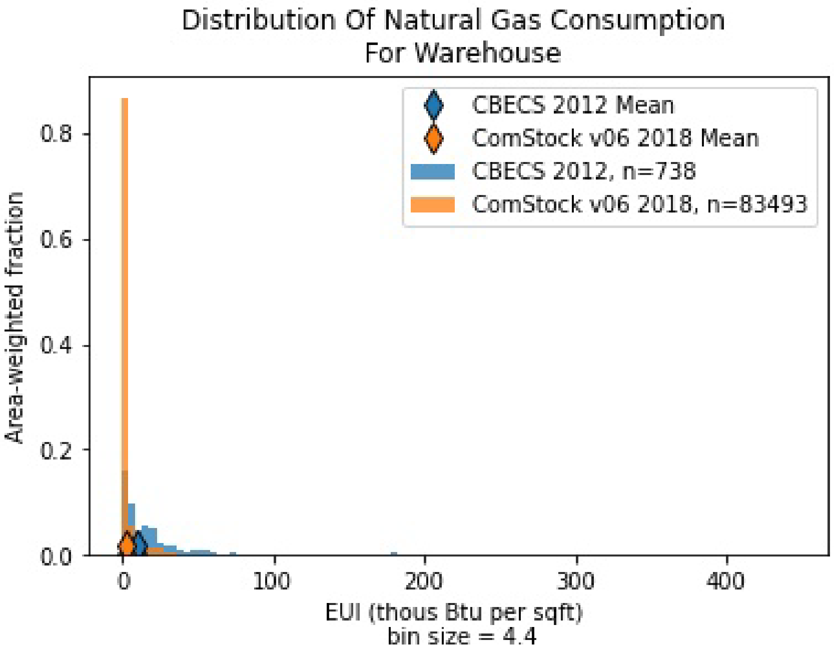
3c - Cherryland, MI | 4a - Maryland | 4b - Tennessee | 4c – Tallahassee, FL | 4d – Horry, SC



Warehouse – CBECS



CBECS n = raw sample count
ComStock n = model count

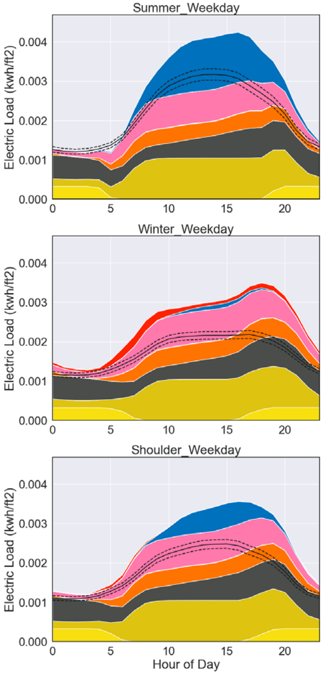


Missing the very low EUI fully unconditioned storage-only warehouses?

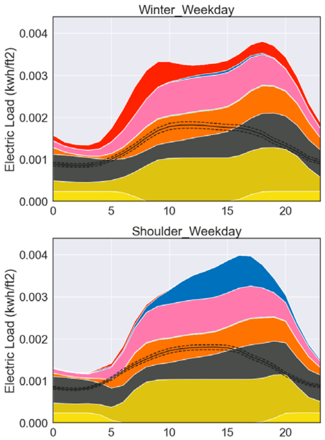
Strip Mall

Strip Mall - AMI

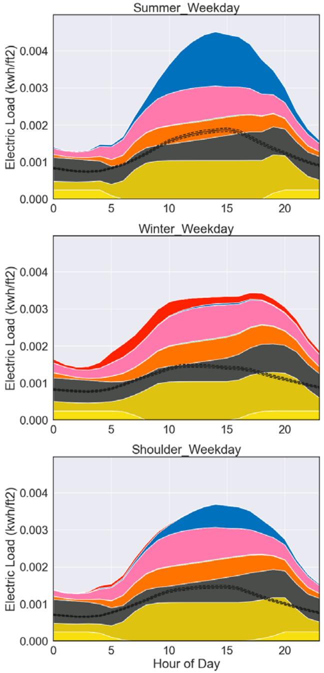
1- Fort Collins



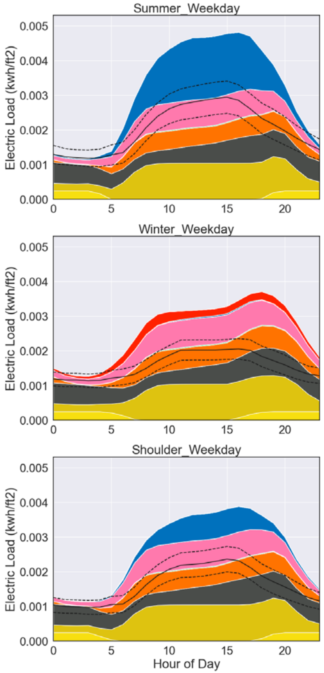
2a - Seattle



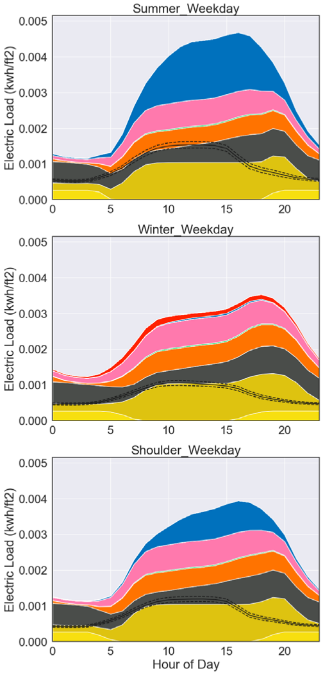
2b - Portland, OR



3a – Portland, ME

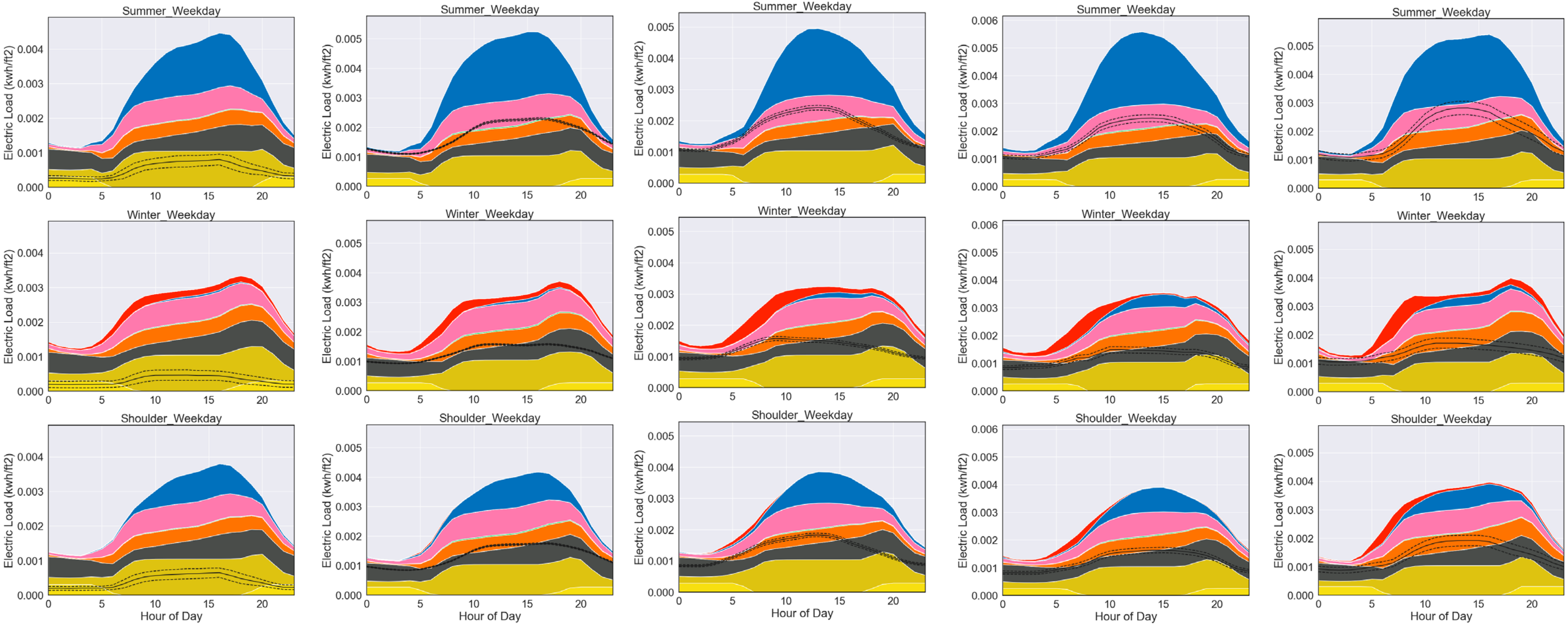


3b - Vermont

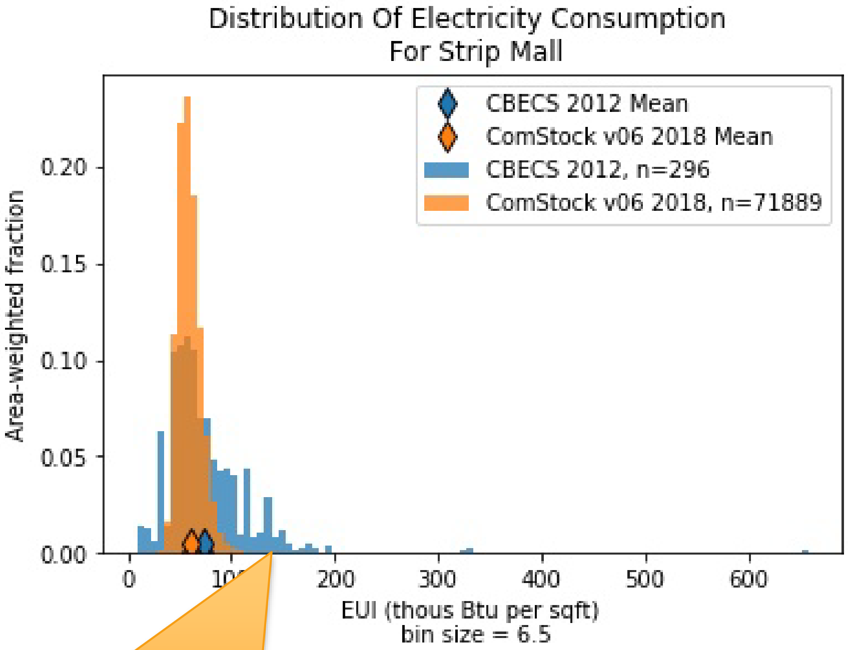


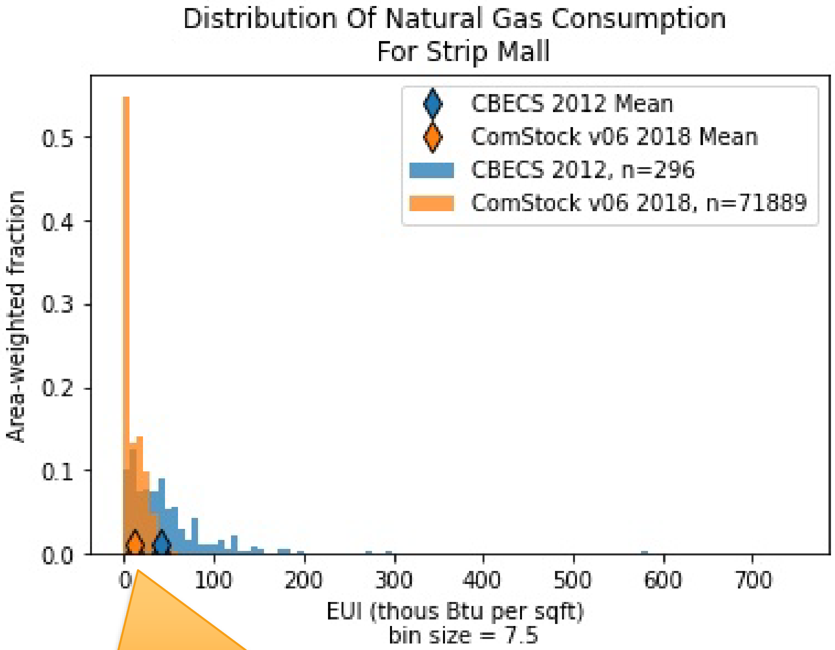
Strip Mall - AMI

3c - Cherryland, MI | 4a - Maryland | 4b - Tennessee | 4c – Tallahassee, FL | 4d – Horry, SC



Strip Mall – CBECS





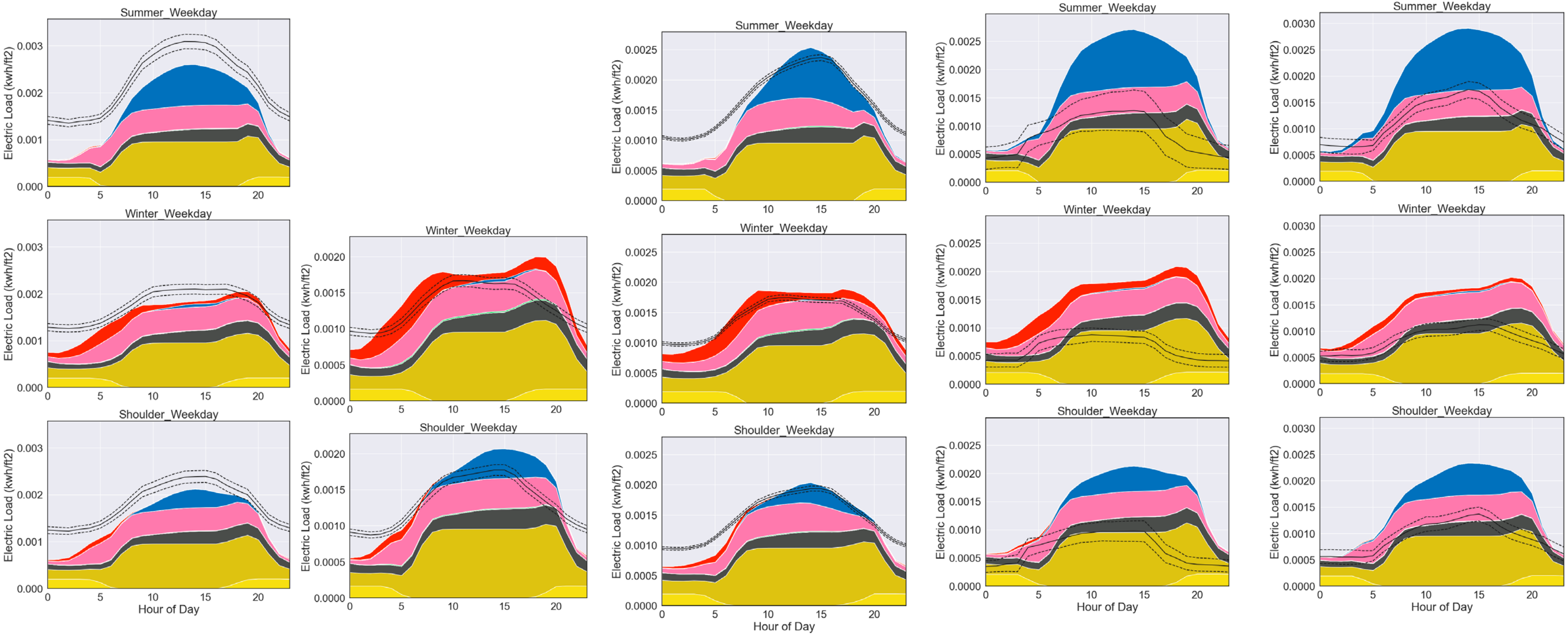
Will have higher EUIs in final run because of restaurant addition to strip malls

May have too many unheated buildings?

Retail

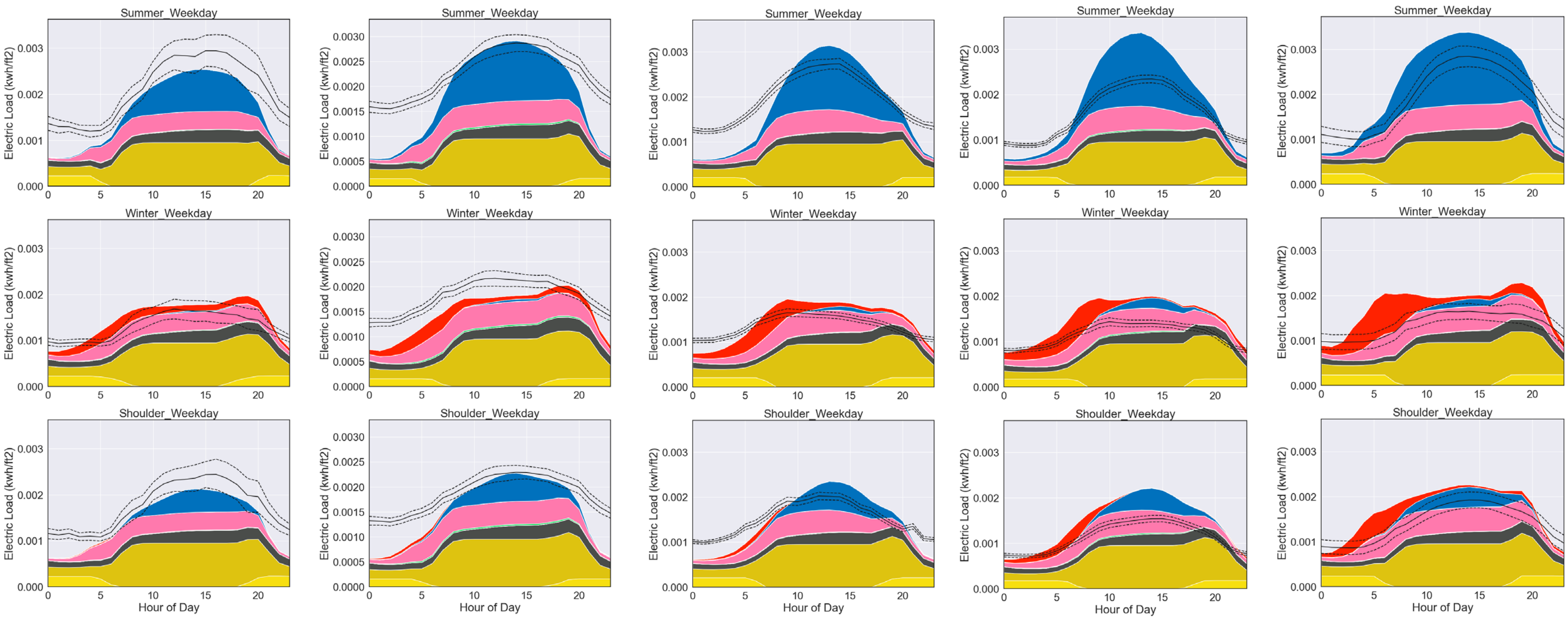
Retail - AMI

1- Fort Collins | 2a - Seattle | 2b - Portland, OR | 3a – Portland, ME | 3b - Vermont

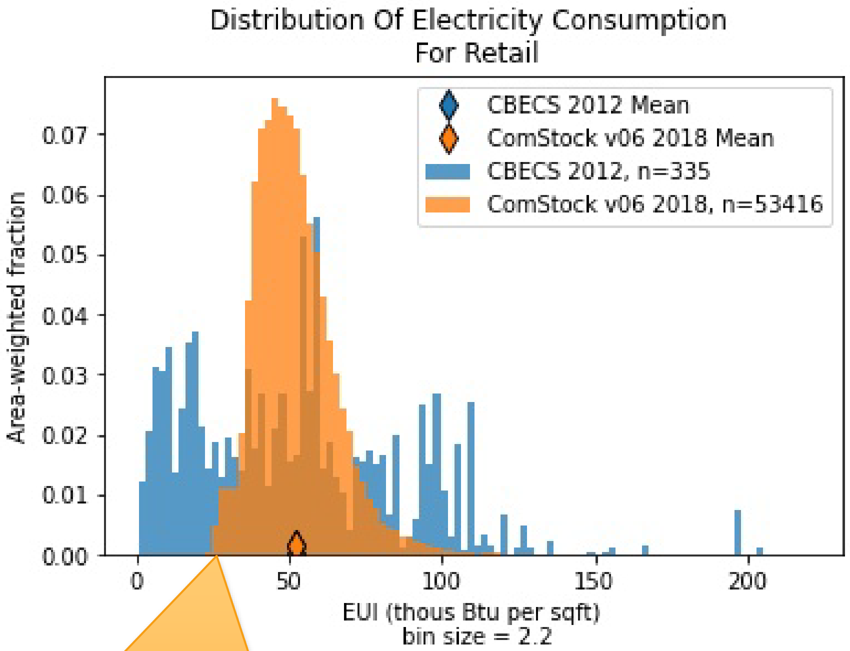


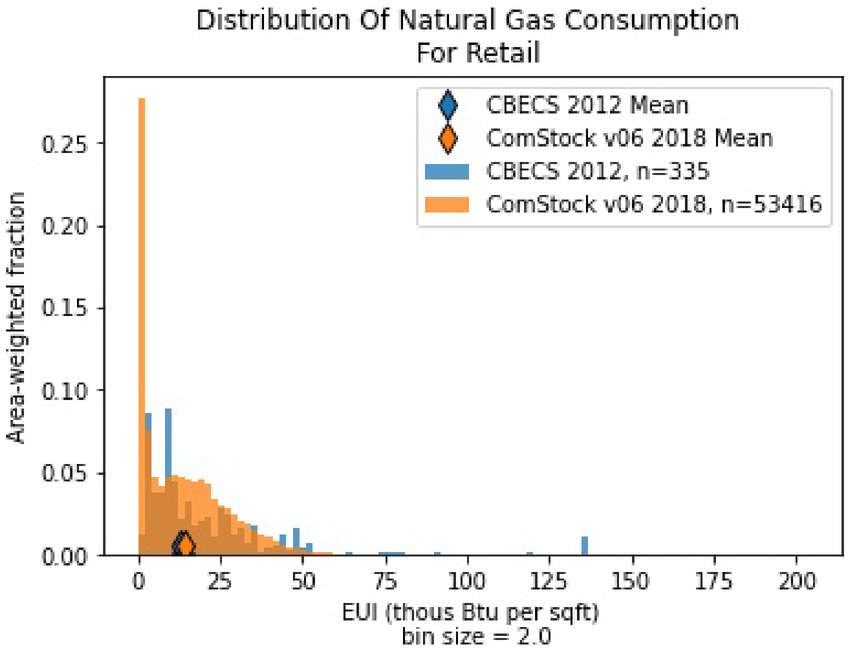
Retail - AMI

3c - Cherryland, MI | 4a - Maryland | 4b - Tennessee | 4c – Tallahassee, FL | 4d – Horry, SC



Retail – CBECS

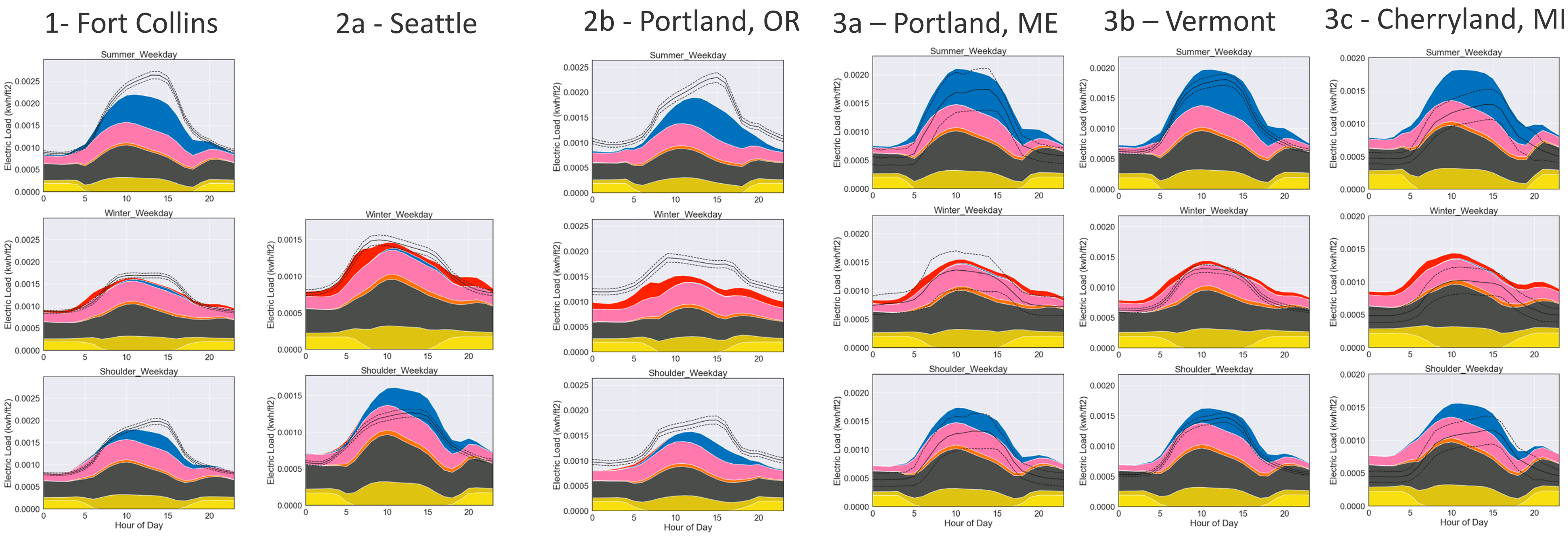




Causes of low EUIs unknown; may need to revisit distributions of hours of operation.

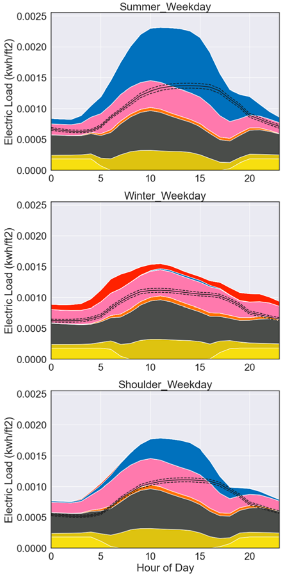
Small Office

Small Office - AMI

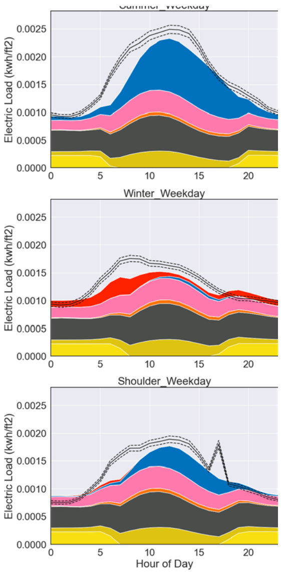


Small Office - AMI

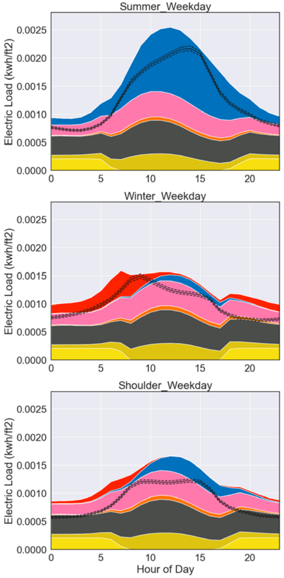
4a – DC



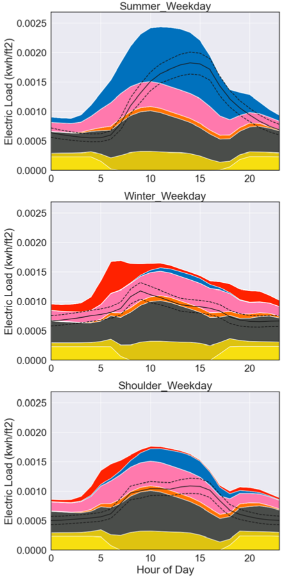
4b - Chattanooga



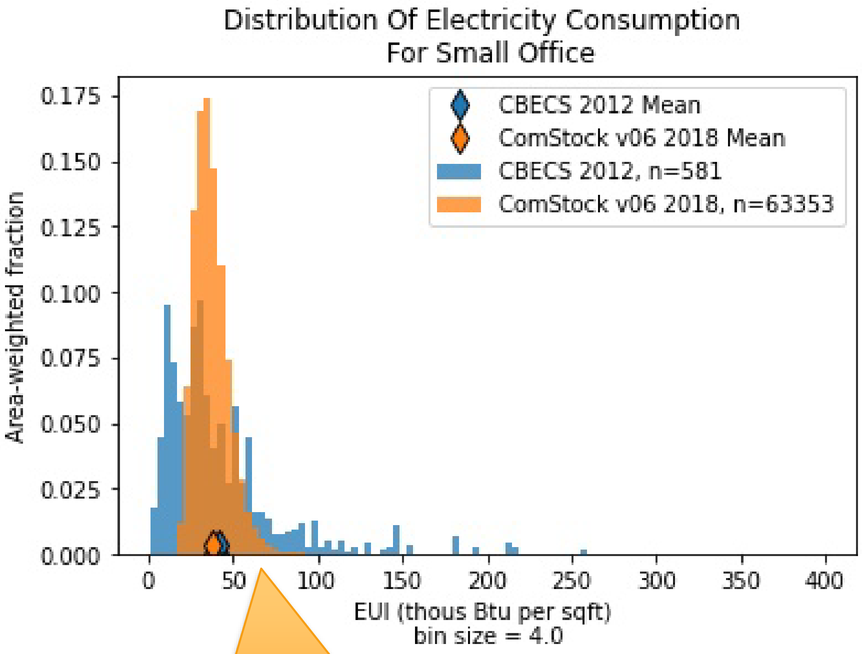
4c – Tallahassee, FL

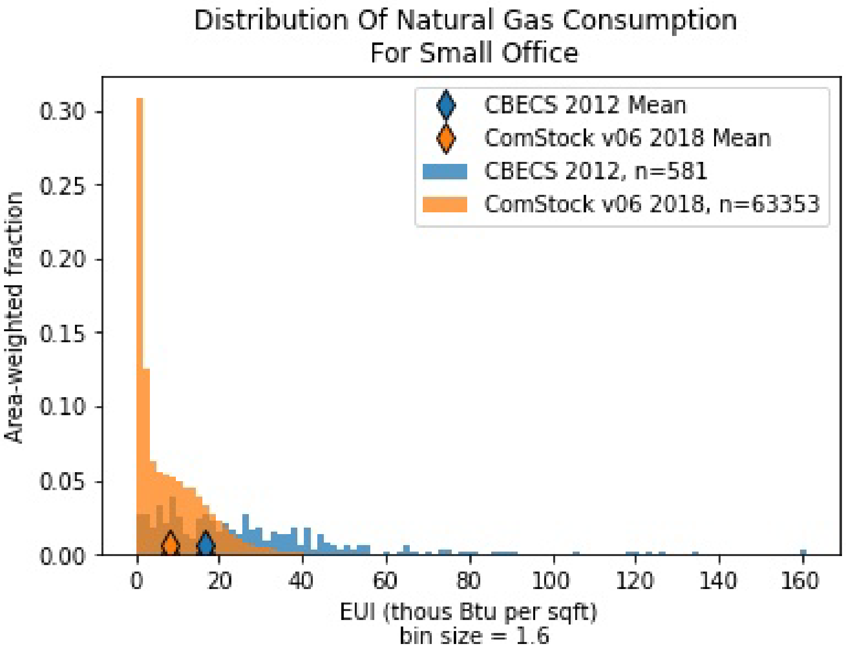


4d – Horry County, SC



Small Office – CBECS





ComStock is missing the higher EUIs

Tracking Quantities of Interest

QOI Changes

- Too much uncertainty in previously-shown regional total QOIs
- Working on QOIs per building type & AMI set
    - This will be a lot of QOIs (~2,000)
    - Working on how to summarize them

Conclusions

Conclusions

1. Results are decent compared to all three datasets (electricity)
   - EUI distributions are reasonable
   - Load shape is reasonable
   - Census-division absolute totals are reasonable
2. We think that these load profiles are significantly better than what is currently available and widely used
3. At some point, there are limits to model refinement based on (truth & stock) data availability
4. Users can look at the results and determine suitability based on their own use cases – transparency

NREL
Transforming ENERGY

Residential Region 5 Calibration

Rajendra Adhikari, Ph.D.
Anthony D. Fontanini, Ph.D.
Lixi Liu, Ph.D.
Andrew Speake
Eric Wilson

September 21, 2021

Residential Calibration Dimensions

ResStock adjusted for blended billing and calendar reporting

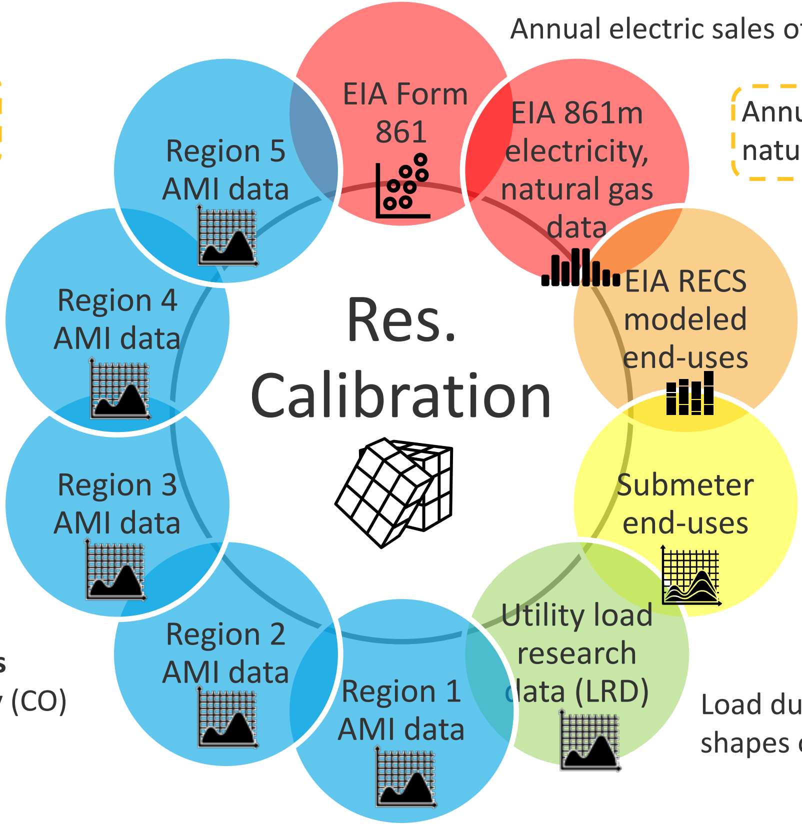
New

AMI data from **Vermont; Cherryland, MI**

AMI data from Electric Power Board of **Chattanooga, TN; Horry Electric (SC);** and City of **Tallahassee, FL**

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

AMI data from **Fort Collins** municipal service territory (CO)



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)

Sub-metered end-use load data (5 datasets)

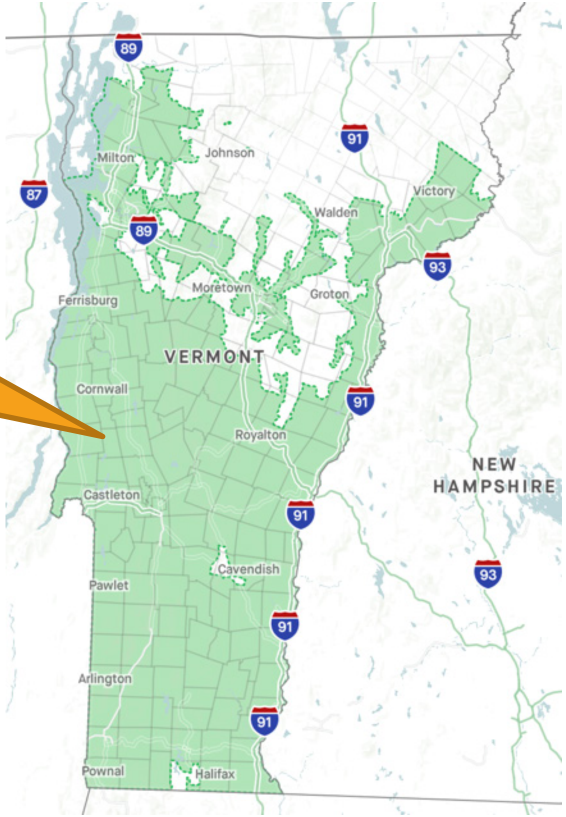
Load duration curves and seasonal load shapes of ~16 utilities around U.S.

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

Region 5 – Data from VEIC, Vermont

- Green Mountain Power Serves ~266,000 customers
- Investor-owned utility
- EULP used AMI data from 2018

AMI data is mainly from Green Mountain Power service territory



Building Type RECS	Saturation
Mobile Home	7.5%
Multi-Family with 2 - 4 Units	13.5%
Multi-Family with 5+ Units	10.4%
Single-Family Attached	3.3%
Single-Family Detached	65.3%

Building Type RECS	Percent Vacant
Mobile Home	13.9%
Multi-Family with 2 - 4 Units	17.9%
Multi-Family with 5+ Units	23.0%
Single-Family Attached	35.0%
Single-Family Detached	22.2%

Heating Fuel	Saturation
Electricity	6.2%
Fuel Oil	43.0%
Natural Gas	16.4%
Other Fuel	18.0%
Propane	16.0%

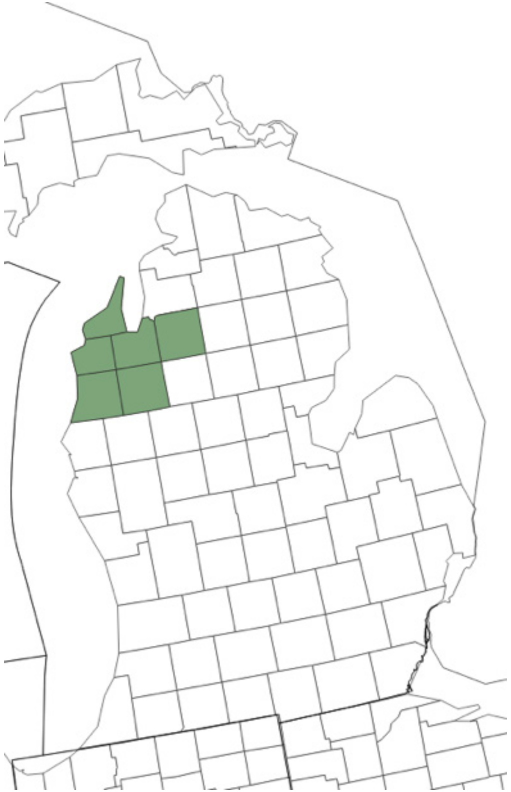
Region 5 – Cherryland Electric Co-op

- Serves ~33,000 customers
- Cooperative
- EULP used AMI data from 2019

Heating Fuel	Saturation
Electricity	11.67%
Fuel Oil	1.63%
Natural Gas	55.95%
None	0.70%
Other Fuel	9.85%
Propane	20.19%

Building Type RECS	Saturation
Mobile Home	8.42%
Multi-Family with 2 - 4 Units	3.51%
Multi-Family with 5+ Units	7.29%
Single-Family Attached	2.37%
Single-Family Detached	78.42%

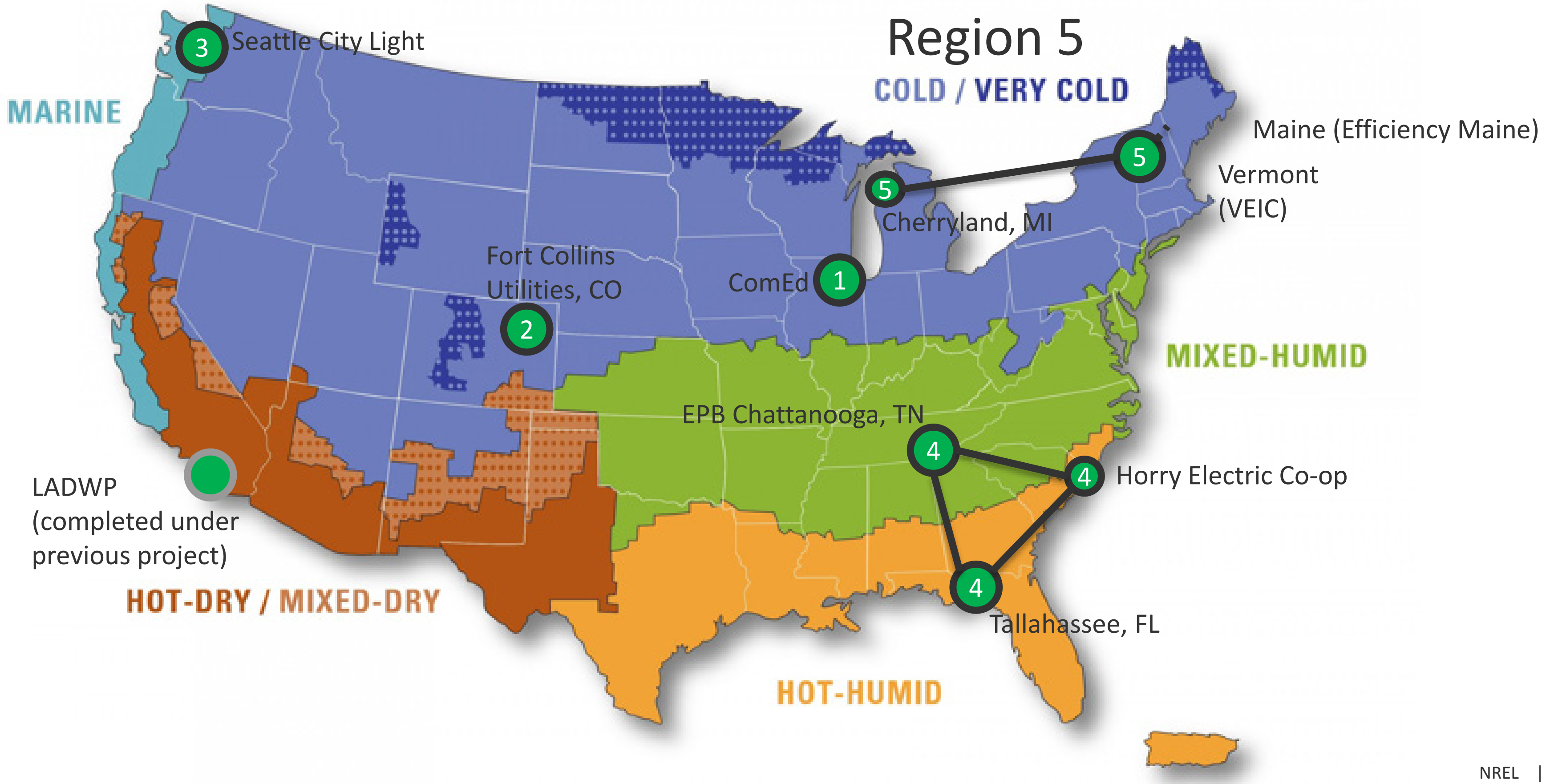
Building Type RECS	Percent Vacant
Mobile Home	35.76%
Multi-Family with 2 - 4 Units	34.76%
Multi-Family with 5+ Units	24.74%
Single-Family Attached	41.46%
Single-Family Detached	31.46%



Where did we end up?

Validation and load shape status

Summary of Residential AMI Calibration Regions



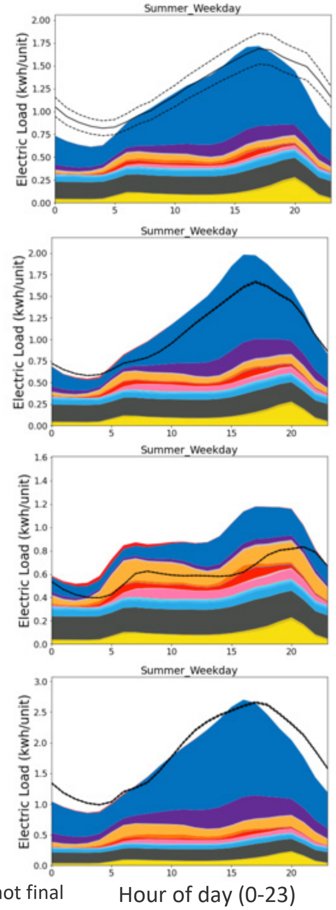
Seasonal end-use loads by day type

ComEd service territory

City of **Fort Collins** service territory

Seattle City Light service territory

Horry Electric service territory

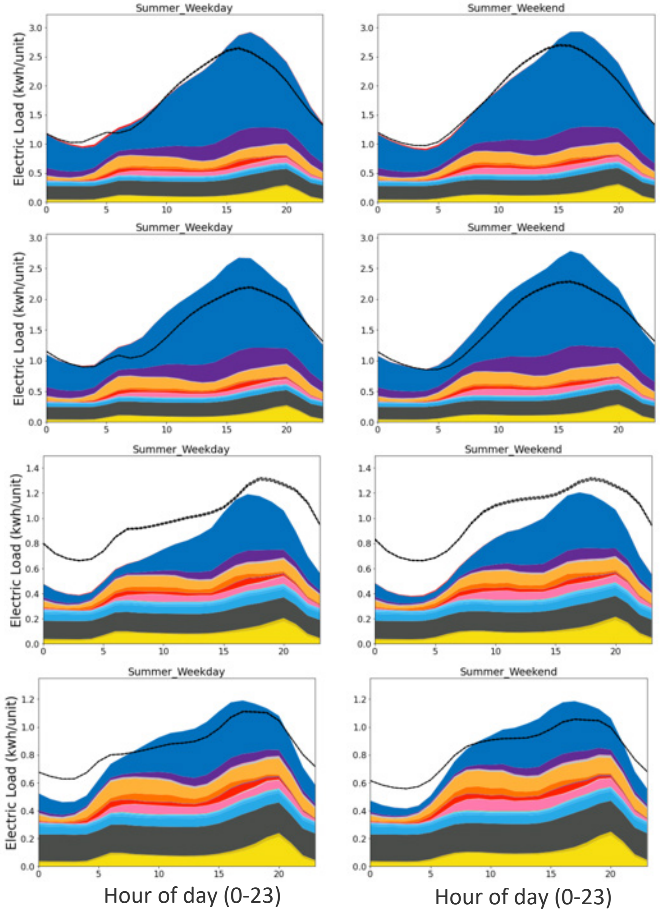


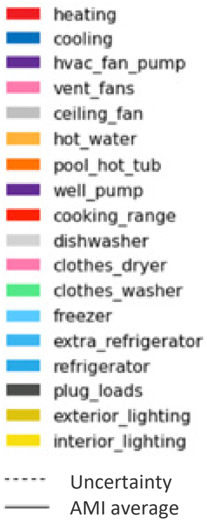
EPB, Chattanooga, TN service territory

City of **Tallahassee** service territory

Cherryland electric co-op service territory

Data from **VEIC**





LRD uncertainty is 10%
AMI uncertainty is the standard error.

*With correction; not final

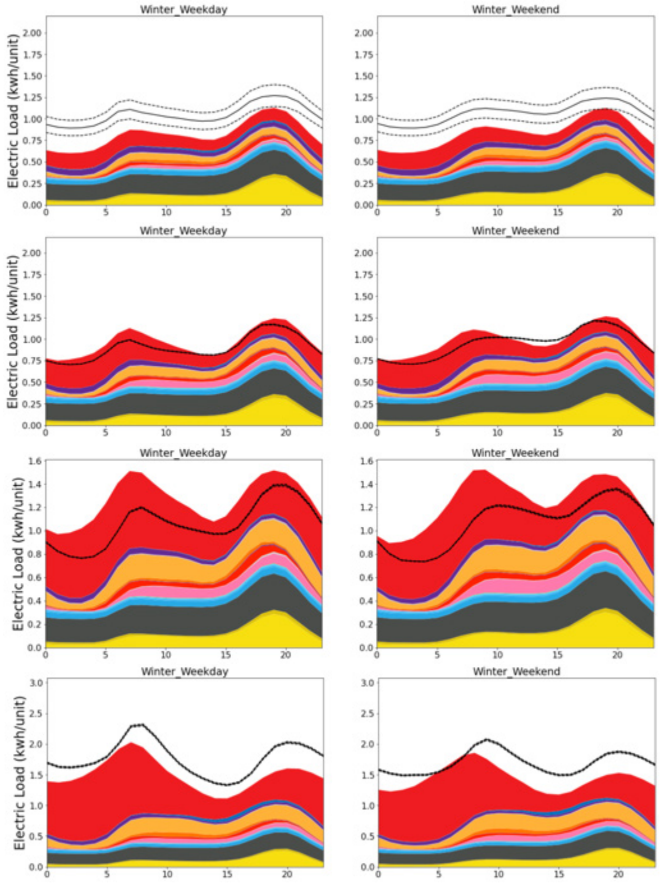
Seasonal end-use loads by day type

ComEd service territory

City of **Fort Collins** service territory

Seattle City Light service territory

Horry Electric service territory



Hour of day (0-23)

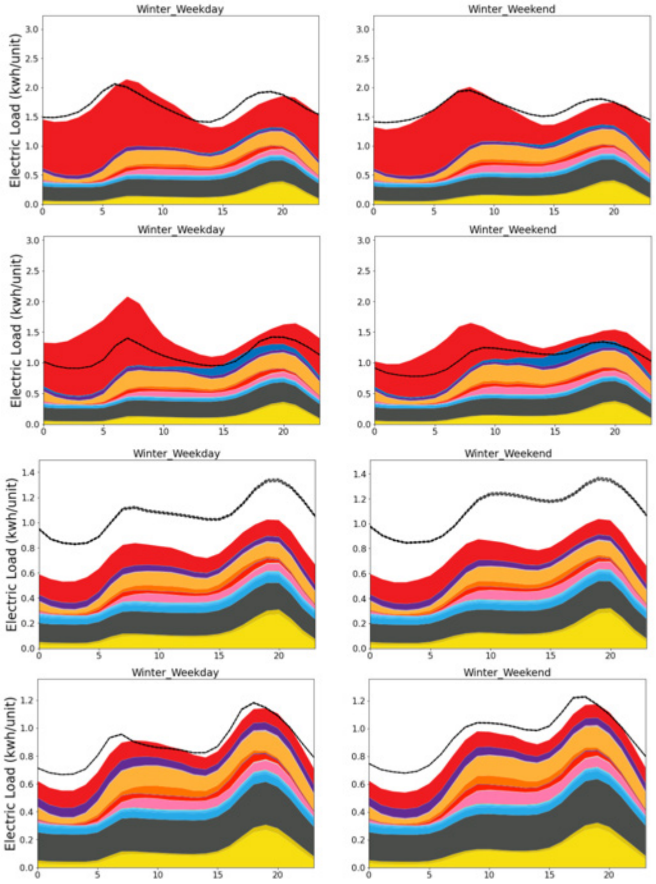
Hour of day (0-23)

EPB, Chattanooga, TN service territory

City of **Tallahassee** service territory

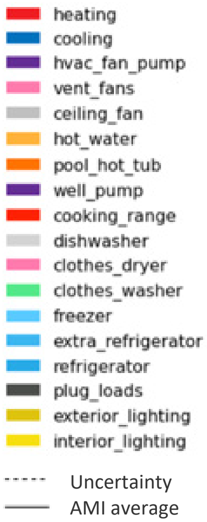
Cherryland electric co-op service territory

Data from **VEIC**



Hour of day (0-23)

Hour of day (0-23)



LRD uncertainty is 10%
AMI uncertainty is the standard error.

*With correction; not final

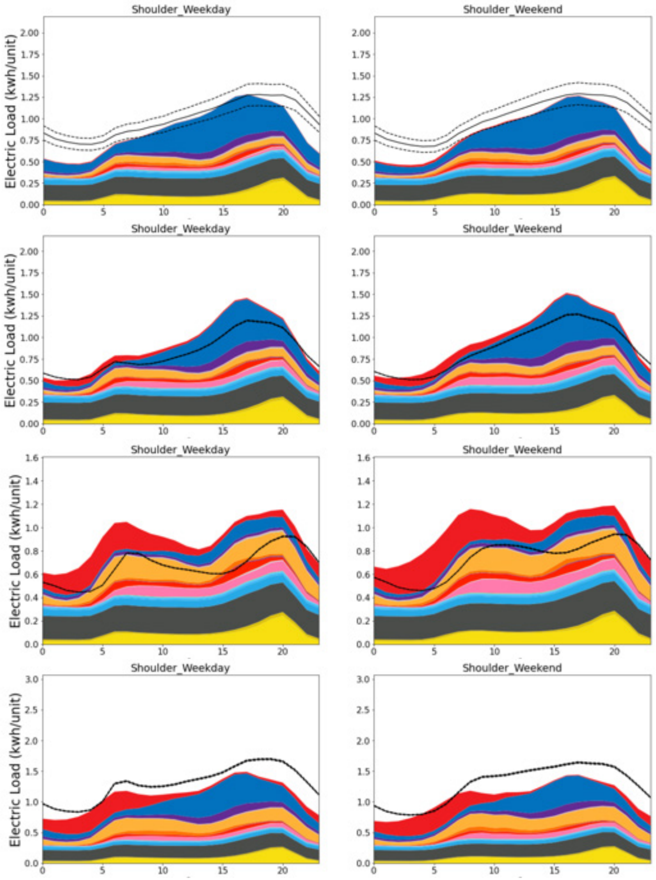
Seasonal end-use loads by day type

ComEd service territory

City of **Fort Collins** service territory

Seattle City Light service territory

Horry Electric service territory

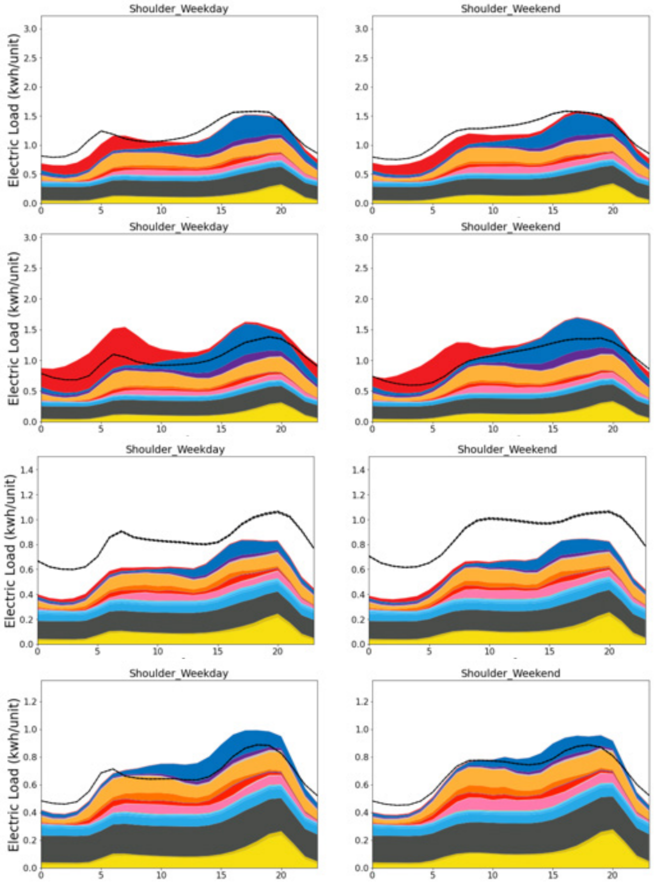


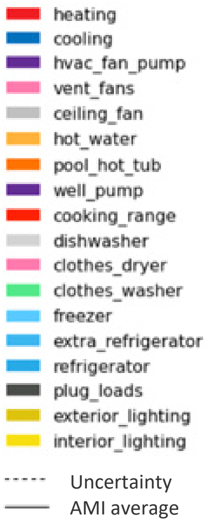
EPB, Chattanooga, TN service territory

City of **Tallahassee** service territory

Cherryland electric co-op service territory

Data from **VEIC**





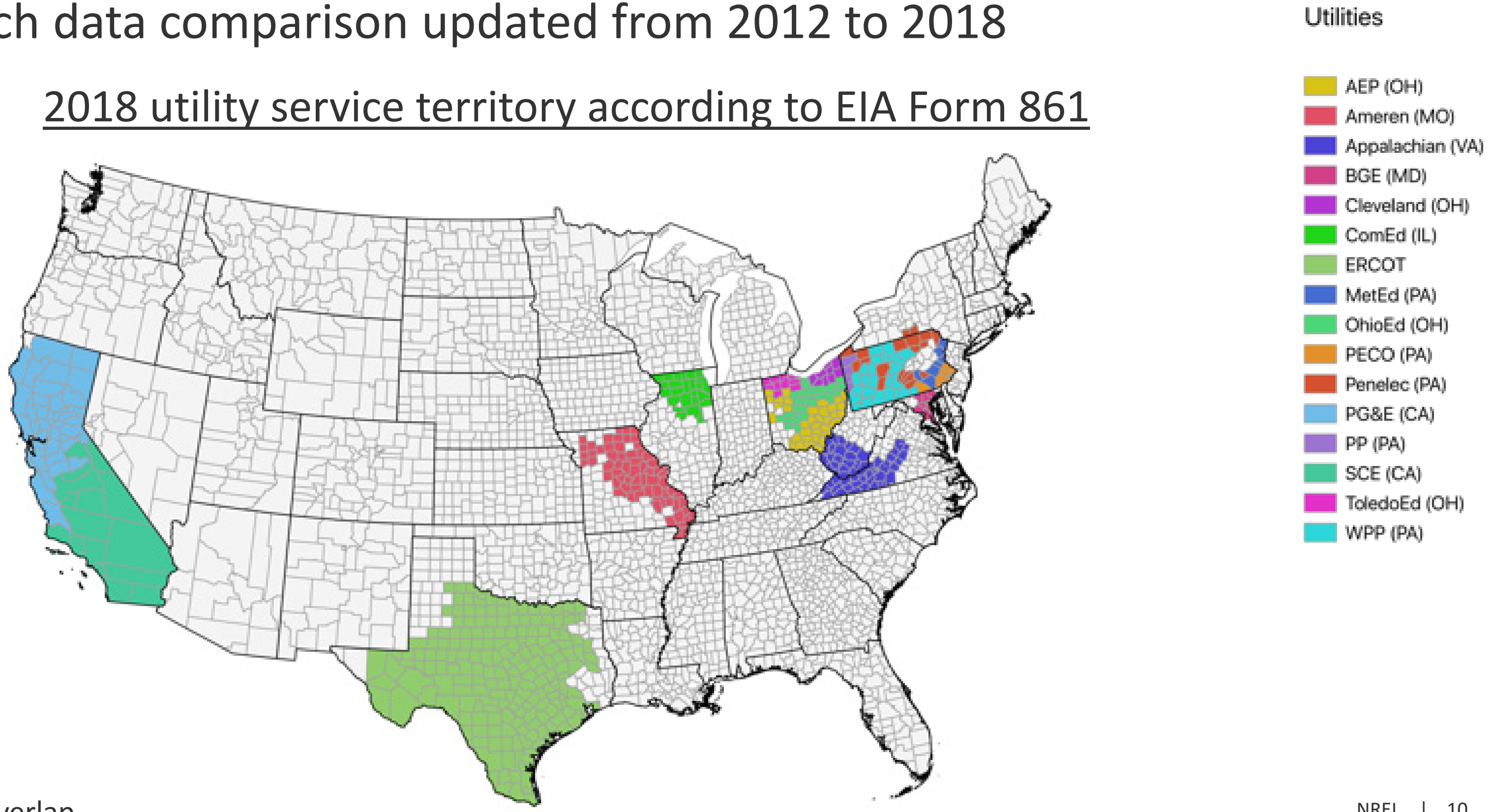
LRD uncertainty is 10%
AMI uncertainty is the standard error.

*With correction; not final

2018 Load Research Data Comparisons

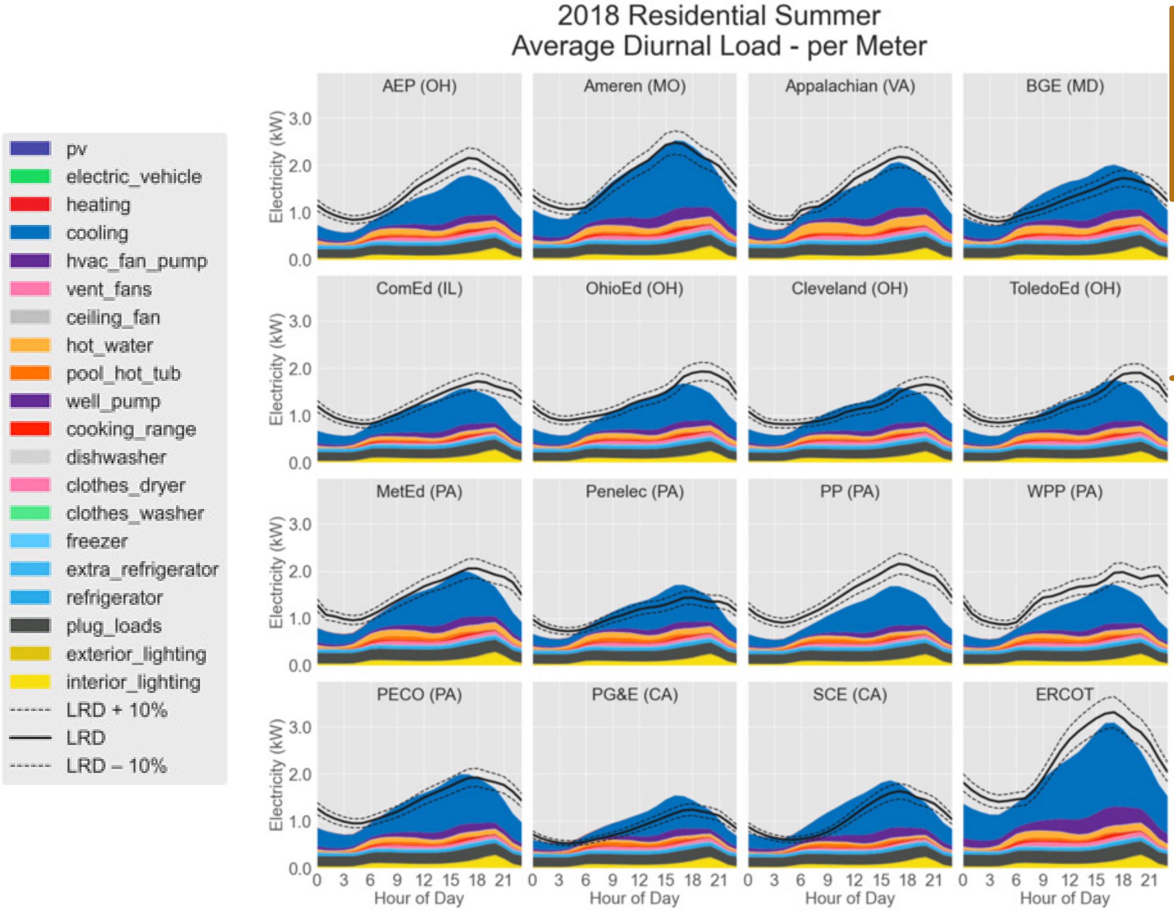
Load research data comparison updated from 2012 to 2018

2018 utility service territory according to EIA Form 861



*Service territories may overlap

2018 Load Research Data Comparisons

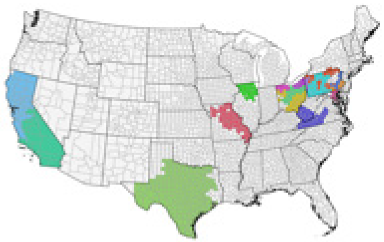


Agreement improved significantly from project start, despite not focusing on these regions for calibration!

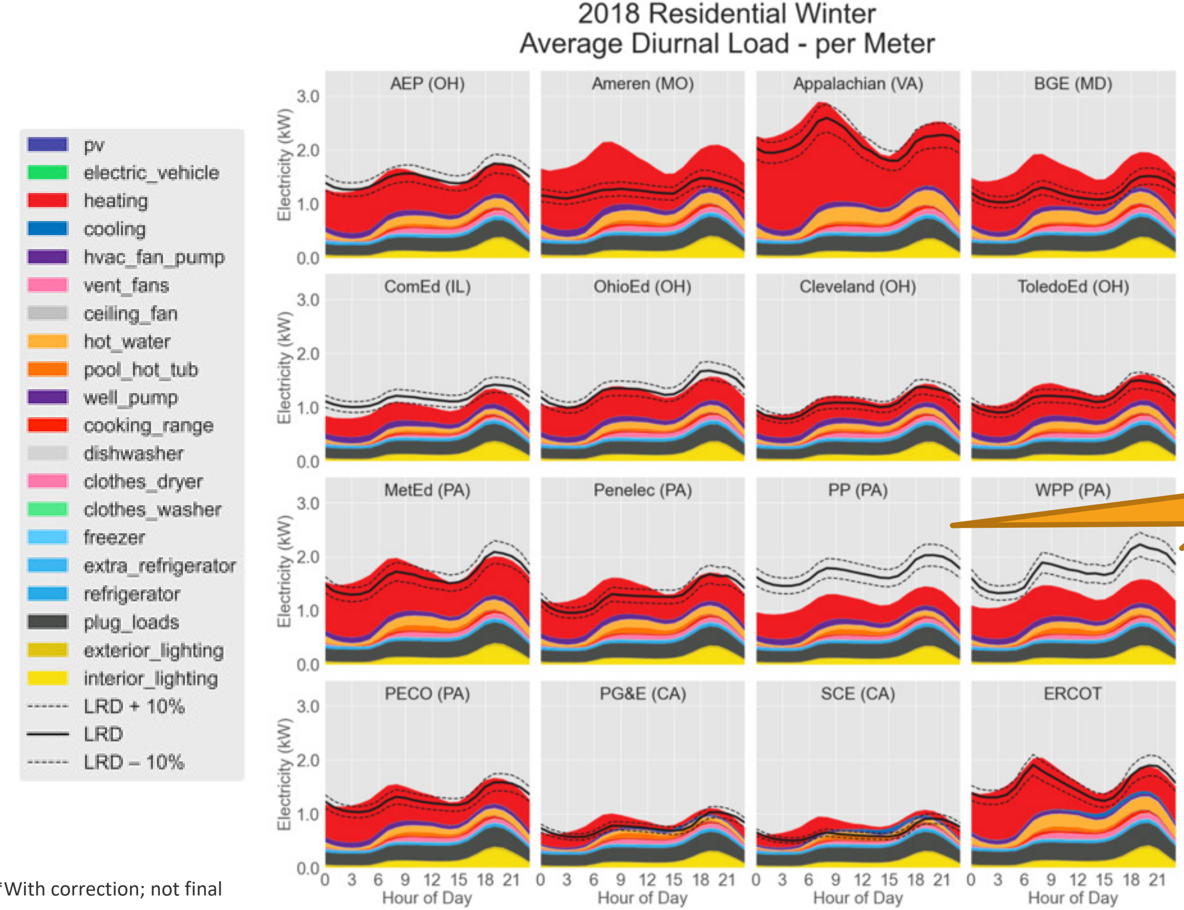
Time shift in some LRD sets

Utilities

- AEP (OH)
- Ameren (MO)
- Appalachian (VA)
- BGE (MD)
- Cleveland (OH)
- ComEd (IL)
- ERCOT
- MetEd (PA)
- OhioEd (OH)
- PECO (PA)
- Penelec (PA)
- PG&E (CA)
- PP (PA)
- SCE (CA)
- ToledoEd (OH)
- WPP (PA)

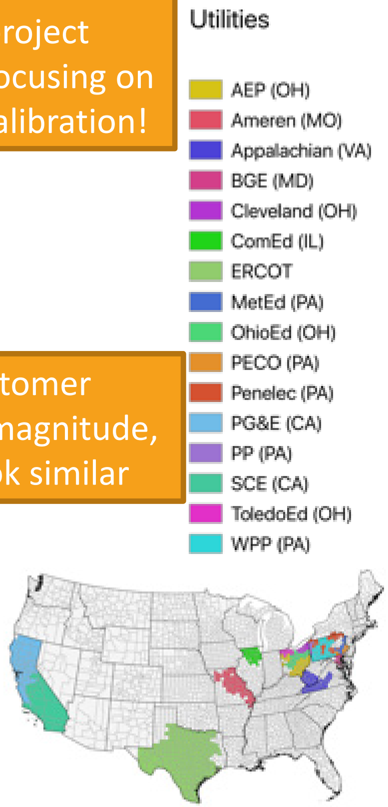


2018 Load Research Data Comparisons



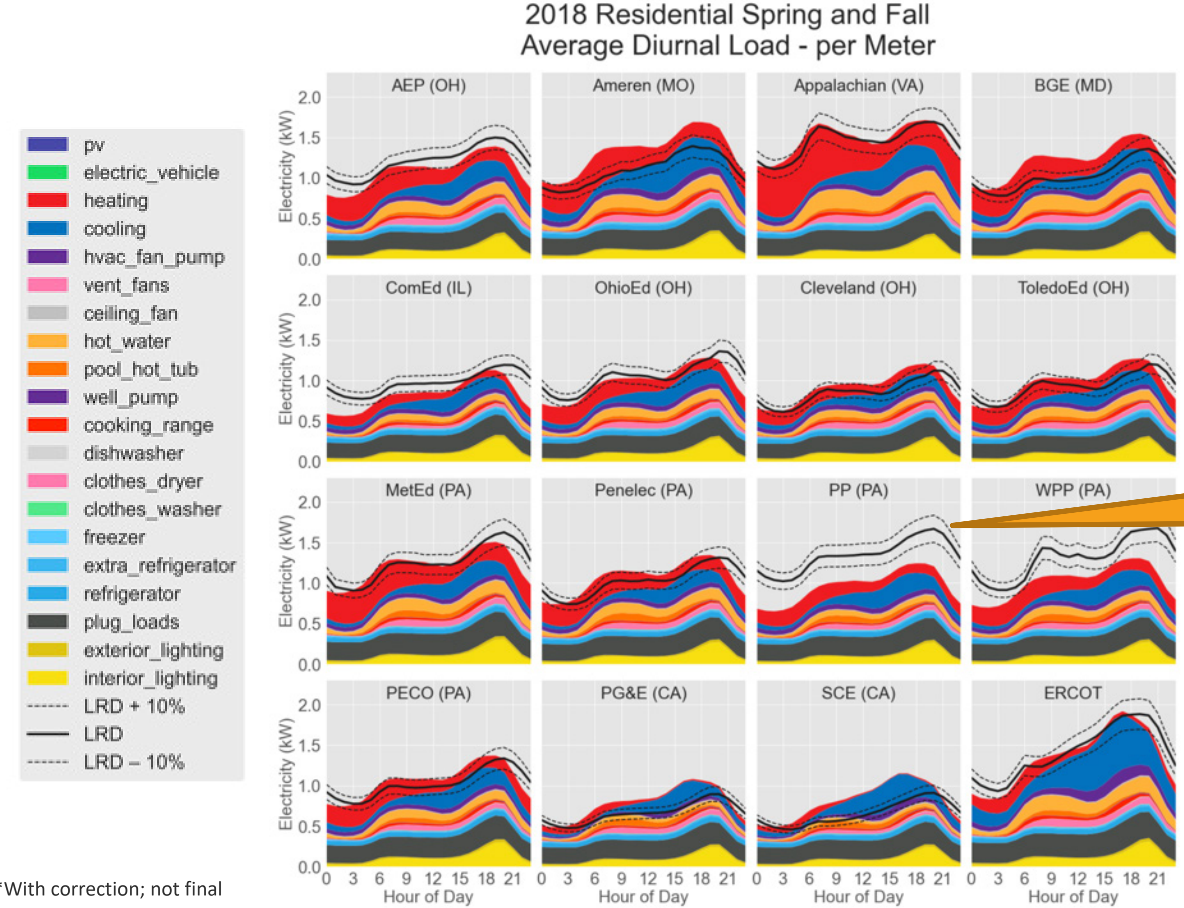
Agreement improved significantly from project start, despite not focusing on these regions for calibration!

Inaccurate customer counts affect magnitude, but shapes look similar



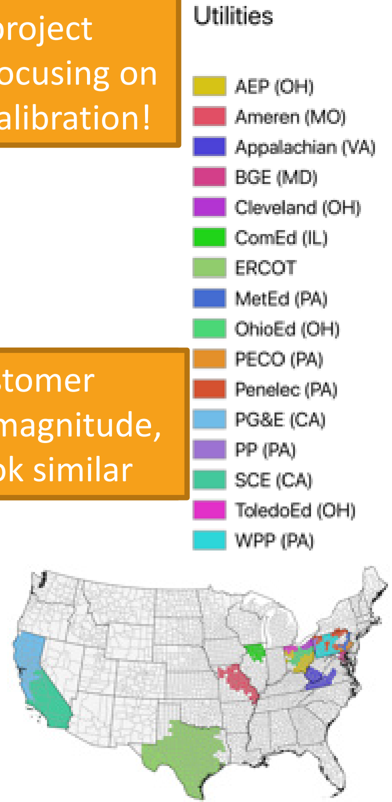
*With correction; not final

2018 Load Research Data Comparisons



Agreement improved significantly from project start, despite not focusing on these regions for calibration!

Inaccurate customer counts affect magnitude, but shapes look similar



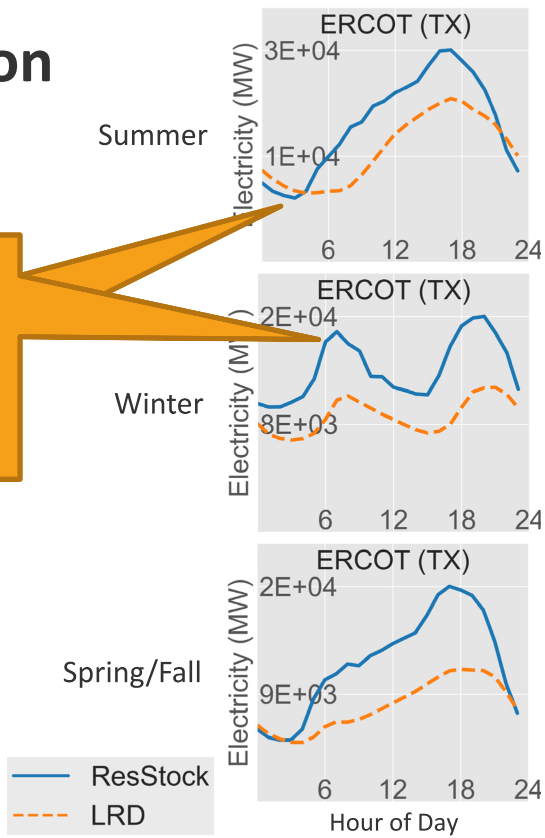
*With correction; not final

Improvement before and after calibration

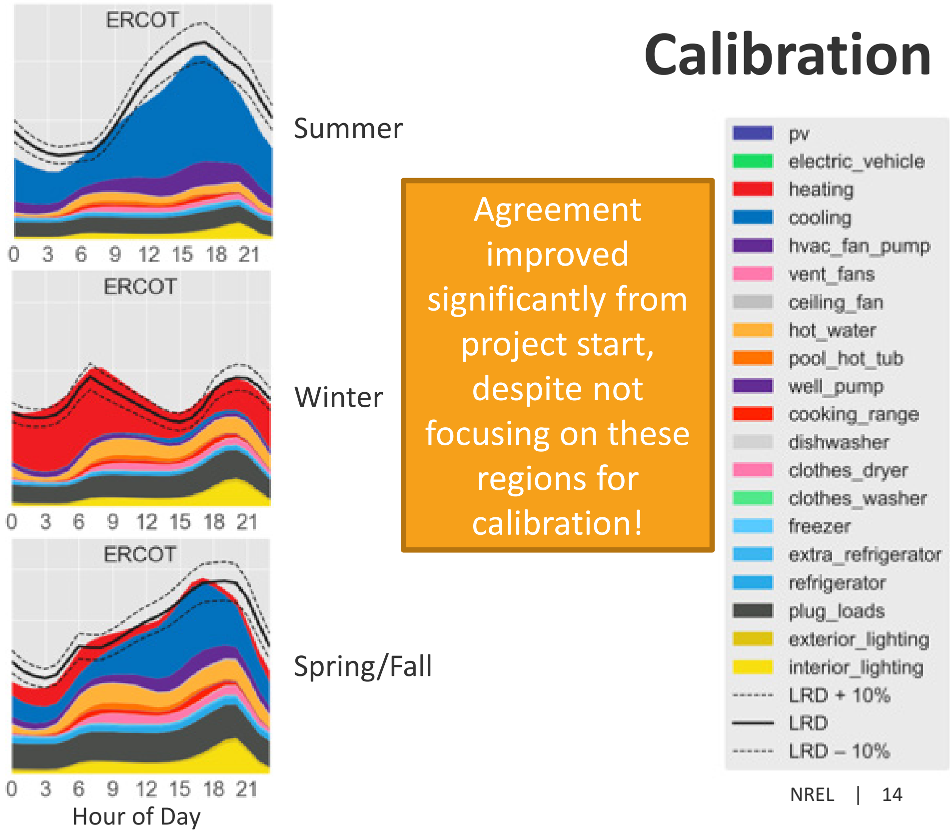
Before Calibration

Too much cooling and electric heating before calibration

2012



2018



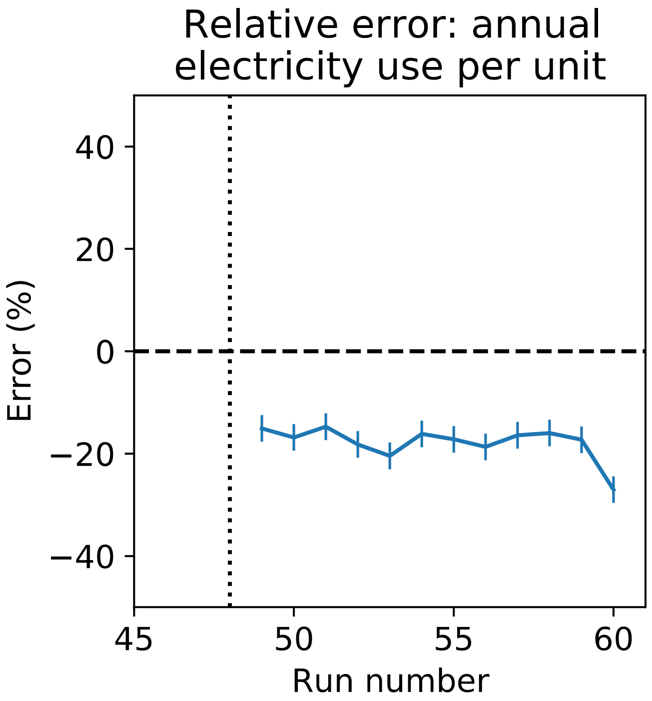
After Calibration

Agreement improved significantly from project start, despite not focusing on these regions for calibration!

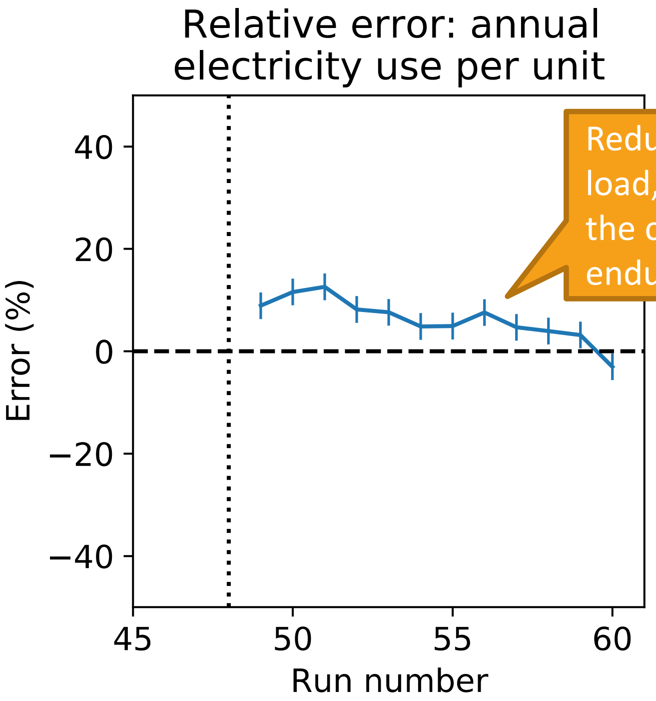
Tracking Quantities of Interest

Annual error: calibration region 5

Cherryland electric co-op



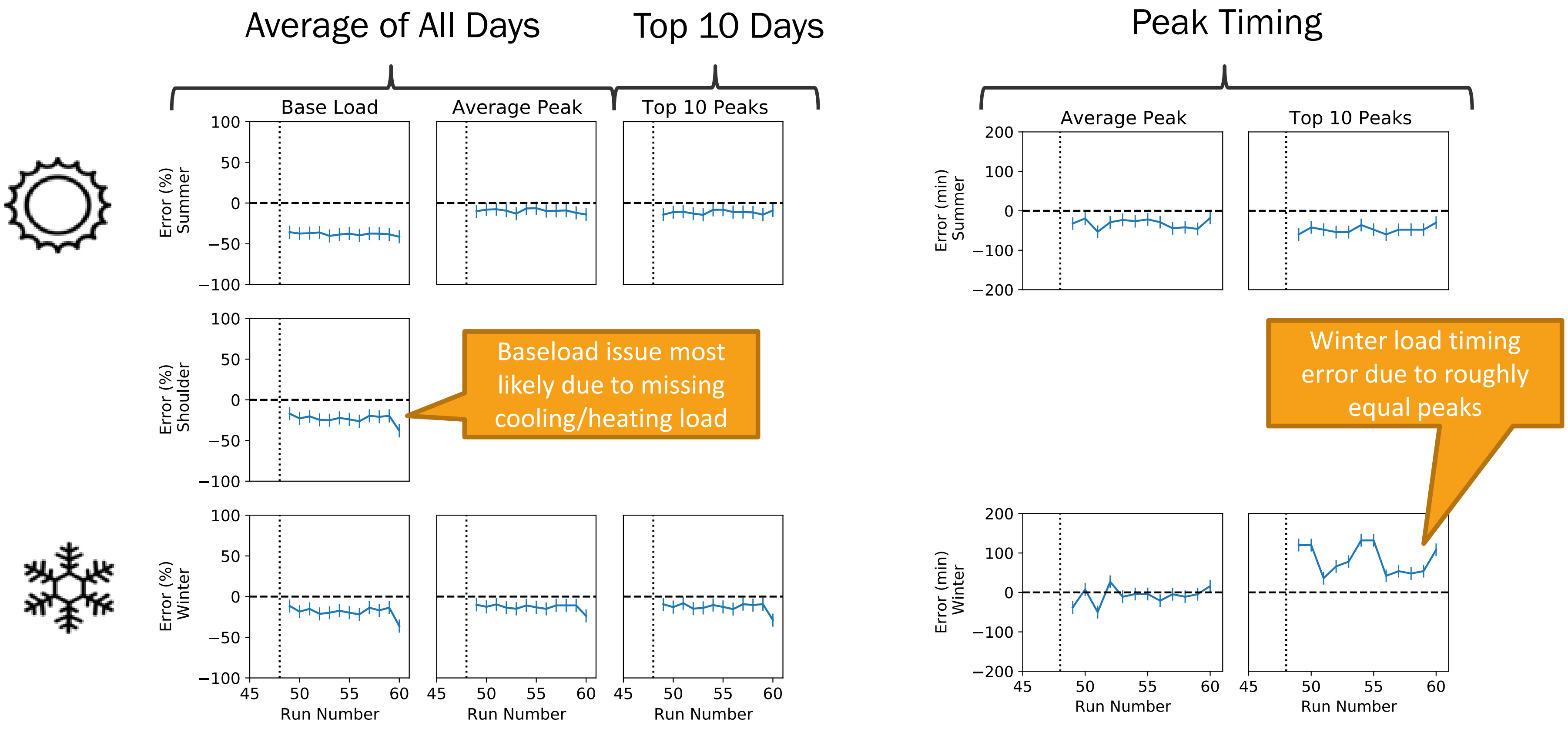
Data from VEIC



Reduction of load, mostly the cooling enduse

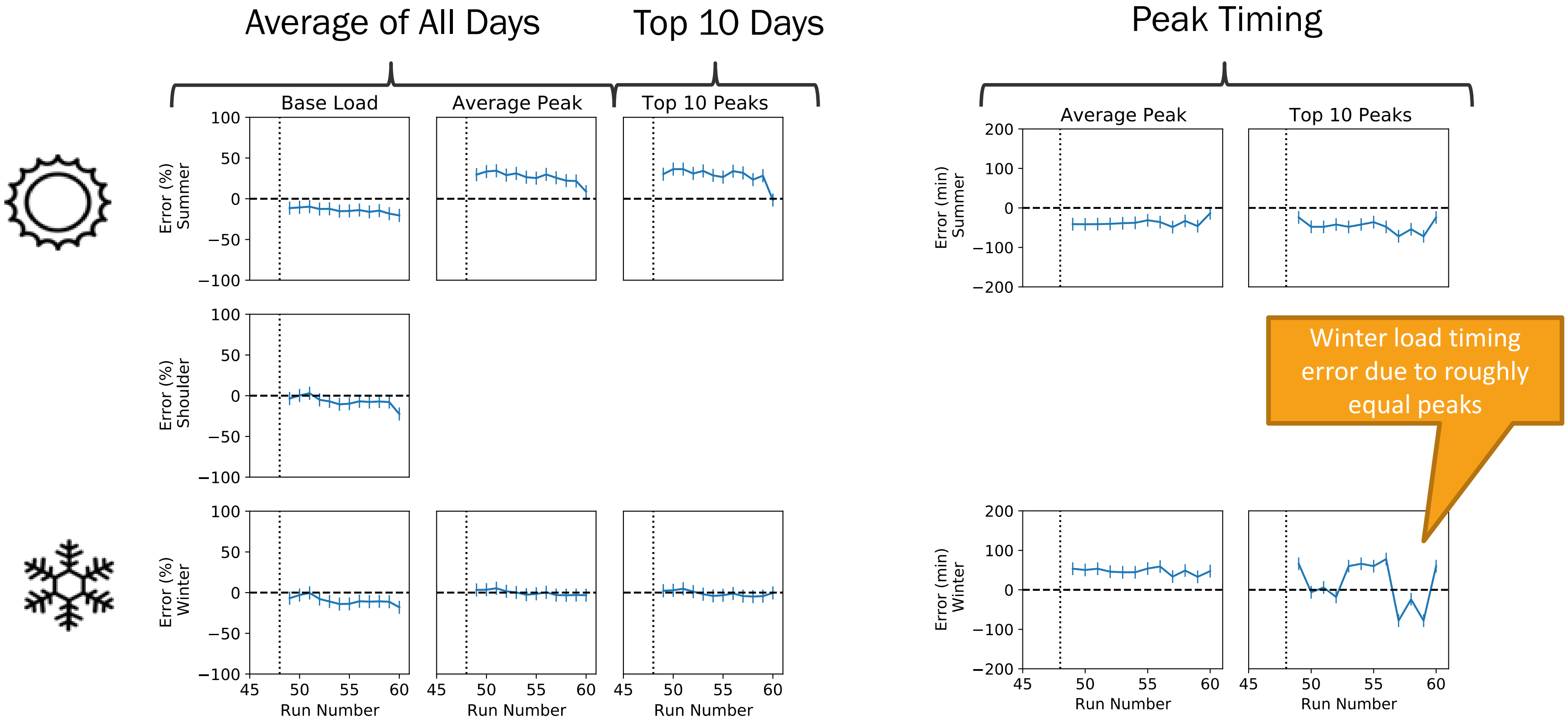
*With correction; not final

Cherryland Electric Co-op service territory: shape error metrics



*With correction; not final

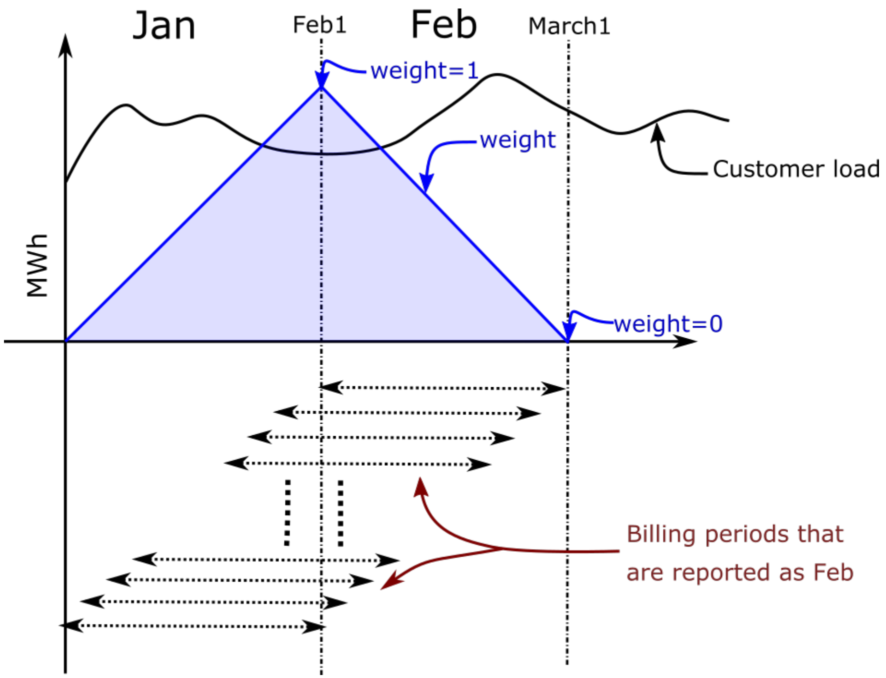
VEIC Vermont service territory: shape error metrics



*With correction; not final

Updated validation comparisons

Updating ResStock results for EIA 861M comparisons



Sometimes utilities report loads to EIA861M in, what is called, "billing months" instead of calendar months.

In billing month reporting, Jan load, for example, impacts reported Feb load.

- The load for all billing periods that end in Feb. is reported as the total load for Feb.
- If billing periods are assumed to be uniformly distributed, then the reported Feb. load can be calculated from the true load using triangular weights.

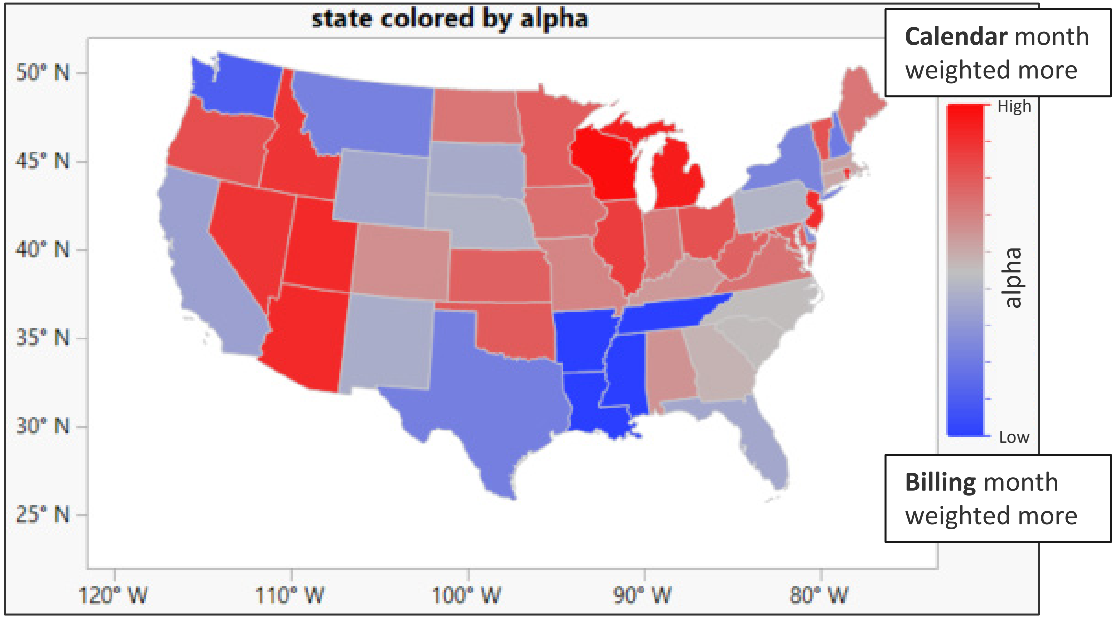
$$Rtw_{m,d} = \frac{d-1}{D_m - 1} \quad for \;\; d = 1 : D_m - 1$$

$$Ftw_{m,d} = 1 - \frac{d-1}{D_m - 1} \quad for \;\; d = 1 : D_m - 1$$

$$Lr_m = \sum_{d=1}^{D_{m-1}} La_{m-1,d} * Rtw_{m-1,d} + \sum_{d=1}^{D_m} La_{m-1,d} * Ftw_{m,d}$$

Why is this important? We use EIA 861M for validation and an output correction model; using the data correctly ensures that do not accidentally ”correct” the peak to be in the wrong month

Updating ResStock results for EIA 861M comparisons



Source: Derived from EIA Form 861M and Climate Prediction Center Population-Weighted Daily Degree Days

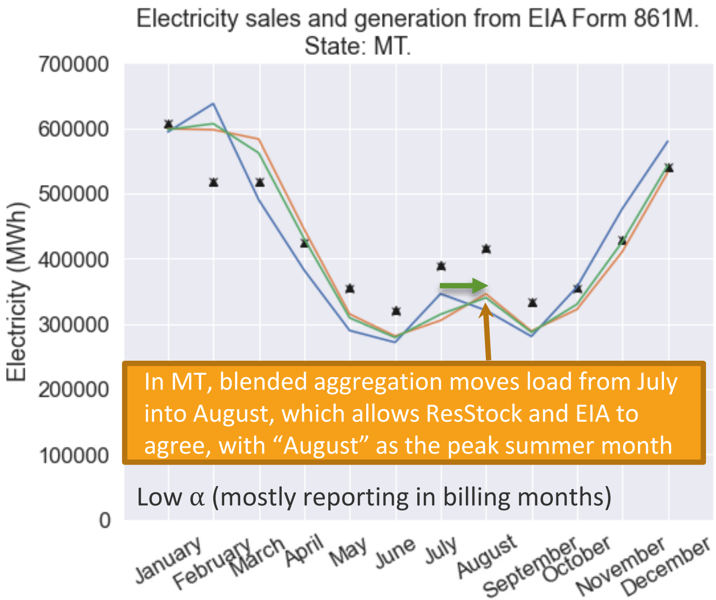
- Assume that each state has a blend of calendar and billing month reporting, with proportion α and (1 - α) such that, reported monthly load is given by

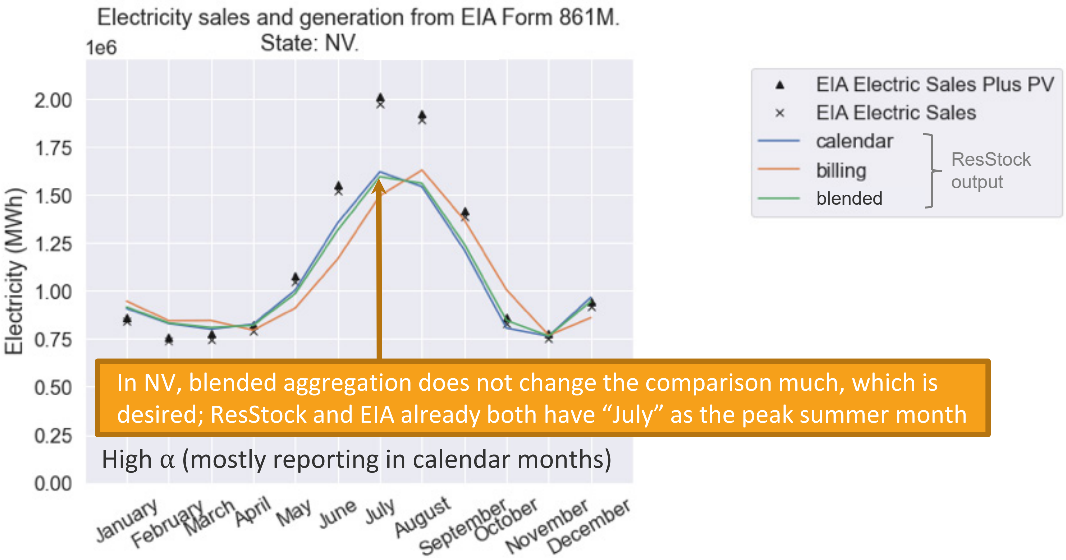
  $L_m = \alpha * \text{calendar\_month\_aggregation} + (1 - \alpha) * \text{billing\_month\_aggregation}$
- α can be solved for each state as part of multi-dimensional optimization that fits a degree day regression model to the state's average temperature and electricity consumption. EIA has performed this optimization and given us these alphas. (More on this later)
- Theoretically, α could be an indication of higher saturation of AMI meters and integration with utility billing and reporting systems.

*Models developed in collaboration with Greg Lawson, U.S. Energy Information Administration
*Modeling approach is still evolving. Model parameters and results are not final.

Updating ResStock results for EIA 861M comparisons

- For state with a small alpha, the values for blended aggregation is closer to billing month aggregation.
- For state with a larger alpha, the values for blended aggregation is closer to the calendar month aggregation.
- By using blended aggregation of ResStock (instead of the original calendar aggregation), we can compare the ResStock values with the corresponding EIA 861M values—enabling an apples-to-apples comparison.



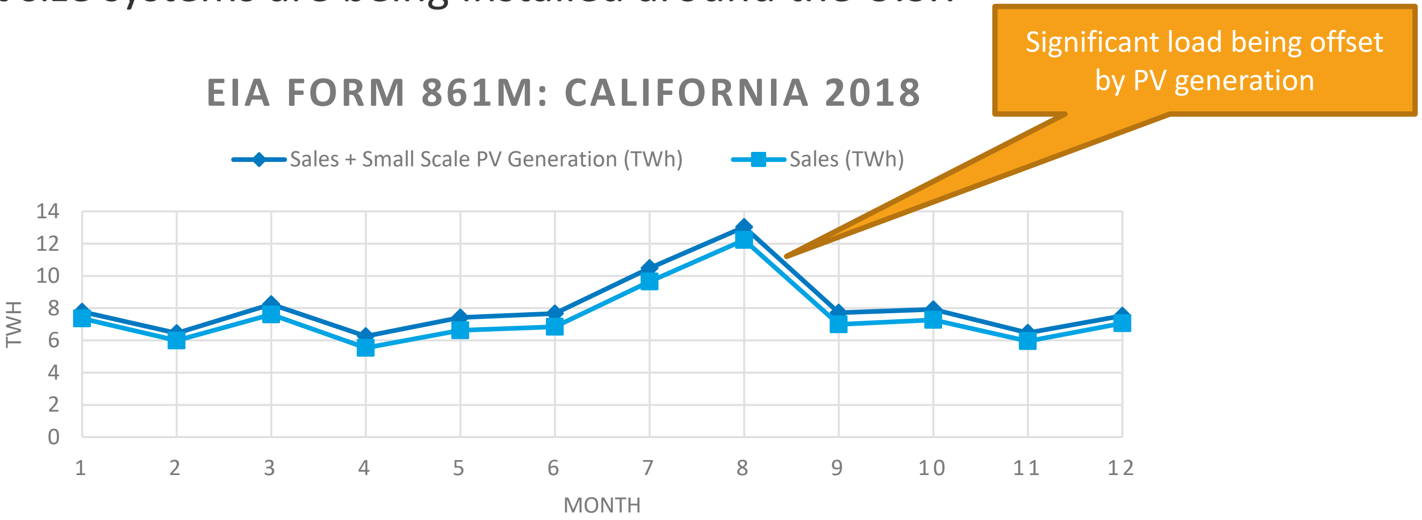


$$Lmixed_m = \alpha * \text{calendar\_month\_aggregation} + (1 - \alpha) * \text{billing\_month\_aggregation}$$

Baseload Updates

Update: Including PV loads into ResStock

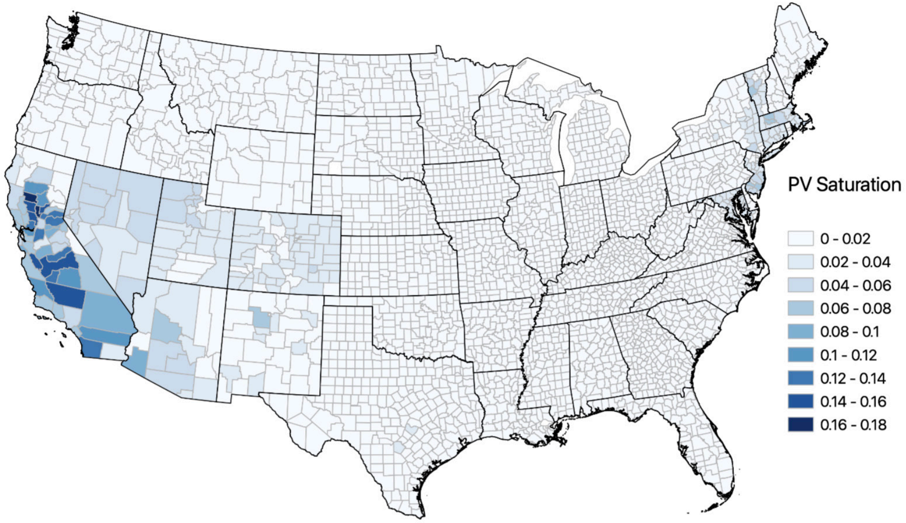
- EIA Form 861M provides estimates of small-scale solar generation
- Some states have a significant load resulting from PV generation (most notably California)
- Can we introduce PV loads into ResStock?
  - What is the PV saturation for different states?
  - What size systems are being installed around the U.S.?

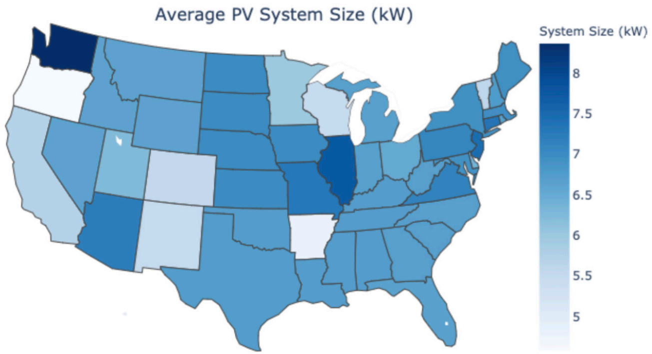


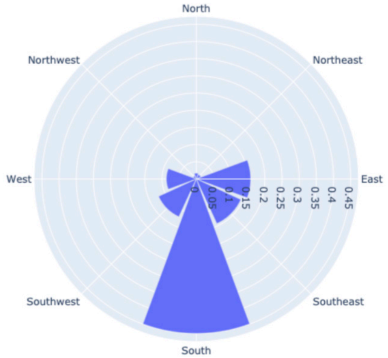
Update: PV saturation and system size

LBNL – Tracking the Sun, reports *individual* PV installation at the zip code level, updates biannually.
Wood Mackenzie/Green Tech. Media, reports *total* installation by state, updates annually.

We reconciled these data sources and used them to estimate PV saturation by county, average kW, and orientation.







HVAC Updates

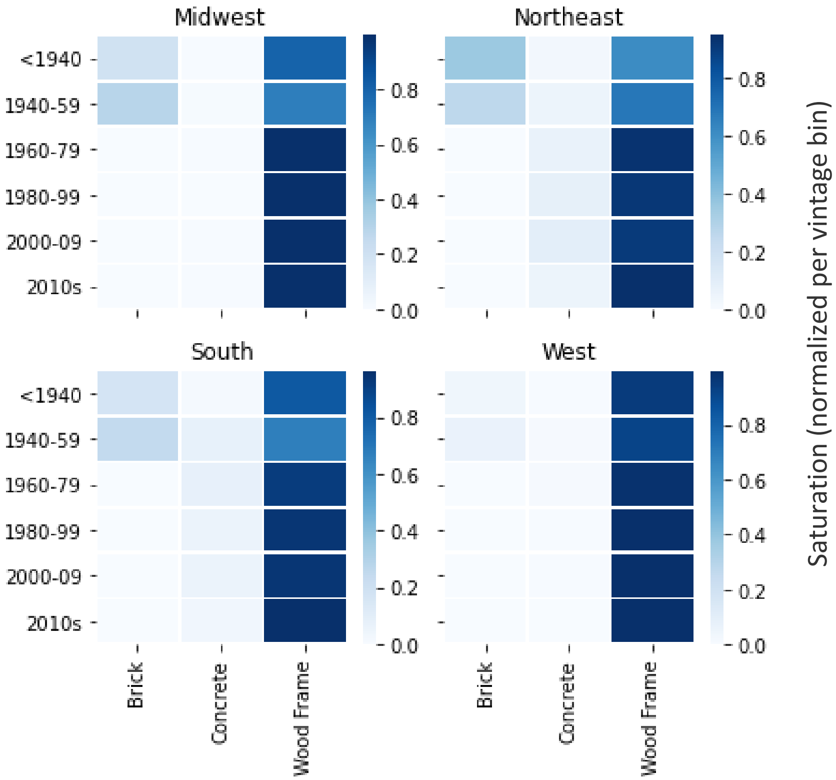
Update: Wall type from assessor data

Previously,

- 2 wall types: Masonry & Wood Frame
- Probability a function of *building type* and *custom region (10)*
- Inferred from RECS 2009 (**N=12K**), question on "Major outside wall material":
    - Ambiguous whether "Brick" means multi-wythe brick masonry wall or wood-framed wall with 4" face brick

Updated,

- 3 wall types: Brick / Concrete / Wood Frame
- Probability a function of *building type*, *state*, and *vintage*
- Queried from HIFLD national parcel data (**N=43M**) from "Code indicating the type of construction (e.g., Brick / Concrete)"



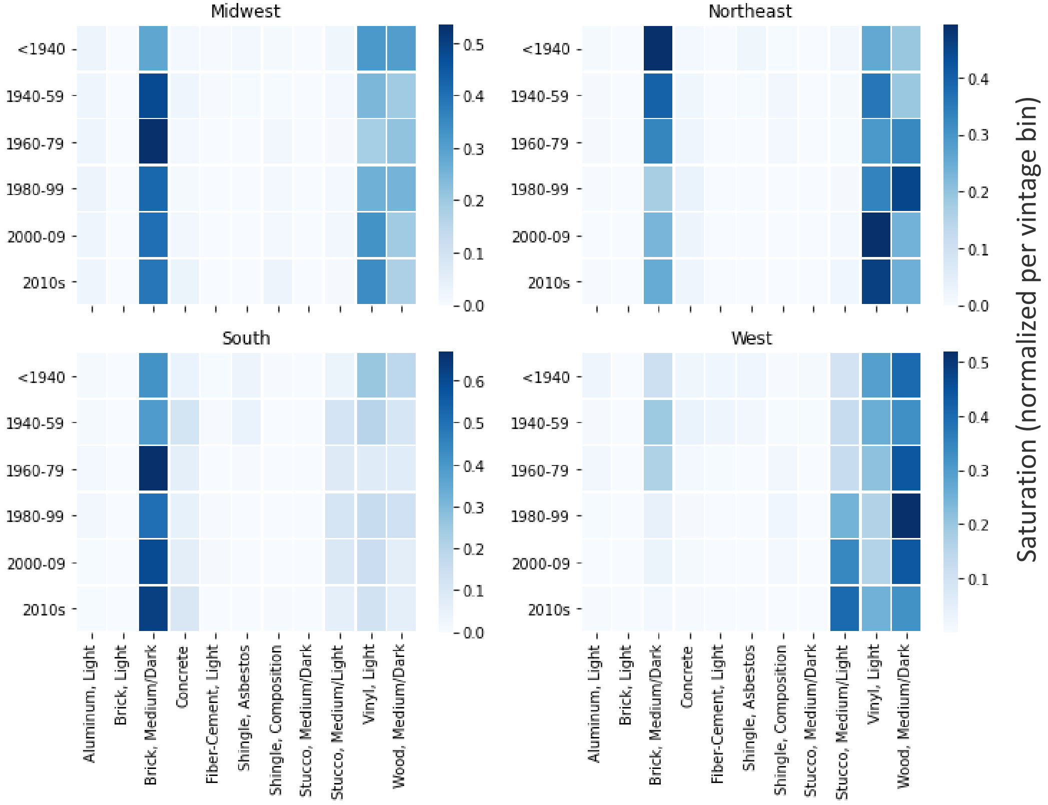
Update: Wall exterior finish from assessor data

Previously,

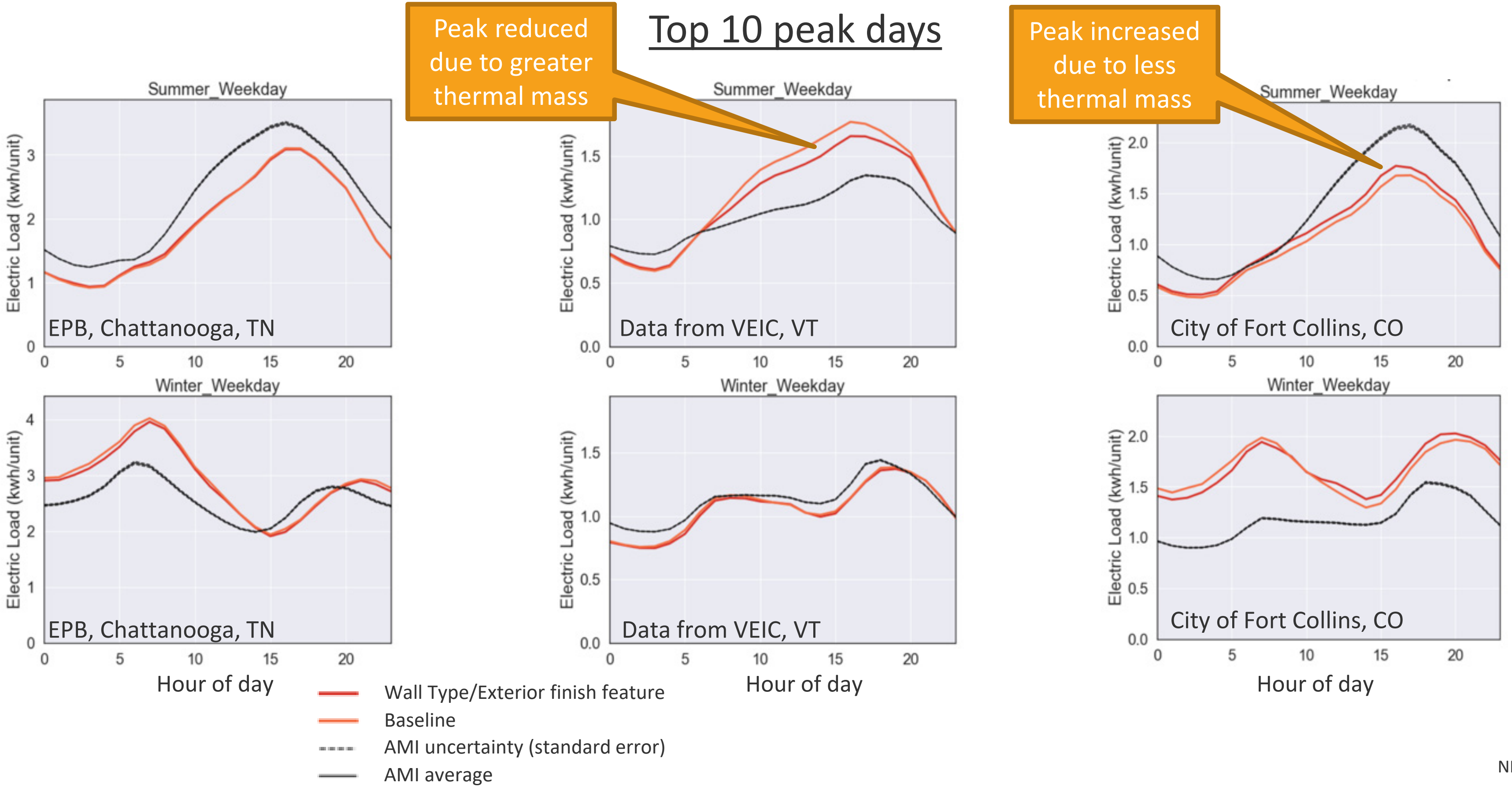
- All *wall exterior finish* was vinyl

Updated,

- *Wall exterior finish* from HIFLD national parcel data (**N=28.2M**) from "Code indicating the type and/or finish of the exterior walls (e.g., Vinyl Siding, Brick Veneer)"
- Probability a function of *wall type*, *state*, and *vintage*
- Med/dark brick is dominant in the Midwest and South, and becoming less popular in the Northeast
- Vinyl and wood are popular in the Northeast and West, in addition to light stucco in the West

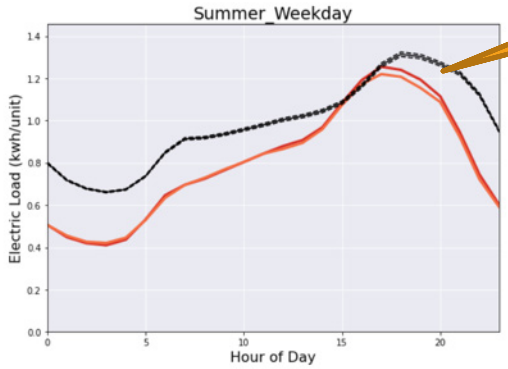


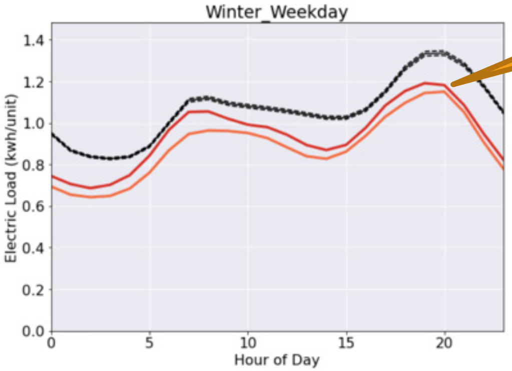
Impact: Wall type and exterior finish



Impact: Multifamily building heights

Cherryland Electric Co-op





Minor **increase** in cooling

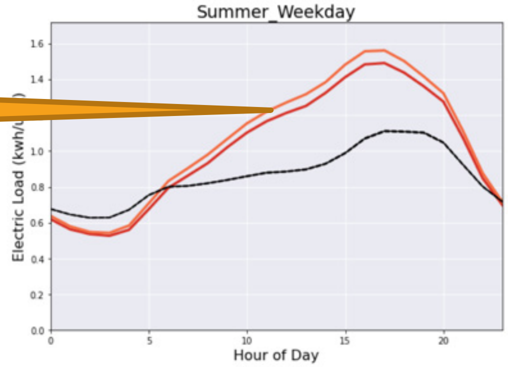
Decrease in cooling

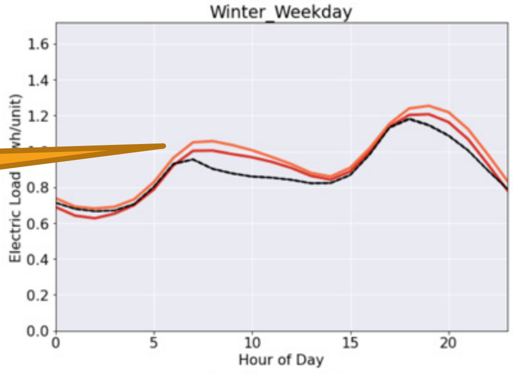
Increase in heating load

Decrease in heating load

Multi-family building heights feature
Baseline
AMI uncertainty (standard error)
AMI average

VEIC data





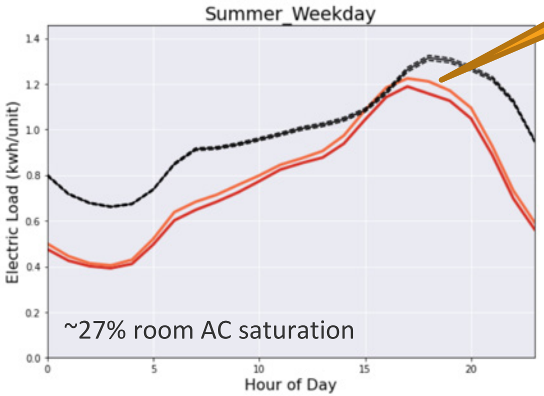
Impact: Room AC Cutler Performance Curves

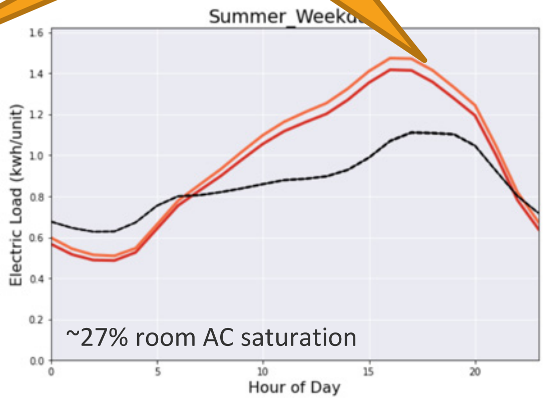
Cherryland Electric Co-op

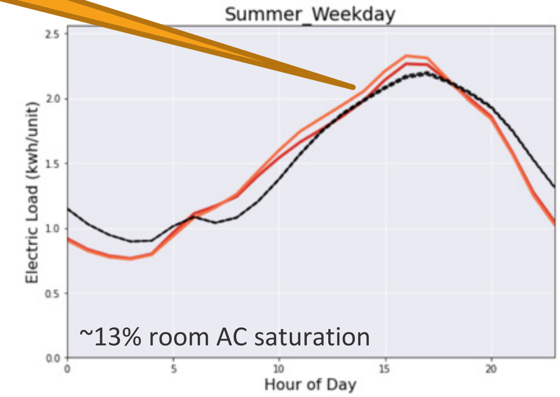
Data from VEIC, VT

City of Tallahassee, FL

New curves decrease cooling load







Room AC using Cutler performance curves

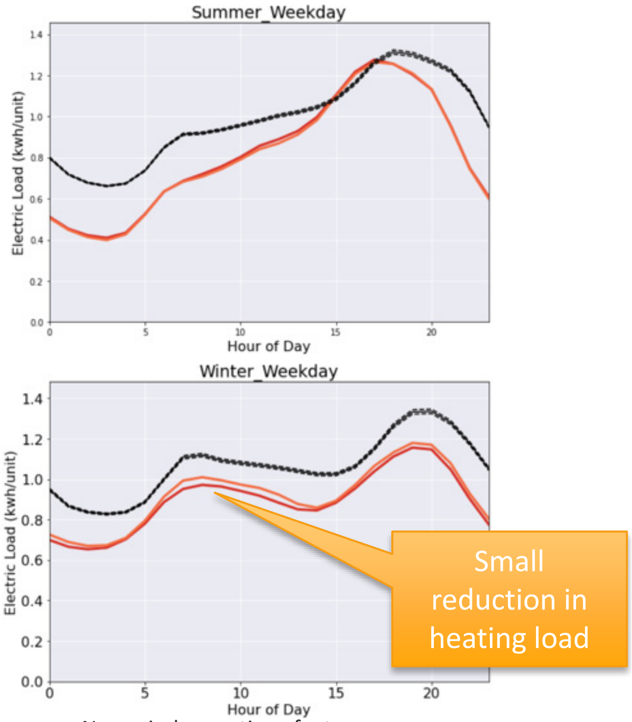
Baseline

AMI uncertainty (standard error)

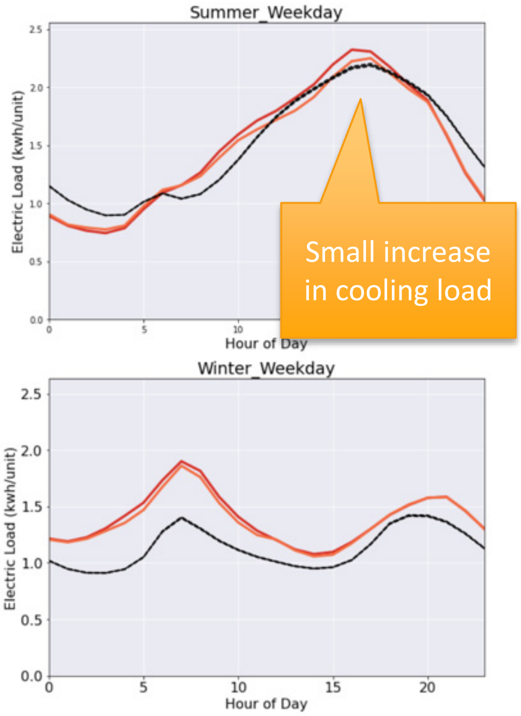
AMI average

Impact: New window options

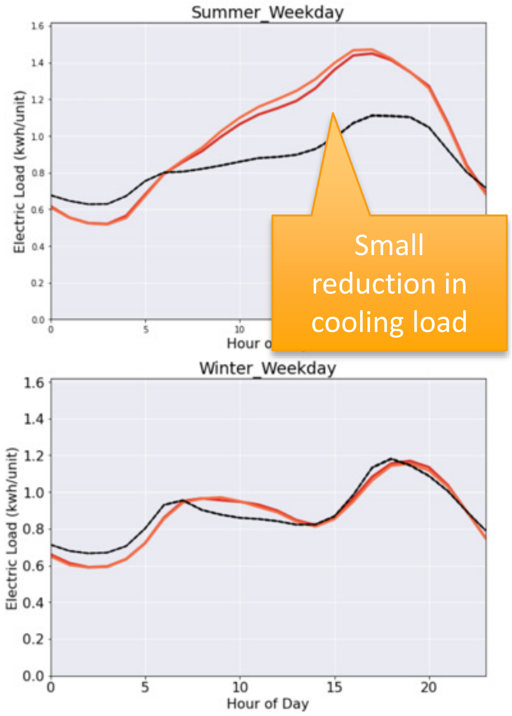
Cherryland Electric Co-op



City of Tallahassee



Data from VIEC



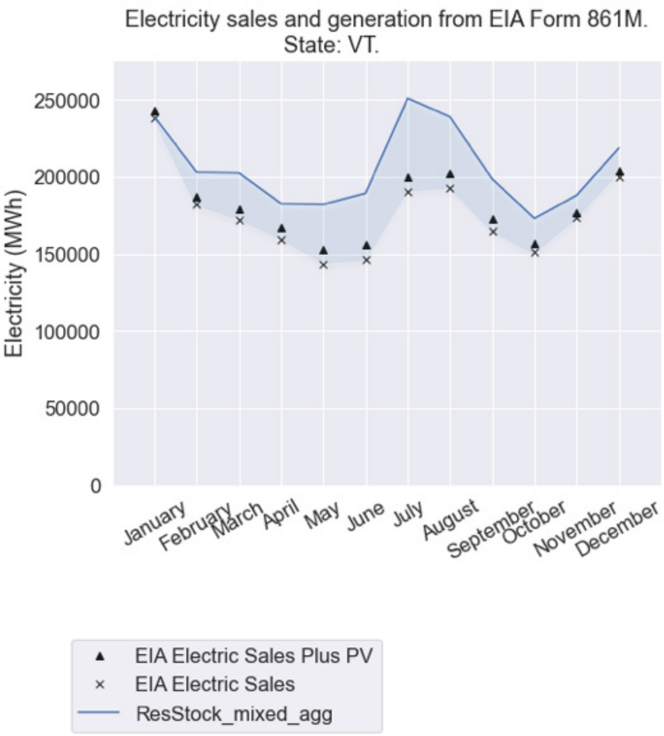
- New window options feature
- Baseline
- AMI uncertainty (standard error)
- AMI average

Added Capabilities

Residential output correction model – Motivation

- ResStock does not capture all behavior
  - Ex: RECS does not capture seasonal changes in setpoints
  - Ex: Mean radiant temperature causes setpoints to change during heat waves
  - Ex: Currently do not model partial space conditioning
- Best available data may not accurately capture all aspects of building stock
  - Ex: Best available data could over or underpredict appliance saturations, age/efficiency, setpoints, etc.
- Guiding Principles:
  - Use universally available data
  - Only correct HVACs
  - Don't correct at hourly resolution
  - Make corrections optional
- Output correction model can also be applied to future ResStock upgrade runs to improve their accuracy

Residential output correction model – Approaches



We need to remove the shaded region out of the ResStock result in order to match the EIA 861M

Different Approaches were considered:

- **Type 1**: Scale all loads

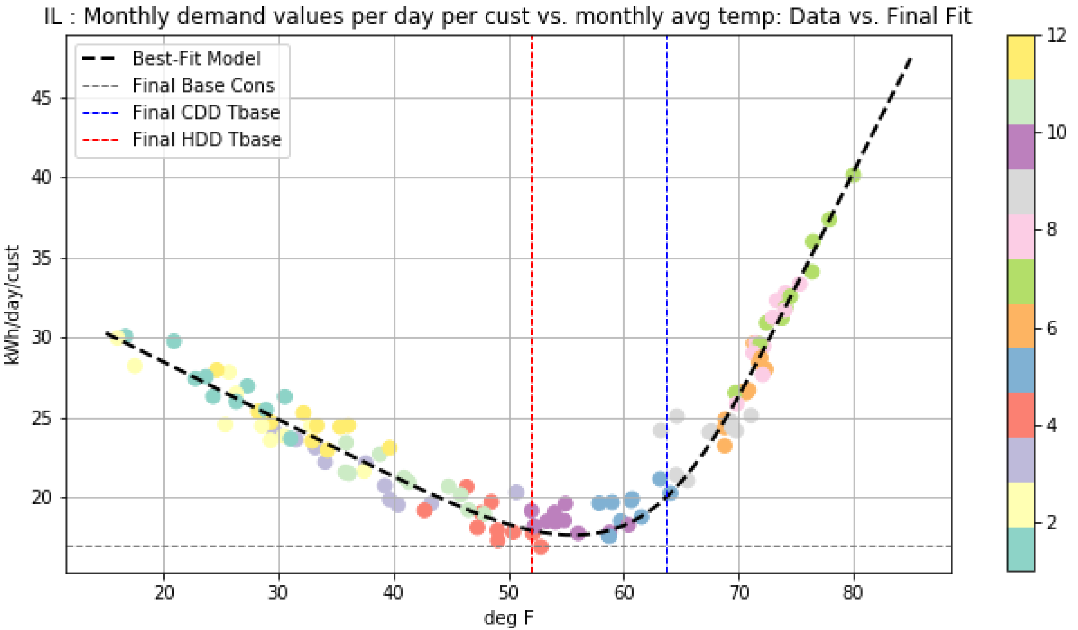
- **Type 2**: Scale only HVAC loads
  - When HVAC loads are scaled, we can choose to scale only the heating (theta0), only the cooling load (theta1) or both heating and cooling loads (theta0_5).
- **Type 5**: Compare the CDD and HDD in each county for each day to the state average CDD and HDD for the whole year, and scale extreme days more than milder days for both heating and cooling.
- **Type 6**: Like Type 5 but scale *milder* days more than *extreme* days.
- **Type 7**: Like Type 5 but scale *extreme* days more for heating and *milder* days more for cooling.
- **Type 8**: Like Type 5 but scale *milder* days more for heating and *extreme* days more for cooling (inverse of Type 7).

- **Type 9:** Scale the state level HVAC load so that the total load per customer per day would match the value estimated by the degree day model from EIA trained on last 10 years of EIA 861M data
- **Type 10:** Like 9, but don't scale the baseload; only make the heating and cooling slope match the change point model
- **Type 11:** Like 9, but apply the state's changepoint model to each county instead of whole state.
- **Type 12:** Like 10, but for each county instead of the whole state.

Residential output correction model – Approaches

Degree-day model from EIA

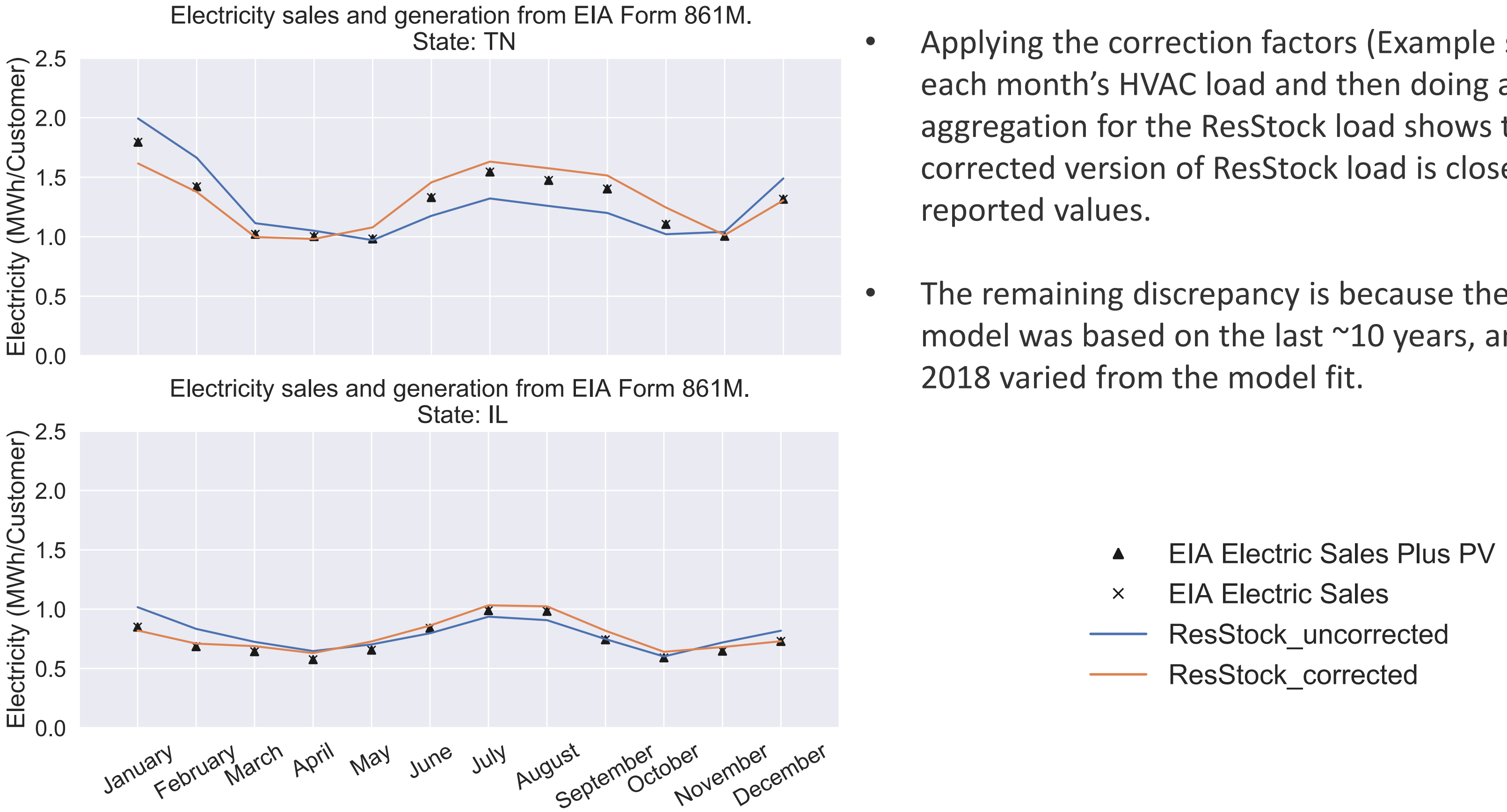
- Trained on last ~10-years of EIA861M and population weighted state avg temperatures
- Model minimizes 6 parameters
  - Alpha (Value between 0 & 1)
  - CDD Tbase (F)
  - HDD Tbase (F)
  - Base Consumption (kWh/day/cust)
  - Cooling Slope (kWh/day/cust/F)
  - Heating Slope (kWh/day/cust/F)



Source: Derived from EIA Form 861M and Climate Prediction Center Population-Weighted Daily Degree Days

*Models developed in collaboration with Greg Lawson, U.S. Energy Information Administration
*Modeling approach is still evolving. Model parameters and results are not final.

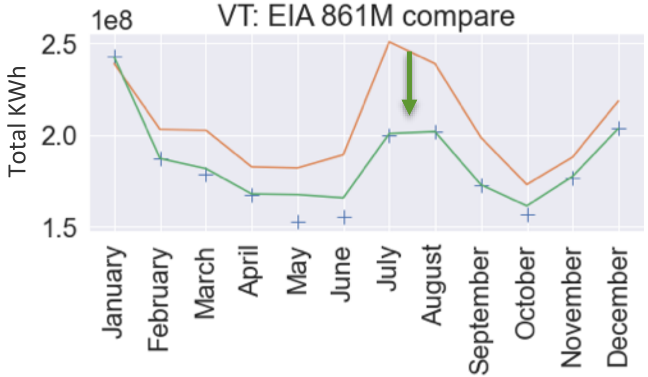
Residential output correction model – Implementation

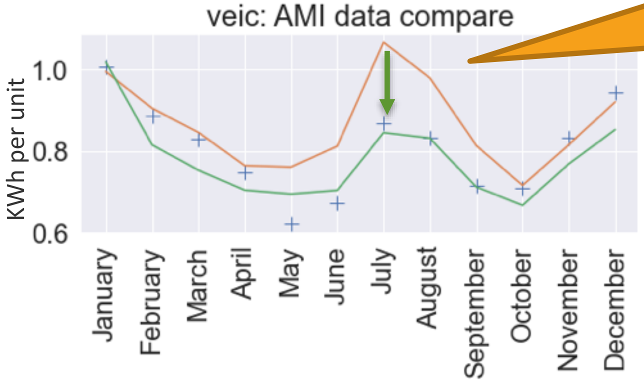


- Applying the correction factors (Example shows: type9) to each month’s HVAC load and then doing a blended aggregation for the ResStock load shows that the corrected version of ResStock load is close to the EIA861 reported values.

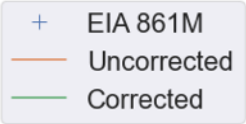
- The remaining discrepancy is because the degree day model was based on the last ~10 years, and actual load in 2018 varied from the model fit.

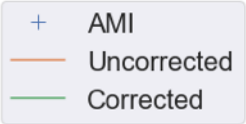
Residential output correction model – Performance



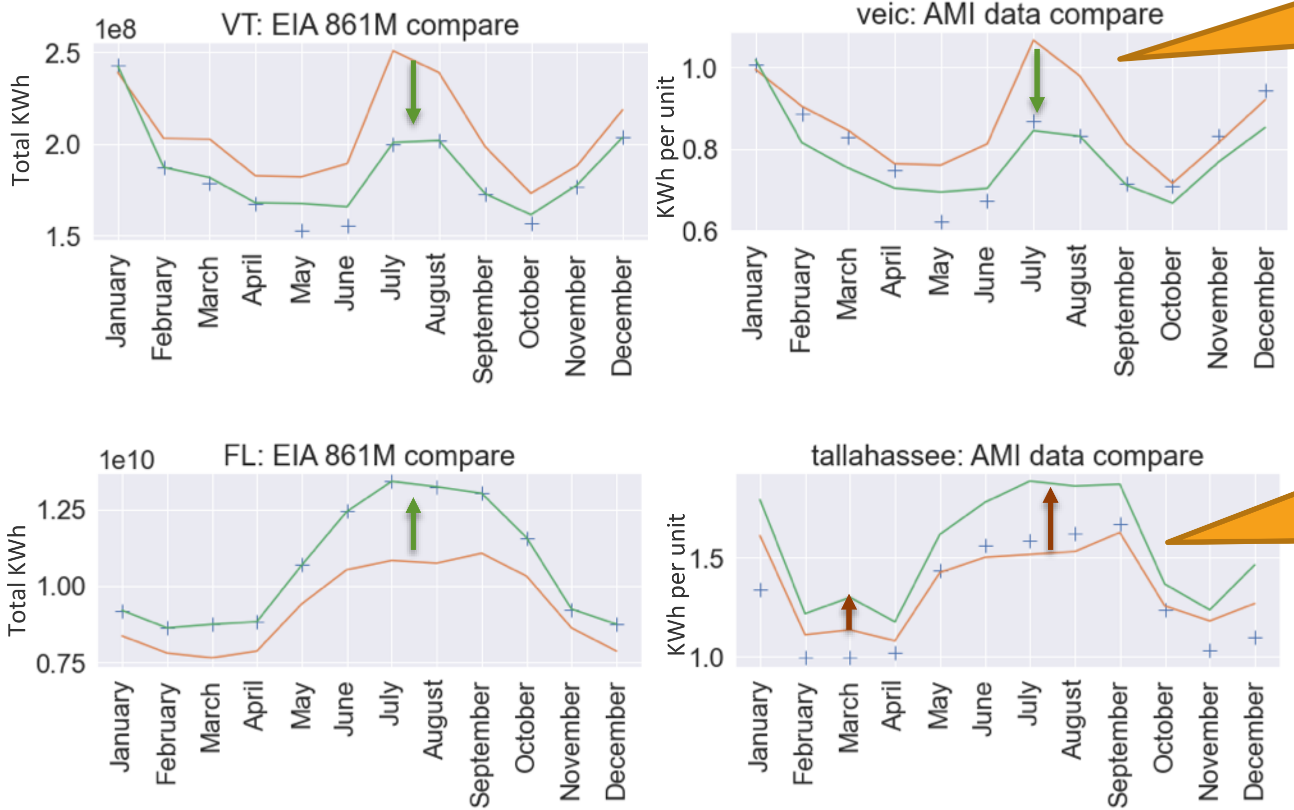


When both AMI and EIA 861M errors are in the same direction, the correction model improves fit to both EIA 861M and AMI data





Residential output correction model – Performance



When both AMI and EIA 861M errors are in the same direction, the correction model improves fit to both EIA 861M and AMI data

When AMI and EIA 861M errors are very different (in direction or magnitude), the correction model improves fit to EIA 861M but the AMI fit deteriorates

Residential output correction model – Performance

Average of hourly CVRMSE, top 100 hours CVRMSE and Monthly CVRMSE

- All correction models achieve similar CVRMSE when averaged across all regions.
- Different correction types achieve best results for AMI and LRD data for different regions.
- None of the correction model improves AMI/LRD fit consistently across all regions
- However, some correction models improve AMI/LRD fit in most regions while only mildly deteriorating fit in others.

- We pick type9 since it is calibrated against generic EIA861M and can be applied to TMY as well as AMY runs, and performs the best in its class.

Average of CVRMSE																	
Utilities	Calibrated using corresponding year's EIA861M												Calibrated using multi-year EIA861M degree day model				
Correction Model Type	type1	type2_theta0	type2_theta0_5	type2_theta1	type5_theta0	type5_theta0_5	type5_theta1	type6_theta0	type6_theta0_5	type6_theta1	type7_theta0_5	type8_theta0_5	type9	type10	type11	type12	Uncorrected
AMI cherryland	0.24	0.25	0.24	0.19	0.25	0.24	0.20	0.25	0.24	0.19	0.24	0.24	0.19	0.18	0.21	0.23	0.20
AMI epb	0.17	0.54	0.17	0.11	0.12	0.20	0.12	0.54	0.20	0.13	0.15	0.25	0.17	0.15	0.17	0.14	0.12
AMI fort_collins	0.11	0.15	0.13	0.25	0.15	0.14	0.23	0.12	0.14	0.24	0.12	0.16	0.16	0.18	0.14	0.10	0.23
AMI horry	0.11	0.16	0.11	0.12	0.17	0.11	0.12	0.16	0.12	0.12	0.12	0.12	0.15	0.11	0.15	0.13	0.17
AMI seattle	0.28	0.27	0.25	0.26	0.42	0.22	0.24	0.25	0.24	0.27	0.30	0.19	0.20	0.19	0.40	0.39	0.24
AMI tallahassee	0.25	0.42	0.30	0.22	0.14	0.40	0.22	0.33	0.26	0.22	0.32	0.28	0.38	0.33	0.39	0.30	0.14
AMI veic	0.09	0.19	0.07	0.06	0.19	0.08	0.19	0.19	0.08	0.06	0.08	0.08	0.07	0.13	0.08	0.11	0.19
LRD AEP (OH)	0.07	0.09	0.09	0.11	0.11	0.12	0.11	0.08	0.08	0.10	0.07	0.12	0.15	0.12	0.13	0.14	0.11
LRD Ameren (MO)	0.28	0.25	0.28	0.36	0.35	0.28	0.36	0.27	0.30	0.36	0.27	0.30	0.28	0.26	0.29	0.33	0.35
LRD Appalachian (VA)	0.10	0.11	0.09	0.12	0.11	0.09	0.12	0.12	0.10	0.12	0.09	0.10	0.11	0.09	0.19	0.14	0.15
LRD BGE (MD)	0.19	0.16	0.18	0.29	0.16	0.18	0.29	0.20	0.21	0.29	0.17	0.21	0.23	0.25	0.26	0.32	0.29
LRD Cleveland (OH)	0.25	0.15	0.28	0.29	0.17	0.33	0.17	0.16	0.24	0.25	0.24	0.33	0.35	0.31	0.49	0.51	0.17
LRD ComEd (IL)	0.17	0.21	0.16	0.14	0.21	0.15	0.18	0.21	0.16	0.14	0.17	0.15	0.13	0.14	0.12	0.17	0.18
LRD ERCOT	0.13	0.15	0.14	0.13	0.10	0.16	0.14	0.14	0.13	0.11	0.14	0.14	0.10	0.14	0.10	0.10	0.10
LRD MetEd (PA)	0.14	0.13	0.13	0.16	0.12	0.13	0.16	0.14	0.14	0.16	0.12	0.14	0.08	0.09	0.13	0.13	0.16
LRD OhioEd (OH)	0.15	0.12	0.17	0.18	0.12	0.22	0.12	0.12	0.15	0.15	0.15	0.21	0.23	0.19	0.28	0.30	0.12
LRD PECO (PA)	0.08	0.08	0.08	0.10	0.08	0.10	0.09	0.08	0.08	0.09	0.08	0.10	0.11	0.10	0.10	0.11	0.09
LRD Penelec (PA)	0.14	0.13	0.13	0.16	0.12	0.14	0.16	0.14	0.14	0.16	0.13	0.15	0.13	0.13	0.16	0.16	0.16
LRD PG&E (CA)	0.25	0.16	0.23	0.22	0.16	0.22	0.16	0.16	0.23	0.23	0.23	0.22	0.12	0.23	0.11	0.19	0.16
LRD PP (PA)	0.30	0.31	0.29	0.27	0.31	0.29	0.28	0.30	0.29	0.28	0.30	0.28	0.25	0.25	0.17	0.17	0.28
LRD SCE (CA)	0.19	0.17	0.19	0.20	0.17	0.21	0.17	0.17	0.19	0.19	0.19	0.20	0.15	0.21	0.17	0.20	0.17
LRD ToledoEd (OH)	0.22	0.16	0.25	0.27	0.18	0.31	0.18	0.16	0.21	0.23	0.21	0.31	0.33	0.29	0.38	0.41	0.18
LRD WPP (PA)	0.25	0.25	0.24	0.21	0.26	0.24	0.22	0.25	0.24	0.22	0.25	0.23	0.22	0.21	0.17	0.17	0.22
Grand Total	0.18	0.20	0.18	0.19	0.18	0.20	0.18	0.20	0.18	0.19	0.18	0.20	0.19	0.19	0.21	0.22	0.18

Residential output correction model – Performance

Average of hourly CVRMSE, top 100 hours CVRMSE and Monthly CVRMSE

- All correction models achieve similar CVRMSE when averaged across all regions.
- Different correction types achieve best results for AMI and LRD data for different regions.
- None of the correction model improves AMI/LRD fit consistently across all regions
- However, some correction models improve AMI/LRD fit in most regions while only mildly deteriorating fit in others.

- We pick type9 since it is calibrated using multi-year EIA-861M degree day model and can be applied to TMY as well as AMY runs, and performs the best in its class, especially when looking at the CVRMSE against EIA-861M for the states.

Average monthly CVRMSE with EIA861M for 2018																	
	Calibrated using corresponding year's EIA861M												Calibrated using multi-year EIA861M degree day model				
State	type1	type2_theta1	type2_theta0	type2_theta0_5	type5_theta0_5	type6_theta0_5	type5_theta0	type6_theta0	type5_theta1	type6_theta1	type7_theta0_5	type8_theta0_5	type9	type10	type11	type12	Uncorrected
AVG	0.01	0.29	0.37	0.05	0.08	0.06	0.38	0.37	0.42	0.29	0.07	0.08	0.24	0.35	0.28	0.38	0.48
AL	0.01	0.04	0.42	0.01	0.01	0.01	0.42	0.42	0.05	0.04	0.01	0.01	0.16	0.15	0.20	0.17	0.42
AR	0.02	0.21	0.59	0.02	0.02	0.02	0.29	0.54	0.21	0.21	0.02	0.02	0.16	0.22	0.16	0.21	0.29
AZ	0.00	0.05	0.48	0.01	0.05	0.01	0.48	0.48	0.48	0.05	0.01	0.05	0.59	0.51	0.63	0.46	0.48
CA	0.02	0.37	0.45	0.28	0.30	0.29	0.45	0.45	0.49	0.38	0.30	0.30	0.38	0.65	0.42	0.63	0.49
CO	0.00	0.54	0.50	0.05	0.11	0.09	0.50	0.50	0.75	0.54	0.09	0.12	0.14	0.30	0.14	0.21	0.75
CT	0.01	0.30	0.21	0.06	0.08	0.07	0.38	0.20	0.38	0.30	0.07	0.07	0.25	0.41	0.26	0.43	0.38
DE	0.01	0.13	0.29	0.01	0.01	0.01	0.32	0.29	0.32	0.13	0.01	0.01	0.15	0.22	0.15	0.19	0.32
FL	0.01	0.01	0.46	0.01	0.01	0.01	0.48	0.46	0.01	0.01	0.01	0.01	0.11	0.12	0.19	0.15	0.48
GA	0.01	0.04	0.44	0.01	0.01	0.01	0.44	0.44	0.06	0.04	0.01	0.01	0.16	0.16	0.16	0.21	0.44
IA	0.00	0.39	0.26	0.01	0.02	0.02	0.26	0.26	0.48	0.39	0.02	0.02	0.24	0.27	0.25	0.27	0.48
ID	0.00	0.19	0.47	0.05	0.15	0.06	0.49	0.47	0.53	0.19	0.10	0.17	0.18	0.32	0.50	0.53	0.53
IL	0.00	0.27	0.22	0.01	0.01	0.01	0.23	0.22	0.36	0.27	0.01	0.01	0.22	0.35	0.27	0.71	0.36
IN	0.00	0.10	0.42	0.01	0.01	0.01	0.42	0.42	0.44	0.10	0.01	0.01	0.22	0.12	0.24	0.27	0.44
KS	0.00	0.43	0.09	0.04	0.07	0.06	0.11	0.10	0.45	0.43	0.07	0.06	0.18	0.45	0.19	0.45	0.45
KY	0.01	0.37	0.37	0.01	0.01	0.01	0.53	0.37	0.53	0.37	0.01	0.01	0.19	0.29	0.20	0.33	0.53
LA	0.02	0.41	0.59	0.03	0.06	0.05	0.65	0.59	0.40	0.41	0.05	0.07	0.14	0.18	0.14	0.18	0.65
MA	0.01	0.74	0.32	0.17	0.24	0.20	0.33	0.34	0.81	0.74	0.19	0.25	0.21	0.53	0.22	0.42	0.81
MD	0.00	0.32	0.12	0.01	0.01	0.01	0.13	0.12	0.36	0.32	0.01	0.01	0.28	0.37	0.29	0.46	0.36
ME	0.00	0.32	0.33	0.10	0.15	0.11	0.34	0.33	0.46	0.32	0.12	0.14	0.22	0.32	0.23	0.28	0.46

Conclusions

Conclusions

- Ran 12 iterations of ResStock incorporating 9 discrete changes
  - Saw general improvements in QOI metrics, both in Region 5 and across the entire U.S.
- New/Updated visualizations
  - Included blended aggregation calendar/billing months to better compare to EIA Form 861M data
  - AMI data from Cherryland Electric Co-op, Michigan
  - AMI data from Vermont
- Finalized output correction model to true up discrepancies between model outputs and a degree day model based on EIA Form 861M data

- Are focusing on creating the frameworks necessary to deliver EULP final products

Data Publication Plan

Same Data, Multiple Scales

Aggregates | Web Viewer | Individual Buildings