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

Technical Advisory Group Meeting #8

May 22, 2020

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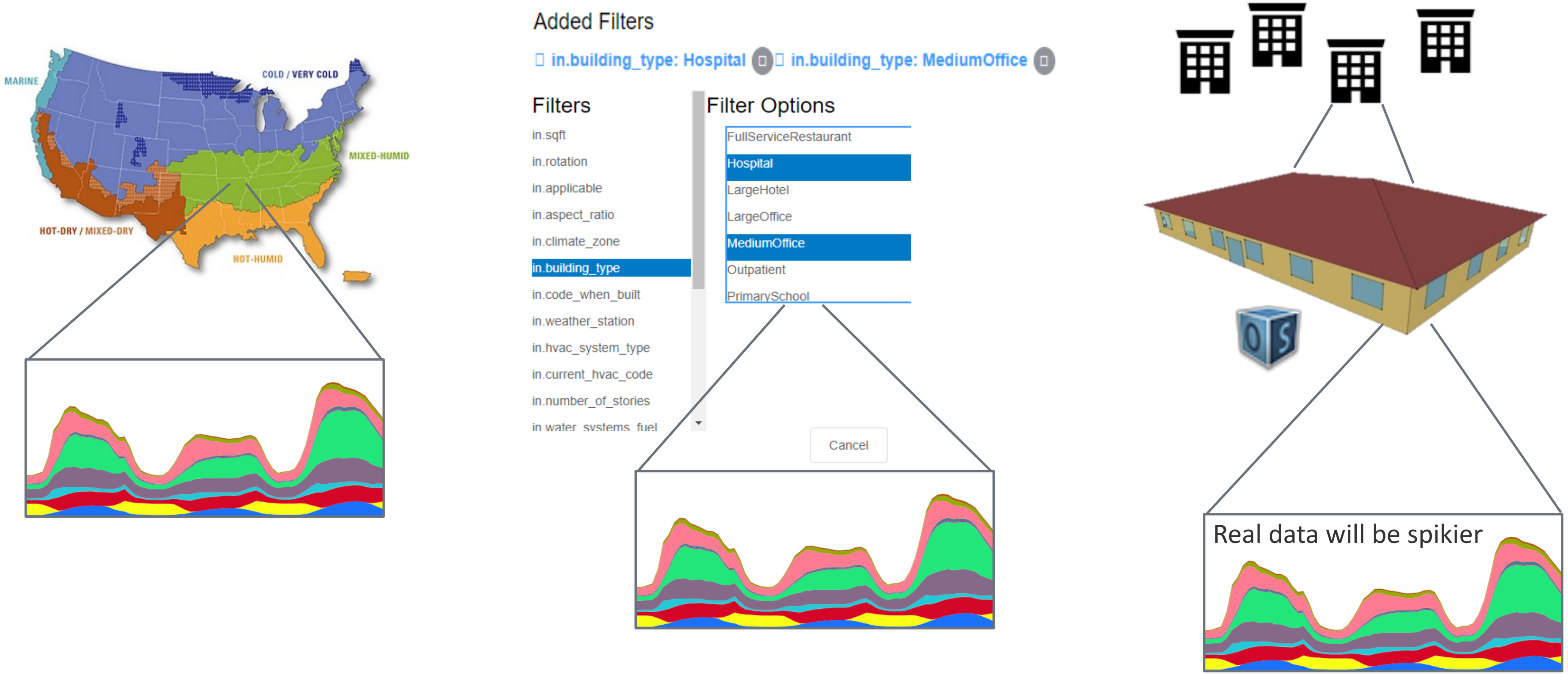
EULP Data Publication

Andrew Parker
September 22, 2020

Same Data, Multiple Scales

Aggregates | Web Viewer | Individual Buildings

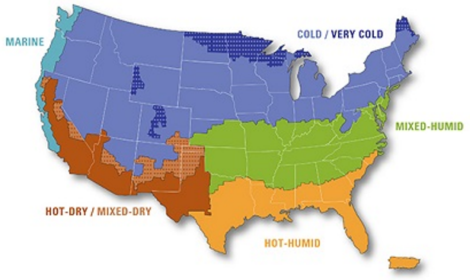


Pre-aggregated Load Profiles

Aggregates | Web Viewer | Individual Buildings

Pre-aggregated EULPs by building type for:

- U.S. States (contiguous)
- ASHRAE Climate Zones
- DOE Building America Climate Zones
- Electric System ISOs
- U.S. Census Public Use Microdata Area*
- U.S. Counties



Format:

- CSV files (for Excel, etc. ease of use)

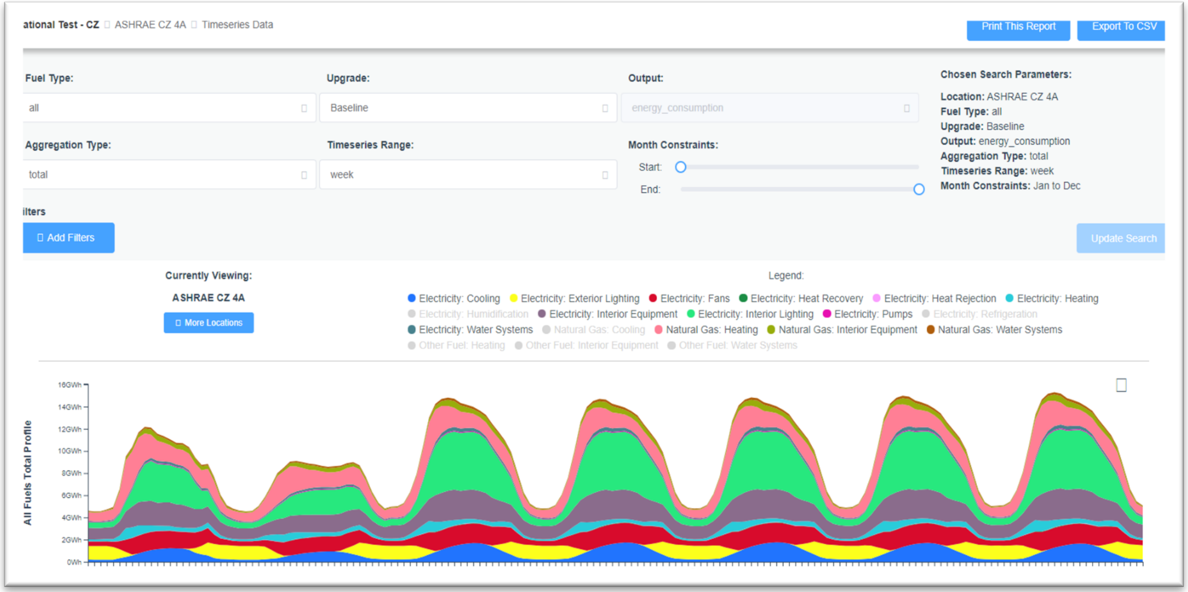
Additional Data:

- Count of models included per aggregation
- List of model IDs per aggregation
- Model characteristics by ID
- Timeseries mean, stdev, and range

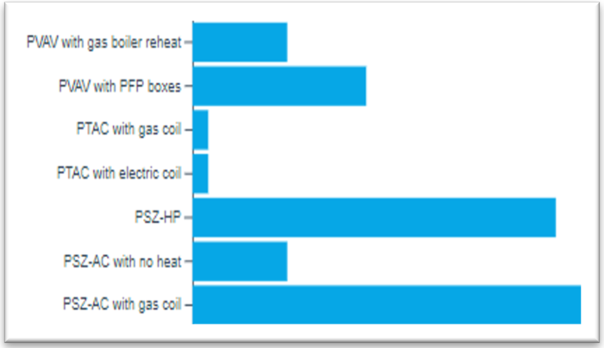
*PUMA is an area with ~200k people; ~2,400 in U.S.

VizStock Web Interface

Aggregates | Web Viewer | Individual Buildings



- View End Use Load Profiles
- View distributions of building characteristics
- Filter by building characteristic
- Filter by geography
- Select time window
- Download CSV of results



Individual Buildings – Load Profiles & Models

Aggregates | Web Viewer | Individual Buildings

Individual Building End Use Load Profiles

- ~450,000 residential
- ~350,000 commercial
- Full dataset will be 10's of terabytes
- Plan to include high-level instructions for loading this dataset using one cloud-based big-data analysis tool

Format:

- Folders with a series of Apache parquet* files
    - Likely 1 file per building, with IDs in names
- In Amazon S3 bucket or similar

Additional Data:

- Model characteristics by ID
- Model in OpenStudio (.osm) format

*https://parquet.apache.org/

2 Sets of Weather Data = 2 Sets of EULPs

Typical Meteorological Year (TMY3)

- Widely accepted/expected by utilities, regulators, etc.
- Weather is not coordinated across regions

	Weather Data from Year	
Month	Denver, CO	Boulder, CO
January	1995	1987
February	1994	1990
March	1991	1981
April	1999	1986

2 locations 40 miles apart use data from different years for the same month

Actual Meteorological Year (AMY)

- Using 2018 NOAA data

Format:

- CSV timeseries data for each location used
  - Dry bulb temperature
  - Relative humidity
  - Solar direct normal irradiation
  - Solar diffuse horizontal irradiation
  - Wind speed
  - Building characteristics
- Location used for each Model

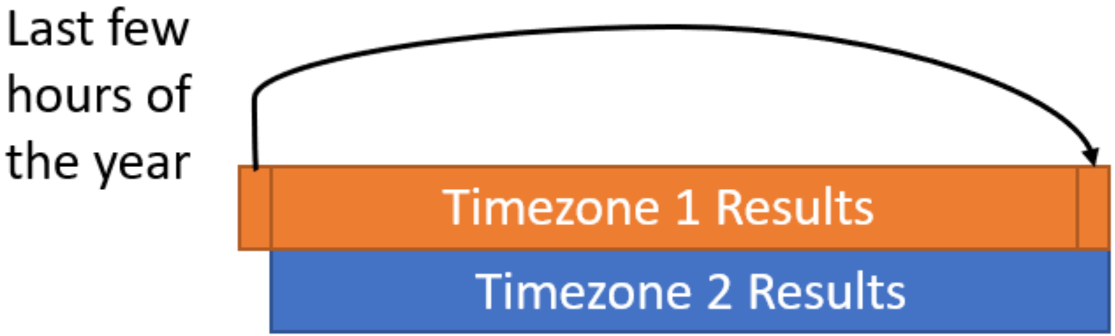
Time Stamps & Time Zones

Time Zones:

- **Data will be provided in UTC**

Time Stamps:

- **Wrap data from first few hours of year back to the end**
- **Creates a single, aligned 1 year worth of data**



Questions & Discussion

Residential Building Types & End Uses

Residential Building Types	Residential End Uses
Single-Family Detached	Heating
Multifamily (low-rise) Single-Family Attached	Cooling
Multifamily (low-rise) 2–4 Units	Furnace/AC fan
Multifamily (low-rise) 5+ Units	Boiler pumps
	Vent. fans
	Water heating
	Interior Lights
	Exterior Lights
	Misc. plug loads
	Refrigerator
	Clothes washer
	Clothes dryer
	Dishwasher
	Cooking Range

Commercial Building Types & End Uses

Commercial Building Types	Commercial End Uses
Small Office	Heating
Medium Office	Cooling
Large Office	Interior Lighting
Stand-alone Retail	Exterior Lighting
Strip Mall	Interior Equipment
Primary School	Exterior Equipment
Secondary School	Fans
Outpatient Healthcare	Pumps
Hospital	Heat Rejection
Small Hotel	Humidification
Large Hotel	Heat Recovery
Warehouse (non-refrigerated)	Water Systems
Quick Service Restaurant	Refrigeration
Full Service Restaurant	
Mid-rise Apartment	
High-rise Apartment	

Residential Building Characteristics

Residential Model Characteristics	(continued)	(continued)
ahs_region	heating_fuel	location_latitude
applicable	heating_setpoint	location_longitude
ashrae_iecc_climate_zone_2004	heating_setpoint_has_offset	location_region
bathroom_spot_vent_hour	heating_setpoint_offset_magnitude	location_state
bedrooms	heating_setpoint_offset_period	mechanical_ventilation
building_america_climate_zone	holiday_lighting	misc_extra_refrigerator
ceiling_fan	hot_water_distribution	misc_freezer
census_division	hot_water_fixtures	misc_gas_fireplace
census_region	hvac_system_cooling	misc_gas_grill
climate_zone_ba	hvac_system_cooling_type	misc_gas_lighting
climate_zone_iecc	hvac_system_heat_pump	misc_hot_tub_spa
clothes_dryer	hvac_system_heating_electricity	misc_pool
clothes_washer	hvac_system_heating_fuel_oil	misc_pool_heater
clothes_washer_presence	hvac_system_heating_natural_gas	misc_pool_pump
cooking_range	hvac_system_heating_none	misc_pool_schedule
cooking_range_schedule	hvac_system_heating_other_fuel	misc_well_pump
cooling_setpoint	hvac_system_heating_propane	natural_ventilation
cooling_setpoint_has_offset	hvac_system_is_heat_pump	neighbors
cooling_setpoint_offset_magnitude	hvac_system_is_shared	occupants
cooling_setpoint_offset_period	hvac_system_shared_electricity	orientation
corridor	hvac_system_shared_fuel_oil	overhangs
county	hvac_system_shared_natural_gas	plug_loads
days_shifted	hvac_system_shared_none	plug_loads_schedule
dehumidifier	hvac_system_shared_other_fuel	puma
dishwasher	hvac_system_shared_propane	pv
door_area	infiltration	radiant_barrier
doors	insulation_crawlspace	range_spot_vent_hour
ducts	insulation_finished_basement	refrigeration_schedule
eaves	insulation_finished_roof	refrigerator
electric_vehicle	insulation_interzonal_floor	roof_material_finished_roof
geometry_building_number_units_hl	insulation_pier_beam	roof_material_unfinished_attic
geometry_building_number_units_mf	insulation_slab	sample_weight
geometry_building_number_units_sfa	insulation_unfinished_attic	solar_hot_water
geometry_building_type_acs	insulation_unfinished_basement	state
geometry_building_type_recs	insulation_wall	units_modeled
geometry_floor_area	interior_shading	units_represented
geometry_floor_area_bin	iso_rto_region	usage_level
geometry_foundation_type	lighting	vintage
geometry_garage	lighting_interior_use	vintage_acs
geometry_perimeter_footprint_ratio	lighting_other_use	water_heater
geometry_stories	location	window_areas
geometry_wall_type	location_city	windows

Commercial Building Characteristics

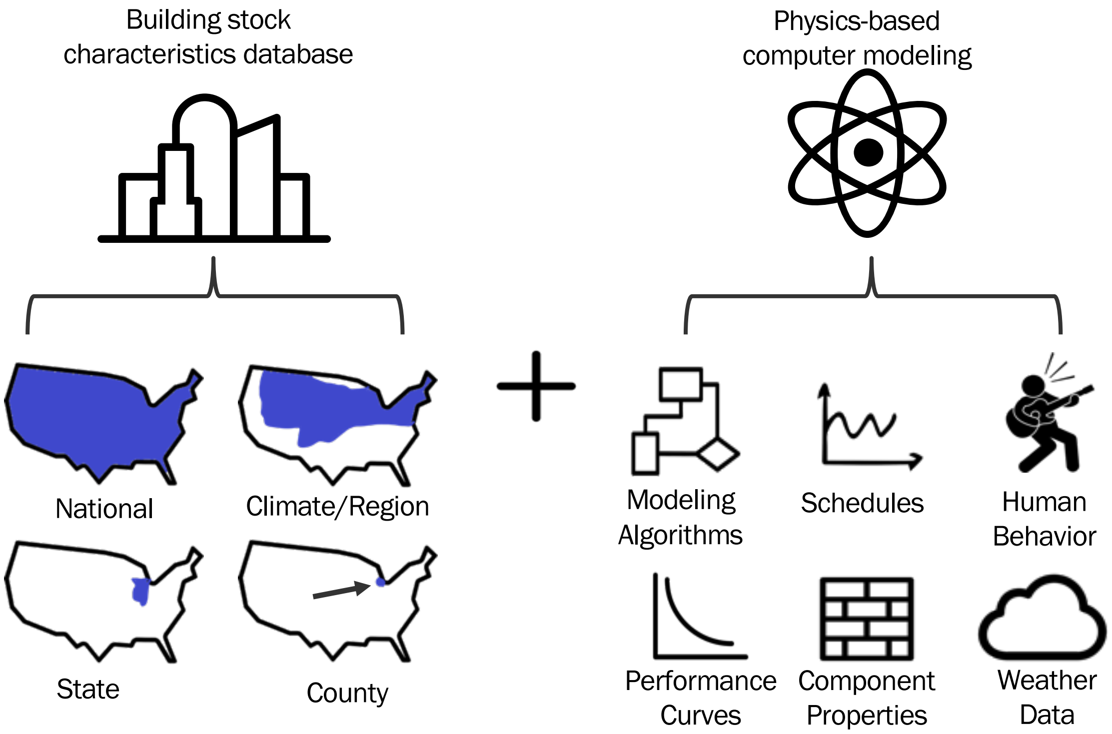
Commercial Model Characteristics	(continued)
building_type	cooling_source_fuel
climate_zone	heating_source_fuel
weather_file_name	hvac_delivery_type
rentable_area	service_water_heating_source_fuel
number_stories	kitchen_makeup
aspect_ratio	exterior_lighting_zone
total_bldg_floor_area	onsite_parking_fraction
bottom_story_ground_exposed_floor	energy_code_when_built
building_height_relative_to_neighbors	energy_code_when_envelope_last_updated
building_rotation	energy_code_when_exterior_lighting_last_updated
floor_to_floor_height	energy_code_when_hvac_last_updated
party_wall_stories_west	party_wall_fraction
single_floor_area	party_wall_stories_east
story_multiplier	party_wall_stories_north
top_story_exterior_exposed_roof	party_wall_stories_south
window_to_wall_ratio	energy_code_when_interior_equipment_last_updated
hvac_system_type	energy_code_when_interior_lighting_last_updated
energy_code_when_service_water_heating_last_updated	
weekday_operation_start_time	
weekday_operation_duration	
weekend_operation_start_time	
weekend_operation_duration	

Commercial Region 1 Calibration

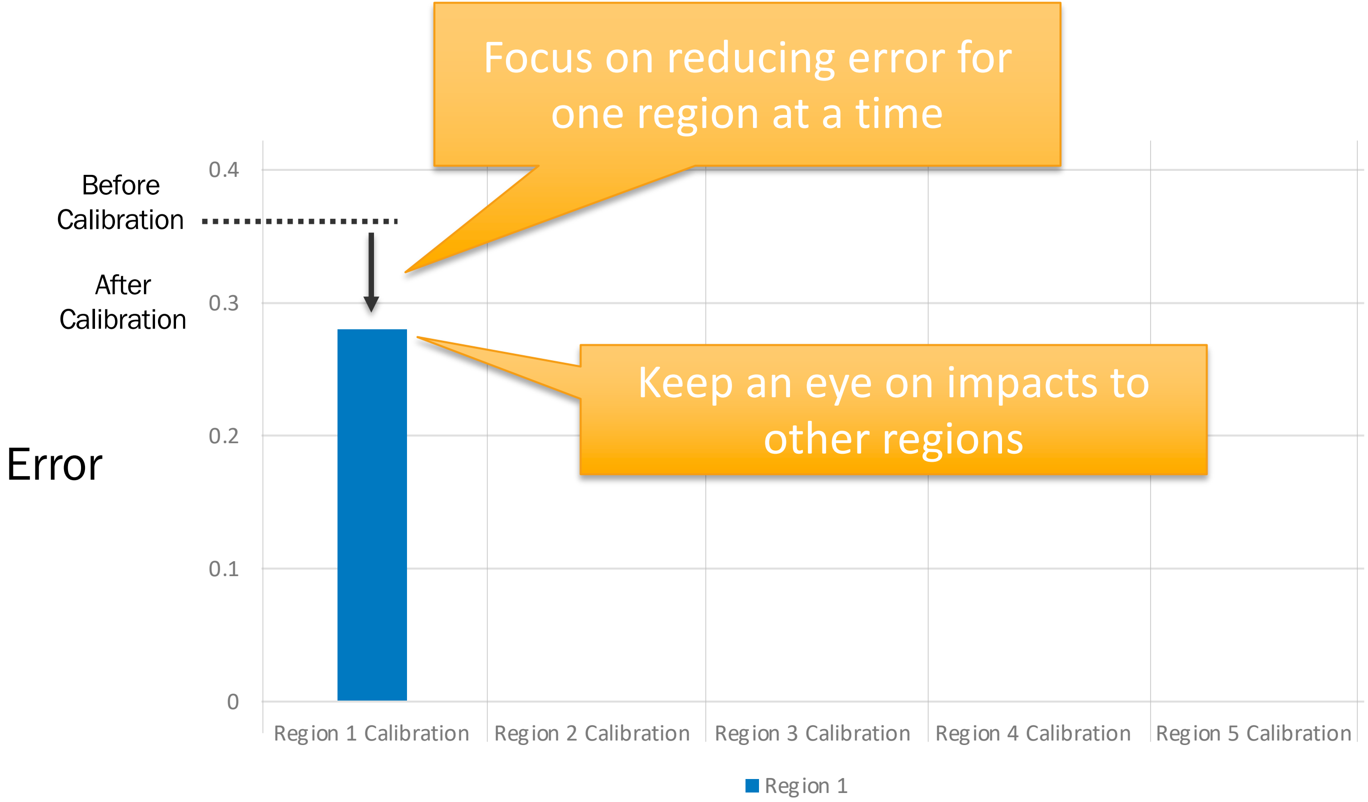
Andrew Parker
Matthew Dahlhausen, Ph.D.
September 22, 2020

Calibration Strategy

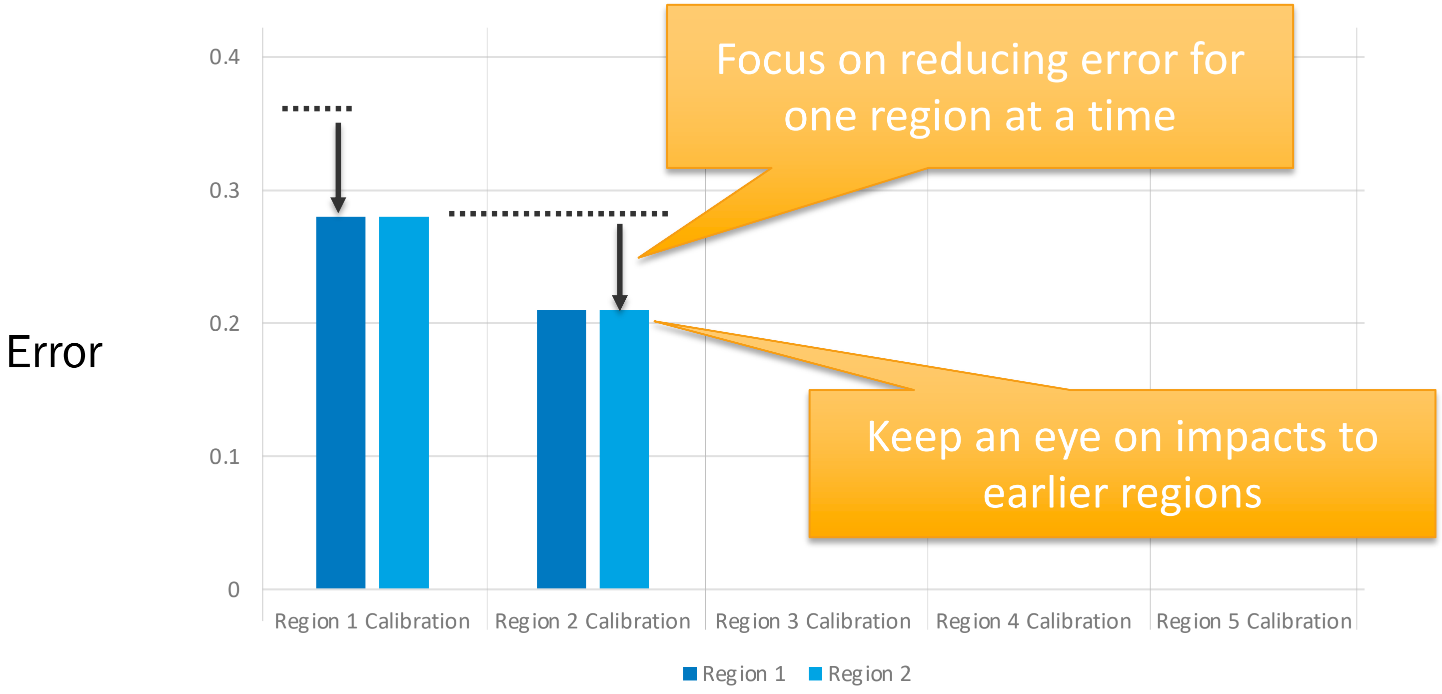
Model Architecture



Calibration Process for One Region

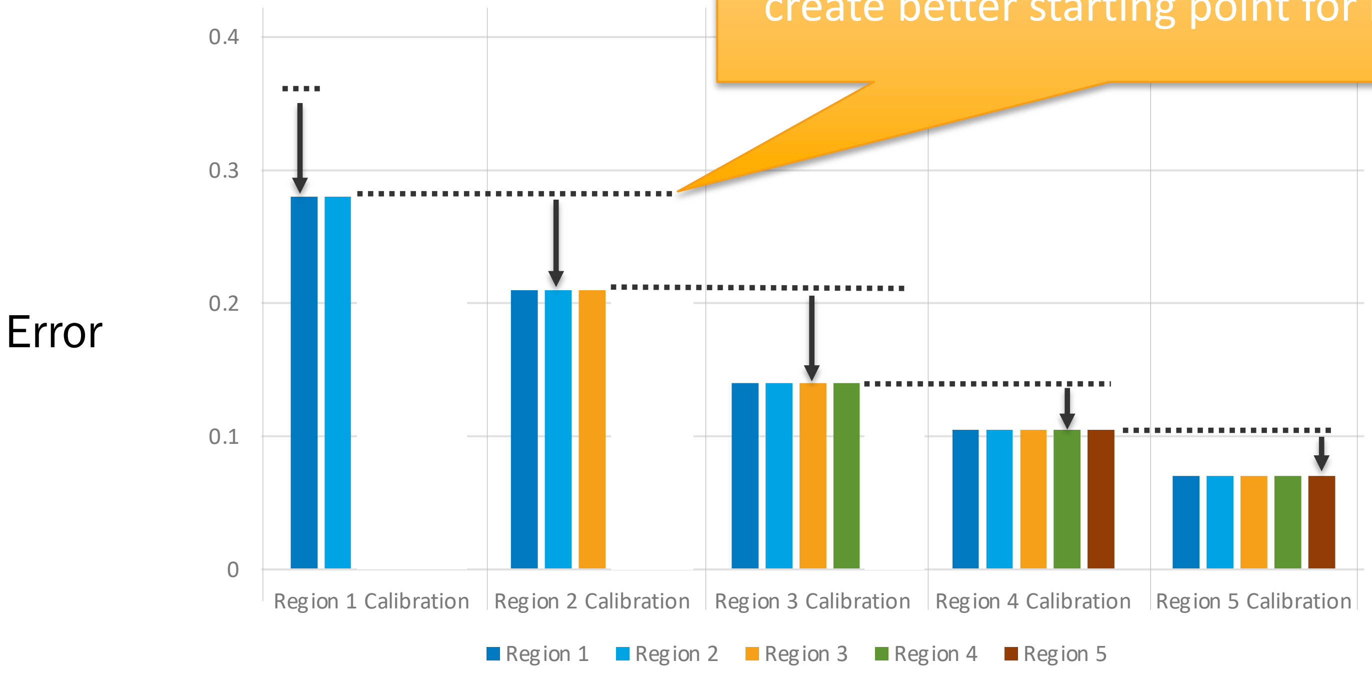


Calibration Process Over Time

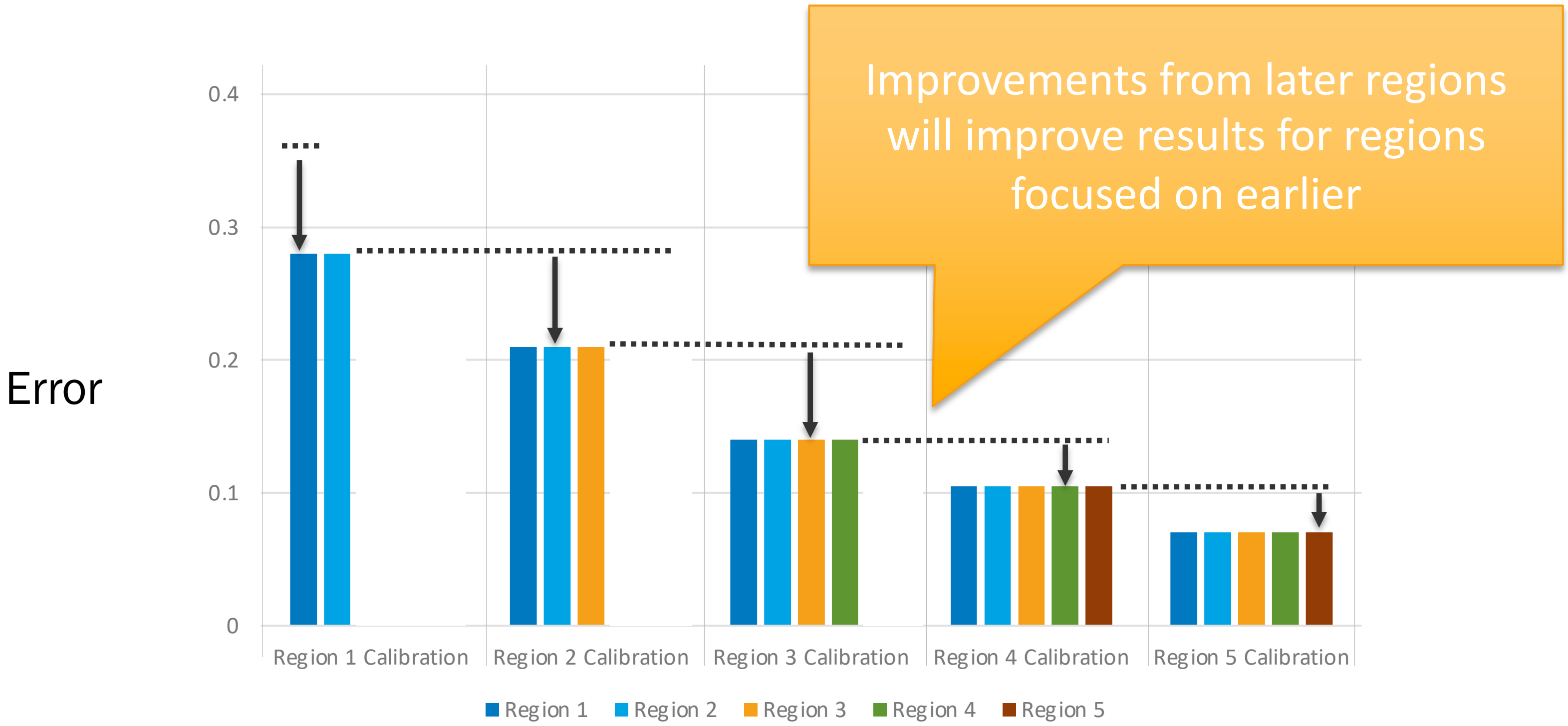


Calibration Process Over Time

Calibration efforts for earlier regions create better starting point for later regions

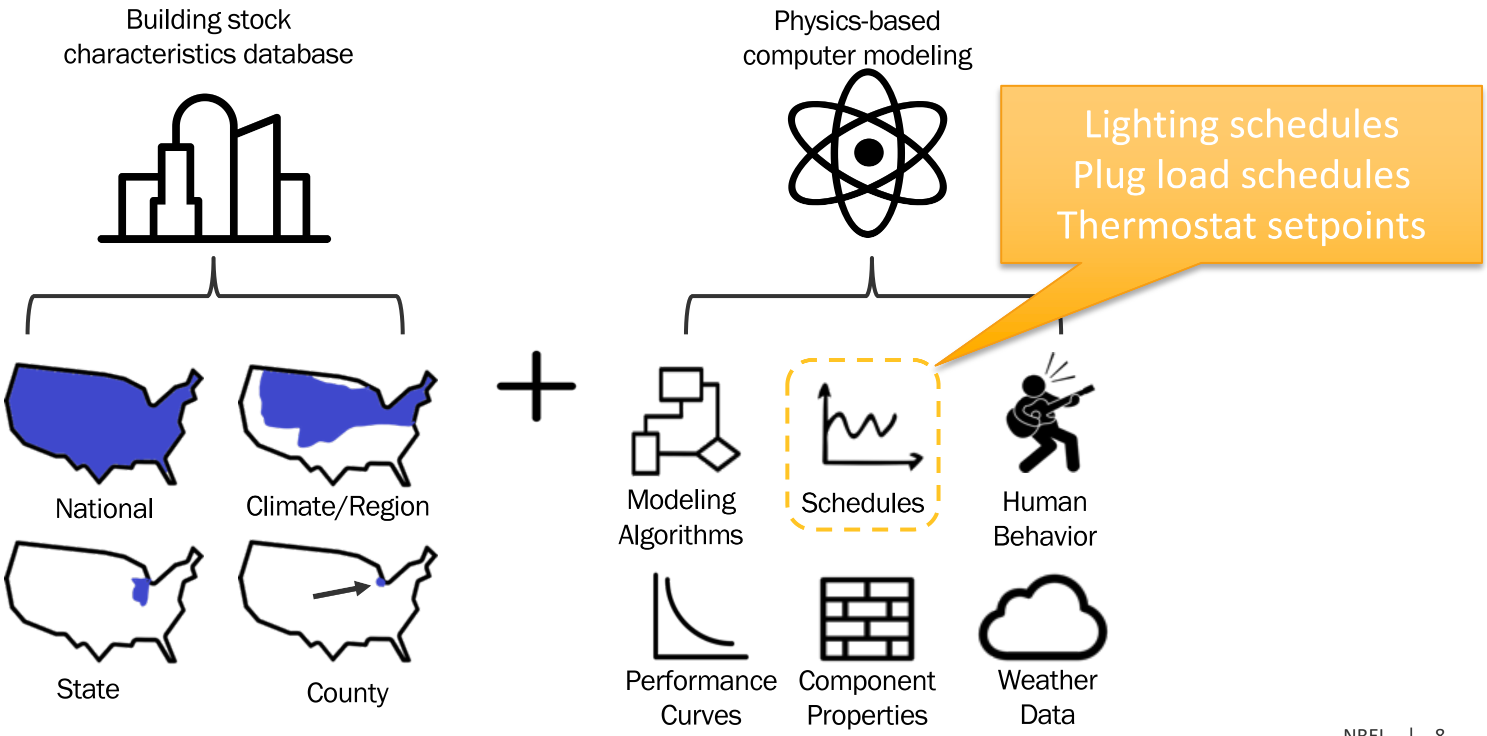


Calibration Process Over Time



Region 1 Focus: Major Schedules

ComStock

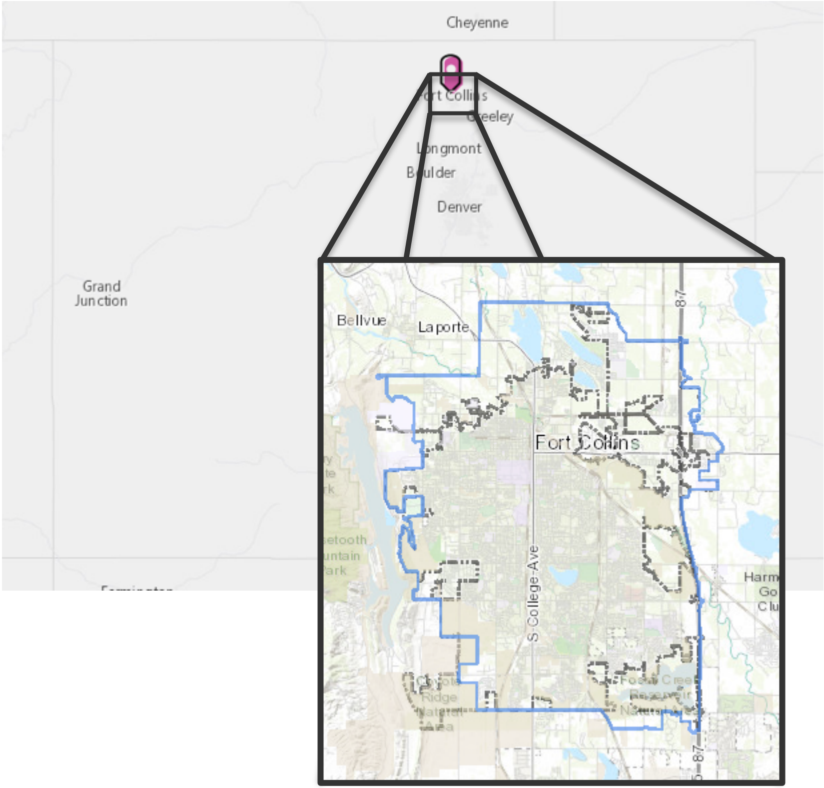


Region 1

- Fort Collins, Colorado (pop. ~160k)
- Municipal Utility
- Commercial Stock Summary

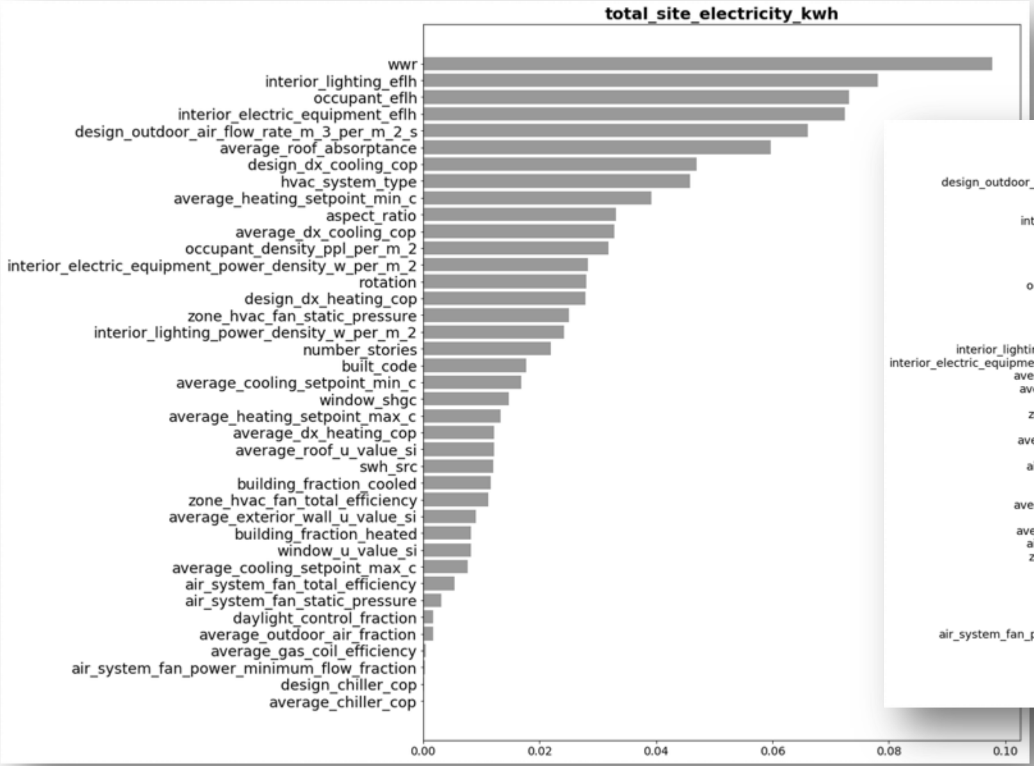
Building Type	Count
small_office	369
strip_mall	223
retail	181
warehouse	153
outpatient	96
full_service_restaurant	72
quick_service_restaurant	29
medium_office	28
primary_school	21
large_hotel	8
small_hotel	7
large_office	4

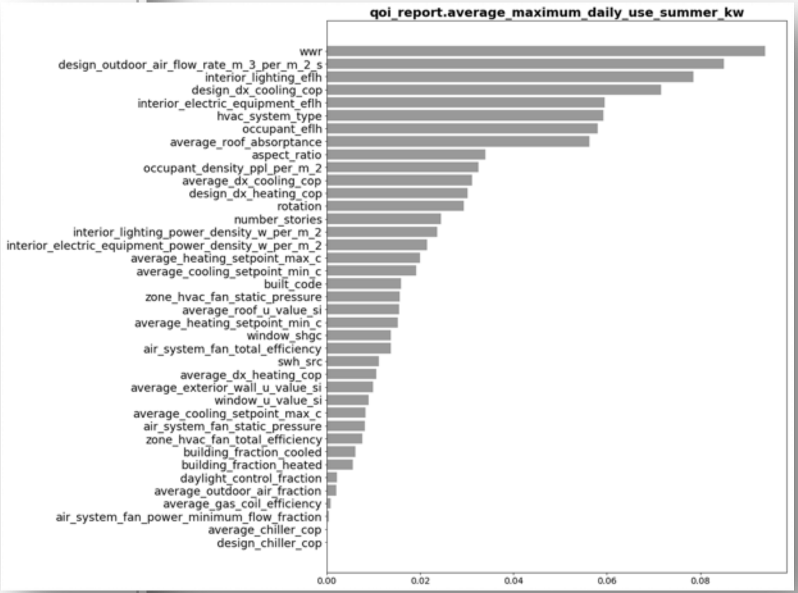
- Primarily used AMI data from 2016



ComStock Sensitivity Analysis

Analyzed impact on ~15 QOIs … focused on inputs highly rated for many QOIs





List of updates

New capabilities

- None

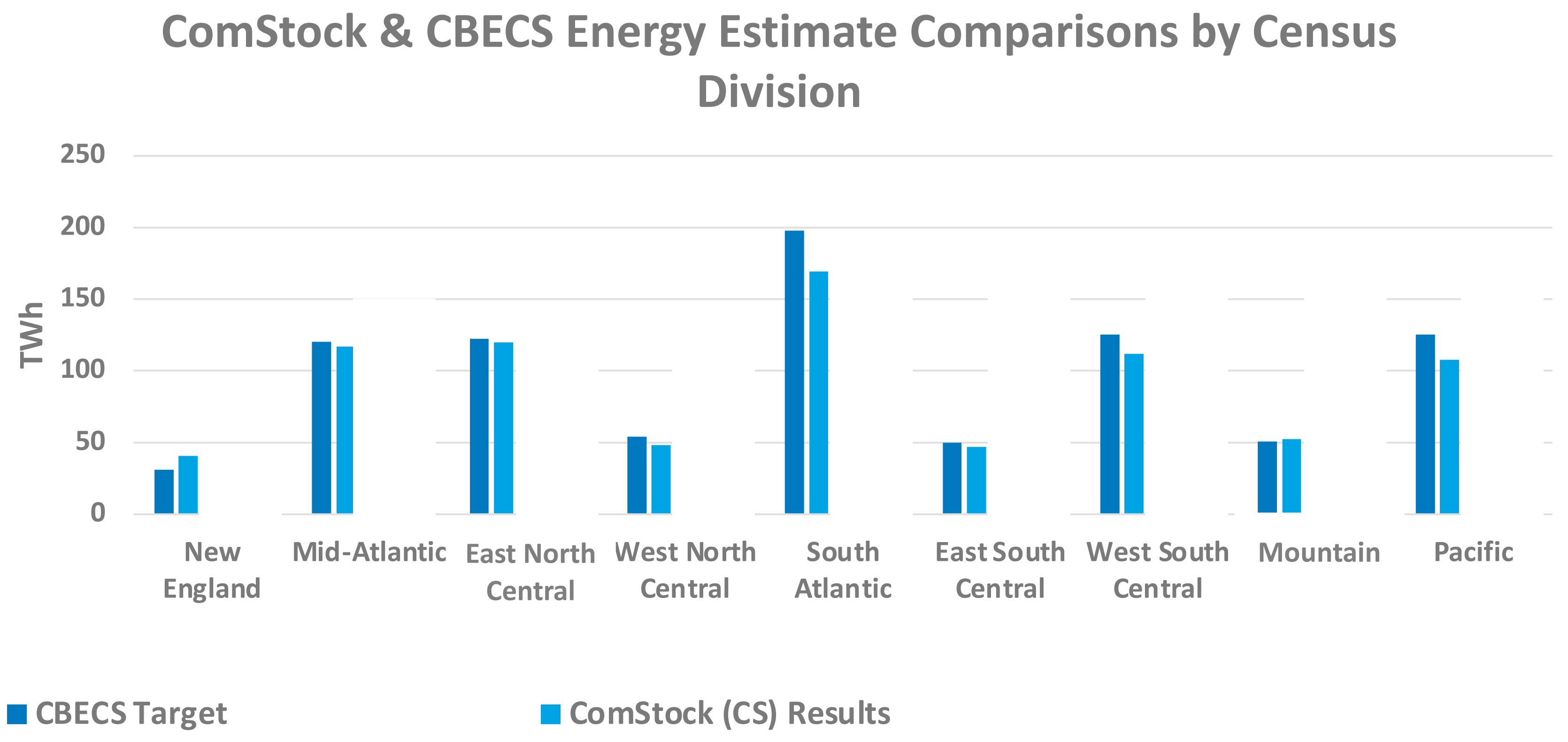
Baseload updates

- Interior lighting schedules
- Plug load schedules

HVAC updates

- Thermostat setpoints

ComStock Calibration Before EULP



Challenges of Commercial AMI data

Sanity Checking AMI Data vs CBECS

building_type	CBECS Mountain Region (kWh/sf)	Fort Collins AMI (kWh/sf)
full_service_restaurant	34*	67
hospital	27	NA
large_hotel	22	12
large_office	14*	16
medium_office	14*	14
outpatient	12	14
primary_school	10	8
quick_service_restaurant	34*	123
retail	24	40
secondary_school	10	NA
small_hotel	22	9
small_office	14*	31
strip_mall	20	25
warehouse	4	22

Mean EUI of AMI data is much higher/lower than CBECS for some building types… why?

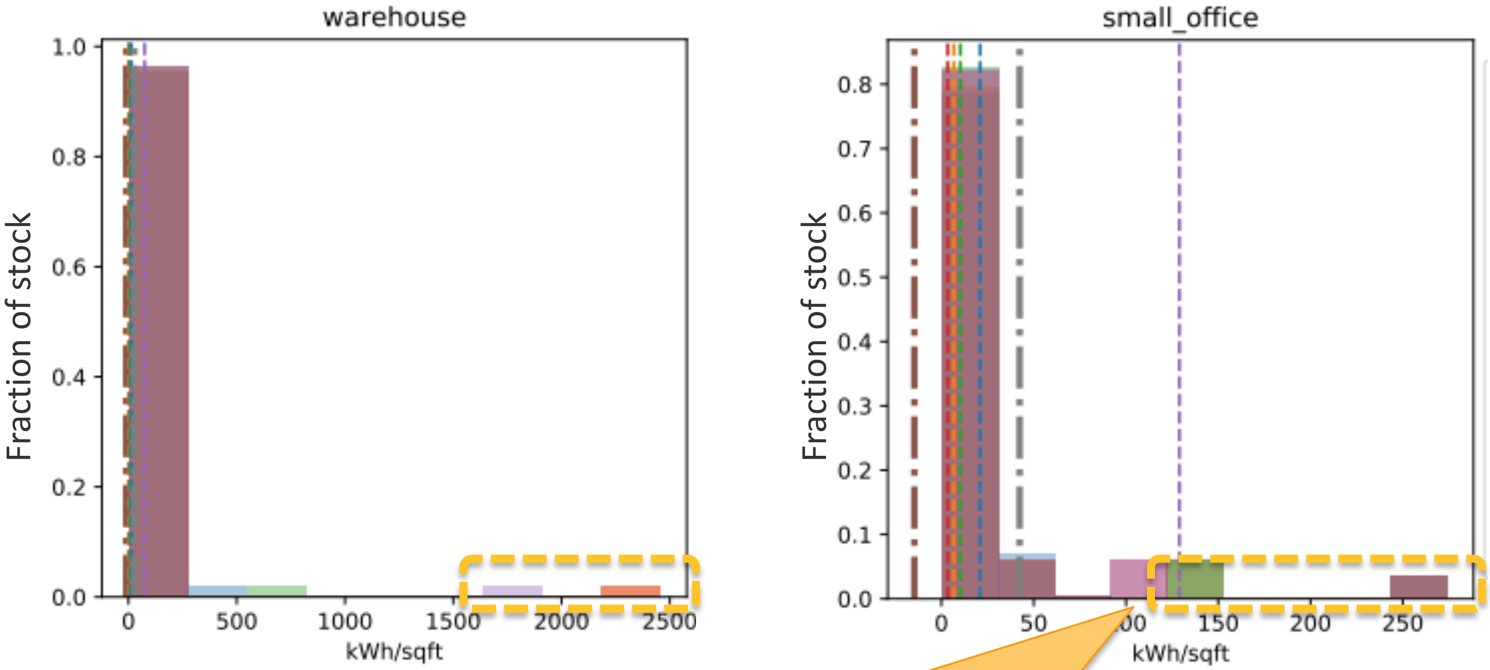
* CBECS doesn't break out quick vs. full svc. Restaurant or office size category

Distribution of AMI Data

	Annual EUI (kWh/sqft)	Percentiles				
	mean	P05	P25	P50	P75	P95
full_service_restaurant	76.8	11.7	26.4	48.1	135.8	215.5
large_hotel	20.2	9.0	15.1	18.1	25.9	31.0
large_office	18.3	7.2	17.4	17.4	24.5	24.5
medium_office	17.0	4.8	12.1	17.9	22.2	36.7
midrise_apartment	29.3	3.4	4.8	6.4	10.7	257.2
outpatient	15.1	3.3	7.8	10.2	17.6	35.5
primary_school	9.1	1.8	6.2	8.0	12.9	16.3
quick_service_restaurant	174.4	48.1	88.5	160.4	215.5	347.7
retail	40.8	2.6	9.0	20.2	49.4	197.7
small_hotel	9.8	1.3	1.3	14.2	14.2	16.4
small_office	30.0	3.8	7.0	10.6	23.1	124.3
strip_mall	28.0	5.0	11.5	18.0	30.3	77.3
warehouse	62.2	1.3	3.8	7.1	13.5	72.3

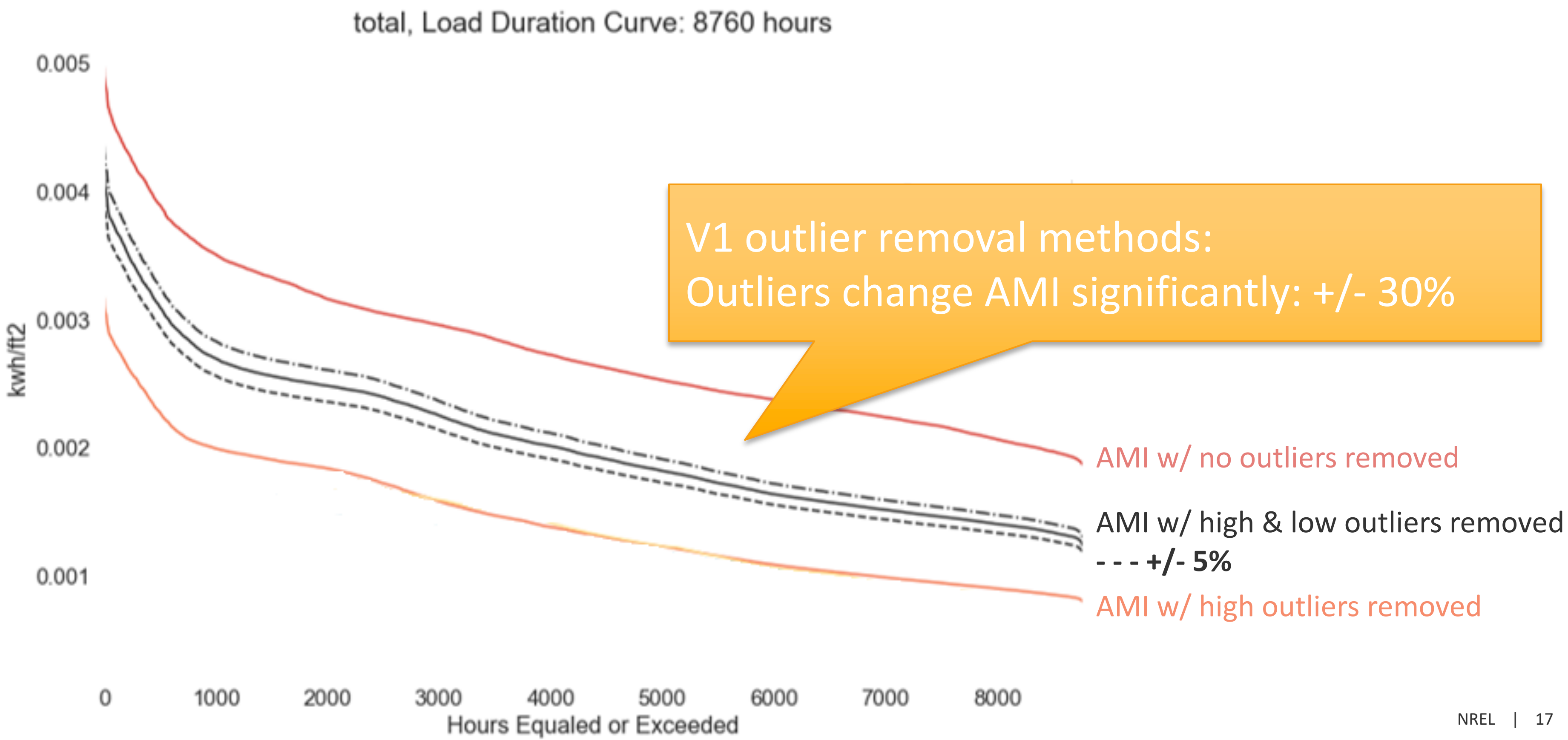
Mean EUI almost as high as 95th percentile!

Outliers Skewing Mean AMI Data



Are these really the building type we think they are?

Impact of Outliers & Classification: Version 1



Investigating V1 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

Identifying Misclassified AMI Systematically

Refine the misclassification/outlier detection process.

Goals:

- Keep as much AMI as possible
- Can't rely on manually classifying every AMI building

Approach:

1. Run each method on AMI
2. Find method that identifies largest number of buildings
3. Manually classify all these outliers using google maps
4. Compare the results of the various methods

Identifying Misclassified AMI - Results

Methods tested:

1. +/- 1.5x IQR: original approach, only removes super high EUIs
2. +/- 1.5x natural log(IQR): incorrectly removes low but realistic EUIs
3. 25th-75th percentile: too conservative, removes half of buildings every time
4. +/- 10x median: misses low EUIs
5. +/- 5x median: slightly better
6. +/- 3x median: best balance we've found

		AMI removed by filter type					
Building type	**Total AMI count**	**+/- 1.5x IQR**	**+/- 1.5x ln(IQR)**	**25th-75th percentile**	**10x median**	**5x median**	**3x median**
small_office	369	28	18	184	11	26	58
strip_mall	223	24	10	110	14	37	65
retail	181	16	6	90	10	23	57
warehouse	153	18	18	76	16	25	45
outpatient	96	4	14	48	9	12	16
full_service_restaurant	72	3	2	36	1	4	10
quick_service_restaurant	29	2	1	14	0	0	1
medium_office	28	1	2	14	2	2	5
primary_school	21	0	2	10	0	0	2
large_hotel	8	0	0	4	0	0	0
small_hotel	7	0	0	2	0	1	2
large_office	4	0	0	2	0	0	0

Final Method Selection: +/- 3x Median

Still uses most of the AMI

Building type	Total AMI Count	True Positive	False Positive	False Positive Rate	Valid AMI Preserved (%)
full_service_restaurant	72	5	5	50%	93%
large_hotel	8	0	0		100%
large_office	4	0	0		100%
medium_office	28	3	2	40%	92%
outpatient	96	9	7	44%	92%
primary_school	21	2	0	0%	100%
quick_service_restaurant	29	0	1	100%	97%
retail	181	46	11	19%	92%
small_hotel	7	1	1	50%	83%
small_office	369	45	13	22%	96%
strip_mall	223	58	7	11%	96%
warehouse	153	38	7	16%	94%
Grand Total	1191	207	54	21%	95%

True Positive: correctly identified a misclassified building
False Positive: identified a building as misclassified, but the original classification was correct

Misclassified AMI: +/- 3x Median

True Positive (actual building types below per google maps)

(original classification) Building type	false positive	quick_service_restaurant	empty or abandoned	residential single family	full_service_restaurant	convenience store	workshop	auto repair	manufacturing	outpatient	self storage	area incorrect	mixed types	unclear	bank	supermarket	church	multiple types	small_office	retail	garden center	nursing home	warehouse	dispensary	emissions testing facility	gym with pod	gymnastics	laboratory	liquor store	preschool in home	residential multifamily	small_hotel	strip_mall	swim school	theater
full_service_restaurant	5	1								1				1																		1	1		
medium_office	2		1									1					1																		
outpatient	7			7																		2													
primary_school																	1													1					
quick_service_restaurant	1																																		
retail	11	10	8	1	4	2	3	2				3	1	3		2	1				1		1	1					1					1	1
small_hotel	1			1																															
small_office	13	1	3	3	5		3		5	8			2	2	6	1	1	2			1							1			1				
strip_mall	7	12	4	6	5	10	1	2				3	4			3			5				1			1	1								
warehouse	7		3				5	7	5		9			1			1	3		3					1										
Grand Total	54	**24**	**19**	**18**	**14**	**12**	**12**	**11**	**10**	**9**	**9**	**7**	**7**	**7**	**6**	**6**	**5**	**5**	**5**	**3**	**2**	**2**	**2**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
		A	**B**	**C**	**D**	**E**	**F**																												

A. Retail or strip malls that are mostly or entirely restaurants
B. Empty or abandoned buildings (don't use much energy)
C. Residential homes that are converted into dentist/doctor/counseling/etc. offices
D. More restaurants
E. Strip malls or retail that are convenience stores, which have refrigeration
F. Warehouses that are light manufacturing of some sort

AMI Classification

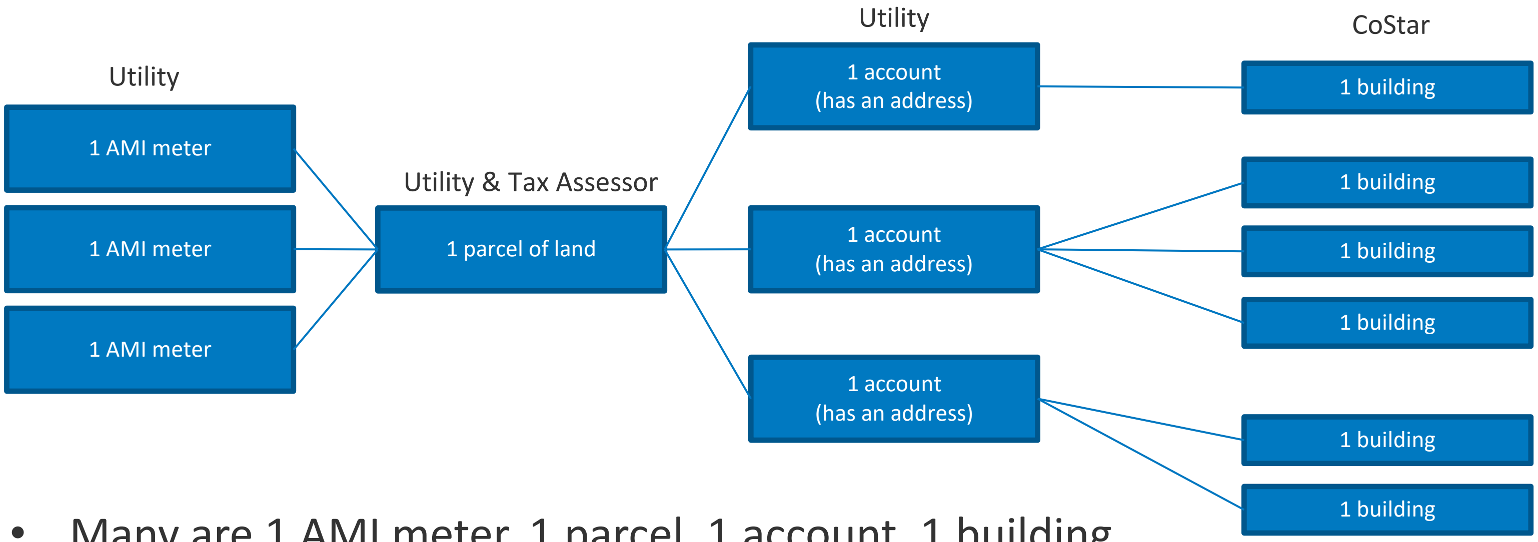
- CoStar (our classification starting point) classifies based on real-estate needs
  - Some are clear: offices, outpatient, standalone retail
  - Some are ambiguous: strip malls, warehouses

- For region 1, addresses were available per-building
  - Were able to investigate specific outliers
  - Must use this opportunity to refine classification & outlier detection

Was important for Region 1
Will be a major focus for Region 2

Matching AMI Data to Buildings

- Some datasets have one service address per-AMI meter
- Ft. Collins…not so simple



- Many are 1 AMI meter, 1 parcel, 1 account, 1 building
- Some are not
- Getting area right is critical for EUI calculation

Processing Commercial end use data

Commercial End Use Data

- Res end use data – typically collected with energy research in mind
- Com end use data – typically collected for another reason & purchased for EULP
    - Data format varies – a few days to reformat/clean up each dataset
    - Labeling/data not always certain
        - A meter is labeled “lighting,” but does that circuit have any other loads on it?
        - How much of the building area is served by a given circuit?

Takes time & effort to use each dataset

Baseload Updates

Update: Lighting Schedules

Task	Affected Building Type	Considerations
Update normalized lighting schedules	retail, full service restaurant, warehouse, office	• Calculated average daily (in hourly interval) profiles for each building type and for each day of week. • Initial understanding of variability of profiles was also explored.
	primary school and secondary school	• Calculated average daily (in hourly interval) profiles for each building type and for each day of week. • Differentiated average profiles between academic and summer break periods.
Update lighting power density	retail, full service restaurant, warehouse, office	• Normalized profile can underestimate usage since it is based on measured peak power. • Quantified approximate difference between design peak power and measured peak power (≈5%). • Lighting power density adjusted.

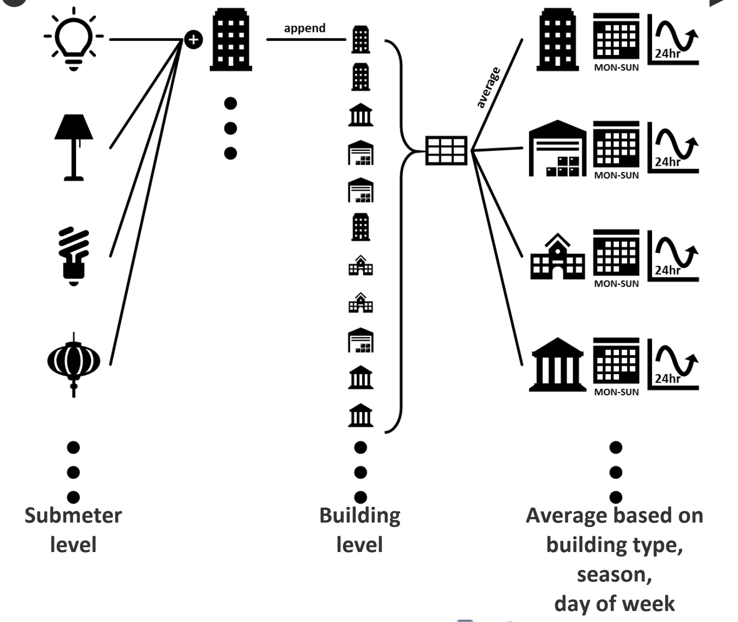
Details of using procured end use data

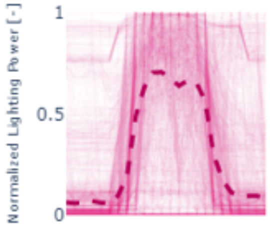
Pre-process

Data source 1 ~300 GB ~3000 buildings 1min interval	Metadata	Timeseries Data
Data source 2 ~50 GB ~70 buildings 15mins interval	Metadata	Timeseries Data

Understand formatting	Review/Classify submeter lables	Review with data owner	Create common metadata	Filter down to certain enduse type	Create common data frame
Two different sources in two different formats	Total of 7355 unique submeter labels	Multiple emails and phone calls	Grouping building types and enduse types separately	~1000 buildings for each enduse type	Ready for post-process

Post-process



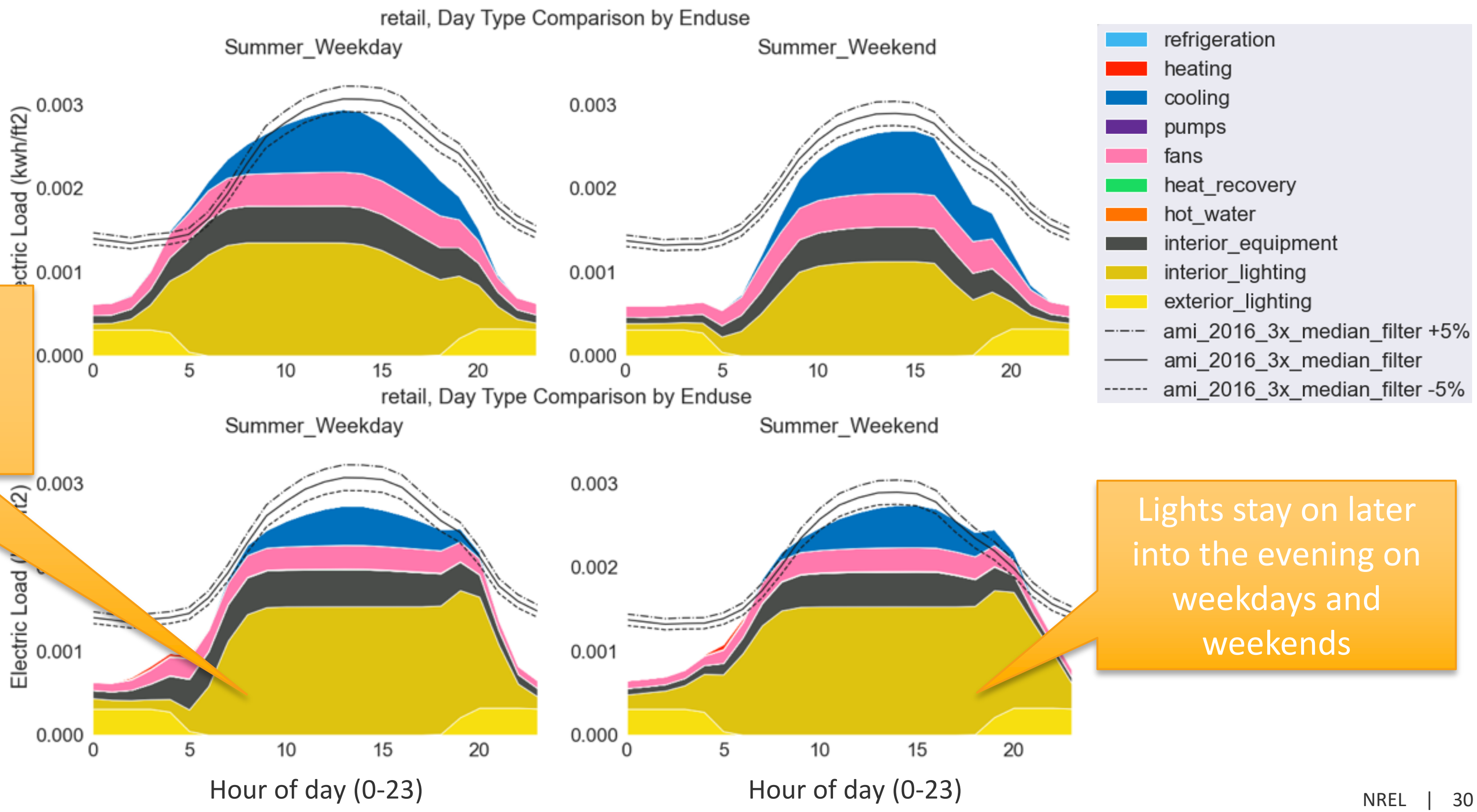


Building Type	Building Count
Mercantile Retail	787
FoodService Restaurant	135
Education School	27
Warehouse	26
Office	25
FoodSales Grocery	23
Other	17
Service	11
Warehouse Refrigerated	5
Data Center	2
Lodging Hotel	1
Office Medical	1

Impact: Lighting Schedules

Before

After



Lights go on later in the morning on weekdays

Lights stay on later into the evening on weekdays and weekends

Update: Plug Load Schedules

Task	Affected Building Type	Considerations
Update normalized plug load schedules	retail, full service restaurant, grocery, warehouse, office	• Calculated average daily (in hourly interval) profiles for each building type and for each day of week.
	primary school, secondary school	• Calculated average daily (in hourly interval) profiles for each building type and for each day of week. • Differentiated average profiles between academic and summer break periods.
Update equipment power density	retail, full service restaurant, grocery, warehouse, office, primary school, secondary school	• Normalized profile can underestimate usage since it is based on measured peak power. • Equipment power density adjusted.

Details of using procured end use data

1

Building Type	Building Count
FoodService_Restaurant	697
Mercantile_Retail	59
Warehouse	31
FoodSales_Grocery	30
Education_School	28
Office	27
Lodging_Hotel	1
Office_Medical	1
Service	0
DataCenter	0
Other	0

Building types with greater than 20 sample buildings were included

2

Manually identified meter data that is not relevant to plug loads. About 90 keywords identified as irrelevant. Examples:

- "Lighting"
- "Air Conditioner"
- "Unknown"

3

Calculated median building plug load schedule for each day of the week and each building type.

4

Visually compared load profiles between the days of the week to determine whether days could be combined. For example, warehouses have similar weekday profiles, but weekends should have a unique schedule.

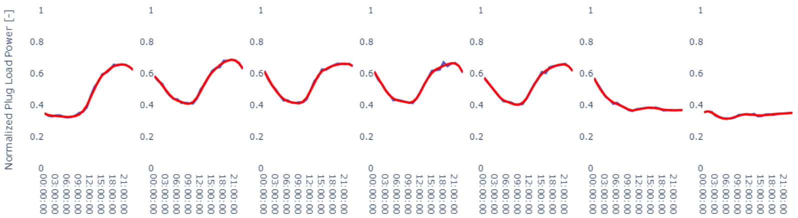


Figure 1. Warehouse profiles

Impact: Plug Load Schedules

Plug loads bring building energy use closer to the base load

HVAC Updates

Update: Thermostat Setpoints

Task	Affected Building Type	Methods
Update normalized thermostat heating and cooling setpoint schedules	retail, strip mall, quick-service restaurant, full-service restaurant, grocery, office	• Calculated average daily (in hourly interval) profiles for each building type and each day of the week. • Initial understanding of variability of profiles was also explored for future calibration efforts.

Details of using procured end use data

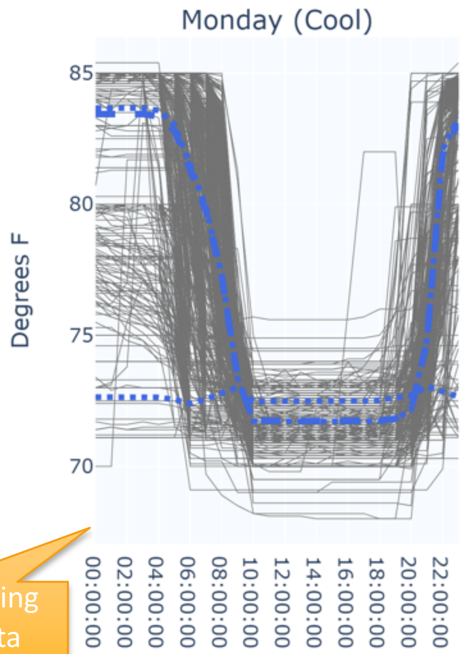
1 Identified heating and cooling thermostat setpoint meters in datasets.

2 Calculated average heating and cooling profiles for each building for each day of the week.

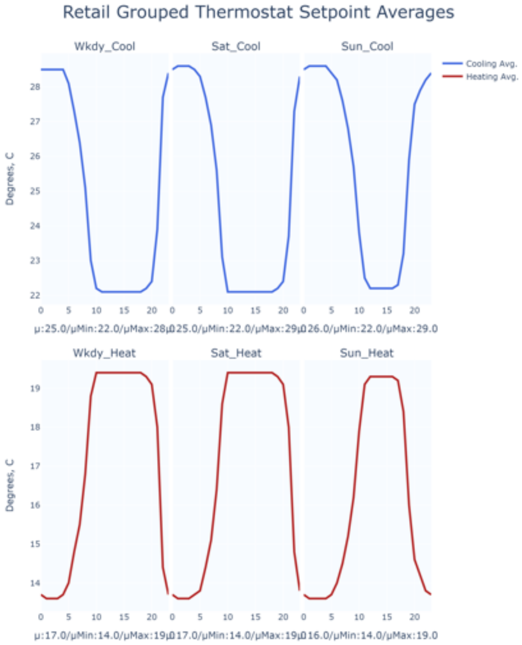
3 Profiles were aggregated to produce representative heating and cooling setpoint profiles

Building Type	Building Count With Thermostat Data
FoodService_Restaurant	1817
Mercantile_Retail	1692
FoodSales_Grocery	164
Office	31
Education_School	16
Warehouse	4
Lodging_Hotel	4
Hospital	2
Outpatient	2

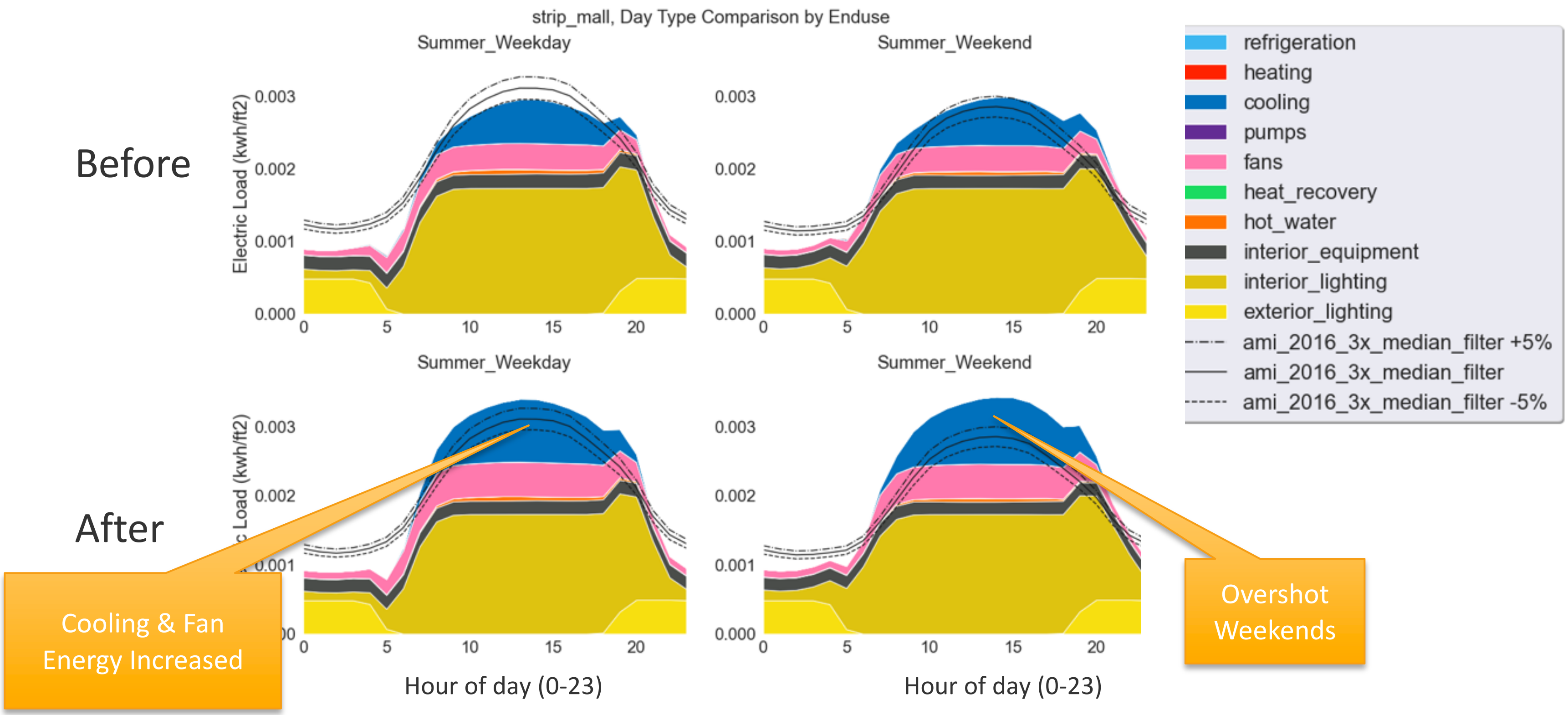
Building types with greater than 20 sample buildings were included



Example of cooling thermostat data producing average Monday profiles

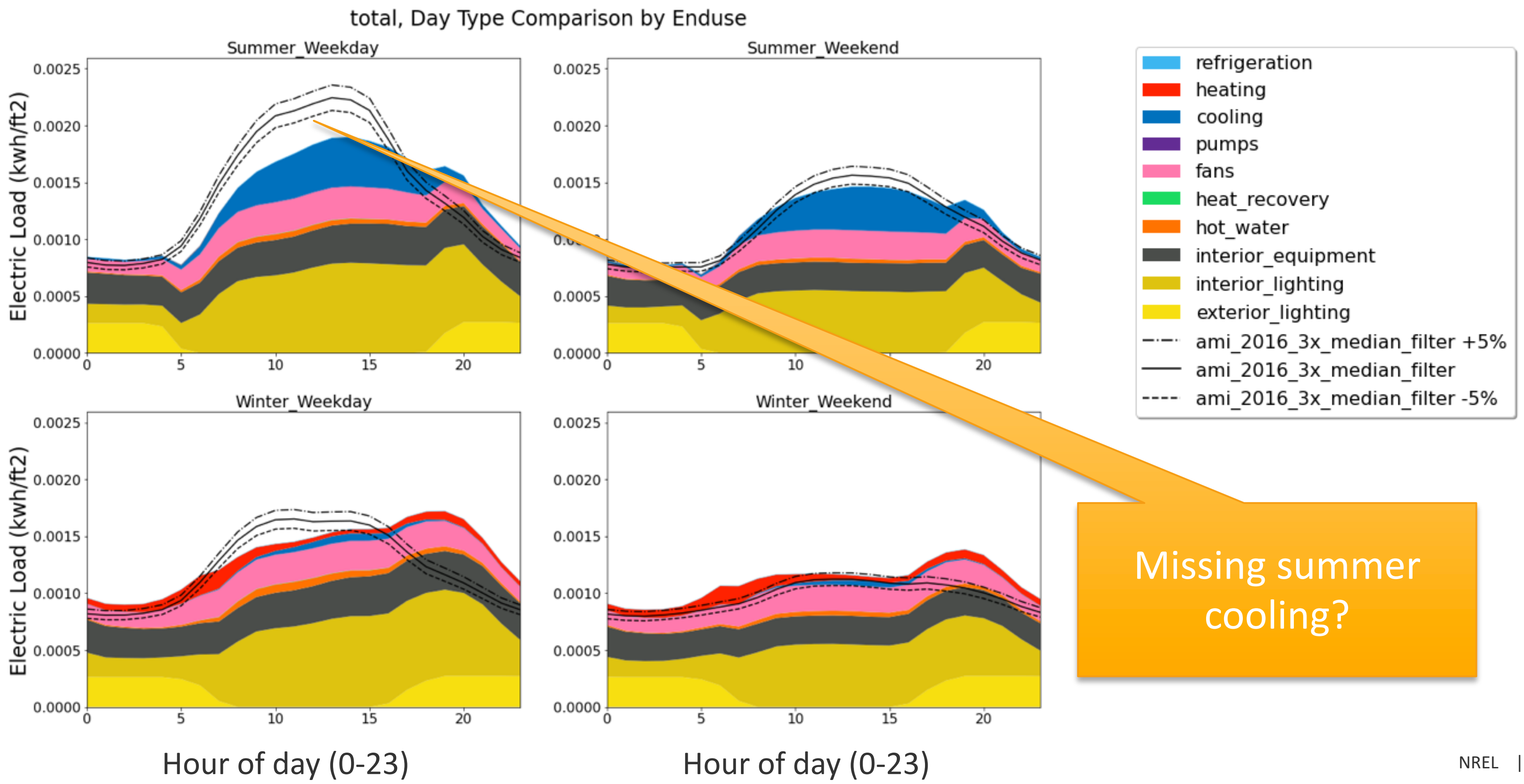


Impact: Thermostat Setpoints

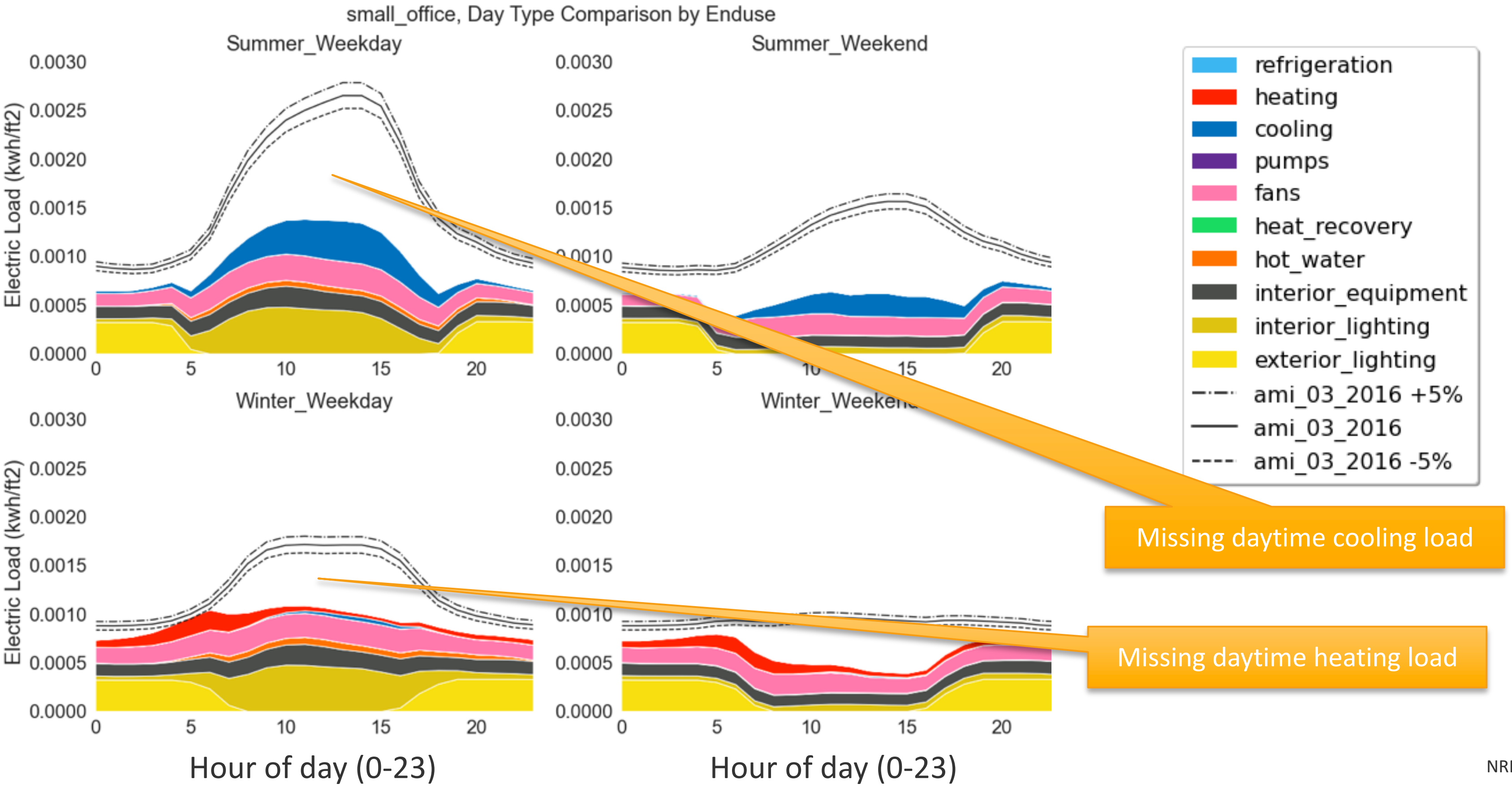


Commercial stock end-use summary

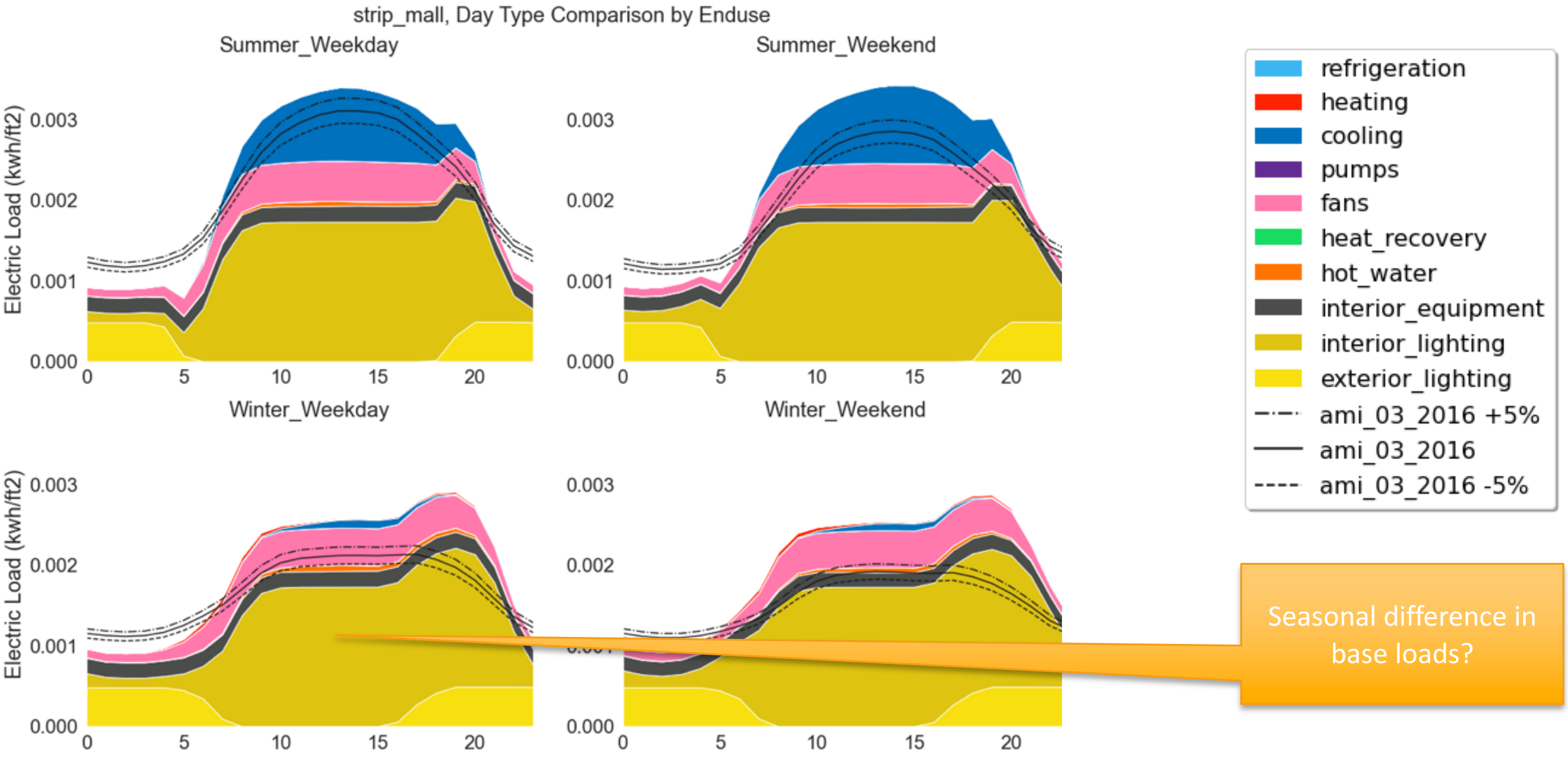
Total building stock load by day type



Small office by day type

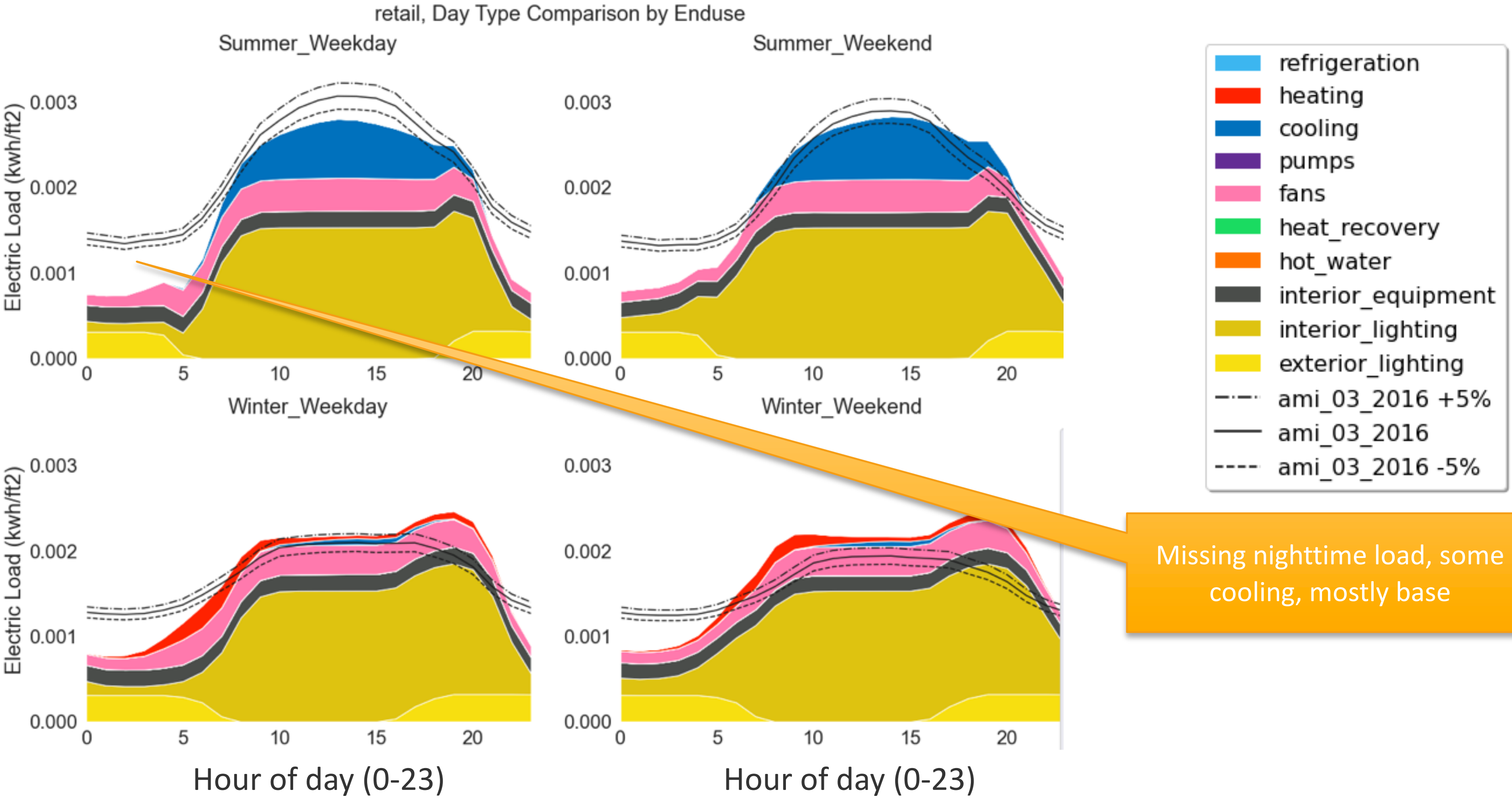


Strip mall by day type



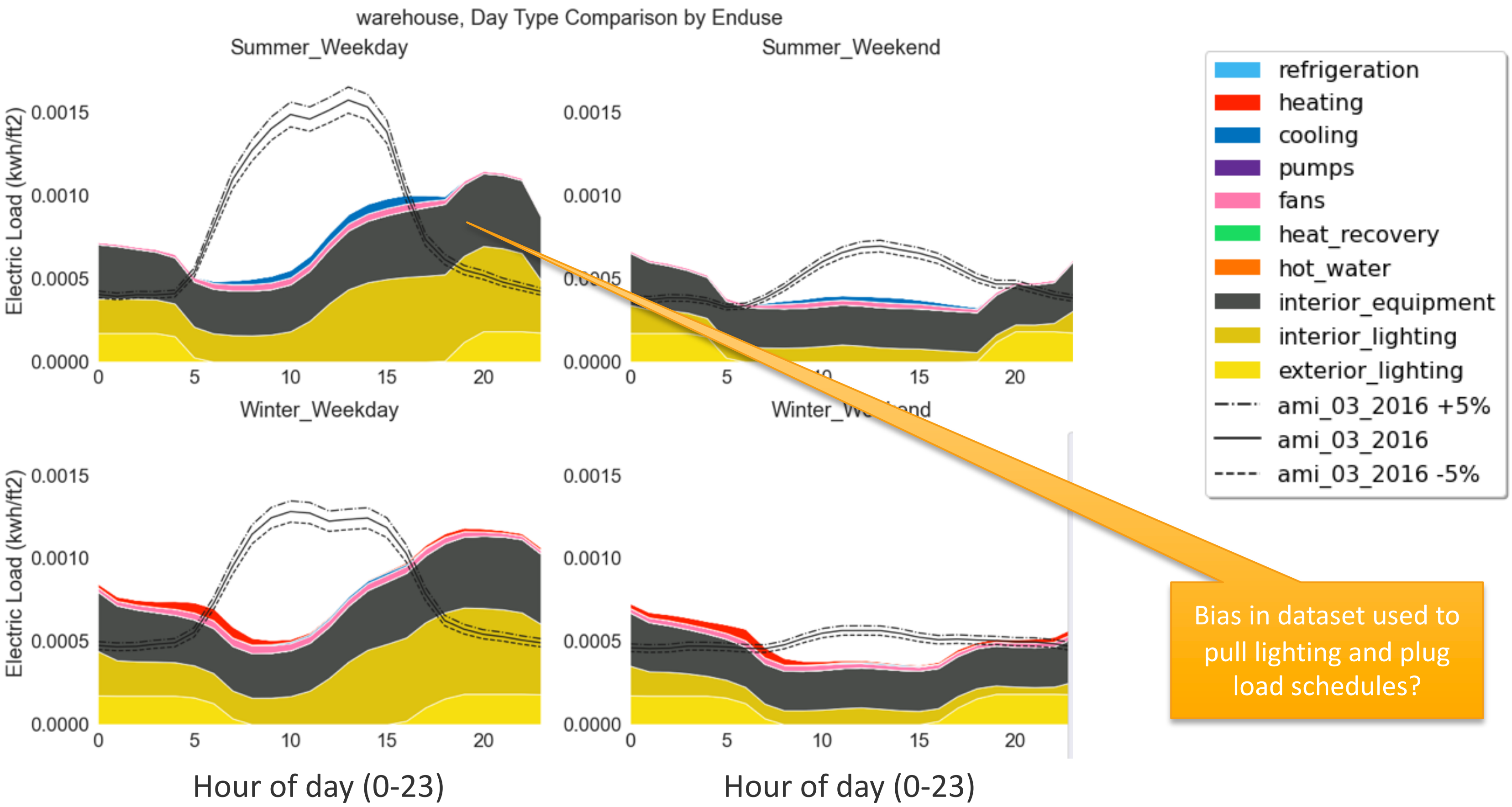
Hour of day (0-23) Hour of day (0-23)

Retail by day type



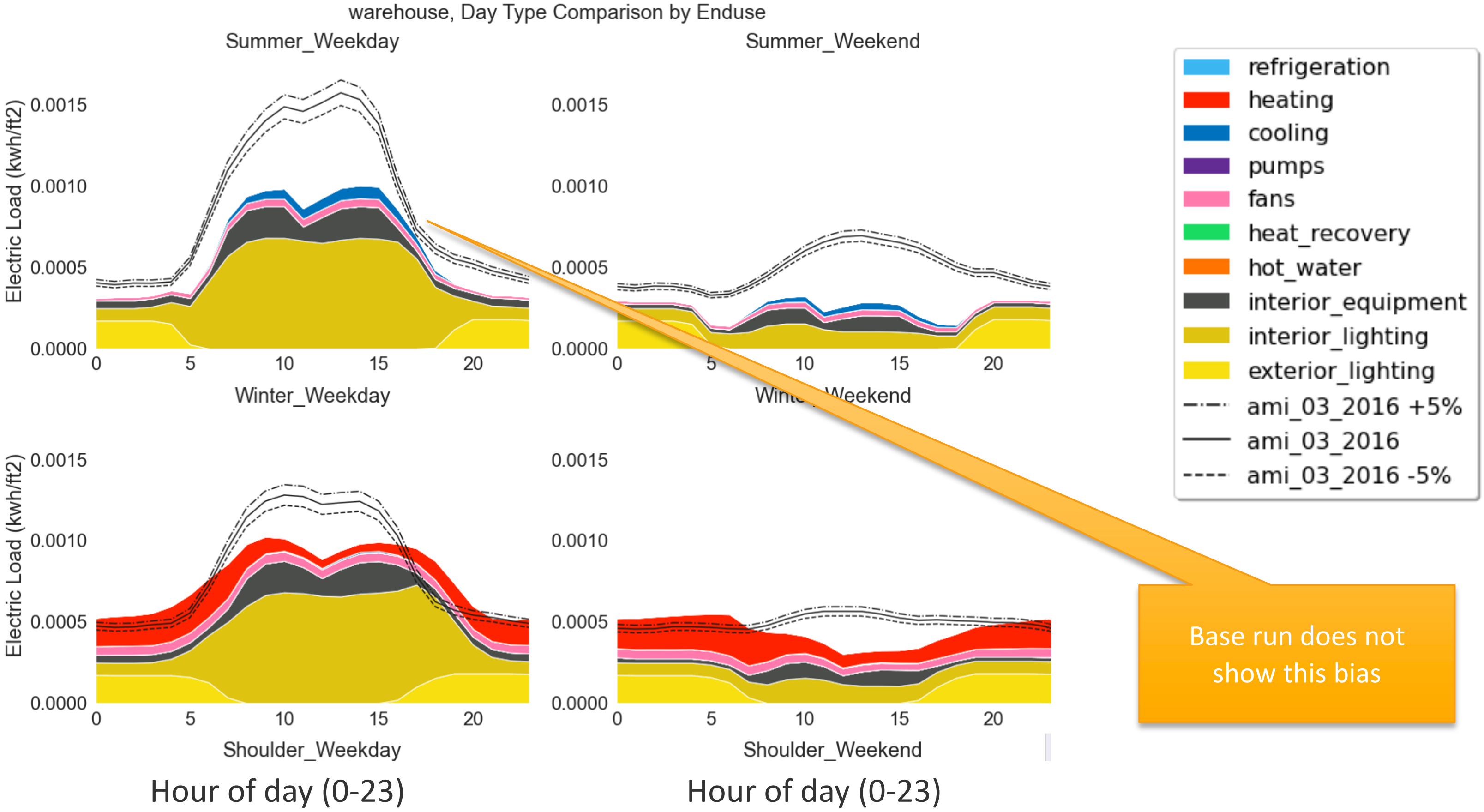
Missing nighttime load, some cooling, mostly base

Warehouse by day type



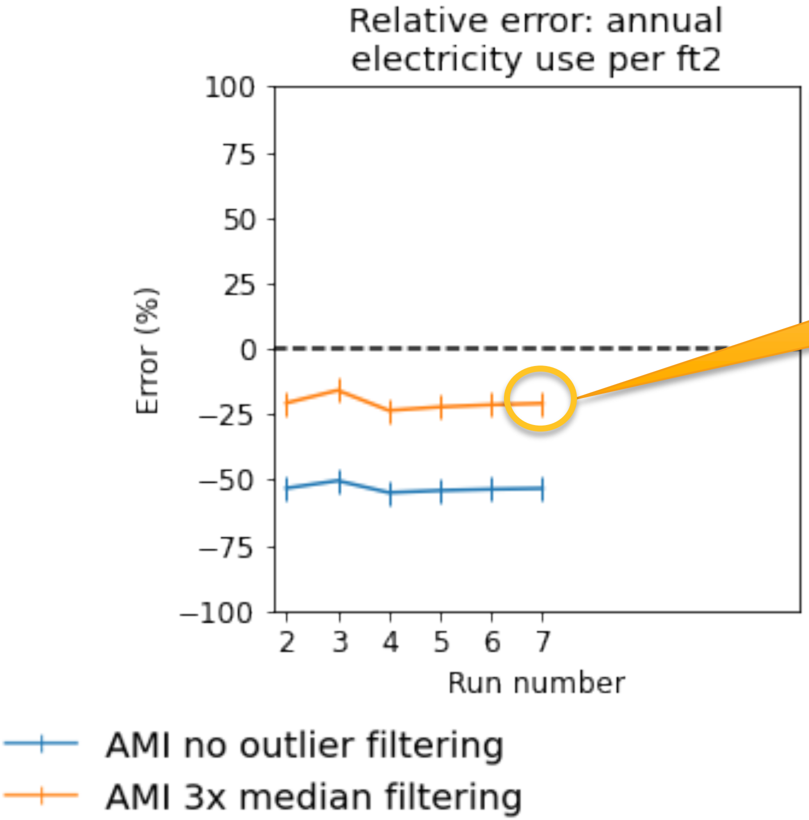
Bias in dataset used to pull lighting and plug load schedules?

Warehouse by day type



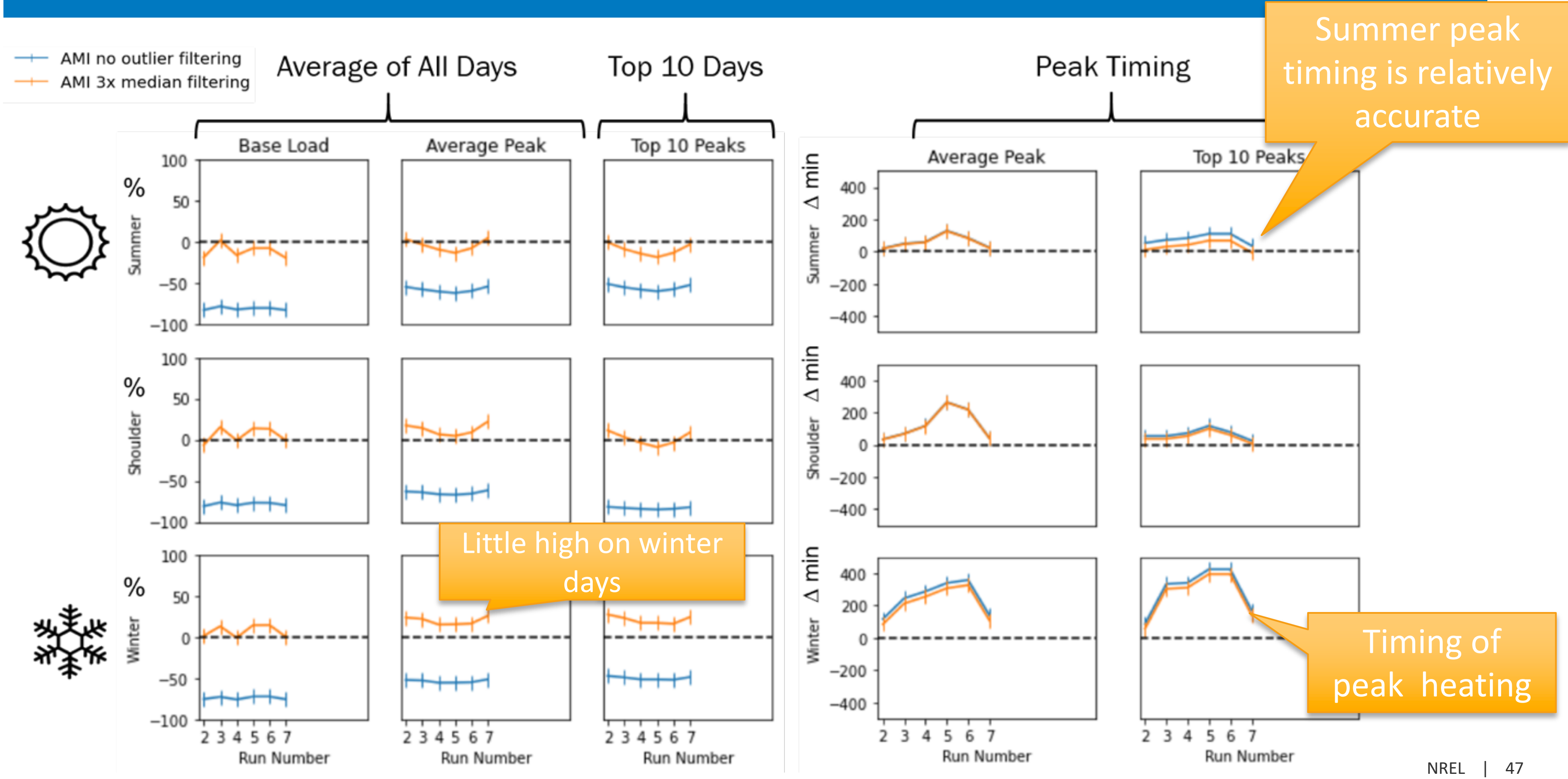
Tracking Quantities of Interest

Region 1 Focus: Annual Error



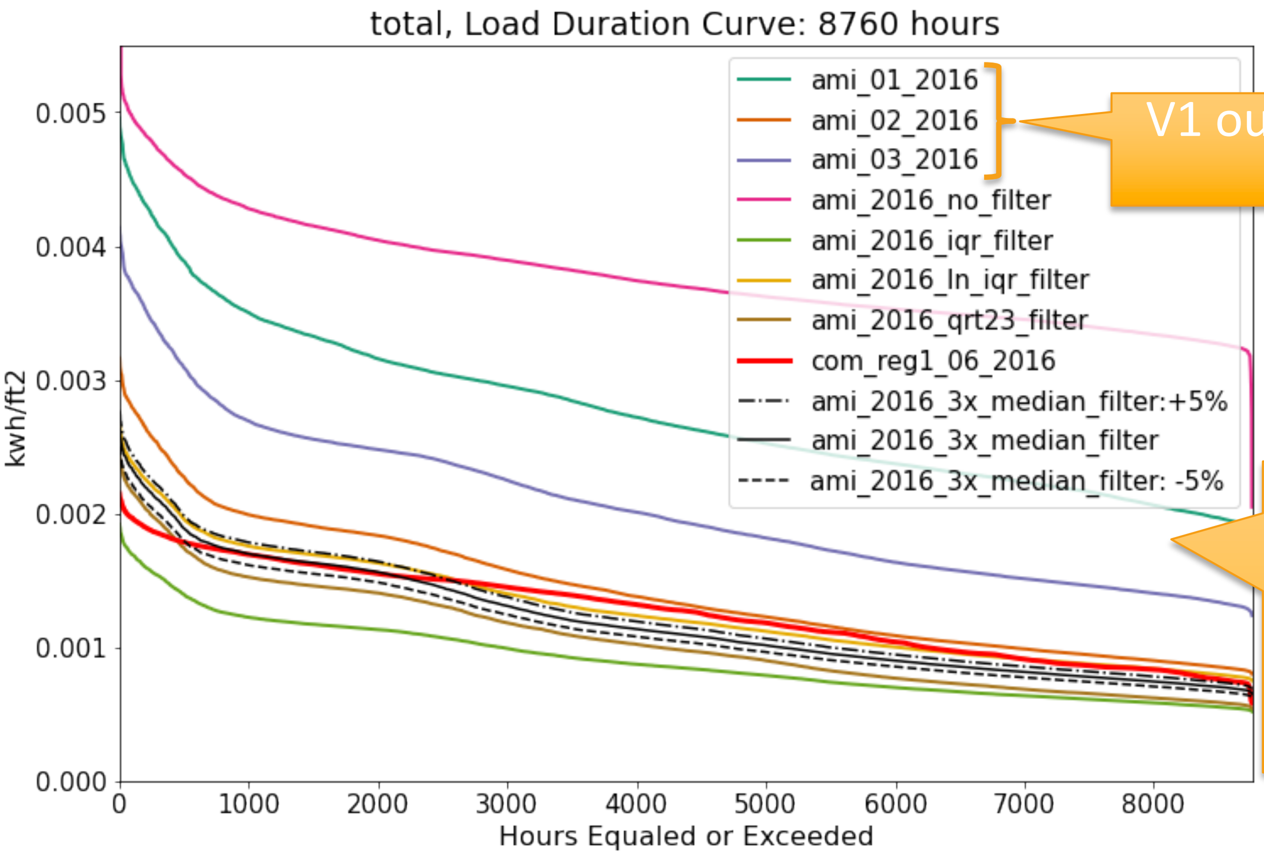
Low annual usage overall; missing nighttime load and summer cooling in some building types

Region 1 Focus: Total Error Metrics



Areas for Improvement

Impact of Outliers



V1 outlier identification methods

Outliers & classification: more impactful than any model changes we've done thus far!

Next Steps: AMI Classification & Outliers

Investigate approach using a much bigger dataset

- Have dataset of ~500k monthly meters from Xcel Energy
- ~200k have CoStar matches (for metadata)

1. Take a random sample and manually classify
2. Calculate rate of true/false positives & true/false negatives
3. Look for systematic misclassifications or reasons for outliers
4. Improve outlier/misclassification detection (if possible)

Next Steps: Model Improvements

- Update energy code adoption by state/year
- Implement RTU efficiency & performance changes
  - RTU data analyzed by excellent intern this summer!

Ensure point of comparison is correct first

- Need to ensure correct classification, perhaps change schedules space use types for things like warehouses, which act more like offices. None of the model updates considered warehouses.
- Consider exterior lighting.
- Add schedule, enduse lighting/equipment variability.
- Restaurant kitchen equipment, particularly hot water use.

Conclusions

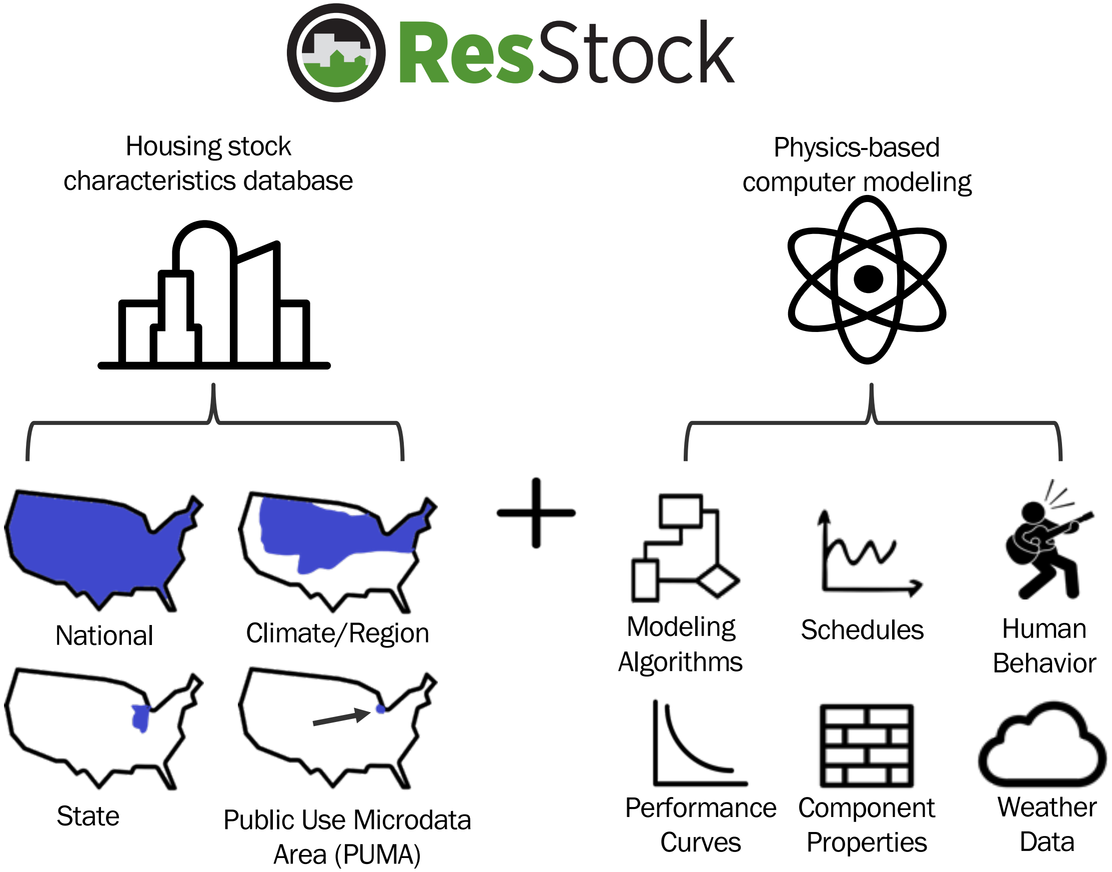
- Ran 6 iterations of ComStock incorporating 3 discrete changes
- Total and individual building type load shapes mostly look good, ignoring magnitude
- Determined that AMI classification & screening needs improvement
  - Will impact AMI comparisons moving forward
  - Have a plan to improve this
- Will be moving on to Region 2, but continue tracking Region 1 metrics

Residential Region 2 Calibration

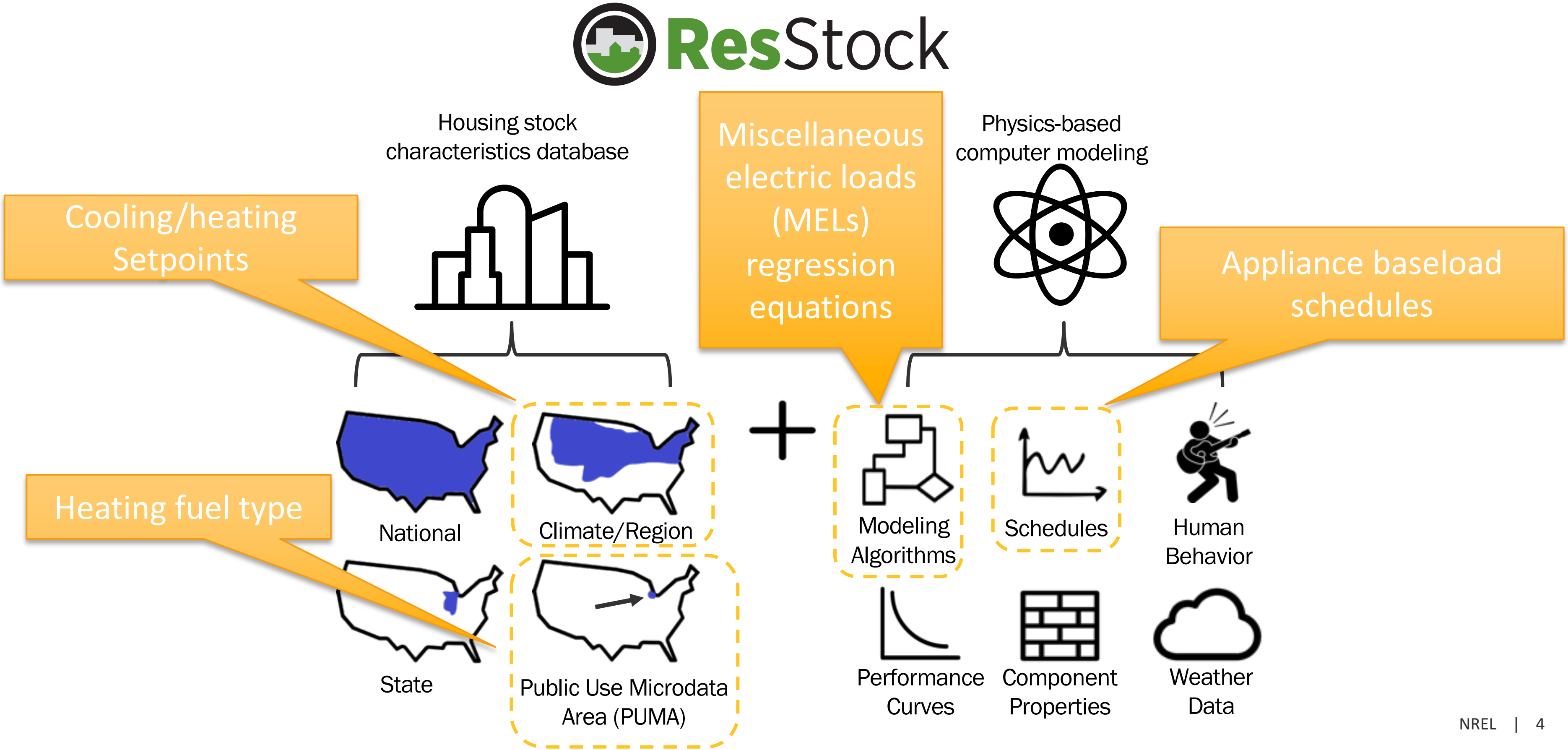
Anthony D. Fontanini, Ph.D.
Eric Wilson
September 22, 2020

Calibration Strategy

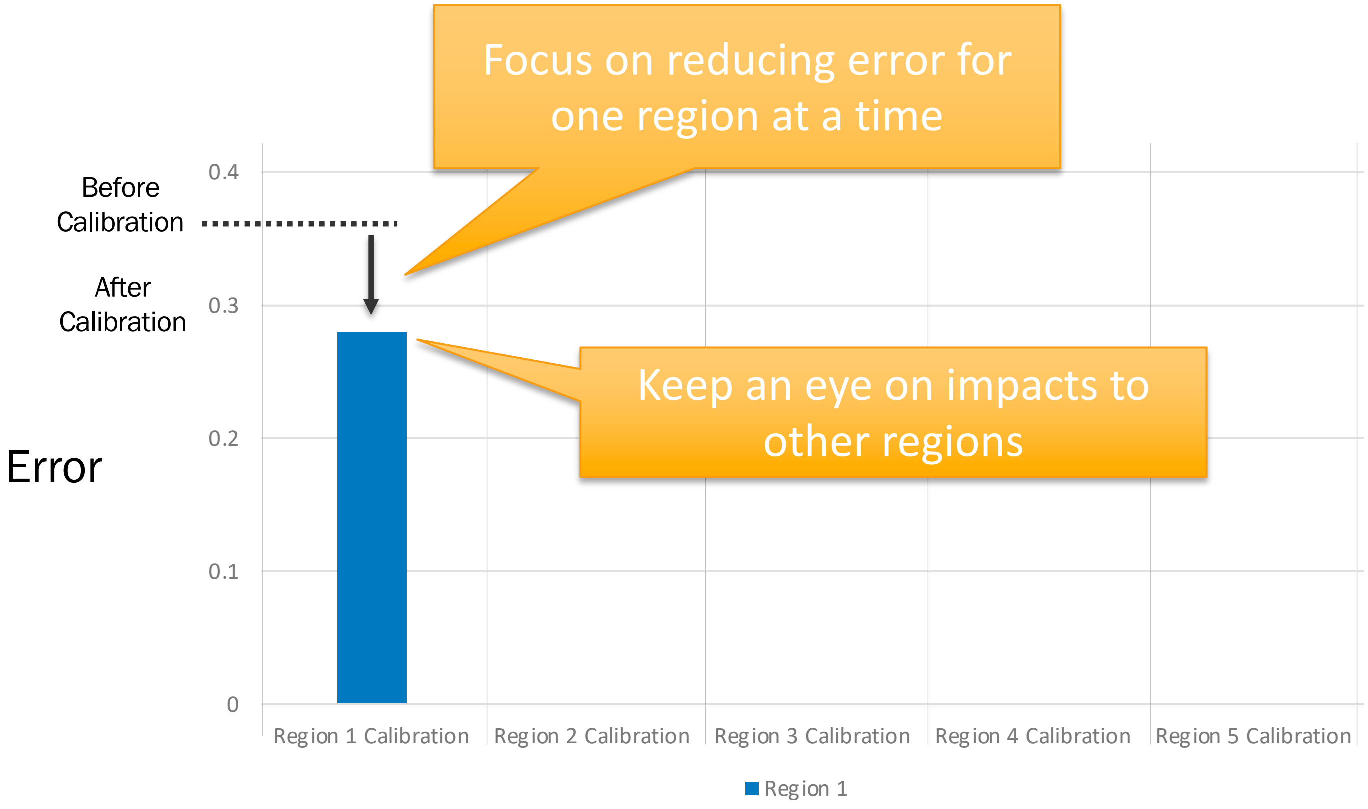
Model Architecture



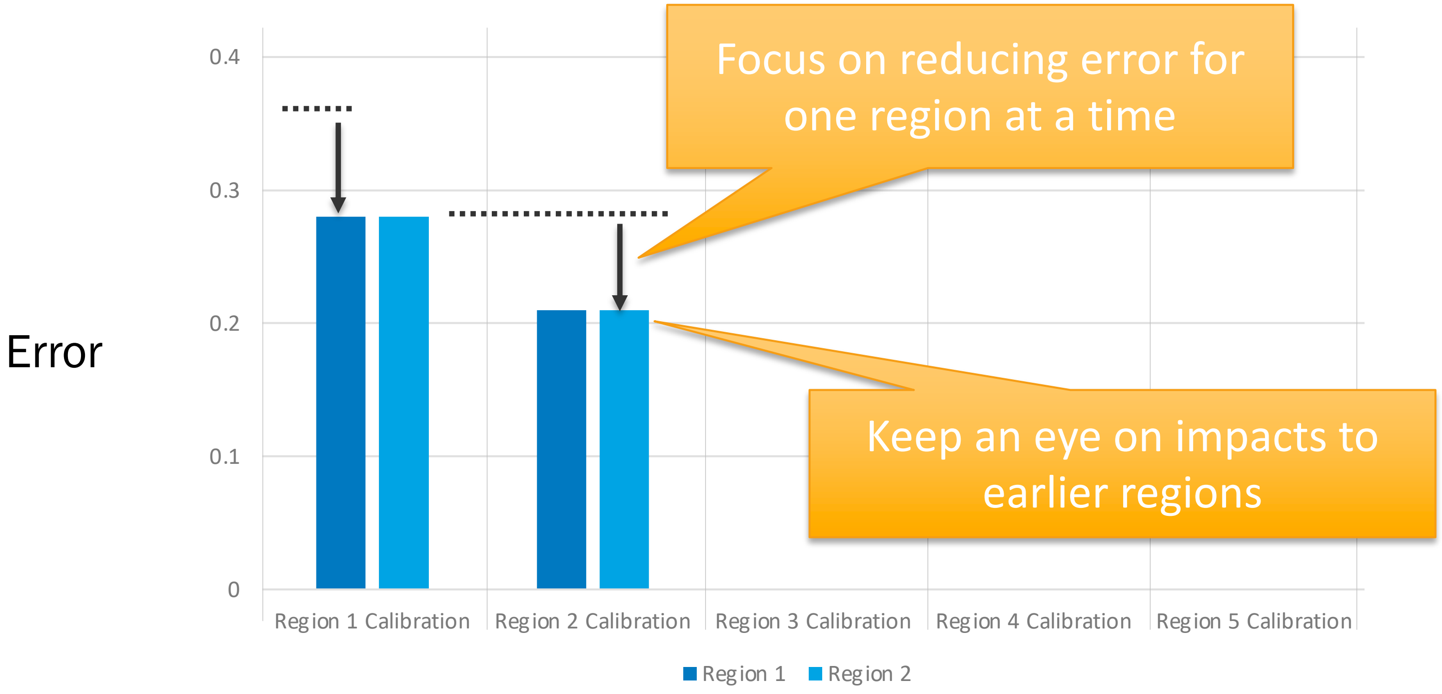
Region 2 Focus: Nationally-Relevant Updates



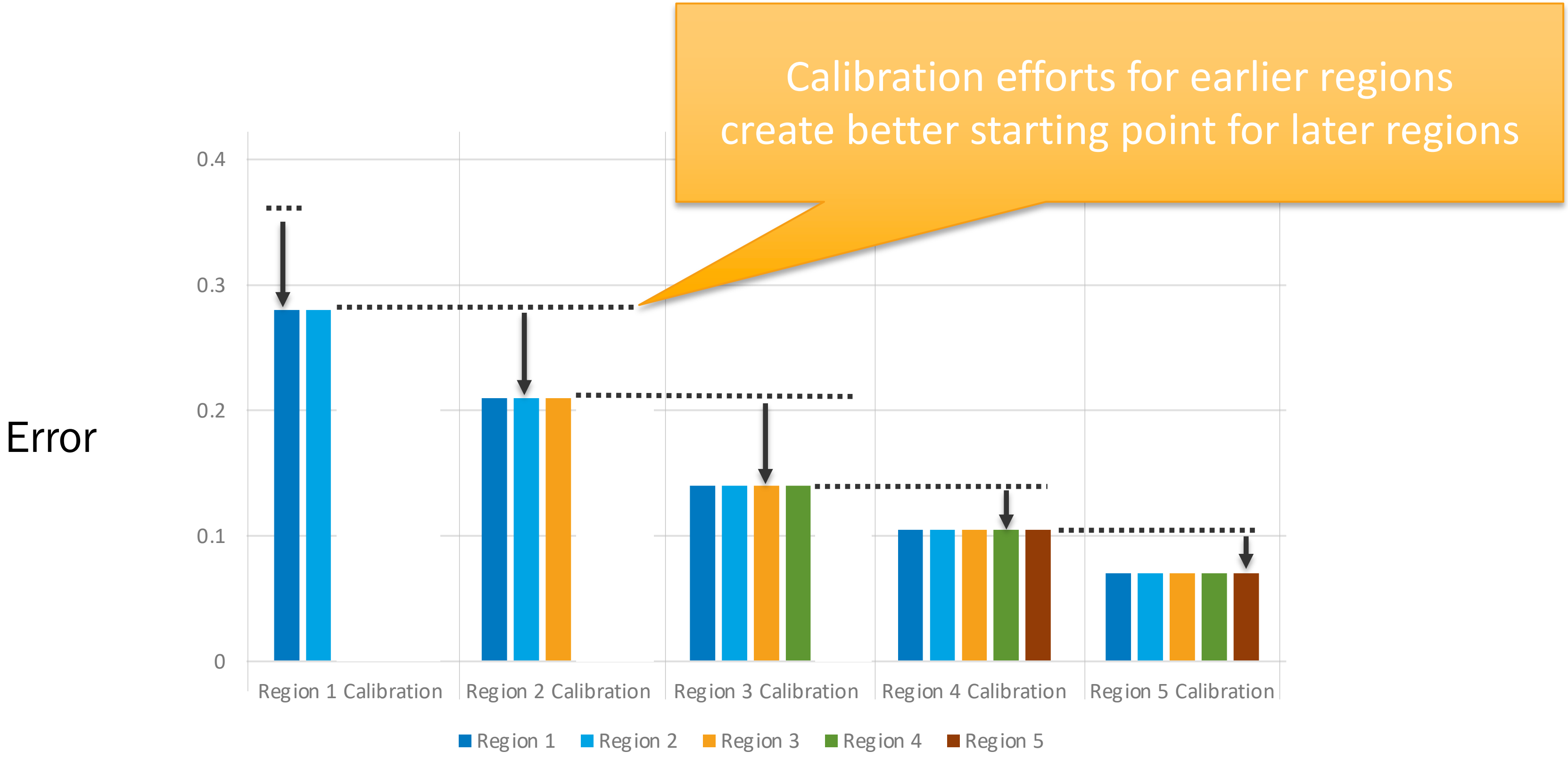
Calibration Process for One Region



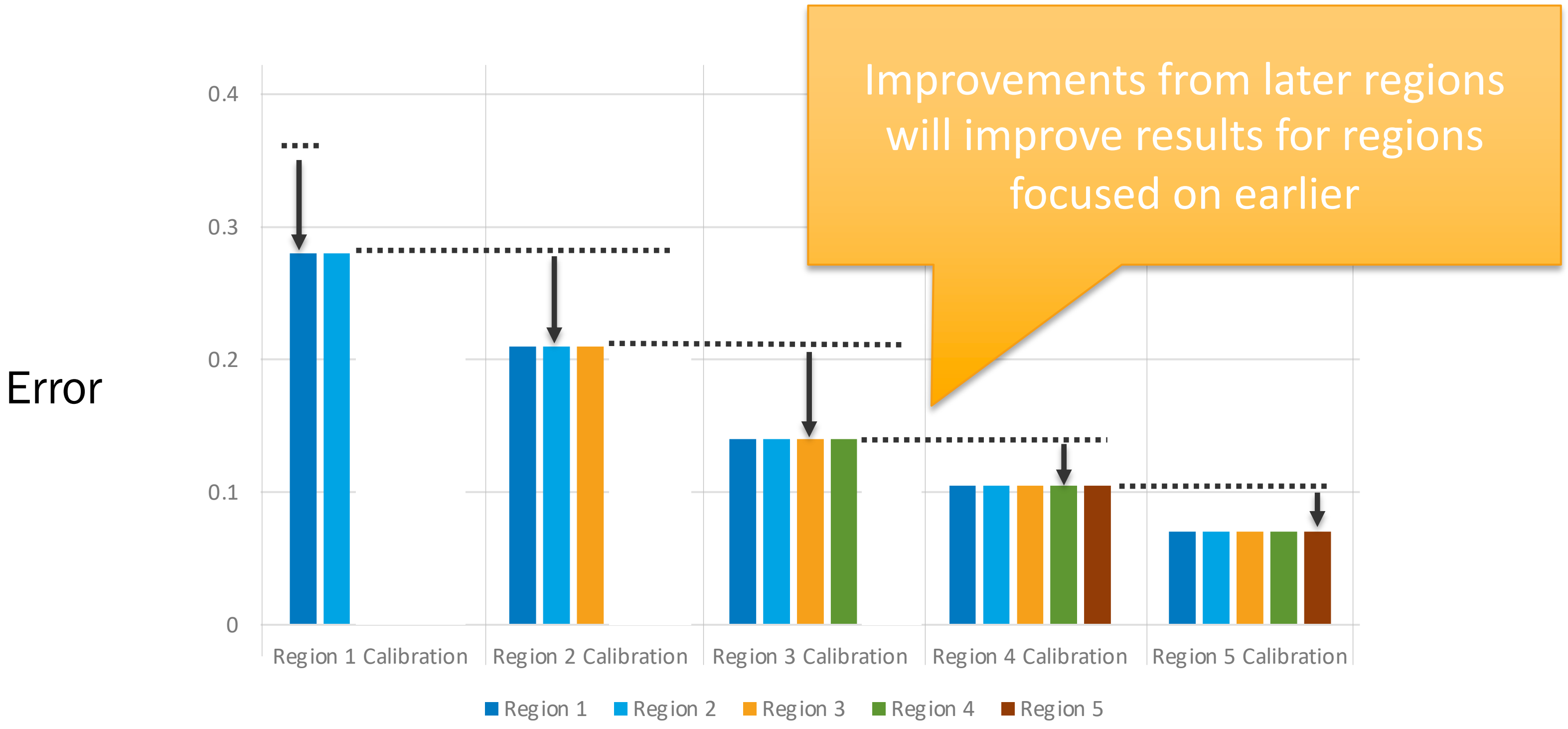
Calibration Process Over Time



Calibration Process Over Time



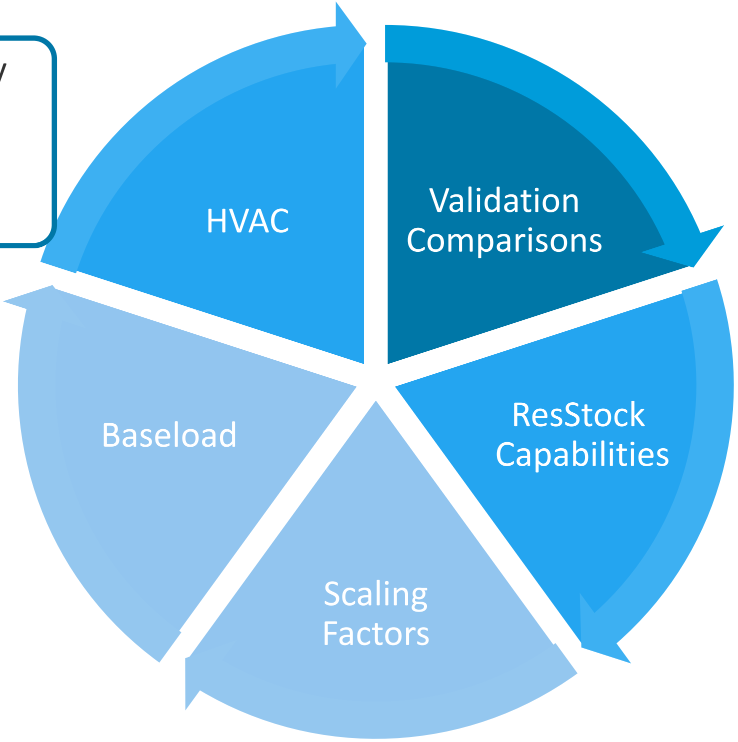
Calibration Process Over Time



Region 2 Calibration Strategy

- Heating fuel type by PUMA
- Cooling/Heating Setpoints

- RECS end-use comparisons
- 2018 Update EIA scatterplots

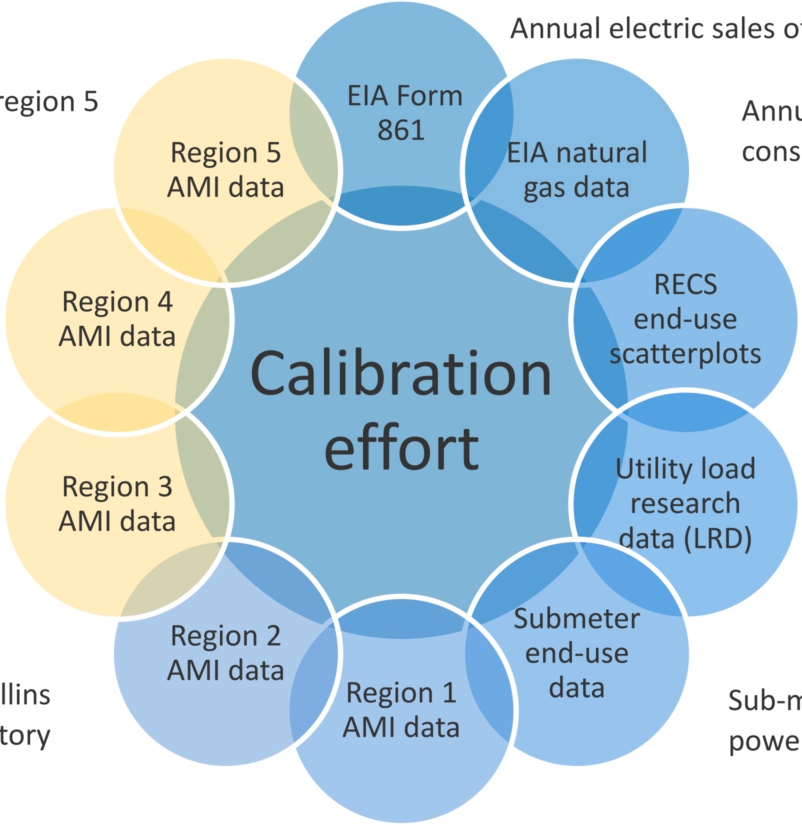


- Baseload schedules
- MELS annual load by building type

- Restructure HVAC housing characteristics
- Vacant units

- Weighting factors for mapping to EIA form 861 service territory

Residential Calibration Dimensions



Annual electric sales of all utilities in U.S.

Annual and monthly natural gas consumption by state

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

AMI data from Fort Collins municipal service territory

AMI data from Seattle City Light, WA

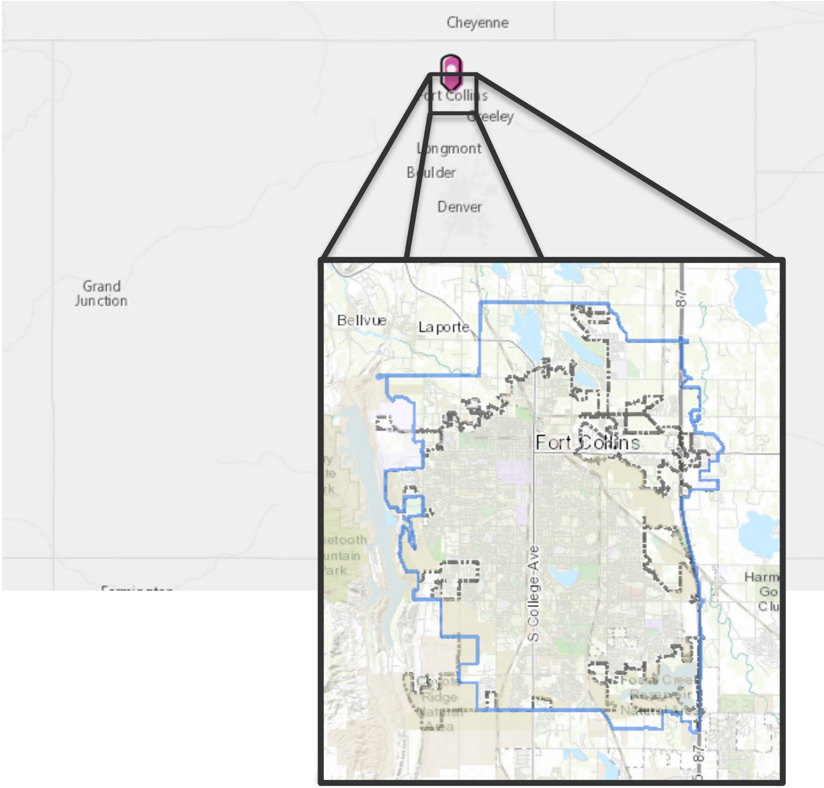
AMI data from future region 4

AMI data from future region 5

Region 2 – Fort Collins, CO

- Fort Collins, Colorado (pop. ~160k)
- Municipal Utility
- Primarily used AMI data from 2018

Residential Building Stock Summary	Percent
Building Type Distribution	
Single-Family Detached	66.0%
Multi-Family 5+ Units	19.7%
Single-Family Attached	7.7%
Multi-Family 2-4 Units	6.6%
Heating Fuel Distribution	
Natural Gas	69.7%
Electricity	23.5%
Propane	4.0%
Other	2.6%



List of updates

New validation comparisons
- Updated EIA form 861 annual residential sales scatterplot to 2018
- Updated EIA natural gas data comparison to 2018
- Updated EIA natural gas data to standard temperature and pressure (STP) by TAG suggestion
- RECS 2009 and RECS 2015 annual end-use scatterplots by fuel type, building type, and climate

New capabilities
- Restructured HVAC housing characteristics to allow for regional and more granular datasets
- Introduced vacant units

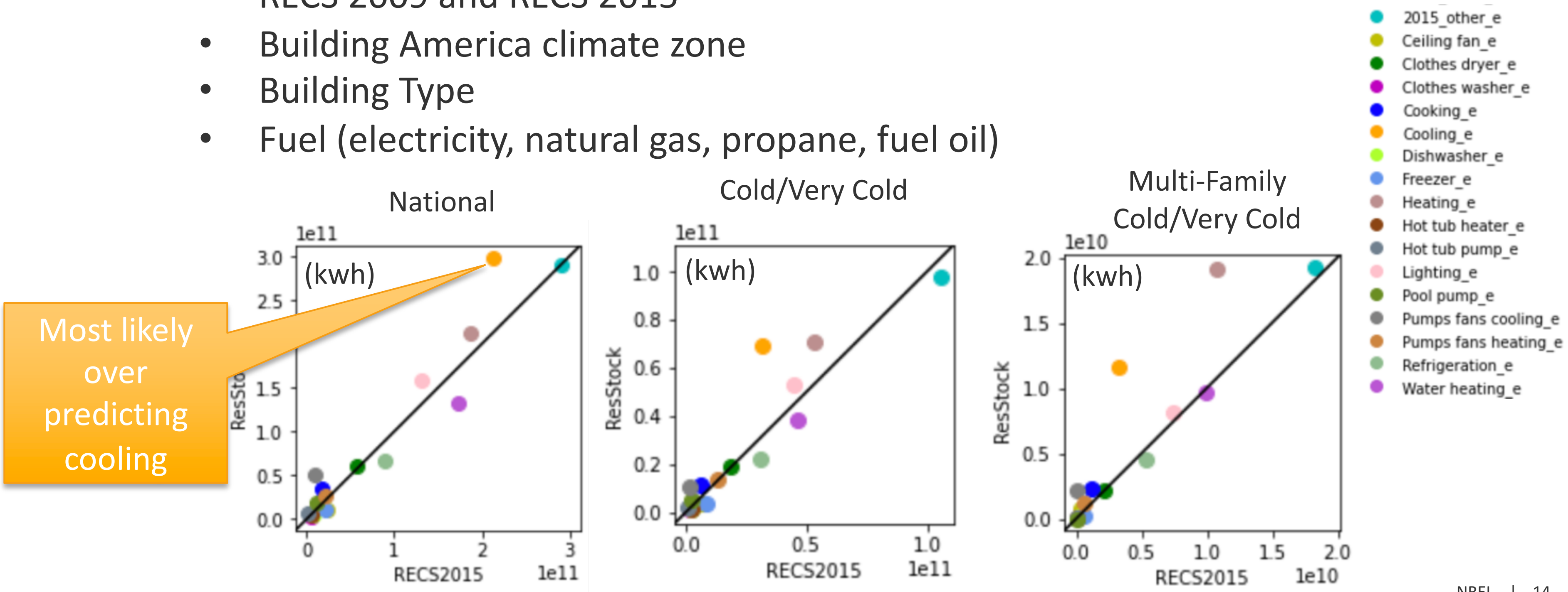
Baseload updates
- Appliance schedules informed by stochastic occupancy model
- Annual miscellaneous electric loads (MELs) broken out by building type

HVAC updates
- Setpoints now described by IECC climate zones and RECS building type
- Heating fuel type described by Public Use Microdata Area (PUMA)
- More diversity added to cooling and heating setback schedules
- Investigated effect of number of days for natural ventilation
- Investigated impact of new HVAC housing characteristics structure

New validation comparisons

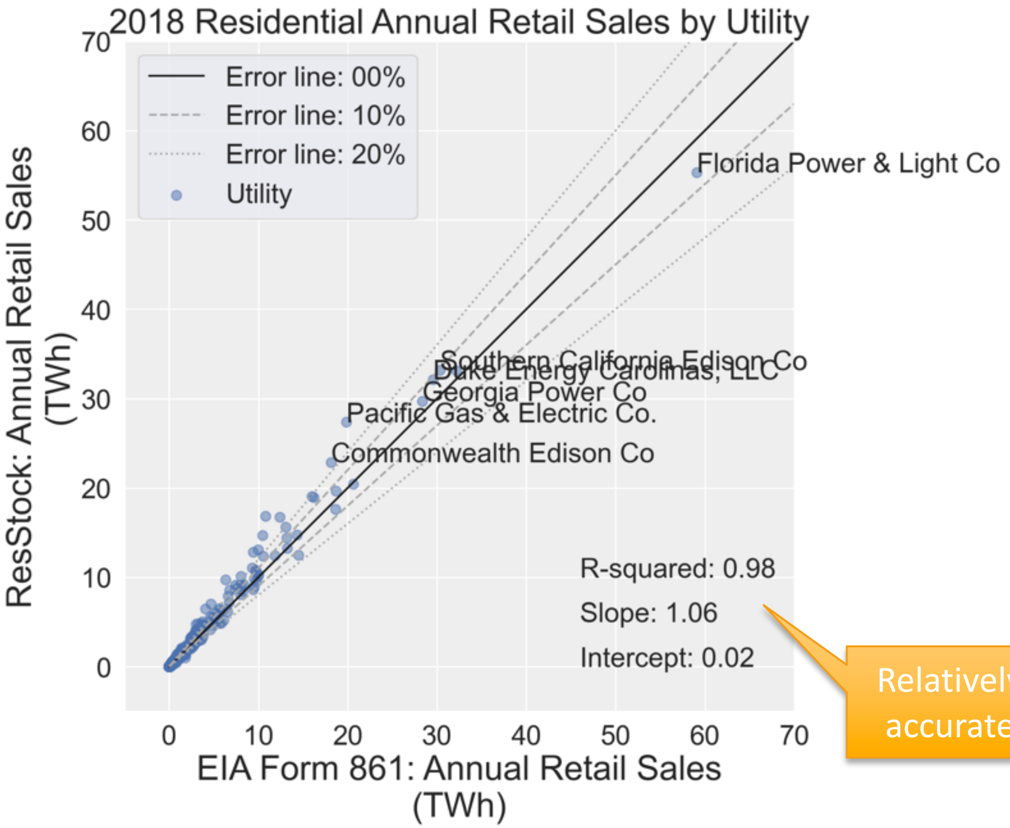
RECS end-use scatterplots

- Scatterplots for annual fuel consumption
- Dimensions:
  - RECS 2009 and RECS 2015
  - Building America climate zone
  - Building Type
  - Fuel (electricity, natural gas, propane, fuel oil)

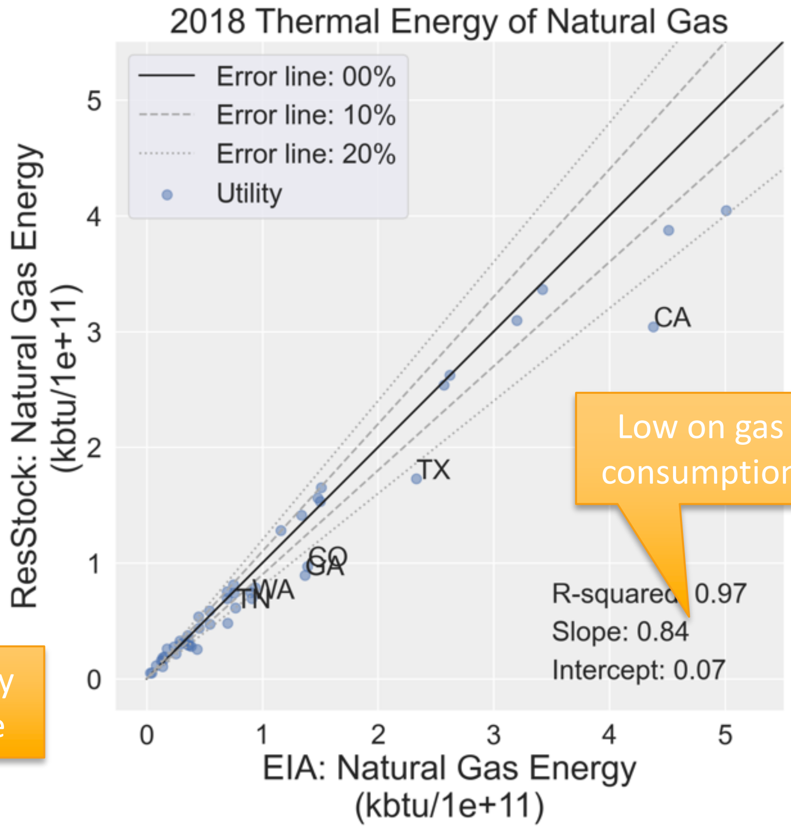


** End-use totals in RECS are **modeled**, but comparisons are useful for determining large errors and potential end-uses to improve.

2018 EIA data comparisons (updated from 2012)



Relatively accurate



Low on gas consumption

Scaling Factors Update

Update: EIA service territory and customer mapping

<u>Before Region 2 calibration</u>

- Data sources
  - Service territory shape files (2012)
  - NSRDB grid cells
  - Census tracts
  - Dwelling unit counts

Only have mapping for 2012

All units get allocated causing errors

Utility service territory to NSRDB grid cell → Dwelling units to NSRDB grid cell → Allocate units based on area service territory weight

Does not preserve number of customers

<u>After Region 2 calibration</u>

- Data sources
  - EIA Form 861
    - Customer counts
    - Service territory (counties)
  - American Community Survey (ACS)
    - Dwelling unit counts by county

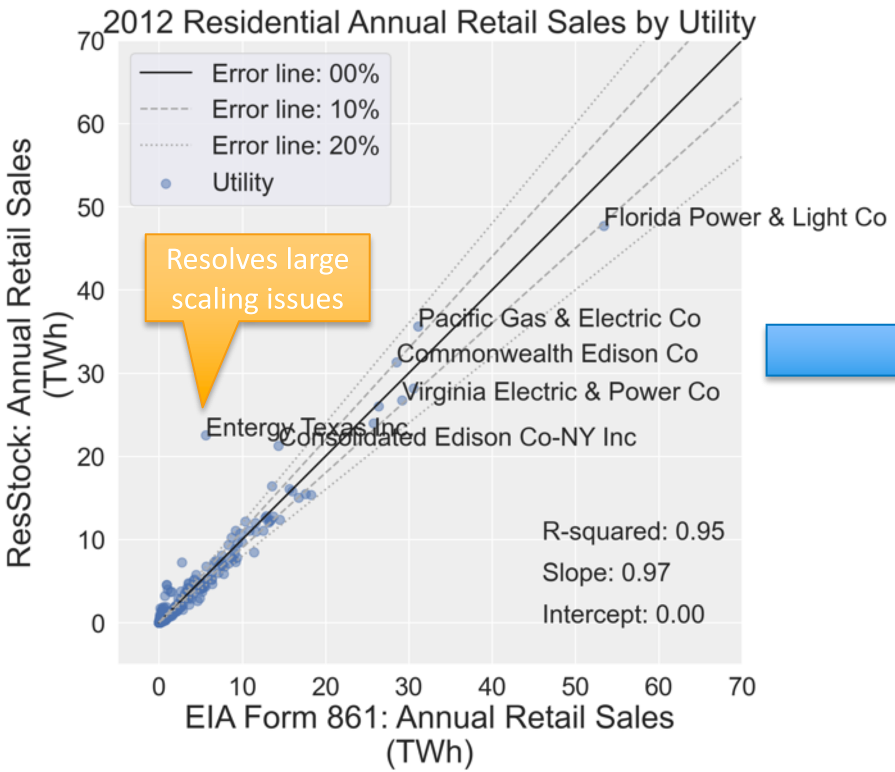
Can be updated for any year

Preserves number of customers

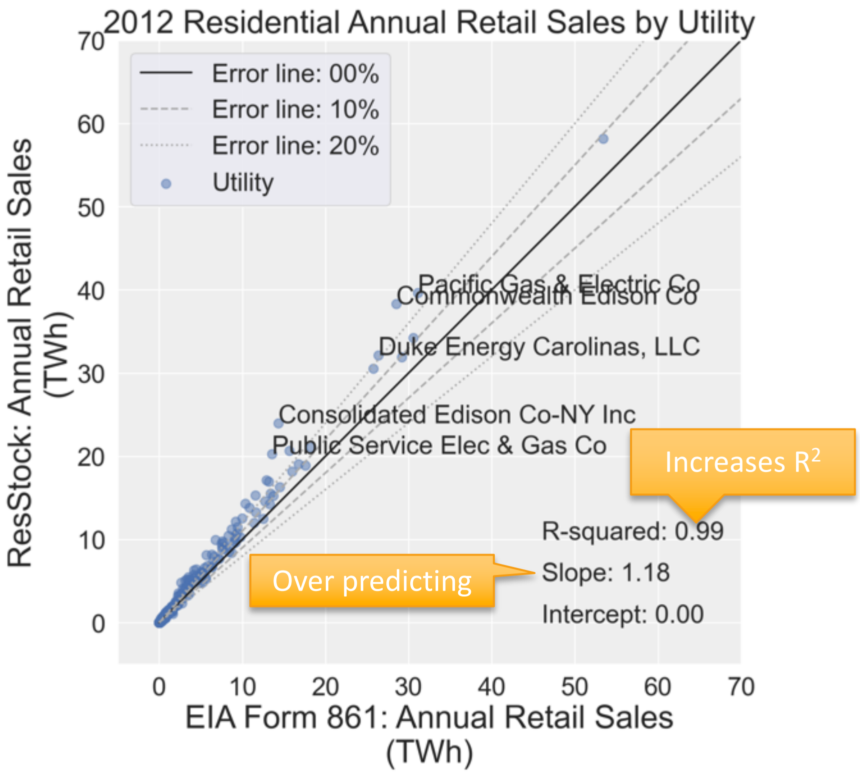
Join EIA form 861 service territory to ACS unit counts → Calculate weighting factors from ACS → Allocate customers based on weights

Impact: EIA service territory and customer mapping

Before mapping update



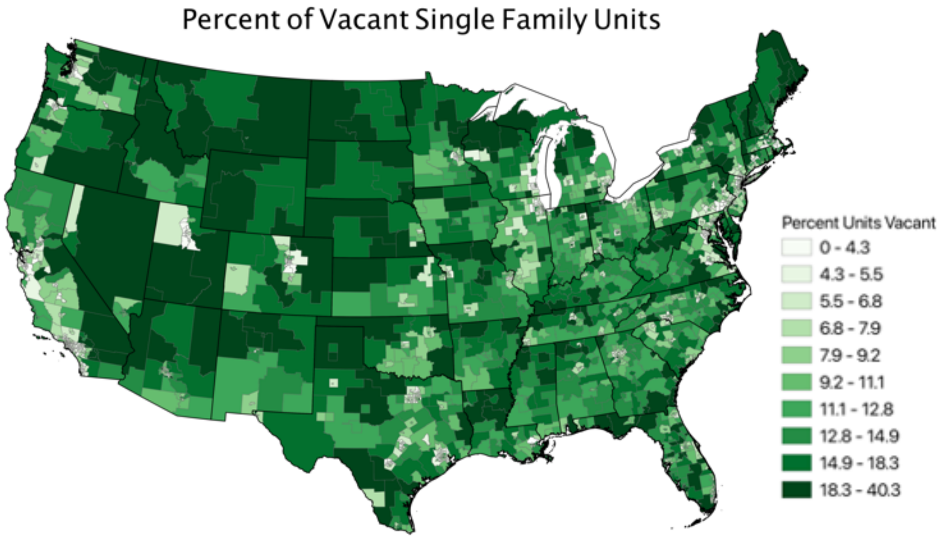
After mapping update

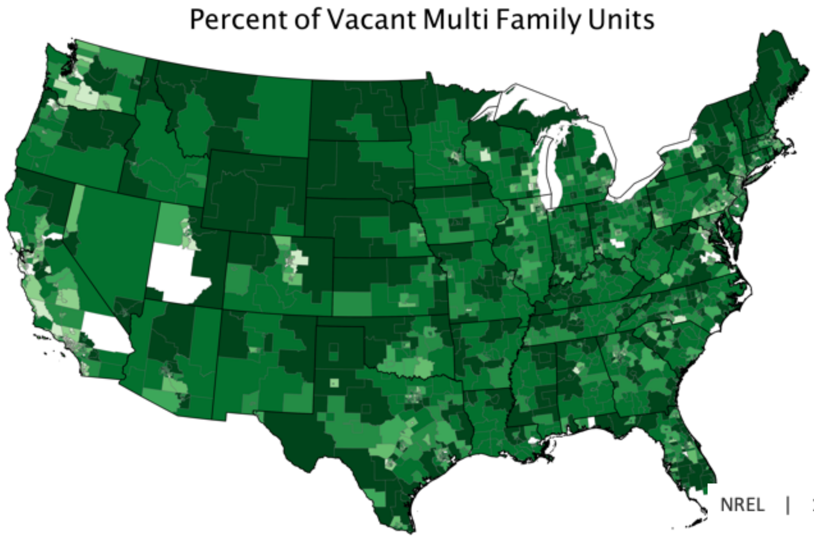


Added Capabilities

Update: Introduce Vacant Units

- American Community Survey (ACS) Public Use Microdata Sample (PUMS) 2016
  - Vacant dwelling units by building type at PUMA-region resolution (N=~2,400)
  - ~14,000,000 vacant units in U.S.
  - Higher fraction of vacant multi-family units in city centers
  - *Modeled reduced baseloads, but buildings still heated and cooled*





Update: Introduce Vacant Units

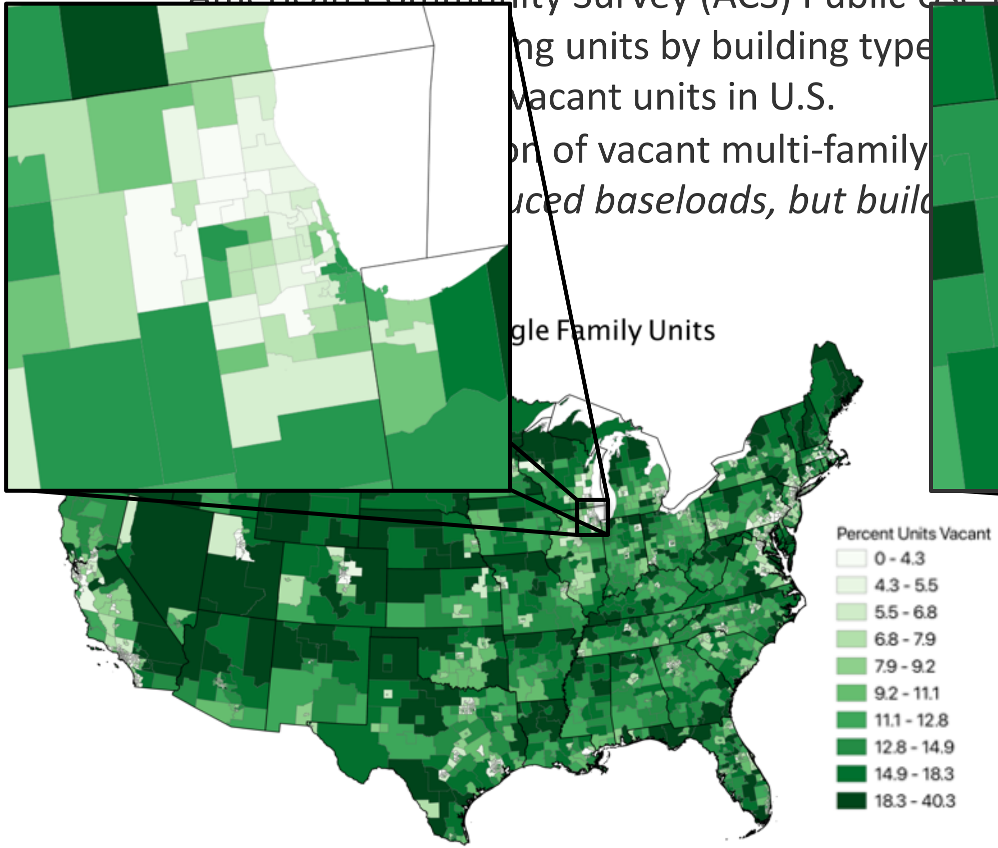
- American Community Survey (ACS) Public Use Microdata Sample (PUMS) 2016

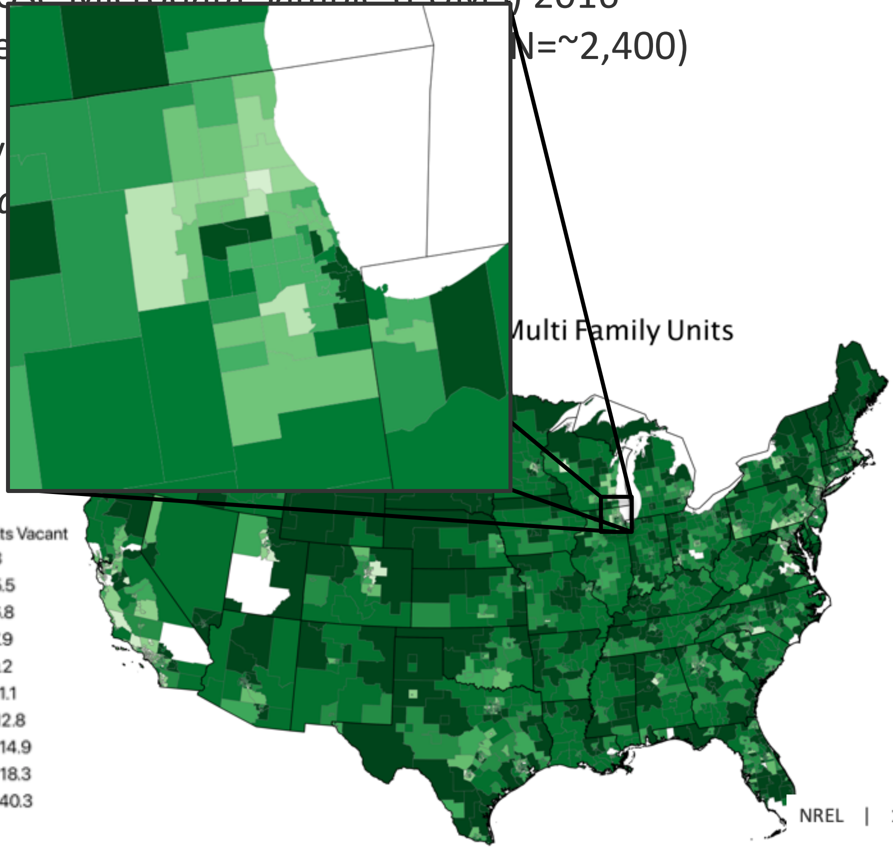
ng units by building type N=~2,400)

vacant units in U.S.

on of vacant multi-family

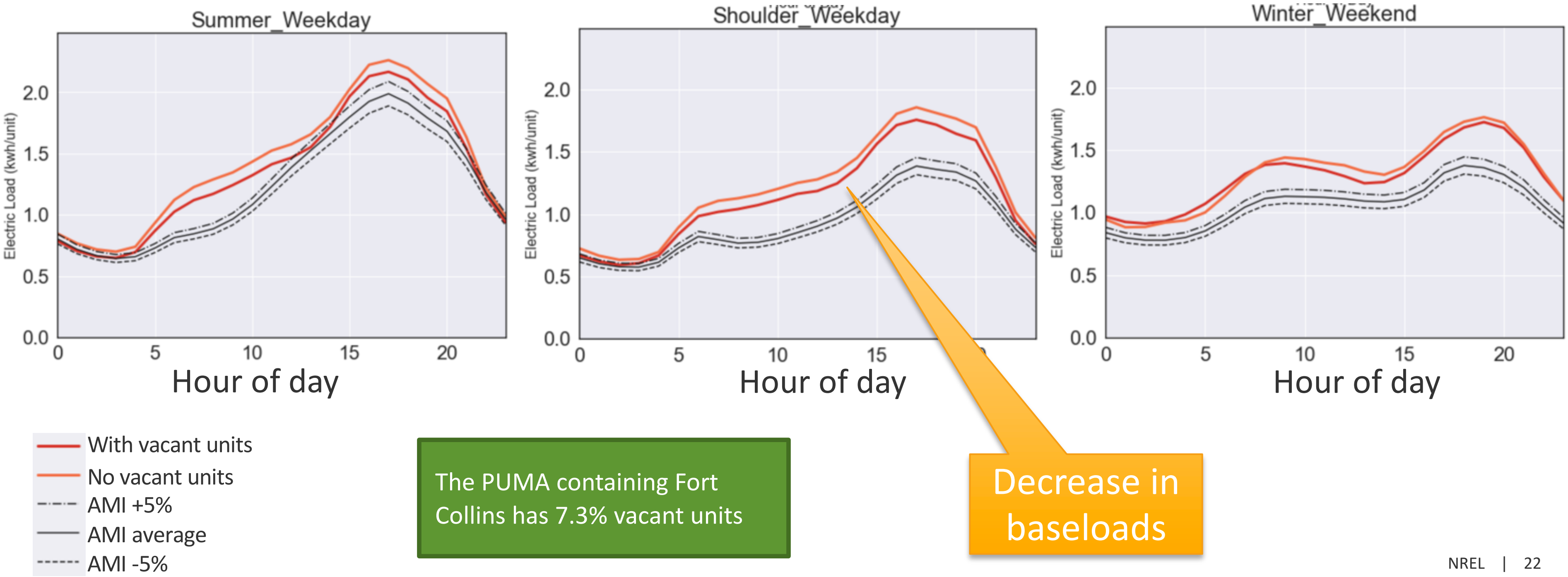
uced baseloads, but buil





Impact: Introduce Vacant Units

Cohort: Single-Family Detached, Fort Collins

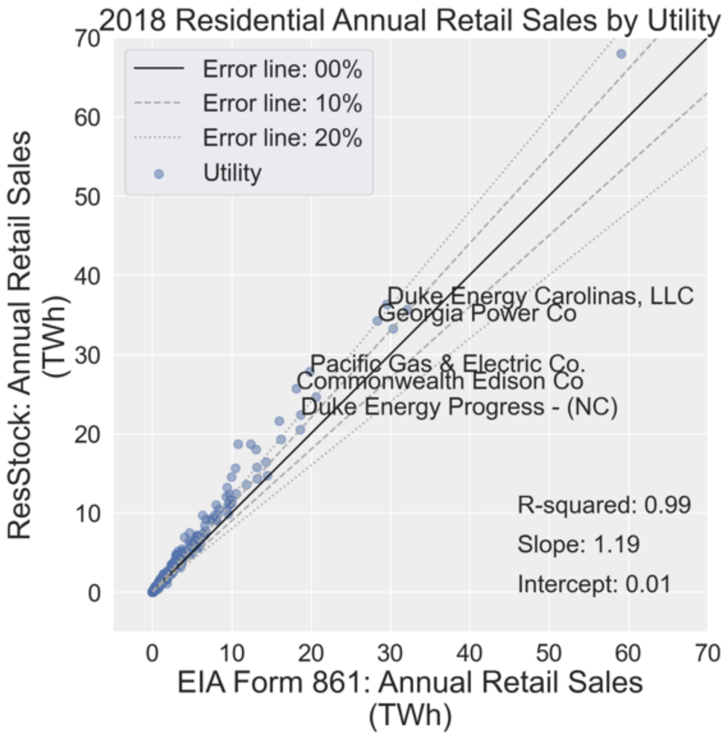


The PUMA containing Fort Collins has 7.3% vacant units

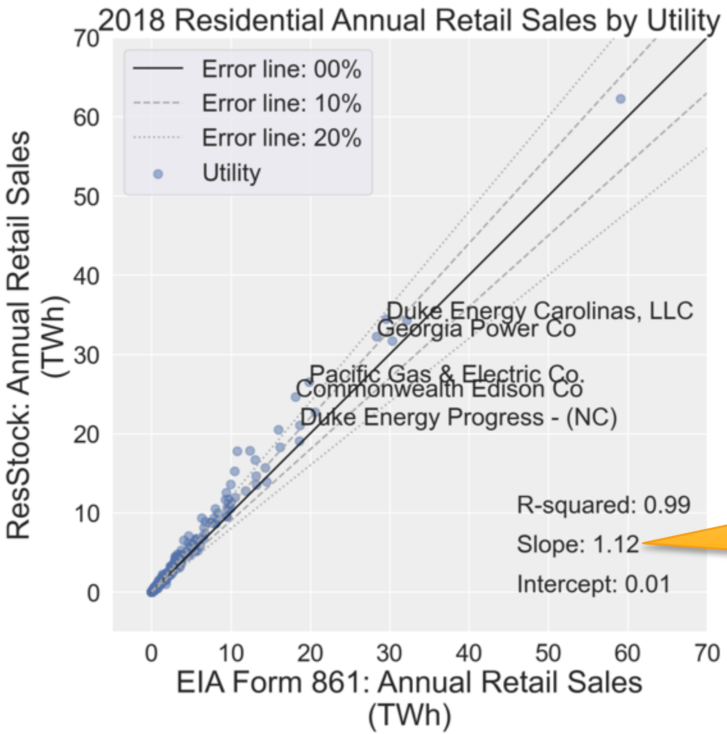
Decrease in baseloads

Impact: Introduce Vacant Units

Without Vacant Units



With Vacant Units



Increased accuracy in slope

Update: Improve HVAC housing characteristics

- HVAC distributions derived from RECS:
  - Heating and cooling equipment type
  - Equipment efficiency levels (based on age of equipment from RECS and efficiency vs. age distributions derived from AHRI data and other sources)
- Automated update process and improved structure of dependencies,
  - Simplified from 37,071 rows in 17 tables to 2,416 rows in 7 tables
  - Will make future updates easier
  - Makes outputs more transparent and easier to understand
  - Simplifies handling of heat pumps and HVAC systems serving multiple units
  - Separates assignment of equipment type (furnace, boiler, heat pump, etc.) from efficiency level
    - Enables us to use American Housing Survey (N=114,860) instead of RECS (N=12,083) for HVAC equipment type, improving geographic resolution
    - Efficiency distributions still depend on equipment type

Update: Improve HVAC housing characteristics

Improved distribution of **Room AC efficiency** using historical ENERGY STAR saturation data, ENERGY STAR minimum efficiency values over time, and federal minimum efficiency values over time.

Year	Product	Metric	Shipment Weighted Value	Federal Minimum Value	ENERGY STAR Minimum	Percent ENERGY STAR
1970	Room AC	EER/CEER	5.8			
…						
1996	Room AC	EER/CEER	9.08			
1997	Room AC	EER/CEER	9.09			
1998	Room AC	EER/CEER	9.08			
1999	Room AC	EER/CEER	9.07			
2000	Room AC	EER/CEER	9.3			
2000	Room AC	EER/CEER	9.3			
2001	Room AC	EER/CEER	9.63	9.79	10.88	
2002	Room AC	EER/CEER	9.75	9.79	10.88	
2003	Room AC	EER/CEER	9.75	9.79	10.88	
2004	Room AC	EER/CEER	9.71	9.79	10.88	
2005	Room AC	EER/CEER	9.95	9.79	10.88	
2006	Room AC	EER/CEER	10.02	9.79	10.88	
2007	Room AC	EER/CEER	9.81	9.79	10.88	
2008	Room AC	EER/CEER	9.93	9.79	10.88	
2009	Room AC	EER/CEER	9.93	9.79	10.88	
2010	Room AC	EER/CEER		9.79	10.88	33%
2011	Room AC	EER/CEER		9.79	10.88	62%
2012	Room AC	EER/CEER		9.79	10.88	58%
2013	Room AC	EER/CEER		9.79	10.88	72%
2014	Room AC	EER/CEER		11	11	50%
2015	Room AC	EER/CEER		11	11	54%
2016	Room AC	EER/CEER		11	12	38%
2017	Room AC	EER/CEER		11	12	34%
2018	Room AC	EER/CEER		11	12	42%

Table sources/notes:

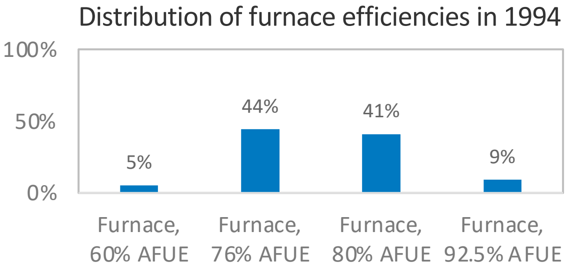
- Shipment weighted values for Room AC comes from AHRI data from Home Energy Score documentation (1970–2008; 2009 is a copy of 2008 values)
- Federal minimum values from a descriptive paragraph at https://appliance-standards.org
- ENERGY STAR, 2014-2015 values are a simplification based on a document at energystar.gov
- ENERGY STAR, 2016-2020 values are a simplification based on a document at energystar.gov
- ENERGY STAR EER value simplification based on data from data.energystar.gov (majority of typical units are EER=12.0)
- Percent ENERGY STAR comes from data found on energystar.gov (no data for 2009 and prior; 2019 and 2020 copied from 2018)

Update: Improve HVAC housing characteristics

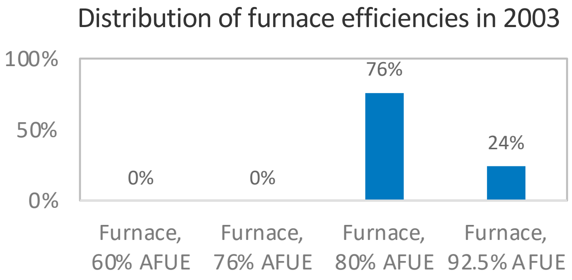
- Updated reference year for HVAC and refrigerator ages (and thus efficiencies) from 2009 to 2018.

For example:

- In 2009, a 15-year-old furnace was made in 1994:

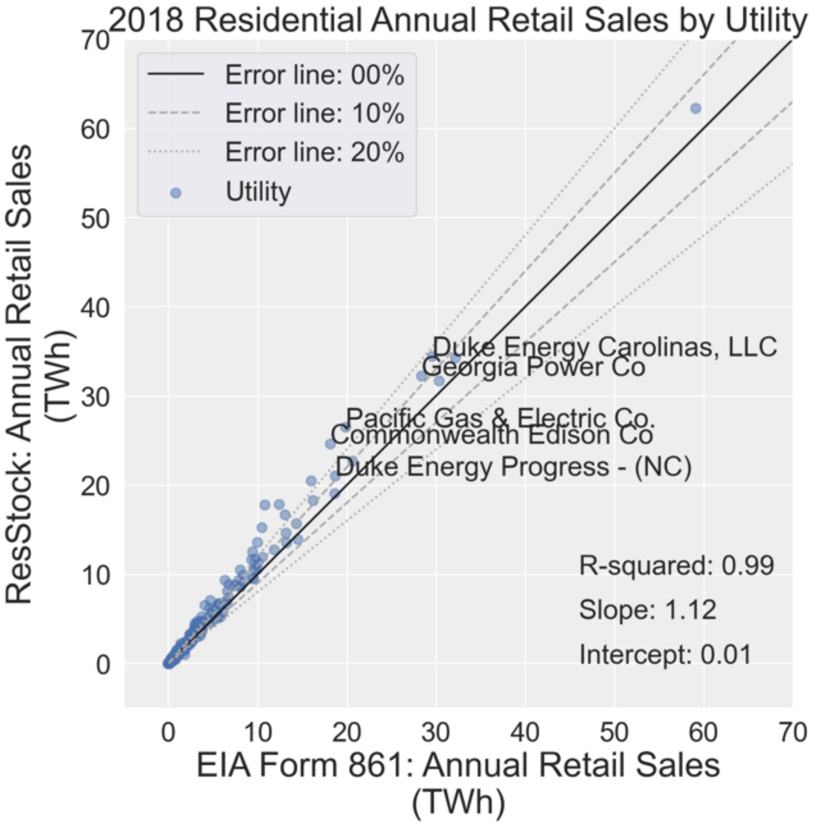


- In 2018, a 15-year-old furnace was made in 2003:

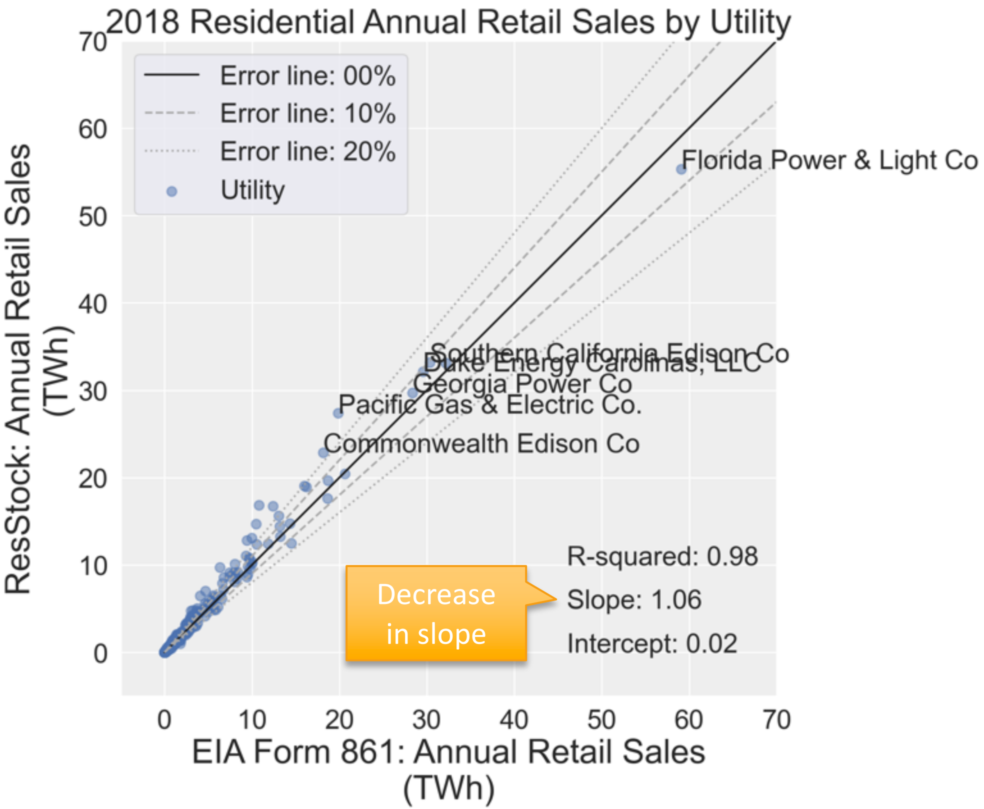


Impact: Improve HVAC housing characteristics

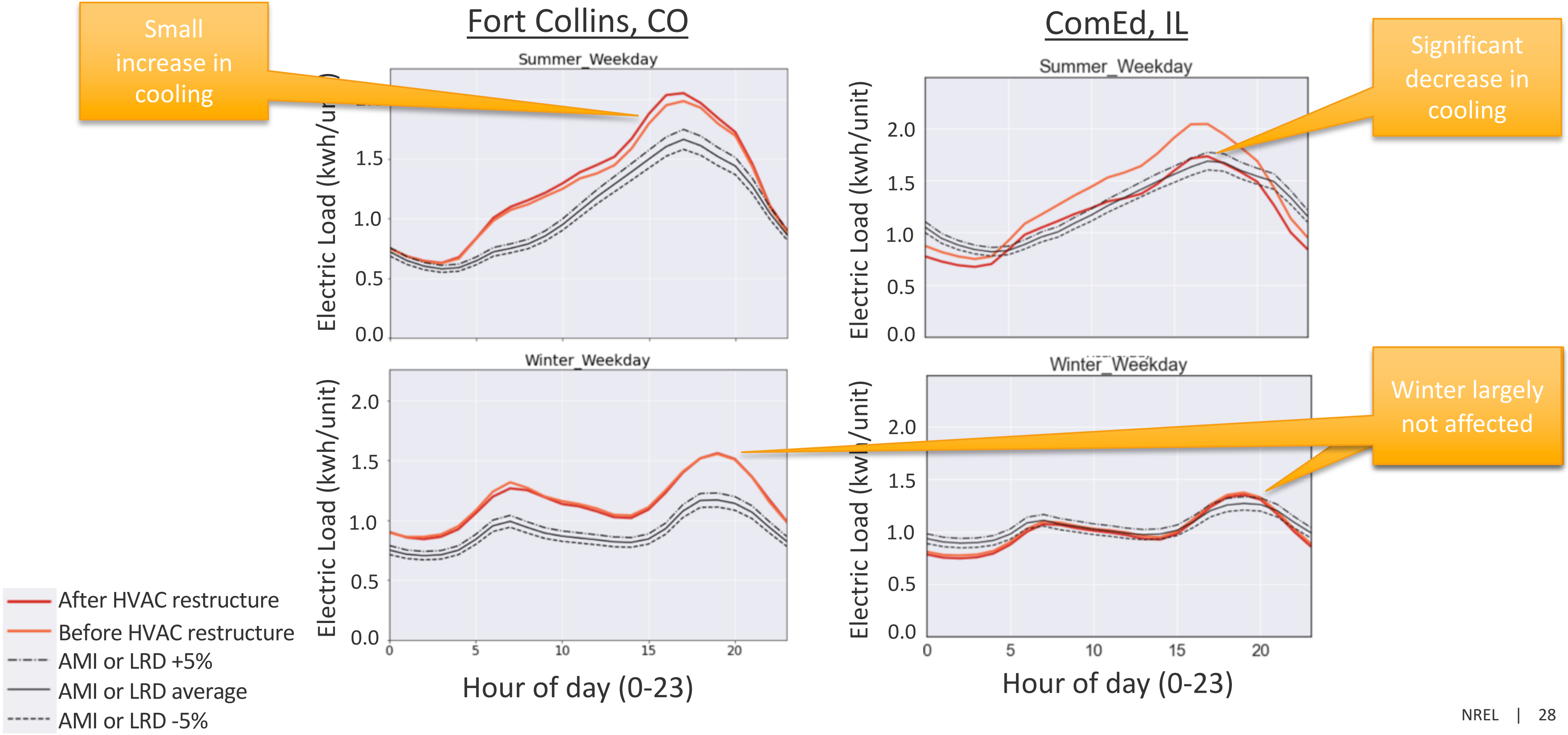
Before HVAC improvement



After HVAC improvement



Impact: Improve HVAC housing characteristics

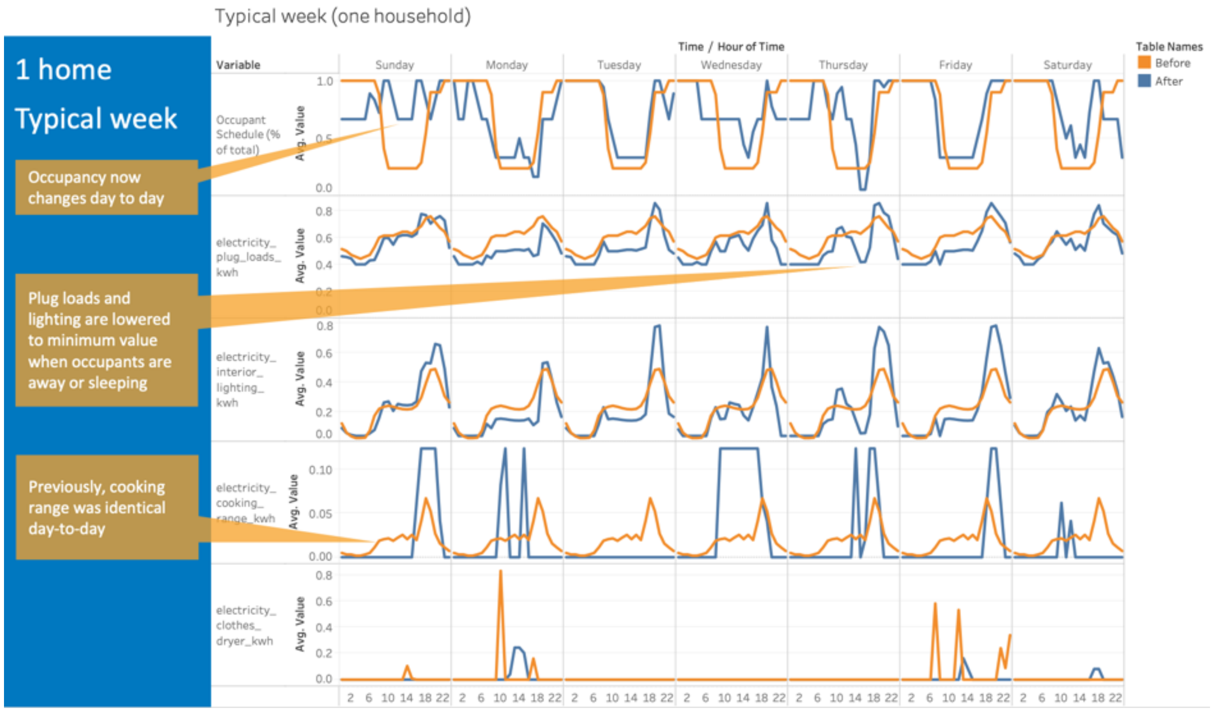


Baseload Updates

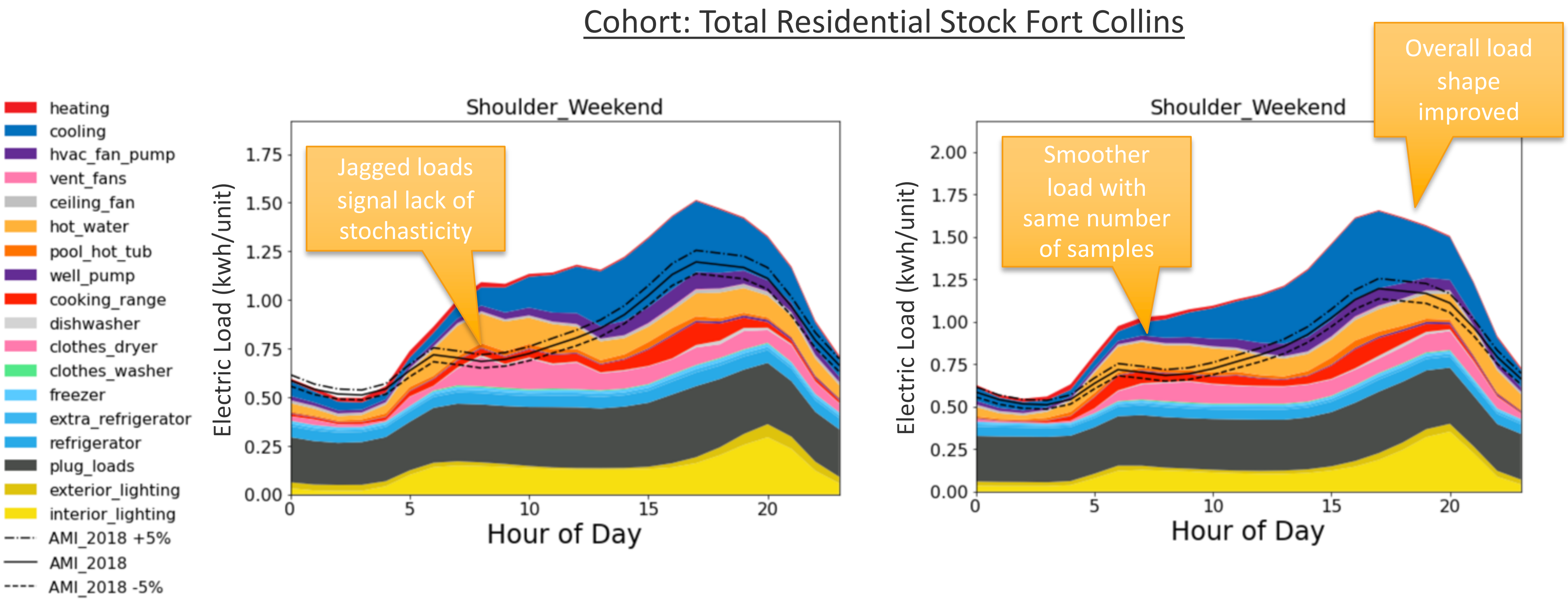
Update: Integrated stochastic occupancy model

→ Stochastic occupant-driven load model is now used for every ResStock run

Example of changes for one home:



Impact: Integrated stochastic occupancy model



Update: MELs equations by building type

Previous approach

- Single regression equation for all building types (RECS 2015)

$$MELS = 908.91 + 277.75 n_{occupants} + 0.39\, ffa$$

New approach

- Separate regression equation for each building type (RECS 2015)

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

$n_{occupants}$: Number of occupants
ffa: Finished floor area
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: MELs equations by building type

Previous approach

- Single regression equation for all building types

$$MELS = 908.91 + 277.75n_{occupants} + 0.39\,ffa$$

New approach

- Separate regression equation for each building type

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

$n_{occupants}$: Number of occupants
ffa: Finished floor area
SFD: Single-Family Detached
SFA: Single-Family Attached
MF: Multi-Family

RECS 2015 percent differences

Building Type	Error: 1 equation	Error: 3 equations
MF	21.4%	6.1%
SFA	13.5%	2.0%
SFD	-12.4%	-9.2%

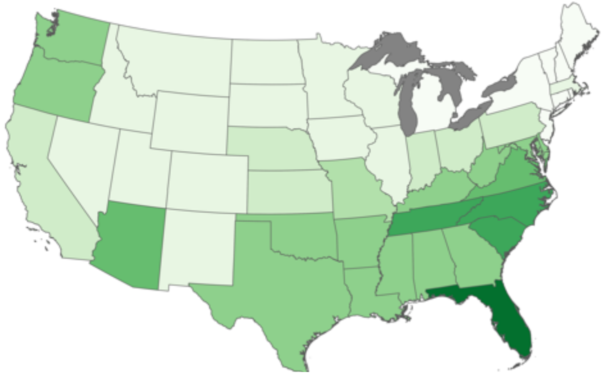
** MELS are defined by the following fields in RECS 2015: televisions, microwaves, humidifiers, and other devices not elsewhere classified

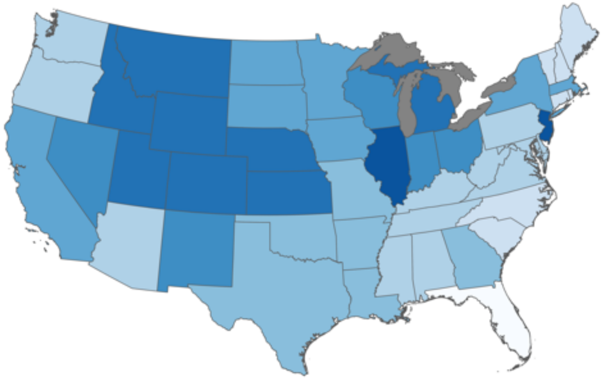
HVAC Updates

Update: Heating Fuel described by PUMA

<u>Before: the EULP project</u>

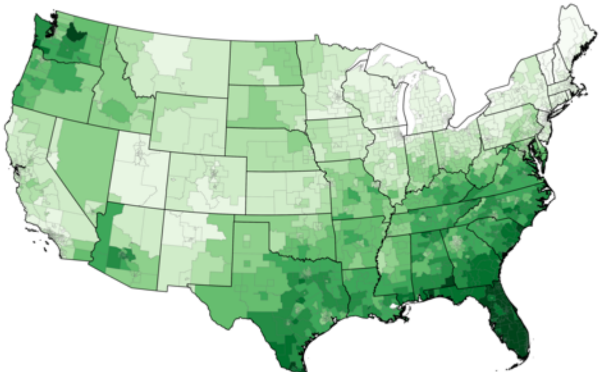
Heating fuel described by groups of states





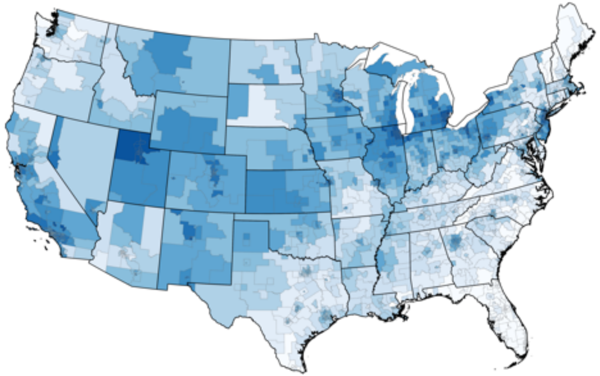
<u>After: Calibration region 2</u>

Heating fuel described by PUMA



Electric heating saturation

- 0 - 0.1
- 0.1 - 0.2
- 0.2 - 0.3
- 0.3 - 0.4
- 0.4 - 0.5
- 0.5 - 0.6
- 0.6 - 0.7
- 0.7 - 0.8
- 0.8 - 0.9
- 0.9 - 1



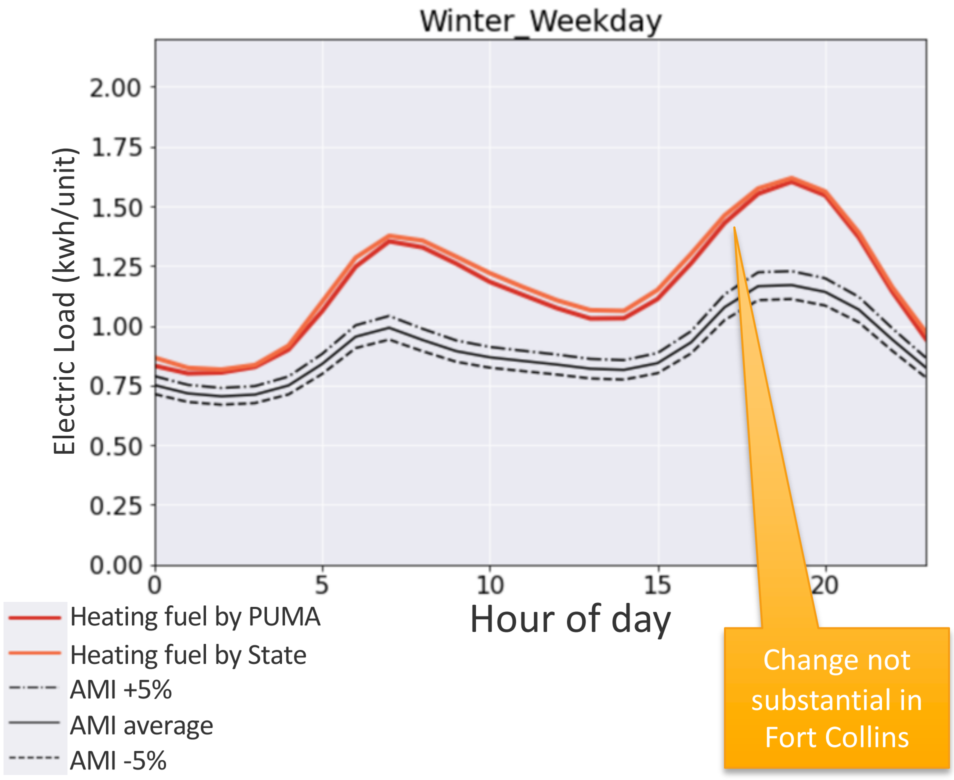
Natural Gas heating saturation

- 0 - 0.1
- 0.1 - 0.2
- 0.2 - 0.3
- 0.3 - 0.4
- 0.4 - 0.5
- 0.5 - 0.6
- 0.6 - 0.7
- 0.7 - 0.8
- 0.8 - 0.9
- 0.9 - 1

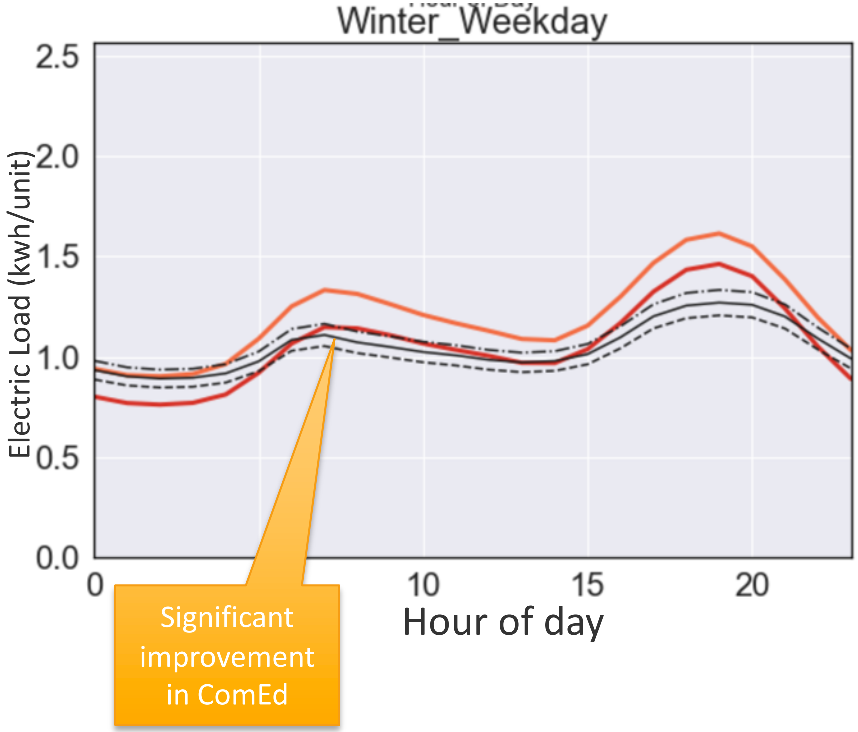
Impact: Heating Fuel described by PUMA

Cohort: Total Residential Stock

Region: Fort Collins

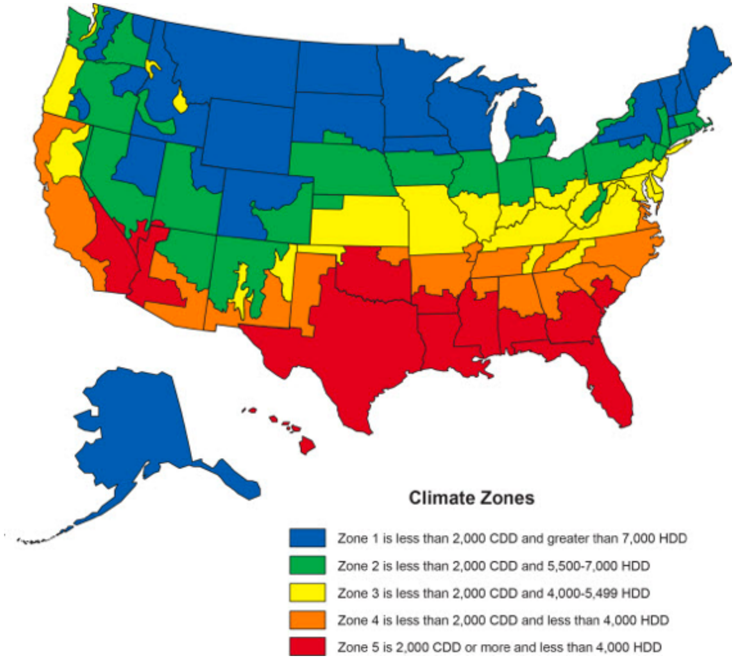


Region: ComEd

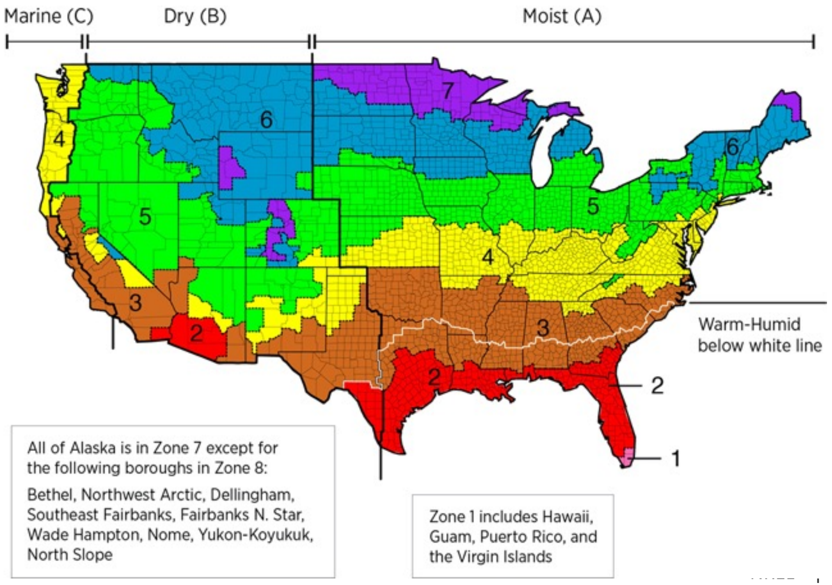


Update: Setpoint & setback distributions and setback time period diversity

- Before Calibration Region 2
  - Setpoints by AIA Climate Zone



- After Calibration Region 2
  - Setpoints by IECC 2004 climate and moisture zone
  - Increased diversity of setback schedules (±5 hours)



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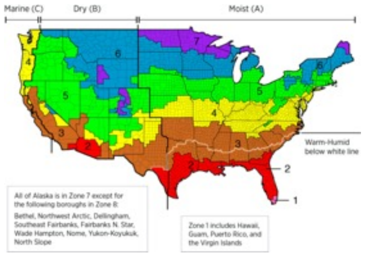
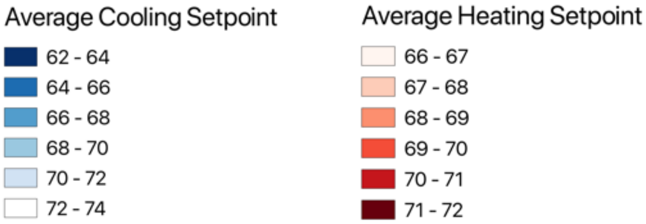
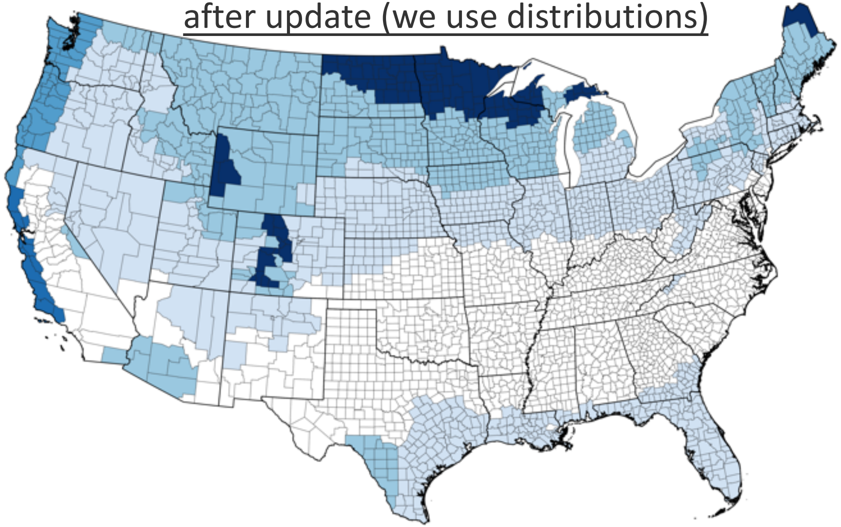
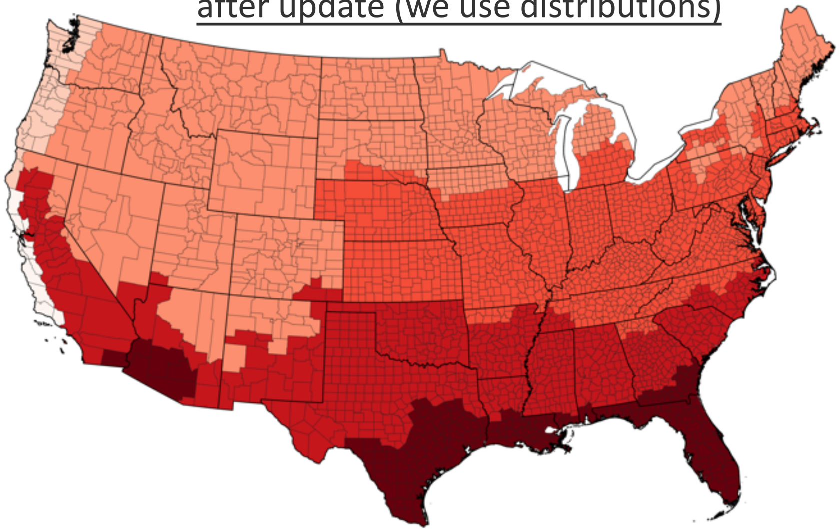




<u>Example: Average Cooling Setpoint after update (we use distributions)</u>



<u>Example: Average Heating Setpoint after update (we use distributions)</u>

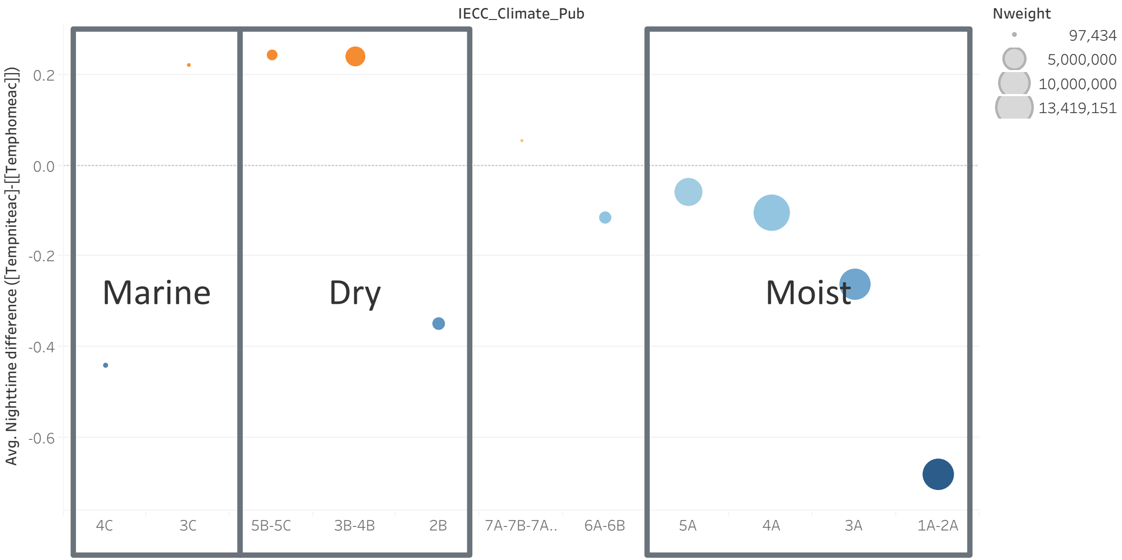


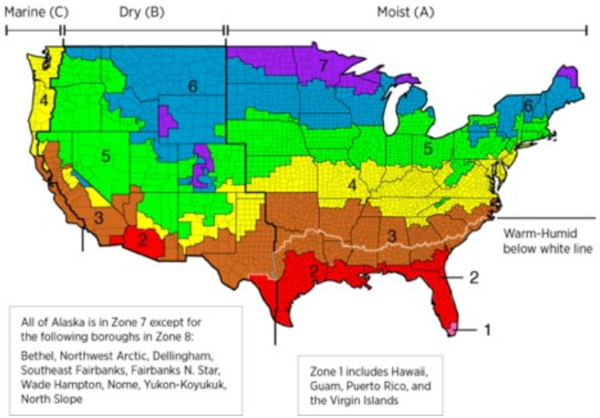
Update: Setpoint & setback distributions and setback time period diversity

On average:

- Dry climates use higher setpoint at night
- Moist climates use cooler setpoint at night

Average difference between nighttime and home AC setpoints, by IECC Climate Zone (source: RECS 2009)

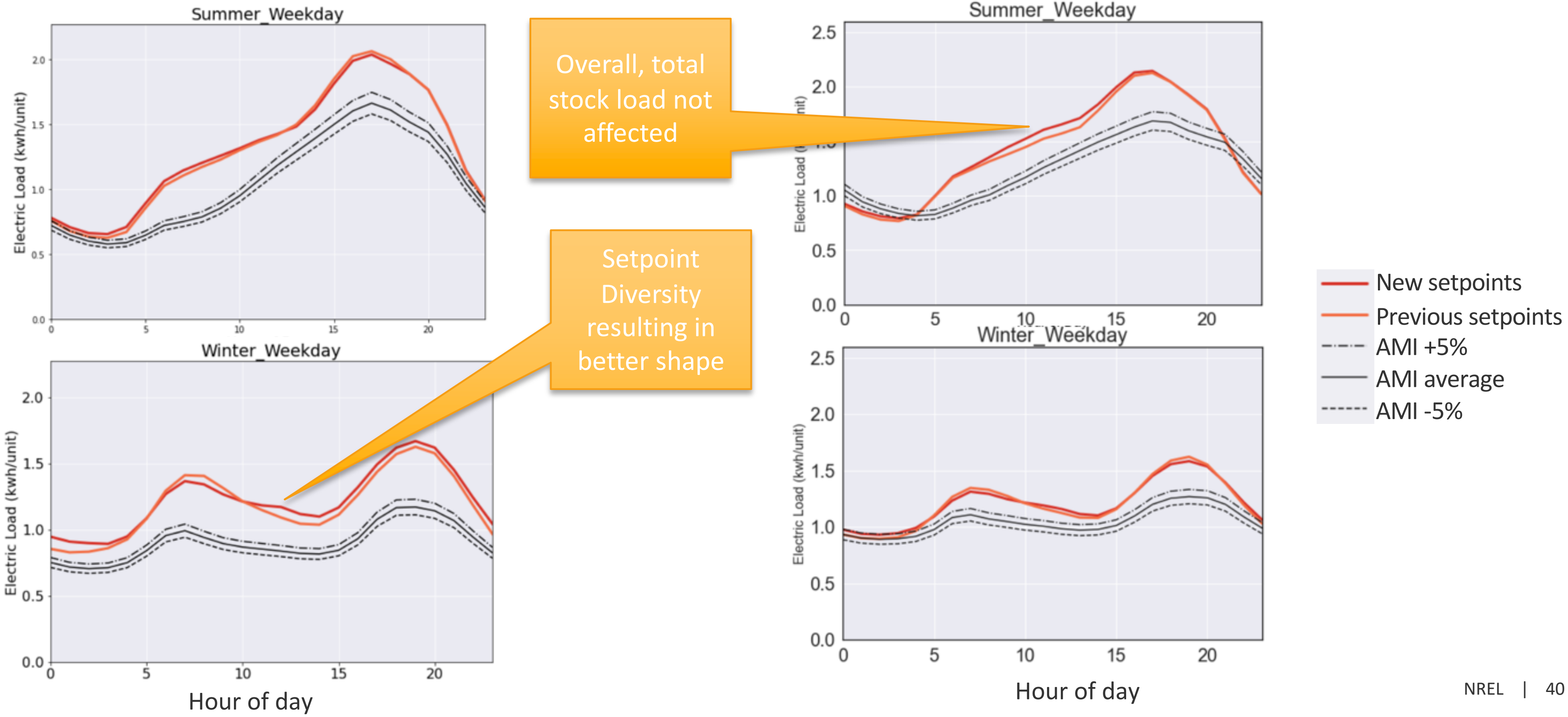




Impact: Setpoint distributions and diversity

Fort Collins, CO
Total Residential Stock

ComEd, IL
Total Residential Stock



Overall, total stock load not affected

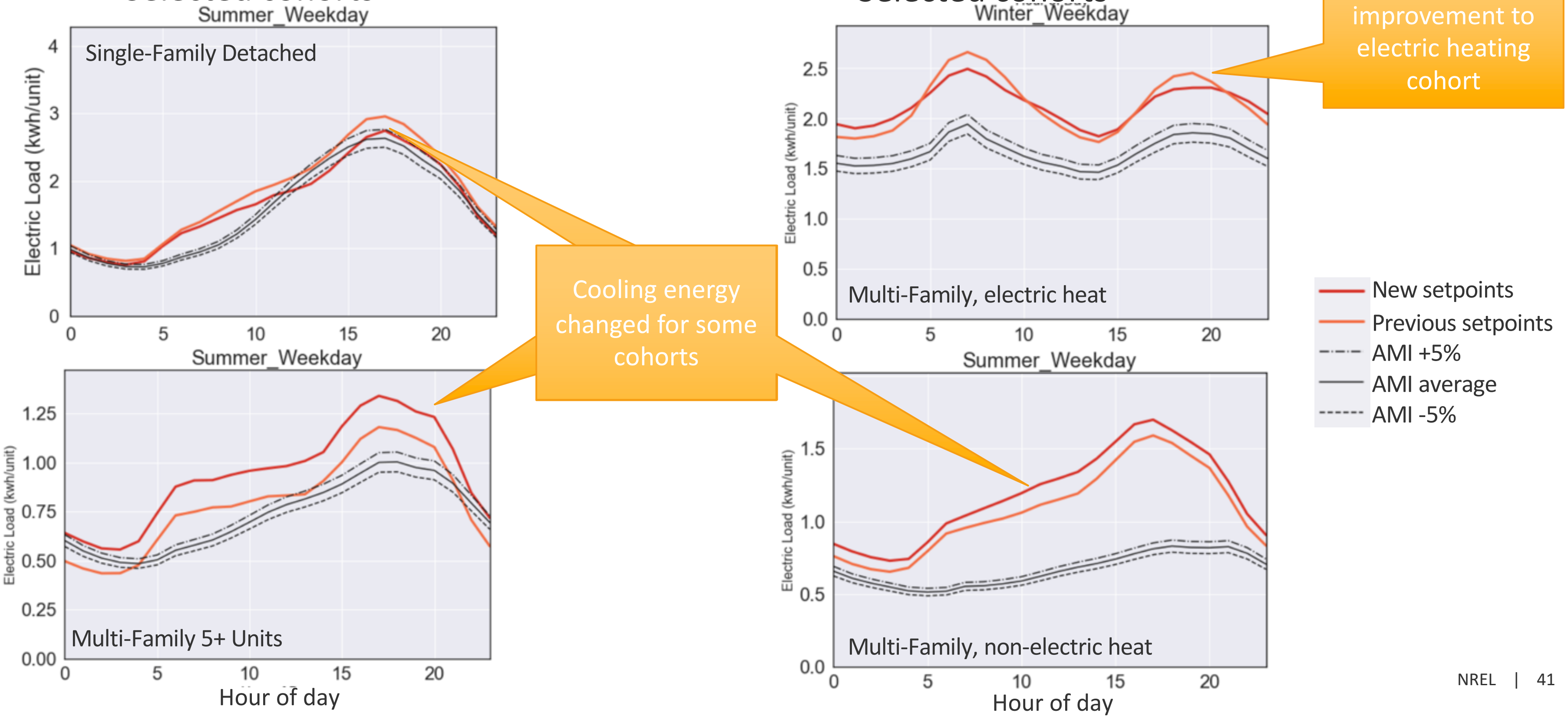
Setpoint Diversity resulting in better shape

Impact: Setpoint distributions and diversity

Fort Collins, CO
Selected cohorts

ComEd, IL
Selected cohorts

Some shape improvement to electric heating cohort

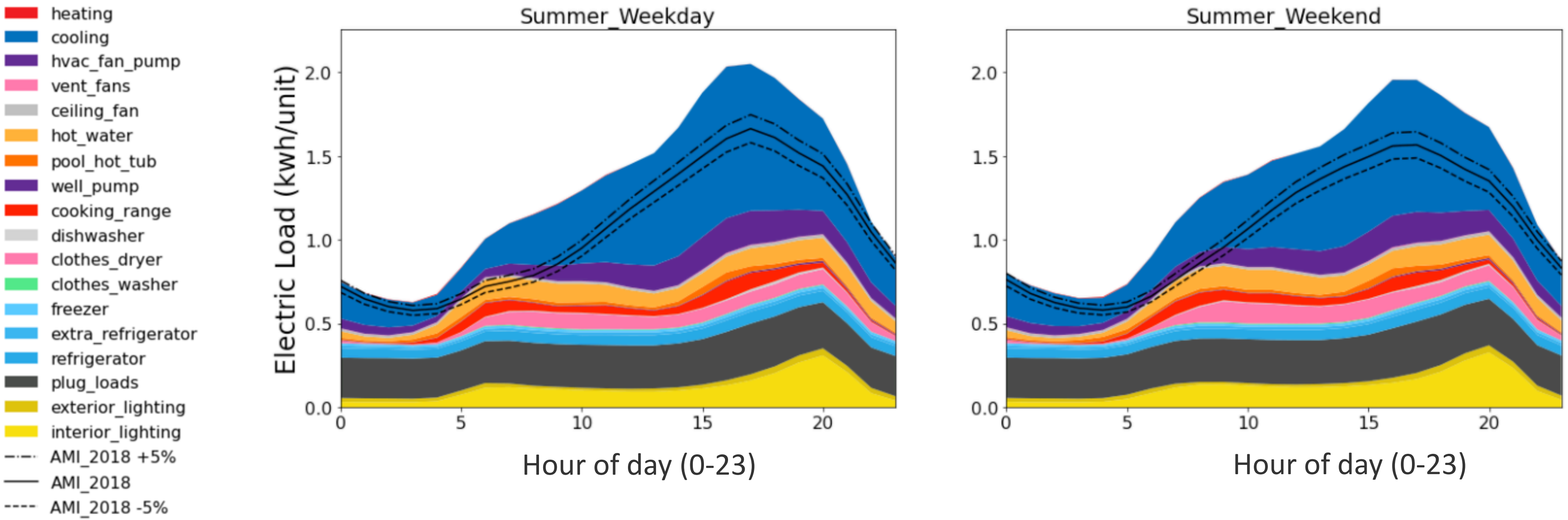


Residential stock end-use summary

Fort Collins municipal utility, CO

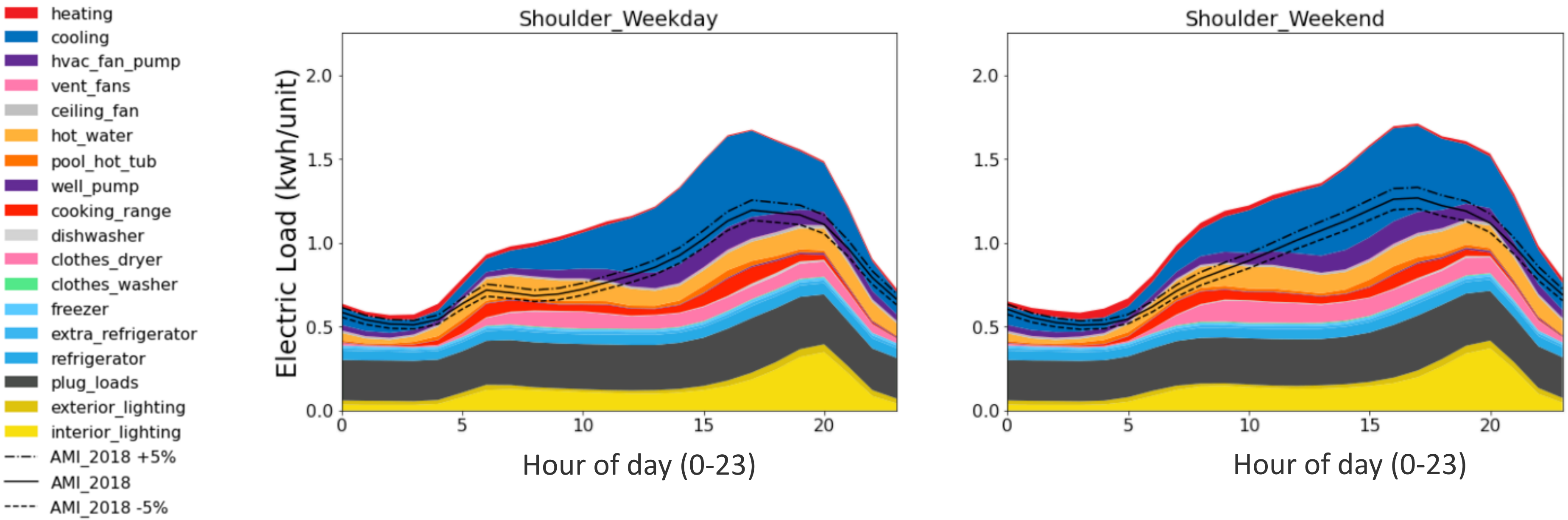
Seasonal end-use loads by day type

Fort Collins municipal utility, CO



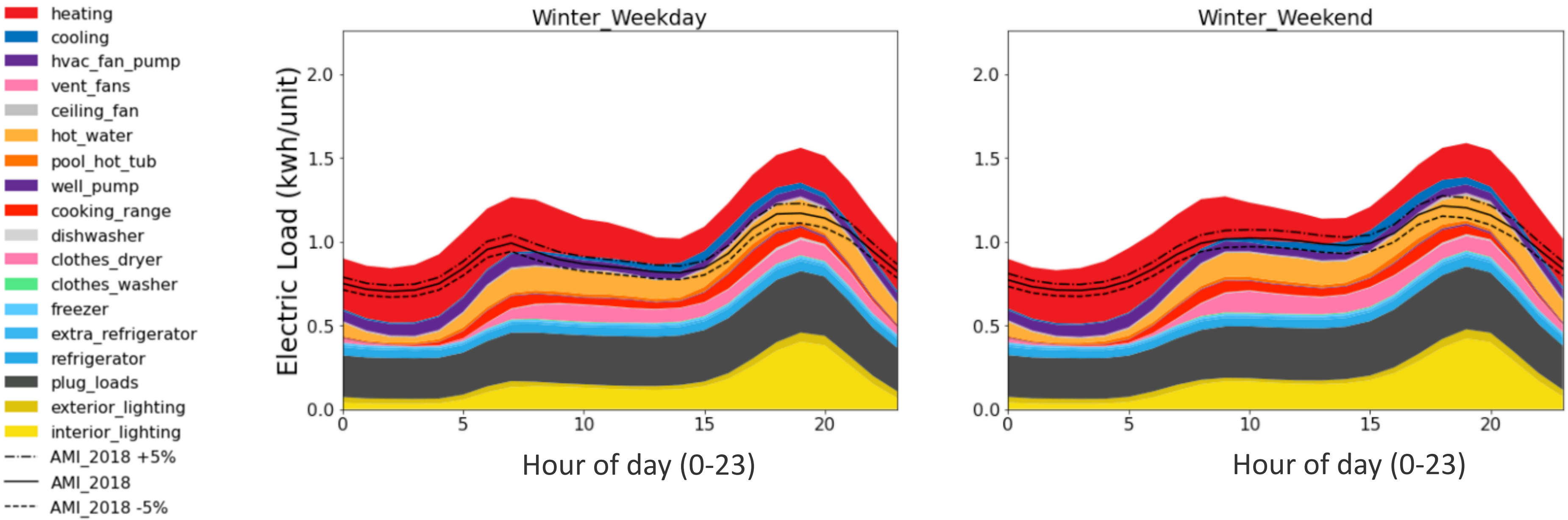
Seasonal end-use loads by day type

Fort Collins municipal utility, CO



Seasonal end-use loads by day type

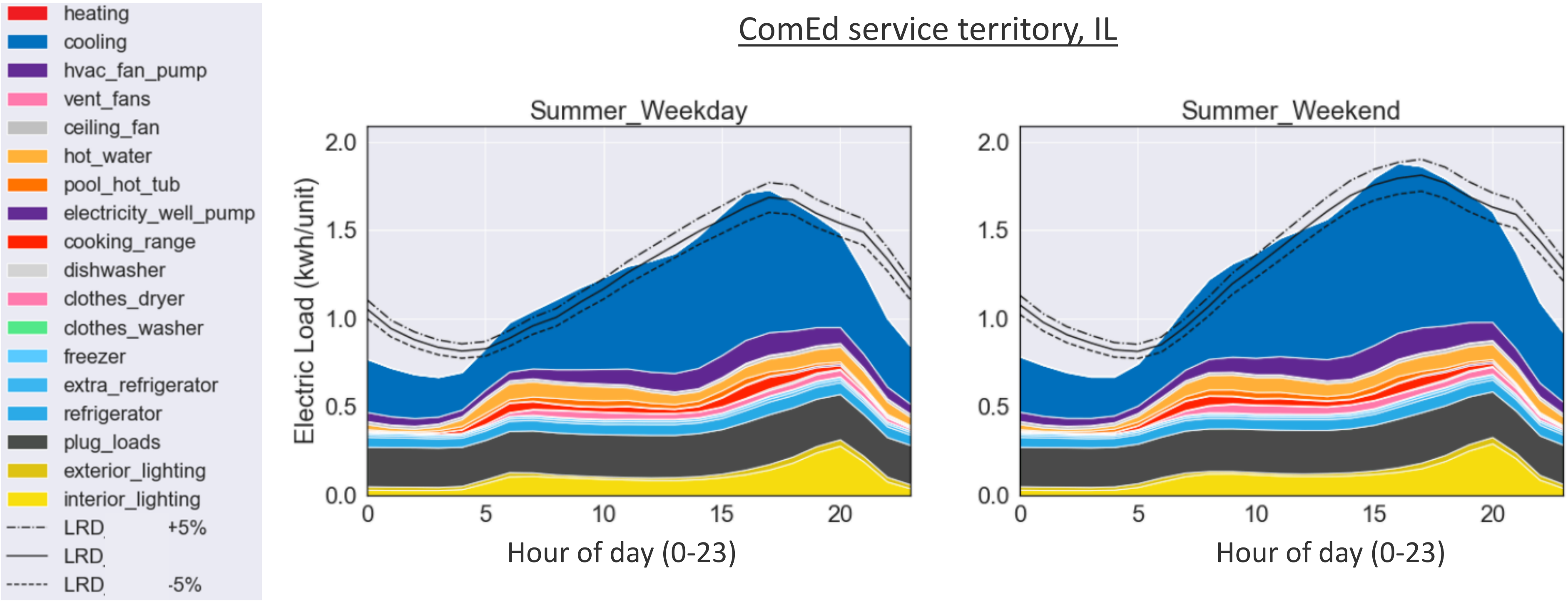
Fort Collins municipal utility, CO



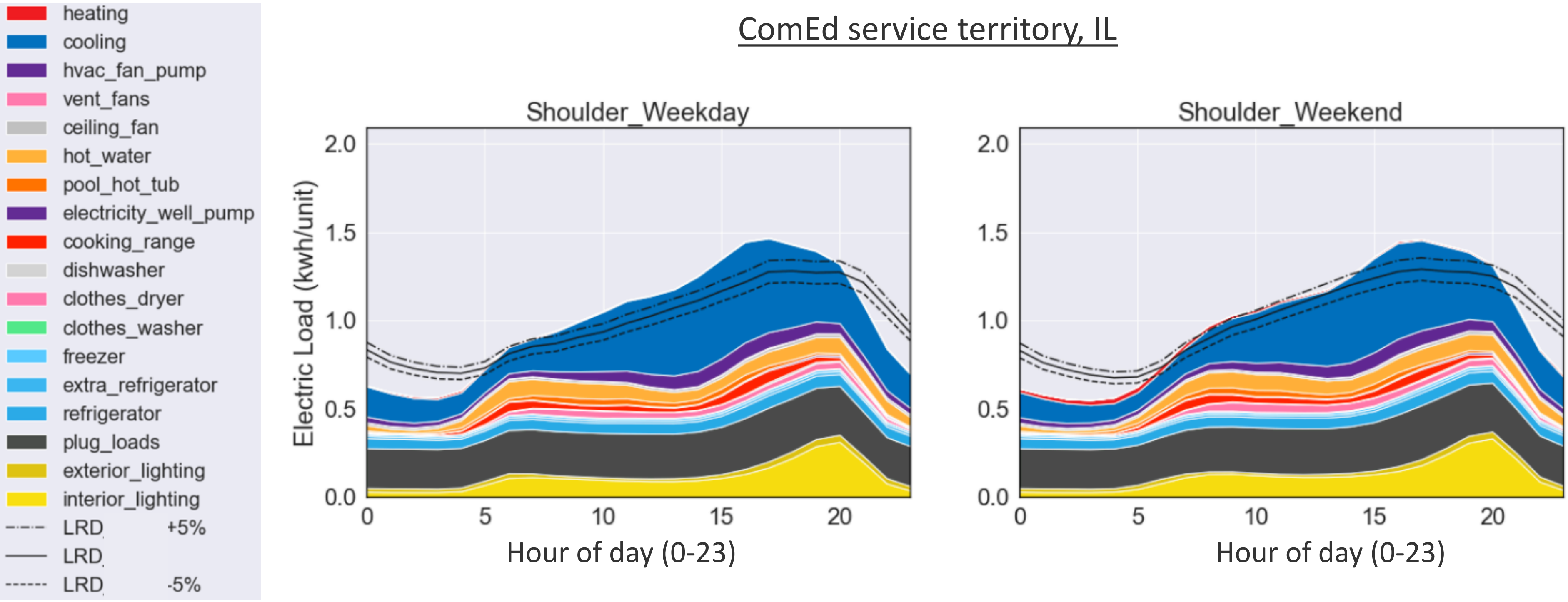
Residential stock end-use summary

ComEd service territory, IL

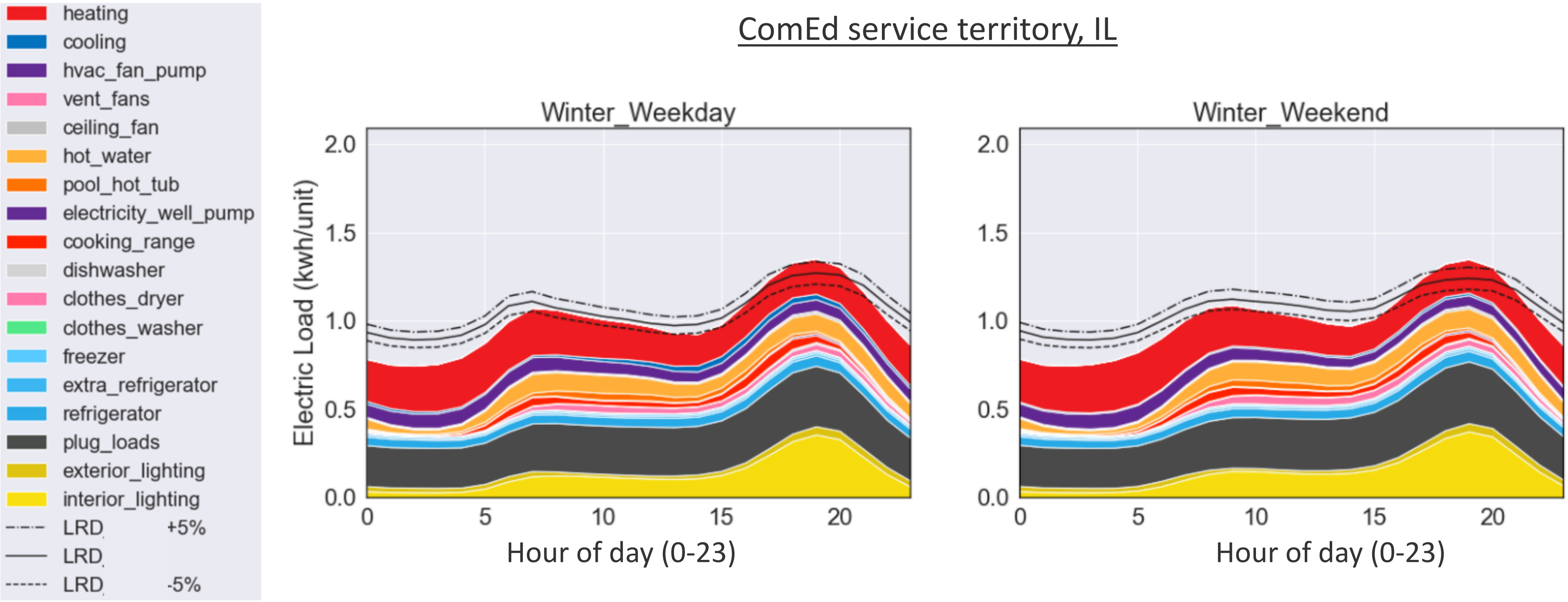
Seasonal end-use loads by day type



Seasonal end-use loads by day type

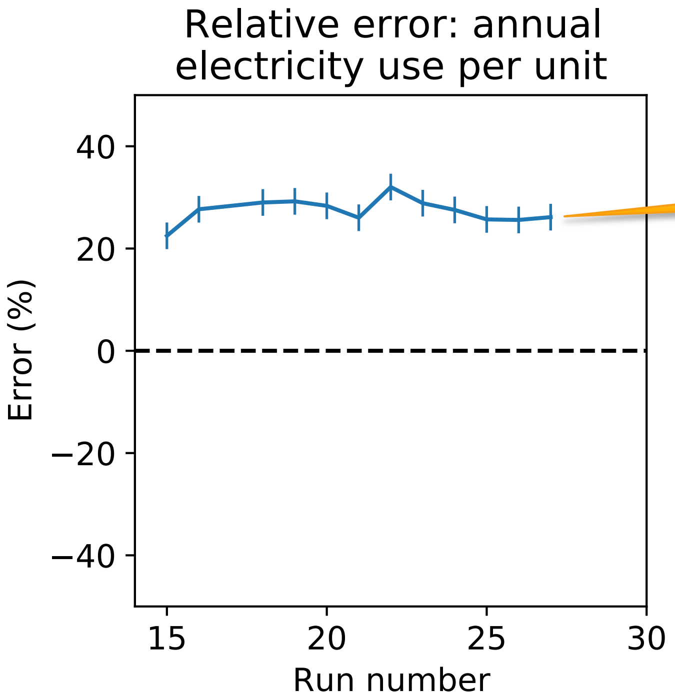


Seasonal end-use loads by day type



Tracking Quantities of Interest

Fort Collins, CO: Annual Error

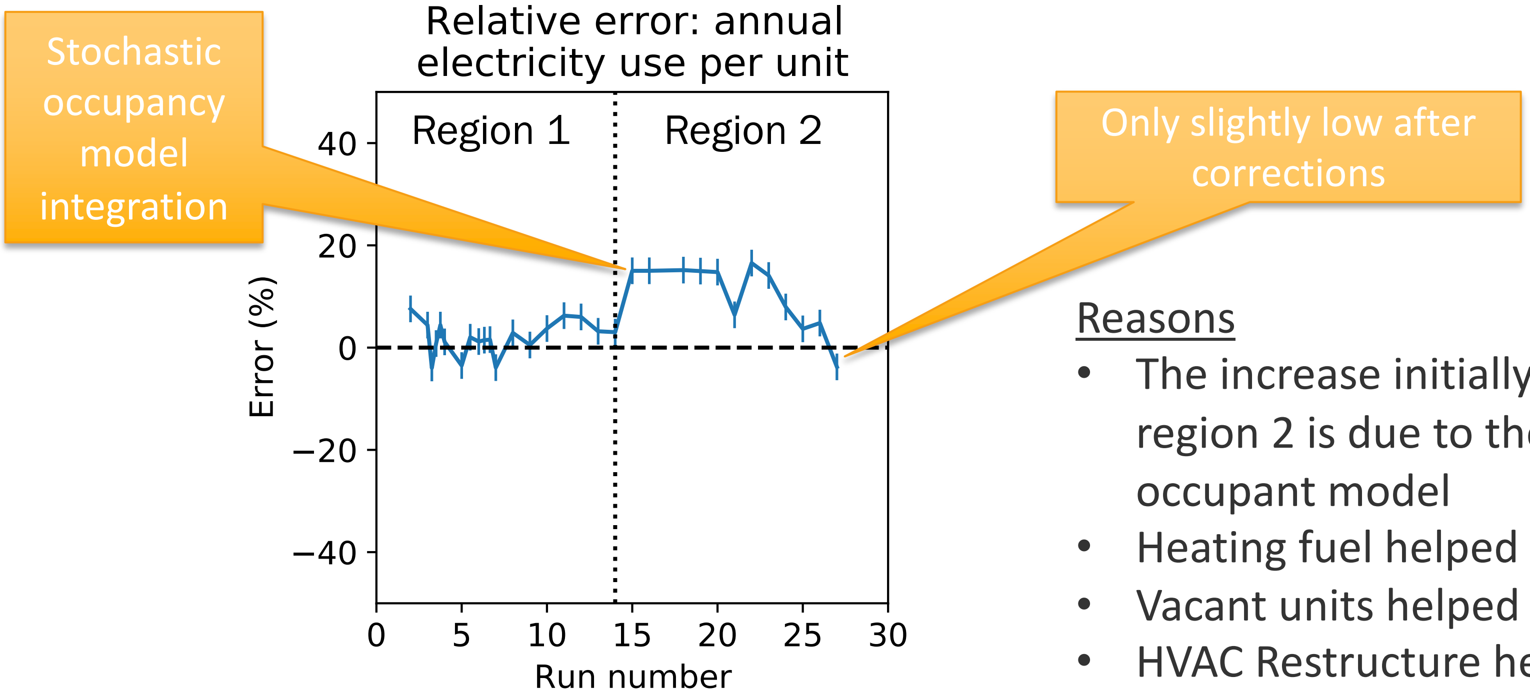


High on annual usage per unit

Reasons

- Combination of a set of end-uses consuming too much electricity
- Cooling energy still too high
- Lighting, water heating, laundry, and/or cooking may also be too high

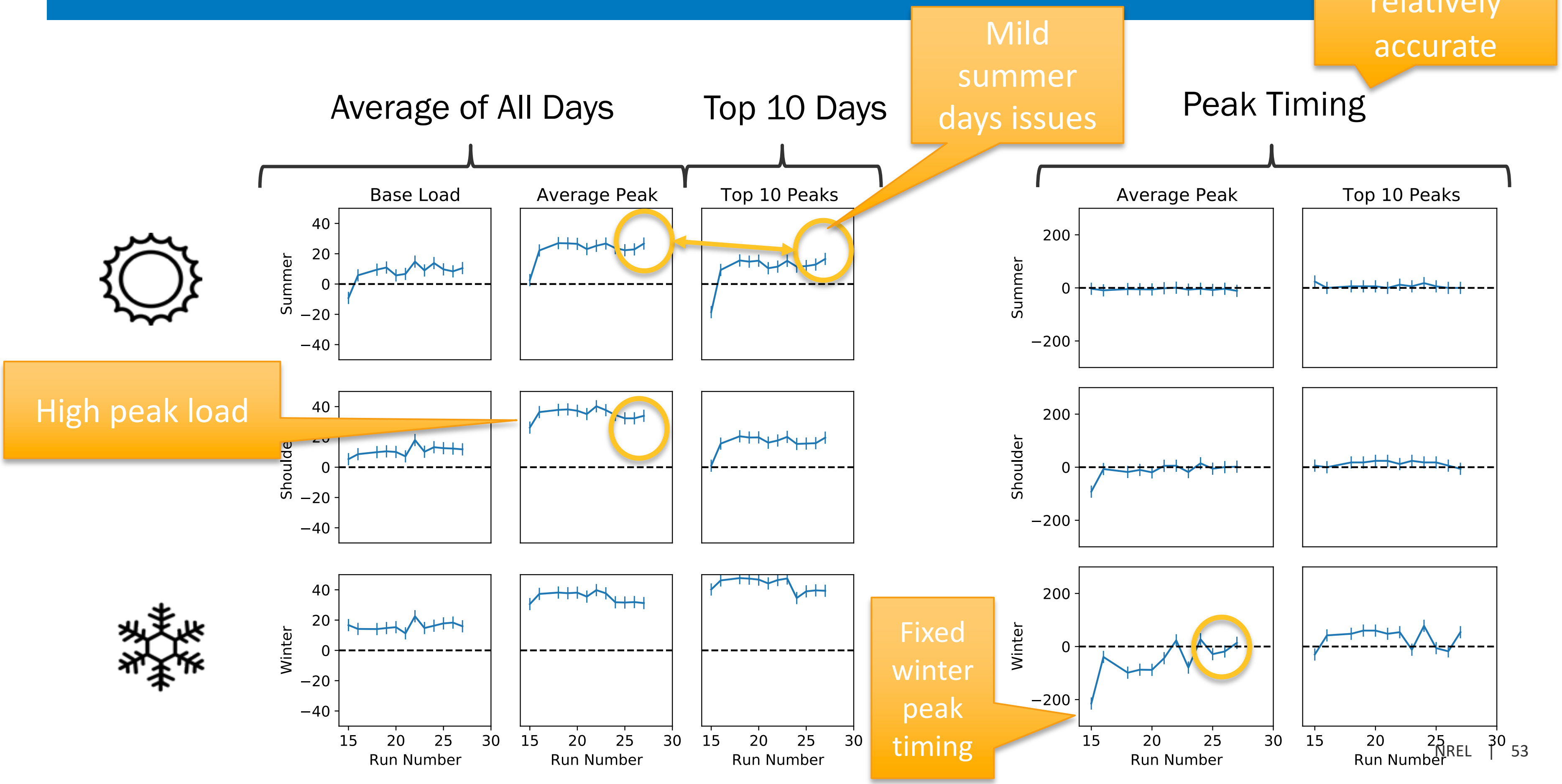
ComEd, IL: Annual Error



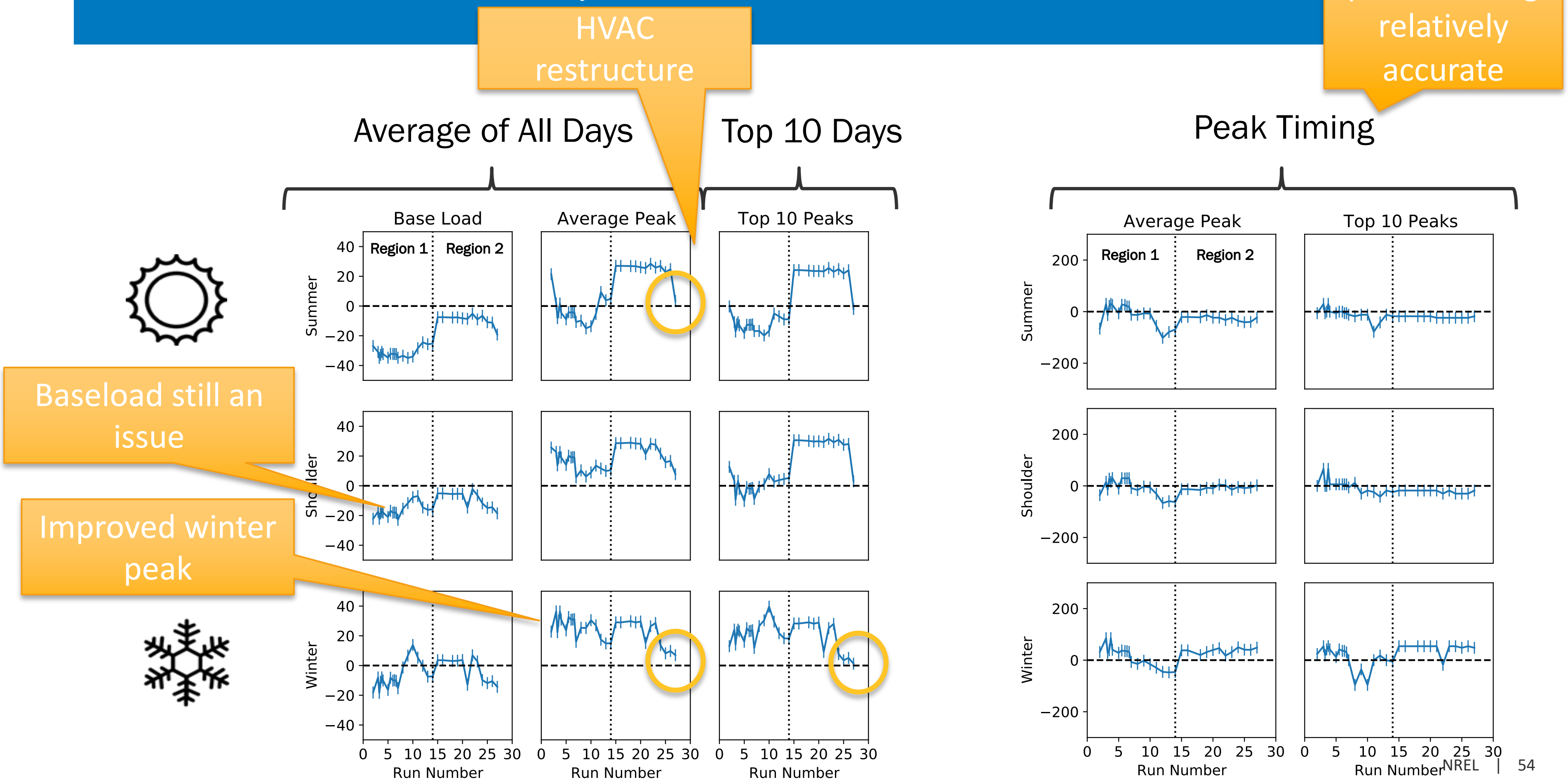
<u>Reasons</u>

- The increase initially at the start of region 2 is due to the stochastic occupant model
- Heating fuel helped correction
- Vacant units helped correction
- HVAC Restructure helped correction

Fort Collins, CO: Total Error Metrics



ComEd, IL: Total Error Metrics

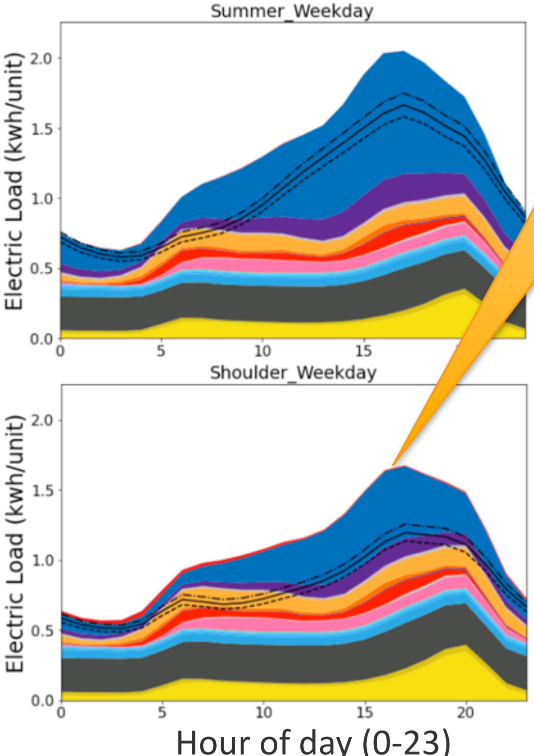


Areas for Improvement

Next Region: Likely Areas for Improvement

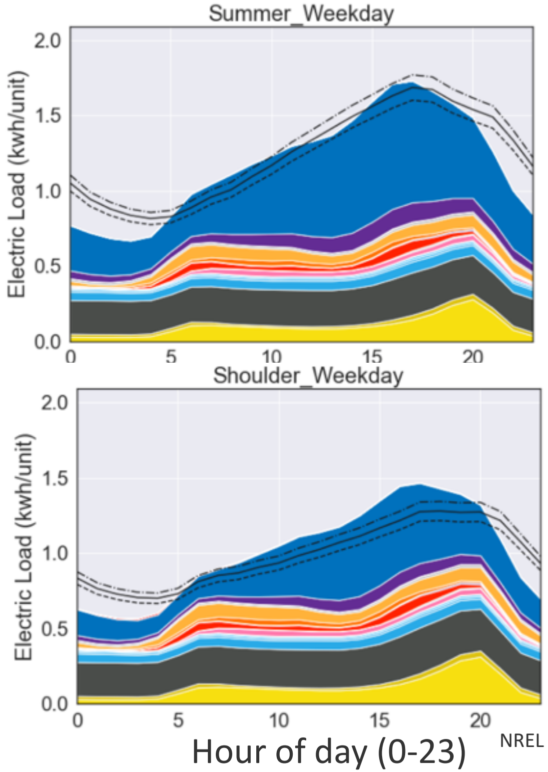
Two regions provides additional insight into areas for improvement

Fort Collins, CO



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

ComEd, IL



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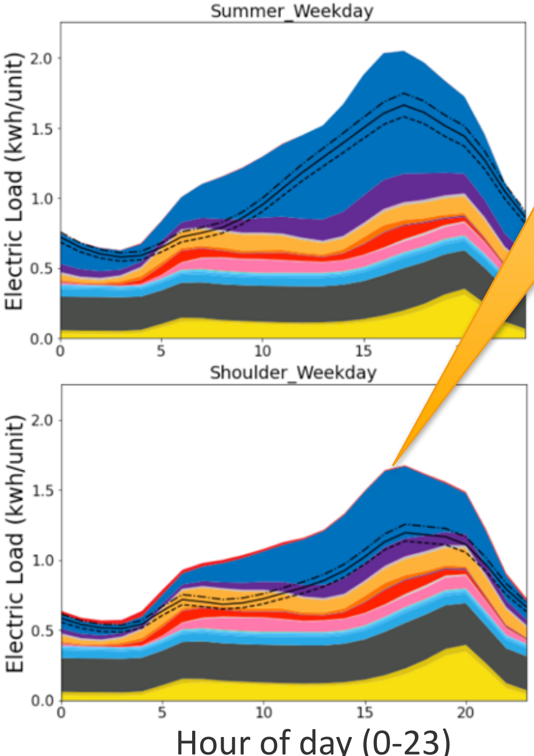
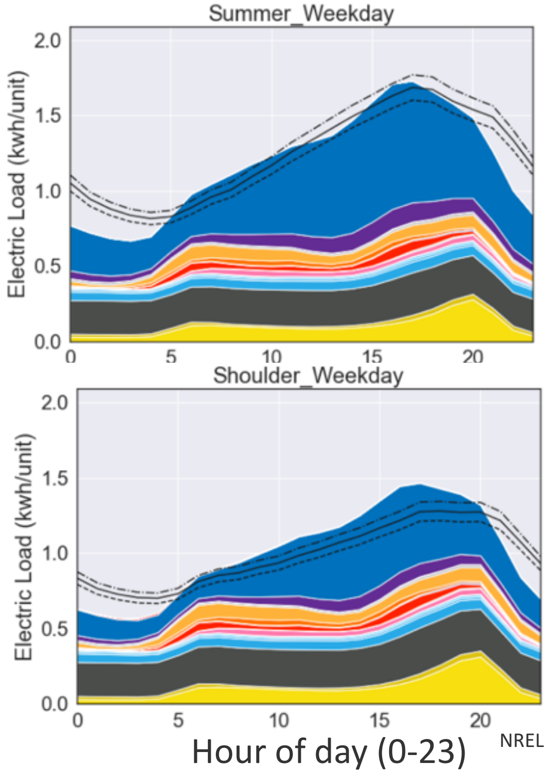


Fort Collins still shows too much cooling, especially in the shoulder season

→ Incorporate more seasonal usage of AC

ComEd, IL



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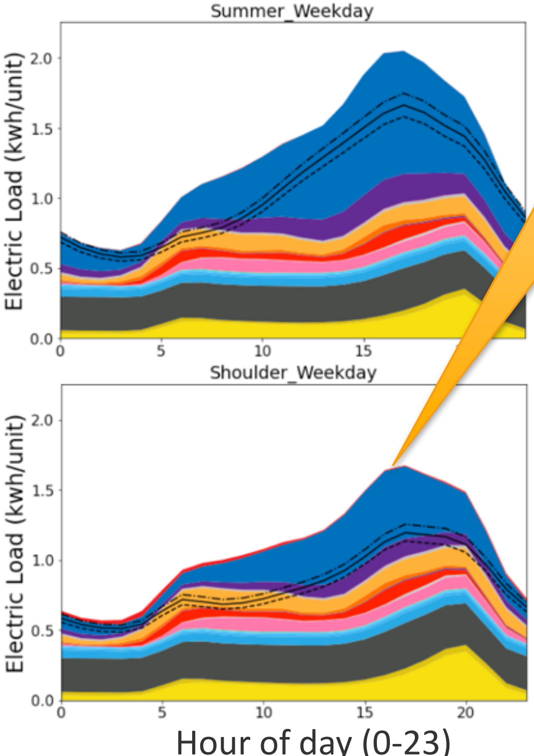
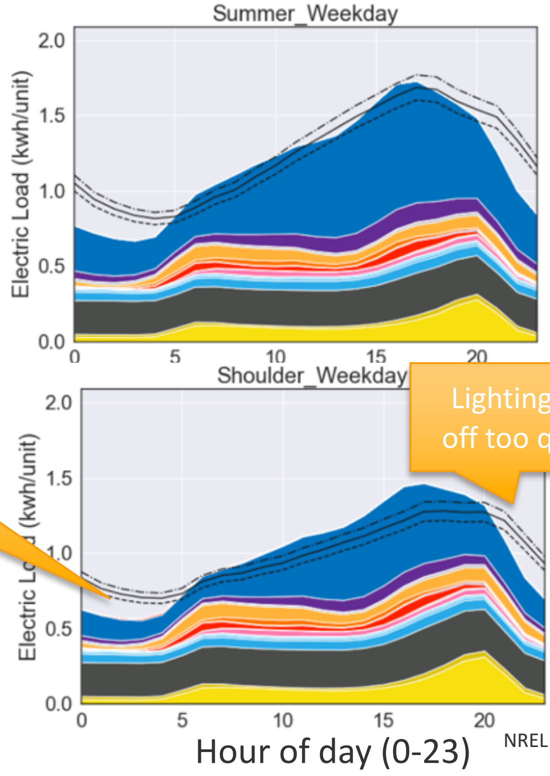


Fort Collins still shows too much cooling, especially in the shoulder season

→ Incorporate more seasonal usage of AC

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

ComEd, IL

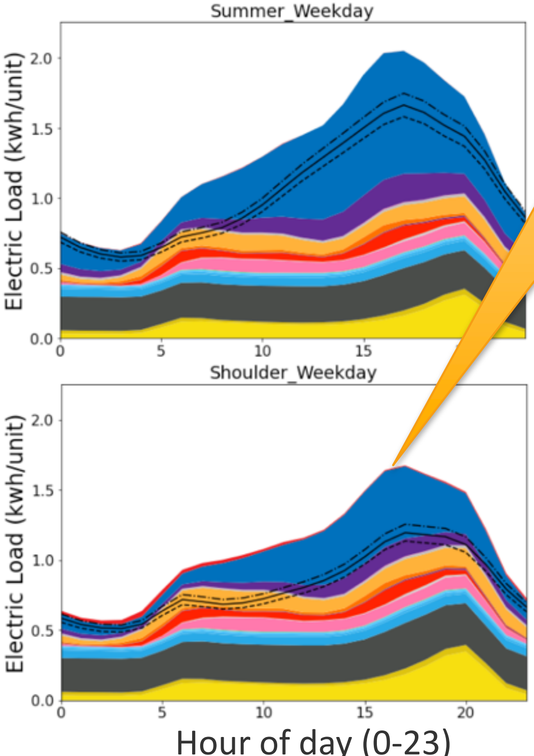


Lighting drops off too quickly?

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

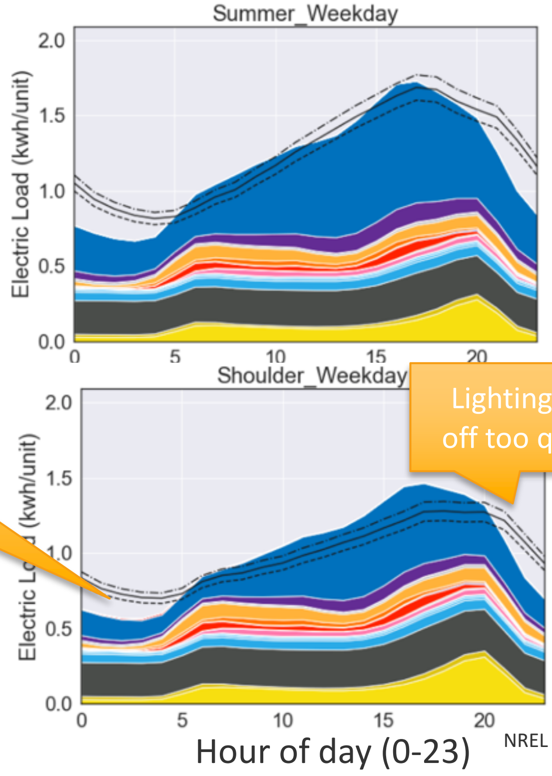
→ Incorporate more seasonal usage of AC

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

→ Use end-use datasets and the American Time Use Survey to investigate regionality of baseload schedules

→ Investigate microclimate and moisture capacitance effects

ComEd, IL



Lighting drops off too quickly?

Next Region: Other Likely Areas for Improvement

HVAC structure improvement enables use of more granular HVAC data:

- Transition from RECS to American Housing Survey (AHS)
  - Cooling saturation and type (central vs. window AC)
  - Heating system type (furnace vs. boiler; electric baseboard vs. heat pump)
  - Water heating fuel type
- AHS is broken into census divisions and the largest 15 metro areas
  - Help towards improving urban and rural models
  - AHS has more samples than RECS, which enables more accurate slicing by vintage, region, and building type

Conclusions (1)

- Ran 14 iterations of ResStock incorporating 8 discrete changes
  - Saw general improvements in QOI metrics
  - Most of the improvements made will carry over to the entire U.S.
- Structural changes to HVAC housing characteristics
  - Enables use for more granular data
  - Will benefit all regions moving forward
- Integrated the residential stochastic occupant-driven load model
  - Now used for every run
- New/Updated visualizations
  - Updated EIA data comparisons from 2012 to 2018
  - RECS 2009 and 2015 end-use scatterplots

Conclusions (2)

- Summary of changes
  - Reduced baseload by adding dwelling unit vacancy
  - More accurate scaling factors for mapping to utility service territories
  - Heating fuel distributions refined with sub-state resolution
  - Improved climate dependence of cooling & heating setpoints and setbacks
  - Improved diversity of cooling and heating setback period start and end times
  - Separated MELs regression equations by building type
- Priority areas for improvement for next region
  - Regionally variable schedule and power level baseloads
  - Potentially missing thermal mass or nighttime baseloads in ComEd service territory
  - Geographically granular HVAC system saturations and water heating fuel type saturations
- Will be moving on to Regional Dataset 3 (Seattle, WA), but continue tracking metrics for the first two region datasets