NORESCO

Single-Family Prototype Model Validation

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Summary

This technical memorandum details the methodology utilized for the validation of single-family prototype models developed for the State of California. The California Prototypes Development project, funded by Southern California Edison's (SCE) Codes and Standards Program, aims to establish a unified set of prototype building models representing California's building stock. This initiative enables the California Energy Commission (CEC) and the California Public Utilities Commission (CPUC) to employ consistent underlying assumptions about the building stock when conducting various analyses, including the evaluation of proposed energy code modifications and the assessment of deemed and custom measures for incentive programs. While the development of these prototype models is documented in a separate report[1], this document focuses on the validation process of the developed models, including the validation methodology and results. It provides detailed descriptions of model enhancements implemented during validation and presents final comparisons to surveyed data and other relevant data sources.

Introduction

Following the development of the single-family prototype models, the next step was to validate the models against energy consumption from the building stock. This was done using data from the 2019 Residential Appliance Saturation Survey (RASS)[2] for single-family buildings. RASS data was collected between October 2018 and September 2019. Since appliance consumption in RASS is specified at the building climate zone level, the prototype model consumption was aggregated to the climate zone level (from four prototype models in four vintages in each climate zone) to enable validation. The climate-zone weighted appliance consumption in RASS was derived using statistical methods (i.e., regression models, as discussed below) and represents the weighted average energy consumption within the sample, which is expected to align with the 50th percentile (2nd quartile) in a normal distribution. Given the significant variability in consumption patterns across the building stock, and the presence of four prototype models and four vintage bins within each climate zone, it is anticipated that aggregated consumption may deviate from the mean but still be considered valid if it aligns with weather (i.e., heating degree-days and cooling degree-days) and other consumption trends (for example, low consumption due to seasonal occupancy in certain locations).

Methodology

The validation process involved the following steps:

1. Unit energy consumption (UEC) data from RASS was extracted for single family buildings by climate zone and end-use. This involved applying filters to the raw surveyed sample data and extracting and weighting end-use consumption to calculate the UEC.
2. Annual end-use consumption data from single-family prototype models (developed in EnergyPlus) in four vintage bins in every climate zone, were aggregated to produce a single value for each end-use within each climate zone (kWh/year for cooling end-use and Therm/year for heating end-use). Floor area weighting factors, as provided in
3. Table 10 (Appendix), were applied.

[1] Prototypes Project Documentation 2023

[2] https://www.energy.ca.gov/publications/2021/2019-california-residential-appliance-saturation-study-rass

4. The inputs for those end-uses that do not vary and/or that vary to a minor degree across climate zones were adjusted to align with RASS data. These end-uses were:
    a. Water heating: Water heaters were modeled based on climate zone-specific water mains temperatures, which account for slight differences in ground temperatures. A monthly temperature schedule was established for each climate zone to accurately reflect seasonal variations in water mains temperature.
    b. Exterior lighting: not expected to vary by climate zone.
    c. Plug and process loads (washer, dryer, and miscellaneous loads): not expected to vary by climate zone.
5. Cooling and heating end-uses, which do vary by climate zone, were validated against RASS data for each climate zone. Validation involved the adjustment of those model inputs that were either assumptions based on industry standards and not based on data from RASS or other sources. For example, thermostat setpoints were based on real-world Ecobee setpoints for modeling and were adjusted during validation.

RASS UEC Calculation Methodology

It is important to understand the procedure used in the RASS analysis to determine the heating and cooling UEC for single family buildings in a climate zone. Specifically, the estimated RASS UECs are determined using a conditional demand analysis (CDA). CDA is a statistical technique used to estimate energy consumption by disaggregating total energy demand into specific end-uses, such as appliances or equipment. This method combines utility billing data, weather information, and customer survey data to produce robust estimates of energy use[3]. The following steps explain the process used in calculating RASS UEC to ensure accurate and consistent results across different climate zones and weather conditions:

1. Data Preparation: This step includes data collection, data cleaning (i.e., eliminating surveys that were determined to have excessive amounts of invalid data, cleaning RASS survey variables, and creating new variables through the cleaning process and the combination of survey variables), data transformation (i.e., normalization, aggregation, and encoding), data integration, data structuring, and data validation.
2. Normalization of Billing and AMI Data: This normalization process converts the varying number of days in consumption data to a standardized one-year period and ensures comparisons across different climate zones by providing annual consumption for long-run normal weather conditions.
3. Degree-Day Models: This step includes utilizing two types of weather files:
    a. Actual year weather data: Separate models for electric and gas consumption are created using actual weather data, including heating degree-days (HDD) and cooling degree-days (CDD) for electricity and primarily HDD for gas. Each model calculates a reference temperature specific to the location of the household.
    b. Normal year weather data: The models are then used to calculate normalized annual consumption (NAC) estimates, reflecting estimated energy consumption for

[3] https://www.energy.ca.gov/sites/default/files/2021-08/CEC-200-2021-005-MTHLGY.pdf

a typical (normal) year (based on most recent weather datasets created for the CEC and PG&E by White Box Technologies[4]).

To calculate the RASS UEC accurately, both actual year weather data and normalized weather data were utilized[3]. The methodology for this calculation involves a two-step process, where the first step uses actual weather data to model energy consumption, and the second step applies this model to normalized weather conditions. The detailed procedure for weather normalization, including the Degree-Day Normalization (DDN) model[3], is outlined below.

- Modeling with actual weather data[5]: The actual weather data (October 1, 2018, to September 30, 2019) helps establish a baseline - understanding of how temperature variations impact energy consumption for each household - as well as creating initial degree days models.
- Using normalized weather data to calculate NAC: The normalized weather data (12-year period from 2006 to 2017) is then used to predict what the energy consumption would be in a typical year, adjusting for any gaps present in the actual data.

Furthermore, RASS UEC data is cleaned after being calculated under that normalization process. Specifically, the methodology used in RASS addressed outliers by trimming the data during the regression analysis phase. For datasets where the model's performance was below a threshold ($R^2 <$ 0.8**Error! Bookmark not defined.**), outliers were identified based on their residuals, with large deviations between observed and predicted values indicating potential outliers. Those outliers were then trimmed to improve model accuracy. The trimming of outliers was part of the normalization procedure applied to daily and monthly usage data for both electric and gas consumption.

Also, in order to utilize the UEC data accurately, it must first be weighted to account for varying sampling processes and corresponding weight calculations for each dataset. Specifically, the data needs to be adjusted to a parameter known as sample weight. These sample weights represent the number of households in the broader population that each response corresponds to, rather than just the survey respondents. The steps for calculating sample weights are outlined below[2]:

1. Sample stage classification: responses were grouped into different stages based on survey timing and methods (e.g., email-only, early/late responses, nonresponse follow-ups).
2. Solo weight calculation: initial weights were assigned for each stage, representing how many households each response accounted for within the population.
3. Blending fractions: blending fractions were calculated to reflect the share of the population represented by each stage, accounting for varying response rates.
4. Base weight creation: solo weights were multiplied by blending fractions to create base weights, adjusting for different survey stages.
5. Calibration (Raking): base weights were fine-tuned using an iterative process to align the weighted data with known population characteristics (e.g., region, dwelling type, income).

[4] https://pda.energydataweb.com/api/downloads/2280/Weather%20webinar%20CALEE2018%207-12-2019.pptx.

[5] Actual weather files were developed as part of the CALLEE2018 file development and are posted on CALMAC.org along with the CALEE2018 version of normal year weather data for each specific city: http://www.calmac.org/weather.asp.

Filtering RASS Data

To perform the heating and cooling validation, raw sample data from RASS was used to determine the heating and cooling consumption by climate zone. This data for single family buildings was filtered to remove certain entries and the values from a few fields were combined to determine the cooling and heating consumption. The following fields were used to determine the cooling and heating consumption:

- Cooling End-Use:
  - Central Air Conditioning Electric UEC
  - Room AC Electric UEC
  - Evaporative Cooler Electric UEC
- Heating End-Use:
  - Primary Heat Gas UEC
  - Auxiliary Heat Gas UEC
  - Conv. Heat Electric UEC
  - Heat Pump Electric UEC
  - Aux. Heat Electric UEC

The following filters were applied:

- Cooling End-Use:
  - Type of building: Single-Family detached
  - Cleaned "Pays for central air conditioning":
    - Yes
    - No, it is part of my rent/condo fee
  - Central Air Conditioning Electric UEC: All none-zero values
- Heating End-Use:
  - Type of building: Single-Family detached
  - Cleaned "Primary heating fuel": Natural Gas

RASS UEC Results

Following the outlined approach, Table 1**Error! Reference source not found.** and Table 2 display the filtered RASS Unit Energy Consumption (UEC) data for heating and cooling, respectively. Each figure presents three metrics per climate zone, represented by box-and-whisker plots. These plots show the weighted mean, first quartile (Q1), and third quartile (Q3) of the distributed data for each climate zone. The first quartile (Q1) represents the value below which 25% of the data fall, while the third quartile (Q3) represents the value below which 75% of the data fall. This spread between Q1 and Q3 is known as the interquartile range (IQR) and is useful for understanding the distribution and variability of the data. Furthermore, distribution of such UEC data is presented in Figure 1 and Figure 2, while heating and cooling data distribution is presented across the 16 climate zones.

Table 1: RASS Heating end-uses (filtered data for single-family homes)

CZT24	RASS Weighted Mean Cooling Consumption (kWh/sf)	Cooling Q1 (kWh/sf)	Cooling Q3 (kWh/sf)	No. of Samples
1	134	135	135	93
2	315	198	405	673
3	256	176	326	2,112
4	252	157	315	1067
5	297	220	349	286
6	155	107	181	1,611
7	139	56	154	1,399
8	122	83	167	1,641
9	163	101	194	2,146
10	160	119	194	1,900
11	222	147	273	315
12	250	158	318	3,045
13	222	151	267	968
14	206	123	242	469
15	89	60	106	207
16	94	44	163	204

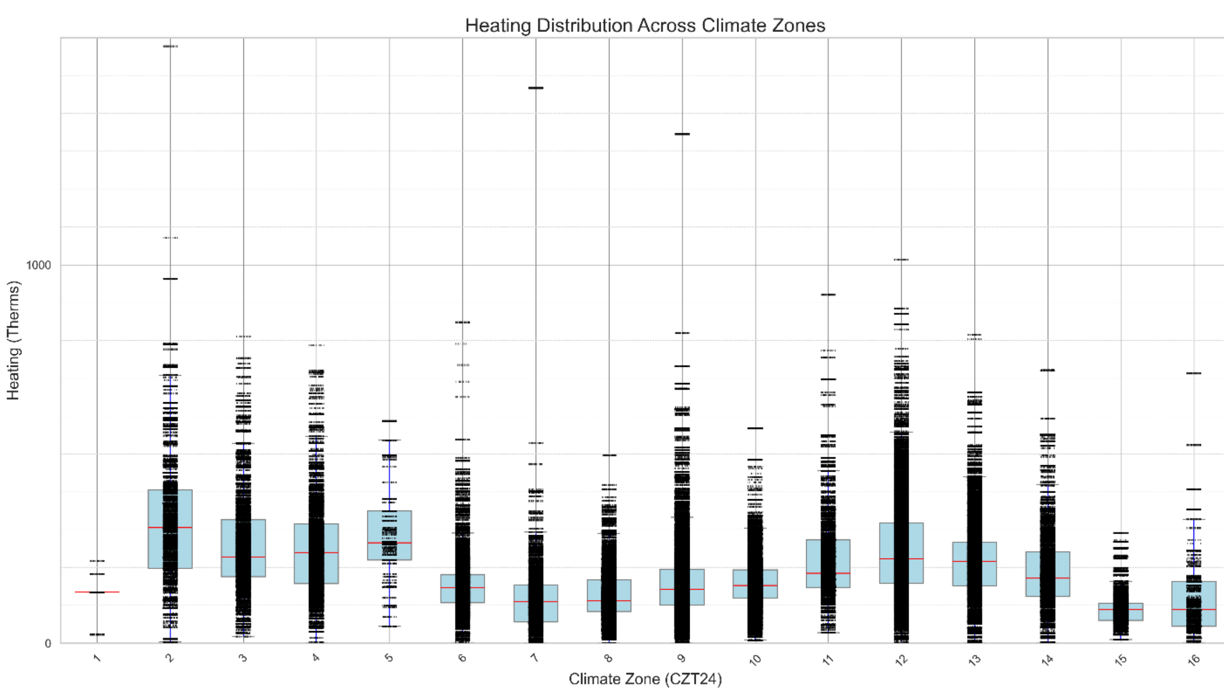

Figure 1: Heating end-use distribution per climate zone - including median, first, and third quartile of the RASS UEC dataset

Table 2: RASS Cooling end-uses (filtered data for single-family homes)

CZT24	RASS Weighted Mean Heating Consumption (Therms/sf)	Heating Q1 (Therms/sf)	Heating Q3 (Therms/sf)	No. of Samples
1	1,362	1,376	1,376	10
2	508	305	581	453
3	588	201	1,117	487
4	654	353	852	834
5	954	271	1,243	51
6	868	498	1,187	886
7	762	390	932	844
8	1,104	611	1,487	1,347
9	1,657	836	2,232	2,126
10	1,680	1,017	2,293	2,211
11	1,766	1,390	2,257	774
12	1,326	800	1,673	3,785
13	2,753	1,891	3,203	1,262
14	2,652	2,078	3,313	579
15	6,938	3,918	9,427	254
16	1,500	1,136	2,422	248

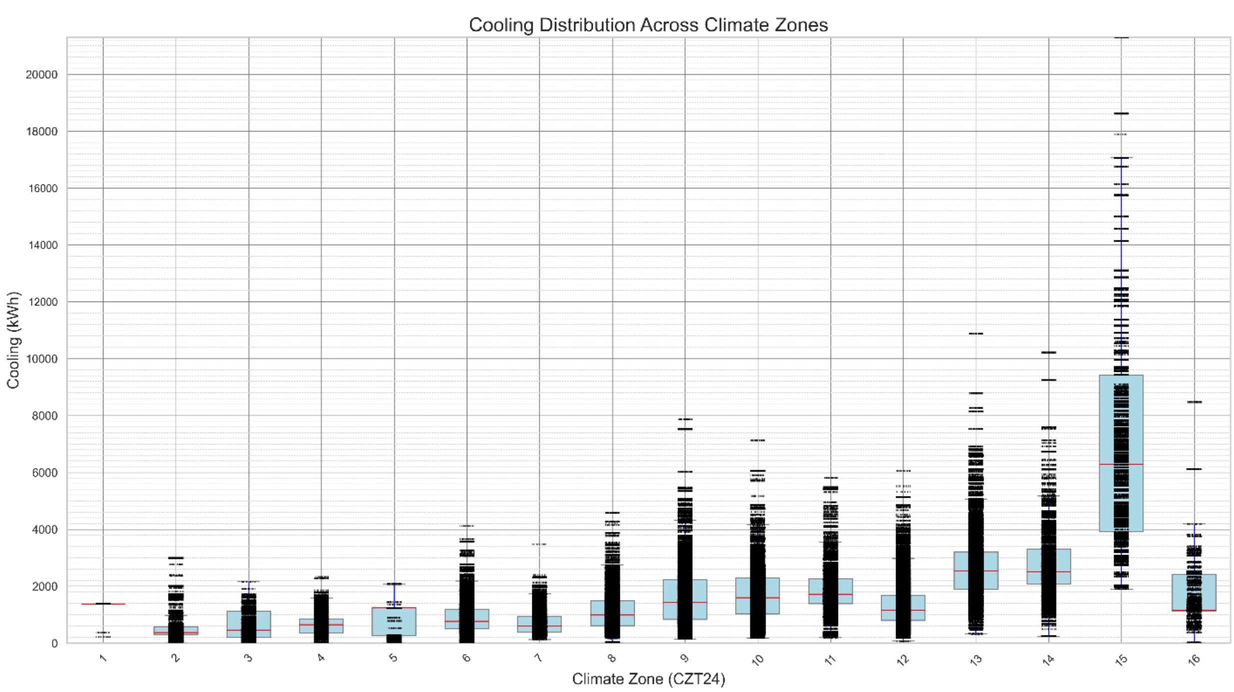

Figure 2: Cooling end-use distribution per climate zone - including median, first, and third quartile of the RASS UEC dataset

Model Adjustments

The initial, non-validated (or unadjusted) modeled heating and cooling consumption by climate zone was found to be higher than the UEC from RASS[2]. To address this discrepancy, a sequential validation process was implemented to refine cooling and heating energy predictions.

For cooling, the modeled cooling was higher than observed. To lower modeled cooling, a list of those variables that could be adjusted to lower cooling energy was developed. The variables to be adjusted were determined based on whether those variables had inputs from the data. For example, the air conditioner efficiency could be lowered to account for in-field degradation. However, this was evaluated during model input development and the COP input was selected based on analysis. Therefore, the air conditioner efficiency was not chosen for adjustment. The first variable to be adjusted were miscellaneous internal loads because they were based on an assumption from PNNL single-family (2006) prototype model[6]. Similarly, the internal lighting power was an assumption from RESNET and not from RASS or other sources with observed data. Next, building envelope improvements were introduced, including reducing the windows' solar heat gain coefficient (SHGC) and incorporating window overhangs and internal window shades to limit solar heat gains. Natural ventilation was then added to simulate occupant behavior, enabling the use of outdoor air to further reduce reliance on air conditioning. Following these measures, infiltration rates were reduced to minimize unwanted air exchange. Finally, the cooling thermostat setpoint temperature was adjusted, with a higher daytime setpoint to lower cooling loads during peak hours. Each of these steps was validated against RASS-derived UEC data, ensuring the models increasingly aligned with observed energy performance across various climate zones and building characteristics.

For heating, the primary strategy was focused exclusively on reducing infiltration rates to address discrepancies in heating energy predictions. All these inputs were based on assumptions and did not have data in RASS[2] or other sources. The rationale for using these specific inputs instead of others was therefore that there is no basis for the starting values used for these inputs other than industry-standard specifications and engineering judgment.

Existing Input Adjustments

More details on the applied adjustments on the existing inputs are listed below.

- Lighting Power Density (LPD) was set to 0.19 W/ft^2 for all models and vintages.
- Plug Loads and Appliances (Equipment Power Density): Plug loads were validated against the 2019 Residential Appliance Saturation Survey (RASS)[2] Unit Energy Consumption (UEC) data for single-family homes. A full list of adjusted plug load densities is presented in Table 3.

Table 3: Adjusted plug loads

Model	Initial Assumption (W/ft^2)	Adjusted (W/ft^2)
Model A (SF 1250)	5.6	1.4
Model B (SF 1750)	4.0	1.0

[6] https://www.energycodes.gov/prototype-building-models#Residential

Model C (SF 2250)	3.1	0.8
Model D (SF 2750)	2.6	0.6

- Infiltration: In order to reduce cooling[7] and heating loads, infiltration was reduced by 34% compared to the initial settings. The adjusted values are presented in Table 4.

Table 4: Infiltration ACH adjusted values

Vintage	Initial Assumption (ACH)	First story (ACH)	Second story (if applicable) (ACH)	Attic (ACH)
Before 1975	0.82	0.62	0.62	0.62
1975-1983	0.76	0.50	0.50	0.50
1984-2005	0.47	0.30	0.30	0.30
2006-2019	0.35	0.26	0.26	0.26

- Window SHGC: 0.44 (applicable to all models and vintages) – replacing the initially specified range of 0.51 to 0.70.
- Thermostat setpoint: For lowering the internal loads further, the cooling schedule was adjusted, while the thermostat heating setpoint (70 °F) has not changed. The adjusted cooling schedule is shown in Table 5. Specifically, the cooling setpoint was increased to 83 °F for daily hours (8 am – 6 pm) and set back to 80 °F for the remaining hours.

Table 5: Adjusted Cooling setpoint

Period	Initial Assumption	Cooling Setpoint
12 am - 8 am	74° F	80 °F
8 am - 6 pm	74° F	83 °F
6 pm - 12 am	74° F	80° F

New Model Inputs

This section describes additional elements incorporated into the models to improve model and validation accuracy. These enhancements include adding window overhangs, implementing internal shading, and integrating natural ventilation.

- Overhangs were added with 2.5 ft depths and zero inch offset.
- Internal window shades (interior blind): To model interior blinds, shades were added only during the months of the year with cooling degree days (i.e., May through October). The schedule of shades can be found in Table 6.

[7] https://doi.org/10.1016/j.buildenv.2020.107459
https://doi.org/10.1016/j.buildenv.2022.108848
https://buildings.lbl.gov/publications/estimation-infiltration-leakage-and

Table 6: Internal window shades schedules

Period	Schedule
January-April, November-December	Always off
May- October	6 am- 8 pm: on Other hours: off

- Natural Ventilation: To further reduce cooling energy consumption, natural ventilation was incorporated into the model. This addition simulates occupant behavior, where occupants frequently open windows to take advantage of cooler outdoor temperatures, thereby minimizing the use of air conditioning and reducing electricity costs. Natural ventilation corresponding to an ACH value was turned on when the indoor and outdoor conditions are deemed favorable for opening windows. Table 7 shows these thresholds for indoor and outdoor temperatures. The corresponding schedules are provided in Table 8.

Table 7: Natural ventilation settings used for validation

Input	Value
ACH	1.25
Minimum Indoor Temperature (F)	75
Maximum Indoor Temperature (F)	80
Minimum Outdoor Temperature (F)	55
Maximum Outdoor Temperature (F)	75

Table 8: Natural ventilation schedules used for validation

Climate Zone	Schedule
15	Always on
All other climate zones	On: May- October
	Off: January-April, November-December

Validated Results

Error! Reference source not found. and Figure 3 present the validated simulation results of all models, adjusted using the weighting factors provided in

Table 10 (appendix section). For each climate zone, the weighted heating and cooling end-uses are shown and compared against the RASS UEC values, including the weighted mean, as well as the 25th (quartile 1) and 75th percentile (quartile 3) consumption from the filtered RASS dataset. The validation process aimed to align the results as closely as possible with the weighted mean values. If aligning with the weighted mean was not achievable, the validated results for each climate zone ensured to fall within the Q1-Q3 range, which represents the middle 50% of the data.

Figure 5 and Figure 6 present a detailed comparison of the observed trends between the simulation results of the validated models (called as “Modeled”) and the RASS UEC data. The comparison focuses on how well the modeled results aligned with the actual energy consumption patterns reflected in RASS. For both cooling and heating end-uses, the validated results show strong alignment with the climate-specific metrics of Cooling Degree Days (CDD) and Heating Degree Days (HDD), indicating that the modeled results are capturing the sensitivity of energy use to outdoor temperature variations. However, the comparison with RASS data exhibits greater variability, and the trends for cooling and heating end-uses from RASS do not always correlate as strongly with CDD and HDD as the modeled results do, especially in climate zones 1 and 16.

The discrepancies between the RASS UEC data and the modeled results can be attributed to several factors. Firstly, the RASS data has a limited number of respondents in certain climate zones, which can significantly affect the accuracy of the results. For example, in climate zone 1, the sample size is particularly small, with as few as 10 filtered respondents for non-zero cooling UEC and only 93 for heating UEC. This low sampling rate can skew the predicted cooling energy consumption for that climate zone. Moreover, the modeled prototypes may not fully capture the diversity of occupant behaviors. For instance, some occupants might choose to leave cooling off even when indoor temperatures exceed 83°F, a behavior that would result in lower cooling energy use than what the model predicts. Additionally, there is the possibility that some of the surveyed homes, such as vacation properties or those located in resort areas, are not fully occupied year-round. This seasonal occupancy, along with other external factors like local climate anomalies or socioeconomic conditions, could further distort the energy consumption patterns observed in the RASS data, leading to discrepancies when compared with the more standardized assumptions in the energy model.

The approach to limit validation adjustments to rational inputs was deliberately chosen to avoid overfitting models to the RASS consumption. This approach allows the models to be used more widely and to generate impacts that are more aligned with the broader building stock as opposed to a small sample.

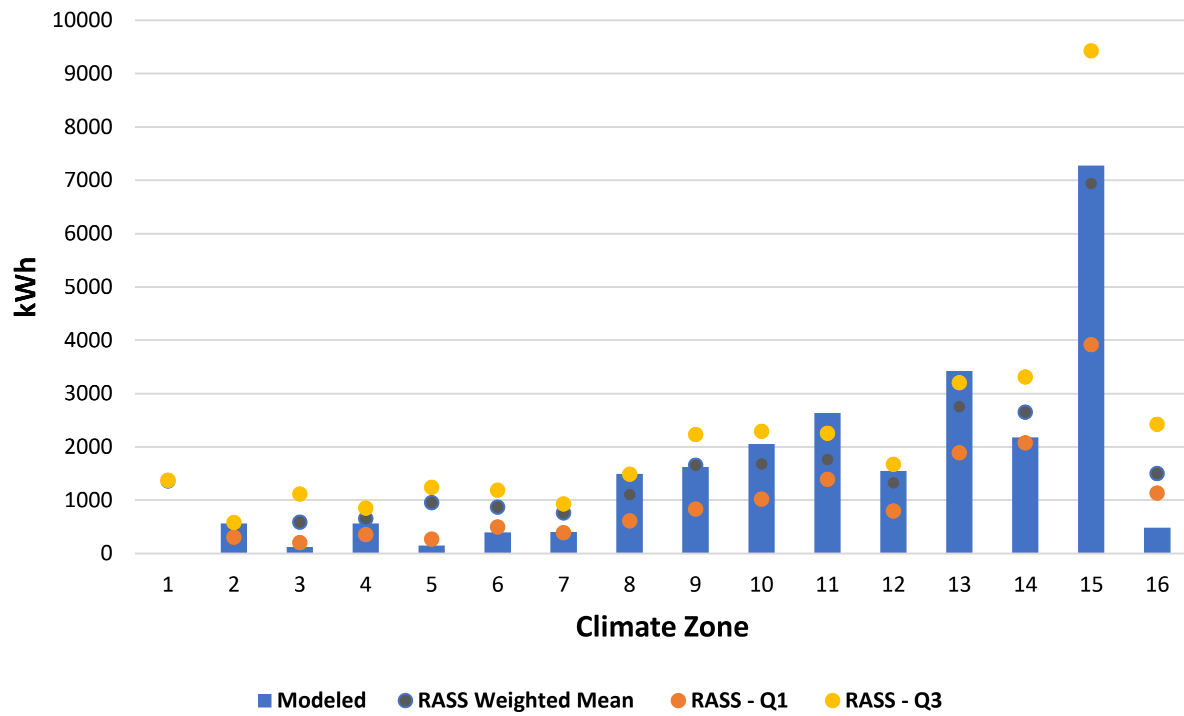

Figure 3: Modeled cooling end-uses compared to RASS 2019

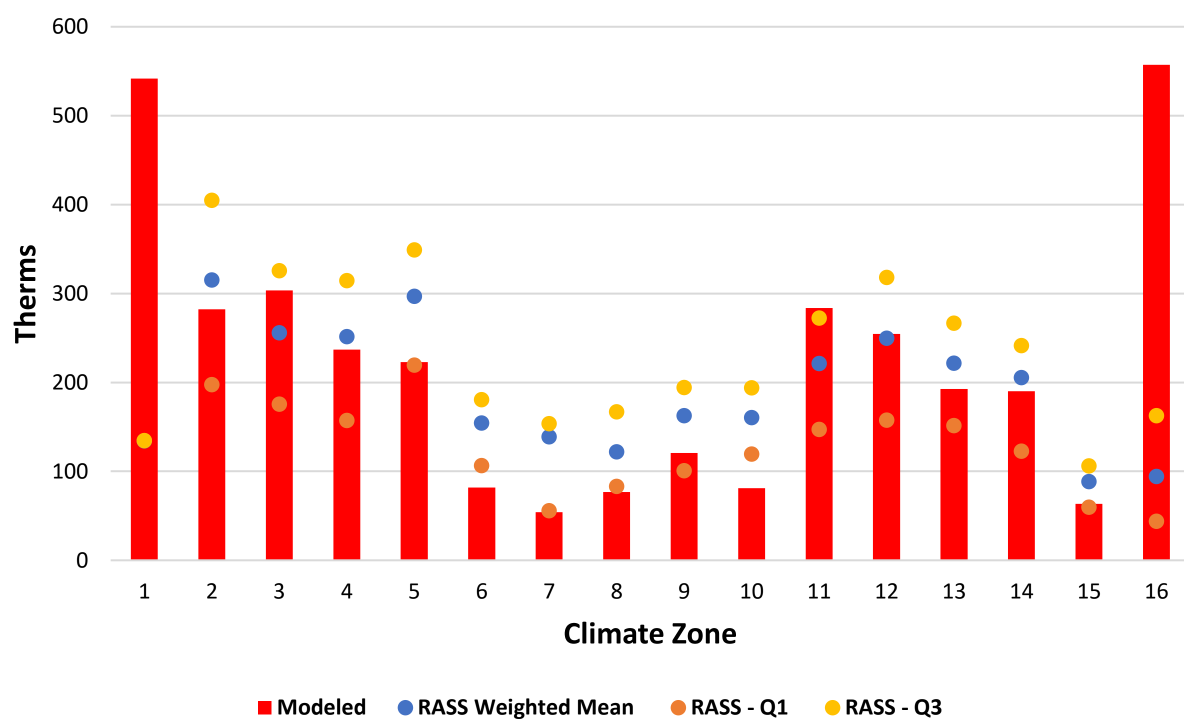

Figure 4: Modeled heating end-uses compared to RASS 2019

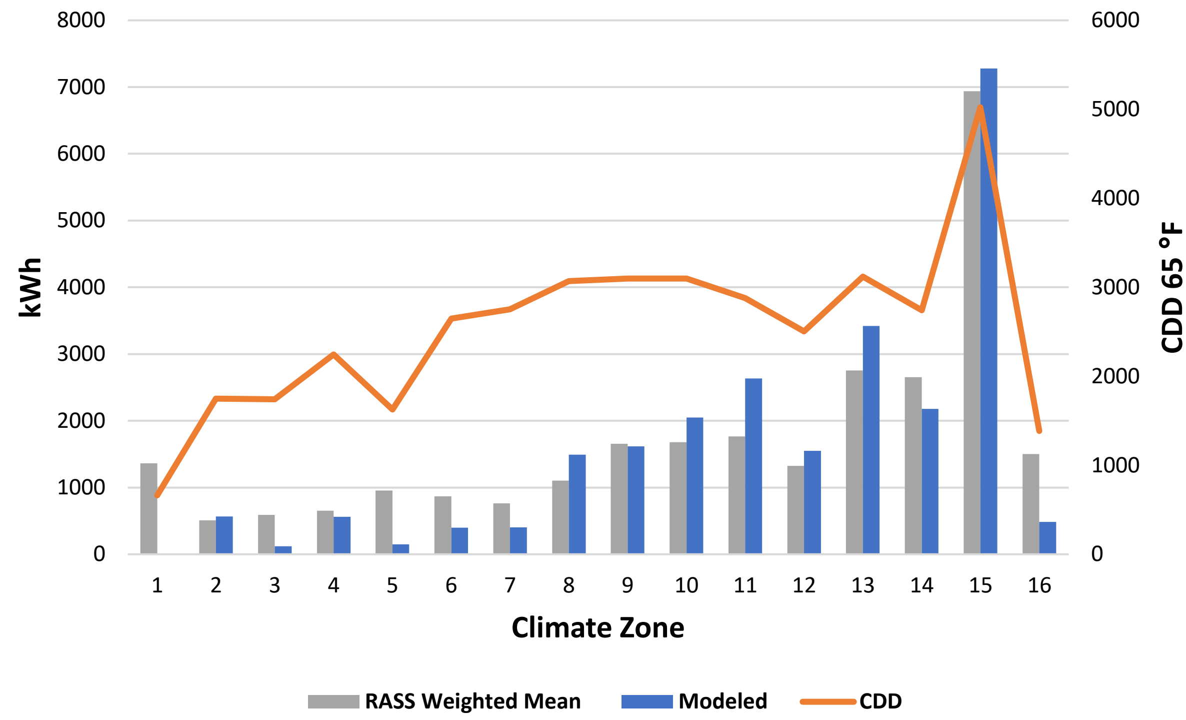

Figure 5: Comparison of cooling end-uses trends from RASS 2019 and modeled consumption

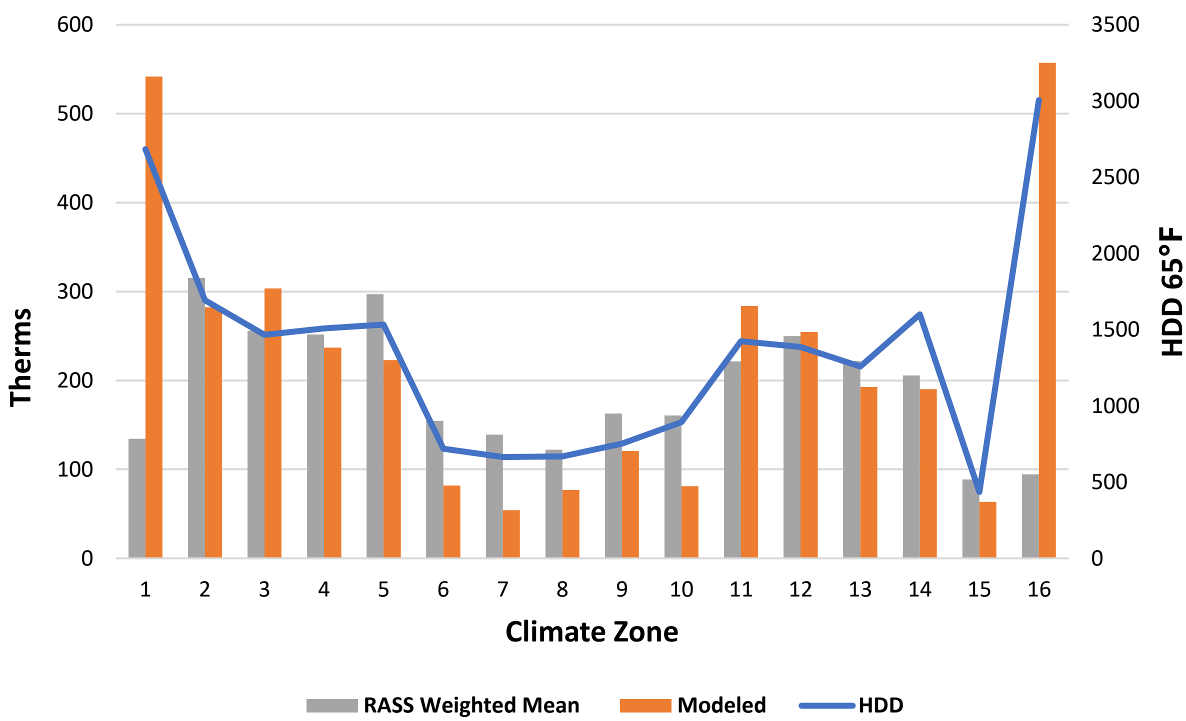

Figure 6: Comparison of heating end-uses trends from RASS 2019 and modeled consumption

Sensitivity of Cooling and Heating End-Uses to Weather

This section evaluates the impact of different weather files on heating and cooling end-uses in the single-family prototype models. Specifically, the models were analyzed using two distinct sets of weather files: one set comprises 16 building climate zone weather files used for Title 24 (T24) compliance analysis, which is a subset of the full CZ2022 dataset[3]; the other set consists of weather station locations utilized by the DEER[8] (Database for Energy Efficient Resources) prototype models. Table 9 shows the weather stations and representative cities for both the Title 24 and DEER weather data sets used in CEC and CPUC analysis. In several climate zones, the CEC and DEER weather data is identical. However, in some climate zones, for example, in climate zone 16, the cooling degree days (CDD) in the selected DEER weather station are more than twice that of the T24 weather station.

Table 9: Title 24 and DEER Representative Weather Cities and Corresponding Weather Stations

CZ	T24 Rep. City	T24 Weather Station Name	T24 WMO Station Number	DEER Rep. City	DEER Weather Station Name	DEER WMO Station Number
1	Arcata	ARCATA-AP	725945	Eureka	EUREKA	725940
2	Santa Rosa	SANTA-ROSA(AWOS)	724957	Napa	NAPA-CO	724955
3	Oakland	OAKLAND-METRO-AP	724930	Oakland	OAKLAND-METRO-AP	724930
4	San Jose-Reid	SAN-JOSE-IAP	724945	San Jose-Reid	SAN-JOSE-IAP	724945
5	Santa Maria	SANTA-MARIA-PUBLIC-AP	723940	Santa Maria	SANTA-MARIA-PUBLIC-AP	723940
6	Torrance	TORRANCE-MUNI-AP	722955	Los Angeles	LOS-ANGELES-IAP	722950
7	San Diego Lindbergh	SAN-DIEGO-LINDBERGH-FIELD	722900	San Diego Lindbergh	SAN-DIEGO-LINDBERGH-FIELD	722900
8	Fullerton	FULLERTON-MUNI-AP	722976	Long Beach	LONG-BEACH-DAUGHTERTY-FLD	722970
9	Burbank - Glendale	BURBANK-GLNDLE-PASAD-AP	722880	Los Angeles Downtown	LOS-ANGELES-DOWNTOWN-USC	722874
10	Riverside	RIVERSIDE-MUNI	722869	Riverside	RIVERSIDE-MUNI	722869
11	Red Bluff	RED-BLUFF-MUNI-AP	725910	Red Bluff	RED-BLUFF-MUNI-AP	725910
12	Sacramento	SACRAMENTO-EXECUTIVE-AP	724830	Stockton	STOCKTON-METRO-AP	724920
13	Fresno	FRESNO-YOSEMITE-IAP	723890	Fresno	FRESNO-YOSEMITE-IAP	723890
14	Palmdale	PALMDALE-AP	723820	Daggett	DAGGETT-BARSTOW-AP	723815
15	Palm Springs-Intl	PALM-SPRINGS-THERMAL-AP	747187	El Centro	EL-CENTRO-NAF	722810
16	Blue Canyon	BLUE-CANYON-AP	725845	Bishop	BISHOP-AP	724800

[8] https://github.com/sound-data/DEER-Prototypes-EnergyPlus/tree/main/weather

The two sets of weather data result in different heating and cooling consumption in each climate zone as shown in Figure 7. This shows that the energy models are responsive to changes in heating and cooling demand coming from the weather data. In climate zone 16, the modeled results using DEER weather files predict a higher cooling energy use, as shown in Figure 7. This outcome is consistent with the higher CDD associated with the DEER weather files for that climate zone, as illustrated in Figure 8.

Similar trends are observed for heating end-uses. In climate zone 16, the use of DEER weather files results in higher predicted heating energy use, as depicted in Figure 9. This finding is aligned with the higher HDD values associated with the DEER weather files, as shown in Figure 10. The comparison between the two sets of weather files highlights how even slight differences in climatic data can lead to meaningful variations in the modeled energy use.

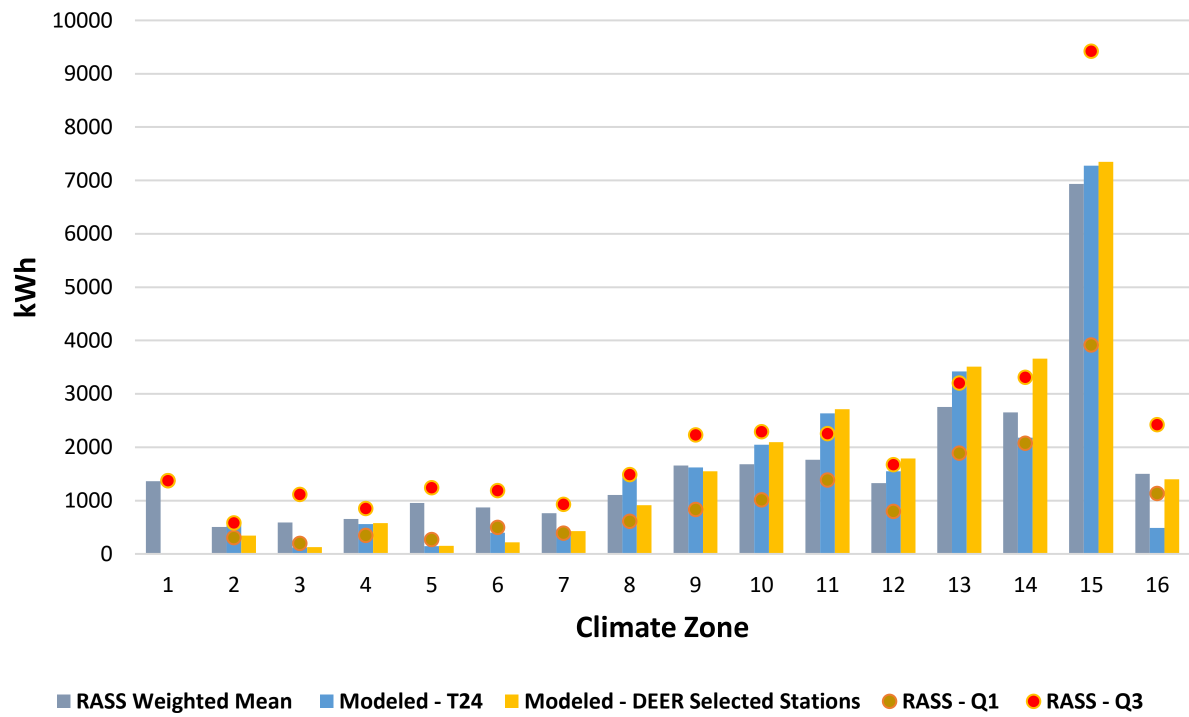

Figure 7: Comparison of cooling end-uses between RASS 2019 and modeled consumption using T24 and DEER weather files

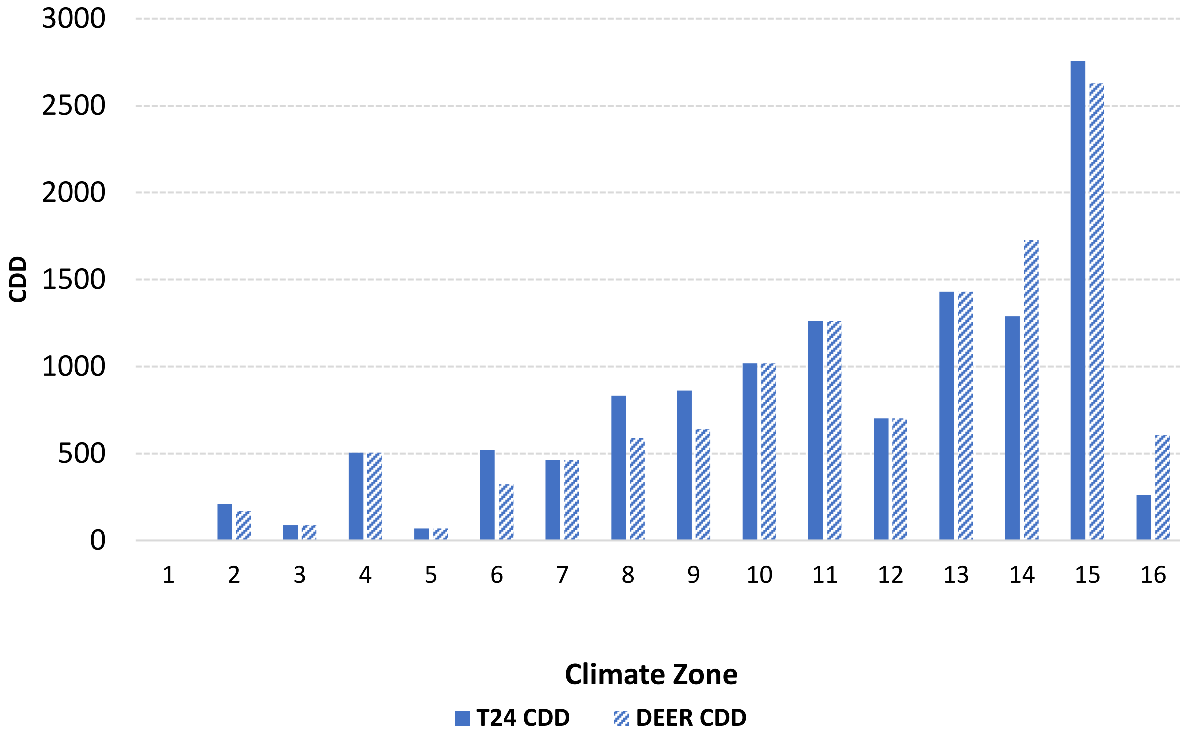

Figure 8: CDD comparison between T24 and DEER weather files

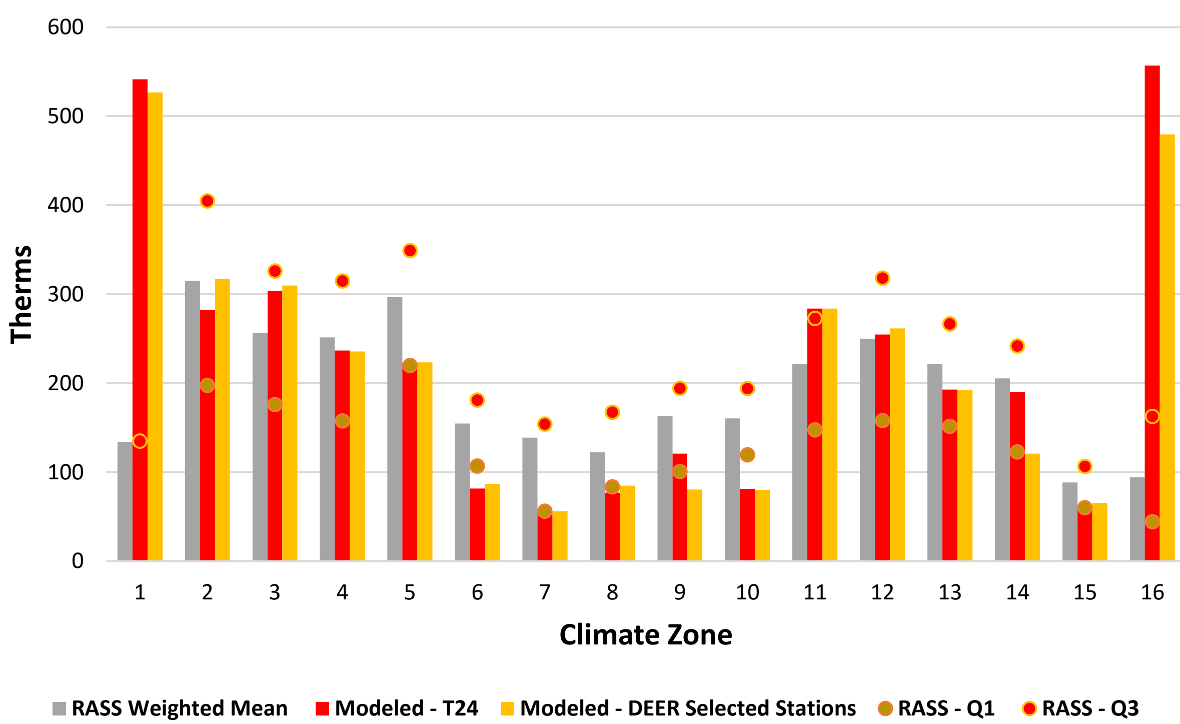

Figure 9: Comparison of heating end-uses between RASS 2019 and modeled consumption using T24 and DEER weather files

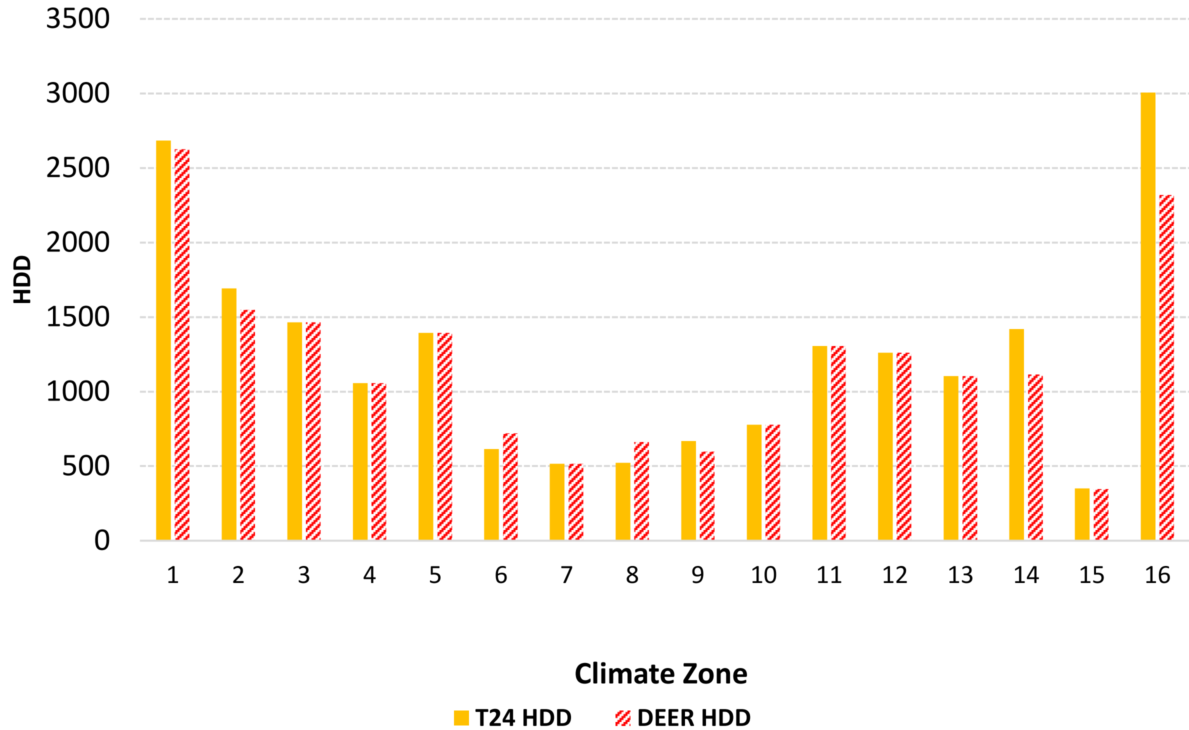

Figure 10: HDD comparison between T24 and DEER weather files

Conclusion

This memo describes the validation process employed for the single-family prototype models to align the simulated energy consumption with the RASS UEC data. Model inputs that did not have a direct source of data were considered candidates for adjusting the modeled consumption. Infiltration, fenestration SHGC, interior lighting power, and the thermostat setpoint were adjusted during the validation process. In addition to these inputs, new inputs were added, such as natural ventilation and overhangs and internal shades on windows, to bring the modeled consumption within range. The results indicate that for most climate zones, the modeled heating and cooling energy consumption aligns with the weighted mean UEC values from RASS. When achieving a close match with the weighted mean was not feasible, the models were adjusted to ensure the results fell within the interquartile range (Q1-Q3) of the RASS dataset.

In some climate zones, the modeled consumption was outside the expected range (Q1-Q3), and this departure is especially evident in climate zones 1 and 16. This variability was attributed to the limited sample size in the RASS dataset and the fact that homes in these climate zones are subject to seasonal occupancy patterns or non-standard thermostat operation. The models could have been adjusted further, for example, by setting the thermostat to off, but the approach taken was to not aggressively attempt to adjust model inputs to RASS data in certain climate zones when observed consumption trends in RASS did not align with HDD/CDD trends.

Additionally, a sensitivity analysis was performed to test how the models respond to changes in cooling and heating demand by using two sets of weather data, one from Title 24 and another from DEER. Even within the same climate zone, using a different weather station with different CDD and HDD resulted in a proportional change to the cooling and heating consumption. This confirms that the models respond appropriately to changes in cooling and heating demand.

Attachment

The attached report details the progress achieved from 2021 to 2023 on the residential segment of the Prototypes project, including building stock assessment, model input development, and model construction.

Prototypes Project
Documentation 202

Appendix 1: Single Family Construction Weighting Factors

Table 10: Single-family prototypes weighting factors

Vintage	Prototype	Climate zone															
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Pre-1975	SF1250	0.0551	0.0979	0.1844	0.0415	0.0588	0.0579	0.1639	0.1709	0.1046	0.0087	0.0712	0.0535	0.0535	0.0190	0.0059	0.3284
	SF1750	0.5506	0.2584	0.4613	0.5585	0.1990	0.5464	0.3260	0.5165	0.5322	0.0629	0.1945	0.2505	0.1881	0.0411	0.1310	0.1540
	SF2250	0.0350	0.0458	0.1394	0.0844	0.0663	0.0887	0.0446	0.0577	0.0839	0.0067	0.0333	0.0284	0.0325	0.0177	0.0194	0.0122
	SF2750	0.0278	0.0250	0.0688	0.0383	0.1167	0.0427	0.0249	0.0172	0.0816	0.0054	0.0018	0.0123	0.0127	0.0005	0.1669	0.0027
1975-1983	SF1250	0.0047	0.0031	0.0013	0.0004	0.0033	0.0002	0.0045	0.0017	0.0017	0.0012	0.0035	0.0031	0.0182	0.0069	0.0020	0.0078
	SF1750	0.0252	0.1789	0.0245	0.0732	0.0230	0.0453	0.0610	0.0298	0.0397	0.0589	0.0585	0.0940	0.0780	0.0304	0.0217	0.0162
	SF2250	0.0049	0.0359	0.0151	0.0224	0.0325	0.0204	0.0702	0.0103	0.0047	0.0204	0.0183	0.0122	0.0178	0.0025	0.0021	0.0164
	SF2750	0.0025	0.0045	0.0057	0.0141	0.0165	0.0340	0.0072	0.0148	0.0049	0.0023	0.0231	0.0163	0.0085	0.0007	0.0224	0.0035
1984-2005	SF1250	0.0011	0.0012	0.0013	0.0023	0.0050	0.0001	0.0011	0.0016	0.0005	0.0067	0.0105	0.0041	0.0242	0.0261	0.0295	0.0424
	SF1750	0.1702	0.2043	0.0301	0.0293	0.2739	0.0124	0.0469	0.0447	0.0211	0.3156	0.2260	0.1425	0.3011	0.6301	0.0720	0.2669
	SF2250	0.0341	0.0308	0.0235	0.0111	0.0291	0.0163	0.0356	0.0371	0.0148	0.0865	0.0498	0.0784	0.0649	0.0447	0.1016	0.0298
	SF2750	0.0136	0.0924	0.0297	0.0608	0.0660	0.0685	0.0713	0.0715	0.0878	0.0596	0.0797	0.0915	0.0306	0.0259	0.1452	0.0862
2006-2019	SF1250	0.0002	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0002	0.0000	0.0004	0.0002	0.0008	0.0003	0.0002	0.0012	0.0005
	SF1750	0.0406	0.0043	0.0044	0.0022	0.0085	0.0012	0.0144	0.0020	0.0007	0.0079	0.1255	0.0424	0.0553	0.0400	0.0553	0.0054
	SF2250	0.0002	0.0036	0.0013	0.0018	0.0274	0.0062	0.0085	0.0016	0.0024	0.0186	0.0451	0.0214	0.0817	0.0441	0.0562	0.0057
	SF2750	0.0339	0.0139	0.0092	0.0597	0.0741	0.0596	0.1200	0.0225	0.0193	0.3381	0.0593	0.1485	0.0326	0.0700	0.1675	0.0218