SAND2021-5552C

ASHRAE VIRTUAL ANNUAL CONFERENCE
June 28-30, 2021

Conference Paper Session #1

Impact of COVID-19 on Energy Consumption and Grid-Interactive Efficient Buildings

Institutional Climate Analysis for Future Heat Wave Scenarios: Sandia National Laboratories California Site

Daniel L. Villa, P.E.

Sandia National Laboratories (SNL)

dlvilla@sandia.gov

+1-505-321-1269

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525
Unlimited Release per SAND2021-XXXX P

Learning Objectives

- Describe the attributes of a load profile.
- Explain why weather-normalization is useful in analyzing electricity consumption.
- Describe how a data-driven grey-box model can be used for modeling classrooms in a school building
- Quantify capability of a school building to provide energy flexibility for a period of time when needed by the grid
- **Understand a method for conducting peak load and energy use analyses for a heat-wave using Building Energy Modeling.**
- **Discern the advantages and disadvantages of using detailed Building Energy Models for heat wave analyses.**
- Describe the requirements and potential approaches to modeling large populations of buildings to investigate coordination of grid flexible loads.
- Describe the possible causes leading to systematic errors in the prediction of aggregate grid loads

Acknowledgements

Thanks to Regina Deola, Gerald Gallegos, Nicole Rinaldi, and Robin Jones for championing this work and providing the NEX-DCP30 parameters for this analysis

Thanks to the internal funding through the Environmental Management department at Sandia National Laboratories to accomplish this research

Thanks for support from my wife Marina. Soli Deo Gloria et Christi.

Outline/Agenda

Introduction

Methods and Data Input

Results and Discussion

Conclusions

Introduction

Background

- **Heat waves** are a prolonged period of abnormally hot weather that cause:
  - Heat related deaths or hospitalization
  - Abnormally high demand on the electrical grid via elevated Air Conditioning (AC) loads
    - AC is the dominant source of increased electricity demand during a heat wave (Choobineh et. al., 2019).
  - Degradation of efficiency for power generation
    - Solar Photo-voltaic efficiency degrades,
    - Line losses increase
    - Heat rejection at thermal plants is less efficient
  - Power outages
    - Directly – equipment failure
    - Indirectly – High temperatures and dryness leads to a fire that damages infrastructure
  - Crop failure
- Global warming is increasing magnitude, duration, and frequency of heat waves (Perkins, 2015; Horton et. al., 2016; IPCC, 2014)
  - Urban environments can expect +14ºC (25ºF) peak waves from normal average (Santamouris, 2020)

https://www.pinterest.com/pin/155303887119794294/

AC/Global Warming/Heat Wave Hazard Causal Loop

In urban environments, heat rejection from AC systems can give positive feedback that elevates external ambient temperatures even further (Viguié et. al., 2020).

HVAC coolant leaks and increased fossil fuel- based power increases green house gasses (GHG)

Increased GHG drives Global warming

Public Domain

Positive feedback between increasing AC use and heat waves calls for a need for clean energy and energy efficient systems

Figure obtained from ASHRAE Kansas City 2019 presentation background

More HVAC installed to keep population cool

Un-conditioned spaces are more likely to be hazardous during heat waves

Resilience to Heat Waves

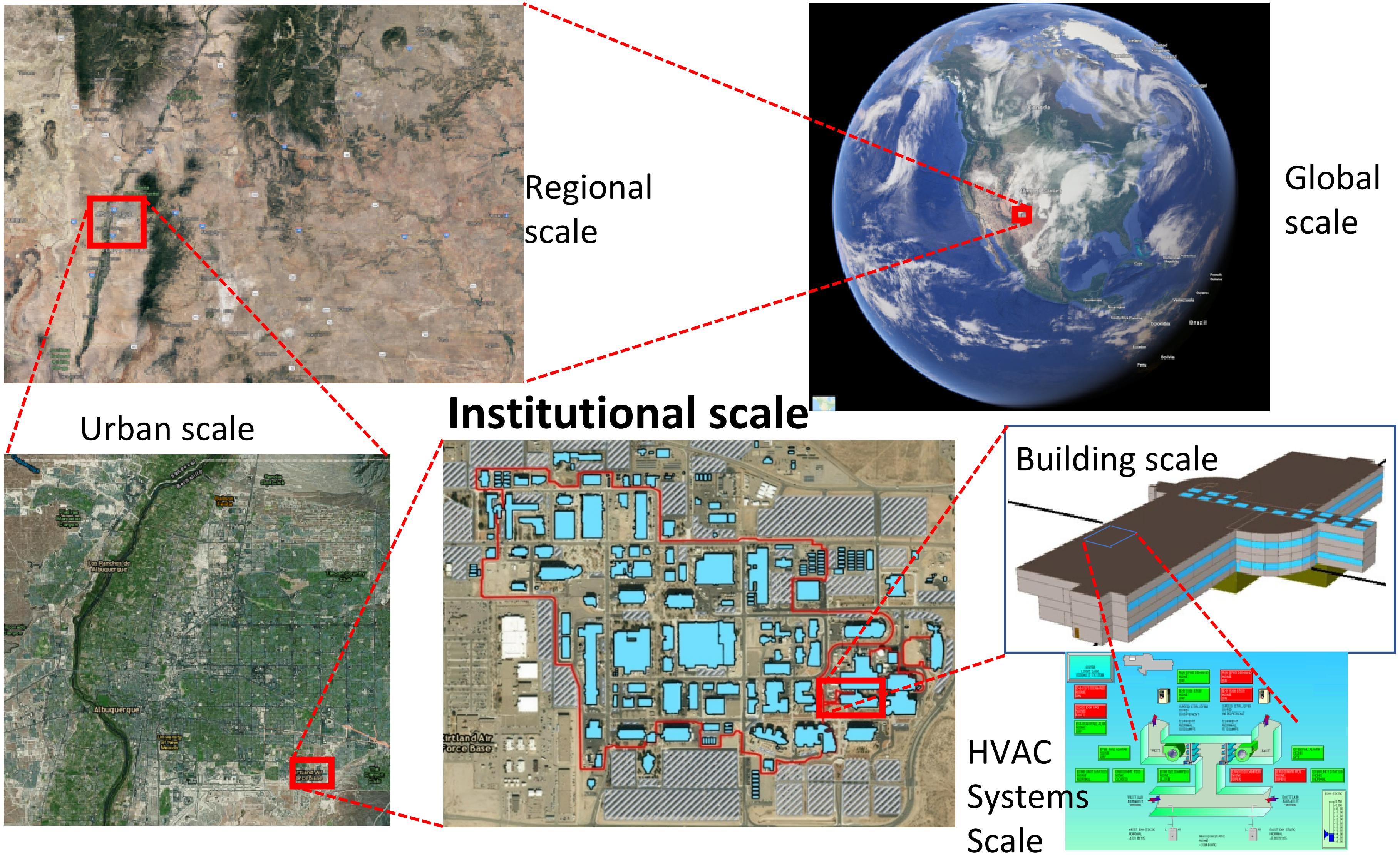
- Resilience to heat wave events can be enhanced by several approaches:

Supply side	Demand side (Buildings)	Outage Performance
Bolster electric generation or transmission	Energy efficiency, Flexible loads	Microgrids, Passive Designs

- Resilience is costly and not always positively correlated to energy efficiency (Sun et. al, 2020)

- The focus here is a necessary step toward any of these approaches: **Quantify heat waves effects on power demand from the built environment**

Scales for resilience analyses



Institutional Heat Wave Analyses

Large institutions often have buildings that support critical operations for which interruption due to a heat wave could cause:

- Economic losses
- Infrastructure downtimes for large populations
- Loss of one-of-a-kind assets that are irreplaceable
- Loss of critical or confidential information
- Damage to the environment
- Injury or death for personnel

Assuring these operations are resilient to heat waves is import to avoid such consequences

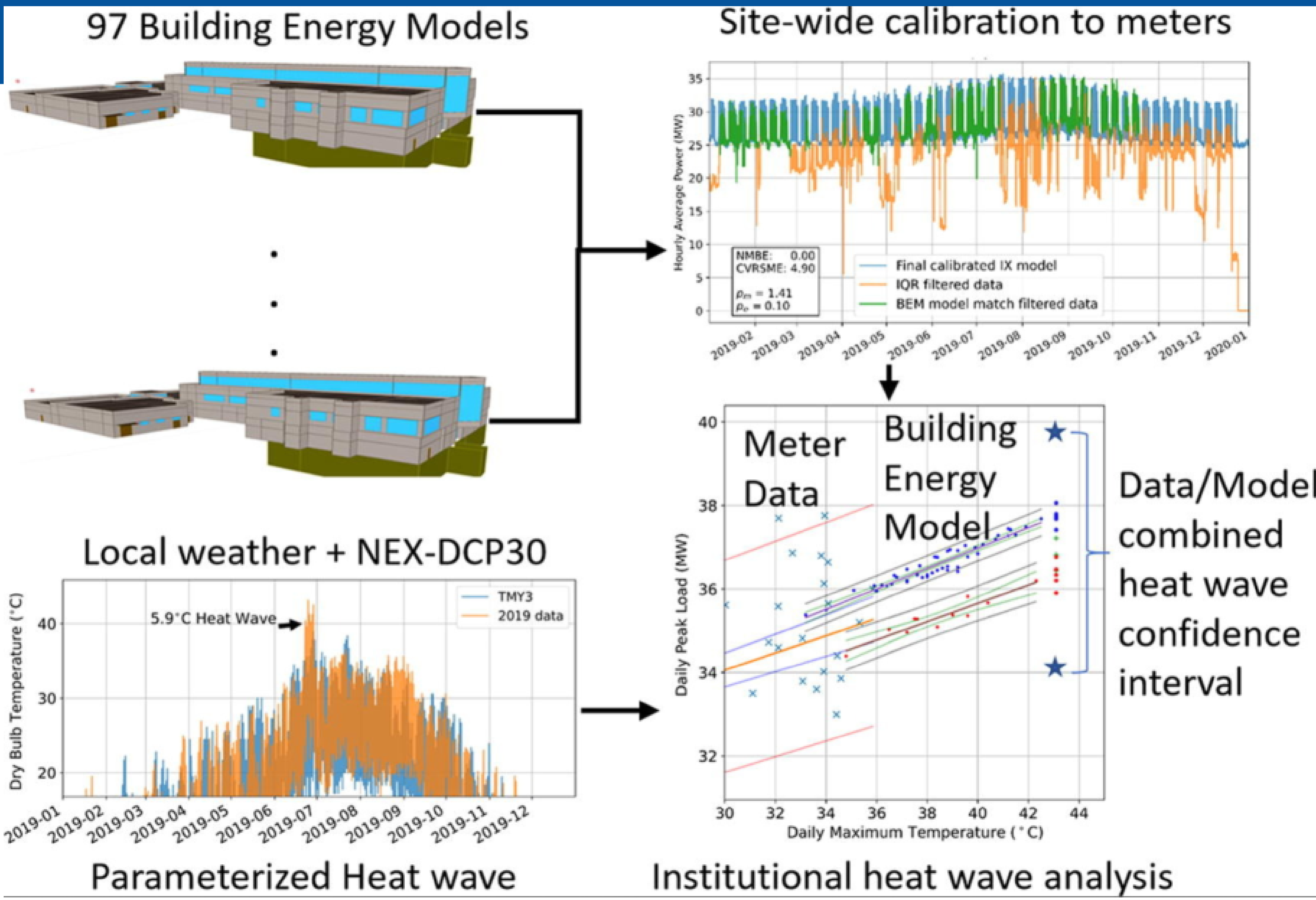
NM SNL Heat wave study

The New Mexico (NM) site heat wave study was conducted rapidly with now need for calibration of any of the individual 97 BEM used.

The NM study has been published in *Energy and Buildings* (Villa, 2021)

The California (CA) site study is the focus of this presentation. **It ended up being much more difficult even though it only involved 23 buildings**

Both studies' objective was to quantify the effect on peak electric load due to heat waves at their respective sites



Methods and Data Input

Methods

Data input:

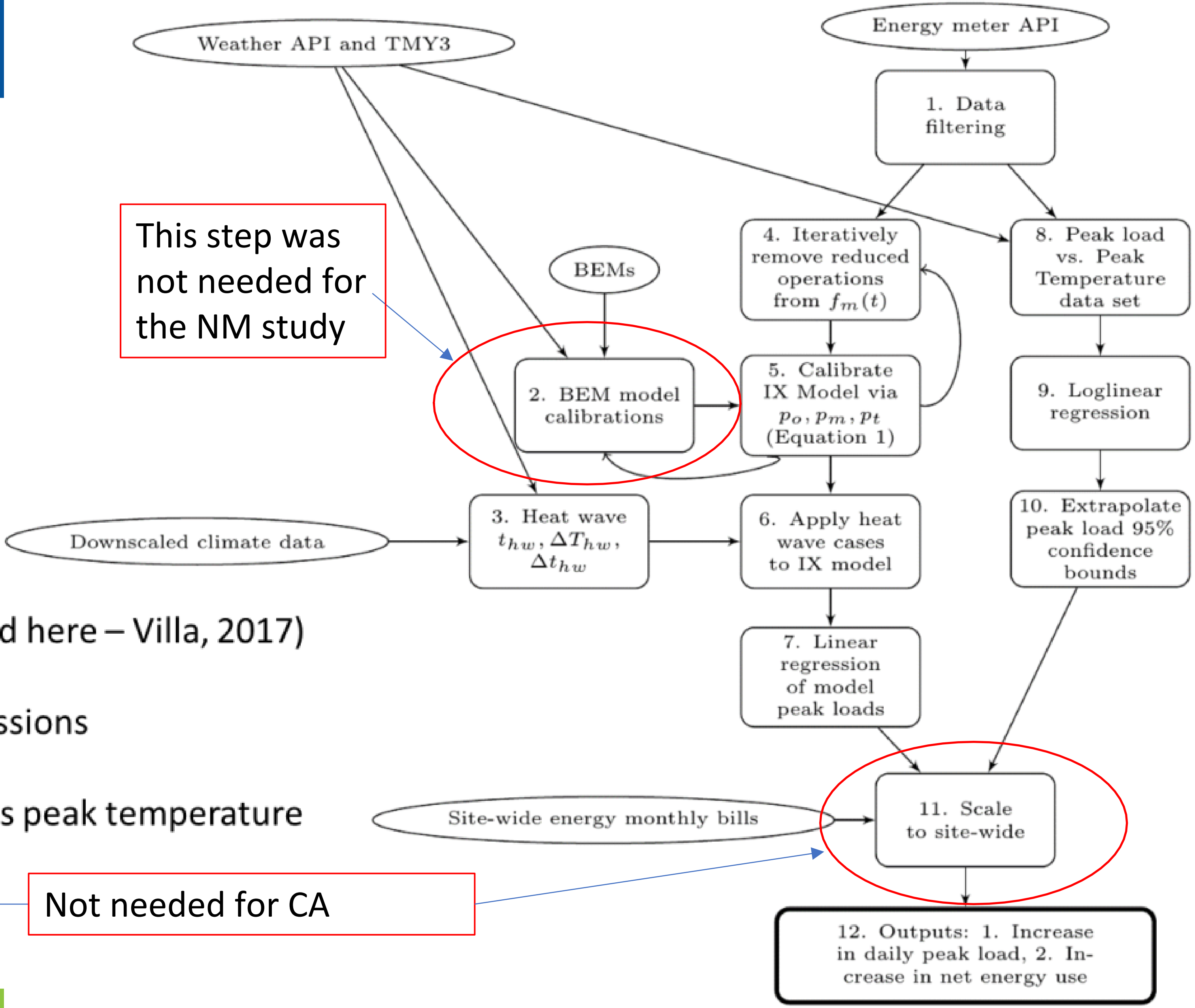
1) Energy meter data for the most recent year.
2) Weather data for BEM
3) Downscaled climate model future temperatures
4) Monthly institution-wide energy use bills

Procedure:

1) Filtering meter data
2) Calibration of indvididual BEM models
3) Deriving the heat wave parameters $t_{hw}, T_{hw}, \Delta t_{hw}$.
4) Removing non-applicable time steps
5) Calibrating the aggregate model (IX = model used here – Villa, 2017)
6) Performing heat wave cases.
7) Calculating model output peak load linear regressions
8) Curating data-driven peak-load dataset
9) Create a log-linear regression of peak load versus peak temperature
10) Extrapolation of the data driven regression
11) Scale the meter results to site-wide results.
12) Compare data and model driven predictions

This step was not needed for the NM study

Not needed for CA



Calibration function

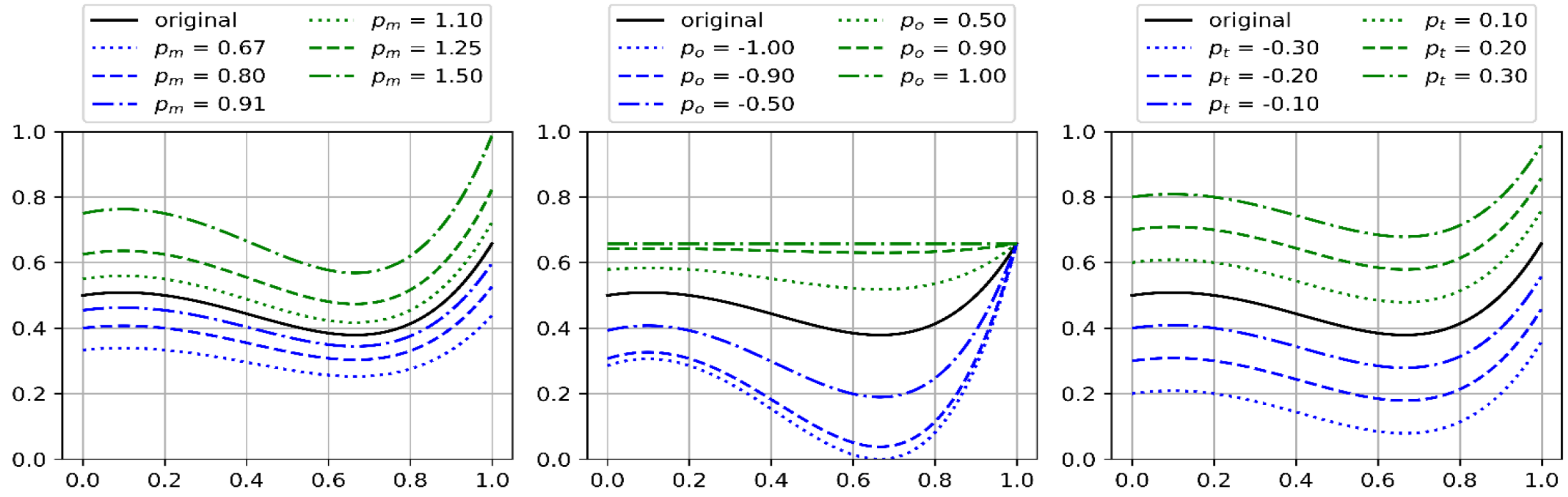
A scaling function is applied to the institution-wide power signal (Step 5)

$$f_{new}(t, p_o, p_m, p_t) = \begin{cases} p_m[(1 - p_o)f(t) + f_{max}p_o] + p_t & 1 \geq p_o \geq 0 \\ p_m[-p_o f_{new_{-1}}(t) + (p_o + 1)f(t)] + p_t & -1 \leq p_o < 0 \end{cases}$$

$$f_{new_{-1}}(t) = \frac{f_{max}}{f_{max} - f_{min}} f(t) - \frac{f_{max} f_{min}}{f_{max} - f_{min}}$$

The calibration function provides scaling (p_m), stretching (p_o), and translation (p_t)

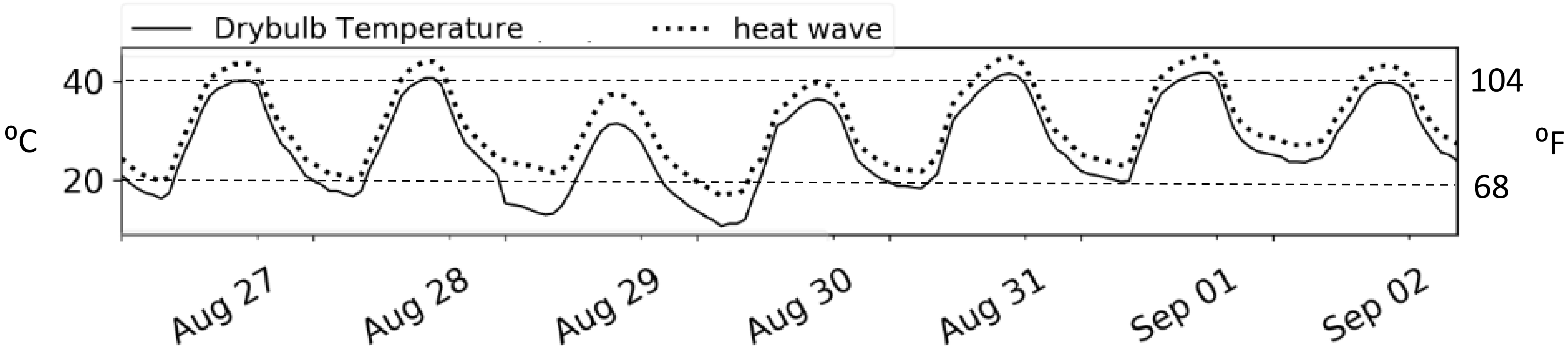
Only p_m and p_o were needed for the NM study



example function used to illustrate parameter effects: $f(t) = t(t + 1)(t - 0.9)(t - 0.2) + 0.5$

Data Input

- Weather data came from the Lawrence Livermore National Laboratory (LLNL) (LLNL, 2020) directly adjacent to the SNL CA site.
  - Missing Total horizontal solar radiation, cloud type, and cloud were filled in with Typical Meteorological Year 3 (TMY3) (Wilcox and Marion, 2008).
- Meter data came from the SNL energy analytics database through a Python API.
  - Verified to be 0.32% variation between the yearly sum of energy between 2019 monthly bills and the 15 min meter data.
- The heat wave scenario from NEX-DCP30 model results (Thrasher et. al., 2013).
  - ΔT_{hw}= 3.4°C (6.1°F), t_{hw}=August 27th, Δt_{hw}= 7 days
  - Unlike the NM case, the 2.0°C (3.6°F) volatility was not used due to lack of information about CA concerning increased volatility.
  - The resulting scenario peak temperature of 45.1°C did not even break the current record high of 46.1°C, yet is still representative of future heat waves according to NEX-DCP30 model results.



Results

Individual model calibration results –Much more work for CA vs NM!

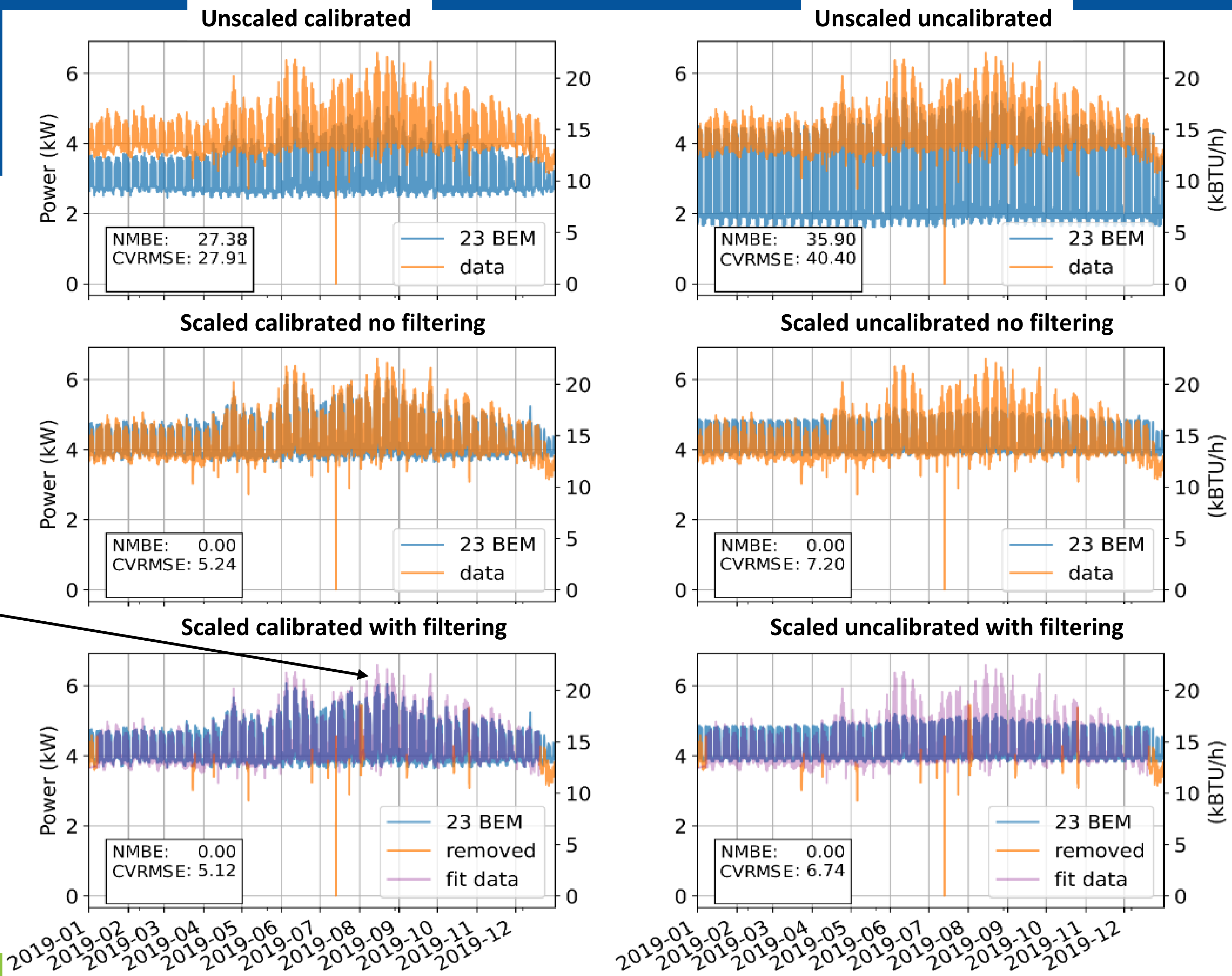
	NMBE (%)		CVRSME (%)		Data Mean Power		Model Mean Power			
	Calibrated	Uncalibrated	Calibrated	Uncalibrated			Calibrated		UnCalibrated	
					(kW)	(kBTU/h)	(kW)	(kBTU/h)	(kW)	(kBTU/h)
1	-3414	-5209	4.228E+04	4.26E+04	1.013	3.458	35.6	121.5	53.79	121.5
2	-5.5	11.41	206.7	206.7	225.3	768.8	237.7	811	199.6	811
3	92.86	87.31	101.9	97.15	193.4	659.9	13.83	47.17	24.56	47.17
4*	8.967	17.57	11.05	21.1	488.4	1667	444.6	1517	402.6	1517
5*	-0.7239	37.61	23.05	45.59	37.98	129.6	38.25	130.5	23.7	130.5
6	-474	-178.6	476.9	226.6	102.7	350.3	589.3	2011	286.1	2011
7*	0.6584	51.78	7.819	56.5	593.2	2024	589.3	2011	286.1	2011
8*	0.6287	-8.661	17.98	81.37	101.6	346.7	101	344.5	110.4	344.5
9*	0.4323	-3.088	25.85	35.3	420.1	1433	418.3	1427	433.1	1427
10	-191.6	-260.1	198.1	282.5	106	361.7	309.1	1055	381.7	1055
11	-44.67	-78.66	69.07	105.9	213.7	729.1	309.1	1055	381.7	1055
12*	-0.2531	-49.1	23.21	99.81	21.09	71.96	21.14	72.14	31.44	72.14
13	-18.89	31.5	42.31	49.83	31.95	109	37.98	129.6	21.89	129.6
14	-90.59	-93.12	147.9	190.1	15.07	51.42	28.72	98	29.1	98
15	-98.79	-192.5	163	310.9	16.69	56.96	33.19	113.2	48.82	113.2
16	-116.7	-120.6	170.5	162.3	70.1	239.2	151.9	518.3	154.6	518.3
17	-42.3	-41.2	51.58	111.2	118	402.6	167.9	572.8	166.6	572.8
18	0.1673	77.76	57.42	97.75	129.7	442.5	129.5	441.8	28.86	441.8
19	24.57	24.57	61.26	61.26	32.91	112.3	24.82	84.69	24.82	84.69
20	27.77	27.77	48.57	48.57	14.73	50.25	10.64	36.3	10.64	36.3
21*	-1.07	47.08	14.6	58.97	36.19	123.5	36.58	124.8	19.15	124.8
22*	-1.371	-43.79	18.49	60.07	110.1	375.7	111.6	380.9	158.3	380.9
23*	-2.128	31.99	27.39	47.27	90.29	308.1	92.22	314.7	61.42	314.7
Unscaled total	27.38	35.9	27.91	40.4			3059	1.044E+04	2700	9214
Scaled total all data	2.563E-08	3.006E-07	5.242	7.202	4213	1.437E+04	4213	1.437E+04	4213	1.437E+04
Scaled total filtered data	4.418E-08	1.469E-08	5.121	6.74	4213	1.437E+04	4231	1.444E+04	4236	1.445E+04

* BEM that were G-14 compliant (NMBE < 10, CVRSME < 30) after calibration.

Data Curation

Effects of:
1) Scaling,
2) Individual BEM model calibration,
3) Data filtering

Peak loads model still could use improvement even though NMBE, CVRMSE greatly exceed ASHRAE Guideline 14 requirements!



NMBE = Normalized Mean Bias Error
CVRMSE = Coefficient for Root Mean Square Error (ASHRAE, 2014)

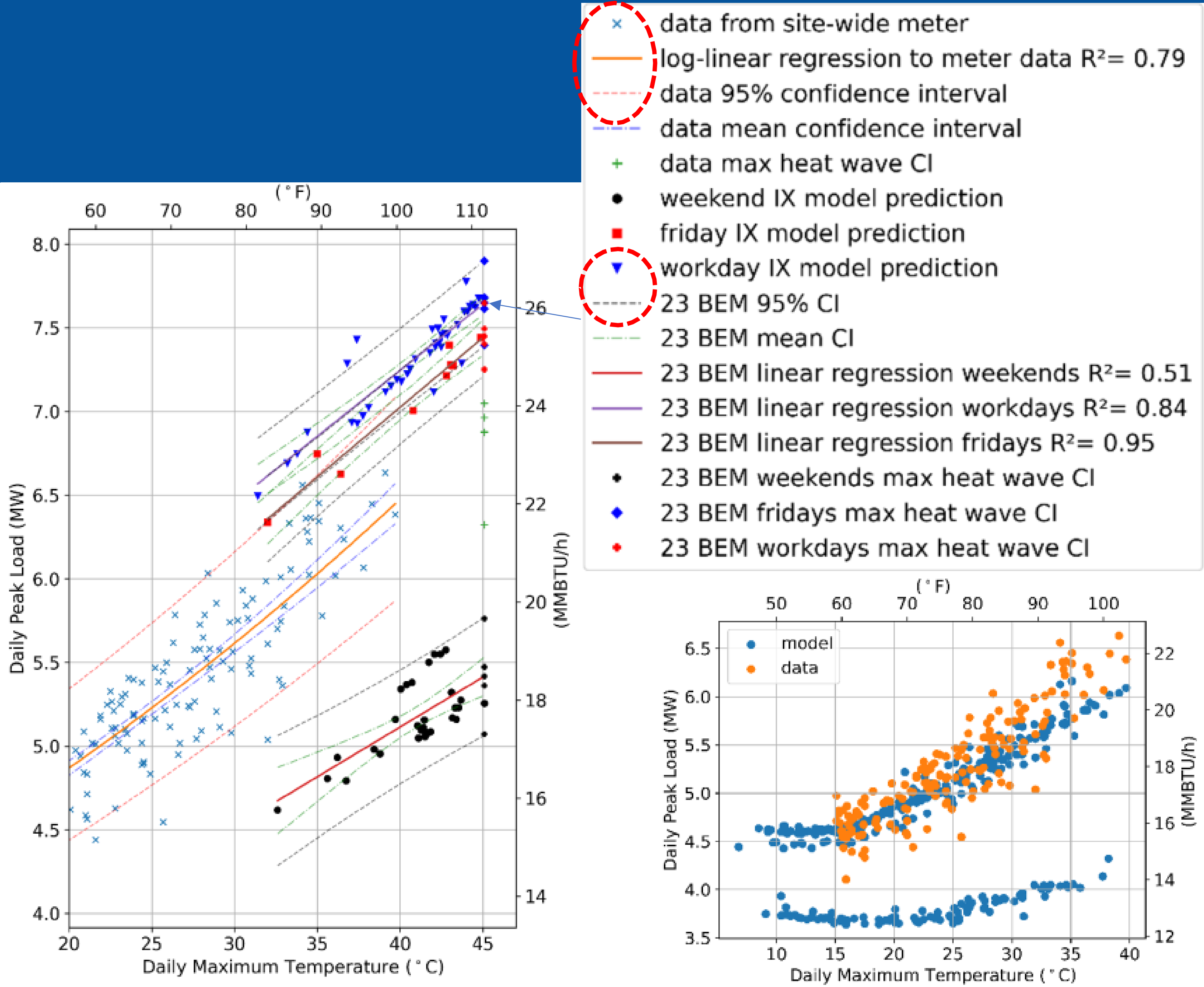
Peak Load Regressions

Even after the manual BEM calibrations the results between data and 23 BEM were not as well aligned.

The right-hand figure shows the 2019 weather data calibration

The left hand shows the model projection based on the heat wave which has been linearly scaled in 10 steps from normal weather to the heat wave shown on slide 15

Note: Confidence intervals help estimate uncertainty but give no information about probability of the occurrence of a given peak load!



Peak Load Regression Results

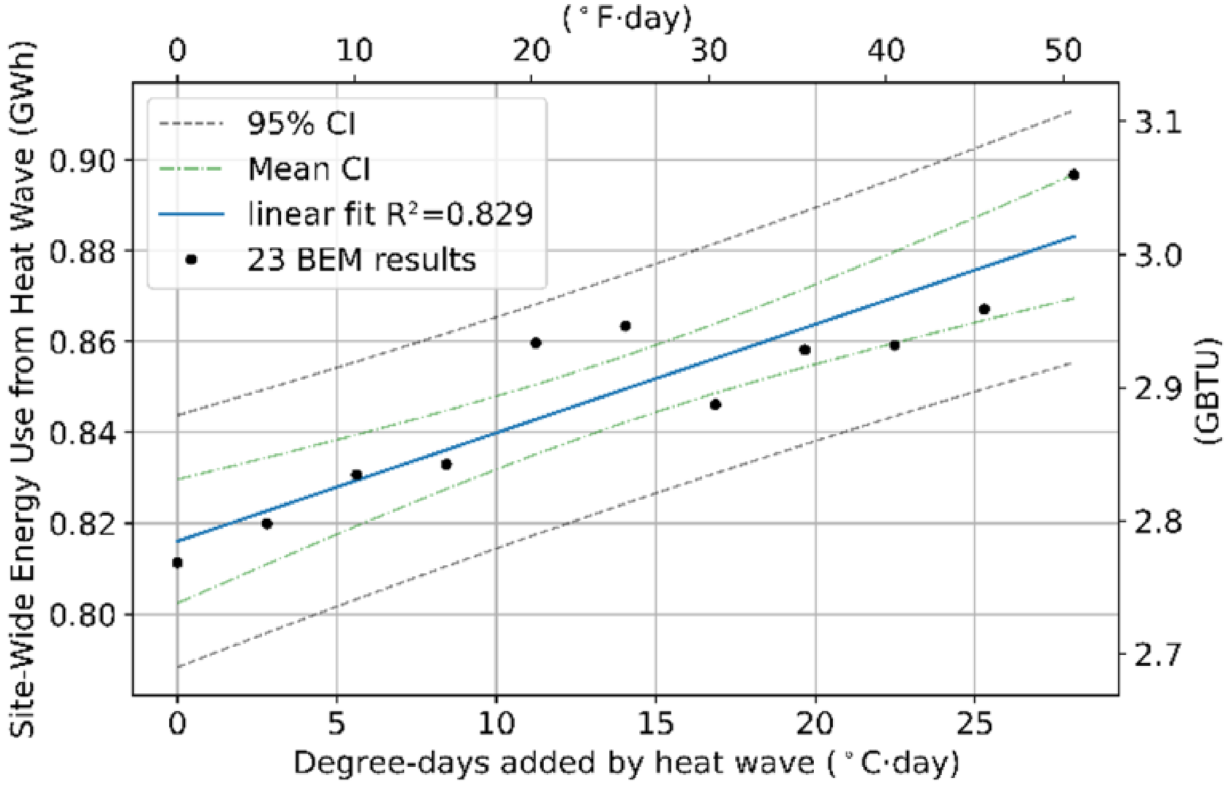
Description	Data (workdays) SI	Data (workdays) English	Workdays SI	Workdays English	Fridays SI	Fridays English	Weekends SI	Weekends English
43.1°C mean predicted peak (MW/MMBTU)	6.962	23.76	7.647	26.09	7.448	25.42	5.417	18.48
— +95% CI	7.669	26.17	7.899	26.95	7.647	26.09	5.762	19.66
— +50% CI	7.049	24.05	7.68	26.2	7.494	25.57	5.473	18.67
— -50% CI	6.877	23.47	7.614	25.98	7.403	25.26	5.361	18.29
— -95% CI	6.321	21.57	7.395	25.23	7.25	24.74	5.072	17.31
37.2°C mean predicted peak (MW/MMBTU)	6.633	22.63	7.379	25.18	7.165	24.45	5.215	17.79
Heat wave to baseline % difference	4.965		3.631		3.949		3.879	
Mean slope (MW/°C or 1/°C) (MMBTU/°F or 1/°F)	0.01425*	0.007918*	0.07881	0.1494	0.08322	0.1578	0.0595	0.1128
— +95% CI	0.01539*	0.00855*	0.09057	0.1717	0.09958	0.1888	0.0823	0.156
— -95% CI	0.01312*	0.007286*	0.06706	0.1271	0.06687	0.1268	0.0823	0.156
Intercept (MW or unitless) (MMBTU or unitless)	8.205		4.093	13.96	3.695	12.61	2.733	9.327
— +95% intercept	8.234		4.572	15.6	4.355	14.86	3.668	12.51
— -95% intercept	8.177		3.614	12.33	3.035	10.36	1.799	6.14
R^2 value	0.7929		0.837		0.9539		0.5051	
Model to data sensitivity % difference	0		-16.64		-11.97		-37.06	
Mean normalized slope (%/°C or %/°F)	1.46	0.8113	1.068	0.5934	1.161	0.6452	1.141	0.6339

* The data regression model was calculated as log-linear [($ln(y/1\ \text{MW}) = ax + b$) or $\ln(y/1\ \text{MMBTU}) = ax + b$) where y is peak power in MW and x is daily maximum temperature. All others are for a linear model ($y = ax + b$).

Increased Energy Use

The analysis was also used to project increased energy use from a heat wave at the site given the heat-content of a heat wave

This information can be very helpful for variable rate price structures during peak demand



Description	Mean	+95% CI	-95% CI
Maximum heat wave 28.10°C·day (GWh)	0.8832	0.9109	0.8554
Maximum heat wave 50.59°F·day (GBTU)	3.014	3.108	2.919
Slope (GWh/°C·day)	0.002389	0.003209	0.00157
Slope (GBTU/°F·day)	0.004529	0.006083	0.002976
Intercept (GWh)	0.816	0.8297	0.8024
Intercept (GBTU)	2.784	2.831	2.738

Conclusions

Conclusions

- The CA analysis has **higher sensitivity to heat waves** equal to 1.46 %/^oC (0.81 %/ ^oF) but **less expected increase in heat wave severity** equal to 3.4^oC (6.1^oF) than the NM results of 0.61 %/^oC (0.34 %/^oF) and 5.9 ^oC (10.6^oF) leading to maximum expected percent increases in peak load of 5.0% for CA and 3.6% for NM.
  - Both these sensitivities are on the low end of values reported in the literature (Santamouris, 2020)
  - This underscores the need for thoroughness in assessing both climate changes and sensitivity to those changes – one size does not fit all for these kinds of analysis!
- The difficulties in the CA analysis suggest that detailed BEM modeling is not always a good approach for heat wave assessments. Though the NM site analysis was easily conducted the models had been maintained more thoroughly (Villa, 2019). This CA analysis showed use of a low-order RC model would have been easier. The best approach to use depends on the purposes of the analysis.
- The reduction of the BEM and data to regression parameters with CI's provides a low-order method with uncertainty for incorporating heat waves into energy master planning analyses (Jeffers, 2020) that consider additional forcing events such as human-attacks, earthquakes, floods, draughts, and fires.

Bibliography

ASHRAE. 2014. ASHRAE Guideline 14-2014, "Measurement of Energy, Demand, and Water Savings." Atlanta: ASHRAE.

Baniassadi, Amir, David J. Sailor, and Harvey J. Bryan. 2019. "Effectiveness of phase change materials for improving the resiliency of residential buildings to extreme thermal conditions." *Solar Energy* 188: 190-199.

Bacher, Peder, and Henrik Madsen. 2011. "Identifying suitable models for the heat dynamics of buildings." Energy and Buildings 43(7): 1511-1522.

Barreca, Alan, Karen Clay, Olivier Deschênes, Michael Greenstone, and Joseph S. Shapiro. 2013. "Adapting to Climate Change: The Remarkable Decline in the U.S. Temperature-Mortality Relationship over the 20th Century." Massashussets Institute of Technology Working Paper CEEPR WP 2013-003. Cambridge, MA USA.

Burillo, Daniel, Mikhail V. Chester, Stephanie Pincetl, Eric D. Fournier, and Janet Reyna. 2019. "Forecasting peak electricity demand for Los Angeles considering higher air temperatures due to climate change." *Applied Energy* Vol. 236: 1-9.

Choobineh, Moein, Andrew Speake, Maxwell Harris, Paulo Cesar Tabares-Velasco, and Salman Mohagheghi. 2019. "End-User-Aware Community Energy Management in a Distribution System Exposed to Extreme Temperatures." *IEEE Transactions on Smart Grid* 10(4): 3753-3764.

DOE, 2015. "Environmental Radiological Effluent Monitoring and Environmental Surveillance." Department of Energy Handbook DOE-HNBK-1216-2015. https://www.standards.doe.gov/standards-documents/1200/1216-bhdbk-2015

Falasca, Serena, Virgilio Ciancio, Ferninando Salata, Iacopo Golasi, Federica Rosso, and Gabriele Curci. 2019. "High albedo materials to counteract heat waves in cities: An assessment of meteorology, building energy needs and pedestrian thermal comfort." *Building and Environment* 163:1-14.

Fennessy, M. J. and J. L. Kinter. 2011. "Climatic Feedbacks during the 2003 European Heat Wave." *Journal of Climate* 24(23): 5953-5967.

Bibliography

Horton, Radley M., Justin S. Mankin, Corey Lesk, Ethan Coffel, and Colin Raymond. 2016. “A Review of Recent Advances in Research on Extreme Heat Events.” *Current Climate Change Reports* 2(4): 242-259.

IPCC, 2014. “Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmenatal Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyers (eds.)]. IPCC, Geneva Switzerland, 151 pp.

Jeffers, Robert. Amanda M. Wachtel, Alexander M. Zhivov, Calum B. Thompson, Avinash Srivastava, and Patrick W. Daniels. 2020. “Integration of resilience goals into energy master planning framework for communities.” *ASHRAE Transactions* 126:803 -823

LLNL, 2020. https://weather.llnl.gov Accessed 1/15/2020. For calibration standards see: https://weather.llnl.gov/cgi-pub/about.pl

Madsen, Henrik, and Jan Holst. 1995. "Estimation of continuous-time models for the heat dynamics of a building." Energy and Buildings 22(1): 67-79.

Perkins, Sarah E. 2015. “A review on the scientific understanding of heatwaves—Their measurement, driving mechanisms, and changes at the global scale.” *Atmospheric Research* Vol. 164 Iss. 165: 242-267.

Santamouris, M., C. Cartalis, A. Synnefa, and D. Kolokotsa. 2015. “On the impact of urban heat island and global warming on the power demand and electricity consumption of buildings—A review.” *Energy and Buildings* 98: 119-124.

Santamouris, M. 2020. “Recent progress on urban overheating and heat island research. Integrated assessment of the energy, environmental, vulnerability and health impact. Synergies with the global climate change.” *Energy and Buildings* 207: 109482.

Schubert, Siegfried D., Hailan Wang, Randal D. Koster, Max J. Suarez, and Pavel Ya Groisman. 2014. “Northern Eurasian Heat Waves and Droughts.” *Journal of Climate* 27(9): 3169-3207.

Bibliography

Sun, Kaiyu, Michael Specian, and Tianzen Hong. 2020. “Nexus of thermal resilience and energy efficiency in buildings: A case study of a nursing home.” *Building and Environment* 177: 106842.

Thrasher, Bridget, Jun Xiong, Weile Wang, Forrest Melton, Andrew Michaelis, and Ramakrishna Nemani. 2013. “Downscaled climate projections suitable for resource management. *Eos, Transactions American Geophysical Union* 94(37): 321-323

Viguié, Vincent, Aude Lemonsu, Stéphane Hallegatte, Anne-Lise Beaulant, Colette Marchadier, Valéry Masson, Grégoire Pigeon and Jean-Luc Salagnac. 2020. “Early adaptation to heat waves and future reduction of air-conditioning energy use in Paris.” *Environmental Research Letters* 15: 075006.

Villa, Daniel L., Jack H. Mizner, Howard D. Passell, Marlin S. Addison, Gerald R. Gallegos, William J. Peplinski, Douglas W. Vetter, Christopher A. Evans, Leonard A. Malczynski, Matthew A. Schaffer, and Matthew W. Higgins. 2017. “Institutional Transformation Version 2.5 Modeling and Planning.” *Sandia National Laboratories Technical Report SAND2017-1498*. February.

Villa, Daniel L., Joshua R. New, Mark Adams, Aaron Garrett, and Gerald R. Gallegos. 2019. “First Steps to Maintain a Large Fleet of Building Energy Models.” *Conference Paper for the ASHRAE 2019 Summer Meeting*. Kansas City, MO. June.

Villa, Daniel. 2021. “Institutional Heat Wave Analysis by Building Energy Modeling Fleet and Meter Data.” *Energy and Buildings* Accepted paper is in revision.

Wilcox, S. and W. Marion. 2008. “*User’s Manual for TMY3 Data Sets*”. *National Renewable Energy Laboratory Technical Report NREL/TP-581-43156*. April.

Questions?

Daniel Villa
dlvilla@sandia.gov
+1-505-321-1269