

# Climate Change and Energy Demand in Buildings

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## ABSTRACT

Linkages between climate change and energy demand are not well understood, yet energy forecasting requires their specification. This paper estimates two parameters that link energy use for space cooling to cooling degree days (CDDs). The first parameter is the set point temperatures for calculating CDDs; the second is the exponent for representing the relationship between changes in CDDs to changes in electricity consumption for space cooling. We find that the best-fitting CDDs have a set point of 67°F, for both residential and commercial buildings rather than the conventional 65°F. (Set points also vary by region, with warmer regions tending to have higher set points.) When CDDs are based on 65°F, the best fitting exponent is 1.5 for both residential and commercial buildings. The higher exponent indicates that space cooling is more climate-sensitive than is specified in the National Energy Modeling System (NEMS), which uses an exponent of 1.1 for commercial buildings.

## Introduction

When climate variables are incorporated in energy demand modeling, many key questions emerge. Should models use temperature data or heating and cooling degree days (HDDs/CDDs), and if degree days are used, what is the preferred reference temperature assumption? Should wind and humidity be included, or are their impacts too insignificant after aggregation (Apadula, Bassini, Elli, and Scapin, 2012; Sailor, 2001)? What other factors need to be controlled to isolate the impact of climate change? This paper examines two methodological questions: what is the value of optimizing cooling degree day (CDD) estimates by allowing the set point for space cooling in buildings to deviate from 65°F and what is the best-fitting mathematical relationship between CDDs and electricity demand for space cooling in buildings? Based on these findings, we tackle one substantive question: how might an increase in CDDs impact electricity use for cooling over the next quarter century?

## Conclusions from the Literature

### Climate as a Determinant of Energy Demand in Buildings

The link between weather and energy use has been widely used to explain and forecast energy consumption and to assist energy suppliers with short-term planning including power purchase contracts. Extending this logic, climate change impacts need to be incorporated into regional energy system planning to ensure an adequate supply of energy throughout the year and to meet peak demand.

There is general agreement that a warmer climate will increase the demand for electricity, which is the dominant source of energy for air conditioning, and will decrease the end-use demand for natural gas and fuel oil, the dominant fuels used for space heating (DOE, 2013). In addition, it is generally agreed that fossil fuel consumption in buildings is more temperature

sensitive (perhaps 62%) than is electricity (at perhaps 16%), because electricity is used for so many end-uses other than space heating and cooling (EIA, 2005).

In southern states the increase in cooling will generally exceed the decrease in space heating while in northern states (those with more than 4000 HDDs per year, specifically), the opposite would likely be the case (DOE, 2013 p.13; USGCRP, 2009). Primary energy consumption may increase with equivalent switching from delivered heating to delivered cooling, because of the energy-related losses associated with electricity generation, transmission, and distribution (ORNL, 2012a). In addition, regional differences in the fuels used for space heating will influence the impact of climate change on overall energy consumption. Amato, Ruth, Kirshen, and Horwitz (2005) investigate the implications of climate change for energy demand as a function of region-specific climatic variables, infrastructure, socioeconomic, and energy use profiles. Using data from Massachusetts, they find that when controlling for socioeconomic factors, degree-day variables have significant explanatory power in describing historic changes in residential and commercial energy demands.

One early regional analysis (for four West Central U.S. states) concluded that “the hypothesized warming trend will translate into only small net increases in energy demand. Only 25% of that region’s energy consumption is climate sensitive, with 20% dominated by heating and cooling in various sectors.” Darmstadter (1993) further concludes that technological possibilities and policy measures are available to mute any serious climatic effects on the energy sector. To illustrate the power of technology transitions and energy policies, it is noted that the U.S. decreased its energy use and yet grew its GDP in the years following the Arab oil embargo’s energy price shock.

More recent publications have estimated larger increases in energy demand with global warming. In the climate change “side case” completed by the Energy Information Administration (EIA, 2005) for the Annual Energy Outlook 2005, warmer winters reduced projected total fossil fuel use by 2.4%, but space cooling requirements increased electricity use by 0.5%. The estimates for the climate change side case in 2008 duplicated the 2.4% decrease for space heating, but resulted in a larger increase for electricity (0.7%). Hadley, Erickson, Hernandez, Broniak, and Blasing (2006) estimate that a 1.2°C increase in temperatures in the U.S. would cause primary energy use to increase by 2% in 2025 over what it would have been without any global warming. By the end of the century Mansur, Mendelsohn, & Morrison (2008) estimate much larger effects.

Evidence to date suggests geographic variation in energy consumption sensitivities. D. J. Sailor (2001), for instance, found that a 2°C temperature increase would result in an 11.6% increase in residential per capita electricity used in Florida, but a 7.2% decrease in Washington. Similarly, research by Scott, Wrench, & Hadley (1994) found that climate change had highly variable impact on commercial building energy demand across four U.S. cities.

There is general consensus that climate change will cause a much greater change in peak demand than in total demand (EIA, 2005). Sathaye et al. (2013) estimate that the peak demand for electricity in California could increase by 10-25% by the end of the century. The U.S. Environmental Protection Agency (EPA, 1989) concluded that climate change could require a 14-23% increase in electricity capacity additions between 2010 and 2055, relative to a future with no climate change. An analysis of the Western Electricity Coordinating Council region by Argonne National Laboratory (ANL, 2008) estimated that 34 GW of additional electricity capacity would be needed by 2050 to meet increasing peak load requirements resulting from climate change. Such impacts pose particular stress on the electric grid, which is already

vulnerable to climate-related outages. The Executive Office of the President (2013) estimates that between 2003 and 2012 severe weather caused power outages that cost the U.S. economy an inflation-adjusted annual average of \$18 billion to \$33 billion. These costs include lost output and wages, spoiled inventory and delayed production, as well as inconvenience and damage to the electric grid. While there is evidence now of climate-related stress on the grid, increasing demand for electricity is not yet precipitating system failures (DOE, 2013).

There is also a general recognition that residential energy consumption is more climate sensitive than commercial energy consumption. This difference is because homes have a higher ratio of building envelope surface area to interior square footage, increasing the importance of outdoor weather conditions. In contrast, energy use in commercial buildings is dominated by internal loads and is also highly affected by the time schedule of use of the premises (e.g., whether or not a school facility is also used in the evenings and on weekends). In a study of 12 U.S. cities, Sailor & Pavlova (2003) found that residential electricity consumption increased 2% to 4% for each degree Celsius increase in ambient temperatures. However, D. J. Sailor (2001) concludes that it is difficult to generalize without first taking into account the many other non-climatic factors that impact energy demand.

### **The Mathematical Relationship between Temperature and Energy Consumption**

The relationship between energy consumption and temperature is modeled in different ways. There are four principal classes of approaches: linear symmetric models, linear asymmetric models, nonlinear models, and semi- or non-parametric models. Each model is unique in some key aspects and has certain advantages.

A typical simplifying assumption in linear symmetric models is that energy demand for heating and cooling use the same balance point temperature and that energy demand responds the same to a marginal change in temperature (either warmer or cooler) which results in a V-shaped relationship between temperature and energy use. This model has historically been used in lieu of more sophisticated building model simulations in building sciences (Day, 2006) and in utility demand forecasting models (Engle, Granger, Rice, and Weiss, 1986).

A base temperature of 65°F is used most often in analyzing the space-conditioning temperature relationship. However, the actual balance point temperature depends on place-specific characteristics of the building stock, non-temperature weather conditions (e.g., humidity, precipitation, and wind), and cultural preferences. The selection of the balance point temperature is critical with this approach, as it directly changes the degree day calculations. This selection can be optimized for the specific region and sector of the economy; for example, Amato et al. (2005) report that the balance point temperature for the commercial sector in Massachusetts was 55°F, below the 60°F balance point temperature for the residential sector. Different types of models use different values, which are determined in different ways (see Brown, Cox, & Baer, 2014).

An example of an application of this model is the National Energy Modeling System (NEMS) utilized by the Department of Energy for national energy forecasts. It models the impact of temperature changes on final energy use by fuel type (f), building type (b), Census division (r), and year (y). This is done through a degree day adjustment in the commercial and residential sectors for space cooling consumption, as shown in the equation 1.

$$SpaceCoolingEnergyUse_{f,b,r,y} = SpaceCoolingEnergyUse_{f,b,r,y} * \left( \frac{DegreeDays_{r,y}}{DegreeDays_{r,2003}} \right)^{1.1} \text{ (Eq. 1)}$$

NEMS uses NOAA-supplied data on historical trends to project degree day values into the future, weighted by population for each census division. This projection takes the past decade average and adjusts it by projected shifts in population. Cooling receives an exponential weighting to model a non-linear relationship between energy consumption for space cooling and temperature; heating is not similarly treated. However, because the exponent is only 1.1, the result is imperceptibly non-linear. Therefore, we characterize the NEMS approach as a linear symmetric model. Other parts of NEMS estimation of heating and cooling service demand are nonlinear, such as, for instance, the inclusion of U-values to incorporate thermal resistance of building envelopes.

An alternative to the V-shaped linear symmetric relationship is a non-linear asymmetric model, as shown in Figure 1. The literature suggests a difference between heating and cooling, in the relationship between weather-related energy consumption and temperature. It is often observed that a range of outdoor temperatures separates the balance points for heating and cooling, in which no indoor comfort equipment is utilized by occupants (ORNL, 2012a). Shorr, Najjar, Amato, and Graham (2009), Miller, Hayhoem, Jin, and Auffhammer (2008), and Hekkenberg, Moll, and Uiterkamp (2009) have incorporated dead zones into their models, but linear models using a single balance point temperature cannot accommodate this. Figure 1b portrays a nonlinear asymmetric relationship when a common 65°F set point is used and the exponent shown in Eq. 1 is significantly greater than 1.

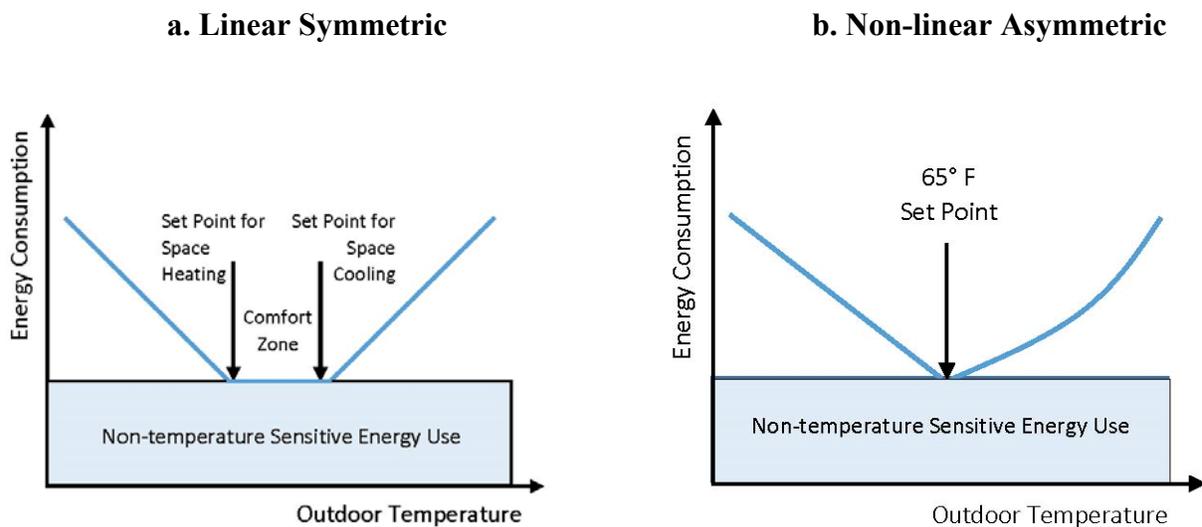


Figure 1. Alternative relationships between temperature and energy use.

### HVAC Equipment Penetration

The impact of climate change on energy demand is strongly influenced by the penetration of HVAC equipment. This leads to regional differences in responsiveness. Warming climates will result in the increased use of existing air conditioning equipment (e.g., greater cooling loads

to compensate for bigger indoor/outdoor temperature differentials, more hours per day of cooling, and longer cooling seasons). Warming climates will also increase the penetration of air conditioning equipment.

An extensive study of residential air conditioning (AC) penetration by Sailor and Pavlova (2003) used census-based data from 1994-1996 for 39 cities to estimate a relationship between climate and residential AC market penetration. More detailed studies of 12 cities showed the wide variation even between cities in the same states. Based on an assumed 20% uniform increase in CDD in those cities, they showed that in some cities increased market penetration accounted for two to three times as much of the increase in AC load and total residential energy as the short-term temperature response. Unfortunately city level data are not available in the residential energy consumption survey (EIA, 2009), so the changes since then are not readily known.

### **Thermostat Management**

Evaluations of the benefits of new cooling and heating technologies often assume specific thermostat behaviors, or set points. California's Title 24 Standards, for example, assume a certain range of settings and frequency of daily changes in those settings. Until recently, data have not been available to test such assumptions. In 2001-02, the California Energy Commission conducted a demand response experiment that produced unique, high frequency observations of residential thermostat settings and internal temperature measurements, which allow testing of assumptions about thermostat behaviors. Comparing the thermostat settings observed in the California experiment with those commonly assumed in policy modeling indicates that people change cooling and heating set points much more frequently than has been assumed. Frequent set point changes, and the extreme diversity of set point behavior across the population, have significant energy implications. Woods (2006) uses Shannon Entropy to assess the consistency of thermostat settings, which can produce both higher and lower levels of energy consumption than is conventionally assumed. Based on these findings, the authors call into question the benefits of energy efficiency programs that focus on equipment replacement and choice.

An hypothesis that thermostat settings have risen over time is tested using a repeated cross-sectional social survey of owners of centrally heated English houses. No statistical evidence for changes in reported thermostat settings between 1984 and 2007 is found (Shipworth, 2011). Contrary to assumptions, the use of programmable thermostat controls did not reduce average maximum living room temperatures or the duration of operation. Regulations, policies, and programs may need to revise their assumptions that adding controls will reduce energy use (Shipworth et al., 2010). Occupant behavior related to choices about how often and where air conditioning is used is important to understanding the impact of global warming on domestic cooling energy consumption. This is broadly confirmed by path analysis, where climate is seen to be the single most significant parameter, followed by behavioral issues, key physical parameters (e.g. air conditioning type), and finally socio-economic aspects (e.g., household income) (Yun and Steemers, 2011).

It is important to take into account regional differences since global climate models predict variable impacts across regions of the U.S., and because energy resources and infrastructures vary across regions. Analysis of survey data shows that there is a substantial difference in reported thermostat settings between states and regions (EIA, 2009), with differences greater than 4°F between the highest and lowest Census divisions. For example, the

average heating thermostat settings range from 65.9°F (Pacific) to 70.2°F (New England, and average cooling thermostat settings range from 71.3° (New England) to 75.5°F (Mountain) (Table 1).

Table 1. Residential thermostat management of space cooling in the U.S., 2009 (in °F)

Census Division	Daytime Temperature When Someone is Home	Daytime Temperature When No One is Home	Temperature at Night	Mean*
East South Central (ESC)	72.4	74.1	72.4	72.9
West South Central (WSC)	73.4	75.9	73.2	74.2
South Atlantic (SA)	73.9	75.4	73.6	74.3
Mid Atlantic (MA)	72.2	74.3	72.4	73.0
New England (NE)	71.3	71.3	71.3	71.3
East North Central (ENC)	72.1	73.3	72.0	72.5
West North Central (WNC)	73.1	74.8	73.2	73.7
Mountain (M)	74.8	76.9	74.8	75.5
Pacific (P)	73.6	77.1	73.7	74.8
U.S. Mean:	73.0	74.8	73.0	73.6

\*The “mean” for each Census Division is calculated by the authors by an equal weighting of the three temperature time-of-day conditions averaged across the columns. The U.S. mean is weighted by electricity consumption for space cooling across the nine divisions. Source: EIA, 2009

A review of 15 studies highlighted the variety of ways that balance points are estimated, and their range for different sectors and regions (Brown, Cox, and Baer, 2014). Five of the 15 studies made exogenous assumptions about balance points, and 18°C (64°F) was the most common choice. Among the studies that estimated balance points endogenously, they ranged widely from 12°C (54°F), for California in 2004-2005 (Franco and Sanstad, 2008) to 24°C (75°F) for UK households in 1989-1990 (Henley and Peirson, 1997).

## Methodology

A three-step methodology was used to estimate the best-fitting space cooling set points for calculating CDDs, and the best-fitting exponent to link increases in CDDs to increases in electricity consumption for space cooling.

### Step 1: Data Collection

Electricity sales data come from EIA-826, a database of monthly state electricity sales by sector and utility, which enables aggregation to the nine census divisions, matching one of the principal scales of analysis used by NEMS. Data were collected for the 2003-2012 time period. Residential and commercial electricity sales data by state and month are compiled for the 50 states plus DC. This enables a sectoral analysis of the relationship between outdoor temperatures and electricity consumption. The consumption data were de-trended for technological changes,

population, and square footage, using the method developed by D. J. Sailor & Muñoz (1997) that is similar to the approach used in NEMS. Detrending involves the following adjustments to raw electricity consumption data:

- $E(y)$  = Average yearly energy consumption over entire period
- $F_{adj}(y) = E(y)^{-1} \text{SUM}(E(m,y))$
- $E_{adj}(m,y) = E(m,y)/F_{adj}(y)$

We then estimate the electricity consumed for space cooling by identifying the “cooling” months typical of each state, and by estimating space cooling based on the increment of electricity consumption occurring during those months compared with the average for non-cooling months. The cooling months range from 2 (in ME and VT) to 6 months across most southern states. Hourly temperature data comes from NOAA.<sup>1</sup> Based on Thornton et al. (2013) and following ASHRAE practices, we use “emblematic” cities to represent the climate of the nine U.S. census divisions:

- ESC – Memphis & Baltimore
- WSC – Memphis & Houston
- SA – Houston, Memphis, & Baltimore
- MA – Baltimore & Chicago
- NE – Chicago & Burlington
- ENC – Chicago & Burlington
- WNC – Baltimore, Chicago, & Burlington
- M – Boise, Helena, Phoenix, Albuquerque, & El Paso
- P – El Paso, San Francisco, & Salem

CDDs are calculated for each of the approximately 10-15 weather stations located in each emblematic city. The monthly values are summed and divided by the number of weather stations to produce average monthly CDDs for each emblematic city, which is then used to represent the states and DC in our study.

After calculating the mean daily temperature for each weather station ( $T_{mean}=0.5 (T_{max} + T_{min})$ ), CDDs are calculated for whole degrees between 55 and 80°F, using the following four-step approach:<sup>2</sup>

Temperature	Day value (above threshold)
$T_{max} \leq T_{threshold}$	0
$T_{min} \geq T_{threshold}$	$T_{mean} - T_{threshold}$
$T_{mean} \geq T_{threshold} \ \& \ T_{min} < T_{threshold}$	$0.5 (T_{max} - T_{threshold}) - 0.25 (T_{threshold} - T_{min})$
$T_{mean} < T_{threshold} \ \& \ T_{max} > T_{threshold}$	$0.25 (T_{max} - T_{threshold})$

These data are used to estimate “best fit” set points, and associated CDDs, weighted by population and aggregated to the census division level. They are also used to evaluate the best-fitting exponent, based on Equation 1.

<sup>1</sup> NOAA’s National Climatic Data Center (NCDC) <http://www.ncdc.noaa.gov/>

<sup>2</sup> <http://www.metoffice.gov.uk/climatechange/science/monitoring/ukcp09/faq.html#faq1.8>

## **Step 2: Analysis Approach**

The set point with the best fit to each state's consumption of electricity in residential and commercial buildings was determined using least squares regression analysis. The best fitting set point was the one with the highest coefficient of determination (e.g., adjusted R<sup>2</sup>). The first analysis holds the set point temperature at 65°F, following current convention. The second analysis matches the CDD data to the electricity consumption data compiled in Step 1, using this data to empirically estimate the best fitting balance point for each state in the sample. Regression analysis is the tool used to estimate the best fit. Using the best-fitting set points, CDDs are calculated, weighted by population, and aggregated to the census division level.

Using both the 65°F set point and the optimized set point, we then evaluate the best fitting exponent to insert into Equation 1. NEMS assumes an exponent of 1.1; in our analysis, we evaluate the best fitting exponent again using regression analysis.

## **Step 3: Comparison of Impact of Change**

The best-fitting version of equation 1 is used as a preliminary estimation of the impact of a 10% increase in CDDs. Based on USGCRP (2009), a 10% increase is illustrative of changing summers in NH (which would resemble NJ in a low emissions scenario by mid-century) and in IL (which would resemble AL in a low emissions scenario by mid century). Both of these shifts would be several times larger than a 10% increase in CDDs.

## **Findings**

The optimized cooling set points range from 59-76°F across the 25 states plus DC in both of the sectors. On average, the best fitting set point temperatures generally resulted in improved the adjusted R<sup>2</sup>s by, on average, 3.3%, when compared with the adjusted R<sup>2</sup>s when a 65°F set point is used.

In the residential and commercial sectors, the lowest best-fitting set points were in the P, NE, and ENC Census divisions, and the highest were in the WSC and SA divisions. Thus, there is a tendency for warmer states to have higher set points, perhaps reflecting cultural preferences, building stock differences, the penetration of cooling equipment, income, and electricity prices.

This pattern is somewhat corroborated by the more aggregated data shown in Table 1, indicating that residential consumers in New England maintained the lowest thermostat settings across the nine Census divisions. The results of our estimates of "best fit" set points aggregated by Census division (Table 2), also shows that the two northern divisions (MA and NE) have lower best-fitting set points than the three southern divisions (ESC, SSC and SA).

Table 2. Best fitting set points and exponents

Census Divisions	Best Fitting Set Points			Best Fitting Exponents with 65°F Set Point		
	Residential	Commercial	Mean	Residential	Commercial	Mean*
ESC	68	67	68	0.98	-0.02	0.73
WSC	73	74	73	1.53	2.14	1.71
SA	72	72	72	1.41	1.87	1.54
MA	63	63	63	1.12	1.09	1.11
NE	61	56	59	1.76	1.56	1.69
ENC	60	59	60	1.43	0.83	1.28
WNC	69	65	68	0.78	0.71	0.76
M	62	62	62	4.18	4.03	4.14
P	52	56	54	0.62	0.63	0.63
Mean*	67.4	66.8	67.3	1.49	1.50	1.41

\* The mean values are weighted by electricity consumption for space cooling across the two building sectors. When the set points are weighted by population, the means are 64.4 (residential), 64.3 (commercial), and 64.4 (both sectors).

When weighting the five division means by average electricity consumption for space cooling, the grand mean set point for both residential and commercial buildings is 67°F—two degrees higher than the standard used in most energy-engineering models, including NEMS.

Our analysis also suggests that the best-fitting exponent is higher than the 1.1 value used by NEMS. The weighted mean of the residential exponents is 1.49, and for the commercial exponents, it is 1.50 (Table 3). In other words, the buildings sector’s electricity consumption is more climate sensitive than is modeled in NEMS. There is no consistent North-South bias to the estimated exponents. But because they are significantly greater than 1.0, we conclude that the form of the relationship between temperature and energy use is nonlinear asymmetric.

Table 3. Difference in average annual electricity use for space cooling (2003 - 2012)

Census Division	Residential		Commercial	
	Exponent	Difference in Average Annual Electricity Use for Space Cooling (GWh)*	Exponent	Difference in Average Annual Electricity Use for Space Cooling (GWh)
<b>ESC</b>	0.98	3,191 (16%)	-0.02	2,129 (30%)
<b>MA</b>	1.12	-112 (-1%)	1.09	31 (0%)
<b>NE</b>	1.76	-410 (-9%)	1.56	-146 (-6%)
<b>SA</b>	1.41	-4,364 (-8%)	1.87	-2,698 (-12%)
<b>WSC</b>	1.53	-1,346 (-3%)	2.14	-1,303 (-7%)
<b>ENC</b>	1.43	-2,422 (-9%)	0.83	671 (8%)
<b>WNC</b>	0.78	746 (6%)	0.71	353 (7%)
<b>P</b>	0.62	-700 (-9%)	0.63	-516 (-9%)
<b>M</b>	4.18	2,397 (20%)	4.03	2,397 (20%)
<b>Mean**</b>	<i>1.49</i>	<i>-336 (-1%)</i>	<i>1.50</i>	<i>-74 (-1%)</i>

\*The difference is between the average annual electricity use for space cooling in each Census Division using the best fitting exponent minus the estimate using an exponent of 1.1 (as in Equation 1).

\*\*The mean values are an average across the nine Census divisions weighted by electricity consumption for space cooling (in 2007).

On average, ceteris paribus, a 10% increase in CDDs evaluated with a 1.1 exponent linking it to electricity consumption would suggest an increase in residential and commercial electricity use for space cooling of approximately 11%. The same projections using an exponent of 1.5 would suggest a 16% increase in electricity demand for space cooling. With an exponent of 1.5 and a 50% increase in CDDs, the expected change in electricity consumption for space cooling would be 87%, which is 31% higher than with an exponent of 1.1. Such an increase in demand would require a significant build-out of new supply capacity and would put upward pressure on rates.

## Conclusions and Remaining Research Gaps

Three conclusions can be drawn from this research. First, the best-fitting set point for calculating CDDs nationwide is 67°F, two degrees higher than the standard of 65°F. Second, set points vary by region, with warmer regions tending to have higher set points. Finally, when CDDs are based on set points of 65°F, the exponent linking CDD to energy use should be higher than the value of 1.1 currently used in NEMS – it should be 1.5 for both residential and commercial buildings. The higher exponent indicates that space cooling is more climate sensitive than is portrayed in NEMS; as a result NEMS underestimates energy use for space cooling, and it would be a significant underestimation if NEMS were to model a climate future that was much warmer than today.

Much still remains to be done to more fully understand climate-driven changes in U.S. energy demand. The first major gap is the influence of climate change on the performance of HVAC equipment. Little research has examined the impact of climate change on the efficiency of heating and cooling equipment, although it is noted as an issue in Oak Ridge National Laboratory (2012a). In theory, HVAC systems should run better if they have variable capacities and are able to modulate effectively.

Second, to what extent will a warming climate cause upward pressure on electricity rates and to what extent will that increase electricity expenditures? Consistent with an increase in space cooling demand that requires new capacity to meet the peak-heavy new load, and without a commensurate increase in generation, the cost of meeting the new load is likely to increase. EIA (2005) estimates that global warming would bring about a much greater change in peak demand than total demand, resulting in higher average electricity prices, but the extent of this upward pressure on rates would benefit from further analysis.

A third major gap pertains to public policies. Few studies have examined how alternative policies have influenced climate-driven impacts on energy consumption or how policies might be influential in the future. For example, how much influence could prospective building codes have, if they were updated to account for likely future climates, so that the building stock can be better prepared for changing climate conditions? Regulations and incentives that encourage planting urban shade trees, using high albedo roofs, and investing in more efficient air conditioning equipment could reduce energy requirements for space conditioning, but the possible range of such impacts on the temperature sensitivity of energy demand are not well characterized. In general, more analysis is needed to better understand policy actions and strategies to achieve such transitions.

## Acknowledgement

The authors thank the U.S. Department of Energy and Oak Ridge National Laboratory (Melissa Lapsa and Roderick Jackson) for sponsoring this project. We also appreciate the valuable comments of two anonymous ACEEE reviewers of this paper.

## References

- Amato, A. D., Ruth, M., Kirshen, P., & Horwitz, J. (2005). Regional Energy Demand Responses To Climate Change: Methodology And Application To The Commonwealth Of Massachusetts. *Climatic Change*, 71(1-2), 175–201. doi:10.1007/s10584-005-5931-2
- Apadula, F., Bassini, A., Elli, A., & Scapin, S. (2012). Relationships between meteorological variables and monthly electricity demand. *Applied Energy*, 98, 346–356.
- Argonne National Laboratory (ANL). (2008). Climate Change Impacts on the Electric Power System in the Western United States. Argonne, IL.
- Brown, M. A., Cox, M., & Baer, P. (2014). “Modeling Climate-Driven Changes in U.S. Energy Demand: Conclusions from a Review of the Literature,” Georgia Institute of Technology, School of Public Policy Working Paper #78.
- Darmstadter, J. (1993). Climate Change Impacts on the Energy Sector and Possible Adjustments in the Mink Region. *Climatic Change*, 24(1-2), 117–129. doi:10.1007/BF01091479
- Day, T. (2006). *Degree-days: theory and application* (p. 106). London: The Chartered Institution of Building Services Engineers.

- EIA. (2005). Impacts of Temperature Variation on Energy Demand in Buildings. *Issues in Focus, AEO2005*. Retrieved from [http://www.eia.gov/oiaf/aeo/otheranalysis/aeo\\_2005analysispapers/vedb.html](http://www.eia.gov/oiaf/aeo/otheranalysis/aeo_2005analysispapers/vedb.html)
- EIA. (2009). Residential Energy Consumption Survey. *Consumption and Efficiency*. Retrieved from <http://www.eia.gov/consumption/residential/>
- Engle, R. F., Granger, C. W. J., Rice, J., & Weiss, A. (1986). Semiparametric Estimates of the Relation Between Weather and Electricity. *Journal of the American Statistical Association*, 81(394), 310–320.
- Executive Office of the President. (2013). *Economic Benefits of Increasing Electric Grid Resilience To Weather Outages*.
- Franco, G., & Sanstad, A. H. (2008). Climate change and electricity demand in California. *Climatic Change*, 87(S1), 139–151. doi:10.1007/s10584-007-9364-y
- Hadley, S. W., Erickson, D. J., Hernandez, J. L., Broniak, C. T., & Blasing, T. J. (2006). Responses of energy use to climate change: A climate modeling study. *Geophysical Research Letters*, 33(17), L17703. doi:10.1029/2006GL026652
- Hekkenberg, M., Moll, H. C., & Uiterkamp, a. J. M. S. (2009). Dynamic temperature dependence patterns in future energy demand models in the context of climate change. *Energy*, 34(11), 1797–1806.
- Henley, A., & Peirson, J. (1997). Non-Linearities in Electricity Demand and Temperature: Parametric Versus Non-Parametric Methods. *Oxford Bulletin of Economics and Statistics*, 59(1), 149–162.
- Mansur, E. T., Mendelsohn, R., & Morrison, W. (2008). Climate change adaptation: A study of fuel choice and consumption in the US energy sector. *Journal of Environmental Economics and Management*, 55(2), 175–193. doi:<http://dx.doi.org/10.1016/j.jeem.2007.10.001>
- Miller, N., Hayhoe, K., Jin, J., & Auffhammer, M. (2008). Climate Change, extreme heat, and electricity demand in California. *Journal of Applied Meteorology and Climatology*, 47(June), 1834–1844.
- Oak Ridge National Laboratory. (2012). Climate Change and Energy Supply and Use. Oak Ridge, Tennessee. Retrieved from <http://www.esd.ornl.gov/eess/EnergySupplyUse.pdf>
- Sailor, D. J., & Muñoz, J. R. (1997). Sensitivity of Electricity and Natural Gas Consumption to Climate in the USA - Methodology and Results for Eight States. *Energy*, 22(10), 987–998.
- Sailor, D., & Pavlova, A. (2003). Air conditioning market saturation and long-term response of residential cooling energy demand to climate change. *Energy*, 28(9), 941–951.

- Sailor, David J. (2001). Relating residential and commercial sector electricity loads to climate—evaluating state level sensitivities and vulnerabilities. *Energy*, 26(7), 645–657.
- Sathaye, J. a., Dale, L. L., Larsen, P. H., Fitts, G. a., Koy, K., Lewis, S. M., & De Lucena, A. F. P. (2013). Estimating impacts of warming temperatures on California’s electricity system. *Global Environmental Change*, 23(2), 499–511. doi:10.1016/j.gloenvcha.2012.12.005
- Scott, M. J., Wrench, L. E., & Hadley, D. L. (1994). Effects of Climate Change on Commercial Building Energy Demand. *Energy Sources*, 16(3).
- Shipworth, M. (2011). Thermostat settings in English houses: No evidence of change between 1984 and 2007. *Building and Environment*, 46(3), 635–642.
- Shipworth, M., Firth, S. K., Gentry, M. I., Wright, A. J., Shipworth, D. T., & Lomas, K. J. (2010). Central heating thermostat settings and timing: building demographics. *Building Research & Information*, 38(1), 50–69. doi:10.1080/09613210903263007
- Shorr, N., Najjar, R. G., Amato, A., & Graham, S. (2009). Household heating and cooling energy use in the northeast USA: comparing the effects of climate change with those of purposive behaviors. *Climate Research*, (39), 19–30. doi:10.3354/cr00782
- U.S. Department of Energy (DOE). (2013). *U.S. Energy Sector Vulnerabilities to Climate Change and Extreme Weather*.
- US Environmental Protection Agency (EPA). (1989). *The Potential Effects Of Global Climate Change On The United States*. Washington, DC: Environmental Protection Agency.
- USGCRP (U.S. Global Change Research Program). (2009). *Global Climate Change Impacts in the United States*. (T. R. Karl, J. M. Melillo, & T. C. Peterson, Eds.). Cambridge, UK: Cambridge University Press. Retrieved from <http://nca2009.globalchange.gov/>
- Woods, J. (2006). Fiddling with Thermostats: Energy Implications of Heating and Cooling Set Point Behavior. *2006 ACEEE Summer Study on Buildings* (pp. 278–287).
- Yun, G. Y., & Steemers, K. (2011). Behavioural, physical and socio-economic factors in household cooling energy consumption. *Applied Energy*, 88(6), 2191–2200.