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Modeling climate-driven changes in U.S. buildings energy demand

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Abstract How climate change might impact energy demand is not well understood, yet energy forecasting requires that assumptions be specified. This paper reviews the literature on the relationship between global warming and the demand for space cooling in buildings. It then estimates two key parameters that link energy for space cooling to cooling degree days (CDDs) using data for nine U.S. Census divisions, which is the spatial resolution of the National Energy Modeling System (NEMS). The first parameter is the set point temperature for calculating CDDs; the second is the exponent for representing the relationship between changes in CDDs and changes in electricity consumption for space cooling. We find that the best-fitting CDDs have a set point of 67 °F (19.4 °C), for both residential and commercial buildings, rather than the conventional 65 °F (18.3 °C). Set points also vary by region, with warmer regions tending to have higher set points. When CDDs are based on the conventional set point, the best fitting exponent is 1.5 for both residential and commercial buildings, indicating that space cooling is more climate-sensitive than is specified in NEMS. As a result, the official projections of U.S. energy consumption would appear to underestimate the energy required for space cooling.

1 Introduction

Climate change could create many difficulties for the U.S. energy system. Recent evidence suggests that it is already doing so, particularly by creating extreme conditions that are hard to anticipate and address (Dell, et al. 2014; IPCC 2014). These include rapid changes in energy demand, resource availability and generation, transmission and distribution efficiency and reliability, as well as challenges related to the energy/water/food nexus. Long term, climate

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change may also impact the settlement patterns within the U.S., potentially resulting in shifts in populations away from low-lying coastal communities, water-scarce regions, and other areas of the country that are most negatively impacted.

Attempts to model some of these impacts could illuminate previously unanticipated interactions between technical aspects of the energy system, energy supply, and energy demand. The existing literature is rich in some areas related to climate and energy use. For example, studies of weather for short-term utility load forecasting date back at least to the 1970s, with climate change studies beginning to appear in the 1990s. Research on the heat loss and heat gain of building structures under different climatic conditions is also well developed.

In contrast, the literature on linkages between climate, energy demand, and behavior is much sparser and many key questions remain unanswered. Yet there are a number of areas where behavioral differences are anticipated to impact how energy is consumed in homes and businesses, including regional differences in thermostat settings and usage, as well as pricing and incentive structures. Furthermore, equipment used to meet demands for heating and cooling may react differently to changes in environmental characteristics like outdoor temperatures and humidity.

When climate variables are carried into 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? What is the best-fitting mathematical relationship? Should wind and humidity be included, or are their impacts too insignificant after aggregation (Apadula et al. 2012; Sailor 2001)? What other factors need to be controlled to isolate the impact of climate change? How sensitive are different sectors of the economy to climate change?

This paper focuses on four questions. The first two are 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 (18.3 °C) and what is the best-fitting mathematical relationship between CDDs and electricity demand for space cooling in buildings? Based on the methodological findings, we tackle two substantive questions: what do the methodological improvements imply about energy projections and how might an increase in CDDs impact electricity use for cooling over the next quarter century?

2 Conclusions from the literature

2.1 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 space cooling, 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 than is electricity, because electricity is used for so many end-uses other than space conditioning (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 (U.S. Department of Energy (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 2012). In addition, regional differences in the fuels used for space heating will influence the impact of climate change on overall energy consumption. Amato et al. (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.

More recent publications have estimated significant increases in electricity 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, et al. (2006) estimate that a 1.2 °C (2.2 °F), 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. Mansur et al. (2008) estimate slightly larger effects. Their discrete choice model estimates that a 1 °C (1.8 °F), temperature increase in January would decrease electricity use in all-electric commercial buildings by 2.6 % (the decrease would be less where fossil fuels are used for space heating); the same temperature increase in July would increase electricity use by 4.6 %.

Evidence to date suggests significantly regional variation in energy consumption sensitivities. Sailor (2001), for instance, found that a 2 °C (3.6 °F) 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 et al. (1994) found that climate change had highly variable impact on commercial building energy demand across four U.S. cities. Auffhammer and Aroonruengsawat (2011) simulated average per-household demand increases of 65–124 % in California by the end of the century relative to a 1980–2000 baseline, while McFarland, et al. (2015) found that temperature increases of 3–6 °C (5.4–10.8 °F) by 2100 would increase electricity consumption by 1.6–6.5 % by 2050.

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 10–25 % by the end of the century. 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 can stress the electric grid, which is already vulnerable to weather-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.

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 and Pavlova (2003) found that residential electricity consumption increased 2 to 4 % for each degree Celsius increase in ambient temperatures. However, Sailor (2001) concludes that it is difficult to generalize without first taking into account the many other non-climatic factors that impact energy demand.

2.2 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 set point temperature and that energy demand responds the same to a marginal change in temperature (either warmer or cooler), producing 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).

A base temperature of 65 °F (18.3 °C), is used most often in analyzing the space-conditioning temperature relationship. However, the actual set 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 set 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 set point temperature for the commercial sector in Massachusetts was 55 °F (12.8 °C), below the 60 °F (15.6 °C), set point temperature for the residential sector. Different types of models use different values, which are determined in various ways (see Brown et al. 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 below.

$$SpaceCoolingEnergyUse_{f,b,r,y} = SpaceCoolingEnergyUse_{f,b,r,y}{}^{*}\left(\frac{DegreeDays_{r,y}}{DegreeDays_{r,2003}}\right)^{x} \quad (1)$$

where x=1.1 for commercial buildings and 1.5 for residential buildings.

The NEMS Reference case uses the 30-year average of heating and cooling degree-days from the National Oceanic and Atmospheric Administration (NOAA) at the State level, adjusted for State population forecasts, to represent future temperatures. As a result of State population shifts, population-weighted heating degree-days are projected to decline slightly, and population-weighted cooling degree-days are projected to increase slightly, relative to the weather normal average, because the population is projected to shift to States with warmer climates (EIA 2005). 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 in the commercial sector (and 1.5 in the residential sector), the result is imperceptibly non-linear.

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

Linear asymmetric models utilize ordinary least-squares regression forms to estimate the relationship between electricity demand and temperature (Deschênes and Greenstone 2011; Mirasgedis et al. 2006). These models tend to control for temperature or degree days, weather variables, and sometimes a range of economic variables. This form has benefits over the V-shaped models described earlier. While still producing linear outputs, and thus describing a linear relationship between electricity consumption and temperature, it allows for variation in the slope of the line on either side of the set point temperature. These researchers acknowledge the nonlinear relationship but achieve success in estimating it through linear parametric models. By incorporating other variables like weather and socio-economic factors, predictive success increases, with some models achieving R^2 values greater than 0.9 (Mirasgedis et al. 2006).

More complicated smooth transition regression forms have been developed to reflect the nonlinear relationship between electricity consumption and temperature. These are typically fixed effects polynomial OLS forms with context-dependent filters; for example, Bessec and Fouquau (2008) control for the month of August when studying Europe to account for the heavy vacationing that typically occurs in that month. An intensive treatment of the OLS residuals typically follows the estimations (Bessec and Fouquau 2008), with empirically fitted

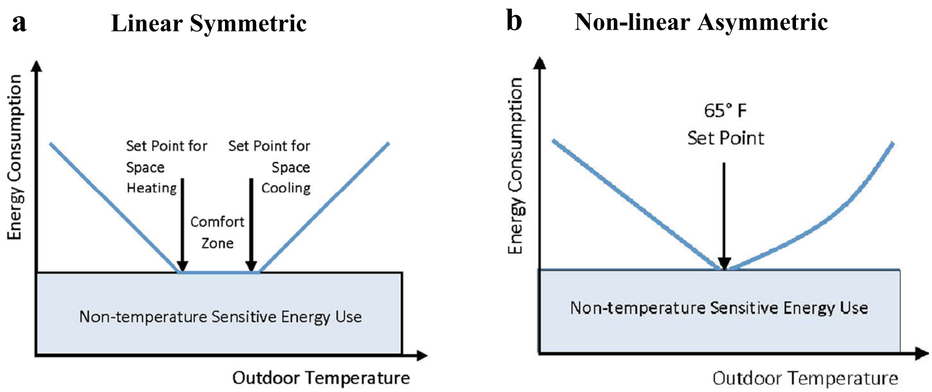

Fig. 1 Alternative relationships between temperature and energy use

set point temperatures. The methods used allow for multiple set point temperatures, and allows for threshold temperatures that bound minimum ranges, where energy consumption is essentially flat.

Semi-parametric and nonparametric models have been used to investigate this relationship as well. Engle et al. (1986) justify this approach on the basis that thermodynamics dictates that heat loss through a barrier is proportional to the fourth power of the temperature differential, and more importantly, that when equipment is operating at 100 %, the effect of more severe weather cannot result in increased energy consumption unless the capacity of the equipment is expanded. Piecewise linear spline (Engle et al. 1986), smoothed kernel regressions (Henley and Peirson 1998), and semi-parametric spline estimates (Gupta 2012) have been applied to utility sales information in the U.S. (Engle et al. 1986), household demand response to differential pricing regimes in the U.K. (Henley and Peirson 1997, 1998), and electricity demand in New Delhi (Gupta 2012).

The non-parametric aspects of the models provide very detailed estimates of the impact of a change in temperature. The semi-parametric models also add parametric determinants for income and price, as well as weather events, like rainfall. These models tend to be robust, require significant data manipulation, and are best suited for more fuel-homogenous geographies. Perhaps as a result, fewer studies use this approach. These approaches are particularly useful in estimating energy demand at extremes, where distance from the mean, behavioral change, and equipment operations generate empirical deviations from the predictions of the other model specifications.

Studies of the relationship between energy consumption and temperature tend to be fuel-disaggregated, but demand-aggregated. In many studies, end uses in the residential, commercial, and industrial sectors are not treated separately; that is, two or three sectors are treated as a whole (Bessec and Fouquau 2008).

Disaggregation by economic sector and end use is important for several reasons, but most importantly because end uses differ in their temperature sensitivity. In addition, disaggregation could help policymakers understand where effective interventions could be pursued. With very sophisticated data and methods, it is possible to construct quite accurate models for homogenous geographies. However, when expanding study horizons to larger regional, national, and international scales, these methods lose utility. In such cases, asymmetric linear ordinary least-squares models and nonlinear smooth transition regression models may provide the best model performance. Where rich data are available at a disaggregated level, it is possible to distinguish factors between regions and then aggregate to larger scales.

2.3 Penetration of heating, ventilation, and air conditioning (HVAC) equipment

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 (AC) 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 AC equipment.

Of course, this finding will apply less to regions where essentially all buildings already have AC equipment. In 2009, homes in the South Census Region had nearly complete market saturation of air conditioning (about 98 %) and 85 % of homes had central air conditioning equipment. In contrast, the Northeast region had only about 65 % market penetration of air conditioning, and window/wall AC units were used in a majority (58 %) of homes with air conditioning. The rest of the country fits somewhere between these two extremes (EIA 2013).

Hamlet et al. (2010) estimated the impact of climate change on market penetration of residential AC in Washington and the Pacific Northwest, an area with relatively low levels of penetration. Because the warming is greatest inland but the population density of Washington is greatest in the coastal areas, the projected impact was low in the initial decades but became significant by 2080.

Several international studies of the impact of increasing market penetration of air conditioning have also been published. Due to expected income growth and continued electrification in developing countries, this factor is expected to play a relatively larger role globally than in the U.S. (Akpinar-Ferrand and Singh 2010; Isaac and van Vuuren 2009); in addition, many countries in Europe that currently have relatively little air conditioning may see significant growth (Auffhammer and Mansur 2012; Day et al. 2009). More generally in the U.S., additional penetration of air conditioning can be expected to be influenced by trends in income distribution and electricity prices, as the poorest citizens are most likely to be without air conditioning (Yun and Steemers 2011).

2.4 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 used 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 author calls into question the benefits of energy efficiency programs that focus on equipment replacement and choice.

A hypothesis that thermostat settings have risen over time has been tested using a repeated cross-sectional social survey of owners of centrally heated English houses; however, no statistical evidence for changes in reported thermostat settings between 1984 and 2007 was found (Shipworth 2011). Contrary to assumptions, the use of 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 impacts 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 (7.2 °C), between the highest and lowest Census divisions. For example, the average heating thermostat settings range from 65.9 °F (18.8 °C), in the Pacific division to 70.2 °F (21.2 °C) in the New England division, and average cooling thermostat settings range from 71.3° (21.8 °C) in New England to 75.5 °F (24.2 °C) in the Mountain division (Table 1).

A review of 15 studies highlighted the variety of ways that set points are estimated, and their range for different sectors and regions (Table A.1). Five of the 15 studies made exogenous assumptions about set points, and 18 °C (64 °F) was the most common choice. Among the studies that estimated set 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 U.K. households in 1989–1990 (Henley and Peirson 1997).

3 Methodology

A three-step methodology is 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 (descried in Section 3.1). We then use the "optimized" exponent to evaluate the climate sensitivity of energy use for space cooling (described in Section 3.2).

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

3.1 Approach to optimizing exponents and set points

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 Sailor and Muñoz (1997) that is similar to the approach used in NEMS. Detrending involves the following adjustments to raw electricity consumption data. For each state, we calculate an average annual electricity consumption for the period 2003 to 2012:

$$\mathrm{E}\left(\overline{y}\right) = \text{Average state–specific annual electricity consumption} \tag{2}$$

The sum of electricity consumption of a state over the twelve months, m, in year y divided by the average state-specific yearly electricity consumption produces an annual adjustment factor as shown in Eq. 3:

$$\mathrm{F_{adj}(y)} = \sum\nolimits_{\mathrm{m}=1,12} \mathrm{E(m,y)}/\mathrm{E}\left(\overline{y}\right) \tag{3}$$

The electricity consumed in month m and year y over the annual adjustment factor creates the detrended electricity consumption for month m and year y (Eq. 4):

$$\mathrm{E_{adj}(m,y)} = \mathrm{E(m,y)}/\mathrm{F_{adj}(y)} \tag{4}$$

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.[1] Based on Thornton et al. (2013) and following practices recommended by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE), 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

We acknowledge that these emblematic cities may not provide optimized climate representations for the nine census divisions; it would appear to be particularly problematic that two of the cities are used to represent more than one census division. These cities may also not reflect future climate conditions, if the climate continues to change as predicted. Nevertheless, use of

[1] NOAA's National Climatic Data Center (NCDC) http://www.ncdc.noaa.gov/

these emblematic cites is standard practice recommended by ASHRAE for representing the climate of the nine census divisions in the U.S.

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 °F (12.8 °C) and 80 °F (26.7 °C), using the following four-step approach.[2] This approach to calculating CDDs from min and max temperatures allows for the possibility of CDDs and HDDs occurring on the same day, which is prohibited when the simpler NOAA method is used. These CDD 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 Eq. 1.

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

Step 2: analysis approach The set point with the best fit to each state's consumption of electricity for space cooling 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 (i.e., adjusted R^2). 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 set point for each state in the sample. Using the best-fitting set points, CDDs are calculated, weighted by population, and aggregated to the census division level.

Using both the 65 °F (18.3 °C) set point and the optimized set point, we then evaluate the best fitting exponent to insert into Eq. 1. NEMS assumes an exponent of 1.1 for residential users and 1.5 for commercial users; 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 Eq. 1 is used as a preliminary estimation of the impact of a 10 % increase in CDDs. Based on USGCRP (2009), such an increase would be illustrative of summers in NH resembling current summers in NJ by mid-century. Similarly, summers in IL would resemble current summers in AL by the same point. The expected change in climate for these regions, as well as the United States over all, are expected to be several times larger than the roughly 10 % increase in CDDs embodied in the USGCRP lower emissions scenario.

[2] http://www.metoffice.gov.uk/climatechange/science/monitoring/ukcp09/faq.html#faq1.8

3.2 Approach to assessing climate sensitivity

We use the "optimized" exponent in NEMS to estimate the impact global climate change might have on energy consumption in residential and commercial buildings. NEMS "is arguably the most influential energy model in the United States" (Wilkerson et al. 2013). It is comprised of twelve modules representing supply, demand, energy conversion, and macroeconomic and international energy market factors. A thirteenth "integrating" module ensures that a general market equilibrium is achieved. Beginning with current resource supply and price data and making assumptions about future consumption patterns and technological development, the model carries through the market interactions represented by the thirteen modules and solves for the price and quantity of each energy type that balances supply and demand in each sector and region represented.

In its Commercial Demand Module, NEMS employs a least-cost function within a set of rules governing the set of options from which consumers may choose technologies. Capital costs are amortized using "hurdle rates," which are calculated for end-uses by year for different subsets of the population by summing the yield on U.S. government 10-year notes (endogenously determined) and the time preference premium of consumers (exogenous inputs to the model). By characterizing nearly 350 distinct commercial building technologies in nine end-uses and eleven types of commercial buildings, across nine census divisions, the model offers the potential for a rich examination of impacts of greater climate sensitivity of energy use for space cooling in commercial buildings. The "Reference case" projection described in this study uses the same computer code as the published Reference case in EIA's *Annual Energy Outlook 2014* (EIA 2014).

NEMS 2014 models climate using a file called "KDEGDAY.TXT" that contains HDDs and CDDs compiled from three data sources. Historic climate (1990–11/2013) is drawn from NOAA's National Climatic Data Center (NCDC) data by state (except AK, DC, and HI, which come from NOAA's Climate Prediction Center (CPC) data. The near future (12/2013–2014) also comes from CPC. The long-term (2015–2040) 30-year trend of full-year climate data is an extrapolation based on the 1984–2013 data. Because the 30-year trend represents only a modest increase in CDDs, we also use a simple off-line calculation to estimate the impact that a higher exponent would have in a future with significant global warming, above and beyond that represented in EIA's Reference case forecast.

4 Findings

4.1 Optimizing exponents and set points

The optimized cooling set points range widely across nine divisions in both of the sectors (Table 2). On average, the best fitting set point temperatures generally improved the adjusted R^2s by, on average, 3.3 %, when compared with the adjusted R^2s when a 65 °F set point is used.

In the residential and commercial sectors, the lowest best-fitting set points were in the Pacific, New England, and East North Central Census divisions, and the highest were in the West South Central and South Atlantic divisions. Thus, there is a tendency for warmer states to have higher set points, presumably reflecting cultural preferences, building stock differences, the penetration of cooling equipment, income, and electricity prices.

Table 2 Best fitting set points and exponents

Census Divisions	Best Fitting Set Points (in °F)			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	1.49

* 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 °F (18 °C) (residential), 64.3 °F (17.9 °C) (commercial), and 64.4 °F (18.2 °C) (both sectors). Weighting by electricity consumption produces higher set points because household electricity use for space cooling is higher in southern states where set points are also generally higher

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 also shows that the two northeastern divisions (MA and NE) have lower best-fitting set points than the three southern divisions (ESC, WSC and SA). 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 2 °F 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. In other words, the commercial 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.

4.2 Assessing climate sensitivity

When NEMS is modified to incorporate a higher exponent reflecting a greater sensitivity of space cooling electricity use to changes in CDDs, the results differ as predicted from the NEMS Reference case forecast. In terms of energy for space cooling in the commercial sector, the exponent of 1.5 produces a forecast of a growing gap in energy consumption, reaching 7.8 % in 2040 (see Fig. 2).

Electricity prices are forecast by the NEMS Reference case to increase as a result of increasing fuel costs and environmental regulations. The laws of supply and demand suggest that electricity prices would also increase, and this is indeed reflected in the NEMS forecast as shown in Fig. 3. Specifically, our analysis suggests that the higher exponent produces

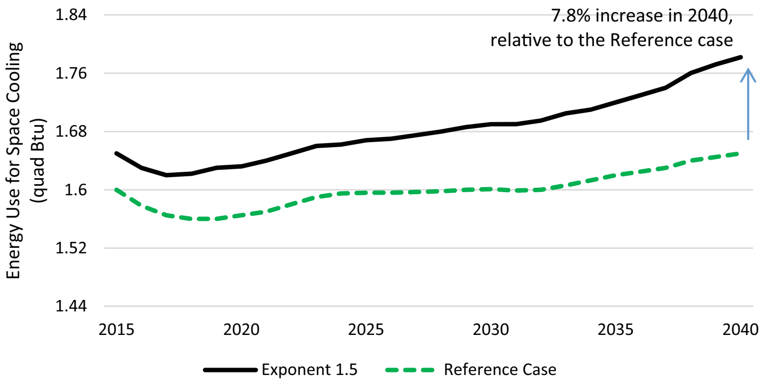

Fig. 2 Impact of higher exponent on energy use for space cooling

electricity rates that by 2040 are 0.3 % higher than in the Reference case. NEMS incorporates only a minimal global warming trend, but it does include southward population migration. Thus, these modest differences in consumption and prices are not surprising.

We use off-line calculations to consider how commercial electricity consumption might alter in a future with significant global warming. We vary these future scenarios from a modest 10 % increase in CDDs, which is consistent with the "climate on the move" characterizations of the U.S. Global Change Research Program (2009), to a more substantial increase of 50 %, representing a combination of warming temperatures and migration to warmer states.

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 put upward pressure on rates, causing second-order effects that would require a model such as NEMS to evaluate. Since NEMS plays a prominent role in U.S. energy forecasting (Wilkerson et al. 2013), it is important that its key parameters be evaluated and improved where gaps and biases are discovered.

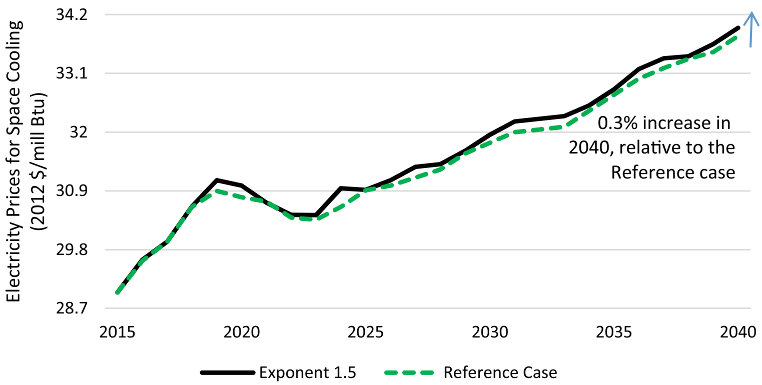

Fig. 3 Impact of higher exponent on electricity rates

5 Conclusions and remaining research gaps

Three conclusions can be drawn from this research. First, our research suggests that the best-fitting set point for calculating CDDs in the U.S. is 67 °F (19.4 °C), two degrees higher than the value used in NEMS. 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 (18.3 °C), the exponent linking CDD to energy use should be higher than the value of 1.1 currently used in the NEMS commercial buildings module. Our research estimates that 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 space cooling would is underestimated in NEMS.

Modeling climate-driven changes in U.S. energy demand has received increasing attention over the past few decades, and a great deal of knowledge has been gained. Nonetheless, the published literature has many gaps. First is the gap in understanding how adaptation measures might play out. Will populations and economic activities migrate? Will consumers buy more of their own on-site generation if the power system becomes more brittle? There are many promising approaches for managing the risks associated with climate change (Brown 2010); however, few researchers have explored the impact of adaptation measures on the relationship between climate change and energy use.

The second 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 ORNL (2012). In theory, HVAC systems should run better if they have variable capacities and are able to modulate effectively. But system efficiencies, including compressor capacity and system sizing, power inverter characteristics, and heat exchanger sizing also impact efficiencies.[3]

Third, to what extent will a warming climate cause upward pressure on electricity rates and bills? 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 revenues from baseload sales, the cost of meeting the new load could challenge electric providers. Alternative business models for utilities need to be examined.

A fourth major gap pertains to public policies. Prospective building codes can be updated to account for likely future climates, regulations and incentives could 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.

Finally, the role of climate change tipping points, disruptive technological innovations, and economic shocks to GDP are sometimes discussed, but are rarely modeled. Methods for incorporating such discontinuities in system dynamics deserve more attention to properly characterize the range of possible future climate change impacts on energy demand (Smith and Brown 2014).

Addressing this array of research gaps will require technology-rich modeling of individual end uses, behavioral research, and further econometric analysis.

[3] Personal communications with Dr. Roderick Jackson (ORNL).

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