Energy 236 (2021) 121273

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Quantification of climate-induced interannual variability in residential U.S. electricity demand

Hadi Eshraghi [a, *], Anderson Rodrigo de Queiroz [b, a], A. Sankarasubramanian [a], Joseph F. DeCarolis [a]

[a] Department of Civil, Construction and Environmental Eng., North Carolina State University, Raleigh, NC, 27695, USA
[b] Department of Decision Sciences School of Business, North Carolina Central University, Durham, NC, 27707, USA

ARTICLE INFO

Article history:
Received 27 September 2020
Received in revised form
1 June 2021
Accepted 15 June 2021
Available online 30 June 2021

Keywords:
Electricity demand
Linear regression
Climate information
Residential heating and cooling
Electricity use intensity

ABSTRACT

We assess the sensitivity of residential electricity demand in 48 U S. states to seasonal climate variations and structural changes pertaining to state-level household electricity demand. The main objective is to quantify the effects of seasonal climate variability on residential electricity demand variability during the winter and summer seasons. We use state-level monthly demographic, energy, and climate data from 2005 to 2017 in a linear regression model and find that interannual climate variability explains a significant share of seasonal household electricity demand variation: in 42 states, more than 70% and 50% of demand variability in summer and winter, respectively, is driven by climate. Our work suggests the need for new datasets to quantify unexplained variance in the winter and summer electricity demand. Findings from this study are critical to developing seasonal electricity demand forecasts, which can aid power system operation and management, particularly in a future with greater electrification of end-use demands.

1. Introduction

US electricity demand has been growing at 1.6% annually since 1990. This rate is higher than other major energy sources used in the residential sector [1]. In 2018, 37% of total US electricity demand was consumed in the residential sector, which is the highest among US end-use sectors [2]. Electricity in the residential sector is used to meet various energy services, some of which are subject to high seasonal variations. Recent surveys show that 46% of the total residential electricity consumption in the continental United States (CONUS) is used for indoor space conditioning [3]. This dependency of aggregate seasonal demand on seasonal climate poses challenges for power system operators and has critical implications for both demand and supply-side planning in the electric sector. Improvements in monthly to seasonal electricity demand forecasts can aid in the development of emergency, contingency management, and system maintenance plans (Mukerji et al., 1991), forward fuel purchases, demand-response programs, and scheduling of hydro and thermal power plants [4]. For example, improved demand forecasts could support seasonal power generation planning [5] and can be used to properly define unit commitment schedules in power systems. Similarly, a 1% reduction in forecasting error for a 10,000 MW utility can provide savings of more than US$ 1.5 million per year [6]. Despite these findings, the role of variability in seasonal temperature on residential electricity demand is not yet fully understood across the CONUS. In addition, climate change will affect future electricity supply and demand [37], thus further motivating the need to understand the degree to which electricity demand is driven by temperature variations.

Electricity as a heating source has been increasing at the expense of other fuels, including natural gas, over the past decade [3]. The Energy Information Administration's Annual Energy Outlook projects this trend will continue [2]. Further, deep decarbonization of the U.S. energy system requires, among other measures, large-scale electrification of end-use services. Numerous studies on deep decarbonization show that electrification of heating services can play a key role in reducing direct emissions from the end-use sectors [7,8].

The dependency of electricity demand on climate has been studied extensively over different spatio-temporal scales. Tso et al. [9] provides a detailed comparison of three types of demand prediction models, including regression, neural networks, and decision

* Corresponding author.
E-mail address: heshrag@ncsu.edu (H. Eshraghi).

https://doi.org/10.1016/j.energy.2021.121273

trees. A review of the common methodologies reveals that regression techniques, mostly due to their ease of application, have been widely used to quantify climate-load relationships [9]. One class of studies estimate future electricity demand, particularly residential cooling and heating loads, over the long-term considering climate change projections, as opposed to other studies that have analyzed the load-temperature relationship at shorter timescales such as hourly. In Table S1 of the Supplementary Information, we reviewed the most closely-related literature published after 2000 for the United States. Recent studies give a clearer picture of the evolving temperature-load relationship in the country.

The seasonality of electricity demand and its association with meteorological variability has been studied extensively. One of the earliest works on this topic, Sailor [10]; used monthly weather and load data to develop residential and commercial sector load sensitivities to specific climate change scenarios and found heterogeneity in load sensitivity to climate change for six states. Amato et al. [11] developed temperature response functions of overall energy consumption using state population, energy prices, daylight hours, and heating and cooling degree days as explanatory variables and found within-state energy consumption was explained well by the identified variables. Using a similar modeling approach, Ruth and Lin [12] identified combined climate and non-climate induced variations in Maryland's energy demand. Lam et al. [13], investigated the seasonal variations in electricity demand in Hong Kong and explained the monthly electricity demand in the residential and commercial sectors using climatic variables as predictors based on regression. OrtizBeviá et al. [14], analyzed the influence of meteorological variability on the daily electricity demand of Spain. Mukherjee and Nateghi [15] incorporated monthly Florida weather data including dew point temperature, mean wind speed, precipitation, monthly electricity consumption, and socio-economic parameters in Bayesian additive regression trees and found more spatio-temporal heterogeneity in the residential sector compared to the commercial sector in Florida. Li [16] analyzed the link between residential electricity demand and outdoor climate in Singapore using regression analysis and found that electricity consumption in different households varies based on outdoor climate variations. Alberini et al. [17] analyzed how sensitive residential demand is to temperature in Italy using a regression model and found that temperature accounts for a very small share of daily electricity demand in the country due to its mild Mediterranean climate. Wang et al. [18] developed a hierarchical Bayesian regression model for predicting summer monthly per capita electricity demand for the coterminous United States (CONUS). Though Wang et al. [18] focused on a national predictive model for summer per-capita consumption over the 48 states, the study did not consider the sensitivity of winter electricity demand to climate and other heating sources. While most studies considered various statistical approaches ranging from simple regression to Bayesian decision trees, none include state-level analysis of residential electricity demand in both the summer and winter seasons at the CONUS scale.

The main objective of this study is to quantify the main drivers of both summer and winter seasonal variability of residential electricity demand over the CONUS. For this purpose, we systematically decompose the explained variance by each driver using linear regression and use that information to explain the role of different seasonal demand drivers across the nation. *Thus, to our knowledge, this manuscript is the first to quantify how population, climate, and alternative heating sources affect interannual variation in total residential electricity demand in the summer and winter seasons across the contiguous United States.* The manuscript is organized as follows: Section 2 of the paper discusses the methodology and data. Section 3 presents the results and Section 4 discusses the findings of the paper.

2. Methods and materials

This study systematically explains the interannual variability of residential electricity demand during the winter (December, January and February, DJF) and summer (June, July and August, JJA) over the CONUS [[19]]. We consider only the summer and winter seasons because power systems face more variability in electric loads during the summer and winter seasons compared to spring and fall [20]. Fig. 1 illustrates the conceptual framework adopted for quantifying the role of the four selected variables – population, climate, natural gas substitution effect, and the previous month's demand – in explaining the winter and summer electricity demand over the CONUS. The procedure quantifies the explained variance by each predictor in a multiple linear regression. We perform this regression sequentially in order to quantify the influence of different predictors on seasonal electricity demand. Monthly electricity demand for the residential sector was obtained from the U.S. Energy Information Administration for the period 2005–2017 [21] and only the seasonal demand during the winter and summer were considered. Data associated with the proposed explanatory variables are described in Sections 2.1–2.4.

2.1. Population

We use state population as a driving factor for the increase in residential electricity demand. A review of electricity demand models by Suganthi and Samuel [22] identifies population as a driving factor to explain the variability of residential electricity demand. Annual population data and housing unit estimates for each county are obtained from the US Census Bureau [23]. Annual data were interpolated linearly to the monthly time scale based on differences between the annual values.

2.2. Population-weighted HDD and CDD

Seasonal climate variabilities are represented by the widely-used metric of heating and cooling degree days (HDD and CDD) [22,24]. The work of Sailor and Munoz [25] compares the application of HDD and CDD in a regression model against the application of temperature and conclude that the former better explains the climate-induced variability in electricity demand. Daily HDD and CDD are defined as the number of degrees the daily average temperature is below and above 65 °F respectively. Monthly heating and cooling degree days are obtained by summing the daily HDD and CDD over all days in the month. Monthly HDD and CDD were obtained for each state from 2005 through 2017 through NOAA's National Climate Data Center [26]. In order to examine the existence of temporal trends in the CDD and HDD data, we performed a Mann-Kendall test on the state-level CDDs and HDDs. First, we calculated the average annual HDD and CDD from the seasonal time series, and then the test was carried out separately for the winter and summer seasons. Across all 48 states, the *p*-values ranged from 0.16 to 1 for winter, and from 0.13 to 1 for summer. These results indicate that there is no long-term trend in the data (p-values > 0.05).

To understand the role of HDD and CDD in explaining the state-level electricity demand variability, monthly state-level HDD and CDD could be obtained by spatially averaging the monthly HDD and CDD by climate division. However, given the role of population in electricity demand, the climate in more highly populated areas is expected to have a larger impact on electricity demand than the climate in less populated areas [27]. Thus, we calculate state-level HDD and CDD using a population weighted average, which

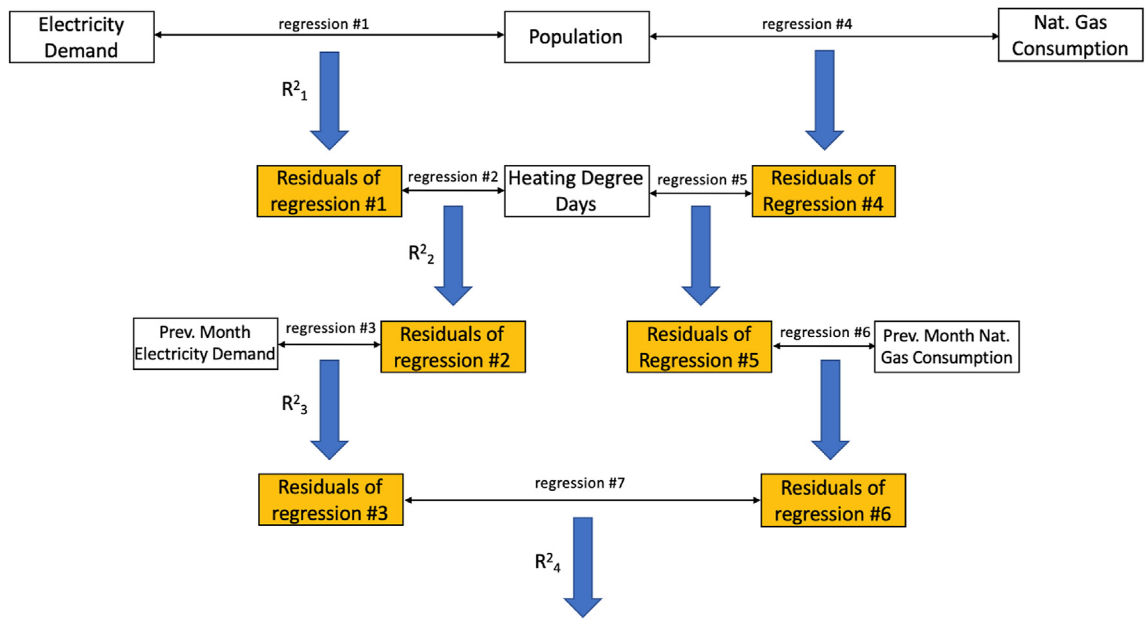

Fig. 1. Schematic diagram illustrating how we quantify variability explained in residential electricity demand by the four explanatory variables for the winter season over the CONUS. The same approach is used to quantify variability for the summer, using CDD instead of HDD.

employs the monthly county population data described above. Given that the county data overlaps with the climate division data, we weighted the HDD and CDD based on the population at the climate division level using Equations (1) and (2).

$$HDD^s_{t,m} = \frac{1}{P^s_{t,m}} \sum_{i=1}^{n_{cd}} P^i_{t,m} \cdot HDD^i_{t,m}, \tag{1}$$

$$CDD^s_{t,m} = \frac{1}{P^s_{t,m}} \sum_{i=1}^{n_{cd}} P^i_{t,m} \cdot CDD^i_{t,m}, \tag{2}$$

where, $P^s_{t,m}$, $HDD^s_{t,m}$ and $CDD^s_{t,m}$ denote the population and state population weighted average HDD and CDD for month m in year t in state 's' with n_{cd} climate divisions and $P^i_{t,m}$, $HDD^i_{t,m}$ and $CDD^i_{t,m}$ denote the population, HDD, and CDD for each climate division within the state, respectively.

2.3. Residential winter natural gas consumption

The space heating market is another structural factor, besides the state population, that affects long-term residential sector electricity demand. This market varies considerably over the CONUS. Over the last decade, natural gas has been the dominant heating fuel in colder areas, and electricity has been used by more homes in milder areas [28]. However, the heating fuel mix by state has changed over time. Since 2005, more houses have been using electricity for space heating at the expense of natural gas, except for the Northeast [3]. We incorporate these long-term changes in the space heating market by adding the monthly state residential winter natural gas consumption as one of the explanatory variables. This data for the period 2005–2017 is drawn from the EIA website [29].

2.4. Electricity demand from the previous month

Similar to the previous studies (e.g. Ref. [18]), we use the previous month's electricity consumption as an additional explanatory variable to capture the monthly persistence in the electricity demand time series. Chronology is an important factor, and we perform the regression with the previous month's demand even if that month belongs to another season. This is the case for December in the winter season and June in the summer season whose previous months are in fall and spring, respectively.

2.5. National analysis of electricity consumption

Our intent is to quantify the interannual variability in electricity demand explained by population, climate, the substitution effect between electricity and natural gas, and the previous month's demand. Recently, Wang et al. [18] developed a hierarchical Bayesian regression model for predicting summer monthly per capita electricity demand. While regression is still central to their analysis, they partitioned the lower 48 states into 8 clusters based on similar historical cooling degree day patterns. The summer season for the states in each cluster is also defined differently according to the duration, start month, and end month and the regression models for individual states in each cluster is related with gross domestic product, electricity price, previous monthly demand, and cooling degree days being the explanatory variables. We take a similar approach by analyzing the variance in seasonal residential electricity demand explained by each explanatory variable using a series of linear regression models (Fig. 1). One could also obtain similar results by using traditional ANOVA techniques. We first quantify the role of population and temperature on electricity demand and natural gas consumption. These regressions provide the variability explained by both population and temperature on winter and summer electricity demand for each state over the CONUS. Then, the resulting residuals (i.e., after regressing with population and temperature) from electricity demand and natural gas consumption are regressed against each other to quantify the role of substituting natural gas with electricity in order to further explain the variation in electricity demand. In the equations below, for ease of exposition, we drop the index s, which denotes the state. We only present the equations for the winter season. The summer season analysis is done in a similar fashion except that the CDD time series is used instead of HDDs. First, we extract the population effect from the electricity demand using Equation (3):

$$ED_t = \alpha_P \times P_t + \beta_P + \varepsilon_t|_P \tag{3}$$

Where P_t is the winter population, ED_t is the winter season electricity demand time series, α_P and β_P are the regression coefficients, and $\varepsilon_t|_P$ is the residual after regressing against population. We define ${R_1}^2$ as the explained variance (i.e., the coefficient of determination in Equation (3)) in electricity demand by population). We then regress $\varepsilon_t|_P$ against the HDDs based on Equation (4) and obtain the explained variance, ${R_2}^2$, by HDDs on electricity demand residuals ($\varepsilon_t|_{P,\ HDD}$):

$$\varepsilon_t|_P = \alpha_{HDD} \times HDD_t + \beta_{HDD} + \varepsilon_t|_{P,\ HDD} \tag{4}$$

where α_{HDD} and β_{HDD} are the regression coefficients and $\varepsilon_t|_{P,\ HDD}$ represents the regression residuals, which represent the unexplained variability in electricity demand by population and HDDs. ${R_2}^2$, is the coefficient of determination from the regression in Equation (4).

Since the regression in Equation (4) is performed using the residual electricity variability conditioned on population, the contribution of HDDs to explaining the variability in electricity demand is given as: ${R_2}^2 \times (1 - {R_1}^2)$. Thus far, the analysis has a total explained variability of electricity demand equal to $[{R_2}^2 \times (1 - {R_1}^2) + {R_1}^2] \times 100$. Next, we consider the role of the previous month's demand and the substitution effect between electricity and natural gas.

In order to capture monthly persistence in the electricity demand time series, we perform regression between $\varepsilon_t|_{P,\ HDD}$ and ED_{t-1}:

$$\varepsilon_t|_{P,\ HDD} = \alpha_{PreMonthELC} \times ED_{t-1} + \beta_{PreMonthELC} + \varepsilon_t|_{P,\ HDD,\ PreMonthELC} \tag{5}$$

Again, $\alpha_{PreMonthELC}$ and $\beta_{PreMonthELC}$ are the regression coefficients, ${R_3}^2$ is the variance explained by the previous month's demand on $\varepsilon_t|_{P,HDD,PreMonthELC}$, which is the regression residual.

The fourth explanatory variable is natural gas consumption in the residential sector. However, since natural gas consumption, just like electricity consumption, is correlated with population and climate conditions, and the previous month's (natural gas) demand, we need to calculate the residuals of natural gas consumption conditioned on population, HDDs, and the previous month's demand, $\nu_t|_{P,HDD,PreMonthNG}$. The steps needed to calculate $\nu_t|_{P,HDD,PreMonthNG}$ are similar to what was done earlier to calculate $\varepsilon_t|_{P,HDD,PreMonthELC}$. Once $\nu_t|_{P,HDD,PreMonthNG}$ is calculated, Equation (6) calculates the substitution effect on electricity demand:

$$\varepsilon_t|_{P,\ HDD,\ PreMonthELC} = \alpha_{ELC-NG} \times \nu_t|_{P,HDD,PreMonthNG} + \beta_{ELC-NG} + \varepsilon_{ELC-NG} \tag{6}$$

where ε_{ELC-NG} is the final unexplained variability in electricity demand, α_{ELC-NG} and β_{ELC-NG} are the regression coefficients and ${R_4}^2$ is the coefficient of determination.

Thus, the total variability explained in the winter season, TV_{winter} due to the four factors can be quantified using Equation (7):

The total explained variance by all four variables in Equation (7) is simply the R^2 of the regression between winter electricity demand against the selected four variables. Since we are interested in quantifying the explained variance by each explanatory variable, we performed the regression sequentially on the residuals obtained in each step. A similar procedure is followed with CDDs to obtain the total variability TV_{summer} explained in the summer. The only difference is that since cooling demand is exclusively met by electricity, we do not consider substitution with natural gas. Results are summarized below on the explained variance by each explanatory variable for both seasons.

Time series data pertaining to the dependent and independent variables were stored in separate.csv files. These files are read into MatLab, where we used the fitlm() function to conduct the linear regressions in the order explained above.

3. Results

Our results indicate that the previous month demand's makes a negligible contribution to explaining the total variability in electricity demand. Therefore, we only present the results pertaining to variability explained by population, climate, and the natural gas substitution effect. Tables S2 and S3, and Figs. S1 and S2 of the Supplementary Information provide the full regression results for the summer and winter seasons with more details.

3.1. Summer season

Fig. 2 shows the amount of variability in electricity demand explained by population and climate for each state in the summer season. Other than Washington and Maine where summers are generally mild, the total explained variability of summer electricity demand across the remaining 46 states is more than 50%. In addition, 42 states out of the 48 states have a total explained variability of more than 70%, as shown in Supplementary Fig. S3.

Fig. 2b generally exhibits greater explanatory power than Fig. 2a and therefore, the largest portion of the household summer electricity demand variation is explained by interannual climate variability. In order to better understand the residential electricity demand-population relationship, in a separate test case (not shown here) we ran the same model with 1990–2005 (rather than 2005–2017) data and we observed that state residential electricity demand was more correlated with the state population. The recent divergence between household electricity demand and population (as indicated by the relatively small numbers in Fig. 2a) can be explained by looking at household electricity consumption intensity trends since 2005. This data is available through a nationwide survey of buildings in selected years [3]. A declining electricity consumption intensity means population growth effects are not translated into electricity demand growth. Fig. 3 shows that the intensity of electricity consumption in American homes increased from 1993 to 2005. This increase is mainly driven by larger home sizes and increased electrification of household energy services [30]. After 2005 however, household electricity consumption intensity has been consistently declining across all nine Census Divisions. While the average square foot per household and

$$TV_{winter} = \Big[{R_1}^2 + {R_2}^2 \times \left(1 - {R_1}^2\right) + {R_3}^2 \times \left(1 - \left({R_1}^2 + {R_2}^2 \times \left(1 - {R_1}^2\right)\right)\right) + {R_4}^2 \times \Big(1 - \Big({R_1}^2 + {R_2}^2 \times \left(1 - {R_1}^2\right) + {R_3}^2 \times \left(1 - \left({R_1}^2 + {R_2}^2 \times \left(1 - {R_1}^2\right)\right)\right)\Big)\Big)\Big] \times 100 \tag{7}$$

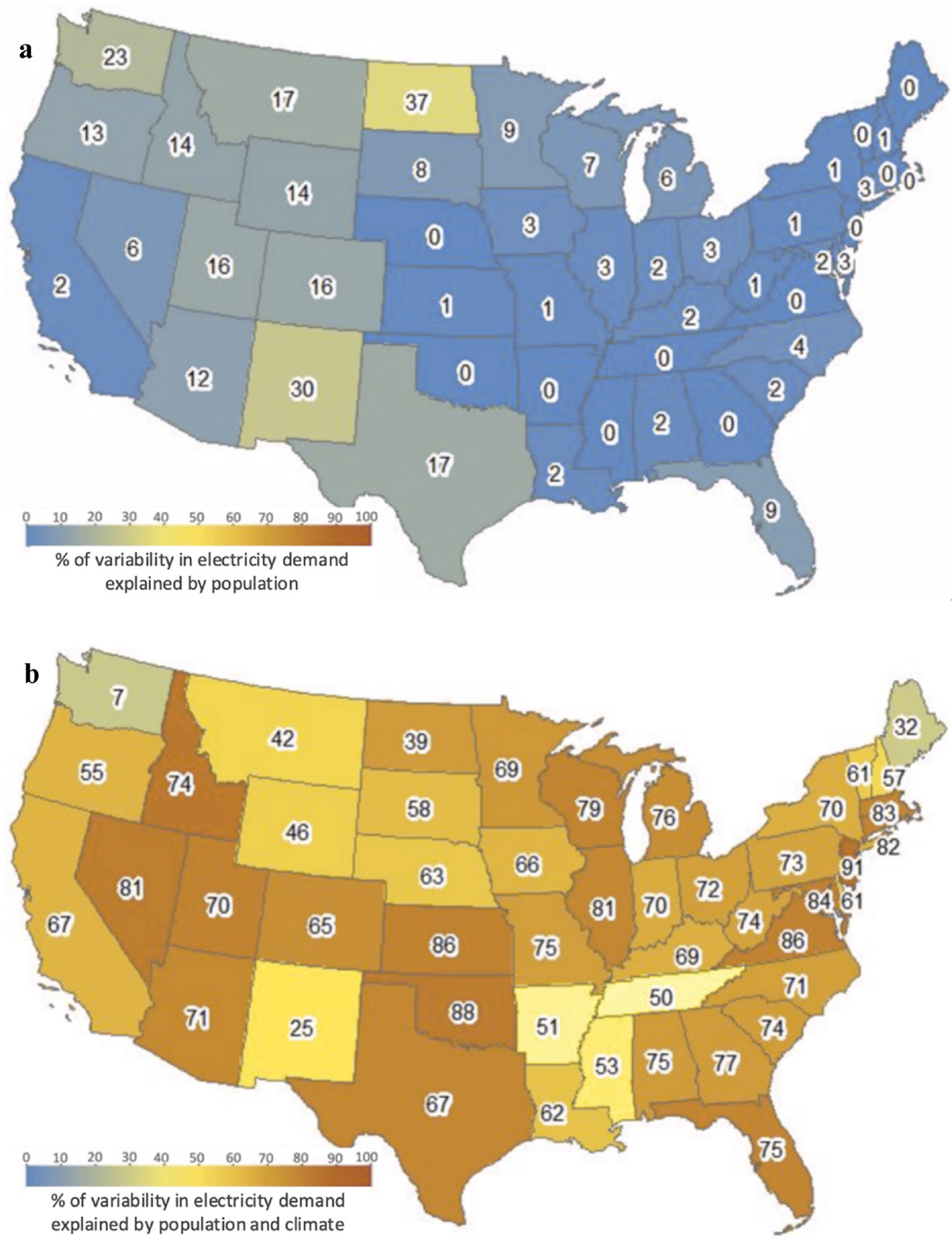

Fig. 2. Variability in residential electricity demand explained by population (a) and climate (b) in the summer season. (a) Both the colors and numbers on the states denote the contribution of population to explaining electricity demand variation in the summer season. Generally, population has greater explanatory power in the western states. (b) Raster colors indicate the cumulative share of population and CDD in explaining total variability of electricity demand in the summer season. Number labels by state indicate the CDD share alone in explaining total variability of electricity demand in the summer season. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

penetration of electric appliances continued to increase from 2005 to 2015 [3], their impact is countered by stricter energy efficiency standards as well as technology improvements at the household level [30]. Fig. S4 in the Supplementary Information visualizes the fitted model against observations in the summer season for four major states: California, Texas, Florida, and New York.

To understand how interannual climate variability modulates electricity demand across the country, we plot the standard deviation of CDD against the interannual variability explained by CDD (i.e., state-level estimates drawn from Fig. 2-b) in Fig. 4. As Fig. 4 shows, even a relatively small variation in CDD can cause a large variation in electricity demand in states such as Florida, Colorado and Louisiana. The main observed pattern is that regardless of states' average temperature, climate-induced variability of household summer electricity demand is correlated with summer climate variability. This pattern is indicated by a 0.3 coefficient of

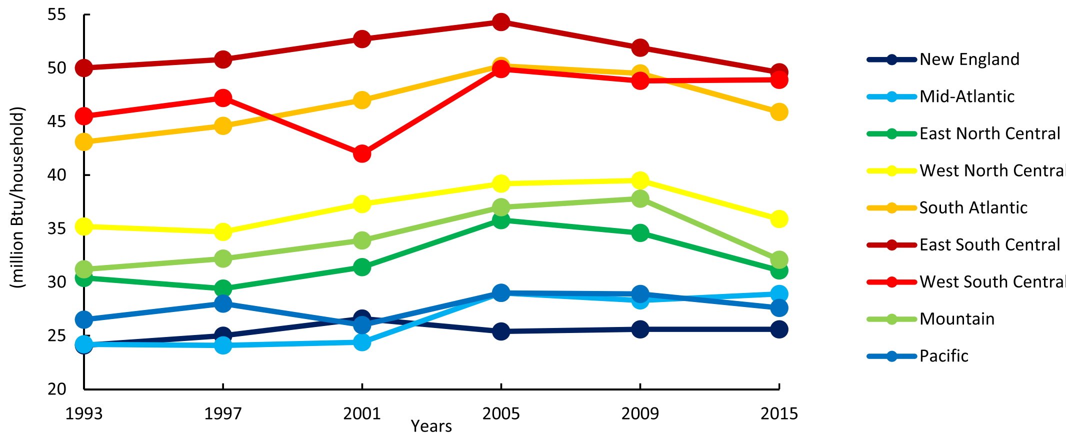

Fig. 3. Household electricity consumption intensities by US Census Division.

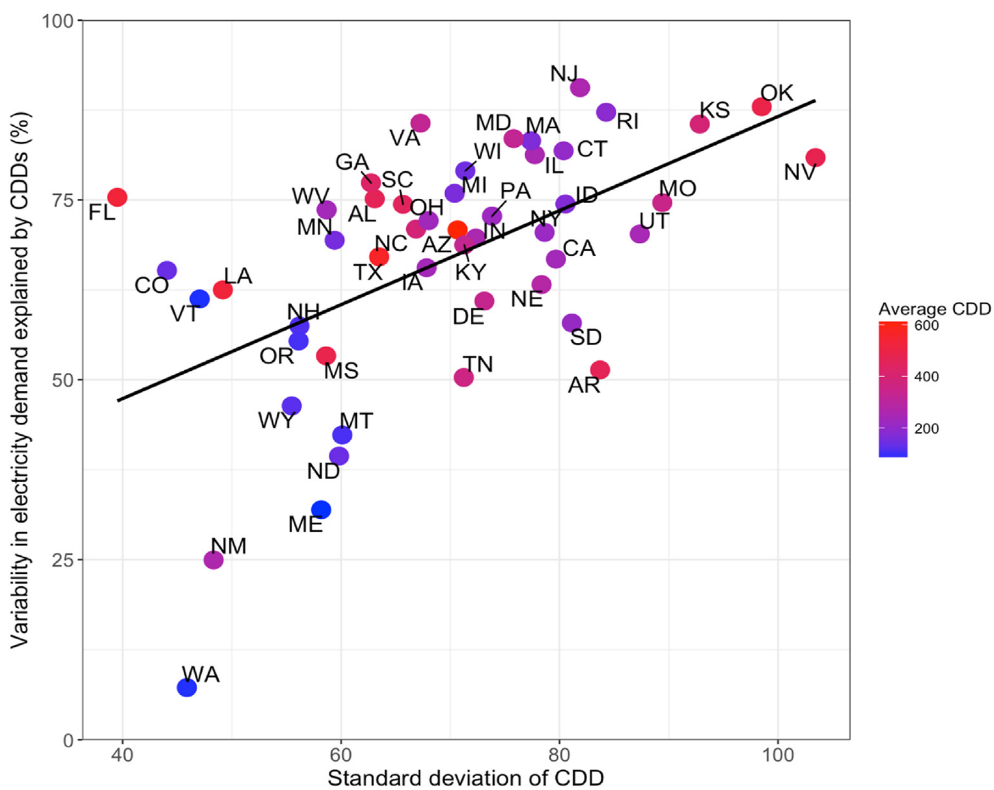

Fig. 4. CDD share in explaining household summer electricity demand variations (as given in Equation (4)) as a function of the standard deviation of CDD for the regression period (2005–2017). Colors indicate the average mean temperature for each state in the summer season. On the vertical axis, only the portion of variability in electricity demand due to climate is plotted. The linear relationship between the two axis is indicated by a 0.3 coefficient of determination, $R^2 = 0.3$. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

determination. Part of the spread around the regression line in Fig. 4 could be due to other state-specific factors, such as humidity and air conditioning penetration levels. The reason for plotting climate-induced demand variability on the vertical axis is that it does not include the effect of other factors, and therefore it isolates the role of climate variability on seasonal load.

3.2. Winter season

Fig. 5 shows the variability in winter electricity demand explained by population and climate, for each state. In winter, similar to summer, only a small portion of interannual variability in electricity demand is due to population alone. The model explains more than 50% of the total variability of winter electricity demand in 42 states, as shown in Supplementary Fig. S3.

The state-specific numbers in Fig. 5b denote the variability in electricity demand explained by HDD alone. Fig. 5b indicates that climate information can explain part of the electricity demand in the upcoming winter season, as the demand variation due to the population is known at the beginning of each season.

Similar to the summer season, we plot climate variability against the climate-induced variability in electricity demand in Fig. 6.

Unlike the summer season where larger climate variations generally translate to larger monthly demand variations, climate-

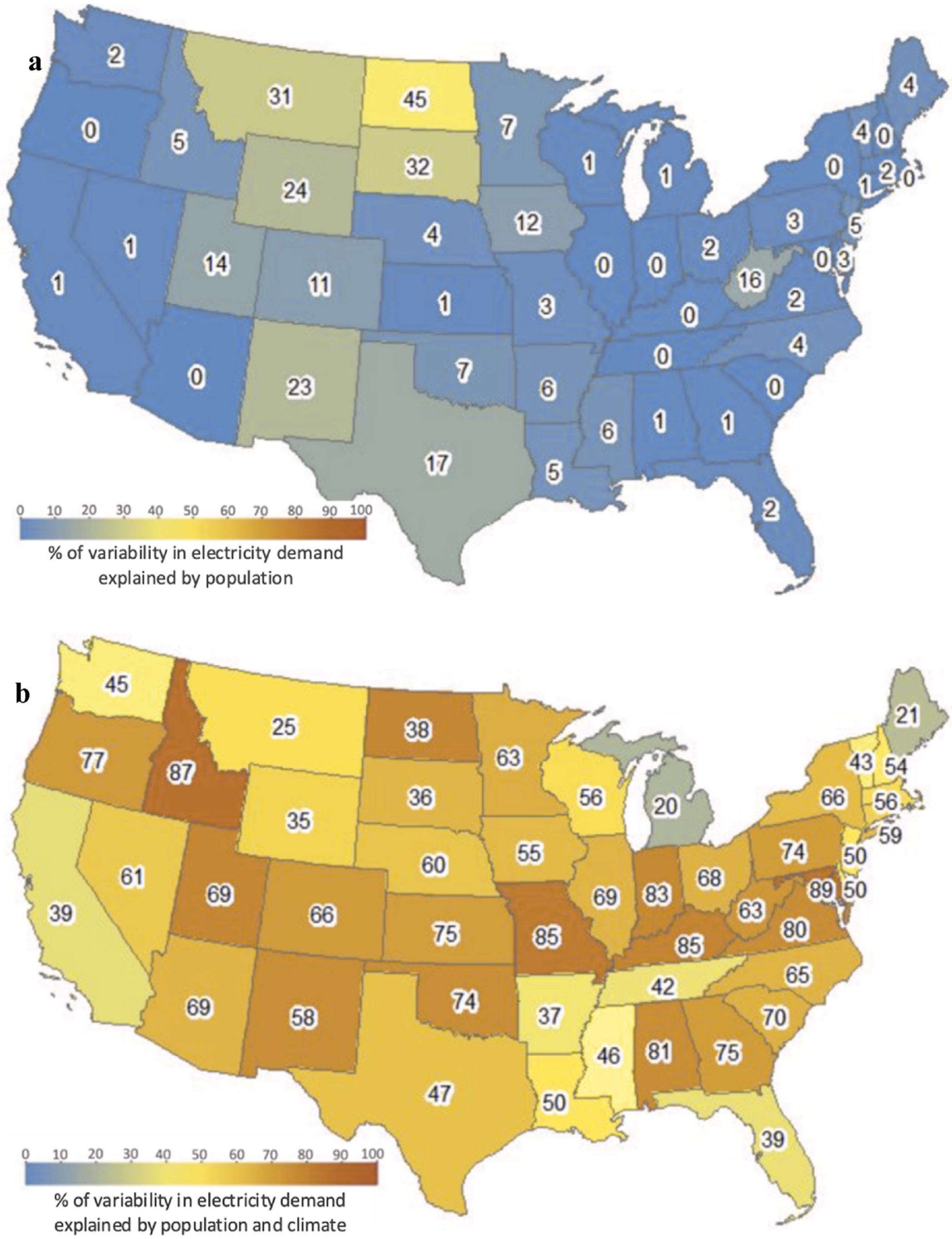

Fig. 5. Variability in residential electricity demand explained by the population (a) and climate (b) in the winter season. (a) Both the colors and numbers on the states denote the contribution of population to explaining electricity demand variation in the winter season. (b) Raster colors indicate the cumulative share of population and HDD in explaining total variability of electricity demand in the winter season. Number labels by state indicate the HDD share alone in explaining total variability of electricity demand in the winter season. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

induced winter electricity demand variability does not appear to be a function of HDD variations. Although we can observe some similarities among the states within the same climate region, large differences in climate-load sensitivities persist even in some neighboring states. This lack of correlation is consistent with the findings of other studies and is the result of a number of factors, including income per capita, choice of heating fuels, housing type, appliance efficiency, building envelopes, other climatic parameters such as humidity, and a host of demographic factors [10]. Among these factors, we speculate that the fraction of heating demand met by electricity could vary significantly, even among neighboring states. In such a case, states with high HDD variability could nonetheless exhibit little variability in electricity demand if other less climate sensitive contributors to winter electricity demand are dominant. Ideally, we could test this hypothesis by isolating the portion of state-level electricity demand used for space heating. Unfortunately, this data is not available at the state-level, but the most recent residential sector energy consumption surveys provide this information for each Census Division [3]; see Supplementary Table S4. We use this Census Division-level data to normalize the

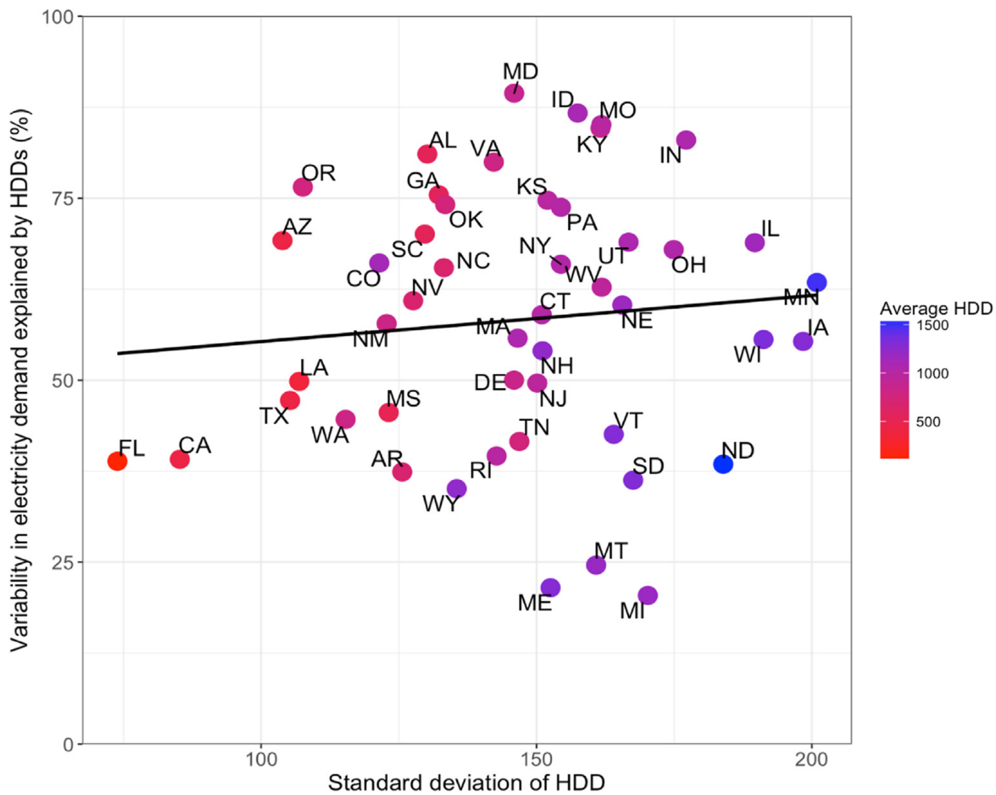

Fig. 6. HDD share in explaining household winter electricity demand variations as a function of the standard deviation of HDD for the regression period (2005–2017). Colors indicate the average mean temperature for each state in the winter season. In this case, the coefficient of determination is negligible, indicating no relationship between the two quantities plotted. $R^2 = 0.01$. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

variability in electricity demand explained by HDDs (the dependent variable in Fig. 6). The result is shown in Fig. 7. The normalized estimates now account for the share of households using electricity for space heating, which in Fig. 7 effectively scales states with less electric heating upward.

As the new coefficient of determination shows, incorporating a measure of states' space heating market helps to better explain seasonal climate-load sensitivity variations by state. However, this scaling is imperfect because it employs the share of household heating met with electricity at the Census Division level, and there are significant variations in electricity used for space heating among some states within the same Census Division.

The substitution effect explains part of the remaining variability in electricity demand (Fig. 8). The state-specific values on the map are higher where substitution of natural gas with electricity (or vice versa) has taken place.

From a national perspective, EIA [3], indicates that electricity has a higher market share, in comparison to natural gas, in meeting household heating needs. In addition, there has been a shift from natural gas to electricity as a heating fuel [3]. Part of this shift is due to population migration further south and west, where the electricity share is increasing, and the natural gas share is declining [3]. The choice of electric heating pumps in the South is a key reason for this substitution with natural gas. This substitution is in contrast to colder parts of the country, particularly the Midwest, where natural gas is still the dominant heating fuel, mainly because the application of heat pumps in very cold climates is more expensive than natural gas furnaces. Nevertheless, even in the Midwest, owing to improvements in electric heat pumps, the electricity share continues to increase [3]. In the Northeast, both electric and natural gas heating shares are increasing at the expense of liquid fuels [3]. To summarize, the ability to explain the variability in winter electricity demand is challenging over the northern states since different fuel types are used for heating. Still, as shown in Figs. 4 and 7, interannual temperature variability explains a significant portion of electricity demand in most states across the CONUS.

With regard to winter electricity demand, no existing US dataset provides space heating demand met by electricity at the state level. As a result, we are not able to isolate the effects of climate on the state-level space heating loads met by electricity. Recent residential energy consumption surveys provide some measure of space heating and cooling, but only at the Census Division level and for select years [3]. This information is more critical for winter than summer because residential cooling demand is met exclusively with electricity, whereas heating demand is met with a wider range of fuel sources. The Energy Information Administration should consider collecting data on state-level heating demand met with electricity, as it would prove valuable in future analyses.

The state-level disparities observed in the winter (Figs. 5 and 8) stem from several factors, such as income levels, choice of heating fuels, housing type, appliance efficiency, and building envelopes. In addition, as discussed in Yang [31]; psychological and behavioral factors are also key to determining thermal comfort zones. Psychological adaption refers to the effects of cognitive, social, and cultural factors in determining human perceptions to thermal comfort, while behavioral adaption, refers to the adjustment of the body temperature balance in order to achieve thermal comfort through actions such as adjusting the physical activity and clothing levels and opening or closing windows and switching on fans [31].

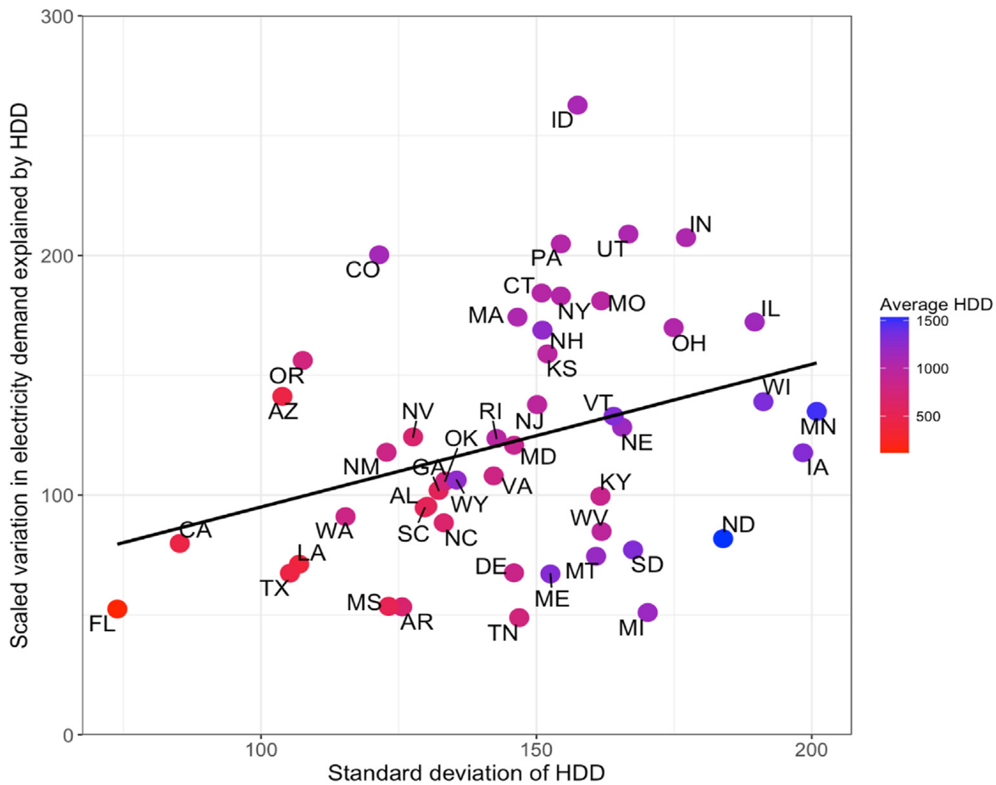

Fig. 7. Winter electricity demand explained by HDD normalized (inflated) by the share of households with electric heating. The household shares are only provided by Census Division, and thus we assigned the same shares to all states in the same Census Division. The coefficient of determination is 0.1, indicating improved explanatory power compared to Fig. 6. $R^2 = 0.105$.

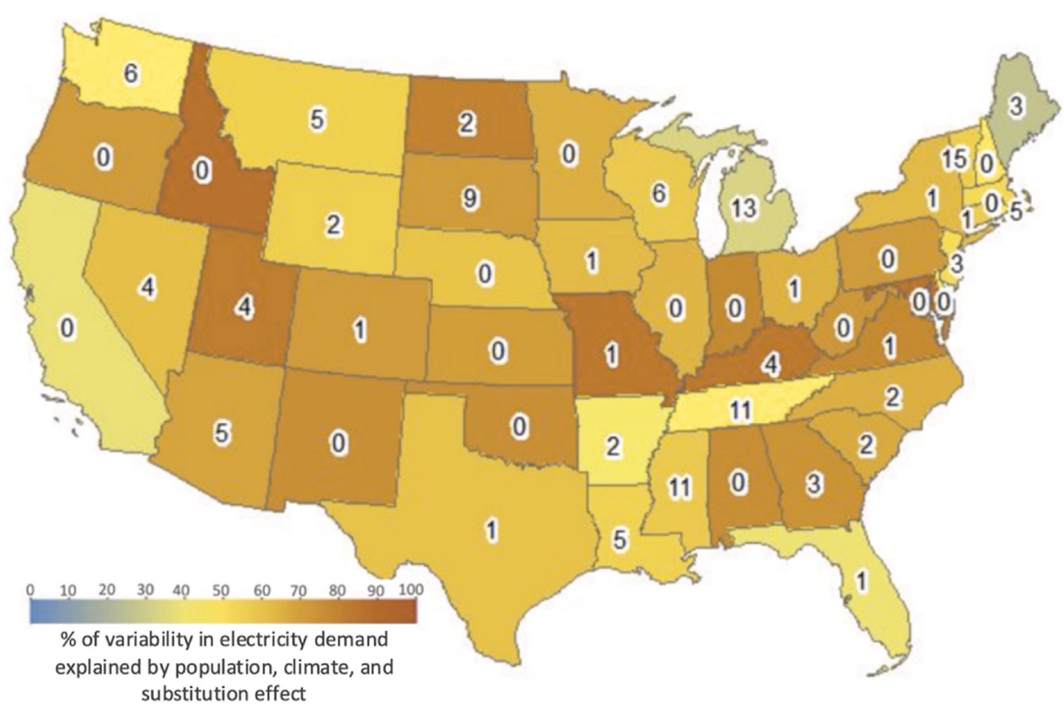

Fig. 8. Role of natural gas substitution in explaining the winter electricity demand variability. Raster colors indicates the cumulative share of population, HDDs and the substitution effect in explaining total variability of winter electricity demand. Numbers in each state indicate the natural gas substitution effect alone in explaining total variability of electricity demand in the winter season. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

4. Discussion and concluding remarks

This study is the first to assess the variation of total seasonal residential electricity demand over the CONUS to population, seasonal climate variation, the substitution of electricity for natural gas, and the month-to-month persistence in electricity demand. These explanatory variables were evaluated sequentially to quantify their incremental contribution to explaining electricity demand variability. Our general observation from the analysis, consistent with Amato et al. [11] and Wang et al. [18]; is that seasonal climate variability plays a crucial role in explaining household electricity demand variations: in 42 states, more than 70% and 50% of demand variability in summer and winter, respectively, is driven by climate. While the ability of climate variability to explain electricity demand is significant, there is substantial spatial variation, especially during winter, across the CONUS. The same level of climate variations in two different states does not necessarily lead to the same demand-side variation in these states.

The methodology presented here can be adopted to better manage electricity demand under a changing energy system. As countries move to reduce greenhouse gas emissions, a key strategy is to decarbonize the electric sector and then electrify many end-use demands. As the share of electricity meeting end-use demands increases under such a scenario, quantifying the role of seasonal climatic variation on seasonal electricity demand will become even more critical. Such seasonal information gleaned from regression models could be used to inform demand-response programs aimed at reducing electricity demand during peak periods and develop contingency measures such as fuel stockpiling for the upcoming season. Future work could extend this analysis to the spring and fall seasons, where the demand variability is likely to be less pronounced. Finally, while this paper is focused exclusively on the residential sector, future work could extend this analysis to include the commercial sector as well, since its electricity consumption is also expected to vary with climatic conditions.

Credit author statement

Hadi Eshraghi: Conceptualization, Methodology, Data collection, Implementation, Original draft preparation. A. Sankarsubramanian, Anderson Rodrigo de Queiroz, and Joseph DeCarolis: Conceptualization, Methodology, Writing- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This material is based upon work supported in whole by the U.S. National Science Foundation under Grant No. CCF-1442909.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2021.121273.

References

[1] EIAa - Energy Information Administration. Monthly energy review. April 2019. available at: https://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf.

[2] EIAb - Energy Information Administration. Annual energy Outlook. 2019. available at: https://www.eia.gov/outlooks/aeo/pdf/aeo2019.pdf.

[3] EIAc - Energy Information Administration. Residential energy consumption survey (RECS). U.S. Department of Energy; 2015.

[4] de Queiroz AR. Stochastic hydro-thermal scheduling optimization: an overview. Renew Sustain Energy Rev 2016 Sep 1;62:382–95. https://doi.org/10.1016/j.rser.2016.04.065.

[5] de Queiroz AR, Mulcahy D, Sankarasubramanian A, Deane JP, Mahinthakumar G, Lu N, DeCarolis JF. Repurposing an energy system optimization model for seasonal power generation planning. Energy 2019 Aug 15;181:1321–30. https://doi.org/10.1016/j.energy.2019.05.126.

[6] Yamin HY. Review on methods of generation scheduling in electric power systems. Elec Power Syst Res 2004 May 1;69(2–3):227–48. https://doi.org/10.1016/j.epsr.2003.10.002.

[7] Bataille C, Waisman H, Colombier M, Segafredo L, Williams J. The deep decarbonization pathways project (DDPP): Insights and emerging issues. https://doi.org/10.1080/14693062.2016.1179620.

[8] The White House. United States mid-century strategy for deep decarbonization. November 2016. http://unfccc.int/files/focus/long-term_strategies/application/pdf/us_mid_century_strategy.pdf.

[9] Tso GK, Yau KK. Predicting electricity energy consumption: a comparison of regression analysis, decision tree and neural networks. Energy 2007 Sep 1;32(9):1761–8. https://doi.org/10.1016/j.energy.2006.11.010.

[10] Sailor DJ. Relating residential and commercial sector electricity loads to climate—evaluating state level sensitivities and vulnerabilities. Energy 2001 Jul 1;26(7):645–57. https://doi.org/10.1016/S0360-5442(01)00023-8.

[11] Amato AD, Ruth M, Kirshen P, Horwitz J. Regional energy demand responses to climate change: methodology and application to the commonwealth of Massachusetts. Climatic Change 2005 Jul 1;71(1–2):175–201. https://doi.org/10.1007/s10584-005-5931-2.

[12] Ruth M, Lin AC. Regional energy demand and adaptations to climate change: methodology and application to the state of Maryland, USA. Energy Pol 2006 Nov 1;34(17):2820–33. https://doi.org/10.1016/j.enpol.2005.04.016.

[13] Lam JC, Tang HL, Li DH. Seasonal variations in residential and commercial sector electricity consumption in Hong Kong. Energy 2008;33(3):513–23.

[14] OrtizBeviá MJ, RuizdeElvira A, Alvarez-García FJ. The influence of meteorological variability on the mid-term evolution of the electricity load. Energy 2014;76:850–6.

[15] Mukherjee S, Nateghi R. Climate sensitivity of end-use electricity consumption in the built environment: an application to the state of Florida, United States. Energy 2017 Jun 1;128:688–700. https://doi.org/10.1016/j.energy.2017.04.034.

[16] Li XX. Linking residential electricity consumption and outdoor climate in a tropical city. Energy 2018;157:734–43.

[17] Alberini A, Prettico G, Shen C, Torriti J. Hot weather and residential hourly electricity demand in Italy. Energy 2019;177:44–56.

[18] Wang S, Sun X, Lall U. A hierarchical Bayesian regression model for predicting summer residential electricity demand across the USA. Energy 2017 Dec 1;140:601–11. https://doi.org/10.1016/j.energy.2017.08.076.

[19] NOAA website: https://www.ncei.noaa.gov/news/meteorological-versus-astronomical-seasons (Accessed on June 15th 2020).

[20] EIAd - U.S. Energy Information Administration, Electric Power Monthly, https://www.eia.gov/todayinenergy/detail.php?id=10211.

[21] EIAe - Energy Information Administration. Electric power sales, revenue, and energy efficiency Form EIA-861 detailed data files. 2018.

[22] Suganthi L, Samuel AA. Energy models for demand forecasting—a review. Renew Sustain Energy Rev 2012 Feb 1;16(2):1223–40. https://doi.org/10.1016/j.rser.2011.08.014.

[23] USCB. Population and housing unit estimates 352. 2018. https://www.census.gov/programs-surveys/popest/data/tables.All.html. [Accessed 15 June 2020].

[24] Ranson M, Morris L, Kats-Rubin A. Climate change and space heating energy demand: a review of the literature. 2014. https://doi.org/10.22004/ag.econ.280923.

[25] Sailor DJ, Muñoz JR. Sensitivity of electricity and natural gas consumption to climate in the USA—methodology and results for eight states. Energy 1997 Oct 1;22(10):987–98. https://doi.org/10.1016/S0360-5442(97)00034-0.

[26] NCDC. National centers for environmental information (formally national climatic data 323 center). found at, http://www.ncdc.noaa.gov/; 2018.

[27] Taylor BL. Population-weighted heating degree-days for Canada. Atmos-Ocean 1981 Sep 1;19(3):261–8. https://doi.org/10.1080/07055900.1981.9649113.

[28] EIAf - Energy Information Administration. Everywhere but Northeast, fewer homes choose natural gas as heating fuel. 2014. https://www.eia.gov/todayinenergy/detail.php?id=18131.

[29] EIAg - Energy Information Administration. Natural gas consumption by end use. 2019. https://www.eia.gov/dnav/ng/ng_cons_sum_a_EPG0_vrs_mmcf_m.htm.

[30] Hojjati B. Drivers of US household energy consumption, 1980-2009. In: Energy & the Economy, 37th IAEE International Conference, June 15-18. International Association for Energy Economics; 2014. 2014 Jun 15.

[31] Yang L, Yan H, Lam JC. Thermal comfort and building energy consumption implications—a review. Appl Energy 2014 Feb 15;115:164–73. https://doi.org/10.1016/j.apenergy.2013.10.062.

[37] Ralston Fonseca F, Craig M, Jaramillo P, Bergés M, Severnini E, Loew A, et al. Effects of climate change on capacity expansion decisions of an electricity generation fleet in the southeast US. Environ Sci Technol 2021;55(4):2522–31. https://doi.org/10.1021/acs.est.0c06547.