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Key Points:

- Data-driven modeling is leveraged to investigate the role of climatic variables on household air conditioning use across the US
- Household demand for air conditioning are projected to increase by up to 13% (range = 11%–15%) under a 2.0-degree warmer world
- Failure to meet this increased demand may lead to prolonged blackouts, with up to 75 million household-days without air conditioning

Supporting Information:

Supporting Information may be found in the online version of this article.

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Implications of Increasing Household Air Conditioning Use Across the United States Under a Warming Climate

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Abstract Soaring temperatures and increased occurrence of heatwaves have drastically increased air-conditioning demand, a trend that will likely continue into the future. Yet, the impact of anthropogenic warming on household air conditioning is largely unaccounted for in the operation and planning of energy grids. Here, by leveraging the state-of-the-art in machine learning and climate model projections, we find substantial increases in future residential air conditioning demand across the U.S.—up to 8% with a range of 5%–8.5% (13% with a range of 11%–15%) after anthropogenic warming of 1.5°C (2.0°C) in global mean temperature. To offset this climate-induced demand, an increase in the efficiency of air conditioners by as much as 8% (±4.5%) compared to current levels is needed; without this daunting technological effort, we estimate that some states will face supply inadequacies of up to 75 million "household-days" (i.e., nearly half a month per average current household) without air conditioning in a 2.0°C warmer world. In the absence of effective climate mitigation and technological adaptation strategies, the U.S. will face substantial increases in air conditioning demand and, in the event of supply inadequacies, there is increased risk of leaving millions without access to space cooling during extreme temperatures.

Plain Language Summary Climate change is leading to increased temperatures around the world. As temperatures rise, the demand for air conditioning increases accordingly, as people strive to keep cool. While the general pattern of projected changes is intuitive (i.e., higher temperatures lead to increased air conditioning use), the specific changes that will be experienced by households is not well understood. Here, we utilize a machine learning model to project changes to household-level air conditioning demand over the contiguous United States. Our results show significant increases to air conditioning demand in projected warming world of 1.5 and 2.0°C levels above pre-industrial ones. In particular, households are projected to experience 8% more air conditioning after surpassing the 1.5°C threshold and up to 13% more after the 2.0°C threshold, when compared to the baseline (2005–2019). We then discuss the implications of these projected changes on possible increase in air conditioner efficiency that would effectively counteract climate-induced increases. In the event that these climate-induced changes are not accounted for, we find that, in some states, the average household could face up to 14 days without air conditioning in a given summer in the 2.0°C warmer world. This will disproportionately impact marginalized communities that are especially vulnerable to heat-related disasters and subsequent health impacts.

1. Introduction

Globally, the electric power system is increasingly stressed, witnessing higher demand and reduced capacity due to more frequent occurrence of extreme weather events under climate change (International Energy Agency, 2018; van Vliet et al., 2012; Yalew et al., 2020). The recent major blackouts in various parts of the United States, including California and Texas, are stark reminders of the high societal costs of not accounting for the climate-induced demand increase (Fuller, 2020; Penn, 2021). In the absence of more proactive approaches towards anticipating demand shifts under climate change, frequent rolling blackouts could become the new norm, leaving millions of households without access to electricity and other electricity-dependent essential services

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such as water, sanitation, mobility, and communication, with significant public health implications (Mukherjee & Nateghi, 2019; van Vliet et al., 2012; Yalew et al., 2020).

Since the majority of the U.S. states are summer-peaking (i.e., the highest peak loads are observed during the summer), characterizing the climate-sensitivity of summer-time electricity demand has become an important pillar in energy adequacy planning (Maia-Silva et al., 2020). Within the residential sector, which is the most heterogeneous segment of the energy sector (Mukherjee & Nateghi, 2017, 2019), air conditioning represents a significant portion of the summer electricity use (Randazzo et al., 2020; US Energy Information Administration, 2018a). Given that over 90% of the U.S. households have air conditioning (US Energy Information Administration, 2018b), the main driver of increased summer-time electricity use within the United States will be climate change (Mukherjee & Nateghi, 2019; Mukherjee et al., 2019; Raymond et al., 2019). While the global demand for cooling is projected to reach a three-fold increase by 2050, better characterizing and addressing the unprecedented increase in cooling demand are often skirted in the sustainability debates (Khosla et al., 2020).

Climate change will result in higher temperatures as well as increased likelihood of extreme heatwaves (Dosio et al., 2018; McGregor et al., 2015), both of which will lead to higher demand for air conditioning (International Energy Agency, 2018). Within the international governance on climate change, there is a focus on limiting warming to 1.5°C or 2.0°C above pre-industrial levels (Intergovernemental Panel on Climate Change, 2018; UNFCC, 2015). A few recent studies have looked into the impact of missing these warming targets in the energy sectors, particularly from the demand-side (Auffhammer et al., 2017; Schaeffer et al., 2012; Yalew et al., 2020; Zhou et al., 2014). Most studies, however, often focus on the energy sector as a whole (Auffhammer et al., 2017; Maia-Silva et al., 2020; Mukhopadhyay & Nateghi, 2017) or consider only a single state (Alipour et al., 2019; Amato et al., 2005; Raymond et al., 2019).

Here, we provide a large-scale assessment and prediction of *household-level* air conditioning use under climate change scenarios across the contiguous United States. This is the first study, to our knowledge, that leverages publicly available datasets to evaluate and predict air conditioning use at the household level under future climate change scenarios, while also adopting a large spatial extent. Moreover, while previous work has focused on annual electricity consumption (Deschênes & Greenstone, 2011) or daily peak load (Auffhammer et al., 2017; Franco & Sanstad, 2008; Kumar et al., 2020; Wenz et al., 2017), the present study focuses on the summer-time air conditioning use as a whole. Finally, we provide information on the shifts in air conditioning demand after two key warming thresholds-1.5 and 2.0°C above pre-industrial levels. The focus on warming thresholds situates the study within the ongoing international discussions on climate change mitigation (Intergovernemental Panel on Climate Change, 2013, 2018), while also presenting high resolution results that are applicable at local levels.

The article is organized as follows. First, we provide an in-depth discussion of the related literature in Section 2. In Sections 3 and 4, we discuss the data and methodology used in this study. Then, in Section 5, we delve into the results and discussion, focusing on the model performance in the observational space, the model projections into the future, and various implications of those projections, including potential changes to air conditioner efficiency and impacts of extreme, unmitigated heat stress. Finally, we conclude the study in Section 6.

2. Background Information Related to Impact of Climate Change on Electricity Consumption

There have been a number of studies focused on the climate sensitivity of electricity use, particularly as it pertains to rising temperatures and air conditioning demand. However, there are a number of gaps that still remain.

One such gap relates to the spatial scale of the study areas considered in the previous research. In particular, a number of studies focus on aggregated study areas, such as cities, states, or even entire countries. For example, Sailor and Pavlova (2003) investigated the impact of climate change on air conditioning demand at the city scale. In particular, the authors considered 12 cities across four U.S. states (Sailor & Muñoz, 1997). Other studies have considered impact of climate change on aggregated energy demands at state-level. Amato et al. (2005) focused on the state of Massachusetts, while Ruth and Lin (2006) evaluated climate impacts on energy demand within the state of Maryland. In a few recent studies, Mukherjee and Nateghi predicted the climate-sensitive portion of the residential and commercial electricity demand for the state of Florida (Mukherjee & Nateghi, 2017), as well as Ohio (Mukherjee & Nateghi, 2019). Similarly, Alipour et al. (2019) focused on the state of Texas. Going beyond

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a single state, Mukherjee et al. (2019) investigated the climate-demand nexus for the residential and commercial electricity sectors across the top eight energy-intensive states in the U.S. Finally, Mirasgedis et al. (2007) projected the electricity demand under climate change across the entire country of Greece. Overall, these studies focus on large-scale areas with aggregated electricity demand data. However, there is a need to evaluate and predict changes at higher resolutions, such as the household-level demand.

There are a few studies that emphasize household-level end-use energy demand changes, as household data can be difficult to obtain and is rarely publicly available. In cases where household-level end-use demand data can be obtained, the scale of the study is generally limited to a small geographic area. For example, Lam (1998) assessed changes to household-level air conditioning use across Hong Kong. In a slightly larger study, Auffhammer and Aroonruengsawat (2011) projected climate-induced changes to household electricity consumption within the state of California. Likewise, Nateghi and Mukherjee (2017) focused on households across the U.S. state of Indiana. These studies demonstrate the importance of conducting household-level studies, but there still remains a need to perform such studies at larger spatial extents.

Another gap within the literature relates to the temporal scale of the studies. Several studies, for example, have focused on the climate impacts to annual electricity consumption. Deschênes and Greenstone (2011), for instance, evaluated the relationship between daily temperatures and annual residential electricity consumption, which they then used to make projections under climate change scenarios. Other studies have considered daily time scales. Franco and Sanstad (2008) considered the relationship between temperature and daily peak electricity load to make future projections for locations within California. Similarly, Auffhammer et al. (2017) simulated the impacts of climate change on total daily electricity consumption, as well as daily peak load. On a broader scale, Wenz et al. (2017) found significant increases to daily electricity consumption (total and peak) across European countries. Finally, Kumar et al. (2020) evaluated the impact of climate change on summer peak load across California. While peak load is a critical metric for managing the electric grid, understanding the climate change impacts at a larger time scale might be more beneficial for long-term planning. However, there is a lack of studies that evaluate changes at seasonal time scales. Evaluating electricity consumption at seasonal time scales is also beneficial for isolating specific end uses. For example, utilities interested in understanding changes in electricity consumed for heating will be primarily interested in the winter season. In this example, a study modeling annual peak load or even total load will not be as helpful as a seasonal study. Similarly, we focus on the summer season, as it is the peak period for air conditioning use within the United States. In addition to the summer season acting as the primary period of air conditioning use, it is also the season with the highest inadequacy risk, which may lead to cascading power outages in the absence of adequate operational planning (Mukherjee & Nateghi, 2019). Therefore, it especially important to understand the future changes to the system during the summer.

In addition, there is a significant variability in the focus of the studies related to climate change and electricity demand, mostly in terms of the types of end-use and/or end-users that are being analyzed. Some studies focus on specific end-uses or users, while other studies focus on various electricity sectors. For example, Zhou et al. (2014) present a study on the impact of climate change on building energy consumption across the U.S. On the other hand, Mukherjee and Nateghi (2017) evaluate the climate sensitivity of the residential and commercial sectors, while Maia-Silva et al. (2020) focus solely on the residential sector. Finally, a recent study by Yalew et al. (2020) assessed the impact of climate change on the energy sector as a whole. Given that the residential sector has been shown to be the most sensitive to changes in climate (Mukherjee & Nateghi, 2017; Mukherjee et al., 2019; Obringer, Mukherjee, & Nateghi, 2020), the present study focuses on the residential sector, as well as the specific end-use of air conditioning.

Another gap that exists in the literature is related to adequate modeling of the complex, nonlinear relationships between energy demand and climate change. The majority of the studies in literature have leveraged parametric, linear models while modeling the climate sensitivity of electricity consumption. For example, Amato et al. (2005) used linear regression to quantify the relationship between climate and electricity consumption. Similarly, Mirasgedis et al. (2007) implemented a series of multiple linear regression models to determine the impact of climate change on electricity consumption in Greece. To model the shifts in peak load under climate climate, Auffhammer et al. (2017) also leveraged multiple linear regression. However, recent work has found that the relationship between the climate and electricity demand is nonlinear, and is best represented by more complex, non-parametric models (Alipour et al., 2019; Mukherjee & Nateghi, 2017; Mukherjee et al., 2019). Here, we build off previous work to implement a state-of-the-art machine learning algorithm to model the impact of climate change on household air conditioning demand. To the best of our knowledge, this is the first time that machine learning algorithms are being leveraged to predict the household-level air conditioning demand under climate change scenarios for the contiguous United States.

To summarize, there have been a number of studies relating climate change to electricity demand. However, these studies often rely on aggregated data at state or regional levels, as well as focus on daily or annual time steps. Moreover, many studies focus on various sectors of the energy system, rather than specific end-uses. Additionally, most of the previous studies assume that the relationship between electricity demand and climate is linear, which often times does not hold good. This may lead to gross underestimation of the predicted demand. Therefore, this study seeks to fill these gaps by (a) focusing on the most climate-sensitive end user, that is, residential households, (b) considering the entire contiguous United States, (c) emphasizing changes based on the summer season, rather than daily or annual, (d) evaluating and predicting changes specifically in air conditioning as an end-use, rather than a whole sector, and (e) most importantly, accounting for the nonlinearities in climate and electricity demand relationships by modeling the nexus using a non-parametric Bayesian learning algorithm.

3. Data Collection, Pre-Processing and Aggregation

In this study, three main types of data were collected: (a) electricity consumption data; (b) observational climate data; and (c) projected climate data.

3.1. Electricity Consumption Data

The electricity consumption data collected for this study were of two types: (a) domain-level residential electricity consumption data; and (b) household-level residential electricity consumption data.

The domain-level residential electricity consumption data was collected from the U.S. Energy Information Administration (EIA). In particular, state-level residential energy consumption data was obtained from the EIA-861M form (US Energy Information Administration, 2019). The electricity sales data across the U.S. was considered as the response variable for the initial analysis. The data was collected on a monthly basis from 2005 to 2019; however, only the summer months (June–September) were used in the final analysis.

Data on household-level electricity consumption for air conditioning was collected at the household-level from the 2009 Residential Energy Consumption Survey (RECS) (US Energy Information Administration, 2018d). This data set contains granular data on a "statistically representative" sample of households based on demographics within each state across the U.S., with the exception of a few states, which are grouped together to form domains. In these cases, the domains are made up of states that are lower in population with similar energy demand patterns. For example, the states of Indiana and Ohio are grouped together to form one domain within the RECS data set. Since the RECS data is aggregated into domains, the total electricity consumption data was aggregated to match the domains. It is important to note that while the EIA has recently published data from the 2015 RECS survey, the sample size was significantly smaller in 2015 when compared to 2009 (US Energy Information Administration, 2018c). The smaller sample size not only resulted in higher standard errors, but also was drawn from different sampling units than previous studies (US Energy Information Administration, 2018c). In order to minimize standard errors in the data, as well as ensure a large spatial extent (i.e., the contiguous United States), we decided to use the 2009 survey. We considered all 27 domains in the 2009 survey, which are listed in Table S1 in Supporting Information S1.

3.2. Observational Climate Data

The observed climate data was collected from the North American Regional Reanalysis (NARR) (Mesinger et al., 2006), which served as the predictor climate variables in the study. In particular, we considered seven key climate indicators: air temperature (TAS), dew point temperature (TDEW), wet bulb temperature (WBA or T_w), simplified wet bulb global temperature (sWBGT), discomfort index (DI), heat index (HIA), and humidity index (Humidex), which have been shown to influence summer electricity demand (Maia-Silva et al., 2020). All of the included variables, with the exception of air temperature, consider the joint impacts of temperature and humidity. Details regarding these measures and their calculations can be found in Buzan et al. (2015) and Maia-Silva et al. (2020).

3.3. Projected Climate Data

The projected climate data were collected from five CMIP5 general circulation models (GCMs): the Geophysical Fluid Dynamics Laboratory - Earth Systems Model (GFDL-ESM2M), the Hadley Centre Global Environment Model (HadGEM2-ES), the Institut Pierre Simon Laplace Model (IPSL-CM5A-LR), the Model for Interdisciplinary Research on Climate - Earth Systems Model (MIROC-ESM-CHEM), and the Norwegian Earth System Model (NorESM1-M). These models were carefully selected after a large community wide study—the Inter-Sectoral Impact Model Intercomparison Project (Warszawski et al., 2014). These five models have been shown to cover the majority of the uncertainty range present across the entire suite of CMIP5 models (McSweeney & Jones 2016; Samaniego et al., 2018). This allows for a more efficient modeling process without significant loss of variation in key climate variables. Additionally, using these five models increases the cross-sector comparability of our results, as these models have been used in a number of studies across different regions and sectors (see Jacob et al. (2018), Samaniego et al. (2018), and Obringer, Kumar, and Nateghi (2020) for examples). The projection data from the RCP 8.5 emission scenario was included in this study. This scenario represents a projection of 8.5 Wm^{-2} in end-of-century radiative forcing and corresponds to the highest projected warming. This scenario is often labeled as the worst case scenario, which will result from unchecked emissions and unmitigated warming. The results presented in this text, therefore, represent the possible future in which there is no large-scale climate action and warming is allowed to continue unmitigated. It should be noted, however, that although this is the worst case scenario, it is not entirely unrealistic. Thus, the results can be interpreted as a potential future and used to build a case for limiting warming and reducing emissions. The climate data were obtained from the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) (Warszawski et al., 2014), which has been used in several climate impact studies, including the recent reports of the Intergovernmental Panel on Climate Change (IPCC) (Intergovernemental Panel on Climate Change, 2013, 2018). The data, which included the seven climate variables considered in this study, was extracted for each domain at a monthly time scale.

3.4. Response Variable Pre-Processing

In order to isolate the climate-sensitive portion of the electricity demand, we implemented a trend adjustment process to limit the impact of non-climatic factors, such as technological advancements or demographic shifts on the energy consumption data (Sailor & Muñoz, 1997). The trend adjustment process consists of calculating an adjustment factor for each year in the study, then dividing the monthly electricity use by the adjustment factor. This method has been used in a number of previous studies that focused on evaluating the impact of climate change on the energy sector (Alipour et al., 2019; Mukherjee & Nateghi, 2017, 2019; Obringer et al., 2019; Obringer, Mukherjee, & Nateghi, 2020). This method effectively removes the trends associated with changing technology and socioeconomic conditions, allowing us to focus on predicting the climate-sensitive portion of the demand. More information on this method can be found in the Supporting Information S1.

To obtain household-level estimates of air conditioning, we used the RECS data provided by EIA, as discussed in Section 3.1. The households in this data set are considered to be "representative". A representative sample in a given domain refers to the fact that the sample population is representative of the actual population within each domain (US Energy Information Administration, 2018d). In other words, as part of the RECS methodology, EIA surveyed a representative sample of households to determine various end-uses of electricity, including air conditioning. In the 2009 survey, this representative sample included 12,083 households across the country (US Energy Information Administration, 2018d). In this study, we used this empirical sample to generate larger sampling distributions, a process which is discussed in greater detail in the Methods section. These sampling distributions were ultimately used to obtain the average amount of electricity used for air conditioning at a household level across the 27 RECS domains.

3.5. Predictor Variables Pre-Processing

Similar to the electricity data, the climate observations were collected on a daily basis from 2005 to 2019 and aggregated to match the temporal and spatial scales of the electricity data. In the temporal dimension, daily data were averaged to get monthly means of the aforementioned climatic variables. This was performed for both the observational data from NARR and the projected data from the CMIP5 models. Spatially, the data were initially

Table 1
Variables Included in Final Data Set

Type	Name	Units	Source
Response	Monthly Household Air Conditioning Consumption	kWh	EIA
Predictor	Air Temperature (TAS)	°C	NARR
	Dew Point Temperature (TDEW)	°C	NARR
	Wet Bulb Temperature (WBA)	°C	NARR
	Simplified Wet Bulb Global Temperature (sWBGT)	°C	NARR
	Discomfort Index (DI)	—	NARR
	Heat Index (HIA)	—	NARR
	Humidity Index (HUMIDEX)	—	NARR

Note. The variables used in the projection analysis were the same, but were obtained from the CMIP5 database, rather than the observational NARR database.

obtained as 32 km (NARR) and 0.5° (CMIP5) grid-level datasets, then averaged to obtain mean values over each domain.

3.6. Final Data Set

Through the processes discussed above, our final data set included several variables. There is the response variable—electricity consumption, which underwent the trend adjustment process (Section 3.4), as well as the predictors, which are the various climate variables and indices. These predictor variables were aggregated to match the spatial and temporal scale of the electricity consumption data (Section 3.5) and were obtained in both the observational and future spaces. It is important to note the difference between these two spaces, as the observational data was first used to train the model (Section 4.1), while the future data was used within the projection analysis (Section 4.2). The variables are summarized in Table 1.

4. Methodology

This study leverages a data-driven technique to first predict household air conditioning use, then project the future demand under climate change scenarios. In particular, the modeling framework proposed in this study consists of three main steps: (a) data collection, aggregation and preprocessing; (b) model development, including model training and testing; and, (c) model projections. These steps are depicted in Figure 1. The first step—data collection, preprocessing and aggregation—has been described in Section 3. In the second step—model development (discussed in Section 4.1)—the proposed algorithm Bayesian Additive Regression Trees (BART) was applied within a cross validation loop. Finally, in the third step—model projections—climate projection analysis (discussed in Section 4.2) and the efficiency assessment of air conditioners (discussed in Section 4.3) were conducted. This framework is generalized enough that can be applied to any study region, contingent on the availability of data.

4.1. Model Development

The model development performed in this study is based on a state-of-the-art statistical learning algorithm, known as BART (Chipman et al., 2010). Statistical learning theory encompasses a wide variety of algorithms used to either predict certain outcomes or discern patterns in the data (Hastie et al., 2009). In this study, the BART algorithm is used to predict the household-level cooling load across the United States because it has been found to best capture the nonlinear relationships between the energy demand and climate, and has been used by a number of studies focused on predicting energy use (Alipour et al., 2019; Mukhopadhyay & Nateghi, 2017; Raymond et al., 2019). However, this is the first study, to our knowledge, that employs this algorithm to project household-level energy use into the future, under climate change scenarios. Below we discuss the algorithm in greater depth, as well as the cross validation scheme used to test the model performance.

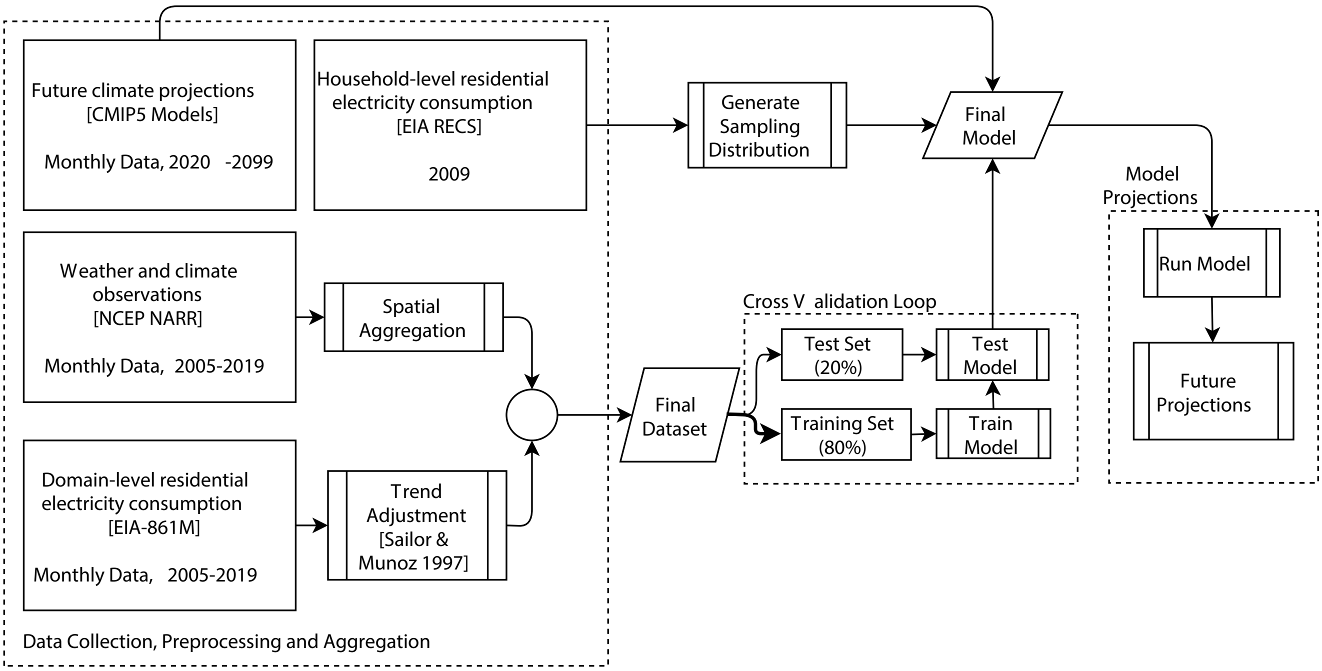

Figure 1. Model framework used to project household-level air conditioning demand across the United States.

4.1.1. Bayesian Additive Regression Trees: Algorithm Specification

In the model development stage, state-level electricity consumption data obtained from the EIA (US Energy Information Administration, 2019) and monthly climate data collected from the North American Regional Reanalysis (Mesinger et al., 2006) were used to develop a predictive model based on the BART algorithm (Chipman et al., 2010). The model was developed for the entire year and the electricity demand for the summer months were extracted later, based on the study scope. The BART algorithm is a sum-of-trees model that aggregates many trees to build a predictive model (Chipman et al., 2010). The algorithm is represented mathematically in Equation 1.

$$Y = \sum_{j=1}^{m} g(X; T_j, M_j) + \epsilon \tag{1}$$

here, $g(X; T_j, M_j)$ is a function that assigns the parameter M of tree T to the predictor variable array X across all m trees. ϵ represents the irreducible error of the model ($\epsilon \sim (N, \sigma^2)$) (Hastie et al., 2009).

4.1.2. Cross Validation

To evaluate the generalization performance of the model, a 5-fold cross-validation technique was implemented. In this technique, 20% of the data is withheld from training the model and used later to test predictive accuracy of the model, while the remaining 80% of the data is used for training the model (Hastie et al., 2009). This process is iterative, in that each iteration uses a different 20% of the data as a test set. Ultimately, this process helps balancing the bias-variance trade-off that is common to evaluate the generalization performance of the statistical learning models (Hastie et al., 2009). We applied the cross-validation scheme once over each domain. In other words, data from each domain was split into fifths, with each fifth being used as a test set once during the model run.

4.1.3. Downscaling Projected Domain-Specific Electricity Consumption to Statistically Representative Households

To downscale aggregate loads and extract household-level cooling demand, we generated sampling distributions of air conditioning use for statistically representative households in each domain. This was done by using the EIA RECS data set, which provides data from a representative sample of households across 27 domains in the contiguous United States (US Energy Information Administration, 2018d). In particular, the RECS data set contains information on the fraction of electricity that is used for space-cooling within a statistically representative household. To generate a sampling distribution, we used the generalization of the central limit theorem (Gnedenko & Kolmogorov, 1954; Voit, 2005) as the basis for fitting the empirical demand data to a normal distribution. Then, using the parameters of this fitted normal distribution, we generated a large sample distribution ($n = 1{,}000$). This generated sampling distribution was then multiplied by the aggregate electricity demand in a region to get an estimate of the household-level demand. Additional details on this process can be found in the Supporting Information S1. It is important to note that this methodology assumes there will be no significant changes to energy consumption, such as technological advances or behavioral shifts. It is important to clarify, therefore, that the results presented in this study will demonstrate the future energy demand, should everything remain the same except the climate. This method has been successfully used in previous studies aimed to project the household-level cooling and heating demand in a region (Nateghi & Mukherjee, 2017; Raymond et al., 2019).

4.2. Climate Projection Analysis

The goal of the projection analysis was to estimate the future change in electricity demand for air conditioning during the summer months due to a warming climate. The analysis was performed by following a methodology laid out in a series of studies in the domain of climate change impact on electricity demand (Maia-Silva et al., 2020; Obringer, Kumar, & Nateghi, 2020), as well as the global recommendations set forth by the IPCC (Intergovernemental Panel on Climate Change, 2018). In this study, two temperature thresholds were selected: 1.5°C and 2.0°C above pre-industrial levels. Then, based on the historical reference period (1971–2000), the corresponding 30-year period when these thresholds will be reached was identified (James et al., 2017). Specifically, the global temperature was calculated for each GCM as a 30-year running mean. Then, by comparing those 30-year means to the reference period (1971–2000), the time periods corresponding to the temperature thresholds (1.5 and 2.0°C above pre-industrial levels) were selected as our future periods. The future climate variables were then extracted from each GCM within the future periods to represent the climatic conditions in a 1.5 and 2.0°C warmer world. Notably, this approach has been used by several recent climate change impact assessment studies (Jacob et al., 2018; Obringer, Kumar, & Nateghi, 2020; Samaniego et al., 2018). In this study, the 30-year periods were identified for five GCMs, however, only the last 15 years of each period were considered for the projection analysis. This selection was made to ensure the future periods did not overlap with the baseline period (2005–2019). In other words, there are a few GCMs that predicted the 1.5°C threshold would be surpassed before 2020, which would lead to a projection analysis that overlapped with the baseline. Selecting the last 15 years of each period, allowed us to avoid this situation. Additional details on this process can be found in the Supporting Information S1.

4.3. Efficiency Calculation

In addition to the projection analysis, we evaluated the hypothetical changes to air conditioner efficiency that would be needed to counteract the increases due to climate change. The efficiency was calculated using a method developed by McNeil and Letschert (2008). The first step was to calculate the consumption (in kWh) of an average air conditioning unit (unit energy consumption; UEC) in each domain. This calculation (Equation 2) is based on income and cooling degree-days (CDD). The CDD data were obtained from the RECS data set for each domain (US Energy Information Administration, 2018d).

$$UEC = 0.345 \times income + 1.44 \times CDD - 823 \tag{2}$$

Here, income is considered to be the state gross domestic product (GSP) adjusted for the cost of living. Using the UEC, the baseline efficiency was calculated using Equation 3, where the demand is the electricity used for air conditioning by the statistically representative household in each domain.

$$efficiency = \frac{demand}{UEC} \tag{3}$$

We then calculated the future efficiency that would be needed to maintain the current UEC, as shown in Equation 4. The difference between the two values (baseline and future efficiency) was considered to be the amount of efficiency improvements needed to counteract the increase in electricity consumption for air conditioning.

$$efficiency_f = \frac{demand_f}{UEC_c} \tag{4}$$

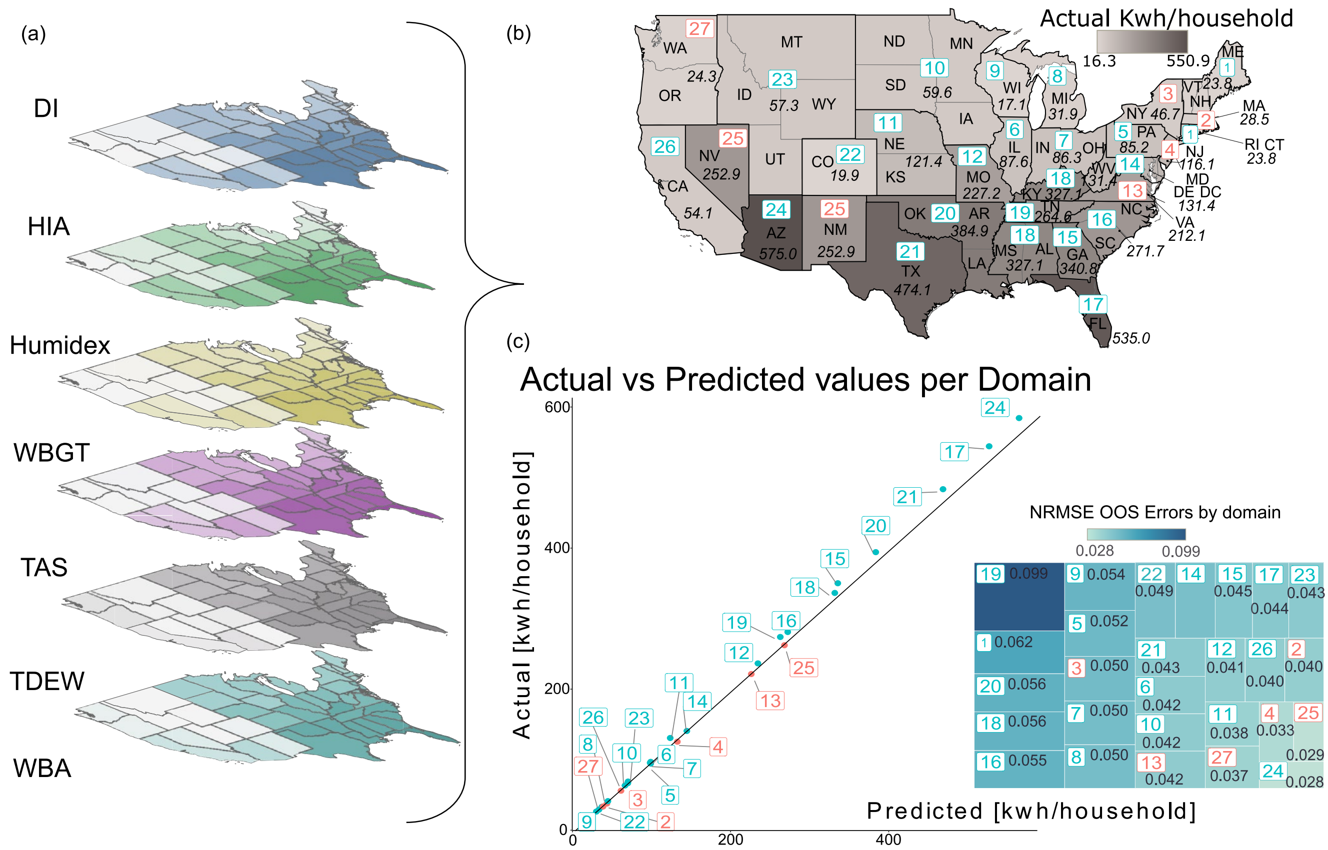

Figure 2. (a) A schematic of the climatic variables and indices considered in building the modeling framework. Note that the gradients depict the basic trends in the input data and are not meant to show specific values. See Table S2 in Supporting Information S1 for further details on these input variables. (b) Mean summer electricity used for air conditioning per household across U.S. domains, labeled with domain numbers (see Methods). (c) The predicted electricity use for air conditioning plotted against the actual values, colored to show over- and under-prediction (red and blue, respectively). The inset plot shows the out-of-sample normalized root mean squared error (OOS NRMSE) as a heat map with darker colors representing larger errors.

5. Results & Discussion

In this section, we will discuss the results of the model performance for each of the 27 US domains (discussed in Section 5.1), followed by the results of projection of air conditioning demand under the extreme warming scenario (RCP 8.5), which is discussed in Section 5.2.

5.1. Model Performance

To conduct this analysis, we leverage a state-of-the-art machine learning approach, grounded in statistical learning theory (see Section 4 for more information), to predict the summer air conditioning demand (in kWh) for a statistically representative household across the contiguous United States. In particular, we consider the 27 domains defined by the US Energy Information Administration Residential Energy Consumption Survey (US Energy Information Administration, 2018d).

We first train a predictive model using an observational data set during the "reference period" of 2005–2019. This initial model predicts the observed electricity consumption for air conditioning based on several key climatic indicators established in previous research (Maia-Silva et al., 2020), including dew point temperature, wet bulb temperature, heat index, and humidity index (see Section 3 and Figure 2). We train each domain separately to account for the domain-specific attributes, such as climate and consumption patterns. As such, different variables may be more or less important in different domains. The influence of predictors within the different domains is reported in Table S1 in Supporting Information S1, which lists the top three predictors in each domain.

Additionally, we perform rigorous cross-validation to ensure the generalization performance of the predictive model and to minimize over-fitting and other model biases.

The model performs well in the majority of the domains (see Figure 2), in terms of both model fit and predictive accuracy. Figure 2c shows the observed versus predictive kWh electricity used per household, demonstrating the ability of the model to fit the data across each domain (see Figure 2b for domain location information). In fact, the majority of the domains are slightly *under*-predicted, suggesting that the model is predicting lower demand than the observations. Of the domains that were over-predicted (i.e., the model predicts higher demand than the observations), the majority are in the Northeast (Massachusetts, New York, and New Jersey) or Northwest (Washington and Oregon). Historically, these domains have been winter-peaking in terms of electricity (Maia-Silva et al., 2020), meaning the electricity use peaks in winter due to space heating, while space cooling in summer remains relatively rare. It is likely that these historical conditions, which have led many households to simply forego the installation of air conditioners, are leading to lower air conditioning use, even in the face of more extreme climatic conditions. Hence, our model, which is based on the climatic conditions, predicts higher air conditioning use than what we observe in these regions. Additionally, the out-of-sample predictive error (NRMSE) is relatively low in most domains (Figure 2c), indicating the reliability and predictive accuracy of the developed model. In particular, our model has a predictive error that is less than 10% (NRMSE < 0.1) across all domains. Given the relatively low errors in the observation space, this model was then used to project the climate-sensitive portion of air conditioning demand into the future, which will be discussed in the following section.

5.2. Projections Under Future Climate Change

The future scenarios are driven by seven key climate variables (see Figure 2a and Section 3) obtained from five bias-corrected Coupled Model Intercomparison Project Phase 5 (CMIP5) projections (Warszawski et al., 2014). We consider the most extreme warming scenario (RCP8.5) to project the shifts in air conditioning use due to unmitigated anthropogenic warming.

Using the developed model trained with the "reference period" (i.e., 2005–2019) data, we project the climate sensitive portion of air conditioning demand into the future following two global mean temperature warming levels of 1.5°C and 2.0°C above a pre-industrial level (Intergovernemental Panel on Climate Change, 2018; Intergovernemental Panel on Climate Change, 2013). We use a time-sampling approach to extract future 15-year periods in which each GCM surpassed and average global temperature of 1.5°and 2.0°C above pre-industrial levels (James et al., 2017). Through this approach, therefore, we had five 15-year slices per temperature threshold that were used to generate the average electricity used for air conditioning due to climate change. This method has been used previously in the literature as a method to characterize climate impacts at different temperature levels (Jacob et al., 2018; James et al., 2017; Obringer, Kumar, & Nateghi, 2020; Samaniego et al., 2018). To remove any bias induced by conducting comparisons between GCM-derived projections and observed values, we first use the ensemble of GCM data to derive the electricity demand during the reference period (see Figure 3a and Figure S3 in Supporting Information S1). We then use this data to project the future electricity demand under climate change. The percent change between the projected electricity demand under the two temperature thresholds scenario and the baseline demand, given an ensemble of five GCMs, are shown in Figure 3. We can also compare the GCM-derived data during the reference period (Figure 3a) to the observational data (Figure 2b) for additional evaluations of accuracy. For further information on this practice, see Obringer, Kumar, and Nateghi (2020) and Maia-Silva et al. (2020). As the two figures show, the GCM-derived data accurately captures the spatial patterns of the electricity use for air conditioning across the study area. See Figure S2 in Supporting Information S1 for additional comparison between the observational data obtained from NARR and the GCM-derived climate variables. Going forward, we use the GCM-derived baseline data set to evaluate the shifts in air conditioning demand following 1.5 and 2.0°C of anthropogenic warming. In terms of planning, the 1.5°C threshold is expected to be reached around 2030, while the 2.0°C threshold is likely to be crossed around 2050 (Intergovernemental Panel on Climate Change, 2018). The associated time-frames of these warming levels also match the commonly used planning horizon in energy systems, underscoring the relevance of this study's insights for integrated adequacy planning in the energy sector (US Energy Information Administration, 2020).

As shown in Figure 3, the model projects increases in household electricity demand for air conditioning use across the 27 domains, although there is some variability in the magnitudes. For example, the increase in household electricity consumption for air conditioning is much more pronounced in Southern and Southwestern parts of the

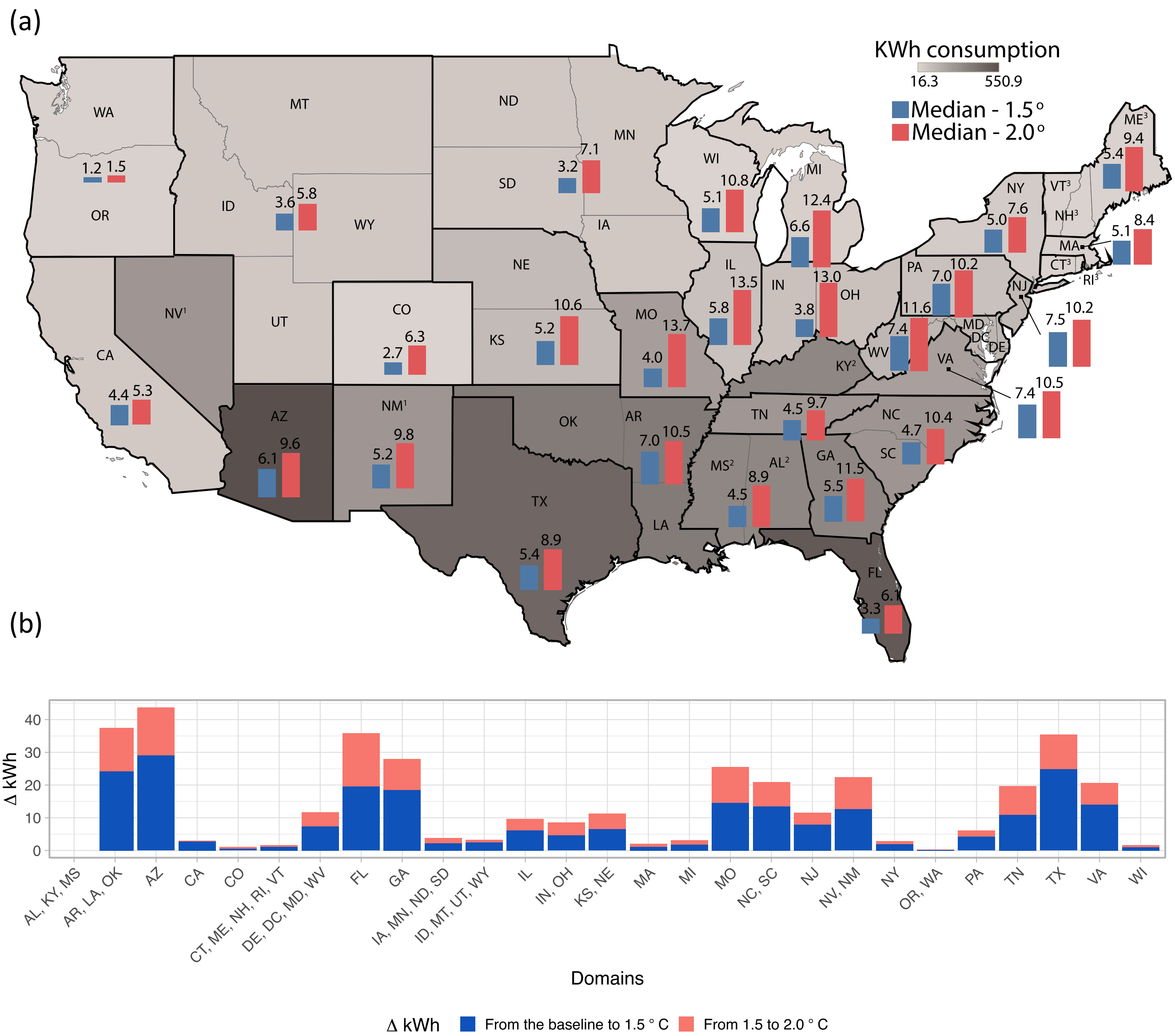

Figure 3. (a) Results of the model projections for each study domain (see Methods) with the overlaying bars representing the median changes in projected demands at two warming level thresholds-1.5°C (blue) and 2.0°C (red), relative to the baseline values. The background shading indicates the GCM-derived baseline consumption (kWh/household) in each domain over the period 2005–2019. (b) Differences in kWh consumed for air conditioning in each domain between the baseline and 1.5°C scenario and the 1.5 and 2.0°C scenarios.

country. In fact, some of the domains with highest per household electricity use are projected to experience more extreme changes under the climate change scenarios. For example, in Arizona (AZ), the use of air conditioning is projected to increase by 6% with a range of 4%–6.5% (see Figure 4) after 1.5°C of warming. This increase represents the projected increase of about 30 kWh per household per month, just for air conditioning use in response to climate change effects. If every household in Arizona were to experience this increase (considering the current average conditions of four persons per household and a population of 7.279 million), there would be an increase in electricity demand by about 54.5 GWh (54.5 million kWh) per month in the summer on average—only for air conditioning. If the population continues to increase, as is likely, this value will be much higher. Furthermore, if global warming exceeds 2.0°C, the change will increase to 10% (with a range of 7%–11%) over the baseline (Figure 3), further increasing the total electricity demand. However, this shift in demand is not so intense across the entire country. For example, in Washington (WA) and Oregon (OR), the model projects a slight increase (1%–2% above the baseline). Since the summer electricity use in these states is not that sensitive to climate (Maia-Silva

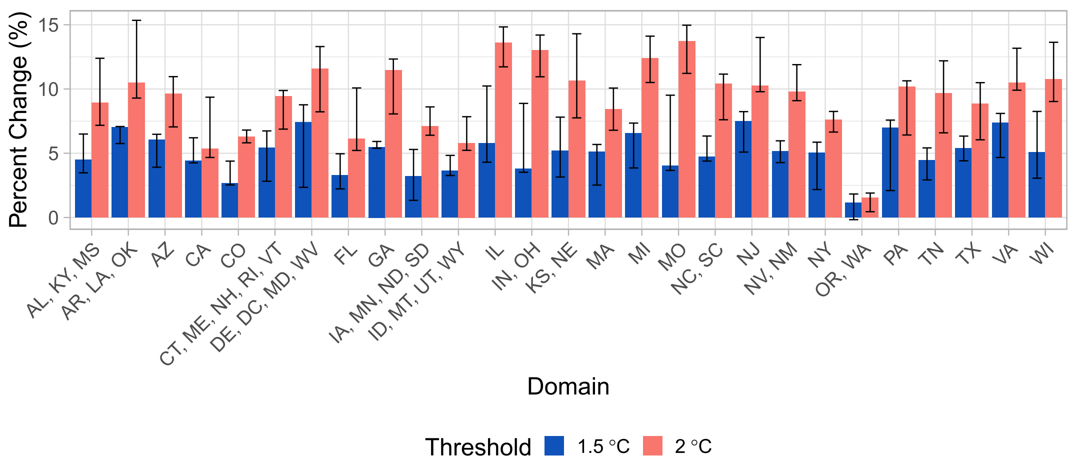

Figure 4. Percent change in electricity use for air conditioning after surpassing 1.5°C and 2.0°C of warming above pre-industrial levels. The colored bars show the median value, while the error bars show the the 20th and 80th percentiles of the different projections obtained from the 5 GCMs considered in the study.

et al., 2020), it is not surprising that our model projects small changes. Nonetheless, in the majority of domains, our model indicates significant increases in household electricity demand for air conditioning, particularly after surpassing a 2.0°C change in global temperature.

In some parts of the country, the 0.5°C increase in global temperature (i.e., from 1.5°C to 2.0°C) could double or, in some cases, triple the increase in climate-driven household electricity demand for air conditioning (Figure 3a). For example, in Indiana and Ohio (IN and OH, respectively), there is a projected 4% (range = 3.5%–9%) increase in electricity use for air conditioning after 1.5°C of warming. This change rises to over 12% (range = 11%–14%) after 2.0°C. This increase in climate-driven electricity demand for air conditioning use, which amounts to over 52.5 GWh, could put serious strain on the energy grid if the utilities are not prepared for such rapid increases. There are similar results across the rest of the Midwestern region, with Illinois (IL), Michigan (MI), and Wisconsin (WI) projected to experience at least twice as large of an increase in the air conditioning demand after the 2.0°C threshold as after the 1.5°C threshold.

5.2.1. Uncertainty in Projected Air Conditioning Use

The results presented in Figure 3 represent the median values across the projections that were derived from the five GCMs used in this study. Due to the differences in these GCMs, there is some uncertainty in the final results. Figure 4 shows this uncertainty across the 27 domains for each temperature threshold. In particular, the figure shows the median value (as does Figure 3) and the 20th and 80th percentiles of the projected change to household-level air conditioning use (see Figure S4 in Supporting Information S1 for the standard deviation). In particular, the figure shows that the percent increase is consistently higher after 2.0°C of warming that it is after just 1.5°C of warming. This is expected, as most regions will experience more extreme increases in temperature under the former threshold. However, the uncertainty is often also larger after surpassing the 2.0°C threshold. This is likely due to the uncertainty within the GCMs, which becomes larger towards the end of the century (Intergovernemental Panel on Climate Change, 2013).

That being said, it is likely that world will cross the 1.5°C threshold within a couple decades (Intergovernemental Panel on Climate Change, 2013; Jacob et al., 2018), if current trajectories persist. As such, focusing on the impacts of reaching 2.0°C of warming may be more beneficial from a practical standpoint. Going forward, we will present some of the implications of surpassing a global temperature of 2.0°C above the pre-industrial levels (the companion results for the 1.5°C warmer world are presented in Figure S1 in Supporting Information S1).

5.3. Required Efficiency Improvements to Offset Increased Demand Due To Anthropogenic Warming

Our results indicate significant increases in air conditioning use at the household level following the 2.0°C warming level threshold (Figures 3 and 4). It may be possible to offset these increases in electricity demand for air conditioning use by improving the efficiency of the air conditioners being used (i.e., on a technological level). Efficiency improvements can lead to a significant reduction in total electricity use, even if there are no behavioral changes (International Energy Agency, 2018; Reyna & Chester, 2017). In other words, one can think of efficiency improvements in air conditioning units as a potential route towards offsetting the climate-driven increases discussed above, thus minimizing the supply inadequacy risk and saving consumers money.

The efficiency of U.S. home appliances has increased rapidly over the last several years, enhancing the energy security in the U.S. In a 2017 scenario-based study, Reyna and Chester (Reyna & Chester, 2017) found that while implementing efficiency measures would not fully offset the future increase in electricity demand, the more aggressive policies significantly reduced energy demand, compared to a scenario with no efficiency measures (Reyna & Chester, 2017). Similarly, according to the International Energy Agency increasing the efficiency of air conditioners would reduce the total cooling load by 45% compared to the baseline scenario (International Energy Agency, 2018). These studies still suggest that there will be an increase in the total consumption. However, if the goal is to offset the climate impacts, further improvements to efficiency will be necessary.

Here, we estimate the efficiency improvements that would be necessary to offset the demand increases caused by climate change. Using the method described by McNeil and Letschert (2008), we calculate the efficiency that would be needed to counterbalance the increases in demand following the 2.0°C temperature threshold (the results from the 1.5°C temperature threshold can be found in Figure S3 in Supporting Information S1; see Section 4.3 for more details on the methods). We find that in most domains, a 1%–8% improvement in air conditioner efficiency is needed to offset the increase in household demand (Figure 5). Specifically, some states such as Arkansas (AR), Louisiana (LA), and Oklahoma (OK) are projected to need close to a 8% improvement in efficiency to maintain the status quo in terms of the electricity supply. It is important to note that these are the efficiency improvements needed to counteract the shifts in electricity demand only induced by climate change. To account for other factors that also influence demand (e.g., population growth, socioeconomic variables, etc.) additional efficiency gains will be necessary in order to effectively offset the demand increases. While estimating these additional efficiency gains are of critical importance for utilities and policymakers to ensure supply adequacy, it falls outside the scope of this study.

The efficiency improvements outlined in Figure 5 may be achievable in terms of technology. There has been an immense improvement of the equipment efficiency over the past several decades, but what accelerates such improvements is effective policy design and enforcement (Reyna & Chester, 2017). In California, for example, the government has enacted strict efficiency requirements for a number of appliances, including air conditioners (Reyna & Chester, 2017). These policies have led to manufacturers working towards improving efficiency of their products, so as to avoid losing out on the Californian market. Consequently, our results indicate that California needs less improvement to efficiency in order to counterbalance the climate-induced changes (see Figure 5).

5.4. Implications of Not Enacting Technological Mitigation Efforts

If utilities fail to proactively manage the supply adequacy to meet the rising demand, rolling outages during extreme heat events could become more frequent (van Vliet et al., 2012; Yalew et al., 2020). We estimate the "household-days" (Figure 5) as the total days without air conditioning experienced by the average household within a domain in a given summer after surpassing the temperature threshold. This measure is calculated by multiplying the average number of days an average household would be without air conditioning by the total number of households under the 2.0°C warmer world (see Figure S1 in Supporting Information S1 for results from a 1.5°C warmer world). In states like Oregon (OR) and Washington (WA), which are not expected to see extreme increases in air conditioning demand, this metric is relatively low (5.8 million household-days, or about one day per household). However, states such as Indiana (IN) and Ohio (OH) could experience 76 million household-days without air conditioning in a given summer season (about 12 days per household).

While the household-days metric is estimated for the average household in different domains, the burden will not be equally felt across all households. Previous work has shown that low income households bear the brunt of extreme heat events within cities (Khosla et al., 2020; Sanchez-Guevara et al., 2019), making them more vulnerable to climate-induced temperature increases and subsequent electricity outages and blackouts (Khosla et al., 2020; Kumar et al., 2020). This higher vulnerability arises often due to a number of factors—from inferior housing structures and residing in areas with higher urban heat island effects to the inability to afford increasing

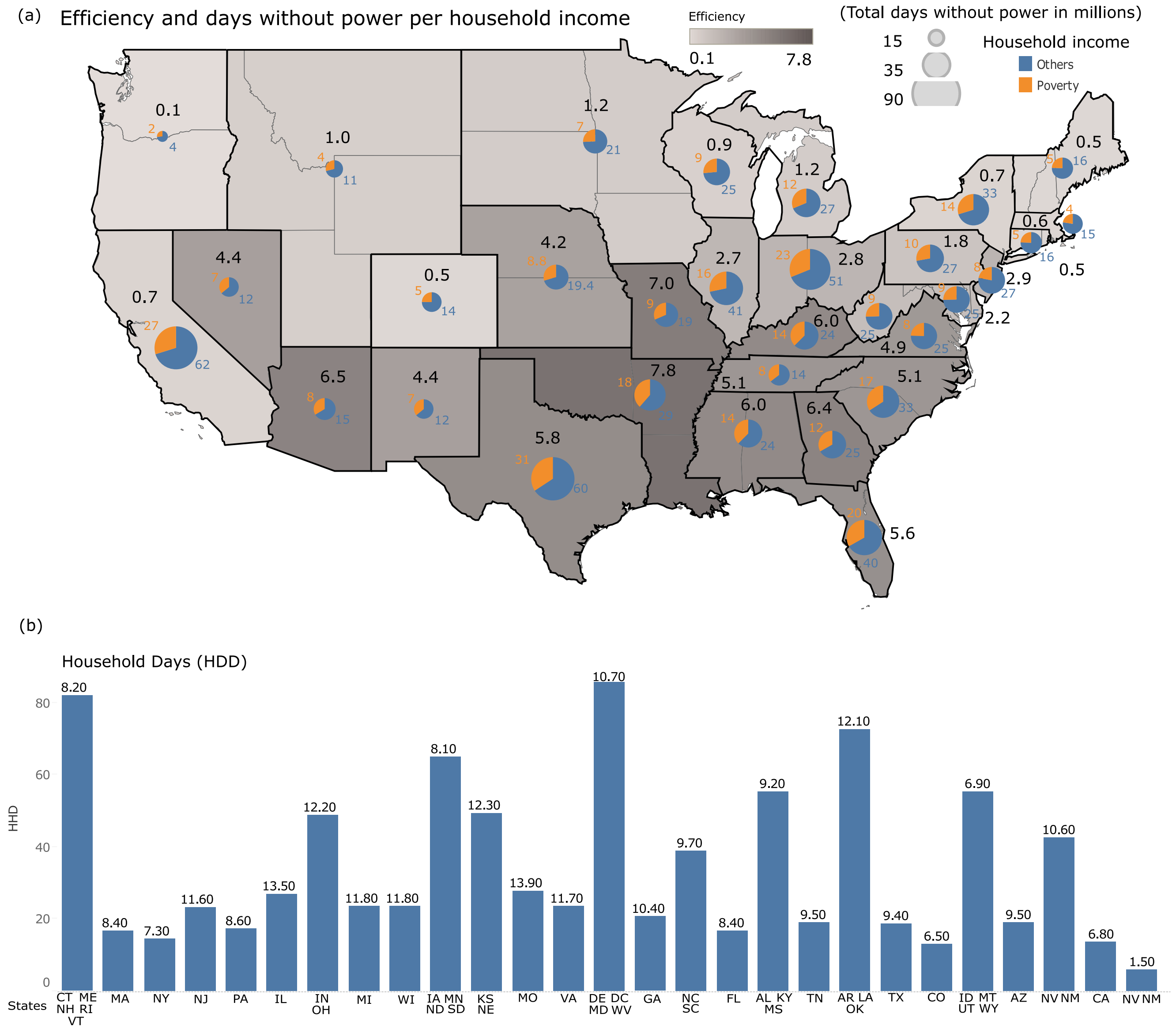

Figure 5. (a) In the background, the map shows the necessary improvements to air conditioner efficiency (%) to offset the increased median demand projected under the 2.0°C warmer climate. This shading is accompanied by a black number indicating the necessary efficiency improvement. In the foreground, there are pie charts–with their sizes representing the total household-days without air conditioning that a domain may face if unable to provide an electricity supply that meets the increased demand. The pie chart is further split between the number of household-days experienced by those that are in poverty (i.e., below 200% of the poverty line - shown in yellow) (Kaiser Family Foundation, 2020) and those that are not (in blue). The accompanying numbers are in the millions of household-days. (b) Bar chart showing the total number of household-days without air conditioning per summer in each domain, with the average days per household (HDD) written above each bar. The accompanying results for the 1.5°C warmer world are presented in Figure S1 in Supporting Information S1.

electricity bills (Drehobl & Ross, 2016; Graff & Carley, 2020; Sánchez-Guevara et al., 2017, 2019). In the light of the vulnerability among marginalized communities, we estimate the impact of inadequate access to cooling energy in low income households based on the recent census reports (Kaiser Family Foundation, 2020) (Figure 5b). For example, Indiana (IN), Ohio (OH), and Texas (TX) are projected to experience high household-days (over 85 million), and have some of the highest proportions of people living in poverty (i.e., below 200% of the U.S. poverty line) (Kaiser Family Foundation, 2020). Thus, should the utilities be unable to meet demand, the population as a whole may not have access to air conditioning. This loss in air conditioning, however, is more likely to negatively impact marginalized communities due to the vulnerabilities associated with poorer housing, urban heat island effect, and lack of access to other cooling infrastructures (e.g., pools) (Sanchez-Guevara et al., 2019).

That being said, this analysis focused on the impact of living in a 2.0°C warmer world. Should society succeed in limiting global warming to 1.5°C, it is likely that the aforementioned impacts will be lessened. For example, in a 1.5°C warmer world, air conditioner efficiency would only need to be improved by 5% in some states (see Figure S1 in Supporting Information S1), a 3% reduction from the 2.0°C analysis. In the event of supply inadequacies, a 1.5°C warmer world would likely leave households without air conditioning up to 8 days in a given summer (Figure S1 in Supporting Information S1), nearly half of what may happen in a 2.0°C warmer world. This reduction in negative impacts would not only help electricity utilities to cope with the shifting demand patterns, but would also limit the effects of climate change felt at the household level, including increased vulnerability to heat stress.

5.5. Study Limitations and Opportunities for Future Work

There were a few limitations in this study. The first of which is the use of domain-wide mean values within the climate data. There has been previous work using population-weighted climate data to model electricity consumption (Kumar et al., 2020; Maia-Silva et al., 2020). However, given that the household air conditioning use data were obtained as domain-wide means, we opted to maintain a similar structure in the climate data. This is a simplification of the real system, since populations are not uniformly spread out across domains. Moreover, this could lead to under- or over-estimations of demand in different areas of each domain. For example, a mountainous area of a domain might be cooler than an urban center situated in a valley. By using the mean temperature, the subsequent estimates of air conditioning, therefore, might be under-estimating the urban center (which is likely to be warmer than average) and over-estimating the mountainous locations (which are likely to be cooler than average). Nonetheless, the work presented here aimed to investigate high level trends across many domains. To this end, this study on the average household-level air conditioning use can be used as a stepping stone to more in-depth analyses evaluating the changes to local communities.

Additionally, the results presented in this study focused on only two global temperature thresholds: 1.5 and 2.0°C above pre-industrial levels. There is, however, a chance that global temperatures will surpass these thresholds, with the worst case scenario often being 4.0°C above pre-industrial levels. As such, it can be beneficial to evaluate the climate impacts that will occur after reaching 2.5, 3.0, and even 4.0°C in global warming. However, in the energy sector, much of the long-term planning is conducted for 2–3 decades in advance, making studies evaluating end-of-century electricity consumption to be impractical for policymakers. In an effort to remain within the current planning horizon for US energy infrastructure, we chose to evaluate only the closest temperature thresholds. Moreover, there are methodological issues when trying to use a predictive model for end-of-century projections. These issues need to be carefully evaluated and accounted for when doing such studies. Future work may focus on fixing these issues, as well as developing new methods that will allow us to investigate shifts in the electricity demand following the larger temperature thresholds.

Similarly, in this study, we used the CMIP5 GCMs for obtaining future climate data. However, the next generation of climate models (CMIP6) has recently been released. As such, work within the climate impacts space is beginning to shift to the CMIP6 models. The CMIP6 models have been shown to exhibit different equilibrium climate sensitivities than previous iterations (Dong et al., 2020; Wyser et al., 2020), as well as an improvement in estimating temperature extremes (Di Luca et al., 2020), which may aid future impact assessment studies. That being said, the CMIP5 suite of models is still widely used and remains a valid source of future climate projections. As the availability of bias-corrected, downscaled CMIP6 data becomes more widely available, we expect that there will be an increase in the use of such data. Future work may focus on leveraging these updated models, potentially evaluating changes in impact assessments between the CMIP5 and CMIP6 studies.

Finally, this study emphasized the climate impact on air conditioning use. This, however, is only part of the equation. There are a number of other factors that might lead to higher or lower air conditioning use than what was presented here. For example, improving insulation within houses can greatly reduce cooling needs (Dehwah & Krarti, 2020). Similar effects have been found through the use of green infrastructure (Perini et al., 2017). This would be especially helpful in older neighborhoods, as well as lower income neighborhoods. This would, in effect, not only reduce the need for cooling, but also help the communities that are most vulnerable to heat stress (Drehobl & Ross, 2016). Future work can start to build off the climate impacts presented here to account for these different solutions, as well as behavioral or cultural changes that might further contribute to changes in the electricity consumed for air conditioning.

6. Conclusion

To summarize, we provide a U.S.-wide assessment on the projected change in summer electricity demand owing to household air conditioning use under two key climate thresholds scenarios-1.5°C and 2.0°C above pre-industrial levels (Intergovernemental Panel on Climate Change, 2018). Our analysis leverages the state-of-the-art machine learning approach to establish a rigorously validated predictive model focused on the *climate-sensitive* portion the electricity demand for air conditioning. In other words, we investigated the impact of climate change alone, without considering potential changes due to technological advancements or socio-demographic shifts. Our results indicate that limiting warming to 1.5°C would have significant benefits to limiting household-level air conditioning demand. However, current trajectories indicate that it is more likely that the world will surpass the 1.5°C threshold within a decade. If this holds true, society will need to work towards minimizing the effects of climate change on the energy sector either by expanding the generation capacity—which if not fully powered by renewable resources, could further fuel anthropogenic climate change—or by improving space conditioning equipment efficiency. The results presented here demonstrates that in most states, a 1%–8% improvement in air conditioner efficiency would be needed to offset the increased demand. If these improvements are not met, there is a possibility of not being able to supply enough electricity to meet the demand. In this scenario, our analysis shows that most domains can expect at least 20 million household-days without air conditioning in a given summer season. These household-days are more likely to disproportionately impact the low-income citizens, potentially leading to increased instances of heat stress induced health concerns in these communities (Khosla et al., 2020; Sanchez-Guevara et al., 2019). In order to protect the most vulnerable citizens, it is crucial that we work to limit warming to 1.5°C above pre-industrial levels, while also working towards ensuring air conditioner efficiency improvements that may ultimately reduce the load on the electric grid. Hence, understanding the probable changes in electricity demand for air conditioning is a crucial step in preparing our electric power system for climate change.

Data Availability Statement

The data and code used in this study are available online via Zenodo (DOI:10.5281/zenodo.5705824).

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