



Managing the water–electricity demand nexus in a warming climate

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Abstract

Models that consider the interconnectivity between urban systems, including water and electricity, are becoming more common, both in research and in practice. However, there are still too few that consider the impact of climate change, and fewer still that look beyond the baseline climate data (i.e., precipitation and temperature). Here, a data-driven, regional model that considers a wider array of climate variables is built and tested to evaluate the impact of climate change on the coupled water and electricity demand nexus in the Midwestern USA. The model, which is based on a state-of-the-art statistical learning algorithm, is first used to compare model runs comprised of different climatic variables. The model runs included a baseline model that considers only precipitation and temperature, as well as a selected feature model that considered a wider array of climatic variables, including relative humidity and wind speed. Following this comparison, the model is used to make future projections of the coupled water and electricity demand as a function of future climate change scenarios. The results indicate that (1) the inclusion of additional climate variables beyond the baseline provides a significant improvement in predictive accuracy, and (2) the climate-sensitive portions of summer electricity and water use are expected to increase in the region by 19% and 7%, respectively. Finally, the regional-scale model is leveraged to make city-level projections, indicating a 10–20% (2–5%) increase in electricity (water) use across the analyzed cities due to a warming climate.

Keywords Water–electricity nexus · Multivariate modeling · Climate change impacts

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1 Introduction

Urban infrastructure systems, and in particular water and electricity systems, are highly interconnected. This interconnectivity, known as the water–electricity nexus, is well-documented in the literature (Newell et al. 2019). There are several ways to analyze the water–electricity nexus, such as evaluating the water needed to generate electricity (i.e., water for electricity) or the electricity needed to treat and distribute water (i.e., electricity for water) (Derrible 2017). Additionally, one can consider the water–electricity *demand* nexus that accounts for end-uses that require both water and electricity, such as running a dishwasher, heating water, or landscaping (Maas et al. 2019; Escriva-Bou et al. 2018). Although research on the water–electricity nexus, as well as other interconnected urban systems, is becoming more commonplace, in practice many utilities operate in isolation, making decisions that may end up being suboptimal at the system level (Hussey and Pittock 2012; Obringer and Nateghi 2019; Obringer et al. 2019). For example, residents in Phoenix, AZ were encouraged to plant drought-tolerant plants in their yards to conserve water. This resulted in a change in microclimate and led to increased electricity use, which ultimately meant more water being used by the electricity utility during generation (Ruddell and Dixon 2014). This example is not a singular instance, but rather something that occurs in many cities across the USA. These isolated efforts contradict the research, which has shown that considering both water and electricity in conservation measures has the potential to achieve savings at no net cost (Bartos and Chester 2014).

These suboptimal management decisions are undesirable under the current conditions, but as urban areas continue to grow in population and the climate continues to change, they could be disastrous. In fact, with estimates that 70% of the world population will live in urban areas by 2050 (The World Bank 2010), utility companies could be experiencing a significant increase in demand, without taking climate into account. By taking climate variability into account, any stress caused by the increase in demand will be exacerbated (Raymond et al. 2018; Mukhopadhyay and Nateghi 2017; Mukherjee and Nateghi 2017). For example, electric grids have been designed to handle specific peak loads, but under climate change, peak loads will likely exceed the capacity margins more frequently (Auffhammer et al. 2017; Lokhandwala and Nateghi 2018; Nateghi et al. 2016). Given that these peaks in usage tend to be more sensitive to variations in climate than average usage (Mukherjee et al. 2019), it is likely that electric utilities will experience a dangerous level of stress, that could result in blackouts and shutdowns, if they do not prepare adequately (Nateghi and Mukherjee 2017; Mukherjee et al. 2018; Cronin et al. 2018). This will be especially true for the residential sector, which is more sensitive to climate variability than the commercial and industrial sectors (Mukherjee and Nateghi 2019). Therefore, it is crucial that electric utilities have access to accurate and credible models that adequately characterize the climate sensitivity of residential electricity use, as it represents the sector that is most likely to be affected by climate change. Moreover, electricity use is affected by water use, especially in the residential sector (Escriva-Bou et al. 2018), making it imperative that these models also account for the impact of climate change on water use.

Water utilities, unlike electric utilities, have the ability to store resources for later use. However, as climate change progresses, droughts are likely to become more intense, potentially reducing storage capabilities of reservoirs that are mainly used for public drinking water supply (Dai 2011; Bruss et al. 2019). Moreover, increased temperatures usually lead to increased water use within the residential sector (Balling et al. 2008; Ashoori et al. 2016), which will put additional stress on the water supply reservoirs. These impacts of climate change are not experienced in isolation, rather, they are interconnected, such that the impacts

on the water sector will affect the electricity sector, and vice versa. For example, in the event of a drought, the water supply reservoirs may experience a significant drop in storage, which will put pressure on the water utility to maintain a certain service level under limited supply. This water supply will be put under additional pressure by the increase in demand that follows higher temperatures and drought conditions. Furthermore, there will be even more pressure brought on by the electric utility which will require an increasing amount of water for cooling generators in regions where the electricity is generated by thermoelectric technology, as is the case in 90% of the USA (Scanlon et al. 2013; Cronin et al. 2018). In this sense, the nexus leads to increased stress on both water and electricity utilities, especially under climate change (Pereira-Cardenal et al. 2014; Gjorgiev and Sansavini 2017). This creates a need for water and electric utilities to work together to prepare for climate change and make decisions that are the best for both sectors.

In order to ensure infrastructure managers and urban planners can make the best decisions now and in the future, there needs to be increased development of accurate, credible, and accessible models that take system interdependencies into account (Rachunok and Nateghi 2019; Rachunok et al. 2019). However, there are only a few models that project the water–electricity nexus into the future and they often only use a small subset of climate variables, generally precipitation and temperature (Venkatesh and Chan 2014; Mostafavi et al. 2018; Dale et al. 2015). The use of precipitation and temperature as climate predictors has been considered the baseline for making demand projections for several years. However, recent work on the climate sensitivity of the water–electricity demand nexus, has shown that there are additional climate variables that need to be considered (Obringer et al. 2019), such as relative humidity and wind speed, which are also considered to play major roles in the *experienced* temperature. That being said, there are improvements to be made within the methodology developed by Obringer et al. (2019). For example, the study focused on building a generalizable model on a city scale rather than at a regional scale (Obringer et al. 2019). Given that climate change is a large-scale phenomenon, it is more reasonable to build regional models if one is interested in making future projections based on climate change scenarios. Additionally, the model by Obringer et al. did not separate the seasons within the model, likely leading to a loss in nuance within the coupled demand profile (Obringer et al. 2019). In this study, we seek to fill these gaps and improve the methodology, while providing a novel analysis of the future water and electricity demand under climate change.

The purpose of this study is twofold: (1) to build and test a generalizable *regional model* for predicting the *interconnected* water and electricity use in different periods throughout the year and (2) use that model to project the water and electricity use into the future under various climate change scenarios. The focus of this study is to isolate the impact of climate change on the water–electricity demand nexus; therefore, only climate variables were considered as predictors within the modeling framework. Additionally, this study considers a wider array of climate variables than previously considered in other future projection studies. The Midwest region of the USA, which has several established cities of varying populations, was selected as the test region; however, the proposed modeling framework presented here could be applied to different regions.

2 Data and methods

There are a growing number of frameworks being developed to model the coupled water–electricity nexus; however, there are few that take a variety of climate variables into account when making future projections. The proposed framework is novel in that it accounts for

a larger array of climate variables to assess their impacts on the coupled water–electricity demand nexus at a regional scale. In this section, we will first describe the study area and the data used in the model before discussing the modeling process and analysis.

2.1 Site description

In this study, the Midwestern region of the USA was selected as the study area (see Fig. 1). Specifically, six established cities were chosen to be included in our regional model: Chicago (IL), Cleveland (OH), Columbus (OH), Indianapolis (IN), Madison (WI), and Minneapolis (MN). These cities, and the region as a whole, can expect to see higher temperatures and increased precipitation due to climate change (IPCC 2013), which will increase the vulnerability of the utility companies. Moreover, these cities have different water and electricity utilities, that do not always work together, which puts them at risk for disadvantageous management decisions in the face of climate change.

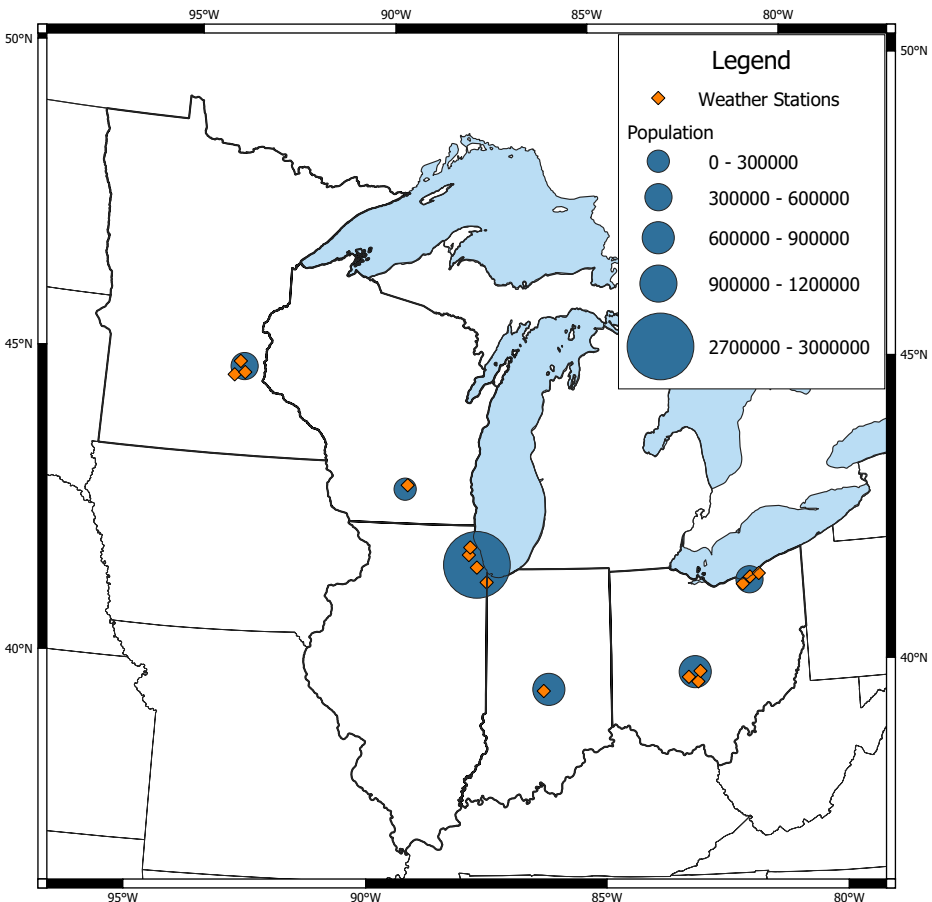


Fig. 1 Study area: Midwestern region of the USA. The blue circles represent the cities included in the regional analysis, sized relative to population, and the orange diamonds represent the weather stations that were used as sources for the observational data

2.2 Data description

There were two stages of data collection in this study: observational data (for model training, testing, and validation) and climate model outputs (for conducting future projections). The first stage included response data (i.e., water and electricity use) from the US Energy Information Administration (EIA) and local utilities, as well as predictor data (i.e., climate variables) from the National Centers for Environmental Information (NCEI) and the National Oceanic and Atmospheric Administration (NOAA). Specifically, the response variables, residential electricity use and residential water use, were obtained through the EIA (US Energy Information Administration 2019) and local utilities, respectively. The predictor variables were obtained from the local climatological dataset maintained by NCEI (NOAA National Centers for Environmental Information 2010) in addition to the El Niño database maintained by NOAA (Wolter and Timlin 1998). This observational data, which are listed in Table 1, were collected from January 2007 through December 2016 on a monthly time scale. The response variables (water and electricity use) were normalized by the service population, so as to make each city comparable in our regional model. Additionally, the response data were de-trended following a procedure that is well-established within the literature (Sailor and Muñoz 1997; Mukherjee and Nateghi 2017, 2019) to remove the trends associated with technological advancements as well as socioeconomic and demographic changes over time. This process, which is further described in the Supplementary Methods, is especially important for this study, since isolating the climate impact was one of the main goals.

The second stage of the modeling process focused on making the future projections using the developed model. For this, climate data were taken from five CMIP5 global circulation models (GCMs), namely 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

Table 1 The input variables used for developing the coupled water–electricity demand nexus model

Variable type	Variable name	Units	Source
Response	Monthly water use (normalized)	L/cap	Local utilities
	Monthly electricity use (normalized)	MWh/cap	EIA-861M ^a
Predictor	Average maximum dry bulb temperature	°C	NCEI ^b
	Average dew point temperature	°C	NCEI ^b
	Average relative humidity	%	NCEI ^b
	Average maximum relative humidity	%	NCEI ^b
	Average wind speed	m/s	NCEI ^b
	Average maximum wind speed	m/s	NCEI ^b
	Accumulated precipitation	cm	NCEI ^b
	El Niño/Southern oscillation index	–	NOAA ^c

Each variable was collected from January 2007 through December 2016 and aggregated to the monthly time scale

^aCitation: (US Energy Information Administration 2019)

^bCitation: (NOAA National Centers for Environmental Information 2010)

^cCitation: (Wolter and Timlin 1998)

Research on Climate—Earth Systems Model (MIROC-ESM-CHEM), and the Norwegian Earth System Model (NorESM1-M). These datasets included both the historical (1971–2005) and the projection time frames (2006–2099). The projection data were considered for two extreme future emission scenarios that have end-of-century radiative forcings equal to 2.6 Wm^{-2} and 8.5 Wm^{-2} , denoted hereafter as RCP2.6 and RCP8.5 respectively. The GCM data were made available from the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) (Warszawski et al. 2014) after screening through multiple GCMs from the CMIP5 archive (see the protocol report available on www.isimip.org for more information). The climate data were downscaled and bias-corrected at a 0.5° global resolution using a trend-preserving approach based on the WATCH observation data (Hempel et al. 2013). Notably, this projection data has been used in several impact assessment studies including the recent AR5 and SR1.5 reports of the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2013, 2018). The data were extracted for the respective cities for each predictor variable included in the final model at a monthly time scale to be used in making future projections of the interconnected water and electricity use.

2.3 Statistical modeling and analysis

The modeling framework used in this study is based in statistical learning theory, and in particular, the branch of statistical learning theory known as supervised learning. Supervised learning is an umbrella term for a variety of algorithms that aim to predict a known response variable(s) given a series of predictor variables (Hastie et al. 2009). Mathematically, supervised learning algorithms can be represented by the following (1):

$$Y = f(X) + \epsilon \quad (1)$$

where Y is the response variable(s), X is the series of predictor variables used to predict the response, and ϵ is the irreducible error ($\epsilon \sim N(0, \sigma^2)$).

The goal of any supervised learning algorithm is to predict Y with as much accuracy as possible. To do this, the algorithms work to minimize the expected error (Hastie et al. 2009), as shown in the following (2):

$$\min \frac{1}{N} \sum_i^N \Delta[\hat{f}(X_i), f(X_i)] \quad (2)$$

Here, $\hat{f}(X_i)$ represents the estimated function, $f(X_i)$ represents the “true” function, and Δ represents some measure of distance (usually based on the Euclidean distance) (Hastie et al. 2009).

One of the subcategories of supervised learning is tree-based algorithms. These algorithms tend to be highly robust, leading to higher predictive accuracies, with the added benefit of being more interpretable than other “black box” algorithms, such as neural networks or deep learning (Caruana and Niculescu-Mizil 2006; Nateghi et al. 2011; Nateghi 2012). In this study, the algorithm used falls under this tree-based algorithm subcategory.

2.3.1 Algorithm description

The algorithm used in this study, multivariate tree boosting, is an extension of gradient tree boosting, which leverages the meta-algorithm boosting to improve predictive accuracy (Friedman 2001). Boosting, mathematically represented in (3), works by iteratively fitting models such that each subsequent model is a better prediction of the response variable(s).

This improvement is accomplished through a weighting process that puts more emphasis on misclassified data points, forcing the algorithm to focus on improving the prediction of those points in future iterations as follows (Friedman 2001):

$$H(X) = \sum_n^N \alpha_n C_n(X) \quad (3)$$

Here, $H(X)$ is the final model produced by the algorithm, N is the total number of iterations, α_n is the weight given to each prediction, and C_n is the model produced using input variables X at iteration n .

Multivariate tree boosting expands upon this algorithm to account for multiple response variables. Specifically, the algorithm leverages the impact of the predictor variables on the response variables as well as the covariance between response variables, resulting in an accurate, simultaneous prediction of multiple outcomes (Miller et al. 2016). This is done through maximizing the covariance discrepancy, such that the predictors that account for the most covariance in the response variable nexus are selected for the final model (Miller et al. 2016). This algorithm is summarized below:

Algorithm 1 Multivariate tree boosting algorithm (Miller et al. 2016).

- 1: **for** n in $1, \dots, N$ steps (regression trees) **do**
 - 2: **for** q in $1, \dots, Q$ quantitative response variables (water and electricity use in this study) **do**
 - 3: train tree $n^{(q)}$ to residuals and estimate the covariance discrepancy $\Omega_{n,q}$
 - 4: **end for**
 - 5: Select the response $y^{(q)}$ corresponding to the regression tree that yielded the maximum $\Omega_{n,q}$
 - 6: Update residuals by subtracting the predictions of the tree fitted to $y^{(q)}$, multiplied by step-size.
 - 7: **end for**
-

Multivariate tree boosting is considered to be the state-of-the-art tree-based algorithm for predicting multiple *response* variables simultaneously. Moreover, this algorithm has been used in a variety of studies, ranging from psychological well-being (Miller et al. 2016) to urban resilience modeling (Nateghi 2018; Obringer and Nateghi 2019). Most recently, the algorithm was leveraged to effectively predict the climate sensitivity of the water–electricity demand nexus (Obringer et al. 2019).

2.3.2 Modeling framework

There are three main steps to the modeling process, as shown in Fig. 2: (1) data collection, aggregation, and preprocessing; (2) model training and testing with observational data; and (3) future projections using climate model output. In this first step, the data were collected as described above. The observational data were aggregated across the cities and grouped into three time periods according to a well-documented energy economy model known as the MARKet ALlocation (MARKAL) model (Loulou et al. 2004): summer months (June–September), winter months (December–March), and intermediate months (April, May, October, November), to account for the seasonal fluctuations in the water–electricity demand nexus. These new datasets were the initial inputs to three separate models—one for each period.

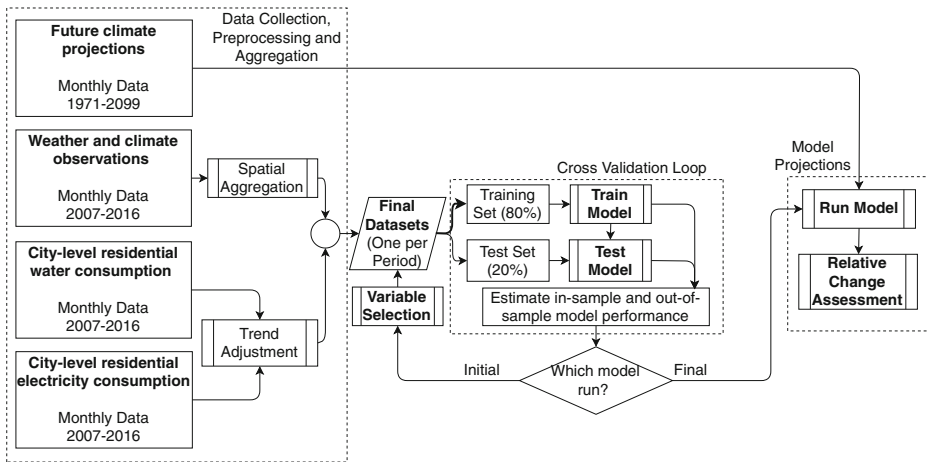


Fig. 2 Schematic for the modeling framework

The model training and testing was the next step. This step used the observational data to first determine the important predictor variables and then validate the predictive accuracy of the model. The important variables were selected based on a threshold criterion: any variable with a relative influence greater than 5% on either response variable in a given period was kept for that period's final model. Ultimately, five variables were kept: average maximum dry bulb temperature, average dew point temperature, average relative humidity, average wind speed, and accumulated precipitation.

The final step was to project the water and electricity use into the future using the climate data obtained from the global circulation models. The data were collected and separated into seasonal periods following the same process described for the observational data. Then, the model was run using the previously selected important variables.

2.4 Future projection analysis

The future projection analysis was performed in accordance with the recent IPCC SR1.5 report (IPCC 2018) to analyze the respective changes in water and electricity use for different global warming levels. Using the historical period (1971–2000) as the reference values, the percent change between the 30-year-historical period and the 30-year-future periods corresponding to three global warming levels (1.5, 2.0, and 3.0 °C above pre-industrial levels) was calculated. A time-sampling approach (James et al. 2017), which has been recently adopted in several impact assessment studies (Jacob et al. 2018; Samaniego et al. 2018; Marx et al. 2018; Singh and Kumar 2019), was used to identify the corresponding 30-year-future periods. In this approach, the warming during the reference period, which was approximately 0.46 °C warmer than the pre-industrial global mean temperature (1881–1910), was established based on several observational datasets (Vautard et al. 2014; Jacob et al. 2018). Using this offset value (i.e., 0.46 °C), the 30-year periods were identified for each of the 10 GCM–RCP combinations (i.e., 5 GCMs × 2 RCPs) in which the global mean temperature increased by 1.04, 1.54, and 2.54 °C respective to the reference period. These periods correspond to the 1.5, 2.0, and 3.0 °C temperature thresholds used in the analysis. The future projections were obtained for each climate model simulation for two warming

scenarios: low warming (RCP2.6) and high warming (RCP8.5). It should be noted that under the low-warming scenario, the 3.0° temperature threshold is not reached, and therefore was not included in the analysis.

3 Results

Following the modeling framework outlined in Section 2.3.2 and Fig. 2, the interconnected water and electricity use was projected into the future under various climate change scenarios. In this section, we first discuss the model performance with the observational data and compare it to a conventional precipitation–temperature model before delving into the future projections of water and electricity use.

3.1 Model performance

As described above, the first part of the analysis in this study was building the regional model for three different periods—summer, winter, and intermediate months. The main goal of this first task was to demonstrate the effectiveness of the proposed modeling framework that makes use of a larger array of climate variables than the baseline model that considers only precipitation and temperature. As shown in Fig. 3, the *Selected Feature* model (i.e., the proposed model) tends to predict the water and electricity use more accurately than the *Baseline* model (i.e., the model that only considers precipitation and temperature, denoted “precip-temp” in the figure). This is especially true in the extreme ends of the consumption patterns, where predictive accuracy is crucial. Moreover, the difference between the selected feature and baseline models is more pronounced in the water use, for both summer and winter periods. This indicates that the additional variables considered in the selected feature model—dew point temperature, relative humidity, and wind speed—are more influential when predicting water use compared to electricity use. Figure 3 shows the results from the summer and winter periods; the results from the intermediate period can be found in the Supplemental Materials (Figure S1).

The improved performance of the selected feature model is further demonstrated in Fig. 4, which compares the model performance measures for both models during the summer and winter periods (see Supplemental Figure S2 for the model performance during the intermediate period). Both the out-of-sample RMSE and out-of-sample R^2 were used to assess the model performance. RMSE is a measure of error, in which lower values are representative of a better prediction (i.e., less error). Often, RMSE is used to evaluate the predictive performance of the model. On the other hand, R^2 can be thought of as a measure that accounts for the percent of variance within the data that is explained by the model. In this sense, a value closer to 1 indicates that the model is explaining more variance in the data. That being said, R^2 is rarely used to assess *predictive* performance, as it is not a measure of error. Together, however, RMSE and R^2 can be used to assess overall model performance—both from a predictive standpoint and the amount variance the model is able to capture.

3.2 Future water and electricity use projections

Following the analysis with the observational data, the selected feature model was used to make future projections of the climate-sensitive portion of the water and electricity use in the region. The predictor variables were obtained from the five CMIP5 global circulation

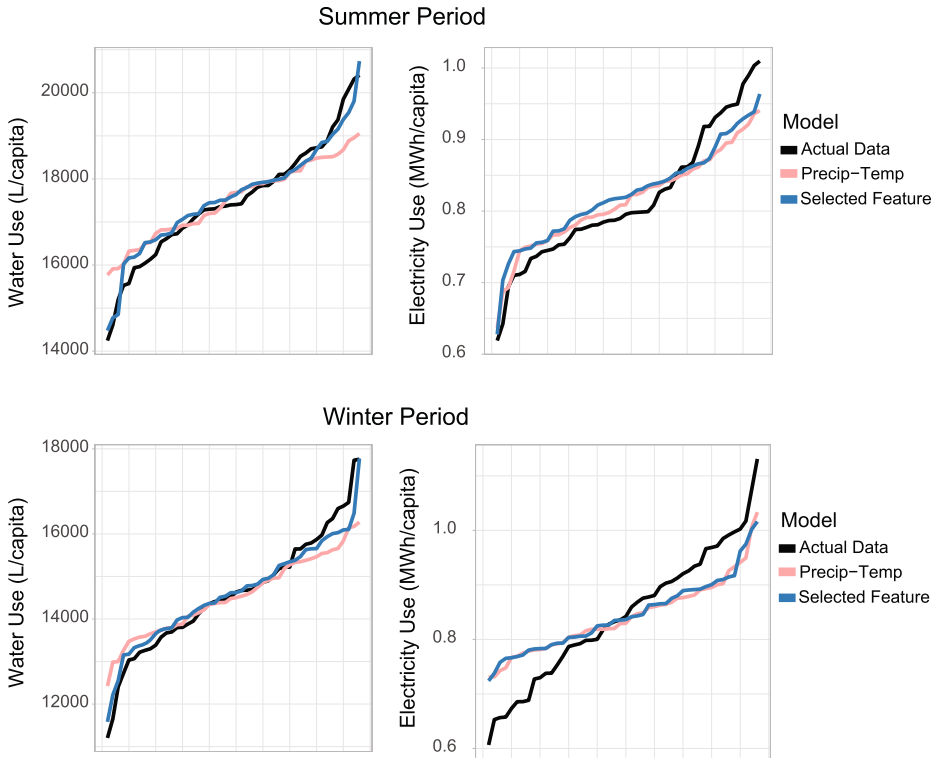


Fig. 3 Observational data compared with the two types of model runs: (1) a baseline model that only considered precipitation and temperature (denoted “Precip-Temp”) and (2) the proposed selected feature model that considers a larger array of climate variables (denoted “Selected Feature”). The results are presented for the summer and winter periods. Note that the data is presented as a line graph, so the x-axis is representative of the count of the data points

models discussed earlier. The purpose of this analysis was to show the potential change in water and electricity use due to climate change alone. In this sense, there was no consideration of technological changes or cultural shifts that would also have an impact on the water and electricity use. To evaluate the potential shifts in future water and electricity use, the percent change was calculated between the “historical” period (1971–2000) and the 30-year period in which key temperature thresholds were reached within the model. The historical baseline data from 1971–2000 can be found in Supplementary Figure S3. These thresholds—1.5, 2.0, and 3.0 °C—were selected based on several recent climate change assessment studies (Jacob et al. 2018; Samaniego et al. 2018; Marx et al. 2018; Singh and Kumar 2019; IPCC 2018). Initially, the percent change was calculated based on all the model output, regardless of the future pathway scenario, followed by a scenario-specific (i.e., RCP2.6 and RCP8.5) calculation. Figures 5 and 6 show the results of this analysis for both the summer and winter periods (see Supplementary Figure S4 for the intermediate period projections).

In general, the water use is projected to increase after all three temperature threshold scenarios and in both periods (see Fig. 5), but the electricity use is only projected to increase in the summer period (see Fig. 6). For water use in particular, as the temperature continues to increase (i.e., higher thresholds are reached), the percent change in median water use also

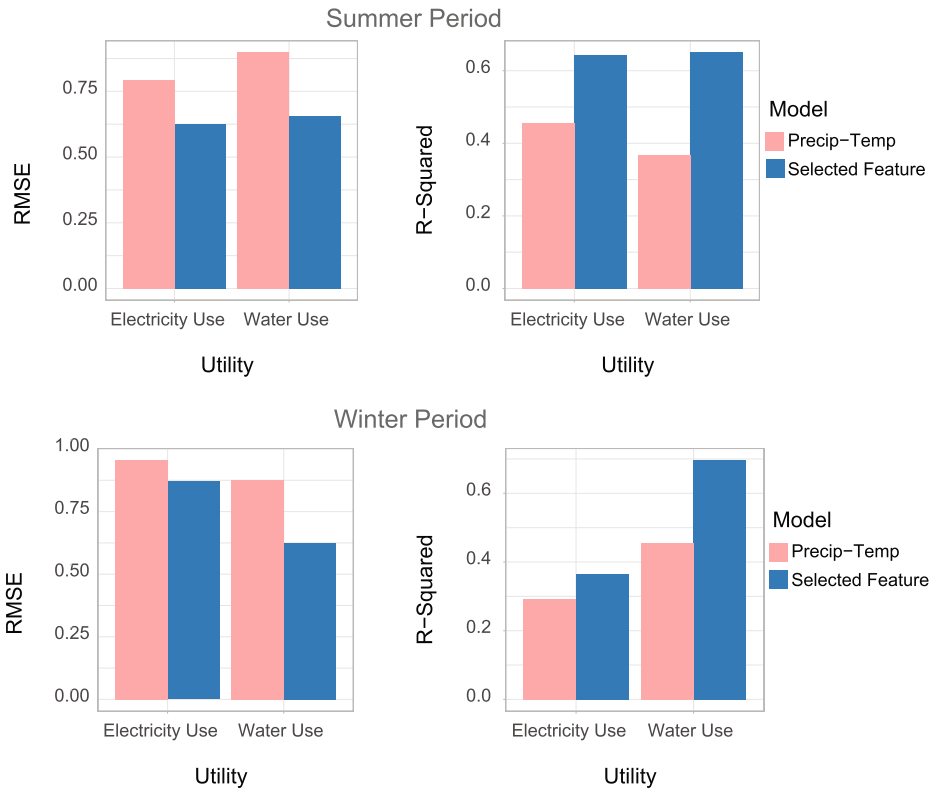


Fig. 4 Out-of-sample model performance results (RMSE and R^2) from the two styles of model runs: (1) a baseline model that only considered precipitation and temperature (denoted “Precip-Temp”) and (2) the selected feature model that considers a larger array of climate variables (denoted “Selected Feature”). The results are presented for the summer and winter periods

increases. In fact, in the summer period, the results indicate a relative increase in water use regardless of the temperature threshold or warming scenario. Given that the 1.5° threshold is approaching, these results demonstrate the necessity for Midwestern water utilities to prepare for increased summer demand in the near future. Similar results were shown for the summer electricity use in Fig. 6. Interestingly, the model shows a median decrease in winter electricity use across all the thresholds and scenarios, but especially after the 3.0° threshold is reached. This is likely due to warming temperatures and a reduced need for space heating in the winter, which is a major contributor to electricity consumption during the winter months. However, this potential reduction in winter electricity use was not offset by the potential increase in summer electricity use, making it imperative that utilities begin to find ways to increase their supply capabilities. In addition to the results presented here, the model-specific projections can be found in the Supplementary Figure S5.

4 Discussion

This study focused on building a regional model to simultaneously project the climate sensitive portion of interconnected water and electricity use into the future under various climate

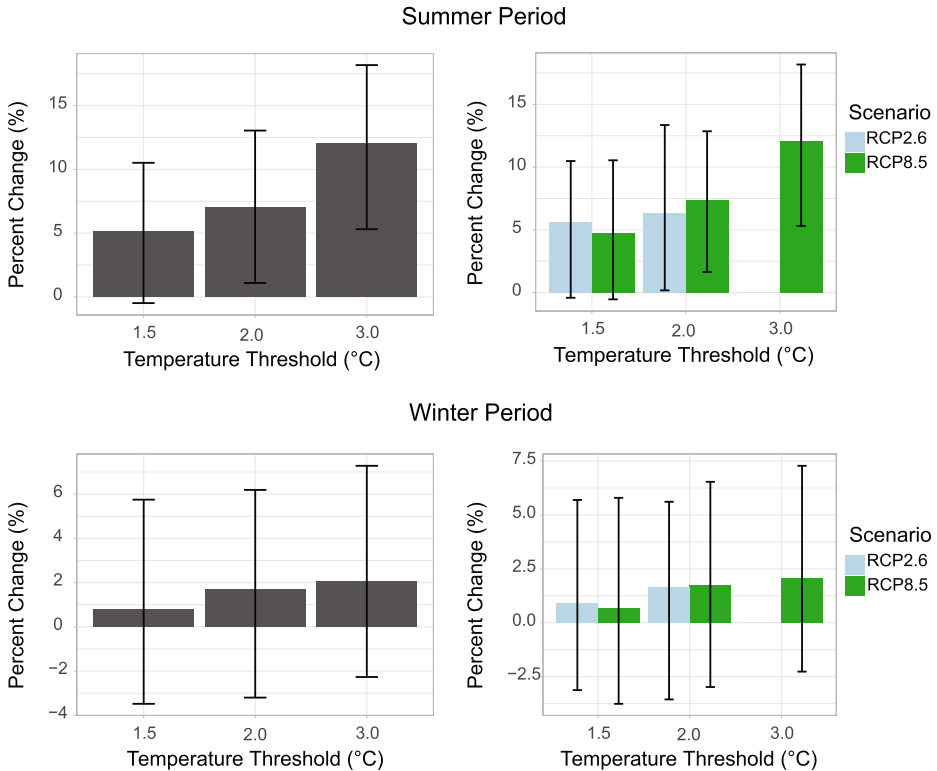


Fig. 5 The median relative change in water use after three different temperature thresholds have been reached in the summer and winter periods. The error bars represent the interquartile range. The left plots show the aggregate of both warming scenarios and the right plots show the same change, separated by scenario. Note that under the low-warming scenario (RCP2.6), the 3.0° threshold is not reached before 2100, and thus is not shown in the figure

change scenarios. There were two main parts of the analysis, the first of which was to build a rigorously tested predictive model (i.e., the selected feature model), using a variety of climate variables, and compare the predictive accuracy to the baseline model that only considered precipitation and temperature. The results from this comparative analysis showed a significant improvement over the baseline model when dew point temperature, relative humidity, and wind speed were included in addition to the standard dry bulb temperature and precipitation. In fact, initial results indicated that by including the average daily maximum values for relative humidity and wind speed, rather than the daily averages included here, there were additional improvements over the baseline model—especially in the winter period. However, the GCM projections of these daily maximum variables are not readily available for downloading, nor are they easily extractable from the model output directly. Since the aim of this modeling framework is to provide practitioners with a tool to make projections for their own systems, it was decided to include the daily averages instead of the maximums, as the climate projections are easier to obtain. In future iterations, including these maximum values in the model may lead to more accurate projections. Nevertheless, the selected feature model developed here did show significant improvement, especially on the extreme ends of the demand profile (see Figs. 3 and 4).

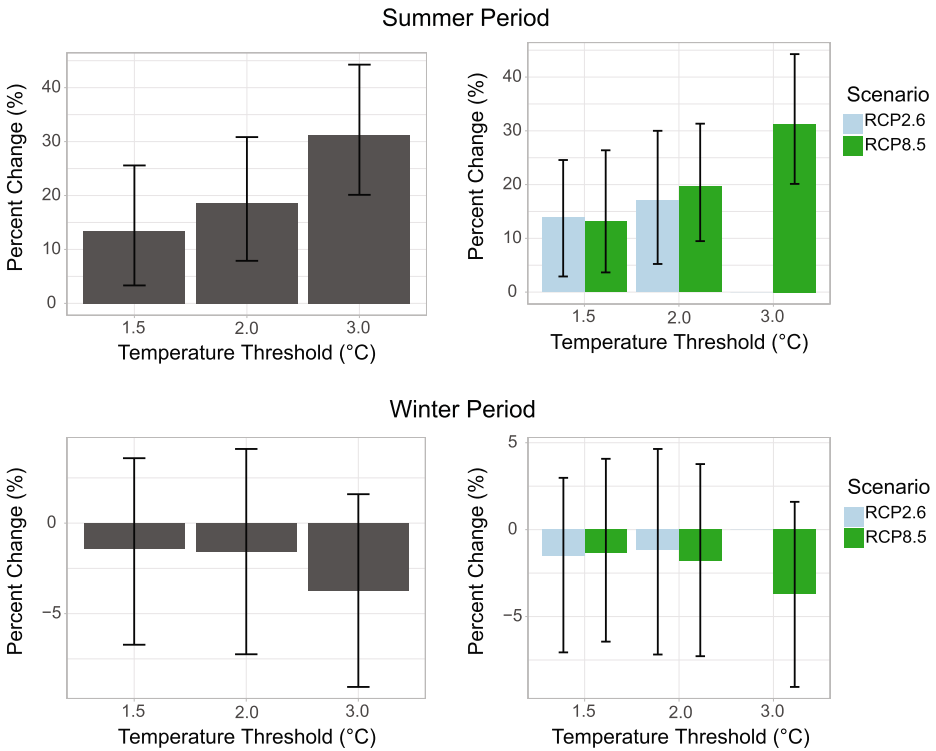


Fig. 6 The median relative change in electricity use after three different temperature thresholds have been reached in the summer and winter periods. The error bars represent the interquartile range. The left plots show the aggregate of both warming scenarios and the right plots show the same change, separated by scenario. Note that under the low-warming scenario (RCP2.6), the 3.0° threshold is not reached before 2100, and thus is not shown in the figure

The selected feature model was used in the second part of the study, which was to make future projections of water and electricity use based on future climate change scenarios. These results indicated a likely increase in both water and electricity use during the summer periods (see Figs. 5 and 6), with minimal uncertainty. During the winter period, however, there was more uncertainty in the projections, although the model still showed a median increase in water use and a median decrease in electricity use. Previous work indicated that warmer temperatures led to increased water use (Obringer et al. 2019), likely due to increased consumption for landscaping purposes. Landscaping, however, is generally only a summer demand pattern. It is possible that the increased temperatures allow for some winter landscaping in the more southern cities, which could explain the slight median increase in water demand. However, the large uncertainty bands make this determination difficult without further investigation beyond the scope of this study. In fact, given the range of possible winter temperature projections, as well as the variance introduced by seasonal shifts in the general climatic conditions, it is possible that winter water use will decrease along with electricity use. This decrease in winter electricity use may be due to the warming temperatures, which would lead to a decreased need for space heating in the winter months (but increased space cooling in the summer, hence the median increase in summer electricity use). Ultimately, this winter decrease paired with the summer increase could put additional

pressure on the electricity utilities to cope with the seasonal fluctuations. Moreover, both cases represent a potential economic loss to the utility—in the summer, there is a higher chance for shortages, while in the winter, there is a higher chance for surplus, both of which are undesirable for electricity utilities.

In addition to the results indicated by the regional model projections, it is possible to use the regional model to predict the water and electricity use for specific cities. The results from these city-specific projections can be found in Fig. 7, which shows the results from the summer period projections for the 1.5 and 2.0 °C temperature thresholds. These two thresholds are the ones that are most likely to be passed in the near future—1.5 °C is projected to be reached around 2030 and 2.0 °C is projected to be reached around 2055—as well as being politically relevant at the international scale. The recent IPCC report, for example, recommended that warming levels be kept below 1.5 °C if the world is to avoid the most detrimental consequences of climate change (IPCC 2018). But the 2015 Paris Agreement, which has been signed by the majority of countries around the world, argues for a 2.0 °C limit (UNFCCC 2015). Either way, these are the main thresholds being discussed at the international level, and are therefore important for utility companies that will need to provide adequate services regardless of the temperature thresholds that are ultimately reached.

In each of these six cities, the patterns of future consumption are similar. Each city, for example, is projected to have increases in both summer water and electricity demand, although the summer electricity is projected to have a larger relative increase. Additionally, there are relative larger changes after the 2 °C threshold than the 1.5 °C threshold, which is to be expected. There are also some differences between the cities. For example, Chicago is more urban (as opposed to suburban) with less residential green space (i.e., yards) than the other cities on the list. This likely leads to lower summer water consumption for outdoor landscaping, and thus a somewhat lower increase in median water demand when compared to the other cities. Minneapolis is the northern-most city in the analysis, and likely to see less of a severe summer temperature increase than the other cities. This could explain the relatively lower increase in summer electricity than Indianapolis and Cleveland, for example. Interestingly, Columbus and Indianapolis, which are close in population and are geographically similar, are projected to experience different magnitudes of changes to the water and electricity demand profile, with Columbus projected to see less intense changes. This may be due to the sprawling nature of Indianapolis (Indianapolis is approximately 160 mi² larger than Columbus), which generally means more single family, detached homes. This would likely lead to increased water use (for landscaping) and electricity use (for space cooling). In general, the cities all follow the same pattern, although there are some differences. That being said, even the small differences between the cities, as well as the differences between the thresholds can lead to large changes in the total demand.

If one focuses on Chicago, which is the largest city in the region, one can see that summer electricity is projected to increase significantly during the summer months with minimal uncertainty. In fact, after passing the 1.5° threshold, Chicago's electric utility could expect to see a 12% increase in per capita demand. Should the economy grow in accordance to the Shared Socioeconomic Pathway (SSP) scenario 1 (i.e., “sustainable growth”), the population in Cook County (covering the city the Chicago), would be 5.39 million by 2030 (Hauer 2019) which roughly corresponds to the crossing of 1.5° threshold. Given a per capita demand estimate of 0.97 MWh/capita in the projected period, this would lead to an additional 745,000 MWh in monthly electricity demand during the summer months, only attributable to climate change. Without technological advances or cultural shifts towards conservation, this increase in demand will become more dramatic which will severely strain

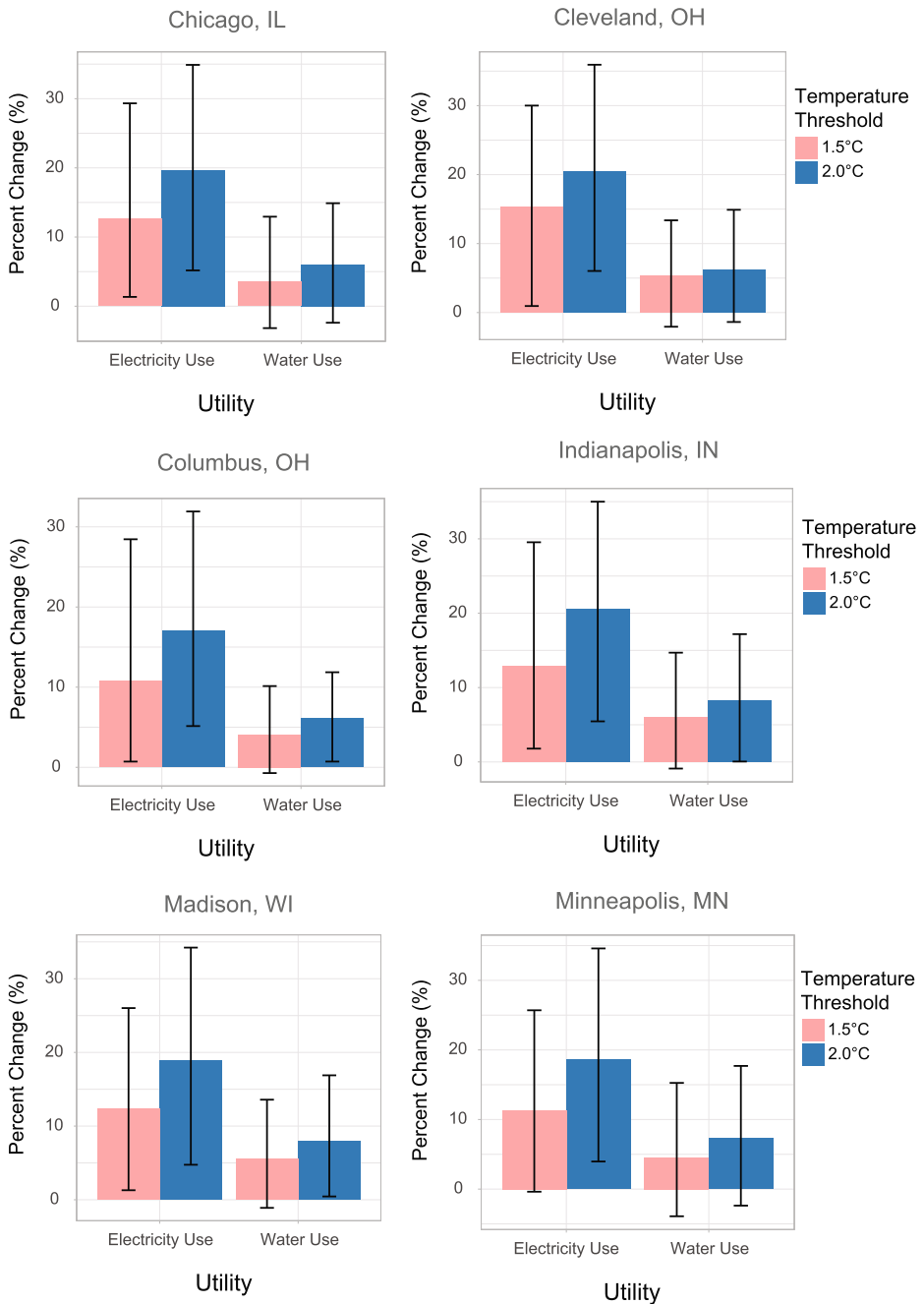


Fig. 7 The median relative change in water and electricity use for the individual cities in the study region for the summer period following two of the three key temperature thresholds. The error bars represent the interquartile range

existing infrastructure. For example, if the SSP5 scenario is followed (i.e., “fossil-fueled development”), the population is projected to be 5.71 million by 2030 (Hauer 2019), which corresponds to approximately 1.06 million additional MWh.

This need for technological advances or cultural changes only increases after the 2.0 °C threshold, which is expected to be crossed in the 2050s, should the current trend hold and no significant climate action plans be implemented. In fact, after this threshold the electricity demand in Chicago could increase by 1.6 million MWh (compared to the reference period) should warming not be capped at the recommended 1.5 °C threshold, assuming a population of 6.09 million in Cook County (Hauer 2019). This intense increase demonstrates the benefit of following the IPCC recommendation and working to cap global emissions from the local utility perspective. Overall, these results signal the importance of making water and electricity use projections and building models that can be adopted by utility managers that need to prepare for future demand shifts.

That being said, the above future changes in water and electricity demand in the Midwestern region of the USA include considerable uncertainty. The uncertainty presented here as the interquartile range (i.e., the error bars in Figs. 5 and 6) demonstrates relatively larger uncertainty during the winter season in both water and electricity use. In fact, the percent change spans over both positive and negative values—leading to highly uncertain projections. This makes preparing for the future more difficult, since it cannot be said, for certain, what will happen. Although the signal is stronger in the summer months (i.e., there is a demonstrable increase in usage across all scenarios), there is still some uncertainty. Part of this uncertainty comes from the climate models themselves (see Supplemental Figure S5 for the model-specific projections). As discussed earlier, only five climate models were selected, as they are most often used within the literature (IPCC 2013, 2018), which introduces bias into the study. However, these are pitfalls that occur with any future projection study. Moreover, this modeling framework has been developed such that it can be applied at a broader scale with a larger number of climate models included. In this sense, although the uncertainty is present, the results can still be interpreted as potential pathways forward, should the outcome of the climate models come to pass.

5 Conclusion

The goal of this study was to build a data-driven, regional model to evaluate the impact of future climate change on the coupled water and electricity demand nexus. The modeling framework leverages the multivariate tree boosting algorithm to simultaneously predict the interconnected water and electricity demand in the residential sector. There were two response variables: monthly water and electricity use, and five final predictor variables: maximum dry bulb temperature, average dew point temperature, average relative humidity, average wind speed, and accumulated precipitation. The proposed selected feature model proved to be more accurate than the baseline model, which only included maximum dry bulb temperature and accumulated precipitation. Many demand projection studies in the past have used only this standard baseline model, which tended to underpredict the higher demand levels. Accurately predicting these higher demand levels, which represent the peak load, is crucial for utility managers. The results presented here indicate that including additional variables, such as relative humidity and wind speed, could greatly improve the predictive accuracy of peak load forecasting models, which will be beneficial for practitioners.

Additionally, the modeling framework was used to make future projections of the water and electricity demand, given the output from several global circulation models. The results from the projection analysis show that the summer water and electricity demands can be expected to increase due to climate change. This means that, ultimately, utilities will either need to rely on technological advances or cultural shifts to limit these increases in demand or spend a significant amount of money to expand their supply capacities. On the other hand, the winter demands were slightly more uncertain, but there is a potential that winter electricity use will decrease due to climate change. This will introduce the additional challenge of managing fluctuations, especially for electric utilities, which lack the storage capabilities of most water utilities.

The modeling framework presented here can be used by utility managers, policymakers, and urban planners, for example, who are interested in gaining a better understanding of how their per capita demand may shift due to climate change. The results presented here can be combined with other research studies that focus on the technological and cultural aspects of demand projections to create a well-rounded understanding of the future for which cities must prepare. Additionally, although the model was built and tested in the Midwestern region of the USA, the framework can easily be applied to different regions around the world.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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