United Nations University
Institute for Water, Environment and Health

Harnessing the Power of AI for Climate Change Impact Assessment

Results presented in this report have been published in the following journal papers:

Obringer, R., Kumar, R., and Nateghi, R. (2020). Managing the water-electricity demand nexus in a warming climate. *Climatic Change*, *159*(2), 233-252.

Obringer, R., Nateghi, R., Knee, J., Madani, K., and Kumar, R. (2023). Contemporary climate analogs project strong regional differences in the future water and electricity demand across US cities. *One Earth*, *6*(11), 1542-1553.

Acknowledgments

UNU-INWEH gratefully acknowledges its host, the Government of Canada, and ongoing financial support from Global Affairs Canada.

Global Affairs Canada Affaires mondiales Canada

Harnessing the Power of AI for Climate Change Impact Assessment

Renee Obringer

Rohini Kumar

Kaveh Madani

United Nations University Institute for Water, Environment, and Health (UNU-INWEH)

2024

Suggested Reference: Obringer, R., Kumar, R. and Madani, K. (2024). Harnessing the Power of AI for Climate Change Impact Assessment, United Nations University Institute for Water, Environment and Health (UNU-INWEH), Richmond Hill, Ontario, Canada.

Download at: https://unu.edu/inweh/publications

ISBN: 978-92-808-6120-4
DOI: 10.53328/INR24ROR012

Image credits: Unless stated otherwise, the images in this report were created by generative artificial intelligence.

About UNU INWEH

UNU-INWEH's mission is to help resolve pressing water, environmental, and health challenges that are of concern to the United Nations, its Member States, and their people through critical analysis and synthesis of existing bodies of scientific discovery; targeted research that identifies emerging policy issues; application of on-the-ground scalable science-based solutions; and global outreach. UNU-INWEH carries out its work in cooperation with the network of other research institutions, international organizations, and individual scholars throughout the world.

UNU-INWEH is an integral part of the United Nations University (UNU)—the academic arm of the UN—which includes 13 institutions located in 12 countries around the world and dealing with various development issues. UNU-INWEH was established in 1996 as a public service agency and a subsidiary body of the UNU. The institute is located in Richmond Hill, Ontario, Canada, and its operations are supported through long-term host-country and core-funding agreements with the Government of Canada.

Contents

List of Figures

Executive Summary

KEY MESSAGES

- Investigating localized climate changes impacts on critical infrastructure is important for developing equitable mitigation and adaptation policies.
- Artificial intelligence (AI) can be used to conduct flexible and computationally efficient climate change impact assessment.
- Input data can range from traditional climate simulations from Earth Systems Models (ESMs) to recently developed proxies for future climate projections.
- AI algorithms can easily handle both types of input data for a variety of applications.

Climate change impact assessment is critical for creating adequate climate change mitigation and adaptation policies and plans. Communicating the results of these impact assessments is equally important for improving the understanding of climate change impacts across various sectors, encouraging local action, minimizing future harm in communities, and making progress towards the UN Sustainable Development Goals (SDGs). Notably, a better understanding of climate change impacts on the water and energy systems would facilitate the fulfillment of SDG2 (end hunger), SDG 6 (clean water and sanitation), SDG 7 (affordable and clean energy), SDG 11 (sustainable cities and communities), and SDG 13 (climate action), with many indirect benefits across many other areas.

Critical infrastructure systems (e.g., water and energy systems) are particularly at risk for climate change impacts. For instance, increased intensity and frequency of droughts due to climate change may lead to reductions in water availability, which can compound with other disasters and lead to cascading impacts throughout the system[1,2]. Likewise, energy systems are impacted by increasing temperatures caused by climate change[3]. In particular, air-conditioning use is expected to increase during summer months in many parts of the world, straining the electricity grid[4]. These impacts propagate through the system, ultimately impacting households. In 2018, the United States Energy Information Administration (EIA) reported that nearly one-fifth of the households in this country chose to forgo necessities (e.g., food, medicine, etc.) in order to pay for their electricity bills[5]. Often, to limit the cost of energy bills, lower-income households will avoid using air conditioning during the summer[6], which leads to heat-related health issues[7]. Similar work has shown that drought-induced demand management programs lead to increased water bills for lower income households[8,9]. It is likely that these issues will become more pronounced under climate change, making it imperative that we work to understand localized climate change impacts.

Nonetheless, conducting climate change impact assessment, particularly at the community-level, is not an easy task. Often, the impact assessment models require access to substantial computational resources to run the complex models, as well as the expertise to work with those models and interpret their results, which may not be possible for all communities. As such, there is a need to expand climate change impact assessment to include more accessible models that can handle high-resolution, local data that is of interest to communities.

This report by the United Nations University Institute for Water, Environment and Health (UNU-INWEH) highlights how climate impact assessment studies can benefit from the power of artificial intelligence (AI). The report details the use of a state-of-the-art machine learning (ML) model to conduct a computationally efficient climate change impact assessment. This model is applied to a case study across the United States of America (U.S.) as an example to showcase the insights it generates in real-world applications. To demonstrate this process, the study will focus on the impacts on coupled water and electricity demand (e.g., the water-electricity demand nexus). In particular, the report leverages data from U.S. cities collected from water and electricity utilities over the past decade. To conduct

A collage of a few climate and weather-related extreme events that are expected to intensify under climate change: loss of glacial ice, wildfires, hurricanes, floods, heatwaves, and droughts (from left to right). Image credit: U.S. National Oceanic and Atmospheric Administration

the impact assessment, the report demonstrates two different means of collecting future climate data—Coupled Model Intercomparison Project 5 (CMIP5) Earth System Models (ESMs) and contemporary climate analogs. ESMs are large physics-based models that simulate how the Earth's physical, chemical, and biological systems work under various scenarios. In particular, the CMIP5 suite of ESMs are focused on simulating the future climate of the Earth using changing CO_2 emissions as the primary force behind shifting climatic patterns. These models are highly specialized and complex, requiring a deep understanding to run and extract information from. Thus, there is a need for more easily understood and implemented means to determine future climatic patterns. This report utilizes climate analogs to fill this need. A climate analog is a location with a modern climate that can be used as a proxy for some other location's future climate. In other words, the climate of location A in 2020 may be similar to the projected climate of location B in 2050, thus location A becomes a climate analog of location B. These analogs are often determined based ESMs, such as the CMIP5 models, but once developed can be used with easily accessible data on current or historical weather and climate. In addition to demonstrating the power of AI for climate change impact assessment, this report aims to compare these two sources of future climate data within an AI framework.

This report demonstrates that AI methodology is effective for conducting computationally efficient climate change impact assessment. In particular, the report focuses on the climate change impacts to water and electricity demand, which are highly interconnected infrastructure systems. Traditional means of conducting climate change impact assessment may not be viable for smaller or underserved communities, thus finding novel, more accessible means of providing these critical results to local areas is crucial for ensuring equitable climate change mitigation and adaptation. Here, AI is used to aid this goal in two primary ways. First, the use of AI allows for flexible, computationally efficient models that can be easily run in web- or cloud-based services. This makes them more accessible to smaller communities. Second, we compare two means of obtaining future climate simulations—the traditional ESM data and contemporary climate analogs. The results in this report demonstrate the power of using the analogs to conduct studies across a wide variety of cities, ranging in population, in the U.S. The report shows that regardless of the input data, AI can be used to project changes in the water and electricity demand under climate change. In particular, the report shows significant increases across the Midwestern U.S. when using ESM-derived data. Similar results were found through the climate analog-derived data, suggesting that the analogs can be used successfully as proxies for traditional ESM data in communities that might not have access to the larger CMIP suite of models.

Understanding the impacts of climate change on critical infrastructure is important for building sustainable and equitable policies for climate change mitigation and adaptation. These infrastructure systems are often interconnected (e.g., the water-energy nexus) and managed by local entities. Thus, while climate change is a global problem requiring cooperation across countries and sectors, many solutions require local action. In this sense, the results presented in this report can be used to deepen our scientific understanding of climate change impacts on the water-energy nexus, as well as develop novel methodologies that integrate ML with traditional climate change impact assessment to better prepare local communities for the future.

The use of AI for climate change impact assessment represents an opportunity to expand the use of impact assessment to communities, ultimately helping society to increase resilience and prepare for the future. AI provides a computationally efficient and flexible means to model the impacts of climate change across a variety of sectors. Moreover, with the growing popularity of data science and breakthroughs in the Fourth Industrial Revolution (Industry 4.0), the use of AI models has increased in various areas, including the private and public sectors. In this sense, in communities where running large-scale impact assessment models is not feasible, there may still be expertise to run web- or cloud-based AI models to understand climate change impacts in their communities.

KEY FINDINGS

- After 2.0°C of warming, Midwestern U.S. cities are likely to experience a median increase of 20% (± 10%) in electricity use under a high warming scenario.
- The Midwestern U.S. region could consume up to 30% (± 10%) more electricity after 3.0°C of warming above pre-industrial levels.
- Midwestern U.S. cities could experience an increase in water consumption up to 7.5% (± 5%) after 2.0°C of warming and 12% (± 7%) after 3.0°C during future summer months.
- Across the entire continental U.S., future increases in summer water and electricity demand under climate change could be up to 15% and 20%, respectively.
- There are strong regional differences across the U.S., with a few cities shown to possibly experience reductions in water and electricity use under climate change.

Introduction

The changing climate will impact every sector on Earth—from droughts and floods reducing agricultural output to heatwaves putting undue stress on electricity systems. Already, society is seeing a significant increase in the number of "billion dollar" events, or climate-related disasters that cause more than one billion U.S. dollars worth of direct damages. These events include storms, hurricanes, wildfires, flooding, and droughts. Further, climate change will create a major public health crisis, particularly in areas that already have high numbers of vulnerable people. As such it is crucial that we work to understand the impacts of climate change across a variety of sectors and regions.

Climate change impact assessment is a key tool for estimating how various sectors may be impacted by the climate crisis, given different warming scenarios[10]. These assessments have provided critical insights into water availability[11] and droughts[12,13], energy supply[14-16] and demand[17,18], and many more applications in both the natural and built environments. Understanding how various sectors may be impacted by climate change is critical for building resilience to future changes. For example, knowing how climate change may reduce water availability in the worst-case scenario allows utilities and infrastructure managers to plan for alternative supply or implement demand management techniques. Further, impact assessment can often be conducted for multiple warming scenarios and time horizons[19]. This allows users to investigate the implications of surpassing seemingly small temperature thresholds (e.g., the difference between 1.5 and 2.0°C)[20]. Yet, there remain challenges associated with these models.

One challenge for conducting climate change impact assessment is the scale and complexity of the models commonly used for such analysis. In particular, many impact assessment models are physics-based models that require in-depth knowledge on how to run the model, as well as how to analyze the output. This can be challenging for small or underserved communities that may not have the funds or expertise to run these large-scale models.

Further, the computational capacity can pose a challenge, as these large-scale climate change impact assessment models often require the use of high-performance super computers, which are costly to operate and maintain. Local communities are unlikely to have access to such computational power, even if they have funding and expertise needed to run the impact assessment models. Additionally, many impact assessment models are dependent on ESM data[21], yet this data is rarely at the scale or specificity needed for impact assessment models[22]. In practice, this means downscaling and bias-correcting output from climate simulations, another computationally extensive process requiring funding and expertise. Thus, if we are to encourage localized climate change impact assessment that can be conducted around the world, there is a need to build models that are (a) easily implemented, (b) accessible, and (c) computationally efficient. Integrating artificial intelligence with these complex climate models is one means of addressing these issues[23].

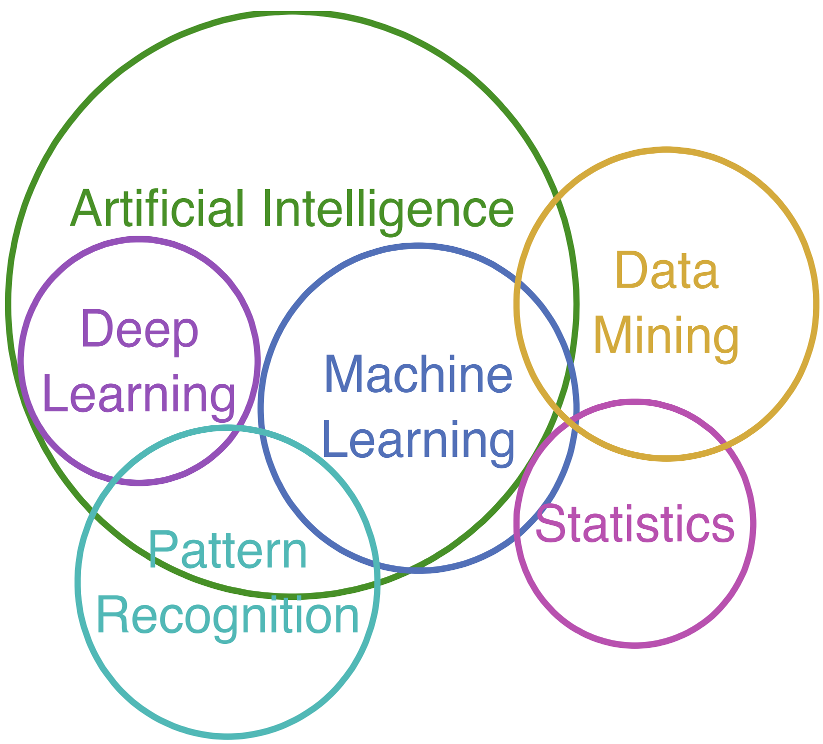
This UNU-INWEH report outlines a study leveraging AI for climate change impact assessment as a means of demonstrating its potential. The report shows that AI is not only flexible and computationally efficient, but also it can provide rapid, highly local estimates of climate change impacts across a variety of sectors. Moreover, with the rapid deployment of web- and cloud-based services, the AI models discussed in this report can be easily accessed around the world with minimal computational resources.

View of Lake Mead from the Arizona side of the Hoover Dam during drought, 2015. Image Credit: Peter Thoeny/Flickr

Why AI for Impact Assessment?

Artificial intelligence (AI) is a growing field, ranging from more traditional statistical machine learning (ML) techniques to advanced deep learning methods. Within this spectrum, there are a number of algorithms that one can use, depending upon the application of interest. For example, leveraging a more interpretable class of algorithms, such as decision tree-based algorithms, can help people understand why a certain phenomenon is occurring. Alternatively, for applications that require highly accurate predictions, but little to no interpretability, deep learning methods can be an effective solution. Regardless of which algorithm one chooses, the goal of most AI algorithms is to predict some quantity (or quantities in the case of multi-outcome modeling) given a series of input variables. This is frequently referred to as *supervised learning*[24]. Using supervised learning algorithms, the model will determine the nonlinear function that best explains the mathematical relationship between the quantity of interest and the input variables. When leveraging AI for climate change impact assessment, this mathematical relationship is assumed to be stationary, such that when the climate changes, the quantity of interest responds to those changes following that same mathematical relationship. This critical assumption allows researchers to quickly project the impacts of climate change for a variety of sectors.

Leveraging AI algorithms for climate change impact assessment exhibits several benefits over traditional models. For instance, AI algorithms aim to minimize expected prediction error, which effectively balances bias and variance[24,25]. By doing this, the algorithms are better able to predict values, even if they were previously unknown. Many traditional models lean towards reducing bias (i.e., being explainable), while allowing variance to increase rapidly. By allowing for some increase in bias, AI algorithms reduce the variance and the overall predictive error[24,25]. Further, AI models can lead to improvements within large impact assessment models, as the results from the AI models can be integrated into these models for scenario testing and other complex techniques. Additionally, AI models are computationally efficient and are able to be run through many web- and cloud-based services. In this sense, AI tools can be used quickly and easily. This is different from traditional impact assessment models, which generally need significant computational resources and can be unwieldy for non-experts.



Connection between artificial intelligence (AI), machine learning (ML), and a number of other data science fields.

In this UNU-INWEH report, we will demonstrate the use of AI for climate change impact assessment to understand how shifting climatic patterns will impact water and electricity demand across the U.S. Specifically, we will be using *domain-informed ML*, which means that we will leverage domain expertise to determine input variables and frame the model. This use of domain-informed ML represents a different branch of AI than more complex deep learning algorithms, where the focus is solely on the prediction, rather than balancing prediction and interpretation.

The focus on domain-informed input variables ensures that the mathematical relationships used within the model are based on physical variables that have been previously shown to have some kind of relationship with the quantity of interest. In other words, it is important to ensure that we are not building our models off of spurious relationships that do not have a physical basis. Further, domain-informed techniques are often easier to communicate with stakeholders, as the relationships picked up by the algorithms are often familiar. Within domain-informed ML, we also emphasize the interpretability of models, rather than relying solely on highly predictive "black box" methods. An ongoing challenge within the AI/ML community is figuring out *why* an algorithm is producing highly accurate predictions. That is, what variables are having an impact and how are they impacting the final prediction. There is a balance between interpretability (e.g., being able to answer the "why" questions thoroughly) and predictability (e.g., having a highly accurate prediction)[24]. Domain-informed ML seeks to maximize both of these qualities, as both are needed to build trust in a given model. When working with climate change impact assessment, it is especially critical to communicate and engage with stakeholders—for that, the stakeholders need to understand and trust the models.

Key Benefits of AI/ML for Climate Change Impact Assessment

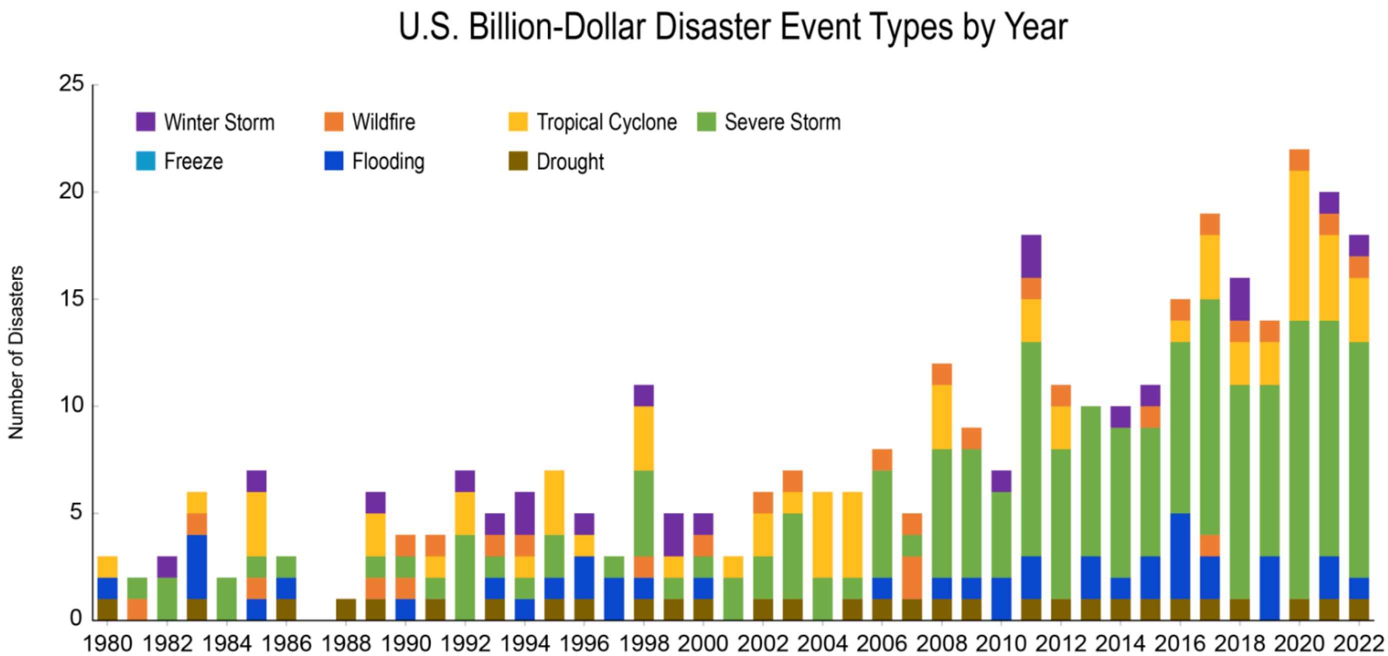
Flexibility:
Artificial intelligence (AI) and machine learning (ML) models are flexible and able to handle a number of different data sources and types. AI/ML has been used across a variety of application areas and geographic domains and its flexibility also improves the transferability of AI/ML models to other areas of interest.

Computational Efficiency:
AI/ML models, particularly those that fall into domain-informed machine learning, are generally computationally efficient and are able to run on web- and cloud-based services. This makes them easy to run outside of academic spaces where resources may be minimal.

Accessibility:
AI/ML models can be integrated into accessible platforms that can be used by local stakeholders. Moreover, as data science and AI/ML become more commonplace in higher education, there will be an increasing number of graduates working in industry and government with AI/ML experience.

Pattern Recognition:
AI/ML models can accurately recognize complex patterns and relationships between predictors and response variables. Often these relationships are nonlinear, making them difficult to recognize without the help of computational technology.

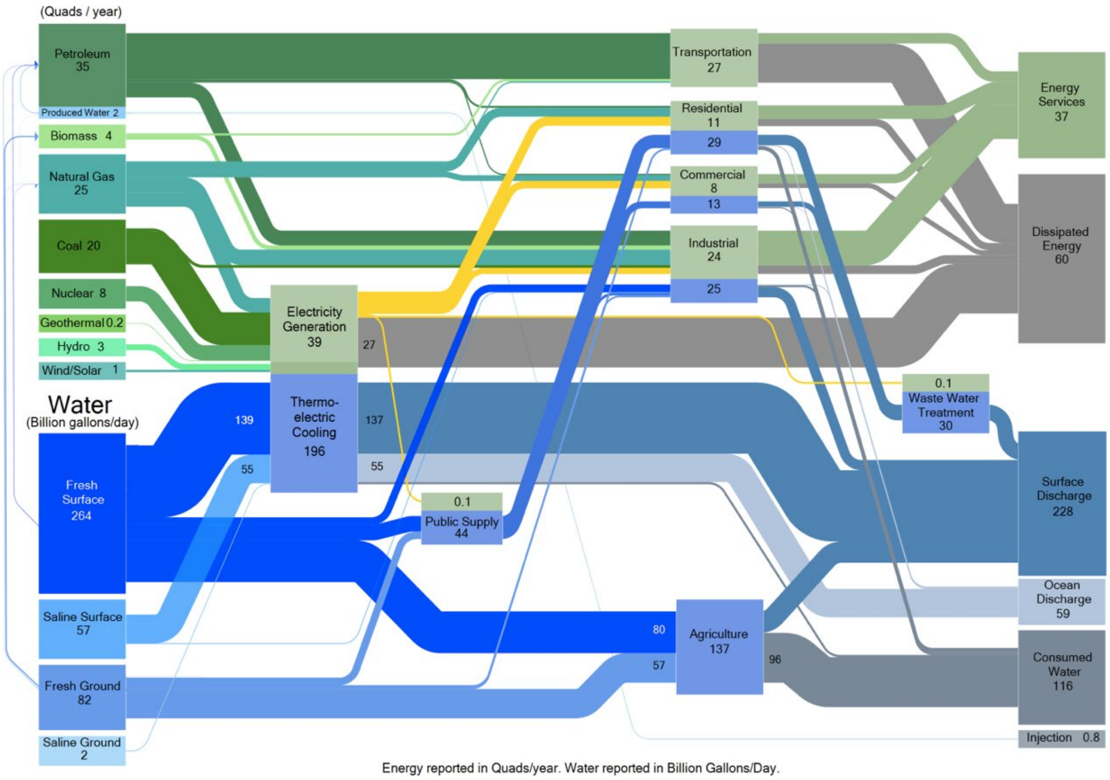
Exploring the Water-Energy Nexus in the United States



A bar chart showing the number of individual weather- and climate-related events that caused more than one billion U.S. dollars of damage each year since 1980. Image credit: U.S. Global Change Research Program

In this UNU-INWEH report, we focus on the United States of America (U.S.) as a case study to demonstrate the utility of AI for climate change impact assessment. Like other parts of the world, the U.S. is experiencing a growing number of extreme climate-related events, which only expected to get more intense as climate change continues to intensify. Further, within the U.S. (as elsewhere), the water and power sectors are highly interconnected, often referred to as the water-energy nexus[26,27]. Thermoelectric plants make up nearly 75% of the power plants in the U.S.[28], which require water for cooling. In terms of hydropower, the U.S. generates just over 6% of its electricity from hydropower, but this makes up over 25% of the total renewable energy profile[29]. Hydropower is highly dependent on the surrounding environment, with minor changes in the timing and quantity of streamflow having major impacts on the generation capacity[30]. Understanding this interconnectivity between water and electricity supply in the U.S. is critical to meeting future clean energy needs. This is particularly true in light of President Joe Biden's ambitious goal to fully decarbonize the U.S. energy sector by 2035[31]. If the U.S. is to meet this goal, it is imperative that the water-energy nexus be accounted for when planning for future power generation capabilities.

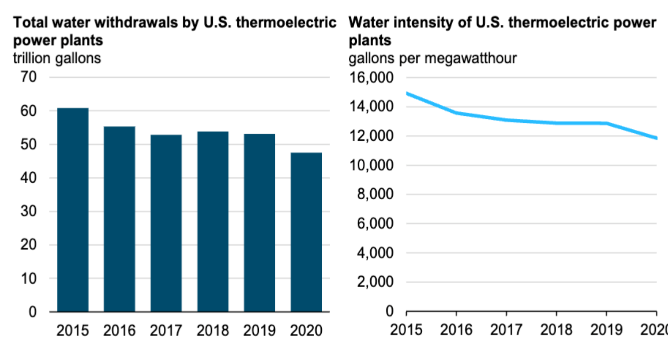
A key strategy of decarbonization is the electrification of the energy sector[32], which reduces reliance on fossil fuel-based heating (e.g., through natural gas or heating oil) and thus reduces greenhouse gas (GHG) emissions. When paired with increased renewable energy penetration, this is an effective strategy for reducing the overall GHG emissions. However, as more sectors become reliant on electricity, the interconnectivity between electricity and other critical infrastructure services increases. For example, in the U.S., the water treatment and distribution infrastructure is already heavily reliant on electricity. It was estimated that in 2012, U.S. water utilities used more than 37,000 GWh for both drinking water and wastewater services[33]. This is equivalent to the electricity consumed by about 1.3 million United Kingdom citizens (just over the population of Birmingham), 4.9 million Indians (about a third of the population of Bangalore), or 14.5 million Nigerians (nearly the population of Lagos). Moreover, it has been estimated that water-related electricity consumption will increase, particularly in those U.S. states that are already experiencing water



Infographic depicting the water-energy nexus within the U.S. Image Credit: U.S. Department of Energy

stress[34]. Additionally, extreme climate events could lead to cascading failures across multiple interdependent systems. For example, during the Texas cold snap caused by winter storm Uri in 2021, there were widespread power outages. These outages impacted the water system, leading to water shortages[35]. Thus, a storm that directly impacted the energy sector, led to cascading failures and indirect impacts on the water sector.

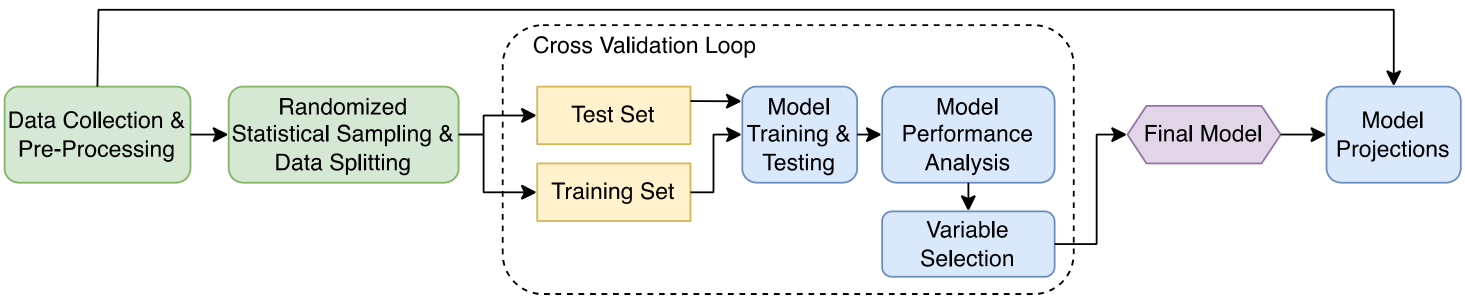
Beyond the climate change impacts on the interconnected water and electricity supply, there is a growing body of work investigating the impacts of climate change on U.S. water and electricity demand, which are projected to shift under climate change. As the U.S. energy sector shifts towards increasing electrification[32], understanding the climate impacts on demand structures will become increasingly important. For example, nearly 90% of U.S. households used air conditioning in 2022[36], with that number expected to continue growing due to higher temperatures and more frequent heatwaves. With this high penetration of air conditioning, electric utilities often experience the peak electricity demand during the summer[37]. Given that climate change is making summers warmer with more extreme heat events[38], it is projected that air conditioning use will increase significantly[4], leading to increases in overall and peak electricity demand[39]. These spikes will, in turn, lead to an increased need to generate electricity, which may lead to increased water consumption by the power sector. Simultaneously, droughts are likely to increase[12,40-42], which are likely to be compounded by increased water demand[1,43,44]. Understanding these impacts is critical for building resilience in our interconnected infrastructure systems, as well as working to mitigate climate change.



Water used by thermoelectric power plants in the U.S. Image Credit: U.S. Energy Information Administration

Model Development and Evaluation in the Observational Space

In this UNU-INWEH report, we are focusing on domain-informed ML, a branch of AI that seeks to provide accurate predictions, as well as allowing for better grounding of models in the physical world. In order to conduct domain-informed ML for climate change impact assessment, the first step is to build the model using observational data. In this step, the model is *learning* the relationship between the response (i.e., dependent) and predictor (i.e., independent) variables. In this report, water and electricity demand are our interdependent response variables, while the observed climatic conditions are our predictors. Thus, ensuring this observational data is accurate and representative is critical to ensuring both an accurate prediction in the observational space and a reliable projection into the future.



The general framework for conducting climate change impact assessment using AI/ML. The process begins with data collection and pre-processing. Then, within a cross-validation loop, the models are trained and tested using observational data. Finally, the best model is selected, often based on predictive accuracy, and is used to make projections using future climate simulations as input data.

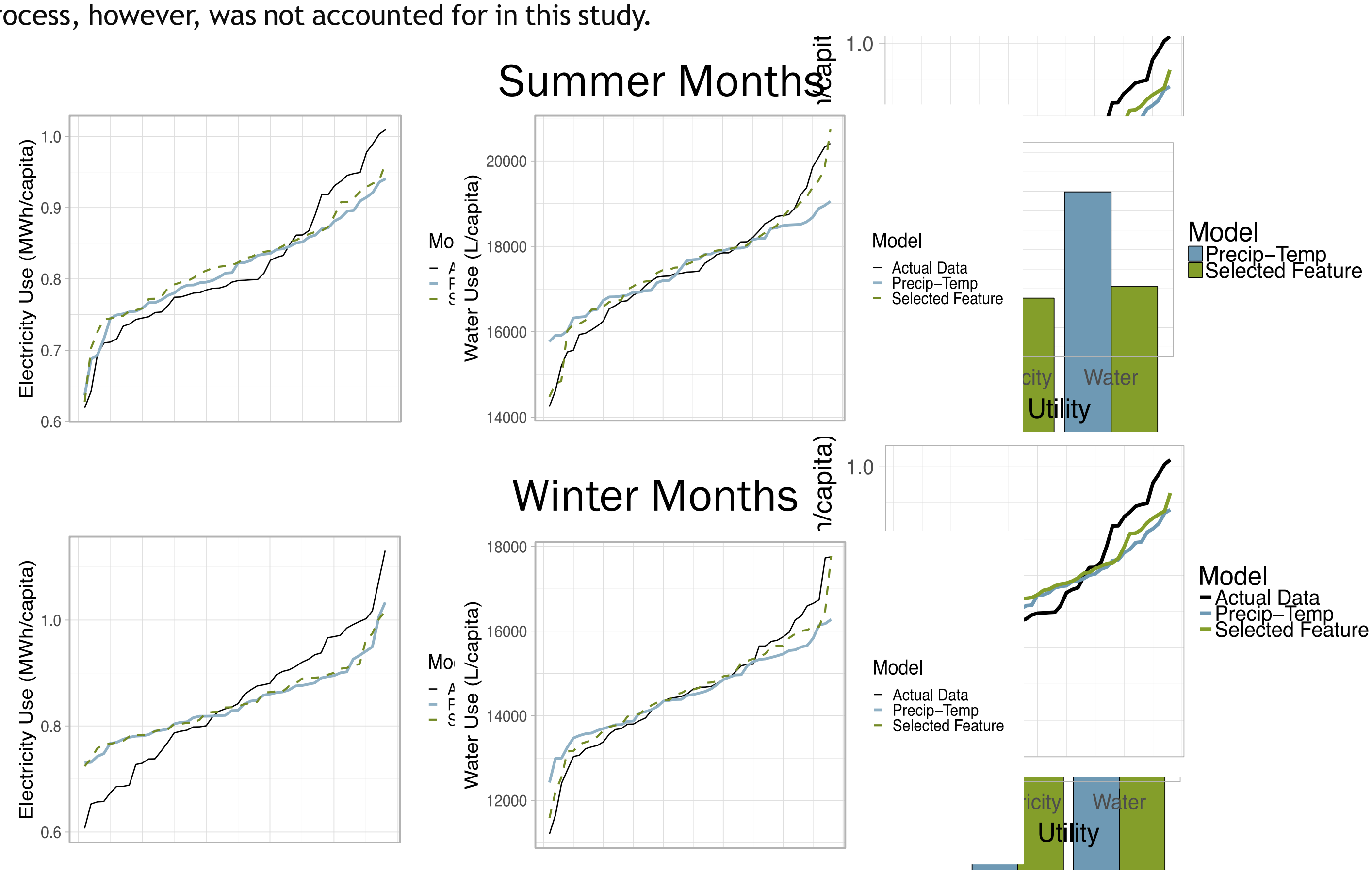
When developing the model, we adopt the following general process. First, we start with data collection and pre-processing. For this study, this involves normalizing the water and electricity demand by the service population, spatiotemporal aggregation to obtain monthly values in both the demand and climate data, and finally, adjusting the trends to focus solely on climate impacts following a statistical process[45]. This statistical trend adjustment is a critical step for climate change impact studies and has been used in a number of demand-based studies[16,17,46]. Then, we randomize the sample and split the data into training and test sets. These different sets are used in a cross-validation loop to iteratively train the model and test the predictive capabilities of the model using the test data, which was not used during the training stage. In this way, we can evaluate how well a model performs when predicting previously unknown data. Within this loop, we also conduct variable selection to determine which variables are the most important for obtaining accurate predictions. These important variables are then used in the final model. Finally, the final model is used to investigate future changes to the coupled water-electricity system, given future climate data as input variables, which we discuss in later sections.

In this UNU-INWEH report, we showcase an example of building the model using observational data from six Midwestern cities: Chicago (IL), Cleveland (OH), Columbus (OH), Indianapolis (IN), Madison (WI), and Minneapolis (MN). In particular, we built this model considering three different seasonal periods—summer (June through September), winter (December through March), and intermediate (April, May, October, and November). Moreover, we tested two variable sets. The first only included dry bulb (or air) temperature and precipitation, which represents the traditional variable set used frequently in both academic literature and managerial practice. We refer to this as the *Baseline* model throughout the study. The second variable set included the results from our larger variable selection, which included relative humidity, wind speed, and other measures of temperature in addition to the traditional variables. We refer to this model as the *Selected Feature* model. To compare these models, we calculated the root mean squared error (RMSE). RMSE is a measure of predictive error, with lower values signifying less error in the model. Thus, lower RMSE values point to a more accurate model.

In particular, the results demonstrate the improved predictive accuracy of the *Selected Feature* model over the *Baseline* model, particularly at the extreme ends of the demand structure. This improvement is more pronounced in the water demand than electricity demand across the seasons, indicating that the additional variables considered in the *Selected Feature* model are critical for accurate water demand predictions. These variables are still important for electricity demand predictions but are less crucial in comparison to the water demand.

Additionally, it is important to note the difference between the summer and winter months. Given that the summer months tend to be more sensitive to climate (i.e., through outdoor landscaping and air-conditioning), it is not surprising to see that the model does much better at predicting the summer water and electricity consumption than in the winter. In particular, the winter electricity is the most difficult to predict, as this region relies primarily on natural gas for heating, rather than electricity. As such, the primary electricity uses in the winter months are lighting, cooking, etc., which are not heavily influenced by climate. As the U.S. shifts towards electrification as a means to combat climate change, it is likely that we will see a stronger climatic influence over winter electricity consumption. This process, however, was not accounted for in this study.

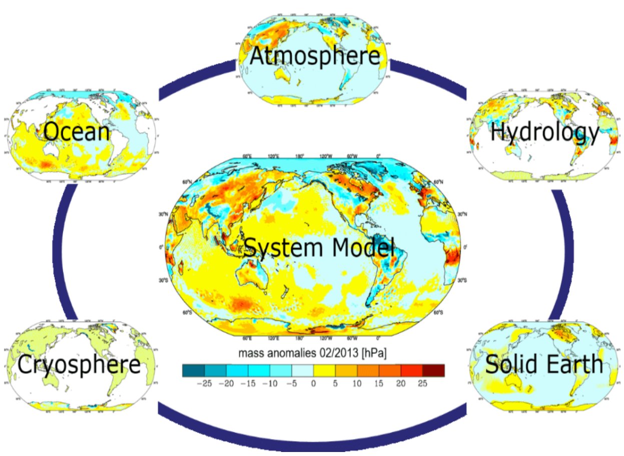
The improved predictive accuracy of the *Selected Feature* model is further demonstrated by the root mean squared error (RMSE) improvement. Here, the out-of-sample (i.e., test set) RMSE is plotted for both variable sets. The RMSE for the *Selected Feature* model is significantly lower than the *Baseline* model, particularly in the summer months. This indicates that (a) the Selected Feature variable set is a more effective predictor of the climate-sensitive coupled water and electricity demand in the Midwest, and (b) that the model is capable of generating accurate predictions of both water and electricity demand across seasons. As such, we continue to leverage this model going forward for use in making projections into the future under climate change.



Observed water and electricity demand data compared to the two types of model runs: the Baseline model (denoted 'Precip-Temp') and the Selected Feature model. The RMSE values for each utility and season are shown on the right hand side of the figure. The results are two-fold: (1) the AI model is able to accurately predict the water and electricity use across the Midwest region; and (b) the consideration of non-traditional variables, such as relative humidity, is important for further improving the prediction.

Integrating Earth System Model Data into the AI Algorithm

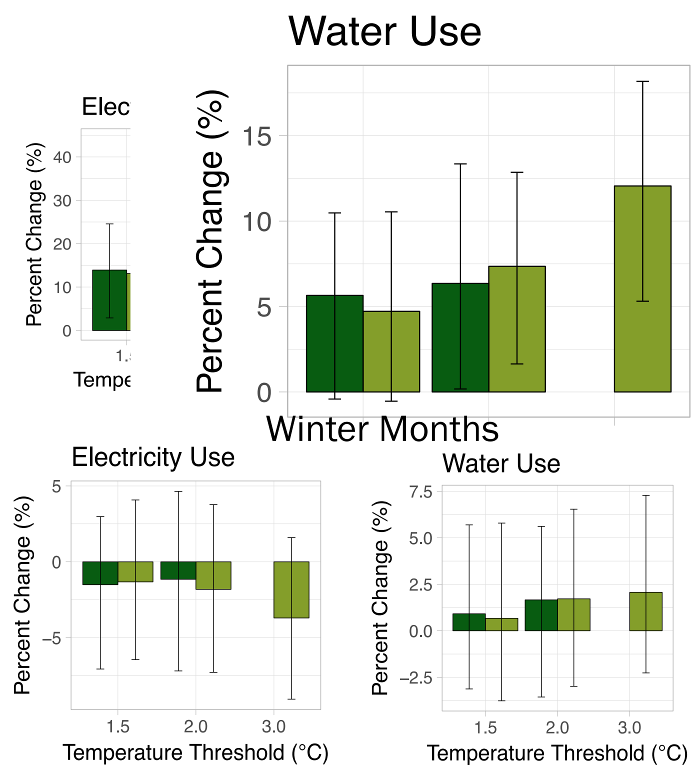
Once the observational model has been trained and tested, it can be used for projection analysis. In order to obtain projections of future water and electricity demand under climate change, there is a need to collect future climate data. In this study, we demonstrate two means of collecting this data, the first is through the Coupled Model Intercomparison Project (CMIP) Earth System Models (ESMs). These large-scale climate simulation models can be downscaled and bias-corrected for use in local impact assessment. Here, we use five models from the CMIP5 era to collect climate data for the six Midwestern cities used in the model development stage (Chicago, Cleveland, Columbus, Indianapolis, Madison, and Minneapolis). The purpose of this projection is to focus on the impacts of climate change, so we do not account for possible techno-demographic shifts, which will also impact how and to what degree society uses water and electricity in the future. In particular, we calculate the percent change between the water and electricity demand predicted in the historical reference period (1971-2000) and the 30-year period in which each ESM surpassed 1.5, 2.0 and 3.0°C of warming compared to pre-industrial levels.



Schematic of an Earth System Model (ESM). Image Credit: The Global Geodetic Observing System (Link to Image)

The developed ML model projects increases in water demand across both seasons and both scenarios, while electricity demand is only projected to increase in the summer months. Moreover, as the world surpasses the higher temperature thresholds, these patterns become more pronounced. This indicates a significant increase in climate-induced water and electricity demand increases that utilities will need to be prepared for, if they hope to maintain adequate service levels. In terms of the winter electricity use, the projected reduction is likely due to less need for electric space heating. However, it is not enough to fully offset the summer increases, possibly leading to more extreme swings in demand over the course of year, a challenge for maintaining a functional grid.

Due to the nature of ESMs, in which each model results in slightly different simulations of future climate variables, our analysis also results in different projections of water and electricity demand, depending on the ESM. In particular, we see more uncertainty in the winter months than the summer months, as well as between electricity demand and water demand. Specifically, the summer demand shows consistently positive changes (i.e., increasing demand) across the scenarios and temperature thresholds, while the winter demand shows more variability. This uncertainty speaks to (a) the variability in the ESM models, particularly in winter months, and (b) the lower climate sensitivity in the winter months, which would lead to a weaker "signal" within the data, thus a more variable projection. Nonetheless, the variance in the winter

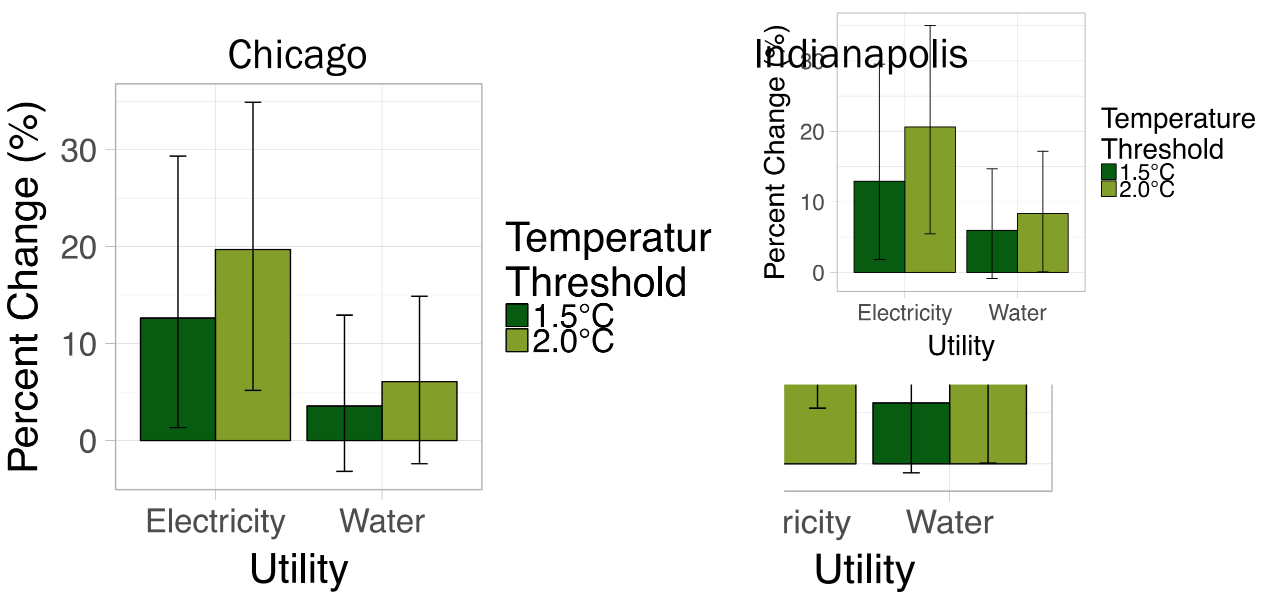


Projected changes to Midwestern U.S. regional water and electricity demand under low (dark green) and high (light green) warming scenarios (RCP2.6 and RCP8.5, respectively) using ESM-derived input data. The bars represent the median, while the error bars show the interquantile range. Note that under the low warming scenario, the world does not surpass 3.0°C of warming, thus there is no projection for that scenario.

months could create further difficulties for the utilities, which are unable to plan for a future in which the demand could increase or decrease, depending on the future climate warming scenarios taken. As the ESM models become more accurate, it is possible that this uncertainty band would shrink, creating an opportunity to better inform management entities and local communities of the possible impacts to the demand structure.

In addition to the regional analysis discussed above, we also conducted the analysis for the cities of Chicago and Indianapolis, the largest cities in the study region. We present results from the high warming (RCP8.5) scenario after the 1.5 and 2.0°C thresholds, as this scenario represents the worst-case scenario over the course of the near- and medium-term future. The results demonstrate similar patterns across both cities, with projected increases in both water and electricity during the summer months. There are differences, however, such as the magnitude of the projected increase in water demand across the two cities. Chicago demonstrates less increase in water demand than Indianapolis, which aligns with the urban form of both cities. In particular, Chicago is more densely urban than Indianapolis, which is likely why they experience less climate-induced water demand increases—they simply don't have the green space that would demand water use in the summer. Indianapolis, on the other hand, is more sprawling with suburban-like neighborhoods fairly close to the city center. This likely leads to an increased use of water for landscaping, which would, in turn, be impacted by climate change.

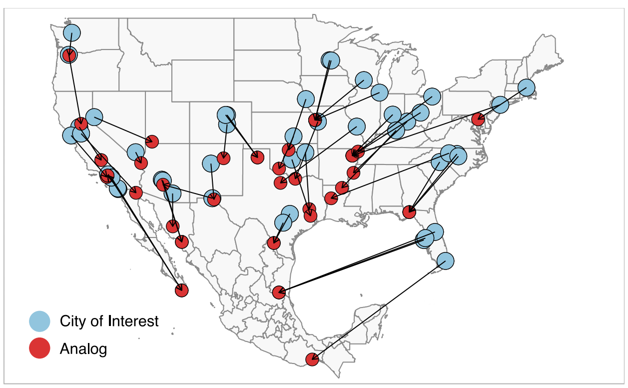
Focusing on Chicago in particular, surpassing the 1.5°C threshold leads to a 12% increase in summer electricity demand, which likely to occur within the next 10-15 years. Should the city's population grow sustainably (i.e., shared socioeconomic pathway 1; SSP1), this could lead to a total increase in 745,000 MWh in electricity demand. Should society continue down fossil-fueled development (i.e., shared socioeconomic pathway 5; SSP5), the increase would jump to a total of 1.06 million MWh after just 1.5°C of warming. Under 2.0°C of warming with SSP1 value could increase to 1.6 million MWh, more than double the increase under the 1.5°C warming threshold. This intense increase highlights the need to cap emissions and limit warming from the local utility and community perspective.



Projected water and electricity demand in the cities of Chicago (Illinois) and Indianapolis (Indiana) during the summer months under the high warming (RCP8.5) scenario using ESM-derived input data. The bars show the median with error bars representing the interquantile range.

Integrating Climate Analogs into the AI Algorithm

Leveraging the ESMs aligns with traditional work on climate change impact assessment, but these data sources are not always accessible to local communities or smaller organizations. As such, it is beneficial to determine alternative means of obtaining future climate data. In this study, we leverage contemporary climate analogs to act as proxies for the ESM data. Climate analogs are determined through a statistical process that identifies the location in which the *current* climate is analogous to the *future* climate in the city of interest. This technique has been used to identify corresponding climate analogs around the world, including cities in the North America[47], Africa[48], and China[49,50]. The approach has also been used for communication- and policy-focused studies[51,52]. We leverage contemporary North American climate analogs[47] to project the water and electricity demand across 46 U.S. cities.



U.S. cities of interest and their contemporary analogs under the high warming (RCP8.5) scenario. These analogs were used to develop proxy data for the model inputs without running any ESMs.

We began this part by building the model in the observational space, following a similar process as before. We split the data into the three main seasonal blocks and leveraged the same data discussed above. The primary difference is the use of reanalysis data for the climate observations, rather than the weather station data. This was a decision made based on the size of the dataset, which would have required multiple weather stations per city to triangulate the city-wide values. Moreover, we needed access to observed climate variables in Mexico, since several U.S. cities have Mexican analogs. As such, we opt to leverage a gridded reanalysis dataset—the North American Regional Reanalysis[53].

The model performance in the observational space was favorable, with median normalized root mean squared error (NRMSE) values of 0.12 and 0.15 for electricity and water demand, respectively. This means that the median error for both water and electricity demand was below 15% across the 46 cities, indicating a strong predictive performance. This aligns with the results from the Midwestern case study, which likewise showed relatively small predictive error.

In this case, the analogs were not for a specific temperature threshold, rather a certain year (2080) and warming scenario (RCP8.5 or high warming). Thus, the results show the projections of water and electricity demand in 2080 under the high warming scenario, only accounting for the climate-induced effects (i.e., not considering the techno-demographic shifts that will have taken place prior to 2080). As such, we will discuss the results in terms of the *climate-sensitive* portion of demand, as in previous sections.

In general, the results show a projected increase in summer electricity demand, while summer water demand is projected to remain the same or increase slightly across much of the U.S. Conversely, winter electricity demand is projected to decrease across the country, with only moderate changes to winter water demand. Our results from the Midwestern cities show some of the highest increases in summer electricity use, as well as some of the largest decreases in winter electricity use. This result aligns with the results from above, which leveraged the ESM data directly. The climate analogs, though based on ESM data, provide an alternative to the traditional approach to impact assessment, thus it is encouraging to see similar results, at least across the Midwestern region.

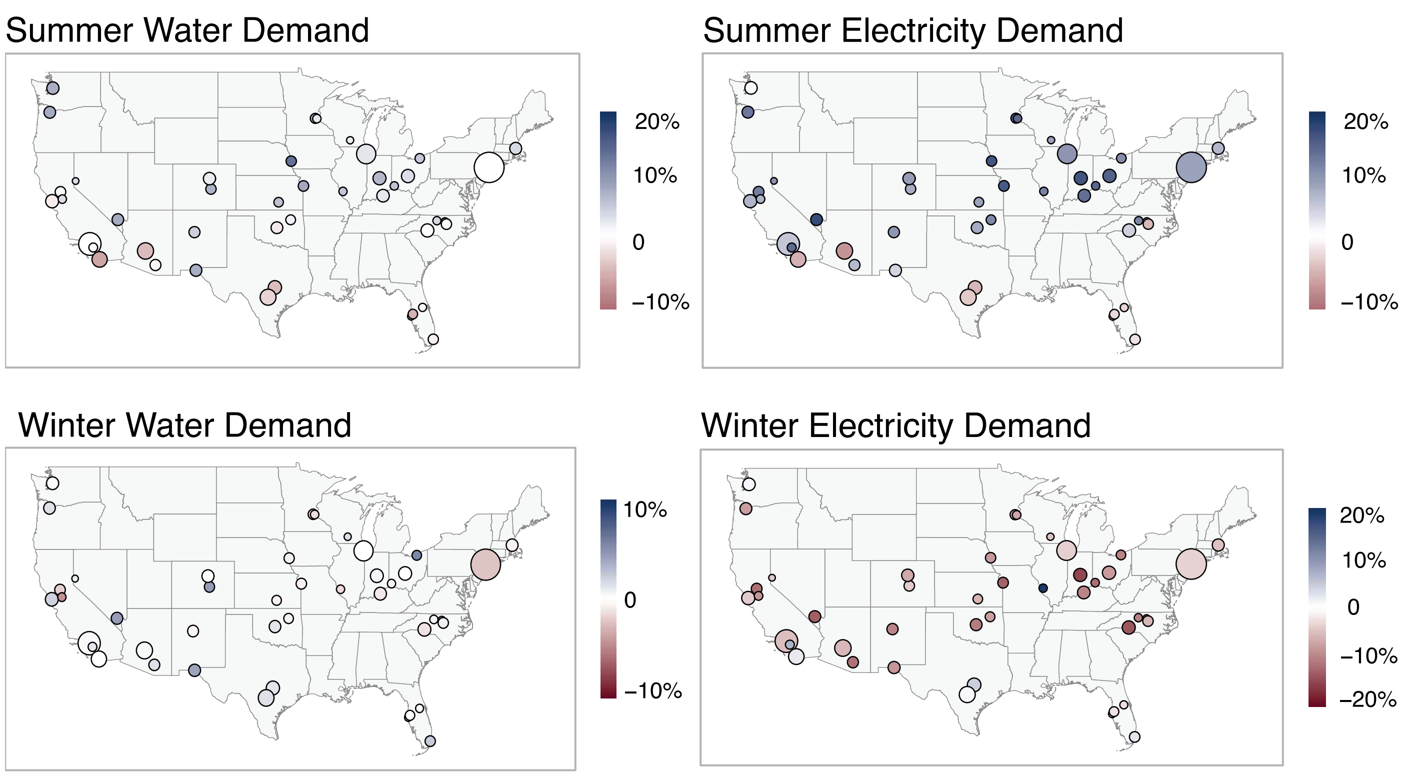
In the Northeast, electricity use is projected to increase in the summer months, while water use is projected to remain relatively stable. Under the high emissions scenario, temperatures are projected to increase in this region, which will likely lead to higher use of air conditioning, thus, increasing electricity consumption in the region. This could pose a challenge for the regional grid management, which historically, has not dealt with extreme demand peaks in the summer[17]. In this sense, it is critical that utilities and grid managers work to ensure their future investments in generation and transmission can handle increased frequency and intensity of summer peak loads.

In terms of the projected water demand, the cities located within the mountain region and the Western

U.S. are likely going to see increases in demand. This increase is going to exacerbate the ongoing issues of drought and water availability[12,54,55], particularly given the complex water governance in the region. Further, the stress put on water systems will be worsened by the simultaneous increase in electricity demand, which could limit the effectiveness of hydroelectric plants[14,56], a key feature of many climate change mitigation plans in the region. Understanding these interconnections is critical for building resilient water and electricity systems, as well as ensuring society does not fall back on carbon-intensive sources during periods of extreme weather.

Although most cities are showing increases in summer water and electricity demand in the high warming scenario, there are a few cities projected to see decreases in the climate-sensitive portion of the demand. These cities are primarily located in the Southern U.S. and have analogs from more tropical regions in coastal Mexico. This north-south gradient could have major implications for the management of the connected electricity grid, as well as the country's major surface water and aquifer systems, yet the gradient itself is counterintuitive. In general, we expect warm, dry regions to get warmer and drier under climate change, however, there is a strong possibility that without adequate mitigation and adaptation, many cities could experience entirely novel climates by the end of the 21st century. In fact, previous work has shown that the likelihood of experiencing a novel climate in any given region increases as the warming becomes more extreme[57]. In fact, in a study conducted across the U.S., it was determined that the Sonoran Desert in Arizona and much of the coastal region off the Gulf of Mexico are the most likely to experience novel climates by the end of the century[57]. This aligns will with our findings, which show projected decreases across much of these regions, as their topical analogs are generally wetter and slightly cooler (on average) during the summer months. In other words, these dissimilar analogs in the Southern U.S. could lead to novel climates, which ultimately leads the model to project decreases in the climate-sensitive portion of the water and electricity demand.

This gradient is not as pronounced in the winter months, in which the majority of the cities are projected to experience decreases in water and electricity demand. The electricity reductions are likely due to the milder winters leading to less need for electric space heating, a finding shown earlier for the Midwestern cities. There are a few cities in the Southern region that demonstrate minimal changes in electricity demand (e.g., Orlando and Tampa, both in Florida), as well as a few cities that are projected to experience increases in demand (e.g., Miami, Florida and Austin, Texas). These latter increases are indicative of winters that become more extreme,



Percent change in water and electricity demand across U.S. cities for the high warming (RCP8.5) scenario using the analog approach.

leading to an increase in space cooling (i.e., air-conditioning). That being said, across the 46 cities, the average reduction in winter electricity consumption is 6.8% (with a maximum of 19%), which is not enough to counteract the increases projected in the summer months (average = 7.7%, maximum = 21.4%). Thus, managing the swings between summer and winter electricity demand could become more difficult for grid managers. In terms of winter water consumption, most cities show little to no change (average = 1.5% increase), but several cities in the Western U.S., including Las Vegas (Nevada) and several Californian cities), are projected to see larger increases. This could ultimately increase the stress on the water resources in the region.

Looking at specific cities, the three most populous cities in the U.S. (New York City, Chicago, and Los Angeles) are projected to have significant increases in summer electricity demand, with minimal changes to the water demand. In fact, the per capita electricity demand is projected to increase between 6 and 12% for each of these cities. Depending on the shared socioeconomic pathway followed, this 6-12% increase could lead to 2.5-9 million MWh of additional electricity consumption for a given summer month. In particular, if we follow shared socioeconomic pathway, SSP5, the most likely pathway with high warming, we estimated that the utilities that serve Chicago would need to generate 5.7 million MWh, while the Los Angeles and New York utilities would have to generate 9.2 million MWh and 9.0 million MWh, respectively. Should the utilities seek to expand renewable energy generation, expanding capacity to account for climate-induced increases to demand could create additional costs and possibly delay decarbonization efforts. For example, generating 3.8 million MWh for Los Angeles residents would require 14,000 1.5 MW wind turbines, which represents about 20% of the operational turbines in the U.S. today—just to supply less than half of Los Angeles County. Overall, the inclusion of these climate-induced changes is critical for adequate planning of both water and electricity systems.

View of Lake Oroville in California (U.S.) during a recent extreme drought. Image Credit: California Department of Water Resources

Discussion & Policy Recommendations

As the climate crisis continues to intensify, understanding the impacts it will have on critical infrastructure is an important aspect to promote sustainable and equitable mitigation and adaptation policies. However, many traditional climate change impact assessment tools can be difficult to obtain and implement at the local level. Communities may not have the resources (financial or experience-based) to run these models, let alone downscale them to the local level. One solution to this issue is to leverage AI models, which are computationally efficient, flexible, and can be integrated into existing cloud- or web-based services. Moreover, the proliferation of AI and ML courses means that it is more likely that local communities can employ someone with the knowledge to run AI models than someone with the knowledge to run specialized climate change impact assessment models. This UNU-INWEH report detailed how one may implement AI for climate change impact assessment, as well the benefits of such an approach. To provide an example of this type of methodology, we presented results from a case study focused on the water-electricity demand nexus.

Specifically, the results presented in this UNU-INWEH report are critical for aiding in decision-making, particularly with regard to preparing water and energy systems for future climate change. Often decisions regarding water and energy systems are made in isolation by individual utilities that are only considering their service (e.g., just the climate impacts on electricity)[58,59]. As the water-energy nexus concept becomes more common in practice, it is likely that these decisions will become more integrated. However, there remains a computational gap for analyzing future changes, particularly for smaller communities, which may not have access to high-fidelity ESM output for representing future climate-related impacts. As such, this report demonstrated two means of leveraging AI for projecting climate change impacts—first using downscaled, bias-corrected ESM data and second using contemporary climate analogs as a proxy for ESM data. The latter method shows great promise for expanding community-scale capabilities for projecting climate change impacts. Further, since the contemporary climate analog dataset contains analogs for 540 North American cities[47], there is ample opportunity to expand this work across the continent and work with smaller municipalities.

Additionally, the analyses reported here show strong regional differences in how climate change may impact demand structures, including extreme increases in summer water and electricity use in some regions, with possible reductions in other regions. These differences could pose issues for our interconnected electric grid and waterways. This could lead to increased inter-state tension, as cities in upstream (watershed) areas may need to withdraw more water, for example, to supply growing demand, leaving downstream cities with less.

Nonetheless, there remain critical gaps for extending this work beyond the U.S. While the AI approach can be used around the world, it is reliant on data availability. That is, if the data on the system of interest and the climate-related variables are not available or of good quality, it is not possible to conduct an AI analysis. However, with the growing use of cloud-based services and increased recognition of the importance of data sharing, these methods are becoming increasingly useful across the globe. In particular, regions within the Global South are seeing increasingly rapid infrastructure development, while also expecting to experience the most intense climate change impacts. In these areas, having access to an accurate AI-based tool to quickly project climate change impacts can help to ensure new developments are as resilient as possible, while also working to mitigate the worst of the impacts.

Going forward, it is imperative that we continue to build and share our climate change impact assessment toolbox, which must include more accessible and flexible models, such as the AI models presented in this report. By ensuring that the climate change impact assessment models are flexible enough to be used anywhere in the world and sharing the resources to not only use the models, but also to collect the necessary data, we can work towards a more sustainable and equitable plan for climate change mitigation and adaptation.

A dry lakebed during a drought in California (U.S.).
Image Credit: U.S. National Oceanic and Atmospheric Administration

References

1. Amir AghaKouchak, Felicia Chiang, Laurie S. Huning, Charlotte A. Love, Iman Mallakpour, Omid Mazdiyasni, Hamed Moftakhari, Simon Michael Papalexiou, Elisa Ragno, and Mojtaba Sadegh. Climate Extremes and Compound Hazards in a Warming World. Annual Review of Earth and Planetary Sciences, 48(1):519–548, 2020. doi: 10.1146/annurev-earth-071719-055228.
2. Amir AghaKouchak, Laurie S. Huning, Mojtaba Sadegh, Yue Qin, Yannis Markonis, Farshid Vahedifard, Charlotte A. Love, Ashok Mishra, Ali Mehran, Renee Obringer, Annika Hjelmstad, Shrideep Pallickara, Shakil Jiwa, Martin Hanel, Yunxia Zhao, Angeline G. Pendergrass, Mazdak Arabi, Steven J. Davis, Philip J. Ward, Mark Svoboda, Roger Pulwarty, and Heidi Kreibich. Toward impact-based monitoring of drought and its cascading hazards. Nature Reviews Earth & Environment, pages 1–14, August 2023. doi: 10.1038/s43017-023-00457-2.
3. Jennifer Cronin, Gabrial Anandarajah, and Olivier Dessens. Climate change impacts on the energy system: A review of trends and gaps. Climatic Change, 151(2):79–93, November 2018. doi: 10.1007/s10584-018-2265-4.
4. Renee Obringer, Roshanak Nateghi, Debora Maia-Silva, Sayanti Mukherjee, Vineeth CR, Douglas Brent McRoberts, and Rohini Kumar. Implications of Increasing Household Air Conditioning Use Across the United States Under a Warming Climate. Earth's Future, 10(1):e2021EF002434, 2022. doi: 10.1029/2021EF002434.
5. US Energy Information Administration. One in three U.S. households faces a challenge in meeting energy needs. Technical report, 2018.
6. Shuchen Cong, Destenie Nock, Yueming Lucy Qiu, and Bo Xing. Unveiling hidden energy poverty using the energy equity gap. Nature Communications, 13(1):2456, May 2022. doi: 10.1038/s41467-022-30146-5.
7. Olivier Deschênes and Michael Greenstone. Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. American Economic Journal: Applied Economics, 3 (4):152–185, October 2011. doi: 10.1257/app.3.4.152.
8. Adam Nayak, Benjamin Rachunok, Barton Thompson, and Sarah Fletcher. Socio-hydrological impacts of rate design on water affordability during drought. Environmental Research Letters, 18(12):124027, November 2023. doi: 10.1088/1748-9326/ad0994.
9. Benjamin Rachunok and Sarah Fletcher. Socio-hydrological drought impacts on urban water affordability. Nature Water, 1(1):83–94, January 2023. doi: 10.1038/s44221-022-00009-w.
10. R. L. Wilby, J. Troni, Y. Biot, L. Tedd, B. C. Hewitson, D. M. Smith, and R. T. Sutton. A review of climate risk information for adaptation and development planning. International Journal of Climatology, 29(9):1193–1215, 2009. doi: 10.1002/joc.1839.
11. Riddhi Singh and Rohini Kumar. Climate versus demographic controls on water availability across India at 1.5 ◦C, 2.0 ◦C and 3.0 ◦C global warming levels. Global and Planetary Change, 177:1–9, June 2019. doi: 10.1016/j.gloplacha.2019.03.006
12. Bradley Udall and Jonathan Overpeck. The twenty-first century Colorado River hot drought and implications for the future. Water Resources Research, 53(3):2404–2418, 2017. doi: 10.1002/2016WR019638.
13. L. Samaniego, S. Thober, R. Kumar, N. Wanders, O. Rakovec, M. Pan, M. Zink, J. Sheffield, E. F. Wood, and A. Marx. Anthropogenic warming exacerbates European soil moisture droughts. Nature Climate Change, 8(5):421–426, May 2018. doi: 10.1038/s41558-018-0138-5.
14. Kaveh Madani, Marion Gu´egan, and Cintia B. Uvo. Climate change impacts on high-elevation hydroelectricity in California. Journal of Hydrology, 510:153–163, March 2014. doi: 10.1016/j.jhydrol.2013.12.001.
15. Leigh Raymond, Douglas Gotham, William McClain, Sayanti Mukherjee, Roshanak Nateghi, Paul V. Preckel, Peter Schubert, Shweta Singh, and Elizabeth Wachs. Projected climate change impacts on Indiana's Energy demand and supply. Climatic Change, January 2019. doi: 10.1007/s10584-018-2299-7.
16. Sayanti Mukherjee and Roshanak Nateghi. A Data-Driven Approach to Assessing Supply Inadequacy Risks Due to Climate-Induced Shifts in Electricity Demand. Risk Analysis, 39(3):673–694, 2019. doi: 10.1111/risa.13192.
17. Debora Maia-Silva, Rohini Kumar, and Roshanak Nateghi. The critical role of humidity in modeling summer electricity demand across the United States. Nature Communications, 11(1):1–8, April 2020. doi: 10.1038/s41467-020-15393-8.
18. Renee Obringer, Rohini Kumar, and Roshanak Nateghi. Managing the water-electricity demand

nexus in a warming climate. Climatic Change, 159(2):233-253, March 2020. doi: 10.1007/s10584-020-02669-7.

19. H. R. Maier, J. H. A. Guillaume, H. van Delden, G. A. Riddell, M. Haasnoot, and J. H. Kwakkel. An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? Environmental Modelling & Software, 81:154–164, July 2016. doi: 10.1016/j.envsoft.2016.03.014.

20. Rachel James, Richard Washington, Carl-Friedrich Schleussner, Joeri Rogelj, and Declan Conway. Characterizing half-a-degree difference: A review of methods for identifying regional climate responses to global warming targets. WIREs Climate Change, 8(2):e457, 2017. doi: 10.1002/wcc.457.

21. Lila Warszawski, Katja Frieler, Veronika Huber, Franziska Piontek, Olivia Serdeczny, and Jacob Schewe. The Inter-Sectoral Impact Model Intercomparison Project (ISI–MIP): Project framework. Proceedings of the National Academy of Sciences, 111(9):3228–3232, March 2014. doi: 10.1073/pnas.1312330110.

22. Michael T. Craig, Jan Wohland, Laurens P. Stoop, Alexander Kies, Bryn Pickering, Hannah C. Bloomfield, Jethro Browell, Matteo De Felice, Chris J. Dent, Adrien Deroubaix, Felix Frischmuth, Paula L.M. Gonzalez, Aleksander Grochowicz, Katharina Gruber, Philipp Härtel, Martin Kittel, Leander Kotzur, Inga Labuhn, Julie K. Lundquist, Noah Pflugradt, Karin Van Der Wiel, Marianne Zeyringer, and David J. Brayshaw. Overcoming the disconnect between energy system and climate modeling. Joule, 6 (7):1405–1417, July 2022. doi: 10.1016/j.joule.2022.05.010.

23. Veronika Eyring, Vimal Mishra, Gary P. Griffith, Lei Chen, Trevor Keenan, Merritt R. Turetsky, Sally Brown, Frank Jotzo, Frances C. Moore, and Sander van der Linden. Reflections and projections on a decade of climate science. Nature Climate Change, 11(4):279–285, April 2021. doi: 10.1038/s41558-021-01020-x.

24. Trevor Hastie, Robert Tibshirani, and Jerome Friedman. The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition. Springer Science & Business Media, August 2009. ISBN 978-0-387-84858-7.

25. Galit Shmueli. To Explain or to Predict? Statistical Science, 25(3):289–310, August 2010. doi: 10.1214/10-STS330

26. Joshua P Newell, Benjamin Goldstein, and Alec Foster. A 40-year review of food–energy–water nexus literature and its application to the urban scale. Environmental Research Letters, 14(7):073003, July 2019. doi: 10.1088/1748-9326/ab0767.

27. Joshua P Newell and Anu Ramaswami. Urban food-energy–water systems: Past, current, and future research trajectories. Environmental Research Letters, 15(5):050201, May 2020. doi: 10.1088/1748-9326/ab7419.

28. US Energy Information Administration. U.S. electric power sector continues water efficiency gains. Technical report, 2023.

29. US Energy Information Administration. Electricity in the U.S. Technical report, 2023.

30. Marta Zaniolo, Matteo Giuliani, Scott Sinclair, Paolo Burlando, and Andrea Castelletti. When timing matters—misdesigned dam filling impacts hydropower sustainability. Nature Communications, 12(1):3056, May 2021. doi: 10.1038/s41467-021-23323-5.

31. The White House. President Biden to Catalyze Global Climate Action through the Major Economies Forum on Energy and Climate. Technical report, April 2023.

32. Daniel Steinberg, Dave Bielen, Josh Eichman, Kelly Eurek, Jeff Logan, Trieu Mai, Colin McMillan, Andrew Parker, Laura Vimmerstedt, and Eric Wilson. Electrification and Decarbonization: Exploring U.S. Energy Use and Greenhouse Gas Emissions in Scenarios with Widespread Electrification and Power Sector Decarbonization. Technical Report NREL/TP-6A20-68214, National Renewable Energy Lab. (NREL), Golden, CO (United States), July 2017

33. Christopher M. Chini and Ashlynn S. Stillwell. The State of U.S. Urban Water: Data and the Energy-Water Nexus. Water Resources Research, 54(3):1796–1811, 2018.. doi: 10.1002/2017WR022265.

34. Kelly T. Sanders and Michael E. Webber. Evaluating the energy consumed for water use in the United States. Environmental Research Letters, 7(3):034034, September 2012. doi: 10.1088/1748-9326/7/3/034034.

35. Helena R. Tiedmann, Lauryn A. Spearing, Sergio Castellanos, Keri K. Stephens, Lina Sela, and Kasey M. Faust. Tracking the post-disaster evolution of water infrastructure resilience: A study of the 2021 Texas winter storm. Sustainable Cities and Society, 91:104417, April 2023. doi: 10.1016/j.scs.2023.104417.

36. US Energy Information Administration. Nearly 90% of U.S. households used air conditioning in 2020. Technical report, 2022.

37. Rohini Kumar, Benjamin Rachunok, Debora Maia-Silva, and Roshanak Nateghi. Asymmetrical response of California electricity demand to summer-time temperature variation. Scientific Reports, 10(1):10904, July 2020. doi: 10.1038/s41598-020-67695-y.

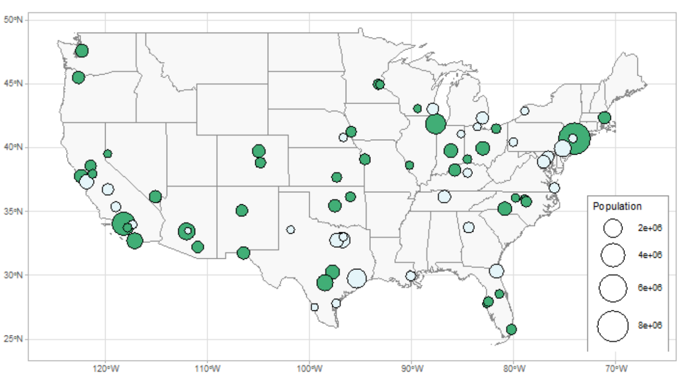
38. Alessandro Dosio, Lorenzo Mentaschi, Erich M. Fischer, and Klaus Wyser. Extreme heat waves under 1.5°C and 2°C global warming. Environmental Research Letters, 13(5):054006, April 2018. doi: 10.1088/1748-9326/aab827.
39. Maximilian Auffhammer, Patrick Baylis, and Catherine H. Hausman. Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. Proceedings of the National Academy of Sciences, 114(8):1886–1891, February 2017. doi: 10.1073/pnas.1613193114.
40. Aiguo Dai. Drought under global warming: A review. WIREs Climate Change, 2(1):45-65, 2011. doi: 10.1002/wcc.81.
41. Benjamin I. Cook, Toby R. Ault, and Jason E. Smerdon. Unprecedented 21st century drought risk in the American Southwest and Central Plains. Science Advances, 1(1):e1400082, February 2015. doi: 10.1126/sciadv.1400082.
42. Toby R. Ault. On the essentials of drought in a changing climate. Science, 368(6488):256–260, April 2020. doi: 10.1126/science.aaz5492.
43. Ryna Yiyun Cui, Katherine Calvin, Leon Clarke, Mohamad Hejazi, Son Kim, Page Kyle, Pralit Patel, Sean Turner, and Marshall Wise. Regional responses to future, demand-driven water scarcity. Environmental Research Letters, 13(9):094006, August 2018. doi: 10.1088/1748-9326/aad8f7.
44. Samaneh Ashraf, Amir AghaKouchak, Ali Nazemi, Ali Mirchi, Mojtaba Sadegh, Hamed R. Moftakhari, Elmira Hassanzadeh, Chi-Yuan Miao, Kaveh Madani, Mohammad Mousavi Baygi, Hassan Anjileli, Davood Reza Arab, Hamid Norouzi, Omid Mazdiyasni, Marzi Azarderakhsh, Aneseh Alborzi, Mohammad J. Tourian, Ali Mehran, Alireza Farahmand, and Iman Mallakpour. Compounding effects of human activities and climatic changes on surface water availability in Iran. Climatic Change, 152(3):379–391, March 2019. doi: 10.1007/s10584-018-2336-6.
45. David J. Sailor and J. Ricardo Muñoz. Sensitivity of electricity and natural gas consumption to climate in the U.S.A.—Methodology and results for eight states. Energy, 22(10):987–998, October 1997. doi: 10.1016/S0360-5442(97)00034-0.
46. Sayanti Mukherjee and Roshanak Nateghi. Climate sensitivity of end-use electricity consumption in the built environment: An application to the state of Florida, United States. Energy, 128:688–700, June 2017. doi: 10.1016/j.energy.2017.04.034.
47. Matthew C. Fitzpatrick and Robert R. Dunn. Contemporary climatic analogs for 540 North American urban areas in the late 21st century. Nature Communications, 10(1):1–7, February 2019. doi: 10.1038/s41467-019-08540-3.
48. Rory G. J. Fitzpatrick, Douglas J. Parker, John H. Marsham, David P. Rowell, Lawrence S. Jackson, Declan Finney, Chetan Deva, Simon Tucker, and Rachael Stratton. How a typical West African day in the future-climate compares with current-climate conditions in a convection-permitting and parameterised convection climate model. Climatic Change, 163(1):267–296, November 2020. doi: 10.1007/s10584-020-02881-5.
49. Cong Yin, Fei Yang, and Juanle Wang. Analogs of Future Climate in Chinese Cities Identified in Present Observations. IEEE Access, 8:219151–219159, 2020. doi: 10.1109/ACCESS.2020.3042548.
50. Shasha Wang, Wenfeng Zhan, Huilin Du, Chenguang Wang, Long Li, Sida Jiang, Huyan Fu, Shiqi Miao, and Fan Huang. Identifying analogs of future thermal comfort under multiple projection scenarios in 352 Chinese cities. Sustainable Cities and Society, 82:103889, July 2022. doi: 10.1016/j.scs.2022.103889.
51. Alexandra Luccioni, Victor Schmidt, Vahe Vardanyan, and Yoshua Bengio. Using Artificial Intelligence to Visualize the Impacts of Climate Change. IEEE Computer Graphics and Applications, 41(1):8–14, January 2021. doi: 10.1109/MCG.2020.3025425.
52. Chiara Binelli, Matthew Loveless, and Brian F. Schaffner. Explaining Perceptions of Climate Change in the US. Political Research Quarterly, page 10659129211070856, May 2022. doi: 10.1177/10659129211070856.
53. Fedor Mesinger, Geoff DiMego, Eugenia Kalnay, Kenneth Mitchell, Perry C. Shafran, Wesley Ebisuzaki, Dušan Jović, Jack Woollen, Eric Rogers, Ernesto H. Berbery, Michael B. Ek, Yun Fan, Robert Grumbine, Wayne Higgins, Hong Li, Ying Lin, Geoff Manikin, David Parrish, and Wei Shi. North American Regional Reanalysis. Bulletin of the American Meteorological Society, 87(3):343–360, March 2006. doi: 10.1175/BAMS-87-3-343
54. John Fleck and Brad Udall. Managing Colorado River risk. Science, 372(6545):885–885, May 2021. doi: 10.1126/science.abj5498.
55. Joel Lisonbee, Elizabeth Ossowski, Meredith Muth, Veva Deheza, and Amanda Sheffield. Preparing for Long-Term Drought and Aridification. Bulletin of the American Meteorological Society, 103(3):E821–E827, March 2022. doi: 10.1175/BAMS-D-21-0321.1.
56. Marion Guégan, Cintia B. Uvo, and Kaveh Madani. Developing a module for estimating climate warming effects on hydropower pricing in California. Energy Policy, 42:261–271, March 2012. doi: 10.1016/j.enpol.2011.11.083.

57. Colin R. Mahony, Alex J. Cannon, Tongli Wang, and Sally N. Aitken. A closer look at novel climates: New methods and insights at continental to landscape scales. Global Change Biology, 23(9):3934–3955, 2017. doi: 10.1111/gcb.13645.
58. Matthew D. Bartos and Mikhail V. Chester. The Conservation Nexus: Valuing Interdependent Water and Energy Savings in Arizona. Environmental Science & Technology, 48(4):2139–2149, February 2014. doi: 10.1021/es4033343.
59. J. Leah Jones and Dave D. White. Understanding barriers to collaborative governance for the food-energy-water nexus: The case of Phoenix, Arizona. Environmental Science & Policy, 127:111–119, January 2022. doi: 10.1016/j.envsci.2021.10.025.
60. US Energy Information Administration. Form EIA-861M Sales and Revenue Data. 2019.
61. NOAA National Centers for Environmental Information. Local Climatological Data (LCD). https://www.ncdc.noaa.gov/cdo-web/datatools/lcd, 2021.
62. S. Hempel, K. Frieler, L. Warszawski, J. Schewe, and F. Piontek. A trend-preserving bias correction- the ISI-MIP approach. Earth System Dynamics, 4(2):219–236, July 2013. doi: 10.5194/esd-4-219-2013.
63. Rich Caruana and Alexandru Niculescu-Mizil. An empirical comparison of supervised learning algorithms. In Proceedings of the 23rd International Conference on Machine Learning, Pittsburgh, PA, USA, 2006.
64. Patrick J. Miller, Gitta H. Lubke, Daniel B. McArtor, and C. S. Bergeman. Finding structure in data using multivariate tree boosting. Psychological Methods, 21(4):583–602, 2016. doi: 10.1037/met0000087.
65. Jerome H. Friedman. Greedy Function Approximation: A Gradient Boosting Machine. The Annals of Statistics, 29(5):1189–1232, 2001.
66. Daniela Jacob, Lola Kotova, Claas Teichmann, Stefan P. Sobolowski, Robert Vautard, Chantal Donnelly, Aristeidis G. Koutroulis, Manolis G. Grillakis, Ioannis K. Tsanis, Andrea Damm, Abdulla Sakalli, and Michelle T. H. van Vliet. Climate Impacts in Europe Under +1.5◦C Global Warming. Earth's Future, 6(2):264–285, 2018. doi: 10.1002/2017EF000710.

Appendix I - Methods and Input Data

Site Description

In this study, we conduct our analysis in cities across the United States. In particular, we started with a case study focused on six cities in the Midwestern United States: Chicago (IL), Cleveland (OH), Columbus (OH), Indianapolis (IN), Madison (WI), and Minneapolis (MN). Then, we expanded the study to include 40 additional cities (46 total) across the country. To select these cities, we initially requested data from 86 cities in the U.S., which were selected based on the population in 2018. In other words, we chose cities that had at least 250,000 residents in 2018. This allowed us to focus on the largest cities in the country, which are where the majority of water and electricity are consumed, and thus are likely to experience significant changes under climate change. Ultimately, of the 86, we were only able to obtain adequate water and electricity demand data from the 46 cities used in the final analysis.



Map of all cities considered in this analysis. Cities in green are those from which we received data. Cities in light blue are those that we requested to provide data, but ultimately did not get any.

Input Data

The data collected for this study included two primary categories: demand data and climate data. The demand data was obtained through local utilities, while the climate data was collected from a variety of sources, including weather towers, renalaysis datasets, and earth system models (ESMs). In particular, the electricity demand data was collected through the U.S. Energy Information Administration (EIA), which manages a database of monthly electricity consumption by utility across the U.S.[60] The water demand data, on the other hand, was collected via freedom of information act (FOIA) requests made directly to the utilities of the select cities. Not all of the 86 cities were able to provide the requested data, thus this dataset became the limiting factor for which cities were included in the final analysis. Both demand datasets were collected at the monthly level from 2007 through 2018. Further, both demand datasets were normalized by service population and the trends adjusted following a statistical method[45]. This method removes the technodemographic trends from the demand data, allowing us to focus on the climate-sensitive portion of the demand.

The climate data were collected from multiple sources. First, we collected data from the U.S. National Centers for Environmental Information (NCEI), which maintains a database of data collected from weather towers across the country[61]. In this case, we collected the tower-based data only for six cities in the Midwest, which served as our initial case study. To collect data across the U.S., we leveraged the North American Regional Reanalysis (NARR) database, which is a gridded dataset that covers much of North America[53]. This dataset was used to expand the initial study to the entire U.S. Finally, we obtained future climate projections through the CMIP5 suite of ESMs. In particular, we collected data form five ESMs: (1) Geophysical Fluid Dynamics Laboratory - Earth Systems Model (GFDL-ESM2M); (2) Hadley Centre Global Environment Model (HadGEM2-ES); (3) Institut Pierre Simon Laplace Model (IPSL-CM5A-LR); (4) Model for Interdisciplinary Research on Climate - Earth Systems Model (MIROC-ESM-CHEM); and (5) Norwegian Earth System Model (NorESM1-M). For the ESMs, we considered two key scenarios: RCP2.6 and RCP8.5 to provide a range of possible futures under climate change. In particular, we collected the ESM data through the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP)[21]. The data were downscaled and bias-corrected at a 0.5° resolution using a trend-preserving approach[62]. Across all these sources, we collected several key variables, including dry bulb temperature, dew point temperature, wet bulb temperature, relative humidity, wind speed, and precipitation. The observational data were collected at the daily level from 2007 through 2018, and later aggregated to monthly values (minimum, maximum, mean, and total, where applicable) to match the demand data.

Methods

Supervised Learning Theory: The primary methodology discussed in this report was a ML algorithm that falls into the category of supervised learning. The goal of any supervised learning algorithm is to predict some value(s), in this case water and electricity demand, given a series of input variables (here, these were the climatic variables). Mathematically, supervised learning algorithms follow Equation 1 where y is the response variable(s), $f(X)$ is the function that connects the predictors (X) to the response variable, and ε is the irreducible error ($\boldsymbol{\varepsilon \sim N(0, \sigma^2)}$). Following this equation, the goal of any supervised learning algorithm will be to find the function, $f(X)$, that minimizes the error between the predicted and actual response variable values, y.

$$\boldsymbol{y = f(x) + \varepsilon} \qquad (\mathbf{1})$$

In this study, we leveraged a multi-outcome tree-based supervised learning algorithms. Tree-based algorithms are a popular non-parametric modeling technique, as they able to balance high predictive accuracy with easier interpretation than a number of other "black box" models (e.g., neural networks)[24,63]. In this report, we leverage multivariate tree boosting to conduct the analysis, which we describe in greater detail below.

Multivariate Tree Boosting: The framework presented in this report was based on an ensemble-of-trees ML algorithm, multivariate tree boosting[64]. The strength of this algorithm is in its ability to simultaneously predict multiple response variables by accounting for the covariance between each response variable to better estimate the complex interactions between real systems. This is an ideal algorithm for estimating the water-energy nexus, as the two systems are highly interconnected.

In particular, multivariate tree boosting leverages the gradient descent boosting meta-algorithm, which works by sequentially fitting decision trees, with each new tree accounting for information from previous tree to improve the prediction[65]. In this case, the algorithm is aiming to minimize error and maximize covariance discrepancy between the previous and current decision trees. Thus, each subsequent tree builds off the previous one to improve the prediction accuracy (i.e., minimizing error), while ensuring the predictors that account for the greatest covariance in the response variables are selected (i.e., maximizing covariance discrepancy)[64].

Variable Selection: An ongoing challenge with ML is overfitting models. In other words, if we train a model too closely to the training data, that model is unlikely to perform well in new situations with previously unknown data. To avoid this pitfall, it is generally recommended to maintain simplicity in the model architecture wherever possible. One way to do this is to conduct variable selection to remove predictors that are not contributing to the predict accuracy. In this study, we conducted variable selection based on variable importance (e.g., how important is the predictor to obtaining a high accuracy). To this end, we used a backward step variable selection process to keep the variables that were contributing most to the predictive accuracy, leaving about 4-6 variables per location out of the original 17. In addition to reducing the complexity of the model, variable selection also improves interpretation.

Modeling Framework: Once we collected and pre-processed our data and conducted variable selection, we began the modeling process. This process involved three key steps: (1) model training and testing; (2) model evaluation; and (3) projections into the future. The first step was conducted through randomized cross-validation, such that a different set of data was held out of the training and used to test the ability of the model to predict based on previously unknown data. This process is repeated until data point has been included in the test data once. For example, a 5-fold cross-validation process would involve splitting the data into five sets, each of which would be considered the test set once over 5 iterations.

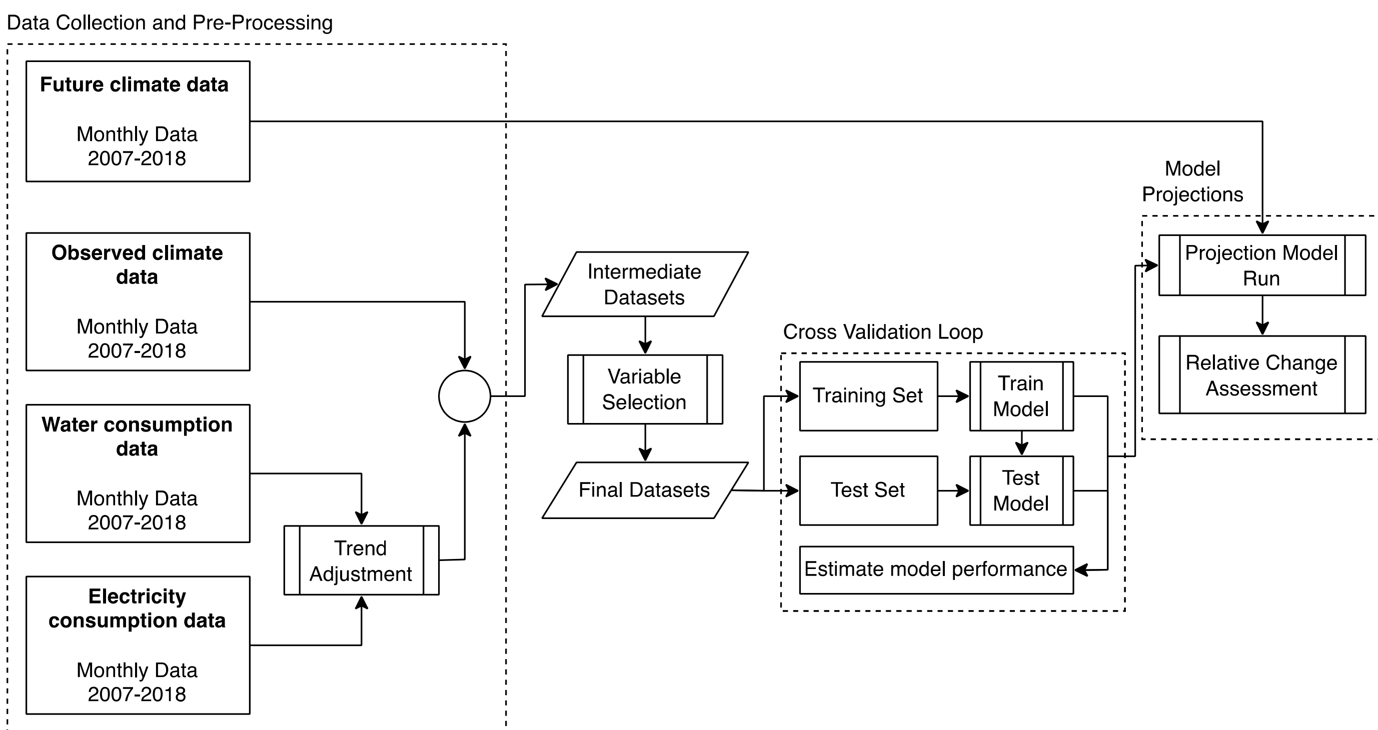
Following the cross-validation, the model performance is evaluated using a quantitative measure, such as root mean squared error or mean absolute error. In this study, we leveraged normalized root mean squared error (NRMSE), which is represented mathematically in Equation 2 below. This measure normalizes the root mean squared error, such that the error can be represented as a percentage. Further, NRMSE is an absolute measure in that it does not require a comparison to other data to known if it is "good" or "bad". Rather, the closer NRMSE is to zero, the more accurate the prediction, regardless of units. We use this measure to discuss the prediction error on the test set, or the out-of-sample error.

$$NRMSE = \frac{\sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}}}{y_{max} - y_{min}} \quad (2)$$

Finally, in the model projection step, we used the historical data from the ESMs (1971-2000) as a reference to build our baseline estimates of water and electricity demand. Then, we leveraged future ESM-derived data from 30-year periods in which the ESM projected the world would cross key temperature thresholds: 1.5, 2.0, and 3.0°C above pre-industrial levels. These 30-year periods were determined through a time-sampling approach[20] that has been implemented in various applications[11,13,66]. In particular, the 30-year periods were identified for each of the 10 ESM-RCP combinations (i.e., 5 ESMs x 2 RCPs) in which the global mean temperature increased by 1.5, 2.0, and 3.0°C, relative to the pre-industrial estimation. The data from each of these 10 ESM-RCP scenarios was used as input variables into the model to project the coupled water and electricity demand. Then, we estimated the percent change between our historical baseline period and the future period. This process, including the steps discussed above.

In the expanded study that considered the entire U.S., we did not leverage ESM data directly. Instead, we used contemporary climate analogs as a proxy for the ESM-derived climate projections. The dataset we used included analogs for 540 cities across North America[47]. The analogs were calculated based on the similarity between 12 key climate variables (minimum temperature, maximum temperature, and precipitation for each season) in the city of interest's future climate and the analog city's current climate. The analysis was conducted by leveraging 27 ESMs and an ensemble mean, leading to 28 possible analogs for each city. Throughout this report, we leveraged the ensemble mean analog.

As an example, New York City has a mean ensemble analog of Jonesboro, Arkansas. This means that using the ensemble of 27 ESMs, the future climate of New York City was the most similar to the climate of present-day Jonesboro. For this report, we then using the NARR data from present-day Jonesboro as a proxy for ESM-derived data for future New York City. Through this process, we were able to obtain estimates of the future climate for 46 U.S. cities without running the ESMs ourselves, thus creating a methodology that could be applied across the country in small communities without access to high fidelity ESM data. Once we obtained the climate analog-based climate data, we followed a similar process described above.



Schematic of the model framework used in this study.

225 East Beaver Creek Road
Richmond Hill, Ontario L4B 3P4, Canada

Tel: +1 905 667-5511
Fax: +1 905 667 5510