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# ENVIRONMENTAL RESEARCH INFRASTRUCTURE AND SUSTAINABILITY



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## Energy forecasting to benchmark for federal net-zero objectives under climate uncertainty

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Supplementary material for this article is available [online](#)

### Abstract

Climate variability creates energy demand uncertainty and complicates long-term asset management and budget planning. Without understanding future energy demand trends related to intensification of climate, changes to energy consumption could result in budget escalation. Energy demand trends can inform campus infrastructure repair and modernization plans, effective energy use reduction policies, or renewable energy resource implementation decisions, all of which are targeted at mitigating energy cost escalation and variability. To make these long-term management decisions, energy managers require unbiased and accurate energy use forecasts. This research uses a statistical, model-based forecast framework, calibrated retrospectively with open-source climate data, and run in a forecast mode with CMIP5 projections of temperature for RCPs 4.5 and 8.5 to predict total daily energy consumption and costs for a campus-sized community (population: 30 000) through the end of the century. The case study of Wright Patterson Air Force Base is contextualized within the existing executive orders directing net-zero emissions and carbon-free electricity benchmarks for the federal government. The model suggests that median annual campus electric consumption, based on temperature rise alone, could increase by 4.8% with RCP4.5 and 19.3% with RCP8.5 by the end of the century, with a current carbon footprint of 547 million kg CO<sub>2e</sub>. Monthly forecasts indicate that summer month energy consumption could significantly increase within the first decade (2020–2030), and nearly all months will experience significant increases by the end of the century. Therefore, careful planning is needed to meet net-zero emissions targets with significant increases in electricity demands under current conditions. Policies and projects to reduce the carbon footprint of federal agencies need to incorporate forecasting models to understand changes in demand to appropriately size electric infrastructure.

## 1. Introduction

Climate variability is an exogenous, stochastic factor that causes energy demand uncertainty and complicates energy consumption modeling. Limited understanding of future energy demand trends can leave energy managers ill-prepared to make long-term decisions, such as whether to advocate for infrastructure modernization or expansion, make facilities more energy efficient, or consider renewable energy resources. Energy managers require forecast models to project future energy demand and inform these decisions and their budgets. Managing energy at the campus level is particularly difficult because resource allocation must be prioritized among many facilities (Kim *et al* 2019). Compounding this energy management challenge is a growing need and demand for transition to renewables and carbon free energy. In particular, the Department of Defense has been directed by recent executive order (EO) 14057 to achieve 100 percent carbon-free electricity on a net annual basis by 2030 and net-zero emissions by 2050. This places a burden on energy managers to transition

energy production while dealing with an increasing demand. In this study we analyze the existing trends of electric consumption at Wright Patterson Air Force Base (WPAFB), build and validate a forecast model for future consumption prediction, and discuss these implications in the context of decarbonization.

Gradual changes to climate and its forecasted impact on energy consumption is a key area of research with important implications for energy management and renewable transitions (De Felice *et al* 2015, Dirks *et al* 2015, Emodi *et al* 2018, Moral-Carcedo and Pérez-García 2019, Mukherjee *et al* 2019, Son and Kim 2017, Zhou *et al* 2014). For example, Emodi *et al* (2018) forecast electrical energy consumption in Australia using climate projections and find that electrical energy consumption may decrease in the first few decades due to reduced heating demand before increasing and surpassing current energy consumption levels by the end of the 21st century as cooling demands rise. Zhou *et al* (2014) forecast the impact of changing climate across the 21st century for United States heating and cooling, finding that heating energy demand will gradually drop for all states, but cooling energy demand will ultimately increase after decreasing slightly from years 2005 to 2020. Importantly, this shift in demand will further increase summer peak demands of electricity, where fossil fuel power plants are already stressed due to drought or heat waves, reducing cooling efficiency (McCall and Macknick 2016, Cook *et al* 2015, Chowdhury *et al* 2021).

Energy prediction and forecast analyses exist at the facility, regional, and multinational scales (Al-bayaty *et al* 2019, Amato *et al* 2005, De Rosa *et al* 2014, Mukherjee *et al* 2019, Mukherjee and Nateghi 2017, Xie and Hong 2017). For example, De Rosa *et al* (2014), at the facility level, addresses how energy savings policy can impact energy consumption, while Amato *et al* (2005) provide a regional level analysis that focuses on how changes to energy infrastructure impact energy consumption spatially. However, at an organization or campus-level, few studies exist, though aggregation or disaggregation methods are most commonly used to achieve results at this level of analysis. Dirks *et al* (2015) acquire facility energy modeling software that houses thousands of facility types, and energy information on an entire geographical region of the US to model energy consumption, and inform energy mitigation and savings techniques. The difficulty of campus-level analyses lies in capturing the different use regimes between facilities along with accessing large quantities of facility-level data.

To meet the objectives of recent EOs, including EO 14057, the DoD must consider how projected changes in climate may impact energy demand and use patterns. Accurate projections of future energy costs are essential for informing short- and long-term decisions and budgets and for meeting renewable energy goals. For instance, in the short-term, accurate year-ahead forecasts can prevent underbudgeting, which drives the need to borrow from other facility sustainment funds. In the long-term, they inform long-range organizational operating budgets, facilitate energy management policy, and motivate investments in energy infrastructure. In this study, we develop and validate a forecasting model based on historical energy demand and climate variables to predict future electric demand based on multiple climate change scenarios. We utilize data from WPAFB as a case study to showcase the increasing energy demands of the Department of Defense. Additionally, we discuss the current trends in renewable energy in southeastern Ohio, where WPAFB is located.

## 2. Background

Statistical, climate-driven prediction models have been used across many fields to gain insight into past and future impacts on operations and to inform policy. Models applied to the management of built and natural systems are applied broadly and produce results with varying degrees of deterministic and probabilistic skill (Delorit *et al* 2017, Graafland *et al* 2020, Theusme *et al* 2021, Zeng *et al* 2020). Models have been developed for the energy sector at a wide range of temporal, spatial, and organizational scales, and are most commonly calibrated to evaluate energy consumption with mention of climate impacts (Amato *et al* 2005, Apadula *et al* 2012, De Felice *et al* 2015, De Rosa *et al* 2014, Dirks *et al* 2015, Emodi *et al* 2018, Mansur *et al* 2008, Moral-Carcedo and Pérez-García 2019, Mukherjee *et al* 2019, Mukherjee and Nateghi 2017, Son and Kim 2017, Zhou *et al* 2014).

Climate-driven, empirical statistical prediction models are developed using a variety of climate inputs, spatial scales, and regression techniques. Many climate variables have been shown to provide value in energy consumption prediction models. In cases of limited access to data, variables are selected based on intuition or expertise in a specific area (Son and Kim 2017). Alternatively, the ability to perform exhaustive analyses may be limited considering that energy managers are typically not modelers or climate scientists. However, existing literature has highlighted specific key climate variables that may help researchers limit their search space, table 1. This study builds on these previous works and investigates a multitude of climate factors for their explanatory power in predicting energy use.

Similar to facility-level models, state- or region-level models can be exported to other states and regions to test the model's stability under a diverse array of climate conditions (Mukherjee and Nateghi 2017, Mukherjee *et al* 2019). Additionally, state-level data can be disaggregated to better understand business sector energy

**Table 1.** Previous research investigated energy demand as a function of several climatological variables.

Climate variable	References	Notes
Temperature	Al-bayaty <i>et al</i> (2019), Amato <i>et al</i> (2005), Apadula <i>et al</i> (2012), De Felice <i>et al</i> (2015), Dirks <i>et al</i> (2015), Ismail and Abdullah (2016), Mukherjee <i>et al</i> (2019), Mukherjee and Nateghi (2017), Psiloglou <i>et al</i> (2009), Xie and Hong (2017), Zhou <i>et al</i> (2014)	Relationship depends on prevalence of electric space conditioning; cooler climates see more linear relationship (negative); warmer climates see a non linear relationship with a higher demand at high temperatures; cooling/heating degree days often used instead
Relative humidity	Al-bayaty <i>et al</i> (2019), Apadula <i>et al</i> (2012), Dirks <i>et al</i> (2015)	Slightly positive, especially in conjunction with high temperatures; also modeled with heat index
Cloud cover	Al-bayaty <i>et al</i> (2019), Apadula <i>et al</i> (2012)	Minimal significance, slightly positive due to increased lighting
Precipitation	Fan <i>et al</i> (2015), Mansur <i>et al</i> (2008), Mukherjee <i>et al</i> (2019), Mukherjee and Nateghi (2017)	Minimal statistical correlation with energy demand
Wind speed	Al-bayaty <i>et al</i> (2019), Mukherjee <i>et al</i> (2019), Mukherjee and Nateghi (2017), Xie and Hong (2017)	Partial correlation with more sensitivity in the residential sector
Irradiation	Al-bayaty <i>et al</i> (2019), De Rosa <i>et al</i> (2014)	Significant in warmer climates with cooling demands

consumption and to capture the spatial heterogeneity of building use within each state (Zhou *et al* 2014). For national or multinational scale, the difficulty lies in data collection. Wenz *et al* (2017) gather electrical energy consumption data from across Europe to develop their wide-reaching study and provided a better understanding of Europe's predicted peak energy consumption under climate change.

Finally, Chandramowli and Felder (2014) present a review of energy consumption prediction methods that found multiple linear regression to be one of the prominent techniques. Other technique types include fuzzy regression (Chukhrova and Johannssen 2019), Bayesian additive regression trees (Mukherjee *et al* 2019, Mukherjee and Nateghi 2017), support vector regression (De Felice *et al* 2015, Son and Kim 2017), and artificial neural networks (Al-bayaty *et al* 2019, Ismail and Abdullah 2016). However, no studies have leveraged principal component analysis (PCA) with regression, much less with cross-validated multiple linear regression to account for multicollinearity and bias present in climate and other predictors.

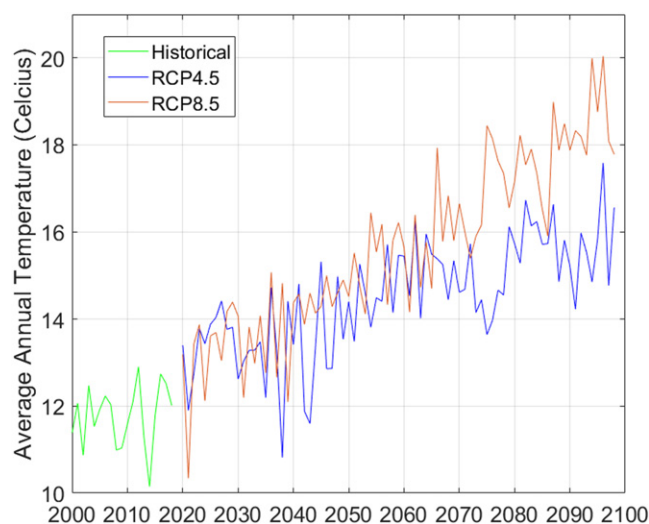
### 3. Methods

#### 3.1. Data

For this study, electric consumption data were provided by WPAFB, located near Dayton, OH, across four consecutive years at the hourly scale, in kilowatt-hours (1 Oct 2015–30 Sep 2019). The scale of these data most closely resemble that of a city, manufacturing complex, or medical or university campus. WPAFB employs over 30 000 people and includes various operation types such as, industrial, commercial, community support, and residential. In all, the data include energy demand from approximately 26 500 facilities. Dayton, Ohio has a temperate climate with moderate rainfall throughout the year, warm to hot summers, and cool to cold winters. While the authors are not permitted to supply billed consumption, or rates, they may be requested via open access request from the installation.

A majority of the climate data used in this prediction framework was retrieved from the National Oceanic and Atmospheric Administration's (NOAA) Local Climatological Data database to include dry bulb temperature, wet bulb temperature, dew point temperature, relative humidity, station pressure, sea pressure, wind speed, precipitation, and cloud fraction. Solar irradiation, cloud opacity, and precipitable water variables were obtained from the commercial solar forecasting company Solcast (Solcast 2019).

Open-source climate projections were obtained through the Lawrence Livermore National Laboratory website (Maurer *et al* 2007). All available models and ensembles for the CMIP5 bias-corrected daily climate projections (BCCAv2-CMIP5-Climate-daily) for maximum and minimum temperature were selected for both RCP 4.5 and RCP8.5 (Reclamation 2013). The two RCPs are used to demonstrate two potential ranges of future energy consumption values. The projection set for RCP4.5 consists of 19 models, with a total of 42 projection ensembles, and RCP8.5 consists of 20 models, with a total of 41 projection ensembles. The median value for all ensembles and each RCP was used to consolidate the ensembles into a single set of deterministic



**Figure 1.** Time series of the historical and forecasted average yearly temperatures. Generally, temperature will gradually increase throughout the century. Between years 2010 and 2040 there is a period of less substantial temperature increase, where a few years may experience average yearly temperatures similar to those experienced in the beginning of the century.

predictions. This approach is consistent with many studies where capturing the general responses to climate change is desired. Figure 1 shows the substantial projected increase in mean annual temperature projected under the two RCP scenarios through the end of the century.

### 3.2. Generating the hindcast

The independent variables collected for the analysis are grouped into three categories: periodicity, climate, and time. We utilize these groups in six different combinations to create the models tested in this study. (1) The *periodicity only* model contains the Fourier transformation, or underlying signal of the observed energy data, as the only input variable. More information on the formulation of the periodicity model can be found in the supporting information, text S2. (2) The *climate only* model contains 12 input variables, including dry bulb temperature, wet bulb temperature, dew point temperature, relative humidity, station pressure, sea pressure, wind speed, precipitation, precipitable water, cloud fraction, cloud opacity, and irradiation. (3) The *periodicity and climate* model consists of 13 variables, including all of the variables from both the periodicity only and climate only models. (4) The *periodicity and time* model consists of 47 input variables, including the single variable in the periodicity only model and all of the categorical time variables (hour of the day [23 variables], day of the week [6], weekday vs weekend [1], month [11], heating vs cooling vs no-heat-no-cool seasons [2], and fiscal year [3]). (5) The *climate and time* model consists of 58 input variables, including all of the variables from the climate only model and all of the categorical time variables. The last model, (6) the *collective* model, consists of all 59 input variables, including all variables from the periodicity only and climate only models, and all categorical time variables. We do not consider a time only model in the study. See the table S1 for the specific inputs within each of the models.

#### 3.2.1. Cross-validated PCR

With the final input variables established, multicollinearity is addressed through cross-validation and PCR (Lins 1985). PCR is a multiple linear regression that uses the principal components (PCs) generated through a PCA of the model inputs. Delorit *et al* (2017) explain that PCR is commonly applied in forecasting and hindcasting to reduce both variable dimensionality and multicollinearity, and result in a set of PCs that represent the variance in a set of predictors. First, PCA is conducted where input variables are broken down into their PCs. Next, a leave-one-out cross-validated hindcast is undertaken across the entire dataset to produce a less biased, deterministic prediction of expected energy consumption for WPAFB. Because this form of cross-validation removes the time-step being predicted, the percentage of variance explained by the model will generally decrease. A leave-one-out cross validation was chosen over k-folds or data split methods to limit bias in the model, though it does increase computation time, significantly. Furthermore, Jolliffe's rule is applied as a PC retention and dimensionality reduction technique (Jolliffe 1972). Only the most influential PCs for the prediction model are retained. The coefficient of variation falls as fewer PCs are retained for the regression. The cumulative effect of the cross-validated PCR is an unbiased and conservative variance explained estimate.



### 3.2.2. Statistical correction

Statistical bias correction, also known as quantile mapping, is prevalent in climate forecast modeling (Cannon *et al* 2015, Maraun 2013, Ringard *et al* 2017). By comparing the fit of the regressed models to the observed data, statistical model bias can be identified and corrected. Statistical correction methods account for consistent bias across a model. To correct the models, the distribution type of the observed energy data is identified. Using the associated distribution parameters, the distribution of the predictions is matched to the distribution of the observations using quantile mapping. The resultant outputs are the final deterministic prediction models.

The observed energy data follows a bimodal normal distribution that necessitates a uniquely tailored statistical correction process. Normal distribution parameters from both distribution ‘modes’ are collected to perform the statistical correction. This method requires both the observed and modeled data to be split at a calibrated point while maintaining time-step position indexing. Each ‘half’ of the modeled data is corrected based on the corresponding ‘half’ of the observed data, and the two ‘halves’ of the model are reassembled to produce the statistically corrected model.

### 3.2.3. Validation metrics

Deterministic model performance is illustrated using mean absolute percent error (MAPE). MAPE is commonly used in energy prediction research and established thresholds are used to determine the skill of prediction models (Adedeji *et al* 2019, Apadula *et al* 2012, Capuno *et al* 2017, De Felice *et al* 2015, Moral-Carcedo and Pérez-García 2019, de Oliveira and Cyrino Oliveira 2018, Panda *et al* 2017, Son and Kim 2017). When utilizing MAPE, a score below 20 signifies a prediction model of ‘good’ quality. If the MAPE falls below 10, the forecast model is said to be of ‘excellent’ quality (Lewis 1982).

Uncertainty is incorporated into the finalized models through prediction ensemble generation. Ensembles are used to calculate ranked probability skill score (RPSS), which is a metric of probabilistic, or categorical, performance and is meant to account for uncertainty in the deterministic models’ outputs. First, a reference climatology is established by separating the distribution of observed data into categories based on the characteristics of the distribution. This becomes the standard against which the prediction ensembles are tested. Climatology is scored based on the percentage of observed data points that fall within each category, while the prediction model is scored based on the number of ensemble predictions that fall in the same category as the observed data. Text S2 in the supporting information contain more details on the calculation of RPSS and category determination.

### 3.2.4. Lean model compilation

Once the skill for each of the six deterministic models is evaluated, a lean model is assembled using only the most dominant input variables from the most skillful model. Dominance is determined by correlating the model’s retained PCs with the original input variables. The following steps were followed to identify the input variables with the greatest signal:

- (a) Isolate the top two-thirds of retained PCs. This decision is arbitrary, but serves to illustrate that an energy manager could down-select to the number of PCs desired based on data availability.
- (b) Select input variables from each PC with the absolute value of correlation coefficients greater than 0.30. This is done as 0.30 is widely regarded as ‘moderate’ correlation.
- (c) Retained input variables are those that occur most often in the remaining PCs.

The new model is then redeveloped through cross-validated PCR, statistical correction, ensemble generation, and skill analysis. The model’s statistical performance is then compared to the initial models to determine the effect of including less but the most important information from the larger input variable set. We recognize that the threshold for inclusion of PCs is arbitrary and a different threshold could impact the overall selection of parameters. However, the intent of this exercise is to evaluate whether model predictive skill is retained with a subset of relevant PCs.

A second lean model is created using only daily temperature averages and categorical time inputs to mimic some of the more readily available data from climate projections. The use of this hindcasts serves to validate the use of a forecast model based on these factors.

## 3.3. Forecast model calibration and validation

Using the lean model developed by down selecting PCs, a forecast of electric consumption is generated. However, the model developed is potentially conservative as it assumes use patterns of the community are unchanging, i.e., the Air Force installation does not grow or change with time. Additionally, it does not consider any efficiency upgrades that would significantly alter overall demand. These assumptions are necessary but could be calibrated for future models based on input from energy managers and new policy. For example,

Table 2. Model performance statistics.

Models	Variance explained ( $r^2$ )	MAPE	RPSS	Dimensionality reduction (%)	Dominant signals for PC1 and PC2 input name, Pearson's coefficient of correlation	
					PC1	PC2
Collective	0.73	6.25	0.57	30.5	FourierTrans (0.87)	FourierTrans (0.94)
Climate and periodicity	0.44	9.62	0.30	61.5	FourierTrans (0.77), irradiation (0.41), DewPtTemp (−0.37)	FourierTrans (0.96)
Climate and time	0.73	6.15	0.59	26.3	DewPtTemp (0.95)	DewPtTemp (0.94)
Periodicity and time	0.55	8.22	0.39	27.7	FourierTrans (0.95)	Wednesday (0.52), weekday/weekend (−0.40), Thursday (0.39)
Climate only	0.43	9.83	0.29	58.3	DewPtTemp (0.94)	DewPtTemp (0.90)
Periodicity	0.27	11.53	0.19	0	FourierTrans (1.0)	

the 2022 Inflation Reduction Act in the United States includes incentives for electrifying facilities, specifically residences. These changes at a campus scale, would increase the winter electric demands through heat pumps, impacting the determined relationship between temperature and consumption patterns.

Forecasts of daily electric consumption are generated by applying CMIP5 forecasted maximum and minimum temperature inputs and categorical time inputs to the coefficients generated by the cross-validated electric consumption prediction model. The electric consumption forecasts are aggregated to total monthly consumption, and placed in decadal categories (2020–2030, 2030–2040, etc) to present a range of possible yearly energy consumption values for each year within a decade. Trends in monthly energy consumption are then compared across the century. One-way ANOVA tests are used to determine the significance of monthly energy consumption changes between the first decade and each subsequent decade to highlight when, during the century, monthly and seasonal trends diverge from current use behaviors.

## 4. Results

### 4.1. Hindcast model results

Deterministically, the top performing models are the collective and climate and time models, as each produces an explained variance of 0.73 ( $r^2$ ) (table 2). Probabilistically, the significance of incorporating statistical correction into model development is manifested as a 9% average increase in RPSS across all models, with the exception of the periodicity only model (1% improvement), which is likely due to the fact it is extracted from the observed data.

Dimensionality reduction compares the number of retained PCs to the initial number of PCs for each model. Specifically, it is the ratio of the difference between the initial number of PCs and the final number of retained PCs in a model to the final number of retained PCs in a model expressed as a percentage. Reducing dimensionality in a model is important because it reduces the complexity of the model and highlights what input variables are not necessary to produce the model skillful. In other words, it narrows the scope of input variables that energy managers must collect and input into a model.

The performance metrics identify that some models do show particularly encouraging skill. All models, except for the periodicity only model, produce MAPE scores consistent with ‘excellent’ prediction/forecast model candidates ( $<10$ ); the periodicity only model is considered ‘good’. A total of approximately 100 ensembles for each model formulation were computed to achieve RPSS convergence ( $<0.01$  score deviation). Clearly, higher RPSSs stem from models with larger deterministic variance explained.

Periodicity provides predictive power only when coupled with categorical time variables. When paired with the climate variables, periodicity provides a slight improvement over the climate only model, and in the collective model, periodicity adds little improvement when compared to the climate and time model. In direct comparison, the climate only model performs substantially better than the periodicity only model. These combined results suggest that the climate inputs provide largely the same information that the periodicity does,

**Table 3.** Median energy consumption value contingency tables for the climate and time model (%); regions: L = low values, ML = mid-low values, MH = mid-high values, H = high values; green = hit, red = extreme miss.

		Modeled			
		L	ML	MH	H
Observed	L	61.6	24.2	2.8	0.5
	ML	36.9	50.6	33.6	8.4
	MH	1.2	12.8	25.6	14.1
	H	0.3	12.4	38.0	76.9

but the climate inputs also provide more additional information. As such, for this research, models with climate inputs are favored over those with the periodicity.

Because the climate and time model was the least complex and highest performing model, it was used to create two lean models consisting of only those input variables with the most dominant signals. After cross-validated PCR, 42 of 58 PCs were retained. Correlating PCs to the specific input variables determined that the inputs with the most dominant signals include the three temperature variables (dew point, dry bulb, and wet bulb) and the time variables weekday/weekend, January, February, June, Sunday, Friday, 1100 h, 1400 h, 1500 h, 1600 h, and 2300 h.

Contingency tables are leveraged to test the categorical performance of the top performing deterministic model (climate and time). Hits and misses are expressed as a percentage of the total number of forecasts in each climatological category. Climatological categories were defined by the histogram of energy consumption, using local minima and maxima as the cutoffs for categorical definition. A breakdown of these categories and their thresholds are shown in figure S2 in the supporting information. In the contingency tables, hits appear along the diagonal from top left to bottom right. It follows that misses appear as a divergence from the diagonal. The hit scores align closely to model RPSS; however, the extreme miss score is new information, and represents cases when the prediction was for low energy consumption, but the actual energy consumption was high, and vice versa (table 3). The hit score of the best performing deterministic model (climate and time model) is 58.6%, and the extreme miss score is 7.9%. Additionally, the hit score for the highest and lowest use categories is 72%. While the overall hit score is unimpressive, the model's performance in the extremes is encouraging. If the energy manager's goal is to avoid extreme misses, and maximize skill in predicting extreme use times, then the model should be preferred over a climatological analog.

Being that the high and low categories are likely to be of greatest importance to energy managers, the contingency tables for the median predictions can also be readapted to consolidate the middle two regions (mid-low and mid-high) to a single category because specificity in these regions may not be necessary or important to energy managers. The result is an increased hit score of 67.7% and a decreased extreme miss score of 0.17%. The increase can be attributed to the higher accuracy in the new 'middle' region due to the consolidation of the mid-high and mid-low regions, and the decrease in extreme misses is attributed to the fewer opportunities for values to fall in extreme miss categories.

#### 4.2. Lean model results

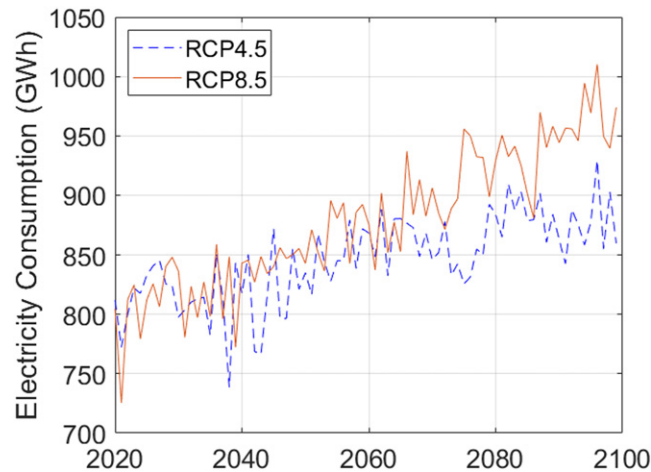
Two lean models are generated with different combinations of input variables to specifically analyze the effect of including categorical time variable types rather than only including specific time variables. Lean model A consists of 44 input variables, including all of the temperature variables (dew point temperature, dry bulb temperature, and wet bulb temperature) and only the most impactful time variable types (hour of the day [23], day of the week [6], weekday vs weekend [1], and month [11]). For example, since several specific hour-of-the-day variables are noted as being impactful, the entire set of hour-of-the-day variables were included in the model. Lean model B further downselects the data to match the daily climate data readily available within CMIP5 projects. The model consists of daily temperature and categorical time variables, including day of the week and month.

Lean model A maintains higher performance results compared to the six original models, while lean model B experiences larger drops in performance (table 4). This result occurs because lean model A contains more total input variables than lean model B. However, lean model B still outperforms three of the six original



**Table 4.** Lean model statistical results table.

Models	Variance explained ( $r^2$ )	MAPE
Lean model A	0.66	6.90
Lean model B	0.46	6.95

**Figure 2.** Time series plot of forecasted total annual energy consumption for RCP4.5 (dashed orange) and RCP8.5 (blue), shows significant increase through the end of the century, with deviation from the 2020 average accelerating around 2040.

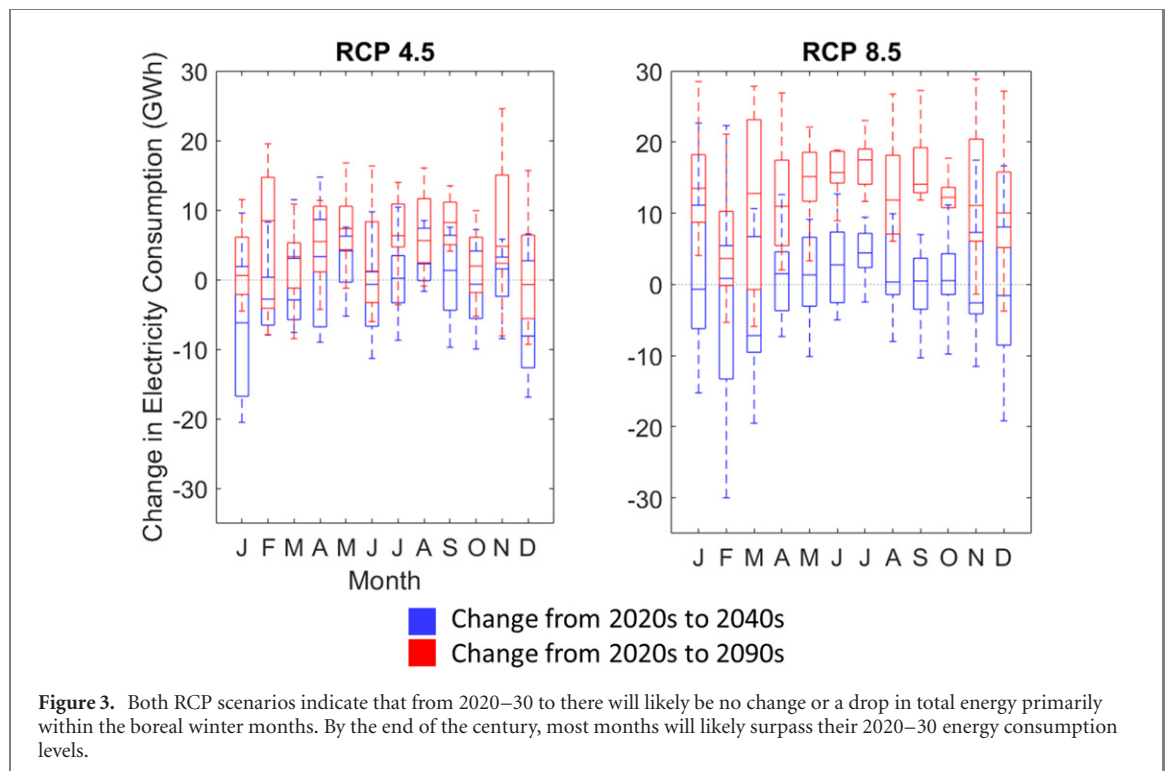
models (periodicity only, climate only, and climate and periodicity) and performs similarly to the periodicity and time model.

#### 4.3. Forecast model results

The previous analyses focused on hindcasts of the electric consumption for WPAFB. Through the identification of the primary driving factors of electric consumption in the hindcast models, we built an electric demand forecast using climate change ensembles. The ‘excellent’ MAPE score ( $<10$ ) provides the basis for the forecasting analysis. We utilize climate ensemble projections for two representative concentration pathways (RCP). RCPs consider a wide array of mitigation efforts for anthropogenic climate change. RCP4.5 is an intermediate scenario with emissions peaking around 2040 before declining. RCP8.5 is a scenario in which emissions continue to increase through the end of the century.

Applying the model in a forecast mode, it is revealed that electric consumption will increase by the end of the century for both RCP cases, though RCP8.5 electric consumption increases more aggressively beginning around year 2065 (figure 2). Between years 2020 and 2040 there is no substantial increase in electric consumption, nor is there a significant difference in consumption predictions for the RCPs. This result could be attributed to the recent observed decreases in temperature since 2017 and milder maximum and minimum temperatures projected for the first two decades following the year 2020. By applying a linear fit to both RCP forecasts, it appears that electric consumption could increase by 0.80 GWh per year for RCP4.5 and 2.14 GWh per year for RCP8.5 through the end of the century. As such, any goals for meeting net-zero energy policies must account for these approximate annual demand changes. Energy managers planning to meet mitigation strategies must build infrastructure and budgets appropriately to meet these projections.

Several months, primarily during the boreal winter and spring, are likely to experience either consistent or falling electric consumption through the year 2040 in both RCP scenarios (figure 3). By the end of the century, the electric consumption across all months will likely meet or surpass 2020–2030 energy consumption totals for both RCP cases. Spring, summer, and fall months achieve greater energy consumption under RCP8.5, with higher degrees of significance, much sooner than RCP4.5 (table 5). Again, while this general result is expected, the onset of significantly elevated electric consumption values, and subsequent costs, was unknown until this point. Also, RCP8.5-informed forecasts produce significant increases in winter energy consumption as early as the decade 2040–2050, while RCP4.5 results show decreases in winter energy consumption in this same period. Additionally, RCP8.5 monthly energy consumption exhibits a higher degree of inter-annual variability than RCP4.5, which could mean more uncertainty in forecasted results or less stability in annual consumption (figure 3). Less stability in consumption would make the task of budgeting on the part of energy managers difficult. Overall, there is high confidence that summer and adjacent seasons’ energy consumption



will increase earlier in the century, while the timeframe for increases of winter energy consumption may be variable.

## 5. Discussion

### 5.1. Limitations of the research

This research is limited in that the models were calibrated to the singular location of Dayton, OH. Future research must be conducted to evaluate the skill of such models across a span of varying climate regions to validate its adaptability. This is particularly important because the aspects of climate that impact energy use are likely to vary. Therefore, exhaustive inclusion of climate input types should be favored in initial model development to identify which are most impactful in the PCA. Additionally, a large and potentially conservative number of PCs for the models with larger input sets were retained using Jolliffe's rule. Adopting other rules (e.g. Kaiser's rule) could further narrow the retained PC count of larger input sets.

Additionally, the analysis is limited in its exploration of only six models in the initial formulation. A more robust iterative approach for evaluating independent variables might be appropriate to better inform future lean models, such as those in Galelli and Castelletti (2013) and Galelli *et al* (2014). However, these iterations should also include weights toward accessibility and ease of access of data for energy managers and other decision-makers.

### 5.2. Model predictive strength

The results demonstrate that skillful predictions of hourly campus-wide energy consumption can be achieved using statistical models informed with mixtures of continuous climate and categorical time variables. Moreover, models can be created with techniques (PCR, cross-validation, and statistical correction) that minimize bias and reduce dimensionality. Furthermore, using uncertainty in deterministic predictions, a model's probabilistic skill can be determined. The skill of the proposed framework and use of open-access data suggests that energy and facility managers could be well-positioned to create their own models. The correlation between the regressed PCs illustrates that temperature and time variables are the most useful in explaining hourly energy consumption. Energy consumption patterns were used to decide which categorical time variables to include, while the temperature data was obtained from an open-access NOAA database. Both of these variable types require limited effort to obtain. However, as the comparison of the climate and time model and lean model B shows, there is a significant tradeoff between reducing dimensionality and maintaining skill.

Though overall predictive strength is important, accuracy at the highest and lowest energy use periods is perhaps of greatest importance to energy managers, who must make operational decisions (e.g. load shedding), and make equipment and policy recommendations to decision-makers. For example, predicting peak

**Table 5.** Significance of the difference in forecasted monthly electric consumption for (a) RCP4.5 and (b) RCP8.5 between the decade 2020–2030 and subsequent decades; dark orange ( $p < 0.05$ ), medium orange ( $0.05 < p < 0.10$ ), light orange ( $0.10 < p < 0.25$ ), no color ( $p > 0.25$ ); ‘–’ represents a negative change and ‘+’ represents a positive change.

a.	<b>RCP 4.5 Significance Compared to 2020–2030 Decade (ANOVA test p-value)</b>						
	2030–2040	2040–2050	2050–2060	2060–2070	2070–2080	2080–2090	2090–2100
Jan	–	–	–				
Feb	–	–		+		+	+
Mar		–			+		+
Apr				+	+	+	+
May		+	+	+	+	+	+
Jun				+	+	+	+
Jul		+	+	+	+	+	+
Aug	+	+	+	+	+	+	+
Sep		+	+	+	+	+	+
Oct				+		+	
Nov				+		+	+
Dec	–	–					

b.	<b>RCP 8.5 Significance Compared to 2020–2030 Decade (ANOVA test p-value)</b>						
	2030–2040	2040–2050	2050–2060	2060–2070	2070–2080	2080–2090	2090–2100
Jan		+	+	+	+	+	+
Feb					+		+
Mar	–		+		+	+	+
Apr		+	+	+	+	+	+
May		+	+	+	+	+	+
Jun	+	+	+	+	+	+	+
Jul	+	+	+	+	+	+	+
Aug		+	+	+	+	+	+
Sep			+	+	+	+	+
Oct		+	+	+	+	+	+
Nov			+	+	+	+	+
Dec			+		+	+	+

energy consumption can inform energy managers of when peaker generators, or those generators only used to compensate for peak energy periods, should be utilized or if energy infrastructure needs expansion to support increased demand. Additionally, hourly predictions facilitate greater integration with renewables that are predictable but vary in availability throughout a day. Predicting low energy periods accurately can inform seasonal decisions to override heating and cooling systems when environmental conditions are mild (e.g. spring and fall) (Delorit *et al* 2020). These predictions offer opportunities both in the short-term for annual budgeting but also in the long-term to develop energy transition pathways to meet net-zero goals for the federal government.

### 5.3. Impact for carbon footprint

The results of the century forecast model illustrate that starting in 2040 there will be significant annual and seasonal deviations from the historic average of electric consumption. For RCP4.5 and RCP8.5 scenarios, an additional demand of 0.80 GWh and 2.14 GWh per year incurs a significant burden not just in terms of cost, but also with respect to reducing emissions. Previous assessments of Dayton, Ohio’s greenhouse gas emission intensity ranged from 370 to 1710 kg CO<sub>2e</sub>/MWh with an average of 684 kg CO<sub>2e</sub>/MWh depending on the accounting method (Siddik *et al* 2020). Utilizing these emissions intensities, this equates to an additional 547 000 kg CO<sub>2e</sub> or 1460 000 kg CO<sub>2e</sub> for RCP4.5 and RCP8.5, respectively, each year. Current emissions from electric consumption at WPAFB total approximately 547 million kg CO<sub>2e</sub> for the year 2020 and could rise to nearly 700 million kg CO<sub>2e</sub> by the end of the century for RCP8.5 considering no change in existing generation mix. Therefore, to meet EO 14057, WPAFB will need to plan for significant additional electric demand by the 2050 deadline for net-zero energy, approximately an additional 50 GWh of demand. Without using appropriate forecasting tools to assess increased electric consumption, the installation could miss these important climate targets.

#### 5.4. Implications for policy and energy managers

The forecasting results are consistent with similar works in this field of study. The energy consumption forecasts developed in this research show a constant, and even a slight decline, in energy consumption approaching the middle of the century. The work of Zhou *et al* (2014) and Emodi *et al* (2018) capture this phenomenon. For example, Zhou *et al* finds that a slight decline in heating demand and a slight decline in cooling demand occur in the first half of the 21st century for the state of Ohio. Since the primary facility energy drain related to climate is heating and cooling, Zhou *et al* appears to explain a large part of what is observed with total energy consumption in the research herein. In contrast to existing studies, the forecasts developed in this research aid in analyzing century-long trends in energy consumption at the campus level using campus-level energy data. This research suggests that energy managers and campus leaders must be prepared for energy consumption, and subsequent costs, to increase over the course of the century. Long-term consumption and cost forecasts, consistent with the type produced here, provide valuable information to mitigate climate impacts and meet renewable and net-zero energy targets.

Energy managers are generally not modelers, and thus tools that are informed with readily available data are likely to be favored. Data accessibility, computational power, modeling ability, and time availability could be factors in model construction. Though models with climate variables tend to outperform less data-intensive constructs, managers may favor a periodicity-based model as it only requires the energy consumption data itself. Ultimately, both approaches are viable and can produce skillful models. The information provided by these forecasts enable campus energy managers to understand the magnitude and timeframe where energy consumption and costs could significantly escalate. Campus managers can decide what risk mitigation strategies to implement, decide when to implement them, and economically justify their investment decisions. To mitigate and overcome cost increases, energy managers should consider policy (near-term) and infrastructure (long-term) adaptations to overcome increases. This model framework can then be used as a tool to justify the economic benefits of infrastructure and renewable resource investments.

## 6. Conclusion

EO 14057 directs federal agencies to achieve 100 percent carbon-free electricity on a net annual basis by 2030 and net-zero emissions by 2050. Using WPAFB, OH as a case study, we demonstrate that electric demand is expected to significantly rise throughout the remainder of the century. To meet these targets, federal agencies need robust predictive practices when building out electric infrastructure to meet not just current demands but also future projections. In this study, we present several options for creating robust forecasts of electric demand at a campus- or installation-scale. These type of analyses are integral to facilitate data-driven decisions focused on climate-informed infrastructure. The methodology developed here provides a flexible framework that can be adapted to any number of continuous or categorical independent variables, utilizes open-source data, and extensively accounts for modeling bias. Each model configuration presented performs skillfully in those areas most important for decision-making and policy development. Energy managers and policy-makers should look to climate projections and skillful forecasts to create robust predictions for net-zero and carbon free infrastructure investments.

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## Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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