The Impact of Neglecting Climate Change and Variability on ERCOT's Forecasts of Electricity Demand in Texas

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Abstract

The Electric Reliability Council of Texas (ERCOT) manages the electric power across most of Texas. They make short-term assessments of electricity demand based on historical weather over the last decade or two, thereby ignoring the effects of climate change and the possibility of weather variability outside of the recent historical range. In this paper, we develop an empirical methodology to predict the impact of weather on energy demand. We use that with a large ensemble of climate model runs to construct a probability distribution of power demand on the ERCOT grid for summer and winter 2021. We find that the ERCOT grid is running with no safety margin, particularly during summer. We estimate a 5% chance that maximum power demand would be within 4.3 and 7.9 GW of ERCOT's estimate of best-case available resources during summer and winter 2021, respectively, and a 20% chance it would be within 7.1 and 17 GW. With such small margins, the unexpected reductions in available power can lead to shortages on the grid. This problem is partially hidden by the fact that ERCOTs seasonal assessments, based entirely on historical weather, are too low. Prior to the 2021 winter blackout, ERCOT forecasted an extreme peak load of 67 GW. In reality, we estimate hourly peak demand was 82 GW, 22% above ERCOT's most extreme forecast and about equal to the best-case available power. Given the high stakes, ERCOT should develop probabilistic estimates using modern scientific tools to predict the range of power demand more accurately.

1. Introduction

Most of the citizens of the State of Texas get electricity from a grid managed by the Electric Reliability Council of Texas (ERCOT). During February 2021, a significant winter storm (Doss-Gollin et al. 2021) caused widespread blackouts throughout the State that left more than 10 million people without electricity (Busby et al. 2021). These blackouts and their downstream impacts led to the deaths of hundreds of people and caused nearly $200B of damages (Frankenfield 2021; Ivanova 2021).

To maintain the robustness of the grid, ERCOT makes short-term seasonal power-demand assessments (e.g., http://www.ercot.com/content/wcm/lists/197378/SARA-FinalWinter2020-2021.pdf) to ensure adequate resources will be available. These assessments are based on the weather from the past decade or so and factors such as population, but they do not account for a changing climate or the possibility of climate variability outside of the conditions described in the historical record. In this paper, we evaluate this methodology and develop a new method for incorporating more realistic predictions of future weather into energy projections.

2. The model ensemble and comparisons to historical data

Our observational data set is daily-average 2-m air temperatures from the ECMWF ERA5 reanalysis (Hersbach et al. 2020), which has a resolution of 0.25° for both latitude and longitude. We also use temperatures from an ensemble of 39 model runs known as the Community Earth System Model Large Ensemble (CESM-LE) (Kay et al. 2015). The members of this ensemble use an identical climate model and the same evolution of historical natural and anthropogenic forcing. The members differ only in their initial conditions, so the variation in climate across the ensemble is entirely due to random climate and weather variability.

To estimate the temperature of Texas, we average the grid points whose centers are within the state border of Texas. The ensemble is bias corrected by adding offsets of 0.7°C and 0.6°C to June-July-August season (JJA) and December-January-February season (DJF) to ensemble member temperatures so that the 40-year seasonal average temperatures from ERA5 is equal to the 40-year seasonal averages of the ensemble. This bias is small compared to the magnitude of the temperature variations we are analyzing.

Figure 1 shows the highest 1-day and 5-day average temperature during each JJA and lowest 1-day and 5-day average temperature during each DJF since 1981 in the ECMWF ERA5 reanalysis. The convention in this paper is that DJF refers to three consecutive months; for example, DJF 2010 is Dec. 2009 and Jan. and Feb. 2010. For the JJA maximum, the highest 5-day average temperature was in 2011 (32.9°C) while the highest 1-day temperature (33.1°C) was in 2020. For the DJF minimum, the coldest 5-day (-6.3°C) and 1-day average temperature (-11.1°C) were both in 2021.

When comparing to the climate model ensemble, the appropriate comparison is between the statistics of the ensemble and the observations, and these agree closely (Figs. 1c and 1d). Fitting the ERA5 and CESM-LE data to a generalized extreme value (GEV) distribution tells us that the 2020 1-day temperature of 33.1°C was a 1-in-7 year event in the ERA5, while it was a 1-in-5 year event in CESM-LE. The 2021 winter 1-day temperature of -11.1°C was a 1-in-55 year event in the ERA5, while it was a 1-in-87 year event in the CESM-LE. The standard deviation of ERA-5 data is 2.0°C and 4.9°C in JJA and DJF, while the average of standard deviation in each member of CESM-LE is 1.8 (1σ of ensemble standard deviation values is 0.22) and 4.0 (1σ=0.58). Based on these comparisons, we feel confident we can use this ensemble to evaluate ERCOT's forecasts.

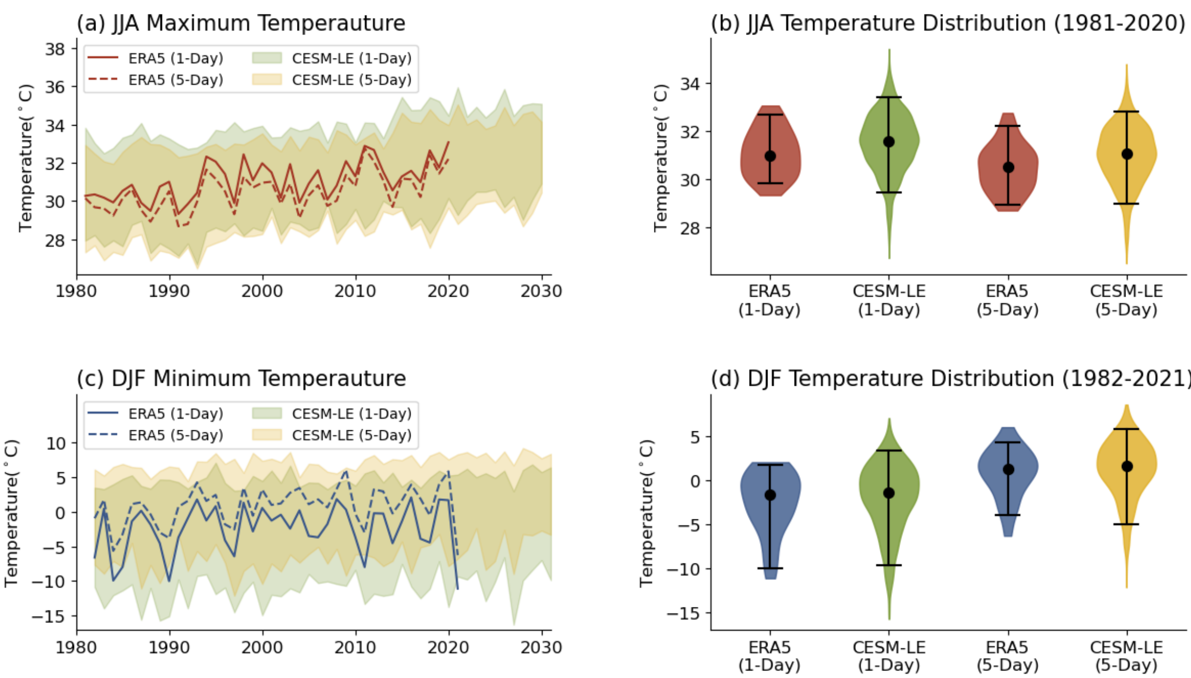

Figure 1. Time series of seasonal maximum and minimum temperature over Texas (these are not population weighted). (a) JJA maximum 1-day (solid line) temperature and 5-day (dashed line) temperature in ERA-5, and green and yellow area each denotes the maximum and minimum ensemble member of 1-day and 5-day temperature in CESM-LE. (b) Violin plot for distribution of 1-day and 5-day JJA maximum temperature in ERA-5 and CESM-LE. Error bars represent the 95th and 5th percentile of the distribution, and the dots represent the median of the distribution. (c, d) Same as (a, b), but for DJF minimum temperature.

3. The connection between electricity consumption and temperature in the historical record

Historical hourly electric power consumption is obtained from ERCOT for the period Jan. 1996-Feb. 2021 (http://www.ercot.com/gridinfo/load/load_hist/). 2001 data are not available, so our analysis excludes DJF 2001, JJA 2001, and DJF 2002. The first step is to regress population-weighted daily average temperature against daily average power. We use a time-invariant population distribution averaged from 2000 to 2020 from CIESIN (2016) for the population weighting.

We perform the regression separately for each season of each year. Figs. 2a and 3a show a tight relationship between temperature and power usage in JJA and DJF for the first and last year of ERCOT's record — other years (not shown) show similarly tight relationships. This indicates that, within a season, variations in temperature are the primary controlling factor for power usage. Based on our examination of the data, we use a linear fit for JJA and a non-linear polynomial fit ($P = C_0 + C_1 T + C_2 T^{1.75}$) for DJF. In Section S1 of the supplement, we discuss this in detail and show how our formulation works better than other potential choices.

From each year's fit, we calculate P_{ref} for that year, which is power usage at a reference temperature (T_{ref}). We use a reference temperature equal to the median temperature for JJA (28.8°C) and DJF (10.9°C). The time series of P_{ref} is plotted in Figs. 2b and 3b; this can be thought of as the seasonal average power usage that would have occurred if the temperature were fixed at the reference temperature. The increase in P_{ref} over time is due to changes in non-climate factors, such as population. We then perform a linear fit to represent P_{ref} as a function of year ($P_{ref}(y)$) (all of the fits can be found in Supplement Section S2).

We expect the coefficients from each year's temperature-power regressions (Fig. 2a and 3a) to be correlated with P_{ref}. For example, increases in population will change the slope of the power-temperature relation because, as population increases, changes in temperature will drive larger changes in power usage. Figs. 2c, 3c, and 3d show that these coefficients are indeed correlated with P_{ref}.

Given this, we can model daily average power usage at as a function of year and daily-average temperature T. For JJA:

$$P_{JJA}(y,T) = P_{ref}(y) + \left(S(y) \times (T - T_{ref})\right) \tag{1}$$

Where $P_{JJA}(y,T)$ is the daily average power for a day in year y with a population-weighted, daily average temperature T. $P_{ref}(y)$ is the value of P_{ref} during JJA in year y, $S(y)$ is the slope of the power-temperature regression in year y, and T_{ref} is the JJA reference temperature. Note that S was plotted in Fig. 2c as a function of P_{ref}, but because P_{ref} is a function of year, we can also express S as a function of year y.

Our equation for DJF is similar to the JJA equation except that the power-temperature relation has higher order terms:

$$P_{DJF}(y,T) = P_{ref}(y) + \left(C_1(y) \times (T - T_{ref})\right) + \left(C_2(y) \times (T - T_{ref})^{1.75}\right) \tag{2}$$

As with the JJA relation, the coefficients C_1 and C_2 correlate with P_{ref} (Figs. 3c and 3d), so we can also express them as functions of year. Also remember that DJF P_{ref} and T_{ref} are different from JJA P_{ref} and T_{ref}.

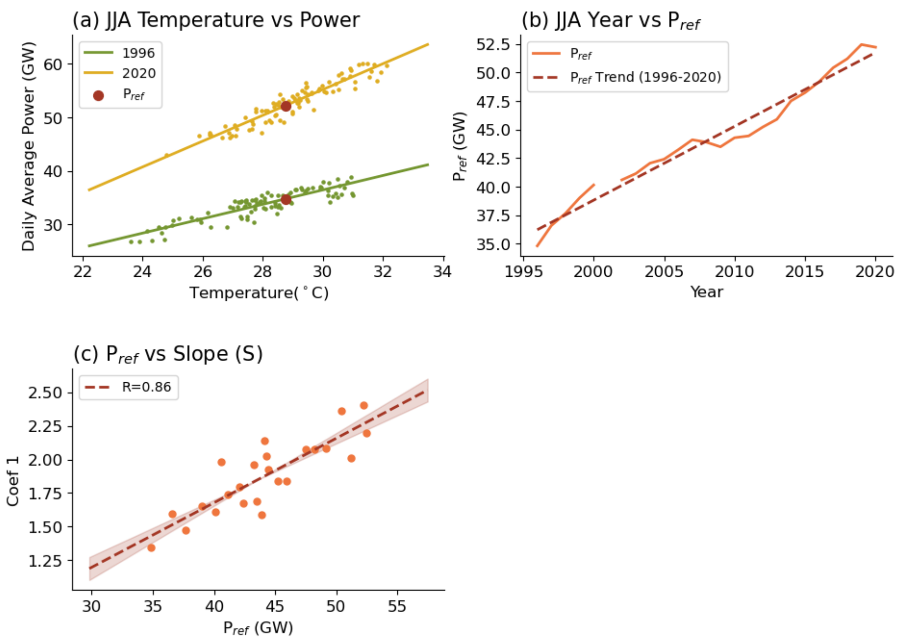

Figure 2. (a) Scatterplot of population-weighted daily average temperature and daily average power usage in the first and last year of ERCOT's historical record. Red circle denotes the power at the reference temperature (P_{ref}). (b) Evolution of P_{ref} over time. The red dashed line is a linear trend. (c) Slope of the temperature-power relation as a function of P_{ref}. Each point represents a value from a single year.

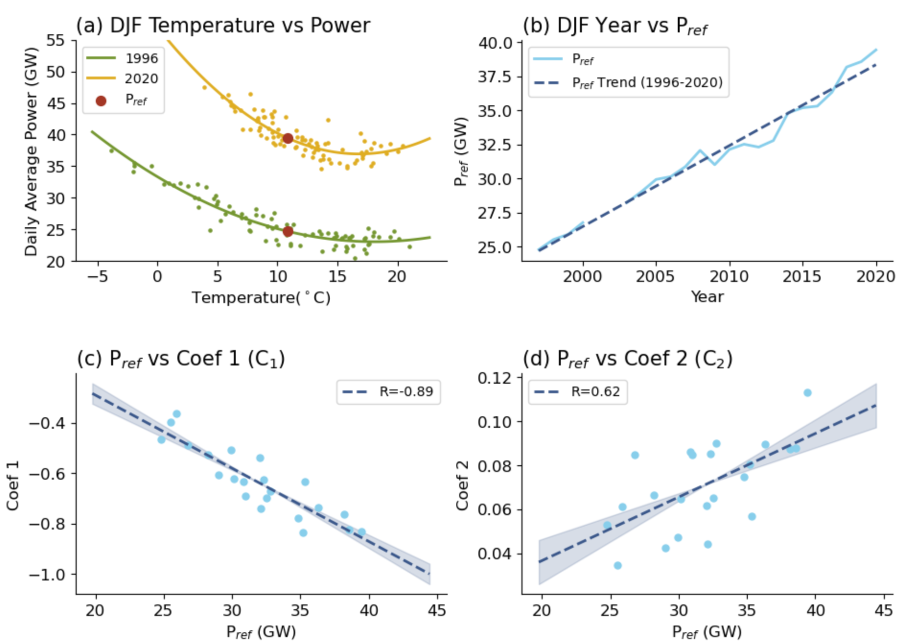

Figure 3. Same as Figure 2, but for DJF. Because we use a 1.75-D power-temperature fit in DJF, we have two constants, and these are plotted in panels c and d.

4. Prediction of future electricity consumption

Using the methodology described in the last section, we can produce an estimate of daily average power usage. For comparison to ERCOT forecasts, we convert this to daily *maximum* power (hereafter DMP), the highest hourly power demand during the day, using a linear regression between daily maximum and daily average power usage developed from the historical data. The correlation between these quantities has R values of 0.99 and 0.98 in JJA and DJF and an RMS error of 1.0 and 1.1 GW, respectively.

Plugging ERA5 temperatures into Eq. 1 and 2, we can reproduce the historical seasonal maximum power (the highest hourly power demand during the season, hereafter SMP) quite closely (Figs. 4a and 4b), with RMS differences of 1.0 GW and 1.5 GW for JJA and DJF, respectively (2021 is excluded from the DJF calculation due to the blackout). This good agreement may be surprising because we left out of our model many factors that one might have anticipated would be important (e.g., weekday vs. weekend, number of hours of sunlight). We investigated many of these factors and found that none of them significantly improved our ability to reproduce the observations.

We also have taken the CESM-LE temperatures and used Eq. 1 and 2 to estimate SMP for the 1996-2021 period. The shaded regions show the range of power predicted by the ensemble and ERCOT's historical power demand falls comfortably within the ensemble's envelope. This result is consistent with the fact that observed temperatures over this period fall within the CESM-LE's range of predicted temperatures (Fig. 1).

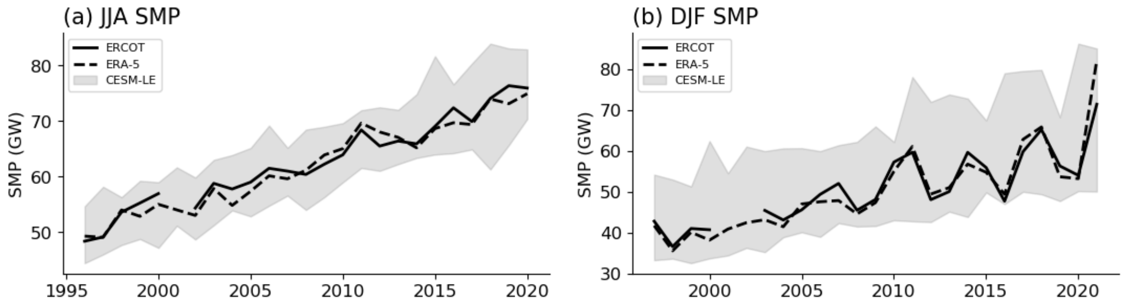

Figure 4. Time series of seasonal maximum hourly power usage (SMP). (a) JJA SMP for 1996-2020. Black solid line represents the historical ERCOT record, and black dashed line represent the historical power usage estimated by us using ERA5 temperatures. The grey area depicts the range of power usage estimated from the CESM-LE. (b) Same as (a), but for DJF 1997-2021.

5. Comparison of seasonal power demand

5a. Comparison of summer power demand

In order to evaluate ERCOT's seasonal 2021 summer resources assessment (http://www.ercot.com/content/wcm/lists/219840/SARA-FinalSummer2021.xlsx), we have calculated a probability distribution of SMP for JJA 2021 using temperatures from the CESM-LE from the period 2016-2025, but with 2021's P_{ref} (Fig. 5a).

ERCOT predicted a most likely SMP of 77 GW, in good agreement with the peak of our probability distribution. ERCOT also predicted an extreme peak-load scenario of 80 GW, which they derived assuming that the worst-case scenario is a repeat JJA 2011 temperatures. Note that ERCOT provides no probabilistic information with which to interpret their extreme scenarios. Is this a 90%, 95%, 99%, etc. confidence interval? We calculate that there is a 17% chance of JJA 2021 SMP exceeding 80 GW (Fig. 5a), suggesting that the use of historical temperatures may not be a good way to estimate of extreme demand.

ERCOT also estimated a best-case of 87 GW of power available to satisfy peak demand. Comparing this to Fig. 5a shows that the ERCOT grid is running with very little margin, with 5% of the summers in the CESM-LE having an SMP within 4.3 GW of ERCOT's estimate of best-case available power and 20% of summers within 7.1 GW. In such a situation, minor but unanticipated declines in available power, such as what happens when several power plants go offline for maintenance at once, puts the ERCOT grid at risk of being unable to satisfy power demand.

5b. Comparison of winter power demand

We now evaluate ERCOT's seasonal resource assessment made right before the DJF 2021 season (http://www.ercot.com/content/wcm/lists/197378/SARA-FinalWinter2020-2021.xlsx). We do that by comparing it to a probability distribution of SMP for DJF 2021 that we calculated using temperatures in the CESM-LE between 2016 and 2025, but with 2021's P_{ref} (Fig. 5b). ERCOT's most-likely SMP is 57 GW, very close to the peak of our predicted distribution. ERCOT's extreme peak load scenario is 67 GW, calculated assuming that the worst case was that Texas would experience temperatures as cold as DJF 2011's, the most recent very cold Texas winter.

Like their summer estimates, this extreme peak load scenario is low — we estimate that there was an 19% chance that SMP would exceed this value. Reality provided support for this: 2021 DJF minimum daily average population-weighted temperatures were 3.4°C colder than 2011's, from which we estimate that peak demand was 82 GW — about 15 GW above ERCOT's worst-case prediction.

ERCOT communicated to us that their estimate of DMP during the 2021 winter storm was 76 GW (Jeff Billo, personal communication, 2021), 6 GW lower than our estimate. We do not know how ERCOT comes up with their number, but we assume that they are using some type of a piecewise-linear fit. Using our own version of a piecewise-linear fit, we find that maximum power demand during the 2021 winter storm was 74 GW, which is close to ERCOT's estimate. However, as shown in Section S1, piecewise-linear fits tend to underestimate power demand at very cold temperatures. Without more information about ERCOT's estimate, though, we cannot confidently identify the source of the disagreement.

This difference has important implications for how much margin the ERCOT grid has. ERCOT estimates that, in the best case, there was 83 GW of power available. If our estimate is correct, then the ERCOT grid had essentially no margin in DJF 2021, meaning that any loss of power, e.g., due to lack of weatherization of energy infrastructure, meant that the ERCOT grid could not satisfy power demand.

More generally, Fig. 5b shows that the ERCOT grid also runs with very little margin in winter, just as it does in summer. For DJF 2021, we estimate that 5% of winters in the CESM-LE had an SMP within 7.9 GW of ERCOT's best-case estimate of available power and 10% and 20% of winters were within 12 and 17 GW, respectively. And 1.5% of the winters had SMP in 2021 DJF exceeding best-case available power, as approximately happened in 2021.

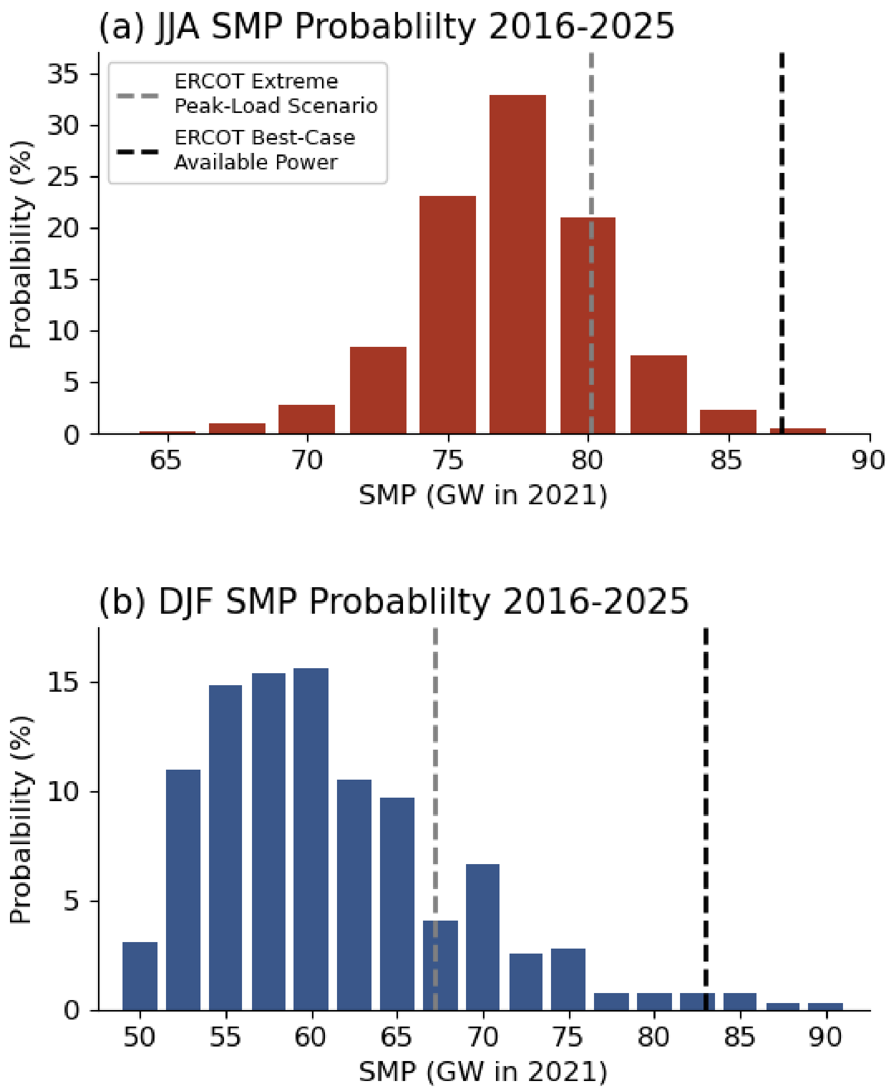

Figure 5. Probability distribution of seasonal hourly maximum power usage (SMP) in (a) JJA 2021 and (b) DJF 2021, predicted by the CESM-LE. Calculations use temperatures from 2016-2025 and P_{ref} for 2021. Grey and black vertical lines represent the ERCOT's seasonal forecast for extreme peak-load and best-case available power.

6. Conclusions

One of ERCOT's most important jobs is ensuring that there is sufficient power available to the Texas electrical grid. In support of this objective, ERCOT makes seasonal assessments of future power demand. However, ERCOT does not take climate change into account or use modern climate forecasting tools to estimate climate variability when making these forecasts. Instead, they exclusively use the historical climate record.

In this paper, we describe an empirical methodology to estimate the impacts of climate change and weather variability on power demand. We then use output from an ensemble of climate model runs (the CESM-LE) to estimate the impact of climate change and variability on ERCOT's forecasts. We find that ERCOT's exclusive use of historical temperatures means that they underestimate the worst-case scenarios. We estimate a 17% and 19% chance that 2021 JJA and 2021 DJF power demand would exceed ERCOT's extreme peak load scenarios, respectively. After the fact, we find that 2021 DJF maximum power demand exceeded ERCOT's extreme peak load scenario by 15 GW or 22%.

ERCOT disputes our estimate of peak demand during the 2021 DJF (82 GW) — they estimate demand was 76 GW. Resolution of this difference is important because it has implications for how much of a safety margin the ERCOT grid has, but ERCOT's model and underlying data are not publicly available so we are unable to identify the source of this disagreement. ERCOT should be transparent about their forecasts and should make their forecast model public so researchers can better evaluate their methodology.

In both summer and winter, we find that ERCOT's electricity grid has little spare capacity. According to ERCOT, best-case power available in 2021 is in the mid-80s GW. We find that power demand can frequently get approach that limit in both summer and winter. That means that unforeseen problems that reduce supply even slightly below the best case can lead to the power grid being unable to satisfy power demand.

Finally, we encourage ERCOT to make probabilistic forecasts of temperature using modern tools, like climate model ensembles. ERCOT's insistence on using historical weather observations means they are underestimating climate variability, leading to underestimates of the most extreme power demand forecast. ERCOT could easily do a better job in this regard — they just need to decide to do it.

Acknowledgments

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Data Availability Statement

Historical hourly power usage data from ERCOT can be publicly downloadable from the hourly load data archive provided by ERCOT (http://www.ercot.com/gridinfo/load/load_hist/). ERA-5 reanalysis data are also publicly downloadable from the Climate Data Store (https://cds.climate.copernicus.eu/#!/home). Gridded population data (GPW v4) is available in NASA's Socioeconomic Data and Applications Center (SEDAC) archive (https://sedac.ciesin.columbia.edu/data/collection/gpw-v4).

References

Busby, J. W., and Coauthors, 2021: Cascading risks: Understanding the 2021 winter blackout in Texas. *Energy Research & Social Science*, **77,** 102106.

CIESIN, 2016: Gridded population of the world, version 4 (GPWv4): Population count. Palisades, NY: NASA socioeconomic data and applications center (SEDAC). *Center for International Earth Science Information Network (CIESIN) Columbia University*.

Doss-Gollin, J., D. J. Farnham, U. Lall, and V. Modi, 2021: How unprecedented was the February 2021 Texas cold snap? *Environmental Research Letters*, **16,** 064056.

Frankenfield, J., 2021: Texas Seeks Relief as Winter Storm Damage Piles Up. *The New York Times*.

Hersbach, H., and Coauthors, 2020: The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, **146,** 1999-2049.

Ivanova, I., 2021: Texas winter storm costs could top $200 billion — more than hurricanes Harvey and Ike. *CBS News*.

Kay, J. E., and Coauthors, 2015: The Community Earth System Model (CESM) large ensemble project: A community resource for studying climate change in the presence of internal climate variability. *Bulletin of the American Meteorological Society*, **96,** 1333-1349.

Supplement

1. Selection of temperature-power relationship

As discussed in the main text, there are several approaches to model the relationship between temperature and power. Linear (Guan et al. 2017; Guan et al. 2014) and piecewise fits have been used in previous studies (Almuhtady et al. 2019; Ihara et al. 2008; Jovanović et al. 2015). Previous work has also used cooling and heating degree-days instead of temperature (Mirasgedis et al. 2007; Psiloglou et al. 2009). Here we show the sensitivity of model selection and describe the best performing model.

1a) Model for DJF

We tested a piecewise-linear fit — where the slope changes at 10°C— and a set of non-linear polynomials ($P = C_0 + C_1 T + C_2\, T^x$ where x = 1.25, 1.5, 1.75, and 2). Because using degree-days is equivalent to a linear fit of temperature over (or below) a certain threshold, this shows similar results to the piecewise fit. After fitting the data using all these models, we calculated each model's mean and RMS error as a function of temperature. These values are then divided by average power usage of each season of the year to account for overall increase of power usage (see Fig. 3 in main text), which yields a relative error.

The results are shown in Fig. S1 for piecewise linear and x = 1.75 and 2. All of the models tested show similar performance between 3°C to 18°C. However, at very cold temperatures, below -3°C, the x = 2 model tends to overpredict the power while piecewise-linear fit underpredicts power. The x = 1.75 model shows the best performance in terms of relative error.

Because of this, we have used the x = 1.75 fit in the paper. The choice of model really only matters at the coldest temperatures, such as DJF 2021. Previous studies also examined the empirical relationship between temperature and daily electricity usage (Auffhammer et al. 2017; Franco and Sanstad 2008). They reported curvature relationship between temperature and electricity usage in cold temperatures, whereas the relationship is linear in hot temperatures, which we will also discuss in the next section.

1b) Model for JJA

Summertime temperature is consistently hot in Texas (see Fig. 1 and 2 in the main text), meaning that the difference between the hottest and coolest summer is small. As a result of the relatively small range of temperatures, the temperature-power relationship in JJA is well described by a linear relation. We tested non-linear fits and found they did no better than a linear model.

2. Description of temperature-power relationship

As discussed in the main text, our model for estimating daily average power usage (DAP) from the daily average temperature are given as follows:

$$P_{JJA}(y,T) = P_{ref}(y) + \left(S(y) \times (T - T_{ref})\right) \qquad (S1)$$

$$P_{DJF}(y,T) = P_{ref}(y) + \left(C_1(y) \times (T - T_{ref})\right) + \left(C_2(y) \times (T - T_{ref})^{1.75}\right) \qquad (S2)$$

Where y indicates year and T denotes temperature (°C). In this section, we provide the coefficients of this fit.

(1) *Coefficients for JJA (Eq. S1)*

a. $P_{ref}(y) = (y \times 0.6470) - 1255.2777$

b. $S(y) = (P_{ref}(y) \times 0.0480) - 0.2424$

(2) *Coefficients for DJF (Eq. S2)*

a. $P_{ref}(y) = (y \times 0.5942) - 1162.0179$

b. $C_1(y) = \left(P_{ref}(y) \times -0.0291\right) + 0.2907$

c. $C_2(y) = \left(P_{ref}(y) \times 0.0029\right) - 0.0213$

With historical hourly power load data from ERCOT, we are able to calculate the linear relationship between daily average power usage (DAP) and daily maximum power usage (DMP). The equations for JJA and DJF are as follows:

$$DMP_{JJA} = DAP_{JJA} \times 1.1290 - 2.0849 \qquad (S3)$$

$$DMP_{DJF} = DAP_{DJF} \times 1.1247 + 0.7091 \qquad (S4)$$

References

Almuhtady, A., A. Alshwawra, M. Alfaouri, W. Al-Kouz, and I. Al-Hinti, 2019: Investigation of the trends of electricity demands in Jordan and its susceptibility to the ambient air temperature towards sustainable electricity generation. *Energy, Sustainability and Society*, **9,** 1-18.

Auffhammer, M., P. Baylis, and C. H. Hausman, 2017: 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,** 1886-1891.

Franco, G., and A. H. Sanstad, 2008: Climate change and electricity demand in California. *Climatic Change*, **87,** 139-151.

Guan, H., S. Beecham, H. Xu, and G. Ingleton, 2017: Incorporating residual temperature and specific humidity in predicting weather-dependent warm-season electricity consumption. *Environmental Research Letters*, **12,** 024021.

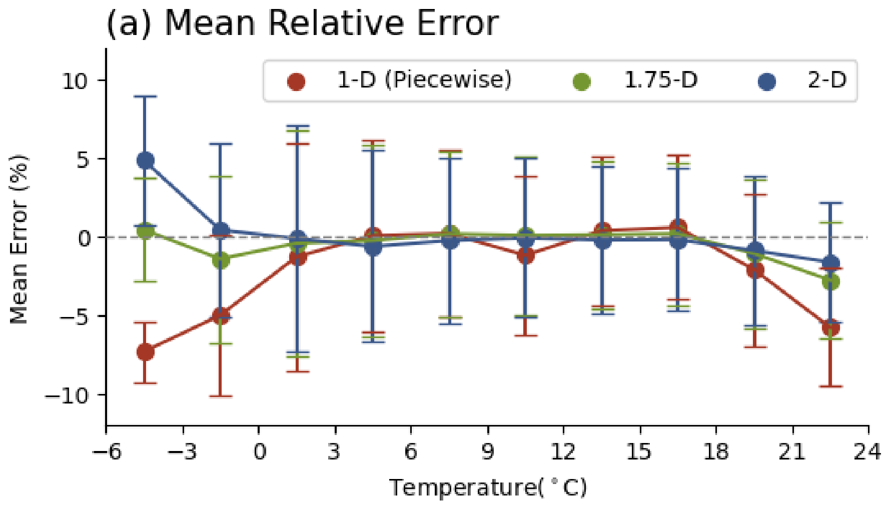
Guan, H., and Coauthors, 2014: Response of office building electricity consumption to urban weather in Adelaide, South Australia. *Urban Climate*, **10,** 42-55.

Ihara, T., Y. Genchi, T. Sato, K. Yamaguchi, and Y. Endo, 2008: City-block-scale sensitivity of electricity consumption to air temperature and air humidity in business districts of Tokyo, Japan. *Energy*, **33,** 1634-1645.

Jovanović, S., S. Savić, M. Bojić, Z. Djordjević, and D. Nikolić, 2015: The impact of the mean daily air temperature change on electricity consumption. *Energy*, **88,** 604-609.

Mirasgedis, S., Y. Sarafidis, E. Georgopoulou, V. Kotroni, K. Lagouvardos, and D. Lalas, 2007: Modeling framework for estimating impacts of climate change on electricity demand at regional level: case of Greece. *Energy Conversion and Management*, **48,** 1737-1750.

Psiloglou, B., C. Giannakopoulos, S. Majithia, and M. Petrakis, 2009: Factors affecting electricity demand in Athens, Greece and London, UK: A comparative assessment. *Energy*, **34,** 1855-1863.



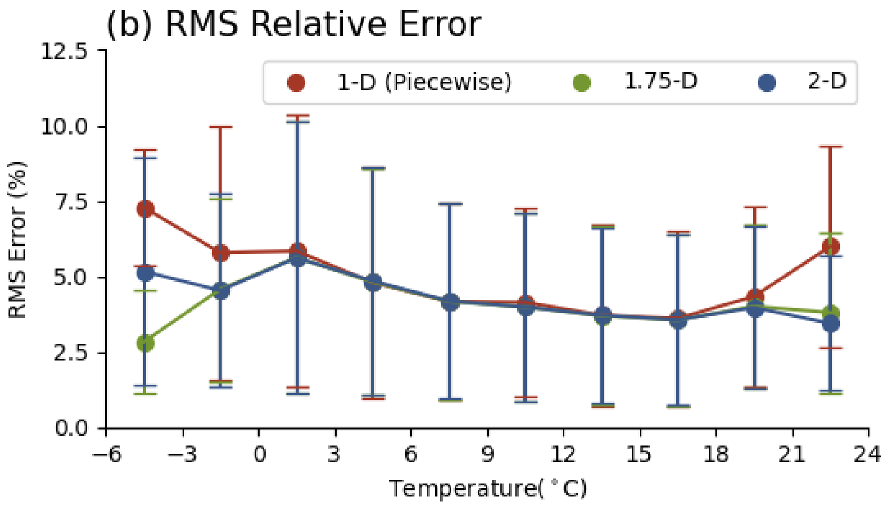


Figure S1. (a) Mean relative error and (b) RMS relative error for 1-D, 1.75-D, and 2-D fit of temperature-power relationship. Relative errors are averaged for every 3°C bins of temperature. The dots represent the mean error in each temperature bins, while the error bars represent the standard deviation of errors in each temperature bins.