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 on the basis of historical weather over the last two decades, thereby ignoring the effects of climate change and the possibility of weather variability outside the recent historical range. In this paper, we develop an empirical method 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 most severe weather events will use 100% of available power—if anything goes wrong, as it did during the 2021 winter, there will not be sufficient available power. More quantitatively, 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. The shortage of power on the ERCOT grid is partially hidden by the fact that ERCOTs seasonal assessments, which are based entirely on historical weather, are too low. Prior to the 2021 winter blackout, ERCOT forecast 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.

KEYWORDS: Climate change; Climate variability; Societal impacts

1. Introduction

Most of the citizens 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 $200 billion of damages (Frankenfield 2021; Ivanova 2021).

To maintain the reliability of the grid, ERCOT makes short-term seasonal power-demand assessments (e.g., https://www.ercot.com/files/docs/2020/11/05/SARA-FinalWinter2020-2021.pdf) to ensure adequate resources will be available. These assessments are based on the weather from the past decade and factors such as population, but they do not account for a changing climate or the likelihood of climate variability outside the very recent historical record. The impact of extreme temperatures resulting from climate change and extreme variability on power demand have been investigated in multiple studies and in different regions (Auffhammer et al. 2017; Franco and Sanstad 2008; Kim and Lee 2019). In this paper, we evaluate ERCOT's method and develop a new method for incorporating more realistic predictions of future weather into energy projections for Texas.

2. The model ensemble and comparisons with historical temperature data

Our observational temperature data are 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 and hourly temporal resolution. Average daily temperature for ERA5 is calculated by averaging the hourly temperatures in a day. While the reanalysis might produce a smoother temperature field than reality, our analysis uses Texas-average temperature, and this large-scale average should be insensitive to smoothing of the temperature field.

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), which has a resolution of 0.94° × 1.25° for latitude and longitude. CESM-LE only has daily average values of temperature, and we take these values from 1981 to 2021 for historical analysis and to 2025 for future analysis. 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. We find a difference of 0.7° and 0.6°C in the June–August (JJA) and December–February seasons (DJF) between the ensemble average and the ERA5 over the last 40 years. Such a bias

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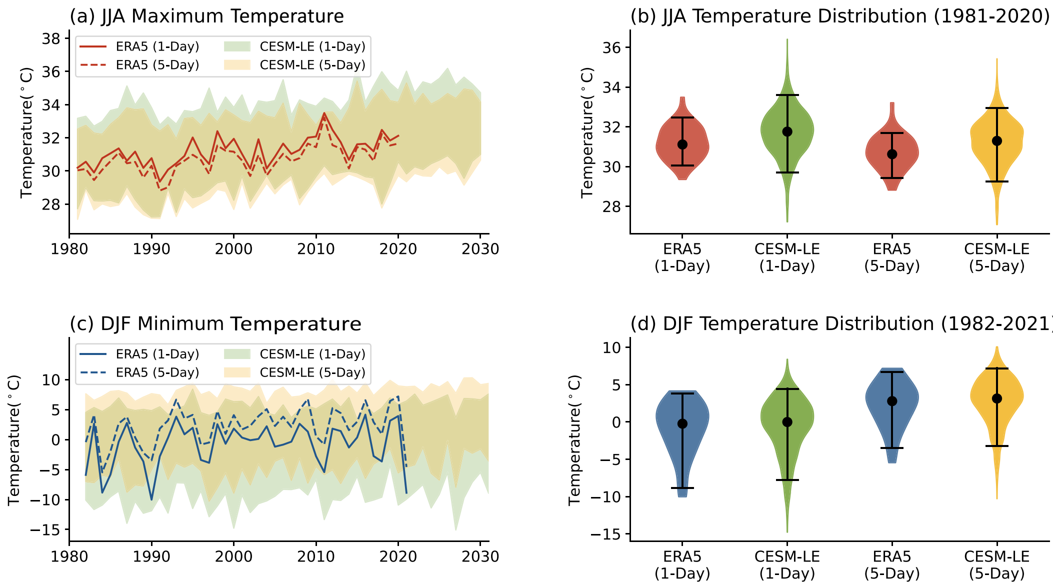

FIG. 1. Time series of seasonal maximum and minimum temperature over Texas (not population weighted): (a) JJA maximum and (c) DJF minimum 1-day (solid line) temperature and 5-day (dashed line) temperature in ERA5, with green and yellow areas each denoting the maximum and minimum ensemble member of 1- and 5-day temperature in CESM-LE, and violin plots for distribution of 1- and 5-day (b) JJA maximum temperature and (d) DJF minimum temperature in ERA5 and CESM-LE. Error bars represent the 95th and 5th percentile of the distribution, and the dots represent the median of the distribution.

is not surprising since the climate model is not tuned to simulate the absolute temperature of Earth. This bias is small relative to the magnitude of the temperature variations that we are analyzing, but we nonetheless adjust for it by adding the offset to each grid point and time step of the model fields so to bring the average values into agreement.

Figure 1 shows the highest 1- and 5-day average temperature during each JJA and lowest 1- and 5-day average temperature during each DJF since 1981 in the ECMWF ERA5 reanalysis and bias-corrected CESM-LE. The convention in this paper is that DJF refers to three consecutive months; for example, DJF 2010 is December 2009 and January and February 2010. For the JJA maximum, the highest 5-day average temperature was in 2011 (32.9°C) and 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.

We note that that focus of this paper is on the temperature extremes, and we see no evidence of larger biases in the tails of the distributions. 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, whereas 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, whereas it was a 1-in-87 year event in the CESM-LE. The standard deviation of ERA5 data is 2.0° and 4.9°C in JJA and DJF, and the average of standard deviation in each member of CESM-LE is 1.8 (1 σ of ensemble standard deviation values is 0.22) and 4.0 (1 σ = 0.58). On the basis of these comparisons, we feel confident that we can use this ensemble to evaluate ERCOT's forecasts.

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

Historical hourly electric power consumption is obtained from ERCOT for the period January 1996–February 2021 (http://www.ercot.com/gridinfo/load/load_hist/). The 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 the population distribution averaged from 2000 to 2020 from CIESIN (2016) for the population weighting. We use time-invariant population distribution since we found there are negligible changes in the population distribution over this period.

We perform the regression separately for each season of each year. Figures 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 nonlinear polynomial fit ($P = C_0 + C_1T + C_2T^{1.75}$) for DJF. Previous studies also discussed power usage increasing with higher temperature in summer and colder temperature in winter (Auffhammer et al. 2017; Craig et al. 2020; Franco and Sanstad 2008; Mirasgedis et al. 2007; Murphy et al. 2019;

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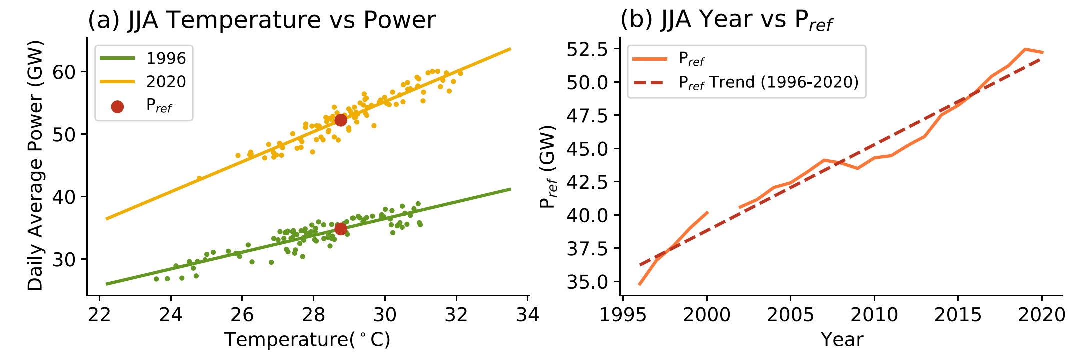

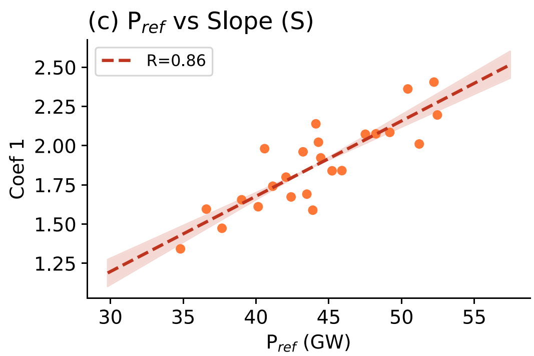

FIG. 2. (a) Scatterplot of population-weighted daily average temperature and JJA daily average power usage in the first and last year of ERCOT's historical record. The red circles denote the power at the reference temperature P_{ref}. (b) Evolution of P_{ref} over time. The red dashed line is a linear trend. (c) Slope of the temperature–power relation as a function of P_{ref}. Each point represents a value from a single year. The shaded area represents the standard error of the linear fit.

Psiloglou et al. 2009). This was done by using everything from a simple linear and piecewise-linear fit (Almuhtady et al. 2019; Guan et al. 2017, 2014; Ihara et al. 2008) to complex regressions up to 5th-degree fit (Jovanović et al. 2015). In section S1 of the online supplemental material, we discuss in detail how we arrive at the form of our fit.

From each year's fit, we calculate $P_{\rm ref}$ for that year, which is power usage at a reference temperature $T_{\rm ref}$. We use a reference temperature equal to the median temperature for JJA (28.8°C) and DJF (10.9°C). The time series of $P_{\rm ref}$ 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 $P_{\rm ref}$ over time is due to changes in nonclimatic factors, such as population. We then perform a linear fit to represent $P_{\rm ref}$ as a function of year [$P_{\rm ref}(y)$] (coefficients for all of the fits can be found in section S2 of the online supplemental material).

We expect the coefficients from each year's temperature–power regressions (Figs. 2a and 3a) to be correlated with $P_{\rm ref}$. 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. Figures 2c, 3c, and 3d show that these coefficients are indeed correlated with $P_{\rm ref}$.

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

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

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

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

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

4. Prediction of future electricity consumption

Using the method described in the last section, we can produce an estimate of daily average power usage. For comparison with ERCOT forecasts, we convert this to daily *maximum* power (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 Eqs. (1) and (2), we can reproduce the historical seasonal maximum power (SMP; the highest hourly power demand during the season) very closely

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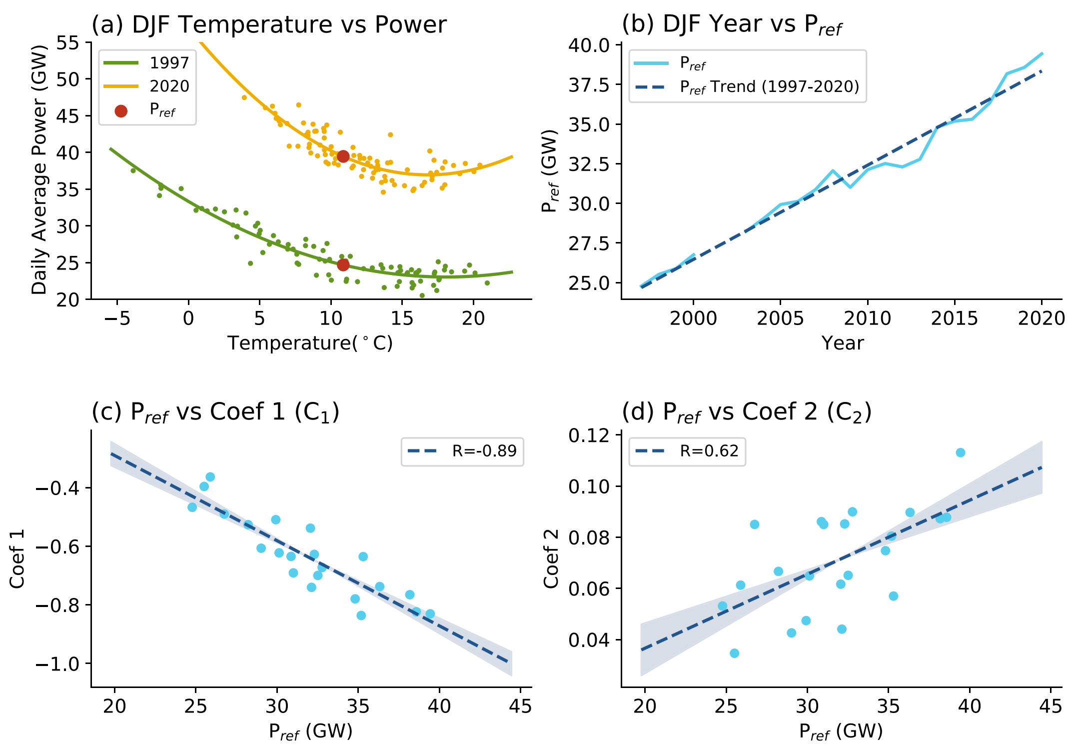

FIG. 3. As in Fig. 2, but for DJF. Because we use a 1.75-degree power–temperature fit in DJF [Eq. (2)], we have two constants, and these are plotted in (c) and (d).

(Figs. 4a,b), with RMS differences of 1.0 and 1.5 GW for JJA and DJF, respectively (2021 is excluded from the DJF calculation because of the blackout). This good agreement may be surprising because we left out factors that one might have anticipated would be important (e.g., weekday vs weekend). We investigated these factors and found that none of them significantly improved our ability to reproduce the observations (section S3 in the online supplemental material). We note that this is true when averaging a large area like the state of Texas, but other factors may be important at smaller scales, such as a county or neighborhood.

We also have taken the CESM-LE temperatures and used Eqs. (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).

5. Comparison of seasonal power demand

a. Summer power demand

To evaluate ERCOT's seasonal 2021 summer resources assessment (https://www.ercot.com/files/docs/2021/05/06/SARA-FinalSummer2021.pdf), we have calculated a probability distribution

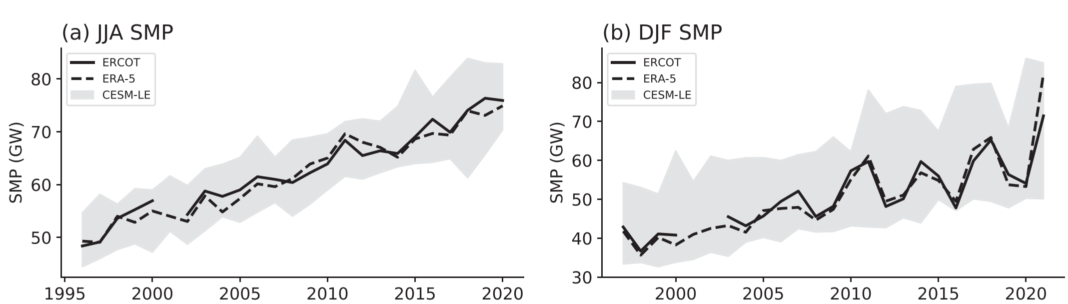

FIG. 4. Time series of seasonal maximum hourly power usage: (a) JJA SMP for 1996–2020 and (b) DJF SMP for 1997–2021. The black solid line represents the historical ERCOT record, and the black dashed line represents the historical power usage estimated by using ERA5 temperatures. The gray area depicts the range of power usage estimated from the CESM-LE.

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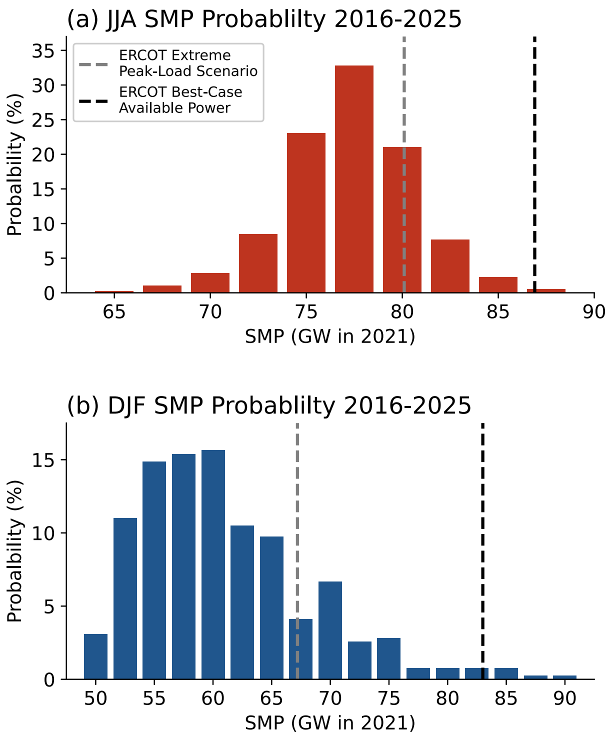

FIG. 5. Probability distribution of seasonal hourly maximum power usage in (a) JJA and (b) DJF 2021, predicted by the CESM-LE. Calculations use temperatures from 2016 to 2025 and P_{ref} for 2021. Gray and black vertical lines represent the ERCOT's seasonal forecast for extreme peak-load and best-case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

of SMP for JJA 2021 using temperatures from the CESM-LE from the period 2016–25 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 of JJA 2011 temperatures. Note that ERCOT publicly provides no probabilistic information with which to interpret their extreme scenarios, although in an email they told us that it should be exceeded in 10% of the years (J. Billo 2021, personal communication). We calculate that there was a 17% chance of JJA 2021 SMP exceeding 80 GW (Fig. 5a), suggesting that the use of limited historical temperatures may lead to an underestimate of the occurrence of extreme demand.

ERCOT also estimated a best case of 87 GW of power available to satisfy peak demand. A comparison of this with 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 because of forced outages (Craig et al. 2020; Murphy et al. 2019), puts the ERCOT grid at risk of being unable to satisfy power demand.

b. *Comparison of winter power demand*

We now evaluate ERCOT's seasonal resource assessment made right before the DJF 2021 season (https://www.ercot.com/files/docs/2020/11/05/SARA-FinalWinter2020-2021.pdf). We do that by comparing it with 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 a 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 (J. Billo 2021, personal communication), 6 GW lower than our estimate. We do not know how ERCOT comes up with their number, and without more information about ERCOT's method, we cannot 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, so that any loss of power, for example, because of 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; 1.5% of the winters had SMP in 2021 DJF exceeding best-case available power, as apparently happened in 2021.

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 use modern climate forecasting tools to estimate climate variability when making these forecasts. Instead, they exclusively use the recent historical climate record.

In this paper, we describe an empirical method to estimate the impacts of 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 variability on ERCOT's forecasts. We find that ERCOT's exclusive use of

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historical temperatures means that they underestimate the worst-case scenarios. In 2021, we estimate a 17% and 19% chance that Texas temperature could have caused the power demand to 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%.

JJA in 2021 was not unusually hot in Texas. Maximum load in JJA 2021 was 74 GW, which is lower than ERCOT's extreme peak-load scenario (80 GW). The CESM-LE tells us that JJA 2021 was at the lower end in the distribution of possible summertime temperatures. There was 88% chance that summer with higher temperature have happened, and 17% chance that it would have exceeded ERCOT's extreme peak-load scenario.

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 robust the ERCOT grid is when power plants unexpectedly go offline, but ERCOT's model and underlying data are not publicly available, and 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 method.

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 of gigawatts. We find that power demand can get close to 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.

Last, we encourage ERCOT to make probabilistic forecasts of temperature using modern tools, like climate model ensembles. ERCOT's insistence on using a relatively short historical record means they are underestimating climate variability, leading to underestimates of the most extreme power demand forecasts. Using a longer historical record would be a poor solution since it would ignore the fact that the climate is changing.

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Data availability statement. Historical hourly power usage data from ERCOT are publicly downloadable from the hourly load data archive provided by ERCOT (http://www.ercot.com/gridinfo/load/load_hist/). ERA5 reanalysis data are also publicly downloadable from the Climate Data Store (https://cds.climate.copernicus.eu/#!/home). Gridded population data (GPW v4) are available in NASA's Socioeconomic Data and Applications Center (SEDAC) archive (https://sedac.ciesin.columbia.edu/data/collection/gpw-v4).

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