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The impact of North American winter weather regimes on electricity load in the central United States

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Extreme wintertime cold in the central United States (US) can drive excessive electricity demand and grid failures, with substantial socioeconomic effects. Predicting cold-induced demand surges is relatively understudied, especially on the subseasonal-to-seasonal (S2S) timescale of 2 weeks to 2 months. North American winter weather regimes are atmospheric tools that are based on persistent atmospheric circulation patterns, and have been linked to potential S2S predictability of extreme cold in the central US. We study the relationship between winter weather regimes and daily peak load across 13 balancing authorities in the Southwest Power Pool. Anomalous ridging across Alaska, the West Coast, and Greenland drive increases in demand and extreme demand risk. Conversely, anomalous troughing across the Arctic and North Pacific reduces extreme demand risk. Thus, weather regimes may not only be an important long-lead predictor for North American electricity load, but potentially a useful tool for end users and stakeholders.

Temperature is a key driver of variability for electricity demand, or consumption, across the world[1–4]. Moreover, the exposure of electrical grids to warm season temperature is more apparent due to anthropogenically-driven temperature increases and more frequent or prolonged heatwaves[5,6], leading to greater use of air conditioning[7–11]. However, wintertime extreme cold conditions can produce similar surges in electrical demand[12,13], associated with an increased use of heating systems. The strain on electrical grids has become notable due to several extreme cold events that have occurred in recent years, termed cold air outbreaks (CAOs) in this study[14].

CAOs are spatially and temporally extended extreme cold events[14–17], which often result in noteworthy socioeconomic and infrastructural impacts, including mortality[18,19]. However, extreme cold also impacts the electrical grid through excessive demand and grid failures, as in the February 2021 event[12] which was one of 37 CAOs affecting the central United States (US) since 1950[14]. Spanning a 2-week duration[14], this extreme event featured compounding impacts across the central US[12,20–22]. Failures in natural gas production, electricity generation, and water systems ultimately left millions of Texans without heat and water for an extended period, with power outages also reported throughout states in the Southwest Power Pool (SPP), which is a regional transmission organization that coordinates the electrical grid and power market in the central US[12,21]. The overall impact of this event across the US resulted in a consumer price index (CPI)-adjusted cost of $27 billion[23]. Therefore, we need to understand how wintertime temperature affects central US electricity demand to better predict large-scale effects on the electrical grid.

Understanding the demand-temperature relationship could be key to those making decisions on energy trading, grid winterization, and preventing potential energy shortfalls on longer lead times, such as the subseasonal-to-seasonal (S2S) timescale of 2 weeks to 2 months[24]. The S2S timescale is a forecasting challenge because it lies between the relatively short memory of atmospheric features on weather timescales, such as midlatitude atmospheric weather systems, and the longer memory in boundary conditions in the ocean and land-surface for seasonal forecasts, such as the El Niño-Southern Oscillation phenomenon[24]. The recent focus on S2S prediction highlights the desire for extended-range forecasts of extreme events, such as CAOs, to enhance preparedness across various sectors. At longer lead times, skillful predictions would aid societal impact mitigation and critical infrastructure protection. As such, this study identifies longer term weather patterns that correlate with severe CAOs and extreme increases in electricity demand.

North American winter weather regimes, atmospheric proxies defined based on recurrent and persistent mid-tropospheric circulation patterns, have been linked with potential longer lead prediction of temperature in the US[14,25,26]. Weather regimes across North America have been connected with various modes of variability that act on S2S timescales, such as the stratospheric polar vortex (SPV) and tropical modes of variability such as the Madden-Julian Oscillation (MJO)[14,26]. Furthermore, recent work has

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highlighted the importance of these regimes and their associated modes of variability in forcing CAOs across the central US[14,20,26]. The longer timescale nature of weather regimes and their connection to extreme weather, namely CAOs, makes them appealing for extended range predictions, particularly in the energy sector[14,27].

Previous literature indicates a non-linear connection between temperature and electricity demand and consumption, often described by a parabolic relationship where colder and warmer ends of the temperature distribution drive increases in electricity consumption, typically in the winter and summer, respectively[2,3,8,10,28–30]. Furthermore, limited research has focused on the impact of wintertime temperature on electricity demand in the central US and the associated cold-induced peak load variability. We contribute to this work by identifying the North American winter weather regimes that strongly correlate with electricity demand, highlighting the usefulness of regimes in predictive models of peak energy demand. Weather regimes have been shown to directly influence renewable energy production and demand in Europe and North America[31–33], and even can provide enhanced subseasonal ensemble forecast skill of European energy variables[34]. Despite increased study of North American weather regimes, their influence on the electrical grid is a relatively unexplored, but important, aspect of their research-to-operation utilization potential. As such, advanced knowledge of the weather regime could be a primary driver for predicting electricity demand in the central US and potentially allow utility operators to anticipate extreme load demands resulting from extreme winter weather.

Results

North American winter weather regimes

To identify the important patterns of variability for central US electricity demand, we start by defining five North American winter weather regimes using European Centre for Medium-Range Weather Forecasts (ECMWF) Fifth Reanalysis (ERA5) geopotential height (GPH) anomalies[35] via a *k*-means clustering analysis used in prior studies, including by the co-authors[14,26]. The Alaskan ridge (AkR) regime is the lowest frequency winter weather regime with 16.5% of days, featuring anomalous ridging in the 500 hPa GPH field (higher-than-normal GPH) over Alaska and anomalous troughing (lower-than-normal GPH) over central North America (Fig. 1a). The second least frequent winter regime is the Arctic High (ArH), with anomalous ridging over northern Canada and Greenland, occurring on 17.3% of days in the record (Fig. 1b). Although the ArH regime is the second least frequent winter weather regime, it is the one frequently associated with disruptions in the SPV due to its connection with Greenland surface pressure and GPH anomalies[36–40], which can lead to CAOs in the midlatitudes[14,26]. Additionally, occupying just over a fifth of all days (20.9%), the Pacific Trough features a strengthened Aleutian Low and anomalous ridging over central North America (Fig. 1c). The West Coast Ridge (WCR) is the second most frequent winter weather regime in the North American domain, occurring on 21% of all winter days, and exhibiting a Rossby wave train across North America with anomalous ridging situated over the West Coast of the US (Fig. 1d). Finally, as the most frequent regime, the Arctic Low (ArL) occupies approximately a quarter of days in the long-term record, demonstrating pan-Arctic anomalous troughing (Fig. 1e).

The five North American winter weather regimes are associated with distinct near surface temperature patterns (Fig. 2). The AkR regime is associated with the coldest weather pattern, with highly negative temperature anomalies extending from Canada into the central US, and across the SPP (Fig. 2a). Indeed, the AkR regime is linked to almost a third of the most extreme central US CAOs since 1950, due to the persistent nature of the anomalous Alaskan ridging[14] and its associated surface cold air advection from northwest North America, as shown in the sea level pressure (SLP) field (Fig. 1a). Cold signals through the central US are also present during WCR regime days, extending into the eastern US due to a north-to-northwesterly flow at the surface (Figs. 1d and 2d). Furthermore, while the ArH demonstrates anomalous ridging which can produce blocking highs that promote CAO development[14,26], negative 2 m temperature (T2M) anomalies are of a lesser magnitude across the central US and SPP associated with a surface flow from a more north-to-northeasterly origin (Figs. 1b and 2b). Finally, the PT and ArL

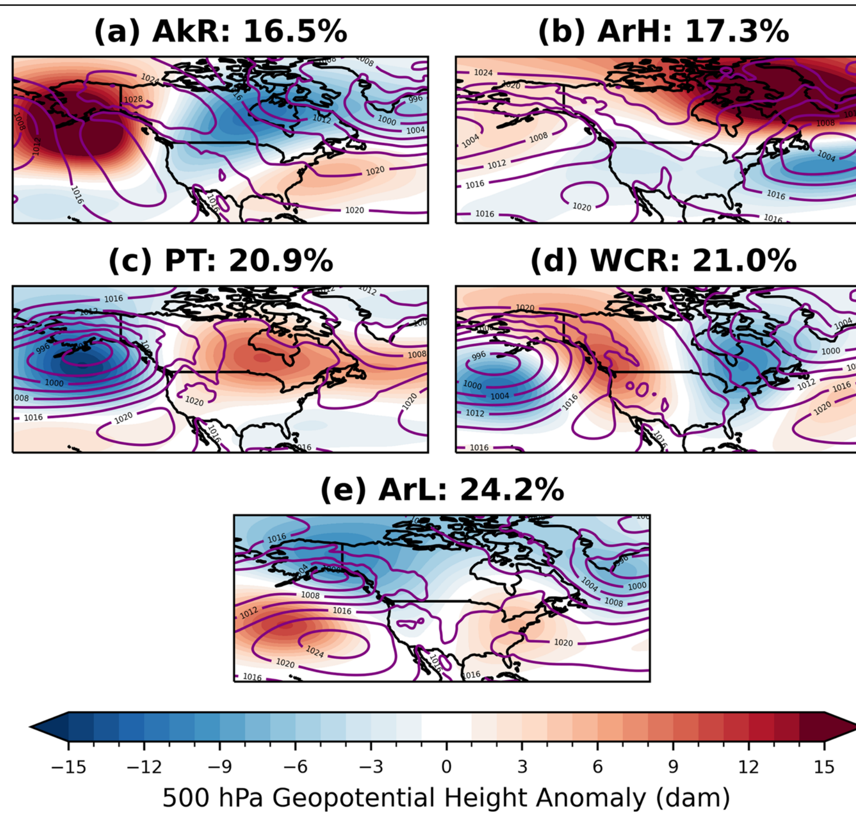

Fig. 1 | North American winter weather regimes. Composite mean maps of ERA5 linearly detrended 500 hPa GPH anomalies (shading, dam) and full-field sea level pressure (contours, hPa) for (**a**) the Alaskan Ridge (AkR), (**b**) the Arctic High (ArH), (**c**) the Pacific Trough (PT), (**d**) the West Coast Ridge (WCR), and (**e**) the Arctic Low (ArL), respectively. Percentages on panels represent the frequency of days occupied by a given winter weather regime in the 1950–2023 period. Anomalies are with respect to the 1979–2020 climatology.

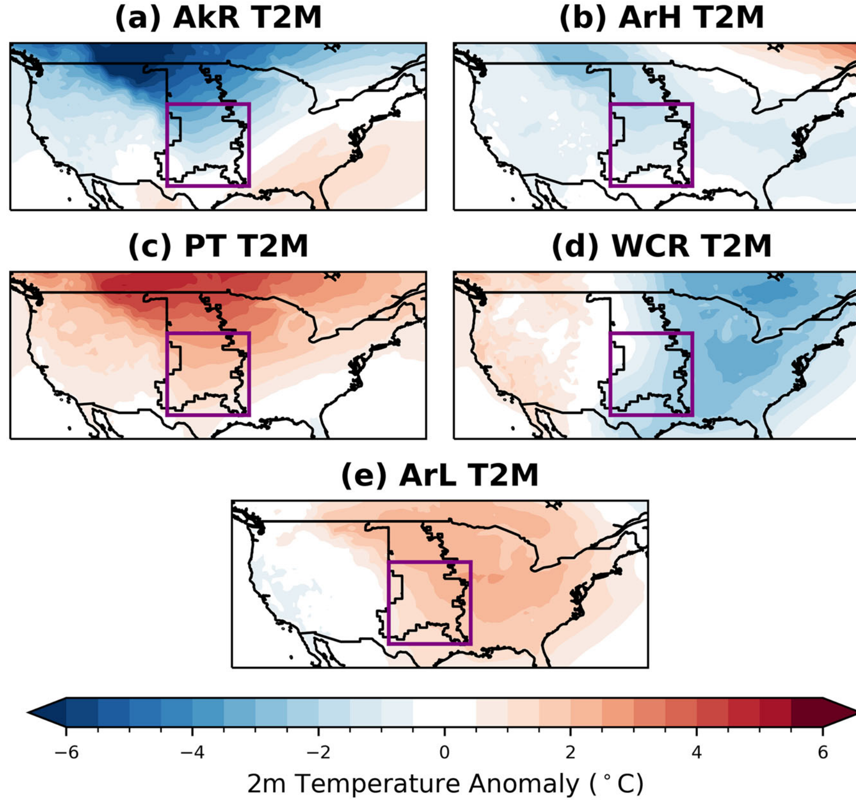

Fig. 2 | T2M patterns for North American winter weather regimes. As in Fig. 1 but for ERA5 linearly detrended T2M anomalies (shading, °C) for (**a**) the Alaskan Ridge (AkR), (**b**) the Arctic High (ArH), (**c**) the Pacific Trough (PT), (**d**) the West Coast Ridge (WCR), and (**e**) the Arctic Low (ArL). The black lines show the region of the entire Southwest Power Pool (SPP) while the purple box (31-43°N, 256-268°E) represents the region of study for electricity load data in the SPP and the area in which T2M is averaged for Fig. 3. A sub-domain of the entire SPP region is used for analysis as it represents the 13 divisions within the SPP that could be consistently matched between load data sources (see methods). Anomalies are with respect to the 1979–2020 climatology also used to calculate the regimes.

winter weather regimes produce anomalous warmth across much of the US due to large-scale continental anomalous ridges and advection of milder maritime air onto the continent (Fig. 2c and e). Overall, North American winter weather regimes have clearly distinct near-surface temperature influences across the central US, which are likely to influence electricity load across the SPP.

Wintertime 2 m temperatures and peak electricity load

Before examining the relationship of electricity load with North American winter weather regimes, we explore how near-surface temperature in the central US relates to electricity load in this region. To quantify this relationship, we combine hourly electricity load data throughout the SPP across 13 balancing authorities between 1999–2022 for November through March (Table S1), scaled by yearly customer counts. The relationship between T2M and peak load anomalies exhibits a parabolic shape, a conclusion found in numerous prior studies across the globe[2,3,10,28–30]. Both the daily mean (Fig. 3a) and daily minimum (Fig. 3b) T2M show a similar relationship with SPP peak load anomalies, with coefficient of determination (R^2) values of 0.38 and 0.39, respectively. Thus, while we show that a quadratic polynomial model represents well the peak load anomaly as a function of T2M parameters, it could be argued that the extreme cold end of the distribution features the weakest non-linearity (Fig. 3). The minimum of this curve could also be useful for end users as it represents slightly below or relatively average peak load, but also a tipping point where deviations in temperature can can lead to increases in electricity demand. For both daily mean and daily minimum T2M, the peak load anomalies are more positive between around 0 to -6°C compared to the minimum in the curve, with the most extreme positive peak load anomalies occurring when both metrics decrease below -6°C (Fig. 3). However, peak load anomalies of ~0.5 MW/1000 customers are possible on the warmer side of the parabola, at ~ 18°C for daily mean T2M and ~ 12°C for daily minimum T2M. We also note that the inclusion of major holidays and weekends has a minimal impact on the relationship between load and daily mean T2M, and thus our results (Fig. S1).

North American winter weather regimes and extreme electricity load

To explore the regime-induced behavior of SPP peak load anomalies, we first examine the mean daily peak load anomalies associated with each winter weather regime (Fig. 4a). The general impact of the winter weather regimes can be quantified by a shift in means, where the AkR, ArH, and WCR regime days feature statistically significant ($p < 0.05$) above average peak load, with AkR regime days having the greatest average peak load anomaly (around 0.13 MW/1000 customers; Fig. 4a). Subsequently, ArL and PT regime days result in significantly below average peak load, with mean peak load anomalies of around -0.10 and -0.15 MW/1000 customers, respectively (Fig. 4a).

We also investigate the probability density functions associated with categories of all days in each regime (Fig. 4b). The AkR and WCR regimes have broader right-hand tails (Fig. 4b), which is not only due to their positive skewness ($\gamma = 0.36$ and $\gamma = 0.47$, respectively), but because their means are shifted toward higher peak load anomalies with slightly higher standard deviations than the other regimes ($\sigma = 0.48$ and $\sigma = 0.47$, respectively). The ArH regime also exhibits a mean shift toward higher peak load anomalies compared to the overall distribution with a more notable positive skew ($\gamma = 0.7$) and positive kurtosis ($\kappa = 0.94$). In fact, Fig. 4b also shows that the relatively higher skewness of the ArH substantially increases the skewness of that in the whole distribution ($\gamma = 0.55$). Since the mean and standard deviations for the ArH are much closer to that of the total distribution, the positive skewness and kurtosis means more weight is placed on higher peak load anomalies with a longer extension of the right-hand tail, which is likely associated with a number of extreme ArH-type CAOs in the region. Indeed, of the ten highest ArH peak load anomaly days, five are associated with Great Plains CAO events between 1950–2021[14] and three belong to an extreme cold event during December 2022[41]. Therefore, excessive demand events may be unlikely in WCR and AkR regimes but are more typical of the circulation, whereas ArH-induced excessive demand events may require a more unique evolution not contained within the regime framework, such as

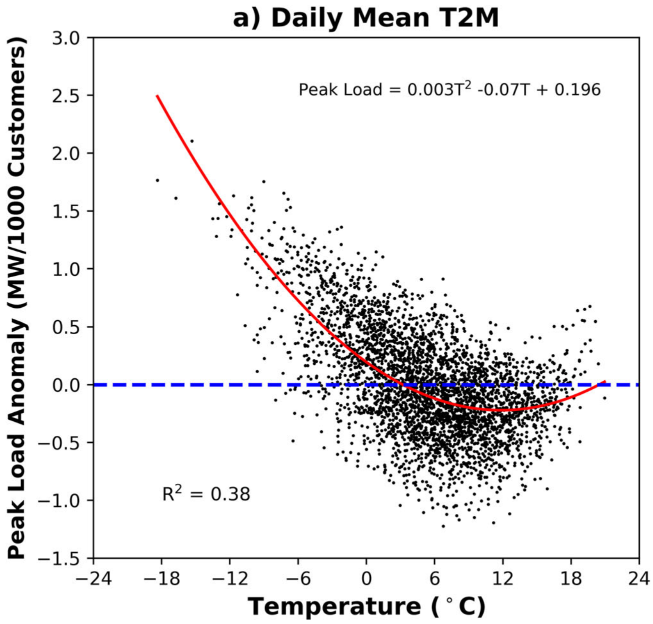

Fig. 3 | The relationship between T2M and SPP electricity load. Scatter plots of peak load anomaly (MW/1000 customers) versus ERA5 (**a**) daily average T2M (°C) and (**b**) daily minimum T2M (°C), where both temperature variables have been averaged over the boxed region in Fig. 2. The red lines represent the second degree polynomial model for the relationship between the two parameters in each plot, with the equation of this polynomial shown on the plot, where T represents the temperature, as well as the the coefficient of determination (R^2) value for peak load anomaly respective to the polynomial model. The blue dashed lines represent an average daily peak load between 1999–2022.

major sudden stratospheric warmings or reliance on other atmospheric blocks.

Conversely, the ArL and PT winter weather regime distributions are slightly positively skewed ($\gamma = 0.43$ and $\gamma = 0.45$, respectively) but have stronger positive kurtosis ($\kappa = 0.71$ and $\kappa = 1.51$, respectively) due to their more peaked distribution. However, these distributions occupy more of the negative peak load anomaly space due to their relatively lower means and standard deviations when compared with the other regimes. The ArL and PT distributions show that they are more likely to produce below average peak load anomalies across the SPP in the winter.

Using risk ratios, i.e., the ratio of the probability of extreme peak load anomalies in a given regime to its sample-wide analog - we quantify the relative likelihood of extreme peak load anomalies in a given weather regime[32]. Risk ratios >1 indicate an increased risk of extreme load compared to the total distribution (i.e., 1.2 equates to a 20% greater risk), whereas values <1 indicate a reduction in risk (i.e., 0.4 equates to a 60% reduced risk). Across all chosen extreme thresholds (90th, 95th, and 97.5th percentiles), the AkR, ArH, and WCR regime days have relative increases in likelihood of extreme peak load anomalies (Fig. 4c). These regimes are most associated with large negative temperature anomalies throughout the SPP (Fig. 2) and fit with our empirical relationship between temperatures (mean and minimum) and peak load anomalies in the region (Fig. 3). AkR regime days are ~1.75–2 times more likely to produce extreme peak load in the SPP. WCR regime days show a risk ratio of around 1.5 and have the largest risk ratio of all the regimes at the 97.5th percentile level (1.84; Fig. 4c). These relative increases in risk for WCR and AkR regime days are statistically significantly different from the baseline risk ratio of 1 at the 95% confidence level (Fig. 4c, gray bars), which also reflects the composite circulation pattern of all extreme days across various load thresholds, showing dominant patterns of anomalous ridging across Alaska and the West Coast similar to their individual regime composites (Fig. S2). ArH regime days are on average associated with negative temperature anomalies in the SPP region, demonstrating a small, but non-significant, increase in likelihood of extremes with risk ratio values of around 1.2. This finding contrasts with the canonical relationship between SPV disruption and midlatitude extreme cold, potentially speaking to the reliance of the ArH on heightened GPH anomalies in other regions to produce extreme cold[20], whereas the AkR and WCR regimes seemingly have a much larger impact on US extreme cold development[26] and thus anomalous peak load. Finally, across all thresholds, the ArL and PT weather regimes show a statistically significant reduction in risk of extreme peak load of around 50–80%. While ArL and PT extreme peak load events are unlikely to happen (only 17 and 9 events, respectively, at the 95th percentile), their circulation patterns are similar to that in Fig. 1, except central US anomalous troughing is stronger (Fig. S2).

The notable patterns in the risk ratio of extreme peak load relate back to the relationship between peak load anomalies and surface temperature. We find that the composite T2M anomaly for extreme peak loads in each regime that exceed their regime-relative 90th percentile show widely differing patterns (Fig. S3). AkR and WCR regime extreme peak load days produce large, negative anomalies throughout the SPP, with the ArH also showing negative anomalies but of less magnitude. Subsequently, PT and ArL regime extreme peak load days show small negative anomalies throughout the SPP with even some positive T2M anomalies in the case of the northern SPP during PT regimes. Thus, North American winter weather regimes have distinct impacts on average and extreme peak electricity load throughout the SPP, with direct links to temperature. However, the upper bound of peak electricity load is significantly modulated by the regimes and their subsequent temperature anomalies.

Discussion

Temperature is a key driver of electricity consumption variability throughout the world[1–4]. The February 2021 CAO demonstrated the vulnerability of power grids to extreme wintertime cold, where demand surges caused widespread outages across the South-Central US[12]. Our results demonstrate that central US wintertime mean and minimum temperature has a parabolic relationship with SPP peak load anomalies, with the coldest temperatures producing the most extreme peak load values (Fig. 3). Anomalous ridging in Alaska (the AkR regime) and along the West Coast of the US (the WCR regime) both yield the greatest wintertime positive peak load anomalies throughout the SPP (Fig. 4a), and the greatest risk for extreme peak load (Fig. 4c). Specifically, AkR and WCR regime days carry a 1.5–2 times greater likelihood of extreme peak load risk. Anomalous ridging

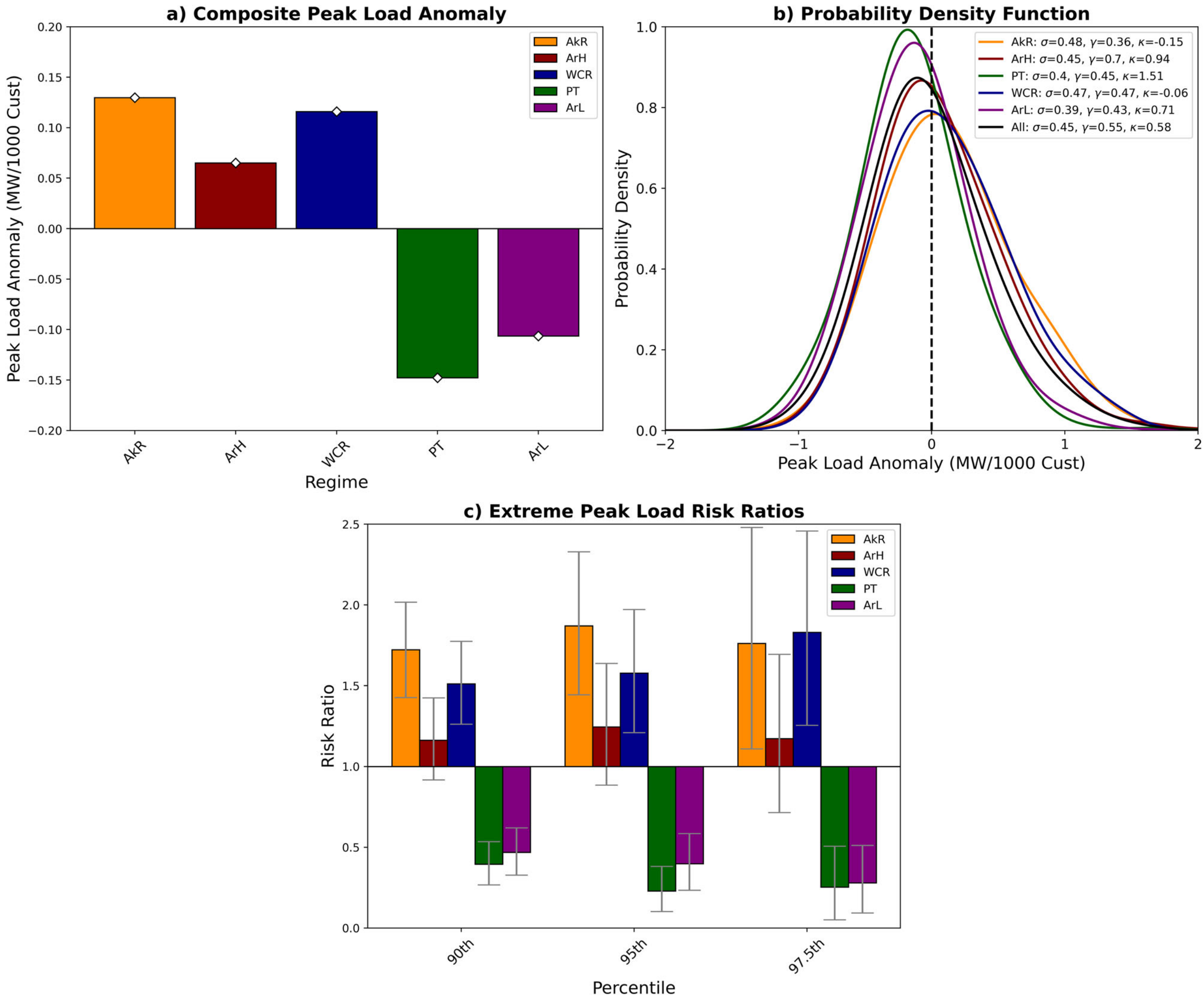

Fig. 4 | The relationship between weather regimes and SPP electricity load. **a** The composite mean peak load anomaly (bars, MW/1000 customers) as a function of North American winter weather regime, where white diamonds indicate that the composite value is statistically significant at the 95th percentile via 5000-iteration bootstrapping with replacement. **b** The probability density function for peak load anomaly (lines, MW/1000 customers) as a function of North American winter weather regime via Gaussian kernel density estimation. σ, γ, and κ represent the probability density function standard deviation, skewness, and kurtosis, respectively. **c** The risk ratios of extreme peak load by North American weather regime (bars) for 90th percentile, 95th percentile, and 97.5th percentile extreme thresholds versus that of the entire distribution. Whiskers represent the 95th percentile confidence interval for each risk ratio from 5000-iteration bootstrapping with replacement. For all plots, AkR is orange, ArH is red, WCR is blue, PT is green, and ArL is purple.

near Greenland (the ArH regime) also causes positive peak load anomalies, but the enhanced risk of extreme peak load is not statistically significant. The relatively lower ArH risk ratios potentially owe to its dependence on other blocking features such as in the AkR[20], internal variability of the flow pattern, and that the connection between SPV disruption and ArH-induced cold conditions may not be as robust over North America. ArL and PT weather regimes are less likely to produce extreme cold, resulting in below average SPP peak load and reduced extreme peak load risk ratios. While wintertime weather regimes help determine the overall risk of extremely high load, they also may be useful for predicting periods of low electricity demand, which is useful for energy traders and showcases their potential for use alongside raw temperature forecasting. Overall, there is the need for ways of forecasting extremes, and regimes offer one avenue to that which is efficient, computationally inexpensive, but also could be used for utility purposes while allowing the interpretation of key dynamical temperature forcings.

The relationship between SPP peak load and North American winter weather regimes suggests that they could be a useful tool for predicting electrical grid demand on the challenging S2S forecast period of 2 weeks to 2 months[24], especially given their longer timescale and more persistent nature, as well as their relation to key modes of variability associated with CAOs[14,25,26]. An important caveat to our results is that this study only considers the SPP. Analyses for other electricity utility domains will likely yield different relationships with the North American winter weather regimes. However, if we can achieve improved prediction capability using regimes, decision makers could be provided with enhanced warning of conditions that produce wintertime electrical grid vulnerability on S2S timescales. Grid vulnerability to extreme cold has become more evident recently due to rising demand within the SPP and aging infrastructure, both adding unique stresses to the system[42]. Therefore, ways of forecasting extremes are needed, and regimes offers one avenue to that goal.

While we have not investigated how numerical weather prediction ensemble suites model peak load, future work could examine peak load as a function of temperature and weather regime in both numerical and machine learning-based forecasting models. Recent work has shown that the forecast skill for Atlantic-European weather regimes appears to be limited to 2 weeks[43], but presently it's uncertain how well North American winter weather regimes can be forecast at different timescales. The unknown prediction skill of North American winter weather regimes is a caveat that future work should study to exploit their added value on the subseasonal timescale, especially regarding potential electricity load prediction. Furthermore, the AkR, ArH, and WCR regimes not only favor CAOs but also could be associated with anomalously windy conditions, which may have use for balancing increased demand from extreme cold via wind energy. Indeed, studies have shown that weather regimes modulate renewable energy production in both Europe and North America[31–33], but how this production could potentially offset shortfalls in CAO-related regimes should be studied. Electricity shortfalls may also be the result of the prolonged nature of extreme cold events. Since extreme cold can often take several days to build, future work should consider how regime persistence affects electricity demand. Finally, some studies have shown that CAO measures, such as frequency, days, and duration, have decreased across North America and are projected to decrease, but the results are uncertain[17,44,45]. Therefore, future work should also explore how changes to the climate system may impact the change in peak load risk to critical energy infrastructure with respect to wintertime cold extremes.

Methods

North American winter weather regime identification

To identify North American winter weather regimes, we follow the method of ref. 14, an extended version of the regime identification used in ref. 26, but in the latest period of 1950–2023. Specifically, 500 hPa GPH anomalies are used to classify the regimes, obtained from ERA5[35] data for November through March between 1950–2023. This process involves k-means clustering, which is a method of vector quantization that aims to group patterns together demonstrating similarities for a given meteorological variable across the North American domain (20–80°N, 180-330°E). Firstly, an empirical orthogonal function (EOF) analysis is performed on the November through March linearly detrended 500 hPa GPH anomalies, where the seasonal cycle is removed from each day respective to the 1979–2020 climatological period to remain in accordance with prior studies[14,26]. Before eigenanalysis, the data are weighted by the square root of the cosine of the latitude. Subsequently, the 12 leading principal component (PC) time series are retained, accounting for around 80% of the explained variance. k-means clustering is then performed on the 12 PC time series to obtain five regimes, by using five clusters in Python's "sci-kit learn" package[46]. Each day in the record is then assigned one of these five regimes based on minimum Euclidean distance from the cluster centroid.

Electricity load data

We collect information on hourly electricity demand for each balancing authority within SPP from ref. 47 for 1999–2010 and from the SPP for 2011–2022. Ref. 47 collects electricity demand data from Federal Energy Regulatory Commission (FERC) Form 714 and uses Least Absolute Shrinkage and Selection Operator (LASSO) to estimate demand based on weather, population, and employment where the FERC data is missing or incomplete. Ref. 47 cross-validates this LASSO estimation, finding that predicted load values are within 4% of their realized values. Our final sample includes the 13 balancing authorities (representing 91% of average annual SPP load) within SPP that could be consistently matched between the load data sources. Specifically, we study peak load in 13 balancing authorities within the SPP across parts of Oklahoma, Kansas, Missouri, Texas, Arkansas, New Mexico, Louisiana, and Nebraska. We keep all observations from November to March of each year during 1999–2022 and compute peak daily load as the maximum amount of electricity demanded in the SPP footprint on each day. We also calculate peak load anomalies for the SPP with respect to the 1999–2022 average, where we remove the seasonal cycle from each day.

To account for trends in the size of the population served by utilities operating in the SPP footprint, we normalize peak daily load by annual customer counts from Energy Information Administration (EIA) Form 861. Since utility names change throughout our sample period as firms merge or disband, we used administrative SPP reports to consistently document customers in the SPP footprint over time.

Polynomial model

To capture the non-linear connection between peak daily load anomaly and ERA5 T2M (both daily average and daily minimum), a linear regression is not suitable. As such, we fit a second degree polynomial (i.e., quadratic) function to the data to better describe the parabolic connection between the two variables. The coefficient of determination (R^2) for this model is computed by first calculating the sum of squares total (SST):

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{1}$$

where y is the observed daily peak load anomaly and overbars denote the mean. Secondly, the sum of squared errors (SSE) between the predicted and observed load data is then calculated via the following equation:

$$SSE = \sum_{i=1}^{n} (y_i - f(T_i))^2 \tag{2}$$

where T is the daily average or daily minimum T2M, and f represents the polynomial function being applied. Finally, the coefficient of determination is then calculated by computing the difference between 1 and the division between the SSE and SST[48].

$$R^2 = 1 - \frac{SSE}{SST} \tag{3}$$

Probability density functions and risk ratios

To investigate the distributions of daily peak load anomalies by weather regime, we use Gaussian kernel density estimation to calculate the probability density functions, with 5-fold cross validation to select the optimal bandwidth. Additionally, we calculate the mean and standard deviation of the daily peak load anomalies in each regime, alongside the skewness and the Fisher (excess) kurtosis (i.e., normal kurtosis = 0). To explore the relationship between North American winter weather regimes and extreme daily peak load anomalies, we calculate risk ratios for exceeding three percentile thresholds: the 90th, 95th, and 97.5th percentiles. The risk ratio describes how much more likely a daily peak load extreme event is in each regime. To compute the risk ratios, we calculate the percentile thresholds in the full distribution of daily peak load anomalies and then calculate the probability of exceeding this threshold in each of the peak demand categories that are split by weather regime. The risk ratio, RR, is then calculated as in ref. 32:

$$RR = \frac{P_{WR}}{P_{clim}} \tag{4}$$

where P_{WR} is the probability of an extreme peak load day in a given weather regime and P_{clim} is the probability of an extreme peak load day in the full distribution.

Data availability

ERA5 reanalysis data can be found in the Copernicus Climate Data Store at https://cds.climate.copernicus.eu/cdsapp#!/home[35]. SPP hourly load data between 1999–2010 and 2011–2022 can be found at https://www.openicpsr.org/openicpsr/project/146801/version/V1/view[49] and https://portal.spp.org/pages/hourly-load, respectively. Customer count data from EIA Form 861 can be found at https://www.eia.gov/electricity/data.php#sales.

Code availability

All code for analyses can be found at https://doi.org/10.5281/zenodo.13948439.

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References

1. Hor, C., Watson, S. J. & Majithia, S. Analyzing the impact of weather variables on monthly electricity demand. *IEEE Trans. Power Syst.* **20**, 2078–2085 (2005).
2. Bessec, M. & Fouquau, J. The non-linear link between electricity consumption and temperature in Europe: a threshold panel approach. *Energy Econ.* **30**, 2705–2721 (2008).
3. Thornton, H. E., Hoskins, B. J. & Scaife, A. A. The role of temperature in the variability and extremes of electricity and gas demand in Great Britain. *Environ. Res. Lett.* **11**, 114015 (2016).
4. Cawthorne, D., de Queiroz, A. R., Eshraghi, H., Sankarasubramanian, A. & DeCarolis, J. F. The role of temperature variability on seasonal electricity demand in the Southern US. *Front. Sustain. Cities* **3**, 644789 (2021).
5. Perkins, S. E., Alexander, L. V. & Nairn, J. R. Increasing frequency, intensity and duration of observed global heatwaves and warm spells. *Geophys. Res. Lett*. https://doi.org/10.1029/2012GL053361 (2012).
6. Perkins-Kirkpatrick, S. E. & Lewis, S. C. Increasing trends in regional heatwaves. *Nat. Commun.* **11**, 3357 (2020).
7. Bartos, M. et al. Impacts of rising air temperatures on electric transmission ampacity and peak electricity load in the United States. *Environ. Res. Lett.* **11**, 114008 (2016).
8. Davis, L. W. & Gertler, P. J. Contribution of air conditioning adoption to future energy use under global warming. *Proc. Natl. Acad. Sci. USA* **112**, 5962–5967 (2015).
9. Hadley, S. W., Erickson III, D. J., Hernandez, J. L., Broniak, C. T. & Blasing, T. J. Responses of energy use to climate change: a climate modeling study. *Geophys. Res. Lett*. https://doi.org/10.1029/2006GL026652 (2006).
10. Auffhammer, M., Baylis, P. & Hausman, C. Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. *Proc. Natl. Acad. Sci. USA* **114**, 1886–1891 (2017).
11. Wenz, L., Levermann, A. & Auffhammer, M. North–south polarization of European electricity consumption under future warming. *Proc. Natl. Acad. Sci. USA* **114**, E7910–E7918 (2017).
12. Doss-Gollin, J., Farnham, D. J., Lall, U. & Modi, V. How unprecedented was the February 2021 Texas cold snap? *Environ. Res. Lett.* **16**, 064056 (2021).
13. Shaffer, B., Quintero, D. & Rhodes, J. Changing sensitivity to cold weather in Texas power demand. *iScience* https://doi.org/10.1016/j.isci.2022.104173 (2022).
14. Millin, O. T., Furtado, J. C. & Basara, J. B. Characteristics, evolution, and formation of cold air outbreaks in the Great Plains of the United States. *J. Climate* **35**, 4585–4602 (2022).
15. Cellitti, M. P., Walsh, J. E., Rauber, R. M. & Portis, D. H. Extreme cold air outbreaks over the United States, the polar vortex, and the large-scale circulation. *J. Geophys. Res. Atmos*. https://doi.org/10.1029/2005JD006273 (2006).
16. Smith, E. T. & Sheridan, S. C. The characteristics of extreme cold events and cold air outbreaks in the eastern United States. *Int. J. Climatol.* **38**, e807–e820 (2018).
17. Smith, E. T. & Sheridan, S. C. Where do cold air outbreaks occur, and how have they changed over time? *Geophys. Res. Lett.* **47**, e2020GL086983 (2020).
18. Analatis, A. et al. Effects of cold weather on mortality: results from 15 European cities within the phewe project. *Am. J. Epidemiol.* **168**, 1397–1408 (2008).
19. Smith, E. T. & Sheridan, S. C. The influence of extreme cold events on mortality in the United States. *Sci. Total Environ.* **647**, 342–351 (2019).
20. Millin, O. T. & Furtado, J. C. The role of wave breaking in the development and subseasonal forecasts of the February 2021 Great Plains cold air outbreak. *Geophys. Res. Lett.* **49**, e2022GL100835 (2022).
21. Bolinger, R. A. et al. An assessment of the extremes and impacts of the February 2021 south-central U.S. arctic outbreak, and how climate services can help. *Weather Clim. Extrem.* **36**, 100461 (2022).
22. Albers, J. R. et al. The February 2021 cold air outbreak in the United States: a subseasonal forecast of opportunity. *Bull. Amer. Meteor. Soc.* **103**, E2887–E2904 (2022).
23. NCEI. *Billion-Dollar Weather and Climate Disasters: Events*. https://www.ncei.noaa.gov/access/billions/events (2024).
24. Vitart, F. & Robertson, A. W. The sub-seasonal to seasonal prediction project (S2S) and the prediction of extreme events. *npj Clim. Atmos. Sci*. **1**, 3 (2018).
25. Michelangeli, P., Vautard, R. & Legras, B. Weather regimes: recurrence and quasi stationarity. *J. Atmos. Sci.* **52**, 1237–1256 (1995).
26. Lee, S. H., Furtado, J. C. & Charlton-Perez, A. J. Wintertime North American weather regimes and the arctic stratospheric polar vortex. *Geophys. Res. Lett.* **46**, 14892–14900 (2019).
27. Grams, C. M., Beerli, R., Pfenninger, S., Staffell, I. & Wernli, H. Balancing Europe's wind-power output through spatial deployment informed by weather regimes. *Nat. Clim. Chang.* **7**, 557–562 (2017).
28. Moral-Carcedo, J. & Vicéns-Otero, J. Modelling the non-linear response of Spanish electricty demand to temperature variations. *Energy Econ.* **27**, 477–494 (2005).
29. Mirasgedis, S. et al. Models for mid-term electricity demand forecasting incorporating weather influences. *Energy* **31**, 208–227 (2006).
30. Deschênes, O. & Greenstone, M. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. *Am. Econ. J-Appl. Econ.* **3**, 152–185 (2011).
31. Garrido-Perez, J. M., Ordóñez, C., Barriopedro, D., García-Herrera, R. & Paredes, D. Impact of weather regimes on wind power variability in western Europe. *Appl. Energy* **264**, 114731 (2020).
32. van der Wiel, K. et al. The influence of weather regimes on European renewable energy production and demand. *Environ. Res. Lett.* **14**, 094010 (2019).
33. Liu, Y., Feng, S., Qian, Y., Huang, H. & Berg, L. How do North American weather regimes drive wind energy at the sub-seasonal to seasonal timescales? *npj Clim. Atmos. Sci.* **6**, 100 (2023).
34. Bloomfield, H. C., Brayshaw, D. J., Gonzalez, P. L. M. & Charlton-Perez, A. Sub-seasonal forecasts of demand and wind power and solar power generation for 28 European countries. *Earth Syst. Sci. Data* **13**, 2259–2274 (2021).
35. Hersbach, H. et al. The ERA5 global reanalysis. *Q. J. R. Meteorol. Soc.* **146**, 1999–2049 (2020).
36. Baldwin, M. P. & Dunkerton, T. J. Stratospheric harbingers of anomalous weather regimes. *Science* **294**, 581–584 (2001).
37. Butler, A. H., Sjoberg, J. P., Seidel, D. J. & Rosenlof, K. H. A sudden stratospheric warming compendium. *Earth Syst. Sci. Data* **9**, 63–76 (2017).
38. Huang, J. et al. The connection between extreme stratospheric polar vortex events and tropospheric blockings. *Q. J. R. Meteorol. Soc.* **143**, 1148–1164 (2017).
39. Domeisen, D. I. V., Grams, C. M. & Papritz, L. The role of North Atlantic–European weather regimes in the surface impact of sudden stratospheric warming events. *Weather Clim. Dyn.* **1**, 373–388 (2020).
40. Afargan-Gerstman, H. & Domeisen, D. I. V. Pacific modulation of the North Atlantic storm track response to sudden stratospheric warming events. *Geophys. Res. Lett.* **47**, e2019GL085007 (2020).
41. Yao, Y. et al. Extreme cold events in North America and Eurasia in November-December 2022: a potential vorticity gradient perspective. *Adv. Atmos. Sci.* **40**, 953–962 (2023).
42. NERC. *2023–2024 Winter Reliability Assessment.* https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/NERC_WRA_2023.pdf (2024).

43. Büeler, D., Ferranti, L., Magnusson, L., Quinting, J. F. & Grams, C. M. Year-round sub-seasonal forecast skill for Atlantic–European weather regimes. *Q. J. R. Meteorol. Soc.* **147**, 4283–4309 (2021).
44. Gao, Y., Leung, L. R., Liu, J. & Masato, G. Persistent cold air outbreaks over North America in a warming climate. *Environ. Res. Lett.* **10**, 044001 (2015).
45. Smith, E. T. & Sheridan, S. C. Projections of cold air outbreaks in CMIP6 earth system models. *Clim. Change* **169**, 14 (2021).
46. Pedregosa, F. et al. Scikit-learn: machine learning in python. *J. Mach. Learn. Res.* **12**, 2825–2830 (2011).
47. Cicala, S. Imperfect markets versus imperfect regulation in US electricity generation. *Am. Econ. Rev.* **112**, 409–41 (2022).
48. Wilks, D. S. *Statistical Methods in the Atmospheric Sciences* 3rd edn, Vol. 100 (Elsevier, Boston, 2011).
49. Cicala, S. *Hourly US Electricity Load.* https://www.openicpsr.org/openicpsr/project/146801/version/V1/view (2022).

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Author contributions

O.T.M. conducted the analyses, wrote the article, and edited the article. C.M. retrieved electricity load data, accounted for the mergers in the chosen balancing authorities, and edited the article. J.C.F. edited the article. All authors contributed toward the development of analyses within the article.

Competing interests

The authors declare no competing interests.

Additional information

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