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LETTER

Unprecedented daily winter extremes for the UK energy sector

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Abstract

As the UK power system transitions towards a greater share of variable renewable energy resources, the system becomes more weather dependent. During winter, the most challenging conditions occur when low wind speeds are accompanied by cold temperatures, driving increased electricity demand and reduced wind power generation. To understand the risks posed by such days, the magnitude and likelihood of these events is assessed, using a large climate model ensemble combined with simple empirical relationships to quantify electricity demand net of wind power (DnW) from meteorological variables. It is demonstrated that the annual probability of experiencing a winter day with higher demand net wind than observed is approximately 1% (1 in 103 years) under the current climate. This represents a 10-fold decrease in probability since the 1960s and is primarily associated with a similar reduction in the probability of an unprecedented cold winter day (a 10-fold decrease to 1.3% each year under present climate). The probability of an unprecedented low-wind day is low (0.4% each year) and has remained largely unchanged over the same period. The large sample size also highlights the meteorological conditions driving these extreme high DnW days. It is found that all high DnW days are associated with low-wind conditions (i.e., very low wind generation is essential for high DnW to occur) but the severity of the DnW event is strongly influenced by the temperature (i.e., the level of demand dictates the magnitude of the DnW). Synoptically, this is associated with a reversal of the climatological pressure gradient over the North Atlantic. The most severe DnW days occur when high pressure is located over Greenland and extends to the UK, leading to a weak but cold northerly airflow over the UK.

1. Introduction

In 2024, wind power became the UK's largest source of electricity generation, overtaking gas for the first time (Staffell *et al* 2025). However, alongside increasing total generation from wind (with a total installed capacity of around 30 GW), wind power output is highly variable, meaning flexible generation sources (such as battery storage, pumped hydropower, and gas) continue to be required when wind speeds drop. By 2030 the UK government aims to reduce reliance on fossil fuels to only 5% of electricity generation (compared to the 25% used today) and triple the installed capacity of offshore wind (DESNZ 2024, Staffell *et al* 2025). This means that cold low-wind days are likely to become more challenging in the future as the increased variability of wind power generation must be managed alongside reductions in flexible gas generation. As a result, energy system operators could benefit from improved understanding of the likelihood of these challenging days to inform the development of the future UK power system.

Thornton *et al* (2017) explored the relationship between high (electricity) demand days and wind capacity factors using observed weather data (from ERA5) and metered demand data (from National Grid). They identified a range of high pressure related synoptic patterns driving peak demand conditions and found a modest recovery in wind power generation during the highest demand conditions, consistent with an earlier study by Brayshaw *et al* (2012). However, due to the short length of observations available (1979–2013), they only had a small sample of peak demand days to explore (Thornton *et al* 2017). Here, we aim to build on the findings of previous studies by quantifying the magnitude and likelihood of extreme demand net wind days using a large climate model ensemble.

To better understand the nature of extremes, and increase the sample of extreme events, the UNSEEN (UNprecedented Simulated Extremes using ENsembles, Thompson *et al* 2017) approach can be applied, which uses coupled ocean-atmosphere forecast systems to capture a wide range of plausible extremes in a changing climate. Using initialised ensembles of near-term climate predictions provides a synthetic event set of winter days two orders of magnitude larger than that available in the observations (Thompson *et al* 2017, Kent *et al* 2022, Kay *et al* 2020, 2023). Insofar as the simulations are able to provide an accurate representation of real weather, this enables a more robust assessment of the likelihood of extreme events and how they change over time. The simulations also allow the exploration of unprecedented events, events that have not occurred in the historical record, but are possible in today's climate.

In this paper, hindcasts from a decadal climate prediction system are used to assess the magnitude and likelihood of the coldest, calmest, and highest demand net wind (DnW) winter days for the UK. Long term trends are identified and discussed, and the weather patterns associated with the most severe events are identified. To our knowledge, this is the first time that decadal climate predictions have been used in this way to inform energy system risk assessment. While the methodology used here is developed for the UK, it is readily applicable to other regions. The paper is structured as follows. Section 2 provides a brief overview of the data and methods used, and section 3 presents an analysis of the climate model's ability to represent relevant aspect of UK climate. Section 4 provides information on the likelihood of seeing these daily extremes and section 5 considers the relationship between temperature and wind speed on such days. Section 6 explores the synoptic patterns which drive these conditions and section 7 summarises the findings.

2. Methods

2.1. Datasets and data preparation

Daily mean 2 m air temperature and 10 m wind speed for the winter (December-January-February), 1961–2025, are used in this study (92 days x 66 years). The model ensemble data are taken from the Met Office Decadal Prediction System (DePreSys3, see Dunstone *et al* 2016), using the HadGEM3-GC31-MM model (Williams *et al* 2018). The model has a spatial resolution of 0.83° longitude by 0.55° latitude (corresponding to a horizontal resolution of around 60 km over the UK), it is initialised on 1st November each year 1960–2018 inclusive and runs for 125 months, such that a model run initialised in November 1960 would provide forecast information up to March 1971 (Dunstone *et al* 2016).

The ensemble comprises 10 members generated from perturbations to a stochastic physics scheme (Dunstone *et al* 2016), which, with the 11 winters of each forecast, provides 110 times as many samples as observations (i.e., 66 winters in the observations, >6600 winters in the model), assuming ensemble member independence at daily timescales. The ERA5 reanalysis data are taken as a proxy of observations (Hersbach *et al* 2020) and are regridded to the models resolution using a linear scheme.

As all forecast winters from the model (i.e., up to 11 winters for a single forecast) are used, the model is expected to drift towards its preferred climate state as the forecast progresses (Boer *et al* 2016). This is accounted for by calculating forecast anomalies relative to the respective means of each forecast year for a common period, using the method specified in appendix E of Boer *et al* (2016).

For each winter, the single coldest and calmest days are determined using the Great Britain (GB) land mean 2 m air temperature and UK grid box mean (6°E to 2°W, 50 to 59.5°N) 10 m wind speed respectively, between 1961 and 2025. This is done separately to isolate the associated impacts of the winter day with the highest demand (coldest) and lowest wind power generation (stillest). The GB land mean temperature is used as this is most closely related to demand (Bloomfield *et al* 2020). The grid box domain is based on the location of current installed (onshore and offshore) wind capacity, based on DESNZ (2025).

Following drift correction, the linear trends from the block minima time series were removed from both the observations and model, pivoting around the final point on the observed trend line (similar to Kay *et al* 2020). The final point on the observed line is used as the pivot point to ensure that past extremes are presented relative to the observed climate of winter 2024–25 and correct the mean bias. The trend is removed from the extremes, rather than from the daily mean, as the trend in the seasonal mean temperatures is different to that in extreme daily temperatures (not shown, see also Gross *et al* 2020, Kay *et al* 2025), and extremes are the focus of the present study. Removing the trend quantified from the full field time series (instead of the extremes) does not change the findings of this study. For consistency, the same detrending methodology is applied to both temperature and 10 m wind speed, though the diagnosed trend is very weak for the latter.

2.2. Modelling demand net wind

To calculate the highest DnW day for each winter, the weather-dependent electricity demand and wind power generation must be modelled for all winter days, assuming stationary demand and wind power generation responses. While solar power generation also contributes to demand net renewables, its contribution is relatively small during the winter (Drax 2024), so is not considered here.

2.2.1. Electricity demand model

Temperature is the primary meteorological driver of electricity demand, with cold temperatures during winter driving an increase in demand associated with heating (Taylor and Buizza 2003, Thornton *et al* 2016). Here, the multiple linear regression model of demand from Bloomfield *et al* (2020) is used to model electricity demand from GB (land) mean temperature, with the parameters representing human-driven components removed to better highlight the weather-driven component (essentially isolating the heating degree day component). This allows for the estimation of weather-dependent electricity demand from 2 m temperature assuming the demand response of 2017. For further detail on the formulation of the demand model used, see section 1.1. of the supplementary material (S1) for Bloomfield *et al* (2020).

2.2.2. Wind power generation model

The daily mean 10 m wind speeds from the model and observations are converted into a national wind power capacity factor using the physical model of wind power generation from Bloomfield *et al* (2020). Although coarse-resolution products tend to underestimate the wind speed relative to station-based observations (Murcia *et al* 2022, Sheridan *et al* 2022, Wilczak *et al* 2024), this study focuses on daily UK-averaged extremes, calculated at the resolution of the model, allowing for a direct comparison of UK-averaged extremes. The results therefore provide a measure of severity relative to the historical record, rather than an absolute estimate of the worst-case magnitude. The distribution of wind farms is updated to include all those operational during March 2024, as in Bloomfield (2025). Capacity factor values are estimated by extrapolating the 10 m wind speeds up to hub height using the power-law relationship (Hsu *et al* 1994), an approach commonly used in power system modelling (see Bloomfield *et al* 2021a), and then passing the converted wind speeds through a power curve. Ideally, wind speeds at hub height (between 100 m to 150 m) would be used, as biases are reduced compared with extrapolation from 10 m (Gruber *et al* 2022), however, hub height wind speeds are not available as model output. This distribution is used to weight the capacity factors values by the installed capacity in each grid box and aggregate to the national level. The national capacity factor is then multiplied by the total installed capacity in 2025 (15.7 GW onshore and 14.7 GW onshore, see Renewable UK 2025) to give the national wind power generation value.

2.2.3. Calculating demand net wind

Demand net wind is calculated by subtracting the modelled daily wind power generation from the modelled daily electricity demand for all the winter days.

3. Model evaluation

Although all models are inherently imperfect in their representation of reality, many can be useful (Box and Draper 1987). Here, the similarity between the model and the reanalysis (referred to as observations) is evaluated to determine whether it provides useful information regarding winter extremes. Previous studies have demonstrated that CMIP6 models (including HadGEM3-GC31-MM) show reduced biases in the frequency and persistence of atmospheric blocking compared with CMIP5 models (Schiemann *et al* 2020, Dorrington *et al* 2022). This is an important consideration as biases in blocking would likely lead to misrepresentation of the associated cold and low-wind conditions during winter. Additionally, the model has passed fidelity tests over the UK for extreme temperatures (Kay *et al* 2024, Kay *et al* 2020, 2025) and over the North Sea for low wind (Kay *et al* 2023), respectively.

Following selection of the single coldest or calmest day of the season, the model performance is assessed using Extreme Value Analysis methods, as in Kent *et al* (2022) and Kay *et al* (2025). A generalized extreme value (GEV) distribution is fitted to the observed dataset of extremes (e.g., the coldest or calmest winter days), resulting in a single value for each of the location, scale, and shape parameters. The model is sampled repeatedly across its members (i.e., for each winter a random member is selected) to produce 10,000 block minima/maxima timeseries with the same length as the observations, and GEV distributions are fitted to these timeseries. If

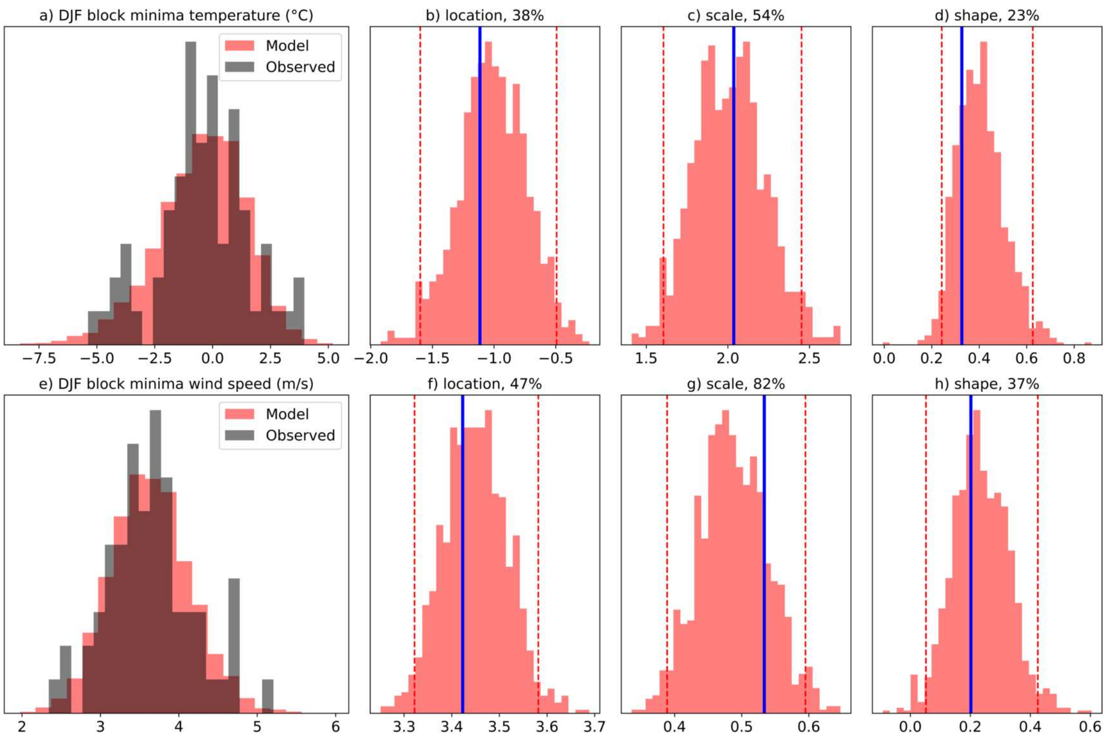

Figure 1. Normalised distributions of winter (DJF) block minima for daily mean UK temperature ((a), coldest winter days) and 10 m wind speed (e, calmest winter days) with the model (HadGEM3-GC31-MM) in red and the observations (ERA5) in grey. Fidelity testing of the model against the observations is shown for the location, scale, and shape parameter of fitted generalised extreme value (GEV) distributions for block minima temperature (b)–(d) and wind speed (f)–(h) respectively. The method for this is described in section 3. The distribution of model parameters is shown in red along with the position of the 2.5th and 97.5th percentiles in thin red dashed vertical lines. The observed value of the GEV parameters is marked as a blue vertical line and the position of this in the model distribution is indicated in the title.

the observed values of the parameters lie within the central 95th percentile of the model distribution, the model is considered to have sufficient agreement with the observations (as in Kay *et al* 2025 and Kent *et al* 2022).

Figure 1 shows the distributions of coldest (1a) and calmest (1e) winter days for the model (red) and observations (grey). The three panels to the right show the bootstrapped distribution of GEV parameters (for location, scale, and shape) for the model (red distribution) and single parameter value for the observations (blue vertical line) for the coldest (1b-d) and calmest winter days (1f-h) respectively. As the observed values of the GEV parameters lie within the central 95th percentile (vertical dashed red lines) of the model distribution for both the coldest and calmest winter days, the model is deemed sufficiently realistic to enable its use to explore such extremes.

As demand net wind is a multivariate index, based on two separate transformed variables and quantified for all winter days, the model performance is evaluated by comparing the distributions of input variables, as in Thompson *et al* (2025). Figure 2 shows the distributions of the meteorological variables (temperature: 2a-b and 10m wind speed: 2e-f), the modelled energy variables (demand: 2c-d and wind power generation: 2g-h), and resulting demand net wind (2i-j), for the model (red) and observations (grey). The two columns show the distributions for the raw (a, c, e, g, and i) and mean bias corrected (b, d, f, h, and j) model variables respectively (see section 2). Even without bias correction of the input variables (temperature and 10 m wind speed), the model distributions show good agreement with the observations. The bias correction ensures that the input meteorological variables are consistent with those in the observations, to prevent errors from compounding during the transformations.

An important caveat to note is that, while the model used provides an indication of how challenging any given day could be given the temperature and wind speed conditions, it does not explicitly represent the economic, social, material, and environmental factors that impact electricity demand/supply. The results presented in this paper therefore only quantify the uncertainty related to weather-dependent demand and renewable supply, rather than the uncertainty arising from non-meteorological factors.

4. Daily extremes in the climate of winter 2024–25

Figure 3 shows the coldest, calmest, and highest DnW days recorded in each winter season for the model (grey, yellow, and red dots) and observations (blue crosses) between 1961 and 2025. Across the coldest days

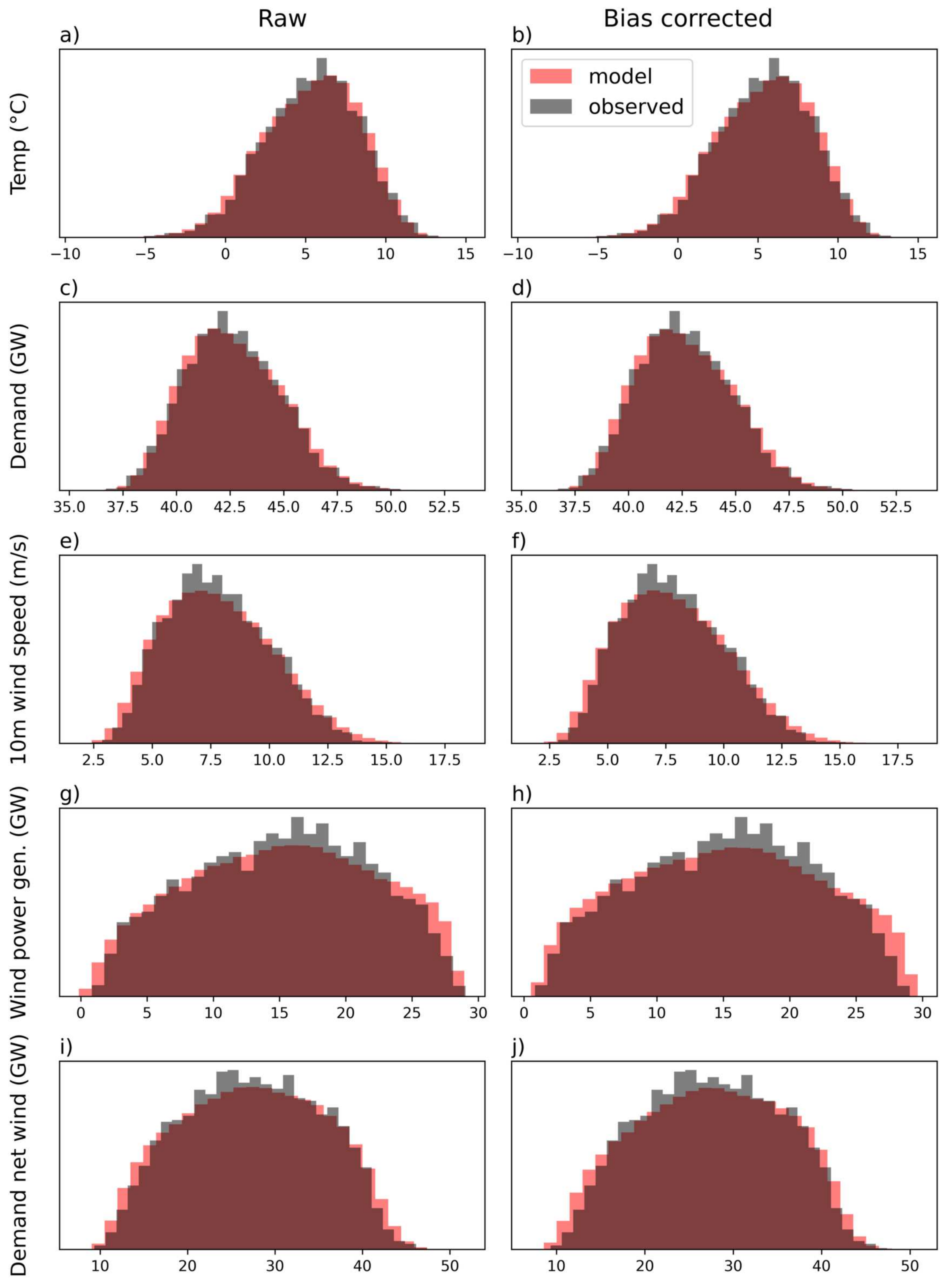

Figure 2. The distribution of meteorological input variables and resulting modelled energy variables (a)–(j). The model (HadGEM3-GC31-MM, red) and observed (ERA5, grey) distributions of 1960 to 2025 winter (DJF) daily means for UK temperature, modelled electricity demand, 10 m wind speed, modelled wind power generation, and resulting demand net wind. The left column shows the raw distributions (a), (c), (e), (g), and (i) and the right column shows the mean bias corrected distributions (see section 2.2, (b), (d), (f), (h), and (j)).

(figure 3(a)), calmest days (figure 3(b)), and highest DnW days (figure 3(c)), the model simulates more severe daily winter extremes than those in the observational record (red dots).

For the coldest winter days (figure 3(a)), there are many examples of simulated days with colder UK mean temperatures than the coldest observed day. For example, this occurred on the 12th January 1987 during a 'cold wave' event (Eden 2008). These unprecedented coldest winter days (red points) are becoming less likely and show a slight warming trend, despite already having had the trend in 'extremes' removed (see section 2.1),

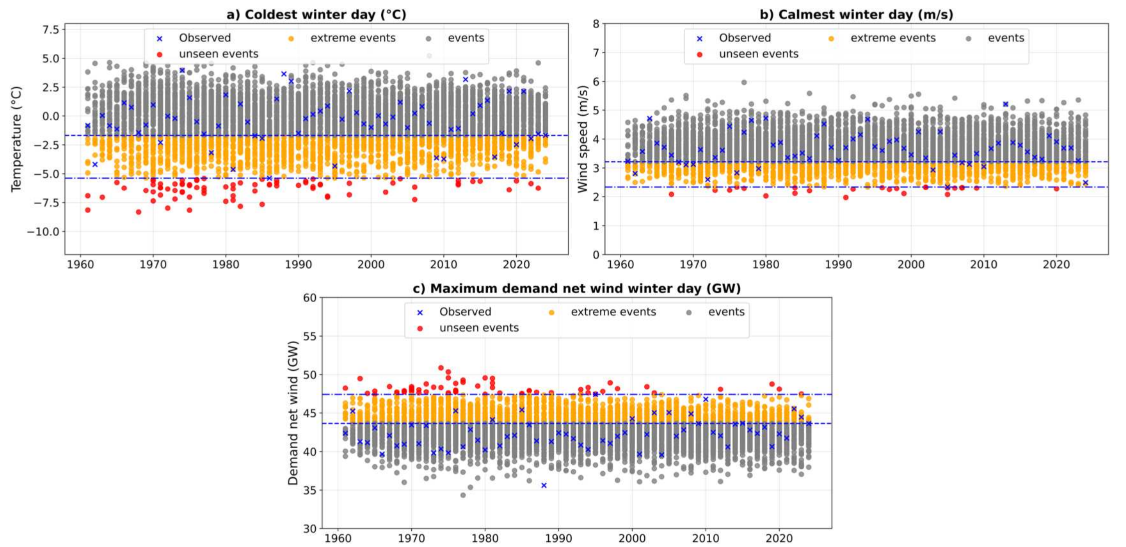

Figure 3. Coldest winter days (a), calmest winter days (b), and highest DnW winter days (c) for the model (dots, HadGEM3-GC31-MM) and the observations (blue crosses, ERA5). For temperature and wind speed in (a) and (b), the blue dashed lines show the 20th percentile of the observed distribution, and the dot dashed lines show the minimum observed values. For demand net wind in (c), the dashed line shows the 80th percentile and the dot dashed line shows the maximum observed value. For (a) and (b) model events above the 20th percentile are plotted in grey, events between the 20th percentile and observed minimum are plotted in yellow, and events below the observed minimum are plotted in red. For (c) model events below the 80th percentile are plotted in grey, events between the 80th percentile and the observed maximum are plotted in yellow, and events above the observed maximum are plotted in red.

suggesting that the temperatures on unprecedented cold winter days are warming faster than the temperatures on the 'typical' annual coldest winter day. This warming trend in unprecedented coldest winter days is consistent with previous studies (Schneider *et al* 2015, Holmes *et al* 2016, Rhines *et al* 2017, Gross *et al* 2020, Seneviratne *et al* 2021, Lo *et al* 2023). One possible mechanism for this is Arctic Amplification, with polar temperatures warming faster than midlatitude regions (Francis and Vavrus 2012, Screen 2014). Consequently, days with northerly winds and colder conditions may be warming more rapidly than days with southerly winds and warmer conditions (Screen 2014). Climate model simulations suggest that this trend is likely to continue as warming increases in the 21st century (Schneider *et al* 2015, Holmes *et al* 2016, Gross *et al* 2020, Lo *et al* 2023).

In contrast with temperature, the calmest winter days simulated by the model (red dots, figure 3(b)) are more comparable to the calmest observed winter day of winter 2005–06. Whilst there is uncertainty in the mean changes of wind speed over Europe with climate change (Wohland *et al* 2019, Wohland *et al* 2021), these forced changes are much smaller in magnitude than multidecadal wind speed variability (Bloomfield *et al* 2021b).

The highest observed DnW day occurred on the 27th December 1995, with a modelled demand net wind of around 47.5 GW. This coincided with a period of extremely cold weather in late December 1995, where the joint coldest UK temperature was recorded, with temperatures falling to −27.2 °C at Altnaharra in North Scotland (Met Office 2012). The model simulates highest DnW days more severe than the one observed in winter 1995–96 (red dots, figure 3(c)). In a similar way to temperature extremes, there is a negative trend in the unprecedented highest DnW days, indicating that unprecedented days are becoming less likely in the present climate. Again, this could be related to Arctic Amplification as discussed above. Therefore, this trend suggests that, assuming a stationary power system, extremely challenging winter days are becoming less likely with climate change.

Figure 4 shows the empirical estimates for the return periods of coldest winter days (figure 4(a)), calmest winter days (figure 4(c)), and highest DnW winter days (figure 4(e)), and how this varies depending on the magnitude of the extreme being considered. To identify the impact of the long-term trend, an additional test is performed, whereby the entire ensemble is detrended to the climate of each year in turn. The resulting impact of the long-term trend on the likelihood of observing an unprecedented extreme event is shown in figures 4(b), (d) and (f).

Using the large ensemble as synthetic observations, the likelihood of seeing a coldest winter day more severe than that of winter 1986–87 (i.e., temperatures colder than −5.3 °C), in the climate of winter 2024–25, is approximately 1.3% each year (1-in-78-year return period, figure 4(a)). Figure 4(a) shows that, using the observations alone, a 1-in-20-year coldest winter day is −4.3 °C, but with a large uncertainty estimate ranging from −3.5 °C to −5.4 °C. Using the UNSEEN approach the uncertainty range can be significantly reduced, with a 1-in-20-year coldest winter temperature estimate between −3.8 °C and −4.0 °C.

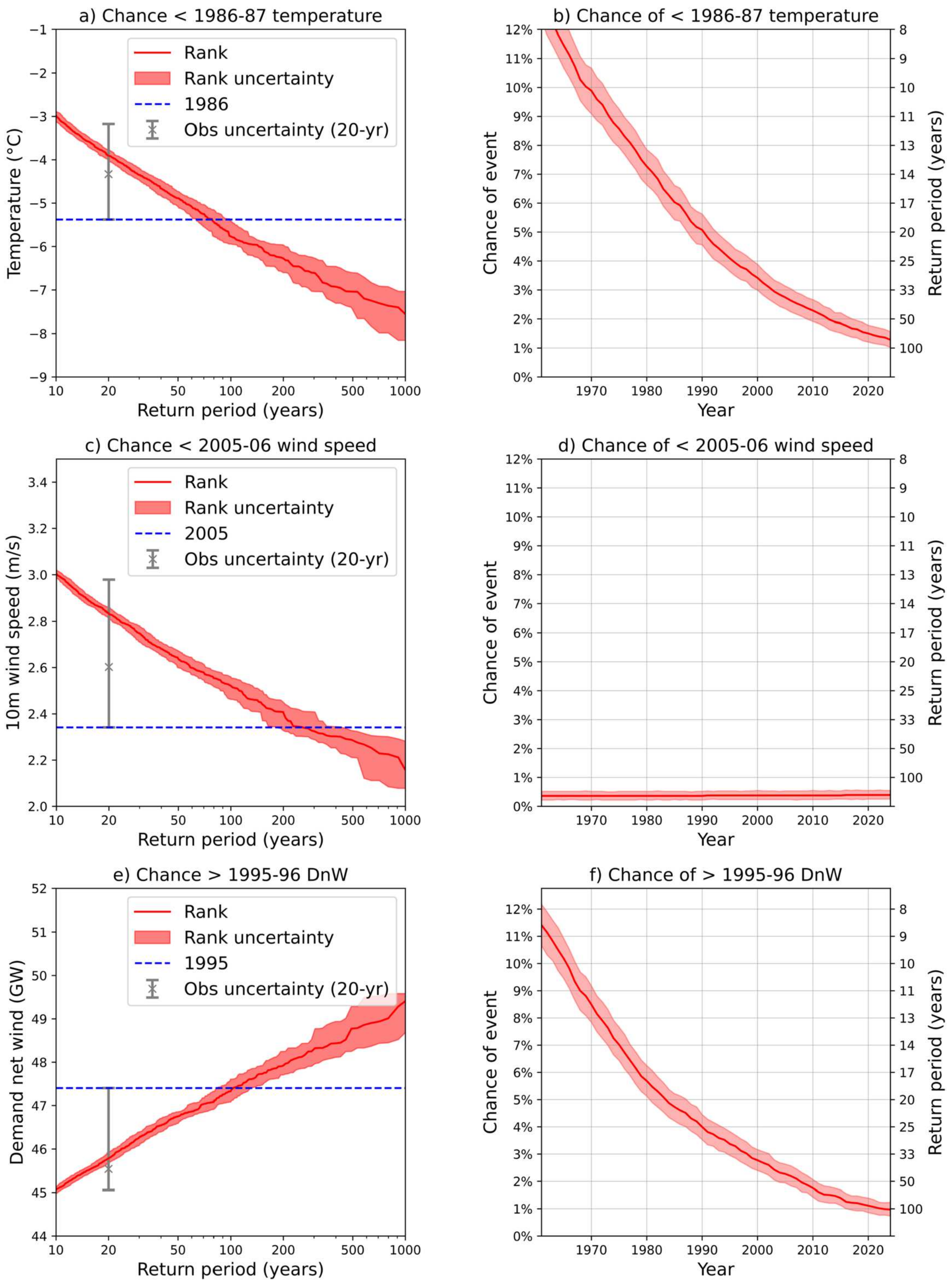

Figure 4. Left column—UNSEEN estimates of the likelihood of exceeding the observed coldest winter day (a), calmest winter day (c), and highest demand net wind winter day (e) in the climate of winter 2024–25. The central estimate is plotted as a solid red line, with the shading indicating the 95% confidence interval obtained via bootstrapping of the ensemble. The observed median value (grey cross) and its 95% confidence interval estimated using bootstrap resampling over time with replacement (grey error bars), are also shown. The dotted blue line indicates the magnitude of the most severe day in the observations. Right column—the change in likelihood of exceeding the most severe day over time (b), (d), and (f), calculated each year from the ensemble adjusted to represent that year's climate. The 95% confidence intervals are indicated by shading and calculated as before.

With time, however, the likelihood of seeing these cold extremes has decreased. For example, while there was approximately a 12% chance (1-in-8-year return period) of seeing a 1986–87-like cold extreme each year in the 1960s, this likelihood has now reduced to approximately 1.3% (a 1-in-78-year event, figure 4(b)). This means that unprecedented coldest winter days are around 10 times less likely now compared to the 1960s. With ongoing climate change, the likelihood of unprecedented coldest winter days is expected to reduce further.

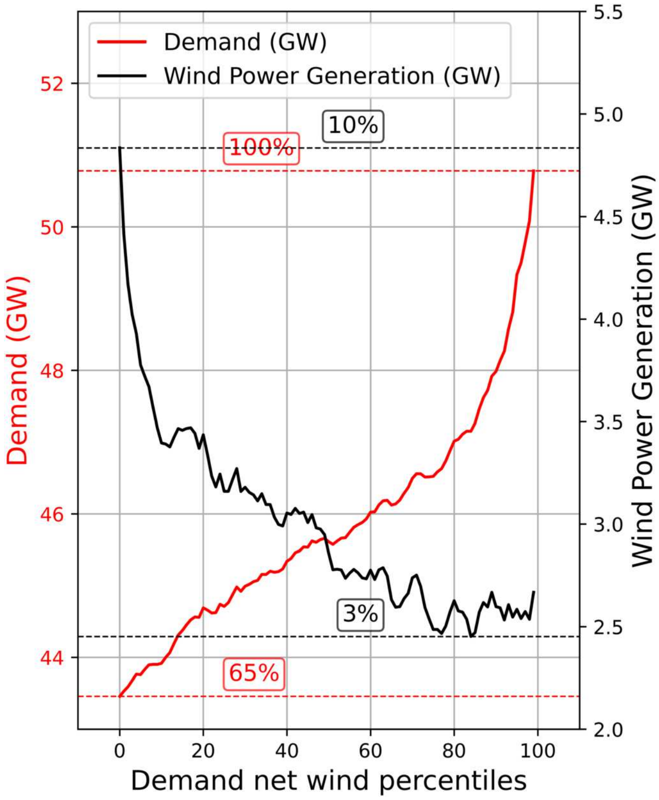

Figure 5. Variation in modelled UK electricity demand (GW, red) and wind power generation (GW, black) with winter (DJF) percentiles of highest demand net wind days averaged over 5% bins for the model. The horizontal lines with values indicate the percentiles of minimum and maximum demand (GW, red) and wind power generation (GW, black) values in the full distributions (i.e., all winter days) of demand and wind power generation respectively.

Applying the same approach to the calmest winter days, the likelihood of seeing a calmest wind day more severe than that of winter 2005–06 (i.e., 10 m wind speed below 2.4 m s^{-1}), in the current climate, is approximately 0.4% each year (1-in-255-year return period, figure 4(c)). The likelihood of an event with such long return periods would be near impossible to quantify using the observations, given that the uncertainty range would be even larger than that shown for the 1-in-20-year event in figure 4(c). Additionally, the model data suggests there has been no significant change in the likelihood of an unprecedented calmest winter day with time (figure 4(d)).

In the current climate, the likelihood of seeing a highest DnW day more severe than that of winter 1995–96 (i.e., demand net wind above 47.4 GW) is approximately 1% each year (1-in-103-year return period, figure 4(e)). Using the large ensemble substantially reduces the uncertainty in estimates of the severity of a 1-in-20-year return period event. Using observations, this event could be anywhere between 45 GW and 47.4 GW, while the model simulated event has greatly reduced uncertainty, with values between 45.7 GW to 45.9 GW. Notably, the model data can be used to quantify the return periods of key historical case studies, such as the highest DnW day of winter 2010–11, which has a return period of approximately 1-in-50 years.

In a similar way to the temperature extremes, and principally driven by the warming trend, unprecedented highest DnW days are also now around 10 times less likely than in the 1960s (figure 4(f)). Therefore, it appears that the probability of seeing these unprecedented demand net wind extremes (in a stationary power system) will continue to decrease with ongoing climate change.

5. The relationship between temperature and wind speed

Figure 5 shows how the modelled electricity demand and wind power generation change as the severity of the highest DnW day increases. As expected, lower wind power and higher demand are associated with higher demand net wind conditions. However, by considering the relative ranking of the demand and wind power generation within the full distribution of winter days, two key observations can be made from this figure. Firstly, it is noted that all of the highest DnW days are associated with very low wind power generation (the days selected rank from the 3rd to 8th percentile out of all winter days for wind power), whereas the demand is much more varied (the demand varies ranks between the 65th to 100th percentile of all winter days). Low wind speeds

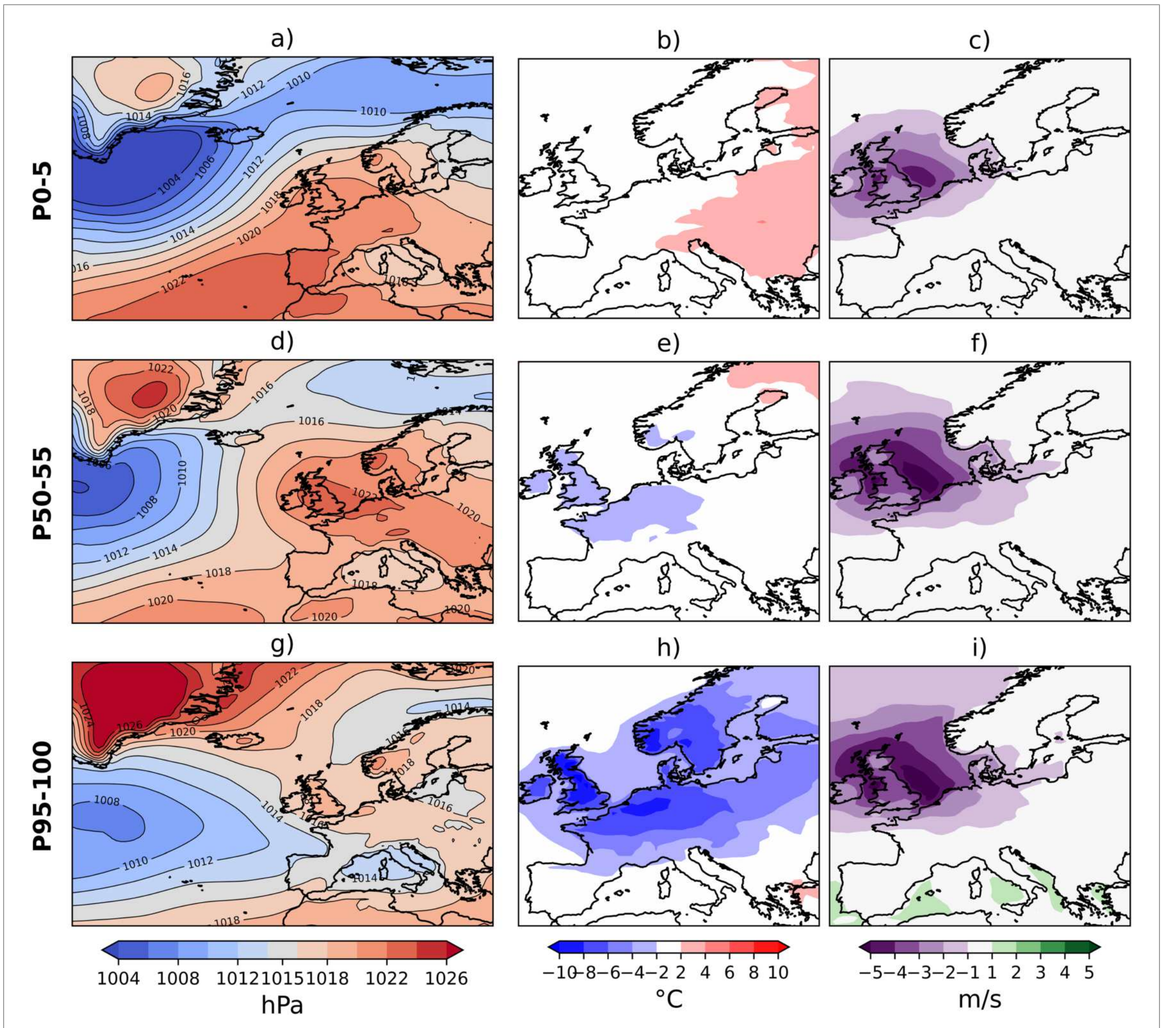

Figure 6. Absolute values of mean sea level pressure (hPa, (a), (d), and (g)), temperature anomalies (°C, centre column, (b), (e), and (h)), and 10 m wind speed anomalies (m/s, (c), (f), and (i)) composited across highest demand net wind days for the UK. The top row is a composite over the 0th–5th percentile (P0-5) of the highest DnW winter days, the middle row corresponds to 50th–55th percentile range (P50-55), and the bottom row corresponds to the 95th–100th percentile range (P95-100). Anomalies are relative to the model's winter climatology, comprised of all winter days between 1960–2018. The temperature field has been linearly detrended at each gridpoint, following the method laid out in section 2.1.

are therefore essential in driving the highest demand net wind conditions seen in any given year. Secondly, for the upper tail of highest DnW days, the level of demand plays a central role in determining the severity of the event. For example, at levels above the 80th percentile of the highest DnW days, the contribution of demand increases rapidly (from 47 GW to 51 GW), whereas the contribution from wind power remains relatively constant (around 2.5 GW). The severity of highest DnW days is therefore more strongly influenced by the demand (and hence temperature) than the wind resources, but only once the condition of very low wind (i.e., the 10th percentile of all winter days) has already been met.

6. Atmospheric conditions associated with UK demand net wind extremes

Figure 6 shows how the synoptic situation changes across different severities of the highest DnW days, and the temperature and 10 m wind speed anomalies associated with this. At the lower tail of the highest DnW days (figure 6(a), the 0th to 5th percentile), a ridge of high pressure over north western Europe leads to lower than average wind speeds (figure 6(c)) and near average temperatures (figure 6(b)). On such days, wind speeds are around 3 m s^{-1} below average in coastal regions. Between the 50th to 55th percentile of the highest DnW days, high pressure is centred over north western Europe (figure 6(d)), resulting in easterly winds which lead to colder temperatures (figure 6(e)) and lower wind speeds (figure 6(f)). On such days, UK temperatures are around 3 °C below average, with wind speeds in coastal regions over 5 m s^{-1} below average. For the upper tail of the highest DnW days (figure 6(g), the 95th–100th percentile) the mean sea level pressure composite shows a region of high pressure over Greenland and generally high pressure over the UK. This pressure pattern results in northerly flow from the Arctic over the UK, leading to temperature anomalies of −8 °C, and wind speeds more than 5 m s^{-1} below average (figures 6(h) and (i)). Thus, whist low wind is essential, the most extreme highest DnW days are dominated by cold temperatures, in agreement with figure 5.

7. Summary and discussion

Using the UNSEEN method we have characterised the most challenging winter days for the UK energy sector and given estimates of the likelihood of the coldest and calmest days individually, as well as the highest DnW day. We find that, for each of the variables considered, more severe extremes than those observed are plausible. In the present-day climate, the annual probabilities for exceeding different types of recorded observational extremes are estimated at approximately:

- 1.0% for extreme highest DnW days (i.e., a 103-year return period for DnW greater the observed maximum of 47.4 GW in winter 1995–96);
- 1.3% for extreme coldest days (i.e., a 78-year return period for temperature less than the observed minimum of −5.3 °C in winter 1986–87); and
- 0.4% for extreme stillest days (i.e., a 255-year return period for 10 m wind speed less than the observed minimum of 2.4 m s^{-1} in winter 2005–06).

Collectively, this suggest that while more extreme high DnW and low temperature events remain possible, more extreme low wind events are rather unlikely.

Many aspects of these exceedance probabilities are, however, non-stationary over time. For an unprecedented coldest winter day, we find such events to be 10 times less likely in the present day when compared to the 1960s. This change in cold extremes is well documented in the literature for the UK (Lowe *et al* 2018, Kendon *et al* 2019), Europe (Forzieri *et al* 2016, Cardell *et al* 2020, Seneviratne *et al* 2021), and on longer timescales out to a season (Sippel *et al* 2024). In the same way, due to the temperature dependence of demand, we also find an unprecedented highest DnW day to be approximately 10 times less likely in the present day when compared to the 1960s. In contrast, for the calmest winter day, we find no significant change in the likelihood of seeing unprecedented extremes over time. Thus, it appears likely that the coming decades will see fewer unprecedented coldest winter days (high demand) and fewer unprecedented high DnW days (assuming the power system's sensitivity to weather remains broadly unchanged).

The large sample of data from the ensemble also provides new insight into the relationship between UK temperature and 10 m wind speed on high DnW days. Although very low wind power generation is a prerequisite for extreme DnW (as all high DnW days were sampled from the lowest 10% of wind generation days), the severity of the DnW extreme was found to be more strongly linked to the level of demand. Meteorologically, this was associated with northerly and easterly flows over the UK (figure 6, consistent with Lücke *et al* 2024). While it is likely that some of the impacts of high DnW can be reduced through interconnections with continental Europe (not modelled here), the meteorological conditions driving these events are often widespread and lead to co-occuring energy droughts across multiple regions (see Van Duinen *et al* 2025).

A key caveat to the research presented is that it is based on a simple empirical relationships between meteorological inputs and the UK power system variables (from Bloomfield *et al* 2020). These relationships therefore hold on the assumption that the UK power system broadly resembles its present-day configuration and meteorological sensitivity, which may not be the case for a future where heating and transport are electrified (Drax 2025). At the same time, the additional installed wind power capacity, as set out in the Clean Power Action Plan (DESNZ 2024), may be able to generate more electricity on low wind days. The balance between the weather dependence of electricity demand, particularly increased demand due to electrified heating, and installed wind power capacity, as explored in Bloomfield *et al* (2018), will likely determine the conditions which cause challenges for the future energy system.

We conclude by noting that, while the UNSEEN approach used here is useful for exploring the magnitude and likelihood of daily extremes, the evolution of demand net wind over days or weeks during the winter is also of concern for the energy system operator, most notably for gas storage (DESNZ 2024). Thus, future studies should consider extending the approaches developed here to look at multi-week demand net wind extremes during the winter.

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Conflicts of interest

The authors declare no conflicts of interest.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5194/gmd-9-3751-2016 (Data 2026).

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