Near-term climate prediction for energy security

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Summary

- As the power system transitions to use more weather-sensitive renewables, the system becomes vulnerable to changes in weather and climate, particularly extremes.
- There is potential for skilful prediction of energy sector relevant quantities on decadal timescales, such as Northern Europe offshore wind capacity factors.
- A large ensemble of decadal predictions can be aggregated to create an event set of physically plausible extremes, such as extended winter wind droughts.

Predicting supply and demand

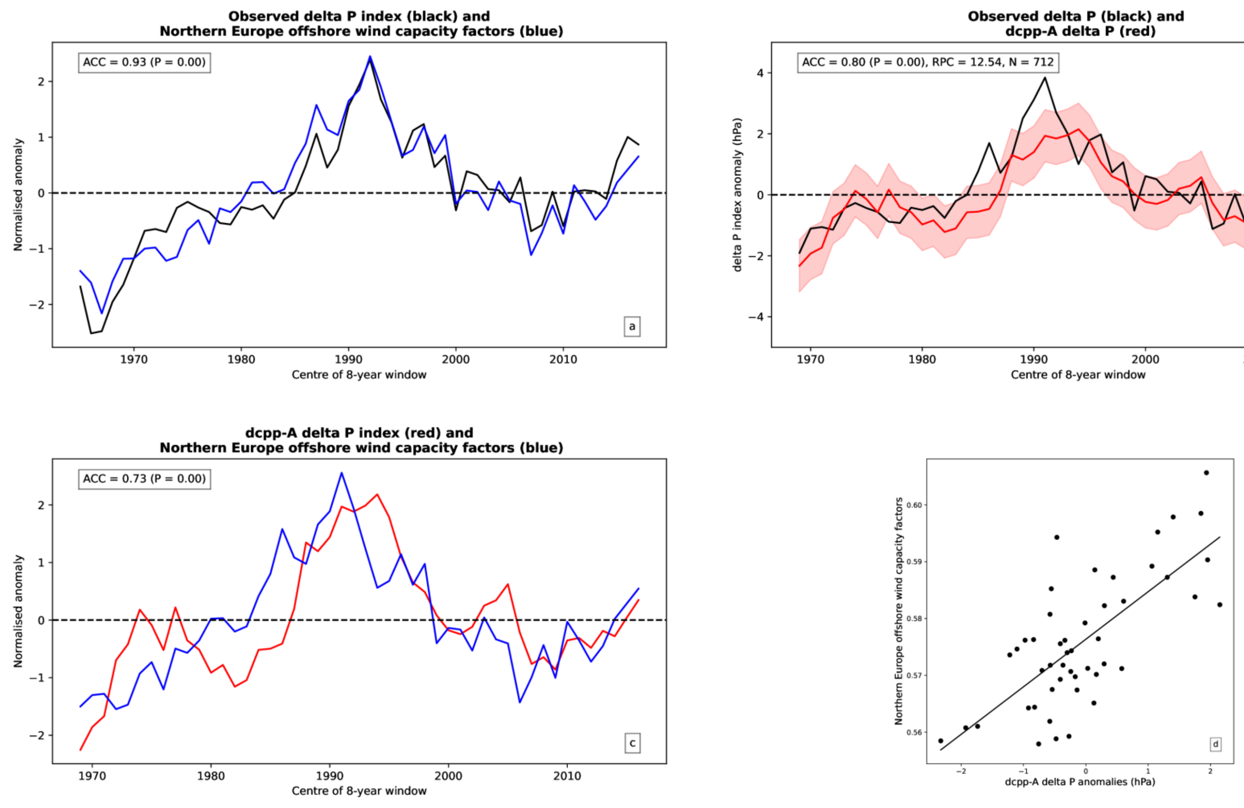

Figure 1 – **a.** Observed time series of the UK delta P index and offshore wind power capacity factors aggregated over the Northern European EEZ regions. **b.** Observed (ERA5) and model (dcpp-A) time series for the UK delta P index. **c.** Time series of model delta P anomalies and wind power capacity factors for the Northern European EEZs. **d.** Scatter plot of **c**. All show extended winter (ONDJFM) and 8-year running means.

- We find predictive skill at decadal timescales for surface variables over Europe during both winter (ONDJFM) and summer (AMJJAS).
- We compare the predictive skill achieved when using either direct model output or pattern based approaches for predicting energy variables over different regions of Europe (**Table 1**).
- We find significant skill when using the difference in pressure over the UK (delta P index) for predicting offshore capacity factors (**Fig. 1**).
- We find significant skill when using the NAO index to predict UK electricity demand, which persists when demand is detrended (**Table 1**).

Energy variable	Climate Index (C)	Obs relationship $r_P(E_{obs}, C_{obs})$	Climate index skill, r_P (C_{obs}, C_{hc})	Energy variable skill, r_P (E_{obs}, C_{hc})
Electricity demand (UK)	Temperature$^{\dagger 1}$	**-0.98**	**0.89**	**-0.84** (-0.33)*
	NAO	**-0.62**	**0.67**	**-0.75 (-0.46)***
	delta P	**-0.64**	**0.80**	**-0.42** (-0.37)*
Offshore wind CFs (Northern Europe)	10m wind speeds$^{\dagger 2}$	**0.90**	**0.56**	**0.53**
	NAO	**0.87**	**0.67**	**0.57**
	delta P	**0.93**	**0.80**	**0.73**
Solar power CFs (Spain)	Solar irradiance$^{\dagger 3}$	**0.99**	**0.46**	0.31 **(-0.62)***
	NAO	**0.69**	**0.67**	**0.63** (0.37)*
	delta P	**0.73**	**0.80**	**0.53 (0.48)***
Precipitation (Scandinavia)	Precipitation$^{\dagger 4}$	-	-	**0.59**
	NAO	**0.76**	**0.67**	**0.64**
	delta P	**0.80**	**0.80**	**0.60**

Table 1 – Column 1: observed Pearson correlation (r_p) between different climate indices and energy variables. Column 2: hindcast skill for predicting the climate index. Column 3: correlation between hindcast climate index and energy variable. Correlations are considered between 1960-2023. Bold values indicate the correlation is significant at the 1% level using the two-sided p-value.

- Although the surface variable (temperature) better captures the forced trend in electricity demand (**Table 1**).
- Therefore, at decadal timescales, large-scale indices may be more useful predictors than direct model output, as in Tsartsali et al. (2023).
- This highlights the potential for skilful prediction of energy sector relevant quantities on decadal timescales

Understanding extremes

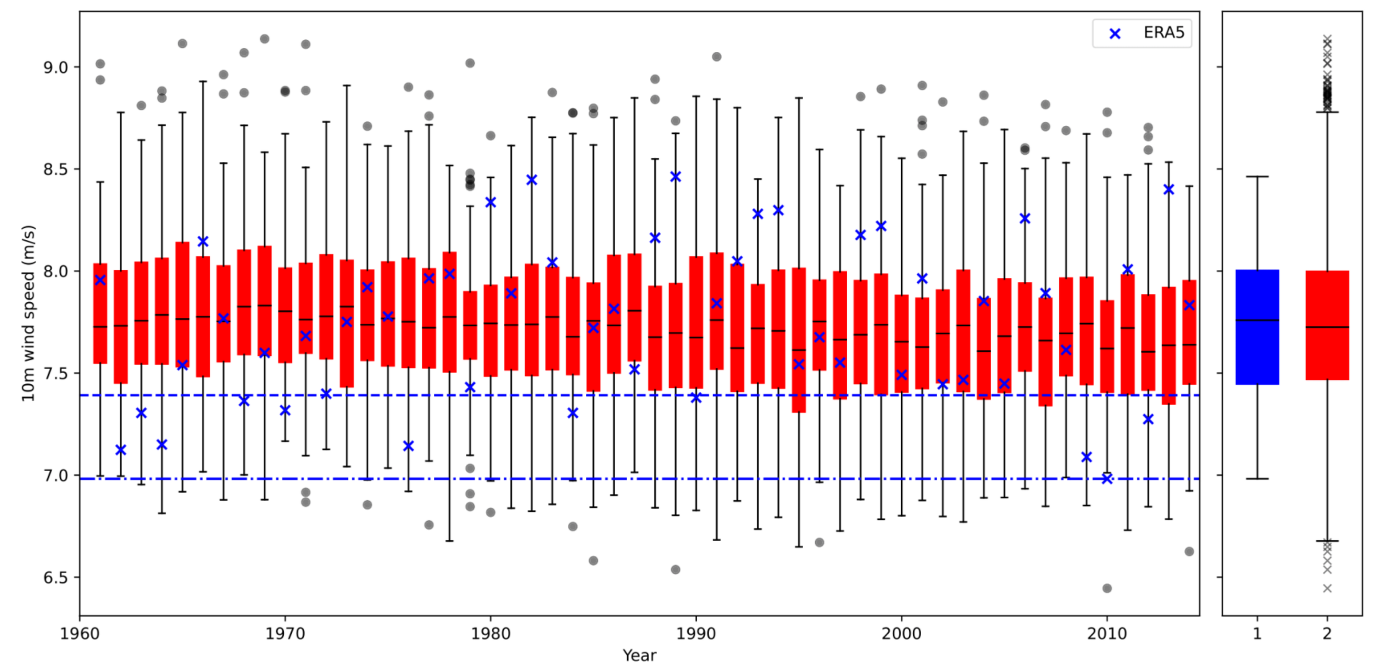

Figure 2 – Time series of 10m wind speeds over the UK from October-March between 1961 and 2014. Blue crosses represent ERA5 and red boxplots represent the HadGEM3-GC31-MM decadal hindcast. The blue boxplot shows the distribution for ERA5, while the red boxplot shows the distribution for HadGEM3-GC31-MM. The dashed and dot-dashed blue line show the 20th percentile and minimum value of the observed distribution from ERA5.

- Large ensembles of decadal predictions produce many more realizations of winters with mean wind speeds below the 20th percentile of the observations than have occurred (**Fig. 2**).
- They also simulate winters where mean wind speeds are lower than the lowest recorded year in the observations, representing unprecedented extremes.
- In future, extremes for demand net wind events will be quantified using observed analogs and power system models.

State of the Climate – Energy Sector

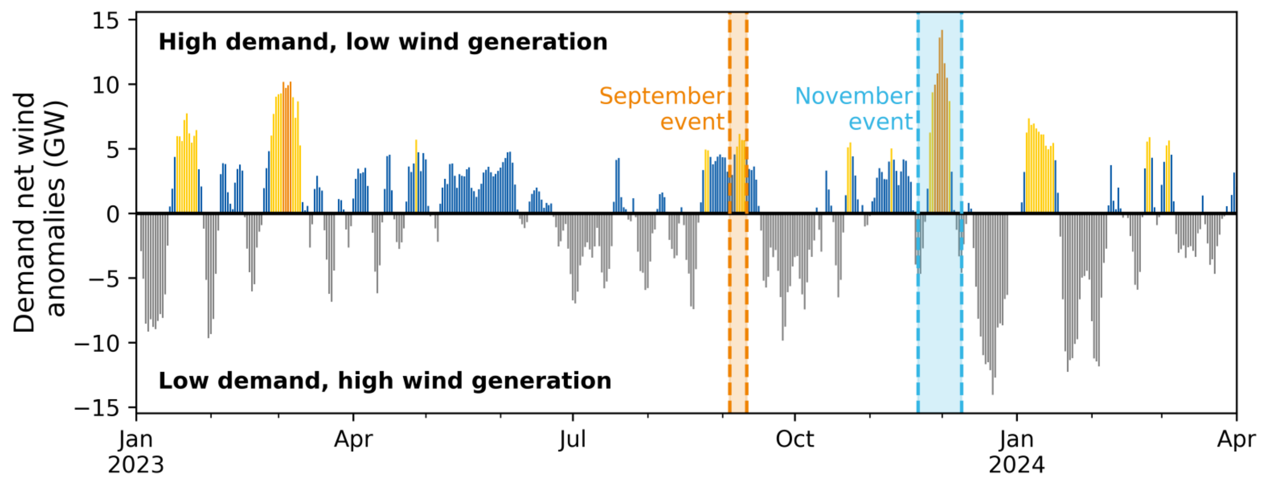

Figure 3 – Daily demand net wind anomalies (GW) for the UK between January 2023 and April 2024, calculated relative to a 14-day rolling mean climatology (1990-2022). Data are smoothed with a 5-day running mean. Anomalies within 1, 2, and 3 standard deviations are shown in blue, yellow, and orange, respectively.

- This report explores the meteorological conditions which impacted the UK electricity system between January 2023 and April 2024.
- We consider the impacts on supply and demand by highlighting high demand net wind events (**Fig. 3**).
- Wo also consider infrastructure damage due to extreme weather events (**Fig. 4**).

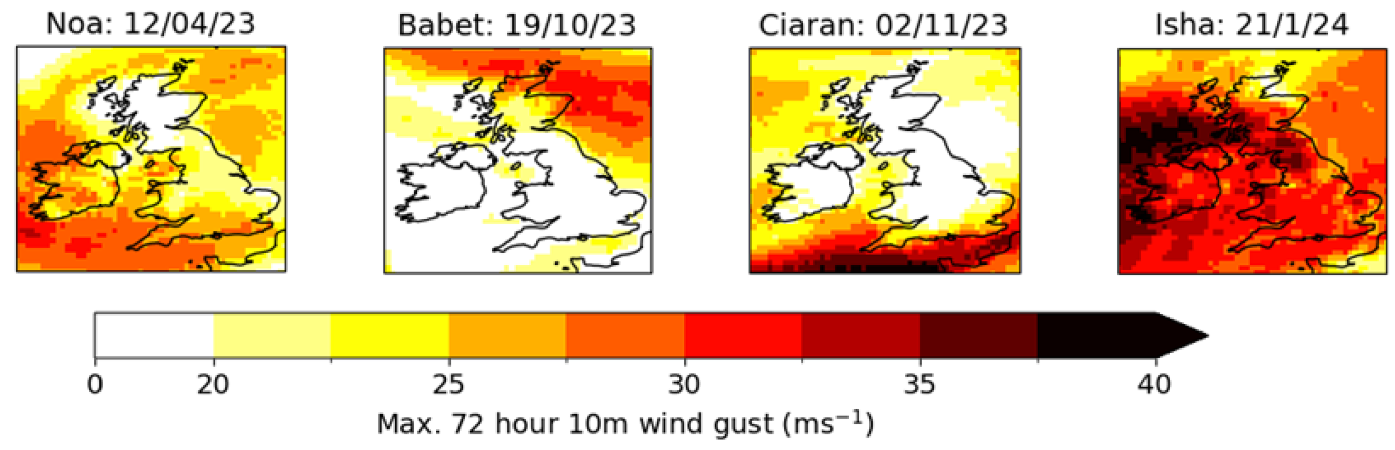

Figure 4 – Storm footprints for notable named storms during 2023 and the 2023-2024 storm season. Based on the max 10m wind gust within a 72-hour period centered around the storm date. Credit: Hannah Bloomfield.

References

1. Tsartsali, E.E. et al. (2023). Predicting precipitation on the decadal timescale: A prototype climate service for the hydropower sector. Climate Services 32, 100422.

Acknowledgements

- I would like to thank my supervisors for all their support and guidance.