Quantification and attribution of uncertainty in wind power modelling

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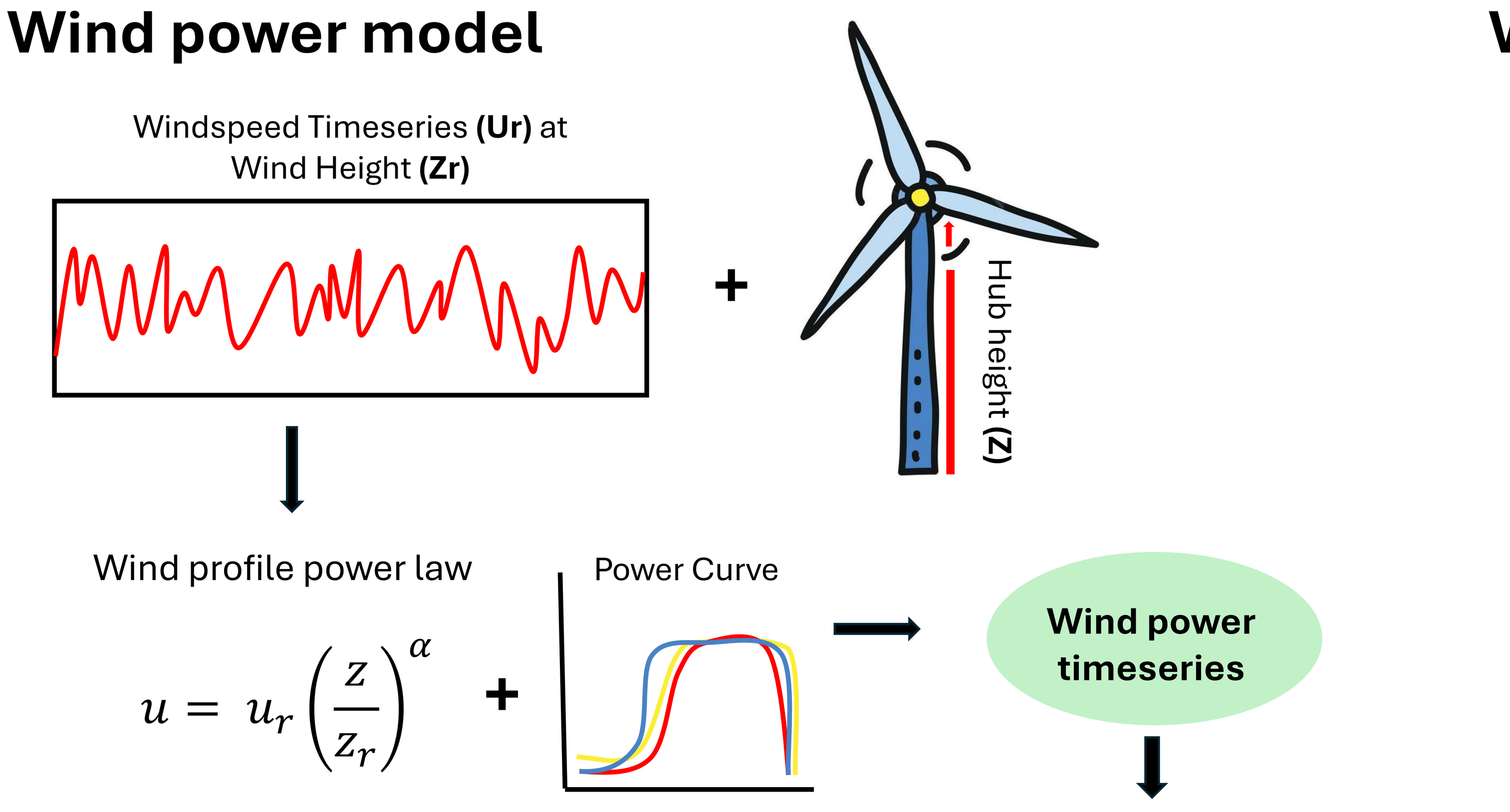
Context

1. In the UK, wind power is a big component of the national energy mix, and the expansion of offshore wind power is vital for meeting the UK's net zero targets.
2. As such, wind power models are useful tools for evaluating wind farm distribution and production (Giddings et a. 2024; Norman et al. 2024) as well as for providing wind power predictions that serve as key inputs to national-scale power systems modelling; these models in turn are commonly used to perform stress tests for energy systems planning across the UK (Climate Change Committee, 2023), as well as to inform large infrastructure investments.
3. It is important that we can trust wind power models and that we understand what are the key modelling choices and assumptions that control their predictions, especially those which could lead to predicting extreme low/high wind conditions.
4. At present, a lot of attention has been given to the influence of climate variability on wind power predictions, particularly when only a short time-period can be used to perform a stress test (Cannon et al. 2015). However, the relative importance of this choice has never been compared to the impact of numerous other uncertain decisions made in the modelling process.

This poster therefore:

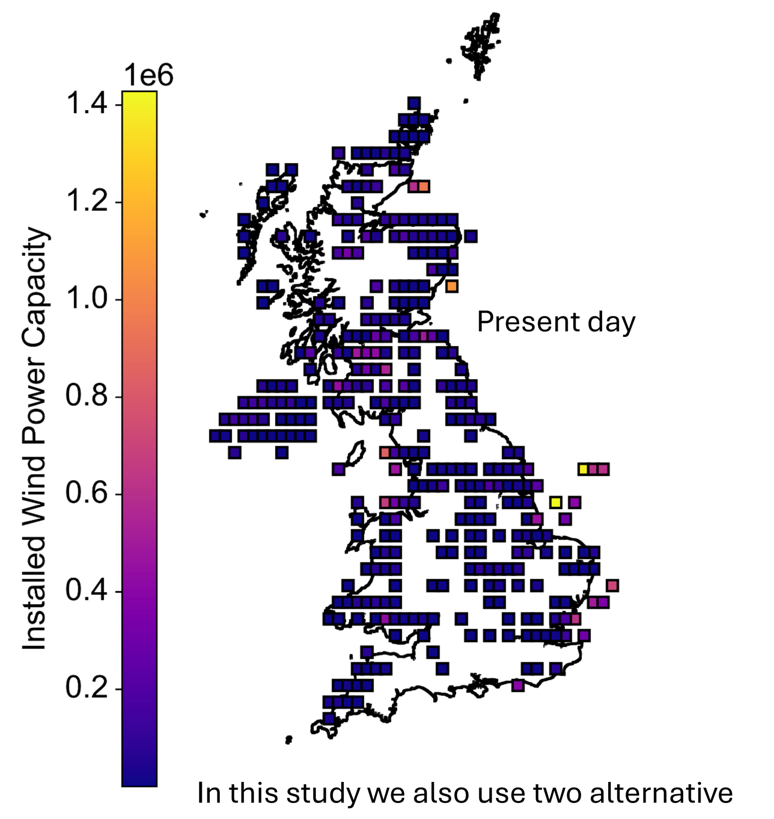
- **Quantifies the uncertainty and sensitivity influencing wind power model predictions (see box to the right)**
- **Explores the spatial pattern of these uncertainties and sensitivities under present and future climate**

Wind power model



MODEL OUTPUTS
Annual-mean capacity-factor, severity, duration and frequency of wind droughts

Wind farm distribution



In this study we also use two alternative future turbine distributions from approved and planned scenarios

Sensitivity analysis and how we do it

Global SA investigate the effects of joint variations of uncertain inputs across their **entire variability space**

Step 1 **propagate** input uncertainties

Monte Carlo simulations

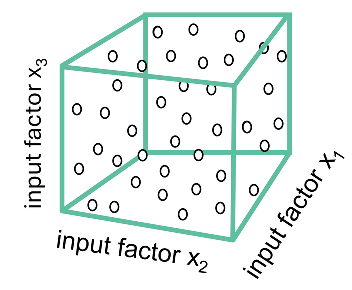
[repeated executions of the model against different combinations of the uncertain inputs]

characterize uncertainty in the inputs → generate N combinations of inputs → execute the model against each inputs' combination

Step 2 **analyze** the input-output dataset

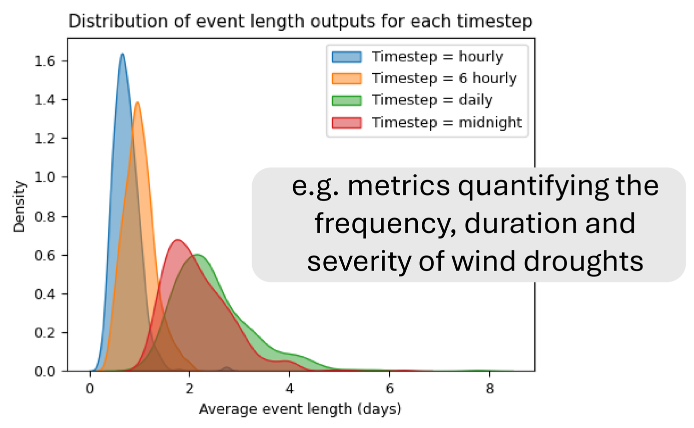
quantifying uncertainty: calculate output(s) ranges or distribution

quantifying sensitivity: calculate (global) sensitivity indices

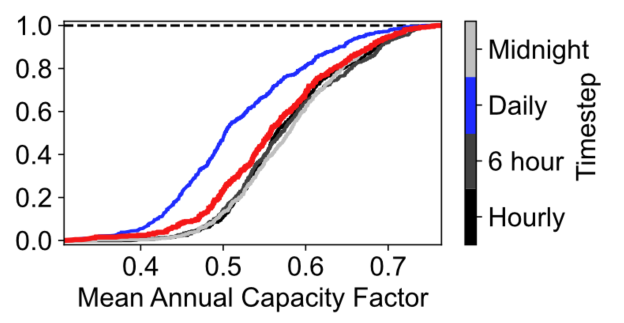


Pianosi et al. (2015)
https://safetoolbox.github.io/

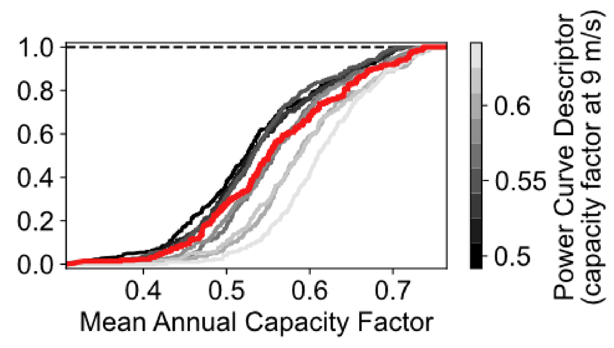
How does the model response change with event-based outputs?



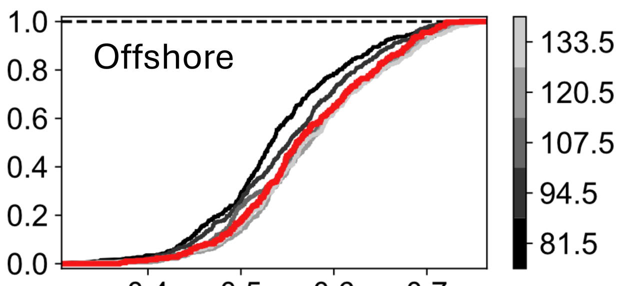
Wind speeds taken from the ERA5 reanalysis from 1940-2022 across all wind farm locations with 3 turbine distribution datasets representing present, approved and planned wind farms

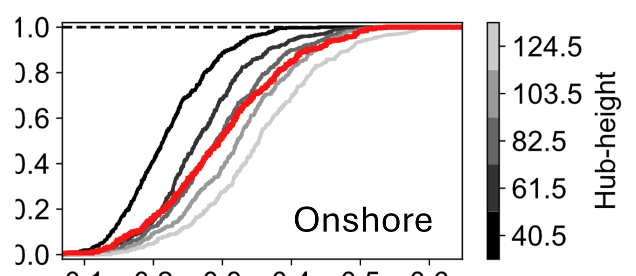


The model output is most sensitive to the daily timestep



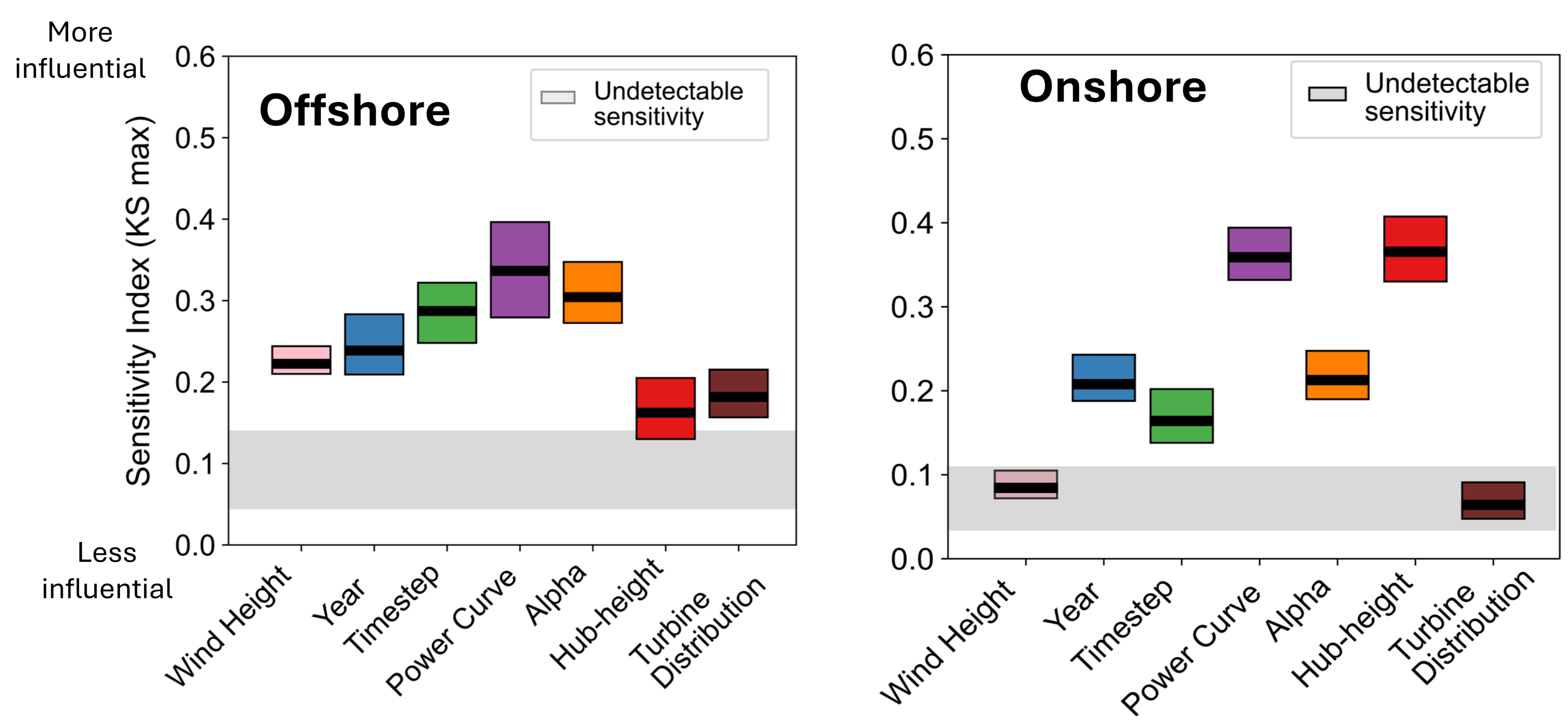
Most of the sensitivity to the power curve comes from the three power curves which rise most quickly





The variation in hub-height for offshore turbines is between 75 and 140m, whereas onshore this varies between 30 and 135 m, most of the sensitivity in the model annual-mean capacity-factor comes from the lower end of these bounds

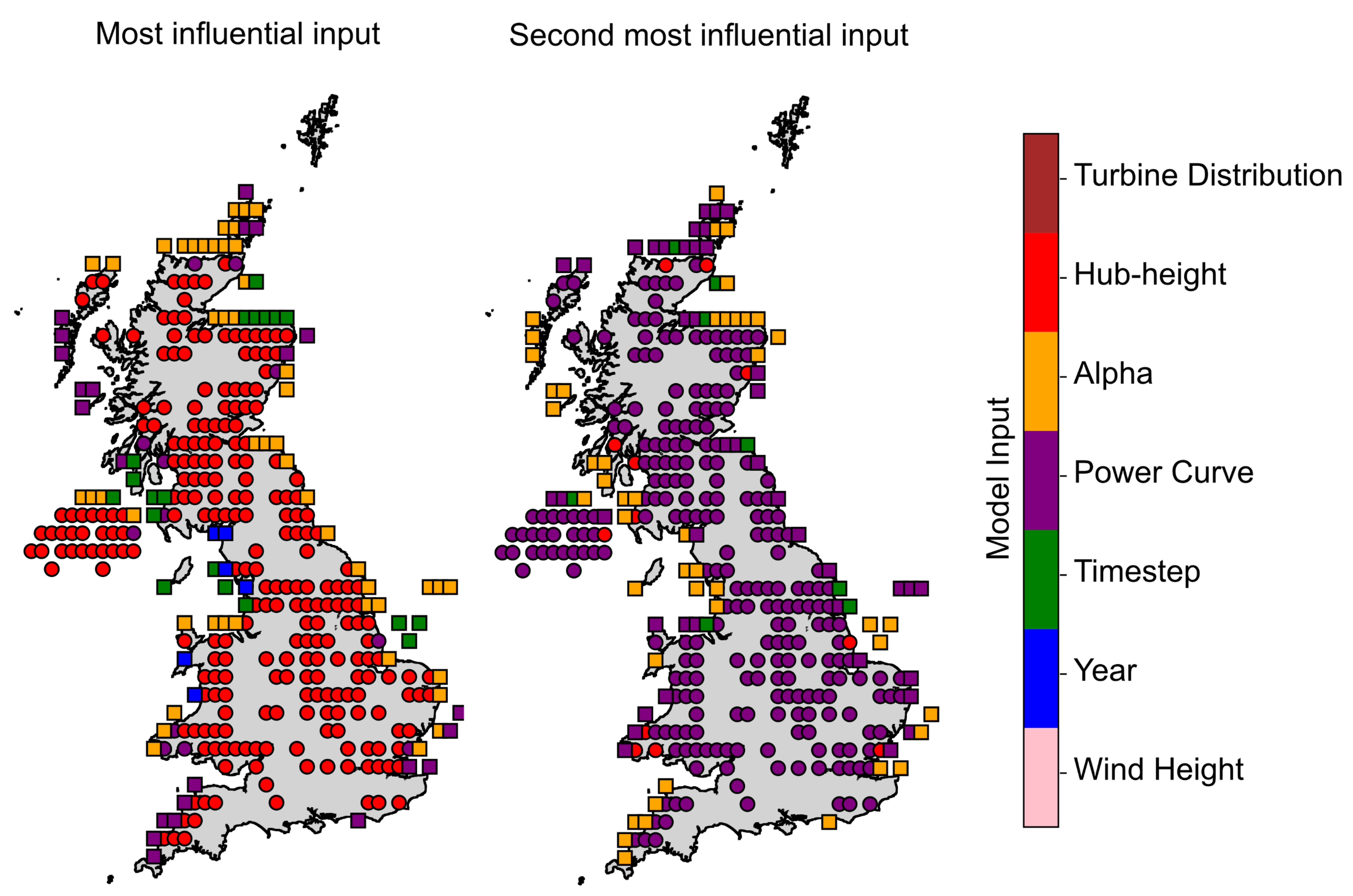
What are the main controls of GB annual-mean capacity-factor – under historical climate?



Key points:

- The climate variability is not as influential on the annual-mean capacity-factor as previously thought
- The power curve is consistently influential across both off-and-onshore turbines
- Hub-height is a much more influential input onshore than offshore
- The influence of the turbine distribution is minimal compared to the other uncertain inputs → the model does not discriminate different spatial investment scenarios well

Does the sensitivity of the annual-mean capacity-factor vary in space?

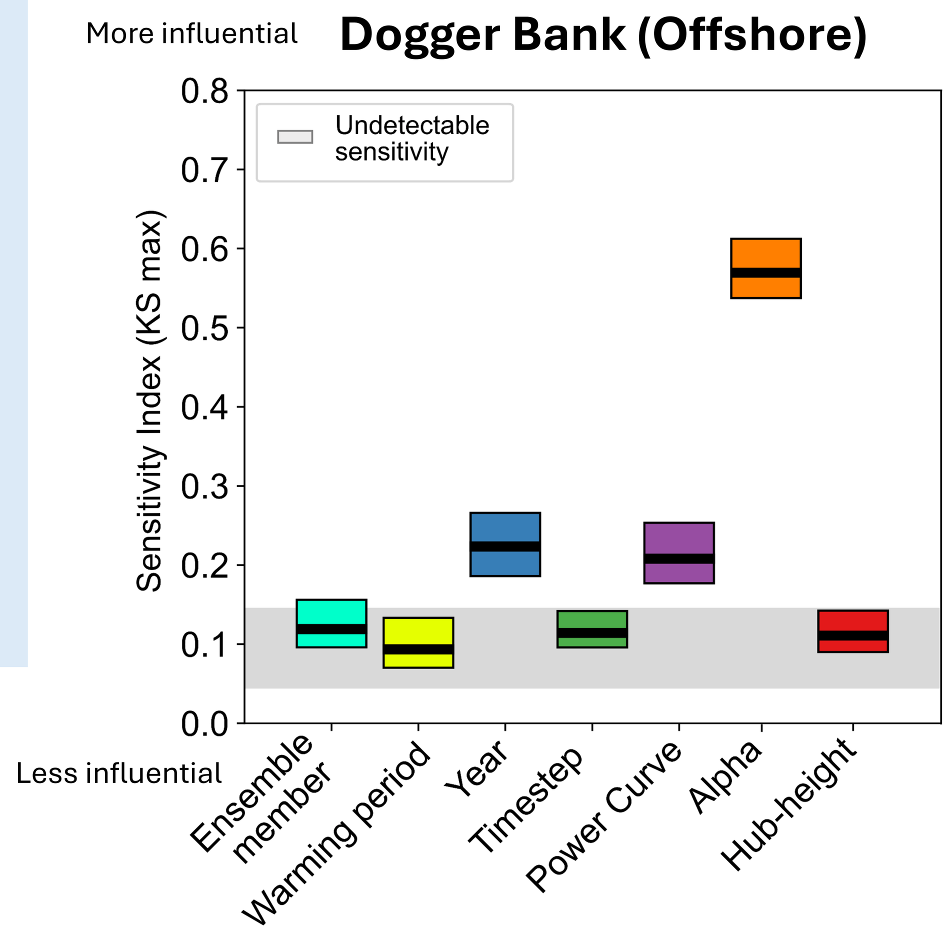


The pattern of sensitivity is much more consistent onshore compared to offshore

Do the controls on annual-mean capacity-factor change when using future climate projections?

Key points:

- By removing the choice of wind height, the alpha parameter has to work much harder to translate the 10m wind speeds to hub-height.
- This shows the importance of hourly data at heights above 10m being easily available from climate models for wind power modelling.
- Future climate uncertainty (represented by ensemble members and warming periods) does not have a strong control on the model output



Here we have used the hourly UKCP18 10m wind speeds available from the CEDA archive. This dataset has 12 ensemble members, and we consider, 1.5 - 4 degrees of warming

References
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