

# ERA 5 calibration to Elexon power

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Calibration to power

# Updates

## New

- Curtailment data to obtain potential generation
- Outage data to exclude periods where capacity is constrained
- Updated power curve comparison to data
- ERA 5 wind speed conversion to power

## Next steps

- Learn power curve from data
- Benchmark models: Quantile mapping, GAMs
- Calibration spatiotemporal model

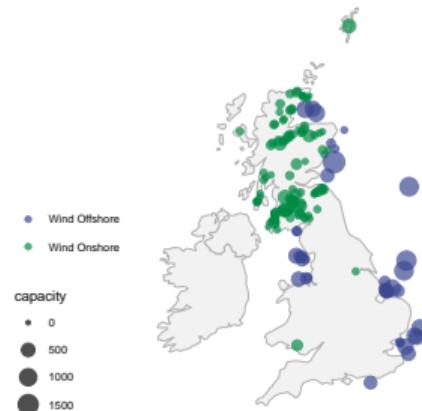
# ERA5 vs Elexon generation

Calibrate a ERA5 driven estimate to **potential generation** accounting for spatiotemporal properties.

ERA5 at wind farms



Elexon wind farms map (2025)



Closest grid point to each wind farm location

# Overview

# Data sources

## Wind speed

- ERA5 at wind farms
  - Hourly data
  - Spatial resolution  $0.25^\circ \times 0.25^\circ$
  - 10m and 100m heights

## Wind power

- Elexon BMU data (since 2019)
  - Half hourly data
  - Generation, curtailment, potential, capacity
  - Outage data (REMIT)
- REPD database
  - Location, turbine height, capacity

# Overview

## 1. ERA 5 to wind farm

Vertical interpolation to turbine height  $h$ .

$$w(h) = w_{100} \left( \frac{h}{100} \right)^{\alpha}, \text{ where } \alpha = 1/7$$

## 2. Wind speed to power

Generic power curves rescaled to wind farm capacity.

$$\hat{PC}_i(w) = PC_i(w) \times \frac{C_i}{\text{Rated power}},$$

where  $C_i$  is the capacity at location  $i$

# Overview of power conversion

## 3. Potential generation

Curtailment and outages are two main events that impact observed generation  $o_{it}$

- Curtailment is added giving rise to potential generation:

$$p_{it} = o_{it} + \text{curt}_{it}$$

- Outage data shows additional limits on capacity
- Currently outage periods are excluded

# Calibration

## 4. Calibration

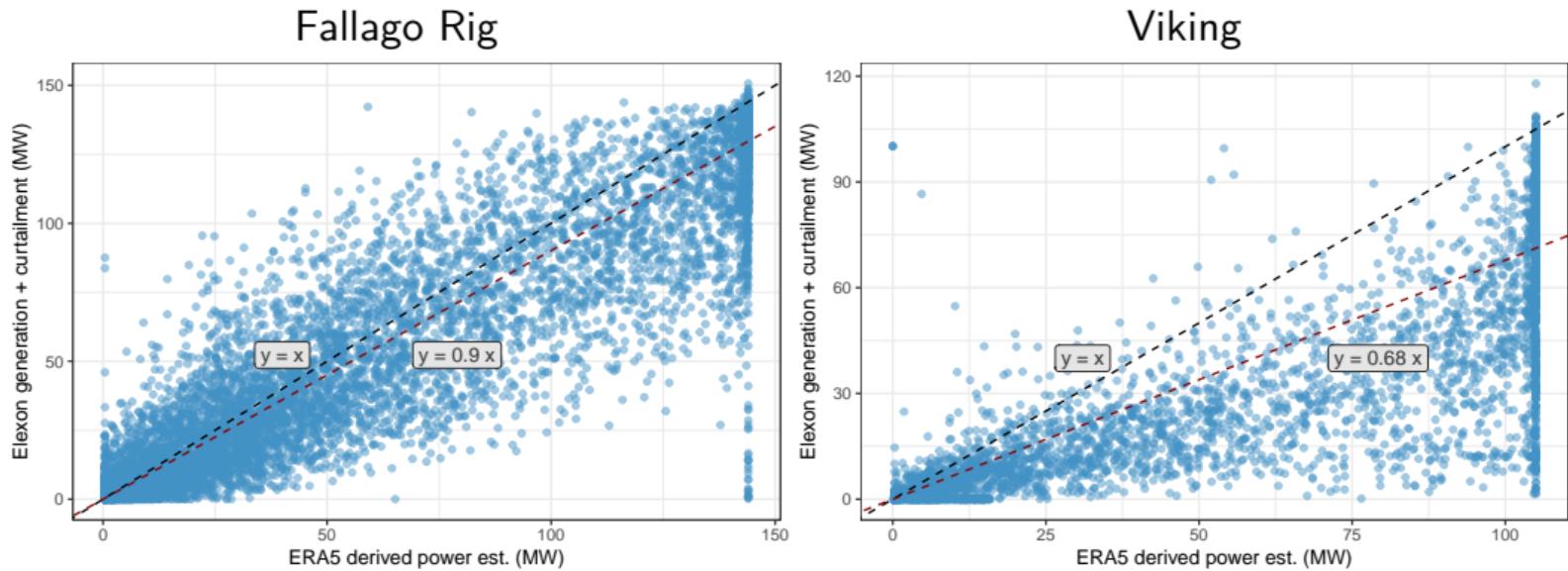
ERA5-derived power estimate  $\hat{p}_{it}$  is compared versus potential power  $p_{it}$

$$\begin{aligned}\hat{p}_{it} &= \hat{P}C_i(w_{it}) \\ p_{it} &= \beta_0 + \beta\hat{p}_{it} + s_i + u_t,\end{aligned}$$

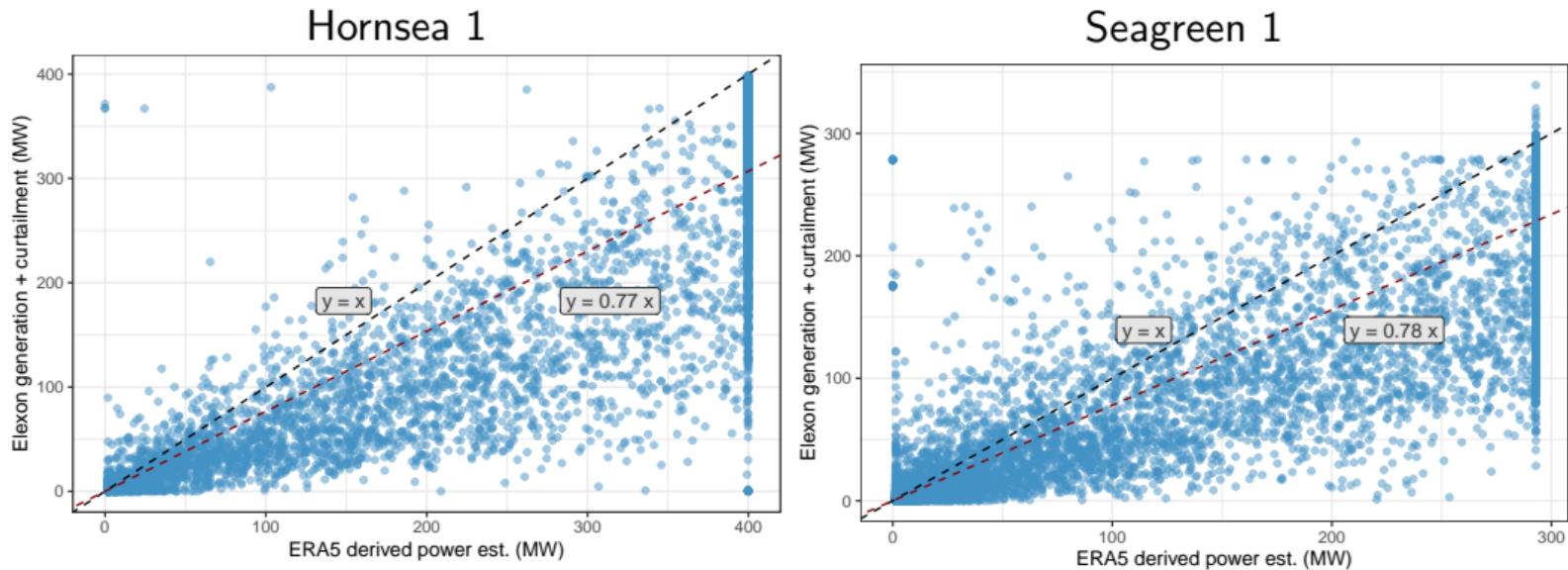
where  $s_i$  and  $u_t$  represent spatial and temporal effects.

## Calibration with linear model

# ERA5 based estimates vs Elexon 2024

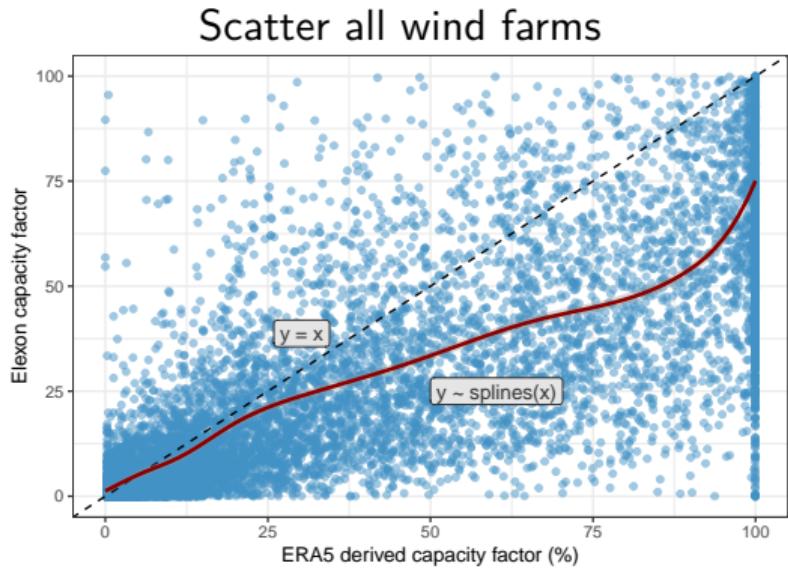


# ERA5 based estimates vs Elexon 2024



# Comparison for all wind farms

- Working with 2024 data only
- Each point represents one hour and one location
- Showin a sample of points to simplify plotting



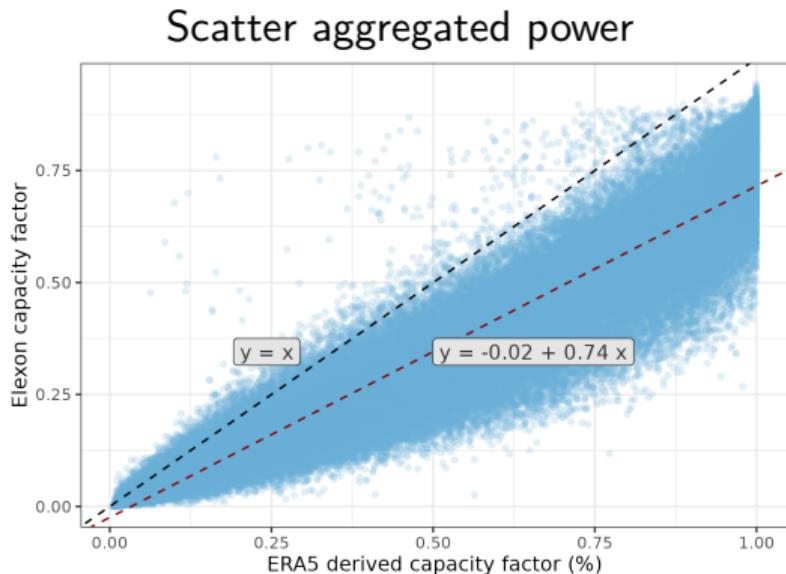
GB level aggregation

# GB level aggregation

- Power aggregated at GB level

$$p_{\text{tot},t} = \sum_i p_{it} / \sum_i C_i$$

- Each point represents one hour
- Overestimation persists but dispersion is lower now

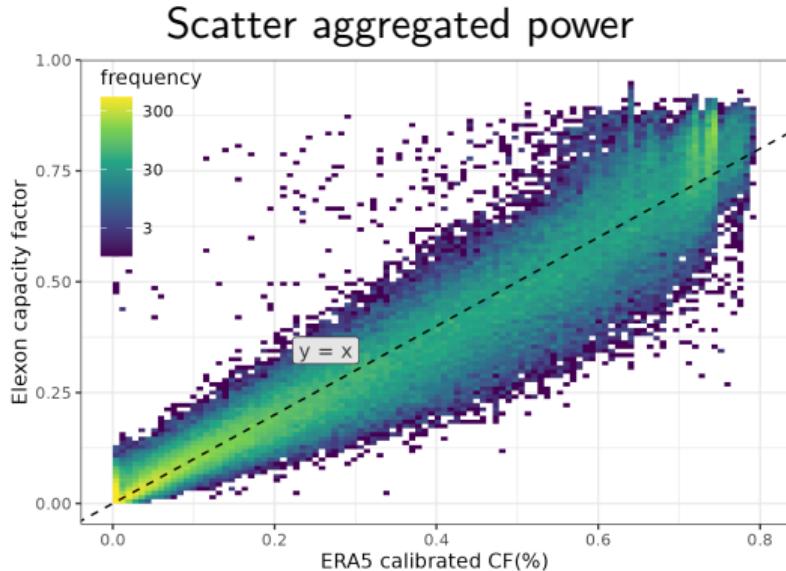


# Calibration with linear model

Features of importance: - month -  
Turbine type (offshore / onshore)

$$p_t^{calib} = \alpha_{k,m} + \beta_{k,m} \hat{p}_t,$$

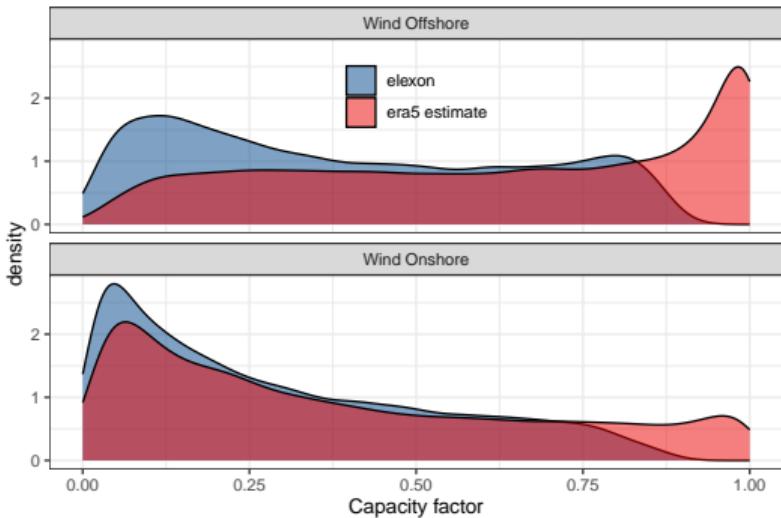
where  $\alpha_{k,m}$  and  $\beta_{k,m}$  represent the intercept and slope, varying by type and month



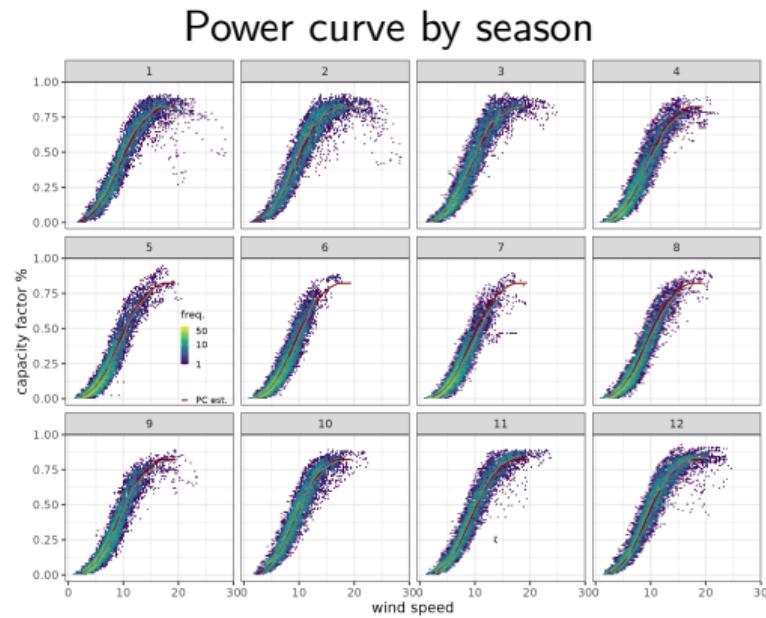
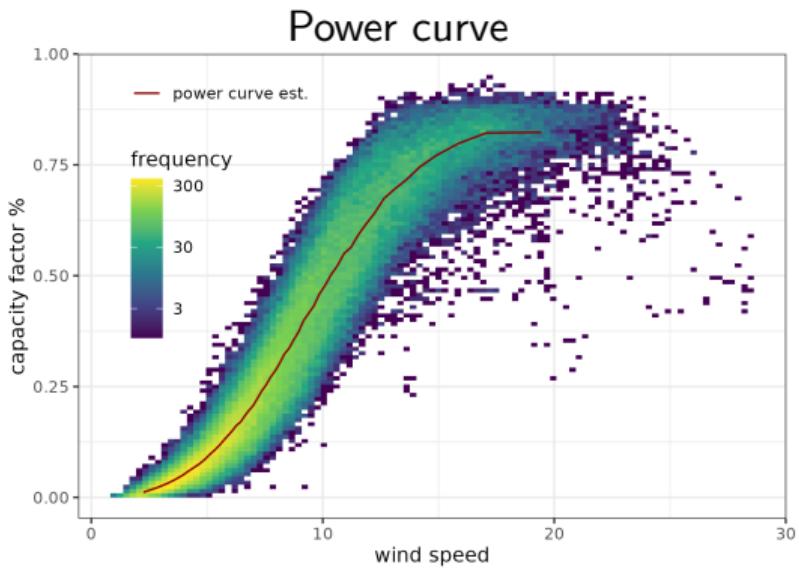
# Density of aggregated power

- Cut-off wind speed isn't capture well by generic power curves
- This issue is markedly present in offshore data

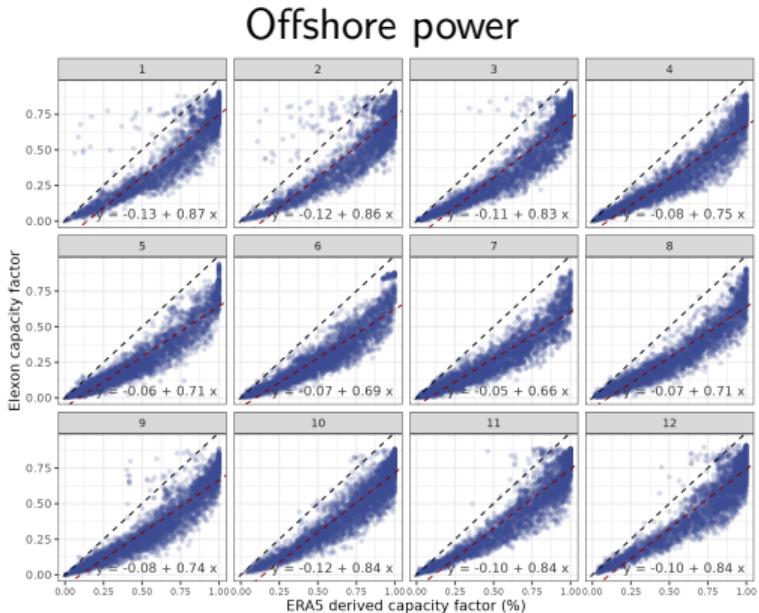
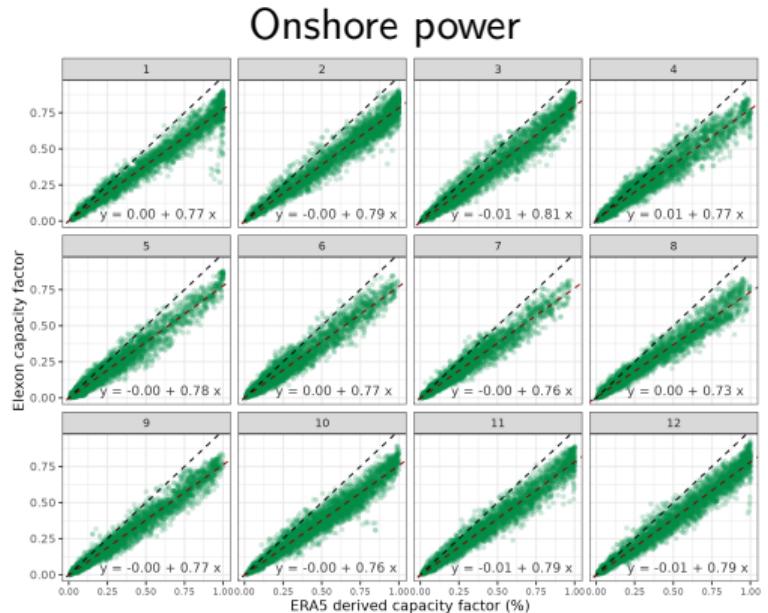
Density of Elexon and ERA5 based estimate



# Power curve by season

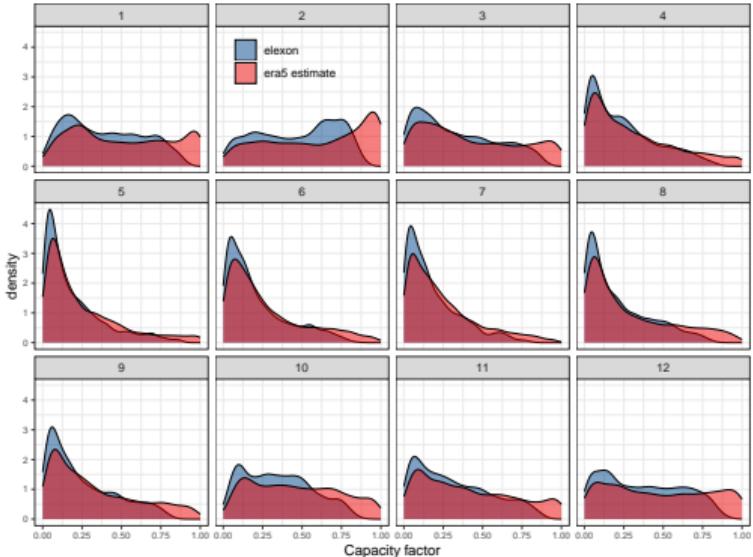


# Linear calibration by season

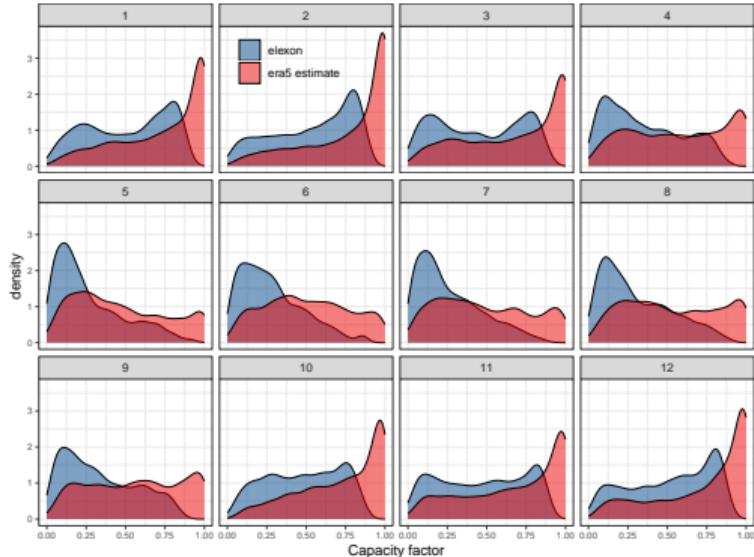


# Difference in density by season

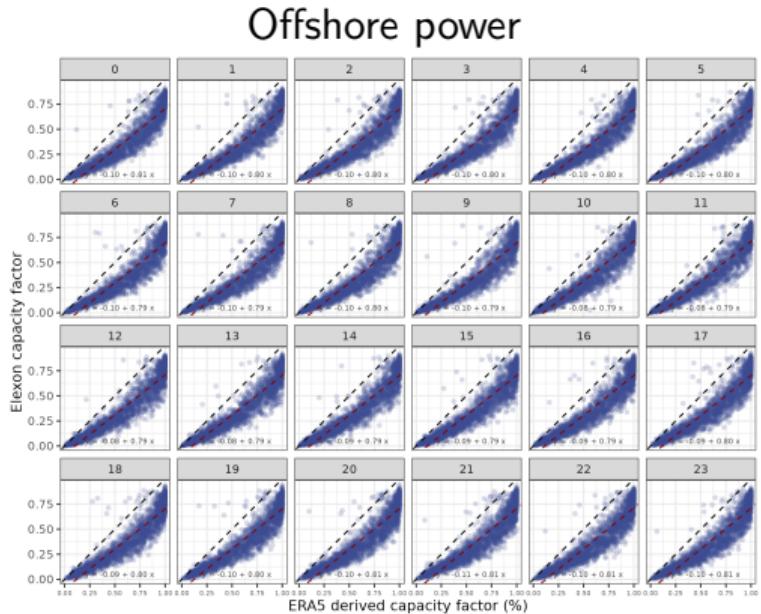
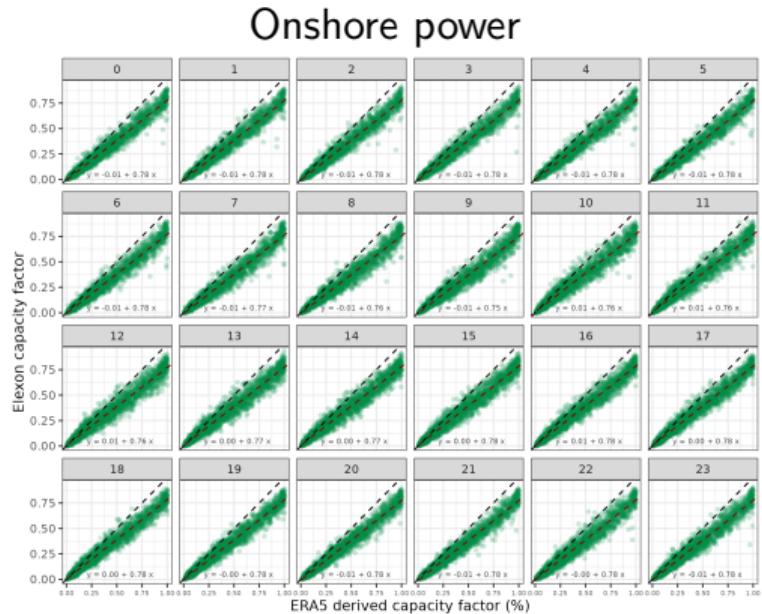
Onshore power



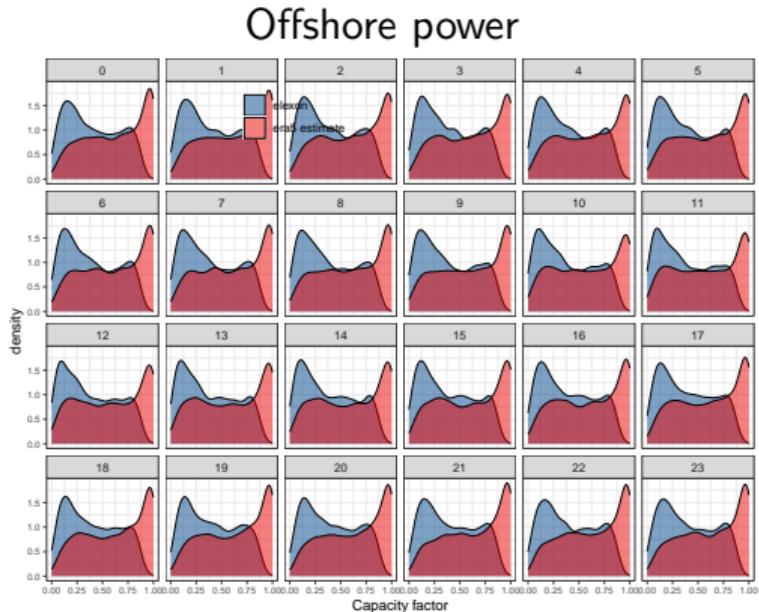
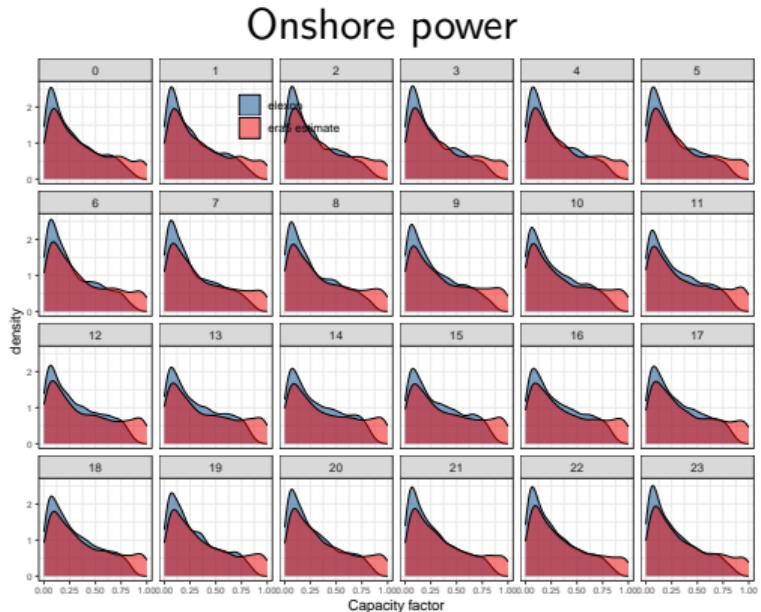
Offshore power



# Linear calibration by time of day



# Difference in density by hour



## Previous research

# Power curve modelling

Binning method

$$P_i = \frac{1}{n_i} \sum_{j=1}^{n_i} P_{ij}$$

where:  $P_{ij}$  is the  $j$  th power observation in bin  $i$  and  $n_i$  no. of observations in bin  $i$

Logistic

$$P(u) = a \frac{1 + m \exp(-u/\tau)}{1 + n \exp(-u/\tau)}$$

where  $a$  represents the upper asymptote,  $n, m$  shape the lower asymptote, and  $\tau$  controls the transition.

# Power curve modelling

5 parameter curve

$$P(u) = D + \frac{A - D}{(1 + (u/C)^B)^G}$$

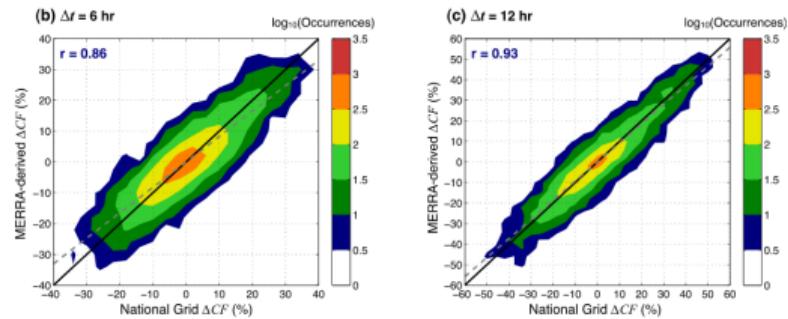
where:  $A$  and  $D$  are the upper and lower asymptotes,  $C$  is the inflection point,  $B$  the slope at inflection point, and  $G$  controls the asymmetry.

# Reanalysis data to quantify extreme wind power statistics

D. Cannon, D. Brayshaw, et. al (2015)

- MERRA wind speed validated with MIDAS
- Vertical interpolation with a logarithmic change
- Calibrated power curves based on manufacturers PC
- Use that to analyse extreme low and high levels, and ramps

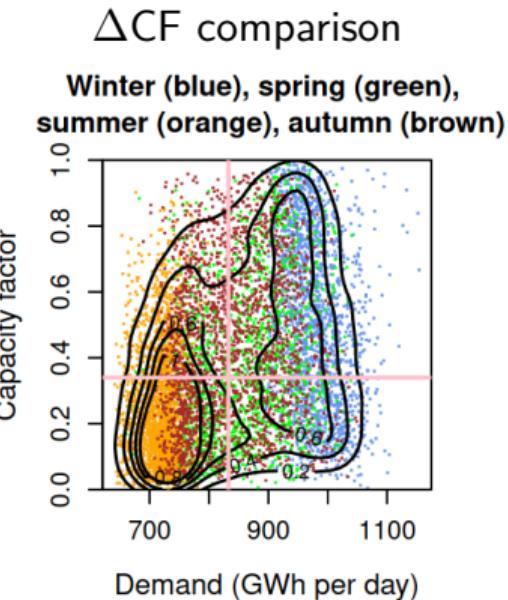
## $\Delta CF$ comparison



# Balancing energy

H. Thornton, D. Brayshaw analyse the relationship between weather, energy demand, and wind power.

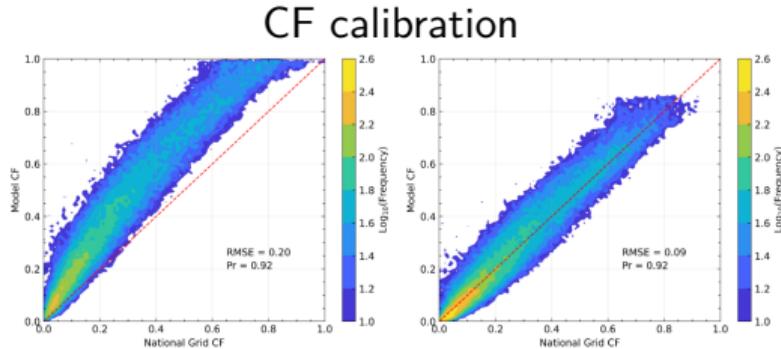
- ERA Interim wind speed
- Cubic power curve with air density correction
- CF compared with GB average from other studies
- Seasonal effects on Demand and



# Analysis of extreme wind droughts

Panit Potisomporn, C. Vogel (2024) perform a extreme value analysis of wind droughts in GB.

- Use ERA5 wind speeds calibrated to MIDAS with QM
- Build a ML algorithm that learns how to extrapolate wind speed from 10m to hub height
- Use a 5 parameter logistic function to model power curve
- Model energy losses with factors by type.



## Next Steps

- Power curve parametric model from data
- Check for spatial correlation
- Quantile mapping calibration