Leveraging turbine-level data for improved forecast performance

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- Overview of methodology
- Case Study and Results

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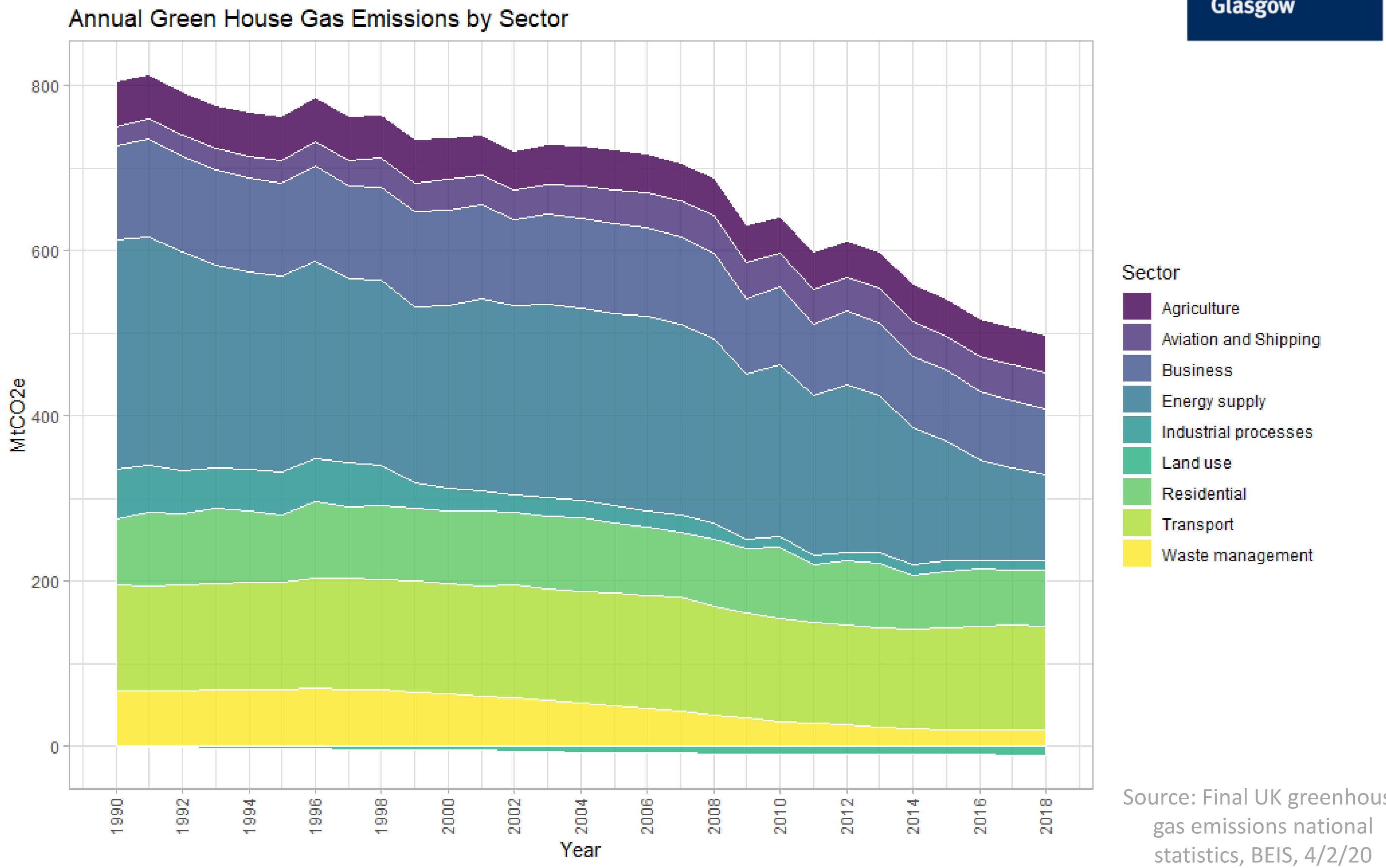


Source: Final UK greenhouse gas emissions national statistics, BEIS, 4/2/20

The future of forecasting for renewable energy

From on work with Conor Sweeney, Ricardo J. Bessa & Pierre Pinson

WIRES Energy and Environment
https://doi.org/10.1002/wene.365

Status Quo

- **National weather centres** produce global and regional numerical weather prediction (NWP)

Weather Forecasts

- **Forecast vendors** produce and sell site-specific weather and power forecasts

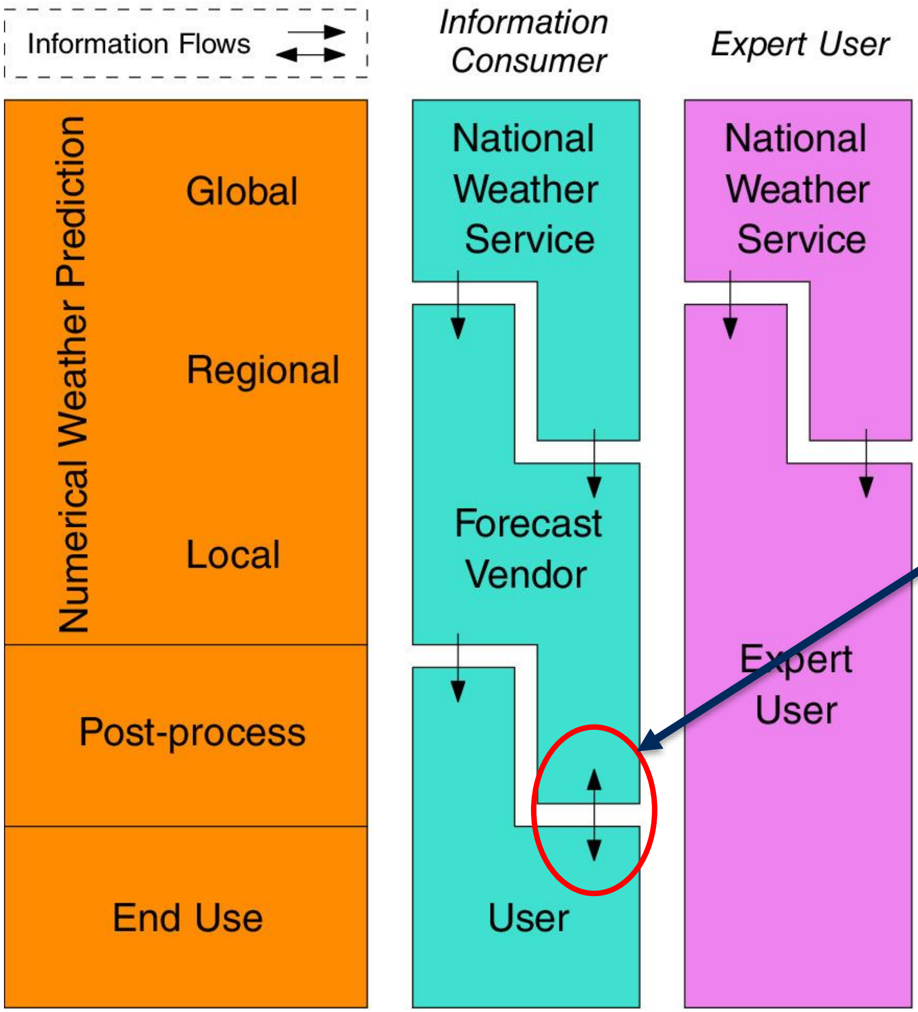
Specialised Weather and **Power** Forecasts

Software tools for interacting with forecasts

- **Forecast users** procure weather and/or power forecast to present to decision-makers on trading desks and in control rooms

Wide range of models from "in-house vendors" to complete dependency on service providers

Status Quo



Two-way data exchange required for quality forecast set-up

Live two-way data exchange required for very short-term forecasting

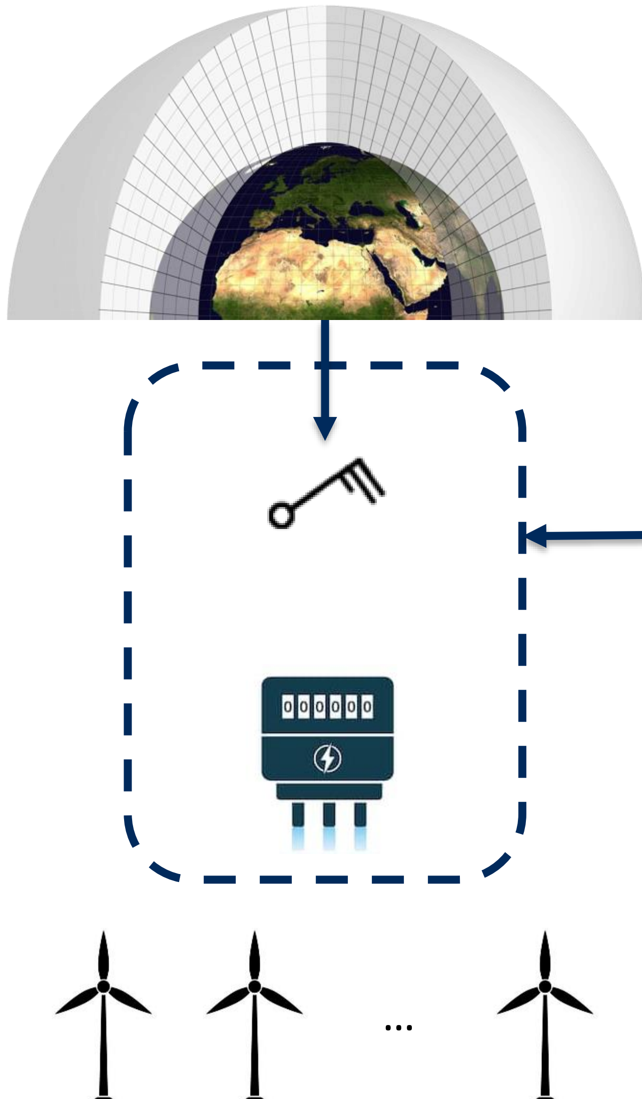
Status Quo

4D Grid of Weather Predictions

"Site" Wind Speed and Direction Forecast

Windfarm Export Meter

Wind Turbine SCADA

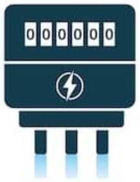


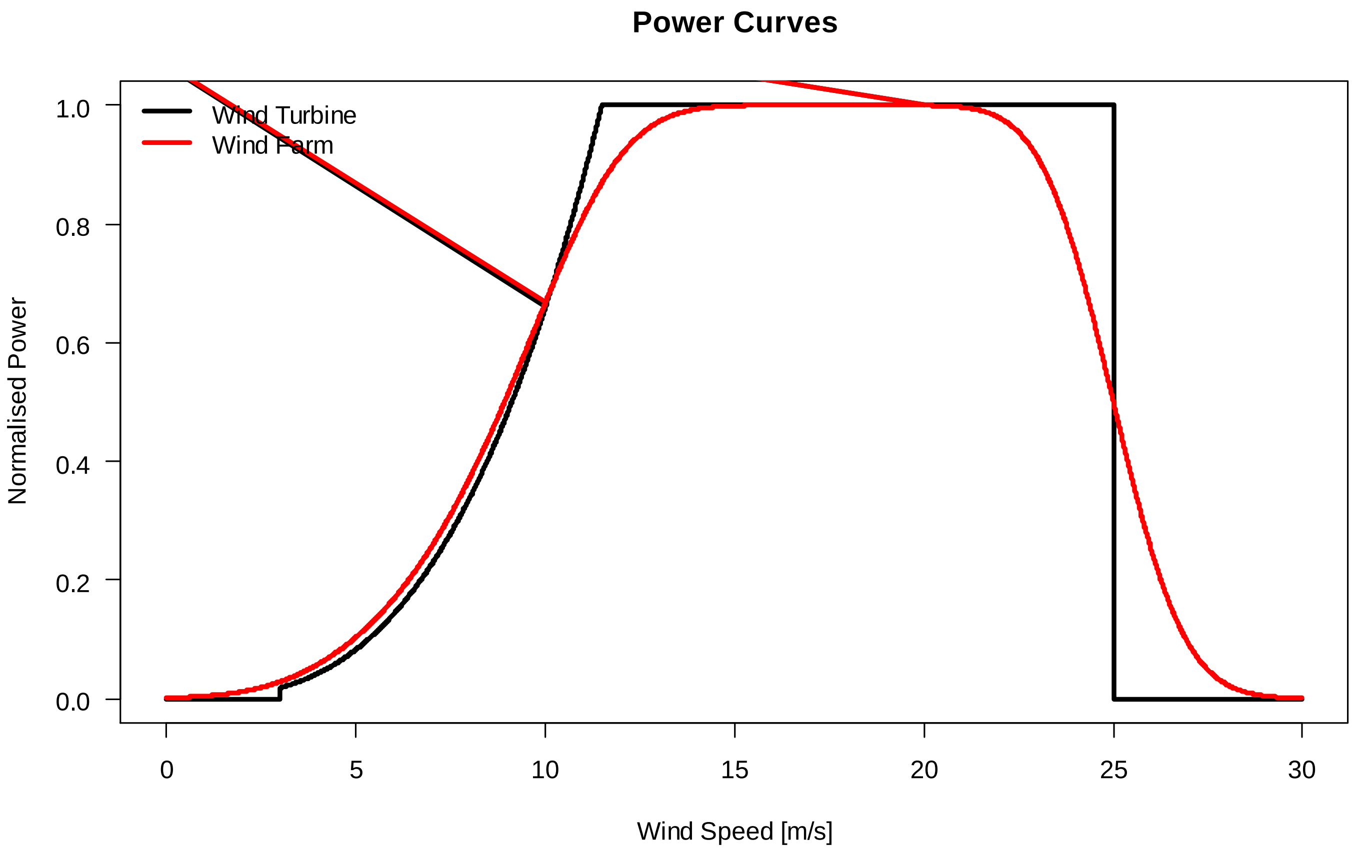
Weather-to-power relationship…

Based on farm-level power curve…

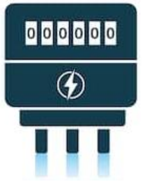
- Weather is a prediction, and therefore uncertain
- Single wind speed and direction for wind farm
- Wind farm power curve is complex and uncertain

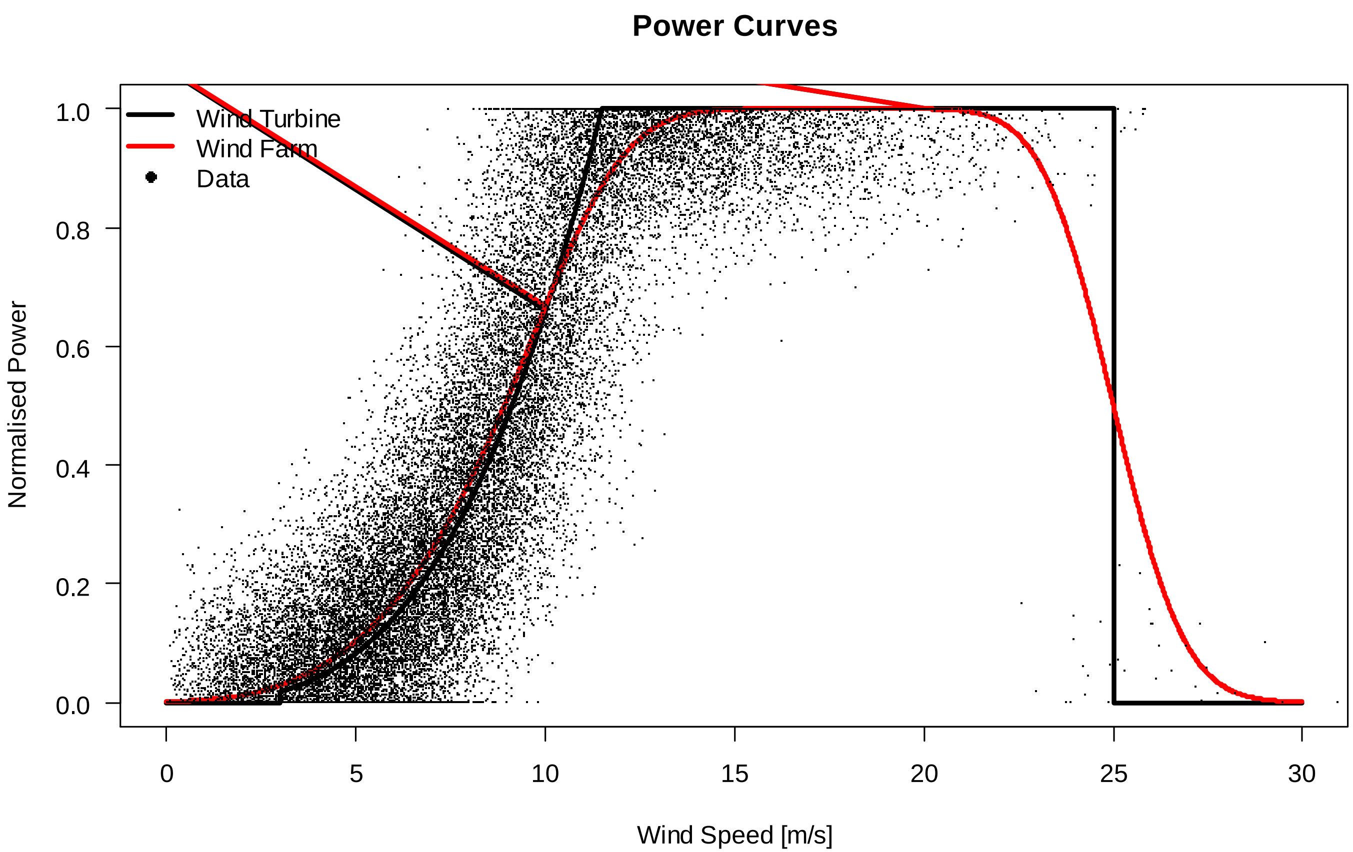
Status Quo




Power Curves
Wind Turbine
Wind Farm
Normalised Power
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25
30
Wind Speed [m/s]

Status Quo

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Data
Normalised Power
Wind Speed [m/s]

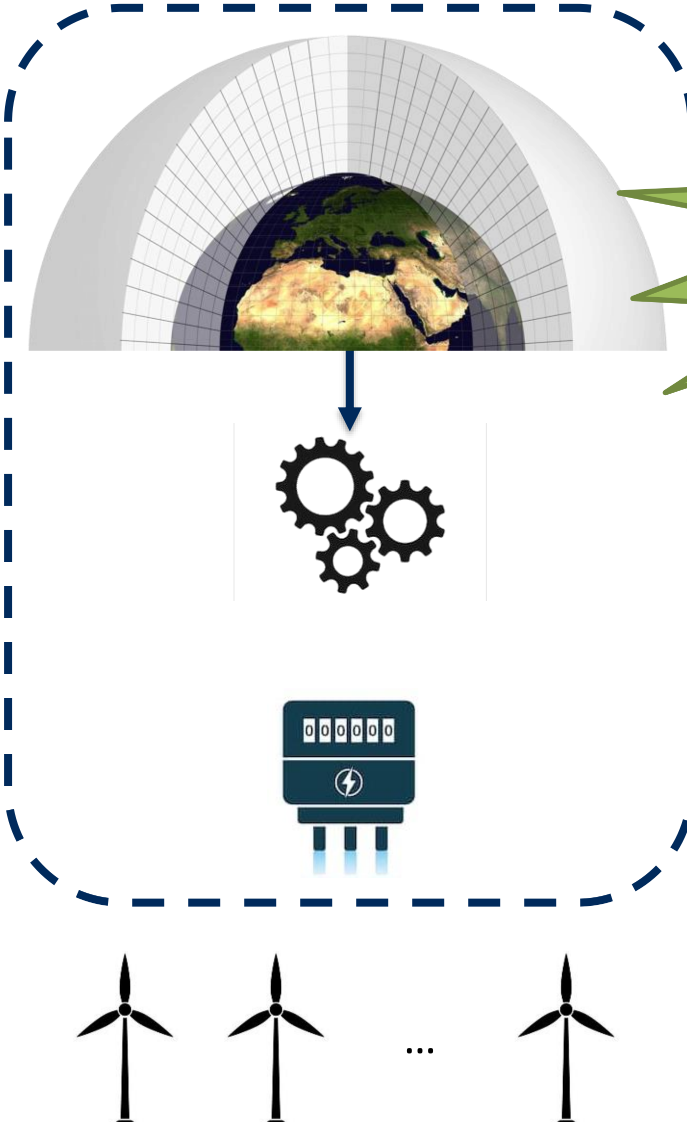
Recent evolution…

4D Grid of Weather Predictions

Feature Engineering

Windfarm Export Meter

Wind Turbine SCADA



>10% reduction in day-ahead MAE and CRPS*

Weather-to-power relationship…

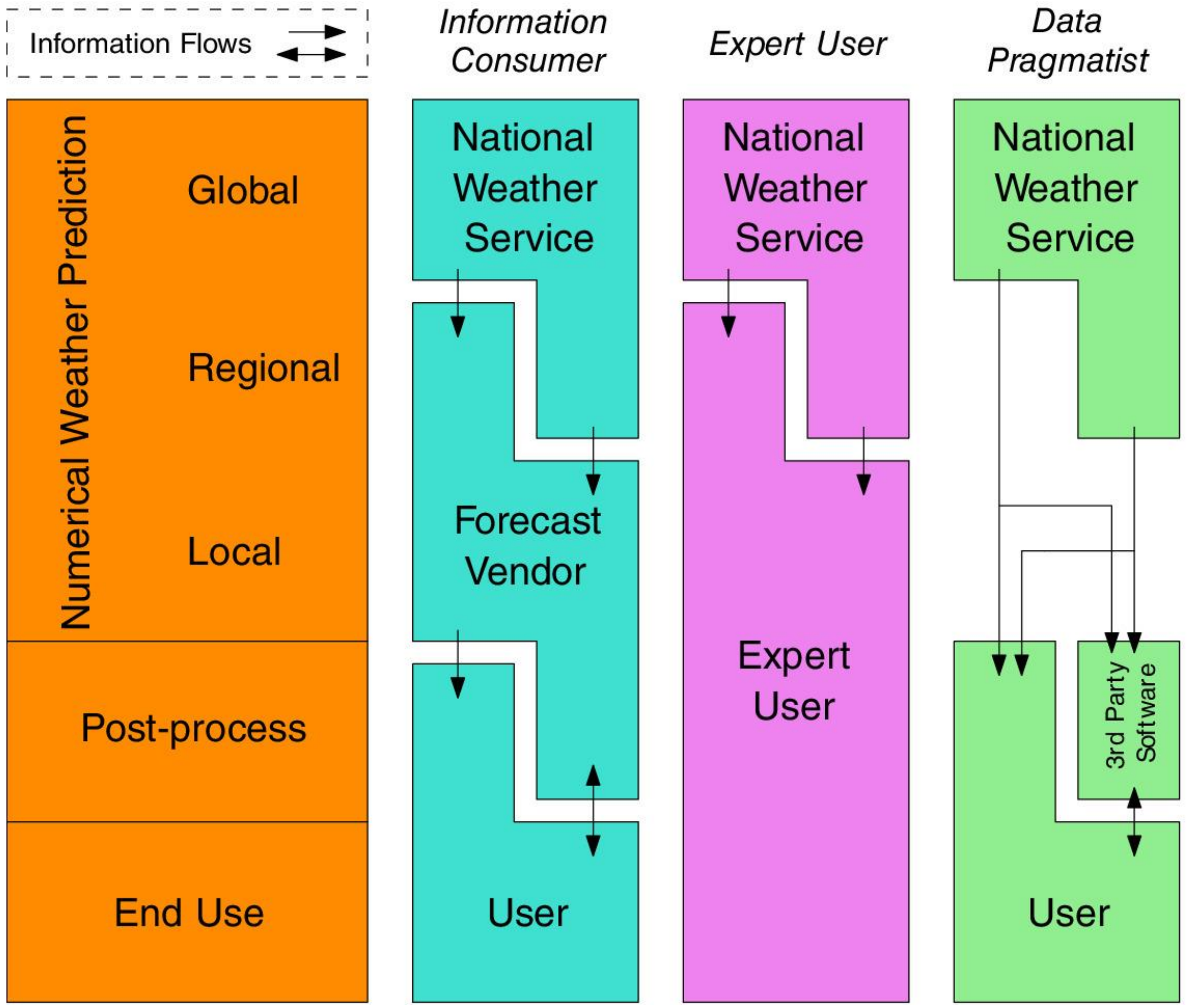
Complex farm power curve…

Engineered features capture:

- common NWP biases, phase and spatial errors
- variation across large areas
- wider weather situation and indicators of uncertainty

*Andrade & Bessa (2017), doi:10.1109/TSTE.2017.2694340

Innovation Reaching BAU



Vendors and expert users can incorporate this type of innovation very easily!

No new data sources or exchanges

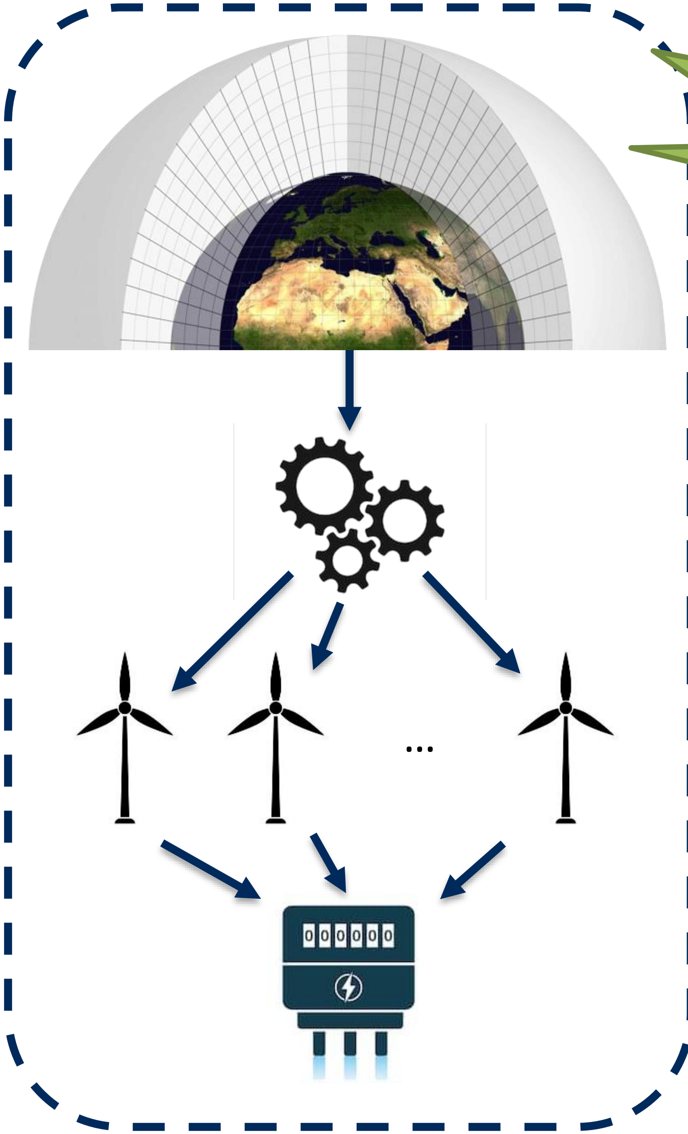
The next evolution?

4D Grid of Weather Predictions

Feature Engineering

Wind Turbine SCADA

Windfarm Export Meter



>5% reduction in day-ahead MAE and CRPS*

Weather-to-power relationship…

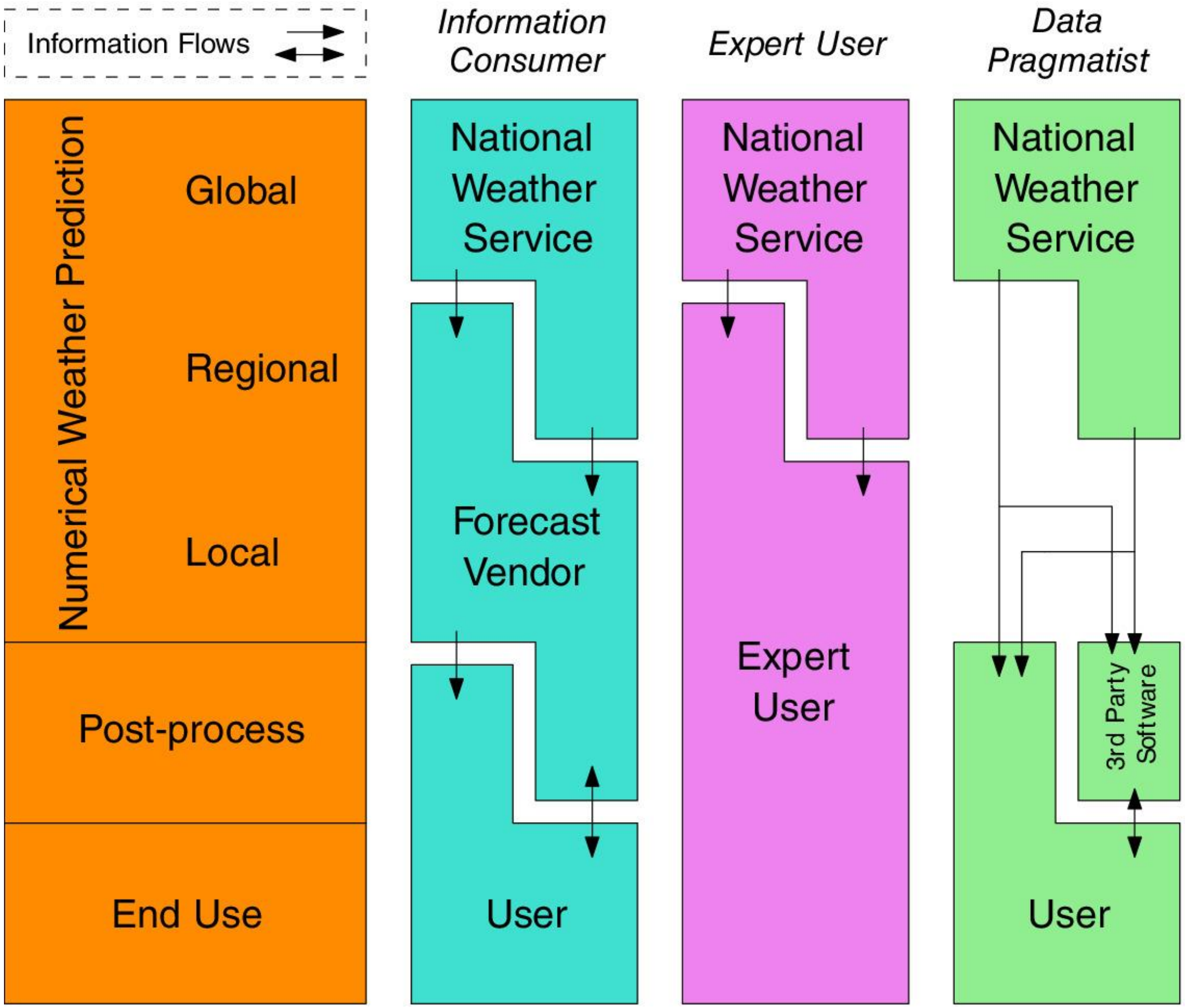
Complex ***turbine*** power curves…

Turbine-level data enables:

- reduction in epistemic uncertainty
- direct incorporation of availability
- advanced very short-term forecasting

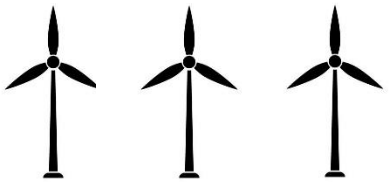
*Gilbert, Browell & McMillan (2019), doi:10.1109/TSTE.2019.2920085

The next evolution?

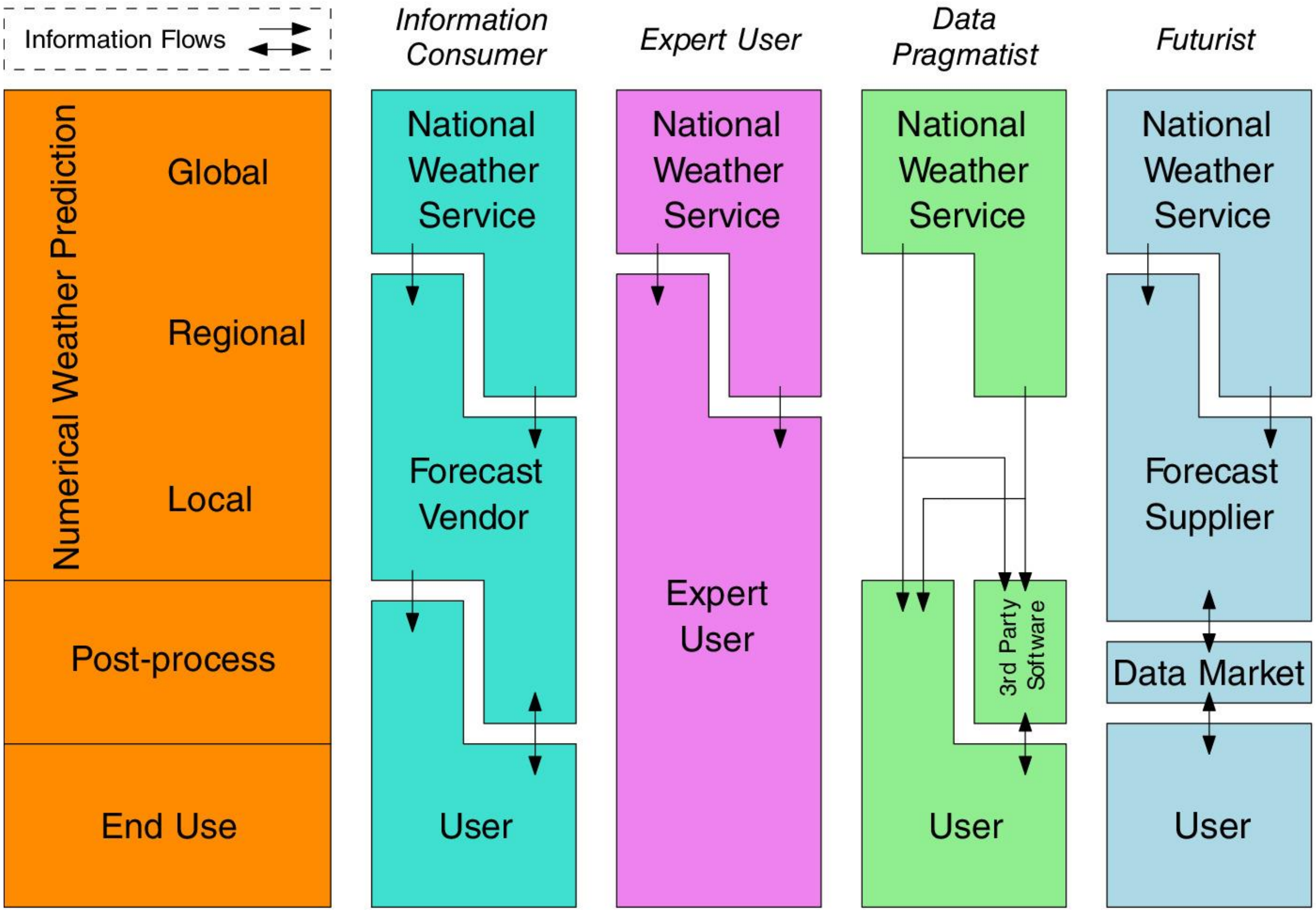


New data:
Turbine SCADA is voluminous and messy

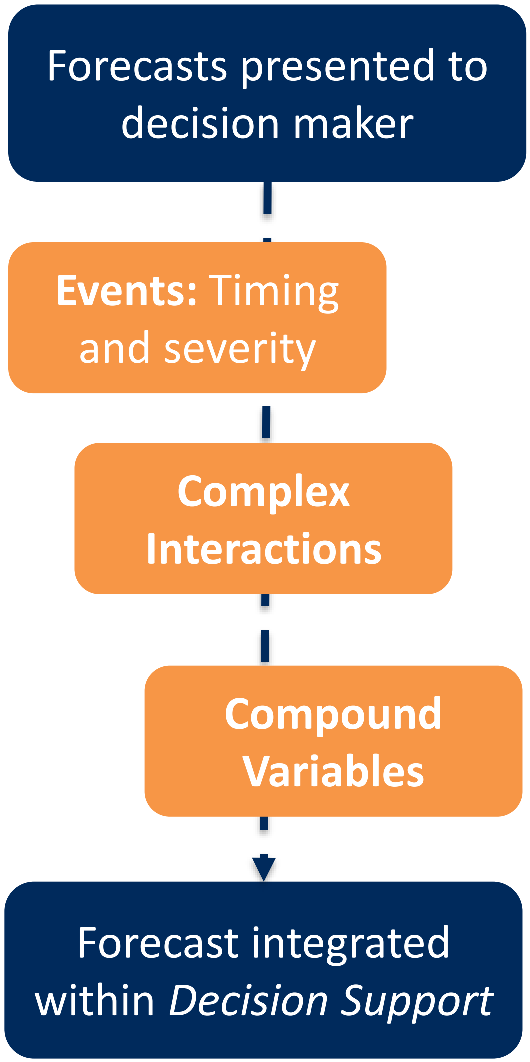
For 3rd party providers:
New info exchange required
OR
Offer as a software product



Something completely different…



What do we want to predict anyway?



- **Energy:** Blocks of energy for trading and generator scheduling
- **Power:** ramps for system operation; instantaneous power for ancillary service provision
- **Interdependency with markets:** risk management**,** algorithmic trading
- **Network flows/constraints:** constraint management and regional balancing

Leveraging turbine-level data for wind power forecasting

Work with Ciaran Gilbert and David McMillan

IEEE Trans. Sustainable Energy
https://doi.org/10.1109/TSTE.2019.2920085

Hierarchies in Forecasting

Motivation:

1. Gather as much information as possible to improve forecast skill
   - Electricity network is a natural hierarchy
   - Turbine – Farm – Region – National/Zone
   - Information from other levels can improve predictive performance
2. Coherency across hierarchy
   - Some applications require that forecasts from lower level to sum to upper level, e.g. market settlement

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Hierarchies in Forecasting

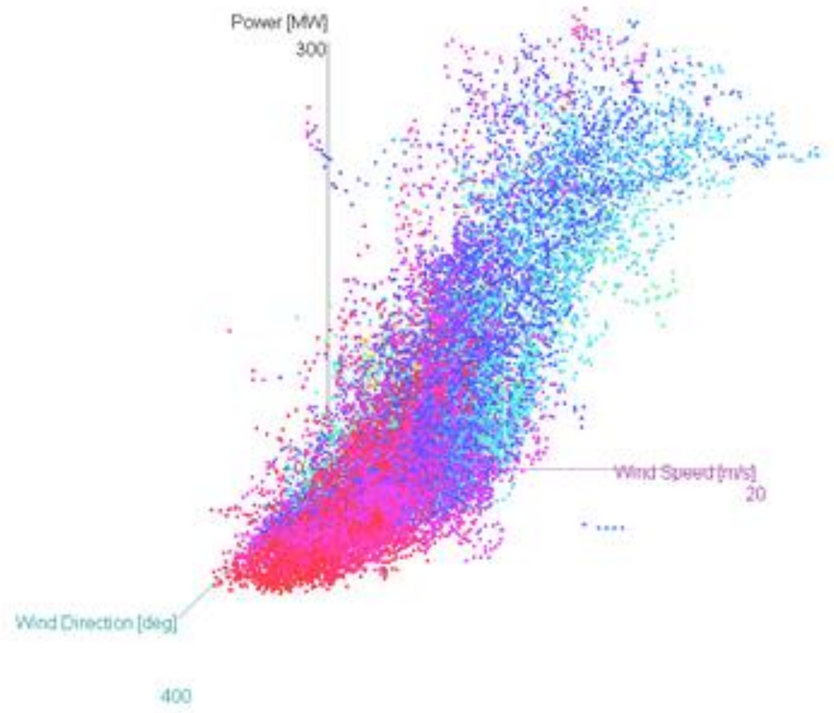
- Wind farm power curve is complicated by many factors: layout, terrain, interactions

- It is difficult to distinguish between random variation and true processes…

Smoothing vs Training Error

- …can looking at individual turbine behaviours can help extract more signal from the noise?

Hierarchies in Forecasting



Methodology Overview

University of Strathclyde Glasgow

Objective

- Produce probabilistic (density) forecasts
- Extend forecasting methodologies to incorporate turbine-level information

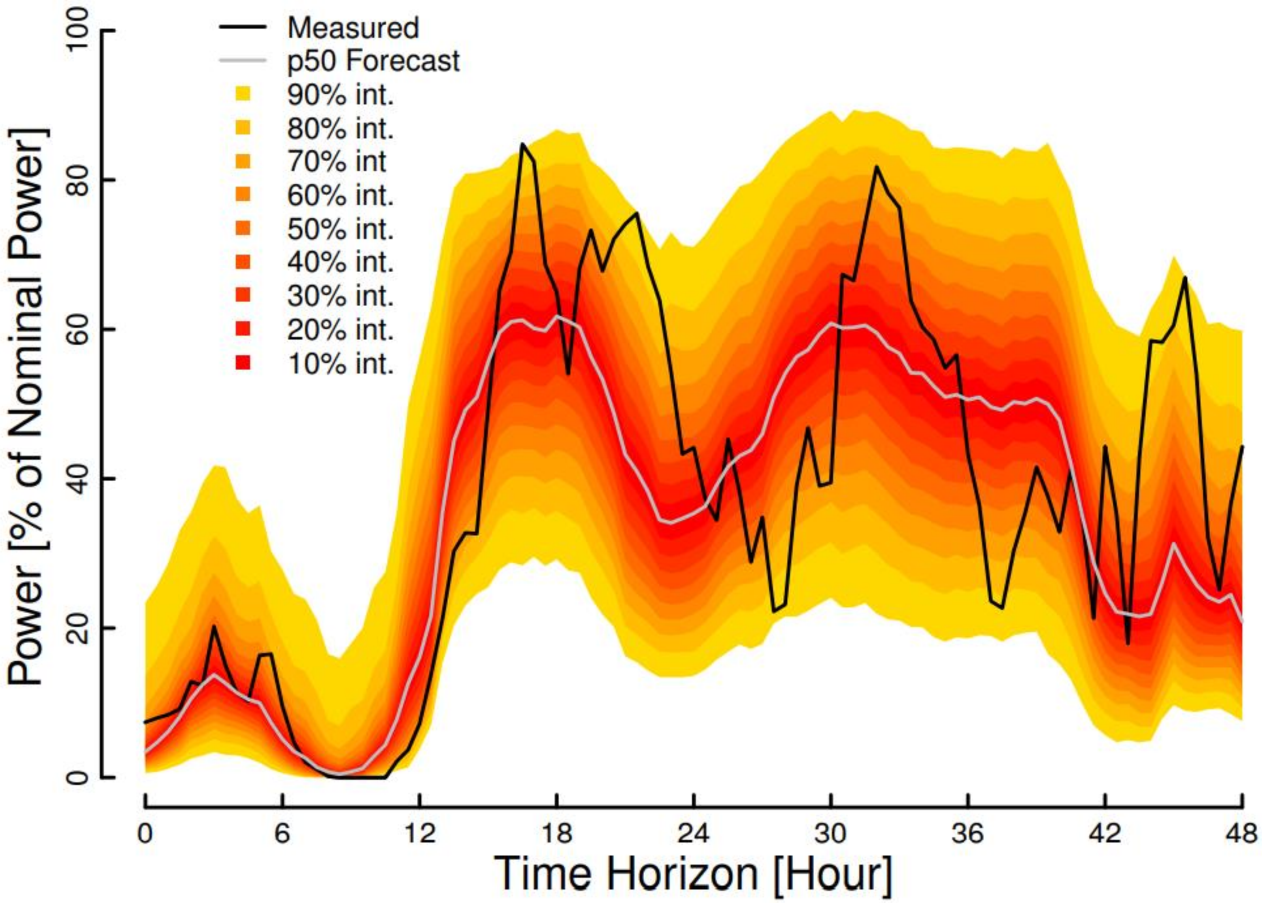
New Approaches

1. Bottom-up: make predictions for individual turbines and use as additional explanatory information
2. Spatial Dependency: predict the full joint distribution of output from all turbines in a wind farm

Benchmarks (using NWP and windfarm data only)

1. Analog Ensemble (*k*NN) – super robust and competitive
2. GBM/quantile regression – leading machine learning algorithm

Objective: Density Forecasts



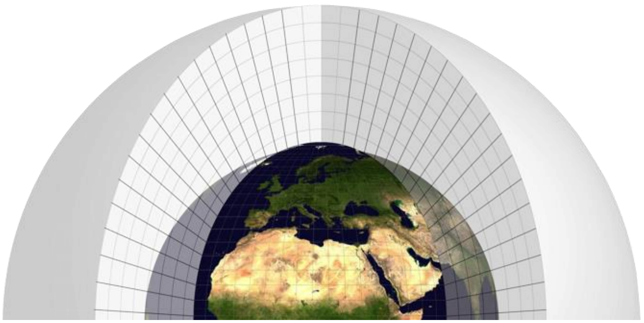
Benchmark

GBM

- Gradient Boosted Decision Tree – a powerful non-linear function approximator
- Quantile regression: one model per quantile: 5,…,95
- Inputs: features derived from NWP
- Target: Windfarm power

Density forecast for wind farm

$$q^{\alpha} = f^{\alpha}_{\mathrm{GBM}}(\boldsymbol{x}_{\mathrm{NWP}})$$



Bottom-up Approach

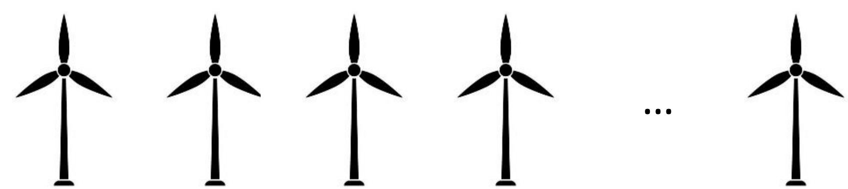
Bottom-up

1. Produce deterministic forecasts for each individual turbine
2. Use these as ***additional features*** in a windfarm power forecasting model

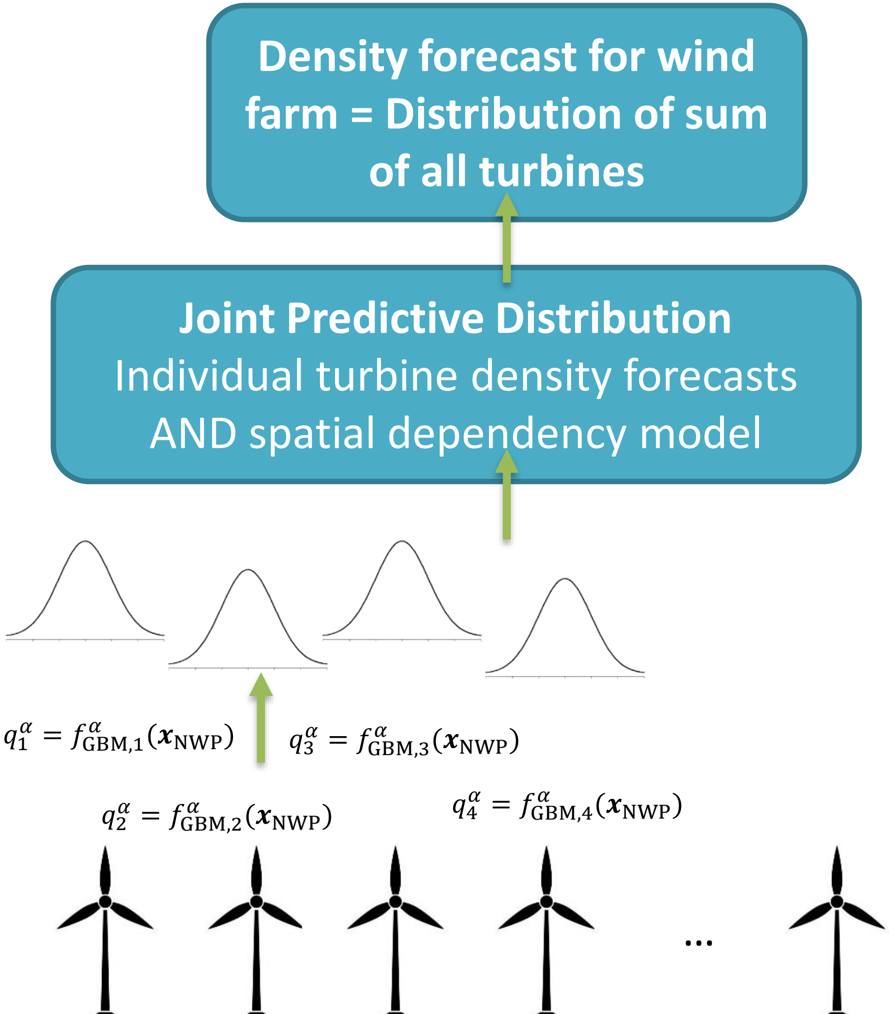
Density forecast for wind farm

$$q^{\alpha} = f^{\alpha}_{\mathrm{GBM}}(\boldsymbol{x}_{\mathrm{NWP}}, \boldsymbol{x}_1, \dots, \boldsymbol{x}_N)$$

$\boldsymbol{x}_{(1)}$ $\boldsymbol{x}_{(2)}$ $\boldsymbol{x}_{(3)}$ $\boldsymbol{x}_{(4)}$ … $\boldsymbol{x}_{(N)}$



Spatial Dependency Approach



Spatial Dependency Approach

1. Produce density forecast for each turbine
2. Model spatial dependency using Gaussian copula with parametric covariance
3. Sample and sum turbine power prediction
4. Construct wind farm density forecast from samples

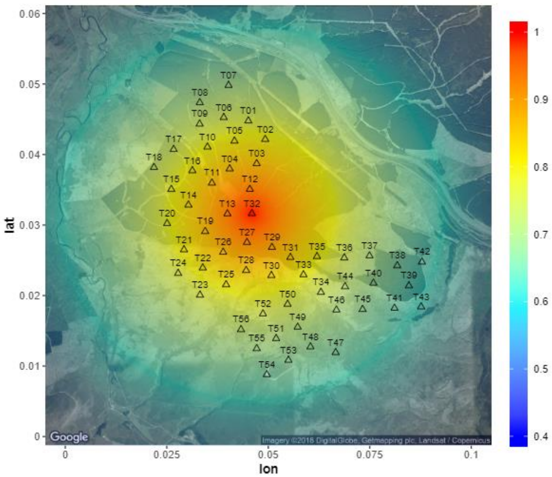
Additional Benchmarks:

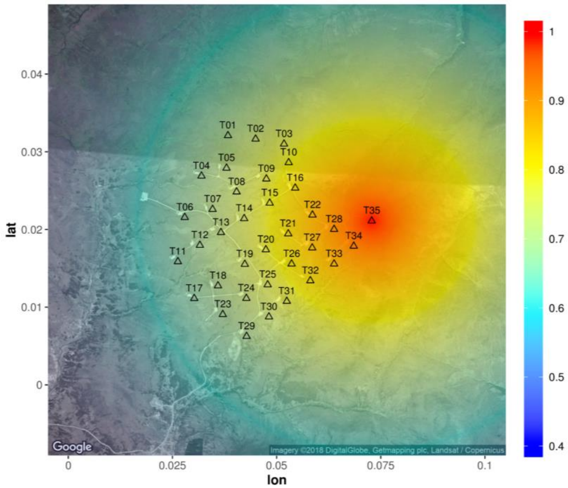
1. Empirical Covariance (data-driven)
2. Vine Copula (facilitates more complex spatial structure)

Case Study

Set up

- 2 Wind Farms with 56 and 35 turbines
- NWP inputs plus ***engineered features***
- 30 minute wind farm production
- 30 minute wind turbine production
- Produce probabilistic (density) forecasts up to 48h ahead

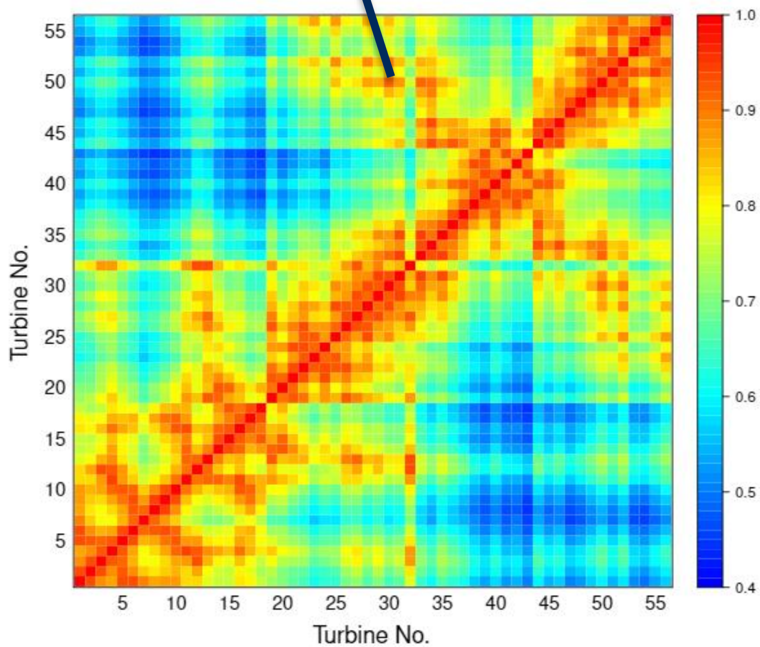


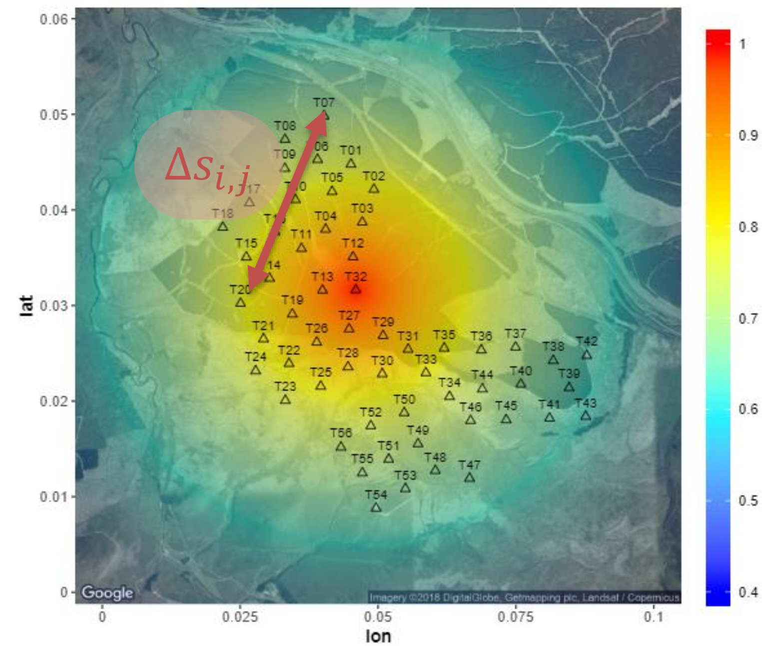


Spatial Structure at WF-A

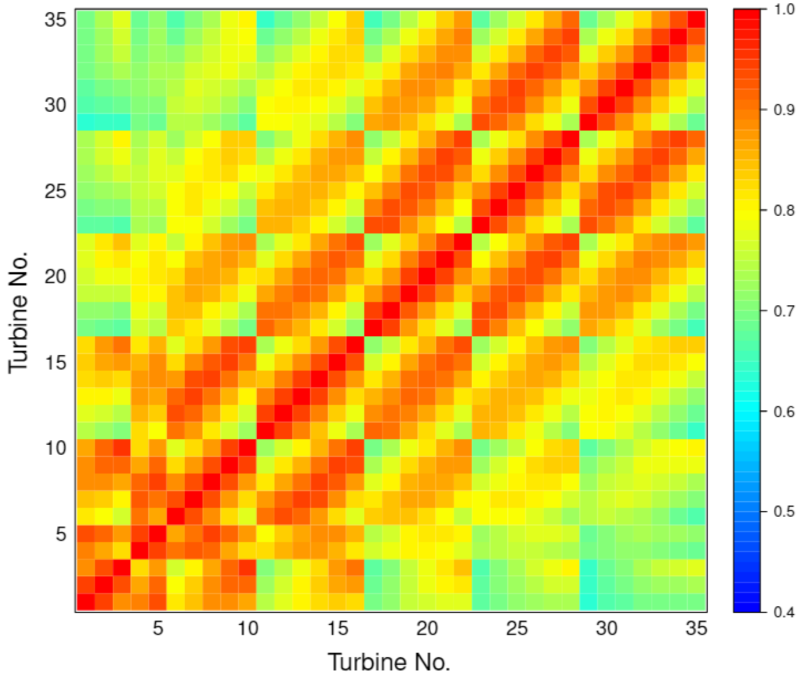
$$\Sigma_{i,j} = \exp\left(-\frac{\Delta s_{i,j}}{\eta}\right)$$

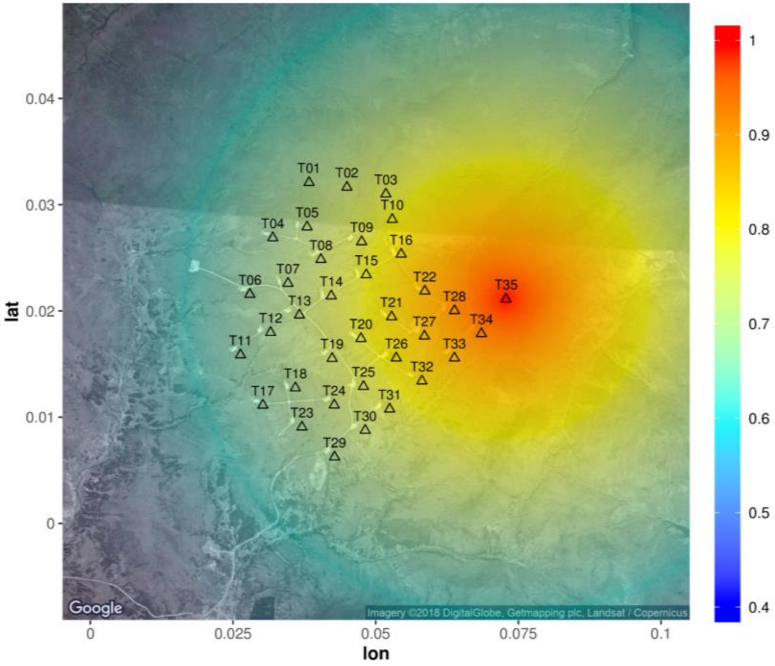
Only one parameter to estimate



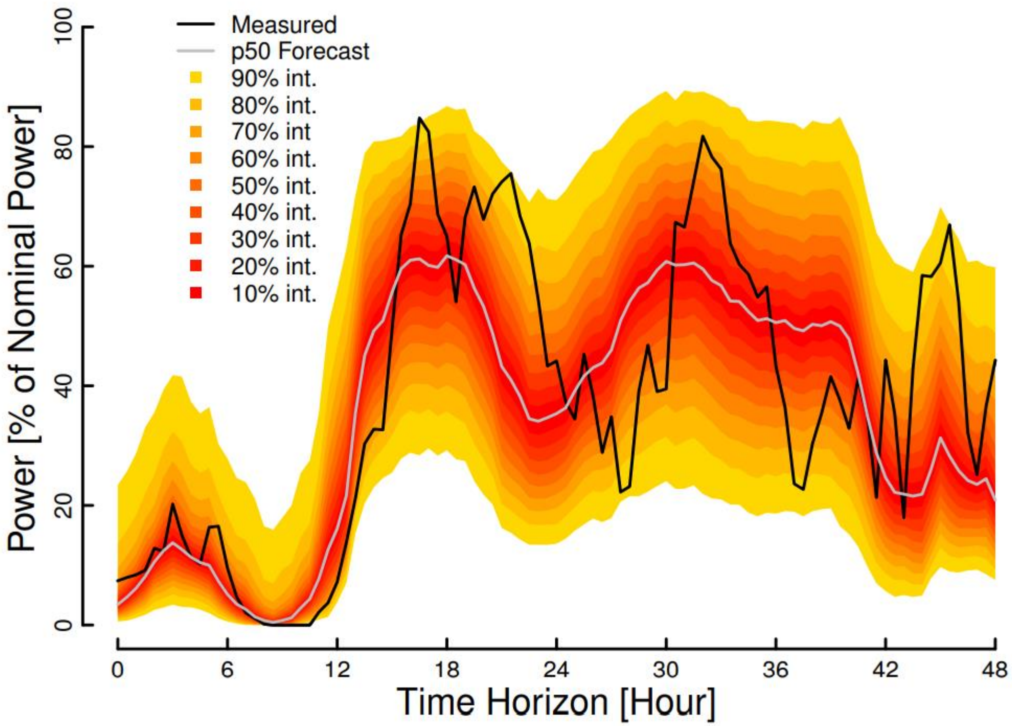


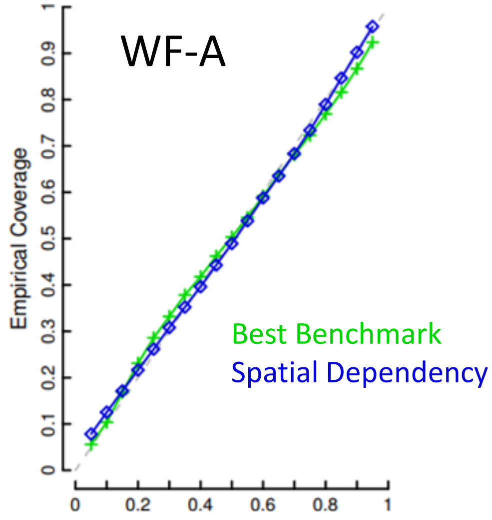
Spatial Structure at WF-B

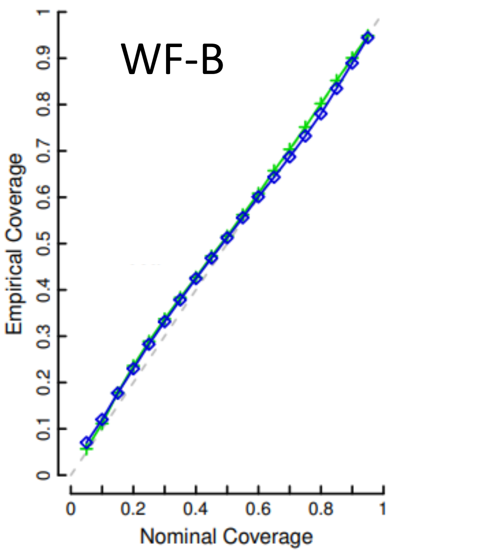




Results: Reliability

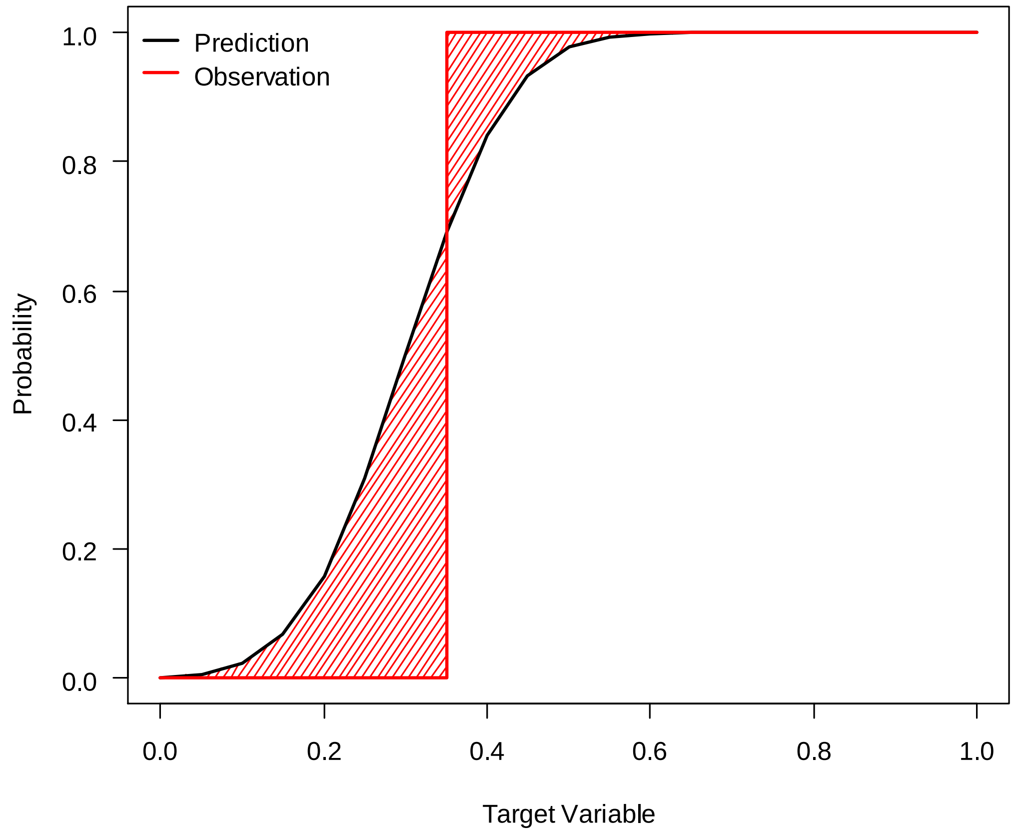






Results: CRPS

Continuous Ranked Probability Score



Rewards both sharpness and reliability

Continuous form of quantile loss

Results: Scores

University of Strathclyde Glasgow

Windfarm	Score	Best Benchmark	Bottom-up	Full Spatial Model
WF-A	**MAE**	9.69	9.27	***9.11*** *(6%)*
	CRPS	7.02	6.74	***6.66*** *(5%)*
WF-B	**MAE**	11.39	***11.21*** *(2%)*	11.26
	CRPS	8.10	***8.00*** *(1%)*	8.02

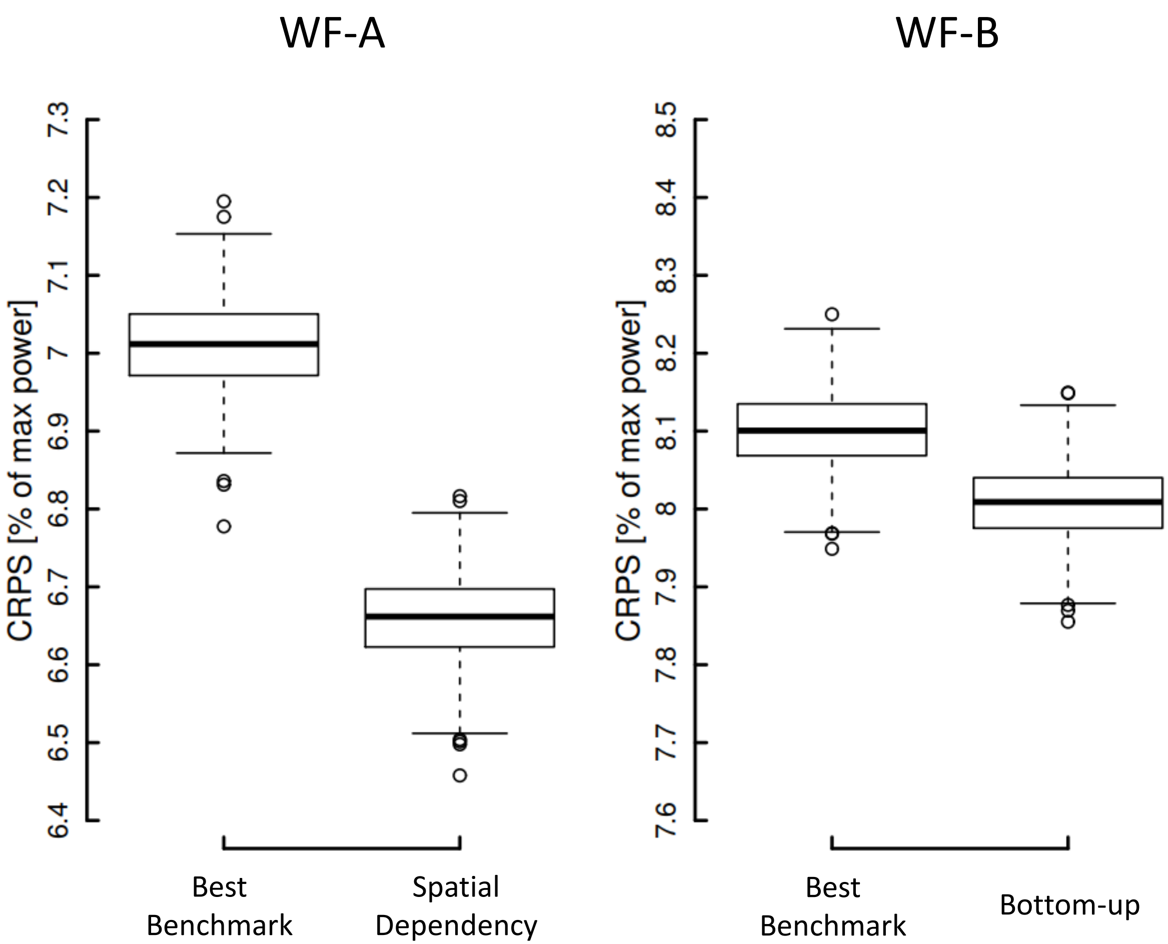
Additional benchmarks…

Empirical Covariance and Vine Copula

…performance a little worse than parametric covariance model.

Results: Scores

Significance of improvement: sampling variation



Forthcoming paper on forecast evaluation in *Wind Energy* by Messner, Browell *et al.*

Summary

- Forecasting practice is evolving rapidly, recent advances coming from data science
  - New business models may emerge as a result
  - Forecasts should get a little better
  - Potentially more ***value*** will come from improving the way we use forecast information in the future…

- We can leverage existing data to improve wind power forecast with software alone!

- Ongoing research includes:
  - Forecasting **ancillary service capability** using high-resolution SCADA (when minimum *instantaneous* power is key)
  - Hierarchical and **spatio-temporal dependency** on Site-Region-National scale
  - **Decision-support** for spatially-constrained problems: regional balancing, network constraints (wind and net-demand)

Thanks! Questions?

Papers and more at jethrobrowell.com