IEA Wind Task 36 Workshop on **Best Practice in the Use of Forecasting in the Power Industry**

University of Strathclyde, Glasgow, UK
21 January 2020

Housekeeping

Time	Description	Presenter/Chair
09:15	Welcome and Introduction	Gregor Giebel (DTU) & Jethro Browell (Strathclyde)
09:30	Presentation: *Leveraging turbine-level data for improved forecast performance*	Jethro Browell (Strathclyde)
10:00	Presentation: *IEA Wind Recommended Practice on Renewable Energy Forecast Solution Selection*	John Zack (AWS Truepower)
10:40	***Coffee***	
11:00	Presentation: *Definitely Uncertain - Wind Power Probability Forecasting*	David Lenaghan (National Grid ESO)
11:30	Presentation: *Benefits of Probabilistic Forecasting in Electricity Trading - a few real world examples*	Tilman Koblitz (WindPoint)
12:00	Forecasting Game	Corinna Möhrlen (WEPROG)
12:30	***Lunch***	
13:30	OpenSpace Discussion and Forecasting Game Analysis	Corinna Möhrlen (WEPROG) and IEA Task Representatives
15:10	***Coffee***	
15:30	Panel: *Bridging the gap between forecast innovation and business as usual*	Industry and IEA Task Representatives
16:45	Closing Remarks	Gregor Giebel (DTU)

- Fire alarm test
- Evening meal

Leveraging turbine-level data for improved forecast performance

Dr Jethro Browell
Research Fellow

University of Strathclyde, Glasgow, UK
jethro.browell@strath.ac.uk

IEA Wind Task 36 Workshop
21 January 2020, Glasgow

Contents

Part 1: The future of forecasting for renewable energy, an academic perspective

- Status quo in wind power forecasting
- Evolving business models in wind power forecasting
- Where does innovation fit in?

Part 2: Leveraging all of that SCADA data operators have been studiously archiving…

- Overview of methodology
- Case Study and Results

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

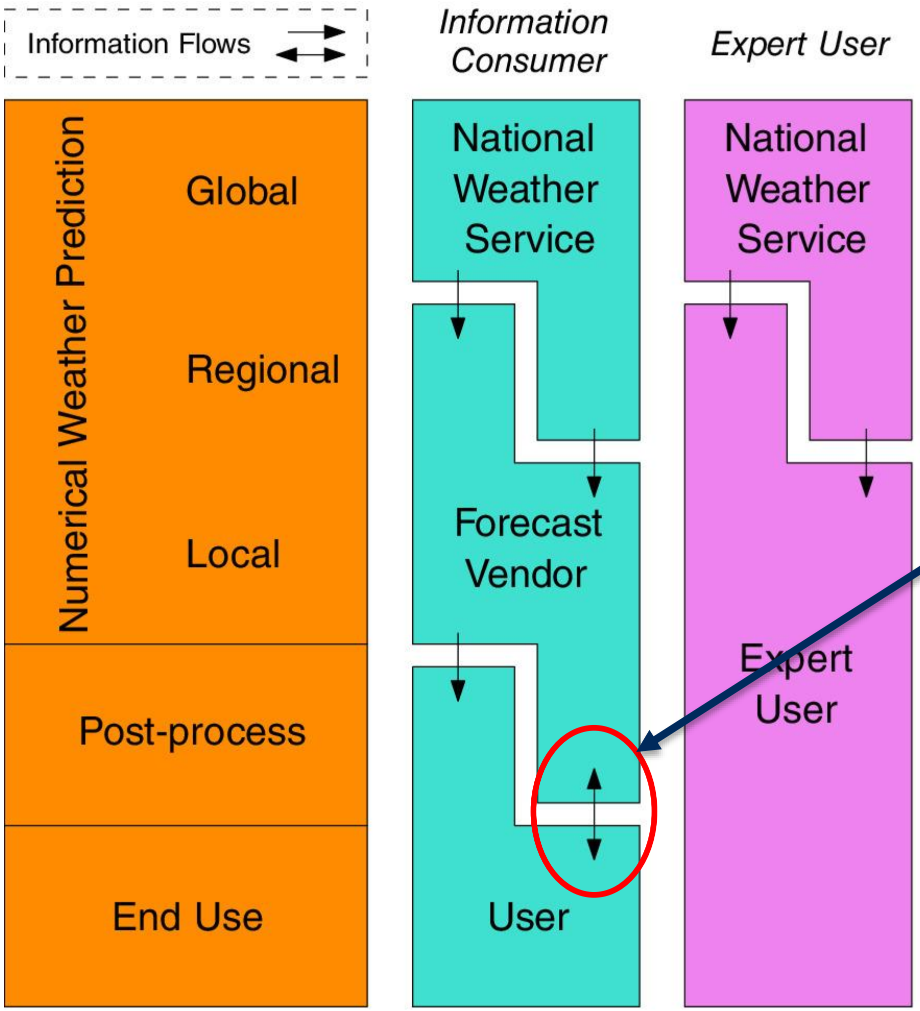
Specialised Weather and **Power** Forecasts

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

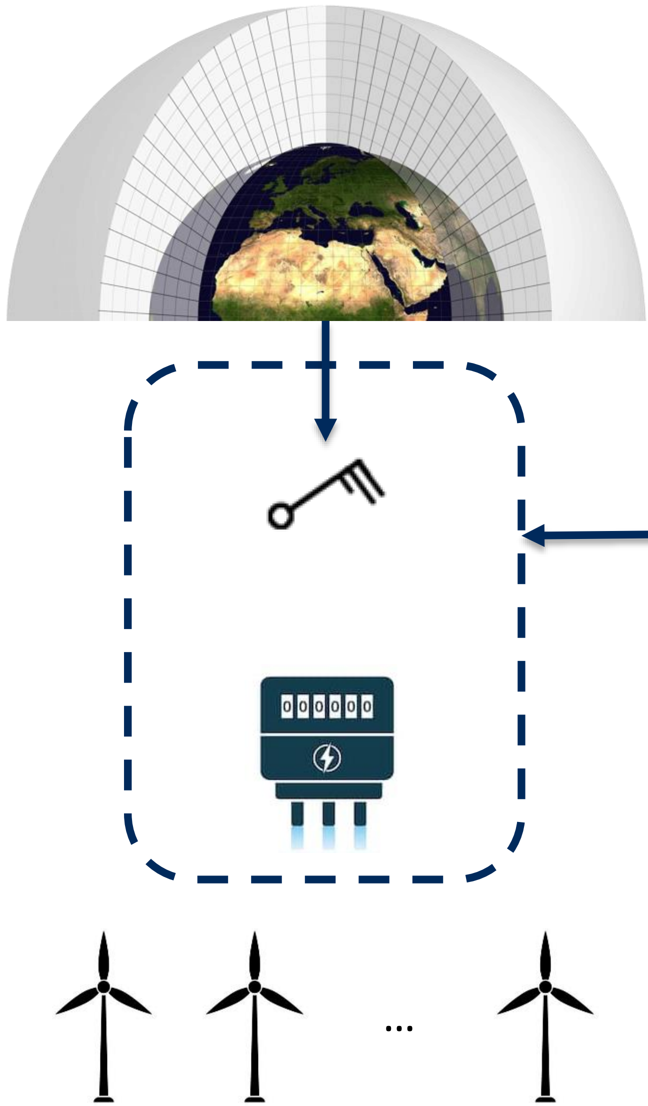


Two-way data exchange required for quality forecast set-up

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

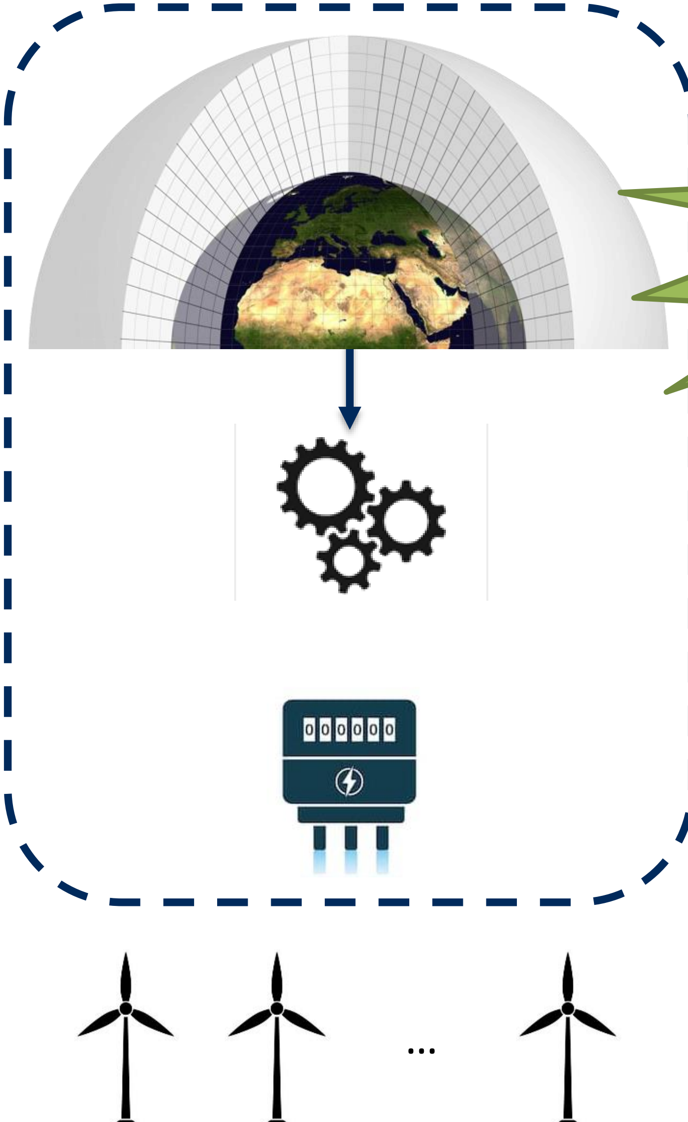
Recent evolution…

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…

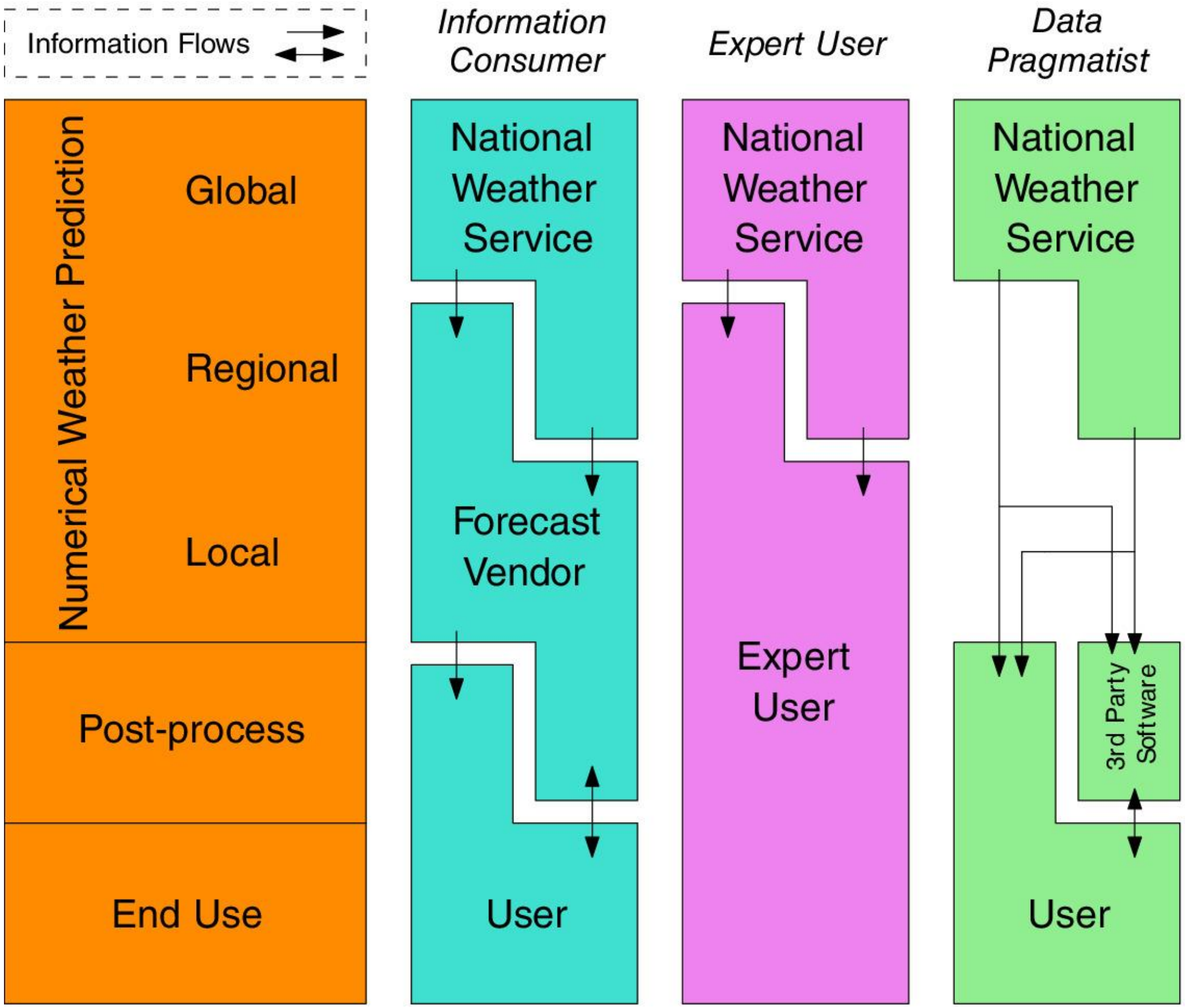
Complex farm power curve…

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

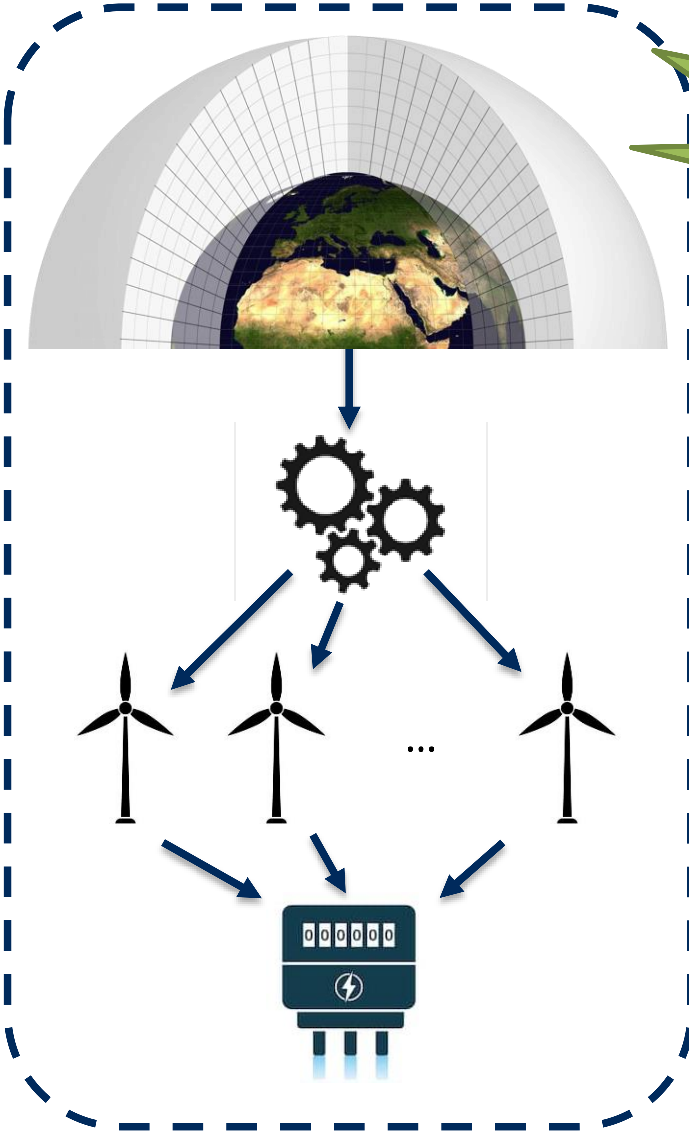
The next evolution?

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…

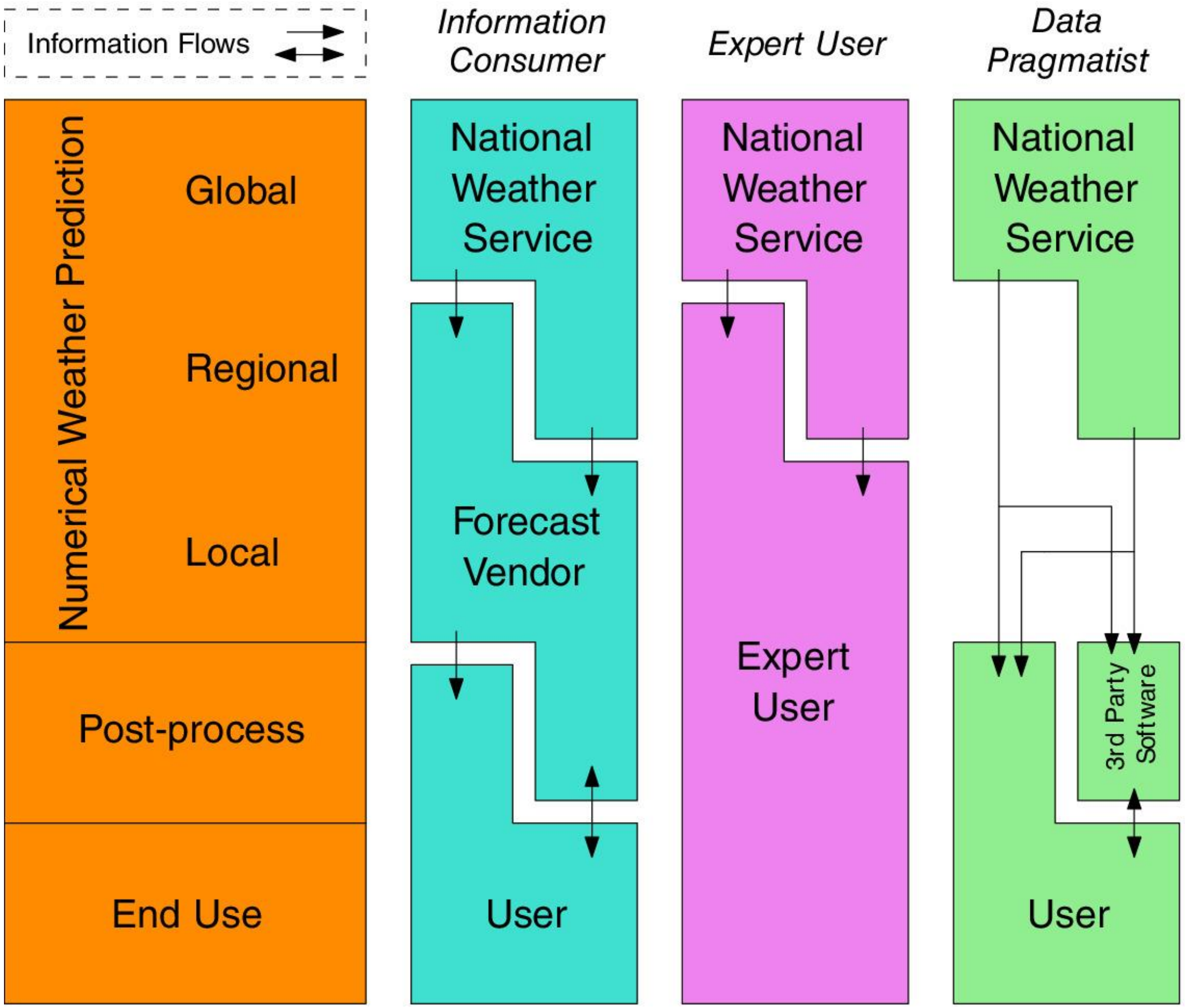
Complex ***turbine*** power curves…

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

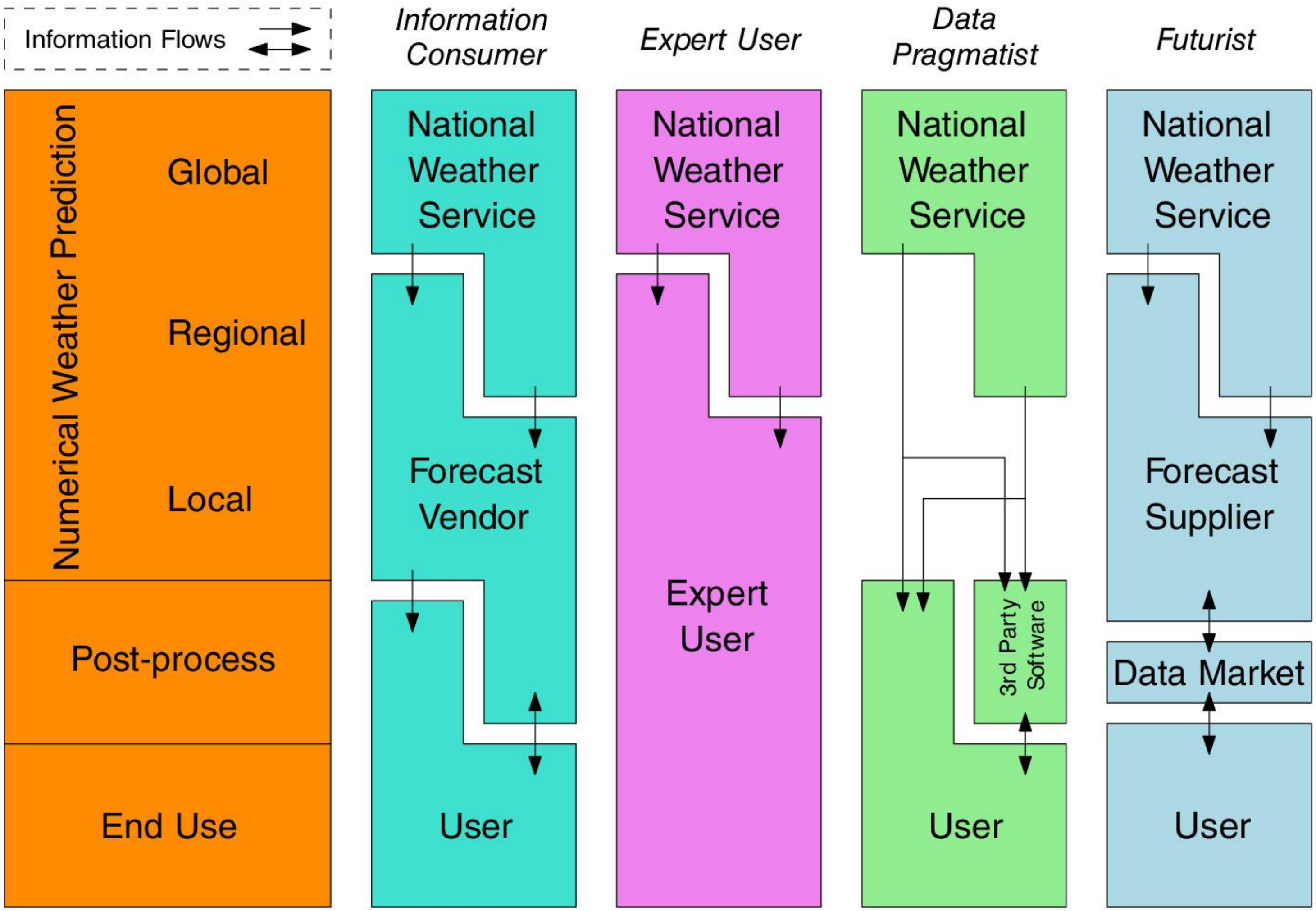
The next evolution?



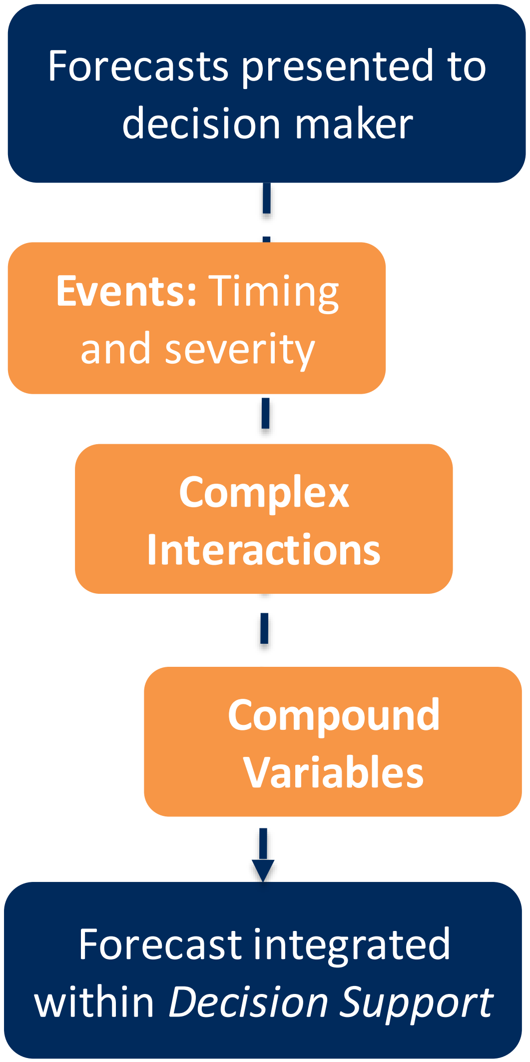
New data:
Turbine SCADA is voluminous and messy

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

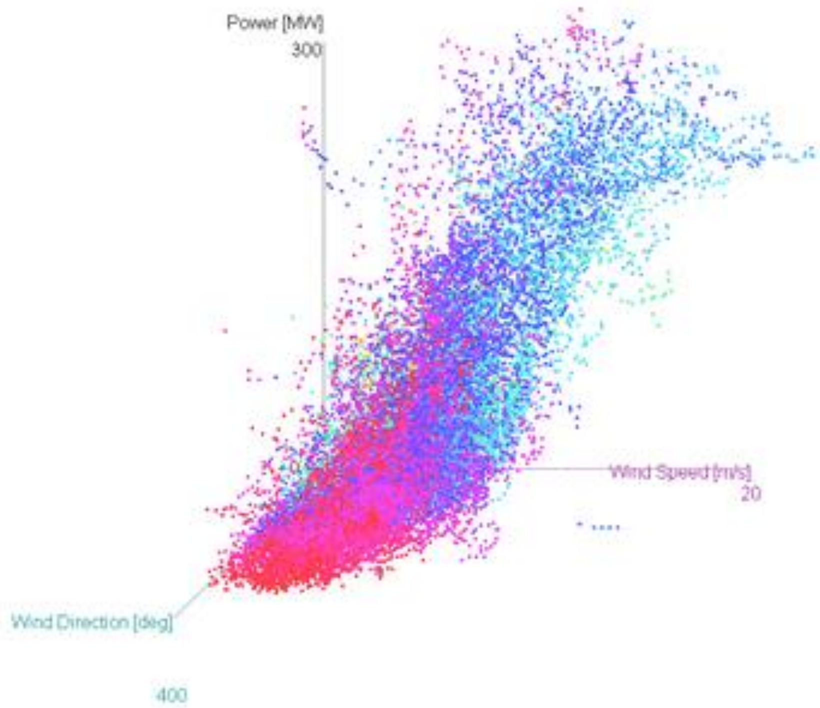
- Wind farm power curve is complicated by many factors: layout, terrain, interactions

- 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



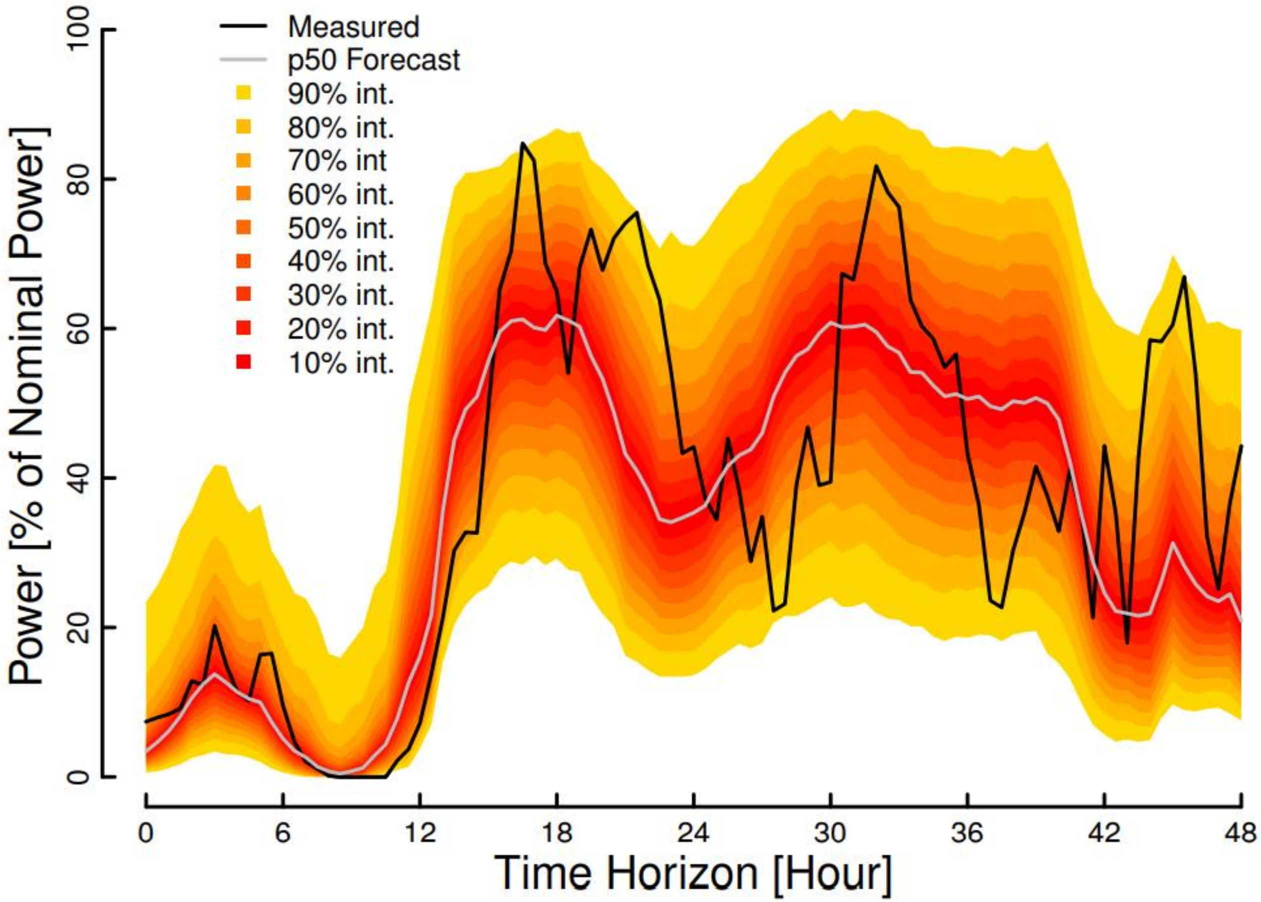
Methodology Overview

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



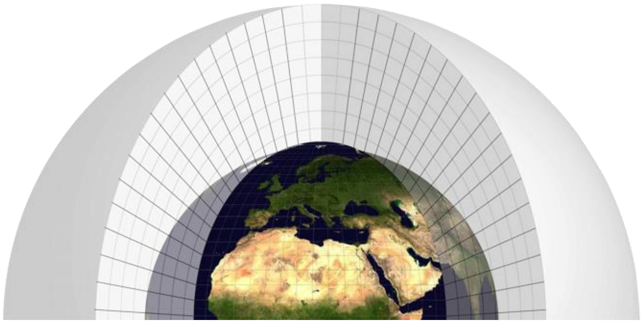
Benchmark

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

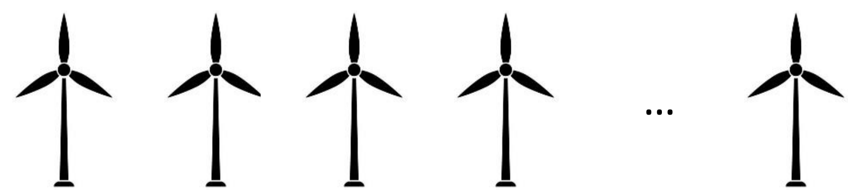
Bottom-up

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

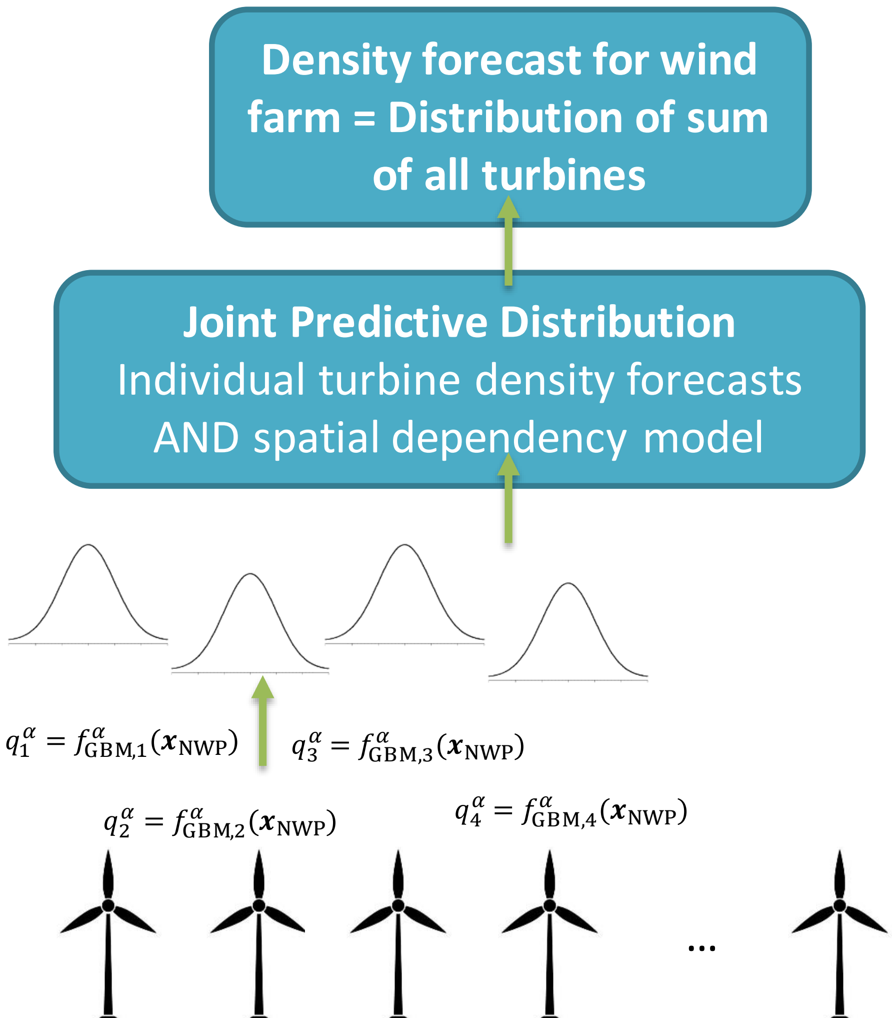
Density forecast for wind farm

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

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



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

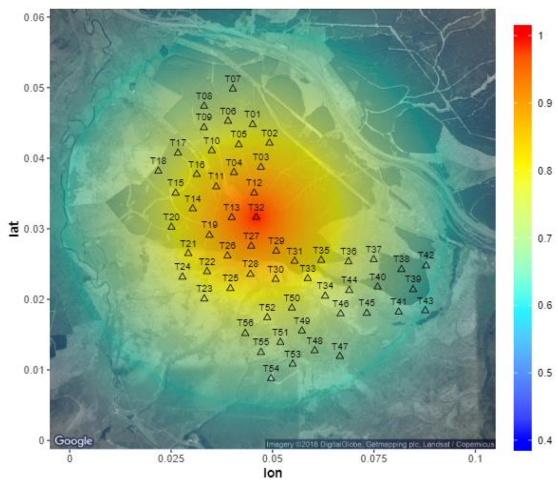
Additional Benchmarks:

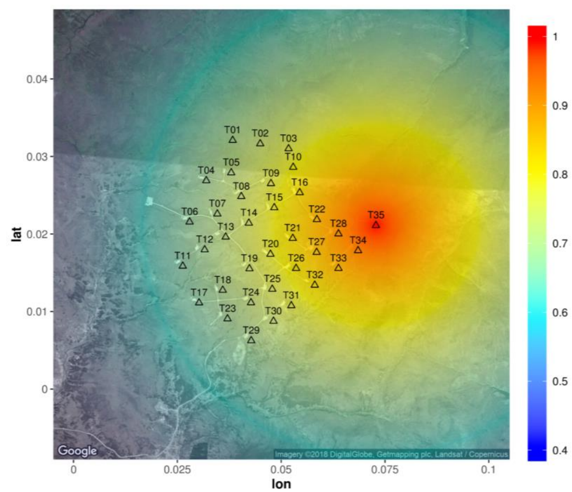
1. Empirical Covariance (data-driven)
2. Vine Copula (facilitates more complex spatial structure)

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

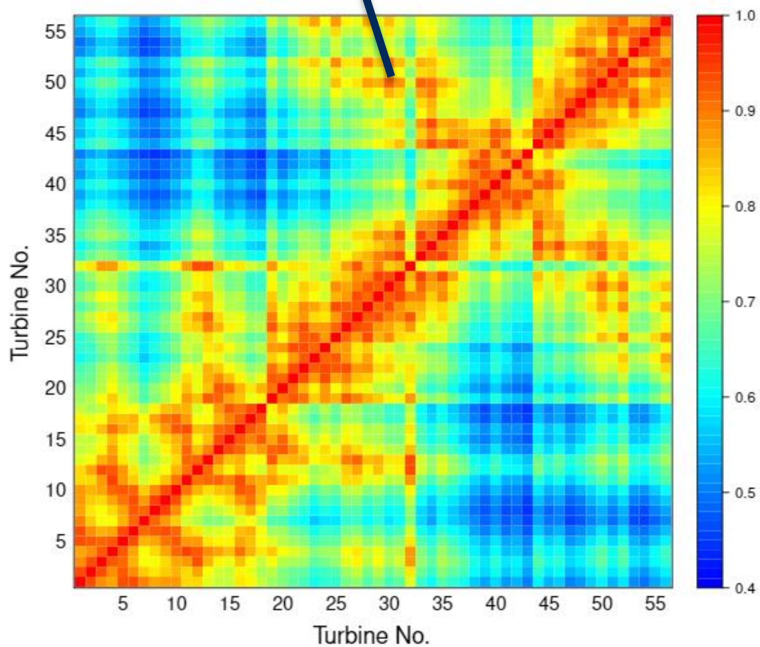


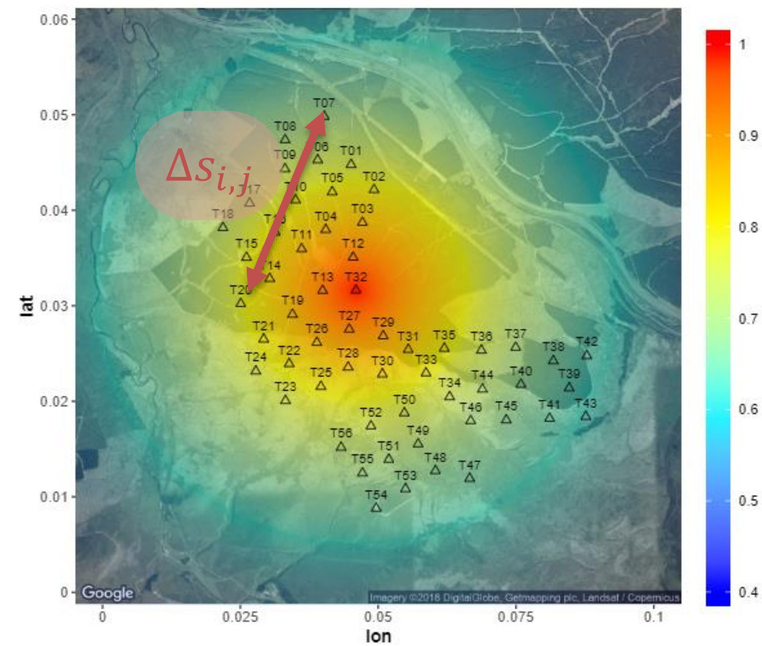


Spatial Structure at WF-A

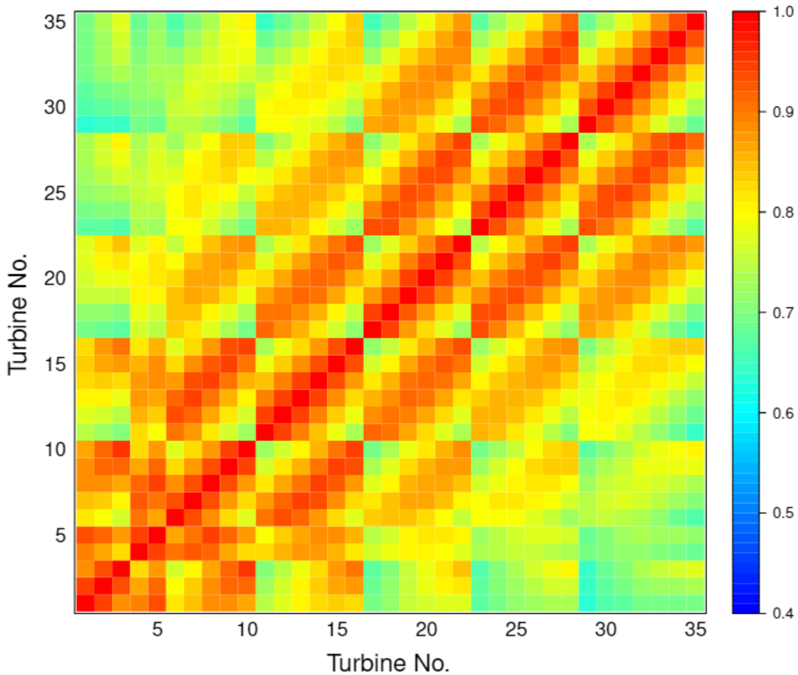
$$\Sigma_{i,j} = \exp\left(-\frac{\Delta s_{i,j}}{\eta}\right)$$

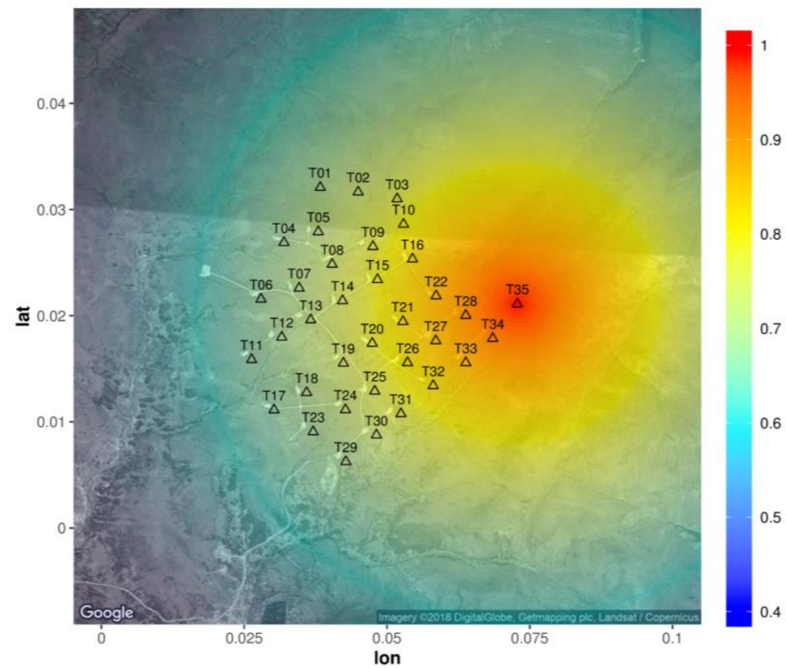
Only one parameter to estimate



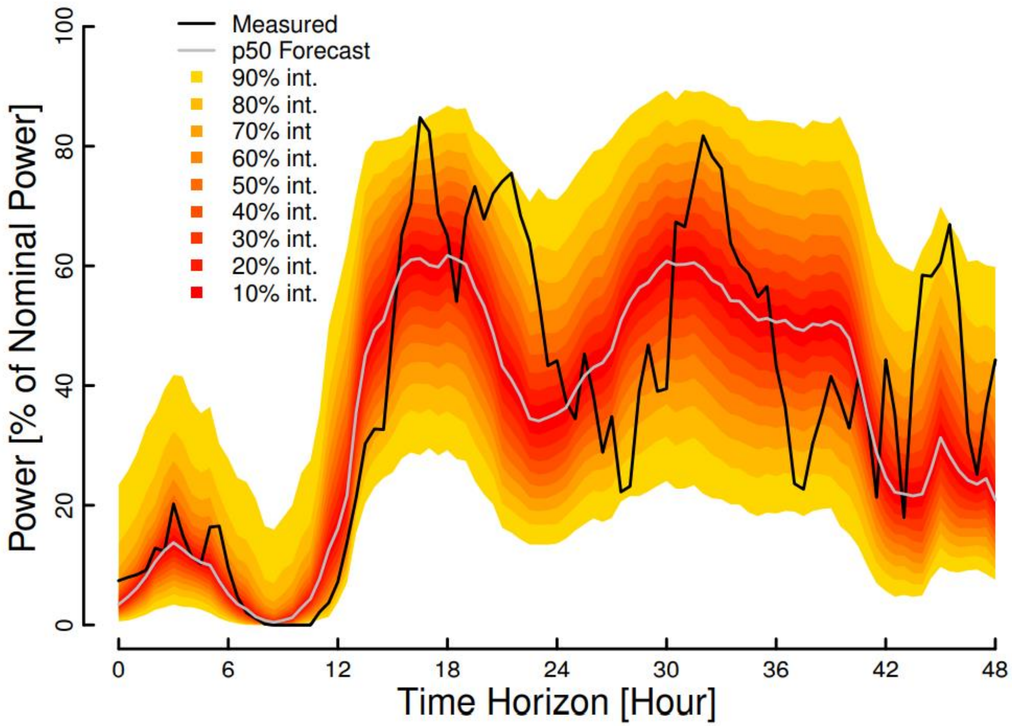


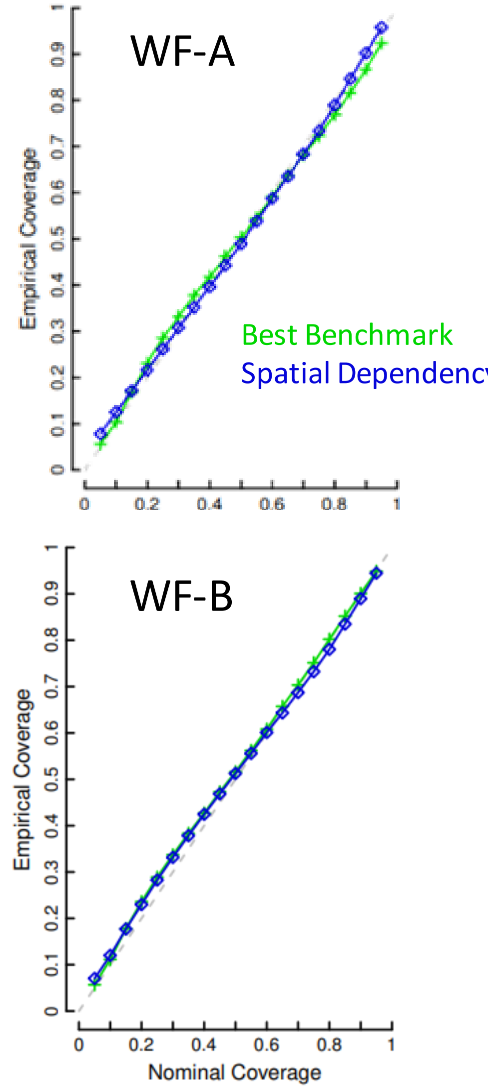
Spatial Structure at WF-B





Results: Reliability





Results: Scores

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

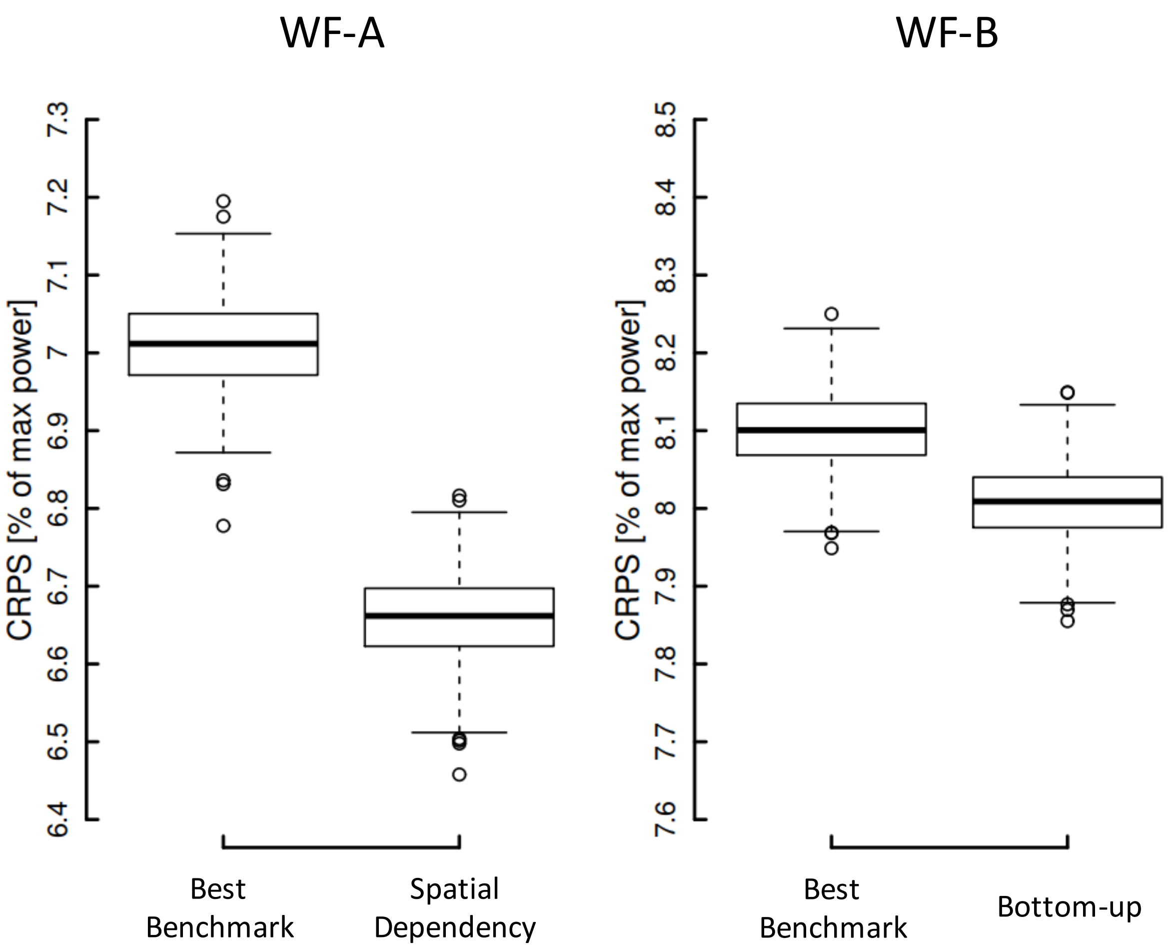
Additional benchmarks…

Empirical Covariance and Vine Copula

…performance a little worse than parametric covariance model.

Results: Scores

Significance of improvement: sampling variation



Recommended Practice (coming up next!)
&
Forthcoming paper in *Wind Energy* by IEA Task Members

Questions for you:

What is 5% reduction in MAE worth to you?

How much effort is required to integrate turbine-level data in to your forecasting systems?

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 for me?

Papers and more at jethrobrowell.com