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THE AWARDS 2020 | UNIVERSITY OF THE YEAR

System-wide probabilistic energy forecasting

Energy Forecasting Innovation Conference

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WORLD CHANGING GLASGOW

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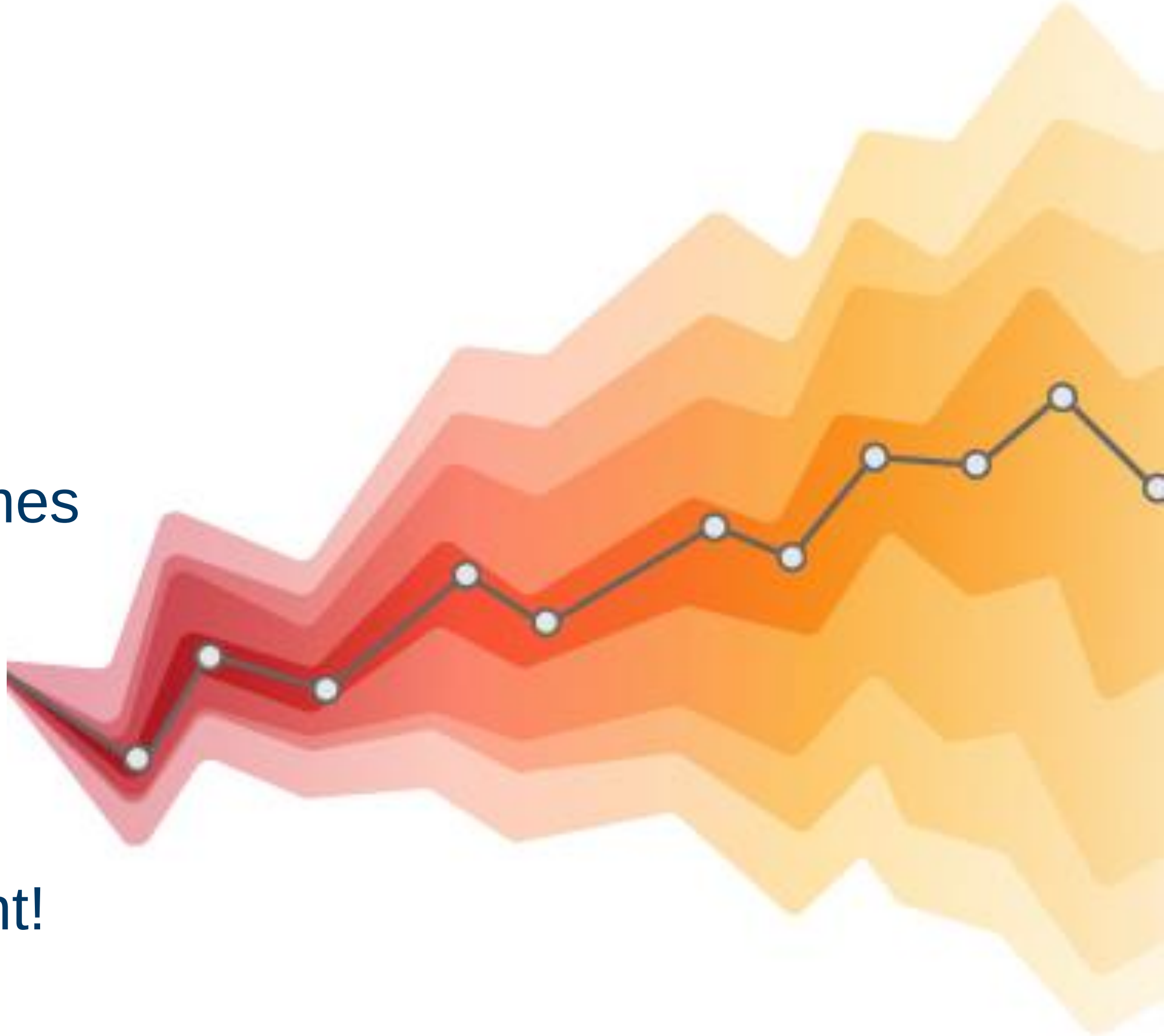
- Summary



Innovation Fellowship EP/R023484/1

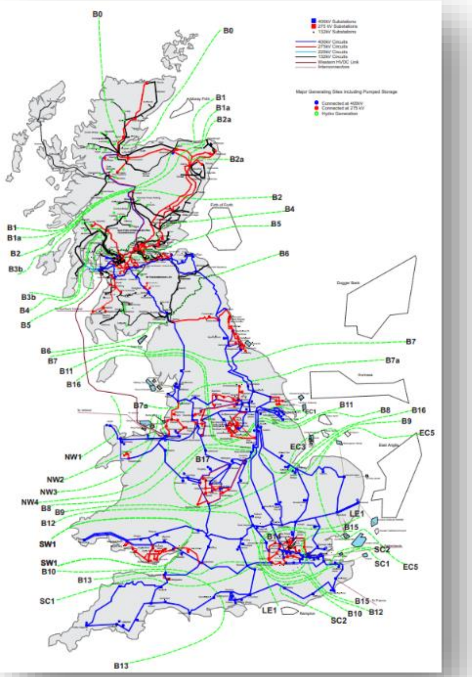
System-wide probabilistic energy forecasting

Motivation

- Energy systems operated under significant and growing uncertainty
- Necessitate that uncertainty is minimised and accurately described to achieve:
  - Efficiency/*“optimisation”*
  - Satisfy risk appetite
- Forecast uncertainty is complex but structured
  - Spatio-temporal
  - Weather and non-weather dynamics

Aim:

- Develop (some of) the statistical methods required to underpin this capability
- Establish potential value for key decision-making problems with partners



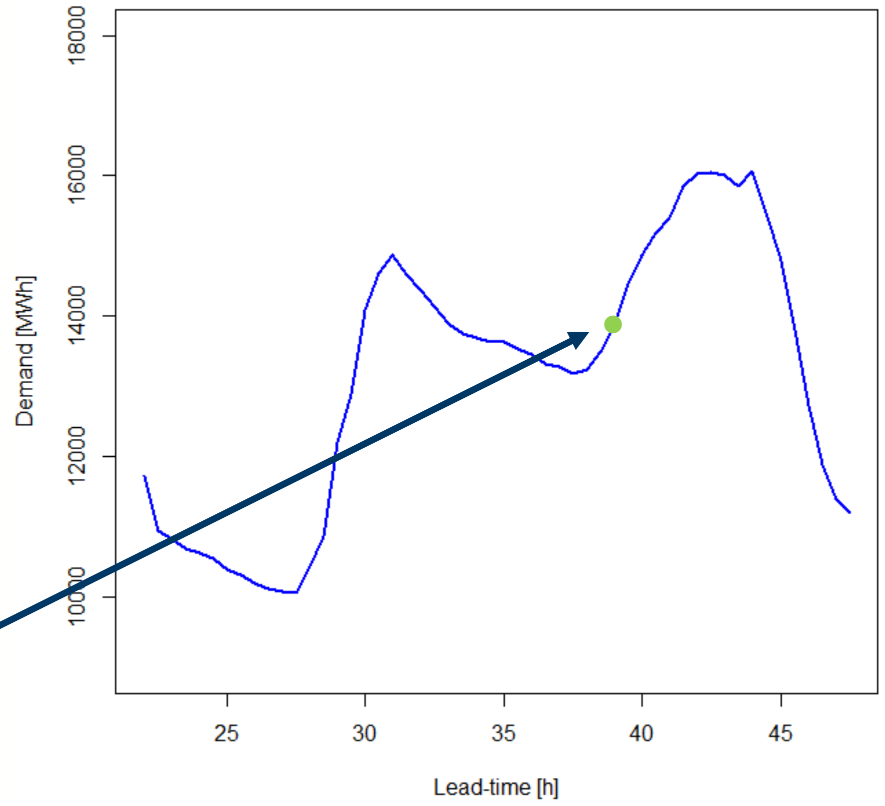
Decisions

- Energy Balancing
- Reserve
- Constraints
- Trading

All are multi-variate, spatio-temporal problems!

Deterministic forecast

Consider this day-ahead forecast of load on the GB transmission system:

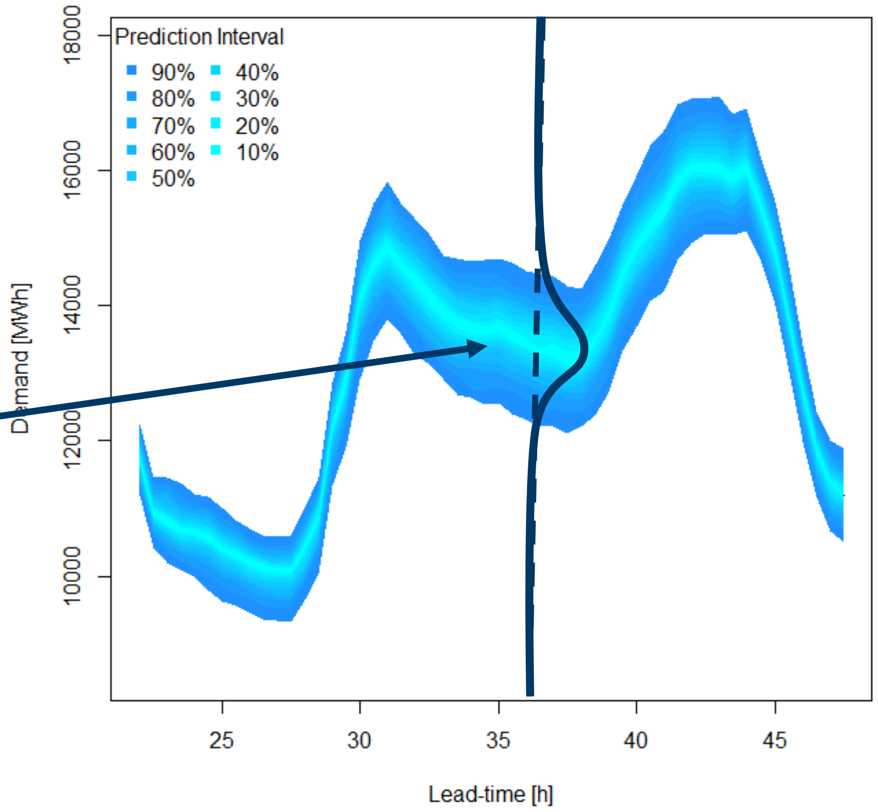


Forecast at each time point is a **single number**

Suitable for decision making if:
1. Cost of over/under predicting is symmetric
2. User is *risk neural*

Probabilistic forecast

Forecast at each time point is a **probability distribution**



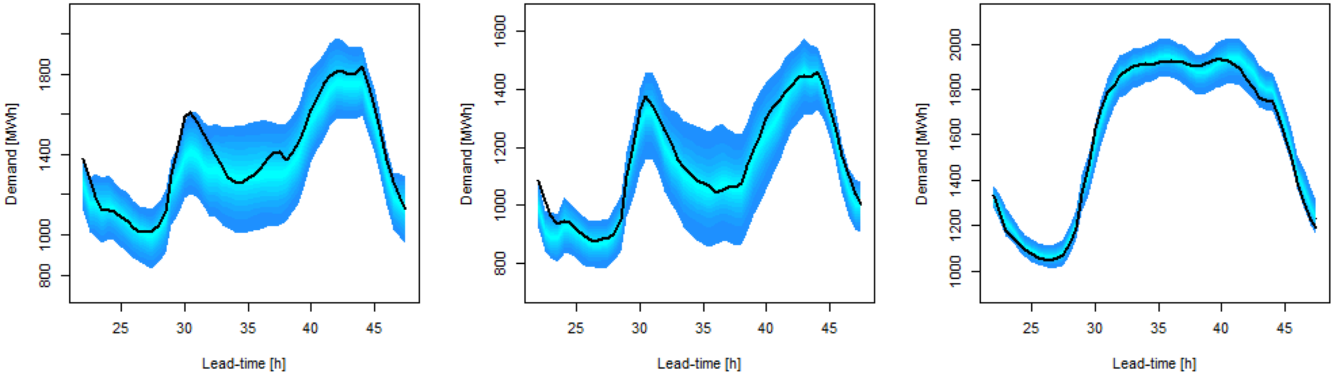
Can make decision based on:

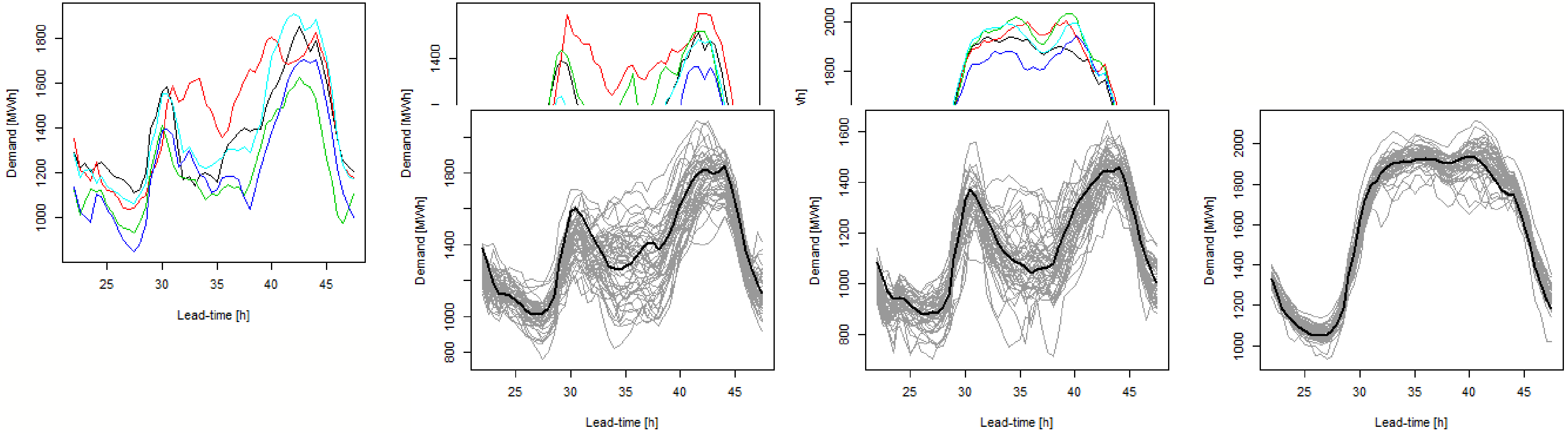
1. **Asymmetric costs** of over/under predicting
2. **Risk** indices/metrics

Probabilistic Forecasting

Probabilistic Forecast, *a forecast that includes uncertainty quantification:*

- Prediction intervals and quantiles
- Density forecasts
- Trajectories or scenarios





Probabilistic forecasting of regional net-load with conditional extremes

Work with Matteo Fasiolo

IEEE Trans. Smart Grid
https://doi.org/10.1109/TSG.2021.3107159

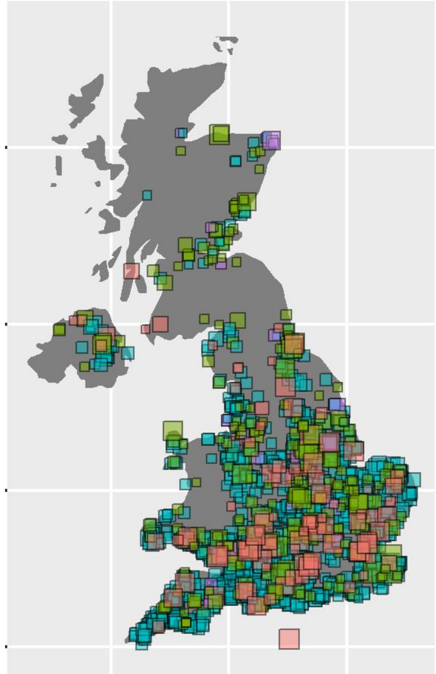
Heilbronn Institute for Mathematical Research
Visitor in Data Science 2019

Motivation

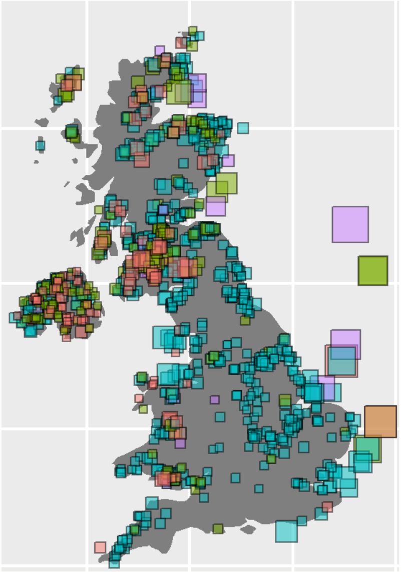
1. Regions can differ greatly in type and capacity of embedded generation
   - ➢ Do we need different input data and methods/models?

2. Regional behaviour important to manage power flow on the grid
   - ➢ Spatial dependency must be retained for probabilistic power flow forecasting

3. Reserve is scheduled by region based on import/export capacity
   - ➢ Volume of reserve based on forecast uncertainty and TSO's risk appetite



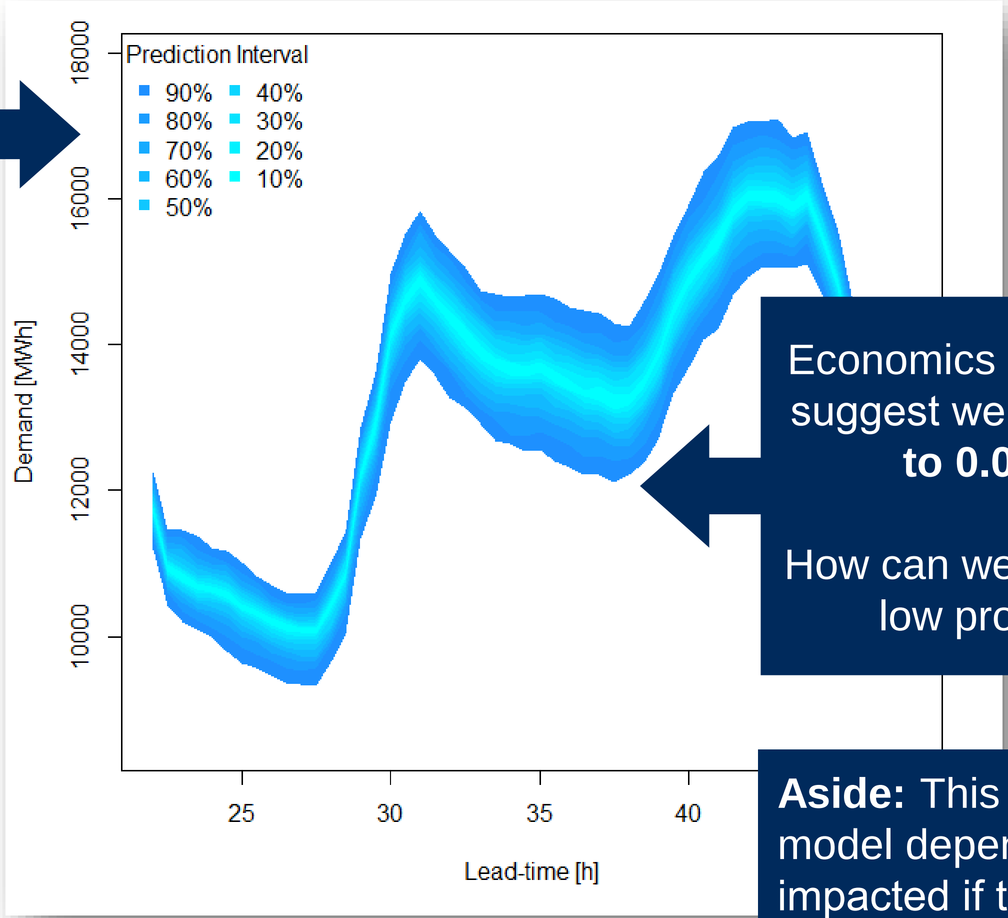
As of March 2021:
1501 Solar Farms (+domestic PV) ↑
1037 Wind Farms →



Net-load is increasingly complex!

Motivation

Probabilistic forecasts quantifies ***forecast uncertainty***



Economics and current practice suggest we're interest in **0.25% to 0.01%** quantiles!

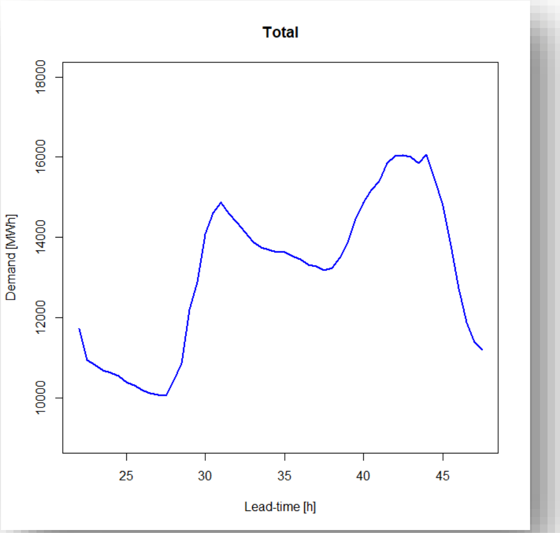
How can we forecast these very low probability levels?

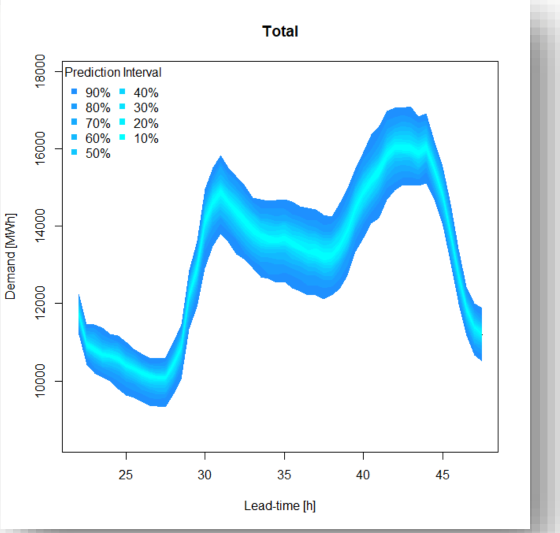
Aside: This is also important if we want to model dependency later this can be negatively impacted if tails are poorly modelled…

Density Forecasting
Overview

Summary:

1. Generalised Additive Model point-forecast
   a) Date/time features
   b) Weather forecast features: temperature, wind speed and solar radiation. Summary statistics by regions
   c) Interactions…
2. Linear Quantile Regression on residuals
   a) Second-order polynomial on point forecast
   b) Linear in date/time and weather features
   c) Quantiles from 0.05%-99.95%
3. Generalised Pareto tails
   a) From 2.5%/97.5% or 5%/95% quantiles



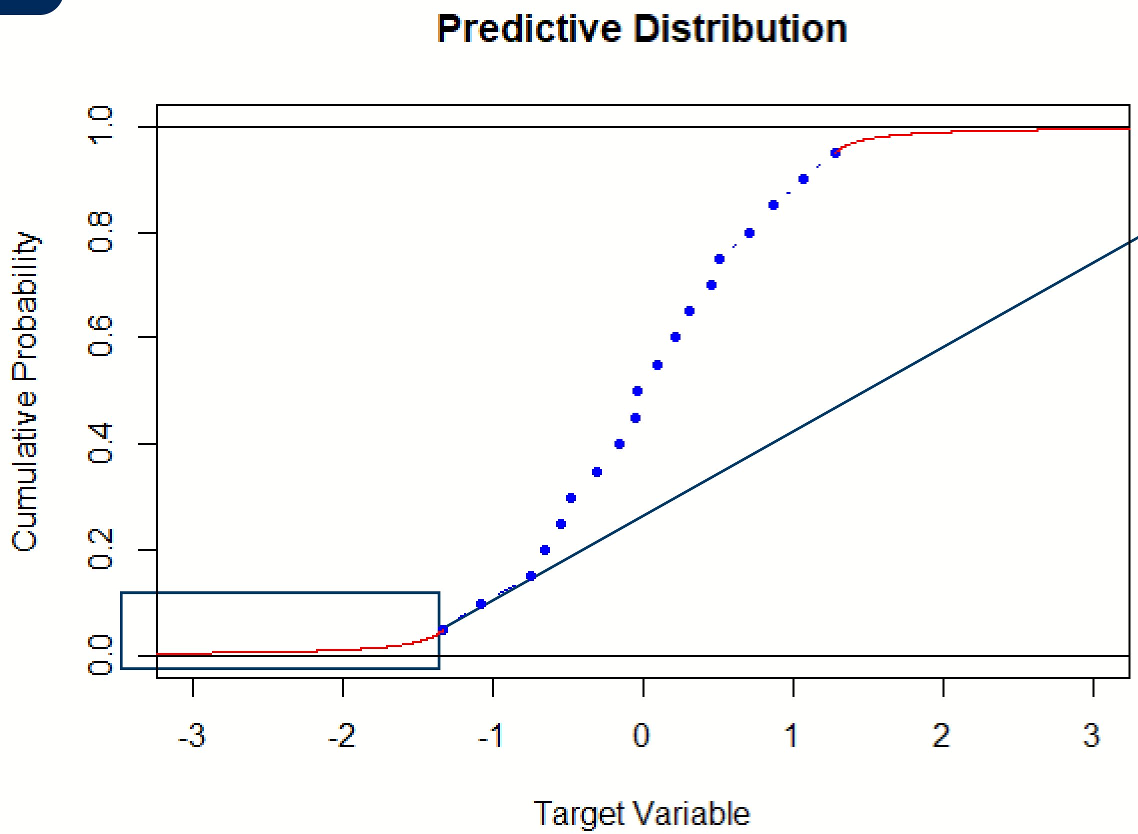


Steps 1 & 2 based on: Pierre Gaillard, Yannig Goude, Raphaël Nedellec, Additive models and robust aggregation for GEFCom2014 probabilistic electric load and electricity price forecasting, IJF 32(3), 2016, 10.1016/j.ijforecast.2015.12.001

Density Forecasting

Generalised Pareto Tails

Tail Distribution
Static Generalised Pareto



$$F(x;\sigma,\xi) = \begin{cases} 1 - \left(1 + \frac{\xi x}{\sigma}\right)^{-\frac{1}{\xi}} & \text{for } \xi \neq 0 \\ 1 - \exp\left(-\frac{x}{\sigma}\right) & \text{for } \xi = 0 \end{cases}$$

Shape and Scale parameters estimated using peak-over-threshold method

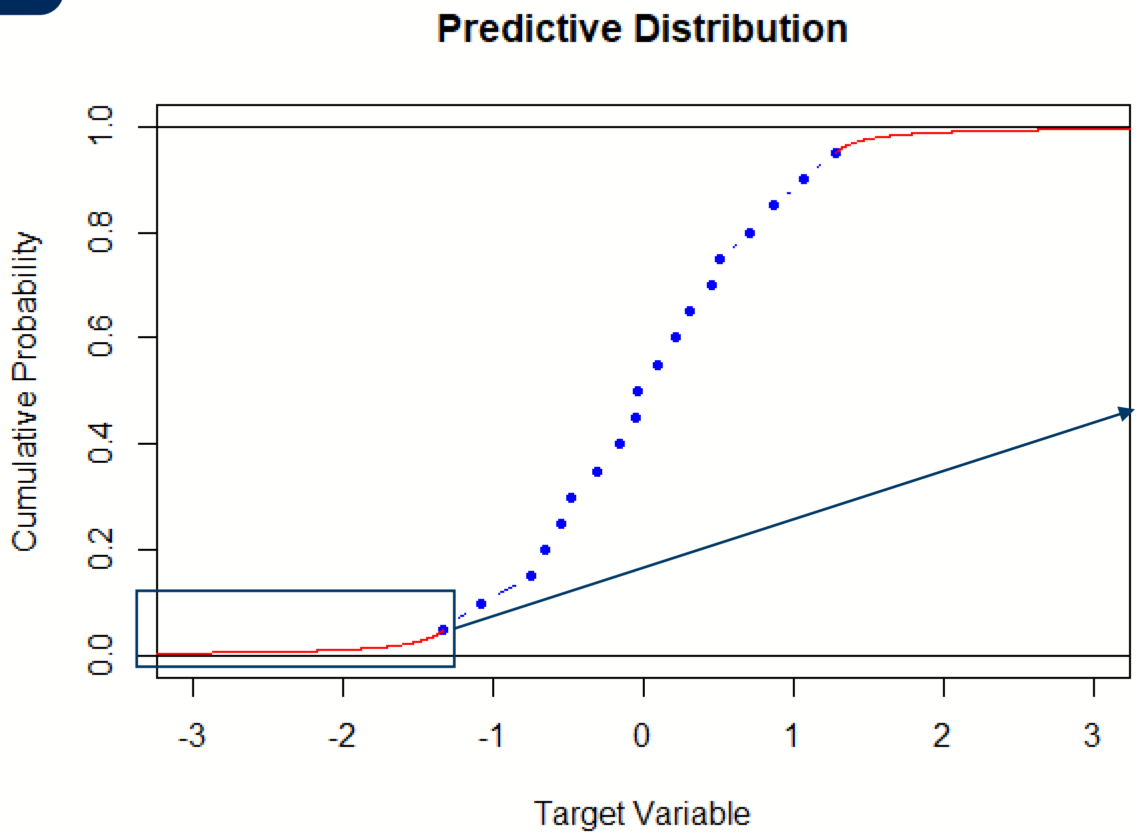
Threshold is last reliable conditional quantile

x = exceedance of quantile

Density Forecasting

GAMLSS Generalised Pareto Tails

Tail Distribution
Conditional Generalised Pareto



$$F_{GPD}(\sigma, \xi)$$

Scale:

$$\log(\sigma) = X_1\beta_1 + \sum_j^{J_1} f_{j1}(x_1)$$

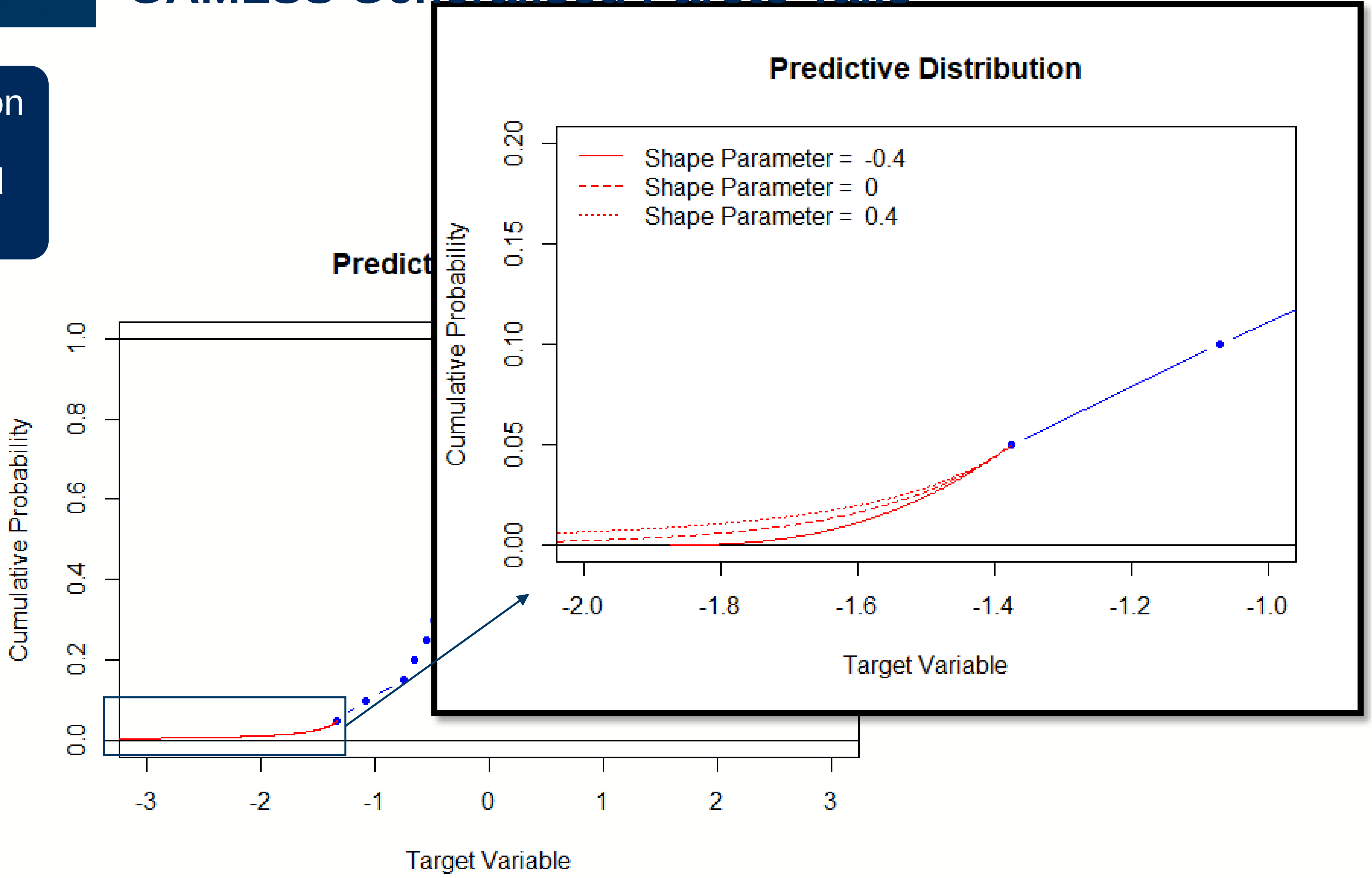
Shape:

$$\xi = X_2\beta_2 + \sum_j^{J_2} f_{j2}(x_2)$$

Density Forecasting

GAMLSS Generalised Pareto Tails

Tail Distribution
Conditional Generalised Pareto

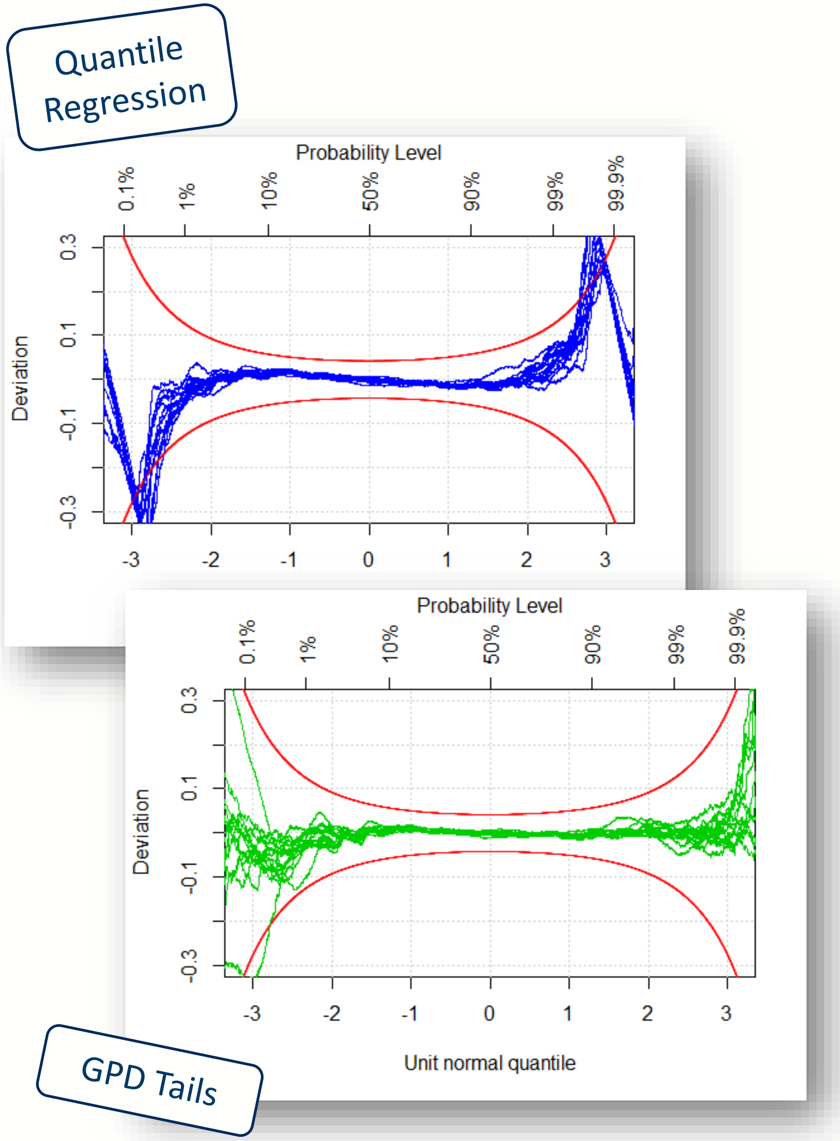


Density Forecasting
Case Study: Results

- Tails are challenging to evaluate:
  - not much data
  - poor discrimination by usual metrics

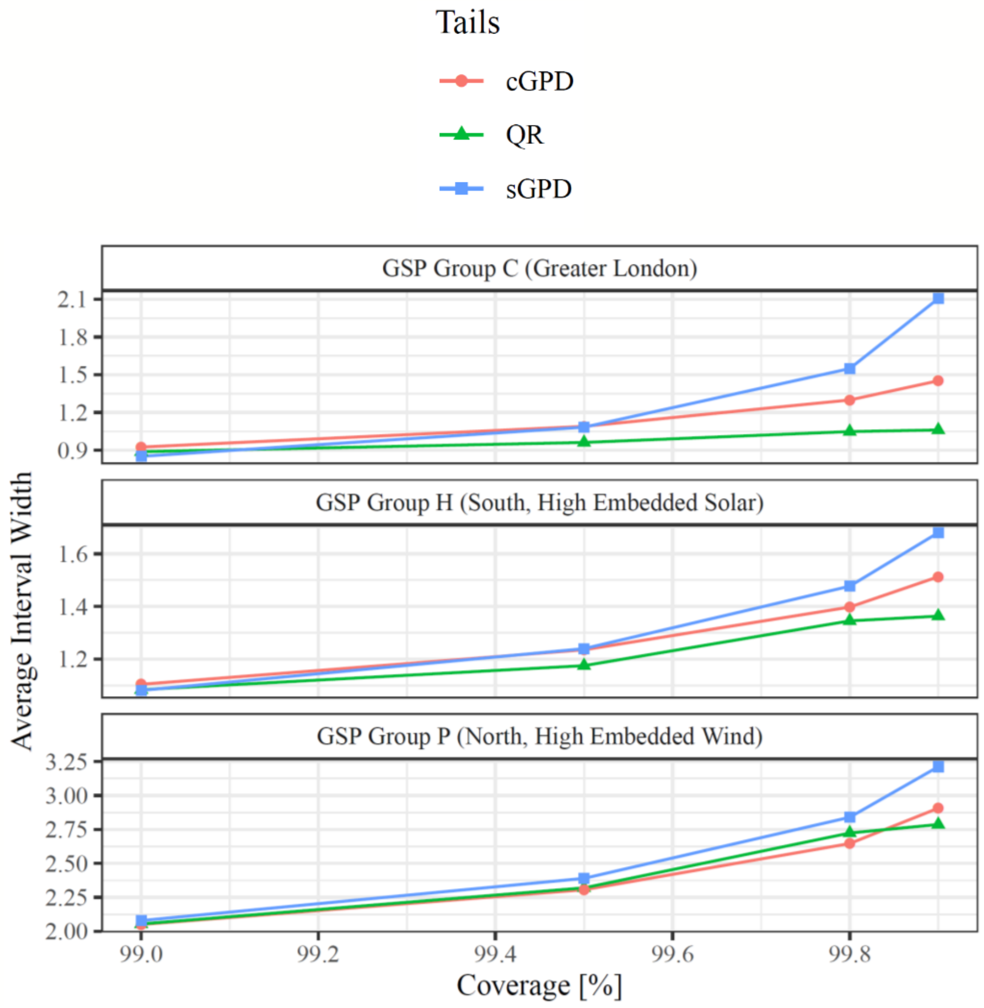
- Worm plot:
  - Shows quantile bias
  - 95% consistency band considering serial corelation

- Quantile regression vs GPD:
  - QR tails uncalibrated, too sharp/over-confident
  - GPD tails calibrated, sharpness can be improved by conditioning on covariates

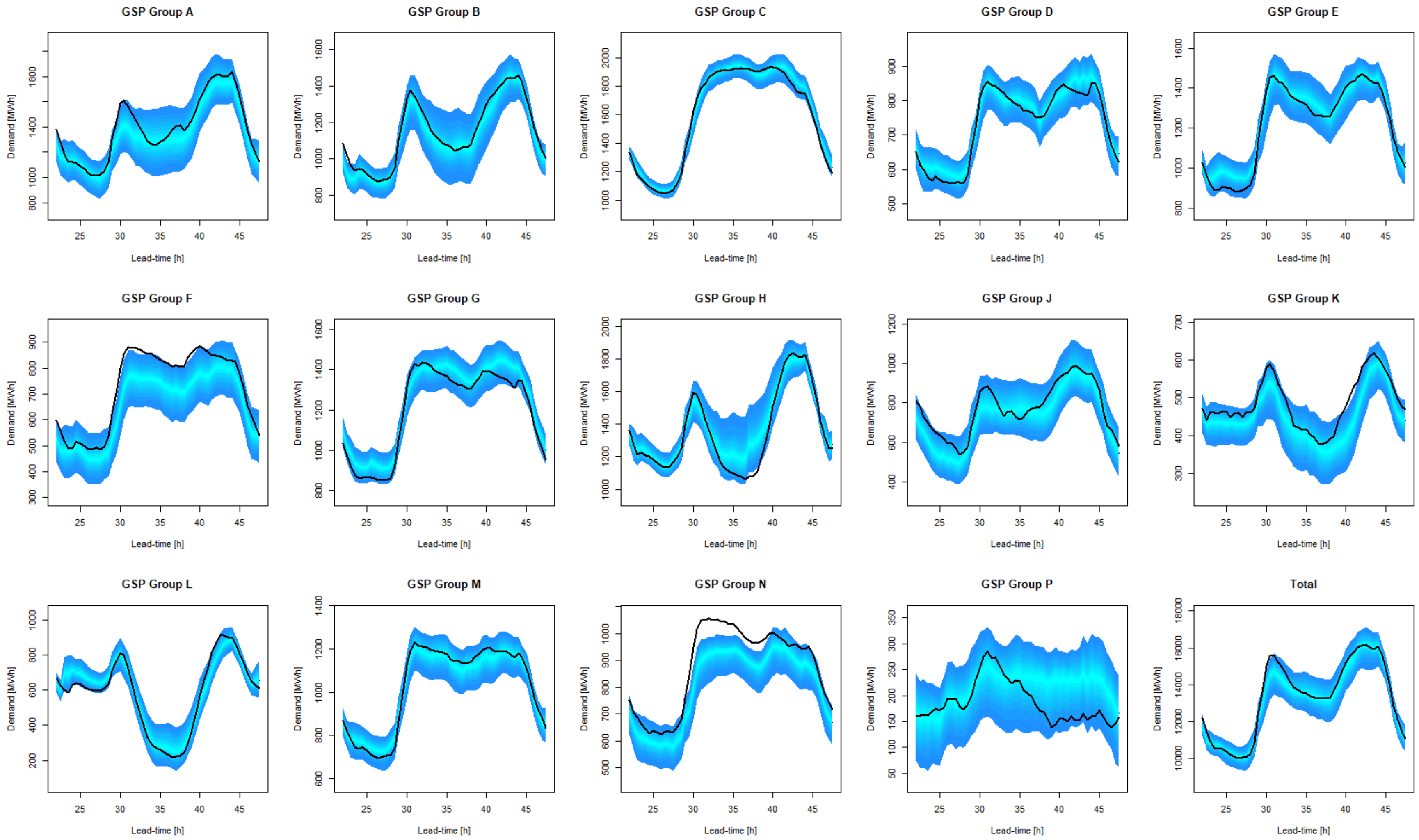


Density Forecasting
Case Study: Results

- **Sharpness = average interval width**
- **Quantile Regression** not calibrated → throw out
- **Conditional GPD** much sharper than **Static GPD**
- Sharper intervals → less uncertainty → *better* decisions?



Density Forecasts



Use-case: Reserve setting

- Reserve energy required in case:
  - Power plant fails
  - Market fails to deliver
  - Forecast is *"wrong"*

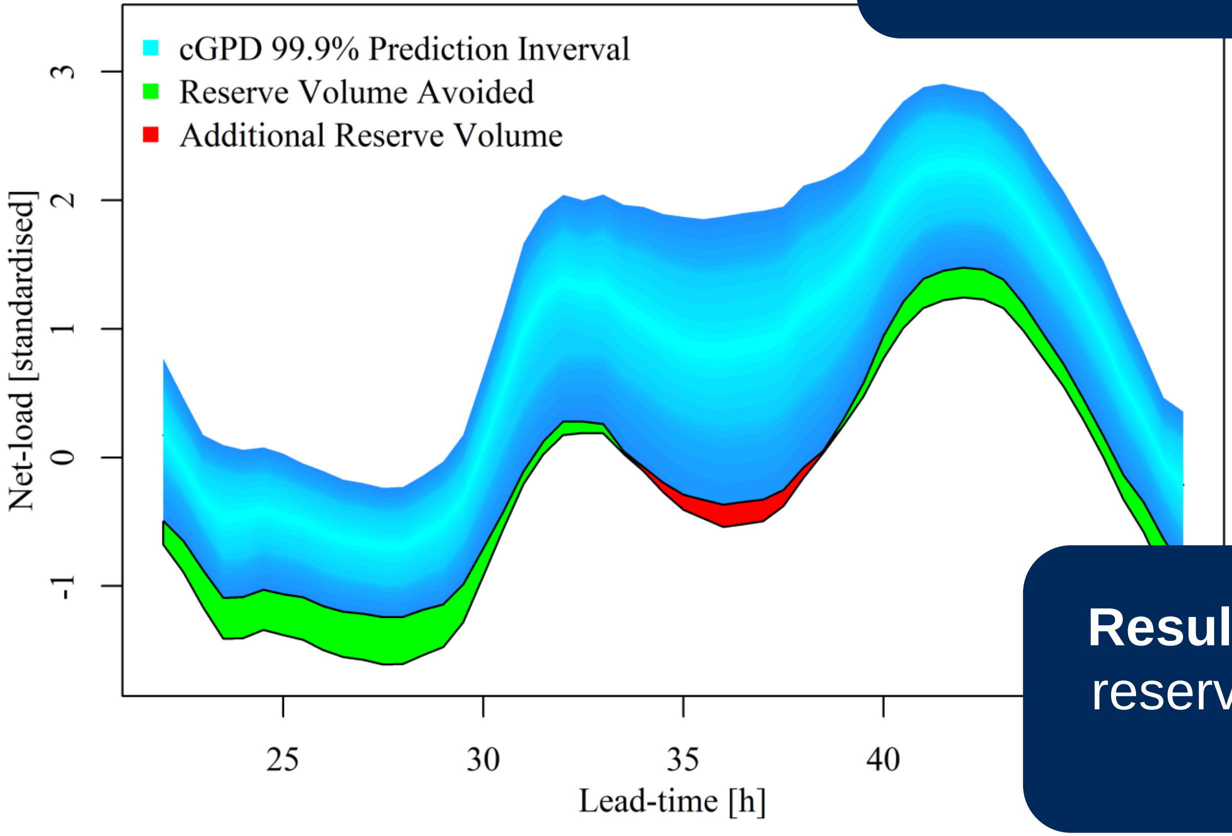
- How much to buy?
  - Risk appetite/policy
  - Cost-Loss: marginal cost of more reserve vs loss if reserve is insufficient

Benchmark: empirical quantile of historic deterministic forecast errors

Here: conditional quantile of density forecast

α = 0.25% to 0.01%

Use-case: Reserve setting



Sometimes (~25%) we need **more** reserve than benchmark to satisfy risk appetite

Mostly we can hold **less** reserve than benchmark

Result: overall reduction in reserve holding, preferable risk profile

Probabilistic Forecasting of Regional Net-load with Conditional Extremes

Summary:

1. Wind and solar weather features are essential to capture embedded generation in net-load forecasting, including in tails *(not shown today)*

2. Generalised Pareto Distribution tails provide reliable extreme quantiles where quantile regression fails

3. Forecasting extreme quantiles reveals opportunities to reduce risk and save consumers £££!

High-dimensional wind power forecasting

Work with Ciaran Gilbert

C. Gilbert, "Topics in high-dimensional energy forecasting", PhD Thesis, University of Strathclyde, 2021, online: https://stax.strath.ac.uk/concern/theses/9306sz801

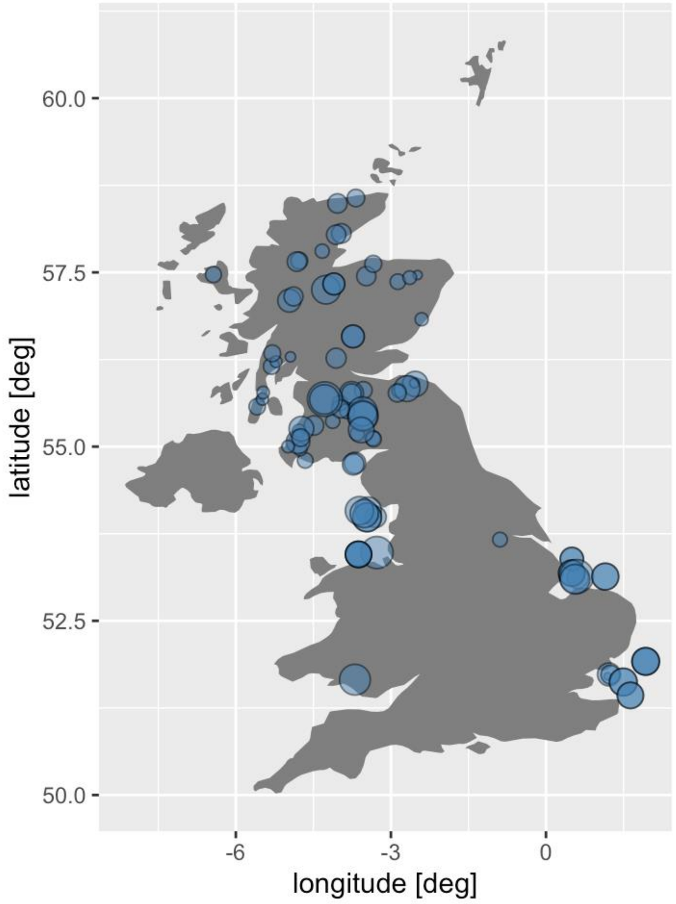
CG PhD Studentship
EPSRC

Spatio-temporal dependency

Motivation

- Spatial dependency:
    - Portfolio effects
    - Power flow & constraints

- Temporal dependency:
    - Trading block products
    - Ramps
    - Storage and plant run times

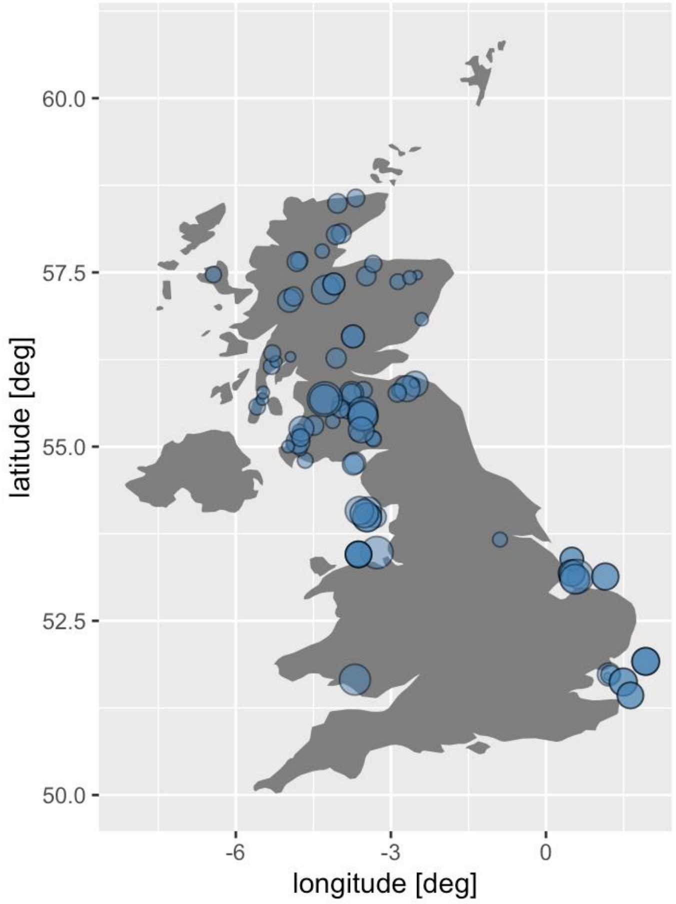


Spatio-temporal dependency

Case study

- 92 Wind Balancing Mechanism Units
- Density forecasting: 92 units × 27 quantiles × 5 cv-folds = 12,420 models to fit!
- Implemented using *ProbCast* on AWS

Density Forecast: **GBT** → Tail Distribution: **Exponential** → Dependency Structure: **Gaussian Copula**

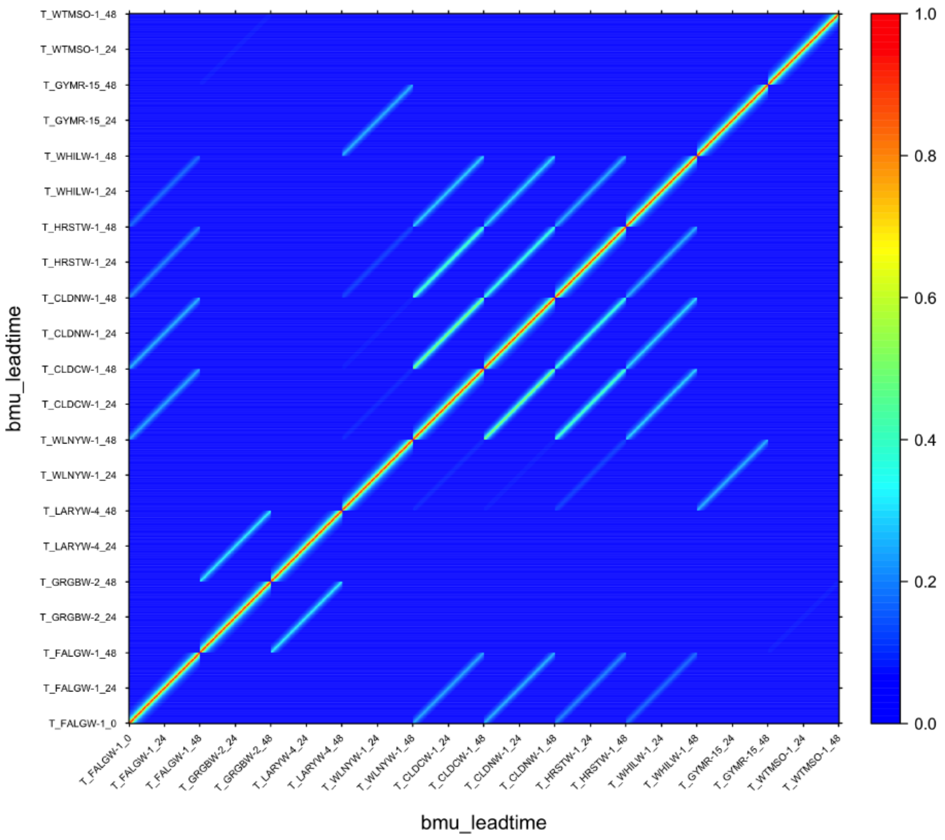


Spatio-temporal dependency

Dependency Structure:
Gaussian Copula

- Very large covariance matrix! Parametrisation necessary
  - Cauchy for temporal
  - Exponential for spatial
  - Interaction (non-separable)

- Probably dynamic!
  - Regime-switching?
  - Dependence on covariate?



$$\Sigma_{(k,t),(k',t')} = \frac{1-\nu}{1+a|\delta t|^{2\tau_t}}\left[\exp\left(-\frac{|\delta k|}{\tau_k(1+a|\delta t|^{2\tau_t})^{\beta/2}}\right) + \frac{\nu}{1-\nu}\mathbf{1}(|\delta k| = 0)\right]$$

Dynamic spatio-temporal dependency

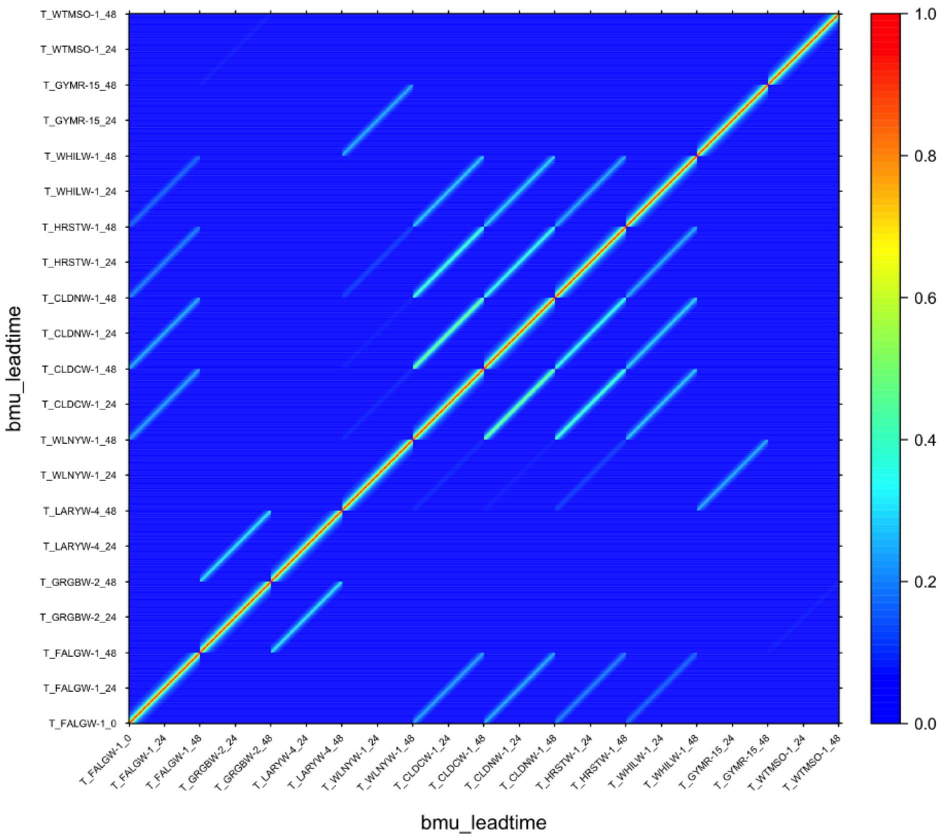
Dependency Structure: **Gaussian Copula**

Regime-switching:

- Estimating separate parameters based on weather regime
- Signs of benefit, but inconclusive

Parameters as functions of covariates:

- Enables more flexible structures
- Explicit time-dependency rather than adaptive updates
- First results to be presented in June. Pre-print of accepted article now online



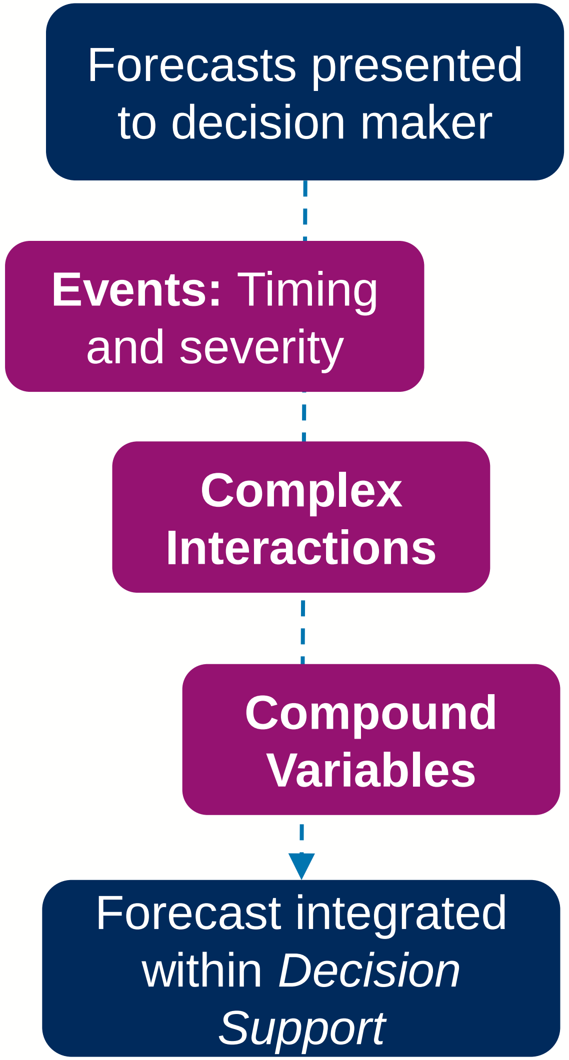
$$\Sigma_{(k,t),(k',t')} = \frac{1-\nu}{1+a|\delta t|^{2\tau_t}}\left[\exp\left(-\frac{|\delta k|}{\tau_k(1+a|\delta t|^{2\tau_t})^{\beta/2}}\right) + \frac{\nu}{1-\nu}\mathbf{1}(|\delta k| = 0)\right]$$

A vision for energy forecasting

Ambitions beyond "better forecasts"

Image source: http://commons.wikimedia.org/wiki/User:Ragnar1904

What do we want to predict anyway?



- **Energy:** Blocks of energy for trading and generator scheduling, risk/reserve requirements
- **Power:** ramps for balancing; instantaneous power for ancillary services, reactive power
- **Interdependency with markets:** risk management**,** algorithmic trading, embedded flexibility
- **Network flows/constraints:** probability of constraint, regional balancing, TSO/DSO flow

Opportunities: data-rich environment!

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Need and opportunities for energy forecasting:

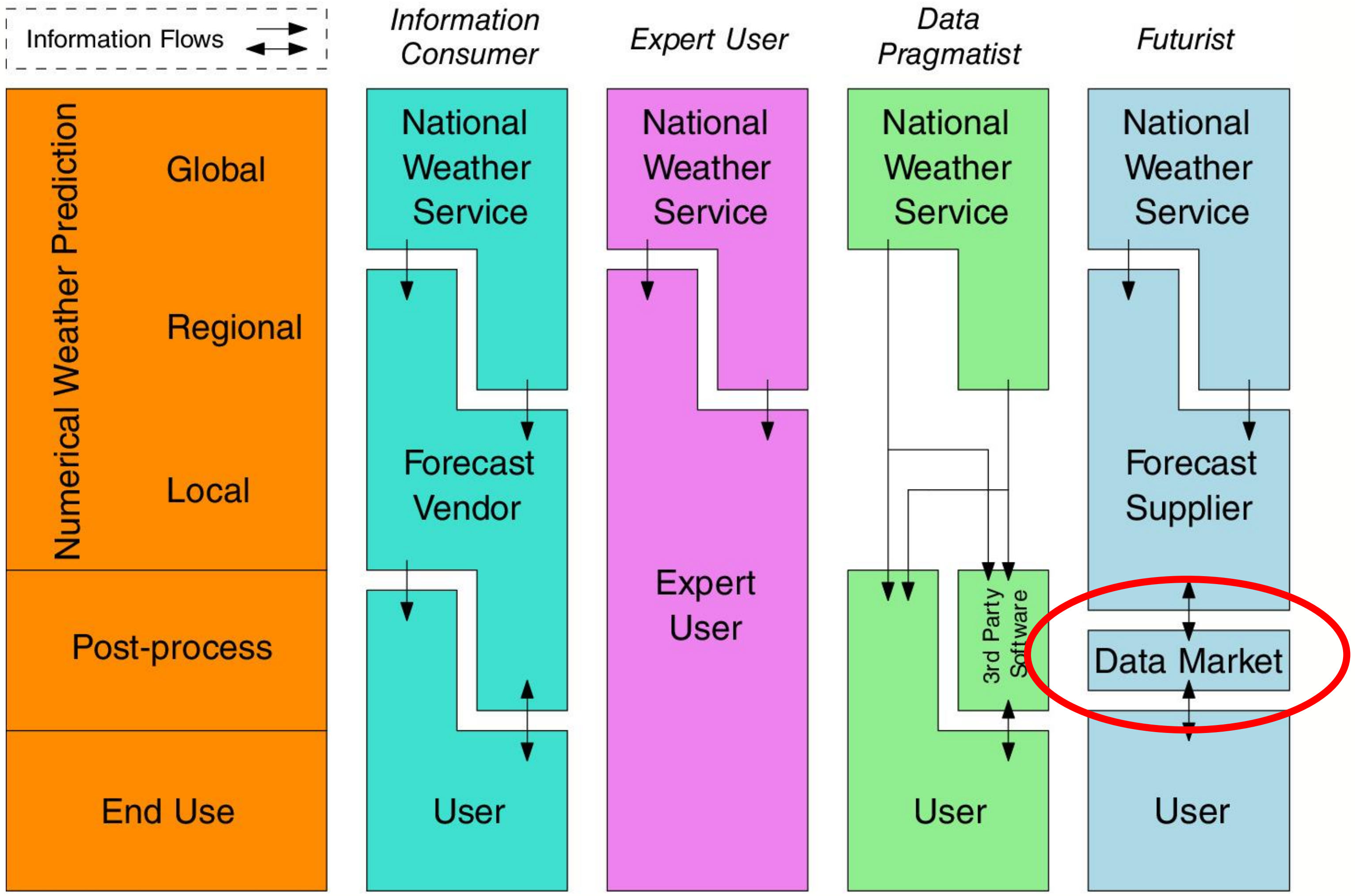
- Critical capability for weather-dependent (weather-led?) energy systems, supporting:
  - Reliability
  - Cost minimisation
  - De-carbonisation***!!!***
- Massive increase in data coverage and availability:
  - Load monitoring and digitization (controllability and automation)
  - Energy networks: metering and asset health monitoring, small flexible (virtual) power plants
  - Weather data availability and forecast performance

Challenges:

- Data 1: coverage and quality never going to be (even close to) perfect!
- Harmonising physical constrains with non-physical systems (digital, markets)
- Data 2: sharing, privacy, (apparent lack of) commercial incentives
- Converting complex forecast information into decisions
- Coherent exchange of forecasts and other data (e.g. TSO-DSO interface)

Fundamental challenges, not simply an IT problem!

The future of energy forecasting?



What do we need from this information exchange?

- "Full" probabilistic forecasts?
- Partial forecasts?
- Covariates?
- Coherence with other data

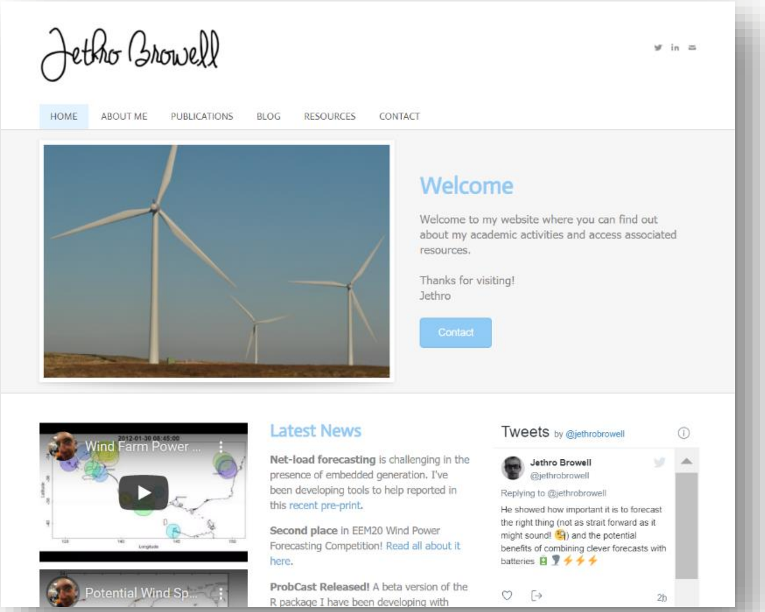
Decision-centric views:

1. Retain "full" information, collapse to only what is required for use:
    - Coherence across all data and forecasts…
    - BUT we lack a parsimonious mathematical framework.
2. Avoid explicit forecasting completely using reinforcement learning…

Figure source: Sweeney, Browell *et al* (2020)

Thanks!

Papers, code etc. linked from www.jethrobrowell.com



Methodologies available in ProbCast – *User feedback welcome!!*

https://github.com/jbrowell/ProbCast

R>>> devtools::install_github("jbrowell/ProbCast")

References

Today:

- J. Browell and M. Fasiolo, "Probabilistic Forecasting of regional net-load with conditional extremes and gridded NWP", IEEE Transactions on Smart Grid, vol. 12, no, 6, pp. 5011-5019, Nov 2021, https://doi.org/10.1109/TSG.2021.3107159
- C. Gilbert, “Topics in high-dimensional energy forecasting”, PhD Thesis, University of Strathclyde, 2021, online: https://stax.strath.ac.uk/concern/theses/9306sz801
- J. Browell, C. Gilbert and M. Fasiolo, "Covariance Structures for High-dimensional Energy Forecasting", Electric Power Systems Research (Special Issue for PSCC 2022), 2022, (preprint at www.jethrobrowell.com)
- C. Sweeney, R.J. Bessa, J. Browell and P. Pinson, "The Future of Forecasting for Renewable Energy," WIREs Energy and Environment, vol. 9, no. 2, 2020, https://doi.org/10.1002/wene.365

Other outputs from *System-wide probabilistic energy forecasting:*

- J. Browell and C. Gilbert, "Predicting electricity imbalance prices and volumes: capability and opportunity", Energies, 15(10), 3645, 2022, https://doi.org/10.3390/en15103645
- M. Farrokhabadi, J. Browell, Y. Wang, S. Makonin, W. Su, and H. Zareipour, "Day-Ahead Electricity Demand Forecasting Competition: Post-COVID Paradigm", IEEE Open Access Journal of Power and Energy, 2022, https://doi.org/10.1109/OAJPE.2022.3161101
- R.M. Graham, J. Browell, D. Bertram and C.J. White, "The application of sub-seasonal to seasonal (S2S) predictions for hydropower forecasting", Meteorological Applications, 29(1), e2047, 2022, https://doi.org/10.1002/MET.2047
- E. Heylen, J. Browell and F. Teng, "Probabilistic day-ahead inertia forecasting", IEEE Transactions on Power Systems, https://doi.org/10.1109/TPWRS.2021.3134811
- R. Telford, B. Stephen, J Browell and S. Haben, "Dirichlet Sampled Capacity and Loss Estimation for LV Distribution Networks with Partial Observability", IEEE Transaction on Power Delivery, vol. 36, no. 5, pp. 2676-2686, Oct. 2021, http://www.doi.org/10.1109/TPWRD.2020.3025125

Q&A

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