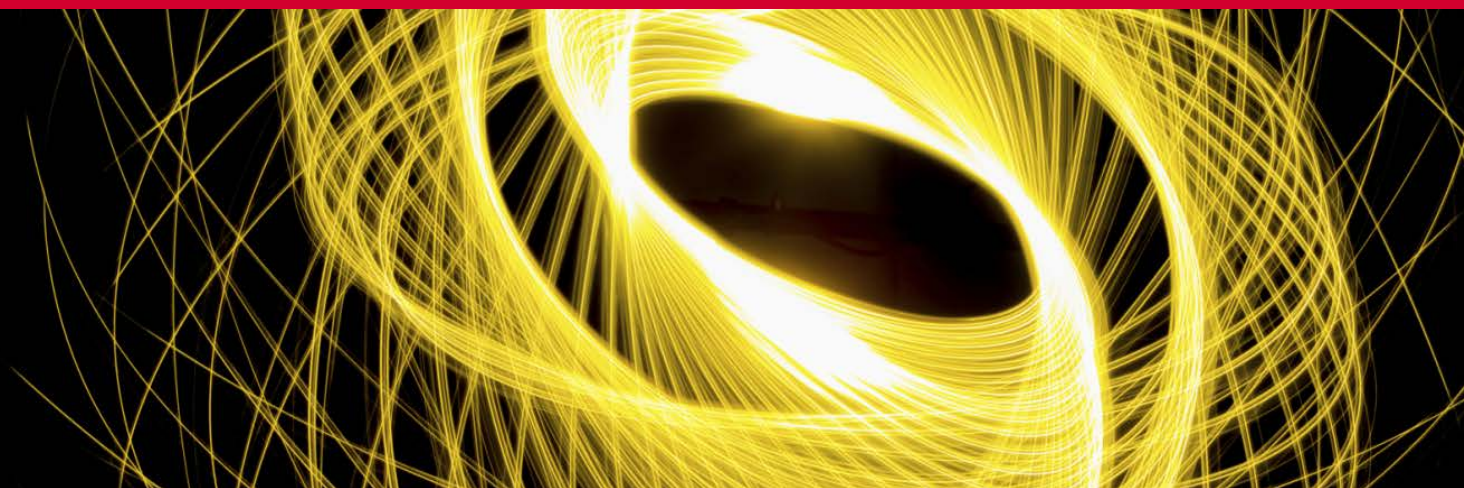


Weather, climate and energy



David Brayshaw

With thanks to students, postdocs and collaborators: Hannah Bloomfield, Dan Drew, Dirk Cannon, Kieran Lynch, Caroline Dunning, Caroline Holmes (nee Ely), Emma Suckling, Dan Hdidouan, John Methven, Len Shaffrey, Andrew Charlton-Perez, Iain Staffell, Chris Dent, Stan Zachary, Alberto Troccoli and others

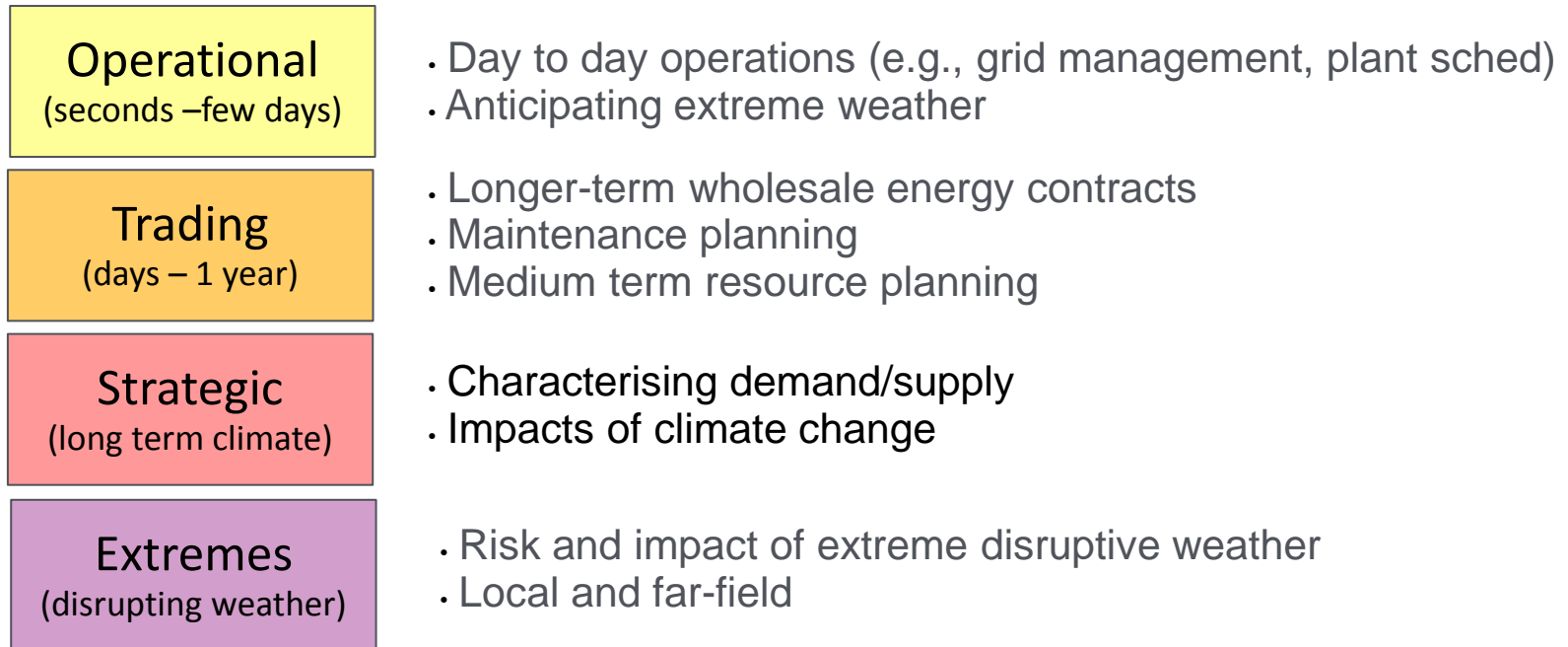


National Centre for
Atmospheric Science
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INSTITUTE

Power systems and meteorology

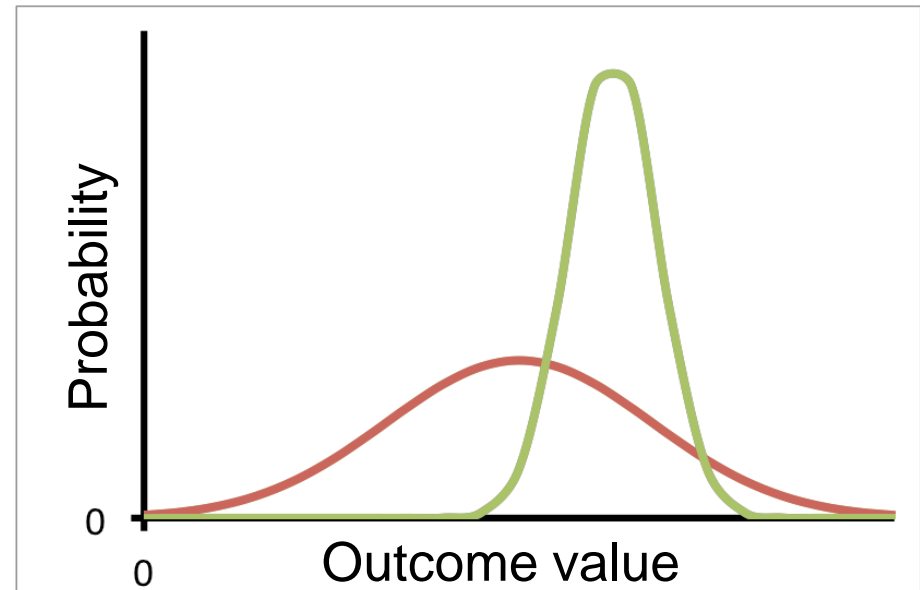
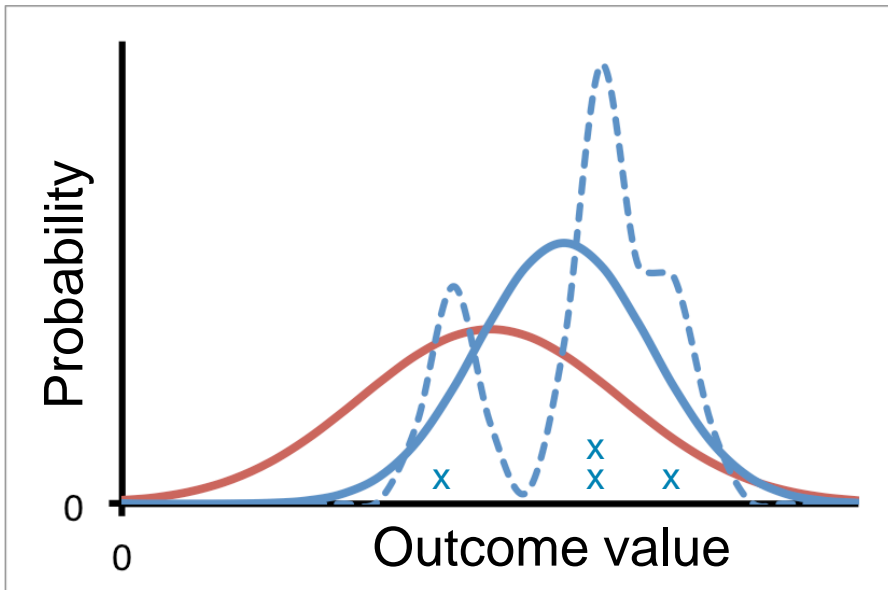
- Many impacts of weather on power (damage, demand, transmission, supply)
- Use of renewables: *Increasing sensitivity* to weather on generation side
- Climate variability and change: *Changing weather*



- Key challenge: how to use weather/climate data effectively to understand behaviour of impacted system and develop risk management strategies
- Today: three examples – operational, strategic and, if time permits, trading
- Power-, Euro-, Renewables- centric (please ask about other areas!)

Types of climate information

- Type 1 – climatologies of risk: understanding range of the possible (blue → red)
 - Reanalysis
 - Climate model projections (GCMs)
- Type 2 – forecasting risk: anticipating outcomes (red → green)
 - Ensemble prediction (subseasonal, seasonal and decadal)



- **Wind-power variability**
 - Reserve holding, system planning, system management
 - Risks: persistent-high, persistent-low and rapid ramps in wind power
- Example 1: Can historical meteorological data better characterize these three risks? (now and into the future)

- **Climate impacts on “integrated” power systems**
 - Load duration and operating opportunity for conventional plant
- Example 2: Are economic “system planning” models robust to climate variations?

- National-aggregate

Wind power climatologies

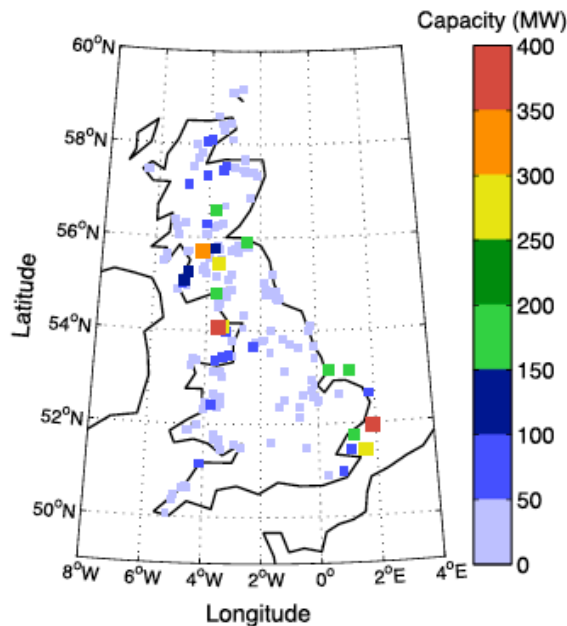
(Cannon et al, 2015; Drew et al 2015; Canon et al, accepted MetZet)

- Insufficient direct power observation records (few years)
- Previous work largely based on met-station data (Sinden, Leahy, Earl, Fruh, ...)
 - Spatially sparse, inhomogenous (spatial, temporal)
 - Wrong height (10m), wrong location (relative to wind farms)
 - → Conversion to “power” problematic
- Reanalysis
 - Full, gridded, homogenous coverage
 - Greater homogeneity, multiple vertical heights
 - Freely available, no need for additional simulations
 - NASA MERRA (Reinecker et al 2011); similar results with ERA-Interim (Dee et al, 2011)
- See also excellent recent work by Ed Sharp, Iain Staffell, Stefan Pfenninger, Lucy Cradden and others

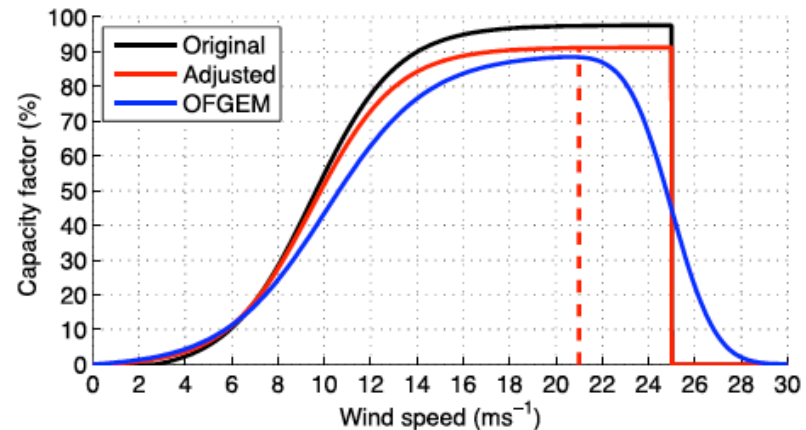
Conversion to wind power

- Interpolate hourly wind-speed to each site in 2012 wind-farm list (2, 10, 50m)
- Extrapolate to turbine height using a fitted logarithmic profile
- Applying simple power curve to estimate capacity factor
- Weight by local installed capacity and aggregate nationally
- Calibrate power curve using observed 2012 wind-power records

(a) September 2012 wind farm distribution

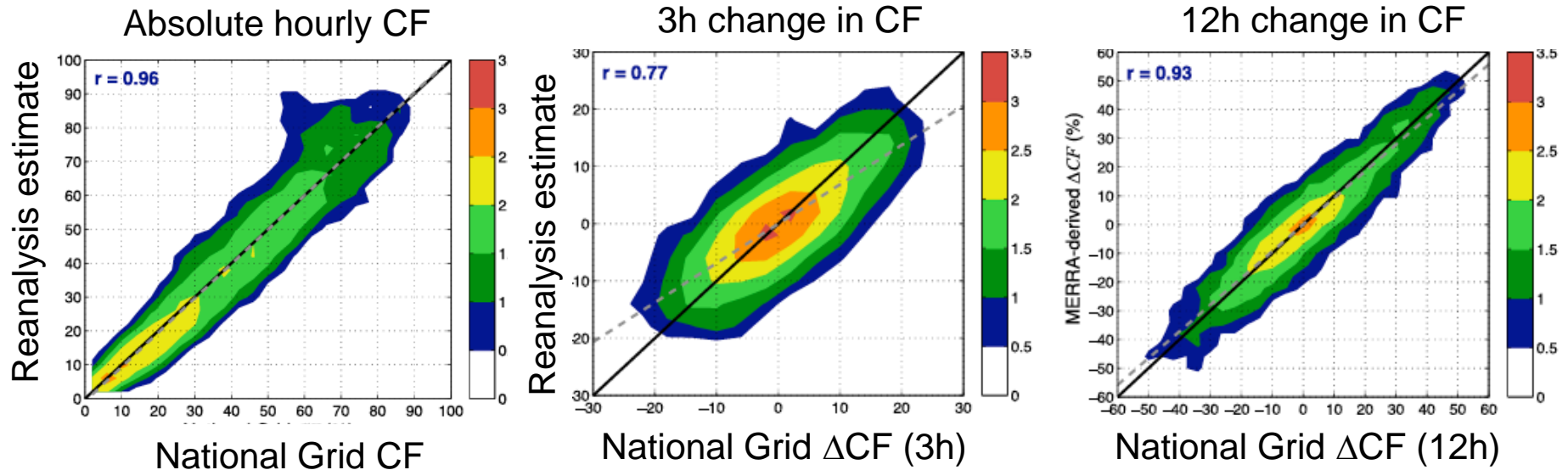
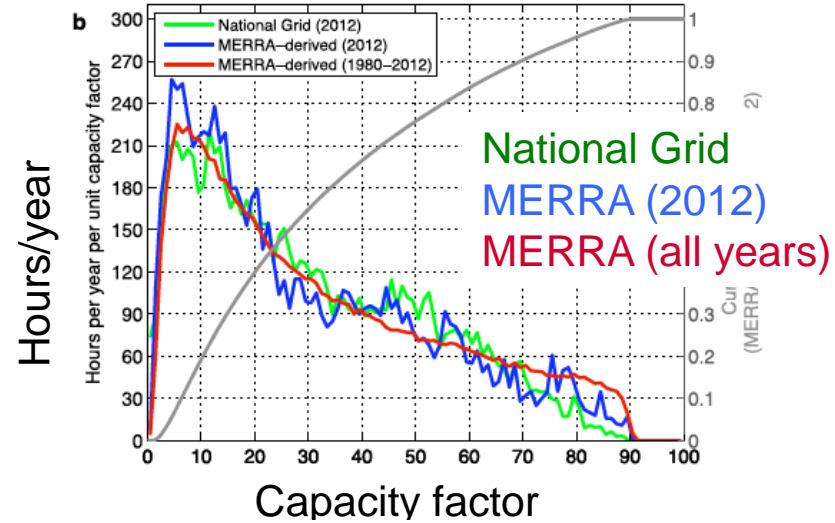


(b) Wind speed to power generation transformations



Wind power – 2012 period

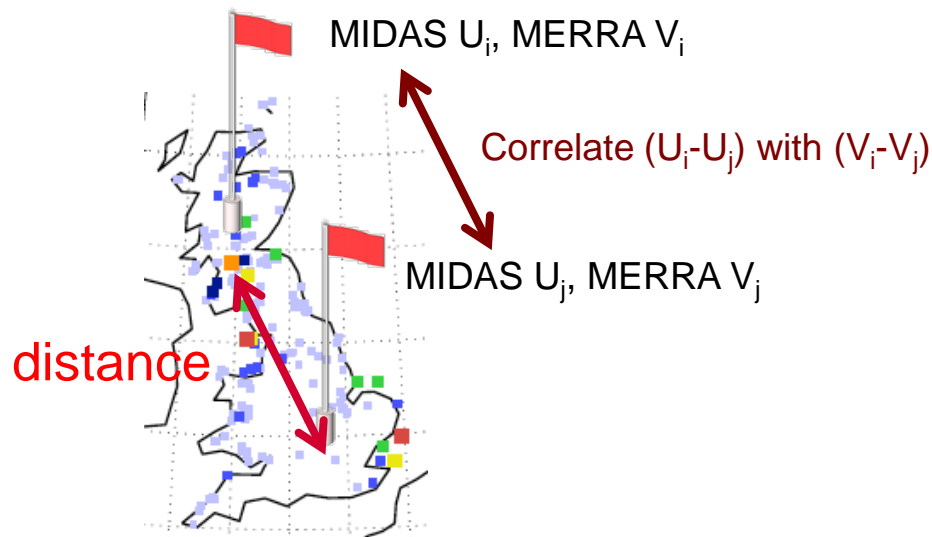
- Calibration performs well
- Good representation of hourly values
- Under estimates ramping < 3-6h
- Good estimation of ramping > 12h
 - Care required at finer spatio-temporal scales



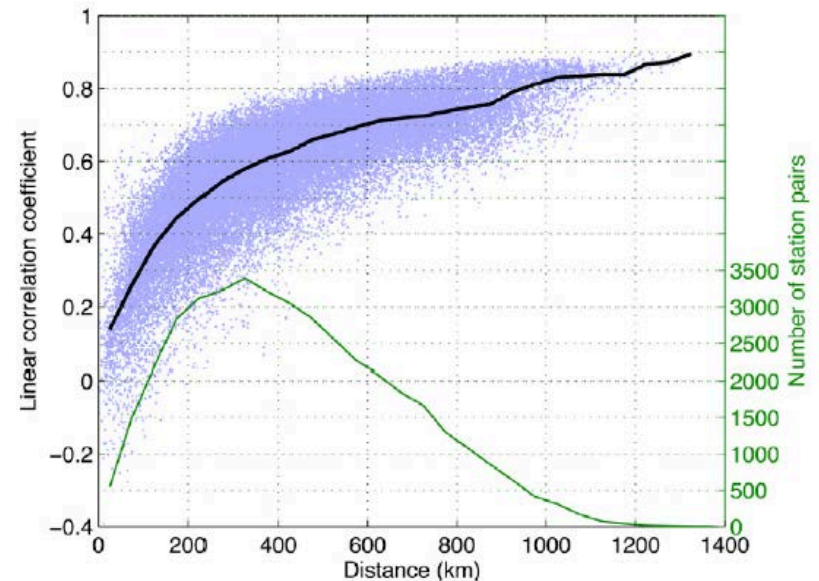
Aside: The limits of reanalysis

GB wind strongly spatially correlated, decreasing with distance ~ 100 's km (Sinden, 2007)

Question: how well does MERRA capture *differences between sites*?



(a) Correlation (δU , δV)



Correlation ~ 0.6 @ 300 km

Interpretation:

- dU contains contribution from “local situation” and “large-scale weather”
- MERRA captures the contribution from “large-scale” but “local” is unresolved
- Effective resolution on scale ~ 300 km

Wind power synthetic record

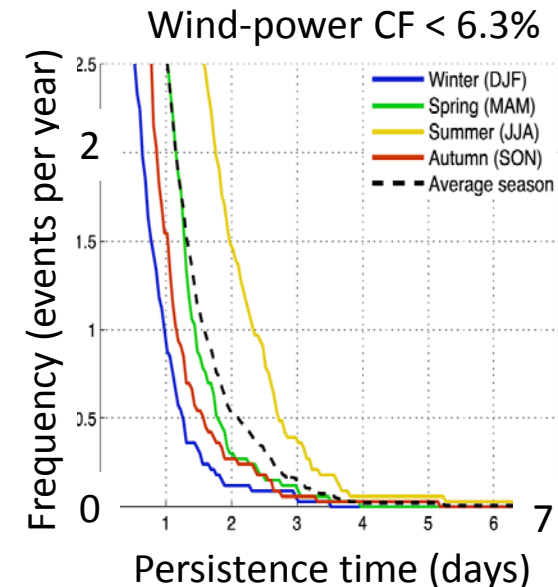
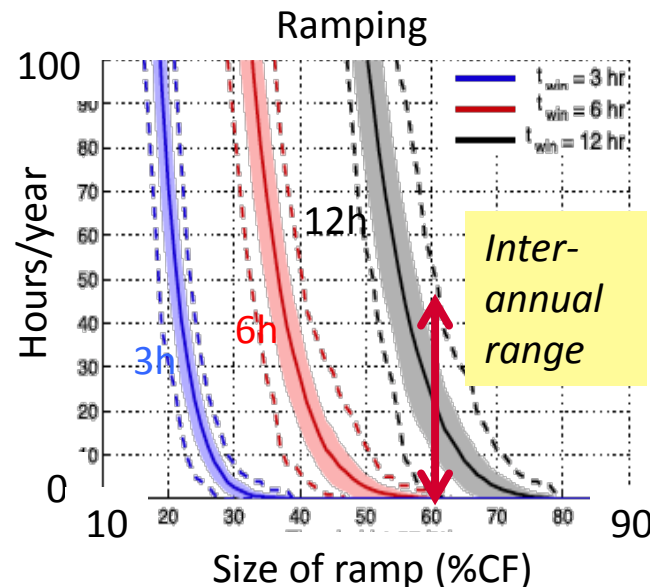
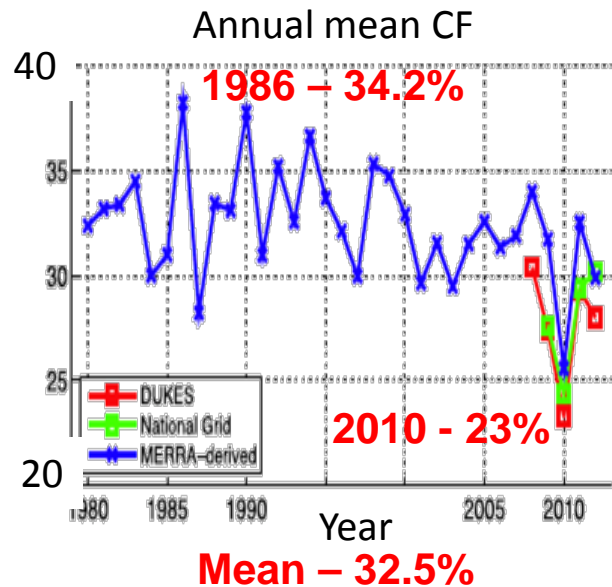
(Cannon et al, 2015, Renewable Energy)

30+ year “synthetic history” of wind power

- Model and data freely available: www.met.reading.ac.uk/~energymet

Key points:

- Better quantification of risks associated with inter-annual climate variability
- Annual-mean capacity factor higher than previous estimates (32.5%) but *highly variable* (15pp range)
- Persistent high/low wind events approximately Poisson-like (exponential decay with persistence)
- Very large ramps can occur – but caution required

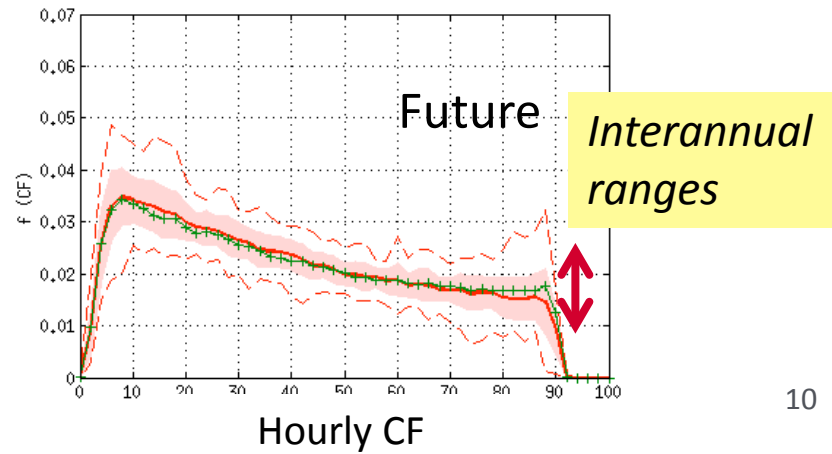
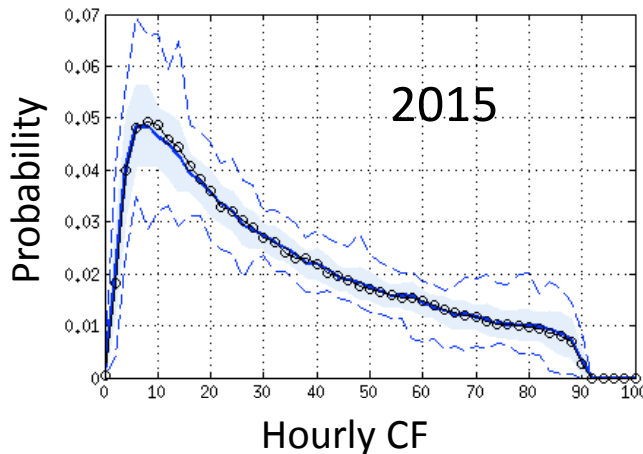
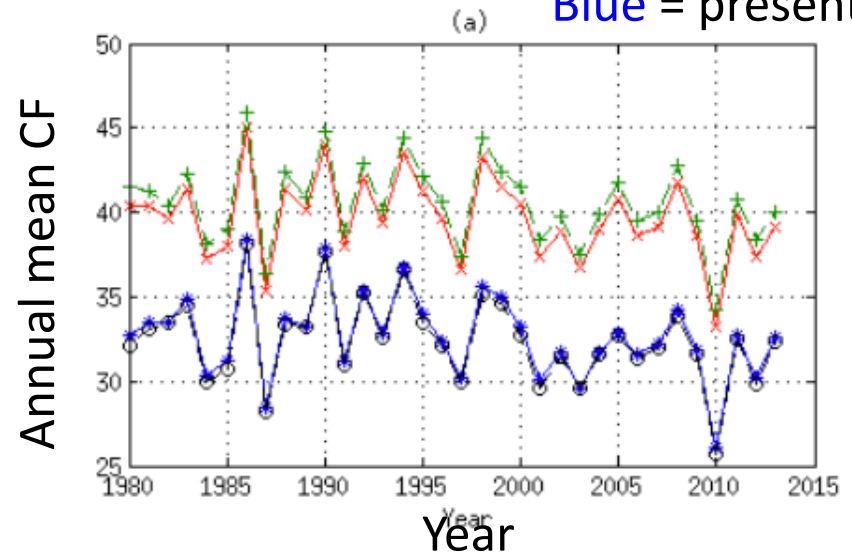
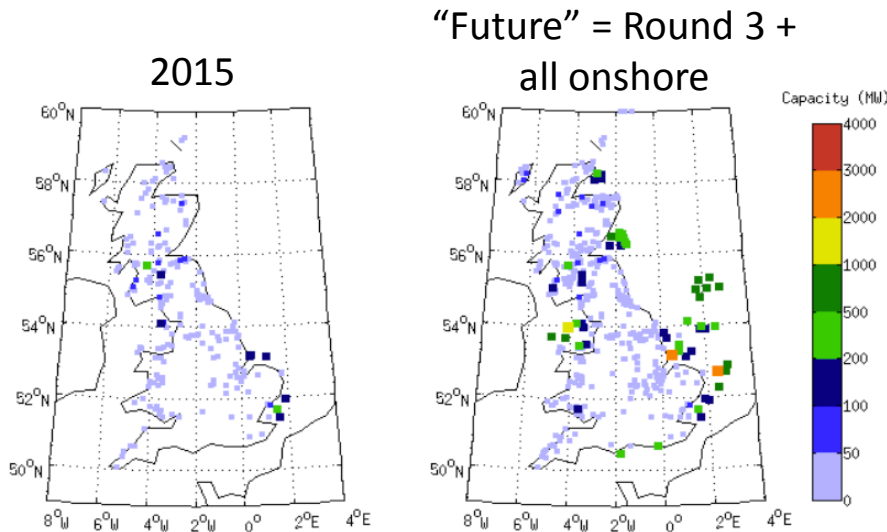


Future wind power installation

(Drew et al, 2015, Resources)

- “What if” scenarios: characteristics of future power systems
- Identify contributions from offshore/onshore

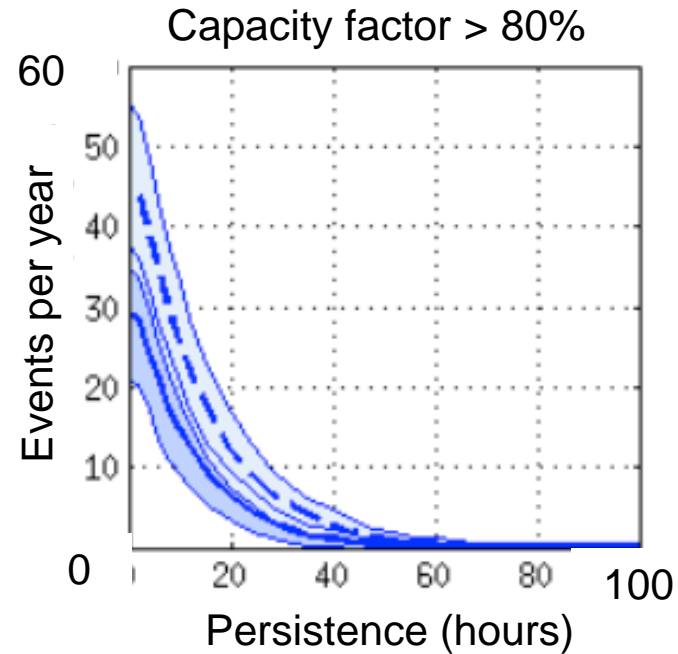
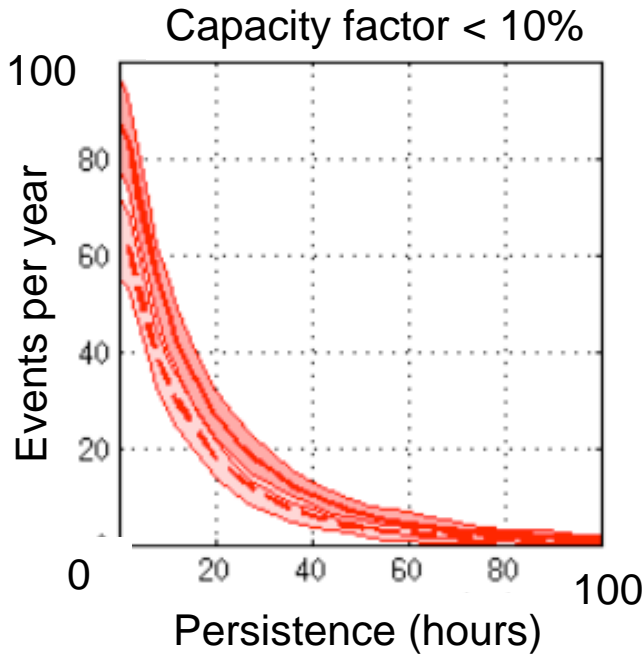
Red = “future”
Blue = present



Future wind power installation

(Drew et al, 2015, Resources)

- Fewer persistent low CF events → much fewer in terms of GW output
- More persistent high CF events → much more in terms of GW output
- Ramps same size in CF terms → larger ramp in GW



Solid lines = present
Dotted = future
Shading = 1 std. dev.

Integrated power systems

(mainly work by Hannah Bloomfield, PhD student)

- Integration of renewables: more sensitive to weather
 - ... but climate impact work usually considers “ingredients”, not power “systems”
- Perspective: two particular “classes” of problem

Short run

Operation of a “fixed” power system

E.g., unit commitment, power flow, loss of load probability

Long run

Design of “best” power system

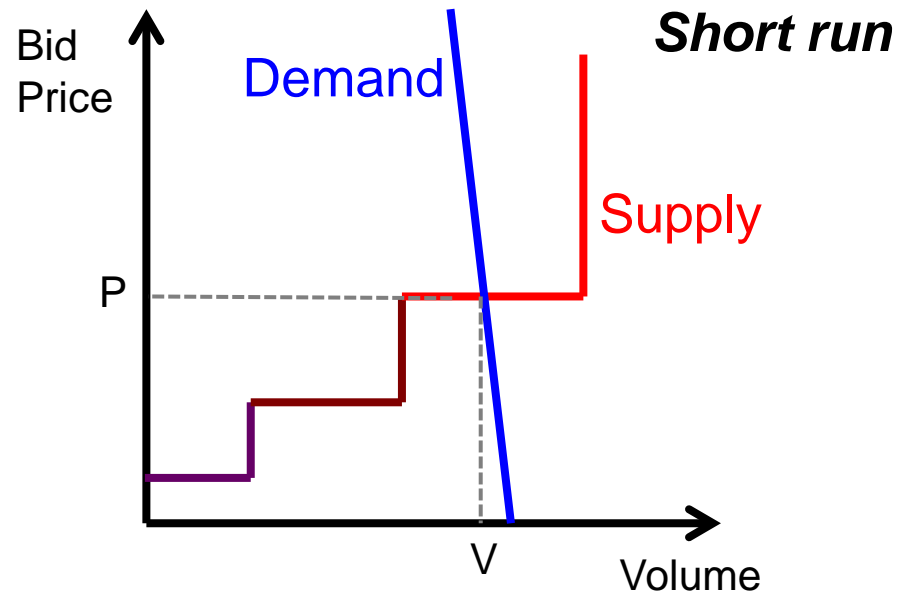
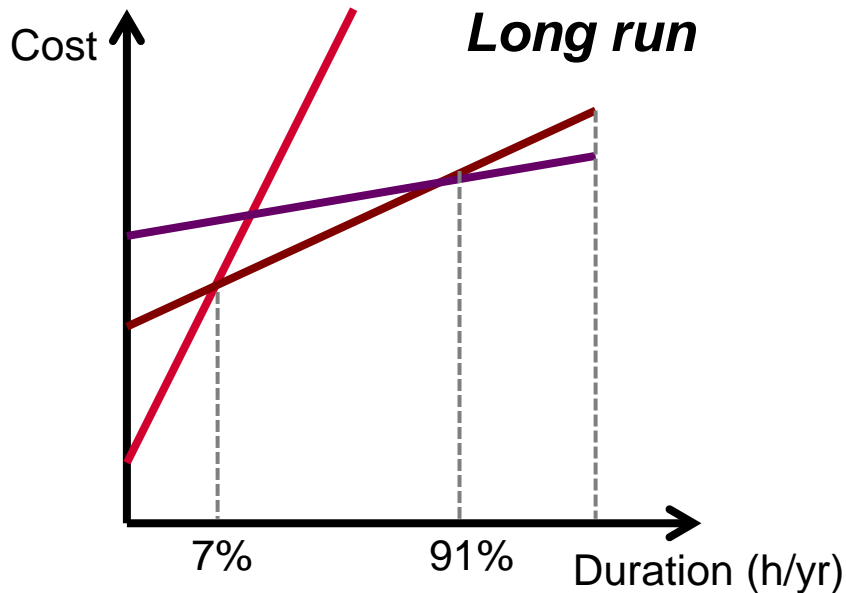
E.g., capacity mix, policy choices, economic optimality

- Both challenging, both important, both focus of much energy-system research
- Highly complex, often drawing on numerical simulation (typically optimisation-based)
- However, many influential studies use short weather/climate records, e.g. (for long-run):
 - Grunewald 2011; Poyry 2009; Green 2010; Gerber 2012; Widen 2011; Buttler 2016; Schaber 2013; Macdonald (in press); EWITS, WWSIS
- **Question: How robust are the results to long-term climate variability?**

Integrated power systems

(work by Hannah Bloomfield, PhD student)

- Simplified approach, based on “merit-order” principles
- Enables approximation of economic decision-making in power sector
- Intention to explore how climate information can/should be used...
- ... not to replace “more complex” power models, or to produce precise predictions

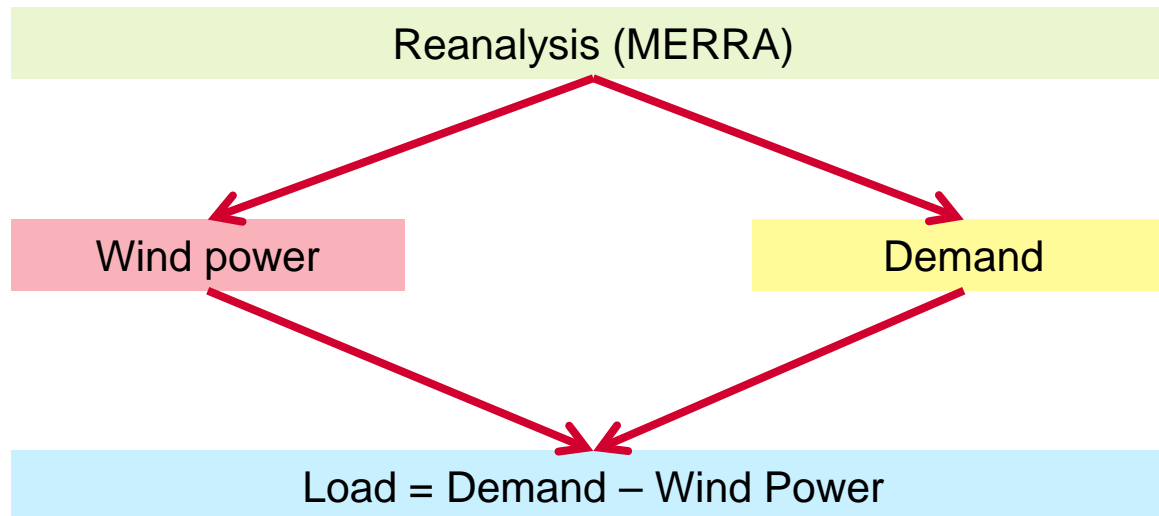


Type	Capital cost	Operating cost	Example
Peaking	Low	High	OCGT, oil
Mid-merit	Medium	Medium	CCGT, coal
Baseload	High	Low	Nuclear

See, e.g., *Stoft (2002)*
 7% and 91% thresholds
 based on *DECC 2013*

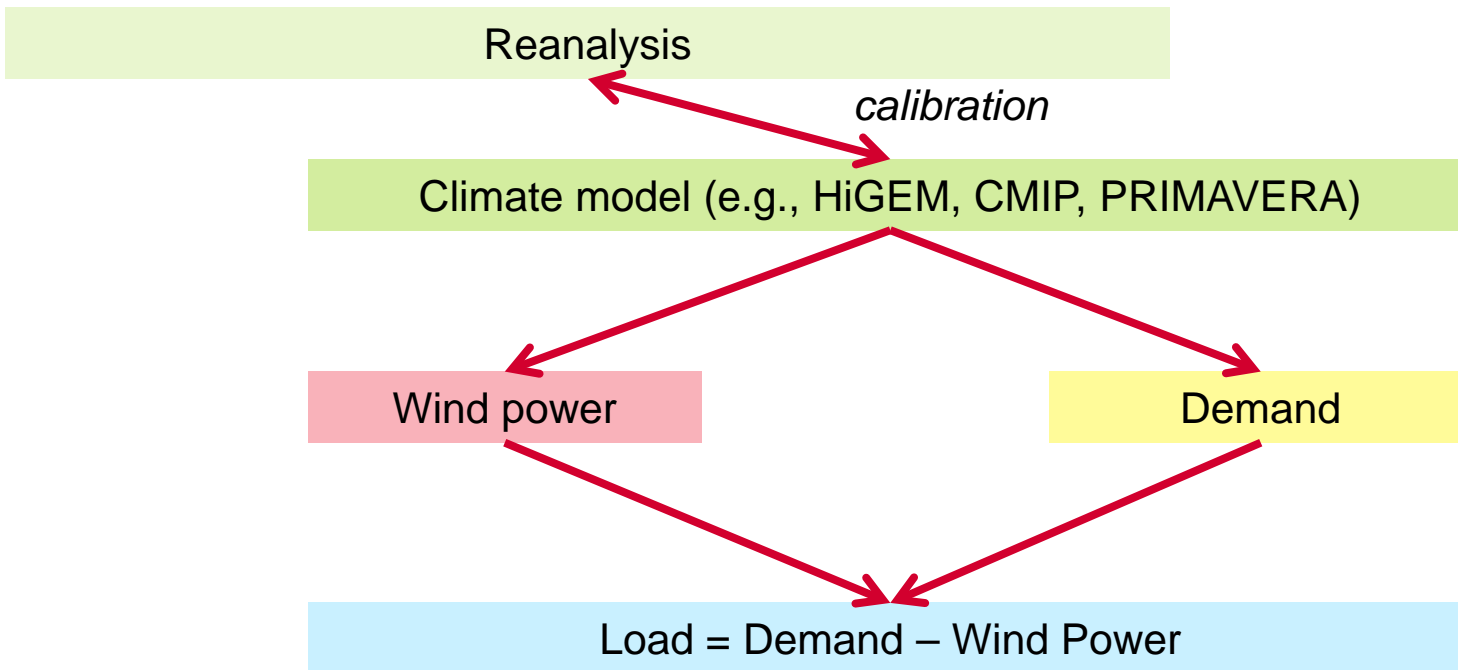
“Model” concept

- Consider a one-zone (copper plate) model of the GB power system
- No transmission constraints, interconnectors, storage or ramping constraints
- Self-consistent weather impact scenarios from reanalysis



“Model” concept

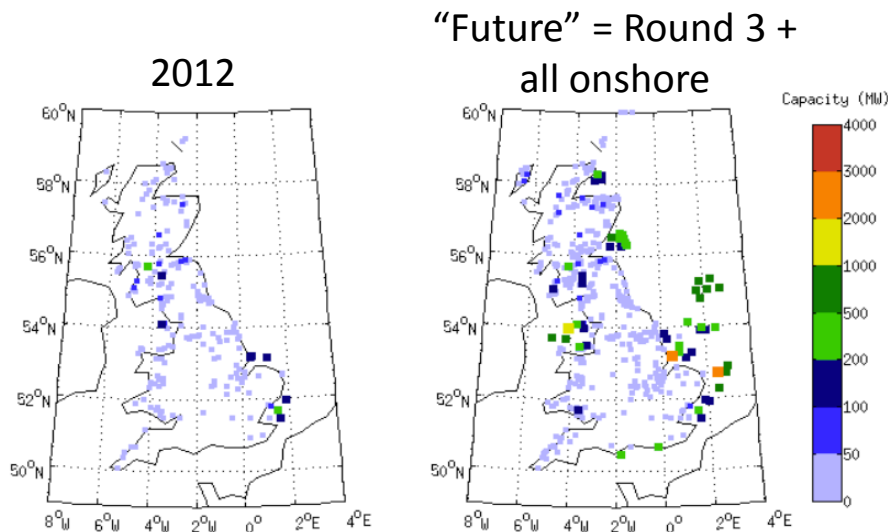
- Consider a one-zone (copper plate) model of the GB power system
- No transmission constraints, interconnectors, storage or ramping constraints
- Self-consistent weather impact scenarios from reanalysis or **climate model**



Wind power scenarios/model

- Constructed as previously, but using four different capacity scenarios:

Scenario	WP capacity	Distribution	Interpretation
NOWIND	0 GW		No use of wind power
LOW	15 GW	2012	Present day (2015)
MED	30 GW	2012	National Grid GG 2025
HIGH	45 GW	Future (Rd3)	National Grid GG 2035



GG =
National Grid Future Energy
Scenarios “Gone Green” (2015)

*Note: interpretive comparisons
indicate approximate
consistencies, not precise
definitions*

Three step approach:

1. Daily demand: multiple linear regression on temperature, c.f. Taylor & Buizza (2003)
 - Trained on recorded national demand 2006-2010; good fit $R^2 \sim 0.93$

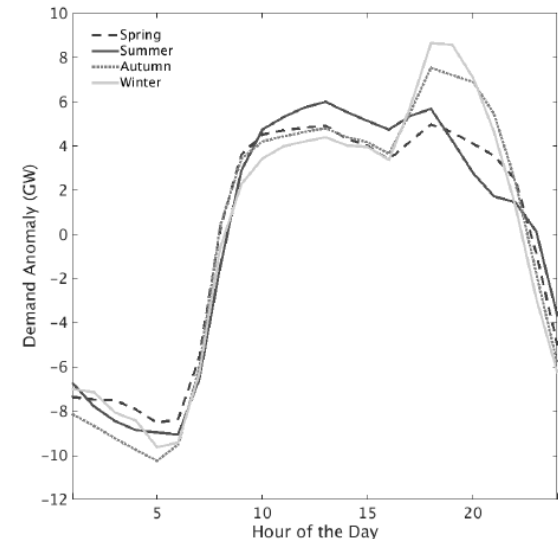
$$\begin{aligned} Demand(t) = & \alpha_1 + \alpha_2(t) + \alpha_3 \sin(\omega t) + \alpha_4 \cos(\omega t) + \alpha_5 T e(t) + \alpha_6 T e^2(t) \\ & + \sum_{k=7}^8 \alpha_k WE(t) + \sum_{l=9}^{12} \alpha_l WD(t) + \alpha_{13} HOL(t) \end{aligned}$$

1. Simplify demand: remove “special days” with no meteorological significance

$$Demand = \alpha_1 + \alpha_3 \sin(\omega t) + \alpha_4 \cos(\omega t) + \alpha_5 T(t) + \alpha_6 T^2(t)$$

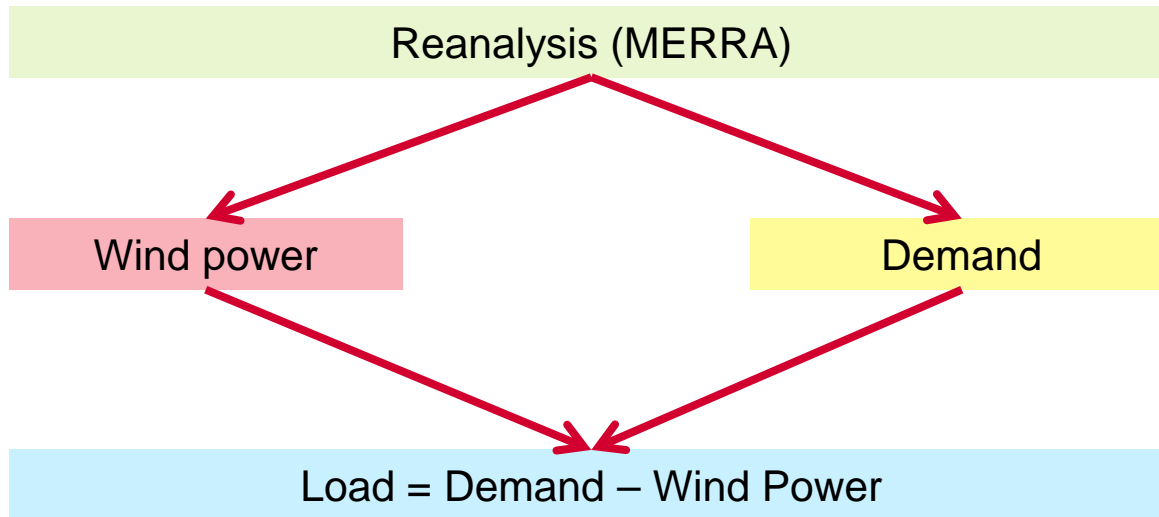
1. Simplified hourly demand:

- “Downscaling” using observed diurnal curves
- One curve per season



“Model” concept

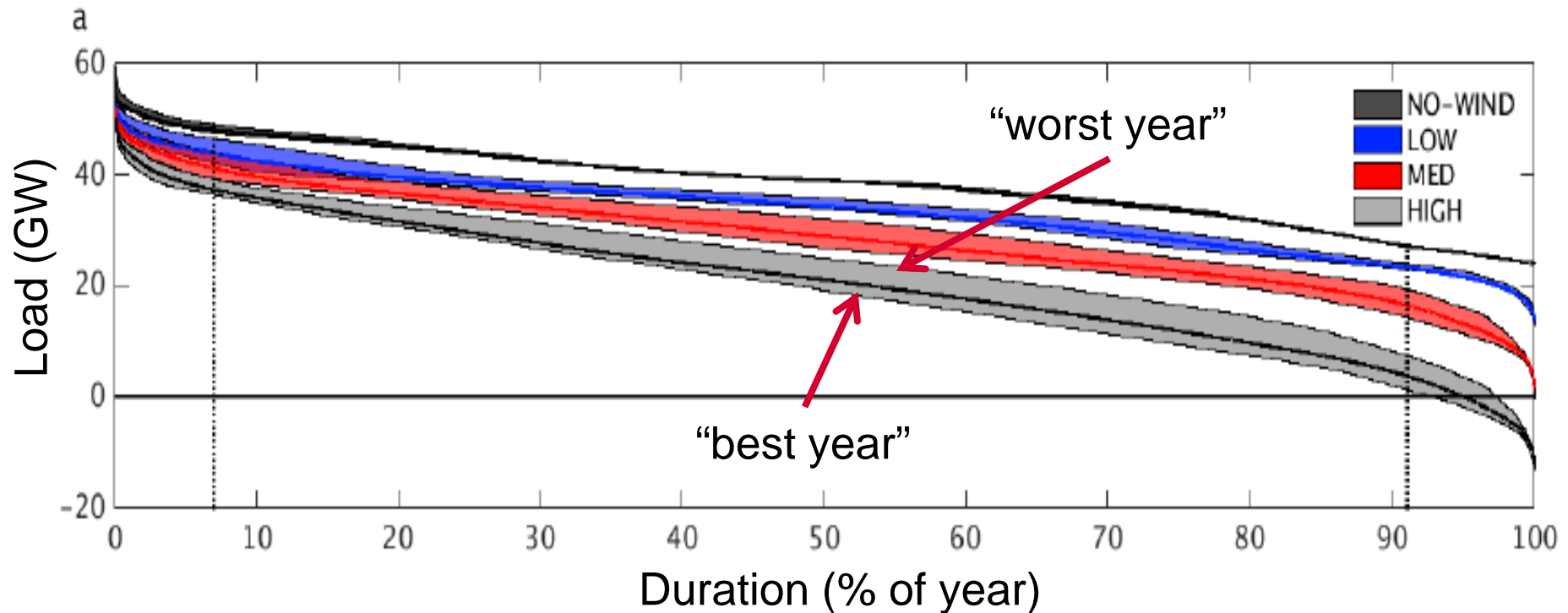
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- Self-consistent weather impact scenarios from reanalysis



Power system “model” concept

Bloomfield et al, Nature Energy (submitted)

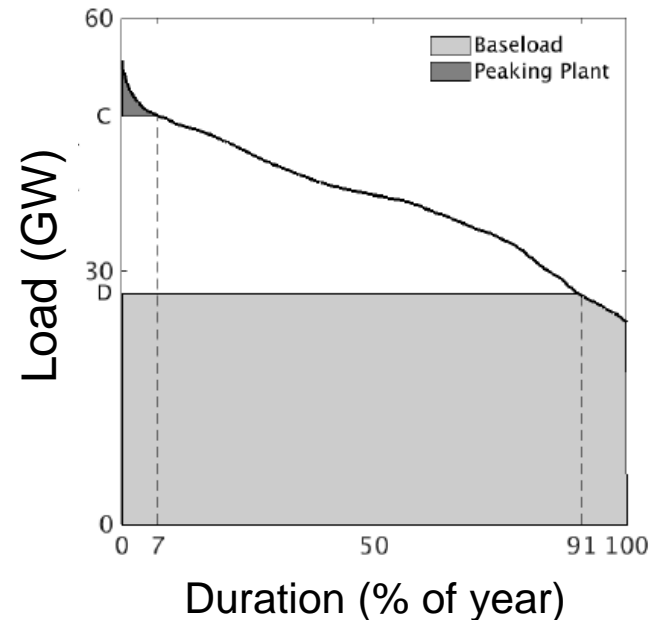
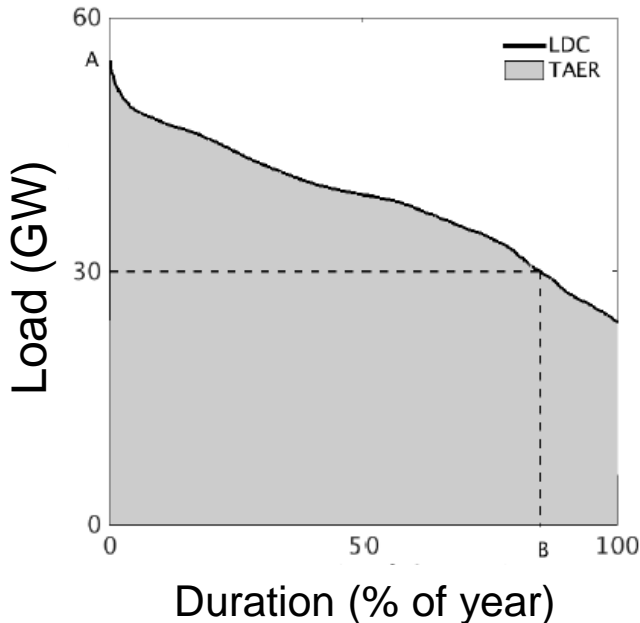
- Result:
 - 4 x 36 year scenarios (NO-WIND, LOW, MED, HIGH); hourly resolution
 - Convenient to display as annual load duration curves (→ 36 LDCs per scenario)



Power system metrics

Bloomfield et al, Nature Energy (submitted)

- Assume “load” must be met by schedulable plant (either peaking, mid-merit, or baseload)
- Six power system “impact metrics” defined
 - Total annual energy required
 - Peak load
 - Curtailed wind energy
 - Threshold of economic opportunity for 7% peaking plant (or volume of energy opportunity)
 - **Threshold of economic opportunity for 91% baseload plant** (or volume of energy opportunity)
 - **Annual operating hours of 30GW marginal mid-merit plant**

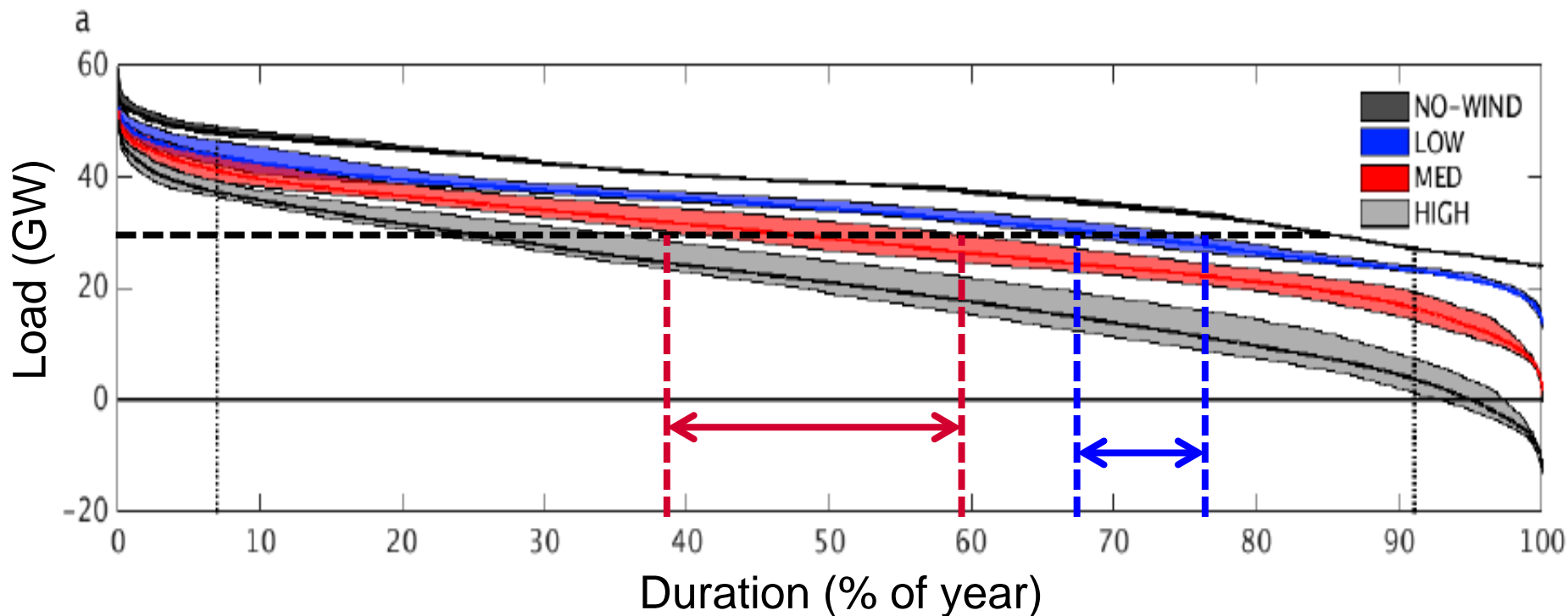


Mid-merit operating hours

Bloomfield et al, Nature Energy (submitted)

Perspective: “Short run” problem

- Substantial decrease in number of hours where load exceeds 30GW (from ~73% to ~50%)
- Also: increase in the year-to-year range
 - Doubling from ~10pp (750h/yr) to ~20pp (1350h/yr)
 - Significantly increased impact of climate on the operation opportunity



Baseload threshold of opportunity

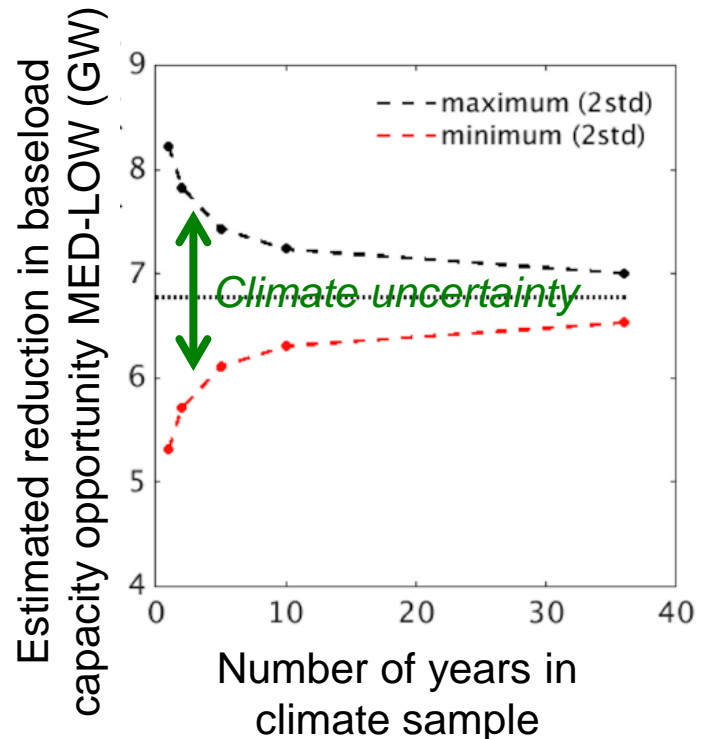
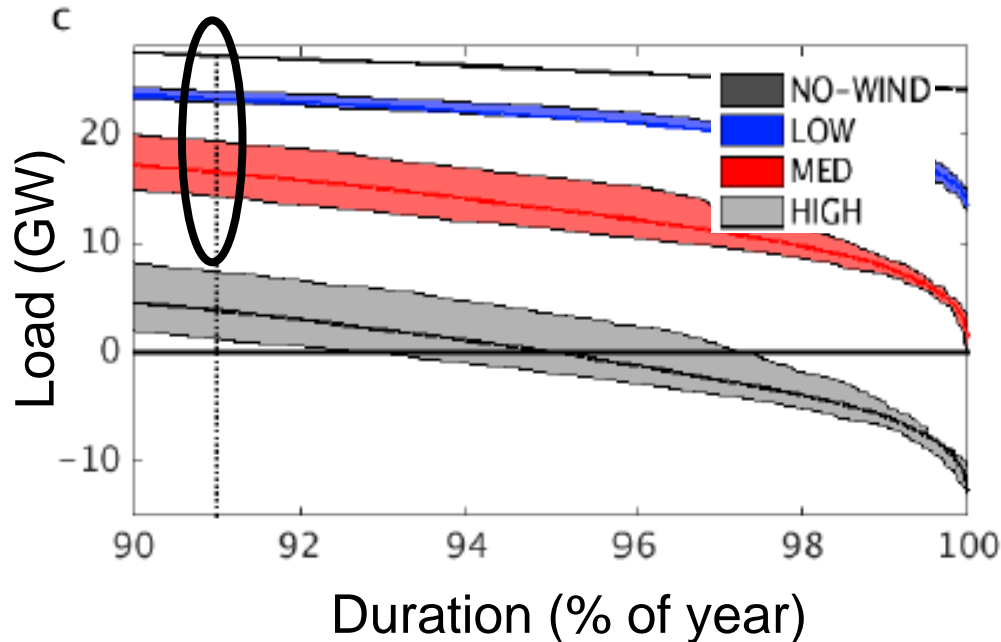
Bloomfield et al, Nature Energy (submitted)

Perspective: “Long run” problem - optimal amount of “baseload type” plant capacity

- Mean decreases dramatically → less opportunity for this type of generation
- Inter-annual range significantly increases → more climate uncertainty

→ Estimates of the economically “optimal” opportunity for baseload which are reliant on short-data may be significantly in error:

- Recall many studies use between 1 and 10 years of data
- 50% error in the change in optimal capacity for single year; 15% error for 10-year

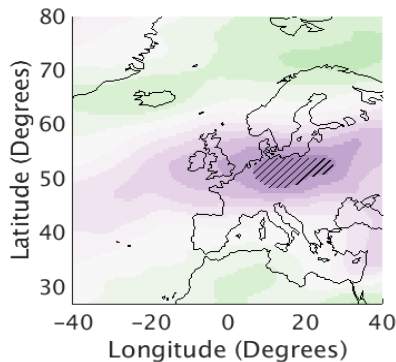


Climate drivers

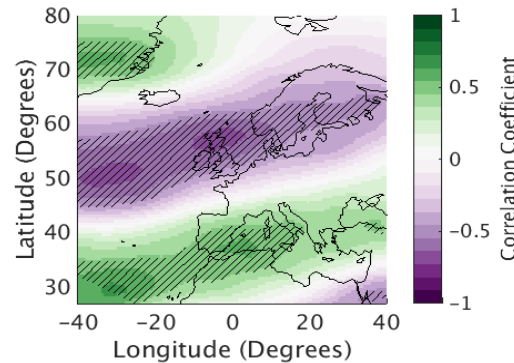
(Hannah Bloomfield, PhD thesis in prep)

- Exploration of what *causes* climate impacts (work in progress)
 - Meteorological drivers sensitive to construction of power system
 - See also Brayshaw, Dent and Zachary (2012) for wind-during-peak-demand

NO-WIND



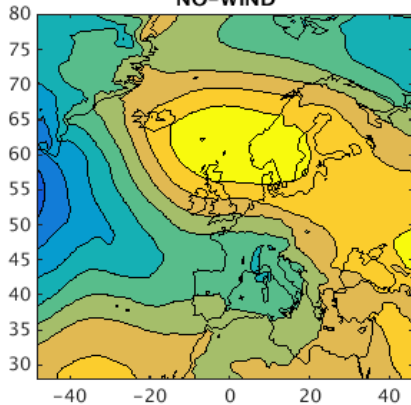
MED (30GW)



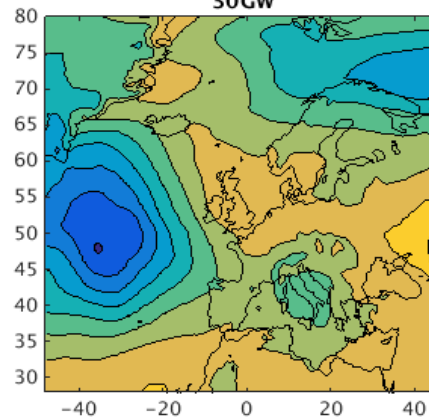
Baseload energy opportunity

Correlation with zonal wind U850

NO-WIND



30GW



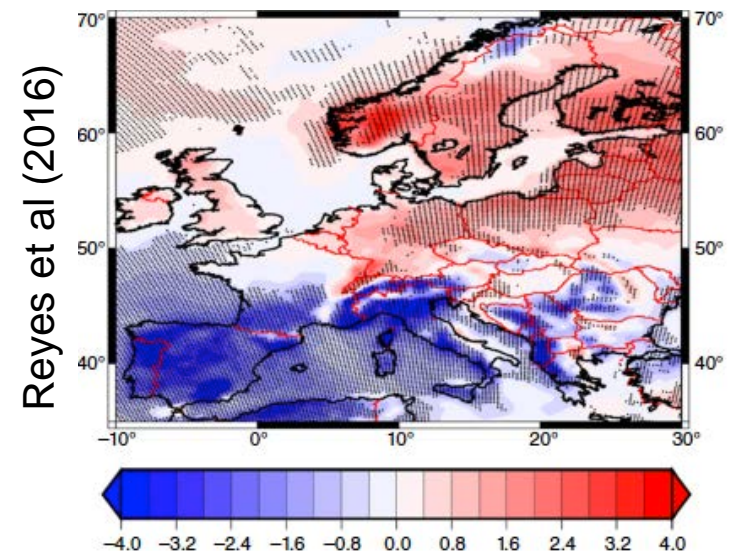
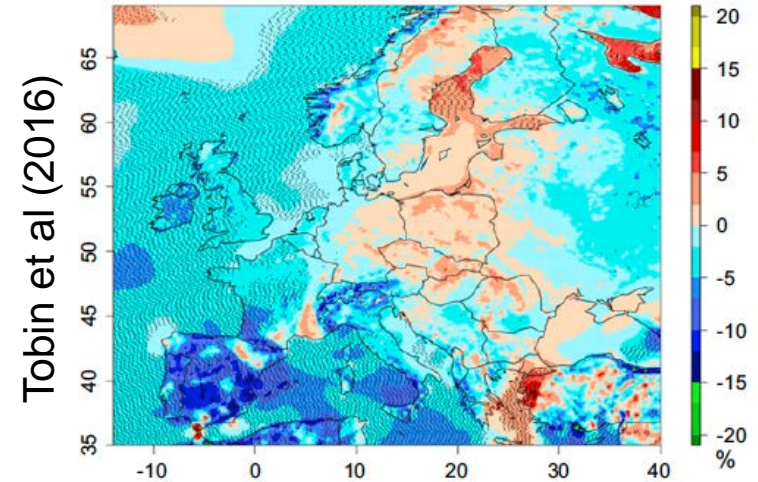
Peak Load

Composite MSLP
(Top 10, 5d separation)

Climate change

- Growing number of studies addressing climate change on energy systems
- General consensus for wind:
 - Changes are “fairly small”
 - Increases in N. Europe
 - Decreases in S. Europe
 - Significant differences between models
 - Differences between studies – even using same model archive!
- See, e.g., Bonjean-Stanton et al (2016) for a recent review across many technologies

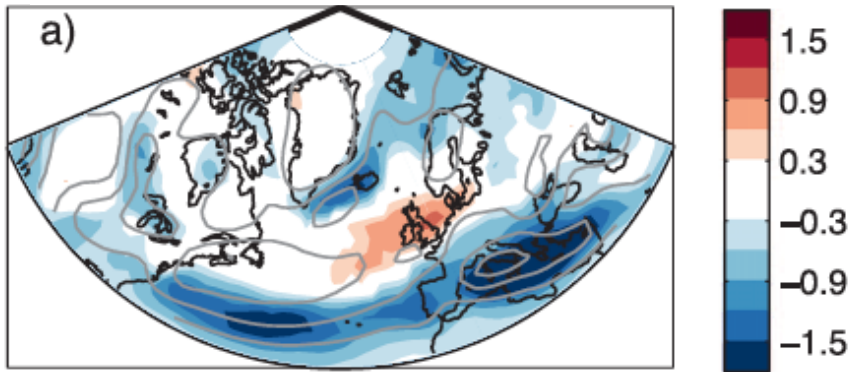
*RCP8.5 late C21 ENS mean
Change in wind power potential*



A note on climate change...

- Understanding the meteorological drivers is important...
- ... forced regional climate change signals can be quite uncertain (note: colour scales!)

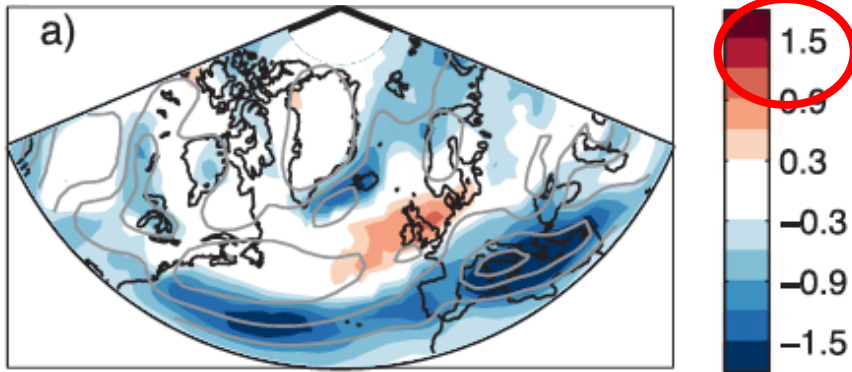
“Climate response”
RCP8.5-HIST Track density DJF
Ensemble mean



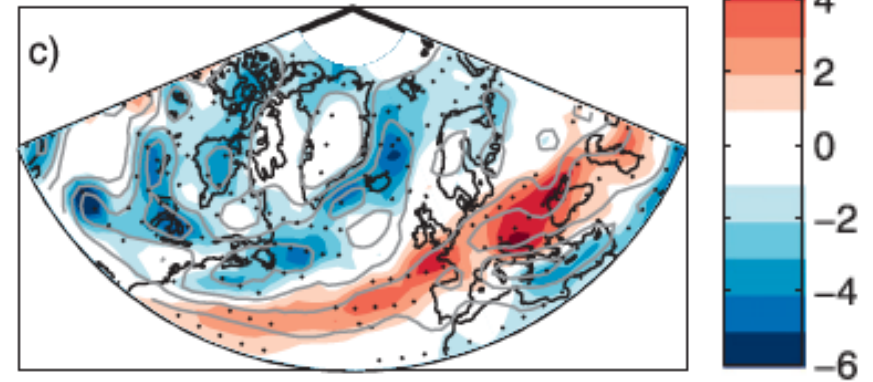
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“Climate response”
RCP8.5-HIST Track density DJF
Ensemble mean

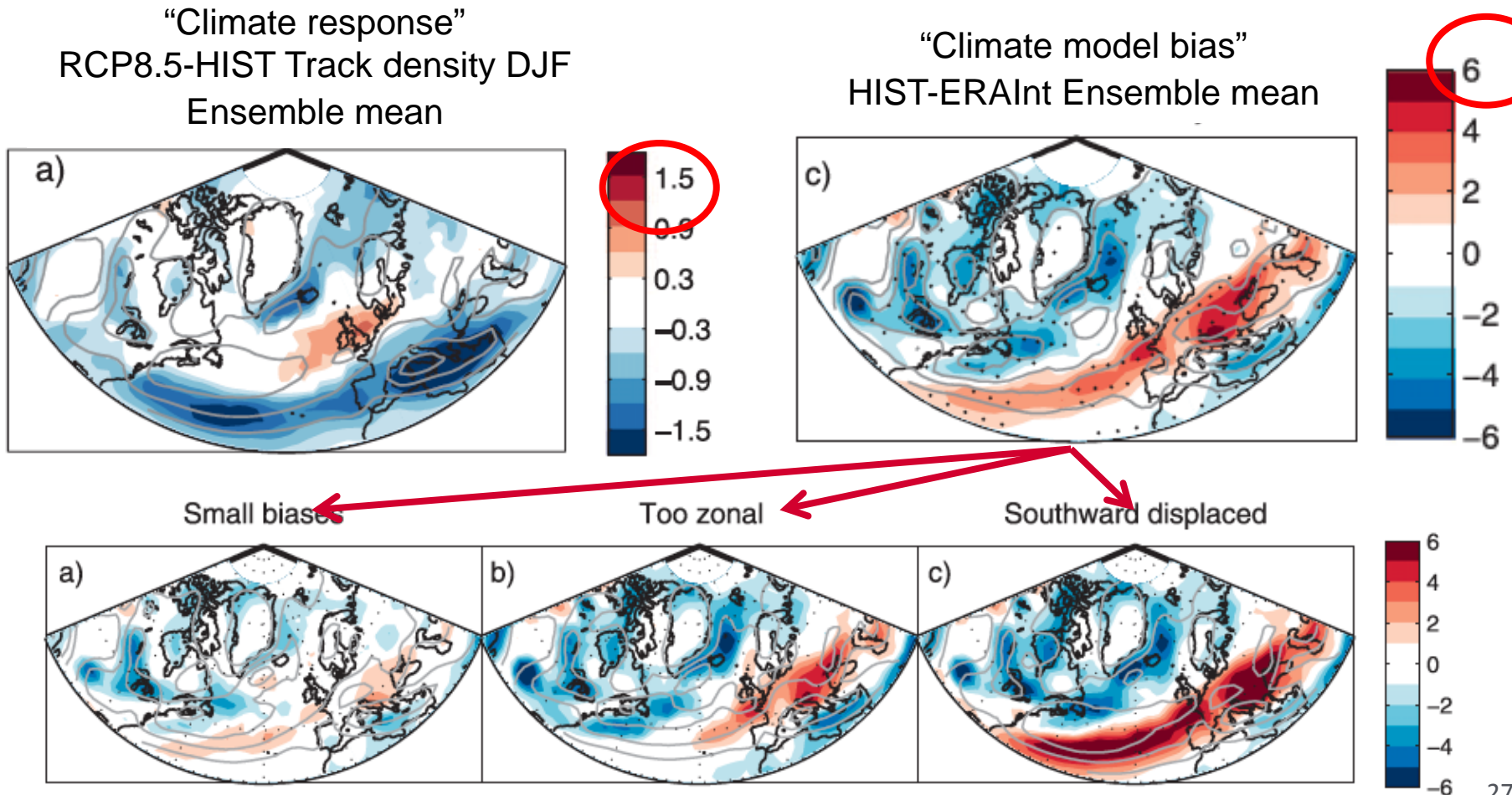


“Climate model bias”
HIST-ERAInt Ensemble mean



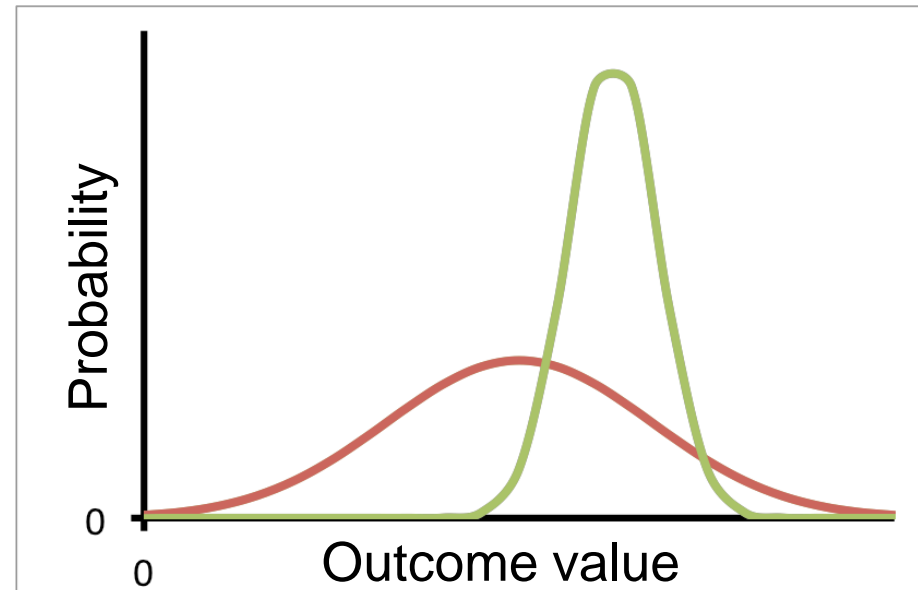
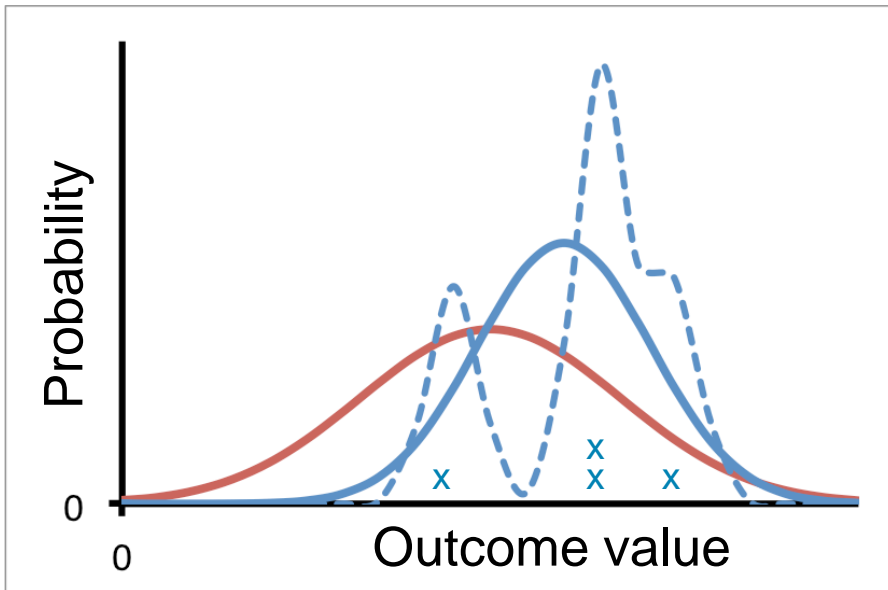
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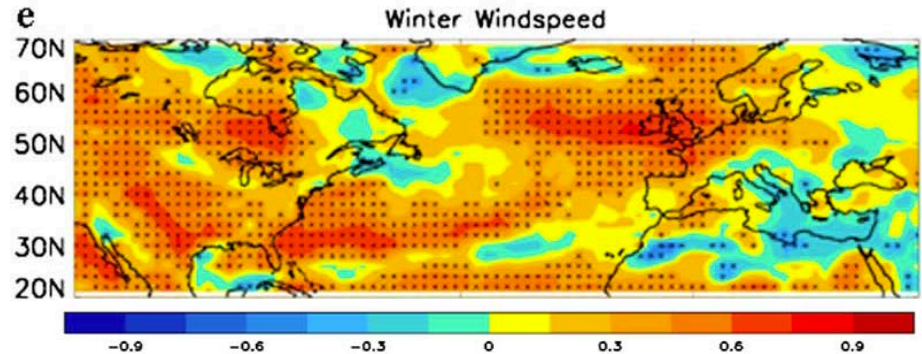
Types of climate information

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- Type 2 – forecasting risk: anticipating outcomes (red → green)
 - Ensemble prediction (subseasonal, seasonal and decadal)



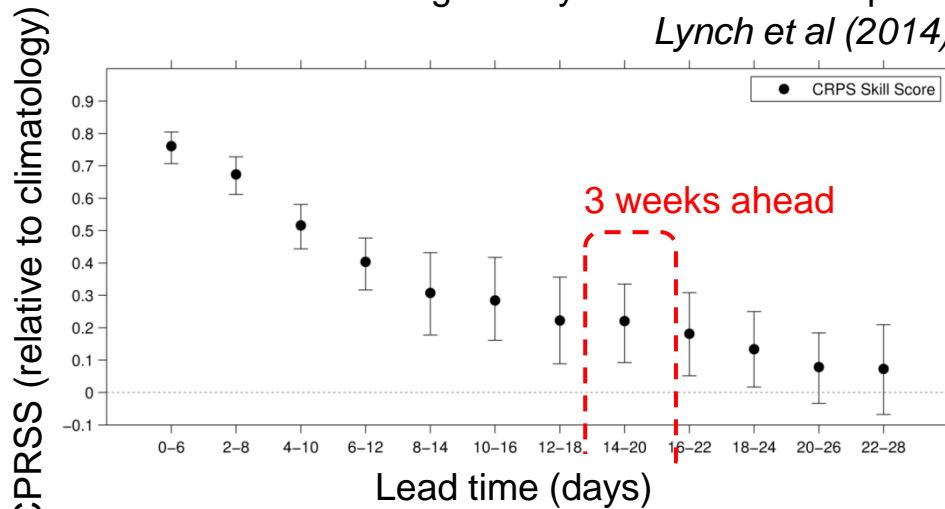
Subseasonal and seasonal forecasting

- Ensemble forecasts
- 3 weeks – 4 months
- Skill at large scales (space & time)
- Inherently probabilistic



3-month average skill in winter wind speed in Met Office seasonal forecast
Scaife et al 2014

ECMWF ensemble forecast
UK-average 7-day mean 10m windspeed
Lynch et al (2014)



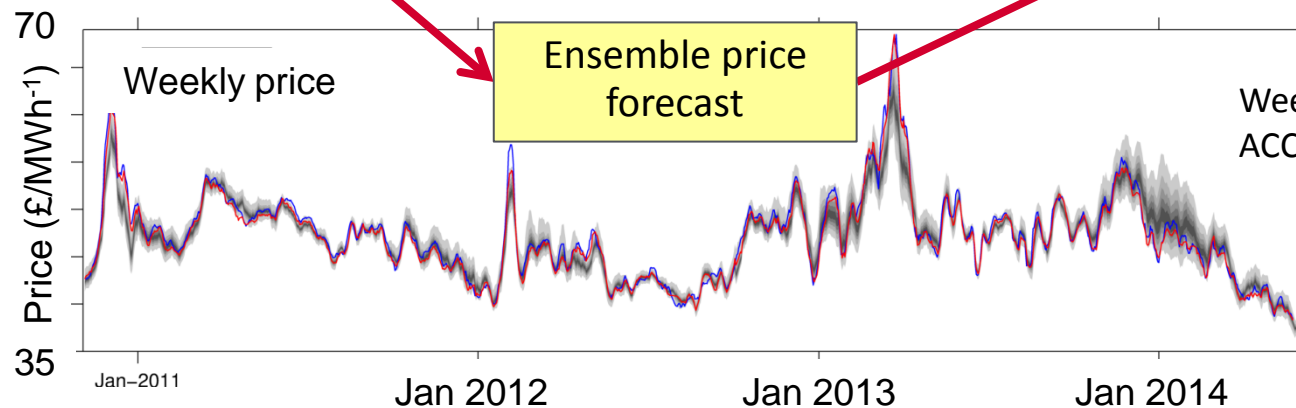
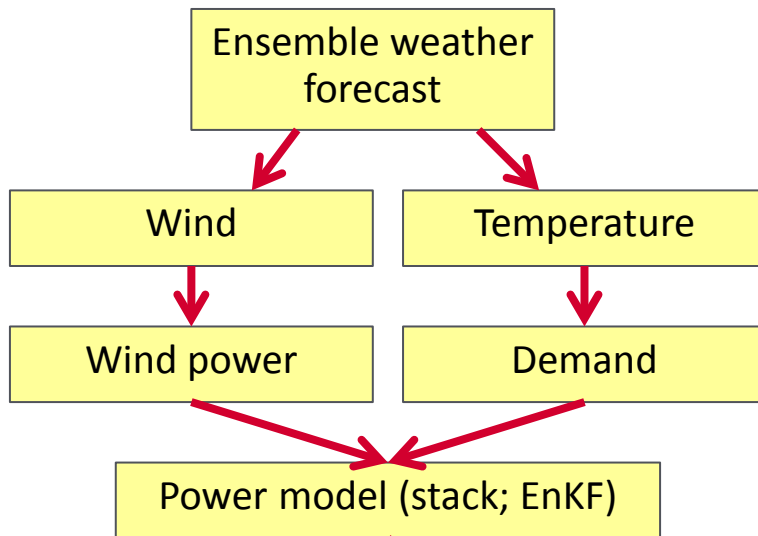
Country-average weekly-mean forecast skill for
Temperature, wind and solar
Suckling (unpublished)

	Temperature	Wind speed	Cloud cover
Europe, wk1	Green	Green	Green
Country 1	Green	Green	Green
Country 2	Green	Green	Green
Country 3	Green	Green	Green
Country 4	Green	Green	Green
Country 5	Green	Green	Green
Europe, wk2	Green	Green	Orange
Country 1	Green	Green	Orange
Country 2	Green	Green	Orange
Country 3	Green	Green	Orange
Country 4	Green	Green	Orange
Country 5	Green	Green	Orange
Europe, wk3	Green	Green	Red
Country 1	Green	Green	Red
Country 2	Green	Green	Red
Country 3	Green	Green	Red
Country 4	Green	Green	Red
Country 5	Green	Green	Red
Europe, wk4	Green	Green	Red
Country 1	Green	Green	Red
Country 2	Green	Green	Red
Country 3	Green	Green	Red
Country 4	Green	Green	Red
Country 5	Green	Green	Red

Using climate forecasts

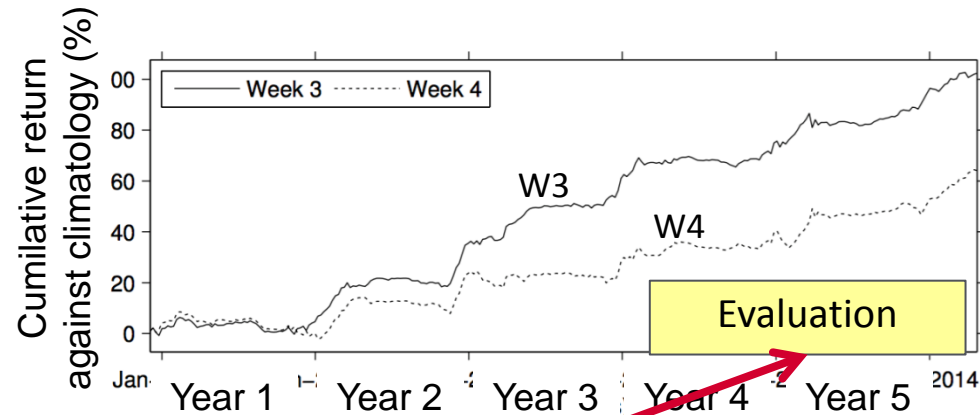
(Lynch et al 2014; Lynch PhD thesis 2016)

- Similar issues to short-range but often more challenging (calibration etc)
- Acting on probabilistic information



Weekly price 3-week ahead forecast:
ACC 0.53; CRPS 0.15 (99% confidence)

It is likely possible to extract more skill

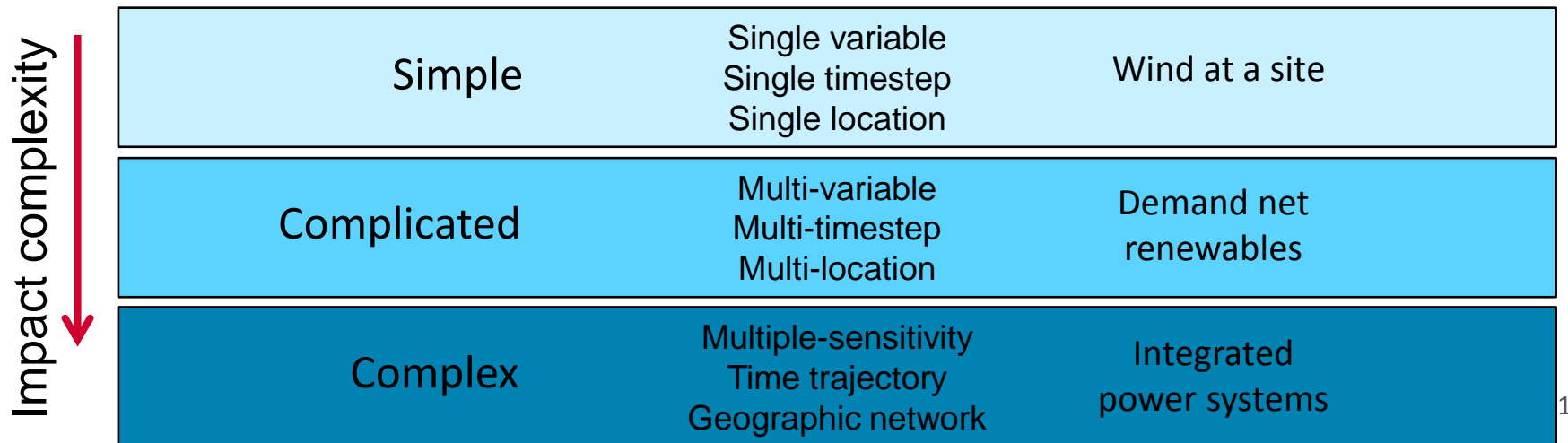


Optimize trading strategy

Lynch et al
(thesis submitted)

Summary

- Weather and climate risk matters for energy applications
 - **Climate variability and change (years-to-decades) produces significant uncertainty**
 - Impacts all parts of the power system, not just renewables
 - Influence on both “short-run” (fixed system) and “long-run” (investment/planning) perspectives
 - Has not been adequately addressed in many previous studies: **CIPSMIP?**
- Opportunities to better manage the risks... but need for interdisciplinary collaboration
 - Reanalysis and GCMs are powerful tools: **but must be used appropriately**
 - Climate drivers need to be understood: **does dataset/model include the relevant processes?**
 - Sub-seasonal, seasonal and decadal forecast systems: **need to integrate with decision-making**



Impact complexity ↓	Simple	Single variable Single timestep Single location	Wind at a site
	Complicated	Multi-variable Multi-timestep Multi-location	Demand net renewables
	Complex	Multiple-sensitivity Time trajectory Geographic network	Integrated power systems

Citations and upcoming

Major projects ongoing:

- ECEM climate services for energy
- PRIMAVERA climate-energy impacts

Recruiting postdoc now!

Contact:

- Website (models and data): www.met.reading.ac.uk/~energymet
- Email: d.j.brayshaw@reading.ac.uk

Citations:

- Bloomfield et al (submitted) Quantifying the increasing sensitivity of power systems to climate variability. *Nature Energy*.
- Cannon, D.J. et al (2015) Using reanalysis data to quantify extreme wind power generation statistics : a 33 year case study in Great Britain. *Renewable Energy*, 75. pp. 767-778.
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- Lynch, K. J. et al (2014) Verification of European subseasonal wind speed forecasts. *Monthly Weather Review*, 142 (8). pp. 2978-2990.
- Ely, C. R. et al (2013) Implications of the North Atlantic Oscillation for a UK–Norway renewable power system. *Energy Policy*, 62. pp. 1420-1427.
- Brayshaw, D.J. et al (2012) Wind generation's contribution to supporting peak electricity demand: meteorological insights. *Journal of Risk and Reliability*, 226 (1). pp. 44-50.
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