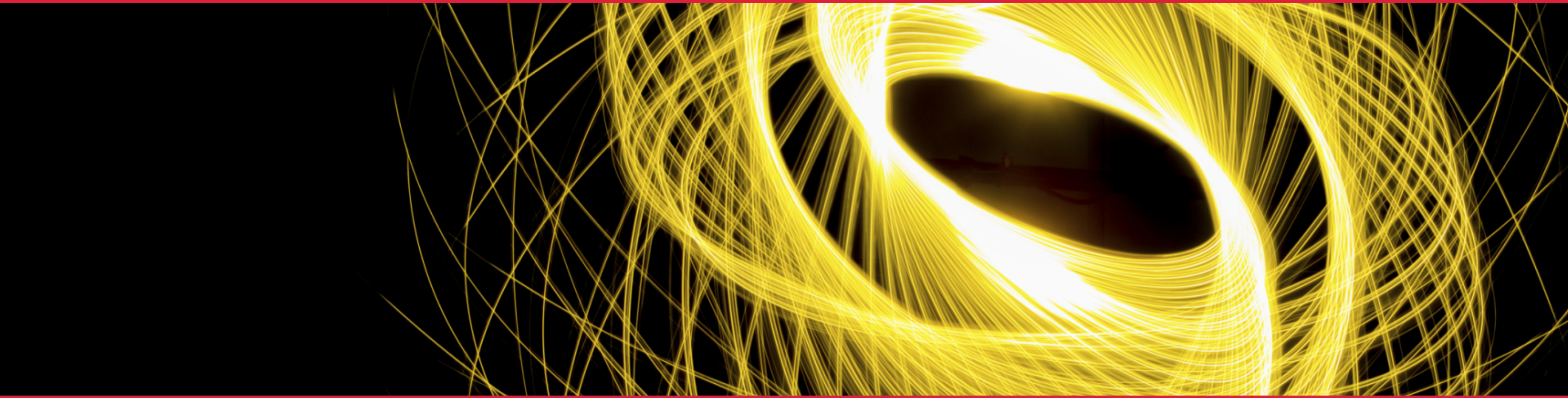
Department of Meteorology
School of Mathematical, Computational and Physical Sciences

University of Reading

Weather and climate impacts on the energy sector



David Brayshaw

Showing work by PhDs and postdocs: Hannah Bloomfield, Dan Drew, Dirk Cannon, Kieran Lynch, Caroline Holmes (nee Ely), Dan Hdidouan, Kostas Phillippopoulos, Francisco Santos-Alamillos & Emma Suckling

With input from John Methven, Len Shaffrey, Andrew Charlton-Perez and others

National Centre for Atmospheric Science
NATURAL ENVIRONMENT RESEARCH COUNCIL

Walker INSTITUTE

Power systems and meteorology

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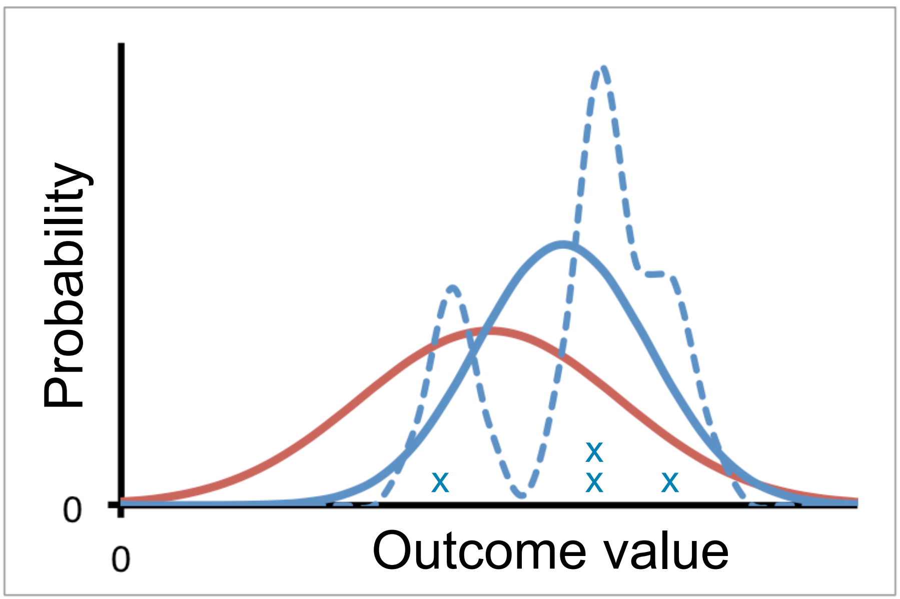
- Many impacts of weather on power (damage, demand, transmission, supply)
- Use of renewables: *Increasing* sensitivity to weather on generation side
- Climate change and variability: effects weather properties

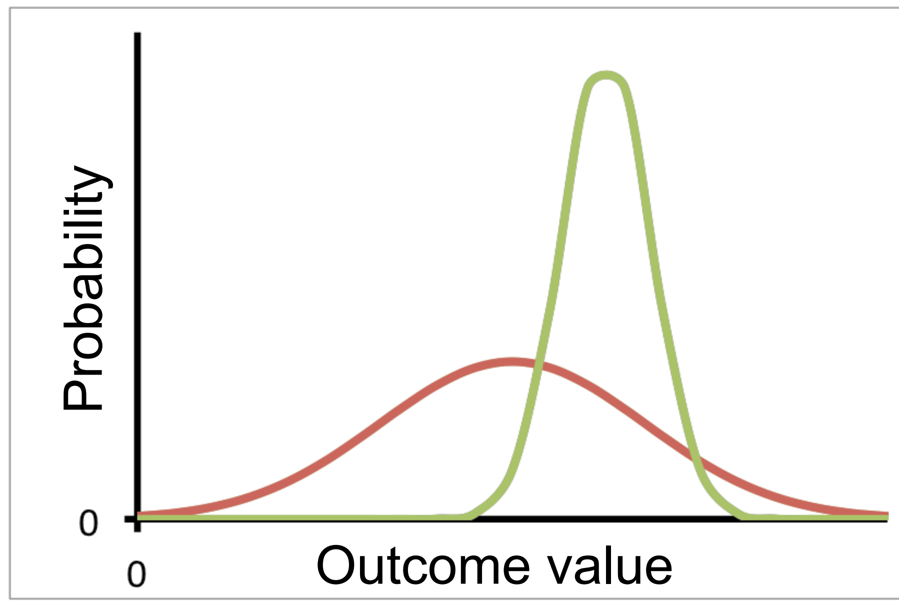
Operational (seconds –few days)	· Day to day operations (e.g., grid management, plant sched) · Anticipating extreme weather
Tactical (days – 1 year)	· Longer-term energy trading · Maintenance planning · Medium term resource planning
Strategic (long term climate)	· Characterising demand/supply · Impacts of climate change · Design of power systems and markets
Extremes (disrupting weather)	· Risk and impact of extreme disruptive weather · Local and far-field

- Key challenge: how to use weather climate data effectively to understand behaviour of impacted system and develop risk management strategies
- Today: examples from operational, strategic and tactical
- Power-, Euro-, Renewables- centric (please ask for other areas!)

Topics

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





Topics

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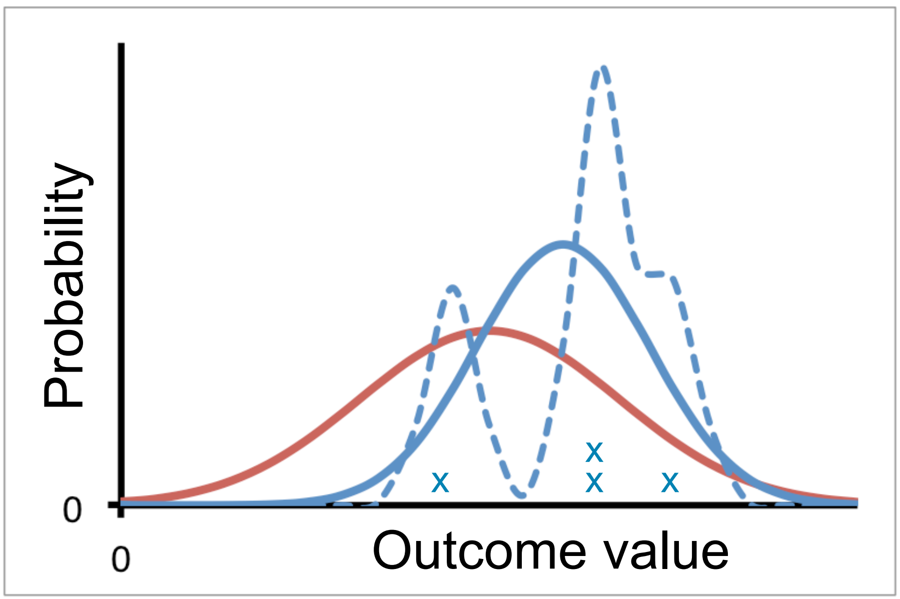
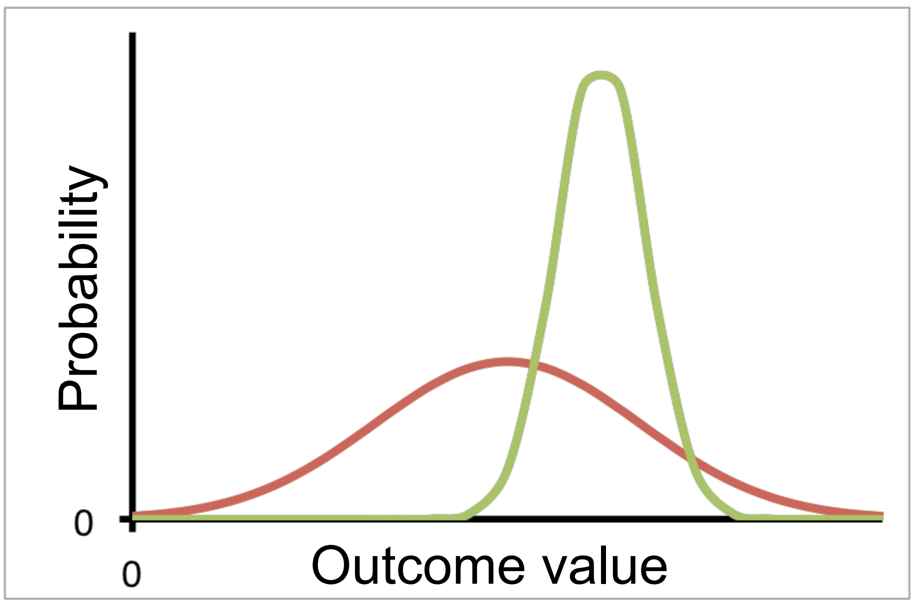




Climatologies of risk

- **Wind-power variability**
  - Reserve holding, system planning, system management
  - Risks: persistent-high, persistent-low and rapid ramps in wind power
- Question 1: To what extent 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
- Question 2: Are economic "system planning" models robust to climate change and variability?

Wind power climatologies

(Cannon et al, 2015; Drew et al 2015; Canon et al, submitted)

- Special thanks to: Dirk Cannon & Dan Drew (postdocs), John Methven & Phil Coker (UoReading), and David Lenaghan (National Grid)

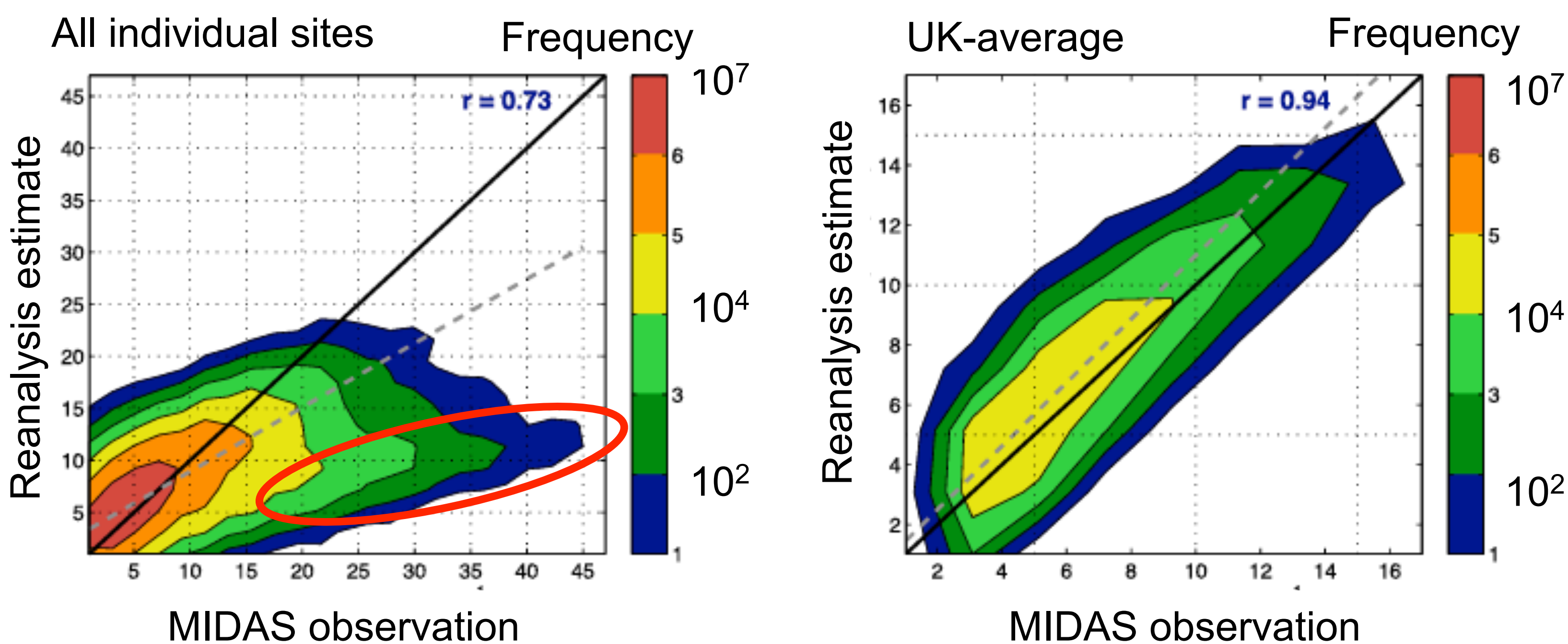
- Insufficient direct power observation records (few years)
- Previous work largely based on met-station data (Sinden, Leahy, Earl, Fruh, …)
  - Spatially sparse, inhomogenous (spatial, temporal)
  - Wrong height (10m), wrong location (relative to wind farms)
  - → Conversion to "power" problematic

- Reanalysis
  - Full, gridded, 30+ years of homogenous coverage
  - Multiple vertical heights
  - Freely available, no need for additional simulations
  - NASA MERRA (Reinecker et al 2011); similar with ERA-Interim (Dee et al, 2011)

Wind evaluation

- MERRA comparison to 328 MIDAS 10m wind-mast observations
  - High altitude sites: likely underestimation of topographic height
  - National average: performs well - compensation of uncorrelated small-scale “errors”

Absolute wind speed (10m, hourly)

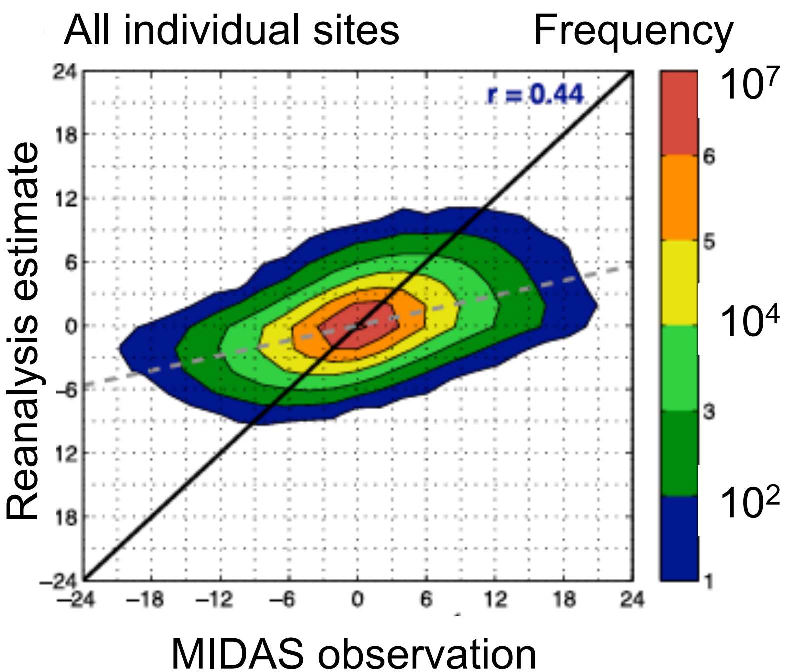


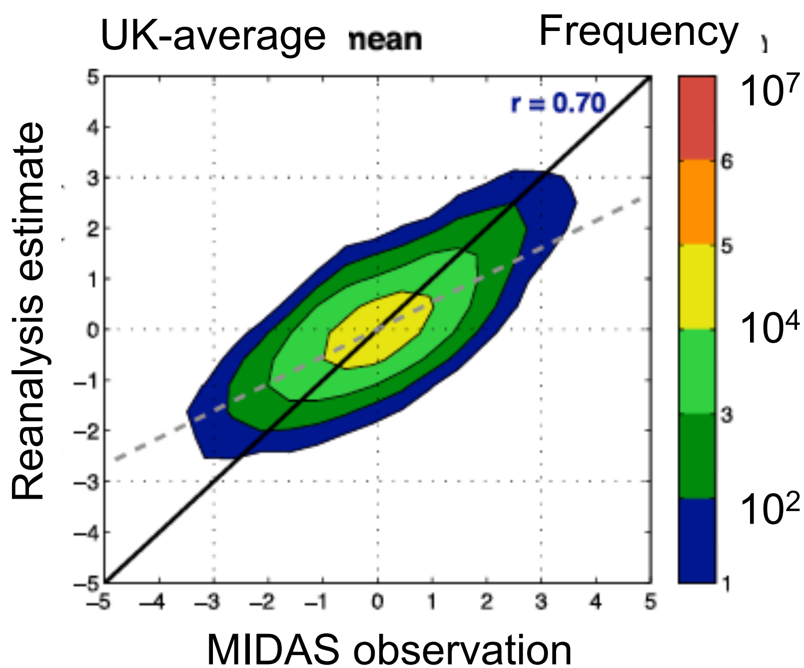
Cannon et al (2015)

Wind evaluation

- MERRA comparison to 328 MIDAS 10m wind-mast observations
  - High altitude sites: likely underestimation of topographic height
  - National average: performs well - compensation of uncorrelated small-scale "errors"
  - National 3-6 hour "deltas" reproduced well

3-hour change in wind speed (10m, hourly)



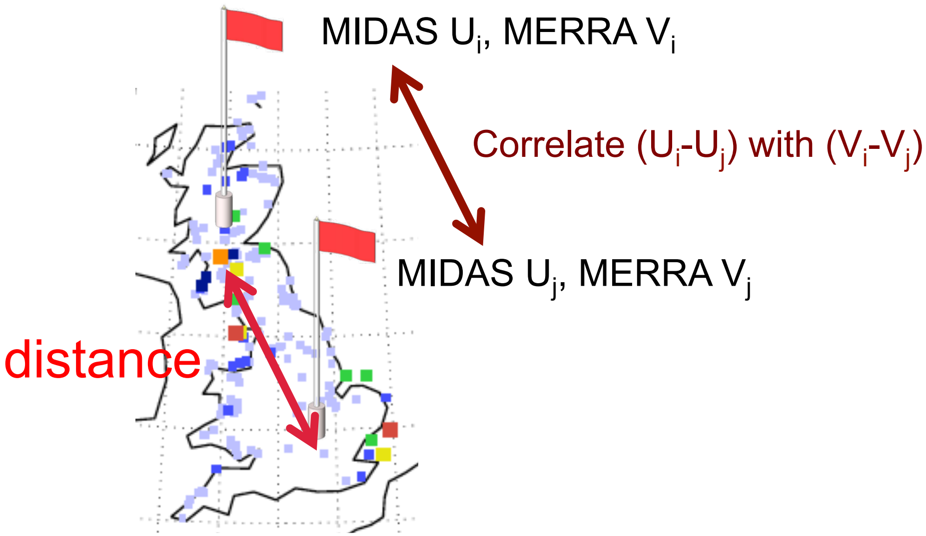


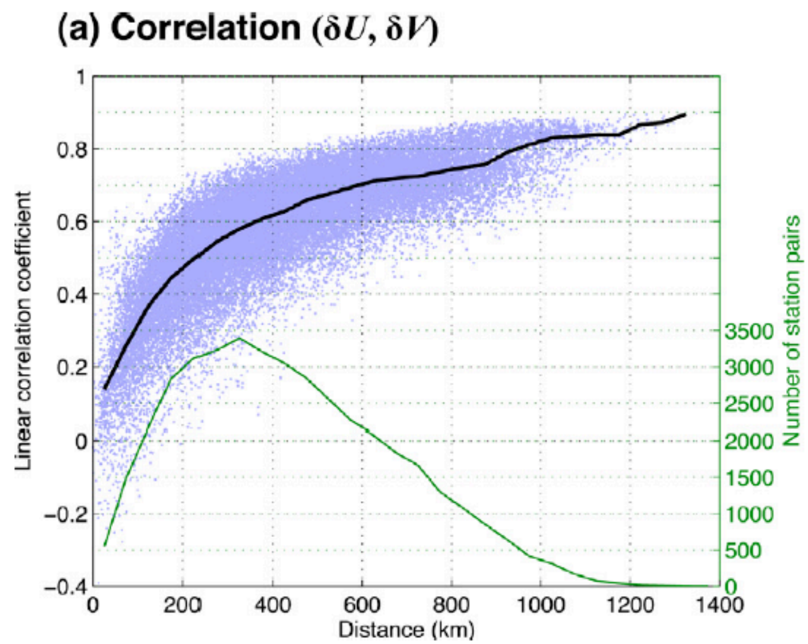
Cannon et al (2015)

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*?





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 ~ 300km

Cannon et al (2015)

Conversion to wind power

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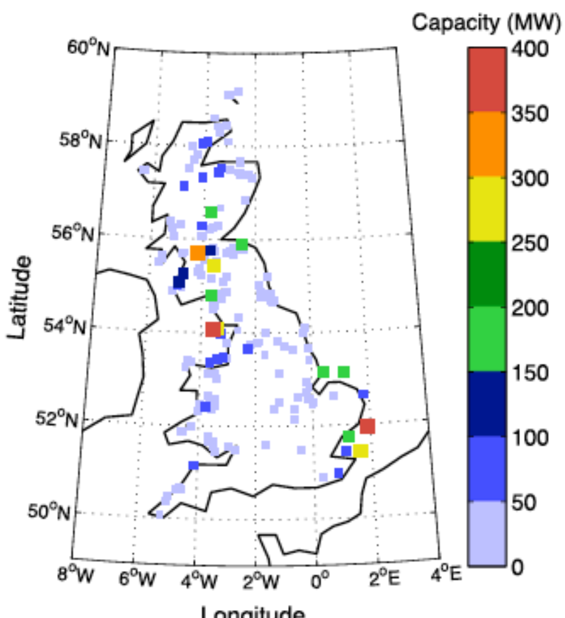
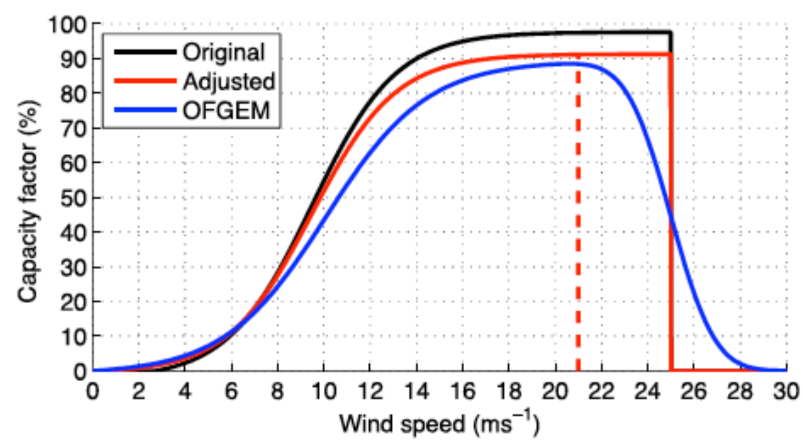
- Interpolate hourly wind-speed to each site in 2012 wind-farm list (2, 10, 50m)
- Extrapolate to turbine height using a fitted logarithmic profile
- Applying simple power curve to estimate capacity factor
- Weight by local installed capacity and aggregate nationally
- Calibrate power curve using observed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

(a) September 2012 wind farm distribution



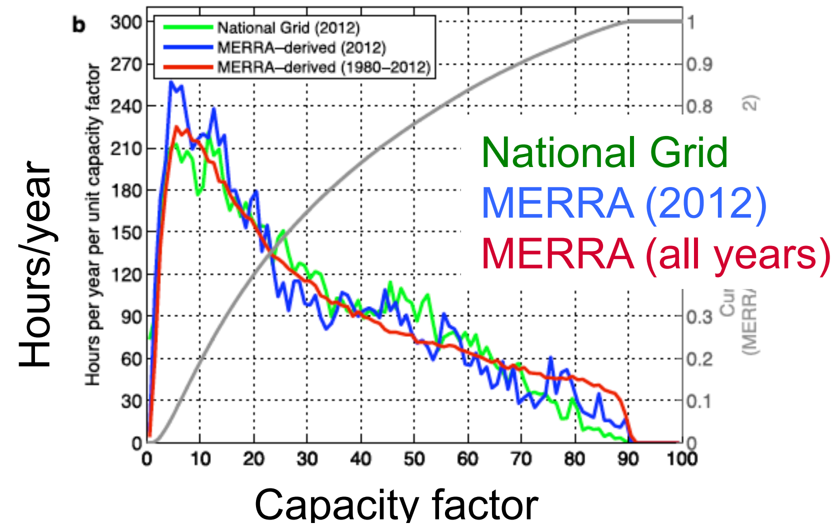
(b) Wind speed to power generation transformations



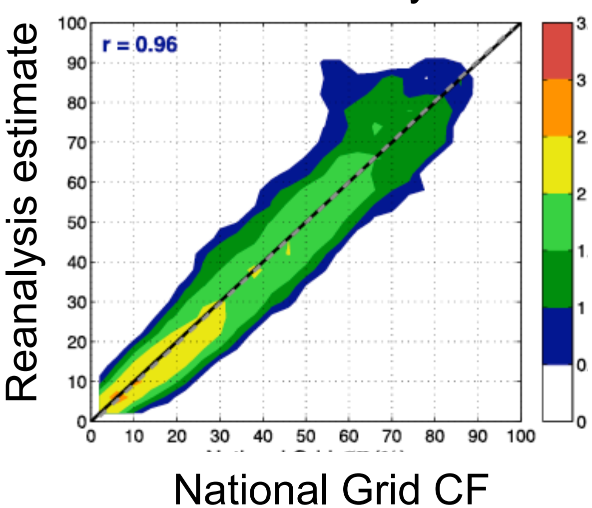
Cannon et al (2015)

Wind power – 2012 period

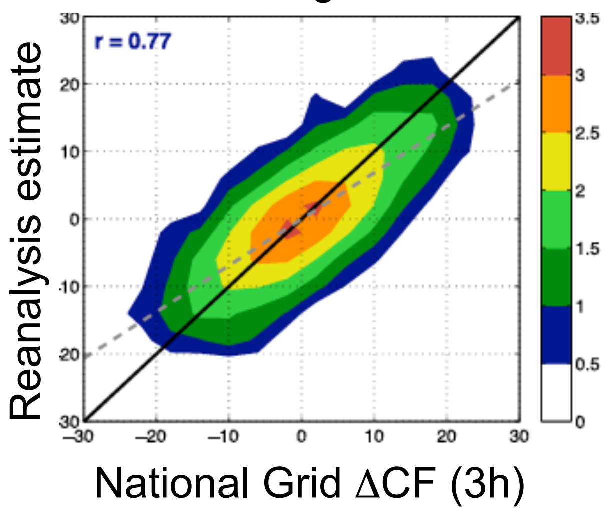
- Calibration performs well
- Good representation of hourly values
- Under estimates ramping < 3-6h
- Good estimation of ramping > 12h



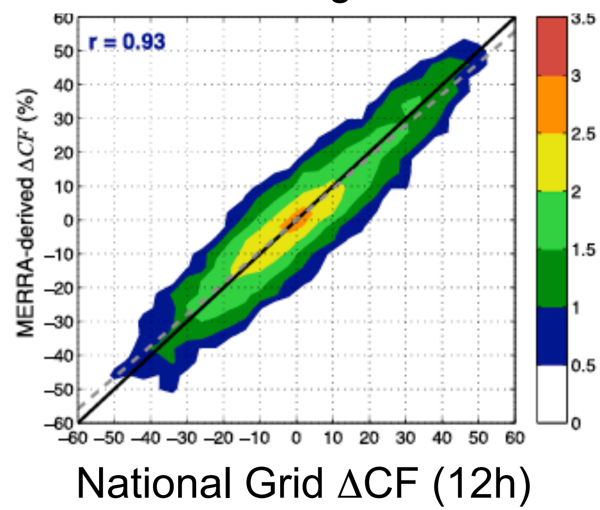
Absolute hourly CF



3h change in CF



12h change in CF



Cannon et al (2015)

Wind power synthetic record
(Cannon et al, 2015, Renewable Energy)

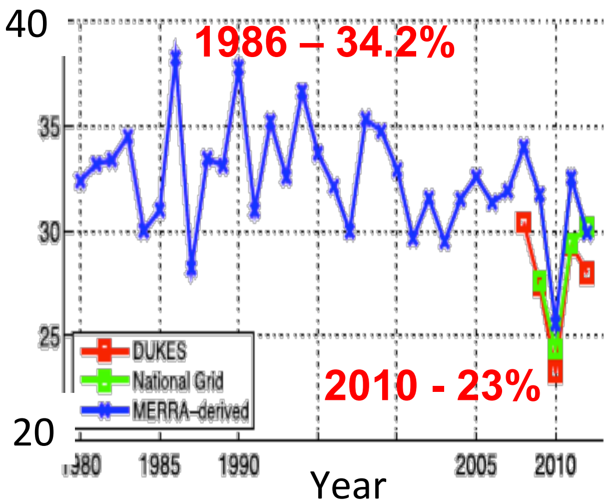
30+ year “synthetic history” of wind power

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

Key points:

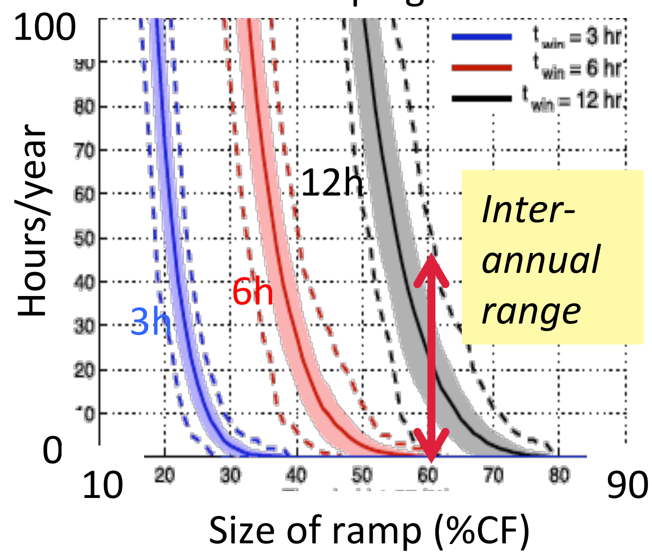
- Better quantification of risks associated with inter-annual climate variability
- Annual-mean capacity factor higher than previous estimates (32.5%) and *highly variable* (15pp range)
- Persistent high/low wind events approximately Poisson-like (exponential decay with persistence)
- Very large ramps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

Annual mean CF

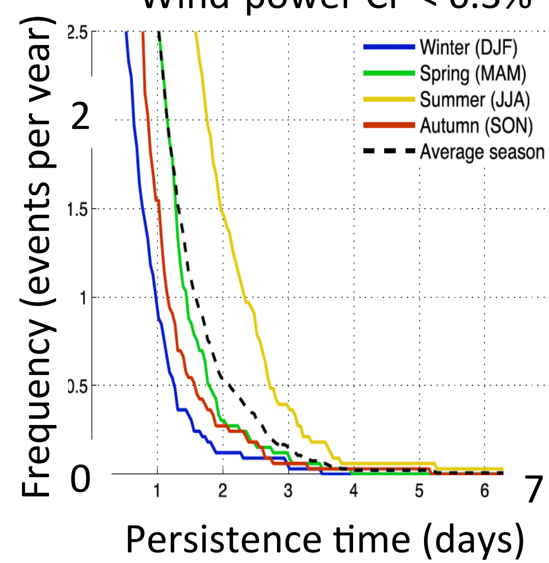


Mean – 32.5%

Ramping



Wind-power CF < 6.3%

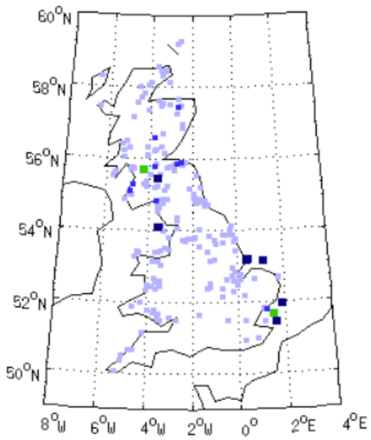


Future wind power installation
(Drew et al, 2015, Resources)

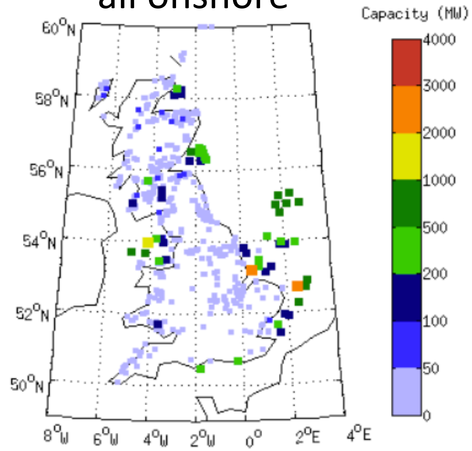
- "What if" scenarios: characteristics of future power systems
- Identify contributions from offshore/onshore

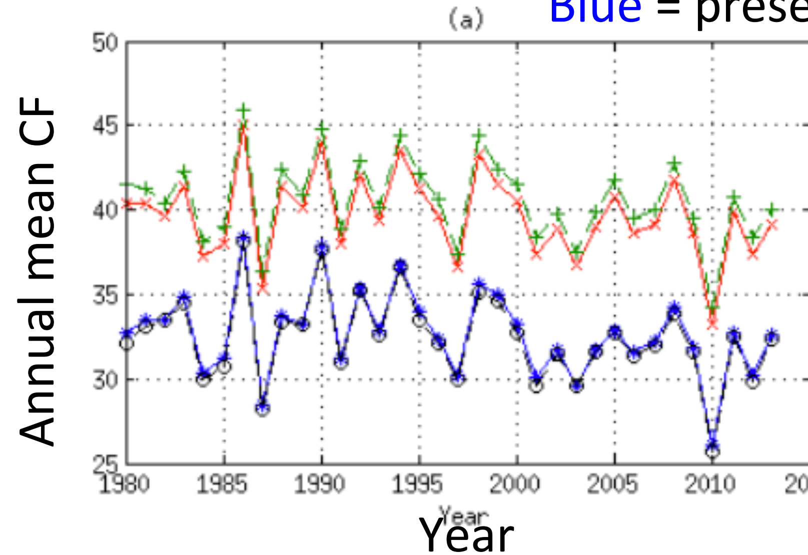
Red = "future"
Blue = present

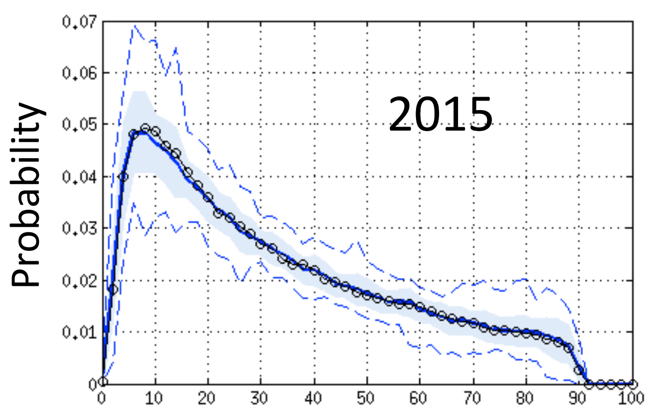
2015



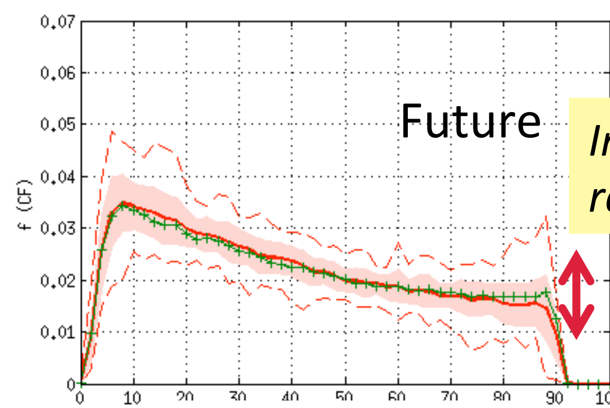
"Future" = Round 3 + all onshore







Hourly CF



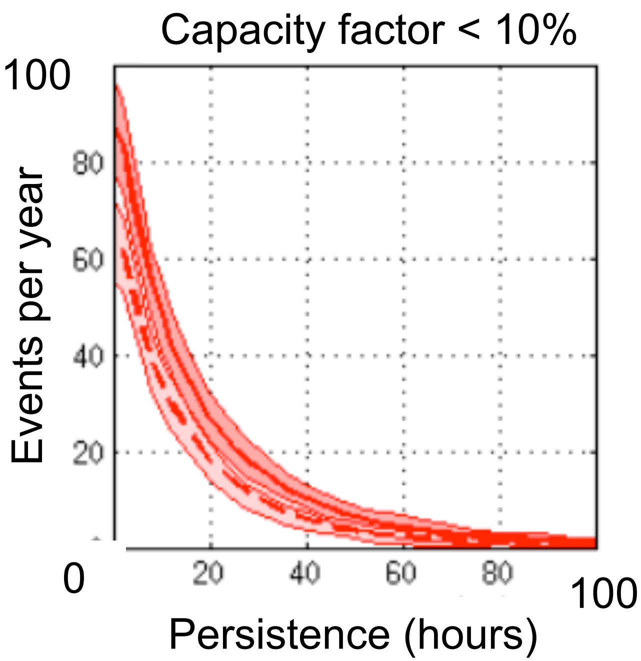
Interannual ranges

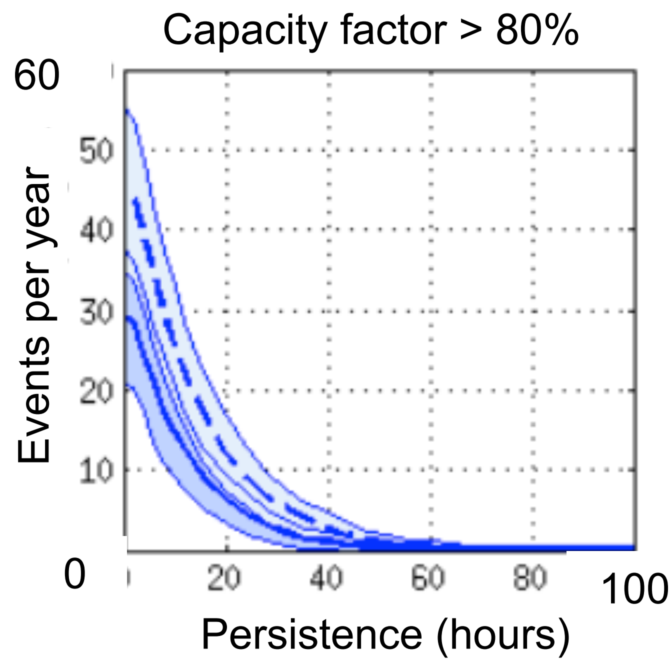
Hourly CF

Drew et al (2015)

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.

Drew et al (2015)

Integrated power systems
(mainly work by Hannah Bloomfield, PhD student)

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- 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	Long run
Operation of a “fixed” power system	Design of “best” power system
E.g., unit commitment, power flow, loss of load probability	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)

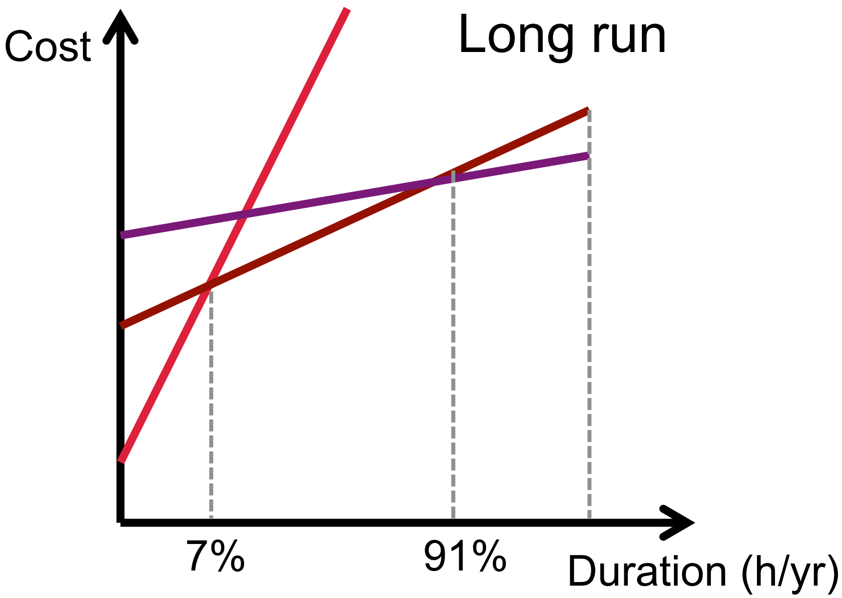
- However, many influential studies use short weather/climate records, e.g. (for long-run):
  - Grunewald 2011; Poyry 2009; Green 2010; Gerber 2012; Widen 2011; Buttler 2016; Schaber 2013; Macdonald (in press); EWITS, WWSIS

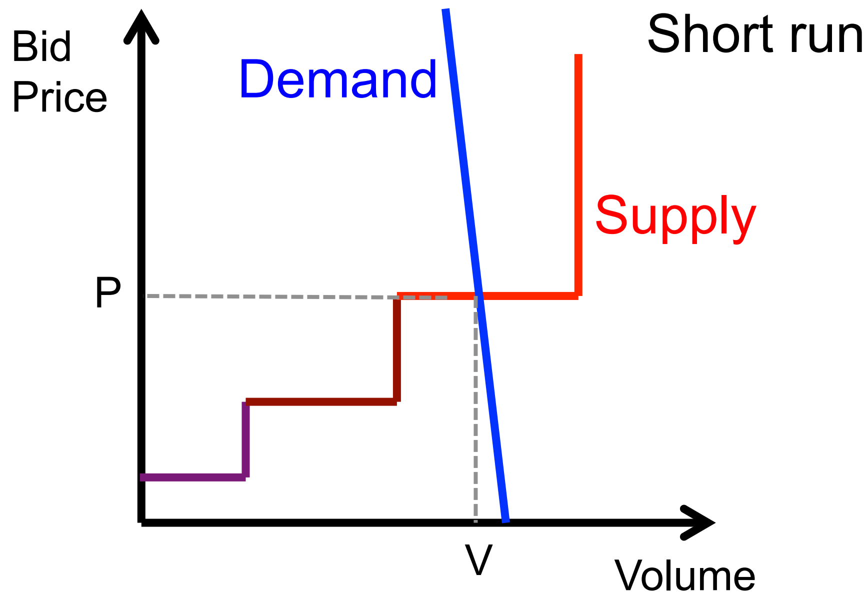
- **Question: How robust are the results to climate variability and change?**

Integrated power systems
(mainly work by Hannah Bloomfield, PhD student)

University of Reading

- 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



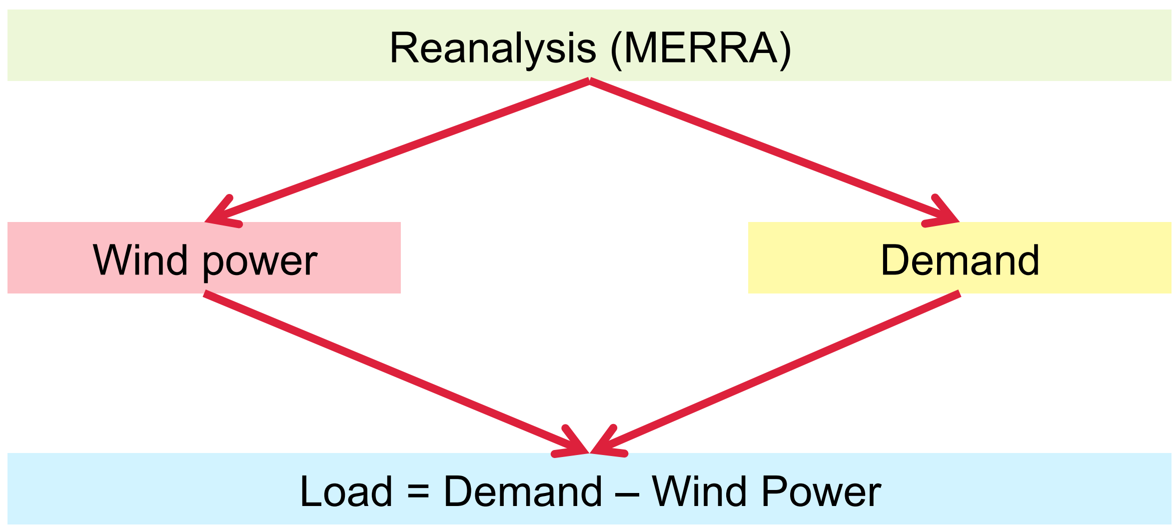


Type	Capital cost	Operating cost	Example
Peaking	Low	High	OCGT, oil
Mid-merit	Medium	Medium	CCGT, coal
Baseload	High	Low	Nuclear

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



Bloomfield et al, Nature Energy (submitted)

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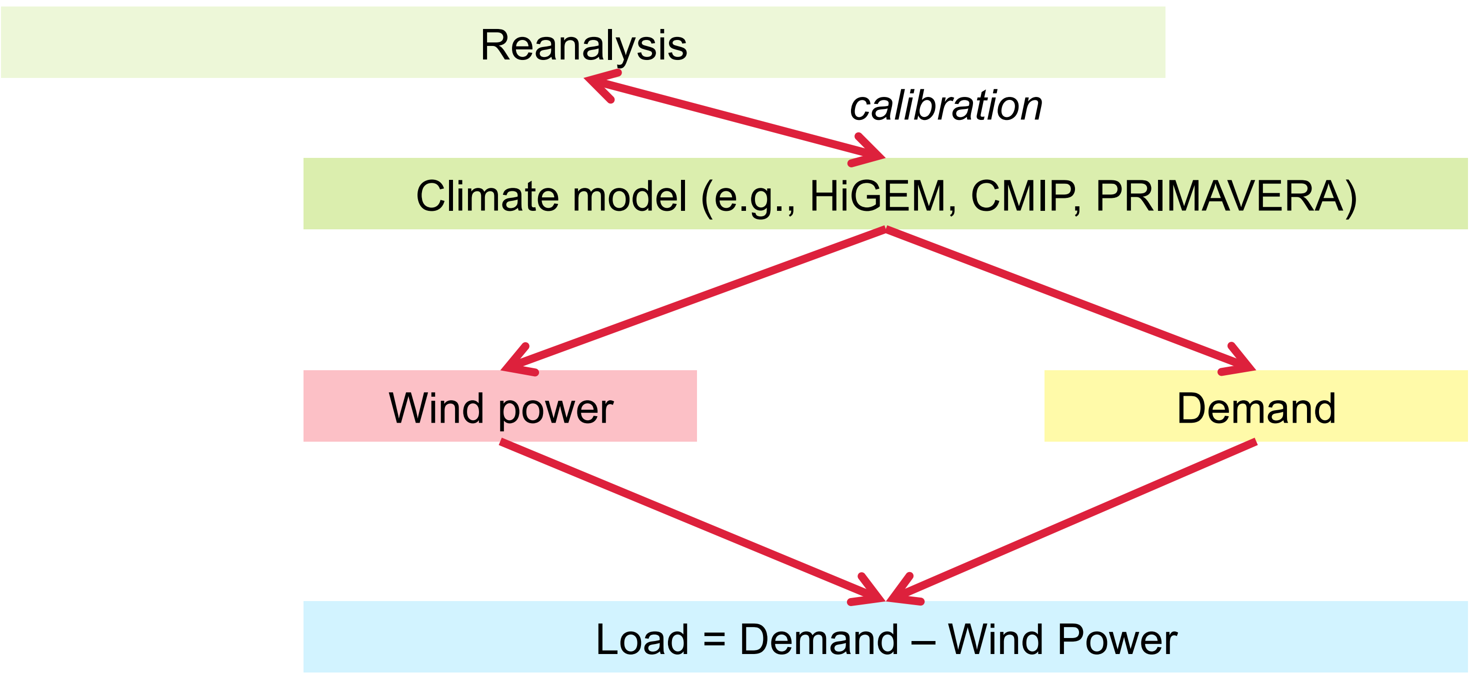

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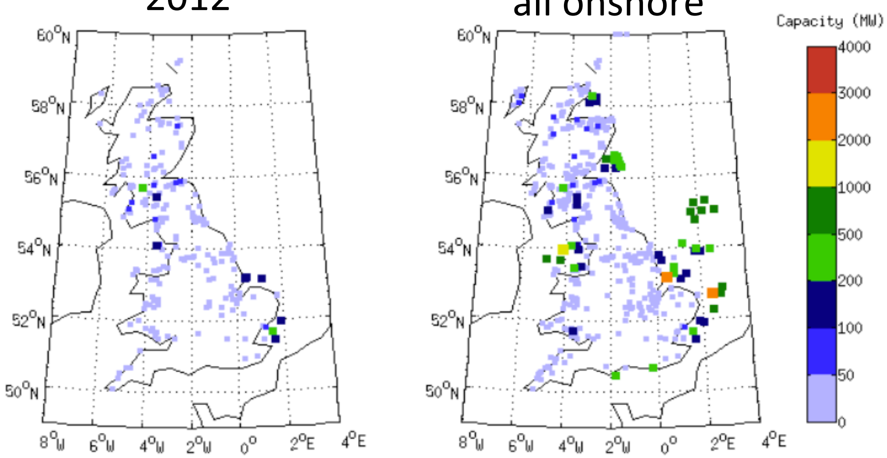
Wind power scenarios/model

- 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

2012

“Future” = Round 3 + all onshore



Bloomfield et al, Nature Energy (submitted)

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

Note: interpretive comparisons indicate approximate consistencies, not precise definitions

Demand model

Three step approach:

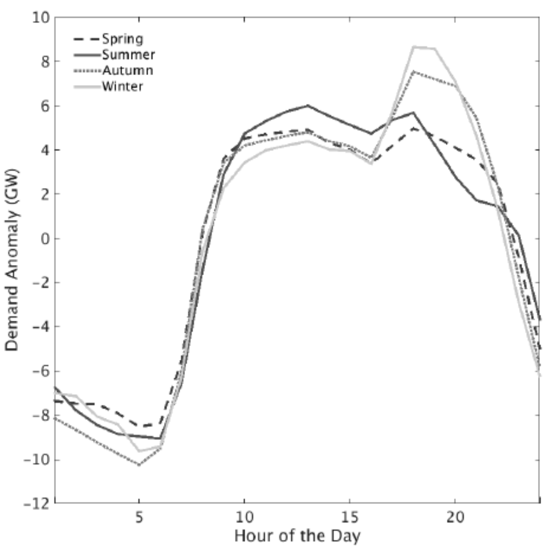
1. Daily demand: multiple linear regression on temperature, c.f. Taylor & Buizza (2003)
   - Trained on recorded national demand 2006-2010; good fit R^2 ~ 0.93

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

2. Simplify demand: remove "special days" with no meteorological significance

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

3. Simplified hourly demand:
   - "Downscaling" using observed diurnal curves
   - One curve per season



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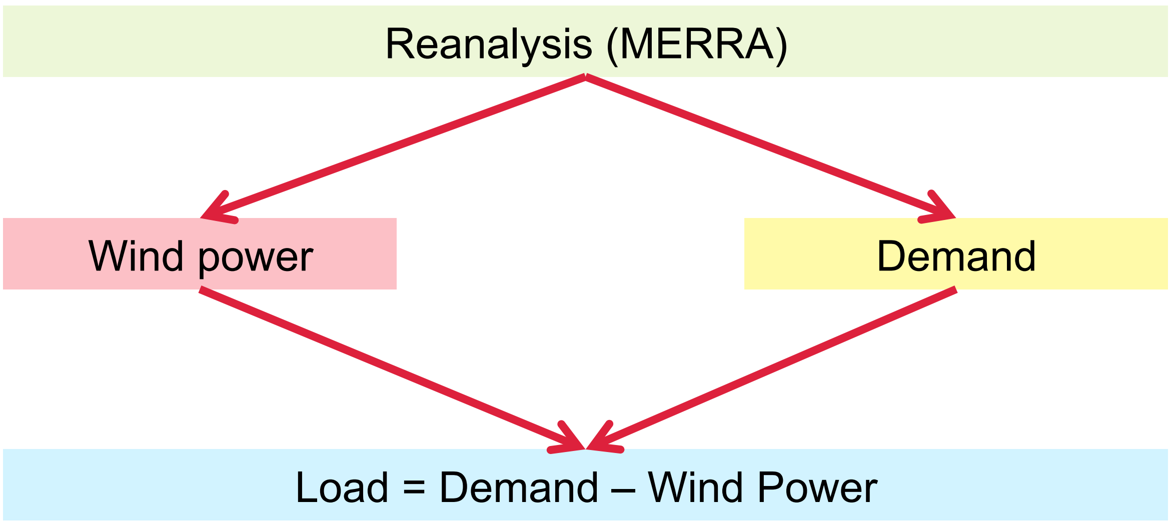
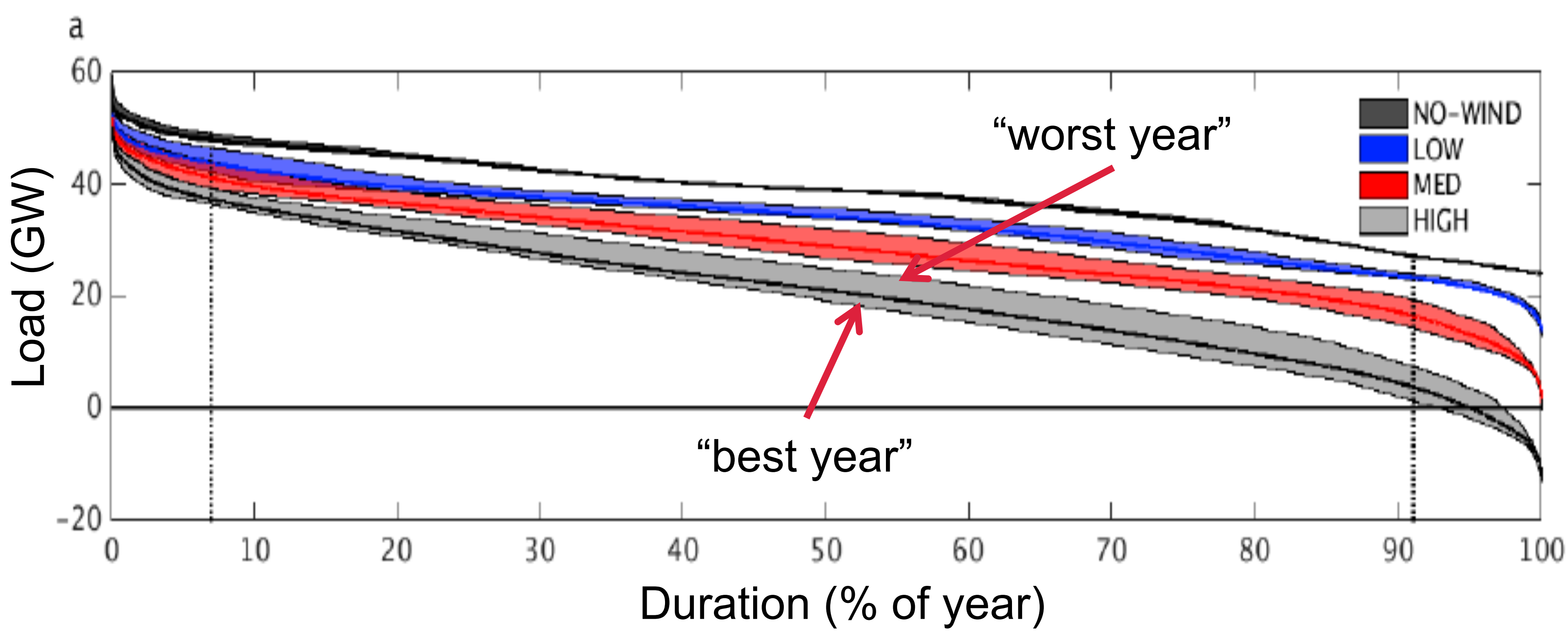


Bloomfield et al, Nature Energy (submitted)

Power system "model" concept

Bloomfield et al, Nature Energy (submitted)

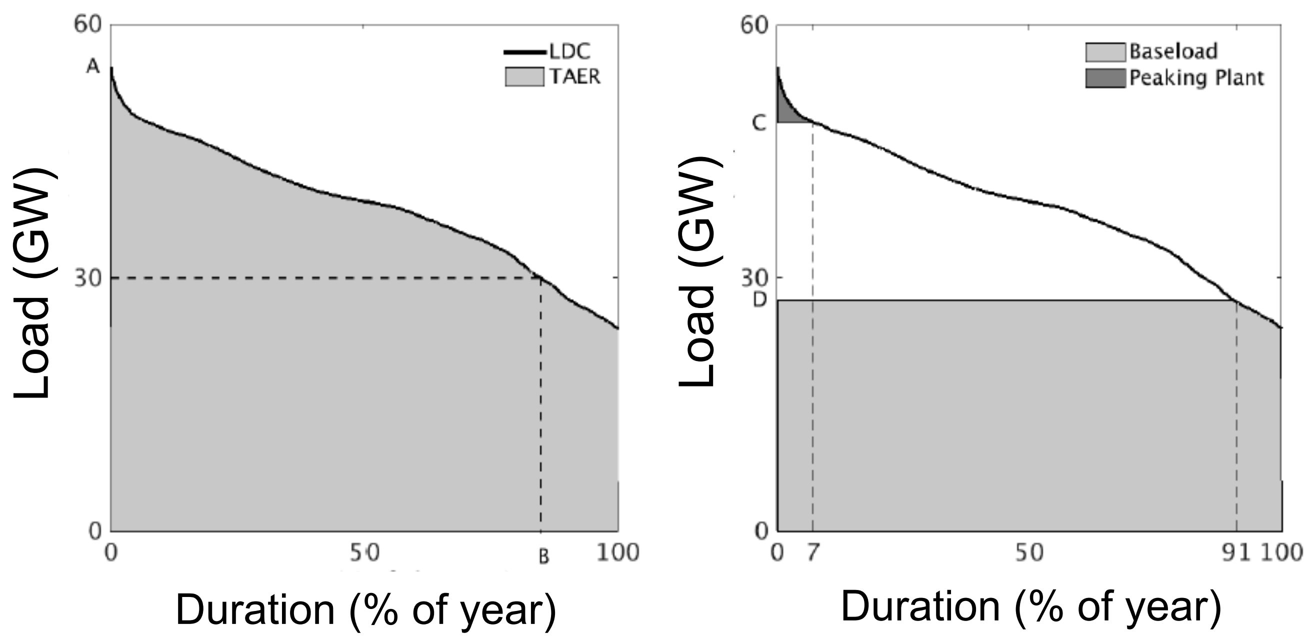
- Result:
  - 4 x 36 year scenarios (NO-WIND, LOW, MED, HIGH); hourly resolution
  - Convenient to display as annual load duration curves (→ 36 LDCs per scenario)



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**

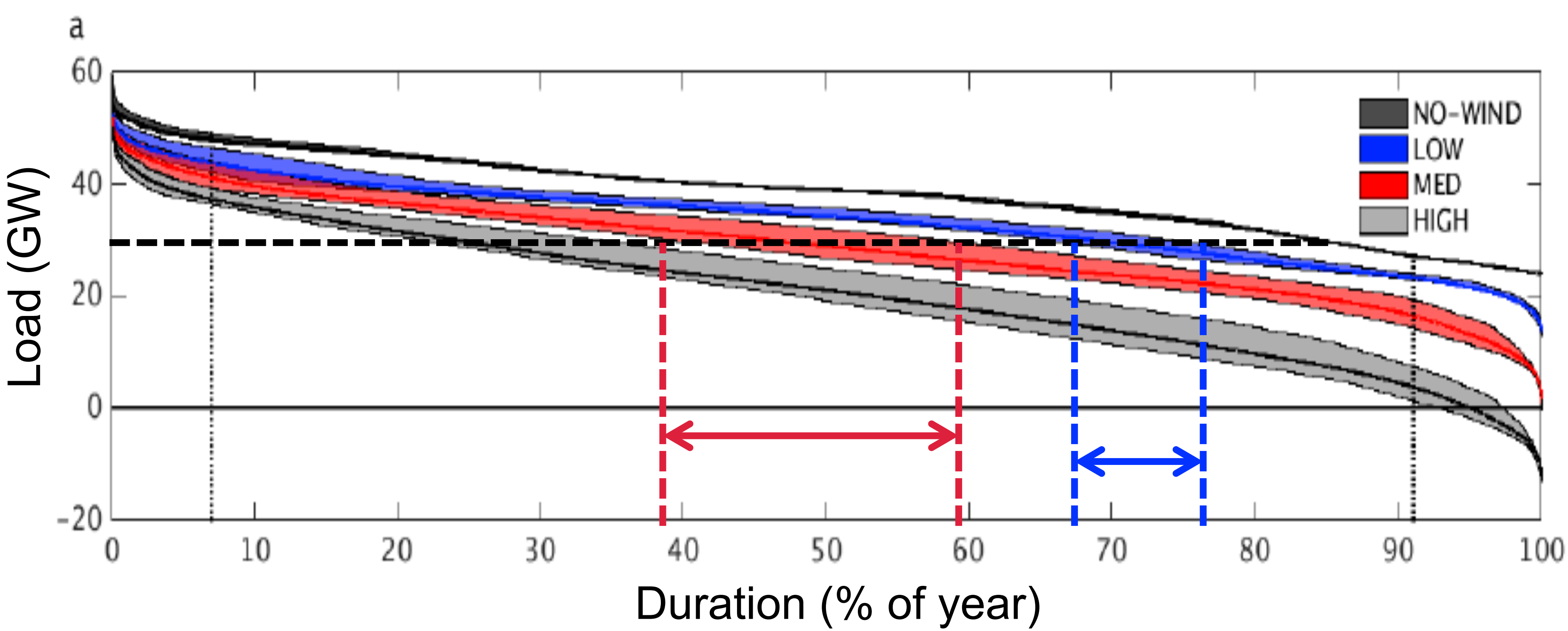


Mid-merit operating hours

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 to ~20pp
  - Significantly increased impact of climate on the operation opportunity



Baseload threshold of opportunity

Bloomfield et al, Nature Energy (submitted)

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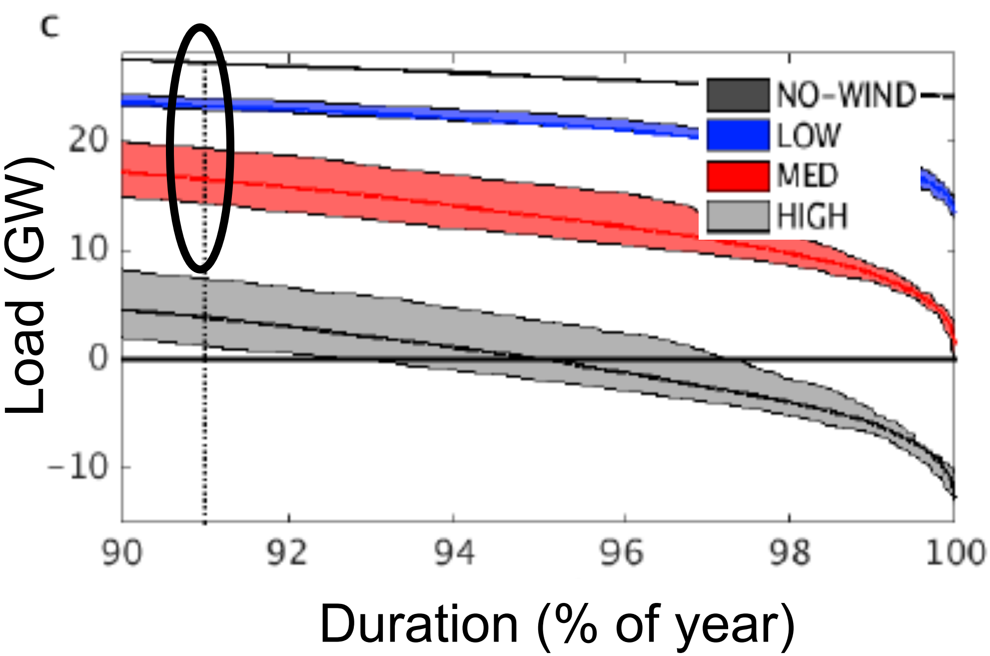
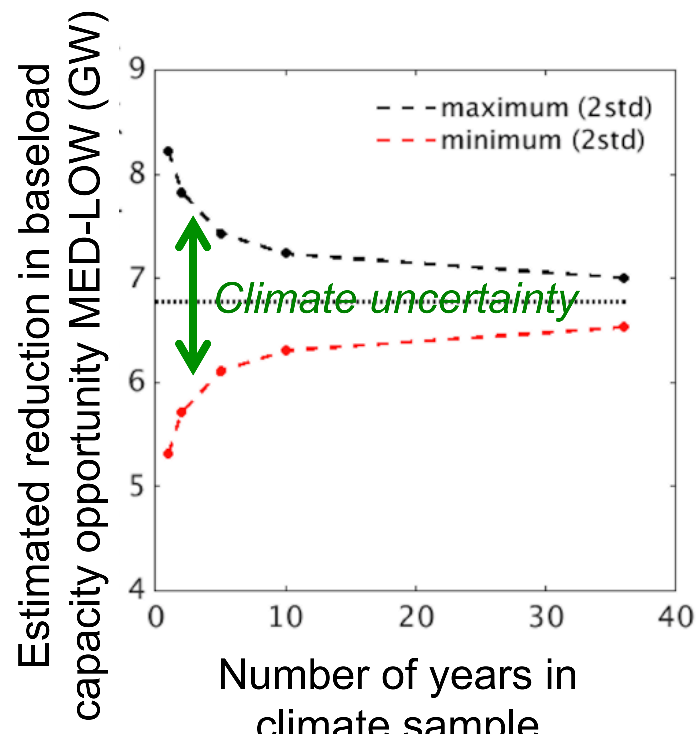
Perspective: "Long run" problem - optimal amount of "baseload type" plant capacity

- 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

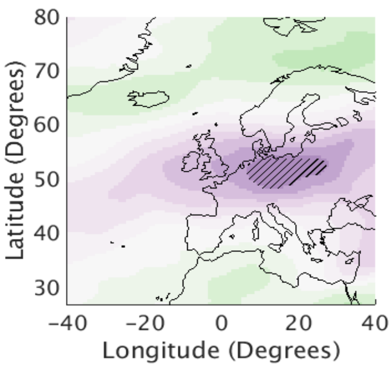




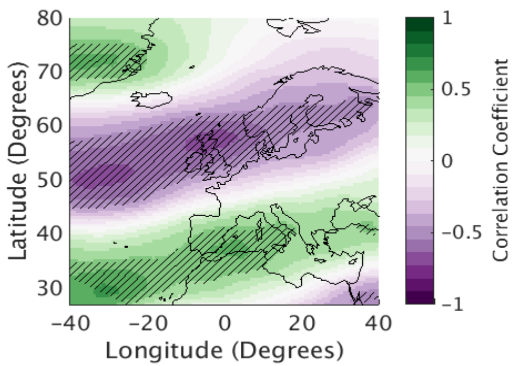
Climate drivers
(Hannah Bloomfield, PhD thesis in prep)

- 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

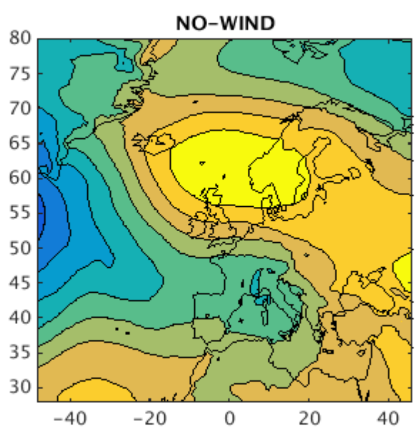


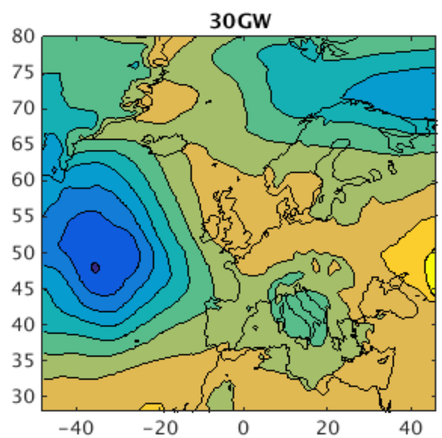
MED (30GW)



Baseload energy opportunity

Correlation with zonal wind U850





Peak Load

Composite MSLP
(Top 10, 5d separation)

Climate change

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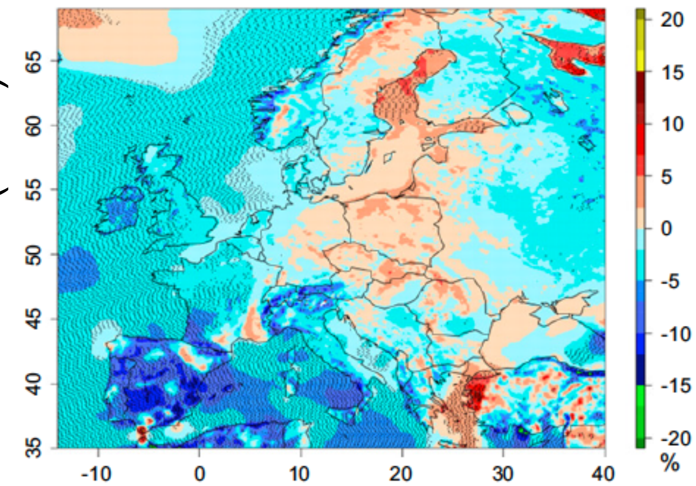
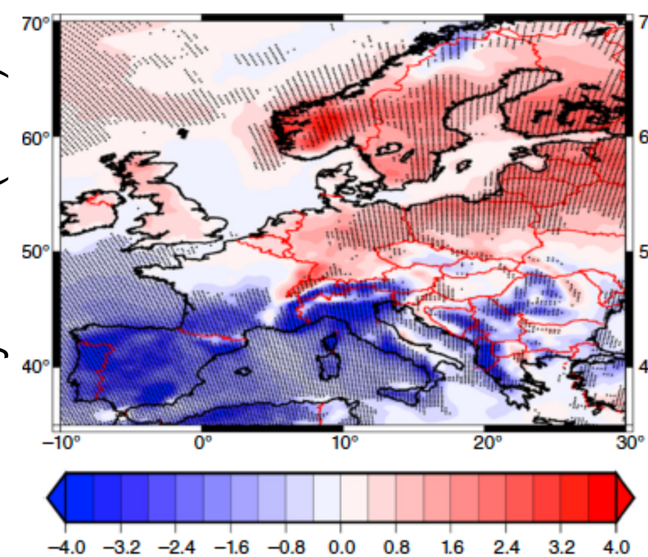
- Growing number of studies addressing climate change on energy systems
- General consensus for wind:
  - Changes are "fairly small"
  - Increases in N. Europe
  - Decreases in S. Europe
  - Significant differences between models
  - Differences between studies – even using same CMIP5 model archive!
- 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

Tobin et al (2016)



Reyes et al (2016)



A note on climate change…

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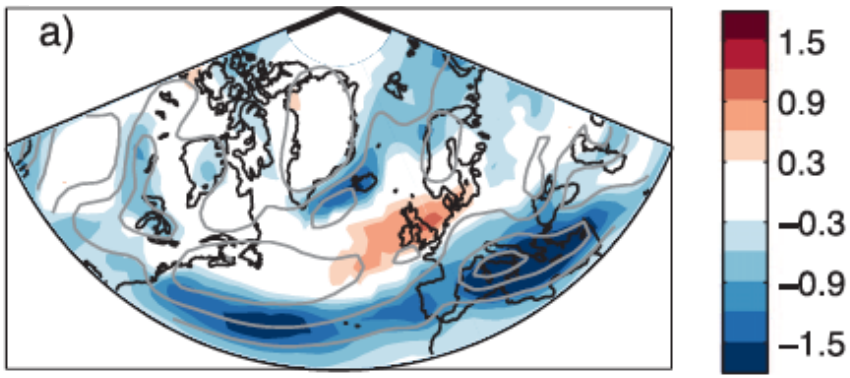
- Understanding the meteorological drivers is important…
- … forced regional climate change signals can be quite uncertain (note: colour scales!)

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



Figures: Zappa et al 2013

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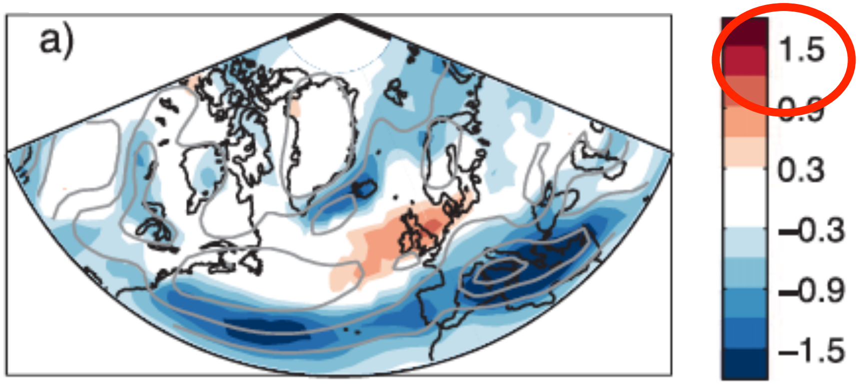
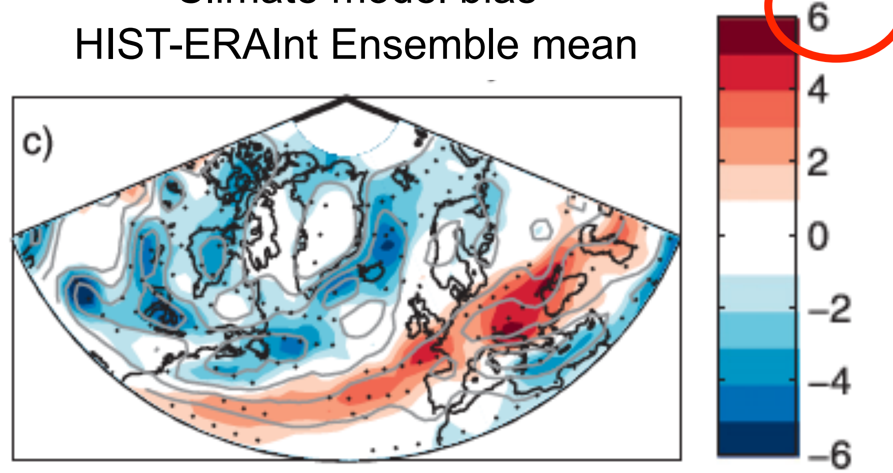


“Climate model bias”
HIST-ERAInt Ensemble mean



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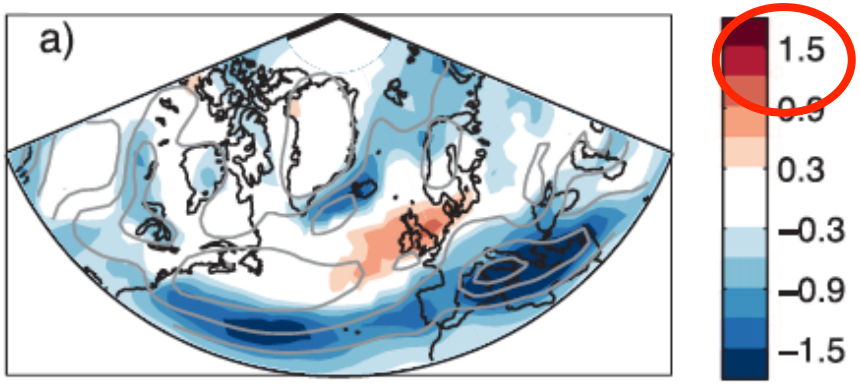

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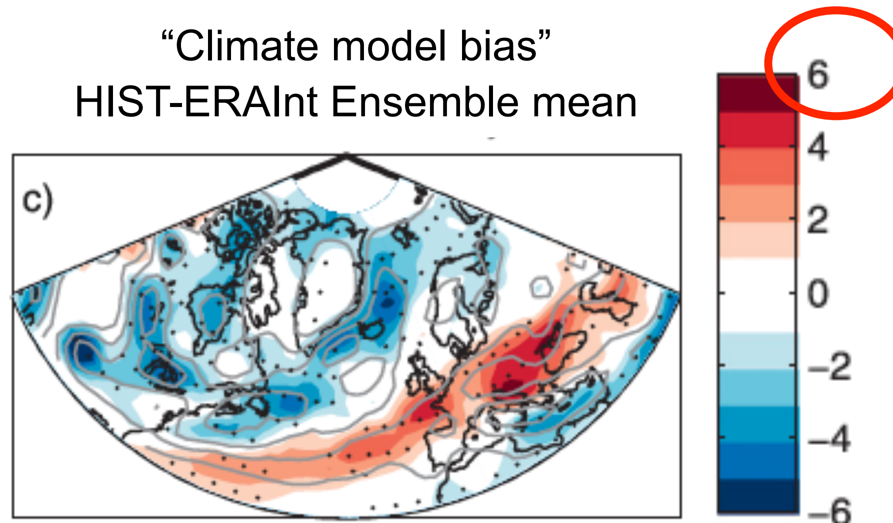
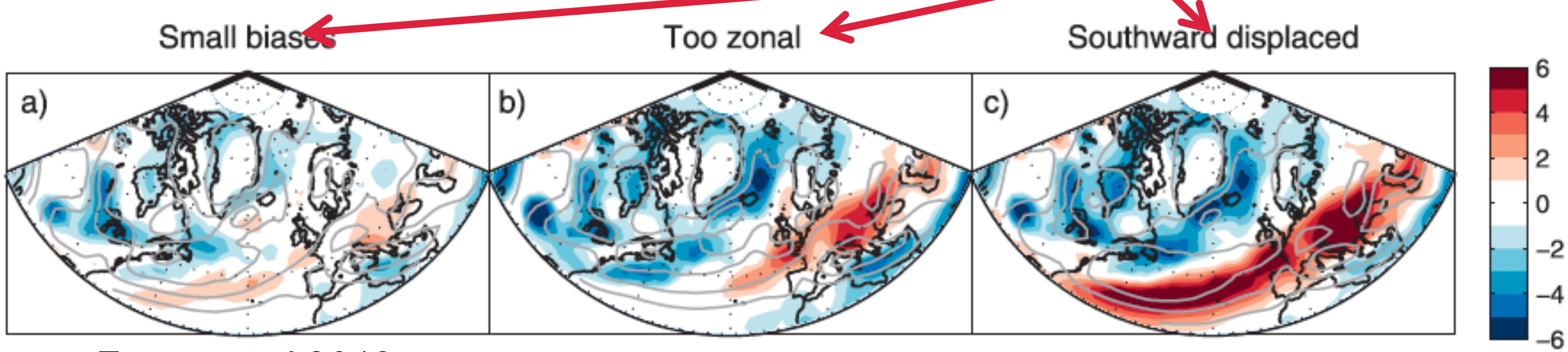


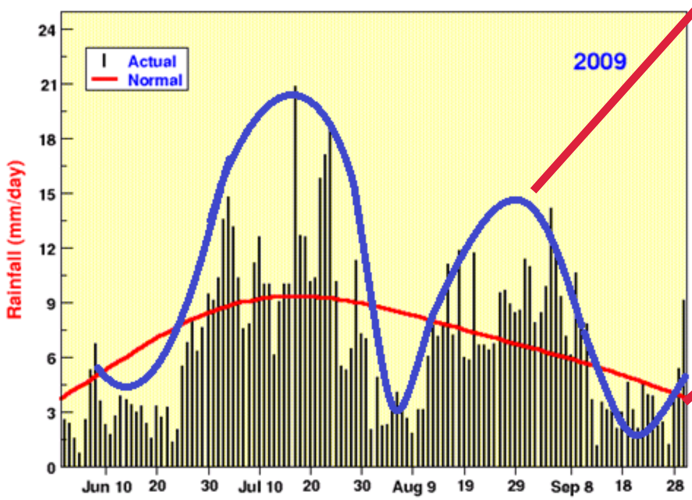


Figures: Zappa et al 2013

Aside: Indian monsoon variability

University of Reading

- India: summer monsoon variability
- Impact on potential demand and resources
- Break events:
  - less wind (and hydro?)
  - More cooling demand, solar

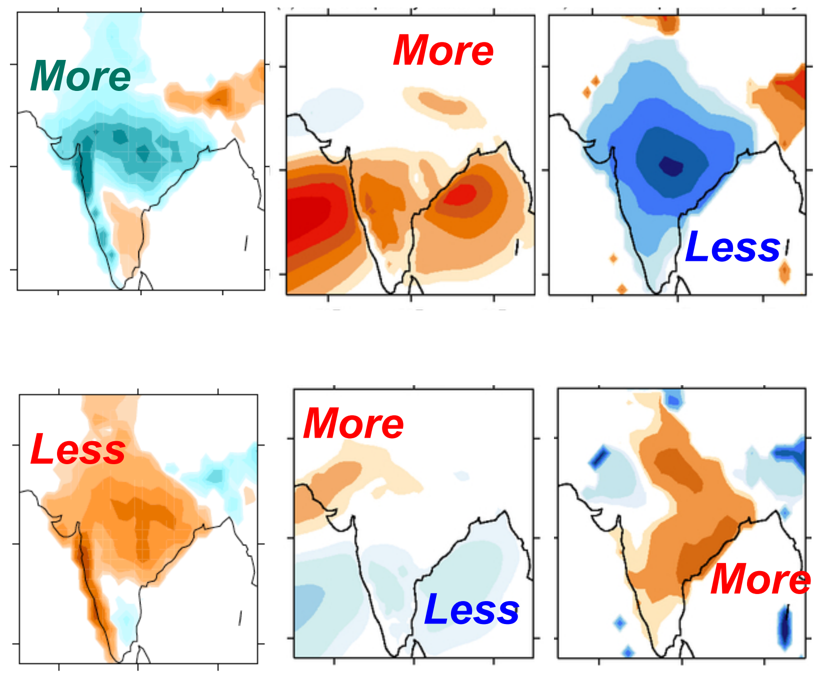


Source: Monsoon Online http://www.tropmet.res.in/

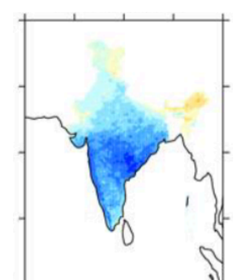
“Active” (anomaly from “normal”)

“Break” (anomaly from “normal”)

Precipitation (hydro?) | *Wind power* | *Temperature (demand)*



Solar: active-break



More in break
Less in active

Dunning et al, 2015 ERL; Stockwell (BSc dissertation)

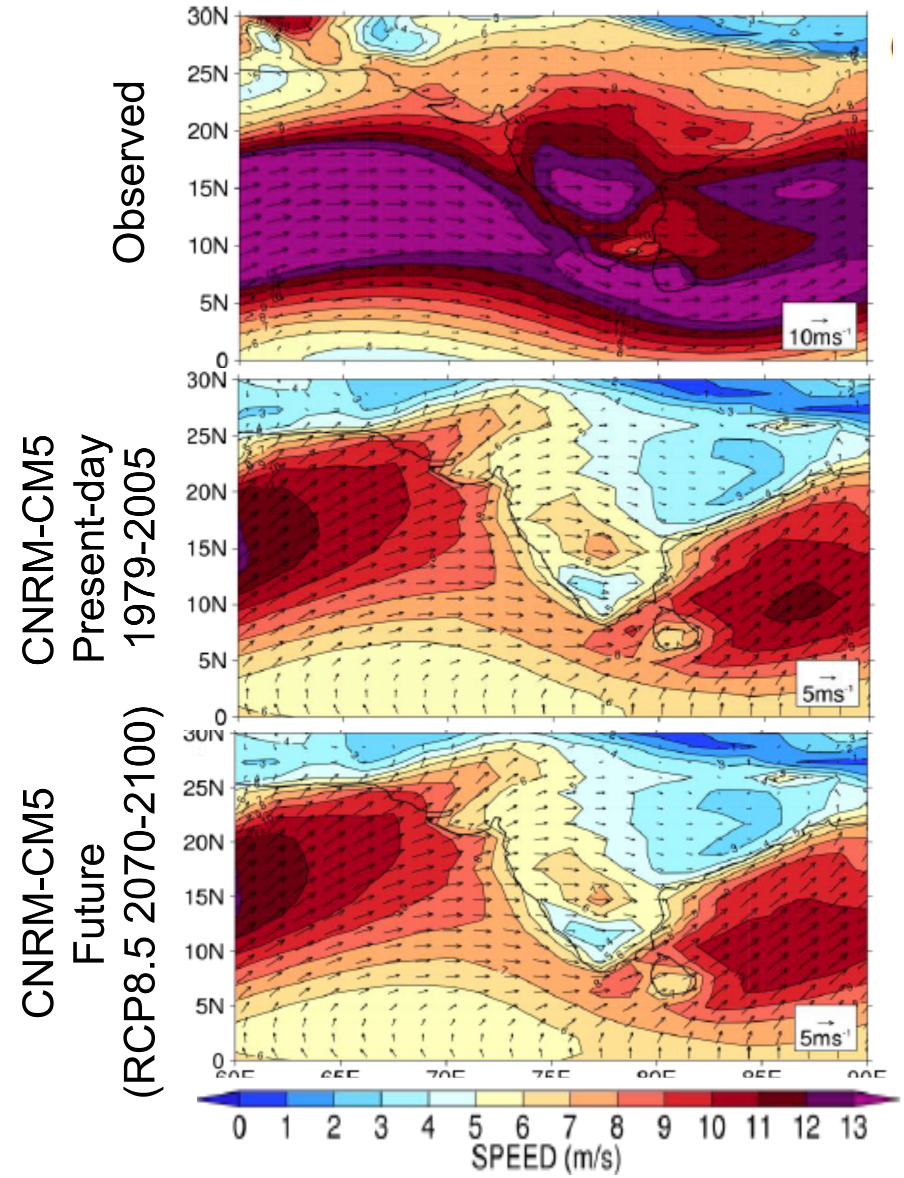
Aside: Indian monsoon variability

University of Reading

- GCM simulation of monsoon winds poor
  - CNRM-CM5
  - Generally thought to be a “good” CMIP5 model for monsoon!

- Simulates slight decrease in wind speed

- Is the climate “response” trustworthy?
  - Change much smaller than bias

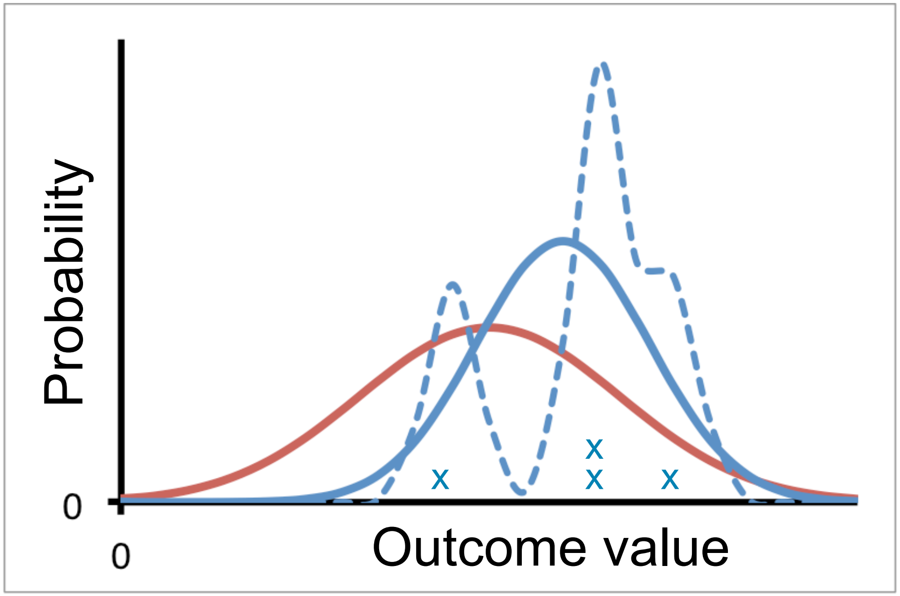


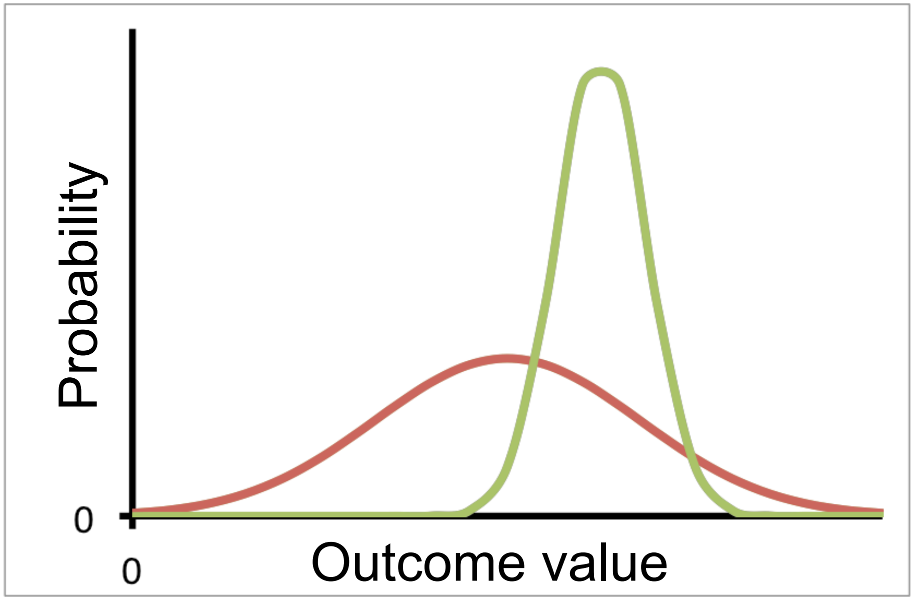
Figures: Lee (MMet dissertation)

Topics

University of Reading

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



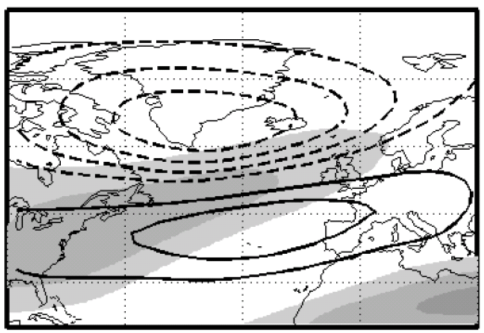


Forecasting risk: Physical basis
Low frequency variability

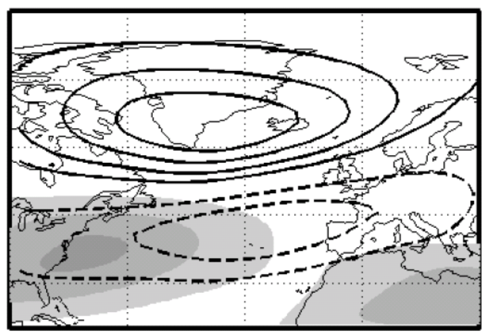
University of Reading

- Low-frequency variability exists in the climate system: ENSO, MJO, NAO, AMO, PDO, …
- Effects regional climate
- NAO vs European wind as a simple example

NAO+



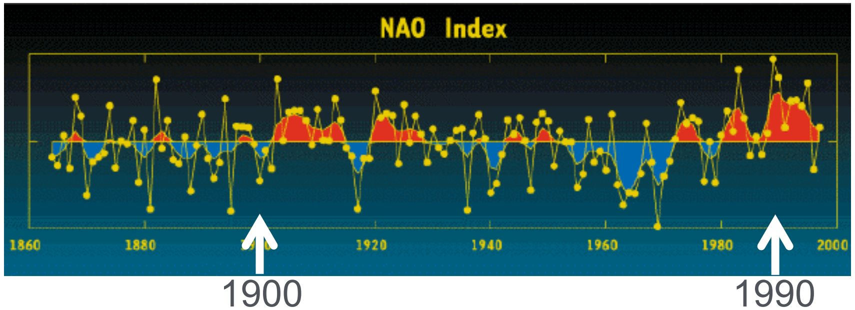
NAO-



From Woollings et al (2010)
Shading = U300, contours = Z500

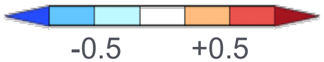
NAO timeseries (annual mean)

From www.ldeo.columbia.edu/res/pi/NAO/



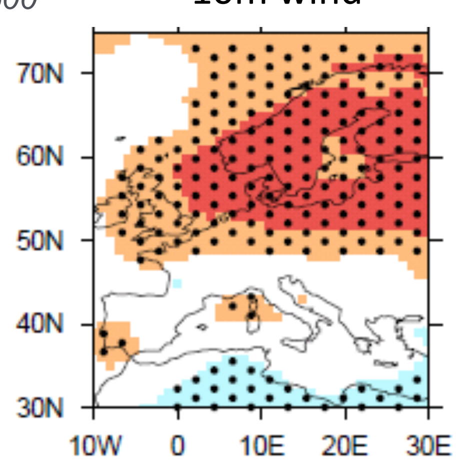
NAO and surface climate

From Ely et al (2013)

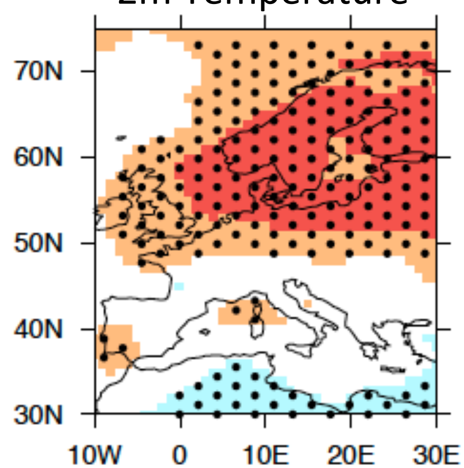


Correlation co-efficient
(for March but qualitatively similar for DJF)
Stippling: significant at 95%

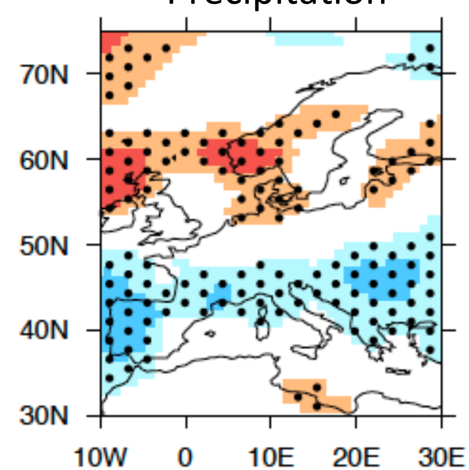
10m wind



2m Temperature



Precipitation



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University of Reading

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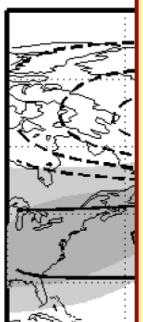
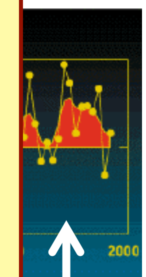
- Effects regional climate
- NAC

NAO   o/





1990

From W
Shading

n

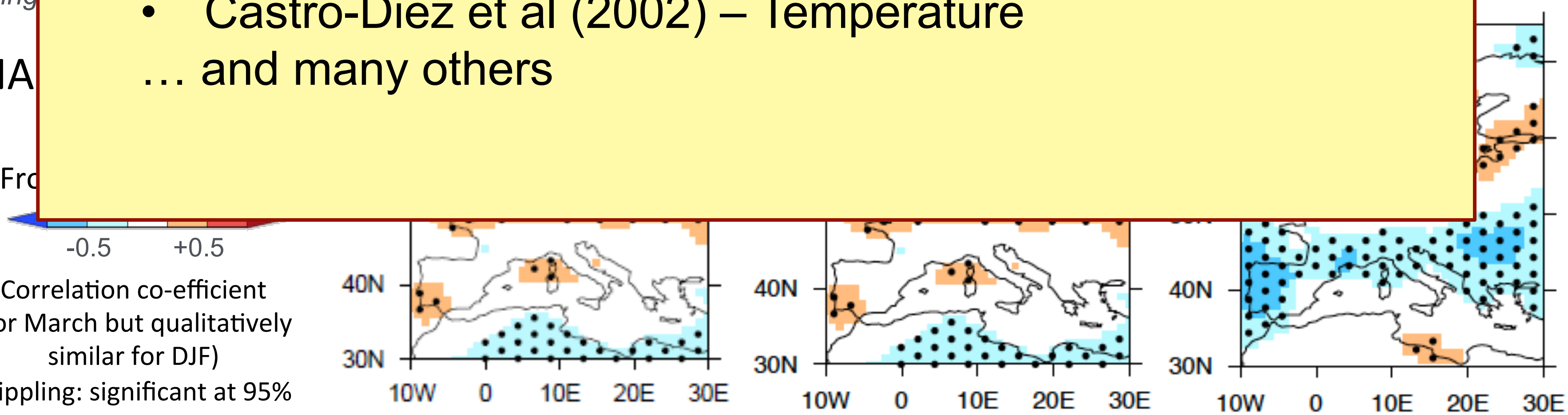
NAO impacts relevant to energy, e.g.:

- Ely et al (2013) – UK-Norway hydro-wind-demand
- Jerez et al (2013) – NAO on renewables in SW Europe
- Trigo et al (2011) – hydrological resources
- Brayshaw et al (2011) - UK wind power
- Pozo-Vazquez et al (2004) – Solar
- Castro-Diez et al (2002) – Temperature

… and many others

NA

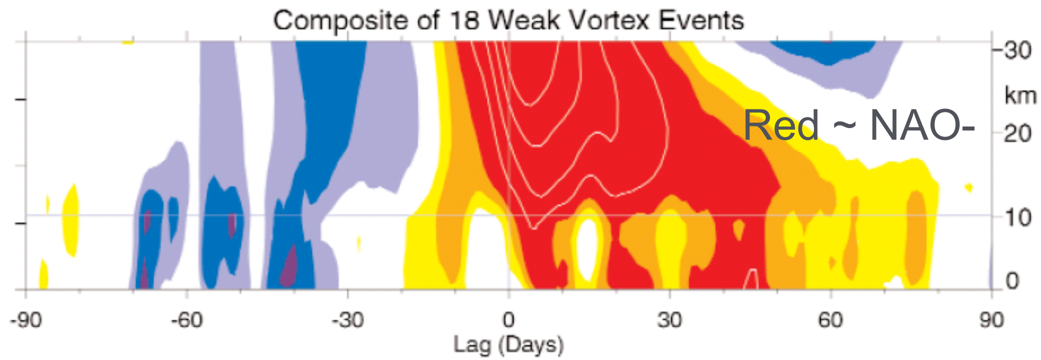
Fr



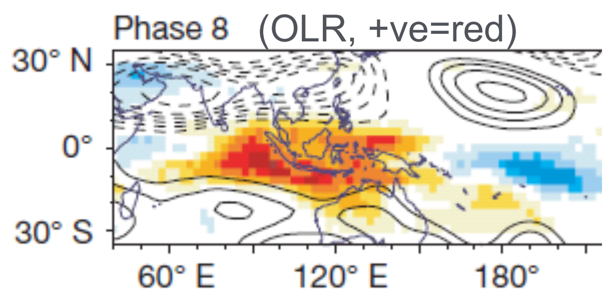
Correlation co-efficient
(for March but qualitatively similar for DJF)
Stippling: significant at 95%

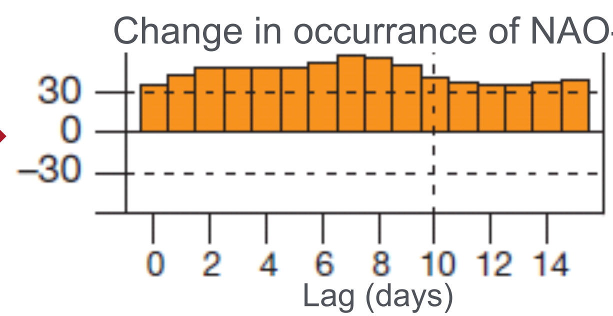
Long-range predictability - examples

Stratospheric "harbingers"
(e.g., Baldwin and Dunkerton, 2001)

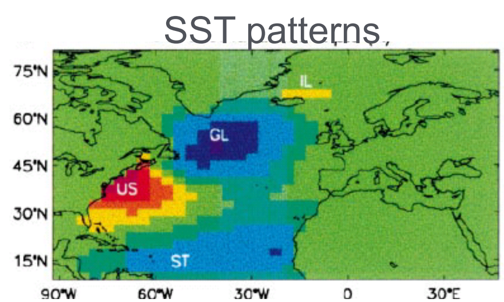


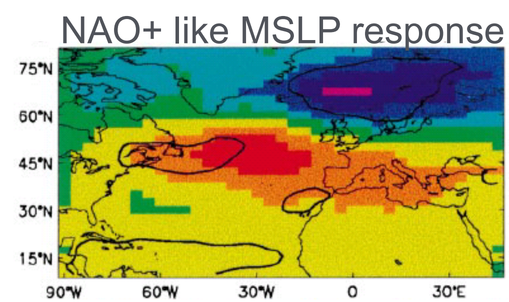
Tropical convection (MJO)
(e.g., Cassou 2008)





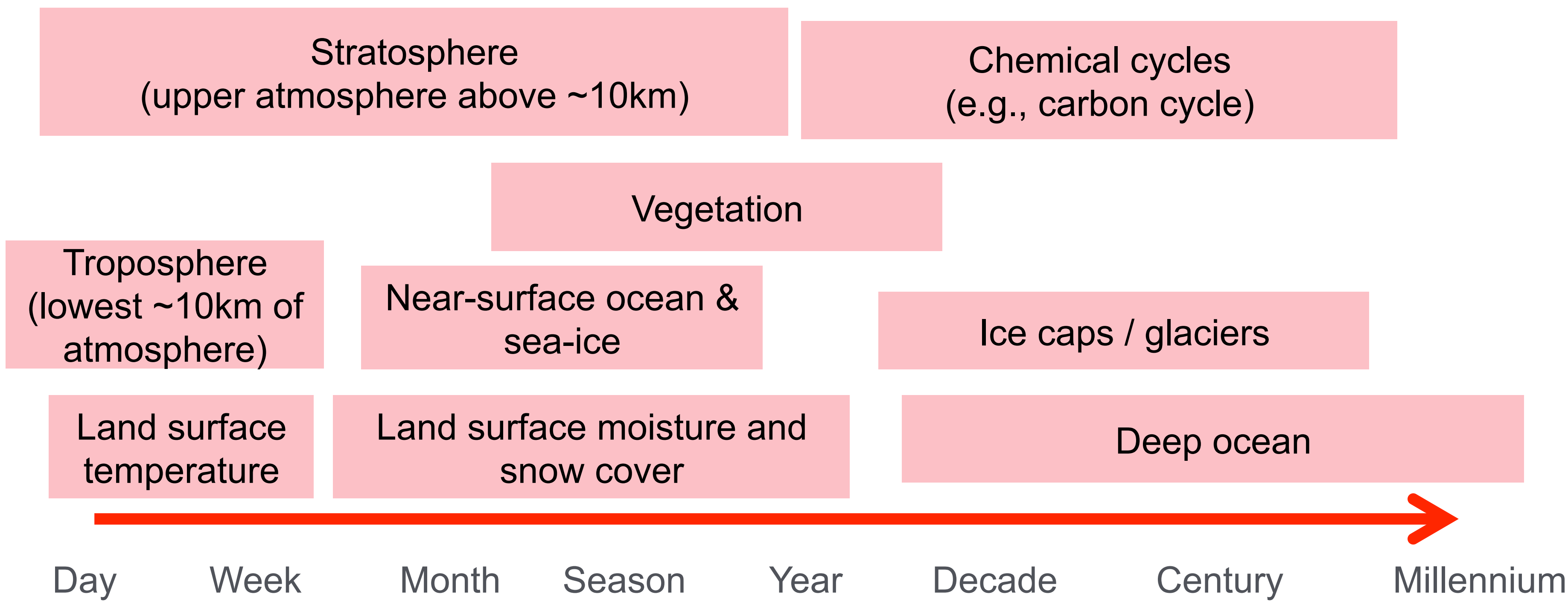
North Atlantic Sea Surface Temp
(e.g., Rodwell et al 1999)





Climate components

- Climate system contains more than just the atmosphere
- Components vary on very different timescales
  - “natural” or “internal” variability (no external forcing required)
- A *very* schematic diagram – many interactions:



Remote communication pathways

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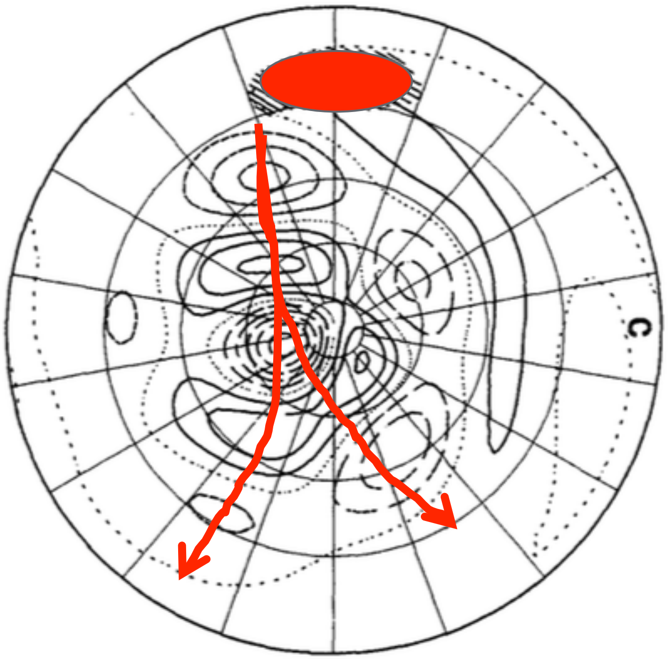
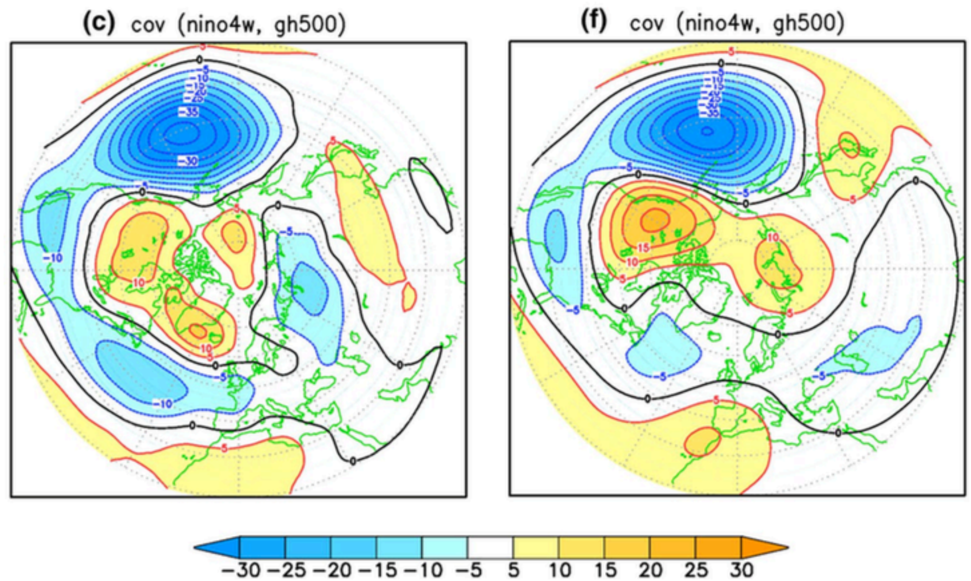
Tropical heating vs geopotential 300 hPa



Nino 4 SST vs Geopotential height 500 hPa



ERA-Interim (reanalysis/"observations")

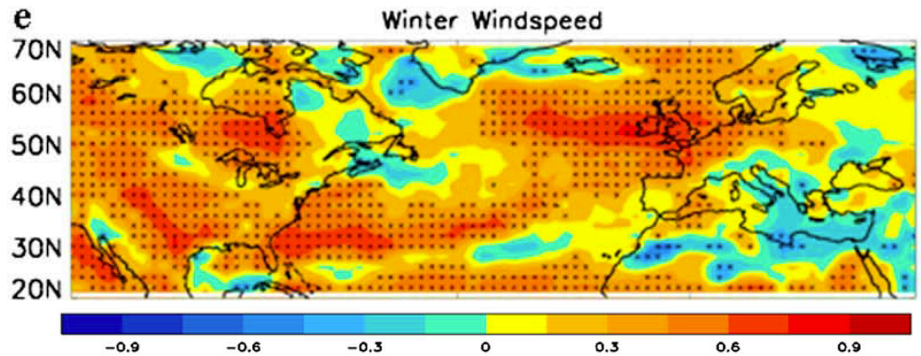
ECMWF System 4 (seasonal forecast)

Wave propagation heavily dependent on background flow

Figures: Hoskins & Karoly 1981; Molteni et al 2015

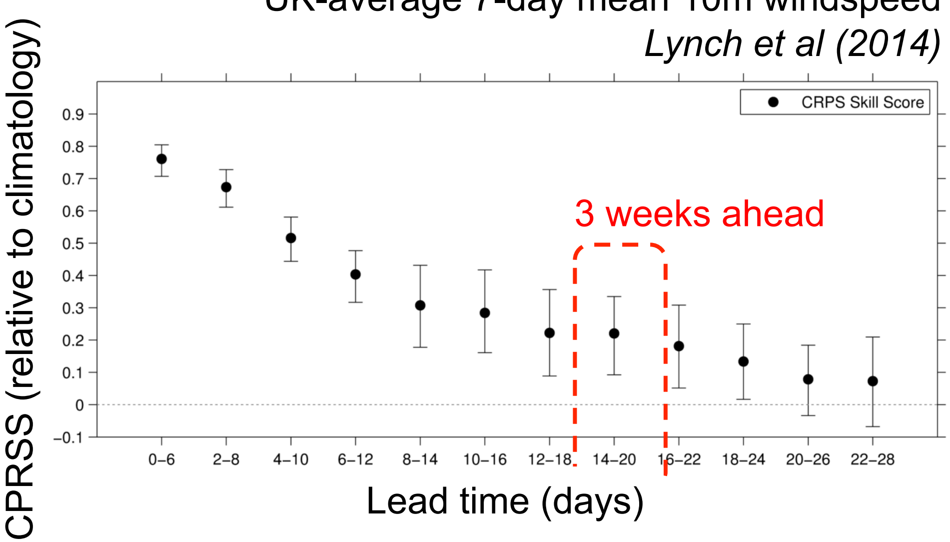
Subseasonal and seasonal forecasting

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

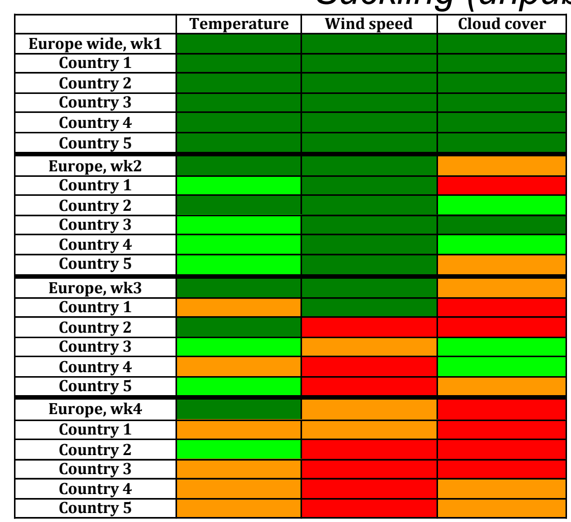


3-month average skill in winter wind speed in Met Office seasonal forecast
Scaife et al 2014

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)



Sub-seasonal prediction for power
(Lynch et al 2014 and PhD thesis)

University of Reading

ECMWF month-ahead forecast system:

- weeks 3 and 4 ahead (focus: week 3 in winter season)
- 51-member ensemble: multiple realisations of possible weather

1. Does it provide skillful predictions of wind and temperature?

2. To what extent does the forecast skill propagate into:
    a. wind power volume
    b. electricity demand
    c. electricity price?

3. How can these forecasts be used to optimise trading decisions?

Datasets used: Elexon (power), ERA-Int (weather), Bloomberg (price)

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Meteorological skill

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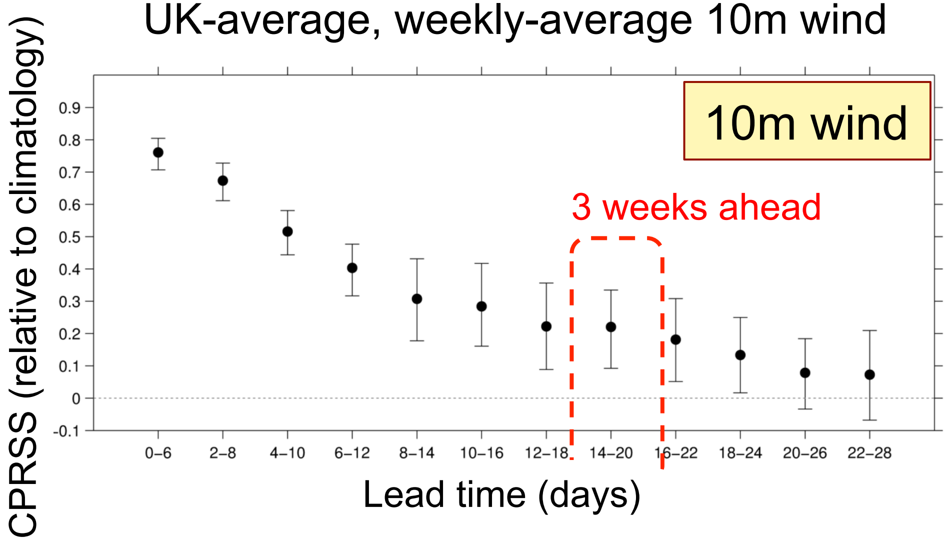
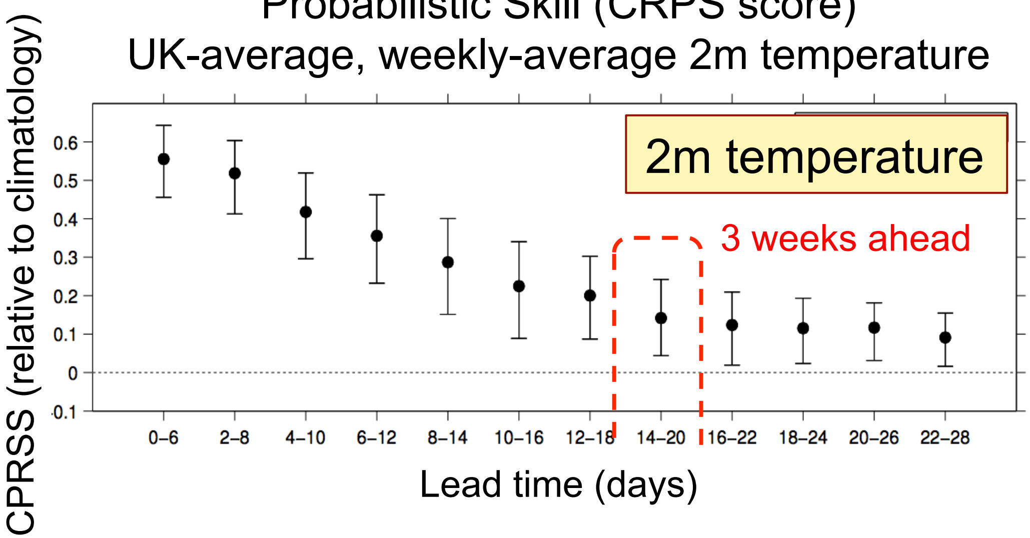
Probabilistic Skill (CRPS score)
UK-average, weekly-average 10m wind



Probabilistic Skill (CRPS score)
UK-average, weekly-average 2m temperature



Analysis shown for **winter** only

3-weeks ahead 7-day UK averages:

- Significant skill above climatology (99% confidence)
- CRPS 0.21 (wind); 0.17 (temperature)
- Consistent ROC / Reliability / ACC / RMSE

- **Lynch et al (2014). *Monthly Weather Review*, 142, 2978–2990.**
- Emma Suckling – other European countries and variables

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University of Reading

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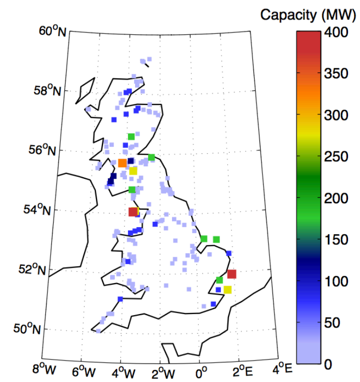
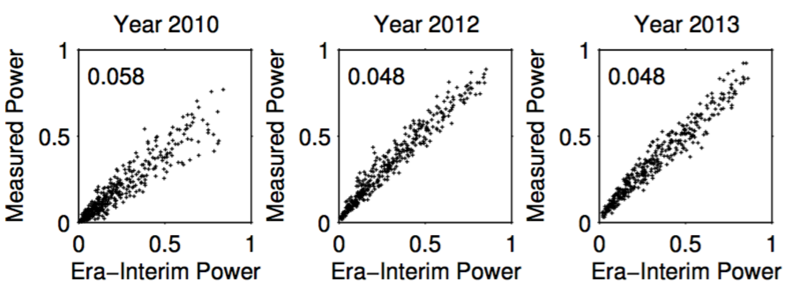
Wind power



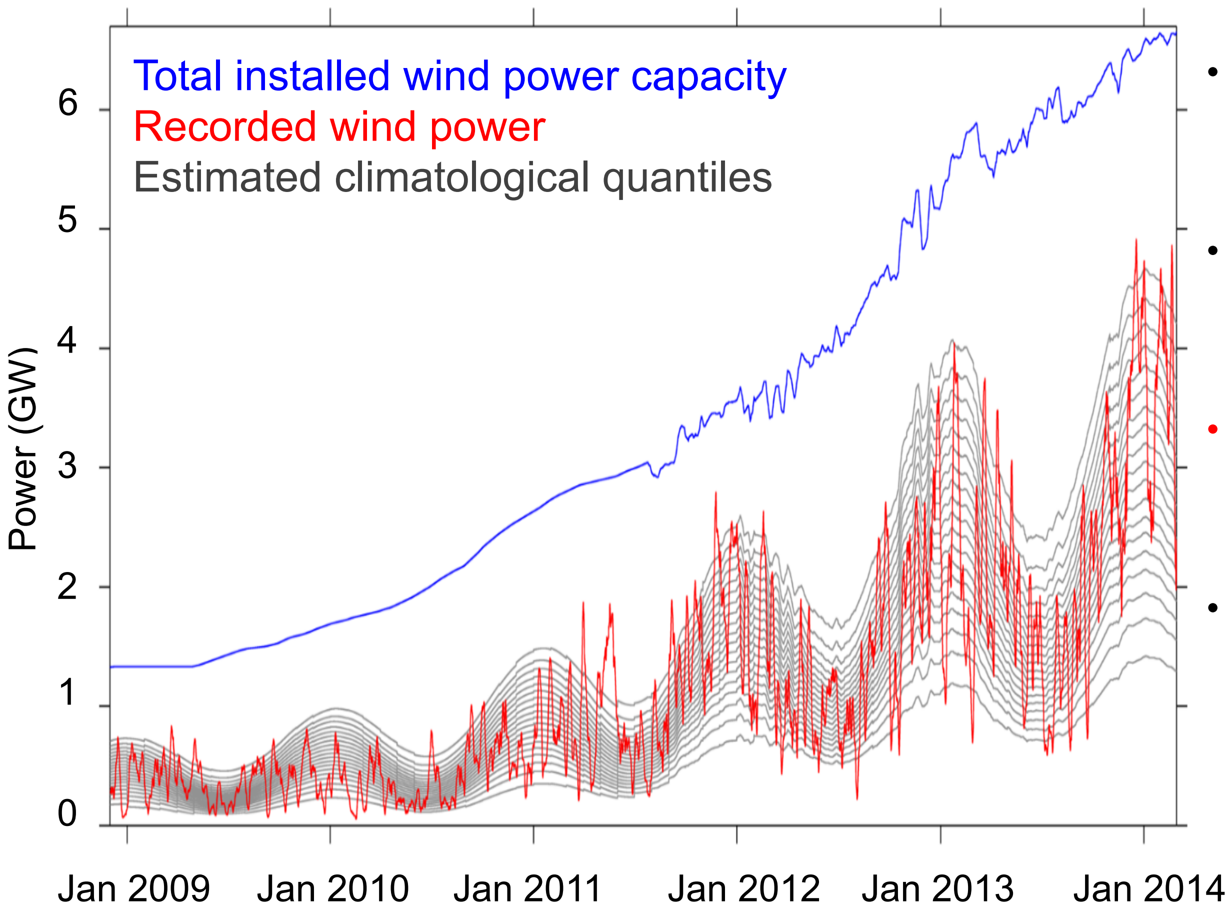
Evolving wind-farm distribution

Aggregate wind-farm power curve

Calibration to observed power data



Wind power forecast



- Use the time-evolving set of wind farms to scale the wind-power PDF derived from ERA-Interim.
- Enables direct comparison with observed wind-power records
- **ACC 0.52; CRPS 0.17 (99% confidence)**
- Similar results if consider a fixed wind-farm distribution and compare entire 33-year synthetic wind-power record.

Use of the 3-week forecast gives significant improvement on climatological expectation

Demand model and forecast

University of Reading

Regression-based model

Trend

Weather (T_{eff} anomalies)

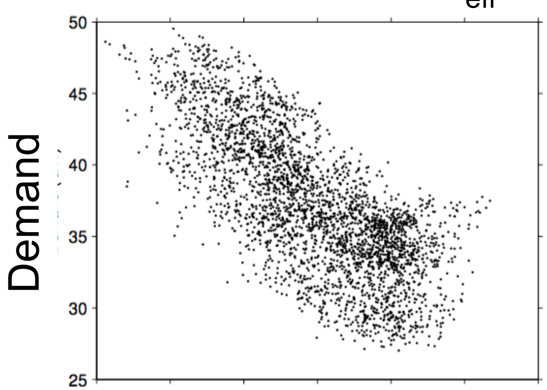
Residual (category-dependent white-noise)

$$D = \beta_1 t + \Phi + \Psi + \beta_2 + \epsilon$$

Seasonality
Day-of-week
Holidays (major/minor)

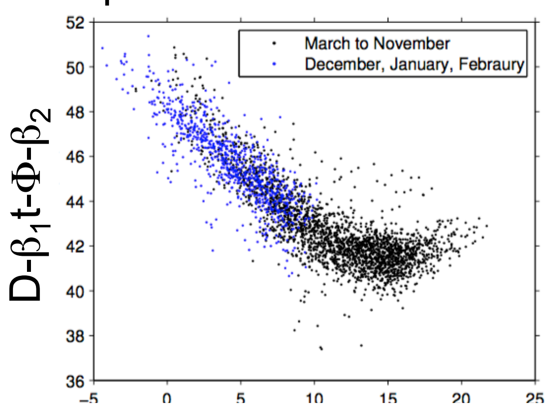
Mean

Raw demand vs T_{eff}



Effective temperature T_{eff}

Temperature-sensitive D vs T_{eff}



Effective temperature T_{eff}

For week-3 average demand:

- **ACC 0.55**
- **CRPS 0.14**
- **95% confidence**

Use of the 3-week forecast gives significant improvement on climatological expectation

Sub-seasonal prediction for power
(Lynch et al 2014 and PhD thesis)

University of Reading

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Datasets used: Elexon (power), ERA-Int (weather), Bloomberg (price)

Modelling concept

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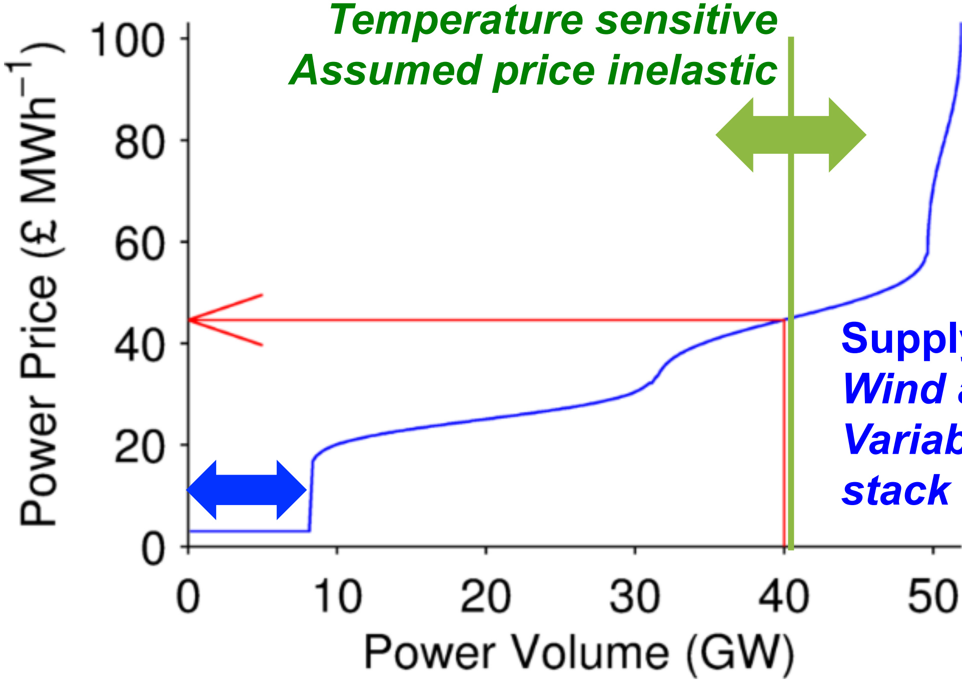
Demand
Temperature sensitive
Assumed price inelastic

Most expensive bid required sets price



Supply stack
Wind as "always on"
Variable contribution shifts stack

High frequency data (6h) used in the met→power conversion but interested in evaluating forecast skill for weekly-averaged blocks

Merit order fitting

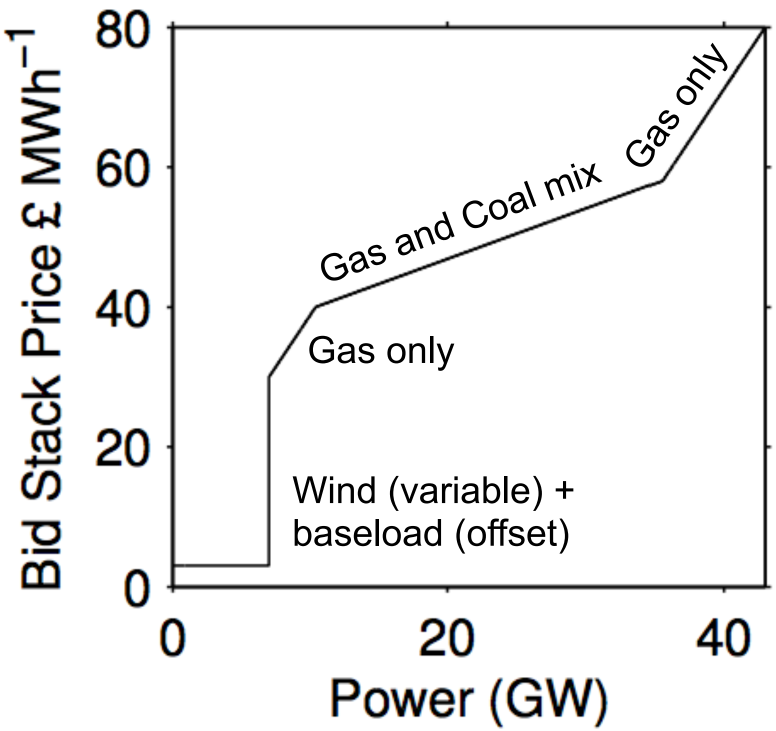
- Need to estimate the form of the supply curve

- Simplified stack model:
  - Three fuels:
    - Wind – always on (price taker)
    - Coal and Gas – fixed (capital) and variable (fuel, carbon) costs
  - No storage
  - No interconnection
  - Copper-plate transmission
  - No ramp constraints

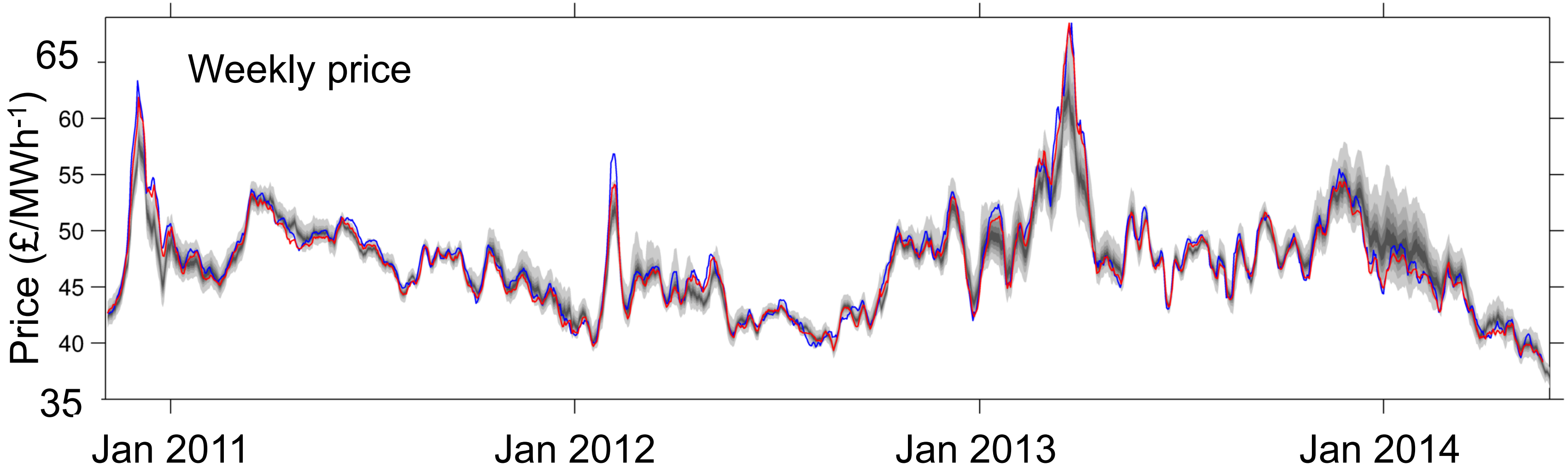
- All assumptions are believed appropriate for an initial analysis of the GB power system

- Range of efficiencies for individual coal and gas plant: assume exponential curve

- Fit time-varying stack parameters – broadly corresponding to plant "efficiency" - using recorded price, demand and wind generation data



Price climatology



Compare blue and red lines:

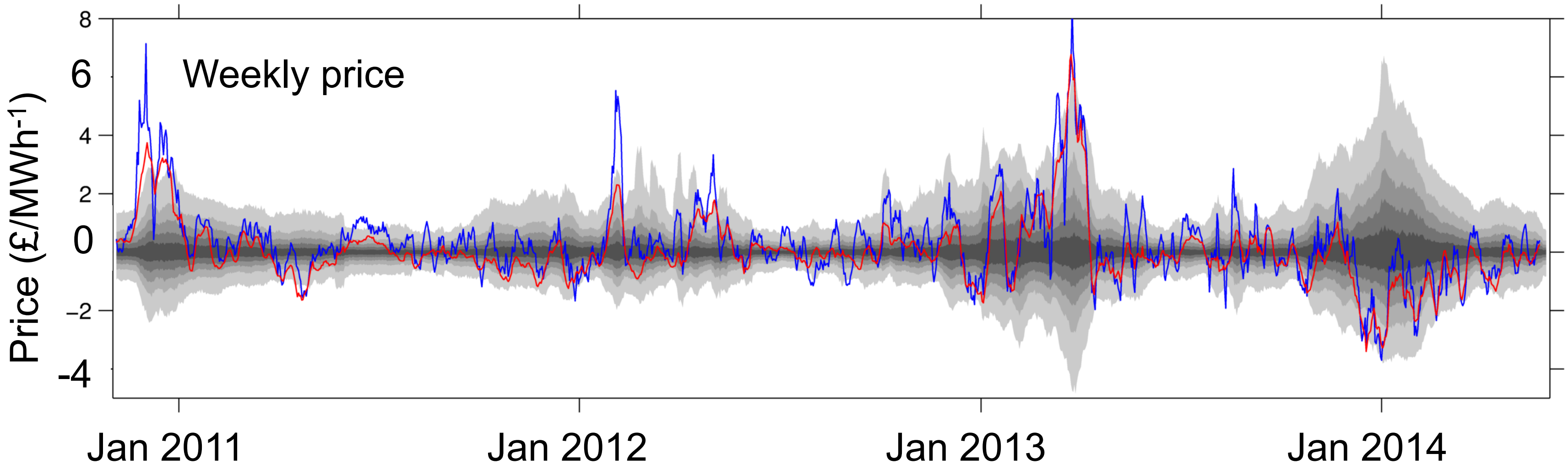
- Blue = actual price
- Red = price simulated by the power model, given perfect knowledge of wind and demand volumes

Grey shading:

- Price quantiles from climatological wind power / demand records (from ERA-Interim)
- Interpretation: Spread of "possible prices" given known historic weather variability

Good estimate of the mean. Climatological quantiles overconfident esp at daily time-scale.

Price forecast



Concerned with predicting price anomalies.

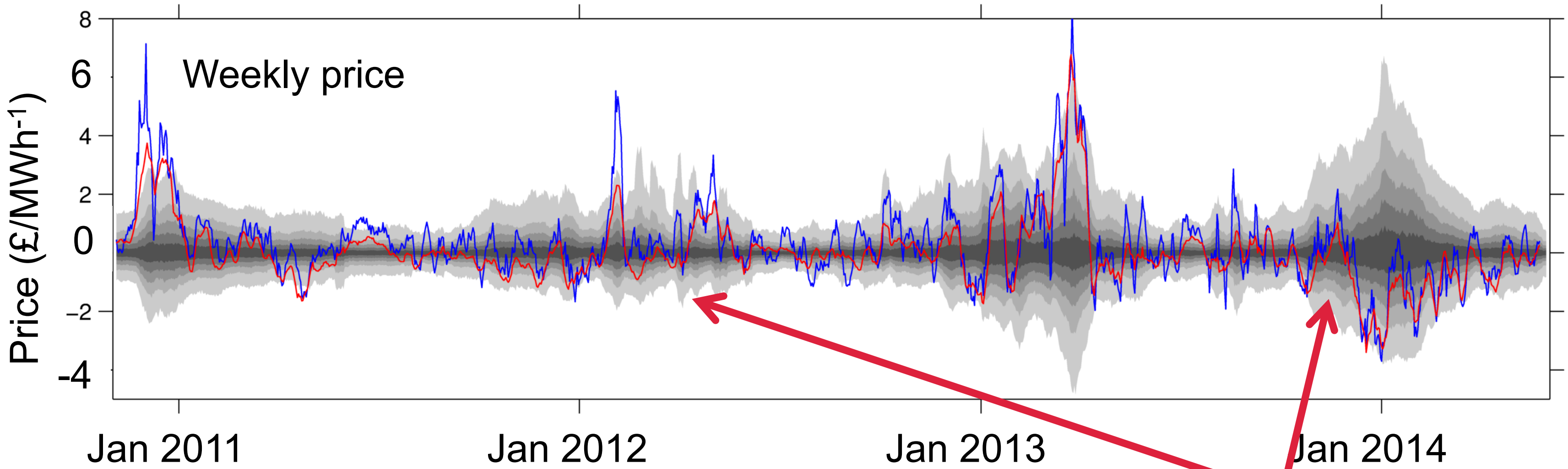
Can the ECMWF week-3 forecast out-perform the climatological PDF shown above?

Answer: Yes.

- ACC 0.53; CRPS 0.15 (99% confidence)

Similar skill for both the "operational" method (using real price records) and "synthetic" method (reconstructing an estimate of price from recorded weather).

Price forecast



Changing "climate spread": seasonally, year-to-year

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Speculative trading application

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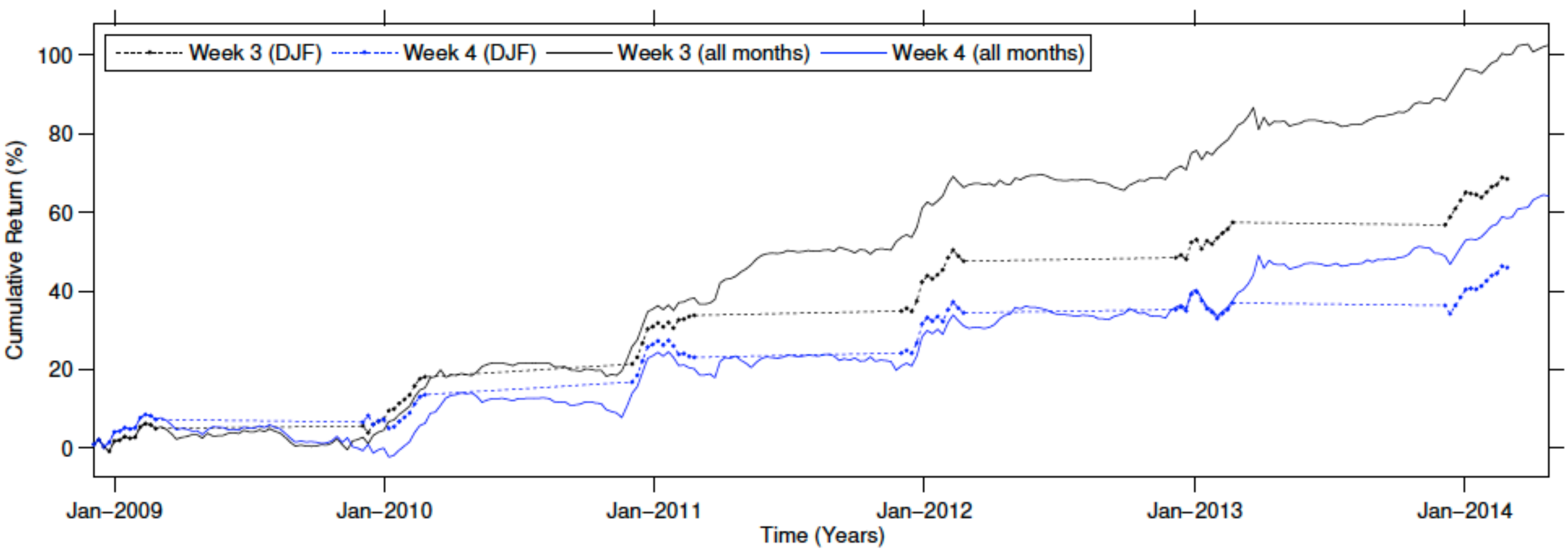
- Simplest speculative strategy:
  - Assume market only acts on climatological expectation (i.e., does not use weather forecast for week 3 and 4)
  - Buy/sell one forward contract each week depending on forecast:
    - Forecast says less DNW / lower price than climatological expectation (i.e., market price is overvaluation) – sell one contract
    - Forecast says more DNW / higher price than climatological expectation (i.e., market price is undervalued) – buy one contract



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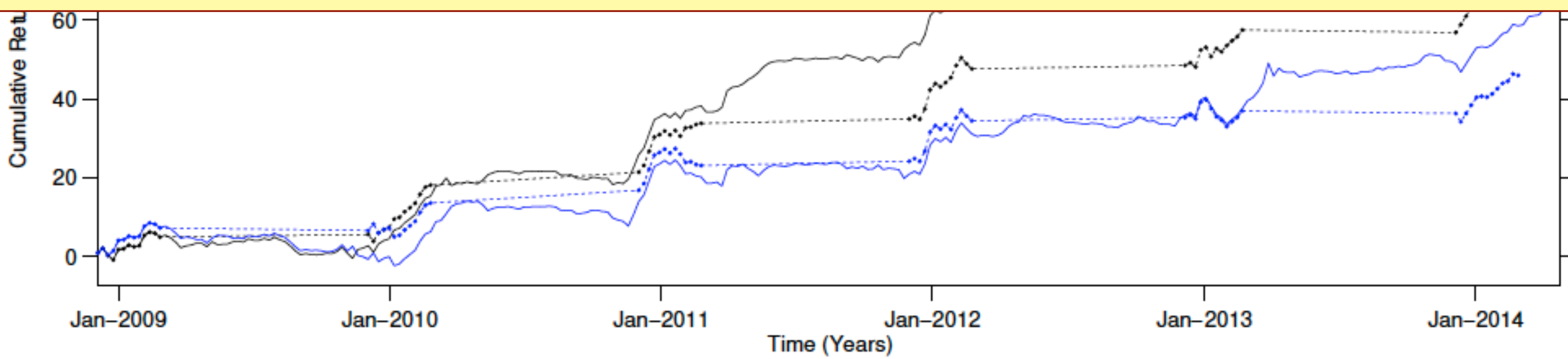
  - Assume market only acts on climatological expectation (i.e., does not use weather forecast for week 3 and 4)
  - Buy/sell one forward contract each week depending on forecast:
    - Forecast says less DNW / lower price than climatological expectation (i.e., market

Demonstrates significant improvement over "mere climatology" but assumes:

- Perfect model of power system impact
- All other actors do not have access to the same information
- Asymmetric returns (c.f., call/put or other risk hedges)



Summary

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- Weather and climate risk matters for energy applications
  - **Climate variability and change (years-to-decades) can produces significant impacts on energy systems**
  - **Opportunities to better manage risk… but end-to-end process understanding and uncertainty quantification important**
- Risk climatologies and climate change:
  - Reanalysis and GCMs are powerful tools but must be used carefully
  - Climate drivers need to be understood: **does dataset include the relevant processes?**
- Forecasting risk:
  - Subseasonal, seasonal and decadal forecast systems beginning to offer predictive skill
  - Evaluation should recognize the **integrated decision-making processes**
- Power system impacts (for climate impact modellers)
  - **Power systems are "more" than just a set of ingredients**
  - Dynamical downscaling is expensive and may not always be necessary (or helpful)

Citations and upcoming

Major projects:

- ECEM climate services for energy
- PRIMAVERA climate-energy impacts
- ODYSEA Ocean drivers of European climate variability

Recruiting now!

Contact details (including website for models and data):

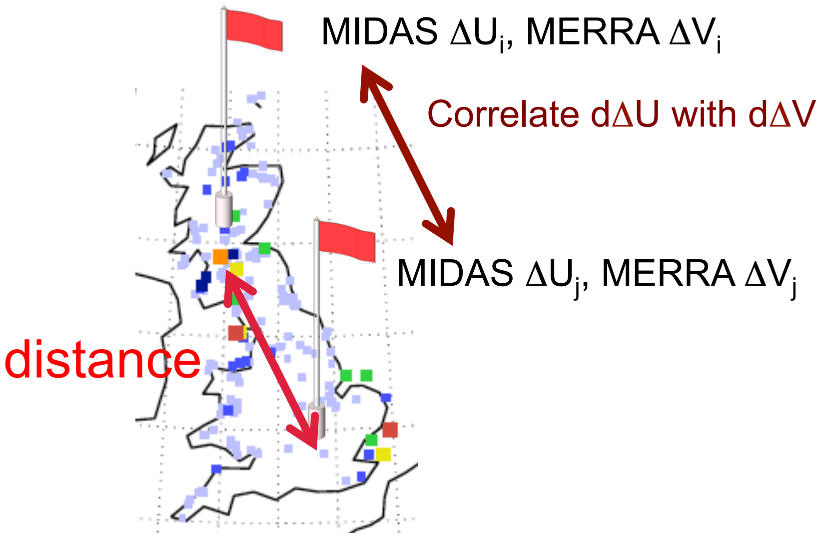
- d.j.brayshaw@reading.ac.uk ; www.met.reading.ac.uk/~energymet

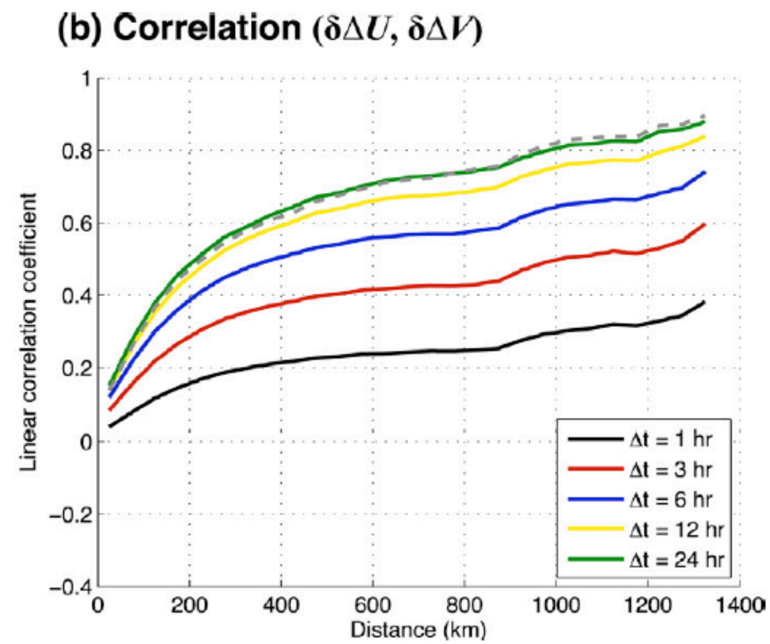
Citations:

- Bloomfield et al (submitted) Quantifying the increasing sensitivity of power systems to climate variability.
- Dunning et al (2015) The impact of monsoon intraseasonal variability on renewable power generation in India. Env. Res. Letters, 10, 064002.
- 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.
- Drew, D. et al (2015) The impact of future offshore wind farms on wind power generation in Great Britain. Resources Policy, 4 (1). pp. 155-171.
- 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.
- Brayshaw, D. J. et al (2011) The impact of large scale atmospheric circulation patterns on wind power generation and its potential predictability: a case study over the UK. Renewable Energy, 36 (8). pp. 2087-2096.

Aside: The limits of reanalysis 2

Extension to time-variability: how well does MERRA capture *differences in changes in wind speed between sites*?





Correlation ~0.5 @ 300 km for 6-hour changes in wind speed

Cannon et al (2015)

Aside: UK-Norway power system
(Ely et al 2013)

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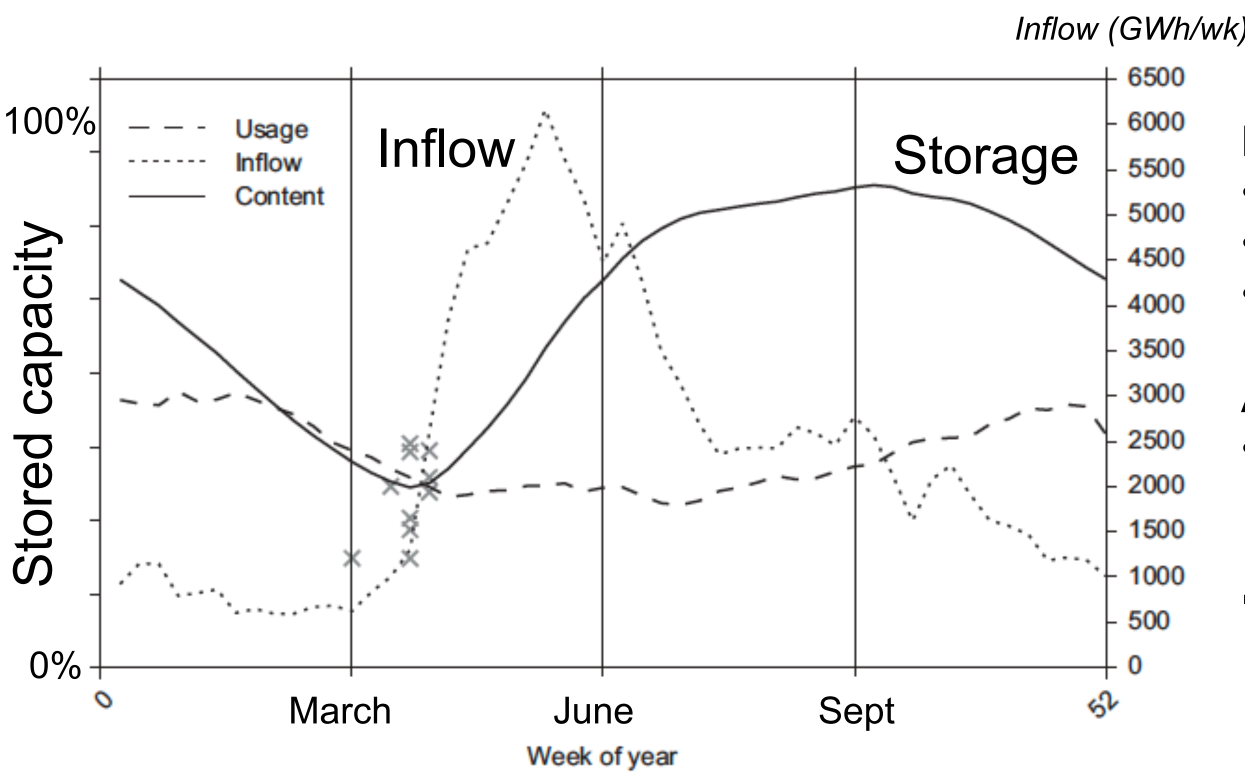
- UK system: power limited (generating capacity to meet peak demand)
- Norway system: energy limited (energy storage to provide for total demand)
    - "what if" UK and Norway were connected?
    - Wind generation UK, hydro generation Norway, demand from both regions
    - Critical period: late winter/early spring



NAO-negative winter/spring:
- Cold (high demand)
- Still (low wind)
- → high load

And
- Cold (inflow from snow delayed)

➔ NAO prediction in spring?

Figures: Ely et al 2013