

Converting climate forecast data to energy variables and understanding weather drivers

Hannah Bloomfield, University of Reading

with thanks to: David Brayshaw, Paula Gonzalez, Andrew Charlton-Perez, David Livings, Phil Coker, Dan Drew, Dirk Cannon, Len Shaffrey, Hazel Thornton.



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4th December 2020





Presentation Outline

Conversion from weather to energy

Motivation

Examples of available datasets



Some common modelling challenges











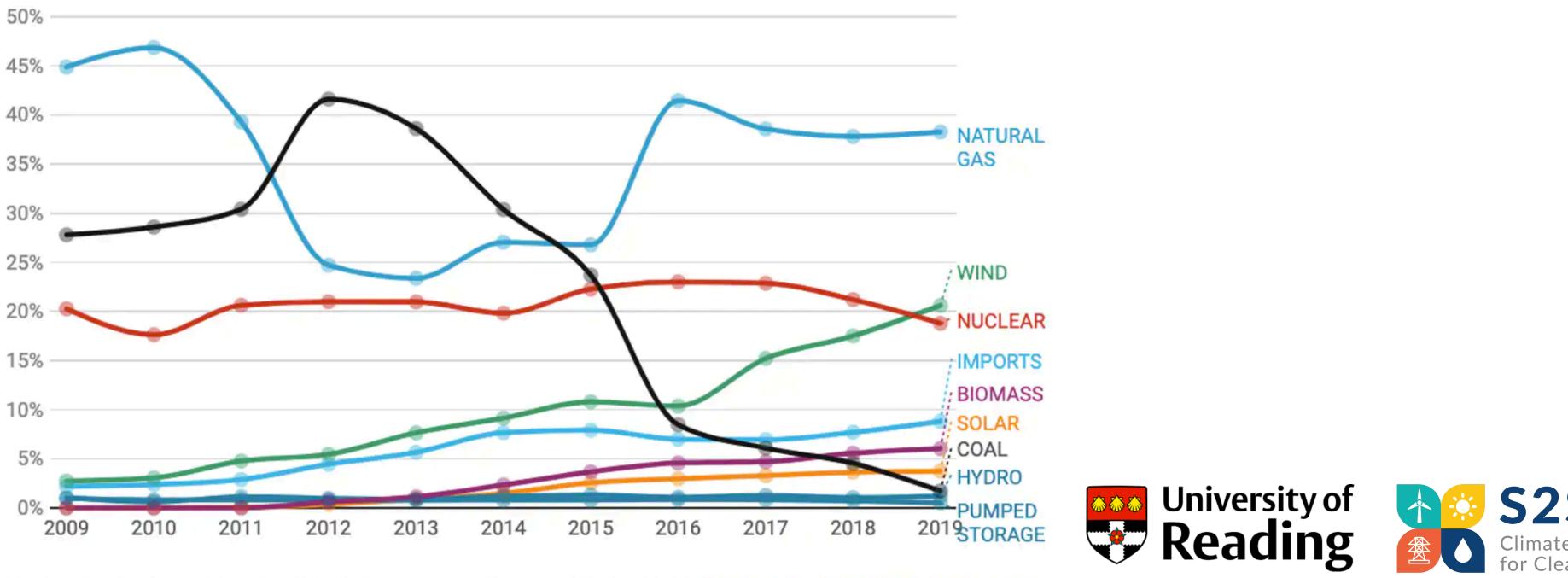
Motivation Why do I need all this weather data?





Why do we need weather and climate data?

- In order to meet government targets power systems are becoming increasingly weather-dependent This weather-dependence results in increases power system variability on numerous timescales from secondsdecades
- Energy systems are rapidly changing to meet climate mitigation targets, so metered data contains large trends, and past years data are less useful.
- Year to year variations in weather can cause large differences in power system modelling results.



Great Britain's electrical generation by fuel type %

Chart: Dr Grant Wilson, University of Birmingham • Source: Elexon and National Grid • Get the data • Created with Datawrapper

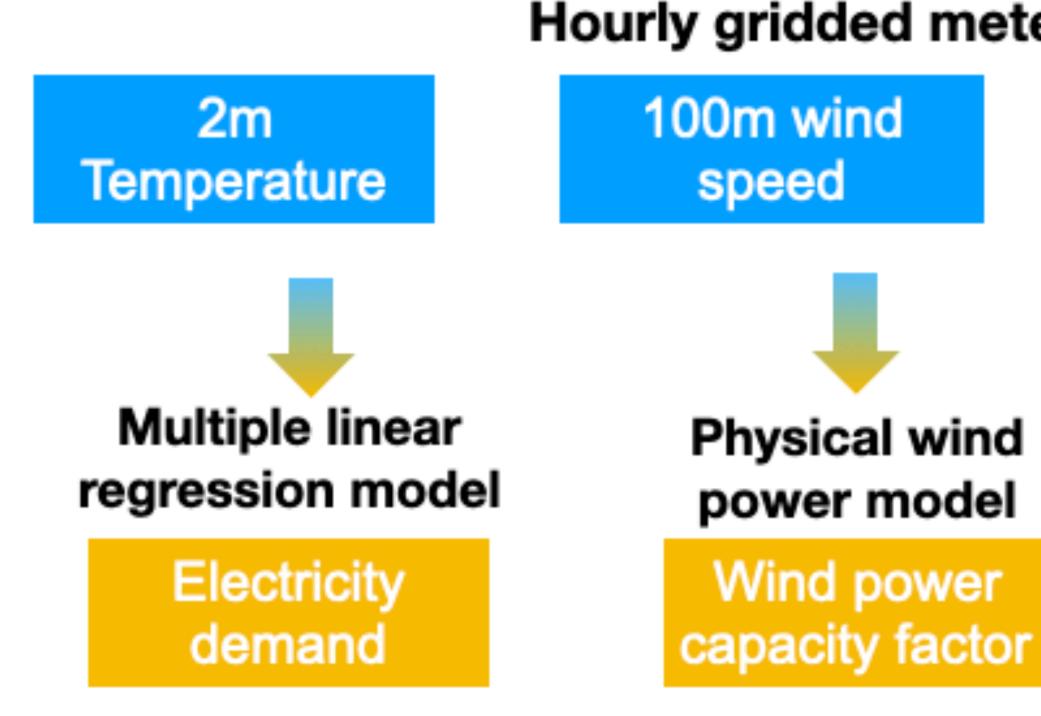


Conversion to energy models

models.

BY

years of weather are passed through models.



Hourly national Energy variables

• Gridded weather and climate data can be converted into energy variables using statistical or physical

Generally the power system setup is fixed (e.g. 2020/2050 levels of demand/wind/solar) and many

Hourly gridded meteorological variables Surface Shortwave 2m Temperature Radiation Empirical solar power model Solar power capacity factor



Conversions to weather How do we do this?



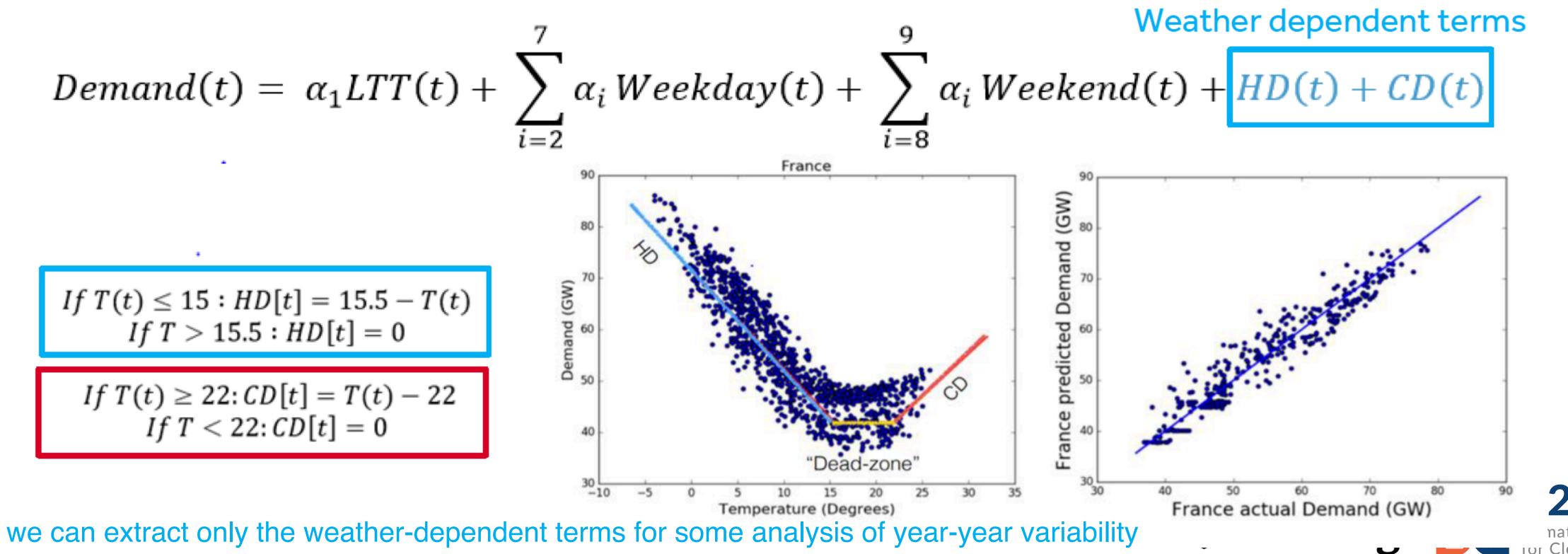
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Demand modelling

- surface wind speeds, cloud cover etc).

- Demand models include both of these factors and generally use a statistical technique (e.g. regression).



pomfield et al., (2020) for further details



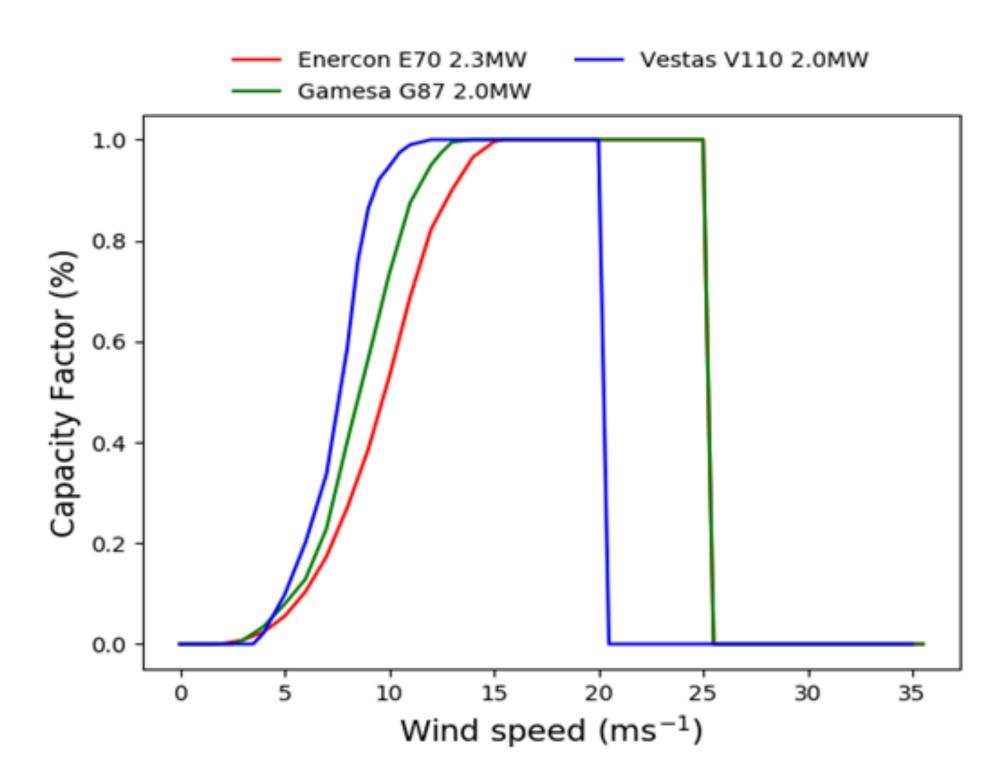
Demand over Europe is predominantly dependent on near surface temperatures (other factors may include near-

Heating Degree Days (HD) and Cooling Degree Days (CD) are a common metric for measuring temperature sensitivity There are both weather-dependent influences and human-induced factors (e.g. long-term trends, day of the week).



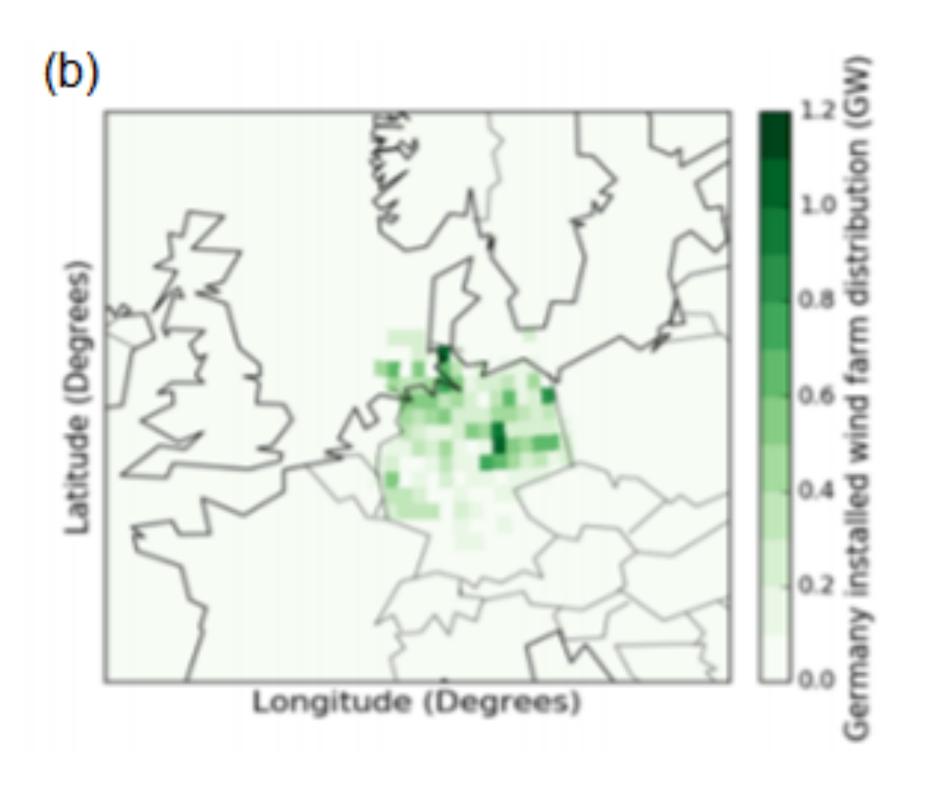
Wind Power modelling

Wind Power models are based on the non-linear relationship between wind speed and wind power. Gridded wind speeds are required at turbine hub-height (~100m) If the locations of wind turbines are known then the gridded wind power output can be calculated, or aggregated over larger regions (e.g. national level).



See Bloomfield et al., (2020) for further details

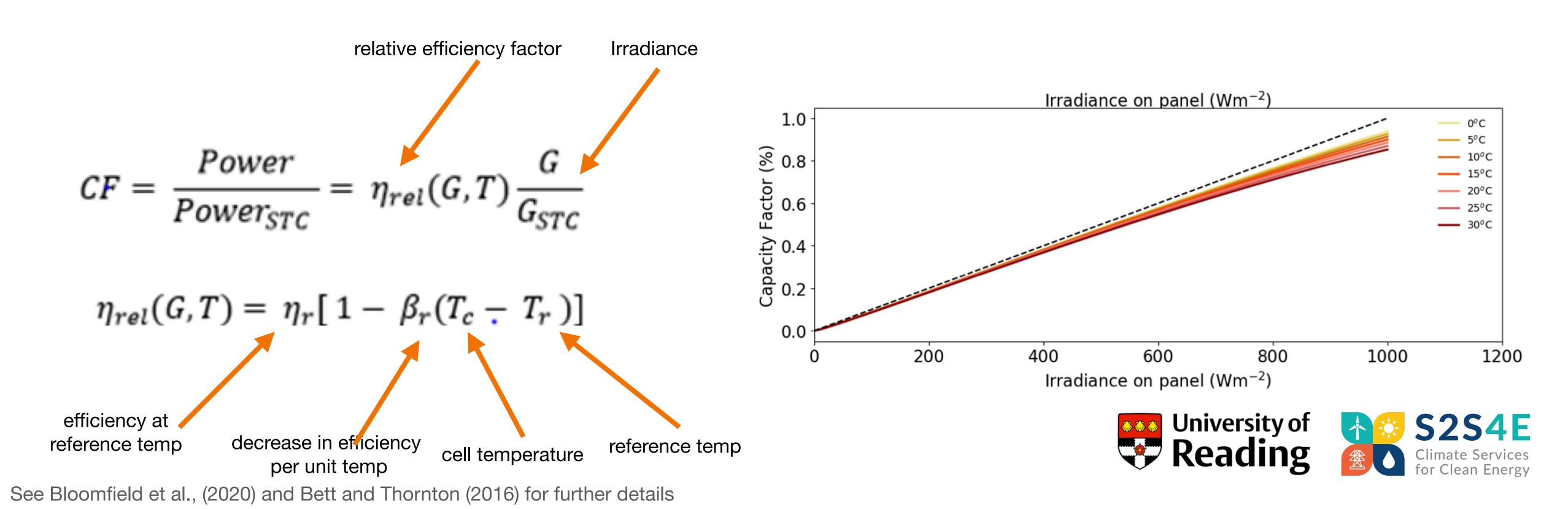






Solar PV modeling

Global Horizontal Irradiance is the main meteorological component required for a solar power model. Information about direct and diffuse components of solar radiation may be required, as well as local temperatures, solar zenith angles and operational characteristics of the chosen solar PV system Physical modelling techniques tend to need more information about local conditions than statistical or empirical solar modelling techniques.





Conversion to weather

Some common problems that are encountered





Challenges in demand/wind/solar PV modelling

Demand

- Statistical models are dependent on the quality of the training data
- All countries have varying levels of weather-dependence, based on power system composition
- Contribution of human and weather factors means that unpacking the various components is complex

- Calibration of the underlying climate data is very important.
- Biases in the wind speed distribution can lead to large errors in wind power
- When looking at future climate simulations or S2S forecasts you are unlikely to have high resolution data
- Wind power generation can be impacted by factors "outside the physical model control" e.g. grid stability issues and the need for wind power curtailment

Wind Power

Solar Power

- There are only very poor records of where solar power generation is located
- A lot of solar/wind models based on the physics of individual panels not aggregated over areas





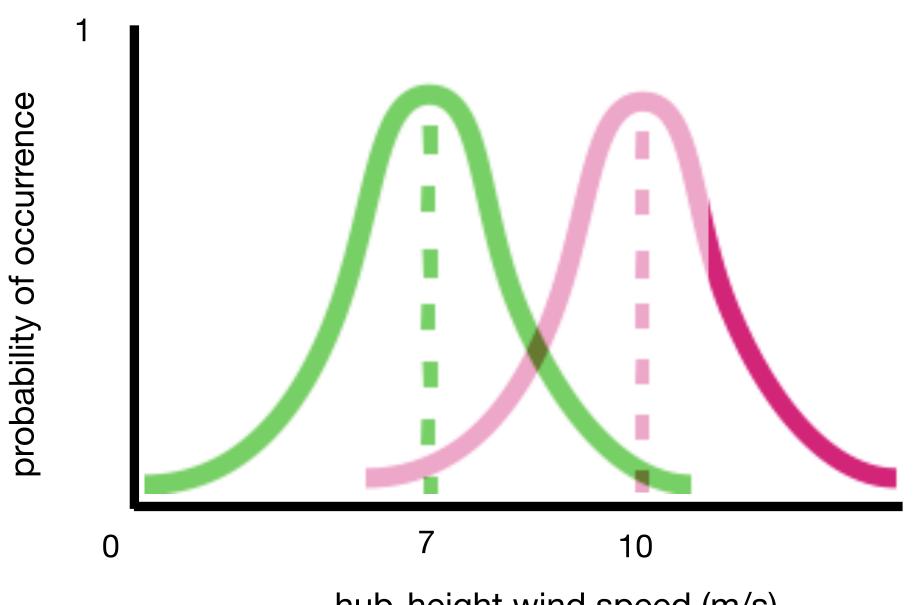




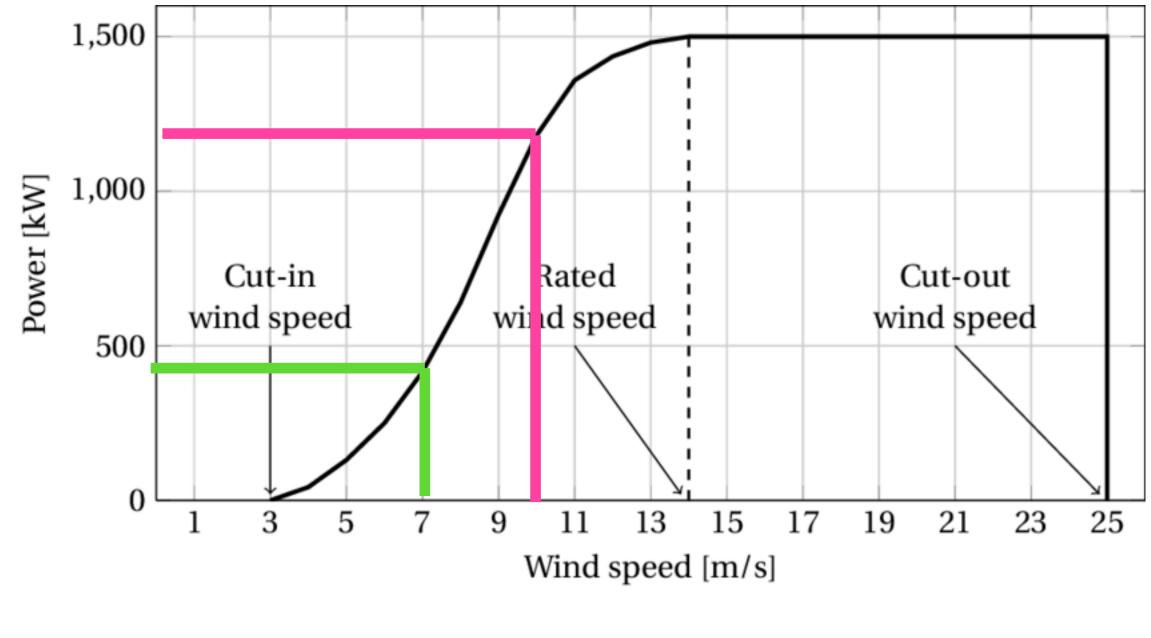


Wind Power modelling Challenges

Calibration of the underlying climate data is very important.
 Biases in the wind speed distribution can lead to large errors in wind power output



hub-height wind speed (m/s)



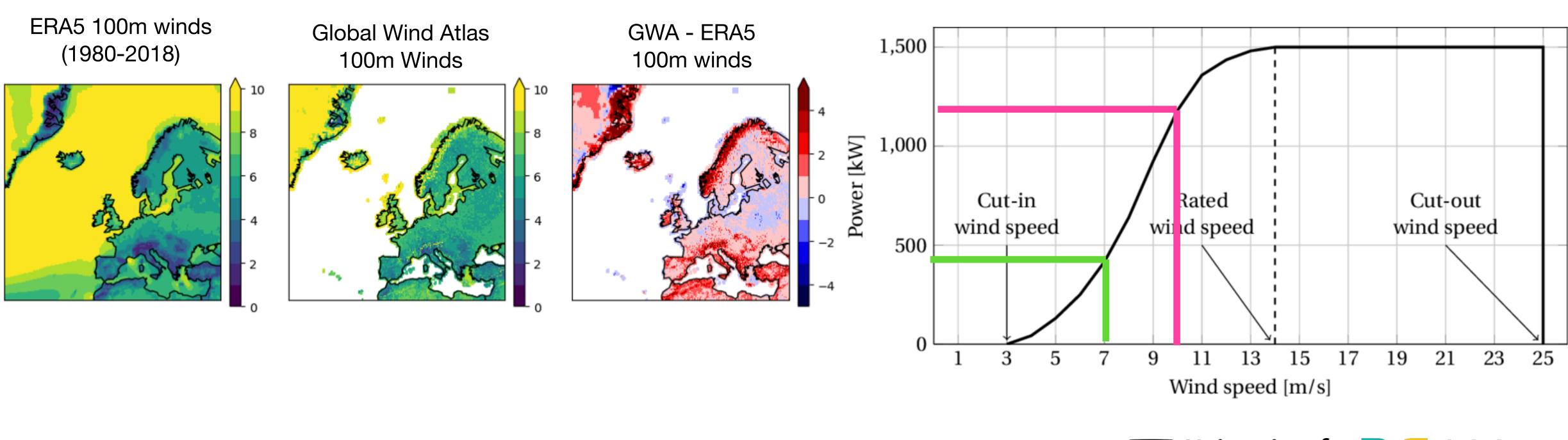






Wind Power modelling Challenges

Calibration of the underlying climate data is very important.
 Biases in the wind speed distribution can lead to large errors in wind power output









Example datasets current, future and S2S timescales



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Examples of available climate data

A list of currently available datasets (all open access) is currently hosted on the opened forum.



Freely available datasets of energy variables

Open data



CC () BY

matteodefelice

Climate reanalysis datasets

(a version of this page is also available on github 1)

This page contains a list of all the freely available datasets of energy variables (electricity de wind/solar/hydro-power) reconstructions based on climate reanalysis or climate change project

The list is a work-in-progress, please reply to this post if you want to add a dataset or suggest correction.

https://forum.openmod-initiative.org/t/freely-available-datasets-of-energy-variables/2291

Historical period

Datasets based on "observed climate" (weather stations, satellite, reanalyses, etc.).

Electricity demand

	Name	Unit	Period	Domain	Spat. res.	Time res.	climate model(s)	data license	updates	URL
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st a	UREAD Energy Reanalysis	Power	1980- 2018	Europe	Country	Hourly	MERRA2	CC Attributions 4.0	no	http://c









Renewables Ninja (wind and solar) renewables.ninja

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1			25%
Hub height (m) 🛛			20% -
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Turbine model 😡			Jan Feb Mar Apr May Jun 2019
Vestas V90 2000	-		Total mean capacity factor: 21.9%
Include raw data			Save hourly output as CSV License: Creative Citation: Staffell at
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S2S4E

ecem.wemcouncil.org

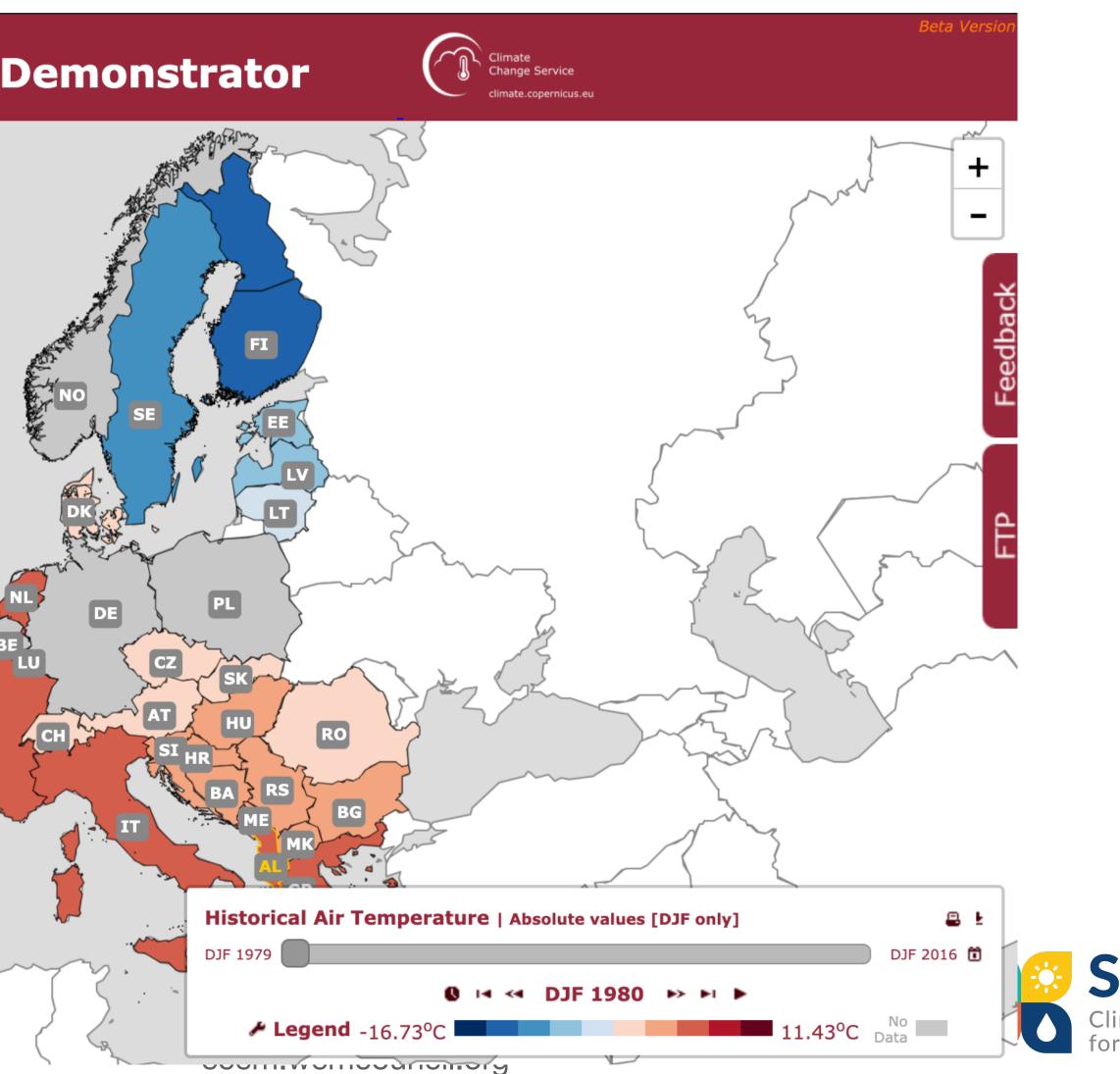




ECEM: demand, wind solar

PROOF OF CONCEPT	COPERFICUS Europe's eyes on Earth	The ECEM
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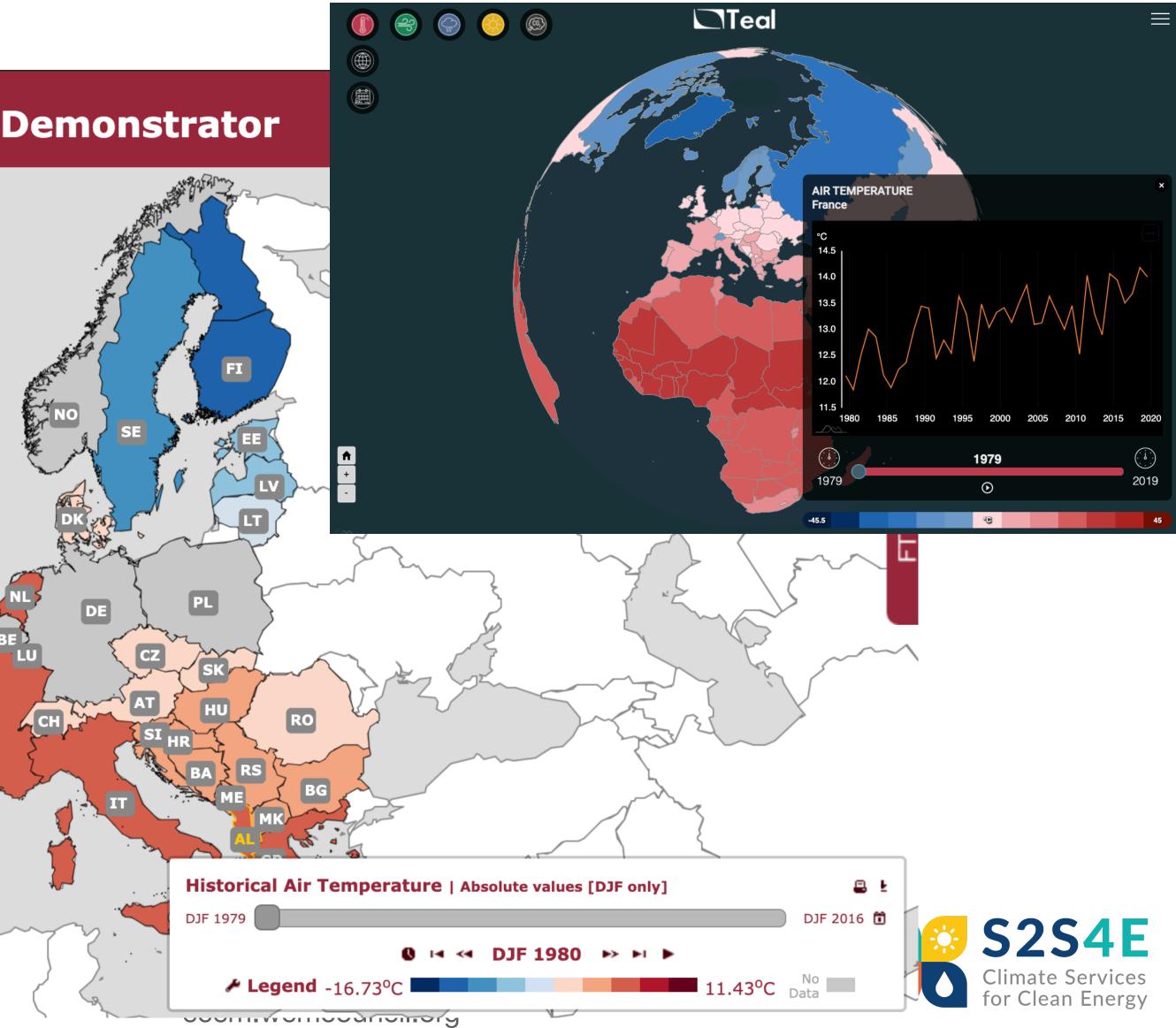


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Timeseries plots		
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New graph Refresh graph	dd to graph	PTES
Labels Off Close Graphs	Reset Map	
Click here for help and informa	tion	

tealtool.earth **ECEM education tool**

http://ecem.wemcouncil.org/





UREAD: demand, wind, solar

https://research.reading.ac.uk/met-energy

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University of Reading Research Data Archive Home <u>Login</u> ERA5 derived time series of European country-aggregate electricity Data Cite XML demand, wind power generation and solar power generation How to cite this Dataset Files Copy Full Archive Bloomfield, Hannah, Brayshaw, David and Charlton-Perez, Andrew (2020): ERA5 derived time series of European country-aggregate electricity demand, wind power generation and **ERA5_energy_update.zip** solar power generation. University of Reading. Dataset. http://dx.doi.org/10.17864/1947.273 This is the latest version of this item. Description **Related CentAUR publications** The ERA5 reanalysis data (1979-2018) has been used to calculate the three-hourly country Characterizing the winter meteorological drivers of theEuropean electricity system using targeted aggregated wind and solar power generation for 28 European countries based on a distribution **<u>circulationtypes</u>** of wind and solar farms which is considered to be representative of the current situation (2017). Meteorological drivers of European power system In addition a corresponding daily time series of nationally aggregated electricity demand is stress provided. The datasets have been produced to investigate the inter-annual variability of the three weather-dependent power system components. ** This is an update on the previous version of the data where there were issues with the Statistics timestamps in the 3-hourly wind and solar power data. ** Loading ... **Resource Type:** Dataset <u>Bloomfield, Hannah 🔟, Brayshaw, David</u> and Creators: Charlton-Perez, Andrew 🕕 University of Reading **Rights-holders:**

Dataset

Bloomfield, Hannah, Brayshaw, David and Charlton-Perez, Andrew (2020): ERA5 derived time series of European country-aggregate electricity demand wind power generation and solar power generation. University of Reading. Dataset. http://dx.doi.org/10.17864/1947.273

Bloomfield, Hannah, Brayshaw, David and Charlton-Perez, Andrew (2020): ERA5 derived time series of European country-aggregate electricity demand, wind power generation and solar power generation: hourly data from 1979-2019. University of Reading. Dataset. https://researchdata.reading.ac.uk/id/eprint/272

Bloomfield, Hannah, Brayshaw, David and Charlton-Perez, Andrew (2020): MERRA2 derived time series of European country-aggregate electricity. demand, wind power generation and solar power generation. University of Reading. Dataset. http://dx.doi.org/10.17864/1947.239

Gonzalez, Paula, Bloomfield, Hannah, Brayshaw, David and Charlton-Perez, Andrew (2020): Sub-seasonal forecasts of European electricity demand, wind power and solar power generation. University of Reading. Dataset. https://researchdata.reading.ac.uk/id/eprint/275

Drew, Daniel, Bloomfield, Hannah, Coker, Phil, Barlow, Janet and Brayshaw, David (2019): MERRA derived hourly time series of GB-aggregated wind power, solar power and demand. University of Reading. Dataset. http://dx.doi.org/10.17864/1947.191

✓ Export

Reanalysis (MERRA2, ERA5) Forecasts (ECMWF, NCEP)





S2S4E: operational forecasts

Clean Exergy Tool			
Search location Q	Check previous forecasts 2020 Nov 27 2020 Nov 27	orecast window 4 −1 2 3 Next 3 months	Forecast for 2020 Nov 23 - 2020 Nov 29 Forecast issued on 2020 Nov 19 Next forecast available on 2020 Nov 26
VARIABLES ③ Select category Essential climate variables Select variable Wind speed	B		O mapbox
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Your feedback helps us improve Hannah 🗸 v1.5.1 Week 1 × (23 - 29 November 2020) Wind speed 0 SUMMARY • • • FORECAST SKILL 18% ABOVE 21% 27% NORMAL (Good) 55% BELOW EXTREMES (p10-p90) 0 FORECAST SKILL MIN MAX MIN MAX 28% 21% 12% 4% FORECAST DISTRIBUTION ① 8.93 m/s 7.72 m/s 6.77 m/s 5.83 m/s DOWNLOAD REPORT

https://s2s4e-dst.bsc.es/#/dashboard

https://research.reading.ac.uk/met-energy for access to the hindcasts (~20 yrs)













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That's a lot of data What can I do with it all?

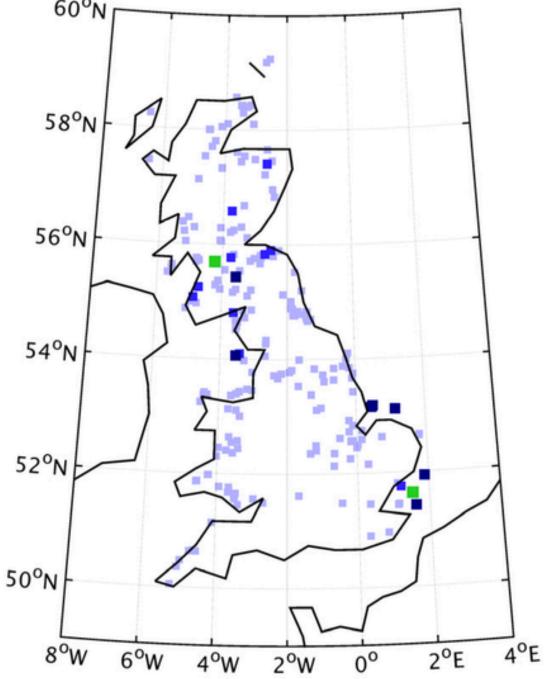


Understand Present/potential power system variability

How might GB baseload capacity reduce in a future power system with more wind power generation?

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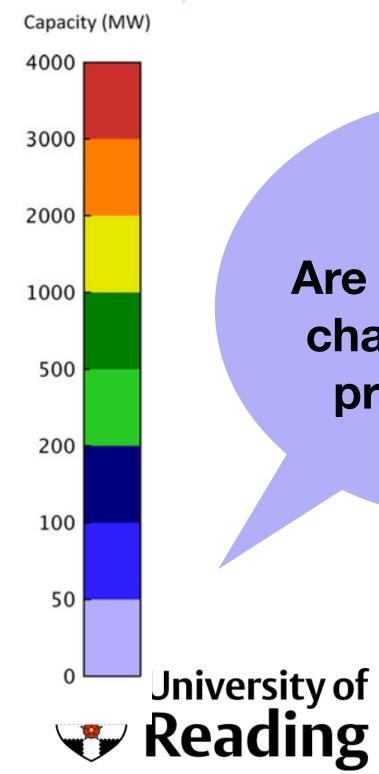
April 2014 (10.2 GW)



How might annualmean CF change with increasing installed WP cap? What weather conditions could cause the most power system stress?

The Future (~50 GW) 60°N 58°N 56°N ÷. 54°N 52°N 50°N 4°E 8°W 00 2°E 6°W 4°W 2°W

What meteorological variables is my power system most sensitive to?



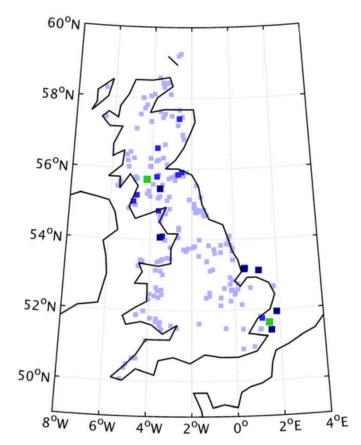
Are any of these characteristics predictable?



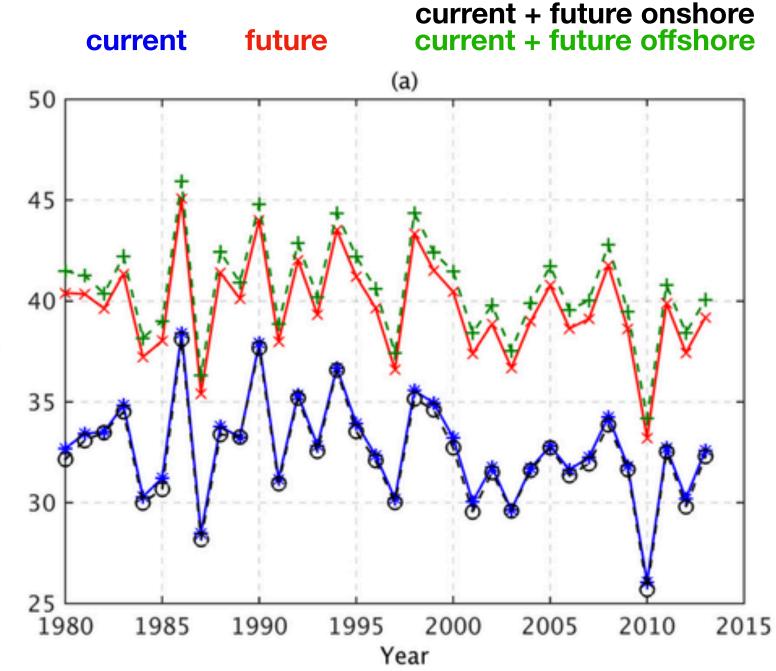


Understand Present/potential power system variability

April 2014 (10.2 GW)



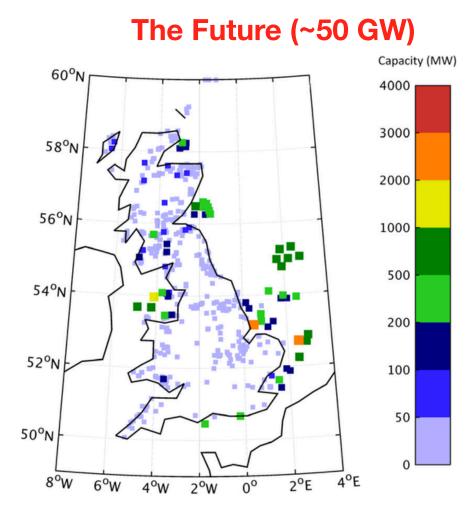
How might annualmean CF change with increasing installed WP cap?



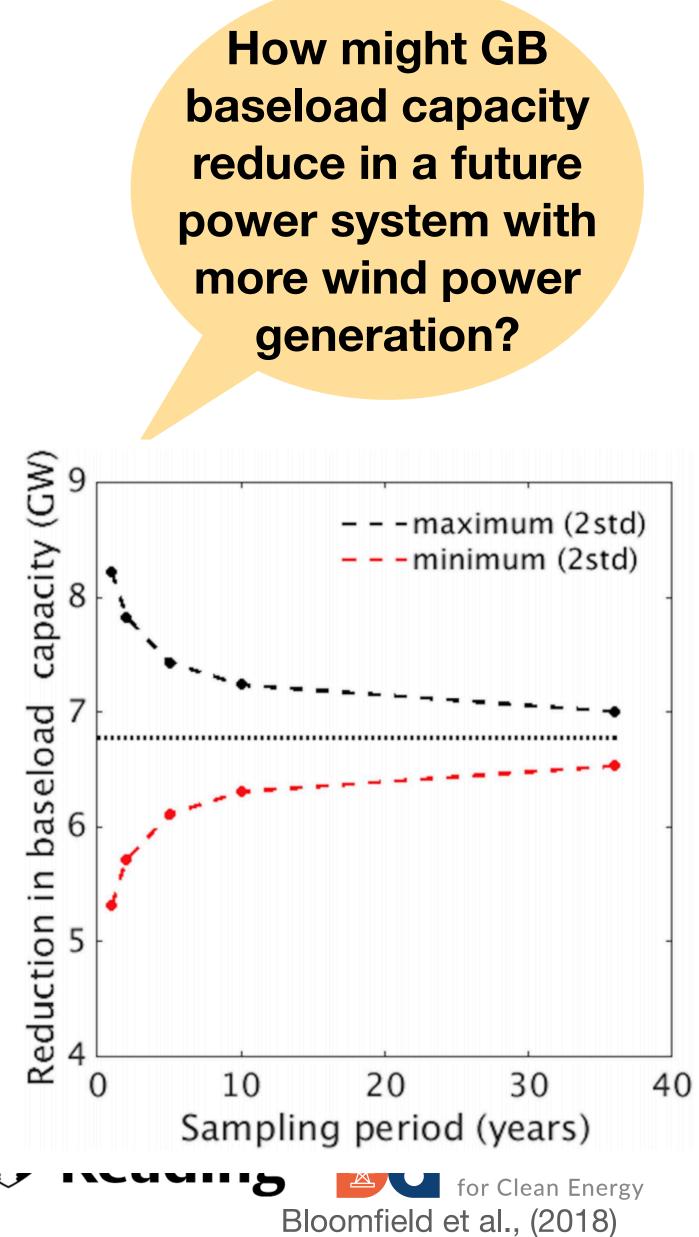
Increase in annualmean CF, but. Still risks of poor generation years.

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Drew et al., (2015)



generation?

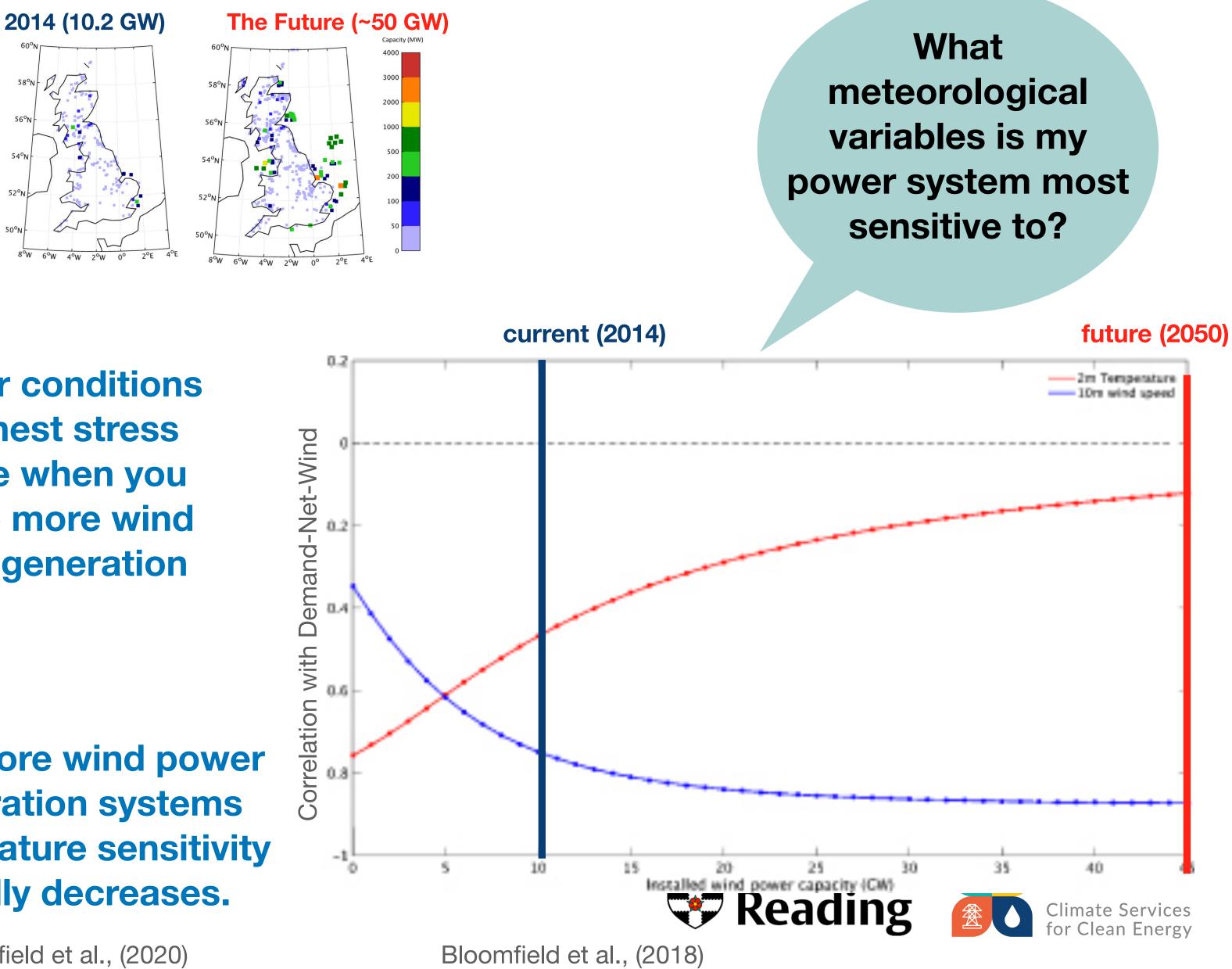


Reduction in BL operation. Much more certainty in the conclusions if you include 30-40 years of data rather than just 1 or 2.

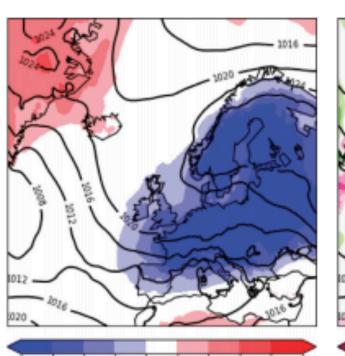
Understand Present/potential power system variability

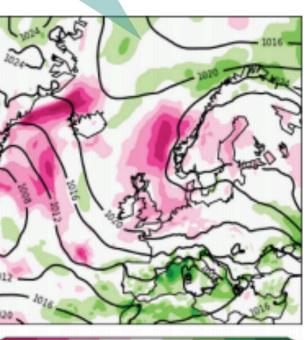
What weather conditions could cause the most power system stress?

April 2014 (10.2 GW)



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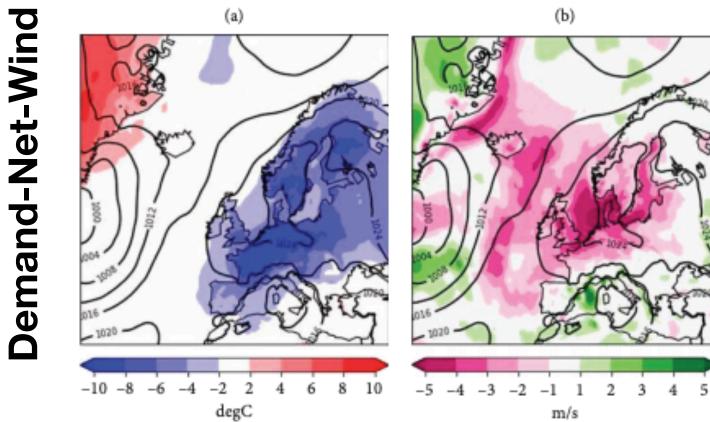


m/s

Weather conditions of highest stress change when you include more wind power generation

with more wind power generation systems temperature sensitivity rapidly decreases.

Bloomfield et al., (2020)



Predict future power system behaviour

Are any of these characteristics predictable?

Pass (calibrated!) forecast data through the models described earlier

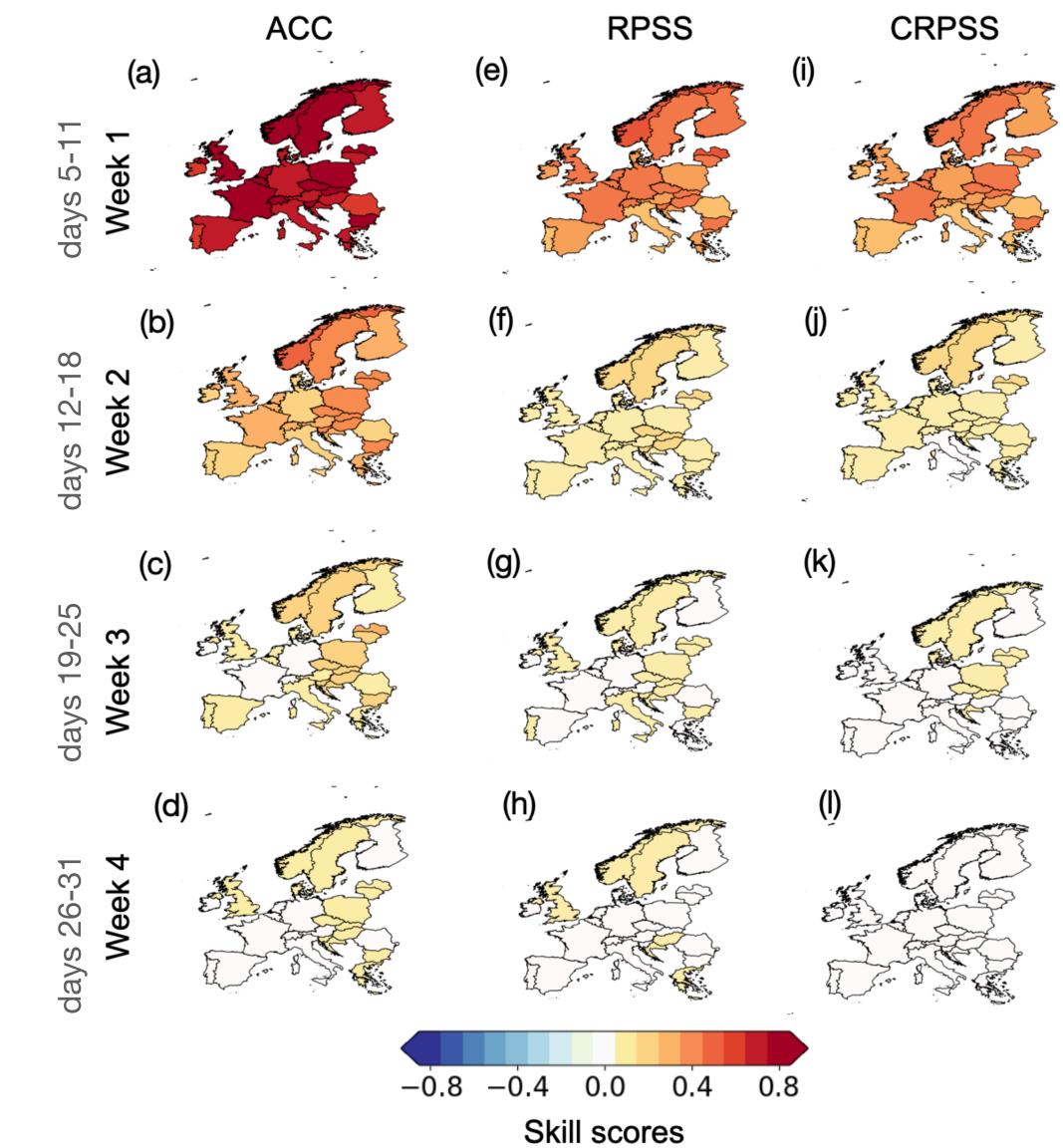
UREAD have published datasets of European Demand, Wind Power, Solar Power hindcasts from 1996-2016 for 2 sub-seasonal models (ECMWF and NCEP, ~40 day forecasts)

Good skill seen in week 1 (days 5-11) useful skill still present at longer lead times

Data: Gonzalez et al., (2020)

CC DY

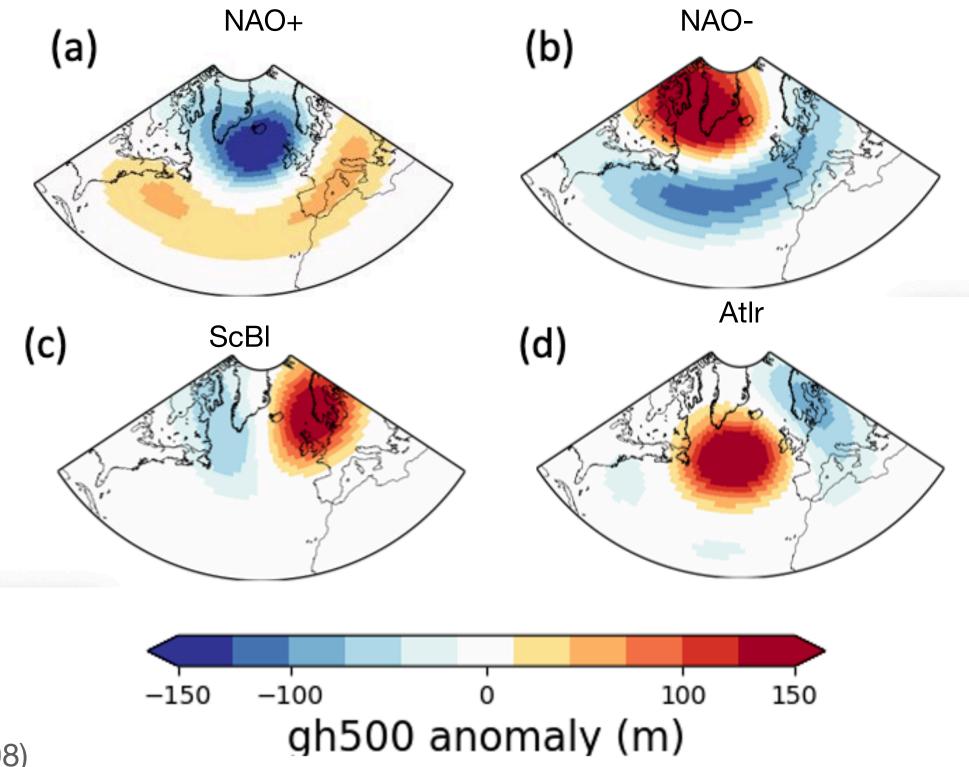
Description: Bloomfield et al., (in review), contact for a copy





Using weather patterns to forecast energy variables

- Weather regimes.
- Patterns based on large scale, upper atmospheric meteorological data.
- Constructed using k-means clustering of principal components of the gridded data.

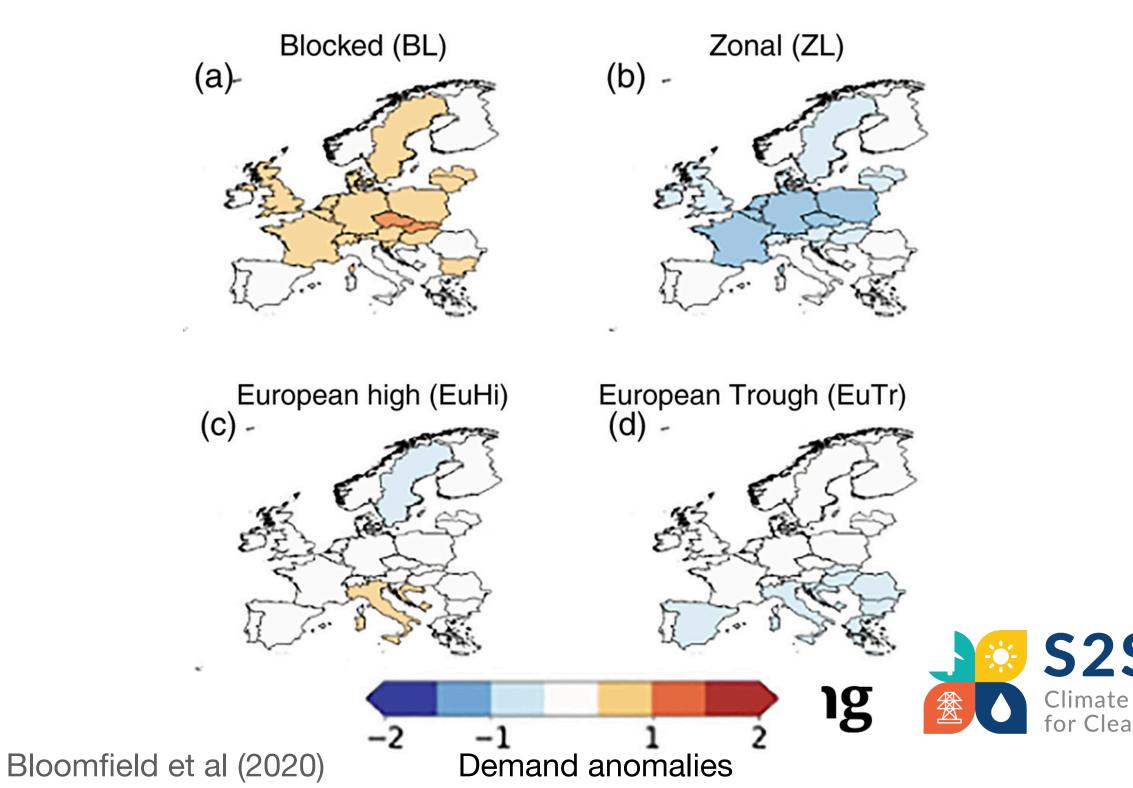


Cassou (2008)

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Targeted Circulation Types.

- Constructed using k-means clustering of principal components of European power system data.
- Better relationship to system of interest than 'traditional' weather regimes.





Using weather patterns to forecast energy variables

A recent S2S4E webinar survey showed pattern methods are commonly used in the energy industry to forecast

- Patterns have the potential to provide enhanced skill compared to grid point based forecasts
- Current work at UREAD is investigating how well pattern based methods (like European weather regimes, or TCTs) compare to using the grid point forecast data.
- Visit the poster later for more details about this.

Motivation European energy variables. Methods weather variables: m Temperature 00m wind spee i00hPa Geo Pattern Assignment WR ecwmi Percent of correct pattern assignments vs ERA5 in each forecast lead week

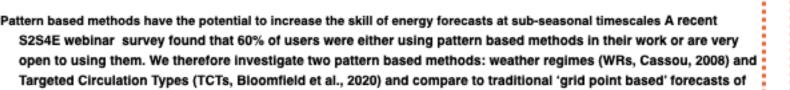
Exploring methods to forecast national energy variables at sub-seasonal to seasonal timescales

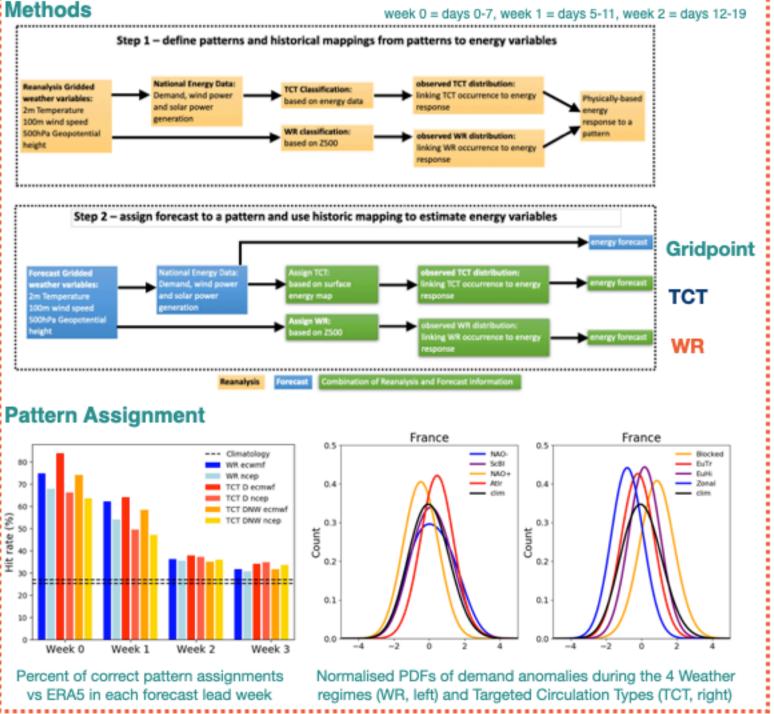




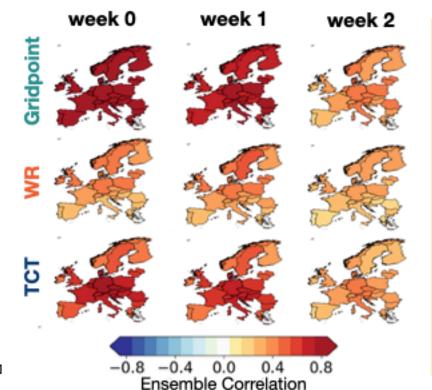


Hannah Bloomfield | David Brayshaw | Andrew Charlton-Perez | Paula Gonzalez





Results: Comparison between patterns and grid point hindcasts



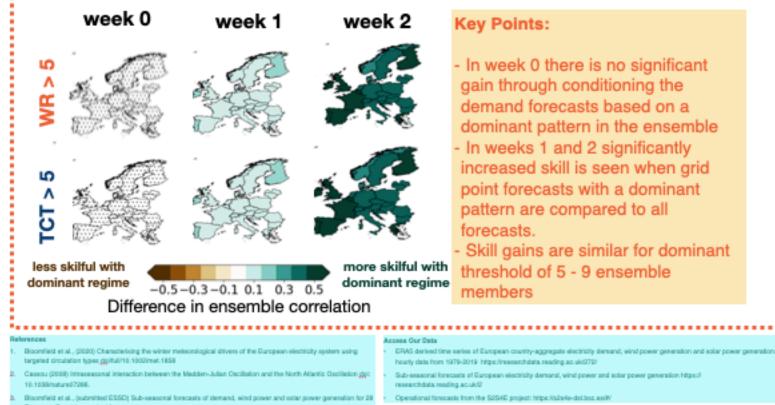
Key Points:

There is high skill in the grid point ased forecasts in a number of orecast metrics. This skill starts to Irop below useful levels in week 2 At all lead times pattern based skill i ess than grid point skill

TCTs provide a better prediction of emand than WRs due to their comparable hit rate and increased elationship to surface energy ariables (see pattern assignment

esults are seen for demand net-renewables and for both the cmwf and ncep hindcasts

Results: Windows of opportunities in grid point hindcasts

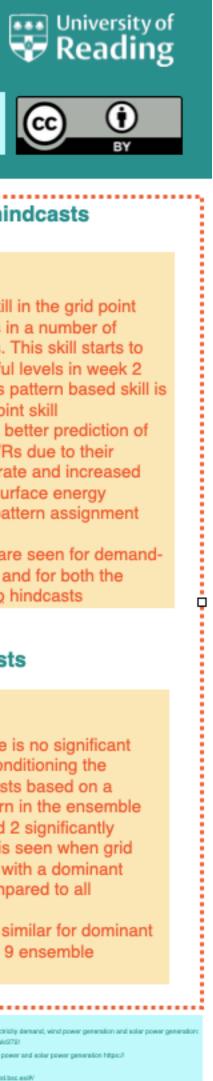


Key Points:

In week 0 there is no significant ain through conditioning the

tern are compared to all

Skill gains are similar for dominant threshold of 5 - 9 ensemble



Summary

- Gridded meteorological datasets from weather forecast models, weather-dependent power system components.
- A number of datasets exist for open-access use which have completed this conversion and published methods.
- These datasets are useful to answer a number of research questions associated with the weather-dependent uncertainty in power system modelling.
- Increased collaboration between the energy and meteorology communities can help tackle future research questions about weather-dependent power system behaviour.

reanalysis and climate model simulations can all be converted into





References and datasets

- Bloomfield et al., (2020) Characterizing the winter meteorological drivers of the European electricity system using targeted circulation type https://doi.org/10.1002/met.1858
- Bloomfield et al., (2020) Meteorological Drivers of power system stress: https:// www.hindawi.com/journals/jre/2020/5481010/
- of Great Britain https://iopscience.iop.org/article/10.1088/1748-9326/aabff9 https://iopscience.iop.org/article/10.1088/1748-9326/11/12/124025
- Bloomfield et al., (2018) The changing sensitivity of power systems to meteorological drivers: a case study Bloomfield et al., (2016) Quantifying the increasing sensitivity of power systems to climate variability Drew et al., (2015) The Impact of Future Offshore Wind Farms on Wind Power Generation in Great Britain
- https://www.mdpi.com/2079-9276/4/1/155
- Reanalysis derived demand, wind and solar power data: ERA5, <u>http://dx.doi.org/10.17864/1947.273</u> MERRA2: http://dx.doi.org/10.17864/1947.239
- S2S forecasts of demand, wind and solar power data: <u>http://dx.doi.org/10.17864/1947.275</u>
- Renewables Ninja renweables.ninja

ECEM future climate/energy data: <u>http://ecem.wemcouncil.org/</u>

With thanks to the whole team energy-met@reading team **Any Questions?**





