Using climate forecast information in decision-making

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Thanks to James Fallon (UREAD), S2S4E collaborators (esp Michael Christoph, EnBW), and UREAD Energy-Met group

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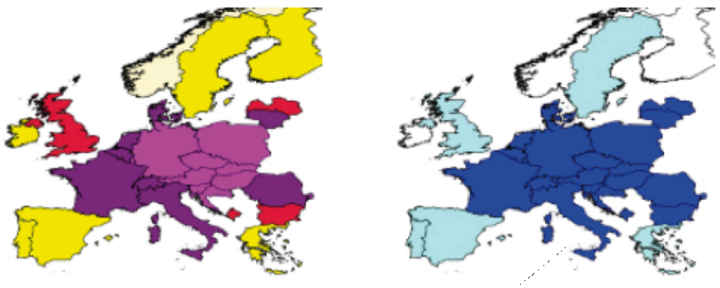
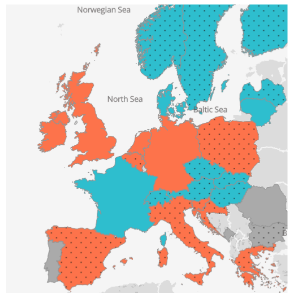
Review and introduction

- From previous speakers, climate variability has a significant impact on Europe. S2S variations:
  - Predictive skill (varying levels depending on lead-time and geography)
  - Relevant to risk-management in energy (e.g., trading, maintenance, security of supply, scheduling).

- 3-year research programme within S2S4E across 5 European research institutions
  - S2S forecast assessment, skill enhancement and use-cases (S2S4E Deliverables 4.1-4.4 + publications/datasets)
    - Calibration, processing and skill assessment (see Andrea Manrique's talk)
    - Modelling impacts of climate on RE and demand (see Hannah Bloomfield's talk)
    - "Seamless" S2S forecast horizons (see Ilias Pechlivanidis's talk)
    - Pattern forecasting (see Llorenc Lledo's talk)
    - Machine learning and multi-model combination (see Paula Gonzalez's talk)



Bloomfield et al, 2020



S2S4E DST

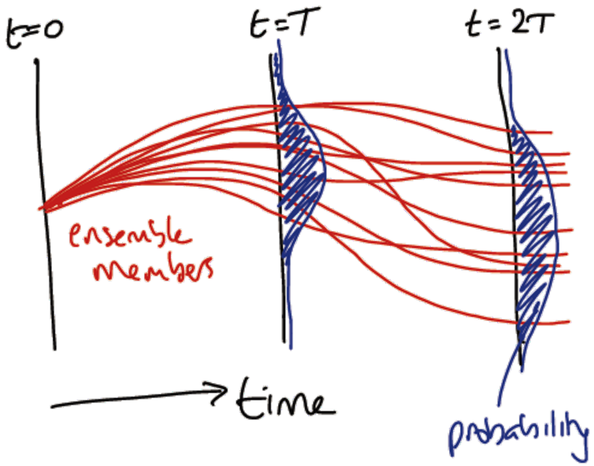
S2S4E Climate Services for Clean Energy

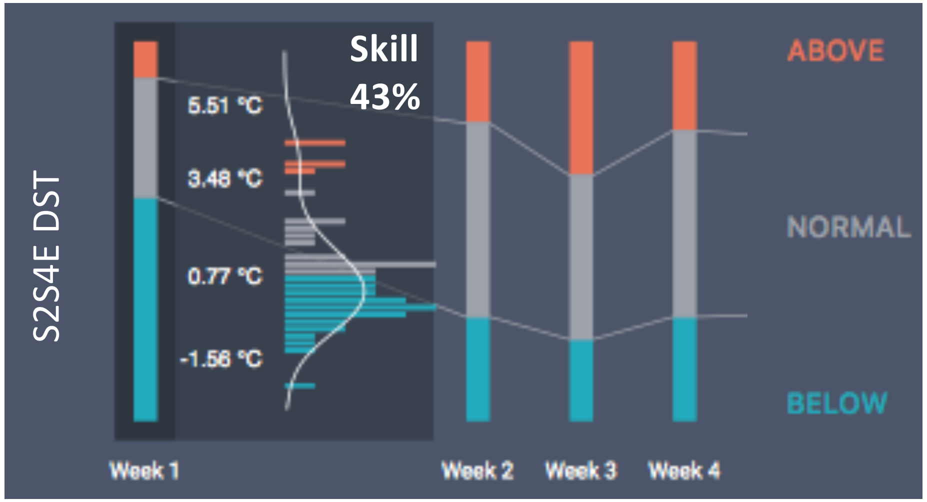
Climate information process

warm

Surface temperature, Germany

cold





Decision

Climate information process

https://www.ecmwf.int/sites/default/files/Cray_Supercomputer_New.png

Decision

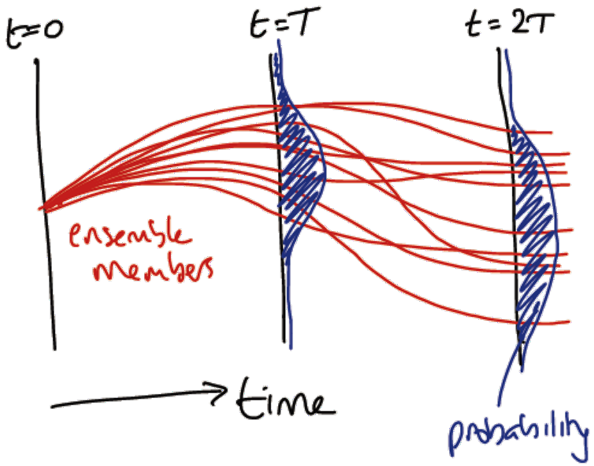
Forecast value

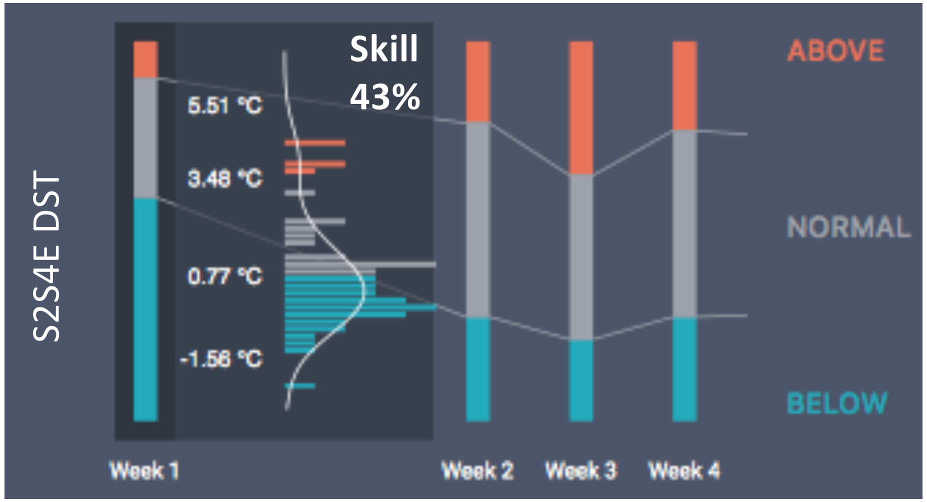
Forecast skill

warm

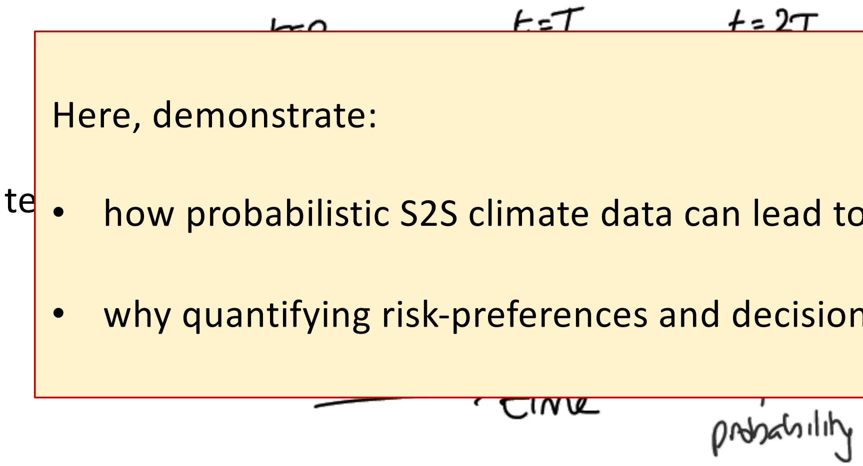
Surface temperature, Germany

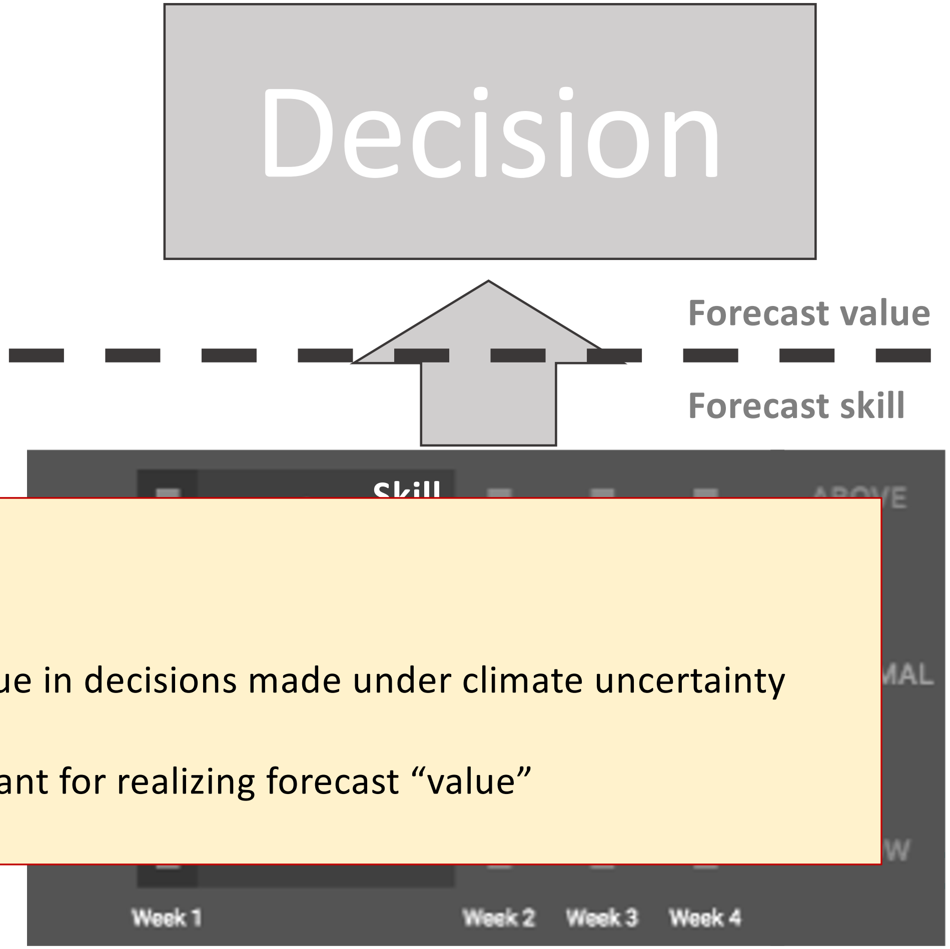
cold





Climate information process





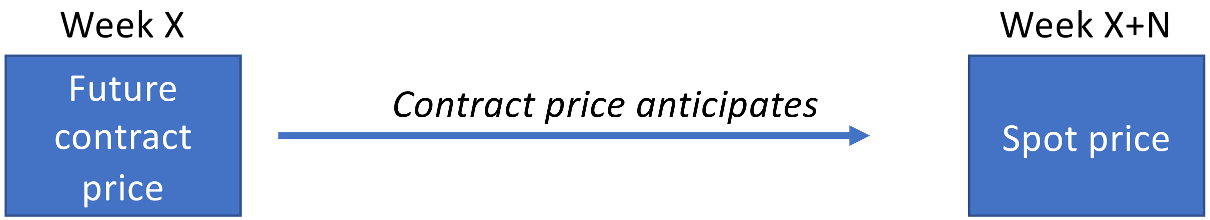
Here, demonstrate:

- how probabilistic S2S climate data can lead to added value in decisions made under climate uncertainty
- why quantifying risk-preferences and decisions is important for realizing forecast “value”

Adding value: energy futures trading

- Forwards and futures
  - Ahead-of-time contracts for management of price or volume risk in energy markets
  - Example: weekly blocks of baseload generation at a fixed price, sold weeks in advance
  - Here: purely financial trades (no transfer of underlying physical asset)

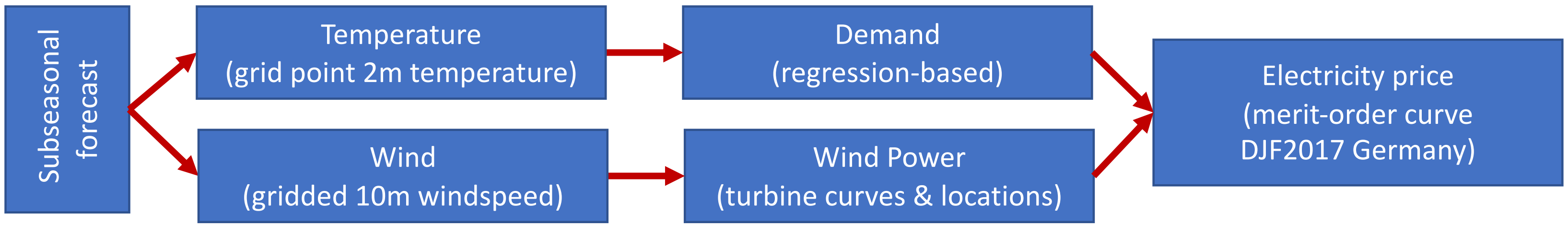
- Need *price* forecast
  - Fundamentals-based price model
  - Converts subseasonal weather forecast ➔ subseasonal price forecast
  - Many approximations and assumptions, but…
  - … added value if trades using forecast better anticipate price N-weeks in advance, compared to the "market"



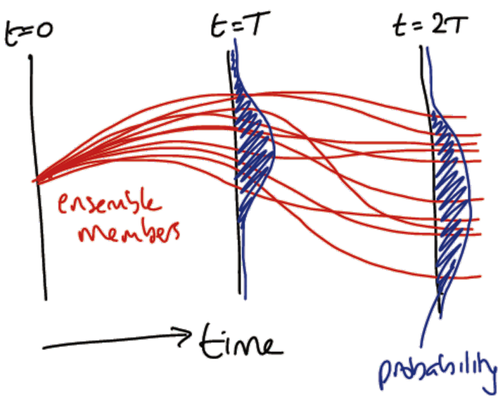
Work with James Fallon (UREAD), Michael Christoph (EnBW), and S2S4E collaborators
With support from the UREAD Energy-Met research group (Hannah Bloomfield, Paula Gonzalez, David Livings)

S2S4E Climate Services for Clean Energy

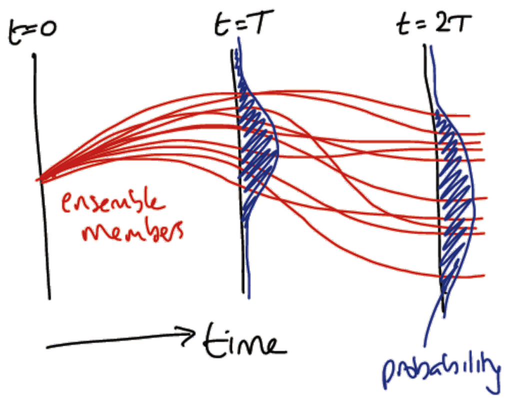
Conversion chain (skill)



Daily-resolution ensembles of temperature & windspeed

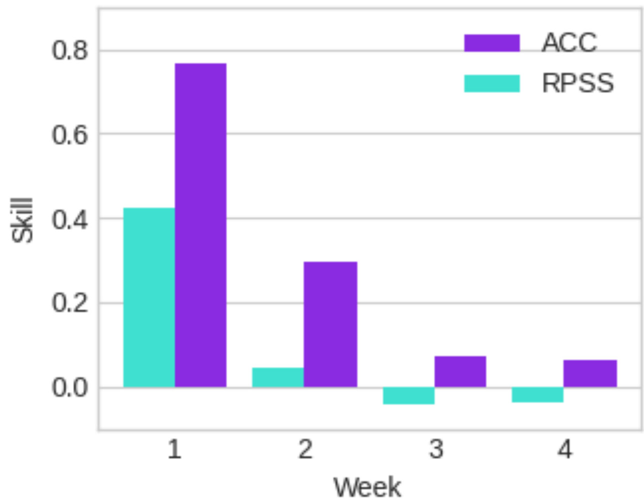


Daily-resolution ensembles of price

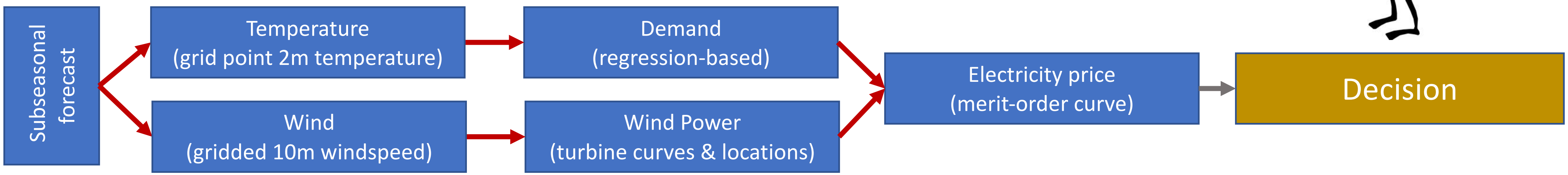


Skill of DJF price forecast compared to climatology

ensemble average and **tercile probability**



Conversion chain **(value)**



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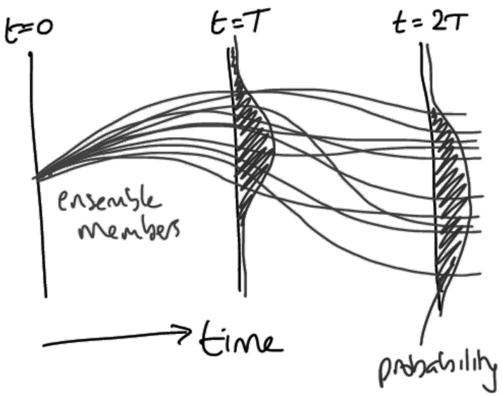

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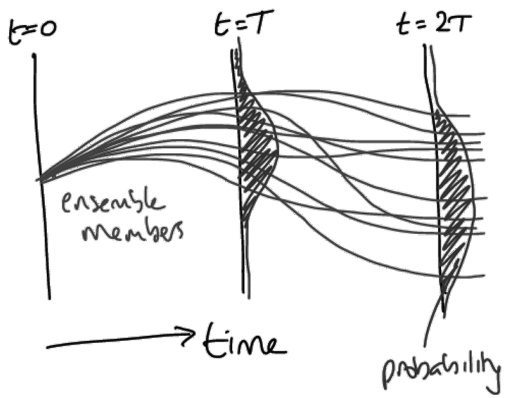
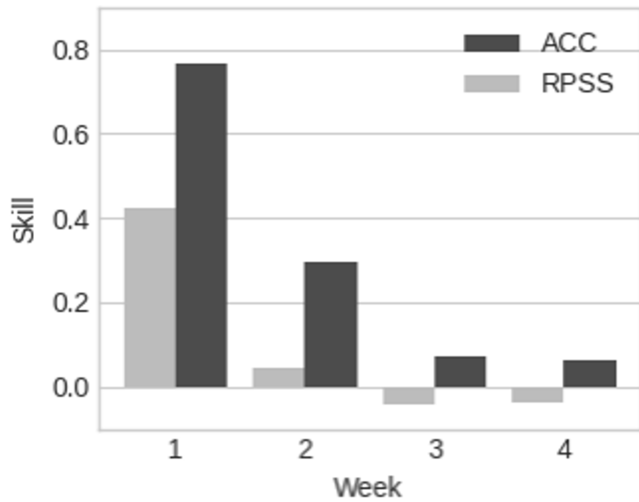


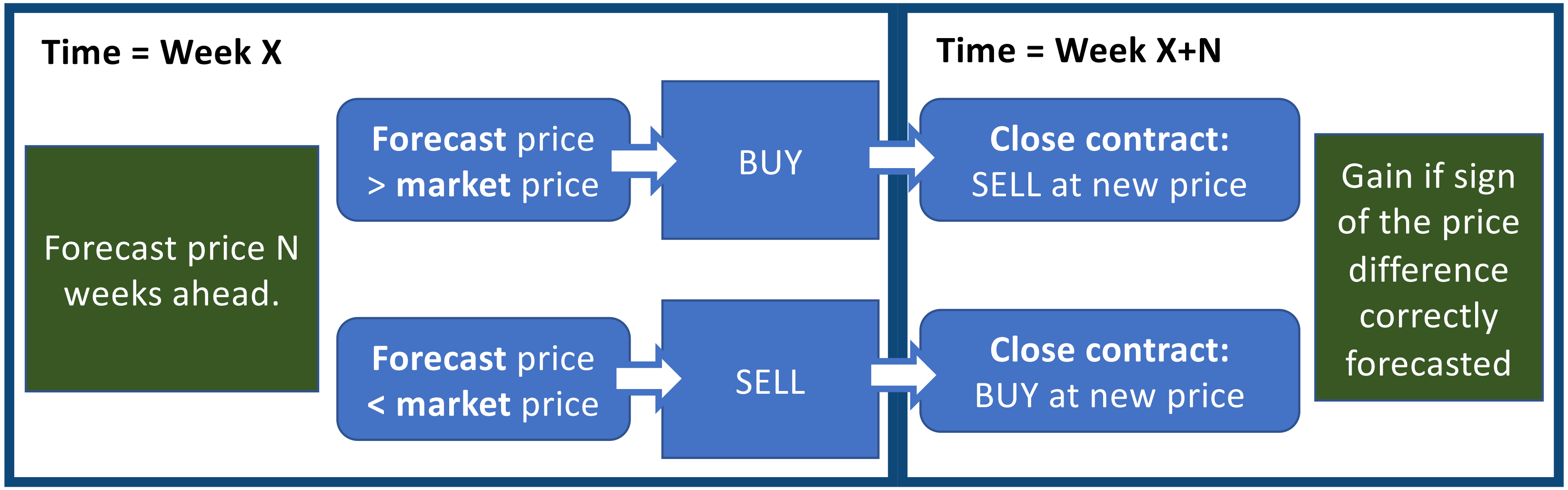
Skill of Price forecast compared to climatology

Ensemble average and **tercile probability**



Decision modelling

- Enter *N*-weeks-ahead futures contract then hold until delivery.
- What is added value of trading on the prices *predicted by S2S forecasts* compared to the *market's expectation*?
- Simplest case using ensemble-mean price forecast – equivalent to, e.g.:
  - If S2S forecast ensemble-average suggests future market price is *undervalued* (forecast price > market price) then
  - *buy* contract for power at market price *N*-weeks-ahead, then *sell* contract at the day-ahead spot price
- Many more advanced variants possible!



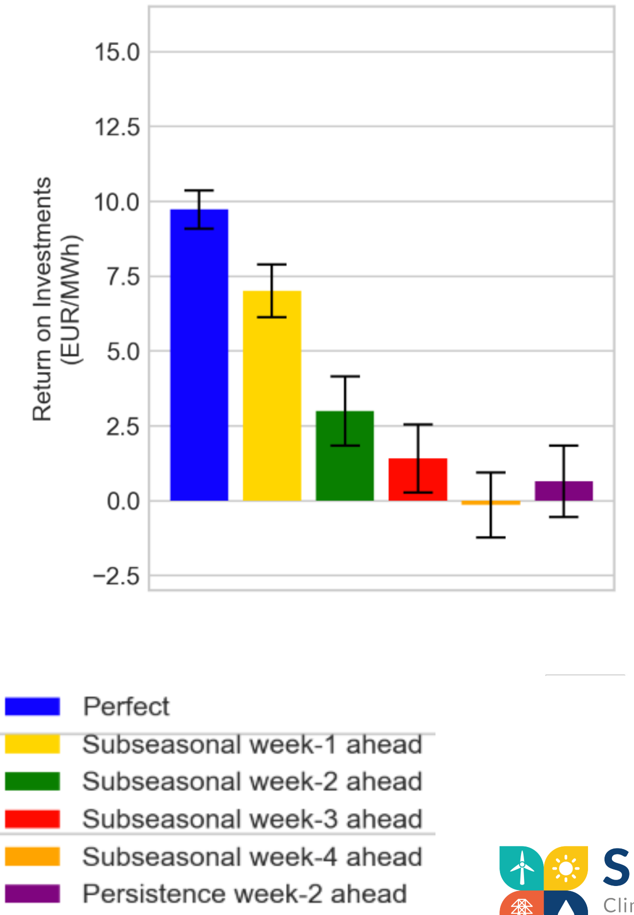
S2S4E Climate Services for Clean Energy

The “total” value of S2S forecasts

- Applied to German market assumed to have *no access to meteorological forecasts* (market has historic data only)

- Significant value add (c.f., nominal unit price ~€40/MWh)
  - **Perfect foresight:** €10/MWh
  - **Subseasonal week-2 forecast (days 11-18):** €3/MWh

- Caveats:
  - Trades every week: not every individual trade “wins”
  - Perfect model assumption (predicts *simulated* prices which exclusively depend on weather)
  - Market access to forecasts (much of the value “priced in”)

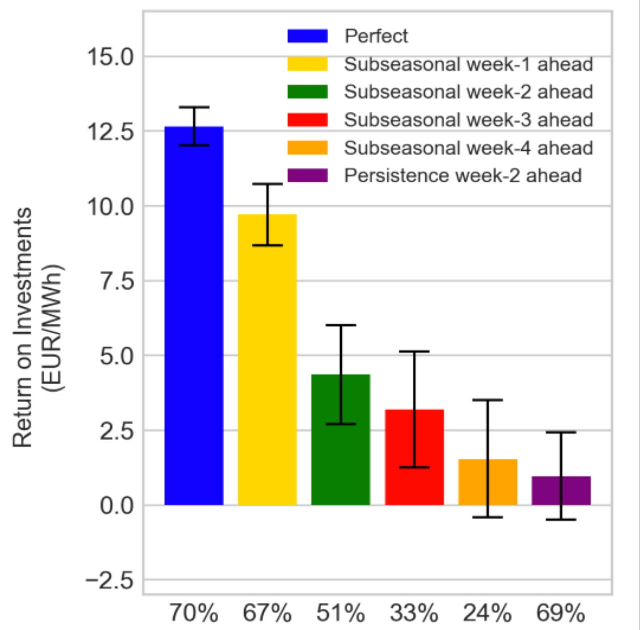


The added value of probabilistic info

- Adjust decision model, trade only if:
  - >45% chance in upper/lower tercile
  - <20% chance in opposing tercile

- Per-trade value add (c.f., the equivalent ensemble-mean trader)
  - **Perfect foresight:** ~25% improvement
  - **Subseasonal week-2 forecast (days 11-18):** ~20-30% improvement

- Caveats (as previous but now also):
  - Trades only on strong signals ➔ many fewer trades made
  - Cumulative value over time less than "ensemble mean" strategy
  - Best strategy depends on risk/return preferences



Fraction of possible trades made (%)

Perfect
Subseasonal week-1 ahead
Subseasonal week-2 ahead
Subseasonal week-3 ahead
Subseasonal week-4 ahead
Persistence week-2 ahead

S2S4E Climate Services for Clean Energy

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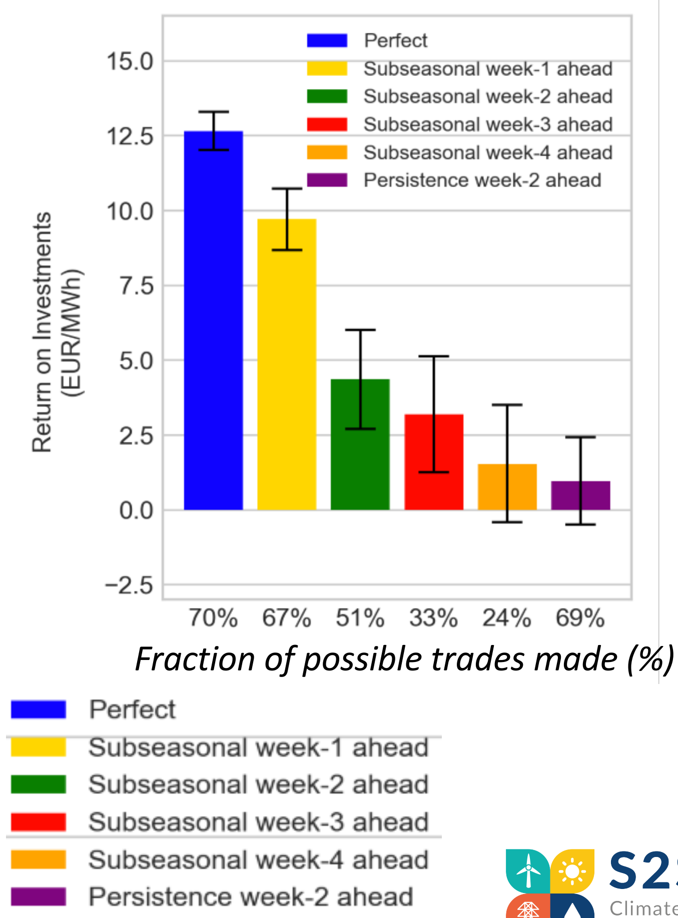
> ***Value*** is in the eye of the beholder…
>
> … it depends on what the user wants to achieve.



Implicit risk preferences

- Case study thinking:
  - "Would a (past) forecast have provided 'useful information' to users?"

- Assessment is subjective but often based on some of:
  - **Mean shift**: What was the 50th centile of forecast distribution?
  - **Direction**: Was there a clearly dominant tercile?
  - **Extremes**: Did any single ensemble member capture an extreme event?
  - If "yes", then forecast said to be "potentially useful" in this case
  - i.e., user would have known to take an "action" if they'd had access to the forecast

- … but these :
  - Imply a view of risk preferences and mission objectives
  - **➔ form an (implicit) decision model!**

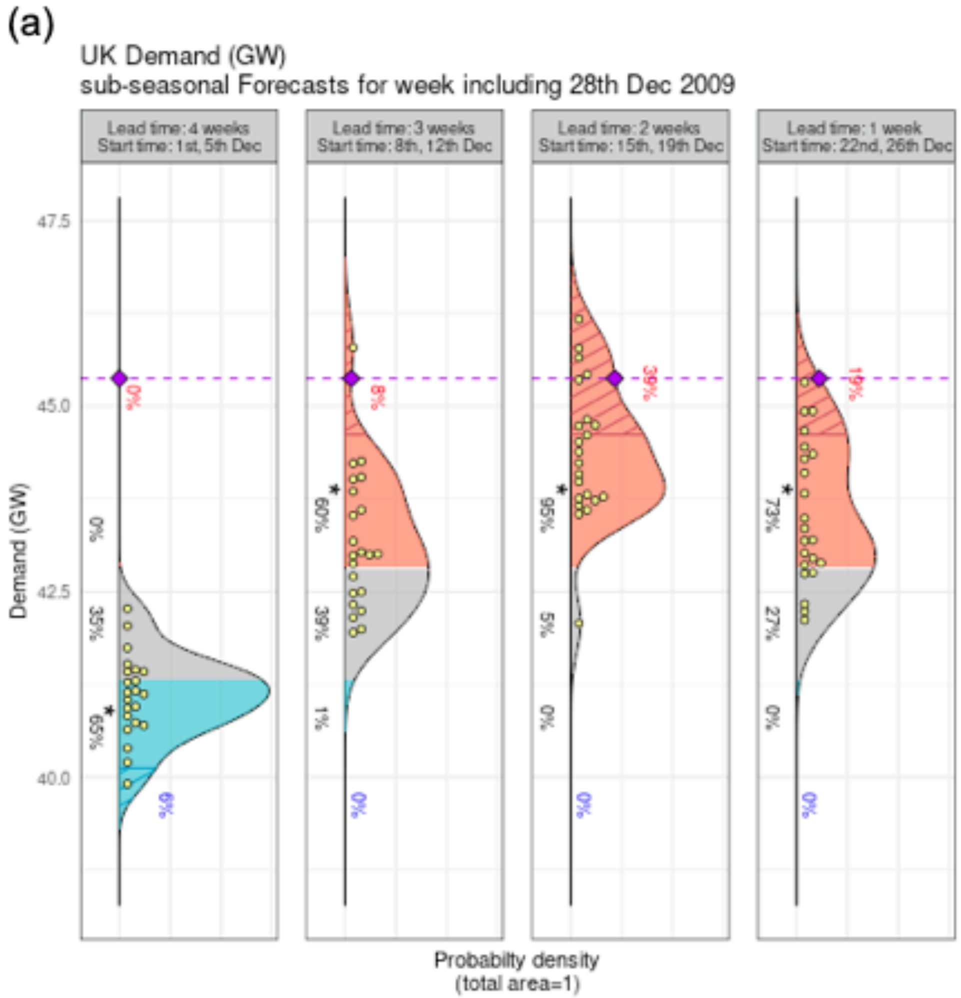


Figure: Bloomfield et al (submitted to ESSD)

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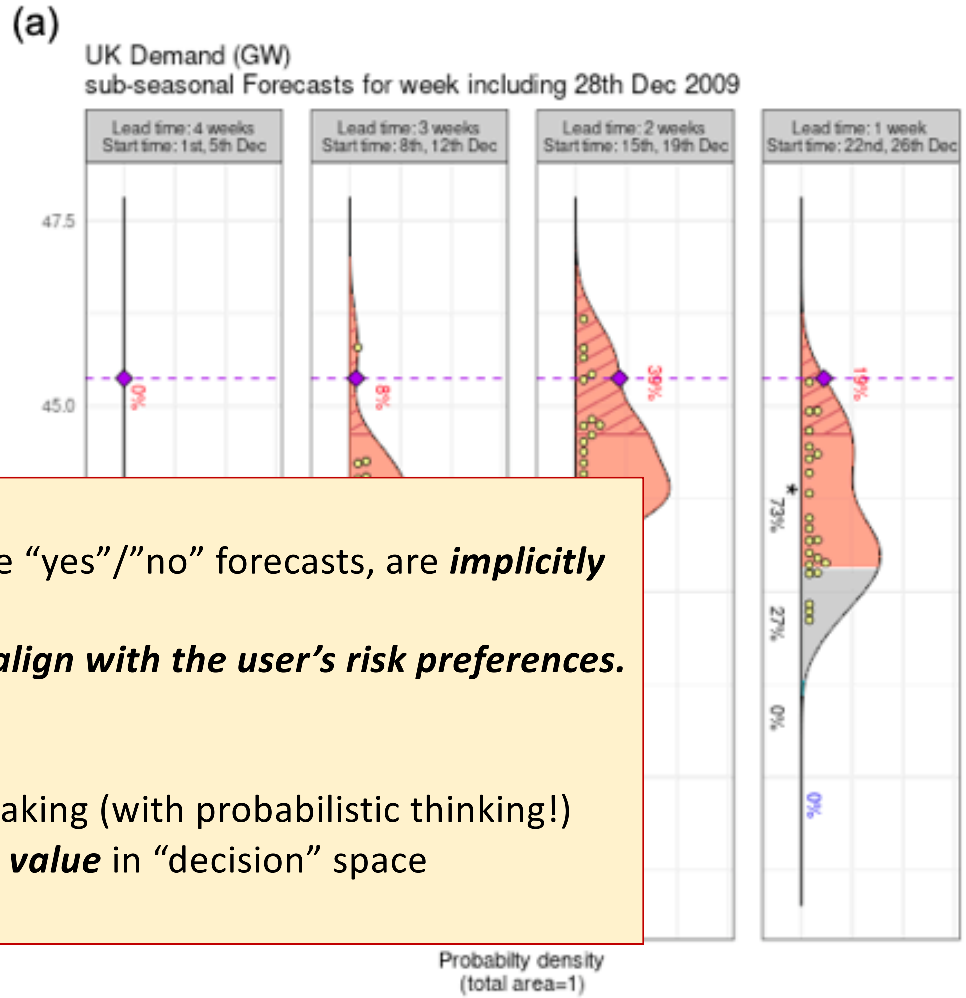


Meteorologists, in seeking (or being asked) to provide "yes"/"no" forecasts, are ***implicitly applying some form of decision model …***

… which may not align with the user's risk preferences.

Need for better:

- Elicitation of user risk preferences and decision-making (with probabilistic thinking!)
- Quantitative modelling/understanding of forecast ***value*** in "decision" space

Figure: Bloomfield et al (submitted to ESSD)

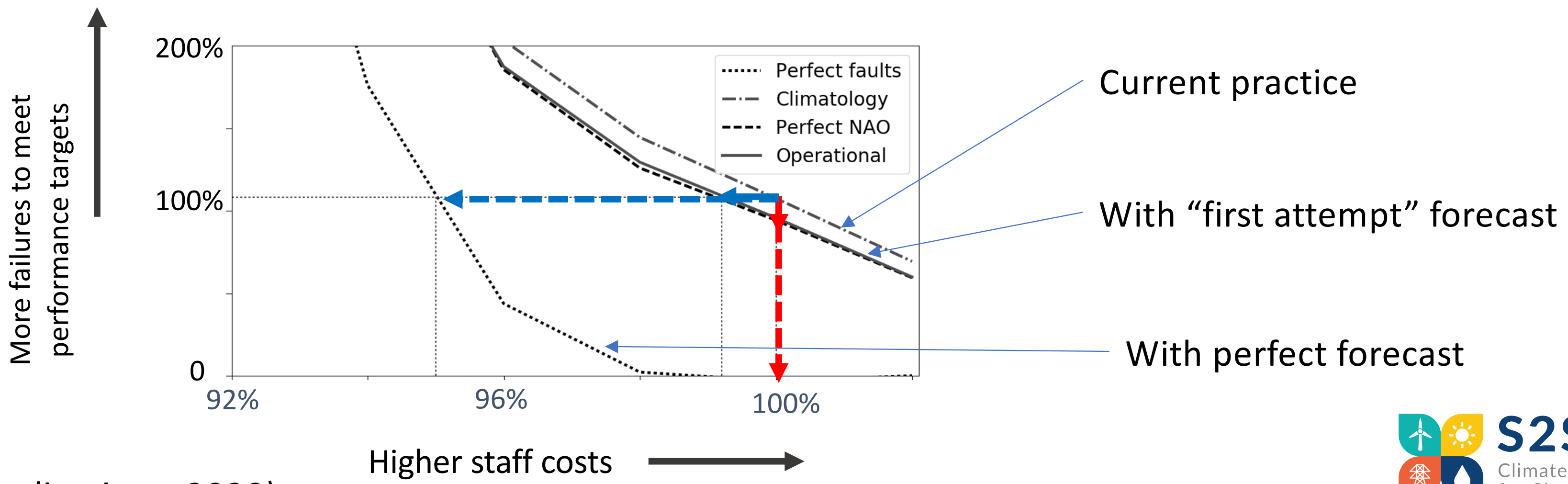
Strategic vs. operational

UK telecoms (not S2S4E, this work co-funded by BT):

- Weather driven fault rates on fixed-line infrastructure: roughly speaking, faults increase when it rains lots
- Need to fix faults quickly: secure additional maintenance resource if required but with ~1-2 weeks notice (➔ forecast needed)

Pattern-based method using ECMWF forecast. Skill translates to potential value in:

- Improve performance for a given staffing cost (fewer operational failures)
- Reduce staffing costs for a given performance level (lower long term costs)



Brayshaw et al (Met. Applications, 2020)

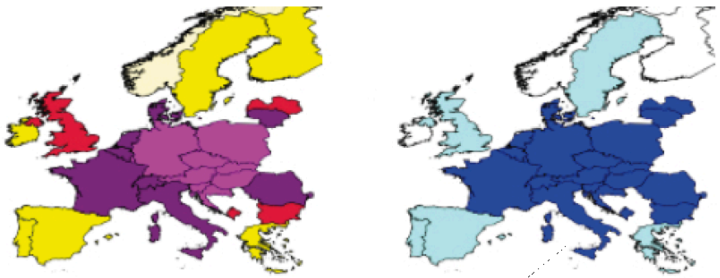
Summary

- Demonstrated translation of subseasonal forecast skill into potential “value” for trading
  - Perfect model experiment suggests ~several % improvement over historic information only
  - Use of probabilistic information offers substantial per-trade improvements over ensemble-average
  - Caveat: limitations → difficult to replicate in short, noisy “real” price data with other external drivers
  - See posters & talks by James Fallon, Paula Gonzalez and Hannah Bloomfield

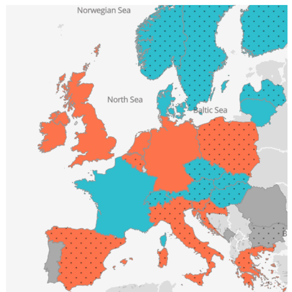
- The decision matters...
  - Explicit modelling of decision ”converts” complex *probabilistic* forecasts to simple *deterministic* outcomes
  - The user (decision-maker) is the expert, not the meteorologist (beware implicit decision modelling)
  - Suggests need for decision makers to engage with probabilistic nature of climate risk:
    - What choices and actions can be taken?
    - Explicit identification of attitudes to “objectives”, “risk”, and “return”.

- Resources to explore S2S forecasts in energy applications: S2S4E research datasets (national wind, demand, solar)
  - https://research.reading.ac.uk/met-energy/data

Research datasets for “energy indicators” (demand, wind, solar):
- Historic observed + ensemble subseasonal forecasts



Bloomfield et al, 2020



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References and links

- Email: d.j.brayshaw@reading.ac.uk
- Personal page: https://research.reading.ac.uk/meteorology/people/david-brayshaw/
- Group page (and links to datasets): https://research.reading.ac.uk/met-energy/data

Papers:

- Bloomfield, H. C., Brayshaw, D. J. and Charlton-Perez, A. J. (2020) Characterizing the winter meteorological drivers of the European electricity system using targeted circulation types. Meteorological Applications, 27 (1). e1858. ISSN 1469-8080 doi: https://doi.org/10.1002/met.1858
- Bloomfield, H. C., Brayshaw, D. J., Gonzalez, P.M. and Charlton-Perez, A. J. (submitted) Sub-seasonal forecasts of demand, wind power and solar power generation for 28 European Countries. For Earth System Science Data.
- Brayshaw, D. J., Halford, A., Smith, S. and Kjeld, J. (2020) Quantifying the potential for improved management of weather risk using subseasonal forecasting: the case of UK telecommunications infrastructure. Meteorological Applications, 27 (1). e1849. https://doi.org/10.1002/met.1849

Datasets

- 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
- 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

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Thank you

Get in touch for more information!

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Public reports of the project will be available for download on the S2S4E website: **www.s2s4e.eu**

Project coordinator: Albert Soret, Barcelona Supercomputing Center (BSC)
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