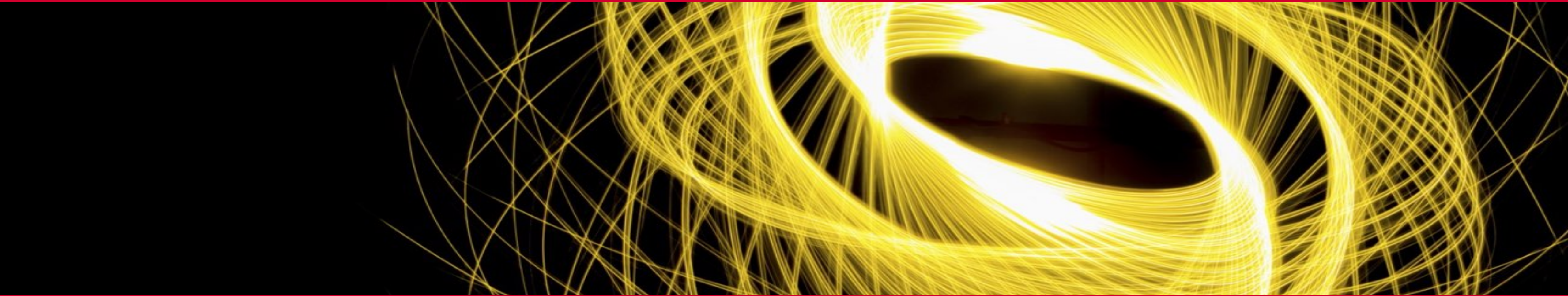
Department of Meteorology
School of Mathematical, Physical and Computational Sciences

University of Reading

S2S Forecasting and Energy

(IEA Task 51 Workshop, 18th May 2023)



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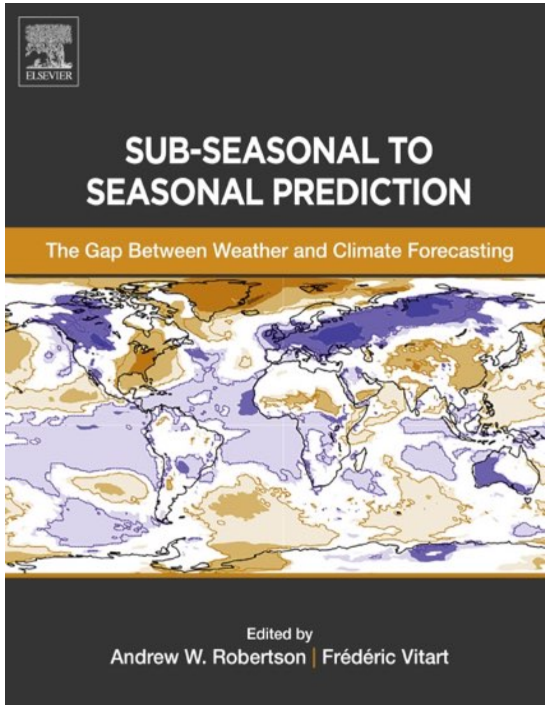
Introduction

- Thanks – especially to Chris (and Kathryn)!

- Welcome to department:
  - 200 academic/research staff; 150 students (includes ~60 PhD students)
  - Host components: NCAS, NCEO, UK Met Office
  - Soon to be joined on campus by ECMWF HQ

- My “Energy Meteorology” research group

- Origin/history of S2S
  - Introductory
  - Version of content in MSc “Climate Impact Modelling and Climate Services” module
    - Online course: https://www.reading.ac.uk/meteorology/online-courses/classes
  - Debt to excellent book (editors Robertson & Vitart, 2019)



- S2S in energy applications
  1. To what extent are subseasonal forecasts able to skillfully forecast energy?
  2. Can this skill be enhanced using advanced techniques (pattern-based, conditional forecasting, sequential learning)?
  3. To what extent could skillful subseasonal forecasts potentially produce *value* in decision-making contexts?

Why S2S?

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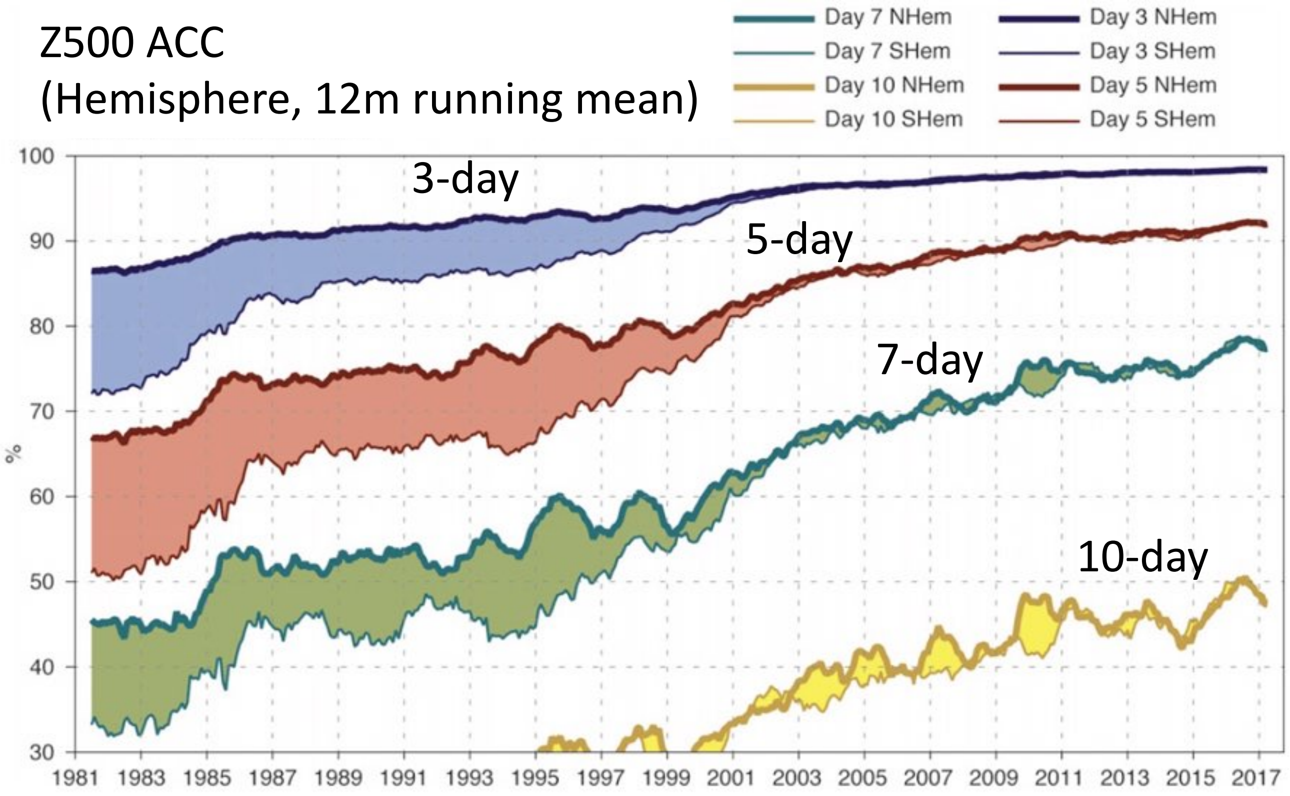
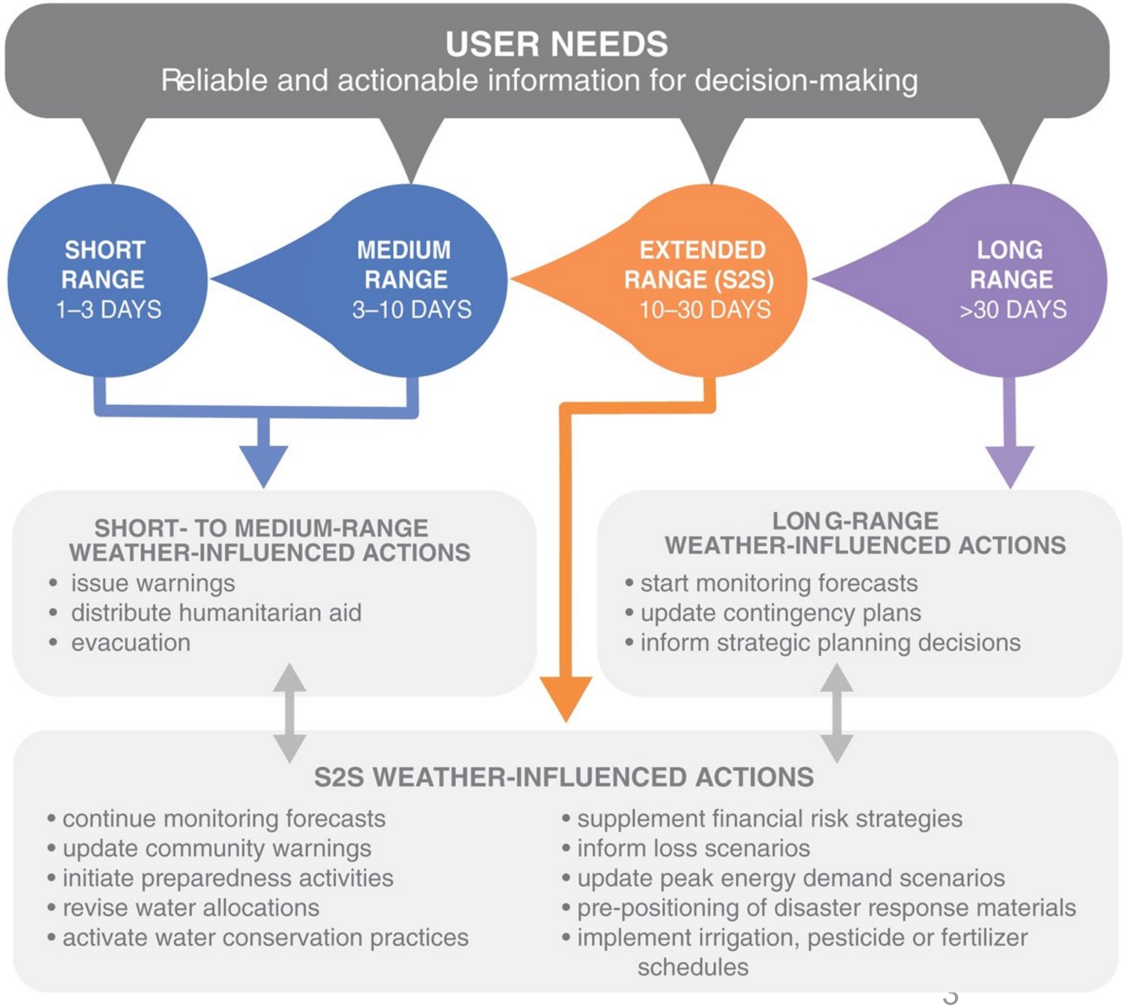
- “Push”: growth of skill of NWP (day per decade)
- “Pull”: user driven interest (need/desire to have S2S forecast)

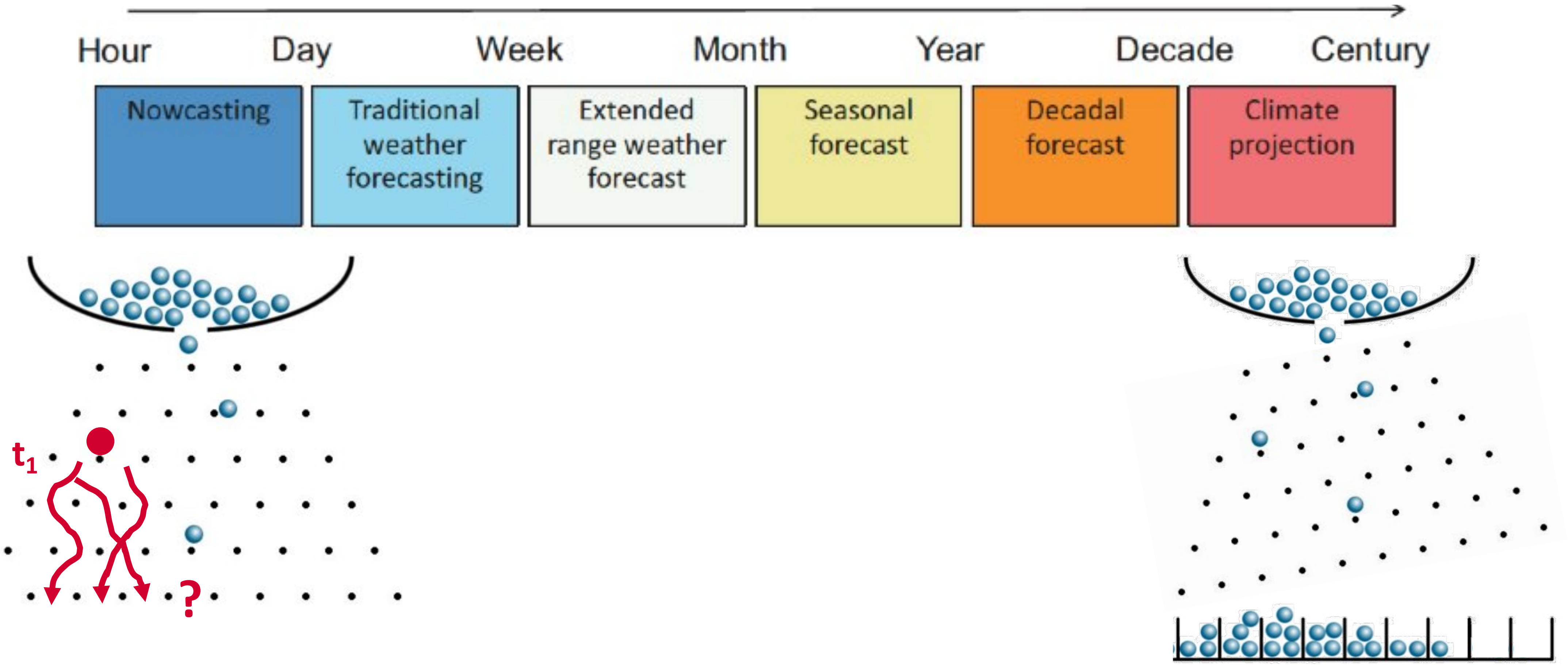




Figs: Toth and Buizza (2019); White et al (2017)

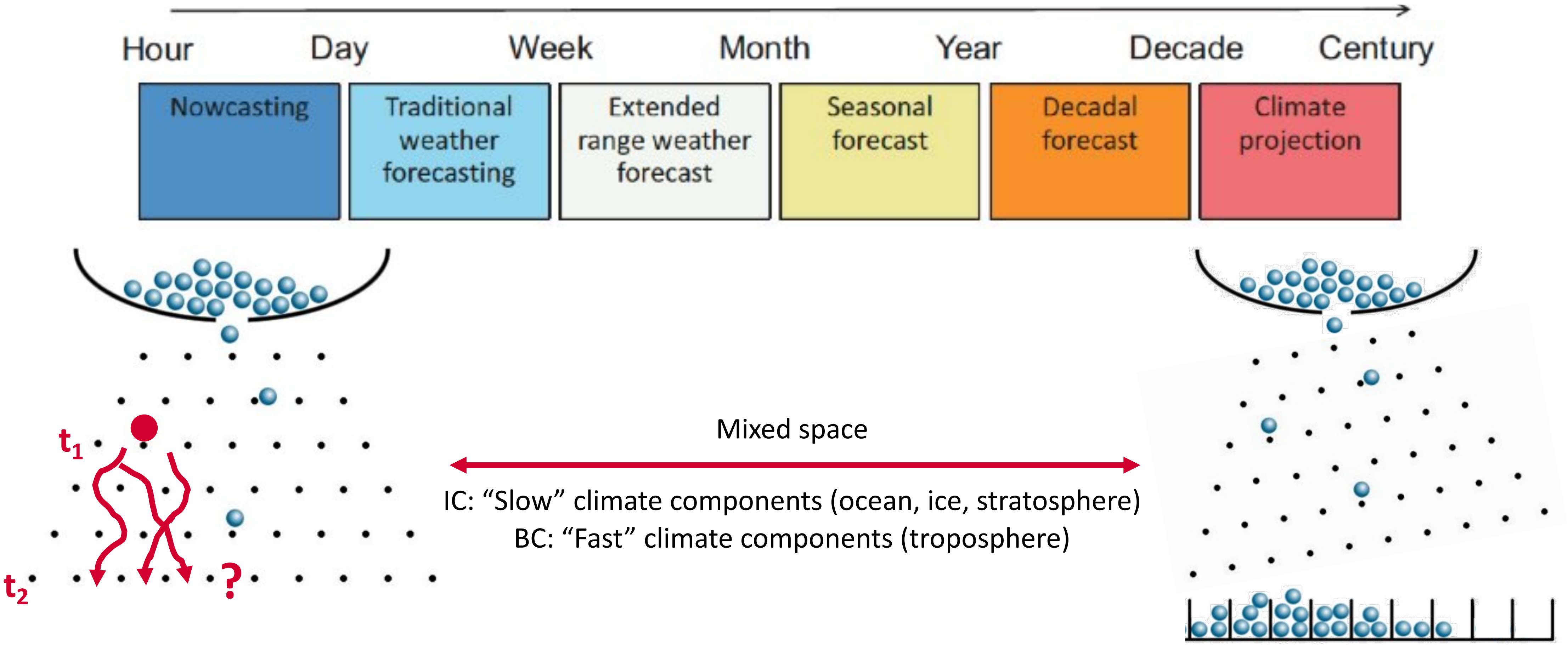
Nature of s2s

- Historically, the S2S "predictability desert" between initial condition and boundary condition predictability
  - IC predictability low *in troposphere*
  - BC predictability from large scale forcing *too weak* on S2S timescale



Nature of s2s

- Historically, the S2S "predictability desert" between initial condition and boundary condition predictability
  - IC predictability low *in troposphere*
  - BC predictability from large scale forcing *too weak* on S2S timescale
- ➔ "Mixture" of IC and BC problems



Origins of S2S

Last decade or so – significant progress in S2S enabled by:

- the identification (and ability to model/simulate) physical sources of initial-condition S2S predictability,
- the scale-dependence of forecast error growth, and
- the use of ensemble-based techniques.

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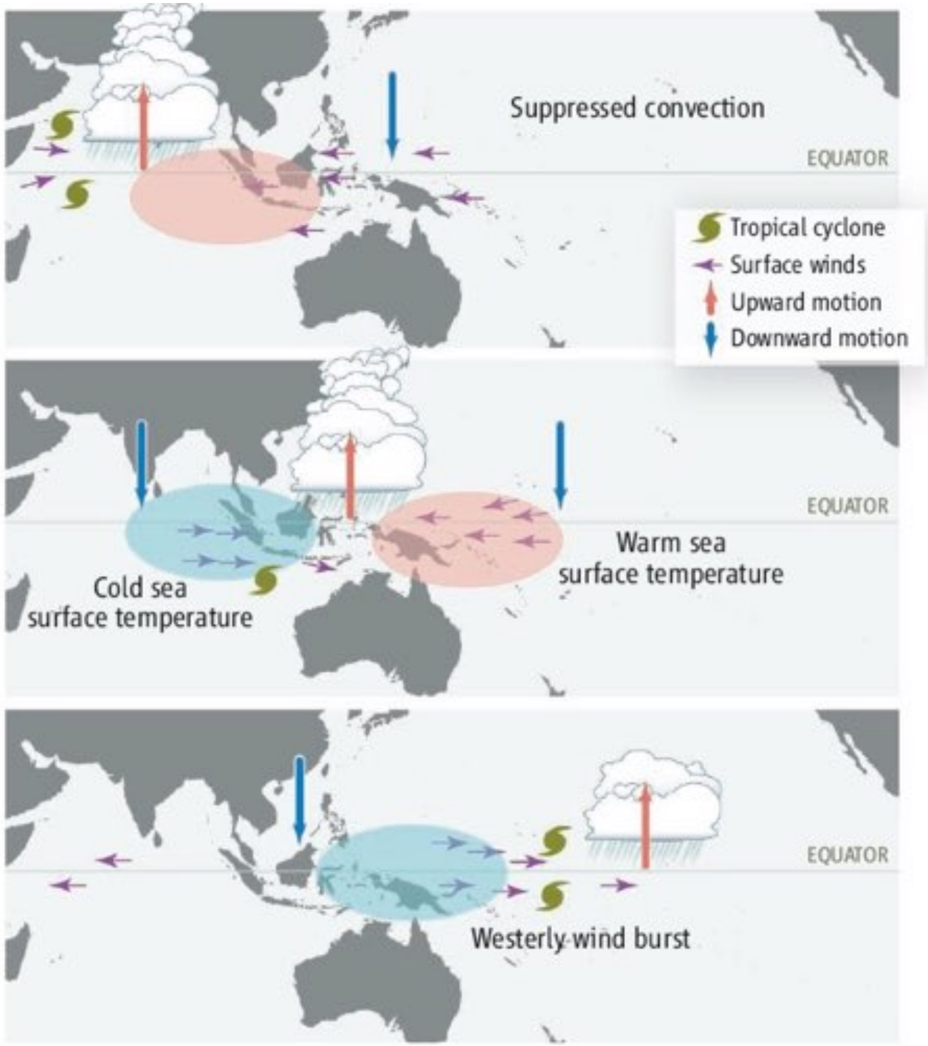
Physical sources

Examples:

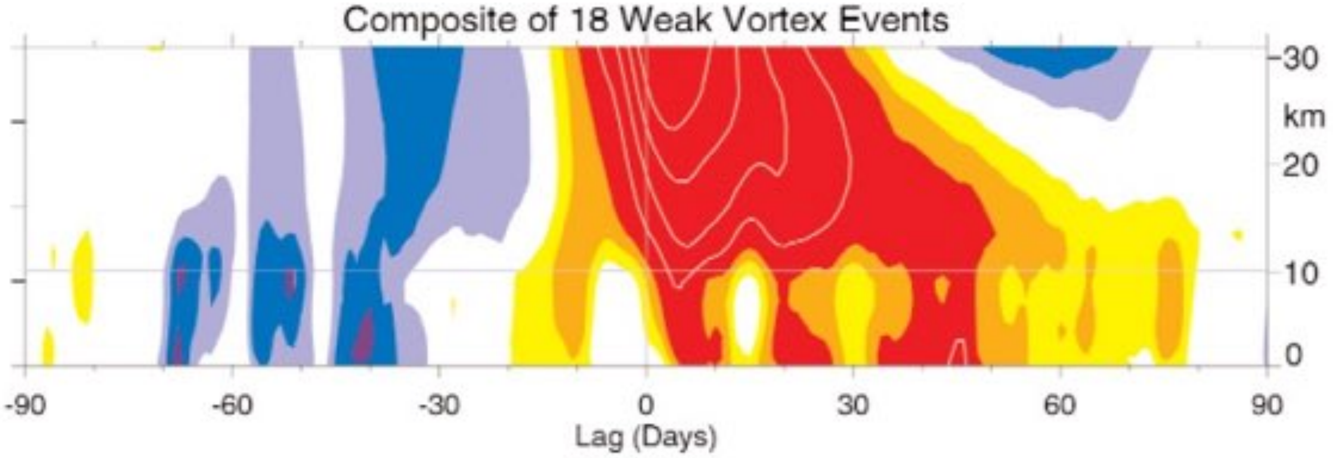
- ENSO
- Madden-Julian Oscillation (MJO)
- Land surface (snow cover, land moisture)
- Stratosphere-troposphere interaction

Evolving on ”S2S timescales” (weeks – months)

MJO (Hartmann and Hendon, 2007)



SSWs (Baldwin and Dunkerton, 2001)



Colour – annular mode index (~ red = NAO-)

Physical sources

Intuitive picture:

- Persistent “external forcing” (e.g., MJO/SSW)
- → preferred large-scale circulate states (e.g., via teleconnection)
- → modified day-to-day regional weather

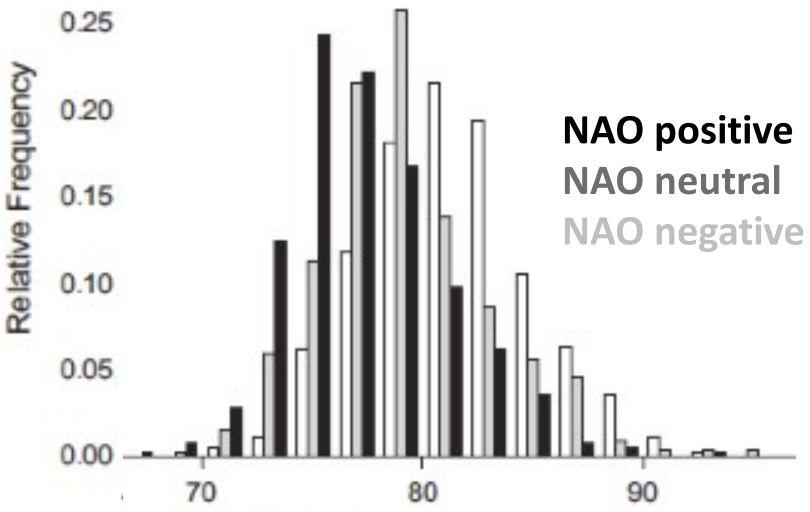
Physical sources

Intuitive picture:

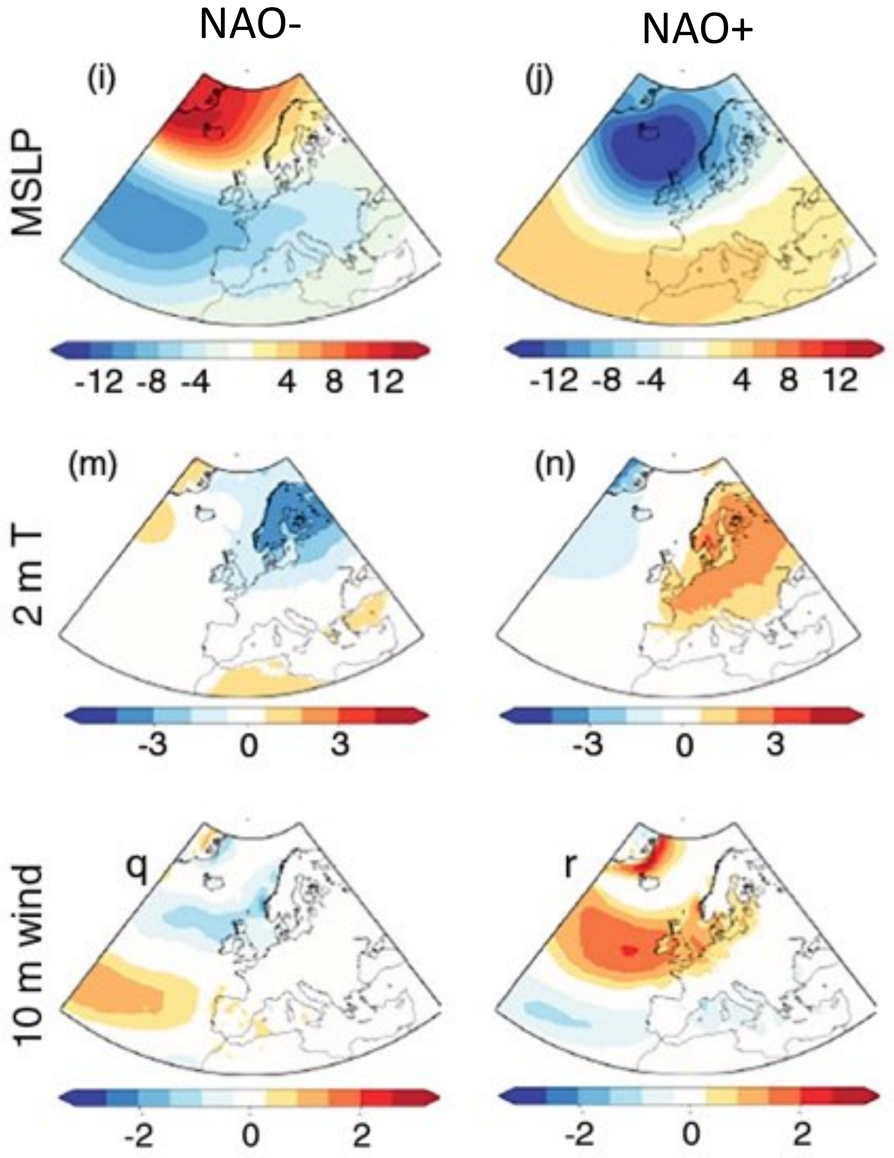
- Persistent “external forcing” (e.g., MJO/SSW)
- → preferred large-scale circulate states (e.g., via teleconnection)
- → modified day-to-day regional weather

Example: winter North Atlantic Oscillation (NAO) / Euro-Atlantic regimes

- Statistical connection to MJO phase (e.g., Cassou 2008)
- Linked to changes in weather impacting Europe / European energy



GB/Norway combined daily demand net wind (GW, simulated system circa 2010)



Left - Ely et al 2013. Above – Bloomfield et al 2019. Also see, e.g., Grams et al 2017; van der Weil 2019.

Origins of S2S

Last decade or so – significant progress in S2S enabled by:

- the identification (and ability to model/simulate) physical sources of initial-condition S2S predictability,
- **the scale-dependence of forecast error growth, and**
- the use of ensemble-based techniques.

Scale dependence of predictability

- OSSE (observing system simulation experiment), atmosphere only
  - “Truth” nature simulation
  - Limited “observations” used to form initial analysis and subsequent forecast of nature simulation
- Error variance “grows” over time

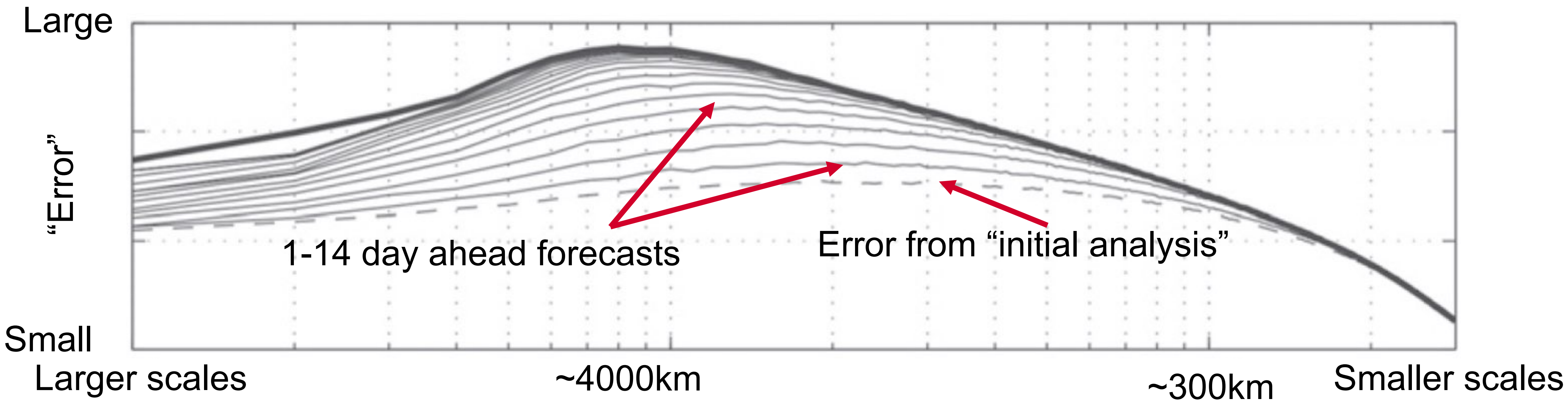


Fig: adapted from Toth and Buizza 2019 (itself adapted from Prove and Errico 2015)

Scale dependence of predictability

- OSSE (observing system simulation experiment), atmosphere only
- Error variance grows over time but…
- … saturates against random forecast later for larger scales
- ➔ **Longer window for predictability at larger scales**

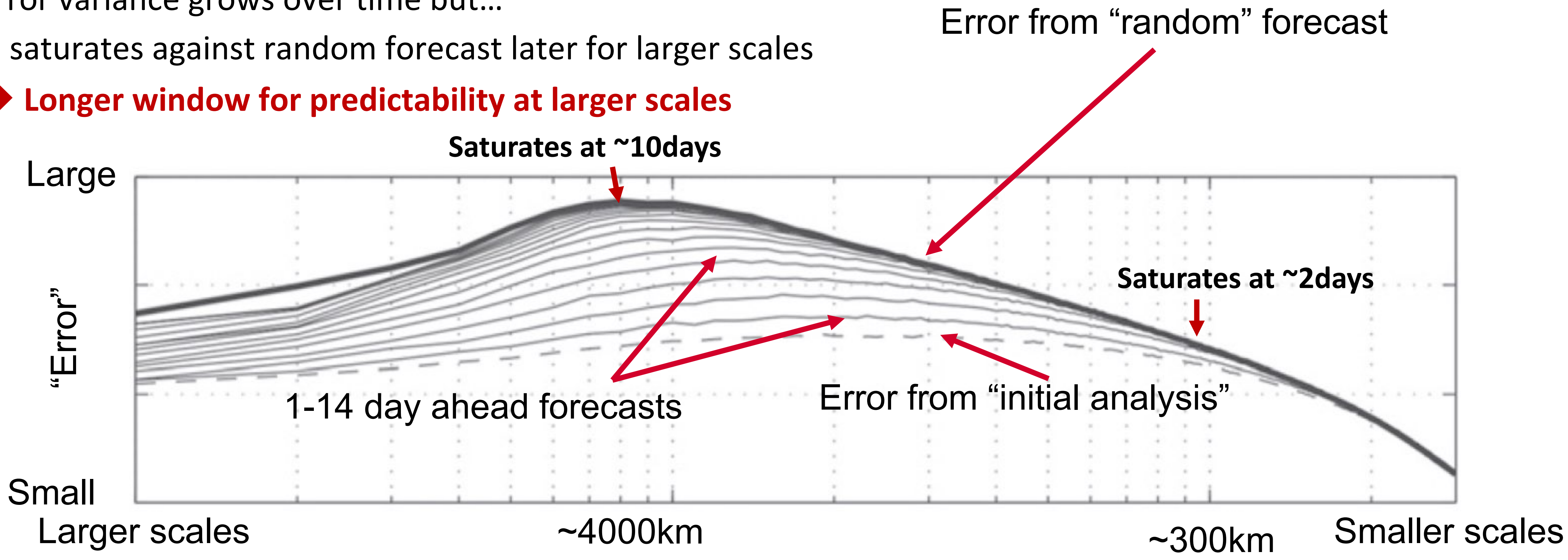


Fig: adapted from Toth and Buizza 2019 (itself adapted from Prove and Errico 2015)

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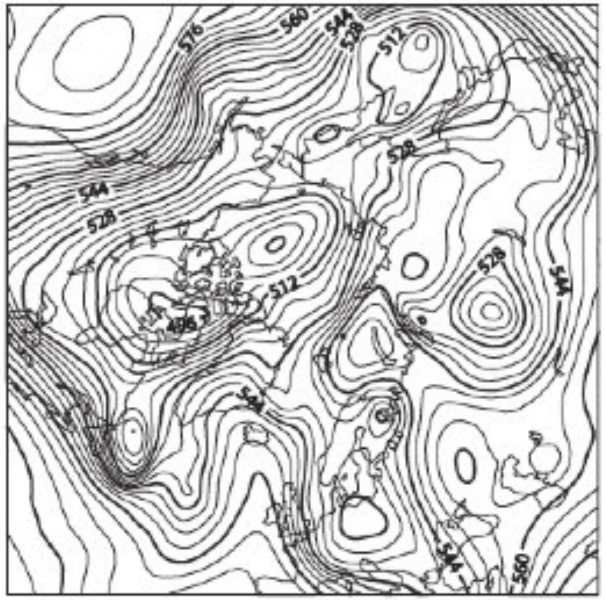
Spatial and/or temporal averaging

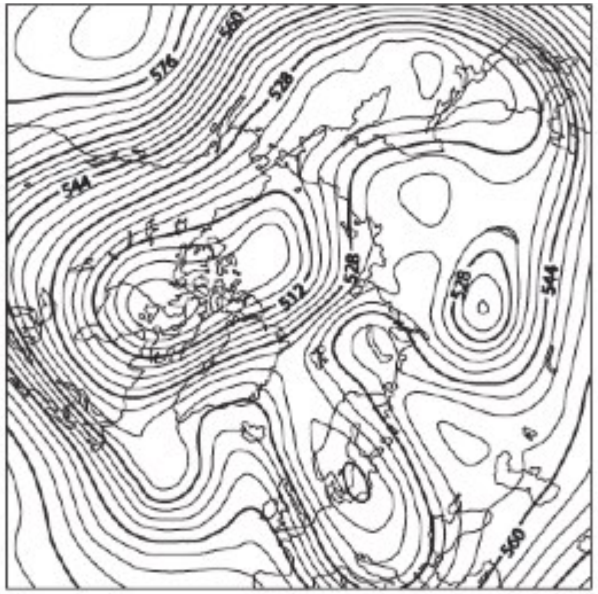
- Weeks - months
- Few 1000’s km

(a) Instantaneous, no truncation (T120)



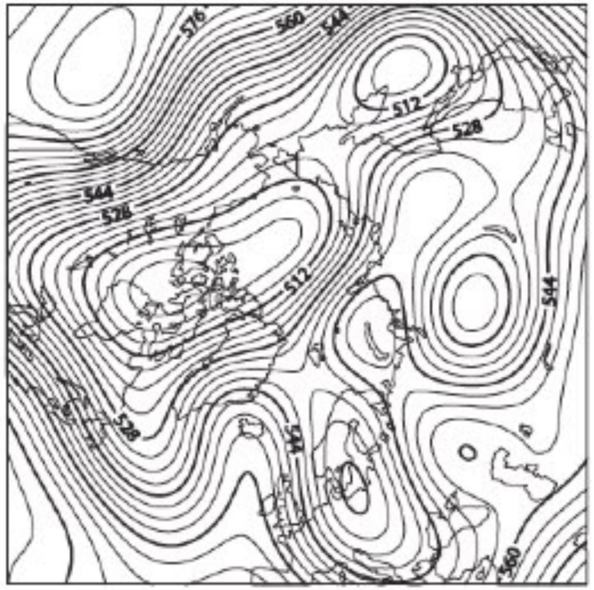
Raw field (Z500)

(b) 48h average, no truncation (T120)



Time-averaging

(c) Instantaneous, truncation (T15)



Spatial-averaging

Origins of S2S

Last decade or so – significant progress in S2S enabled by:

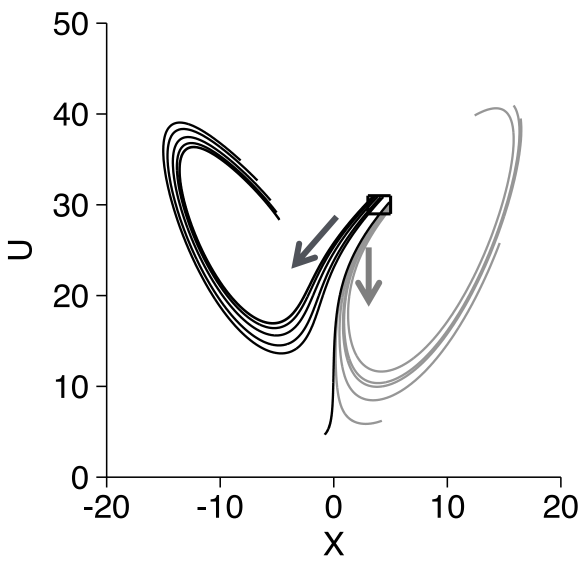
- the identification (and ability to model/simulate) physical sources of initial-condition S2S predictability,
- the scale-dependence of forecast error growth, and
- **the use of ensemble-based techniques.**

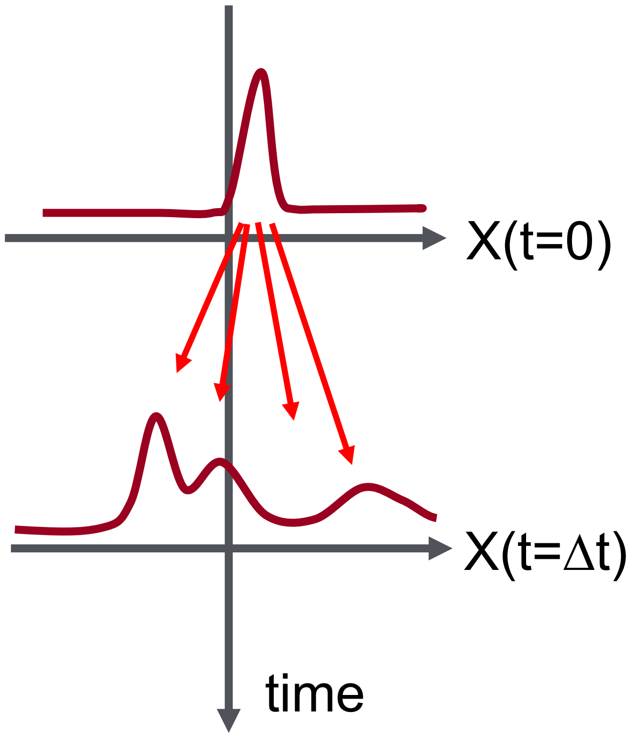
Ensembles

- Most commonly: initial condition ensembles

- Latterly: stochastic physics ensembles, multi-model ensembles

Lorenz-63 model





Ensembles

- Typically used in aleatoric fashion: “average” over “noise” to reveal “signal”

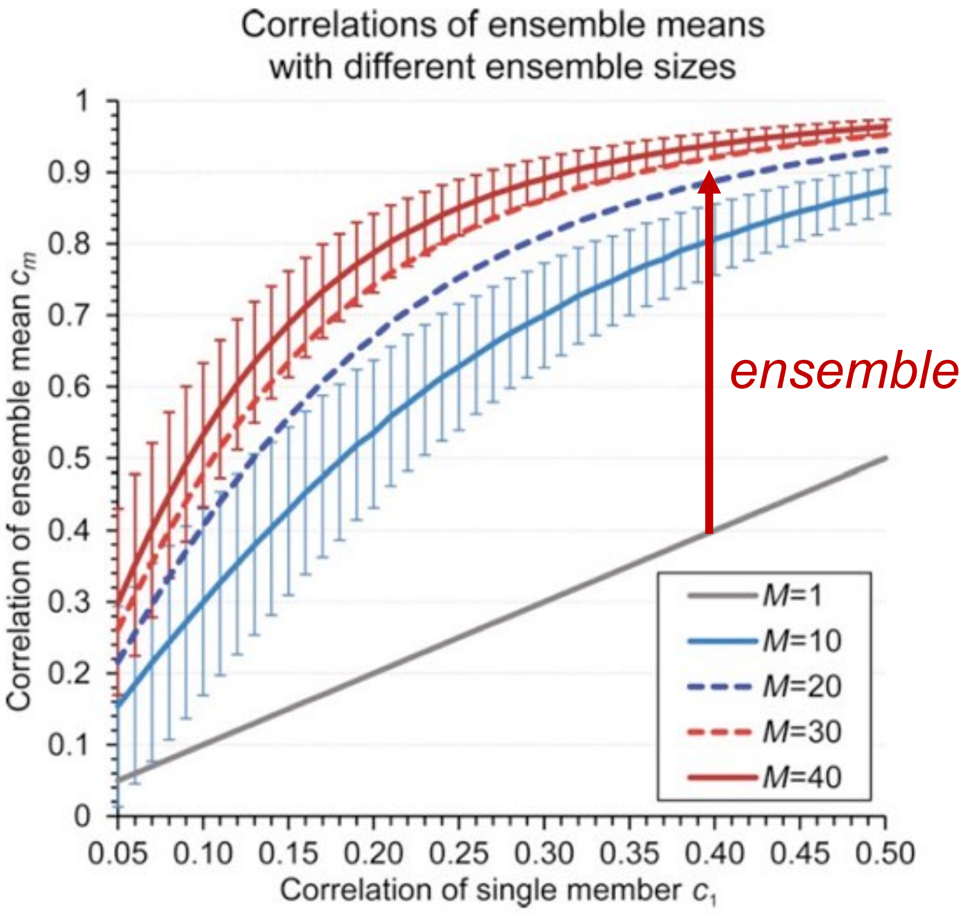


Fig: Takaya (2019)

Origin of S2S – summary

Neglected many practical and scientific issues:

- ensemble construction
- drift/calibration
- central role of data assimilation and initialisation

However, fundamentals:

- Traceable (event-wise) S2S predictability occurs at large scales in time and space
- Relies on existence of "slow evolving" source with some level of initial condition predictability
- Climate (statistical) S2S predictability occurs when large-scale conditions influence "fast evolving" / "small scale" weather
- Averaging used to extract the "signal" from "noise" (over ensemble members, over space or over time)

- The useability challenge:
  - Extent to which "weak" meteorological skill translates into energy forecasts
  - Connecting skill to potential *value* in energy-facing applications

S2S in energy applications

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- S2S4E "climate service for energy"
  - ~3 year research programme over 5 EU institutes
  - Overall lead: Albert Soret (BSC)

S2S4E Climate Services for Clean Energy

- Here present work from team at UReading (thanks: Paula, Hannah, James, David and Andrew)
  1. To what extent are subseasonal forecasts able to skillfully forecast nationally-aggregated load/generation?
  2. Can this skill be enhanced using:
     a. Pattern-based forecasting?
     b. Conditional forecasting?
     c. Multimodel ensembles and sequential learning algorithms?
  3. To what extent could skillful subseasonal forecasts potentially produce *value* in energy market trading?

Focus on principles and methods rather than quantitative precision

This project has received funding from the Horizon 2020 programme under grant agreement n°776787. The content of this presentation reflects only the author's view. The European Commission is not responsible for any use that may be made of the information it contains.

Figs: Bloomfield (2019 & 2021)

Models and data (in brief)

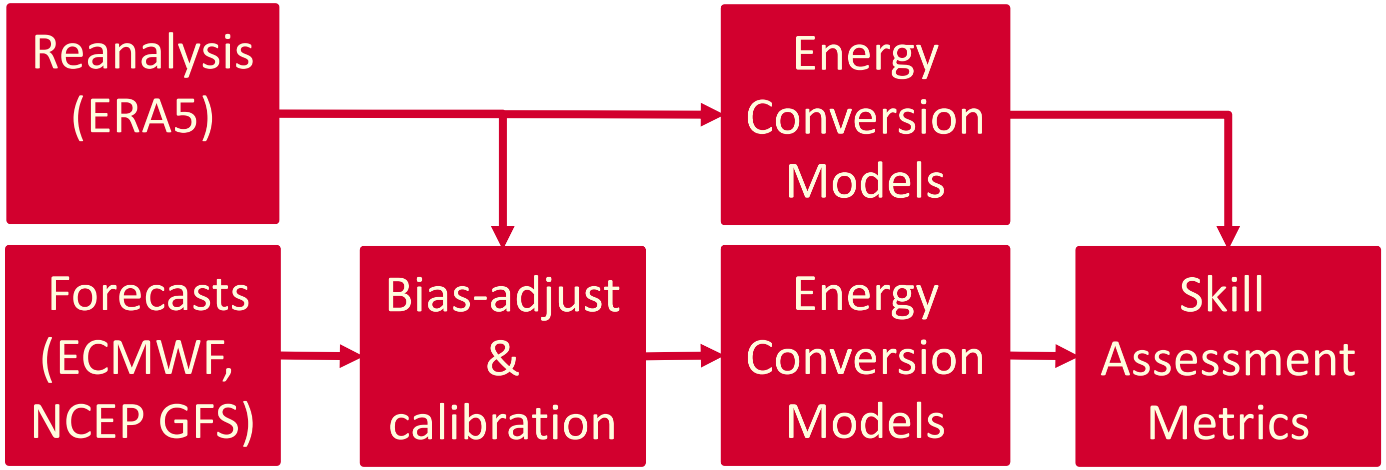
Simple physical/statistical models linking “weather” to “energy”

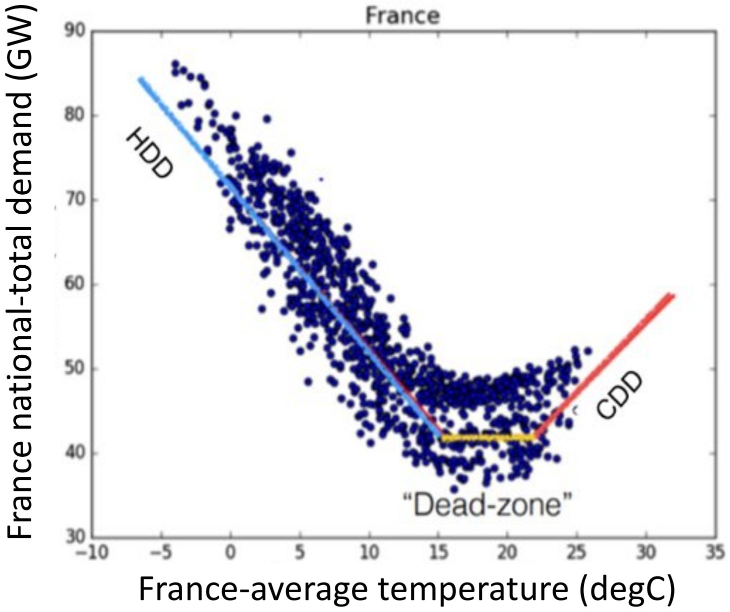
- ERA5 meteorology linked to ENTSO generation/load data (circa 2016/2017)
- Hourly wind, solar PV, demand at national level
- Reasonable performance (average R^2 ~0.8-0.9, RMSE ~5-10%)

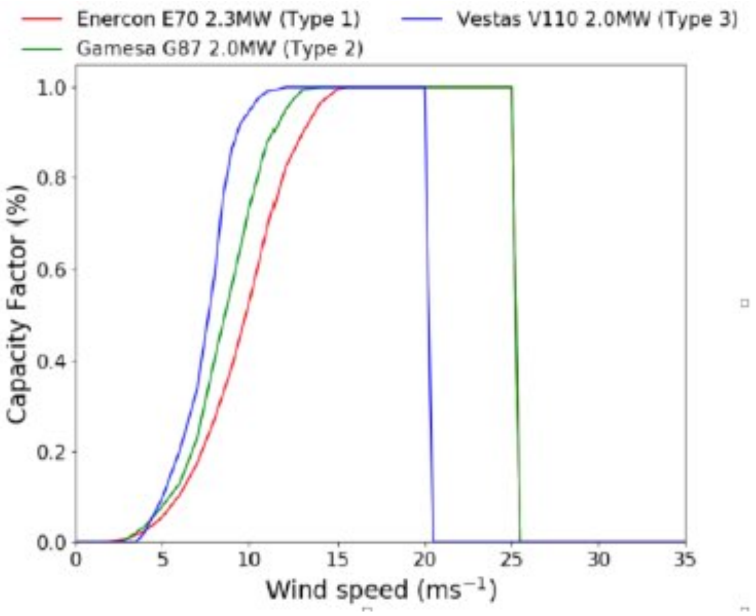
Perfect model experiments: examine skill/value of subseasonal (up to ~week 6) forecasts

- See, e.g., Cannon et al (2017) for discussion of “conversion” vs “forecast” error
- ERA5 nationally-aggregated hourly wind, solar, demand 1950-2020 (“truth”)
- Two extended-range reforecast datasets for energy (models current ~2016)
  - ECMWF-ER → 11 member hindcast 1995-2015
  - NCEP-GFS → lagged 12-member hindcast 1999-2010

Open Access research dataset (**publication: Bloomfield et al, 2021**)





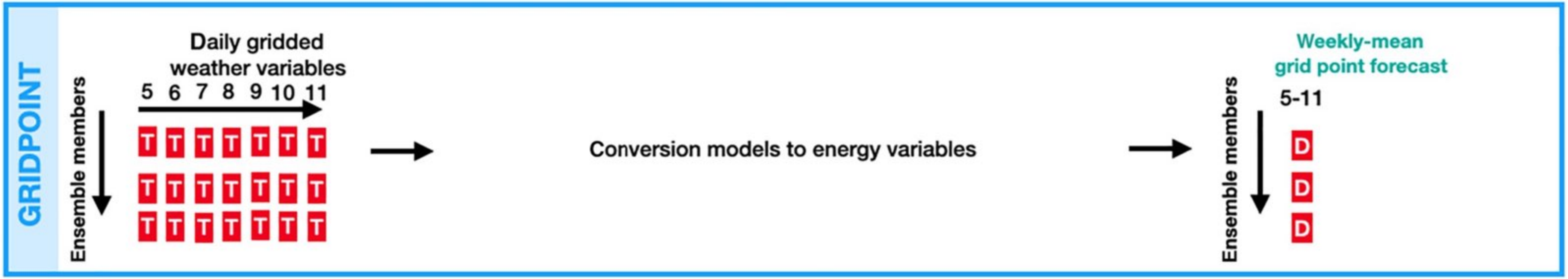


Figs: Bloomfield (2019 & 2021)

Baseline “gridpoint” forecast

Question 1: To what extent are gridpoint-based subseasonal forecasts able to skillfully forecast nationally-aggregated load/generation?

- NB: grid-points are spatially averaged (e.g., to national-level) prior to “conversion” to energy



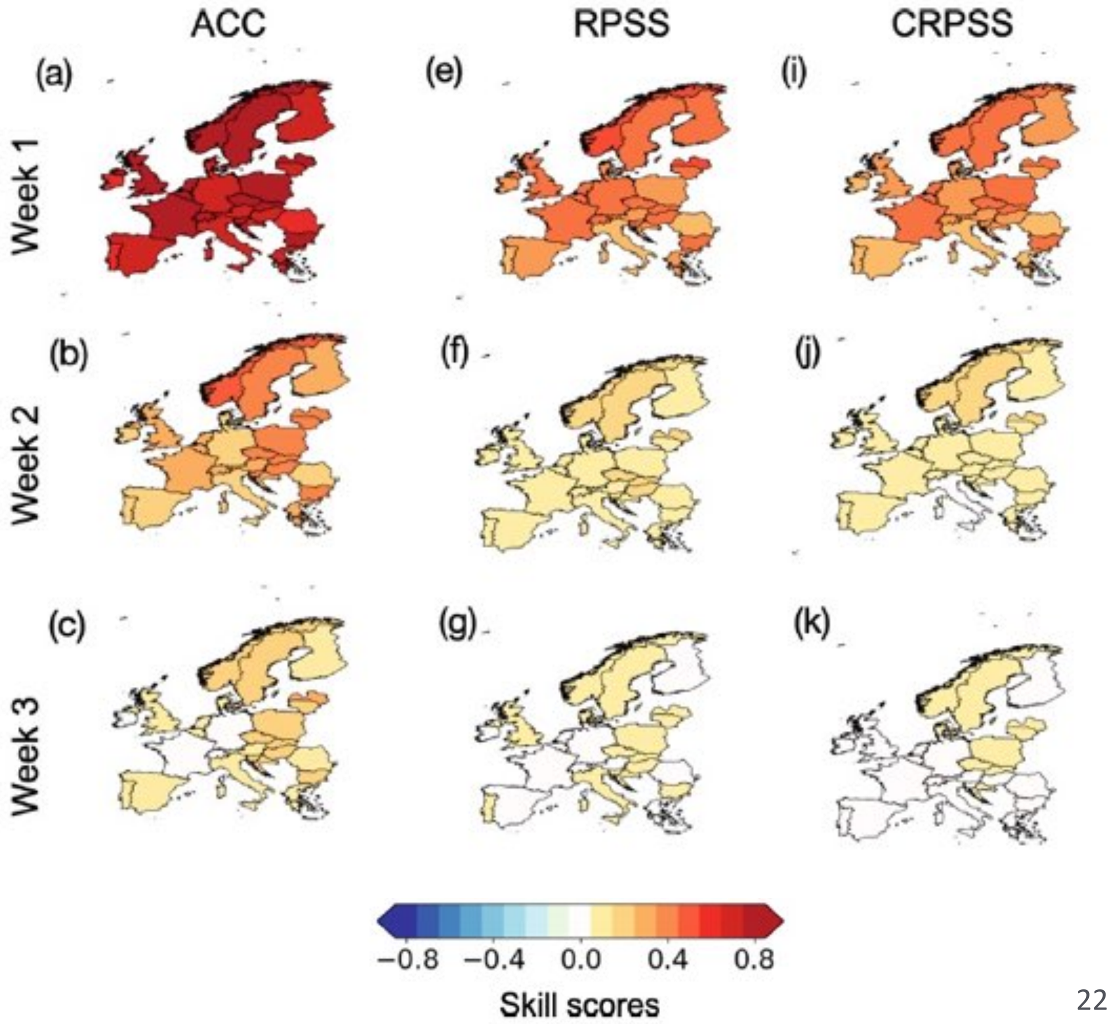
Figs: Bloomfield et al (2021)

Gridpoint forecast skill

- Evidence for skill (to at least week 2)
- Skill depends on metric chosen
  - Typically less skill in more complex metrics

- [Confirms earlier studies, e.g., Lynch et al 2014]

Winter (DJF) Demand-Net-Wind, weekly-mean ECMWF forecast, skill w.r.t. climatological forecast



Week #	Day #
1	5-11
2	12-18
3	19-25
4	26-32

Figure: Bloomfield et al, 2021, ESSD

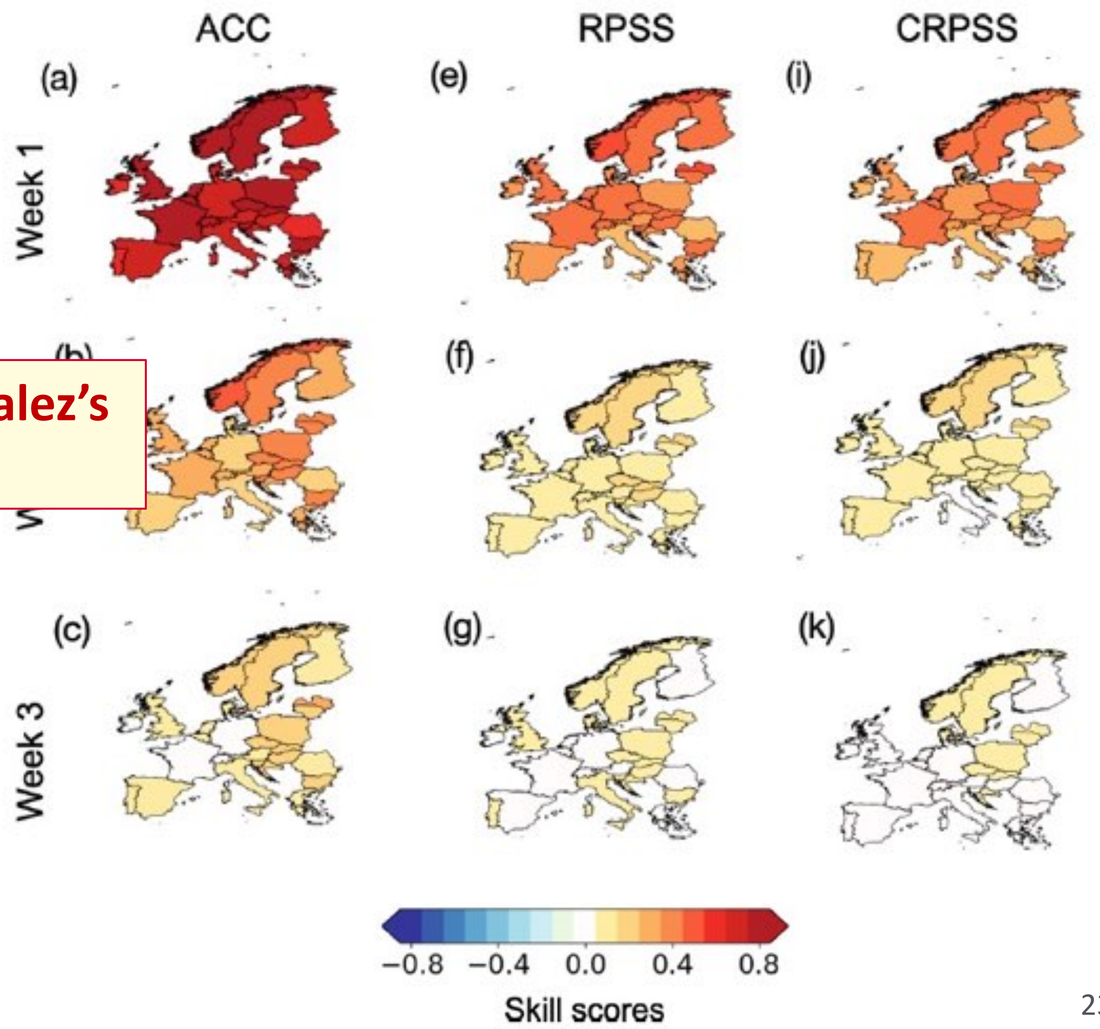
Gridpoint forecast skill

- Evidence for skill (to at least week 2)
- Skill depends on metric chosen
    - Typically less skill in more complex metrics

- *Question 2: can skill be improved?*
    a. *Pattern-based forecasts*
    b. *Conditional predictability*
    c. *Sequential learning algorithms*

See Paula Gonzalez's talk later today

Winter (DJF) Demand-Net-Wind, weekly-mean ECMWF forecast, skill w.r.t. climatological forecast



Week #	Day #
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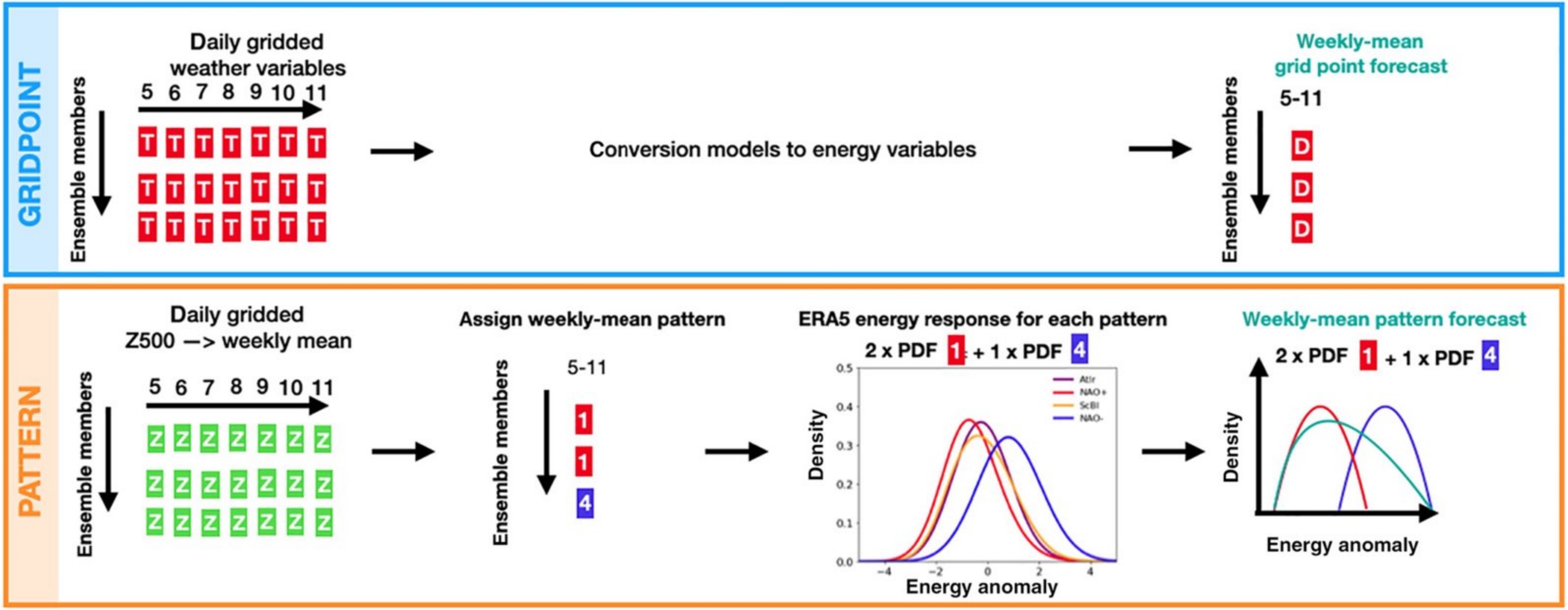
Figure: Bloomfield et al, 2021, ESSD

Q2a: Pattern-based forecasting



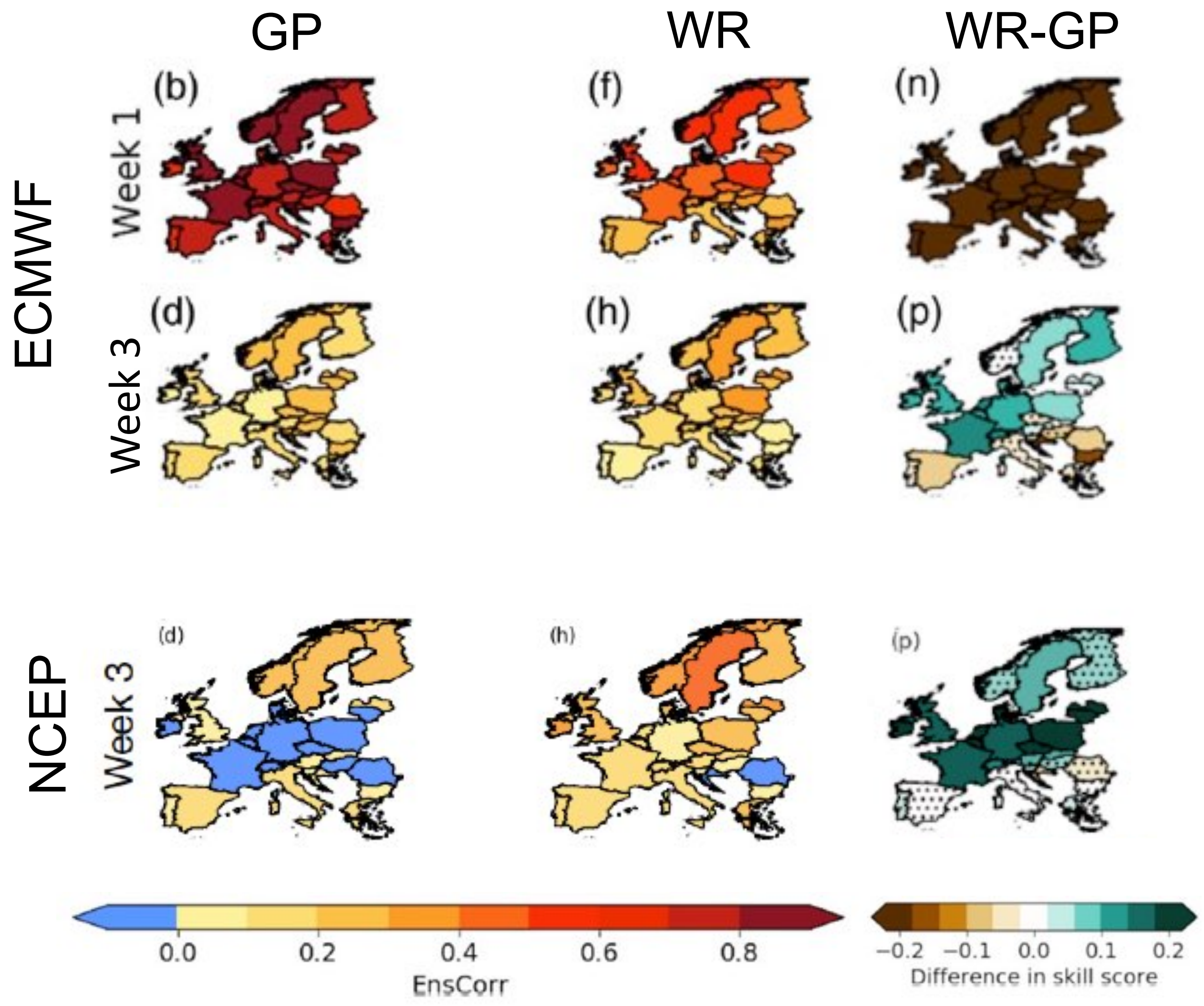
Predict the large-scale weather pattern (weekly-mean) → Use historic (observed) relationship between the large-scale weather pattern and the energy "impact"

Figs: Bloomfield et al (2021)

Pattern-forecast skill

- Week 1:
  - Pattern forecast outperformed by gridpoint
- ECMWF week 3:
  - Significant skill *improvement* in EnsCorr
  - No change in RPSS/CRPSS
- NCEP week 3:
  - Significant skill improvement in EnsCorr,
  - *Also improvement* in RPSS & CRPSS

Winter (DJF) Demand-Net-Wind, weekly-mean EnsCorr
Skill w.r.t. climatological forecast



Week #	Day #
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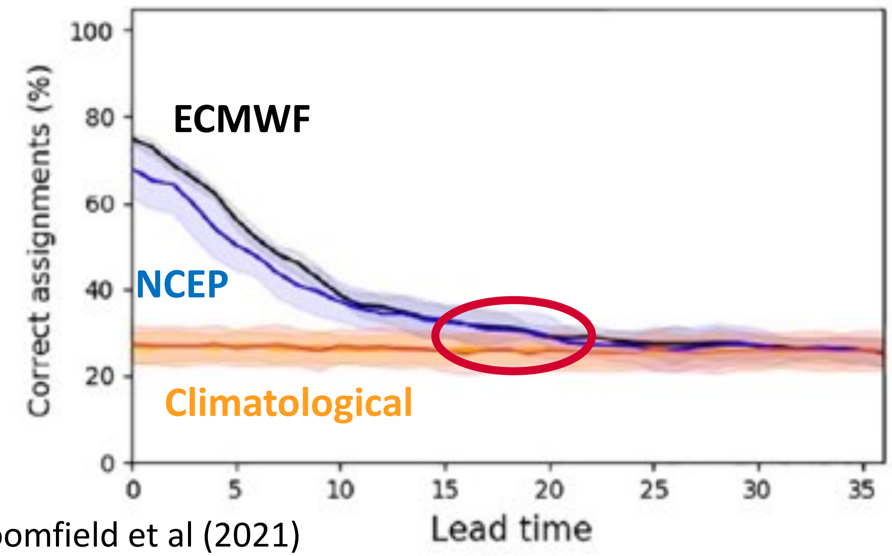
Figs: Bloomfield et al (2021)

Pattern-forecast discussion

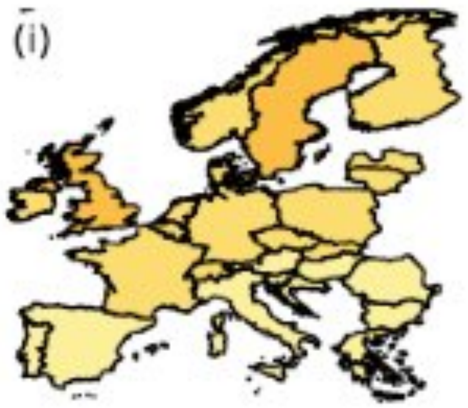
- Interpretation:
  - Forecast = (NWP-derived prediction of large-scale pattern) x (reanalysis-derived impact model)
  - NCEP-GFS more biased (w.r.t. ERA5 “truth”) than ECMWF-ER so benefits more from 2-step process
- However:
  - Predictive skill for weekly-weather patterns at leads of 15-20 days
  - Weather-patterns with stronger link to energy-system impacts (e.g., TCTs; Bloomfield et al 2019) but with some loss of predictive skill (here led to overall weaker performance than standard weather-patterns)
- Challenge: ***seeking optimal patterns to maximize pattern predictability and energy-system impact***

Weather regime forecast assignment

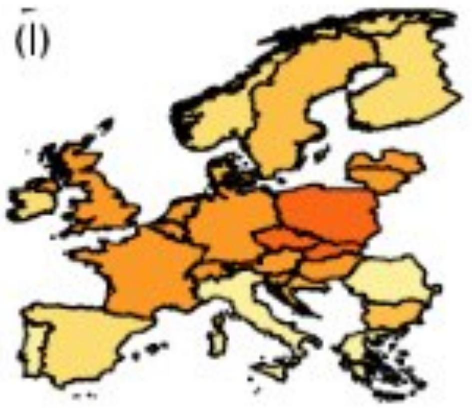


Figs: Bloomfield et al (2021)

Standard Weather Regimes

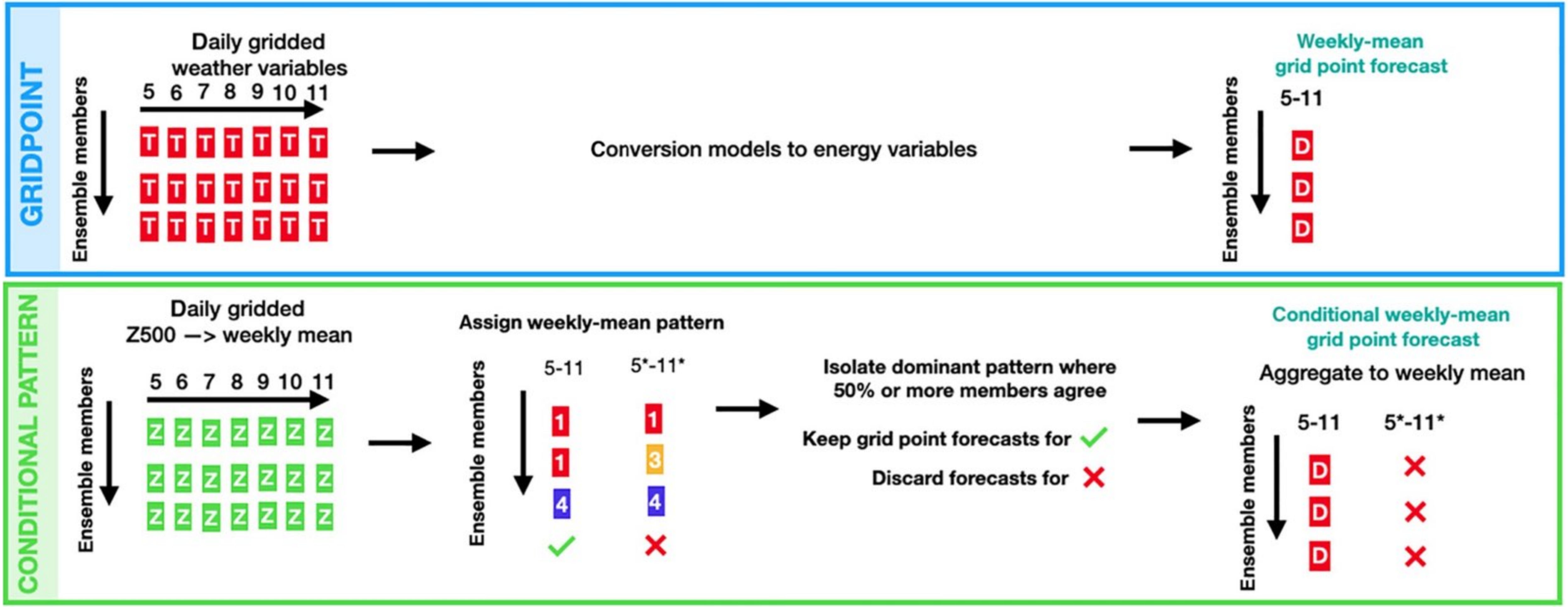


Targeted Circulation Types



DJF DNW CRPSS skill *assuming* perfect pattern forecast

Q2b: Conditional forecasting



Predict the large-scale weather pattern (weekly-mean) → Use gridpoint forecast only if >50% of weather pattern assignments agree on a pattern

Figs: Bloomfield et al (2021)

Conditional gridpoint forecast skill

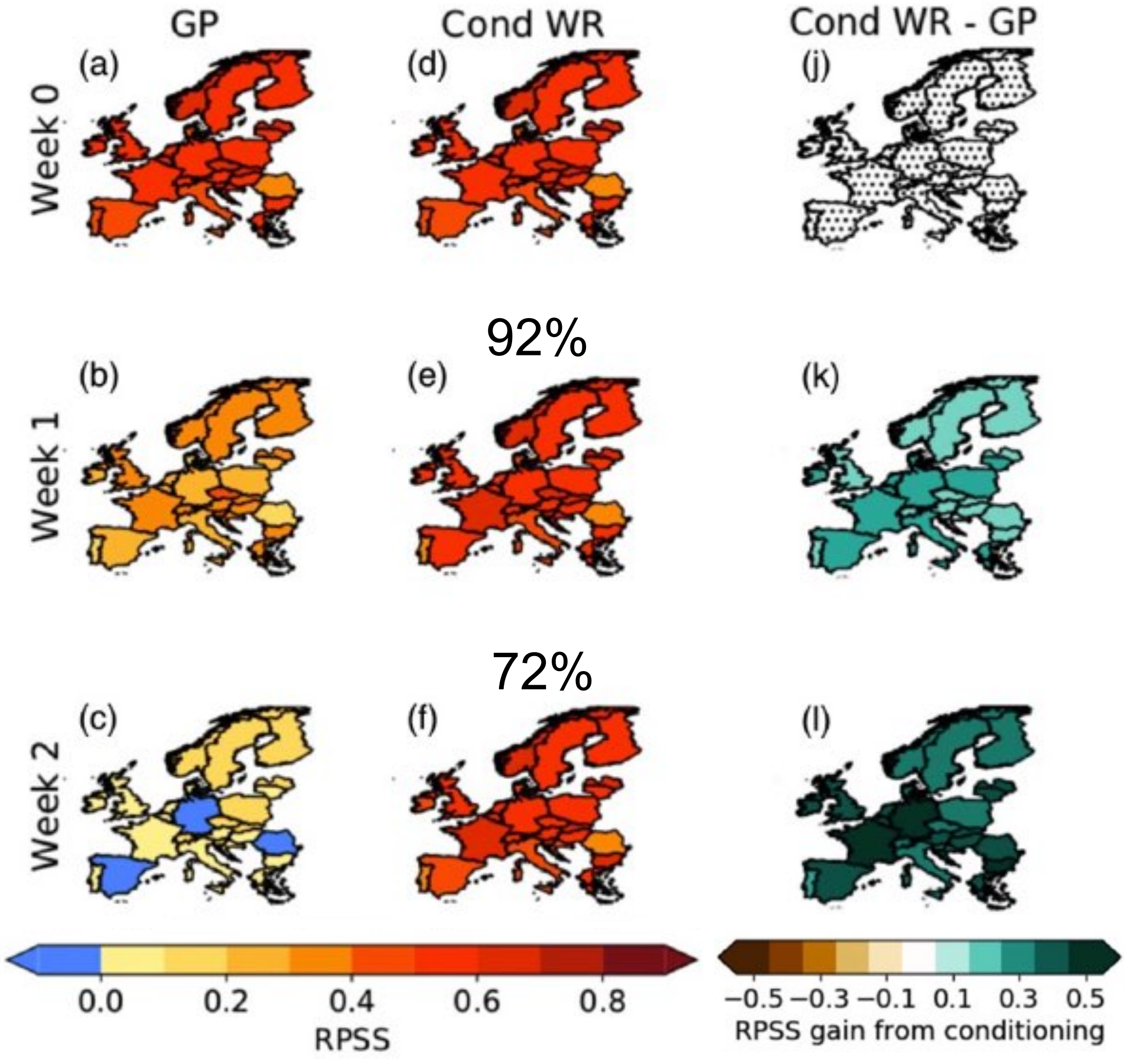
- Significant improvement in skill
  - ~0.2 RPSSS week 1
  - Up to ~0.5 in week 2

- Modest number of forecasts discarded
  - 8% week 1
  - 28% week 2

- Methodological decisions could be optimized, e.g.:
  - Thresholding for discard/accept

Week #	Day #
1	5-11
2	12-18
3	19-25
4	26-32

Winter (DJF) Demand-Net-Wind, weekly-mean RPSS terciles
NCEP forecast skill w.r.t. climatological forecast



Figs: Bloomfield et al (2021)

Conditional gridpoint forecast skill

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Winter (DJF) Demand-Net-Wind, weekly-mean RPSS terciles
NCEP forecast skill w.r.t. climatological forecast

- Moc
- Met

Summary for Q2 (skill-enhancement methods)

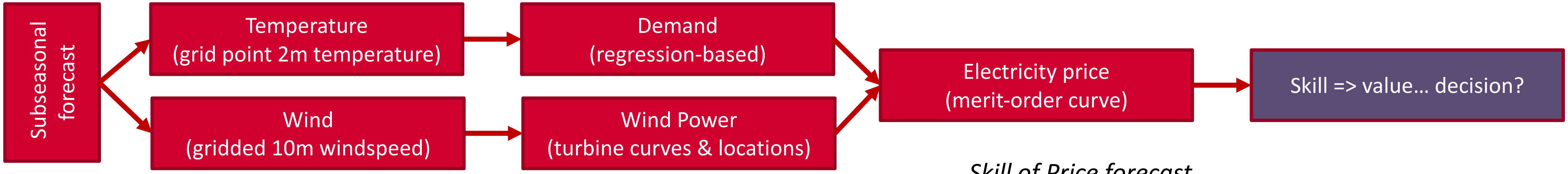
- Significant possibilities for enhancing “modest skill” NWP at extended range
- Weekly-mean weather regimes predictability at leads of ~10-15 days
- Pattern-forecast “2-step approach” compensates for deficiencies in NWP surface representation
- Conditional forecasting enables intelligent use of grid-point forecasts
- Sequential Learning Algorithms (not shown, see Paula’s talk and Gonzalez et al 2021) a powerful way to combine forecast systems and statistical predictors with many operational advantages

Figs: Bloc

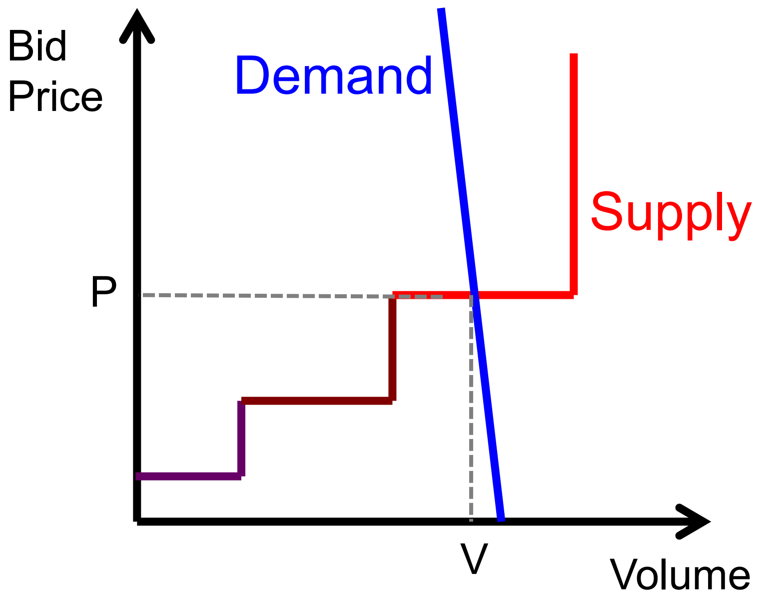
Forecast skill to forecast value

Question 3. To what extent could skillful subseasonal forecasts potentially produce *value* in energy market trading?

Unpublished work with James Fallon, but also see Lynch et al (2014) for related discussion

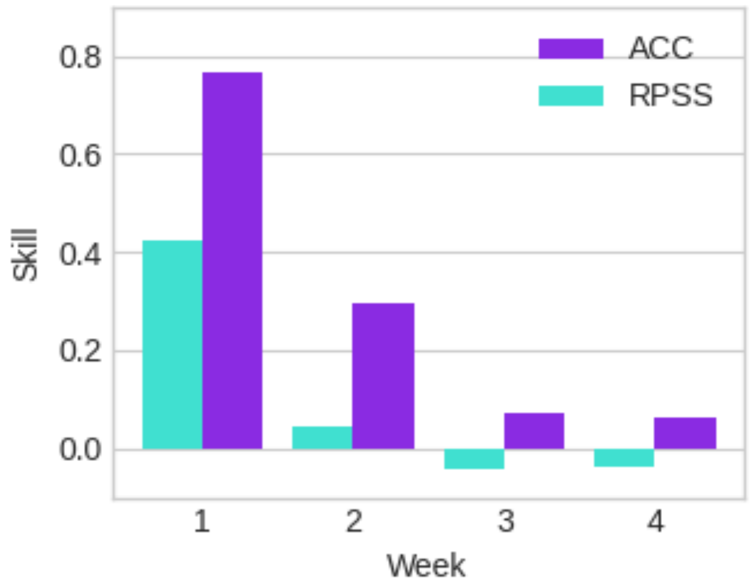


Merit order (illustration)



Skill of Price forecast compared to climatology

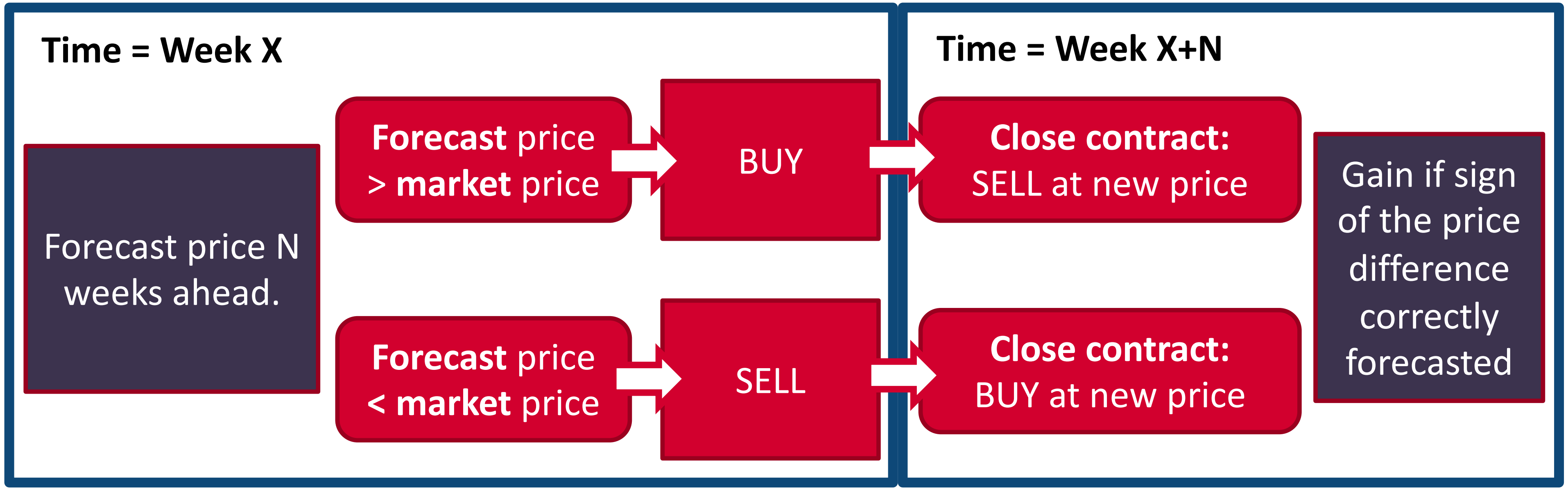
Ensemble average and **tercile probability**



S2S4E Climate Services for Clean Energy

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!

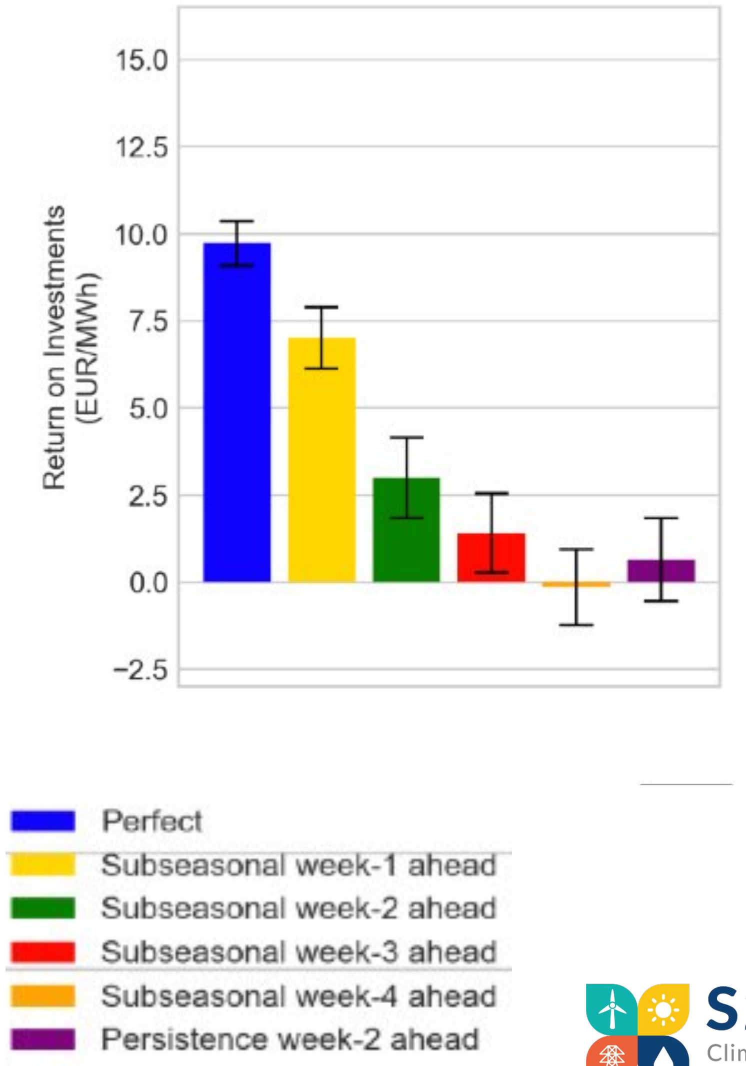


The “total” value of S2S forecasts

- 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”)



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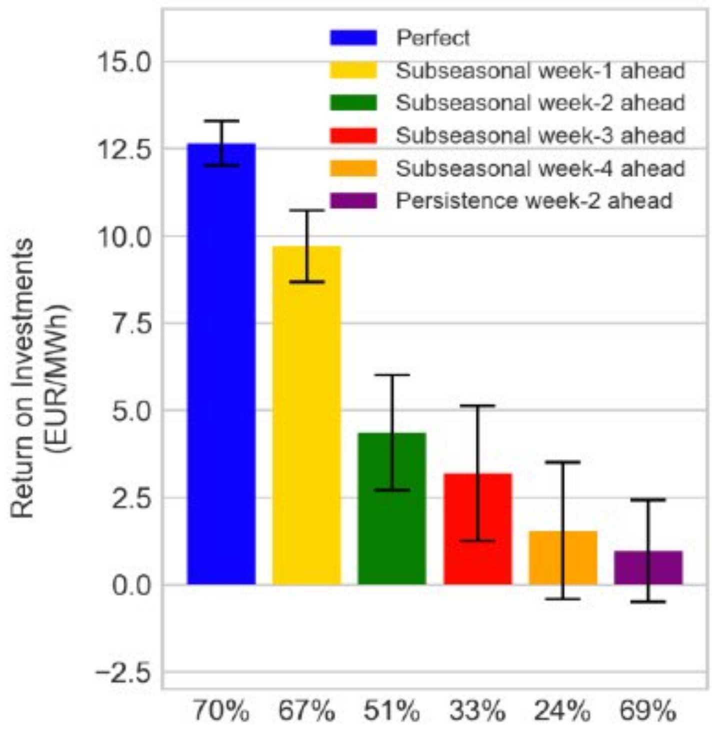
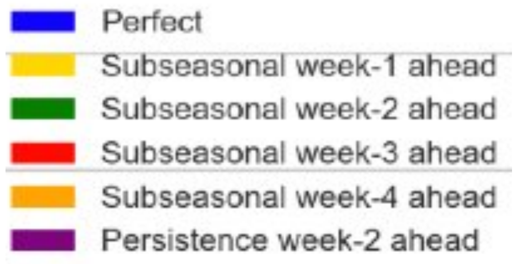
S2S4E Climate Services for Clean Energy

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 (%)



The added value of probabilistic info

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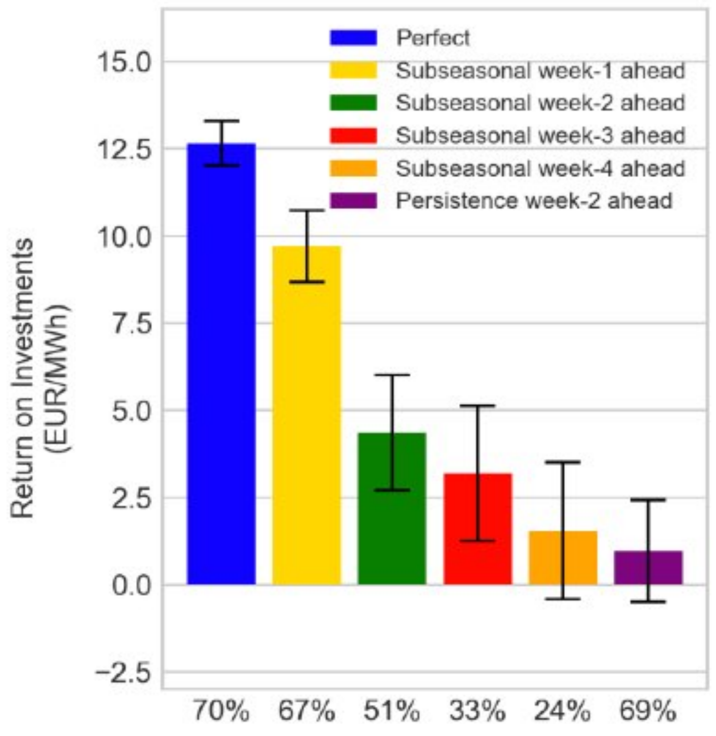
- Per-trade value add (c.f., the equivalent ensemble-mean trader)
  - **Perfect foresight:** ~25% improvement
  - **Subseasonal week-2 forecast (days 11-18):** ~20-30% improvement
- Caveats (as previous but now also):
  - Trades only on strong signals ➔ many fewer trades made
  - Cumulative value over time less than "ensemble mean" strategy
  - Best strategy depends on risk/return preferences

Value is in the eye of the beholder…

… it depends on what the user wants to achieve.



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

Forecast value in decision-making

- Need more consideration about how forecast skill propagates into value via *decision-making*

- Example: telecommunication faults (see Brayshaw et al 2020 for details)
  - UK £33bn/year or ~1.5% GDP net economic contribution (Kelly, 2015)
  - BT / Openreach responsible for ~90% of fixed line infrastructure
  - Weather highlighted as a contributor to increased fault rates
  - Associated with service delays, disruptions and challenging conditions

- Seek subseasonal (weeks-ahead) fault rate forecast and establish “value” in maintenance/repair scheduling

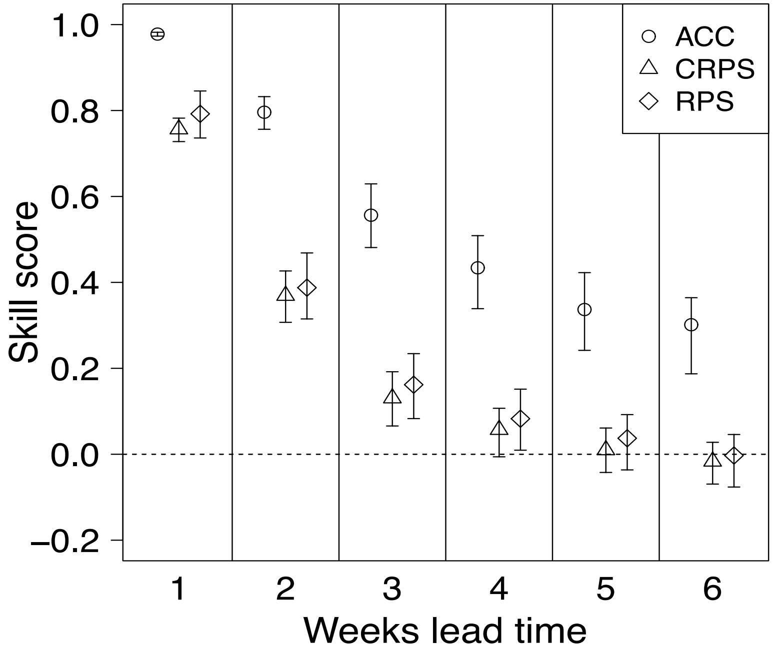
Methodology (abridged)

- Fit statistical relationship between observed faults and reanalysis (here, ERA-Int)

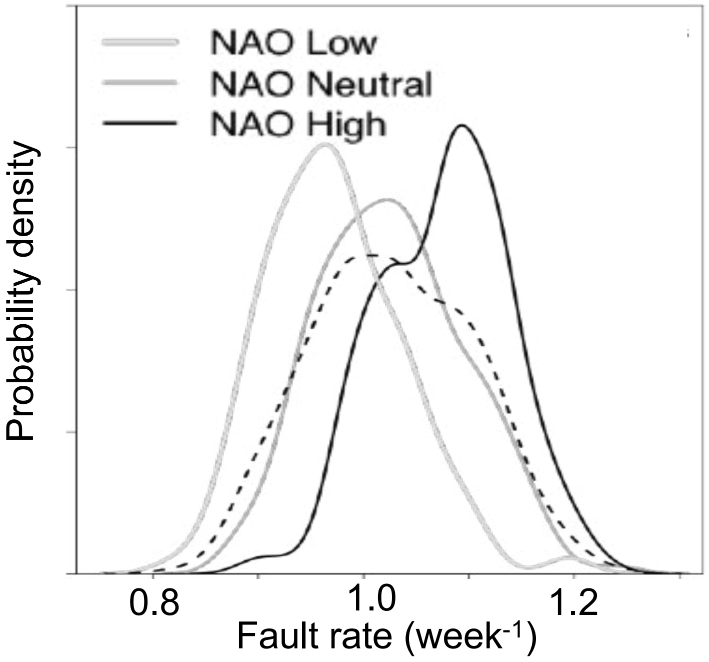
$$FRA_i^{VOICE} = \alpha_0 + \alpha_1 PS + \alpha_2 PT + \alpha_3 T + \alpha_4 W + \alpha_5 WT + \alpha_6 RHT + \alpha_7 HOL + \varepsilon_i(0,\sigma)$$

- Establish:
  1. ECMWF-ER can skillfully predict weekly-NAO (20yr 11-member hindcasts, system Dec16-Feb17)
  2. Weekly-NAO has a strong influence on fault rates
  3. Predict NAO then use climatological NAO-faults relationship ➔ skillfully predict weekly fault rates

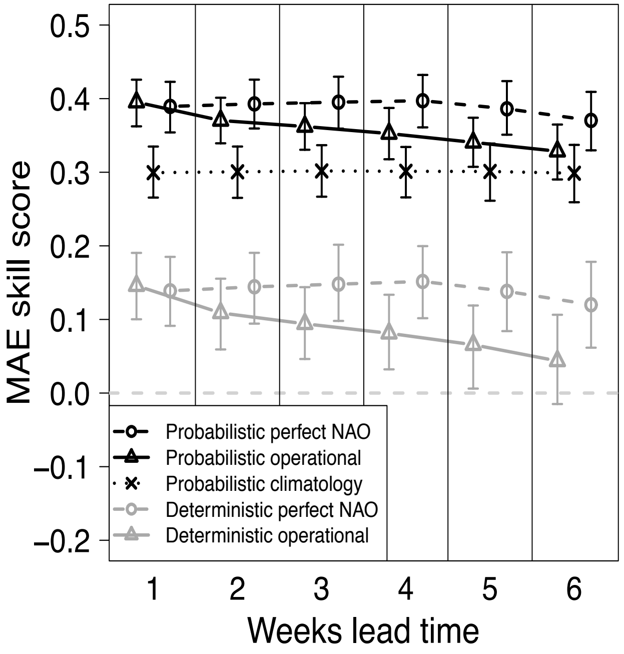
NAO forecast skill (w.r.t. climatology)



NAO impact on fault rate



Fault rate skill compared to deterministic climatology



Figures: Brayshaw et al 2020

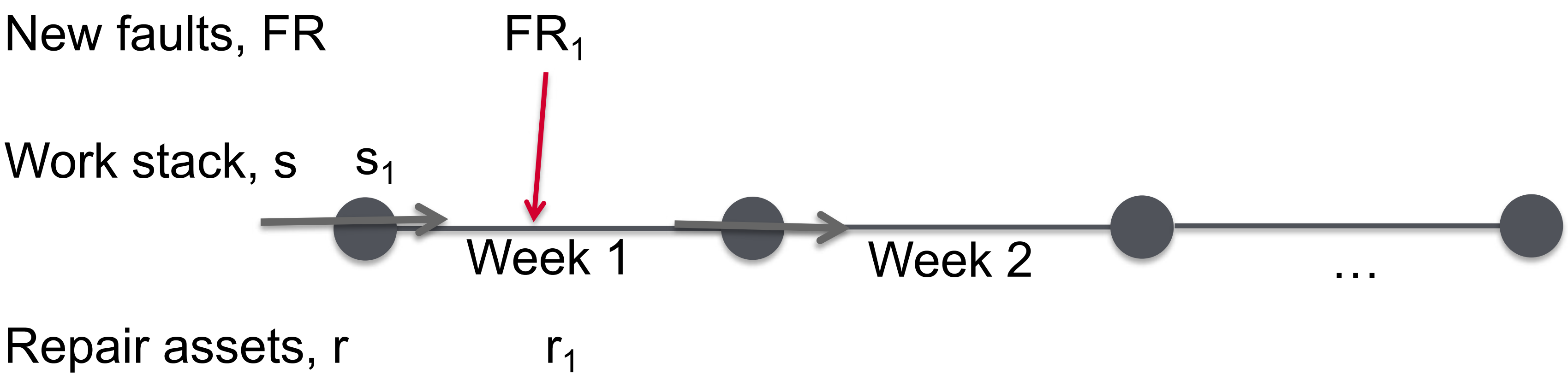
Decisions and value

- Goal is *fixing faults promptly*, not just predicting faults
  - Required meet a target for fixing faults within a given window
  - Can hire additional engineers but requires notice and incurs a cost

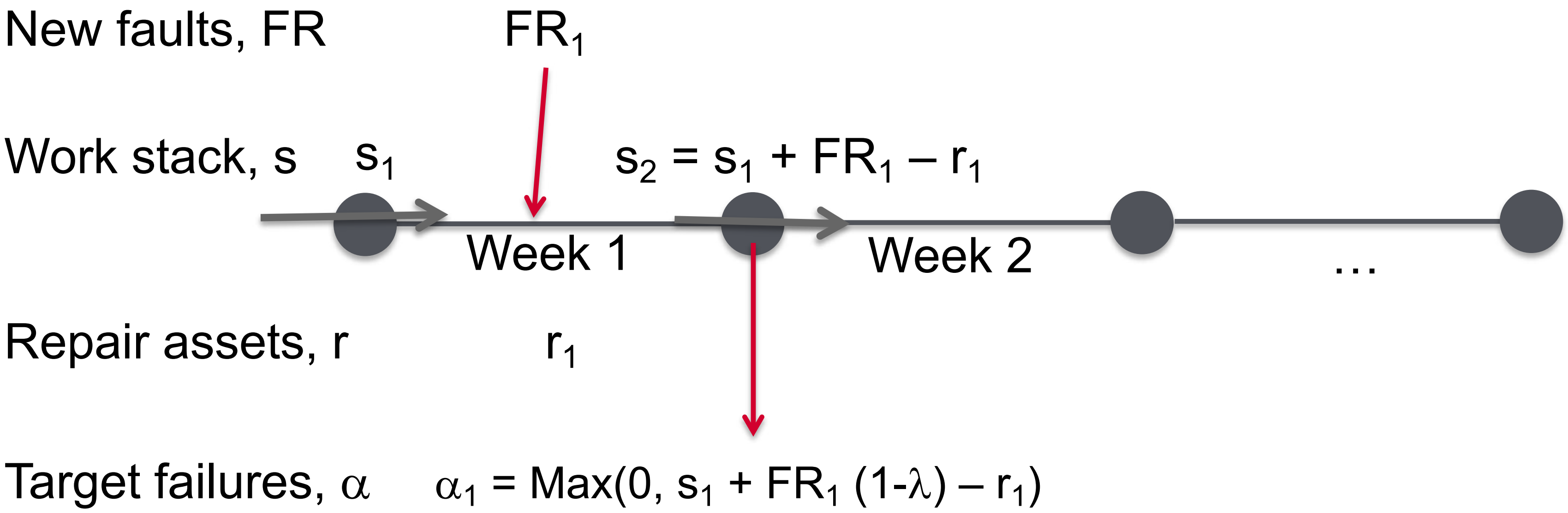
- Toy model of decision process
  - Target: fix a fraction ($1-\lambda$) of incoming faults during any week
  - Assume engineers only fix faults ("repair capacity")
  - Unfixed faults carryover into next week and must be fixed before new work
  - Can employ 'extra' engineers (increase repair capacity) but with 1-week lead

- Aside - real decision is far more complex:
  - Daily resolution
  - Multi-objective (e.g., same engineers install new lines, with associated targets)
  - Decisions on multiple time-horizons from ~week-4 to near real time

Decisions model



Decisions model



Decisions model

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New faults, FR — FR_1

Work stack, s — s_1 — $s_2 = s_1 + FR_1 - r_1$

Week 1 — Week 2 — …

Repair assets, r — r_1 — r_2

Target failures, α — $\alpha_1 = \text{Max}(0, s_1 + FR_1\,(1-\lambda) - r_1)$

Need to decide r_2 during week 1

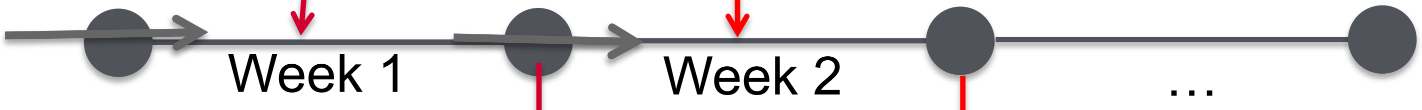
➔ locks in decision of repair assets one-week in advance

Decisions model

Forecast fault rate

New faults, FR $\quad FR_1 \quad FR_2^f$

Work stack, s $\quad s_1 \quad s_2 = s_1 + FR_1 - r_1$



Repair assets, r $\quad r_1 \quad r_2$

Target failures, α $\quad \alpha_1 = \mathrm{Max}(0, s_1 + FR_1 (1-\lambda) - r_1) \quad \alpha_2^f = \mathrm{Max}(0, s_2 + FR_2^f (1-\lambda) - r_2)$

Forecast failure rate

Decisions model

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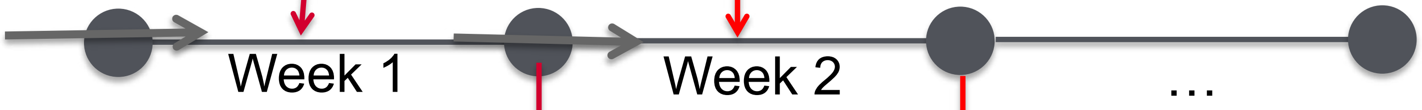
Forecast fault rate

New faults, FR $\quad FR_1 \quad FR_2^f$

Work stack, s $\quad s_1 \quad s_2 = s_1 + FR_1 - r_1$



Repair assets, r $\quad r_1 \quad r_2$

Target failures, α $\quad \alpha_1 = \mathrm{Max}(0, s_1 + FR_1\,(1-\lambda) - r_1) \quad \alpha_2^f = \mathrm{Max}(0, s_2 + FR_2^f\,(1-\lambda) - r_2)$

Forecast failure rate

Choose r_2 as: $\underset{r_2}{Min}(c_{fail}\alpha_2 + c_{repair}r_2)$

$$r_{\min} \le r_2 \le r_{\max}$$

Decisions model

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Forecast fault rate

New faults, FR $\quad FR_1 \quad FR_2^f$

Work stack, s $\quad s_1 \quad s_2 = s_1 + FR_1 - r_1$

Week 1 $\quad$ Week 2 $\quad$ …

Repair assets, r $\quad r_1 \quad r_2$

Target failures, α $\quad \alpha_1 = \mathrm{Max}(0, s_1 + FR_1\,(1\text{-}\lambda) - r_1)$ $\quad \alpha_2^f = \mathrm{Max}(0, s_2 + FR_2^f\,(1\text{-}\lambda) - r_2)$

Forecast failure rate

Choose r_2 as: $\underset{r_2}{Min}(c_{fail}\alpha_2 + c_{repair} r_2)$

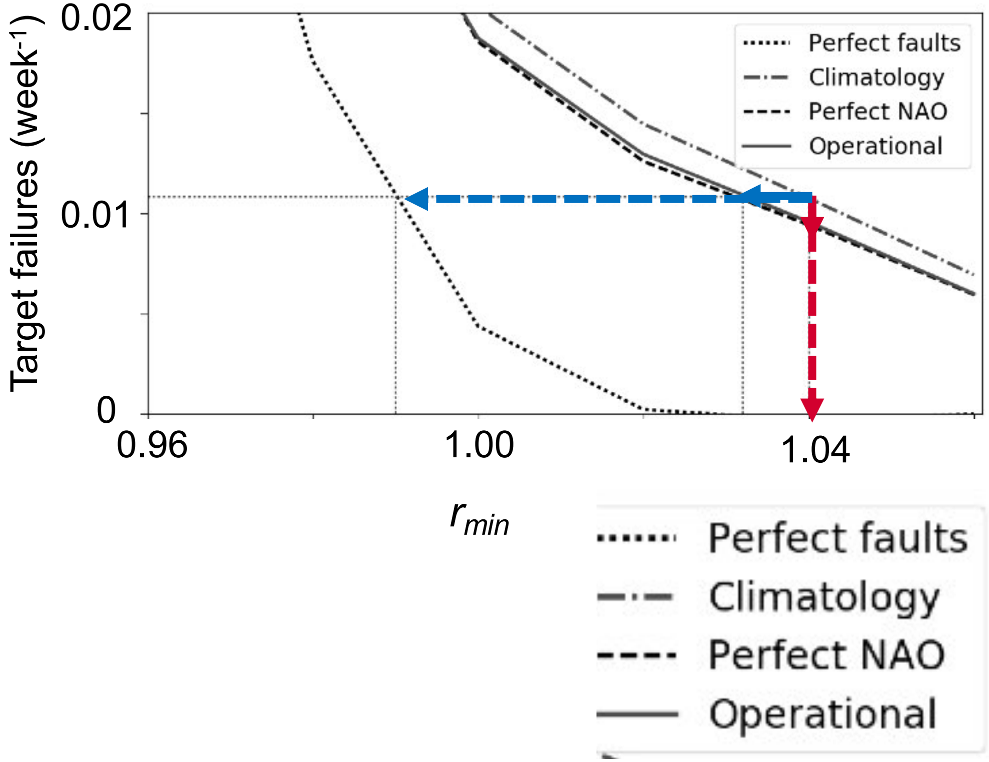
$$r_{\min} \leq r_2 \leq r_{\max}$$

Then step forward to calculate **actual** α_2 using r_2 and the **actual** fault rate FR_2

Iterate over 'perpetual winter' from ECMWF hindcasts (neglect end years)

Decisions and value

- Experiment: constant contingency
  - (r_{max}-r_{min} = 0.15 week^{-1})
  - Vary minimum repair capacity (r_{min})
- **Operational**:
  - For a given repair capacity, improved forecasts reduce target failure rate (~10%, up to 100%?)
  - ➔ "Better" performance with given resources
- **Planning**:
  - For a given target failure rate, improved forecasts reduce required repair capacity (~1%, up to 5%?)
  - ➔ "Reduced cost" for same performance level



Context: Annual staffing cost ~£500M, max penalty for failures up to ~£1M/day

Figure: Brayshaw et al 2020

Summary

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- Origins of S2S forecasting
  - Physical sources
  - Scale dependence
  - Use of ensembles

- S2S applied to energy
  - Skill exists and techniques to enhance (pattern, conditional, SLA etc) but…
  - … remains modest and key challenge is finding ways to convert weak skill to strong value-add in decisions

Climate truth → Climate sample or simulation → Simple impact → Complex impact → Decision or outcome

- Contact: d.j.brayshaw@reading.ac.uk; https://research.reading.ac.uk/met-energy/
- Online courses: https://www.reading.ac.uk/meteorology/online-courses

Contact and references

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