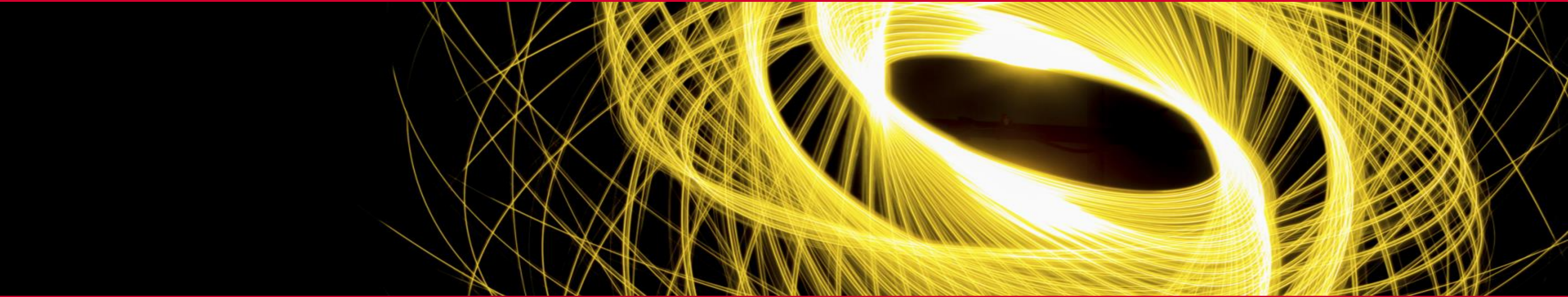
Department of Meteorology
School of Mathematical, Physical and Computational Sciences

University of Reading

Anticipating Weather & Climate Risk in Energy Systems



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Challenges in Energy-Climate Modelling

- Climate change is driving a complete transformation of the electricity sector
  - Rapid growth of renewables such as wind & solar (global investment of US$242 billion in 2020)
  - Electrification of other sectors: transport & heating

- Fundamentally changes exposure of energy-system to weather
  - Need supply (generation) and demand (use of power) to balance quasi-instantaneously
  - Imperfect foresight as both highly weather-dependent

- Key issues:
  - Managing weather/climate risk in the power system *today* (i.e., operations)
  - Designing power systems that are robust to *climate uncertainty in the future* (i.e., planning)

- *Today:*
  - *Role of numerical modelling but combining with statistical methods*
  - *Illustrate with "S2S" subseasonal forecasts for energy applications*

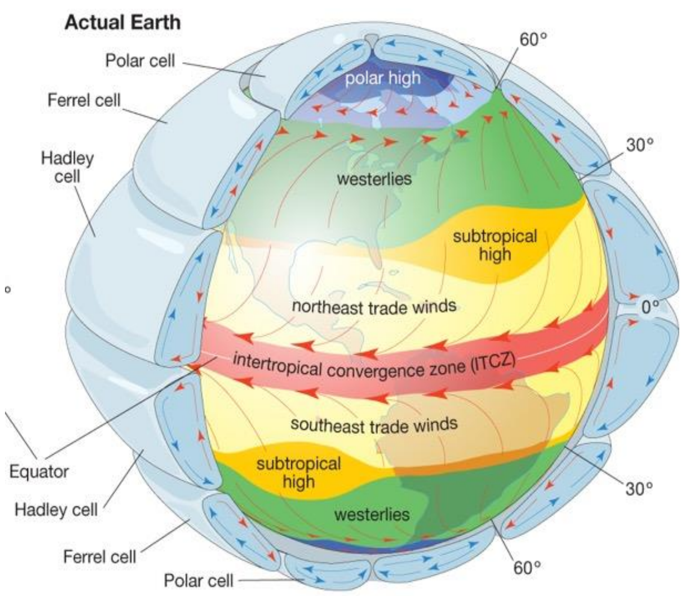
  - *Focus on "operational" weather/climate risk management*
  - *Very happy to discuss planning (e.g., capacity expansion under climate uncertainty offline!).*

Image: pxhere.com/en/photo/1408472

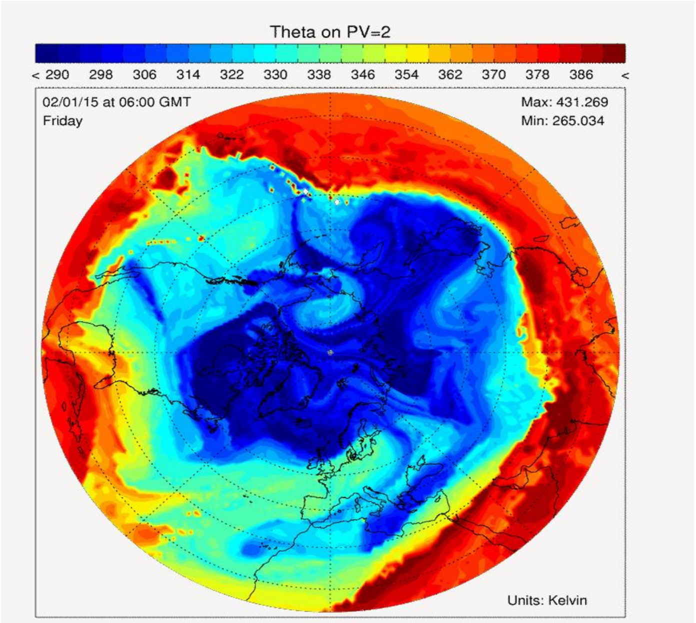
Why physical/numerical models?

- Drivers: differential insolation and rotation
  - Gross large-scale time-average structure of atmospheric/ocean circulation well understood…
  - … but great complexity for understanding, simulating and predicting variations

- Physically-based numerical GFD models encode representation of ‘real’ atmospheric structure and behaviour
  - *… correlations, co-dependencies, co-evolution etc*

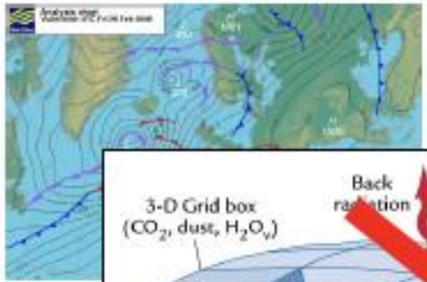


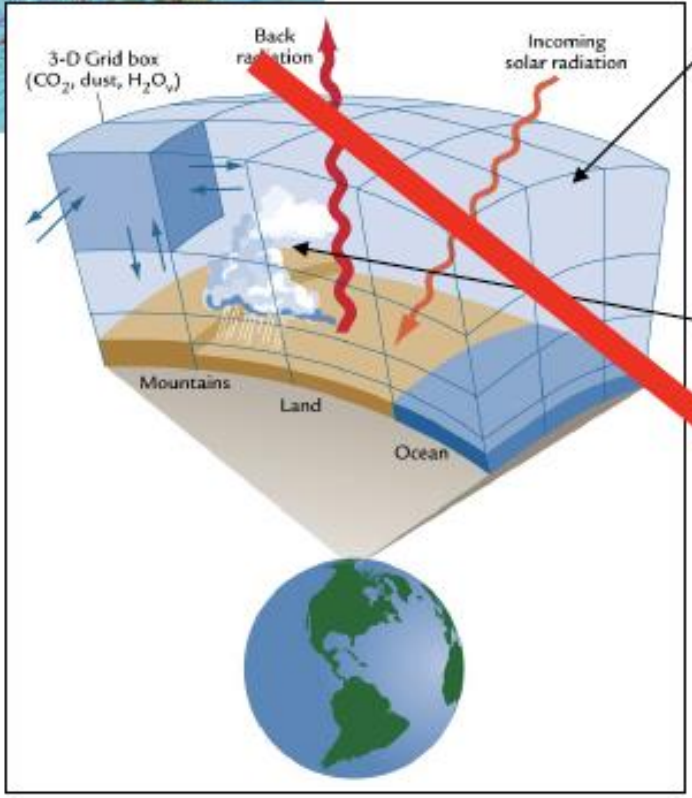
Encyclopedia Brittanica



What is a physical NWP model?

Initial state analysis





Dynamical "core" ~ based on Navier-Stokes eqns

$$\rho\left(\frac{\partial u_r}{\partial t}+u_r\frac{\partial u_r}{\partial r}+\frac{u_\varphi}{r\sin(\phi)}\frac{\partial u_r}{\partial \theta}+\frac{u_\theta}{r}\frac{\partial u_r}{\partial \phi}-\frac{u_\varphi^2+u_\theta^2}{r}\right)=-\frac{\partial p}{\partial r}+\rho g_r$$
$$\mu\left[\frac{1}{r^2}\frac{\partial}{\partial r}\left(r^2\frac{\partial u_r}{\partial r}\right)+\frac{1}{r^2\sin(\phi)^2}\frac{\partial^2 u_r}{\partial \theta^2}+\frac{1}{r^2\sin(\phi)}\frac{\partial}{\partial \phi}\left(\sin(\phi)\frac{\partial u_r}{\partial \phi}\right)-2\frac{u_r+\frac{\partial u_\theta}{\partial \phi}+u_\theta\cot(\phi)}{r^2}+\frac{2}{r^2\sin(\phi)}\frac{\partial u_\varphi}{\partial \theta}\right]$$

$$\rho\left(\frac{\partial u_\varphi}{\partial t}+u_r\frac{\partial u_\varphi}{\partial r}+\frac{u_\varphi}{r\sin(\phi)}\frac{\partial u_\varphi}{\partial \theta}+\frac{u_\theta}{r}\frac{\partial u_\varphi}{\partial \phi}+\frac{u_r u_\varphi+u_\varphi u_\theta\cot(\phi)}{r}\right)=-\frac{1}{r\sin(\phi)}\frac{\partial p}{\partial \theta}+\rho g_\theta$$
$$\mu\left[\frac{1}{r^2}\frac{\partial}{\partial r}\left(r^2\frac{\partial u_\varphi}{\partial r}\right)+\frac{1}{r^2\sin(\phi)^2}\frac{\partial^2 u_\varphi}{\partial \theta^2}+\frac{1}{r^2\sin(\phi)}\frac{\partial}{\partial \phi}\left(\sin(\phi)\frac{\partial u_\varphi}{\partial \phi}\right)+\frac{2\frac{\partial u_r}{\partial \theta}+2\cos(\phi)\frac{\partial u_\theta}{\partial \theta}-u_\varphi}{r^2\sin(\phi)^2}\right]$$

$$\rho\left(\frac{\partial u_\theta}{\partial t}+u_r\frac{\partial u_\theta}{\partial r}+\frac{u_\varphi}{r\sin(\phi)}\frac{\partial u_\theta}{\partial \theta}+\frac{u_\theta}{r}\frac{\partial u_\theta}{\partial \phi}+\frac{u_r u_\theta-u_\varphi^2\cot(\phi)}{r}\right)=-\frac{1}{r}\frac{\partial p}{\partial \phi}+\rho g_\phi$$
$$\mu\left[\frac{1}{r^2}\frac{\partial}{\partial r}\left(r^2\frac{\partial u_\theta}{\partial r}\right)+\frac{1}{r^2\sin(\phi)^2}\frac{\partial^2 u_\theta}{\partial \theta^2}+\frac{1}{r^2\sin(\phi)}\frac{\partial}{\partial \phi}\left(\sin(\phi)\frac{\partial u_\theta}{\partial \phi}\right)+\frac{2}{r^2}\frac{\partial u_r}{\partial \phi}-\frac{u_\theta+2\cos(\phi)\frac{\partial u_\varphi}{\partial \theta}}{r^2\sin(\phi)^2}\right]$$

Physical "parameterisation" schemes

- Cloud/moisture processes
- Surface energy and momentum exchange
- Radiation…

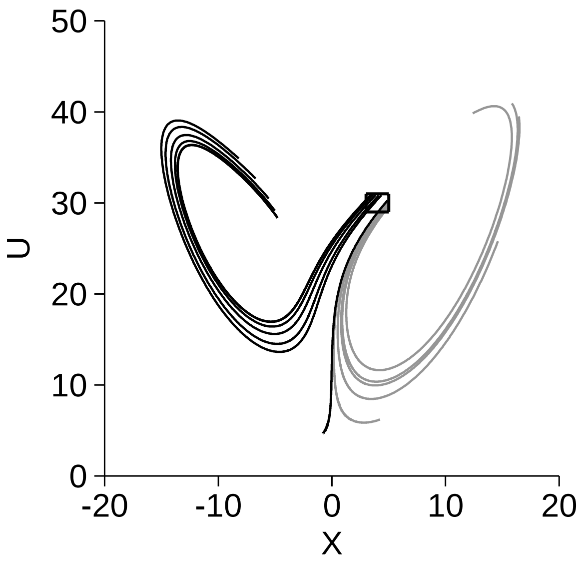
Forecast

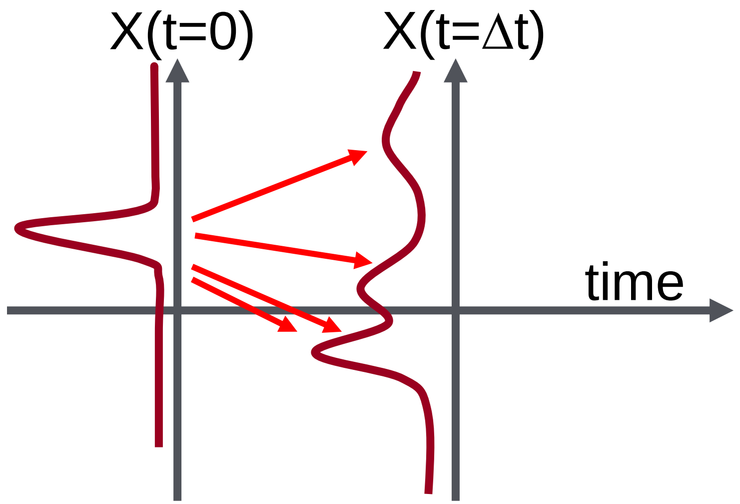
Initial condition ensembles

- Initial condition error grows rapidly (~days in the lower atmosphere)

- Illustration: Lorenz-63 model
  - Analogies to NWP

- Skill in longer-range forecasts (> weeks) involves initialization and/or modelling of “slower evolving” climate-system components (sea-ice, upper atmosphere, near-surface ocean, etc)





Subseasonal forecasting

- Subseasonal (or "extended-range") forecasts: approximately 1-4 weeks ahead
- Bridge "gap" between long-range outlooks and short-range weather forecasts
- Applications in planning, trading / financial risk management, scheduling (e.g., maintenance, hydropower), …

- Previous studies suggest modest but positive forecast skill for wind over Europe (Lynch et al 2014) but…
  - Inherently probabilistic
  - Require large ensembles
  - Spatio-temporal 'aggregation'
  - Time-varying: 'windows of opportunity'

- Here - statistical/NWP hybrids for energy forecasting:
  - Introducing the models, data and preliminary skill assessment
  - Part 1 - Pattern forecasting / conditioning
  - Part 2 - Sequential learning algorithms

H2020 S2S4E project – particular thanks to UREAD team:
Paula Gonzalez, Hannah Bloomfield, David Livings,
Emma Suckling, James Fallon & Andrew Charlton-Perez

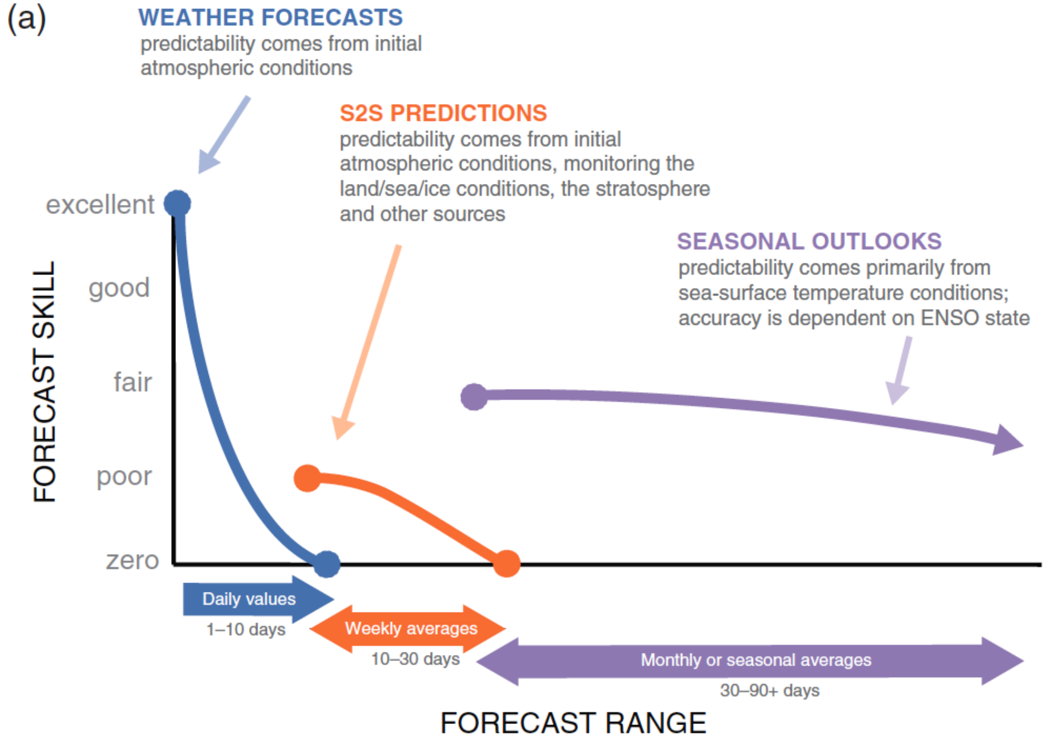
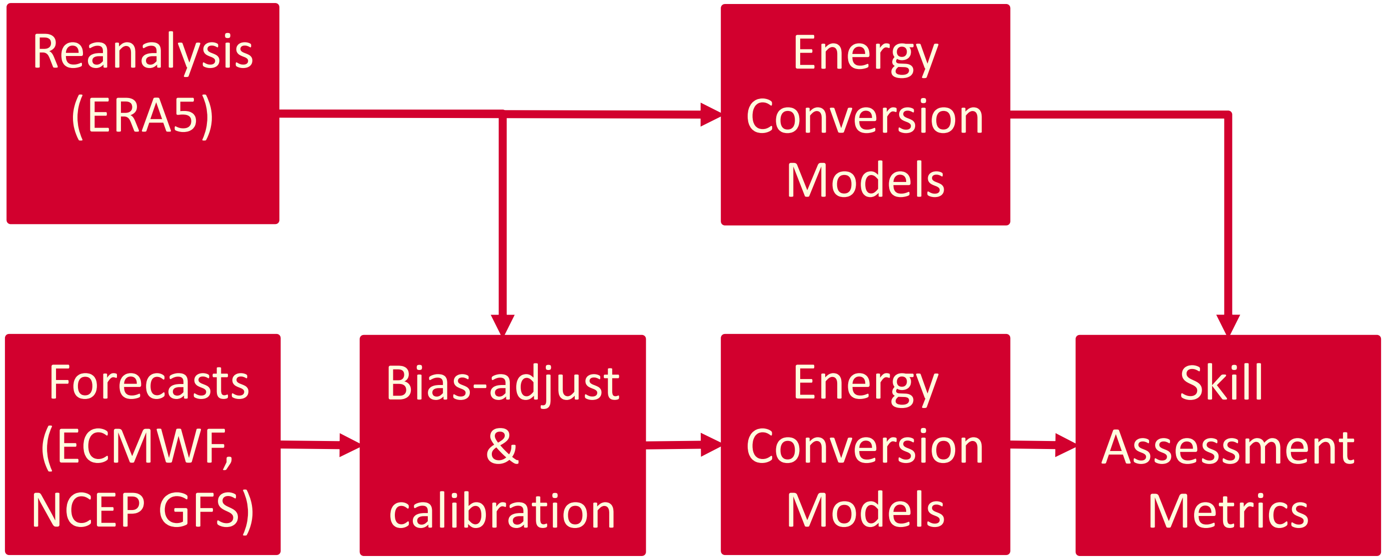


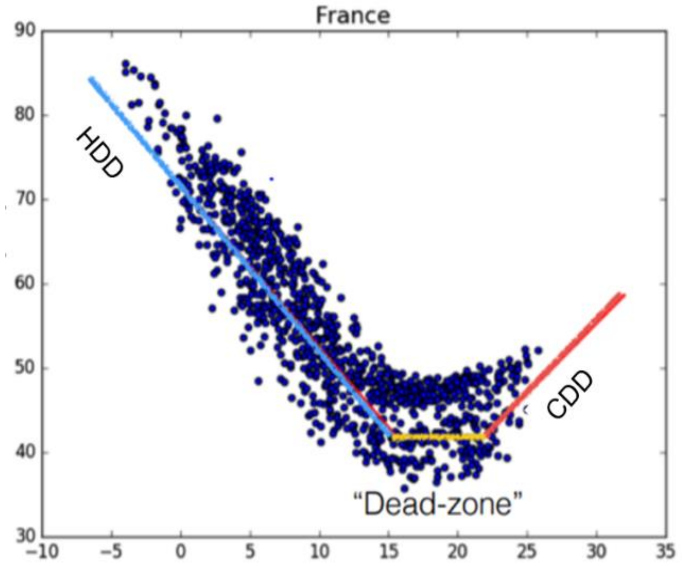
Figure: White et al (2017)

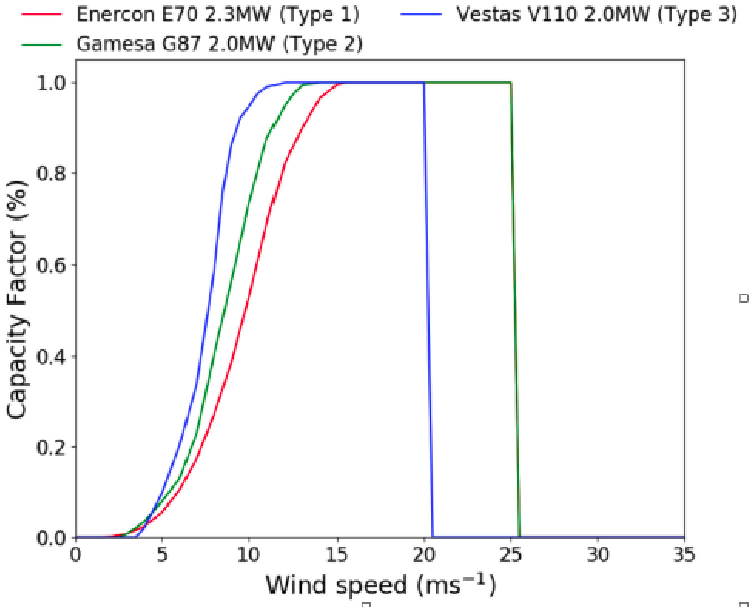
Background: models & data

- S2S4E project: Prototype "climate service for energy"
  - ~3 year research programme over 5 EU institutes

- Open Access research dataset (**publication: Bloomfield et al, 2021**) includes:
  - Nationally-aggregated hourly wind, solar, demand 1950-2020 (from ERA-5 and MERRA2)
  - Two extended-range reforecast datasets for energy (versions current ~2016)
    - ECMWF-ER → 11 member hindcast 1995-2015
    - NCEP-GFS → lagged 12-member hindcast 1999-2010

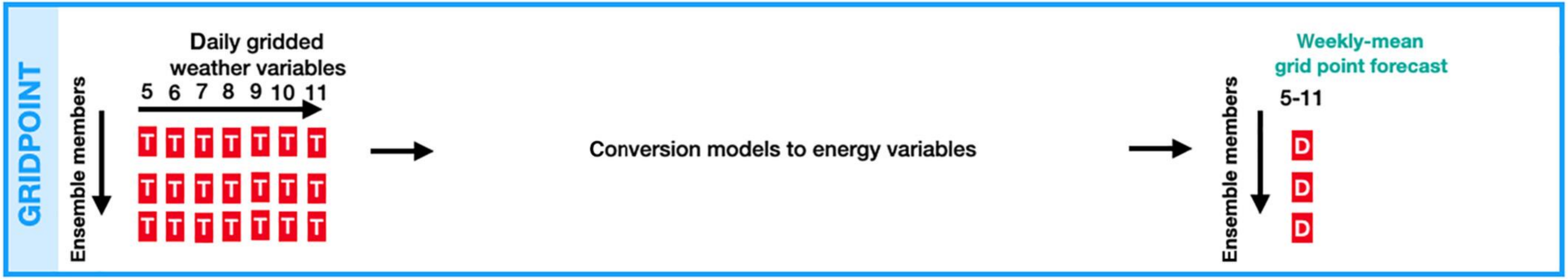






Figs: Bloomfield (2019 & 2021)

Baseline gridpoint forecast



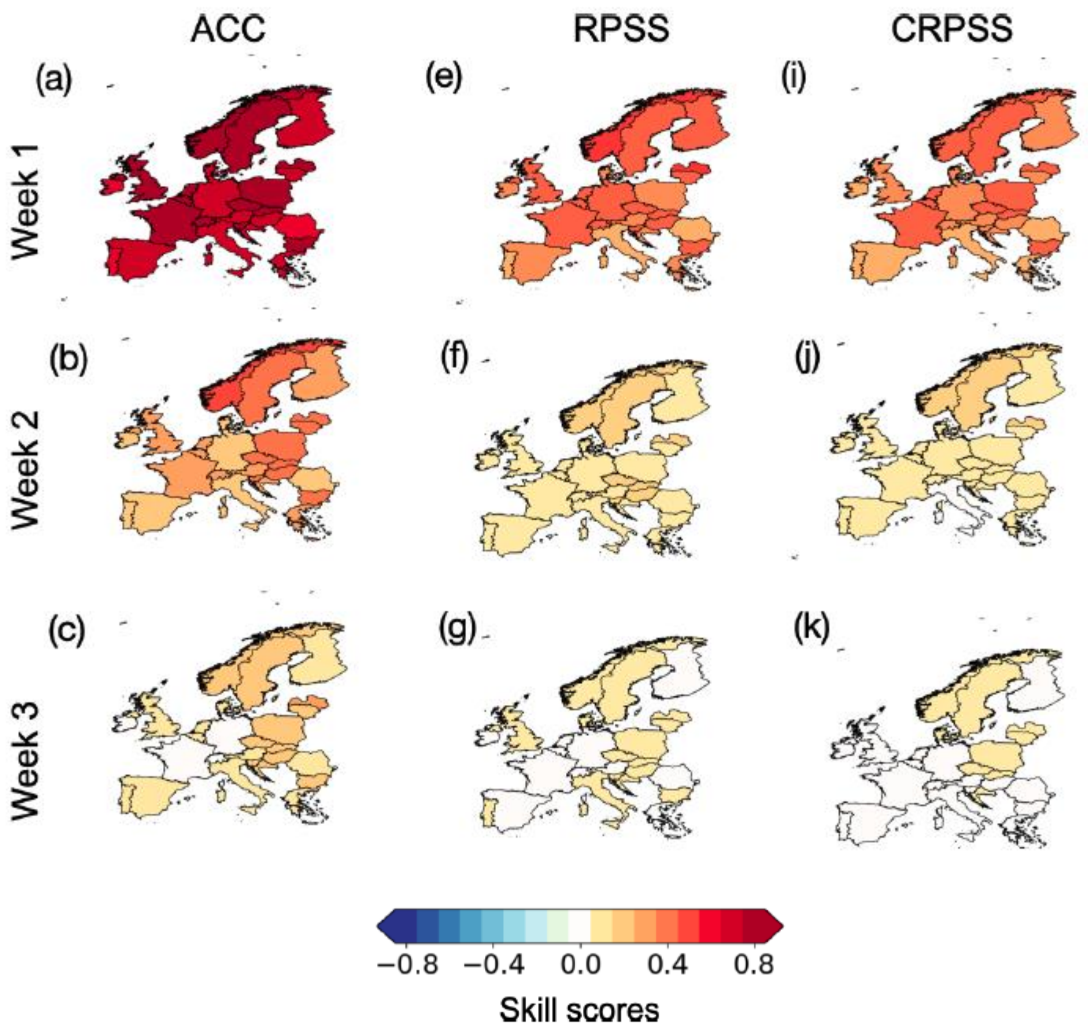
Figs: Bloomfield et al (2021)

Gridpoint forecast skill

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

- *Question: can skill be improved?*
  - *Pattern-based methods*
  - *Sequential learning algorithms*

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

Part 1 – Pattern-based techniques

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This section:

- **Bloomfield et al (2020 & 2021, Met Applications)**

European surface climate/energy strongly influenced by large-scale circulation, e.g.:

- Brayshaw et al 2011; Santos-Alamillos et al 2012; Ely et al 2013; Grams et al 2017; van der Weil et al 2019; Bloomfield et al 2020

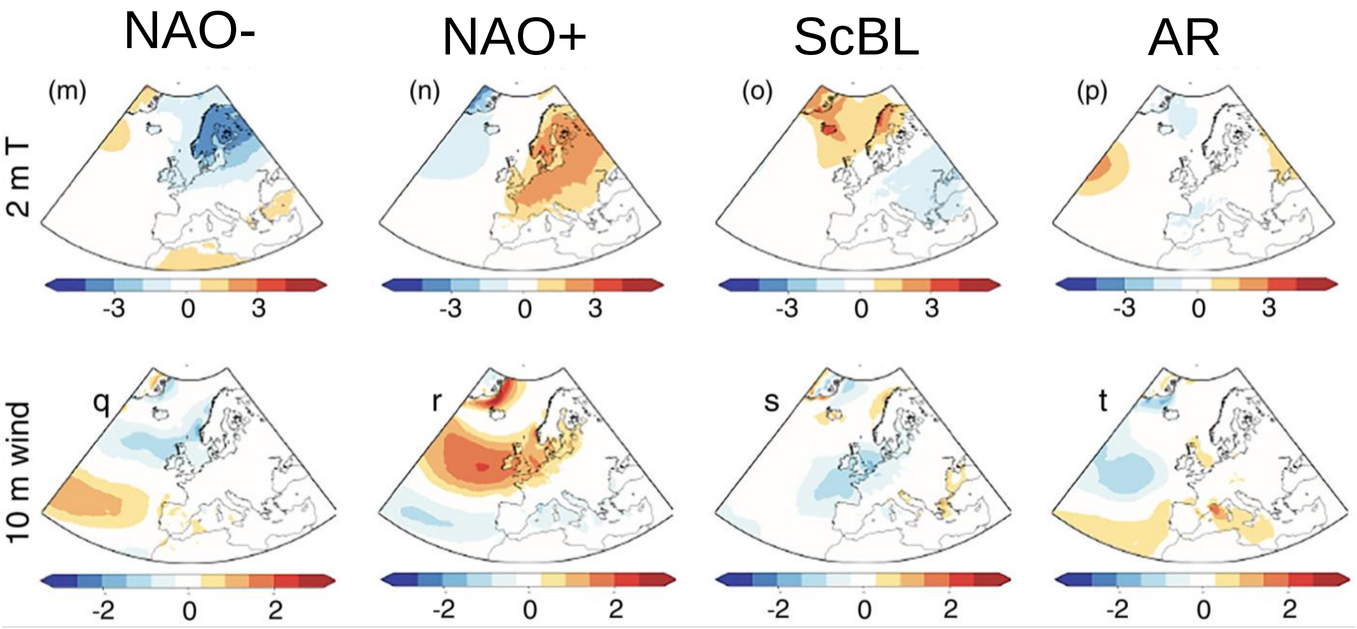
“Weather-regimes” (e.g., Cassou 2008)

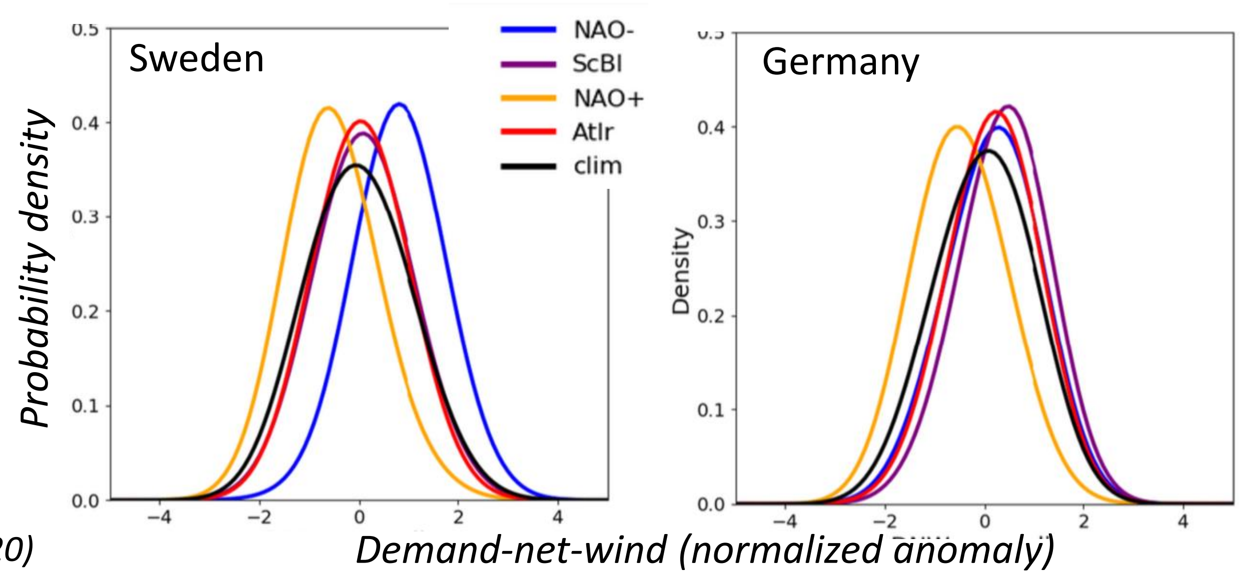
Large-scale circulation potentially offers predictability:

- Error growth from initial condition (type-I) uncertainty saturates at longer leads
- Spatio-temporal averaging enhances signal-to-noise
- Physical “drivers” typically large-scale

Two approaches:

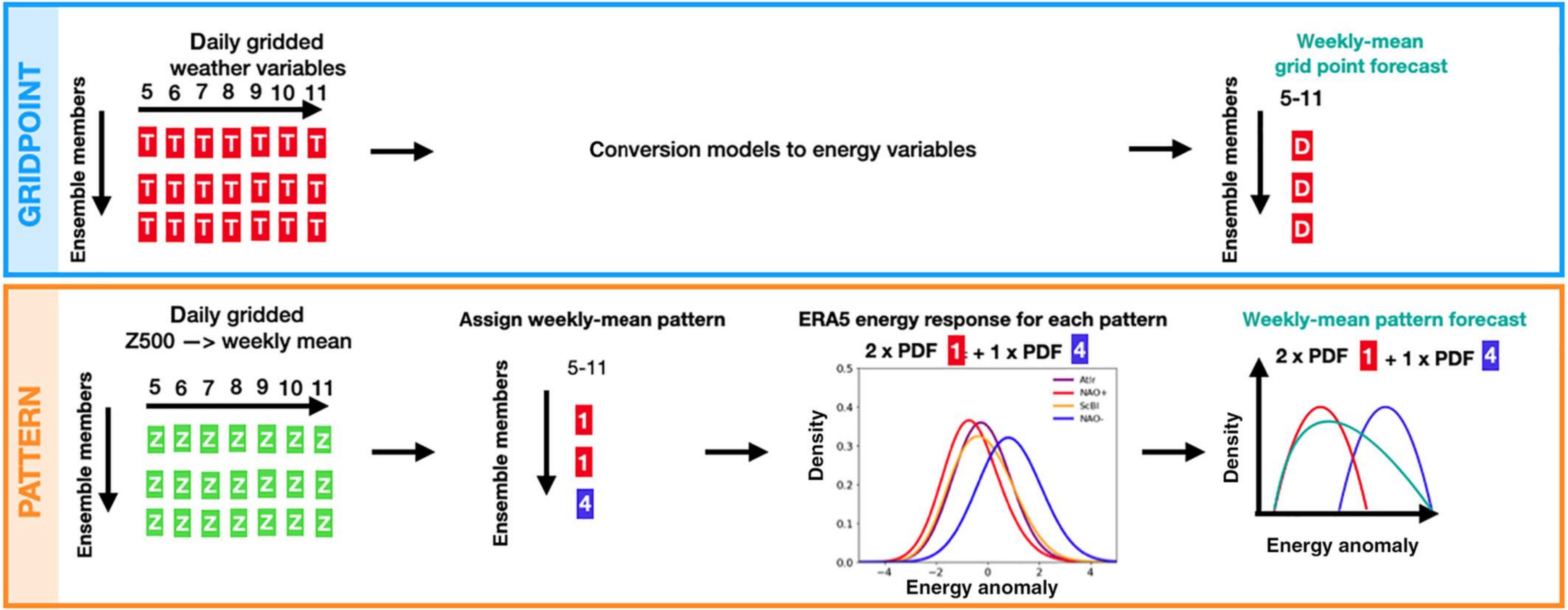
- Pattern-forecasting
- Conditional-prediction





Figs: Bloomfield et al (2020)

Approach 1 – Pattern 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

Week #	Day #
1	5-11
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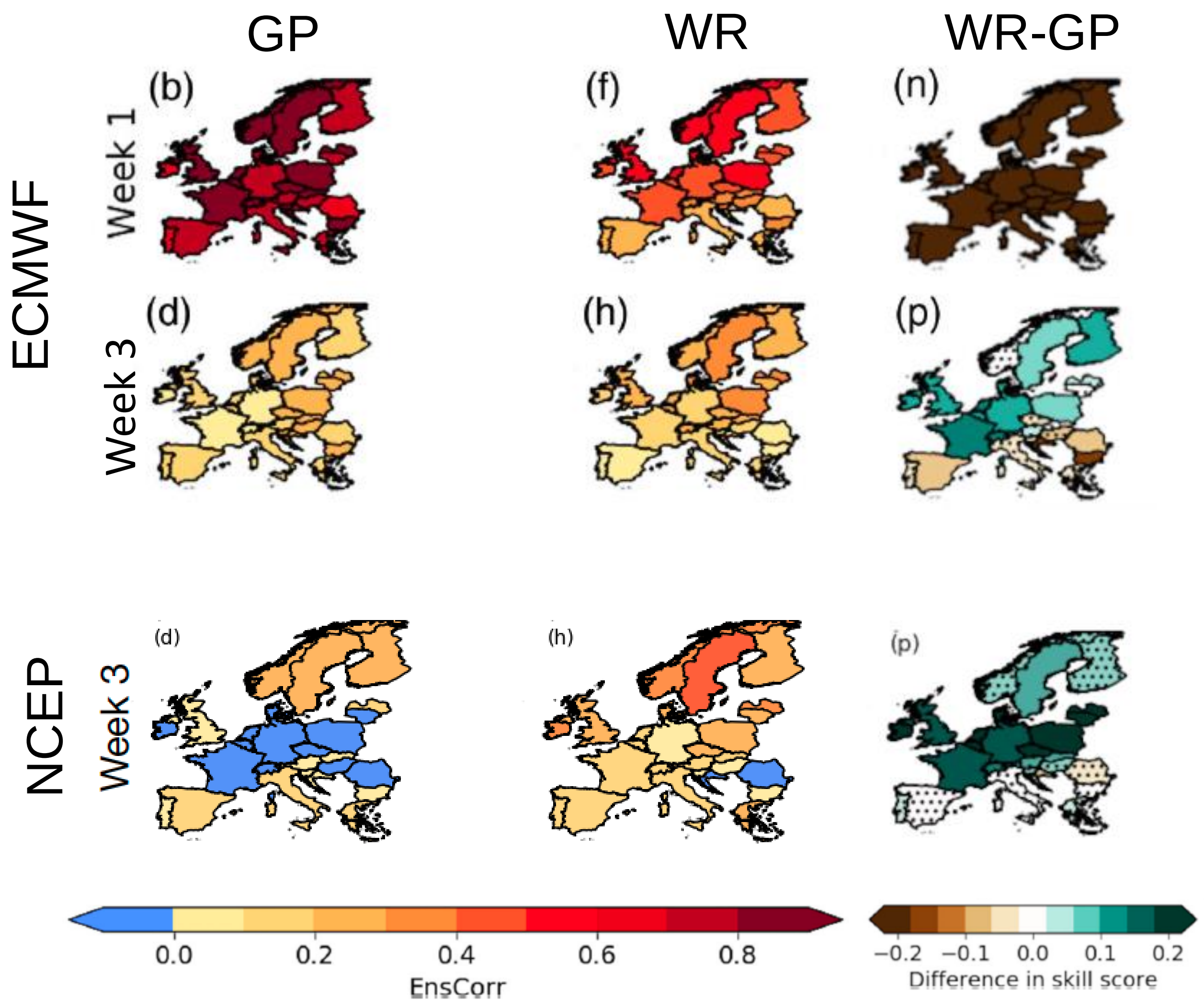
Winter (DJF) Demand-Net-Wind, weekly-mean EnsCorr
Skill w.r.t. climatological forecast

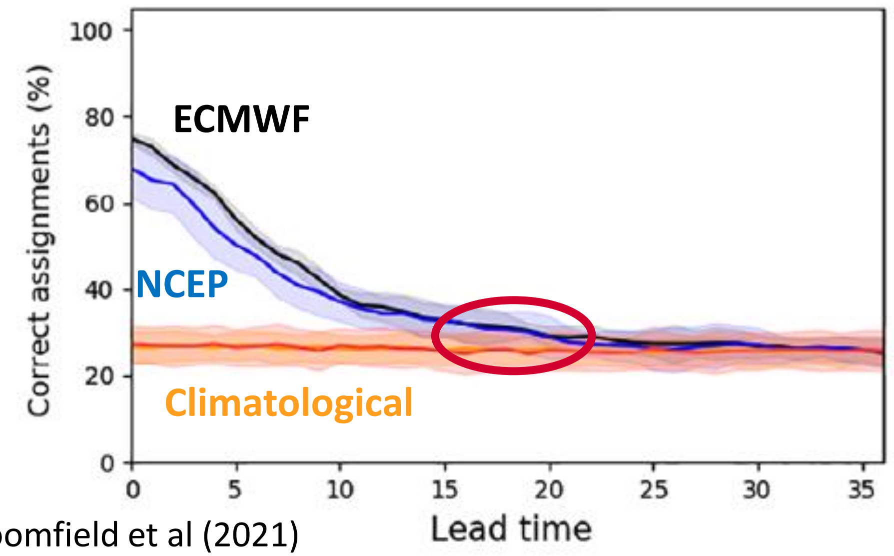


Figs: Bloomfield et al (2021)

Pattern-forecast discussion

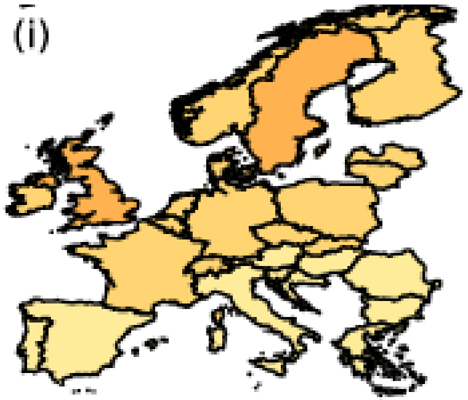
- Interpretation:
  - Forecast = (NWP-derived prediction of large-scale pattern) x (reanalysis-derived impact model)
  - NCEP more biased (w.r.t. ERA5 truth) than ECMWF so benefits more from 2-step process
- However:
  - Predictive skill for weekly-weather patterns at leads of 15-20 days
  - Weather-patterns 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

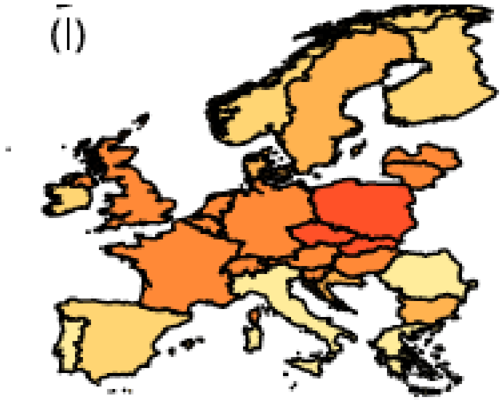


Figs: Bloomfield et al (2021)

Standard Weather Regimes

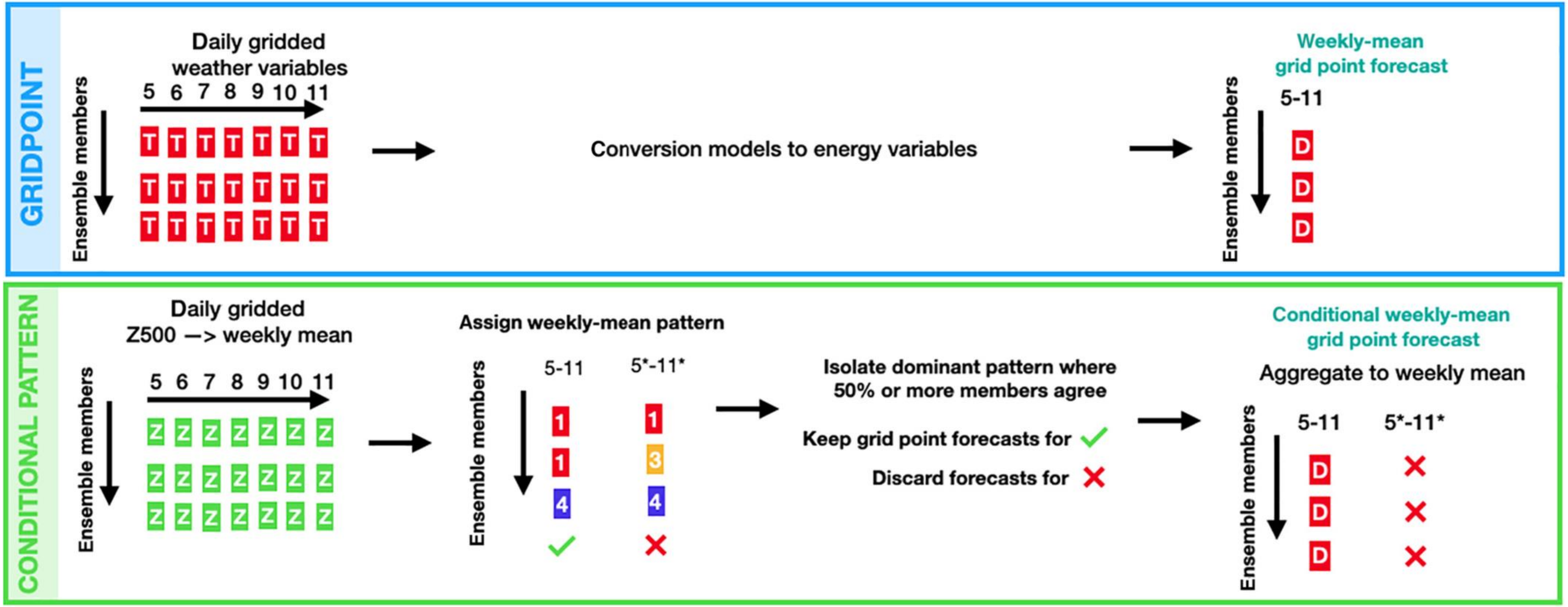


Targeted Circulation Types



DJF DNW CRPSS skill *assuming* perfect pattern forecast

Approach 2 - Conditional forecasting



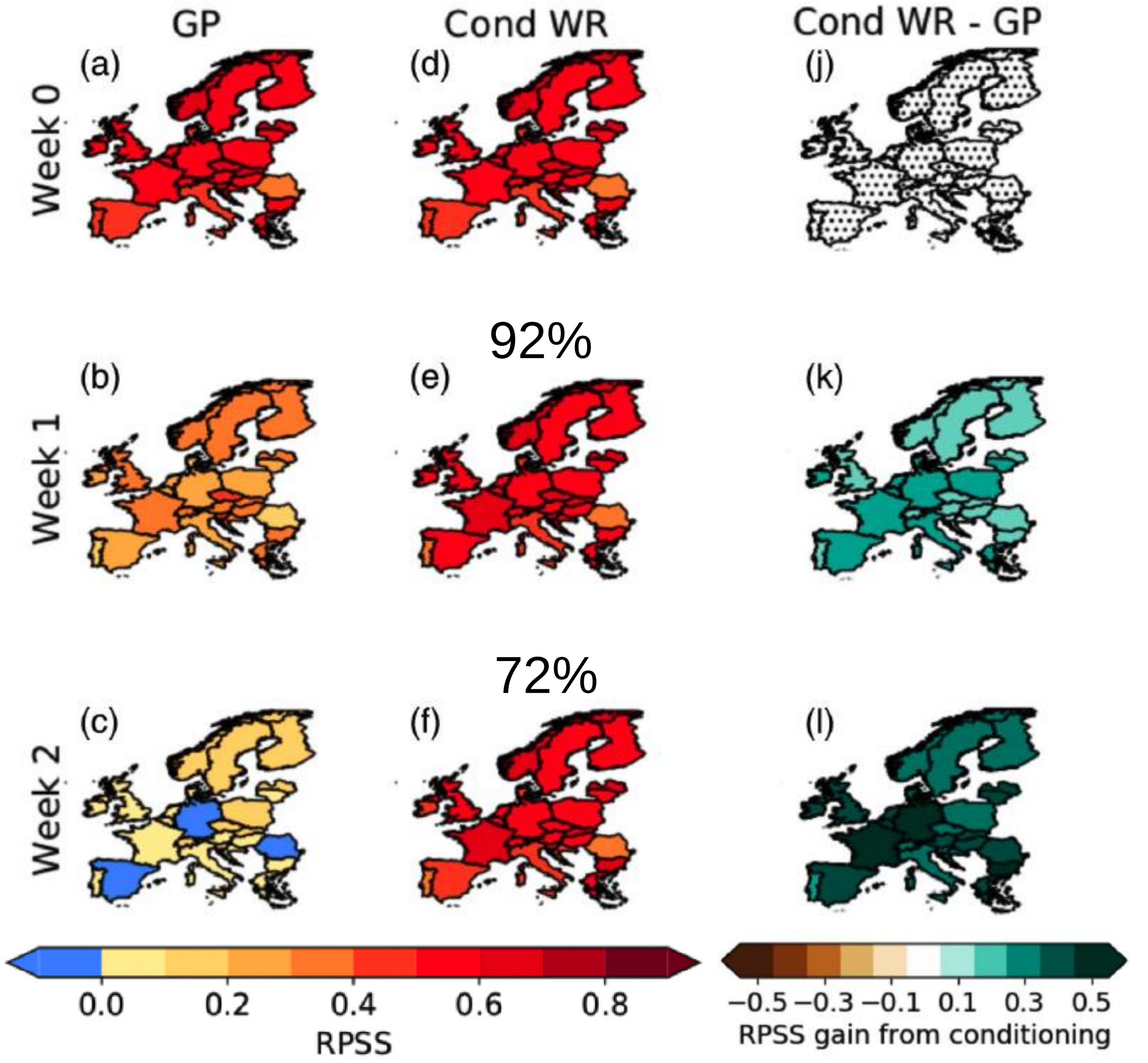
Predict the large-scale weather pattern (weekly-mean) → Use gridpoint forecast only if >50% of weather pattern assignments agree on a pattern

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

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



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

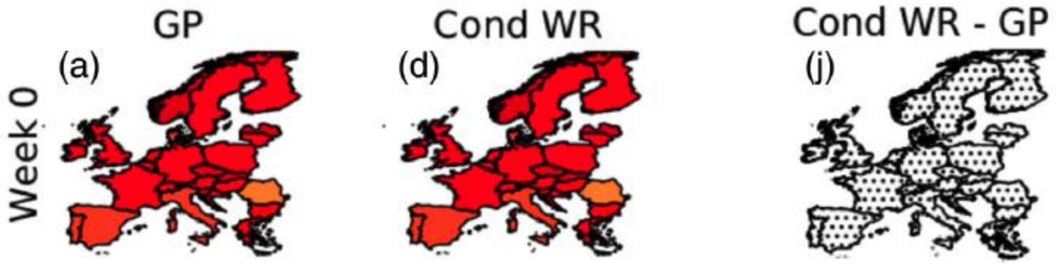
Conditional gridpoint forecast skill

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

- Modest number of forecasts discarded
  - 8% week 1

- Met

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



Part 1 – Summary for pattern-based 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

4 26-32

0.0 0.2 0.4 0.6 0.8
RPSS

−0.5 −0.3 −0.1 0.1 0.3 0.5
RPSS gain from conditioning

Figs: Bloomfield et al (2021)

Part 2 – Sequential Learning Algorithms

- **This section follows Gonzalez et al 2021 (QJ Royal Met Soc)**

- Multiple NWP systems (here NCEP-GFS/ECMWF-ER but also UKMO, DWD, MeteoFrance etc)
  - All have deficiencies, all have limited ensemble size
  - Wish to 'combine' to produce a single 'best' forecast
  - Possible also other expert datastreams (e.g., statistical forecasts) with predictive power

- Most approaches applied to NWP presently tend to:
  - Apply 'fixed weighting' schemes to component forecasts (based on a prior skill assessment)
  - Produce deterministic 'point forecast' output
  - Combine NWP forecasts but not other expert datastreams

- *Sequential learning algorithms (SLAs)* <u>may</u> offer many benefits:
  - Weighting evolves dynamically (adapts to skill changes, no need for offline retraining)
  - Probabilistic forecast output
  - Combine multiple types of forecast expert (not limited to NWP)

SLA - Methods

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- Language & terminology (for those more familiar with NWP!):
  - NWP ensemble properties (e.g., quantiles) ➔ 'experts'
  - Also reanalysis, statistical predictors etc ➔ 'experts'
  - *Thanks INI "Maths of Energy Systems" programme (2019).*

- Here, using the *converted-to-energy* datasets discussed previously over a common period (1999-2010):
  - ECMWF ER 11-member hindcast
    - ➔ Experts: MIN, Q10, Q35, Q50, Q65, Q90, MAX
  - NCEP GFS lagged 12-member hindcast
    - ➔ Experts: MIN, Q10, Q35, Q50, Q65, Q90, MAX
  - ERA5 'observations'
    - ➔ Experts: Climatology Q10, Q35, Q50, Q65, Q90
    - ➔ Experts: Seasonal climatology MAX MIN
    - ➔ Expert: Last week's weather PERS
    - ➔ Expert: Last year's weather PERS_1YR

- 4 different SLAs (of 2 basic types) – open source packages
  - *In all cases, a 'genuine' forecast is being made*

Name	Description
BOA	Bernstein Online Aggregation
EGA	Exponentiate Gradient Algorithm
BOA_NWP	BOA restricted to NWP experts
EGA_NWP	EGA restricted to NWP experts

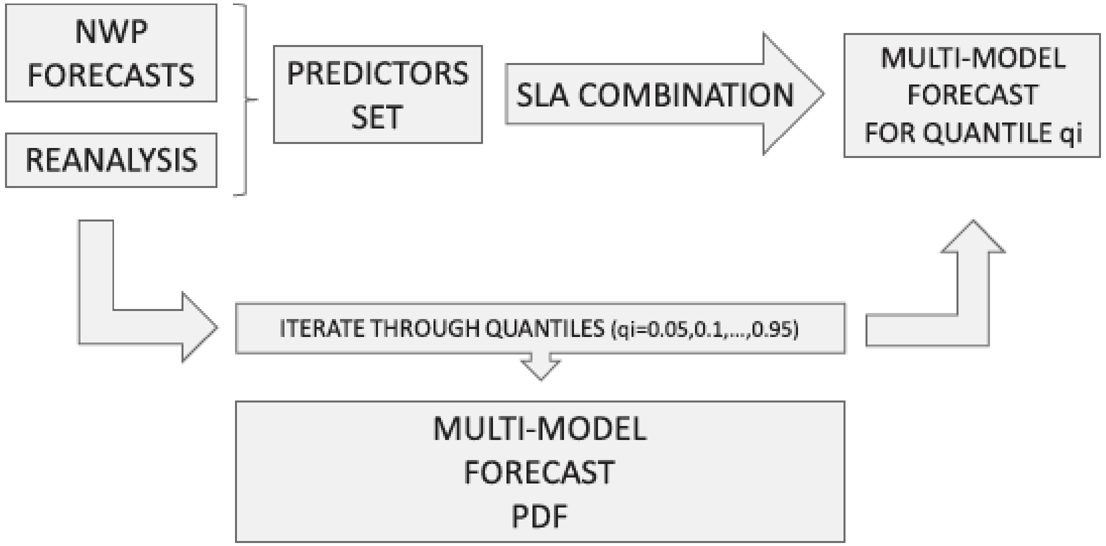

Fig: Gonzalez et al 2021

SLA methods – example weight evolution

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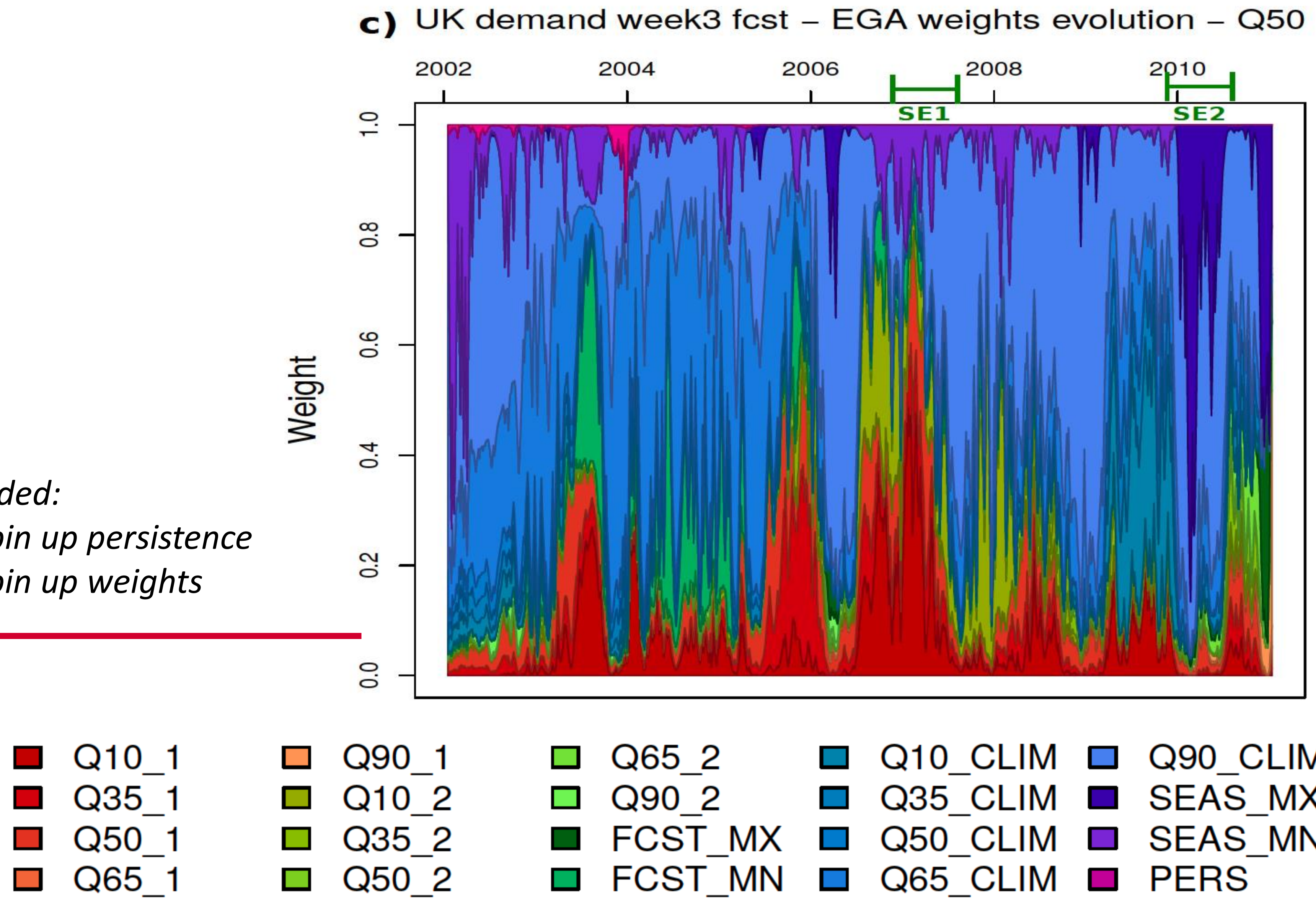

ERA5 experts (_CLIM)

NCEP experts (_2)

ECMWF experts (_1)

Discarded:
1-yr spin up persistence
2-yr spin up weights

Fig: Gonzalez et al 2021

SLA methods – example weight evolution

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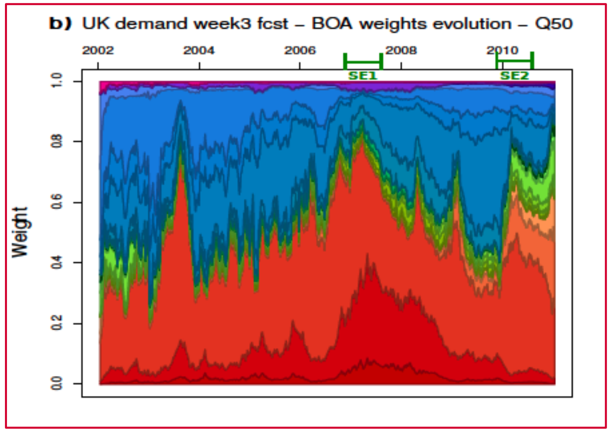

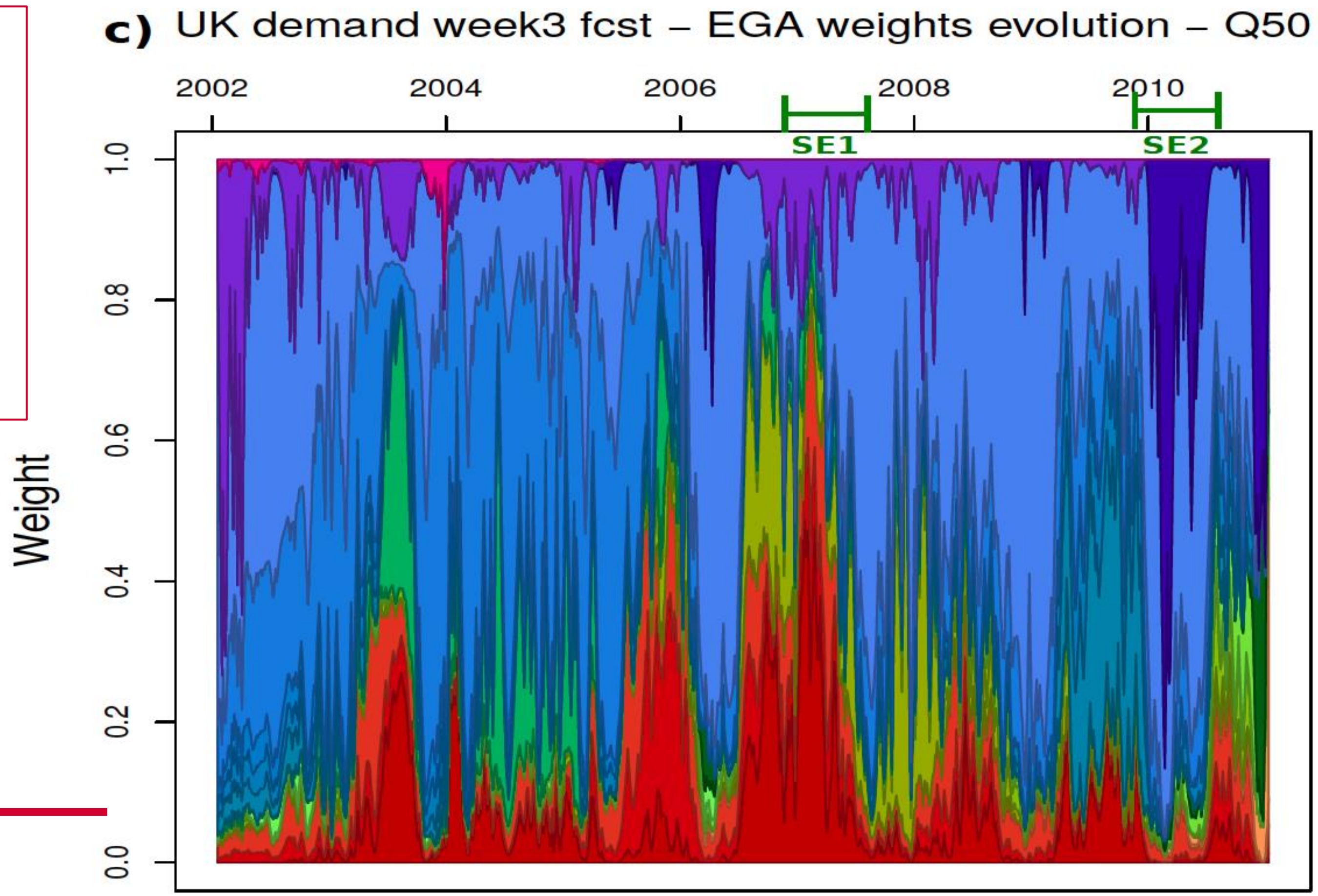

ERA5 experts (_CLIM)

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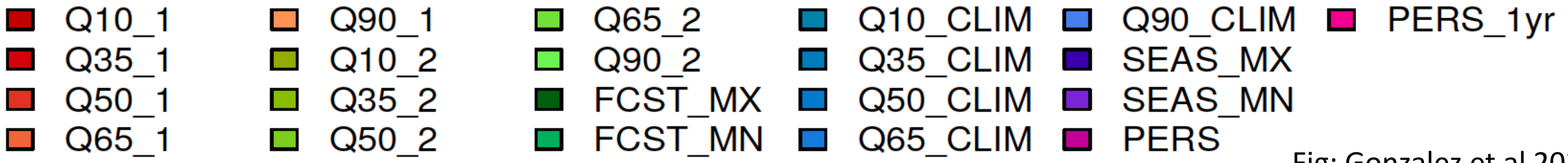


Fig: Gonzalez et al 2021

SLA forecast skill

- Pinball loss (~CRPSS) referenced to “Equal Weights NWP”
- UK Demand forecast
- Schemes ordered L→R on week 3
  - week 1: days 1–7;
  - week 2: days 8–14;
  - week 3: days 15–21;
  - week 4: days 22–28;
  - week 5: days 29–35.

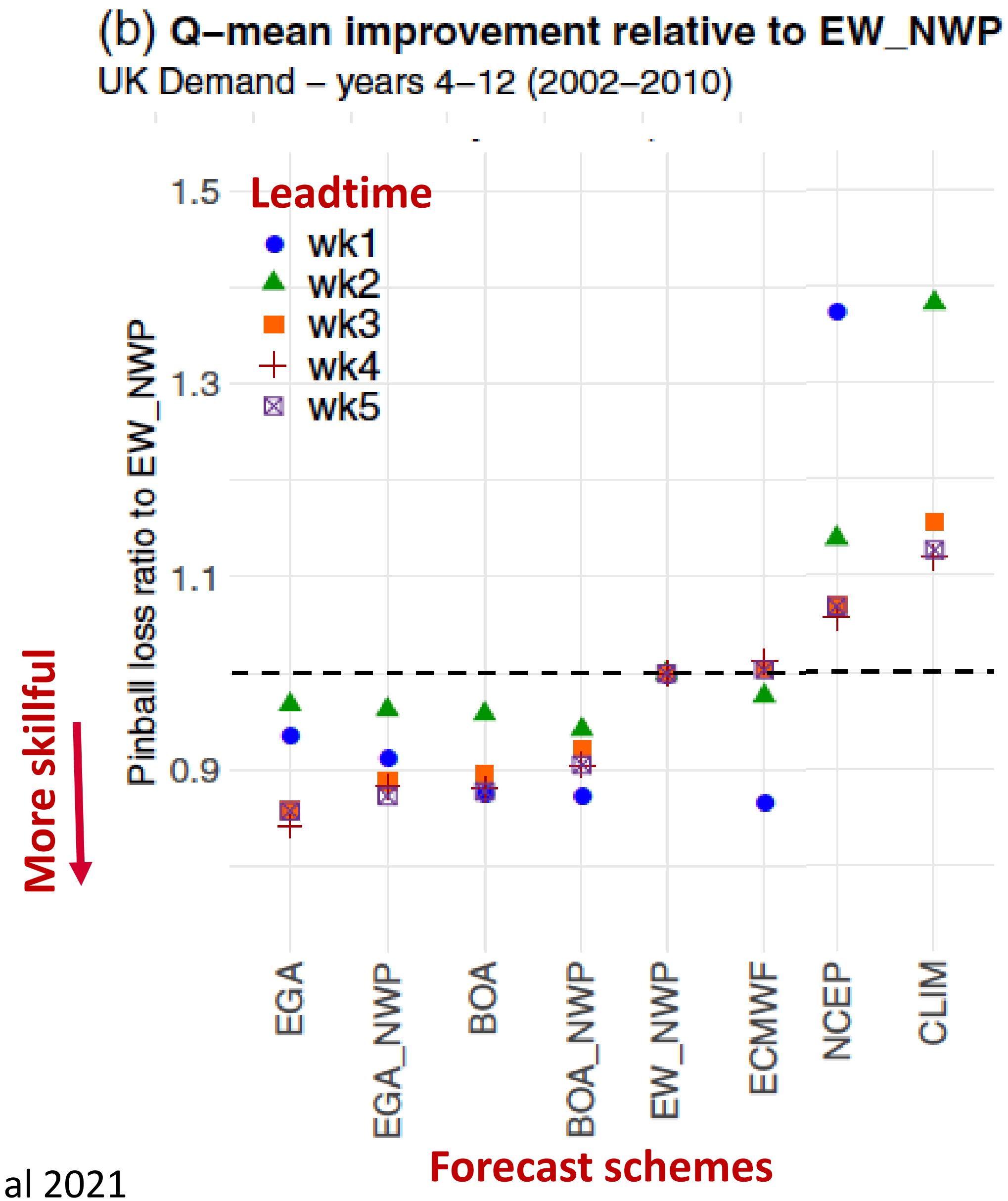


Fig: Gonzalez et al 2021

SLA forecast skill – week 1

- Pinball loss (~CRPSS) referenced to "Equal Weights NWP"
- UK Demand forecast
- Schemes ordered L→R on week 3
    - week 1: days 1–7;
    - week 2: days 8–14;
    - week 3: days 15–21;
    - week 4: days 22–28;
    - week 5: days 29–35.
- Week 1 (**blue dots**):
    - ECMWF best forecast (beats any combinations)
    - CLIM worst forecast (and NCEP poor**)
    - SLAs (BOA, EGA, BOA_NWP, EGA_NWP):
        - Outperform "Equal Weights"
        - Are outperformed by ECMWF

** Note: NCEP's relatively poor performance compared to ECMWF can be partly attributed to the use of ERA-5 (based on the ECMWF model) as the reference 'truth'

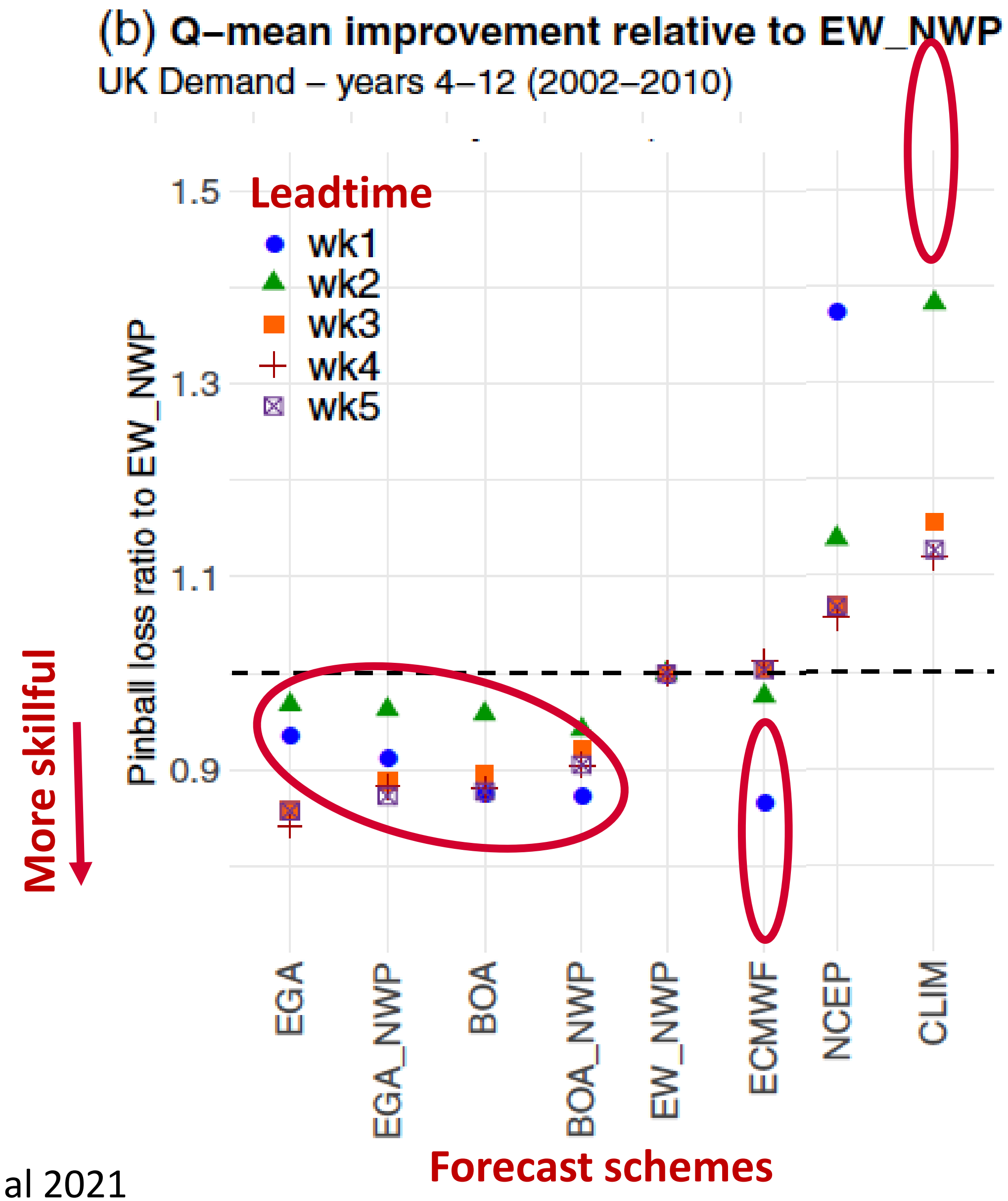


Fig: Gonzalez et al 2021

SLA forecast skill – week 3

- Week 3 (days 15-21) – orange squares
- SLAs (EGA and BOA):
  - Outperform any single forecast
  - Outperform Equal Weights (~10%)
- Adding "reanalysis experts" advantageous (few %)
  - EGA > EGA_NWP
  - BOA > BOA_NWP
- ECMWF best single forecast but outperformed by all combination schemes (EGA, BOA and, marginally, Equal-weights)
- *Note: qualitative behaviour is robust across case studies examined but "best" SLA (and quantitative improvement) varies*

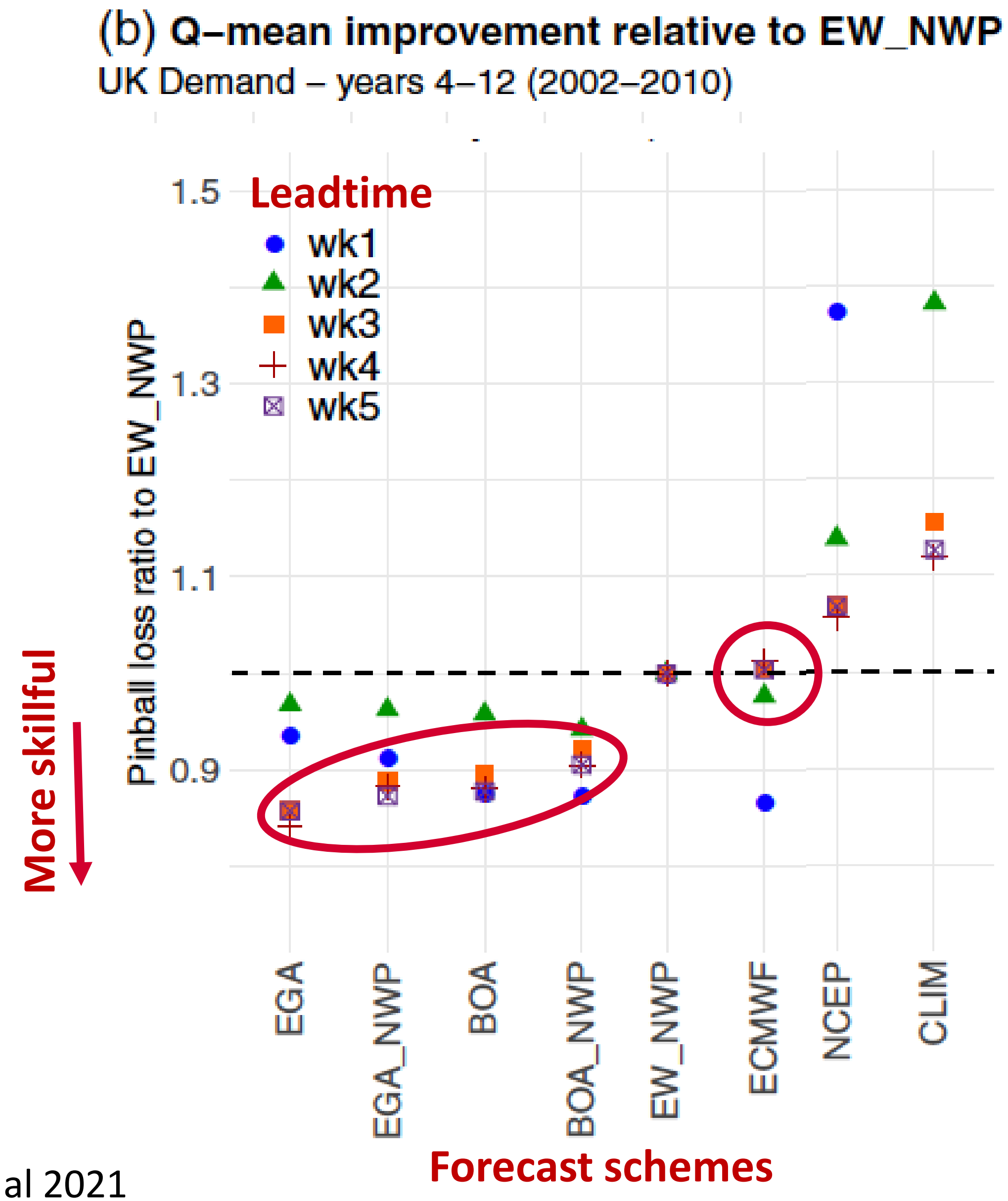
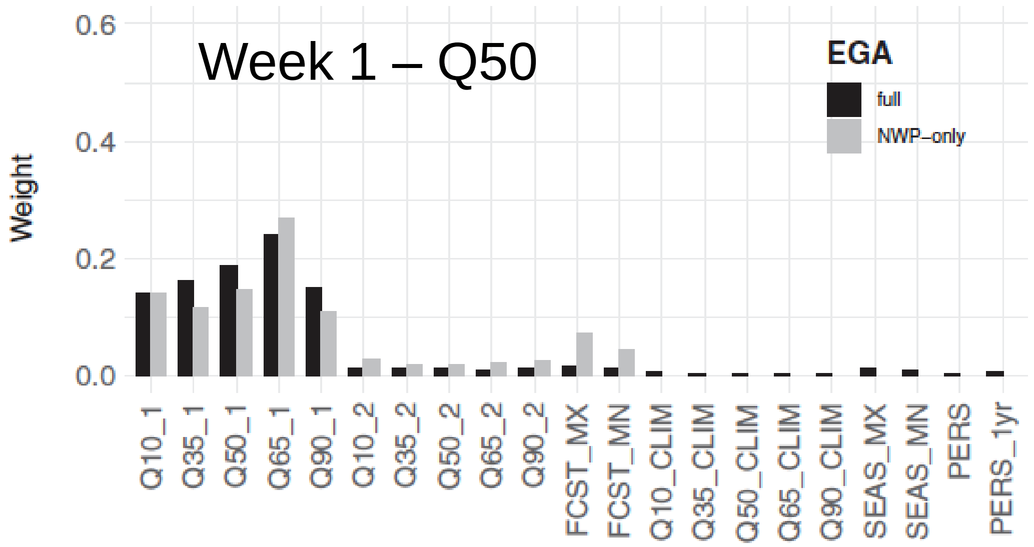
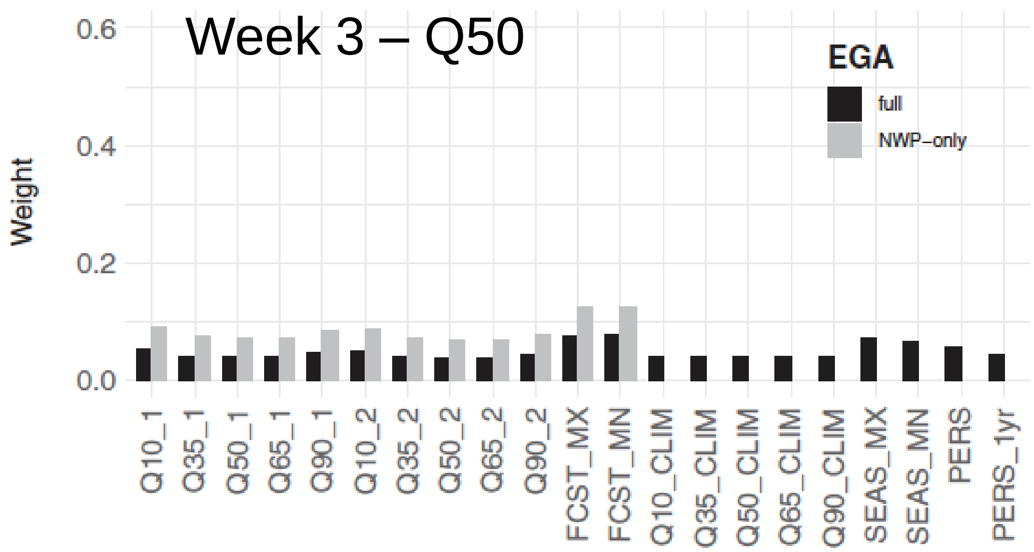


Fig: Gonzalez et al 2021

The role of weights



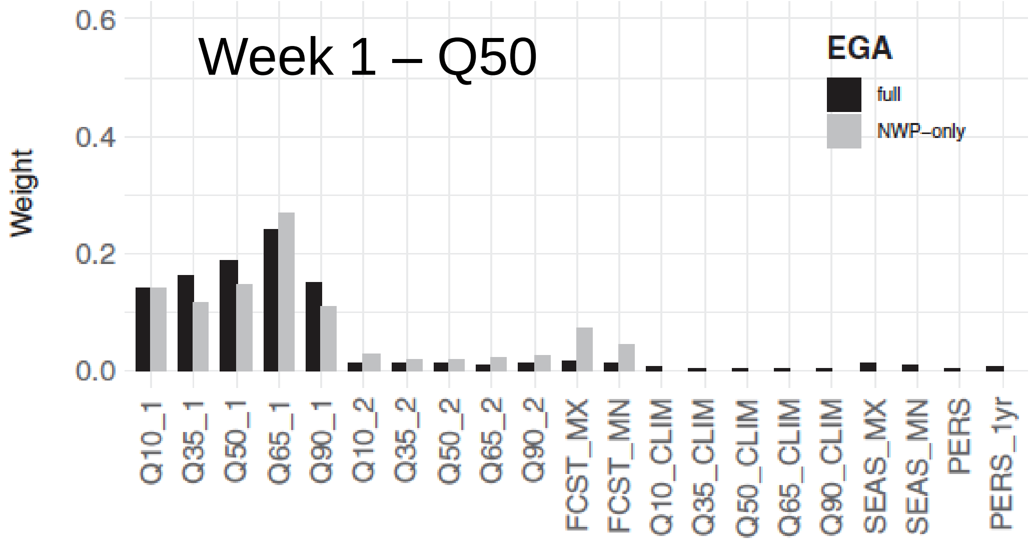


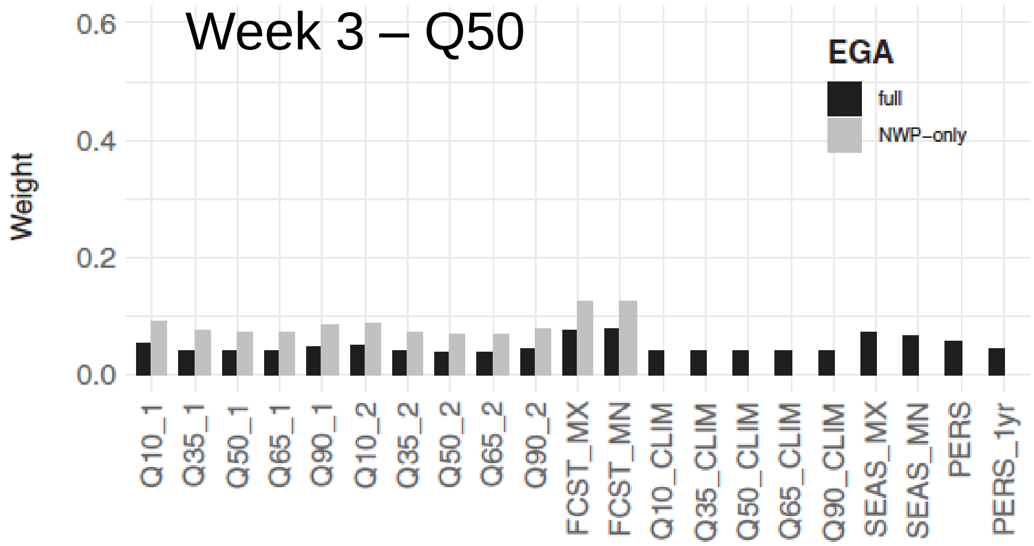
ECMWF > NCEP

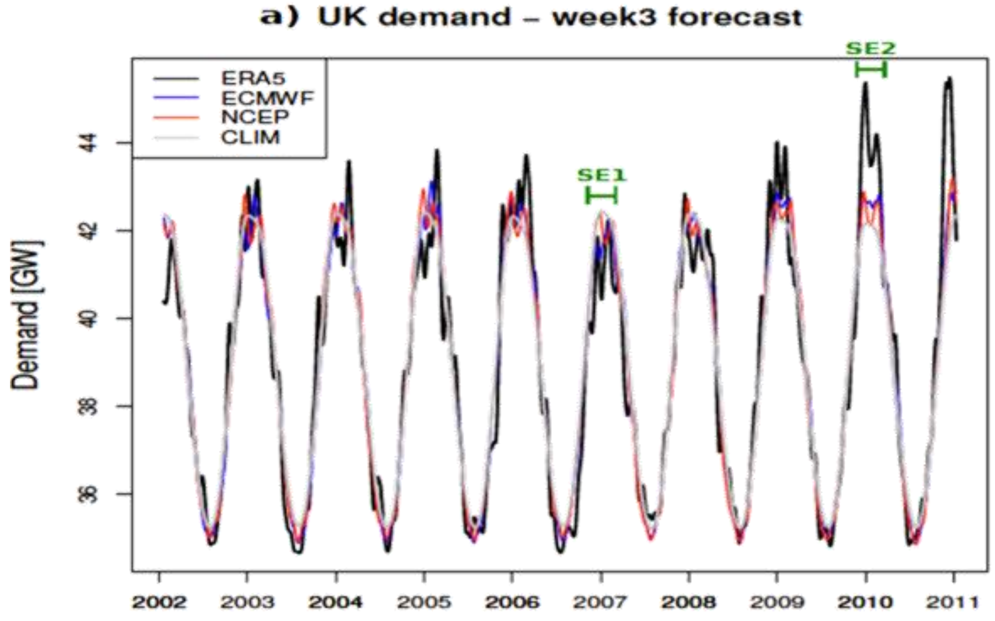
Longer leads ➔ more “climatology”

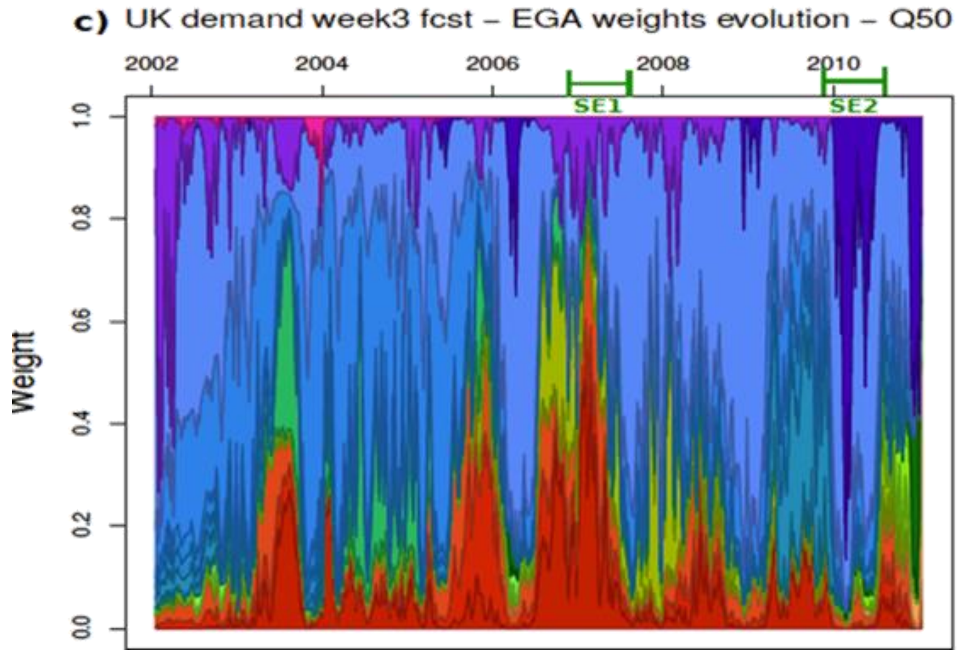
Skew in forecast quantiles

The role of weights



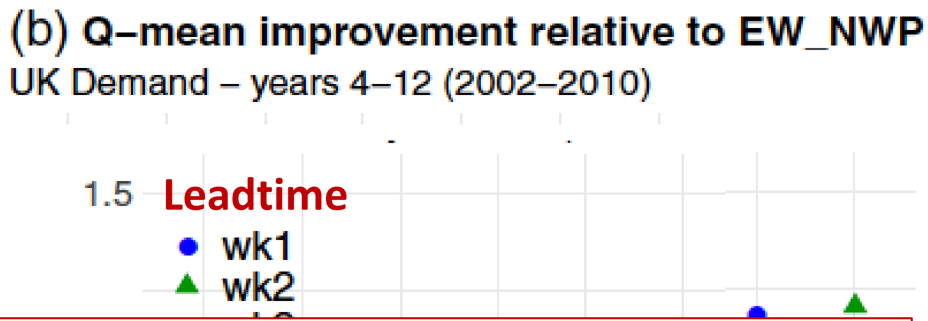






SLA forecast skill – week 3

- Week 3 (days 15-21) – orange squares
- EGA and BOA:
  - Outperform any single forecast
  - Outperform Equal Weights (~10%)



Part 2 – Summary for Sequential Learning Algorithms

- Significant possibilities for enhancing "modest skill" NWP (here, at extended range)
- By construction well-suited to operations, no need for offline training / refitting
- Able to combine multiple datastreams and adapt to change in skill
- Need for further understanding of the role played by the weights:
  - Residual bias adjustment, responding to "slow" evolution or learning "new" predictability?

Forecast schemes

Fig: Gonzalez et al 2021

Summary

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- Numerical Weather Prediction (NWP) models are a powerful tool
  - High-quality probabilistic (ensemble) forecasts, embedding physical behaviours and structures

- Nevertheless, in many cases NWP can be enhanced by statistical methods, e.g.:
  - Pattern-based and conditional forecasts
  - Sequential Learning Algorithms

- **Sequential learning algorithms** highly flexible
  - Significant improvements in skill
  - Open source code/packages
  - Well-suited to operations (no need for offline training, adapts when models/skill changes)
  - Combine multiple ”expert” prediction streams
  - … but somewhat “black box” regards weight evolution – need for more understanding

- Not discussed the decision-process
  - Forecast skill into forecast value (decision outcomes) – often related to optimization
  - See Brayshaw et al (2020, Met. Applications) for discussion (operations and planning)

Closing remarks

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- Next Generation Challenges in Energy-Climate Modelling workshop
  - 14th – 16th September 2022
  - Free to attend, highly interactive and opportunity to present research
  - See also Bloomfield et al (2021, Bull. Am. Met. Soc.) for overview of past events

- Climate Services and Climate Impact Modelling course
  - Starts January 2023
  - https://www.reading.ac.uk/meteorology/online-courses/classes

Contact and references

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