Enhancing skill through multi-model aggregations

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Climate Forecasting for Energy

S2S4E / openmod

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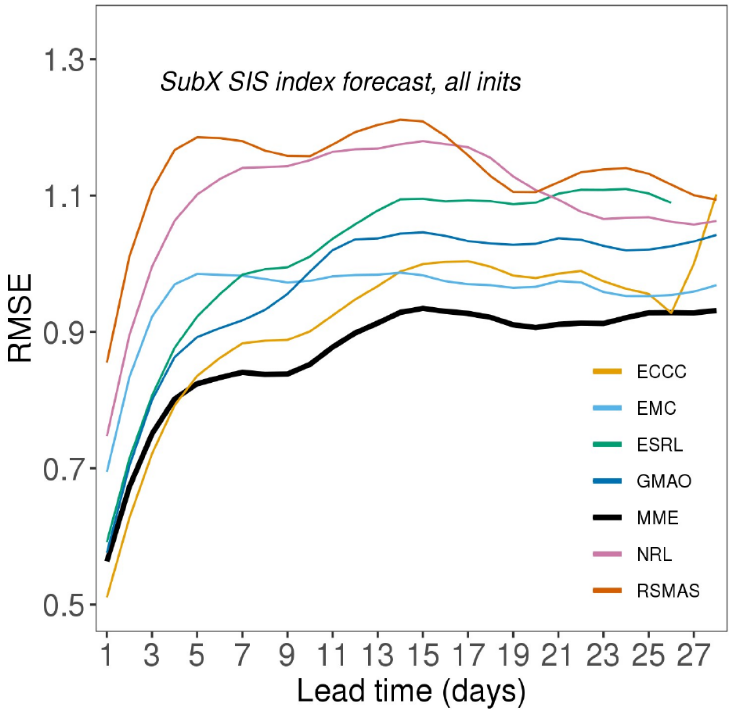
MOTIVATION

Multi-model combinations have been extensively shown to **enhance prediction skill** at different forecasting ranges (e.g., Hemri et al. 2020, Siebert and Stephenson 2019, Sansom et al. 2013, Weigel et al. 2008, DelSole 2007, Hagedorn et al. 2005).



Deterministic prediction skill of the SubX ensemble for an intraseasonal index.
Alvarez & Vera, CLIMAX project
(DOI: 10.13140/RG.2.2.30839.04009)

MME: standard, equal weight multi-model combination

- At short leads (weather forecast), some individual forecasting systems might outperform the MME;
- at longer leads, the MME shows reduced RMSE (root mean squared error) and improved ACC (anomaly correlation).

References: Hagerdorn et al. (2016) / Doblas-Reyes et al. (2016) The rationale behind the success of multi-model ensembles in seasonal forecasting. https://doi.org/10.3402/tellusa.v57i3.14657

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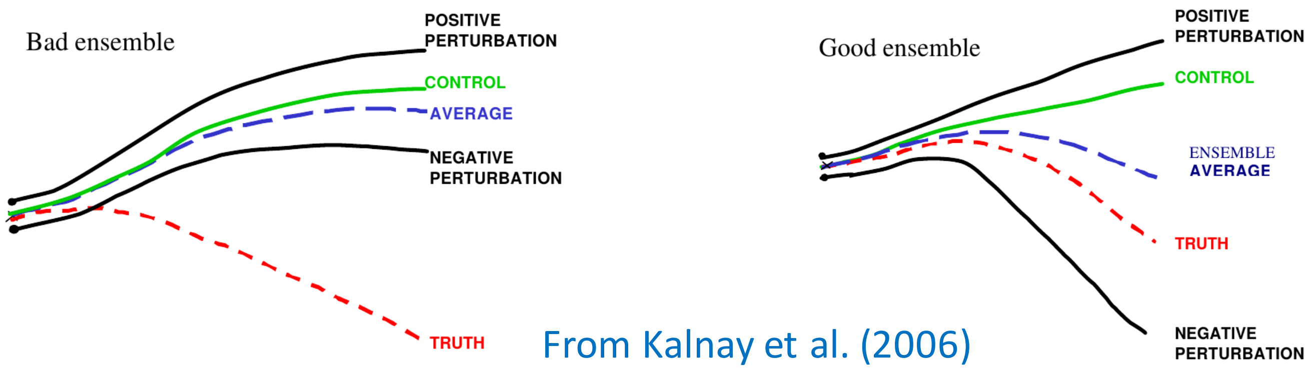
MOTIVATION

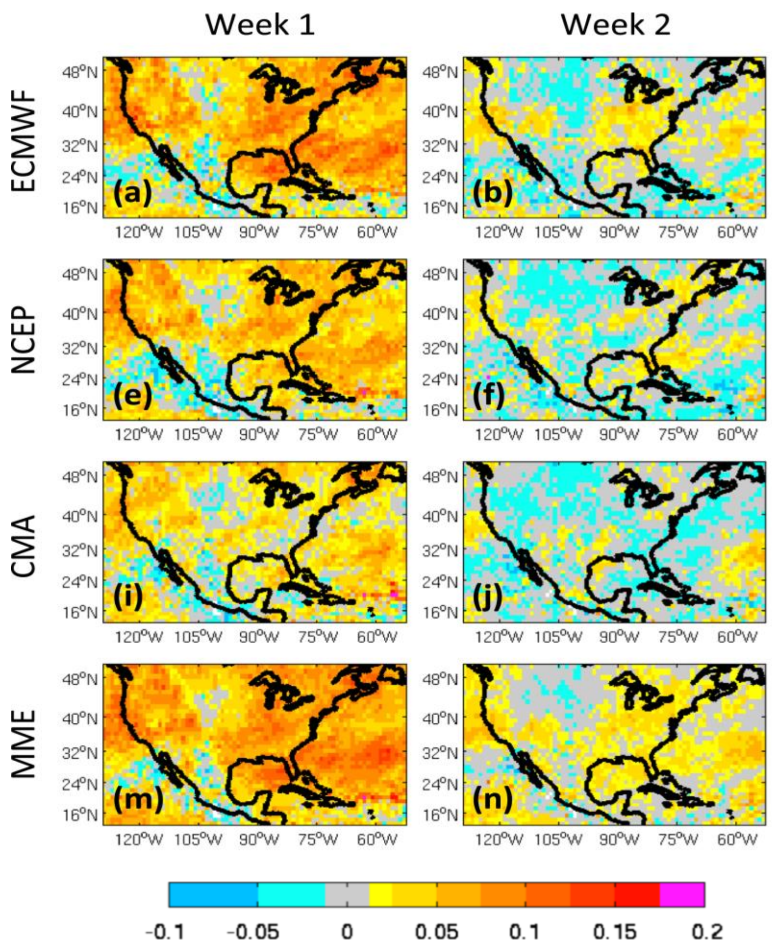
The improvements linked to multi-model combinations arise from several aspects, including:

- the **compensation of model errors** --> enhanced signal-to-noise ratio:
  - Different models have different dynamical cores and different sub-grid processes parameterizations
- the generation of a **larger ensemble** --> better representation of forecast uncertainty:
  - Single-model ensembles can be overconfident



From Kalnay et al. (2006)

JFM Precipitation RPSS – S2S ensemble



From Vigaud et al. (2017)

References: Hagerdorn et al. (2016) / Doblas-Reyes et al. (2016) The rationale behind the success of multi-model ensembles in seasonal forecasting. https://doi.org/10.3402/tellusa.v57i3.14657

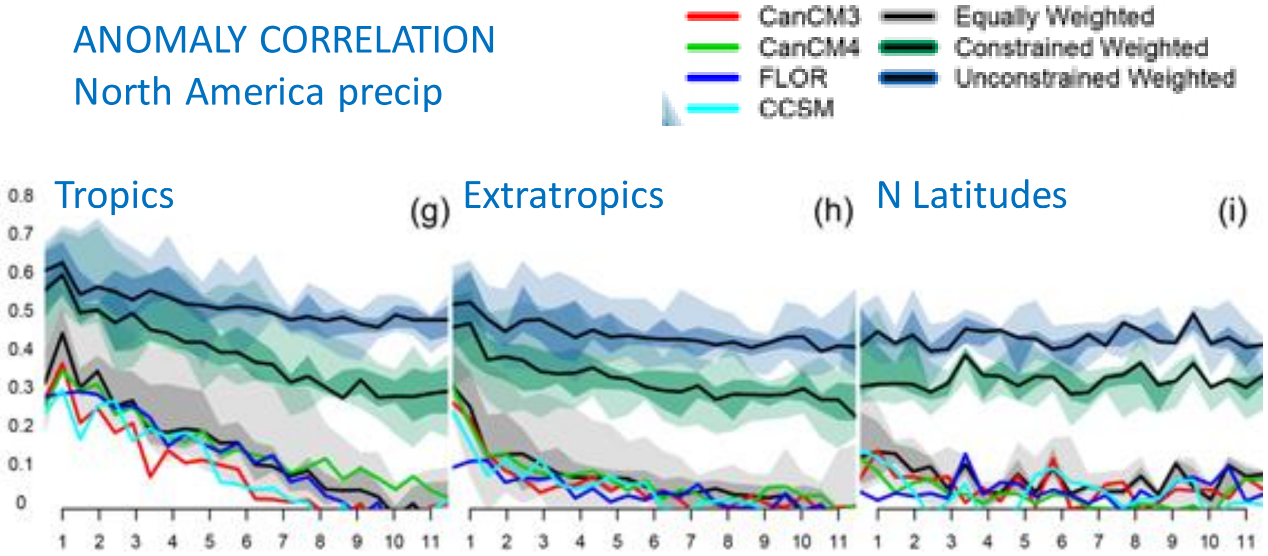
IMPLEMENTATION

The **combination** of multiple forecasting systems **is not trivial**:

- different ensemble generation methodologies and ensemble sizes,
- different launching calendars,
- different resolutions, vertical levels, etc.,
- lack of independence between systems.

Standard and innovative methods

- Equal weights / skill-based weight assignment
- Methods targeted towards probabilistic prediction: ensemble pooling, logistic regression, Bayesian model averaging
- Time-varying weights: machine learning methods (e.g., sequential learning/online prediction algorithms)



From Wanders & Wood (2016)

References: Manrique-Suñen et al. (2020) https://doi.org/10.1175/MWR-D-20-0067.1
Wanders and Wood (2016) https://doi.org/10.1088/1748-9326/11/9/094007

IMPLEMENTATIONS WITHIN S2S4E

In the context of **S2S4E**, **multi-model** combinations were explored both in the **subseasonal and seasonal forecast ranges**, using **standard methodologies** such as poolig or equal wights, but also more **innovative ML-based methods.**

1. **Llorenç Lledó et al. Seasonal prediction of Euro-Atlantic Teleconnection patterns.** Equal weight and ensemble pooling methods applied to the seasonal prediction of EATCs.
2. **Ilias Pechlivanidis et al. Seasonal prediction of European river streamflows.** Equal weight combination of seasonal predictions of the forcings to a hydrologic model.
3. **Franco Catalano et al. Definition of a metric of model independence** to aid the selection and combination of seasonal predictions.
4. **Paula Gonzalez et al. Use of sequential learning algorithms in subseasonal prediction** of energy variables.

All the **multi-model combinations resulted in improved predictions** with respect to individual systems, either through:

- higher skill,
- larger geographical extent of skill,
- longer predictability limits,
- or a combination of the above.

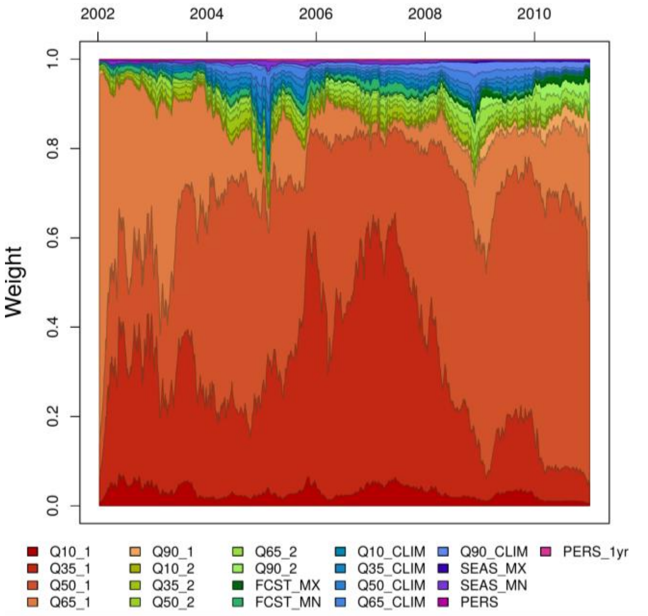
References: S2S4E Deliverable 4.4 (https://earth.bsc.es/s2s4e/lib/exe/fetch.php?media=s2s4e_d4.4.pdf)

Machine learning multi-model ensembles for subseasonal energy prediction

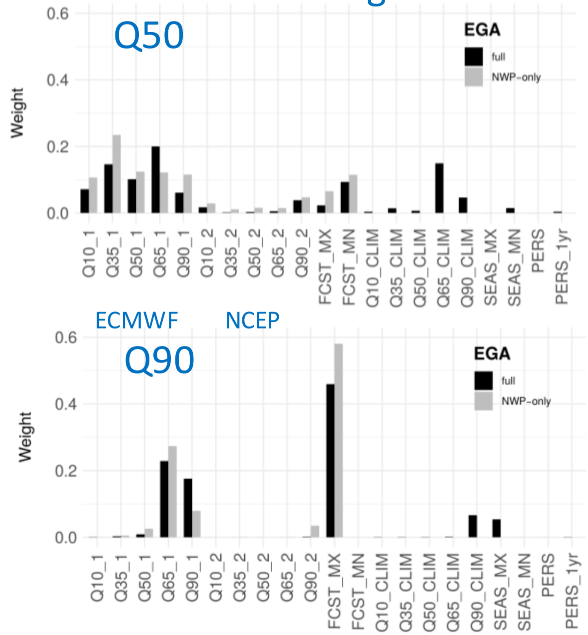
Motivation: ML sequential learning algorithms **combine 'experts' with time-varying weights** and have potential advantages :

- Combination **weights updated in every forecast step** to minimize a loss function;
- A different combination can be obtained **for different quantiles** of the predictand distribution,
- **Irrelevant experts are discarded** through minimal weights
- Admit experts of **different types**, allowing to explore 'seamless' prediction

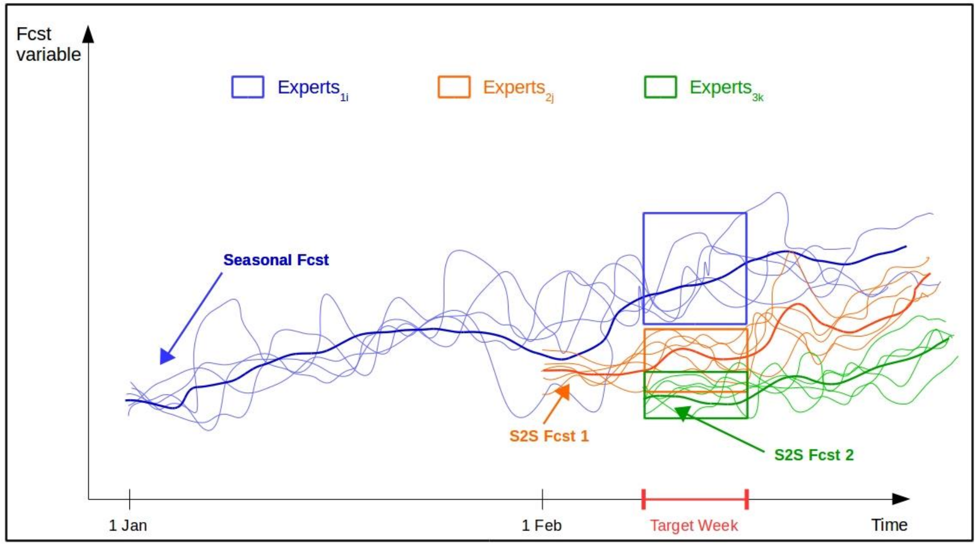
UK demand – week 2 hindcasts
Weights evolution



UK demand – week 2 hindcasts
Mean weights



Combining different types of forecasts



Reference: Gonzalez PLM, Brayshaw DJ, Ziel F. (2020) A new approach to subseasonal multi-model forecasting: sequential learning algorithms. In preparation.

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Subseasonal prediction of country level energy variables

Country-level energy **weekly** variables (demand, windpower) derived from two s2s systems (ECMWF ER, NCEP CFSv2) and ERA5 (All available from UREAD's Research Data Archive: https://researchdata.reading.ac.uk/)

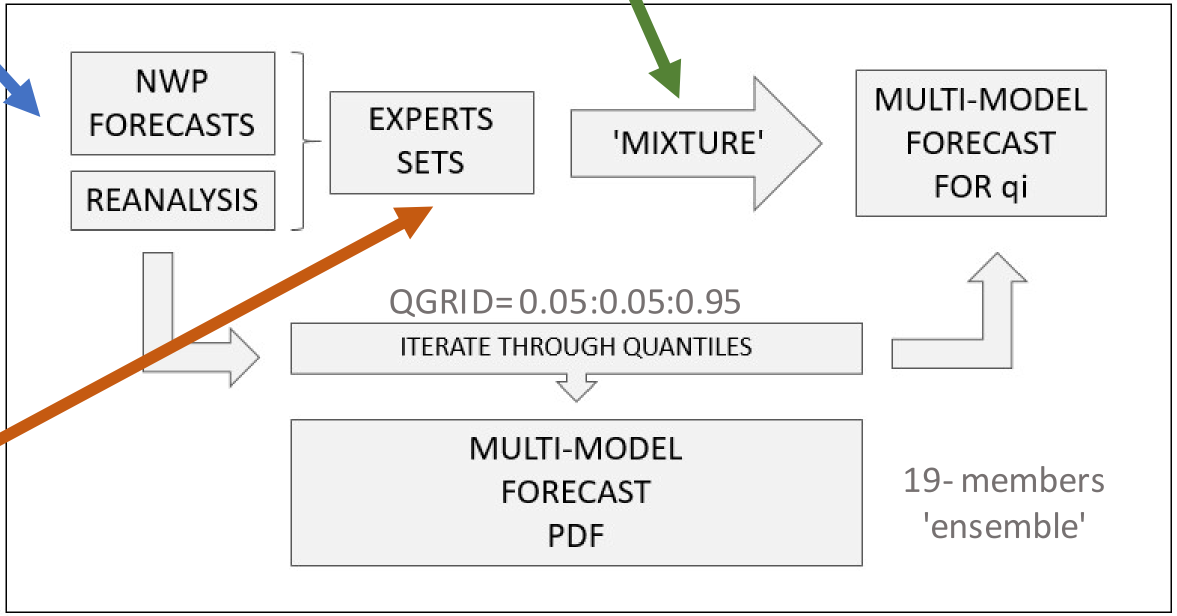
EXPERTS

NWP-based:
- quantiles of the forecasts' distributions
- seasonal max/min

Reanalysis-based:
- quantiles of the climatology
- seasonal max/min
- persistence
- 1yr persistence

ALGORITHMS

- **BOA**: Bernstein online aggregation -> **evolving learning rate**
- **EGA**: Exponentiated gradient algorithm -> **fixed learning rate**



SET-UPS

- **full**: considering all experts
- **NWP-only**: with only the experts from the hindcasts

(And with further optimizations explored)

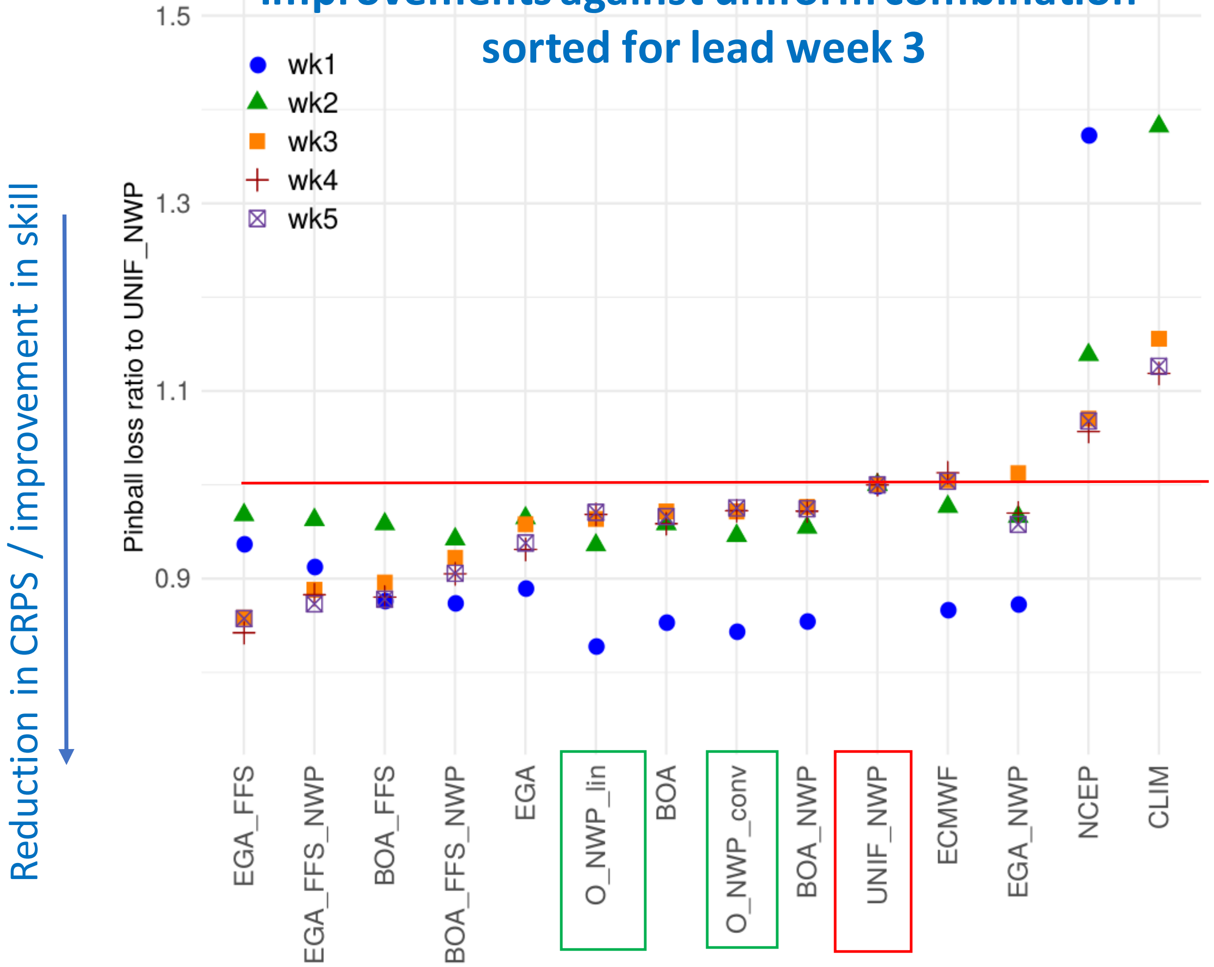
Reference: Gonzalez PLM, Brayshaw DJ, Ziel F. (2020) A new approach to subseasonal multi-model forecasting: sequential learning algorithms. In preparation.

Subseasonal prediction of country level energy variables

RESULTS

- SKILL METRIC: Quantile-mean pinball loss: ~ **CRPS**
- The two multi-model aggregation algorithms showed **significant skill improvements** with respect to the climatology, standard multi-model methods and the individual best NWP system (ECMWF) for **weeks 2-5**.
- The optimized BOA and EGA mixtures, which were the most skillful combinations, resulted in average **improvements ranging around 7-15% in the ~ CRPS for weeks 3, 4 and 5**.
- In the results presented here, some **additional skill** was obtained when the mixtures included **reanalysis-based experts**.
- Results from **other countries and variables are consistent**.

UK demand
Improvements against uniform combination sorted for lead week 3



'oracles': optimal lineal combinations --> knowledge of the full period

Reference: Gonzalez PLM, Brayshaw DJ, Ziel F. (2020) A new approach to subseasonal multi-model forecasting: sequential learning algorithms. In preparation

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DISCUSSION

- **Multi-model combination** have the potential to result in **improved predictions** with respect to individual systems.

- The different methodologies can be **more applicable to specific situations** (region, timescale, variable). There is no 'one-size-fits-all' and they **should not be applied as a 'black box'**. (e.g., Knutti et al. 2010, Mishra et al 2019)

- The more innovative **sequential learning algorithms** were shown to outperform other conventional multi-model methodologies, particularly for longer lead times. Their benefits extend beyond multi-model prediction since they have the potential to improve prediction through:
  - the incorporation of reanalysis-based and other **non-conventional 'experts'** (e.g., regimes);
  - the incorporation of **prior starts** of the same system,
  - the design of a **'seamless' forecasting system**, merging seasonal and sub-seasonal products,
  - the possibility to **correct remaining biases** in the systems, etc.

- Machine learning and AI methodologies are promising and increasingly recognized as **'emerging data science tools'** in earth system research due to their capabilities to identify recurring patterns, reduce noise, etc.

THANKS!

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References: Knutti et al. (2010) https://doi.org/10.1175/2009JCLI3361.1
Mishra et al. (2019) https://doi.org/10.1007/s00382-018-4404-z

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