

About ECMWF

Playing a unique role

Reading

Bonn

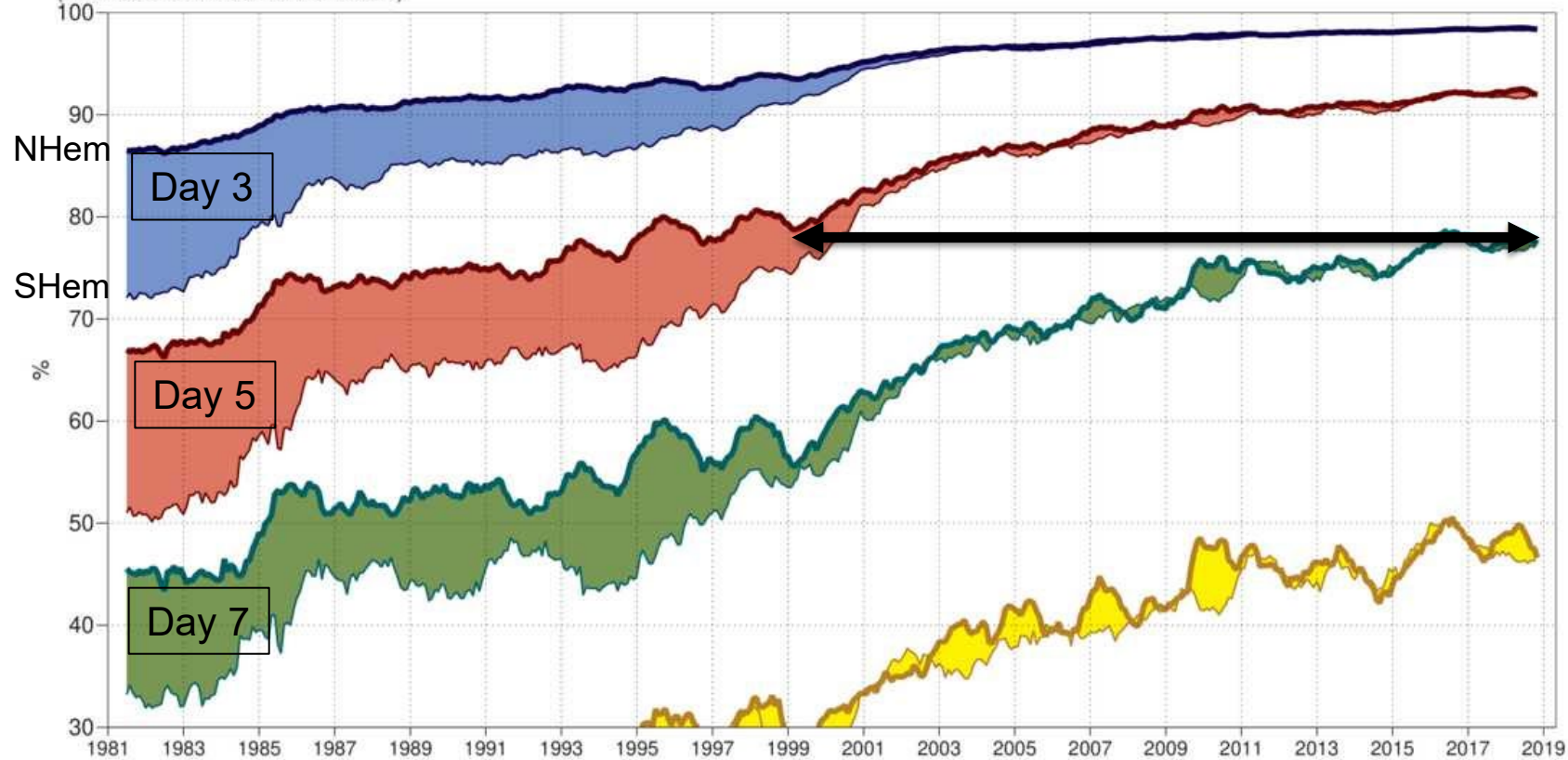
Bologna

ECMWF's role is to address the critical and most difficult research problems in medium-range NWP that no one country could tackle on its own

Dramatically improving accuracy.....

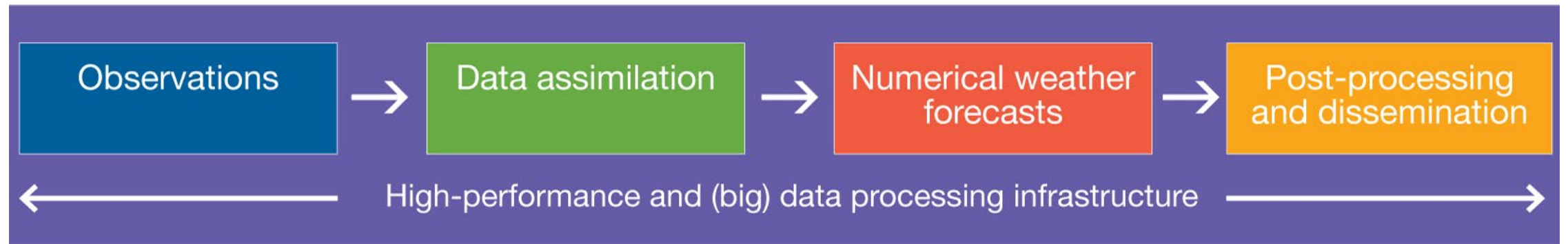
500hPa geopotential height
Anomaly correlation
12-month running mean
(centered on the middle of the window)

- Day 7 NHem
- Day 7 SHem
- Day 10 NHem
- Day 10 SHem
- Day 3 NHem
- Day 3 SHem
- Day 5 NHem
- Day 5 SHem

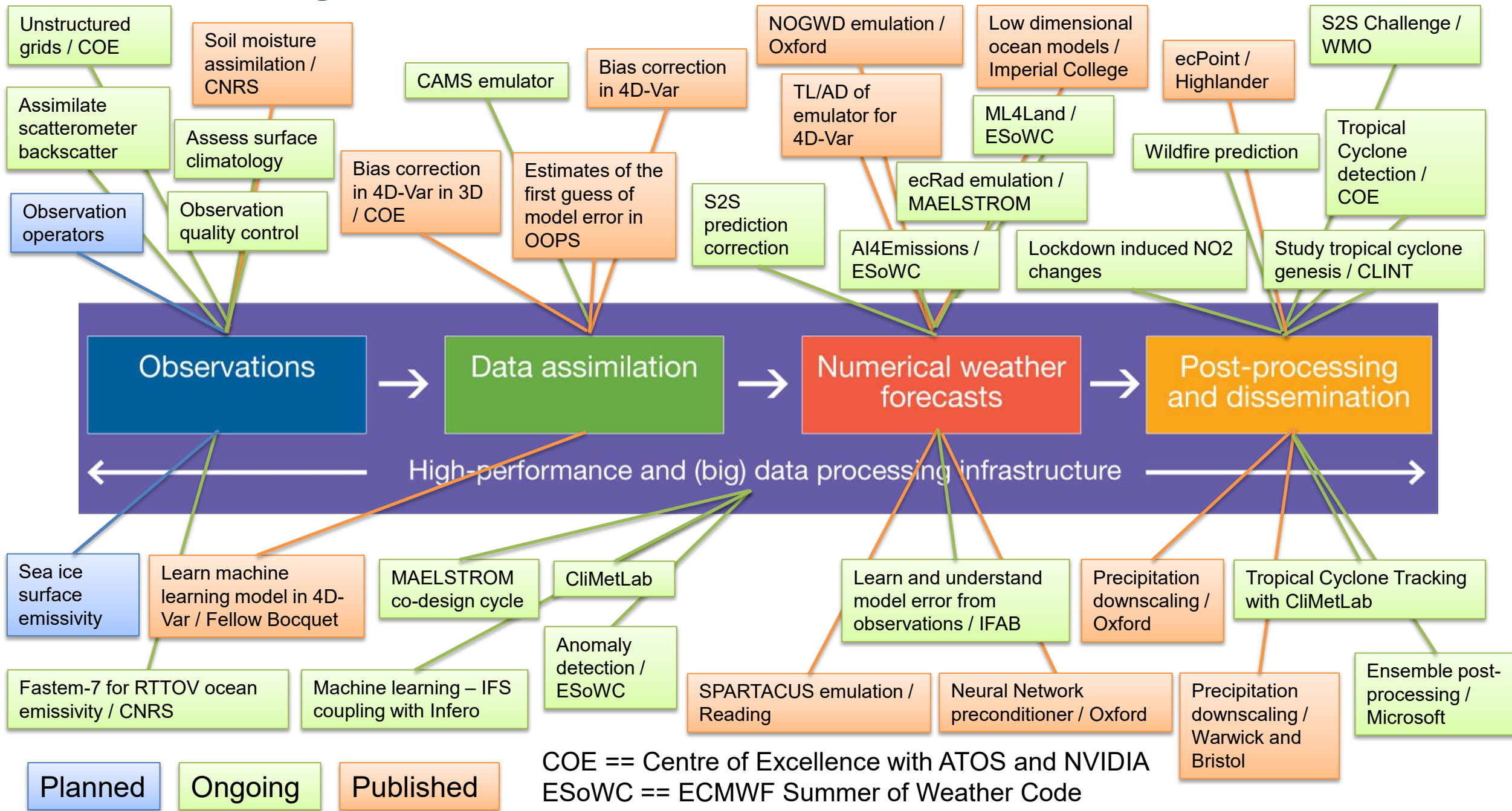


Improving

Numerical Weather Prediction




Machine learning at ECMWF



Machine learning roadmap

<https://www.ecmwf.int/en/eLibrary/19877-machine-learning-ecmwf-roadmap-next-10-years>

Technical Memo

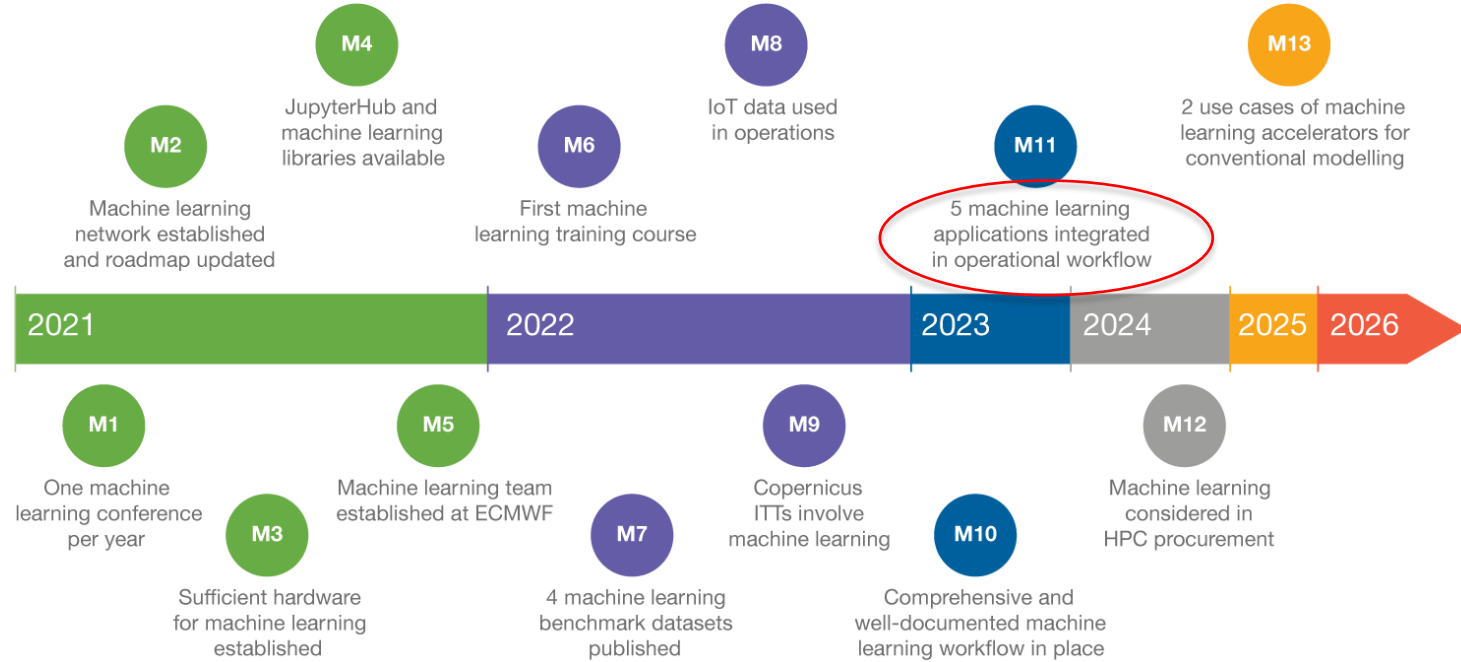


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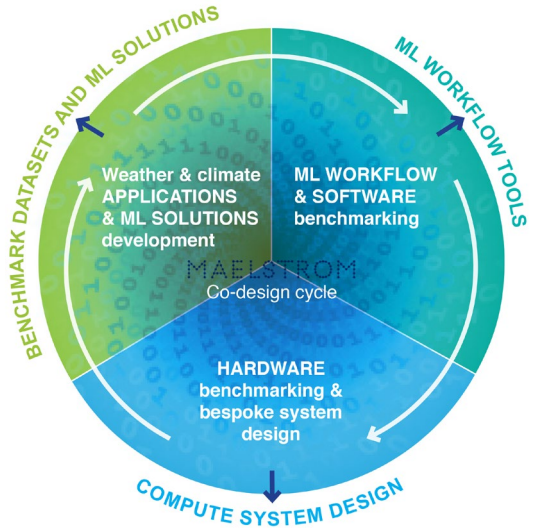
Machine learning at ECMWF: A roadmap for the next 10 years

Peter Dueben, Umberto Modigliani, Alan Geer, Stephan Siemen, Florian Pappenberger, Peter Bauer, Andy Brown, Martin Palković, Baudouin Raoult, Nils Wedi, Vasileios Baousis

January 2021



- Vision 2031**
- It is difficult to distinguish between machine learning and domain sciences
 - Data handling fully capable to serve machine learning needs
 - Fully supported diagnostic tools via trustworthy AI
 - Physical constraints can be represented in deep learning
 - Use of machine learning as easy and normal as data re-gridding
 - Unsupervised learning and causal discovery used on a regular basis
 - Machine learning solutions from end-users integrated in workflow

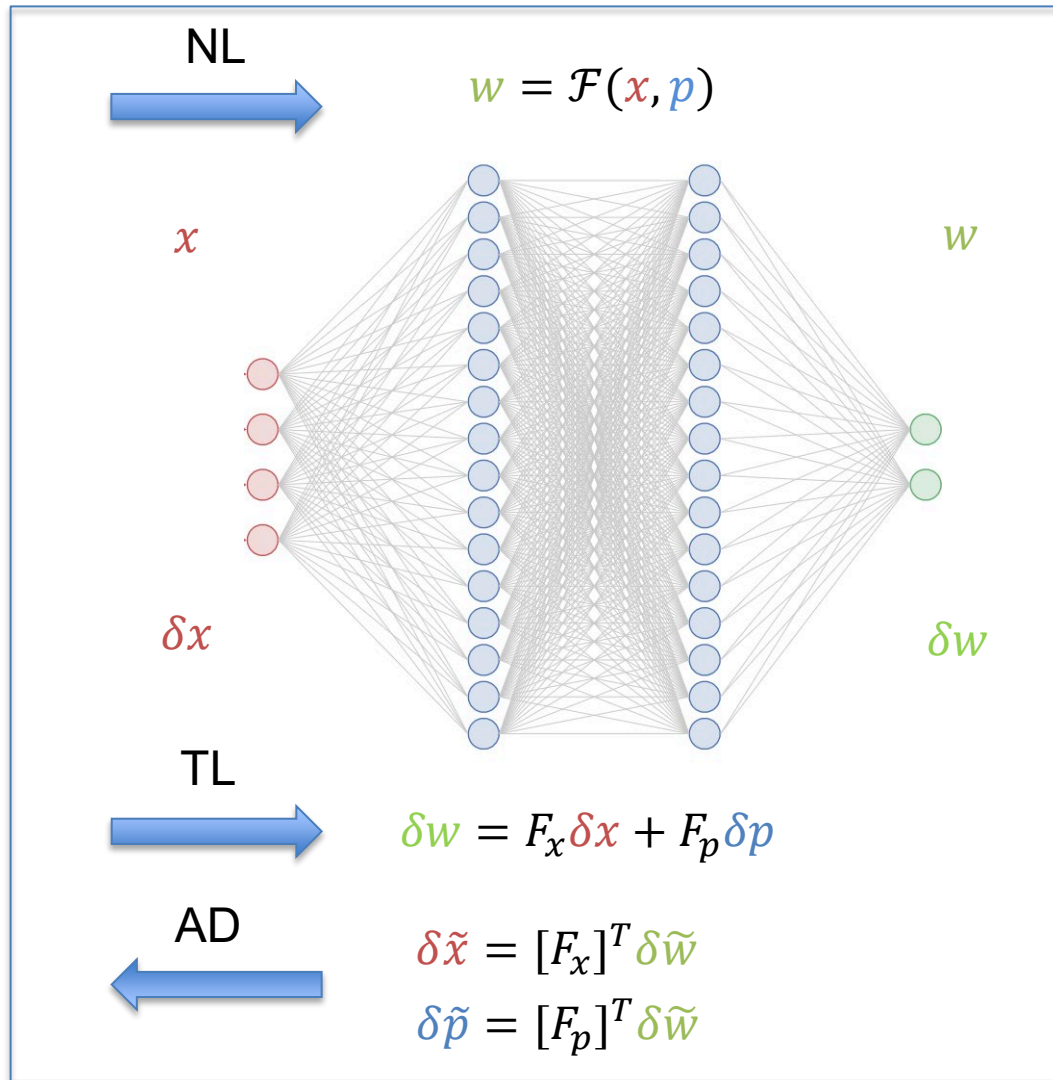


- Objective 1** Explore machine learning applications across the weather and climate prediction workflow and apply them to improve model efficiency and prediction quality.
- Objective 2** Expand software and hardware infrastructure for machine learning.
- Objective 3** Foster collaborations between domain and machine learning experts with the vision of merging the two communities.
- Objective 4** Develop customised machine learning solutions for Earth system sciences that can be applied to various applications and at scale on current and future supercomputing infrastructure.
- Objective 5** Train staff and Member and Co-operating State users and organise scientific meetings and workshops.

MAELSTROM

Research highlight: Data assimilation

Towards online training of neural networks in the IFS 4D-Var



From offline, TensorFlow-based training of Neural Networks towards **online learning** within the **ECMWF 4D-Var** framework






FNN (Fortran Neural Network) library

- Fortran implementation of sequential Neural Networks equipped with tangent linear and adjoint operators required by incremental 4D-Var
- Tested for learning model error in a QG model (Farchi et al., 2022) and now implemented in the IFS.
- Potential applications: model error, observation bias, physics parametrizations, ..

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Online model error correction with neural networks in the incremental 4D-Var framework

Authors

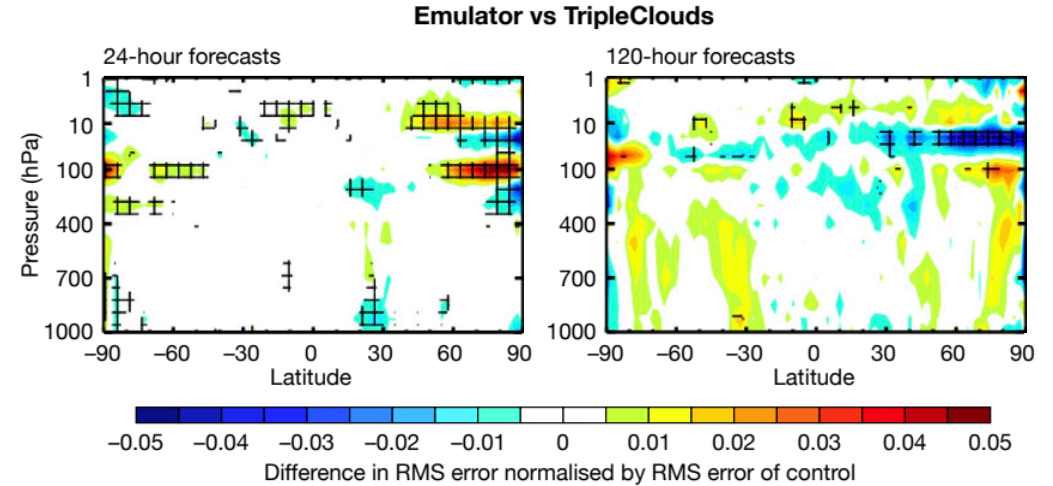
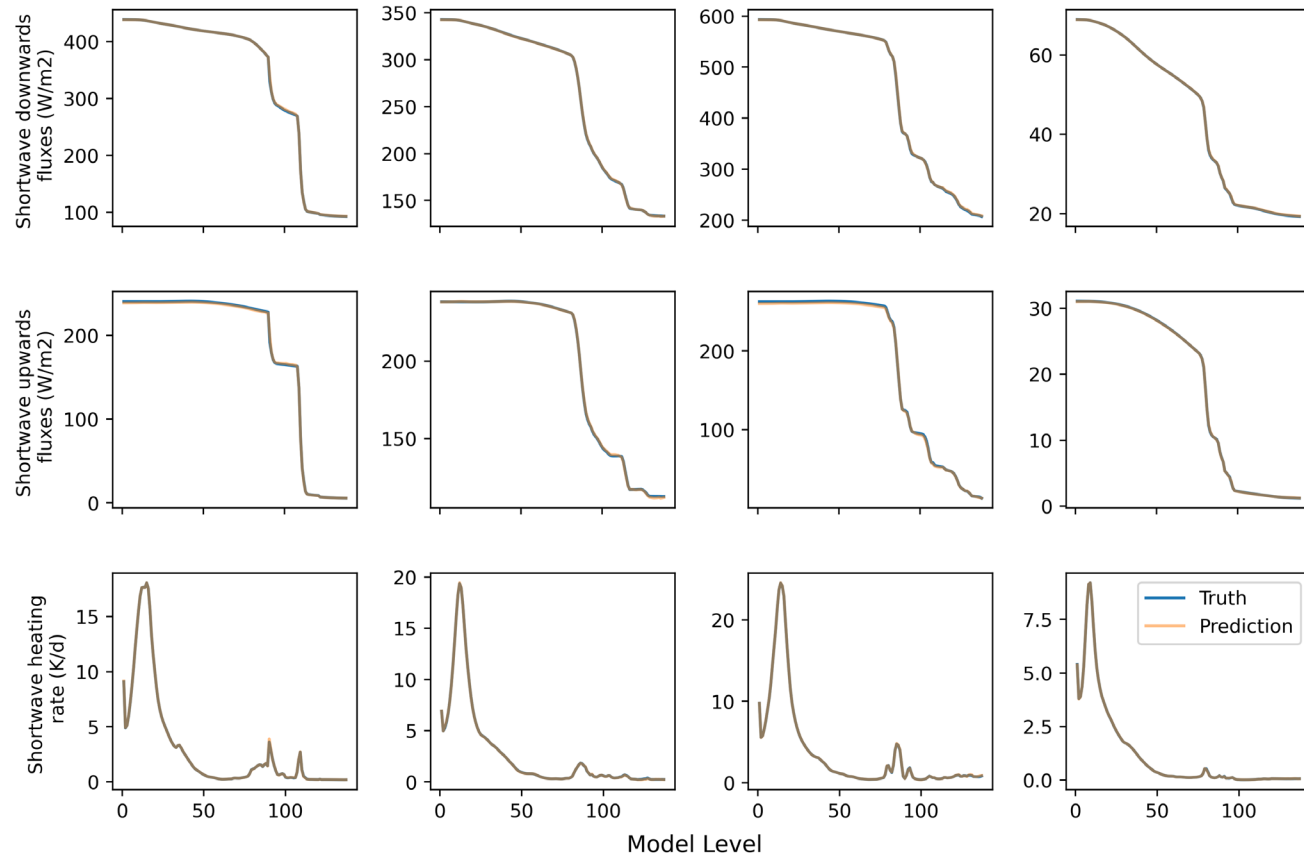
Alban Farchi   , Marcin Chrust, Marc Bocquet, Patrick Laloyaux , Massimo Bonavita 

Published Online: Sun, 30 Oct 2022 | <https://doi.org/10.1002/essoar.10512719.1>

Research highlight: application in model component

The radiation scheme is an expensive model component, being run at with a coarser timestep and spatial grid.

Can we accurately emulate the radiation scheme using neural networks?



No degradations in forecast below 100hPa.
Faster than existing scheme decoupled from IFS.

Next steps: GPU use within IFS.

Example column predictions comparing existing scheme with neural network.

Matthew Chantry, Robin Hogan, Peter Dueben @ ECMWF
Peter Ukkonen @ DMI

Research highlight: application in post-processing, collaboration with Microsoft

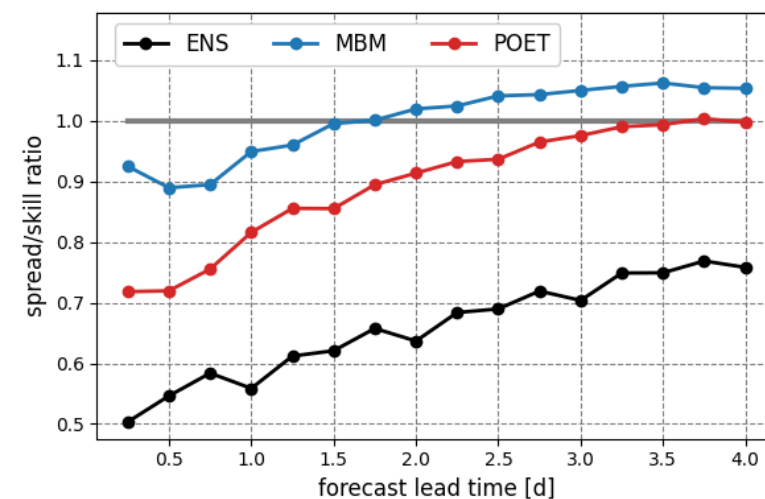
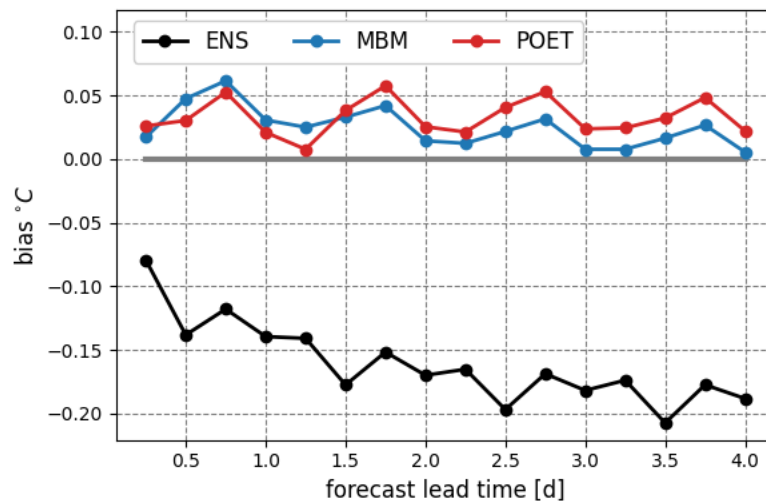
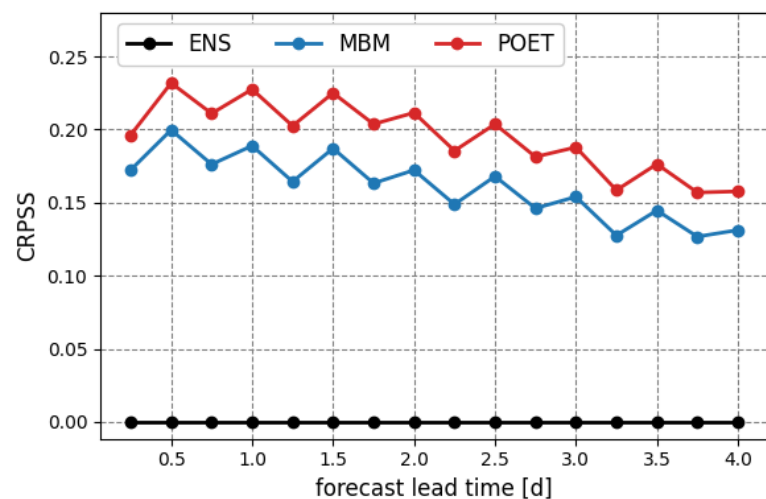
Can we correct the bias and spread of the operational ensemble?

Can we do this by training on a smaller ensemble hindcast?

Focus on 2m-temperature predictions.

Compare transformer-based neural network (POET, 10^6 parameters), with member-by-member approach (10^8 parameters).

20% improvement in CRPS, significant reduction in bias, better calibrated spread/skill ratio.



Zied Ben Bouallegue, Matthew Chantry, Peter Dueben, Jesper Dramsch, Mariana Clare @ ECMWF
Jonathon Weyn @ Microsoft

Massive Open Online Course (MOOC) on Machine Learning in Weather & Climate

FREE course. Explores application of Machine Learning across main stages of numerical weather and climate predictions: from processing of input observations to their assimilation into models, and finally to forecasting and post-processing.

Register now at <https://www.ecmwf.int/mlwc-mooc>

- Launch on 9 Jan 2023, continues to March 2023. Estimated 3-4 hours of study per week, 36 hours total.
- In partnership with International Foundation on Big Data and Artificial Intelligence for Human Development (IFAB).
- Three tiers:
 - Tier 1: Introduction to Machine Learning in weather & climate
 - Tier 2: Concepts of Machine Learning
 - Tier 3: Practical Machine Learning applications in weather & climate
- Includes videos, podcasts, Jupyter notebook practicals, interactive applications, challenges and much more...
- Will bring together experts and provide a shared vision across the communities of Earth system sciences, high-performance computing and Machine Learning.



in partnership with

A promotional banner for the MOOC. The background is a vibrant blue with a stylized globe on the right side, overlaid with white and green network lines. The text is white and blue. At the top left, the ECMWF logo and 'in partnership with IFAB' are displayed. The main title 'MOOC Machine Learning in Weather & Climate' is prominently featured in the center. Below the title, it says 'Register now for our FREE online course'. At the bottom left, there is a dark blue button with the text 'SIGN UP' and a white right-pointing arrow.

