Machine Learning for Weather and Climate Prediction

Peter Dueben

Head of the Earth System Modelling Section and Coordinator for Machine Learning and AI Activities

ECMWF | EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS

The strength of a common goal

MAELSTROM

esiwace
CENTRE OF EXCELLENCE IN SIMULATION OF WEATHER AND CLIMATE IN EUROPE

Funded by the European Union

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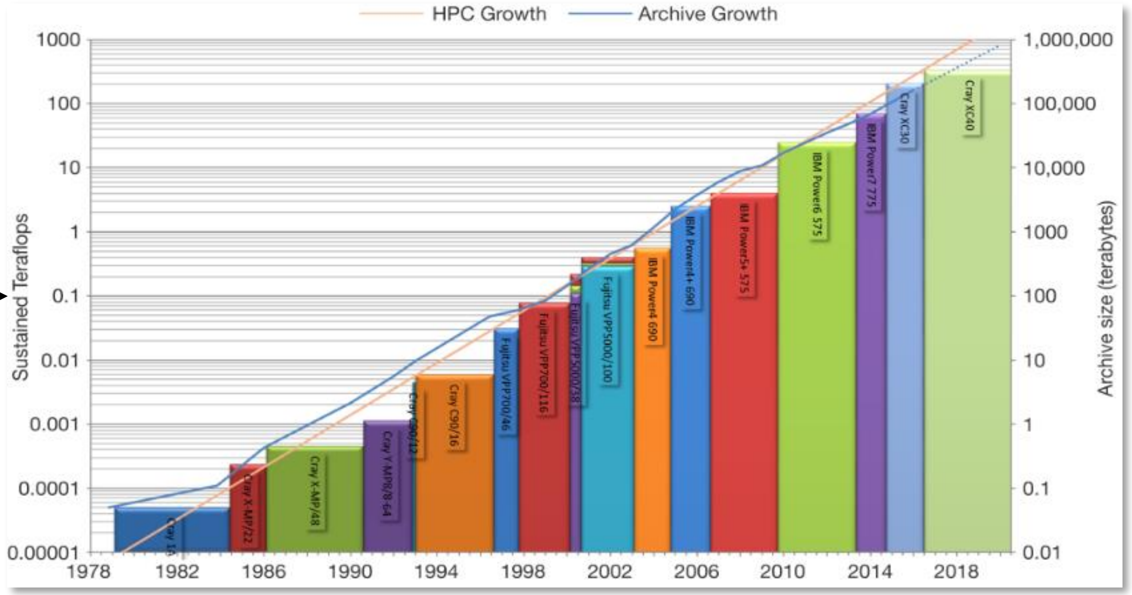
Why now?

Increase in data volume



New computing hardware

New machine learning software

TensorFlow
Keras
PyTorch

Increase in knowledge

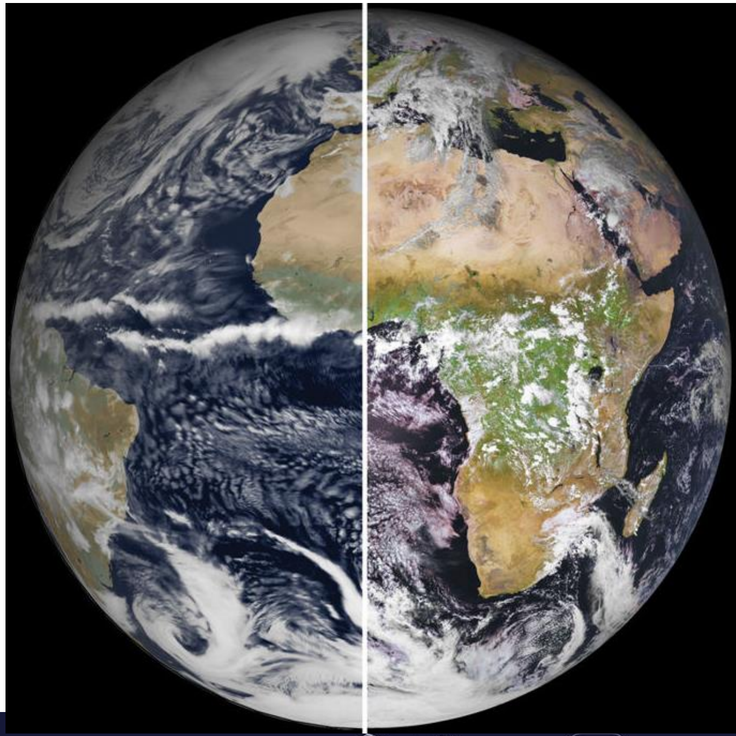
Why would machine learning help in Earth system sciences?

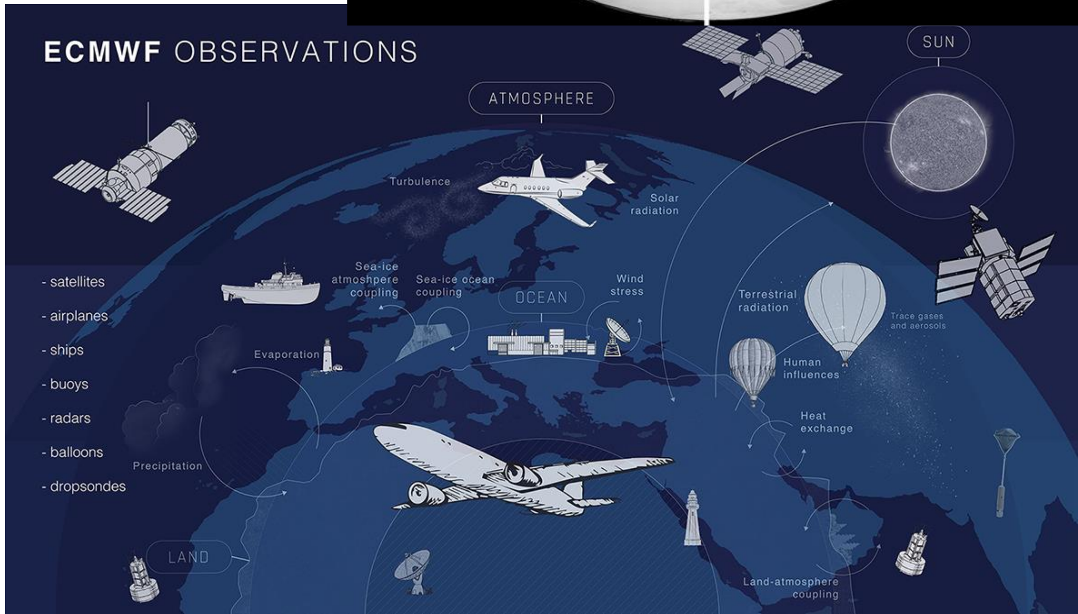
Inputs → machine learning → Outputs

Earth system science is difficult as the Earth system is huge, complex and chaotic, and as the resolution of our models is limited

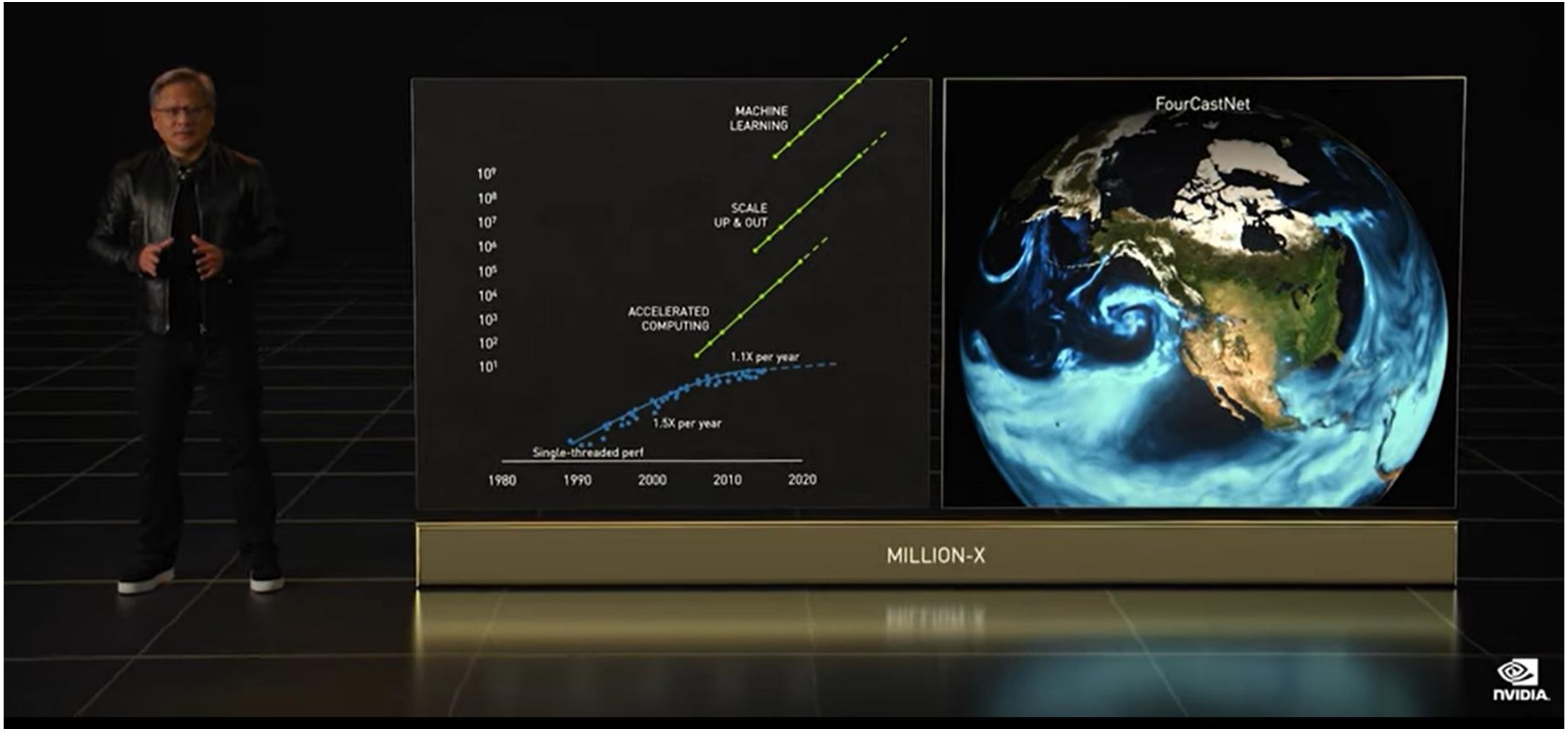
However, we have a huge amount of observations and Earth system data

- ➢ **There are many application areas for machine learning in Earth system science**





The perspective of a full ML model for weather and climate

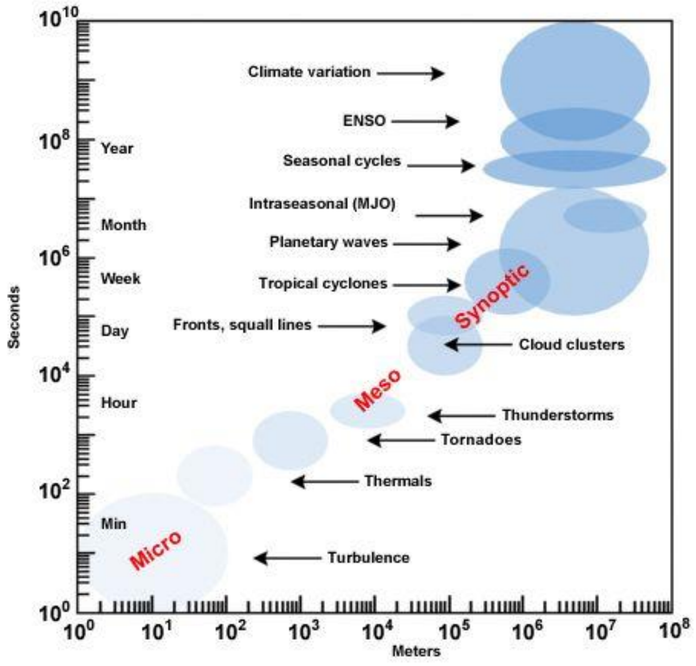


NIVIDA's Earth-2 is coming with FourCastNet

Climate?

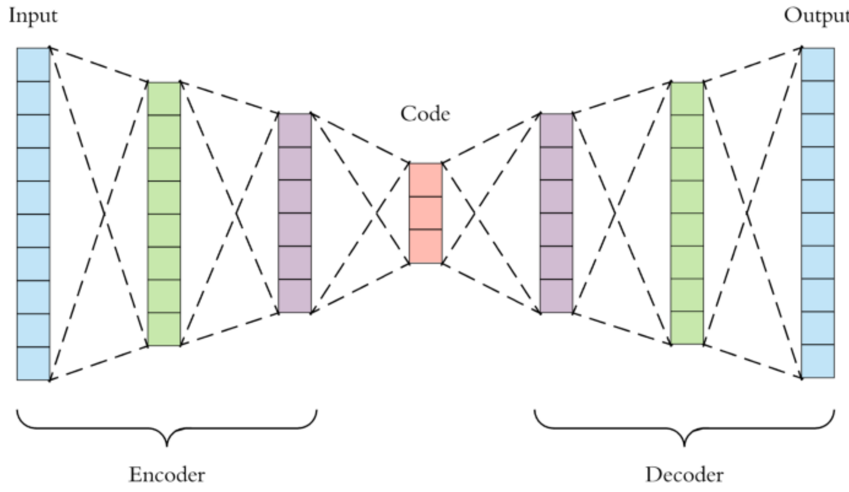
Use the magic of machine learning for our domain ⟶ Science

The Earth system is multi-scale

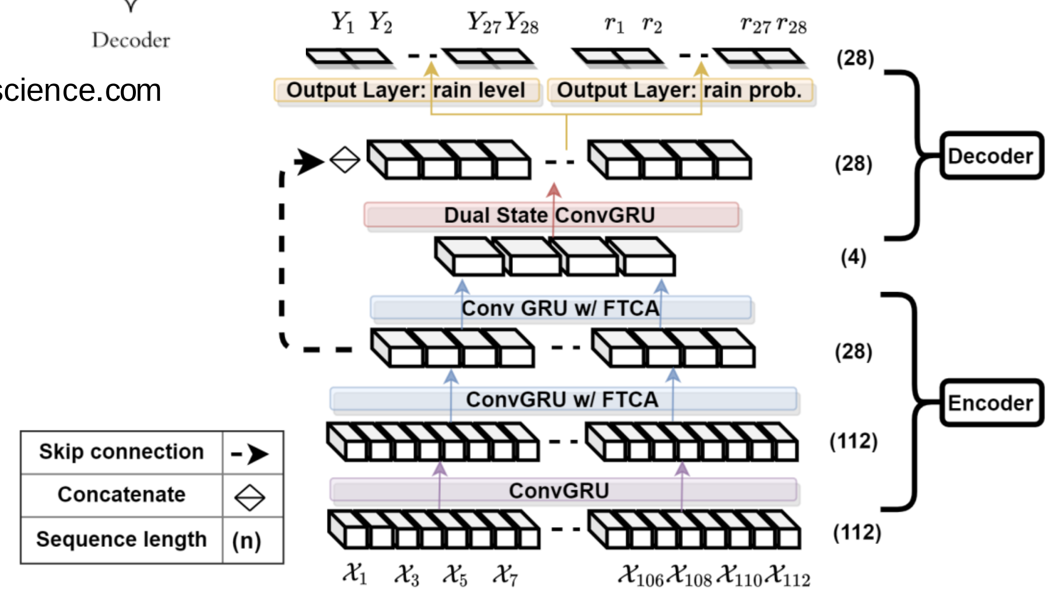


Source: UCAR

Machine learning can also be multi-scale



Source: https://towardsdatascience.com

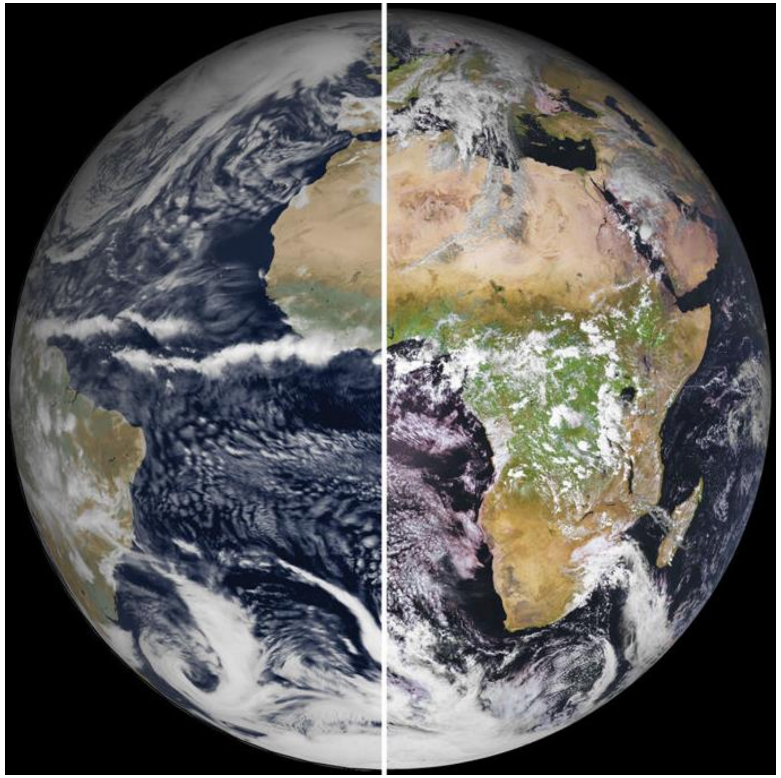


Let's learn how to use that capability!

Adewoyin, Dueben, Watson, He, Dutta Machine Learning 2021

Machine Learning and AI for Earth system science

Improve understanding
- Fuse information content from different datasources
- Unsupervised learning
- Causal discovery
- AI powered visualisation
- Uncertainty quantification
- …

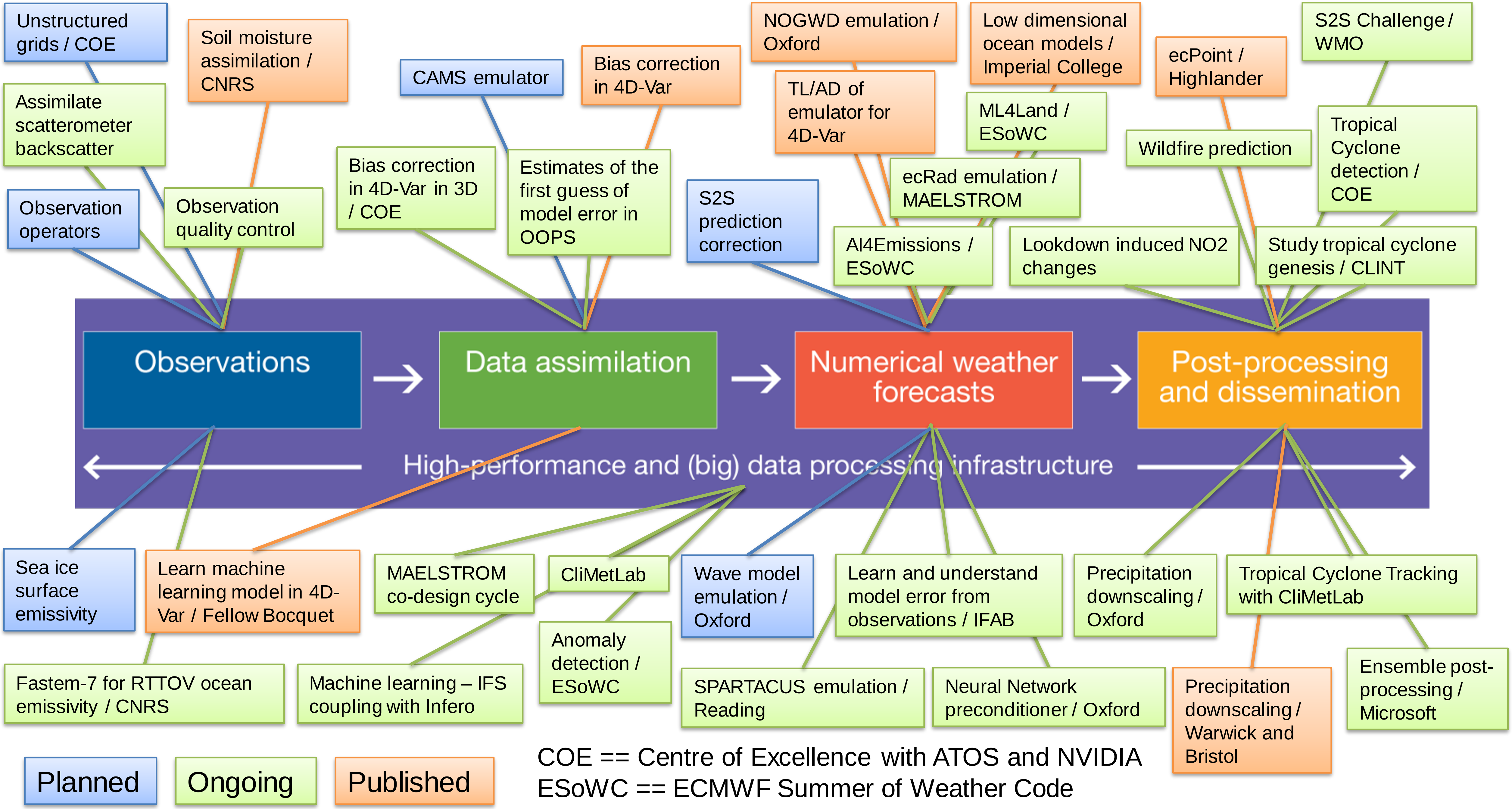


Speed up simulations and green computing
- Emulate model components
- Port emulators to heterogeneous hardware
- Use reduced numerical precision and sparse machine learning
- Optimise HPC and data workflow
- Data compression
- …

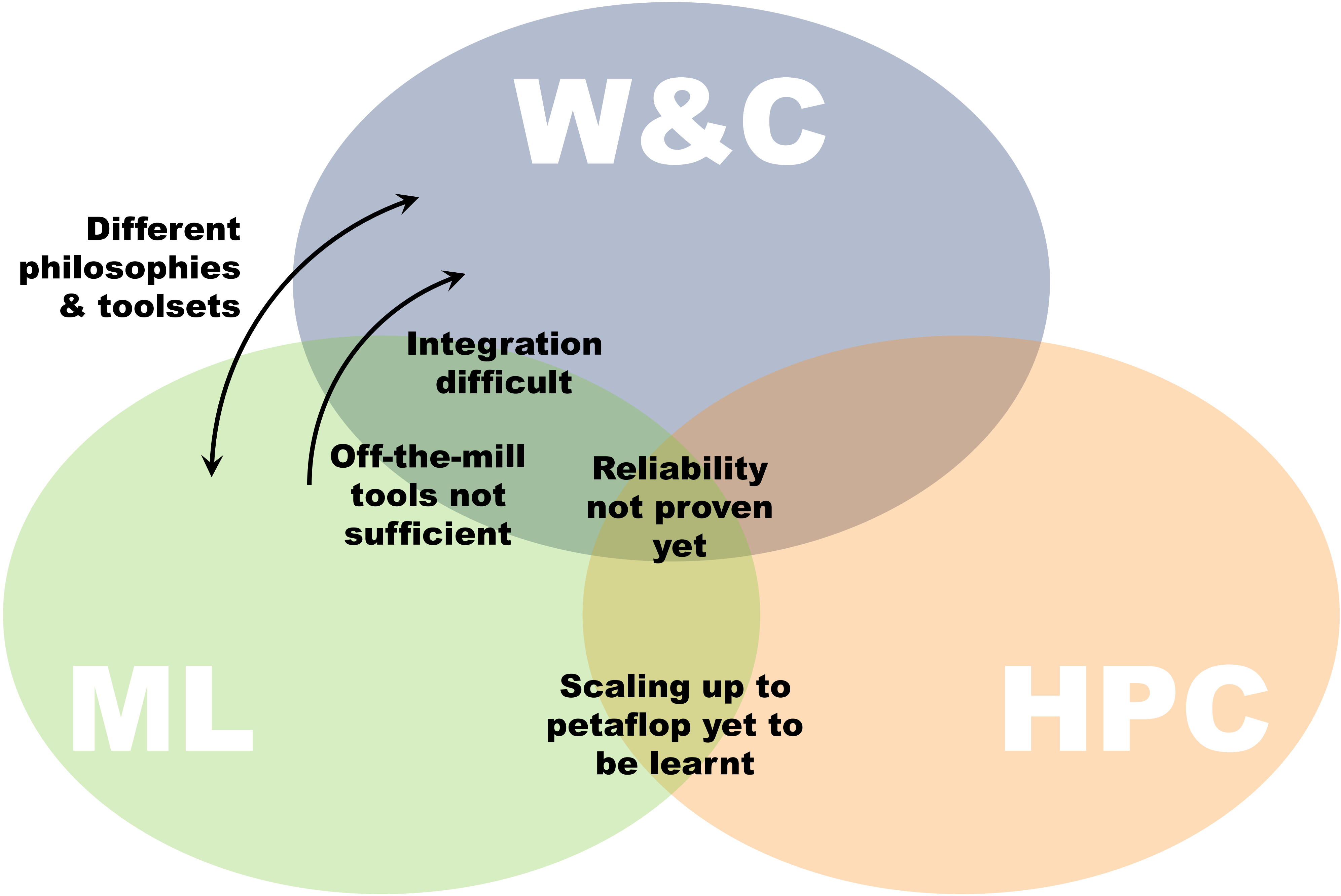
Improve models
- Learn components from observations
- Correct biases
- Quality control of observations and observation operators
- Feature detection
- …

Link communities
- Health – e.g. for predictions of risks
- Energy – e.g. for local downscaling
- Transport – e.g. to combine weather and IoT data
- Pollution – e.g. to detect sources
- Extremes – e.g. to predict wild fires
- …

AI – Where? – Machine learning at ECMWF



Challenges


W&C
Different philosophies & toolsets
Integration difficult
Off-the-mill tools not sufficient
Reliability not proven yet
ML
Scaling up to petaflop yet to be learnt
HPC

The ECMWF Machine Learning Workshop – https://events.ecmwf.int/event/294/

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MAELSTROM dissemination workshop (28 March) and Machine Learning Workshop (29 March - 1 April)

Overview

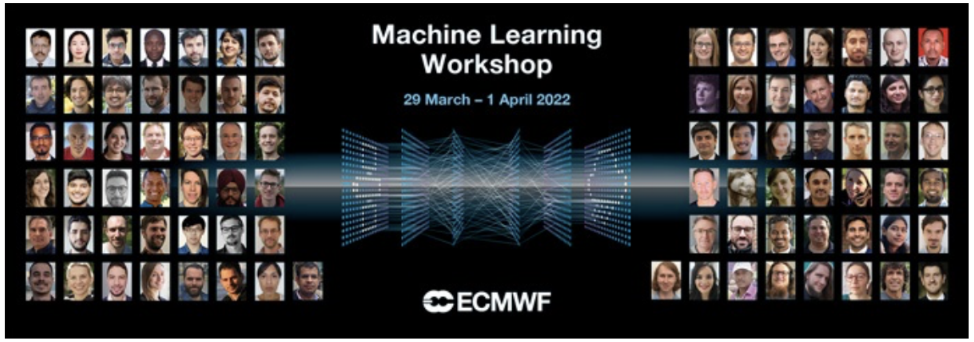
Presentations and recordings

Posters

Organising committee

Code of conduct

Virtual | 28 March 2022 to 1 April 2022



#MLWS2022

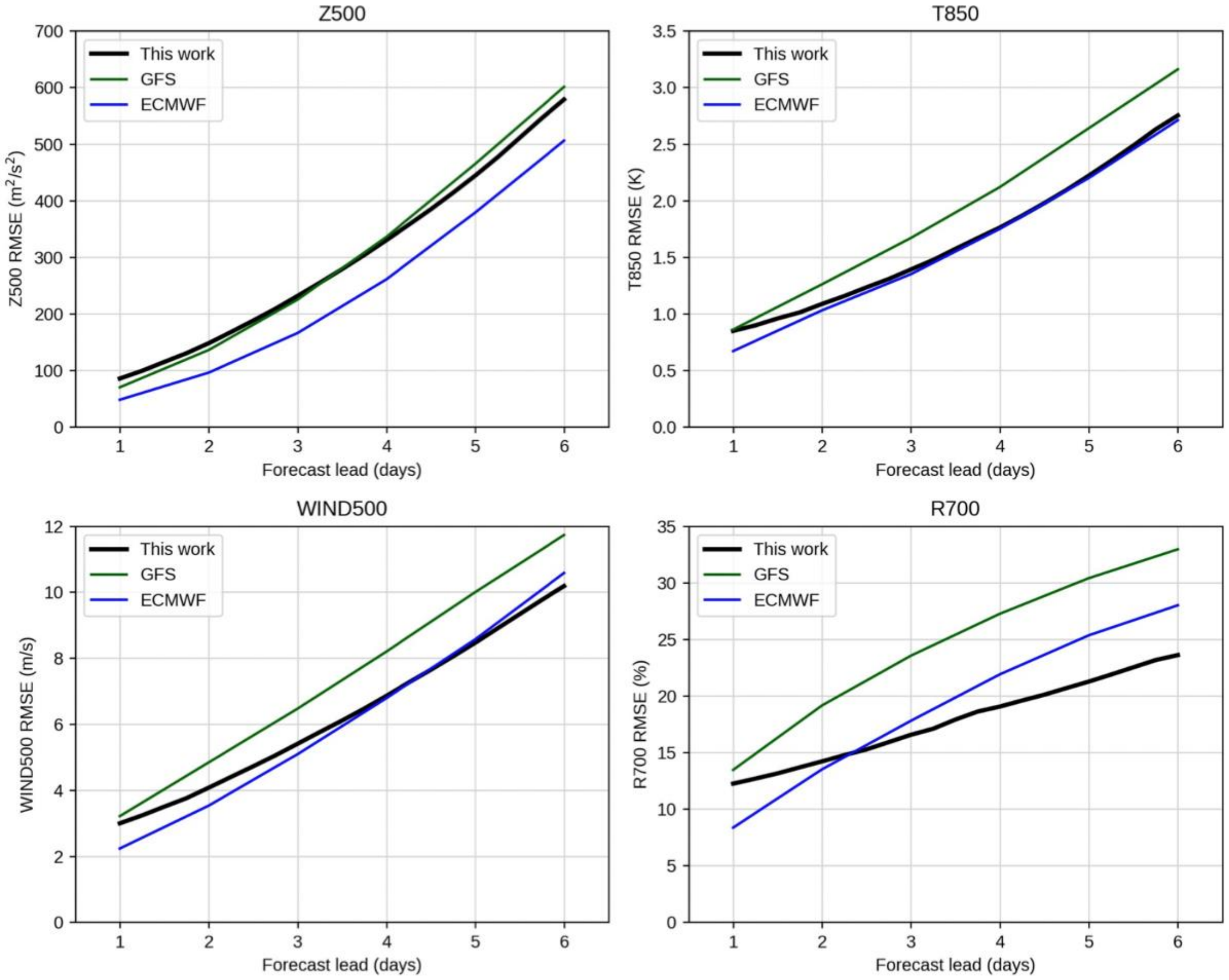
MAELSTROM

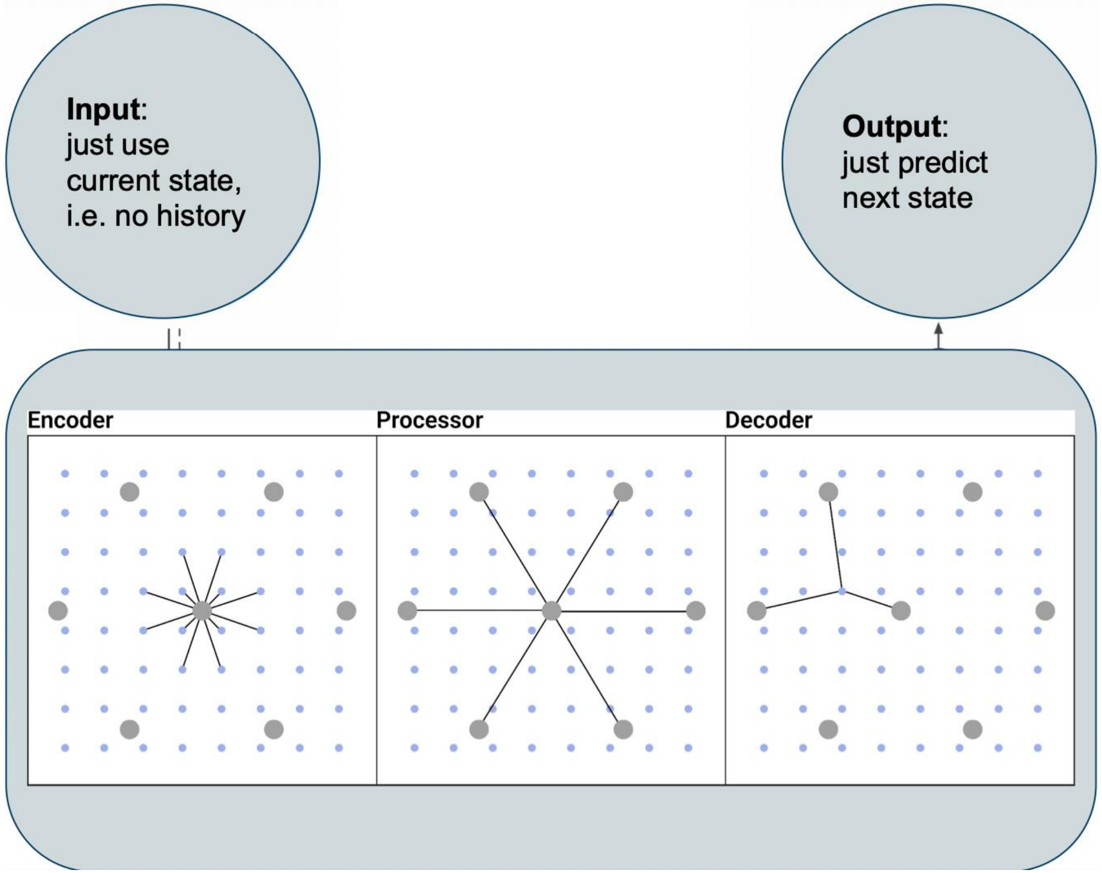
Example talk 1: Ryan Keisler – Forecasting Global Weather with Graph Neural Networks

WeatherBench-type problem
Input: ERA5 fields / **Output:** ERA5 fields at a later time

In this work, I used a 2 TB subset of ERA5:

- Horizontal resolution: 1.0 degrees in lat/lon
- Vertical resolution: 13 pressure levels
- Time: every 3 hours, from 1979 through 2020
- Fields: 6 fields (z, q, t, u, v, w)



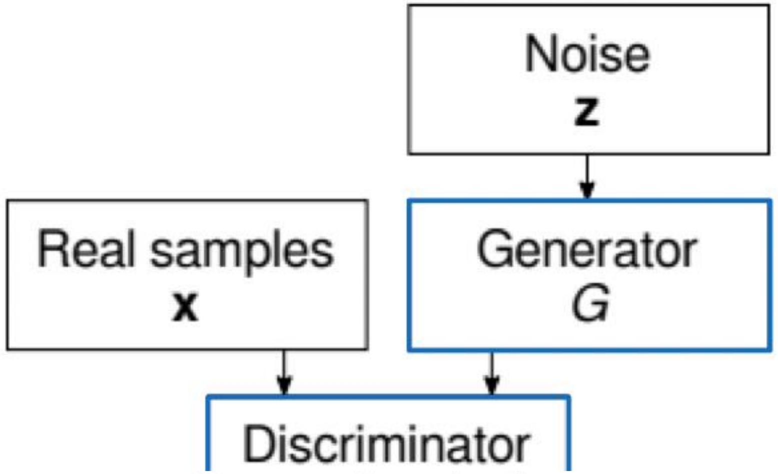


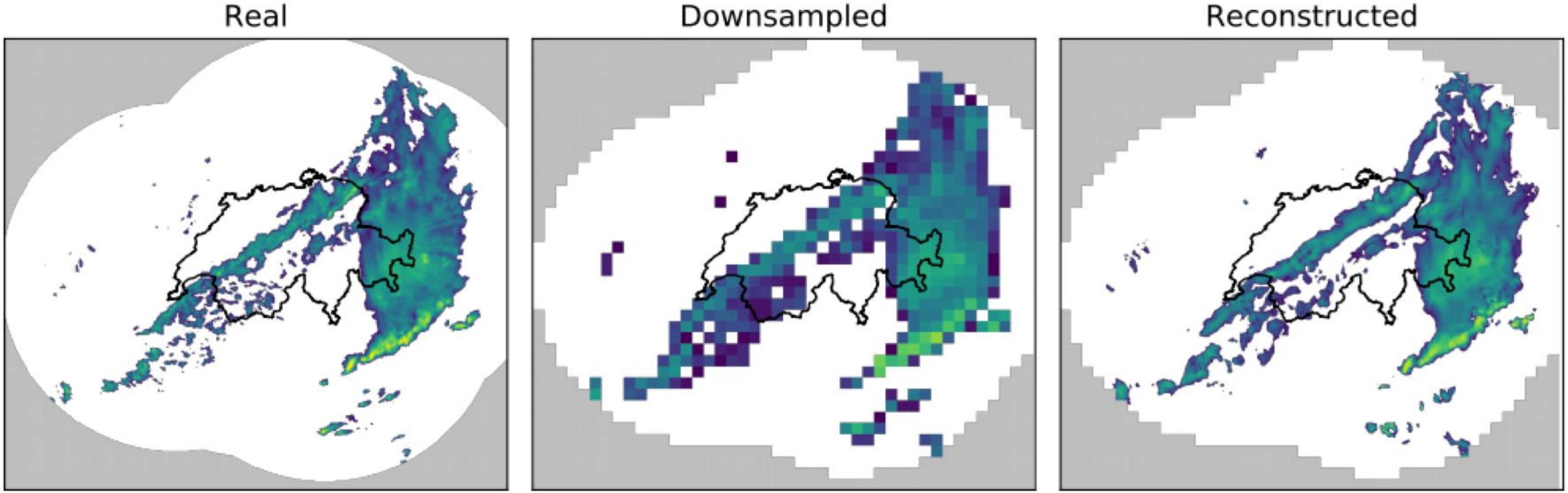
Example talk 2: Jussi Leinonen – Time-Consistent Downscaling of Atmospheric Fields with Generative Adversarial Networks

Input: Precipitation observations on coarse grid
Output: Precipitation observation on fine grid

Two competing (usually convolutional) neural networks:

- Discriminator tries to distinguish real samples from generated ones
  - CNNs are powerful image classifiers

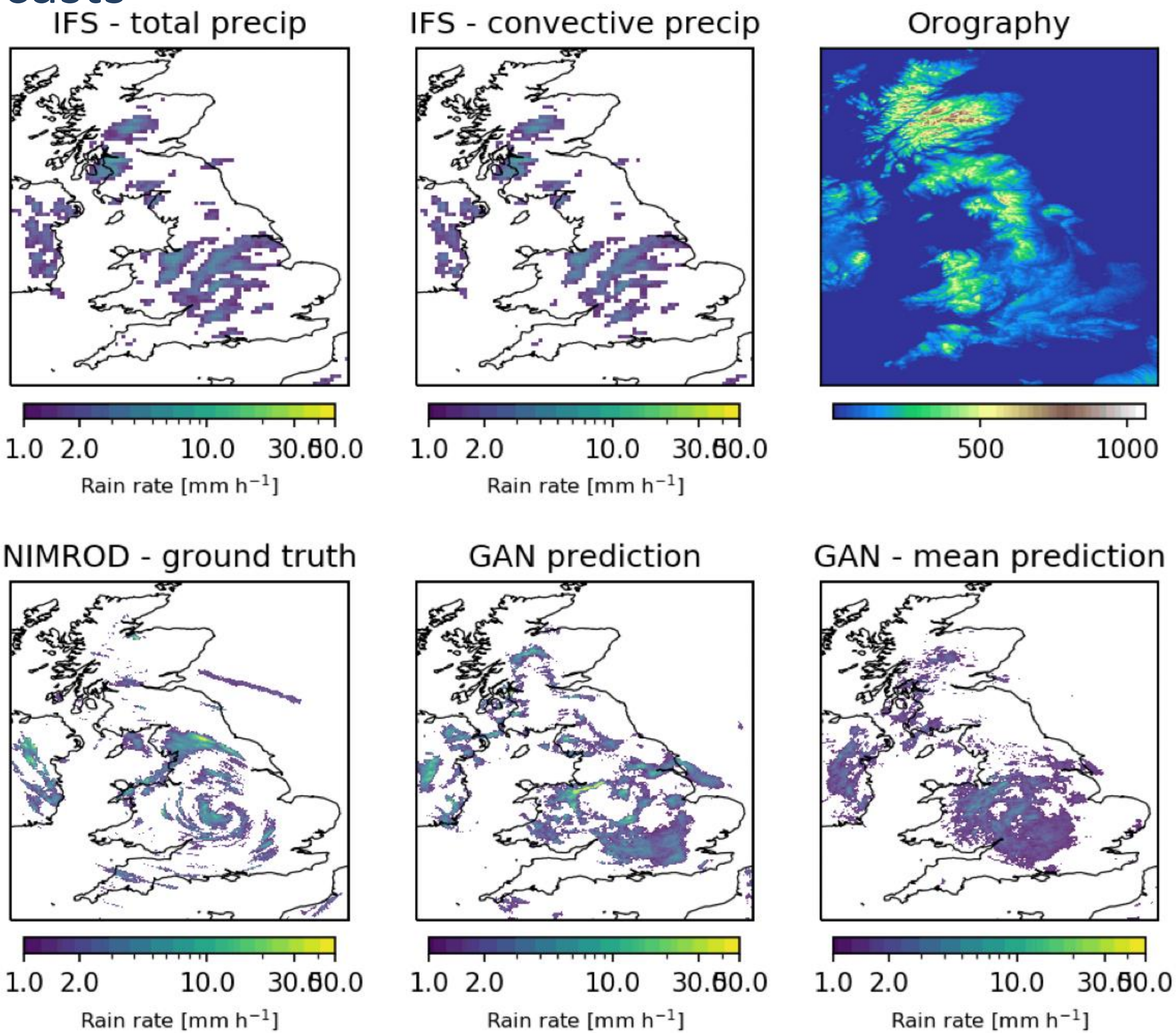




Example talk 3: Lucy Harris – A machine Learning Approach to Stochastic Downscaling of Precipitation Forecasts

Input: IFS Model Simulation fields on coarse (9 km) grid
Output: Precipitation observation on fine (1 km) grid

Also, see talk by Suman Ravuri later ;-)

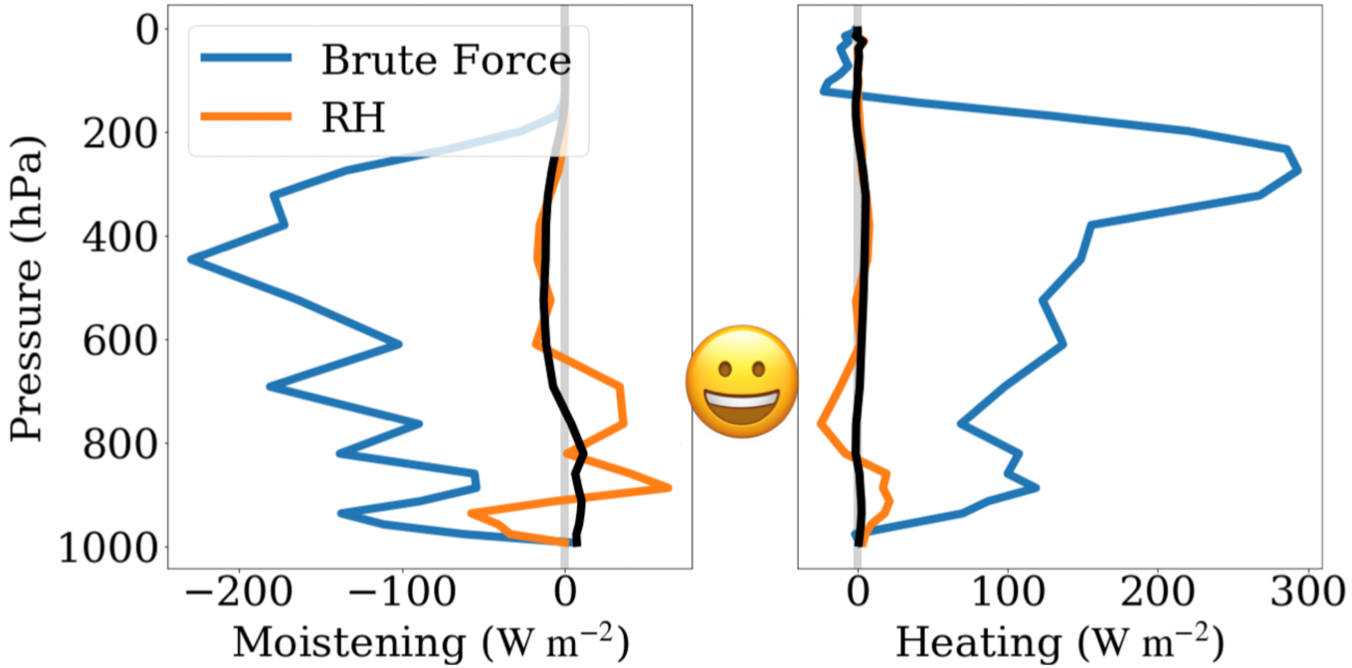


Example talk 4: Tom Beucler – Climate-Invariant, Causally Consistent Neural Networks as Robust Emulators of Subgrid Processes across Climates

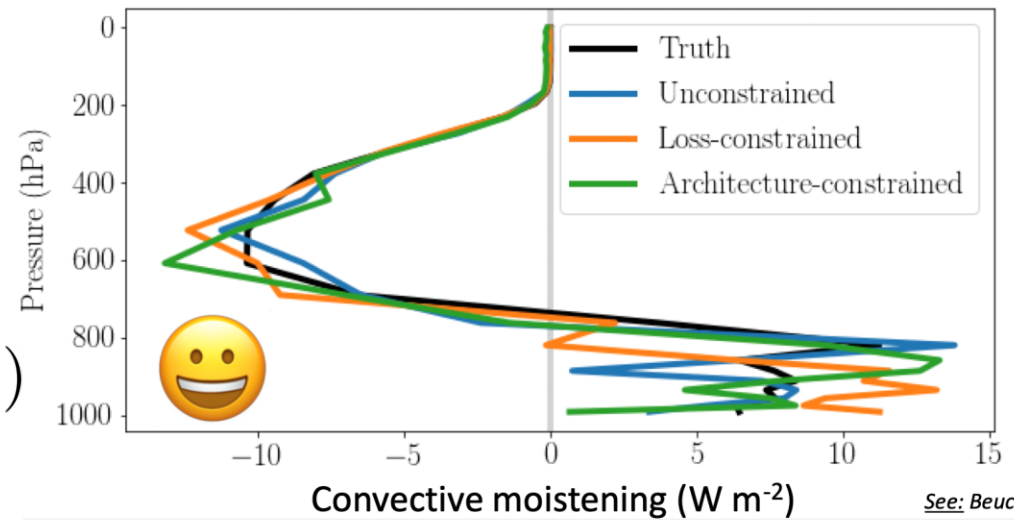
Input: Physical state of climate model
Output: Physical tendency of super-parametrised model

$$\text{Specific humidity}\,(z) \;\rightarrow\; \text{Relative humidity}\,(z)$$

Generalization improves dramatically!

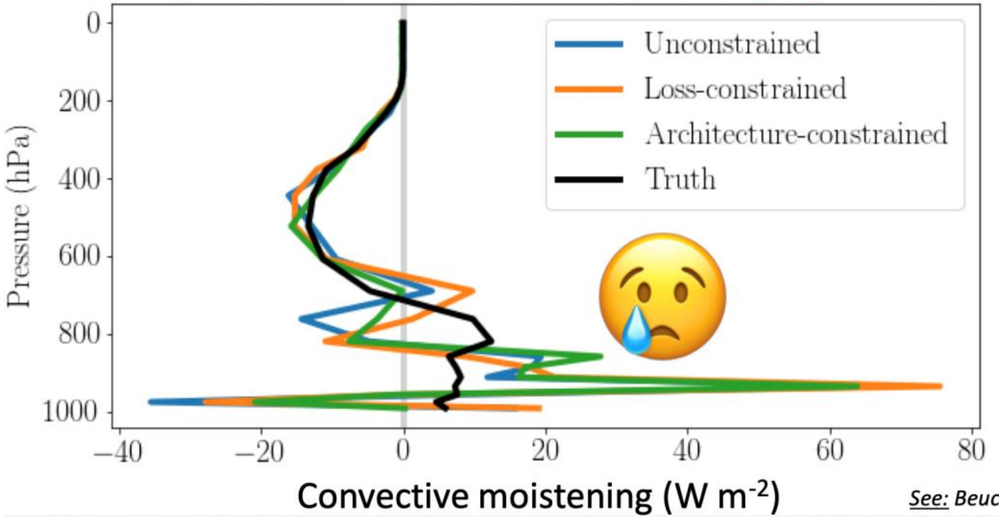


Daily-mean Tropical prediction in reference climate



See: Beucler et al. (2019)

Daily-mean Tropical prediction in (+4K) warming experiment



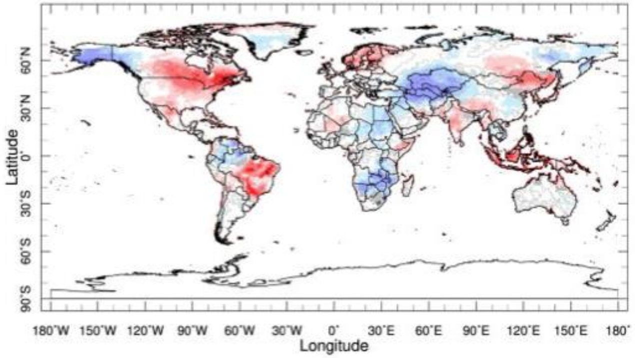
See: Beucler et al. (2019)

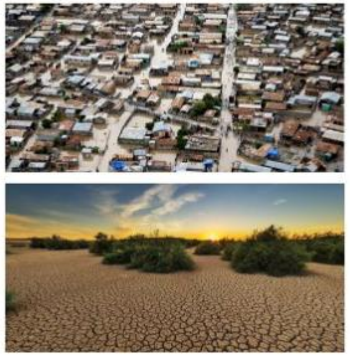
Example talk 5: David Landry – Opportunistic mixture model for post-processing S2S temperature and precipitation forecasts using convolutional neural networks

WEATHER CLIMATE WATER

WORLD METEOROLOGICAL ORGANIZATION

PRIZE CHALLENGE TO IMPROVE SUB-SEASONAL TO SEASONAL PREDICTIONS USING ARTIFICIAL INTELLIGENCE **1 June - 31 October 2021**





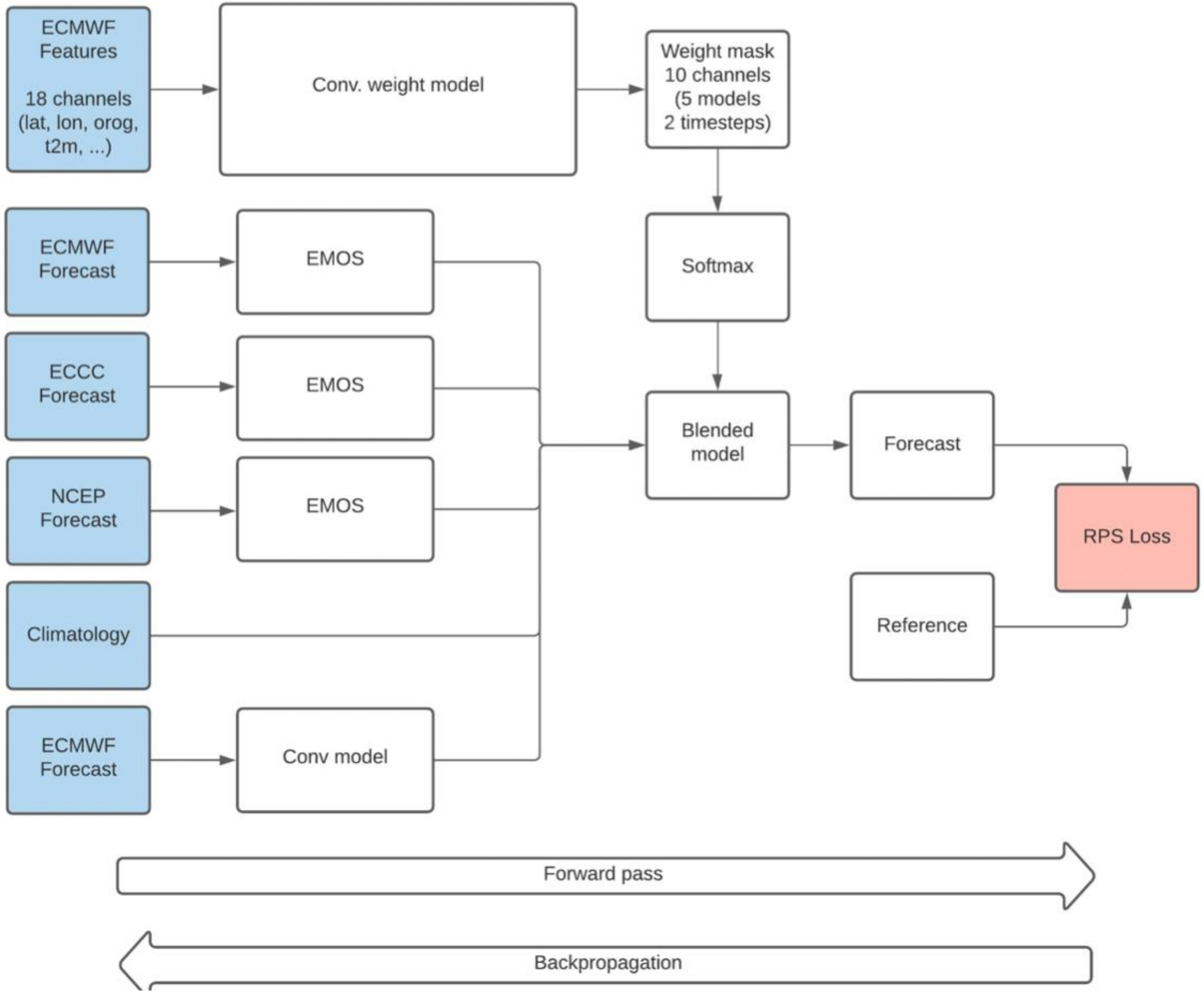
Improved sub-seasonal to seasonal (S2S) forecasts could enhance food security, the sustainable management of energy and water resources, and reduce disaster risk by providing earlier warnings for natural hazards.

The World Meteorological Organization (WMO) is launching a competition to improve, through Artificial Intelligence and/or Machine Learning techniques, the current precipitation and temperature forecasts for 3 to 6 weeks into the future from the best computational fluid dynamic models available today.

All the codes and scripts will be hosted at Renkulab, developed by the Swiss Data Science Center, and training and verification data will be accessible from the European Weather Cloud and IRI Data Library. Data access scripts will be provided. After the competition, open access will be provided to all the codes and results.

Timeline
Opens: 1 June 2021
Closes: 31 October 2021
Winners announced: Early February 2022

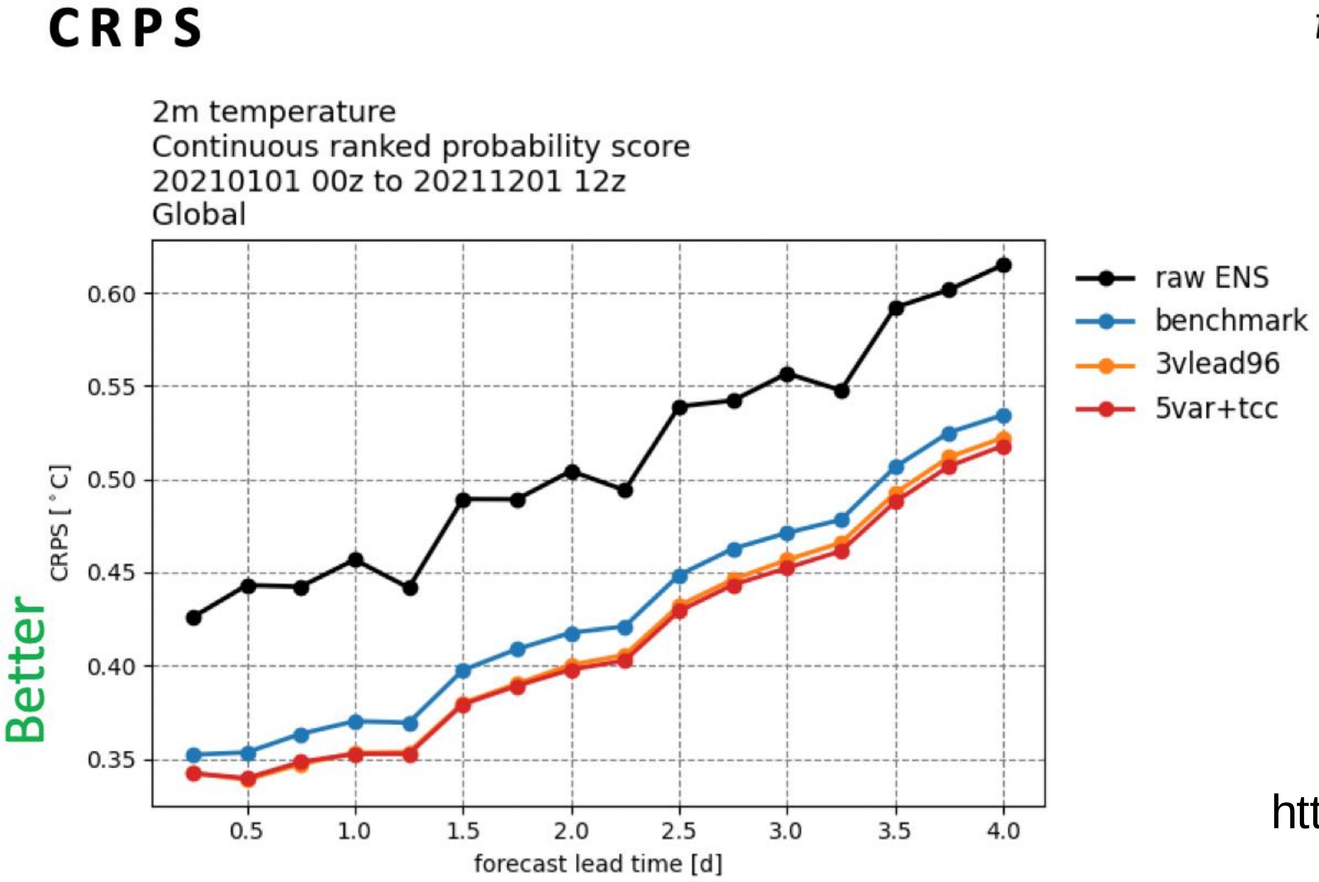
Prizes
Winning team: CHF 15 000
Second team: CHF 10 000
Third team: CHF 5 000

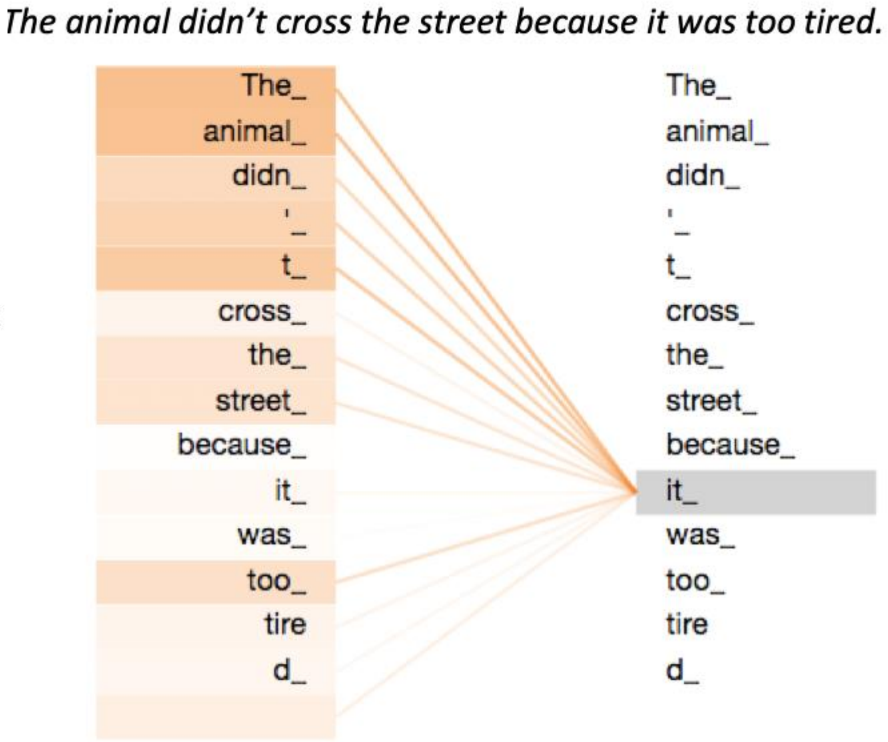


Example talk 6: Jonathan Weyn – Improving medium-range ensemble forecasts with transformers

Input: ECMWF ensemble forecast
Output: ECMWF ensemble forecasts improved

See also work by Tobias Finn ;-)





https://jalammar.github.io/illustrated-transformer/

Example talk 7: Karthik Kashinath – Building Digital Twins of the Earth for NVIDIA's Earth-2 Initiative

See later ;-)

Make developments comparable via benchmark datasets

Benchmark datasets include:

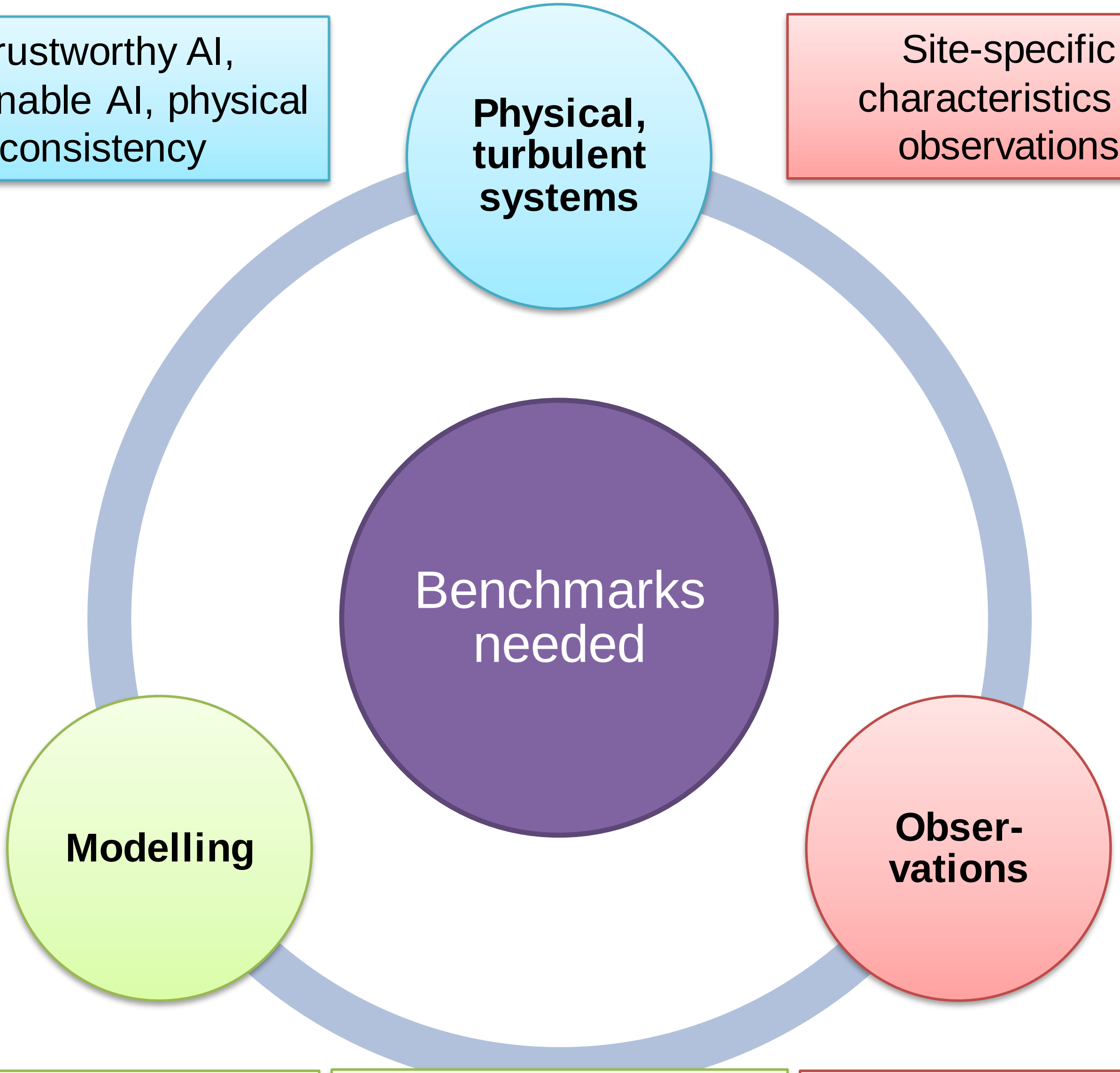
- A problem statement
- Data that is available online
- Python code or Jupyter notebooks
- A reference machine learning solution
- Quantitative evaluation metrics
- Visualisation, diagnostics and robustness tests
- Computational benchmarks

Benchmark datasets are useful because:

- They allow a quantitative evaluation of machine learning approaches
- They reduce data access and help scientists to get access to relevant data
- They allow for a separation of concerns between domain sciences and machine learning experts
- They allow for a separation of concerns between domain sciences and HPC experts,
  e.g. towards green computing

Missing machine learning benchmark datasets for atmospheric sciences

- Transfer learning
- Online and reinforcement learning
- Training of machine learning tools in a changing climate
- Unstructured grids on the sphere
- Multi-scale interactions in space and time
- Dataflow and handling of huge datasets
- Trustworthy AI, explainable AI, physical consistency



- Hybrid modelling and coupling
- Uncertainty quantification and representation
- Weather and climate predictions based on machine learning
- The emulation of model components
- Post-processing and down-scaling

- Site-specific characteristics of observations
- Composite distributions of observations
- Extreme value predictions
- Missing data and irregular spacing of monitoring sites
- Auto correlation and periodic patterns
- Physical constraints
- Data anonymity
- Fusion of diverse datasets
- Air-quality applications
- Nowcasting applications
- Uncertainty estimates
- Feature detection

Dueben, Schultz, Chantry, Gagne, Hall, McGovern

What is the single most important development to achieve progress?

Domain scientists

Machine learners

Machine learning domain scientists

What is the direction? – Imagine if…

- …we could collect and centralise most datasets of observations from the past and presence, as well as model output and reanalysis data
- …we would have mapping tools from any point in time and space to any point in time and space for all datasets available
- …we would have interpretation tools for physical reasoning including the extraction of physical laws and the understanding of causality
- …we would have a tool to estimate uncertainties of all datasets based on mappings between different datasources
- …we would have machine learning powered, fly-trough visualisation tools
- …all of these tools were scalable and easy to use from Python, Jupyter, Julia…

Many thanks!

Peter.Dueben@ecmwf.int **@PDueben**

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The strength of a common goal