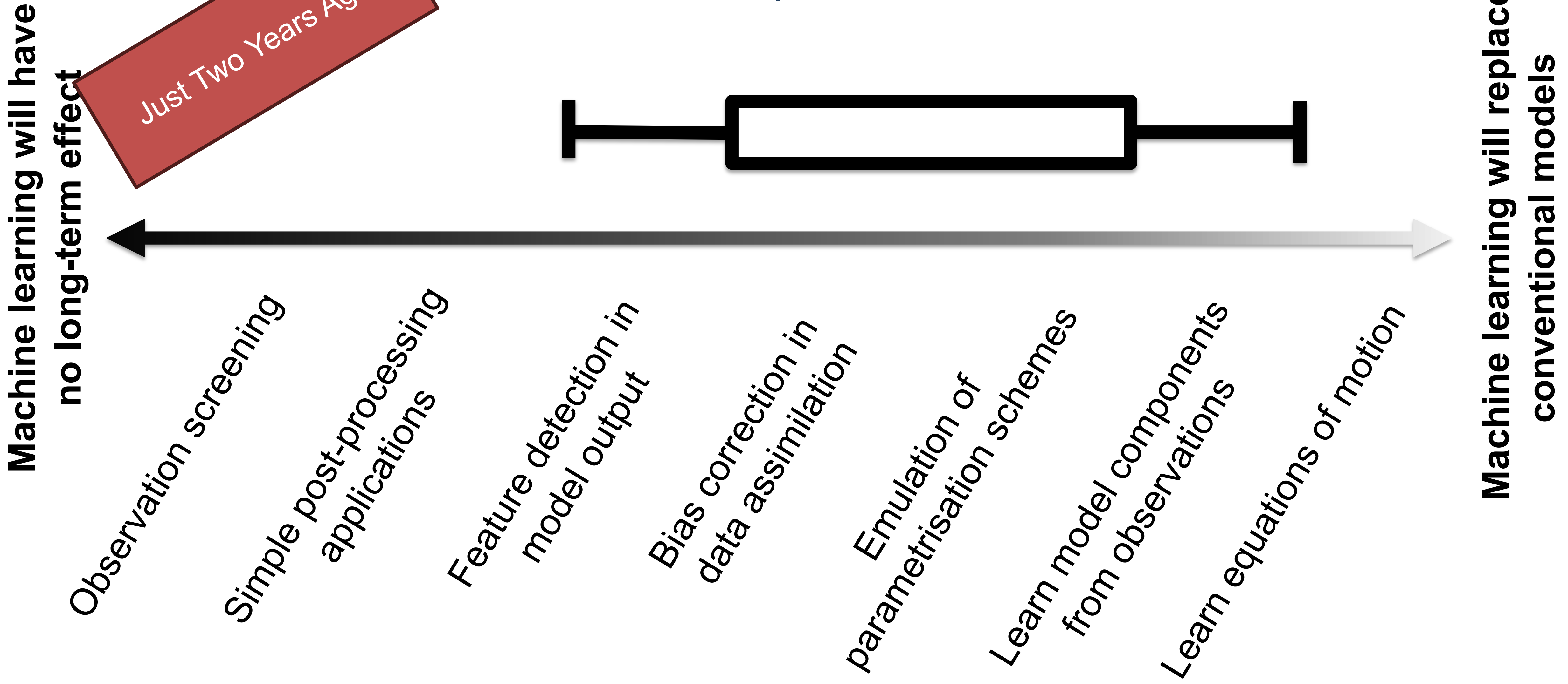
Machine Learning in Weather and Climate

Jesper Dramsch

Scientist for Machine Learning

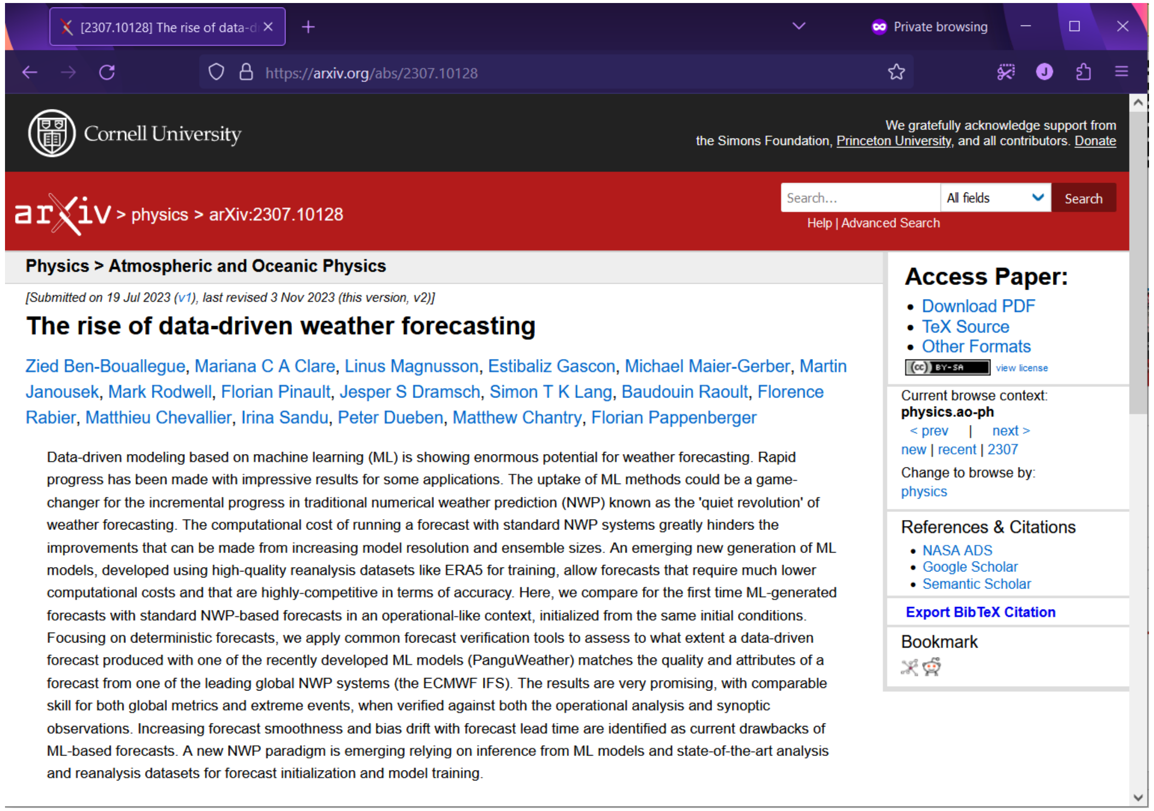
Jesper.Dramsch@ecmwf.int

What will machine learning for weather and climate predictions look like in 10 years from now?



The uncertainty range is still very large...

The rise of data-driven weather forecasts



Cornell University

We gratefully acknowledge support from the Simons Foundation, Princeton University, and all contributors. Donate

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[Submitted on 19 Jul 2023 (v1), last revised 3 Nov 2023 (this version, v2)]

The rise of data-driven weather forecasting

Zied Ben-Bouallegue, Mariana C A Clare, Linus Magnusson, Estibaliz Gascon, Michael Maier-Gerber, Martin Janousek, Mark Rodwell, Florian Pinault, Jesper S Dramsch, Simon T K Lang, Baudouin Raoult, Florence Rabier, Matthieu Chevallier, Irina Sandu, Peter Dueben, Matthew Chantry, Florian Pappenberger

Data-driven modeling based on machine learning (ML) is showing enormous potential for weather forecasting. Rapid progress has been made with impressive results for some applications. The uptake of ML methods could be a game-changer for the incremental progress in traditional numerical weather prediction (NWP) known as the 'quiet revolution' of weather forecasting. The computational cost of running a forecast with standard NWP systems greatly hinders the improvements that can be made from increasing model resolution and ensemble sizes. An emerging new generation of ML models, developed using high-quality reanalysis datasets like ERA5 for training, allow forecasts that require much lower computational costs and that are highly-competitive in terms of accuracy. Here, we compare for the first time ML-generated forecasts with standard NWP-based forecasts in an operational-like context, initialized from the same initial conditions. Focusing on deterministic forecasts, we apply common forecast verification tools to assess to what extent a data-driven forecast produced with one of the recently developed ML models (PanguWeather) matches the quality and attributes of a forecast from one of the leading global NWP systems (the ECMWF IFS). The results are very promising, with comparable skill for both global metrics and extreme events, when verified against both the operational analysis and synoptic observations. Increasing forecast smoothness and bias drift with forecast lead time are identified as current drawbacks of ML-based forecasts. A new NWP paradigm is emerging relying on inference from ML models and state-of-the-art analysis and reanalysis datasets for forecast initialization and model training.

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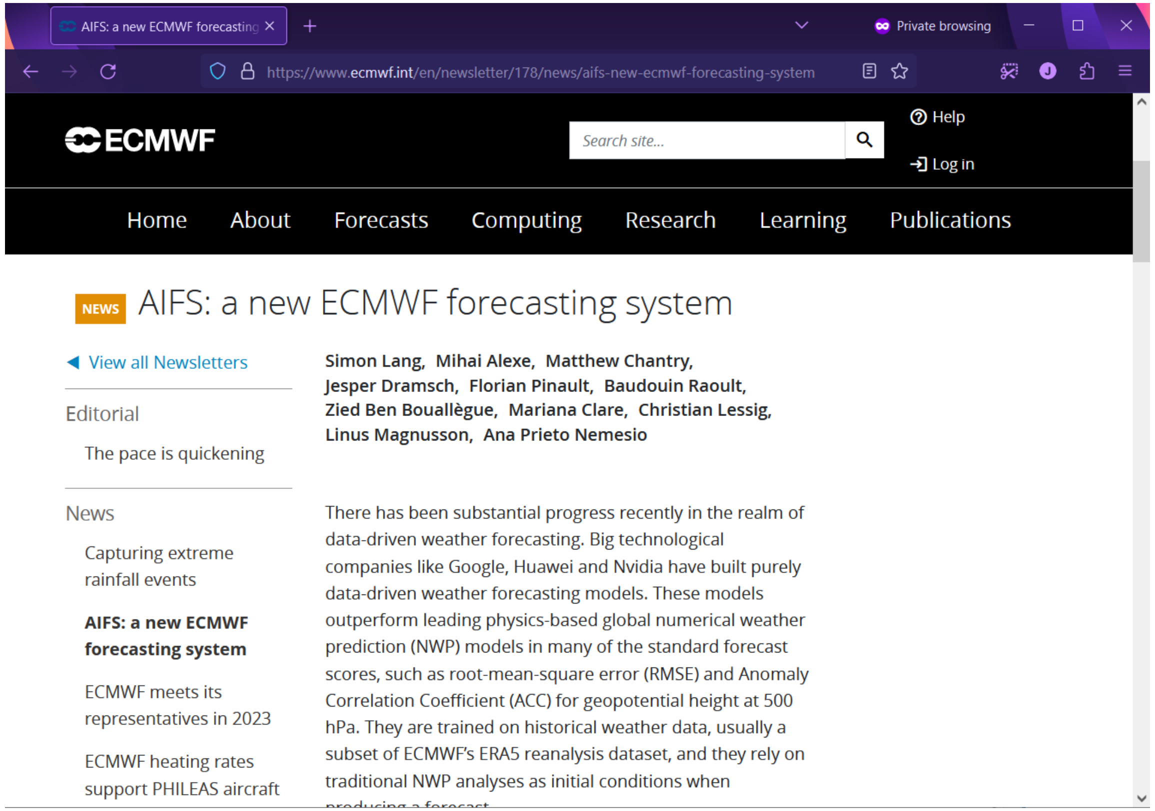

ECMWF

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Simon Lang, Mihai Alexe, Matthew Chantry, Jesper Dramsch, Florian Pinault, Baudouin Raoult, Zied Ben Bouallègue, Mariana Clare, Christian Lessig, Linus Magnusson, Ana Prieto Nemesio

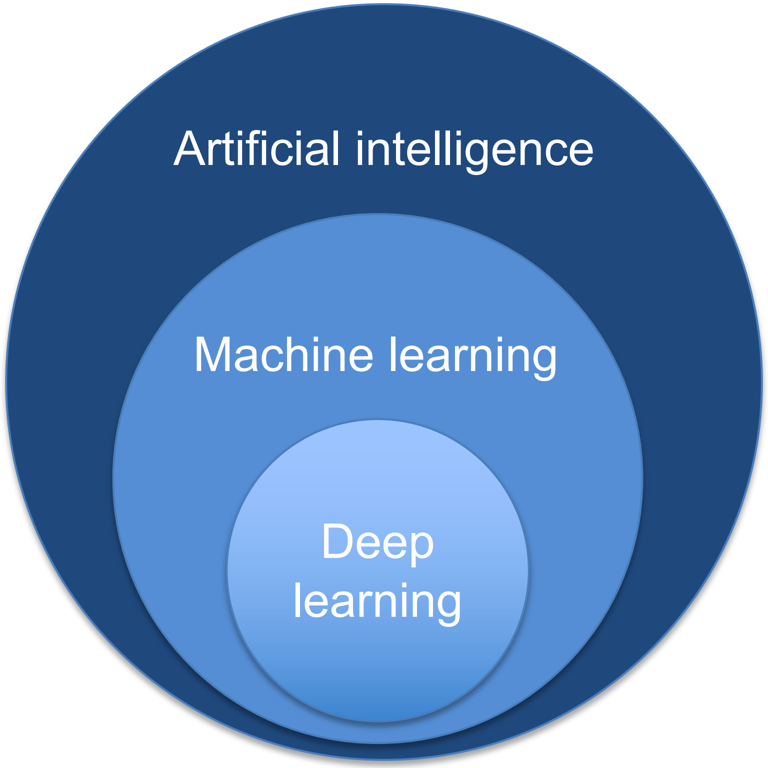
There has been substantial progress recently in the realm of data-driven weather forecasting. Big technological companies like Google, Huawei and Nvidia have built purely data-driven weather forecasting models. These models outperform leading physics-based global numerical weather prediction (NWP) models in many of the standard forecast scores, such as root-mean-square error (RMSE) and Anomaly Correlation Coefficient (ACC) for geopotential height at 500 hPa. They are trained on historical weather data, usually a subset of ECMWF's ERA5 reanalysis dataset, and they rely on traditional NWP analyses as initial conditions when

ECMWF

Outline

- What are AI and Machine Learning?
- Showcase of Machine Learning Applications
- Tackling Machine Learning in Physical Disciplines
- The Rise of Data-Driven Numerical Weather Forecasts
- Selected Challenges and Opportunities

Let's start with definitions

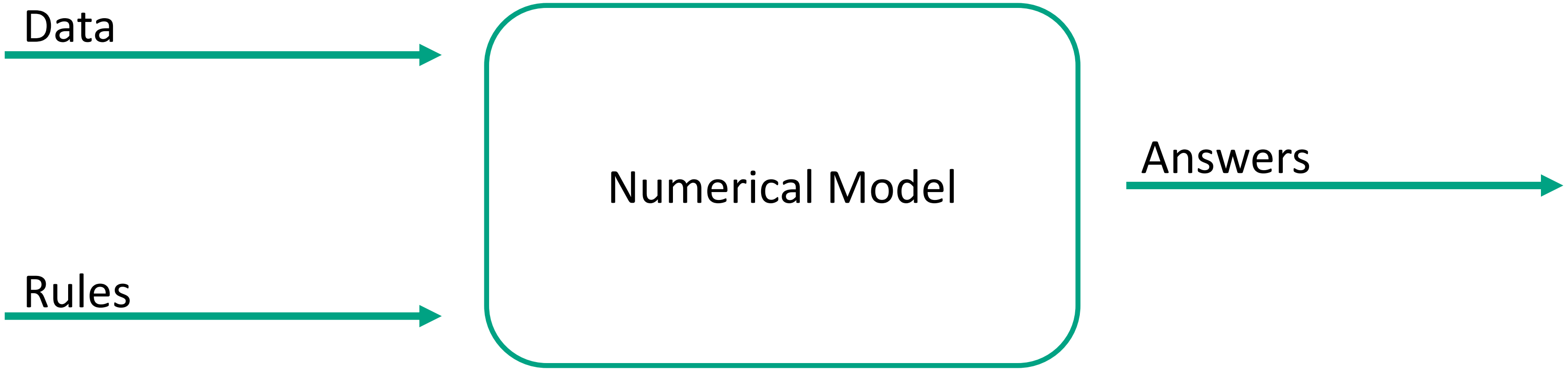


Artificial intelligence (AI) *is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans (Wikipedia)*
Example: A self-driving car stops as it detects a cyclist crossing

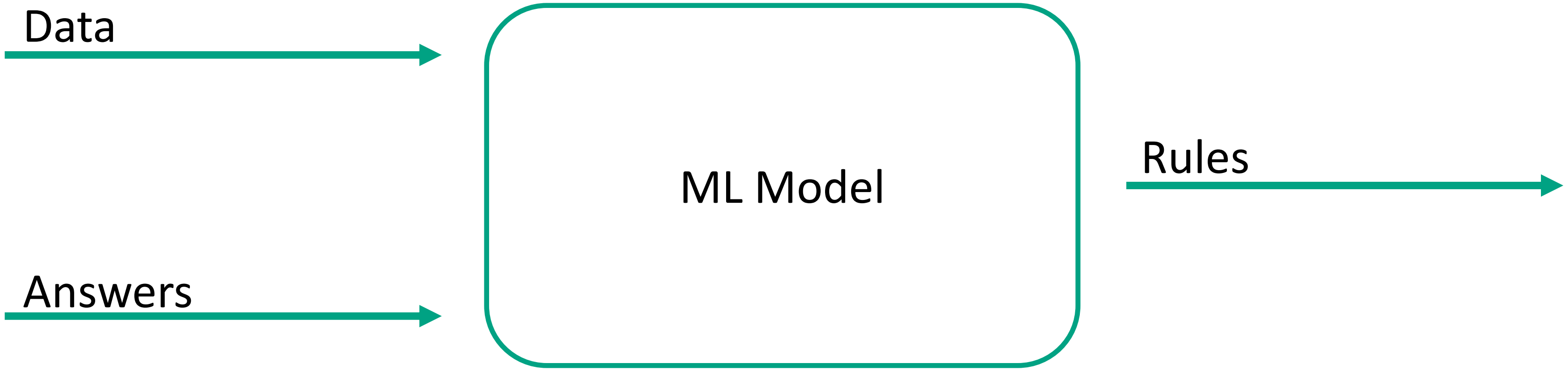
Machine learning (ML) *is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions… (Wikipedia)*
Example: To learn to distinguish between a cyclist and other things from data

Deep learning *is part of a broader family of machine learning methods based on artificial neural networks (Wikipedia)*
Example: The technique that is used to detect a cyclist in a picture

Classical Modelling



Supervised Machine Learning Modelling



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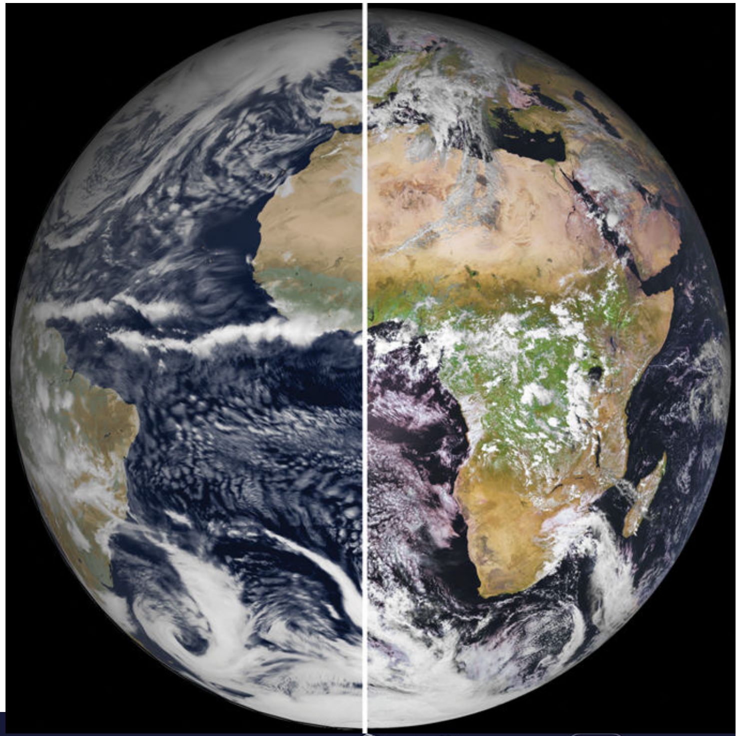
Why would machine learning help in weather and climate predictions?

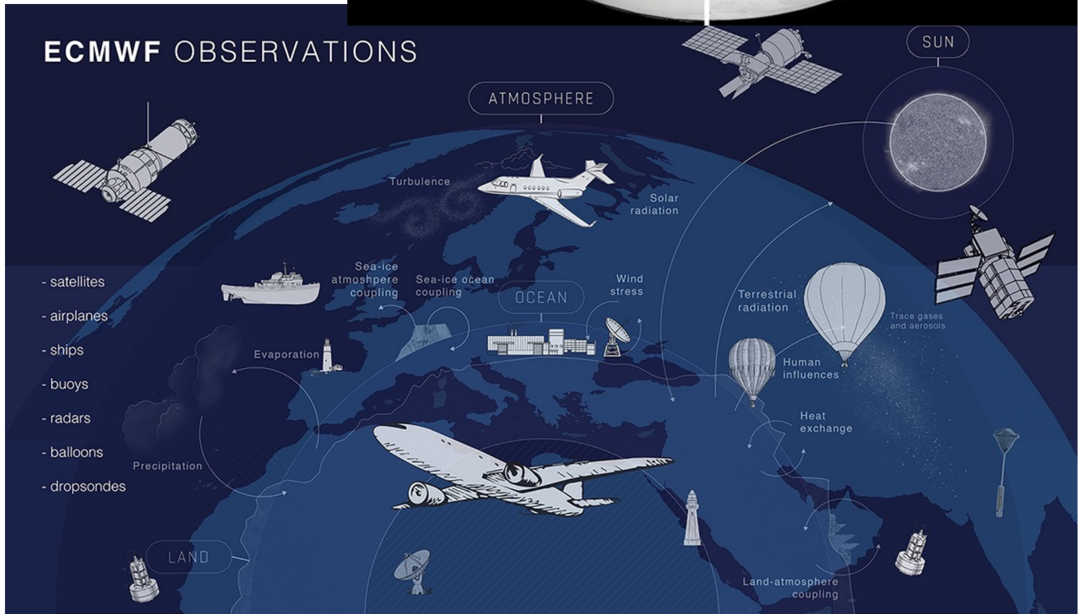
Predictions of weather and climate are difficult:

- The Earth is huge, resolution is limited and we cannot represent all important processes within model simulations
- The Earth System shows “chaotic” dynamics which makes it difficult to predict the future based on equations
- All Earth System components (atmosphere, ocean, land surface, cloud physics,…) are connected in a non-trivial way
- Some of the processes involved are not well understood



However, we have a huge number of observations and Earth System data

➢ **There are many application areas for machine learning in numerical weather predictions**



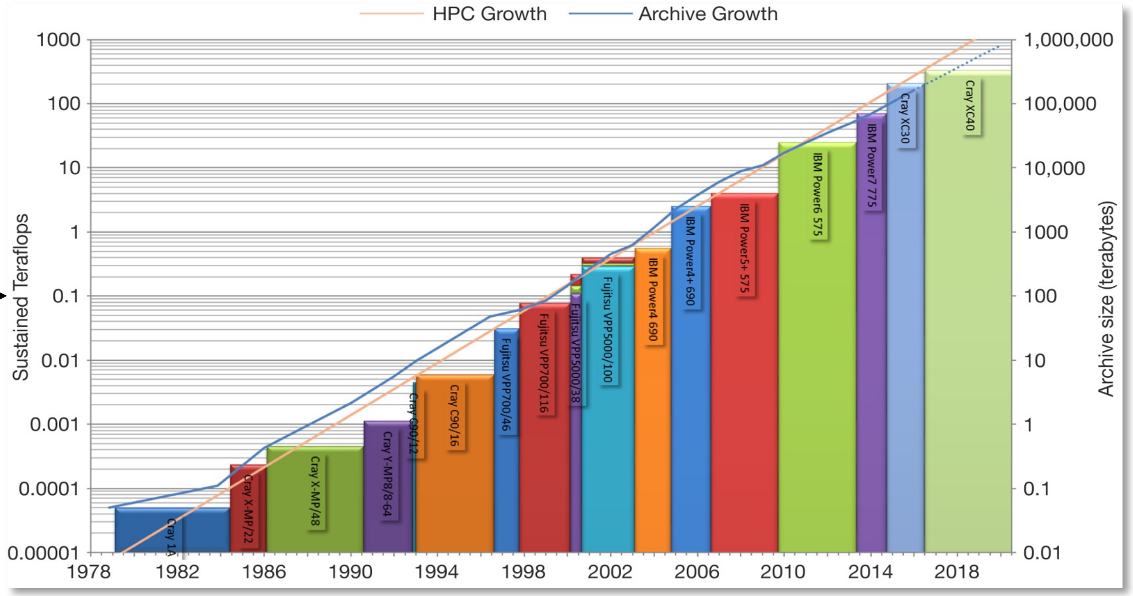
Why now?

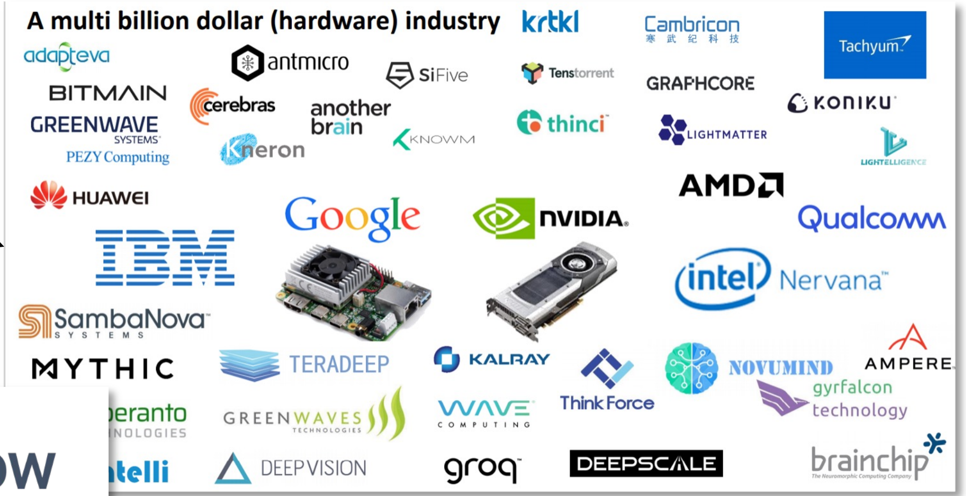
Increase in data volume

New computing hardware

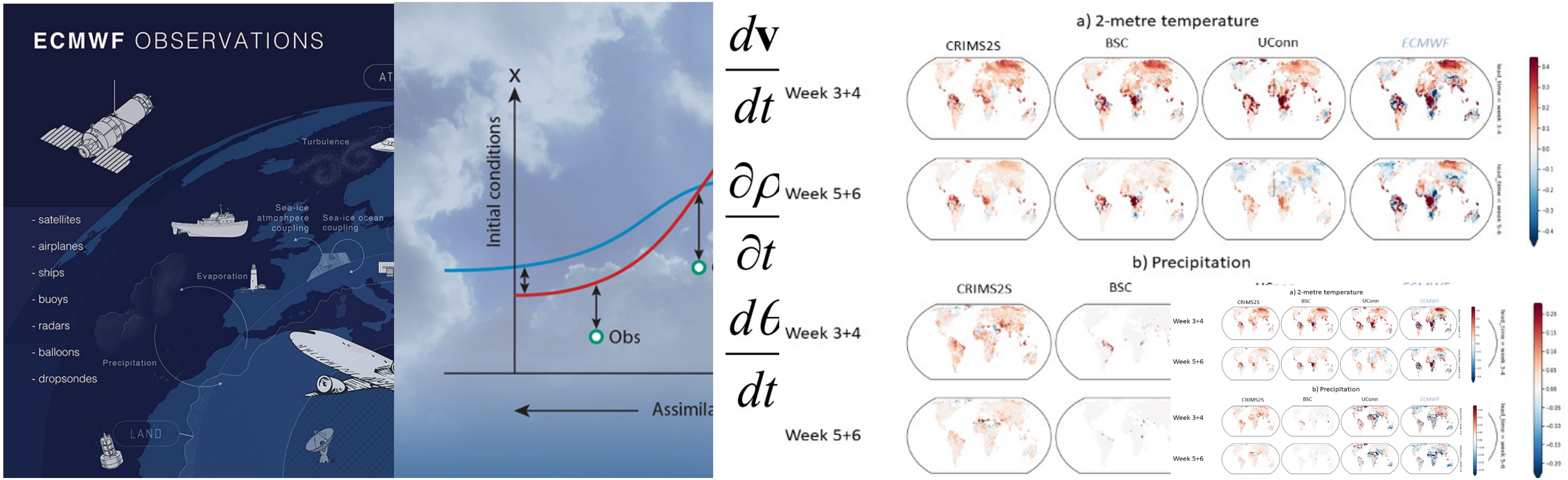
New machine learning software

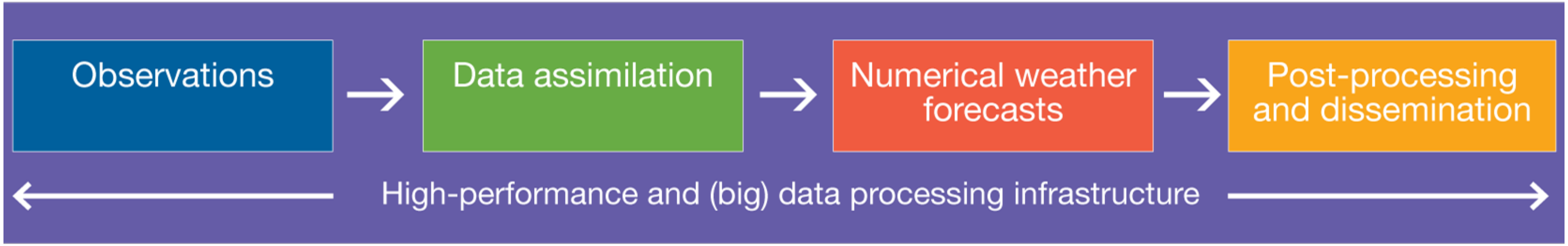
Increase in knowledge





Numerical Weather Prediction





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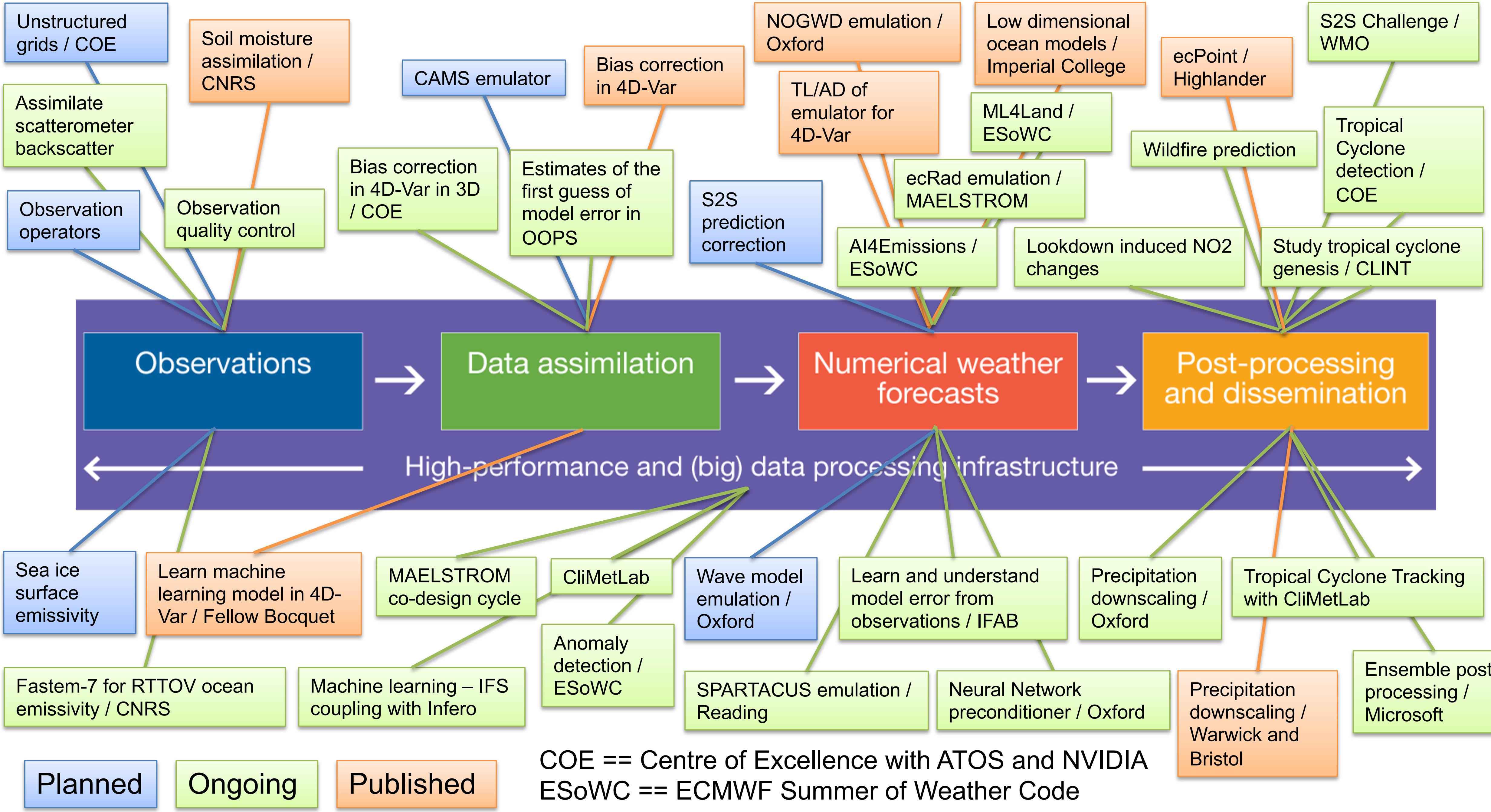
Machine learning at ECMWF



Get organised! → A machine learning roadmap


Technical Memo

ECMWF
European Centre for Medium-Range Weather Forecasts

878

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 Palkovič, Baudouin Raoult, Nils Wedi, Vasileios Baousis

January 2021

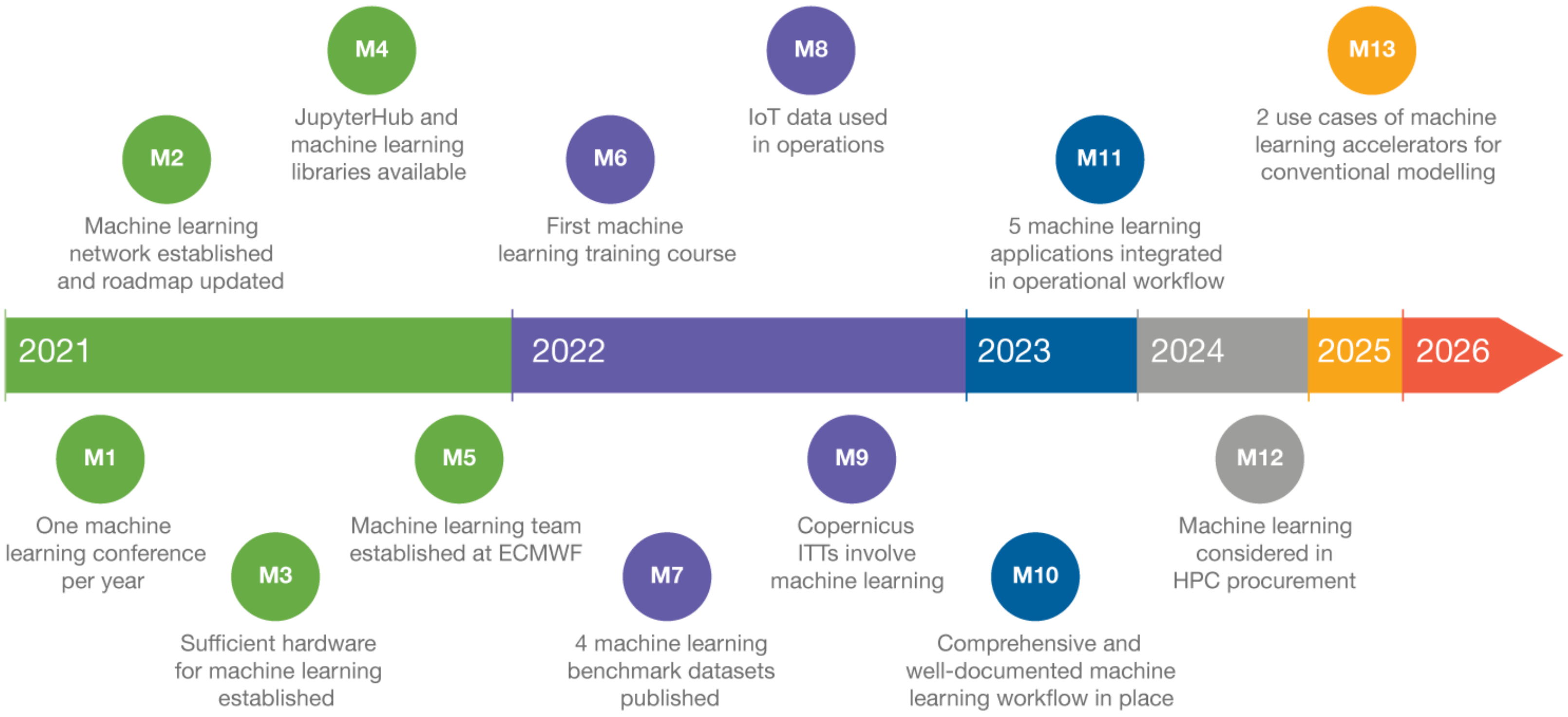
Objective 1
Explore machine learning applications across the weather and climate prediction workflow and apply them to improve model efficiency and prediction quality.

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.



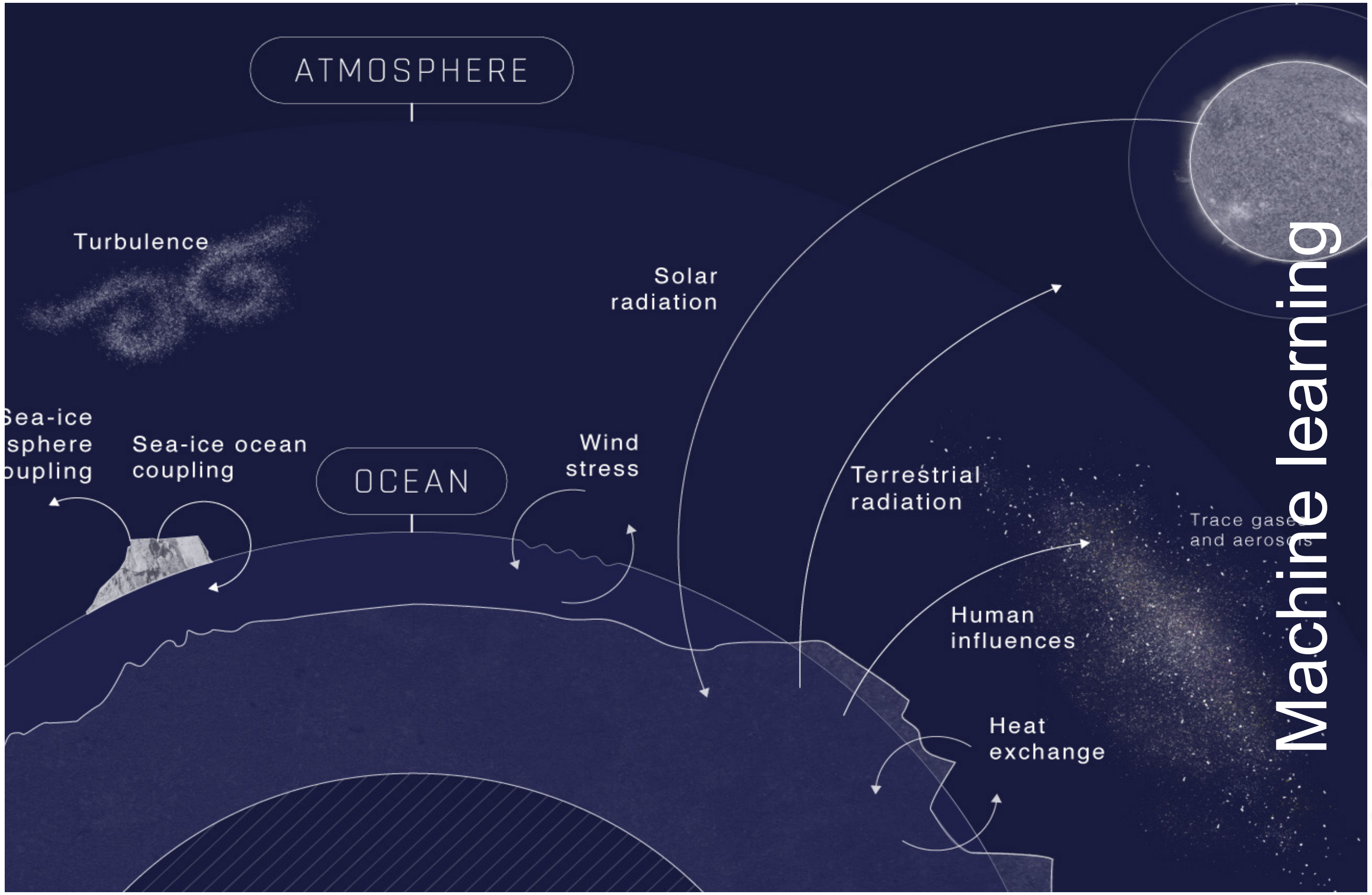
Vision 2031

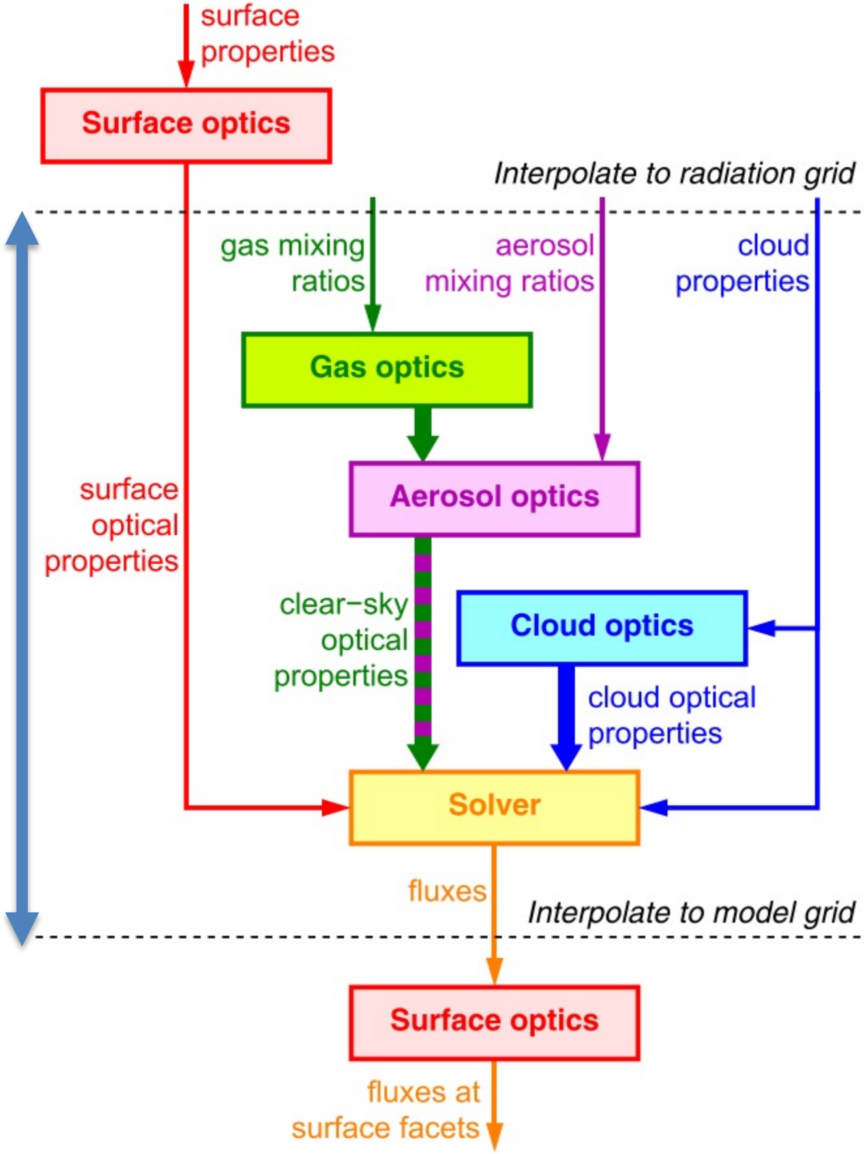
- It is difficult to distinguish between machine learning and domain sciences
- Data handling fully capable to serve machine learning needs
- Fully supported diagnostic tools via trustworthy AI
- Physical constraints can be represented in deep learning
- Use of machine learning as easy and normal as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

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

Showcase of Machine Learning Applications

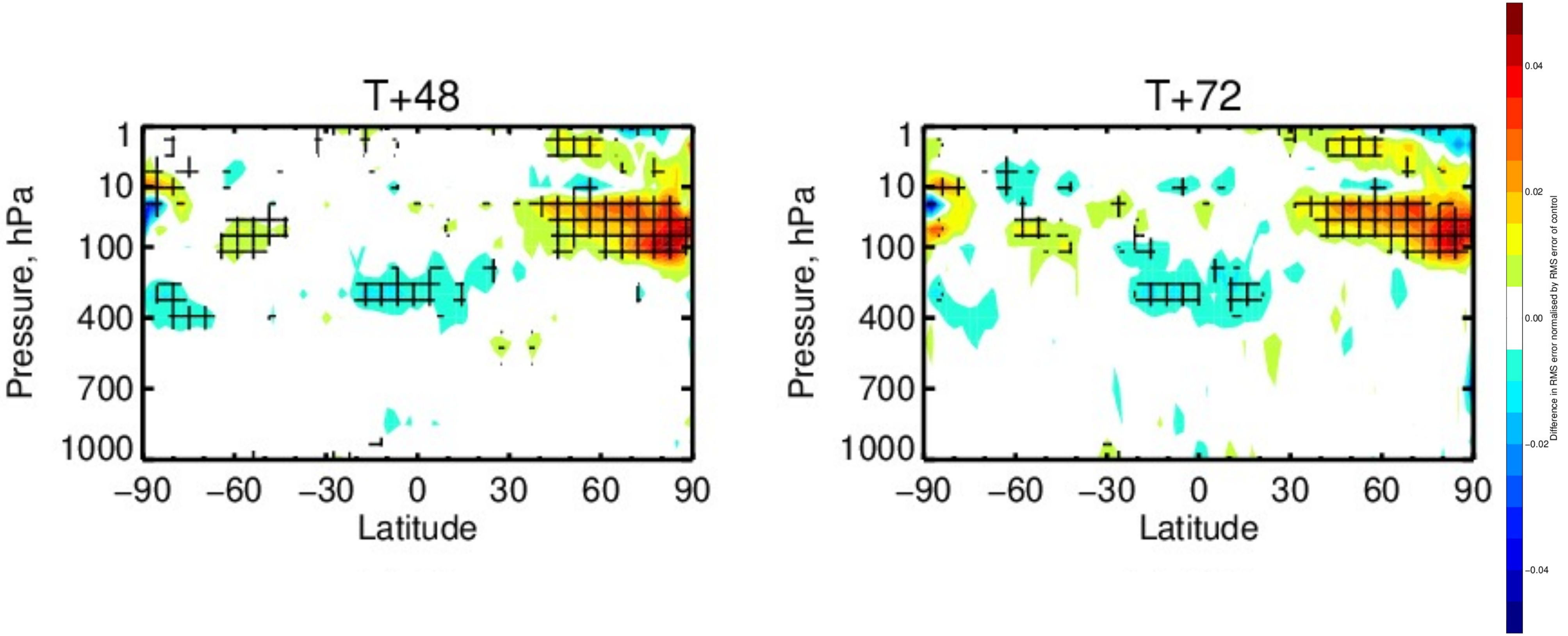
Machine learning for parametrised physics





Chantry, et al.

Machine learning for parametrised physics

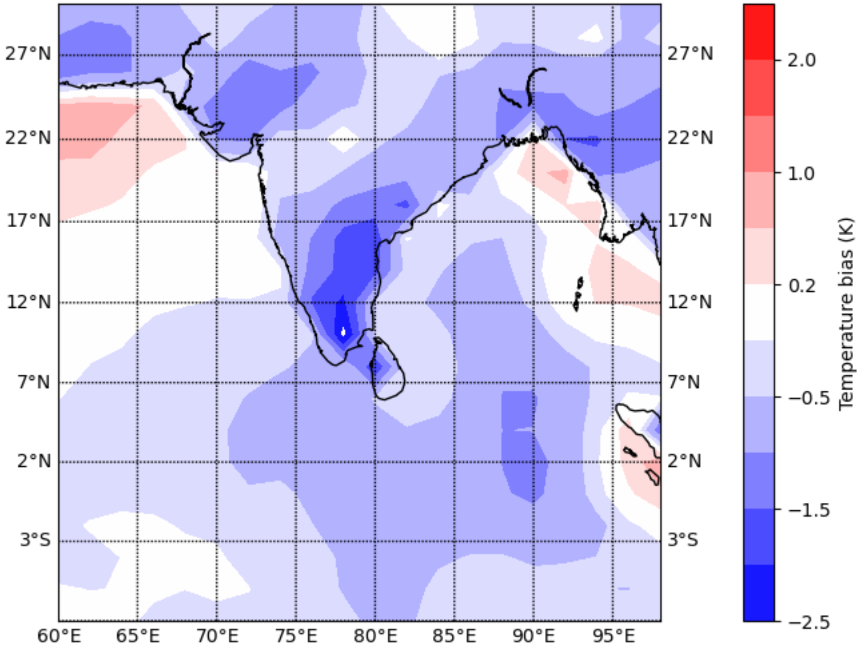


Change in temperature RMSE during JJA deterministic forecasts at TCo399 versus existing radiation scheme.

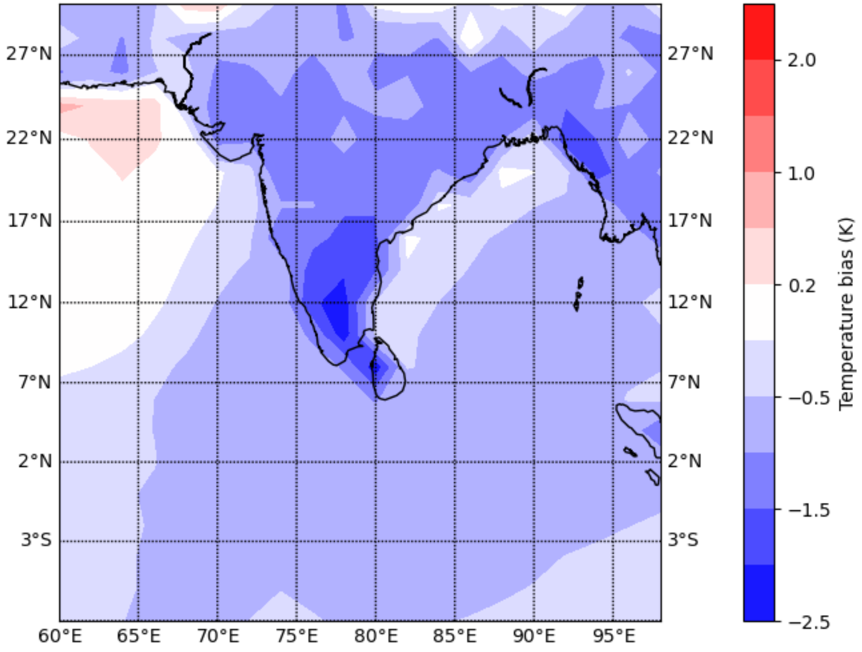
Chantry, et al.

Predict Bias from Deterministic Forecast using Machine Learning

Target Bias (Average 2011)

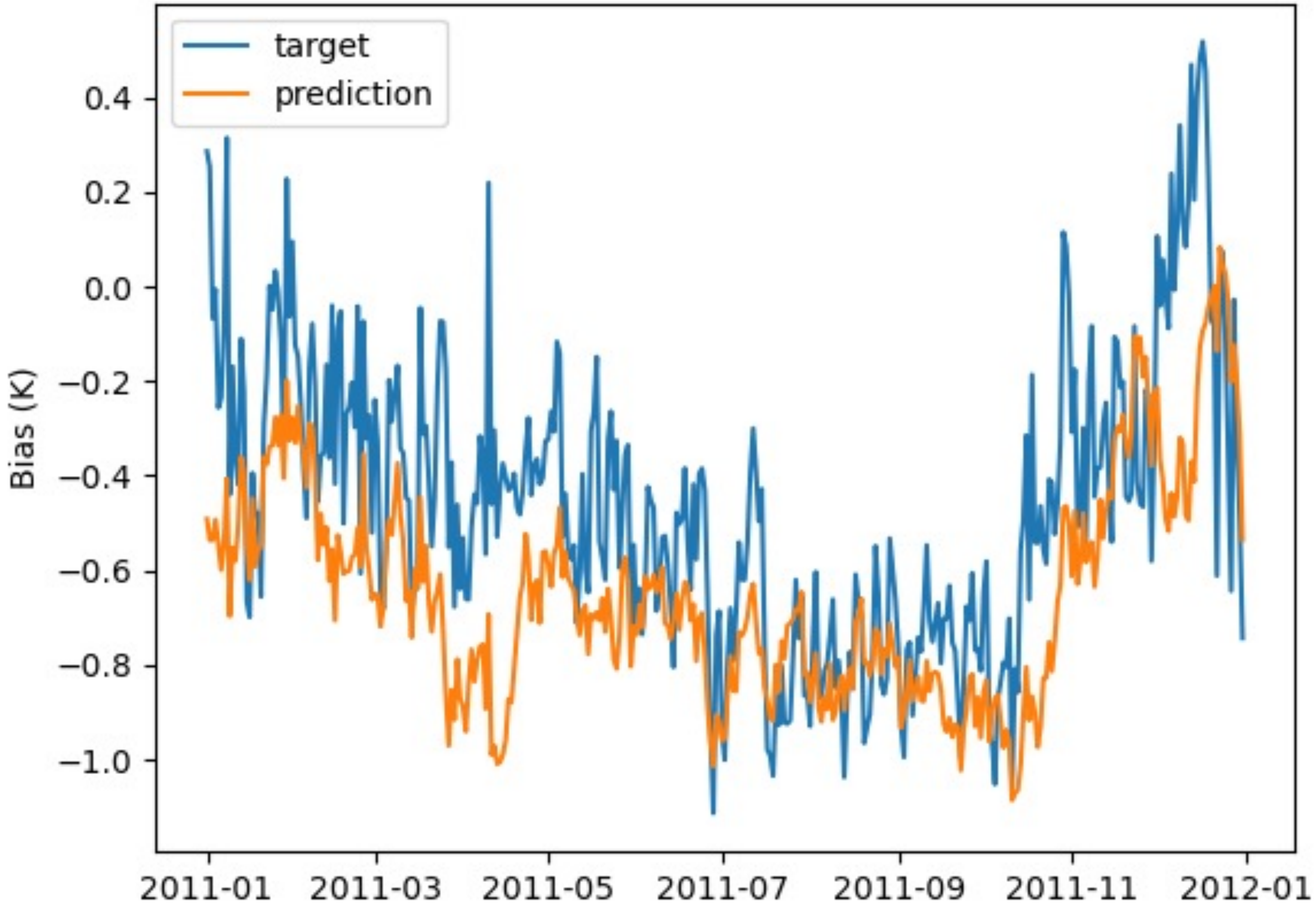


Predicted Bias

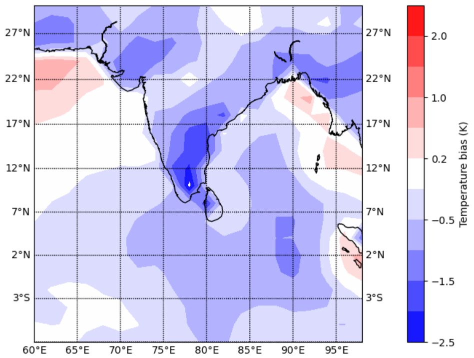


Clare, et al.

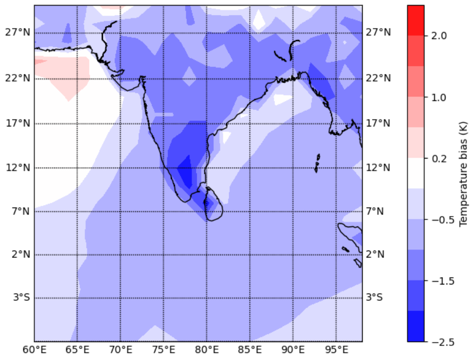
Predict Bias from Deterministic Forecast using Machine Learning



Target Bias (Average 2011)



Predicted Bias

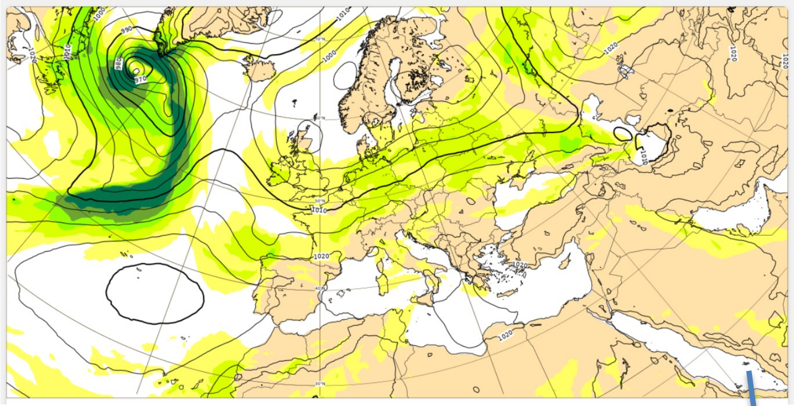


Clare, et al.

Data-Driven Weather Forecasts

How to go from physical NWP to fully data-driven NWP

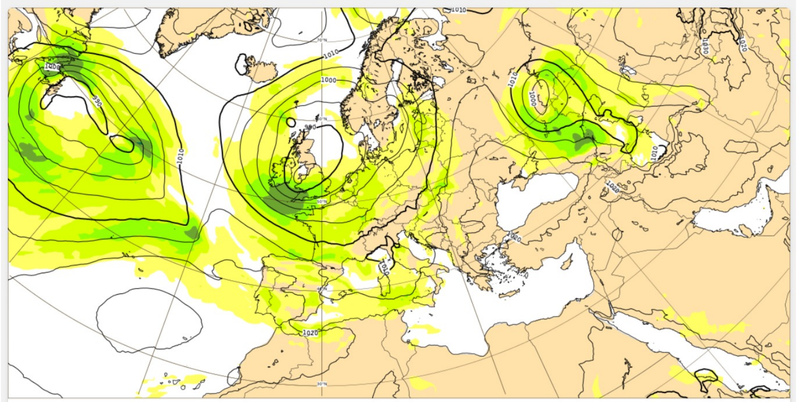
Analysis



Fusion of short-range forecast
with latest observations

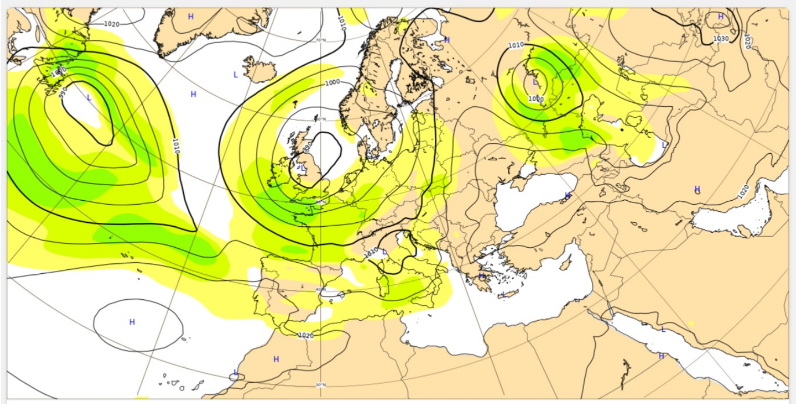
NWP Model

Forecast

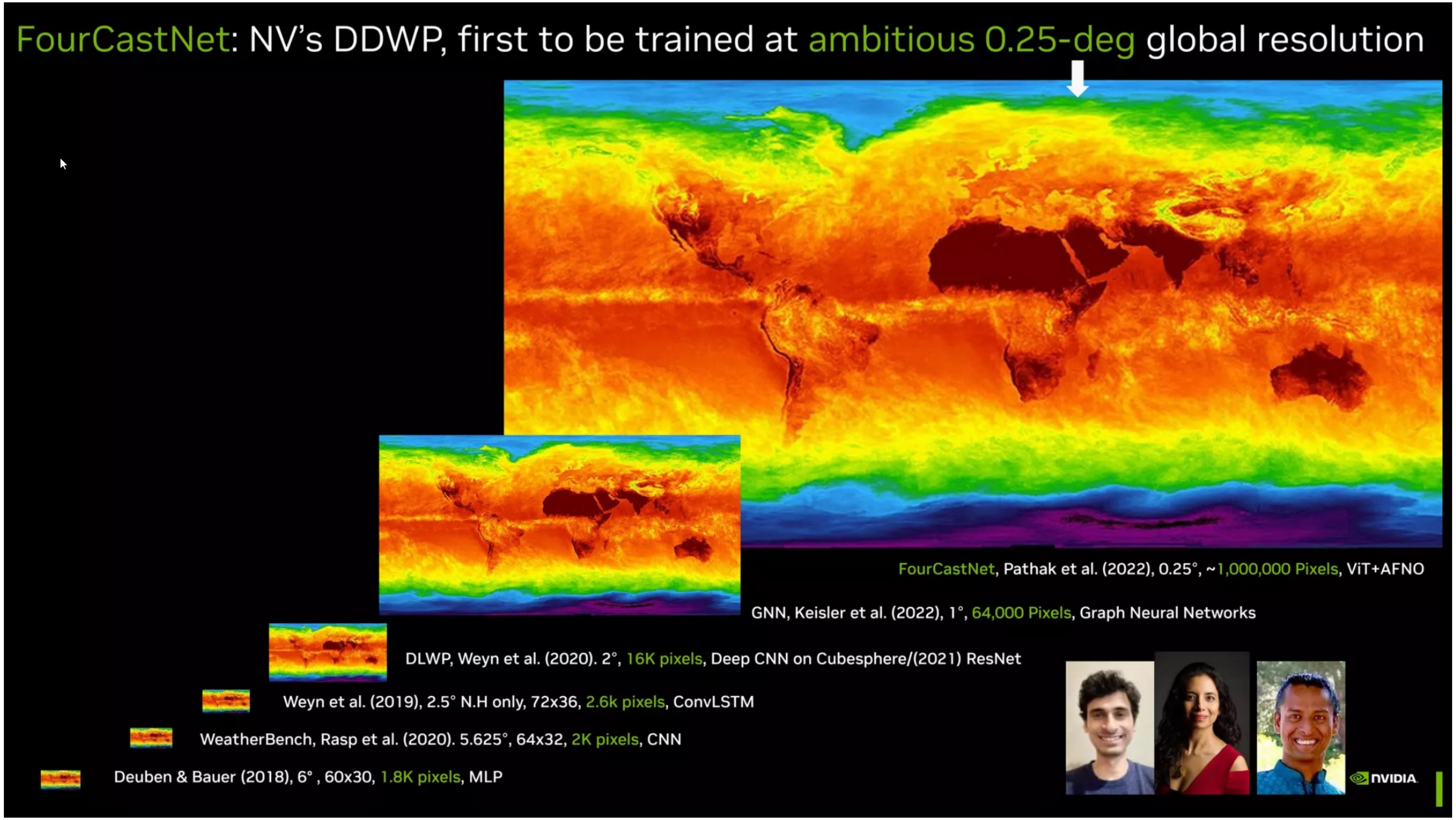


Data Driven Model

Learned from 40
years of analyses

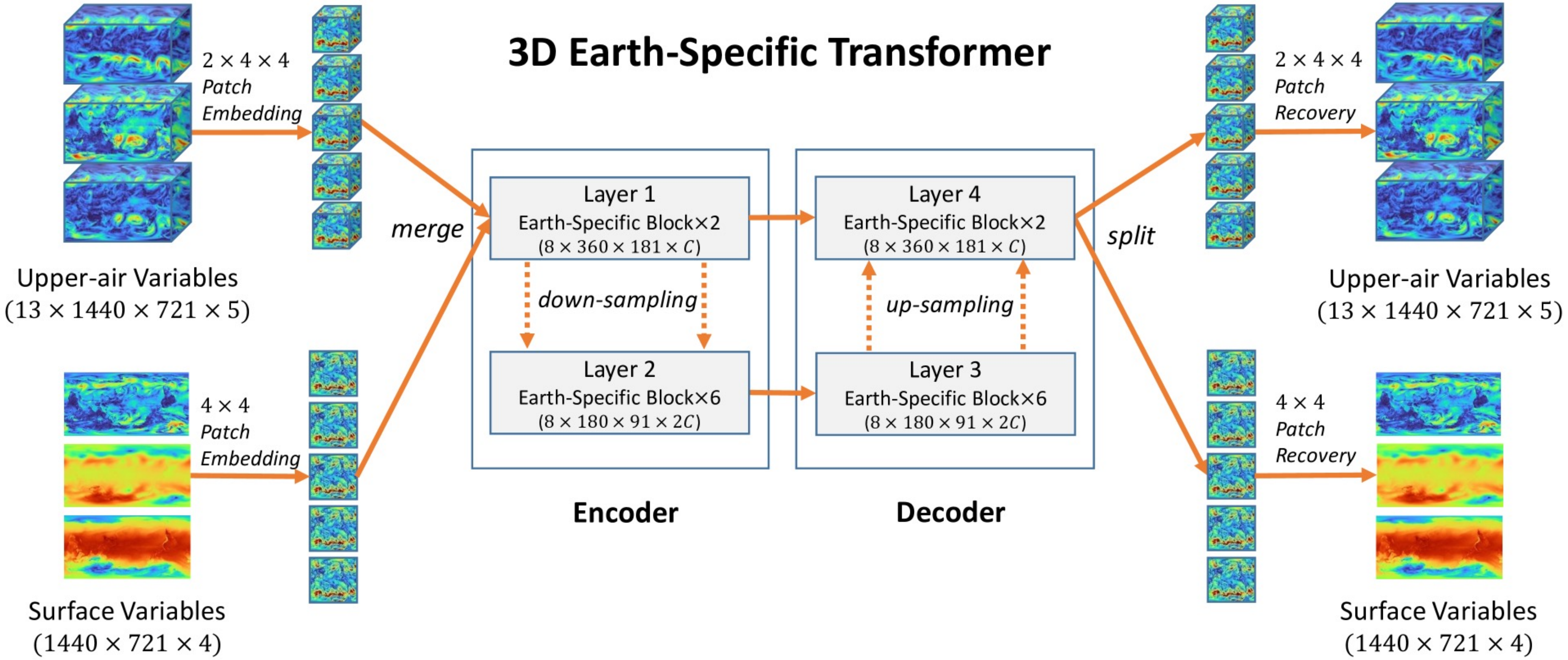


FourCastNet



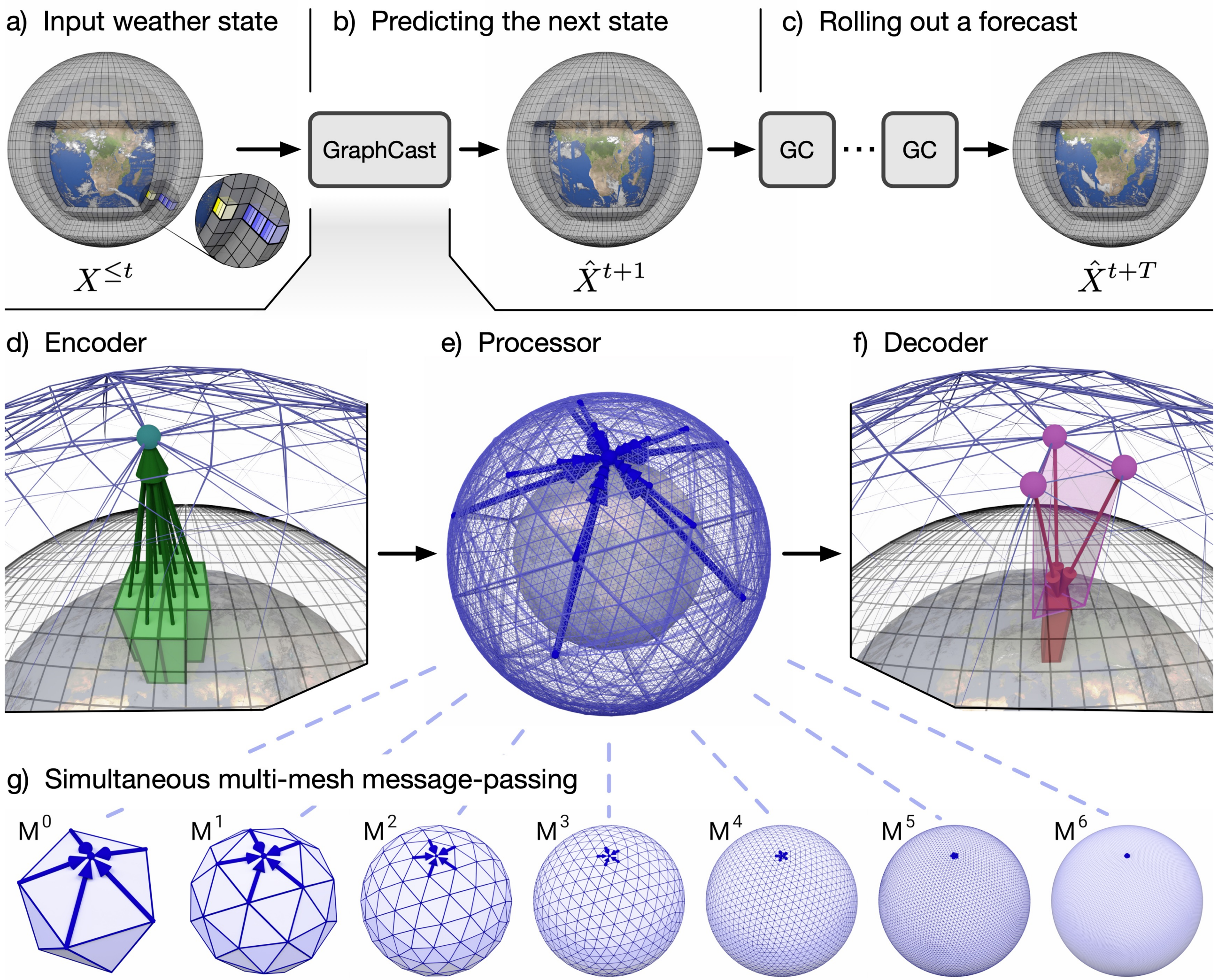
https://ar5iv.labs.arxiv.org/html/2202.11214

Pangu Weather



https://ar5iv.labs.arxiv.org/html/2211.02556

DeepMind GraphCast



A very fast and evolving landscape

2018
Exploring the concept

ECMWF staff
~500km_ERA5 to predict future z500.
Similar work from Rasp and Weyn.

2020 WeatherBench

Defining the dataset, split, headline fields and metrics

Feb 2022
Full medium-range NWP

Keisler - GraphNN 1°, competitive with GFS

NVIDIA – FourCastNet
Fourier+ , 0.25°

O(10^4) faster & more energy efficient than IFS

Nov 2022
Tropical cyclones

Huawei – PanguWeather
0.25° hourly product

"More accurate tracks" than the IFS.

Dec 2022
Extensive predictions

Deepmind – GraphCast
0.25° 6-hour

Many variables and pressure levels with comparable skill to IFS.

Jan 2023
Global & Limited Area

Microsoft – ClimaX

Forecasting various lead-times at various resolutions, both globally and regionally

Apr 2023
7-day+ scores improve

FengWu – China academia + Shanghai Met Bureau
0.25° 6-hour product

Improves on GraphCast for longer leadtimes (still deterministic)

Jun 2023

Spherical harmonics

NVIDIA – SFNO
0.25° 6-hour product

Extension of FourCastNet to Spherical harmonics, improved stability

Diffusion modelling

Alibaba – SwinRDM
0.25° 6-hour product

Sharp spatial features

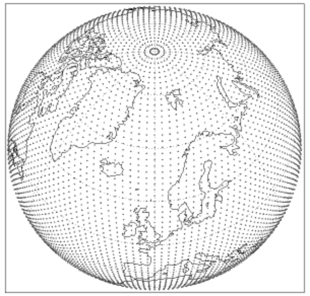
Last months
AIFS
FuXi
AtmoRep
FuXi-extreme
NeuralGCM
GenCast
…

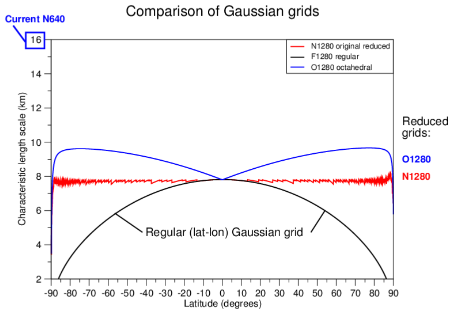
impossible to keep this figure up

AIFS V0.1

Model:

- O96 ERA5 grid, ~1-degree
- "Level 5" hidden grid, ~2-degree

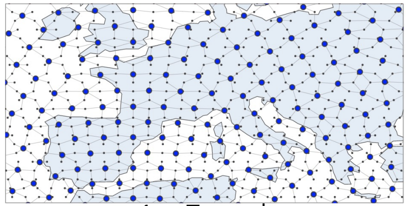




+ (equi-)area weights
+ weighting along plevs (vertical
+ per-variable weights in the loss

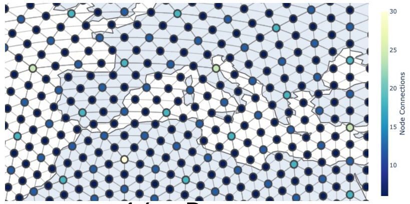
Variables:

13 pressure levels – u, v, w, q, t, z
surface: 2t, 10u, 10v, 2d, sp, msl, sst

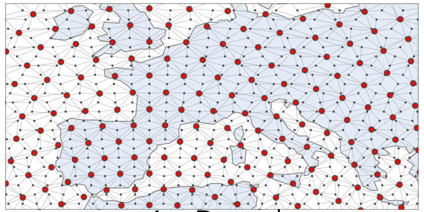


1 x Encoder

Skip-connection (residual)



16 x Processor



1 x Decoder

e.g. Hidden mesh "l6" ~ 40 000 Nodes
Multi-scale interconnectivity
~ 320 000 edges

Training:

Step 1: 4 days on 16 GPUs to minimise errors for single 6h step
Step 2: 34 hours on 16 GPUs to minimise errors up to 3 days
Step 3: 4 hours on 16 GPUs minimising errors up to 3 days on operational analysis

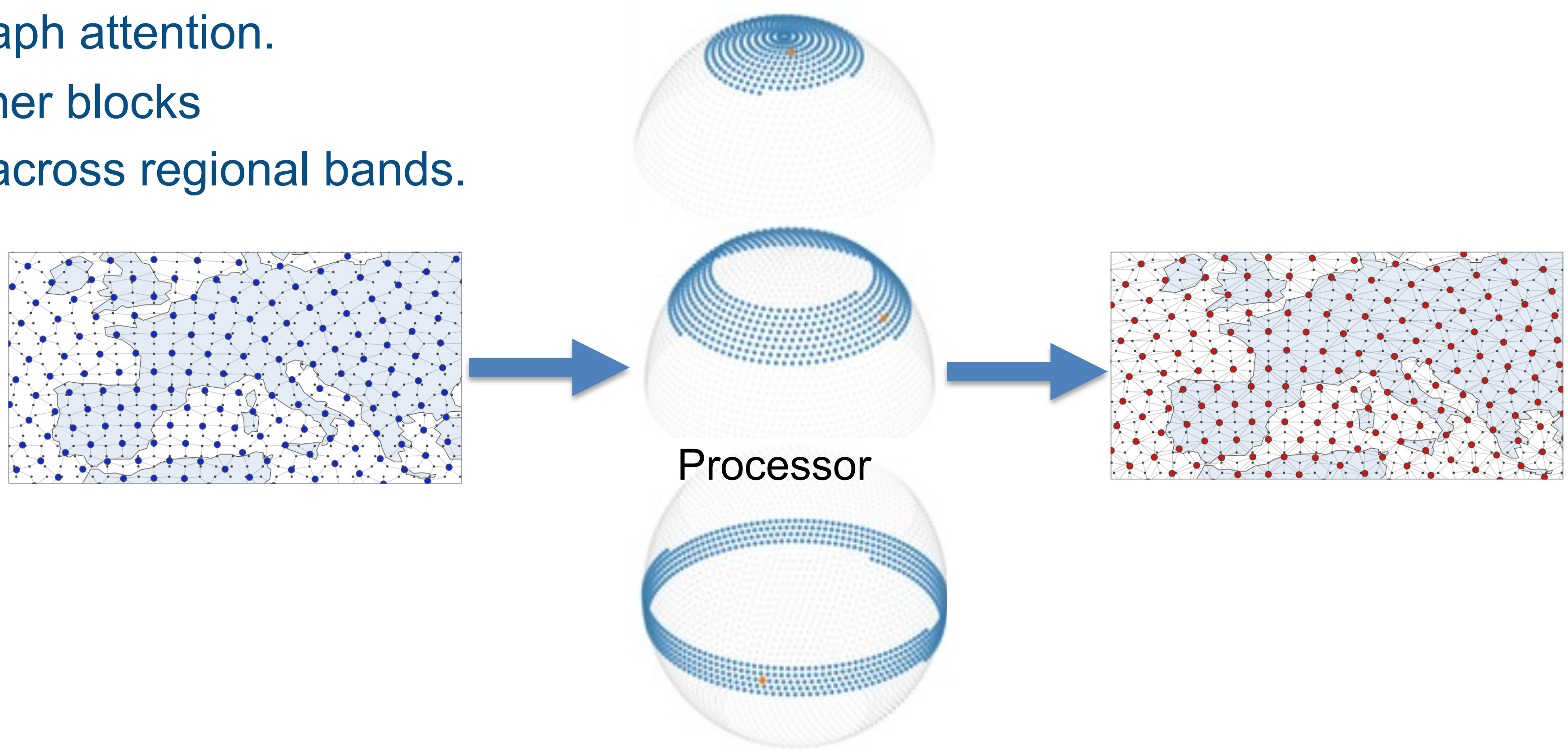
Total ~6 days on 16 GPUs

Live from Jan 2024.

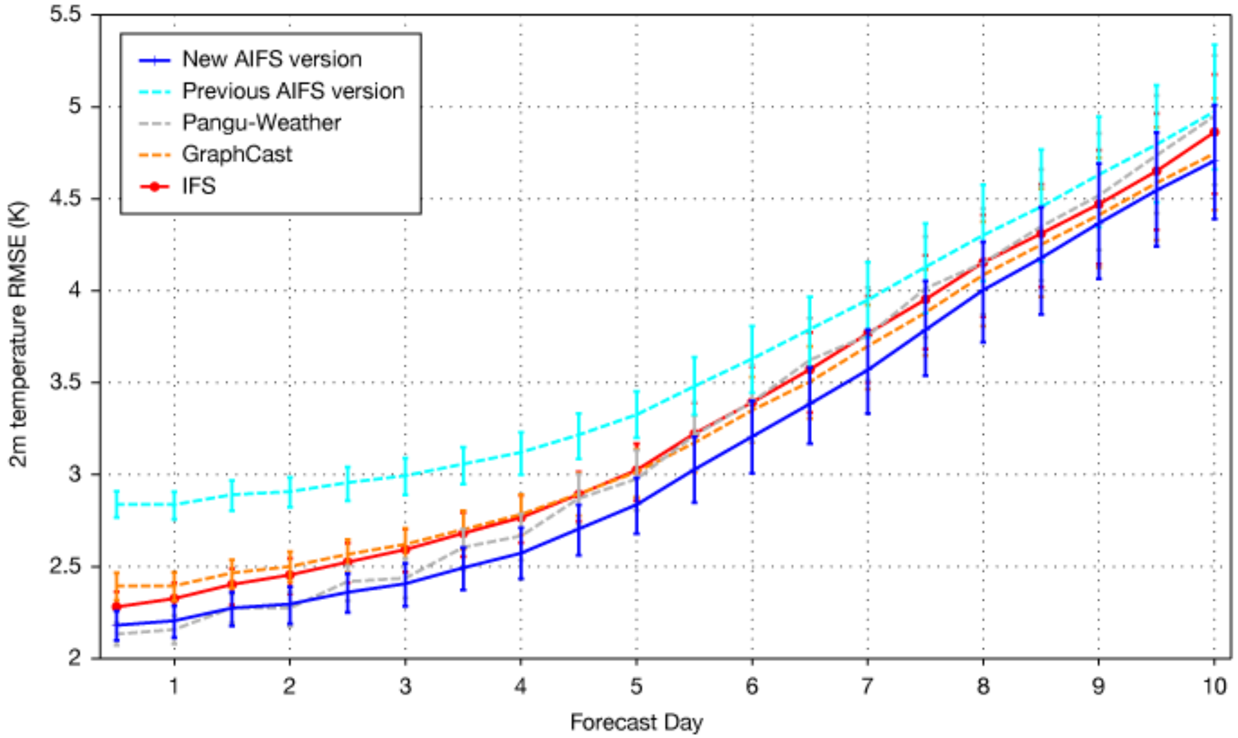
Resolution 0.25 degrees (4x finer)

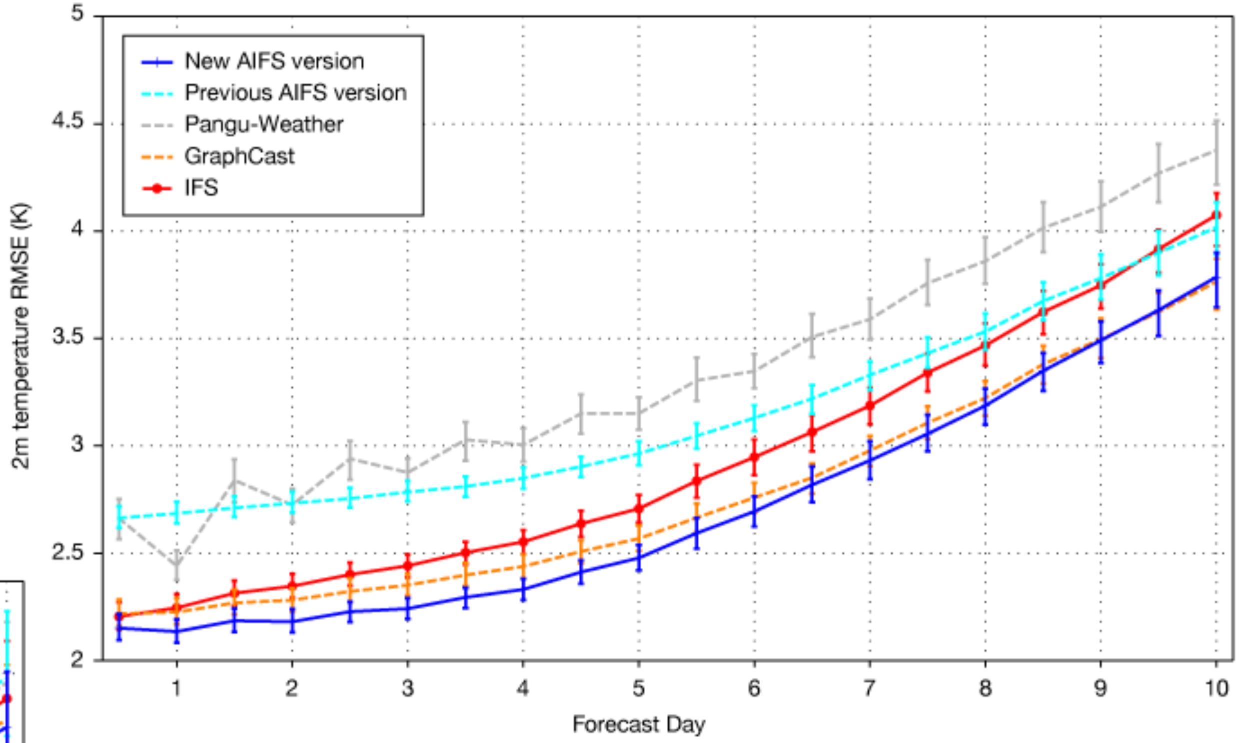
New architecture.

- Encoder/decoder: graph attention.
- Processor: Transformer blocks
  - attention across regional bands.



AIFS v0.2 against surface obs.

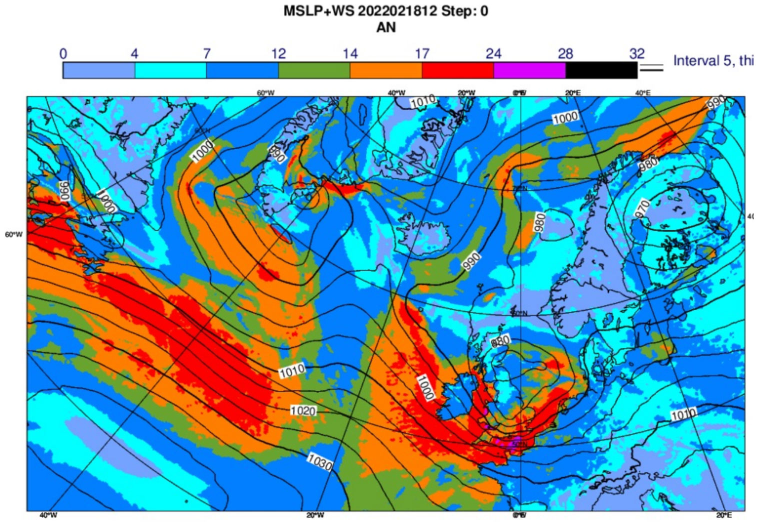




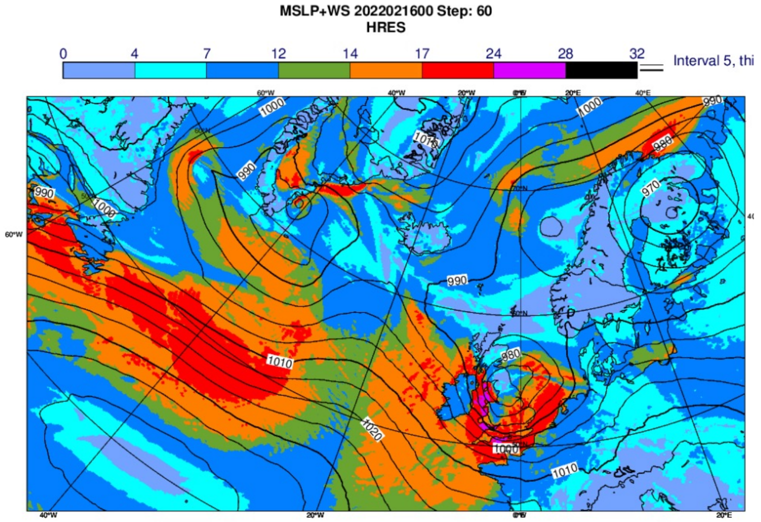
Evaluation Storm Eunice over UK 2022-02-16 00z + 60h

See ECMWF Newsletter 176

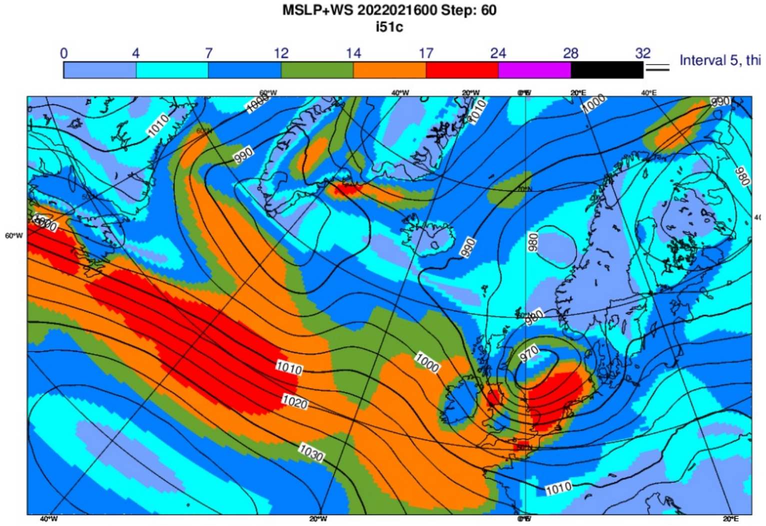
Analysis



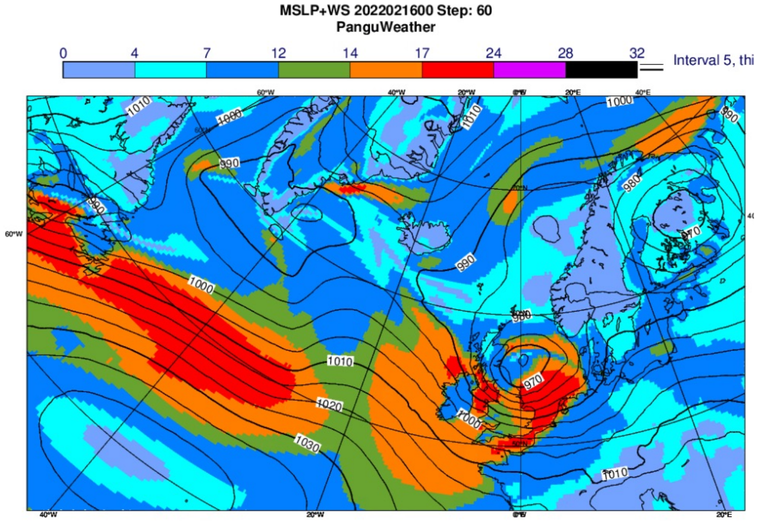
HRES



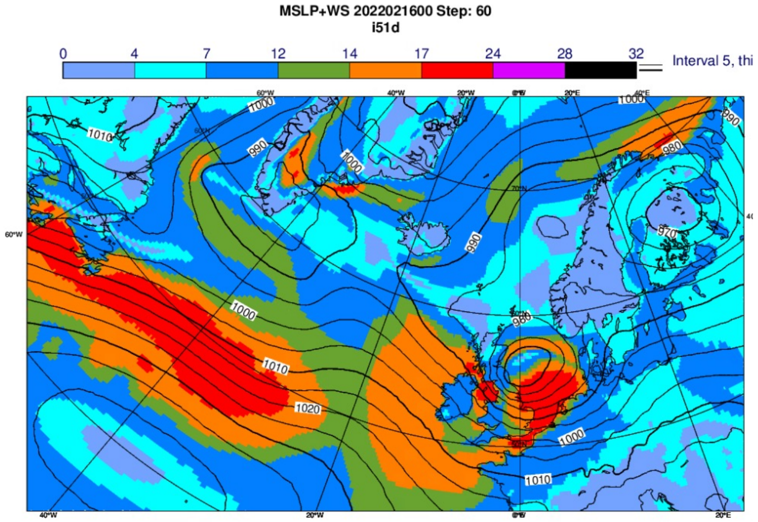
Fourcastnet



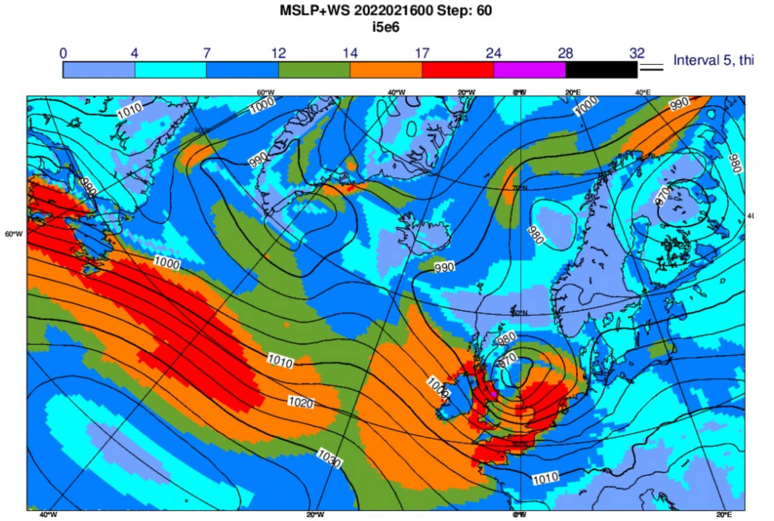
PanguWeather



Graphcast

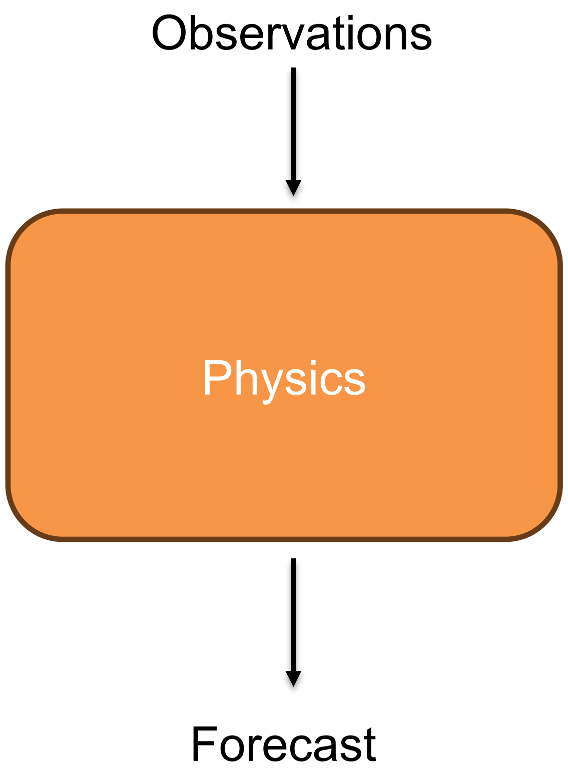


AIFS n320



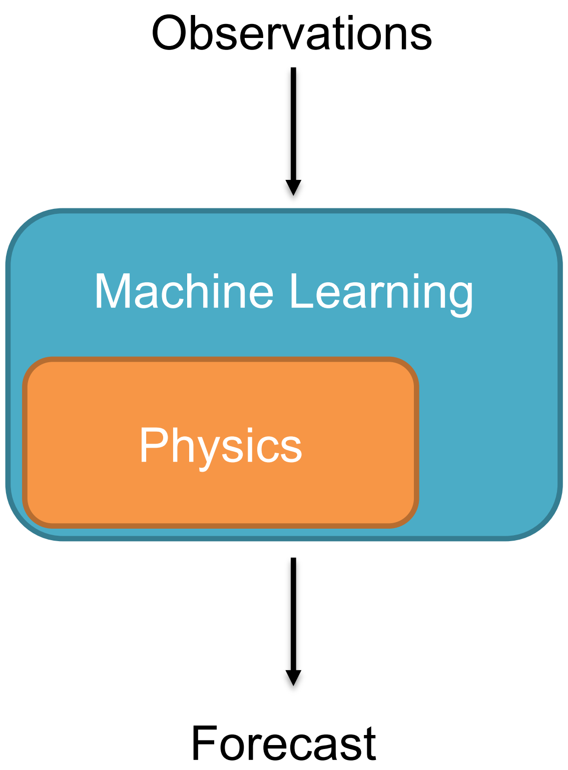
Tackling Machine Learning in Physical Disciplines

Classic Physical Model



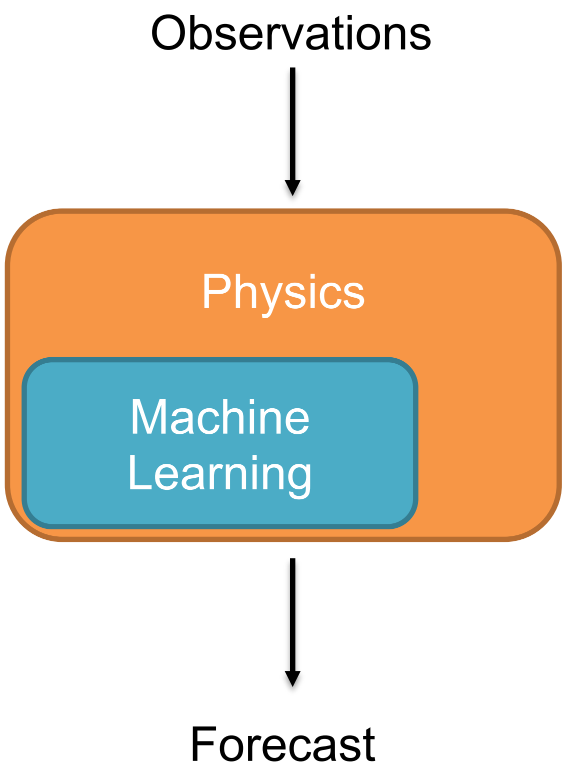
Keisler, 2021

“Physics-informed” Machine Learning



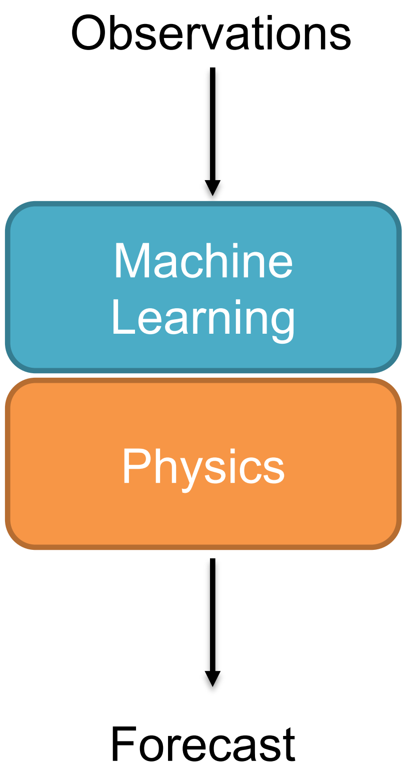
Chantry, et al.

Hybrid Models – Machine Learning Model inside Physics



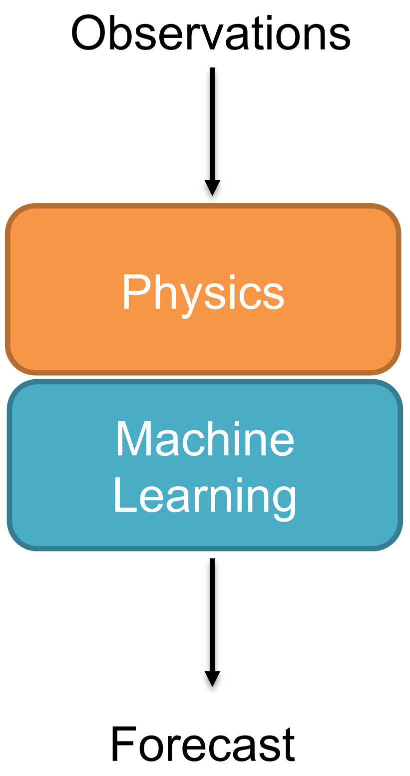
Chantry, et al.

Hybrid Models – Machine Learning Pre-conditioning



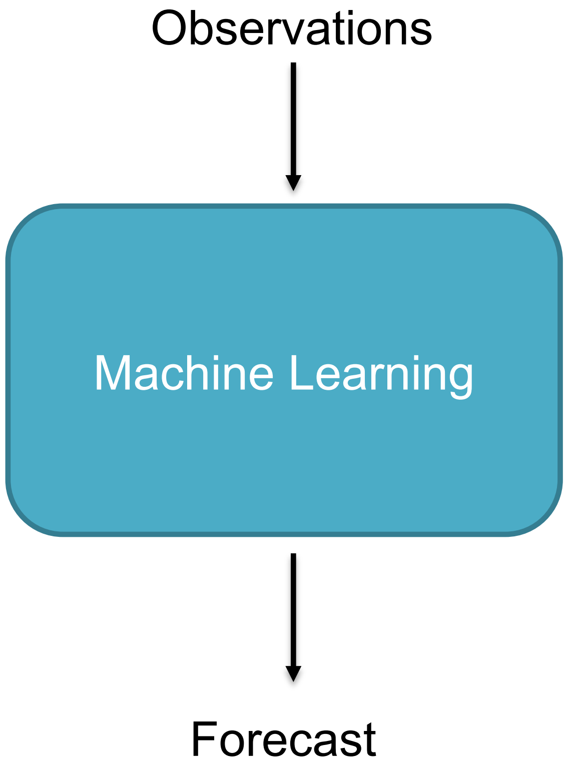
Bonavita, M., & Laloyaux, P. 2020

Hybrid Models – Machine Learning correction of Physics (errors)



Bonavita, M., & Laloyaux, P. 2020

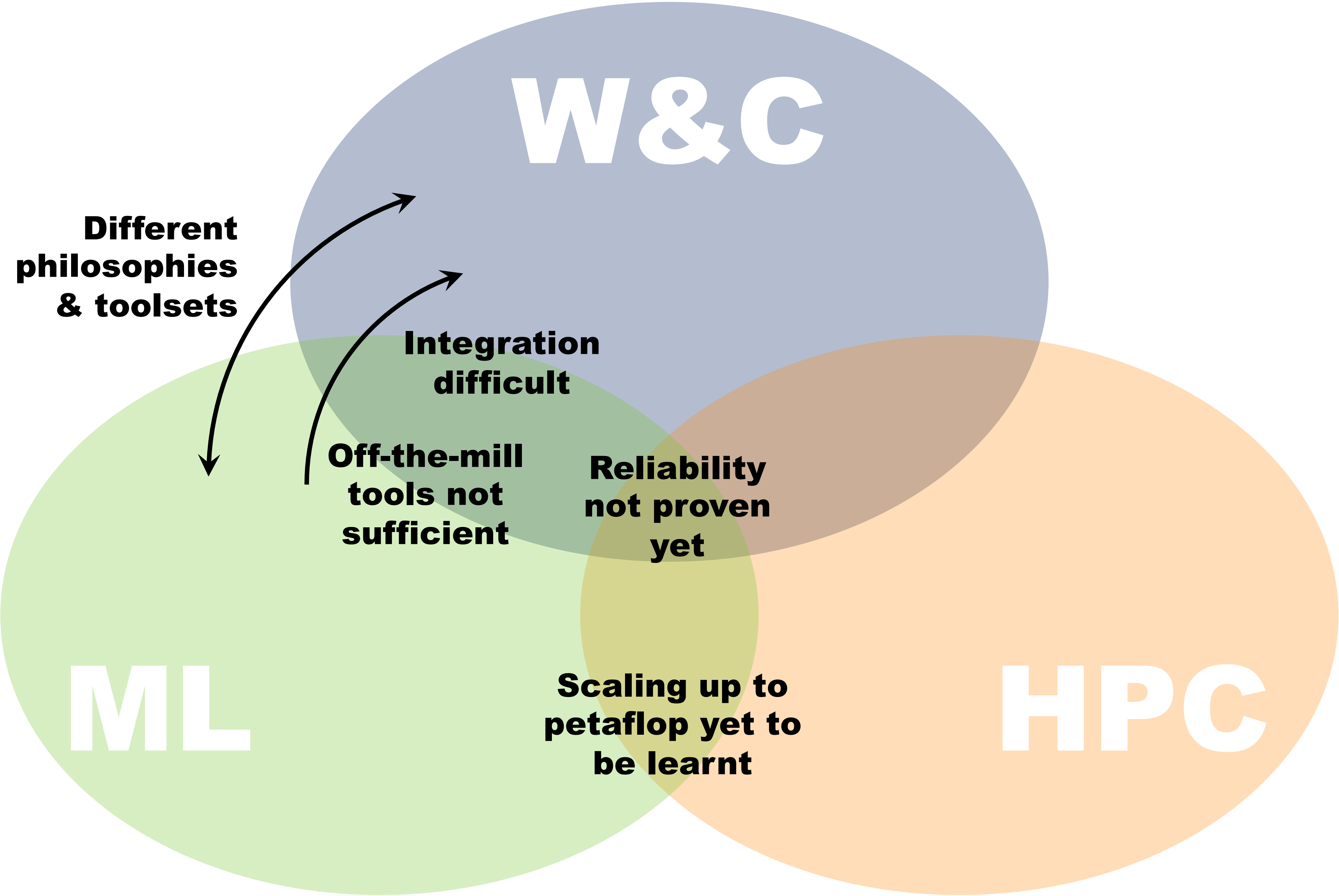
Full Machine Learning Model



Keisler, 2021

Selected Challenges in ML in NWP

Challenges


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

How can you build trust in ML tools and make them reliable?

Trustworthy AI, explainable AI and physics informed machine learning

Ways to incorporate physical knowledge into machine learning models:

- Change the architecture of the neural network
- Formulate the machine learning problem in a physical way
- Close the budget for the output variables
- Correct the outputs to fulfil the constraint
- Incorporate physical constraints into the loss function

Evaluate the machine learning solution for reproducing the correct physics

- Consider specific use cases and weather regimes
- Perform sensitivity tests on the inputs or outputs
- Test for physical reasoning (e.g. for extreme events)
- Benchmarking on existing solutions

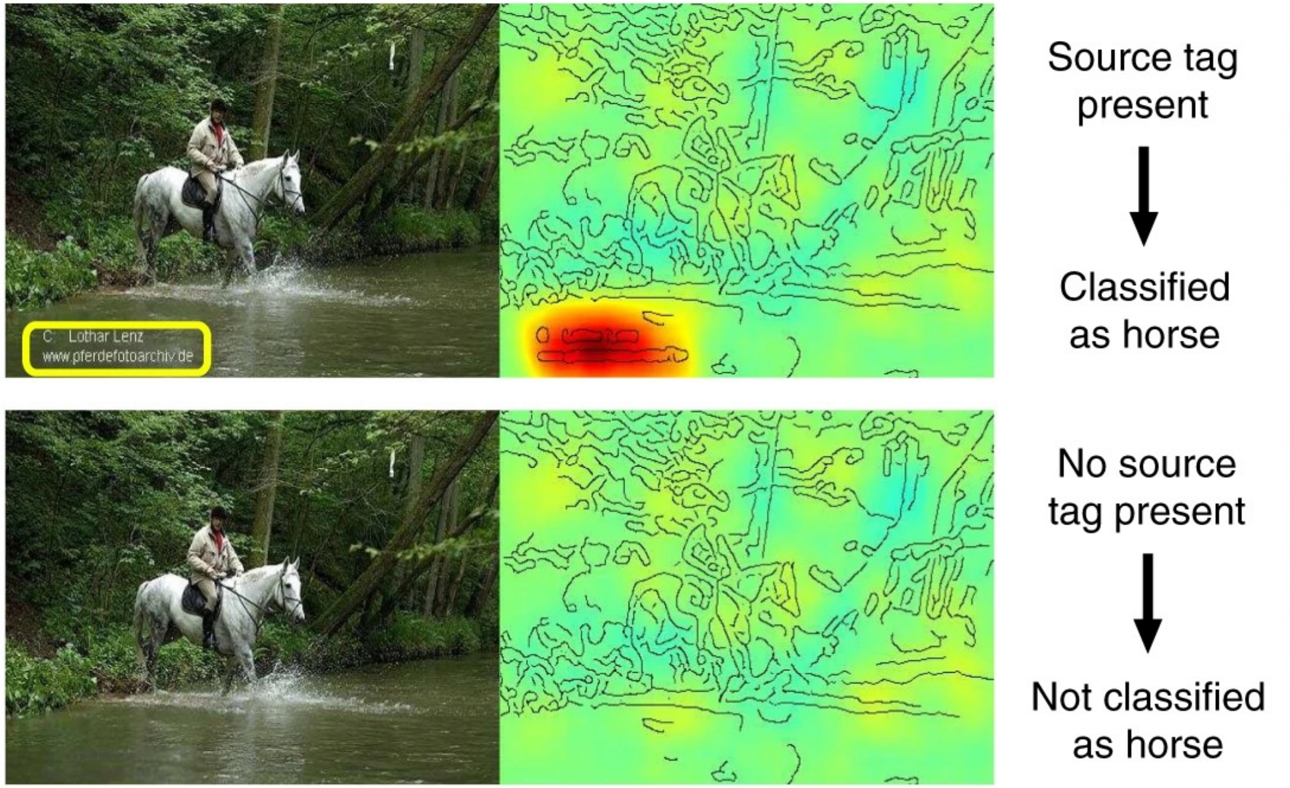
Reichstein, M. et al. Deep learning and process understanding for data-driven Earth system science. Nature 566, 195–204 (2019).

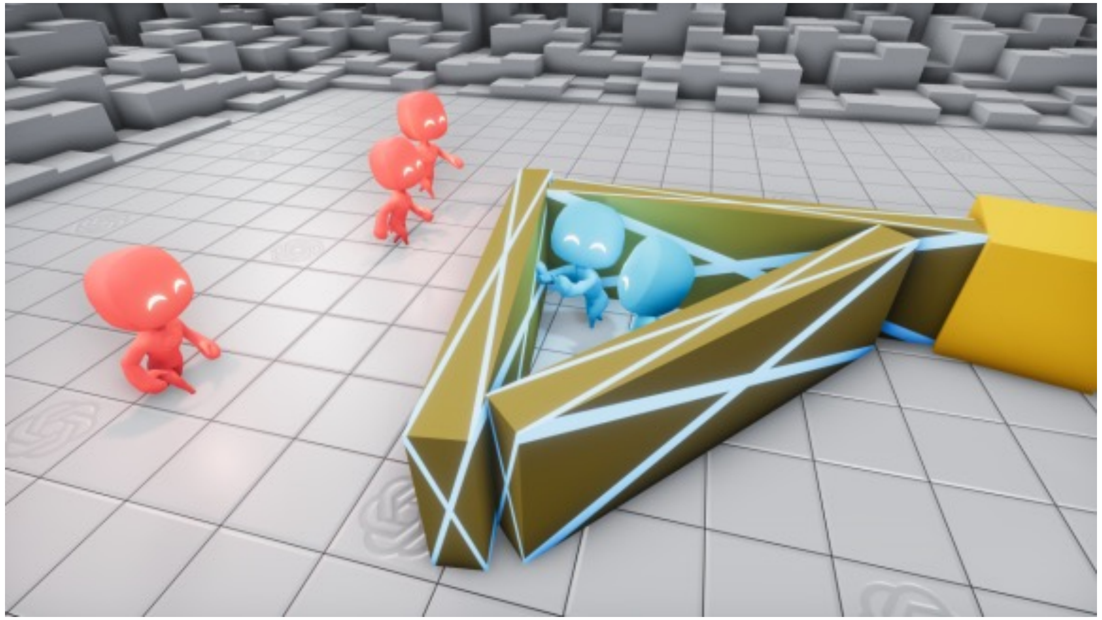
McGovern, et al. Making the Black Box More Transparent: Understanding the Physical Implications of Machine Learning, Bulletin of the American Meteorological Society, 100(11), 2175-2199 (2019)

Are we worried about Hallucinations?

Machine Learning does ”exactly what it’s trained for”.

Horse-picture from Pascal VOC data set





[Lapuschkin Wäldchen Binder A. *et al. Nat Commun* 2019](#)

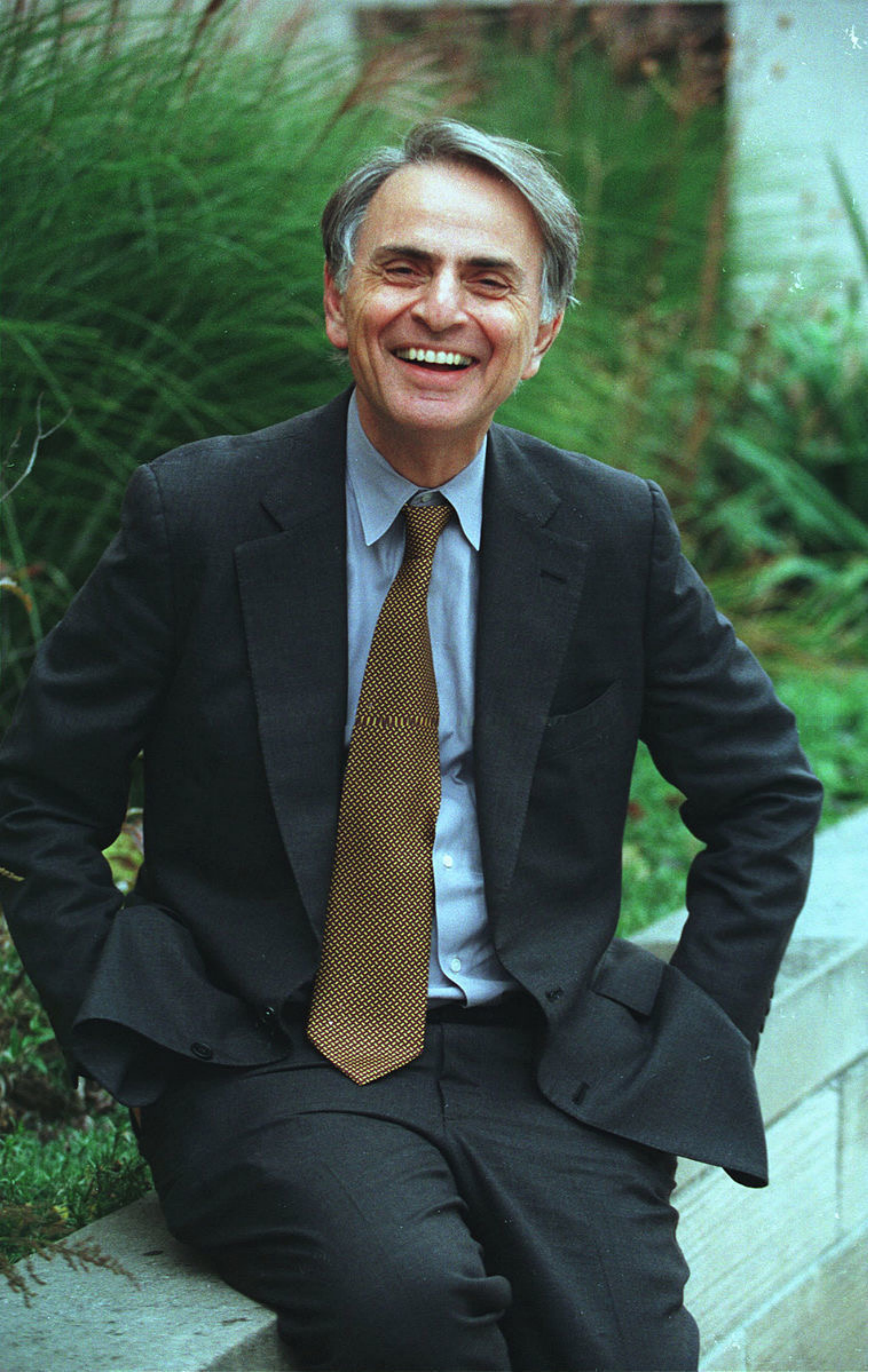
Will we hallucinate tropical cyclones?

- Probably not.

- ChatGPT and other Large language models
are trained to sounds convincing.

- Data-driven weather forecasts are trained to give accurate forecasts.

- Metrics matter!



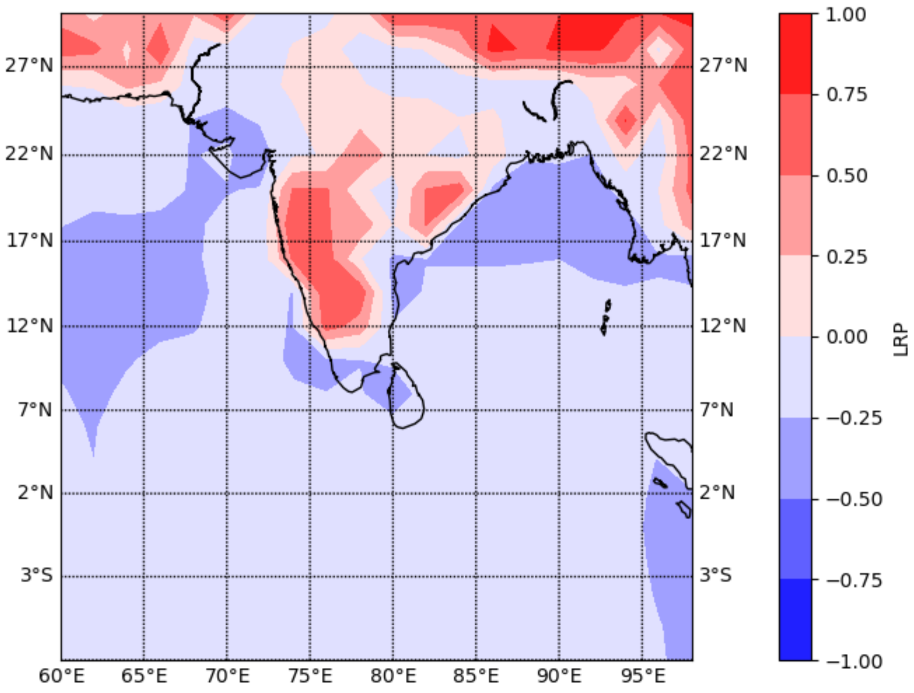
extraordinary claims
require
extraordinary evidence

Carl Sagan

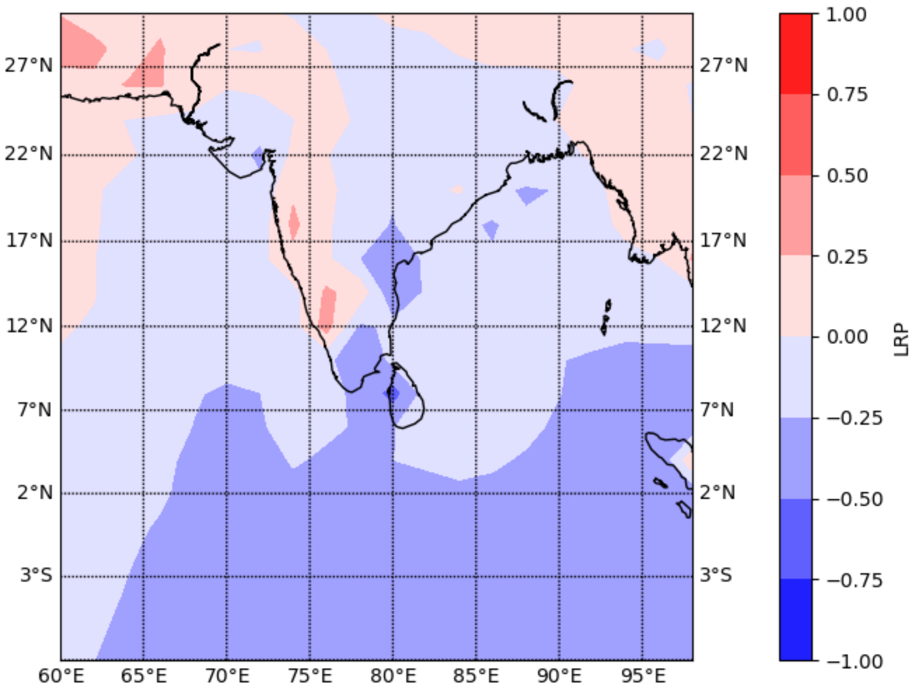
How can you build trust in ML tools and make them reliable?

Explainable AI – Layer Relevance Propagation

LRP Orography



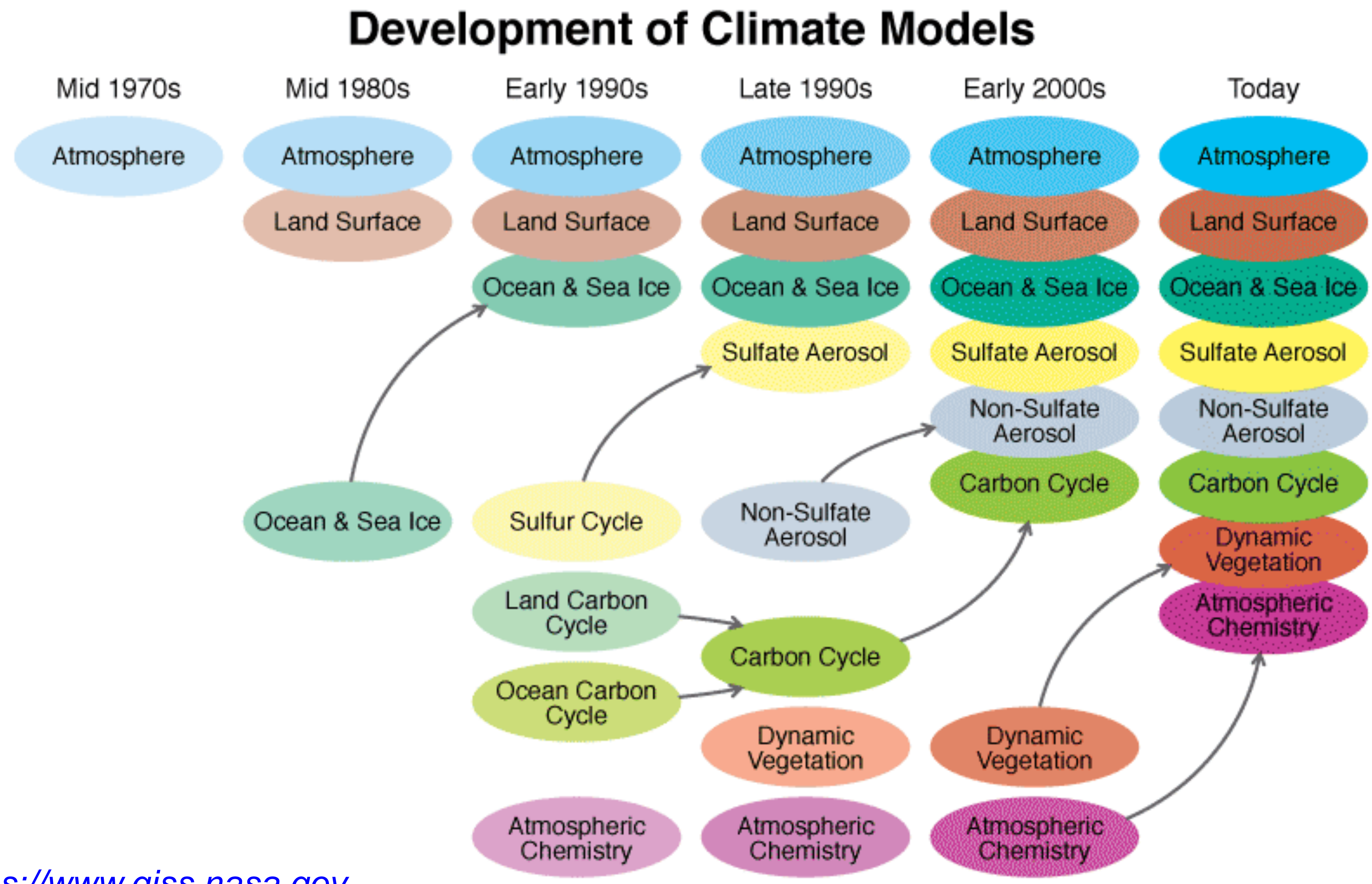
LRP Land Sea Mask



ECMWF

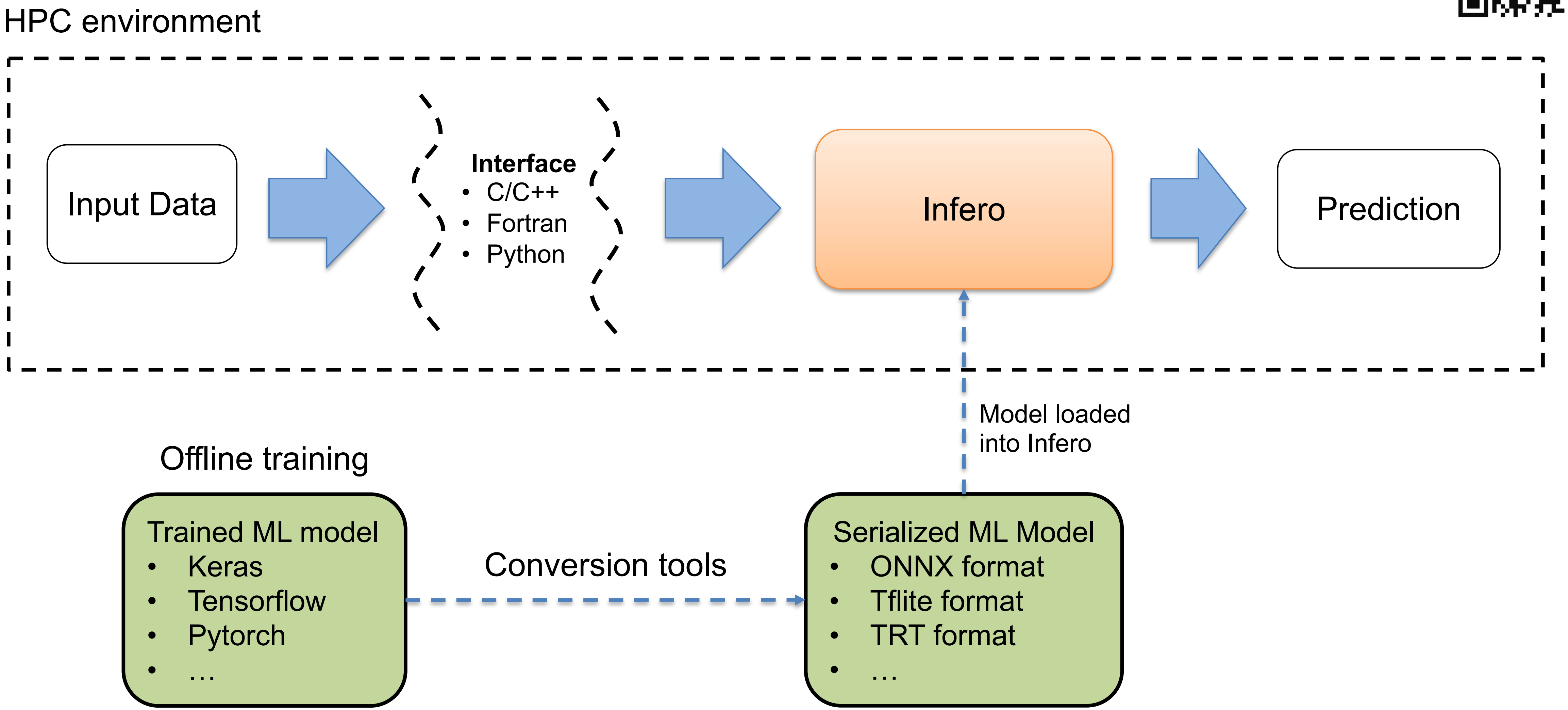
Clare, et al.

Learn how to combine models and machine learning



Source: https://www.giss.nasa.gov

How do you link ML software and conventional models?



Bonanni, Quintino

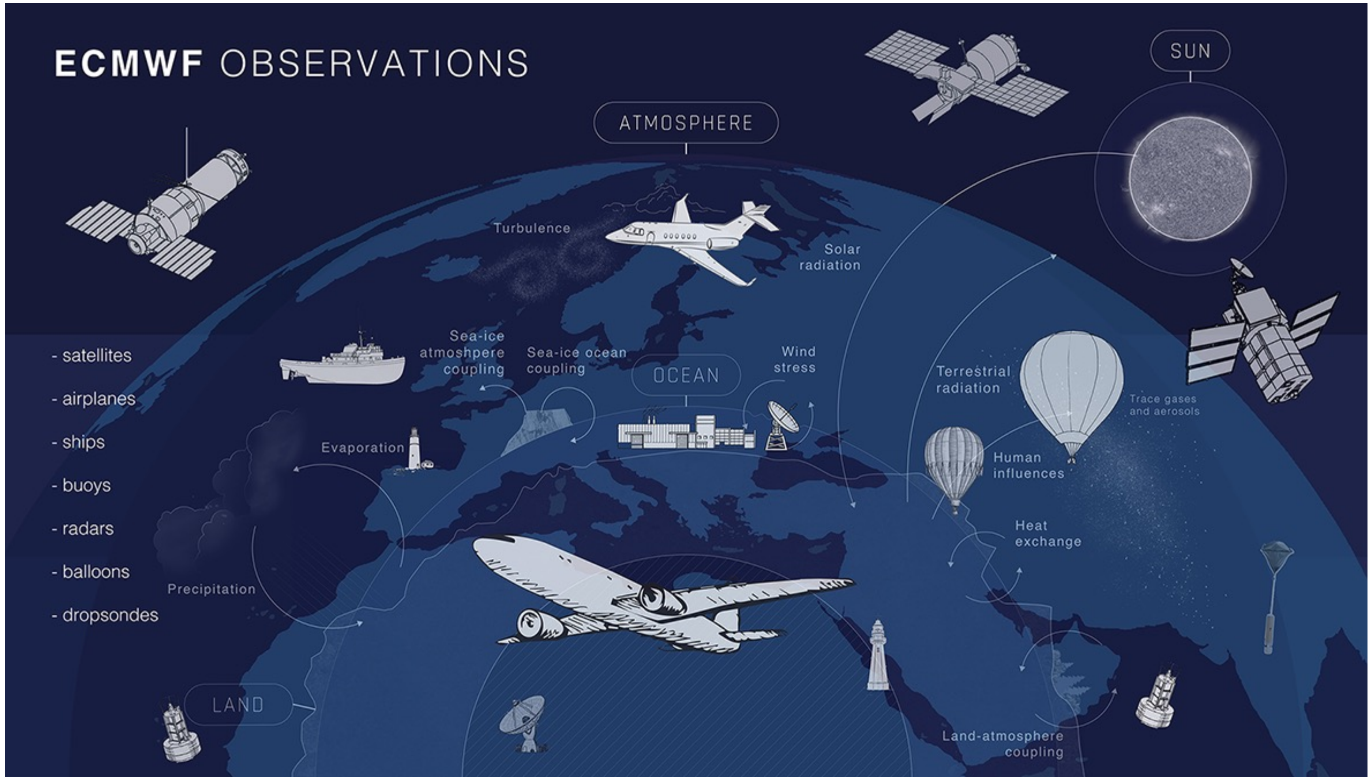
DATA

Diverse

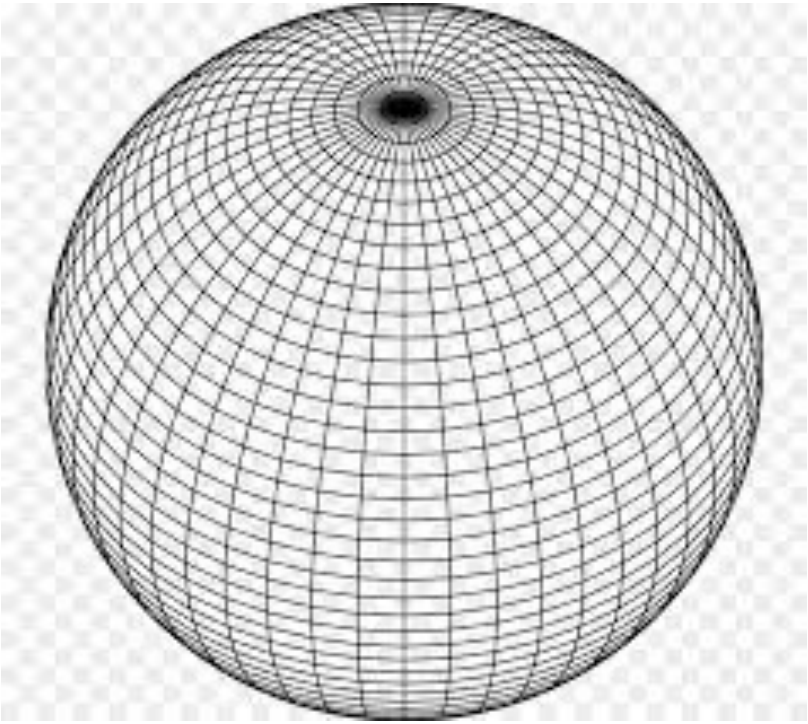
Big

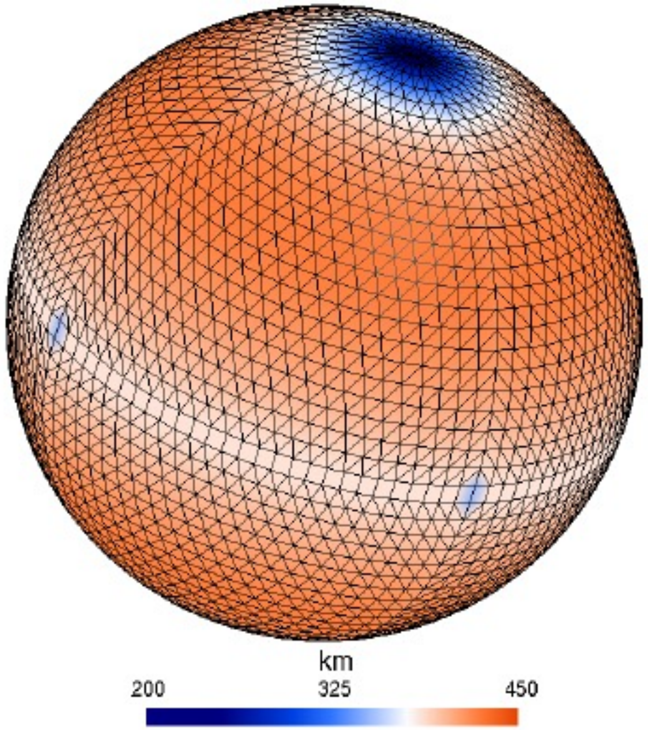
Restricted

Work intensive

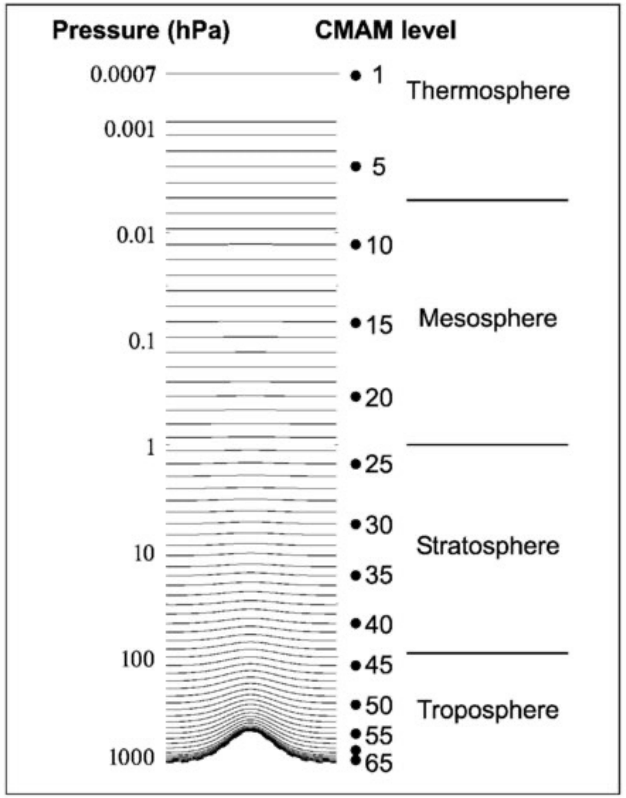


The sphere and unstructured grids





Source: Willem Deconinck



Source: Polavarapu et al. 2005

Longitude/latitude vs. reduced Gaussian cubic octahedral grid

Problem: Find a three-dimensional machine learning solution that work on unstructured grids.

Geometric deep learning and Graph Neural Networks may help to solve this problem

What is the single most important development to achieve progress?

Domain scientists

Machine learners

Machine learning domain scientists

Code for Earth in one slide

Code for Earth – Quick facts

- key innovation action run by ECMWF, supported by Copernicus and Destination Earth, the European Environment Agency, Helmholtz-Zentrum Hereon and IFAB.
- welcomes each summer individuals and developer teams from different backgrounds in earth sciences, computer sciences and software development to work on solutions for pre-defined challenges
- It's about innovation, collaboration and open source software development
- Grants selected teams, that successfully complete their projects, a €5,000 stipend.

Code for Earth – 3 Stream and 19 challenges, 64 mentors

- Joint partner challenges with CESOC / University of Bonn, European Environment Agency, Helmholtz-Zentrum Hereon and University of Reading
- Stream 1 – Data visualization and visual narratives
- Stream 2 – Machine Learning for Earth Sciences applications
- Stream 3 – Software development for Earth Sciences applications

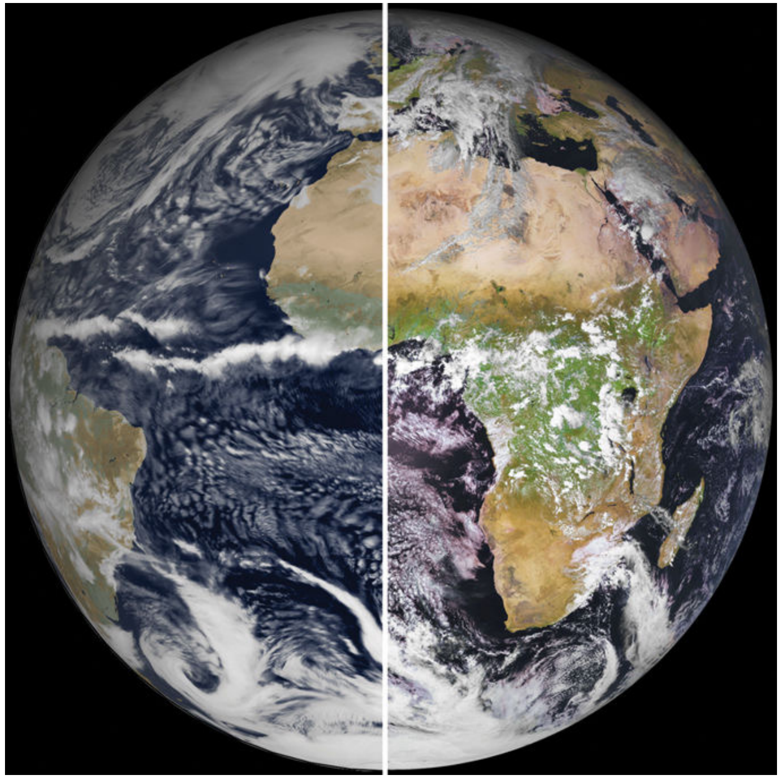
Useful links and further information

- Upcoming **Q&A Webinar, 21. March 2024**, register on our website
- Code for Earth Website – https://codeforearth.ecmwf.int/
- **Submit your proposal by 09. April 2024**

CODE FOR EARTH ECMWF

Opportunities: A high-level view how ML/AI will be used in Earth system science

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



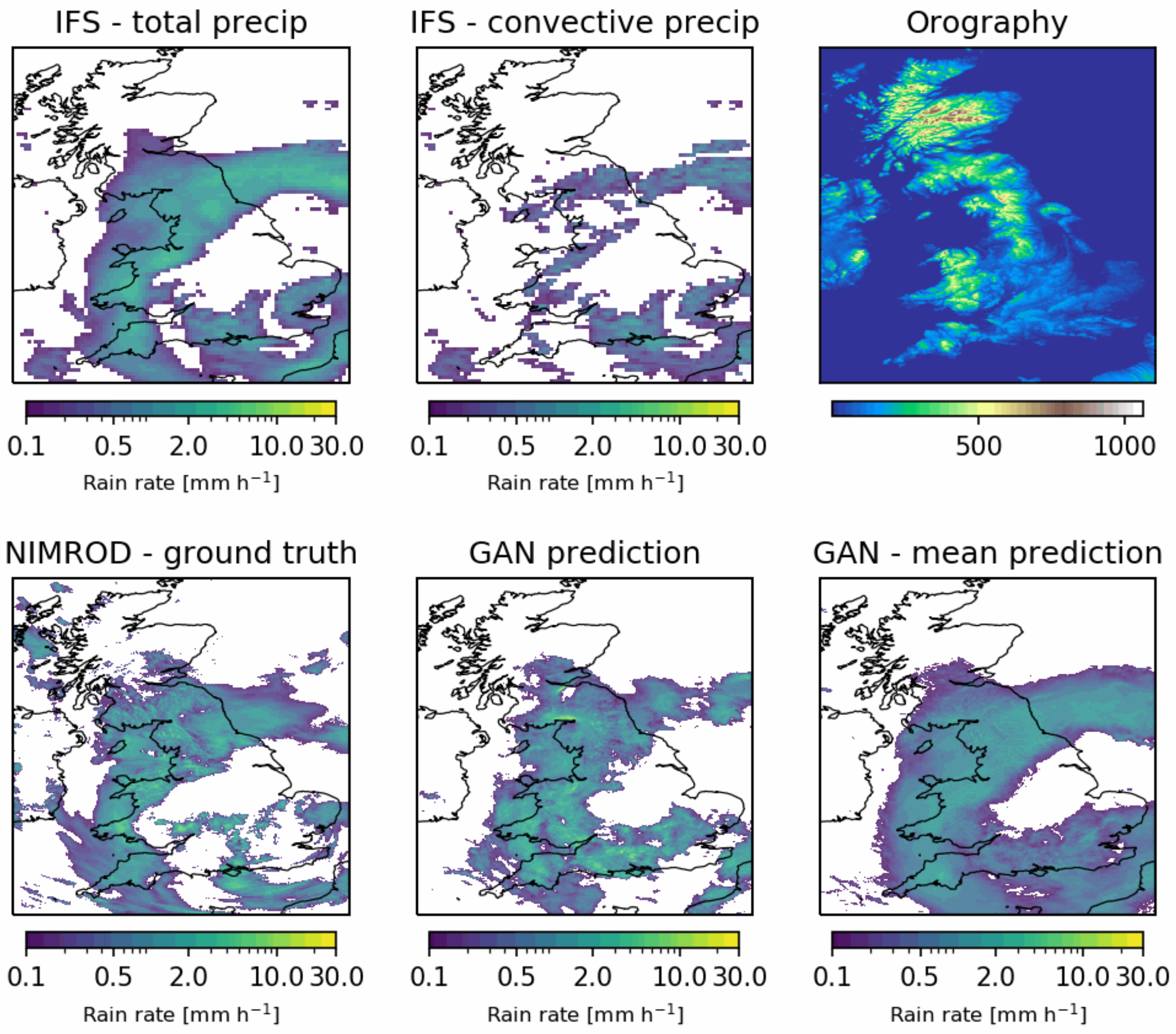
Speed up simulations and green computing
- Emulate model components
- Port emulators to heterogeneous hardware
- Use reduced numerical precision and sparse machine learning
- Optimise HPC and data workflow
- Data compression/Tethering
- …

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
- …

Opportunities: A story of uncertainties

- Map IFS model data at ~10 km resolution to NIMROD precipitation observations at ~1 km resolution
- Test Generative Adversarial Networks (GANs) and Variational Autoencoders (VAs)
- Generate ensembles to represent the uncertainty of the mapping.

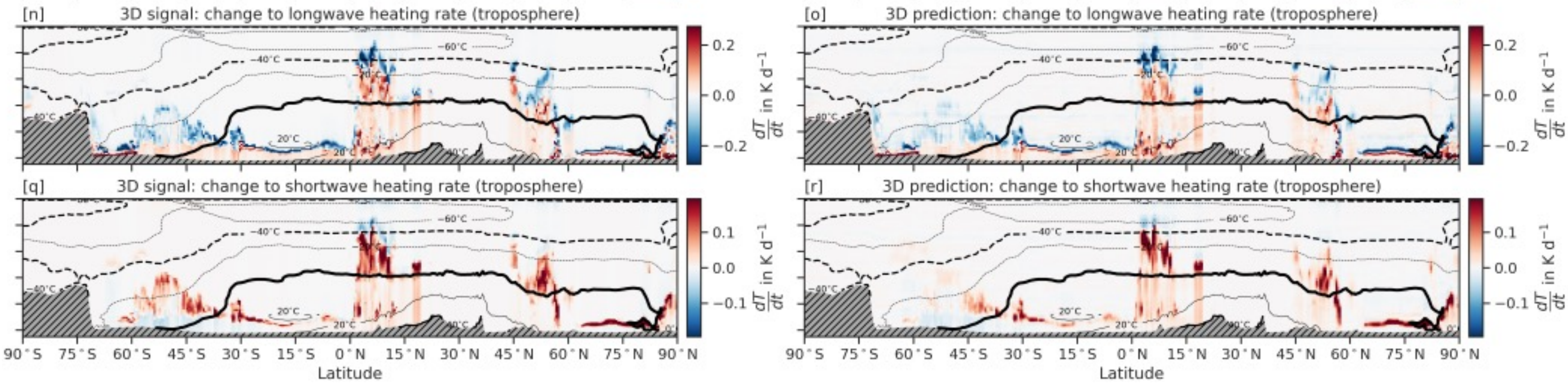


Harris, McRae, Chantry, Dueben, Palmer

Opportunities: Make expensive things cheap via emulation

To represent 3D cloud effects for radiation (SPARTACUS) within simulations of the Integrated Forecast Model is four time slower than the standard radiation scheme (Tripleclouds)

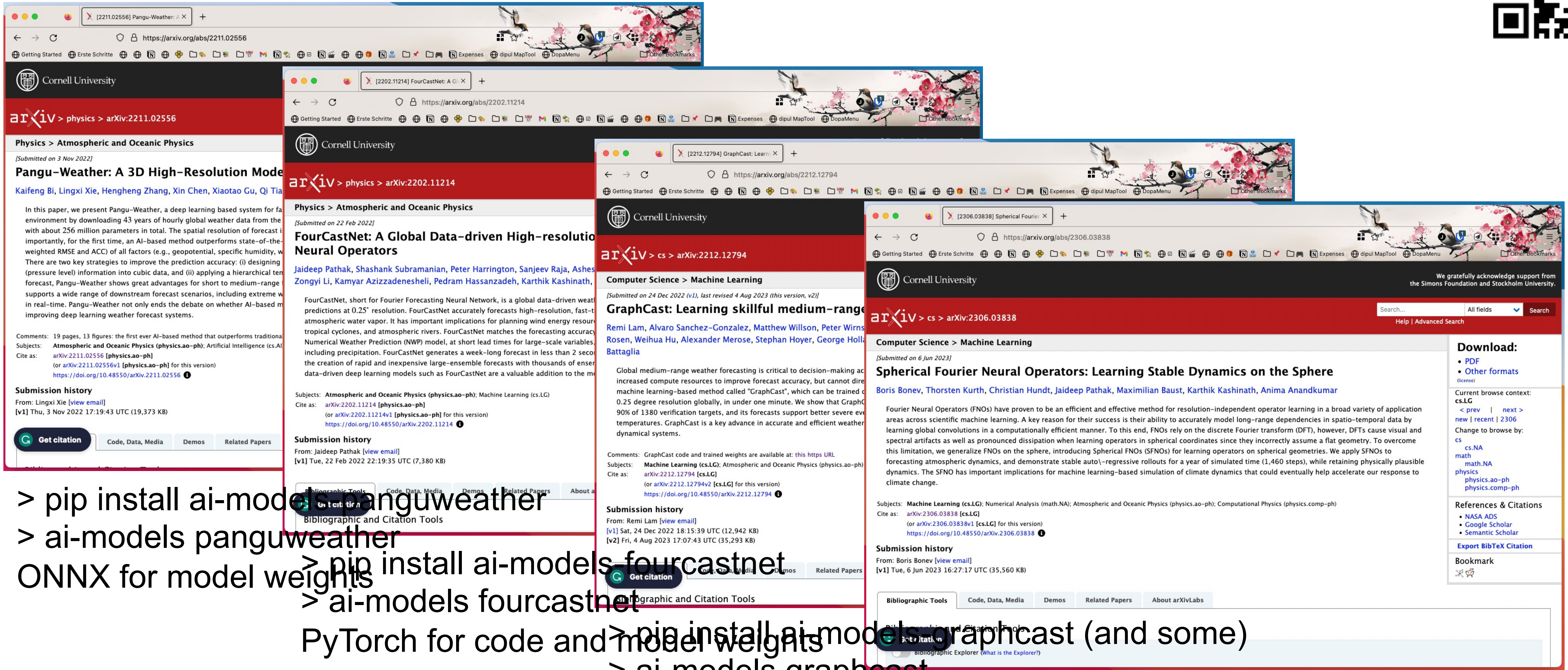
Can we emulate the difference between Tripleclouds and SPARTACUS using neural networks?



Rel. Cost	Tripleclouds	SPARTACUS	Neural Network	Tripleclouds+Neural Network
	1.0	4.4	0.003	1.003

Meyer, Hogan, Dueben, Mason JAMES 2022

AI-Models Plugins for FOSS Data-Driven NWP



> pip install ai-models-panguweather
> ai-models panguweather
ONNX for model weights

> pip install ai-models-fourcastnet
> ai-models fourcastnet
PyTorch for code and model weights

> pip install ai-models-graphcast (and some)
> ai-models graphcast
Jax for code and model weights

> pip install ai-models-fourcastnetv2
> ai-models fourcastnetv2
PyTorch for code and model weights

There's a lot to do!