UEF 2024
6th June 2024

Machine Learning Activities at ECMWF: an overview

Mariana Clare

with thanks to all involved in Machine Learning activities at ECMWF

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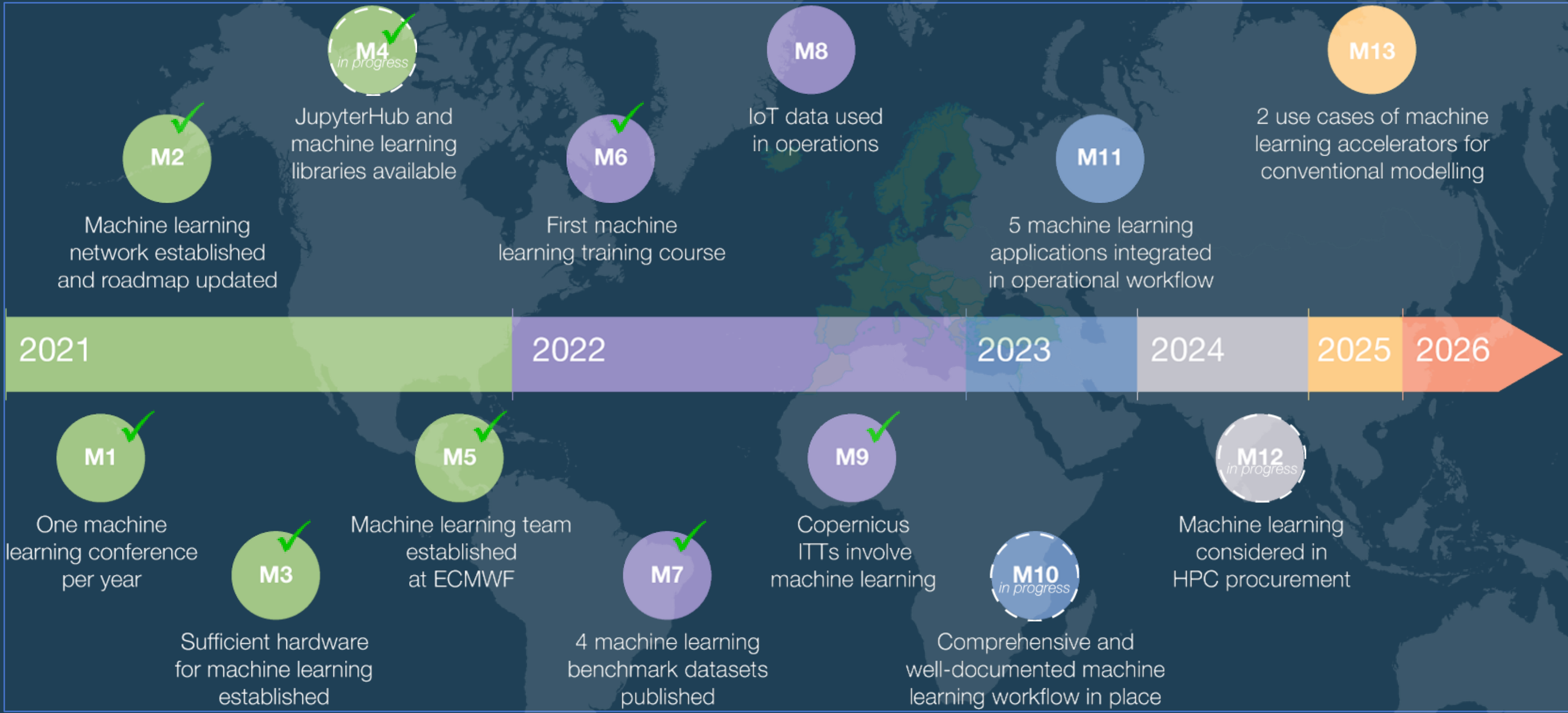
What the ML Roadmap has achieved so far



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

a very busy and FAST evolving landscape

2018 ECMWF's ML scientific publication

ECMWF's
Peter Dueben and Peter Bauer publish a paper on using ERA5 at ~500km resolution to predict future z500.

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

An overview of machine learning at ECMWF

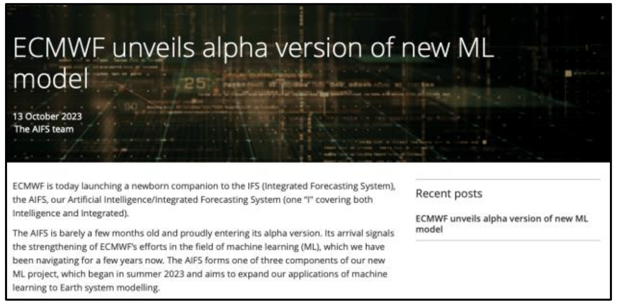
DestinE

ML Project

Member State Pilot Project

DestinE partners

Led by MET Norway & MeteoSwiss



ECMWF unveils alpha version of new ML model

13 October 2023
The AIFS team

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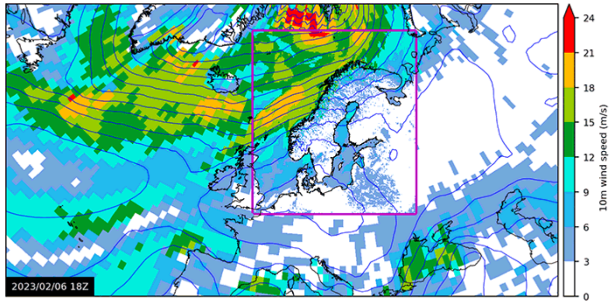


ML Project overview: different paths towards an ML ensemble prediction system at ECMWF

The hybrid model

Enhanced and accelerated implementation of ECMWF ML Roadmap

Delivering results

Development of a ML ensemble forecast

Data-driven model initialised with NWP analysis hence requiring conventional data assimilation.

Embracing novelty

Observations-driven ML system

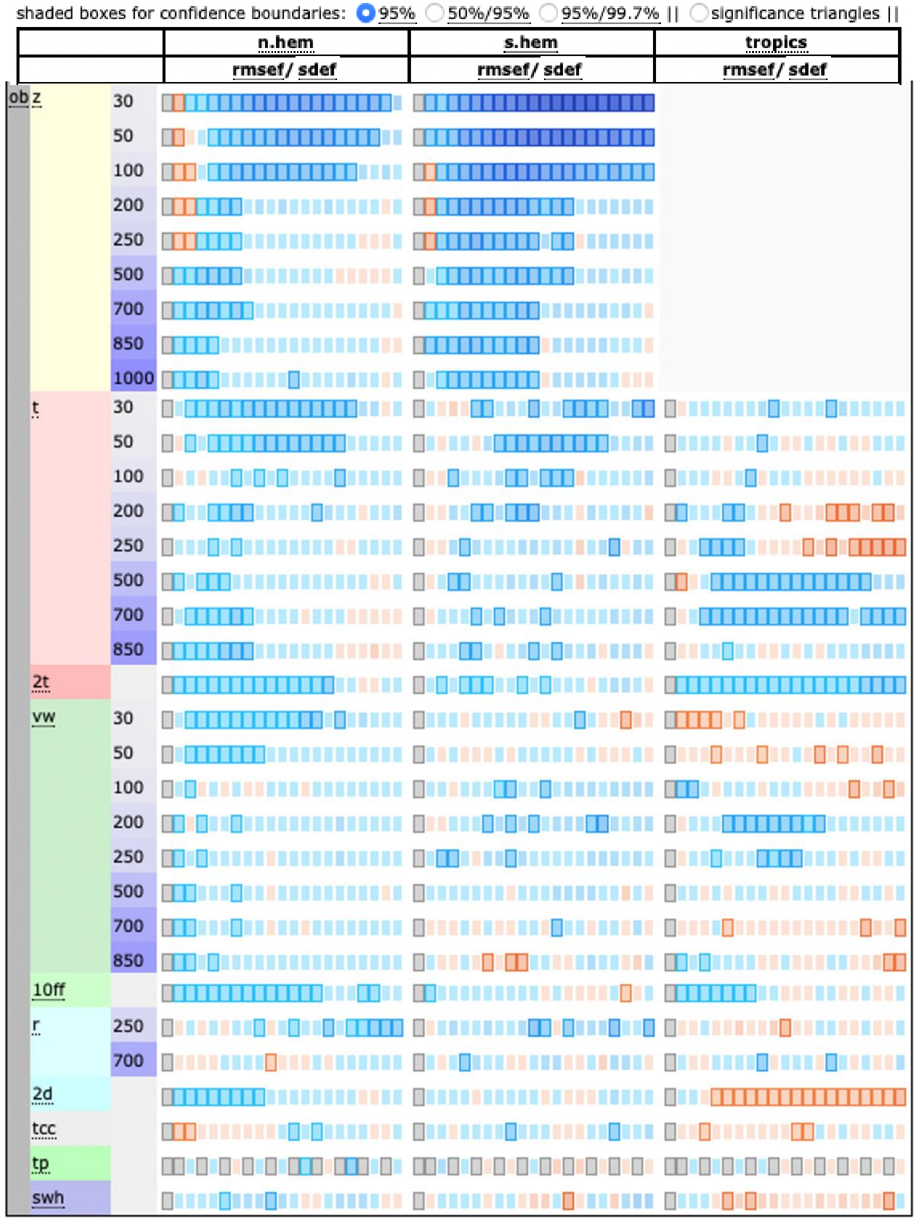
A whole system reinventing the path from observations to predictions.

A scientific challenge

Exploiting Neural Networks (NN) to correct model error (hybrid modelling)

NN is trained **offline** to learn analysis **increments** ,then **applied online** state dependent corrections within the DA, but also online in the medium (extended) range forecast.

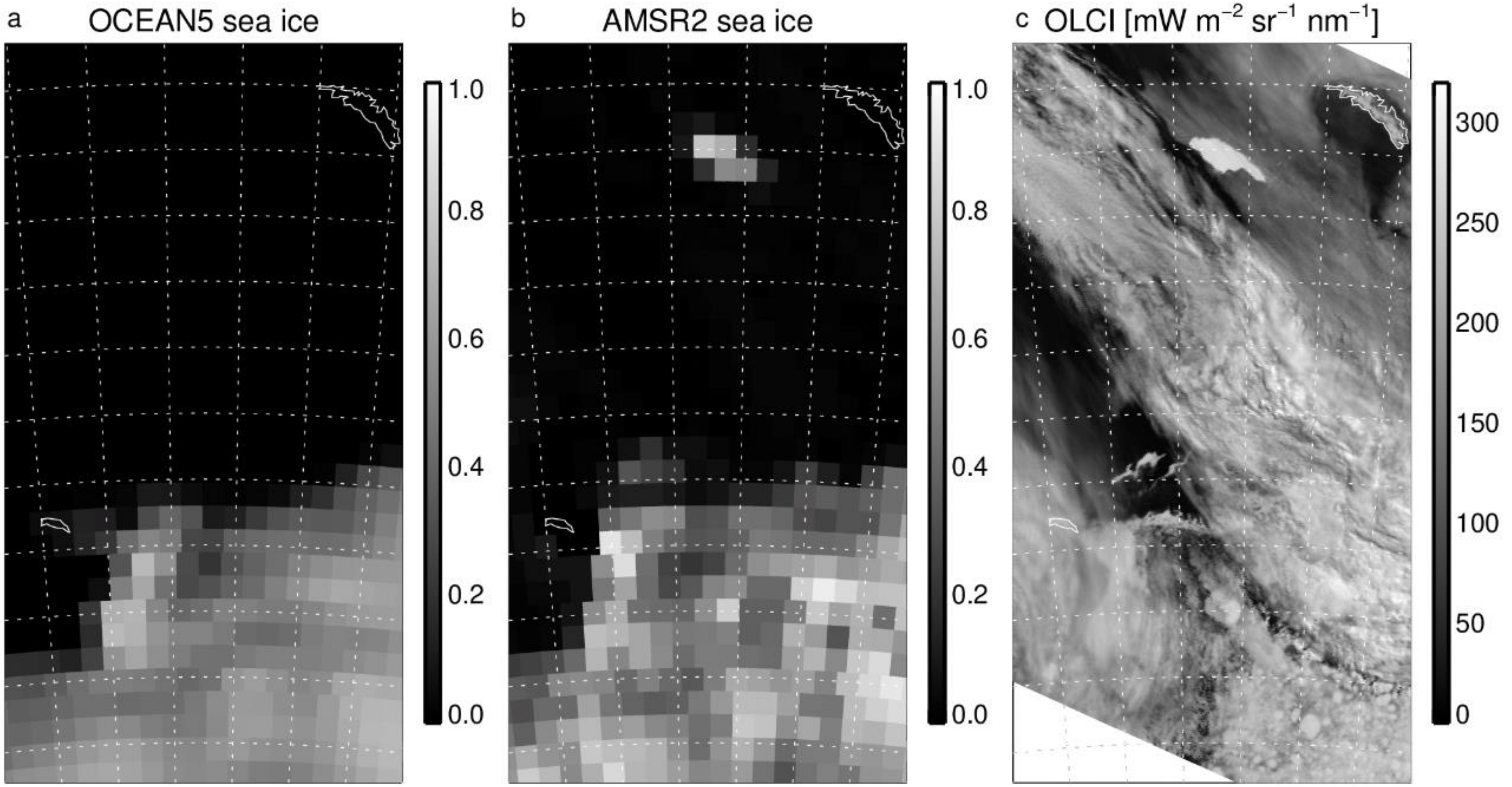
NN online bias correction will be included as part of ERA6



Farchi et al. (2024)

Using microwave radiances to improve the ocean and sea-ice

Geer (2023)

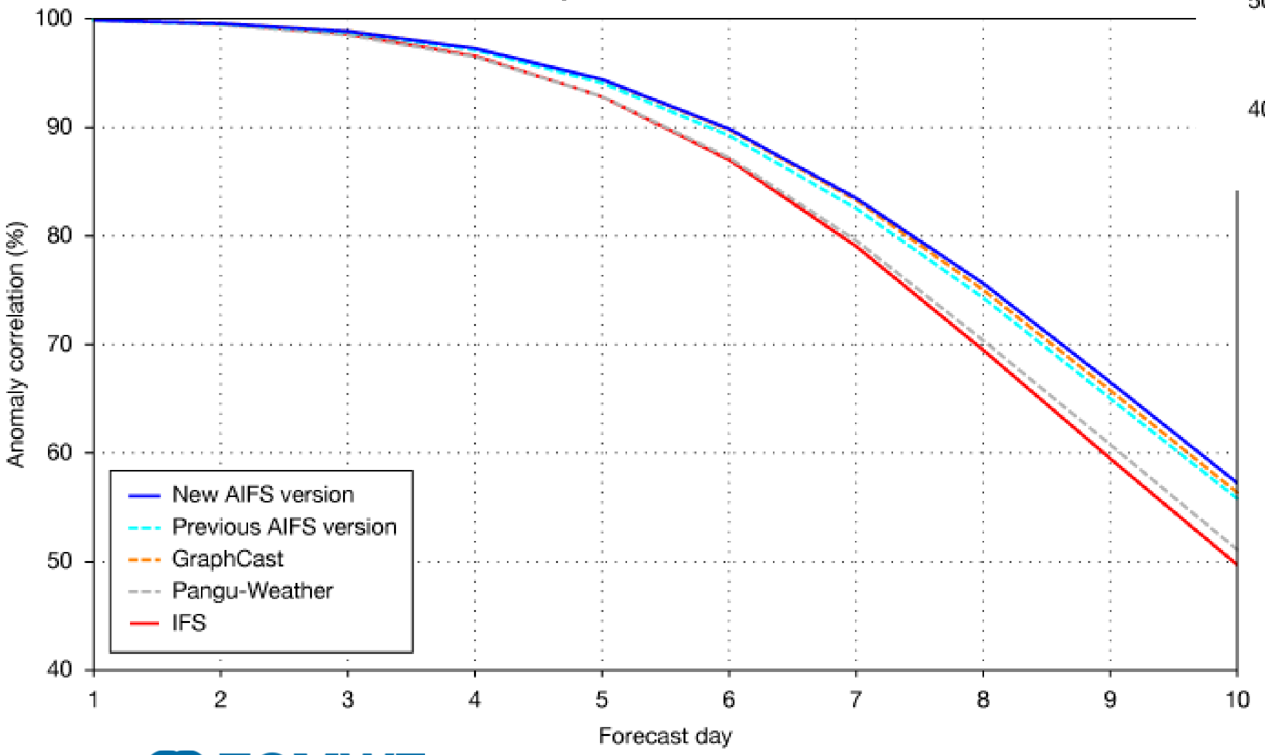


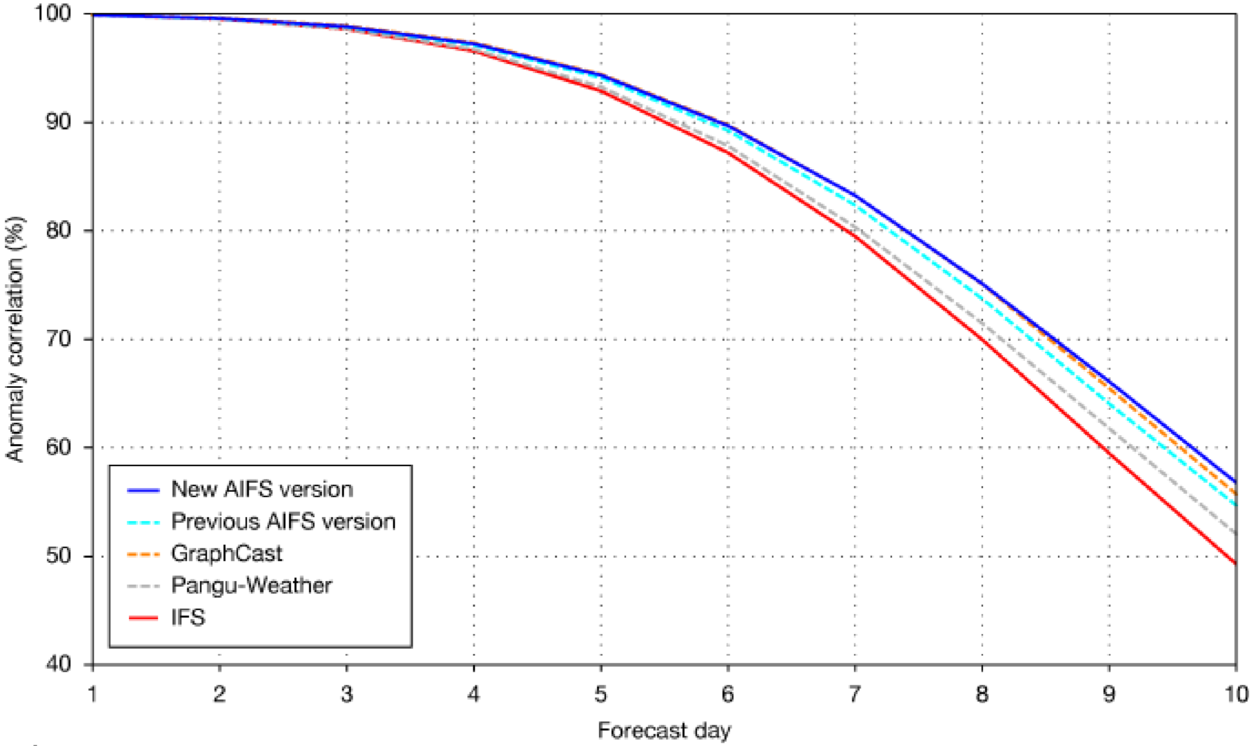
12 UTC 4th Dec 2020 – A68A (100 km by 60 km)

Iceberg approaching island of South Georgia. Copernicus sentinel data 2020

Data driven models
AIFS v0.2 – atmospheric skill

Northern hemisphere z500 ACC





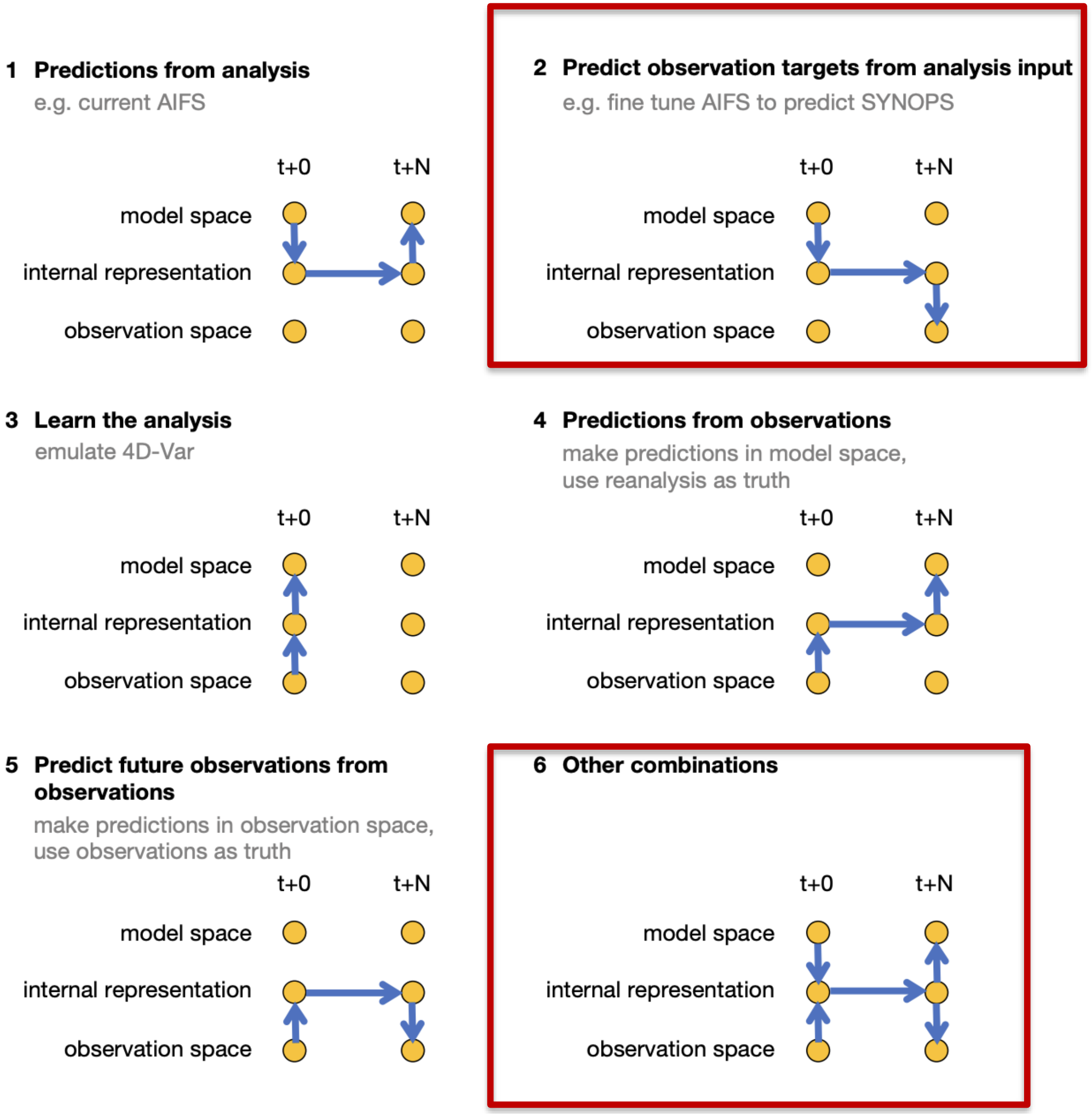
Southern hemisphere z500 ACC

Higher = better

see Simon Lang and Linus Magnusson's talks and Lang et al. (2024)

Learning from observations

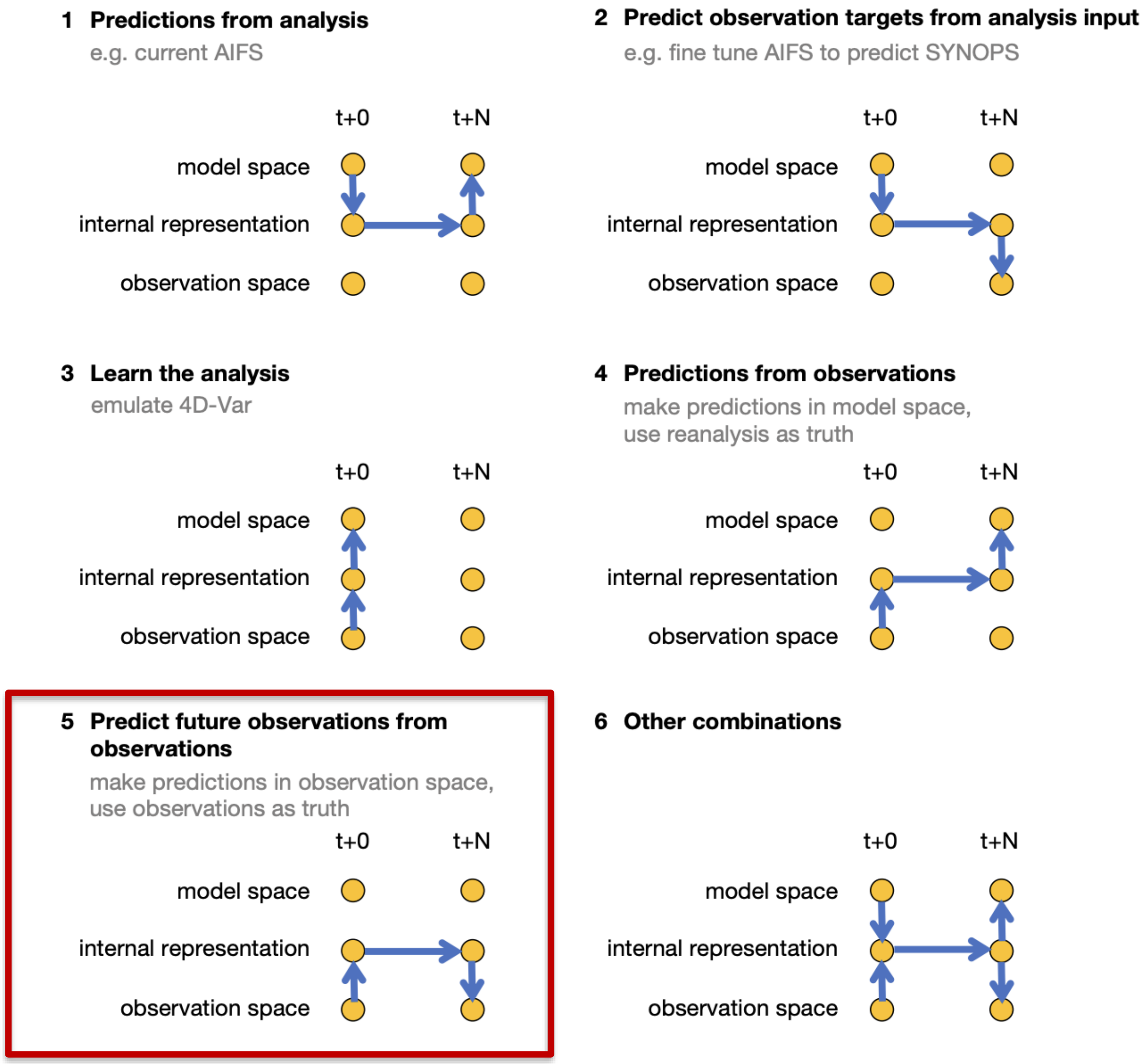
Can we “augment” AIFS using observation data?



McNally et al. (2024)

Learning from observations

Can (re)analysis be bypassed altogether



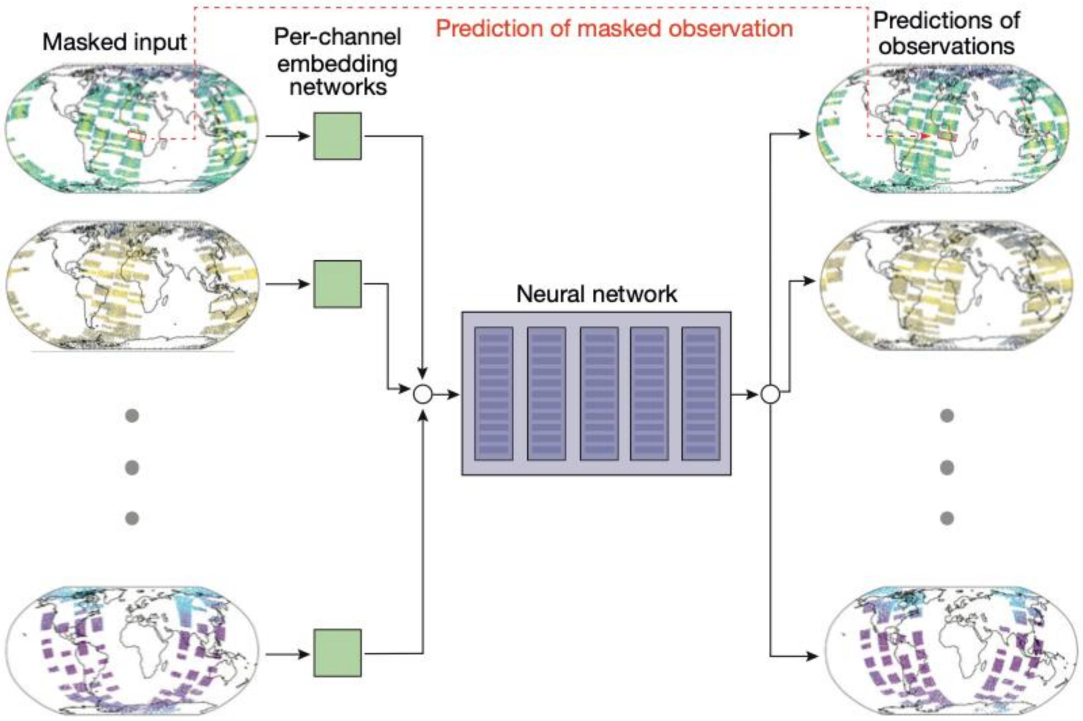
ECMWF

McNally et al. (2024)

Data Driven Machine Learning Forecast trained / initialised from observations

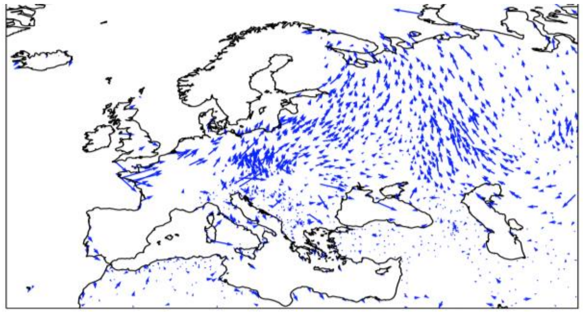
- Using historical measurements (10yrs ++) the network learns correlations between observations from different sources, at different locations and (crucially) at different times.

- Then from an input set of real-time observations the network can <u>predict</u> an observation of any <u>type</u> at any required future <u>location</u> and <u>time</u>.

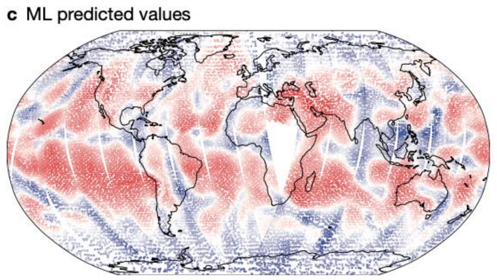


DOP

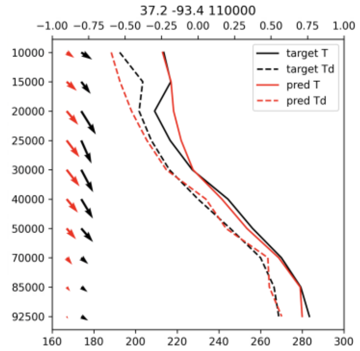
McNally et al. (2024)



Future SYNOP (T2m / wind)

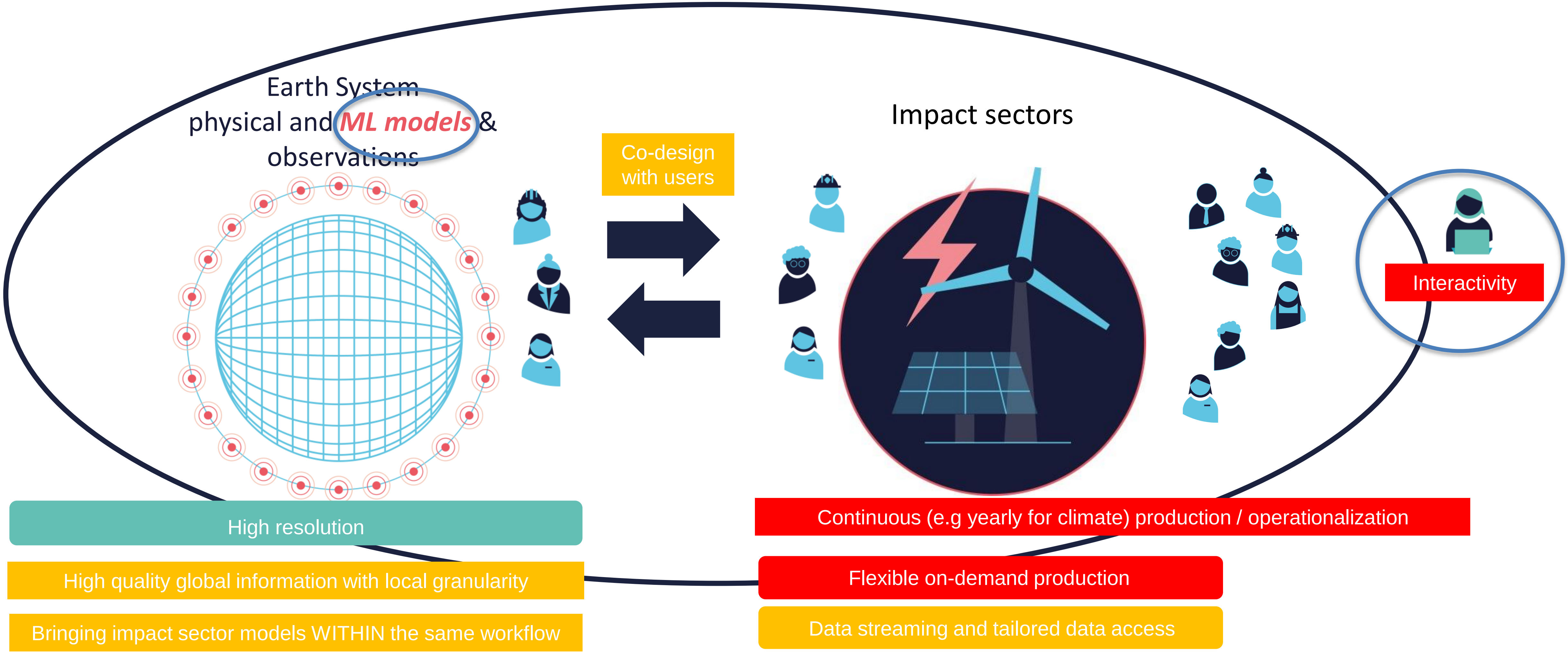


Future radiances (MW/IR/VIS)

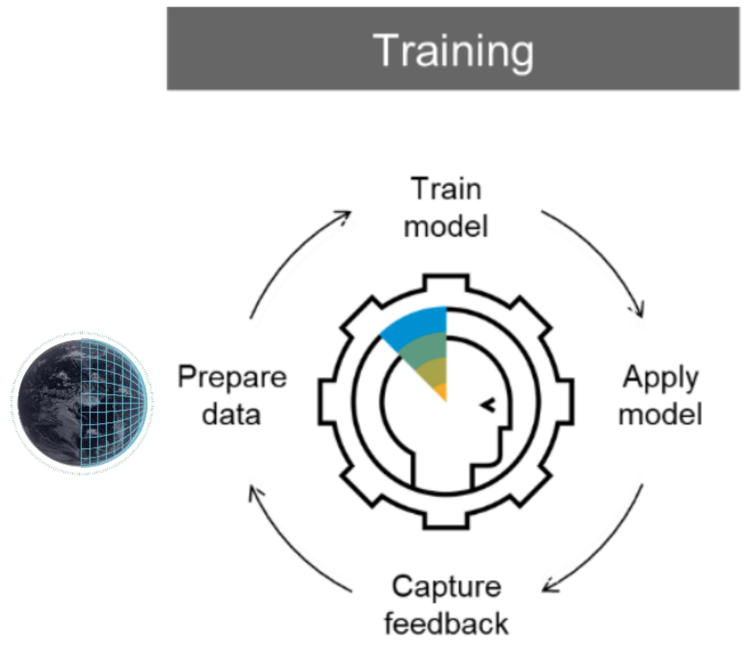


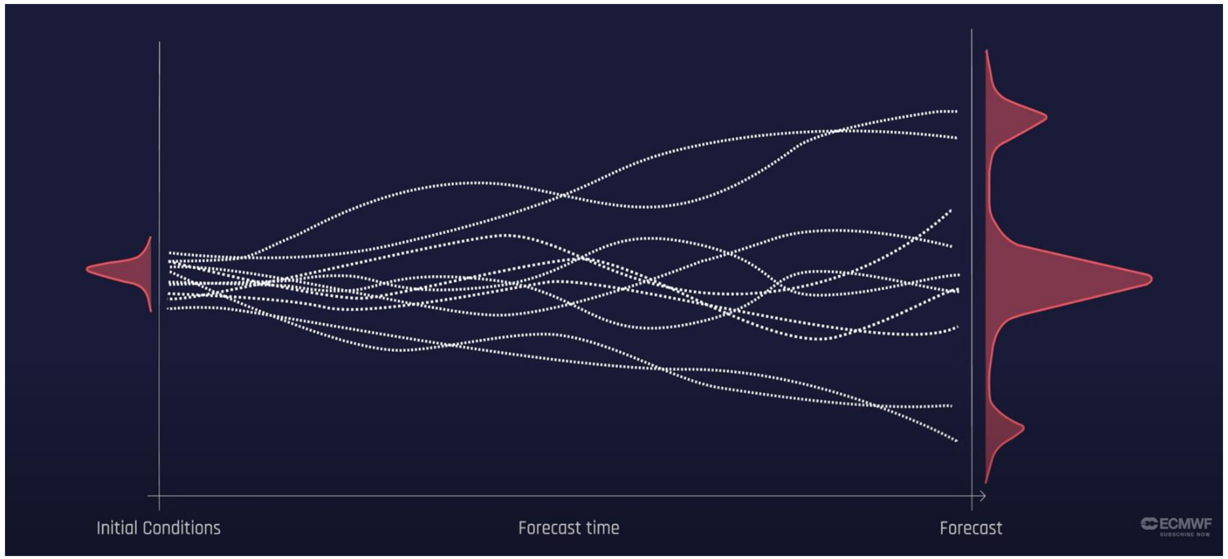
Future SONDES (T / Q / wind)

DestinE


Earth System
physical and *ML models* &
observations
Co-design
with users
Impact sectors
Interactivity
High resolution
High quality global information with local granularity
Bringing impact sector models WITHIN the same workflow
Continuous (e.g yearly for climate) production / operationalization
Flexible on-demand production
Data streaming and tailored data access

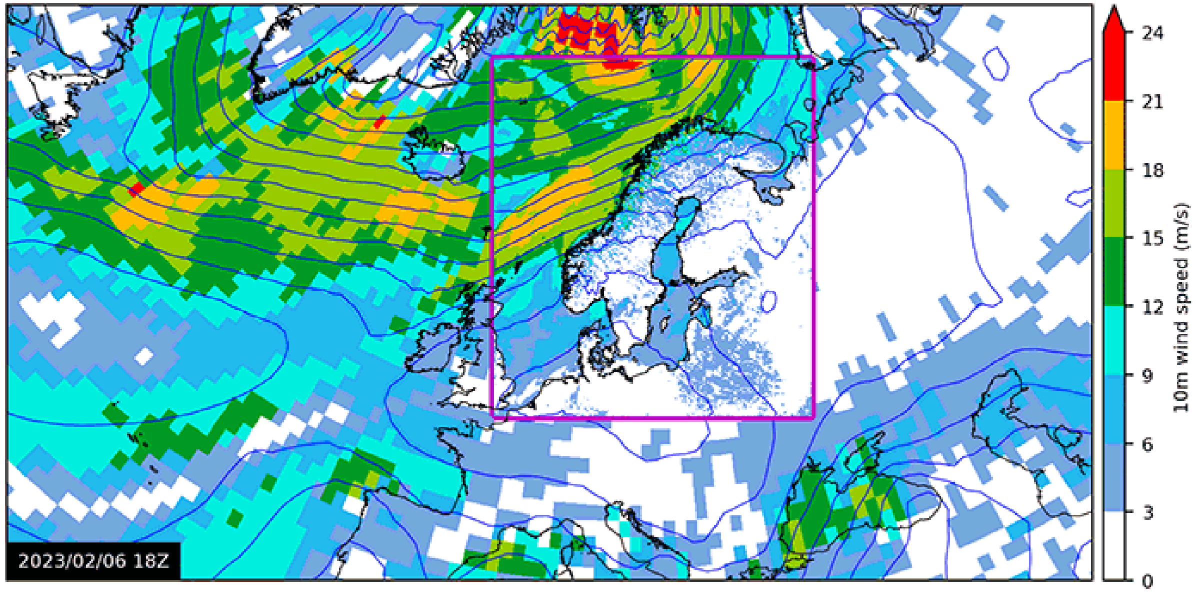
Data driven forecasts for uncertainty quantification



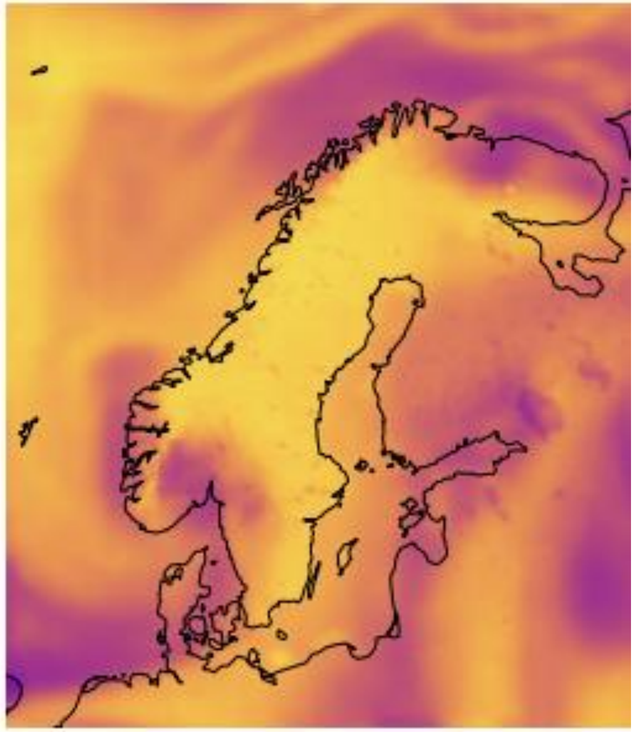


Developing & running both global & local data-driven models to create ensembles that complement DestinE simulations

Limited area models



Stretched grid model (Met Norway, Nipen et al. 2024)

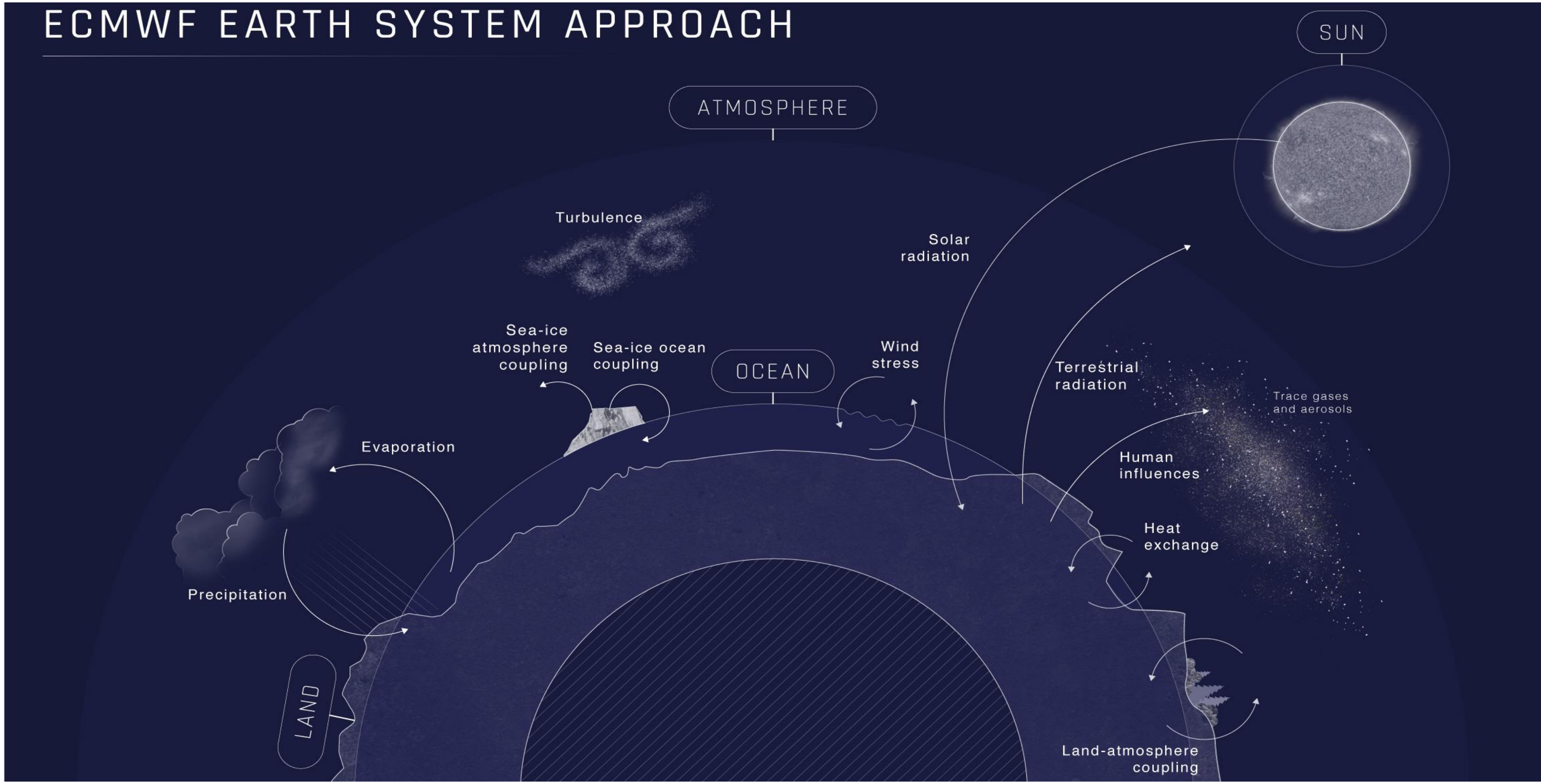


Limited Area Model (Oskarsson et al., 2023)

AI Earth System Model

Build full Earth System model with land, ocean, sea-ice and hydrology components

Leverage developments made in the ML project especially ensemble developments and learning from observations

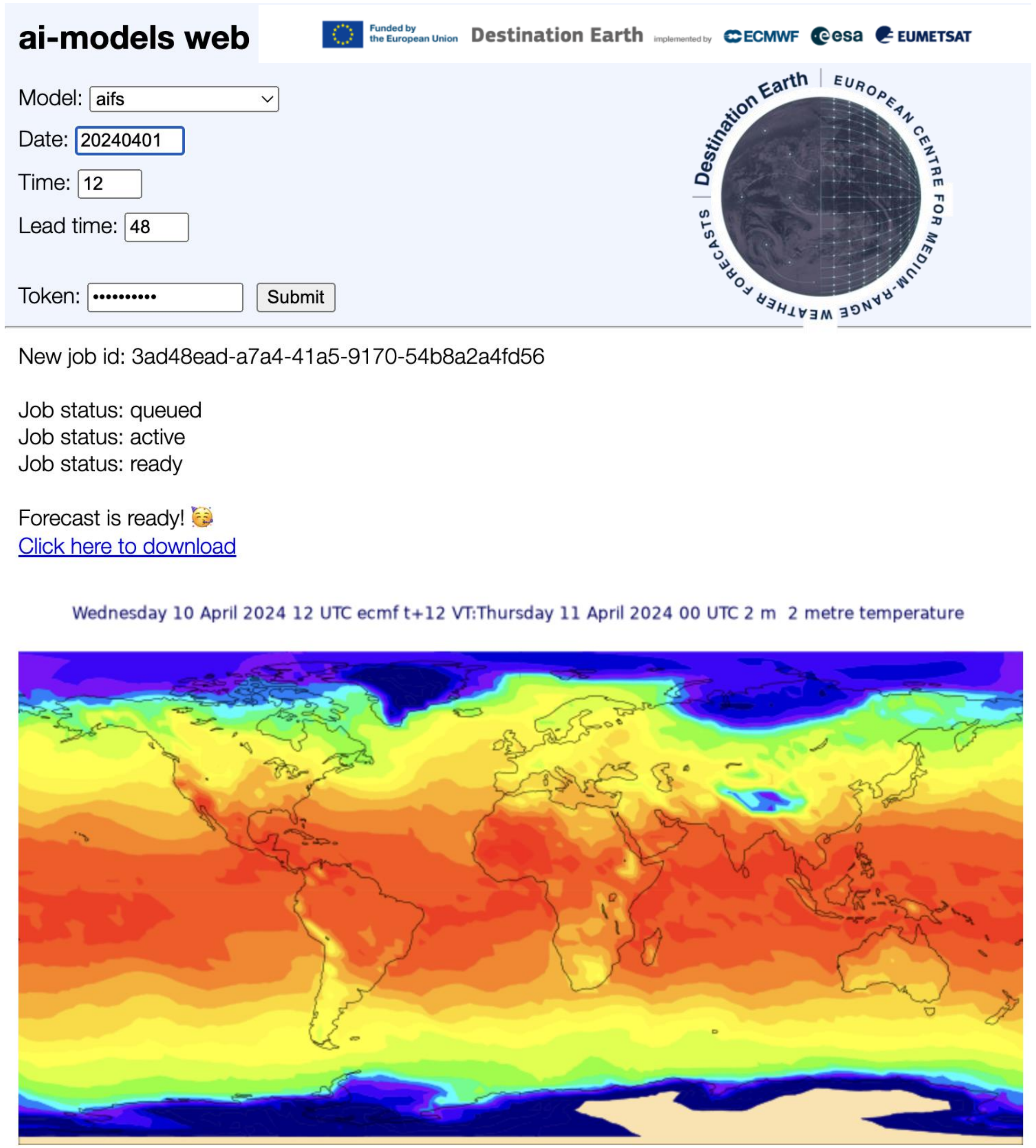


Forecast-in-a-box

Providing a packaged system with data-retrieval, forecasting & postprocessing.

This system runs on local hardware or cloud and is delivered in a matter of minutes

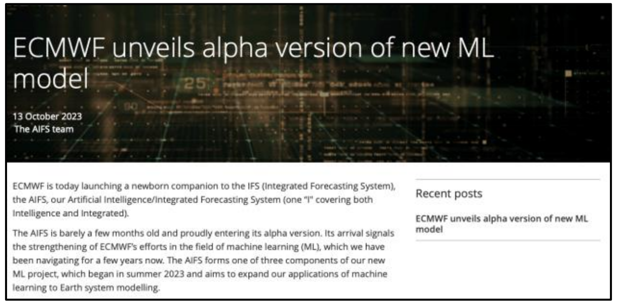
It is configurable for Earth-System components and user-defined outputs.



An overview of machine learning at ECMWF

DestinE

ML Project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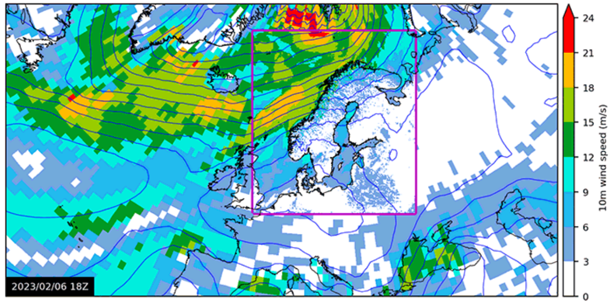

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