Machine learning as game changer in forecasting

Matthew Chantry on behalf of many colleagues across ECMWF

Strategic Lead for Machine Learning

Matthew.chantry@ecmwf.int

ECMWF

Neural networks as universal approximation systems

Given enough compute and data any relationship can be learnt….

For which problems is this true?

A short history of data-driven weather forecasting

2018 – Concept explored (ECMWF and others)…

February 2022 – First competitive medium-range systems

- **Keisler –** GraphNN**,** competitive with GFS (USA)
- **NVIDIA** – **FourCastNet** Fourier+ , 0.25°**, O(10^4) faster & more energy efficient than IFS**

November 2022

- **Huawei – PanguWeather**

Vision Transformer
0.25° **"More accurate tropical cyclone tracks" than the IFS.**

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- **Deepmind – GraphCast**

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January-June 2023

- **Microsoft – ClimaX**
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- **…**

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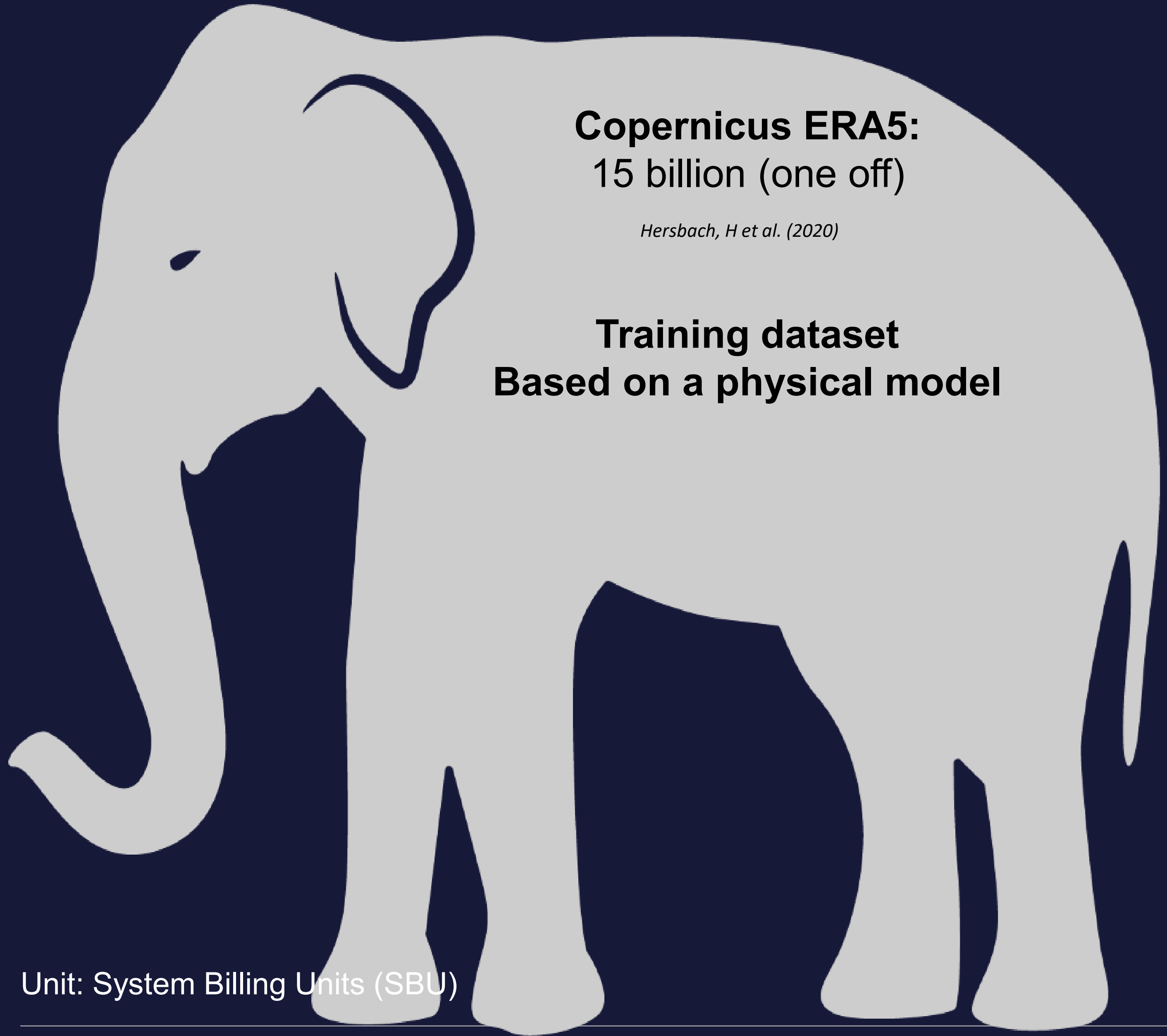
"Outperforming the leading operational ensemble forecast" (aka ECMWF)

June 2024

- **Microsoft – Aurora**

Higher resolution – 0.1°
Atmospheric composition

ECMWF



Copernicus ERA5:
15 billion (one off)

Hersbach, H et al. (2020)

Training dataset
Based on a physical model

Physics-based Forecast:
180 000
per forecast

AI Model:
0.3
per forecast

~1000x
reduction in
energy
Forecast time
reduced from
~30minutes to
~3minutes

Unit: System Billing Units (SBU)

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Early 2023 Prototype AIFS developments begin

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June 2023 ECMWF – ML project begins

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Embracing novelty

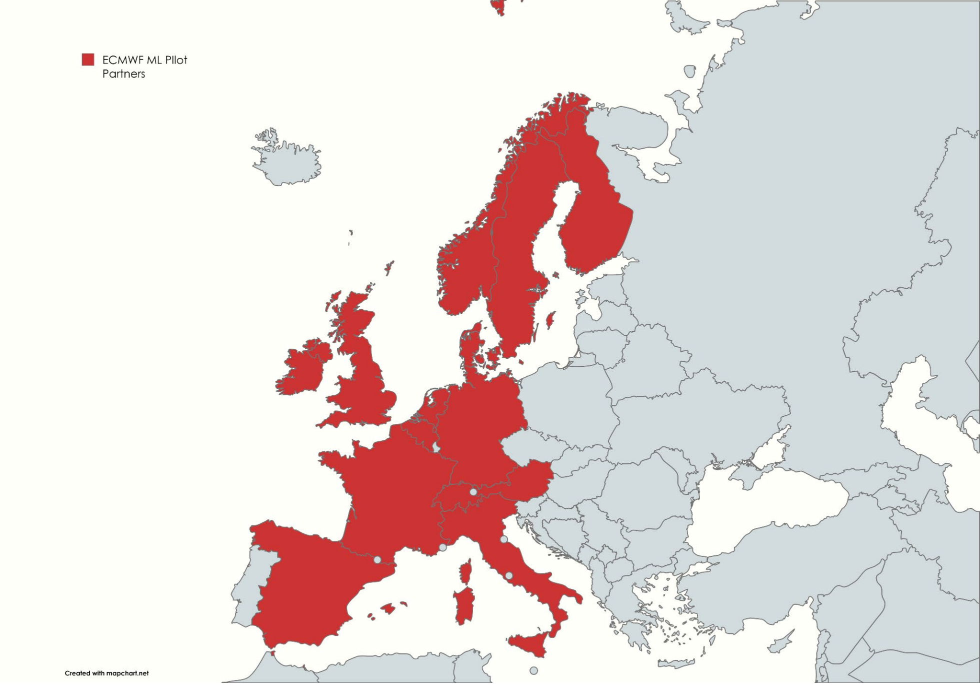
Observations-driven ML system

A whole system reinventing the path from observations to predictions.

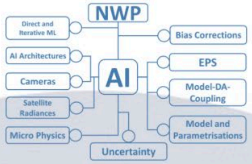
A scientific challenge

Member State Pilot project

- 14 Member States and ECMWF.
- Working together across 4 work packages.
- Sharing technical and scientific developments on:
  - Data-driven modelling.
  - Data-driven ensembles.
  - Data-driven data-assimilation.
  - MLOps



Part of
EUMETNET E-AI initiative



“Artificial Intelligence and Machine Learning for Weather, Climate and Environmental Applications” (E-AI) Optional Programme

High level objectives:

- To enhance the collaboration of European NMHSs and external partners in the area of AI/ML in weather, climate and environment.
- To share the developments which take place under E-AI using a commonly-used permissive open-source licence.

Coordinating Member for E-AI: DWD (Roland Potthast)

EUMETNET

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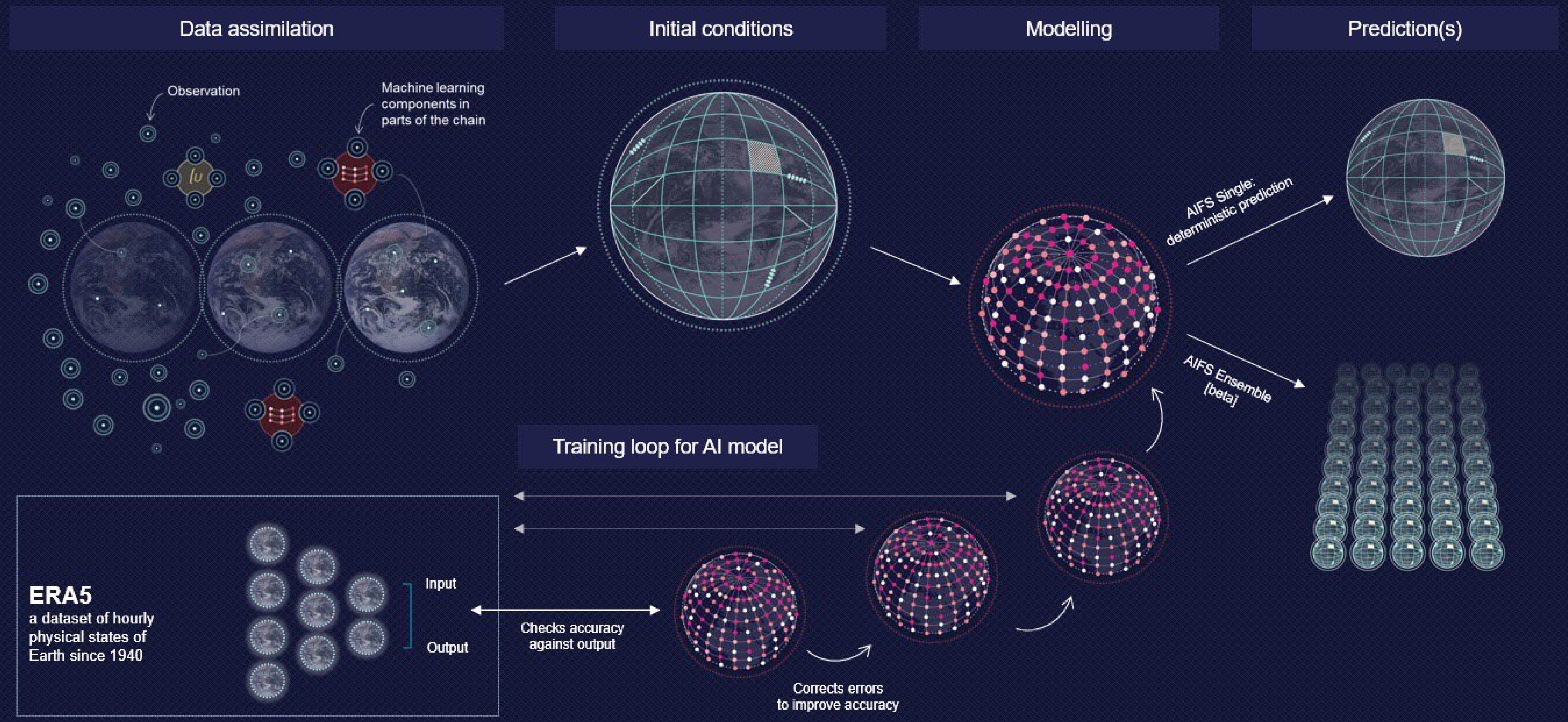
AIFS: Artificial Intelligence Forecasting System



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June 2023 ECMWF – ML project begins

October 2023 ECMWF – AIFS experimental forecasts live

Jan/Feb 2024 ECMWF – AIFS first updates

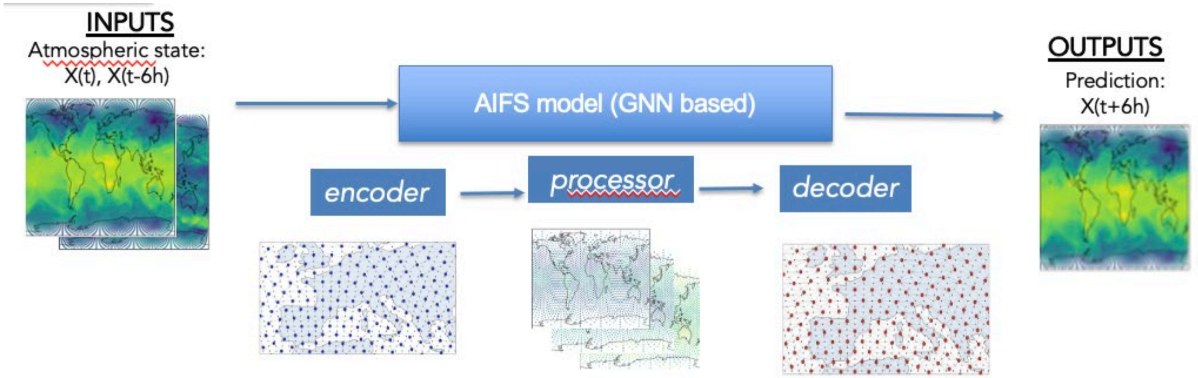
July 2024… ECMWF – First AIFS ENS experimental

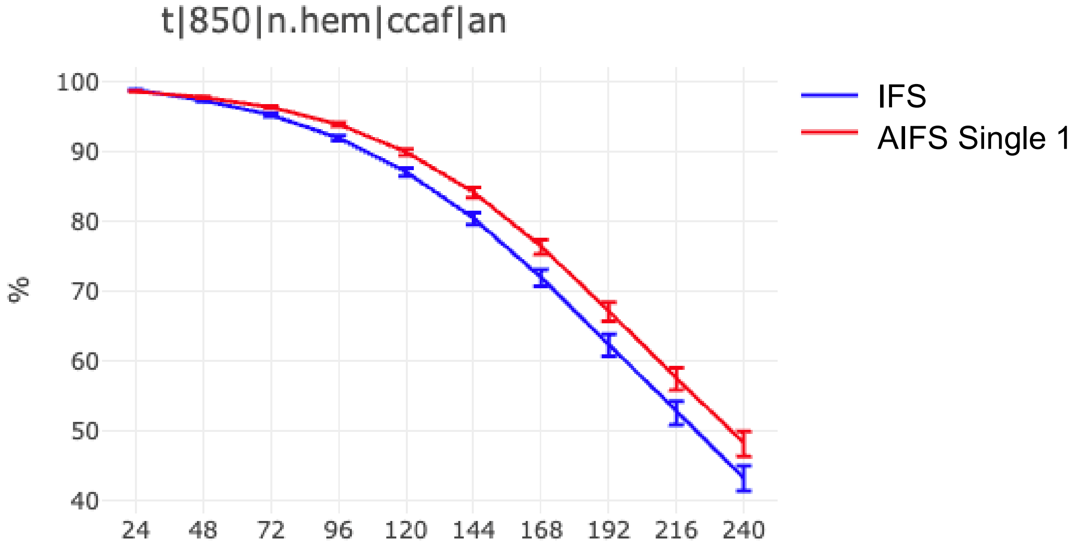
Feb 2025: ECMWF – AIFS Single 1 operational

ECMWF

AIFS Single vs IFS

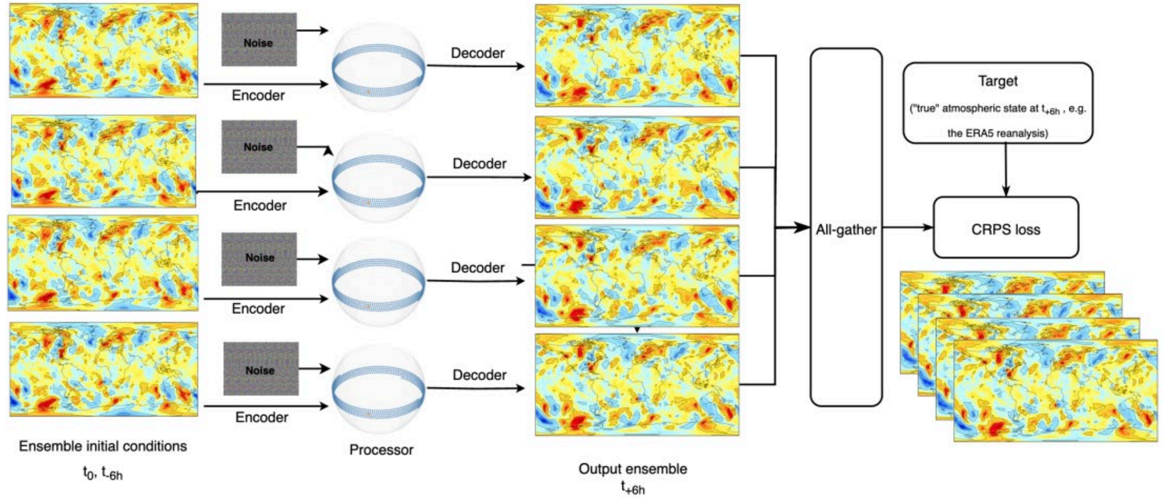
Lang et al 2024a
Operational system from 25/2/25

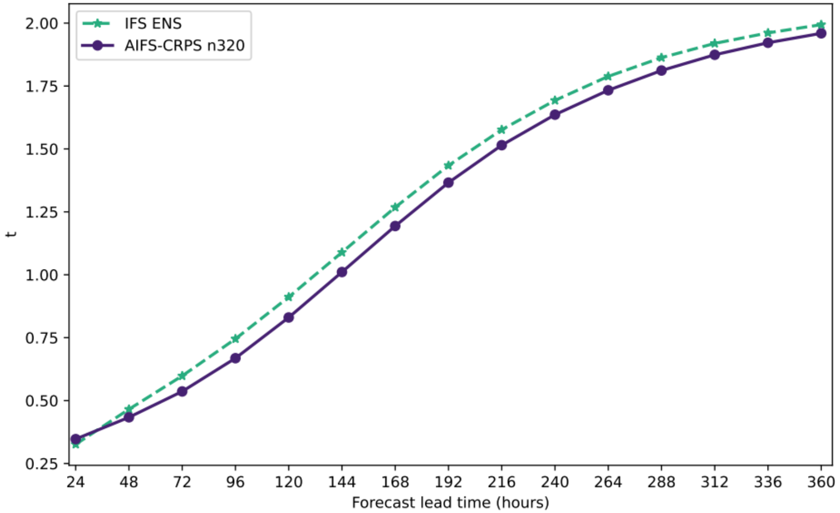




AIFS ENS CRPS vs IFS ENS

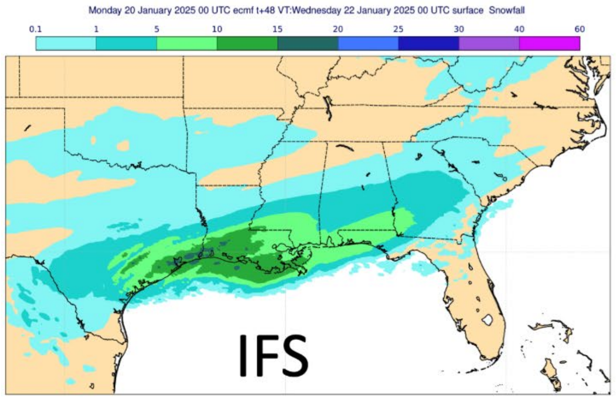
Lang et al 2024b
Operational system later this year



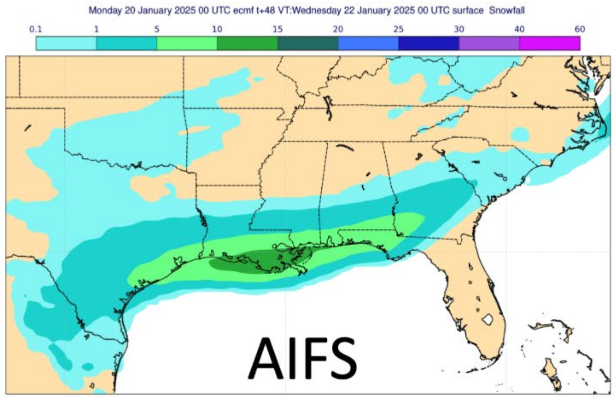


More on AIFS from Simon on Thursday

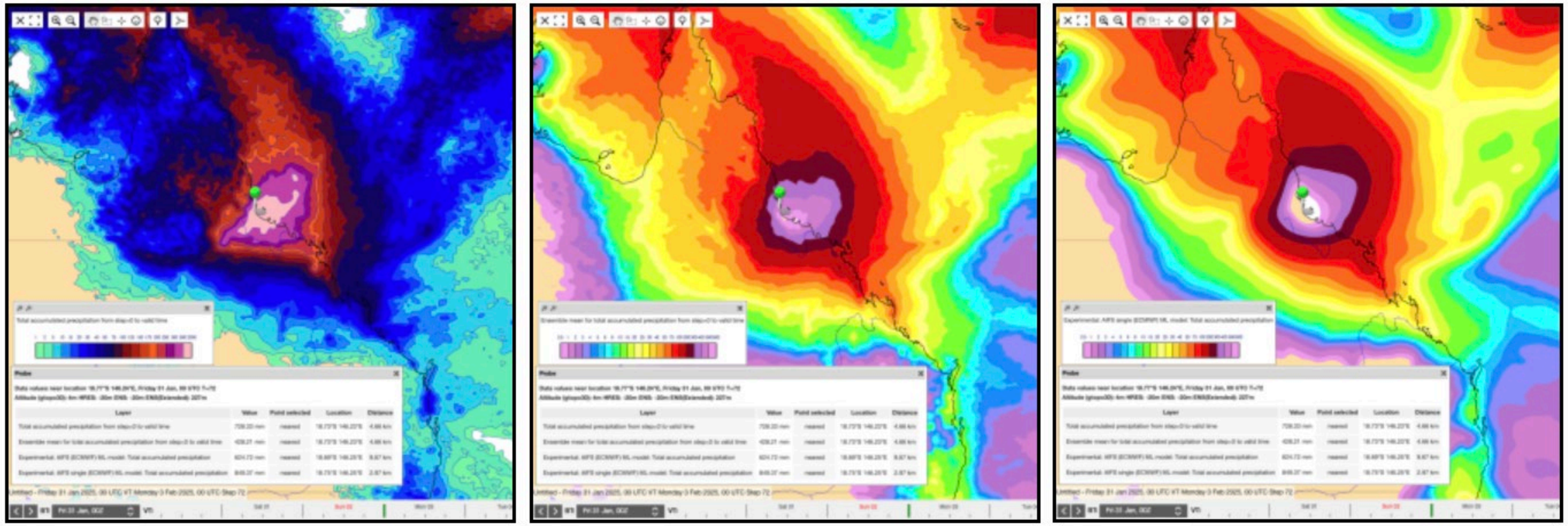
Case Studies: AIFS Single v1



24h snowfall; T+24-48h
VT: 21 January 2025



Rare snow along the Gulf Coast
Structure well-predicted but underestimated intensity.



Heavy precipitation event in Queensland
AIFS predicts more extreme precipitation than the IFS

More on AIFS case studies from Linus on Thursday

Anemoi

Open source ML software framework for earth system modelling. Underpins AIFS, DestinE AI activities and more activities across Europe.

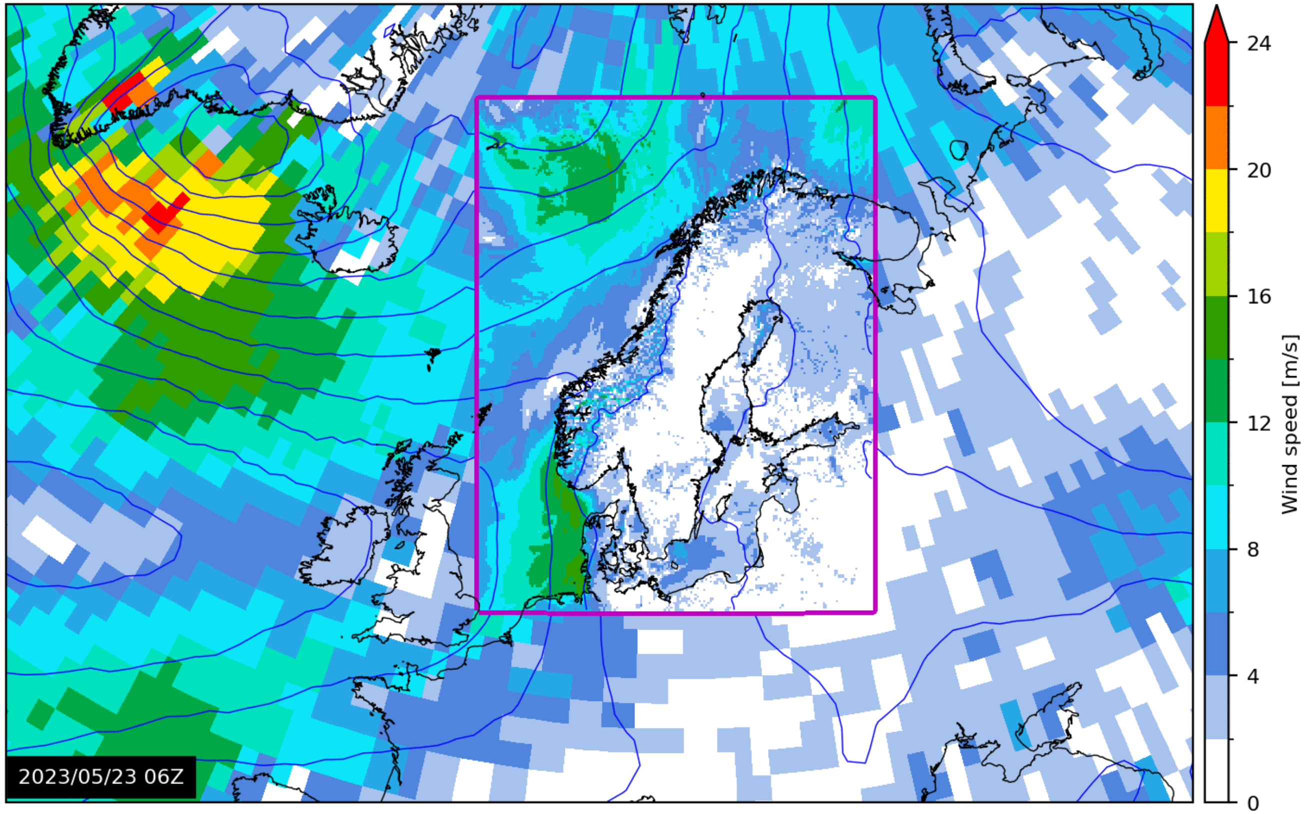
Open recipes for training the AIFS and open models.

<u>Developed</u> and <u>used</u> by meteorological centers across Europe.
AEMET, DWD, FMI, GeoSphere, KNMI, MET Norway, Meteo Swiss, Meteo France, RMI, & ECMWF

anemoi

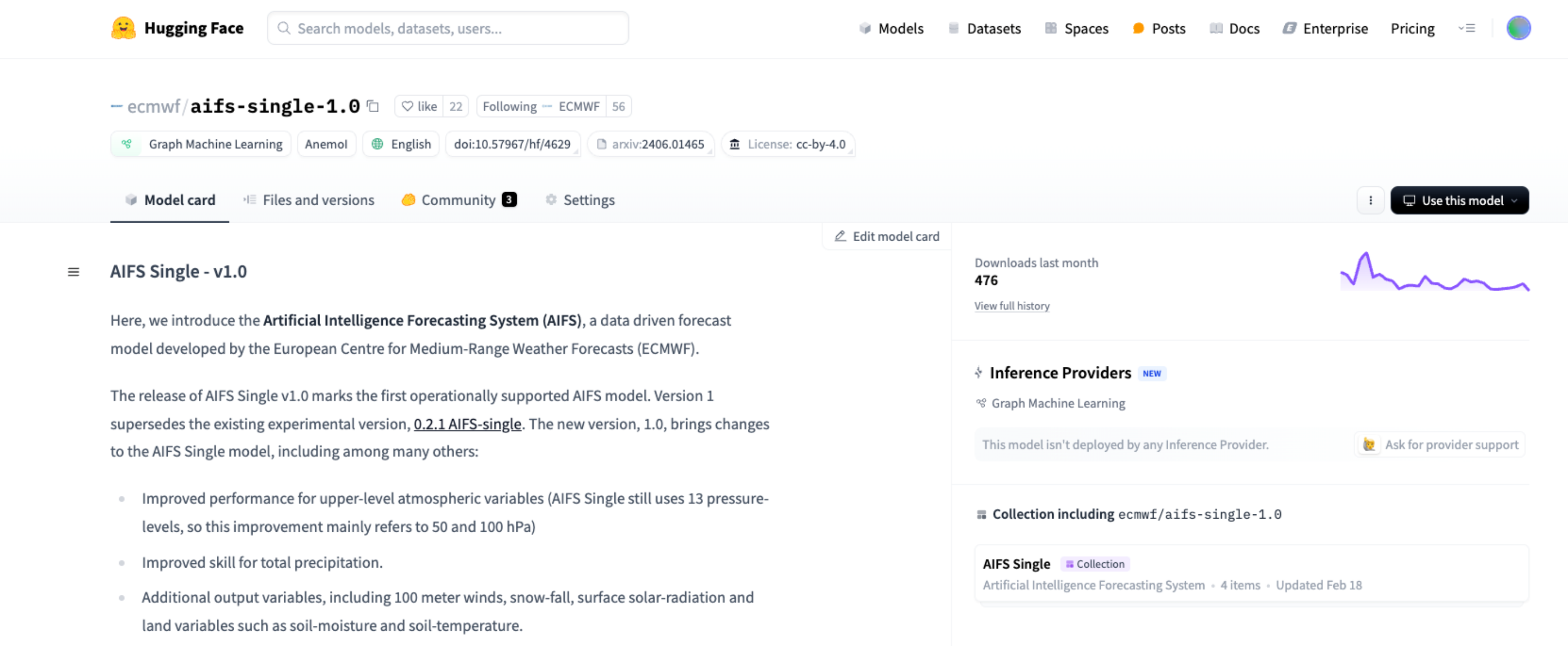
Pooling of resources without resulting in a single forecasting model.

ANEMOI in action: developing weather model for the Nordics
See Jorn's talk for more!



Running AIFS yourself interactively

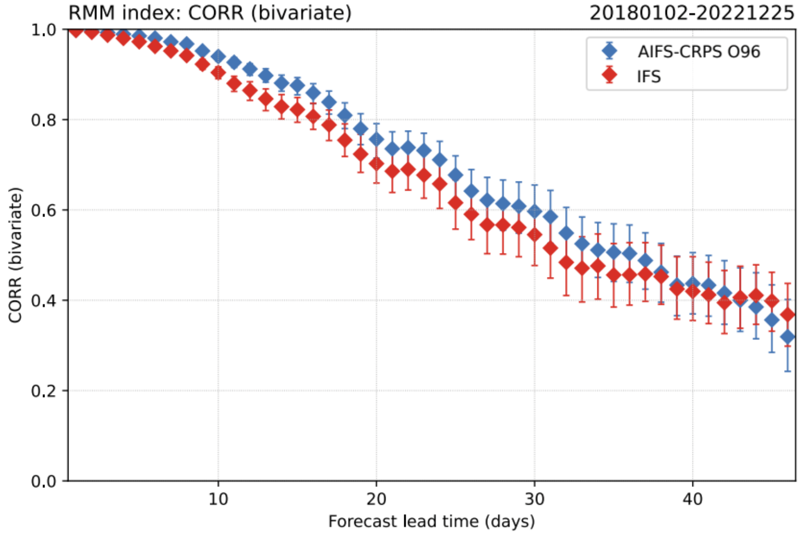
https://huggingface.co/ecmwf/aifs-single-1.0

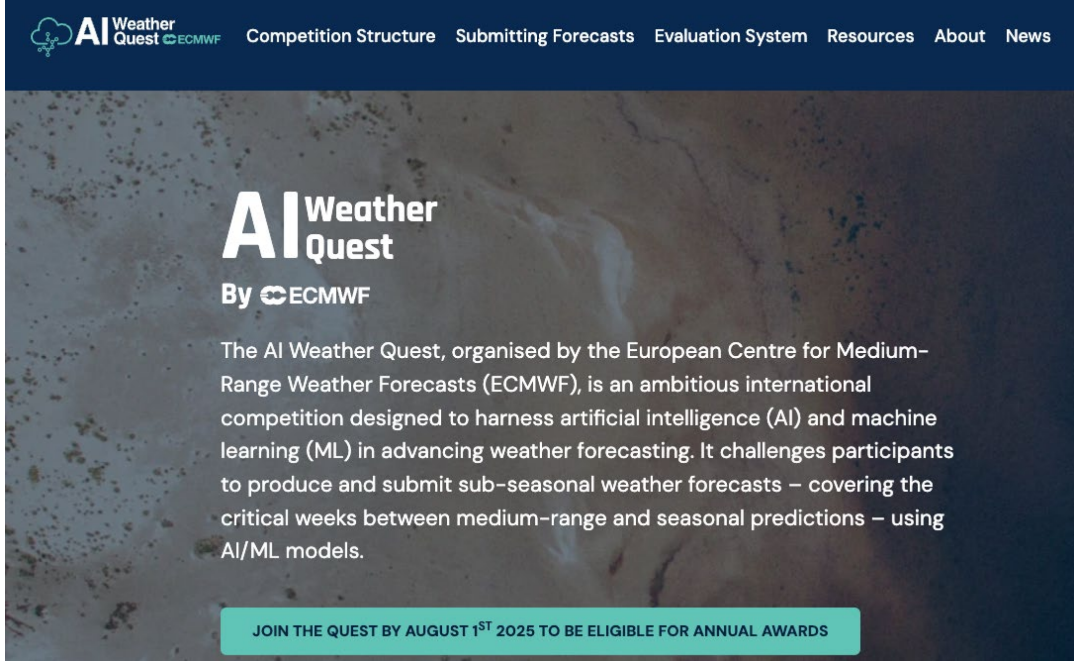


- AIFS Single 1 on Hugging Face – an open platform for sharing the models.
- Includes interactive notebook on how to run from ECMWF open data, can be adapted for other sources.

Sub-seasonal and beyond

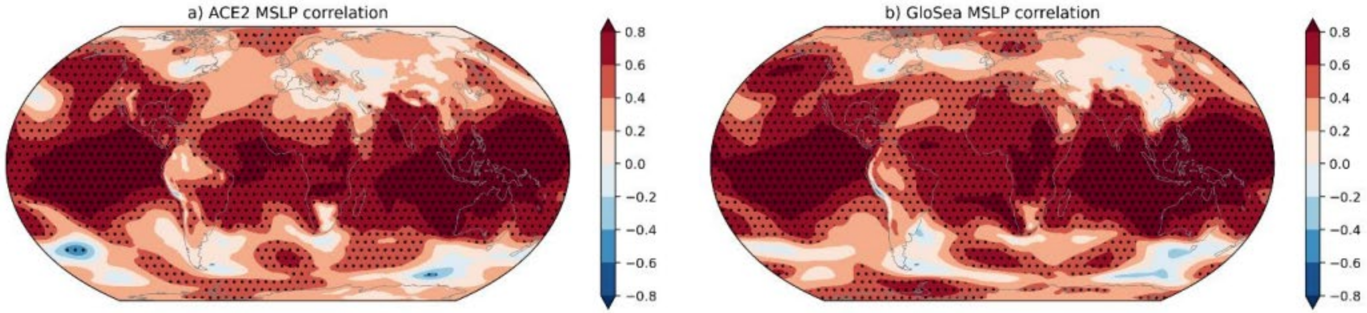
Clear skill for AIFS on sub-seasonal (Lang et al 2024b)



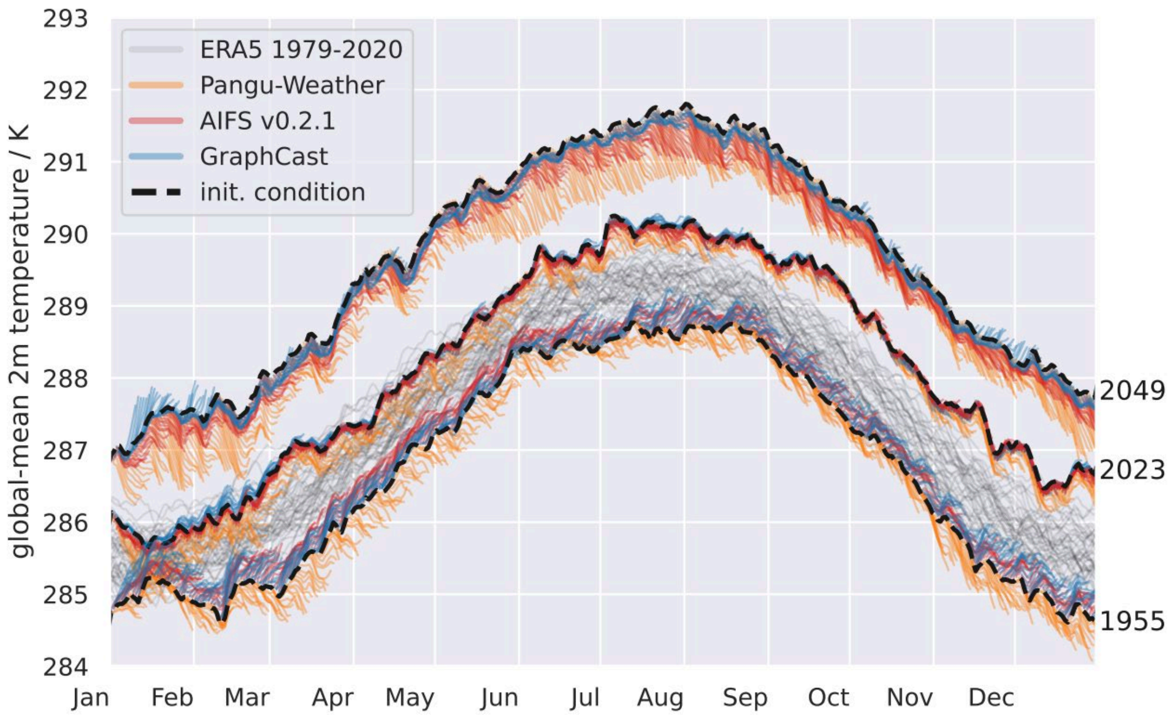


ECMWF organising a sub-seasonal competition this year

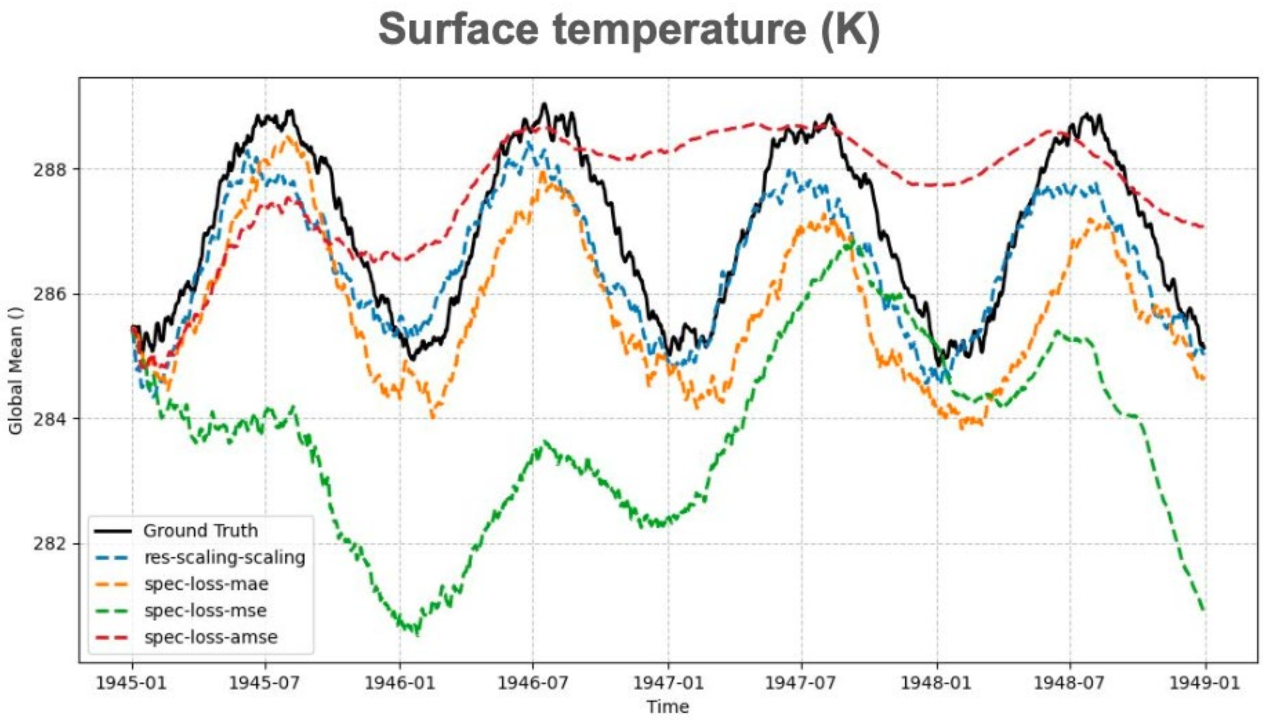
First model development and evaluation for seasonal
Kent et al. 2025



What about climate?



Exploring robustness of data-driven weather models in changing climate
Rackow et al. 2024



Developing Climate emulator in Destination Earth
See Chris Bretherton for more on Climate.

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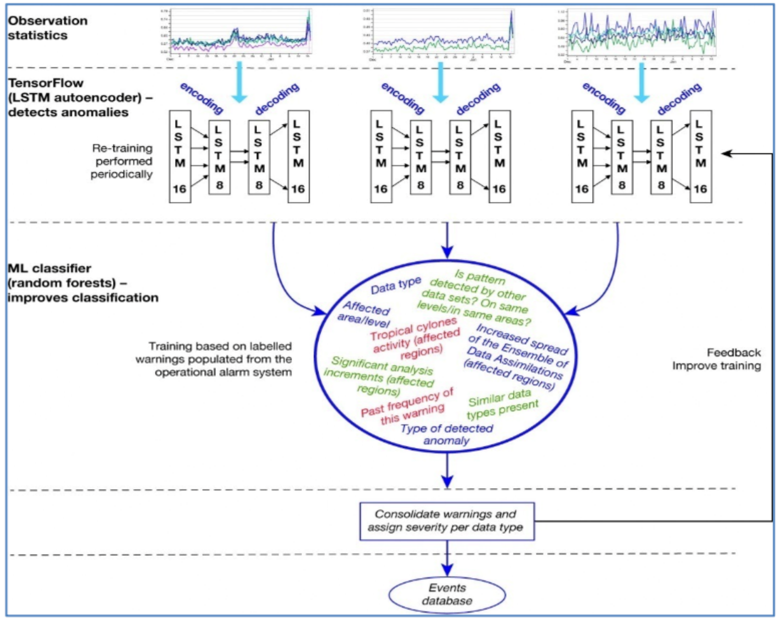
Hybrid applications of ML

Many applications across the Centre.

- Observation operators.
- Observation monitoring.
- Ensemble of DA emulation.
- Learning model error within IFS DA systems

Observation and DA System Monitoring



O-B departures timeseries

↓

Anomaly detection module
(LSTM autoencoder)

↓

Event classifier
(Random Forest)

Dahoui, M. (2023). Use of machine learning for the detection and classification of observation anomalies, *ECMWF Newsletter N. 174, Winter 2023*

Model Error Estimation and Correction in the IFS

Training the NN parameters inside 4D-Var results in further forecast skill improvements for most variables.

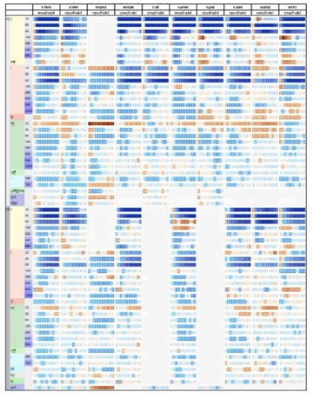
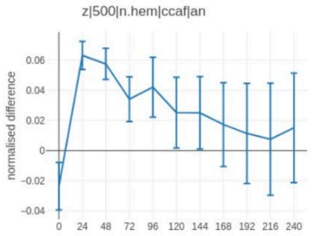


Figure: Score card 2022/06/03 to 2022/08/31. 12H assimilation window with NN model error correction trained **online**.



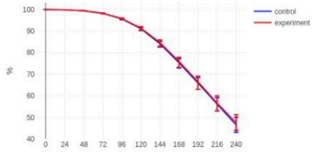
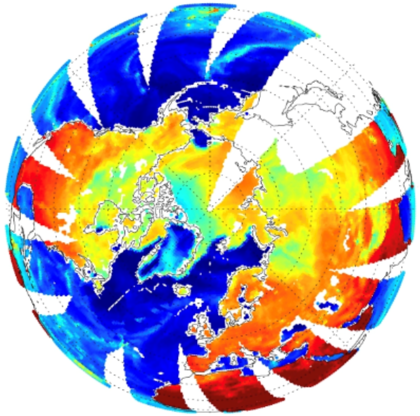


Figure: Z500 NH anomaly correlation. 2022/06/03 to 2022/08/31. 12H assimilation window with NN model error correction trained **online**.

From Marcin Chrust (ECMWF)

Hybrid Physical-ML models of the observations (H)

Satellite observations



SSMIS F-17 channel 13 (19 GHz, v)
Microwave brightness temperatures
3rd December 2014

Geophysical variables

Equations & parameters – where sometimes knowledge is quite uncertain

$$y = h\left(\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_{\dots} \end{bmatrix}, \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_{\dots} \end{bmatrix}\right)$$

Forward function

Gas spectroscopy

Scattering from hydrometeors

Cloud and precipitation micro and macro-structure

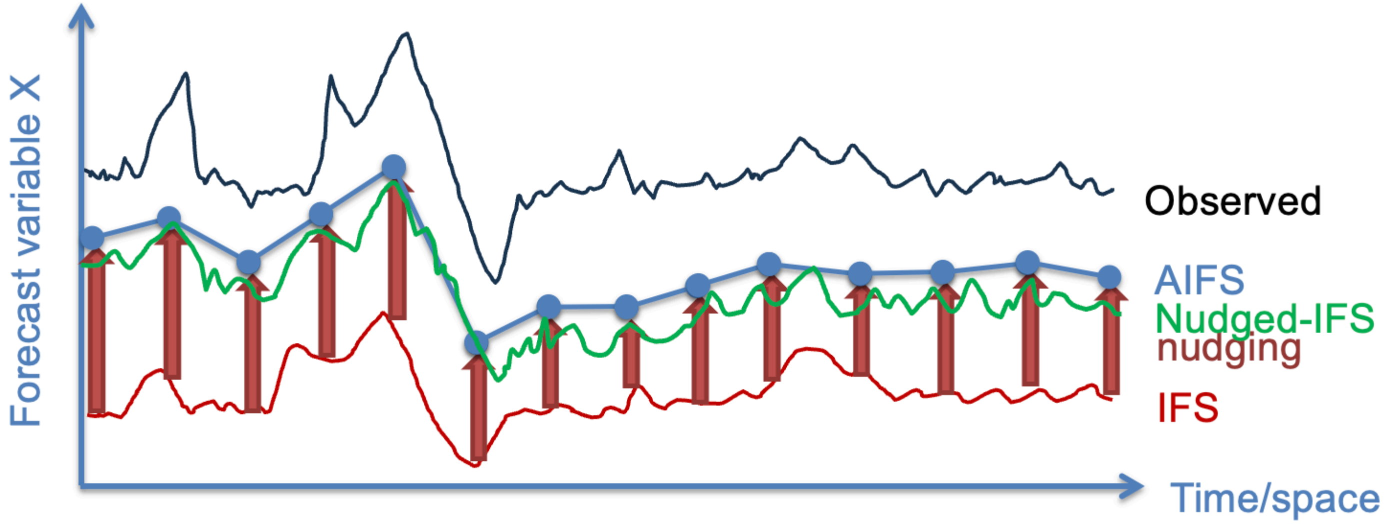
Snow / ice grain size and structure

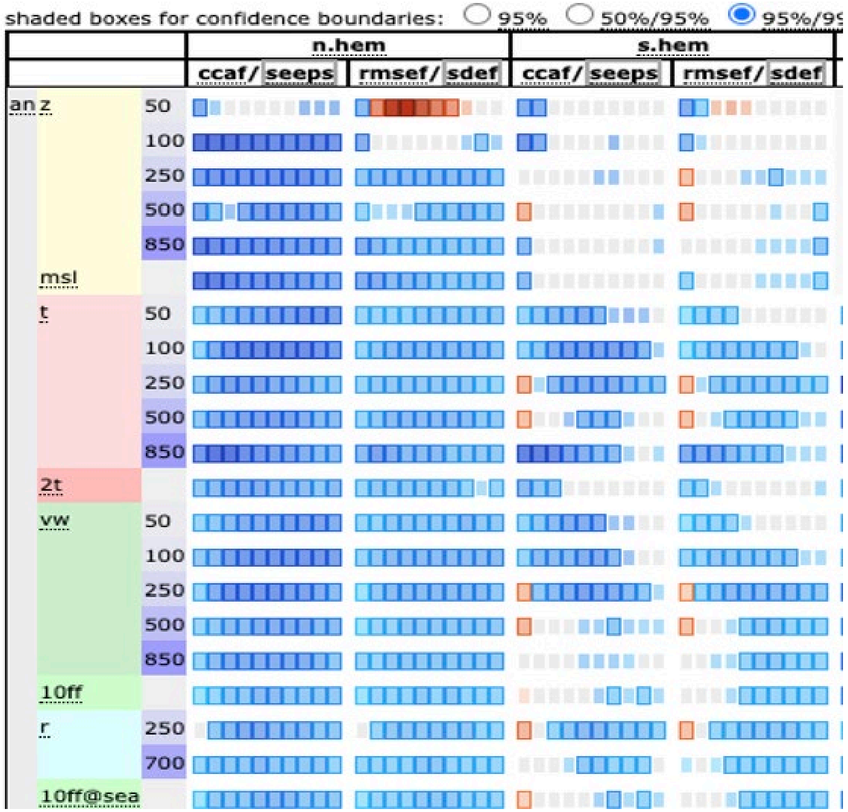
…..

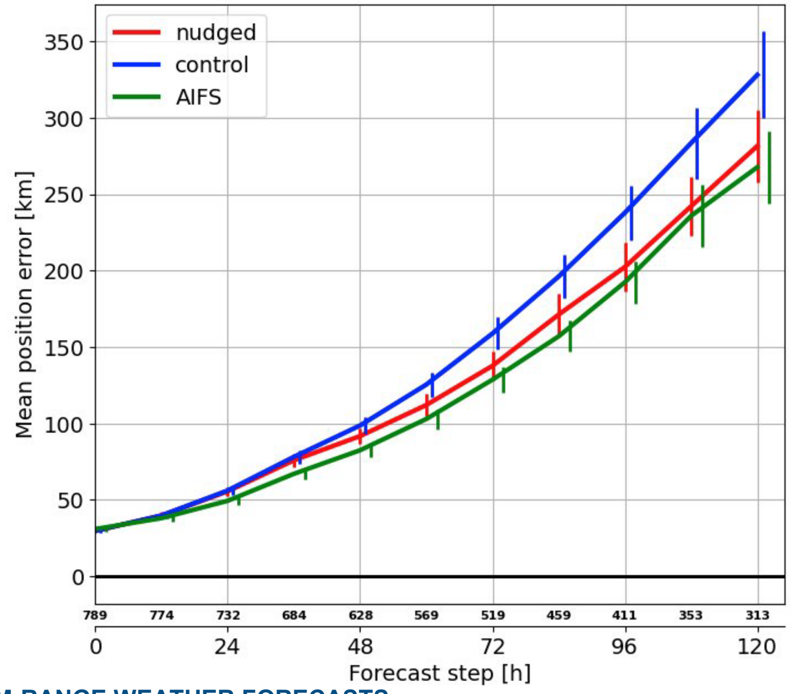
From Alan Geer, ECMWF

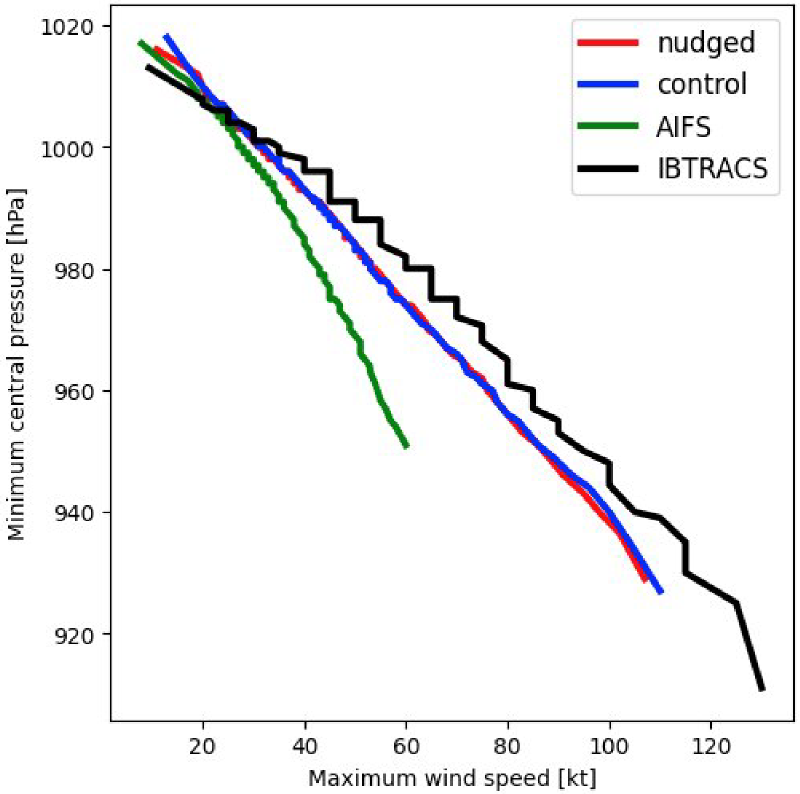
Driving the IFS with the AIFS

- Following the work by Hussain et al (2024)
- Develop custom AIFS version that operates on 137 model levels.
- Up to 15% improvements in ACC/RMSE









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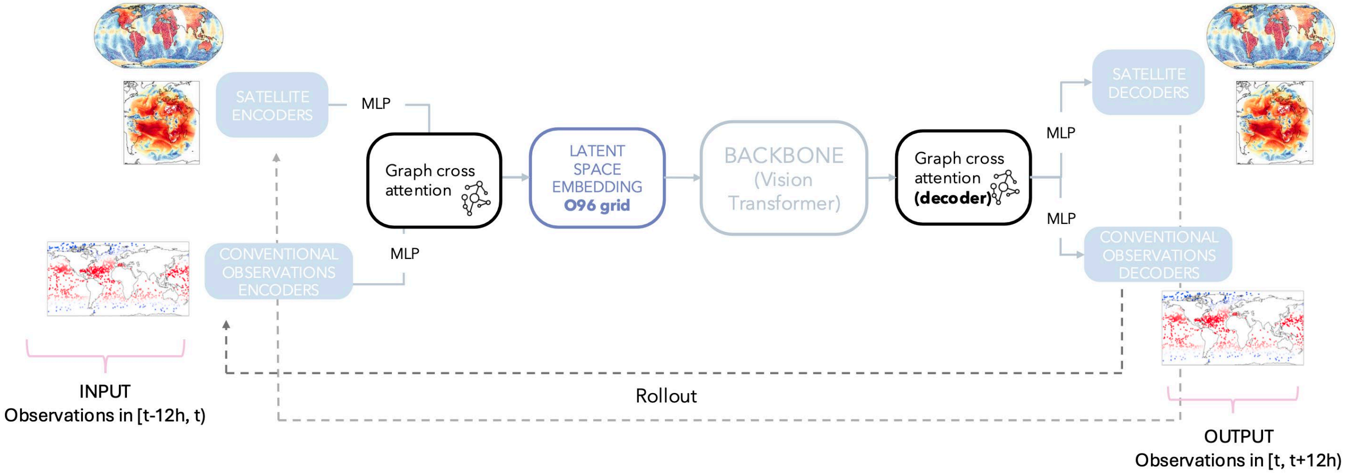
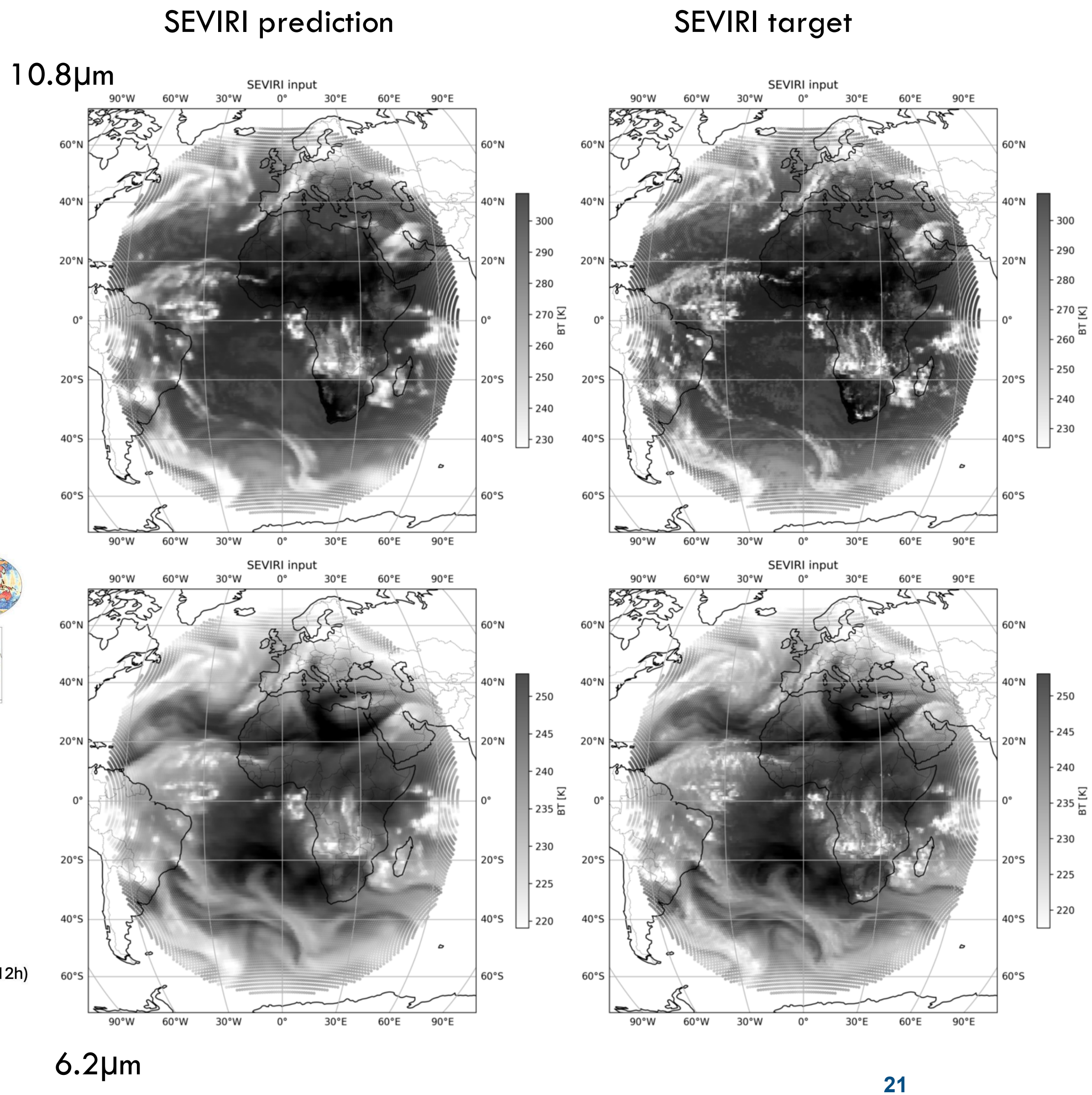
AI-DOP: How to learn a forecast from observations

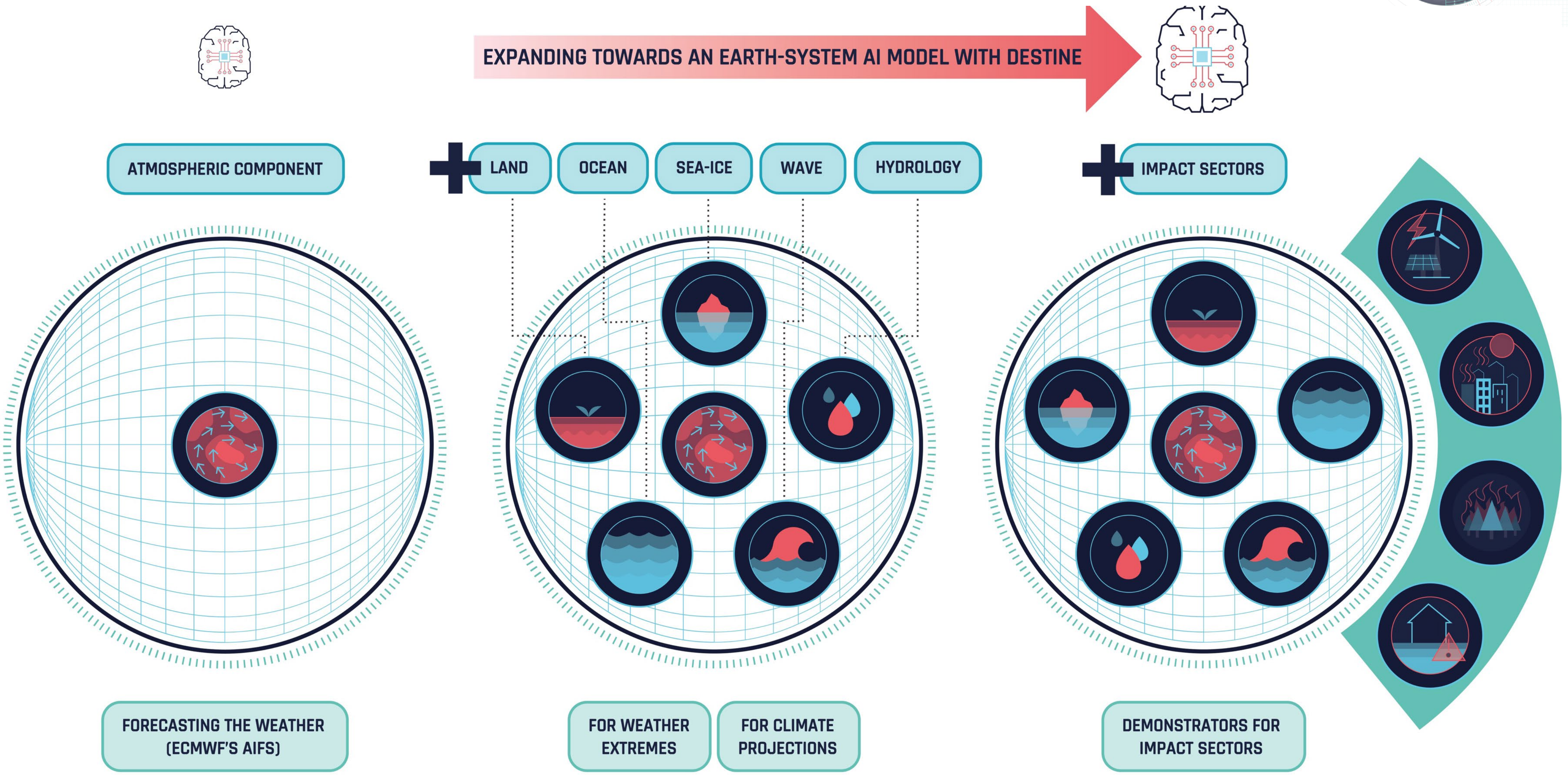
- Use historical observations to train a Neural Network to forecast <u>future</u> observations (don't need analyses)
- Include all available observations of the <u>full Earth system</u> (atmosphere, ocean, land) simultaneously
- Once trained, initialize the model <u>directly</u> with the observations themselves
- The model can produce a forecast at unobserved locations (e.g., on a grid)



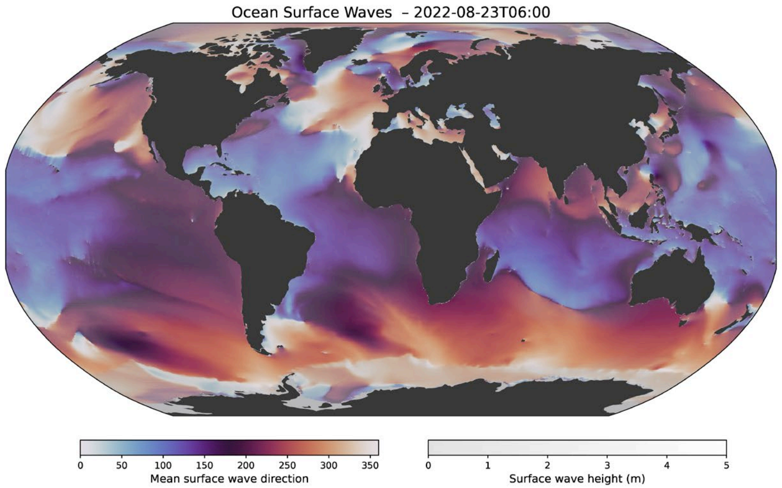


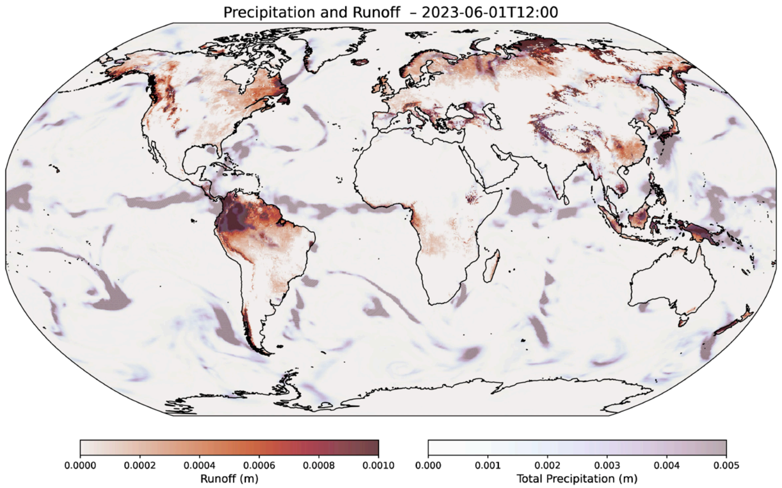
ECMWF

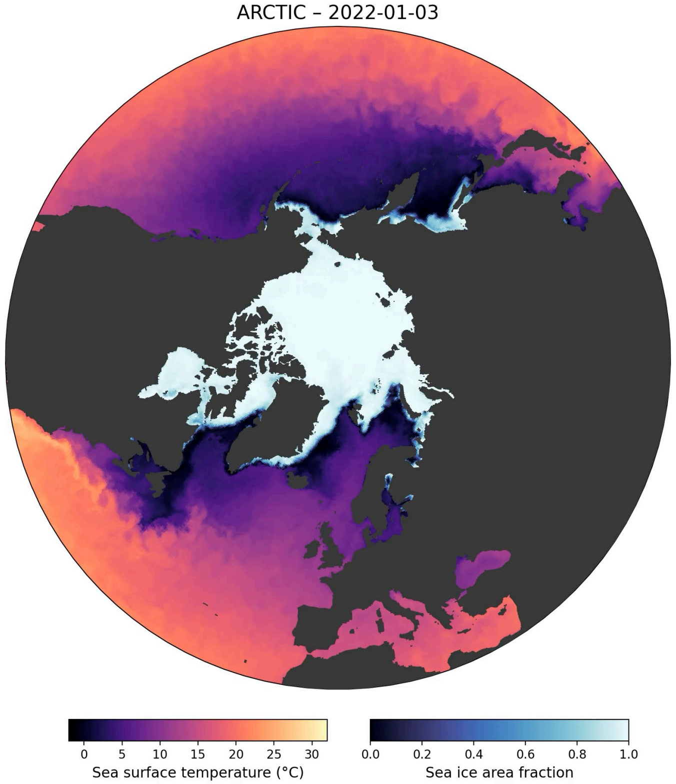
More from Tony (Tuesday) and Mihai (DA workshop, Thursday)


EXPANDING TOWARDS AN EARTH-SYSTEM AI MODEL WITH DESTINE
ATMOSPHERIC COMPONENT
LAND
OCEAN
SEA-ICE
WAVE
HYDROLOGY
IMPACT SECTORS
FORECASTING THE WEATHER (ECMWF'S AIFS)
FOR WEATHER EXTREMES
FOR CLIMATE PROJECTIONS
DEMONSTRATORS FOR IMPACT SECTORS

Status: First protypes across the Earth System



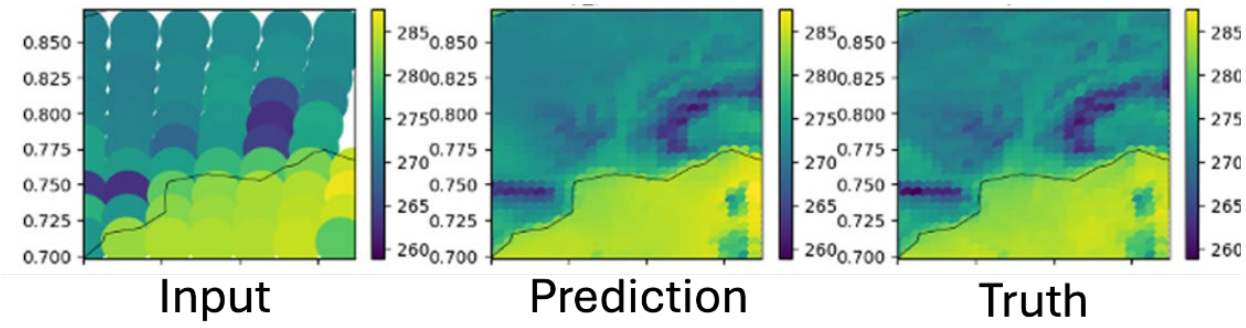




AI in Copernicus

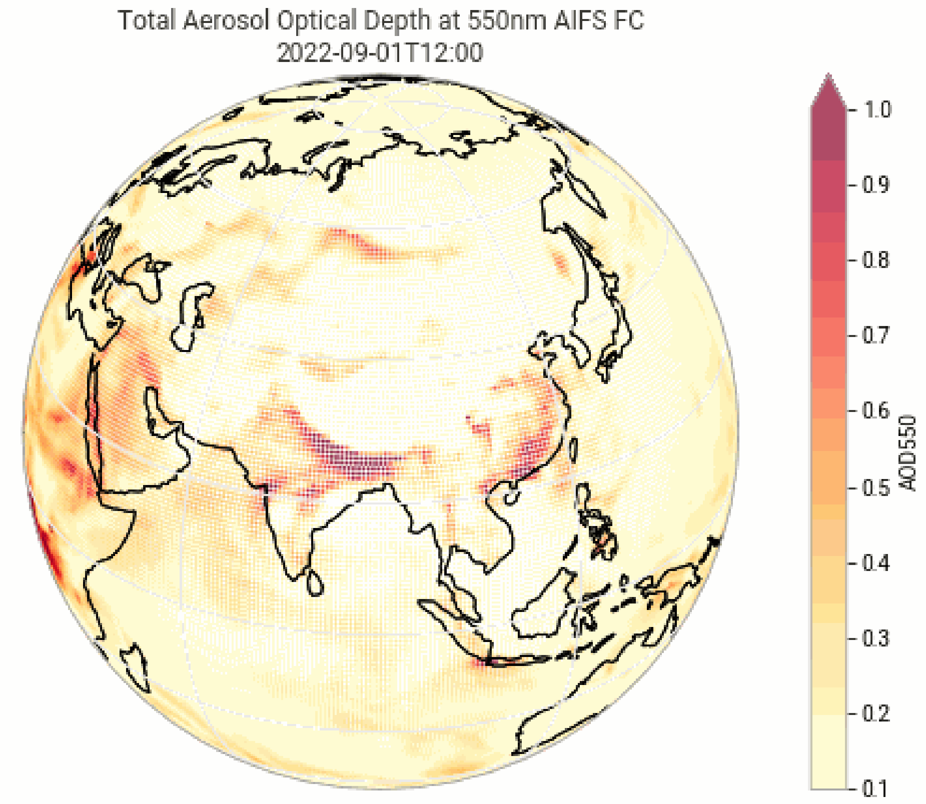
C3S

- Leverage developments in ML-based downscaling.
- Create near-real-time regional reanalysis using ML downscaling system and ERA5T.
- Downscaling for regional climate projections.



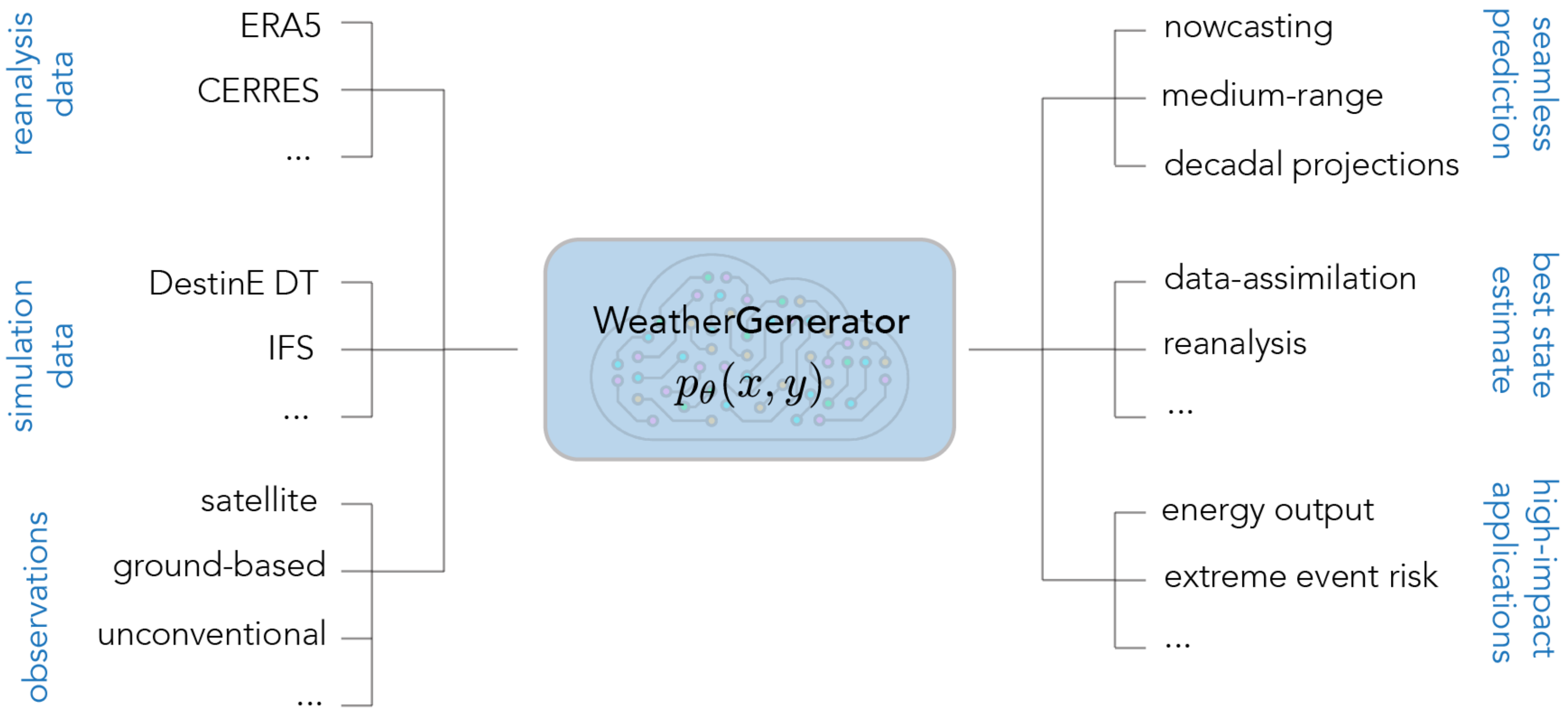
CAMS

- Leverage AIFS/Anemoi/CAMS datasets.
  - Build AIFS-compo.
  - First prototypes in development.
- Also explore hybrid approaches for IFS-compo



Weather Generator

WeatherGenerator



Exploring the next generation of ML models.
Single foundation models across time, space and task

https://www.ecmwf.int/en/about/media-centre/news/2024/weathergenerator-project-aims-recast-machine-learning-earth-system

JÜLICH Forschungszentrum

Norwegian Meteorological Institute

MAX PLANCK INSTITUTE FOR BIOGEOCHEMISTRY

Royal Netherlands Meteorological Institute Ministry of Infrastructure and Water Management

METEO FRANCE

SMHI

Met Office

cmcc Centro Euro-Mediterraneo sui Cambiamenti Climatici

netherlands eScience center

buluttan Weather Intelligence

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Swiss Confederation

Federal Department of Home Affairs FDHA
Federal Office of Meteorology and Climatology MeteoSwiss

MeteoSwiss

ECMWF EUROPEAN CENTRE FOR MEDIU

KAJO

LT

Statkraft

ETH zürich

Outlook

- Empowering Member States to leverage data-driven modelling through Anemoi.
  - Collaboration via EUMETNET E-AI and ECMWF ML Pilot Project [See Jorn’s talk on Tuesday]
- Operationalisation of the AIFS ENS CRPS. [See Simon’s talk on Thursday]
  - Learn from data in the hands of users. [See Linus’s talk on Thursday]
  - Machine learning offers the idea of faster cycles to improve.
- Experimental subseasonal forecasting and beyond.
- How can we build trust beyond experience? [See Amy’s talk on Thursday]
- Will ML teach us something about predictability? [See Greg’s talk on Friday]
- Widen use of ML across ECMWF activities.
- Like increase in number of forecasting systems.
  - Bespoke forecasting systems for specific use-cases?
  - How to communicate well about optimal use of many systems to users?

Neural networks as universal approximation systems

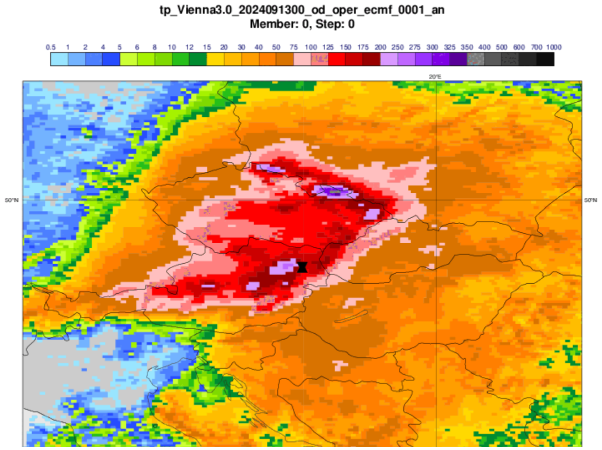
Given enough compute and data any relationship can be learnt….

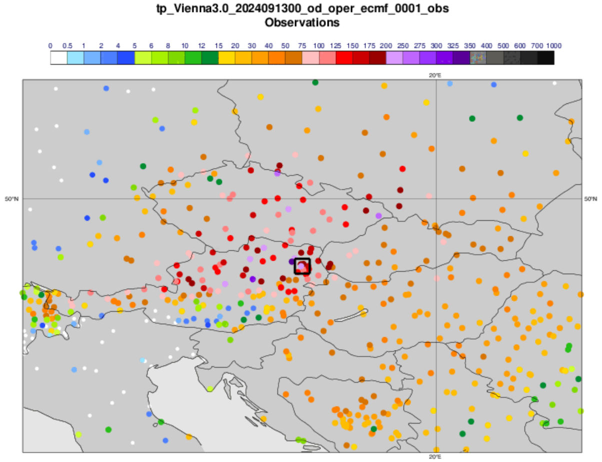
For which problems is this true?

Answer: Many...

Extremes: Extreme precipitation in Central Europe, storm Boris

- AIFS-nudged less jumpy than IFS (48r1 & 49r1). No under-estimation like in AIFS Single.





0-3 day lead time

3-6 day lead time

4-7 day lead time

3-day accumulated precipitation