Adding Land Variables to the AIFS and introduction to Direct Observation Prediction (AI-DOP)

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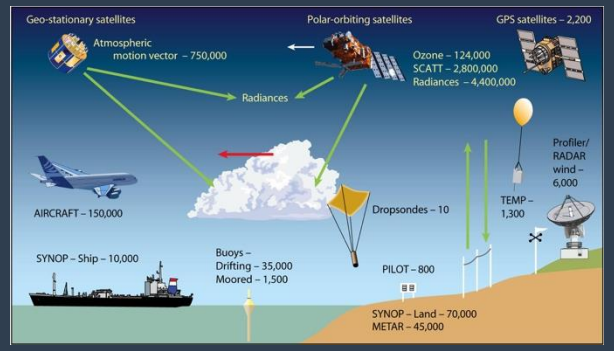
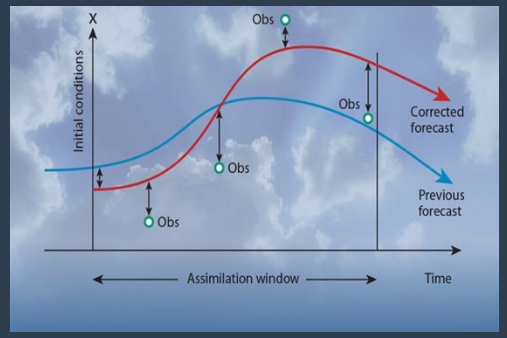
ECMWF

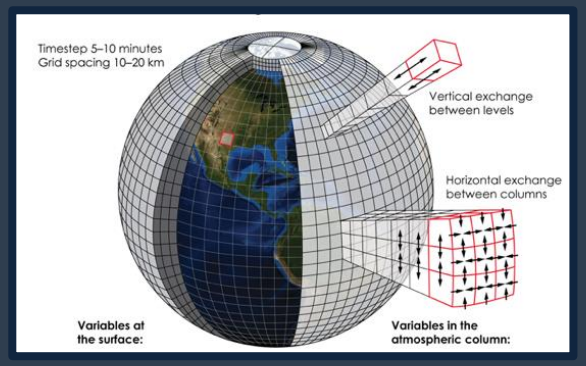
Overview

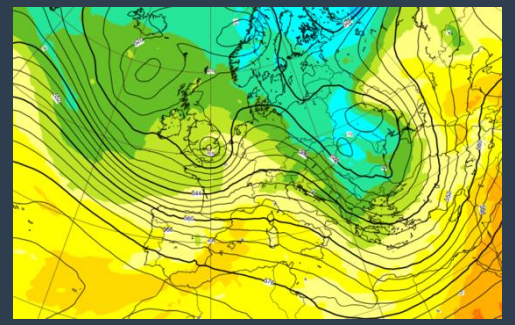
- Traditional Weather Forecasting Workflow:
  - How are Weather Forecasts made with the traditional system
- Artificial Intelligence Forecasting System (AIFS):
  - Where are we starting to use Machine Learning (ML) for weather forecasting?
  - How have we added land variables into these new ML systems
- Direct Observation Prediction (AI-DOP):
  - Making Weather Forecasts directly from observations using ML
- Summary

How do we make Weather Forecasts





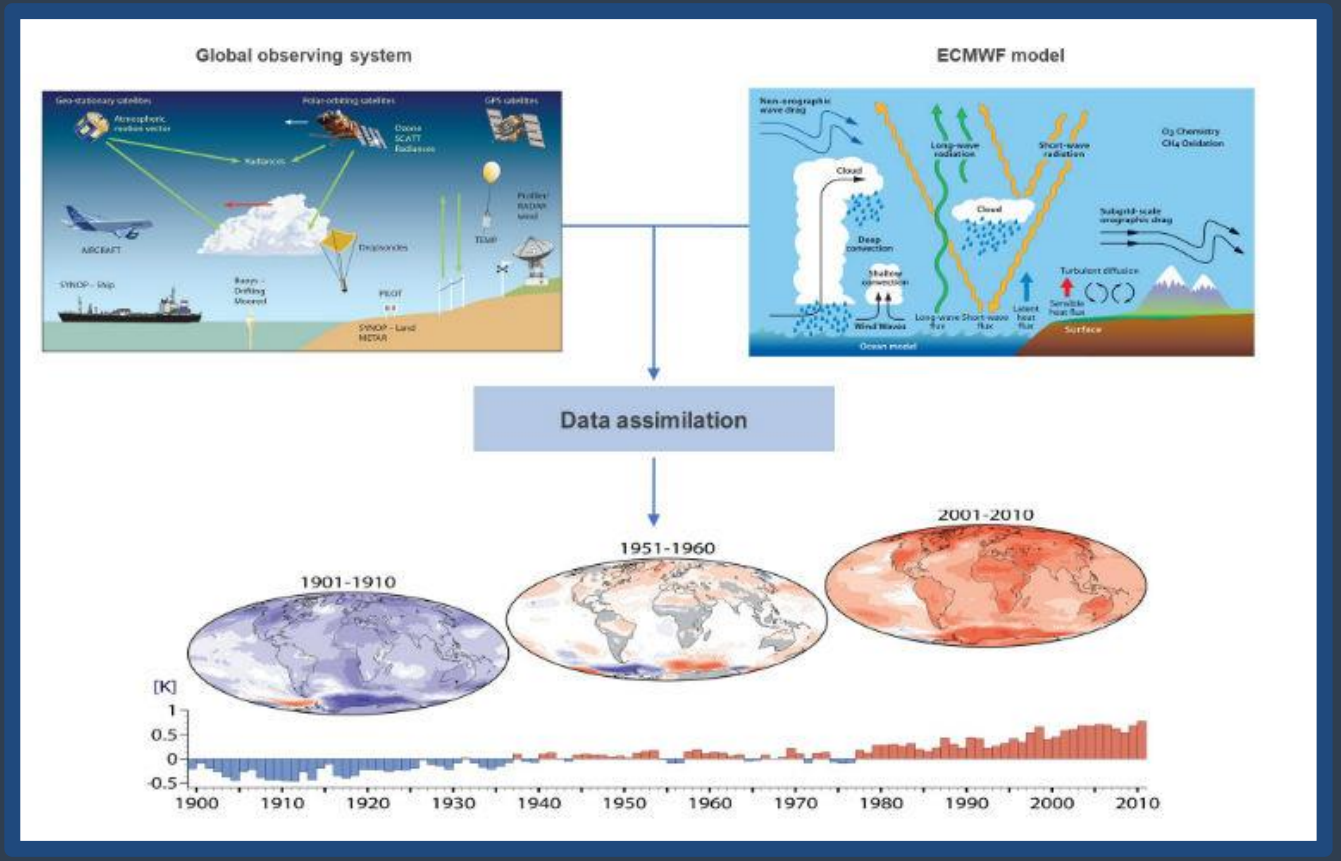




Observations → Data assimilation → Physics based forecast model → Post-processing and dissemination

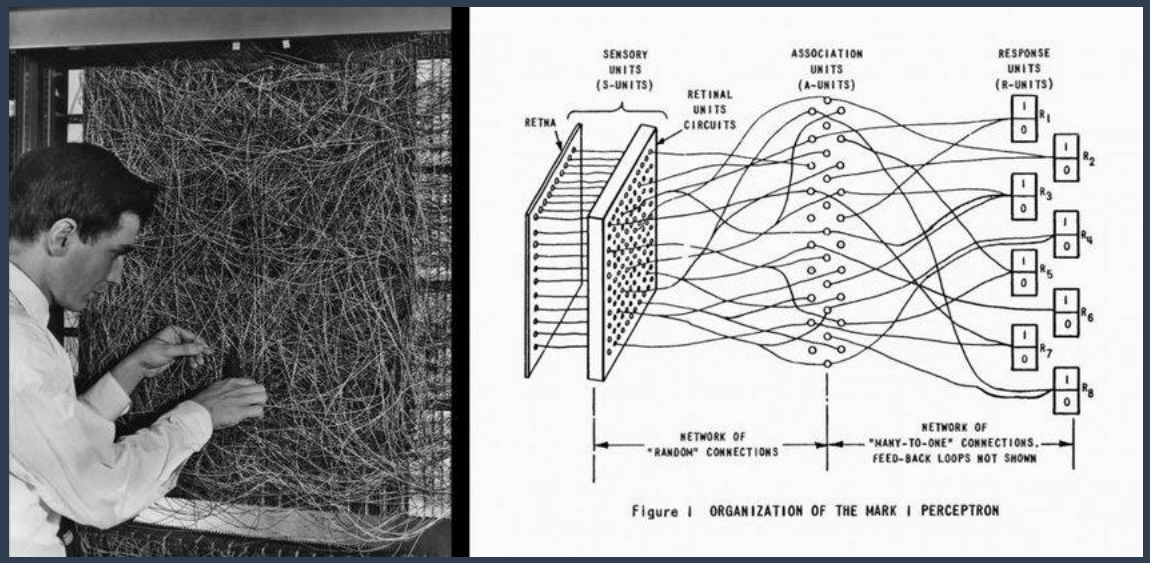
ERA5: blended observations and physics for over 50 years

- Run Data Assimilation system with available historical observations to get best estimates to the state of the atmosphere
- Available 1940 to present
- ~ 0.25 degree resolution
- Hourly estimates to state of the atmosphere combining observations and model physics
- Very large dataset! < 5 Petabytes
- ERA6 entering production soon!



Step-back: Rise of Machine Learning…

- Machine Learning not a “new” idea
- Combination of access to ever increasing data volume and progress in compute (GPUs) makes its application possible and much more effective now
- Increased compute power (and available data) makes machine learning possible today
  - Explosion in data volumes following digitisation
  - “Domain specific compute architectures” e.g. GPUs
- Data produced by ECMWF presents significant opportunity for training a “Data-Driven” model



Frank Rosenblatt programming his Perceptron, 1970s

Step-back: Rise of Machine Learning…

Defining the dataset, split, headline fields and metrics

2020 WeatherBench

ECMWF staff
~500km ERA5 to predict future z500. Similar work from Rasp and Weyn.

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)

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

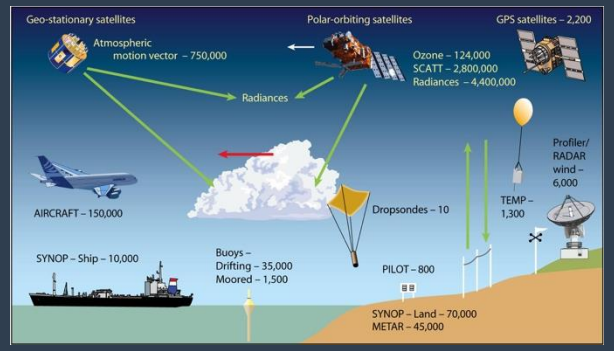
Sharp spatial features

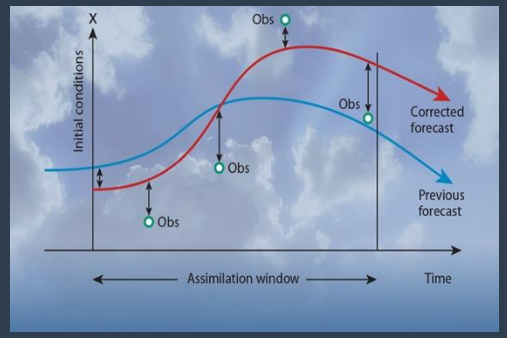
Jun 2023

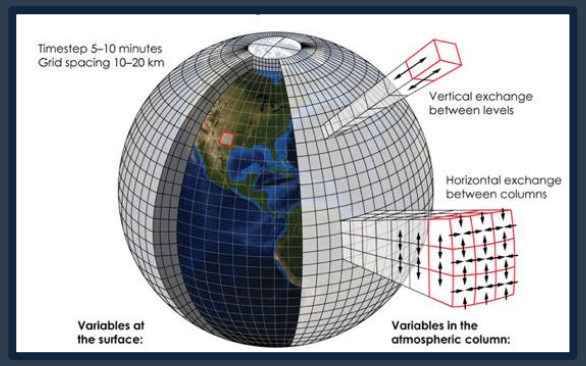
And so on…
AIFS
FuXi
AtmoRep
FuXi-extreme
NeuralGCM
GenCast
…

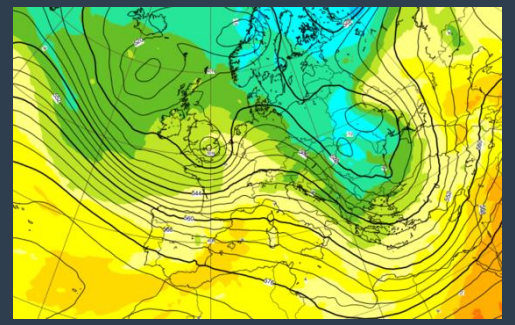
impossible to keep this figure up!

AIFS: Data-driven Weather Forecasting System









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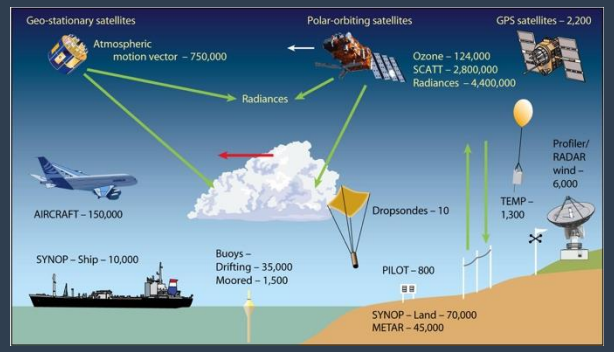
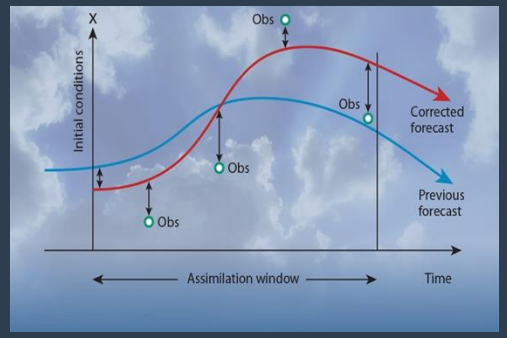
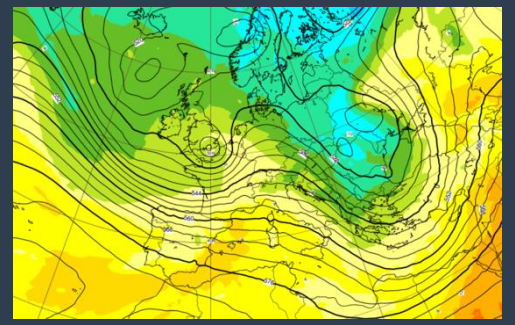
AIFS: Data-driven Weather Forecasting System





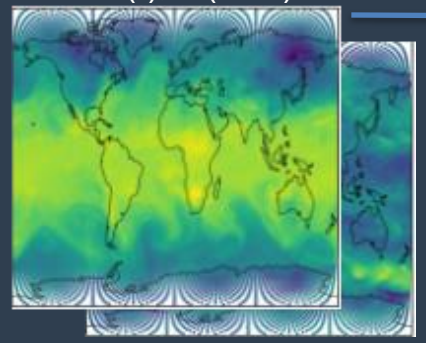


Observations → Data assimilation → "Data-driven" forecasting model → Post-processing and dissemination

AIFS: Data-driven Weather Forecasting System

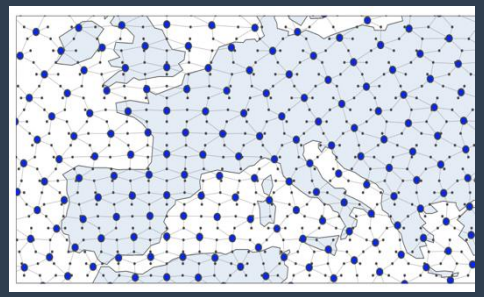
Lang et al. 2024a
https://arxiv.org/abs/2406.01465

Input
Atmospheric state:
X(t), X(t-6h)

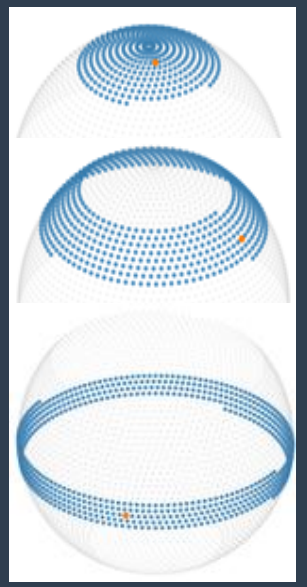


AIFS MODEL

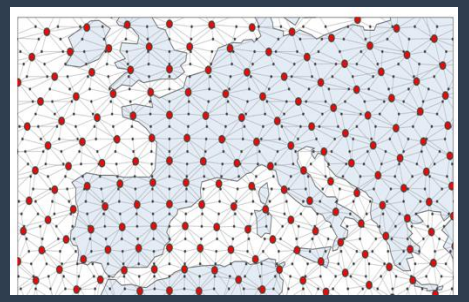
encoder → processor → decoder



Graph attention

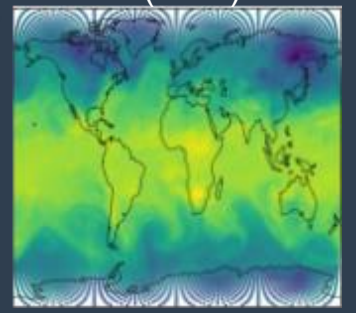


Transformer blocks and windowed attention (attention across regional bands). On a coarser grid than input grid



Graph attention

Output
Prediction:
X(t+6h)

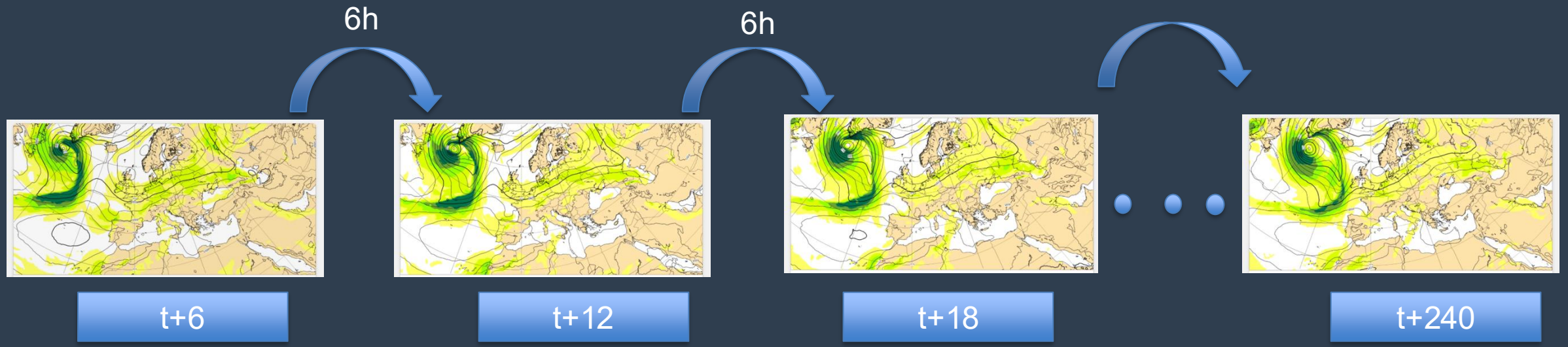


Implemented in

anemoi

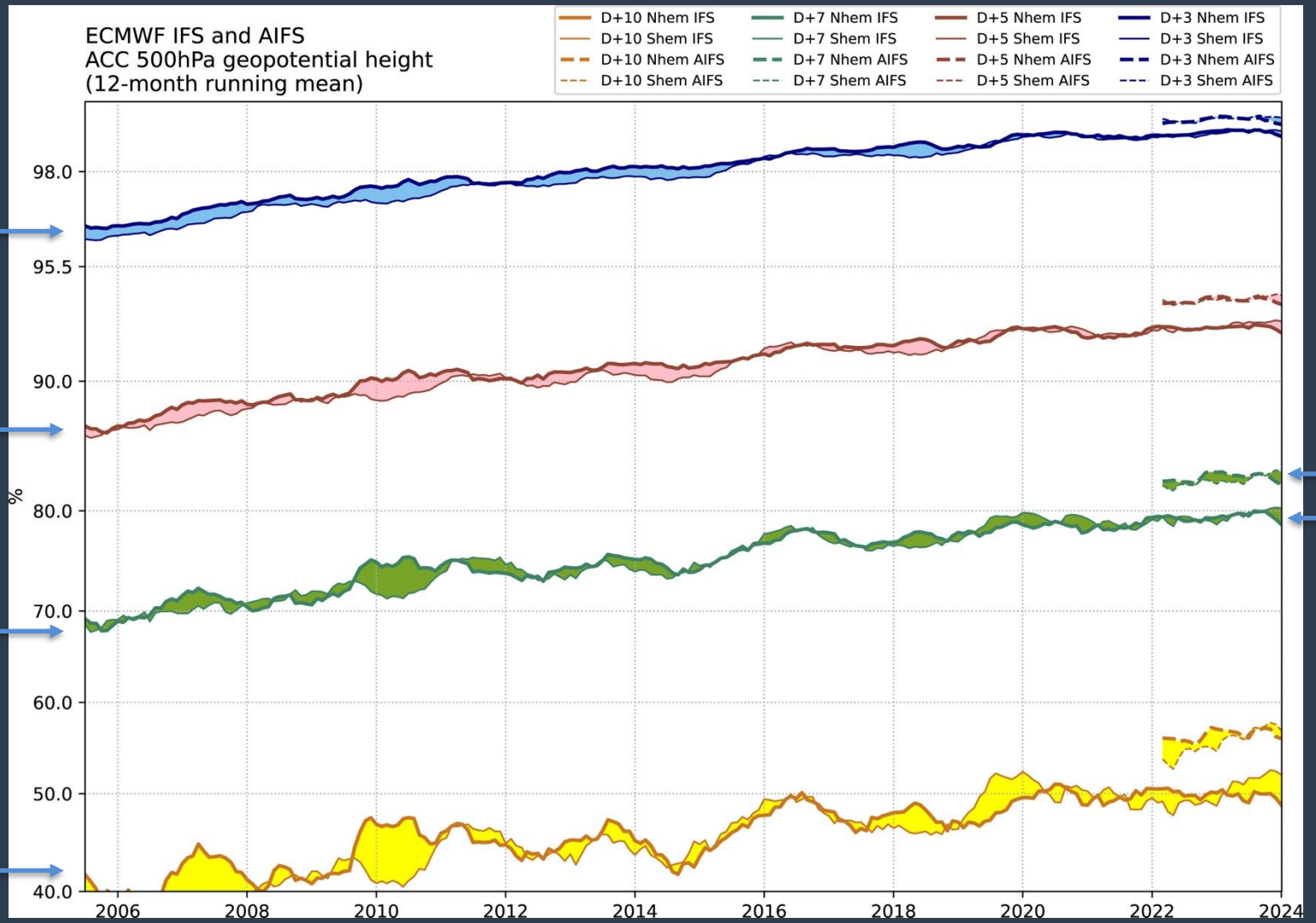
INFERENCE

Once the model is trained, we can generate predictions stepping e.g. 6h from analysis to analysis



The forecast is then autoregressively stepping 6h into the future $x_n = f(x_{n-1})$ …

AIFS: Forecast Performance



3-day forecast

5-day forecast

7-day forecast

10-day forecast

AIFS

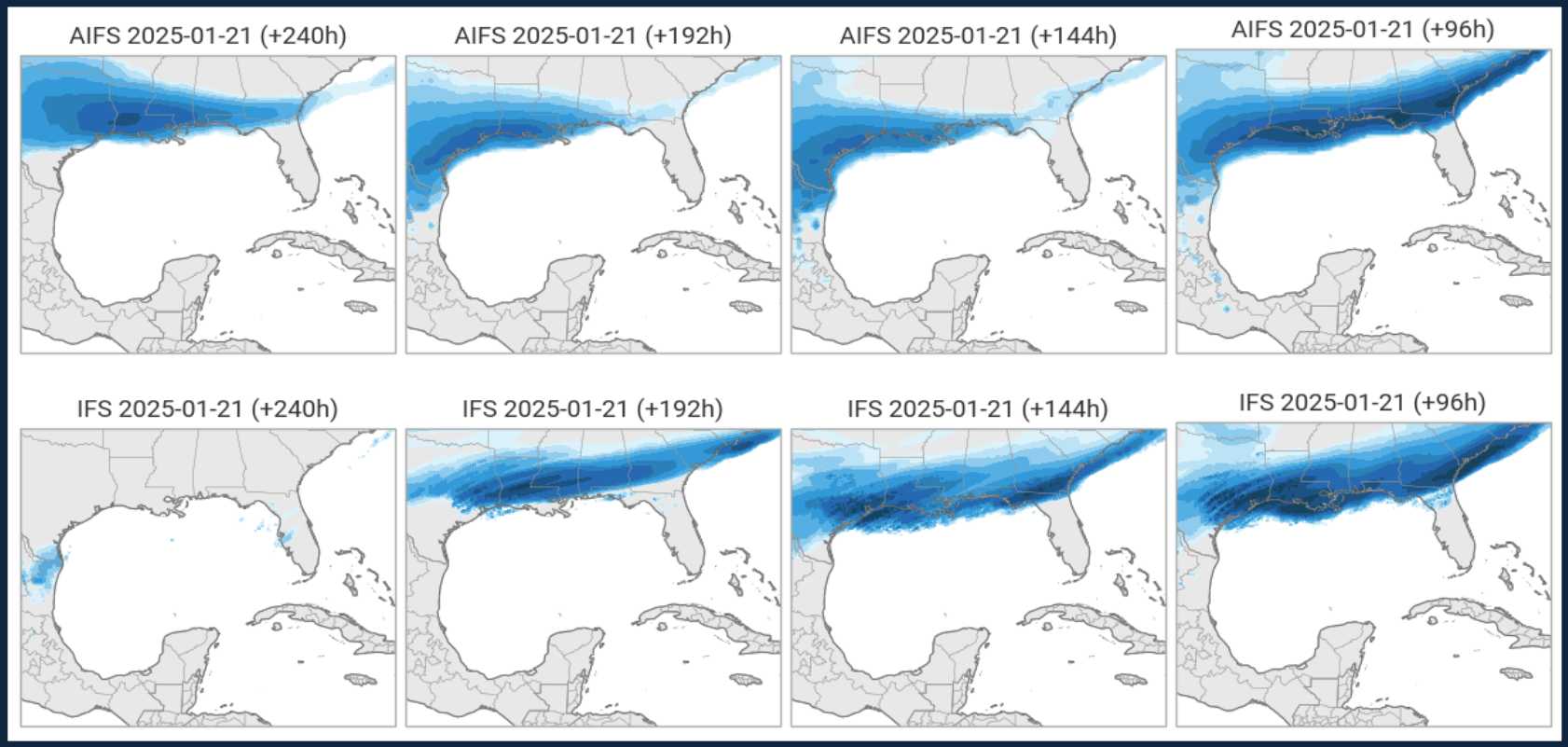
IFS

AIFS: Case Study

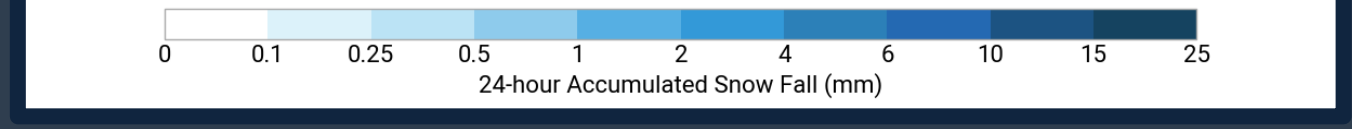
Forecast Lead Time

DAY 10 | DAY 8 | DAY 6 | DAY 4

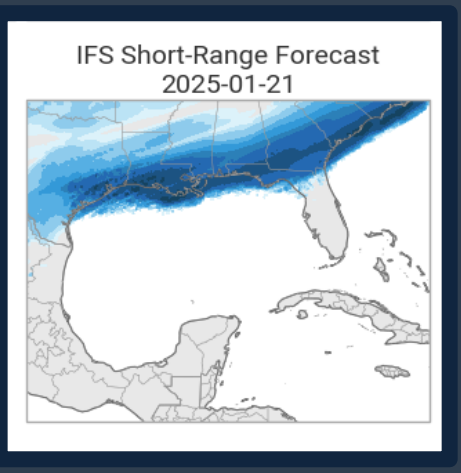
AIFS



IFS



Best estimate



AIFS: Efficiency and Cost

Gain in time and energy

ERA5:
15 billion (one off)

Hersbach, H et al. (2020)

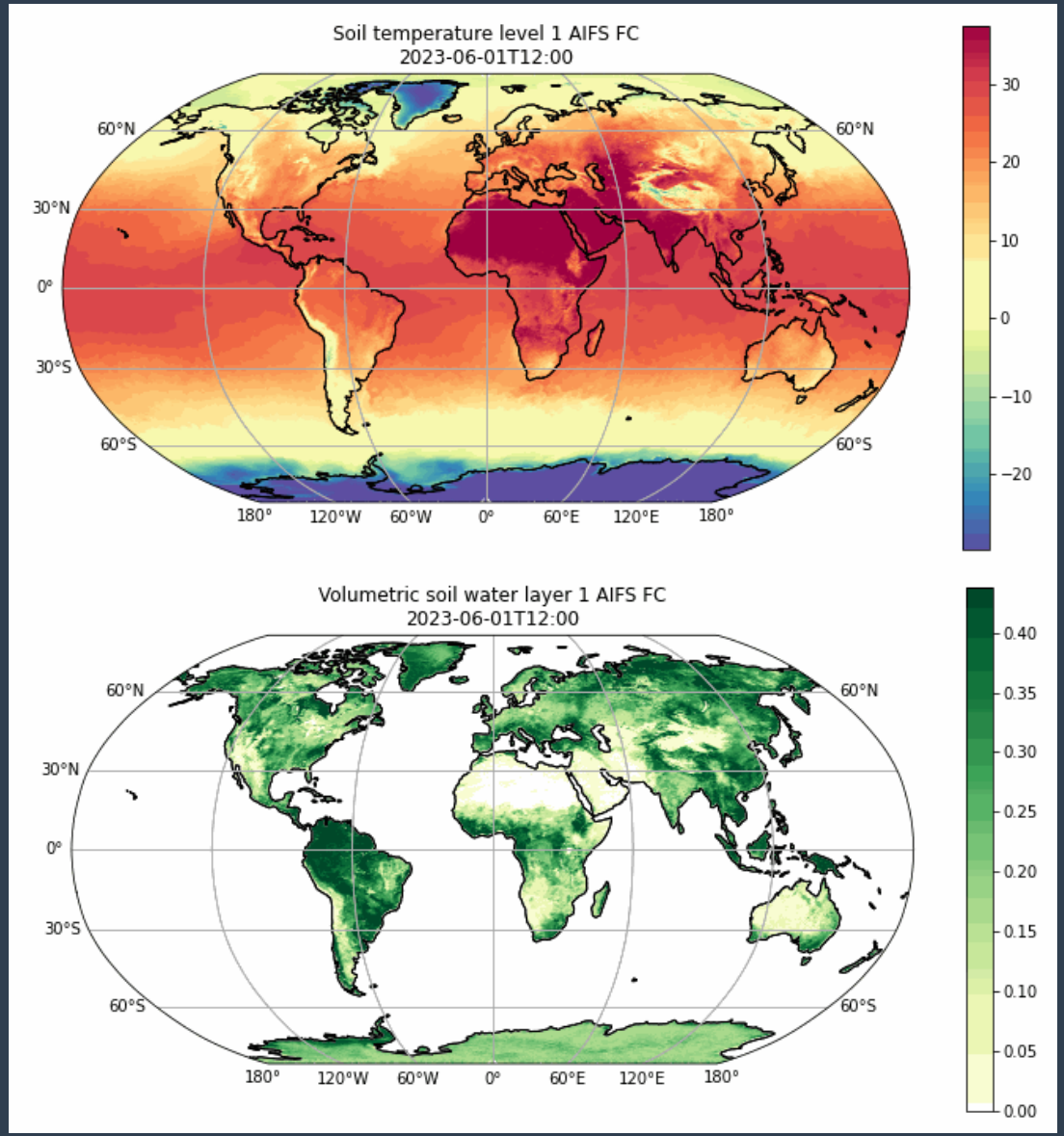
ECMWF HRES:
180 000
per forecast

AI Model:
0.3
per forecast

ECMWF

AIFS Single 1.0 – Adding Land and Energy Sector Variables

- As part of first operations release new variables included in AIFS 1.0 model
- New variables added to AIFS 1.0
  - Prognostics:
    - Soil moisture (layer 1 + 2) 💧
    - Soil temperature (layer 1 + 2) 🌡️
  - Diagnostics:
    - Cloud covers (tcc, lcc, mcc, hcc) ☁️
    - Surface radiations (strd, ssrd) ☀️
    - 100m winds (100u, 100v) 🌬️
    - Snow fall (sf) ❄️
    - Runoff (ro) 🏃



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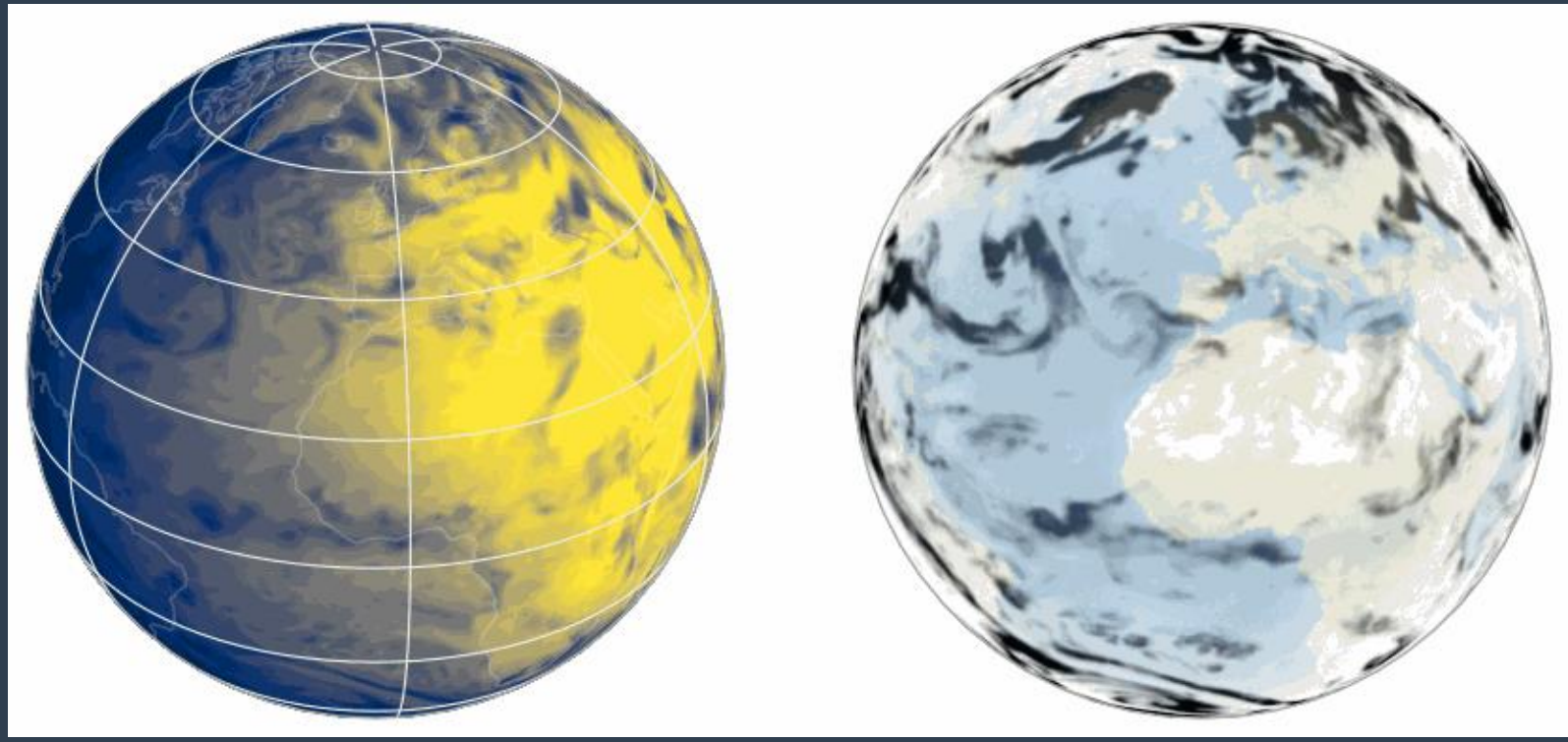
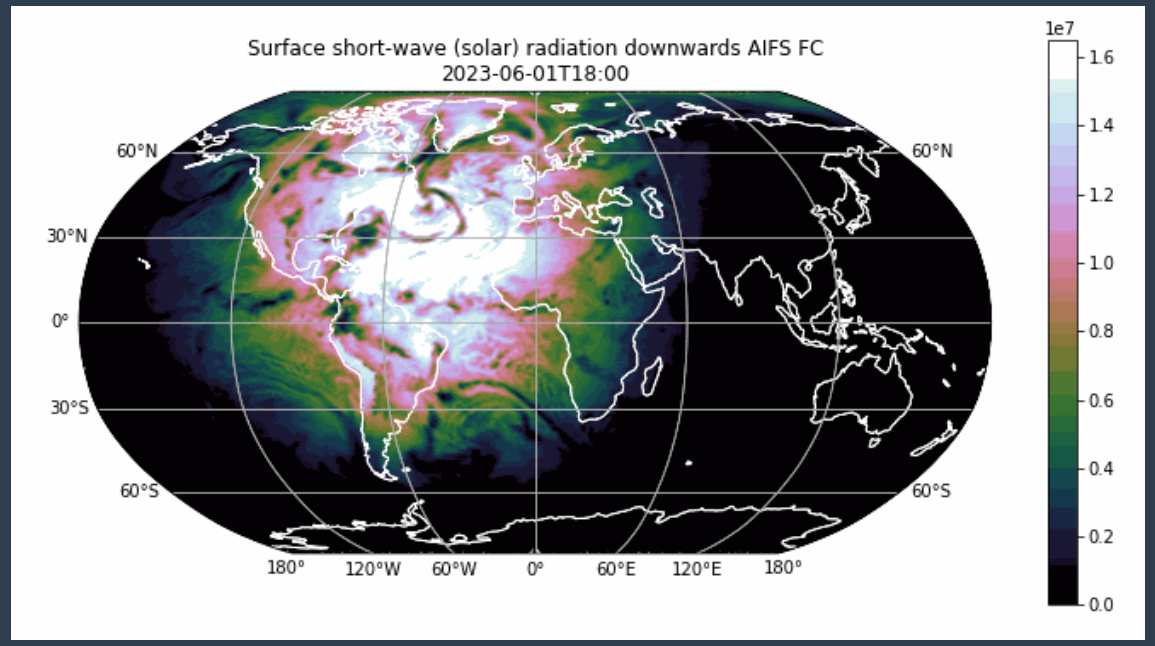


Surface Solar Radiation

Cloud Cover

AIFS Single 1.0 – Development Procedure

- Build new datasets through `anemoi-datasets` github.com/ecmwf/anemoi-datasets
  - New variables, new years of data, etc.
  - Now training on
    - ERA5: 1979-2022 (1-step, 6-hour forecasts)
    - IFS-Operations: 2016-2022
      (fine-tuning/rollout, 6 to 72-hour forecasts)
- Decide which features to include in release from `anemoi-core` github.com/ecmwf/anemoi-core
- Train example models at **o96** (~1 degree) resolution with varying configurations
- For most promising models train versions at **n320** (~30 km) resolution
- Perform more rigorous validation and decide on final candidate



ECMWF

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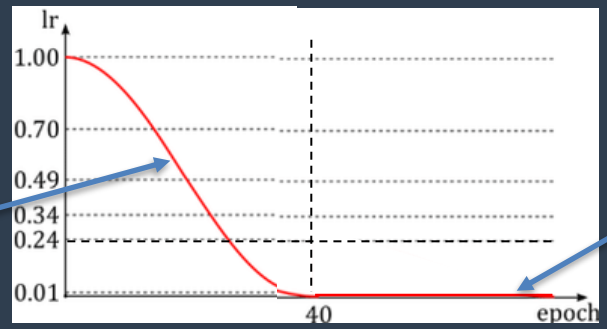
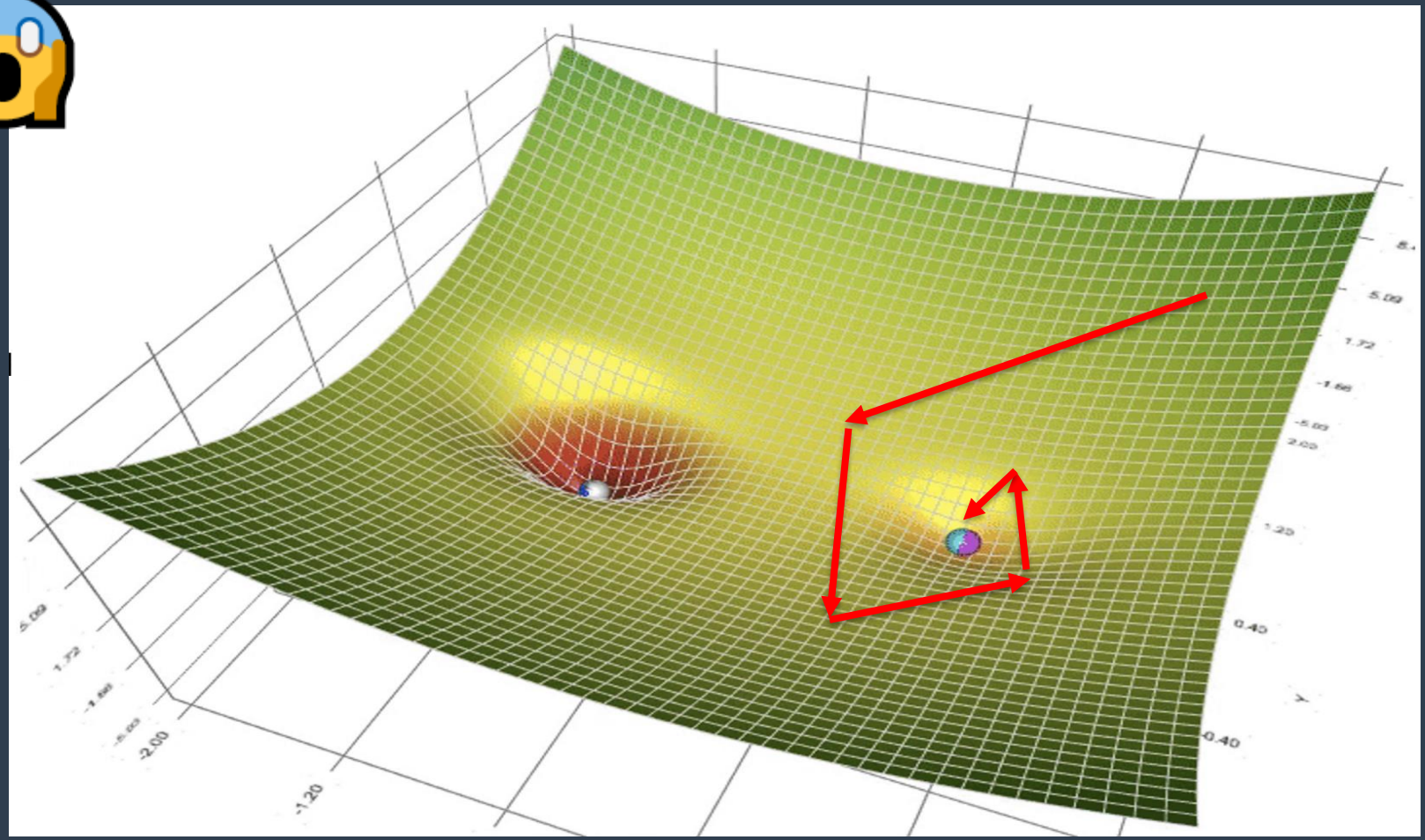
Learning Rate



ERA5 training

Fine-tuning to operations

AIFSv1 candidate1 vs AIFSv0.2.1



ECMWF

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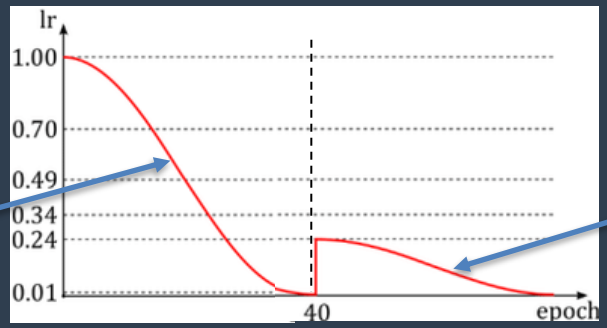
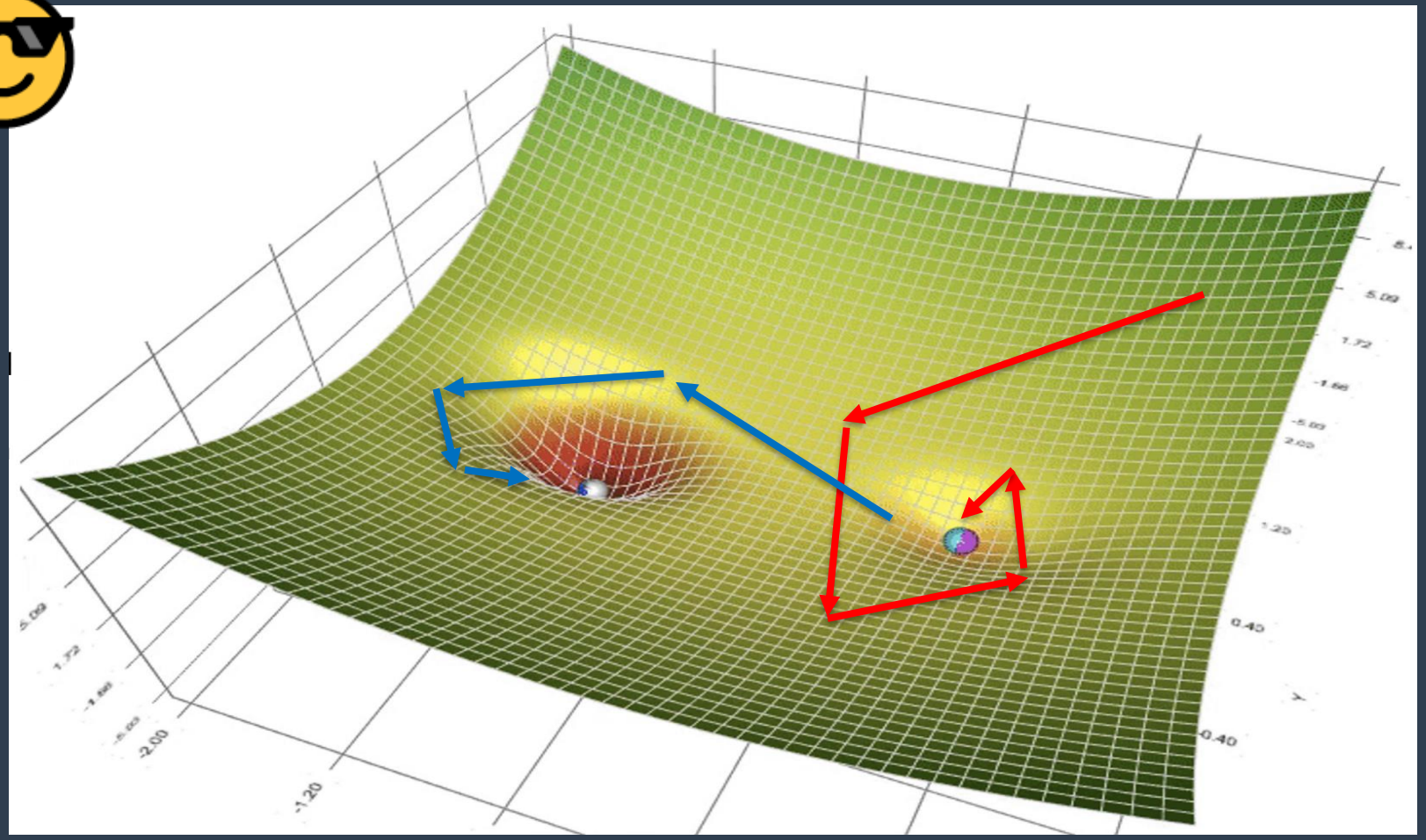


ERA5 training

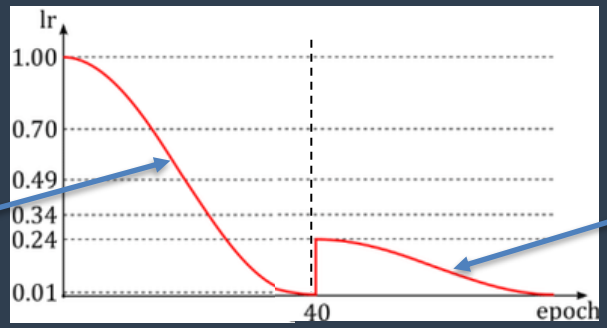
Fine-tuning to operations

AIFSv1 candidate2 vs AIFSv0.2.1



ECMWF

Learning Rate



ERA5 training

Fine-tuning to operations

AIFSv1 candidate1 vs AIFSv0.2.1

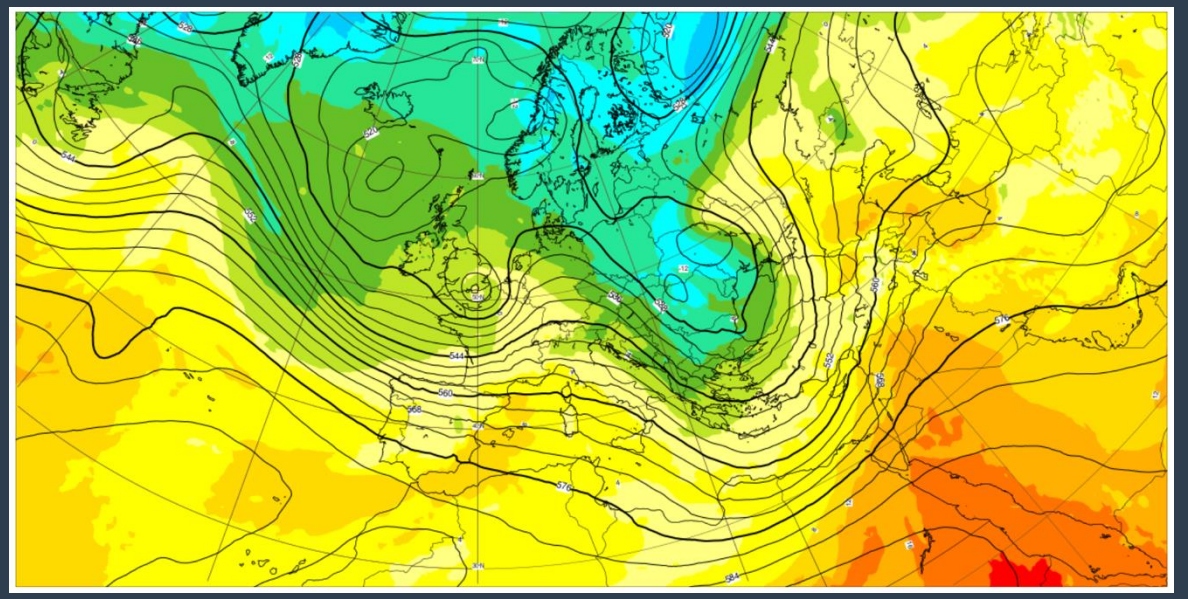
AIFSv1 candidate2 vs AIFSv0.2.1

AIFSv1 candidate2 vs IFS

ECMWF

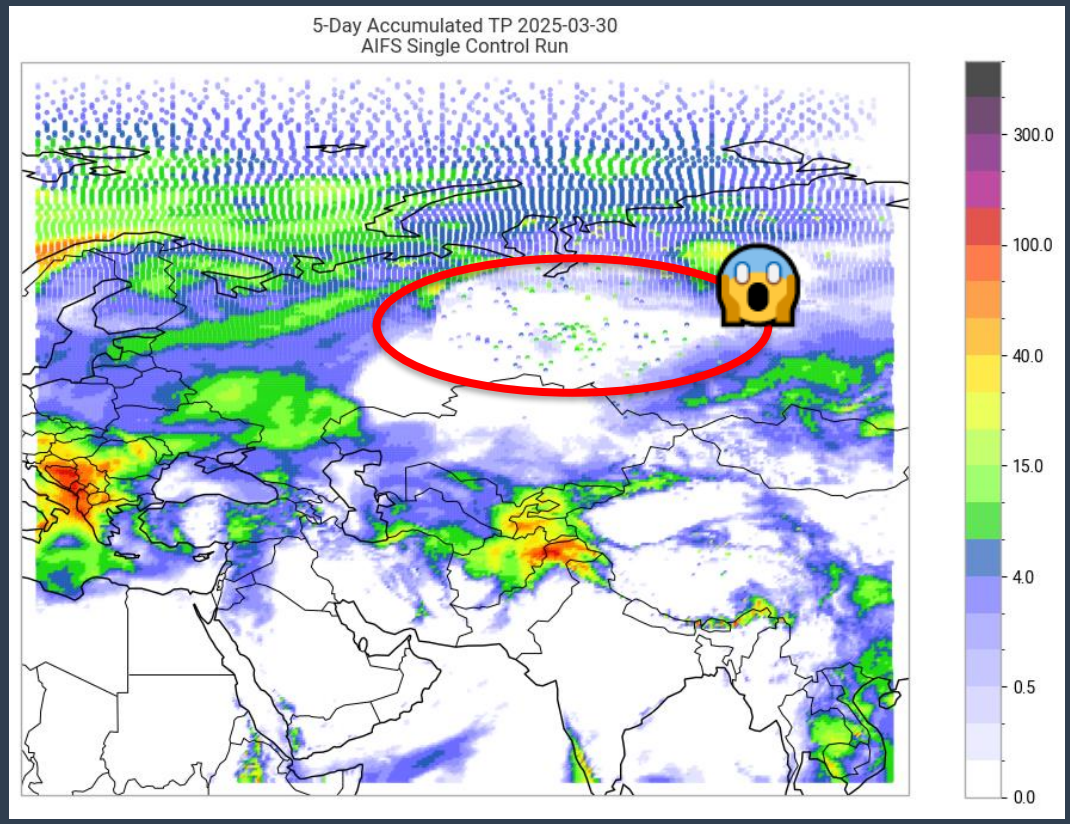
AIFS Single 1.0 – Into Operations

- AIFS-Single Operational as of Feb 2025
- AIFS-ENS Operational as of June 2025
- Outputs now available on: https://charts.ecmwf.int/
- Initially very good performance!
- But then…



AIFS Single 1.0 – Rain Pox! 🤒

- Blobs of unphysical rainfall in locations far away from real weather systems
- Causes:
  - Change in initial soil moisture conditions as new IFS cycle introduced at ECMWF
  - AIFS model had “learnt” an unphysical relationship between soil moisture and rainfall
- Fix:
  - Fix issues in IFS initial conditions from new cycle
  - Re-train AIFS with down-weighted loss parameter on soil moisture
  - Encourages model to learn dominant relationship:
    - Rainfall ➡️ Soil Moisture ✅
    - Soil Moisture ➡️ Rainfall ❌
- Find small improvements to scores too!



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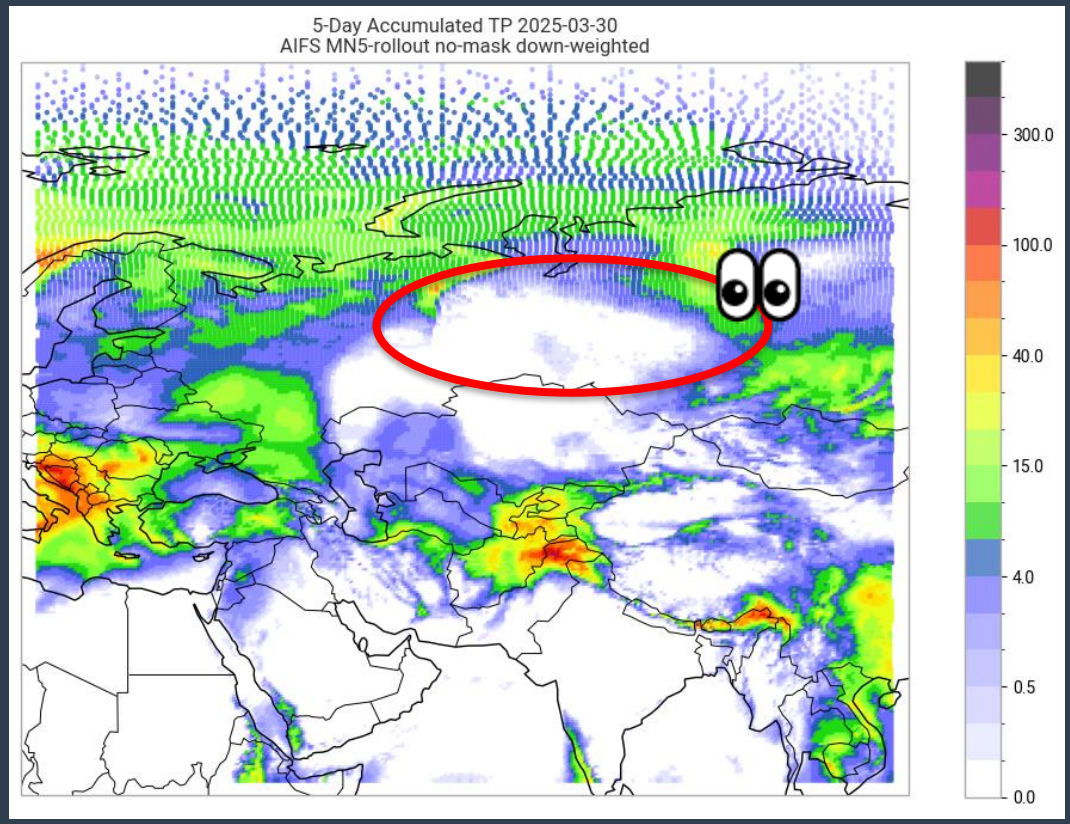
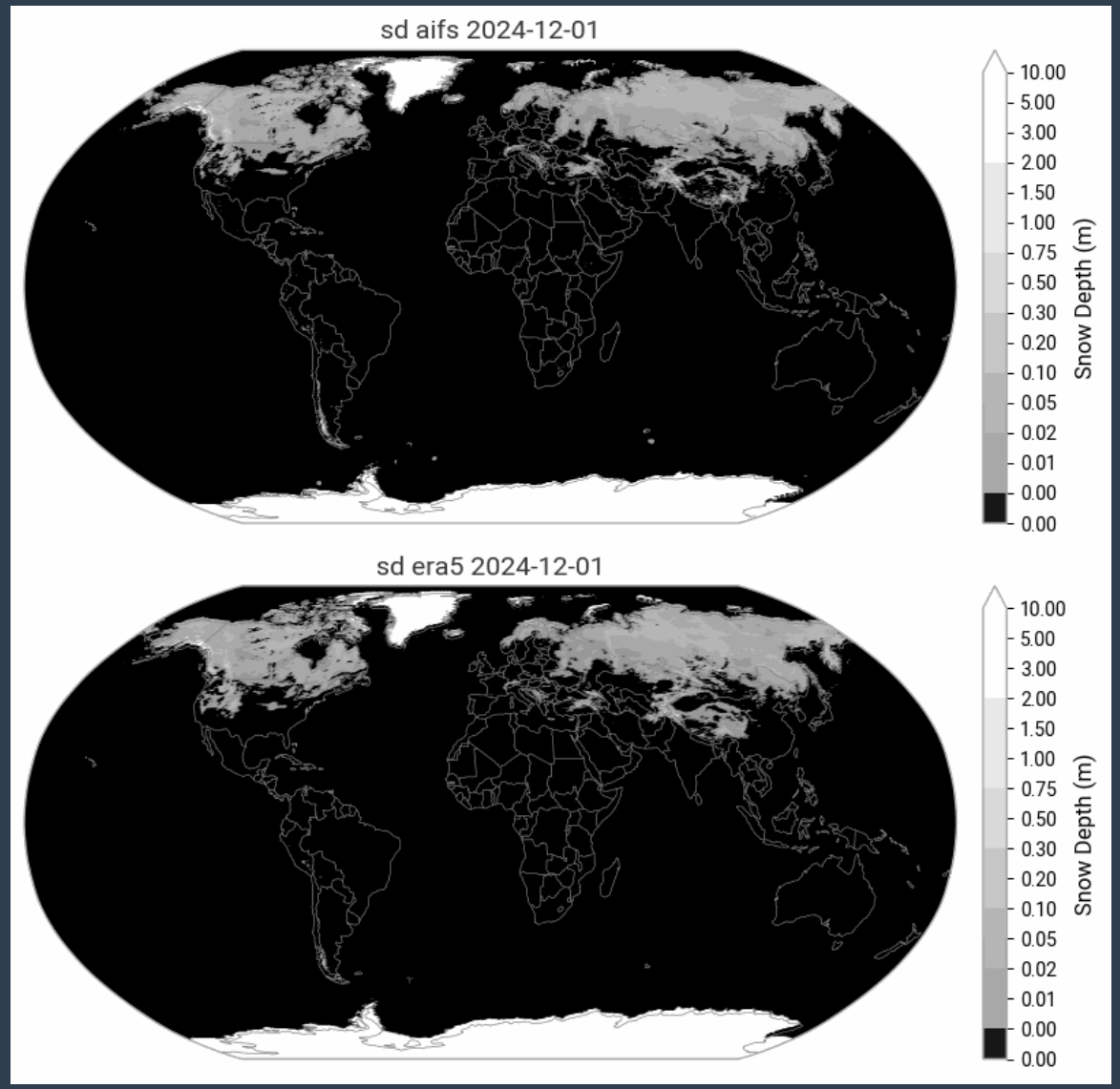
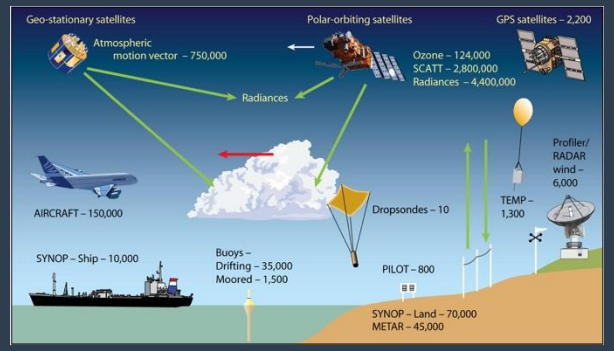


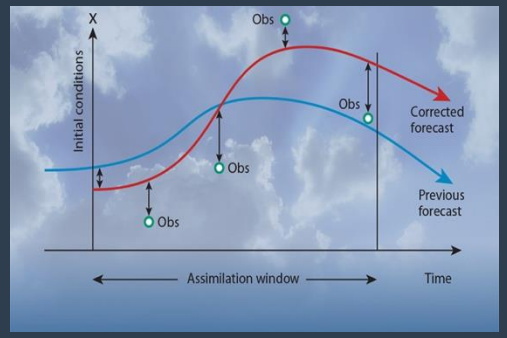
AIFS Single 1.0 – What's Next?

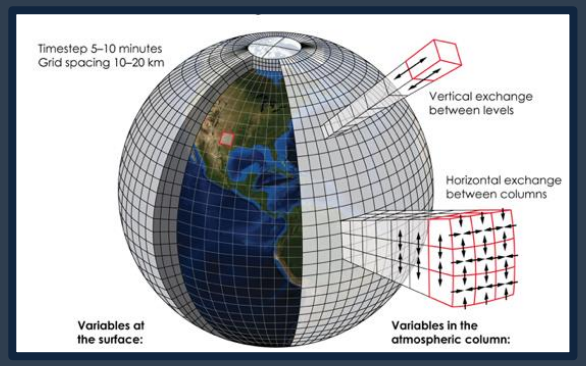
- Outputs now available on:
  - https://charts.ecmwf.int/
- All trained under open-source Anemoi repos:
  - github.com/ecmwf/anemoi-core
- Next Steps
  - More variables
  - Higher resolution
  - More collaboration (Anemoi)
  - Observations

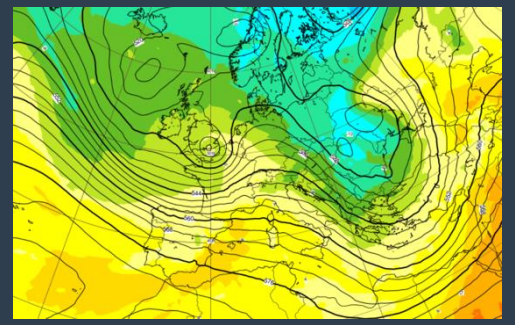


AI-Direct Observation Prediction (AI-DOP)









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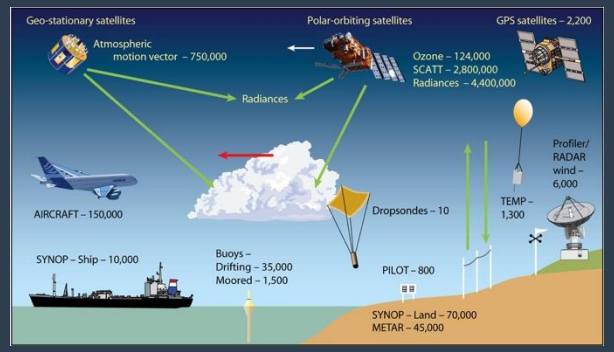
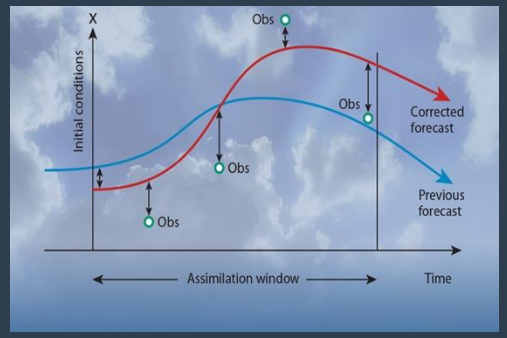
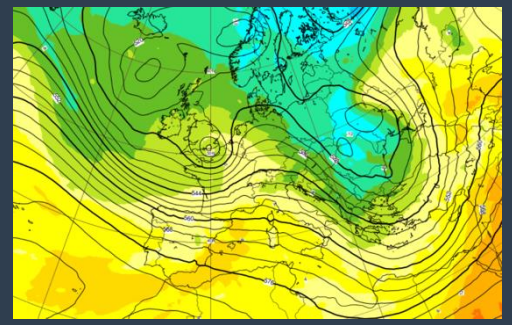
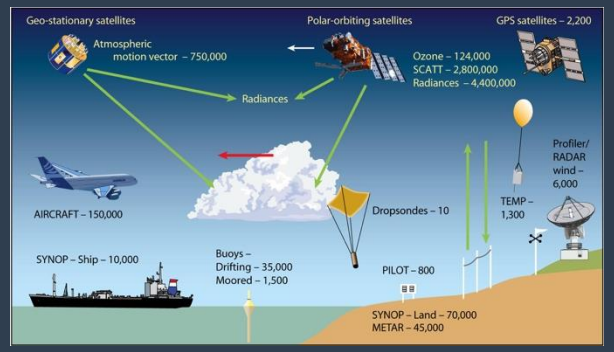


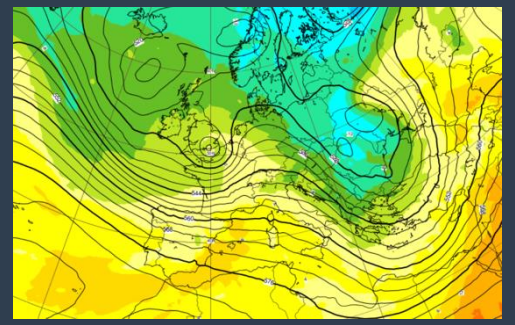




Observations → Data assimilation → "Data-driven" forecasting model → Post-processing and dissemination

AI-Direct Observation Prediction (AI-DOP)





Observations → "Data-driven" forecasting model → Post-processing and dissemination

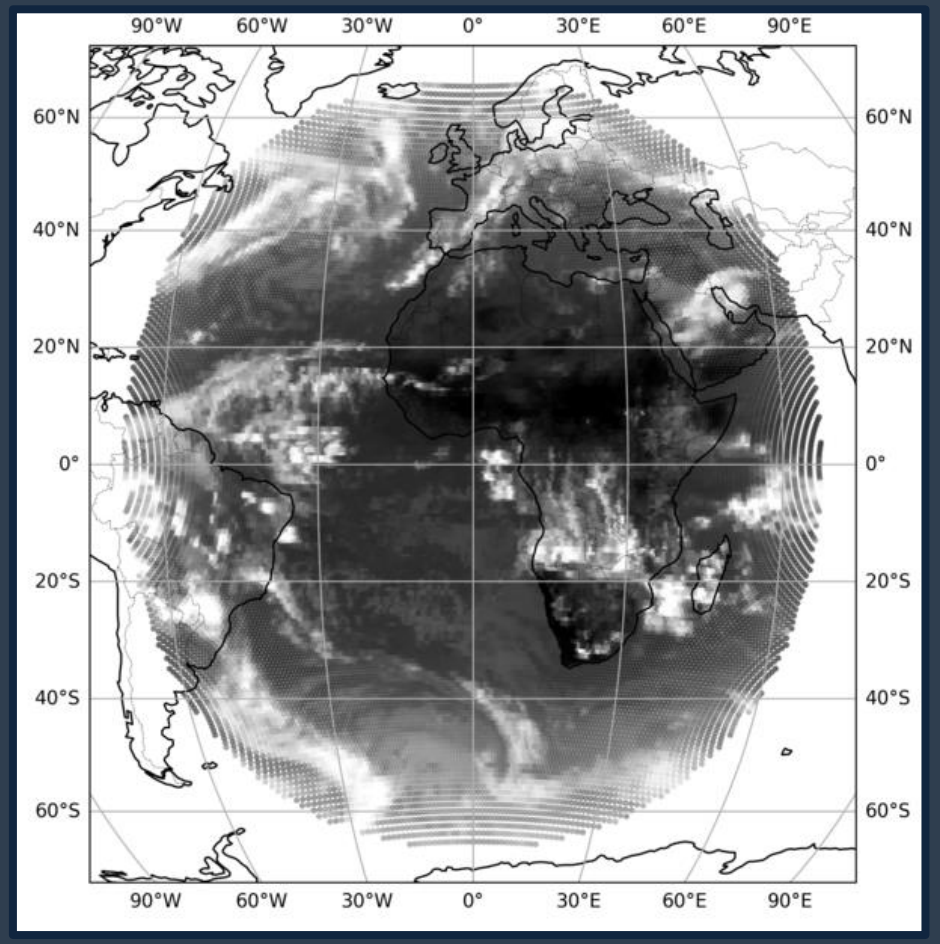
AI-Direct Observation Prediction (AI-DOP)

- We use historical observations to train a Neural Network (NN) to forecast future observations

- Include observations of the full Earth system (atmosphere, ocean, land) simultaneously

- Use all observations, without demanding a detailed physical model of the measurement

- Initialize model directly from observations:
  - Lower latency for forecasts
  - Faster access to warnings



AI-Direct Observation Prediction (AI-DOP)

GRAPHDOP: TOWARDS SKILFUL DATA-DRIVEN MEDIUM-RANGE WEATHER FORECASTS LEARNT AND INITIALISED DIRECTLY FROM OBSERVATIONS

A PREPRINT

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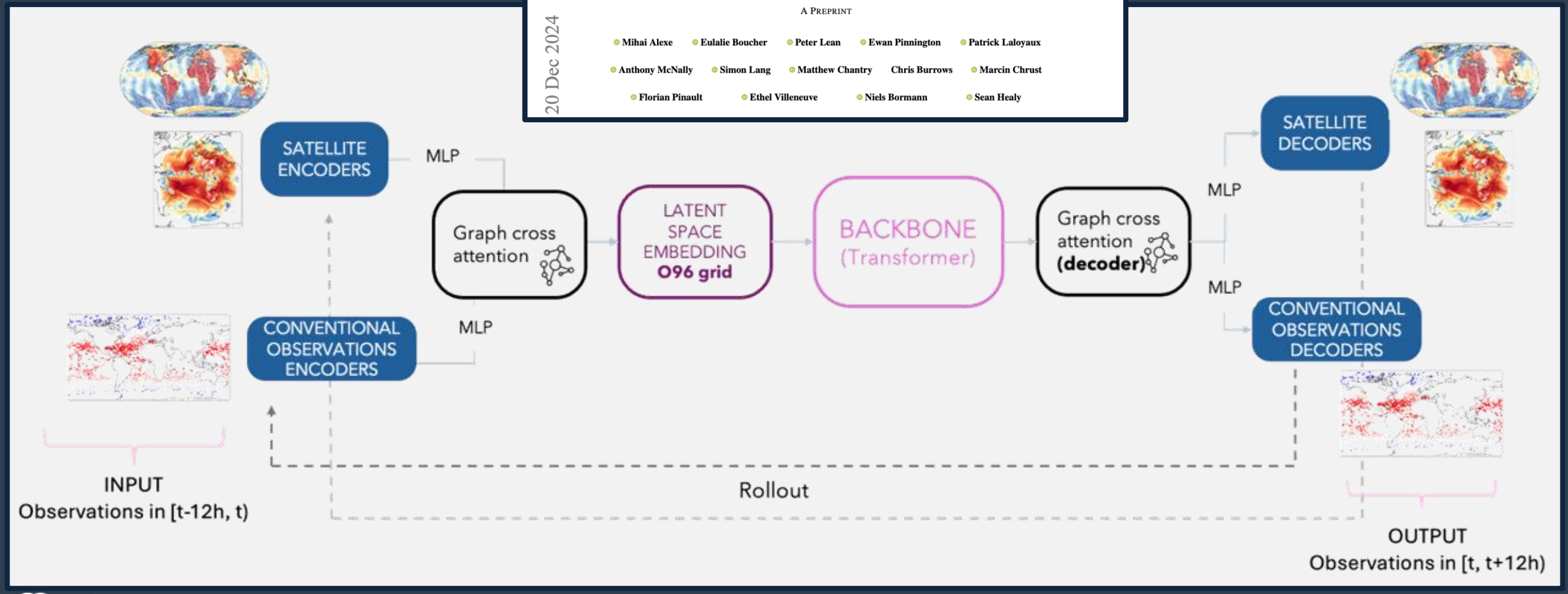
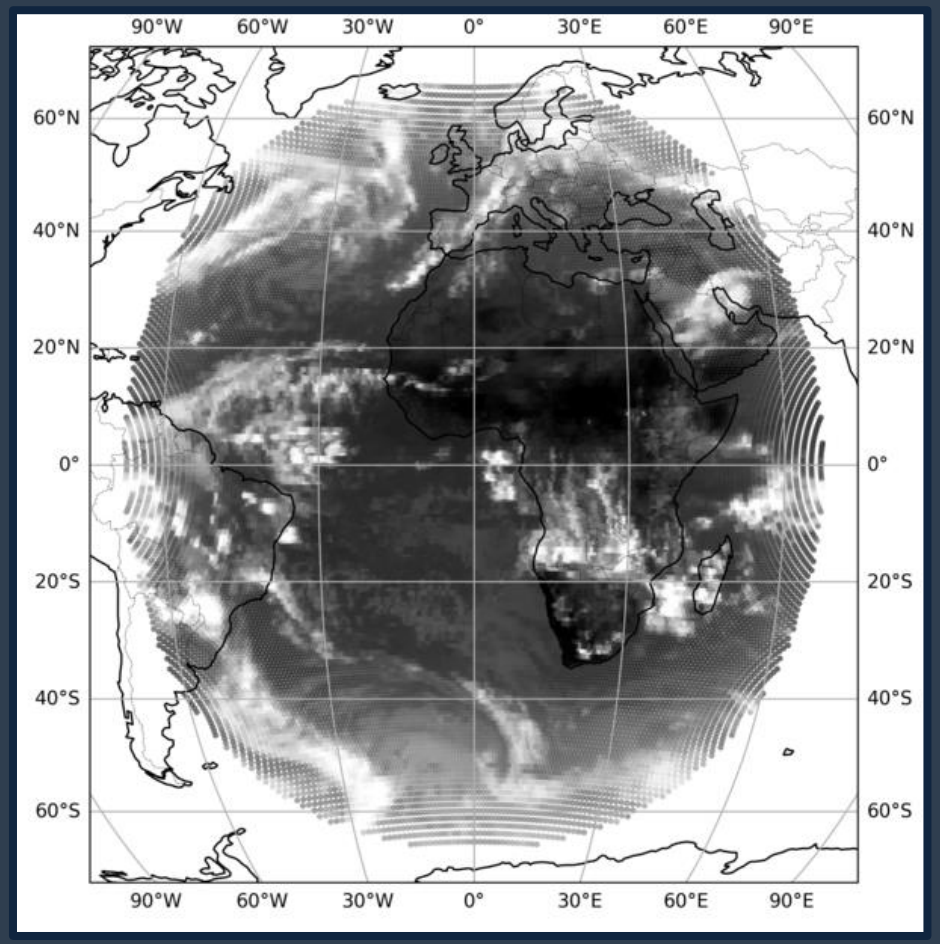
Florian Pinault · Ethel Villeneuve · Niels Bormann · Sean Healy

20 Dec 2024

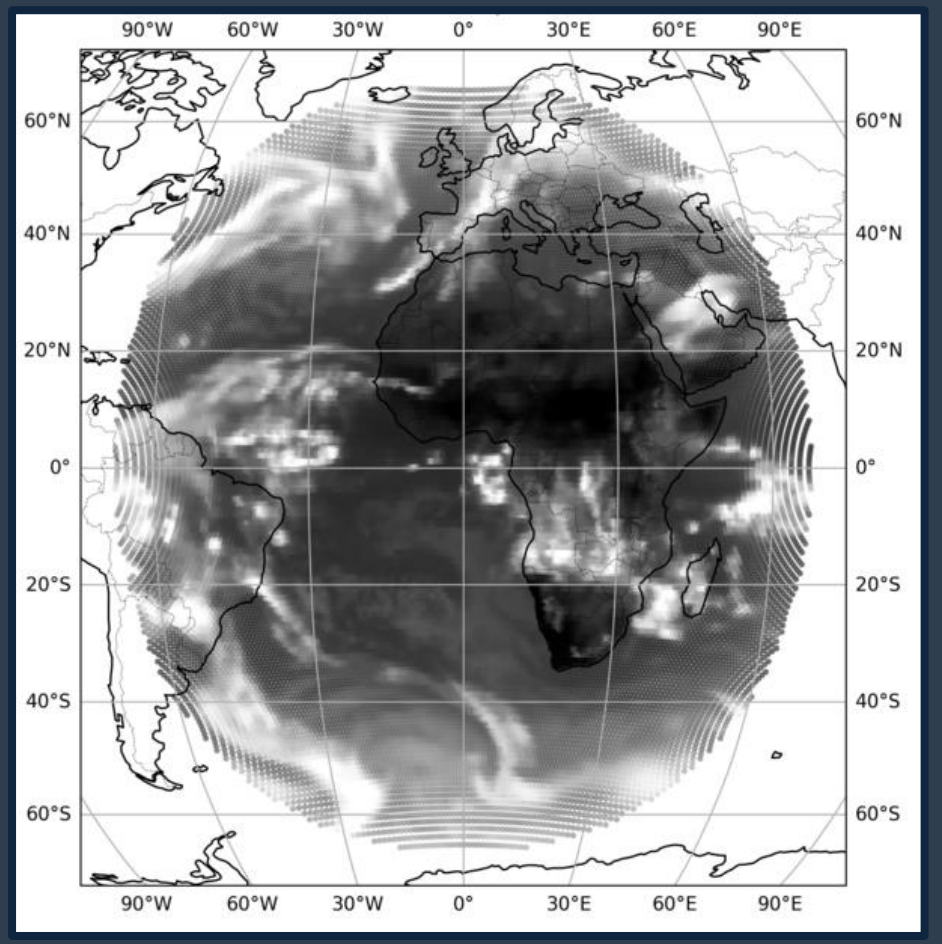


First medium-range forecasts directly from observations

Target Real Observations

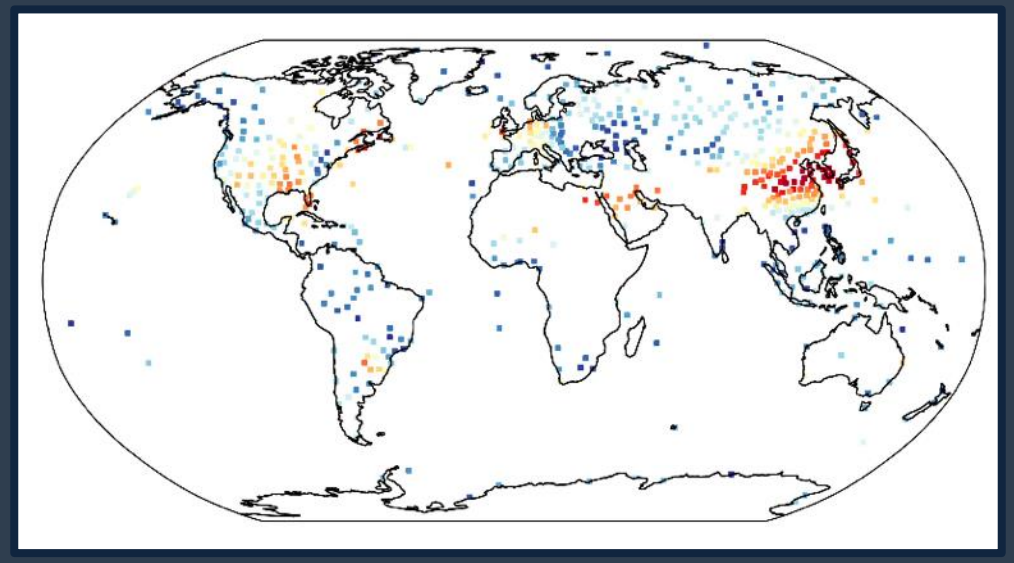


AI-DOP Model

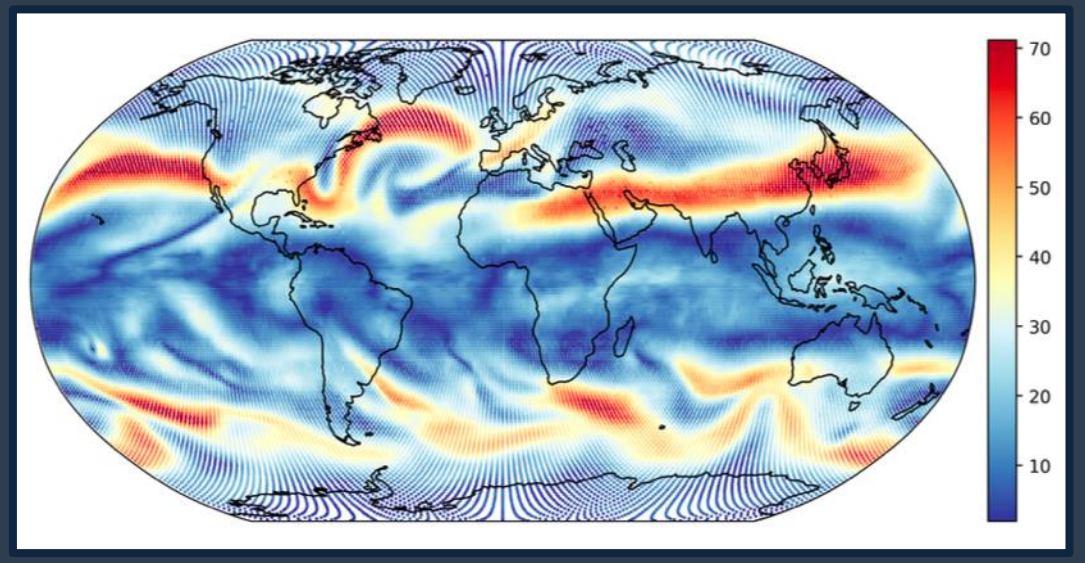


Predict observations in locations which are not observed

Input Wind Observations

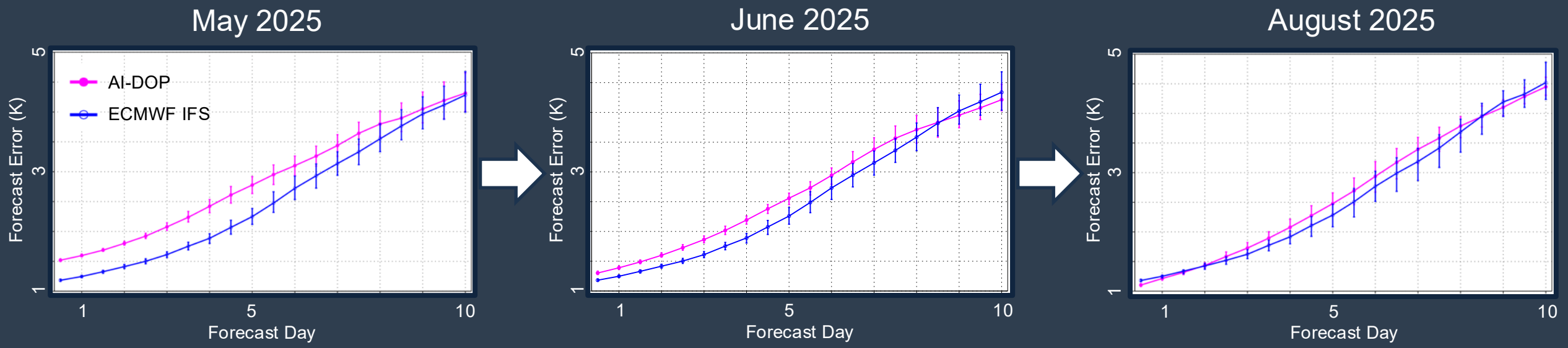


AI-DOP Predicted Wind



- Model fills gaps from traditional observations using learnt relationships to satellite observations
- Allows us to forecast physical variables (e.g., wind, temperature, pressure, humidity)

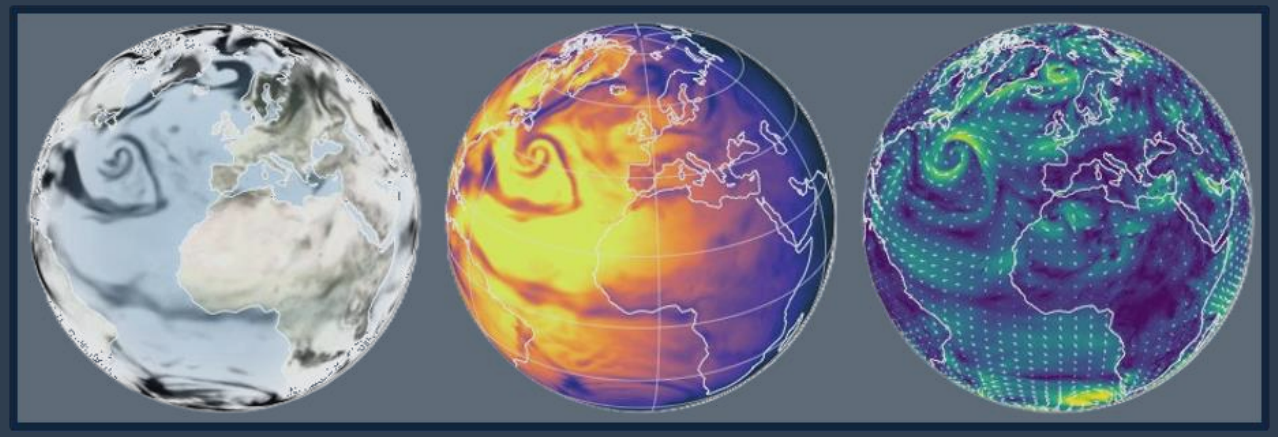
AI-DOP: How do forecast scores compare?



- Progress in skill of AI-DOP forecasts for successive model developments

Summary

- AI/ML becoming larger part of weather forecasting
- First “Data-Driven” forecast models now operational
  - AIFS Single
  - AIFS Ensemble
- Starting to expand to other Earth System Components… Land!
- Using observations directly could present some opportunities:
  - Exploit a wider range of innovative satellite sensor technologies
  - Potential to produce more accurate weather forecasts
  - Deliver forecasts and critical warnings faster than currently possible



AIFS Single Forecasts (cloud, solar, wind)