ECMWF strategy and research directions

Andy Brown

Director of Research

UNIFIED MODELING AND PREDICTION OF WEATHER AND CLIMATE

A 25-Year Journey

BY ANDREW BROWN, SEAN MILTON, MIKE CULLEN, BRIAN GOLDING, JOHN MITCHELL, AND ANN SHELLY

Practical experience in developing and using the U.K. Met Office Unified Model for both weather and climate prediction provides lessons about both the benefits and challenges of seamless prediction.

The concept of a unified or seamless framework for weather and climate prediction has attracted a lot of attention in the last few years (Hurrell et al. 2009; Brunet et al. 2010; Shapiro et al. 2010; Nobre et al. 2010; Hazeleger et al. 2010; Senior et al. 2011). Traditionally the weather and climate prediction problems have been seen as different disciplines. Numerical weather prediction (NWP) is crucially dependent on defining an accurate initial state and running at the highest possible resolutions, while climate prediction has sought to incorporate the full complexity of the Earth system in order to accurately capture long time-scale variations and feedbacks determining the current climate and potential climate change. Unifying modeling and prediction across time scales stems from a recognition that the evolution of the weather and climate are linked by the same physical processes in the atmosphere–ocean–land–cryosphere system operating across multiple space and time scales. In addition, there is an increasing requirement to include Earth system complexity in NWP models (e.g., atmospheric chemistry for air quality predictions) and growing evidence that improvements to the resolution and initialization of coupled climate models are required to accurately capture important modes of atmospheric and oceanic variability on monthly to decadal time scales (e.g., Scaife et al. 2011).

What does seamless prediction look like in practice? The aim of this paper is to discuss the Met Office experiences over the last 25 years as we have moved toward a fully unified framework for our global and regional atmospheric, land, and ocean prediction systems, highlighting the clear benefits but also the potential drawbacks and pitfalls encountered along the way. We will also discuss the current status of our unified prediction systems and vision for the future.

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The abstract for this article can be found in this issue, following the table of contents.
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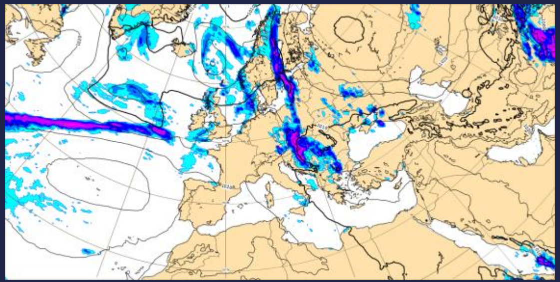
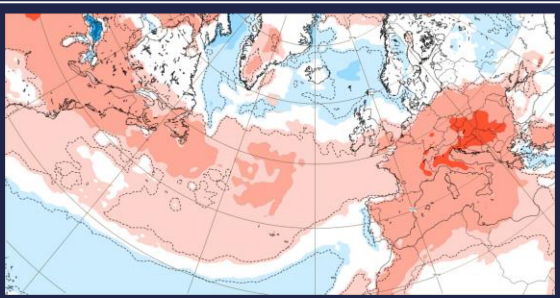
HISTORICAL DEVELOPMENT OF THE MET OFFICE WEATHER AND CLIMATE MODELS. *Phase 1 (1960–90): Separate NWP and climate models.* As in most other modeling centers, the Met Office initial development of numerical models for weather forecasting and climate was entirely

Brown et al, BAMS, 2012

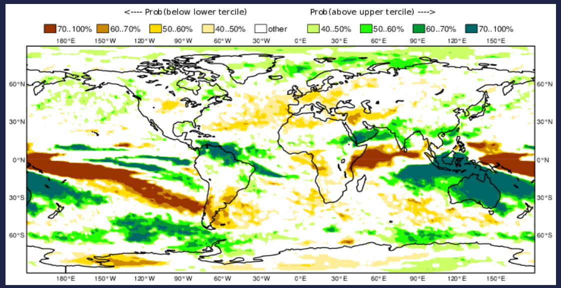
Medium range: up to 2 weeks



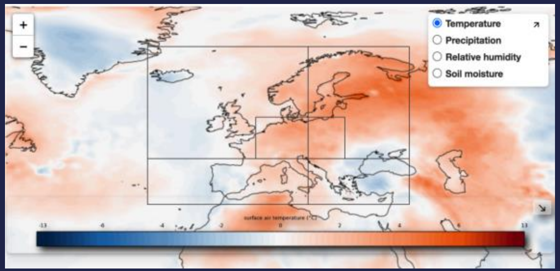
Sub-seasonal range: up to 6 weeks



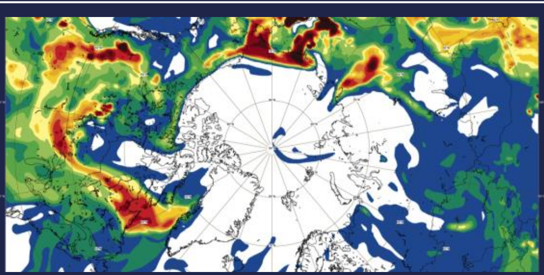
Seasonal range: up to 2 years



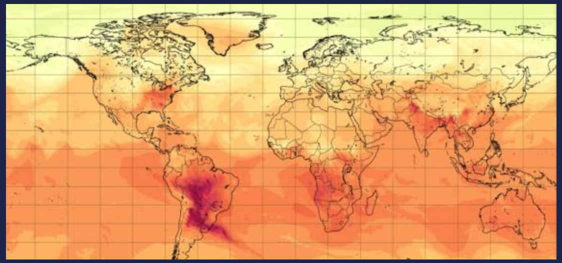
Climate monitoring



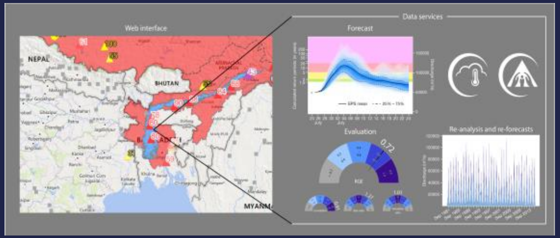
Air quality forecasts and monitoring



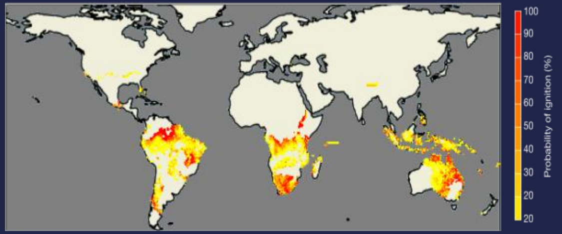
Greenhouse gas forecasts and monitoring



Hydrological forecasts

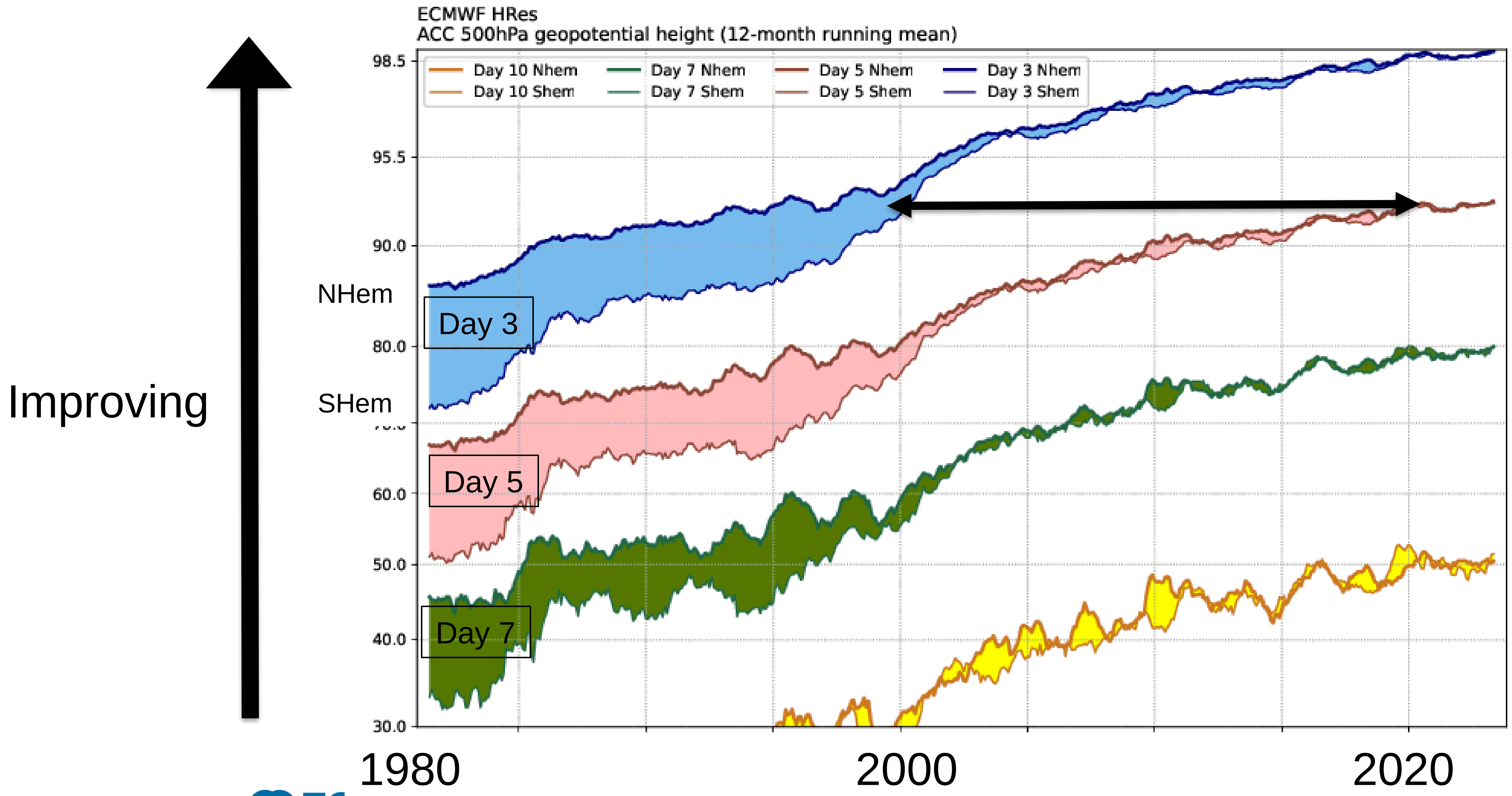


Wildfires: probability of ignition by lightning

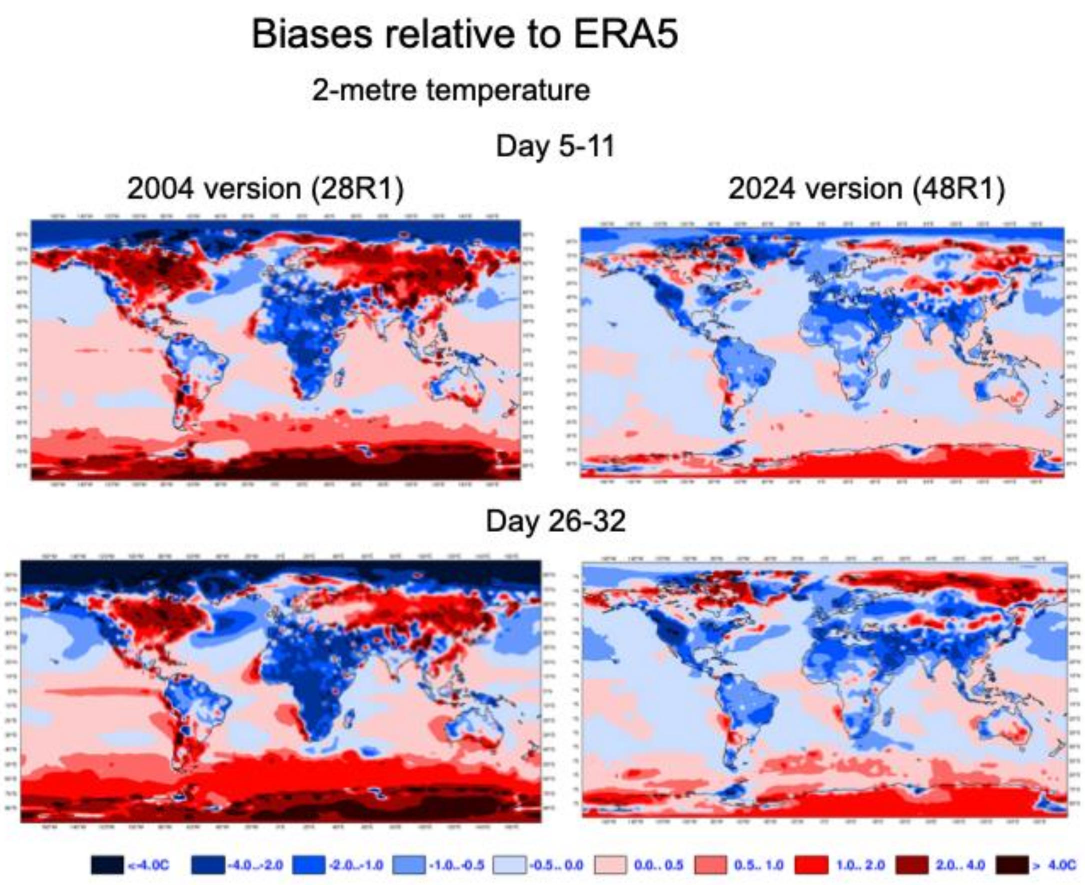


Use of IFS as basis for climate modelling (EC-EARTH, Destination Earth)

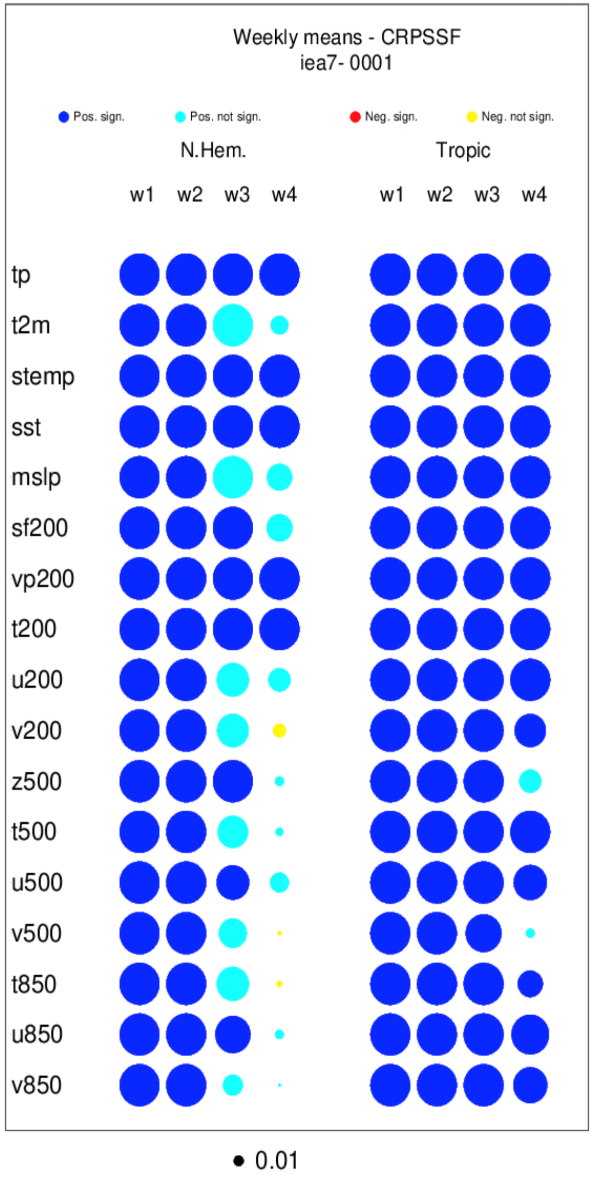
Dramatically improving accuracy…………



Progress over 20 years of subseasonal prediction



2024 vs 2004 version



48r1 Reforecasts: Same re-forecast period and start dates as 2004 re-forecasts.

MJO 28 days (+8 days)

SSW 26 days (+4 days)

PNA 18 days (+4 days)

NAO 14 days (+4 days)

What has made things better?

More and better observations

- Number, accuracy, variety

Bigger supercomputers

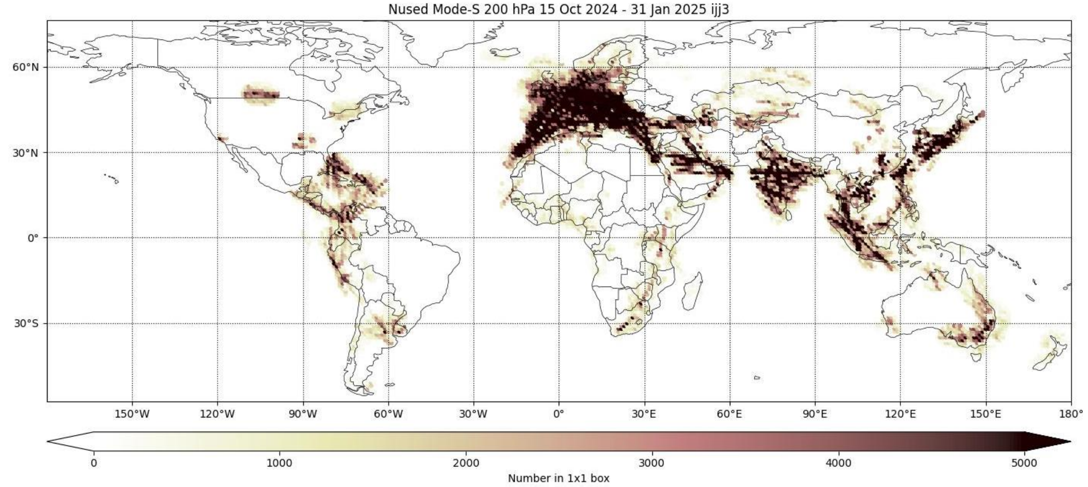
- More expensive choices possible (e.g. model resolution)

Better science

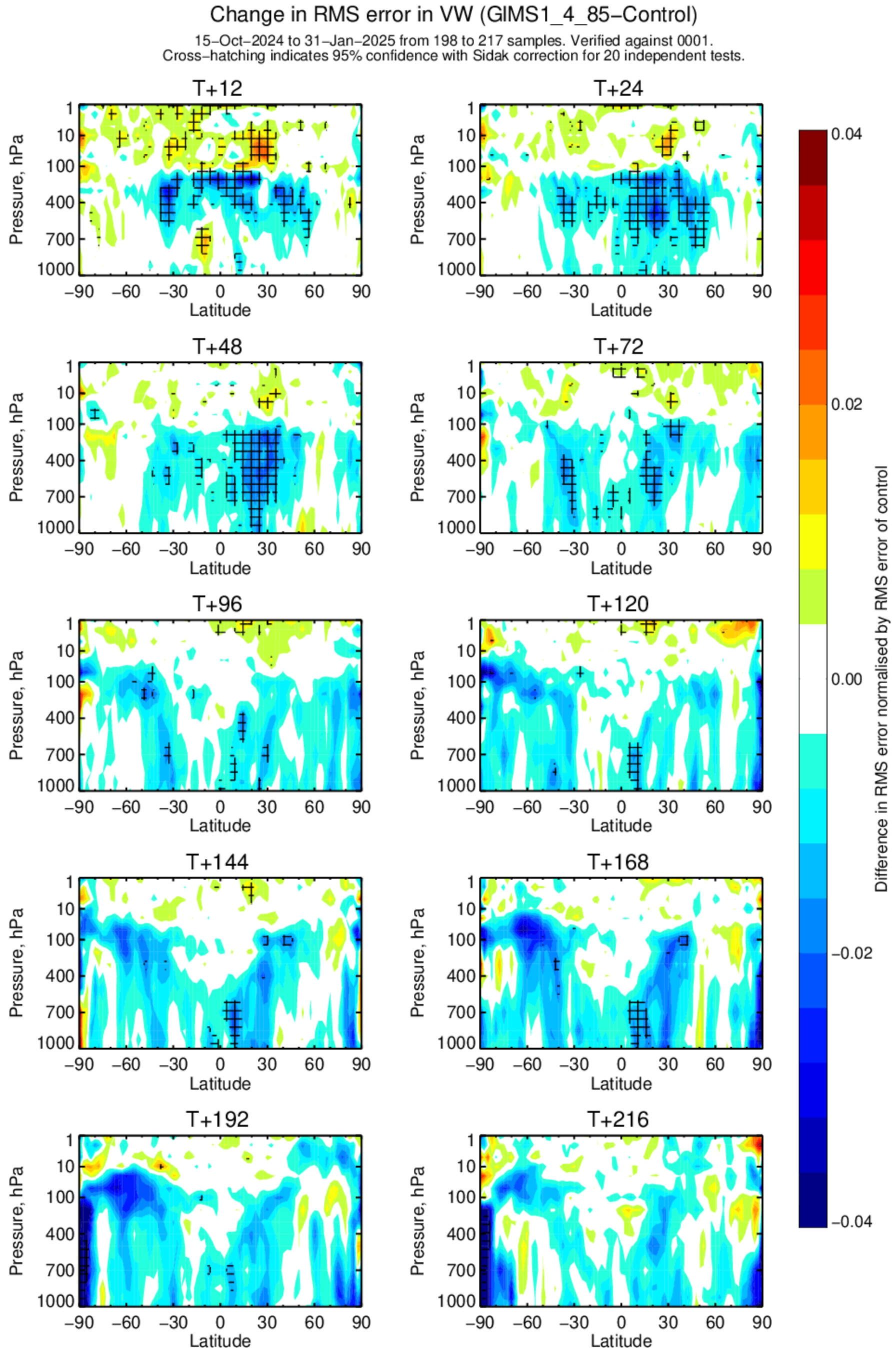
- Clever people!
- Partnerships
- Seamless(?)

Global Mode-S aircraft data:

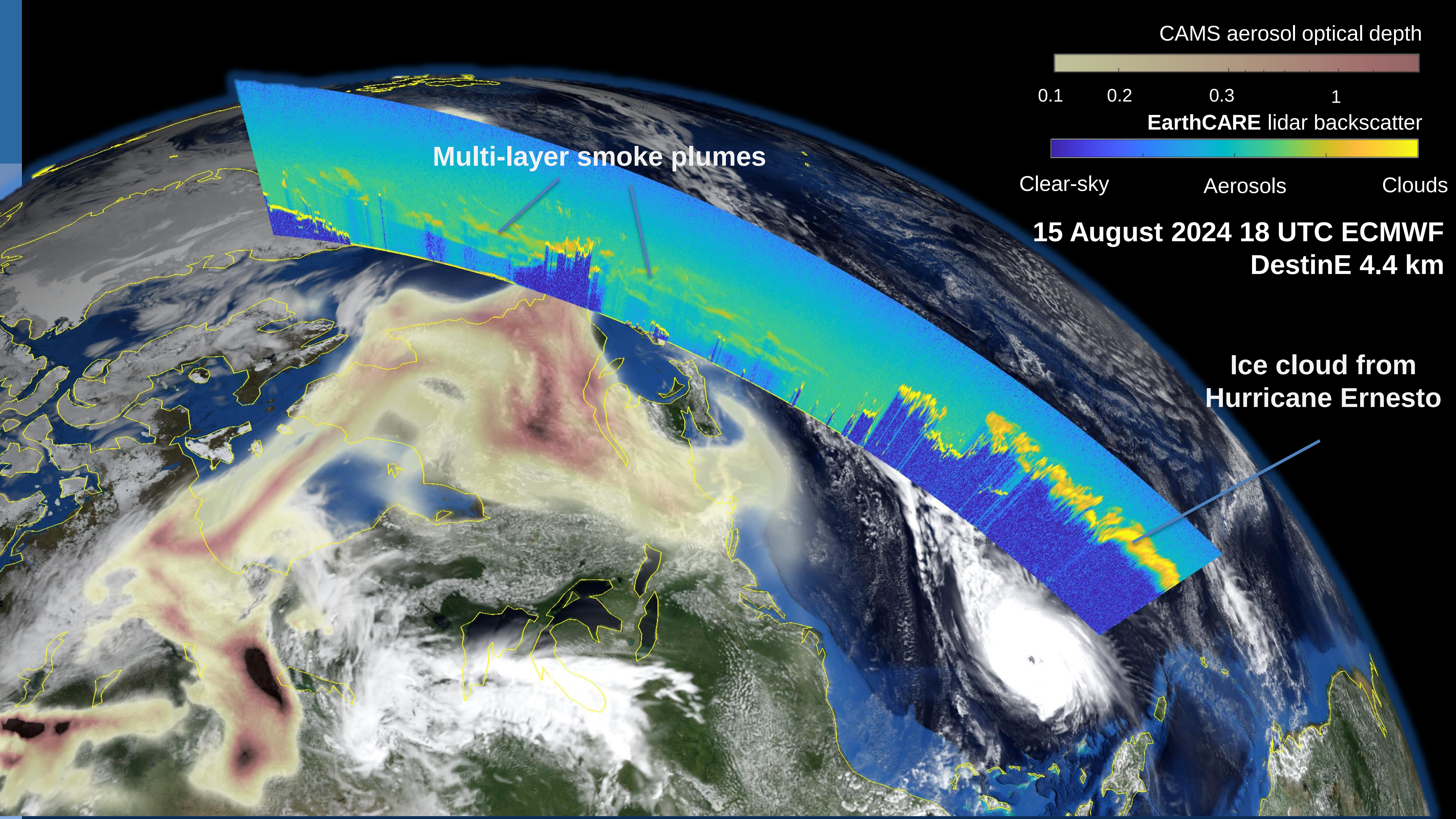
- Large numbers in parts of middle east, India, Japan, SE Asia, at 200 hPa
- Moderate numbers in Caribbean, SE Australia
- Low numbers elsewhere



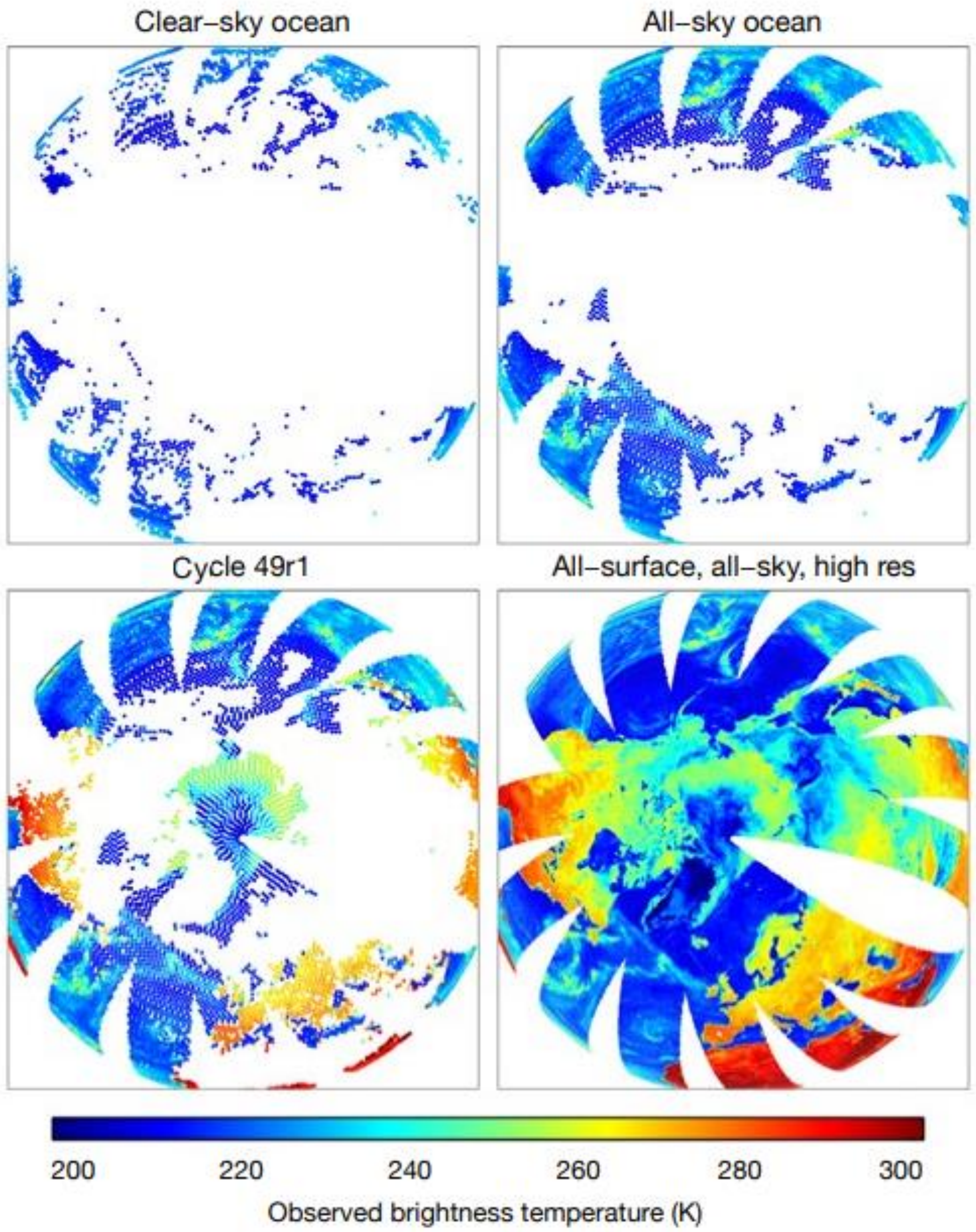
- Benefit from 60S to 60N up to 150 hPa for winds, up to day 8
- Especially in the Tropics
- Hatching shows 95% confidence



Blue is better


CAMS aerosol optical depth
0.1
0.2
0.3
1
EarthCARE lidar backscatter
Clear-sky
Aerosols
Clouds
15 August 2024 18 UTC ECMWF
DestinE 4.4 km
Multi-layer smoke plumes
Ice cloud from
Hurricane Ernesto

Innovating in the exploitation of satellite data:
towards all-sky, all-surface

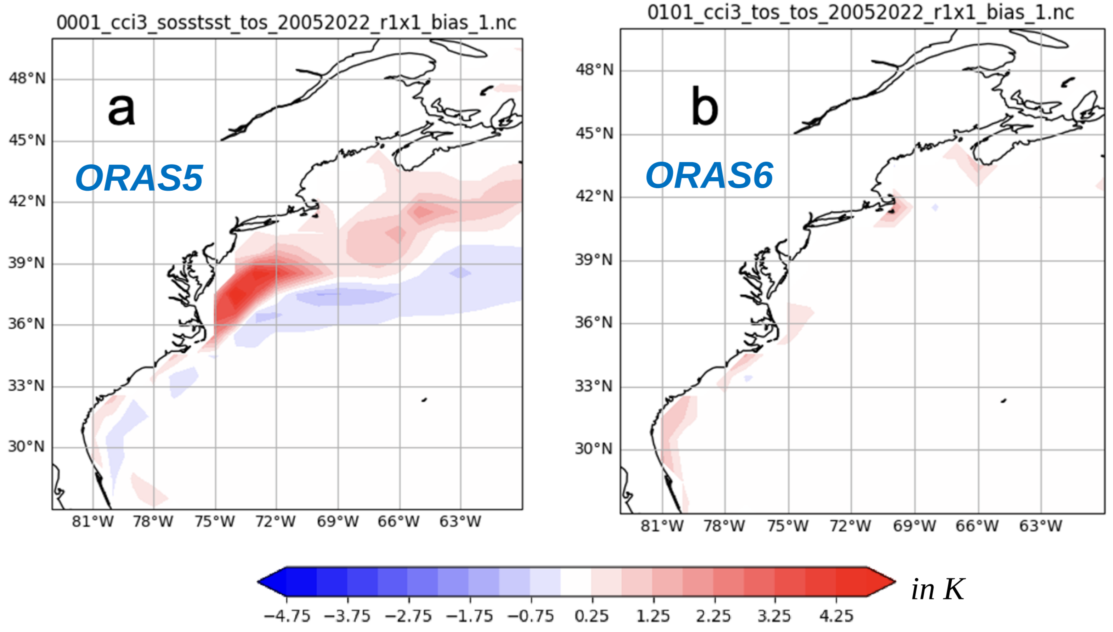


AMSR2 observed brightness temperatures
37 GHz v-polarised channel

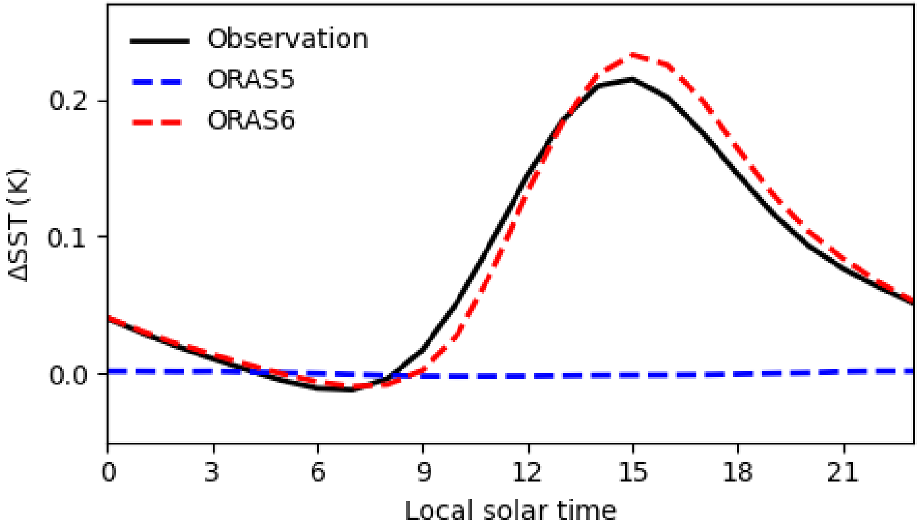
ORAS6 performance – SST

- Greatly reduced SST biases in the GS regions – partial coupling no longer needed
- Good representation of SST diurnal cycle – possible for hourly coupling

SST biases in the Gulf Stream regions
(2015-2022, against CCIv3)



Global mean SST diurnal cycle
(2019, against drifter data)

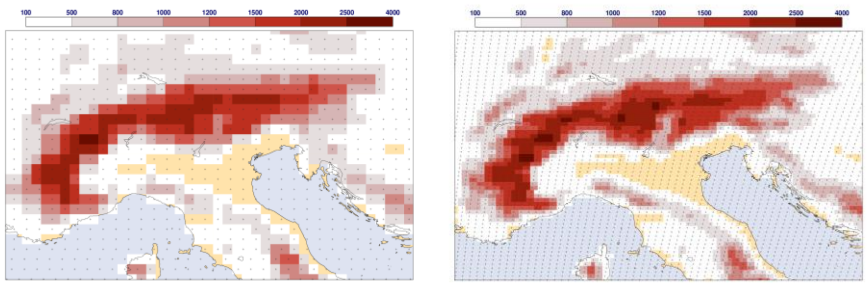


New ocean model (with no partial coupling) to next NWP cycle (50r1)

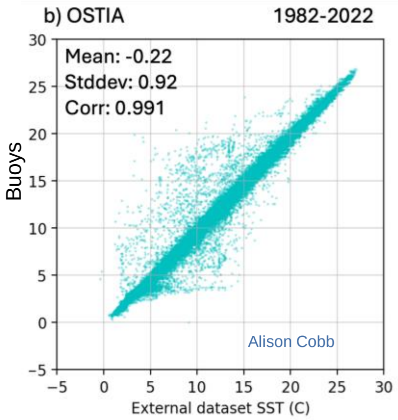
ERA6 preliminary results

Horizontal grid

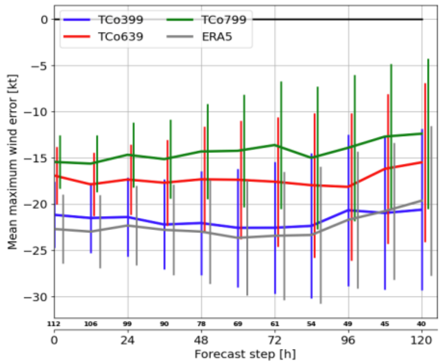
ERA5 Tl 639 **ERA6 TCo799**

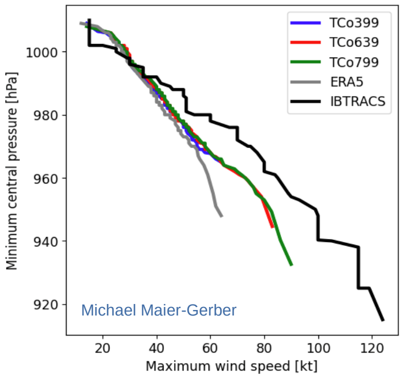


Great Lakes

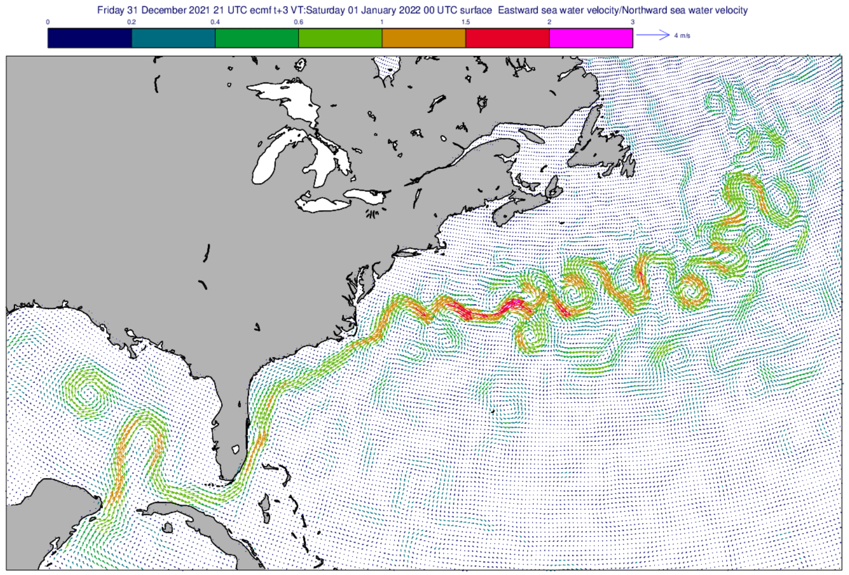


Tropical cyclones

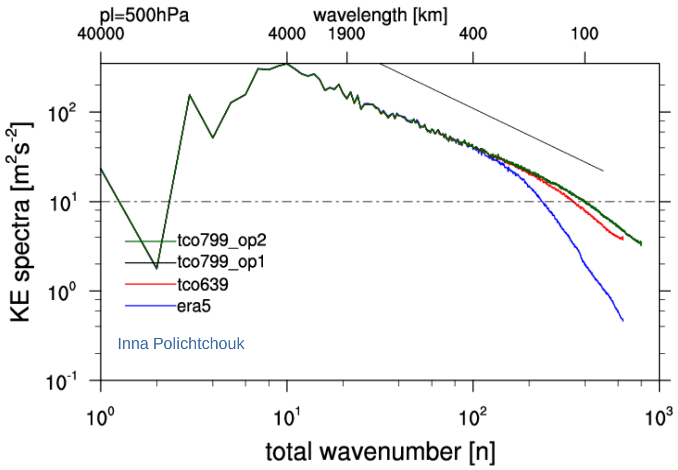




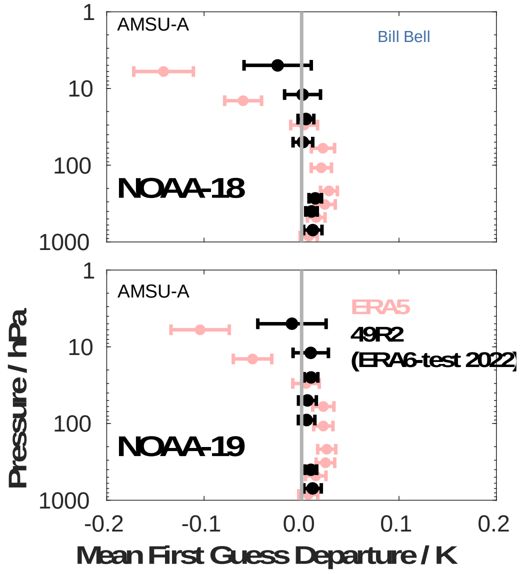
Hourly ocean currents, SST, sea ice



Energy spectra



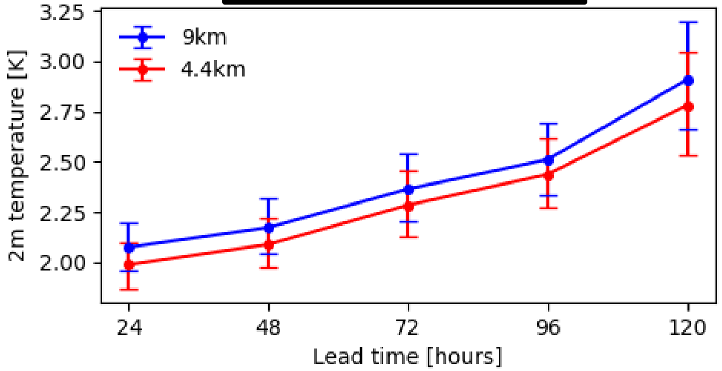
Departure statistics



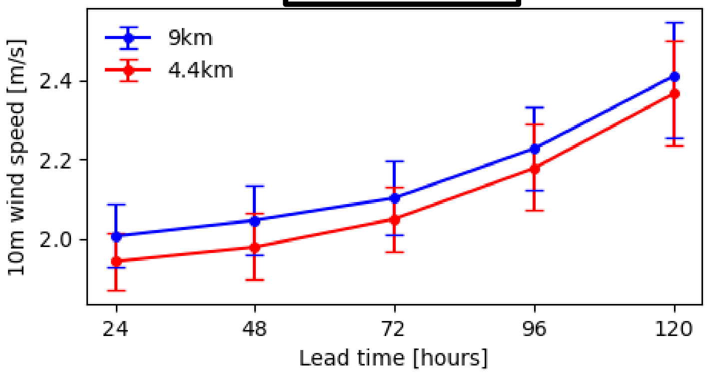
What does km-scale global modelling give?

Improved statistics of European near-surface weather

2m temperature

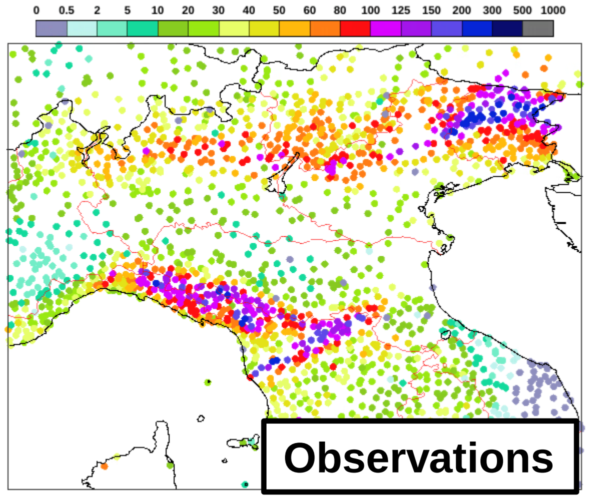


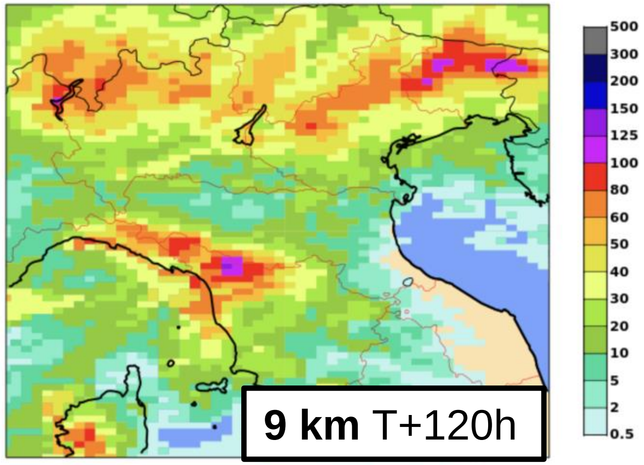
10m wind

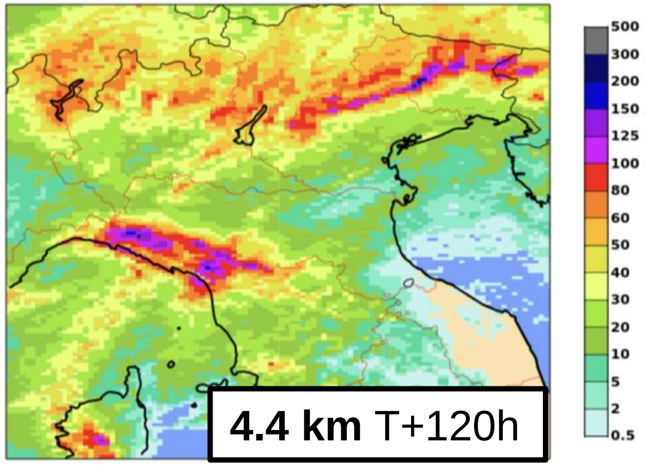


Improved prediction of high-impact weather

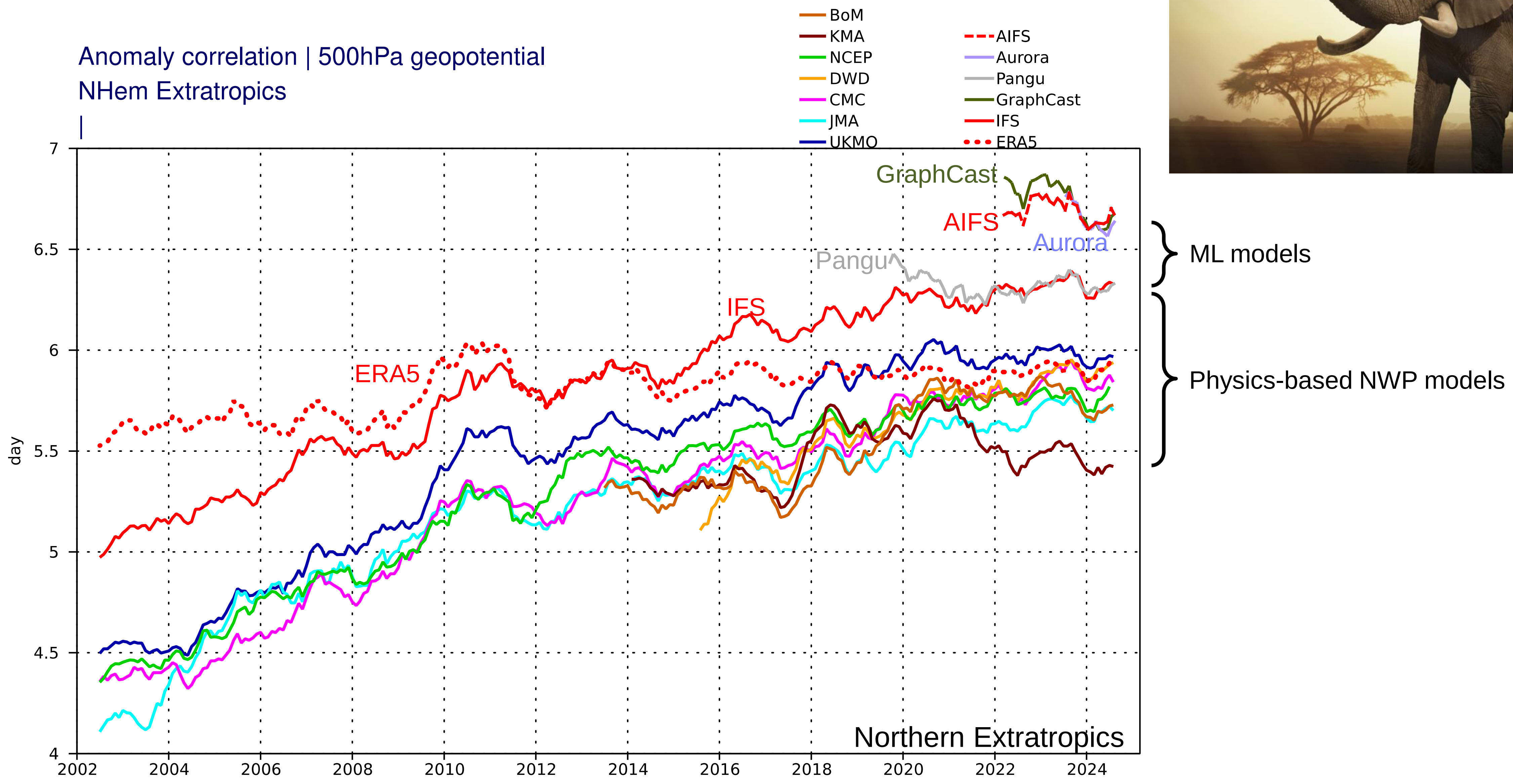
Total precipitation
2 Nov 2023







The elephant in the room……



Machine Learning at ECMWF

ECMWF collaborative project with Member States is one project of wider EUMETNET programme

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

+ development of Foundation Model (WeatherGenerator)

Three strands of the machine learning project

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A short history of data-driven weather forecasting

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**

December 2022

- **Deepmind – GraphCast**

GraphNN
0.25° **Many parameters with comparable skill to IFS.**

November 2022

- **Huawei – PanguWeather**

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

January-June 2023

- **Microsoft – ClimaX**
- **China academia/Shangai Met – FengWu**
- **Alibaba – SwinRDM**
- **NVIDIA – SFNO**
- **…**

December 2023

- **Deepmind – GenCast**

Probabilistic forecast (ensemble) – 0.25°
"Outperforming the leading operational ensemble forecast" (aka ECMWF)

June 2024

- **Microsoft – Aurora**

Higher resolution – 0.1°
Atmospheric composition

2018 – Concept explored (ECMWF and others)…

Early 2023
Prototype AIFS developments begin

June 2023
ECMWF – ML project begins

October 2023
ECMWF – AIFS experimental forecasts live

Jan/Feb 2024
ECMWF – AIFS first updates

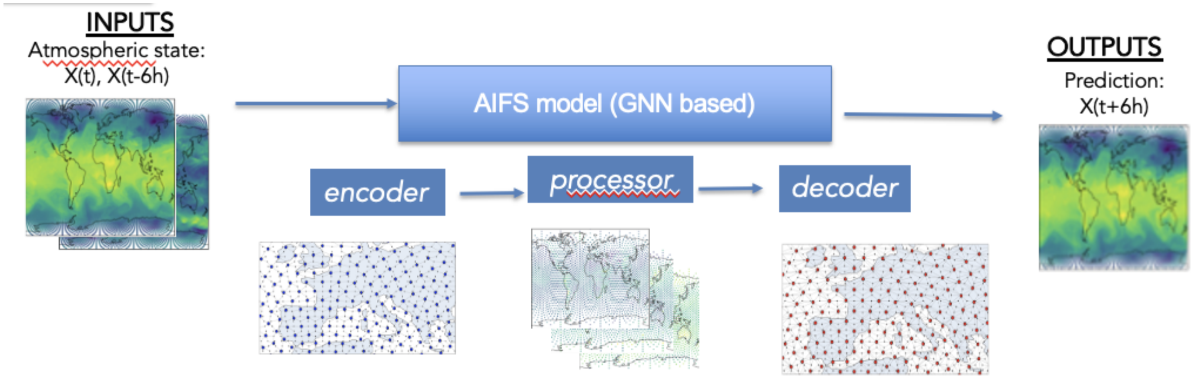
July 2024…
ECMWF – First AIFS ENS experimental

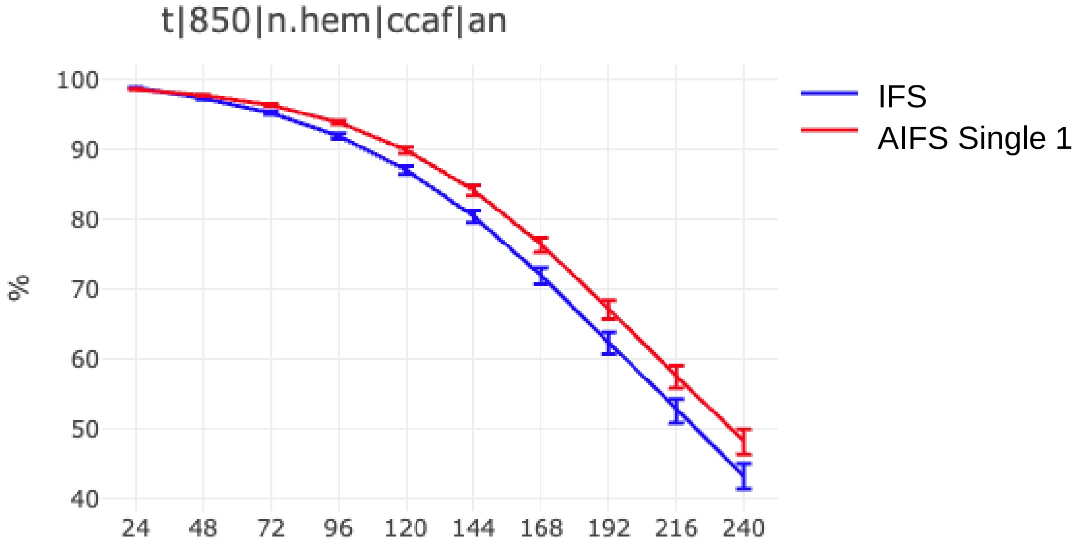
Feb 2025: ECMWF – AIFS Single 1 operational

ECMWF

AIFS Single vs IFS

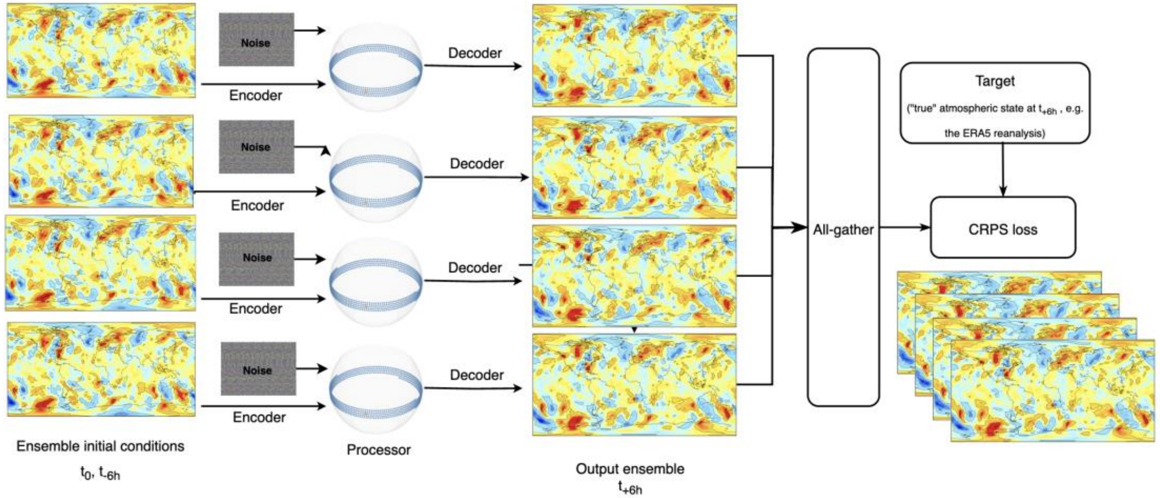
Lang et al 2024a
Operational system from 25/2/25

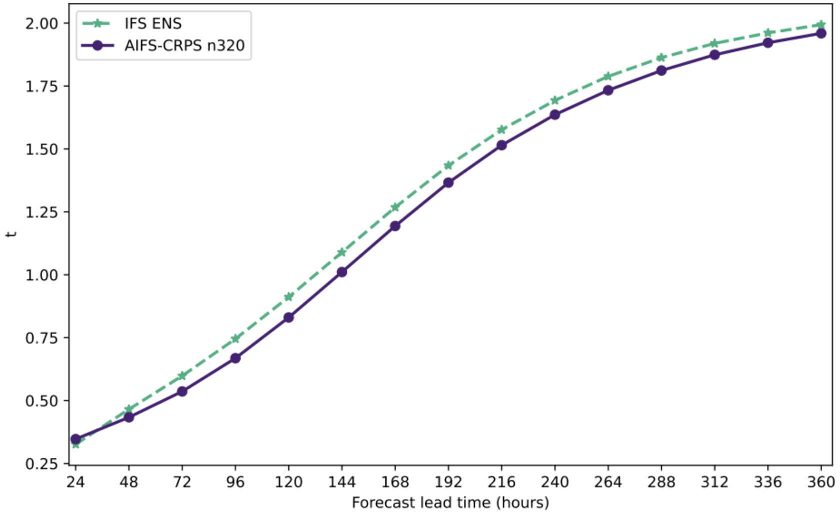




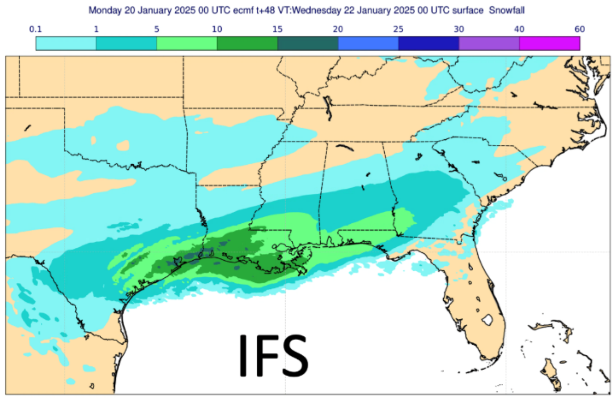
AIFS ENS CRPS vs IFS ENS

Lang et al 2024b
Operational system later this year

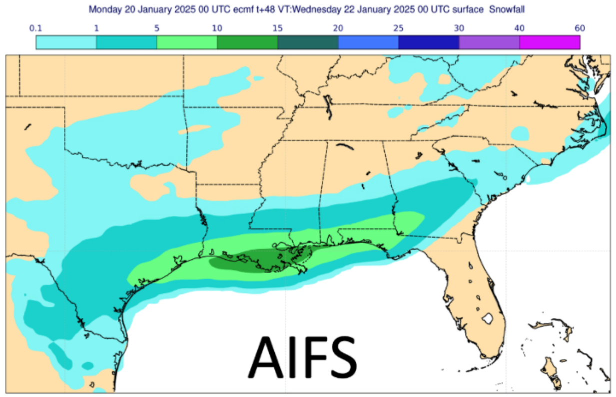




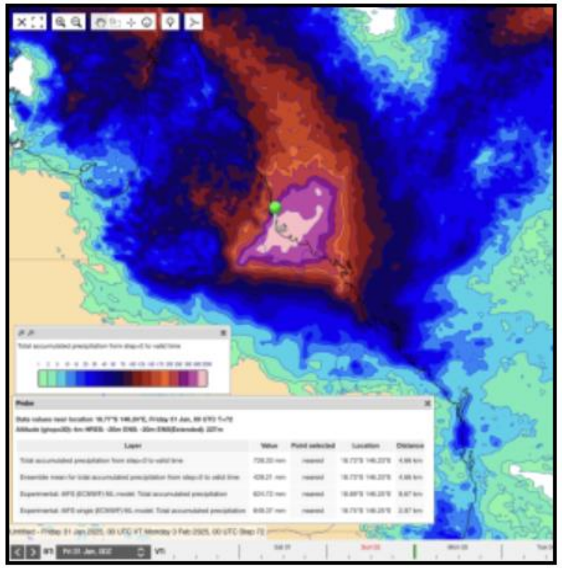
Case Studies: AIFS Single v1

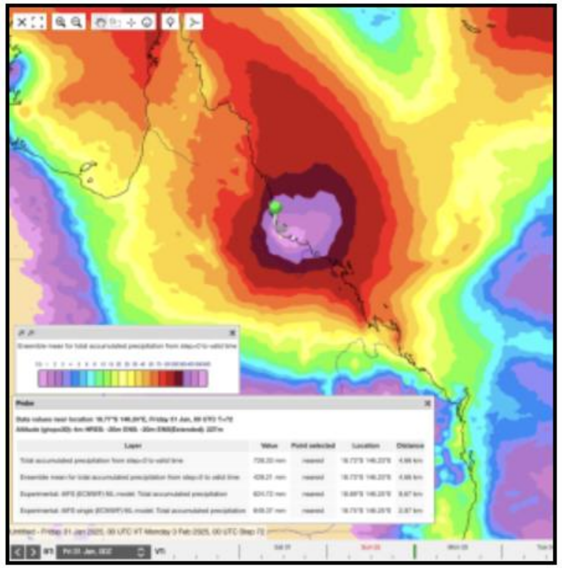


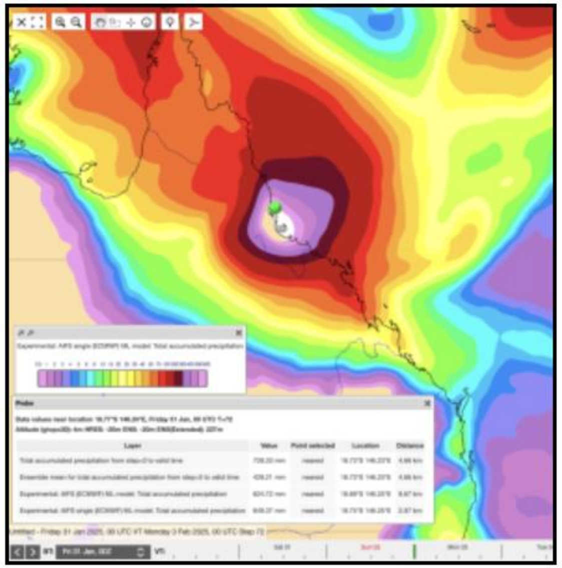
24h snowfall; T+24-48h
VT: 21 January 2025



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

Anemoi

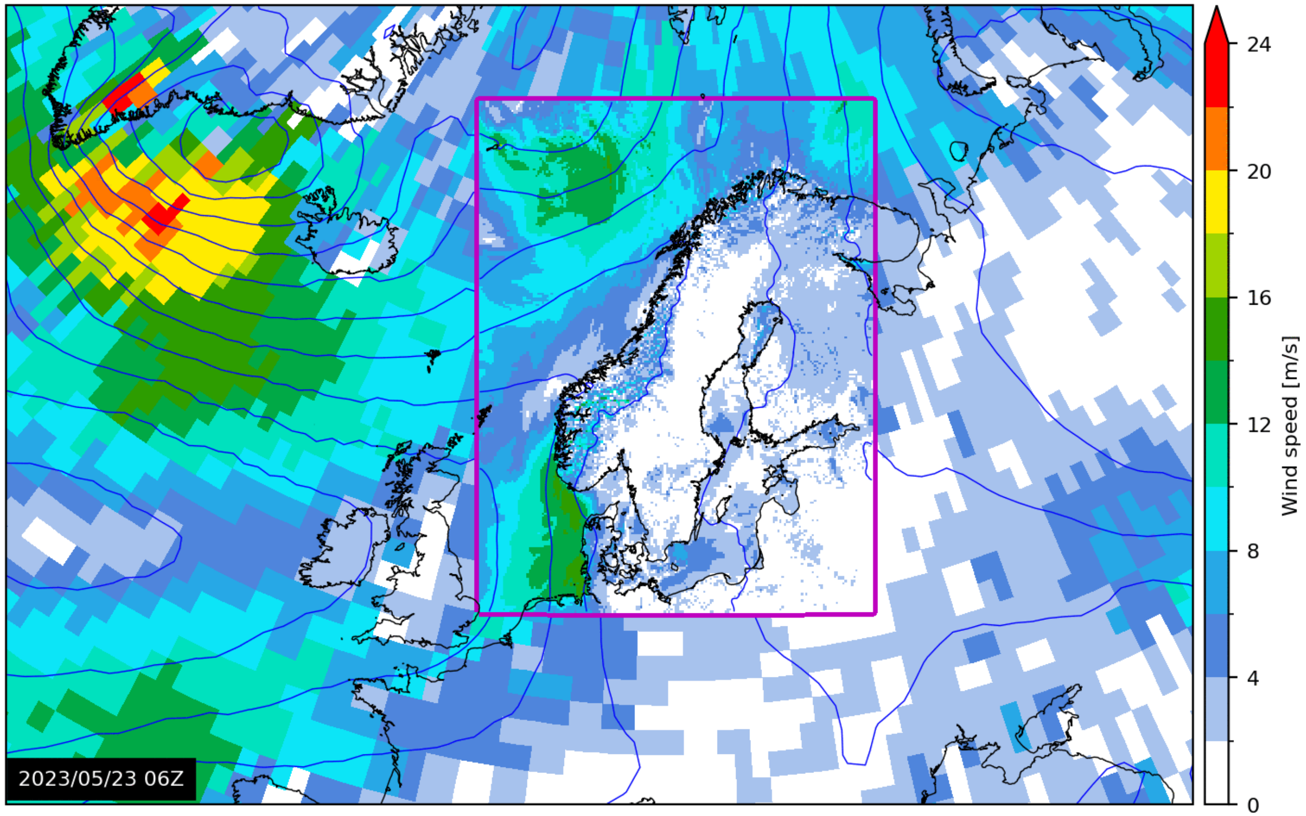
Pooling of resources without resulting in a single forecasting model.

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.

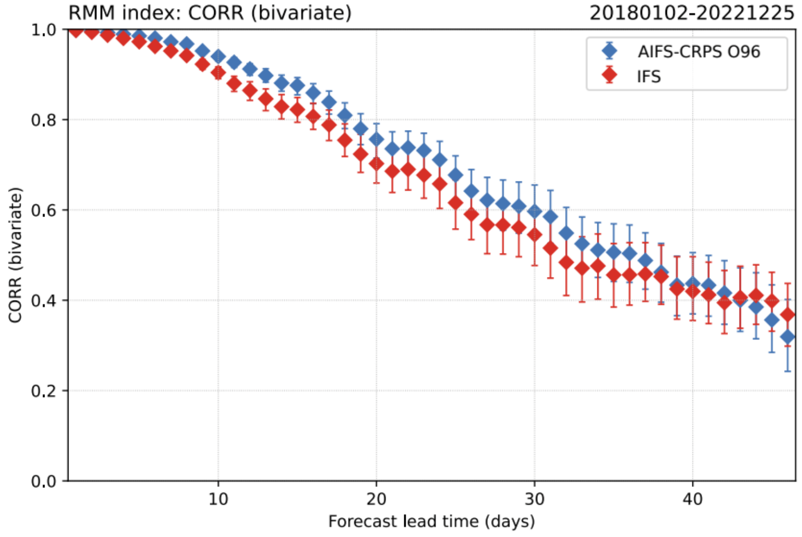
<u>Developed</u> and <u>used</u> by meteorological centers across Europe.
AEMET, DWD, FMI, GeoSphere, KNMI, MET Norway, Meteo Swiss, Meteo France, RMI, & ECMWF

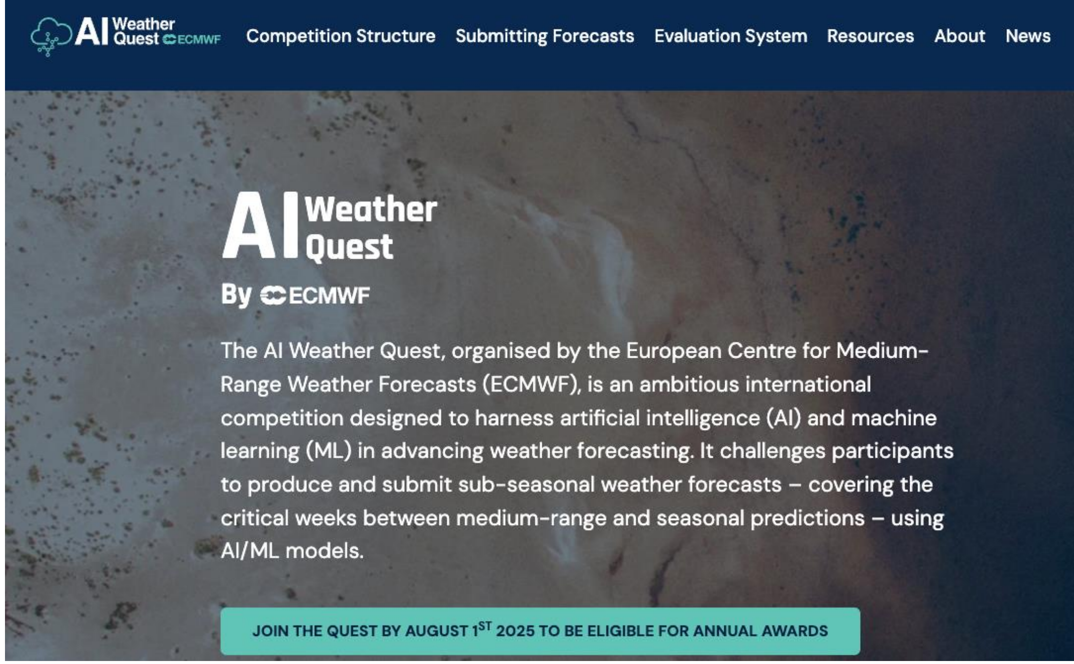
ANEMOI in action: developing weather model for the Nordics



Subseasonal and beyond

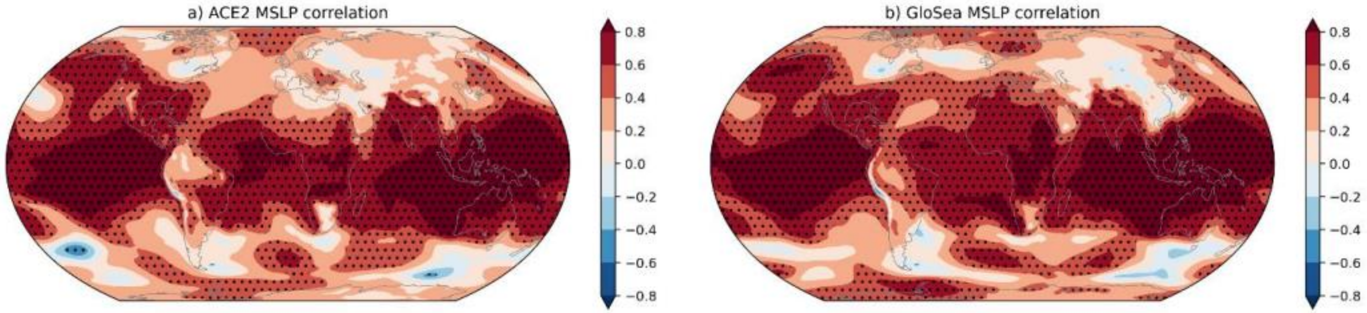
Clear skill for AIFS on sub-seasonal (Lang et al 2024b)





ECMWF organising a sub-seasonal competition this year

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



Ongoing ECMWF work on
- ML emulators of Earth System components (land, waves, ocean, ice)
- Subseasonal specific training

Three strands of the machine learning project

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.

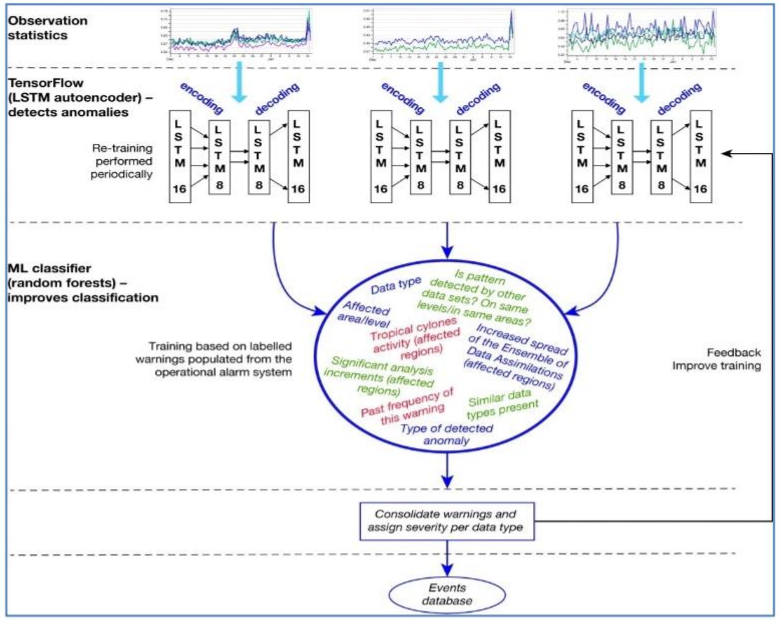
A scientific challenge

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.

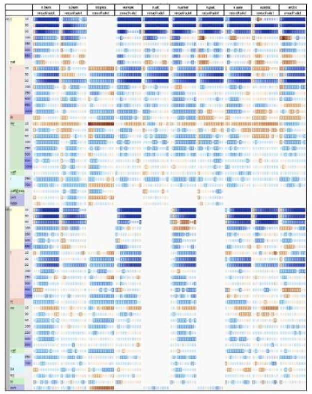


Figure: Score card 2022/06/03 to 2022/08/31. 12H assimilation window with NN model error correction trained **online**.

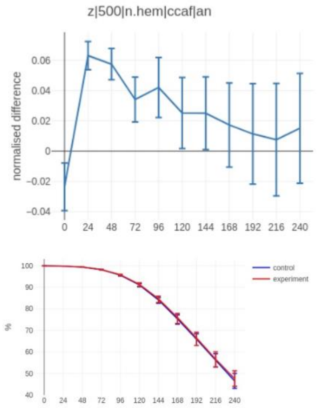
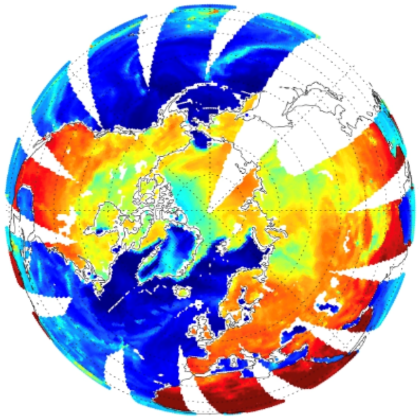


Figure: Z500 NH anomaly correlation. 2022/06/03 to 2022/08/31. 12H assimilation window with NN model error correction trained **online**.

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

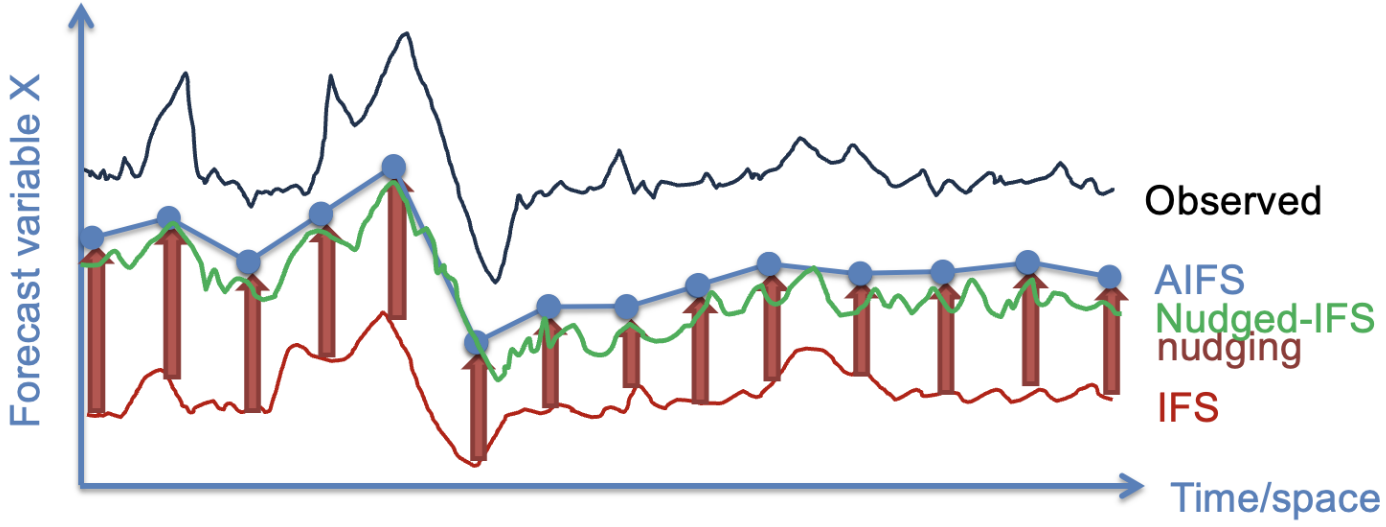
Snow / ice grain size and structure

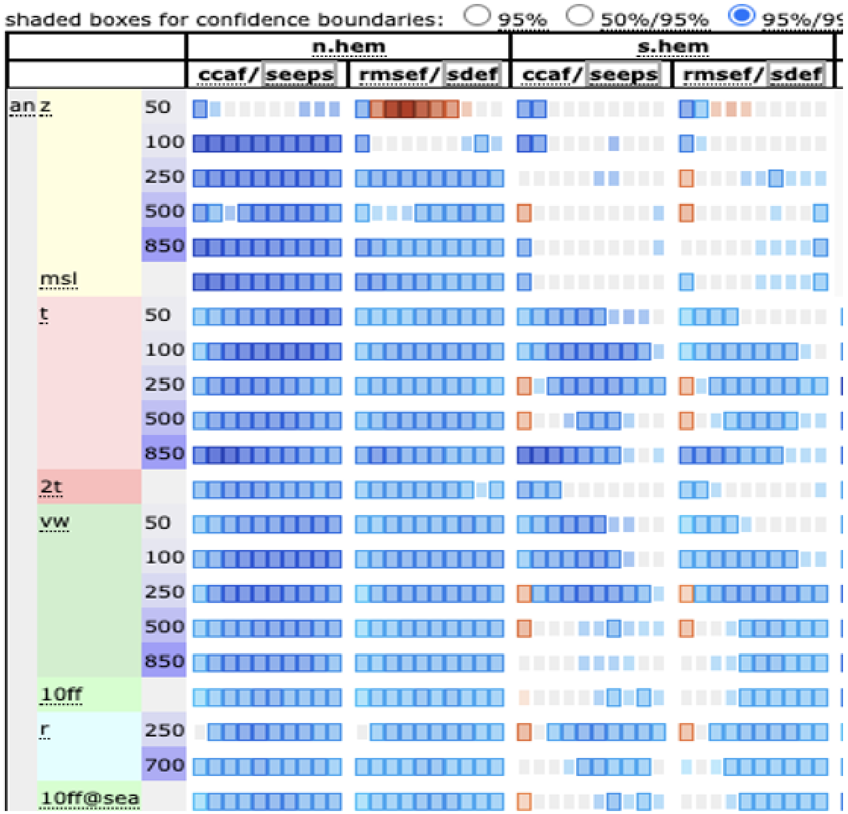
…..

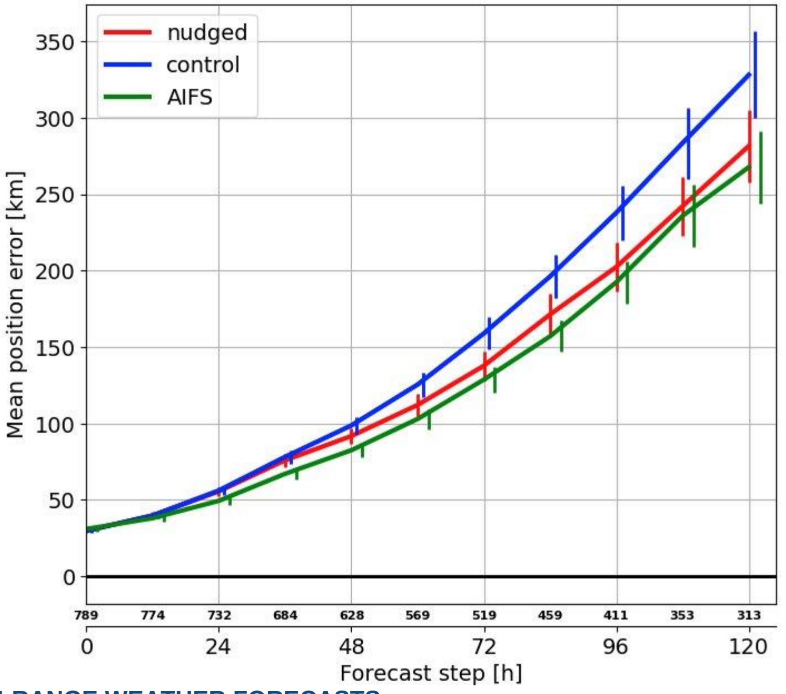
From Alan Geer, ECMWF

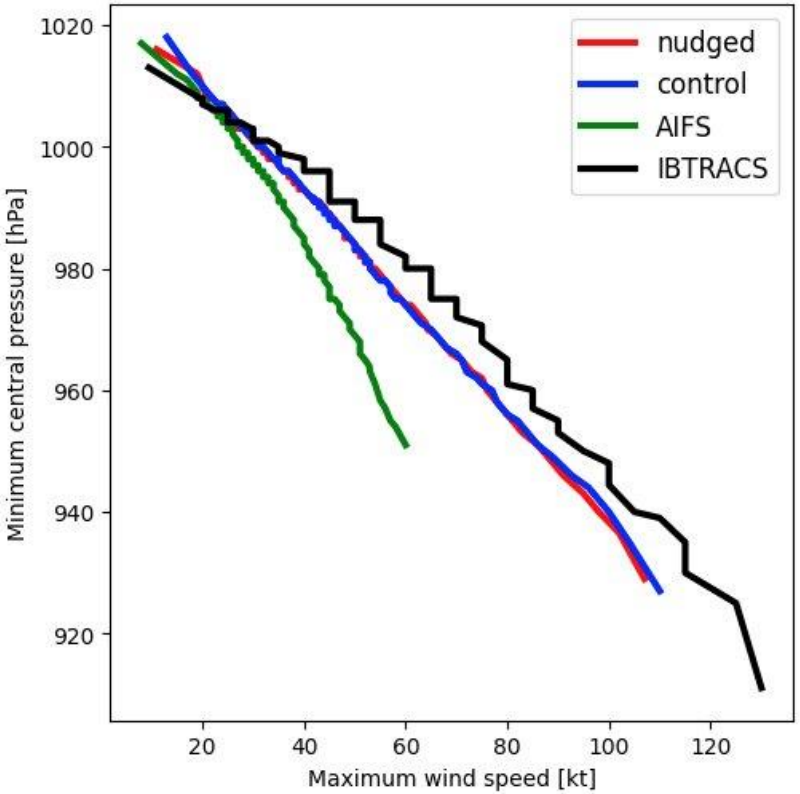
Driving the IFS with the AIFS

- 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



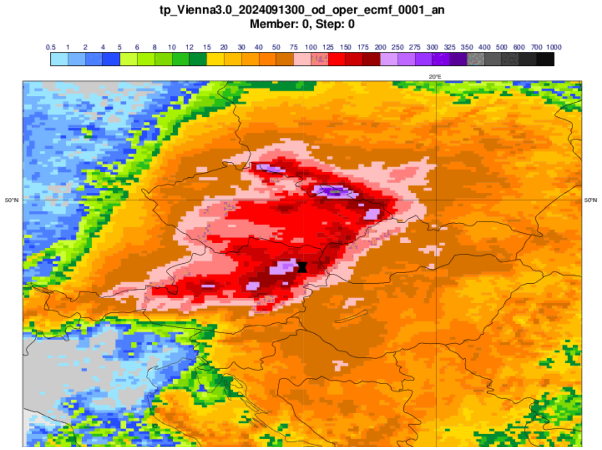


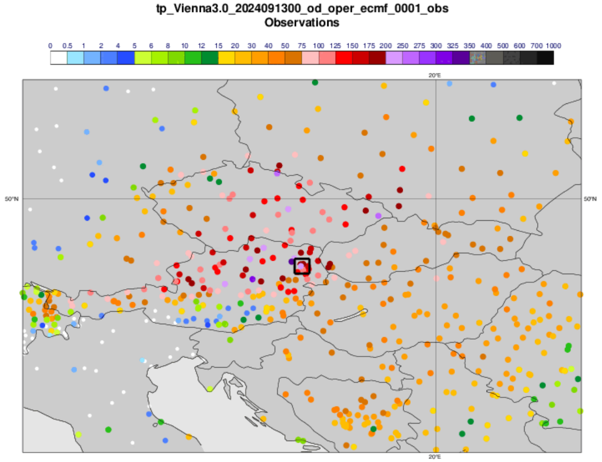


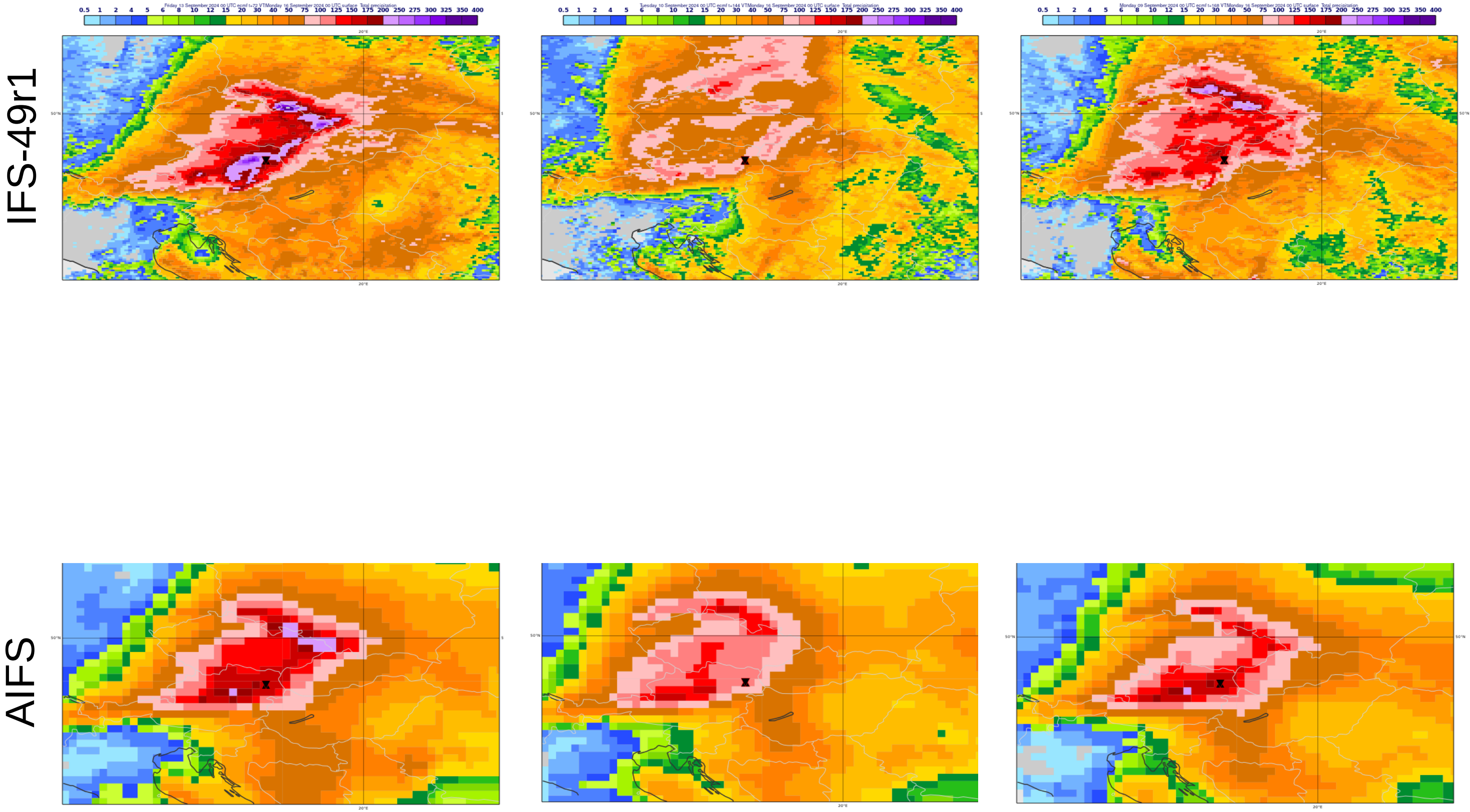


Extremes: Extreme precipitation in Central Europe, storm Boris

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





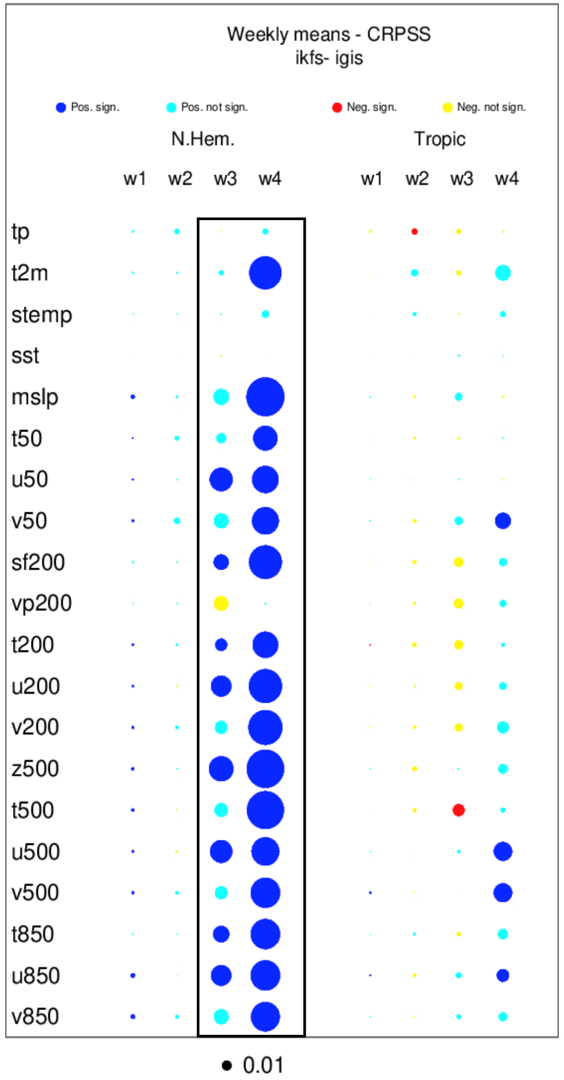


0-3 day lead time | 3-6 day lead time | 4-7 day lead time

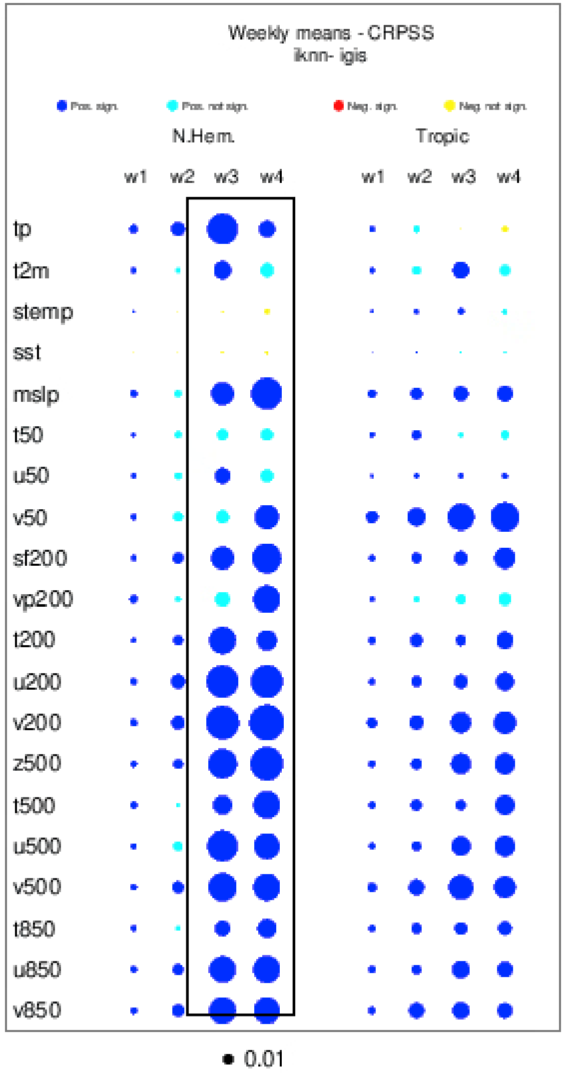
3-day accumulated precipitation

Impact of online bias correction through nudging of subseasonal predictions

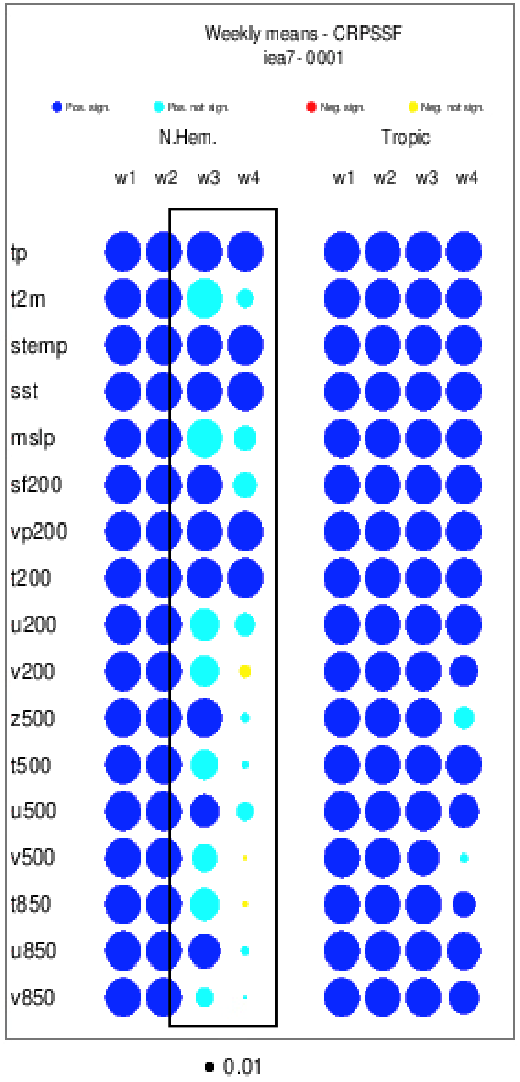
North Pole



Global



2024 vs 2004



Three strands of the machine learning project

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

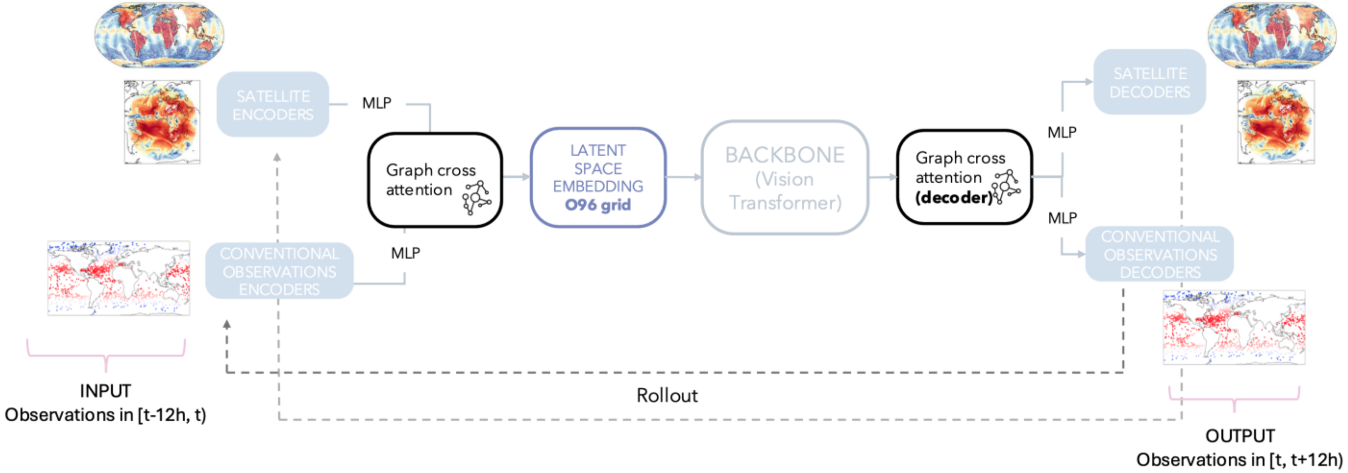
Observations-driven ML system

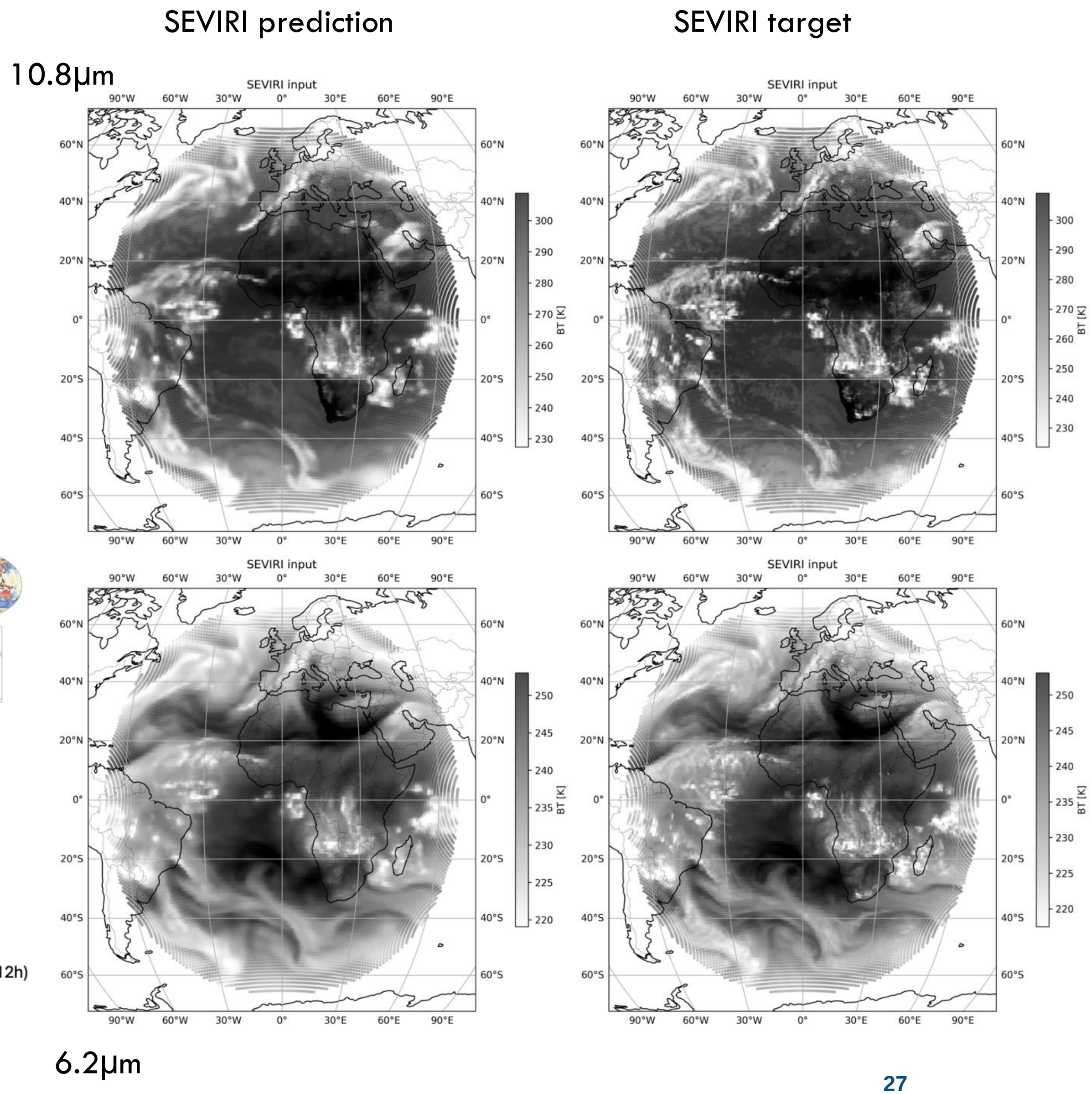
A whole system reinventing the path from observations to predictions.

A scientific challenge

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)





The quiet revolution of numerical weather prediction?

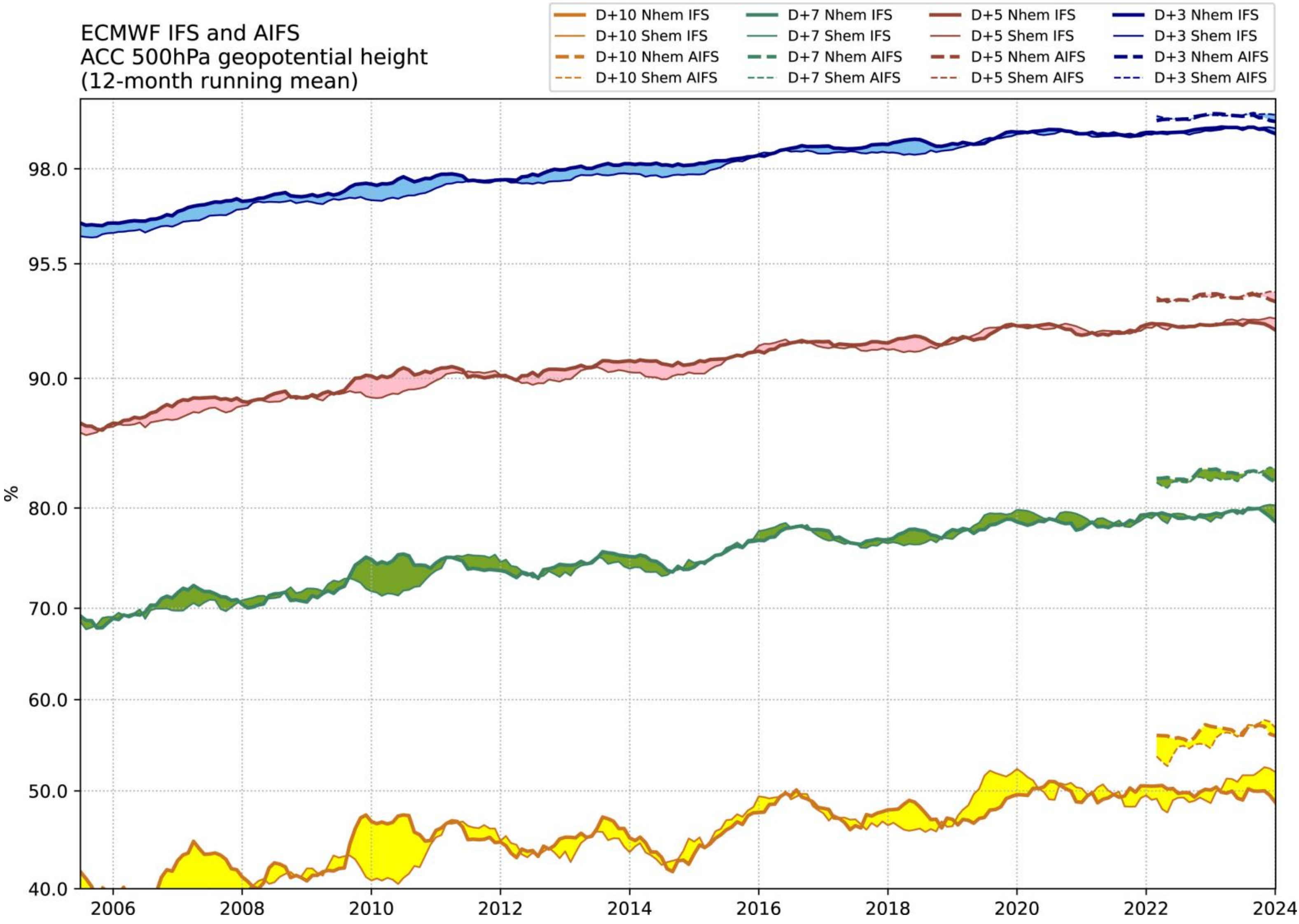
The quiet revolution is dead…

…long live the machine learning revolution.

AIFS is years ahead of IFS in terms of forecast scores for deterministic and ensemble predictions.

If you want to have competitive scores with IFS, you need to nudge it to AIFS.

And we can trust weather predictions of machine-learned models.



The changing role of the model

- Operational real-time predictions will NOT be directly with seamless ‘pure’ physical model
  - Fully data-driven likely to play major role for real-time weather predictions (maybe alongside nudged for transition period?)
  - Pure physics subseasonal unlikely to be competitive with data-driven or some form of hybrid
  - More open as go to longer timescales, composition etc
- But we still need a model
  - Use in data assimilation / reanalyses (subject to AI-DOP progress)
  - Creation of training datasets (km-scale for training more than operational use?)
  - Likely long-term operational use in some applications (especially climate), although maybe in some cases with application-specific hybrids/nudging etc
  - Understanding and hypothesis testing
- With changed purpose, relative balance of metrics of success change
- Still benefits of seamless behind the scenes, but not an end in itself and more focus on application specific optimization

THE STRENGTH OF A COMMON GOAL

ECMWF STRATEGY 2025–2034

Our Vision:

World-leading monitoring and predictions of the Earth system enabled by cutting-edge physical, computational and data science, resulting from a close collaboration between ECMWF and the members of the European Meteorological Infrastructure, will contribute to a safe and thriving society

ECMWF in 2035:

- Innovating at the cutting edge of physical, computational and data science for environmental monitoring and prediction
- Delivering forecast tools and products of unprecedented quality, exploiting data-driven methods anchored on physics-based modelling
- Integrated in and collaborating with the wider European meteorological community to deliver maximum value to society

Our Mission: Deliver global numerical weather predictions focusing on the medium-range and monitoring of the Earth system to and with our Member States

Strategic Pillars and Actions:

Science & Technology	Impact	Organisation & People
Improve use of observations & Earth system data assimilation	Meet users' needs & deliver world-leading quality products	Increase organisational performance, resilience & effectiveness
Improve seamless Earth system models	Optimise provision & sharing of data, tools & resources	Enable a thriving multi-site environment with an emphasis on sustainability
Exploit high-performance computing, technology & computational science for numerical weather prediction	Enhance partnerships, training & communications	
Harness artificial intelligence/machine learning for data-driven forecasting		
Optimise system design & enhance flow from research to operations & vice versa		

https://www.ecmwf.int/en/about/what-we-do/strategy

ECMWF in 2035……

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