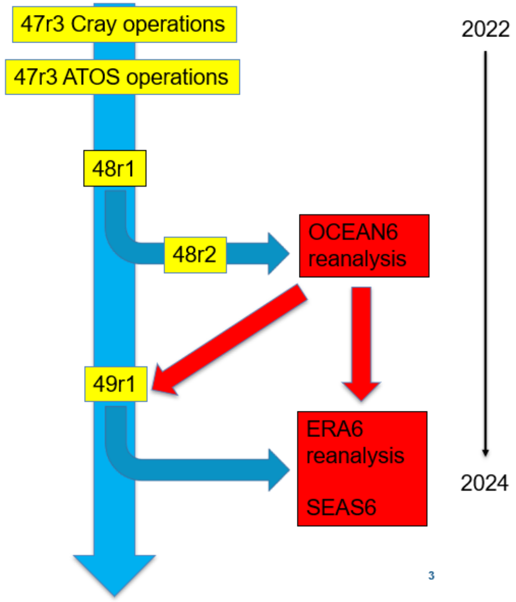
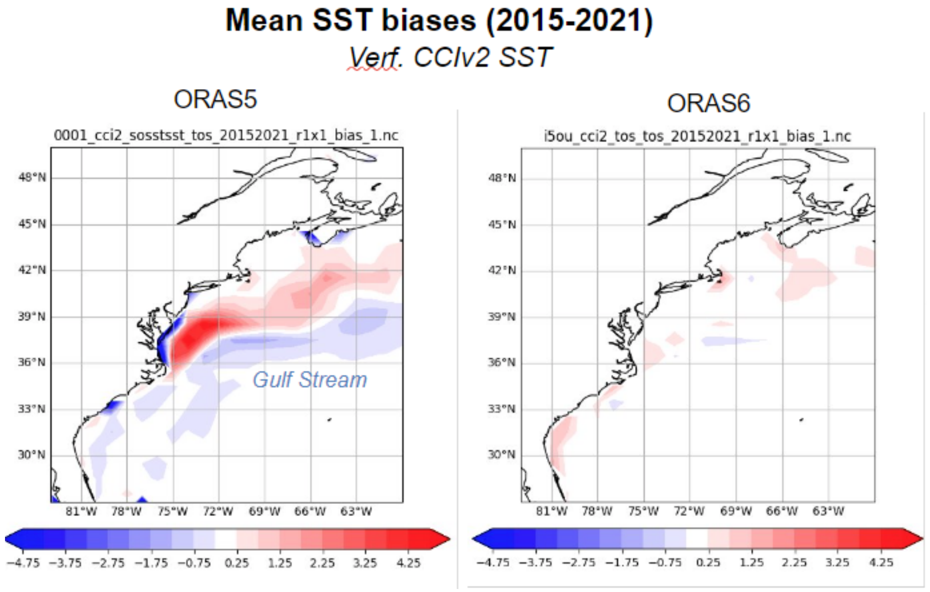
Centre update: ECMWF

Inna Polichtchouk

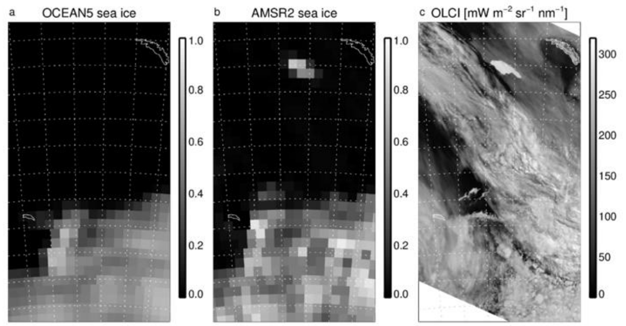
Operational upgrades



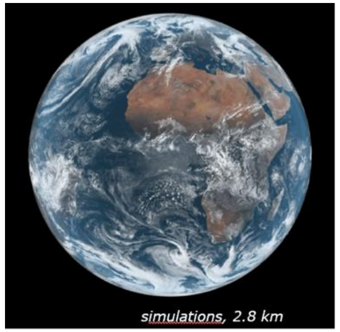
Reanalyses

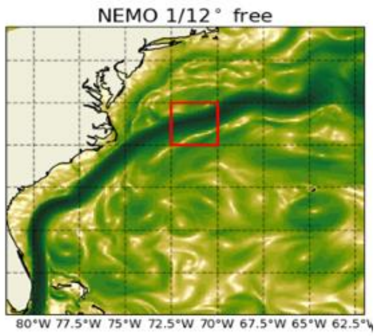


Coupled; all-sky, all surface

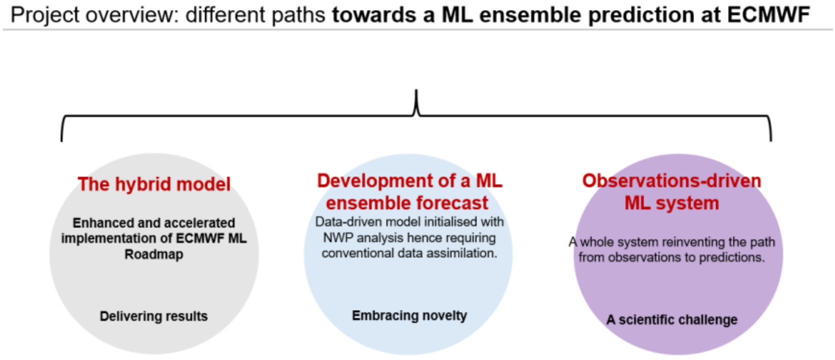


Towards high resolution (physical and computational science)



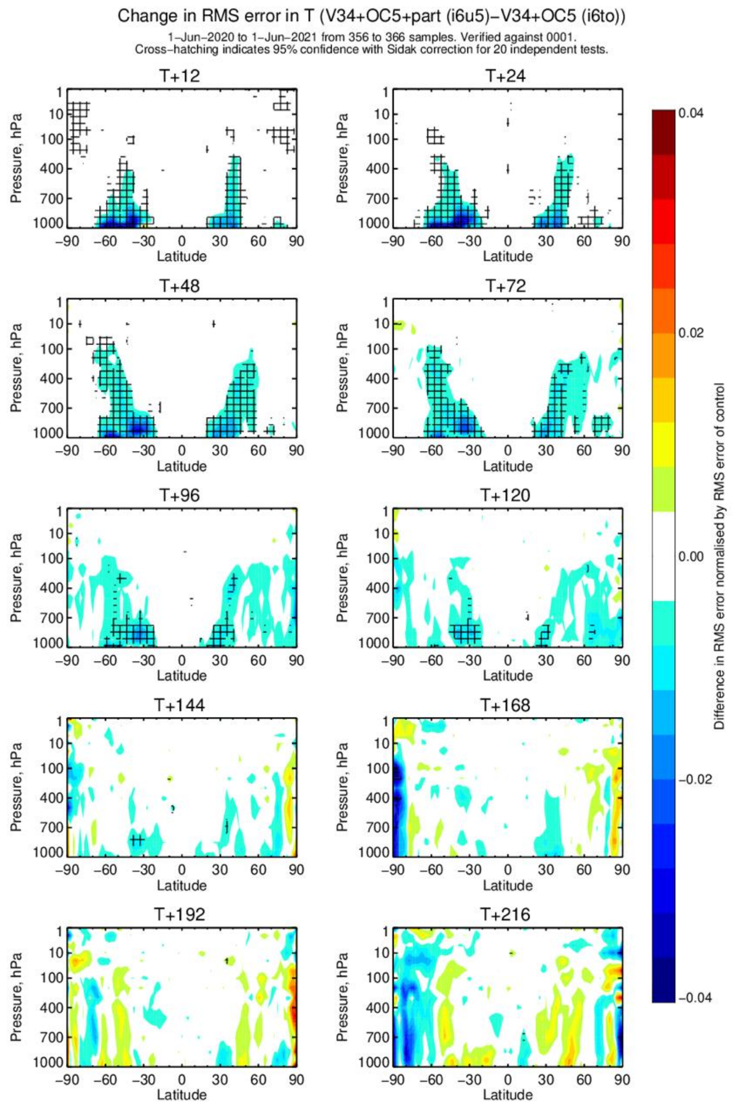


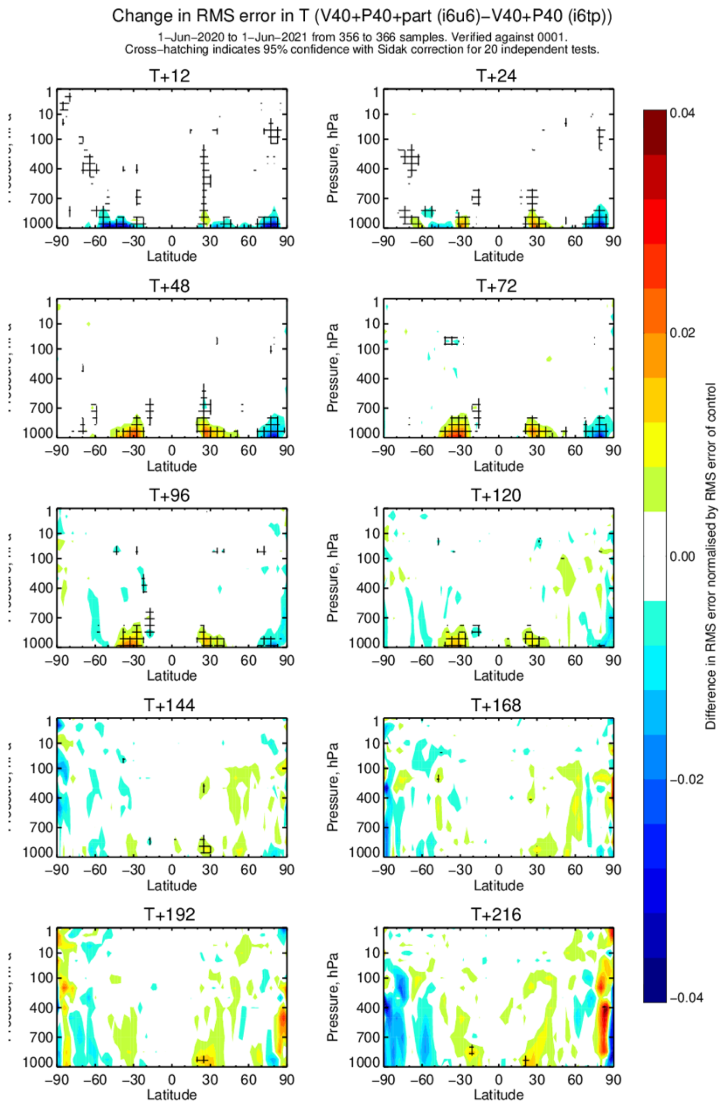
Machine learning



Effect of partial coupling in NEMO V40 compared to NEMO V34

V34





V40

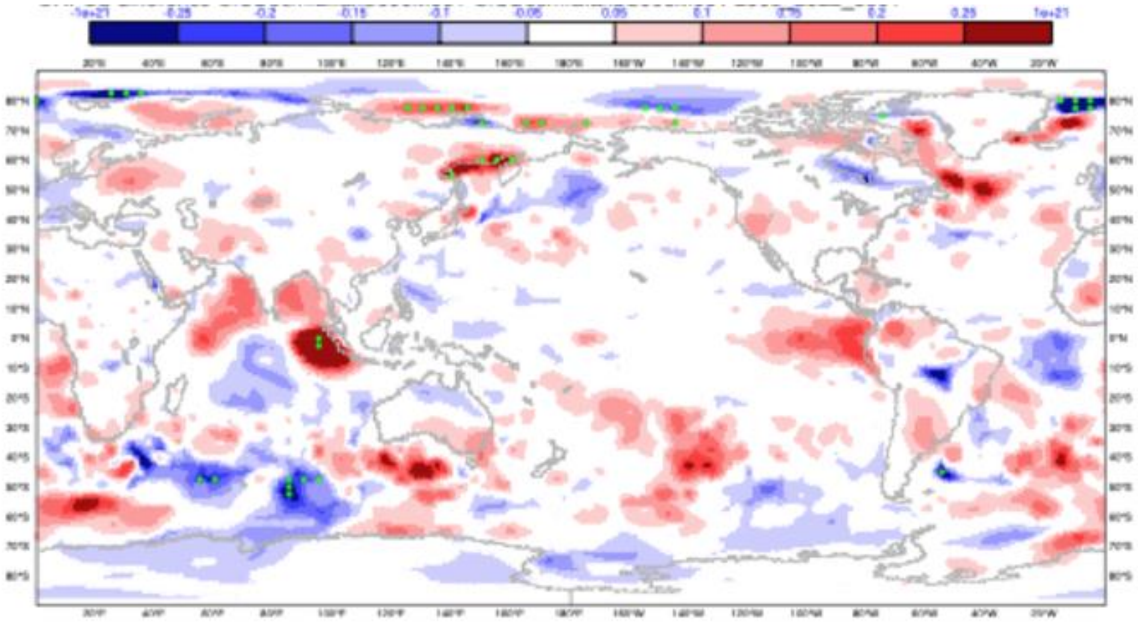
- Due to improvement in the ocean initial conditions, the positive impact of partial coupling we have in the old system is gone and replaced with negative impact (at least after 24 hours)
- Based on these results we will not use partial coupling for any NEMO V40 based systems

Evaluating 49r2: Seasonal forecast scores

Skill in equatorial upwelling regions improves with Nemo4 and ORAS6.

49r2v5 – 49r1: 2mT CRPSS difference

JJA (month 2-4)

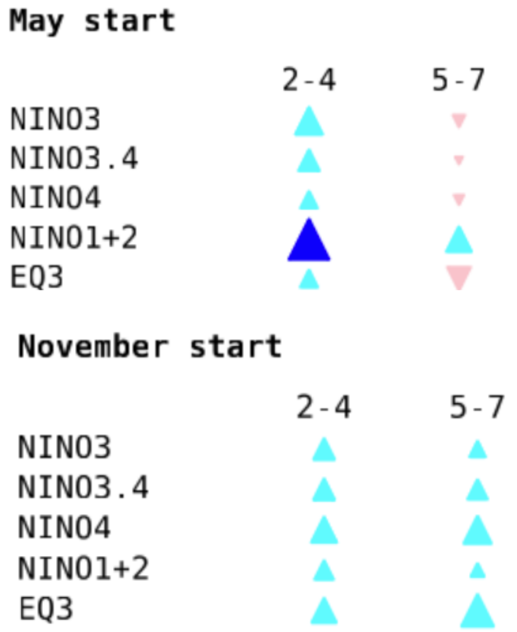


Red – improvement Blue - degradation

Anomaly scores

49r2v5 NEMO4 vs. 49r1 NEMO3.4

Sign test based on MAE



Tco319 ORCA025, 51 members, May 1 and Nov 1, 2005-2022

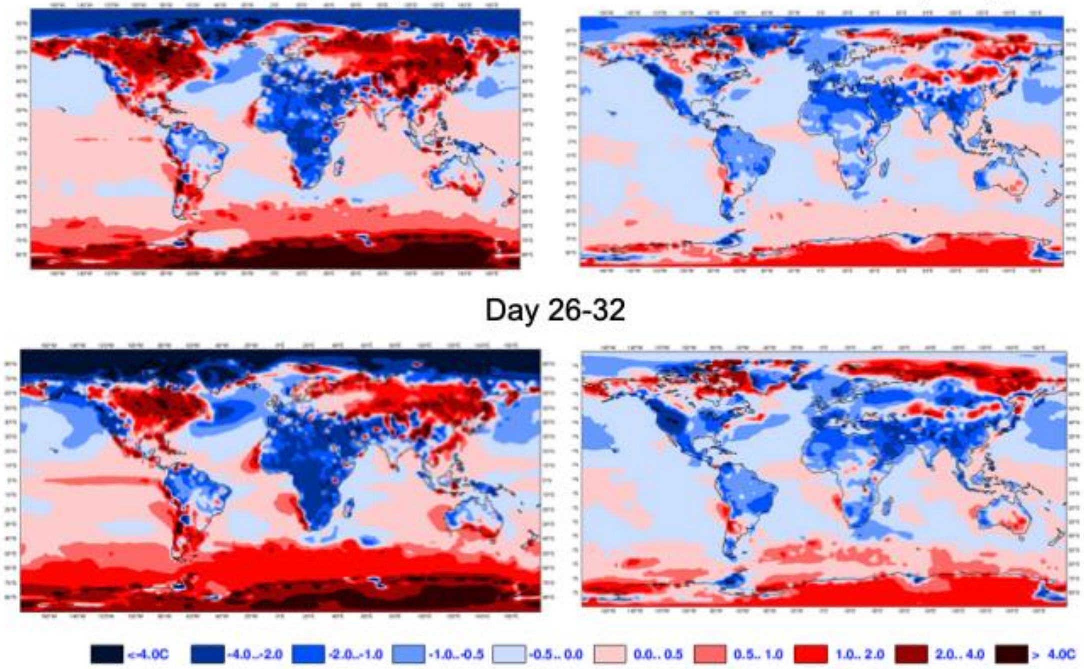
20 Years of Sub-seasonal prediction

Biases relative to ERA5

2-metre temperature

Day 5-11

2004 version (28R1) | 2024 version (48R1)



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

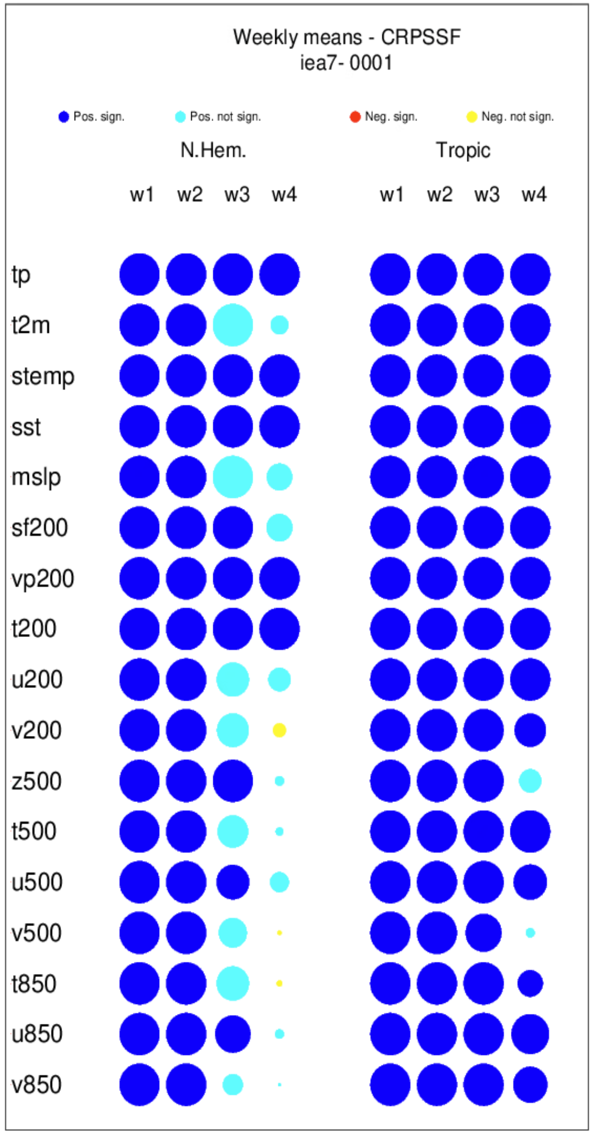
MJO 28 days (+8 days)

PNA 18 days (+4 days)

SSW 26 days (+4 days)

NAO 14 days (+4 days)

2024 vs 2004 version



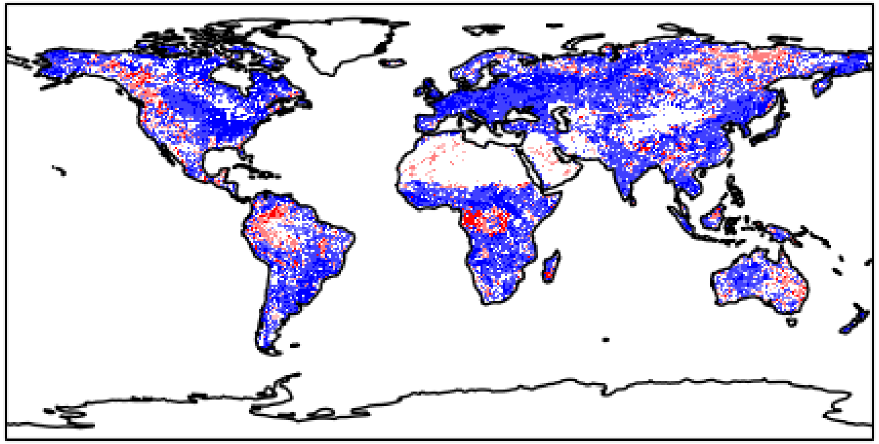
• 0.01

Land parameter optimisation for surface fluxes

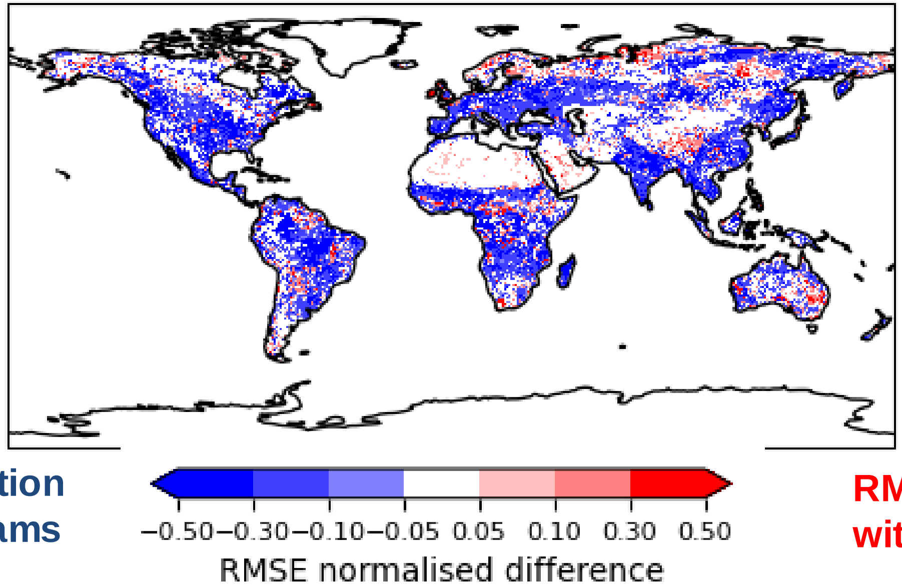
What and how:

- **Offline optimisation of 2D land-surface parameters**
- **BFGS optimization with variational cost function**
- **Clustering based on surface characteristics and errors wrt observations**

Offline: Normalised RMSE difference wrt CLASS; **latent heat**



Offline: Normalised RMSE difference wrt CLASS; **sensible heat**



RMSE reduction with opt params

RMSE increase with opt params

High-resolution ENS

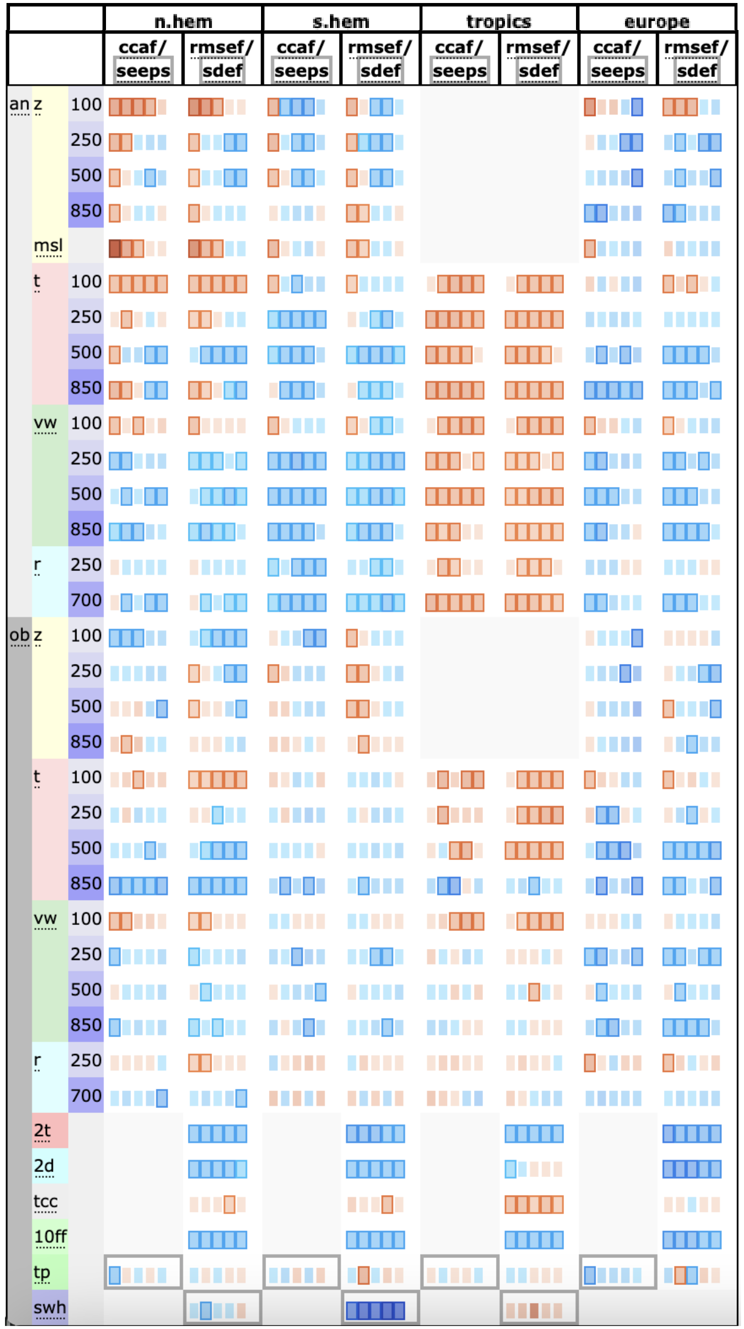
Improvement (~ 2-8%) in fCRPS for surface variables

Ensemble upper air variables like deterministic except for:

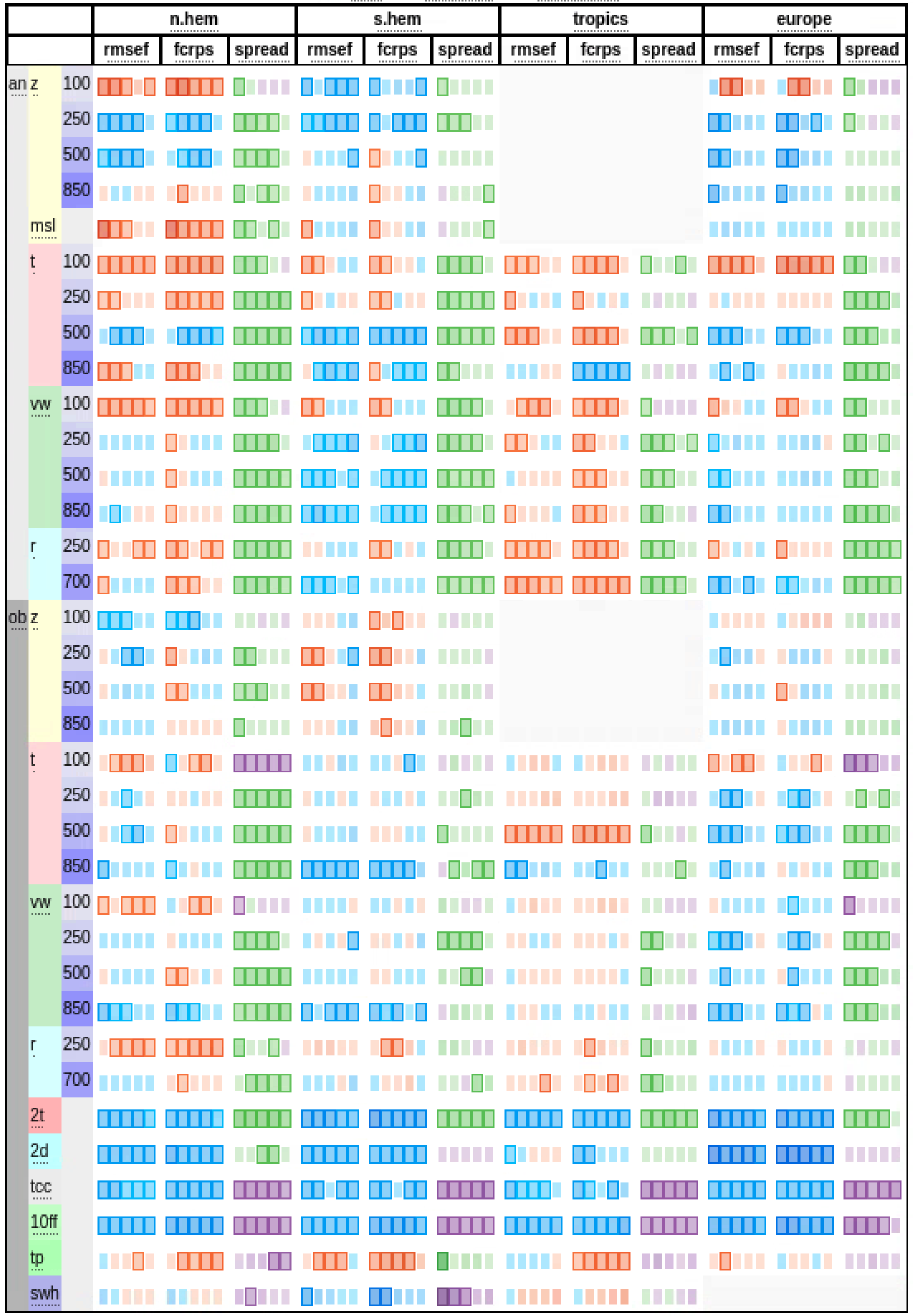
- Smaller error in the tropics
- More improvement in NH Z500 & Z250

Sample : JJA 2023 and DJF 2023/4 every 48h (85 dates)
Range : 5 days

det : 4 vs 9km



ens : 4 vs 9km

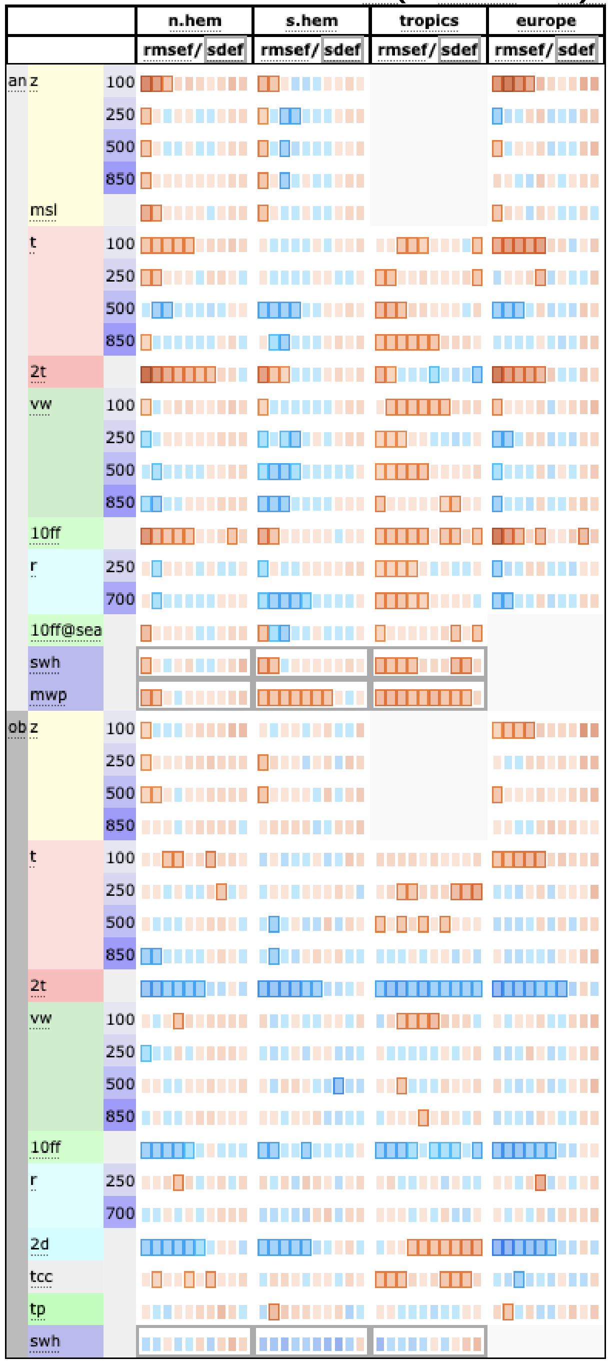


High-resolution DA

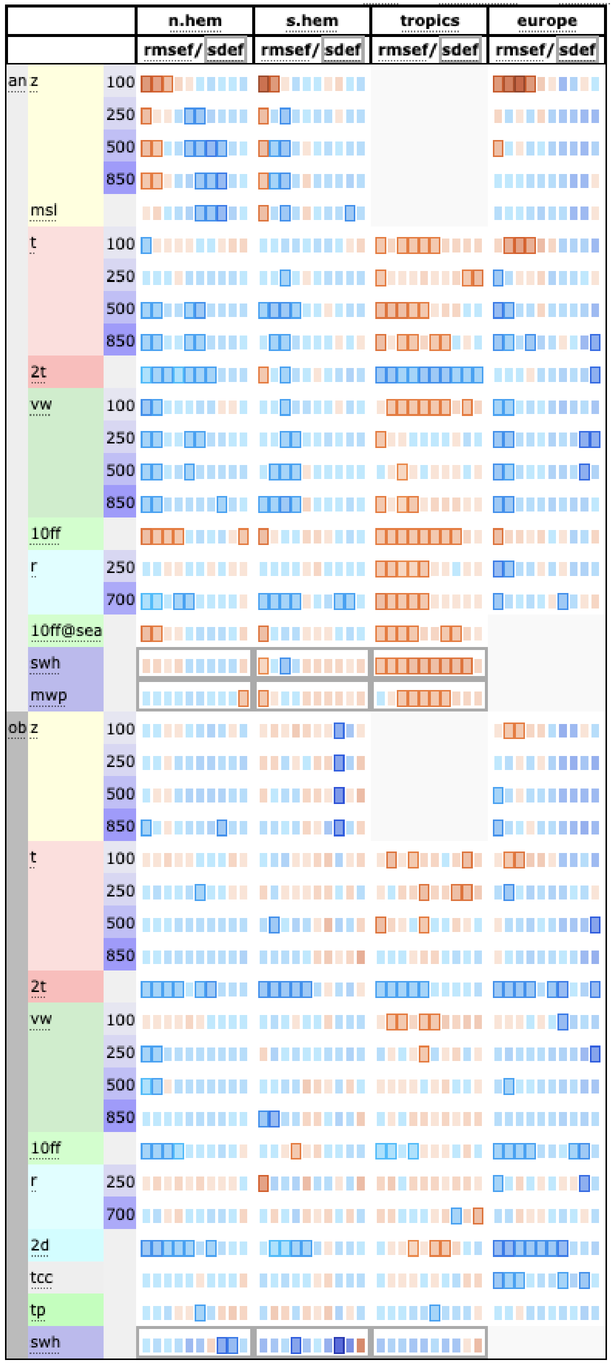
Setup of the high-resolution DestinE analyses:

- TCo2559 (4.4 km) trajectory using latest 49r1 DestinE forecast, including new mean orography
- Improved resolution of minimisation (TL319/TL399/TCo399/TCo511)
- Observation time-slots reduced from 1800s to 400s
- Observation rescreening
- High-resolution geostationary satellite data (125 km thinning to 75 km) :

FC 4km vs 9km (**AN** 9km)



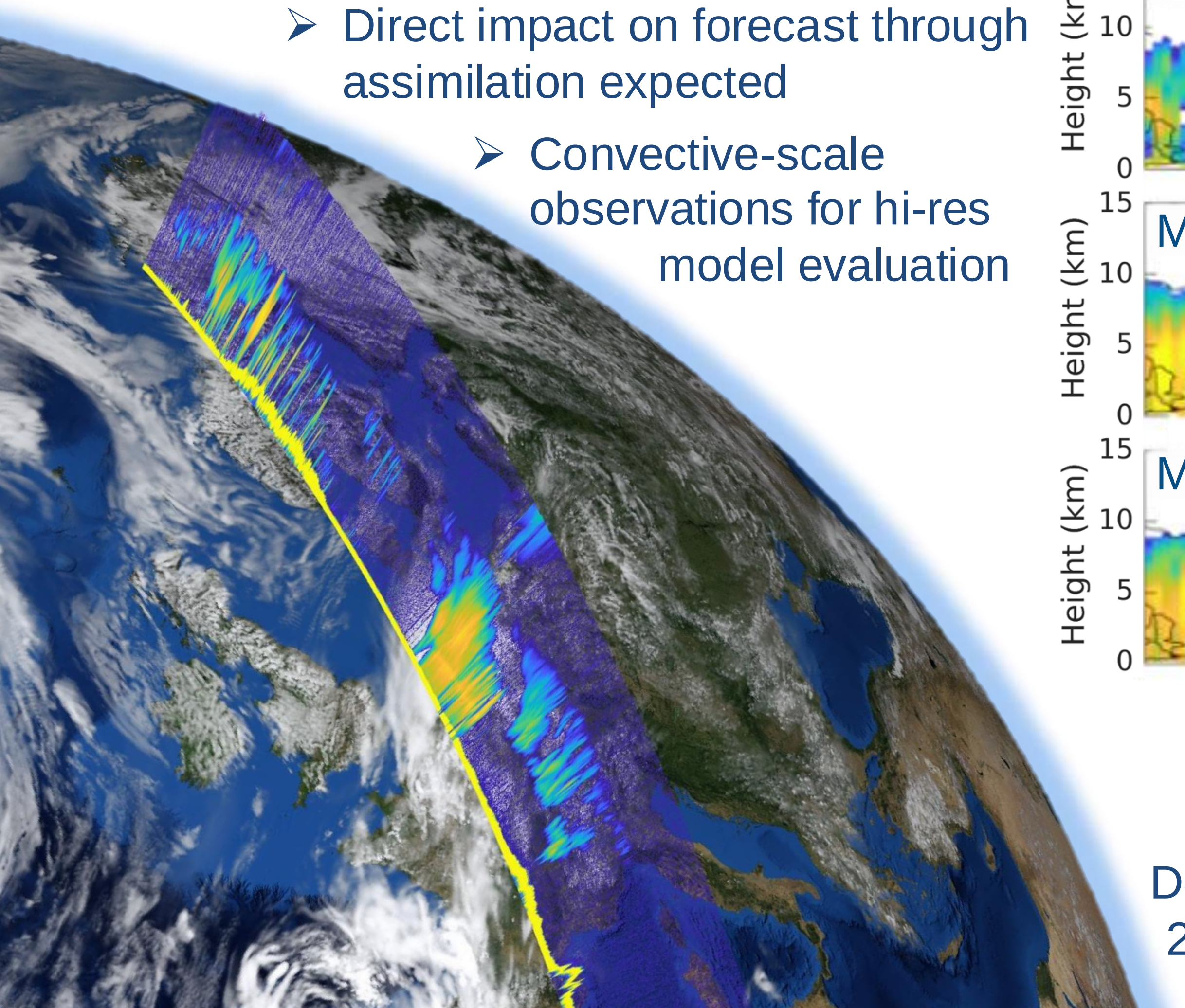
AN+FC 4km vs 9km

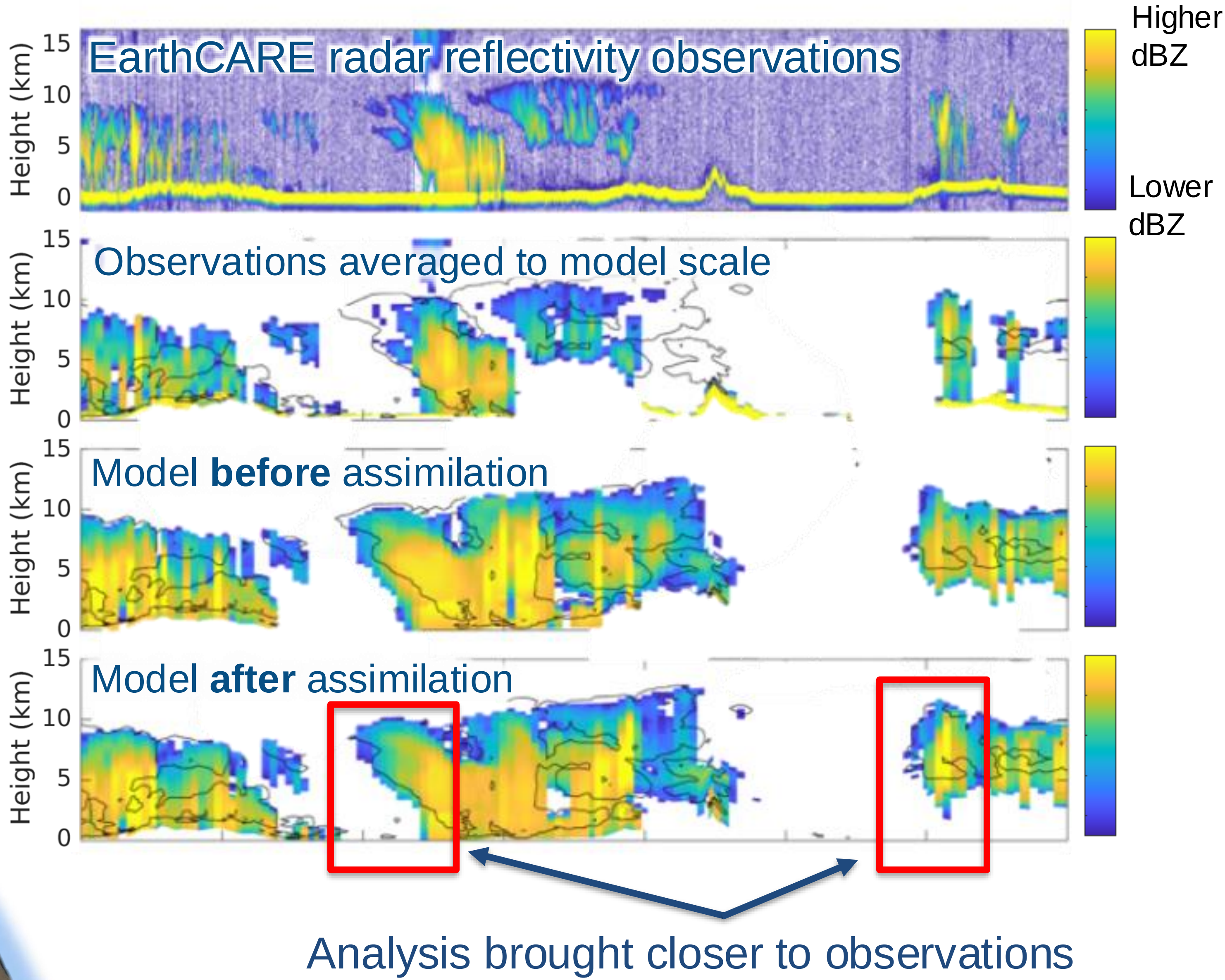


Sample : 20230901 to 20231004 every 24h (34 dates)
Range : 10 days

Monitoring, assimilation and **evaluation** using EarthCARE

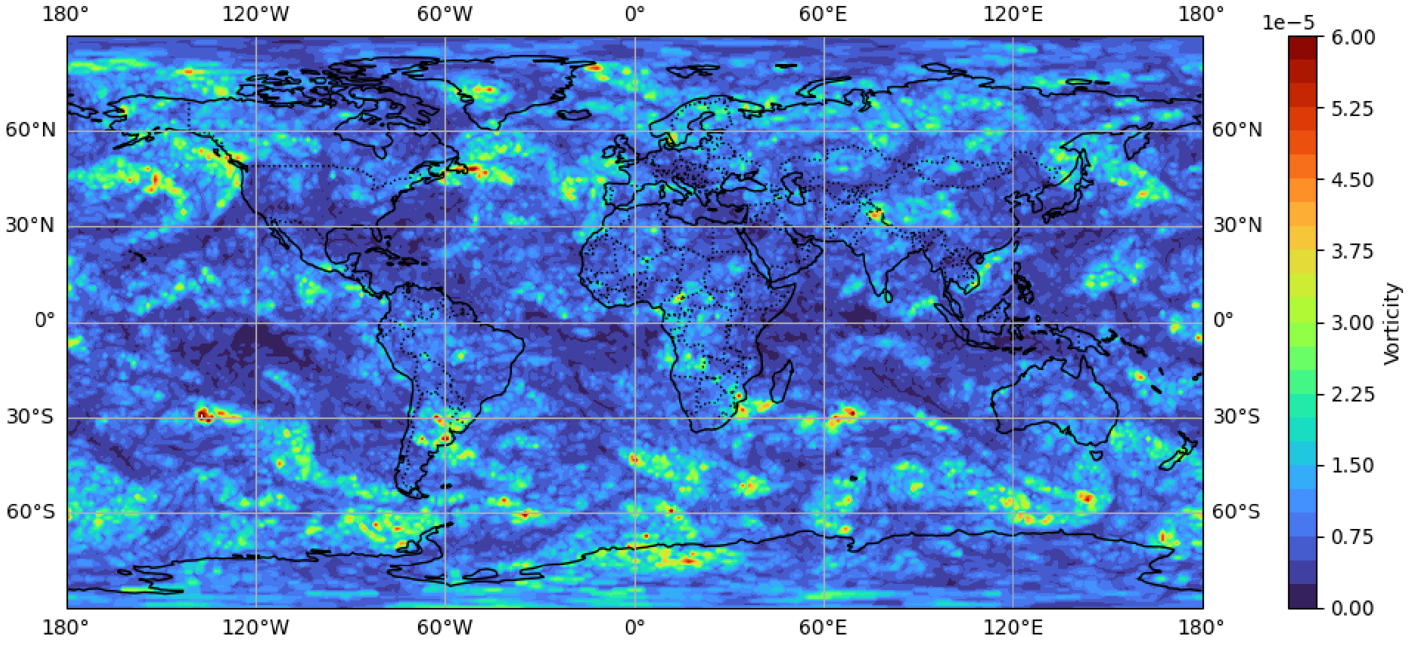
- Rapid detection of instrument issues through O-B monitoring
- Direct impact on forecast through assimilation expected
- Convective-scale observations for hi-res model evaluation





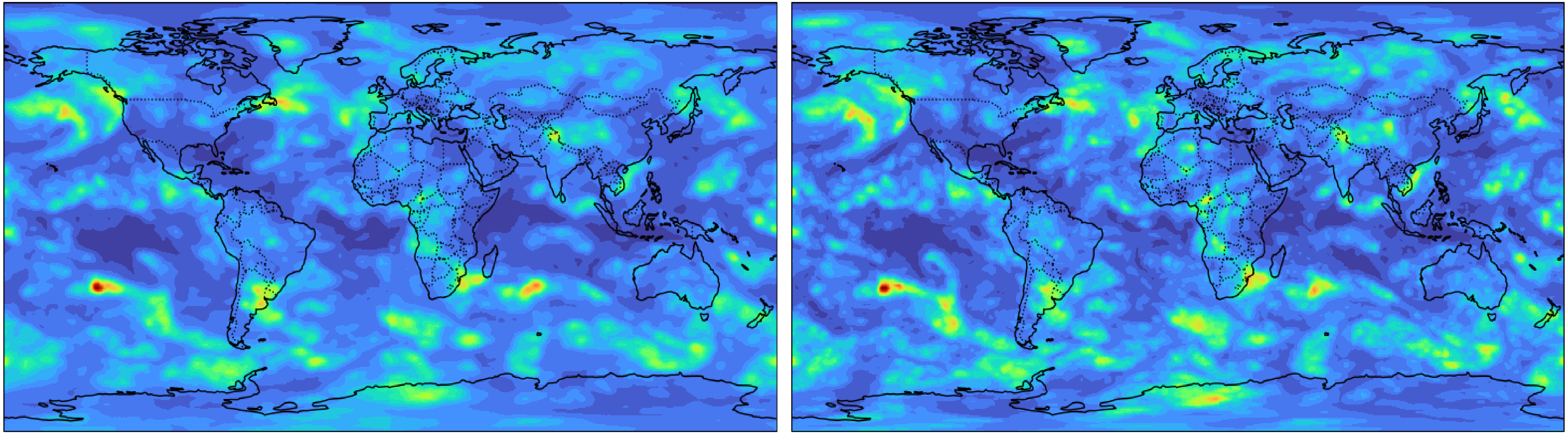
DestinE 4.4 km cloud fields
2024-06-18 00UTC + 14h

Emulation of EDA background error variances: Turing test



Input: 5-EDA es, F80 grid, L100
2023-10-16 0900

Which one is ML generated?

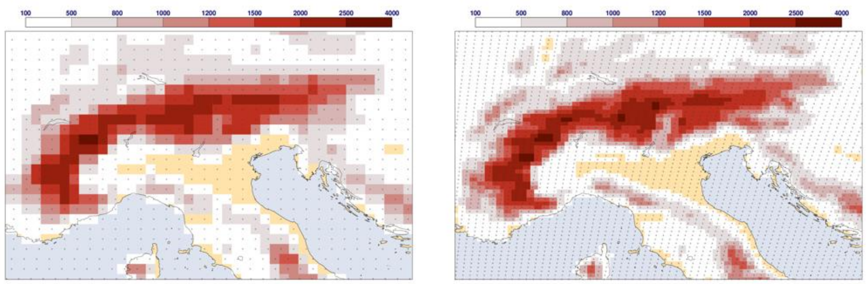


Reanalyses

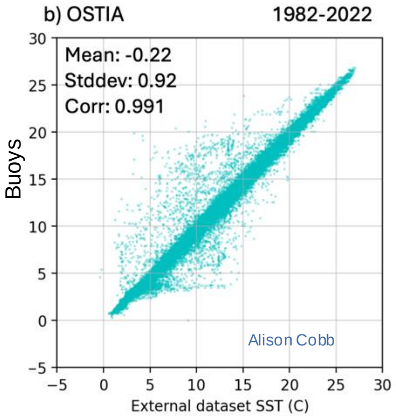
ERA6 preliminary results

Horizontal grid

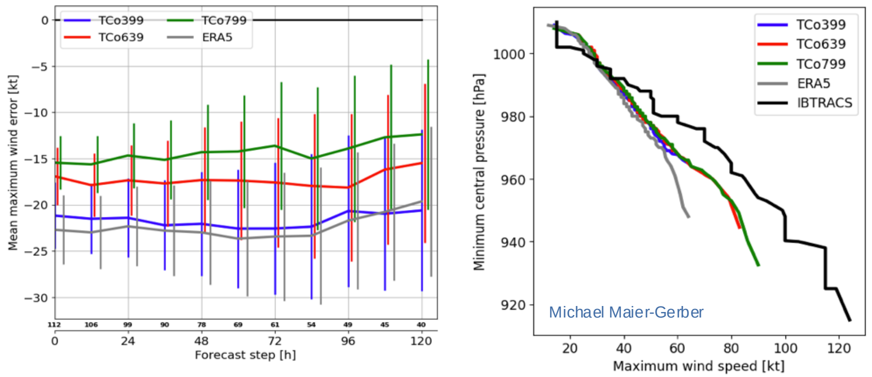
ERA5 Tl 639 ERA6 TCo799



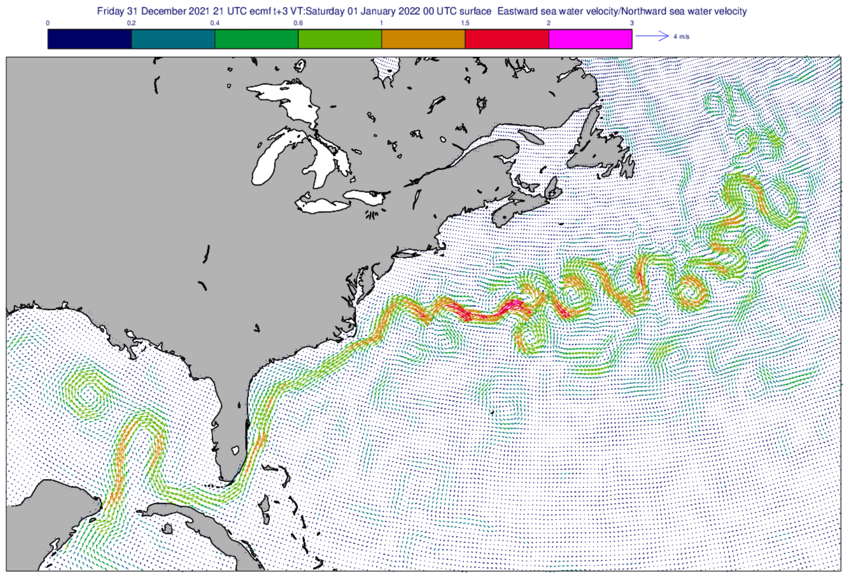
Great Lakes



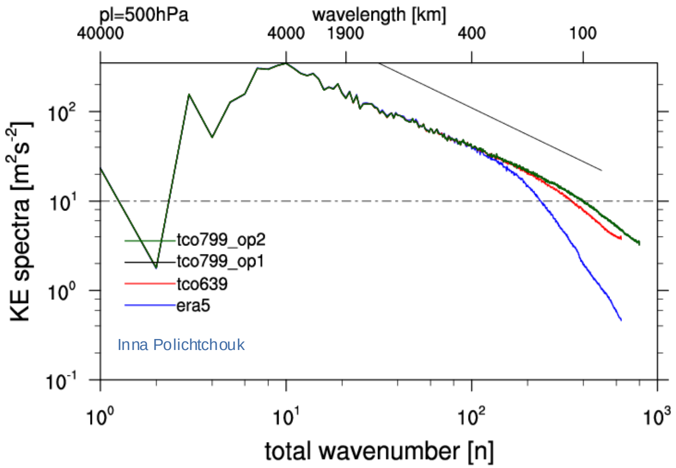
Tropical cyclones



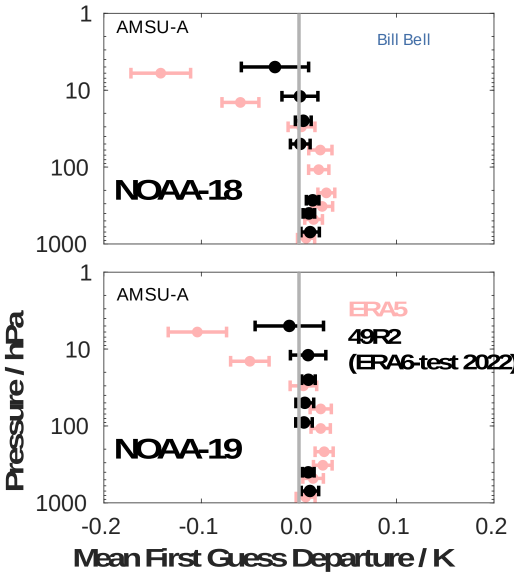
Hourly ocean currents, SST, sea ice



Energy spectra



Departure statistics



ORAS6 performance

The performance of ORAS6 is significantly improved compared to its predecessor ORAS5. Fit-to-observations error standard deviations have been reduced by ~15% for sea-water temperature, and by ~7% for sea-water salinity.

O-B RMSE changes w.r.t ORAS5

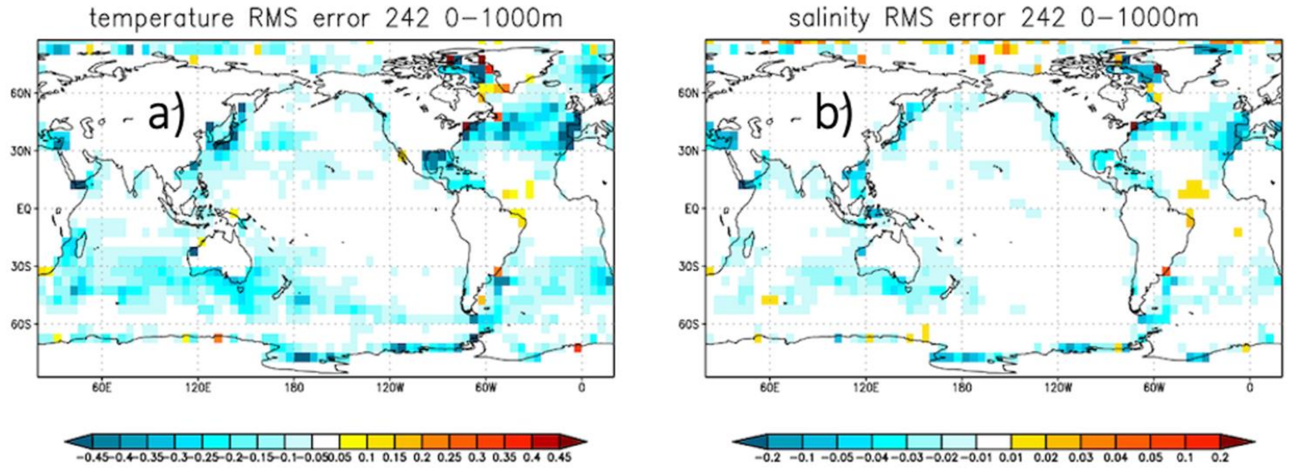
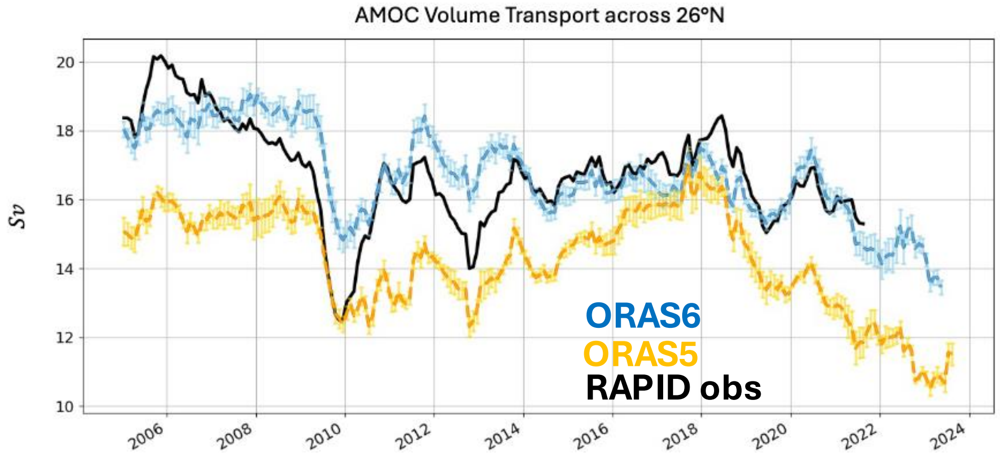


Figure 11 Changes in RMS O-B departures in a) temperature (in K) and b) salinity (in PSU) from ORAS6 w.r.t ORAS5. RMS errors are computed using model short-range forecasts (background) against all active in-situ observations, over 2010-2020 period, and averaged from sea surface to 1000 m depth. Blue colours indicate ocean state variables are closer to observations in ORAS6 than in ORAS5.



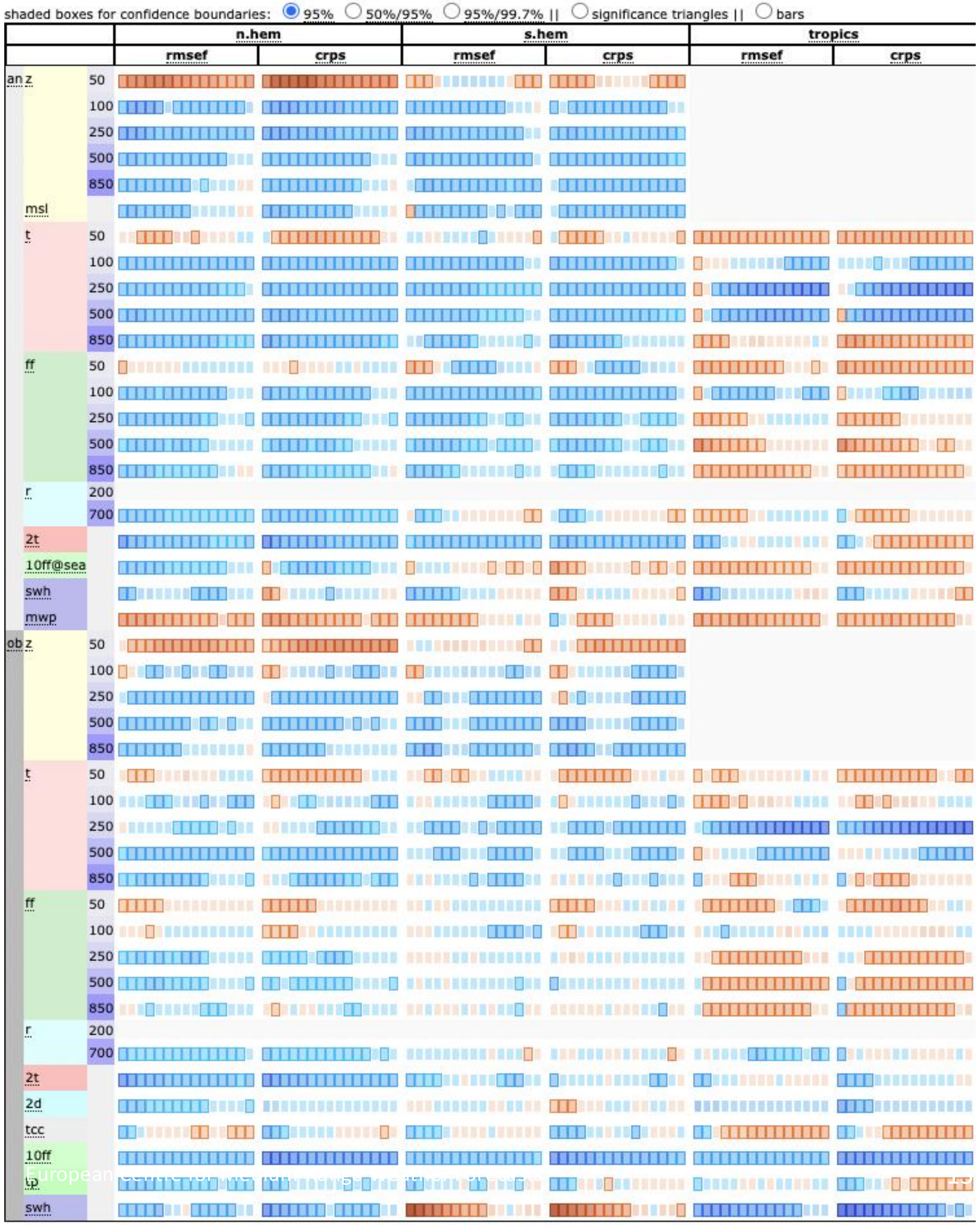
R2O

Cy49r1

- Final 50-member ensemble scorecard for Cy49r1 from initial research testing leading up to release of the Cycle (summer and winter combined, 152 forecasts).
- Particularly strong for 2m temperature and 10m wind

Main changes:

- assimilation of 2m temperature observations
- Land-surface model updates
- activation of the stochastically perturbed parameterisations (SPP) model uncertainty scheme in all ensemble configurations.

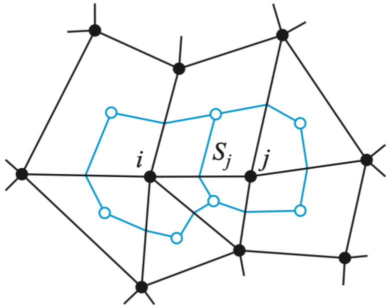


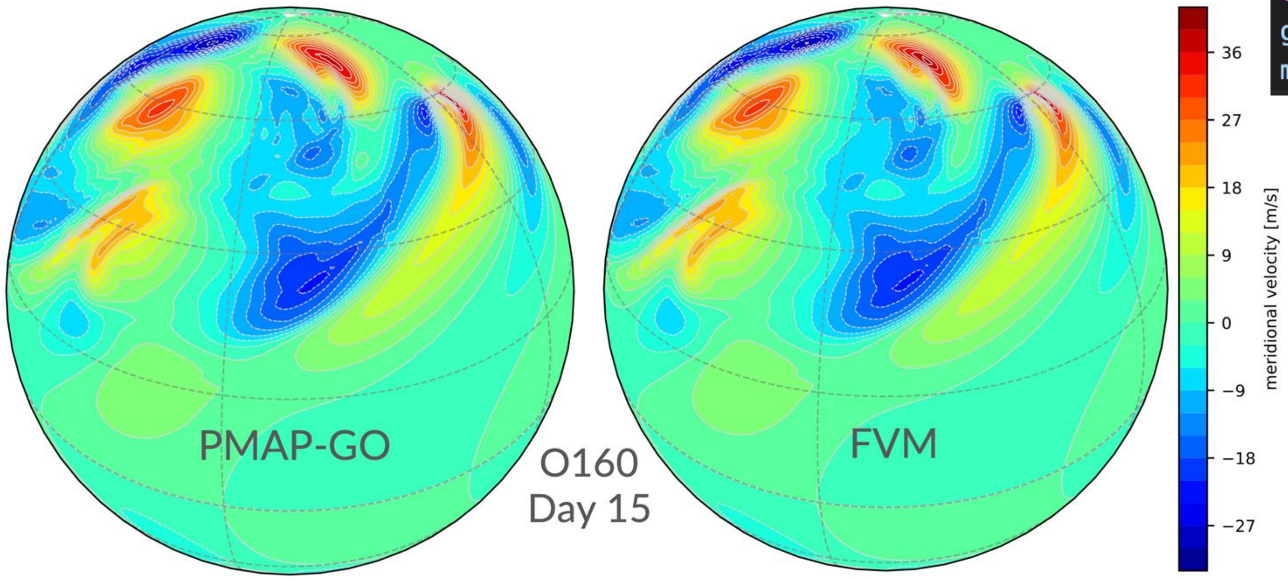
Hybrid 2024 – Adapting IFS to GPUs and accelerators

Model component		Porting method	CPU run time	GPU (Nvidia)			GPU (AMD)	
				Status	Performance	Expected Completion	Status	Perf.
Dynamical core	Spectral Transform	Manual, OpenACC	16%	Done	Good	MS1 (Q1-24)	Optimising	GPU-MPI
	Grid point dynamics	FIELD API + Loki	10%	Porting		MS2 (Q4-24)	Porting	Blocked by compiler
	Semi-Lagrangian	FIELD API + Loki	12%	Optimising	Data transfer MPI comms	MS2 (Q4-24)	Porting	
Physics	EC-physics	FIELD API + Loki	30%	Porting	Data transfer	MS1 / MS 2 *	Porting	
	Surface model	FIELD API + Loki		Porting		MS2 (Q4-24)	Porting	
	Radiation	Loki	5%	Porting	Memory use	MS2 (Q4-24)	Porting	
	Perturbation	FIELD API + Loki	N/A	Porting		MS2 (Q4-24)	Porting	
Wave model	Dy-core	Manual, OpenACC	8%	Done	Good	Q3 2024	Porting	
	Source term	FIELD API + Loki					Porting	
Atmospheric composition		FIELD API + Loki	N/A					
Diagnostics	DDH	CPU-only	N/A					
	FULLPOS	Manual	6%					
Ocean model (NEMO)		CPU-only, PSyclone	6%	Exploring				

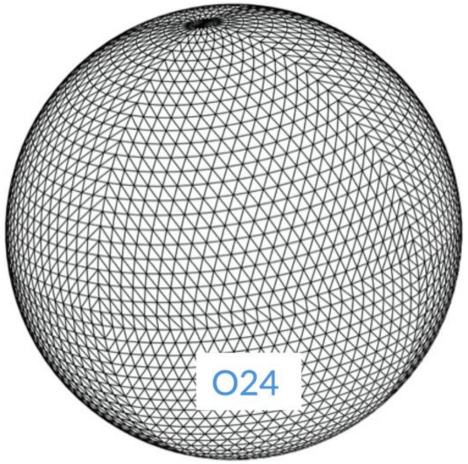
Complete | **Demonstrated** | **Working on it** | **External issues** | **Not started yet** | **Out of scope**

PMAP-GO: Global FVM on Octahedral grid in Python with GT4Py.next

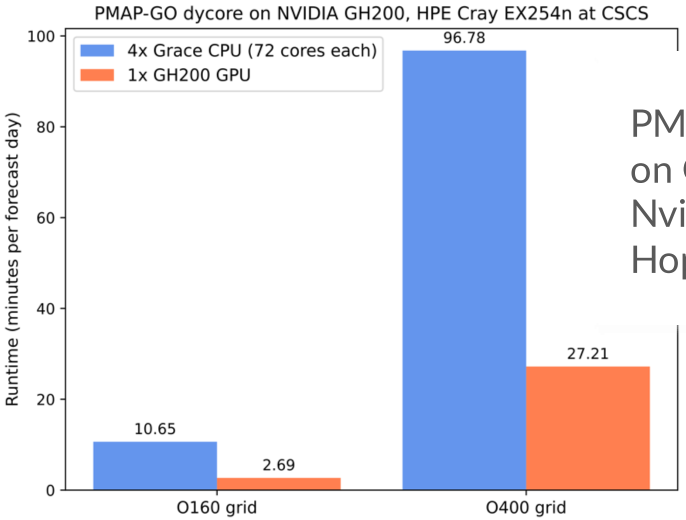





```python
from atlas4py import StructuredGrid
grid = StructuredGrid("O24")
mesh = AtlasMesh.generate(grid)
```




```python
@field_operator
def advection_scheme_upwind(
    rho: Field[[Vertex], float],
    dt: float,
    vel: tuple[Field[[Vertex], float], Field[[Vertex], float]],
    vol: Field[[Vertex], float],
    dual_face_orientation: Field[[Vertex, V2EDim], float],
    dual_face_normal: tuple[Field[[Edge], float], Field[[Edge], float]],
    dual_face_length: Field[[Edge], float]
) -> Field[[Vertex], float]:
    flux = upwind_flux(rho, vel, dual_face_normal, dual_face_length)
    return rho - (dt / vol) * neighbor_sum(
        flux(V2E) * dual_face_orientation, axis=V2EDim)
```



PMAP-GO completely runs on GPU including the latest Nvidia GH200 Grace Hopper Superchip at CSCS

CSCS
Centro Svizzero di Calcolo Scientifico
Swiss National Supercomputing Centre

ECMWF
EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS

ML Project: different paths **towards a ML ensemble prediction 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.

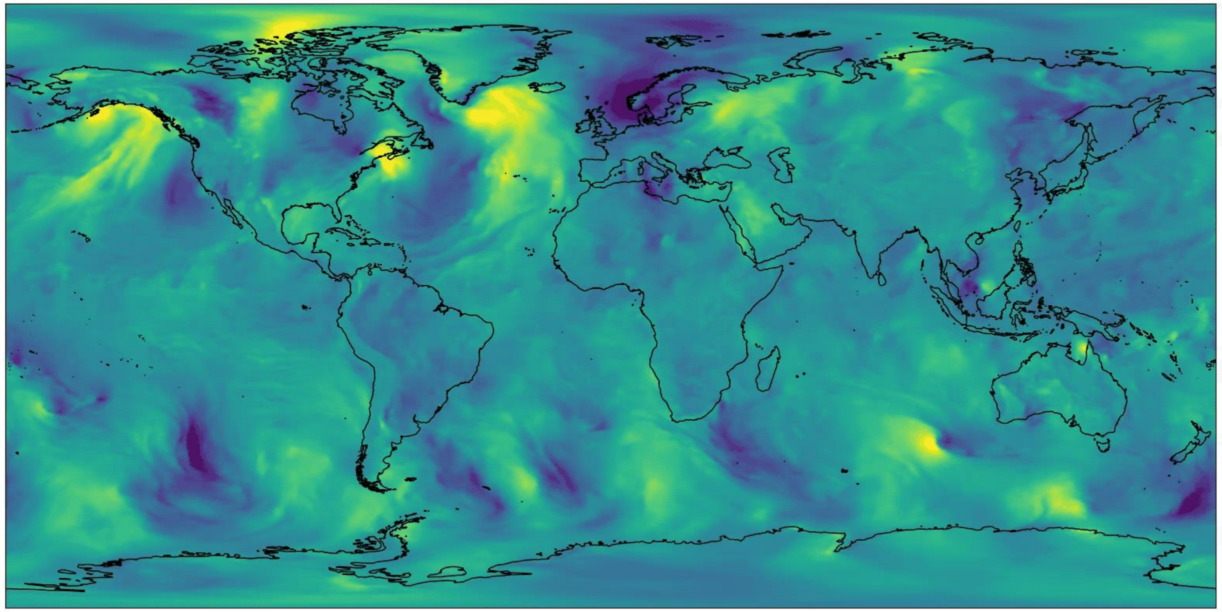
A scientific challenge

Anemoi

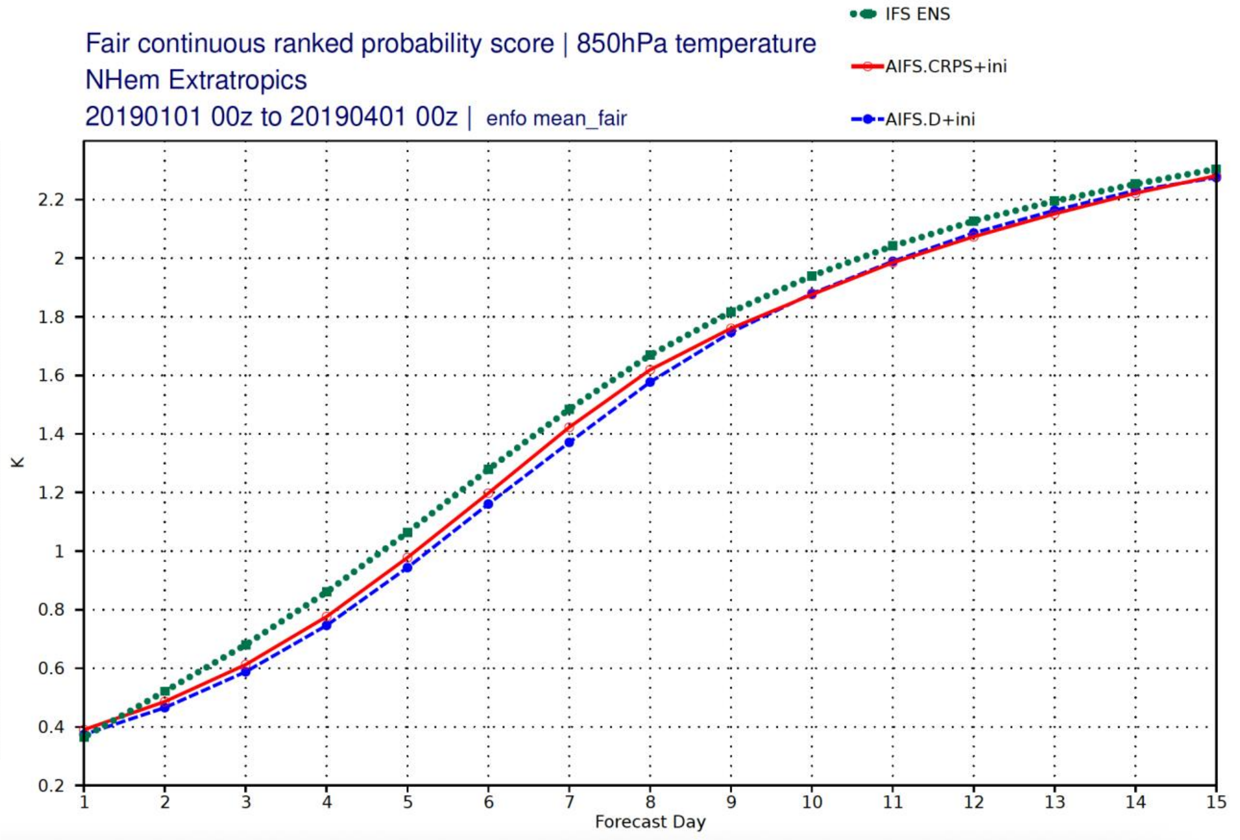
Ensemble AIFS forecast

Preliminary results, ~ 1 deg resolution models (O96)
Two approaches, both outperforming IFS for some headline scores
Diffusion method running live since June 2024, providing data and plots

IFS ENS
AIFS.CRPS+ini
AIFS.D+ini



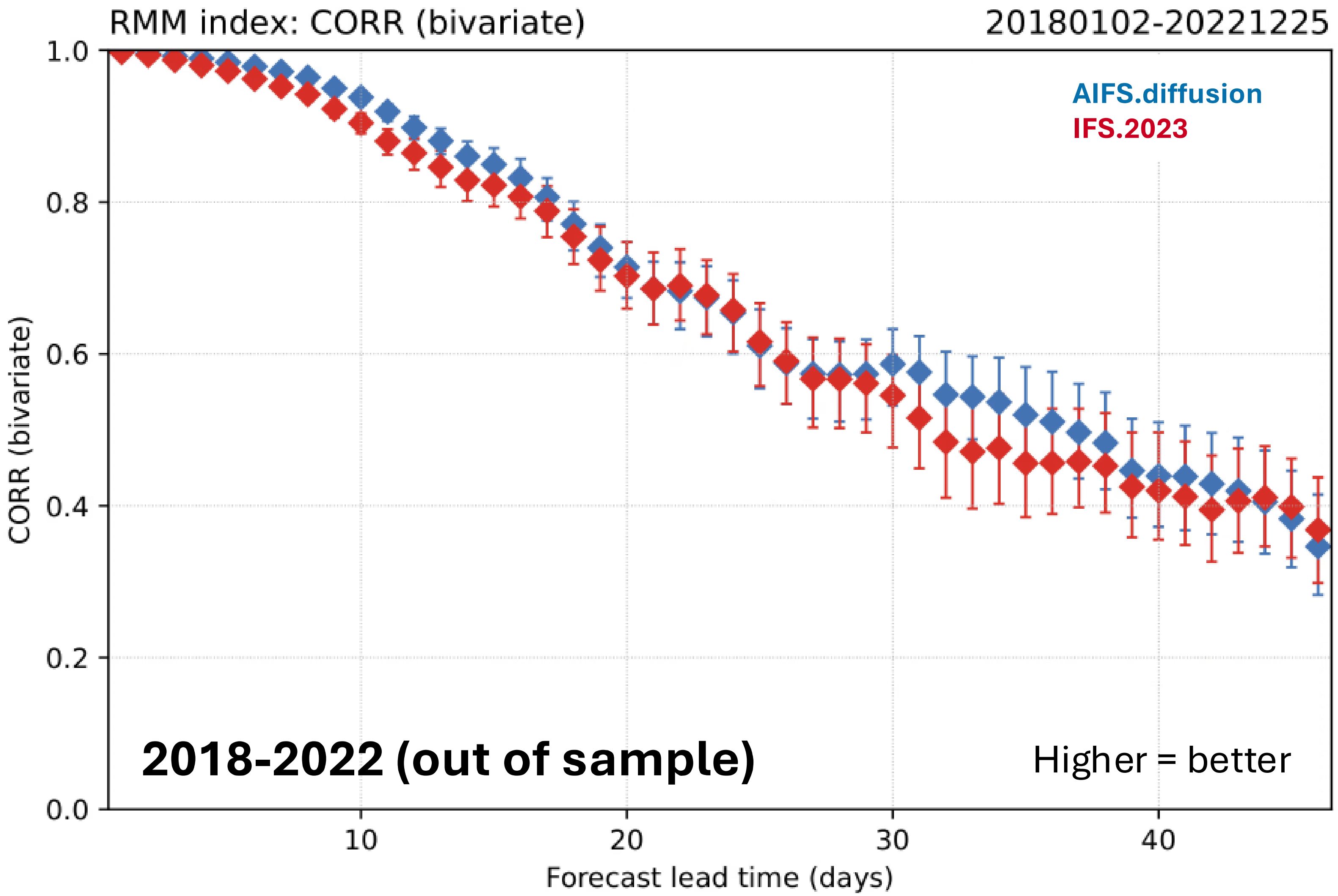
Probabilistic framing encourages prediction of small scales



Lower = better

ECMWF

Sub-seasonal AIFS prediction, first look ...
Madden-Julien Oscillation



Stable predictions with lower biases than the IFS.

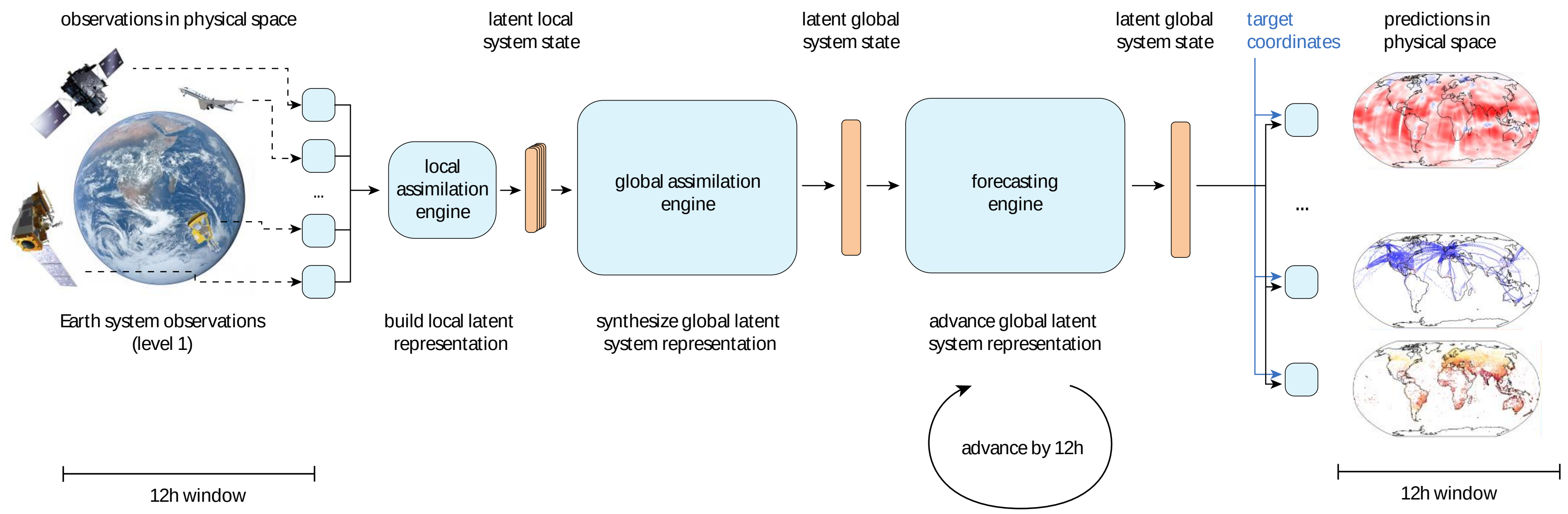
Expect introduction of Earth-system processes to further boost skill.

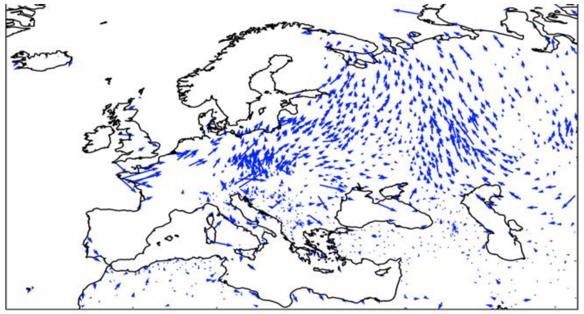
Pushing towards operational sub-seasonal AIFS system.

Data Driven Machine Learning Forecast trained / initialised from observations

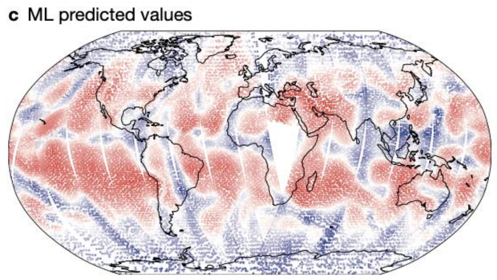
- Using historical measurements (10yrs ++) the network learns correlations between observations from different sources, at different locations and (crucially) at different times.

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

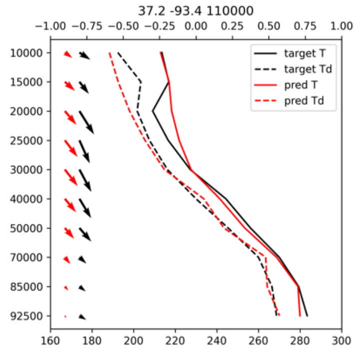




Future SYNOP (T2m / wind)



Future radiances (MW/IR/VIS)

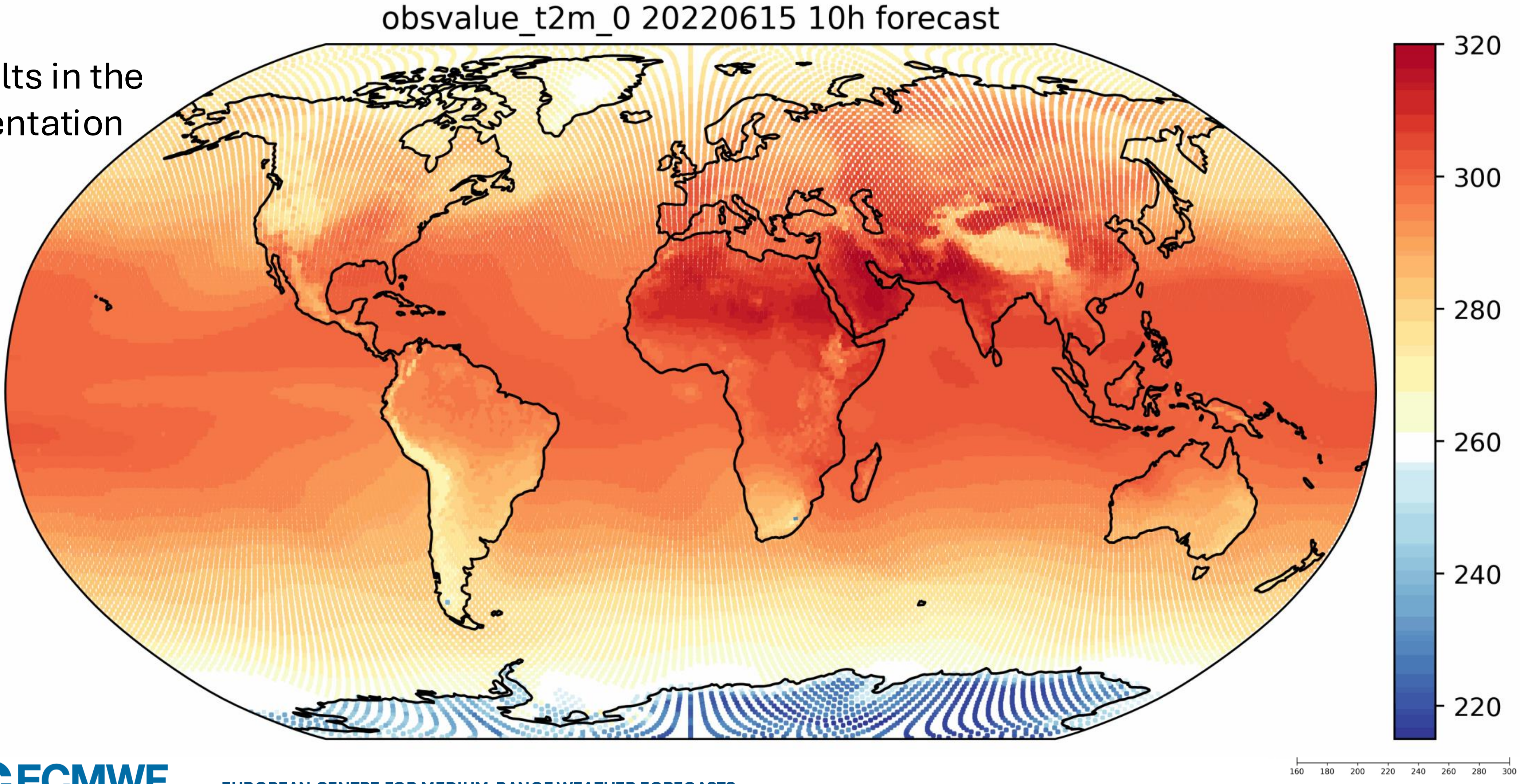


Future SONDES (T / Q / wind)

Data Driven Machine Learning Forecast trained / initialised from observations

10-day forecast trained and initialised only from observations

More results in the ML presentation



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