A machine learning revolution for weather forecasting?

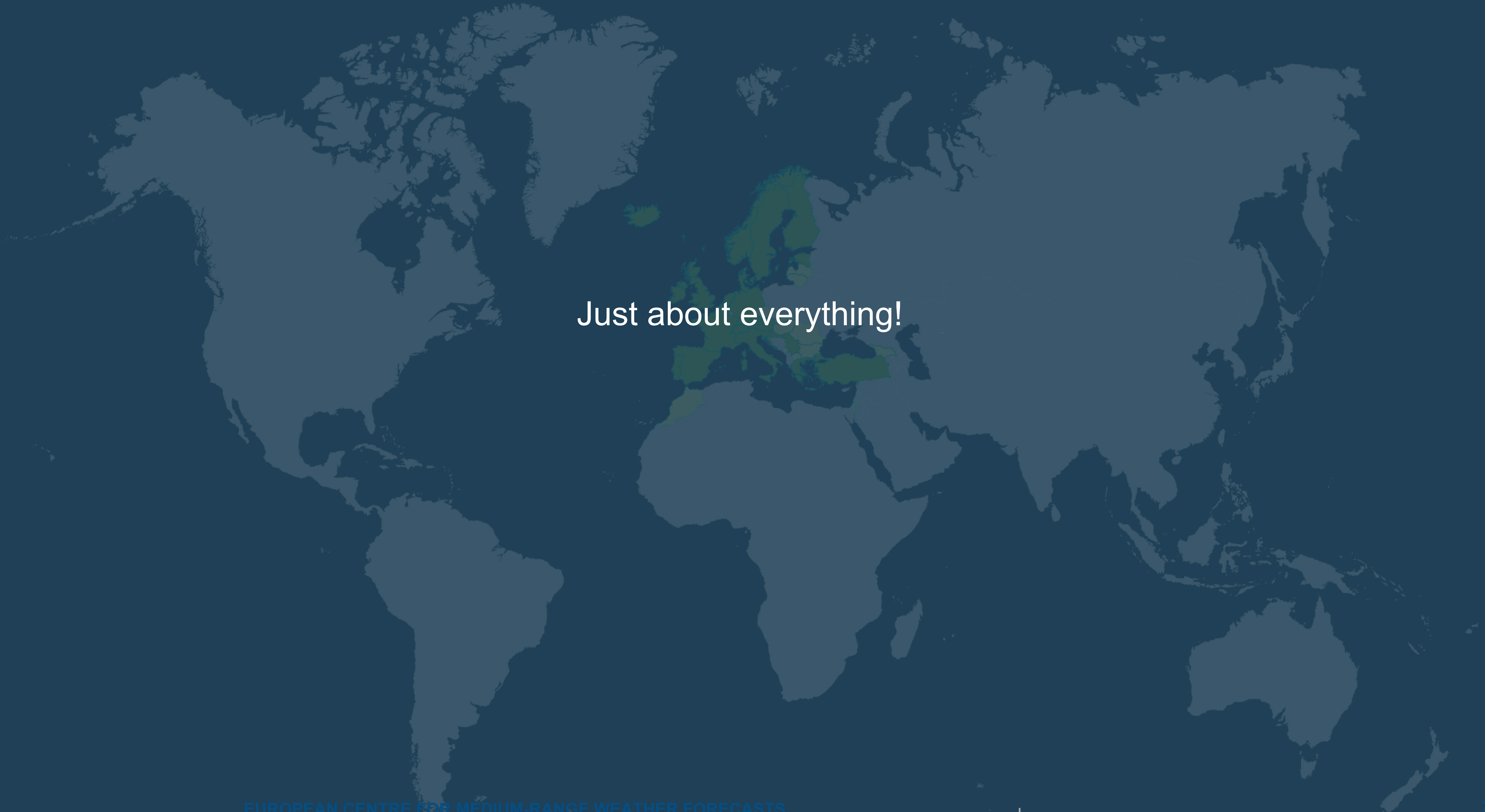
Matthew Chantry

Zied Ben Bouallegue, Linus Magnusson, Simon Lang, Mark Rodwell, Mariana Clare, Mihai Alexe, Jesper Dramsch, Baudouin Raoult, Florian Pinault, Florian Pappenberger and many many more

What’s behind the boom in machine learning?

- Big advances in machine learning architectures, training algorithms and frameworks.
  - Transformer architectures.
  - Self-supervised training, diffusion modelling.
  - PyTorch (and others) with huge community and big-tech support.
- Big advances in computational power.
  - GPUs and other accelerators.
  - NVIDIA (and others) investing in improving the efficiency of basic algorithmic components.
- Consuming huge amounts of data.
  - OpenAI (and others) have trawled the web for all text/images etc.
  - Bad data will lead to bad models.

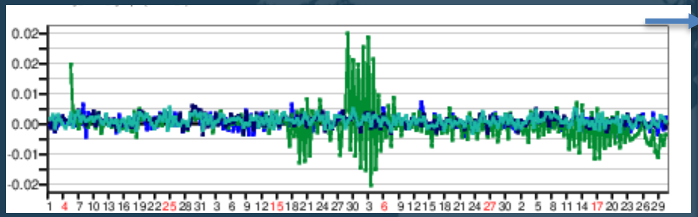
What kind of things are people using ML to do in the earth system?



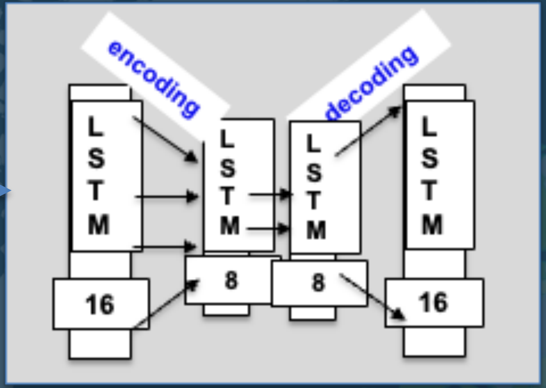
Just about everything!

Machine learning **automated anomaly attribution**

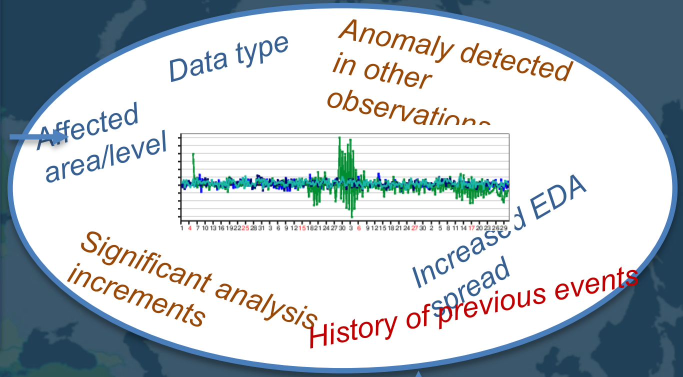
Observation anomaly



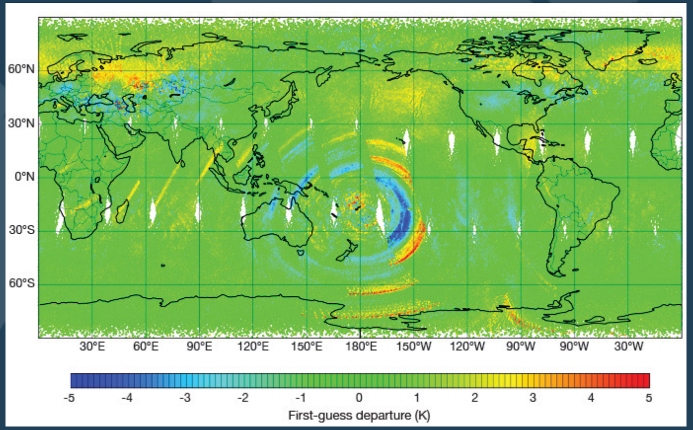
LSTM autoencoder
Detect Anomalies



Random forest classifier
Improves classification



Hunga-Tonga eruption



M. Dahoui

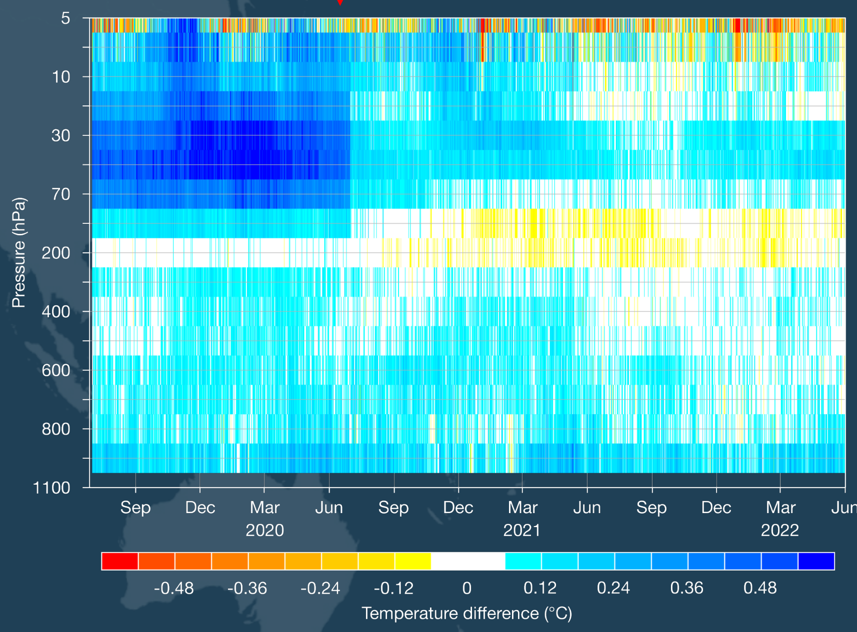
Hybrid NWP+ML – collaboration with CEREA, France

- Hybrid models augment standard physics-based models with a data-driven component:

$$\mathbf{x}_{k+1} = \mathbf{M}^{phys}(\mathbf{x}_k) + \mathbf{F}^{stat}(\mathbf{x}_k, \mathbf{p})$$

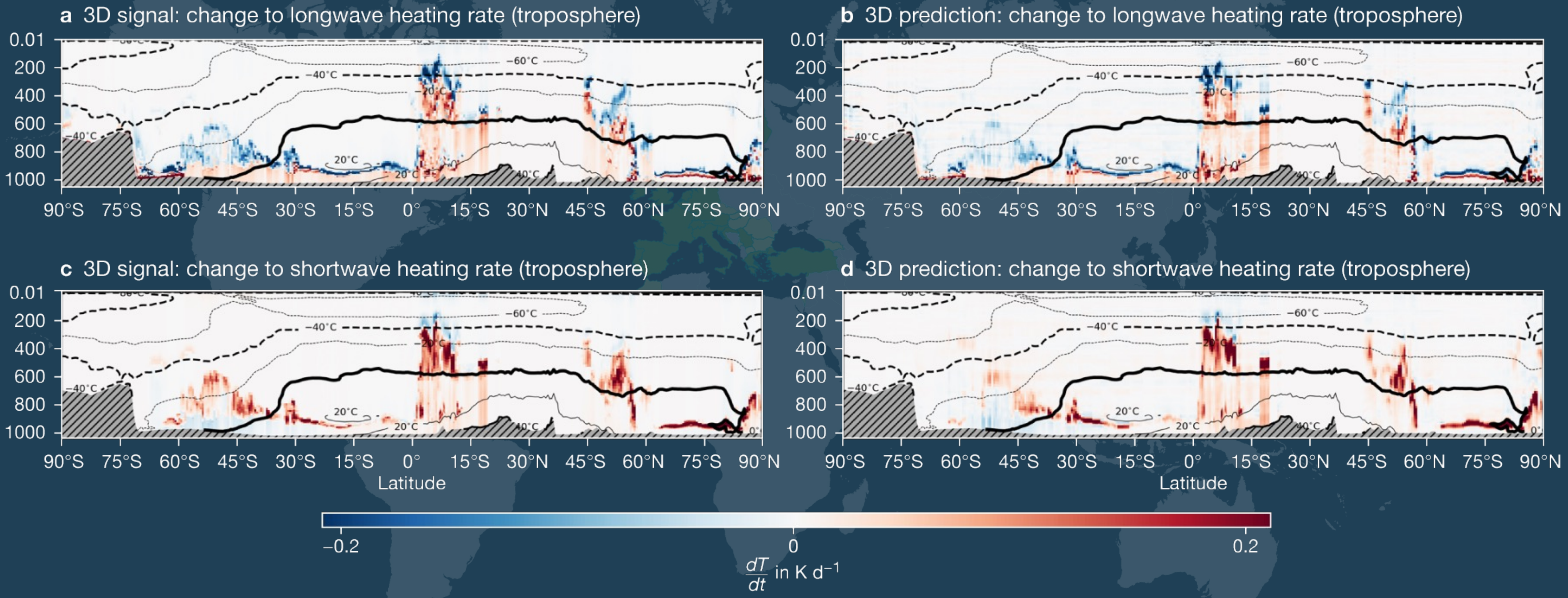
- A hybrid model is already used in the ECMWF weak constraint 4DVar analysis. Can the hybrid model approach be extended to the forecast?
- Bonavita & Laloyaux, 2020 trained offline a neural network (NN) to learn model errors, showing improved forecast skill scores in the full IFS
- Farchi et al., 2022 developed this idea introducing online training of the NN inside 4DVar: this outperforms results from offline training in simplified models.
- Current work, testing in the full IFS: results appear promising!

Introduction of bias correction within 4D-var improved stratospheric representation.
Next step NN trained within 4D-var…

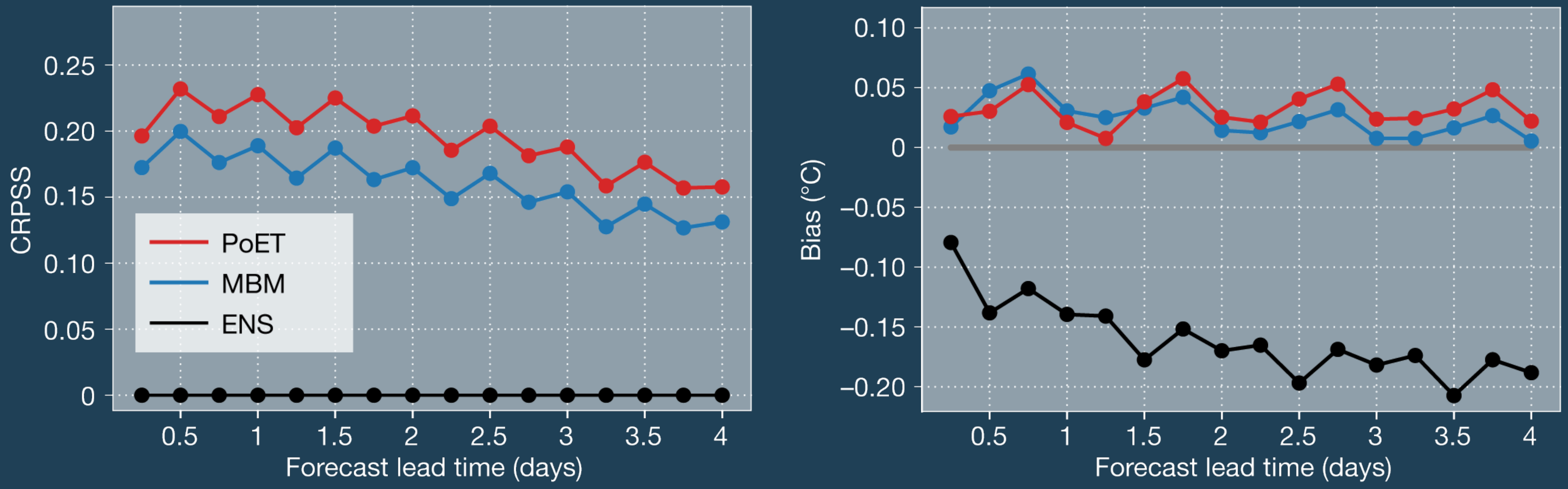


Alban Farchi & Marc Bocquet
@ CEREA

Using neural network emulators



PoET – Postprocessing Ensembles with Transformers (collaboration with Microsoft)



- Improving 2m-temperature ensemble predictions.
- Using transformers to debias and improve the calibration of forecasts.
- Forecasts have smaller bias and better calibration, and compares favourably to a leading method from statistical postprocessing.

Jonathan Weyn, Microsoft
Visiting Scientist at ECMWF

What's behind the boom in machine learning?

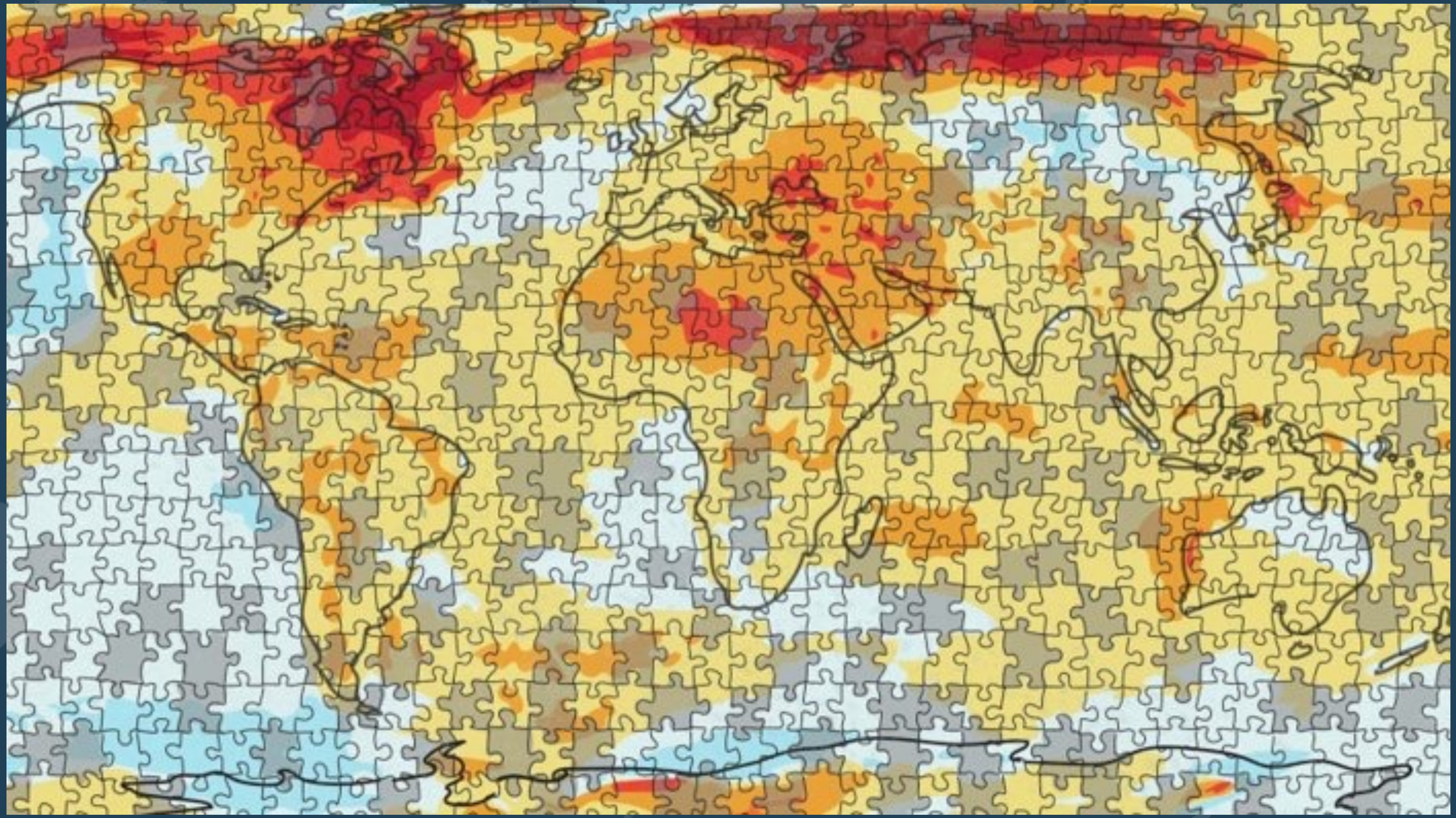
- Big advances in machine learning architectures and training algorithms.

- Big advances in computational power.

- Consuming huge amounts of data.
  - Learning from observations is hard.
    - Data is stored in many different places, and formats.
    - Observations change over time.
    - Data has biases and errors.
    - Requiring multiple variables can mean using multiple observation datasets.

Reanalysis for machine learning

- Reanalysis provides singular point of “truth”.
- Many variables.
- All times.
- All points in space.
- All accessible from one access point.



Is reanalysis sufficient to learn a global forecasting system?

Simple problem framing.

- Given state of ERA5 at a random point in time, x(t).
- Construct a model F, a neural network parametrised by weights.
- Predict a future state of ERA5, $x(t+dt) \simeq F(x)$.
- Seek to minimise $[x(t+dt) - F(x(t))]^2$ using gradient descent.
  - i.e. change the weights in such a way to decrease the MSE.
- Randomly draw a new x and repeat.

Is reanalysis sufficient to learn a global forecasting system?

Simple problem framing.

- Given state of ERA5 at a random point in time, $x(t)$. Typically u, v, t, z, q on ~10 pressure levels and 2t, 10u/v, sp.
- Construct a model F, a neural network parametrised by weights. Big models, $O(10^7)$ parameters.
- Predict a future state of ERA5, $x(t+dt) \simeq F(x)$. Typically 6-hour timestep!
- Seek to minimise $[\, x(t+dt) - F(x(t)) \,]^2$ using gradient descent.
    - i.e. change the weights in such a way to decrease the MSE.
- Randomly draw a new x and repeat. Many many times, passing through ERA5 O(100) times.

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

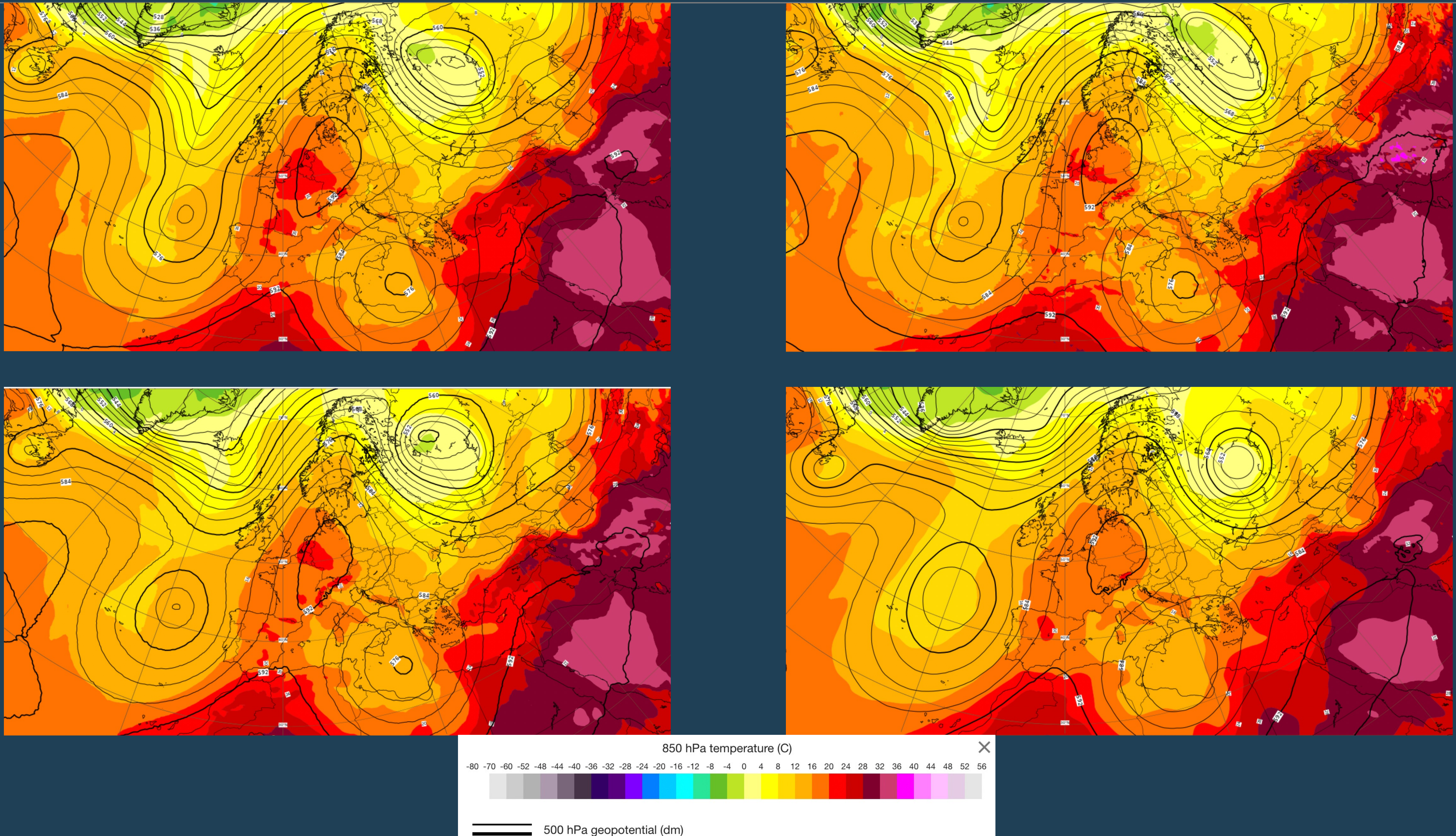
Diffusion modelling

Alibaba – SwinRDM
0.25° 6-hour product

Sharp spatial features

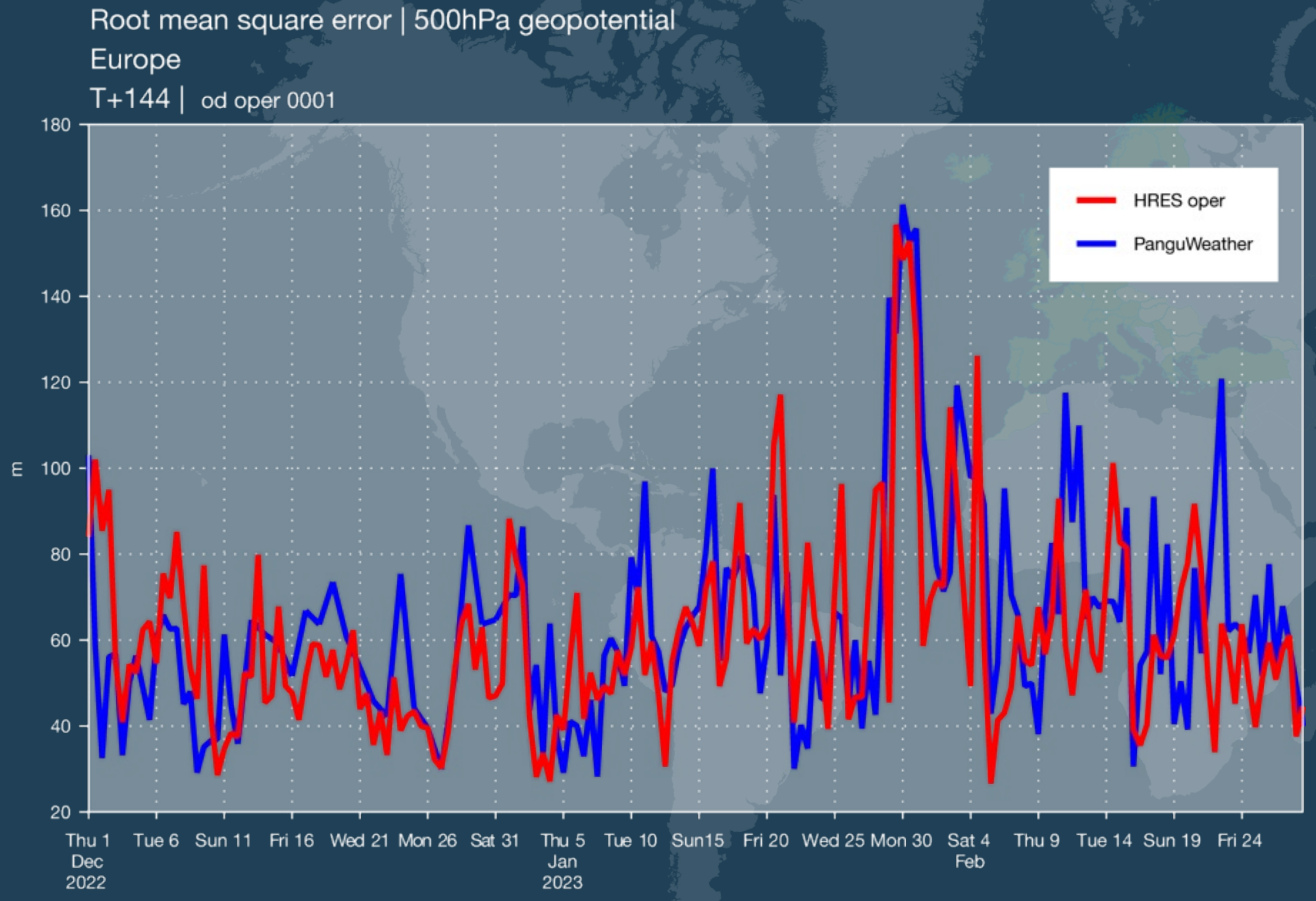
What ML models are showing...

Day 4 forecasts over Europe (valid 7 Sept 2023 12UTC)

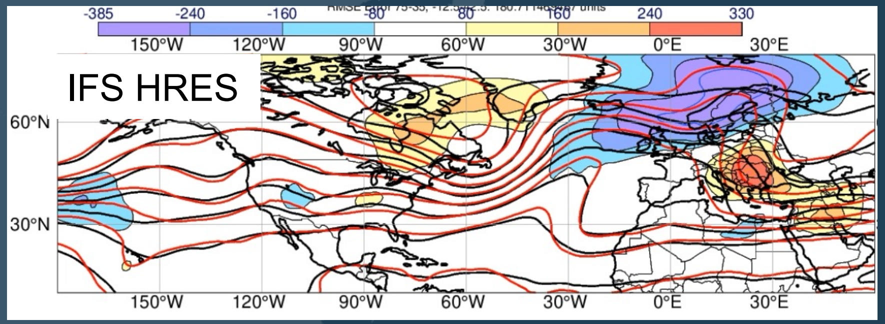


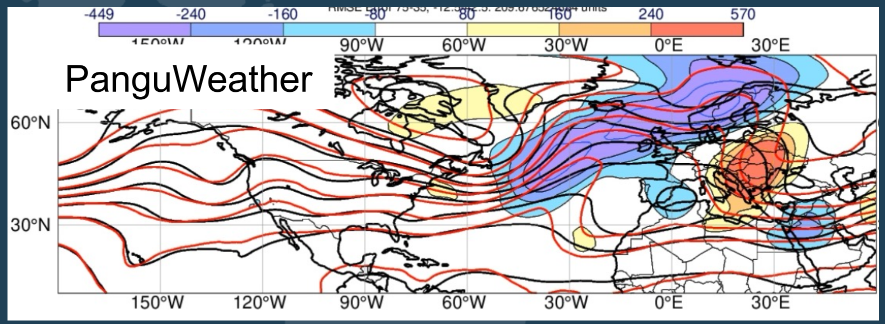
Time-series of day 6, RMSE over Europe

Same starting point....similar results

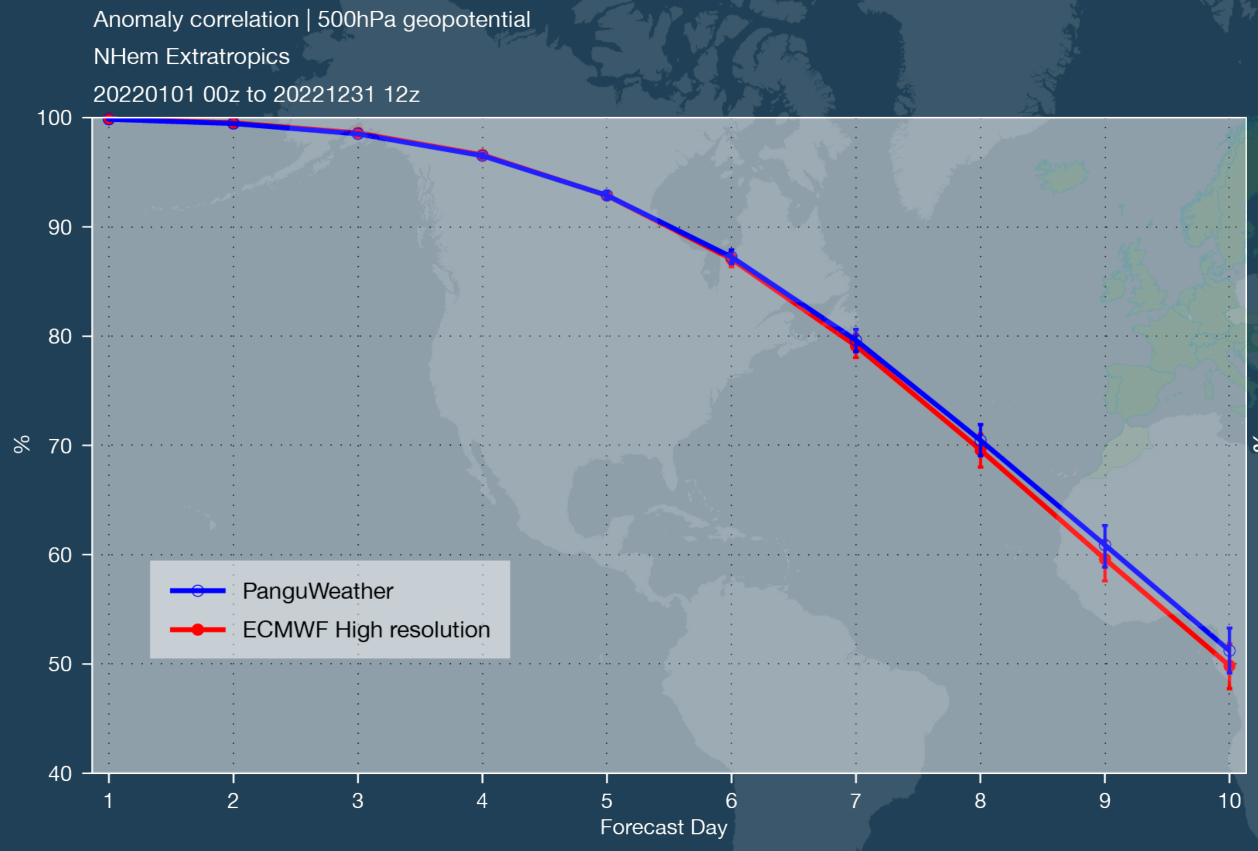


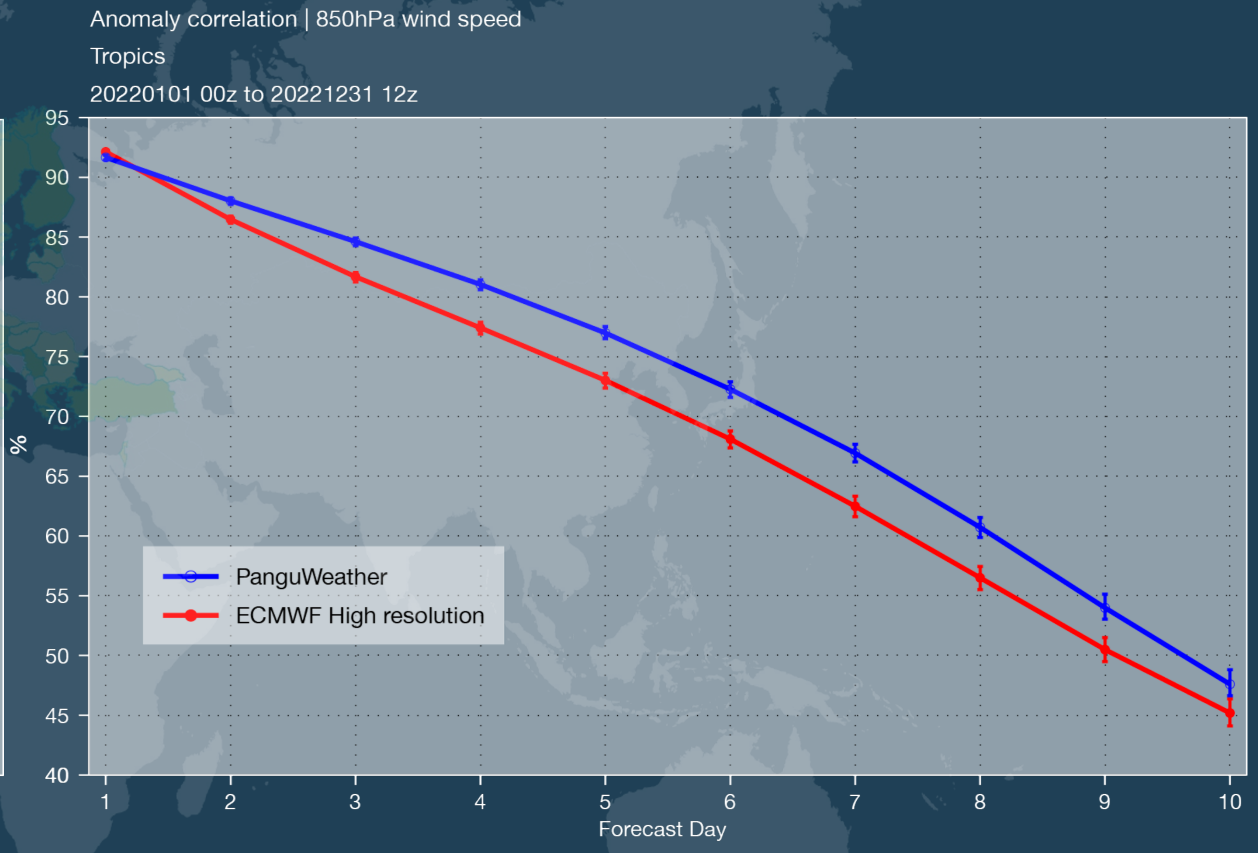
+144h forecast errors 30 January 00UTC



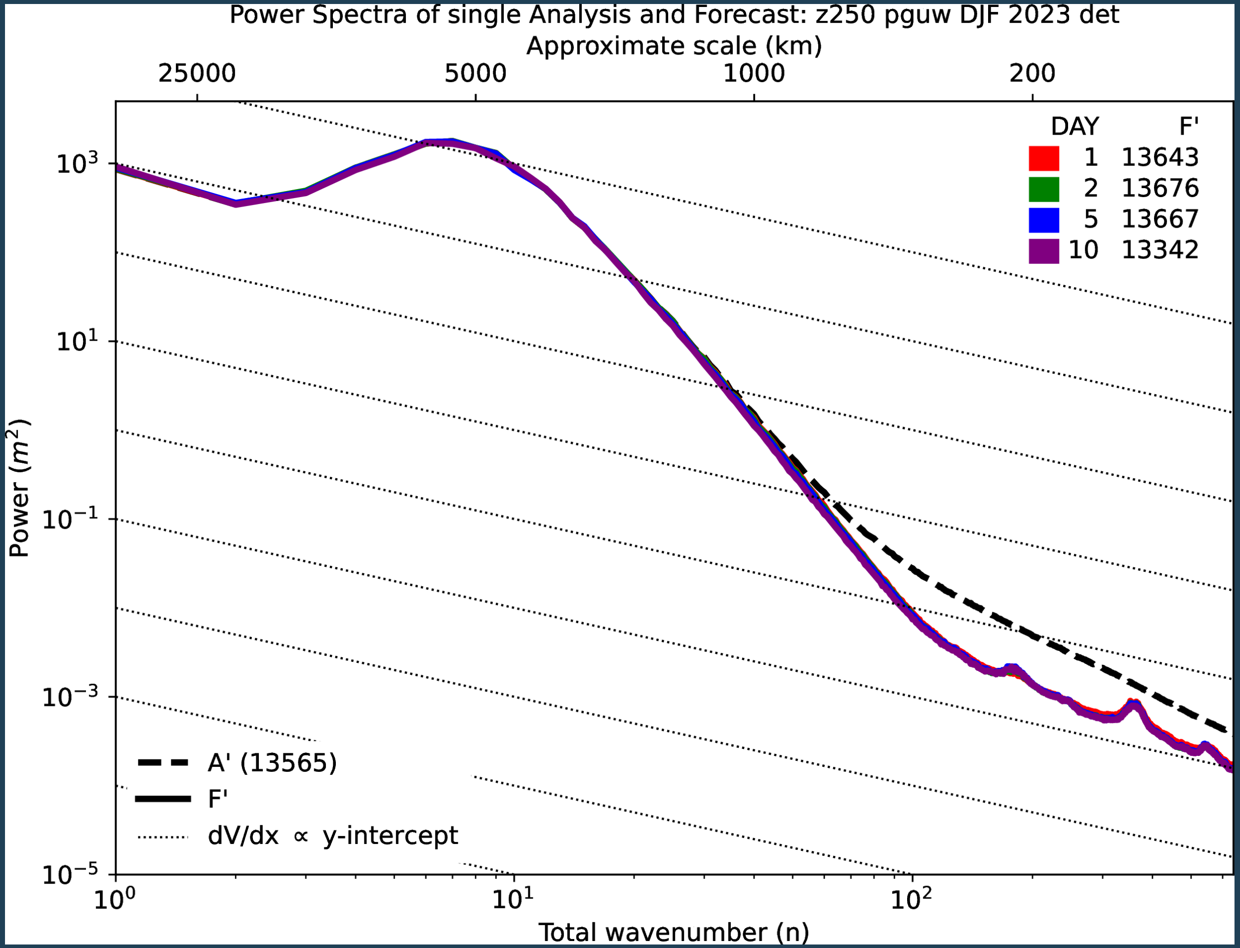


What the analysis is showing: **an undeniable skill**





Digging into the scores: RMSE, bias and forecast variability DJF 2022/2023



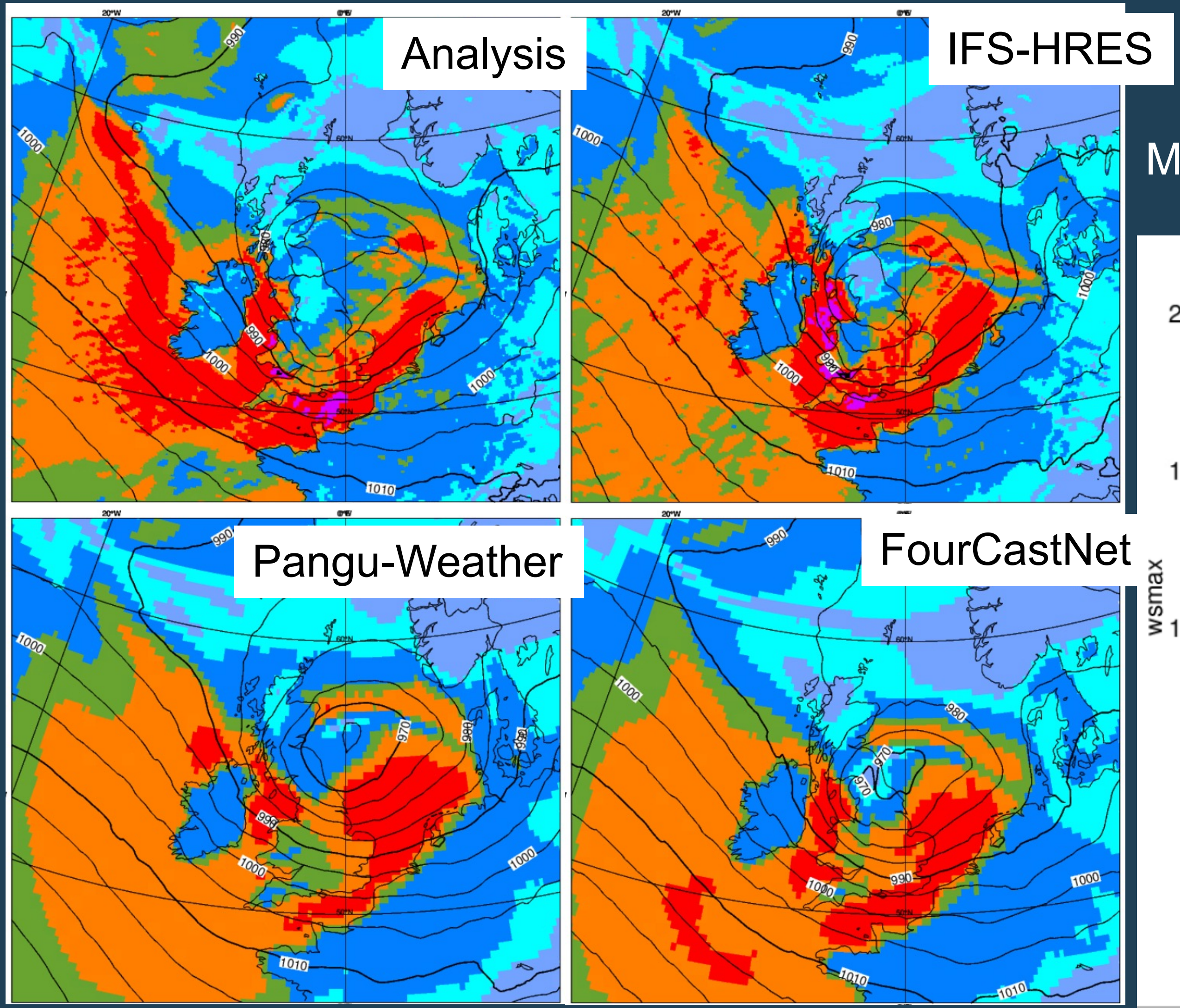
Why is the RMSE lower in PanguWeather?

- Not a clear reduction in forecast activity in PanguWeather
  - …but smoothing of small scales
- Strong model drift in Pangu
  - …but regional biases are improved

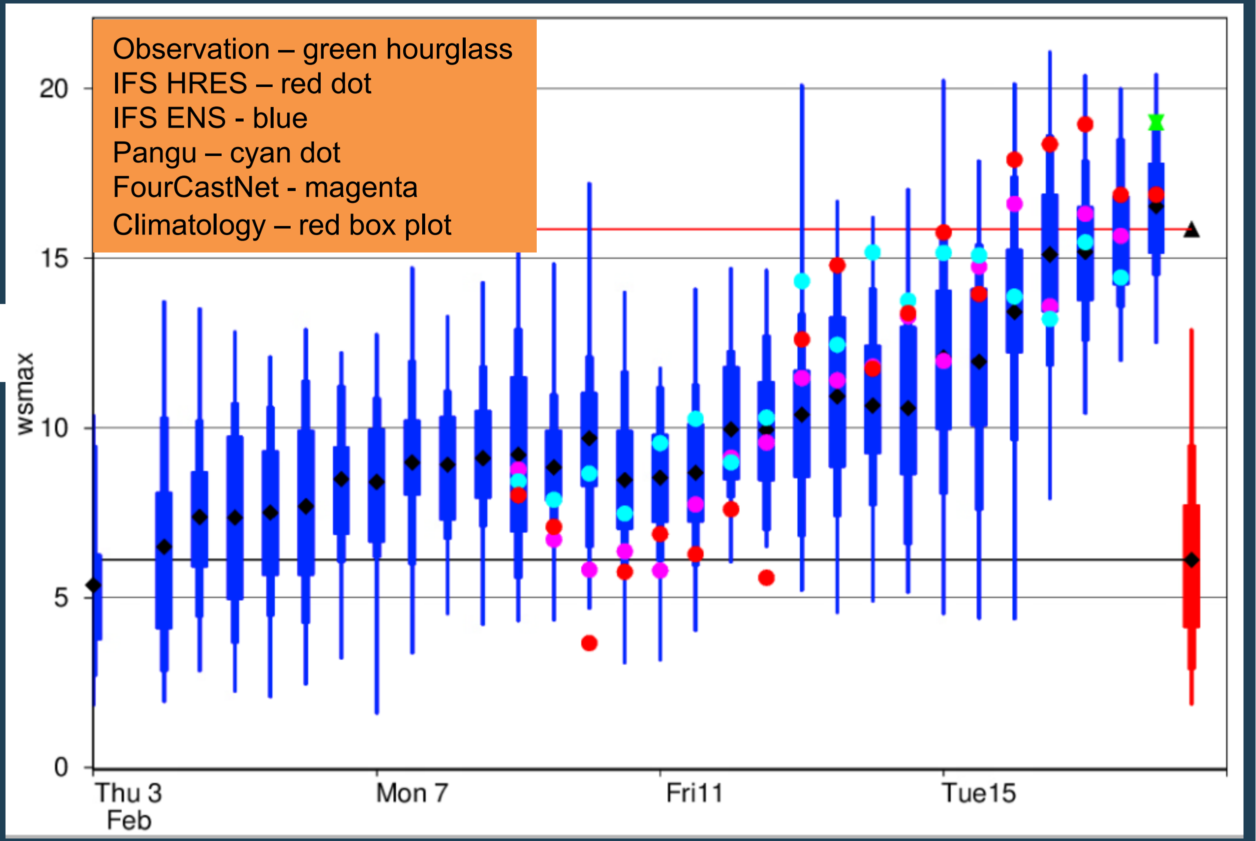
Scope for further investigations to understand the differences

What about high-impact events?

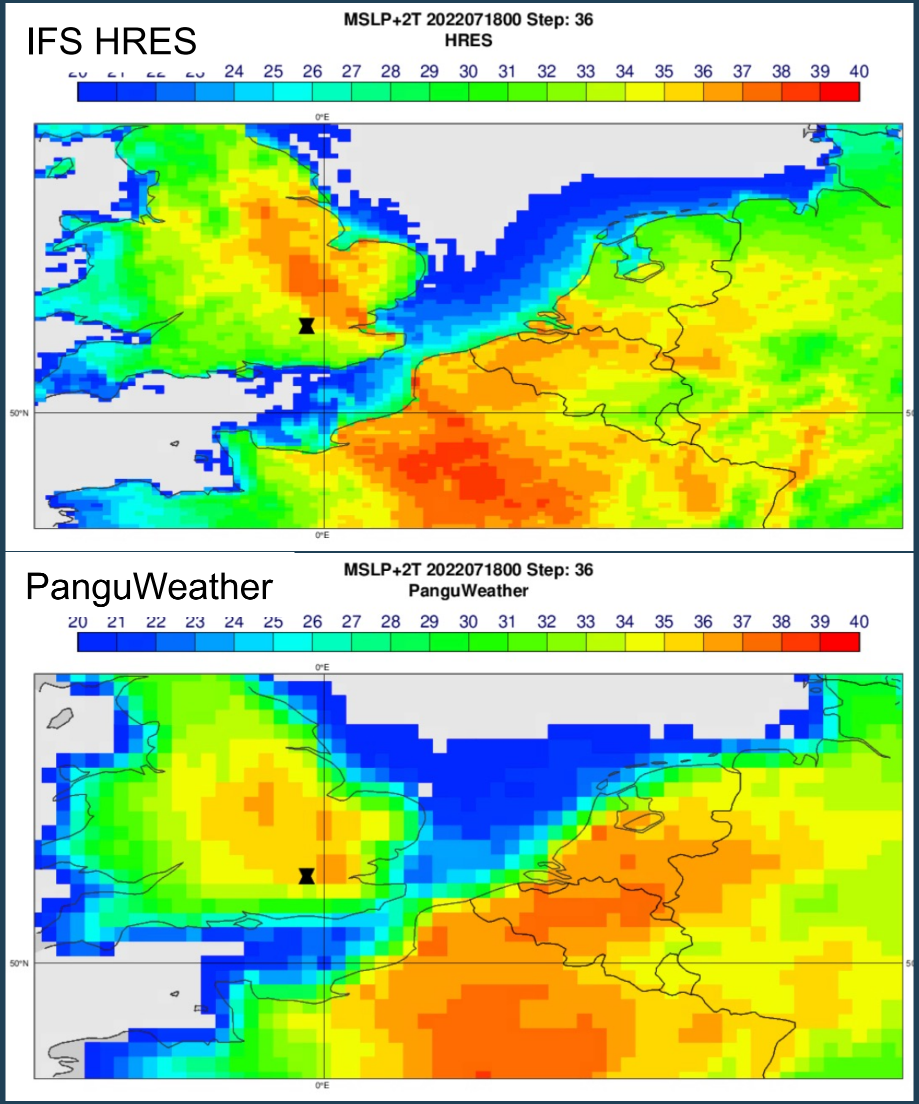
Storm Eunice (2.5-day forecasts valid18th Feb 2022 12UTC)



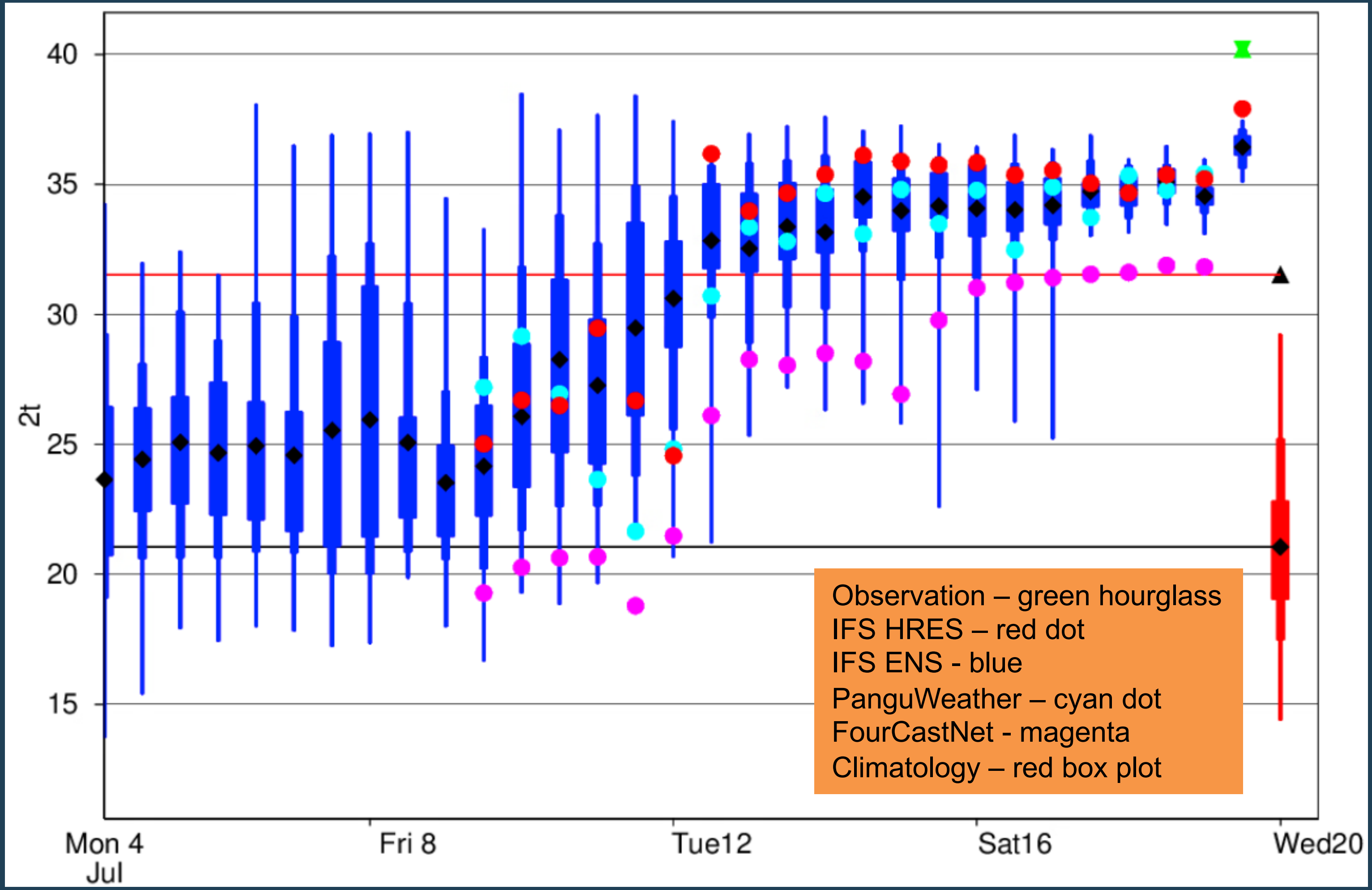
Maximum mean wind Heathrow 18 Feb (00, 06, 12 and 18



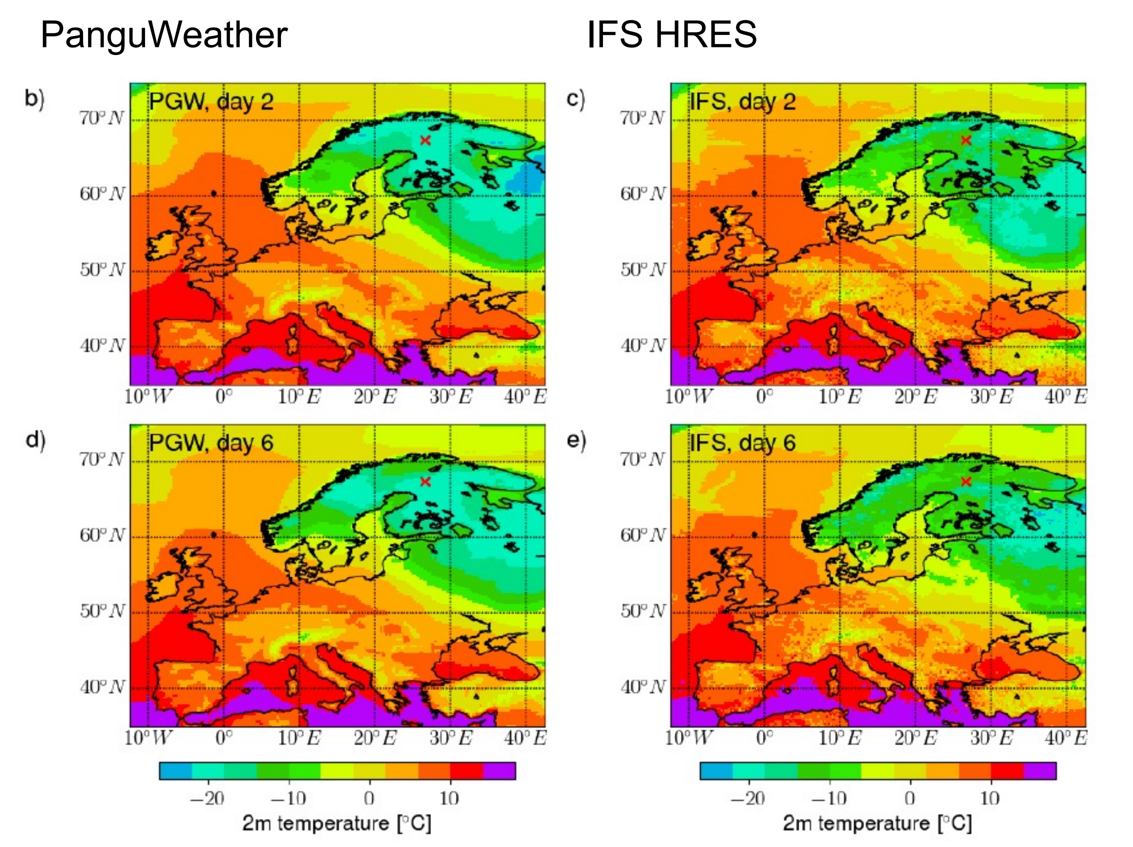
UK heatwave 2022



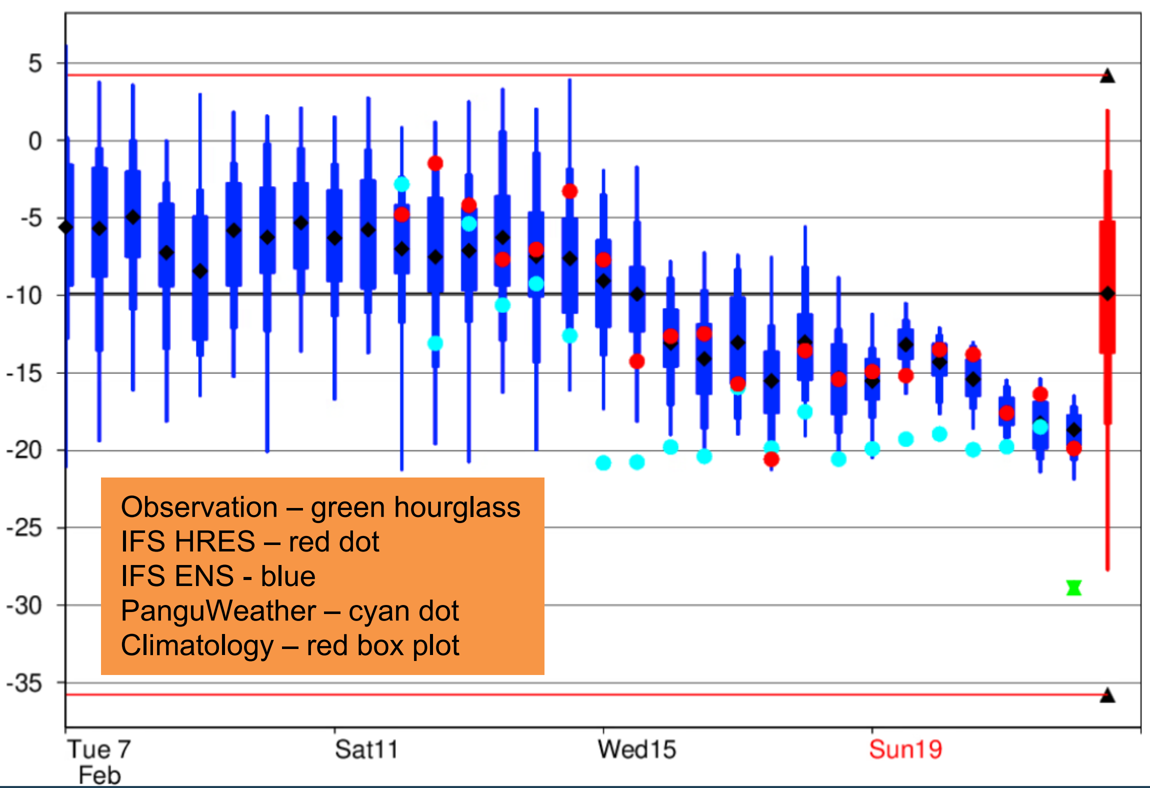
2m temperature Heathrow 19 July 12UTC



Cold snap over northern Europe Feb 2023



2m temperature Sodankyla 22 February 00UTC

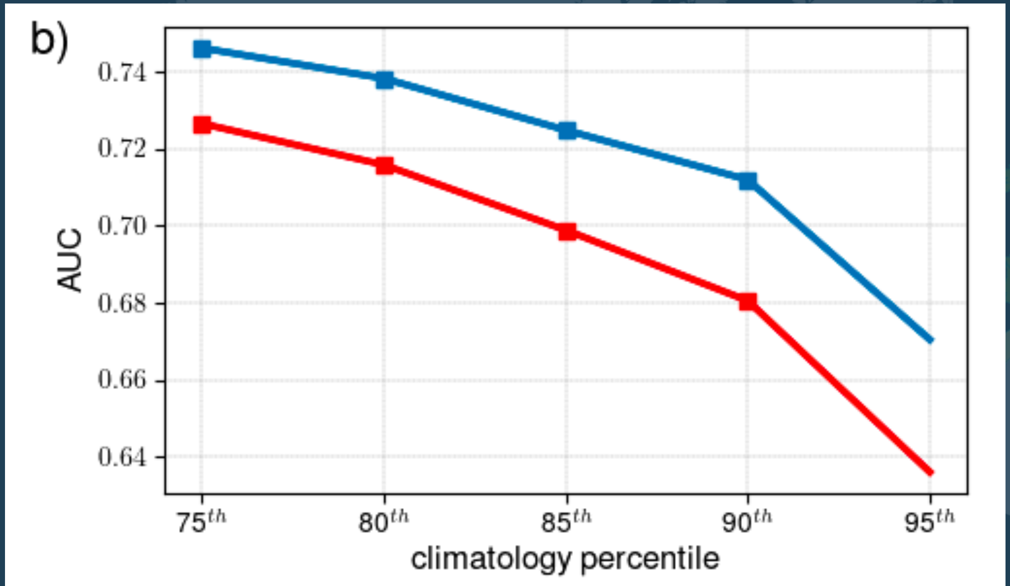


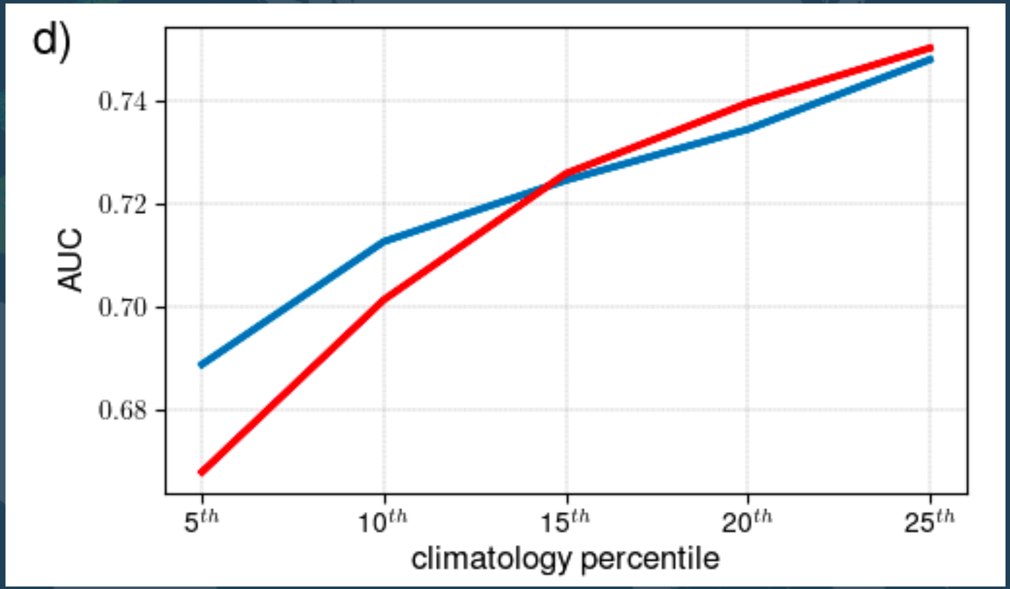
Potential discrimination ability (ROC area) for day 6 forecasts

warm **summer** day

IFS –red
PanguWeather - blue

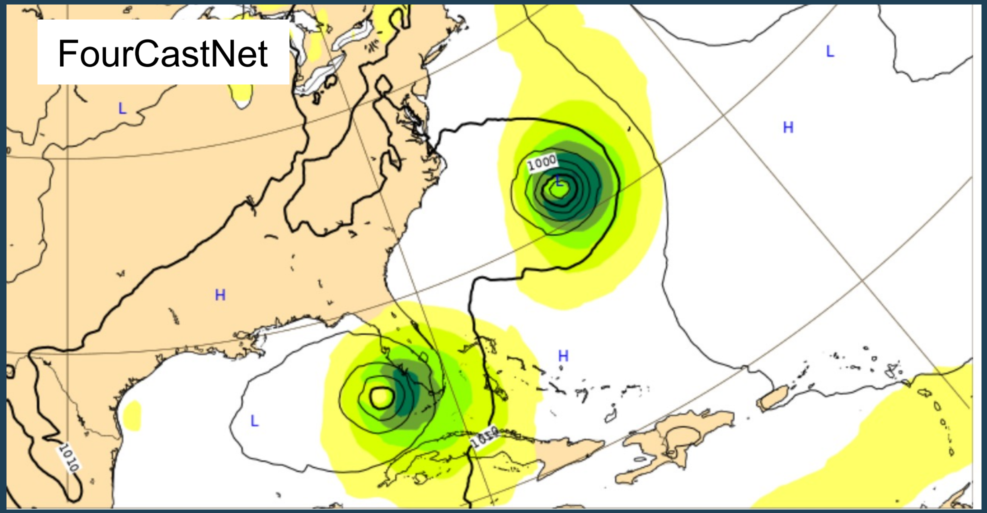
cold **winter** days

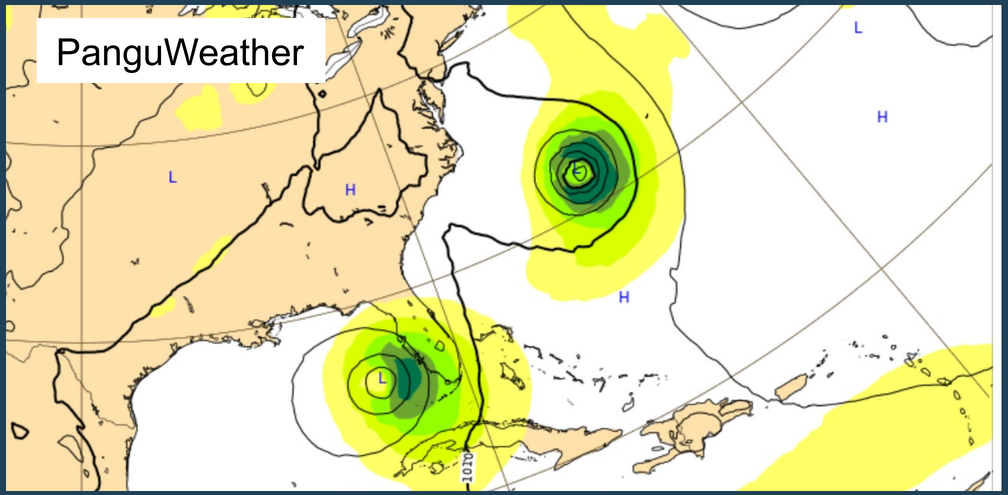


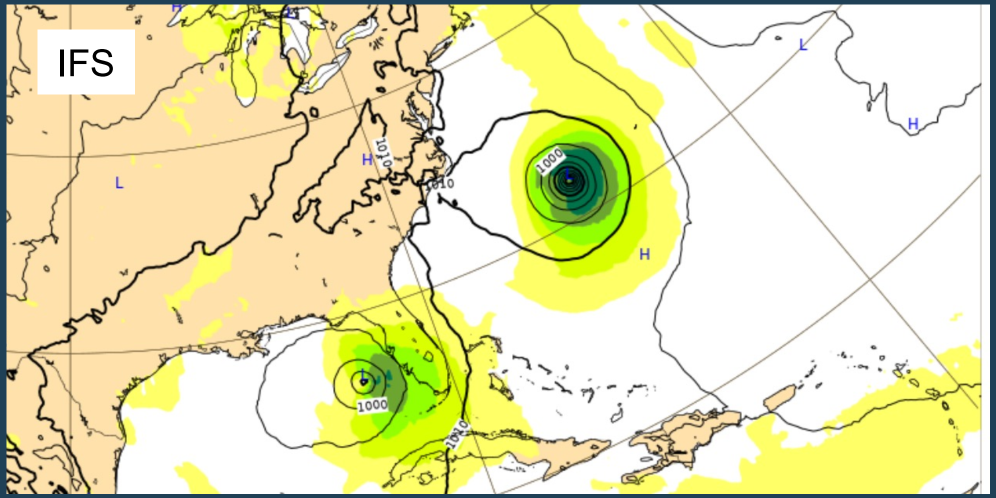


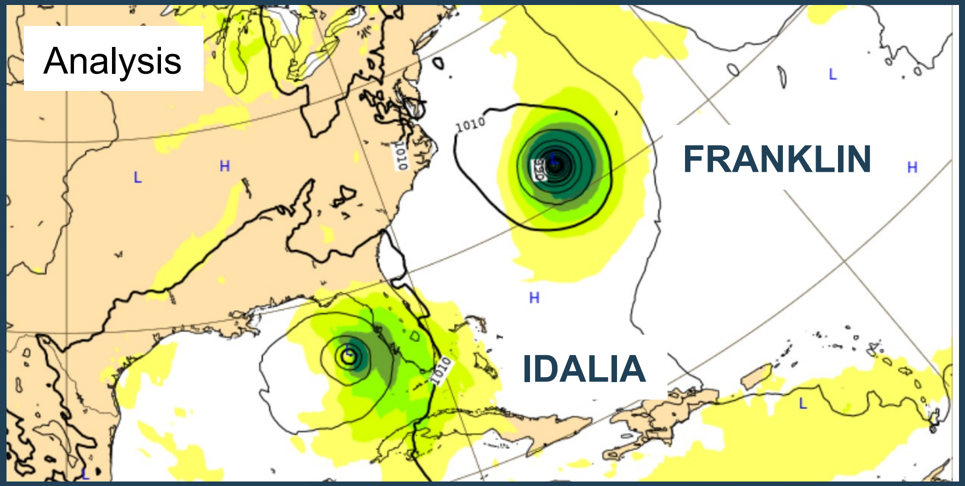
PanguWeather better for both warm and cold extremes, based on climatological threshold from own climate

Tropical cyclones Idalia and Franklin (day 2 forecasts, valid on 30 Aug 2023 00UTC)





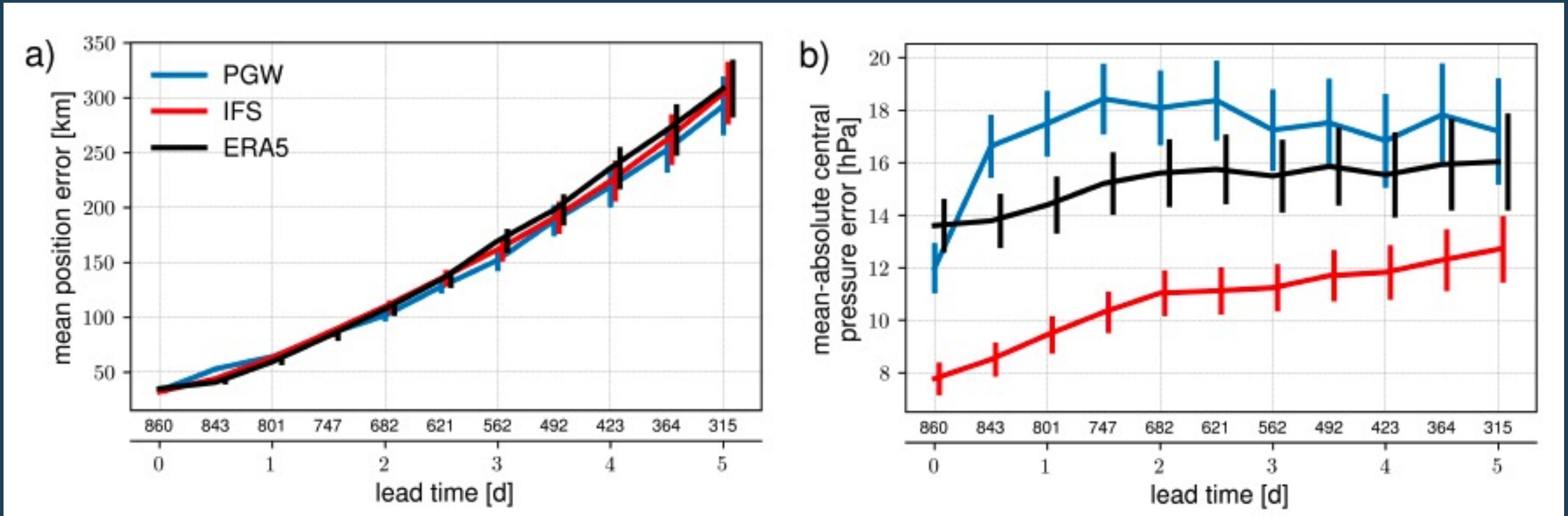




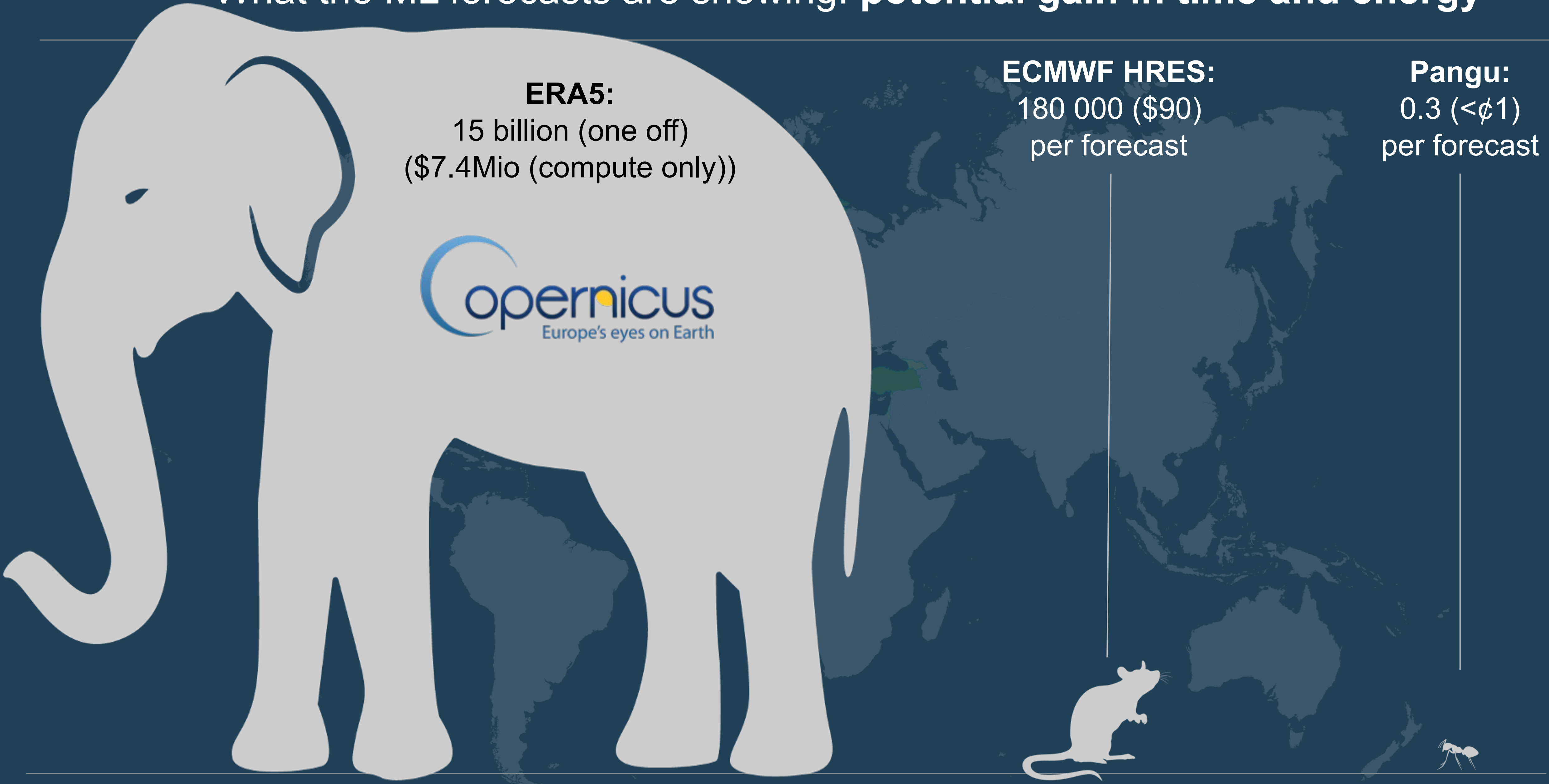
Tropical cyclone verification

Position error

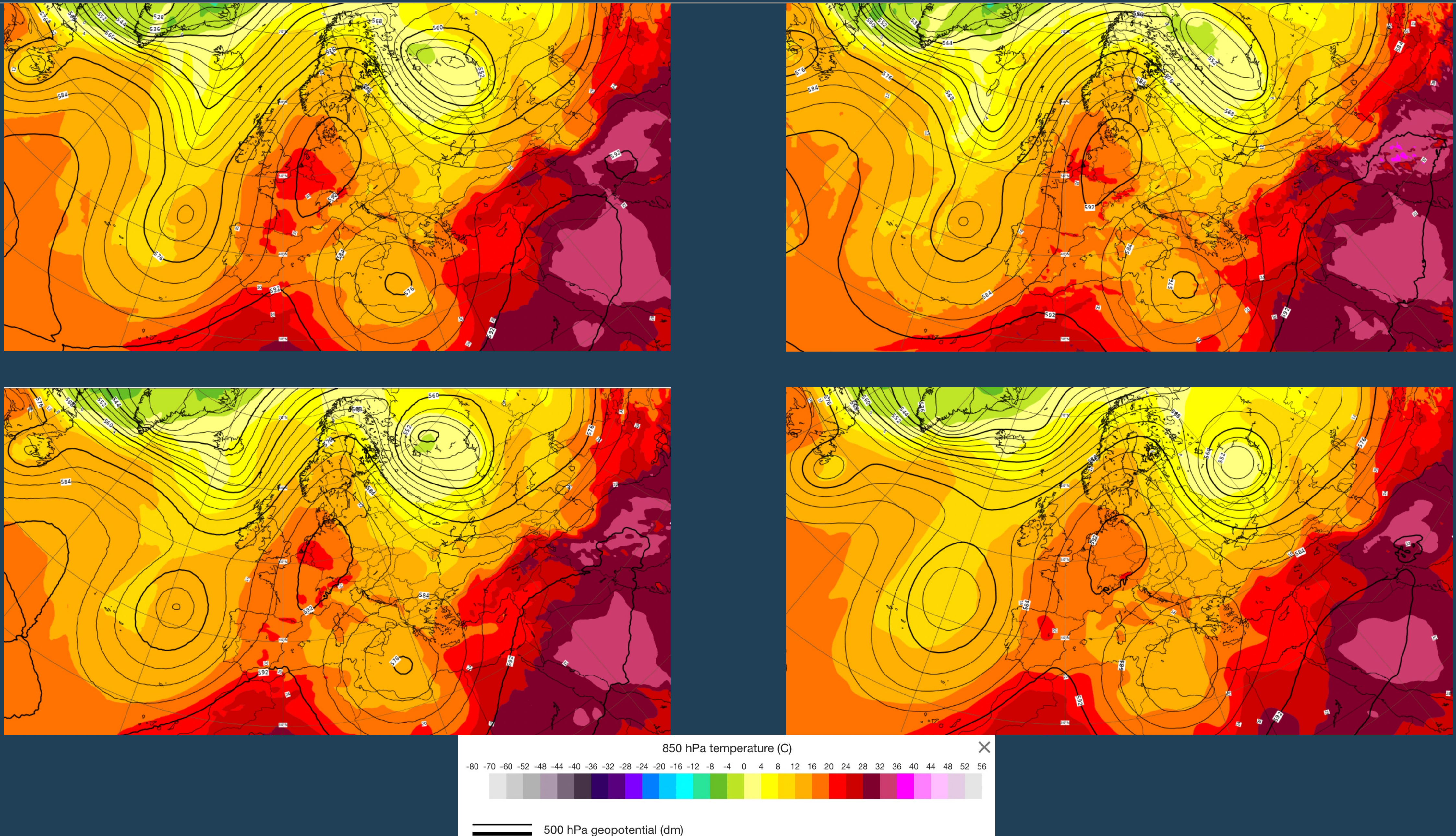
Intensity bias



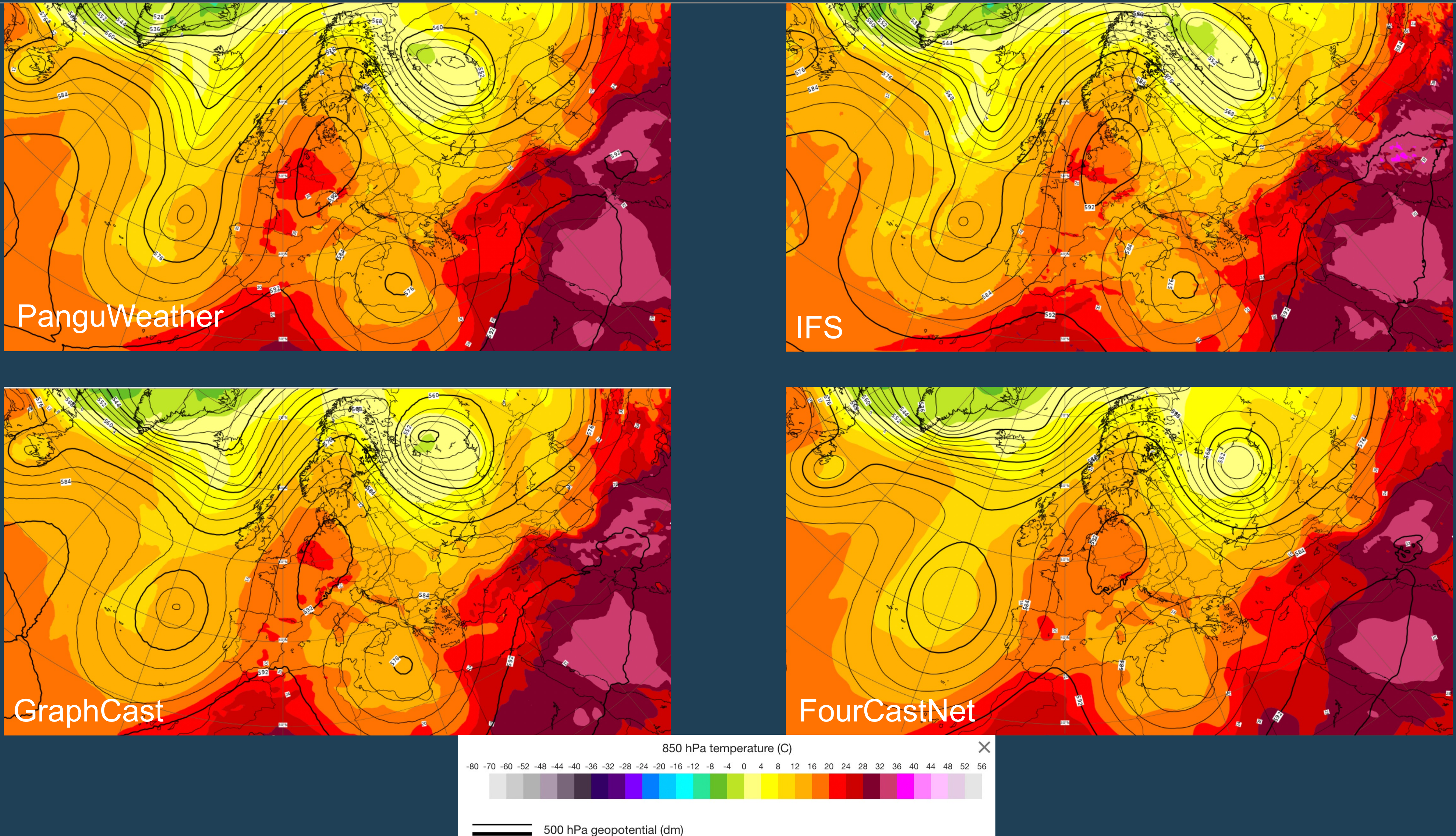
What the ML forecasts are showing: **potential gain in time and energy**



Day 4 forecasts over Europe (valid 7 Sept 2023 12UTC)

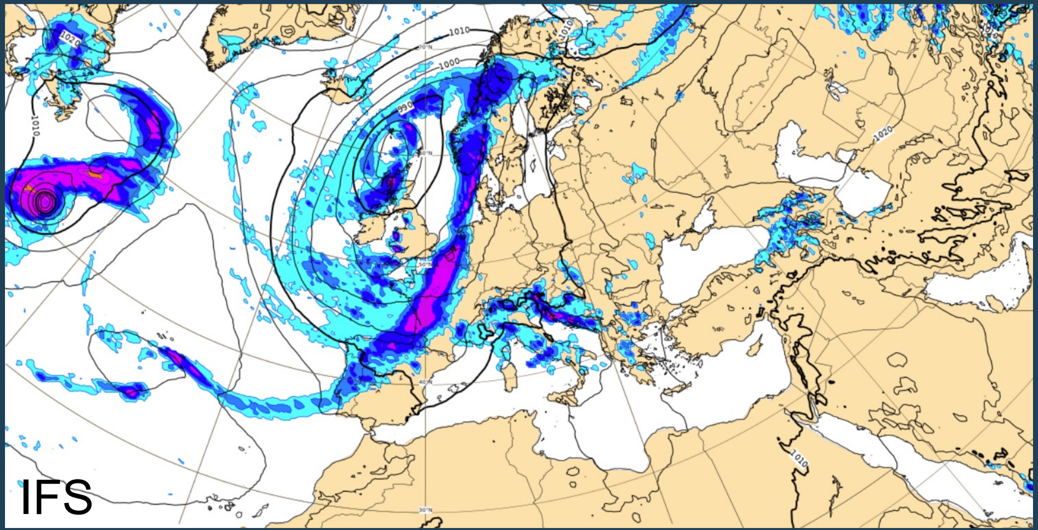


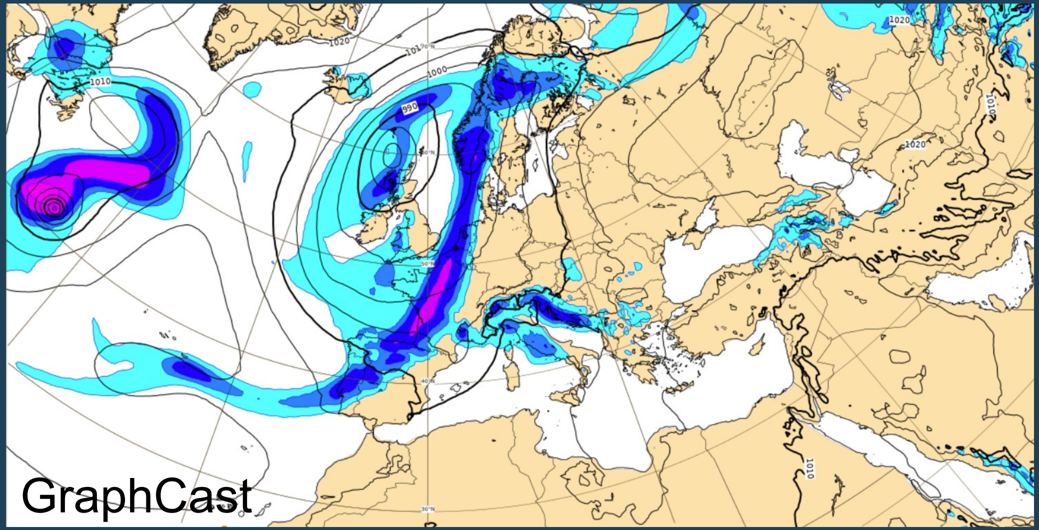
Day 4 forecasts over Europe (valid 7 Sept 2023 12UTC)



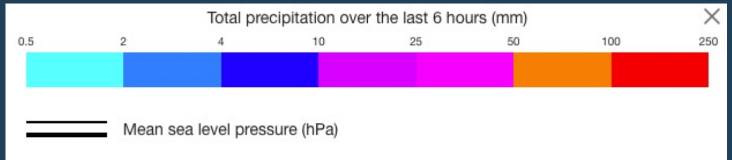
+60h forecasts over Europe (valid 21 Sept 2023 12UTC)

PanguWeather





FourCastNet



Summary/Outlook

- Very good scores for PanguWeather initialised from ECMWF analysis
- Temperature extremes, cyclogenesis of both extra-tropical and tropical cyclones can be captured
- Similar perturbation growth rate from initial perturbations on synoptic scales

- Problem with structure of very intense cyclones
- Smooth small scales

- Many don’t predict precipitation and there has been limited evaluation
- Missing model uncertainty in ensemble mode

What’s next?

Results in this talk are mainly from:

arXiv > physics > arXiv:2307.10128

Search...

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Physics > Atmospheric and Oceanic Physics

[Submitted on 19 Jul 2023]

The rise of data-driven weather forecasting

Zied Ben-Bouallegue, Mariana C A Clare, Linus Magnusson, Estibaliz Gascon, Michael Maier-Gerber, Martin Janousek, Mark Rodwell, Florian Pinault, Jesper S Dramsch, Simon T K Lang, Baudouin Raoult, Florence Rabier, Matthieu Chevallier, Irina Sandu, Peter Dueben, Matthew Chantry, Florian Pappenberger

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news

Exploring machine-learning forecasts of extreme weather

Linus Magnusson