AIFS: a data-driven probabilistic forecasting system

EuroCC Webinar

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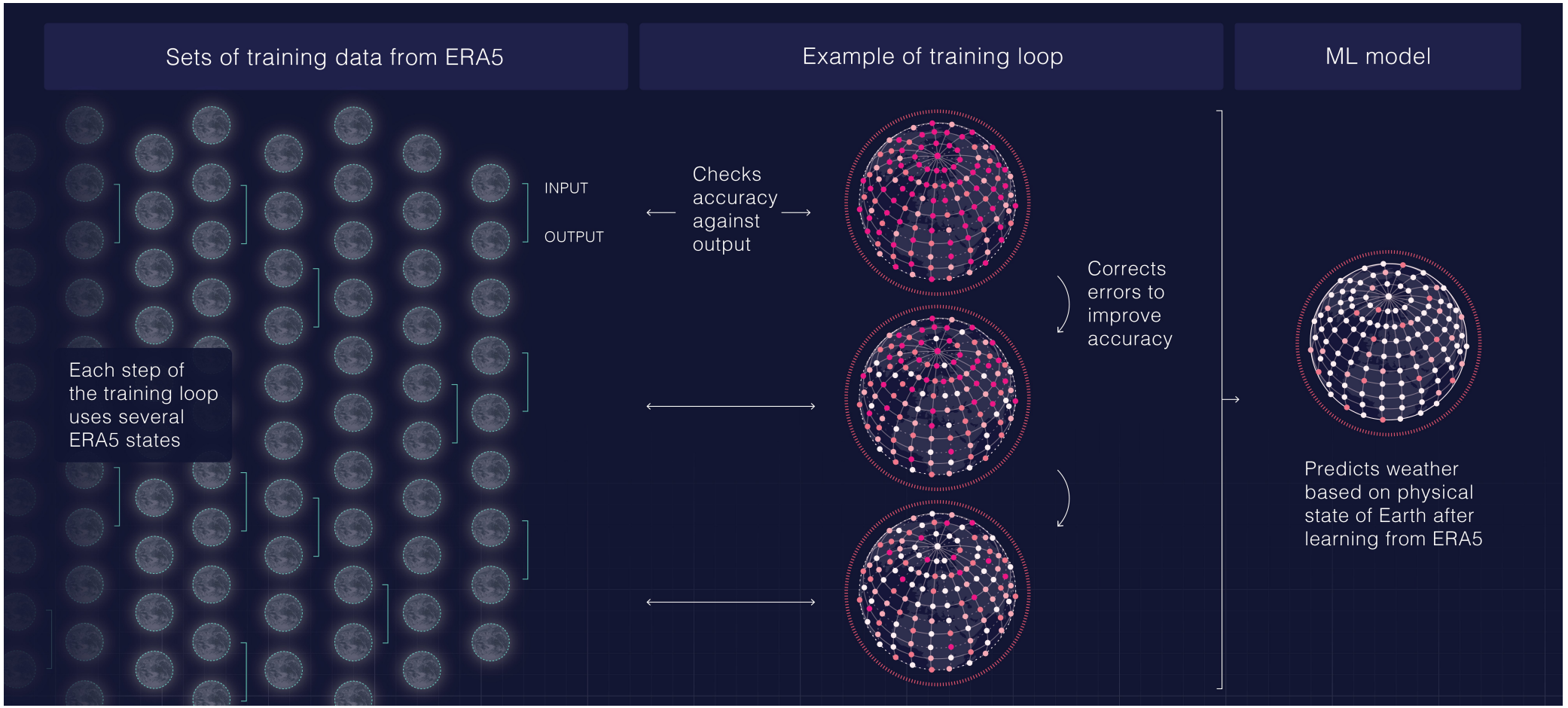
Training the AIFS Machine Learning Model

The model is highly accurate due to ERA5, a dataset of hourly states of the Earth's atmosphere since 1940



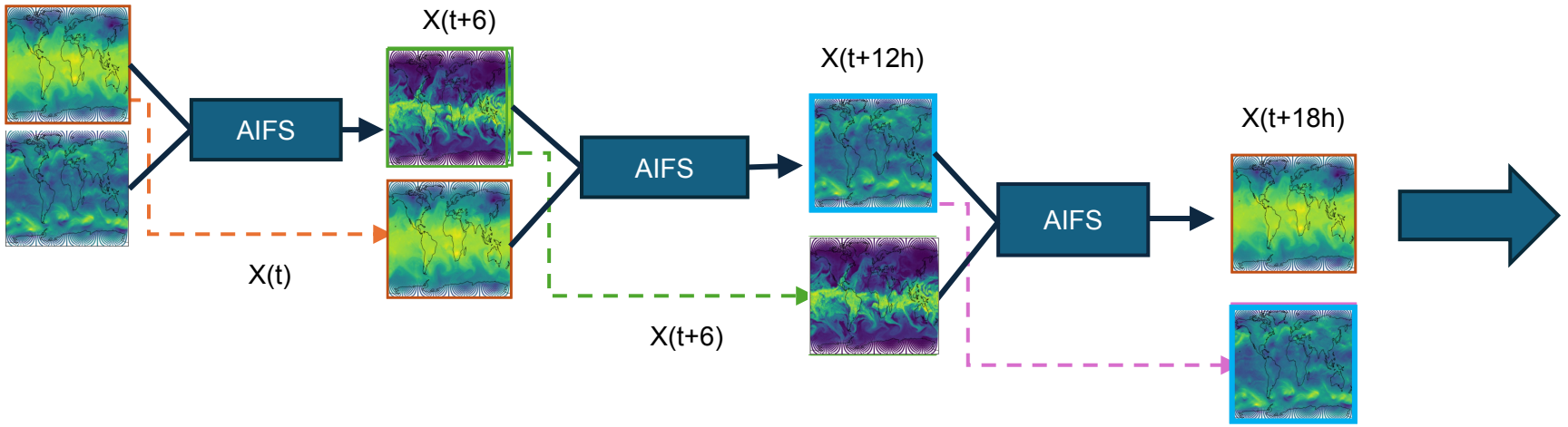
Lang et al. (2024) *arXiv preprint arXiv:2406.01465v1*

Artificial Intelligence Forecasting System

TRAINING SCHEME – Step 2

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

WMSE - area-weighted mean squared error



AR predictions
Up to rollout 12 (72 hours)

WMSE t+6h + WMSE t+12h + WMSE t+18h + ... + WMSE t+72h

model is trained to produce forecast up to 72 hr ahead by aggregating the WMSE

ROLLOUT 1 - 6h

ROLLOUT 2 - 12hr

ROLLOUT 3 – 18hr

ROLLOUT 12- 72hr

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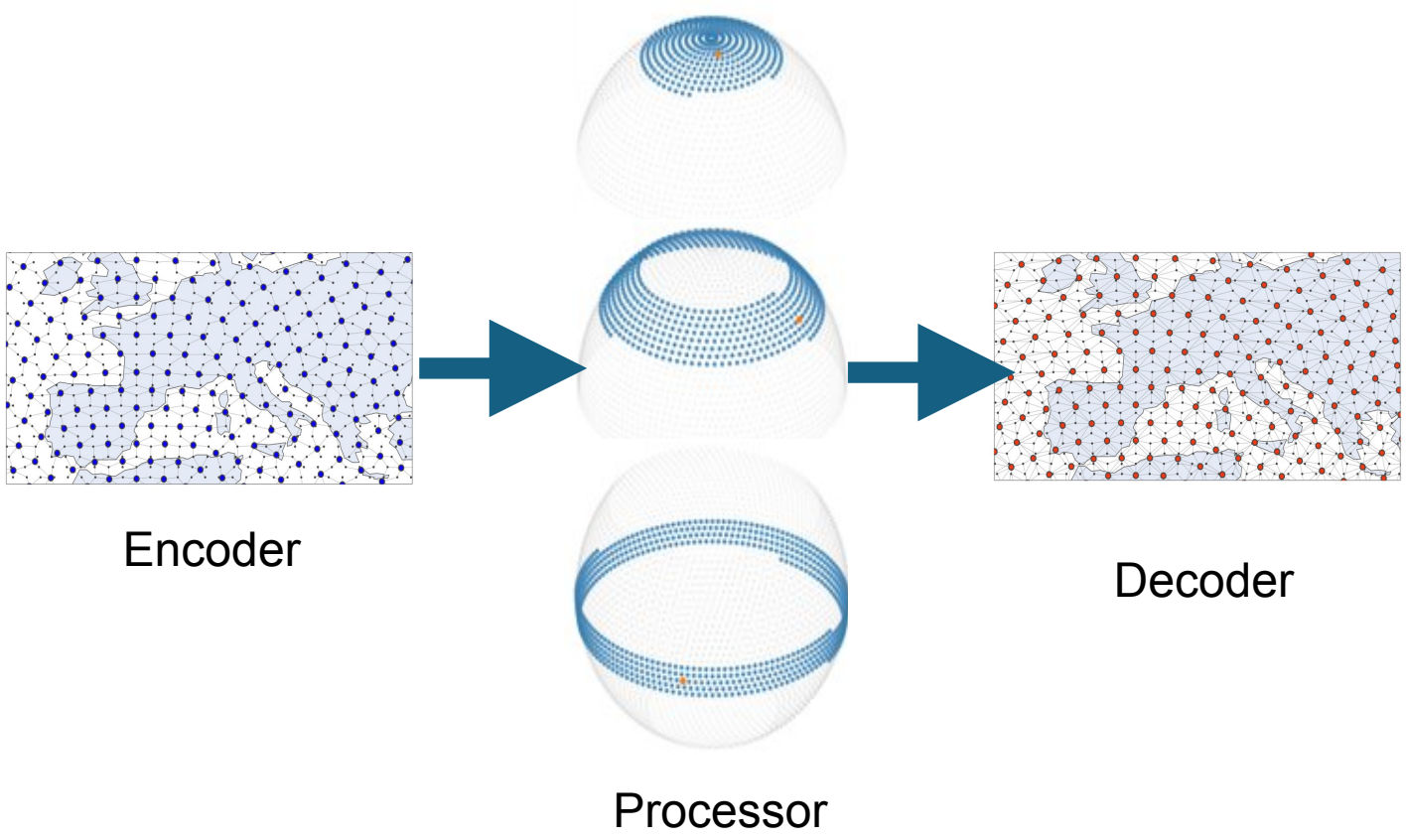
Latest AIFS v0.2(1) – hybrid of graphs & transformers

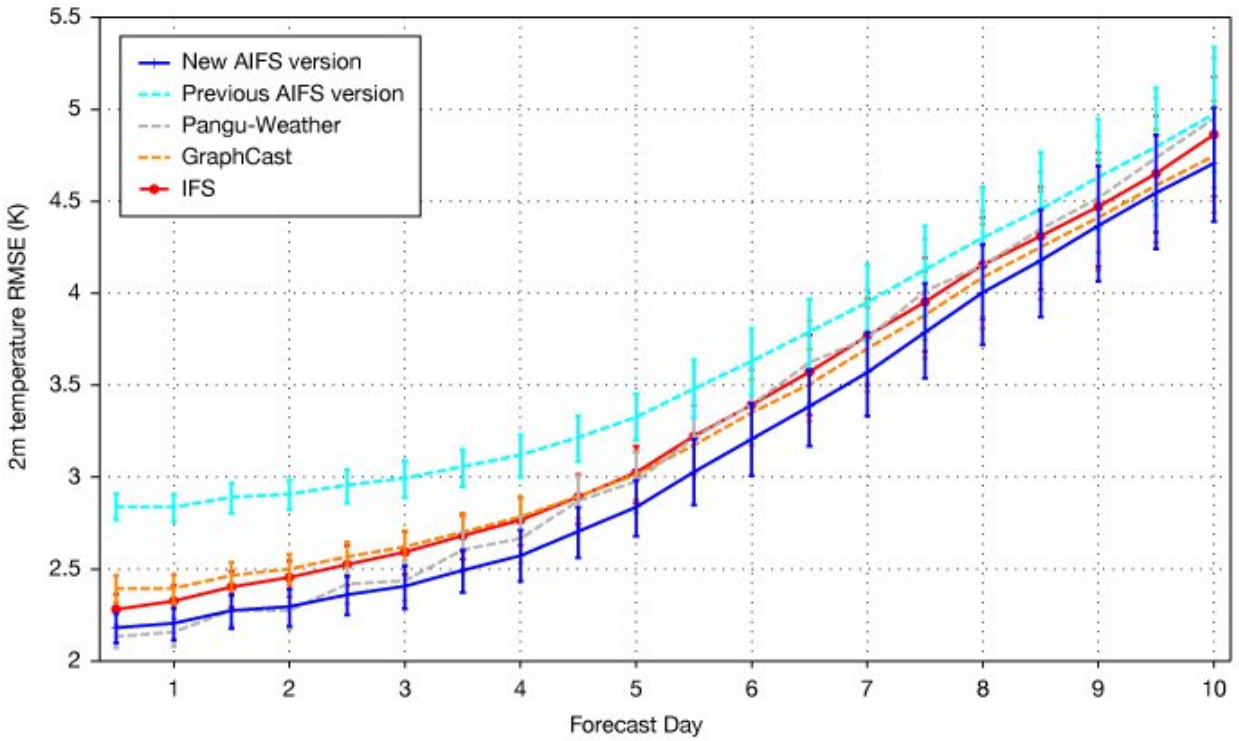
- Live from Jan 2024.
- Resolution 0.25 degrees (4x finer)
- New architecture.
  - Encoder/decoder: graph attention.
  - Processor: Transformer blocks and windowed attention (attention across regional bands).



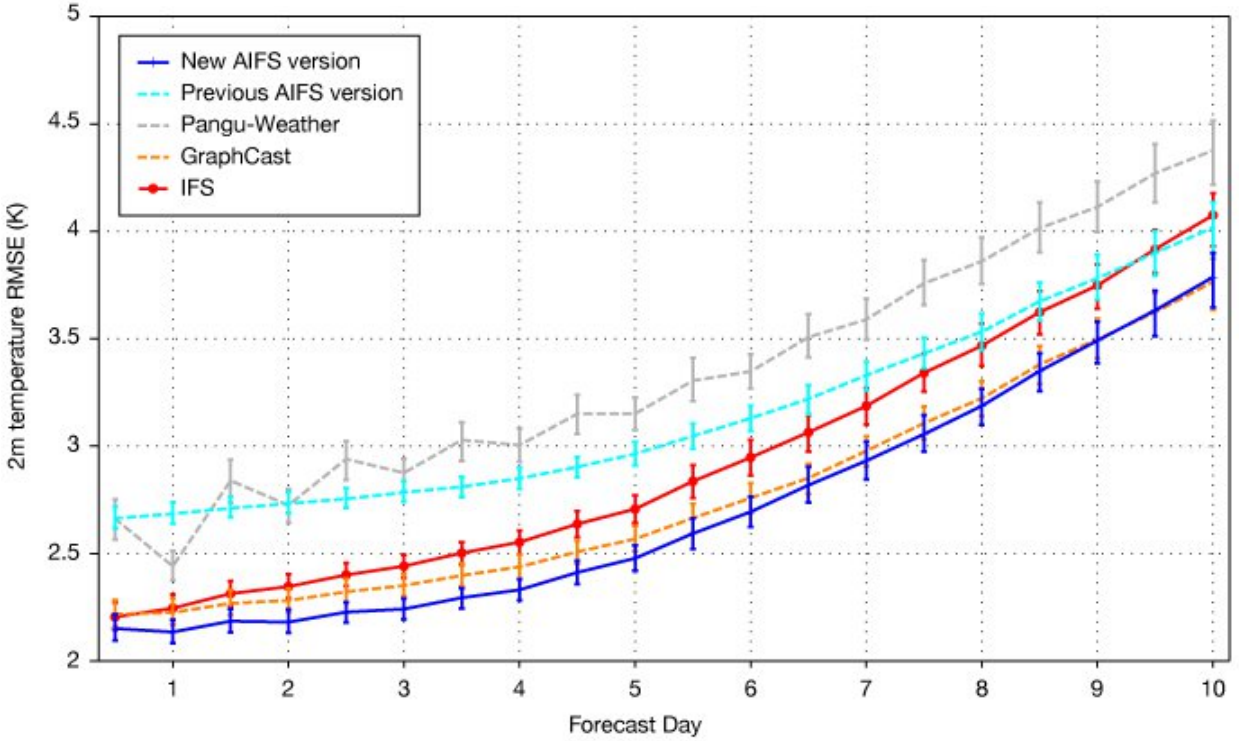
https://www.ecmwf.int/en/about/media-centre/aifs-blog/2024/first-update-aifs

Verification of surface against observations

Northern hemisphere 2m-temperature



Southern hemisphere 2m-temperature



Lower = better
Sept-Oct-Nov 2023

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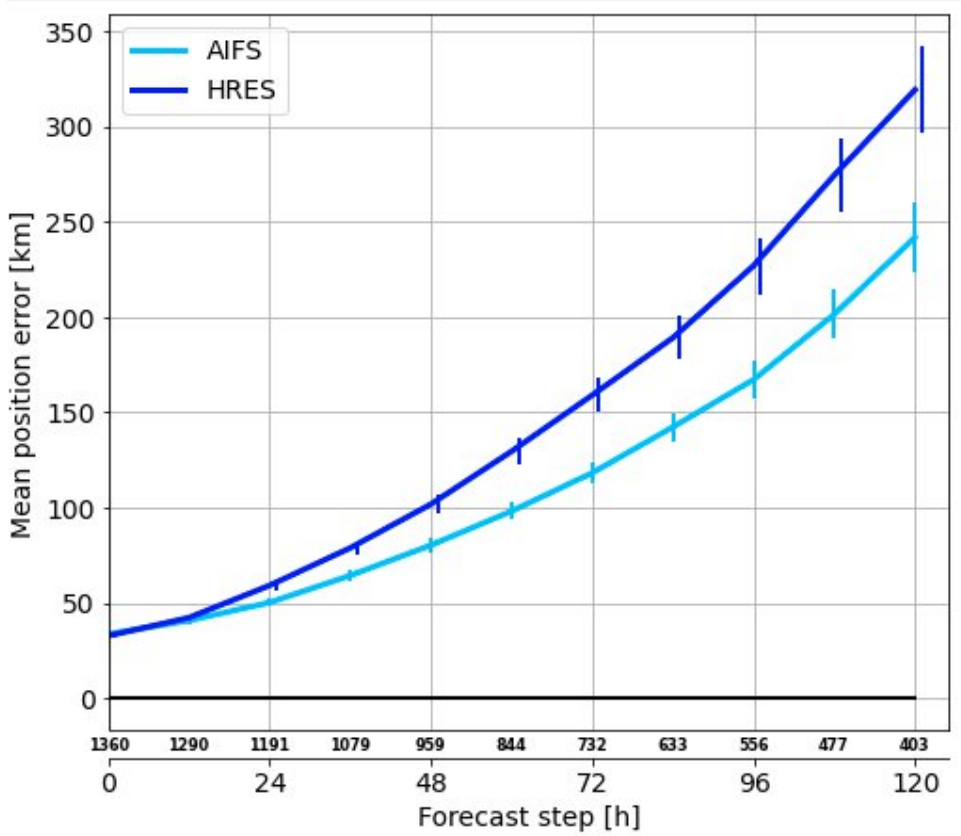
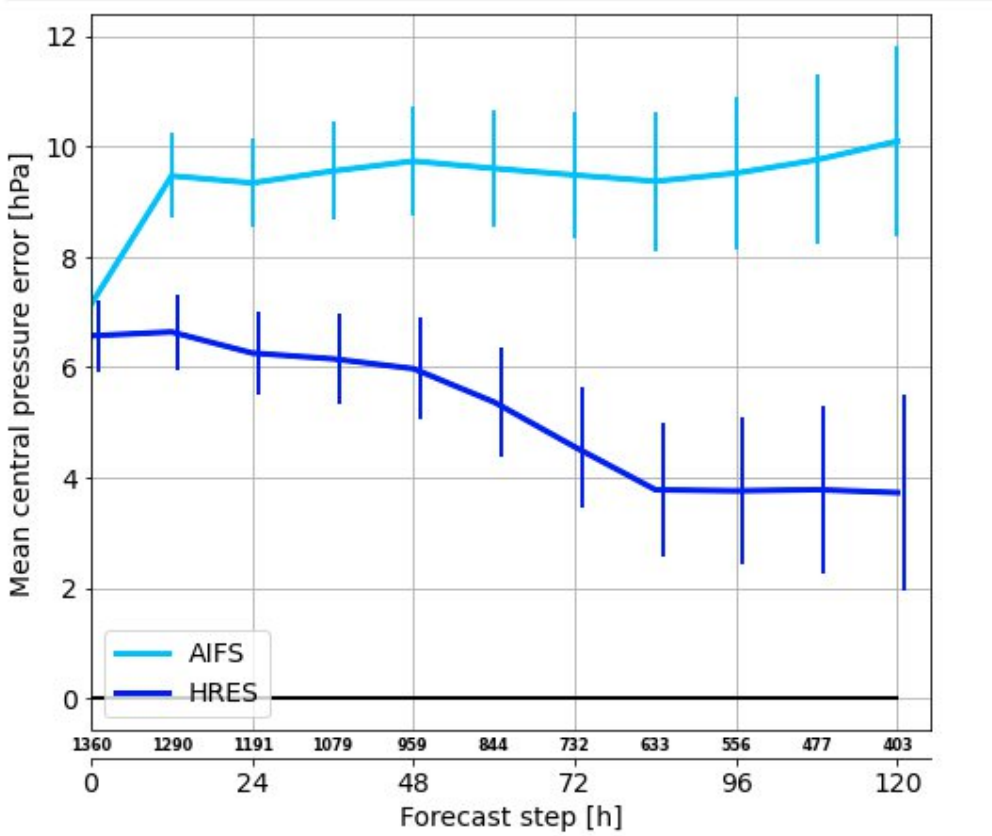
Forecast skill TCs, 2022-2023:

Position error



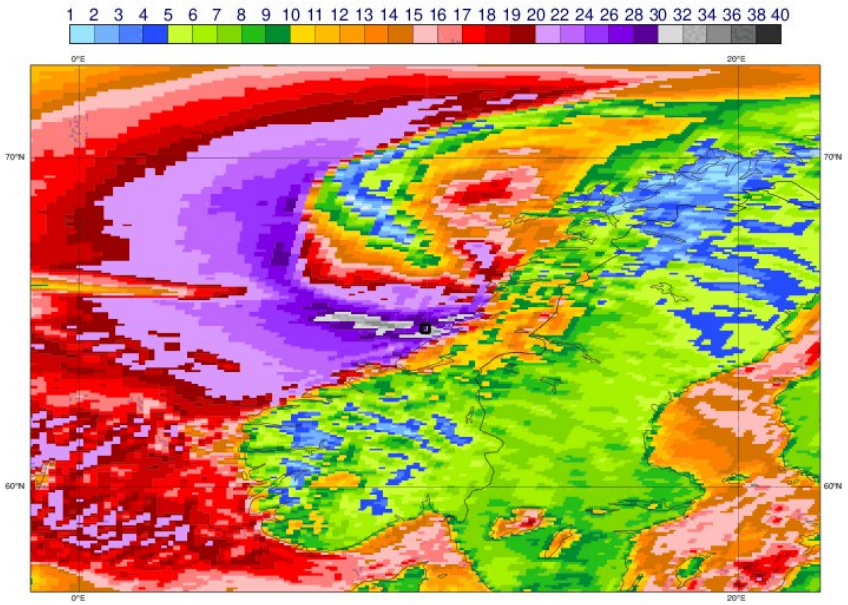
Central pressure bias



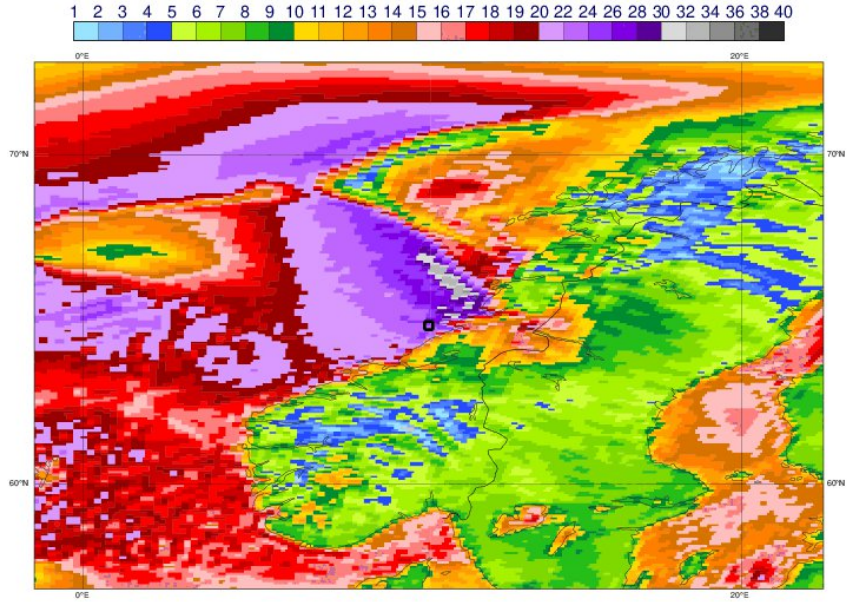
Case study: Wind storm Ingunn

Day 2 forecasts

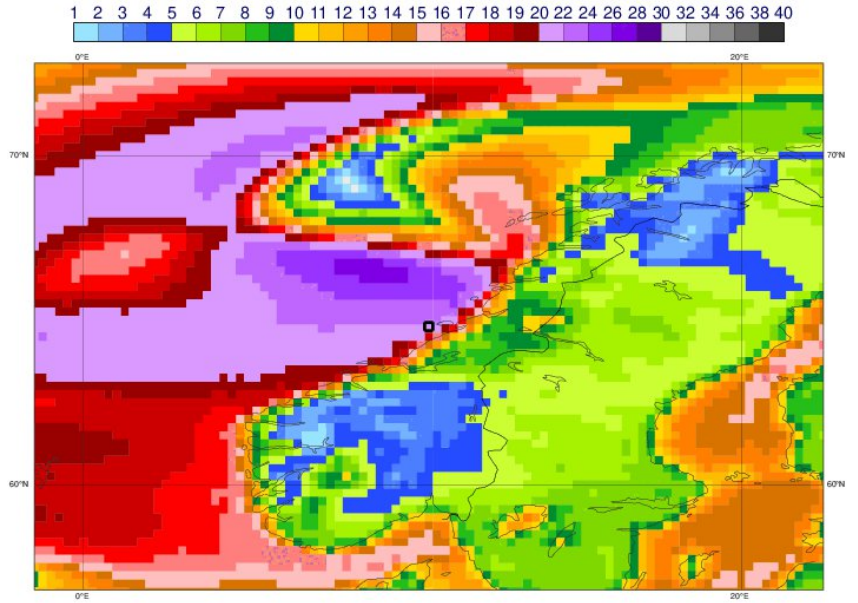
Analysis



IFS - control

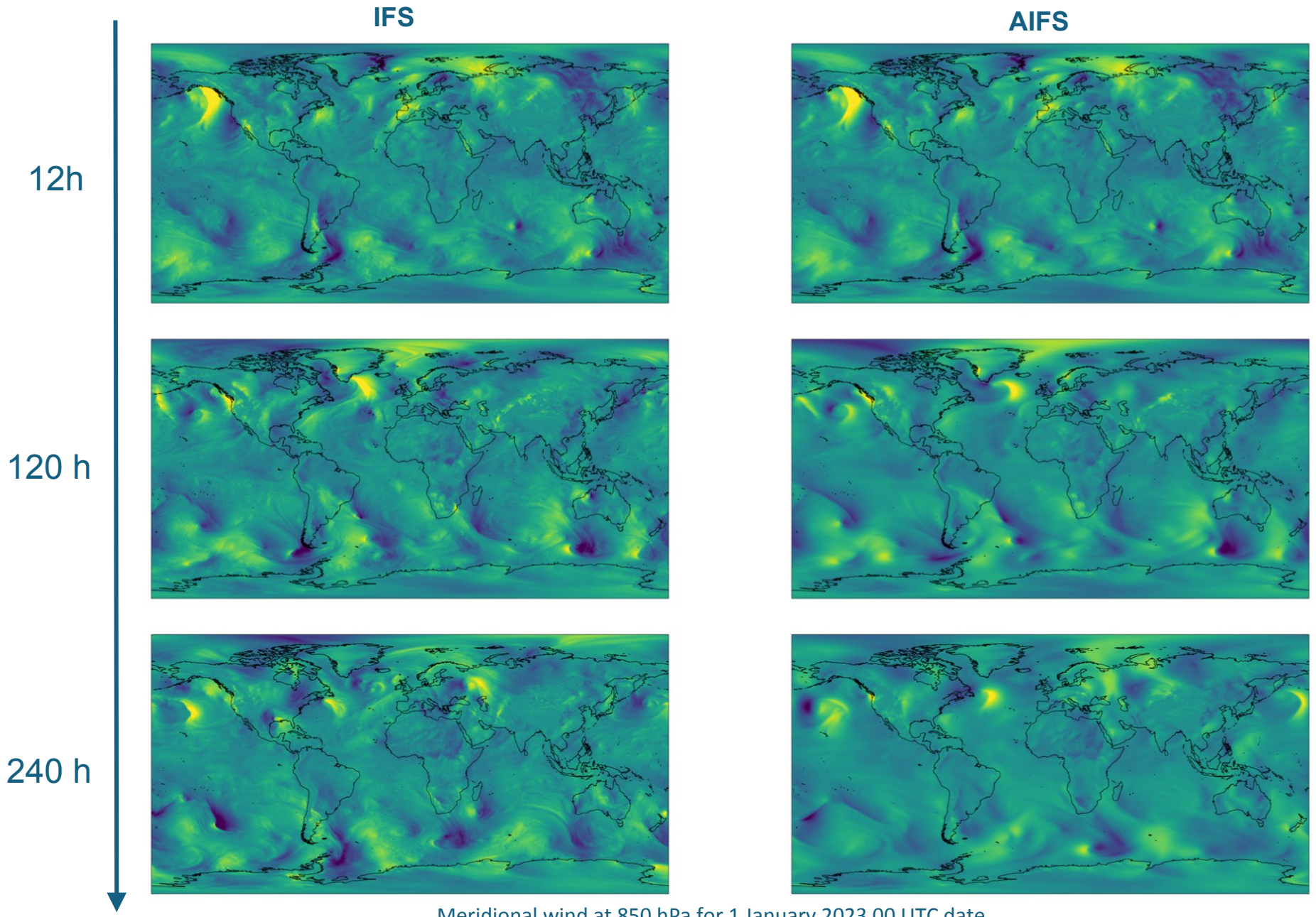


AIFS - deterministic



AIFS improved structure and location.
AIFS underestimated maximum windspeed.

Consistent with verification and other case studies



Meridional wind at 850 hPa for 1 January 2023 00 UTC date

Ensemble Forecasts

Toward ensembles

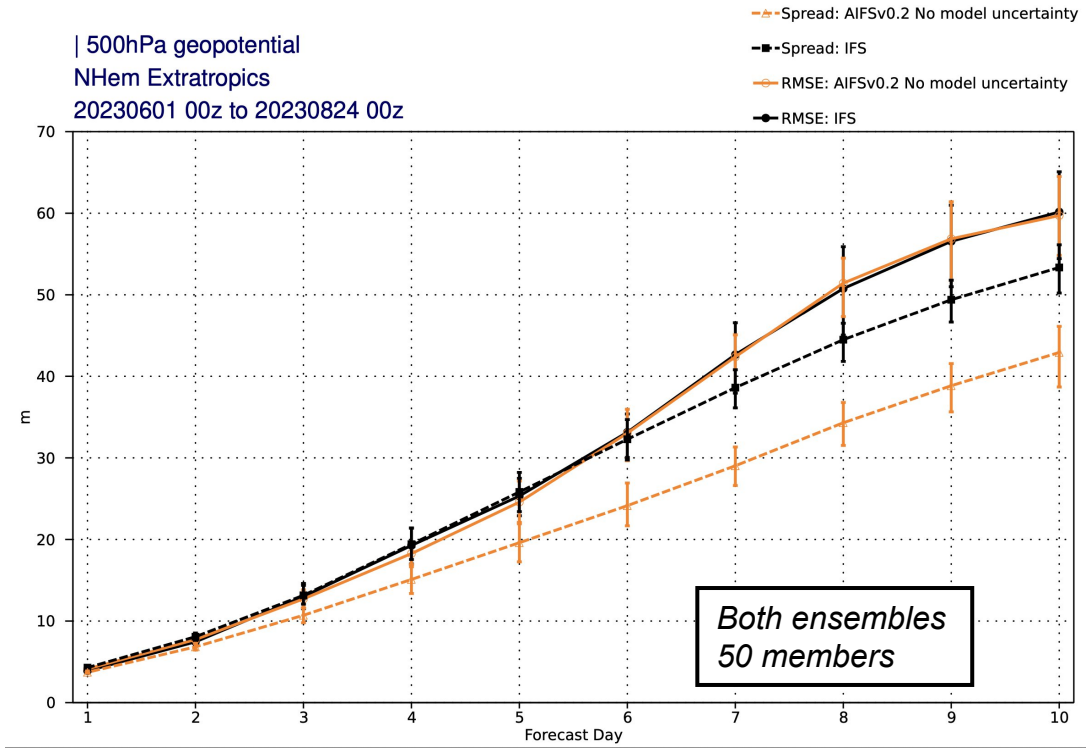
Initial Condition Uncertainty

Use the **ensemble initial conditions** to initialise the AI model compared with latest IFS ensemble (9km) *(Lang et al. 2023)*

Considerable gap
between spread (dashed)
and error (full)

Overconfident!

Aiming for
Dashed = Full
Lower -> better



Similar approach taken in Bi et al. (2023) [Pangu], Pathak et al. (2023) [FourCastNet]

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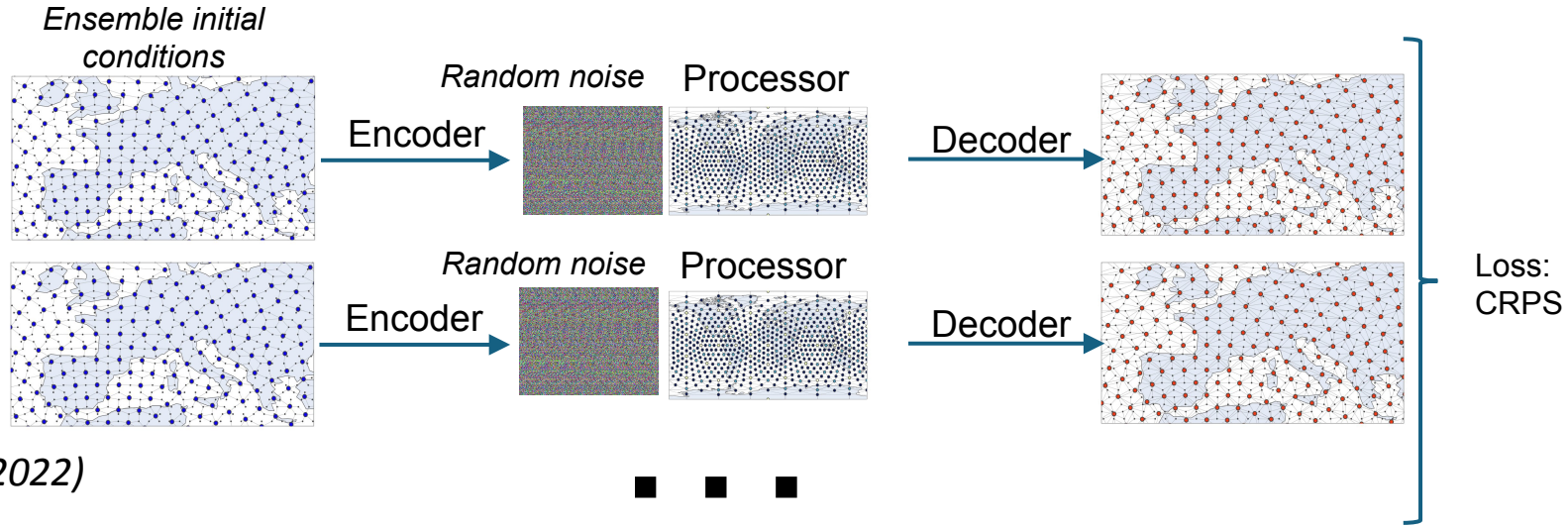
Ensemble forecasts …

a) Instead of a MSE loss, learn an ensemble via optimizing probabilistic scores

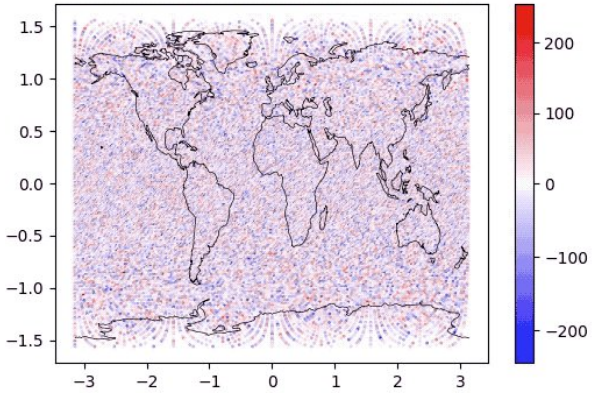


Pacchiardi et al. (2022)

b) Create a forecast as de-noising task (diffusion training)

for example:

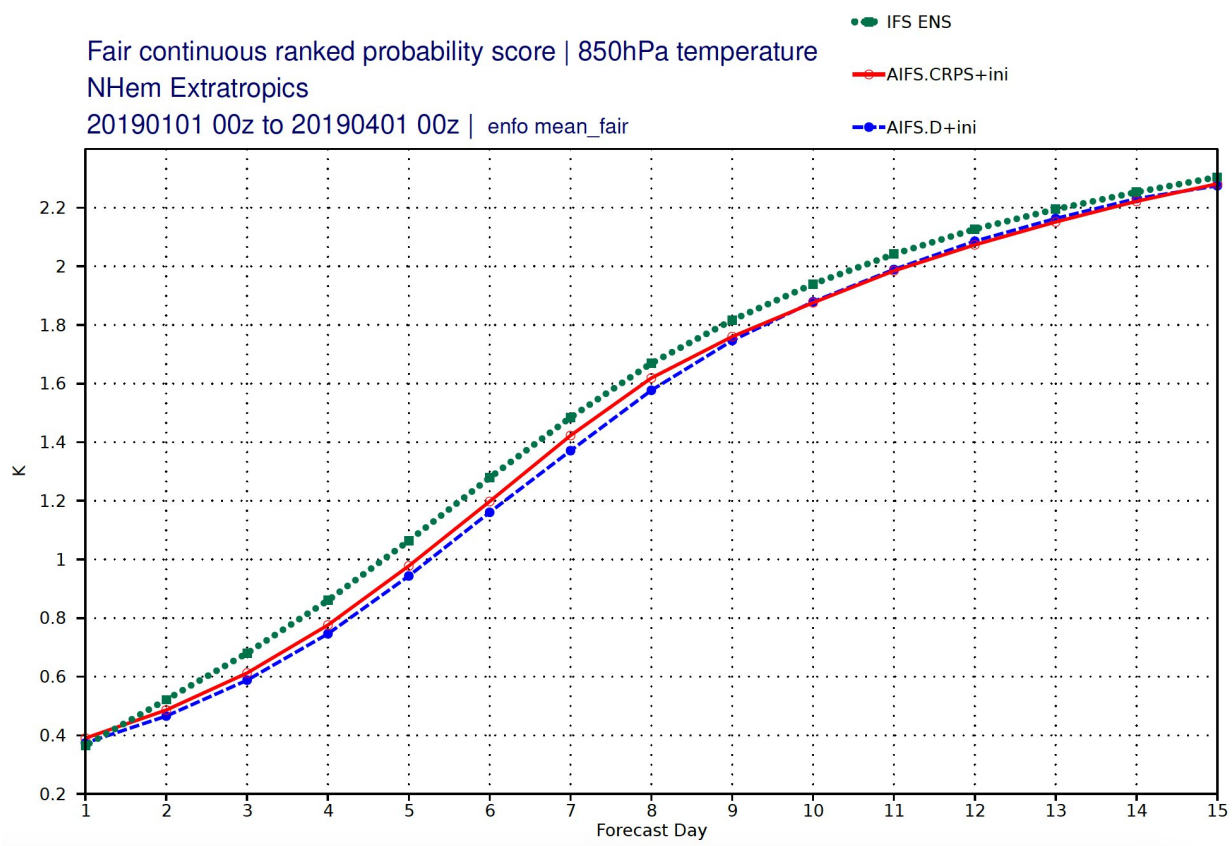
- Stable diffusion -> Images
- Sora -> Video
- Gencast -> Weather
  (Price et al. (2023))

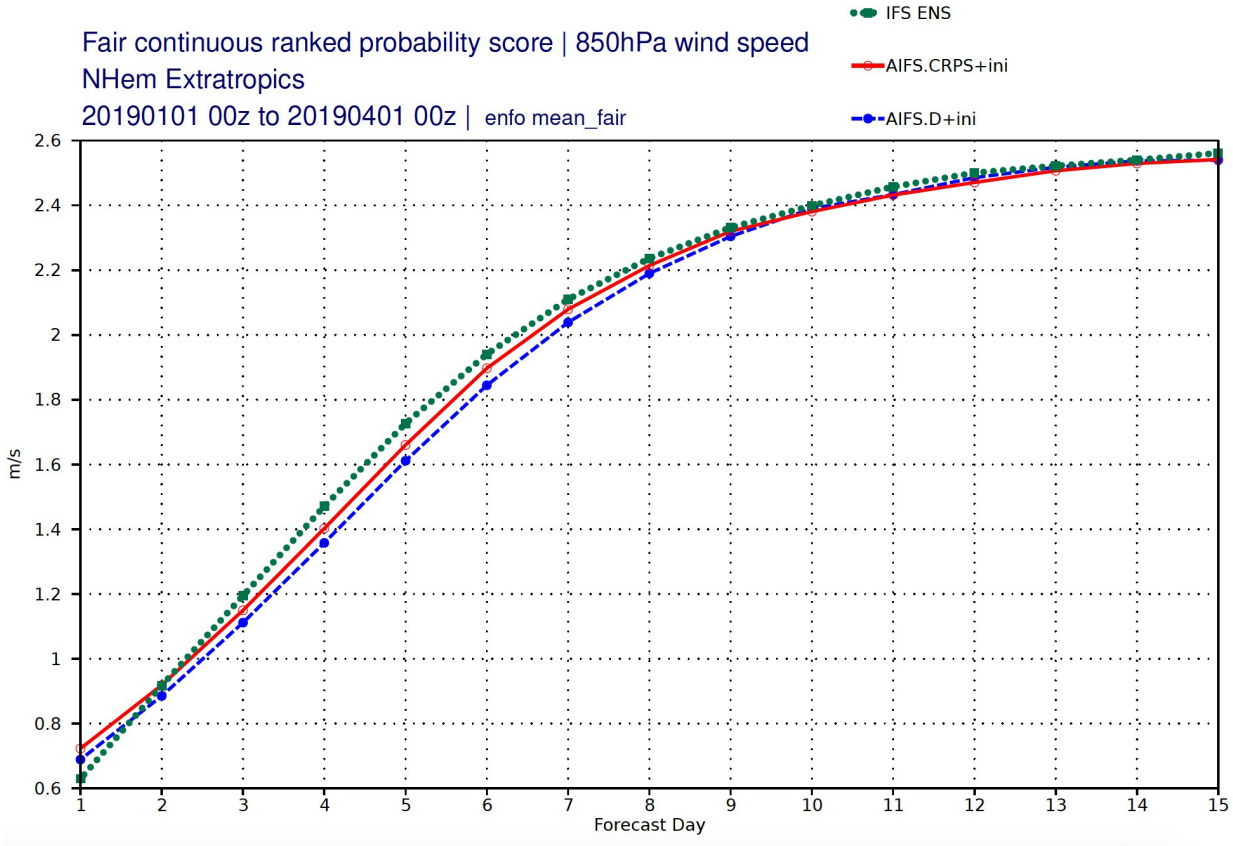


CRPS Scores

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

Preliminary results, ~ 1 deg resolution models (O96)





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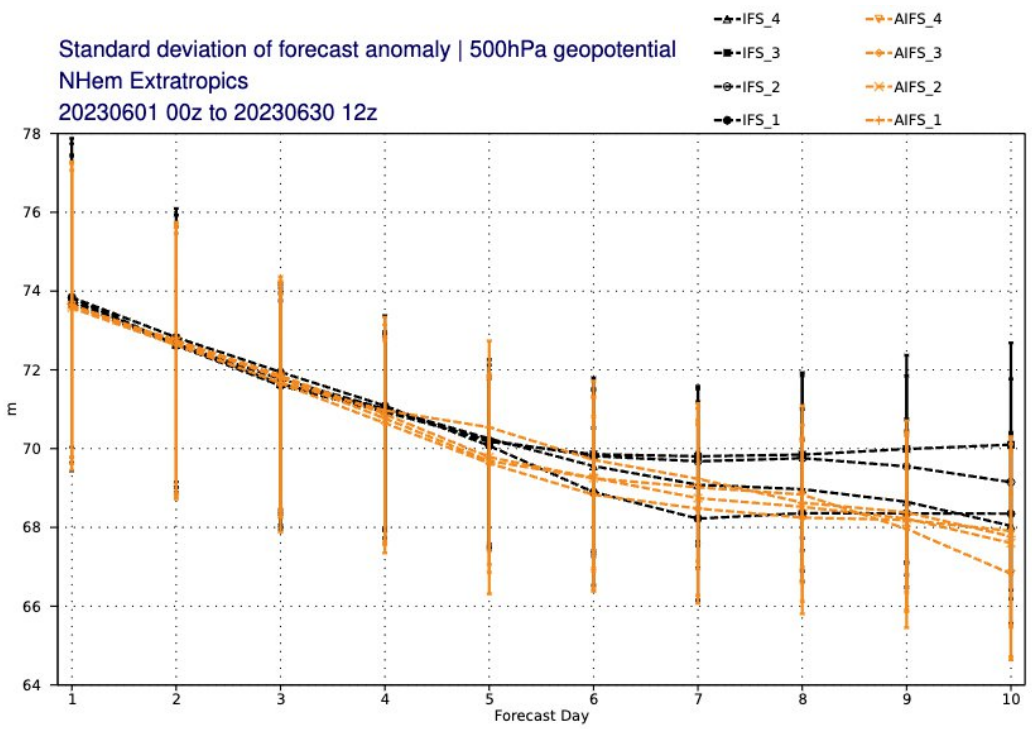
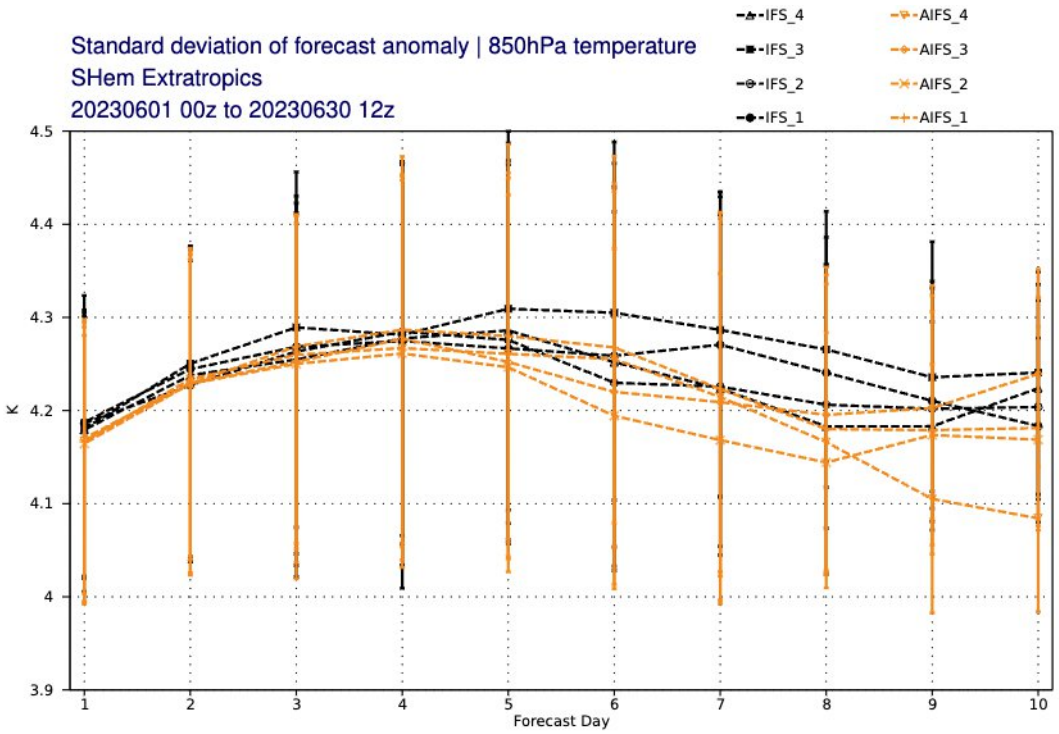
What do the ensemble members themselves look like?

Forecast activity (measure of forecast smoothness)





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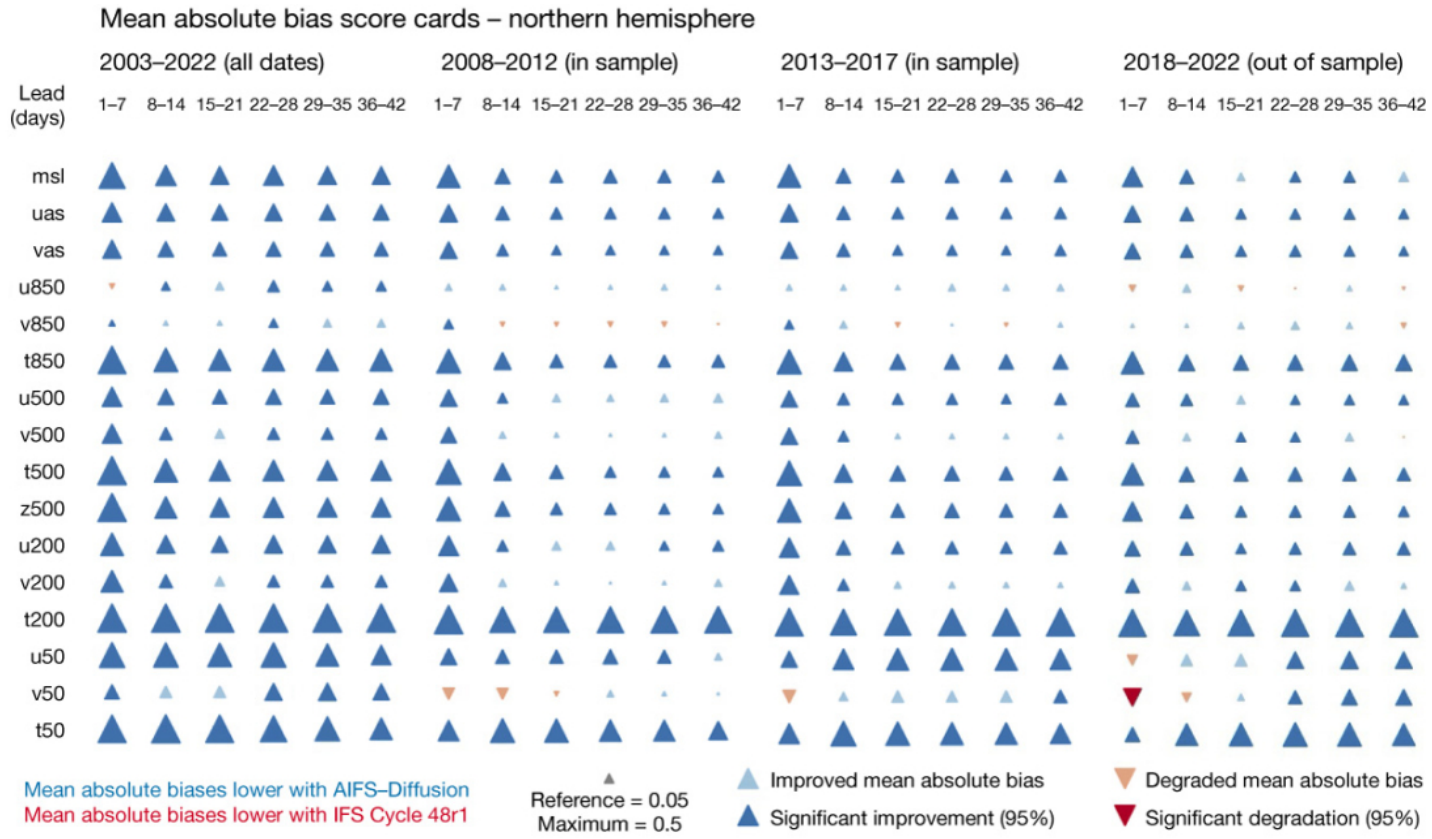
Sub-seasonal time scales



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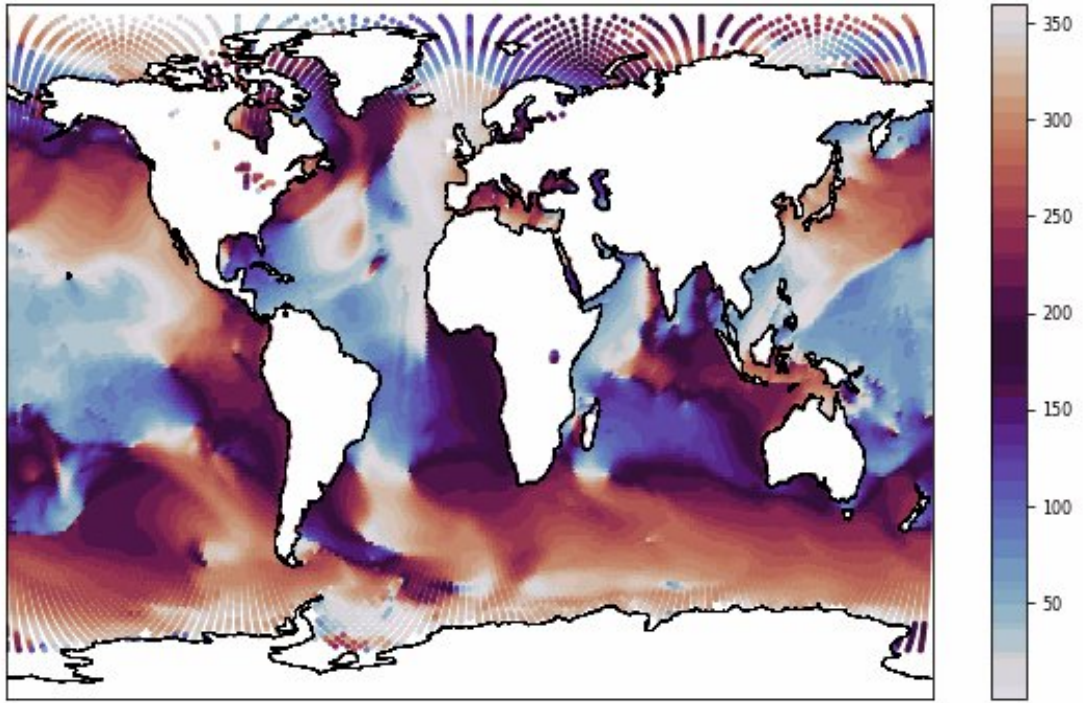
And there’s more to come…

AI Earth System Model

Mean wave direction (14-day forecast)



Study how to represent full Earth System model with land, ocean, sea-ice, waves and hydrology components within the DestinE framework

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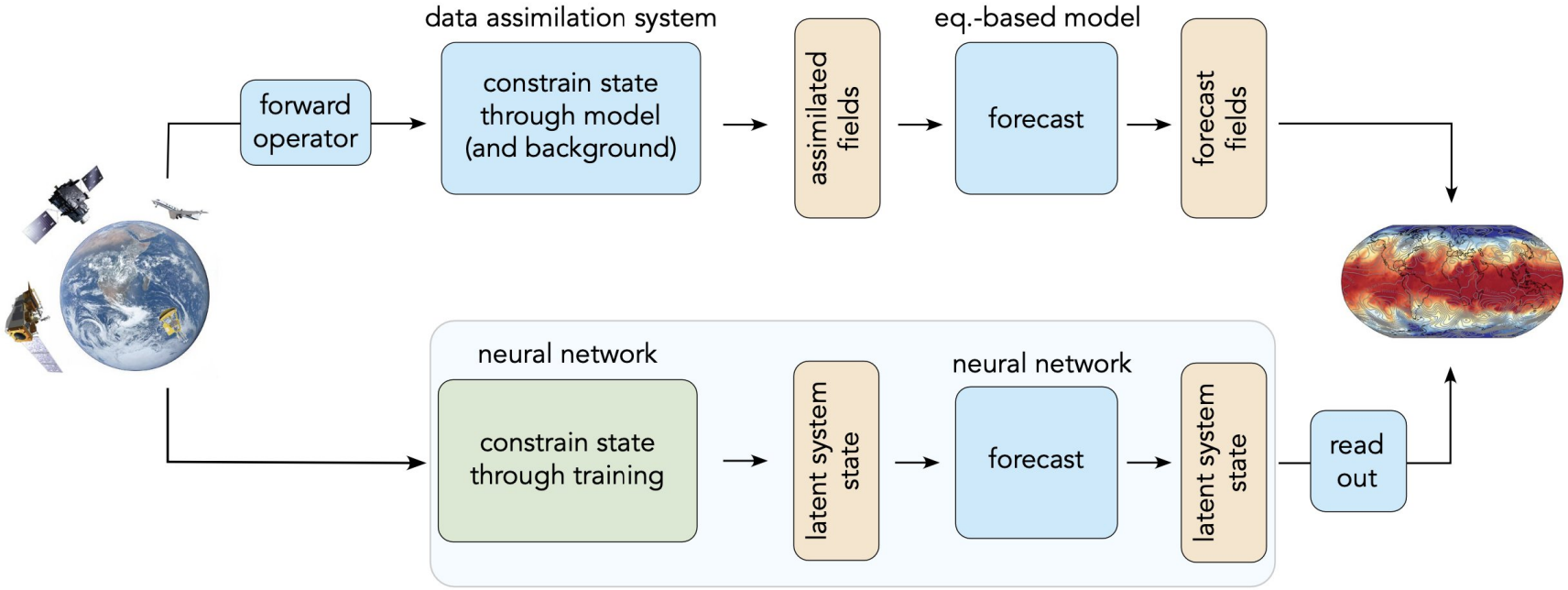
Can machine learning models do data assimilation or replace it?

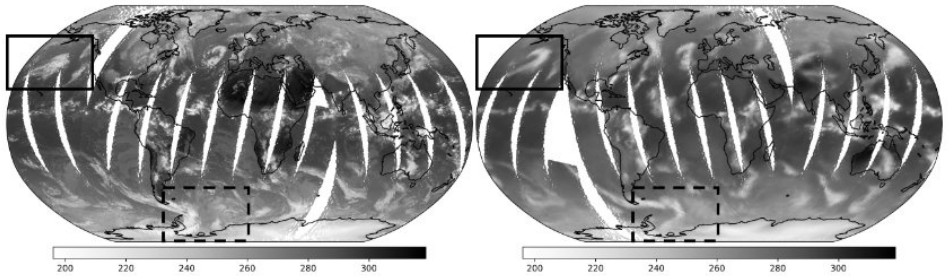
Reason it *can't* work: significant parts of the atmosphere are not directly observed.

Reason it *may* work: current data-assimilation approaches need to throw away significant data and make significant approximations.



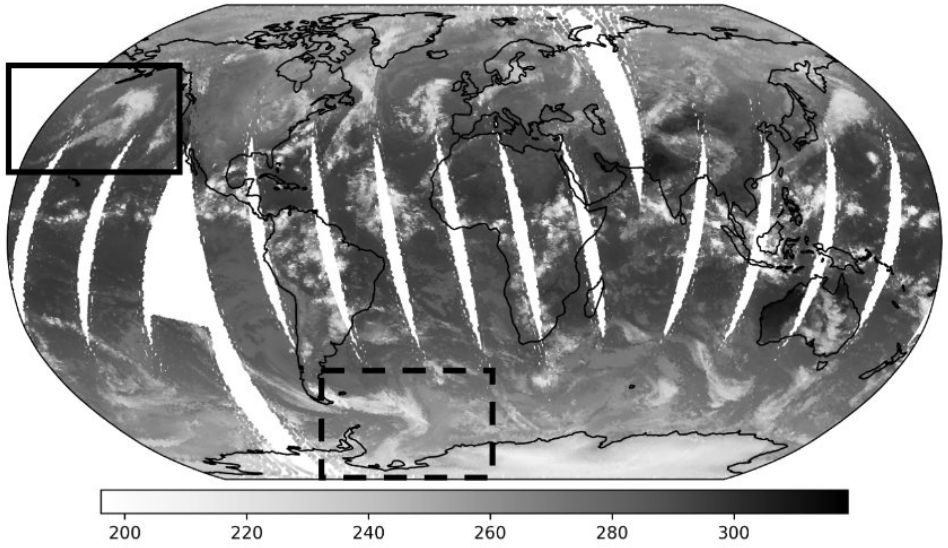
McNally et al., *arXiv:2407.15586,* 2024.

Preliminary Results

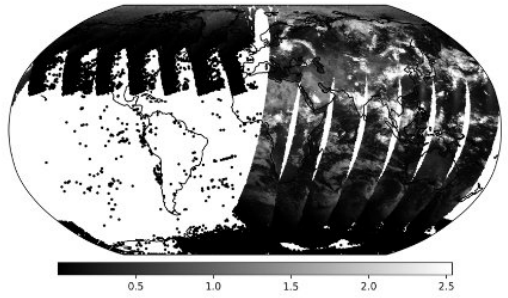


(a) Input IASI channel 921 radiances

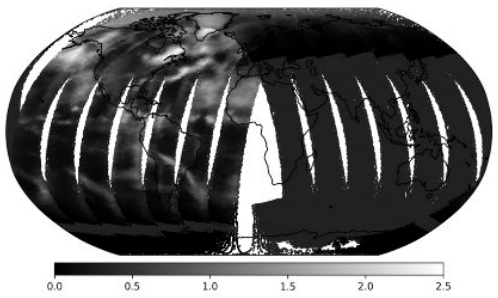
(b) Predicted IASI channel 921 radiances



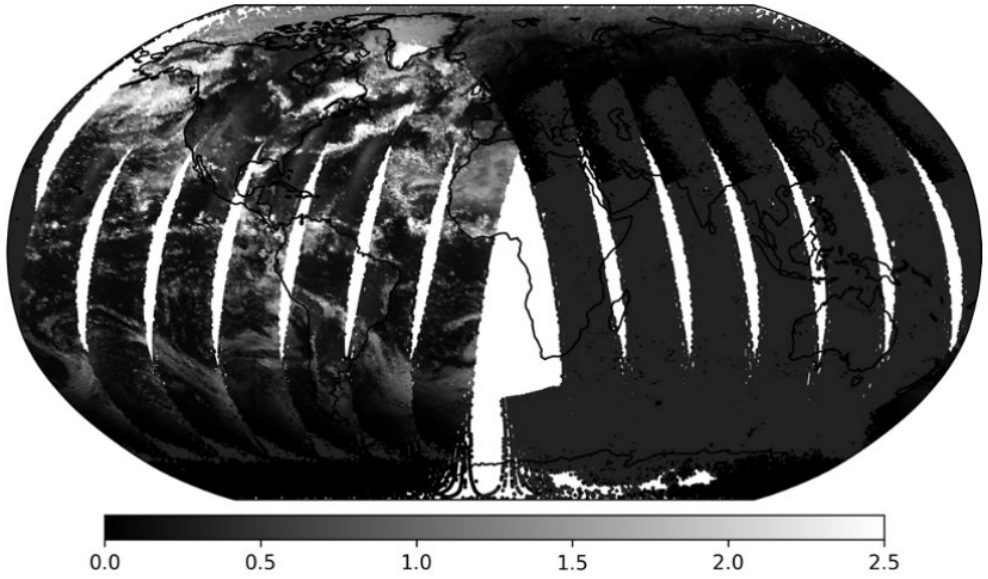
(c) Target IASI channel 921 radiances



(a) Input AVHRR visible reflectances



(b) Predicted AVHRR visible reflectances



(c) Target AVHRR visible reflectances

How to get involved:
Open source data and code

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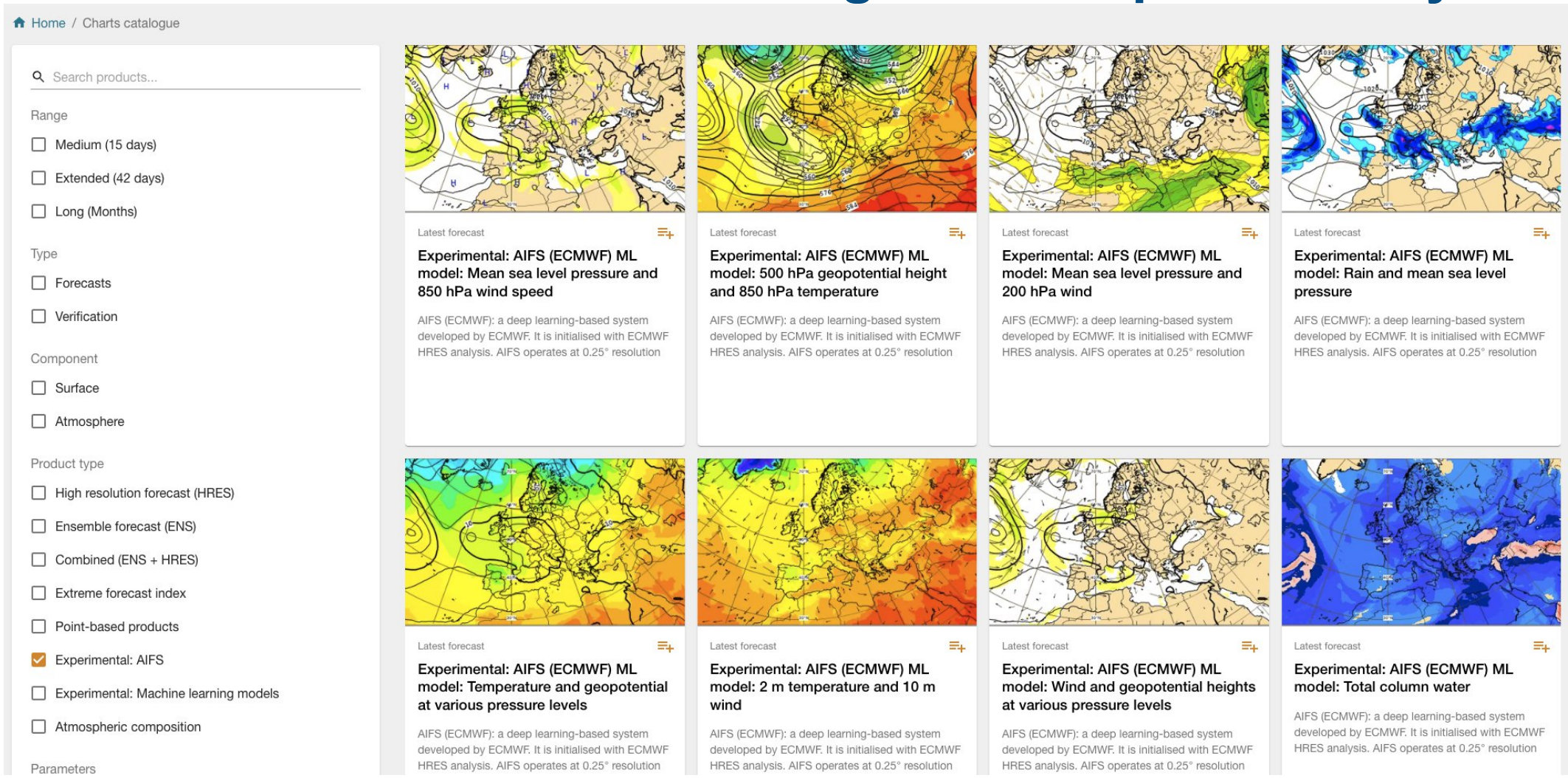
IFS, AIFS and other machine learning models open to everyone!

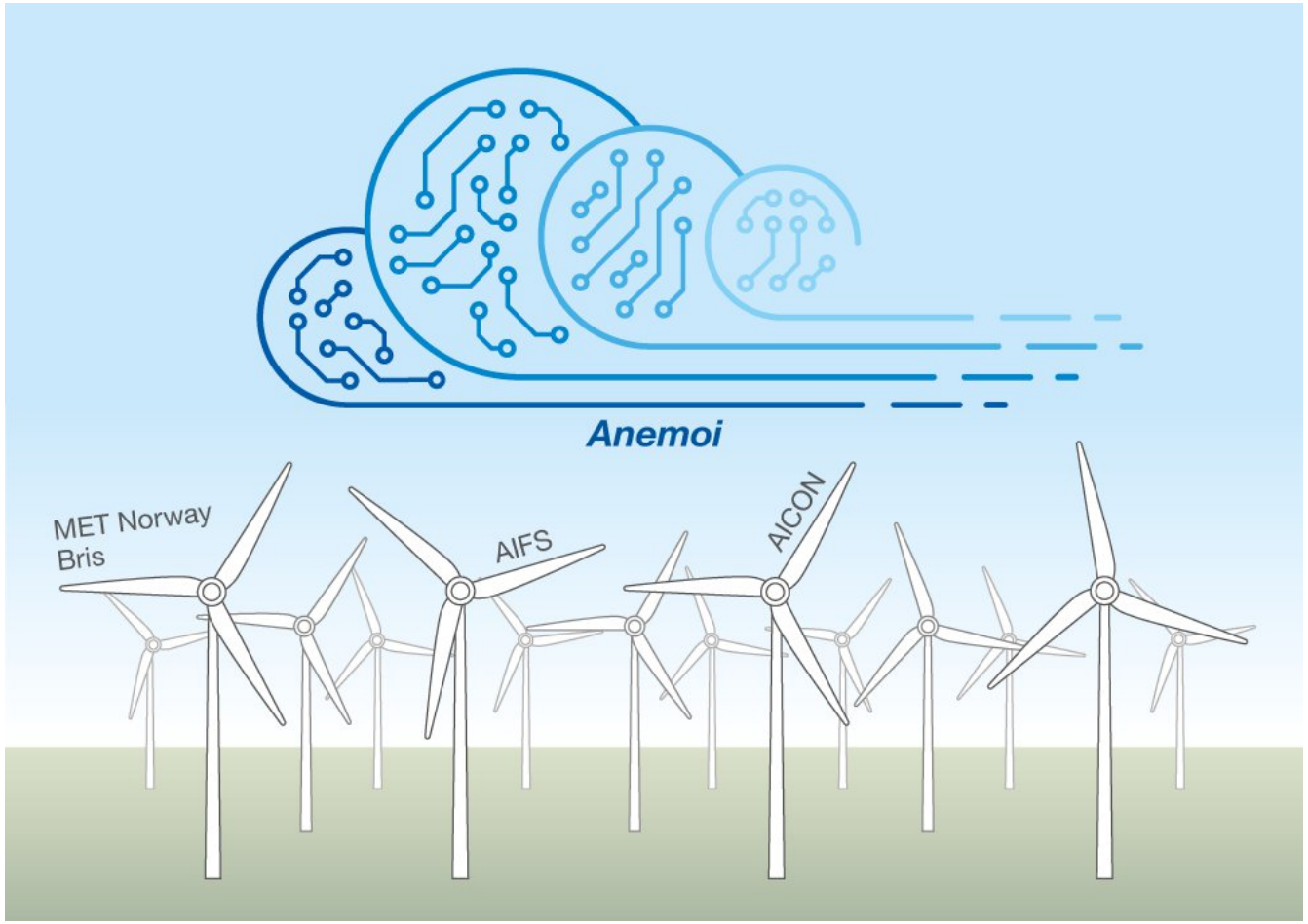


https://charts.ecmwf.int/

Anemoi and AIFS: Open Source Code

Aspiration
Set of tools, shared/co-developed across Europe, and beyond, for building data driven forecasting systems.
Users can bring their data and pick a suitable architecture and training method.
More advanced users can add new architectures and training methods.

Anemoi will be open source, with many pieces already being open.



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AI Weather Quest

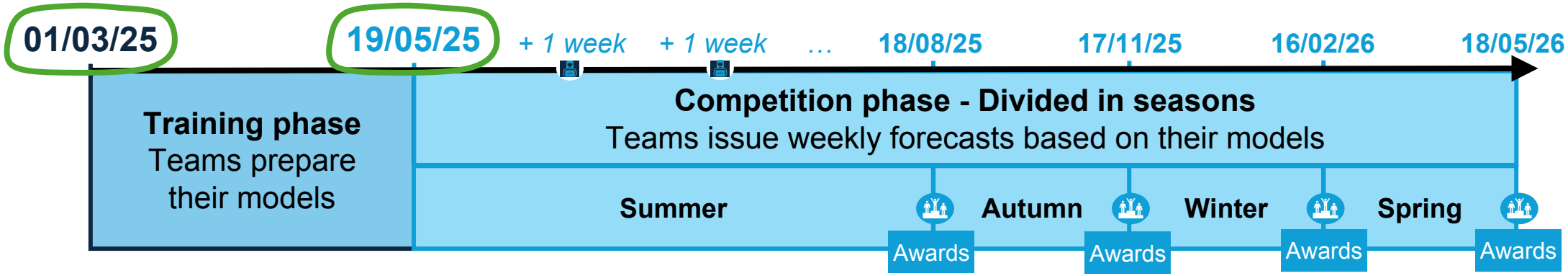
What? A **global competition** for the best-performing AI/ML models for sub-seasonal to seasonal weather predictions.

Who is it for?

- No prior expertise in weather forecasting required.
- **Anyone who can leverage AI/ML to improve weather predictions welcome**.

Why participate?

Gain global recognition for your work, increase your knowledge about AI/ML-based forecasting models, and make connections with the best experts working on similar topics.
Interested? Contact olga.loegel@ecmwf.int.



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Key References

AIFS:
Lang, S., Alexe, M., Chantry, M., Dramsch, J., Pinault, F., Raoult, B., ... & Rabier, F. (2024). AIFS-ECMWF's data-driven forecasting system. arXiv preprint arXiv:2406.01465.

AIFS Ensembles:
https://www.ecmwf.int/en/about/media-centre/aifs-blog/2024/enter-ensembles
https://www.ecmwf.int/en/newsletter/181/earth-system-science/data-driven-ensemble-forecasting-aifs

Anemoi:
https://github.com/ecmwf/anemoi-datasets
https://github.com/ecmwf/anemoi-graphs
https://github.com/ecmwf/anemoi-models
https://github.com/ecmwf/anemoi-training