Numerical methods for weather prediction

Machine learning for weather prediction

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Machine learning for weather prediction

- Small neural networks have been used / experimented with since the 1990s
- First attempt by Dueben and Bauer with convolutional neural networks
- Steady progress over the coming years by Rasp, Wayne, Keisler, ...

Machine learning for weather prediction

"To do [medium range weather forecasting] with the same level of skill using AI would likely require an exceptional (and hence unrealistic) amount of training data. [...]"[1]

"We expect that the success of DL weather forecast applications will hinge on the consideration of physical constraints in the NN design. So [...] there might be potential for end-to-end DL weather forecast applications to produce equal or better quality forecasts for specific end-user demands [...]"[2]

[1] T. Palmer. A vision for numerical weather prediction in 2030, 2022; https://arxiv.org/abs/2007.04830

[2] M. Schultz, C. Betancourt, B. Gong, F. Kleinert, et al.. Can deep learning beat numerical weather prediction? Philosophical transactions of the Royal Society of London / A, 379(2194):20200097, 2021.

Machine learning for weather prediction

Feb 2022 — **Dec 2022** — **Jun 2023** — **October 2023**

Full medium-range NWP

Keisler - GraphNN
1°, competitive with GFS

NVIDIA –
FourCastNet
Fourier+ , 0.25°

O(10^4) faster & more energy efficient than IFS

Tropical cyclones

Huawei – PanguWeather
0.25° hourly product

“More accurate tracks” than the IFS.

Extensive predictions

Deepmind – GraphCast
0.25° 6-hour

Many variables and pressure levels with comparable skill to IFS.

Global & Limited Area

Microsoft – ClimaX

Forecasting various lead-times at various resolutions, both globally and regionally

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

AtmoRep
0.25° 1-hour product

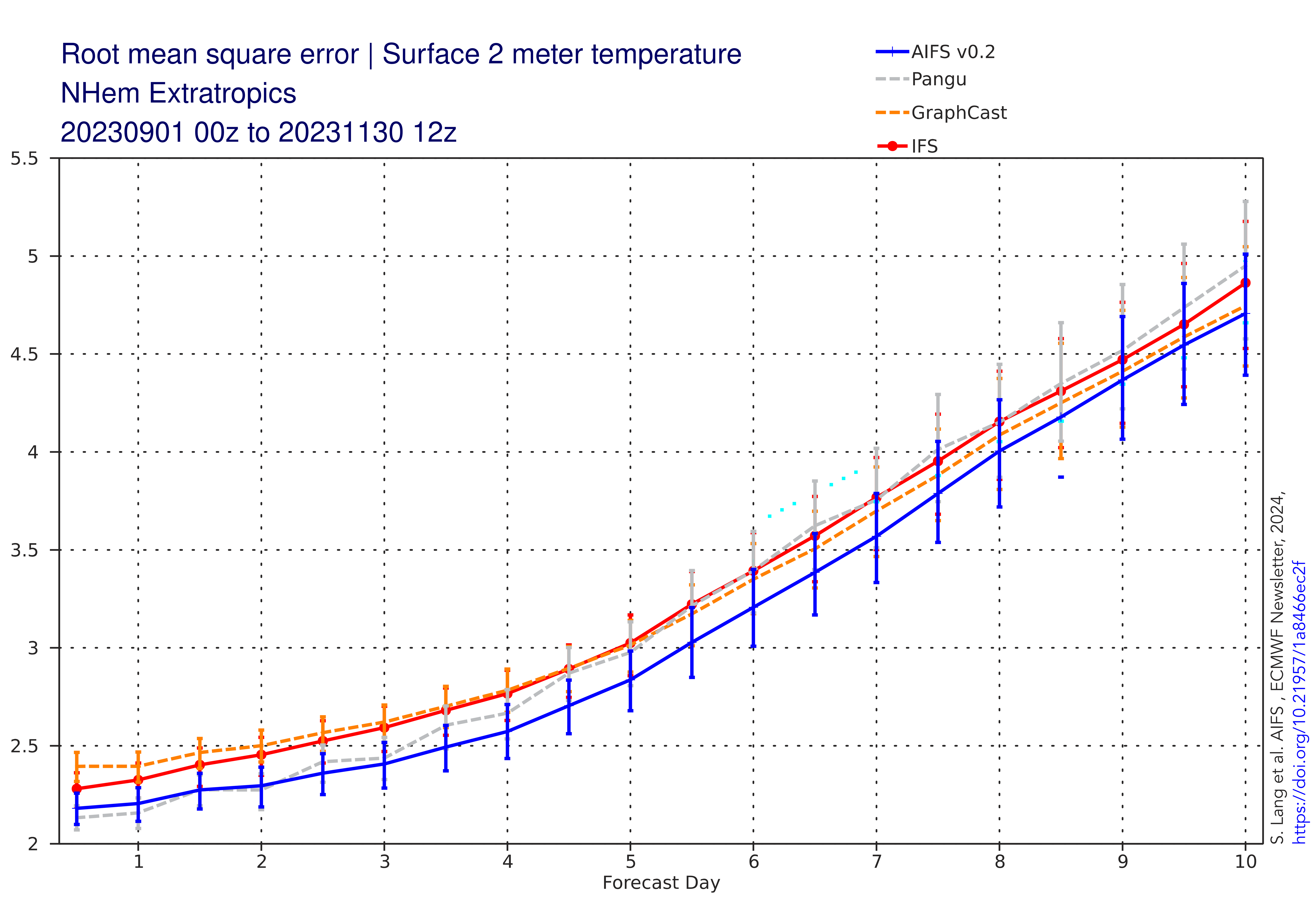
First large-scale representation learning model for atmospheric dynamics (i.e. foundation model)

AIFS
0.25° 6-hour product

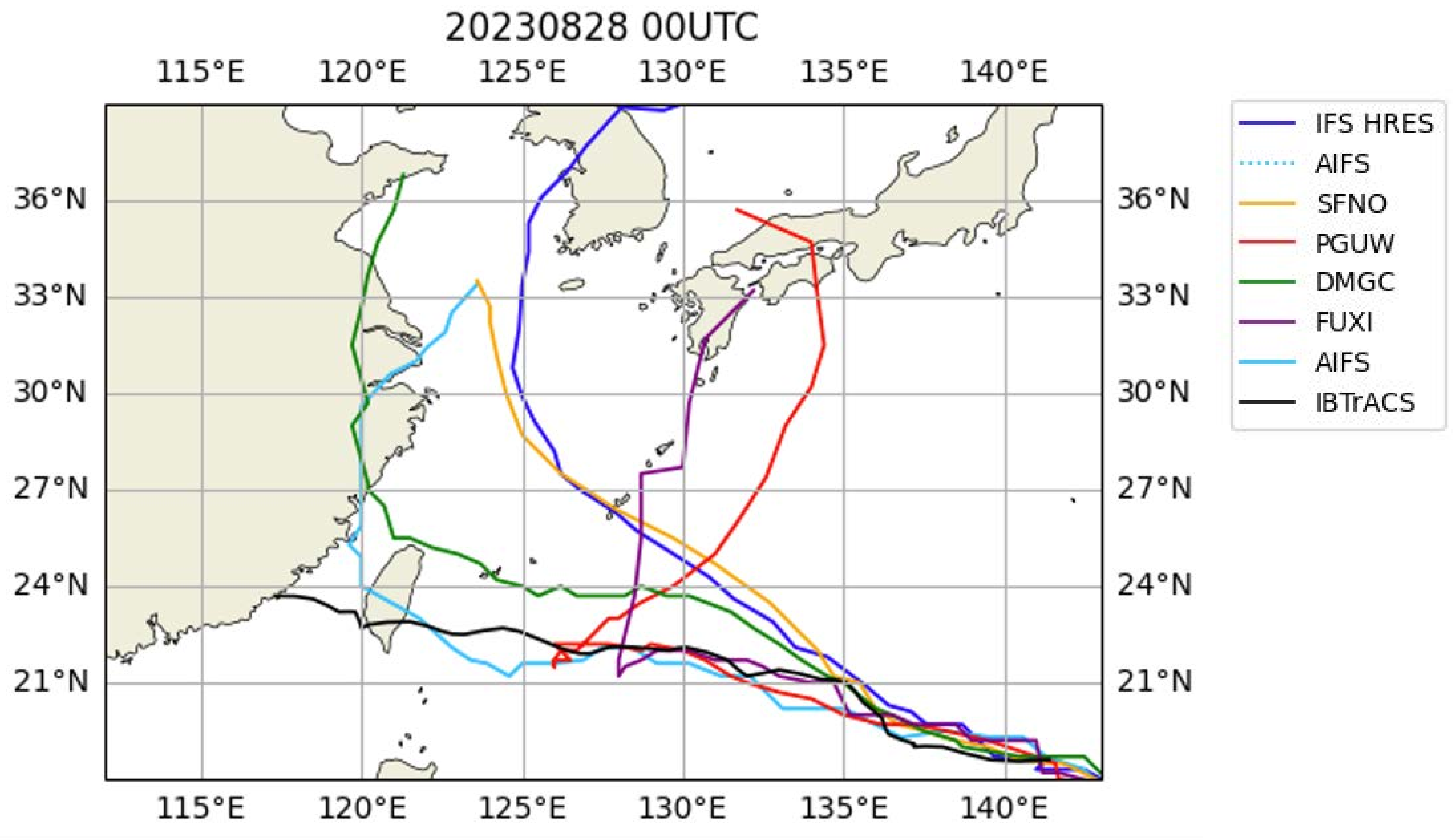
First prototype of ECMWF’s data-driven forecast model

Many more:
FuXi
FuXi-extreme
NeuralGCM

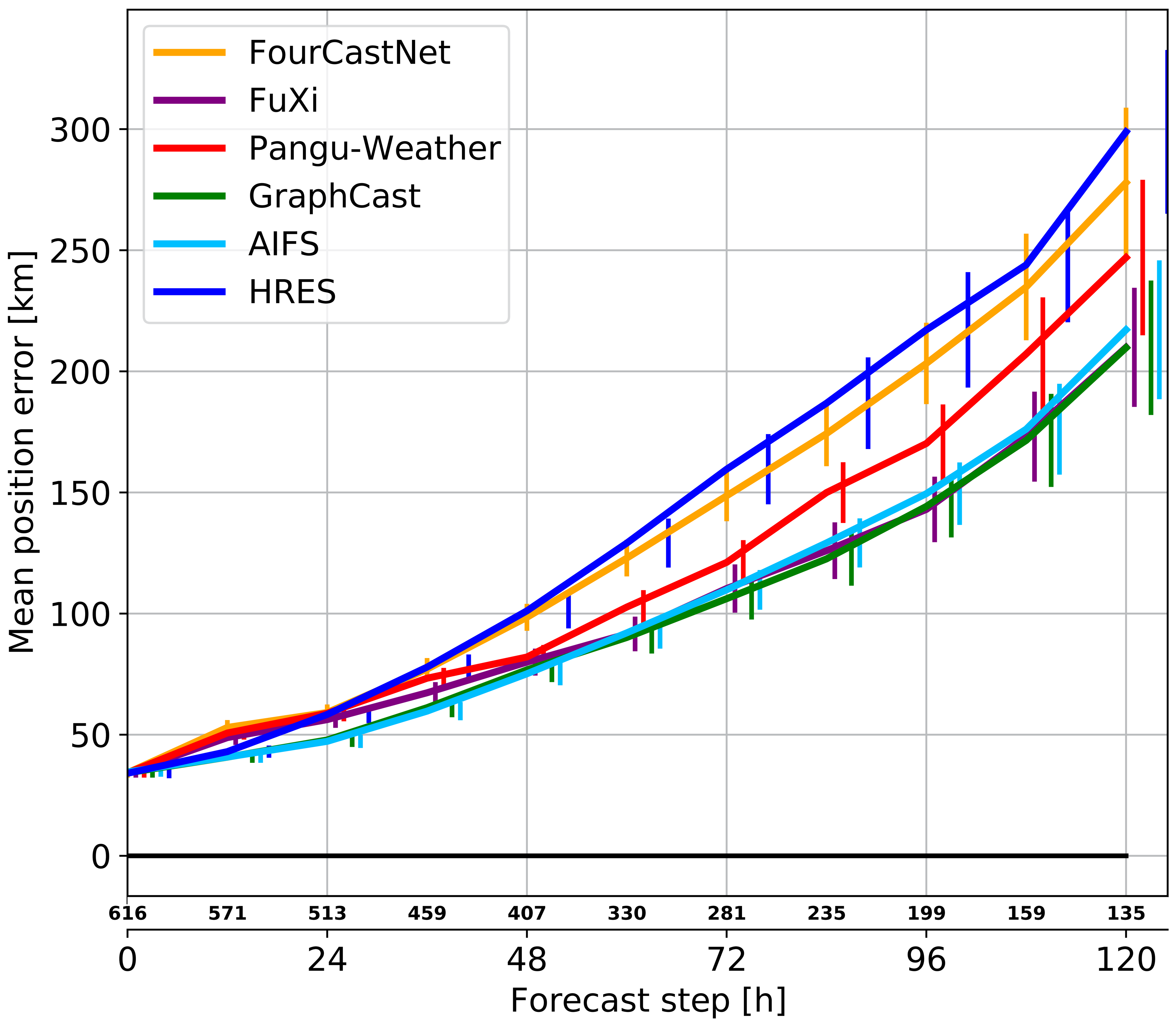
Machine learning for weather prediction

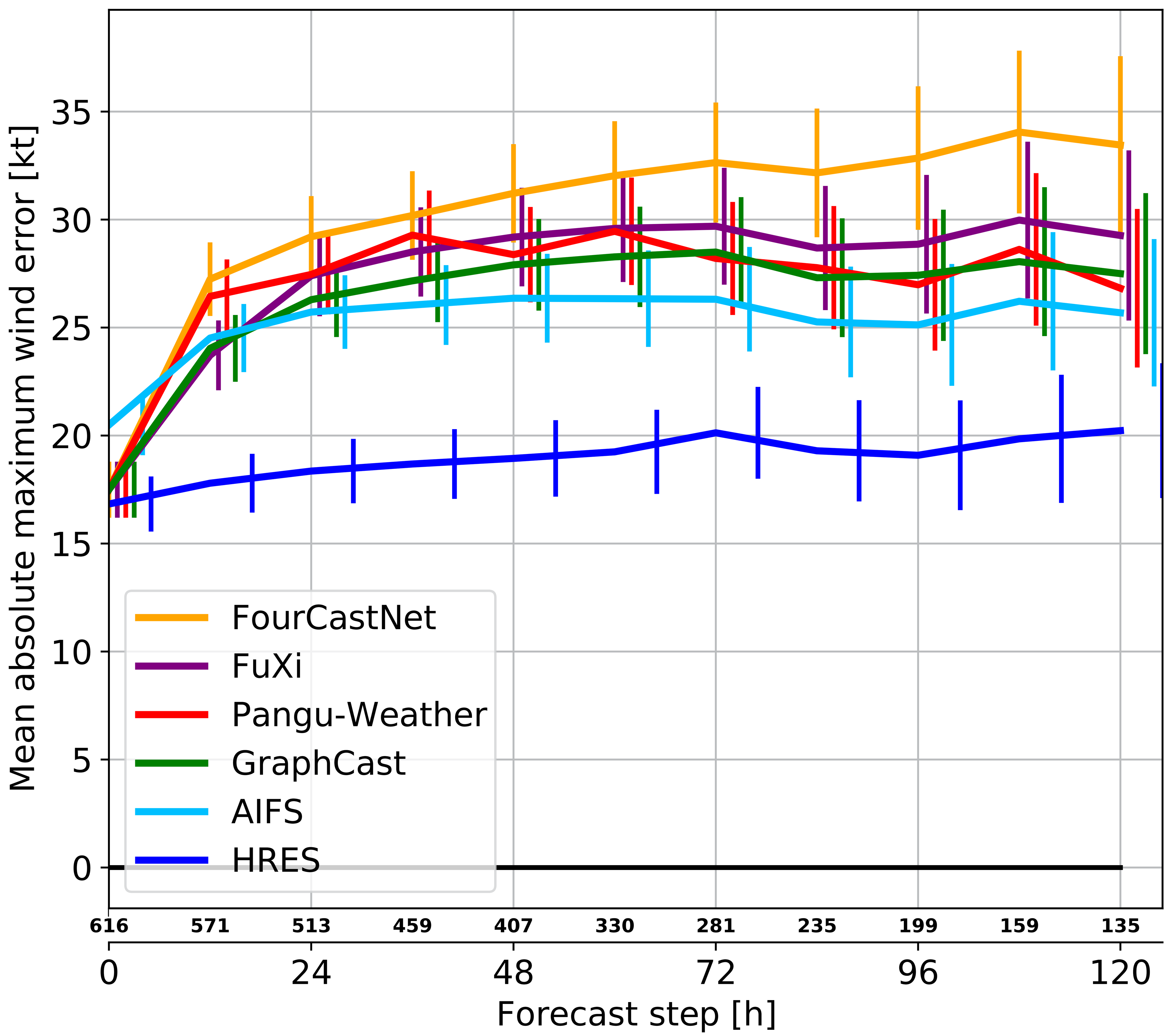


Machine learning for weather prediction



Machine learning for weather prediction





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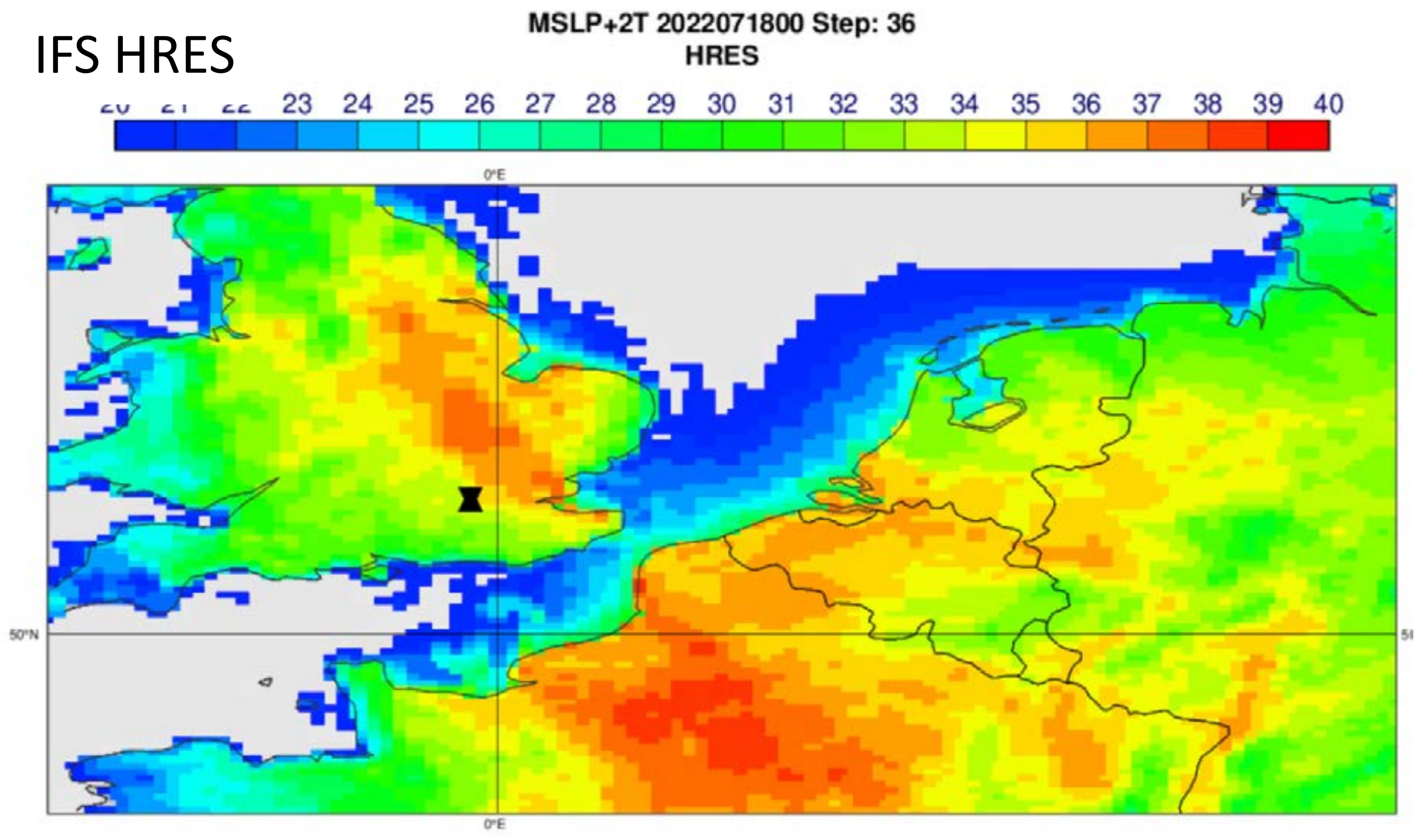
IFS HRES



PanguWeather

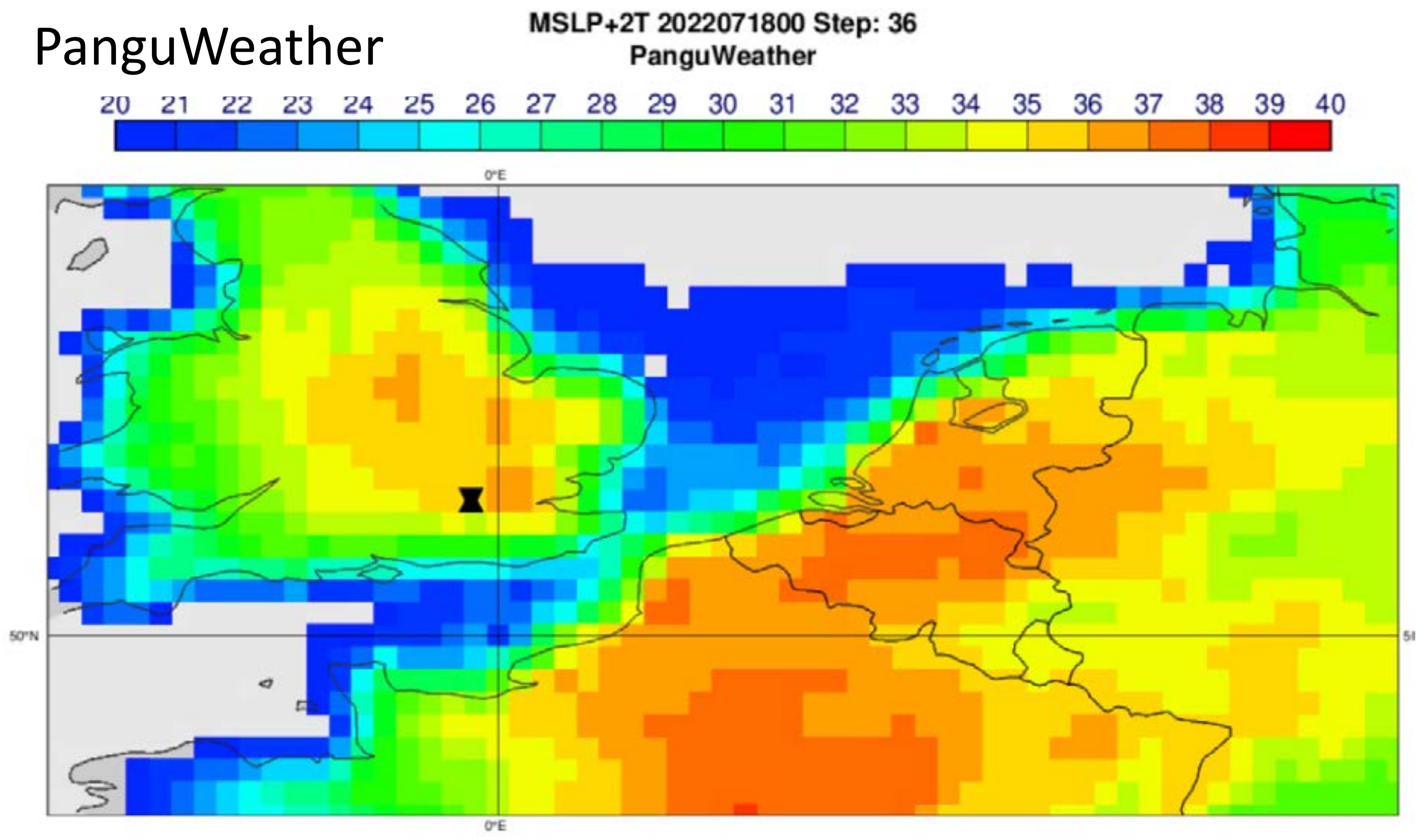


Figure from Zied Ben-Bouallegue, ECMWF

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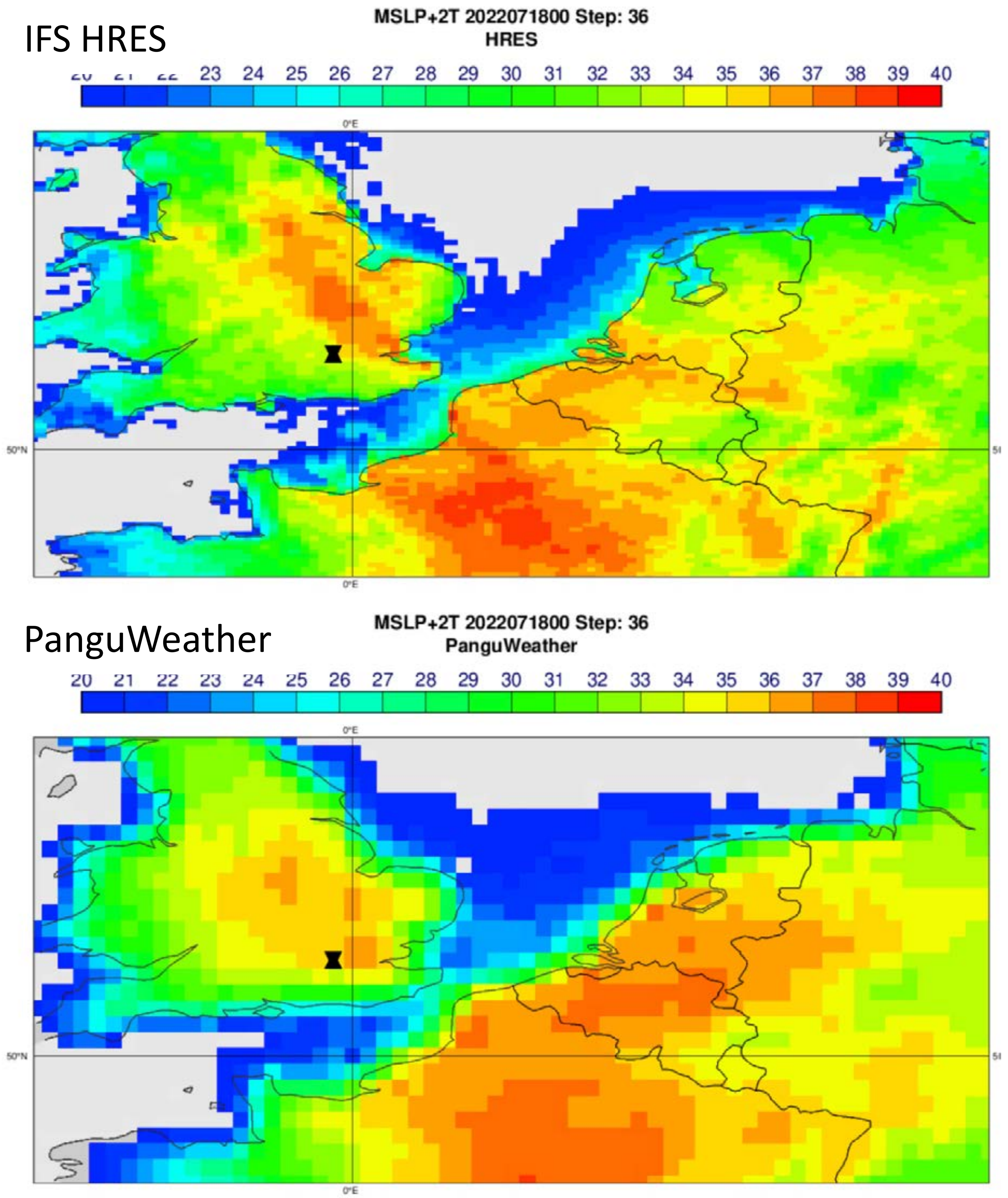

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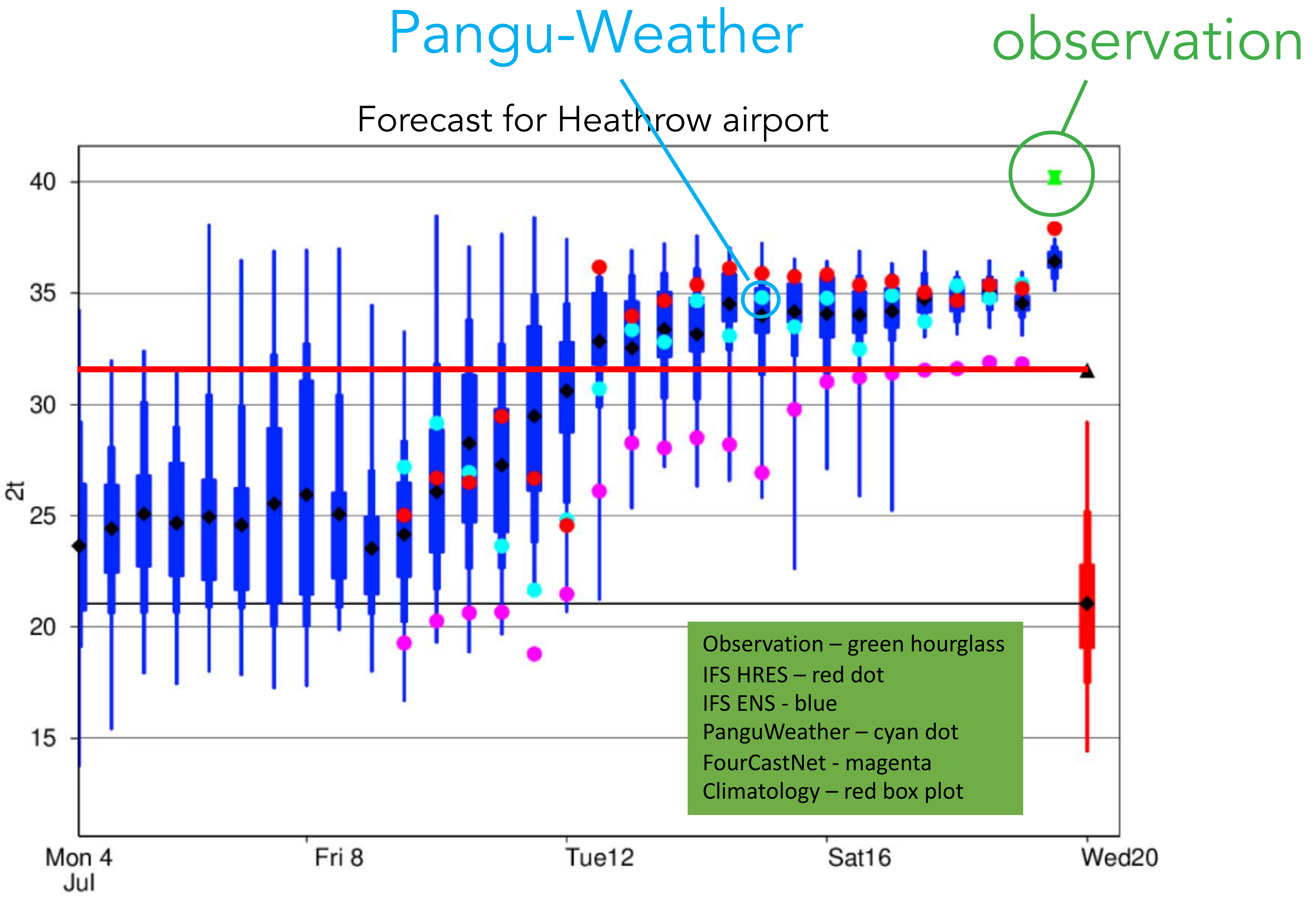

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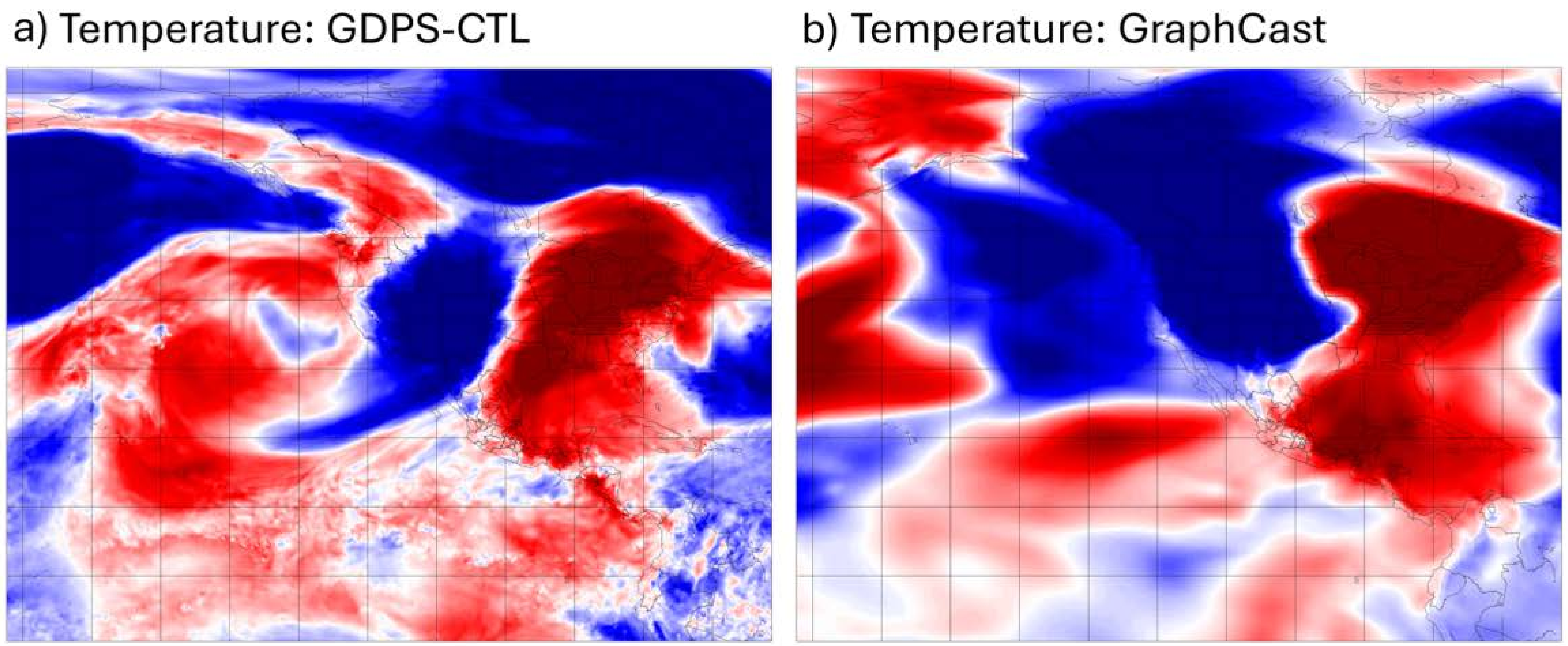
- Machine learning models outperform conventional ones for a wide range of weather scores and variables
- Inference is 3-4 orders faster than with conventional model
- Range of network architectures achieve similar scores
- Trained on historical weather data in ERA5 reanalysis
  - Optimal blend between observations and physical models

Machine learning for weather prediction

- Forecasts are too smooth
  - Consequence of training with weighted MSE loss



Machine learning for weather prediction

- Forecasts are too smooth
  - Consequence of training with weighted MSE loss
- Most current models are deterministic
  - Predict mean of multi-modal distribution
  - But neural networks are naturally suited for ensemble predictions
    - diffusion models
    - training with score-based loss function

Machine learning for weather prediction

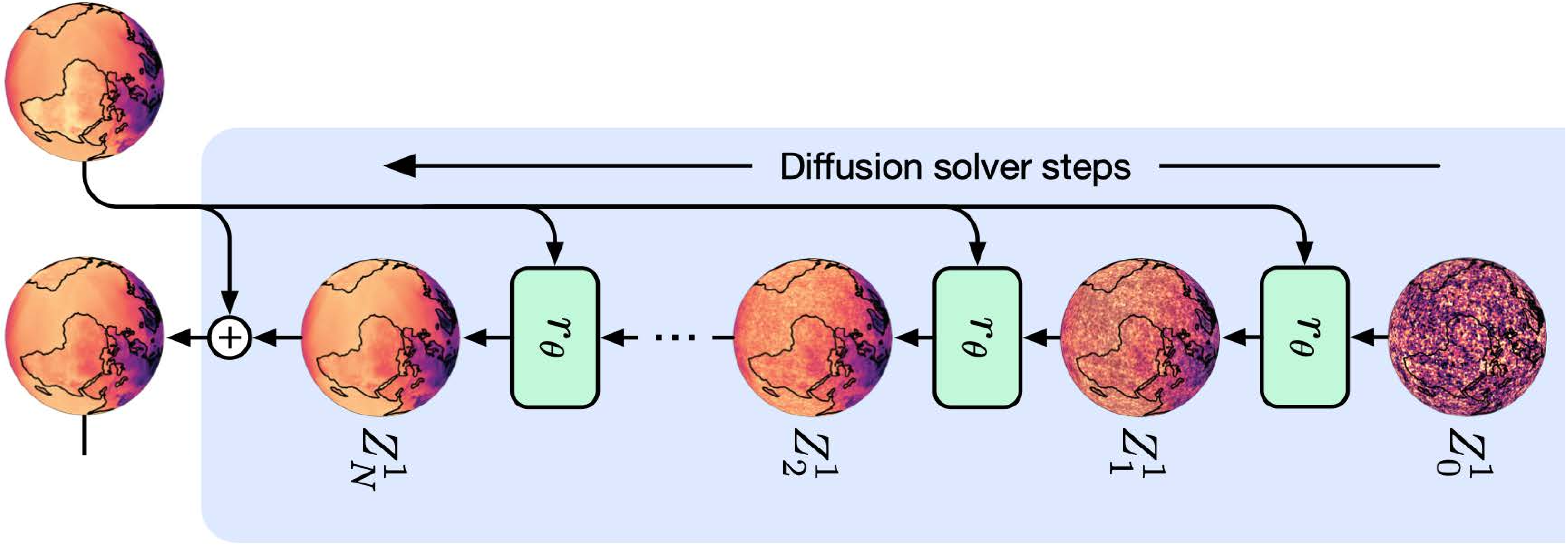
- GenCast:

Machine learning for weather prediction

- GenCast:

https://arxiv.org/abs/2312.15796

Machine learning for weather prediction



https://arxiv.org/abs/2312.15796

Machine learning for weather prediction

- Forecasts are too smooth
  - Consequence of training with weighted MSE loss
- Most current models are deterministic
  - Predict mean of multi-modal distribution
- Network use and output limited number of physical quantities
  - More required for operational forecasting
  - But networks have to have (fairly) complete state model for skilful medium-range forecast

Design space

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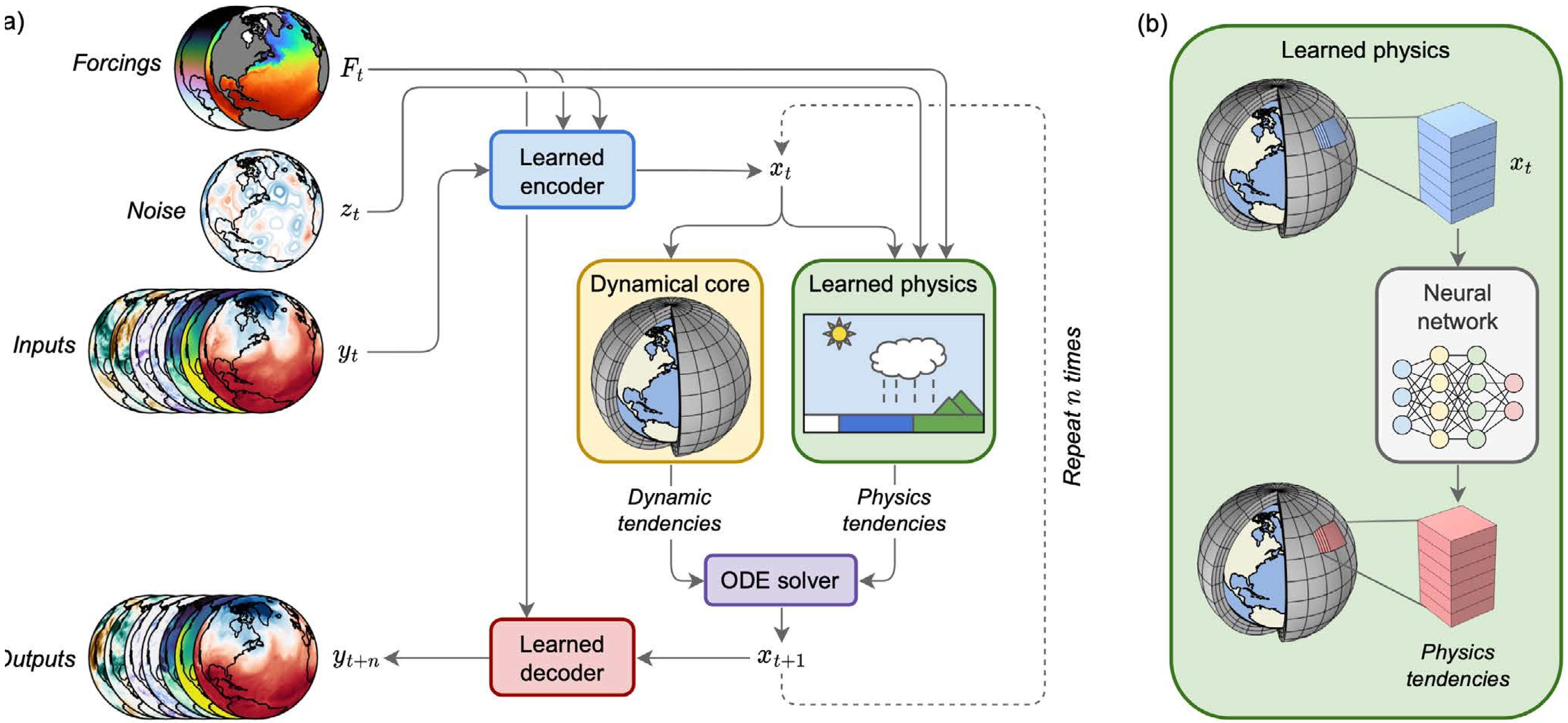
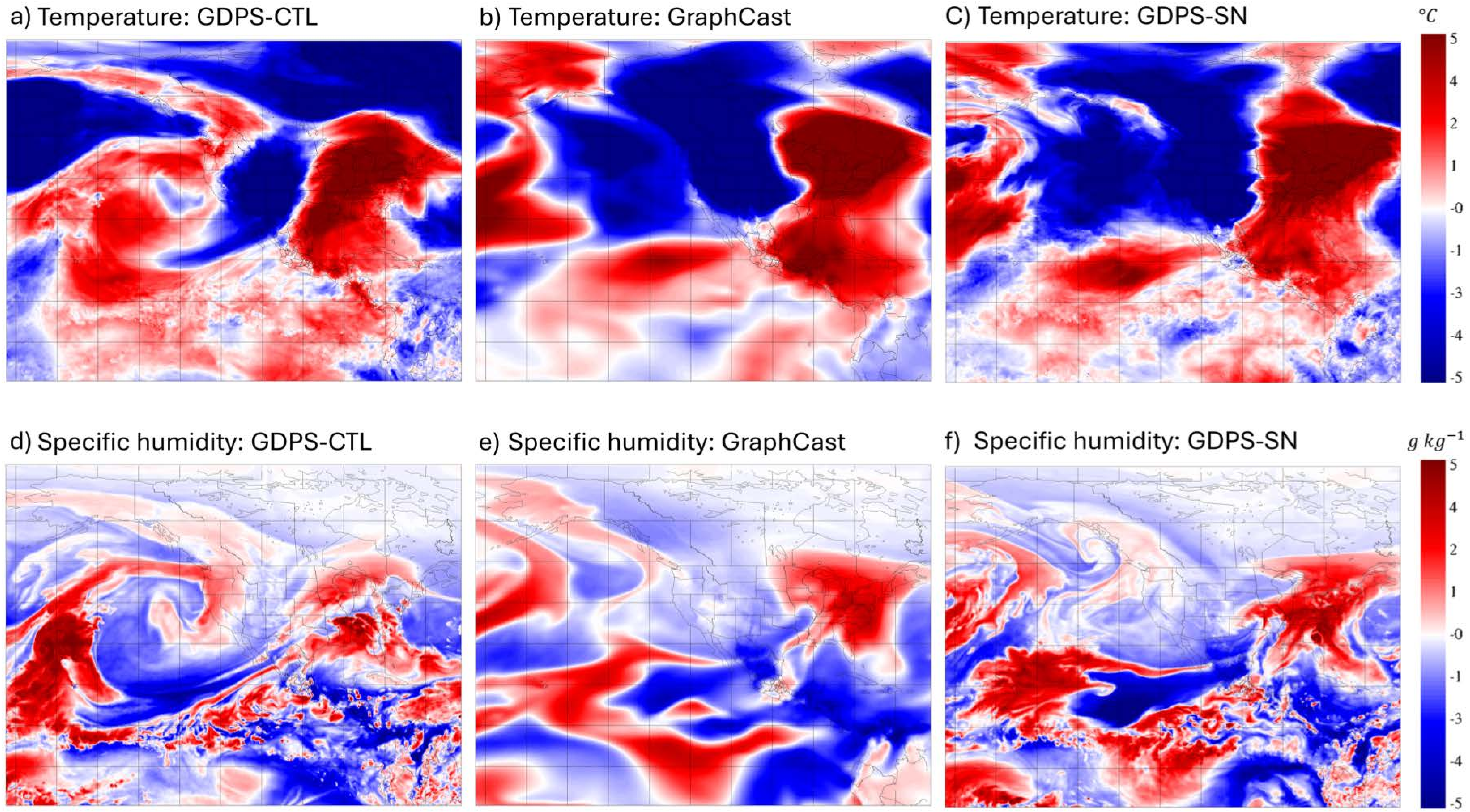
- NeuralGCM: use conventional dynamical core and complement with with per-column neural network for parametrization



https://arxiv.org/abs/2311.07222

Design space

- GDPS-SN: nudge conventional model to AI forecast



https://arxiv.org/abs/2407.06100

Design space

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Summary

- Currently machine learning revolution in NWP
  - Machine learning models outperform best conventional models in wide range of scores
- Can machine learning models become much better than conventional models, e.g. for extended range?
- How can machine learning models become operational?