

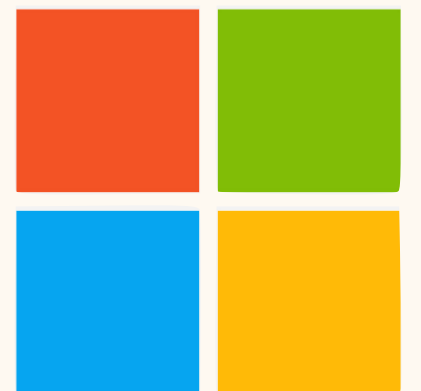
Aurora: A Foundation Model for the Earth System

Wessel Bruinsma

The Alan Turing Institute
Work was done at Microsoft Research

UCL AI Centre, London, 24 July 2025

**The
Alan Turing
Institute**

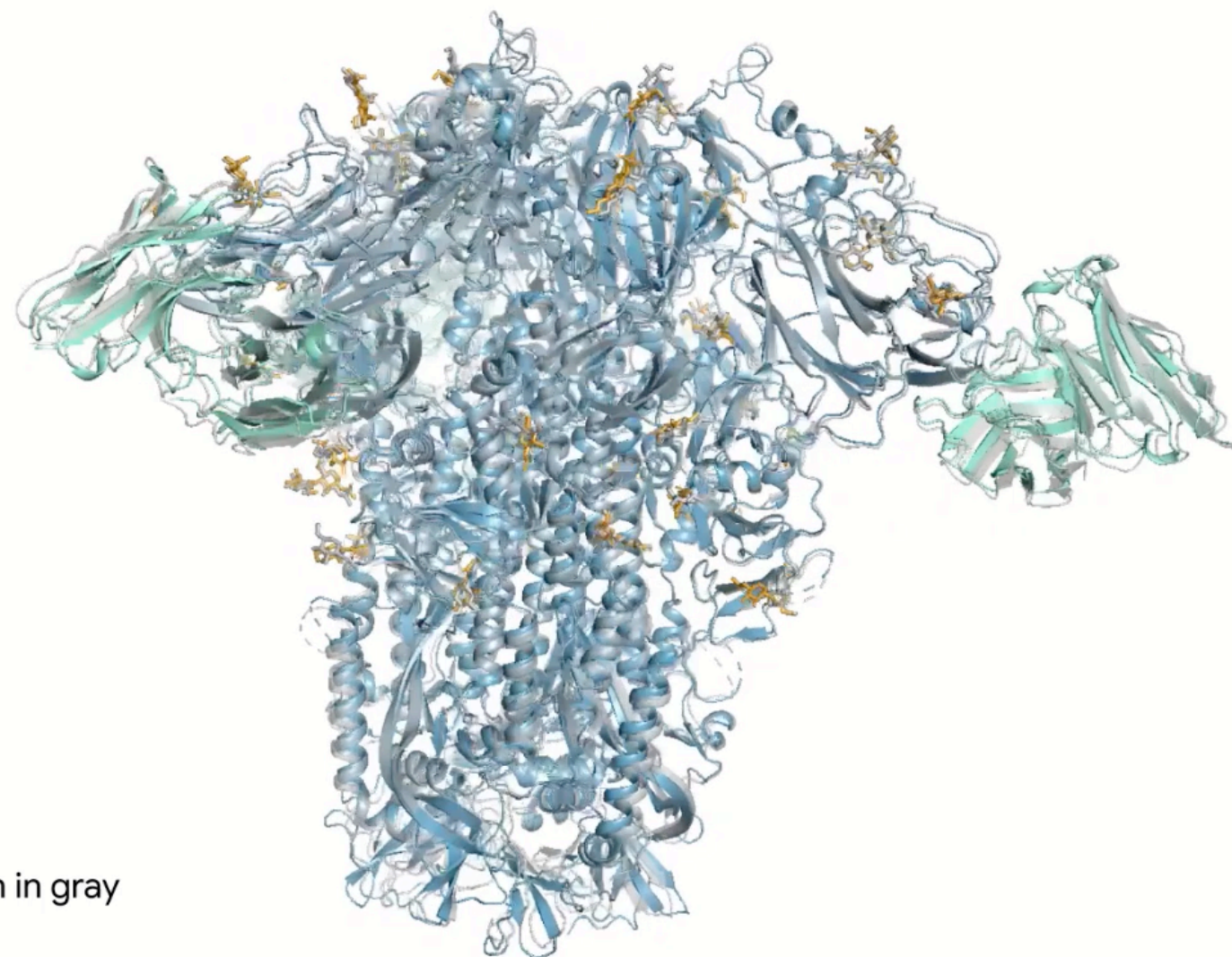


The AI Revolution in Science

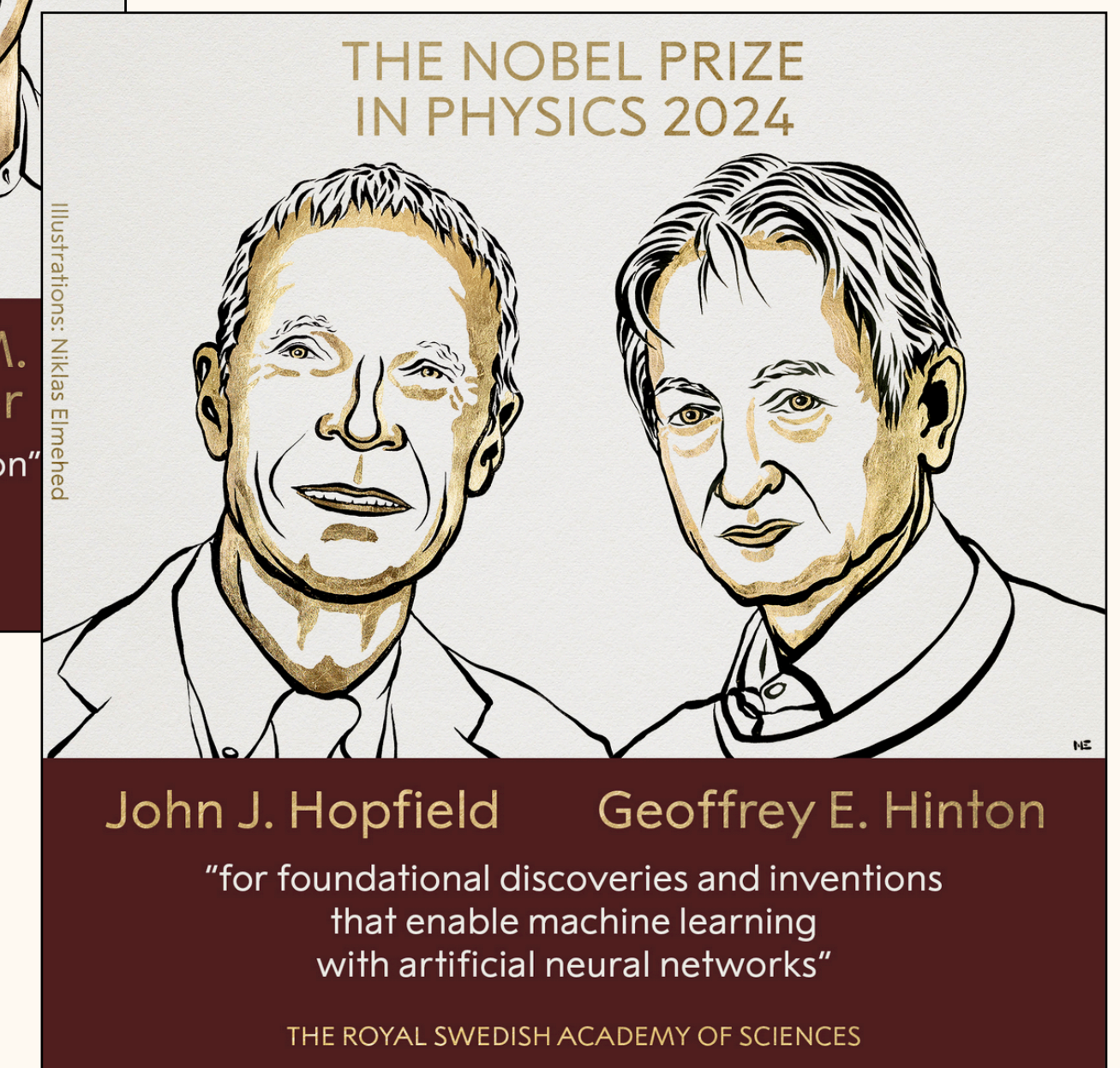
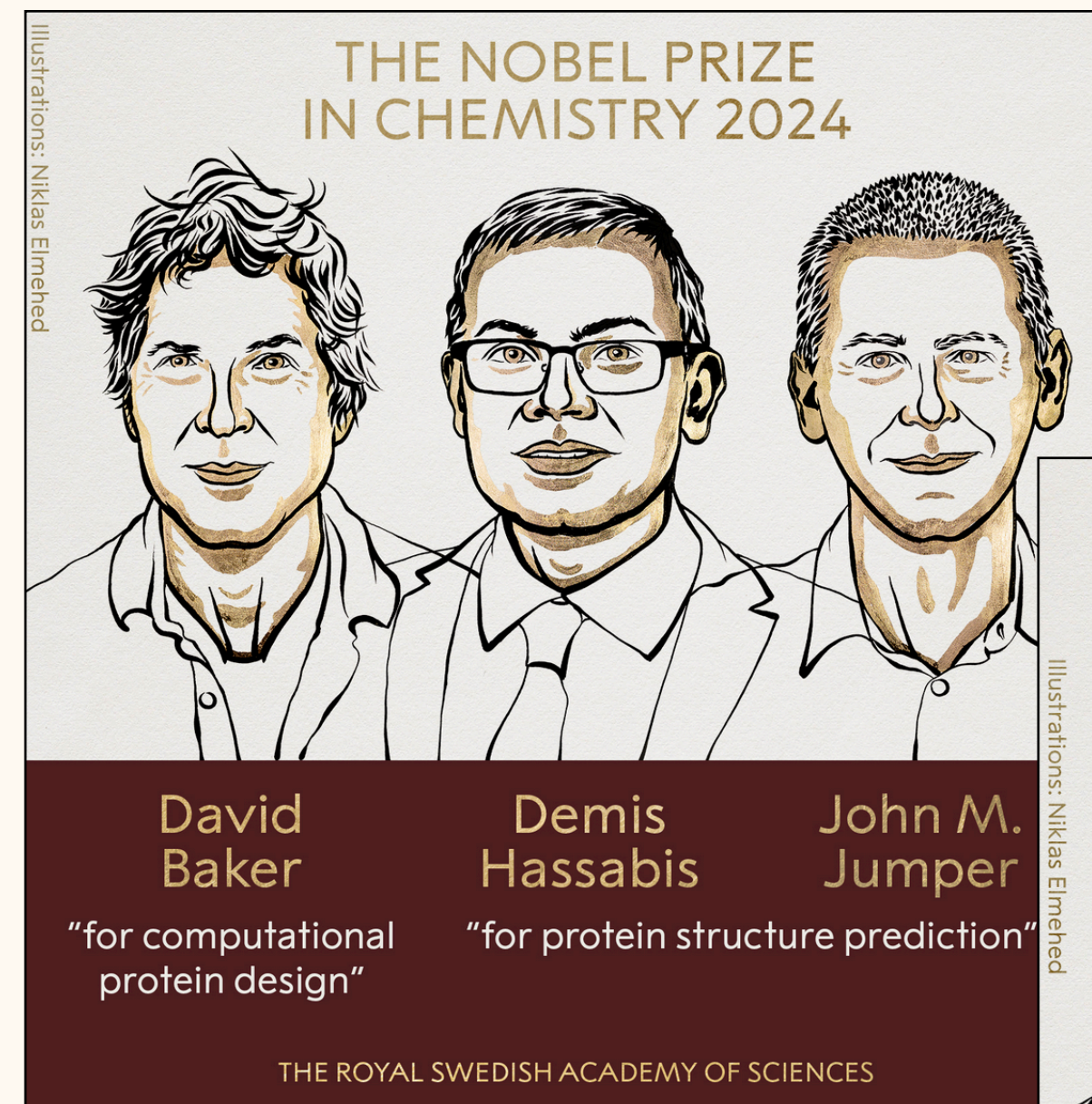


AlphaFold
Protein folding

7PNM



Ground truth shown in gray



The AI Revolution in Weather Forecasting

2018

First serious efforts to compare AI models to physics baselines

Dueben and Bauer (2018)

2019

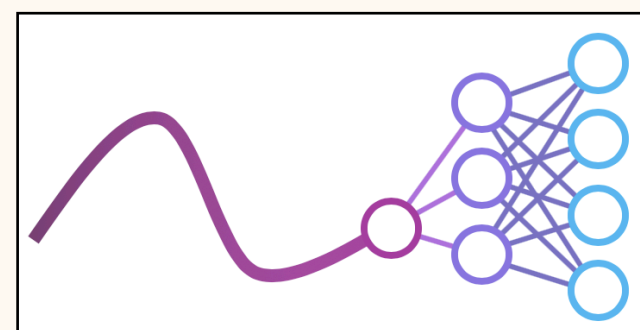
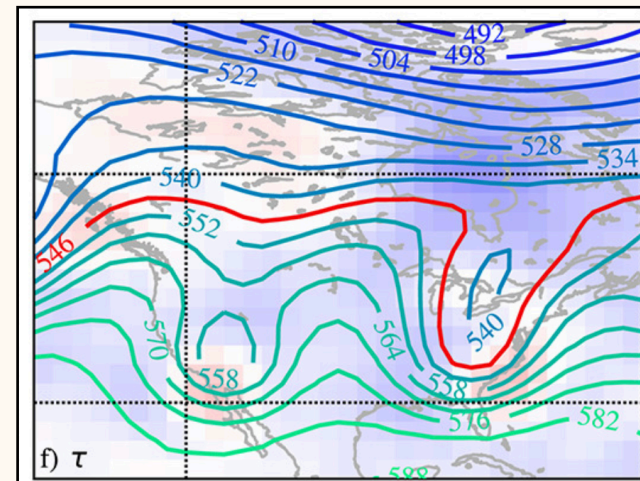
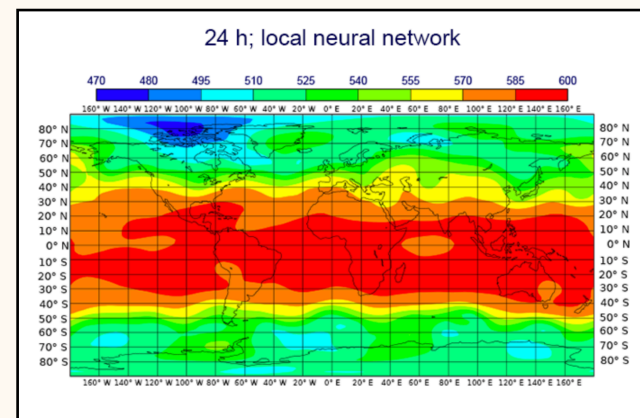
AI models skillful to multiple days

Weyn et al. (2019)

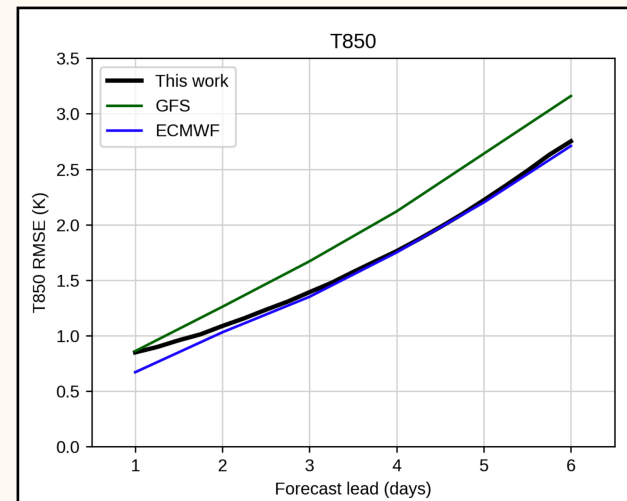
2020

WeatherBench starts to drive ML development

Rasp et al. (2020)



The AI Revolution in Weather Forecasting



2022

GNN outperforms GFS at 1°

Keisler (2022)

2022

Pangu-Weather outperforms HRES at 0.25°

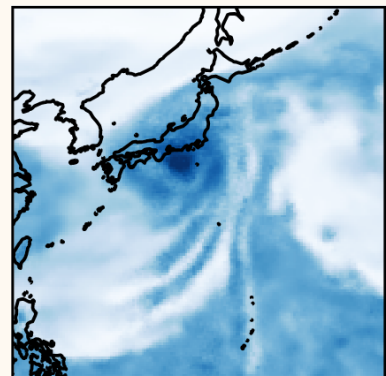
Bi et al. (2023)

The AI Revolution in Weather Forecasting



2022–2023

Tech companies start to work in this space



2023

GenCast outperforms IFS ensemble
Price et al. (2024)



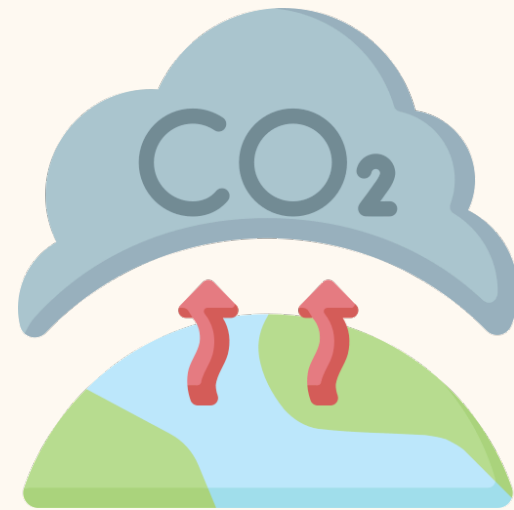
2024

ECMWF launches AIFS

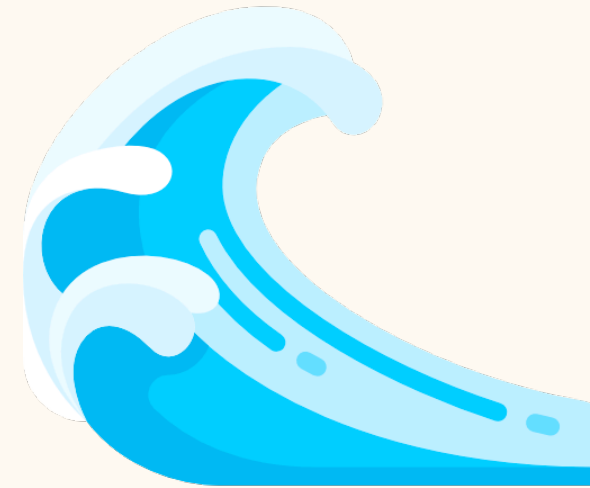
What About Other Forecasting Tasks?



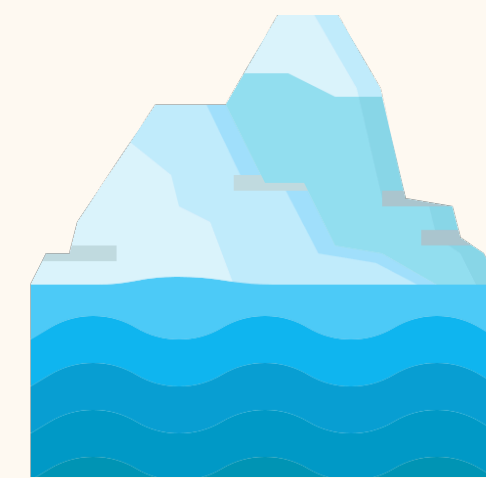
Air
pollution



Atmospheric
composition



Waves



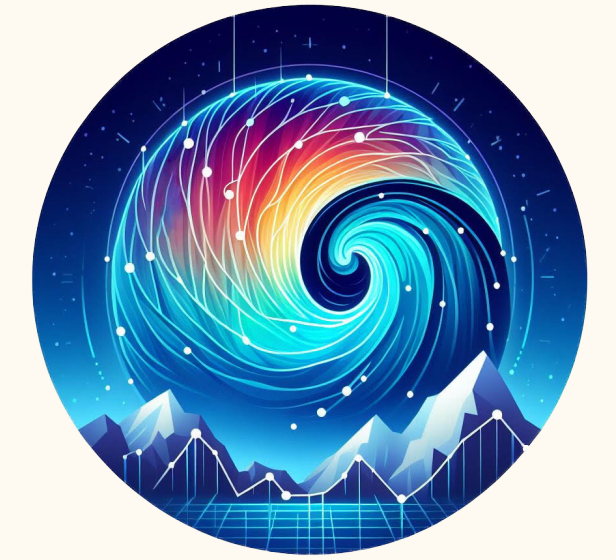
Sea ice



Ocean

- Current models are impressive, but **limited to one setting**.
- Unified approach?

Aurora



pretraining

- Train a single neural network a *large* body of Earth system data
- Learn general-purpose representation of dynamics that govern atmospheric and oceanic flow
- Slow and data hungry

fine-tuning

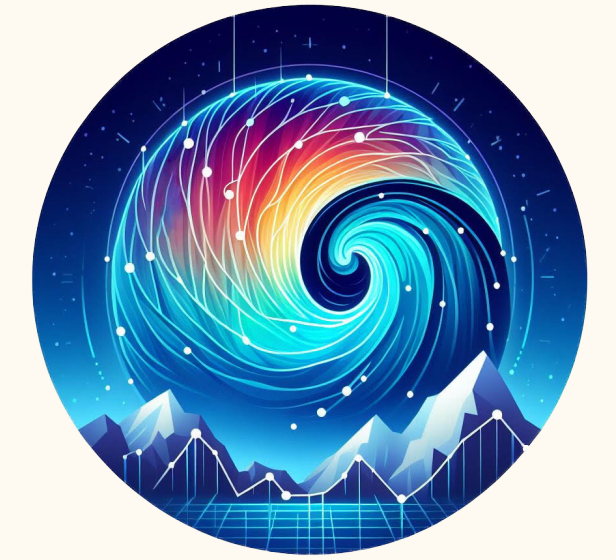
- Leverage learned representation to **efficiently adapt to new domains!**
- Fast and data efficient

Aurora: a **foundation model** for the Earth system

The Model

A dramatic photograph of a massive supercell storm cloud, featuring a large, dark, and textured wall cloud extending from the horizon. A bright, vertical column of white cloud, likely a developing funnel or a wall cloud, is visible on the right side of the storm. The foreground shows a flat, green agricultural field with some distant structures and a few small figures, emphasizing the scale of the storm. The sky is filled with dark, heavy clouds, and the overall atmosphere is ominous and powerful.

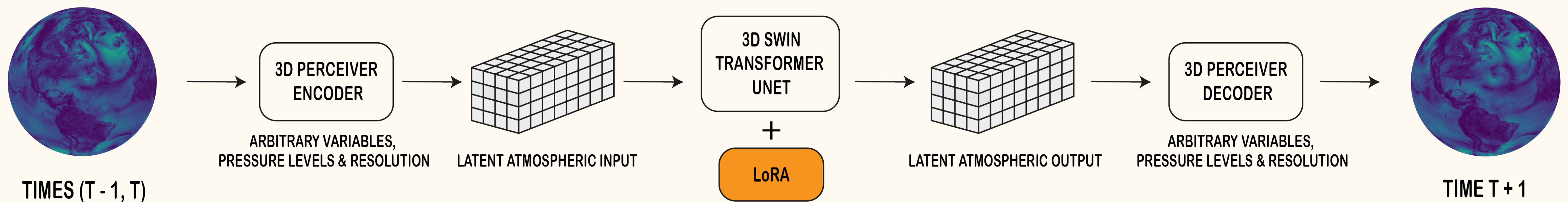
The Model



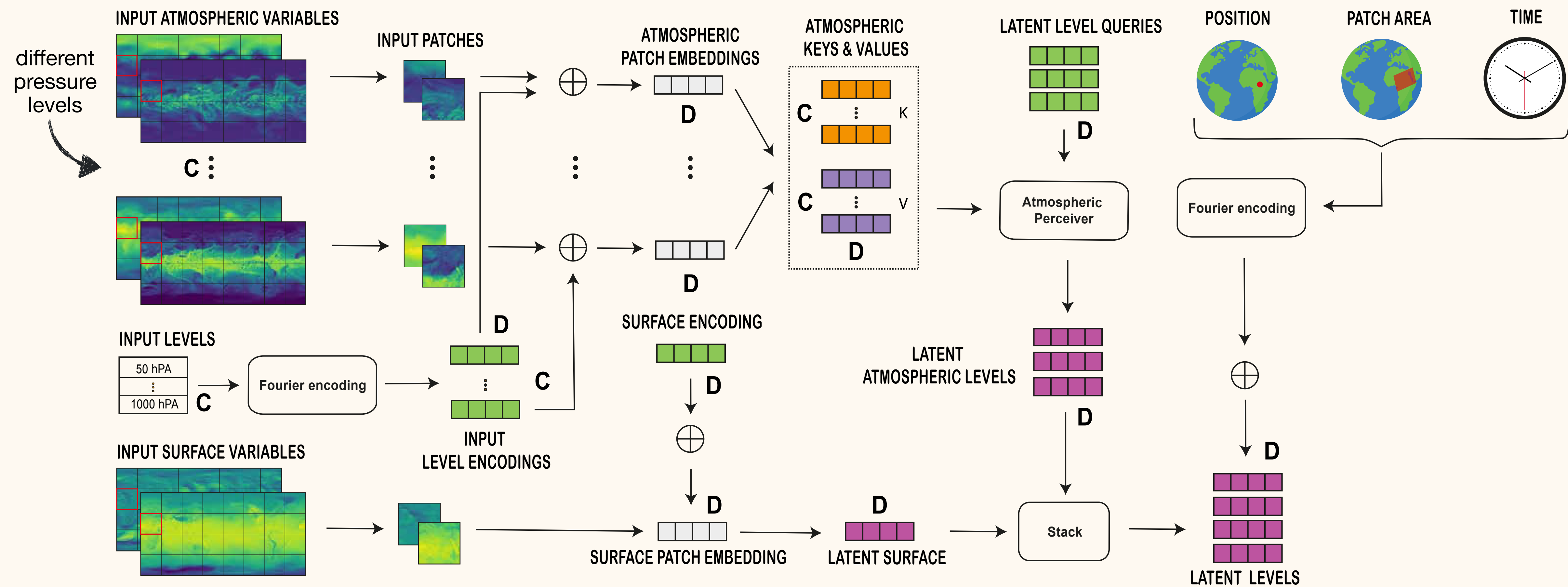
- Predict global state of **any variables** at **any resolution** 6 h ahead:

$$\begin{aligned}\hat{X}^{t+6h} &= \Phi(X^t, X^{t-6h}), \\ \hat{X}^{t+12h} &= \Phi(\hat{X}^{t+6h}, X^t), \\ \hat{X}^{t+18h} &= \Phi(\hat{X}^{t+12h}, \hat{X}^{t+6h}), \\ &\vdots\end{aligned}$$

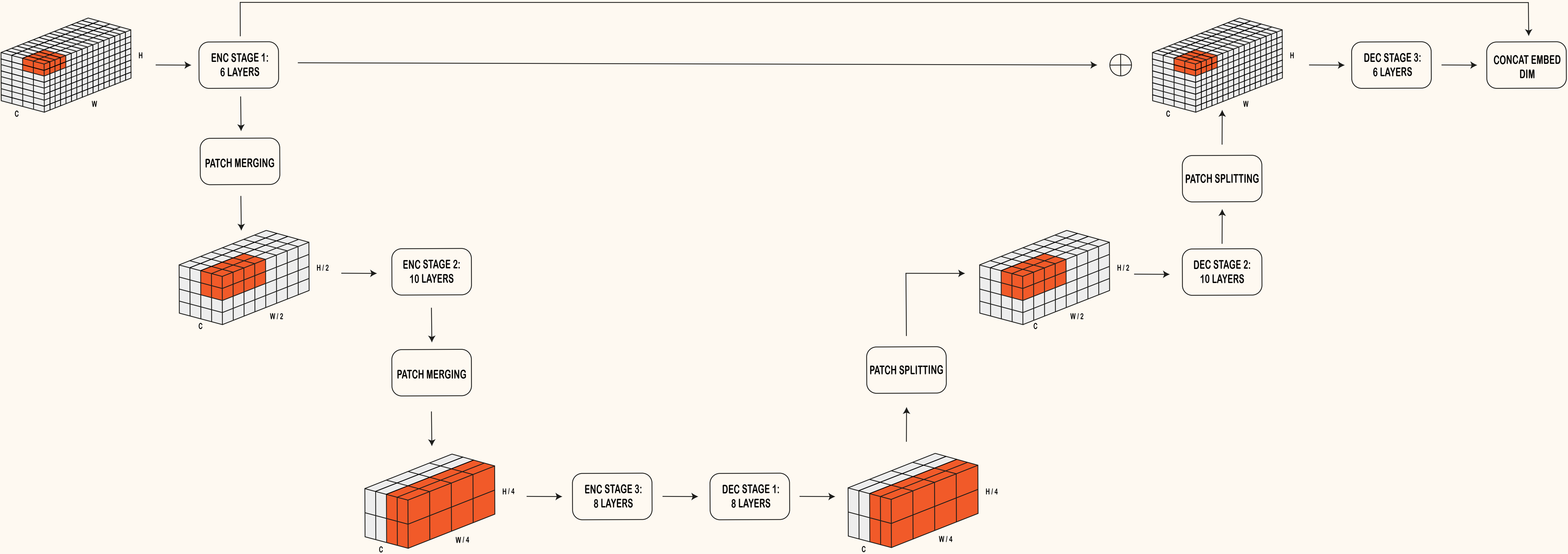
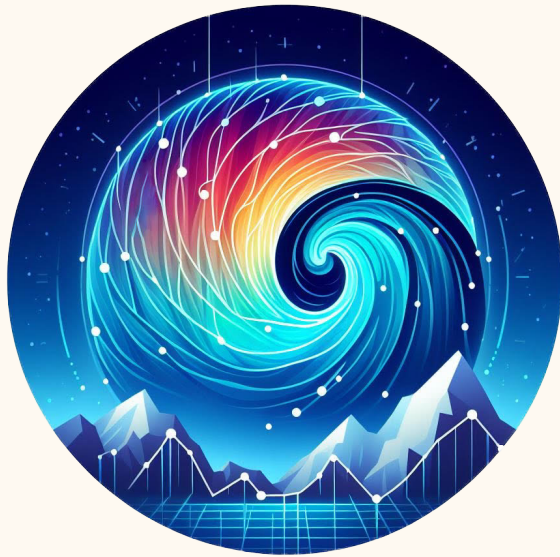
- Transformer-based encoder–decoder architecture:



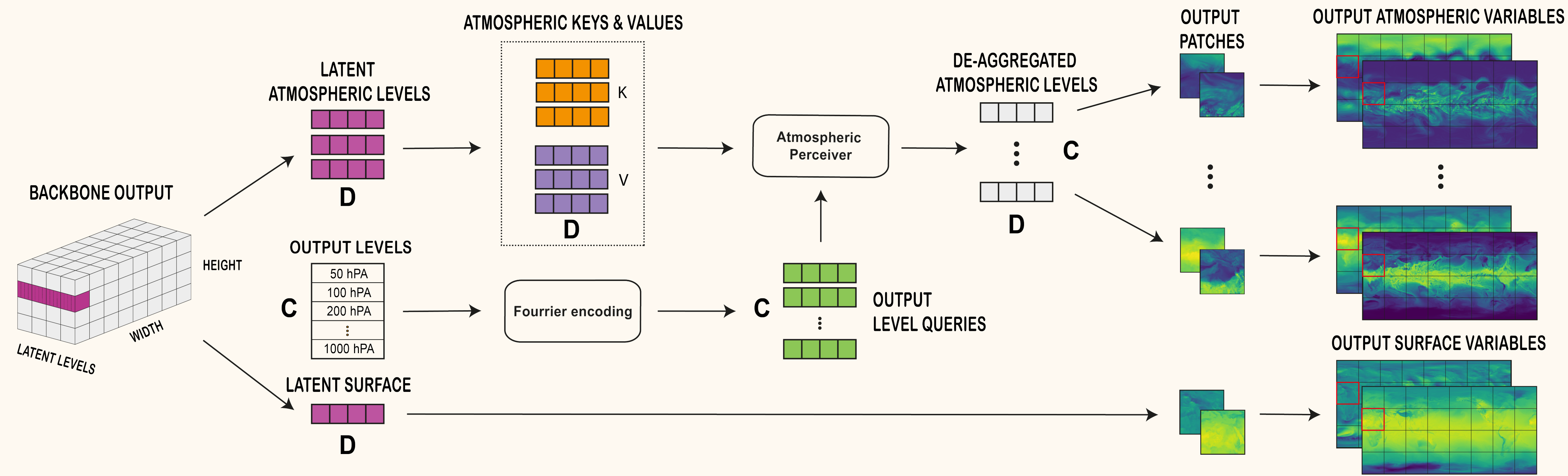
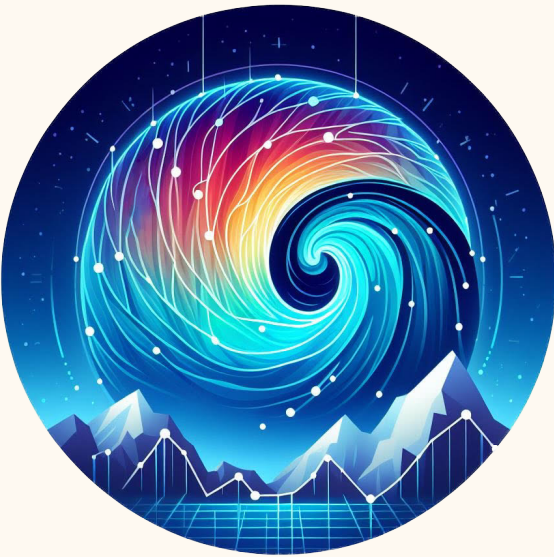
Encoder



Backbone



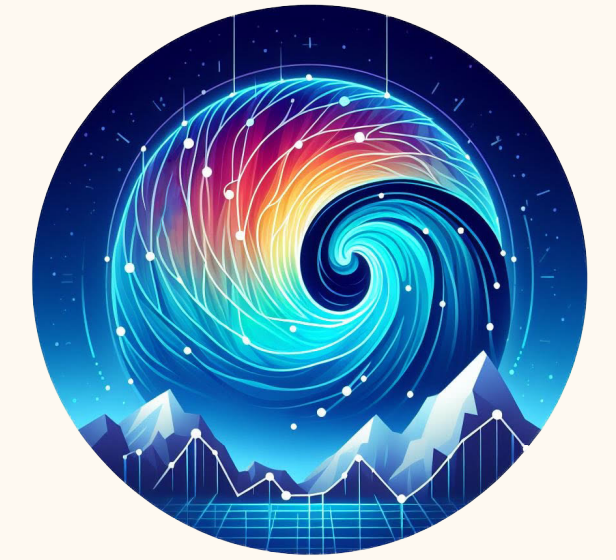
Decoder



Pretraining



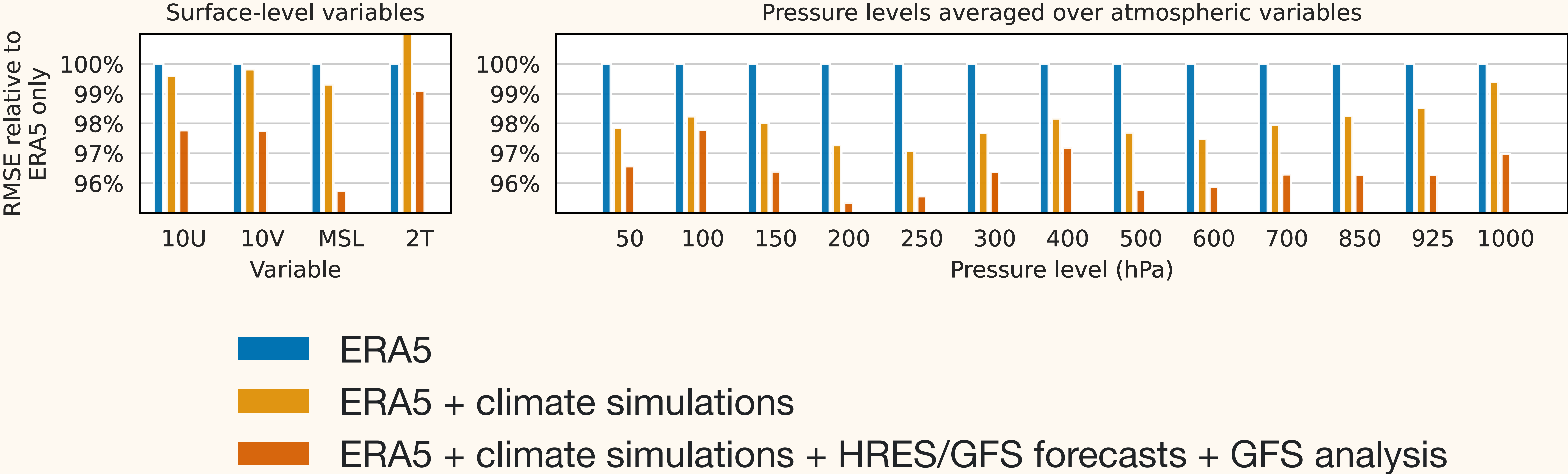
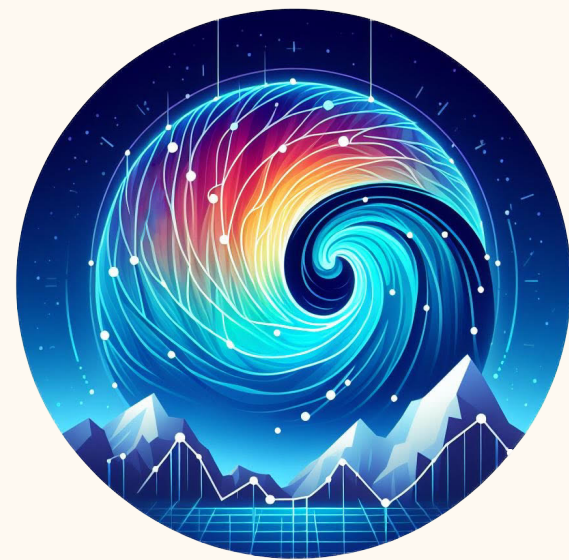
Pretraining



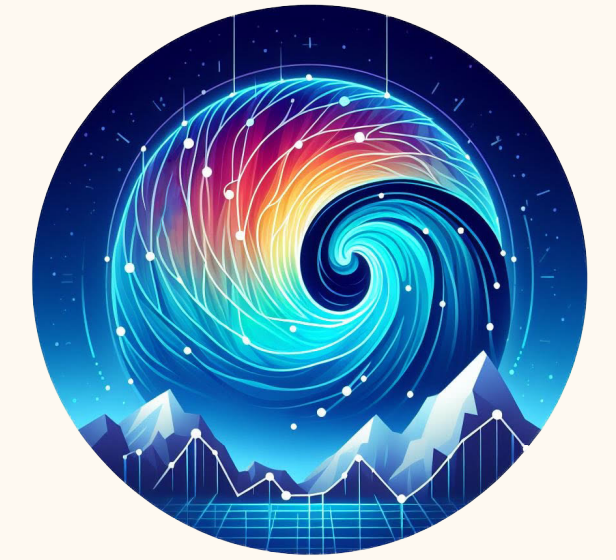
Name	Resolution	Timeframe	Surf. variables	Atmos. variables	Levels	Steps	Size
ERA5	$0.25^\circ \times 0.25^\circ$	1979–2020	2T, 10U, 10V, MSL	U, V, T, Q, Z	13	368.18 k	105.50 TB
HRES-0.25 forecasts	$0.25^\circ \times 0.25^\circ$	2016–2020	2T, 10U, 10V, MSL	U, V, T, Q, Z	13	149.81 k	42.93 TB
IFS-ENS-0.25	$0.25^\circ \times 0.25^\circ$	2018–2020	2T, 10U, 10V, MSL	U, V, T, Q, Z	3	6.69 M	527.54 TB
IFS-ENS-0.25 mean	$0.25^\circ \times 0.25^\circ$	2018–2020	2T, 10U, 10V, MSL	U, V, T, Q, Z	3	133.71 k	10.55 TB
GFS forecasts	$0.25^\circ \times 0.25^\circ$	Feb 2015–2020	2T, 10U, 10V, MSL	U, V, T, Q, Z	13	354.40 k	101.56 TB
GFS T0	$0.25^\circ \times 0.25^\circ$	Feb 2015–2020	2T, 10U, 10V, MSL	U, V, T, Q, Z	13	8.64 k	2.48 TB
GEFS reforecasts	$0.25^\circ \times 0.25^\circ$	2000–2019	2T, MSL	U, V, T, Q, Z	7	2.96 M	454.61 TB
CMCC-CM2-VHR4	$0.25^\circ \times 0.25^\circ$	1950–2014	2T, 10U, 10V, MSL	U, V, T, Q	7	94.96 k	12.62 TB
ECMWF-IFS-HR	$0.45^\circ \times 0.45^\circ$	1950–2014	2T, 10U, 10V, MSL	U, V, T, Q, Z	7	94.96 k	4.75 TB
MERRA-2	$0.625^\circ \times 0.50^\circ$	1980–2020	2T, 10U, 10V, MSL	U, V, T, Q	13	119.81 k	5.58 TB
Total						10.97 M	1,268.12 TB

- 150 000 steps on 32 GPUs (A100)
- The magic: **data scaling** and **model scaling**!

Data Scaling

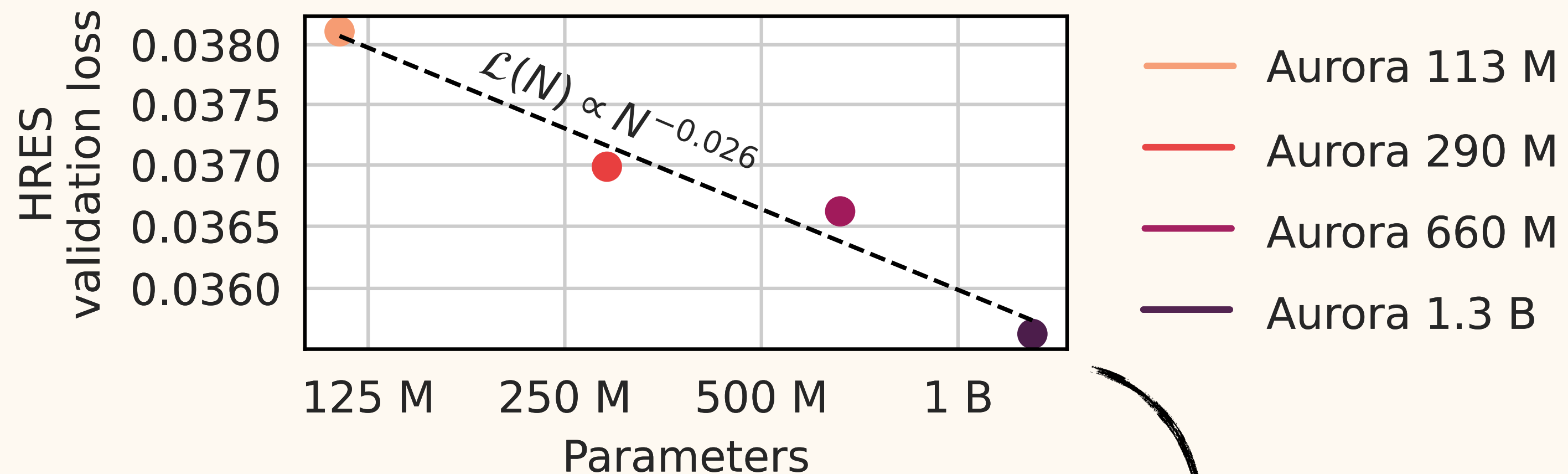


Model Scaling



Economical to train big models!

Validation loss at fixed computational budget



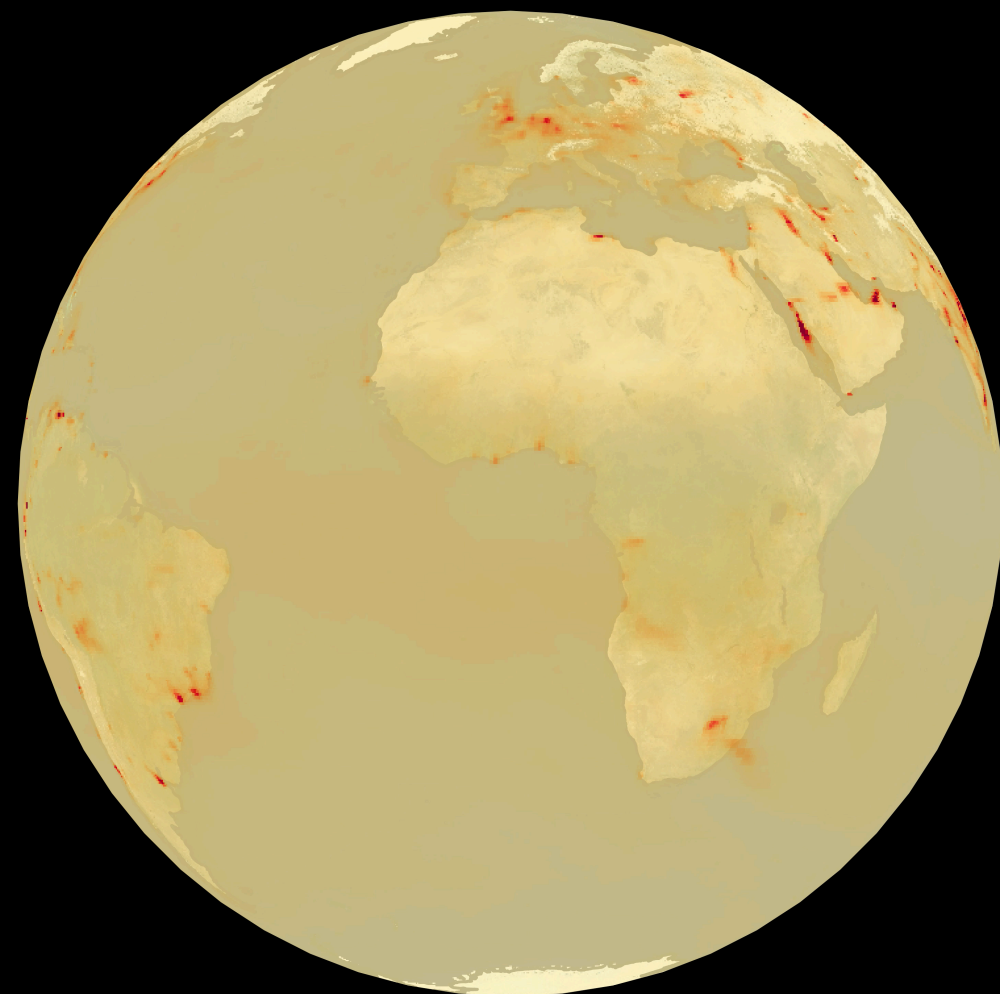
6% reduction per 10x model size!

Fine-Tuning

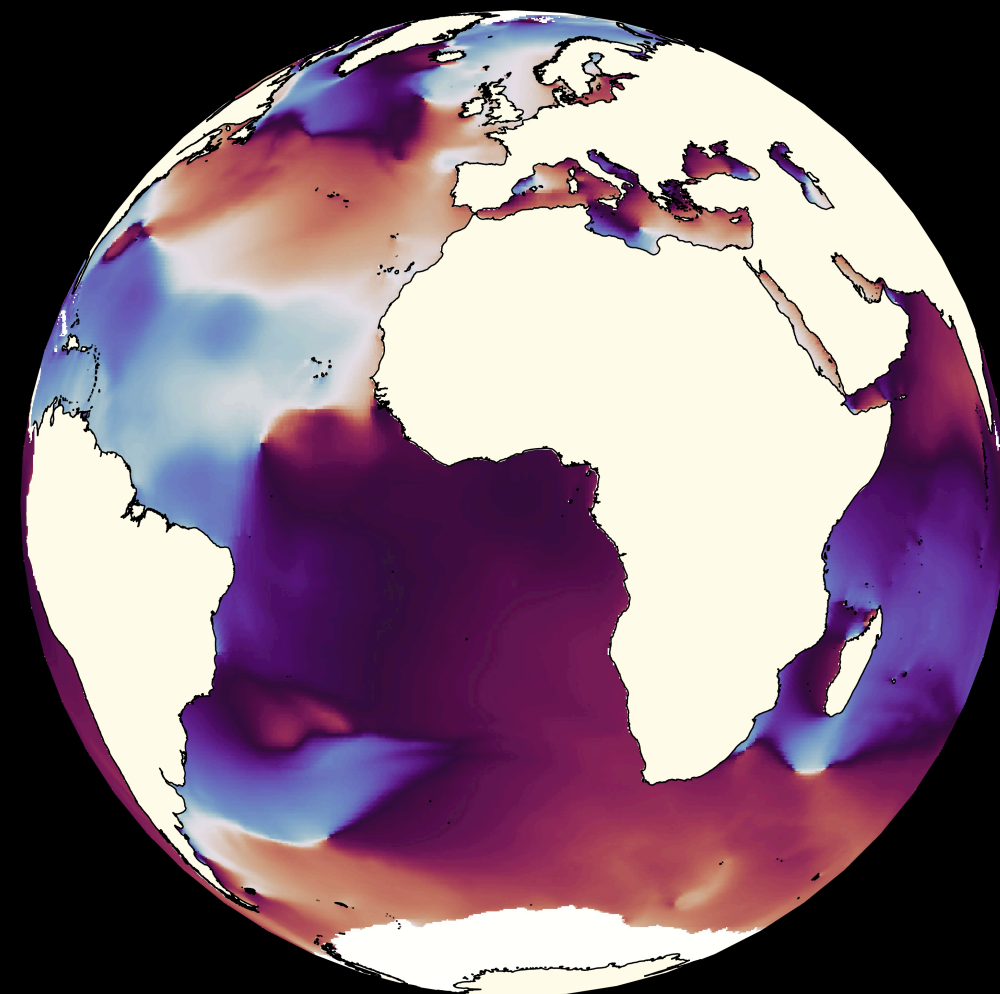
The background image is a dramatic landscape featuring a massive, dark, and textured storm cloud formation that dominates the upper half of the frame. A bright, vertical light beam or rain shaft descends from the center of the cloud formation, creating a stark contrast with the dark sky. The foreground shows a flat, green field with some distant structures and a few small figures, suggesting a rural or agricultural setting. The overall mood is intense and powerful.

Applications

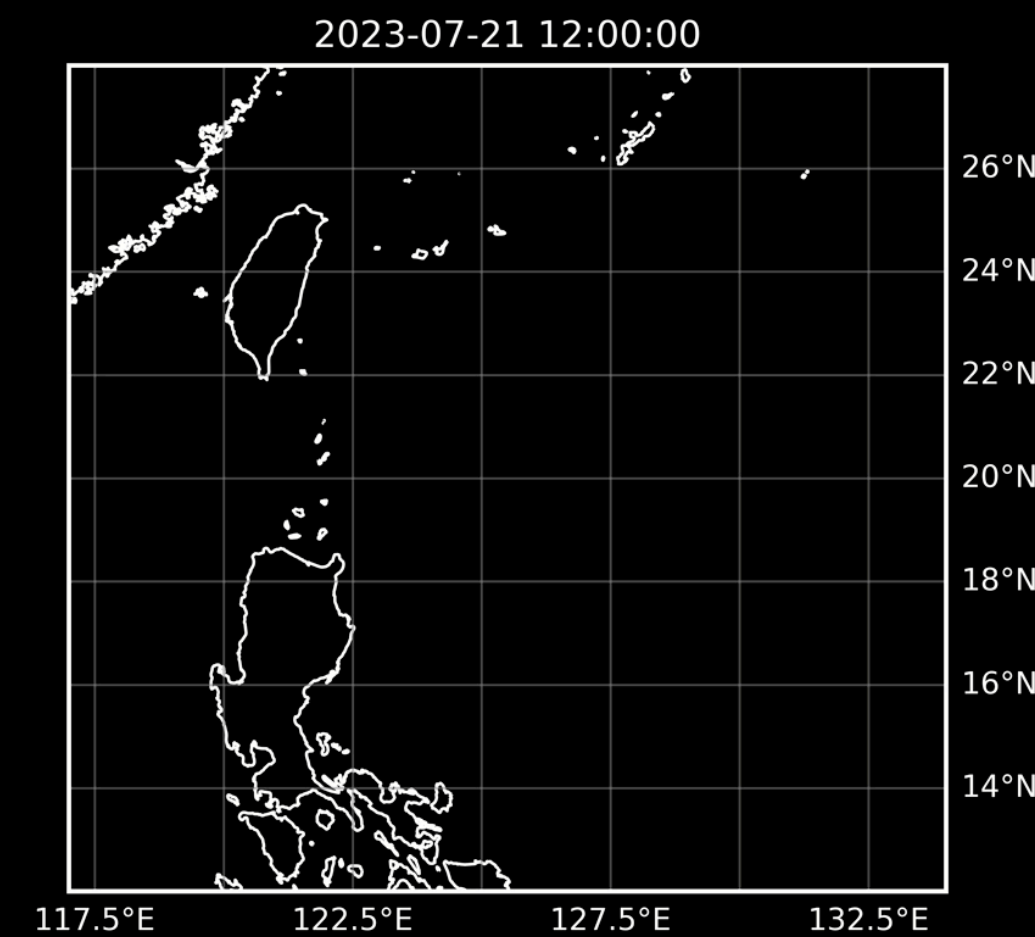
Operational in all settings!



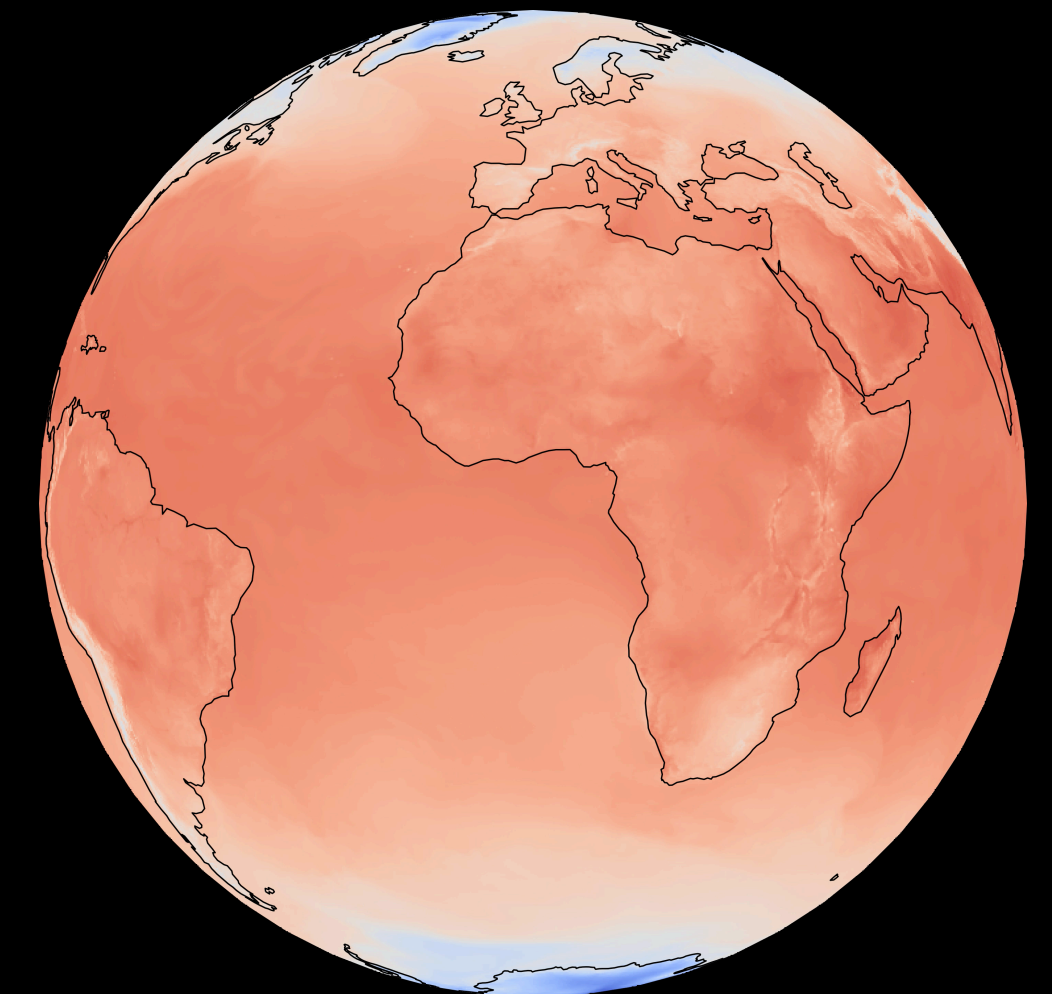
Atmospheric comp.
and air pollution



Ocean
waves

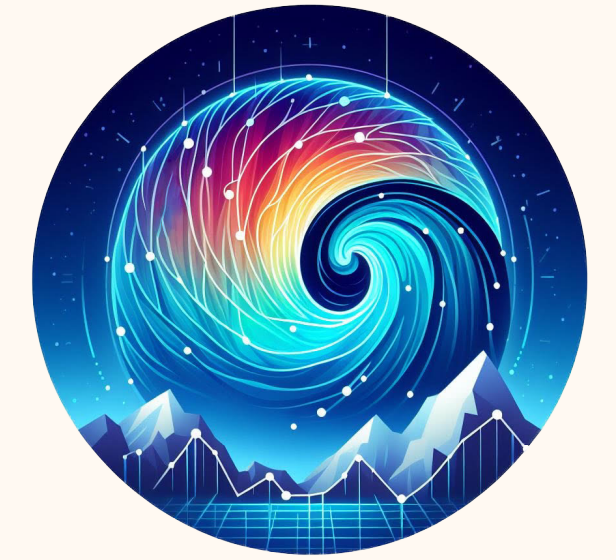


Tropical cyclone
tracks



High-resolution
weather

Air Pollution Forecasting

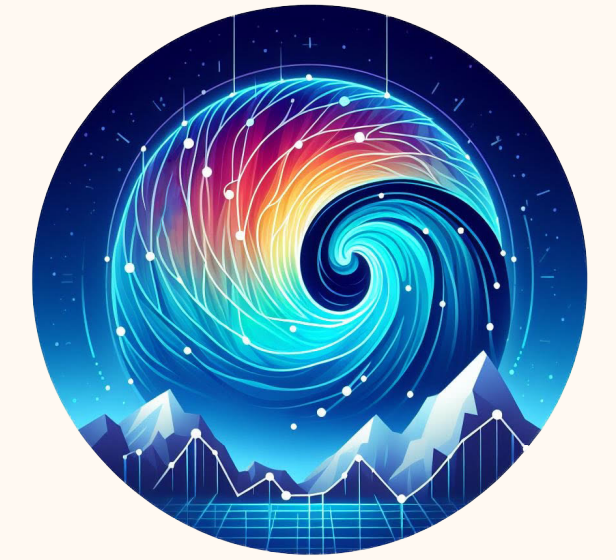


- **Setup:** model PM_{10} , $\text{PM}_{2.5}$, PM_{10} , CO, NO, NO_2 , SO_2 , O_3
- **Data:** Copernicus Atmospheric Monitoring Service (CAMS) analysis
- **Baseline:** CAMS forecasts

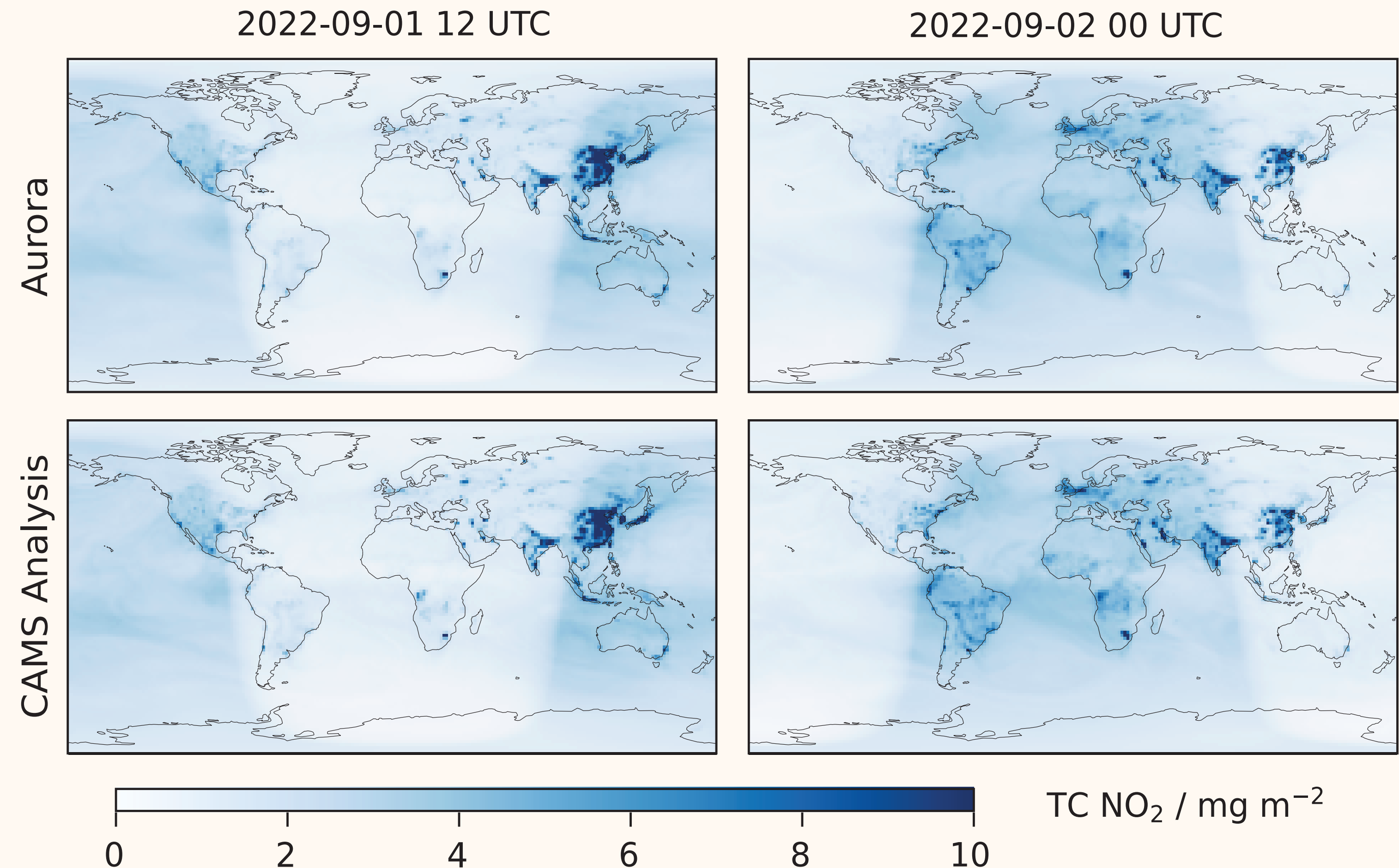
Coupled to IFS, ~10x more expensive:
~16 node-hours per hour lead time!

Aurora: **~0.5 s per hour lead time**

Air Pollution Forecasting



- Heterogeneous and spikey
- Anthropogenic factors
- Scarce
- Non-stationary



Overall:

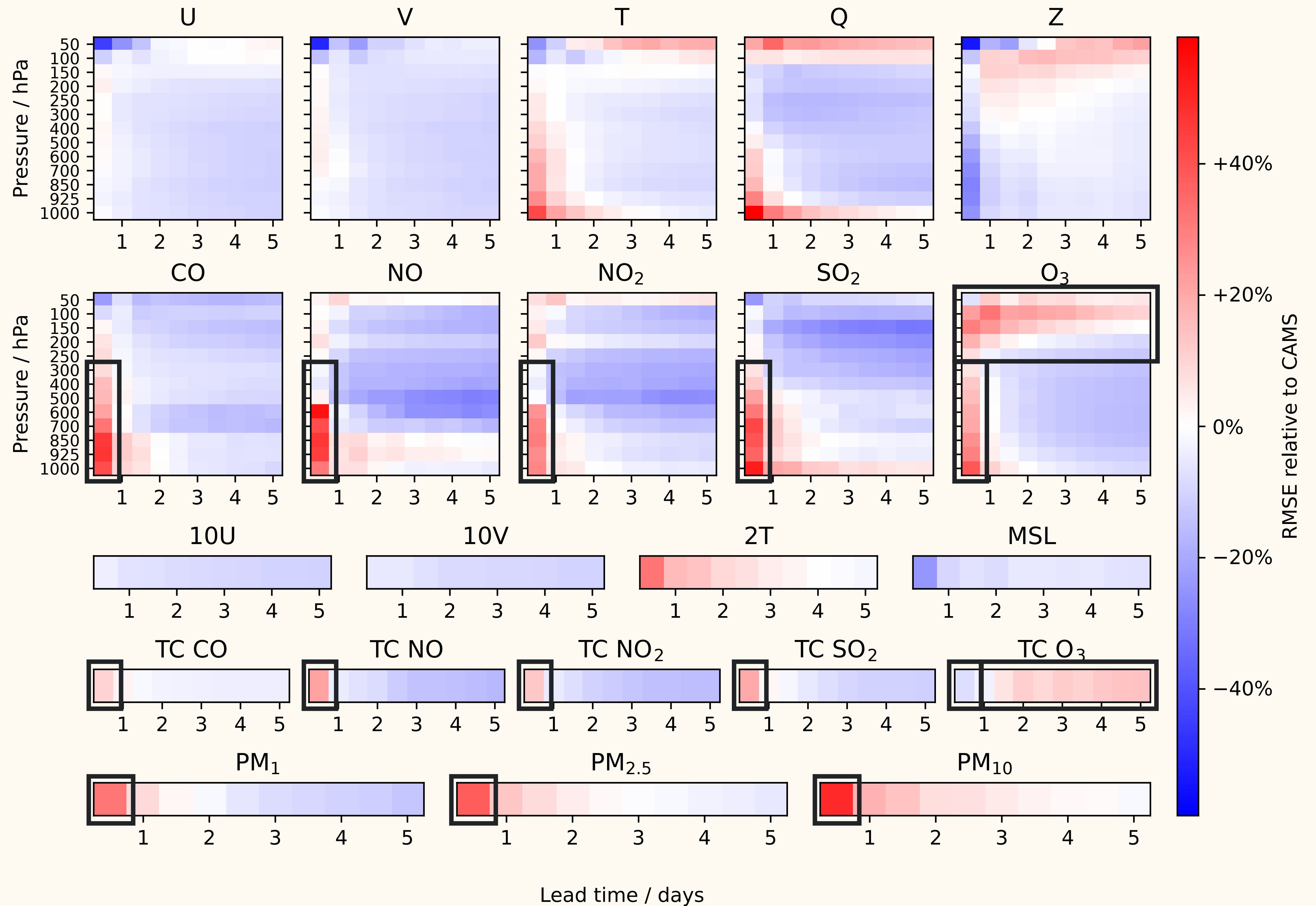
Competitive on
95%
($\leq 20\%$ RMSE)

Better on 75%

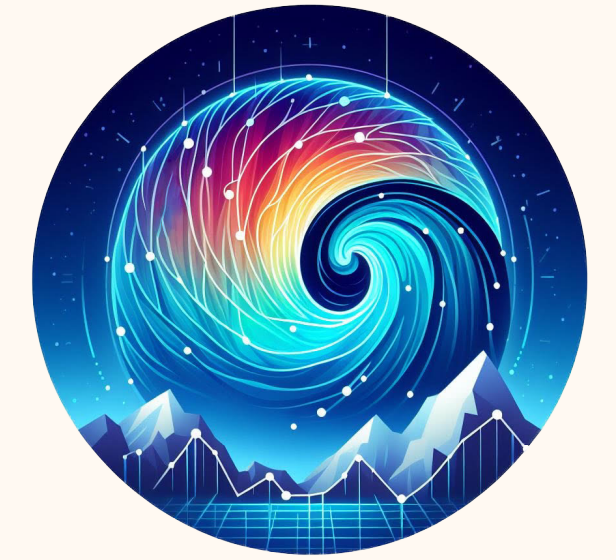
Three days:

Competitive on
100%
($\leq 20\%$ RMSE)

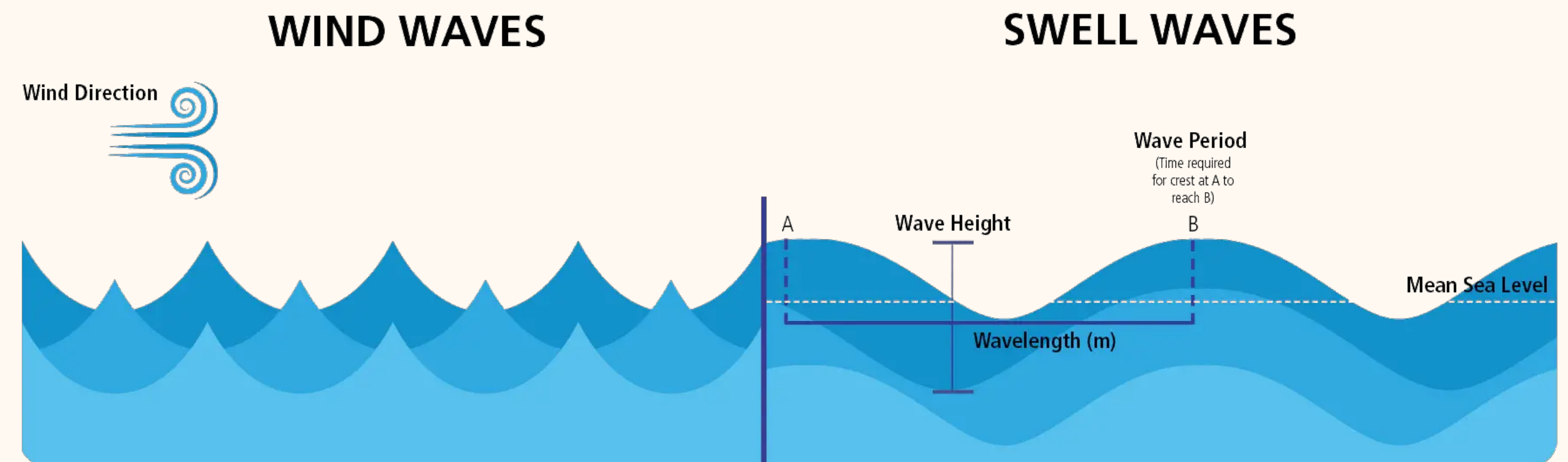
Better on 86%



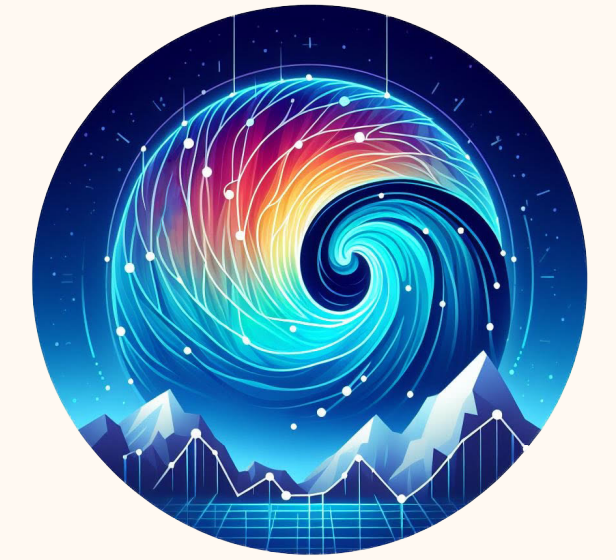
Ocean Wave Forecasting



- **Setup:** model height, direction, and period of wave components
- **Data:** HRES-WAM analysis
- **Baseline:** HRES-WAM forecasts

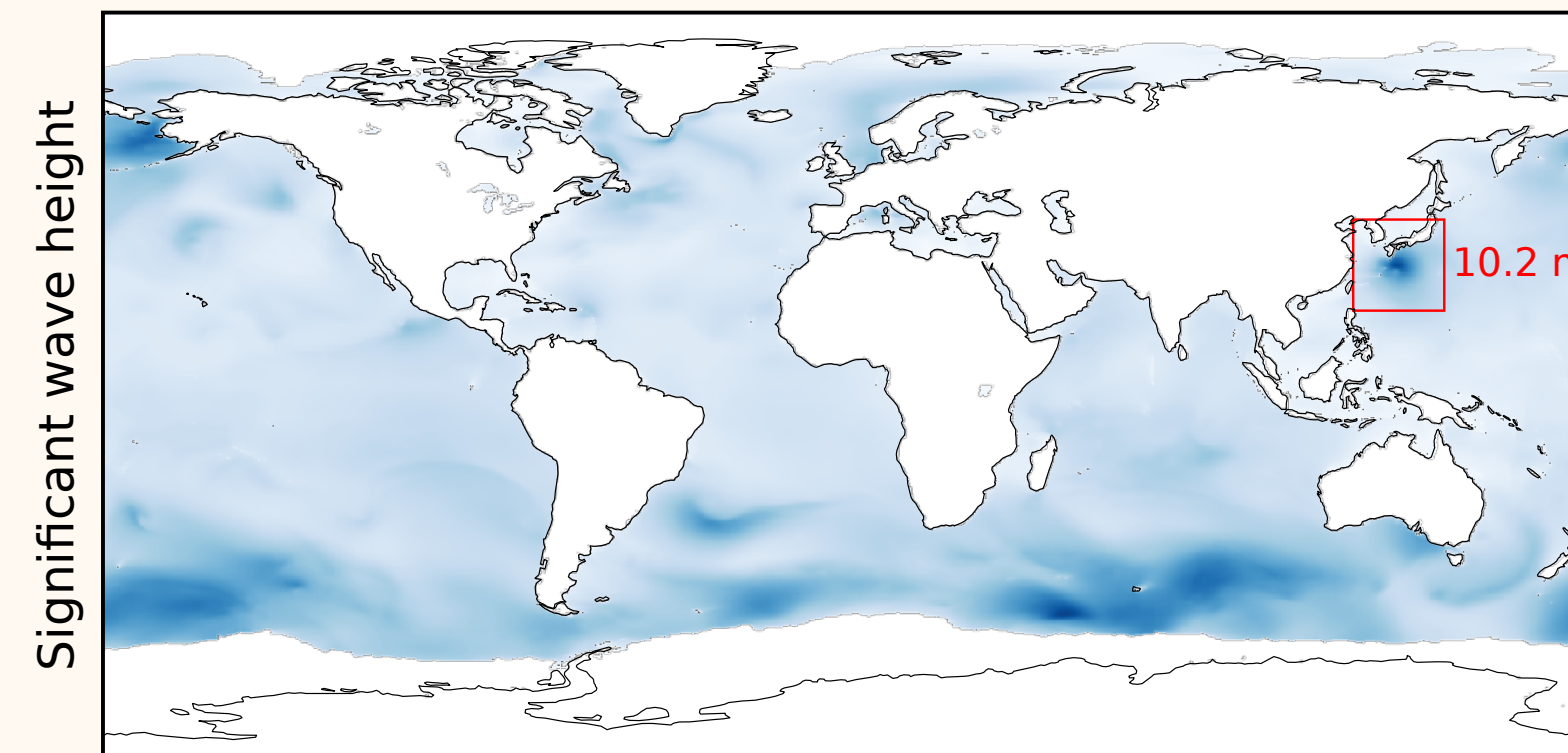


Ocean Wave Forecasting

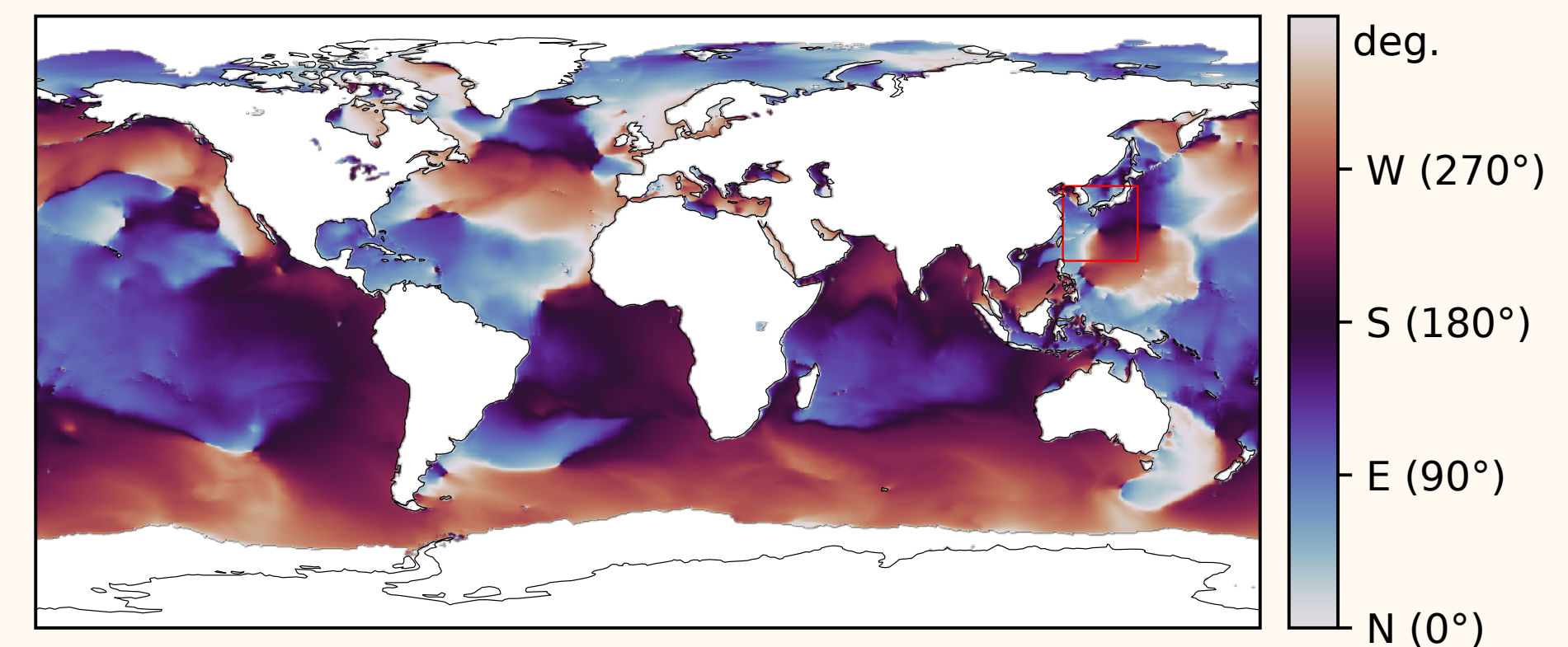
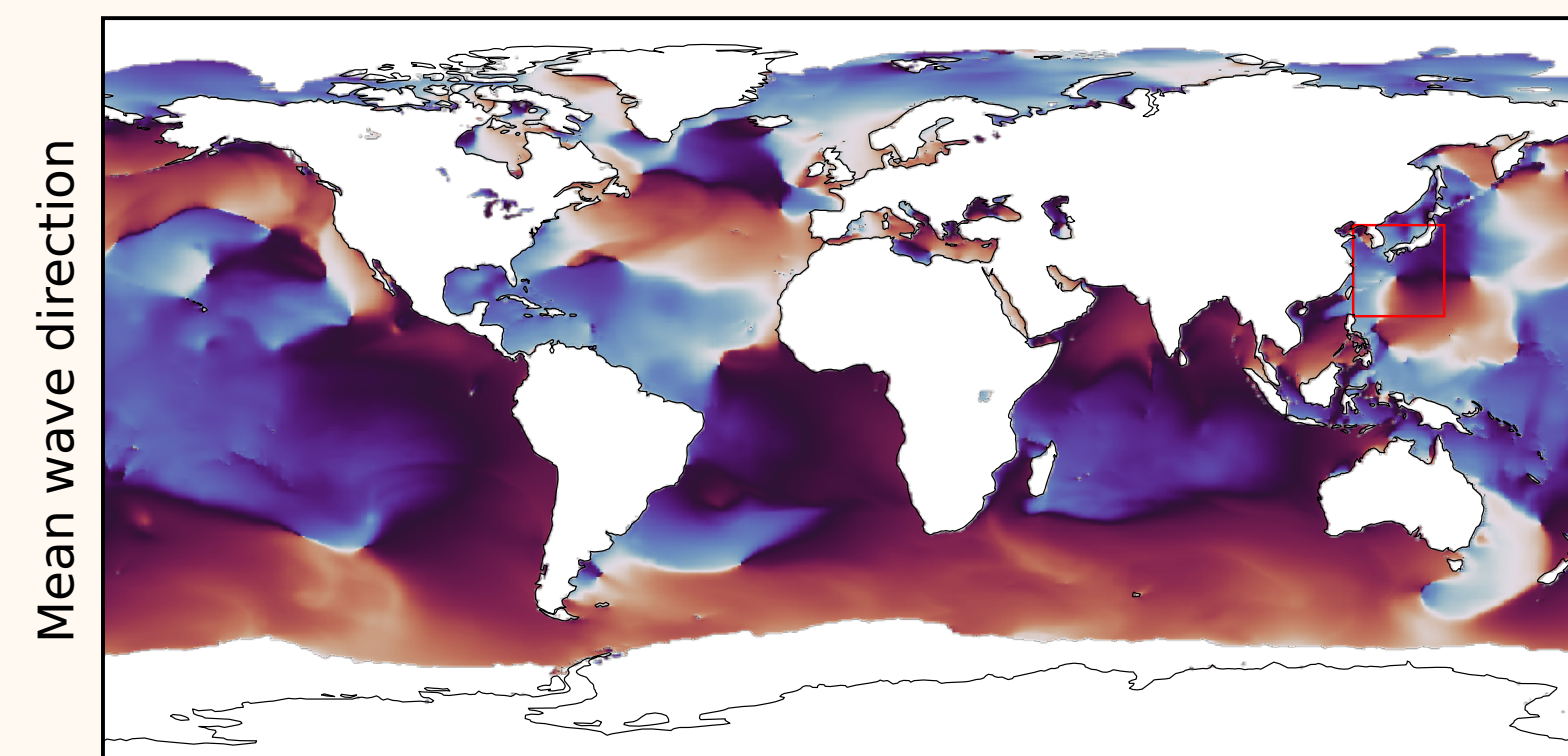
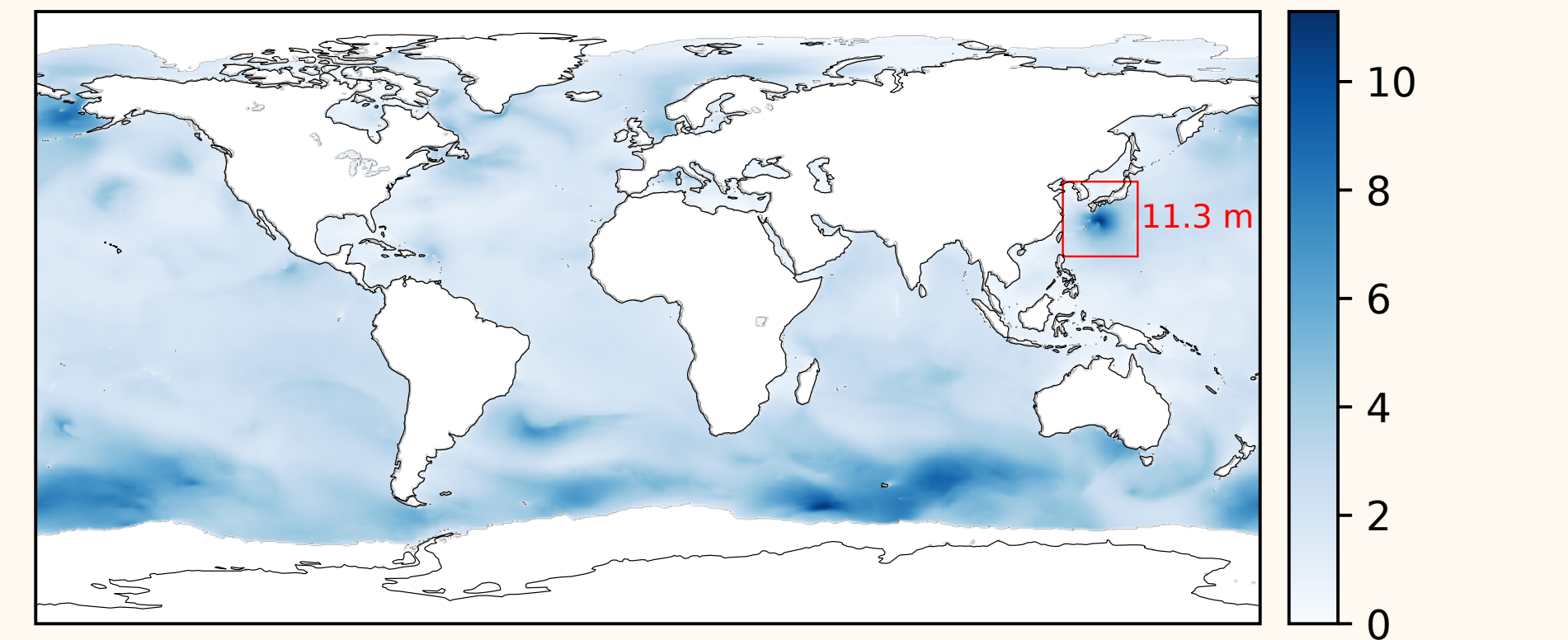


- Angle-valued variables
- Absence of wave components

Aurora 0.25° (1 day lead time)



IFS HRES-WAM 0.25° Analysis



Overall:

Competitive on
96%

($\leq 20\%$ RMSE)

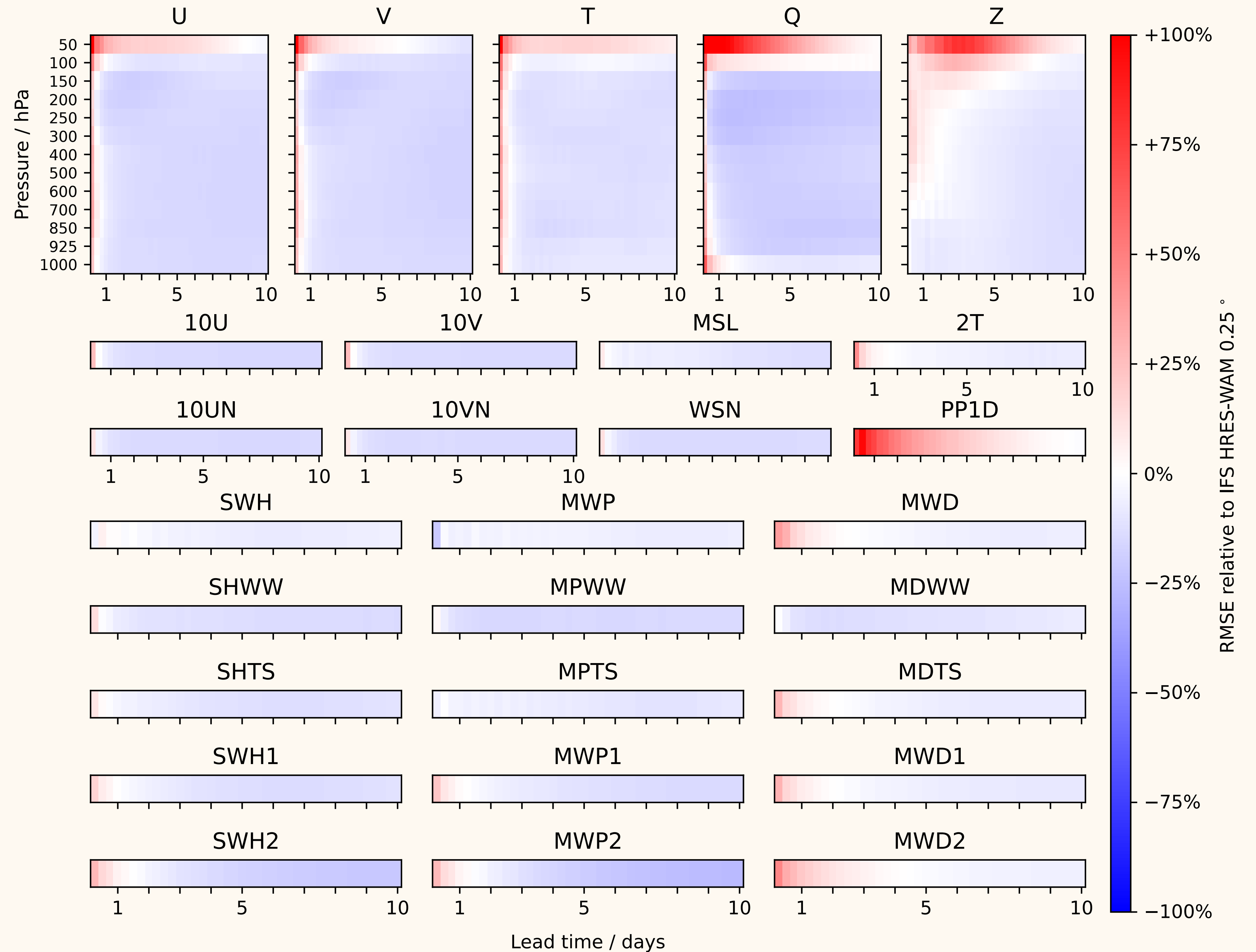
Better on 86%

Three days:

Competitive on all
but PP1D

($\leq 20\%$ RMSE)

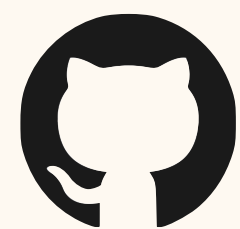
Better on 91%



Open Source

- All models open source under **MIT licence!**

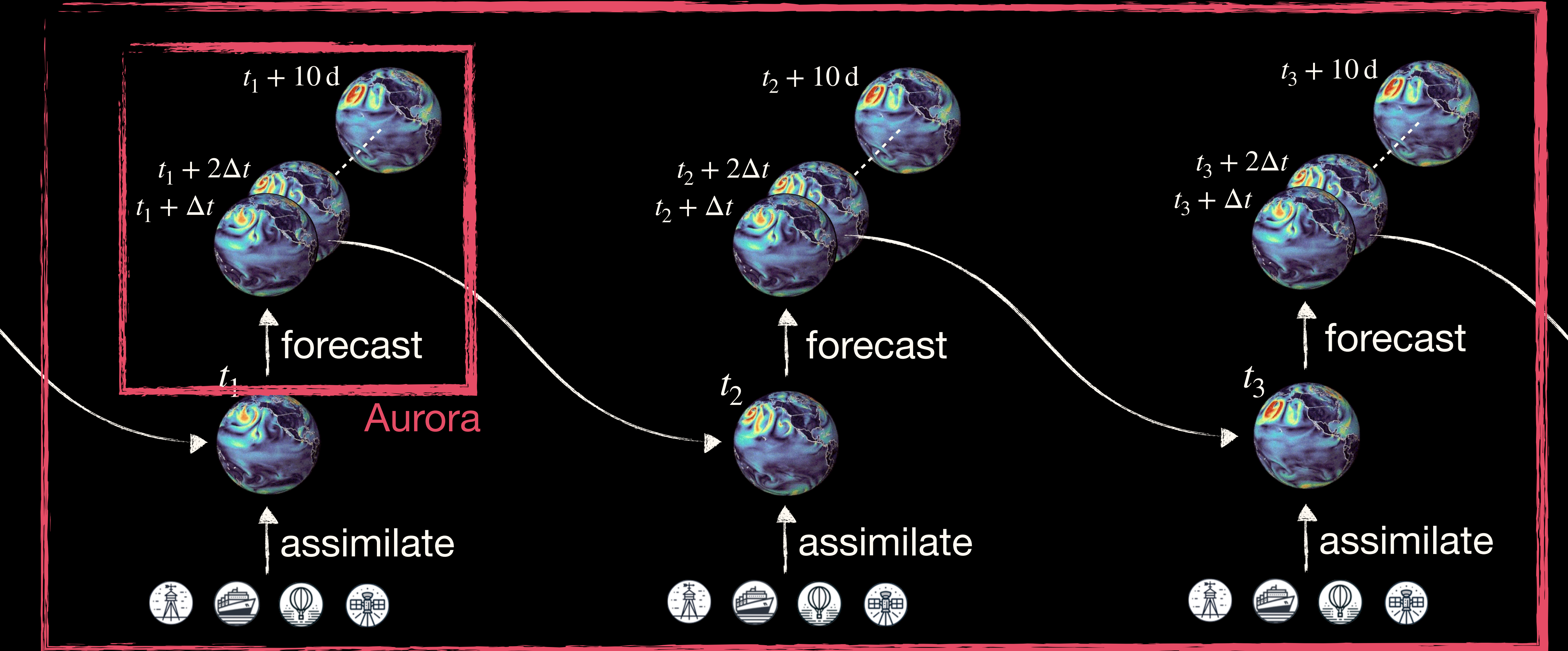
```
1 import torch
2
3 from aurora import Aurora, Batch, rollout
4
5 model = Aurora()
6 model.load_checkpoint()
7
8 model.eval()
9 model.to("cuda")
10
11 batch = Batch(...)
12
13 with torch.inference_mode():
14     for prediction in rollout(model, batch, steps=10):
15         ... # Do something with `prediction`.
16
```



<https://github.com/microsoft/aurora>
`pip install microsoft-aurora`

The Weather Forecasting Pipeline

Aardvark-Weather



The Aurora Team



Paris Perdikaris

University of Pennsylvania,
formerly MSR



Wessel Bruinsma

**The Alan Turing Institute,
formerly MSR**



Cristian Bodnar

Silurian, formerly MSR



Ana Lučić

University of Amsterdam,
formerly MSR



Megan Stanley

MSR



Richard Turner

U. of Cambridge, The Alan
Turing Institute, formerly MSR



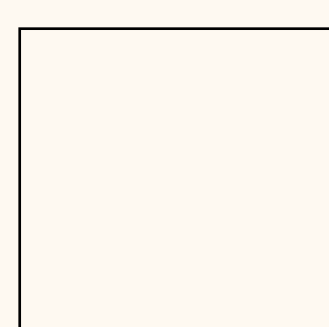
Anna Allen

University of Cambridge, The
Alan Turing Institute



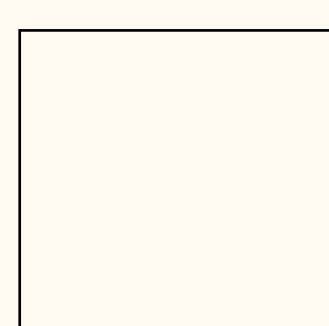
Johannes Brandstetter

JKU Linz, Emmi AI, formerly MSR



Patrick Garvan

IONQ, formerly MSR



Maik Riechert

MSR



Max Welling

University of Amsterdam,
CuspAI, formerly MSR



Elizabeth Heider

Book tour, formerly MSR



Conclusion

- Medium-term weather forecasting has seen incredible progress
- **Pretraining–fine-tuning paradigm** to extend these advancements to other domains
- Aurora only scratches the surface!

 wessel.ai/pdf/aurora

 wessel.ai/pdf/aardvark

 hi@wessel.ai

Bodnar, C., Bruinsma, W.P., Lučić, A., Stanley M., Allen, A. *et al.* A foundation model for the Earth system. *Nature* **641**, 1180–1187 (2025).

Allen, A., Markou, S. *et al.* End-to-end data-driven weather prediction. *Nature* **641**, 1172–1179 (2025).