Aurora: A Foundation Model for the Earth System

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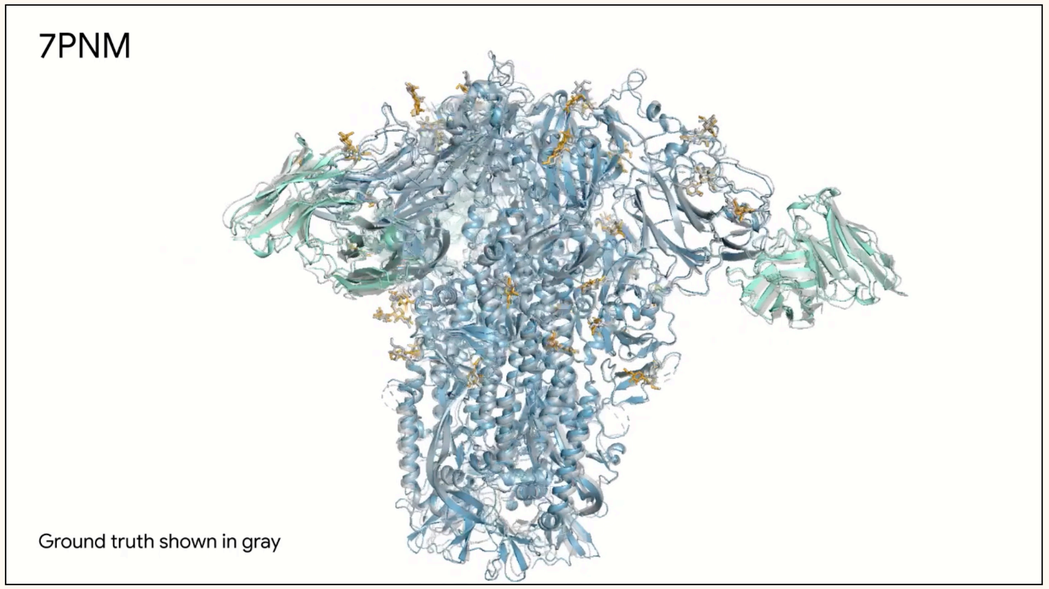
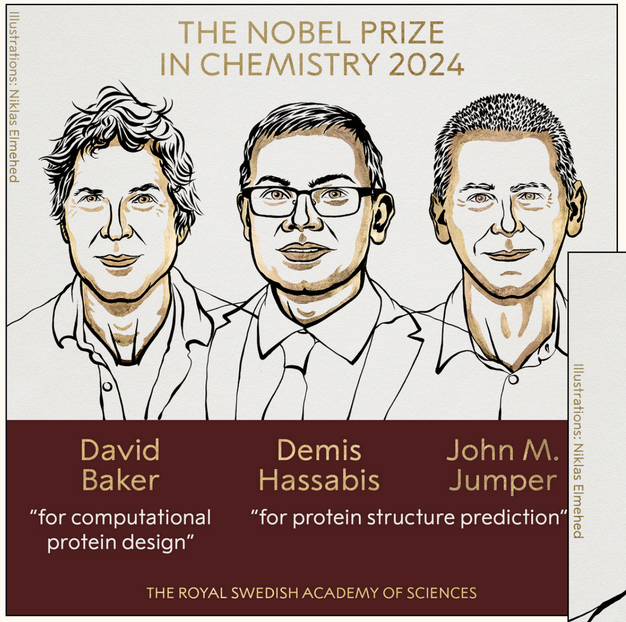
The Alan Turing Institute
Work was done at Microsoft Research

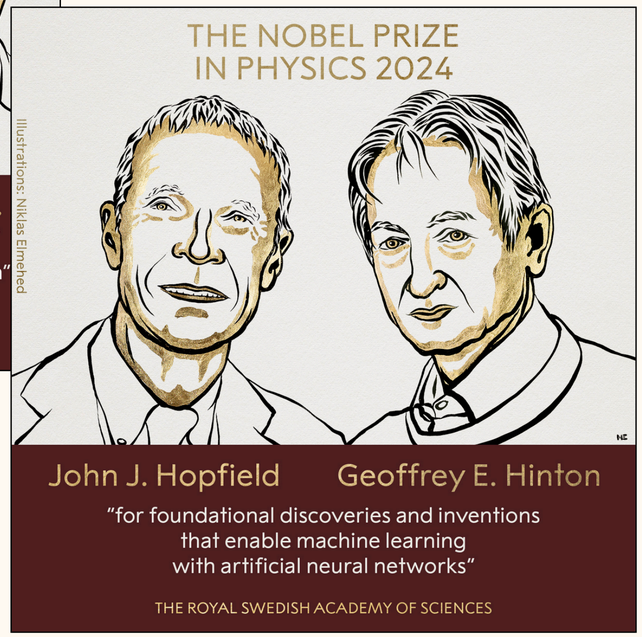
CDI AI/ML Webinar, USGS, Online, 22 July 2025

The AI Revolution in Science

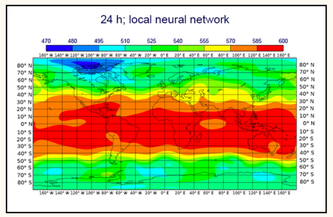
AlphaFold
Protein folding







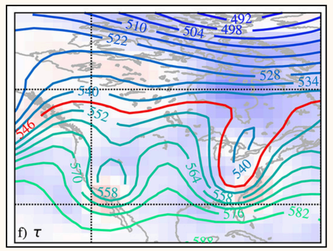
The AI Revolution in Weather Forecasting



2018

First serious efforts to compare AI models to physics baselines

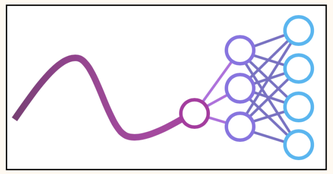
Dueben and Bauer (2018)



2019

AI models skillful to multiple days

Weyn et al. (2019)

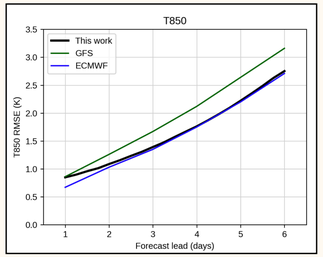


2020

WeatherBench starts to drive ML development

Rasp et al. (2020)

The AI Revolution in Weather Forecasting



HUAWEI

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

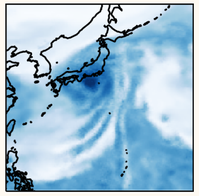
NVIDIA

Microsoft

Google DeepMind

2022–2023

Tech companies start to work in this space



2023

GenCast outperforms IFS ensemble

Price et al. (2024)

ECMWF

2024

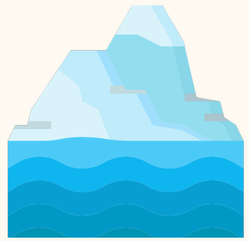
ECMWF launches AIFS

What About Other Forecasting Tasks?

Air pollution

Atmospheric composition

Waves

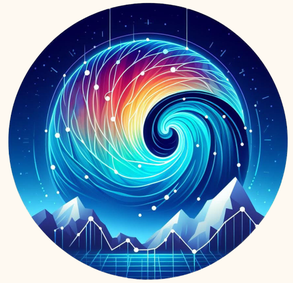


Sea ice

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

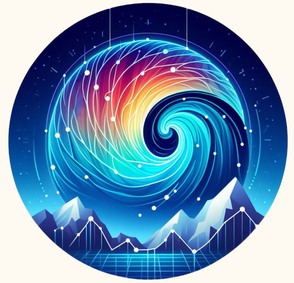
fine-tuning

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

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

The Model

The Model



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

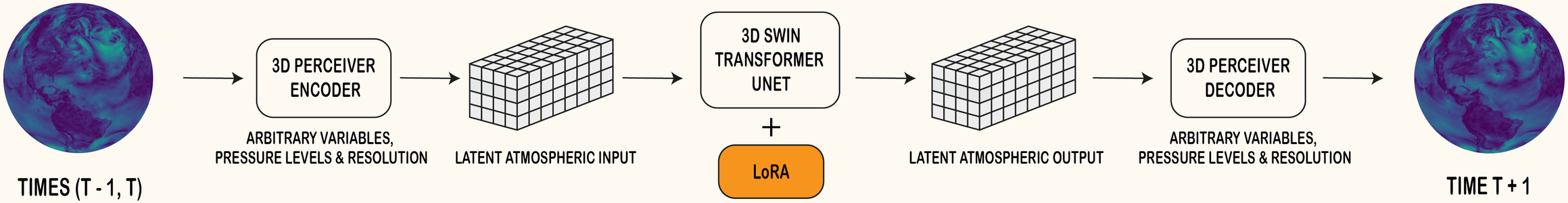
$$\hat{X}^{t+6\,\mathrm{h}} = \Phi(X^{t}, X^{t-6\,\mathrm{h}}),$$

$$\hat{X}^{t+12\,\mathrm{h}} = \Phi(\hat{X}^{t+6\,\mathrm{h}}, X^{t}),$$

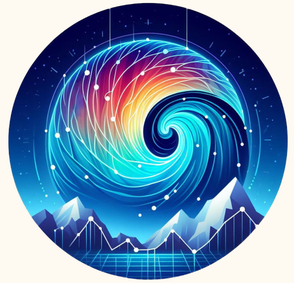
$$\hat{X}^{t+18\,\mathrm{h}} = \Phi(\hat{X}^{t+12\,\mathrm{h}}, \hat{X}^{t+6\,\mathrm{h}}),$$

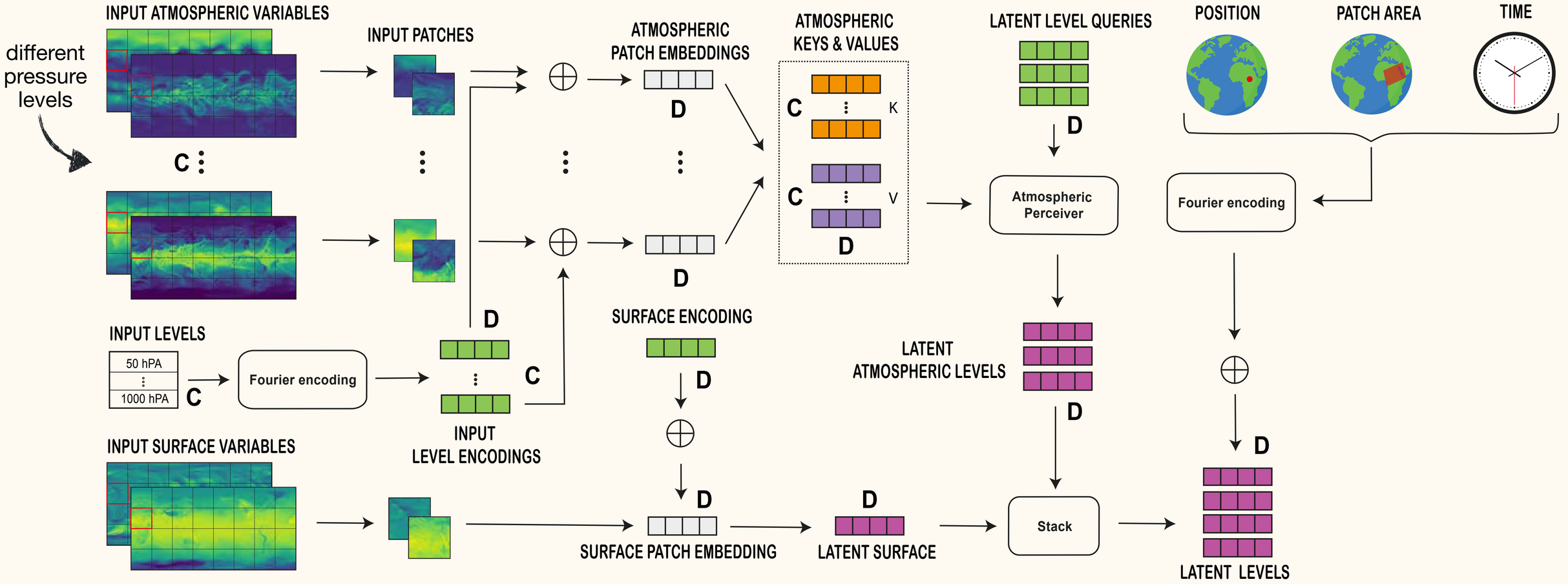
$$\vdots$$

- Transformer-based encoder–decoder architecture:

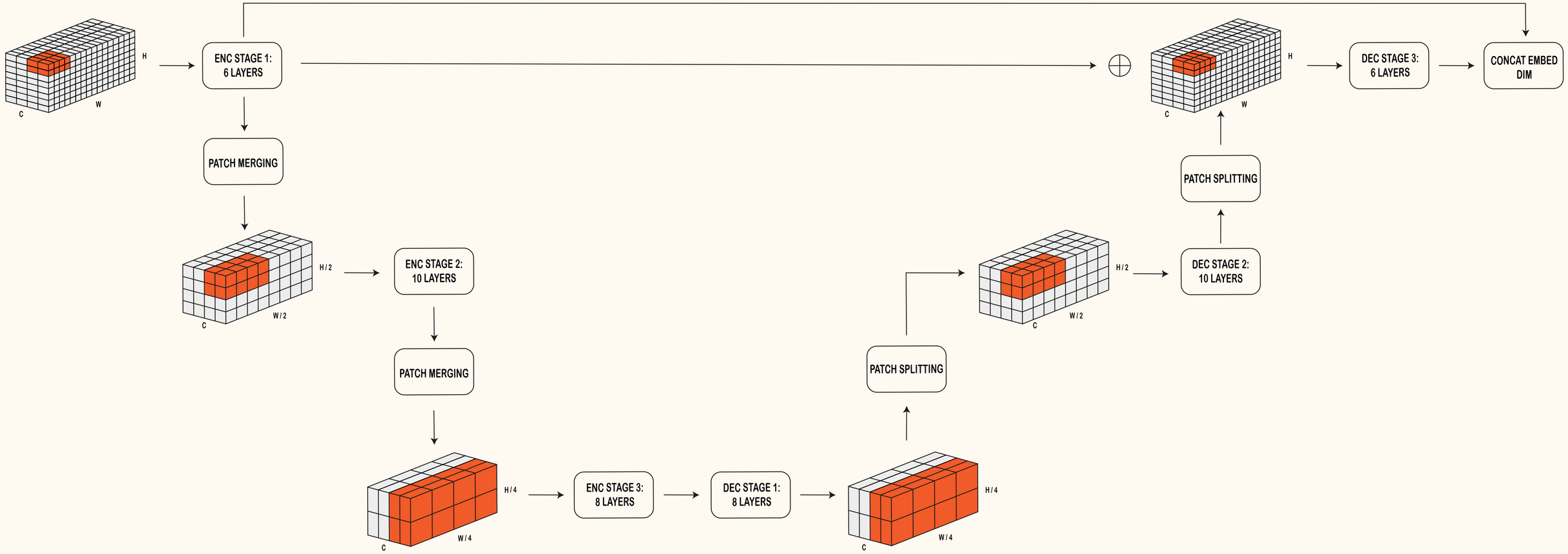


Encoder

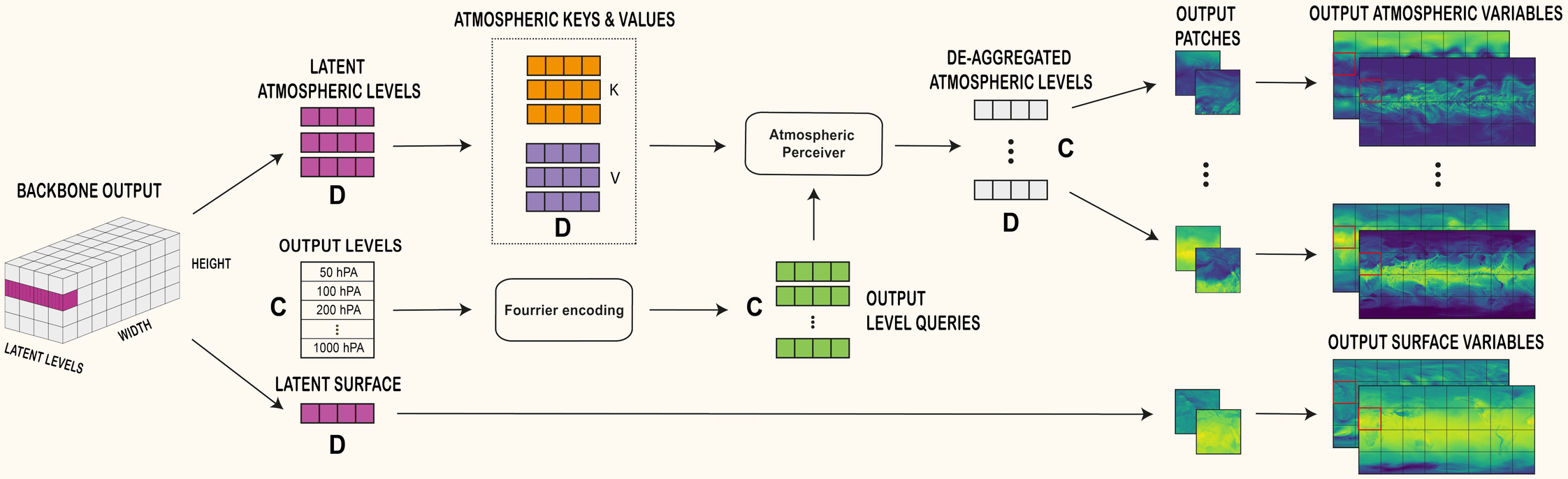



INPUT ATMOSPHERIC VARIABLES
different pressure levels
C
INPUT PATCHES
ATMOSPHERIC PATCH EMBEDDINGS
D
ATMOSPHERIC KEYS & VALUES
C
K
C
V
D
LATENT LEVEL QUERIES
D
POSITION
PATCH AREA
TIME
Atmospheric Perceiver
Fourier encoding
INPUT LEVELS
50 hPA
1000 hPA
C
Fourier encoding
D
C
INPUT LEVEL ENCODINGS
SURFACE ENCODING
D
LATENT ATMOSPHERIC LEVELS
D
INPUT SURFACE VARIABLES
D
SURFACE PATCH EMBEDDING
D
LATENT SURFACE
Stack
D
LATENT LEVELS

Backbone

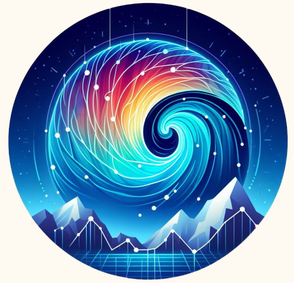

H
C
W
ENC STAGE 1:
6 LAYERS
PATCH MERGING
H / 2
C
W / 2
ENC STAGE 2:
10 LAYERS
PATCH MERGING
H / 4
C
W / 4
ENC STAGE 3:
8 LAYERS
DEC STAGE 1:
8 LAYERS
PATCH SPLITTING
H / 2
C
W / 2
DEC STAGE 2:
10 LAYERS
PATCH SPLITTING
H
C
W
DEC STAGE 3:
6 LAYERS
CONCAT EMBED
DIM

Decoder


BACKBONE OUTPUT
HEIGHT
WIDTH
LATENT LEVELS
LATENT
ATMOSPHERIC LEVELS
D
OUTPUT LEVELS
C
50 hPA
100 hPA
200 hPA
1000 hPA
LATENT SURFACE
D
ATMOSPHERIC KEYS & VALUES
K
V
D
Fourrier encoding
Atmospheric
Perceiver
C
OUTPUT
LEVEL QUERIES
DE-AGGREGATED
ATMOSPHERIC LEVELS
C
D
OUTPUT
PATCHES
OUTPUT ATMOSPHERIC VARIABLES
OUTPUT SURFACE VARIABLES

Pretraining

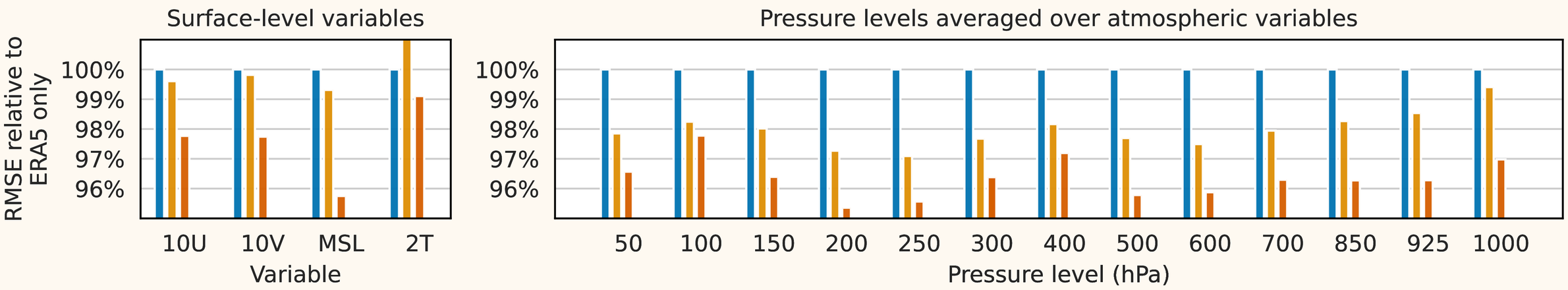
Pretraining



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

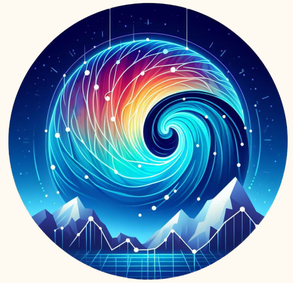


ERA5

ERA5 + climate simulations

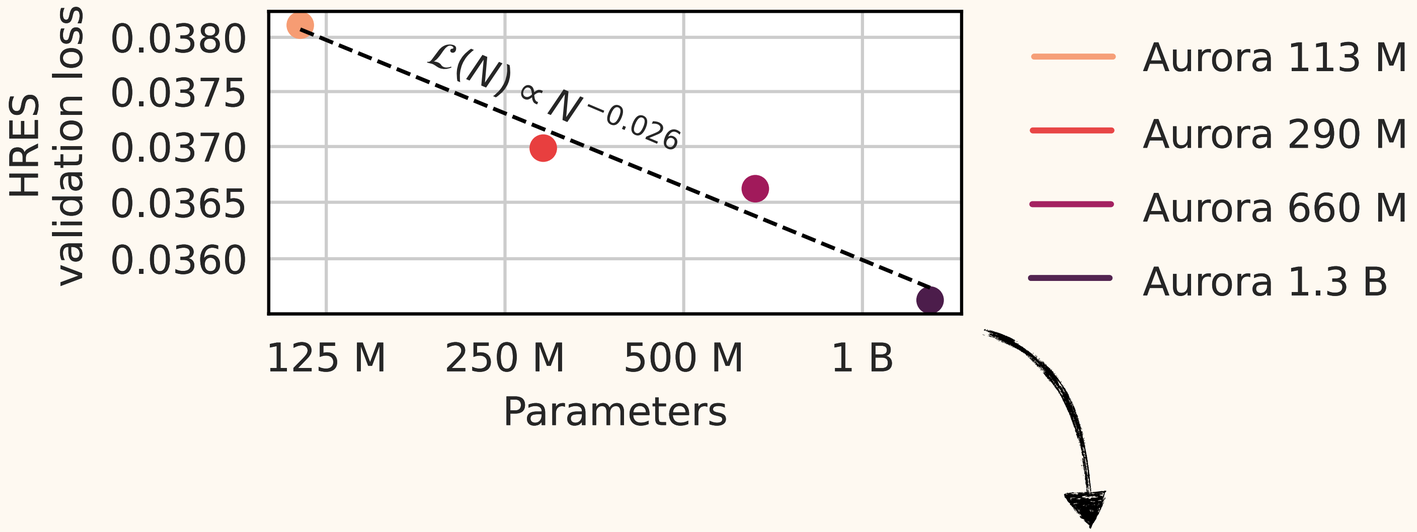
ERA5 + climate simulations + HRES/GFS forecasts + GFS analysis

Model Scaling



Economical to train big models!

Validation loss at fixed computational budget

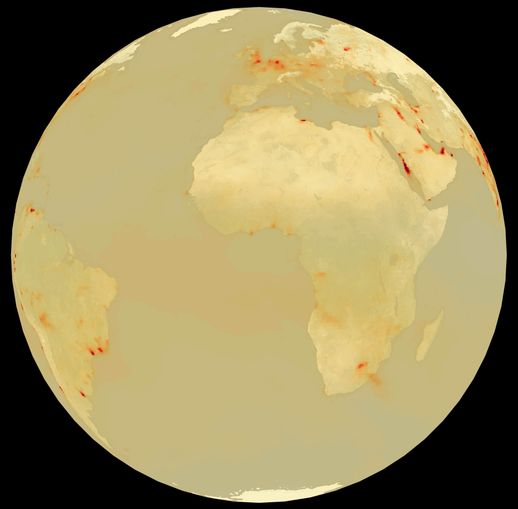


6% reduction per 10× model size!

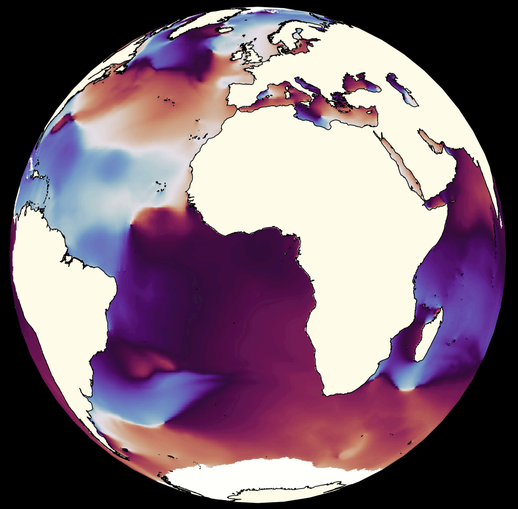
Fine-Tuning

Applications

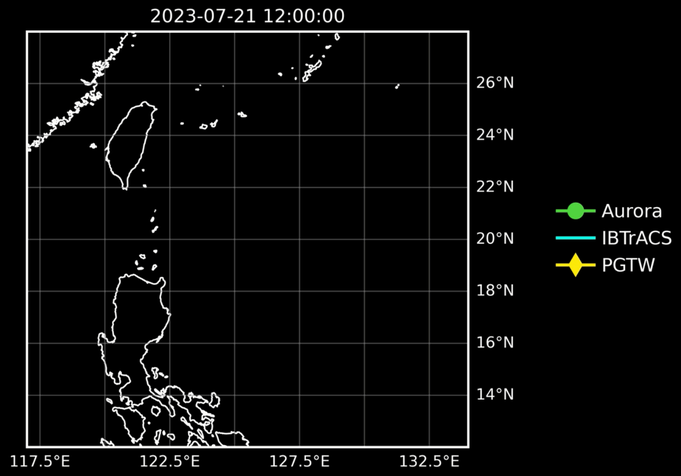
Operational in all settings!



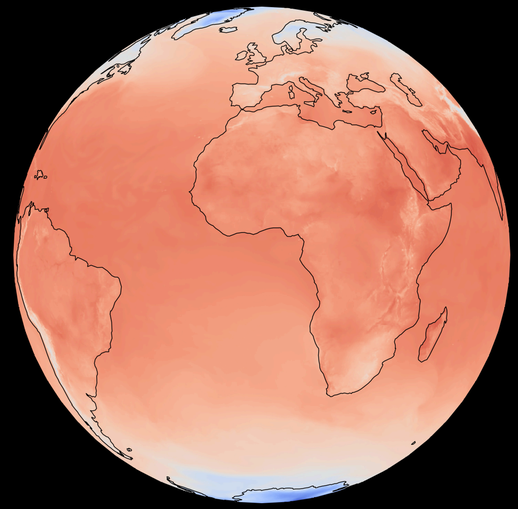
Atmospheric comp. and air pollution



Ocean waves



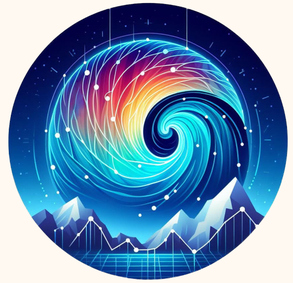
Tropical cyclone tracks



High-resolution weather

Animations created by Megan Stanley

Air Pollution Forecasting



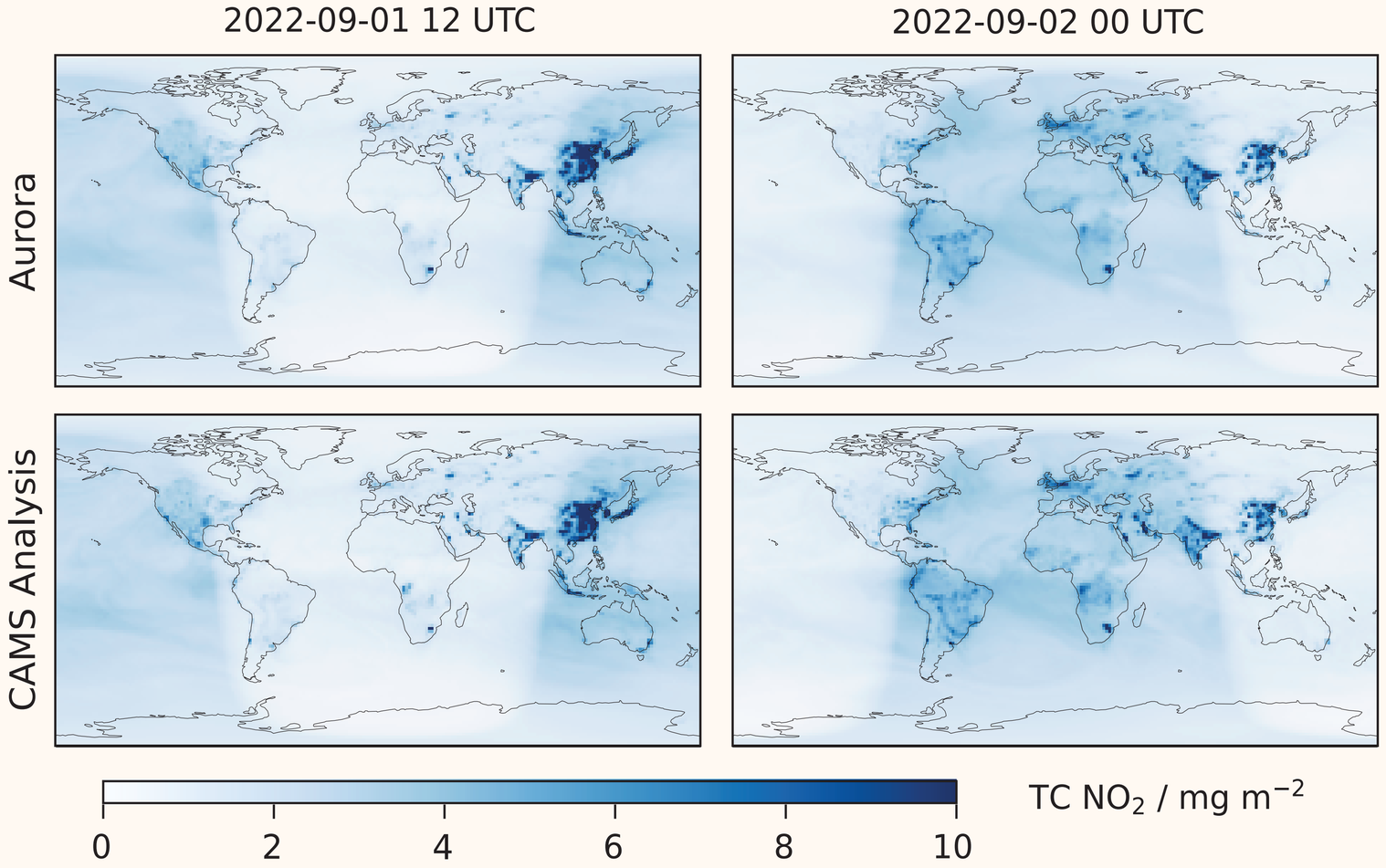
- **Setup:** model PM_1, $PM_{2.5}$, PM_{10}, CO, NO, NO_2, SO_2, O_3
- **Data:** Copernicus Atmospheric Monitoring Service (CAMS) analysis
- **Baseline:** CAMS forecasts

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:

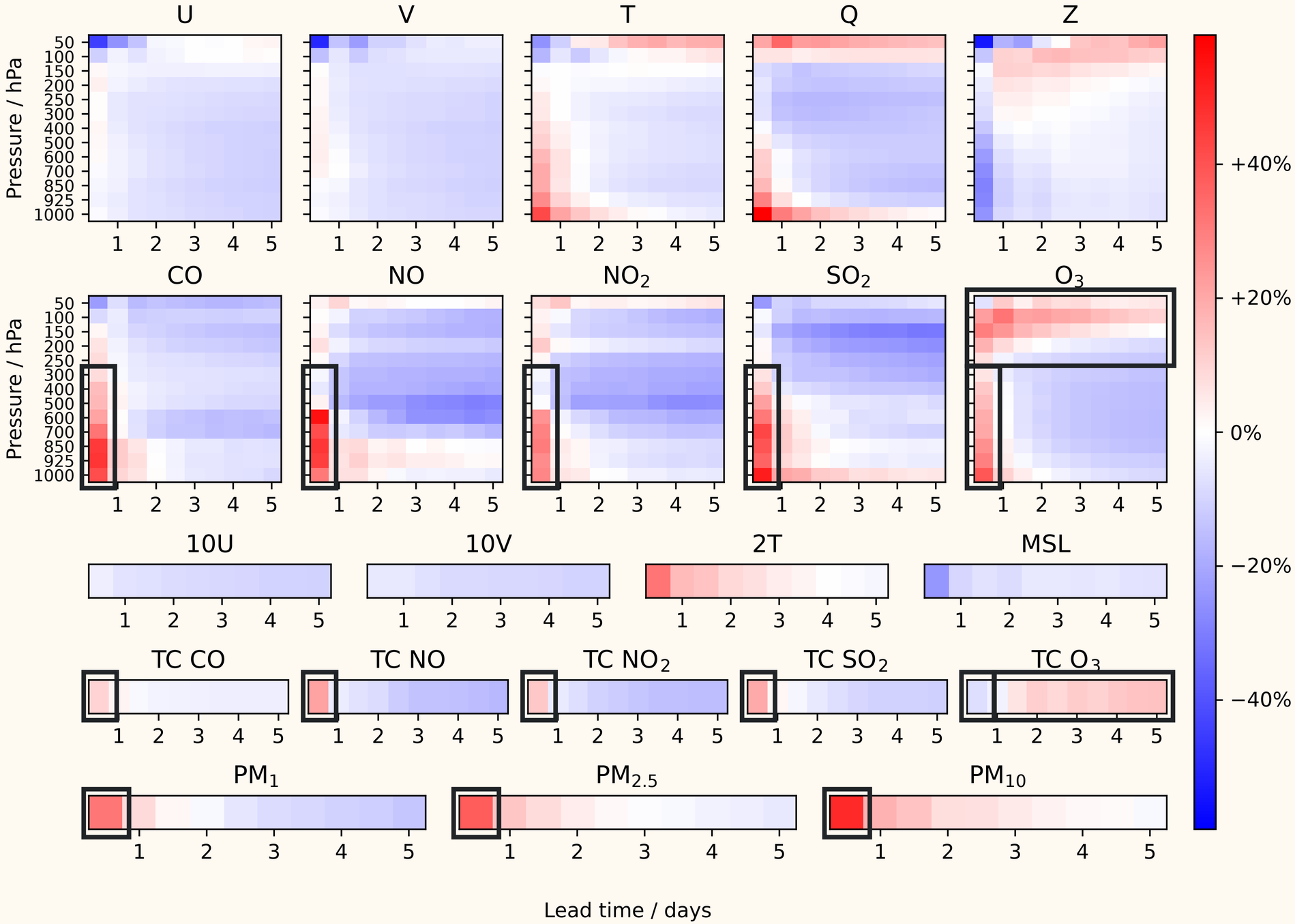
Competitive on 95%
(≤ 20% RMSE)

Better on 75%

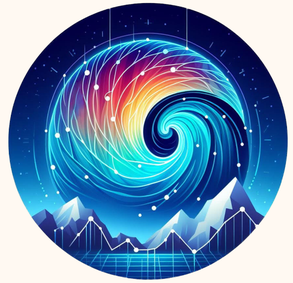
Three days:

Competitive on 100%
(≤ 20% RMSE)

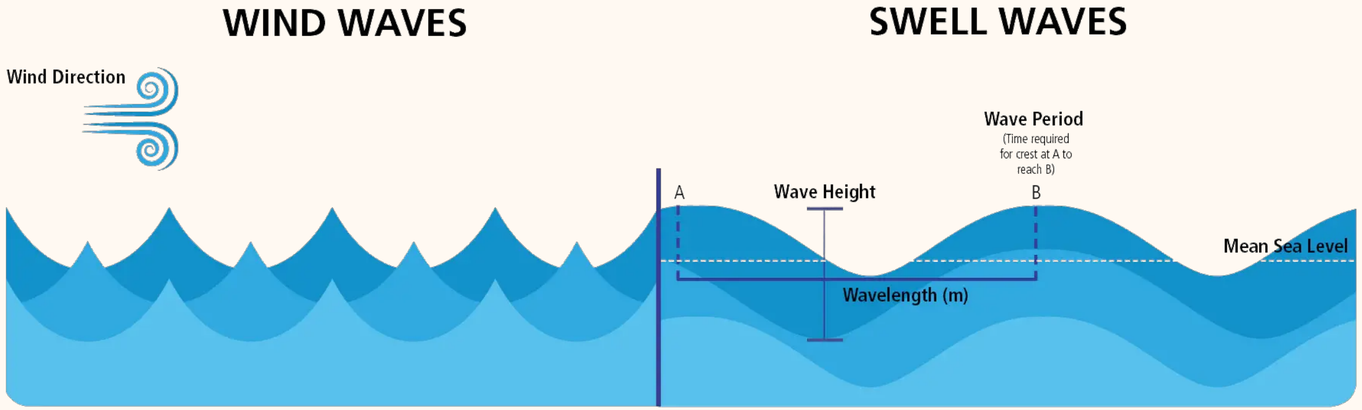
Better on 86%



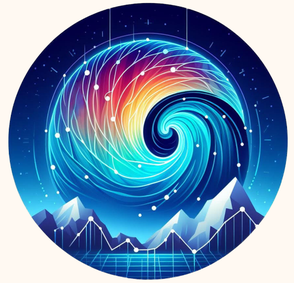
Ocean Wave Forecasting



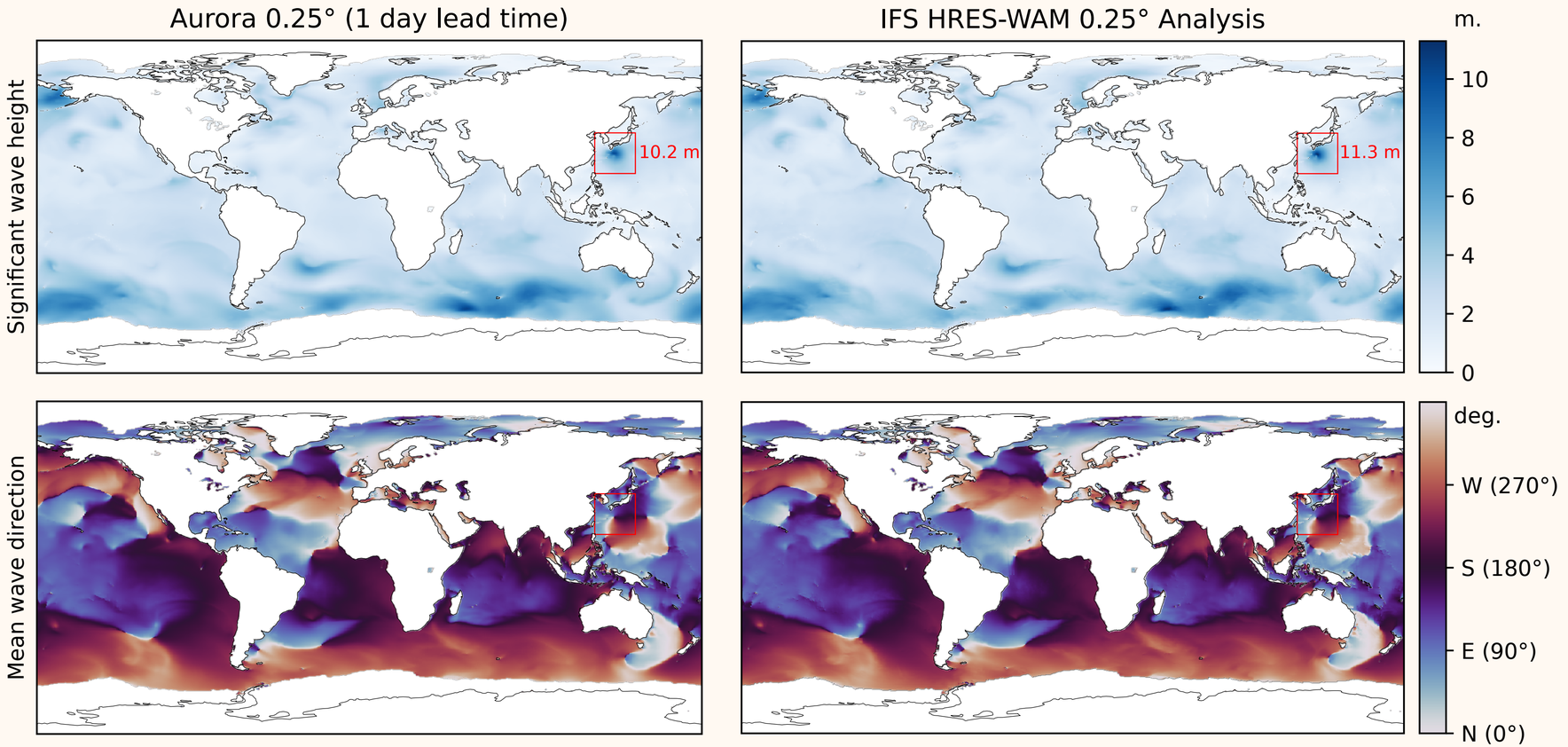
- **Setup:** model height, direction, and period of wave components
- **Data:** HRES-WAM analysis
- **Baseline:** HRES-WAM forecasts



Ocean Wave Forecasting



- Angle-valued variables
- Absence of wave components



Overall:

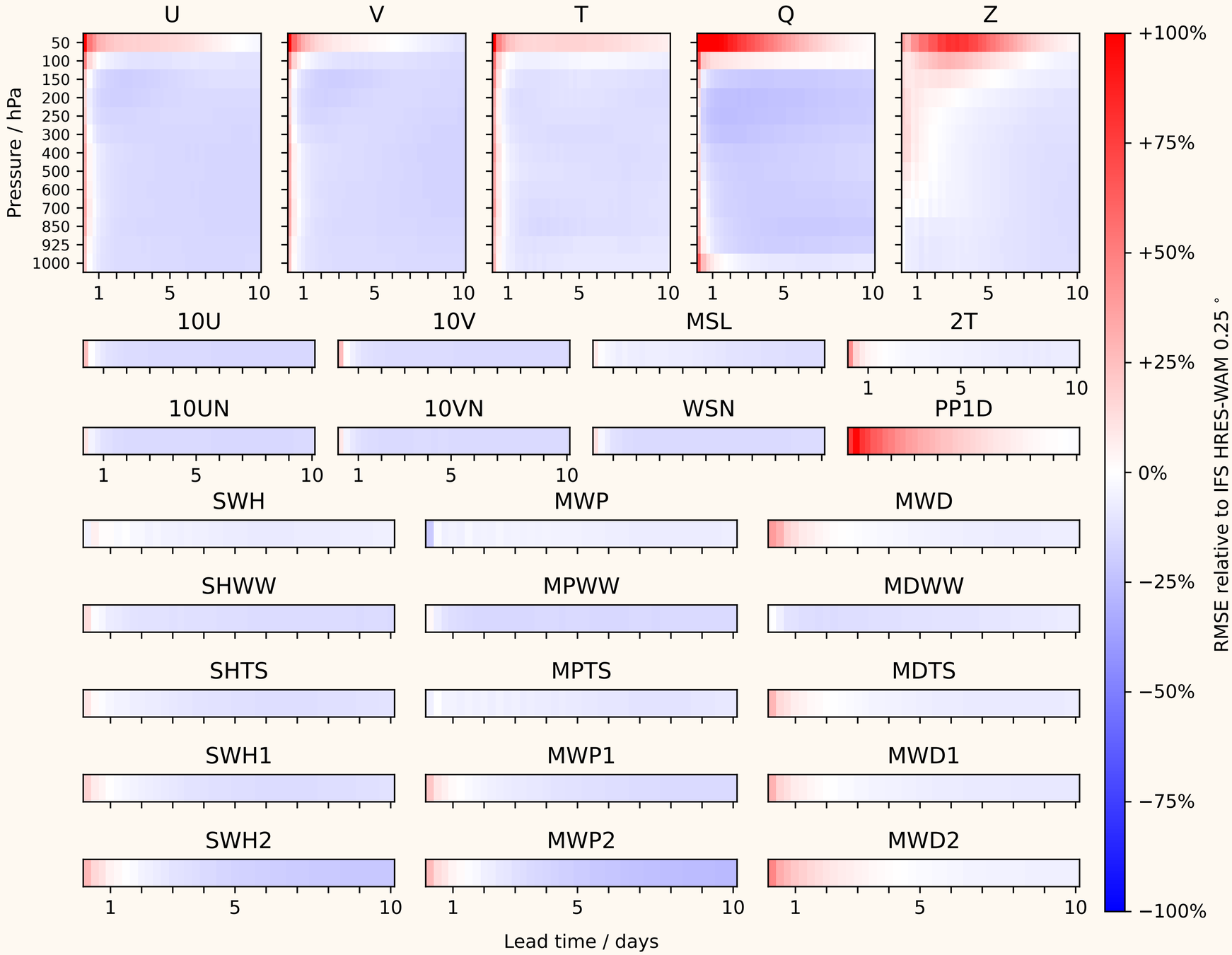
Competitive on 96%
(≤ 20% RMSE)

Better on 86%

Three days:

Competitive on all but PP1D
(≤ 20% RMSE)

Better on 91%



Open Source

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

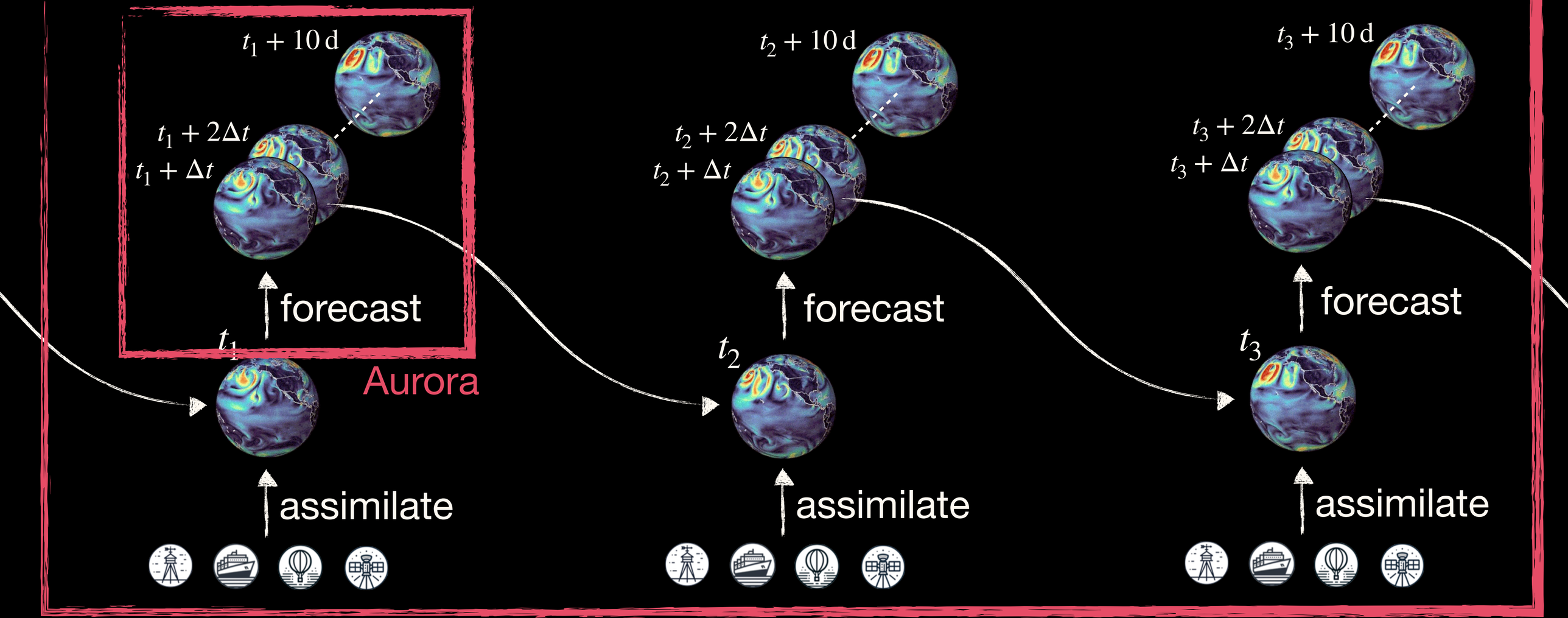
```python
import torch

from aurora import Aurora, Batch, rollout

model = Aurora()
model.load_checkpoint()

model.eval()
model.to("cuda")

batch = Batch(...)

with torch.inference_mode():
    for prediction in rollout(model, batch, steps=10):
        ...  # Do something with `prediction`.

```

https://github.com/microsoft/aurora

pip install microsoft-aurora

The Weather Forecasting Pipeline

Aardvark-Weather



The Aurora Team

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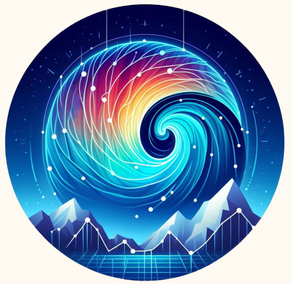
University of Amsterdam, CuspAI, formerly MSR

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).