FOURCASTNET: A STEP TOWARDS BUILDING DIGITAL TWINS OF THE EARTH FOR NVIDIA'S EARTH-2 INITIATIVE

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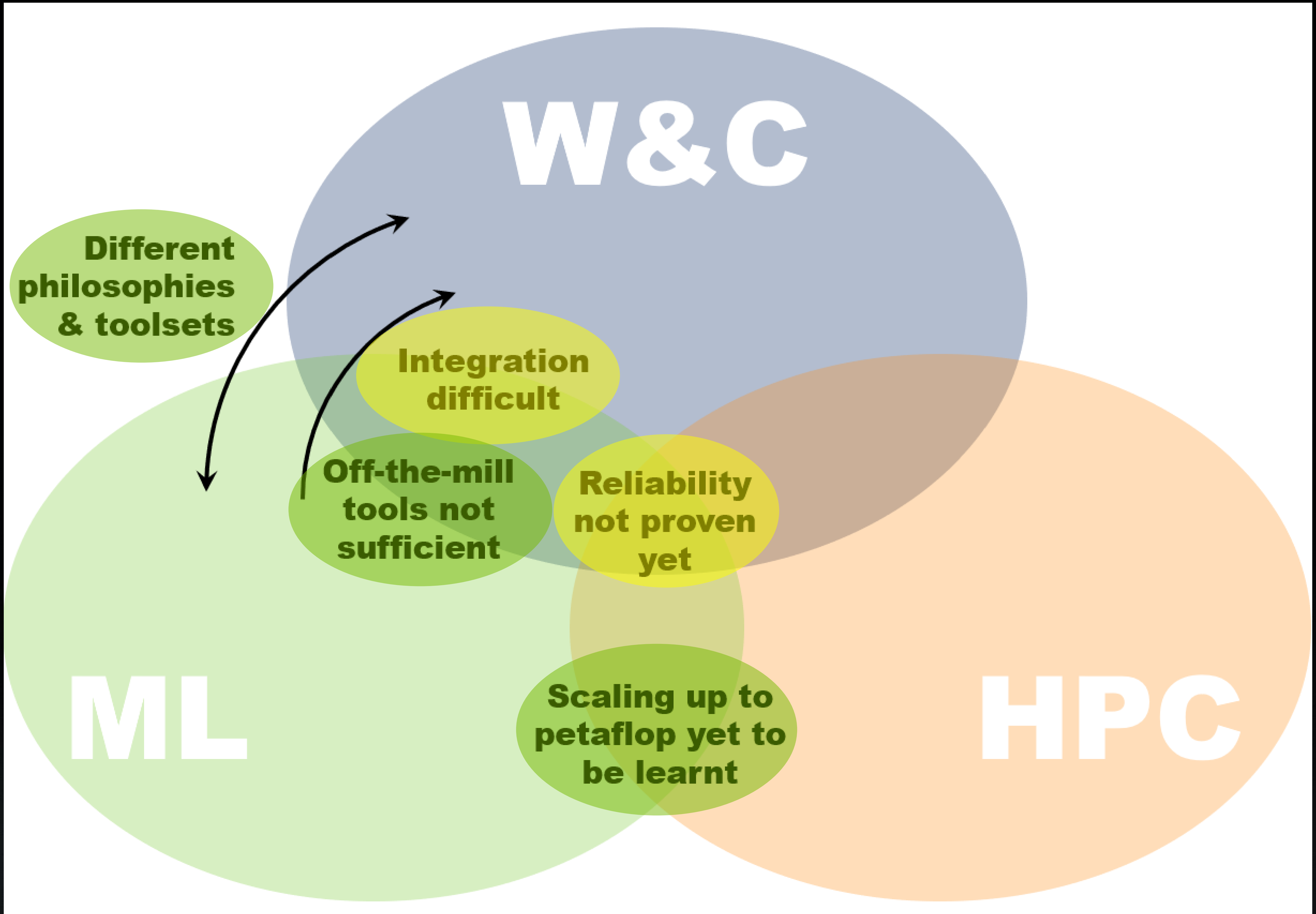
EARTH DIGITAL TWIN
MACHINE LEARNING CHALLENGES AND APPROACHES



Source: Peter Dueben (ECMWF) on "Machine Learning for Weather and Climate Predictions" at the 7th ENES HPC Workshop 2022

EARTH DIGITAL TWIN
MACHINE LEARNING CHALLENGES AND APPROACHES

CHALLENGES

- Weather ⟶ Climate
- Extrapolation
- Physical consistency & causality
- Uncertainty quantification & Calibration
- Data fusion & assimilation
- Scale up & out
- …

APPROACHES

- Spatio-temporal modeling
- Super-resolution
- Segmentation
- Online learning
- Reinforcement Learning
- …

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FourCastNet

Global data-driven high-resolution Earth digital twin for Extreme Weather

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S. Subramanian
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P. Harrington
LBL

S. Raja
U. Michigan

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Rice. U.

M. Mardani
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Z. Li
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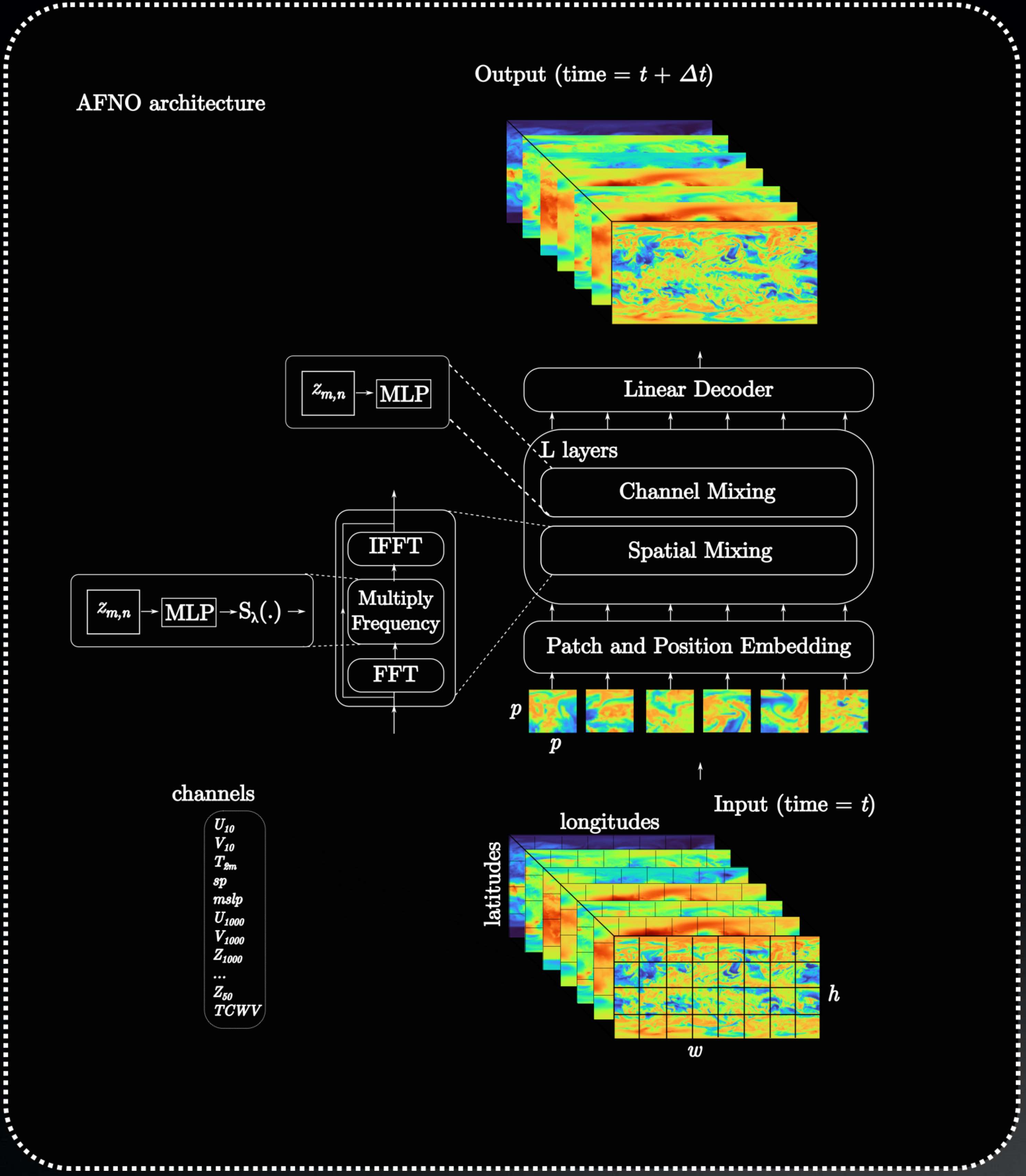
A. Anandkumar
Caltech/NVIDIA

FOURCASTNET (FOURIER FORECASTING NETWORK)



- Purely data-driven ML surrogate weather model
- Trained on ERA5 reanalysis data at the native resolution of 0.25 degrees

Vertical Level	Variables
Surface	$U_{10}, V_{10}, T_{2m}, sp, mslp$
$1000hPa$	U, V, Z
$850hPa$	T, U, V, Z, RH
$500hPa$	T, U, V, Z, RH
$50hPa$	Z
Integrated	$TCWV$

Extending to include radiation processes, vapor transport, clouds

Training set: 1979 to 2015
Validation set: 2016, 2017
Held out: 2018 onwards

Pathak et al. (2022), FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators, arXiv:2202.11214

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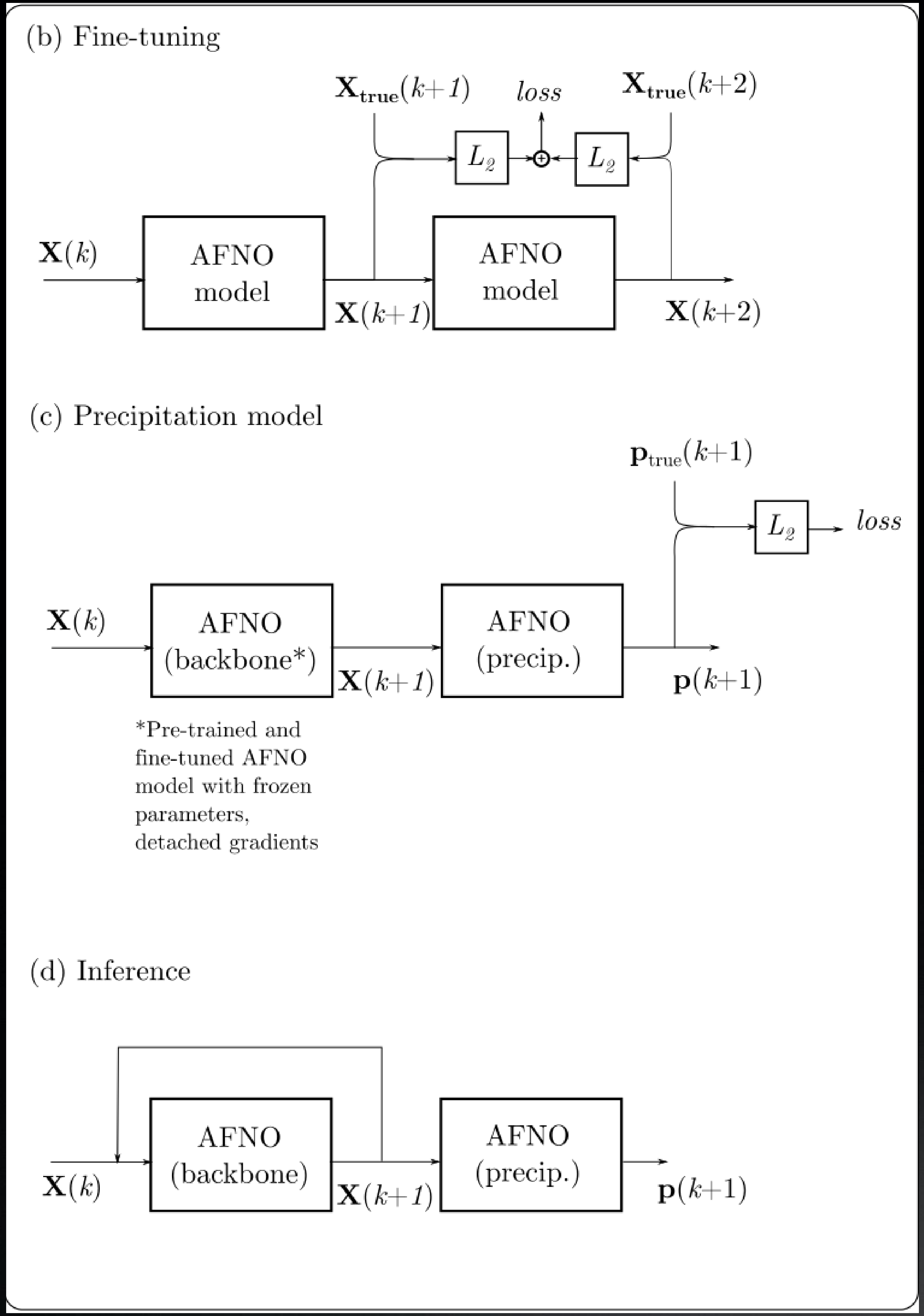

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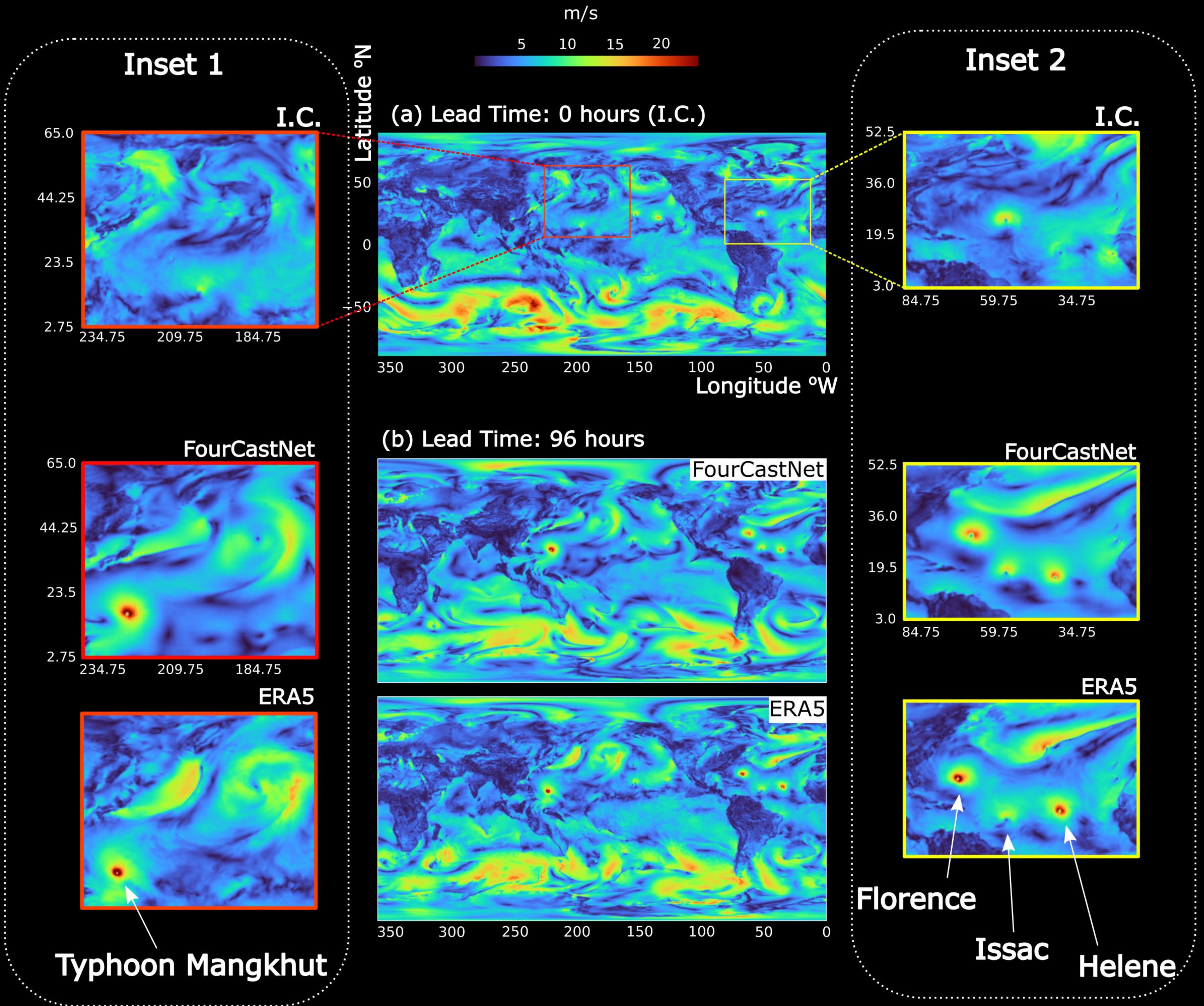
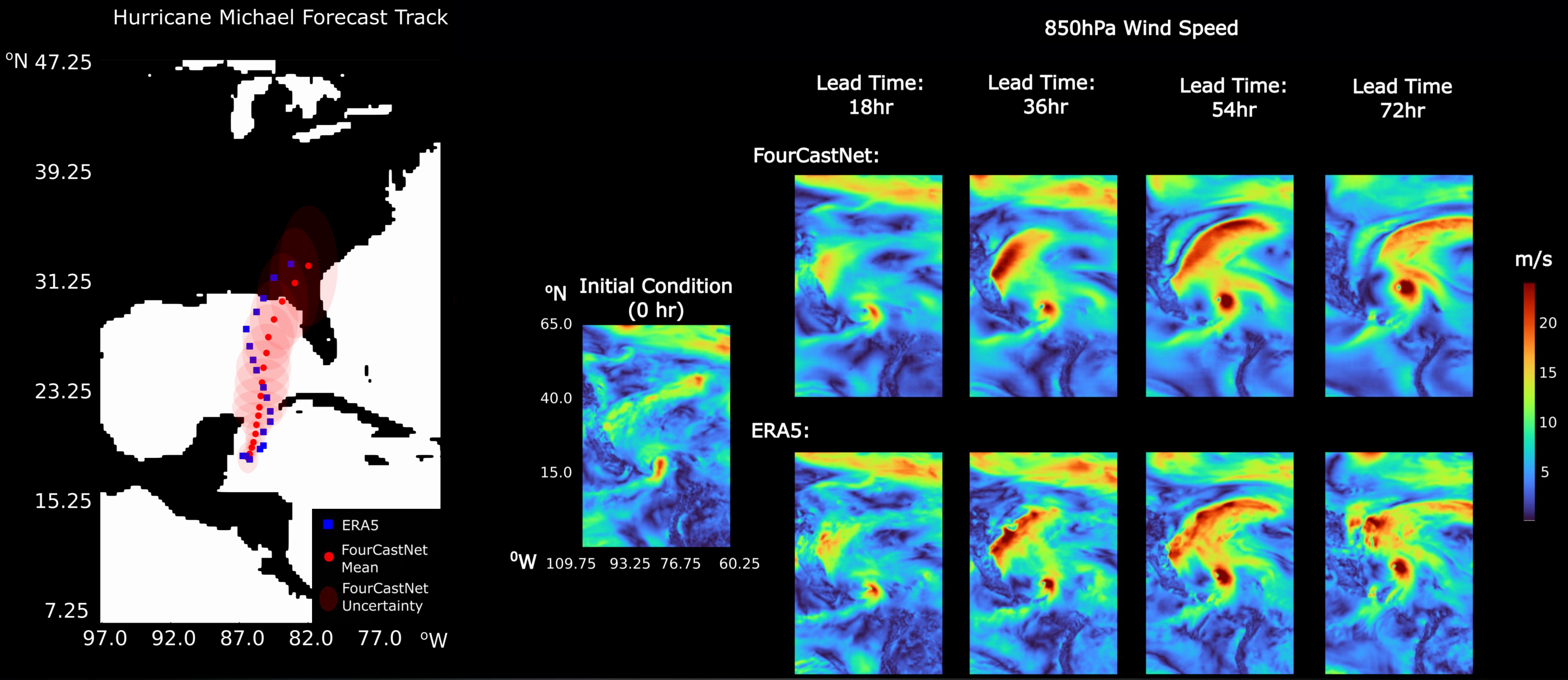
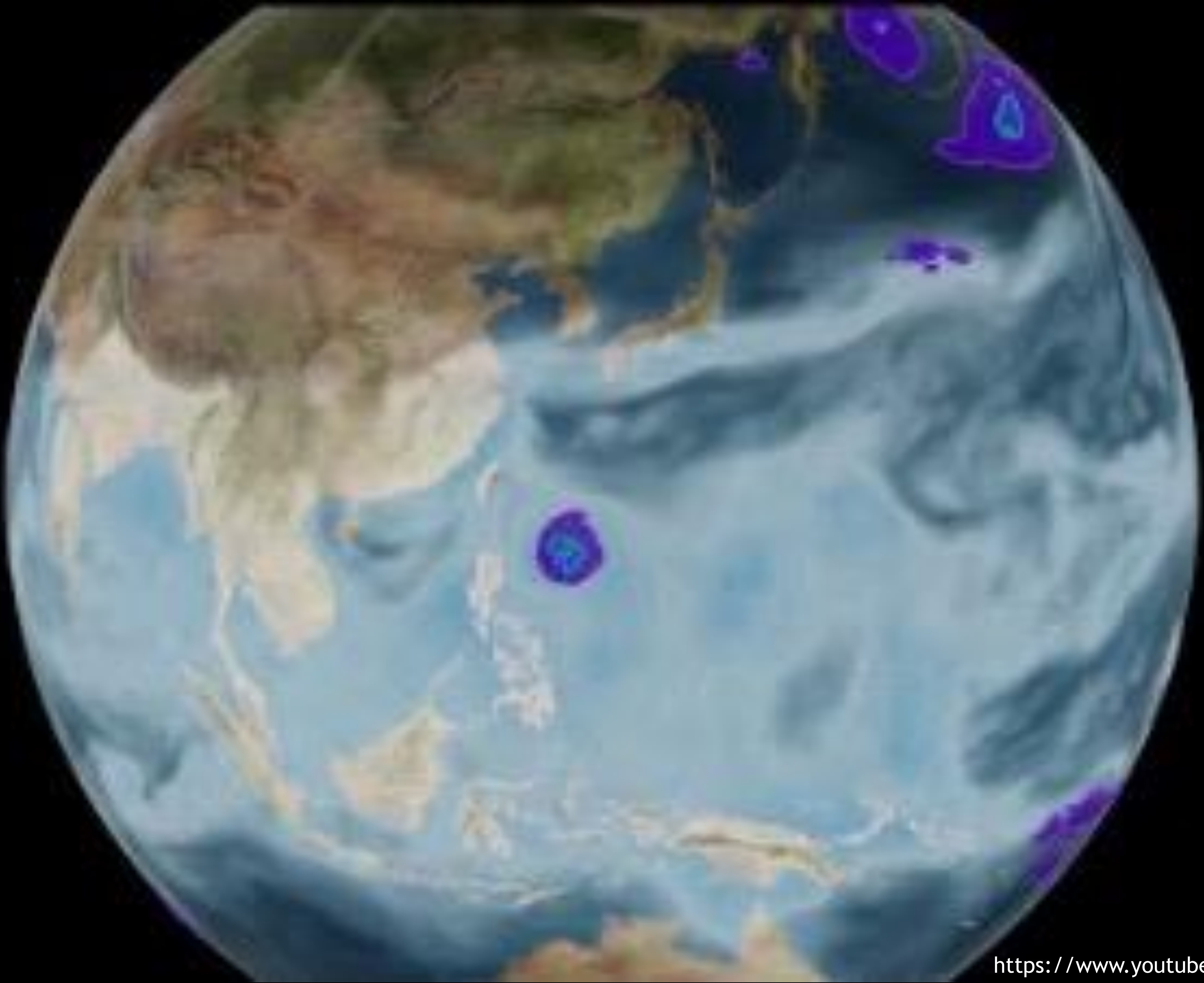
EXCELLENT SKILL ON FORECASTING SURFACE WINDS



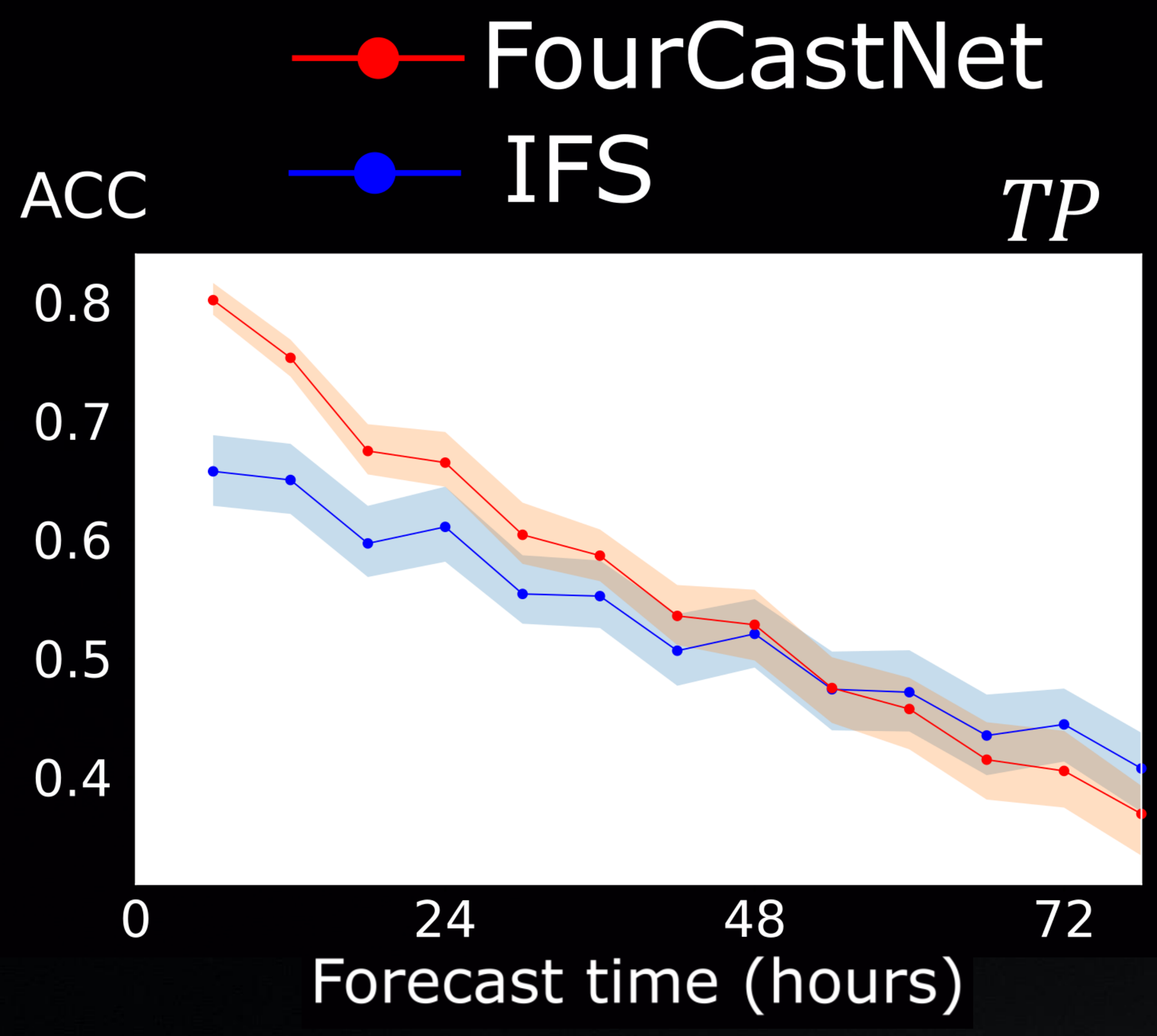
FOURCASTNET PREDICTS HURRICANE PATHS AND INTENSITIES

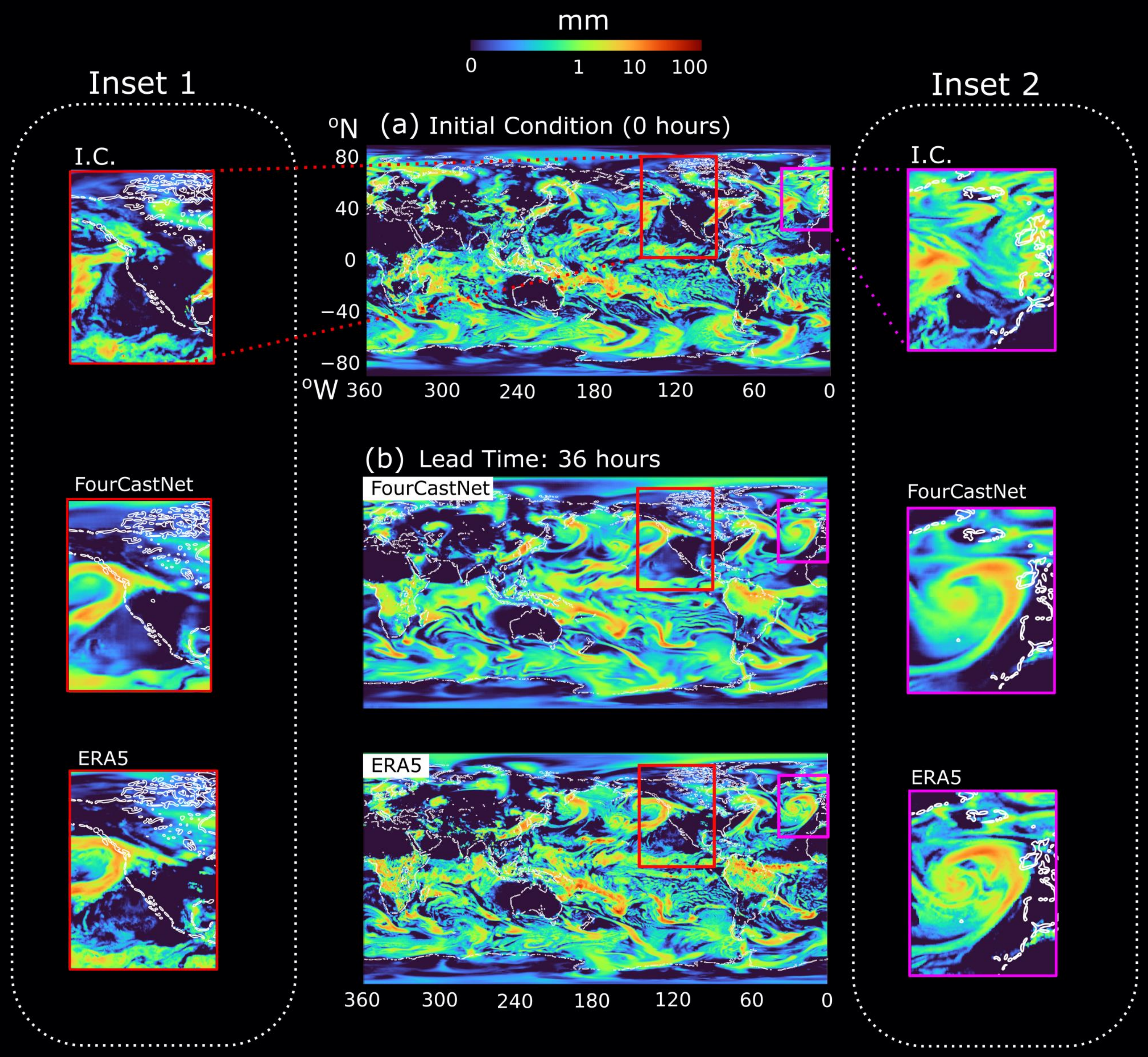




https://www.youtube.com/watch?v=JnGPxZ9glVk

UNPRECEDENTED SKILL ON PRECIPITATION FORECASTS

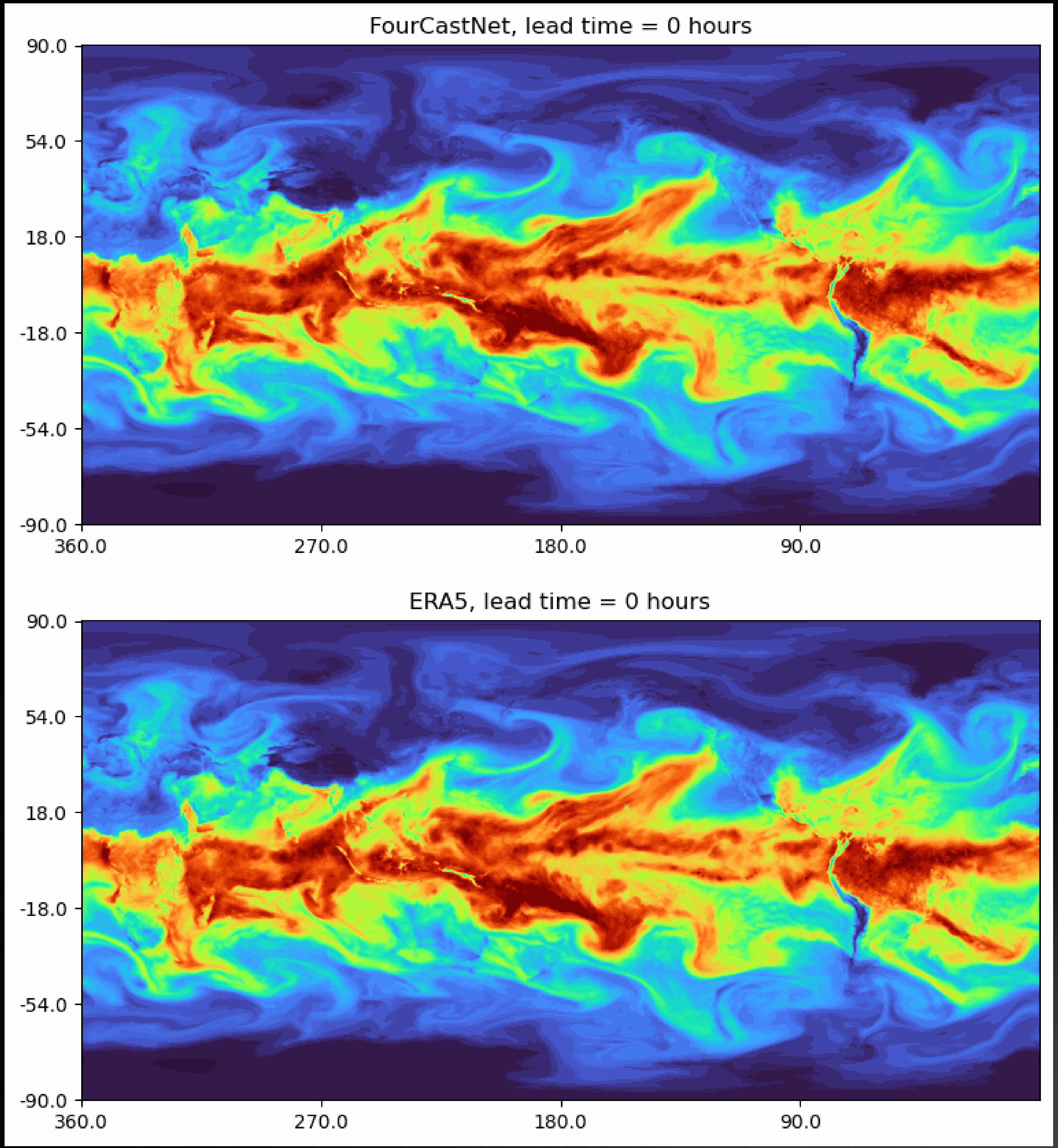


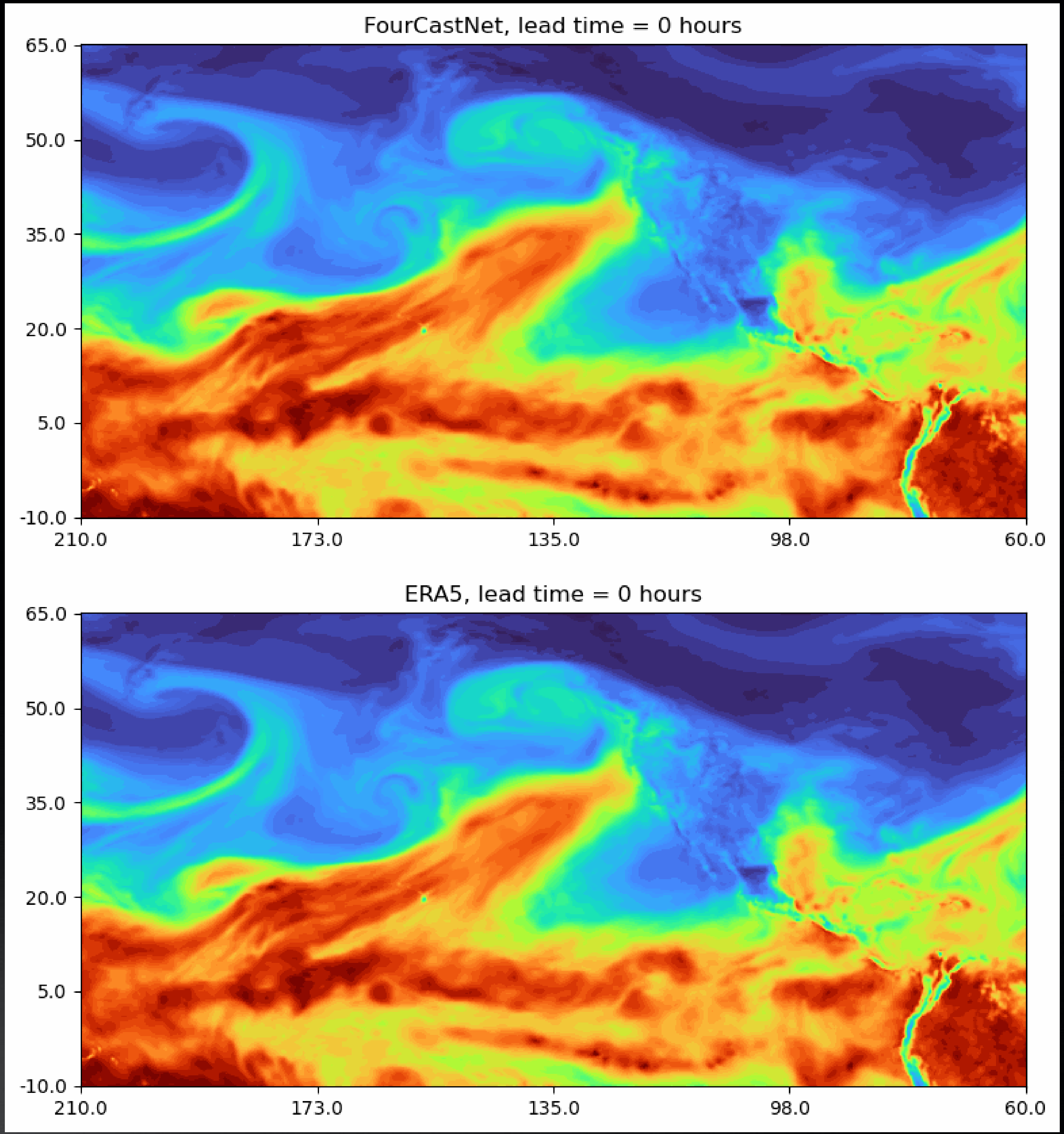


Note: Ground truth is ERA5, NOT observations

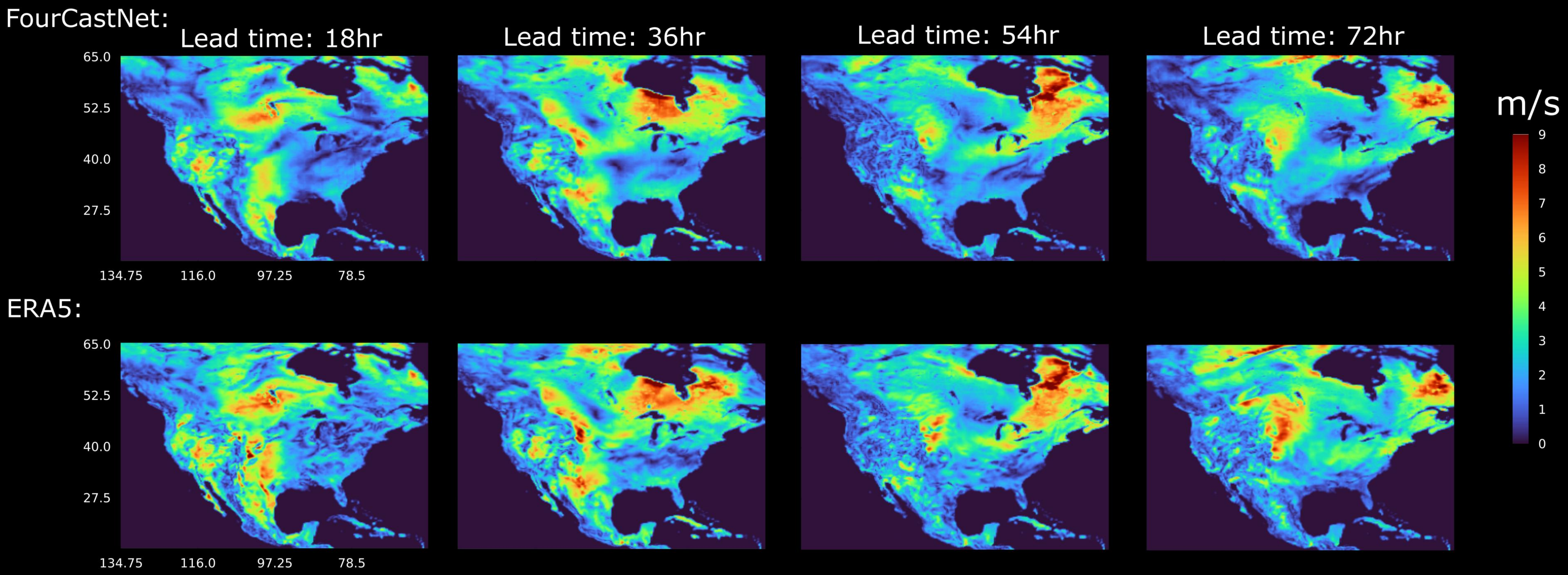
Pathak et al. (2022), FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators, arXiv:2202.11214

ACCURATE TOTAL COLUMN WATER VAPOR DYNAMICS

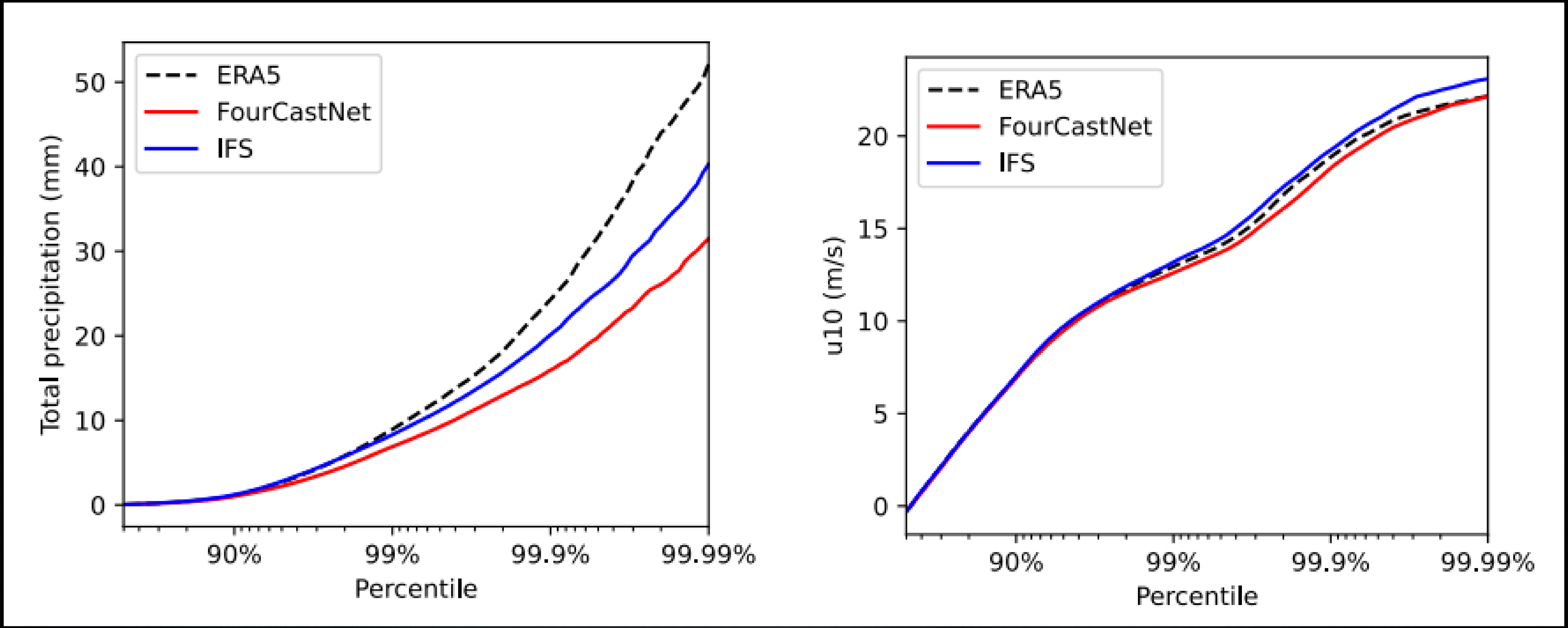




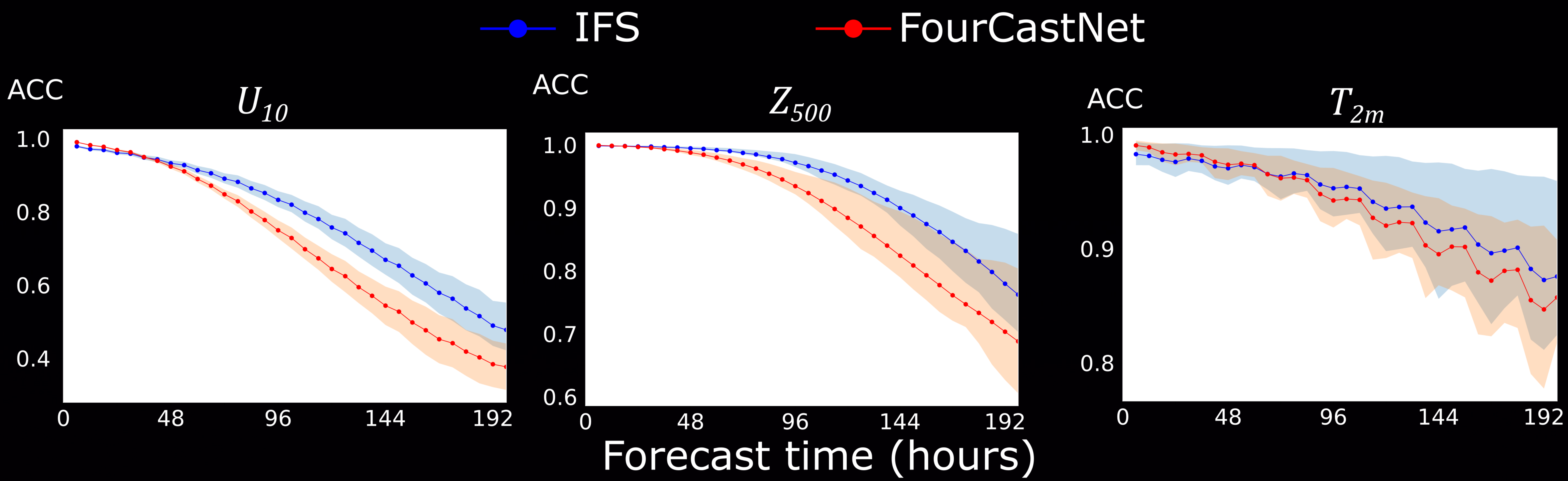
FOURCASTNET PREDICTS NEAR-SURFACE WIND FIELDS ACCURATELY: IMPORTANT IMPLICATIONS FOR WIND ENERGY PLANNING



PERFORMANCE ON EXTREME PRECIPITATION AND WIND EVENTS



SHORT-TERM FORECAST SKILL APPROACHING IFS



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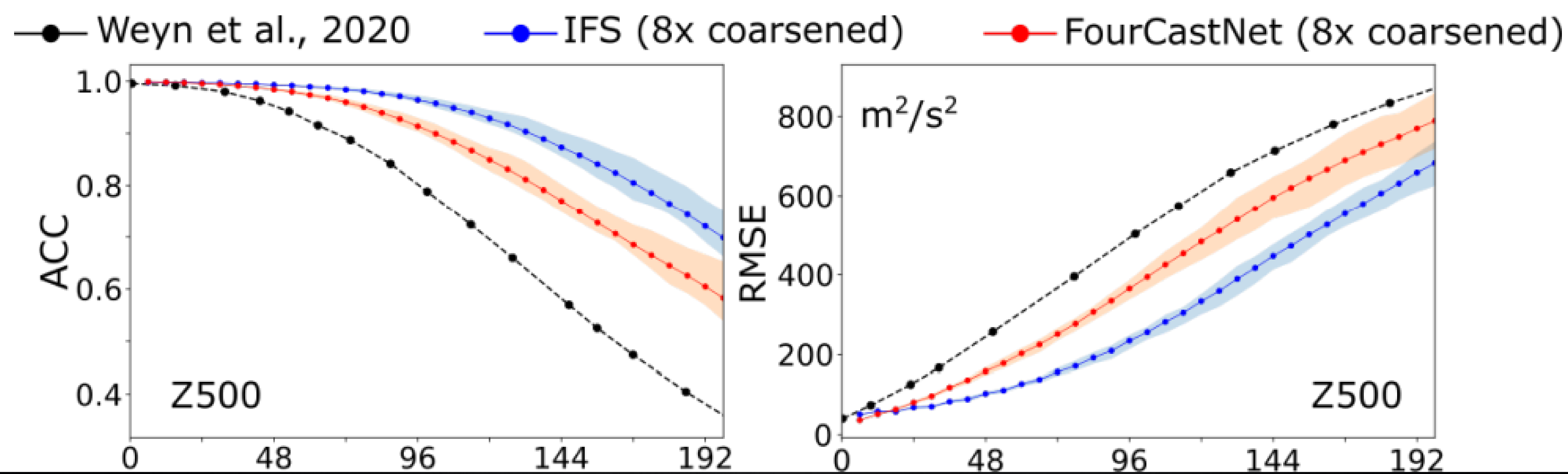
COMPARISON AGAINST STATE-OF-ART (DLWP, WEYN ET AL.)

8X higher resolution, significantly higher skill at weather timescales



Note: DLWP can predict reliably at S2S timescales

COMPUTATIONAL PERFORMANCE

Latency and Energy consumption for a 24-hour 100-member ensemble forecast				
	IFS	FCN - 30km (actual)	FCN - 18km (extrapolated)	IFS / FCN(18km) Ratio
Nodes required	3060	1	2	**1530**
Latency (Node-seconds)	984000	7	22	**44727**
Energy Consumed (kJ)	271000	7	22	**12318**

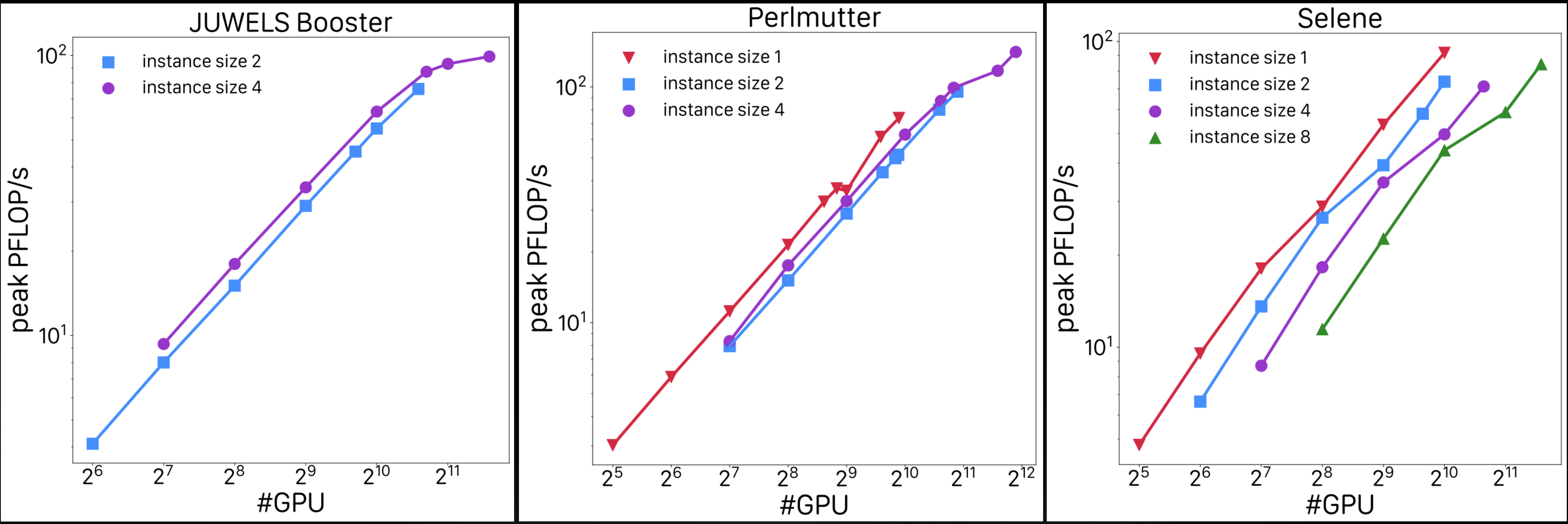
- 100-member ensemble forecast in 7 seconds
- 100-member ensemble forecast consumes 7 kJ
- 4 to 5 orders-of-magnitude speedup over NWP
- 4 orders-of-magnitude smaller energy footprint

Caveats

- FourCastNet is *not* physics constrained
- Orders-of-magnitude *fewer* variables and levels

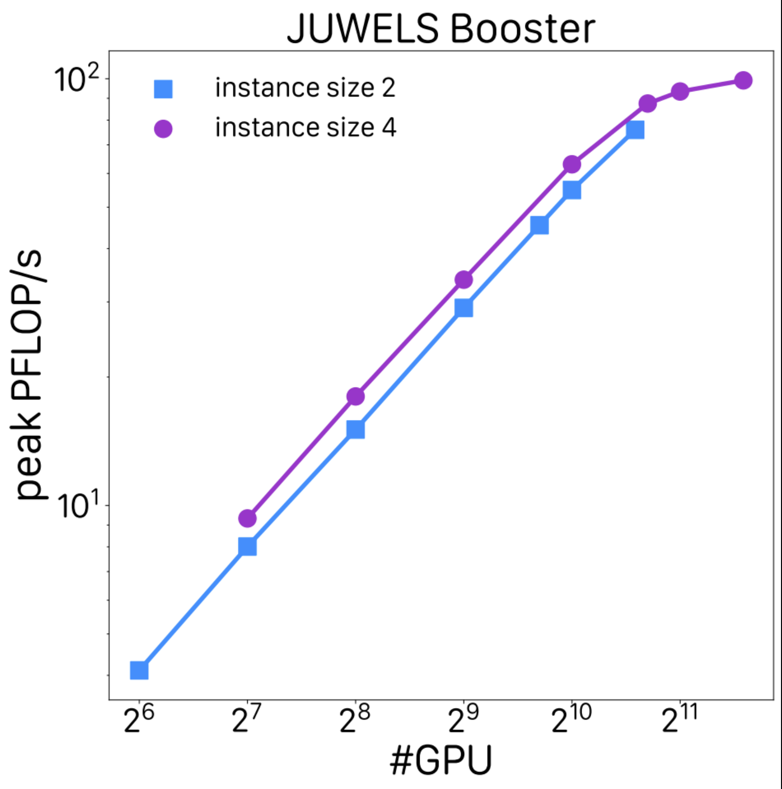
SCALING RESULTS (1 OF 3)

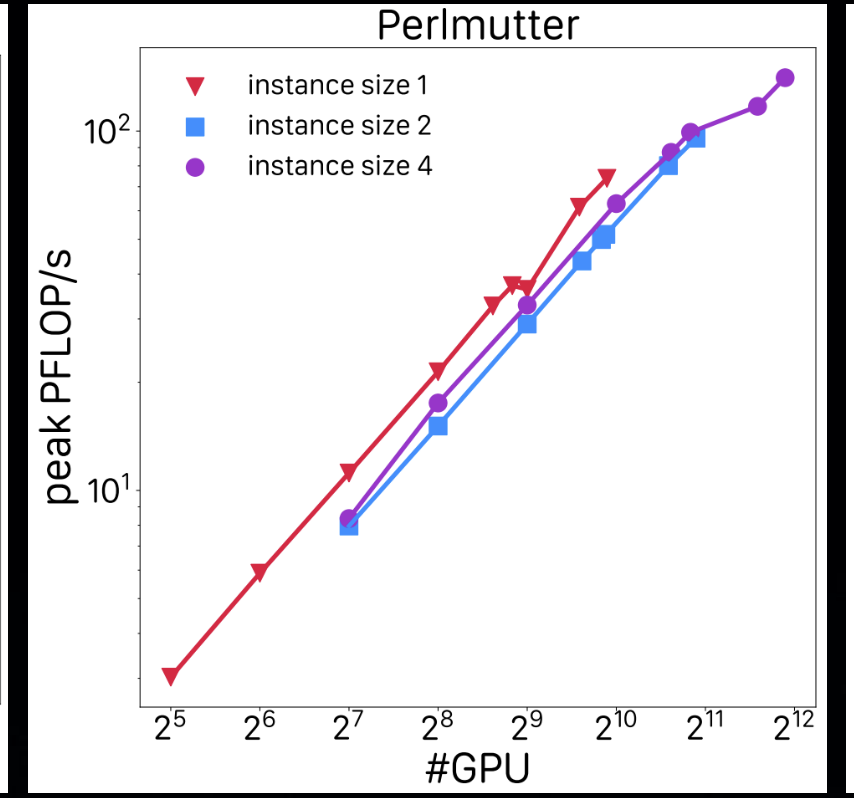
FourCastNet scaled efficiently upto ~ 4000 GPUs on three supercomputing systems:
JUWELS Booster, Perlmutter, and Selene

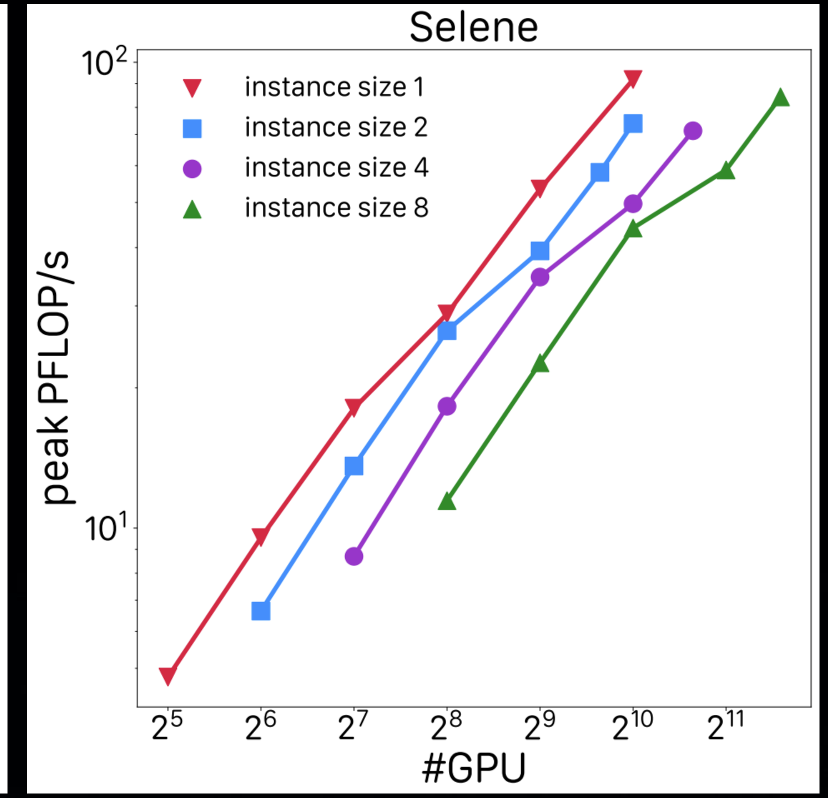


SCALING RESULTS (2 OF 3)

FourCastNet scaled efficiently upto ~ 4000 GPUs on three supercomputing systems: JUWELS Booster, Perlmutter, and Selene







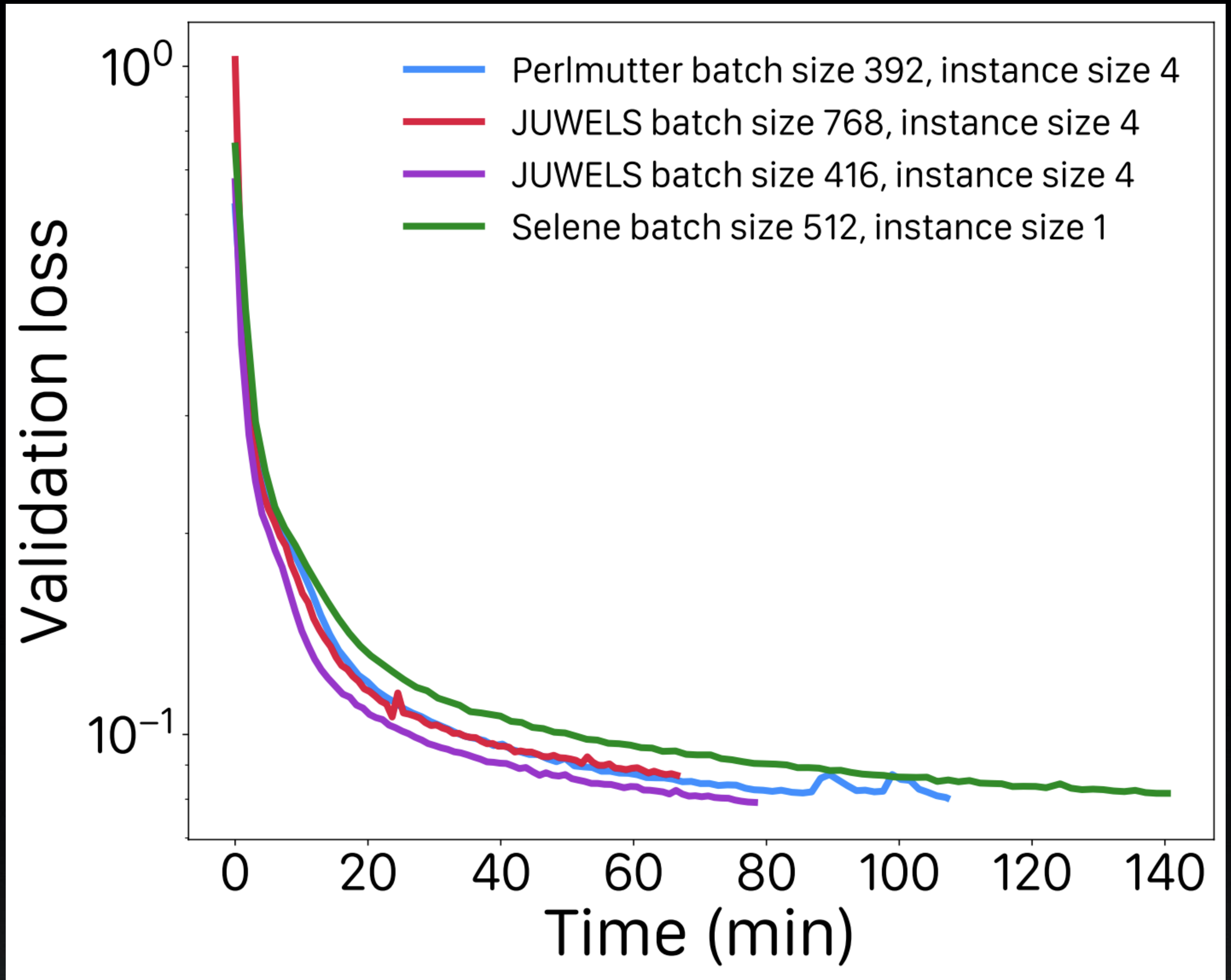
Peak performance is 140.8 petaFLOPS in mixed precision (averaged over a full epoch)

Model instance size	Phase	FP32	FP16	Tensor
1	training	28	6	8298
	validation	13	4	2840

FLOPS count per iteration per GPU for different precisions in units of 10^9 .

SCALING RESULTS (3 OF 3)

Model and data parallelism reduces training time from ~ 24 hours to 67.4 minutes



SCALING CHALLENGES HEADING TOWARDS 1 KM RESOLUTION

Model	Complexity (FLOPs)	Parameter Count	Interpretation
FNO	$Nd^2 + Nd \log N$	Nd^2	Global Conv.
AFNO	$Nd^2/k + Nd \log N$	$(1 + 4/k)d^2 + 4d$	Adaptive Global Conv.

p = patch size,
N = sequence size = ***dim_x * dim_y*** / ***p***^2;
d = embedding dimension, ***k*** = block count

	Current (25 km)	Intermediate (5 km)	Large (1 km)
N (p = 1)	1M	25M	625M
FFTs	720 x 1440 (***d*** of them)	3600 x 7200 (***d*** of them)	18k x 36k (***d*** of them)
Matrix Multiplies	[4***d*** x ***d***] * [***d***] (***N*** of them)	[4***d*** x ***d***] * [***d***] (***N*** of them)	[4***d*** x ***d***] * [***d***] (***N*** of them)

EARTH DIGITAL TWIN FOR EXTREME WEATHER

MONITOR | FUSE DATA | ASSIMILATE DATA

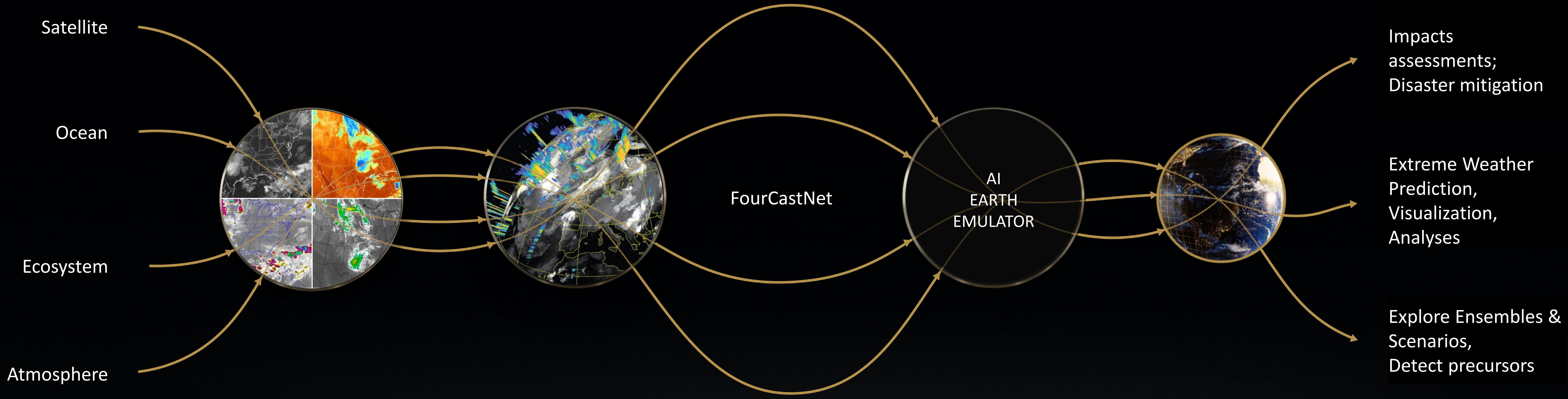
ERA5 Reanalysis Data (ECMWF) / Hi-res simulations

PHYSICS-ML EMULATION

Modulus Model Training and Inference

PREDICT | ANALYZE | VISUALIZE

Omniverse



Current Data Input:
Atmospheric winds and geopotential heights ~ 20 channels
10 TB, 30-km spatial resolution, 5 vertical pressure levels

Future Data Input:
Atmosphere, Ocean, Land, Ecosystems, Ice
10 PB, 5-km resolution, 20 vertical levels, 300 variables

Current Training and Inference:
16 hours on 128 GPUs, 0.25 seconds for 7-day forecast

Future Training and inference:
200 hours on 16384 GPUs, 4 seconds for 7-day forecast
(projected estimates – W.I.P)

1. Predict, visualize, detect and track extremes
2. Compare skill to traditional NWP models
3. Checkpoint / restart ensembles around events
4. Assess extreme weather impacts, mitigate disasters
5. Interactively investigate impact of changing climate scenarios on behavior of extremes
6. Detect precursors of extremes

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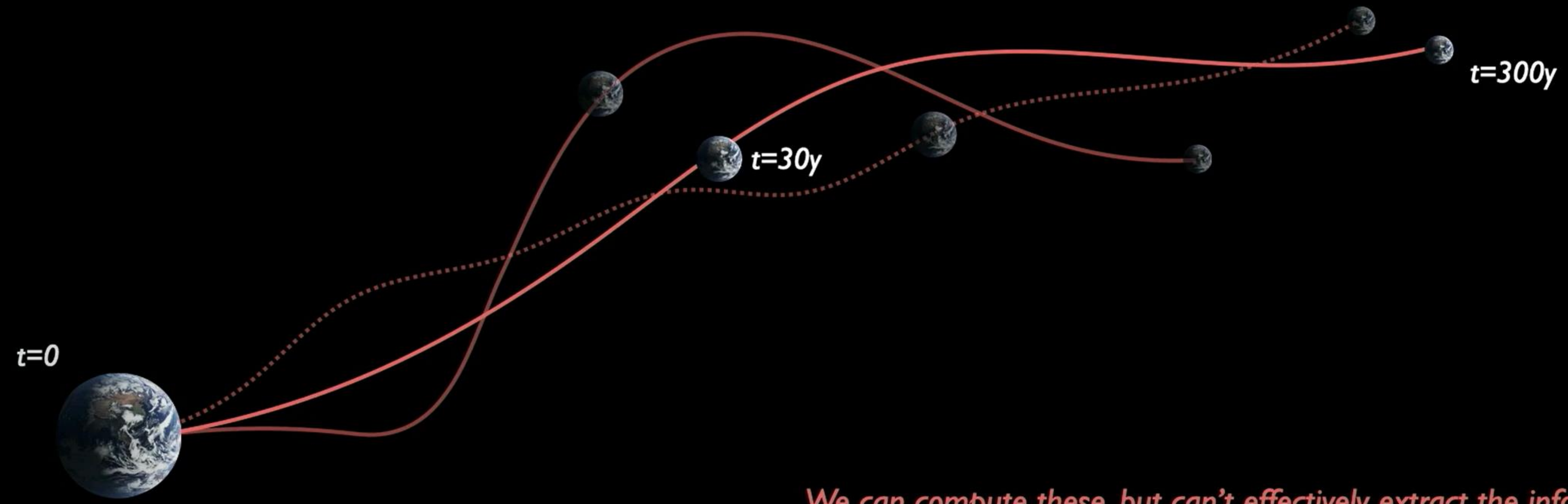
TODAY

- Unprecedented skill
- 1000-member ensemble in seconds
- 4 to 5 orders-of-magnitude speedup over NWP
- 4 orders-of-magnitude smaller energy footprint

LOOKING AHEAD

- Physics constraints
- Full state vector (ocean, land, sea ice)
- Higher resolutions
- Generative models for fine-scales
- Uncertainty Calibration
- Observational ground truth / diagnostics
- Weather ⟶ Climate
- ML Data Assimilation

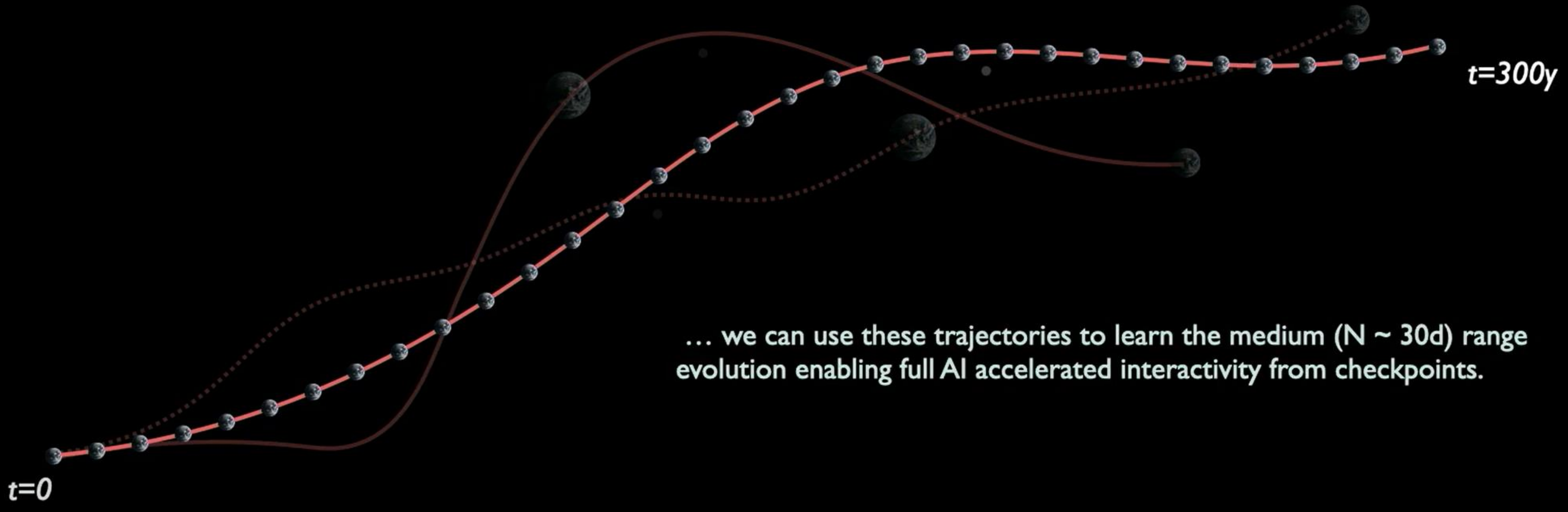
Climate as a trajectory in a Tera-dimensional (10^{12}) trajectory phase space



We can compute these, but can't effectively extract the information content from an XByte trajectory, let alone interact with it.

Source: Bjorn Stevens' keynote on "Digital Twins for Understanding and Adapting to Climate Change" at GTC Spring 2022

If we can compute these trajectories

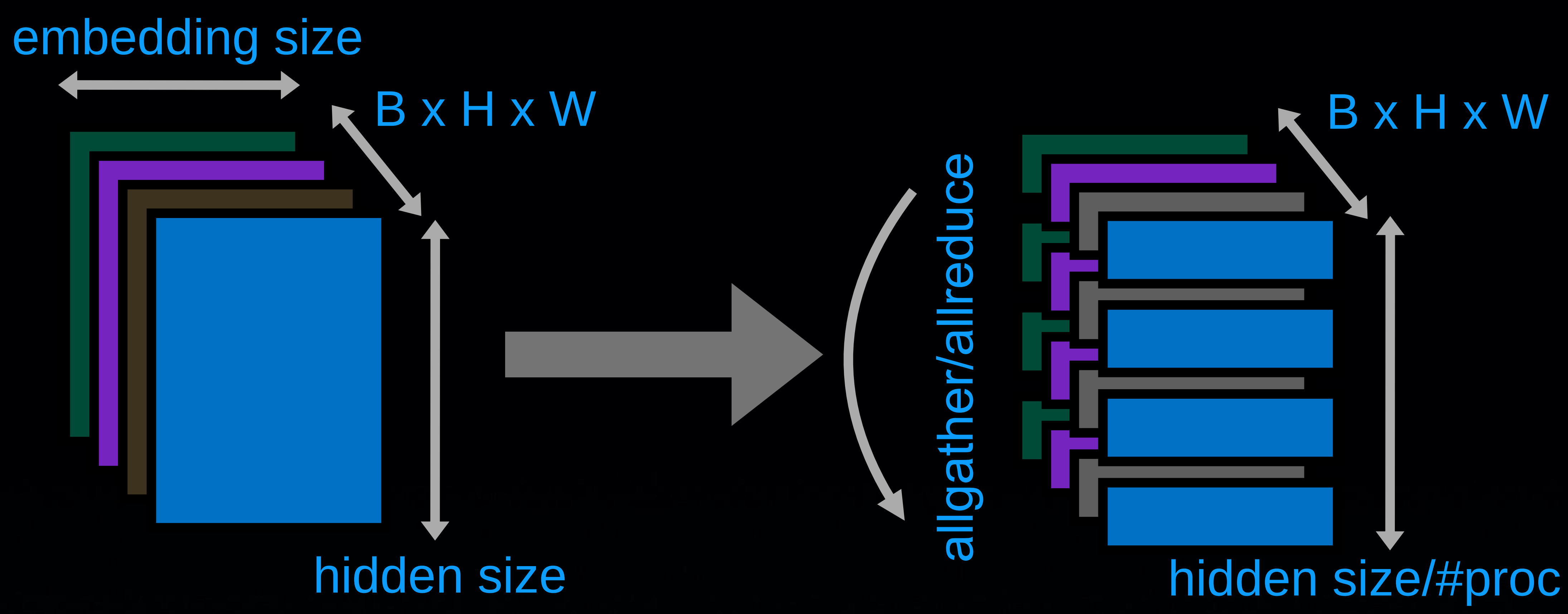


… we can use these trajectories to learn the medium (N ~ 30d) range evolution enabling full AI accelerated interactivity from checkpoints.

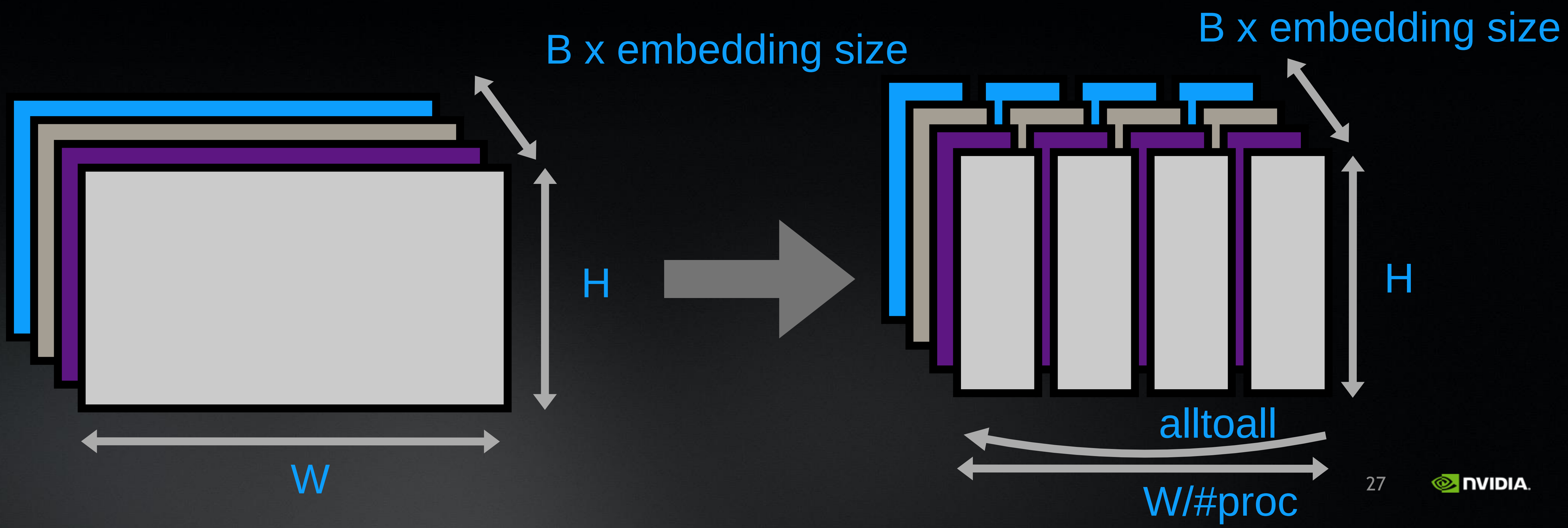
If only as a first step for learning the entire system $N \rightarrow \infty$

PARALLELIZATION METHODS I

Feature parallelization
splitting channel dim, dense layers become distributed matrix multiplications



Domain decomposition
splitting height and width, FFTs become distributed, LayerNorm needs to exchange stats



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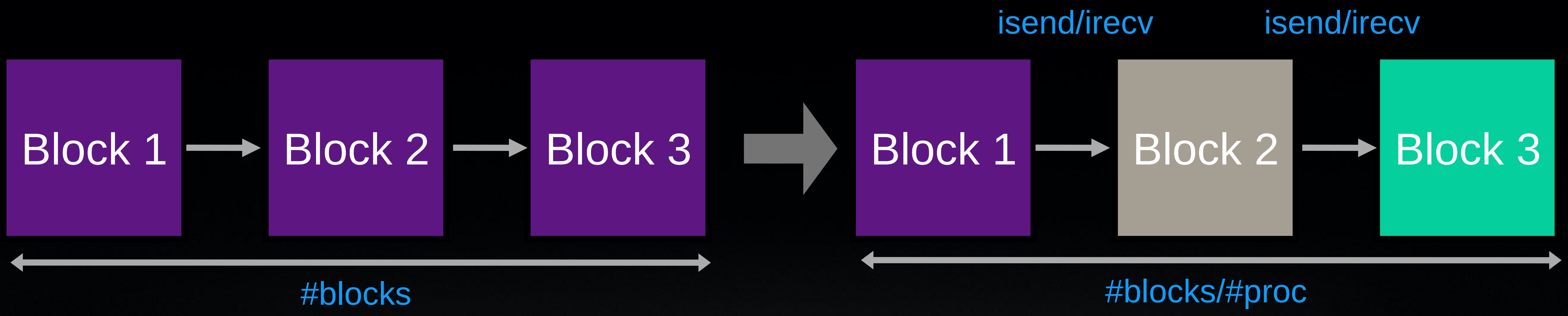
PARALLELIZATION METHODS II

Layer pipelining
place only a few transformer blocks
on each GPU



Data parallelism
split the global batch across GPU

Hybrid parallelism
mix and match different types