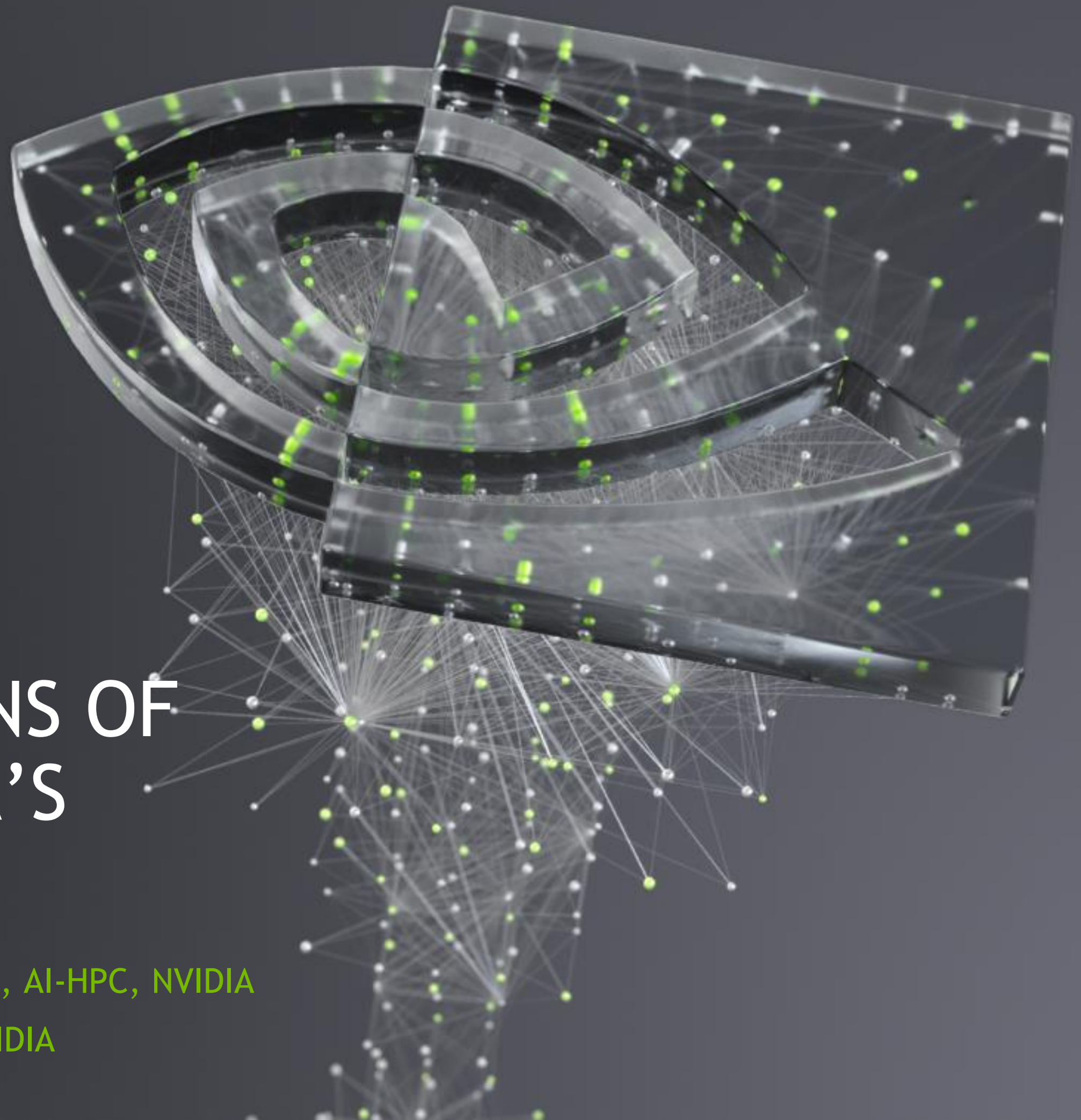




BUILDING DIGITAL TWINS OF THE EARTH FOR NVIDIA'S EARTH-2 INITIATIVE

Karthik Kashinath, Senior AI Developer Technologist, AI-HPC, NVIDIA

Jaideep Pathak, Senior Deep Learning Engineer, NVIDIA



CLIMATE SCIENCE REQUIRES MILLION-X SPEEDUPS

Computational constraints limit model resolution

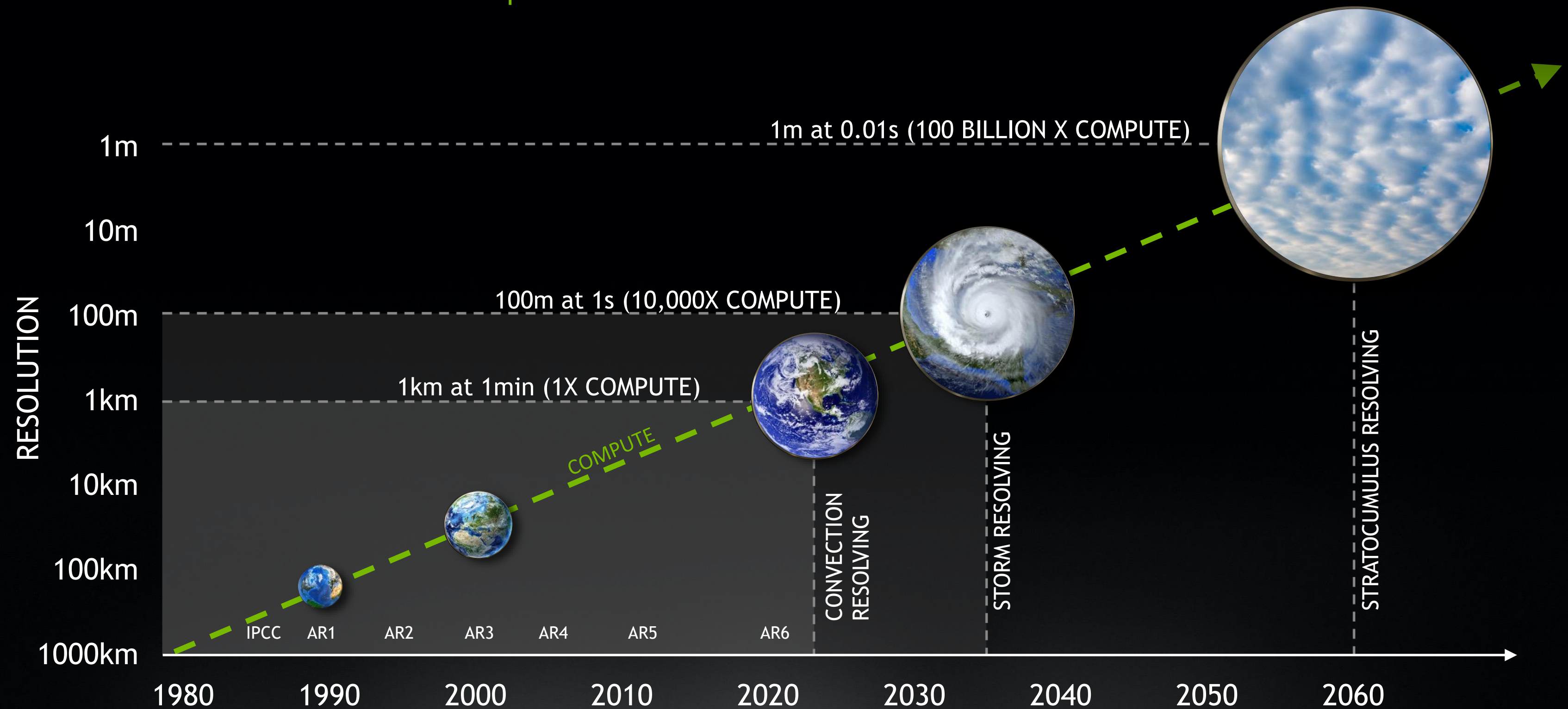
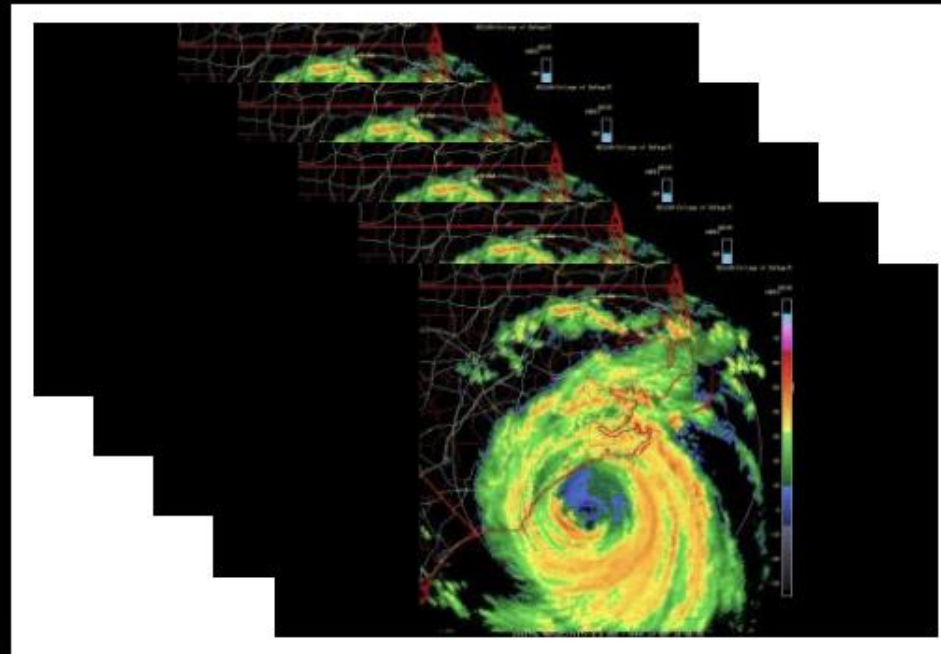


Figure adapted from: Schneider, T., Teixeira, J., Bretherton, C. *et al.* Climate goals and computing the future of clouds. *Nature Climate Change* 7, 3–5 (2017). <https://doi.org/10.1038/nclimate3190>

CLIMATE SCIENCE REQUIRES MILLION-X SPEEDUPS

Computational constraints limit the size of ensembles and how many scenarios can be explored

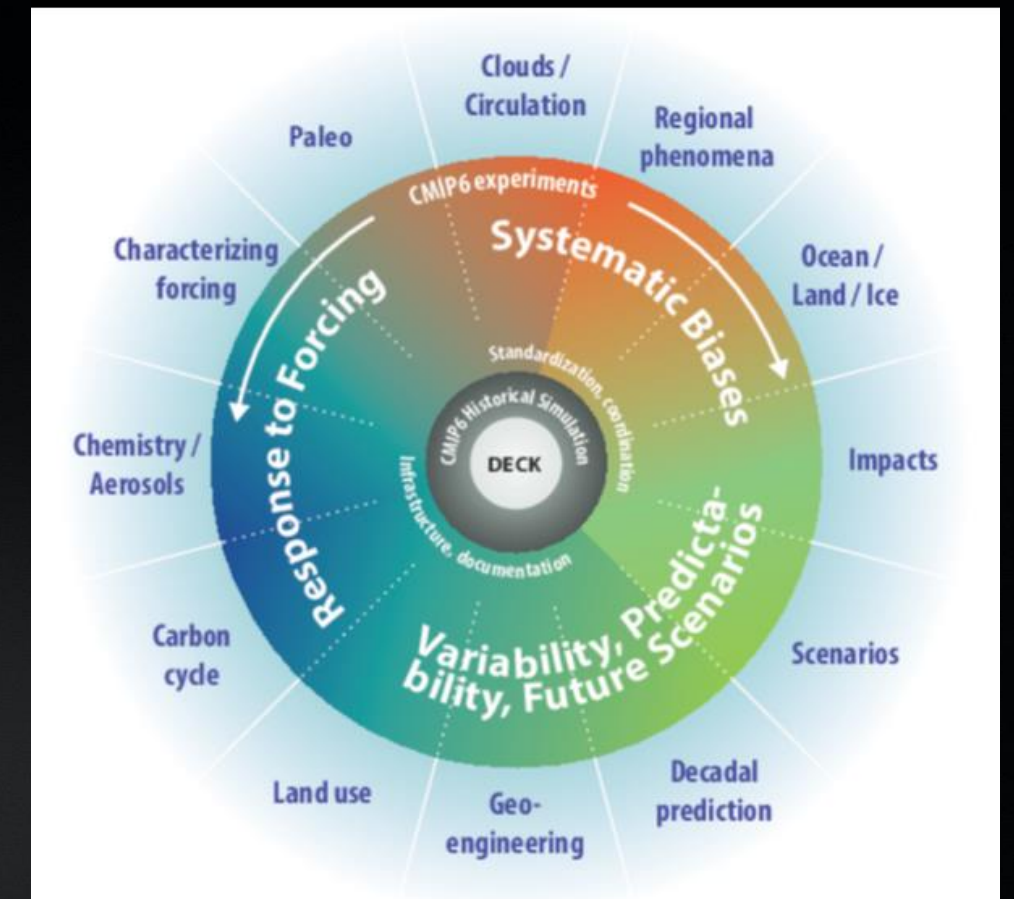
10s → 1000s OF MEMBERS



ENSEMBLES

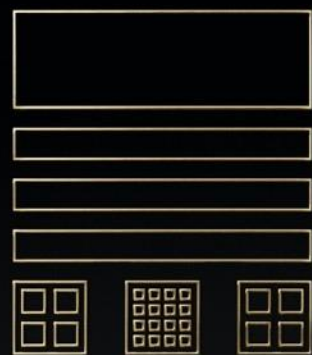
SCENARIOS

10s → 1000s OF SCENARIOS

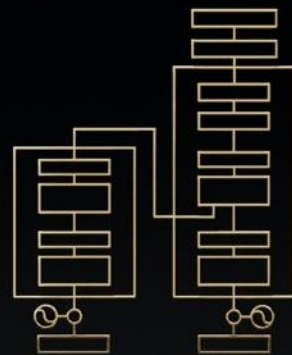


ADVANCES IN COMPUTING AND ML PROMISE MILLION-X SPEEDUPS

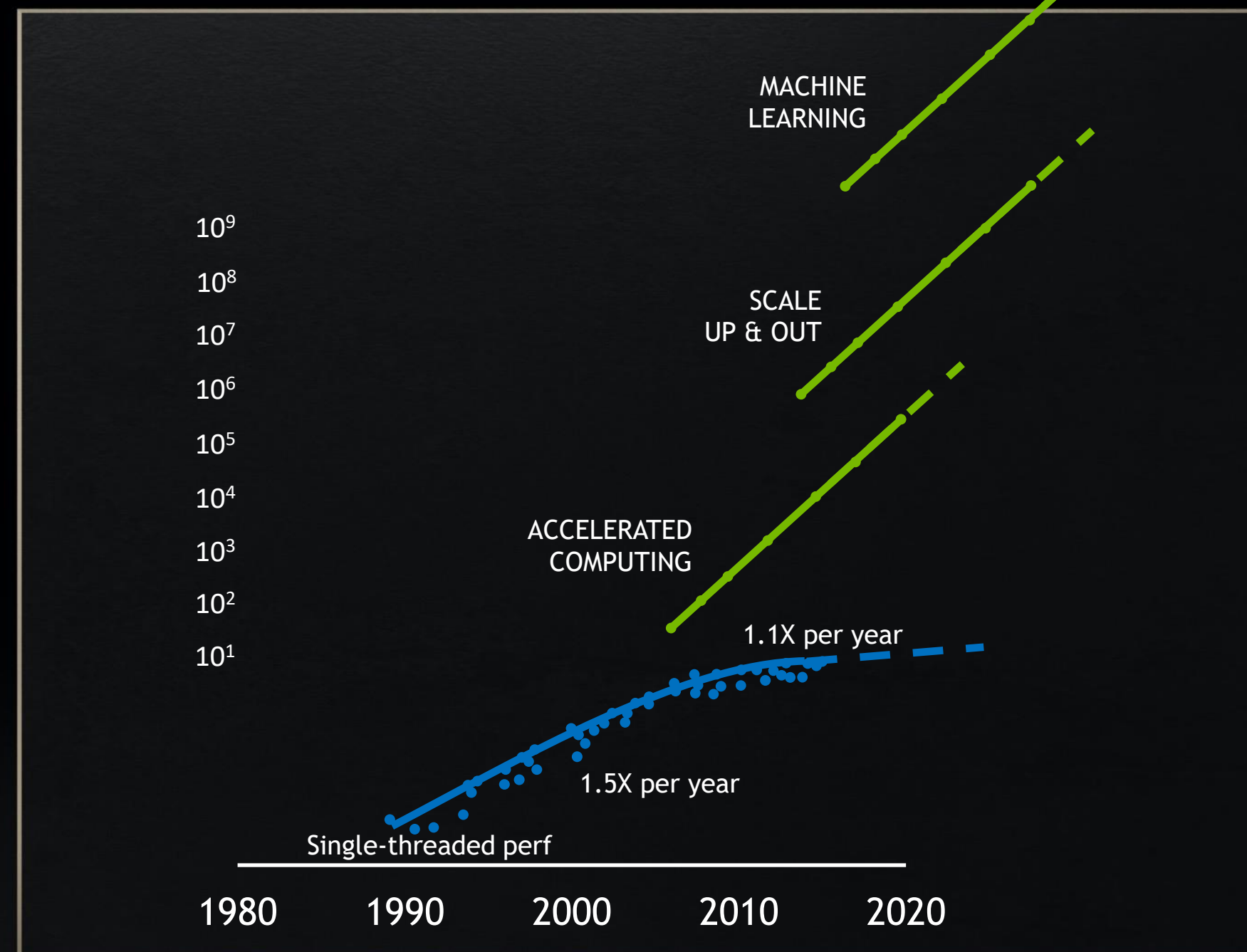
Accelerated Computing



AI



Data Center Scale

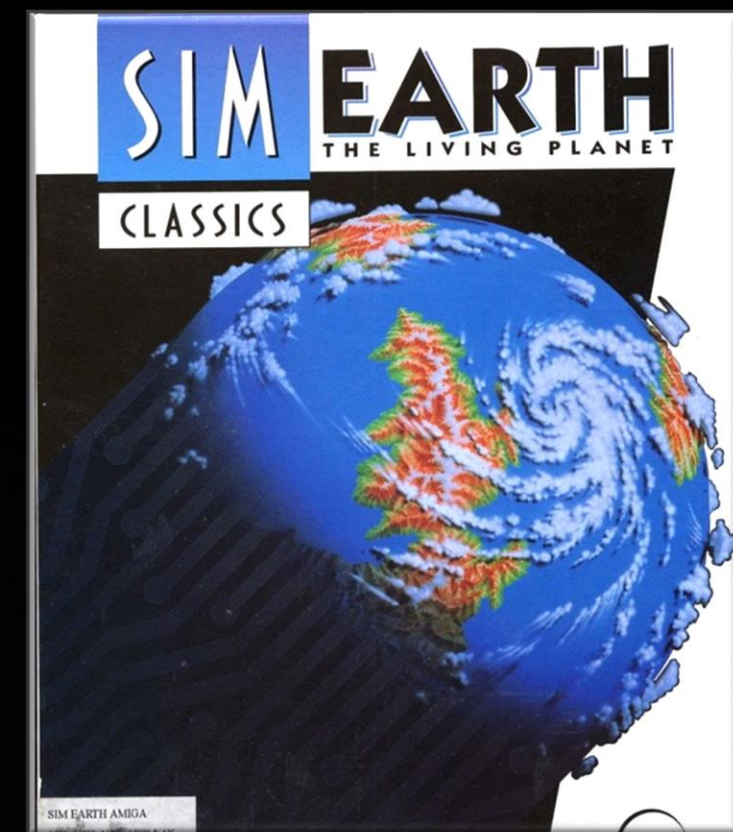


DESTINATION-EARTH: DIGITAL REPLICAS OF EARTH

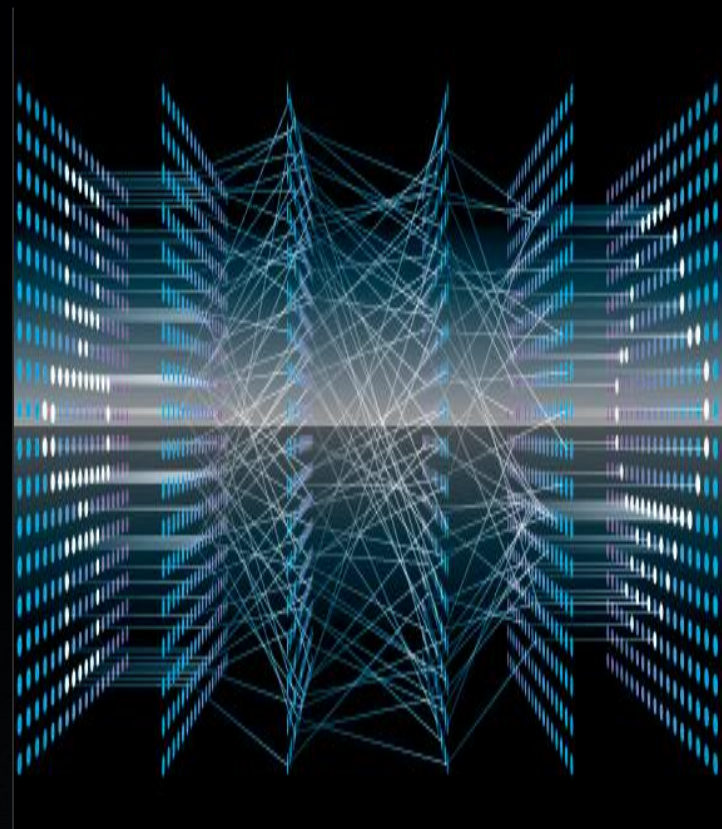
Project DestinE envisions what Earth-system modeling could be

Intuitive User Interface:

What-if Q & A



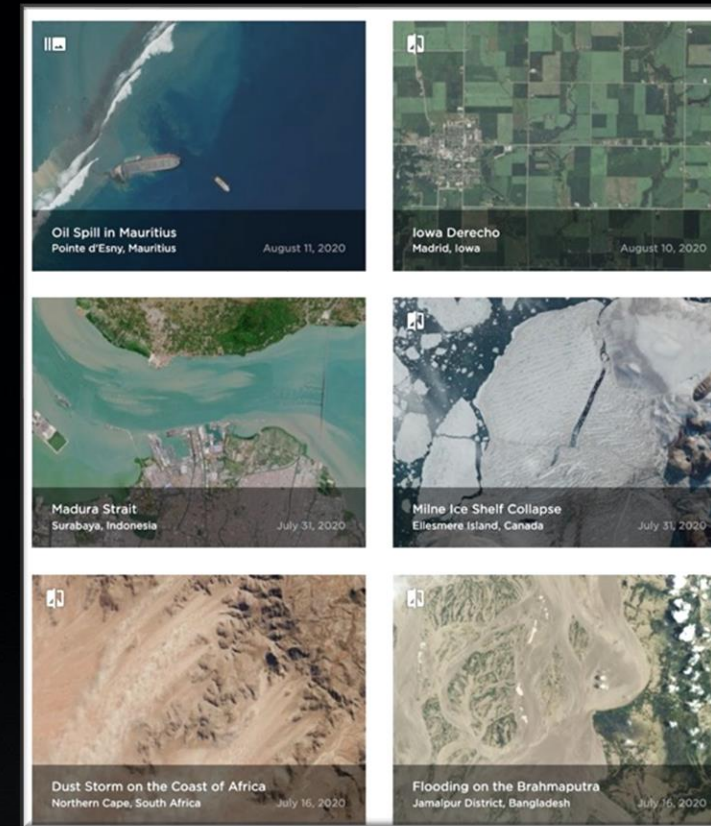
Data-driven Models



Storm-resolving Models



Unified Observations



Exascale Compute



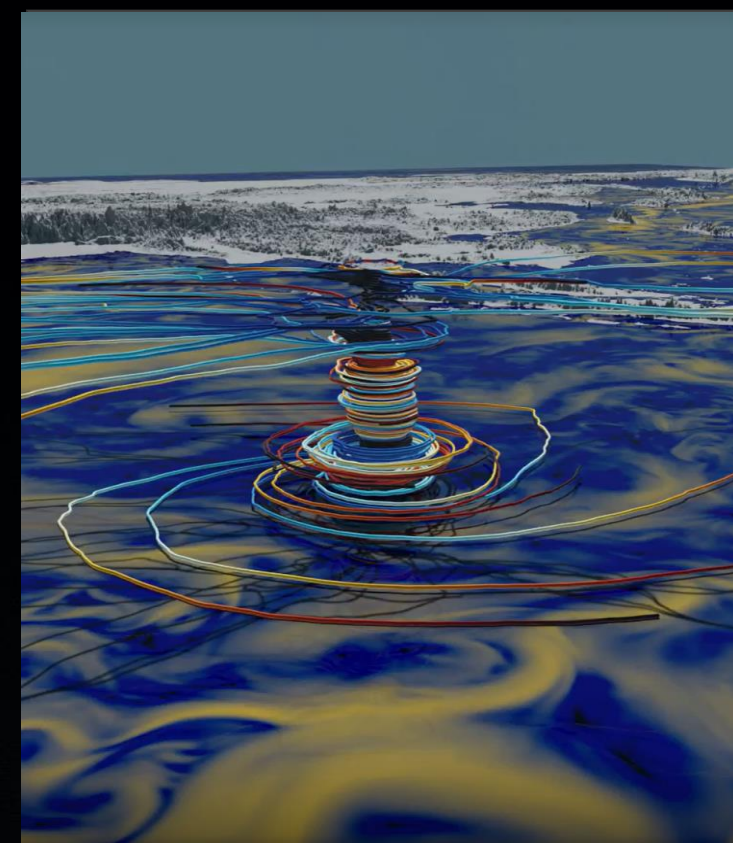
<https://digital-strategy.ec.europa.eu/en/library/destination-earth>

DESTINATION-EARTH: DIGITAL REPLICAS OF EARTH

NVIDIA has technologies needed to make this vision a reality

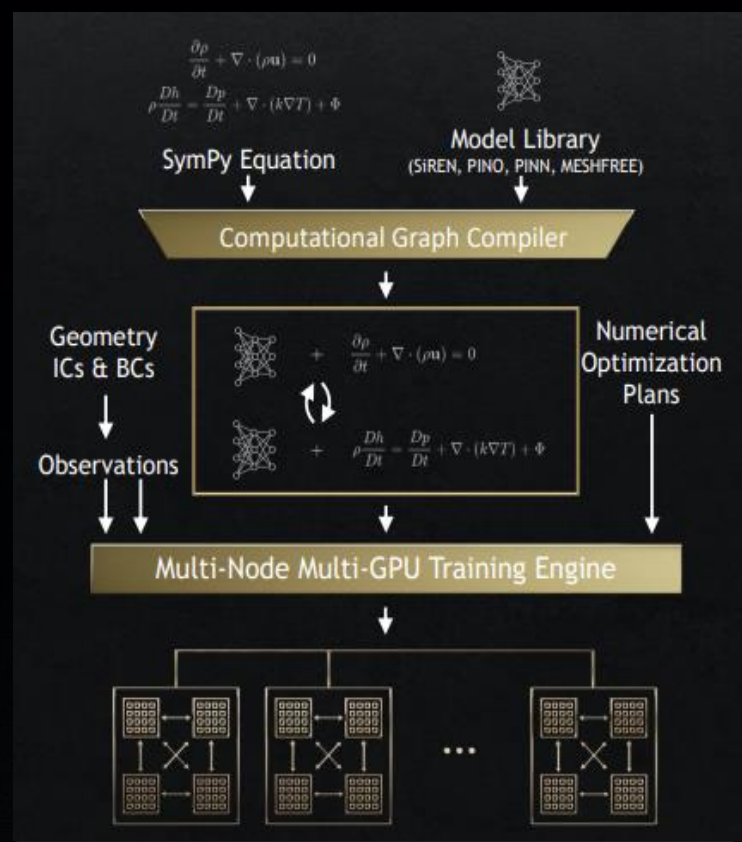
Intuitive User Interface:

What-if Q & A



OMNIVERSE

Data-driven Models



PHYSICS-ML /
MODULUS

Storm-resolving Models



GPU-ACCELERATION

Unified Observations

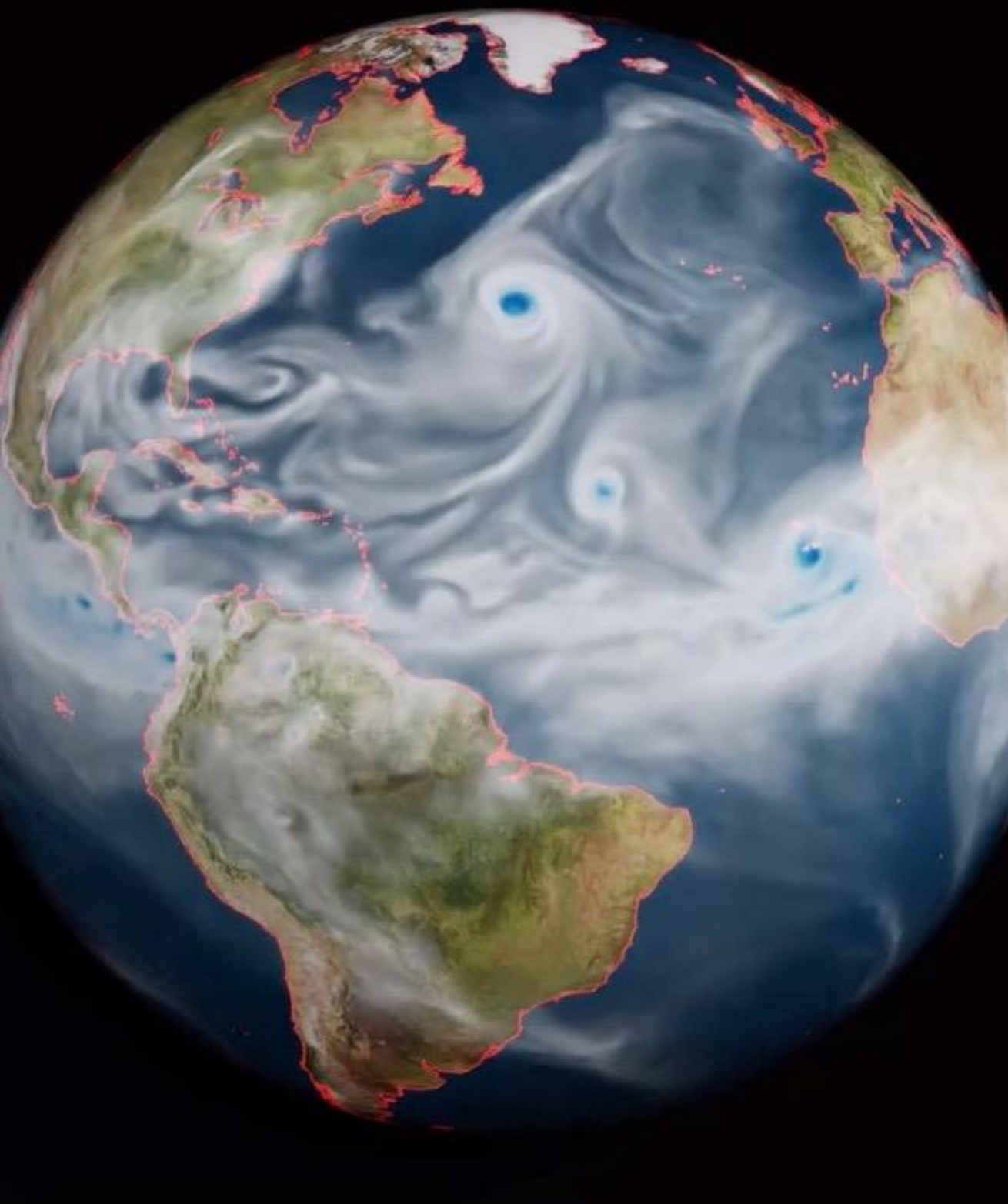


OMNIVERSE NUCLEUS

Exascale Compute



OVX SUPERPOD



Earth-2

WHY?
INTERACTIVITY AT SCALE:
UNFOLD AND EXTRACT
INFORMATION

HOW?
DIGITAL TWINS TO MONITOR,
PREDICT, MITIGATE, AND
ADAPT

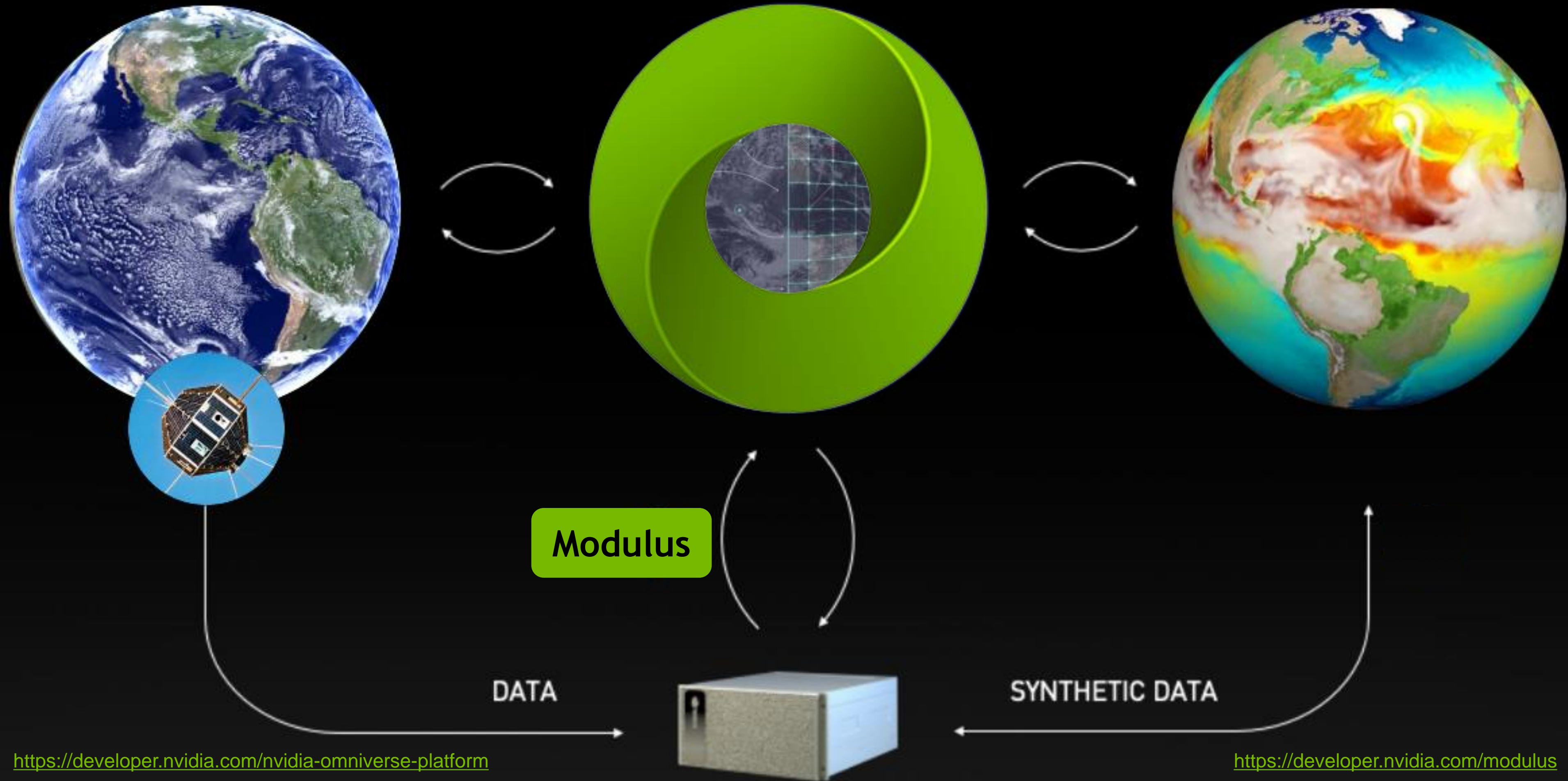


<https://blogs.nvidia.com/blog/2021/11/12/earth-2-supercomputer/>

PHYSICAL WORLD

DIGITAL TWIN

SIMULATION



EARTH DIGITAL TWIN

DEEP LEARNING CHALLENGES AND APPROACHES

CHALLENGES

- Extrapolation
- Physical consistency & causality
- Uncertainty quantification & Calibration
- Data fusion & assimilation
- Scale up & out
- ...

APPROACHES

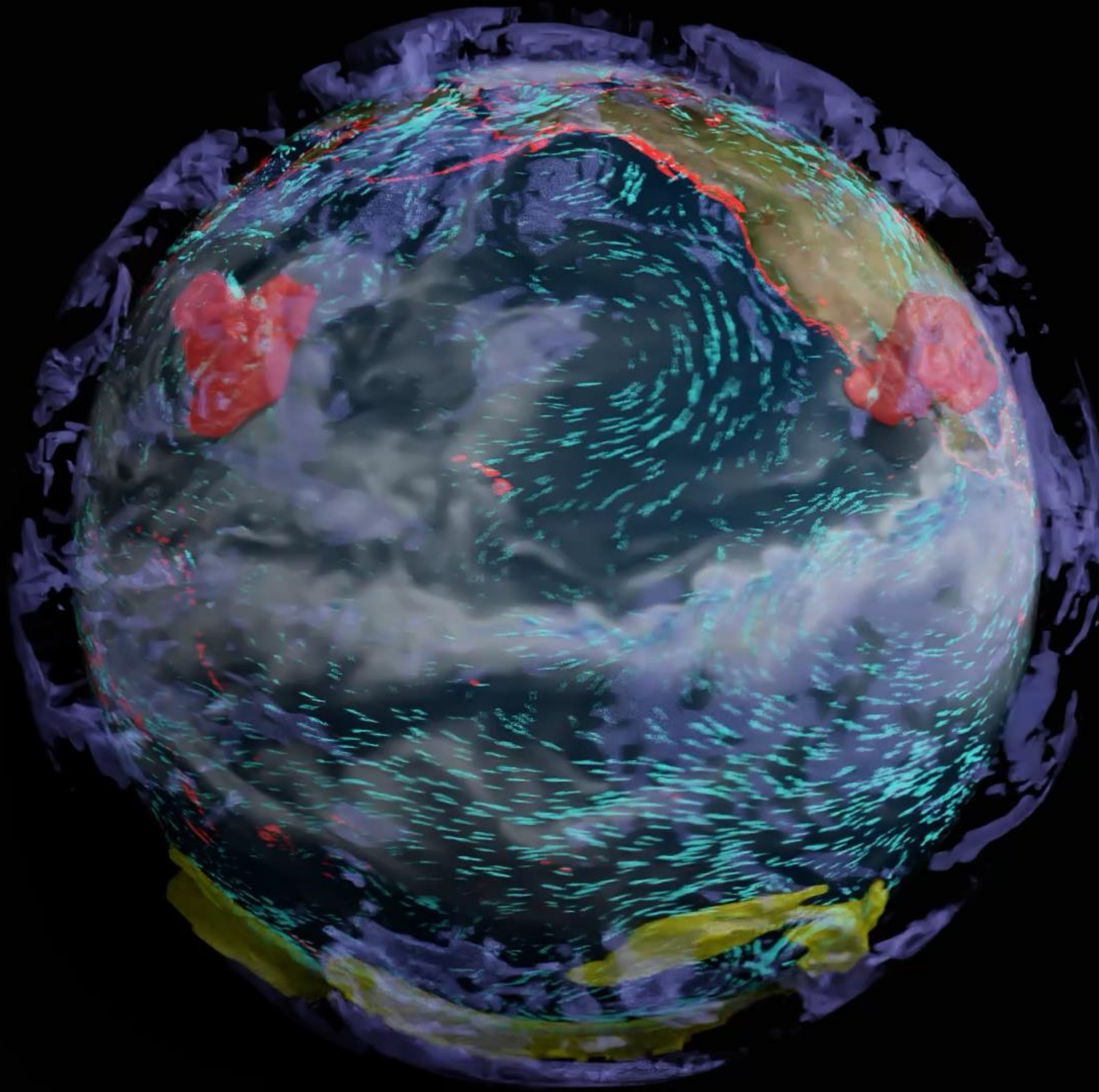
- Emulation
- Super-resolution
- Segmentation
- Online learning
- Reinforcement Learning
- ...

YEAR 2100

+3 C Global Temperature

+60% Extreme Tropical Cyclones

+400% Extreme Atmospheric Rivers

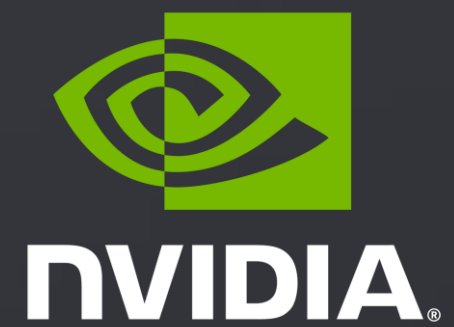


2100, SEP 14

- TROPICAL CYCLONES
- ATMOSPHERIC RIVERS
- CLOUDS
- WINDS

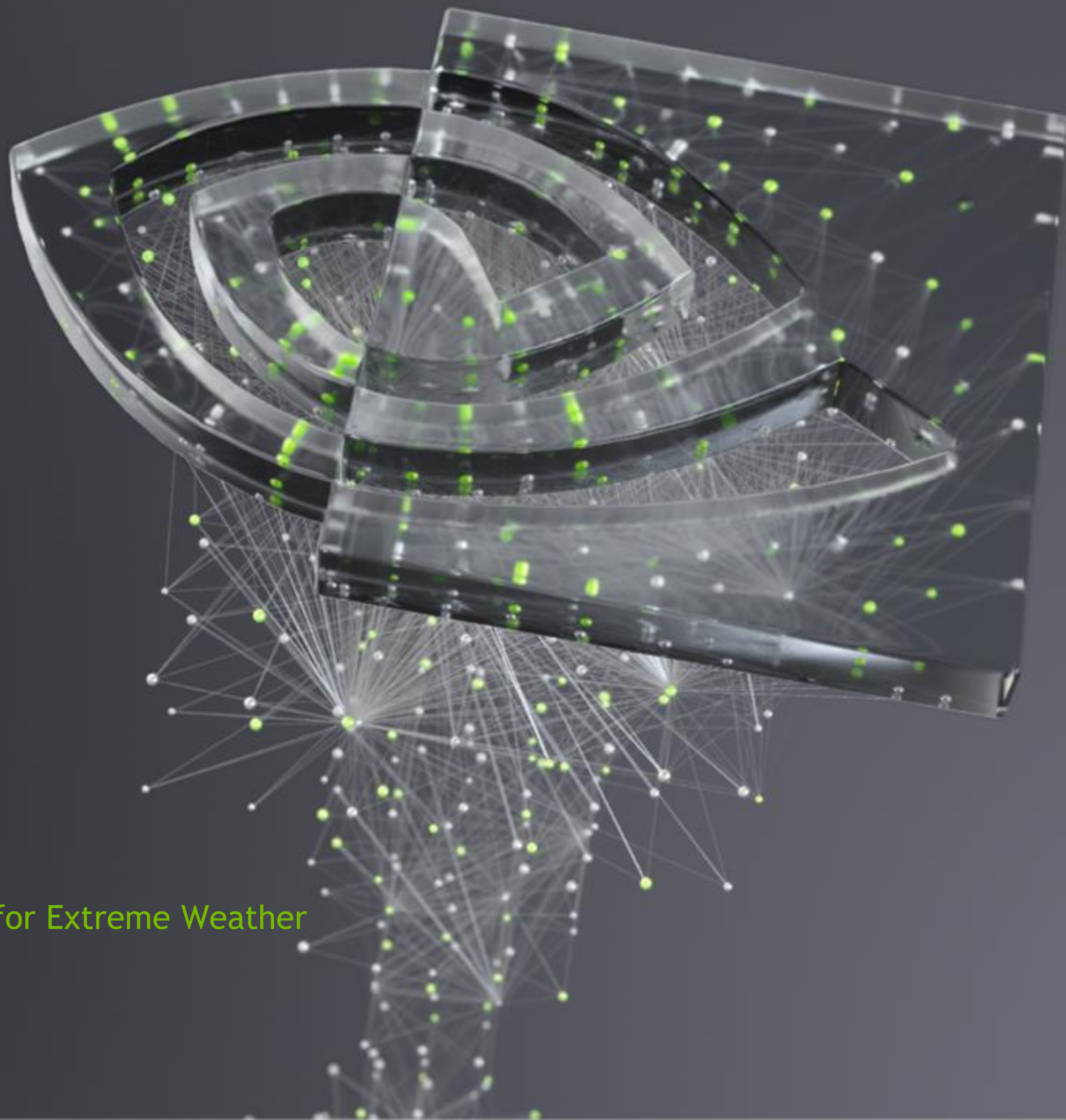


NVIDIA.



FourCastNet

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





J. Pathak
NVIDIA



S. Subramanian
LBL



P. Harrington
LBL



S. Raja
U. Michigan



A. Chattopadyay
Rice. U.



M. Mardani
NVIDIA



T. Kurth
NVIDIA



D. Hall
NVIDIA



Z. Li
Caltech



K. Azzizzadenesheli
Purdue



P. Hassanzadeh
Rice U.

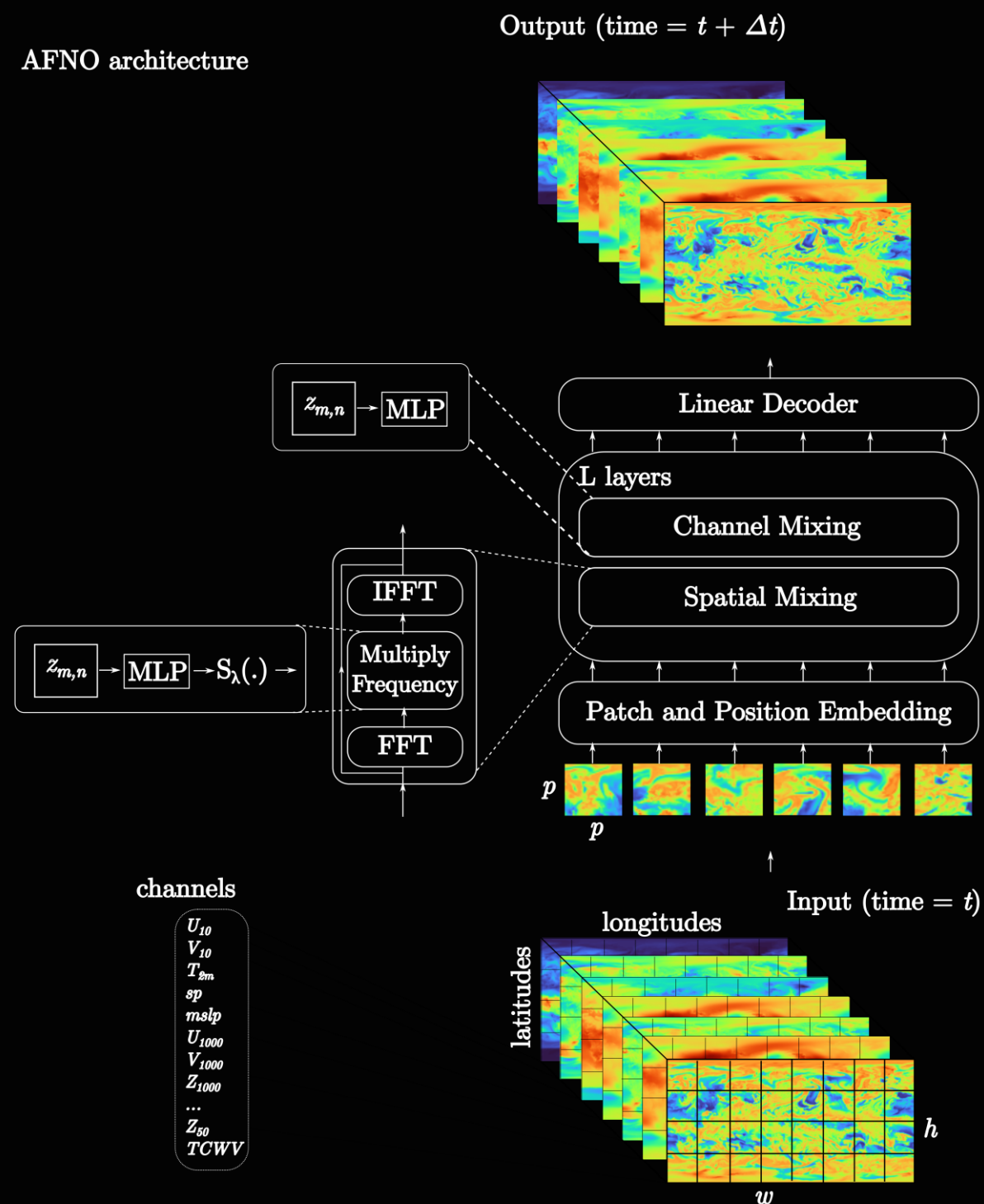


K. Kashinath
NVIDIA



A. Anandkumar (PI)
Caltech/NVIDIA

FOURCASTNET (FOURIER FORECASTING NETWORK)



Purely data-driven machine learning surrogate weather model

Trained on ERA5 reanalysis data at the native resolution of 0.25 degrees.

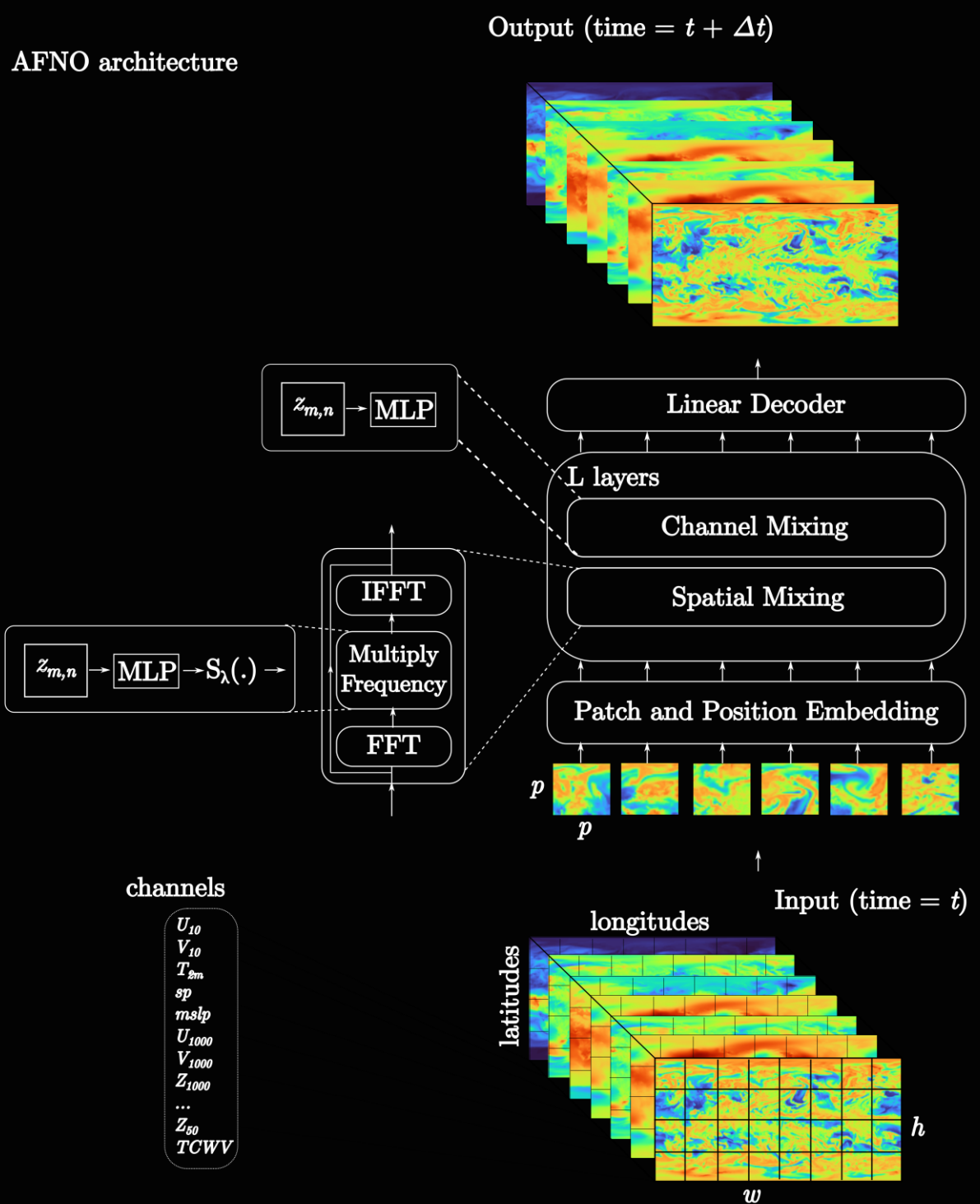
State-of-the-art for Deep Learning based weather surrogate models.

Highest resolution data driven model ever trained.

Guibas et al. (2022), Adaptive Fourier Neural Operators: Efficient Token Mixers for Transformers, ICLR 2022.

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

FOURCASTNET (FOURIER FORECASTING NETWORK)



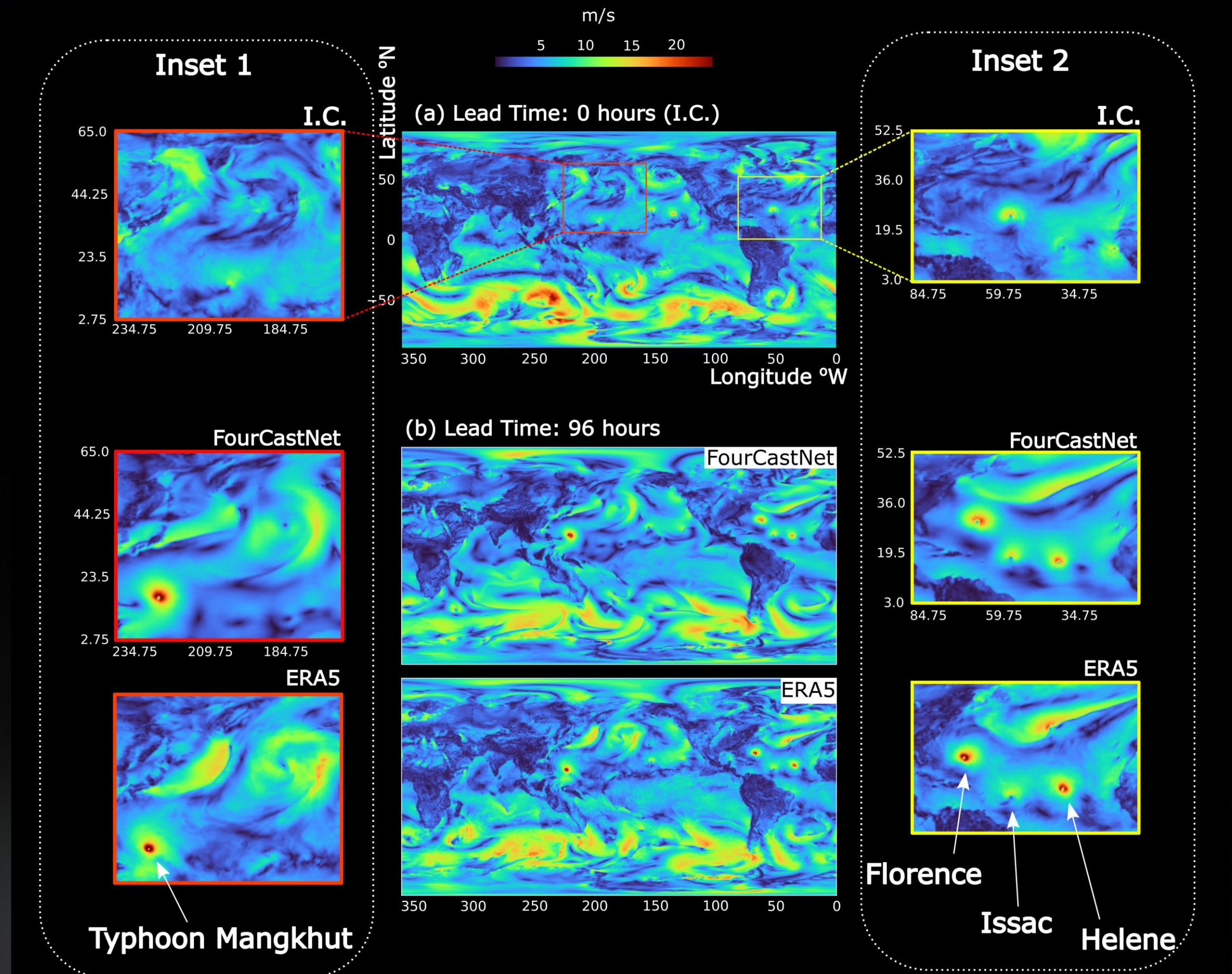
Vertical Level	Variables
Surface	$U_{10}, V_{10}, T_{2m}, sp, mslp$
1000hPa	U, V, Z
850hPa	T, U, V, Z, RH
500hPa	T, U, V, Z, RH
50hPa	Z
Integrated	$TCWV$

Currently models 21 atmospheric variables.

Soon to be extended to a larger set of variables to include radiation processes, vapor transport, more moisture variables, clouds.

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

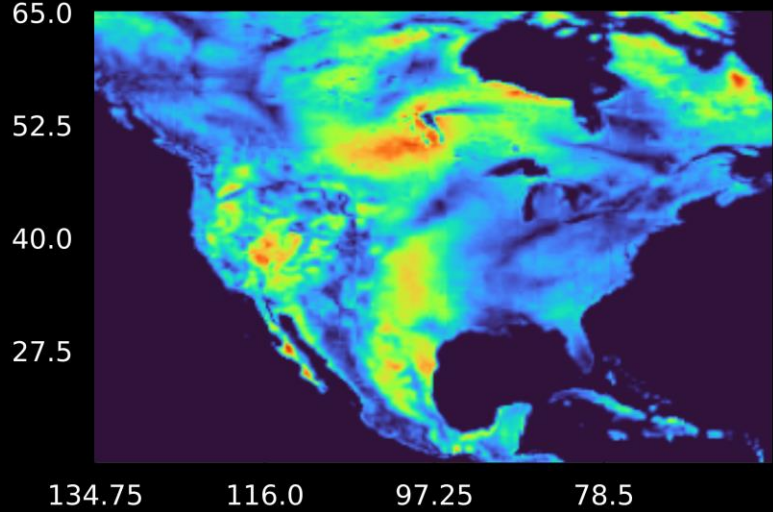
EXCELLENT SKILL ON FORECASTING SURFACE WINDS



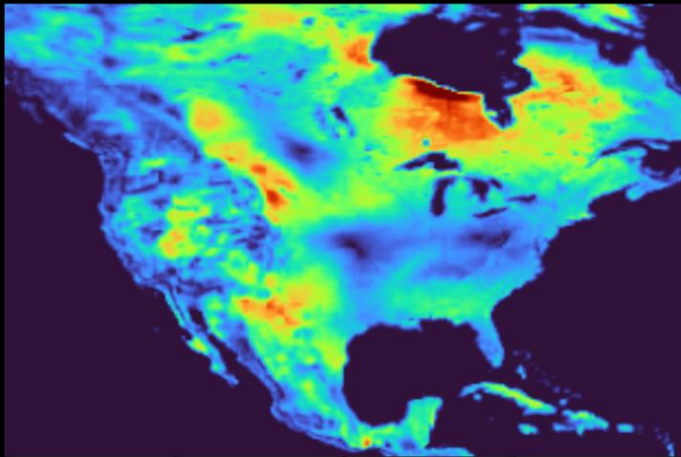
FOURCASTNET PREDICTS NEAR-SURFACE WIND FIELDS OVER LAND ACCURATELY: IMPORTANT IMPLICATIONS FOR WIND ENERGY PLANNING

FourCastNet:

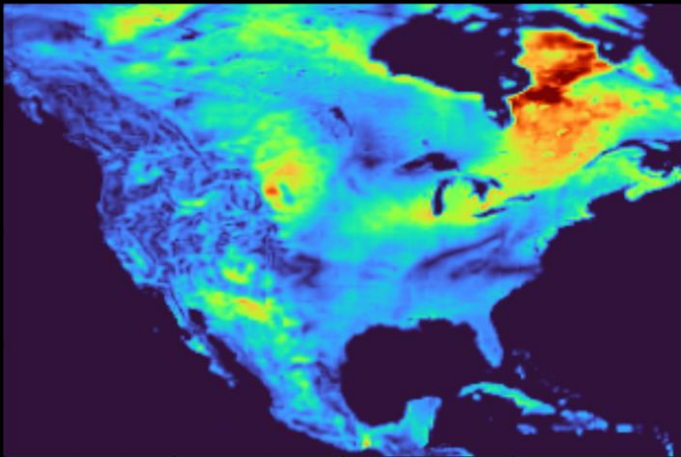
Lead time: 18hr



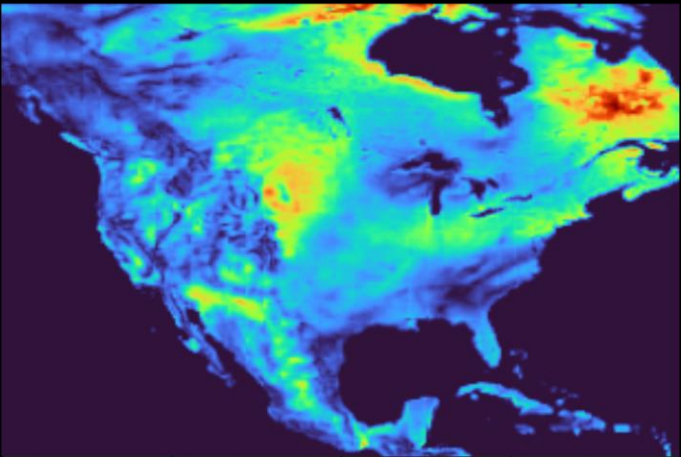
Lead time: 36hr



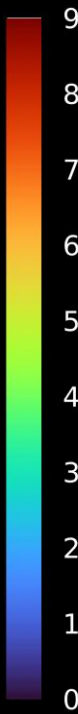
Lead time: 54hr



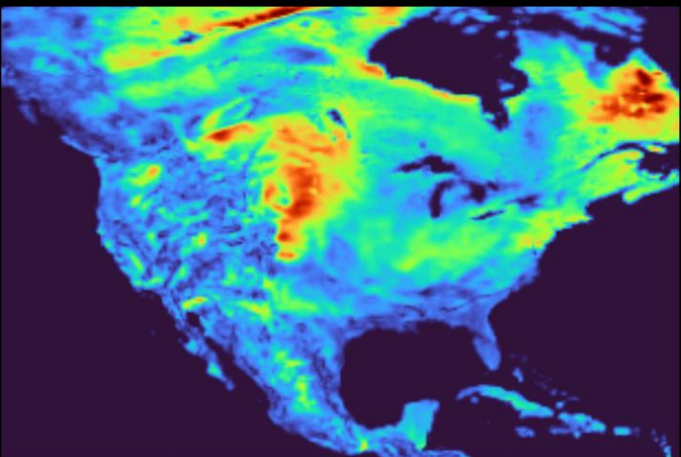
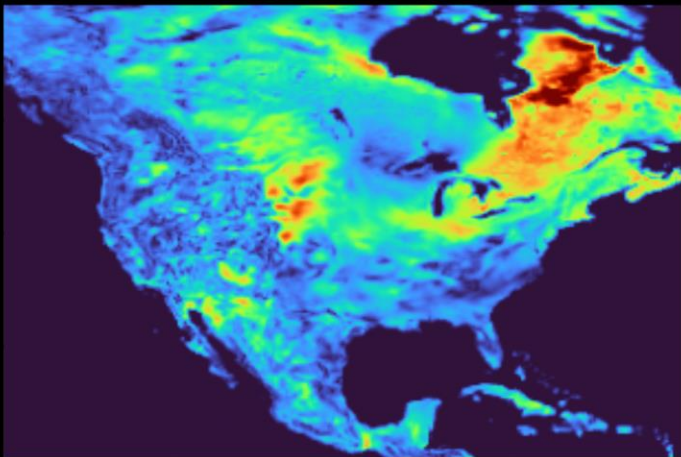
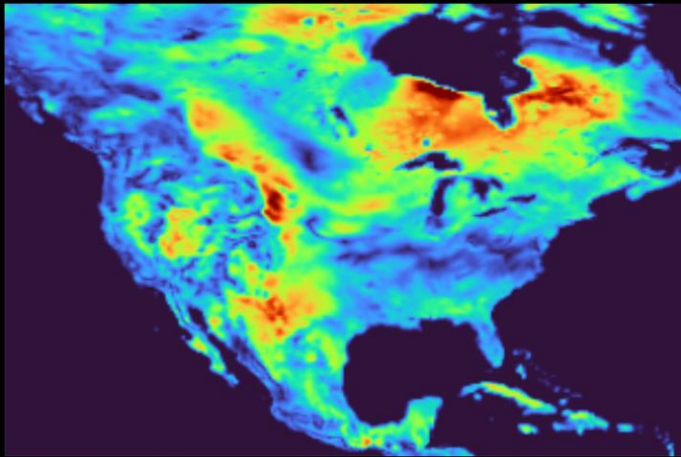
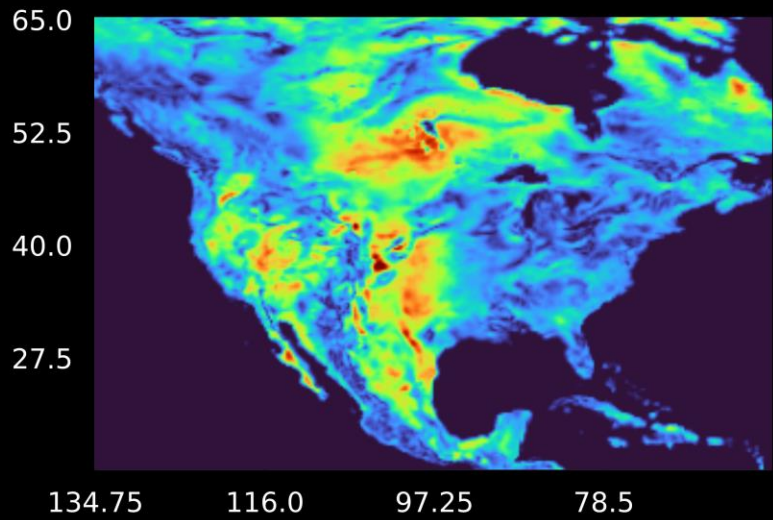
Lead time: 72hr



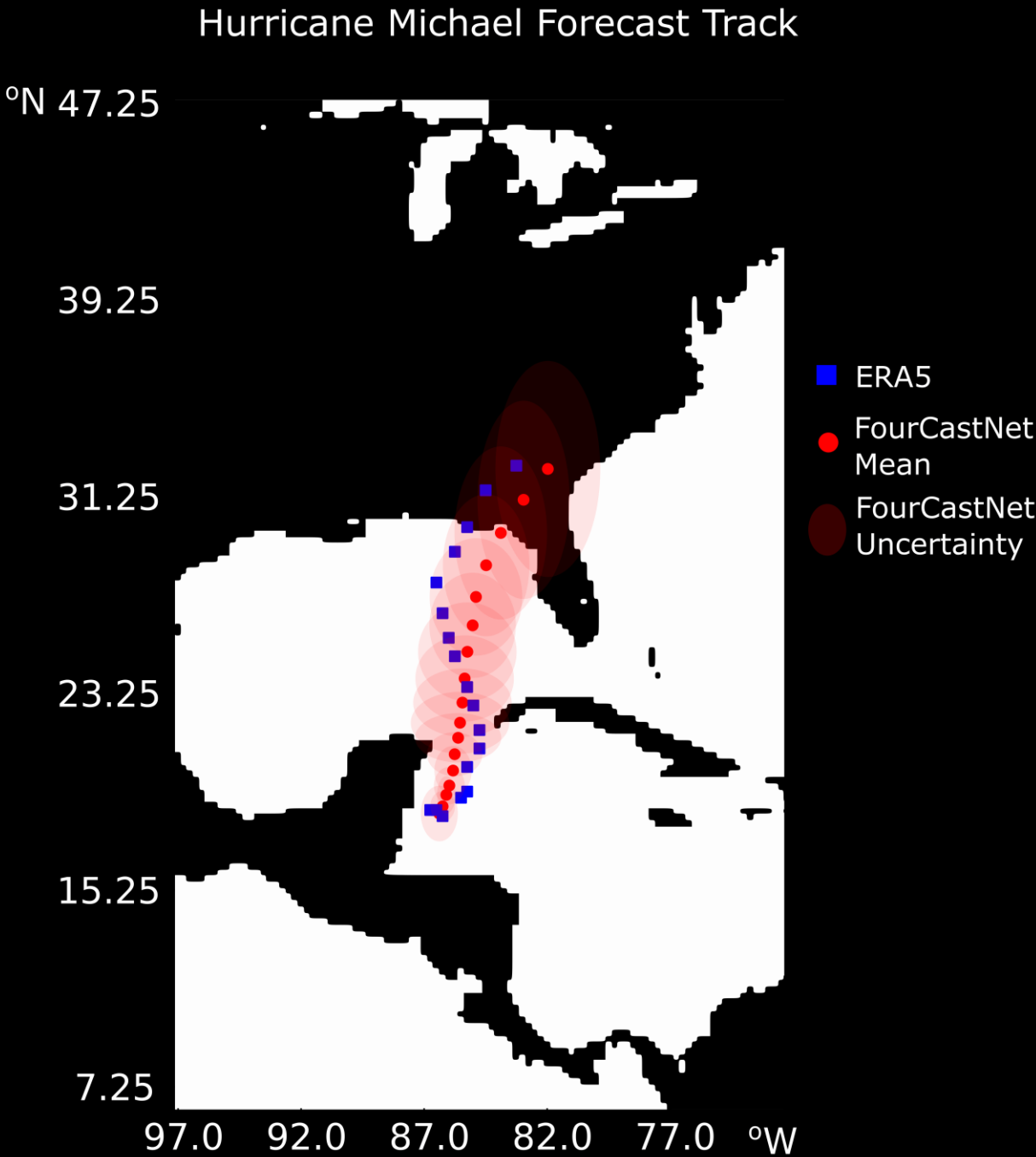
m/s



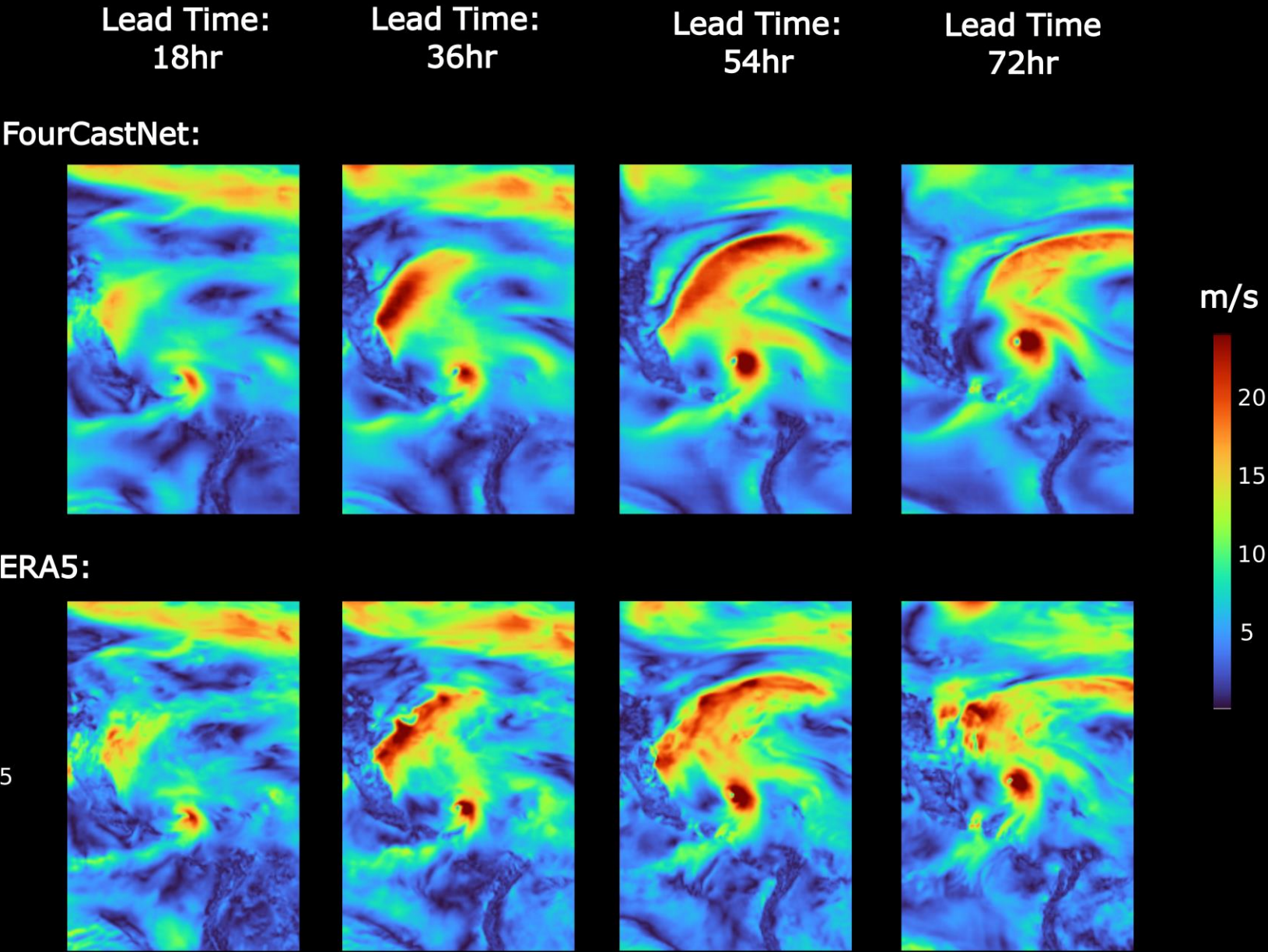
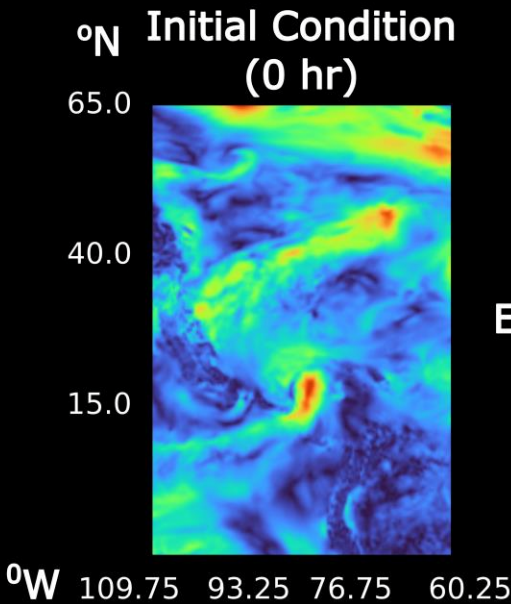
ERA5:



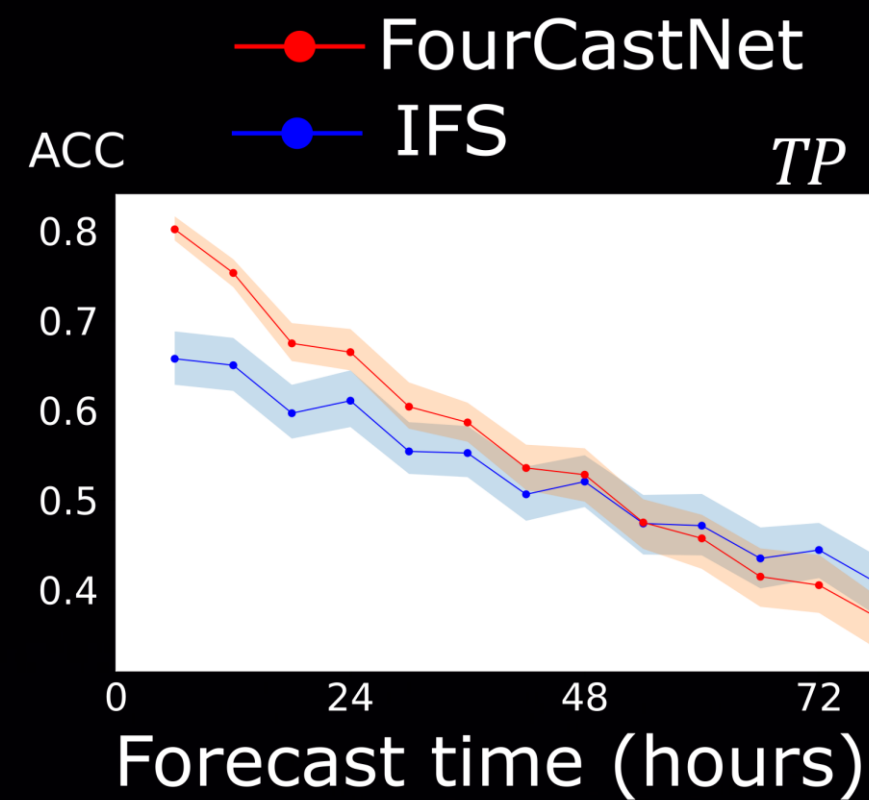
FOURCASTNET PREDICTS HURRICANE PATHS AND INTENSITIES



850hPa Wind Speed

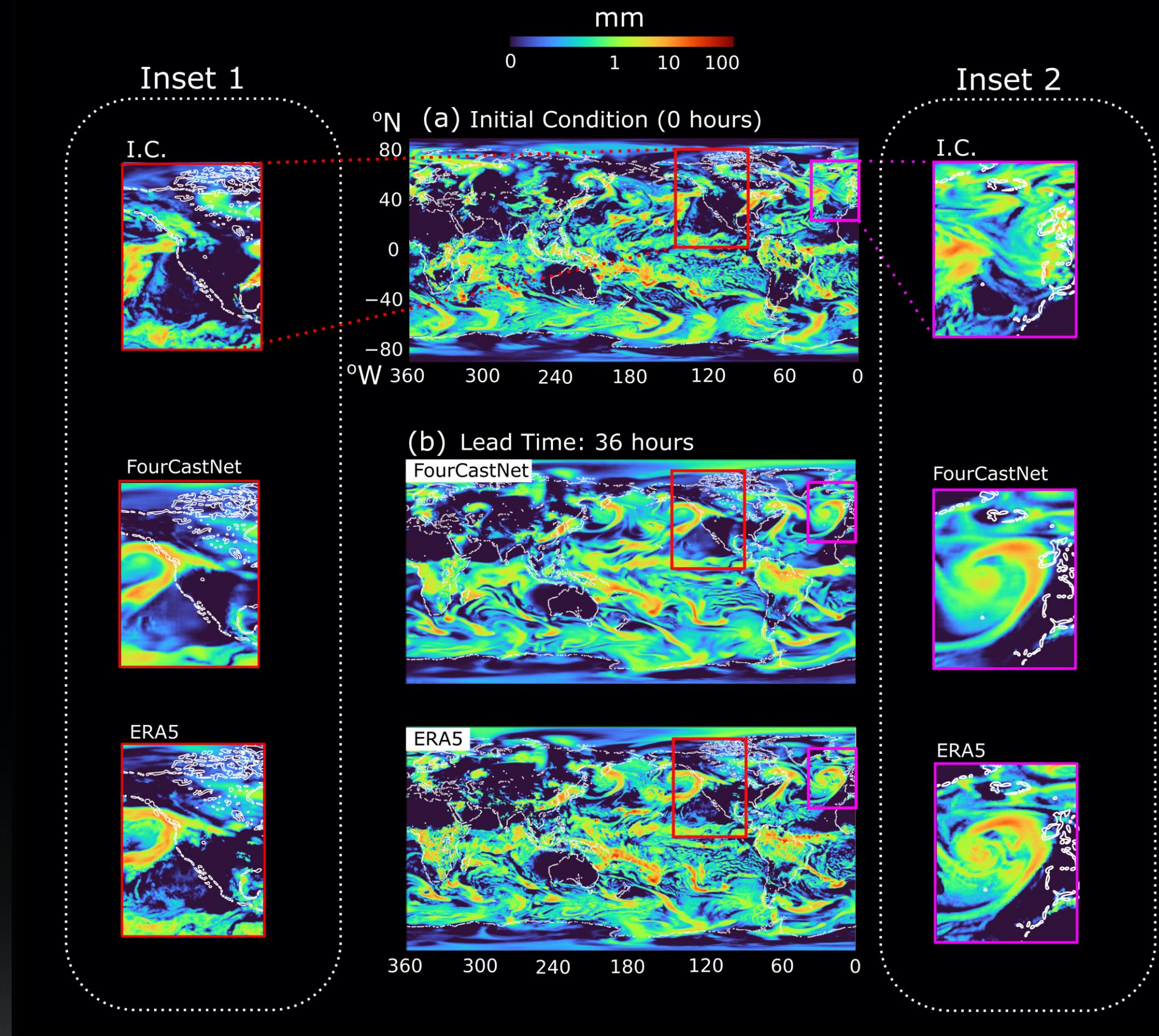


PRECIPITATION

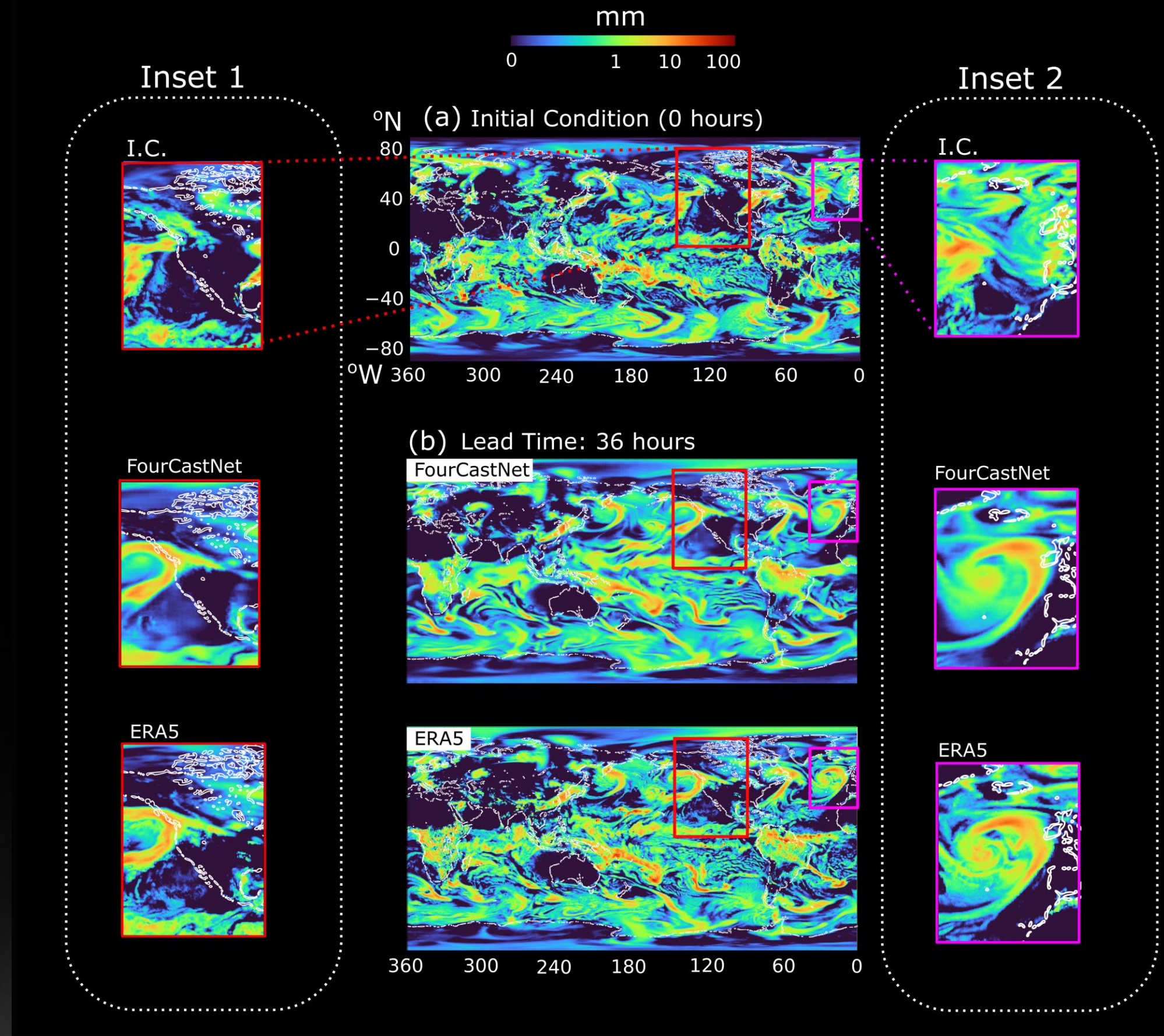
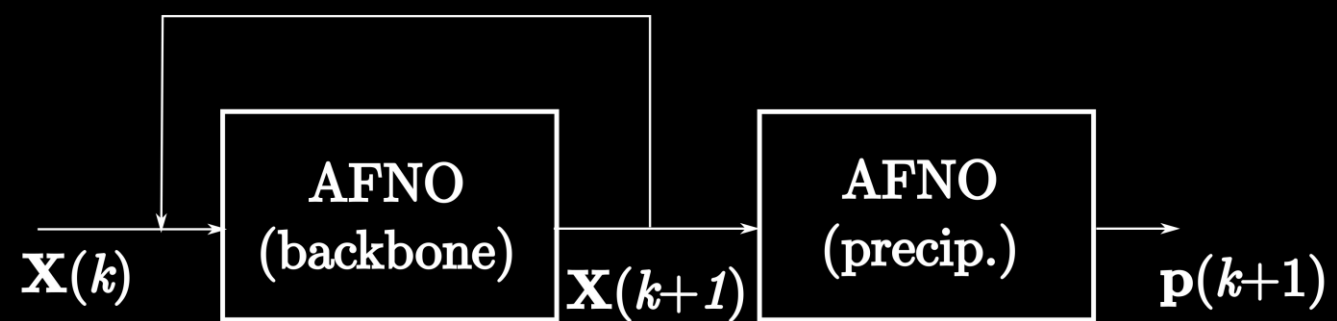
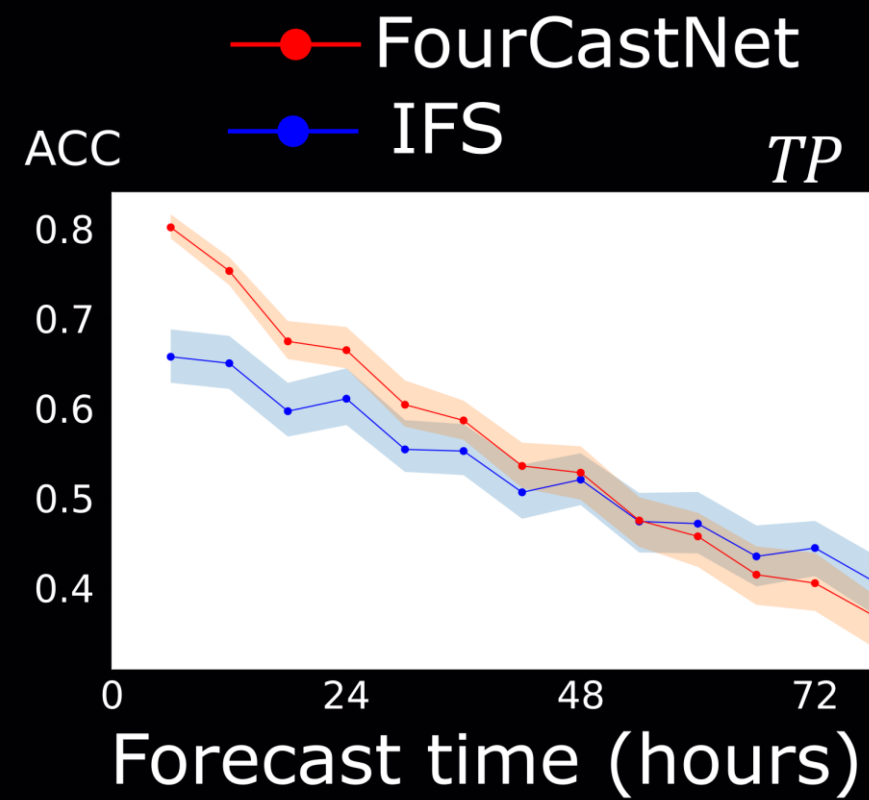


Excellent performance on forecasting precipitation with small scale features captured really well.

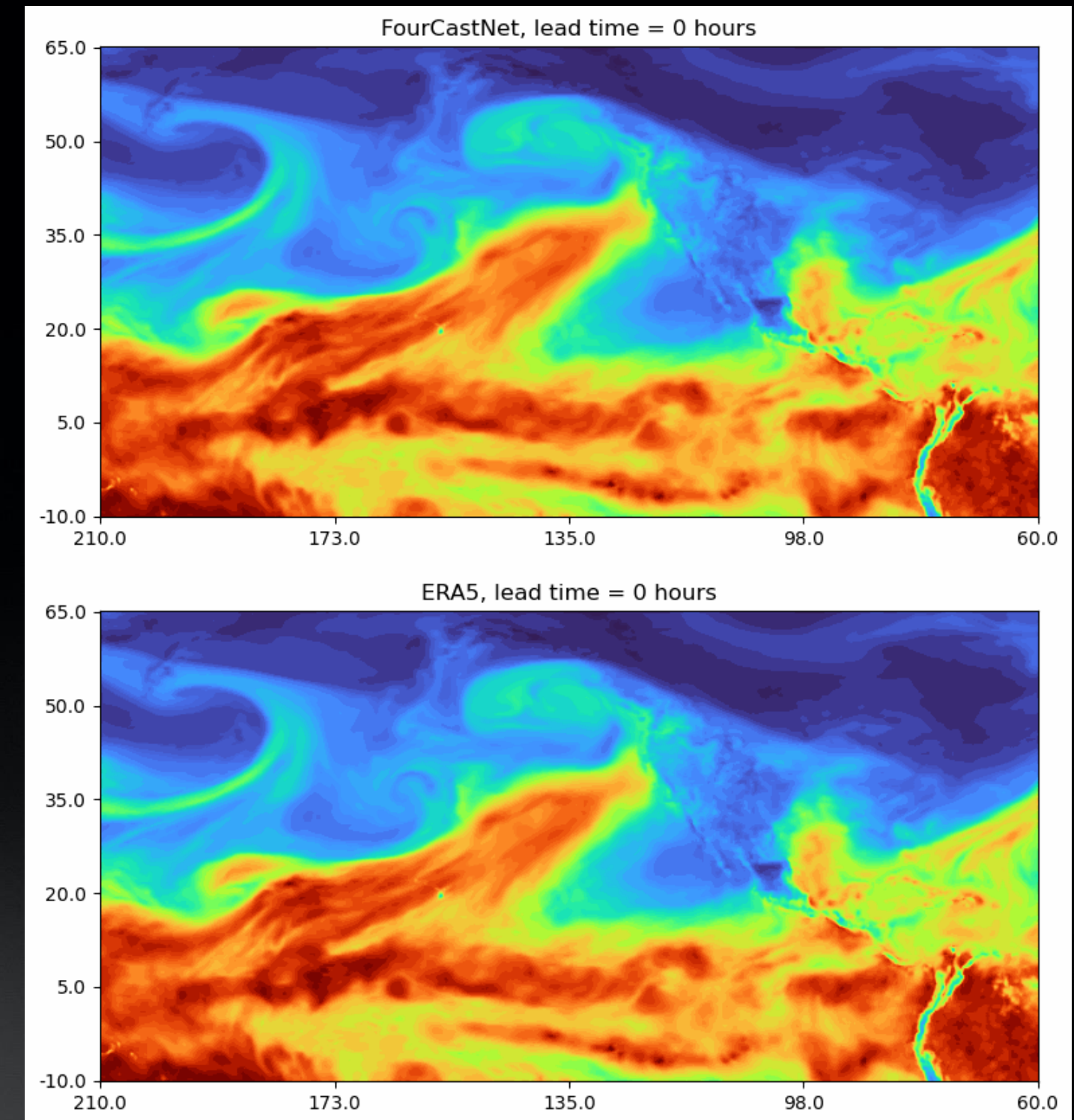
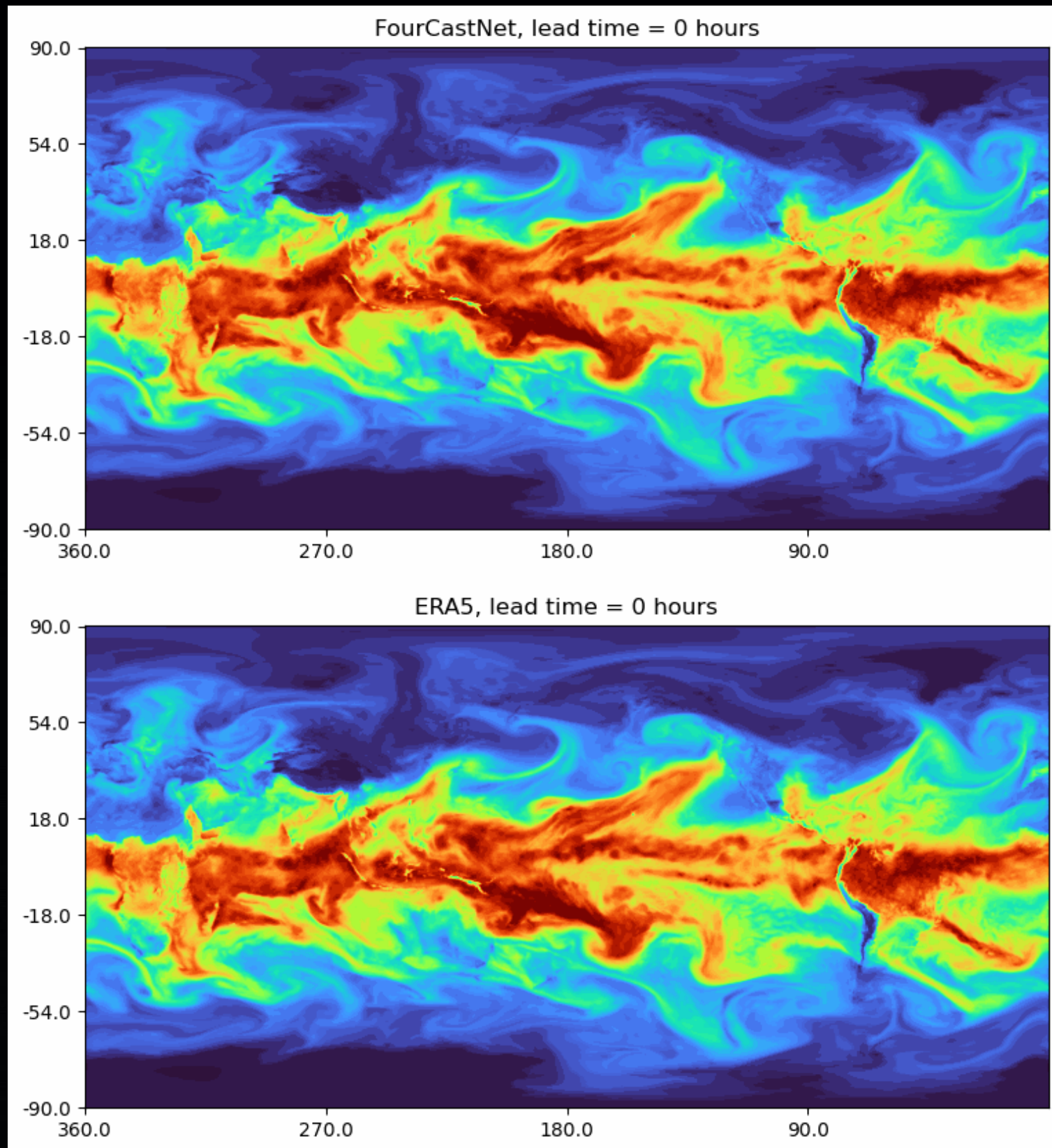
Currently we compare our forecasts to ERA5 rather than observations



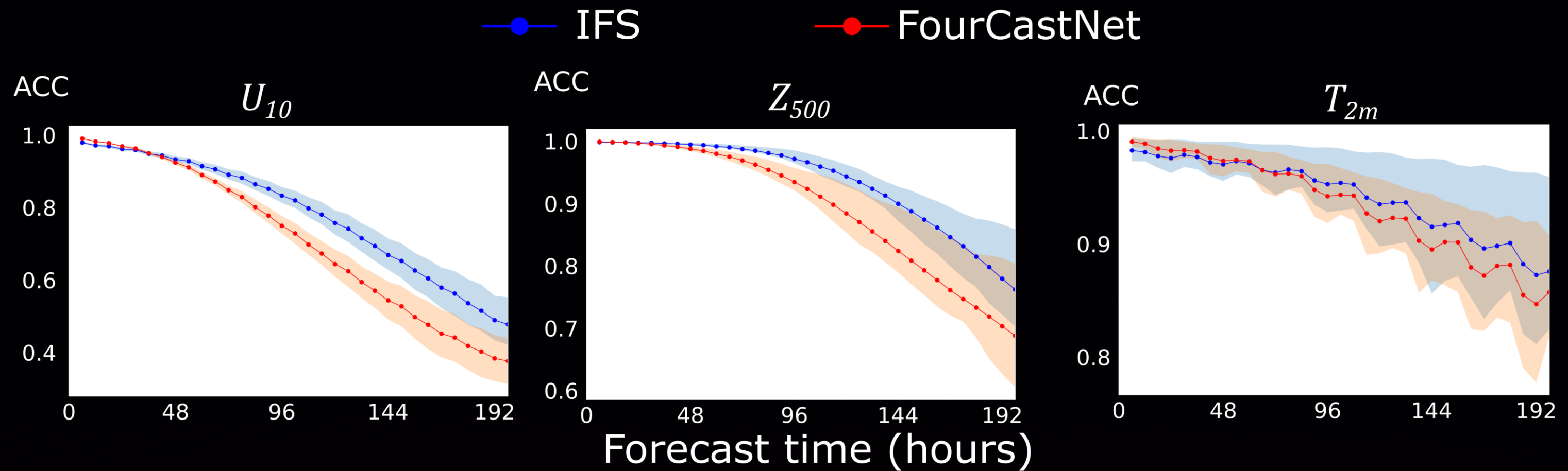
PRECIPITATION



MOISTURE VARIABLES: WATER VAPOR



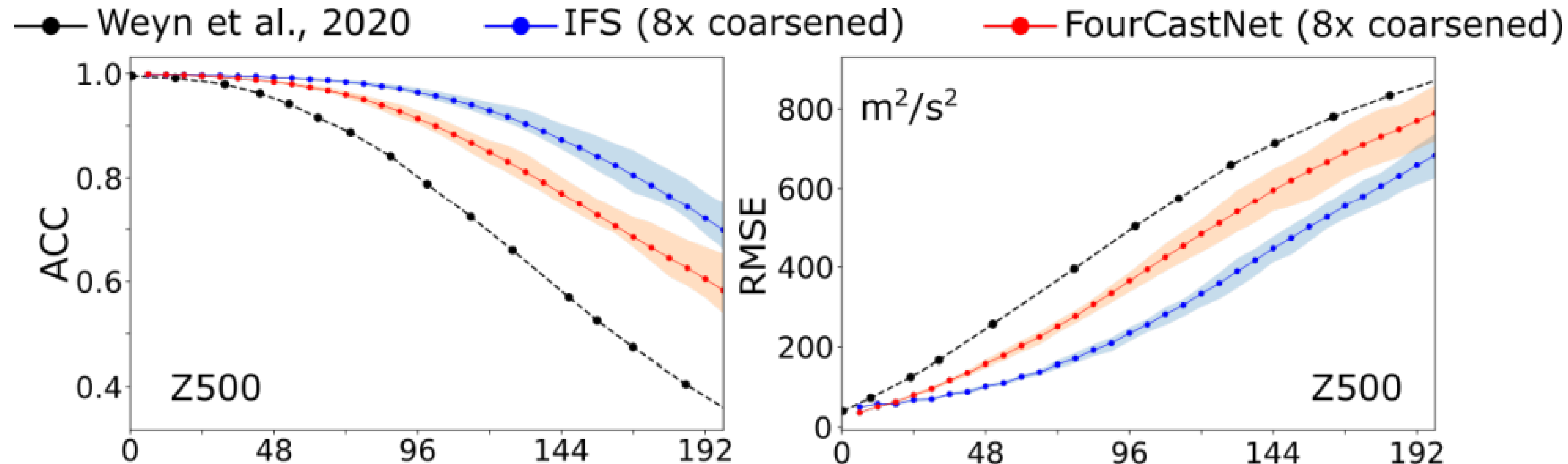
SHORT-TERM ACC CLOSE TO IFS



Caveat: Comparisons are made to ERA5 rather than directly to observations.

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

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

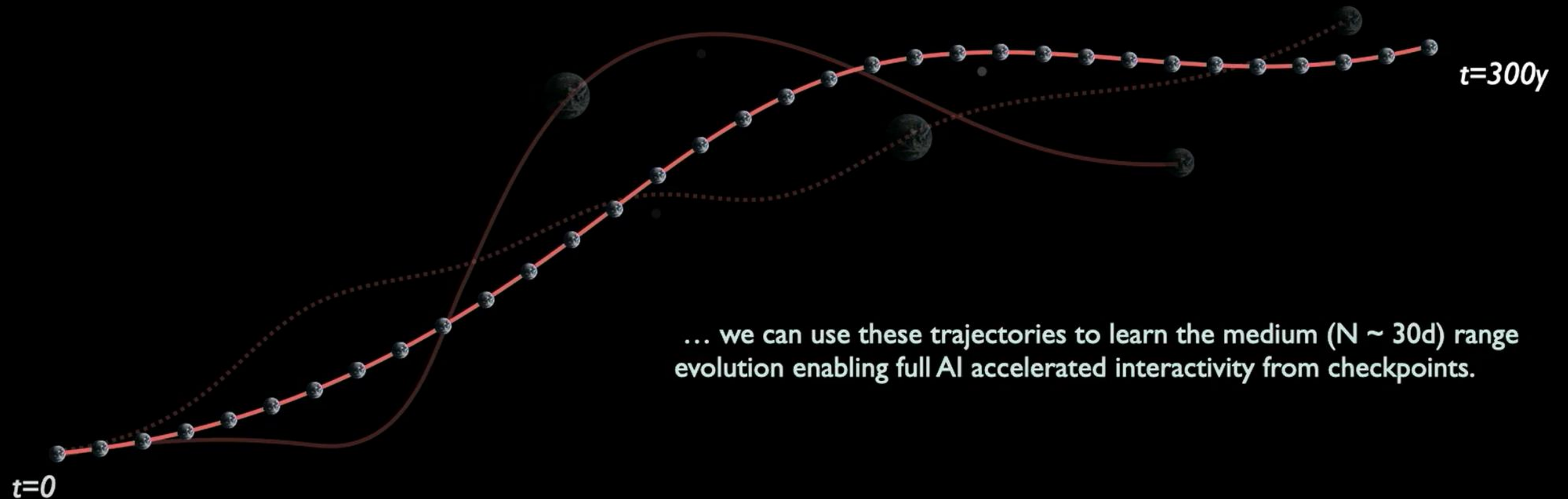
- Physics constraints
- Full state vector
- Generative models for fine-scales
- Uncertainty Calibration
- Observational ground truth / diagnostics

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.

If we can compute these trajectories



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