CAN DEEP LEARNING REPLACE CURRENT NUMERICAL WEATHER PREDICTION MODELS?

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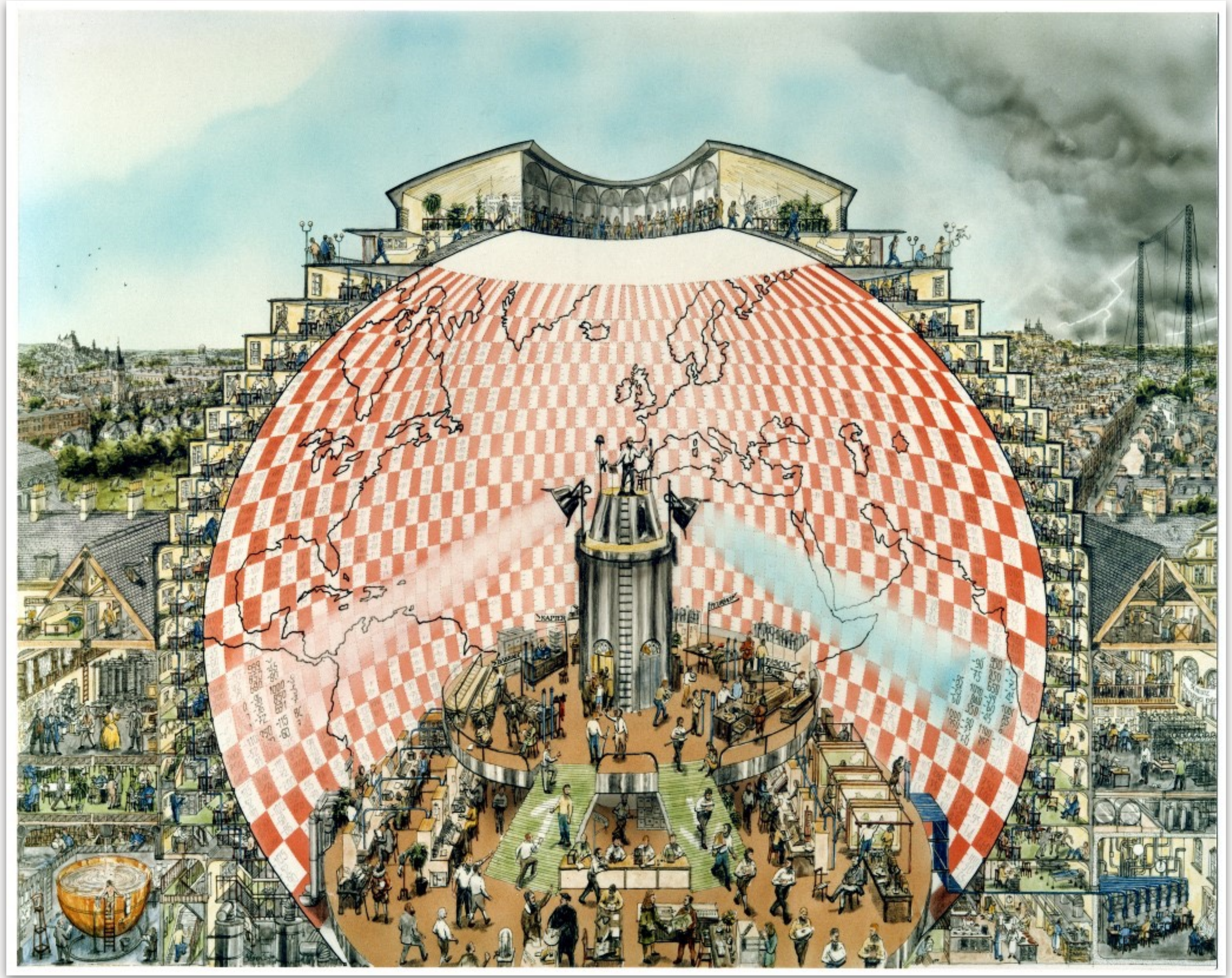
A Vision of Numerical Weather Prediction (NWP)

"Imagine a large hall like a theatre… the walls of this chamber are painted to form a map of the globe…. A myriad computers are at work upon the weather of the part of the map where each sits, but each computer attends only to one equation or part of an equation."

–Lewis Fry Richardson, Weather Prediction by Numerical Process, 1922



"Weather Forecasting Factory" by Stephen Conlin, 1986

Made Practical by Advancements in Computing and Numerics

- Jule Charney and John Von Neumann led the first numerical weather prediction experiment in 1950

- They integrated the barotropic vorticity equation on 500-hPa surface

$$\frac{\partial \nabla^2 \psi}{\partial t} = \frac{1}{a^2}\left[\frac{\partial \psi}{\partial \mu}\frac{\partial \nabla^2 \psi}{\partial \lambda} - \frac{\partial \psi}{\partial \lambda}\frac{\partial \nabla^2 \psi}{\partial \mu}\right] - \frac{2\Omega}{a^2}\frac{\partial \psi}{\partial \lambda}$$

- 24-hour forecast took about 24 hours to compute on ENIAC computer

Can We Trust NWP Models?

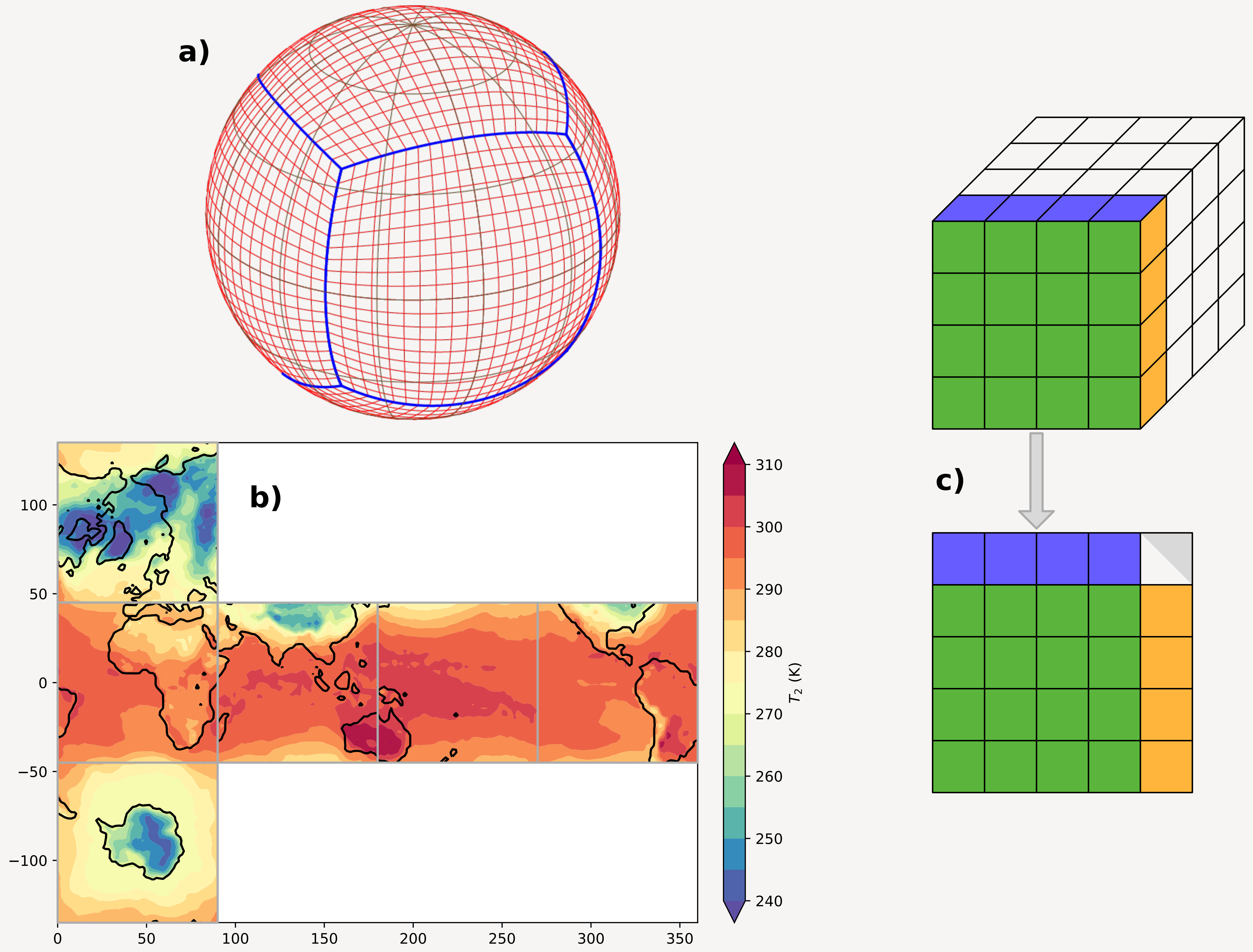
- Dynamical core: equations for conservation of mass, energy and momentum …
  - Inviscid motions and wave propagation
  - Numerical approximation can be evaluated for order of accuracy, stability, …
- Operational Models Rely on Parameterizations
  - Clouds and precipitation
  - Influence of the Earth's surface (surface temperatures)
  - Heat transfer by electromagnetic radiation
- *Parameterizations are evaluated empirically!*

AI and NWP

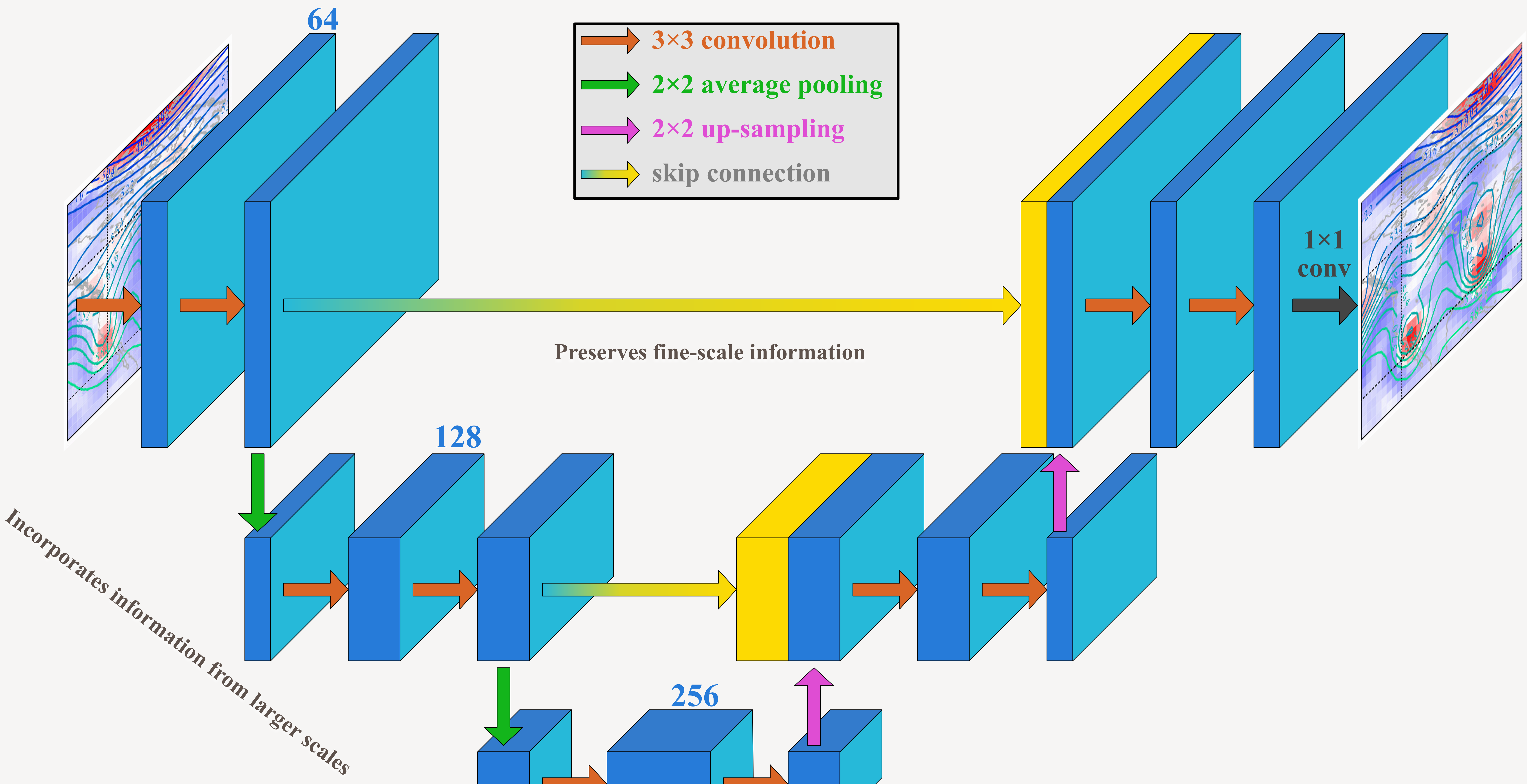
- Parameterizations are empirical and major limitations in the accuracy of NWP
  - Many groups are trying to improve parameterizations using AI
- State-of-the-art NWP models require enormous computer resources for each forecast
- Completely replacing NWP with Deep Learning Weather Prediction (DLWP) could
  - Reduce the time required for each forecast by orders of magnitude
  - Thereby addressing uncertainty
    - Allowing a *large* number of simulations of likely future states (*ensembles*)
    - Giving better probabilistic forecasts
    - Capturing extreme events

DLWP Building Blocks: Cubed Sphere Grid

- Convolutional neural network (CNN)
  - 3x3 spatial stencil
- Train identical filters for
  - 4 equatorial-centered faces
  - 2 polar faces
    - sense of rotation reversed between polar faces



DLWP Building Blocks: U-Net Architecture

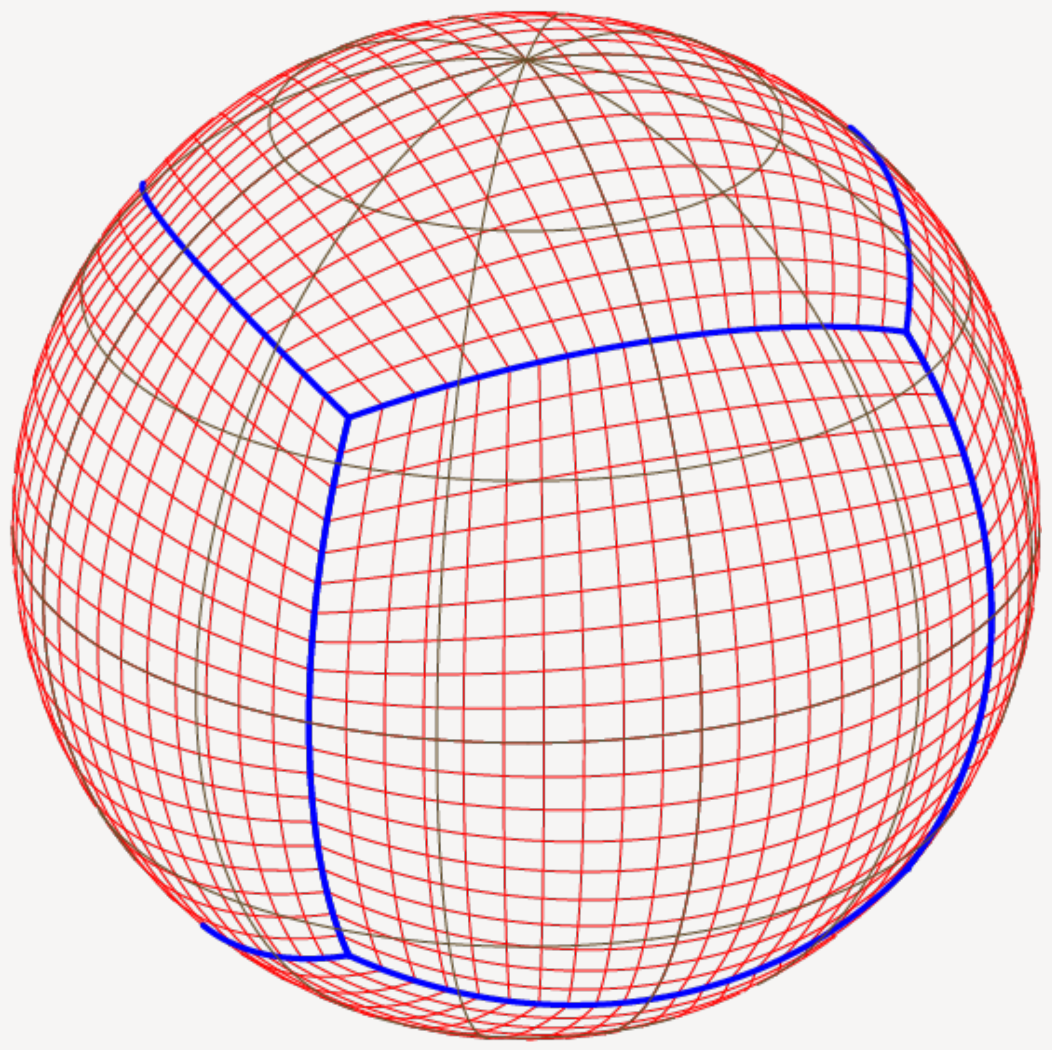


DLWP Building Blocks: Data

- ERA5: observations blended with NWP model output
  - Retrieved on 1° lat-lon grid
  - Re-gridded to cubed sphere (Ullrich & Taylor, 2015)
- Model *training*: 1979-2012
  - ~100,000 samples
- Model *validation* set: 2013-2016
- *Test* set: final performance evaluation: 2017-2018
  - twice weekly: 208 cases

2D Fields on Spherical Shells

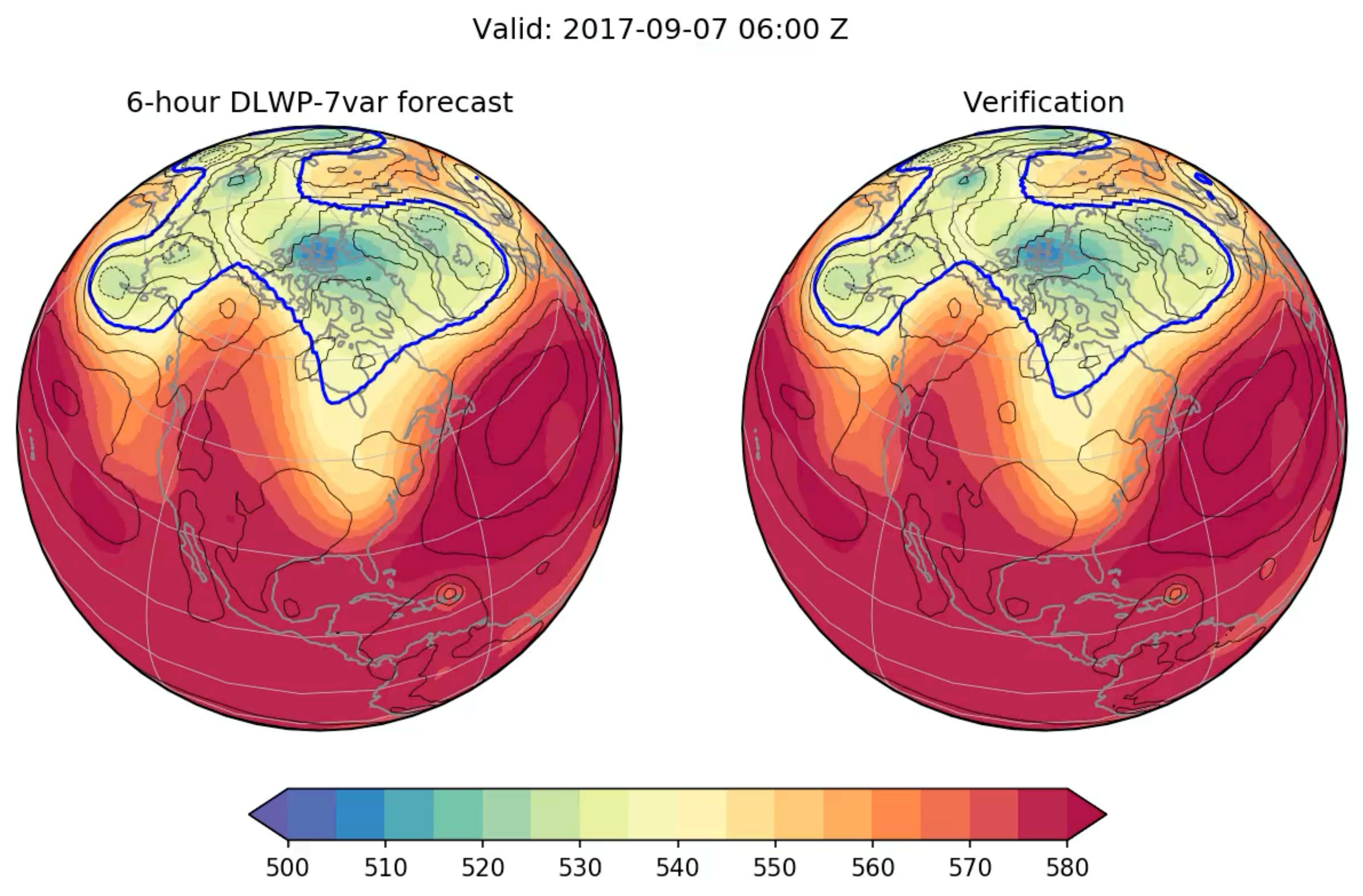
- 6 or 7 prognostic variables
  - 1000-hPa height
  - 500-hPa height
  - 300-700-hPa thickness
  - 2-m temperature
  - 850-hPa temperature
  - Total column water vapor
  - 250-hPa height
- 3 prescribed fields
  - TOA incoming solar radiation
  - land-sea mask
  - topographic height



- Resolution
  - 64x64 points on each face of the cube sphere (figure is 20x20)
  - ~1.4° x 1.4° at the equator

Hurricanes Irma & Jose

- 4-day single model forecast
- 1.4° x 1.4° resolution
- Plotting
  - 1000-hPa height (black)
  - 500-hPa height (color fill)
- 7 prognostic variables

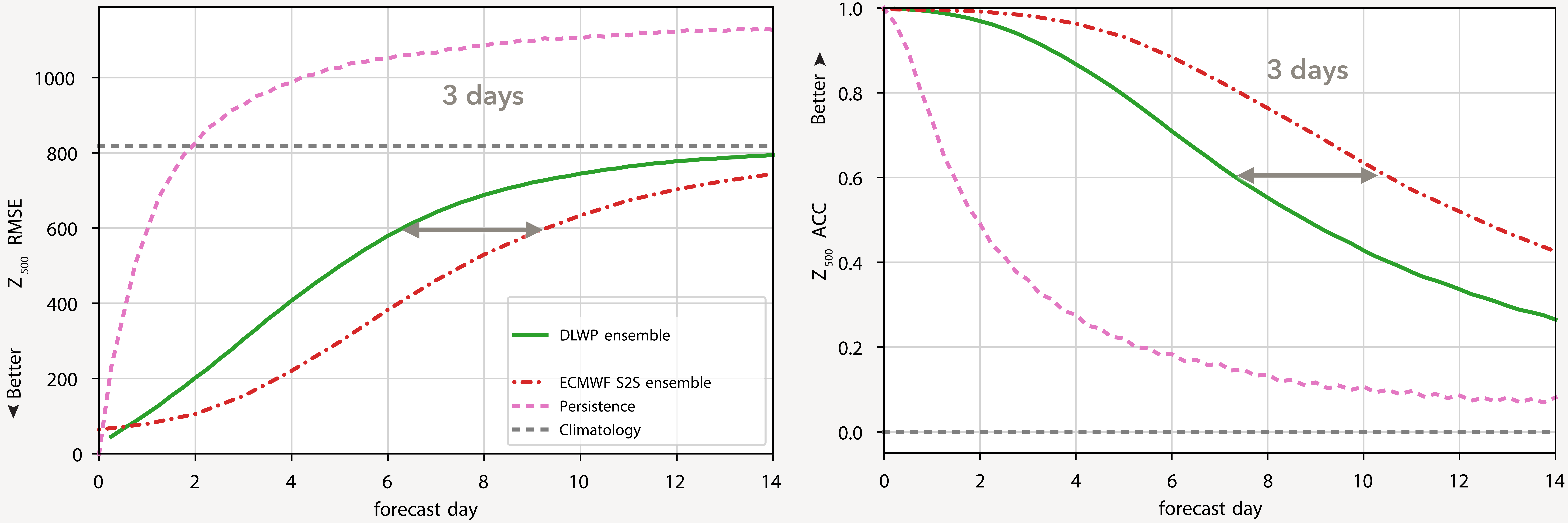


DLWP-NWP Comparison

Comparison of Key Attributes of Our DLWP Ensemble and Those of the State-of-the-Art ECMWF Ensemble for Extended-Range Forecasting

	DLWP	ECMWF
Atmospheric fields	6 2-D variables	9 prognostic 3-D variables; 91 vertical levels
Horizontal resolution	150 km	18 km (36 km after day 15)
Atmospheric physics	3 prescribed inputs	Many physical parameterizations
Coupled models	None	Ocean, wave, and sea ice models
Initial condition perturbations	10 (ERA5 uncertainty)	50 (SVD/4DVAR)
Model perturbations	Perturbed CNN weights	Stochastic physics
Ensemble members	320 (+control)	50 (+control)

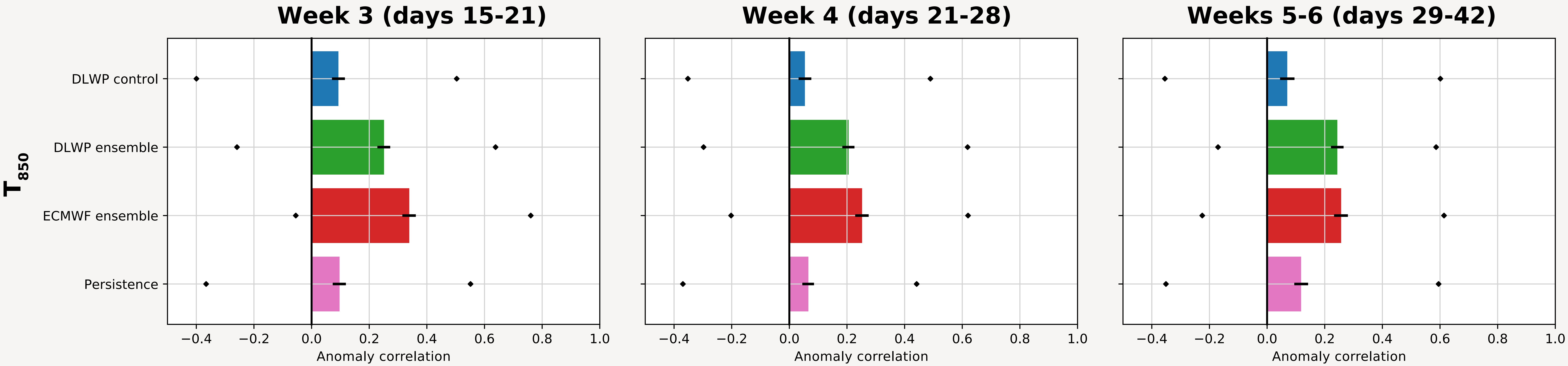
Ensemble Performance: Deterministic Lead Times



DLWP grand ensemble: 32 stochastically perturbed models x 10 initial conditions = 320 members

Ensemble Performance: S2S Lead Times

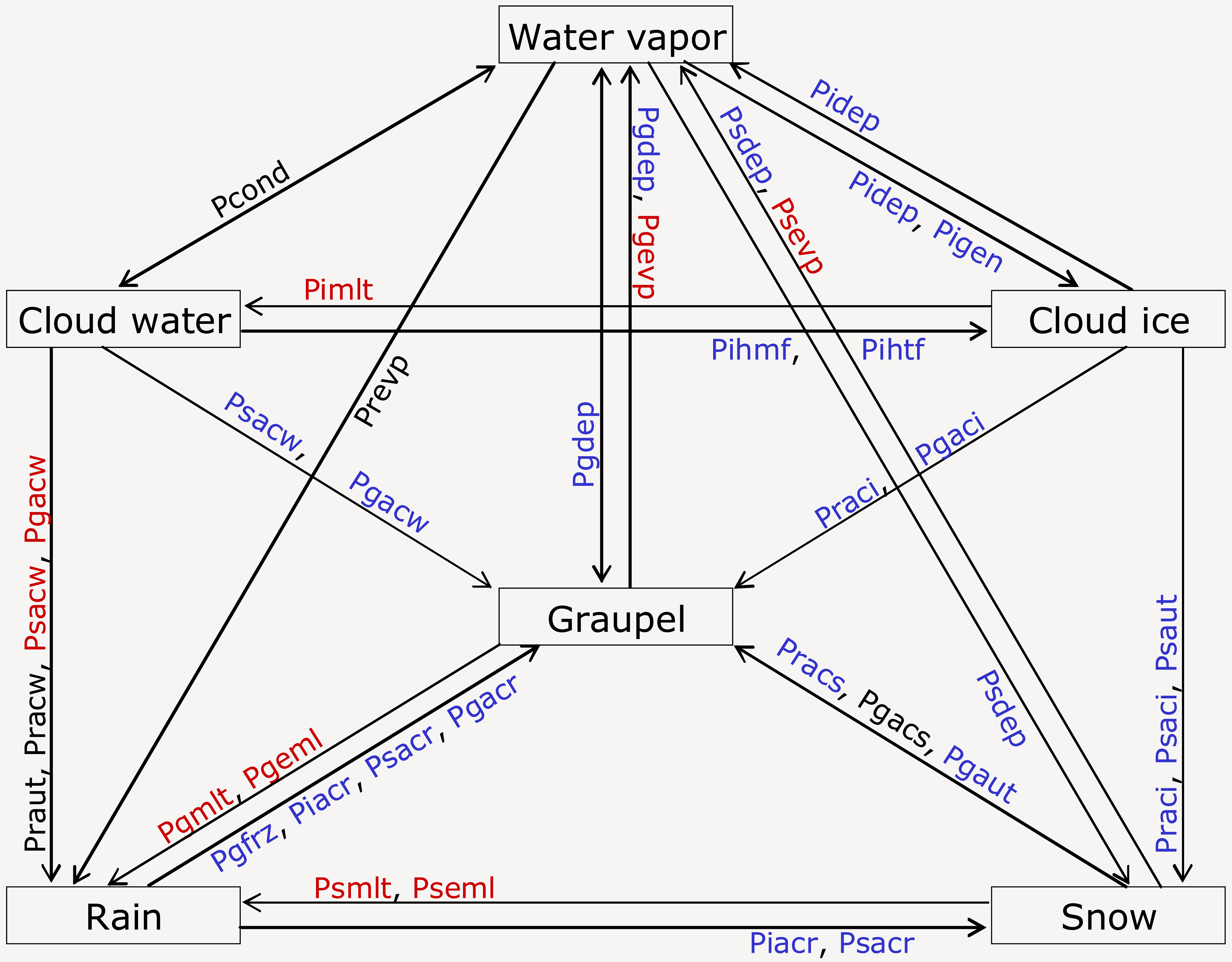
Anomaly correlation coefficient of the ensemble mean



Persistence is computed as the 1- or 2-week-averaged anomaly just prior to the initialization

Black bar: 95% confidence interval. Black dots: best and worst forecast.

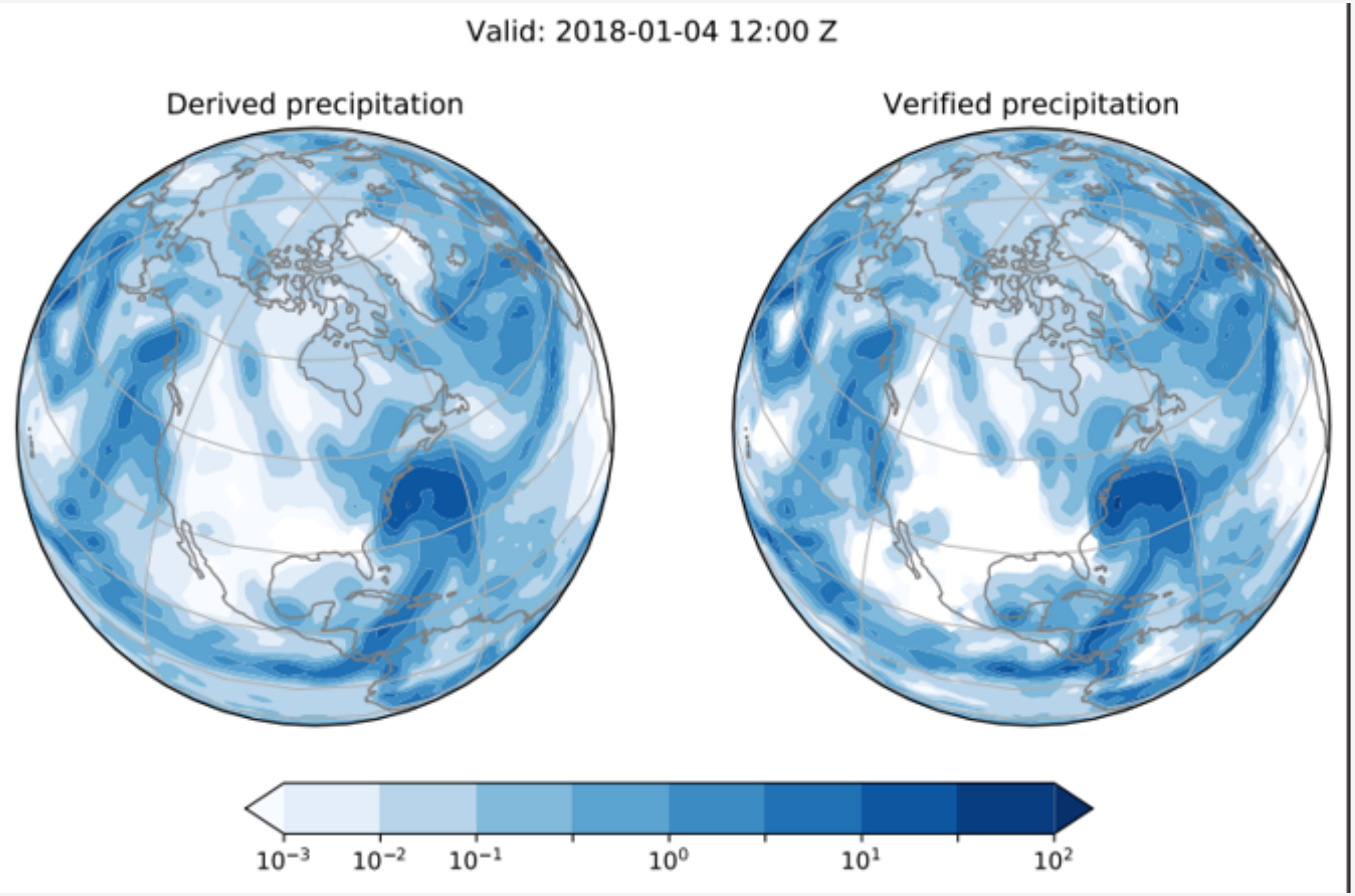
6-Variable Cloud & Precipitation Parameterization



Hong and Lim, 2006

U-NET DIAGNOSIS OF PRECIPITATION

- Same 6 variables as prognostically forecast in DLWP model
- But precipitation is diagnosed from the ERA5 analysis
- Can be used to diagnose precipitation in DLWP forecasts



Conclusions

- DLWP has the potential to revolutionize weather forecasting, echoing of the impact produced by the introduction of NWP in the 1950's
  - Data-driven AI-based weather prediction has been enabled by advances in algorithms and hardware.
  - 1-week forecast stepped forward with 12-hr time step (and 6-hr resolution) requires just 1/10 of a second on one Nvidia V100 GPU
- The speed of DLWP allows us to make much larger "ensembles" of near-twin forecasts.
  - Better defines the probable distribution of future atmospheric states
  - Better capture extreme events.
- DLWP has the potential to improve the representation of processes crudely parameterized in NWP.

Further Reading:

Weyn, J.A., Durran, D. R., Caruana, R., and Cresswell-Clay, N. (2021). Sub-seasonal forecasting with a large ensemble of deep-learning weather prediction models. *J. Adv. Modeling Earth Sys*, 13, e2021MS002502 https://doi.org/10.1029/2021MS002502

Weyn, J. A., Durran, D. R., & Caruana, R. (2020). Improving data-driven global weather prediction using deep convolutional neural networks on a cubed sphere. *J. Adv. Modeling Earth Sys*, 12, e2020MS002109 https://doi/10.1029/2020MS002109

Weyn, J. A., Durran, D. R., & Caruana, R. (2019). Can machines learn to predict weather? Using deep learning to predict 500 hPa geopotential height from historical weather data. *J. Adv. Modeling Earth Sys*, 11, 2680-2693. https://doi/10.1029/2019MS001705