DeepSphere-Weather : Deep Learning on spherical unstructured grids for weather / climate applications

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(Image credit: ECMWF)

Objective of our work

- A scalable deep learning framework to perform convolution on the spherical unstructured grids commonly used by NWP and climate models
- Working on native spherical unstructured grid is:
  - computationally more efficient than previous approaches
  - provide similar / better results than modelling on planar projections of the data

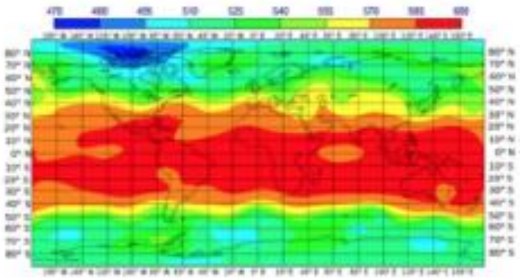
Data-driven weather forecasting

- <u>WeatherBench Challenge</u> (Rasp et al., 2020)
  - ❑ Provide a standardized dataset to benchmark DL models

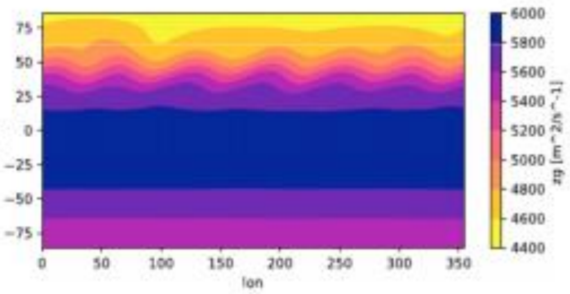
Previous solutions – “2D / image projection”

Planar projections

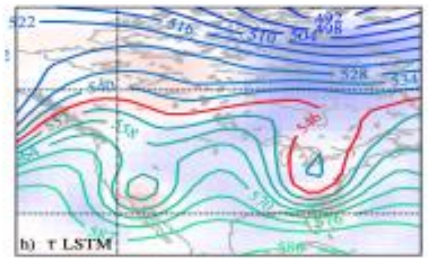
Düben and Bauer, 2018



Scher, 2018

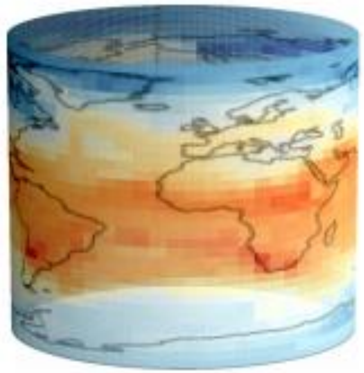


Weyn et al., 2019



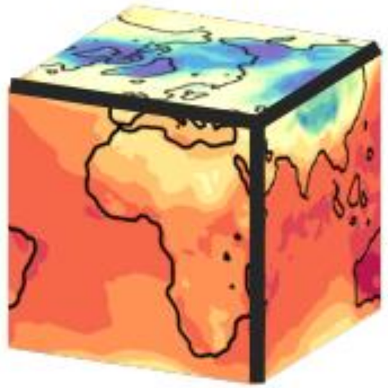
Spherical approximations

Rasp et al., 2020



Adapted from Rasp, S., Dueben, P. D., Scher S., Weyn, J. A., Mouatadid, S., and Thuerey, N. (2020). WeatherBench: A benchmark dataset for data-driven weather forecasting. arXiv.

Weyn et al., 2020



Adapted from Weyn, J . A., Durran, D. R , and Caruana, R. (2020). Improving data-driven global weather prediction using deep convolutional neural networks on a cubed sphere. JAMES.

A possibility – Classical spherical convolutions

Method

1. Compute spectral projections of the data
   - Spherical Harmonic transform (SHT)
2. Convolution correspond to multiplication in the spectral domain
3. Inverse SHT transforms

SHT disadvantages

- Computational cost: $O(n^2)$
- For isolatitude sampling (i.e. equiangular, gaussian grids) cost can be reduced to $O(n^{3/2})$
- It’s a global operation. Need to access all nodes and induce high communication on HPC.

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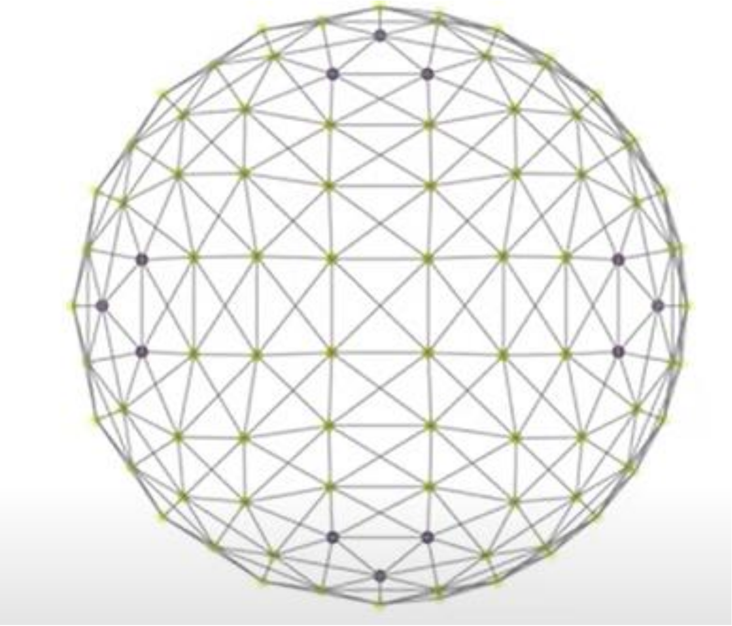
DeepSphere – Graph-based spherical convolutions

Method

- Spherical unstructured grids are represented as a graph of connected pixels
- The eigenvector of the graph Laplacian approximates the the spherical harmonics basis
- Spectral graph convolutions are <u>local operations:</u>

$$W(L, w)x = \sum_l w_l L^l x$$

A weighted average of neighboring pixels



Advantages

- No need to compute the Spherical Harmonic transform (SHT)
- The convolution operation scales linearly with number of grid nodes: O(n)
- Convolutions on a sub-region of a sphere cost the number of nodes involved

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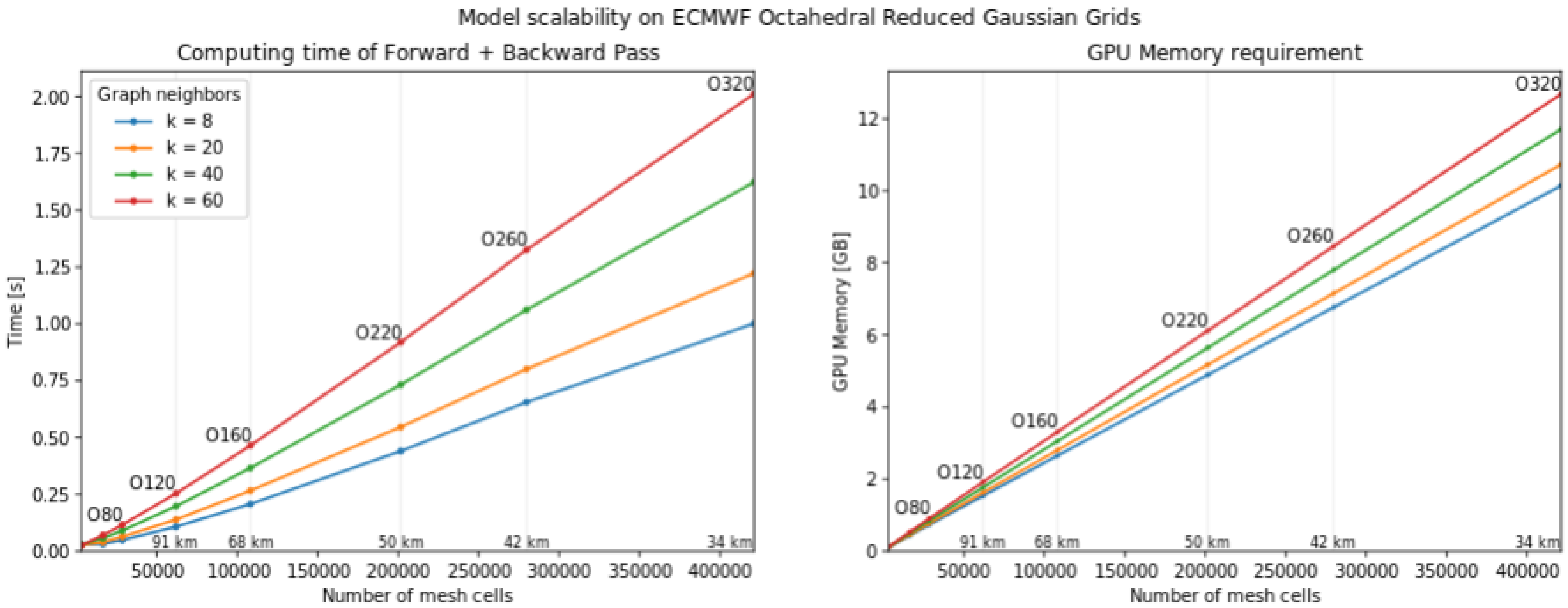
Scalability



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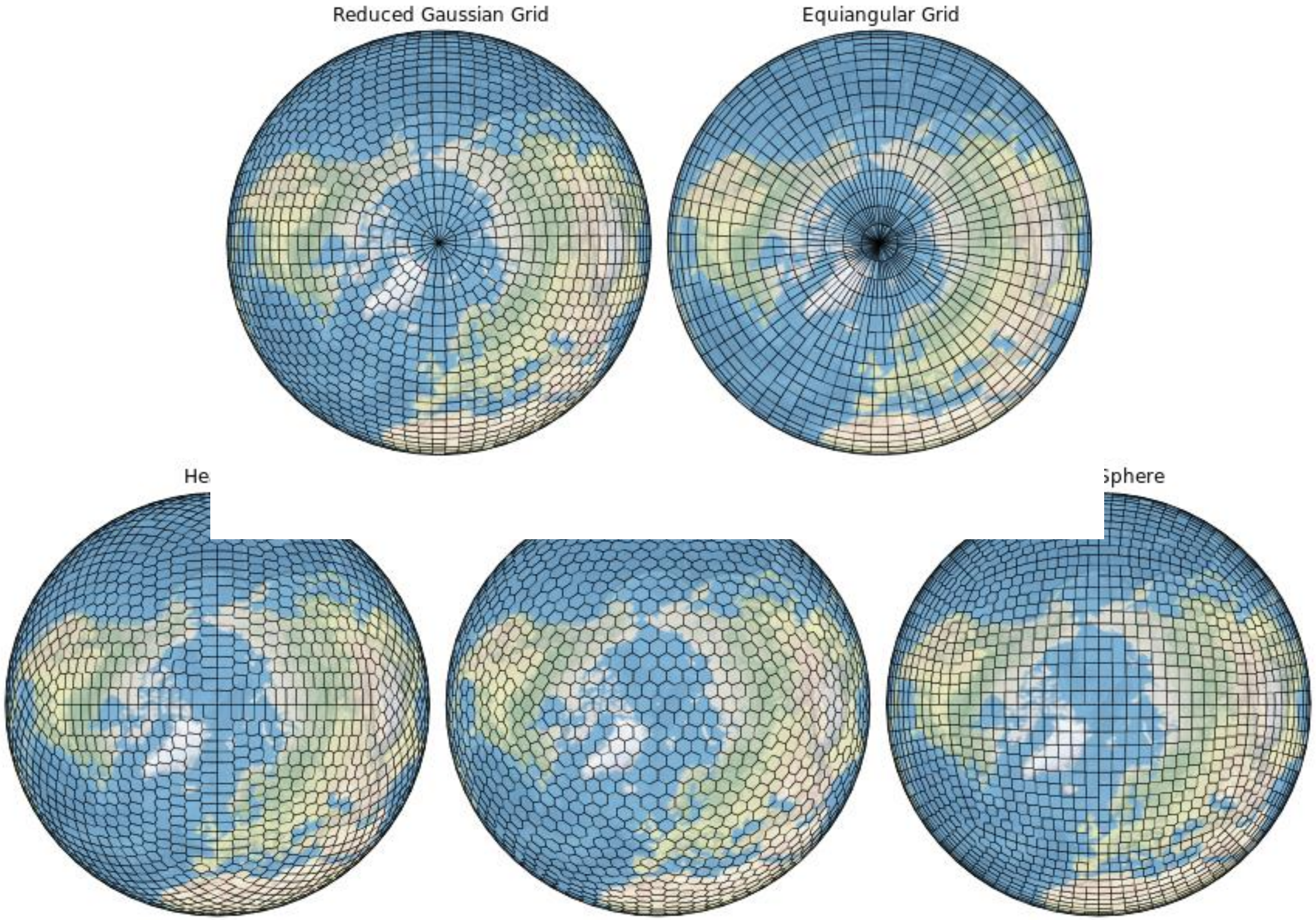
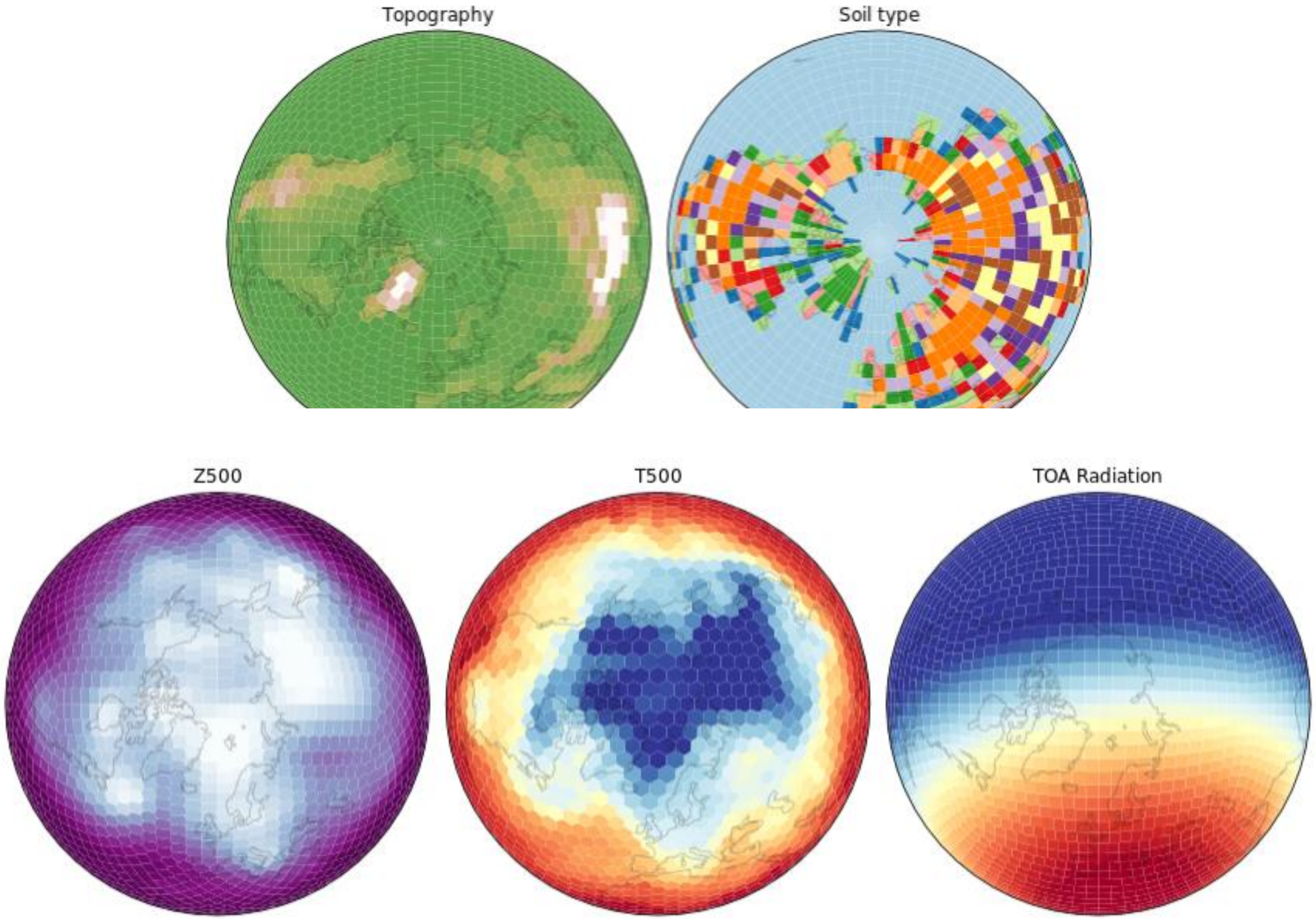
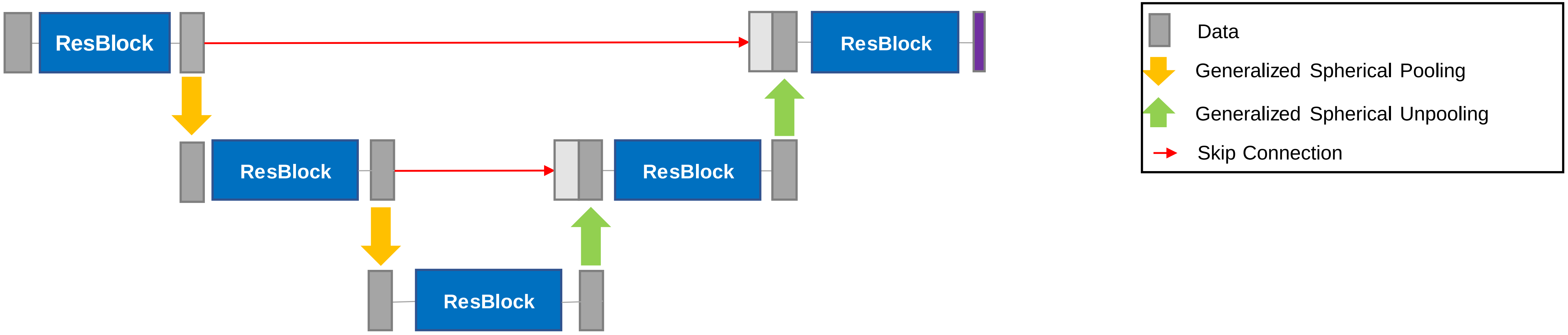
Spherical grids



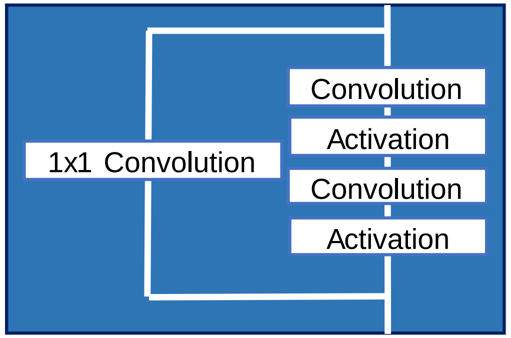
Model variables



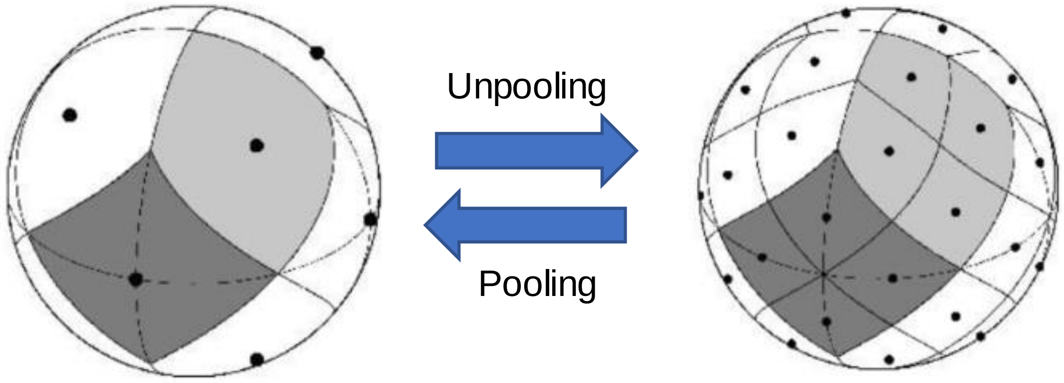
Residual UNet Model



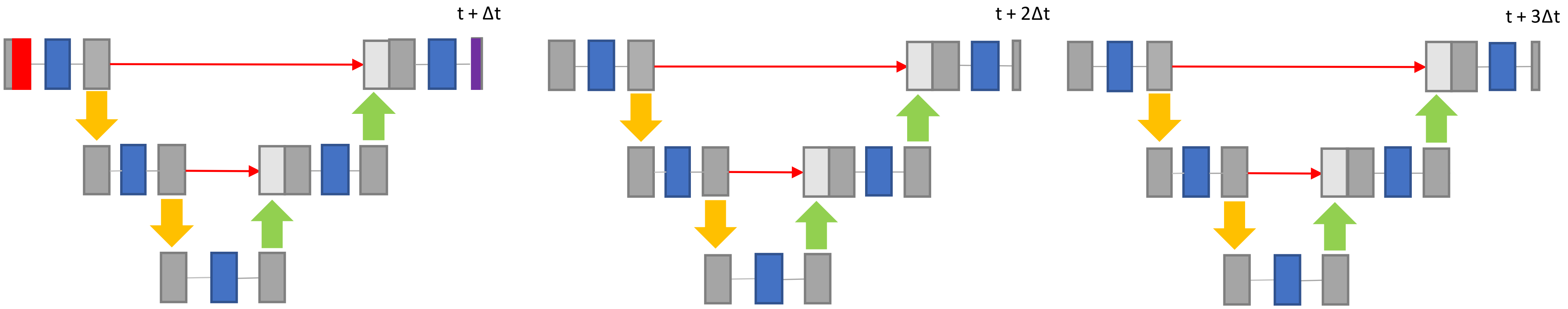
ResBlock



Generalized Spherical Pooling / Unpooling

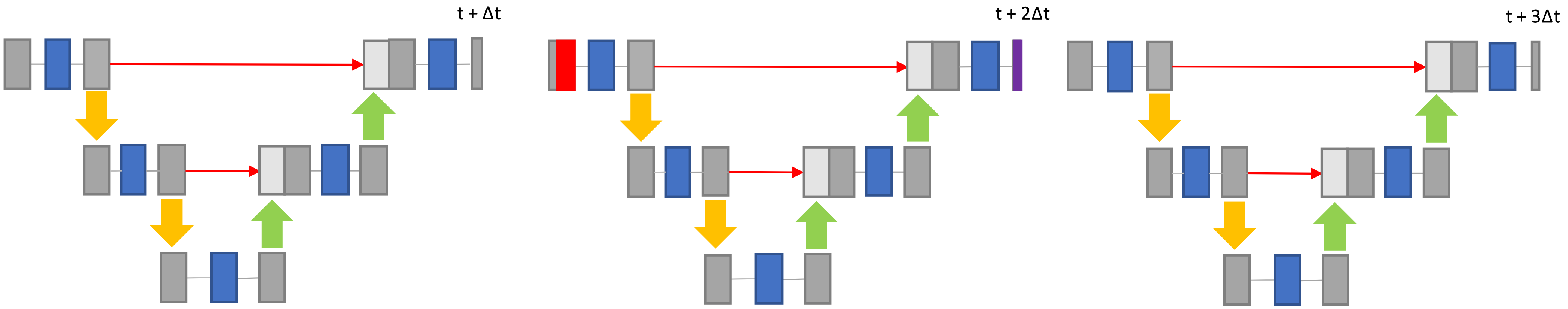


Autoregressive training



<u>AR settings</u>
Forecast cycle: 6h
Input k: [-18h,-12h,-6h]
Output k: [0h]
AR iterations: 6

Autoregressive training



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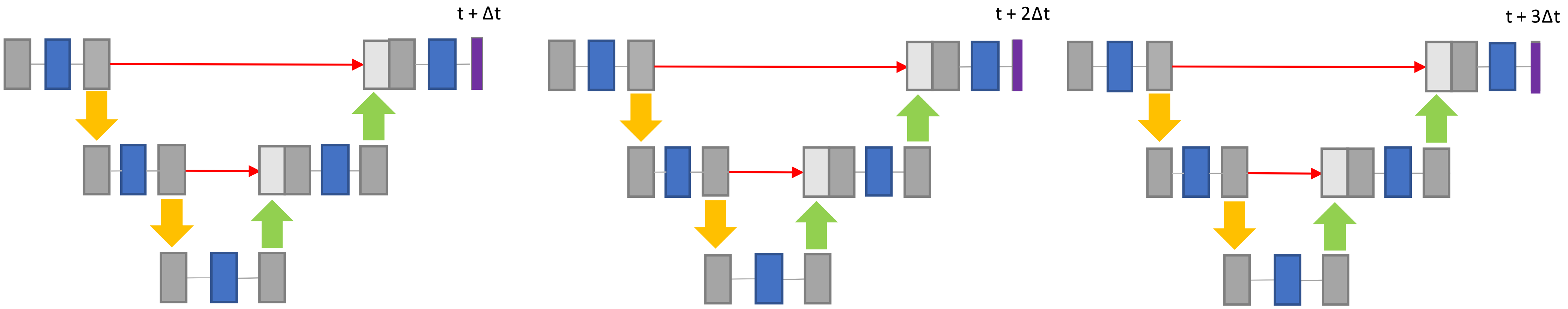

Loss function = L(, )

<u>AR settings</u>
Forecast cycle: 6h
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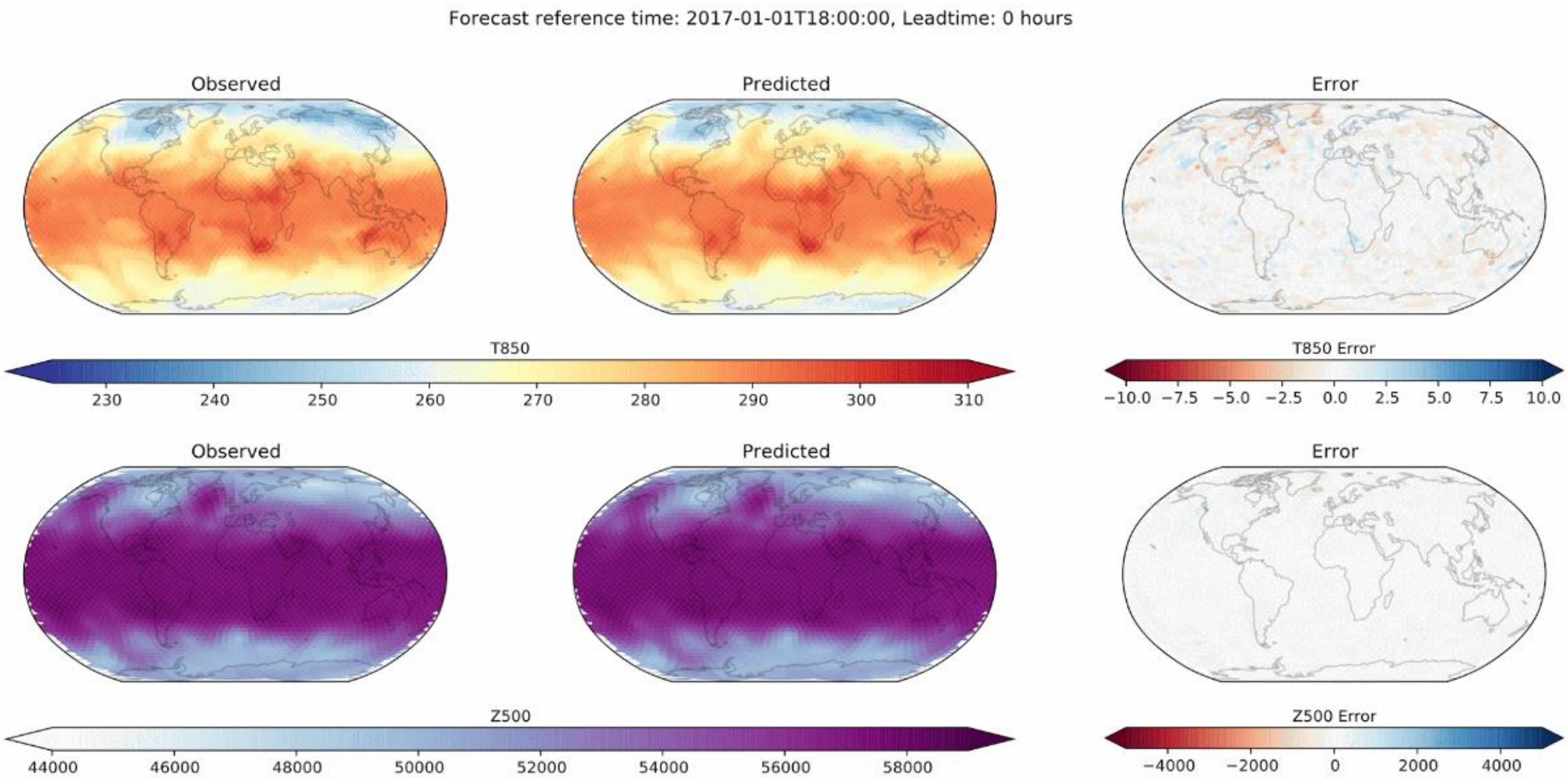
How predictions look like …



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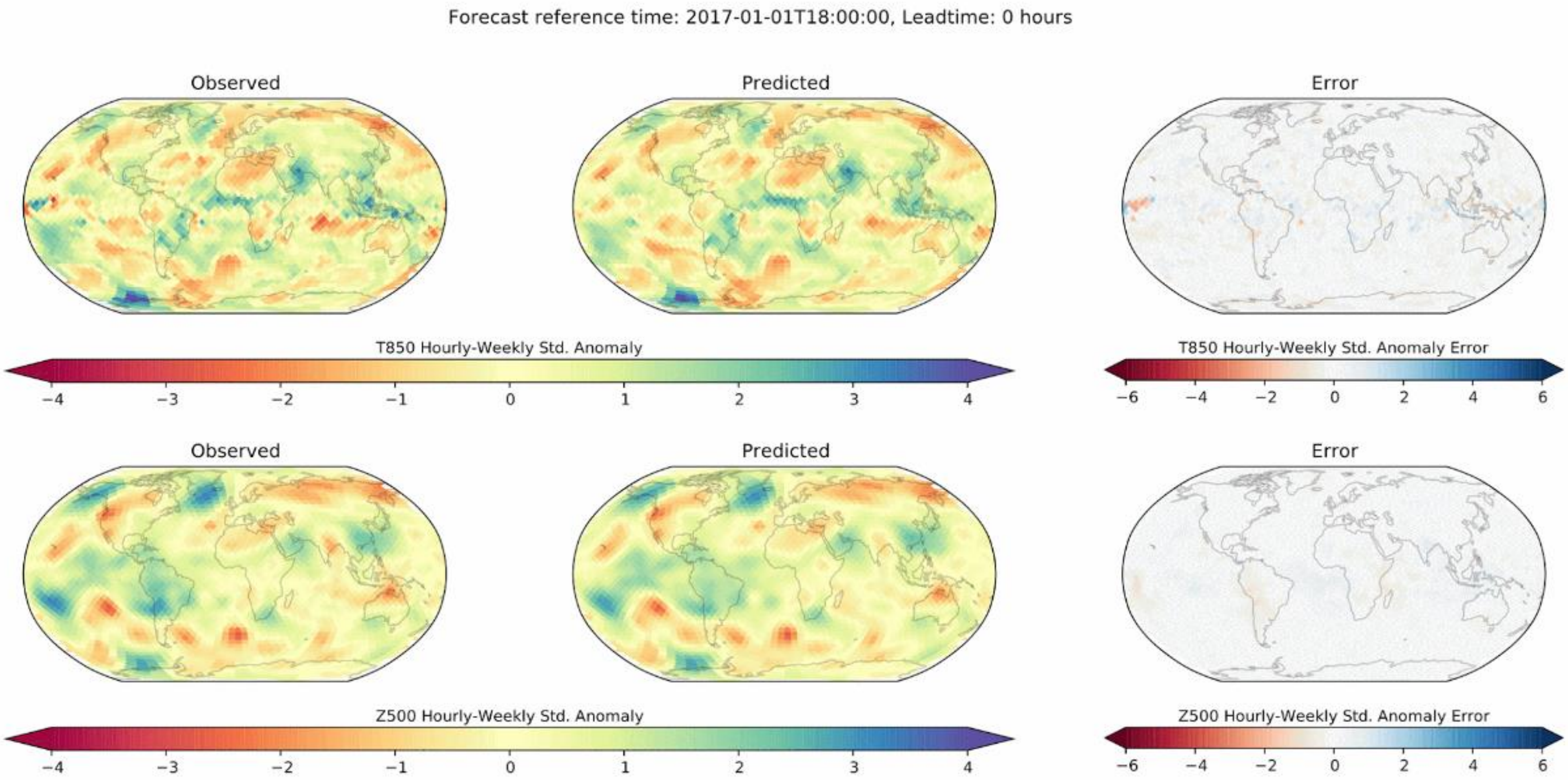
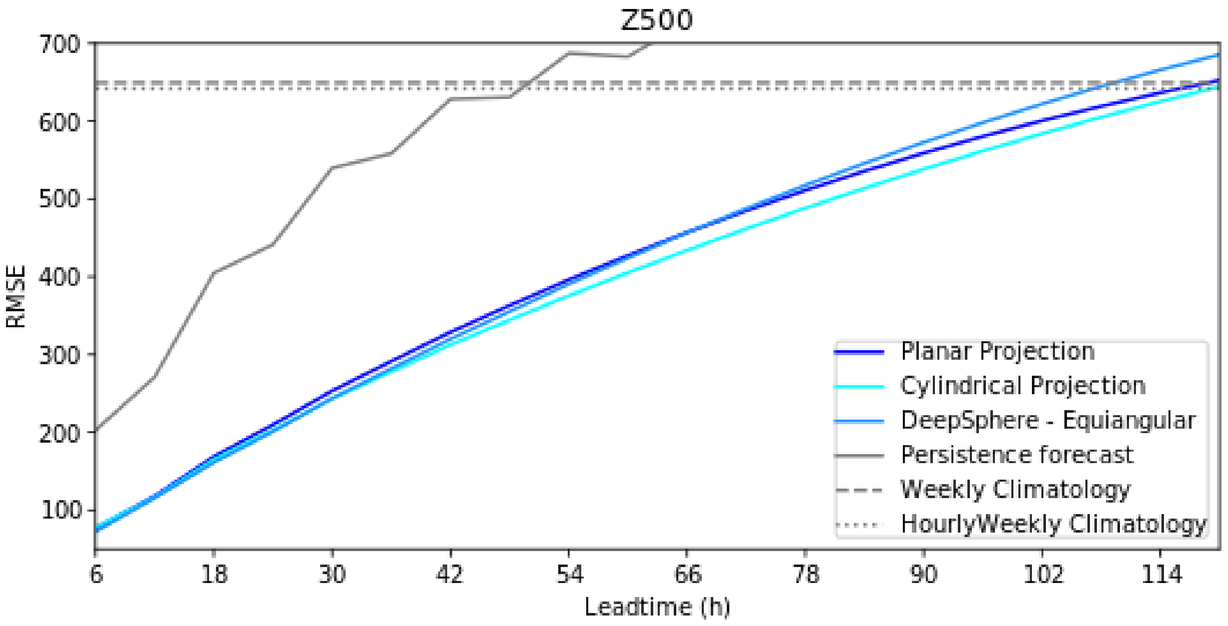
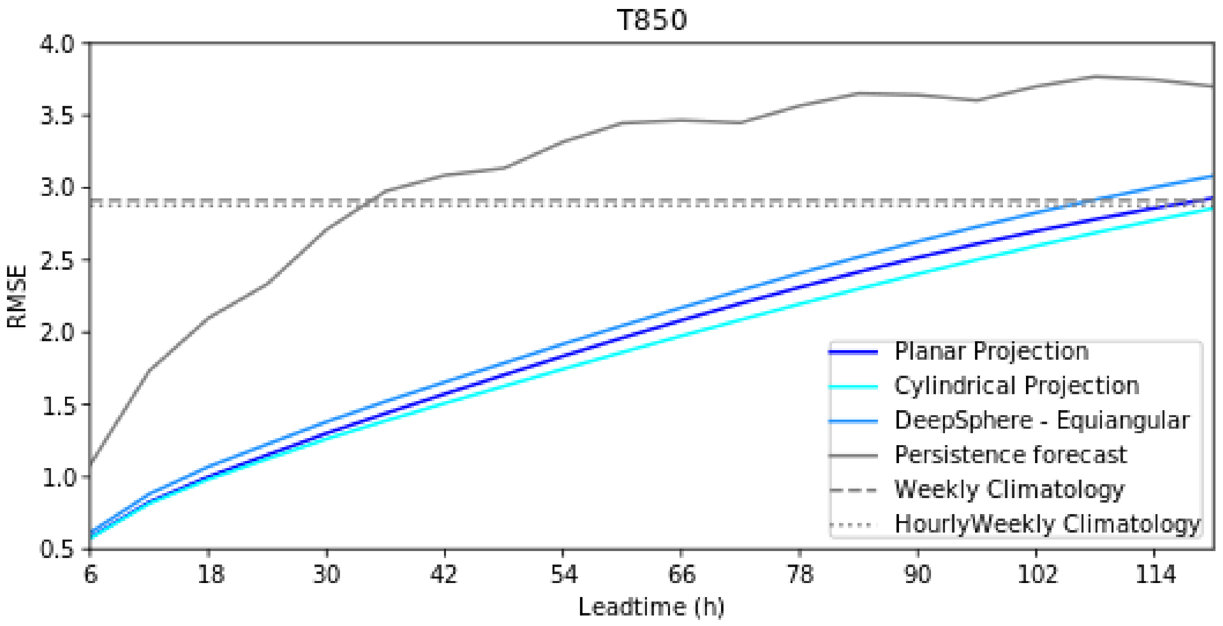
How predictions look like …

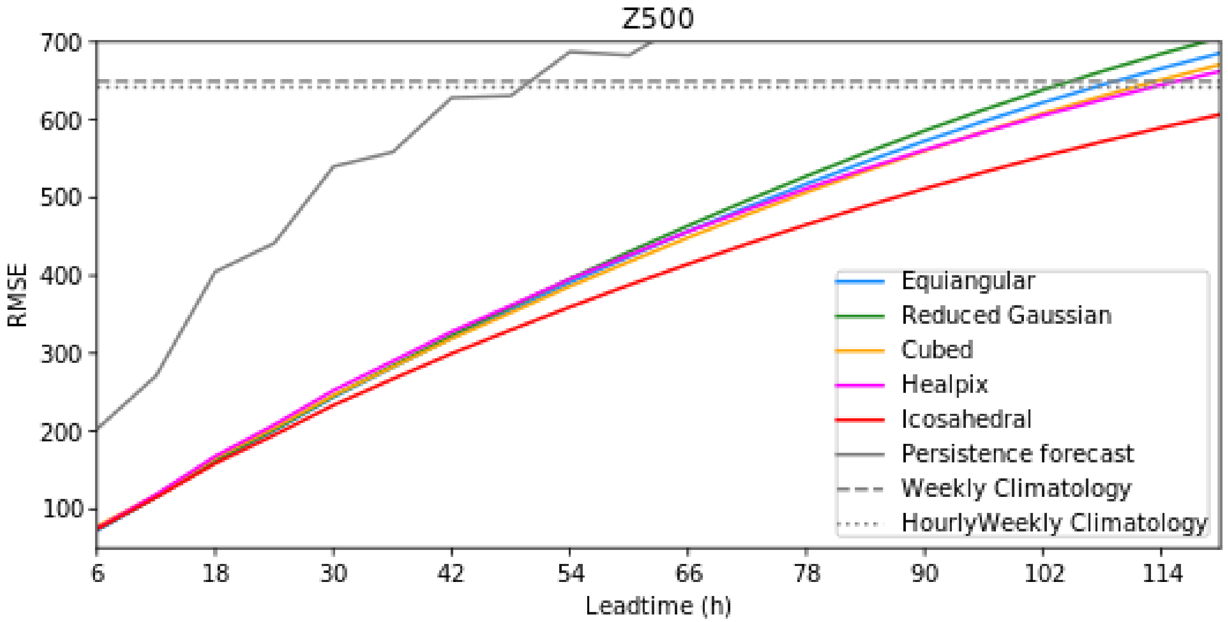


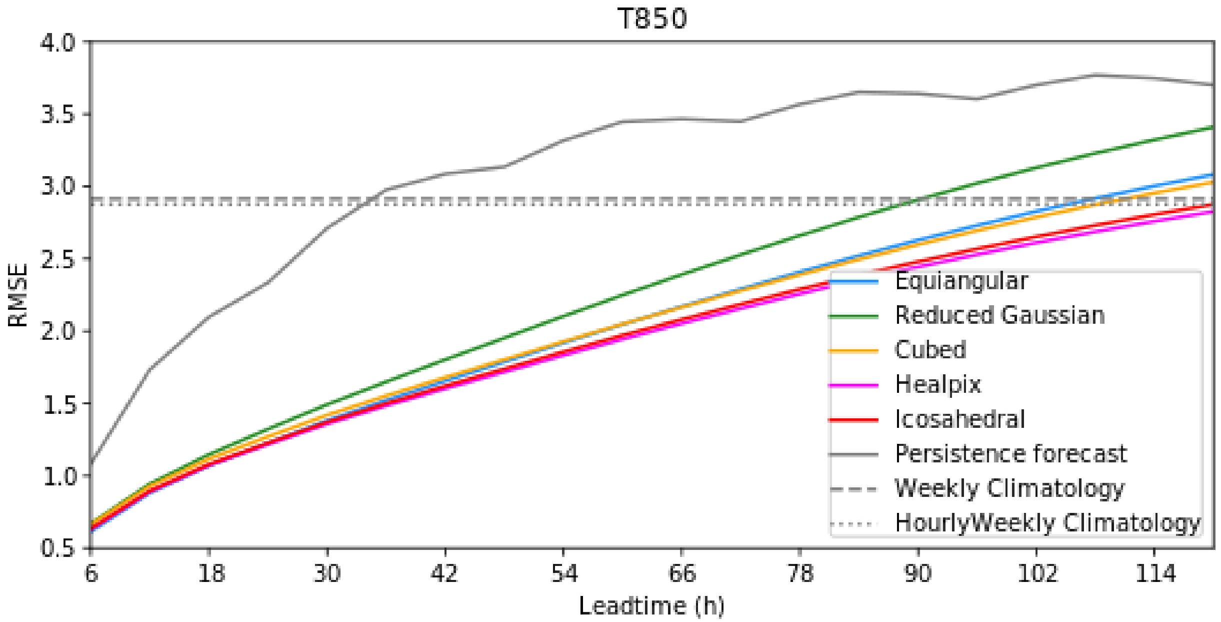
Planar vs. Cylinder vs. Sphere



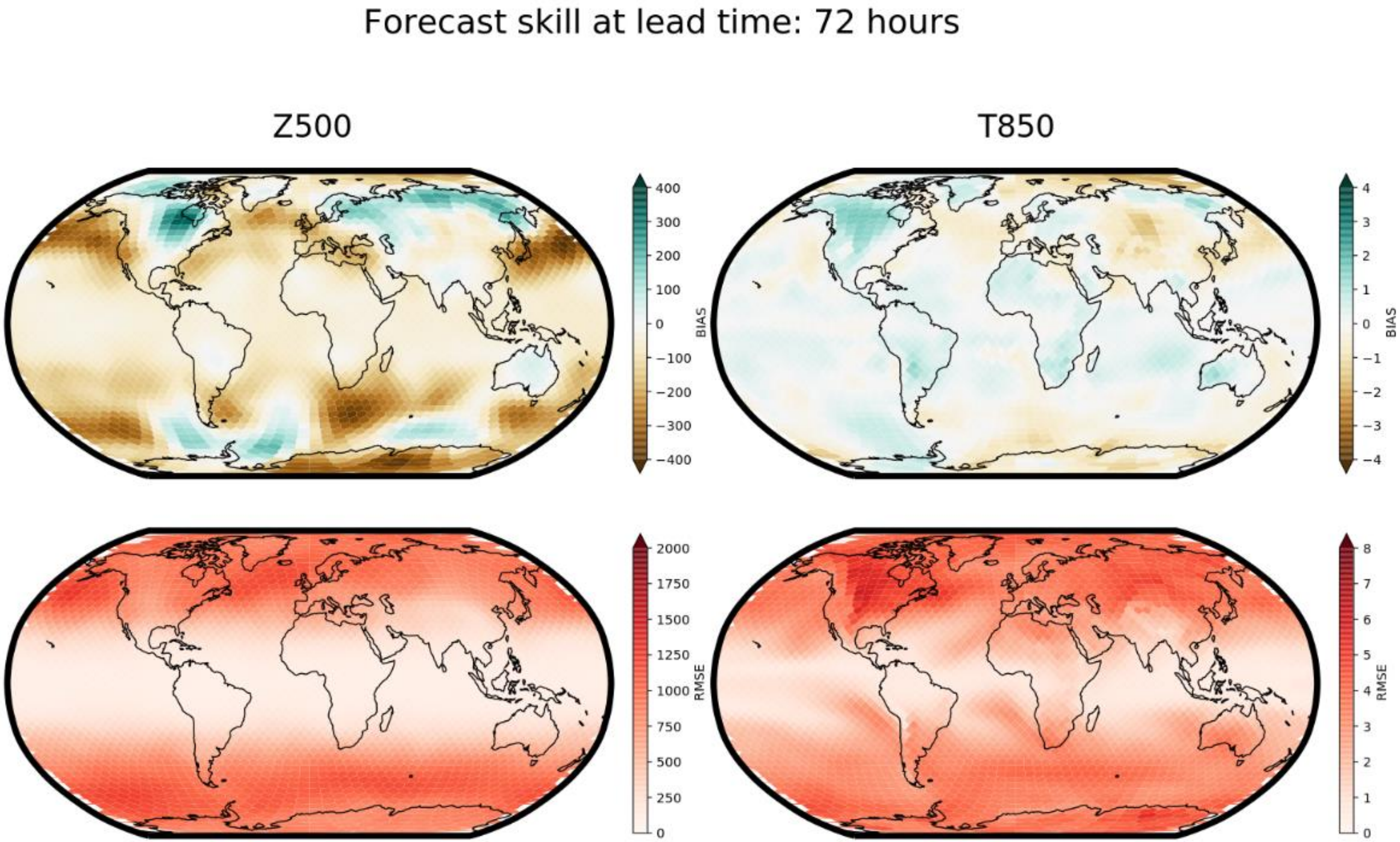


Spherical samplings





Spatial skill summary



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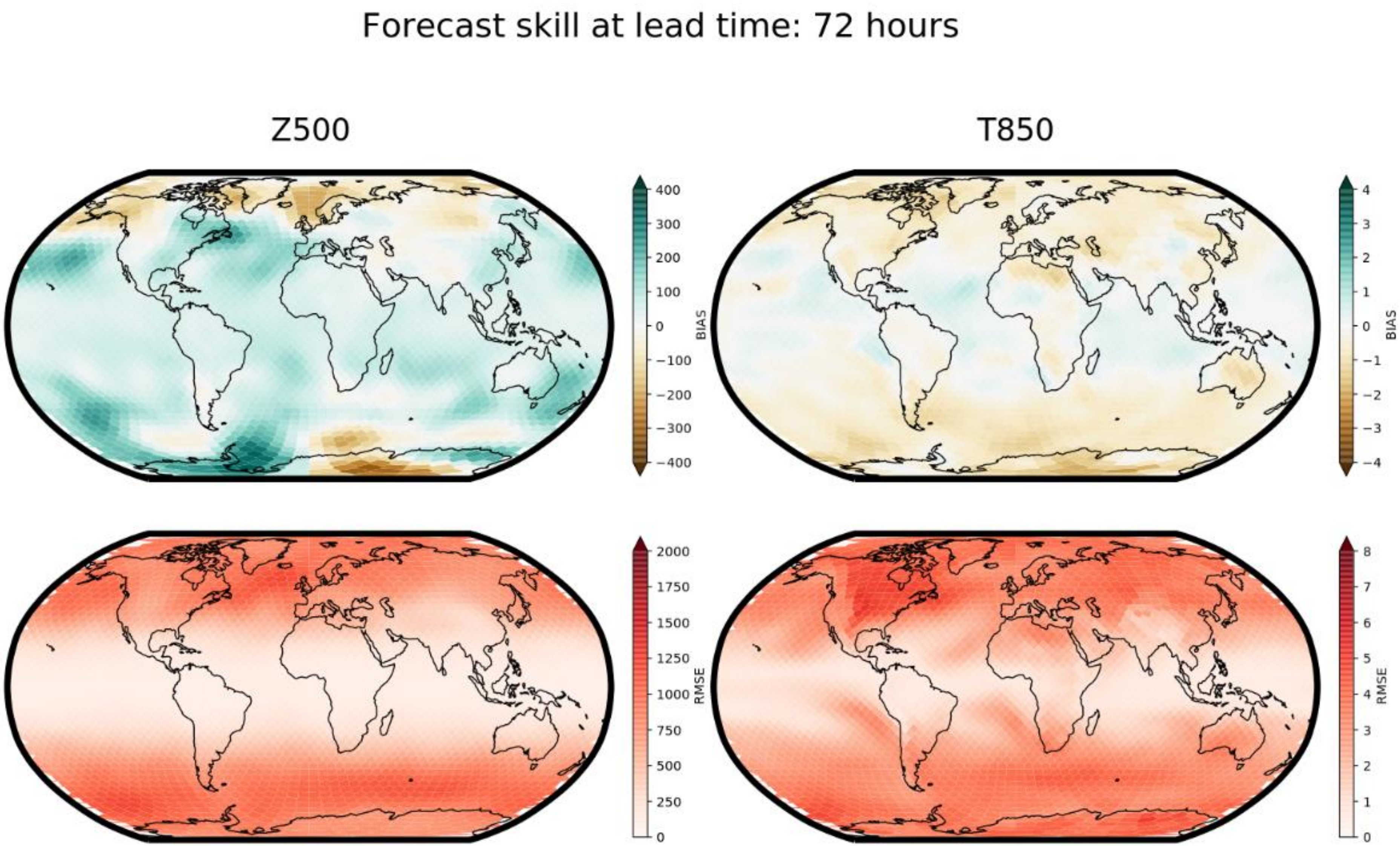
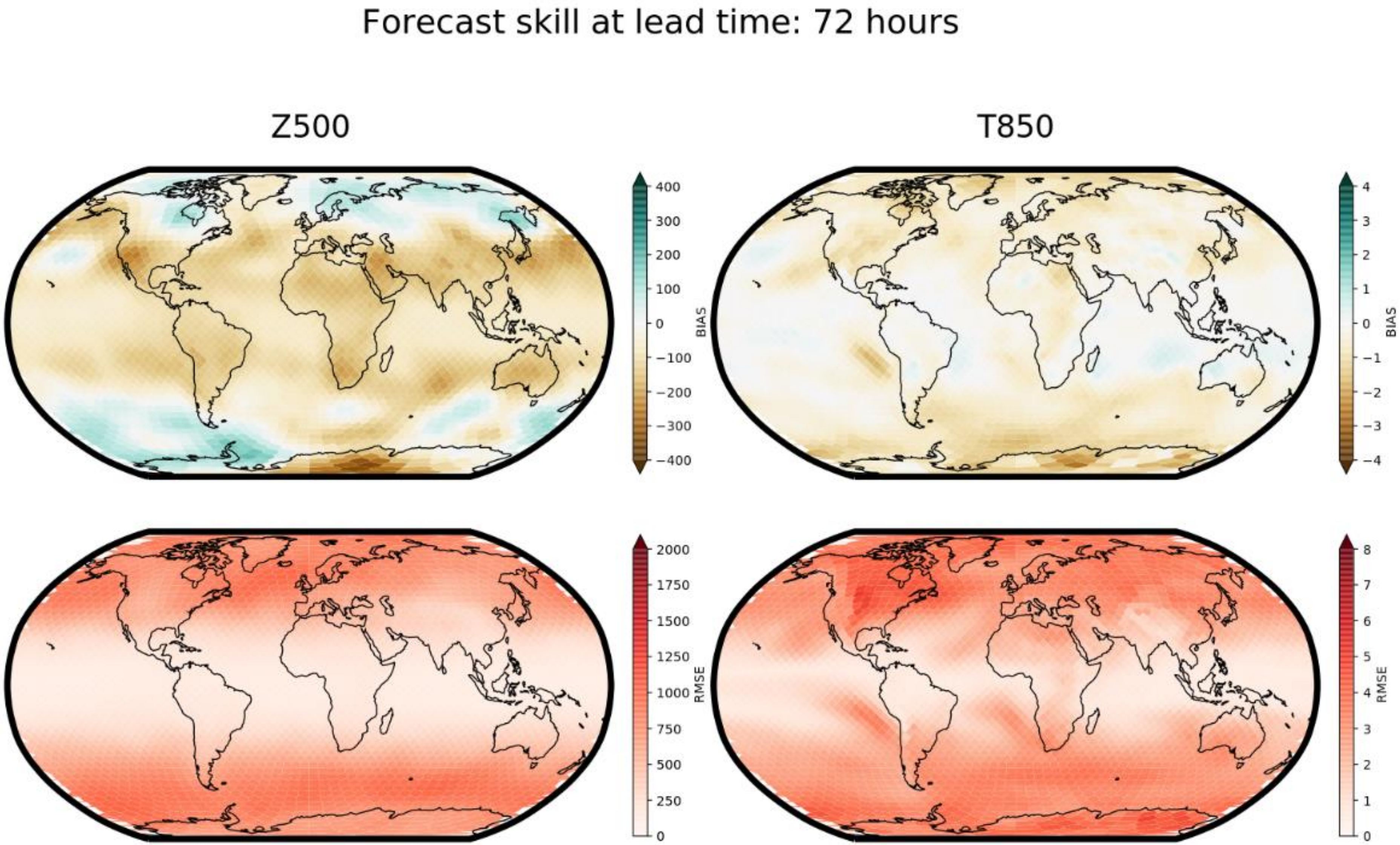
Spatial skill summary



Spatial skill summary



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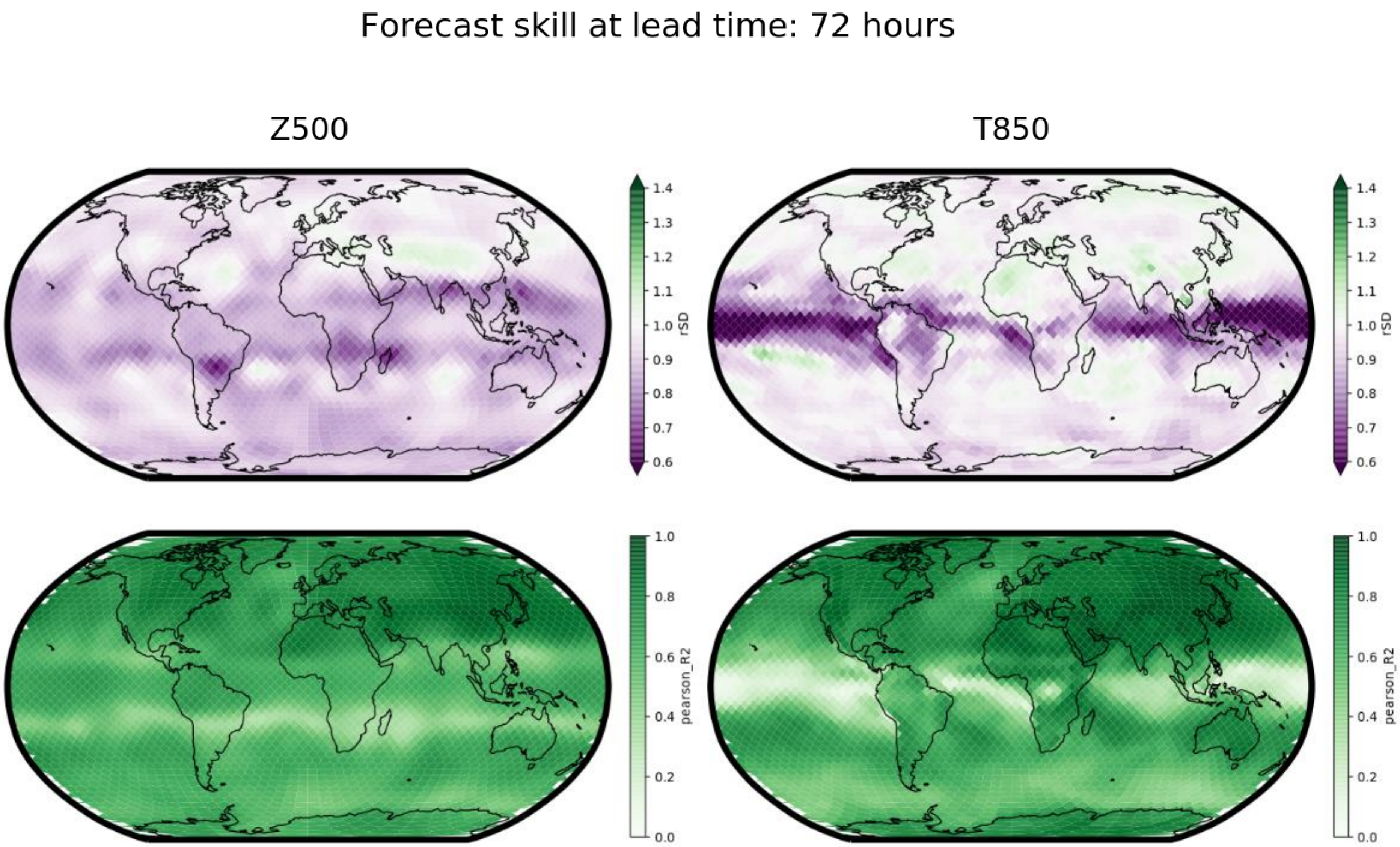
Spatial skill summary



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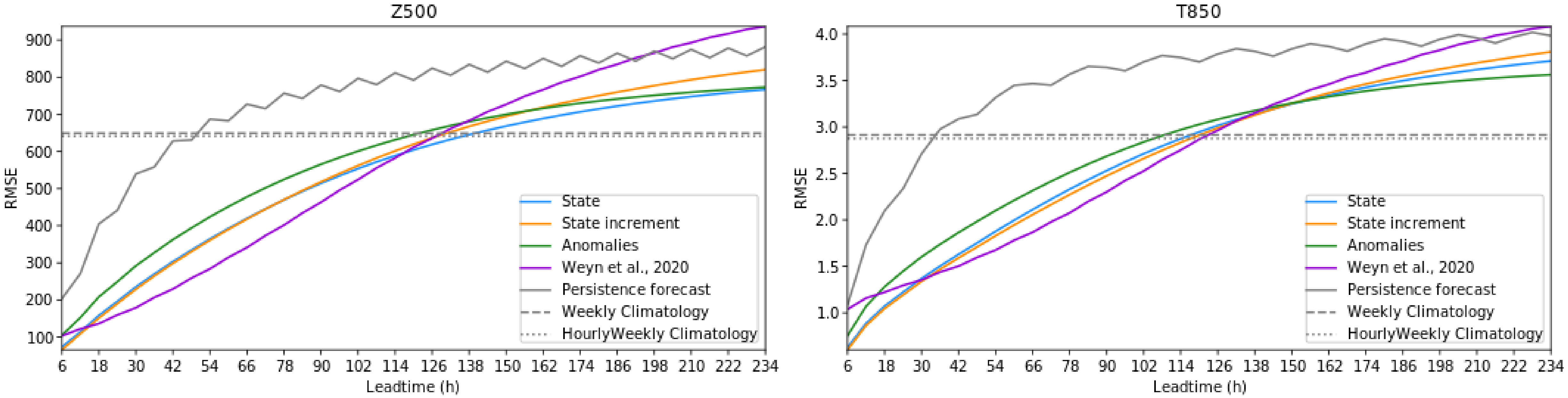
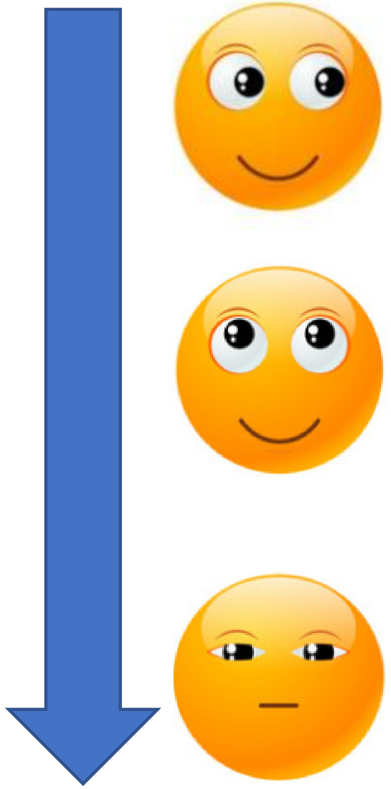
Modelling strategies



Foreseen applications

- Bias-correction, downscaling, post-processing of NWP model output
- Classification tasks (i.e. feature detection, segmentation, …)
- Emulation of climate model outputs
- Stochastic space-time realizations
- Model (i.e. PDE) error correction
- Model component emulation
- ….



References

Papers

- Ghiggi, Feng, Bolon Brun, Lloréns Jover, …, Defferrard.
  DeepSphere-Weather: scalable deep learning on spherical unstructured grids for weather/climate applications,
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- Defferrard, Milani, Gusset, Perraudin.
  DeepSphere: a graph-based spherical CNN, ICLR, 2020.
  [arXiv, ICLR, OpenReview, latex, slides, video, code]
- Defferrard, Perraudin, Kacprzak, Sgier.
  DeepSphere: towards an equivariant graph-based spherical CNN, RLGM workshop at ICLR, 2019.
  [arXiv, RLGM@ICLR, reviews, latex, poster, code]

Code

- https://github.com/deepsphere
- https://github.com/deepsphere/deepsphere-weather