WeatherBENCH: A Benchmark Dataset For Data-driven Weather Forecasting

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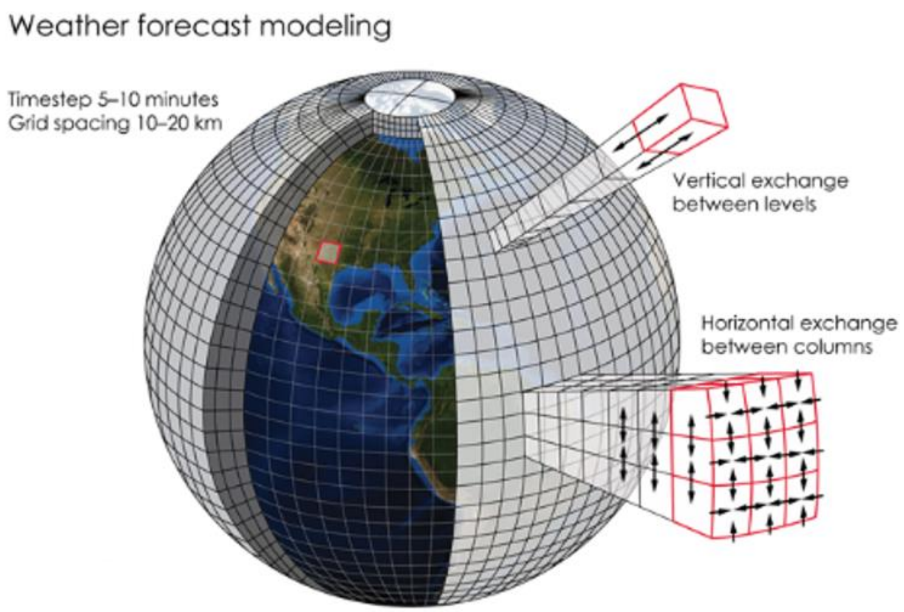
Goals

- **Awareness:** Inter-comparability of machine learning weather forecasting studies
- **Crowdsourced science:** WeatherBench dataset
- **Physics / Machine learning baselines:** numerical weather prediction models, neural network models, etc

How weather forecasting is done today

Traditional weather forecasting involves:

- Observation gathering
- Data assimilation
- Numerical weather prediction
- Forecast post-processing and evaluation

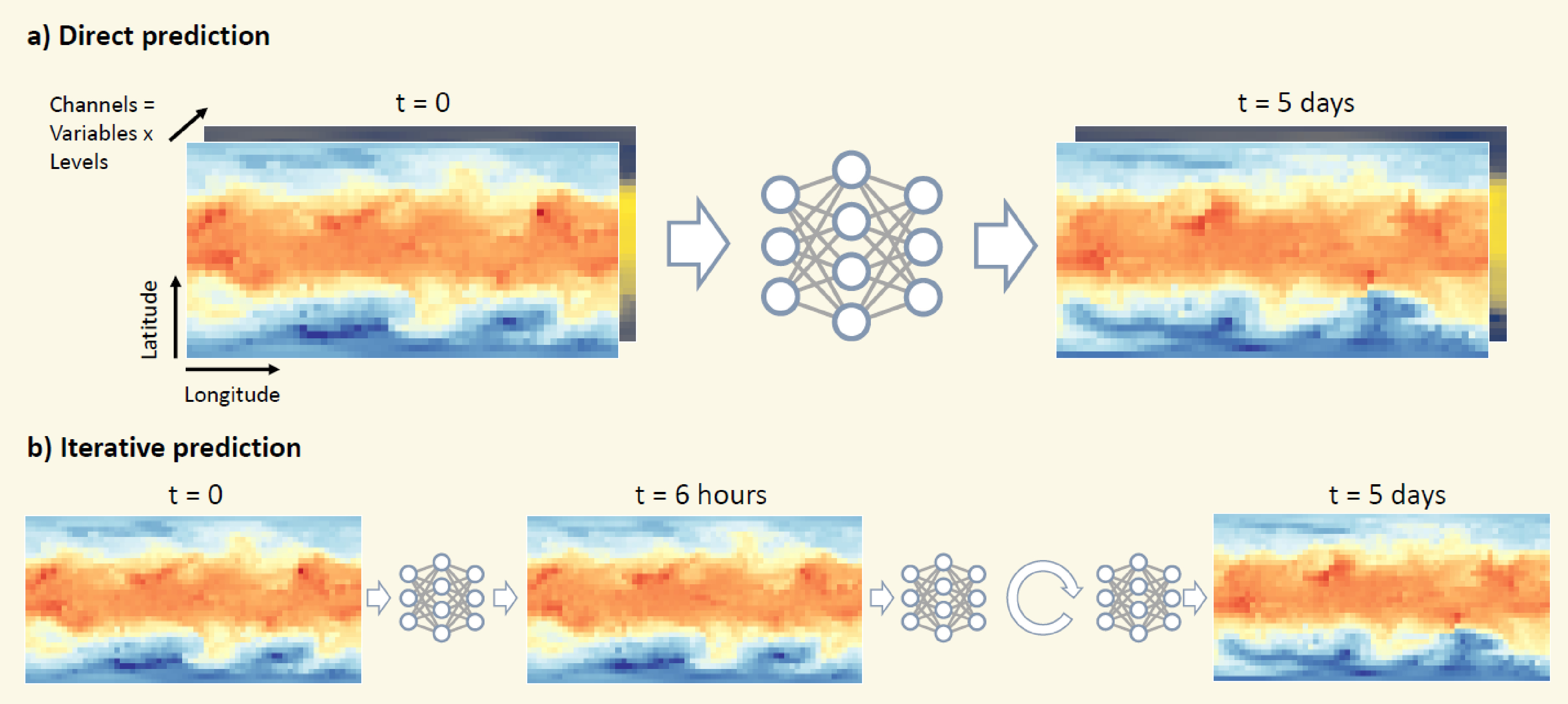


Credit: K. Cantner, AGI.

Concern:

- computationally **expensive**
- Poor performance on **extreme events**

Data-driven weather forecasting



Data-driven weather forecasting: SOTA?

Recent studies:

- NNs to predict 500 hPa geopotential 1 hour ahead (*Dueben and Bauer, 2018*)
- CNNs to predict GCM outputs 14 days ahead (*Scher, 2018; Scher & Messori, 2019*)
- CNNs to predict reanalysis derived Z500 at different lead times (*Weyn et al., 2019*)

Concern:

- different settings of general circulation models as ground truth
- different spatial and temporal resolutions
- different neural network architectures evaluated using different metrics

WeatherBENCH dataset

Goal:	Evaluate deep learning models for global medium range weather forecasting
Data:	ERA5 reanalysis dataset for training and evaluation
Spatial resolution:	40 years of hourly data (1979-2018)
Temporal resolution:	Data re-gridded to 5.625°, 2.8125° and 1.40525° Selected 10 vertical levels between 1 and 1000 hPa

WeatherBENCH dataset

3-D fields	2-D fields	Time-invariant fields
Geopotential	2-meter temperature	Land-sea mask
Temperature	10-meter wind	Soil type
Humidity	Total cloud cover	Orography
Wind	Precipitation	Latitude, longitude
	Top-of-atmosphere incoming solar radiation	

WeatherBENCH evaluation

Target fields: 500 hPa geopotential and 850 hPa temperature

Years: 2017-2018

Resolution: 5.625°

Metric:

$$RMSE = \frac{1}{N_{forecasts}} \sum_{i}^{N_{forecasts}} \sqrt{\frac{1}{N_{lat} N_{lon}} \sum_{j}^{N_{lat}} \sum_{k}^{N_{lon}} L(j)\,(\hat{y}_{i,j,k} - y_{i,j,k})^2}$$

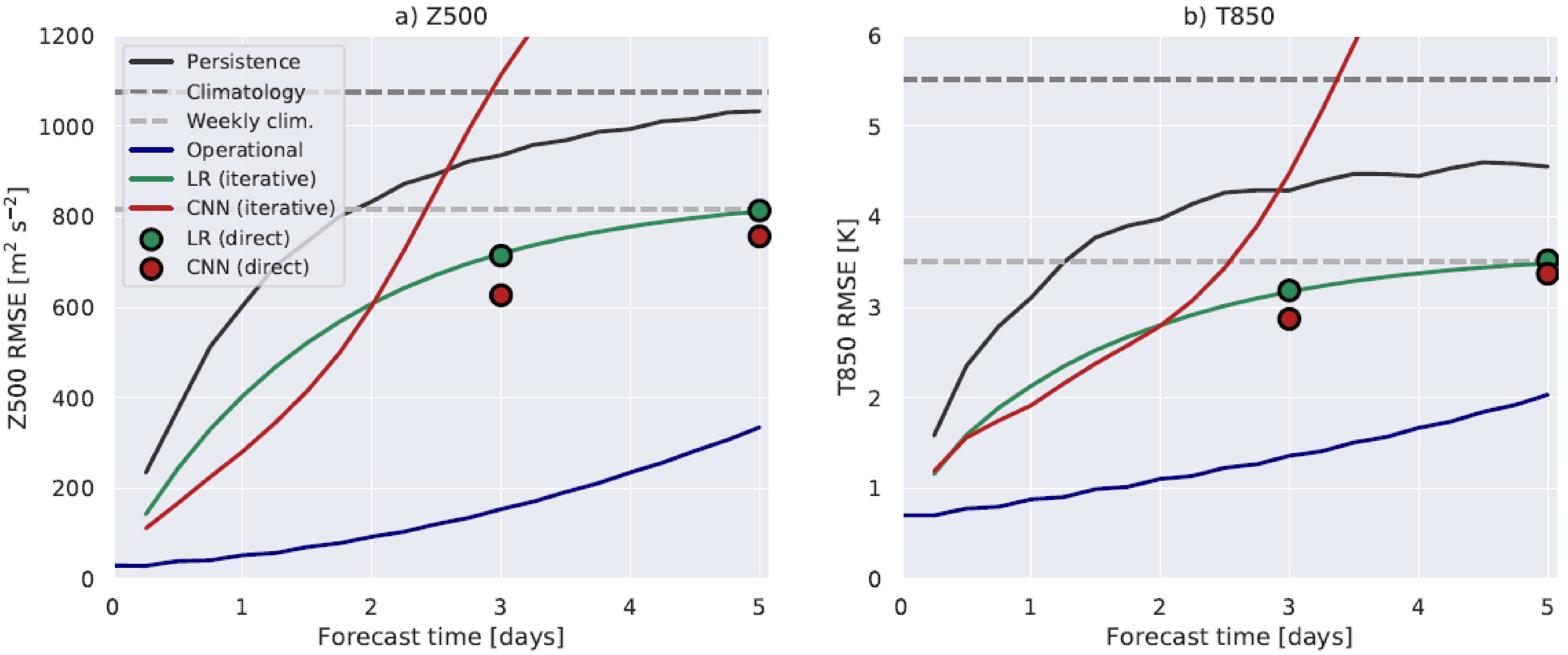
with $L(j)$, the latitude weighting factor for the latitude at the j^{th} latitude index

$$L(j) = \frac{\cos(lat(j))}{\frac{1}{N_{lat}} \sum_{j}^{N_{lat}} \cos(lat(j))}$$

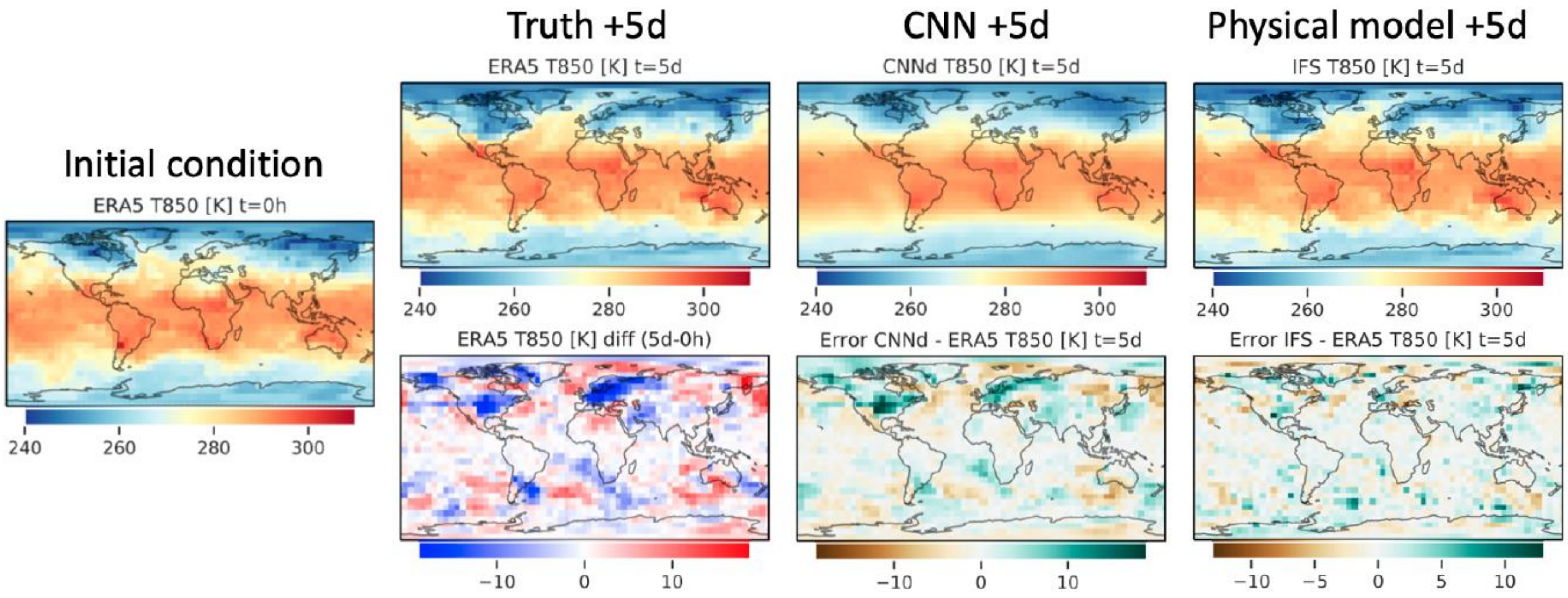
Meaningful baselines

Persistence:	Tomorrow's weather is today's weather
Climatology:	Mean over 1979 – 2016
Operational NWP model:	Operational IFS (Integrated Forecast System) from the ECMWF
Linear regression	
Convolutional neural network:	Five layer CNN with a filter size of 5

Meaningful baselines



Climate forecasts



Conclusion

We hope the benchmark can provide a starting point for:

- Scientific understanding
- Challenge for data science
- Clear metric for success
- Quick start
- Reproducibility and citability
- Communication platform

The end

For more details, see:

WeatherBENCH: A benchmark dataset for data-driven weather forecasting

https://arxiv.org/abs/2002.00469

The benchmark development is ongoing and we encourage you to develop and evaluate your own solutions!

https://mediatum.ub.tum.de/1524895

https://github.com/pangeo-data/WeatherBench

Sources

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