Deep learning-based bias adjustment of decadal climate predictions

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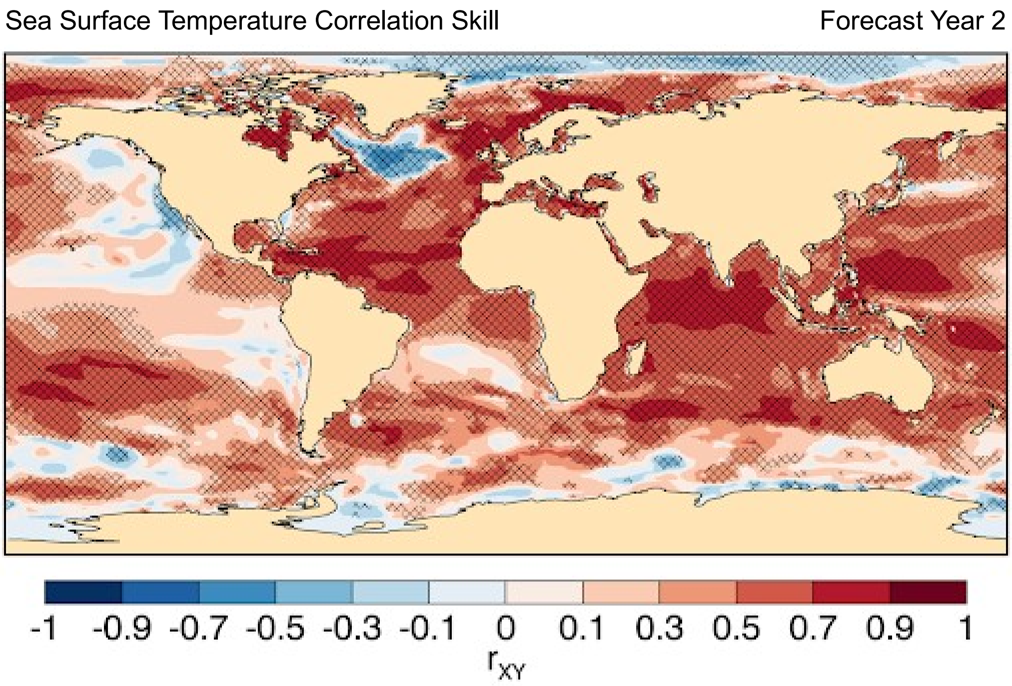
Introduction: Decadal climate predictions

Forecasts from 1 to 10 years

Provide key information to inform adaptation strategies

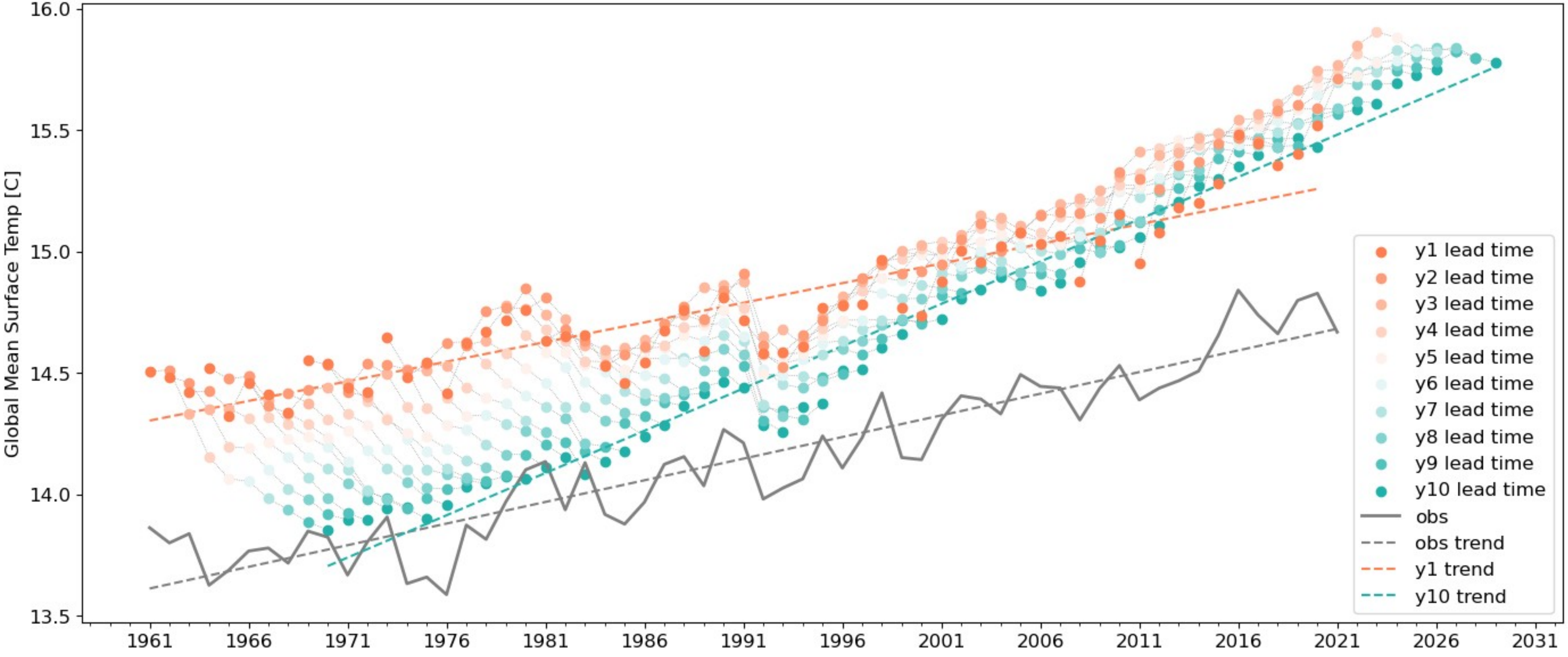
Retrospective forecasts initialized every year (1961-2021) used to assess **prediction skill**



CanESM5 model forecast [Sospedra-Alfonso et al. 2021]

Decadal climate predictions are biased

CanESM5 raw forecasts, near-surface air temperature



Decadal climate predictions are biased

Time dependent bias (Drift)
Forecasts drift away from observations with increasing lead time

Systematic bias
Climate models have systematic model error (climatological bias)

Trend bias
Modelled and observed trends generally differ

Forecast adjustment: usually done with simple linear methods [Meehl et al. 2022]

Difficulties of climate models

Climate model biases have non-linear **spatial** and **temporal** correlations

spatial correlations

- Teleconnections (ENSO, PDO)
- Relatively strong covariance in neighboring points and long range covariance for teleconnected regions

temporal correlations

- Lead time dependence (drift)
- Dependence on initialization year (bias, trend)

non-stationary target

- Climate change leads to accelerated data shift → out-of-distribution data
- Trend difficult to approximate

Other solution?

Current adjustment methods don't capture the special characteristics of decadal forecasts

Climatological bias correction [Boer et al., 2016]

Linear trend correction [Kharin et al., 2012]

Linear drift dependence on initial conditions [Fuckar et al., 2014]

Polynomial representation of drift [Pasternack et al, 2018]

Dynamic modeling of the drift [Nadiga et al., 2019]

Debiasing using Neural Networks

Idea: Use neural networks to learn and correct model biases

Already applied to sub-seasonal forecasts
[Kim et al. 2021, Han et al. 2021, Lerch & Polsterer 2022, François et al. 2021, Wang et al. 2022]

So far no application for decadal forecasts

Challenge of climate data:
- non-stationary, correlations in space and time, multiple time scales

Challenge of decadal forecasts:
- longer lead times, larger impact of bias on forecast
- two temporal dimensions for bias: lead time and initialization year

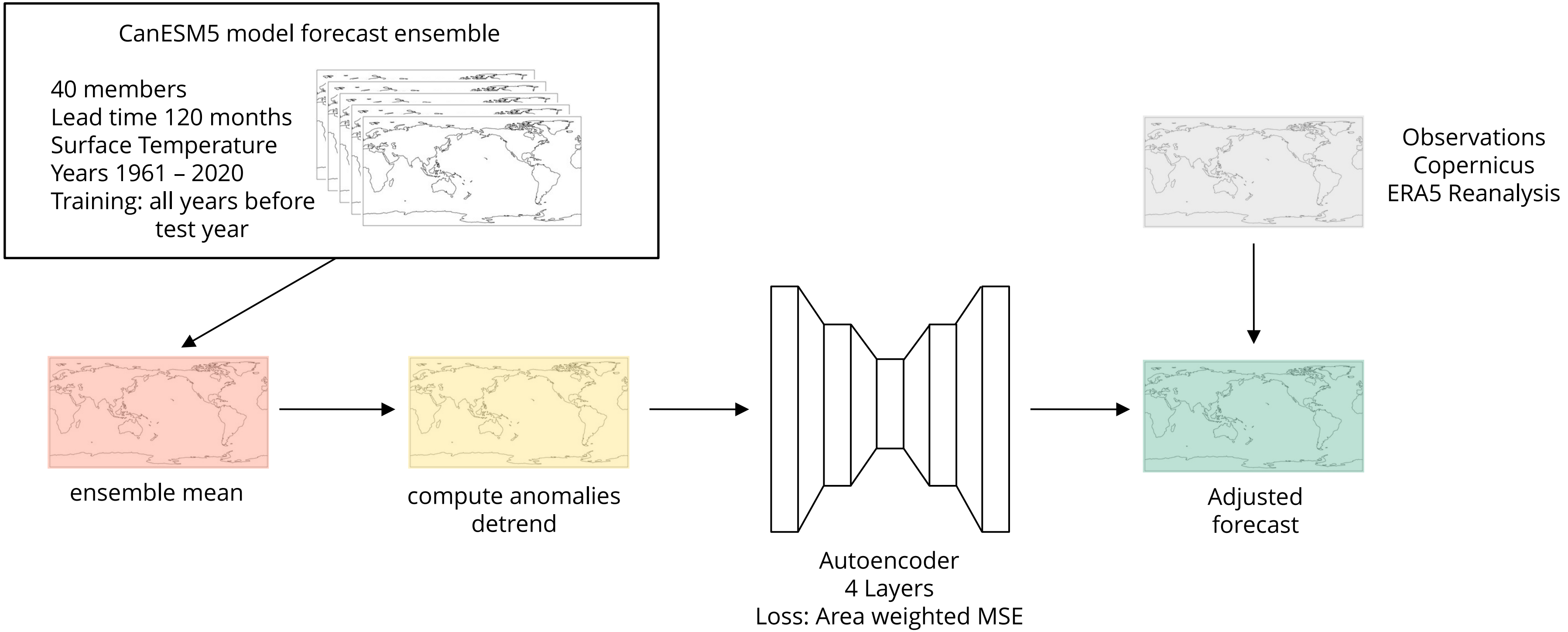
Forecast adjustment using Neural Networks

First tests: simple fully-connected autoencoder

Focus on lead times up to 24 months

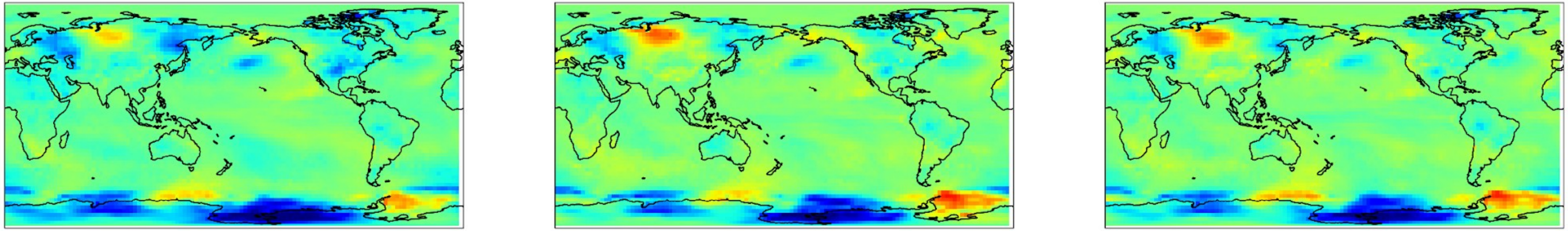
Variable: Near-surface air temperature

Forecast adjustment using an Autoencoder

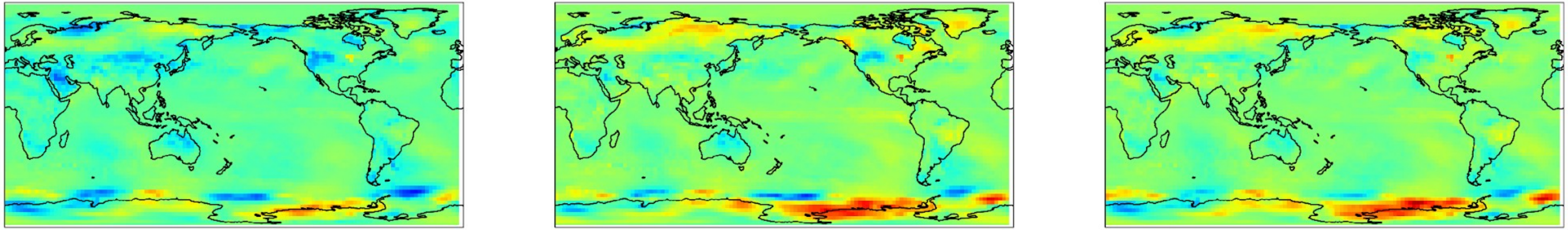


Preliminary Results: Near-Surface Air Temperature

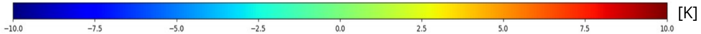
NN adjusted forecast error | Linear bias adjusted forecast error | Raw forecast error



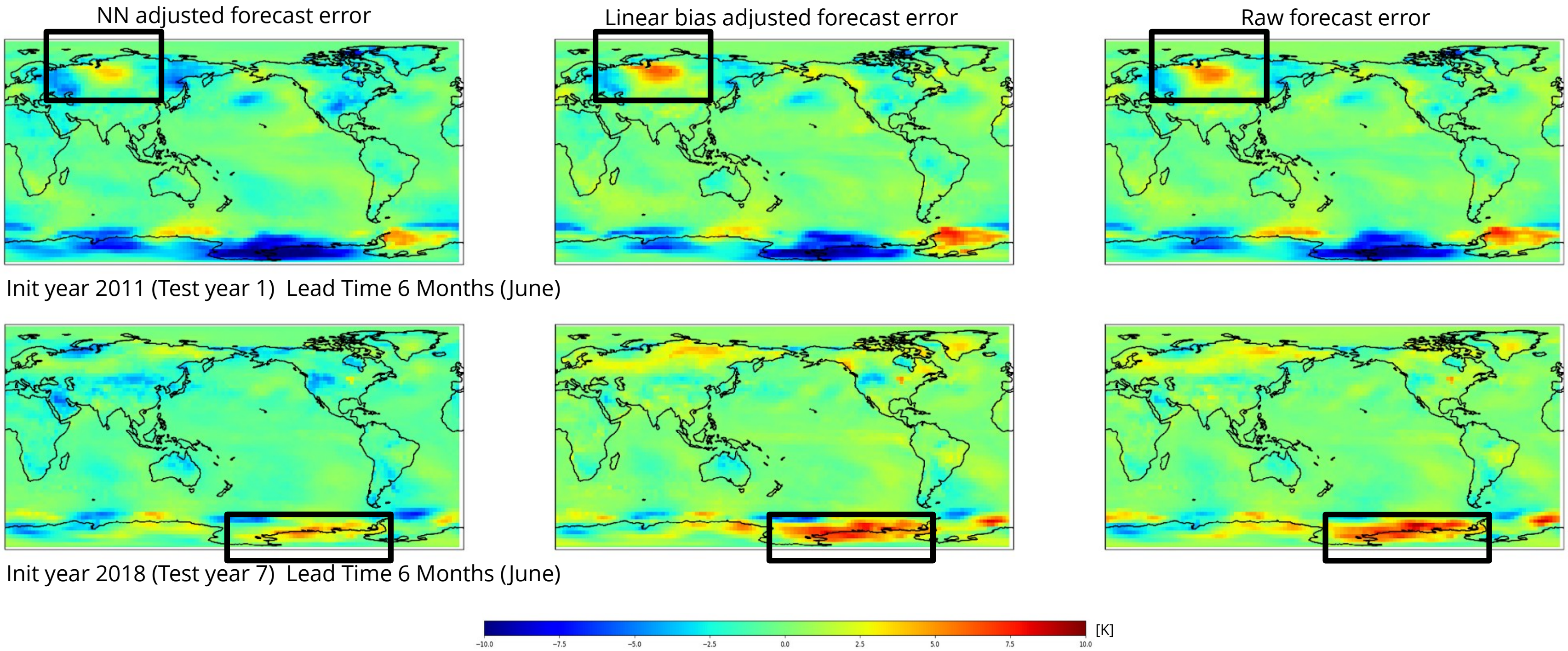
Init year 2011 (Test year 1) Lead Time 6 Months (June)



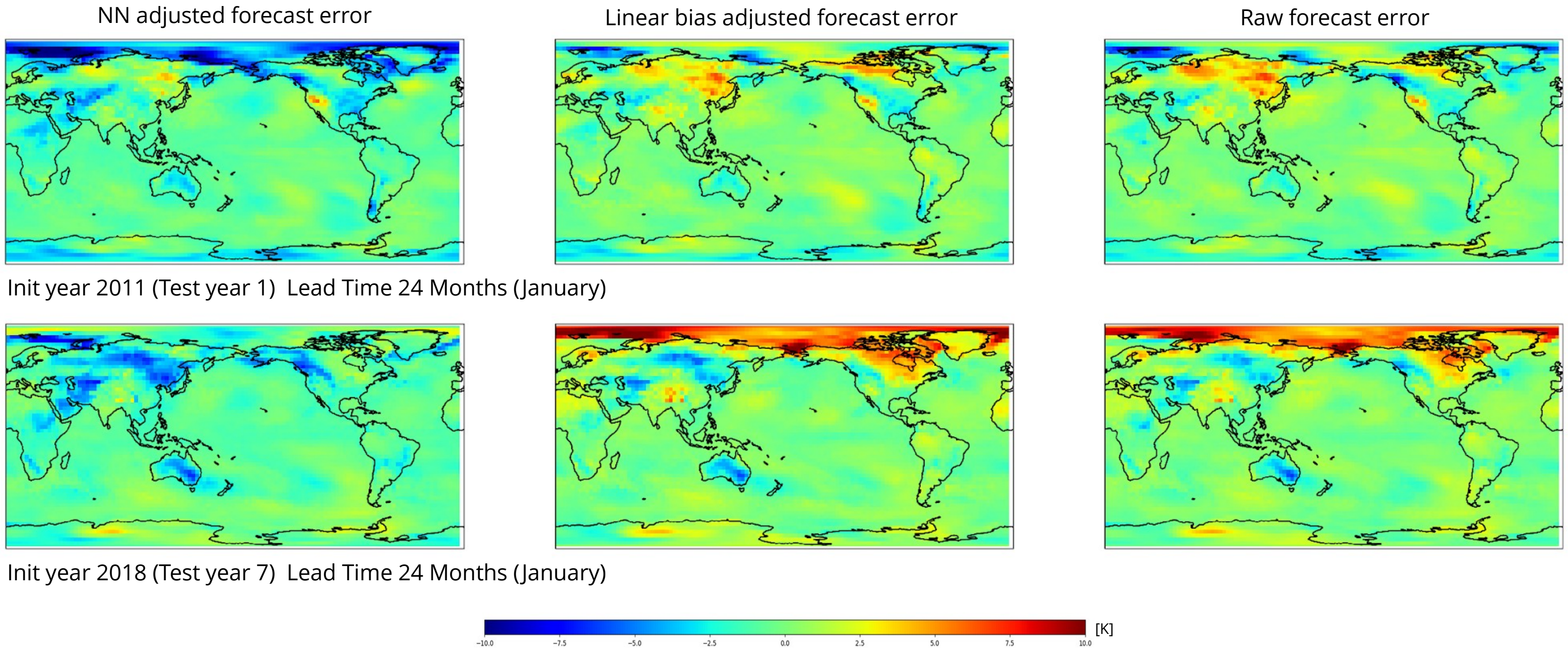
Init year 2018 (Test year 7) Lead Time 6 Months (June)

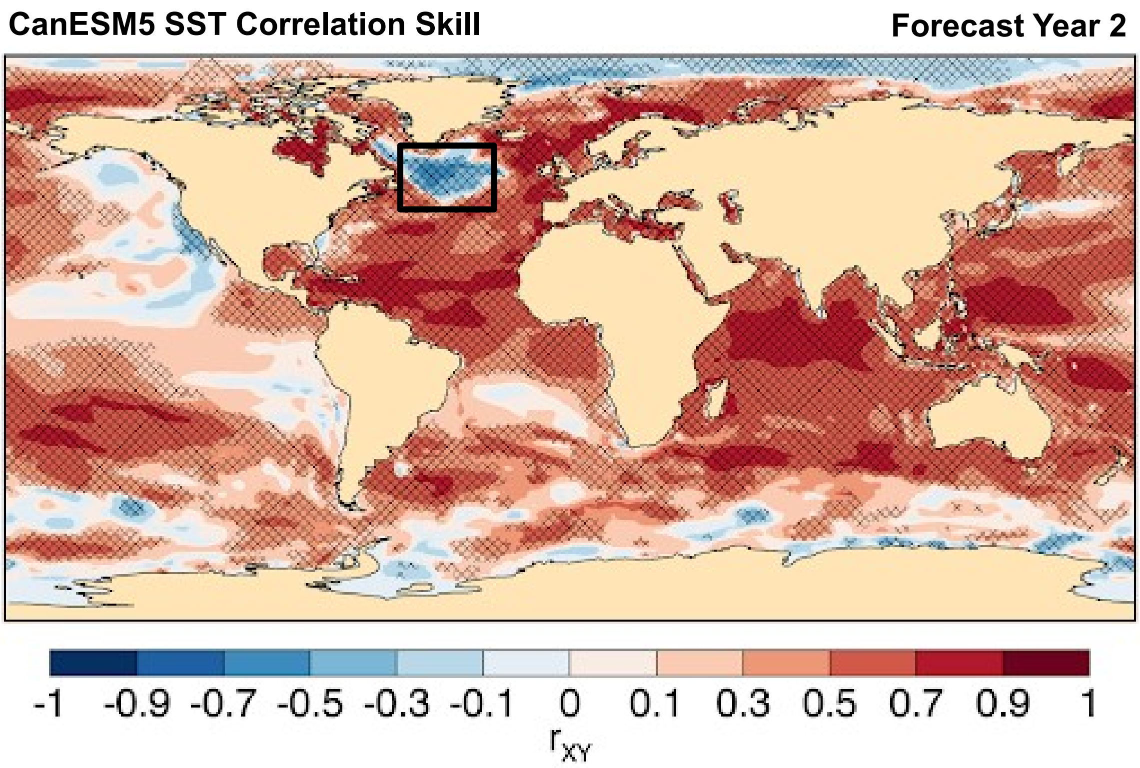


Preliminary Results: Near-Surface Air Temperature



Preliminary Results: Near-Surface Air Temperature



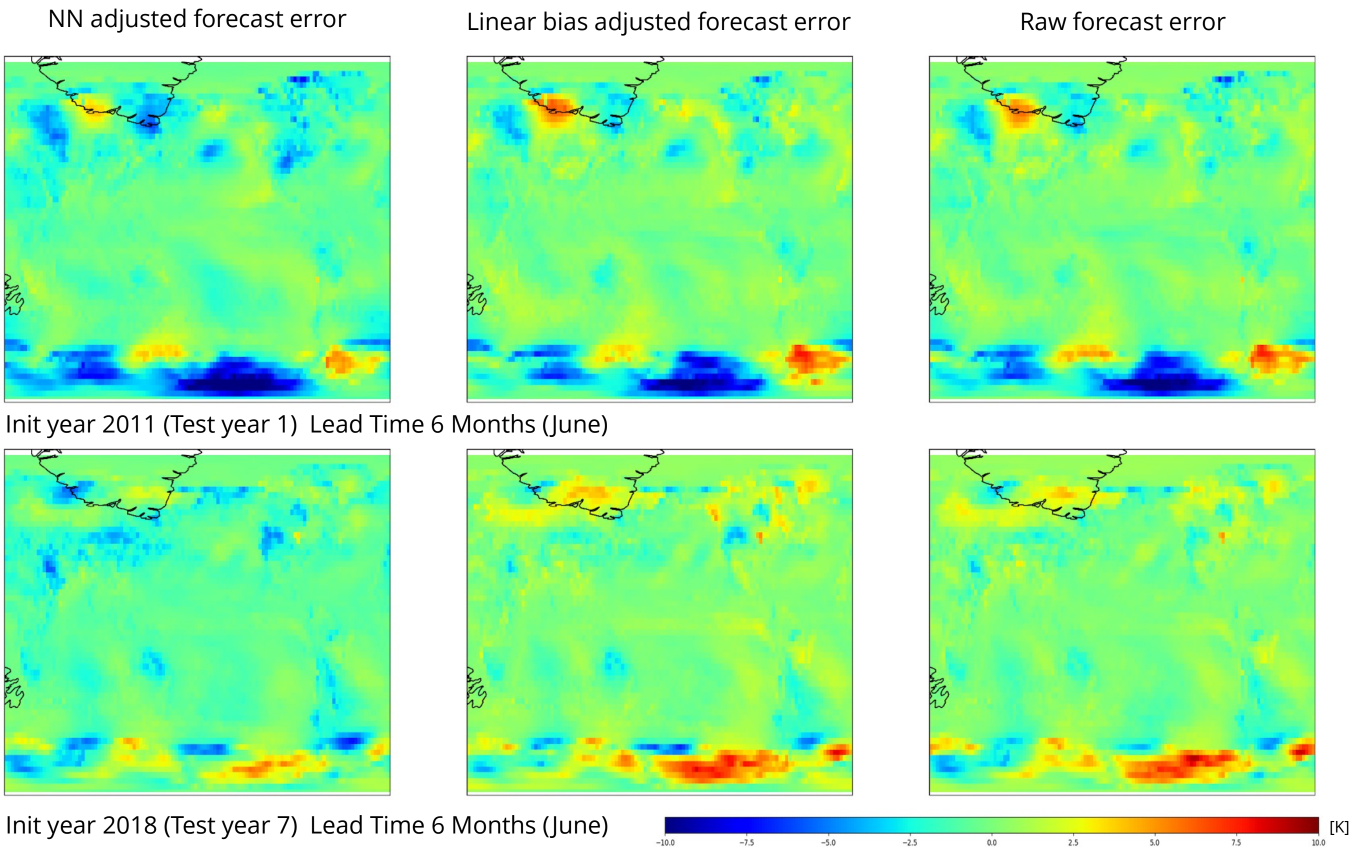


Western Subpolar North Atlantic

Area of large errors partly due to erroneous trends in the reanalysis used for initialization, and to strong model climatological bias

[Sospedra-Alfonso et al. 2021]

Preliminary Results: Near-Surface Air Temperature



Init year 2011 (Test year 1) Lead Time 6 Months (June)

Init year 2018 (Test year 7) Lead Time 6 Months (June)

Conclusions and next steps

Early model still lead-time and initialization year independent

Current focus: learning temporal structure of bias

Challenge: consideration of bias along two temporal dimensions
(lead time, initialization year)

Improvements to architecture: ConvLSTM [Shi et al. 2015]
Spatially-aware loss functions

Capture model and forecast uncertainties

Model Comparisons and Preliminary Results

Model comparison and preliminary results

Model 1: Fully-connected Autoencoder

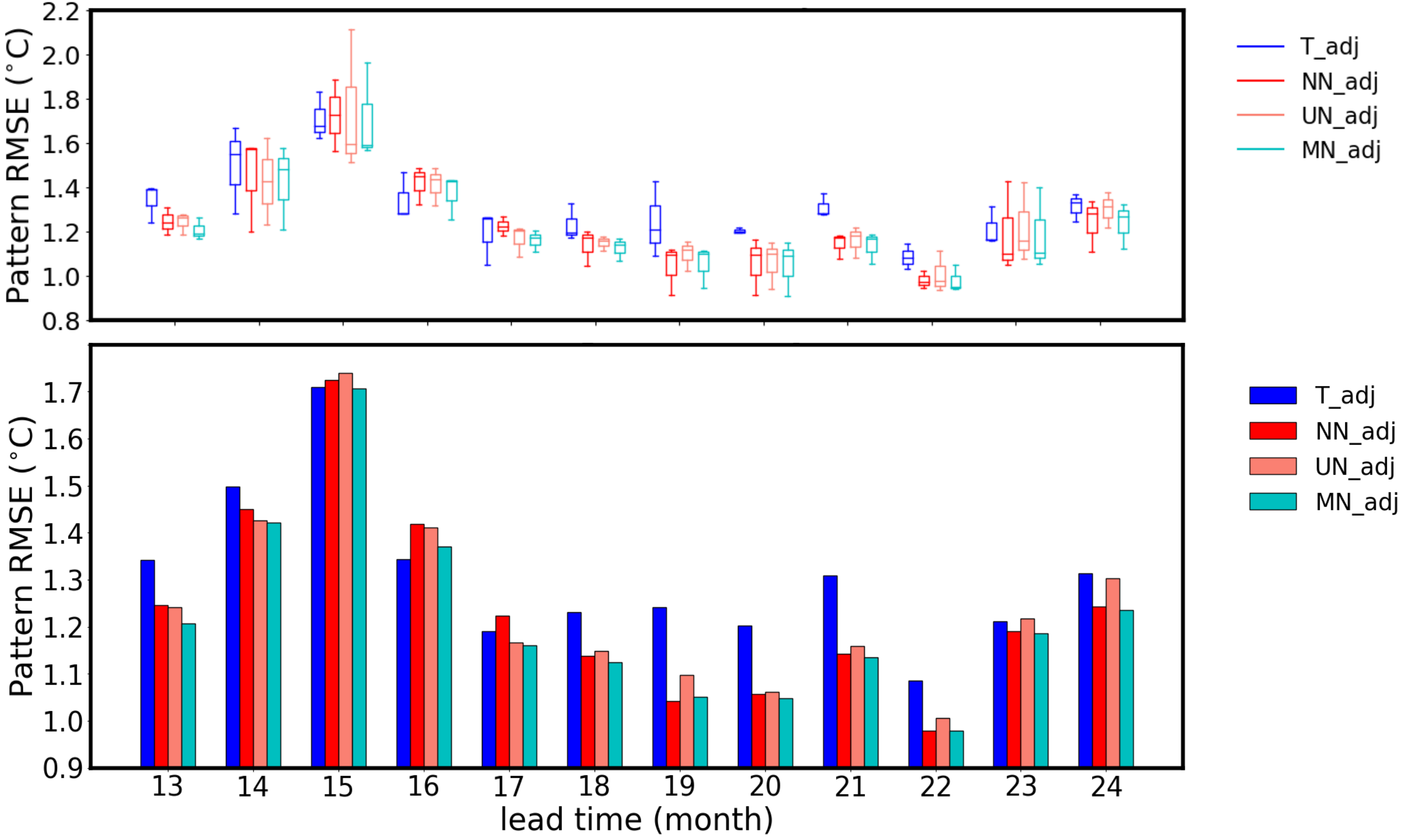
Model 2: Convolutional Autoencoder with skip-connections (U-Net like architecture)
Already applied for sub-seasonal forecast adjustment, fe. [Han et al. 2021]

Training performed on all lead times (focus on lead times 1 – 24)

First results:

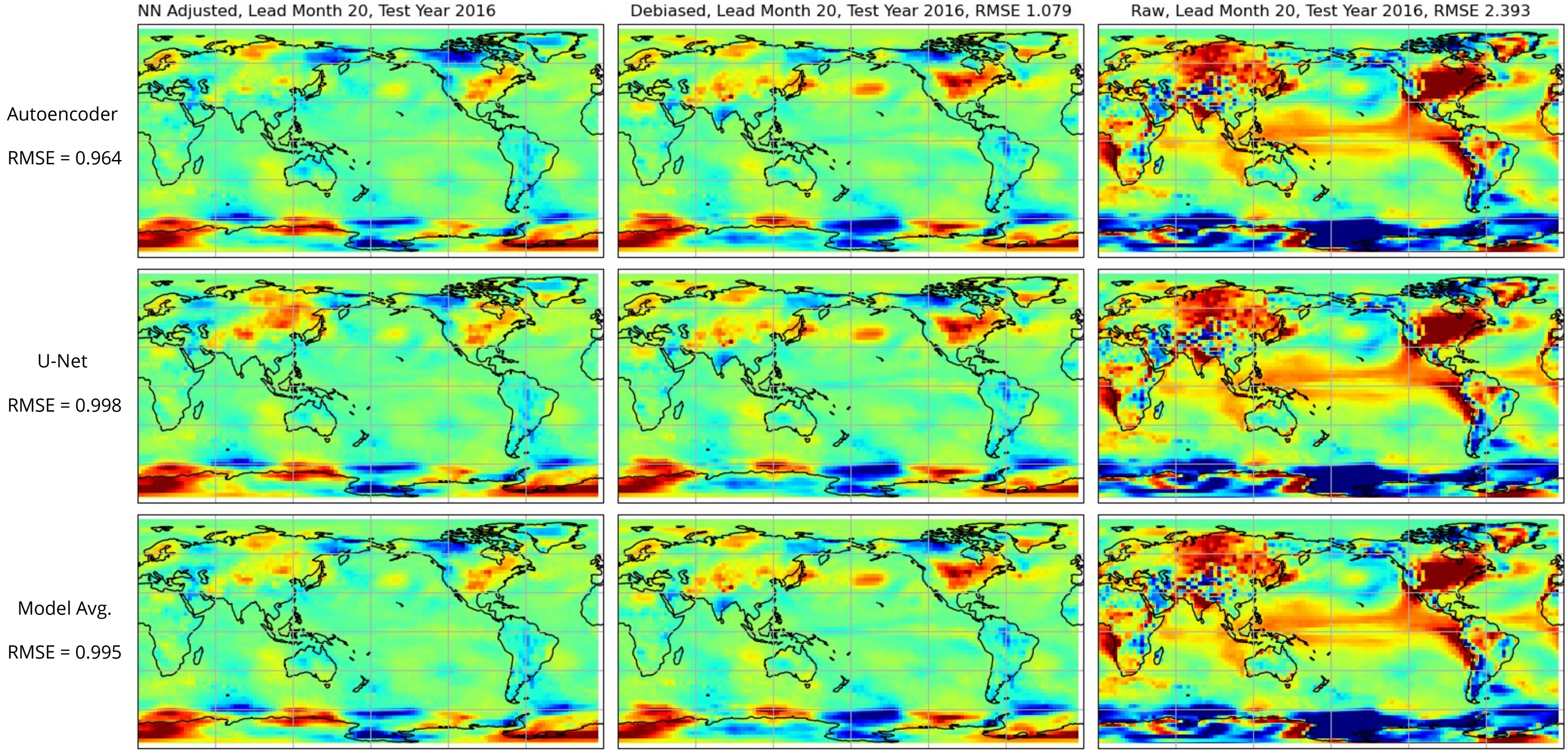
- NN-based adjustment improves upon traditional debiasing methods for *some* lead times
- training single model on all lead times shows better performance than using a separate model for every lead time
- Conv. Autoencoder with skip-connections does not outperform fully-connected Autoencoder

Pattern RMSE distribution over test years (global)

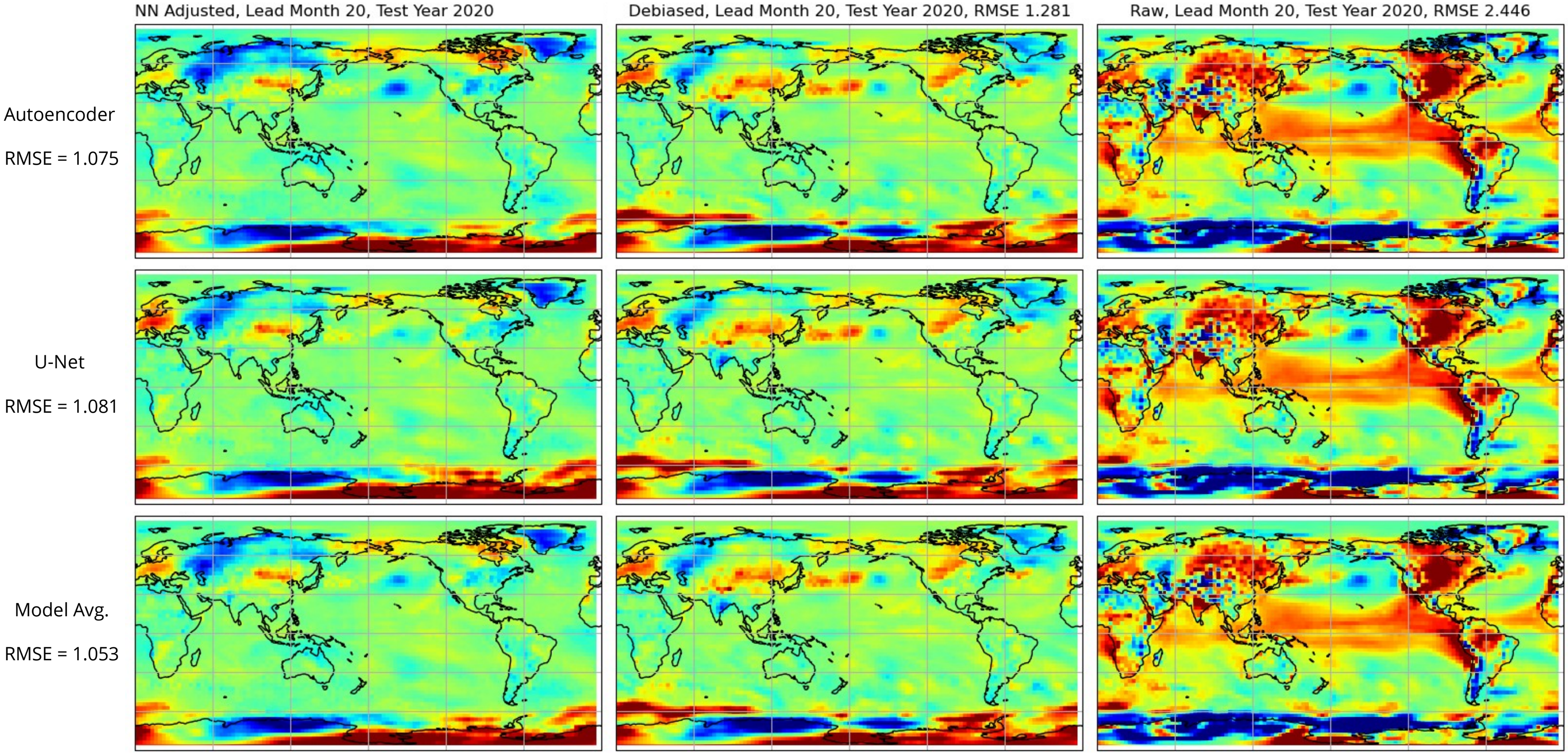


Model RMSE, Test Year 2016

A3



Model RMSE, Test Year 2020



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