



NSBC: Deep learning for non-stationary bias correcting of future climate projection

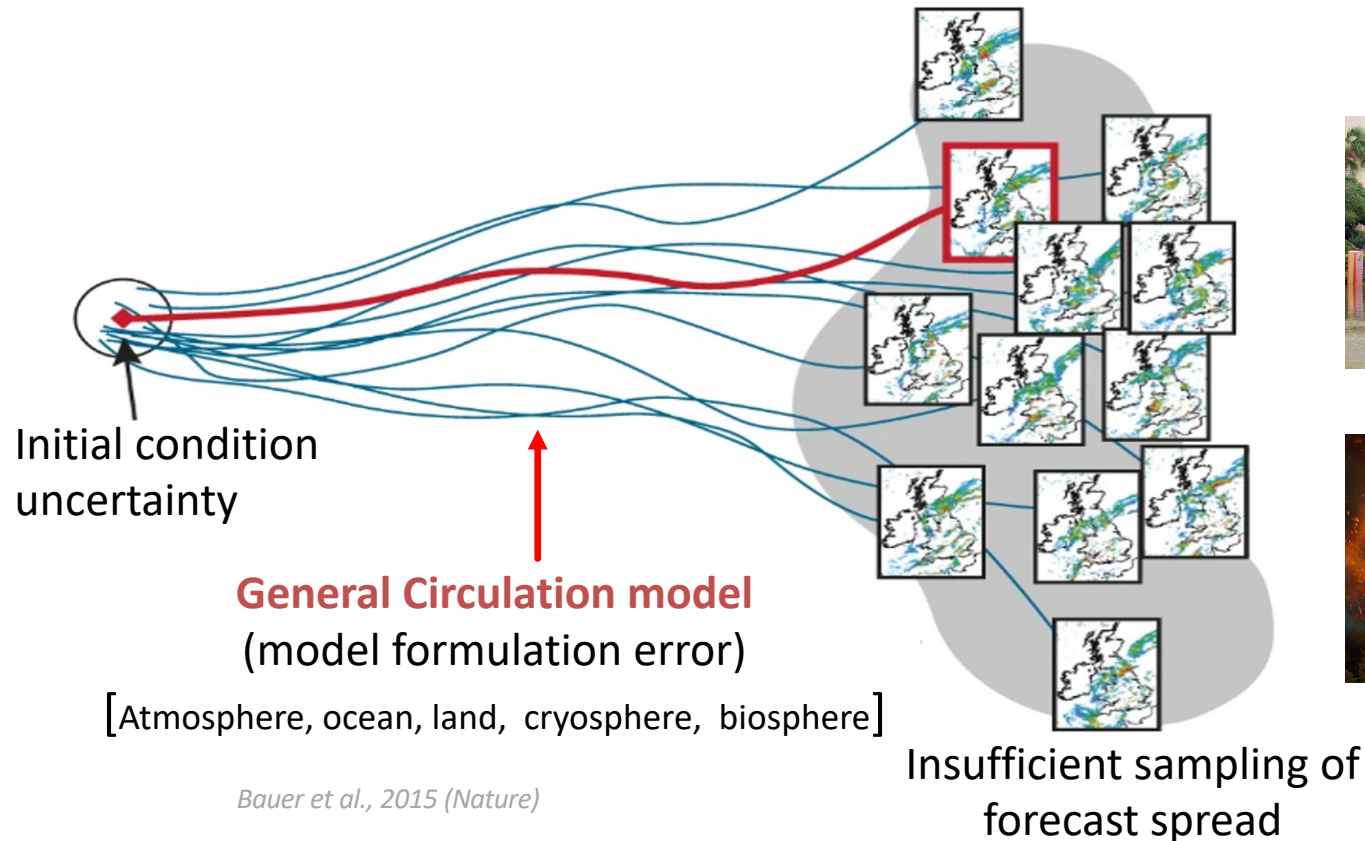
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Lawrence Livermore National Laboratory



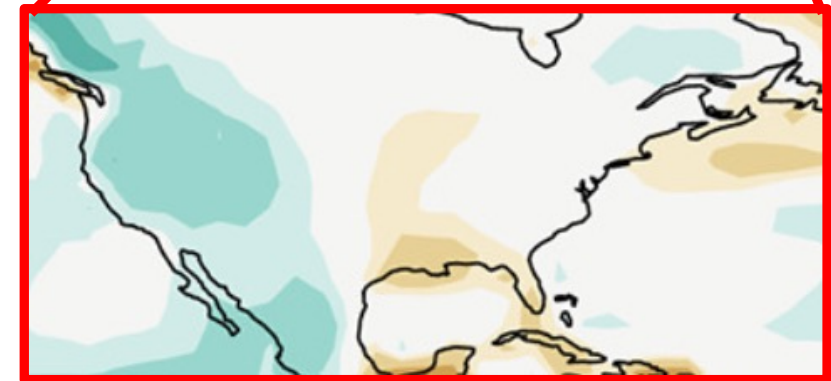
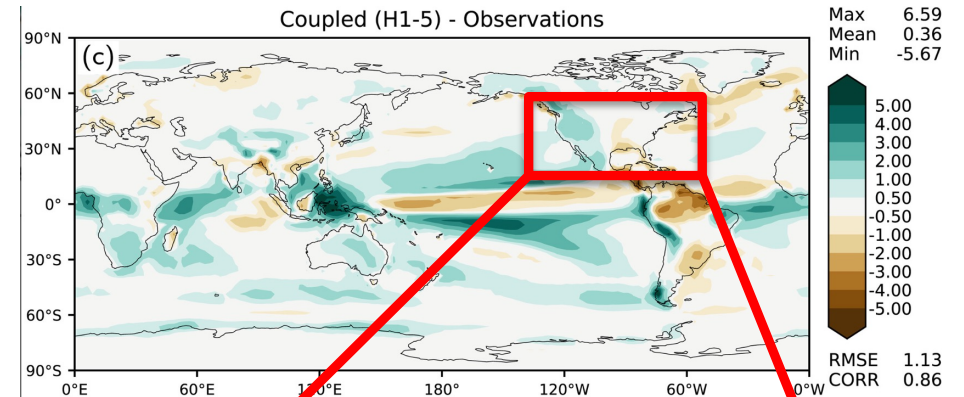
Global Climate Models (GCMs) have bias



- GCM biases: due to the parameterization and misrepresentation of physical processes, and coarse grid resolution.
- Reduce and correct the biases of GCM outputs through **post-processing** and statistical analysis.

E3SM (Energy Exascale Earth System Model) precipitation Bias

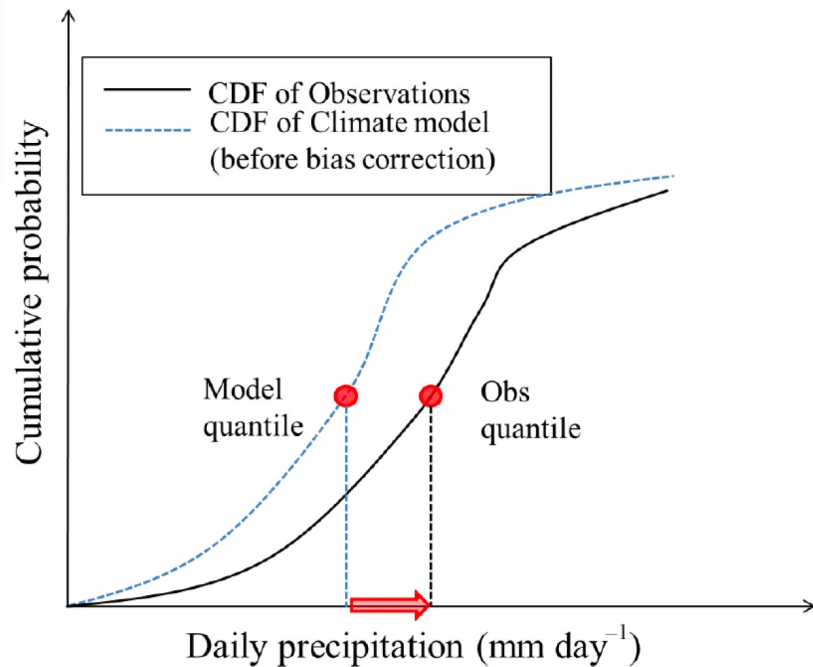
- too frequent, too weak
- Over predicts precipitation occurrence for rainfall rates less than 15mm/day and under predicts the occurrence of large rain events.
- Within CONUS, under-estimation of annual precipitation at the Gulf Coast and over-estimation at the West-Coast.
- AI-3 = 3 AMIP
- H1-5=five ensemble his



Golaz et al (2019)

Current bias correction methods — Quantile mapping

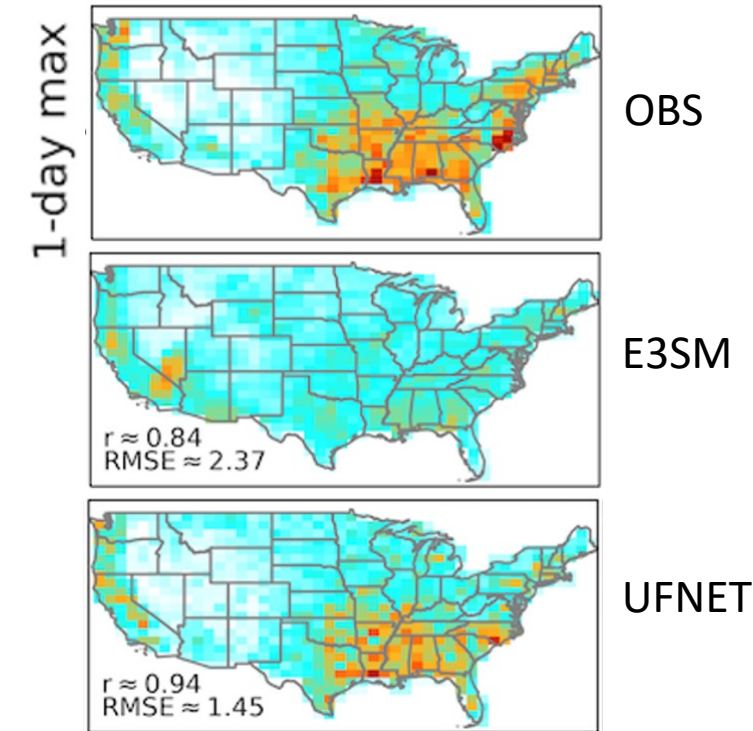
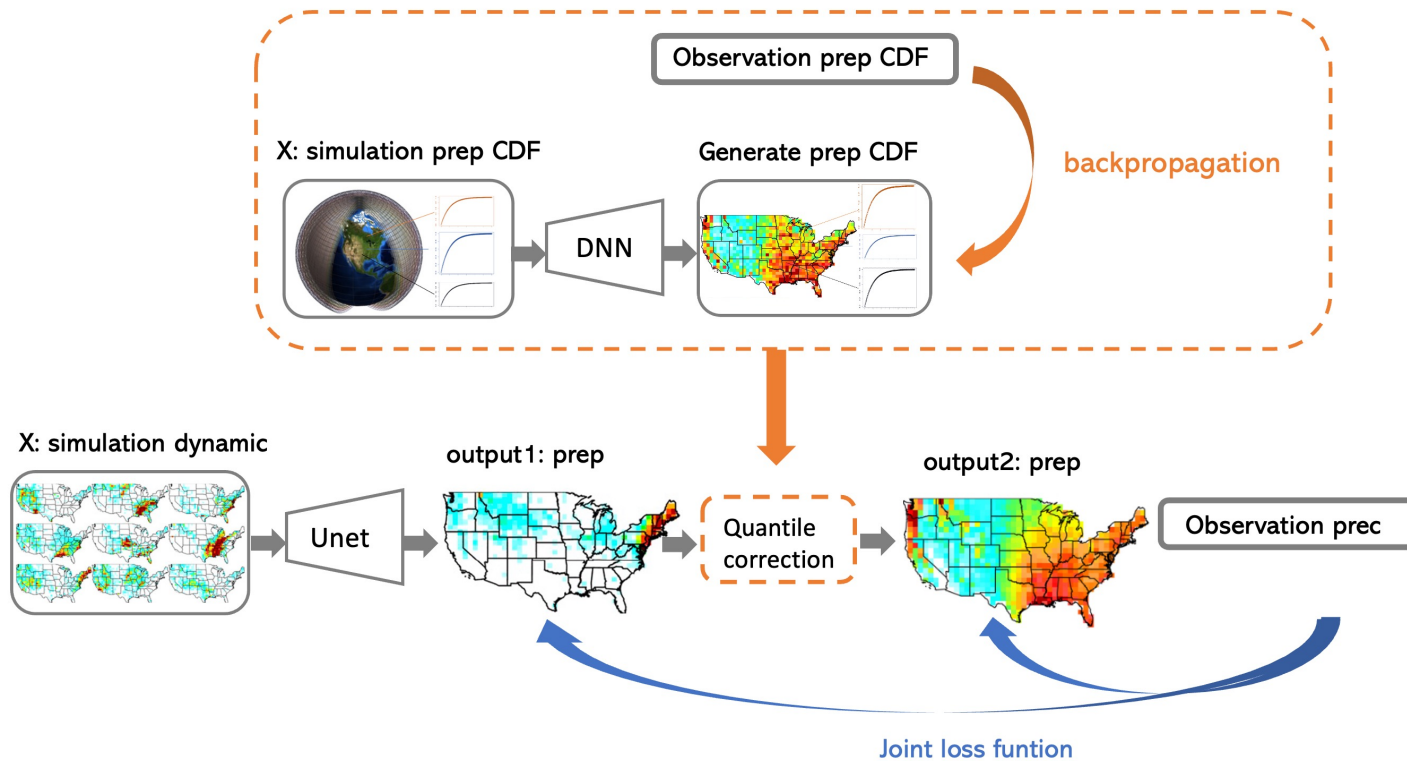
Quantile Mapping



- Post-processing bias correction method to correct systematic distributional biases within the climate model.
- maps the 1-D CDF of the simulated precipitation to that of the observed precipitation for a given historical period.
- Hard to improve the spatial structure.
- Can lead to unrealistic distributions.
- Accuracy deteriorates as historical and future simulation periods diverge.

Source: Kim, K. B., Kwon, H. H., & Han, D. (2016).

Deep learning based bias correction—— UFNet



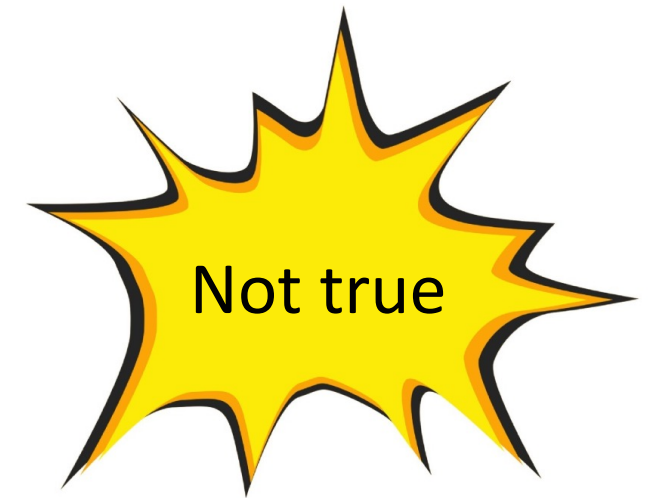
- UFNet combines two different deep learning architectures to effectively simulate highly realistic precipitation fields.
- UFNet bias corrects the spatial distribution of precipitation and represents extreme precipitation well.

Summary: current bias correction methods

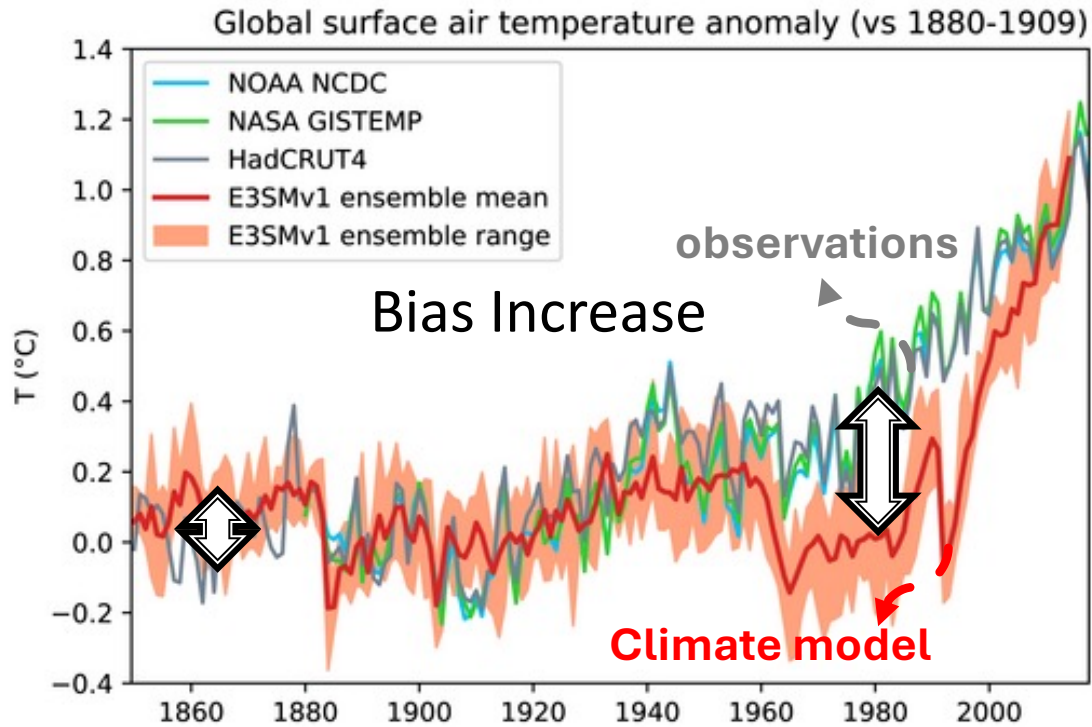
Basic thinking:

Train the bias correction based on historical period, but apply it on the current and future climate.

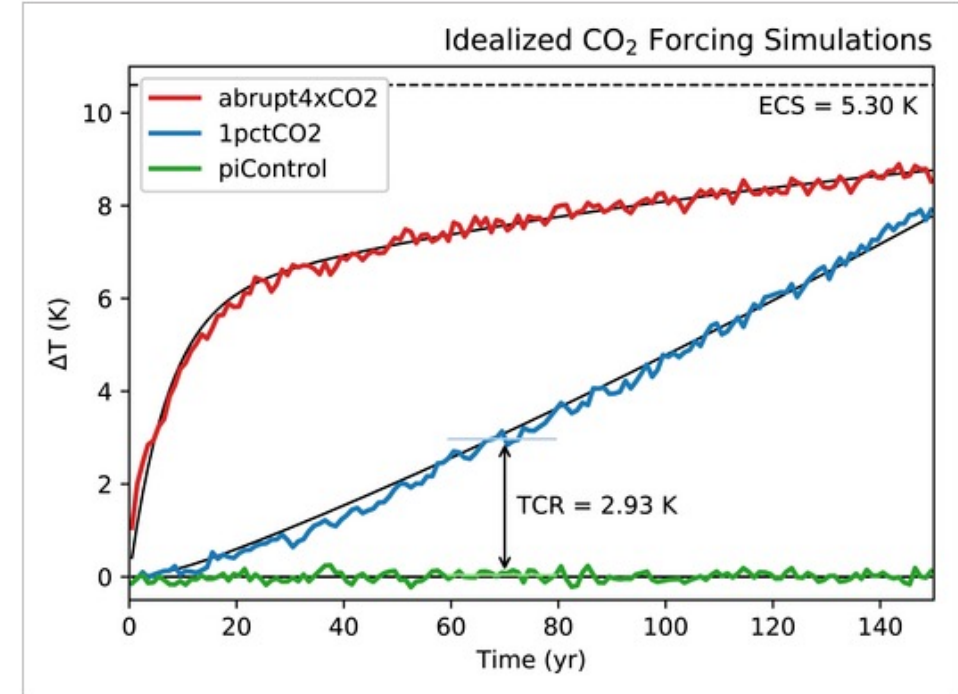
Assumption: stationarity of the bias from historical and future.



E3SM temperature bias changes



Bias increase from historical and current period.



The sensitivity of Climate model to CO₂ concentration is complex.

Golaz et al (2019)

Challenge

1. **How to capture the bias changes in the future and correct it?**

Develop a deep learning based bias correction framework, which can predict the changes of bias in the future.

2. **How to evaluate the performance of the bias correction model in the future?**

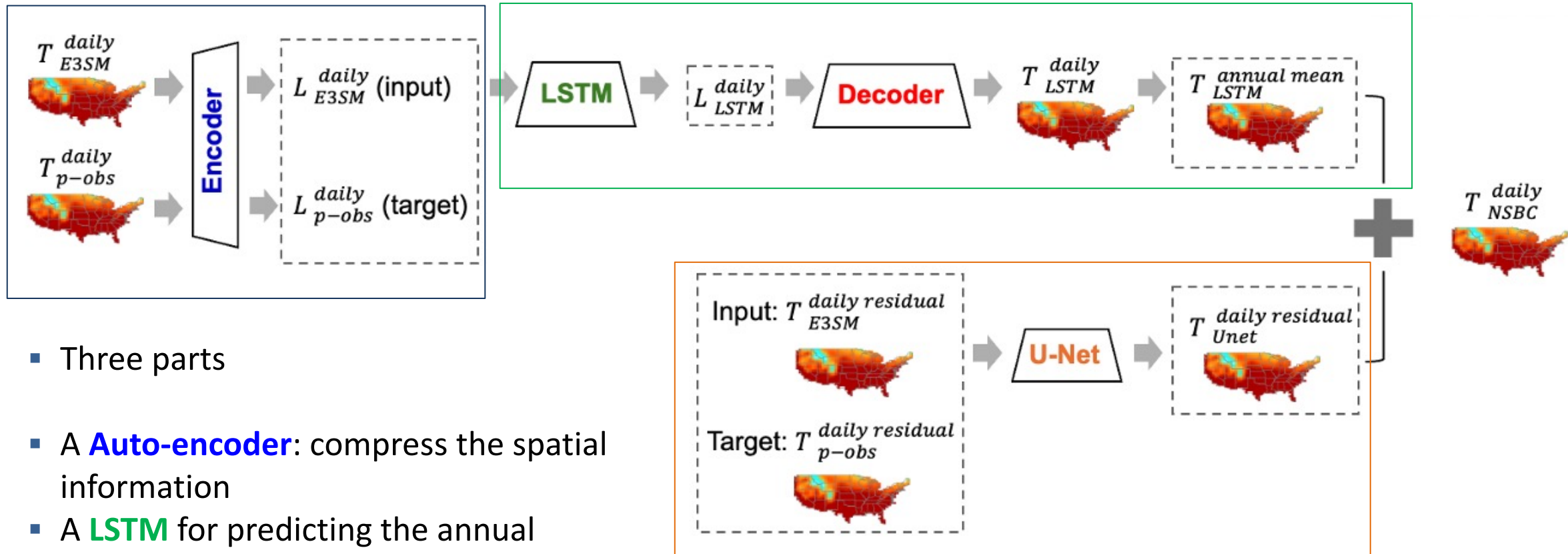
pseudo observation : GFDL

- High performance; large difference with E3SM temperature; long time period (1850-2099)

Data and Method

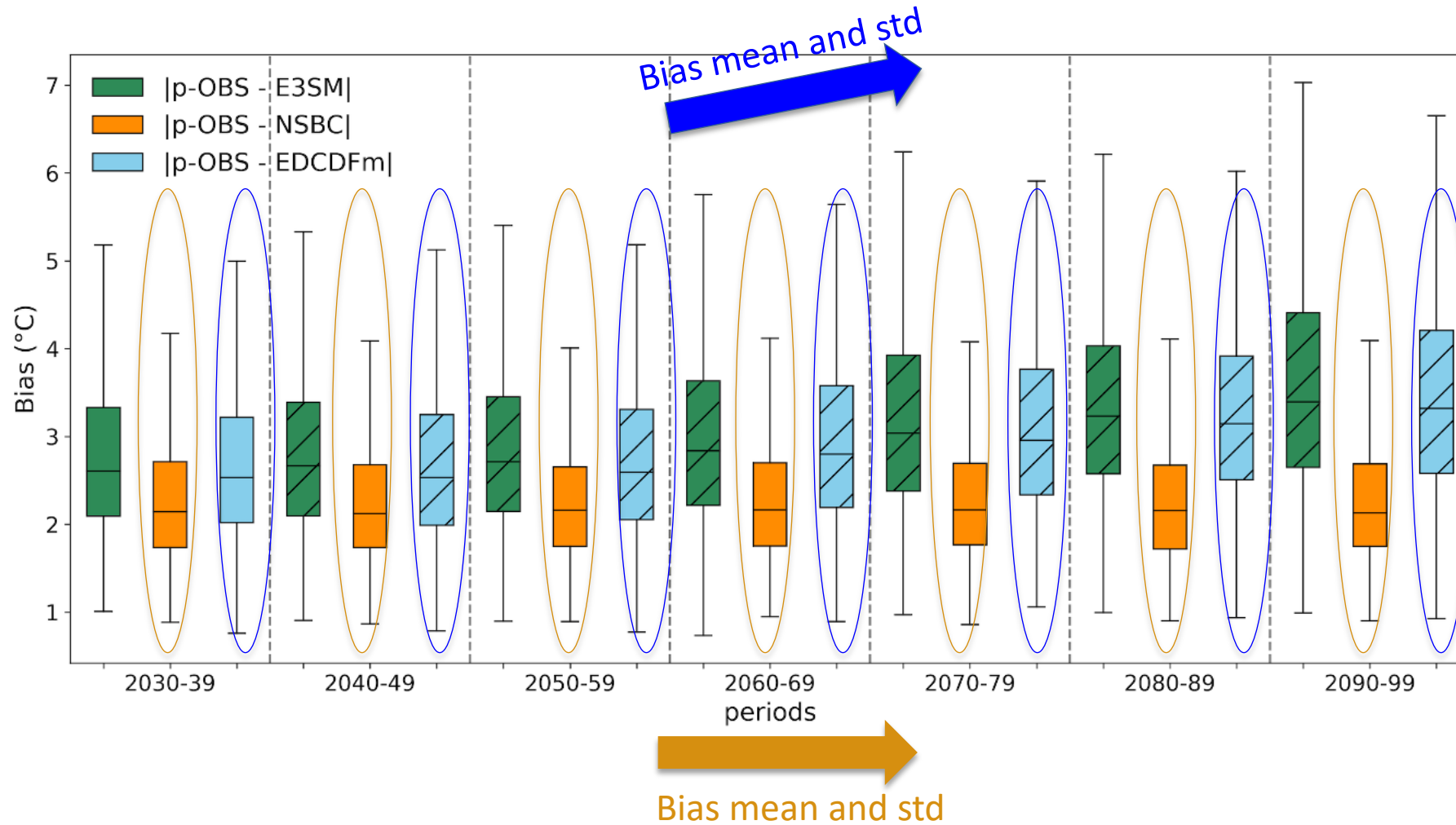
- Input feature: 2m temperature from E3SM
- pseudo observation : 2m temperature from GFDL
- Resolution: 1 degree, daily
- Training period: 1950-2021
- Test period : 2022-2099
- Baseline: EDCDFm bias correction method

NSBC structure

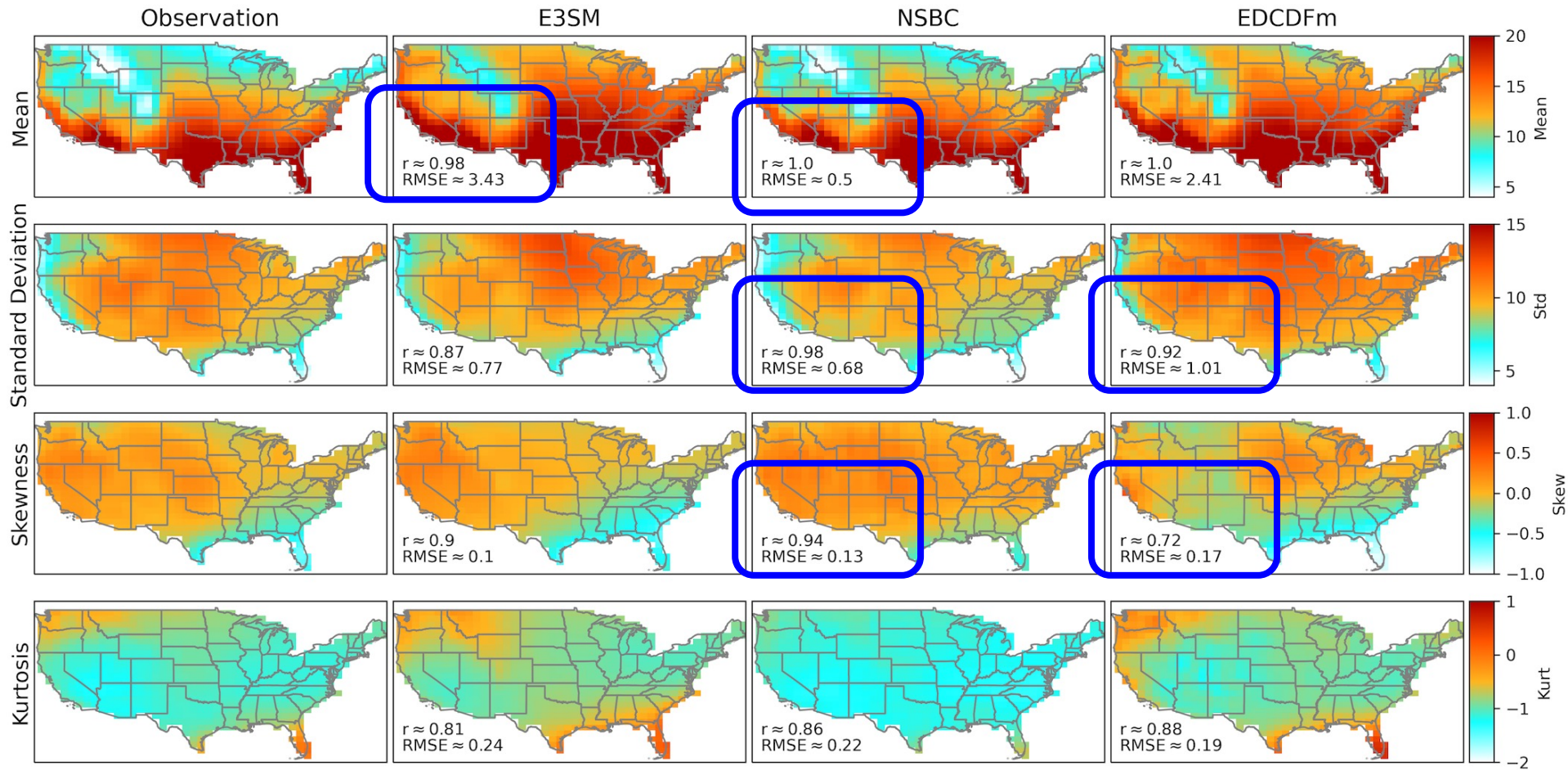


- Three parts
- A **Auto-encoder**: compress the spatial information
- A **LSTM** for predicting the annual temperature mean
- A **U-Net** for capture the daily residual bias in temperature.

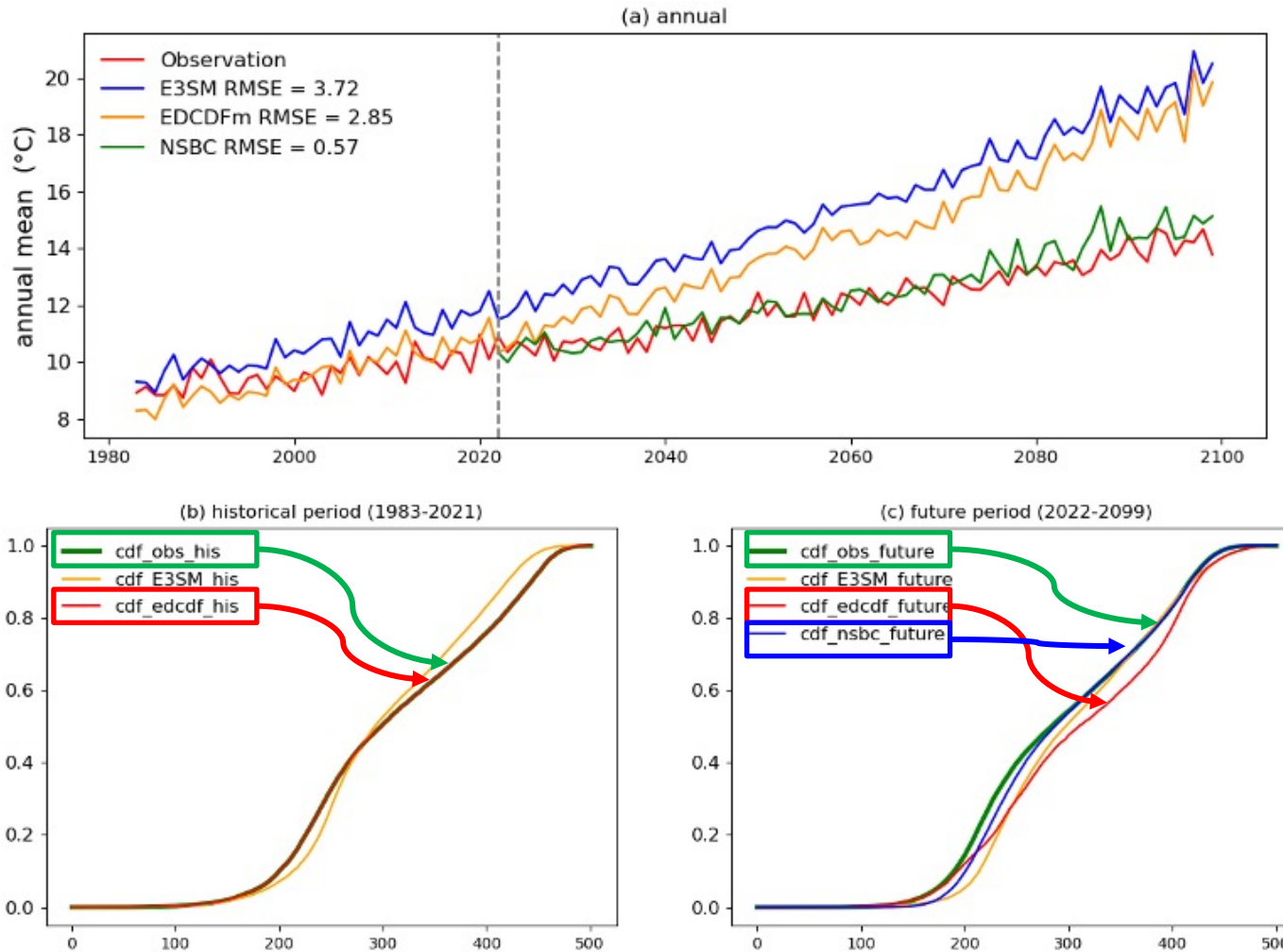
Evaluation: correct the mean and std of bias



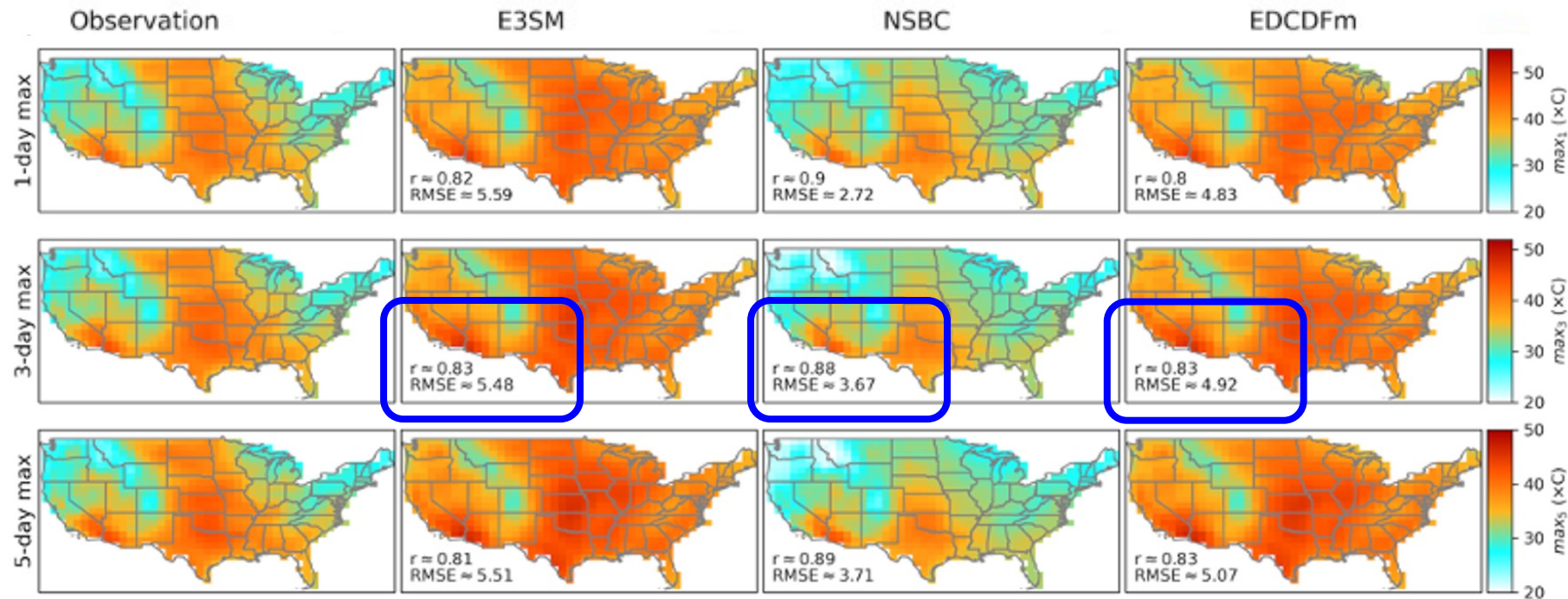
Evaluation: mean, std, skew, kurt



Evaluation: annual changes of temperature in the future



Evaluation: extremes



Summary

- NSBC combines three different deep learning architectures to effectively simulate highly realistic temperature fields, addressing the non-stationarity of biases - a significant challenge in bias correction for future climate projections.
- NSBC uses LSTM to extrapolate future mean temperature and captures future climate change features more accurately while preserving the spatial information's relevance.
- NSBC can make precise corrections to extreme temperature data, especially for heatwave events, which is crucial for studying extreme events and conducting risk assessments.

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