Deep Learning for Climate Model Output Statistics

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Motivation

- Numerical climate models provide important information for the prospective effects of climate change
- But they also suffer from **systematic errors** and **deficiencies in climate process representation**
- **Model output statistics (MOS)** use statistical techniques to reduce these errors
- Can MOS based on deep learning reduce these errors further?

Source: https://str.llnl.gov/december-2017/bader

Outline

- Model Output Statistics (MOS)
- Deep Learning for Climate MOS: ConvMOS
- Experiment
- Results
- Conclusion & Future Work

Model Output Statistics (MOS)

- Goal: Correct modeled climate variable (e.g. precipitation) to correspond more closely to observational data
- Previously published approaches:
  - Linear Regression ([Paeth 2011], [Eden et al. 2014])
  - Random Forests ([Sa'adi et al. 2017], [Noor et al. 2019])
  - Support Vector Machines ([Sa'adi et al. 2017], [Pour et al. 2018], [Ahmed et al. 2019])
  - Multilayer Perceptrons ([Moghim et al. 2017])
- Study area often represented as a 2D grid of locations

→Typically one MOS model per location of interest

Deep Learning for Climate MOS

- What types of errors are there in climate models?
  - Location specific errors
  - Systematic errors

- How to efficiently reduce both types of errors?
  - Combination of **per-location model parameters** (location specific errors) and **global model parameters** (systematic errors)

- Two types of modules:
  - Local network
  - Global network

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Deep Learning for Climate MOS

data science

Local Network

- Linear regression per location/cell
- Implemented with a 1D CNN
  - Easy integration into architecture
  - 1 Filter per location (groups = C_{in})

Input (C_{in}, H, W) → Reshape $(\mathrm{H} * \mathrm{W}, C_{in})$ → Conv C_{in} $(\mathrm{H} * \mathrm{W}, 1)$ → Reshape $(1, H, W)$

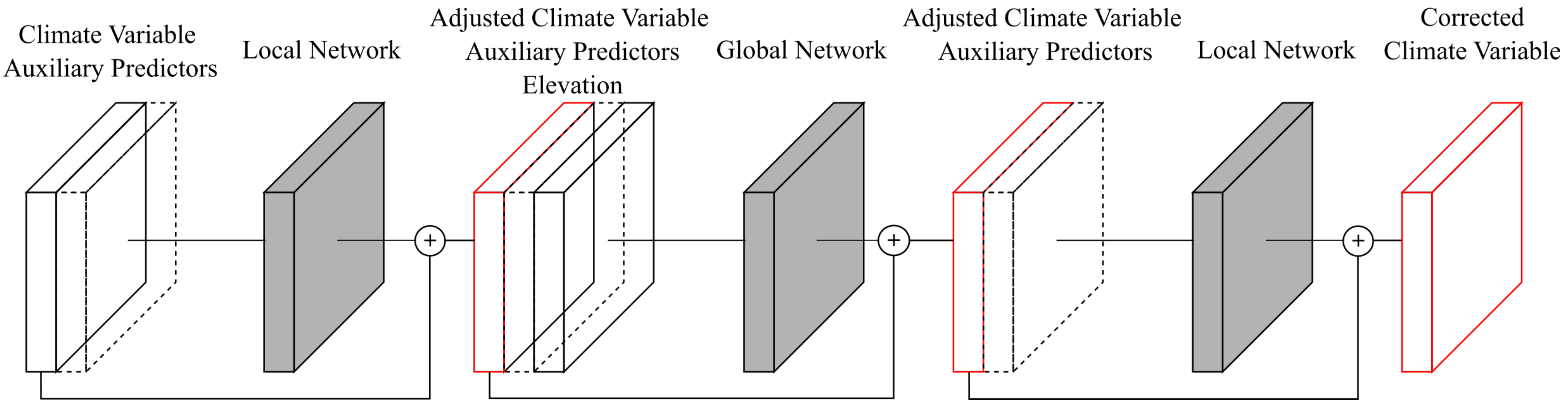
Global Network

- 2D CNN
- Activation: ReLU
- Padding: Keep height/width same

Input (C_{in}, H, W) → Conv 9x9 $(4, H, W)$ → Conv 1x1 $(8, H, W)$ → Conv 5x5 $(16, H, W)$ → Conv 3x3 $(1, H, W)$

C_{in} = # input channels = # number of predictors, H = Height, W = Width

ConvMOS



Climate Variable
Auxiliary Predictors
Local Network
Adjusted Climate Variable
Auxiliary Predictors
Elevation
Global Network
Adjusted Climate Variable
Auxiliary Predictors
Local Network
Corrected
Climate Variable

Experiment

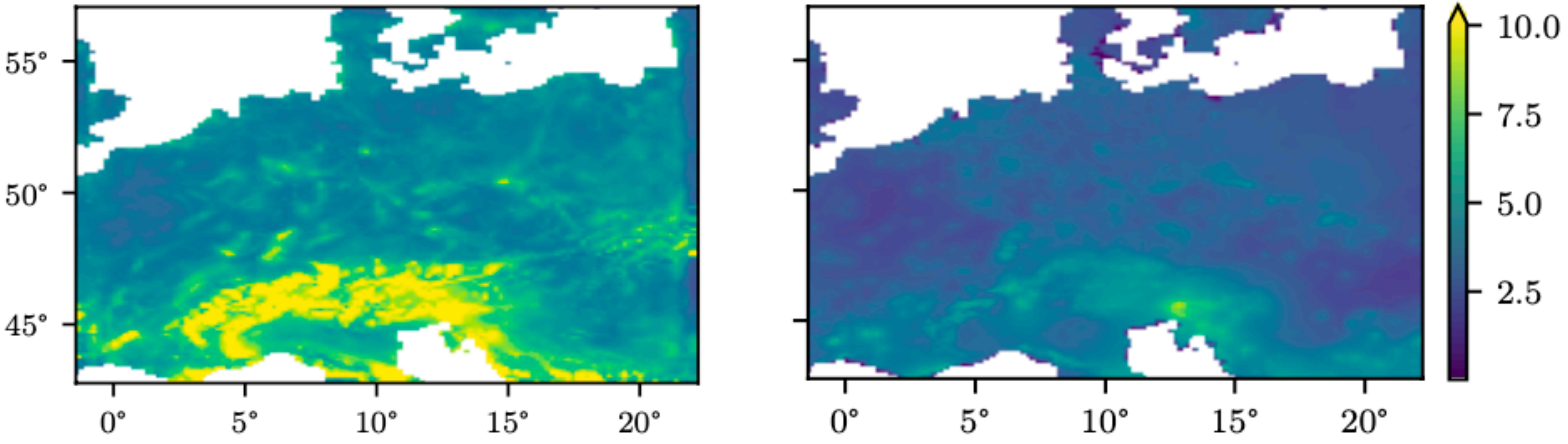
- Apply MOS for **daily precipitation** data of the climate model **REMO**
  - Study area: Extended German region at 0.11° resolution ($-1.43\circ$ to $22.22\circ$ E and $42.77\circ$ to $57.06\circ$ N)
  - **23 predictors** per cell (e.g. precipitation, temperature, wind, …)
  - Predictand: Observed precipitation from the **E-OBS** 19.0e dataset
  - Data split: Training set (2000-2009), Validation set (2010), Test set (2011-2015)
- Baseline MOS approaches for comparison:
  - Local linear regression (Lin)
  - Non-local Principal Component Regression (NL PCR)
  - Non-local Random Forest (NL RF)

Results

Metric / MOS	RMSE	Corr.	Skill	R^2	Bias
None	5.32	0.49	**0.93**	–28.24	0.31
Lin	3.77	0.49	**0.93**	0.23	0.03
NL PCR	3.37	0.62	0.92	0.36	**0.02**
NL RF	3.39	0.61	0.81	0.36	0.03
ConvMOS	**2.99 ± 0.01**	**0.72 ± 0.00**	0.92 ± 0.00	**0.49 ± 0.01**	–0.10 ± 0.06

Note: RMSE and Bias in mm, other metrics without unit

Results (RMSE in mm)



(a) REMO raw

(b) ConvMOS

Conclusion & Future Work

- Our work shows good results for Deep Learning MOS

  → Further work in this direction is promising
- Improved MOS allows for more accurate climate data especially at high spatial resolutions

  → More accurate information on prospective effects of climate change

- Future Work:
  - Further analysis
  - Additional comparisons (different study areas, different climate variable, …)
  - Incorporate time

Thank you for your attention