Assessing historical patterns of regional extreme precipitation change in observations and climate models using quantile regression and machine learning

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Research Questions

- How have different extreme precipitation levels changed over time?
- How do changes in observations compare to changes simulated by models in CMIP6?
- How have thermodynamics vs. dynamic climate changes affected extreme precipitation? Does this explain differences between observations and models?

Data

Global Precipitation Datasets:

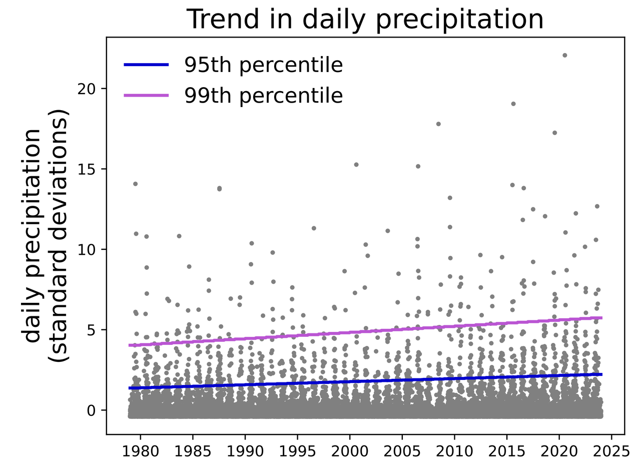
- CPC Global Unified Gauge-Based Analysis of Daily Precipitation **(CPC)** from 1979-2023
- Climate Hazards Group InfraRed Precipitation with Station data **(CHIRPS)** daily precipitation from 1981-2023
- Global Precipitation Climatology Centre **(GPCC)** monthly precipitation data from 1891-2019

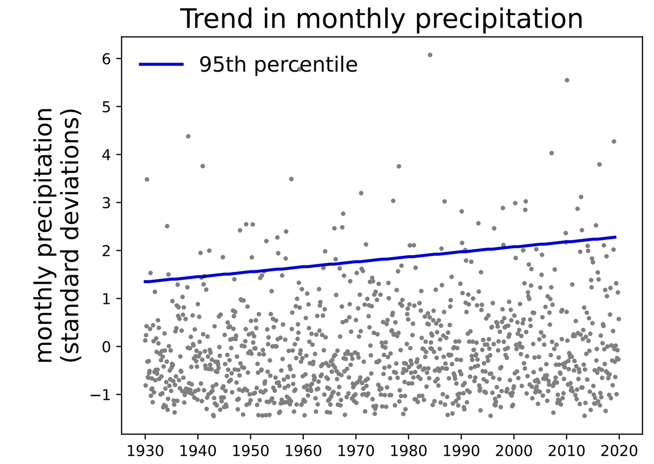
22 CMIP6 Model Simulations:

- **historical** + **SSP-585** simulations (r1i1p1f1 variant) (ACCESS-CM2, ACCESS-ESM1-5, AWI-CM-1-1-MR, BCC-CSM2-MR, CESM2, CESM2-WACCM, CMCC-CM2-SR5, CMCC-ESM2, CanESM5, EC-Earth3-CC, EC-Earth3-Veg-LR, FGOALS-g3, IITM-ESM, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, KIOST-ESM, MIROC6, MPI-ESM1-2-HR, MPI-ESM1-2-LR, MRI-ESM2-0, TaiESM1)

Quantile Regression

- Quantile regression estimates the conditional quantile of Y as a linear function of X (Koenker and Bassett, 1978)
- We use quantile regression to calculate trends in extreme precipitation percentiles over time





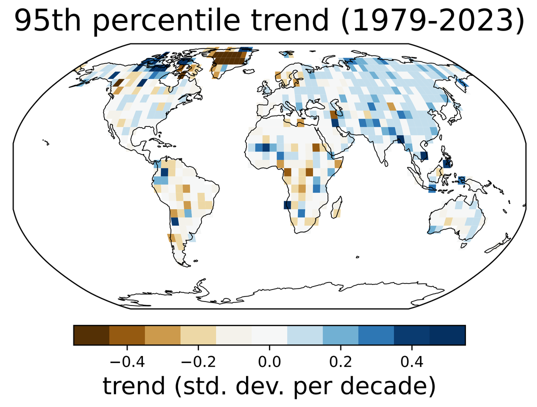
Quantile regression coefficients are calculated using the pyqreg Python library

Trends in **Daily** Extreme Precipitation

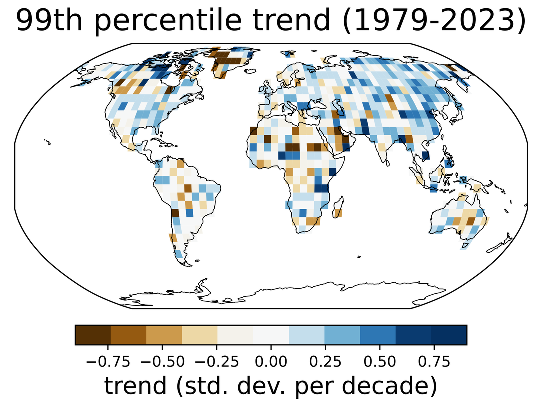
- We calculate trends in the 95th and 99th percentile of daily precipitation over **1979-2023**
- There are generally larger changes (both negative and positive) in the 99th percentile vs. the 95th percentile. In both cases, the sign of the trends are variable across the globe, likely due to a shorter 44-year record
- Many of the observed trends fall at the upper or lower end of the CMIP6 distribution

Observations (CPC):

95th percentile trend (1979-2023)

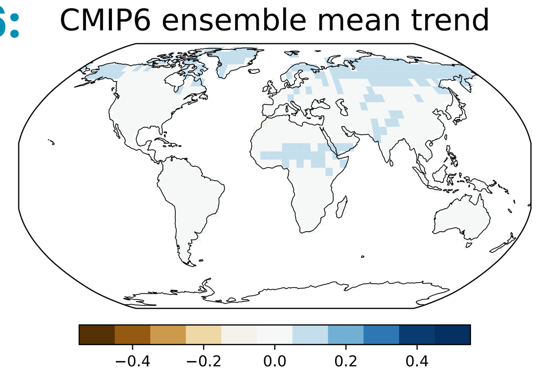


99th percentile trend (1979-2023)

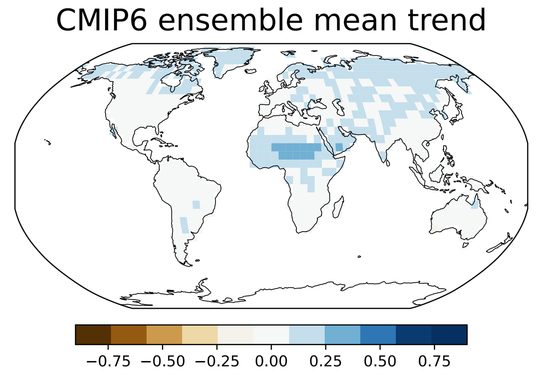


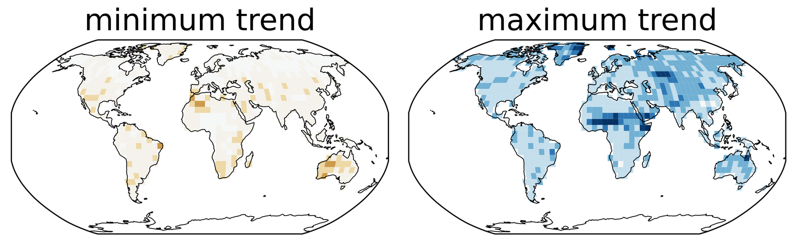
CMIP6:

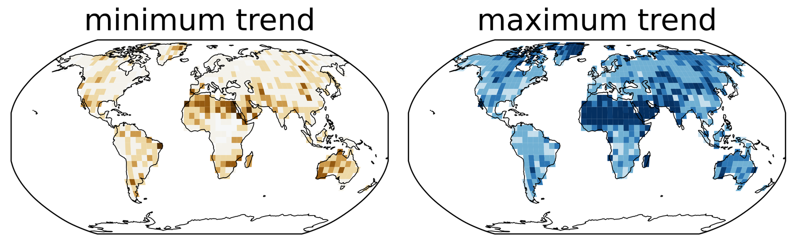
CMIP6 ensemble mean trend



CMIP6 ensemble mean trend

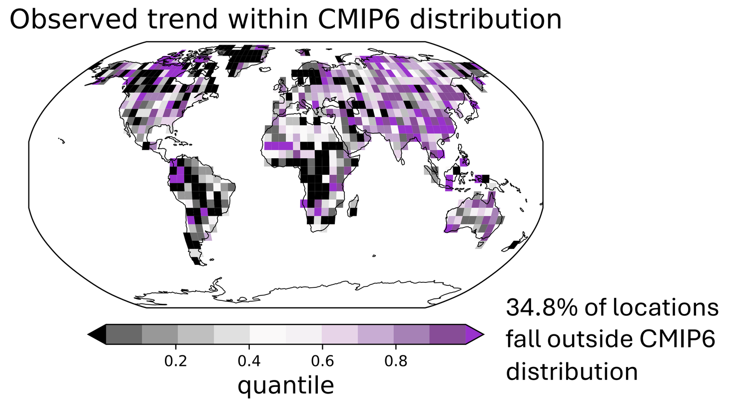




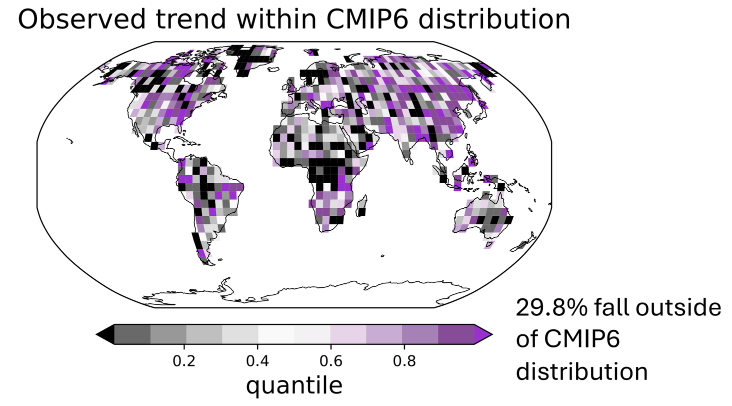


Observations vs. CMIP6:

Observed trend within CMIP6 distribution



Observed trend within CMIP6 distribution

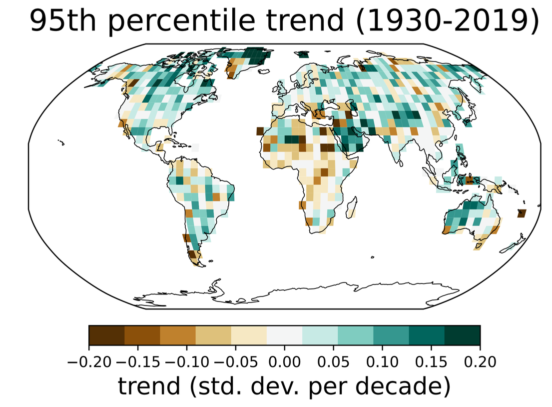


Trends in **Monthly** Extreme Precipitation

- We calculate trends in the 95th percentile of monthly precipitation over **1930-2019**
- Most regions show increases in extreme monthly precipitation, but the sign of the trends varies across the globe
- Many observed trends fall at the upper or lower end of the CMIP6 distribution

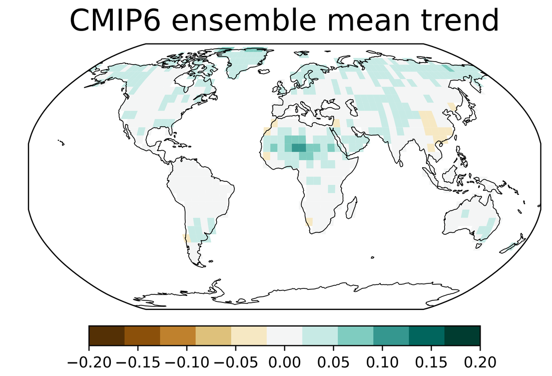
Observations (GPCC):

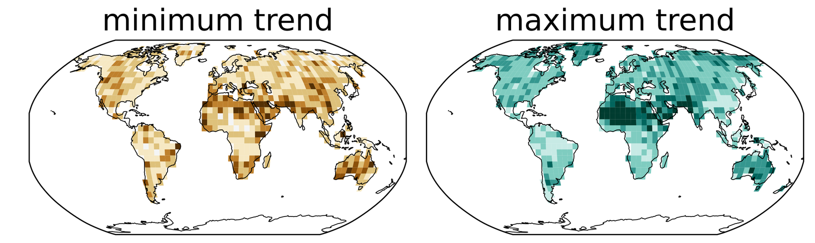
95th percentile trend (1930-2019)



CMIP6:

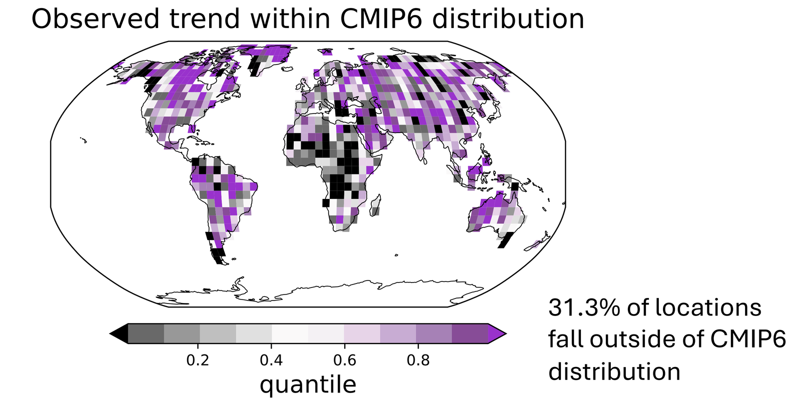
CMIP6 ensemble mean trend





Observations vs. CMIP6:

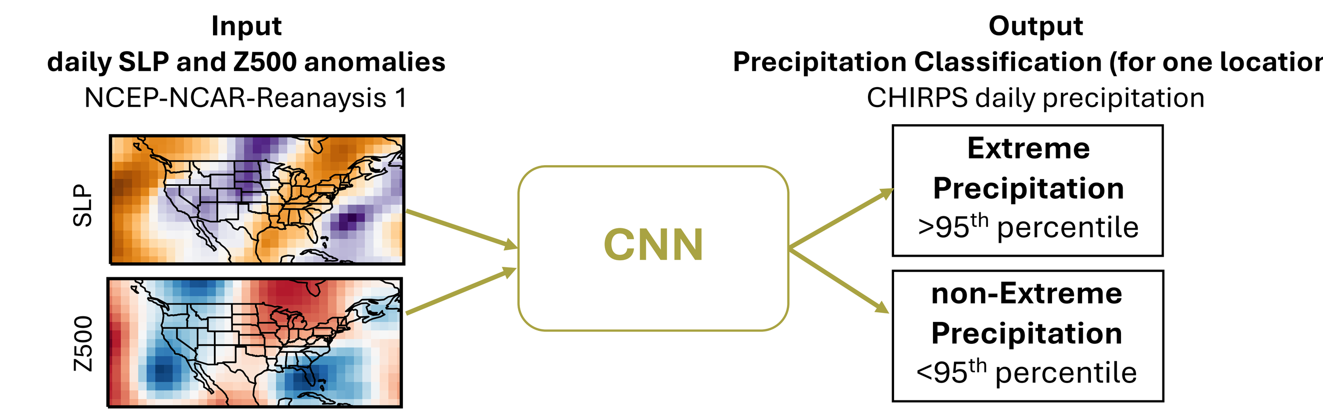
Observed trend within CMIP6 distribution



Identifying **atmospheric circulation patterns** associated with extreme precipitation using **neural networks**

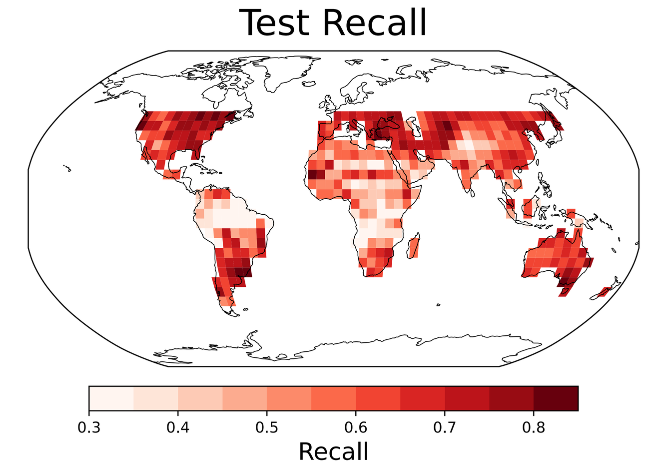
Methods

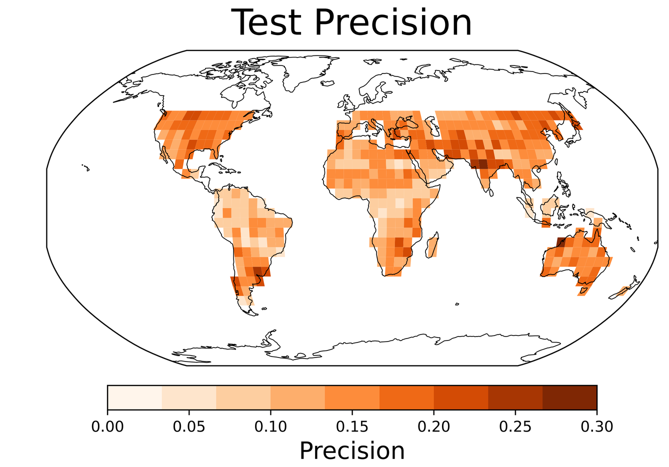
- Train a convolutional neural network (CNN) to learn "extreme precipitation circulation patterns"
- Each CNN learns to predict extreme precipitation **for one location** (5°x5° grid cell)
- *Adaptation of methods from Davenport and Diffenbaugh (2021)*
- Example CNN to predict extreme precipitation over Central US:

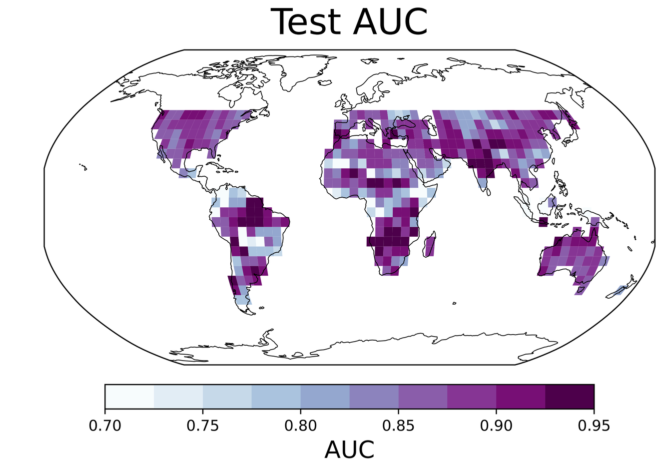


CNN Training Results

- **Recall** = fraction of true extremes that were correctly predicted
- **Precision** = fraction of extreme predictions that were true extremes
- **AUC** = "area under the ROC curve" (1 = perfect model)
- Maps show results on the testing data (days that the CNN doesn't see during training)



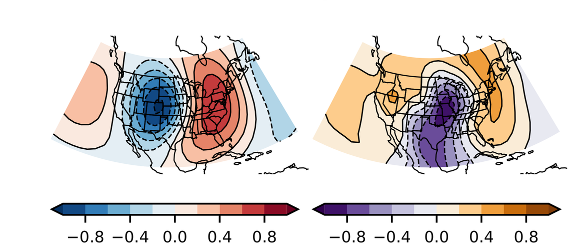




Next Steps!

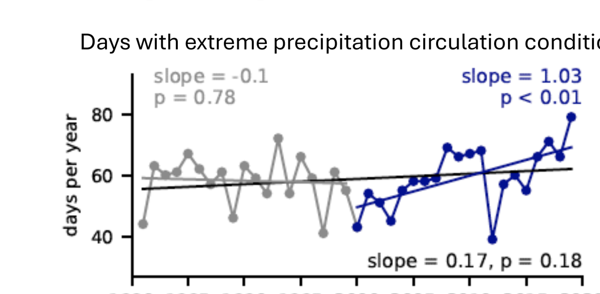
- Investigating circulation patterns learned by the CNNs in different regions

example composite **extreme precipitation circulation** condition in the Central US:



- **Applying the CNNs to GCM simulations**: Can the CNNs predict extreme precipitation in GCM simulations? **Are there model biases in extreme precipitation circulation patterns?**
- **How has the occurrence of extreme precipitation circulation patterns changed over time?**

example **changes in the frequency** of extreme precipitation circulation conditions in the Central US:



- Increasing the number of CMIP6 simulations analyzed
- Analyzing additional observational datasets (including regional datasets with longer temporal coverage)
- **Are there regions where historical extreme precipitation trends consistently fall outside the CMIP6 distribution?**

References

Davenport, F. V., & Diffenbaugh, N. S. (2021). Using machine learning to analyze physical causes of climate change: A case study of U.S. Midwest extreme precipitation. *Geophysical Research Letters*, 48, e2021GL093787. https://doi.org/10.1029/2021GL093787

Koenker, R. and Bassett, G. (1978). Regression Quantiles. Econometrica 46, 33. https://doi.org/10.2307/1913643