EGU24-6408, updated on 15 Aug 2024
https://doi.org/10.5194/egusphere-egu24-6408
EGU General Assembly 2024

Trend-Preserving Deep Learning for Multivariate Bias Correction and Downscaling of Climate Models

Di Tian and Fang Wang
Auburn University, Auburn, United States of America (tiandi@auburn.edu)

Global climate models (GCMs) or Earth system models (ESMs) exhibit biases, with resolutions too coarse to capture local variability for fine-scale, reliable drought and climate impact assessment. However, conventional bias correction approaches may cause implausible climate change signals due to unrealistic representations of spatial and intervariable dependences. While purely data-driven deep learning has achieved significant progress in improving climate and earth system simulations and predictions, they cannot reliably learn the circumstances (e.g., extremes) that are largely unseen in historical climate but likely becoming more frequent in the future climate (i.e., climate non-stationarity). This study shows an integrated trend-preserving deep learning approach can address the spatial and intervariable dependences and climate non-stationarity issues for downscaling and bias correcting GCMs/ESMs. Here we combine the super-resolution deep residual network (SRDRN) with the trend-preserving quantile delta mapping (QDM) to downscale and bias correct six primary climate variables at once (including daily precipitation, maximum temperature, minimum temperature, relative humidity, solar radiation, and wind speed) from five state-of-the-art GCMs/ESMs in the Coupled Model Intercomparison Project Phase 6 (CMIP6). We found that the SRDRN-QDM approach greatly reduced GCMs/ESMs biases in spatial and intervariable dependences while significantly better reducing biases in extremes compared to deep learning. The estimated drought based on the six bias-corrected and downscaled variables captured the observed drought intensity and frequency, which outperformed the state-of-the-art multivariate bias correction approach, demonstrating its capability for correcting GCMs/ESMs biases in spatial and multivariable dependences and extremes.