Exploring variability in seasonal average and extreme precipitation using unsupervised machine learning.

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Focal Area(s)

We will use unsupervised machine learning methods to identify and quantify the influence of large scale natural modes of climate variability to gain insight into the observed and simulated seasonal average and extreme precipitation changes.

Science Challenge

A recent paper, led by co-PI Mark Risser, finds that although much of the variability in seasonal average and extreme precipitation over CONUS is unforced, the effect of large-scale modes of circulation variability (such as ENSO, AMO, PNA, etc.) can be detected and attributed. However, it is unclear whether or not unsupervised learning methods can (a) replicate this finding or (b) yield insight into possible nonlinear behavior that was not captured in the initial statistical analysis. Further work would entail extending this framework to other global land areas.

Rationale

Understanding the mechanisms behind present day year-to-year variability in seasonal average and extreme precipitation is critical for predictability of seasonal precipitation, water resource management, and understanding any future changes to variability. The key question in future climate change is how external forcing from anthropogenic changes to the composition of the atmosphere combines with natural variability. For precipitation metrics, this undoubtedly varies across the planet depending on both long distance teleconnections as well as the local influence of circulation variability and changes. Machine learning provides an alternative to traditional statistical analyses as well as opens the possibility of undiscovered influences (including nonlinear behavior with known modes) on seasonal average and extreme precipitation.

Narrative

We propose to apply Artificial Neural Networks (ANNs) and Multilayer Perceptrons (MLPs) directly to observed seasonal average and extreme CONUS precipitation and test the machine learned relationships to those found in Risser et al. (2021). This approach has two aims: first, the statistical methodology in Risser et al. (2021) assumed a fixed set of known modes of variability (e.g., ENSO, PNA) and applied these to all of CONUS, while also assuming linear relationships between the climate indices and seasonal precipitation. The potential benefits of using ML methods to replicate this work are twofold: first, ANNs can capture asymmetries or nonlinearities in these relationships (e.g., the La Niña influence

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is not equal to the negative of the El Niño influence). Determining whether or not such nonlinearities exist is the first step to quantifying them. The existence of such nonlinearities would enable improvements in predictability from these indices and a deeper understanding of the upstream process drivers associated with these modes. Second, while the Risser et al. (2021) methodology estimated relationships between modes of variability and seasonal precipitation locally, there may be additional modes of variability (which may themselves be unknown) that vary across CONUS with respect to how they influence seasonal precipitation. If our efforts to replicate Risser et al. (2021) are judged successful, we would extend the analysis to REGEN, an observed global daily precipitation dataset over land (Contractor et al., 2019). We would further the AI analysis to projected precipitation quantities from the CMIP5 and CMIP6 model ensembles.

References

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