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Latent Linear Adjustment Autoencoder: a novel method for estimating dynamic precipitation at high resolution

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A key challenge in climate science is to quantify the forced response in impact-relevant variables such as precipitation against the background of internal variability, both in models and observations. Dynamical adjustment techniques aim to remove unforced variability from a target variable by identifying patterns associated with circulation, thus effectively acting as a filter for dynamically induced variability. The forced contributions are interpreted as the variation that is unexplained by circulation. However, dynamical adjustment of precipitation at local scales remains challenging because of large natural variability and the complex, nonlinear relationship between precipitation and circulation particularly in heterogeneous terrain.

In this talk, I will present the Latent Linear Adjustment Autoencoder (LLAAE), a novel statistical model that builds on variational autoencoders. The Latent Linear Adjustment Autoencoder enables estimation of the contribution of a coarse-scale atmospheric circulation proxy to daily precipitation at high resolution and in a spatially coherent manner. To predict circulation-induced precipitation, the LLAAE combines a linear component, which models the relationship between circulation and the latent space of an autoencoder, with the autoencoder's nonlinear decoder. The combination is achieved by imposing an additional penalty in the cost function that encourages linearity between the circulation field and the autoencoder's latent space, hence leveraging robustness advantages of linear models as well as the flexibility of deep neural networks.

We show that our model predicts realistic daily winter precipitation fields at high resolution based on a 50-member ensemble of the Canadian Regional Climate Model at 12 km resolution over Europe, capturing, for instance, key orographic features and geographical gradients. Using the Latent Linear Adjustment Autoencoder to remove the dynamic component of precipitation variability, forced thermodynamic components are expected to remain in the residual, which enables the uncovering of forced precipitation patterns of change from just a few ensemble members. We extend this to quantify the forced pattern of change conditional on specific circulation regimes.

Future applications could include, for instance, weather generators emulating climate model simulations of regional precipitation, detection and attribution at subcontinental scales, or statistical downscaling and transfer learning between models and observations to exploit the typically much larger sample size in models compared to observations.