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Machine Learning for Multivariate Downscaling: A Generative Model Inspired by Forecast Evaluation

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To complement computationally expensive regional climate model (RCM) simulations, machine learning methods can predict the high-resolution RCM data from low-resolution global climate model (GCM) input. Instead of merely targeting the conditional mean of the RCM field given the GCM data, more recent works are based on generative adversarial networks or diffusion models and aim to learn the full conditional distribution. In this spirit, we present a novel generative model that relies on statistical tools from forecast evaluation. The model can sample several plausible RCM realisations and enables assessing their variability. To achieve this goal, we use a simple neural network architecture that predicts Fourier coefficients of the high-resolution fields for multiple variables jointly (temperature, precipitation, solar radiation and wind). The loss function of our model is a proper scoring rule that measures the discrepancy between the model's predictive distribution and the RCM's true distribution. The score is minimised if both distributions agree. Our generative model is trained on multiple GCM-RCM combinations from the Euro-Cordex project. Furthermore, we show how the framework can be augmented to perform a bias-correction task: With a modified loss function, it is possible to generate data from the observational distribution, for example resembling gridded E-OBS data. To summarise, our work presents a machine learning method that allows us to generate multivariate high-resolution climate data, and can be extended flexibly to include further variables or downscale and bias-correct future projections.