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Revisiting Tabular Machine Learning and Sequential Models to Advance Climate Downscaling

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Recent advancements in the empirical downscaling of climate fields using Machine Learning have predominantly leveraged computer vision approaches. These methods treat a climate field as an image channel, applying image processing techniques to automatically extract features for the downscaling model from its latent space embeddings. In contrast, this work aims to revisit and validate the potential of tabular and sequential models in the context of grid-by-grid downscaling, where each grid cell in a map is individually downscaled and input features for the downscaling model are selected manually by a climate expert. We present downscaling results for precipitation and evapotranspiration using three distinct models: Long Short-Term Memory (LSTM), Multi-layer Perceptron (MLP), and a hybrid approach that combines Linear Regression with Random Forest. Our discussion includes the setup and optimization strategies for these models to enhance their ability to capture extremes. The merits of this grid-by-grid approach are highlighted, focusing not only on performance and effectiveness in preserving spatial features but also on its flexibility, spatial transferability, ease of model fine-tuning, and training efficiency.