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A Convolutional Neural Network approach for downscaling climate model data in Trentino-South Tyrol (Eastern Italian Alps)

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Statistical downscaling is a very popular technique to increase the spatial resolution of existing global and regional climate model simulations and to provide reliable climate data at local scale. The availability of tailored information is particularly crucial for conducting local climate assessments, climate change studies and for running impact models, especially in complex terrain. A crucial requirement is the ability to reliably downscale the mean, variability and extremes of climate data, while preserving their spatial and temporal correlations.

Several machine learning-based approaches have been proposed so far to perform such task by extracting non-linear relationships between local-scale variables and large-scale atmospheric predictors and they could outperform more traditional statistical methods. In recent years, deep learning has gained particular interest in geoscientific studies and climate science as a promising tool to improve climate downscaling thanks to its greater ability to extract high-level features from large datasets using complex hierarchical architectures. However, the proper network architecture is highly dependent on the target variable, time and spatial resolution, as well as application purposes and target domain.

This contribution presents a Deep Convolutional Encoder-Decoder Network (DCEDN) architecture which was implemented and evaluated for the first time over Trentino-South Tyrol in the Eastern Italian Alps to derive 1-km climate fields of daily temperature and precipitation from ERA-5 reanalysis. We will show that in-depth optimization of hyper-parameters, loss function choice and sensitivity analyses are essential preliminary steps to derive an effective architecture and enhance the interpretability of results and of their variability. The validation of downscaled fields of both temperature and precipitation confirmed the improved representation of local features for both mean and extreme values, even though lower performances were obtained for precipitation in reproducing small-scale spatial features. In all cases, DCEDN was found to outperform classical schemes based on linear regression and the bias adjustment procedures used as benchmarks. We will discuss in detail the advantages and recommendations for the integration of DCEDN as an efficient post-processing block in climate data simulations supporting local-scale studies. The model constraints in feature extraction, especially for precipitation, over the limited extent of the study domain will also be explained along with potential future developments of such type of

networks for improved climate science applications.