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Spatially-Coherent Probabilistic Downscaling of Daily Precipitation in Ungauged Mountain Locations: a Transfer Learning Study in the Swiss Alps and the Langtang Valley, Nepal.

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Accurate downscaling of daily precipitation is crucial for hydrological and climate modeling, especially in regions with complex terrain and a lack of observational data. In such regions, climate reanalysis are not reliable and thus accurate downscaling is usually limited to those locations captured by a (discrete) network of in-situ measurements instead. For this reason, learning to downscale in ungauged locations, whilst maintaining the spatial structure of precipitation, is crucial to effectively downscale (gridded) climate simulations.

This study introduces a Gaussian Process - Multi-Layer Perceptron (GP-MLP) latent variable model tailored for the probabilistic downscaling of daily precipitation in ungauged locations. By generating spatially coherent precipitation fields, this model addresses key challenges in regional climate impact assessments and water resource management.

The GP-MLP model consists of an MLP that performs non-linear regression, mapping a set of inputs to distributional parameters of a given probability distribution for each spatio-temporal locations, and we induce spatial correlation between locations with a latent variable modelled by a GP We jointly learn the GP and MLP parameters using variational inference, which critically allows us to model non-Gaussian probability distributions.

We test our approach in two geographically and climatologically diverse regions: the Swiss Alps and the Langtang Valley in Nepal. The Swiss Alps, with their complex terrain and relatively dense observational network, serve as an ideal region for the initial training of our model. In the Langtang Valley, a high-mountain region with limited ground-based observations, we employ a transfer learning strategy on the model pre-trained in the Swiss Alps. This process involves fine-tuning the model parameters to the unique climatic and topographical features of the Himalayas, thereby enhancing its performance in predicting daily precipitation in this data-sparse region.

Our preliminary findings demonstrate the model's strong capability in producing accurate and spatially coherent predictions of daily precipitation for ungauged locations. The probabilistic nature of the model's outputs is particularly valuable, providing not only predictions of daily precipitation but also quantifying the associated uncertainties - a crucial aspect for risk management in hydrology and agriculture in areas where the paucity of data has traditionally

limited detailed climate impact analysis.