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# Next-Gen Climate Projections for Switzerland: Blending Bias Correction with Machine Learning across Scales

Shivanshi Asthana<sup>\*1</sup>, Erwan Koch<sup>1</sup>, Sven Kotlarski<sup>2</sup>, and Tom Beucler<sup>1</sup>

<sup>1</sup>University of Lausanne – Switzerland

<sup>2</sup>Swiss Federal Office of Meteorology – Switzerland

## Abstract

Shivanshi Asthana, Erwan Koch, Sven Kotlarski, Tom Beucler

Regional climate models (RCMs) are key tools for projecting future climate, but their coarse spatial resolution (e.g., 12 km EURO-CORDEX ensemble) limits their usability for local impact studies. Machine-learning (ML) downscaling pipelines (both deterministic and generative) offer a promising complement to dynamical methods for kilometer-scale projections.

Firstly, we investigate three bias-correction approaches alongside deterministic and generative ML architectures to produce 1 km Swiss climate scenarios from the EURO-CORDEX 12 km ensemble. Four climate fields are downscaled using the MeteoSwiss Spatial Analysis as target data: daily mean temperature, daily maximum and minimum temperature, and daily precipitation. We combine dynamical Optimal Transport Correction (dOTC) for bias correction with a residual U-Net for super-resolution. Baselines include empirical quantile mapping for bias correction and bicubic interpolation for super-resolution. When evaluated for the standard climatological period (1981-2010), we find significant improvements in the representation of interannual cycles, decadal variability, and distributional tails, as quantified by 20, 50, and 100-year return levels across climate regimes represented by cities such as Bern, Geneva, Locarno, Lugano, and Zürich.

Secondly, beyond coupling RCMs with bias correction and super-resolution, we assess whether emerging generative ML approaches, such as latent and heavy-tailed diffusion, can directly generate realistic ensembles of kilometer-scale climate fields from CMIP6 model outputs. After an intermediate bias-correction step, we map coarse prognostic fields to the four kilometer-scale targets. Overall, we show that (1) multivariate bias correction remains essential to preserve statistical fidelity across spatial scales, and (2) residual ML methods hold promise for actionable, high-resolution information on climate timescales.

**Keywords:** Climate Change, Climate Downscaling, Generative Models, GCMs, RCMs, Climate Scenarios

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<sup>\*</sup>Speaker