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The Added Value of Remote Sensing Data in Downscaling Regional Climate Models

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Small-scale, subgrid processes on the ice sheets, such as localized surface melt, remain unnoticed by current coarse-resolution Regional Climate Models (RCMs), leading to uncertainties in climate reanalyses and projections. Deep learning allows us to enhance the spatial resolution of RCMs but requires sophisticated model development. Earlier studies have shown that rudimental techniques, such as single-image super-resolution, have failed to capture Antarctic surface melt patterns accurately, because the spatial transferability of these models is low. In this study, we add remote sensing data to a super-resolution model: daily observations of surface albedo from MODIS are used to guide the downscaling of low-resolution surface melt (RACMO2, 27 km) to a high-resolution version (RACMO2, 5.5 km) for a 20-year period, between 2001-2019. We extend a conventional SRResNet and add the MODIS data in different configurations (i.e., spatial-channel communication, content communication, and empirical-physical activation). The models are trained over the Antarctic Peninsula, for which RACMO2 simulations are available at 5.5 km resolution (Van Wessem et al., 2016). We verify the performance of the models with three independent datasets to inspect (1) the overall performance (using QuickSCAT); (2) spatial patterns (using Sentinel-1); and (3) temporal patterns (using automatic weather stations). Our work shows the potential of adding remote sensing data to deep learning-based downscaling models, leading to improved spatial transferability compared to single-image downscaling models.