Towards a spatially transferable super resolution model for downscaling Antarctic surface melt

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Abstract

Surface melt on the Antarctic Ice Sheet is an important climate indicator, yet the spatial scale of modeling and observing surface melt is insufficient to capture crucial details and understand local processes. High-resolution climate models could provide a solution, but they are computationally expensive and require finetuning for some model parameters. An alternative method, pioneering in geophysics, is single-image super resolution (SR) applied on lower-resolution model output. However, often input and output of such SR models are available on the same, fixed spatial domain. High-resolution model simulations over Antarctica are available only in some regions. To be able to apply an SR model elsewhere, we propose to make the single-image SR model physics-aware, using surface albedo and elevation as additional input. Our results show a great improvement in the spatial transferability of the conventional SR model. Although issues with the input satellite-derived albedo remain, adding physics awareness paves a way toward a spatially transferable SR model for downscaling Antarctic surface melt.

1 Introduction

The Antarctic Ice Sheet (AIS) is an important, but poorly constrained contributor to global sea level rise during the past century. The stability of ice shelves, the floating margins of the AIS, is compromised by increased surface melt caused by (local) atmospheric warming (1; 2; 3). On the AIS, in-situ observations are very scarce, making calibrated regional climate models (RCMs) the backbone for estimating climatological parameters. The current spatial resolution of leading RCM simulations is coarse for the entire AIS, typically $\sim$25 km (e.g., Regional Atmospheric Climate Model, RACMO2(4); Modèle Atmosphérique Régional, MAR (5)). It hence poses a challenge for studying surface melt features beyond the grid scale, where higher-resolution observations and/or simulations are required. To date, some higher-resolution ($\sim$5 km) simulations have been developed, but they are only over some Antarctic regions (e.g., (6)) during a certain time period. It is because generating such high-resolution RCM simulations requires substantial computational resources, and very careful finetuning for some model parameters. In this context, a fast, affordable, and accurate method of producing surface melt in a high spatiotemporal resolution over AIS is needed, to enhance our understanding of the Antarctic surface melt dynamics.

As an alternative to running RCMs at a high spatial resolution, image super resolution (SR) (7) is a competent computer vision technique to downscale the low-resolution RCM simulations. With the development of convolutional neural networks (CNNs), Dong et al. (2016) (8) proposed SRCNN,

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which is a pioneer study applying deep learning to SR tasks. Presently, the dominant SR models are still mostly CNN-based, e.g., SRResNet (9), and HAN (10). SRResNet can be combined with a discriminator to build conditional GANs, like SRGAN (9) or ESRGAN (11). In parallel, there has been a recent development to use transformers (12) in SR. Transformers are the state-of-the-art method in natural language processing, and show promising application in computer vision tasks, like the Swin Transformer (13; 14), including SR. In the field of geoscience, deep-learning-based SR techniques have already been applied for downscaling precipitation (15; 16), temperature (17; 18), wind (19), Antarctic bed topography (20), and satellite remote sensing images (21). Among these studies, a sole generator, particularly SRResNet, is prevalently applied. Meanwhile, some studies also applied conditional GANs (e.g., (19; 20)).

For this study, we downscaled RACMO2 surface melt from 27 km to 5.5 km over the entire AIS using a proposed SRResNet-backboned and physics-aware network. It takes advantage that both 27 km to 5.5 km resolution surface melt simulations exist over the Antarctic Peninsula based on RACMO2, as the training input pairs. The proposed SR model uses the SRResNet (9) as the backbone, while fed by the high-resolution albedo and high-resolution elevation at the end of its upsampling part. The latter part is physics-aware because surface melt is known to be strongly related causally by albedo and elevation (by means of a solid physical relation between air temperature and elevation). Our model shows good performance over the Antarctic Peninsula, and we demonstrate that the estimate of surface melt estimates has significantly improved over all of Antarctica, compared to the sole SRResNet.

2 Methods and materials

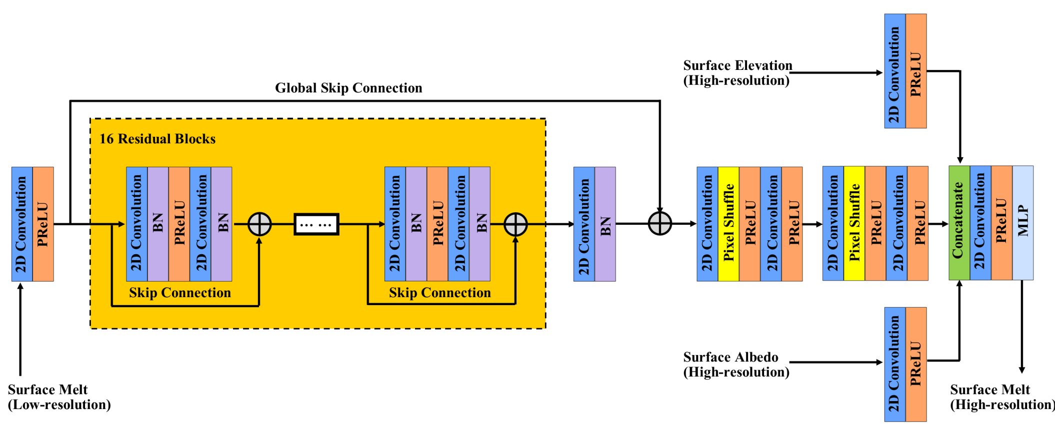

Figure 1: Overview of the proposed physics-aware SRResNet architecture.

2.1 Data sets

The Regional Atmospheric Climate Model version 2.3p2 (4), RACMO2, is a leading regional climate model adapted for the simulation of the weather over snow and ice surfaces, for a more accurate representation of surface mass and energy balance. The daily surface melt pairs are derived from RACMO2 simulations at horizontal resolutions of 27 and 5.5 km. Over the entire AIS, RACMO2 simulates at a horizontal resolution of approximately 27 x 27 km^2, for the period 1979–2019, forced by ERA-Interim. Also, it has a contemporaneous 5.5 x 5.5 km^2 (6), covering the Antarctica Peninsula, which makes them ideal image pairs for training supervised SR models.

The Moderate Resolution Imaging Spectroradiometer (MODIS) satellites provide continuous observation of the Earth's surface. In this study, we deployed the bi-hemispherical reflectance (i.e. white-sky albedo) for shortwave broadband from the MCD43A3 albedo product (22) archived in the *Google Earth Engine* (23) as daily albedo input. Besides, the elevation information is obtained from the TanDEM-X 90 m digital elevation model (24). Given the high cloudiness over the Antarctic Ice Shelves, even after upscaling the MCD43A3 albedo product to 5.5 km, there are still pixels with missing data. Therefore, we applied spatial (2×2) and temporal (5-day) median filters to reduce the influence of missing data, as well as a 3×3 Lee filter to reduce noise, especially in mountain areas.

2.2 Super resolution architecture: physics-aware SRResNet

In this study, we propose a physics-aware SR architecture. It has two major modules, the backbone of SRResNet (9), and the physics-aware part with elevation and albedo as the two physical parameters. The model architecture is illustrated in Fig. 1. The left part consisting of 16 residual blocks learns a high-level representation of the input low-resolution inputs, then it is upsampled with the pixel shufflers. Together with high-resolution contemporaneous static elevation and dynamic surface albedo input through a multilayer perceptron layer, the high-resolution surface melt is predicted.

3 Results and discussion

3.1 Experiments

During the training phase of the vanilla and physics-aware SRResNet models, we first separated the RACMO2 surface melt simulations into the training (October to June 2001—2006), validating (entire years during 2007—2010), and testing (entire years during 2011—2019) data sets. The boundary conditions for the division into these periods are given by RACMO2 archival procedures and the availability of QuikSCAT observations for evaluation (25). The accuracy assessment results in a RMSE $\approx$ 0.51 (0.52) mm.w.e. per day, $R^2 \approx$ 0.89 (0.83), MAE $\approx$ 0.10 (0.10) mm.w.e. per day, and Structural Similarity Index (SSIM) $\approx$ (0.99) 0.98 based on training (testing) data set, on the Antarctic Peninsula. There is no significant difference between the vanilla and physics-aware SRResNet models.

3.2 Improvement compared to a simple single image super resolution

We demonstrate the annual surface melt over the entire Antarctic in Fig. 2, in which we compare the results from both the vanilla SRResNet and our proposed physics-aware SRResNet. On the Antarctic Peninsula, both the vanilla and physics-aware SRResNet reconstructed high-resolution surface patterns. The key messages are summarized below by geographical area type:

Grounding Line: Areas near the grounding lines are often characterized as high surface melt areas, because of their relatively low albedo, and consistent katabatic winds removing high-albedo snow (26). The physics-aware SRResNet is indeed able to simulate increased surface melt close to the grounding line (green circle in Fig. 2).

Blue ice areas (melt-induced): Outside the Antarctic Peninsula, melt-induced blue ice areas are experiencing cyclic melt-refreeze processes (27), making them areas of low albedo but high elevation. Surface melt is well retrieved by physics-aware SRResNet (blue arrows in Fig. 2).

Blue ice areas (wind-induced): Unlike melt-induced blue ice areas, wind-induced blue ice areas, especially those in high-elevated areas (red arrow in Fig. 2), are experiencing sublimation and wind-erosion rather than surface melt. However, the physics-aware SRResNet still erroneously produced high surface melt. It can mean that the model puts too much weight on albedo and too little on elevation, and/or that this surface type is not represented in the training set. Indeed, in the Antarctic Peninsula, we have no low-albedo, high-elevation areas.

Ice rises: Antarctic ice rises occur when the flowing part of an ice shelf is diverted around the grounded region (28). However, the ice rise on the Shackleton Ice Shelf (white arrows in Fig. 2), is not well-characterized by RACMO2 27 km simulations due to the coarse resolution, neither by the vanilla nor physics-aware SRResNet model. It is because of the applied DEM, which is generated from Synthetic Aperture Radar (SAR) observations. And SAR can penetrate dry snow, which ultimately failed to provide information about this ice rise.

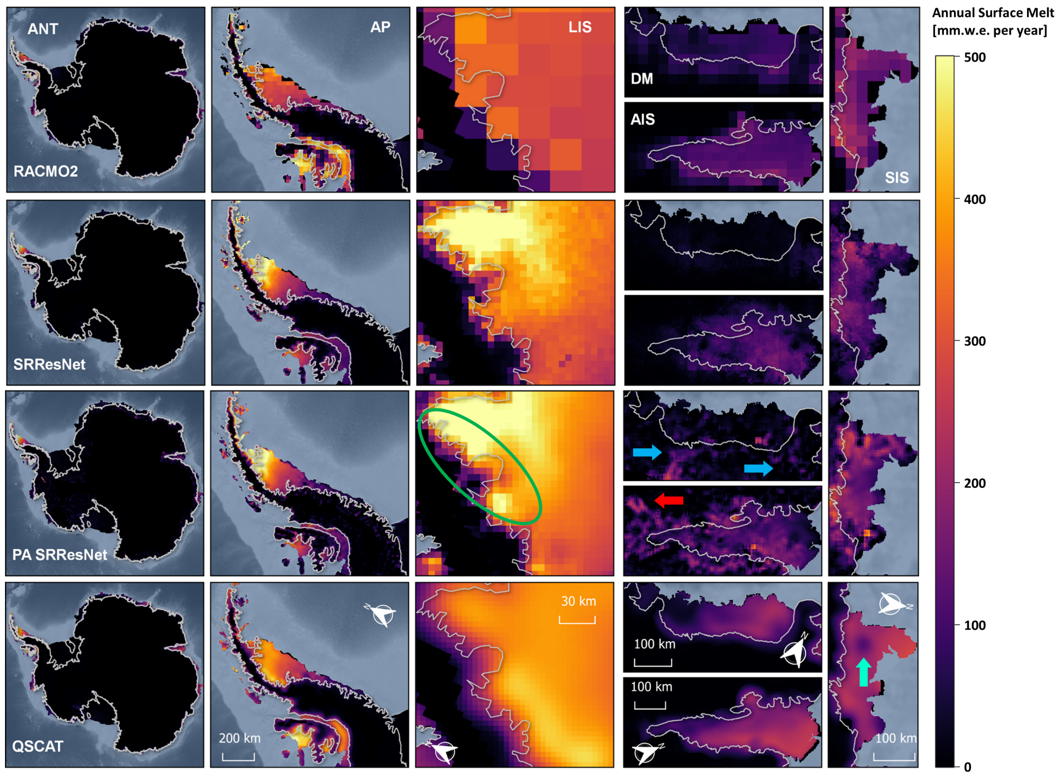

Figure 2: Annual surface melt in the year 2005 from Regional Atmospheric Climate Mode version 2.3p2 (RACMO2) 27 km simulations, and results from the vanilla and physics-aware SR deep residual network (SRResNet), and QSCAT-derived surface melt, over entire Antarctica, and zoom-ins over the Antarctic Peninsula (AP), Roi Baudouin in Dronning Maud Land (DM), Amery Ice Shelf (AIS), and Shackleton Ice Shelf (SIS).

3.3 Towards an Antarctica-wide surface melt product

Improvements are still needed to push the product towards a better Antarctic product. First, the quality of input data should be improved, including cloud removal and missing data handling in the daily MODIS albedo product, as well as snow penetration correction for DEM especially in ice rise areas, and void-filling. Second, it is necessary to *teach* the model how to handle and balance the input physical parameter, for instance in high-elevated low albedo areas (e.g., wind-induced blue ice areas), which is not presented in the training data set. Third, it is worth trying more complex model architectures, including physics-informed parts in the loss function, to make the results not only photo-realistic but also physics-realistic.

4 Conclusions

We present a physics-aware and SRResNet-backboned network to downscale the surface melt simulations from a regional climate model (RCM) from 27 km to 5.5 km over the entire Antarctica. It takes advantage that both 27 km to 5.5 km resolution surface melt simulations exist over the Antarctic Peninsula based on the same RCM, RACMO2, as the training input pairs. The SR model uses the SRResNet as the backbone while feeding the high-resolution albedo and high-resolution elevation at the end of the upsampling part. The presented work shows an improvement in spatial transferability in low-albedo areas (near the grounding line, over the melt-induced blue ice areas), but is still weak over the wind-induced blue ice areas and ice rise areas.

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