Supplementary material

Deep learning applied to glacier evolution modelling

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1. Filtering of DEM rasters

Before computing the glacier-specific Δh parameterized functions, some preprocessing is done to the regional French Alps DEM raster files in order to filter artefacts and noise. The processing chain works as follows:

1. The regional DEM files are cropped using the 2003 glacier inventory shapefile outlines, thus obtaining glacier-specific rasters with the DEMs from 1979 and 2011.
2. The glacier surface altitude difference for this period (so-called dh/dt) which corresponds to the change in ice thickness is computed glacier by glacier by subtracting the two previously mentioned DEM rasters.
3. A first empirical filter is applied to all rasters to filter unrealistic values coming from artefacts (*e.g.*, presence of clouds or saturation on the images used to generate de DEMs).
4. The filtered ice thickness difference (dh/dt) and DEM rasters are paired together as in Figure 12, and a low-order polynomial fit is applied in order to get the main trend of the scatterplot between the ice thickness difference *vs.* altitude.
5. A dynamic envelope/buffer around the polynomial fit line is computed for each glacier based on a quantile between maximum and minimum values for each altitude. In order to smooth the computed envelope for each altitude, a convolutional filter is applied to these values in order to smooth them and to follow the polynomial fit. A dynamic sliding window size is used to adjust the averaging process to the characteristics of each glacier.
6. A second filter is then applied using the computed smoothed envelope buffer to remove outliers
7. A final polynomial fit is computed with a variable order depending on the number of remaining data values of each glacier.
8. The percentage of pixels of information available for computing the polynomial fit (the parameterized function) is displayed for each glacier at the end of the processing chain.

2. SMB statistical error analysis

In order to determine the error due to each predictor, a Lasso model was trained with the same training matrix as the ANN, but instead of using SMB as ground truth data the errors generated by the ANN without weights were used. As discussed in section 4.1, Lasso performs a regularization on the training dataset, thus keeping only certain predictors and removing the rest. By looking at the resulting coefficients of the model, we can estimate the linear contribution of each predictor to the final model error. Latitude and longitude appear as the most important error predictors, but their contribution might in fact indicate the different magnitude of errors between glaciers or regions, since the pair of coordinates specifically identifies each glacier. October, August and March temperature follow behind, indicating that changes in temperature during these months have an influence in the simulation errors. It is not surprising that two of these months appear as top predictors as seen in Fig. 5 as changes in temperature during these months at the transition between the accumulation and ablation season can have a strong importance on the surface mass balance processes.

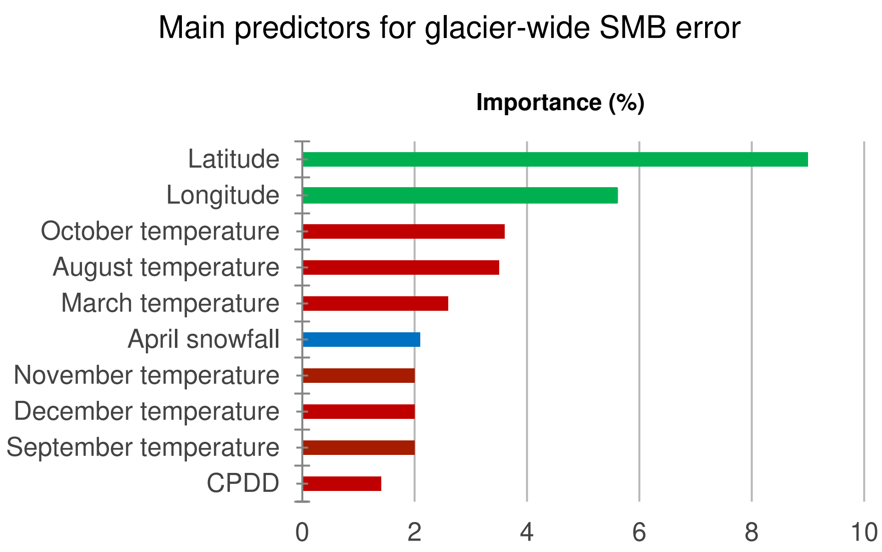

Figure S1: Importance (%) of the first 10 predictors using Lasso to predict residual error from the ANN SMB model. Green bars indicate topographical features, red bars temperature-related features and blue bars precipitation-related features.

Such an approach to analyze the influence of the different predictors into the quantification of uncertainties is of course limited, since a linear model is trained with nonlinear results. But these results are useful to determine the main contributors to errors rather than quantifying these errors, which has been done with the LOGO, LOYO and LSYGO cross-validations.

3. Supplementary figures

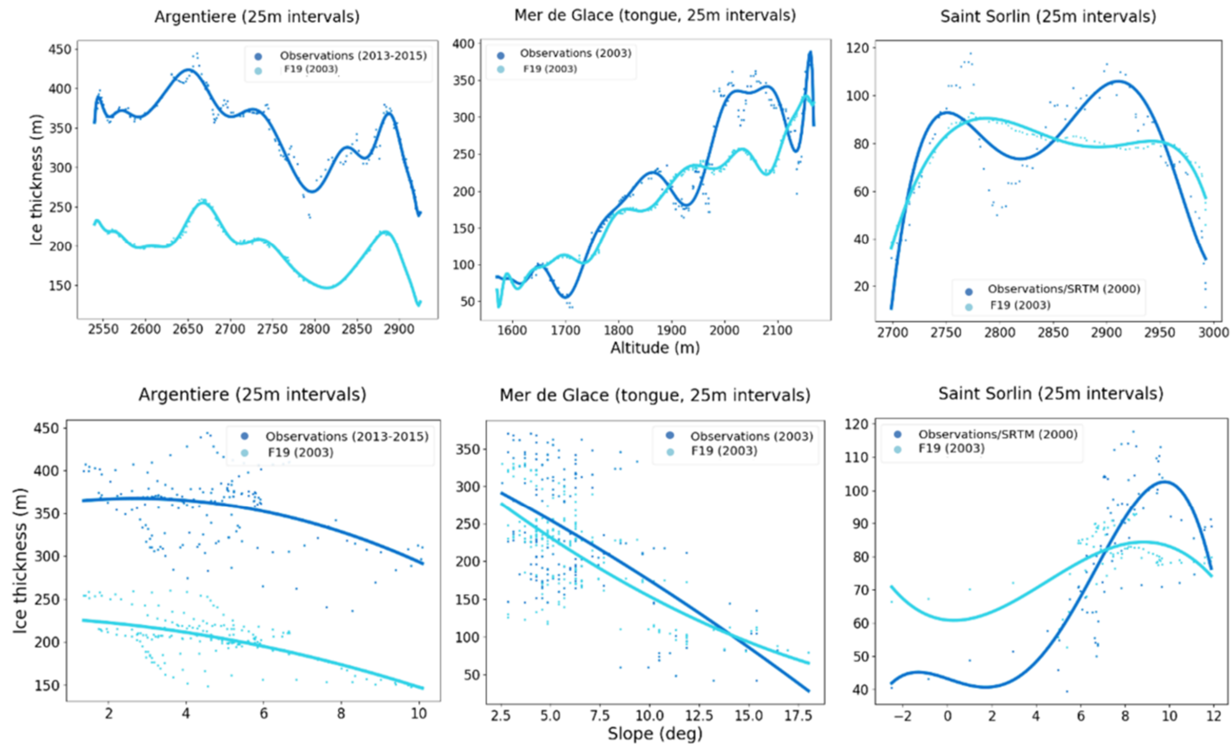

Figure S2: Comparison of simulated glacier ice thicknesses from F19 with observations from the GLACIOCLIM observatory. Points are compared at 25 m intervals on the glacier flowline. The polynomial fits have less degrees of freedom for the slope plots. Note that for some glaciers the dates are not the same

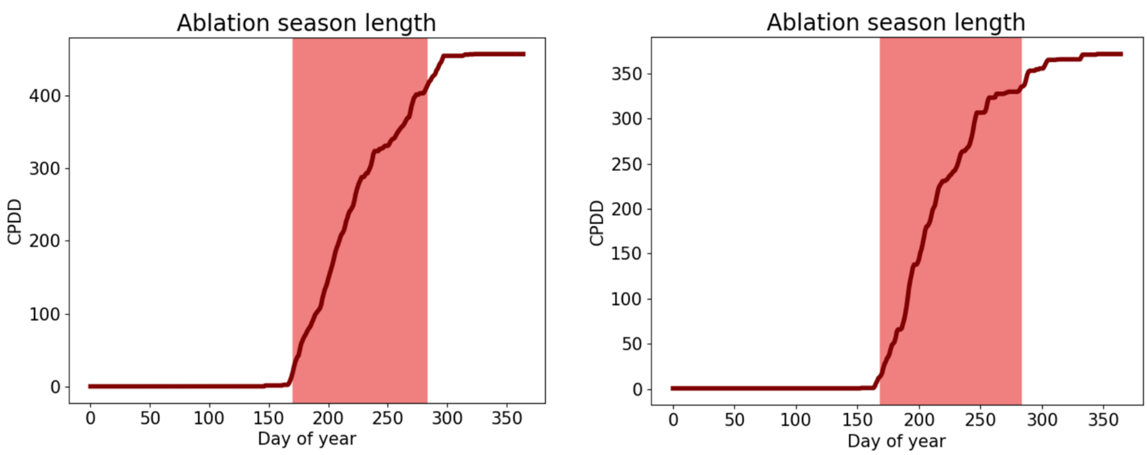

Figure S3: Example of dynamical calculation of ablation season length used for computing the annual CPDD value for Glacier Blanc (Écrins cluster) in 1963 (left) and 1984 (right)

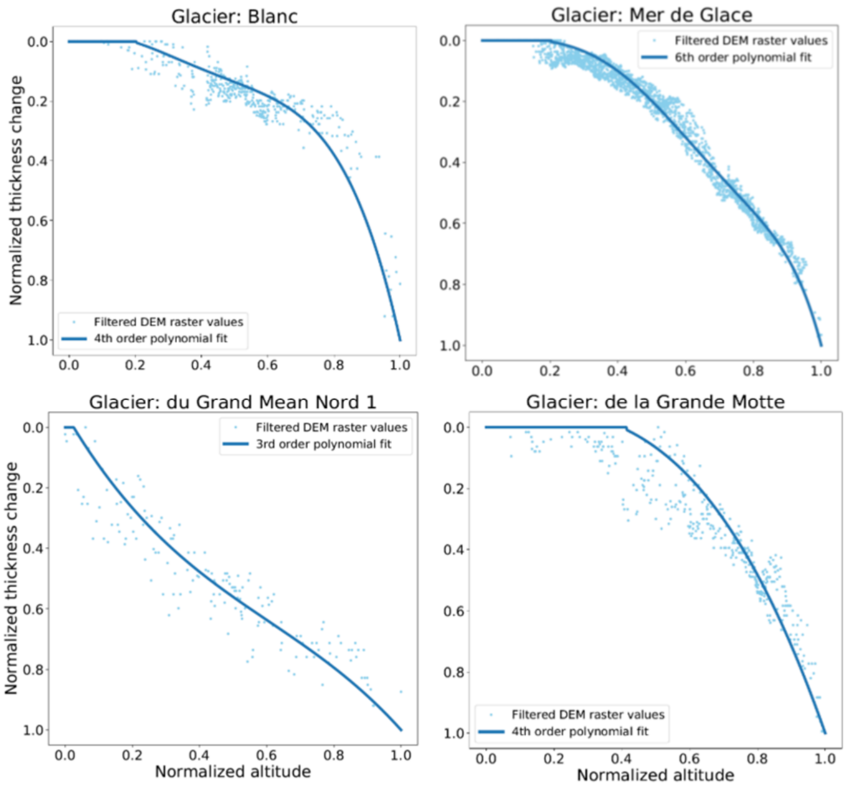

Figure S4: Examples of glacier specific Δh parameterized functions generated by ALPGM. The order of the polynomial fit depends on the number of available pixels.

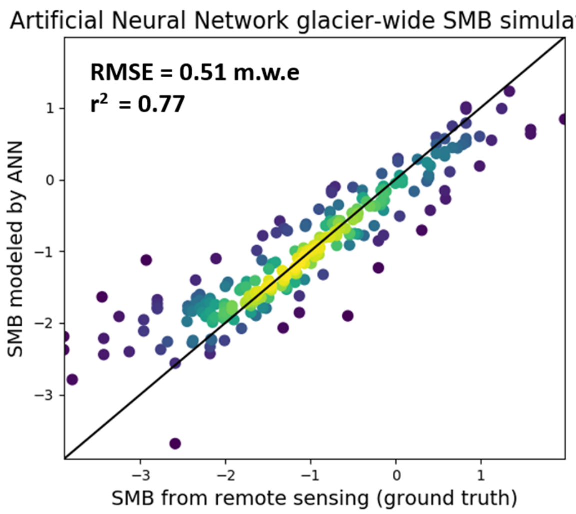

Figure S5: Results for the spatiotemporal cross-validation using Leave-Some-Glaciers-and-Years-Out (LSYGO). SMB values are in m.w.e. Compared to the other scatter plots from 3.2, there are less values available for test due to the severity of the spatiotemporal independence.