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A deep learning reconstruction of mass balance series for all glaciers in the French Alps: 1967-2015

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Abstract. Glacier surface mass balance (SMB) data are crucial to understand and quantify the regional effects of climate on glaciers and the high-mountain water cycle, yet observations cover only a small fraction of glaciers in the world. We present a dataset of annual glacier-wide surface mass balance of all the glaciers in the French Alps for the 1967-2015 period. This dataset has been reconstructed using deep learning (i.e. a deep artificial neural network), based on direct and remote sensing SMB observations, meteorological reanalyses and topographical data from glacier inventories. This data science reconstruction approach is embedded as a SMB component of the open-source ALpine Parameterized Glacier Model (ALPGM). An extensive cross-validation allowed to assess the method's validity, with an estimated average error (RMSE) of 0.49 m.w.e. a^{-1}, an explained variance (r^2) of 79% and an average bias of +0.017 m.w.e. a^{-1}. We estimate an average regional area-weighted glacier-wide SMB of -0.72±0.20 (σ) m.w.e. a^{-1} for the 1967-2015 period, with moderately negative mass balances in the 1970s (-0.52 m.w.e. a^{-1}) and 1980s (-0.12 m.w.e. a^{-1}), and an increasing negative trend from the 1990s onwards, up to -1.39 m.w.e. a^{-1} in the 2010s. Following a topographical and regional analysis, we estimate that the massifs with the highest mass losses for this period are the Chablais (-0.90 m.w.e. a^{-1}) and Ubaye and Champsaur ranges (-0.91 m.w.e. a^{-1} both), and the ones presenting the lowest mass losses are the Mont-Blanc (-0.74 m.w.e. a^{-1}), Oisans and Haute-Tarentaise ranges (-0.78 m.w.e. a^{-1} both). This dataset - available at: https://doi.org/10.5281/zenodo.3663630 (Bolibar et al., 2020a) - provides relevant and timely data for studies in the fields of glaciology, hydrology and ecology in the French Alps, in need of regional or glacier-specific meltwater contributions in glacierized catchments.

1 Introduction

Among all the components of the Earth system, glaciers are some of the most visibly affected by climate change, with an overall worldwide shrinkage despite important differences between regions (Zemp et al., 2019). The European Alps are among the regions with the strongest glacier mass loss over recent decades, with expected mass losses between 60% and 95% by the end of the 21st century (Zekollari et al., 2019). These major glacier mass changes are likely to have an impact on water resources,

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society and alpine ecosystems (e.g. Huss and Hock, 2018; Immerzeel et al., 2020; Cauvy-Fraunié and Dangles, 2019). In order to study and quantify all these potential consequences, the availability of glacier mass balance data is of high relevance. Therefore, open historical datasets are crucial for the understanding of the driving processes and the calibration of models used for projections. Unlike glacier length, glacier surface mass balance (SMB) provides a more direct indicator of the climate-glacier interactions (Marzeion et al., 2012). Glacier SMB is classically measured using the direct or glaciological method, by separately determining the ablation and accumulation totals. Direct measurements quantify the surface mass balance at different points of the glacier, and these values must be integrated at the glacier scale in order to assess the glacier-wide SMB (Benn and Evans, 2014). These different points can show a high nonlinear variability, which can complicate this integration process towards glacier-wide estimates (Vincent et al., 2018). Moreover, field measurements require a lot of manpower, time and economic resources in order to be sustained for a meaningful period of time. On the other hand, recent advances in remote sensing allow estimating glacier SMB changes at a regional level with unprecedented efficiency using geodetic and gravimetric methods (Kääb et al., 2012; Berthier et al., 2016; Fischer et al., 2015; Brun et al., 2017; Dussaillant et al., 2019). Due to constraints related to the availability of digital elevation maps (DEMs) or airborne data, these mass balance estimates normally encompass several years or decades. Some studies are bridging the gap towards an annual temporal resolution (Rabatel et al., 2005, 2016; Rastner et al., 2019), but the coverage is still limited to glaciers without cloud cover or acquisition-related artefacts. This means that these mass balance datasets are often restricted to certain glaciers and years within a region. All these new datasets are extremely beneficial for data-driven approaches, fostering the training of machine learning models capable of capturing the regional characteristics and relationships (Bolibar et al., 2020b). This type of approach allows to fill the spatiotemporal gaps in the SMB datasets, therefore, it can be seen as a complement to remote sensing and direct observations. On the other hand, SMB reconstructions have already been carried out in the European Alps, providing a basis for comparison between different approaches. For example, Marzeion et al. (2012, 2015) reconstructed annual SMB series of all glaciers in the Randolph Glacier Inventory - including the European Alps - for the last century. They used a minimal model relying only on temperature and precipitation data, based on a temperature-index method, with two optimized parameters to calibrate the temperature sensitivity and the precipitation lapse rate. Huss (2012) presented an approach to extrapolate SMB series of a limited number of glaciers to the mountain-range scale. By comparing multiple methods, he found the best results with a multiple linear regression based on 6 topographical parameters. From this relationship he reconstructed area-averaged SMB series of all the glaciers of the European Alps between 1900-2100 and analysed the trends for the different alpine nations and different glacier sizes.

Here, we introduce a dataset of annual glacier-wide SMB of all the glaciers in the French Alps (Bolibar et al., 2020a), located in the westernmost part of the European Alps, between 5.08° and 7.67°E, and 44° and 46°13'N. Glacier-wide SMBs have been reconstructed for the 1967-2015 period, using deep learning (i.e. a deep artificial neural network). This approach was introduced in Bolibar et al. (2020b), for which a deep artificial neural network (ANN) was trained with data from 32 French alpine glaciers, as part of the ALPGM glacier evolution model (Bolibar, 2020). Annual glacier-wide SMB values are reported for each glacier in the French Alps found in the 2003 glacier inventory (Gardent et al., 2014). An overview of the methodology used to produce the dataset and a review of the associated uncertainties is presented in Sect. 2, followed by a dataset overview

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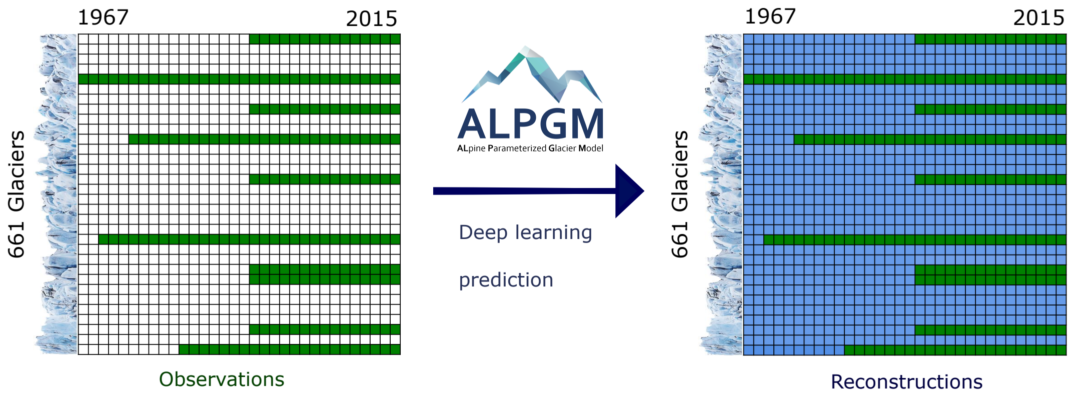

Figure 1. Summary of the deep learning regional SMB reconstruction approach. From the available annual glacier-wide SMB observations, a deep learning model is used to reconstruct the full dataset, thus filling the spatiotemporal gaps in the observational dataset. Green indicates glaciers and years with SMB observations and blue indicates reconstructed SMB values. The grid size with glaciers and years is schematic and only serves to illustrate the concept.

in Sect. 3, where the data structure and regional trends are described and where the dataset is compared to a previous study and observations.

2 Methodology and uncertainties

The annual glacier-wide SMB dataset for the 661 French alpine glaciers has been reconstructed using a deep artificial neural network (ANN), also known as deep learning. ANNs are nonlinear statistical models inspired by biological neural networks (Fausett, 1994; Hastie et al., 2009). Recent developments in the field of machine learning and optimization enabled the use of deeper ANN architectures, which allow to capture more nonlinear and complex patterns in data even for small datasets (Ingrassia and Morlini, 2005). For the reconstruction presented here, a deep feed-forward ANN has been trained with a dataset of 32 French alpine glaciers, covering most of the massifs within the French Alps, which exhibit a great variability of topographical characteristics (Fig. 4 in Bolibar et al., 2020b). Four glaciers include direct SMB measurements from the GLACIOCLIM observatory, some of which between 1949 and 2018 (Vincent et al., 2017), and 28 glaciers include estimates of annual glacier-wide SMB from remote sensing between 1984 and 2014 (Rabatel et al., 2016). Training data consists of: (1) annual glacier-wide SMB for each of the 32 glaciers as a reference dataset; (2) climate data from the SAFRAN meteorological reanalyses (Durand et al., 2009), with: cumulative positive degree days (CPDD), cumulative winter snowfall, cumulative summer snowfall, mean monthly temperature and mean monthly snowfall, all variables being quantified at the altitude of the glacier's centroid; and (3) annually interpolated topographical data from the 1967, 1985, 2003 and 2015 glacier inventories in the French Alps (update of Gardent et al., 2014), with: mean and maximum glacier altitude, slope of the lowermost 20% altitudinal range of the glacier, surface area, latitude, longitude and aspect. These parameters were identified as relevant for glacier-wide SMB modelling in the French Alps (Bolibar et al., 2020b), and the dates of the glacier inventories determined the time interval for

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the reconstructions presented here. This modelling approach is part of the SMB component of ALPGM (Bolibar, 2020), an open-source data-driven parameterized glacier evolution model. For a detailed explanation of the methodology, please refer to Bolibar et al. (2020b). For the final reconstructions presented here, a cross-validation ensemble approach was used, in which the individual predictions of each of the Leave-One-Glacier-Out (LOGO) cross-validation models were averaged to produce a single output. An ensemble approach has the advantage of further improving generalization, and reducing overfitting as well as the inter-model high variance typical from neural networks (Krogh and Vedelsby, 1995). On the other hand, for the 32 glaciers with glacier-wide SMB observations used for training, an ensemble of 50 models trained with the full dataset was used, in order to achieve the best possible performance for this subset of glaciers, which represents a substantial fraction (45% in 2003) of the total glacierized surface area in the French Alps.

The uncertainties linked to the deep learning approach used in this study have been assessed through cross-validation, for which deep learning predictions were compared with observations. A detailed presentation of the method's uncertainties and performance from the cross-validation study can be found in Bolibar et al. (2020b). Block cross-validation ensured that all the 32 glaciers in the dataset were evaluated, with spatiotemporal structures formed by glaciers and years being considered in order to prevent the violation of the assumption of independence (Roberts et al., 2017). This means that three different deep ANNs were produced: one for reconstructing glacier-wide SMB in space, one for the reconstruction in time (future and past), and another one for both dimensions at the same time; each of these with a different calibration and performance. It was shown that the deep ANN performs better in the spatial dimension, in which the SMB signal relationships with the predictors are the simplest. SMB interannual variability is mostly driven by climate, whereas geography and local topography (i.e. differences between glaciers) modulate the signal in space in a simpler way (Vincent et al., 2017; Bolibar et al., 2020b). Therefore, deep learning is capable of finding more structures in the spatial dimension, accounting for a better accuracy and explained variance compared to the temporal dimension. The deep ANN used in this study presents an RMSE of 0.49 m.w.e a^{-1} with an r^2 of 0.79 in LOGO cross validation. Nonetheless, only one glacier in the training dataset is smaller than 0.5 km^2 (Glacier de Sarennes, 0.3 km^2 in 2003), implying that uncertainties for very small glaciers (< 0.5 km^2) might differ from those estimated using cross-validation. In 2015, very small glaciers in the French Alps represented about 80% of the total glacier number, but they accounted for only 20% of the total glacierized area. This means that their importance is relative, for example in terms of water resources, but a user of this dataset should bear in mind that SMB from these very small glaciers might carry greater uncertainties than the ones assessed during cross-validation. This might be especially true for extremely small glaciers (< 0.05 km^2) which can be considered as spatial outliers for the deep ANN. Since there is only one glacier with SMB observations for very small glaciers and none for extremely small glaciers, there is no precise way to quantify these uncertainties. On the other hand, the ANN is mostly trained with glacier-wide SMB data between 1984 and 2014, with a reduced amount of values between 1967 and 1984 (986 and 62 values, respectively). Since this early period contains on average more positive and neutral glacier-wide SMB values than the 1984-2014 period, the performance of the ANN was specifically assessed for this period. An additional cross-validation was performed with four folds, each with a glacier including glacier-wide SMB data before 1984. For each fold, all SMB data of that glacier and time period were hidden from the ANN, and the simulated glacier-wide SMBs between 1967 and 1983 were tested in order to assess the model's performance. The results showed that the ANN is capable of correctly reconstructing glacier-wide SMB for glaciers and years before 1984 (Fig. S3), with an estimated accuracy (RMSE) of 0.47 m.w.e. a^{-1} and an estimated explained variance (r^2) of 0.65. This uncertainty assessment is based on roughly 10% of the full dataset, meaning that these estimates lack the robustness of the full cross-validation from Bolibar et al. (2020b), but they serve to show that the model can accurately reconstruct glacier-wide SMB data outside the main cluster of years used during training.

3 Dataset overview

3.1 Dataset format and content

The SMB dataset is comprised of multiple CSV files, one for each of the 661 glaciers from the 2003 glacier inventory (Gardent et al., 2014), named with its GLIMS ID and RGI ID with the following format: *GLIMS-ID_RGI-ID_SMB.csv*. Both indexes are used since some glaciers that split into multiple sub-glaciers do not have an RGI ID. Split glaciers have the GLIMS ID of their "parent" glacier and an RGI ID equal to 0. Every file contains one column for the year number between 1967 and 2015 and another column for the annual glacier-wide SMB time series. Glaciers with remote sensing-derived observations (Rabatel et al., 2016) include this information as an additional column. This allows the user to choose the source of data, with remote sensing data having lower uncertainties (0.35±0.06 (σ) m.w.e. a^{-1} as estimated in Rabatel et al. (2016)). Columns are separated by semicolon (;). All topographical data for the 661 glaciers can be found in the updated version of the 2003 glacier inventory included in the Supplementary material and in the dataset repository.

3.2 Overall trends

We estimate an average area-weighted regional glacier-wide SMB of -0.72±0.20 (σ) m.w.e. a^{-1} between 1967 and 2015 (Fig. 3). As reported in previous studies (Huss, 2012; Rabatel et al., 2016; Vincent et al., 2017), our reconstructed SMB data show a slightly negative average value during the 1970s, even less negative in the 1980s, and then increasingly negative values in recent decades with an abrupt change in 2003 (Fig. 2 and 3). For this period (1967-2015), the year 2003 with its remarkable heatwave remains the most negative glacier-wide SMB year (-2.26 m.w.e. a^{-1} on average), with 1984 being the most positive year of the study period (+0.85 m.w.e. a^{-1} on average).

3.3 Regional and topographical trends

Here we analyse the main trends for the glacierized massifs and for some relevant topographical parameters. The reported glacier-wide SMBs are only area-weighted if specifically mentioned. Interesting differences appear once the dataset is divided into mountain ranges (Fig. 4). The Mont-Blanc massif presents the lowest mass loss over the entire study period, with an average cumulative loss over the 1967-2015 period of 36.42 m.w.e. This is probably due to its northern location within the French Alps and its large high altitude accumulation areas, which resulted in more positive or less negative SMBs, especially during the 1980-2000s. Oisans is the massif with the second lowest average cumulative mass loss (38.35 m.w.e.). Its glaciers

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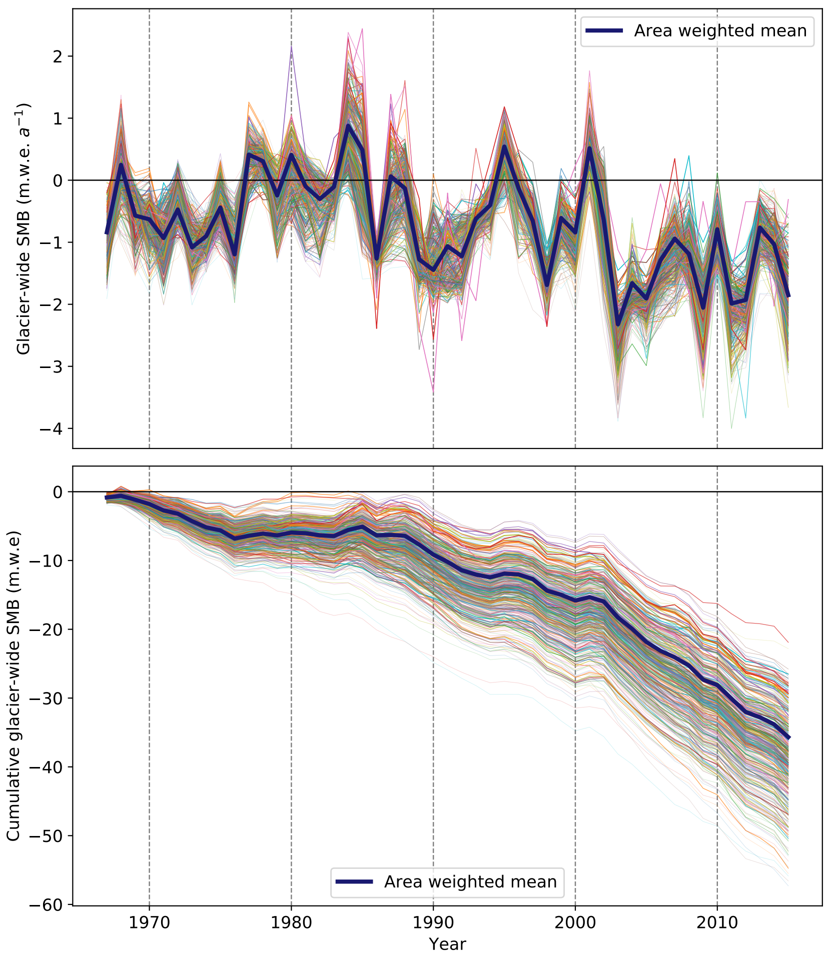

Figure 2. Annual glacier-wide SMB reconstruction of all the glaciers in the French Alps (N = 661) between 1967 and 2015. For each individual glacier, line thickness depends on glacier area, with smaller glaciers having thinner lines.

have average altitudes ranging from 2290 to 3470 m.a.s.l., with around 50% of them having mean altitudes over 3000 m.a.s.l. and with about 40% of glaciers (including most of the large ones) having a northern aspect. Glaciers in Haute-Tarentaise present similar characteristics to those from Oisans, with mean altitudes ranging between 2300 and 3600 m.a.s.l., with about 60% of the glaciers above 3000 m.a.s.l. This less negative trend was especially important during the recent years with high mass losses from 2003 onwards. On the other hand, the Ubaye, Champsaur, Chablais and Haute-Maurienne massifs appear as the most affected mountain ranges with cumulative mass losses reaching between 44 and 45 m.w.e. for the four massifs over the 1967-2015 period. The Chablais range has a very small number of glaciers remaining, all of them at rather low altitudes (2200-2900 m.a.s.l.), relatively small (0.01 - 1.1 km^2), and with a northwestern aspect. Despite being the northernmost mountain range in the French Alps, its low altitude is most likely the main reason for the very negative SMBs, which were under the

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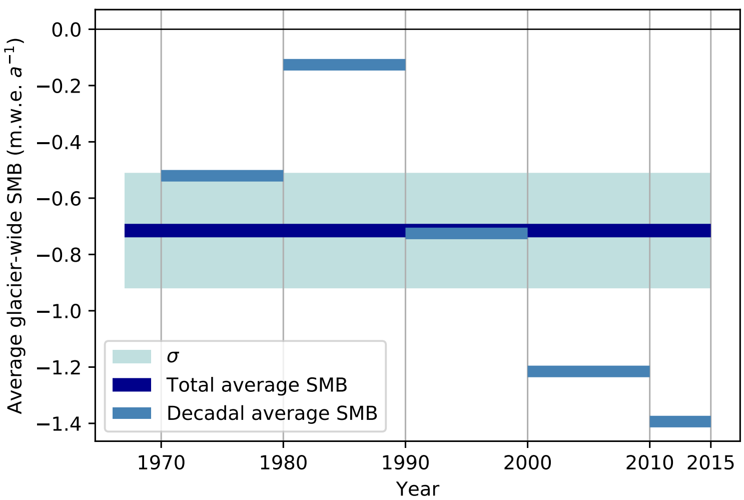

Figure 3. Averaged area-weighted decadal glacier-wide SMB for the French Alps. The total area-weighted glacier-wide SMB is estimated for the 1967-2015 period

regional average even during the positive years in the 1980s. The Champsaur range shows a similar situation, with very small glaciers (0.03 - 0.89 km^2) lying at relatively low altitudes (2300-3100 m.a.s.l.) in the southernmost latitudes of the Alps (44º7'). Finally, the situation of the Ubaye massif is quite similar to the one of Champsaur, being the southernmost glacierized massif in the French Alps, with a strong mediterranean influence. Such glaciers are remnants of the Little Ice Age, far from being in equilibrium with the warming climate, and can quickly lose a lot of mass through non-dynamic downwasting (Paul et al., 2004).

When classifying the SMB time series by glacier surface area, we encounter the following patterns, with n being the number of glaciers in the subset and s its standard deviation: (1) Very small glaciers (< 0.5 km^2; n = 534; $\overline{SMB}_{1967-2015}$ = -0.82 m.w.e. a^{-1}; s = 0.21 m.w.e. a^{-1}) present more negative glacier-wide SMBs than (2) small/medium glaciers (ranging from 0.5 to 2 km^2; n = 93; $\overline{SMB}_{1967-2015}$ = -0.76 m.w.e. a^{-1}; s = 0.16 m.w.e. a^{-1}) and (3) large glaciers (> 2 km^2; n = 34; $\overline{SMB}_{1967-2015}$ = -0.72 m.w.e. a^{-1}; s = 0.10 m.w.e. a^{-1}). Very small glaciers present a larger spread of values than small/medium and large glaciers (s = 0.21 m.w.e. a^{-1} versus 0.17 and 0.10 m.w.e. a^{-1}, respectively). As explained in Sect. 2, the uncertainties for very small glaciers are greater due to their underrepresentation in the training dataset, meaning that analysis based on small glaciers have to be taken with greater care. On the other hand, a clearer relationship between the glacier slope (computed here as the lowermost 20% altitudinal range slope) and glacier-wide SMB arises, with steeper glaciers having less negative glacier-wide SMBs (Fig. S4 and S7). Glaciers with a gentle tongue slope generally present longer response times and higher ice thickness, which are associated with more negative mass balances (Hoelzle et al., 2003; Huss and Fischer, 2016). These results are in agreement with the findings by Fischer et al. (2015), who computed the geodetic mass balance of

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all the Swiss glaciers for the 1980-2010 period. Overall, the topographical relationships found here are similar, although more negative than for the Swiss Alps (Huss, 2012; Huss and Hock, 2015), showing how the southernmost glaciers in the Écrins and Vanoise regions present stronger glacier mass losses. This is mostly due to their mediterranean climatic influence compared to the more continental Swiss and Austrian glaciers, which results in more negative SMB in a warming climate (Oerlemans and Reichert, 2000). Nonetheless, results from this type of bivariate analysis can show rather biased trends, since the topographical variables are highly intercorrelated, with for example small glaciers having steeper slopes and *vice versa* (Gardent et al., 2014). The position and evolution of the equilibrium line can totally reverse the trends of small or steep glaciers, so these relationships can strongly vary depending on the region or time period observed.

3.4 Comparison with previous studies and observations

In order to put into perspective the reconstructions presented in this study, we compare them to an updated version from the Marzeion et al. (2015) reconstructions (B. Marzeion, personal communication, October 2019 - January 2020), and to all the available glacier-wide SMB observations in the French Alps. The goal of this comparison is not to draw conclusions on the quality of either reconstruction, but to analyse the differences among them and to try to understand the causes. In the updated version of Marzeion et al. (2015) - referred as M_{15U} from now on - a global SMB model relying on temperature and solid precipitation was used to reconstruct SMB time series for all the glaciers in the world present in the Randolph Glacier Inventory (Consortium, 2017). This model was optimized based on three parameters: the temperature sensitivity of the glacier, a precipitation correction factor and a bias correction. As in Bolibar et al. (2020b), the approach by M_{15U} was cross-validated respecting the spatiotemporal independence in order to evaluate its performance for unobserved glaciers and years. Prior to contrasting the results, three important different aspects between our approach and the one of M_{15U} need to be highlighted: (1) M_{15U}'s model works with simplified physics, with a temperature-index model calibrated on observations; in this study we use a fully statistical approach based on deep learning, where physics-based considerations only appear in the predictor selection. (2) M_{15U} calibrated their model with SMB observations of 38 glaciers, most of them located in Switzerland for the 1901-2013 period; in this study we used observations of 32 glaciers, all located in the French Alps for the 1967-2015 period. (3) M_{15U} force their updated model with CRU 6.0 (update of Harris et al., 2014), with 0.5° latitude/longitude grid cells, which has a significantly lower spatial resolution and suitability to mountain areas than the SAFRAN reanalysis (Durand et al., 2009) used in this study, in which altitude bands and aspects are considered for each massif, and meteorological observations from high-altitude stations are assimilated. The cross-validations of both studies determined a performance with an average RMSE of 0.66 m.w.e. a^{-1} and an r^2 of 0.43 for M_{15U} for the European Alps, and an average RMSE of 0.49 m.w.e. a^{-1} and an r^2 of 0.79 for this study. However, due to the highly different methodologies and forcings of the two models, a direct comparison is not possible, so the following analysis is focused on the overall trends and sensitivities in the reconstructions and their potential sources.

As shown in Figure 5, the interannual variability, driven by climate, is quite similar between the two reconstructions. Conversely, important differences are found for different subperiods in the amplitude of the area-weighted mean glacier-wide SMB series. These differences are the greatest in the 1970s, 1980s and 2010s, with similar average values for the 1990s and 2000s

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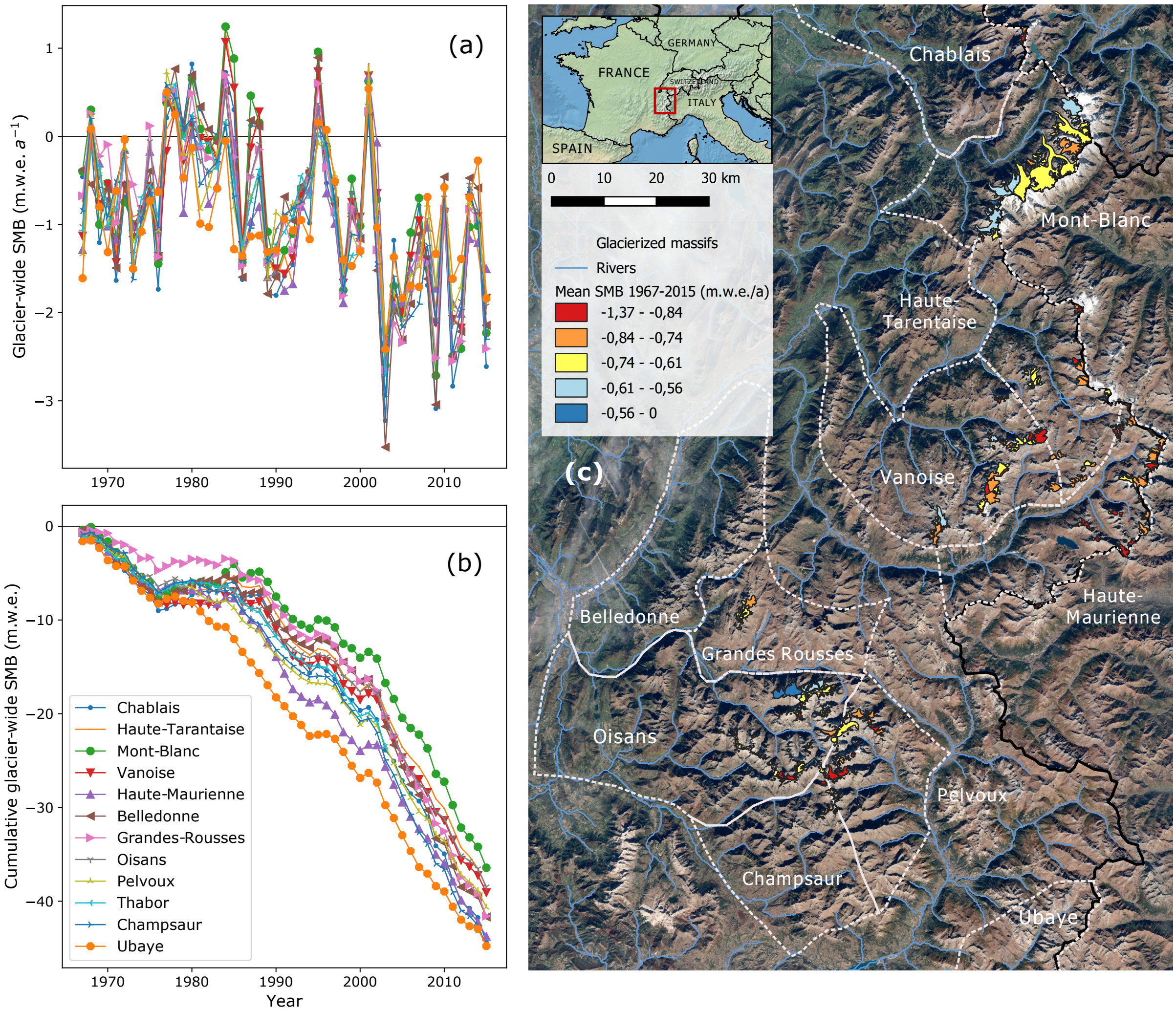

Figure 4. (a) Averaged annual glacier-wide SMB and (b) cumulative averaged glacier-wide SMB time series for each of the massifs in the French Alps between 1967 and 2015. (c) Glacierized massifs in the French Alps with the average glacier-wide SMB for the 1967-2015 period. Coordinates of bottom left map corner: 44º32' N, 5º40' E. Coordinates of the top right map corner: 46º08' N, 7º17' E. (Basemap © imagico.de)

(Fig. 5 and S5). M_{15U} presents less negative and more positive glacier-wide SMB values in the 1970s, but on the contrary, it presents more negative values in the 1980s compared to our results. We believe there might be two potential reasons for this: (1) In 1976 there was a shift in the winter mass balance regime in the French Alps, with more humid winters bringing more accumulation; and in 1982 there was a shift in the summer mass balance, resulting in increased ablation (Thibert et al., 2013). Since both models use parameterized or statistical relationships for SMB response to precipitation and temperature, they are

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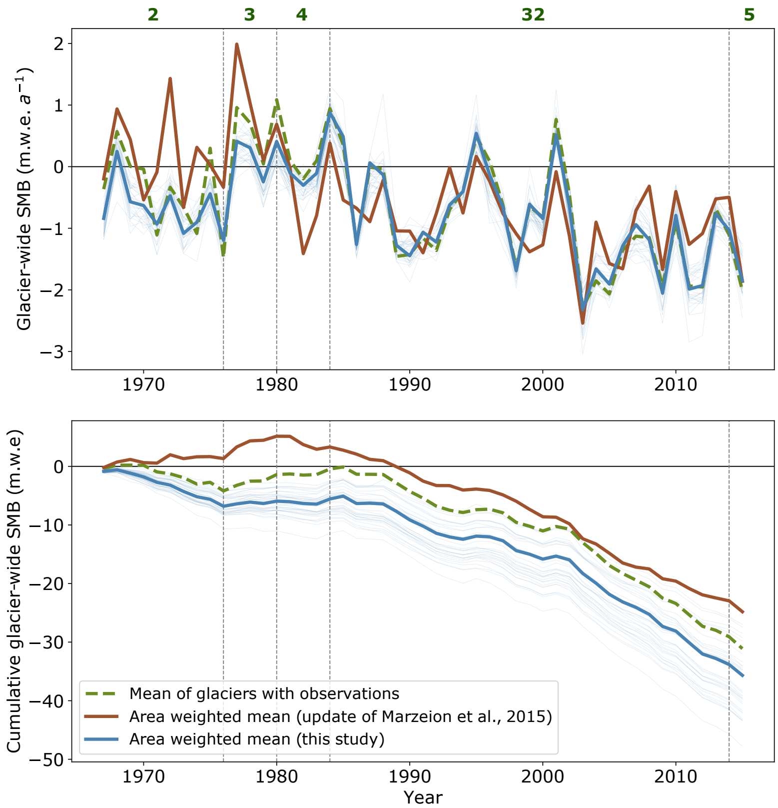

Figure 5. Comparison of annual and cumulative glacier-wide SMB simulations in the French Alps between this study, reconstructions from an update from Marzeion et al. (2015) and the mean of all observations available in the French Alps. Green numbers indicate the number of glaciers with SMB observations for each period and thin light blue lines indicate the area-weighted mean of each of the cross-validation ensemble members.

likely to react differently to these changes. A similar situation is found from the year 2003 onwards, where there was a substantial increase in temperatures and mass loss (e.g. Six and Vincent, 2014). Our reconstructions show a marked change in 2003 (change of slope in the cumulative plot in Fig. 5), whereas M_{15U} present a rather linear trend. (2) For the 1967-1983 interval, the amount of available glacier-wide SMB data for training is much lower than for the rest of the period (green numbers in Fig. 5). This is likely the reason why the differences between our reconstructions and observations are greater for that period (Fig. 5). On the other hand, the similarities between our reconstructions and the observations for the 1984-2014 period are explained by the fact that the 32 glaciers with observations represent around 45% of the total glacierized area in the French Alps in the year 2003. For the periods before and after this interval, differences and uncertainties in the reconstructed values are greater because of the smaller sample size.

Important similarities between observations and the reconstructed glacier-wide SMB values for the 1984-2015 period in this study (Fig. 5) question a possible overfitting of the reconstructions to the training data. First, for the vast majority of the 661

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French glaciers, the reconstructions are based on an ensemble of cross-validated models, which intrinsically limits overfitting (see Sect. 2). Second, we analysed the deviation to the climatological mass-balance signal of the SMB for each cluster of glacier-sizes. This analysis is presented in the Supplementary. It reveals that the similarities between observations and the reconstructed glacier-wide SMB values for the 1984-2015 period in Fig. 5 proceed from big glaciers, that dominate both in the area-weighted reconstructions and in the observations. However, for the other glacier-size classes, our reconstruction shows different patterns from the data in the observations, which suggests that the model is not overfitting (Fig. S1).

4 Data availability

The full glacier-wide SMB dataset and the detailed topographical information of all the French alpine glaciers is available in the following Zenodo repository: https://doi.org/10.5281/zenodo.3663630 (Bolibar et al., 2020a).

5 Conclusions

We presented a dataset of annual glacier-wide SMB of all the glaciers in the French Alps (44° - 46°13'N, 5.08° - 7.67°E) for the 1967-2015 period (Bolibar et al., 2020a). This dataset has been reconstructed using deep learning (i.e. an artificial neural network), based on direct and remote sensing annual glacier-wide SMB observations, climate reanalysis and topographical data from multitemporal glacier inventories. The deep learning model is capable of reconstructing glacier-wide SMB time series for unobserved glaciers in the same region based on patterns and structures learnt by the artificial neural network from the observations and their relationships with predictors. An extensive cross-validation was implemented to understand the characteristics of the SMB signal in the region and to assess the method's validity and uncertainty. The average accuracy (RMSE) of the dataset is estimated at 0.49 m.w.e. a^{-1} with an explained variance (r^2) of 79%. Reconstructions show a mean area-weighted glacier-wide SMB of -0.72±0.20 (σ) m.w.e. a^{-1} for the 1967-2015 period. Important differences are found among different massifs, with the Mont-Blanc (-0.74 m.w.e. a^{-1}), Oisans and Haute-Tarentaise ranges (-0.78 m.w.e. a^{-1} both) presenting the lowest mass losses and the Chablais (-0.90 m.w.e. a^{-1}), Ubaye and Champsaur (-0.91 m.w.e. a^{-1} both) showing the highest losses. In order to put these results into perspective, this reconstruction was compared to all available glacier-wide SMB observations in the French Alps as well as the physical/empirical reconstructions from another study (update from Marzeion et al., 2015). Interesting differences were found between the two methods, highlighting the different sensitivities and responses of different approaches to climate shifts that occurred during the study period. These differences are particularly relevant in the 1970s and 1980s, previous to a winter precipitation and summer temperature shift that occurred in the French Alps in the years 1976 and 1982, respectively. Moreover, after the famous 2003 European heatwave, glaciers experienced an acceleration in mass loss which is well captured by our reconstruction. This open glacier-wide SMB dataset can be useful for hydrological or ecological studies in need of meltwater contributions of glacierized catchments in the French Alps. Moreover, the publication of such open datasets is the cornerstone of future community-based data-driven scientific studies.

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6 Code availability

The source code of ALPGM v1.1 is accessible at https://github.com/JordiBolibar/ALPGM, with its DOI: 10.5281/zenodo.3609136 (Bolibar, 2020).

Author contributions. All authors contributed to writing and editing the manuscript. JB performed the simulations, processed the data and plots and performed the analysis. AR provided the surface mass balance remote sensing data and contributed to the glaciological analysis, IG participated in the climate and regional analysis and CG contributed to the statistical aspects of the methods.

Competing interests. The authors declare that they do not have any competing interests.

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