



Deriving Distributed Mass Balance Patterns of Swiss Glaciers from Remote Sensing Data

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10 Abstract [word limit: 250].

Glacier mass balance (MB) is central to understanding glacier change and calibrating glacier evolution models, yet direct MB observations remain sparse. Recent efforts to infer distributed MB fields from the mass continuity equation have so far mainly been limited to individual glaciers, used simplified elevation-dependent approaches, and/or relied on glacier models for the inversion. Here, we present one
15 of the first regional applications of a continuity-based inversion to derive spatially distributed MB fields directly from remote sensing observations of ice thickness, surface velocity, and surface elevation change, for all glaciers larger than 2 km² in the Swiss Alps.

Using in-situ MB observations from the Swiss Glacier Monitoring Network, we optimize and evaluate
20 our inversion framework for regional performance and transferability. We show that numerical filtering of the ice flux divergence is essential to obtain physically meaningful MB fields. After filtering, the inferred MB fields closely match observations (RMSE = 0.76 m w.e. yr⁻¹). Sensitivity analyses indicate robust performance across different ice thickness products, including for global reconstructions that do not integrate local ice thickness observations, while emphasizing the importance of temporal
25 consistency between the input datasets.

Our results demonstrate that observation-based distributed MB fields can be derived at regional scale from widely available remote sensing products, offering the method a strong potential for application in other regions worldwide. The resulting MB fields, together with derived equilibrium line altitudes and
30 MB gradients, provide new and independent constraints for glacier model calibration.



Short non-technical summary (500 characters incl spaces)

Direct measurements of glacier mass change are scarce, limiting our understanding and modelling of glacier evolution. We show that 2D maps of mass change can be derived for glaciers in the Swiss Alps by combining multiple observation products from satellites. Our results closely match field
 35 measurements. Our map can provide independent information in places without direct measurements and be used to improve glacier models. Our approach could also be applied to other glacier regions worldwide.

1 Introduction

The mass balance (MB) of a glacier is a key variable for understanding glacier response to climatic
 40 conditions and for modelling its temporal evolution. In recent decades, rising global temperatures have led to progressively more negative MBs, contributing to widespread glacier mass loss (Dussaillant et al., 2025; The GLAMBIE Team et al., 2025; Wouters et al., 2019; Zemp et al., 2019). Because the glacier MB directly reflects local climatic conditions, its spatial distribution is essential for monitoring and interpreting glacier change, as well as for constraining and calibrating glacier evolution models (Huss
 45 and Hock, 2015; Maussion et al., 2019; Rounce et al., 2023; Zekollari et al., 2022). In particular, distributed mass balance fields provide crucial information to better represent processes such as spatial variability in precipitation, avalanching (Kneib et al., 2024, 2026), and debris cover ((Bhushan et al., 2024). Additionally, distributed MB fields help overcome a key limitation of current large-scale glacier modelling, where calibration is typically based on a single glacier-wide geodetic mass balance (e.g.,
 50 Hugonnet et al., 2021). Because this integrated quantity can often be reproduced by multiple combinations of tunable model parameters, model calibration suffers from parameter equifinality. Distributed MB fields provide additional spatial constraints that help reduce this ambiguity.

Despite its importance, glacier MB remains poorly constrained due to limited observations in space and
 55 time. Traditional measurements rely on in-situ stake readings and snow pit measurements, which are sparsely distributed and available for only a small number of glaciers (ca. 200 of roughly 270,000 glaciers; WGMS, 2026). Geodetic methods, based on surface elevation changes derived from airborne or satellite data, provide broader spatial coverage and have been widely applied at local to regional scales to estimate glacier mass change (e.g, Brun et al., 2017; Davaze et al., 2020; Sommer et al., 2020).
 60 However, surface elevation change reflects the combined effect of mass balance and ice dynamics and therefore does not directly provide the spatial distribution of MB (Berthier et al., 2023; Berthier and Vincent, 2012). By combining observations of surface elevation change with estimates of glacier dynamics, expressed through the ice flux divergence, the continuity equation can be inverted to estimate distributed MB fields (Figure 1). The ice flux divergence represents the local emergence or
 65 submergence of ice due to glacier flow and can be estimated from observations of ice thickness and surface velocity.



A growing number of studies have applied this mass continuity approach to derive MB patterns from remote sensing data (Bhushan et al., 2024; Bisset et al., 2020; Cook et al., 2023; Hubbard et al., 2000; Kneib et al., 2024; Kraaijenbrink and Immerzeel, 2025; Miles et al., 2021; Reynaud et al., 1986; Van Tricht et al., 2021; Zeller et al., 2023). These methods differ in their spatial discretization, data requirements, representation of ice flow, and solution strategies, and are often constrained by data resolution, quality and associated uncertainties. In many cases, this necessitates smoothing of input data or flux divergence fields, or the use of simplified approaches such as flux gates or elevation band methods. As a result, these studies have either focused on high-resolution 2D MB reconstructions for individual glaciers (e.g., Kneib et al., 2024; Van Tricht et al., 2021) or on regional-scale estimates in a simplified one-dimensional (elevation based) framework (Miles et al., 2021). Recent studies retrieving regional 2D MB fields have relied on glacier models during the inversion process (Cook et al., 2023; Herrmann et al., 2026; Zöller et al., 2026), limiting their use as independent constraints for model calibration.

Consequently, spatially distributed MB estimates derived directly from observations are not yet available at regional scales, despite the growing availability of high-resolution datasets of glacier properties at regional to near-global scale (e.g., Gardner et al., 2025; Hugonnet et al., 2021; Millan et al., 2022). Here, we present a regional application of the method introduced by Van Tricht et al. (2021), which derives distributed MB fields from remote sensing data by solving the continuity equation. Using extensive in-situ observations, we apply and evaluate this approach over the Swiss Alps. The distributed MB fields are used to calculate the equilibrium line altitude (ELA) and mass balance gradient for each glacier, which are valuable metrics for glacier model calibration. In addition, we perform a sensitivity analysis to assess the robustness, transferability and potential of the method for application at larger (global) scales.

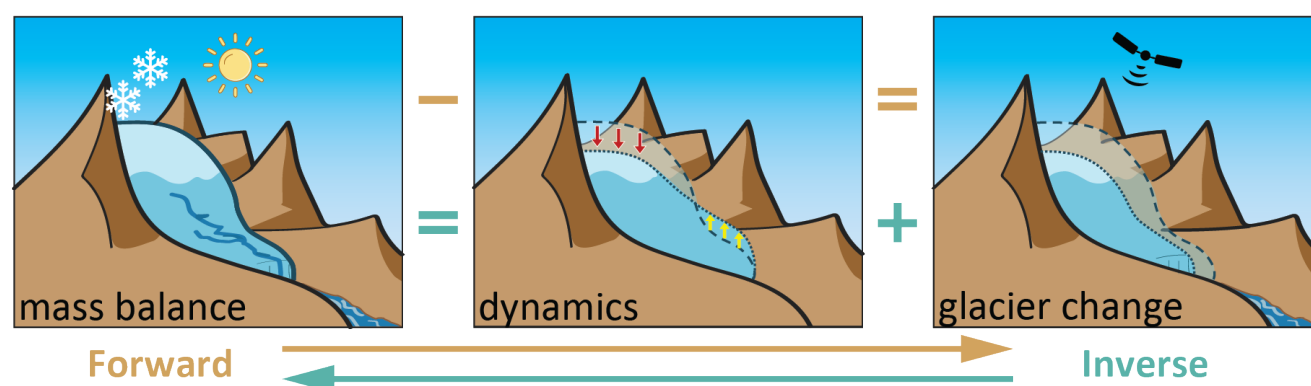


Figure 1 Schematic of studying glacier change patterns using the continuity equation. To simulate glacier change, a ‘forward approach’ is used where the modelled glacier mass balance and glacier dynamics (flux divergence) are combined to derive the glacier change. This requires that the components governing the mass balance (e.g., temperature and precipitation) are well known. In an ‘inverse approach’, observations of glacier change and its dynamic components are used to infer the mass balance.

2 Study area and Data

2.1 Glaciers of Swiss alps

We focus on the Swiss Alps, where an extensive network of in-situ mass-balance observations is available to evaluate our method, making it a suitable test region for a regional-scale application. The Swiss Alps host over 2000 glaciers, with a total volume of $\sim 59 \cdot 10^9 \text{ m}^3$ (Grab, 2020). In this study, we restrict the analysis to glaciers with an area $A > 2 \text{ km}^2$ to ensure a sufficient number of data pixels in the 50-m surface velocity remote sensing datasets used to estimate glacier dynamics, while excluding very small glaciers where ice dynamics are typically weak. This selection results in 100 glaciers that cover more than 85% of the regional volume ($\sim 51 \cdot 10^9 \text{ m}^3$), of which 17 have in-situ mass-balance measurements provided by Glacier Monitoring in Switzerland (GLAMOS - Glacier Monitoring Switzerland, 2023a).

2.2 Ice thickness data

We use ice thickness data for the glaciers from the SwissGlacierThicknessR2020 data package (Grab, 2020), published in the framework of Grab et al. (2021). Specifically, we employ the gridded ice thickness product (Figure 2a), which was derived from ice thickness point measurements obtained using airborne Ground Penetrating Radar (GPR) up to 2020 and combined with glaciological modelling using two independent algorithms (GlaTE and ITVEO; see Grab, 2020; Langhammer et al., 2019). This dataset provides spatially continuous ice thickness fields over entire glaciers at 10 m resolution and covers 81% of all Swiss glaciers. The dataset is consistent with the outlines of the Swiss Glacier Inventory SGI2016 (Linsbauer et al., 2021). Most glaciers have a measurement reference year of 2015 or later, while a smaller subset (15 glaciers) has reference years between 2008 and 2014.

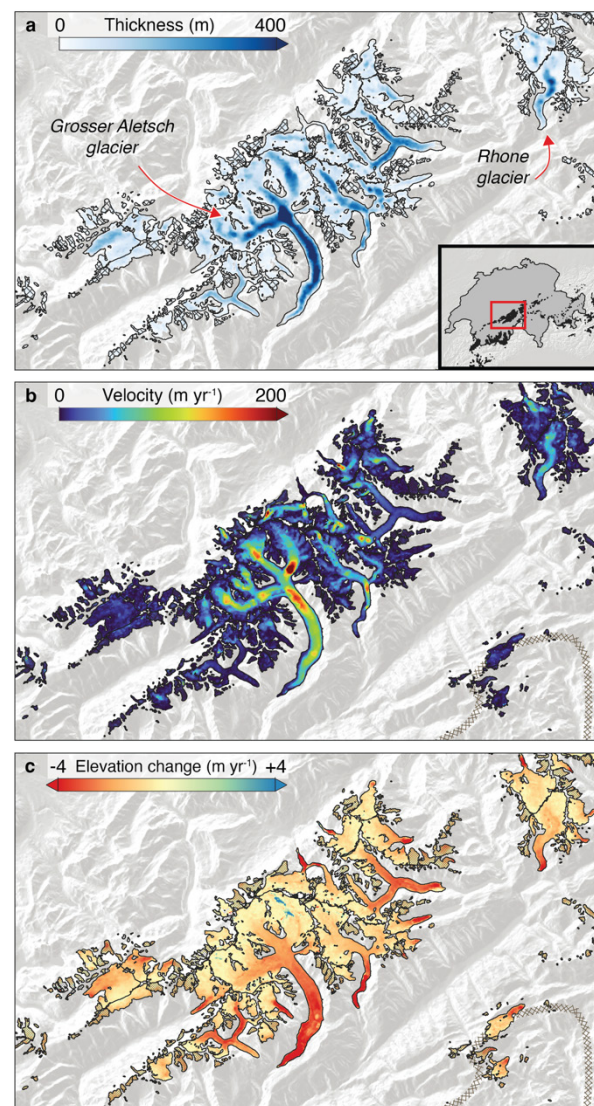


Figure 2 Used datasets, derived from remote sensing observations, shown for Swiss Alps Region D, which includes the Aletsch glacier and the Rhone glacier (EPSG:2056). (a) Ice thickness from Grab et al. (2021), (b) velocity from Millan et al. (2022), (c) Elevation change from Hugonnet et al. (2021).



135 2.2 Ice velocity data

We use the horizontal surface velocity components (v_x, v_y) from Millan et al. (2022). In this dataset, glacier surface velocities were mapped globally from image pairs acquired between 2017 and 2018 using Landsat 8, Sentinel-2 and Sentinel-1. Glacier motion was derived for each image pair using a cross-correlation approach that tracks the displacement of surface features or speckle (Michel and Rignot, 1999; Millan et al., 2019; Mouginot et al., 2017), and the results were assembled at 50 m spatial resolution. The velocity maps for RGI region 11 (covering Switzerland) are provided in the WGS 84 / UTM zone 32N coordinate system (EPSG:32632) and are masked using RGI 6.0 outlines (RGI Consortium, 2017).

145 The velocity dataset is reported to have a global precision and accuracy better than 10 m yr⁻¹, although local uncertainties may differ. From this dataset, we select the 100 studied Swiss glaciers. Median errors for these glaciers are 8.0 m yr⁻¹ and 95th percentile 16.1 m yr⁻¹

2.3 Glacier elevation change

150 We use glacier surface elevation change data from Hugonnet et al. (2021), who provide global estimates of surface elevation change between 1 January 2000 and 31 December 2019 (hereafter referred to as the 2000–2020 period) at 100 m spatial resolution. These estimates are primarily derived from stereo imagery acquired by NASA’s Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and are validated against high-precision measurements.

155 Hugonnet et al. (2021) provide elevation change maps over 5-year, 10-year, and 20-year periods within 2000–2020. Reported uncertainties for 5-year periods are generally below 0.5 m yr⁻¹ for glaciers larger than 1 km², although uncertainties vary spatially and temporally, and are typically higher in low-contrast accumulation areas. In this study, we use the 2000–2020 period for the main MB estimates (Figure 2c), and use the 2010–2020 and 2015–2020 periods to assess the impact of the selected period on the retrieved MB fields. Median elevation change errors for the studied glaciers are 2.13, 2.99, and 6.24 m yr⁻¹ for these periods, respectively, with lower errors in ablation areas and substantially higher errors in accumulation areas, sometimes exceeding 10 m yr⁻¹.

160 Although the elevation change maps are not clipped to individual glacier extents, Hugonnet et al. (2021) use RGI 6.0 outlines to aggregate glacier-wide changes; we adopt the same outlines for consistency. The elevation change maps for RGI region 11 (Central Europe) are provided in WGS 84 across multiple UTM zones (31N–33N). We reproject them to a common coordinate system (EPSG:32632) and resample them from 100 m to the 50 m grid of the velocity data using bilinear interpolation, which

170 introduces minor smoothing of the elevation change fields.



2.4 In-situ surface mass balance data

For optimizing and assessing our MB inversion approach, we rely on in-situ GLAMOS MB observations that are available for 17 of the studied glaciers. Two main GLAMOS products are
175 considered. First, we use point mass-balance observations obtained from stake measurements and snow pits to optimize and evaluate the spatial patterns of the reconstructed MB fields. These measurements are sparsely distributed and vary in spatial coverage. For some glaciers, they are concentrated in the ablation zone, while for others, they extend more evenly across the glacier surface.

180 Second, we use binned mass-balance data which provide glacier mass balance per elevation bin for the whole elevation range of the glacier. These values were derived from direct glaciological observations combined with a distributed accumulation and temperature-index melt model that were calibrated against geodetic mass changes (GLAMOS, 2023). While these binned mass balance data capture the altitudinal (1D) variability in MB rather than the full spatial (2D) distribution, they cover the entire
185 glacier and thus provide a complementary dataset to the point measurements.

For both datasets, we use annual mass-balance values, covering a time interval of approximately one hydrological year (from October to September in the subsequent year). To ensure consistency with the elevation change data, we filter the observations to match respective analysis periods (2000-2020, 2010-
190 2020 or 2015-2020).

3 Methods

3.1 Continuity equation method

The continuity equation for glacier flow with constant density (Eq. 1) links the local MB (b) and the ice flux divergence per unit width in the local vertical ice column ($\nabla \cdot \mathbf{q}$) with local changes in the ice
195 thickness ($\partial H / \partial t$) (see e.g. Berthier and Vincent, 2012; Hubbard et al., 2000; Van Tricht et al., 2021):

$$\frac{\partial H}{\partial t} = b - \nabla \cdot \mathbf{q}. \quad (1)$$

Equation (1) shows that the difference between the local MB and ice flux divergence must be compensated by a change in local ice thickness. For mountain glaciers, basal and internal mass balance are commonly considered to be much smaller than surface mass balance (b_s), such that $b \approx b_s$ (Beraud
200 et al., 2023; Huss et al., 2015; Kaser et al., 2003).

Assuming a constant bedrock and negligible firn compaction, the local ice thickness (H) change can be approximated by the surface elevation (h) change. However, this assumption is generally only valid in the ablation area, where the entire column predominantly consists of ice. In the accumulation area, firn
205 compaction can significantly influence surface elevation changes. To account for this, surface elevation changes are converted to mass-equivalent changes by scaling with an effective density relative to water



($\rho_w = 1000 \text{ kg m}^{-3}$). Equation (1) can then be reformulated as (Berthier and Vincent, 2012; Hubbard et al., 2000; Kneib et al., 2024; Miles et al., 2021):

$$b = \frac{\rho_{dh}}{\rho_w} \frac{\partial h}{\partial t} + \frac{\rho_{\nabla q}}{\rho_w} \nabla \cdot \mathbf{q}, \quad (2)$$

210 where the mass balance b is expressed in meter water equivalent per year (m w.e. yr^{-1}). Following Kneib et al. (2024) and Miles et al. (2021), we assume that all ice fluxes consist of glacier ice only, such that $\rho_{\nabla q} = \rho_{ice} \approx 900 \text{ kg m}^{-3}$. The effective density associated with elevation change (ρ_{dh}) is determined based on the physical interpretation of the observed elevation change and calculated flux divergence. Where both elevation change and flux divergence are positive, the signal is interpreted as accumulation and a density of 600 kg m^{-3} is assigned. Where both are negative, indicating ice ablation, 215 a density of 900 kg m^{-3} is used. In cases where elevation change and flux divergence have opposing signs, an intermediate density of 850 kg m^{-3} is adopted, consistent with the commonly used density conversion factor in geodetic surveys (Hugonnet et al., 2021; Huss, 2013).

3.2 Ice flux divergence calculation

220 The local ice flux divergence translates into a local vertical component of ice flow at the glacier surface. It is defined with a positive term for divergent flow (Eq. 1), corresponding to a local removal of mass at the surface which is expected in the accumulation area and referred to as submergence velocity. In contrast, the ice flux divergence term is negative for upward motion, with a local supply of mass to the surface, which typically occurs in the ablation area and is referred to as emergence velocity. Under the 225 shallow ice approximation (Cuffey and Paterson, 2010; Hutter and Morland, 1984), the ice flux $\mathbf{q}$ can be expressed as a function of ice thickness H and surface velocity $\mathbf{u}$ using a depth-averaged glacier velocity ratio ($F = \bar{\mathbf{u}}/\mathbf{u}_s$) to account for the relative contributions of basal sliding and vertical ice shear deformation,

$$\mathbf{q} = HF\mathbf{u}_s. \quad (3)$$

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This approximation allows efficient computation of the flux but requires assumptions of the sliding regime of the glacier (Hubbard et al., 2000). For purely deformational flow without sliding, the depth-averaged glacier velocity ratio is (Cuffey and Paterson, 2010)

$$F = \frac{\bar{\mathbf{u}}}{\mathbf{u}_s} = \frac{n+1}{n+2}, \quad (4)$$

235 where n is the exponent of Glen's flow law. While commonly $n = 3$ is appropriate for many glacier modelling scenarios, lower exponents ($n \approx 2$) might exist at lower stress (Cuffey and Paterson, 2010; Schulson and Duval, 2009) and fast flowing ice might reach $n \approx 4$ (Millstein et al., 2022). These ranges in n would yield $F = 0.75$ to 0.83 in absence of basal sliding. For maximum sliding $F = 1$ and $\bar{\mathbf{u}} = \mathbf{u}_s$. As both basal sliding and ice rheology are poorly constrained, we explore F values between 0.75 240 and 1 . Ice flux divergence vector $\mathbf{q}$ can then be written as:



$$\begin{aligned}\nabla \cdot \mathbf{q} &= \frac{\partial q_x}{\partial x} + \frac{\partial q_y}{\partial y}, \\ &= \frac{\partial}{\partial x} (HF u_{s,x}) + \frac{\partial}{\partial y} (HF u_{s,y}), \\ &= F \left(\frac{\partial H}{\partial x} u_{s,x} + H \frac{\partial u_{s,x}}{\partial x} + \frac{\partial H}{\partial y} u_{s,y} + H \frac{\partial u_{s,y}}{\partial y} \right)\end{aligned}\quad (5)$$

Where each component can be calculated from the spatial gradients of ice thickness and surface velocity components (Reeh et al., 2002).

3.2.1 Spatial gradients and filtering approaches

245 Spatial gradients of ice thickness and the surface velocity components are computed on a pixel basis using second-order central differences. However, directly computing ice flux divergence from these gradient fields produces a resolution-dependent product that is highly noisy and physically unrealistic (Van Tricht et al., 2021) (Figure 3a) due to input uncertainties and local variability. Moreover, glacier flow depends not only on local geometry but also on surrounding geometry through longitudinal stress coupling acting over distances of several ice thicknesses (Kamb and Echelmeyer, 1986; Zekollari et al., 2014), which is not represented in the SIA. The characteristic length scale of longitudinal coupling typically ranges from 1–3 times the ice thickness for valley glaciers and 4–10 times for ice sheets and can reach up to 12 times the ice thickness in specific cases (e.g. surging glaciers) (Reeh et al., 2003; Rounce et al., 2018).

255 To account for both noise and non-local effects while ensuring that the approach is independent of the spatial resolution of the input datasets, we apply a distance-weighted exponential filter (Figure 3e). The filter decay length is scaled to local ice thickness, following the approach of Van Tricht et al. (2021). This effectively incorporates non-local influences on the ice flow while retaining sensitivity to local variations better than uniform filters (e.g., moving averages), which tend to oversmooth spatial features.

The exponential filter is applied on each grid pixel (x, y) with a decay length ℓ (m) determined locally from the local ice thickness multiplied by a longitudinal coupling factor N :

$$\ell_{x,y} = N \cdot H_{x,y}. \quad (6)$$

265 A filter kernel is then defined around every individual pixel that assigns exponentially decreasing weights to its neighbouring pixels (x_i, y_j) :

$$W(x_i, y_j) = \exp \left(-\frac{1}{\ell(x, y)} \sqrt{(x_i - x)^2 + (y_j - y)^2} \right). \quad (7)$$

The filtered value $(\hat{g})$ of each pixel is computed as the normalized weighted sum of the kernel:

$$\hat{g} = \frac{\sum g \cdot w}{\sum w}. \quad (8)$$

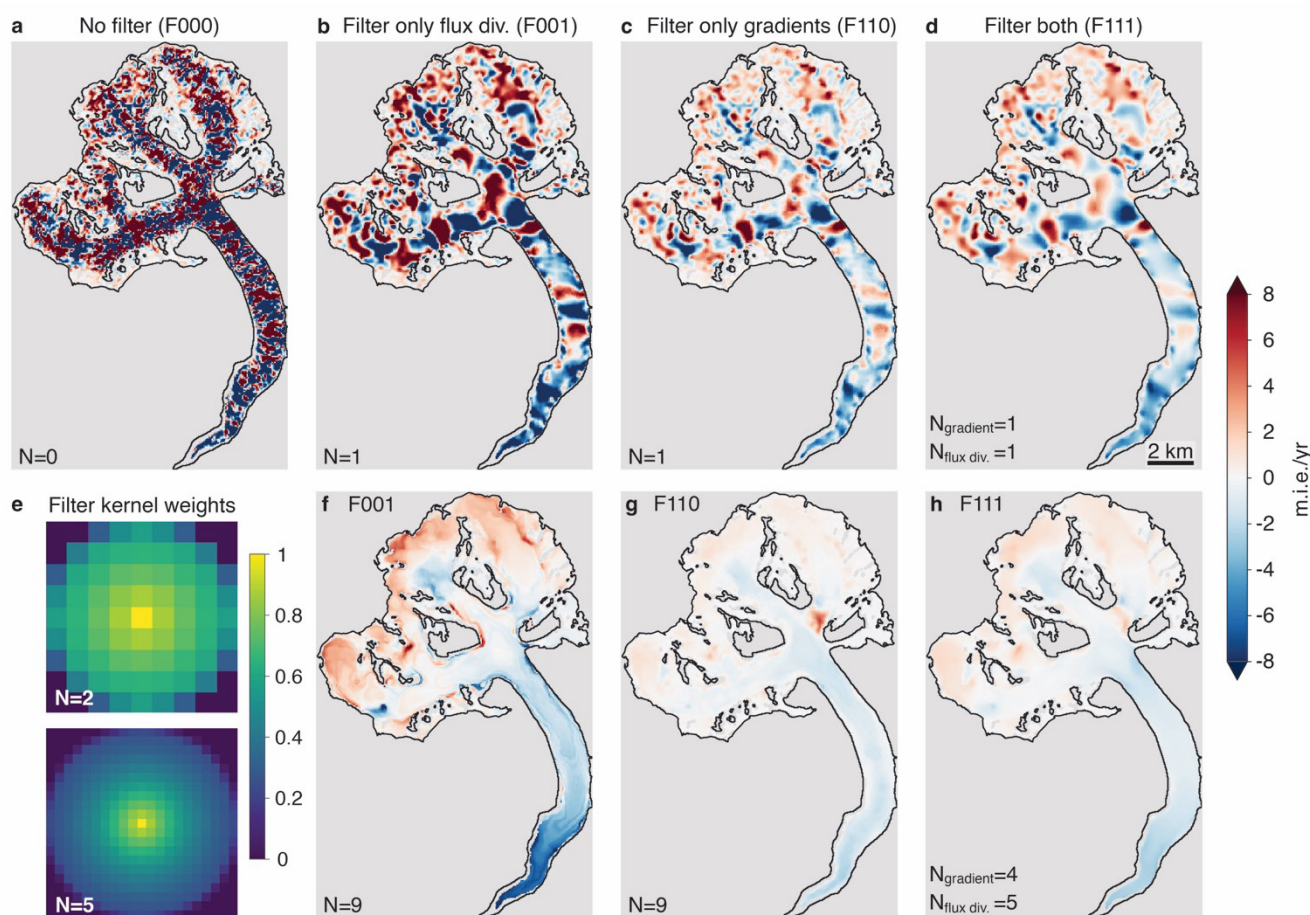


Figure 3 Effect of exponential filter applied in different steps of the flux divergence calculation for varying longitudinal coupling factors N , showcased for the Grosser Aletschgletscher (hereafter “Aletsch Glacier”). (a) displays the unfiltered reference case, (e) shows example kernel size and weights for different N for a local ice thickness of 100 m. For all other panels: top and bottom row show the same filter approach for different N .

Thicker ice results in a larger decay length and thus a broader effective filter window, whereas thinner ice leads to a narrower window (Figure 3e), thereby mimicking the longitudinal coupling of ice flow in a numerical scheme. A minimum decay length of 100 m is imposed (two pixels). Pixels outside the glacier mask are excluded from the filtering procedure, to avoid cross-contamination of closely situated glaciers. We do not impose a maximum decay length.

We test three implementations at which stage to incorporate the longitudinal coupling in the ice flux divergence calculation (Figure 3; Figure 4): (A) not filtering the spatial gradients of velocity and thickness but instead filtering only the resulting ice flux divergence field (referred to as F001), (B) filtering the spatial gradients of velocity and thickness, but not the resulting ice flux divergence (referred to as F110), and (C) applying both filtering steps (F111).



3.2.2 Hyperparameter space

In addition to the choice of filtering stage, two key parameters are explored: (1) the filter length governed by the longitudinal coupling factor N and (2) the sliding parameter F .

For the filter length in approaches F001 and F110 we vary the coupling factor N in Equation 6 over the range $N \in [0, 10]$ in steps of 1 (11 values), where $N = 0$ corresponds to no filtering. For approach F111, where filtering is applied both before and after flux divergence calculation, we restrict the parameter space to $N \in [1, 5]$ (5 values each step), as the combined smoothing scale is proportional to $N_{001} + N_{110}$. For the sliding parameter, we vary F over the range $F \in [0.75, 1]$ in steps of 0.05 (6 values) to account for possible variations in both Glen's flow law exponent n and the contribution of basal sliding. In total, this results in an ensemble of 246 ice flux divergence realizations (per glacier).

3.3 Regional application

3.3.1 Aligning datasets in space and time

The ice velocity, thickness and elevation change datasets are reprojected to a common coordinate system (EPSG:32632, WGS 84 / UTM zone 32N) to compute ice flux divergence and MB fields consistently. For the evaluation, the results are transformed to EPSG:21781 (Swiss CH1903 / LV95), the native projection of the GLAMOS data, while visualizations are produced in EPSG:2056, the updated Swiss reference system.

The ice thickness data are based on the SGI2016 glacier outlines (Linsbauer et al., 2021), whereas the velocity and elevation-change datasets are based on the RGI v6.0 outlines (RGI Consortium, 2017). Because these outlines do not always coincide, the velocity and elevation change fields are extended to the SGI2016 outlines where needed, using linear interpolation or nearest-neighbour extrapolation (i.e. extending boundary values).

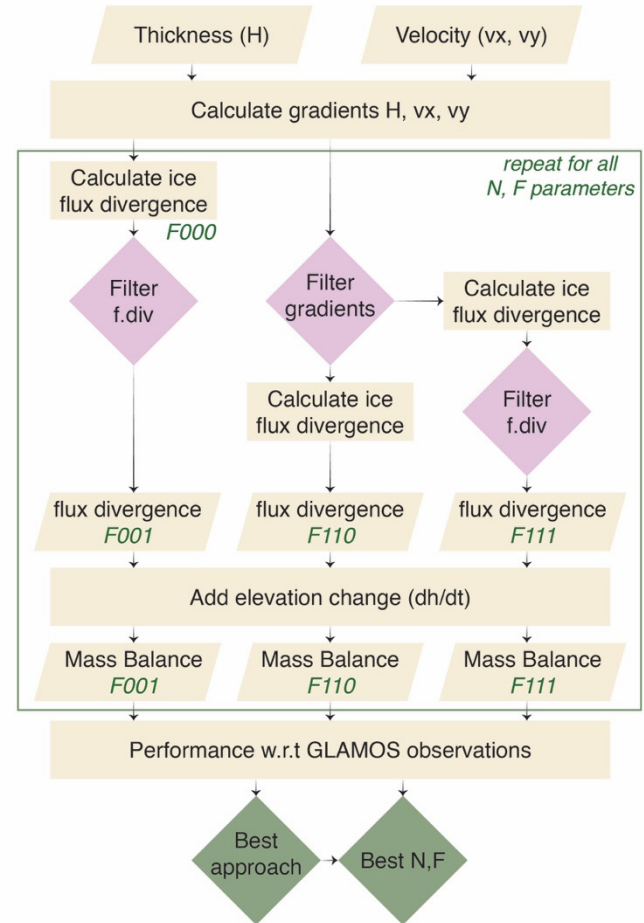


Figure 4 Flowchart of explored approaches to derive the MB from observational datasets, with different choices of when to apply the exponential filter.



325 The available datasets are not fully contemporaneous. Surface velocities are derived from observations
acquired between 2017 and 2018, whereas the ice thickness data predominantly represent the period
2015–2020. The resulting flux divergence fields therefore approximate conditions for the period 2015–
2020. Surface elevation change rates are considered over the periods 2000–2020, 2010–2020, and
2015–2020, to assess the sensitivity of the retrieved MB fields. Longer averaging periods reduce
uncertainties but are less temporally consistent with the ice flux divergence estimates. GLAMOS
330 observations are filtered for the same 20-, 10- or 5-year period to match the temporal coverage of the
chosen elevation change period in the MB estimates. The range of the individual GLAMOS
observations within each period is used as an estimate of observational uncertainty, assuming that it
exceeds the measurement error.

335 3.3.2 Partition train and test glaciers

To determine the best choices for filtering approach and hyperparameters, we partition the 17 glaciers
with available GLAMOS observations into a training and test set. The training set contains 13 glaciers,
and the test set 4 glaciers. The three filtering approaches and hyperparameters are optimized using the
training glaciers by minimizing the root mean square error (RMSE) relative to the in-situ MB
340 observations. The optimized setup is then applied to the unseen test glaciers, and the resulting RMSE is
used as an estimate of the overall performance.

The partitioning into training and test sets is based on key glacier characteristics from the GLAMOS
inventory, including winter, summer, and annual mass balance, glacier area, and minimum and
345 maximum elevation (see Table 1). This ensures that the test set, although limited in size, captures a
representative range of glacier properties. This approach reduces the risk of overfitting to glaciers with
extensive in-situ observations and enables a first assessment of its transferability to other glaciers.
Although the small size of the test set limits our ability to robustly assess transferability to all glaciers in
Switzerland, it still provides a first-order estimate of the regional performance.



350 **Table 1 Overview of glaciers used for method optimization and evaluation, partitioned in a ‘training’ and ‘test’ set. All reported values are from the GLAMOS dataset (GLAMOS - Glacier Monitoring Switzerland, 2023a) and show the diversity of glaciers for both sets.**

SGI-ID	Name	set	Average annual MB (m w.e.)	Average winter MB (m w.e.)	Average summer MB (m w.e.)	Area (km ²)	Min. elevation (m)	Max. elevation (m)	Obs. Period	Corresponding RGI-ID
B36-26	Grosser Aletschgletscher	train	-1.19	1.27	-2.45	78.5	1605	4120	2000-2021	RGI60-11.01450
B82-27	Glacier d'Otemma	train	-1.08	1.24	-2.32	12.6	2464	3785	2019-2021	RGI60-11.02801
B56-14	Adlergletscher	train	-0.43	0.84	-1.27	2.1	2980	4175	2005-2021	RGI60-11.02764
B52-29	Allalingsgletscher	train	-0.53	0.91	-1.43	9.1	2682	4182	2000-2021	RGI60-11.02704
B52-32	Hohlaubgletscher	train	-0.66	1.04	-1.70	2.2	2839	4024	2000-2021	RGI60-11.02679
A51e-37	Tiefengletscher	train	-1.16	1.73	-2.89	2.2	2500	3379	2013-2017	RGI60-11.01296
E22-03	Vadret Pers and Vadret da Morteratsch	train	-0.90	1.30	-2.20	14.9	2032	4006	2001-2021	RGI60-11.01946
B22-01	Glacier de Tsanfleuron	train	-1.49	1.66	-3.14	2.4	2504	2964	2009-2021	RGI60-11.02249
B52-24	Schwarzberggletscher	train	-0.76	1.19	-1.95	5.1	2664	3570	2000-2021	RGI60-11.02746
B56-03	Findelgletscher	train	-0.48	1.09	-1.57	13.9	2554	3914	2004-2021	RGI60-11.02773
B82-14	Glacier du Giètro	train	-0.77	1.09	-1.85	5.1	2738	3816	2000-2021	RGI60-11.02774
A55f-03	Glacier de la Plaine Morte	train	-1.47	1.34	-2.81	7.3	2477	2957	2009-2021	RGI60-11.02072
B45-04	Griesgletscher	train	-1.37	1.57	-2.94	4.6	2426	3332	2000-2021	RGI60-11.01876
A10g-05	Silvrettagletscher	test	-0.89	1.41	-2.30	2.7	2469	3103	2000-2021	RGI60-11.00804
A50i-19	Claridenfirn	test	-0.80	1.34	-2.14	4.7	2464	3256	2000-2021	RGI60-11.00817; RGI60-11.00819; RGI60-11.00843; RGI60-11.00878
B43-03	Rhonegletscher	test	-0.71	1.54	-2.25	14.6	2209	3621	2006-2021	RGI60-11.01238
B83-03	Glacier de Corbassière	test	-0.75	0.97	-1.73	14.9	2311	4311	2000-2021	RGI60-11.02766

3.4 Comparison to observations

- 355 For all training and test glaciers we compare the reconstructed MB against both the elevation-binned and point MB observations from GLAMOS using the RMSE. In both cases, we average annual MB values over the temporal range covered by each selected elevation bin or stake record, and the corresponding interannual range is used as an estimate of observational uncertainty within the period.
- 360 For the comparison against elevation-binned MB, we aggregate the retrieved MB into 100 m elevation bins based on the elevation fields of (Grab, 2020), consistent with the ice thickness data used. For each bin, we calculate both the area-weighted mean and standard deviation, with the latter serving as an estimate for within-bin MB variability. The resulting $RMSE_{bins}$ is calculated as an unweighted mean over all bins.



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For the comparison against point MB, we extract the derived MB at the pixel corresponding to each stake location and use the standard deviation within a 3×3 pixel neighbourhood as an estimate of local MB variability. GLAMOS point MB measurements are generally repeated at the same locations each year, with stakes repositioned to account for ice flow. This allows for direct comparison of mass balance observations over time. However, most glaciers have multiple stake records that are not measured over the same temporal range (i.e. some stakes are measured once or twice in most recent years, whereas others are measured consistently for multiple years). Therefore, for the point-based evaluation, we weight each stake by its number of observations when calculating $RMSE_{point}$.

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375 The binned and point-based RMSE values are then combined into a single error metric for each glacier and hyperparameter combination:

$$RMSE(N, F, glacier) = \overline{RMSE_{bin} + RMSE_{point}}.$$

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The optimal hyperparameter combinations are selected based on both a low overall $RMSE_{glacier}$ across the training glaciers and low inter-glacier variability in $RMSE_{glacier}$ (small min-max range of RMSE), thereby favouring combinations that perform well and consistently across the training set.

4. Results

4.1 Model performance

4.1.1 Evaluation of parameter space and filter approach

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All filtering approaches reproduce the general pattern of the GLAMOS elevation-binned mass balance within the training set glaciers (solid black line with shaded range, Figure 5a-b). A no-filter estimate ($N=0$, F000, green lines) is included as a baseline to highlight the effect of the filtering strategies. This solution varies only with the sliding parameter F and shows relatively little variability (shaded range), indicating that the method is more sensitive to the choice of coupling factor N than to F (Figure 5a).

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Although the elevation-binned averages of the no-filter approach, F000, agree reasonably well with observations, the corresponding ice flux divergence fields are physically unrealistic (Figure 3a) and show extremely large variability within each bin (Figure A1). This demonstrates that agreement in elevation-binned values alone can mask substantial errors in the spatial distribution.

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Among the filtering approaches, the largest sensitivity to hyperparameter choice is observed for the approach where only the flux divergence is filtered (F001, yellow lines), which exhibits the widest spread across the solutions. In contrast, approaches with filtering before the flux divergence calculation (F110 and F111) show more consistent behavior but systematically overestimate MB in the ablation zone and underestimate it in the accumulation zone. This indicates that filtering the gradients strongly influences the retrieved MB values. For F001, although some parameter combinations perform poorly, optimal choices of N and F yield the closest agreement with observations. Across all approaches, MB

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values in the lowest elevation bin are often overestimated and higher than the next-to-lowest bin. This may reflect reduced filtering effectiveness in thin-ice regions, uncertainties in the input data, the imposed minimum filter length, or the limited number of pixels in these bins.

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To systematically quantify the effect of the filtering, $\text{RMSE}_{\text{glacier}}$ values are computed for all hyperparameter combinations and aggregated across the training glaciers (Figure 6). The optimal configurations are identified based on both low mean $\text{RMSE}_{\text{glacier}}$ ($\overline{\text{RMSE}_{\text{glacier}}}$) and a low min-max range of values across $\text{RMSE}_{\text{glacier}}$. The best performance is obtained for the F001 approach with $N = 9$ and $F = 0.80$ (and similar results for $N = 10$, $F = 0.75$ to 0.90), yielding a $\overline{\text{RMSE}_{\text{glacier}}}$ of $0.78 \text{ m w.e. yr}^{-1}$ and a $\text{RMSE}_{\text{glacier}}$ range of $0.69 \text{ m w.e. yr}^{-1}$ across glaciers. Although for the other filtering approaches (F110 and F111) the best-performing hyperparameters also yield relatively low $\overline{\text{RMSE}_{\text{glacier}}}$ of $\sim 1.1 \text{ m w.e. yr}^{-1}$ (Figure 5c-h, Figure 6), their performance across glaciers is less robust (range $\text{RMSE}_{\text{glacier}} = 2.5 \text{ m w.e. yr}^{-1}$). The reference, no-filter approach F000 results in substantially higher RMSE values than all filtered approaches ($\overline{\text{RMSE}_{\text{glacier}}} > 2.7 \text{ m w.e. yr}^{-1}$ and range $\text{RMSE}_{\text{glacier}} > 8 \text{ m w.e. yr}^{-1}$), confirming the importance of filtering to obtain accurate MB patterns. Across all approaches, the influence of the sliding parameter F on the RMSE values is small compared to that of the smoothing length N (Figure 6).

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These results show that the F001 approach provides the best overall performance. Although the optimal coupling factor ($N = 9$) exceeds commonly assumed longitudinal coupling scales for valley glaciers (typically 1–3 times ice thickness), the use of an exponential decay filter limits the influence of distant pixels. For example, for an ice thickness of 100 m and $N = 9$, the effective filter length of 900 m (18 pixels in our data), with weights decreasing from 1 at the center to 0.13 at the edge.

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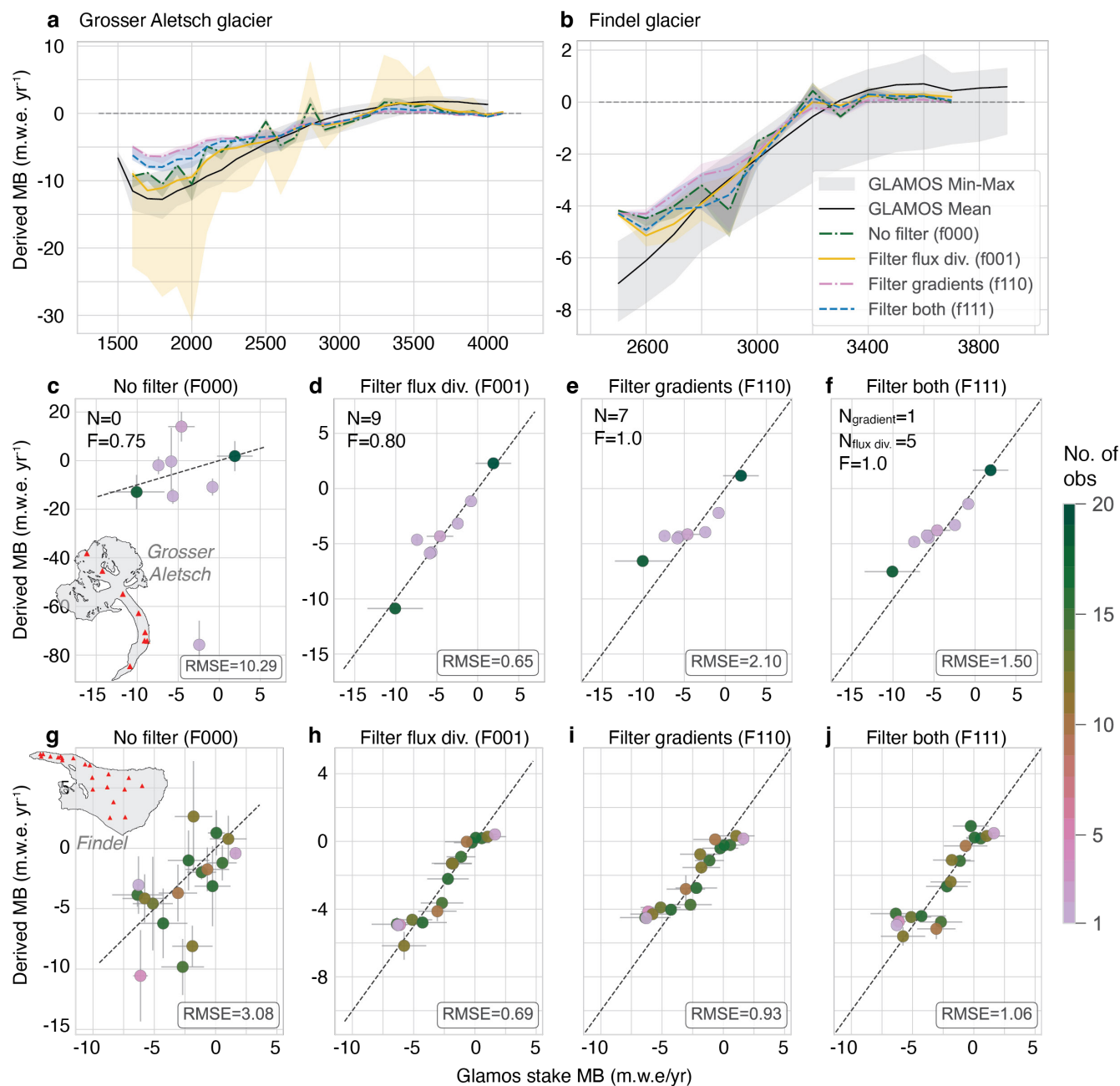
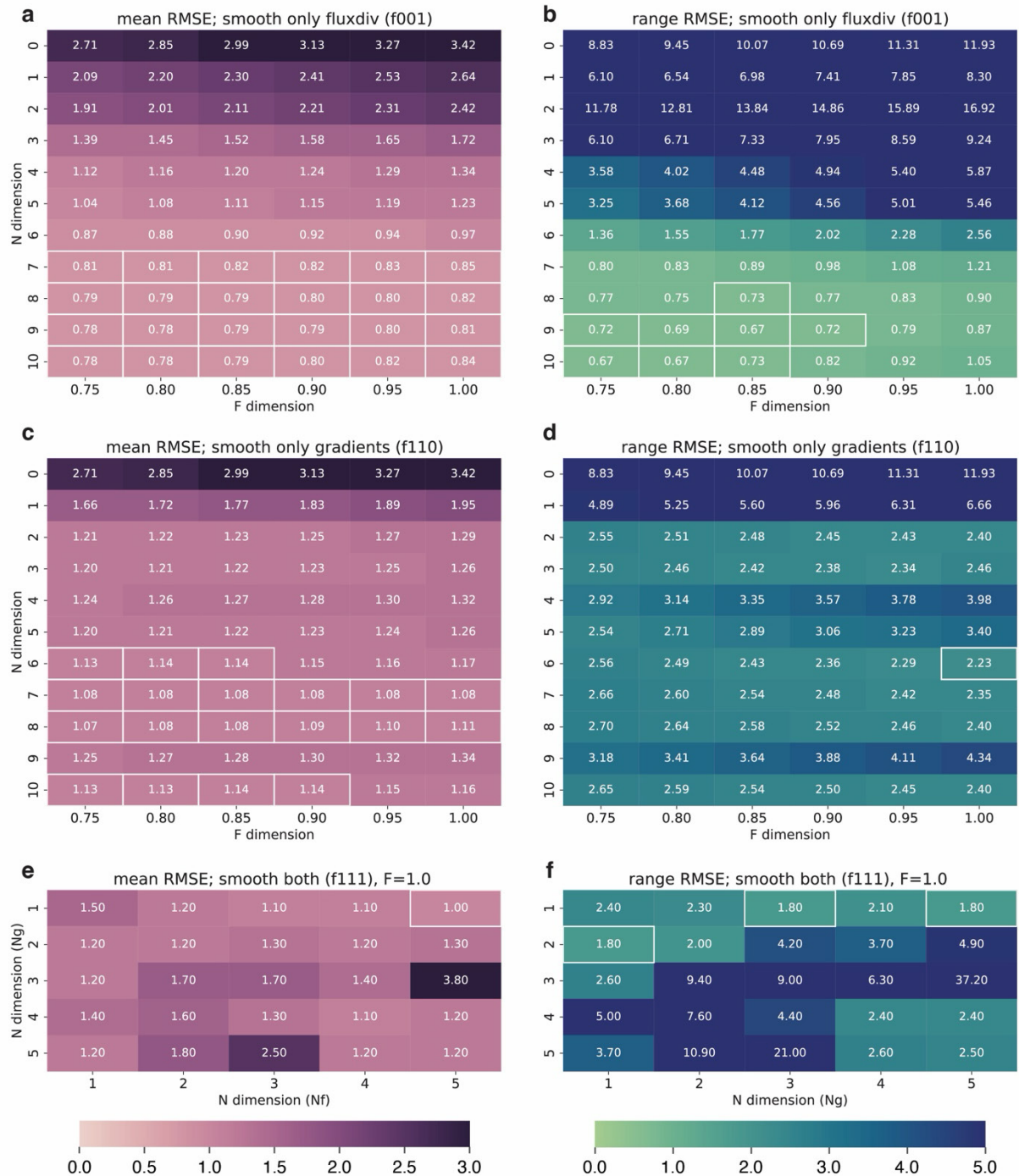


Figure 5 Comparison between derived MB and observed GLAMOS MB values for different filtering approaches. (a,b) Elevation-binned MB for full parameter space (shaded) and best performing parameters (thick lines) of each filter approach. (c-j) Point MB values for the best parameters per filter approach. Example for two glaciers in the train-set: Grosser Aletsch (a; c-f) and Findel (b; g-j).

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435 **Figure 6** Parameter space optimization for each filter approach, N and F. RMSE values are aggregated for all 13 glaciers in the train set and per parameter combination, including N=0 for no-filter approach. (a/c/e) Heatmap showing the mean RMSE over all glaciers, (b/d/f) heatmap showing min-max range of RMSE across glaciers. (e) and (f) show the parameter space for two-step filter approach F111 with one selected value F=1.0. White boxes indicate the lowest RMSE values (1 decimal accuracy).



440 4.1.2 Evaluation of best parameters

The performance of the selected optimal approach, with filtering applied to the ice flux divergence field with a coupling factor of $N = 9$ times the local ice thickness and a sliding parameter $F = 0.8$, is evaluated on the four glaciers in the test set (Figure 7, Table A1). The agreement of the derived MB to point MB observations is similar between the test and training set, with an overall $RMSE_{point}$ of 0.70 m w.e. yr^{-1} and 0.73 m w.e. yr^{-1} , respectively. For elevation-binned MB observations, the test set yields an $RMSE_{bins} = 0.81$ m w.e. yr^{-1} , again comparable to the training set that had $RMSE_{bins} = 0.84$ m w.e. yr^{-1} .

For three of the four glaciers, Corbassière, Rhône, and Silvretta glaciers, the retrieved MB agrees well with GLAMOS observations for both elevation-binned and point observations. Corbassière Glacier shows $RMSE_{bins} = 0.56$ m w.e. yr^{-1} and $RMSE_{point} = 0.95$ m w.e. yr^{-1} , Rhône Glacier $RMSE_{bins} = 0.73$ and $RMSE_{point} = 0.51$ m w.e. yr^{-1} , and Silvretta Glacier $RMSE_{bins} = 0.54$ and $RMSE_{point} = 0.51$ m w.e. yr^{-1} . For Claridenfirn, the agreement with point observations is similarly good ($RMSE_{point} = 0.84$ m w.e. yr^{-1}), while the RMSE for elevation-binned values is higher ($RMSE_{bins} = 1.42$ m w.e. yr^{-1}). For this assessment the lowest elevation bin of Claridenfirn (<2500 m a.s.l.; 0.01 km²) is excluded, as it represents a small, thin glacier remnant below a rock cliff that experienced substantial frontal ablation during the observation period (Figure 7 c1, Appendix A2).

Overall, these results demonstrate that the method performs well on independent test glaciers and provide a solid baseline for its transferability to other glaciers.

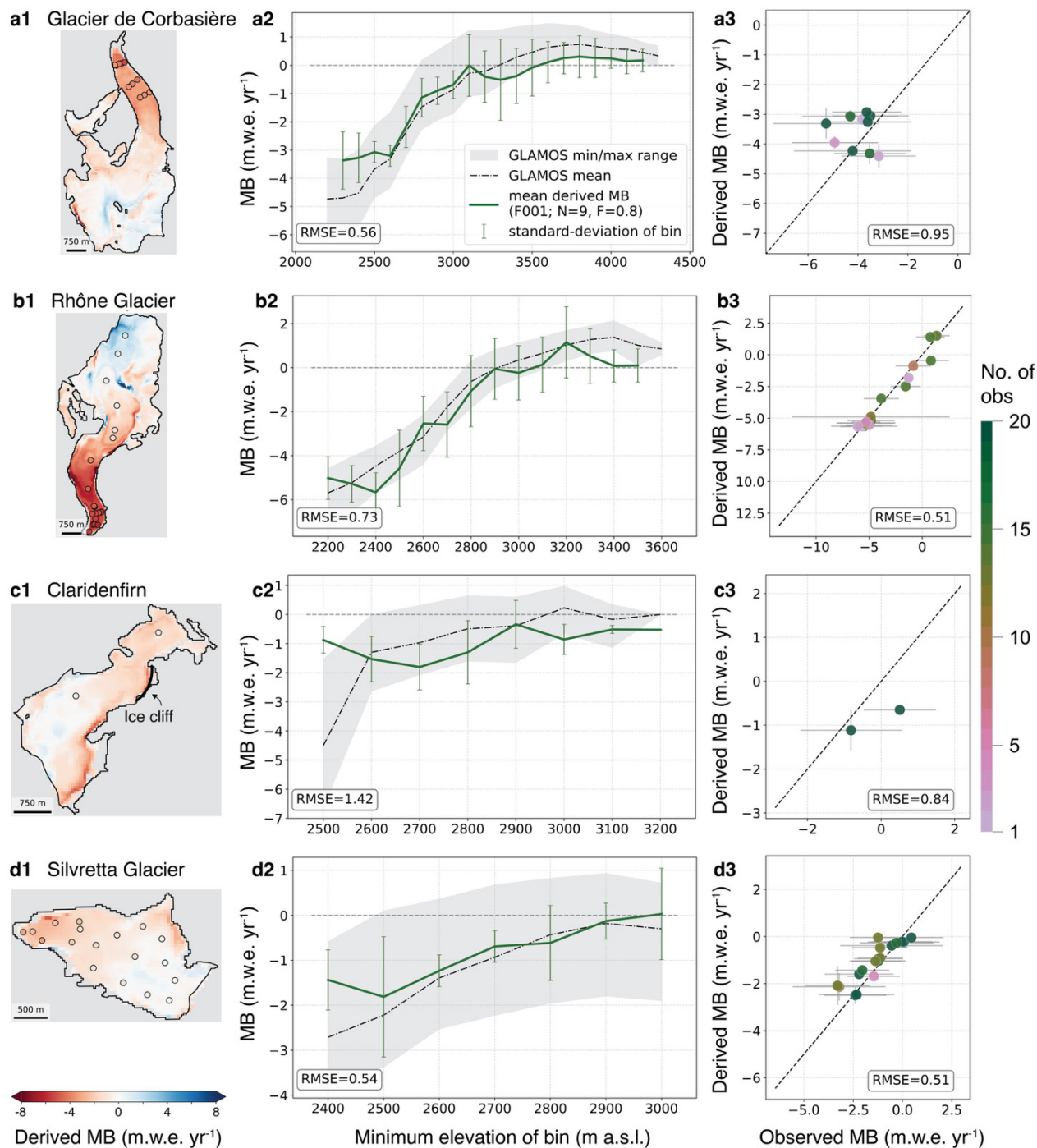


Figure 7 Comparison of derived MB to GLAMOS observations on test glaciers for the optimal approach in which the ice flux divergence is filtered (F001) with hyperparameters N=9 and F=0.8. Left column (a1-d1) shows retrieved spatial MB patterns, middle column (a2-d2) the evaluation to binned MB values and right column (a3-d3) the evaluation to point MB values. In the latter, the vertical bars show variability of derived MB in 3x3 window around the pixel of the stake and horizontal bars represent the temporal (5-95 percentile) range of observations. Figure A2 shows the results for all other GLAMOS (train) glaciers.



4.2 Distributed mass balance for Swiss Alps

We apply the optimized method to all glaciers in the Swiss Alps with an area larger than 2 km² with available ice thickness observations, which results in a total of 100 glaciers. The reconstructed ice flux divergence fields are shown in Figure 8 and the corresponding mass balance fields for 2000–2020 are presented in Figure 9. For almost all glaciers (97%) we retrieve net negative mass balance. Across the study region, the average glacier mass balance is -0.84 m w.e. yr⁻¹, ranging between -1.75 to 0.61 m w.e. yr⁻¹ (min-max range of average glacier MB). These regional values compare well to GLAMOS annual Swiss-wide mass balance of -0.90 m w.e. yr⁻¹ in the 2000-2020 period (GLAMOS - Glacier Monitoring Switzerland, 2023b) and the estimates of Cremona et al. (2026) whom report annual mass balance ranging between -1.5 to -0.6 m w.e. yr⁻¹ for Swiss glaciers between 2010-2024. When converted to mass change, our regional mass balance corresponds to -0.62 Gt yr⁻¹.

We estimate distributed uncertainties of the MB fields by performing 100 Monte Carlo simulations (using F001 approach, N=9 and F=0.8) where we perturb the input velocity and elevation change fields using their distributed error estimates (Hugonnet et al., 2021; Millan et al., 2022). To account for spatial dependency of errors during the differencing and filtering steps, we generate spatially correlated noise from the distributed error values (correlation length of 250 m for velocity and 1000 m for elevation change (Huss et al., 2021; Kochtitzky et al., 2022)). The distributed uncertainty of the flux divergence and MB estimates is then determined as the standard deviation (σ) from the Monte Carlo simulations, providing values at pixel level (Figure A3 and A4). The separate uncertainty contributions of the input data on the retrieved MB are, regionally averaged, $\sigma = 0.82$ m w.e. yr⁻¹ from velocity errors, and $\sigma = 1.87$ m w.e. yr⁻¹ (Figure A5) from the elevation change errors. These estimates reflect the high uncertainty of elevation change values, especially in the accumulation area. When using the more contemporaneous elevation change data of the 5- and 10-year periods, the uncertainties of the derived MB values for 2010-2020 and 2015-2020 are further increased to 2.63 and 5.46 m w.e. yr⁻¹ (regional average), respectively. This shows a strong decrease in the reliability of mass balance values for shorter periods of elevation change.

Using the 20-year MB estimates, we segment the distributed mass balance fields into an accumulation ($MB \geq 0$) an ablation zone ($MB < 0$) to calculate the Accumulation Area ratio (AAR) of the glaciers. The regional AAR is on average 18.5%, varying from 0 to 57.9%. For the 17 GLAMOS glaciers only, our estimated AAR is on average 19.2% while the reported average AAR is higher at 31.9 % (2000-2020 period).

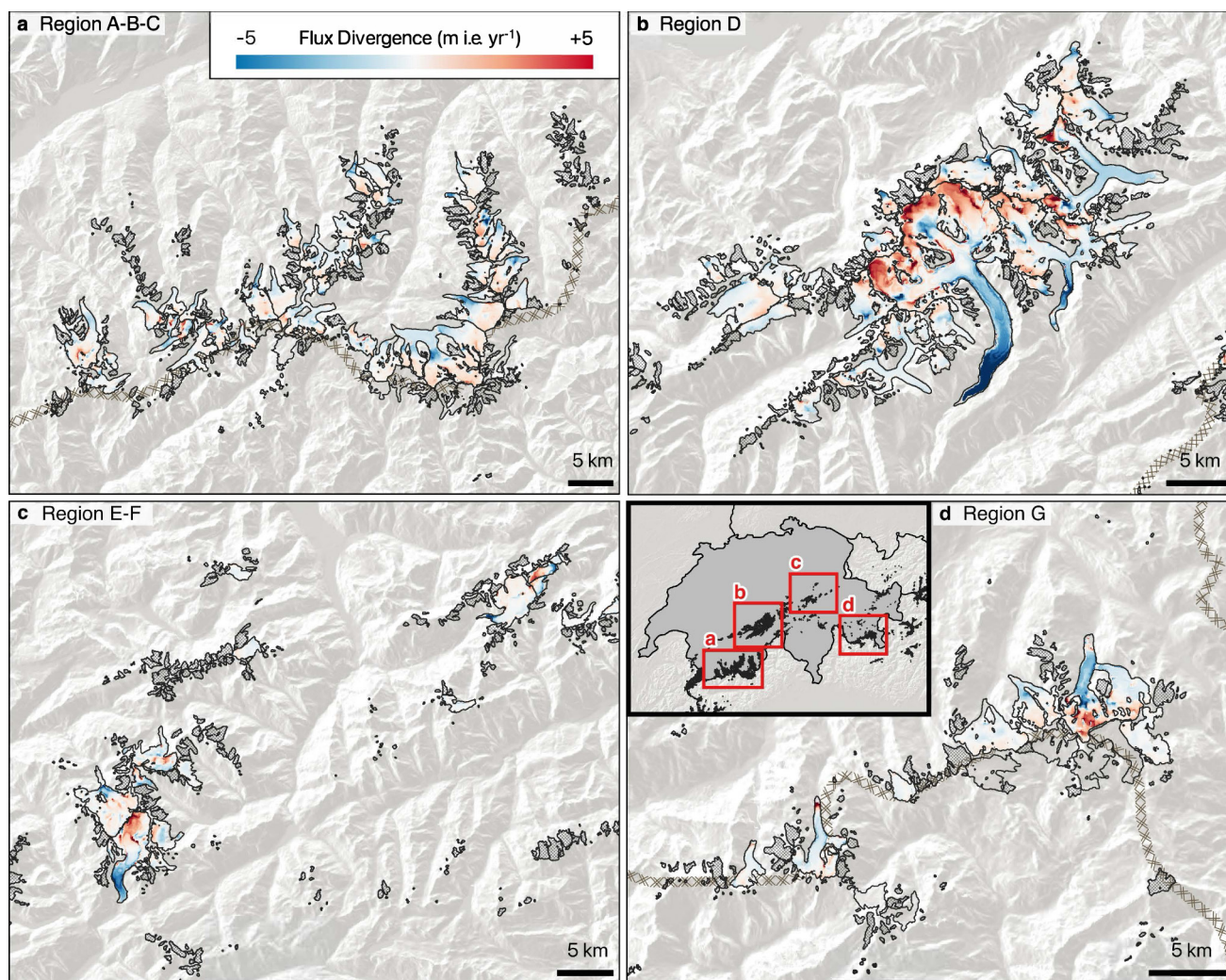


Figure 8 Distributed ice flux divergence (m i.e. yr^{-1}) for all Swiss glaciers $> 2 \text{ km}^2$. Glacier outlines from RGI v6.0 inventory are shown. Negative flux divergence corresponds to an upward velocity (emergence velocity). Background: hill shade of EU DEM (European Commission, 2012). Hashed glaciers: smaller than 2 km^2 ; empty glaciers: no data available. Swiss borders are indicated with a line of crosses.

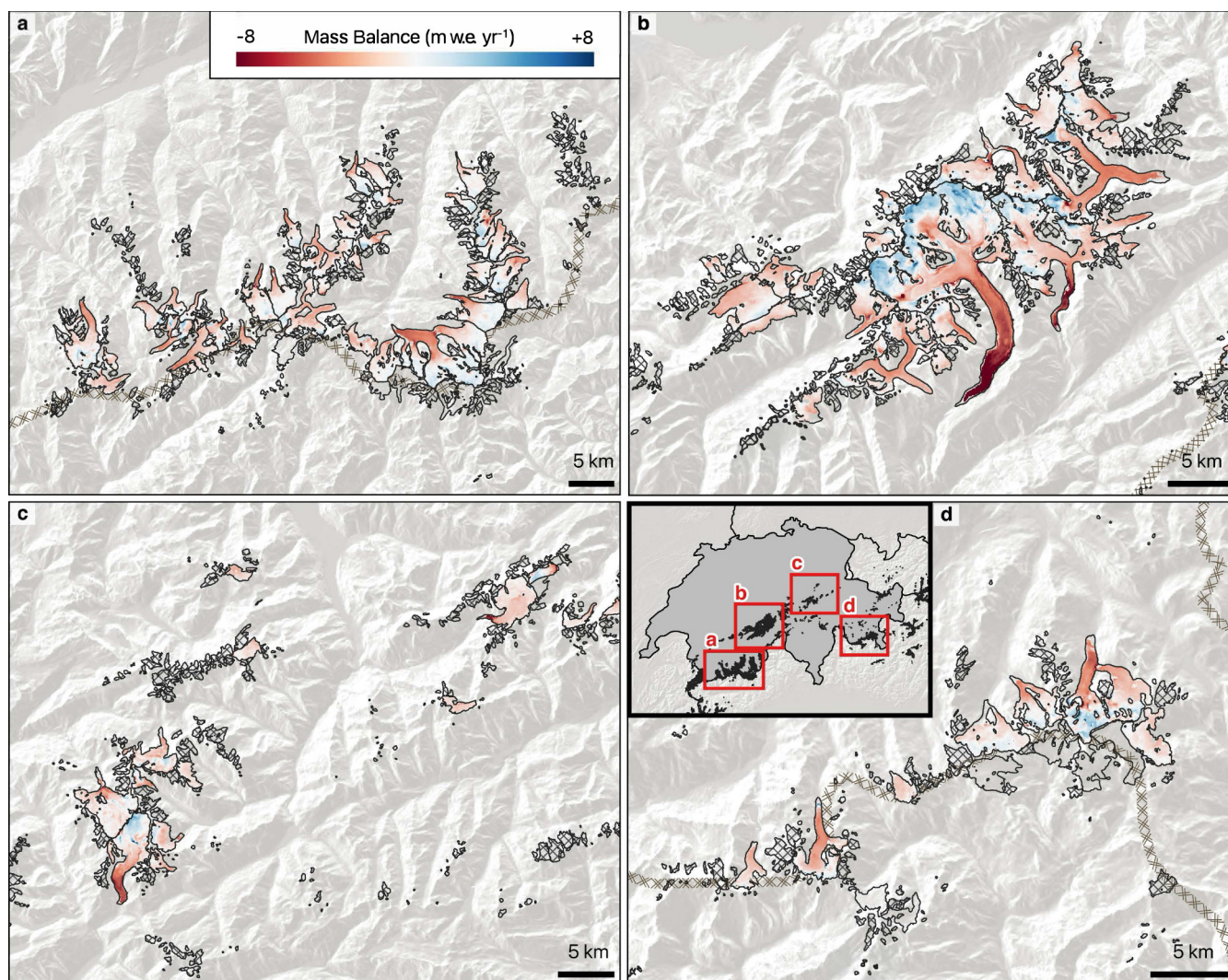


Figure 9 Spatial MB for all Swiss glaciers $> 2 \text{ km}^2$ in 2000-2020 period. Glacier outlines from RGI v6.0 inventory are shown. Background: hill shade of EU DEM (European Commission & DG ENTR, 2012). Hashed glaciers: smaller than 2 km^2 ; empty glaciers: no data available. Swiss borders are indicated with a line of crosses.

4.3 ELA and mass balance gradient estimates for Swiss Alps

We extract the equilibrium line altitude (ELA) and MB gradient in the ablation area from the distributed mass balance estimates. The ELA is derived by (1) segmenting the distributed MB estimates into a labelled accumulation and ablation area, and then (2) aggregating all pixels from the identified ablation zone and fitting a linear regression to these points. We exclude the lowest elevation bin(s) from this regression in cases where this bin has a higher MB estimate than the subsequent higher-elevation bin(s) (i.e., a negative MB gradient within the first bin(s), as seen for example in Figure 7 b2 and d2). The elevation at the intersect of the linear fit with MB=0 is taken as the ELA, and the slope as the MB gradient in the ablation area.

Our results yield an ELA range from 2715.6 to 3965.2 m a.s.l. for the studied glaciers in the period 2000-2020, with a mean of 3304.4 m a.s.l... Evaluation to the ELA extracted in the same way from elevation-binned MB values on GLAMOS glaciers shows a good agreement, with a Pearson correlation of 0.80, a RMSE of 122.5 m and mean error (bias) of 82.7 m (Table 2). The differences can be partly attributed to the lack of contemporaneity in the datasets used to obtain our estimates, favoring more recent years corresponding to the thickness and velocity observations – and yielding a higher ELA. The mass balance gradients in the ablation area that we model agree well with those from GLAMOS. The MB gradient in the ablation area has a mean error of -1.75 (MAE of 2.25) m w.e. yr⁻¹ km⁻¹.

Table 2 Extracted Equilibrium Line Altitude (ELA) and the mass balance gradient in ablation area for all 17 GLAMOS glaciers (GLAMOS - Glacier Monitoring Switzerland, 2023a), estimated for 2000-2020 period. *Note that our values are estimated for the Morteratsch-Pers glacier complex, whilst the elevation-binned GLAMOS values are reported only for Pers glacier.

Glacier Name	ELA	GLAMOS ELA	Difference	Mass balance gradient in ablation area	GLAMOS mass balance gradient in ablation area	Difference
	m a.s.l.	m a.s.l.	m	m w.e. yr ⁻¹ km ⁻¹	m w.e. yr ⁻¹ km ⁻¹	m w.e. yr ⁻¹ km ⁻¹
Silvrettagletscher	2992.22	-	-	4.06	4.51	-0.45
Claridenfirn	3126.05	3200	-73.95	4.15	13.02	-8.87
Tiefengletscher	3391.46	3266.6	124.86	2.78	3.44	-0.66
Glacier de la Plaine Morte		2894.8	-	-	3.40	-
Glacier de Tsanfleuron	3365.77	-	-	2.81	4.74	-1.93
Grosser Aletschgletscher	3202.14	3048.5	153.62	6.79	8.00	-1.21
Rhonegletscher	3055.15	2955.3	99.8	10.24	8.55	1.69
Griesgletscher	3322.19	-	-	3.53	4.15	-0.62



Schwarzberggletscher zentral	3261.04	3134.7	126.38	4.71	8.17	-3.46
Allalngletscher	3392.95	3468.7	-75.76	7.5	4.20	3.3
Hohlaubgletscher	3442.83	3299.7	143.14	4.6	8.18	-3.58
Findelgletscher	3299.54	3288.2	11.38	9.52	9.33	0.19
Adlergletscher	3714.05	3491.3	222.78	2.52	5.36	-2.84
Glacier du Giéto	3391.56	3327	64.57	4.41	7.98	-3.57
Glacier d'Otemma zentral	3319.47	3336.6	-17.15	5.34	5.93	-0.59
Glacier de Corbassière	3492.43	3352.2	140.24	3.05	5.02	-1.97
Vadret Pers & Vadret da Morteratsch*	3182.15	3026.4	155.72	4.65	8.04	-3.39

5. Dependency on input data

5.1 Sensitivity to ice thickness data

540 Since many glaciated regions lack the observational coverage of ice thickness observations that is available in the Swiss Alps, we assess the transferability of our method to other regions by investigating the sensitivity of the MB estimates to ice thickness data input. For this, we use the ‘minus’ and ‘plus’ uncertainty estimates of Grab et al. (2021) to obtain a lower and upper thickness estimate, as well as use globally available ice thickness reconstructions from a multi-model inversion effort (Farinotti et al., 545 2019) and an inversion relying on satellite-derived surface velocities (Millan et al., 2022).

The ice thickness product of Farinotti et al. (2019), commonly referred to as the ‘G2TI’, provides a multi-model estimate derived from up to five independent ice thickness models, which inverts ice thickness from surface characteristics using principles of ice-flow dynamics. Although G2TI is not 550 purely observation-based, this dataset is widely used in the community and serves as a robust benchmark to our method. The G2TI dataset was constrained using observations from the Glacier Thickness Database 2.0 (WGMS, 2016), which includes measurements from 1955 to 2015. The Millan et al. (2022) thickness dataset derives the ice thickness from satellite-based estimates of surface velocity and slopes using the shallow-ice approximation, primarily around the period of 2017-2018. They report 555 an overall uncertainty of 30% on the global glacier thickness estimates, and an overall agreement with observed thicknesses of 9 ± 87 m. The lower and upper uncertainty bounds of Grab et al. (2021) are on average -18.9 m (minus) and 29.8 m (plus) for the studied (100) glaciers. The Grab-, Farinotti- and Millan thickness datasets yield total ice volumes of 5.05×10^{10} , 6.92×10^{10} and 6.54×10^{10} m³, respectively. While the Farinotti dataset represents the largest overall ice volume, the Millan dataset 560 generally estimates thicker ice in the central parts of the glacier tongues (Figure A6).

Here, we generate new MB estimates by relying on the Farinotti et al. (2019) and Millan et al. (2022) thickness datasets and our optimized setup and hyperparameters (F001 approach, N=9, F=0.8). Results



are compared to the GLAMOS glaciers (Figure 10). For these 17 glaciers, the average
565 $\overline{MB_{point}} = -2.65 \text{ m w.e yr}^{-1}$. Our estimates are $\overline{MB_{point}} = -2.37 \text{ m w.e yr}^{-1}$ when using
Grab ice thickness, $\overline{MB_{point}} = -2.65 \text{ m w.e yr}^{-1}$ for Farinotti ice thickness and $\overline{MB_{point}} = -2.64 \text{ m}$
w.e yr^{-1} for Millan ice thickness; yielding respective MAEs of 0.64, 0.74 and 0.98 m w.e. yr^{-1} . For the
Grab thickness bounds, $\overline{MB_{point}}$ varies from -2.56 (thinner) to -2.61 (thicker) m.w.e yr^{-1} and the
MAE is between 0.73 and 0.66, respectively. All estimates provide similar values of mass balance with
570 good agreement to GLAMOS point MB observations, indicating spatial patterns are robust across
different ice thickness products.

The average GLAMOS $\overline{MB_{bins}} = -1.39 \text{ m w.e. yr}^{-1}$, compared to respective Grab-, Farinotti- and
Millan derived MB values of -1.31 , -1.22 , -1.42 m w.e (MAE of 0.72, 0.88, 1.08 m w.e. yr^{-1}); the
575 Grab thickness bounds yield average $\overline{MB_{bins}}$ of -1.53 (thinner) and -1.57 (thicker) with MAE of 0.79
and 0.78, respectively. Also here our method retrieves mass balance values with good agreement to
observations, although the binned values tend to slightly overestimate the MB (underestimate the ice
ablation), for all ice thickness datasets.

580 The most notable difference with respect to MB observations, is obtained when relying on the Millan
ice thickness for reconstruction, which tends to produce more negative and more positive MB extremes.
In this setup, the negative and positive extreme MB values are typically found at the edges of the glacier
(Figure 10). This behaviour results from the Millan dataset having higher ice thickness estimates in the
centre of glacier tongues than the other datasets, while having similar thickness values near the glacier
585 margins (Figure A6). This leads to comparatively strong ice thickness gradients towards the glacier
boundary, which in turn produce larger flux divergence values. At the same time, because the ice is
relatively thin near the glacier bounds, the associated filter size is smaller, and the result is more
sensitive to (errors in) the input data. This suggests that the filter hyperparameters may require
recalibration when using the Millan ice thickness dataset, e.g. by setting a larger minimum filter size or
590 with a reduced dependency of the filter size on the local ice thickness.

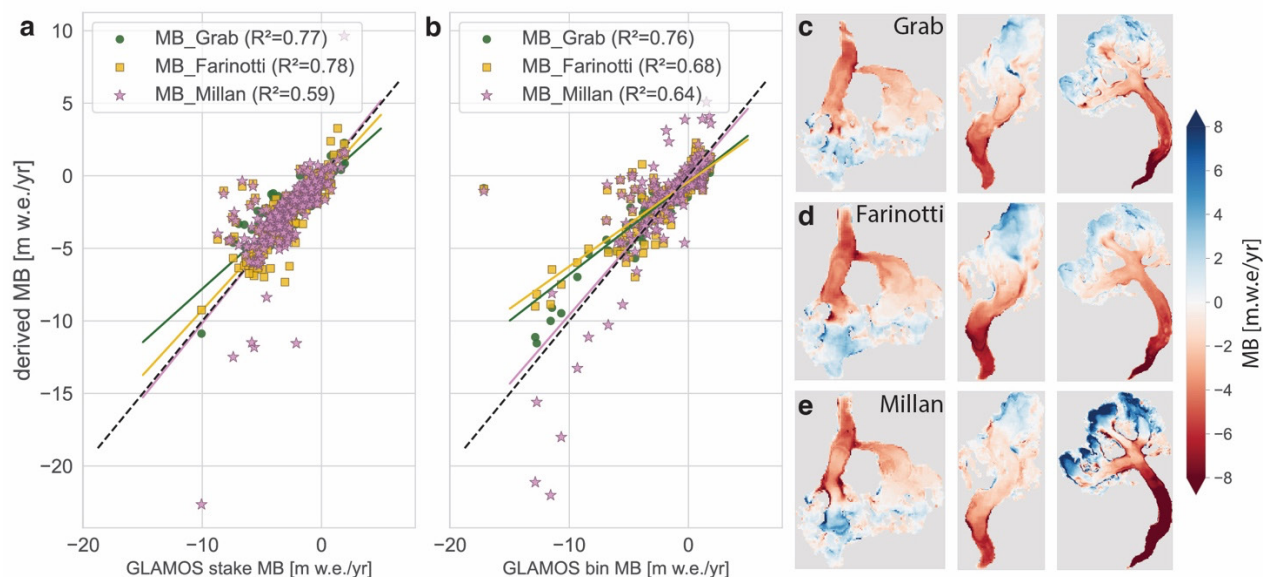


Figure 10 MB estimates (2000-2020) using different ice thickness datasets. Comparison to (a) all stakes on the 17 GLAMOS glaciers and (b) all binned MB values on these glaciers. (c) Panels with derived MB patterns based on the different thickness data for three example glaciers: Morteratsch-Pers (left), Rhône (middle) and Grosser Aletsch (right) glaciers.

5.2 Comparison to a glacier with high-res UAV data

We also assess the sensitivity of our method to the spatial resolution and contemporaneity of the input data by comparing our results with independent estimates of ice flux divergence and MB patterns for the Morteratsch-Pers glacier. These estimates were derived using the same mass continuity inversion approach applied to high-resolution Unoccupied Aerial Vehicle (UAV) data and GPR data (Van Tricht et al., 2021). Van Tricht et al. acquired digital surface models from UAV surveys between 2017 and 2020 at a spatial resolution of 0.05–0.09 m, which were resampled to a 25 m grid for the derivation of surface elevation changes and ice flow velocity. While the underlying methodology is the same, Van Tricht et al. optimized their hyperparameters specifically to match in-situ MB observations on this glacier and used near-contemporaneous datasets, achieving a mean absolute error (MAE) and RMSE of 0.29 and 0.35 m.i.e. yr⁻¹, respectively. Differences with our derived MB can therefore be interpreted as a result from using lower-resolution and/or less contemporaneous input data, as well as from our application of a single regionally calibrated approach rather than one specifically tailored to the individual glacier. Our MB estimates for the Morteratsch-Pers glaciers yield a RMSE of 0.82 and 1.14 m w.e. yr⁻¹ with respect to binned and point mass balance observations of GLAMOS, respectively.

The comparison between distributed MB fields (Figure 11) is performed without applying a density conversion, such that the mass balance is expressed in m i.e., consistent with Van Tricht et al. (2021). The results show good agreement between the two datasets with RMSEs typically around 1 m.i.e. yr⁻¹, and reaching up to 1.38 m.i.e. yr⁻¹ (2000-2020 period), supporting the validity of our approach when working with data that are not perfectly contemporaneous and of lower resolution. Agreement between the MB values improves when using elevation change data that has better temporal alignment to the



UAV observations. The MAE decreases from 1.19 m i.e. yr^{-1} (2000–2020) to 0.77 m i.e. yr^{-1} (2015–2020), while the Pearson correlation coefficient (R^2) increases from 0.80 to 0.84. However, overall our retrieved MB values tend to provide less pronounced ice ablation, especially at the terminus of Morteratsch-Pers, which likely results from a slight overestimation of the local flux divergence (Figure A7). The terminus has been thinning strongly in the past decades to years (Rossini et al., 2018; Van Tricht et al., 2021; Zekollari et al., 2014), and now mostly consists of dead ice, which explains part of the disagreement.

Despite the existence of some differences, the retrieved MB patterns are roughly similar: the ablation area of Pers glacier has a slightly higher MB than Morteratsch-Pers. We do reproduce some of the ablation hotspots near the terminus when using 2015-2020 data, showcasing that not only the filtering approach but also the choice of elevation change product impacts how well local features are resolved in our method.

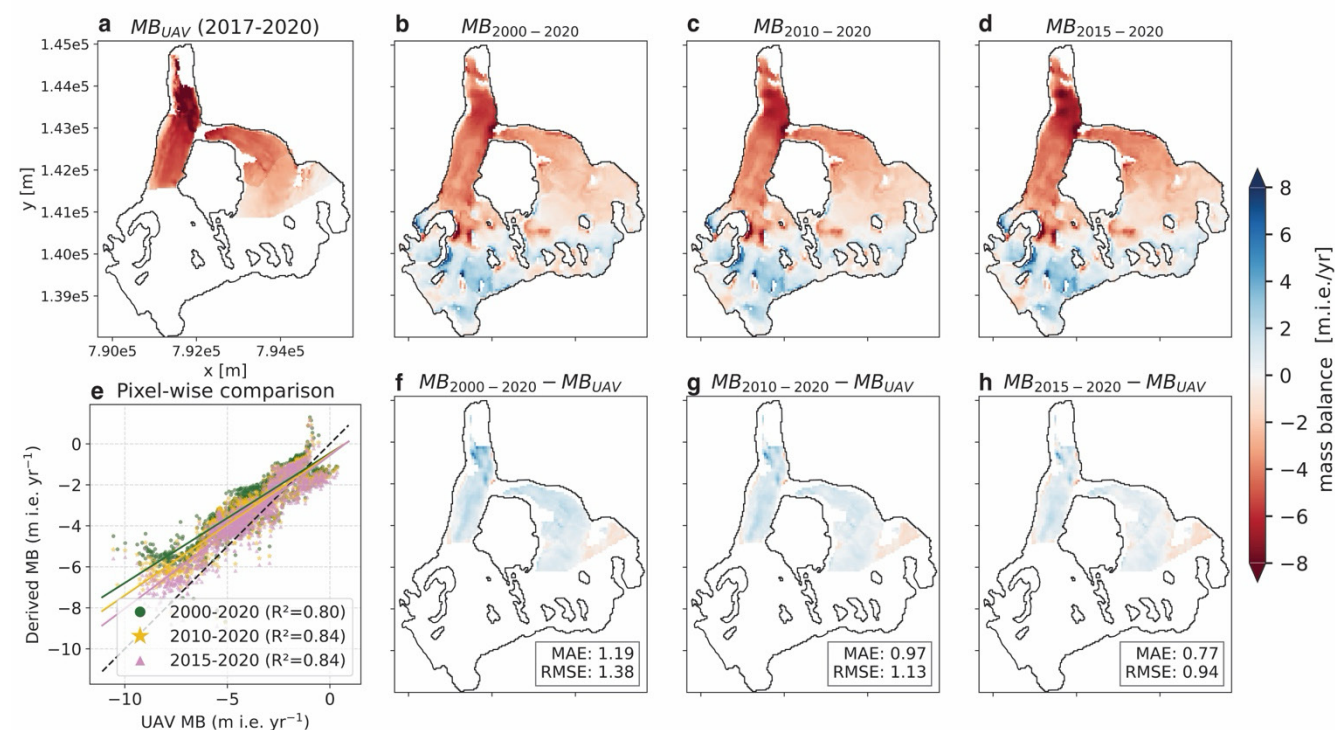


Figure 11 Comparison to independent spatial MB patterns obtained from high-resolution UAV observations on the Morteratsch-Pers glacier complex. (a) Average MB obtained from UAV over three-year observation period 2017-2020 (Van Tricht et al., 2021). (b-d) Retrieved MB fields using different periods of elevation change observations (Hugonnet et al., 2021), (e) Agreement of pixel values in overlapping area. (f-g) Pixel-wise difference for derived MB values per period. All values in m i.e. yr^{-1} , all maps plotted in EPSG:21781.



6. Discussion

6.1 Method performance and robustness

The method to derive spatially distributed MB fields yields consistent and accurate estimates across glaciers in the Swiss Alps. After exploration of configurations of the hyperparameters, the agreement with in-situ observations is strong with binned and point MB RMSE of 0.81 and 0.70 m w.e. yr⁻¹, respectively. The performance of the method depends on several methodological choices, in particular the filtering strategy, the filtering length, and the sliding parameter.

The importance of filtering in obtaining physically meaningful results is evident from the unfiltered approach, which can reproduce elevation-binned averages, but does so by producing unrealistic spatial patterns and higher errors when evaluated against point measurements. This insight emphasizes the necessity to inspect the 2D flux divergence fields in inversion approaches and to not rely solely on the 1D MB curve. Among the tested configurations, filtering the ice flux divergence field after computation (F001) provides the best performance, with a higher coupling factor N providing an optimal balance between noise reduction and preservation of spatial variability. In contrast, filtering the gradient fields prior to computing the ice flux divergence (F110 and F111) generally leads to (stronger) overestimation of the MB in the ablation area, regardless of the chosen factor N .

The longitudinal coupling factor N is the most sensitive parameter in the method. Increasing N reduces noise in the ice flux divergence field but also increases spatial averaging. The optimal value ($N = 9$) is larger than typical estimates of longitudinal coupling length for valley glaciers, likely reflecting the need to compensate for noise and uncertainties in the input datasets and the numerical differentiation. Because the longitudinal coupling length is implemented as an exponential decay, the influence of distant pixels remains limited, which explains why relatively large values of N still produce physically possible results.

In contrast, the method shows limited sensitivity to the sliding parameter F . Variations in F have only a minor effect on the resulting MB fields compared to the choice of N . This suggests that approximating depth-averaged velocities using observed surface velocities is sufficient at the regional scale, and that the method is relatively robust to unknown basal conditions.

The robustness of the method is further supported by the comparison with independent high-resolution estimates (e.g., relying on UAV data) from the Morteratsch-Pers glacier. Despite differences in input data resolution and parameter tuning, the retrieved MB fields show good agreement in both magnitude and spatial patterns. In this comparison exercise, improved agreement is achieved when using data with better temporal alignment, highlighting the importance of data consistency while also demonstrating that the method performs well with currently available (regional) datasets.

Lastly, other regional results from MB inversion by Zöller et al. (2026) and Herrmann et al. (2026) have reported similar performances in their evaluation to GLAMOS observations. Zöller et al., who



performed MB inversions using the Instructed Glacier Model (IGM) (Jouvet, 2023; Jouvet and Cordonnier, 2023) for Swiss glaciers with area $> 1 \text{ km}^2$, report a regional RMSE to GLAMOS of $0.22 \text{ m w.e. yr}^{-1}$ for the mass balance and 98 m for the ELA, whereas we obtained a RMSE of $1.28 \text{ m w.e. yr}^{-1}$ and 90.3 m , respectively. While Zöller et al. achieve a better agreement to the GLAMOS mass balance values, we note that they compare to the glacier averaged MB value and we compare to the point and elevation-binned MB, and are hence more susceptible to spatial disagreements. Herrmann et al., using the FROST framework to retrieve ELA and other SMB parameters for glaciers in the Alps with area $> 1 \text{ km}^2$, report a mean error of 106.63 m with respect to GLAMOS ELA, and mean errors of 4.50 and $2.35 \text{ m w.e. yr}^{-1} \text{ km}^{-1}$ for the ablation and accumulation gradient, respectively. Our results perform better for each aspect, with mean error for ELA 82.7 m and mean errors of $-1.75 \text{ m w.e. yr}^{-1} \text{ km}^{-1}$ for the ablation gradient. Overall, this indicates that our method achieves performance of a comparable magnitude, while providing a complementary and model-independent approach.

6.2 Limitations and uncertainties

Despite the overall robust performance, a few limitations and sources of uncertainty should be considered when interpreting the results.

6.2.1. Limits of numerical method

For many of the observed glaciers, MB values are overestimated in the lowest elevation bin. This overestimation is reduced as N increases, but remains persistent even for our optimal $N=9$. These low-elevation areas often combine thin local ice thickness with high gradients in thickness and/or velocity, yielding relatively high flux divergence values but small filter sizes, resulting in an overestimation of the flux divergence (underestimation of emergence velocity). The choice for $N=9$ reflects a trade-off to achieve robust performance across glaciers at regional scale but may not be optimal for detailed studies on individual glaciers. Moreover, N is partly dependent on data resolution (e.g., lower resolution masking the very low and very high ice thickness values), is inherently linked to uncertainties of the input datasets, and would therefore require recalibration when applied to different grids or data sources.

Although our method performs well across glaciers with different shapes, sizes, and topographical settings, applying the method to glaciers with complex flow or geometric configurations is challenging. This limitation arises from the discretized nature of the method and the applied filter. While the exponential filter incorporates a physically motivated longitudinal coupling length, it does not account for directional effects in ice flow. This may be particularly relevant for glaciers with multiple tributaries or flow basins that contribute unevenly to the overall dynamics (e.g., such as on Glacier de Corbassière), although we have not encountered clear issues in this regard.



6.2.2. Physical assumptions

720 The conversion from surface elevation change to mass balance introduces additional uncertainty through the assumed density. Although we partition the glacier into different density regimes rather than assuming a constant density, the conversion remains simplified and neglects temporal variability in firn and ice density, which is particularly relevant in accumulation areas.

725 Secondly, our methodology cannot separate the individual mass balance components. The inversion of the continuity equation retrieves the residual mass balance required to satisfy mass conservation, but cannot distinguish between surface, basal, internal and frontal mass balance contributions. Previous studies often assume negligible basal and internal mass balance components and equate the retrieved field to the climatic mass balance (Bhushan et al., 2024; Kneib et al., 2024; Van Tricht et al., 2021). However, the inversion itself is agnostic to this distinction, and we therefore referred to the retrieved estimates simply as ‘mass balance’ (Miles et al., 2021). For most glaciers in this study, this distinction has little practical consequence. However, the results for Claridenfirn show that the approach becomes 730 unreliable where frontal ablation contributes substantially to the (local) glacier mass budget, and that additional observations, modelling or postprocessing are required to account for these processes.

6.2.3. Contemporaneity of data

735 An important source of uncertainty is the limited contemporaneity (i.e., temporal mismatch) of the input datasets. Ideally, ice thickness, surface velocity, and elevation change should represent the same time period. In this study, the datasets overlap but are not fully synchronous, which introduces uncertainties that are difficult to quantify. However, while the magnitude of the ice thickness and velocity may vary over time, their spatial distribution is assumed to be more stable. As a result, the spatial structures of derived ice flux divergence fields and MB patterns are expected to be relatively robust to moderate temporal mismatches (i.e., on the order of a few years). On the other hand, the 740 magnitude of the derived MB is especially sensitive to temporal mismatch of input data for local areas undergoing fast thinning and/or other (geometric) changes, as was shown for the Claridenfirn glacier and Morteratsch-Pers glacier.

745 The evaluation approach is also affected by temporal inconsistencies: although we select GLAMOS observations from the same periods as the elevation change datasets, and weigh by the number of observed years, the temporal coverage of GLAMOS differs between glaciers. Consequently, the evaluation does not reflect the same degree of contemporaneity for all glaciers.

6.2.4. Elevation change error

750 The uncertainty and contemporaneity of the elevation change data (Hugonnet et al., 2021) further propagates into the MB estimates. Shorter time intervals provide better temporal alignment with other datasets but are associated with higher noise levels, whereas longer periods reduce elevation change related uncertainty but also decrease contemporaneity. In this study, we have prioritized the longer time series to obtain more stable regional estimates. For local scale applications, which may include higher

resolution elevation change data (both in space and in time), a different prioritization may be more suited.

6.3 Implications for glacier modelling

Because the MB fields are derived solely from (remote sensing) observations, they provide an independent dataset for the calibration and evaluation of glacier models. More specifically, the spatial distribution of MB, and the derived mass balance gradients and equilibrium line altitudes, can serve as additional constraints beyond the currently most used approach that relies solely on geodetic glacier mass balance observations (Hugonnet et al., 2021) to calibrate the mass balance component of glacier evolution models (e.g., Marzeion et al., 2020; Rounce et al., 2023; Zekollari et al., 2024; Schuster et al., 2025; Van Tricht et al., 2026). Having these additional constraints is also valuable for more focused studies that focus on (a selection) of individual glaciers, where they can be used to complement in-situ measurements. Moreover, the distributed values, including distributed uncertainty estimates, can potentially be used as a new source for the development of data-driven (machine learning) models. And lastly, the distributed fields of mass balance can provide new insights to the distribution of precipitation and temperature that are usually parameterized from low resolution climate models.

6.4 Potential for global application

Accurate surface velocity and elevation change datasets are now becoming available at near-global scale, enabling the application of this method beyond the Swiss Alps. In this study, we demonstrate the approach using globally available surface velocity and elevation change data, which we combine with high-resolution ice thickness data, while also assessing the sensitivity of our approach to relying on ice thickness datasets. This provides a first indication of the promising scalability of the method, and although further calibration is advised if relying on global ice thickness data, the method generally produces robust mass balance estimates.

The application of the method to different glacier types does require some caution. In particular, the current framework does not explicitly account for multiple flow basins or complex ice divides as found in ice caps and large ice fields, nor for processes such as avalanches or debris cover that influence spatial distribution of mass balance (Kneib et al., 2024; Kraaijenbrink and Immerzeel, 2025). For such cases, our method should be adapted through additional processing steps and/or modifications to the filtering approach. Moreover, the method should be further tested and developed for glaciers with strong frontal, internal and/or basal ablation components. Although we show that the methodology is not sensitive to the sliding parameter F (including a full sliding regime), we acknowledge that our evaluation in the Swiss Alps does not constrain the effects of complex basal conditions, which may be important for marine-terminating glaciers.



7. Conclusions

790 In this study, we present one of the first regional applications of a continuity-based inversion to derive spatially distributed mass balance fields from remote sensing observation. The approach combines ice thickness, surface velocity, and surface elevation change datasets, and is applied at regional scale across the Swiss Alps. Using an extensive set of in-situ MB observations from GLAMOS, we systematically evaluate methodological choices and quantify model performance, demonstrating the feasibility of
 795 deriving observationally based distributed mass balance fields at regional scales.

The method yields consistent and accurate distributed mass balance estimates across a diverse set of 17 glaciers, with good agreement to both point and elevation-binned mass balance observations. Our results show that filtering is essential to obtain physically meaningful flux divergence fields. While
 800 previous studies have similarly highlighted the need to consider large spatial scales in ice flux divergence calculations, we show that physically unrealistic flux divergence fields may still reproduce realistic average elevation-binned MB curves and emphasize the need to evaluate the flux divergence fields directly. Among the tested configurations, applying an exponential filter after the flux divergence computation provides the best balance between noise reduction and preservation of spatial variability.
 805 The longitudinal coupling factor is the most sensitive parameter, whereas the method shows limited sensitivity to the sliding parameter, indicating robustness to uncertainties in basal conditions.

Comparison with independent high-resolution UAV-based estimates of distributed MB demonstrates that the method reproduces spatial patterns of distributed mass balance despite relying on substantially
 810 lower-resolution regional datasets. Mass balance values nevertheless tend to be slightly overestimated in the ablation areas, which may partly result from (temporal) inconsistencies between the input datasets. We further show consistent performance of the method when different ice thickness datasets are used, also with global datasets, opening the door for an application to other regions around the globe. Together, these results demonstrate that the approach is sufficiently robust to exploit widely available
 815 regional to global remote sensing products for deriving distributed mass balance fields.

At the same time, the results highlight the importance of temporal consistency between input datasets. Elevation change estimates over longer periods are generally more robust and lead to lower
 820 uncertainties in the derived mass balance values. However, longer elevation-change periods increase the temporal mismatch to the velocity and thickness data, leading to large local overestimations of mass balance in glacier areas that experienced strong thinning or retreat during the observation period.

The distributed mass balance fields, ELA and mass balance gradient estimates offer a valuable, independent dataset for glacier model calibration and evaluation, allowing to expand the calibration of
 825 glacier models beyond solely relying on geodetic mass balance estimates. Given the increasing availability of global datasets of glacier surface velocity and surface elevation change, the method holds strong potential for application beyond the Swiss Alps.



830 2 Appendices

A1. Supplementary Figures and Tables

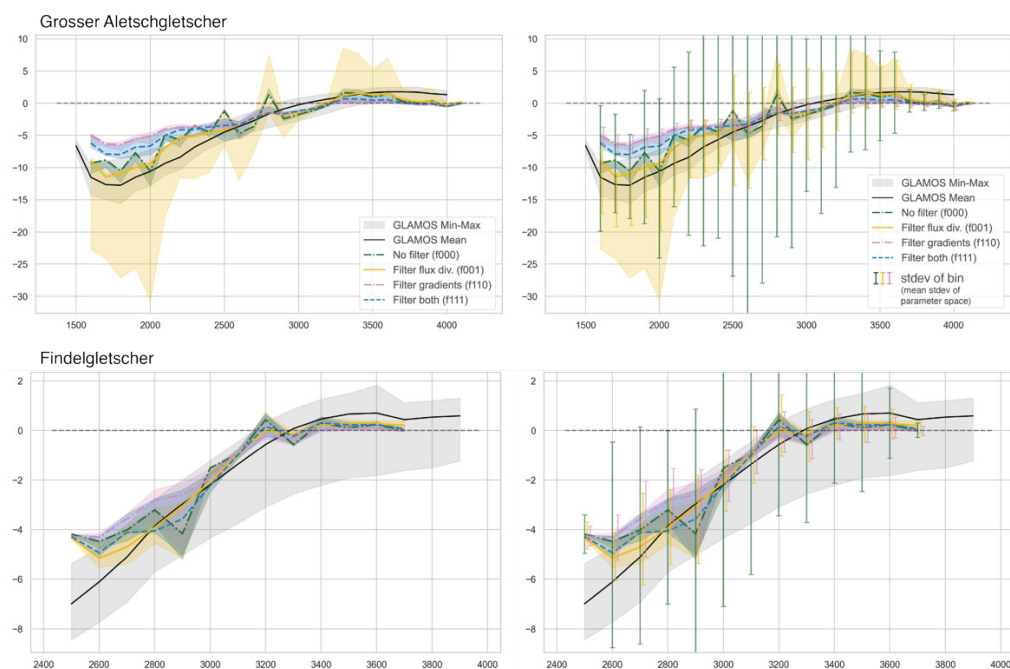
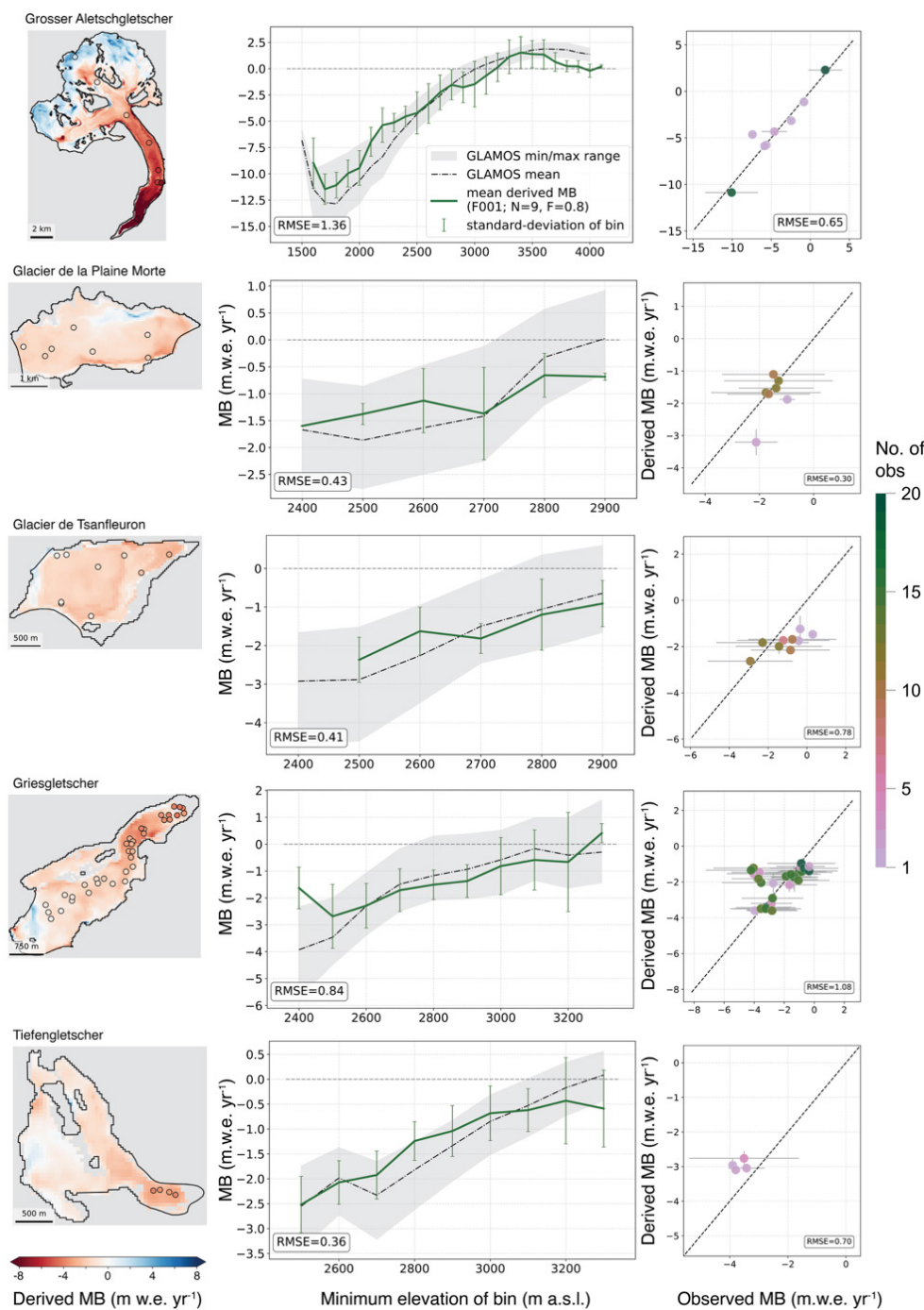


Figure A1: Demonstration of MB variability in binned values for Aletsch and Findel glaciers. Error bars represent the standard deviation of MB values in each elevation bin. Left and right panel show same profiles.



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Figure A2: Comparison of derived MB to GLAMOS observations on train glaciers for the optimal (F001, N=9, F=0.8). Left column shows retrieved spatial MB patterns, middle column the evaluation to binned MB values and right column the evaluation to point MB values. In the latter, the vertical bars show variability of derived MB in 3x3 window around the pixel of the stake and horizontal bars represent the temporal (5-95 percentile) range of observations.

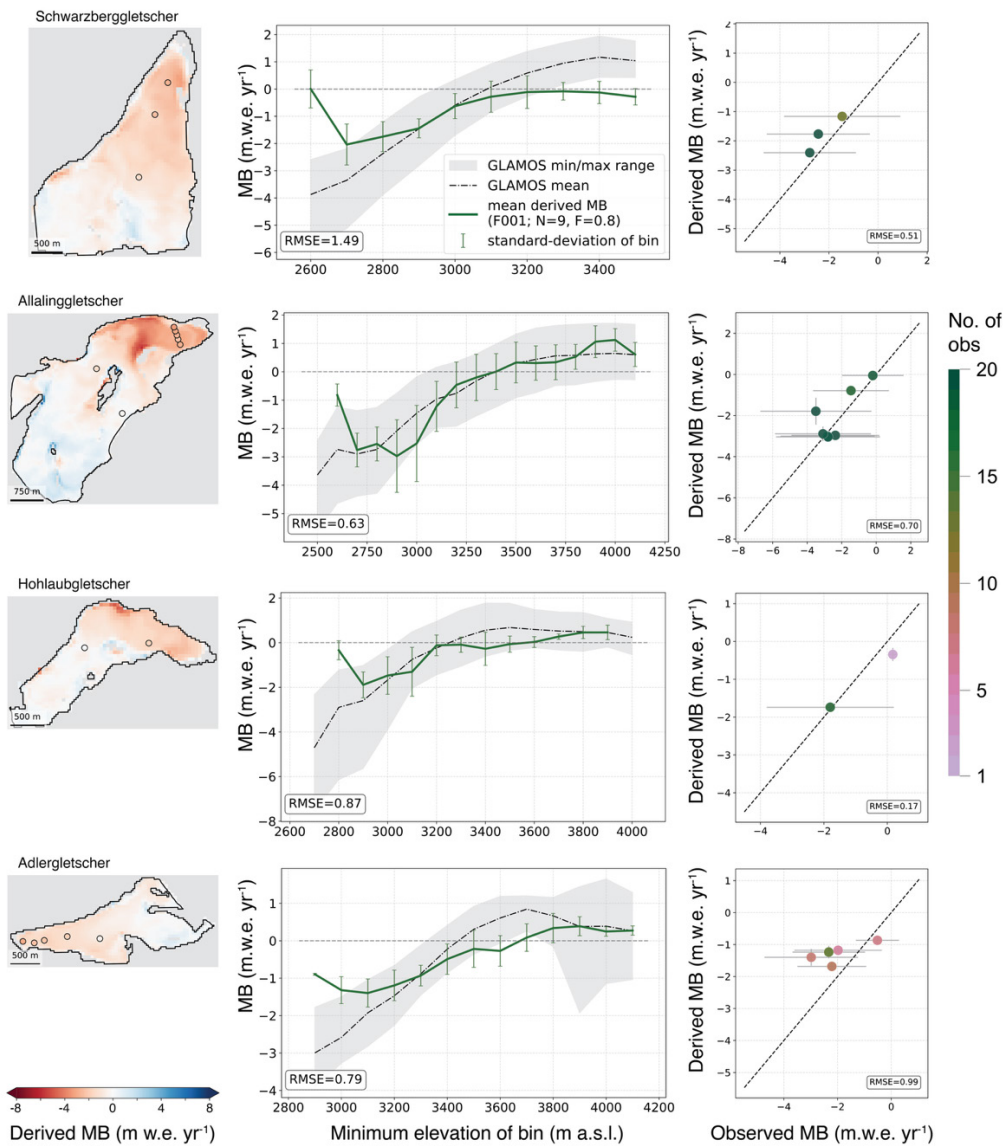


Figure A2 continued

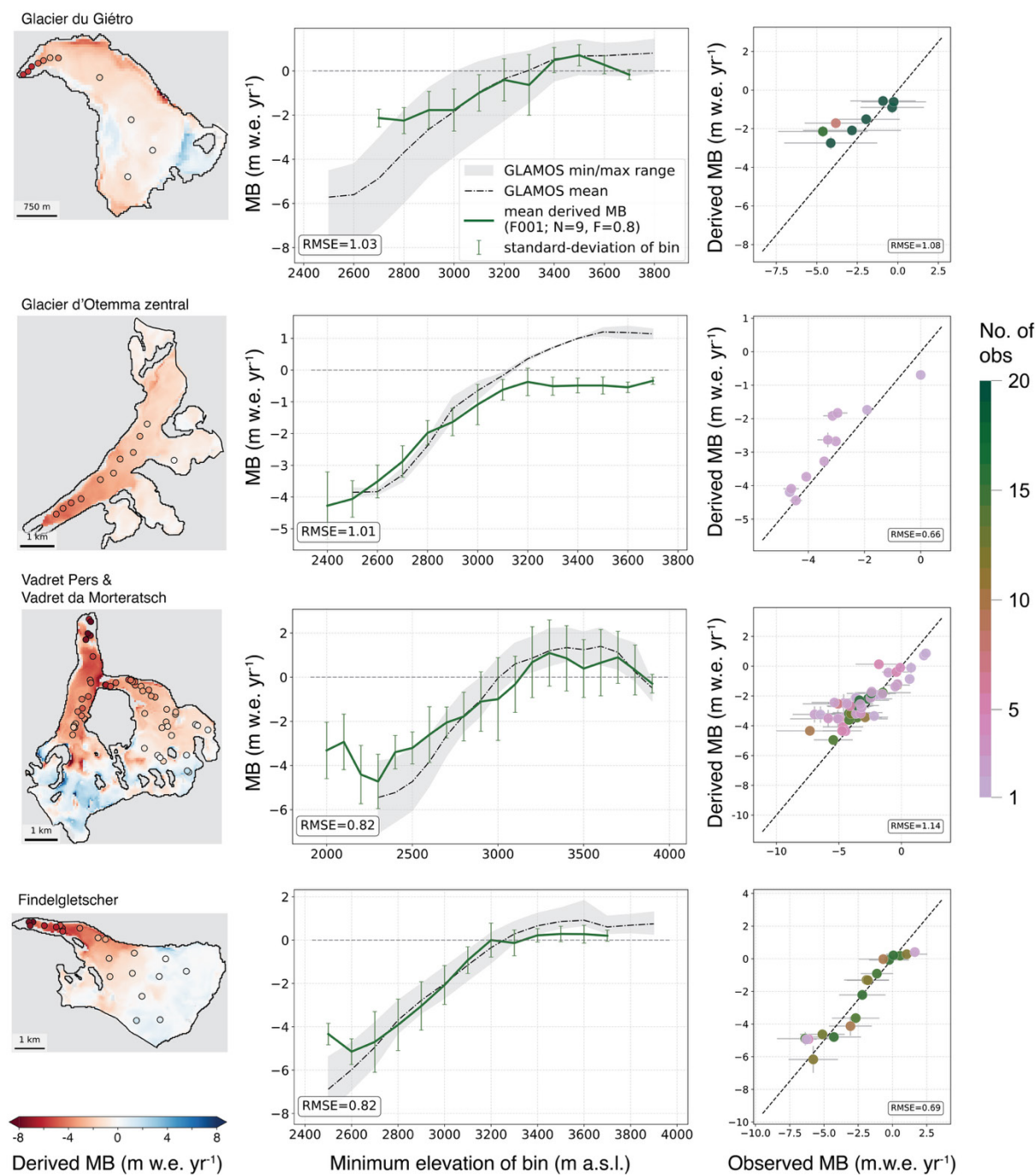


Figure A2



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Table A1: Table with all RMSE values for the selected filter approach (F001; N=9, F=0.8) for all evaluated glaciers in 2000-2020 period. $RMSE_{glacier}$ is the average of $RMSE_{bins}$ and $RMSE_{point}$.

Glacier SGI ID	Glacier Name	Set	N	F	$RMSE_{glacier}$	$RMSE_{bins}$	$RMSE_{point}$	Area (km ²)
B36-26	Grosser Aletschgletscher	train	9.0	0.80	1.01	1.36	0.65	78.5
B82-27	Glacier d'Otemma	train	9.0	0.80	0.83	1.01	0.66	12.6
B56-14	Adlergletscher	train	9.0	0.80	0.89	0.79	0.99	2.1
B52-29	Allalingletscher	train	9.0	0.80	0.67	0.63	0.70	9.1
B52-32	Hohlaubgletscher	train	9.0	0.80	0.52	0.87	0.17	2.2
A51e-37	Tiefengletscher	train	9.0	0.80	0.53	0.36	0.70	2.2
E22-03	Vadret Pers and Vadret da Morteratsch	train	9.0	0.80	0.98	0.82	1.14	14.9
B22-01	Glacier de Tsanfleuron	train	9.0	0.80	0.60	0.41	0.78	2.4
B52-24	Schwarzberggletscher	train	9.0	0.80	1.00	1.49	0.51	5.1
B56-03	Findelgletscher	train	9.0	0.80	0.75	0.82	0.69	13.9
B82-14	Glacier du Giétro	train	9.0	0.80	1.06	1.03	1.08	5.1
A55f-03	Glacier de la Plaine Morte	train	9.0	0.80	0.37	0.43	0.30	7.3
B45-04	Griesgletscher	train	9.0	0.80	0.96	0.84	1.08	4.6
A10g-05	Silvrettagletscher	test	9.0	0.80	0.53	0.54	0.51	2.7
A50i-19	Claridenfirn	test	9.0	0.80	3.22	(5.60) 1.42	0.84	4.7
B43-03	Rhonegletscher	test	9.0	0.80	0.62	0.73	0.51	14.6
B83-03	Glacier de Corbassière	test	9.0	0.80	0.75	0.56	0.95	14.9

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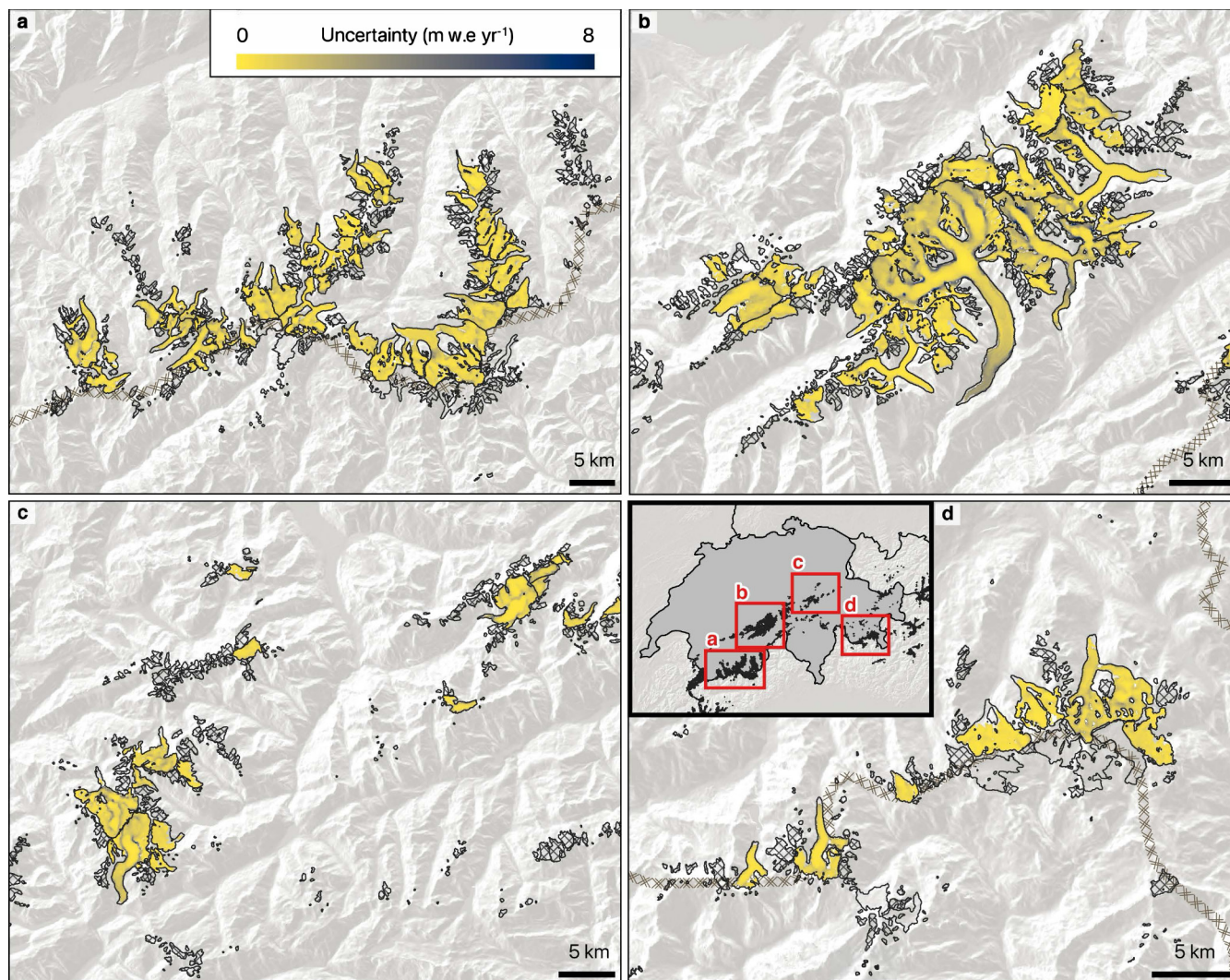


Figure A3: Distributed uncertainty of ice flux divergence due to errors in velocity field, obtained from 100 Monte Carlo simulations perturbing the velocity components with spatially correlated noise (250 m correlation length).

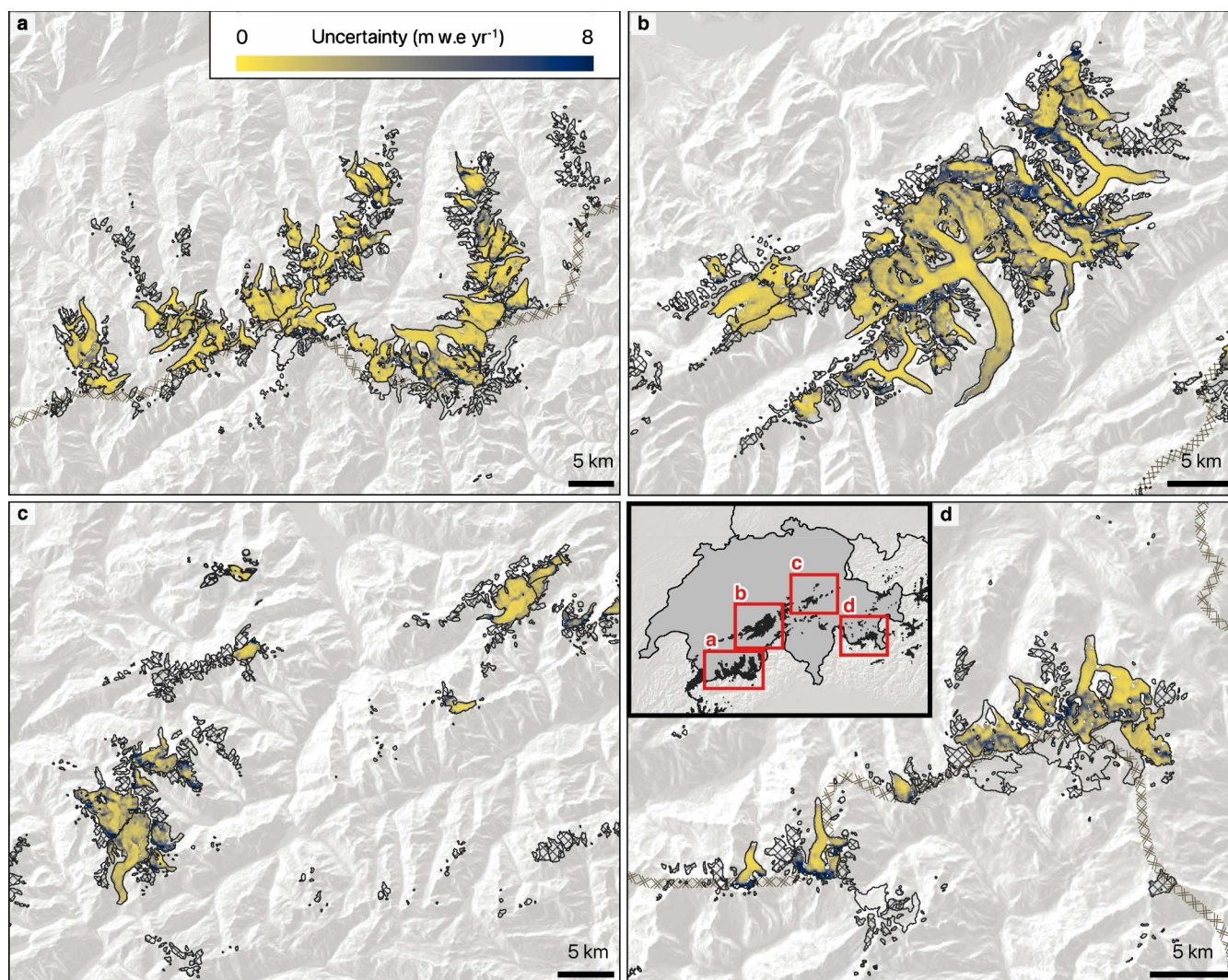
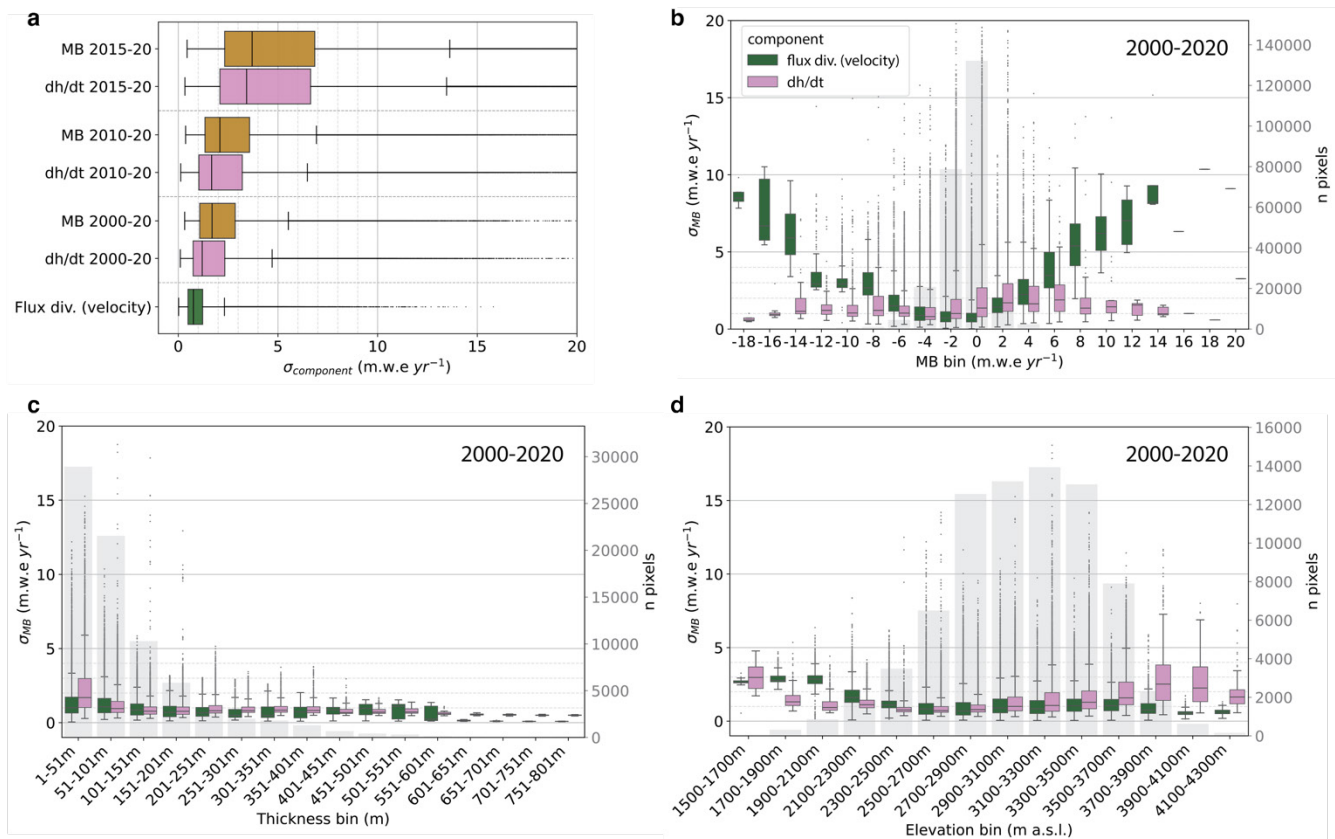


Figure A4: Distributed uncertainty of mass balance obtained from 100 Monte Carlo simulations, combining uncertainty of velocity- and elevation change (2000-2020) components. Spatially correlated noise was generated for each simulation from velocity errors (250 m correlation length) and elevation change errors (1000 m correlation length).

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865 **Figure A5: Uncertainty of mass balance (MB) realizations obtained from 100 Monte Carlo simulations, aggregated over all studied**
870 **glaciers. (a) MB uncertainty of the combined velocity- and elevation change error contributions (yellow), and the individual**
contribution to that uncertainty (velocity: green; elevation change for different periods: pink). MB uncertainty contribution of
components grouped (b) by local mass balance value (c) by local ice thickness value and (d) by local elevation. (b-d) are only for
estimates of 2000-2020 period, and show corresponding data distribution in gray on background (right y-axis). Grid lines are for
left y-axis.

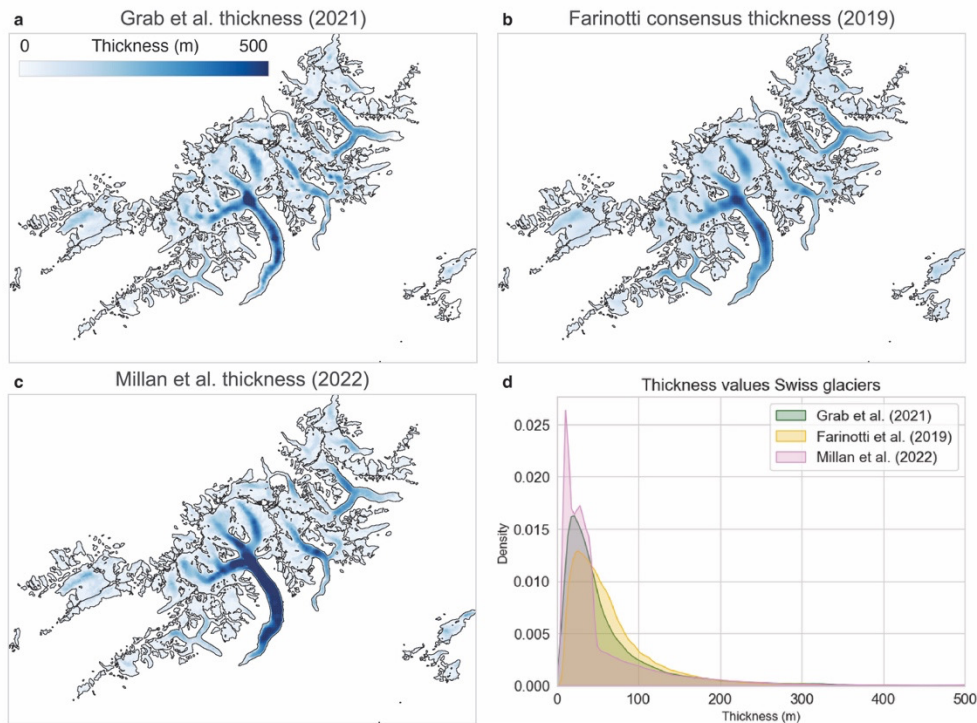


Figure A6: Different thickness datasets for Swiss Alps region used in the sensitivity tests, shown for Swiss glaciated region D.

875 Table A2 Preview of aggregated glacier values. Full table for all 100 studied glaciers is be available at zenodo (see data availability section).

Glacier RGI ID	SGI ID	Glacier Name	Mean Mass Balance	Median MB uncertainty (2000-2020)	AAR	ELA	MB gradient in ablation area (2000-2020)
			m w.e. yr ⁻¹	m w.e. yr ⁻¹	%	m a.s.l.	m w.e. yr ⁻¹ km ⁻¹
RGI60-11.00781		Jamtalferner	-0.73	1.29	0	-	-
RGI60-11.00804	A10g-05	Silvrettaletscher	-0.77	1.11	7.16	2992.2	4.06
RGI60-11.00830			-1.31	2.07	0	2894.6	3.74
RGI60-11.00833			-1.71	1.37	0	-	-
RGI60-11.00843			-0.48	1.97	47.85	2905.2	29.07
RGI60-11.00872			-1.12	1.5	2.95	2958.9	5.20
RGI60-11.00817; RGI60-11.00819; RGI60-11.00843; RGI60-11.00878 (merged)	A50i-19	Claridenfirn	-1.06	1.89	10.44	3126.1	4.15



RGI60-11.00918	Limmern	-1.09	2.57	0	5986.4	0.37
RGI60-11.00932		-0.64	4.35	10.49	3289.5	1.76
RGI60-11.00994		-0.83	1.71	0	3070.0	2.65
RGI60-11.01120		-1.04	1.78	0	3965.2	1.02
RGI60-11.01144		-0.89	2.81	12.78	3343.0	2.08
RGI60-11.01187		-0.71	4.66	0	3472.3	1.28
RGI60-11.01193	Chelengletscher	-0.96	2.93	22.82	3049.1	6.56
RGI60-11.01198		-0.71	2.26	16.66	3072.1	4.19
RGI60-11.01222		-0.62	1.94	20.44	3157.3	3.80
RGI60-11.01238	B43-03 Rhonegletscher	-1.13	2.03	27.11	3055.2	10.24
RGI60-11.01246	Dammagletscher	-0.76	4.15	24.73	3125.1	2.91
...	...	...	...	...	...	...
...	...	...	...	...	...	...

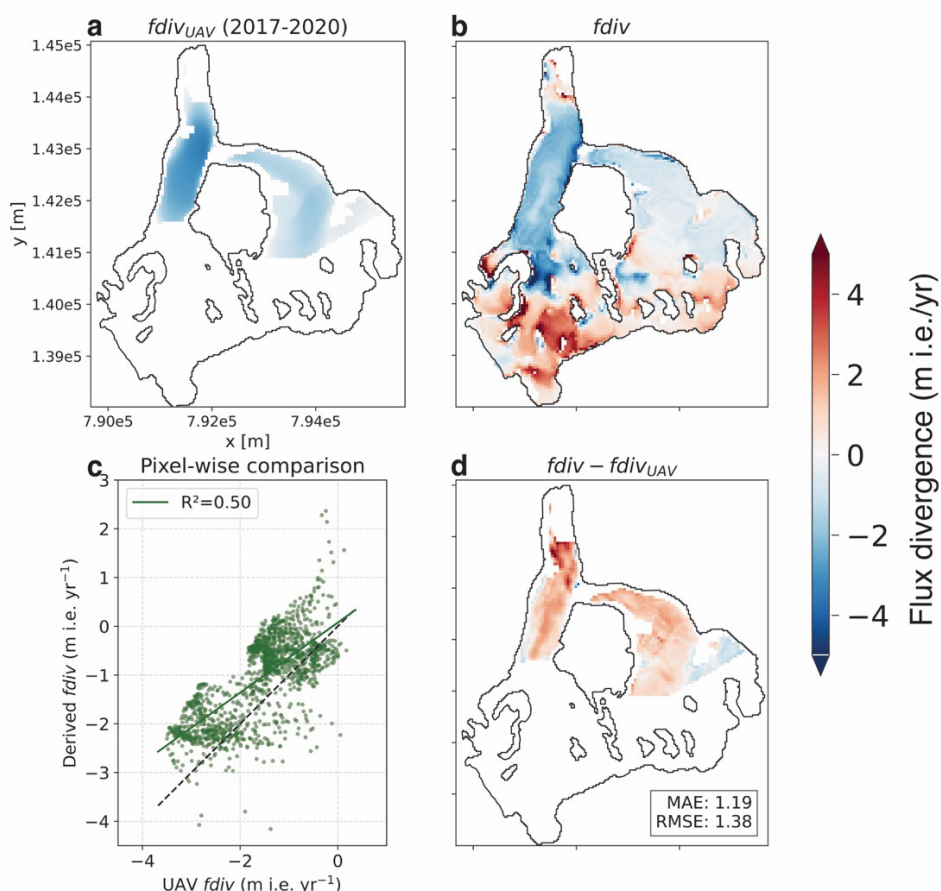


Figure A7: Comparison of flux divergence field on Morteratsch-Pers Glacier obtained from (a) UAV data by Van Tricht et al. (2021) (b) this study; (c) regression of all overlapping points, (d) difference between the two maps

A2. Treatment of ice cliff of Claridenfirn in evaluation

For Claridenfirn, the agreement between the derived MB and elevation-binned GLAMOS MB is strongly affected by the lowest elevation bin (2400-2500 m a.s.l.). When including this bin, the $RMSE_{bins}$ for Claridenfirn is 5.60 m w.e. yr^{-1} , which increases the overall $RMSE_{bins}$ of the four test glaciers from 0.81 to 1.86 m w.e. yr^{-1} .

This lowest elevation bin represents only a very small glacier area (0.01 km²) of thin ice (1.8–6 m) located below a rock cliff (Figure A8 below). The small ice thickness results in a small filtering area, making these pixels particularly sensitive to uncertainties in the input data. In addition, the principal terminus of Claridenfirn experienced frequent ice avalanches over a vertical rock cliff until



approximately the 2010s, with frontal ablation contributing substantially to its mass balance. Frontal
 ablation has subsequently decreased to almost zero due to glacier retreat (Huss et al., 2021). This
 process is not explicitly represented in the mass-continuity inversion but is reflected in the observed
 elevation changes and GLAMOS observations over the 2000–2020 period.

The discrepancy may additionally be affected by the limited contemporaneity of the input datasets. The
 strong retreat of the glacier tongue, particularly in these small, low-elevation areas, is represented
 differently by the ice thickness (reference year of 2010 for this glacier (Grab et al., 2021)) and velocity
 datasets (2017–2018) than by the elevation-change and GLAMOS observations covering 2000–2020.
 Using the more contemporaneous 2010–2020 and 2015–2020 elevation-change datasets would reduce
 the $RMSE_{bins}$ for Claridenfirn from 5.6 to 2.60 and 2.37 m w.e. yr^{-1} , respectively, while including the
 2400–2500 bin.

Given the very small area of the lowest elevation bin and the specific processes affecting this part of the
 glacier, this bin was excluded from the test-set evaluation presented in the main text, and Figure 7
 (panel c2).

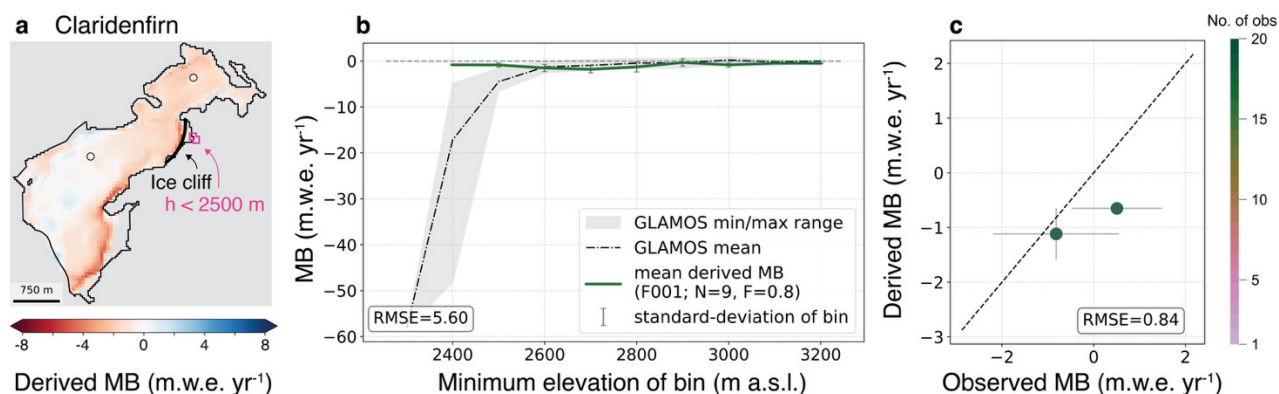


Figure A8 Comparison of derived MB to GLAMOS elevation-binned MB observations for Claridenfirn; alternative version for
 main Figure 7c; indicating (a) the location of the excluded low-elevation bin and (b) the full GLAMOS elevation-binned profile.
 Panel (c) is the same as in Figure 7.



Code and data availability

- 915 The produced spatially distributed MB estimates over 100 Swiss glaciers, as well as the method to
derive these values as presented in this manuscript, are published on Zenodo:
<https://doi.org/10.5281/zenodo.23086392>.
- This study uses previously published observational or remote sensing-derived data products. The used
ice thickness data was obtained from Grab (2020) at <https://doi.org/10.3929/ethz-b-000434697>. Ice
920 velocity data from Millan et al., (2022) was accessed at <https://doi.org/10.6096/1007> and elevation
change from Hugonnet et al., (2021) at <https://doi.org/10.6096/13>. Glacier mass balance observations
from GLAMOS at <https://doi.org/10.18750/MASSBALANCE.POINT.2021.R2021> for the point mass
balance observations and at <https://doi.org/10.18750/massbalance.2023.r2023> for the binned mass
balance values (GLAMOS-Glacier Monitoring Switzerland, 2021; GLAMOS - Glacier Monitoring
925 Switzerland, 2023a). Glacier outlines were used from both the Randolph Glacier Inventory (RGIv6, at
<https://doi.org/10.7265/4M1F-GD79> (RGI Consortium, 2017)) and Swiss Glacier Inventory (SGI2016,
<https://doi.org/10.3389/feart.2021.704189>, Linsbauer et al., 2021).

Supplement link

- 930 *The link to the supplement will be included by Copernicus, if applicable.*

Author contributions

MI, HZ and LVT designed the experiments. MI developed the model code and performed the
simulations. All authors contributed to the analyzing of the results and contributed to the writing of the
manuscript.

935 Competing interests

The authors declare that they have no conflict of interest.

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n/a



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