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Committed Ice Loss in the European Alps Until 2050 Using a Deep-Learning-Aided 3D Ice-Flow Model With Data Assimilation

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Key Points:

- We present a novel, fast, accurate deep-learning method for glacier model initialization and forward simulation at a regional scale
- We calculate glacier climatic surface elevation change without needing calibration across the whole of the European Alps for the first time
- We find committed ice loss in the European Alps to be 34% by 2050, rising to 46% with linear extrapolation of 2000–2020 mass-balance trends

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Modeling the short-term (<50 years) evolution of glaciers is difficult because of issues related to model initialization and data assimilation. However, this timescale is critical, particularly for water resources, natural hazards, and ecology. Using a unique record of satellite remote-sensing data, combined with a novel optimisation and surface-forcing-calculation method within the framework of the deep-learning-based Instructed Glacier Model, we are able to ameliorate initialization issues. We thus model the committed evolution of all glaciers in the European Alps up to 2050 using present-day climate conditions, assuming no future climate change. We find that the resulting committed ice loss exceeds a third of the present-day ice volume by 2050, with multi-kilometer frontal retreats for even the largest glaciers. Our results show the importance of modeling ice dynamics to accurately retrieve the ice-thickness distribution and to predict future mass changes. Thanks to high-performance GPU processing, we also demonstrate our method's global potential.

Plain Language Summary Modeling glaciers is highly challenging over the next few decades because setting up models correctly is a big issue. This is unfortunate, because we really want to know what is going to happen on that timescale, as it will directly affect our lives, homes and jobs. We present a new modeling approach, taking advantage of new data and machine-learning methods, that allows us to set our model up much more effectively. We thus work out how much ice will be lost in the European Alps between now and 2050, even if the climate does not change further, and find that a third of the ice will be lost, come what may. Even the largest glacier fronts will retreat by several kilometers. We show that modeling glaciers properly, with a well-set-up model, is really important to make accurate predictions.

1. Introduction

Prognostic large-scale glacier simulations often focus on the 2100 horizon to predict long-term changes in global mean sea level or ice cover (B. Marzeion et al., 2012; Maussion et al., 2019; Radić et al., 2014; Rounce et al., 2023; Zekollari et al., 2019). The evolution of glaciers over shorter timescales is however more difficult to predict, owing to issues surrounding model initialization and data assimilation, with glacier models typically initialized using mismatched data sets that introduce inconsistencies, requiring a relaxation period to dissipate (e.g., Seroussi et al., 2019; Zekollari et al., 2019). Additionally, to define the initial glacier geometry at a regional scale, ice-flow models use ice-thickness estimates calculated using various forms of the Shallow Ice Approximation (SIA) (e.g., Farinotti et al., 2019; Maussion et al., 2019; Millan et al., 2022), introducing inaccuracies in areas of basal sliding or complex ice flow. This then becomes the starting point for a prognostic simulation, which may use a simplified flowline approximation of the real glacier geometry (e.g., Maussion et al., 2019; Zekollari et al., 2019) and require time-consuming tuning of model parameters. This mismatch of model physics with reality inevitably creates further unphysical model artifacts, requiring a longer relaxation period to dissipate, at the end of which the model glacier may have diverged significantly from its real-world counterpart (something particularly studied in ice-sheet modeling, e.g., Goelzer et al., 2018; Seroussi et al., 2019). Over longer simulations, these differences are outweighed by the uncertainty in climate scenarios (and thus the glacier surface mass balance, SMB, whose calculation at a large scale is itself difficult; e.g., Miles et al., 2021; Van Tricht et al., 2021)

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used to force the glacier model (see Figure 10 in Marzeion et al., 2020)—but on shorter timescales (a few decades), they may induce significant biases in projections of glacier mass losses.

However, the favored model timescale (2100) is too long-term for mountain communities exposed to changes in water availability and tourism potential, and/or the hazard of glacier lake outburst floods (GLOFs) (Carrivick & Tweed, 2016; Huss & Hock, 2018; Taylor et al., 2023); it also does not address the important contribution, likely exceeding that of the ice sheets, mountain glaciers will make to global sea-level rise in the coming decades (Edwards et al., 2021; Farinotti et al., 2019; Mukherji et al., 2023). The shorter timescale also comes with the advantage of depending little on the climate scenario chosen, as all the IPCC scenarios show little divergence over the next 20–30 years, with much of the forecast ice loss on that timescale being a committed response to current climate (Mukherji et al., 2023; Zekollari et al., 2019). By constructing an ice-flow model that avoids model initialization problems and parameter calibration whilst fully assimilating the latest data, therefore, the short-term committed distributed evolution of mountain glaciers to 2050, an absolute lower bound on future ice loss, can be predicted with a higher degree of certainty than hitherto achievable.

Here, we use the Instructed Glacier Model (IGM; Jouvet, 2022), a deep-learning-based 3D ice-flow model, that can assimilate all available data, optimize the model glacier and make projections with a consistent inverse and forward model without post-initialization parameter calibration, thereby resolving traditional initialization problems due to inconsistencies between actual ice flow regime, reconstructed glacier geometry, and ice flow assumptions between forward and inverse modeling. We therefore simulate the evolution of all Alpine glaciers under today's climate to the middle of the 21st century, forced with the mean climatic-surface-elevation-change (CSEC, see methods below) distribution for 2000–2019. We thus present a scenario of committed ice loss in the European Alps (hereafter referred to as "the Alps") over the coming decades.

2. Methods

To invert ice thickness across the Alps, we use the IGM Stokes-flow emulator, detailed in Jouvet (2022), at a resolution of 100 m. This is a deep-learning-driven emulator (based on a convolutional neural network) trained on full-Stokes simulations of 10 Alpine glaciers, which has shown 90% accuracy in matching physical solutions while running a thousand times faster (see Text S1 in Supporting Information S1 for details). For inversion purposes, we split the Alps into 12 glacier clusters (Figure 1). Glacier outlines are taken from the Randolph Glacier Inventory (RGI) version 6.0 (RGI Consortium, 2017). For each cluster, we use the full optimisation scheme described in Jouvet (2022) using ice-thickness observations from v3.1.0 of GlaThiDa (Welty et al., 2020). Otherwise, parameter values and model setup are the same as in Jouvet (2022) (see Text S2 in Supporting Information S1 for details). The optimisation problem is solved by minimizing a cost function that penalizes model deviations from observed surface velocities, calculated flux divergence, surface topography and ice thickness (where available; see Text S4 in Supporting Information S1 for details on inversion performance when no thickness observations are available), with the model allowed to adjust three controls to find the minimum cost: ice thickness, surface topography and a combination of ice viscosity and basal sliding (the $\tilde{A}$ variable introduced by Jouvet, 2022).

For our initial thickness and surface-velocity values in the optimisation problem, we take those calculated by Millan et al. (2022). Consequently, we ignore the negligible proportion of alpine glaciers (<1%) for which the Millan et al. (2022) products are unavailable. Surface topography is from the 90 m Copernicus digital elevation model (DEM) 2020 release. From this DEM and the surface-velocity observations, the optimisation process calculates the flux divergence, which we add to the 20-year (2000–2019) thickness-change-rate product from Hugonnet et al. (2021) to obtain the glacier CSEC distribution (assuming basal and internal mass balance to be negligible, Figure 1b; see Text S3 and Figure S1 in Supporting Information S1 for details). This, to our knowledge, marks a novel approach to calculating CSEC at both the level of the individual glacier and regionally (though we have not fully evaluated this method by comparison to observations in this paper). We then keep the CSEC distribution constant for a 30-year prognostic simulation (2020–2050) in IGM to examine the impact of maintaining today's climate on Alpine glaciers, regardless of future warming. We also performed simulations using the 5- and 10-year thickness-change-rate products from Hugonnet et al. (2021) (2015–2019 and 2010–2019, respectively) to assess the impact of using different CSEC distributions, but found a negligible difference so do not consider them further, as well as performing three further simulations: (a) using a variable CSEC calculated from the 20-year thickness-change-rate product, (b) including the SMB-elevation feedback, (c) extrapolating the warming trend over the last 20 years.

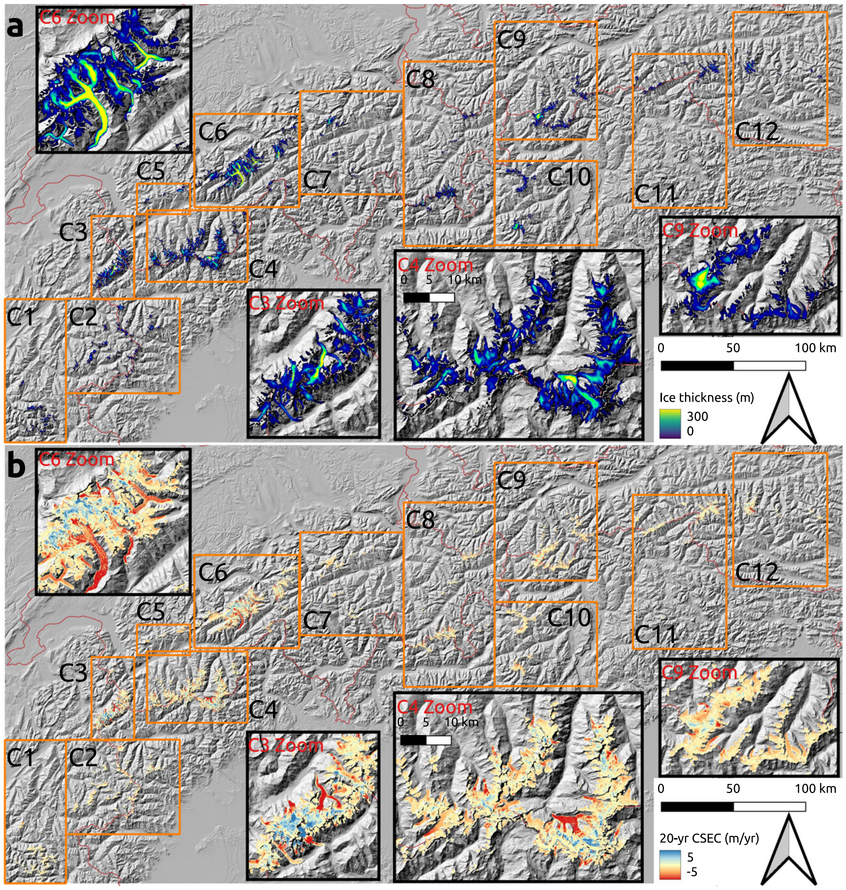

Figure 1. (a) Map of the Alps, showing inverted glacier thickness for 2020, and the 12 clusters (orange boxes) used for inversion. Insets show zoomed major glaciers. Background image is the 90 m Copernicus DEM. (b) The same, but showing our CSEC distribution based on the 20-year product from Hugonnet et al. (2021).

For (i), we modify the thickness-change-rate value (and therefore the final CSEC value) for each year by adding the associated error for each location, multiplied by a random value in the interval $[-1, 1]$. This multiplier is the same for all locations in a given year, such that we approximate Alpine-wide higher and lower accumulation. The purpose of this simulation is to assess how sensitive the results are to interannual CSEC variations; it is not meant to replicate observed SMB, nor be a scenario for future SMB.

For (ii), we include the SMB-elevation feedback to test whether this makes a significant difference at the 2050 horizon. We perform a linear regression of our calculated CSEC across all glaciers against elevation and then use the gradient of this line to scale CSEC at each point during each timestep based on the difference between its initial elevation and its current elevation (see Figure S2 in Supporting Information S1 for details).

For (iii), rather than assuming no further climate change, we linearly extrapolate the trend in glacier SMB for each glacier in the Alps from 2000 to 2022 and for 2010–2022 from the observations in Dussaillant et al. (2023) and apply these to our calculated CSEC based on the 20-year thickness-change product (see Text S3 in Supporting Information S1 for further details). This is to provide two more plausible cases (please note, we do not mean we have devised a plausible climate scenario, only that adding an observationally based trend to the CSEC is closer to reality than assuming it remains fixed) to act as a comparator to our no-further-climate-change scenario.

3. Model Validation

We initially validate the model by simulating the volume of Grosser Aletschgletscher, a focus of previous work by the authors (Jouvet et al., 2011; Jouvet & Huss, 2019), from 1999 to 2019, the period represented by the 20-year thickness-change-rate values (Hugonnet et al., 2021) we are using to calculate our CSEC. We take our

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bed calculated from the present-day thickness inversion and apply the 1999 surface DEM, derived from aerial photography (Bauder et al., 2007), to construct the initial geometry, with an ice volume of 14.9 km^3, in line with the ∼15 km^3 previously calculated for the 1999 glacier volume (Farinotti et al., 2009). We then run an ensemble of 101 simulations over the 20-year period, one with the fixed CSEC and 100 with the variable CSEC described above, to derive a 2019 glacier volume (Figure 2a), which, from our thickness inversion, we estimate to be ∼13 km^3. Using the fixed CSEC in IGM very closely reproduces the expected volume change (OptCSECFix, dashed red line, final volume 12.9 km^3). Taking the mean value of the ensemble of variable CSEC simulations (OptCSECVarAvg, solid red line) shows a small overestimation of volume in 2019 (13.3 km^3) compared to the fixed-CSEC case. We attribute this difference to our randomised set of CSEC anomalies for this experiment being biased slightly positive (note, e.g., the outlying very positive simulation in Figure 2a). Taking this further, we examine the mismatch between our modeled surface DEM at the end of the fixed-CSEC run (2019) and our optimized DEM (based on the Copernicus 90 m DEM) at the start of the prognostic runs (2020) (Figure 2b). This shows our transiently modeled DEM is generally underestimating ice thickness with respect to the optimized DEM in the accumulation area and upstream of Konkordiaplatz, where the three branches of the glacier join. However, ice thickness in the glacier trunk is overestimated, the two effects balancing out in terms of overall volume. The mean absolute mismatch between the two surface DEMs is below 20 m; this translates to a volume difference of 0.4 km^3 (3% of the total volume) across the whole glacier; a similar difference was found between using fixed and variable CSEC. This limited mismatch makes us confident that our approach can largely replicate observed change on large, dynamic glaciers in the Alps over decadal timescales and is suitable for making predictions about the majority of Alpine glacier mass loss to 2050 (see Text S4 in Supporting Information S1 for further information on validation, including on small glaciers).

We also demonstrate the added value of our method by performing a suite of alternative simulations. We run two simulations using an unoptimized ice-thickness field derived by Millan et al. (2022) using an approach based on the SIA (purple line in Figure 2a). In the first simulation (UnoptSIA, dotted purple line), we use this thickness field as our starting ice thickness and replace the emulator with an SIA flow model. In the second simulation (UnoptEmu, dashed purple line), we use the emulator with the unoptimized thickness to represent the not-uncommon case of having mismatched forward and inversion models in a higher-order flow model (Jouvet & Huss, 2019; Réveillet et al., 2015). In both cases, the initial ice volume is overestimated by 1.5 km^3 (i.e., 10%), with both simulations (Figures 2d and 2e) more than doubling the error with respect to the optimized 2020 surface compared to our optimized simulation. This underlines the importance of having accurate initial conditions in a glacier model, regardless of the ice-flow-model physics; this is an area where our optimisation method is able to deliver a substantial improvement on existing methods. We also perform a simulation starting from our optimized thickness field but with the SIA as the ice-flow model (OptSIA, dash-dot purple line), which ends with a mismatch over 1.5 times greater than our fully optimized simulation (Figures 2a and 2c). This also underscores the limitations of the SIA as a flow model and the issue of using different physics for the inversion and forward-modeling exercises, as the glacier starts to gain mass toward the end of the simulation. This non-physical mass gain results from the high surface slopes in the upper accumulation area driving very high SIA velocities, leading to over-export of ice into the too-slow-flowing trunk. Our results, in line with Zekollari et al. (2019), therefore confirm the need for including ice dynamics in even short-term models of glacier evolution.

We then perform four further simulations (Figure 2a) where we optimize glacier thickness, but leave out the thickness observations in two (i.e., thickness is optimized purely using surface-velocity observations; OptNoThk, blue lines), and the velocity observations in the other two (i.e., the thickness is optimized purely using thickness observations; OptNoVel, cyan lines). In all four cases, we drop $\tilde{A}$ from the control parameters and therefore specify A (Arrhenius factor) of 78 $Pa^{-3}\ y^{-1}$ in all cases and a sliding coefficient, c, of 0 and 12, respectively, within each pair of runs, to demonstrate the impact of parameter choice. The relevant mismatches between the end-of-simulation surface DEMs and the optimized surface DEM can be seen in Figures 2f–2i, respectively.

The key outcome from these four simulations is that, for a reasonable value for the sliding parameter ($c = 12$), the partial optimisation performs: (a) 10%–20% better than an SIA flow model starting from the fully optimized glacier (compare Figure 2c with Figures 2g and 2i); (b) in volumetric terms, the simulations are very close to our fully optimized case, certainly by the end of the validation period; and (c) having no thickness observations and relying solely on velocity only leads to a 10% increase in the surface-elevation mismatch (Figures 2g and 2i), while improving the volumetric match (Figure 2a). This demonstrates the value of our approach over simpler flow models and in its own right even in less data-rich environments. However, for a poor choice of c ($c = 0$), we

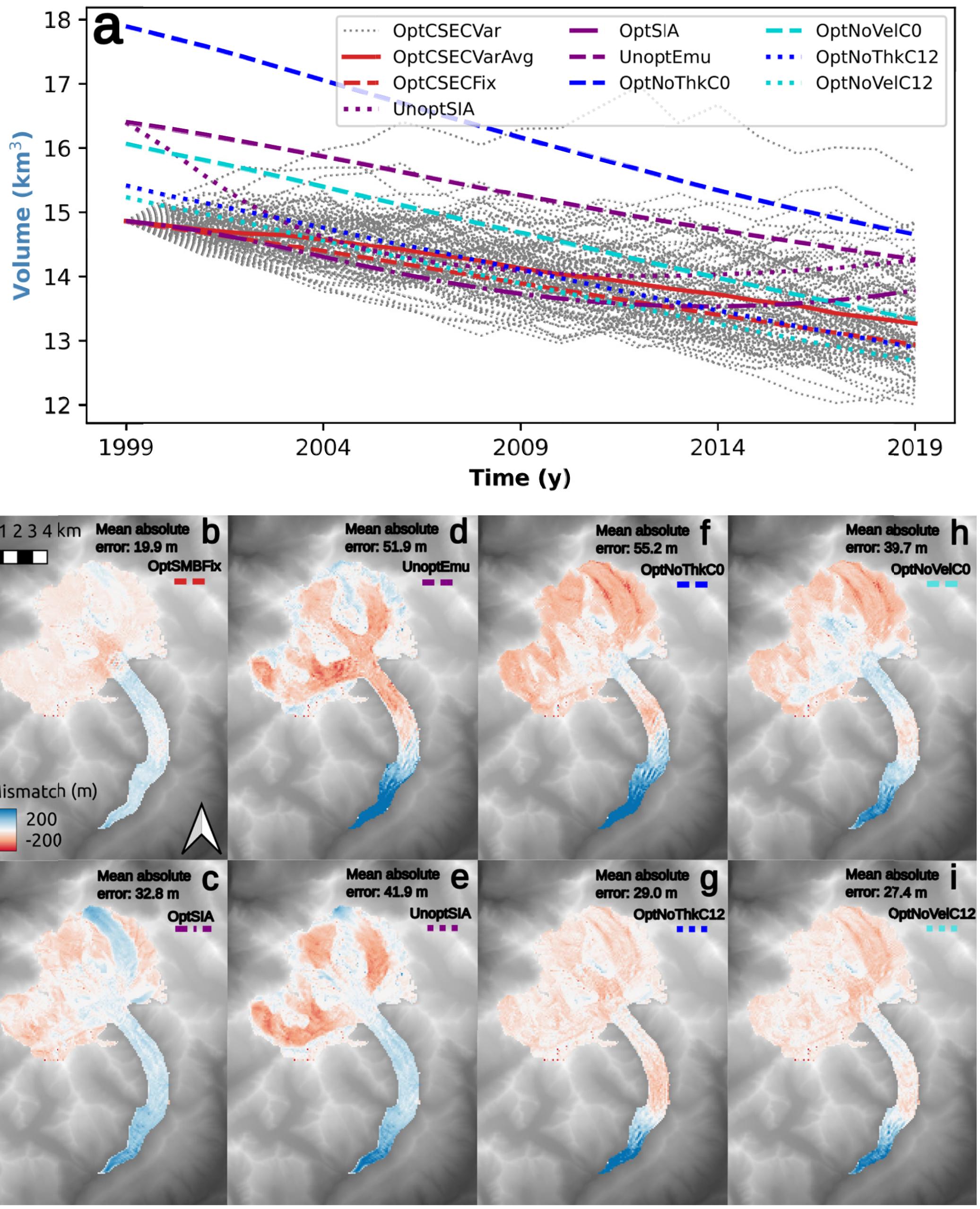

Figure 2. Validation of model on Grosser Aletschgletscher. (a) Modeled volume of Grosser Aletschgletscher 1999–2019 using a constant CSEC (OptCSECFix) and an ensemble of 100 variable CSEC simulations (OptCSECVar); the mean of the ensemble is shown by OptCSECVarAvg. UnoptSIA shows a simulation with unoptimized thickness (that reconstructed by Millan et al. (2022) using an SIA-based approach) using the SIA as a flow model; UnoptEmu shows a simulation with unoptimized thickness, but using the emulator in IGM as a flow model. OptSIA shows a simulation using the optimized thickness, but with the SIA as the flow model. OptNoThkC0 shows a simulation where the initial thickness was optimized without including thickness observations and $c = 0$; OptNoThkC12 shows the same, but with $c = 12$. OptNoVelC0 shows a simulation where the optimisation did not include velocity observations and $c = 0$; OptNoVelC12 shows the same but with $c = 12$ (b–i) The mismatch between the surface DEM at the end of the validation simulations in a and the optimized surface DEM used as the starting point for the prognostic simulations (label at top-right of each panel shows which simulation).

see a much greater divergence in performance (Figures 2a, 2f, and 2h) and an increased importance of thickness observations, highlighting the major benefit of our method in obviating the need for parameter choices in data-rich regions.

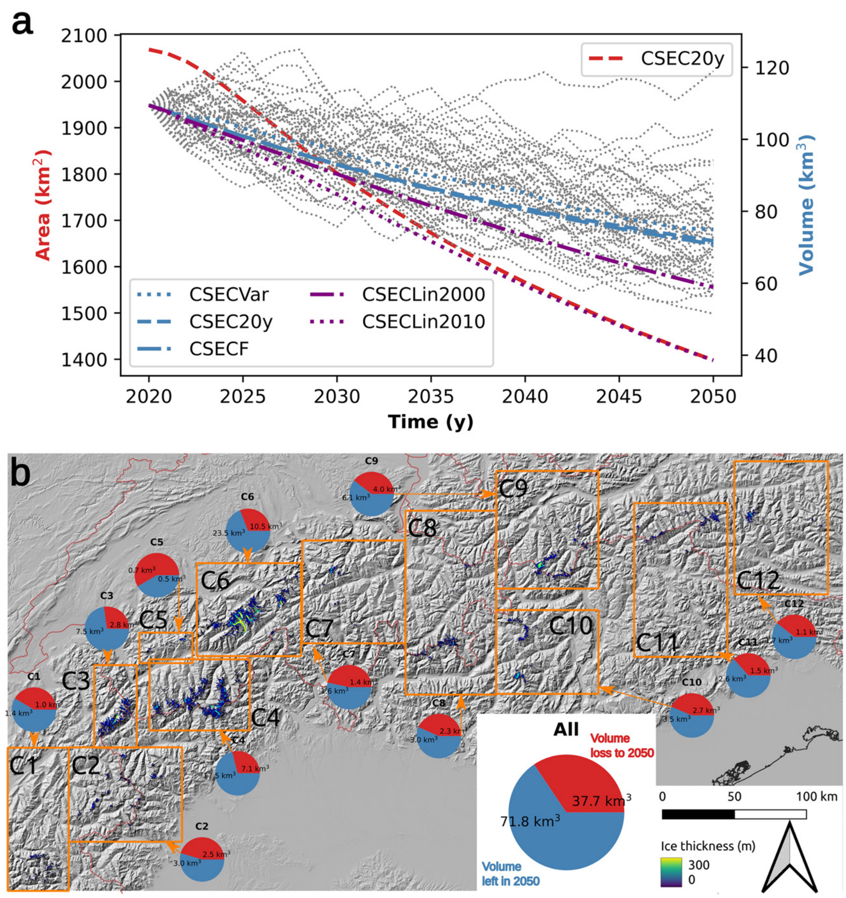

Figure 3. (a) Simulated change in Alpine glacier area (red line, counting cells with ice thickness >5 m) and volume (blue lines) 2020–2050. The dashed lines show the simulation using a fixed CSEC derived from the 20-year thickness-change-rate product from Hugonnet et al. (2021). The gray dotted lines show the volume from the simulations using the variable CSEC based on the 20-year average, with the dotted blue line showing the mean. The blue dash-dot line shows the simulation incorporating the elevation-SMB feedback (note how close it is to the blue dashed line without using this feedback). The purple lines show the volume when extrapolating forward the trend in glacier SMB 2000–2022 (dash-dot) and 2010–2022 (dotted) to 2050. (b) Volume evolution of Alpine glaciers over 2020–2050 by regional cluster (see Figure 1) for the simulations using the fixed 2000–2019 CSEC. Red pie-chart segments show ice volume lost, blue show remaining 2050 ice volume. The background image shows ice thickness in 2050 overlaid on the 90 m Copernicus DEM.

4. Prognostic Simulation Results

Overall, we find a 34% committed reduction in Alpine ice volume and a 32% reduction in area (defined by counting pixels with >5 m of ice thickness) over 2020–2050, that is, based on current CSEC (2000–2019) and irrespective of future additional climate change (Figure 3). Using a variable rather than constant CSEC (CSECVar) leads to only a 3% volume change. Including the elevation-SMB feedback (SMBF), meanwhile, leads to only a 2% volume difference. Thus, henceforward, we will only reference the simulations using the constant CSEC as we find little meaningful difference when using a non-constant one.

If, however, we model CSEC by linearly extrapolating the trend from the best-available yearly record of SMB observations since 2000 (2000–2022) (Dussaillant et al., 2023, CSECLin2000) forward to 2050—that is, by considering what might be called a "more plausible" climate scenario, rather than no further climate change—we find a 46% volume loss by 2050. This is a third higher than our committed scenario, which underlines the importance to the cryosphere of every tenth of a degree in warming. If we instead extrapolate based on the 2010–2022 SMB trend (CSECLin2010) to give more weight to the most recent years of observations, we find a 65% volume loss by 2050, suggesting the possibility of worse outcomes.

At a more local level, our results (Figure 3b) show that ice loss will be stronger at lower altitudes, with clusters containing lower-altitude, smaller-size glaciers (C5, C2, C7) faring considerably worse than larger, higher-altitude

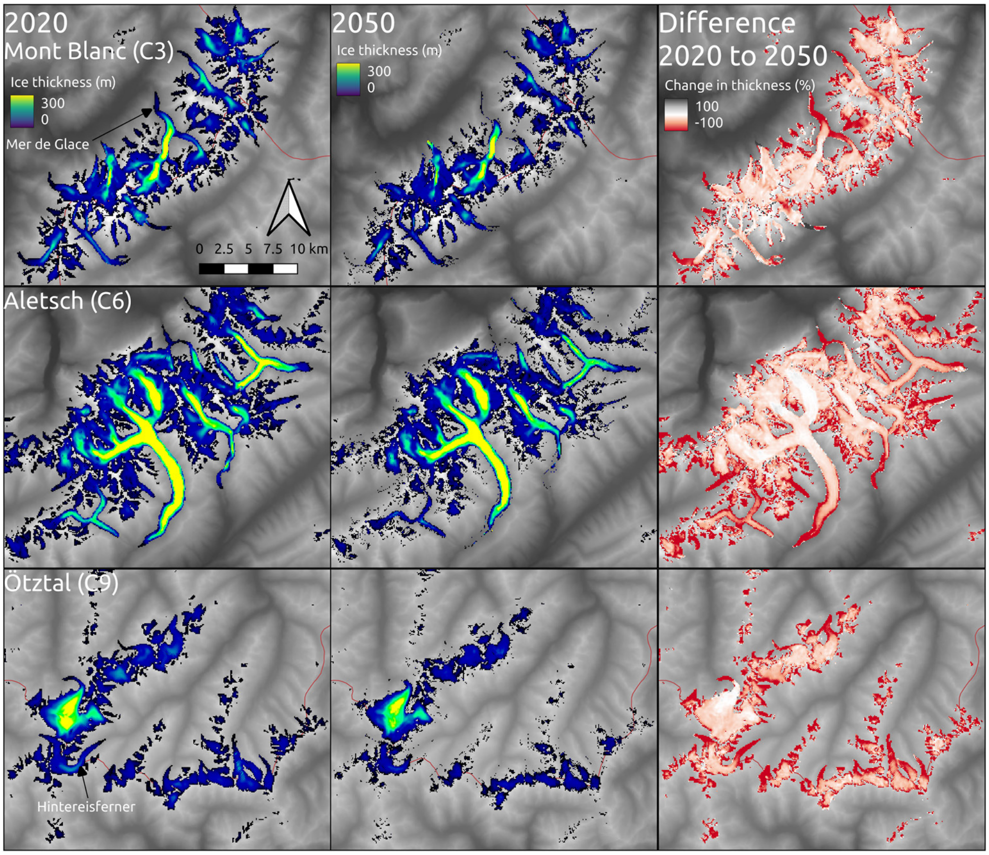

Figure 4. Ice thickness in 2020 (first column) and 2050 (second column), and the difference between them (third column) for the Mont Blanc massif (first row), Aletsch region (second row) and Ötztal Alps (third row). Background image is the Copernicus 90 m DEM.

glaciers (C3, C4, C6). This is in line with observed glacier change (Huss et al., 2010), and confirms the general viability of our approach. Even within clusters with larger, higher-altitude glaciers, however, we can expect to see significant ice loss (Figure 4) with, for example, the complete disconnection of one branch of the Mer de Glace (France) and a 3 km terminus retreat, a 3 km retreat at Grosser Aletschgletscher, and the loss of nearly half the length of Hintereisferner (Austria). By mid-century, therefore, only the largest, highest glaciers will retain substantial ice volumes.

5. Discussion

Our committed Alpine ice volume loss, representing an absolute minimum for future ice loss, by 2050 (34%) agrees very well with that found by 2100 by Zekollari et al. (2019) (35%), and the 40% (up to about 2070) found by Zekollari et al. (2020), suggesting a rapid increase in rates of Alpine melting. The prognosis for glaciers in the Alps is thus likely even worse than previously thought, especially when we find a 65% reduction in ice volume by 2050 when we linearly extrapolate the 2010–2022 trend in SMB, fitting with recent predictions of extensive Alpine mass loss this century (Rounce et al., 2023). Similarly, our area loss (32%) nearly equals the 35% by 2100 of Zekollari et al. (2019), though we note that the absolute (much less the relative quoted here) values would change had we used the Paul et al. (2020) glacier outlines (14% area loss compared to the RGI). This points to a greater-than-expected risk of GLOFs, streamflow reductions and depleted reservoirs in the Alps in the coming decades, though small-scale, accurate modeling of glacier mass changes, taking into account snow-firn-ice densification processes and glacier thermal regime would be needed to fully quantify this. We also note our modeling does not take into account the recent (2022–2023) extreme mass loss in the Alps (GLAMOS, 2023), so we re-emphasize that the ice-loss figures in this study are very much absolute lower bounds, not climatically driven projections.

Our approach presents several major novelties in ice-flow modeling. For the first time, thanks to the application of deep learning, we are able to present results, for both inversion and forward modeling, equivalent in accuracy to a 3D full-Stokes model (Jouvet et al., 2021) at high resolution in 2D across an entire glacierised region. Moreover, we also show that we can initialize our forward simulations with self-consistent model glaciers that match their real counterparts, avoiding many initialization issues that affect traditional glacier models. These advances will be of great benefit to the glacier modeling community going forward.

This advance is only possible, however, owing to the greater availability of both surface velocity (Millan et al., 2022) and thickness-change-rate (Hugonnet et al., 2021) data, allowing us to both invert ice thickness and calculate a 2D distribution of CSEC across entire regions for the first time. We are further not dependent on the choice of climatic forcing scenario, as we use only observed climate at this short timescale, and we require far less data processing, nor do we need to tune any model parameters to achieve accurate results.

Finally, the emulation capabilities of IGM allow our forward and inversion models to run extremely fast on graphical processing units (GPUs). For reference, the inversions performed here at 100 m resolution took only one hour in total to run on a single GPU (NVIDIA RTX A3000 12GB); the entirety of the forward modeling for each simulation shown in Figure 3a (i.e., one simulation of the whole Alps for 30 years) took another 5 minutes. This speed and the success of the method presented here allow us to consider applying our model at a larger and potentially global scale.

6. Conclusion and Further Work

We have presented simulation results, requiring no parameter tuning or recalibration after initialization and based on a novel and simple method for calculating glacier CSEC, for committed ice loss in the Alps up to 2050 through physically consistent inversion and forward modeling using IGM. We show that, in a committed-ice-loss-only scenario, representing an absolute lower bound on future ice loss, where we project 2000–2019 CSEC forward to 2050, the Alps will lose 34% of its current ice volume. If we instead extrapolate the trend linearly from glacier SMB observations since 2010 (2010–2022), we find a loss of 65% by 2050. By validating this method with the case of Grosser Aletschgletscher, we show its potential to be applied elsewhere or globally, as well as demonstrate its technical innovativeness and ability to ameliorate initialization issues that frequently bedevil glacier simulations thanks to the application of deep-learning techniques. Our validation exercise also shows the importance of fully modeling ice dynamics when predicting mass loss, even on short timescales.

Data Availability Statement

All data and the IGM v1.0 code used for the simulations is freely available from Zenodo (Cook et al., 2023). The latest version of IGM (v2.0 at time of writing) is freely downloadable from https://github.com/jouvetg/igm.

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