Bedrock estimation with AI, two approaches evaluated on Vatnajökull, Iceland.

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1. Introduction

Accurate estimation of basal topography underneath glaciers has remained a difficult task even though much progress has been made in the last decades (Farinotti et al., 2017) Most methods combine surface data (e.g. glacier surface elevations, surface slopes, and surface velocities) with existing radio echo sounding (RES) measurements (profiles and/or point measurements) to create bedrock maps. Early attempts utilizing artificial intelligence (AI) methods to infer bedrock topography led to promising results (Clarke et al., 2009) and proved to be as accurate as many other approaches (Farinotti et al., 2017).

Bed topography maps are key information for various glaciological research, both theoretical and practical. This includes modelling the feature development of glaciers in response to changing climate, studies on glacial hydrology and how marginal lakes evolves, with glacier retreat. Ice thickness maps provide assessments on the amount of water stored in glaciers and their potential contribution to see level rise. Accurate bed topography maps are essential for risk assessments of jökulhlaups caused by geothermal and volcanic activity beneath glaciers, as well when studying potential changes in locations of river outlets from glaciers in the coming decades. The Icelandic Road and Coastal Administration has therefore, a direct interest in glacier bed topography mapping being as accurate as possible.

We investigate two methods which utilize AI technology to generate detailed bedrock maps of Skeiðarárjökull, South Iceland, with the aim to improve existing datasets. The first method is based on an inversion approach of ice flow physics whereas the second method aims to directly predict bedrock elevations underneath glaciers from surface observations.

After describing both methods, we summarize our findings and give an outlook for further research.
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2. Methods and Data

2.1 Data

Both AI methods heavily rely on surface data, namely surface elevation and surface velocity maps for the region of interest. The glacier surface used in this study is a digital elevation model of Skeiðarárjökull in autumn 2021, deduced from optical stereo images acquired by the SPOT7 and Pléiades satellites corrected using GNSS profiles acquired the mass balance measurement trip in October 2021 (Eyjólfur Magnússon et al., in prep.). The velocity field of Skeiðarárjökull used in this study is annual velocity field spanning 1 October 2019 to 30 September 2020, extracted from Sentinel-1 high resolution radar images (Wuite et al., 2022). This annual velocity field appears free of any clear artifacts, observable for the annual velocity fields in 1 October 2020 to 30 September 2021 and 1 October 2021 to 30 September 2022.

Extensive RES surveys have been carried out on Skeiðarárjökull. This includes ~1500 km of survey profiles mostly measured in the spring of 1993 and 1994 with low frequency (5 MHz) analogue radar (Björnsson and Pálsson, 2020). In the lower part of Skeiðarárjökull ~90 RES point measurements were carried out in 1997, 1998 (Björnsson et al., 1999) and 2008 (Magnússon et al., 2009) to obtain ice thickness and bedrock elevation. Currently available bedrock map deduced from the exiting RES data is from Magnússon (2008) and Magnússon et al. (2009). All input data used in the AI methods was subsampled to grid-files with 100 m X 100 m cell size prior to the inversions (see overview map of RES data in Fig. 1).

2.2 Methods

We now give a short overview of the two bedrock estimation methods used in this study.

2.2.1 Inversion approach with surrogate model (IASM)

The first method builds upon the assumption that for every physical forward model an exact backward model exists that allows for an inversion of the processes at hand.

In our case, the forward model (or process) is ice flow. This process is controlled by basal topography of a glacier. Distinct features of the bedrock (eg. hills, troughs and such) result in distinct features within surface data such as surface elevation changes and patterns in surface velocity. It has been realized early on that these imprints from the bedrock onto the surface are (1) attenuated by the transfer through the ice body and (2) non unique (Gudmundsson, 2003). Especially both, hills and slippery spots at the base can result in very similar surface deformation signals. This ambiguity complicates basal topography estimations from surface data, which is the inverse model to ice flow, and hence requires a thorough statistical treatment during this step. Often, forward models with sufficiently high fidelity for an inverse approach (Gagliardini et al., 2013) demand a lot of computational resources and time. Thus replacing the costly forward model with a fast computing surrogate model is often preferred in inverse approaches. Such a surrogate model, however, is required to represent all important dynamical features of a system sufficiently well to be useful.

Convolutional neural networks, a form of AI technology, have been successfully used to speed up ice flow models substantially (Jouvet et al., 2022). Building upon this type of surrogate ice flow model, an efficient basal topography estimation technique has been presented (Jouvet, 2023), which we have tested for its applicability to Skeiðarárjökull. This method attempts to find an optimal balance between known (surface elevation and surface speed) and unknown (bed topography) input data to the forward model, and optimizes for bed topography based on ice flow dynamics and known bed topography measurements.

Being an AI based approach, this inversion technique requires training data which has been generated by glaciating now deglaciated landscape with a suitable numerical forward model (Jouvet et al., 2022), a method to produce suitable training datasets already suggested earlier (Clarke et al., 2009). The used landscape is not specific to Iceland nor to large ice caps common in Iceland and we discuss the implications of this later in section 4

2.2.2 Direct artificial neural network approach (DANNA)

Another, more direct approach to bedrock topography estimation is to train an artificial neural network (ANN) to directly infer bedrock elevations from surface data (surface elevation and surface velocity). Several different architectures of ANNs exist, such as feedforward or recurrent neural networks (Bishop, 2016), but we restrict our approach to basic feedforward neural networks (FNN) with back-propagation training techniques. Such methods, being a substantial extension of statistical models, require lots of training data to learn the process connections between bedrock topography and surface data. One could also take the viewpoint that the FNN learns the inverse model described in section 2.2.1 directly from data.

For Skeiðarárjökull (cf. Sect. 2.1) a substantial amount of radio sounding data exists, thus this location is ideal to test training data intensive methods such as our DANNA approach.

We examine two different FNN architectures: (1) a FNN which utilizes surface elevation along with ice surface velocities as well as 250 spatial registration points to predict bedrock elevation in a given location (DANNA1) and (2) a FNN which uses a neighbourhood of 100 points both in surface elevation and surface flow speed magnitude above a given location to predict bedrock elevation below that location (DANNA2).

We expect DANNA1 to have more spatial interpolation qualities as it utilizes distances to spatial registration points and thus learns spatial patterns to some degree. DANNA2 however is completely independent of location and only utilizes pixel neighbourhoods (e.g. 50x50 pixels) in surface data for its predictions. It can, however, learn surface data gradients, such as surface slope, from these neighbourhoods. This make DANNA2 generally more transferable to different regions, however we did not test for such properties of our AI approaches.

3. Results

First we tested our IASM approach on Skeiðarárjökull, utilizing surface velocity fields (Wuite et al., 2022) and surface elevation data (Eyjólfur Magnússon et al., in prep.) in the inversion approach. As described by the optimization function, eq. (5), in (Jouvet, 2023), several optimization parameters are available and have been tested by us. Our best fitting results are presented in Figs 2-4. In Fig 2 the optimization towards surface elevation (usurf) is displayed, alongside the error in surface, between optimized and initial surface. Fig 3. displays the optimization of surface velocity (velsurf_mag) and in Fig 3. our best fitting results for ice thickness are compared to the initial ice thickness estimates (Magnússon, 2008; Magnússon et al., 2009).

Important to note is that outside the region of existing ice thickness radar data, the errors in inversion estimations (cf. Figs 2. and 4, right panels) become large, which is expected. However in Fig 5, the resulting ice thickness estimates at the tongue of Skeiðarárjökull (blue spot, left panel), is a persistent pattern of thickness overestimation and indicate a failure of the method in that location. This error pattern could not be removed by variations in inversion parameters, which points to a fundamental problem in slow flowing, shallow glacier tongue regions.

Our results for the bed elevation estimation methods DANNA1 and DANNA2 are presented in Fig 5 along with the initial bed elevation estimates (Magnússon, 2008; Magnússon et al., 2009). In contrast to the IASM approach, DANNA directly estimates bed elevations (in m a.s.l.). Comparing DANNA1 and DANNA2 to the existing bed elevation map (Fig 5 right panel), we see DANNA1 creates smooth bed estimates, similar to the existing map. DANNA2 however is more prone to surface data noise and thus creates a somewhat noisier bed estimation. However the power of DANNA2 is to be able to estimate bed elevations quite correctly outside the data area (red outline in Fig 5), a capability only DANNA2 has, IASM and DANNA1 fail to do so meaningfully.

Comparing results of DANNA1 and DANNA2 to a hold out dataset of radar bed estimations, i.e. bed estimations which were not used to train the ANN method, reveals the following error estimates. A mean absolute error in bed elevation of MAE_{DANNA1} = 7.2 m for DANNA1 and MAE_{DANNA2} = 12.3 m for DANNA2.

4. Conclusion

Even though the IASM approach is scientifically very interesting as it is an inversion approach to a physics base ice flow model, it demonstrated downsides in a practical application. As can be seen in Fig 4, right panel, the algorithm does perform poorly outside the data region. Also a strong imprint of the radar measurement profiles persists through all configurations we have tried.

Another downside of the IASM approach is that the surrogate ice flow model, which is used for this approach, has been trained on alpine-style valley glacier data (compare Jouvet et al. (2022), Fig. 6). This also explains the persistent overdeeping estimates in ice thickness (cf. Fig 4, right panel, blue area at terminus). In that case the method can not handle slow flowing, Icelandic glacier terminus situations, as the surrogate model has never been trained to deal with such configurations.

To make IASM work for Iceland, a substantial amount of resources (financial and computational) would have to be invested to re-create a new surrogate forward model, suitable for Icelandic conditions. This avenue for progress has not been possible in this study.

Our DANNA approaches, however, demand a lot less resources and proofed themselves to be very useful for bed topography estimations. They do depend on a large enough training dataset, however such datasets exist for Icelandic glaciers. Especially DANNA2 is a promising method and as a next step we suggest to study the data noise behaviour of DANNA2 in the attempt to make it even more useful for future applications.

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Expenses in the years 2022 and 2023

Fund to the project from The Icelandic Road and Coastal Administration research fund was 3,600,000 ISK combined in 2021 and 2022.
Contracted work paid to ThetaFrame Solutions in 2021 (0.7 man months) 578,230 ISK (3,850 €)
Contracted work paid to ThetaFrame Solutions in 2022 (1.0 man month) 782,820 ISK (5,500 €)
Contracted work paid to ThetaFrame Solutions in 2023 (5.0 man months) 4,101,300 ISK (27,500 €)
Work on data preparation by EM (0.6 man months): 600,000 ISK.
Overhead (2.5%): 90,000 ISK.
Total expenses: 6,152,350 ISK

Figures

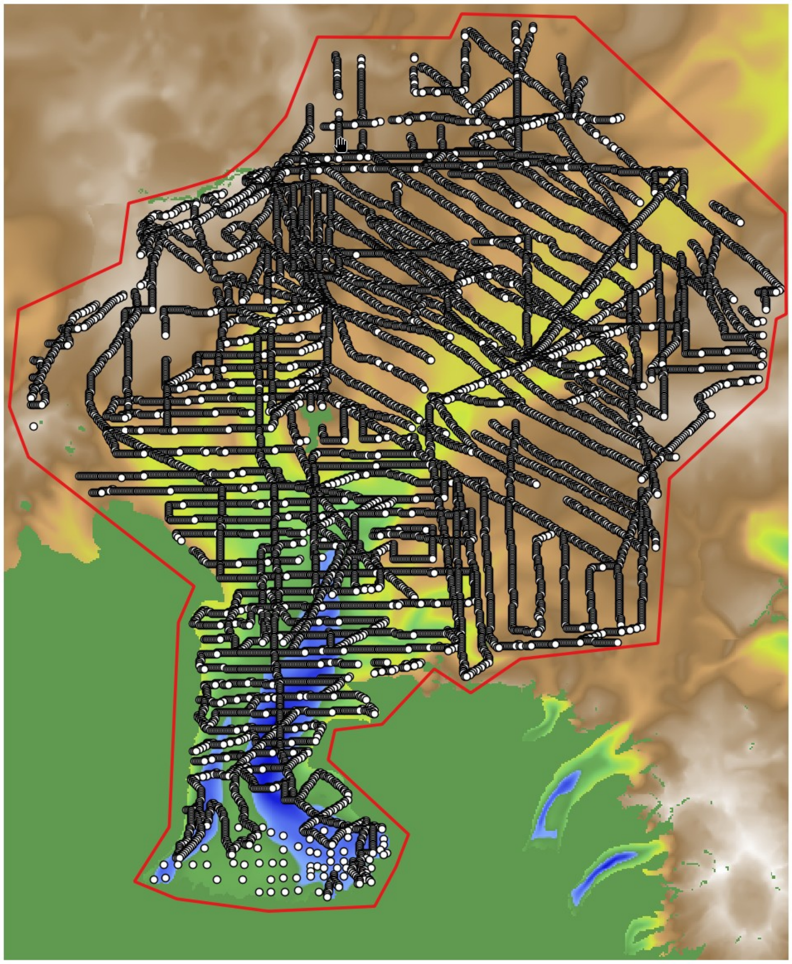

Fig. 1: Locations of the RES measurements used in this study as white dots on top of the reference bedrock map.

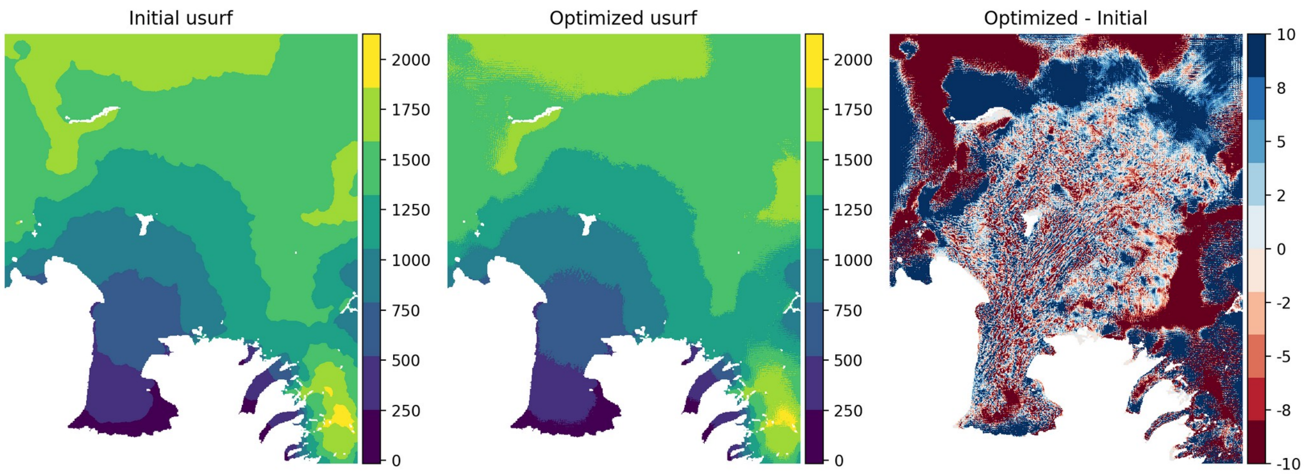

Fig. 2: IASM result for surface elevation at Skeiðarárjökull. Initial surface elevation (usurf) on the left, inversion optimized surface elevation in the middle and the error between both on the right. Vertical elevation is in meters.

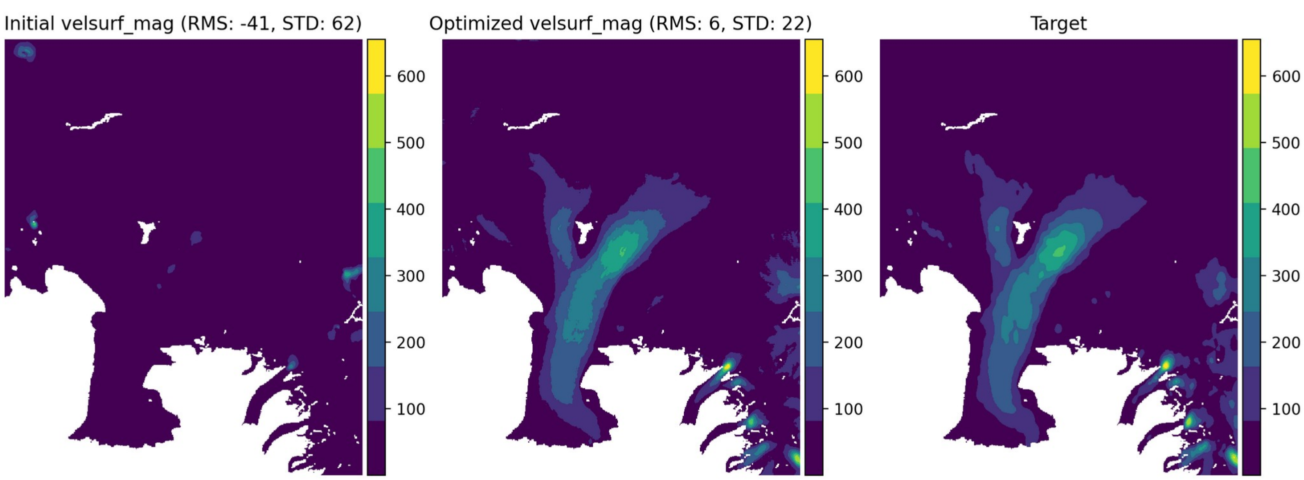

Fig. 3: IASM result for surface velocity magnitude at Skeiðarárjökull. Initial surface velocity (velsurf_mag) on the left, inversion optimized surface velocity in the middle and target surface velocity data on the right. Units is m/year.

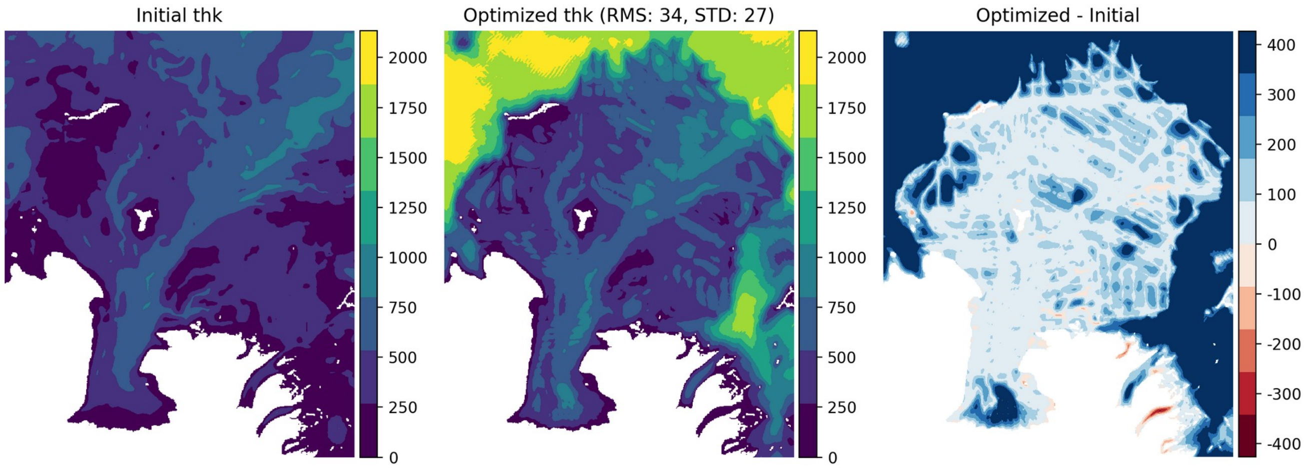

Fig. 4: IASM ice thickness results Skeiðarárjökull. Initial ice thickness (thk) on the left, inversion optimized ice thickness in the middle and the error between both on the right. Ice thickness is in meters.

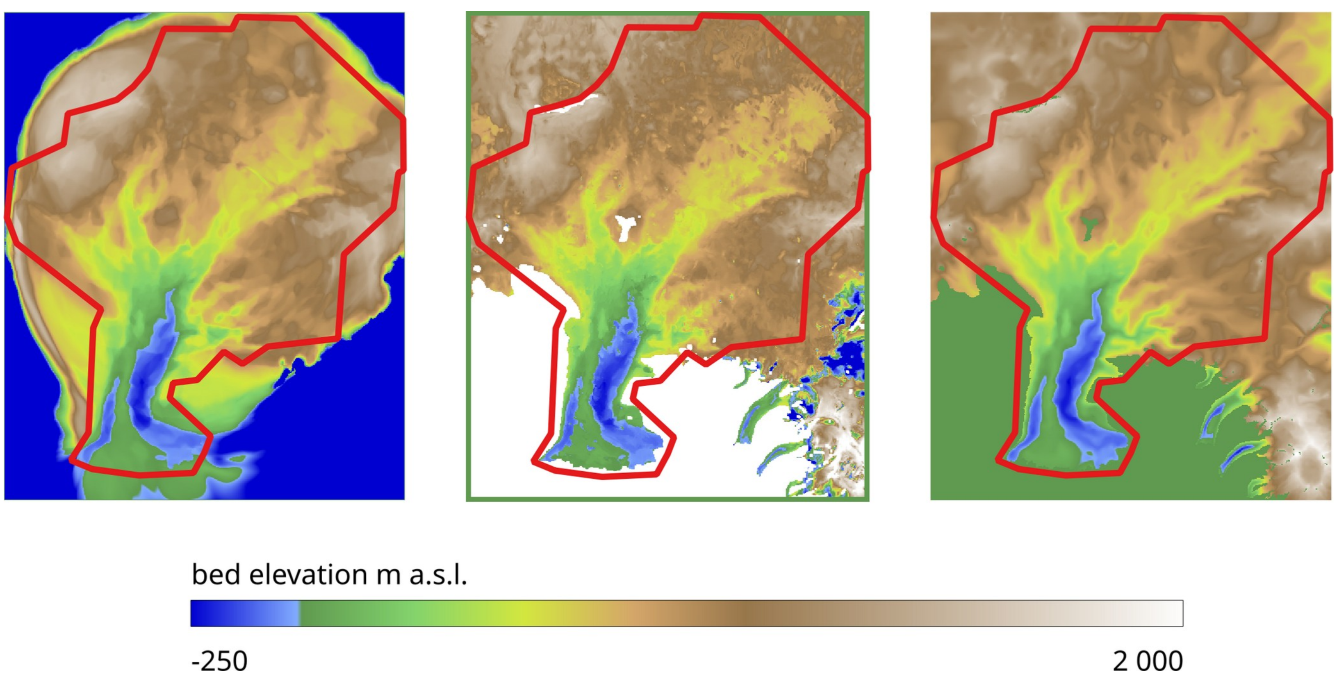

Fig. 5: DANNA bed elevation results. On the left, DANNA1 results, in the middle DANNA2 results and on the right the reference bed elevation map. Bed elevation below sea level are in shades of blue. Red marks the area in which we have bed elevation radar measurements.