Mapping glacier basal sliding applying machine learning

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Key Points:

- Seismic and GPS data are examined to study physical processes controlling glacial basal motion
- Decision tree model uses beamforming catalog and statistical features of time series to constrain correlations with GPS recorded motions
- Glacial on-ice velocity is strongly modulated by activity at the base of the glacier

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Abstract

During the RESOLVE project ("High-resolution imaging in subsurface geophysics: development of a multi-instrument platform for interdisciplinary research"), continuous surface displacement and seismic array observations were obtained on Glacier d'Argentière in the French Alps for 35 days in May 2018. The data set is used to perform a detailed study of targeted processes within the highly dynamic cryospheric environment. In particular, the physical processes controlling glacial basal motion are poorly understood and remain challenging to observe directly. Especially in the Alpine region for temperate based glaciers where the ice rapidly responds to changing climatic conditions and thus, processes are strongly intermittent in time and heterogeneous in space. Spatially dense seismic and GPS measurements are analyzed applying machine learning to gain insight into the processes controlling glacial motions of Glacier d'Argentière. Using multiple bandpass-filtered copies of the continuous seismic waveforms, we compute energy-based features, develop a matched field beamforming catalogue and include meteorological observations. Features describing the data are analyzed with a gradient boosting decision tree model to directly estimate the GPS displacements from the seismic noise. We posit that features of the seismic noise provide direct access to the dominant parameters that drive displacement on the highly variable and unsteady surface of the glacier. The machine learning model infers daily fluctuations and longer term trends. The results show on-ice displacement rates are strongly modulated by activity at the base of the glacier. The techniques presented provide a new approach to study glacial basal sliding and discover its full complexity.

Plain Language Summary

Alpine glaciers are a major component in the dynamic cryospheric environment. They are characterized by a multitude of processes occurring side by side, including but not limited to melt water flow, crevasse formation, and frictional basal sliding of the ice mass over the rigid and obstructive bedrock. Each of these processes generates distinctive acoustic signals that can be recorded by seismic instruments and the changing on-ice motions are resolvable with GPS. Considering the rapidly changing glacial environment, there is an increasing need for reliable models to predict glacial dynamics to properly assess any associated hazard. Understanding basal sliding is of particular interest to this problem. Investigated here is how to overcome the challenge of describing glacier sliding using

seismic signals since the records often contains multiple "loud" signals originating from associated surface processes within the glacier. To uncover specific processes occurring at the ice-bedrock interface, we design a machine learning model to incorporate signals recorded on the glacier to predict the on-ice surface motions. The results provide valuable insights into the spatiotemporal dynamics of an active Alpine glacier with the potential to contribute to a better understanding of the driving mechanisms of glacier sliding.

1 Introduction

The cryosphere is one of the most rapidly changing environments on Earth and transformations are accentuated by the ongoing evolution of climatic conditions. In mountainous regions, glacier dynamics can be used as a local marker of climate change, and can cause major damage to human infrastructure, so it is of common social interest to study spatiotemporal processes within the ice with high resolution (Faillettaz et al., 2015). The rapidly emerging field of "cryoseismology" addresses processes within the glacial environment, such as crevassing, hydrofracturing, failure and calving of ice fragments or supraglacial, englacial and subglacial water discharge via the analysis of continuous seismic records (Podolskiy & Walter, 2016). Special emphasis has been put on the investigation of glacier sliding, which is still not completely understood, but affects large-scale ice flow, ice sheet stability, and thus ultimately sea level rise (Ritz et al., 2015).

Glaciers flow via two processes, internal deformation (or "creep") and basal sliding (Cuffey & Paterson, 2010). The stress-strain relationship for internal deformation of the glacier itself describes viscous deformation associated with ice creep and can be approximated by "Glen's flow law" (Glen, 1955). Basal sliding is responsible for fast flow of ice-streams; "sliding" is used as an umbrella term here for actual sliding of the ice sole and deformation of soft subglacial till beds (e.g., Helanow et al., 2021). In view of steep, unstable ice tongues, it is of great interest to scientists and stakeholders to understand the physical basis of glacier sliding given that catastrophic break-off events threaten mountain communities world-wide (Faillettaz et al., 2015; Shugar et al., 2021).

The first theoretical concept of glacier sliding was introduced by postulating that normal forces on undeformable bed undulations produce local shear resistance (Weertman, 1957). Here, a frictionless glacier bed was considered with sliding driven by enhanced deformation and regelation around stiff bed obstacles. Weertman's theory of "hard" bed sliding (Weertman, 1957) was modified to account for subglacial water cavity formation (Iken, 1981; Schoof, 2005; Gagliardini et al., 2007) and deformable subglacial till layers (Murray, 1997). Both mechanisms can explain observations of melt-water enhanced ice flow and basal sliding (Cuffey & Paterson, 2010). Modern sliding theories (e.g., Schoof, 2005; Zoet & Iverson, 2020) are still influenced by these concepts. However, recent cryoseismological studies show that glacier sliding is not always smooth, but interrupted by distinct slip events (Aster & Winberry, 2017). This points to frictional processes, where sudden shear failure at the glacier bed emits seismic waves, analogous to the behavior of tectonic faults. Such stick-slip motion cannot be explained by traditional Weertman-type or soft-bed theories, which describe sliding as a continuous, slow, and smooth process. Instead, frictional processes add to the complexity of basal sliding and thus ice flow. A pivotal challenge in glaciological research is to formulate new or extend existing sliding laws, including conventional concepts but also considering glacier frictional sliding as an additional flow mechanism (e.g., Sergienko et al., 2009; Winberry et al., 2011; Lipovsky & Dunham, 2017; Lipovsky et al., 2019; Zoet & Iverson, 2020).

Evidence from polar and non-polar ice masses suggests that microseismic stick-slip motion is a widespread (see Podolskiy & Walter, 2016, and references therein) and potentially pervasive form of basal sliding (Barcheck et al., 2019; Hudson et al., 2020; McBrearty et al., 2020; Walter et al., 2020; Gräff et al., 2021; Kufner et al., 2021). Individual microseismic stick-slip events are very small with negative magnitudes and shear displacements on millimeter scales or less (Helmstetter et al., 2020). Successive events may coalesce into sustained ice-tremor resulting in ice-stream wide sliding episodes with surface displacements of tens of centimeters per day. The spectral signature of the sliding tremor is characterized by spectral peaks at frequencies corresponding to the inverse of inter-event times between individual stick-slip events (Lipovsky & Dunham, 2016). First detected at rapid Antarctic ice streams, sliding tremor may be a widespread phenomenon with observational evidence for these sliding tremors beneath Greenlandic (McBrearty et al., 2020) and Alpine glacier ice (Umlauft et al., 2021), and the slip displacement may be measurable at the ice surface. Detection of these tremors with conventional on-ice seismometers is challenging because the signals can be masked by the extensive glacial noise from other cryoseismic sources, especially englacial and subglacial water flow (Röösli et al., 2014; McBrearty et al., 2020; Eibl et al., 2020; Umlauft et al., 2021). Thus, in Alpine regions, with temperate glacier ice and high meltwater production, frictional sliding in the form of microseismic stick-slip tremors may be completely overlooked and far more predominant than presently understood.

Analogous to tectonic faults, stick slip motion across glacial faults emits seismic energy and is commonly measured by seismometers (Podolskiy & Walter, 2016). The frictional state of a tectonic fault and information about the current position within its seismic cycle are still challenging to access. As the fault's rupture, nucleation and magnitude, and future earthquake occurrence are directly controlled by the fault frictional state, its quantification is of interest for understanding the underlying physics (Marone, 1998). Numerous theoretical simulations and laboratory experiments contributed to the determination of frictional characteristics (e.g., Rabinowicz, 1956; Scholz, 1968; Rubinstein et al., 2004; Kaproth & Marone, 2013; Madariaga & Ruiz, 2016; Dorostkar et al., 2017). Recently, analyses of seismic signals from laboratory faults (Rouet-LeDuc, Hulbert, Bolton, et al., 2018) and faults in earth (Johnson & Johnson, 2021) applying machine learning have yielded remarkable results indicating that the seismic waves contain information about the fault characteristics at all times.

We use this analogy to guide the choice of research methodology to monitor the physical state of the glacier. So far, direct and continuous quantification of fault friction cannot be achieved using conventional geophysical approaches, whereas supervised machine learning models are suitable to directly quantify instantaneous fault friction in laboratory experiments and fault properties in tectonic environments (Rouet-LeDuc, Hulbert, Bolton, et al., 2018; Rouet-LeDuc, Hulbert, & Johnson, 2018; Hulbert et al., 2019; Johnson & Johnson, 2021; Ren et al., 2020; Wang et al., 2021, 2022).

In laboratory experiments it was demonstrated that frictional properties can be accessed through the statistical characteristics of continuous seismic records (range of the data, root mean square, variance, skewness, kurtosis, quantile ranges) and that even different modes of slip along these laboratory faults were captured, which demonstrates that seismic data are a rich archive that allows one to directly observe the physical state of a fault (Rouet-LeDuc, Hulbert, Bolton, et al., 2018; Hulbert et al., 2019). These processes are similar to basal motion in the glacial environment where the displacement takes place at the ice-bed-interface.

With the aim to uncover the signals related to sliding that are not directly observable, we applied a decision tree model to a new data set from a dense on-ice network on Glacier d'Argentière (French Alps) comprising continuous measurements of local seismicity, surface velocities, and meteorological observations. Due to the highly variable and noisy glacial environment, extensive preprocessing of the seismic and geodetic measurements is essential for a robust feature space with the goal of directly estimating glacier sliding behavior from the surface of the ice and hence, to monitor its dynamics.

2 Methods

2.1 Resolve data collection

As part of the RESOLVE project "High-resolution imaging in subsurface geophysics: development of a multi-instrument platform for interdisciplinary research"), researchers from ISTerre and IGE Grenoble (France) and ETH Zürich (Switzerland) installed a unique sensor infrastructure at the surface of Glacier d'Argentière (Fig. 1) (Gimbert et al., 2021). A dense seismic monitoring array with 98 geophones, 7 GPS stations, a meteorological station, and a water discharge station were operational during approximately one month in May 2018 (24/04/2018-27/05/2018). Five of the GPS stations were installed directly on the surface of the ice (ARG1-ARG4, ARGG) with four of them integrated with the seismic array (ARG1-ARG4). The remaining two stations (ARG5, ARGR) were placed on solid bedrock next to the glacier near the seismic array.

The GPS derived displacement rate (velocity) was computed using a centered moving time window of size ± 3 hrs with a 1 hr time step for east, north, and vertical components, and the combined horizontal components (east + north). This sampling was found to provide the best agreement between errors and signal-to-noise ratio.

Seismic observations were continuously recorded at a sample rate of 500 Hz in a grid-like dense array (Ø 700 m). The stations were deployed into snow about 30 cm below the surface within the ablation zone of Glacier d'Argentière (see Gimbert et al., 2021, for specific details). Signal preprocessing includes removing the instrument response, detrending and demeaning the continuous waveforms.

Temperature and precipitation were monitored at a 10 min sampling rate using one station situated on solid bedrock about a kilometer to the north of the array. Water discharge was measured every 15 min by the Emosson power supply company in excavated tunnels below the glacier tongue (Vincent & Moreau, 2016; Gimbert et al., 2021).

2.2 Matched Field Processing

Matched field processing (MFP) is the natural extension of plane wave beamforming and yields for the location of seismic noise sources in range, depth and azimuth by analysing spherical waves in the close environment of the underlying seismic array (Bucker, 1976). The approach was originally developed in ocean acoustics (Baggeroer et al., 1993; Kuperman & Turek, 1997), but a broad spectrum of applications can be found in environmental seismology to study near-surface processes on the exploration scale (Vandemeulebrouck et al., 2010; Cros et al., 2011; Corciulo et al., 2012; Umlauft & Korn, 2019) and the rapidly emerging special research field of cryoseismology to better understand dynamics within e.g., Alpine glacial ice (Walter et al., 2015, 2020; Umlauft et al., 2021; Nanni et al., 2021, 2022).

Assuming the spatial coherence of the wave field across the array, a systematic correlation of portions of continuous seismic field records and the model-based Green's function (replica) is performed at various candidate source positions. The approach is performed in the frequency domain and can be considered as an equivalent of shift-and-stack techniques in the time domain. For a certain frequency, replica parameterization allows improved data fitting by velocity inversion (Gradon et al., 2019) or polarity optimization for the location of double-couple sources (Umlauft et al., 2021). The procedure is aimed to estimate phase matches between the data wave field and the replica field with the beampower maximum representing the most probable source location.

2.3 Data Features

Data features are statistics of the continuous seismic records from a five-node subarray with high signal-to-noise-ratio, meteorological and water discharge measurements, and events spatially binned from a beamforming catalogue (see Fig. 2 for station locations and a snapshot of the beamforming catalogue). Statistical features were computed for the continuous seismic record of five selected stations shown as inverted white triangles in Fig. 2. We made four copies of the records using a bandpass filter between 10-50 Hz: 10-20 Hz, 20-30 Hz, 30-40 Hz, and 40-50 Hz to cover the frequency bands related to the most dominant processes in glacial ice, such as water flow, crevassing, icequakes or stick-slip tremors (Podolskiy & Walter, 2016). A moving time window of 1 hr is applied to compute the variance, kurtosis, mean, root mean square, skewness, range and interquantile ranges (0.025, 0.25, 0.5, 0.75, 0.95) using ± 3 hrs before and after the respective time stamp. This sampling matches the GPS data sampling resolution. Hence, statistical features at every hour reflect the distribution of the seismic data within the same 6-hours-windows as the averaged GPS data. The meteorological data (temperature and precipitation) and water discharge measurements are applied by computing the average of 30 data points (meteorological data) / 24 data points (water discharge measurements) corresponding to 6 hrs of seismic data (1 data point is the average of the data during the previous 10 min / 15 min) to obtain consistent feature time windows.

We extracted information from an extensive beamforming catalog which was developed using an advanced matched field processing localization scheme based on a gradient-decent optimization that meets the challenging, seismically "loud" environment. A complete detailed description on the methodology and the MFP implementation can be found in (Nanni et al., 2022). We used four sub-catalogues with center frequencies of 5 Hz, 10 Hz, 15 Hz and 20 Hz. Each catalogue was limited in x,y,z with respect to the dimension of the array and the depth of the glacier. The seismic velocities were limited to 1300-3800 $\frac{m}{s}$ and we expect that range to cover Rayleigh wave, P- and S-wave velocities within glacial ice (Podolskiy & Walter, 2016). We additionally reduced each catalogue to normalized beampower values between 0.2-1.0. Fig. 2 shows a 1 hr snapshot of a 10 Hz-catalogue together with the ice surface and the bedrock topography. To use the high-resolution catalogue results as features in the gradient tree boosting model, we spatially binned the MFP derived sources within 8 predefined source regions of the same ice volume (voxels V1-V8). Voxels 1-4 capture the deeper part of the glacier, close to its base, and voxels 5-8 capture the surface equivalent. For each voxel we sum the number of sources and sum their beampower respectively. For consistency with the other data, we apply a moving time window of 1 hr using ± 3 hrs before and after the respective time stamp to match previous feature and label sampling. Virtual cut surfaces and voxel notations are indicated in Fig. 2.

2.4 Xtreme Gradient Boosting Model for Glacier d'Argentière

Gradient tree boosting (Friedman et al., 2000) is a widely used and scalable supervised machine learning approach. It is a very powerful tool that is based on, but usually outperforms, decision tree ensembles (Breiman, 2001; Chen & Guestrin, 2016). Decision tree ensembles use multiple shallow trees that can be built in a serial manner, in parallel or even independently from each other and combined in a next step in order to enhance model performance. Gradient tree boosting is an extension of decision tree ensembles. The ensemble learner can be used for classification or regression problems. In order to predict a target variable (label), a model is trained based on simple decision rules learned from the data (feature). Depending on the purity of the individual leaves of the tree, the prediction is weighted through a comparison with the respective label. The deviation is represented by an arbitrary loss function. The model is trained sequentially by adding a gradient term to the current decision tree model iteration, with the aim to minimize the loss function for the weighted ensemble of all previous decision trees. Usually, trees that are added in each iteration are shallow (weak learners), but the full ensemble contains a large number of them in total quantity. Once the model is trained, the feature importance (SHAP values) can be evaluated to get more insight into the model drivers allowing one to learn which input observations yield the best estimates on the output label (Lundberg & Lee, 2017).

To estimate the GPS velocity on the surface of Glacier d'Argentière, we develop a gradient boosted tree regression model using the features extracted from the data. Specifically, we use the XGBoost package and routines form scikit-learn (Chen & Guestrin, 2016; Pedregosa et al., 2011). When selecting model hyperparameters, the choice of data split, and feature preprocessing is done by iteratively optimizing the model using 5 fold cross validation on the training data to minimize the average mean-squared-error for the folds. A Bayesian optimizer is implemented for a search space to select the best hyperparameters (Head et al., 2018). The procedure randomly selects hyperparameters for 100 iterations, then gradient descent is applied to converge on the best selection for an additional 100 iterations. Initially the search space is large, then expanded or narrowed for specific parameters to avoid final values converging at the upper and lower limits. For each optimization run the evolution of parameters is viewed to update the search space, then the procedure is repeated. The workflow is distributed on a GPU server to train multiple models with different hyperparameters simultaneously to select the final model based on convergence.

2.5 Model development and optimization

To analyze the ability of the model to perform predictions for data with a temporal distance to the training data, we experimented with different train/test splits. First, we experimented with a random train/test split, such that for each test sample, training samples in close temporal proximity are available. We subsequently increased the length of consecutive train/test intervals from 24 to 96 hours. For longer intervals, the model needs to learn time-invariant, globally valid features to still be able to achieve good performance. As extreme cases, we experimented with 50%/50% splits (where the first half of the time series is used for training, and the other half is used as test data) and 80%/20% splits (where the first 80% of the time series is used for training and the last 20% for testing). Feature preprocessing included standard scaling (S), quantile transformation (Q) ($n\_quantiles = 50$), principal component analysis (P) ($n\_components = 50,\ whiten = True$), and a random forest regressor (R) ($n\_estimators = 200,\ \ max\_depth = 3,\ \ n\_features\_to\_select = 20,\ \ step = 1$). All routines are available in the scikit-learn package (Pedregosa et al., 2011; Buitinck et al., 2013). We optimized the hyperparameters for each type of split on the training fraction using the original data and each possible combination of S, Q, P and R. The results show that the best-fit model hyperparameters with the lowest loss, hence, the best model, strongly depends on the choice and combination of data split and feature preprocessing. For each GPS velocity time series we evaluate the type of split with the choice of preprocessing and accordingly apply the respective model hyperparameters which yield the highest possible prediction score. Comparison of data and best-fit model are expressed through the coefficient of determination (R^2), the root-mean-squared-error ($RMSE$), and the correlation coefficient (CC). These metrics are applied to allow direct comparison between models and do not reflect the absolute quality of the results. To further improve predictions, we tested different applications of a low-pass filter to the GPS velocity time series to reduce the high-frequency 'spiky' fluctuations inherent to the time series. The cutoff frequency was optimized to maximize the evaluation score.

3 Results

Results are presented to show the capability of the model to predict the velocity time series for all available RESOLVE GPS stations and specifically highlight the model predictions for three GPS stations that yield the highest scores (ARG2, ARG3 and ARGG in Fig. 1). Additionally, we provide details on the best-fit model hyperparameters for station ARG3 considering the implementation of different data splits and feature preprocessing.

We assess the different types of data splitting for model evaluation and provide results for a direct comparison of the performance and robustness of each technique. In Fig. 3 we show the prediction scores for CC and $RMSE$ using the testing fraction of the GPS velocity time series of ARG3 for different short-term and long-term splits, and the dependence on feature smoothing window length between 1-24 hrs to reduce bias from temporary signals. The results indicate the model performance is strongly dependent on the type of data split and that it generally improves when larger smoothing windows are applied. The best results are observed when using random splits, where the entire time series is shuffled before selecting the training and test data, with a $CC > 0.8$ for a smoothing window >5 hrs. Increasing the smoothing window length further improves the predictions towards $CC = 1$ (Fig. 3 [a]). Similar metrics are observed with the $RMSE < 1$ using a window length >7 hrs and further decreasing to $RMSE = 0.25$ with longer windows (Fig. 3 [b]). These results show the best model fit but this split does not encourage the model to learn time-invariant features, as no predictions for data with large temporal distance to the training data have to be made.

To maintain temporal sequencing, we split the data into uniform temporal blocks with sizes between 24-96 hrs for the entire duration of the data. The best results are found using temporal block sizes of 24 and 36 hrs with $CC > 0.6$ ($RMSE < 1.2$) for a window length >9 hrs. The results improve to $CC = 0.8$ ($RMSE = 0.75$) for the largest smoothing windows tested and increase with an approximate linear trend (Fig. 3). Applying block sizes >36 hrs show inconsistent, alternating behavior with little improvement above $CC = 0.6$ ($RMSE < 0.6$). This is consistent when using even larger fractions of the data for the long-term splits (80%/20% split, 50%/50% split). In general, these models show a $CC < 0.2$ ($RMSE > 0.65$) with the maxima derived using a smoothing window between 9-13 hrs.

The sensitivity of the best-fit model hyperparameters applying different data splits and feature preprocessing is illustrated in Fig. 4. Variations in the hyperparameters are strongly dependent on and significantly differ for the type of split and the choice of feature preprocessing. Except for $n\_estimators$ ranging between about 1000-1200 for all types of split, no trend can be observed for other hyperparameters and types of split (4 [a]). Just as the data split alters the model, different choices and combinations of feature preprocessing lead to inconsistent model hyperparameters. Values of min_child_weight seem to be lower when less preprocessing is applied, but overall the response of the model hyperparameters shows no clear pattern for different choices of preprocessing. Comparing the models of three equally 50%/50% split GPS stations (ARG2, ARG3, ARGG) in terms of hyperparameters, preprocessing, and low-pass filtering indicates the requirements for the best prediction score ($CC = 0.25 - 0.46$) are also fundamentally different and significantly influence the model performance (Fig. 1).

3.1 Short-term sliding predictions

The model predictions for the velocity time series of GPS station ARG3 using three different types of train/test split are shown in Fig. 5. For the testing set, data versus model correlations are shown in the inset. Without any additional preprocessing applied to the features except smoothing to suppress noise (smoothing window of 15 hrs), the random split yields outstanding performance (Fig. 5 [a]) with $RMSE = 0.42$, $CC = 0.94$, and $R^2 = 0.88$. The model is able to capture hourly fluctuations by randomly training and testing on the time sampling domain of the data (1 hr).

Next, we increase the length of train/test intervals in the range of 24 and 96 hours. The most robust and performant model with a reasonable agreement between smoothing and prediction score was achieved using blocks of 36 hrs and smoothed features with a smoothing window of 15 hrs (Fig. 5 [b]). Compared to using blocks of 24 hrs, the 36 hrs block split model shows slight deficiencies expressed by a lower RMSE in the range of about 0.2, which is not reflected by the CC. This marginal shortcoming is counterbalanced by the gain in block size from 24 hrs to 36 hrs, leading to a gain in prediction horizon of 12 hrs which serves the scientific motivation of this study. Without any additional feature preprocessing applied, the model scores with $RMSE = 0.84$, $CC = 0.75$ and $R^2 = 0.5$ (Fig. 5 [b]). Apart from some infrequent failures and not fully capturing the amplitude at all times, the model is able to predict fluctuations with daily resolution.

3.2 Long-term sliding predictions

With the aim to stretch the prediction horizon, we apply a 50%/50% split, since the model seems to be less sensitive towards smoothing than the one using the 80%/20% split we consider it more robust (Fig. 3). We train the model on the first half of the data and test it on the remaining half. Analogous to the short-term splits, we use the raw features and only apply a smoothing window length of 15 hrs in a first iteration, which results in a significantly lower prediction score ($CC < 0.4$, $RMSE > 0.9$, see also Fig. 3). Extensive feature preprocessing involving S, Q, P and R, and the additional application of a low-pass filter with a cutoff frequency of 16.5 hrs improves the correlation coefficient up to $CC = 0.47$ (Fig. 5 [c]). While short-term dynamics can not be captured by the model, it is able to predict the long-term behavior of the GPS velocity, notable the varying trend but with a static offset.

3.3 Sliding predictions across Glacier d'Argentière

Next we evaluate short-term model predictions (block split, 36 hrs) and long-term model predictions (50%/50% split) for three GPS stations (ARG2, ARG3 and ARGG in Fig. 1), which yield the highest prediction scores within the network. We do not apply any feature preprocessing except a smoothing window of 15 hrs, unlike the feature preprocessing (S, Q, P, R) and an additional lowpass filter for long-term predictions to enhance the model performance.

For GPS station ARG2, which was located within the seismic array and situated close to seismic node 64 (Fig. 2), we derive a model score of $CC = 0.25$ using a 50%/50% split with preprocessing P and a low-pass filter with a cutoff frequency of 2.5 hrs applied (see Table 1 for best-fit model hyperparameters). The SHAP features show that statistical features of node 12 contributed most to the model (Fig. A2 [a]). It is important to note that node 12 was situated on the north-western flank of the glacier while ARG2 was located in the central-north close to the glacier tongue. The interstation distance and the model's decision "against" favoring features from the closest node 64 posit that the long-term behavior of the surface velocity of the ice is likely not locally driven by e.g., an opening crevasse, but rather controlled by some seismic activity along the north-western flank. As displayed in Fig. 6 [a] short-term predictions (36 hrs blocks, smoothing window of 15 hrs) for ARG2 yield an increase in CC by a factor of 2.64. The SHAP features (Fig. 7 [a]) show that beamforming features replace statistical features when analyzing shorter time windows. Explicitly, the low-frequency source locations (5 Hz) within lower voxel V1 (Fig. 2) contributed most to the model predictions followed by the skewness of seismic node 12 in the 30-40 Hz filter band.

GPS station ARG3 was situated in line with ARG2 and integrated with the seismic array as well. More precisely it is located next to seismic node 60. For long-term predictions (50%/50% split), we derive a model score of CC = 0.46 with preprocessing S, Q, P and R and a low-pass filter with a cutoff frequency of 16.5 hrs applied (see Table 1 for best-fit model hyperparameters). When comparing to ARG2, more preprocessing and a stronger filter are applied. As a result of the smoother GPS data from the low-pass filter data, the model shows a CC value with a 2x increase. As revealed by the SHAP features and as for ARG2, statistics from node 12, situated at the north-western flank of the glacier, are of upmost importance (Fig. A2 [b]). Fig. 6 [b] shows the equivalent short-term predictions (36 hrs blocks, smoothing window of 15 hrs) for ARG3 which result in $CC = 0.75$. Again, statistical features important for long-term predictions are here replaced by low-frequency beamforming features (5 Hz) from the lower voxels V1 and V2 (Fig. 7 [b], Fig. 2). Additionally, the 0.5 interquartile range of the 30-40 Hz filtered record of seismic node 80 strongly contributes to the model predictions.

For GPS station ARGG situated within the accumulation zone of the glacier <3 km north-west from the seismic array, the best long-term model score based on a 50%/50% split is $CC = 0.37$ with a low-pass filter with a cutoff frequency of 1.39 hrs applied (see Table 1 for best-fit model hyperparameters). The data features were best suited in the original format (no preprocessing) using the filter to suppress short-term dynamics. As for ARG2 and ARG3, the SHAP features again indicate the importance of statistical features from seismic node 12 (Fig. A2 [c]). For short-term predictions (36 hrs block split) we derive a $CC = 0.6$, which is mostly dependent on beamforming features of the lower voxel V2 (Fig. 2) in the 20-30 Hz filter band followed by the 0.5 interquartile range of the 40-50 Hz filtered record of seismic node 64 and the skewness of the 40-50 Hz filtered record of seismic node 12.

The long-term model results and the related feature ranks for the three GPS stations analyzed show consistent results that suggest glacial surface velocity is being controlled by activity at the north-western flank of the glacier. Interestingly, the meteorological features and surface beamforming voxels generally play a subordinate role for the model estimates. For short-term model predictions we observe that beamforming features of the lower voxels close to the glacier bed are most important followed by high-frequency statistical features (30-50 Hz), such as the 0.5 interquantile range and the skewness.

4 Discussion

The application of machine learning using continuous seismic records continues to show success in describing physical processes of complex natural systems. While the glacier motion model predictions are not as robust as those for laboratory stick-slip studies (Rouet-LeDuc, Hulbert, Bolton, et al., 2018; Shokouhi et al., 2021; Corbi et al., 2019; Jasperson et al., 2021; Wang et al., 2021), slow slip in Earth (Hulbert et al., 2020), future prediction (Laurenti et al., 2022; Wang et al., 2022), or stick-slip processes in Earth (Johnson & Johnson, 2021), they are nonetheless predictive for the log-term sliding behavior and especially performant for short-term variations. Ice deformation is considered mostly aseismic through viscous creep (Gimbert et al., 2021), which is inherent to the material properties. The data features are designed to capture such deformation using information in the continuous signal emitted from internally deforming slip boundaries during viscous flow, which occurs at a range of pressures and temperatures. The glacial system dynamics are highly complex and variations in signals produced by the sources of noise appear to be more heterogeneous than in a laboratory system or an earthquake fault.

This study shows for the first time that surface displacement rates can be linked to distinct areas, and even in-depth activity, of a temperate Alpine glacier based on the seismic beamforming features. The addition of seismic beamforming as a data feature provides additional information to the model space and enables the estimate of surface displacement rates on Alpine glacial ice in an highly dynamic and noise-prone environment, and the ability to locate its driving process. To our current state of knowledge, basal motion is most likely the driver for deep cryoseismogenic processes which drive the displacement rates at the surface of Glacier d'Argentière and outrivals internal deformation through viscous creep due to its strong seismic fingerprint (Podolskiy & Walter, 2016).

Data splits strongly influence the decision tree models outcome with sample-wise or short-term train/test fractions leading to the highest prediction scores and longer train/test fractions to a subsequent decrease in performance together with a loss in robustness. Even though the short-term models outperform the long-term models in terms of evaluation metrics, they provide less insights into the physics and dynamics of glacial sliding. Hence, there is a tradeoff between model performance and long-term predictions.

We found that the best agreement between prediction horizon and model performance is given by using block splits with block sizes of 24-36 hrs ($CC = 0.75$). Those models are robust towards feature smoothing, meaning that within each block the dynamics and processes are similar and hence 'understandable' for the model.

The best long-term model captures the long wavelength characteristics, suggesting that the highly variable temporal fluctuations are generated by a number of incoherent processes and the model can not isolate into these unique characteristics in the feature space. A possible cause is the seismic features contain a combination of information from multiple weak processes and expanding the feature space might improve the high frequency estimates. With the current best model and features, the surface ice velocity can be predicted with an accuracy of up to 46% for the longer term behavior in the range of 16.5 hrs.

Intensively studying the hyperparameter space and the dependence on data split, different choices of preprocessing and low-pass filters shows that each station-related model has to be tuned independently and model settings may not be generalized in the Alpine cryospheric environment. We found that individual station estimates generally score better than averages of multiple on-ice velocity time series and that bedrock stations were less suited for the analysis.

Overall, we observe that the relevant features for model predictions differ for GPS stations that were situated in the noise-prone ablation zone (ARG2, ARG3) compared to ARGG, which was situated in the accumulation zone. For ARGG, less influenced by cryoseismic sources as e.g. crevassing or water flow, which can potentially mask in-depth activity of the glacier, the long-term model and short-term model can both pick up processes at the glacier's base relevant for sliding (lower beamforming voxels V2 and V4, 20-30 Hz). For long-term model predictions of ARG2 and ARG3 those features are revised by statistical features, as they potentially reflect the dominant local sources such as crevassing or water flow. The short-term models of ARG2 and ARG3 however capture in-depth activity. We observe consistent results for both stations in favoring low-frequency beamforming features from the bottom voxels V1 and V2 (5 Hz).

The RESOLVE experiment design was most advantageous for capturing the spatio-temporal seismic and geodetic behavior driven by glacial processes in the one month of data collection. Limitations to the seismic and geodetic measurements as applied to this analysis include the discrepancy in sampling rate (500 Hz for seismic observations vs. 1 hr for geodetic observations). This mismatch requires several steps of preprocessing to properly align the data features and labels, specifically the moving time window analysis and smoothing of the time series data or the compilation of the highly resolved beamforming catalogue. Those procedures come with a potential loss of information regarding short-term variations of the glacier's activity. Furthermore, seismic observations were solely collected in the ablation zone of the glacier, while GPS station coverage spanned over the entire length of Glacier d'Argentière (<3 km). The accumulation zone of temperate based glacial ice is typically less active than the ablation zone. The ablation zone, however, is characterized by a multitude of physical processes such as crevasse formation, meltwater flow or avalanches and rockfalls provoked by increasing temperatures in lower altitudes (Nanni et al., 2022). Even though the geodetic observations show coherent behavior across the network and the glacier's extent (Fig. A1), model predictions of distant stations which were situated in the accumulation zone may be challenged due to regime differences. Compared to predictions made on GPS stations which were integrated with the seismic array, model estimates of high-altitude geodetic observations show reasonable performance, but might have benefited from nearby seismic observations.

The mild power threshold of the beamforming catalogue (0.2-1.0) subsequently leads to the integration of poorly resolved seismic sources in our analysis which poses the risk to decrease the model performance due to random, physically unconstrained locations. However, in view of the high noise level in Alpine glacial environments, locations with a lower resolution likely carry relevant information from deep processes at the glacier bed, as e.g. basal stick-slip (Umlauft et al., 2021) or subglacial water flow (Nanni et al., 2020). As revealed by the feature importance for model estimates of GPS ARGG (Fig. 7 [c]) the 20 Hz beamforming catalogue as applied to this analysis carries information enabling the best model prediction. The surface displacement itself but also the center frequency of the catalogue reasons that glacier basal motion, potentially coupled with subglacial water flow, is most likely the driving mechanism for the displacement of ARGG, as pure subglacial water flow is characterized by lower frequencies (3-7 Hz) (Nanni et al., 2020) and does not ultimately lead to surface displacement.

We have learned that this line of analysis could potentially contribute to an improvement of glacial sliding laws by considering relevant drivers for model parameterizations that are revealed by the feature importance.

5 Conclusions

A profound understanding and the formulation of sliding laws for glacier basal motion are still a major challenge for the scientific community and needed for hazard assessment and the generation of new prediction models. Especially for temperate glaciers in Alpine regions, sliding is difficult to monitor with conventional geophysical approaches. On-ice seismological records prove to be a very rich archive of glacial activity, but due to glacial noise from other cryoseismic sources, stick-slip events and tremors are often masked and remain unnoticed. New approaches are needed which involve on-ice seismological measurements densely sampled in space and time, as well as modern tools that efficiently analyze such large datasets and reveal previously hidden signals.

We applied a supervised ML approach gradient tree boosting to a seismic array data set acquired in course of the RESOLVE project on Glacier d'Argentière and showed its general suitability for the identification of seismic signatures of ice beds in the presence of melt-induced microseismic noise. The analysis is designed to verify if model estimates are driven by basal motion. Our results demonstrate that gradient tree boosting is a suitable tool to estimate ice surface displacement rates from seismic data collected at glaciers and that information about basal processes can be accessed from on-ice seismometers, analogous to frictional behavior of tectonic fault zones, at least at long period. We have learned that other than for quiet laboratory faults (Rouet-LeDuc, Hulbert, Bolton, et al., 2018) or reasonably long monitoring time series along tectonic faults (Rouet-LeDuc, Hulbert, & Johnson, 2018; Johnson & Johnson, 2021), using only statistical properties of continuous seismic records are not sufficient to describe glacial environments. We adapted the ML model by creating expressive beamforming features using array processing that meet the challenging, seismically "loud" environment. As revealed by the feature importance, the spatio-temporal compilation of seismic source locations provides the essential information for the model to relate estimates of surface velocities to in-depth activity.

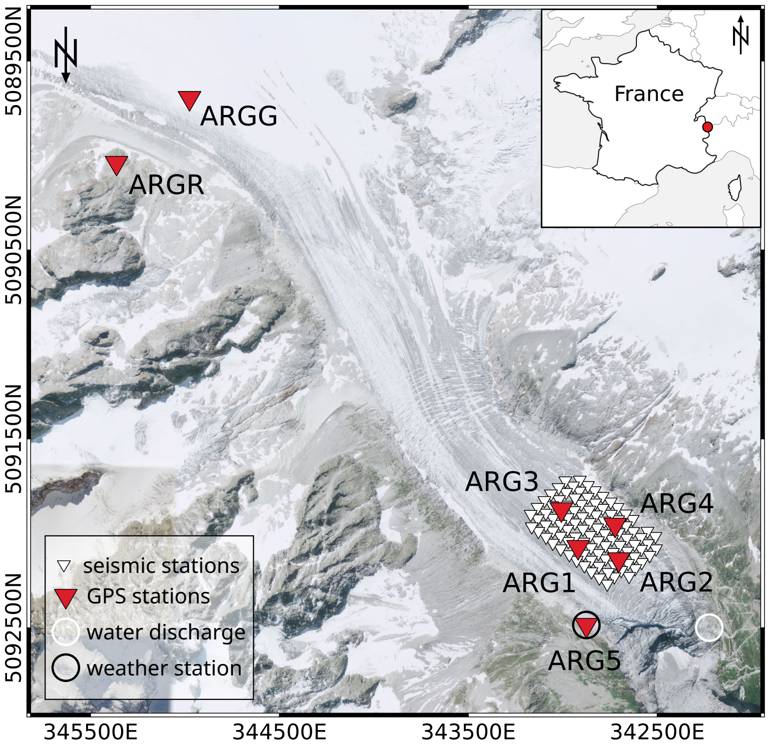

Figure 1. Overview map of Glacier d'Argentière together with the RESOLVE sensor infrastructure (Gimbert et al., 2021) including the locations of the seismic nodes (white triangles), the GPS stations (red triangles, ARGx), the weather station (black circle around ARG5) and the location of the borehole for measurements of water discharge (white circle). The GPS stations ARG1, ARG2, ARG3, ARG4 and ARGG were installed on the surface of the glacier (on-ice stations), GPS stations AGR5 and ARGR were installed on solid ground / bedrock (off-ice stations).

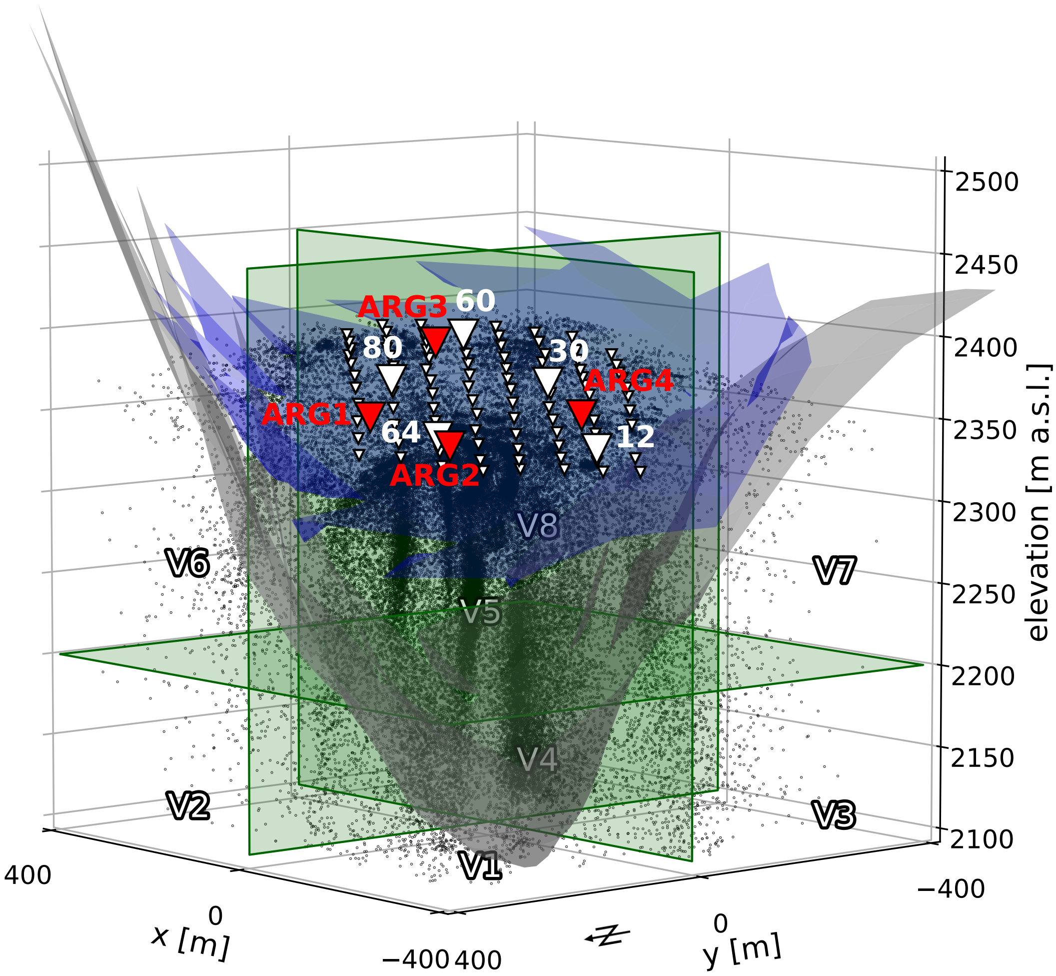

Figure 2. Snapshot of the thresholded beamforming catalogue together with the drone derived ice surface (shades of blue) and the bedrock topography measured by radio-echo sounding (shades of grey). Black dots represent seismic source locations during 1 hr (temporal resolution of 1 sec), for a center frequency of 10 Hz and beampower values between 0.2-1.0. The white triangles indicate the seismic array with the five heightened ones being the selected stations for the computation of the statistical features (12, 30, 60, 64, 80). The red triangles display GPS stations (ARG1-ARG4) situated within the seismic array. The green planes indicate the cut surfaces that divide the glacier into eight voxels (V1-V8) with V1-V4 capturing the lower part close to the glacier bed and V5-V8 encompassing portions of the ice surface.

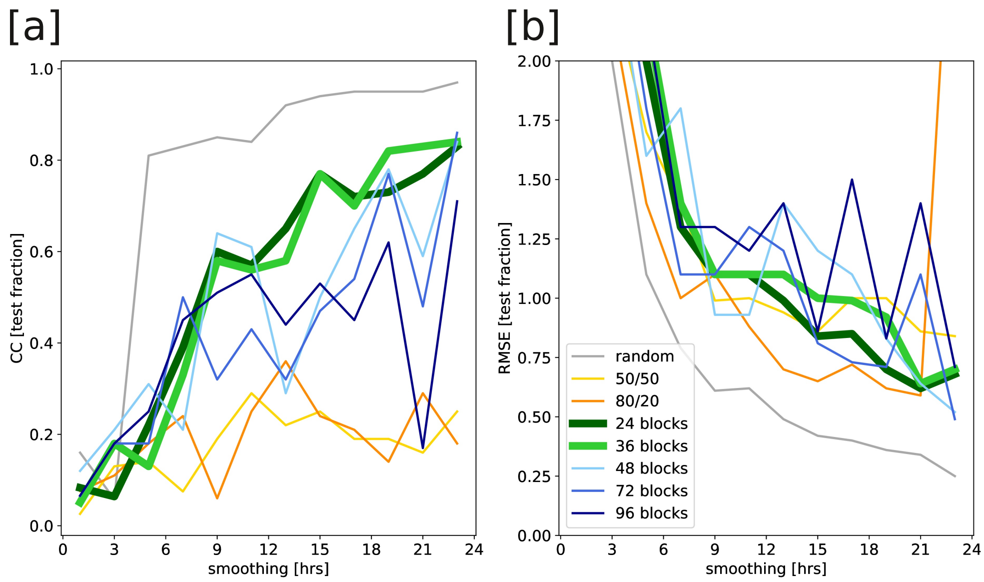

Figure 3. Model prediction scores ([a] CC and [b] $RMSE$) of the testing velocity time series of GPS station ARG3 in dependence on the degree of smoothing window duration applied to the features. Blocks refer to the lengths of the train/test intervals. No additional feature preprocessing was applied.

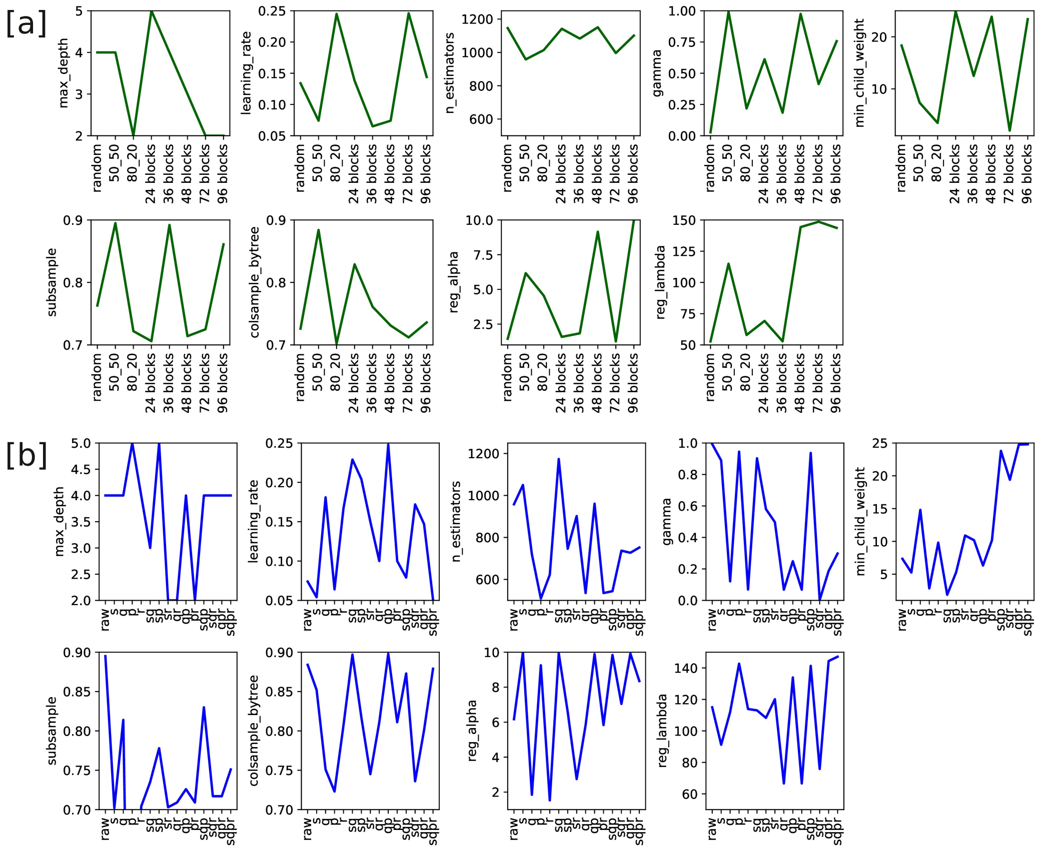

Figure 4. [a] Best-fit model hyperparameters optimized for different types of data split applied to the model of GPS station ARG3. The data was used in the original format with no additional preprocessing applied. [b] Best-fit model hyperparameters optimized for the raw data and all available combinations of preprocessing. Data were split 50%/50%.

Table 1. Overview of best-fit model hyperparameters, choices of preprocessing and low-pass filters applied to GPS stations ARG2, ARG3, ARGG using a 50%/50% split.

		GPS stations		
		ARG2	ARG3	ARGG
Hyperparameters	max_depth	5	4	3
	learning_rate	0.052	0.051	0.052
	n_estimators	514	752	527
	gamma	0.816	0.298	0.696
	min_child_weight	1.28	24.803	23.946
	subsample	0.708	0.751	0.738
	colsample	0.771	0.879	0.732
	reg_alpha	9.849	8.349	1.929
	reg_lambda	100.271	147.171	134.623
Preprocessing		P	S,Q,P,R	-
Low-pass filter [hrs]		2.5	16.5	1.39
Correlation coefficient		0.25	0.46	0.37

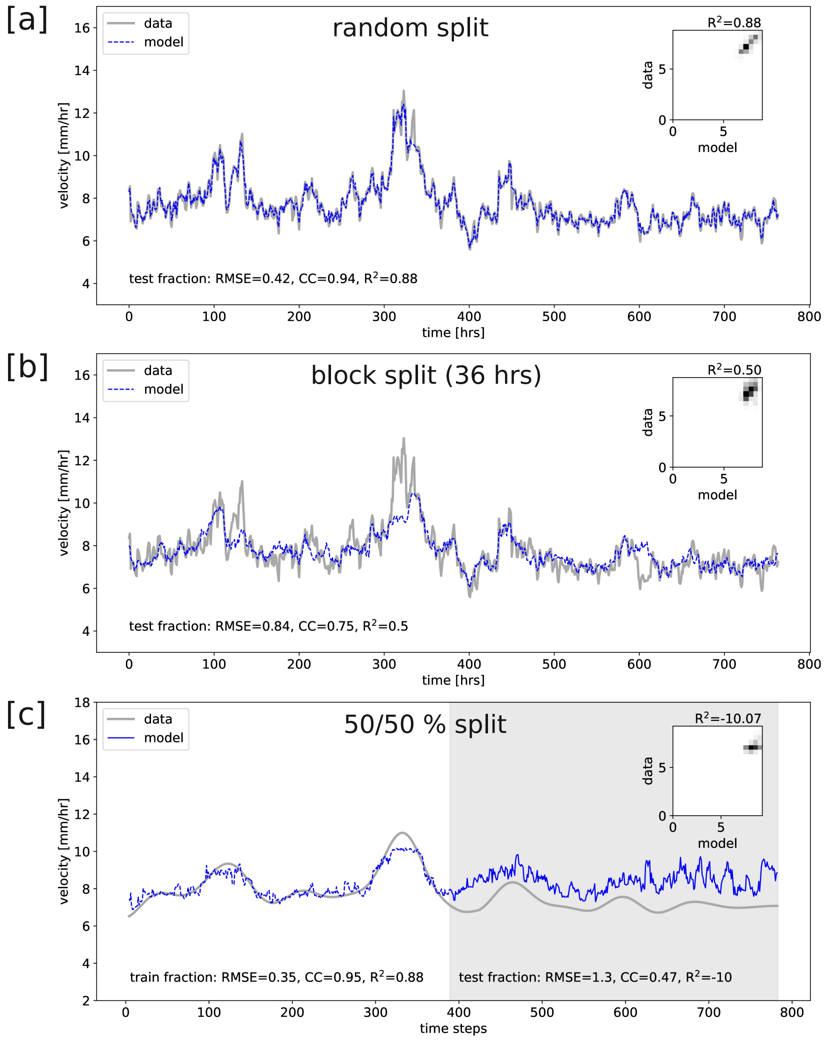

Figure 5. Performance of the XGB model to predict surface velocity [mm/hrs] trained on GPS station ARG3 (see Fig. 1 and Fig. 2), which was situated within the seismic array in the ablation zone of Glacier d'Argentière. The model performance is compared for different types of split applying the respective best-fit model hyperparameters. The data curve is displayed in grey and the model predictions in blue. [a] The model was trained and tested on random samples. No additional preprocessing was applied. [b] The model was trained and tested using blocks of 36 hrs. No additional preprocessing was applied. [c] The model was trained on 50 % of the velocity time series (white facecolor) and tested on the remaining 50 % (grey facecolor). Preprocessing involved S,Q,P,R and a low-pass filter with a cutoff frequency = 16.5 hrs was applied.

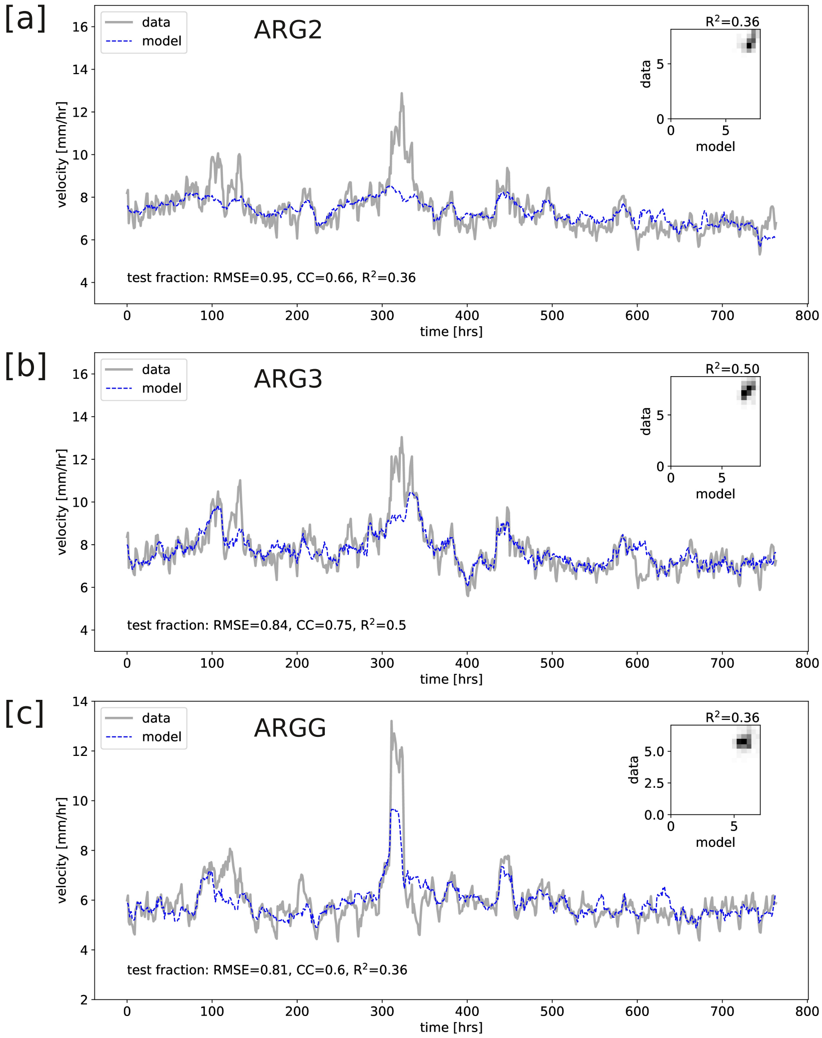

Figure 6. Performance of the XGB model to predict surface velocity [mm/hrs] using blocks of 36 hrs for training and subsequent testing. The model was trained and tested on GPS station ARG2 [a], ARG3 [c] and ARGG [e] (see Fig. 1 and Fig. 2). The feature importance is expressed through SHAP values to the right of the predictions respectively ([b], [d], [e]). The best-fit model hyperparameters were optimized for all three models and data were smoothed over 15 hrs. No additional preprocessing was applied.

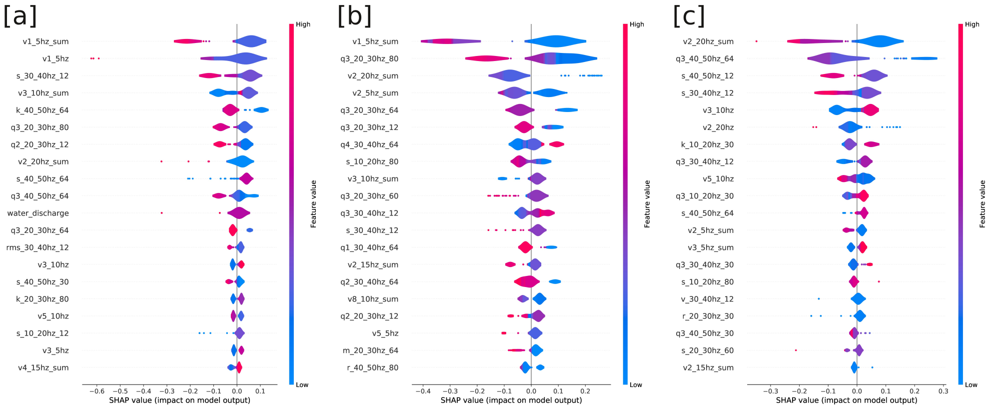

Figure 7. Feature importance (SHAP values) for model predictions using block sampling (block size = 36 hrs) shown in Fig. 6: [a] ARG2, [b] ARG3, [c] ARGG.

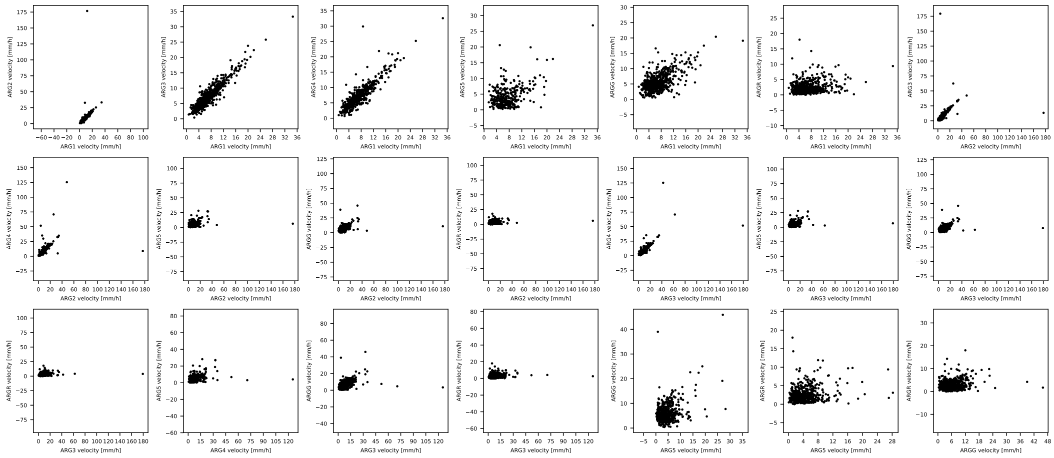

Figure A1. Station-wise correlation of geodetic observations.

Appendix A

The RESOLVE GPS (GNSS) analysis has been performed by a static, differential positioning using the GAMIT software (Herring et al., 2018) in a network combining the 5 RESOLVE GNSS stations (ARG1-4 on the glacier and ARG5 beside the glacier on the bedrock), plus the ISTerre long-term station ARGG on Glacier d'Argentière outside the RESOLVE network, with 14 permanent and stable RENAG (http://renag.resif.fr) stations in less than 180 km distance (including ARGR on bedrock close to Glacier d'Argentière at 3 km distance from the RESOLVE network). This set of stations has been analyzed in 6-hours-sessions (corresponding to 30-40 mm of displacement of stations on Glacier d'Argentière) shifted by 1 hour to obtain hourly positions for each of the stations. The formal uncertainties of each of the position estimates are 2-3 mm on the horizontal components. The positioning of the bedrock site ARG5, close to the glacier stations and therefore in a comparable environment, indicates a dispersion of 4-6 mm. This value is probably a realistic estimate of the hourly positioning precision of the glacier stations.

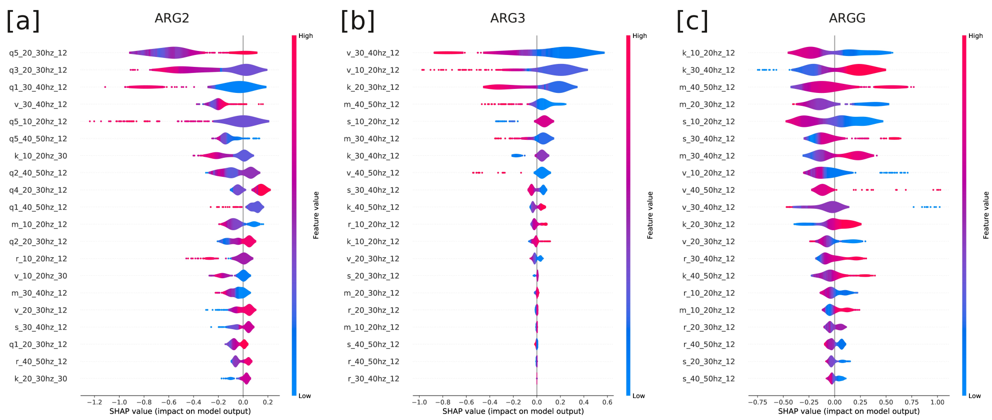

Figure A2. Feature importance (SHAP values) for model predictions using a 50%/50% split on the velocity time series of [a] ARG2, [b] ARG3, [c] ARGG.

Acknowledgments

The authors acknowledge the financial support by the Federal Ministry of Education and Research of Germany and by the Sächsische Staatsministerium für Wissenschaft Kultur und Tourismus in the program Center of Excellence for AI-research "Center for Scalable Data Analytics and Artificial Intelligence Dresden/Leipzig", project identification number: ScaDS.AI CWJ and PAJ acknowledge support by the U.S. Department of Energy, Office of Science, Office of Basic Energy Sciences, Chemical Sciences, Geosciences, and Biosciences Division under grant 89233218CNA000001. CWJ also acknowledges Institutional Support (Laboratory Directed Research and Development) at Los Alamos National Laboratory. This work has been conducted in the framework of the RESOLVE Project (https://resolve.osug.fr/; LabEx OSUG@2020, Investissement d'avenir – ANR10LABX56 and IDEX Université Grenoble Alpes). The seismic nodes and GPS stations were provided and operated by the French seismological and geodetic network Rèsif-Epos. The computations of the beamforming catalogue were performed using the GRICAD infrastructure (https://gricad.univ-gre-noble-alpes.fr), which is supported by Grenoble research communities, and with the CiGri tool (https://github.com/oar-team/cigri) that was developed by Gricad, Grid5000 (https://www.grid5000.fr) and LIG (https://www.liglab.fr/). The machine Learning model was developed using the resources of the Leipzig University Computing Centre.

Open Research Section

Data Availability

The MFP source codes are described and available via https://lecoinal.gricad-pages.univ-grenoble-alpes.fr/resolve/ (last access: 11/11/2021) under a creative commons attribution 4.0 inter- national license. The data derived from the MFP analysis (i.e., 29 sources localizations per second over 34 days and for 20 frequency bands) together with 1 day of raw seismic signal recorded over the 98 seismic stations are available via https://doi.org/10.5281/zenodo.5645545 under a creative commons attribution 4.0 international license (Nanni, Roux, et al., 2021). The complete set of raw seismic data can be found at https://doi. org/10.15778/resif.zo2018 under a creative commons attribution 4.0 international license. The GPS data are available on request through Andrea Walpersdorf (andrea.walpersdorf@univ-grenoble-alpes.fr).

Credit Author Statement

J.U. and C.W.J. formulated most of the manuscript, computed the data features and performed the machine learning analysis including hyperparameter optimization. All steps were supported by P.A.J. throughout the project. P.R. and A.L. performed MFP and compiled the beamforming catalogue. A.W. processed the GPS data. U.N. and F.G. supported the study with discussions on characteristics of Alpine glaciers. S.L and S.M. implemented data split techniques. Together with D.T., B.R.-L., C.H. and P.A. the first authors conceptualized the project and had fruitful discussions on the machine learning analysis.

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