**An Unsupervised Machine-Learning-Approach to Understanding Summer Seismicity at an Alpine Glacier**

*Theresa Sawia, Meredith Nettlesa, Ben Holtzmana, John Paisleyb, Fabian Walterc*

*aLamont Doherty Earth Observatory, Columbia University, bDepartment of Electrical Engineering, Columbia University, cETH Zürich Versuchsanstalt für Wasserbau, Hydrologie und Glaziologie*

**Key points:**

* We use unsupervised machine learning to cluster spectrograms of glacial icequakes and seismic “noise” based on their characteristic time-dependent spectral features.
* We introduce a novel method of physically interpreting the learned features, and reveal waveform and spectral properties that would be overlooked by simpler machine learning or seismic analysis techniques.
* Based on these findings, we suggest new timing constraints on the subglacial component of a glacial outburst flood, and identify other possible seismic signatures of variable subglacial hydrology.

**Abstract**

Continuous, long-term observations of glaciers and ice sheets are vital for understanding cryospheric dynamics, yet the sub- and englacial environments that control many aspects of ice behavior are inherently difficult to observe. Cryoseismology offers tools for monitoring interior, basal, and surface processes of glaciers and ice sheets, with seismic sources ranging from discrete “icequakes” to sustained, high-frequency seismic tremor. The varied, complex, and sometimes subtle nature of ice-derived seismic signals, however, can pose challenges for typical seismic analysis techniques. Here, we use an unsupervised feature extraction algorithm, now called “SpecUFEx” (Holtzman et al., 2018), on previously cataloged icequakes, as well as intermittently sampled, minute-long, “icequake-free” spectrograms of seismic noise from June-July 2007 at Gorner Glacier, Switzerland (Walter, 2009). We discover that groups spectrograms vary systematically in time corresponding with important hydrologic and dynamic events, including a glacial outburst flood and afternoon meltwater production. We recover a stationary approximation of the spectral features extracted during SpecUFEx using a novel method of “reverse engineering” the unsupervised output, aiding direct physical interpretation. By using SpecUFEx, we are able to provide new insight about the timing of the glacial outburst flood and detect other, more subtle seismic fluid signatures. This work utilizes a fully interpretable, unsupervised machine-learning approach for exploration of long-term continuous seismic data from a temperate glacier, with possible applications to other geologic settings of fluid-driven seismicity.

**Introduction**

Rapid changes in the cryosphere could have substantial implications for our climate and oceans, yet the sub- and englacial conditions that control ice dynamics are inherently difficult to observe. Cryoseismology offers tools for monitoring surface, basal, and interior processes of glaciers and ice sheets over long periods of times and vast spatial scales. Decades of research have revealed a diverse range of cryoseismic sources, largely impulsive “icequakes” caused by ice flow and deformation (see review by Podolsy and Walter, 2016) and more recently high-frequency (.5-20 Hz) tremor caused by turbulent water flow and bedload transport in sub- and englacial channels (e.g., Bartholomaus et al., 2015; Gimbert et al., 2016 Vore et al., 2019, Eibl et al.2020, Linder et al., 2020). These signals can be spotted visually in spectrograms (e.g., Röösli et al., 2014), but visual inspection is an infeasible method when scaling to accommodate larger datasets.

Gaining insight from the tremendous volume and variety of cryoseismic data poses a challenge for typical seismic analysis techniques, leading to growing interest in the use of machine learning methods. Supervised machine learning algorithms — those trained on up to millions of example data points — have shown remarkable success at detecting and classifying tectonic earthquakes when large, labeled datasets are available (e.g., Ross et al 2018 and 2019; Zhu and Beroza, 2018; Mousavi et al., 2020; Park et al., 2020), including at fluid-rich volcanic or geothermal settings (Ren et al., 2020, and reviews by Malfante et al., 2018; Carniel and Guzman, 2020), whose fluid-mediated seismic behavior could be considered analogous to temperate glacial settings.

Labeled datasets, however, do not exist for most geophysical studies, highlighting the need for unsupervised machine learning (UML) methods. UML models infer patterns in data without being trained on labeled data, and are typically used to discover groups of similar data (i.e., clustering, e.g., Trugman and Shearer, 2017; Chamarczuk et al., 2019; Lamb et al., 2020; Seydoux et al., 2020; Steinmann et al., 2021) or to characterize the data using lower-dimension, statistically derived “features” (e.g., Yoon et al., 2015, Lindenbaum et al., 2018) or both (e.g., Sick et al., 2015; Holtzman et al., 2018; Ren et al., 2020; Jenkins et al., 2021). Unlike supervised machine learning, the output from UML can be abstract, difficult to interpret physically because no labels are predicted and the features or clusters being identified may not be of scientific interest.

One unsupervised spectral feature extraction algorithm (now called “SpecUFEx,” Holtzman et al., 2018) has proven especially well-suited for characterizing subtle, fluid- and thermal-driven effects in seismic data. SpecUFEx revealed time-varying spectral features of injection-induced earthquakes at a geothermal energy field that corresponded with nearby fluid-injection levels (Holtzman et al., 2018). Here, we show the advantages and limitations of using an unsupervised machine-learning approach to understanding seismicity at a temperate glacier where dynamic, fluid-driven processes are continuously taking place.

**Background**

Gorner Glacier is the second largest glacier in the Swiss Alps, spanning approximately 57 square kilometers at an average elevation of 2500m. Gorner Glacier converges with another glacier, Grenzgletcher, as they flow westward at a speed on the order of centimeters per day (Table 1, and Garcia et al., 2019). An ice-marginal lake, Gorner See, forms every spring at the confluence of the two glaciers and by midsummer drains catastrophically in a “jökuhlaup”; a glacial outburst flood, releasing up to 60 million cubic meters/s of water in some combination of sub-, en-, and supraglacial flow (Huss et al., 2007, Werder et al., 2009a, 2010). Proglacial discharge has been measured continuously for over 50 years by a hydro-electric company about 4.5 km away from Gornersee (e.g., Huss et al., 2007).

A timeline of reported events for the 2007 Gorner See glacial outburst flood is given in Table 1. Lake drainage began on July 4th, as Gorner See breached its shore and flowed over the surface of the glacier to a lake-proximal moulin. From July 7-15, the majority of the lake drained through an en- and subglacial conduits, ending when the lake was mostly empty and the lake level meter subaerially exposed (Werder et al., 2009a - *but I need to ask Fabian/Jonny/Meredith about the hydrological timeline in this study, because I don’t understand some parts of it|||*). Although sediment transport data were not collected during the 2007 study period, historical (1973-1990) and more recent (2016, 2017) observations show high sediment concentration in proglacial runoff (~1kg/m^3), with peak sediment transport during lake drainages (e.g., Collins, 1989; Delaney et al., 2018). The annual outburst floods typically accelerate the flow and surface deformation of Gorner glacier (Sugiyama et al., 2007, 2008 & 2010), which can increase icequake activity (Riesen, 2007; Roux et al., 2010; Garcia et al., 2019). A burst of surficial icequakes marked the onset of the 2007 lake drainage, but no such increase in activity in basal seismicity was observed (Walter et al., 2009).

Meltwater runoff is another hydrologic driver of seismicity at Gorner Glacier. Surface seismicity rates peak in the afternoon as melt water flow at the ice/bed interface raises the glacier to near-flotation levels, allowing for uninhibited basal sliding and increased ice deformation (Walter 2008 and 2009; Roux et al., 2010). Walter et al., (2009) detected 100s to 1000s of icequakes daily in June-July 2007, with the vast majority (>99%) caused by tensile openings of crevasses in the top twenty meters of the ice. A few tens of basal icequakes – driven by subglacial waterflow– were also detected daily, typically in the early morning hours when subglacial water pressure is at its lowest.

**Data**

Our seismic data come from an 8-instrument array of three-component Geospace GS-11D geophones deployed on-ice at Gorner Glacier in shallow boreholes between June-July, 2007. The instruments have an aperture of about 200 m, and are no farther than about 200 m from the shore of Gorner See at its maximum height prior to drainage. The seismometers sampled continuously at 1000 sps, and were leveled daily to account for melting of the ice. Only the vertical seismic velocity components are used in this study.

Our first experiment is concerned with surficial icequakes. Walter (2009) reports over 100,000 surficial icequakes in June-July 2007, detected using a modified STA/LTA trigger algorithm. A subset (N= ~24,000) of those detected events were located with a grid-search inversion algorithm (Lee and Steward, 1981). Errors in location range from ~1 m within the array footprint, to over 200 m (with a mean error of 70m). The icequakes are high frequency (~50 Hz), low magnitude (M<1), short-duration (~1s), and can be easily distinguished from basal events and background noise by their prominent Raleigh wave arrival. Complete details about the icequake catalog can be found Walter (2009).

Eight seismic stations operated throughout the entire experiment (numbered J1-8) data from stations J3, J6 and J7 are discarded because of persistent instrument malfunction that interfered with the sensitive nature of this method. Data are analyzed exhaustively for stations J4, J5 (*|||This was true 2 months ago, but I have not made the most recent batch of figures on stations J4 and J5|||)* and J8, but without loss of generalization, only results from station J8 are shown. We limit our study to icequakes located within the array footprint where locations are most accurate, and focus on icequakes in the top 50 meters of ice. We use a STA/LTA filter to confirm that the icequake records have exactly one event in the window, and are left with a catalog of 1411, two-second long icequake records (**Figure 1a**). The icequakes’ timing is shown in **Figure 2b**, along with the auxiliary geophysical data from Garcia et al. (2019; Figure 2a).

A parallel experiment is performed on 1521, minute-long records of seismic “noise” that is free of icequakes, sampled every ten minutes during the same two-month time period as the icequakes (**Figure 2c**). We use a STA/LTA filter to identify and discard records with prominent icequakes in them. We also discard records if they have detectable icequakes in the five-seconds preceding, or the two-seconds following the record of noise, to account for sustained icequake codas and possible precursory signals, respectively. The pervasiveness of icequakes (at times >5 icequakes per minute) prevents a uniform temporal distribution of noise records that would expected from consistent ten-minute sampling, which is especially clear in the hourly distributions of the data (**Figure 2d,e**). The high rates of icequakes in the afternoon hours mean that there is systematic under-sampling of noise in that time period.

To understand how environmental factors are interacting with seismicity, we utilize local GPS, lake level, temperature and precipitation measurements collected simultaneously with the seismic data (**Figure 2a**; Sugiyama et al., 2007; Garcia et al., 2019). The four GPS stations are located between 100 m and 3 km down-glacier from Gorner See, sampling continuously every 2 minutes with a horizontal and vertical accuracy of +/-1.4 mm and +/-3 mm, respectively. We use the GPS displacement measurements from Garcia et al. (2019) relative to their location at the beginning of our study, subtract the pre-drainage GPS velocity reported for each station in (Table 1), then take an hourly rolling average. This allows us to see diurnal periodicity as well as the larger surges caused by the outburst flood, temperature, and rainfall.

Lake levels were measured by a pressure transducer sampling continuously every minute. Temperature and precipitation data come from an automated weather station located on the northern margin of Gorner Glacier, 2.5 km from the seismic array and 600 m in elevation above it (Garcia et al., 2019).

**Methods**

**Spectrogram generation:**

We calculate spectrograms of the ground velocity data using a short-time Fourier transform (STFT). Table 2 lists the parameters used to generate the spectrograms, including STFT window length, overlap, and number of windows for the icequake or noise observations. The spectrograms are then filtered according to the values in Table 2. The upper frequency constraint is chosen to avoid the sharp spectral peaks in the noise data at around 90 Hz (see **Figure 3b,** top panel) and the prominent lobes in icequake data around 160 Hz (**Figure 3a**, top panel). Our experiments show that these features are instrument artifacts which can strongly impact results. The lower frequency bound is chosen to be near the theoretical limit allowed by the STFT window length, keeping in mind that there must be numerous enough STFT windows for robust analysis by the hidden Markov Model (which learns on reoccuring time-varying patterns). Our experiments show that using at least 30 STFT windows are recommended. Following the original study on SpecUFEx (Holtzman et al., 2018), we then normalize each spectrogram by its mean, convert it to decibels, and force negative values, if they occur, to zero.

**SpecUFEx**:

SpecUFEx applies two layers of unsupervised feature extraction to the spectrograms, beginning with nonnegative matrix factorization (NMF; **Figure 4a**). NMF reduces spectrograms into a basis “dictionary” of sparse and meaningful spectral patterns, and an activation coefficient matrix (ACM) that shows how those patterns vary over time (Lee and Seung, 1999). The NMF dictionary is shared for all spectrograms, but the ACMs are generated uniquely for each spectrogram. Unlike other unsupervised dimensionality reduction techniques (e.g., principal or independent component analysis, vector quantization) the linear, additive nature of NMF allows for highly interpretable output, evident by comparing the spectrogram and ACM in **Figure 4a and b**.

The ACMs are then used as input for a hidden Markov model (HMM, Figure 4b). The HMM assumes that the temporal evolution of the ACM’s spectral patterns depends on unobservable “hidden states,” where each hidden state is a combination of spectral patterns from the NMF dictionary that tend to cooccur in time. Those states are given in the “emissions matrix” (EB), which, like the NMF Dictionary, is shared for all events. The state transition matrices (STM, **Figure 4C**) show how those states vary in time, and are generated uniquely for each ACM. The final product, the fingerprints (**Figure 4D**), show the probability of each state transitioning to another (or itself) from one time step to the next. For further details of the SpecUFEx algorithm, see the appendix of Holtzman et al. (2018).

**PCA dimensionality reduction**

The fingerprints are sparse, 255-dimensional representations of spectrograms, so to improve statistical representation we further reduce their dimensionality prior to clustering using principal component analysis (PCA, i.e., Pearson, 1901; Lever et al., 2017). We choose the number of principal components to cluster on so that at least 86% of the variance (about two standard deviations above the mean) in the original fingerprints is preserved. This results in a 67-dimensional dataset for the icequake fingerprints, and a 3-dimensional dataset for the noise fingerprints. All said, reducing the fingerprints at this step does not drastically change clustering results for this particular dataset, but regardless, it should be standard practice. (see, “The curse of dimensionality,” e.g., Bellman 1966).

**Clustering**

We evaluate how well-clustered each datapoint is using silhouette scores (Rousseeuw, 1987). Silhouette scores range from -1 to 1 with high scores indicating well-clustered data. The silhouette score, **S(i)**, of a datapoint (**i**)is

,

where **a** is the mean Euclidean distance of point **i** to every other point in its cluster, and **b** is the mean distance of point **i** to every point in the closest neighboring cluster. Negative silhouette scores imply an incorrectly clustered datapoint, but only 84 of 1411 icequake fingerprints (< 6%) and 17 of the 1521 noise fingerprints (< 2%) have negative silhouette scores; too few to impact the overall clustering trends in this study. By maximizing the mean silhouette score (MSS) of a dataset, we can qualitatively evaluate how well-clustered the dataset is for a given number of clusters.

**Results**:

Clustering analysis results in 3 clusters for the icequake data (maximum MSS=.11, **Figure 5c**) and 4 clusters for the noise data (maximum MSS=.63, **Figure 5d**). **Figure 5a** shows the fingerprints colored by their cluster assignment, projected onto their first three principal subspaces (for icequakes, ~28% of the original fingerprint variance is preserved in this image). The clusters are organized for clarity by randomly assigned colors, and we note that no similarities between the icequake and noise experiments are suggested based on shared colors. To characterize the observations within each cluster, it is useful to work with a select subset: the top 20 events in each cluster with the highest silhouette scores. These are the “representative events” from each cluster, marked with black x’s in **Figure 5a and b** (60 events total for the icequakes, 80 total for noise). Some of the fingerprints (and therefore their PCA reductions) are identical, resulting in overlapping x’s.

**Figure 6** shows the waveforms of the representative icequakes (left column) and spectra for the representative noise (right column). For visualization of the icequakes, we normalize the waveforms by their maximum amplitude, time-lag them to maximize their correlation with each other, stack them, and then visualize a .8 second window containing the majority of the waveform energy. This process brings out subtle features that characterize the clusters. For example, the S-phase of each event takes on a distinct shape for each cluster (thick black arrows, **Figure 6**). Additionally, the first icequake cluster (blue) has a visibly lower signal-to-noise ratio than the other two clusters due to a constant background noise around 30-70 Hz (seen in representative spectrograms; not shown). The blue and orange cluster both have remarkably coherent reverberations in their codas (thin black arrows, **Figure 6**).

We calculate the spectra by summing the noise spectrograms’ frequency amplitudes through time (right column, **Figure 6**). Although there are many ways of calculating the amplitude spectra of a waveform, we choose this one because it is the most similar to the spectrograms that were the input data for SpecUFEx. For example, the spectra reflect the median-normalization that was applied to the spectrograms during preprocessing. We stack the spectra and notice distinguishing peaks between clusters (black arrows), as well as some differences in median-normalized amplitude and overall shape. The second (red) cluster retains energy in the higher frequencies compared to the other three clusters, resulting in a distinctly flatter spectra. We attempted to align the noise waveforms as we did with the icequakes, but found that results were indistinguishable from the same method applied to random time series.

The highly similar waveforms for the second (red) and third (orange) clusters suggest a similar source and path, yet analysis of the icequakes’ locations shows that is not always the case. **Figure 7** shows the icequakes’ locations in map view colored by cluster. The dots with black outlines are the 20 most representative events in each cluster. The representative red dots appear largely concentrated on lake-marginal clusters, whereas the blue and orange are more dispersed. There are linear features in the ice (the formation of crevasses) that are primarily orange or red, but not blue.

**Figure 8 (a, b)** describes the station-event distances for the 20 representative events in each cluster using “box-and-whisker plots”. The boxes enclose the 25th-75th percentiles of the distance measure, with a line indicating the 50th percentile (median). The whiskers extend to 1.5 times the interquartile range (the range between the 25th and 50th percentiles), and individual points beyond the whiskers are considered outliers. Depths between all icequake clusters are very similar, although the epicentral distance of icequakes in the red cluster are on average greater than icequakes in the other clusters (consistent with the red icequakes’ spatial clustering on lake-marginal crevasses). **Figure 8** **(c-f)** shows box-plots of all of the waveforms and spectrograms within each cluster for icequakes (left column) and noise (right column). **Figure 8c,e** (“log10(RSAM)”) is based on the “real-time amplitude measurement” of the waveform,

,

where ***x(t)*** is the band-passed waveform (ground velocity) signal. RSAM measures the overall energy of the waveform, and is frequently used in volcano-seismology as an indicator of volcanic activity (Endo & Murray, 1991). **Figure 8d,f** shows the top 20 representative waveforms’ mean spectral centroids (SC); the spectral center of mass of a waveform (Klapuri & Davy, 2007). To calculate the spectral centroid, each time frame of the spectrogram (i.e., a spectra) is treated as a distribution over frequency bins from which a centroid can be found. SC(t) is calculated as:

,

where **s** is the magnitude spectrum, and **f** is the array of frequencies for a given time frame of the spectrogram.

To understand the clusters’ connection to glacial behavior, we compare the timing of the observations in each cluster to auxiliary geophysical data, including ambient temperature, on-ice GPS displacement, precipitation measurements and lake-level data. **Figure 9** shows the clusters binned by hour of the day (UTC) for the entire study period, along with the mean temperature difference from daily mean (dark red dashed line). There is little diurnal variation between icequake clusters, but the noise data appears to separate strongly related to time of day. The first (blue) and fourth (purple) clusters peak in the evening (04-22 UTC), with the purple peak preceding the blue by 2-4 hours. The second (red) cluster strongly resembles the timing distribution of the original dataset (top bar plot, in black). The third (orange) cluster has most of its noise events in the morning hours (00-12 UTC).

**Figure 10** shows the timing of clusters alongside the auxiliary data shown in **Figure 2.** The GPS surge and the reported onset of the outburst flood both coincide roughly with the timing of the blue icequake cluster and the red noise cluster, although both of these clusters continue after the GPS surge has passed. Beyond this, there is no strong seasonal trend in the clustering of icequake clusters. For the noise data, however, all clusters seem to respond to the flood, summarized in Table 1. The blue, orange and purple clusters are all active in the pre-drainage season, but within hours of supraglacial lake drainage (July 4th), the purple noise cluster pauses. About a day later (late on July 5th, or early July 6th), the blue and orange clusters cease as well. About 99% (594/601) of the noise events in the red cluster begin on or after July 5th; two days prior to the reported sub- and englacial components of the flood. The purple and orange cluster resume on July 15th and 17th (respectively), but the blue cluster never reappears.

**Reconstructing spectral features**

We introduce a novel method for recovering the spectral features that were most important for the clustering assignments, allowing for direct physical interpretation of the unsupervised output. We first choose a “key state” for each cluster based on which element in the fingerprint matrix has the highest value, then map that state back into the frequency domain. **Figure 11** shows the fingerprint with the highest silhouette score from each cluster with the key state circled and numbered in green. Qualitatively, we see that the fingerprints are more sparse for the noise experiment (right column) than the icequakes (left column). The noise fingerprints are composed primarily of one or two states on the main diagonal, suggesting that the entire spectrogram can be represented by one or two states occurring repeatedly through time. The icequake fingerprints are more complicated, with many off-diagonal elements in addition to “key states” on the diagonals.

**Figure 12** shows the “reconstructed spectra” (dashed lines) from key states chosen from the fingerprints in Figure 11, along with “median spectra” (solid lines) from each cluster, calculated by taking the median value at each frequency bin for all spectra in a cluster. The reconstructed spectra are generated and visualized as such:

1) We choose a key state for each cluster based on which element in the fingerprint has the highest value.

2) We then multiply the HMM emissions matrix (“EB,” **Figure 4**) with the transpose of the NMF dictionary (“Dict,” **Figure 4)**, and use it to map the key states to a frequency vector (the “reconstructed spectra”).

3) To allow for clear comparison between the shapes of the reconstructed and median spectra, we scale them by their maximum value, that is, we divide all of the spectra by the maximum value among all spectra, and likewise divide all of the reconstructed spectra by the maximum value among all reconstructed spectra (*not* by cluster). We display the results in logarithmic scale so the lower-amplitude details at the uppermost frequencies are not lost in visualization.

It is important to remember that since the spectrograms were median-normalized prior to SpecUFEx, the reconstructed spectrograms reflect that normalization. One outcome of this is that the median spectra for the red cluster is in reality is the highest amplitude signal across all frequencies. At times, the reconstructed spectra recover incredibly minute details found in the natural spectra, such as a small local peaks around 25 Hz for the orange, blue and purple clusters. The reconstructed spectra also capture some general trends of the actual spectra, including the broadband, relatively low (median-normalized)-amplitude, flat-frequency characteristic of the red cluster. At higher frequencies, however, the reconstructed noise spectra diverge significantly from the actual noise spectra, where the low-amplitude dips in the reconstructed spectra due to sparse NMF spectral patterns are highlighted with the logarithmic scaling.

**Discussion**

SpecUFEx is demonstrated as an efficient and effective way to extract characteristic time-varying spectral features from large seismic datasets in an unsupervised matter, and, when combined with further dimensionality reduction, unsupervised clustering, and ground-truth measurements, can help reveal seismic trends at dynamic, fluid-driven systems. Some of the clusters characterized using SpecUFEx could have been found using simpler methods. The noise cluster associated with the onset of lake drainage (red cluster), for example, could have been identified by using k-means directly on the spectra, or on the features depicted in **Figure 8 c-d.** The other noise clusters, however, are less distinct in their differences. Performing K-means on the noise spectra, for example, does not produce the orange and purple clusters. Additionally, since the phases aren’t aligned between records in time, performing k-means directly on the waveforms or spectrograms would fail to produce these results as well. Therefore, SpecUFEx is advantageous in blindly discriminating subtle spectral features of seismic data that elude simpler detection techniques.

The PCA projections and silhouette scores of the k-means-clustered fingerprints help decipher the SpecUFEx’s unsupervised output. The PCA projections show that the datasets form continuous branches connected to one center mass, and that, for the noise especially, these branches seem to relate to changing hydrologic conditions at the glacier. We interpret the continuous nature of the branches as reflective of possible subglacial parameters, which are themselves distributed over continuous values (e.g., conduit geometry, hydraulic pressure, bedload properties, turbulence). The silhouette scores help us quantify our clustering choices, and also lets us isolate characteristic end-members of the different branches. Although other unsupervised clustering techniques can be used (e.g., hierarchical clustering), our analysis reveals incredibly coherent detail between representative cluster members in these data, while allowing for enough members for robust statistical analyses — both important criteria for unraveling the physical sources of the signals.

The majority of the spectral energy in all of the noise clusters occur in the 5-40 Hz band; a signal which could be explained by subglacial turbulent water flow and saltation from sediment transport. The reported timing of the subglacial drainage (Werder et al., 2009a) was chosen based on the peak lake level before drainage, shown by the second dotted black line in **Figures 2, 10.** It is almost certain that subglacial drainage initiated prior to that, however, given that continuous meltwater input to the lake would delay the visible drop in lake level by minutes to hours. This leads us to conclude that the timing of the red noise cluster (July 5th or 6th) is a better indicator of subglacial drainage than surface lake level observations.

Characteristics of the purple and orange clusters are especially intriguing, given that their diurnal trends are markedly different from the noise dataset as a whole (see **Figure 9**). The purple cluster peaks 2 to 4 hours after the hottest time of day; a lag time that could be determined by the storage capacity/residence time [I’m blanking on the better term for this] of the glacier. The peak in the orange cluster precedes the hottest time of day by about 6 hours. The orange and purple clusters are interrupted during the lake drainage, but afterwards return with an even more prominent diurnal trend. One possibility for the clusters’ timing is that they contain the seismic signatures of two separate, stable modes of subglacial meltwater runoff (purple, high runoff; orange, low runoff), which are interrupted by the catastrophic flooding period. Subglacial conduit networks that were deformed or destroyed during the flood could reform, eventually exhibiting the same stable modes of subglacial meltwater and leading to a return of the purple and orange clusters.

There are alternative hypotheses for the sources of the spectral features that we see in the noise clusters. The second (red) cluster, for example, coincides with the surge in GPS displacement, and so could be a signal related to sliding or grinding at the ice/bed interface, or from minute fractures in the ice or firn caused by increased ice flow and deformation. Although we cannot rule this out, the fact that the noise cluster trends continue long past the end of the GPS surge suggests that this noise is hydrologically-sourced.

One of the novel aspects of this study is the reconstruction of the unsupervised output back into the frequency domain, allowing for direct physical interpretation of results. For the noise cluster, the reconstructed spectra in **Figure 12** very closely resemble the shapes of the actual spectra in the 5-40 Hz range. This demonstrates how a single state in a fingerprint can represent highly resolved spectral details of the data, but only for stationary time series such as sustained tremor. The noise waveforms do not correlate in time, and so would be impossible to identify using cross-correlation.

For the icequakes, the reconstructed spectra in **Figure 12** fail to emulate the actual spectra, but can still be instructive for deciphering why the icequakes are clustered as they are. For example, the first (blue) icequake cluster in **Figure 6** has a sustained background noise throughout the record. That noise is likely represented by state 12 in the icequake fingerprints, which has a broad peak in amplitude from 30-50 Hz. A signal in this frequency range could be caused by turbulent water flow and sediment saltation in subglacial conduits; a hypothesis that is supported by the timing of the blue icequake cluster with respect to lake drainage.

The remarkable, fine-scale coherence between waveforms in **Figure 6** demonstrates how SpecUFEx could be a useful tool for identifying repeating earthquakes. Rather than auto-correlating a dataset or manually choosing templates for cross correlation (which can be time-consuming, computer-intensive, or both), SpecUFEx can identify groups of highly similar waveforms in a semi-automated, unsupervised fashion. Additionally, cross-correlation coefficients can be impacted by factors such as azimuth and epicentral distance (Gao et al., 2021), but SpecUFEx appears insensitive to these changes. Future studies will be undertaken to understand what physical aspects of the source and/or path are causing the subtle differences between waveforms and spectra in **Figure 6,** especially the features indicated with the black arrows.

**Conclusion:**

We use an unsupervised features extraction algorithm, SpecUFEx, and k-means clustering to characterize two months of glacial seismic data based on characteristic time-varying spectral features in spectrograms. To help decipher results, we use PCA, silhouette scores, auxiliary geophysical data collected during the study period, and a newly introduced method for “reverse engineering” the output of SpecUFEx back into the frequency domain. We analyze both previously cataloged icequakes and intermittently sampled icequake-free noise, and discover discriminating characteristics between clusters in both datasets that are at times incredibly subtle and would elude more simple machine learning or seismic analysis techniques. Based on this analysis, we present updated constraints on the timing of the subglacial component of the glacial outburst flood, and identify other possible seismic signatures of subglacial conduit reorganization. This work demonstrates the value of unsupervised feature extraction as a seismic monitoring and discovery tool, especially in systems where complex fluid-driven processes occur.

Works cited

1. Bartholomaus, T. C., Amundson, J. M., Walter, J. I., O’Neel, S., West, M. E., & Larsen, C. F. (2015). Subglacial discharge at tidewater glaciers revealed by seismic tremor. Geophysical Research Letters, 42(15), 6391–6398. https://doi.org/10.1002/2015GL064590
2. Bellman R. Dynamic programming. Science. 1966 Jul 1;153(3731):34-7. doi: 10.1126/science.153.3731.34. PMID: 17730601.
3. Bergen, K. J., Johnson, P. A., De Hoop, M. V., & Beroza, G. C. (2019, March 22). Machine learning for data-driven discovery in solid Earth geoscience. Science, Vol. 363. <https://doi.org/10.1126/science.aau0323>
4. Carniel, R., & Guzmán, S. R. (1989). Machine Learning in Volcanology: A Review. Volcanoes - Updates in Volcanology [Working Title] Dr. Karoly Nemeth, 32(tourism), 137–144.
5. Chamarczuk, M., Nishitsuji, Y., Malinowski, M., & Draganov, D. (2019). Unsupervised learning used in automatic detection and classification of ambient-noise recordings from a large-n array. Seismological Research Letters, 91(1), 370–389. <https://doi.org/10.1785/0220190063>
6. Collins, D. N. (1989). Seasonal development of subglacial drainage and suspended sediment delivery to melt waters beneath an alpine glacier. Annals of Glaciology, 13(May), 45–50. <https://doi.org/10.1017/s026030550000762x>
7. Delaney, I., Bauder, A., Werder, M. A., & Farinotti, D. (2018). Regional and Annual Variability in Subglacial Sediment Transport by Water for Two Glaciers in the Swiss Alps. Frontiers in Earth Science, 0, 175. <https://doi.org/10.3389/FEART.2018.00175>
8. Eibl, E. P. S., Bean, C. J., Einarsson, B., Pàlsson, F., & Vogfjörd, K. S. (2020). Seismic ground vibrations give advanced early-warning of subglacial floods. Nature Communications, 11(1). https://doi.org/10.1038/s41467-020-15744-5
9. Gao, D., Kao, H., & Wang, B. (2021). Misconception of Waveform Similarity in the Identification of Repeating Earthquakes. Geophysical Research Letters, 48(13). <https://doi.org/10.1029/2021GL092815>
10. Garcia, L., Luttrell, K., Kilb, D., & Walter, F. (2019). Joint geodetic and seismic analysis of surface crevassing near a seasonal glacier-dammed lake at Gornergletscher, Switzerland. Annals of Glaciology, 60(79), 1–13. <https://doi.org/10.1017/aog.2018.32>
11. Gimbert, F., Tsai, V. C., Amundson, J. M., Bartholomaus, T. C., & Walter, J. I. (2016). Subseasonal changes observed in subglacial channel pressure, size, and sediment transport. Geophysical Research Letters, 43(8), 3786–3794. https://doi.org/10.1002/2016GL068337
12. Huss, M., Bauder, A., Werder, M., Funk, M., & Hock, R. (2009). Glacier-dammed lake outburst events of Gornersee, Switzerland. Mitteilungen Der Versuchsanstalt Fur Wasserbau, Hydrologie Und Glaziologie an Der Eidgenossischen Technischen Hochschule Zurich, 213, 65–84.
13. Holtzman, B. K., Paté, A., Paisley, J., Waldhauser, F., & Repetto, D. (2018). Machine learning reveals cyclic changes in seismic source spectra in Geysers geothermal field. Science Advances, 4(5), eaao2929. <https://doi.org/10.1126/sciadv.aao2929>
14. Jenkins II, W. F., Gerstoft, P., Bianco, M. J., & Peter, D. (2021). Unsupervised Deep Clustering of Seismic Data : Monitoring the Ross Ice Shelf , Antarctica. ESSOAr Preprint Archive, 1–40. https://doi.org/10.1002/ESSOAR.10505894.1
15. Klapuri, A., & Davy, M. (Eds.). (2007). Signal processing methods for music transcription, chapter 5. Springer Science & Business Media.
16. Karl  Pearson  F.R.S. . (1901). LIII. On lines and planes of closest fit to systems of points in space. The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, 2(11), 559–572. <https://doi.org/10.1080/14786440109462720>
17. Kong, Q., Trugman, D. T., Ross, Z. E., Bianco, M. J., Meade, B. J., & Gerstoft, P. (2019). Machine learning in seismology: Turning data into insights. Seismological Research Letters, 90(1), 3–14. <https://doi.org/10.1785/0220180259>
18. Lamb, O., Lees, J., Marin, L. F., Lazo, J., Rivera, A., Shore, M., & Lee, S. (2020). Investigating potential icequakes at Llaima volcano, Chile. Volcanica, 3(1), 29–42. <https://doi.org/10.30909/vol.03.01.2942>
19. Lever, J., Krzywinski, M., & Altman, N. (2017). Points of Significance: Principal component analysis. In Nature Methods (Vol. 14, Issue 7, pp. 641–642). Nature Publishing Group. <https://doi.org/10.1038/nmeth.4346>
20. Lindner, F., Walter, F., Laske, G., & Gimbert, F. Glaciohydraulic seismic tremors on an Alpine glacier. 14(1). <https://doi.org/10.5194/tc-2019-155>
21. Malfante, M., Dalla Mura, M., Metaxian, J. P., Mars, J. I., Macedo, O., & Inza, A. (2018). Machine Learning for Volcano-Seismic Signals: Challenges and Perspectives. IEEE Signal Processing Magazine, 35(2), 20–30. <https://doi.org/10.1109/MSP.2017.2779166>
22. Mousavi, S. M., Ellsworth, W. L., Zhu, W., Chuang, L. Y., & Beroza, G. C. (2020). Earthquake transformer—an attentive deep-learning model for simultaneous earthquake detection and phase picking. Nature Communications, 11(1), 1–12. <https://doi.org/10.1038/s41467-020-17591-w>
23. Park, Y., Mousavi, S. M., Zhu, W., Ellsworth, W. L., & Beroza, G. C. (2020). Machine-Learning-Based Analysis of the Guy-Greenbrier, Arkansas Earthquakes: A Tale of Two Sequences. Geophysical Research Letters, 47(6), 1–8. https://doi.org/10.1029/2020GL087032
24. Podolskiy, E. A., & Walter, F. (2016). Cryoseismology. In Reviews of Geophysics (Vol. 54, Issue 4, pp. 708–758). Blackwell Publishing Ltd. <https://doi.org/10.1002/2016RG000526>
25. Ren, C. X., Peltier, A., Ferrazzini, V., Rouet-Leduc, B., Johnson, P. A., & Brenguier, F. (2020). SUPP Machine Learning Reveals the Seismic Signature of Eruptive Behavior at Piton de la Fournaise Volcano. Geophysical Research Letters, 47(3), 1–11. https://doi.org/10.1029/2019GL085523
26. Riesen, P., Sugiyama, S., & Funk, M. (2010). The influence of the presence and drainage of an ice-marginal lake on the flow of Gornergletscher, Switzerland. Journal of Glaciology, 56(196), 278–286. <https://doi.org/10.3189/002214310791968575>
27. Röösli, C., Walter, F., Husen, S., Andrews, L. C., Lüthi, M. P., Catania, G. A., & Kissling, E. (2014). Sustained seismic tremors and icequakes detected in the ablation zone of the Greenland ice sheet. Journal of Glaciology, 60(221), 563–575. https://doi.org/10.3189/2014joG13j210
28. Ross, Z. E., Meier, M. A., Hauksson, E., & Heaton, T. H. (2018). Generalized seismic phase detection with deep learning. Bulletin of the Seismological Society of America, 108(5), 2894–2901. <https://doi.org/10.1785/0120180080>
29. Ross, Z. E., Yue, Y., Meier, M. A., Hauksson, E., & Heaton, T. H. (2019). PhaseLink: A Deep Learning Approach to Seismic Phase Association. Journal of Geophysical Research: Solid Earth, 124(1), 856–869. <https://doi.org/10.1029/2018JB016674>
30. Roux, P. F., Walter, F., Riesen, P., Sugiyama, S., & Funk, M. (2010). Observation of surface seismic activity changes of an Alpine glacier during a glacier-dammed lake outburst. Journal of Geophysical Research: Earth Surface, 115(3), 1–13. <https://doi.org/10.1029/2009JF001535>
31. Seydoux, L., Balestriero, R., Poli, P., Hoop, M. de, Campillo, M., & Baraniuk, R. (2020). Clustering earthquake signals and background noises in continuous seismic data with unsupervised deep learning. Nature Communications, 11(1). https://doi.org/10.1038/s41467-020-17841-x
32. Sick, B., Guggenmos, M., & Joswig, M. (2015). Chances and limits of single-station seismic event clustering by unsupervised pattern recognition. Geophysical Journal International, 201(3), 1801–1813. <https://doi.org/10.1093/gji/ggv126>
33. Steinmann, R., Seydoux, L., Beauce, E., & Campillo, M. (2021). Hierarchical exploration of continuous seismograms with unsupervised learning. May, 1–26.
34. Sugiyama, S., Bauder, A., Weiss, P., & Funk, M. (2007). Reversal of ice motion during the outburst of a glacier-dammed lake on Gornergletscher, Switzerland. Journal of Glaciology, 53(181), 172–180. <https://doi.org/10.3189/172756507782202847>
35. 2008\_Sugiyama\_Triggering and drainage mechanisms of the 2004 glacier-dammed lake outburst in Gornergletscher, Switzerland.pdf. (n.d.).
36. Sugiyama, S., Bauder, A., Riesen, P., & Funk, M. (2010). Surface ice motion deviating toward the margins during speed-up events at Gornergletscher, Switzerland. Journal of Geophysical Research: Earth Surface, 115(3). <https://doi.org/10.1029/2009JF001509>
37. Trugman, D. T., & Shearer, P. M. (2017). GrowClust: A Hierarchical clustering algorithm for relative earthquake relocation, with application to the Spanish Springs and Sheldon, Nevada, earthquake sequences. Seismological Research Letters, 88(2), 379–391. https://doi.org/10.1785/0220160188
38. Vore, M. E., Bartholomaus, T. C., Winberry, J. P., Walter, J. I., & Amundson, J. M. (2019). Seismic Tremor Reveals Spatial Organization and Temporal Changes of Subglacial Water System. Journal of Geophysical Research: Earth Surface, 124(2), 427–446. https://doi.org/10.1029/2018JF004819
39. Walter, F., Deichmann, N., & Funk, M. (2008). Basal icequakes during changing subglacial water pressures beneath Gornergletscher, Switzerland. Journal of Glaciology, 54(186), 511–521. <https://doi.org/10.3189/002214308785837110>
40. Walter, F. (2009). SEISMIC ACTIVITY ON GORNERGLETSCHER DURING GORNERSEE OUTBURST FLOODS. Dissertation, 31(1–2), 14–27. https://doi.org/10.1007/BF03322148
41. Walter, F., Clinton, J. F., Deichmann, N., Dreger, D. S., Minson, S. E., & Funk, M. (2009). Moment tensor inversions of icequakes on Gornergletscher, Switzerland. Bulletin of the Seismological Society of America, 99(2 A), 852–870. <https://doi.org/10.1785/0120080110>
42. Walter, F., Dreger, D. S., Clinton, J. F., Deichmann, N., & Funk, M. (2010). Evidence for near-horizontal tensile faulting at the base of gornergletscher, a Swiss alpine glacier. Bulletin of the Seismological Society of America, 100(2), 458–472. <https://doi.org/10.1785/0120090083>
43. Werder, M. A., Loye, A., & Funk, M. (2009). Dye tracing a jökulhlaup: I. Subglacial water transit speed and water-storage mechanism. Journal of Glaciology, 55(193), 889–898. <https://doi.org/10.3189/002214309790152447>
44. Werder, M. A., Schuler, T. V., & Funk, M. (2010). Short term variations of tracer transit speed on alpine glaciers. Cryosphere, 4(3), 381–396. https://doi.org/10.5194/tc-4-381-2010
45. Yoon, C. E., O’Reilly, O., Bergen, K. J., & Beroza, G. C. (2015). Earthquake detection through computationally efficient similarity search. Science Advances, 1(11). https://doi.org/10.1126/sciadv.1501057