A Little Data goes a Long Way: Automating Seismic Phase Arrival Picking at Nabro Volcano with Transfer Learning

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Key Points:

- Transfer learning using existing model trained on California earthquake data produces effective new model for monitoring at Nabro volcano
- Nabro transfer learning model shows improved S-wave picking resulting in smaller location errors than even manual phase picks
- Changing task from classification to segmentation results in more efficient model processing 14 months of data from 7 stations in 4 hours

Abstract

Supervised deep learning models have become a popular choice for seismic phase arrival detection. However, they tend to perform poorly on out-of-distribution data and require large training sets to aid generalization and prevent overfitting. This presents an issue when using these models in new monitoring settings. In this work, we develop a deep learning model for automating phase arrival detection at Nabro volcano using a limited amount of training data (2498 event waveforms recorded over 35 days) through a process known as transfer learning. We use the feature extraction layers of an existing, extensively-trained seismic phase picking model to form the base of a new all-convolutional model, which we call U-GPD. We demonstrate that transfer learning reduces overfitting and model error relative to training the same model from scratch, particularly for small training sets (e.g., 500 waveforms). The new U-GPD model achieves greater classification accuracy and smaller arrival time residuals than off-the-shelf applications of two existing, extensively-trained baseline models for a test set of 800 event and noise waveforms from Nabro volcano. When applied to 14 months of continuous Nabro data, the new U-GPD model detects 31,387 events with at least four P-wave arrivals and one S-wave arrival, which is more than the original base model (26,808 events) and our existing manual catalogue (2,926 events), with smaller location errors. The new model is also more efficient when applied as a sliding window, processing 14 months of data from 7 stations in less than 4 hours on a single GPU.

Plain Language Summary

Seismic monitoring increasingly relies on automated signal processing as the rate of data acquisition grows. Supervised deep learning models have proven to be effective for detecting and characterizing seismic events, but training such highly parameterized models generally requires large amounts of manually labelled data. Once trained, however, these models extract general seismic waveform features that can be used to train new models with more limited training data. In this work, we use the generalized knowledge of seismic data from a model trained on millions of earthquakes in California to train a new model for detecting volcanic earthquakes at Nabro volcano, Eritrea, a recently active and, prior to its 2011 eruption, poorly monitored volcano. Using

a small training set of waveforms, the new model more accurately detects phase arrivals and noise than off-the-shelf applications of two baseline models. The new model is efficient, processing 14 months of data in less than 4 hours. It is also effective, detecting more volcanic events and showing improved levels of S-wave arrival picking. The result is smaller event location errors than even our manual picks. This level of efficiency and consistency highlights the role that machine learning can play in volcano-seismic monitoring.

1 Introduction

Seismic monitoring plays a fundamental part in mitigating hazards at volcanoes. During periods of unrest, thousands of earthquakes can occur each day, producing a diverse range of seismic signals that reflect a multitude of interlinked volcanic processes (e.g., migrating fluids, fault movement, explosions, rockfalls). These earthquakes are generally recorded by broadband seismometers, which are highly sensitive to ground motion across a wide range of frequencies and record signals at high sample rates (typically 100 times or more per second). This level of detail, however, comes at the cost of generating vast amounts of data. Many seismic networks utilize tens or even hundreds of seismometers at a given time (e.g., Hansen & Schmandt, 2015), making real-time manual inspection of these time series practically infeasible. Previous seismic deployments have also generated extensive legacy datasets that can offer insights into historical volcanic activity and opportunities to further our understanding of volcanic processes. The main challenge is therefore to identify and characterize volcanic earthquakes in a robust and timely manner so as to provide vital clues regarding the state of a volcano and the likelihood or impact of an eruption or hazard, as well as be able to accurately and efficiently process large existing datasets for further analysis within a reasonable timeframe.

Identifying earthquake phase arrivals, particularly the initial primary (P-) and secondary/shear (S-) wave arrivals, forms the basis of most seismic processing tasks (e.g., determining locations, magnitudes and source parameters). Manually identifying these phase arrivals yields greater accuracy and estimates of arrival time uncertainty than automated approaches but is extremely time-consuming. Alternatively, most automated approaches are orders

of magnitude quicker but typically require clear phase arrivals, existing 'templates' of previously catalogued earthquakes (e.g., Gibbons & Ringdal, 2006; Lengliné et al., 2016; Shelly et al., 2007), or pre-processing / feature extraction steps calibrated for a small set of earthquake characteristics (e.g., trigger algorithms based on the ratio of short-term average to long-term average signal amplitude, STA/LTA; Withers et al., 1998). A challenge for application to volcanology is that volcanic earthquakes can exhibit widely varying time-frequency characteristics, often with low amplitudes or obscured phase arrivals, and new phases of unrest can produce previously unseen seismic signals that differ from existing earthquake templates. Furthermore, methods based on existing seismic catalogues are unsuitable for new seismic deployments where a catalogue of events has not been collected.

A recently successful approach for seismic phase arrival detection is the use of supervised deep learning models (e.g., Dokht et al., 2019; Mousavi et al., 2019; Ross et al., 2018; Woollam et al., 2019; Zhu & Beroza, 2019). These methods are based on convolutional neural networks (CNN), a variant of classical neural networks that employ convolution operations, as opposed to matrix multiplication, in at least part of the model. These operations are employed in 'hidden' convolutional layers that allow the network to learn a large set of filters to extract useful features from the input data and map them to a desired output (e.g., to identify phase arrivals in earthquake waveforms; Fig 1). Typically, multiple convolutional layers are applied in succession and in combination with other operations, such as non-linear 'activation', down-sampling and normalization, to extract complex patterns from the data using a hierarchy of simpler filter kernels. These extracted features can then be fed into a standard fully-connected neural network or other machine learning architecture for classification, segmentation, regression, clustering or inference (e.g., Mousavi et al., 2019; Ross et al., 2018; van den Ende & Ampuero, 2020). As such, the 'convolutional' part of CNNs act as the model's feature extraction system. With each successive convolutional layer, the extracted features move from lower-level, general signal features (resembling, for example, long/short period wavelets in seismological waveform models; Fig 1A inset) to more task specific, high-level features (Yosinski et al., 2014). The final 'classification' layers of the model map these features to the desired output and can be considered the most task specific part of the model, empirically tuned to the distribution of the training data (Yosinski et al., 2014). Such an approach gives these models a strong advantage over traditional algorithms

that require considerable manual intervention or rely on a small set of manually determined characteristics and simple threshold criteria. Supervised deep learning models, however, require substantial amounts of labelled data during training to generalize to out-of-sample data (the amount dependent on various factors, such as network architecture, number of network parameters and training hyperparameters; e.g., D'souza et al., 2020; He et al., 2019; Sun et al., 2017). They can also suffer significant loss in performance when faced with data that differs in source or distribution from their training data (e.g., Barbedo, 2018; Zech et al., 2018). This requirement can place the traditional paradigm of supervised learning (i.e., using a large amount of hand-labelled data to train a single model for a desired domain or problem) out of reach for many real-world applications.

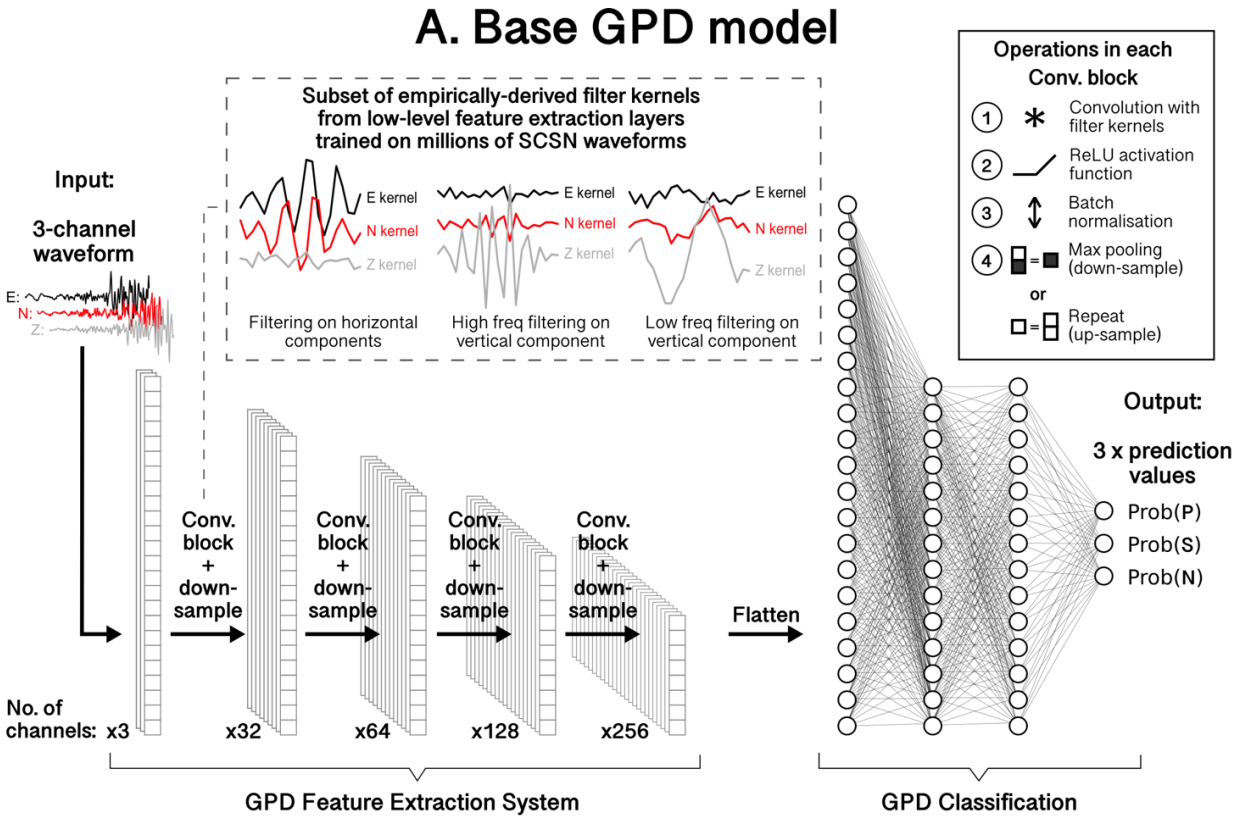
Transfer learning is based on the idea of knowledge transfer from one task to another (Pan & Yang, 2010; Zhuang et al., 2020) and can be a powerful tool when we do not have sufficient labelled data to train a reliable model from scratch. At its simplest, the first *n* convolutional layers and their weights from the feature extraction part of an existing model are copied to the first *n* layers of a new model for a related or similar task, with the remaining layers either re-initialized with randomized weights or replaced (e.g., Razavian et al., 2014; Yosinski et al., 2014). These tasks need not be near-identical or even superficially related, as long as low-level data characteristics are shared between tasks (e.g., Efremova et al., 2019; Tran et al., 2020; Zamir et al., 2018). The intuition is that generalized knowledge of data structure and properties from one model trained with abundant labelled data (or 'big data') can guide a learning algorithm towards a good solution for a new task with far more limited, or even no, labelled data.

In this paper, we evaluate the utility of inductive transfer learning (i.e., when labelled data are available for both the source and target tasks) for small seismic training sets and produce a deep learning model that accurately and robustly picks phase arrivals from a deployment at Nabro volcano in Eritrea, a region with little or no prior seismic monitoring. We leverage the knowledge acquired from training a model on millions of seismic waveforms recorded by the Southern California Seismic Network (SCSN), hereby referred to as the GPD model (Generalized seismic Phase Detection; Ross et al., 2018), and apply it to seismograms from Nabro volcano in Eritrea, for which we have limited hand-labelled data (manual phase arrival picks) from the first couple of

months of a 14-month seismic deployment (Goitom, 2017; Hamlyn et al., 2014). The new model task differs from the original GPD model task in that it is modified from one of *classification* (assigning a single class label *P-wave*, *S-wave* or *noise* to an entire 4-second waveform; Fig 1A) to one of *segmentation* (assigning a class label *P-wave*, *S-wave* or *noise* to *each datapoint* within that 4-second waveform; Fig 1B). We achieve this by replacing the fully-connected uppermost layers of the original GPD model with further convolutional layers, creating an all-convolutional model commonly referred to as a U-Net (Ronneberger et al., 2015). We refer to this specific model design as the U-GPD model, utilizing GPD model weights within a U-Net architecture. The new data from Nabro volcano also exhibit differences in instrument calibration and sample rates from the original GPD model training data, as well as differing waveform characteristics between tectonic and volcanic event types (Lahr et al., 1994; Lapins et al., 2020; McNutt & Roman, 2015).

In the following section, we introduce transfer learning and recent applications in seismological deep learning. In Sections 3 and 4, we present our proposed transfer learning method, U-GPD model architecture and seismic data recorded at Nabro volcano. In Section 5, we present a series of model comparisons. We first use common training metrics to demonstrate that transfer learning reduces overfitting and model error, particularly for very small training sets (< 1000 waveforms), when compared with a model reinitialized with randomized weights before training (i.e., trained from scratch with no transfer learning). We then apply these new models to a test dataset of known P-/S-wave arrivals and sections of noise and compare performance with off-the-shelf applications of the base GPD model and another extensively-trained phase-picking model, PhaseNet (Zhu & Beroza, 2019). We find that the U-GPD transfer learning model yields improved phase arrival identification, particularly for S-waves, and false detection rate at Nabro volcano. Altering the model task from classification to segmentation also improves pick time residuals over the base GPD model for these test data. Finally, we apply both our new U-GPD transfer learning model and the original base GPD model to the full 14-month seismic deployment at Nabro volcano through a sliding window approach. The new U-GPD model identifies more useable S-wave arrivals than the base GPD model, yielding smaller subsequent location errors than even our manual analyst's phase arrival picks. The new model also runs an order of magnitude faster, processing 14 months of data from 7 broadband seismometers in less than 4 hours on a single GPU. Our findings indicate that transfer learning can be extremely useful for volcano

seismic monitoring, even with limited computing resources and data. We conclude this paper with a discussion of our findings, methodology and practical considerations of transfer learning in Section 6. All data and code used throughout this paper are made fully and publicly available (see *Data Availability Statement*).


A. Base GPD model
Operations in each Conv. block
1 Convolution with filter kernels
2 ReLU activation function
3 Batch normalisation
4 Max pooling (down-sample)
or
Repeat (up-sample)
Subset of empirically-derived filter kernels from low-level feature extraction layers trained on millions of SCSN waveforms
E kernel
N kernel
Z kernel
Filtering on horizontal components
High freq filtering on vertical component
Low freq filtering on vertical component
Input:
3-channel waveform
E:
N:
Z:
Conv. block + down-sample
Flatten
Output:
3 x prediction values
Prob(P)
Prob(S)
Prob(N)
No. of channels: x3
x32
x64
x128
x256
GPD Feature Extraction System
GPD Classification

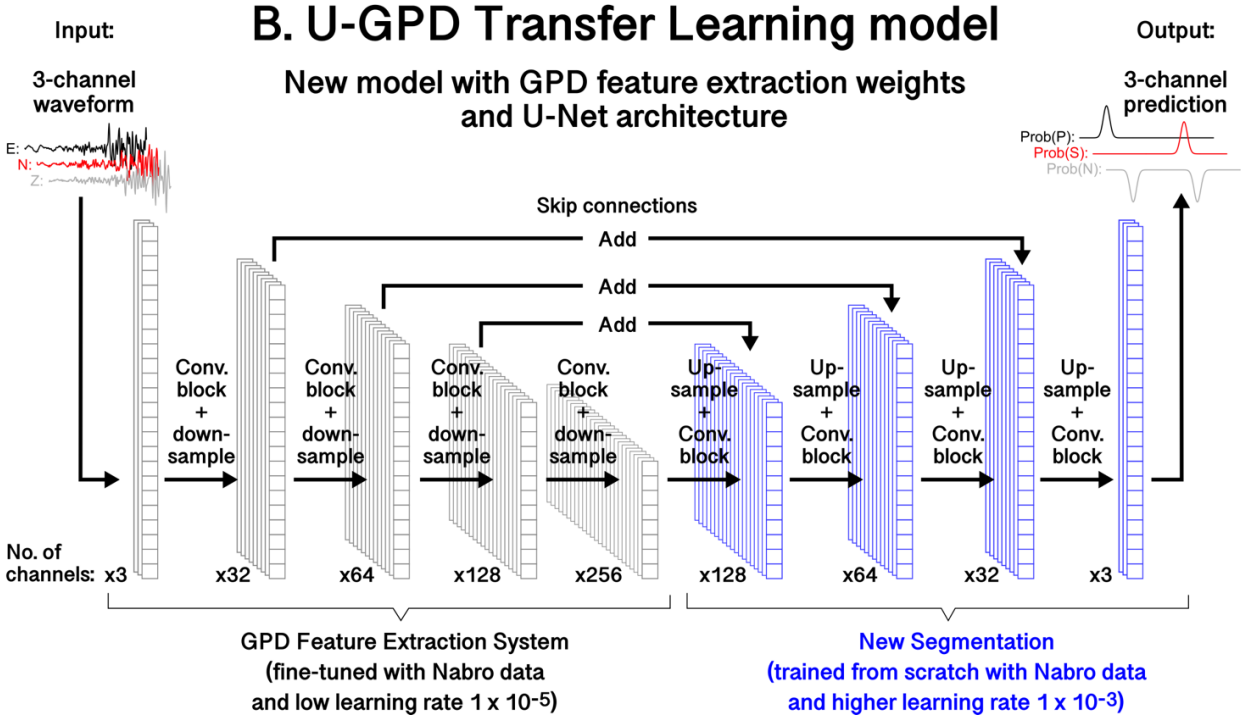

B. U-GPD Transfer Learning model
New model with GPD feature extraction weights and U-Net architecture
Input:
3-channel waveform
E:
N:
Z:
Output:
3-channel prediction
Prob(P):
Prob(S):
Prob(N):
Skip connections
Add
Add
Add
Conv. block + down-sample
Up-sample + Conv. block
No. of channels: x3
x32
x64
x128
x256
x128
x64
x32
x3
GPD Feature Extraction System
(fine-tuned with Nabro data
and low learning rate 1 x 10-5)
New Segmentation
(trained from scratch with Nabro data
and higher learning rate 1 x 10-3)

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Figure 1. **a)** Model architecture for Generalized seismic Phase Detection (GPD) CNN model (Ross et al., 2018). Model can be considered as two parts: a feature extraction system (convolutional layers) and classification part (fully connected layers). GPD model outputs 3 x prediction values (probability of P, S or noise) for an entire 400-sample 3-component waveform (i.e., output dimensions: 1 x 3). Examples of filter kernels (dashed line inset) from lowest convolutional layer that extract generalized seismic waveform features determined through model training on extensive SCSN dataset. These indicate that the GPD model has learnt to extract different features from vertical and horizontal components. **b)** Proposed transfer learning model architecture ("U-GPD"). GPD model feature extraction system is copied to new model and fine-tuned with new Nabro data and low learning rate. Low learning rate ensures that useful features are not 'unlearned'. New convolutional layers replace the GPD classification layers and are trained using new Nabro data and higher learning rate. Model outputs 3 x prediction values for each datapoint in 400-sample 3-component waveform (i.e., output dimensions: 400 x 3).

2 Transfer Learning

There are many approaches to transfer learning (see Pan & Yang, 2010; Zhuang et al., 2020 for comprehensive surveys), including using 'off-the-shelf' feature extraction systems from existing state-of-the-art CNNs (e.g., Maqsood et al., 2019; Razavian et al., 2014), learning domain-invariant or global representations across multiple tasks (e.g., Glorot et al., 2011; Li et al., 2014; Tzeng et al., 2015; Zhuang et al., 2015), applying pre-processing steps to make input data representations more similar between datasets (e.g., Daumé, 2007; Sun et al., 2016) and the use of domain-adversarial models (e.g., Ganin et al., 2016). Here we employ the first of these approaches for P- and S-wave arrival time picking at Nabro volcano, utilizing pre-trained filters from an existing, extensively trained CNN model (the GPD model; Ross et al., 2018) to train a new model with different output dimension and task type (see *Section 3.1, U-GPD Model Architecture*). Other seismological studies that have employed transfer learning in this way have used pre-trained filters from models designed for non-seismological tasks, such as image recognition. For example, filters trained to recognize photographic images or handwritten characters have been used to detect earthquakes and classify volcano-seismic event types from spectrograms (Huot et al., 2018; Lara et al., 2020; Titos et al., 2020) and interpret seismic facies (Dramsch & Lüthje, 2018).

Some studies have chosen to fine-tune entire seismic deep learning models, essentially updating the models with new data (or equivalently 'pre-training' the models with larger datasets, depending on perspective). El Zini et al. (2020) pre-train an autoencoder with abundant unlabeled data to learn compressed data representations of 2D seismic images. These model weights then serve as a starting point for a model that segments seismic images, with weights fine-tuned using limited labelled training data. This approach was shown to outperform the transfer of weights from image recognition models and training a model from scratch. Bueno et al. (2020) fine-tune a Bayesian neural network (BNN) to improve classification of volcano-seismic event characteristics between datasets and time periods. They show that this approach increases model accuracy and reduces epistemic uncertainty when applied to new volcanic systems or phases of activity. With a similar aim but different approach to the work of this paper, Chai et al. (2020) utilize pre-trained weights from another existing phase arrival detection model, PhaseNet (Zhu & Beroza, 2019), to pick phase arrivals from hydraulic fracturing experiments. They use the entirety of the PhaseNet model and its pre-trained weights as a starting point for training and then fine-tune all model weights equally using just 3,500 seismograms. They present improved results over the original PhaseNet model, which was trained using 700,000 seismograms of regional Californian seismicity, when applied to higher sample rate data (2 kHz) from a very different setting (i.e., hydraulic fracturing). Whilst these studies show that fine-tuning entire models can be an effective strategy, poor hyperparameter choices (model learning rate, number of training epochs, etc.) can inadvertently retrain the model (also known as 'catastrophic forgetting'; e.g., Kirkpatrick et al., 2017) or lead to settling on a non-global minimum within the parameter space, reopening the potential for overfitting when the number of model parameters is large and the training dataset is small (El Zini et al., 2020; Yosinski et al., 2014). The work in this paper differs from that of Chai et al. (2020) in that only the weights from the feature extraction part (i.e., the first 'half') of the GPD model are transferred to our new U-GPD model. These weights are fine-tuned using a much lower learning rate (weight update step size) to retain useful learned knowledge from the original model but optimize cohesion with the rest of the new model, which is redesigned to reduce the total number of trainable parameters, among other optimizations (see Section 3.1, Model Architecture), and initialized with randomized weights (Fig 1).

3 Proposed Model

3.1 U-GPD Model Architecture

As outlined briefly above, we utilize pre-trained parameters from the convolutional layers of the GPD model as a starting point for our U-GPD transfer learning model. The original GPD model was trained using 4.5 million hand-labelled seismograms (1.5 million of each class *P*, *S* and *noise*) recorded by the Southern California Seismic Network (SCSN) between the years 2000 and 2017. These training data were all 400-sample (4 sec) 3-component waveforms, high-pass filtered above 2 Hz and (re)sampled at 100 Hz. All events had epicentral distances less than 100 km and magnitudes between -0.81 and 5.7 M (various magnitude scales). The GPD model was chosen as a base for our transfer learning model as these data characteristics are comparable to those observed and recorded by volcano observatories. Furthermore, the short input length of 4 seconds (400 samples at 100 Hz sample frequency) means there is less chance of erroneously labelling or missing relatively small magnitude or overlapping phase arrivals. Finally, the GPD model's 'sequential' architecture, with each layer being solely connected to the layers directly before and after, also means the model is more interpretable and makes it easier to isolate its feature extraction system.

During model training, we fine-tune these pre-trained parameters using a very small learning rate (1×10^{-5}), rather than keep them fixed (e.g., Yosinski et al., 2014). The aim of this fine-tuning step is to modify any highly specific features from the source domain (particularly in the higher-level feature extraction layers) and overcome optimization difficulties arising from splitting the GPD convolutional layers from co-adapted classification layers (Yosinski et al., 2014) without unlearning the important generalized waveform features we wish to exploit. We then replace the GPD model's fully-connected layers (i.e., the task-specific classification part of the model) with further convolutional layers and up-sampling operations, combined with ReLU activation function (Nair & Hinton, 2010) and batch normalization (Ioffe & Szegedy, 2015), to produce a model output with the same dimensions as model input (400 samples x 3 channels; Fig 1). Each of the three output channels represents the model's prediction (or 'probability') of a P-wave arrival, S-wave arrival or neither (hereby referred to as *noise*), respectively, at each datapoint

in the waveform. This all-convolutional approach has been adopted by other phase arrival picking models (e.g., Woollam et al., 2019; Zhu & Beroza, 2019) and has several distinct advantages when applied to seismic phase arrival detection: i) it provides less ambiguous labelling of phase arrivals when compared to the original GPD model's approach of assigning a single class prediction (*P*, *S* or *noise*) to an entire 400-sample 3-channel waveform; ii) convolutional layers tend to have fewer parameters than fully connected neural network layers so less training data is required to avoid overfitting; iii) by producing a model with input and output traces of same dimension, we require less overlap when applied as a rolling window method, producing a model that runs orders of magnitude faster on continuous sections of data. These new convolutional layers are initialized with completely randomized weights and trained with a higher learning rate (1×10^{-3}) than the pre-trained GPD weights. We use dilated filter kernels in these new convolutional layers (e.g., van den Oord et al., 2016; Yu & Koltun, 2016) to increase the size of the model's receptive field (or 'field of view') and aggregate multi-scale context. Finally, the new layers are subjected to spatial dropout (Tompson et al., 2015), where 30% of the feature maps (output of filter operations) in each convolutional layer are effectively dropped (set to zero) at the start of each training epoch. This step promotes independence between the features the model extracts and prevents overfitting (Tompson et al., 2015). Precise details of U-GPD model dimensions and hyperparameters are provided in *Supplementary Materials*.

The overall network architecture outlined above is sometimes referred to as a U-Net (Ronneberger et al., 2015). With each step through the network, the input data are progressively downsampled with an increasing number of features extracted, creating a contracting network path that is forced to sacrifice detail and learn a more compressed, general representation of the input waveform to discriminate between classes (*P*, *S* or *noise*). The model then follows a symmetrically expanding path, where the data are progressively upsampled and the number of features reduced, to regain precise temporal or spatial detail and return an output with equal dimension to the model input (Ronneberger et al., 2015). Skip connections (addition operators), which act as direct, one-way pathways between layers in the contracting and expanding sides of the model (Fig 1B), are used to retain precise waveform details that may be lost through this contraction/expansion process and have been shown to greatly improve the likelihood of model parameters settling on the global minimum during training (Li et al., 2017).

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304 **3.2 Phase Arrival Labels and Model Hyperparameters**

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306 Each 3-component waveform in our training dataset has a corresponding 3-channel 'mask'
307 that provides a ground truth label (*P*, *S* or *noise*) for each waveform datapoint. During training, the
308 model aims to minimize the difference between its predictions and these ground truth labels.
309 Labels are presented as binary values (0's or 1's), with P-wave arrivals indicated by a +/- 0.14 sec
310 boxcar function, centered on the manually picked P-wave arrival time, and S-wave arrivals
311 indicated by +/- 0.19 sec boxcar function, also centered on the manually picked S-wave arrival
312 time. These boxcar widths provide a good balance between phase arrival detection rate and arrival
313 time precision and compensate for human error in the ground truth labels. Previous studies have
314 used Gaussian-style probability masks, with values ranging between 0 and 1, for labelling phase
315 arrivals (e.g., Woollam et al., 2019; Zhu & Beroza, 2019). We find that label accuracy on our test
316 data (e.g., Fig 5) and event location error distributions from the full deployment (e.g., Fig 8C &
317 D) are near-identical when using either approach but training with boxcar masks produces a model
318 that detects ~ 10% more events when run over continuous data.

319

320 As with the original GPD model, our new U-GPD model was trained using a categorical
321 cross entropy loss function (see Supplementary Materials) and the Adam optimization algorithm
322 (Kingma & Ba, 2014). The model weights that produced lowest loss value on the validation dataset
323 during training were selected as our final model weights. Other loss functions that address the
324 imbalance between arrival and noise labels (as the majority of labels in any given waveform are
325 not a phase arrival), such as a focal loss function that effectively adds weighting parameters to
326 cross entropy loss (Lin et al., 2017), were trialed but yielded no improvement in model
327 performance.

328

329 **4 Data**

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331 Nabro volcano is one of two calderas that form the Bidu Volcanic Massif on the Eritrea-
332 Ethiopia international border (Fig 2). Located in the Afar region at the northern end of the Main

Ethiopian Rift, it erupted unexpectedly for the first time in recorded history on 12th June, 2011, disrupting continental aviation and initiating a significant humanitarian crisis (Bojanowski, 2011; Donovan et al., 2018; Goitom et al., 2015). At the time, there were no seismic or other monitoring networks operating in Eritrea but earthquakes were felt around the volcano several hours and days prior to eruption, prompting evacuation (Goitom et al., 2015). This seismicity is the first of note in global catalogues for the region (Goitom et al., 2015). Despite this fortuitous warning, at least seven people were tragically killed and about 12,000 were displaced (Bojanowski, 2011; Goitom et al., 2015; Hamlyn et al., 2014). The eruption is particularly notable for the vast amount of SO_2 emitted into the atmosphere, one of the largest eruptive SO_2 masses globally since the eruption of Mount Pinatubo in 1991 (Fromm et al., 2014; Goitom et al., 2015; Theys et al., 2013), and the comparative rarity of recorded historical eruptions in the region (Goitom et al., 2015; Hamlyn et al., 2014).

In August, 2011, approximately two months after the eruption began, eight 3-component broadband seismometers (5 x Guralp CMG-6T, 3 x Guralp CMG-40T; Fig 2) were deployed around the volcano to monitor ongoing activity (Hamlyn et al., 2014). These stations remained operational for 14 months until October, 2012. The first two months of data were collected at a sample rate of 100 Hz before dataloggers were switched to a sample rate of 50 Hz for the remainder of the deployment to maximize data recovery while minimizing service runs. Manual phase arrival picking conducted on the first four months of data (2011-08-30 to 2011-12-31; Goitom, 2017; Hamlyn et al., 2014) identified a total of 2926 events, from which the first 35 days of data (all 100 Hz sample rate) were quality checked and used for training and validating our transfer learning model. Five subsequent days of data (2 x 100 Hz days, 3 x 50 Hz days) were selected and quality checked to serve as test data. The reason to exclude 50 Hz data from model training is to emulate data availability in the early stages of this seismic deployment and demonstrate that changes in sample rate can be overcome without compiling new training datasets through a process known as data augmentation. The raw data for all datasets (training, validation and testing) were self-normalized, with linear trend removed, and left unfiltered.

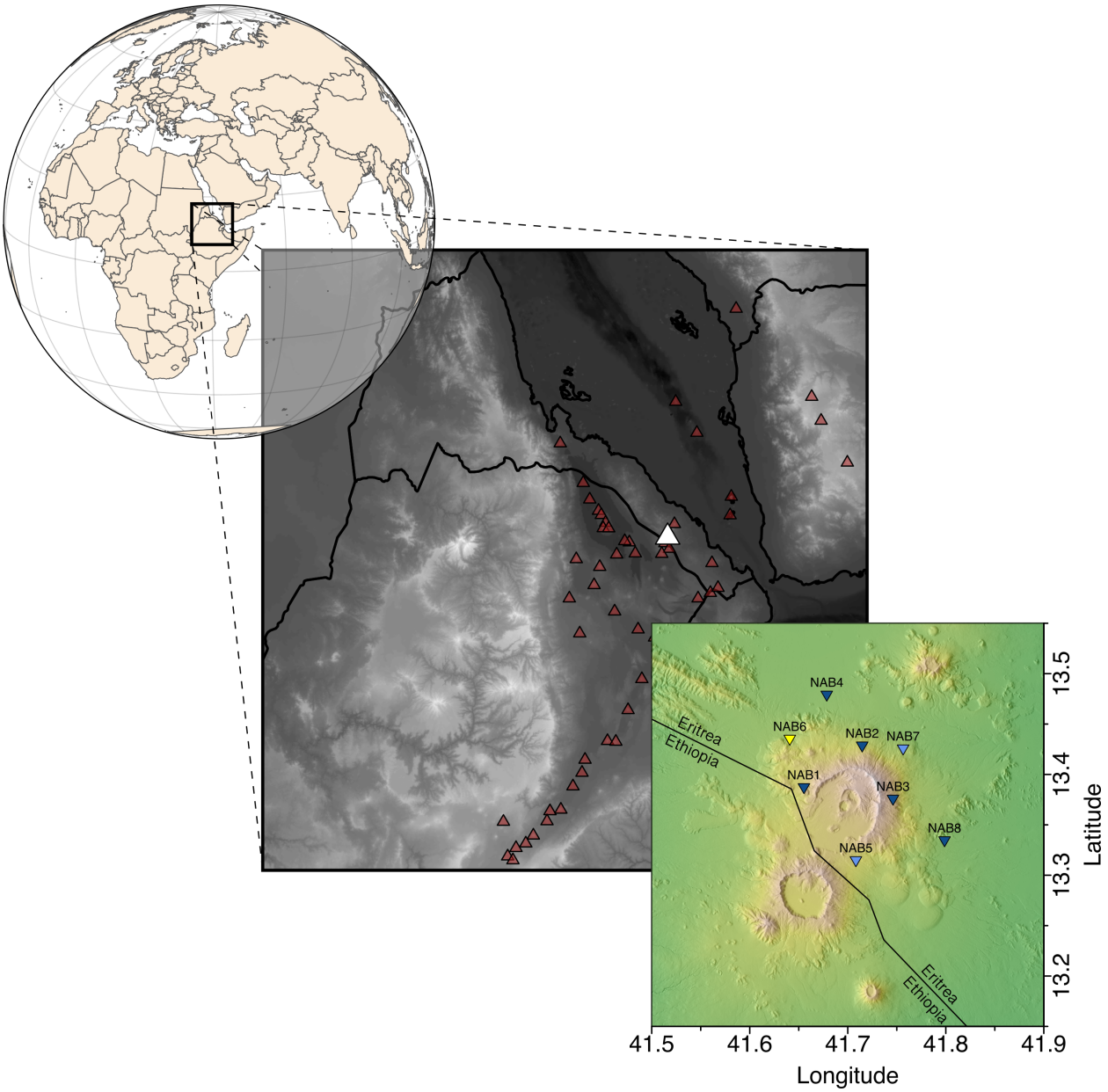


Figure 2. Regional topographic map (90 m CGIAR Shuttle Radar Topography Mission and GEBCO bathymetry model, grey-scale map center) and seismic deployment (30 m ALOS Digital Surface Model, color map bottom right) around Nabro volcano. Red triangles (center map) indicate Holocene volcanoes (Global Volcanism Program, 2013) with Nabro volcano highlighted in white. Inverted blue triangles (bottom right map) indicate operational broadband seismic stations deployed around Nabro volcano from August 2011 to October 2012 (station NAB6, inverted yellow triangle, was flooded shortly after deployment and not operational). Training and validation data were taken from dark blue stations only (NAB1, NAB2, NAB3, NAB4 and NAB8).

A total of 2921 waveforms with labelled P- and S-wave arrivals from 978 events (2011-08-30 to 2011-10-03) and five stations were used as training and validation data (only five stations were consistently operational during this time; dark blue stations in Fig 2 bottom right map). Training and validation data were grouped and divided so that no event appeared in both datasets to avoid data leakage (the model being trained on event data that also appears in validation or testing). 857 events (2498 waveforms) were used for model training and 121 events (423 waveforms) were used for model validation, a training-validation split of approximately 85%-15%. 624 sections of noise (20 secs length) were manually identified across all five stations (2011-08-31 to 2011-09-27), with 500 sections (2500 waveforms) and 85 sections (425 waveforms) used for model training and validation, respectively. Two noise waveforms were randomly dropped from each dataset so that the training and validation noise data comprise 2498 and 423 waveforms, respectively, to match the number of event waveforms.

A separate test dataset of 400 event waveforms with labelled P- and S-wave arrivals (132 events) and 400 noise waveforms (80 sections of noise) was also produced for subsequent model testing. These data come from a different time period than those used for training and validation data, with 200 waveforms from a period where data were recorded at 100 Hz sample rate (2011-10-04 and 2011-10-05) and 200 waveforms from a period with 50 Hz sample rate (2011-10-14, 2011-10-15 and 2011-11-27) for each category. All training, validation and test data were manually identified and quality checked.

The success of U-Net architectures relies on an effective data augmentation strategy when working with smaller datasets (Ronneberger et al., 2015). This allows the network to learn invariance to certain changes in input signal without them needing to appear in the annotated dataset. Here we outline a data augmentation strategy that improves performance of our U-GPD transfer learning model (Supplementary Materials). First, as all stations were switched from 100 Hz sample frequency to 50 Hz sample frequency part way through the seismic deployment, we randomly select subsets of the training data (all originally sampled at 100 Hz) to be decimated to 50 Hz sample frequency throughout training. Each training sample (i.e., each 3-component waveform) has a probability of 0.5 of being selected for decimation before each training epoch,

with an anti-aliasing, low-pass finite impulse response (FIR) filter applied and linear phase shift removed. Second, we randomly time-shift our P- and S-wave arrivals relative to the model input 'window', so that our waveforms differ slightly from epoch to epoch and the model must learn signal features that indicate arrivals rather than where they occur within the input window (i.e., arrivals don't need to occur in the center of the window for the model to detect them). With our noise data, a random 400-sample window is chosen at each training epoch from our 20-second noise sections, introducing more waveform variety between training epochs.

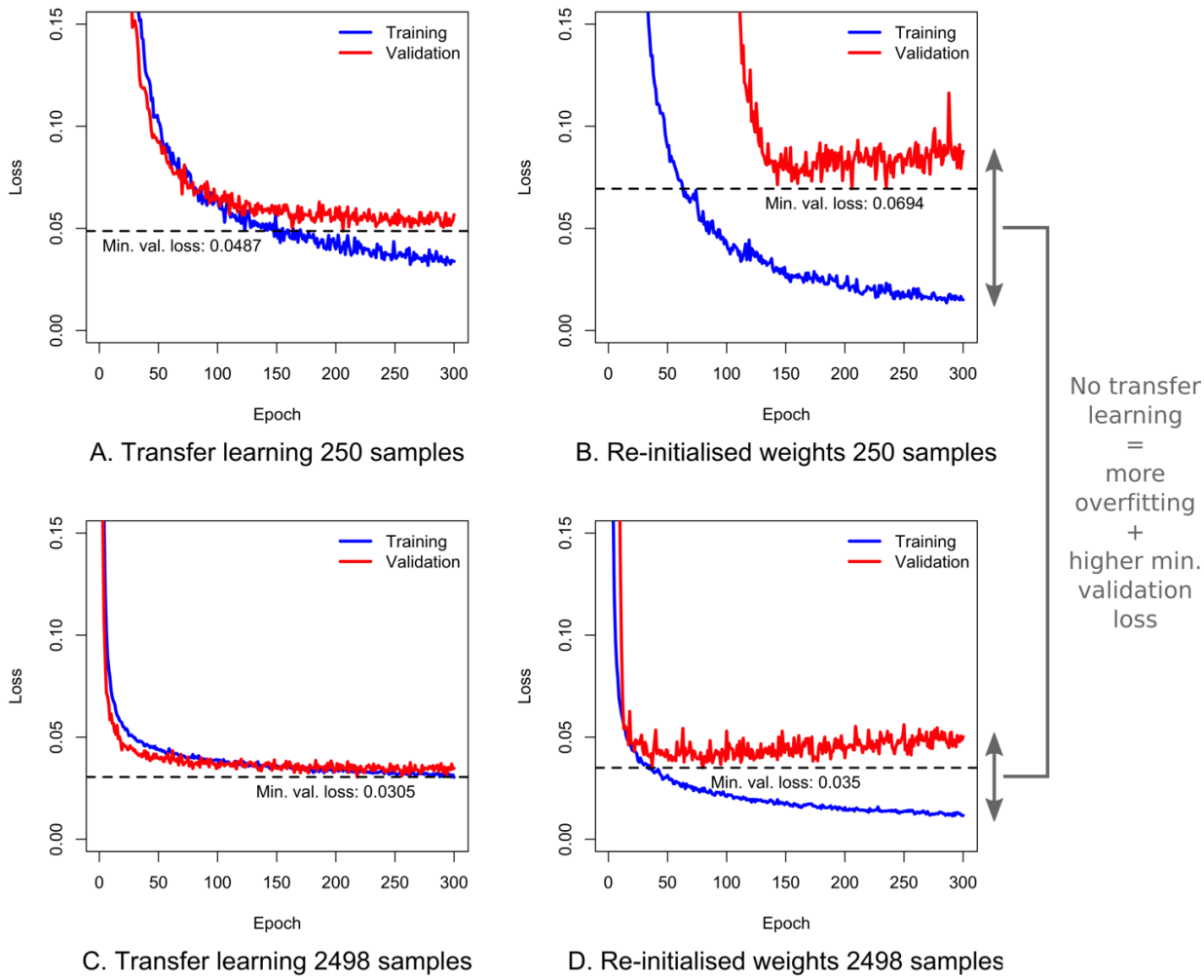
All data processing and model training/testing were performed in Python using the ObsPy (Beyreuther et al., 2010; Krischer et al., 2015; Megies et al., 2011), TensorFlow (Abadi et al., 2015; https://tensorflow.org) and Keras (Chollet et al., 2015; https://keras.io) libraries.

5 Results

5.1 Training Metrics (Transfer Learning vs No Transfer Learning)

To examine the impact of transfer learning and determine how much training data is required to produce an effective model, we use varying sized subsets of the training data throughout model training (i.e., 250, 500, 750, …, 2000, 2250 and 2498 training samples). Figure 3 compares how model loss (measure of distance between model predictions and ground truth labels) on training and validation data evolves throughout training between our transfer learning model and the same model with completely re-initialized weights (i.e., with no transfer learning) for our smallest and largest subsets of training data (250 and 2498 training samples, respectively). The learning rate is set to be equal (1×10^{-3}) across the whole re-initialized model as we are no longer fine-tuning existing knowledge. All other hyperparameters, including dropout rate, are kept the same. The models trained without transfer learning (Fig 3B and D) show a much greater degree of overfitting: the model loss on the training data continues to decrease with more training while the loss on validation data (data that the model does not use during training) hits an inflection point and starts increasing, reflecting that the model is 'memorizing' the precise features of the training data at the cost of generalization (Shorten & Khoshgoftaar, 2019). By contrast, the validation loss continues to decrease for the models trained with transfer learning (Fig 3A and C). Furthermore,

433 the minimum validation loss achieved by the transfer learning models for each training dataset size
434 is lower than when transfer learning is not employed (Fig 3 horizontal dashed lines). Such
435 diagnostics indicate that transfer learning is successfully preventing overfitting to the training data
436 and will likely produce a model that generalizes better to non-training data (Shorten &
437 Khoshgoftaar, 2019). The greatly improved performance on validation data using the smallest
438 subset of training data (Fig 3A and B) shows that transfer learning is particularly useful for
439 reducing overfitting and model loss when training data are very limited, but this advantage is
440 progressively diminished with increasing training dataset size (Figs 3 and 4).
441



442
443
444 **Figure 3.** Model loss vs. training epoch number. **a)** Transfer learning model and 250 training
445 samples of each class (P, S or neither). **b)** Model trained without transfer learning (i.e., initially

randomized weights) and 250 training samples of each class. **c)** Transfer learning model and full training dataset (2498 training samples of each class). **d)** Model trained without transfer learning (i.e., initially randomized weights) and full training dataset. Blue curve shows model loss for training data, red curve shows model loss for validation data (not seen during training). A lower model loss on training data (blue) than validation data (red) means the model shows signs of overfitting. The degree of overfitting (gap between blue and red curves) is much greater for the models without transfer learning (**b** and **d**) with validation loss hitting an inflection point then increasing whilst training loss continues to decrease. The transfer learning models also achieve a smaller minimum validation loss (horizontal dashed line) for each training set size.

Figure 4 shows the highest model accuracy (the proportion of labels the model classifies correctly) and lowest model loss achieved by our transfer learning and re-initialized models on validation data when trained using each subset size of training data. The transfer learning model achieves lower model loss regardless of training dataset size (Fig 4B). As training dataset size increases, the difference between the lowest loss achieved by the two models (gap between red circles and red triangles, Fig 4B) decreases and the advantages of transfer learning diminish. Generally, loss is considered a more robust metric than accuracy for model performance on future data as it measures the distance between model predictions and ground truth labels, whereas accuracy simply measures a binary true/false score. However, accuracy still provides useful information regarding model performance. In particular, the transfer learning model shows a stable relationship between maximizing model accuracy and minimizing model loss (gap between black and red circles is very small for all training subset sizes), where the training strategy of minimizing model loss appears to achieve the same goal as maximizing model accuracy, again a sign of reduced overfitting. The re-initialized model (black and red triangles), on the other hand, shows a much less stable relationship in this regard, with diverging training scores (Fig 4) indicating that high model accuracy comes at the cost of higher model loss and low model loss comes at the cost of lower model accuracy for these small training set sizes when transfer learning is not employed. The increased model loss for model weights with highest model accuracy (black triangles) also suggests that the model has become overconfident in its predictions (it has large errors on the small proportion of labels it gets wrong) and is therefore likely to perform worse on out-of-distribution

data, with more false or missed phase arrival detections (e.g., a phase arrival being labelled as noise with high model confidence, or vice versa).

Model performance between the two approaches (transfer learning vs re-initialization) converges as training set size increases, indicating that the need for transfer learning decreases with increased training set size, as expected. In fact, model performance with transfer learning appears to plateau, or possibly even degrade, at training subset sizes of more than 1500 samples. This suggests that, with enough training data, transfer learning could potentially inhibit the model's ability to learn useful features in the new data that are absent in the original GPD training data. This apparent variance in performance may also simply be a result of the stochasticity arising from training using randomized weights in the new part of our transfer learning model.

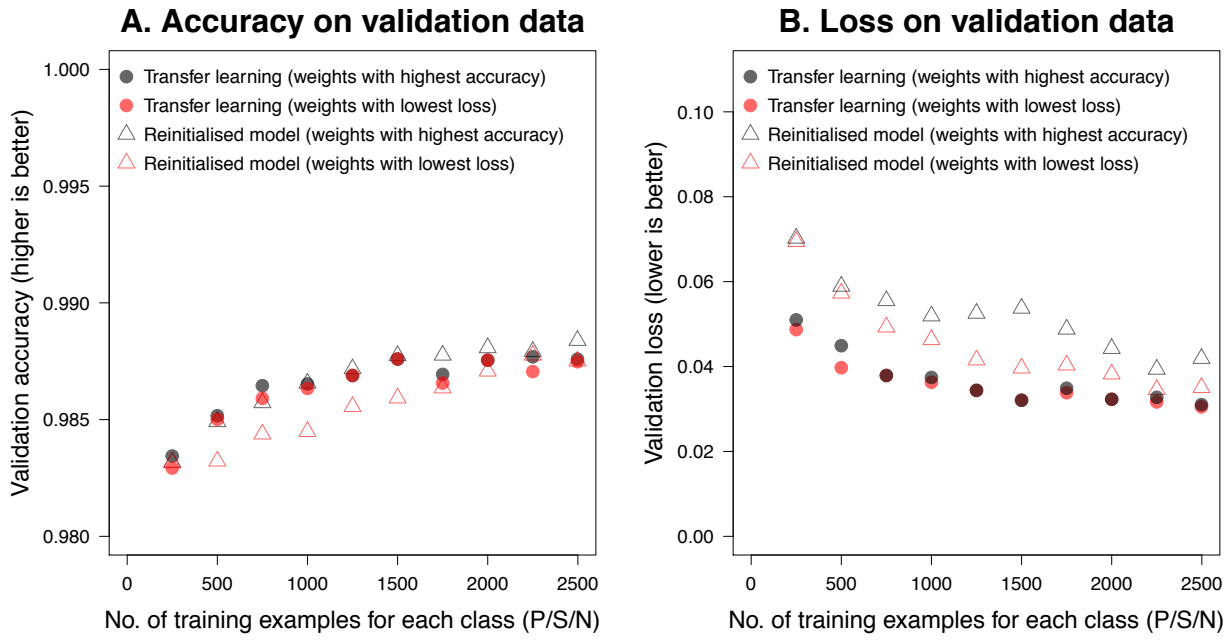


Figure 4. Model accuracy (**a**) and loss (**b**) for various subsets of training data. Open red circles are transfer learning model weights from epoch that achieves lowest validation loss (e.g., dashed horizontal lines in Fig 3), open black circles are transfer learning model weights from epoch that achieves highest validation accuracy, solid red triangles are re-initialized model (no transfer learning) weights from epoch that achieves lowest validation loss, and solid black triangles are re-initialized model weights from epoch that achieves highest validation accuracy.

496

497 **5.2 Test Dataset (Known Arrival Times)**

498

499 Following model training, we test the above models (i.e., new model with and without
500 transfer learning) and two baseline models (GPD and PhaseNet) using the test dataset outlined in
501 Section 4. We examine the proportion of correct class predictions (Fig 5) and the residuals between
502 model and manually determined phase arrival pick times (Fig 6). Due to differences in model task
503 types (classification vs segmentation), we apply all models as sliding windows over 1000-sample
504 waveforms (note that the PhaseNet model takes a 3000-sample waveform as input so we examine
505 only the middle 1000 samples for this model). To account for human picking error in collating our
506 test set, we define a true positive for each phase arrival type (P or S) as the model prediction
507 exceeding a given threshold value for that arrival type within 0.5 secs of the manually determined
508 arrival, such that predicted arrival times very close to the manually determined arrival time are
509 considered accurate. A true positive for sections of noise is defined as no phase arrival prediction
510 exceeding a given threshold value at any point within that section of data. The test data are pre-
511 processed as per the training data for each model (i.e., GPD model tested on 2 Hz high-pass filtered
512 data and all other models, including PhaseNet, tested on raw data; all detrended and self-
513 normalized).

514

515 The GPD model is tested using four different threshold values (Fig 5A – D) as this value
516 strongly controls the number of false or missed phase arrival detections generated by this model.
517 When the threshold is set to be whichever class label (P, S or N) has the highest predicted value
518 for a given waveform, nearly all P- and S-wave arrivals are detected by the GPD model (99.75 %
519 and 95 % detection rate, respectively; Fig 5A). However, this threshold criterion makes the GPD
520 model extremely prone to false phase arrival detections in sections of noise, with 44 % of 1000-
521 sample noise waveforms in our test dataset containing at least one false phase arrival detection
522 (Fig 5A, bottom right square) and many of our 1000-sample event waveforms containing multiple
523 phase arrival triggers (not shown). When this threshold criterion is applied to continuous sections
524 of data from Nabro, the number of false phase arrival detections overwhelmingly outweighs the
525 number of true phase arrival detections and becomes unmanageable in terms of correctly

associating phases, identifying true events and processing the data within computational memory constraints.

One way to lower the number of false phase arrival detections is to use a higher threshold value for P- and S-wave predictions. Figure 5B shows the GPD model's performance on our test data using a 0.9 threshold value (i.e., a P or S prediction 'probability' must exceed 0.9 to be included). The number of false detections in sections of noise is greatly reduced (down from 44 % of waveforms to 10 % of waveforms) but at the cost of reduced true phase arrival detections (~ 95% and ~82% of P- and S-wave arrivals, respectively). Part of this performance dip is undoubtedly due to the difference in sample rates between one half of the test data (50 Hz) and the GPD model's training data (all 100 Hz). When the threshold value is increased further (i.e., P or S prediction must exceed 0.95 or 0.99; Fig 5C and D), the GPD model yields even fewer false phase arrival detections in noise sections but at the cost of fewer P- and S-wave arrivals.

Figure 5E shows the performance of the PhaseNet model on our test dataset. This model is included as it adopts the same U-Net segmentation approach as our new model and is trained on data from a variety of instrument types, although the training data is still exclusively from southern California. The PhaseNet model is much less prone to false phase arrival detections than the GPD model (Fig 5E, bottom right square); as such, a much lower threshold value (0.4) can be used to maximize the number of true phase arrival detections. This model accurately identifies ~ 89% and ~ 83 % of P- and S-wave arrivals in our test dataset, which is better than the GPD model with a threshold value that achieves a similar false detection rate (e.g., Fig 5D), but detects fewer phase arrivals than our transfer learning and reinitialized models trained with Nabro data (Fig 5F – I).

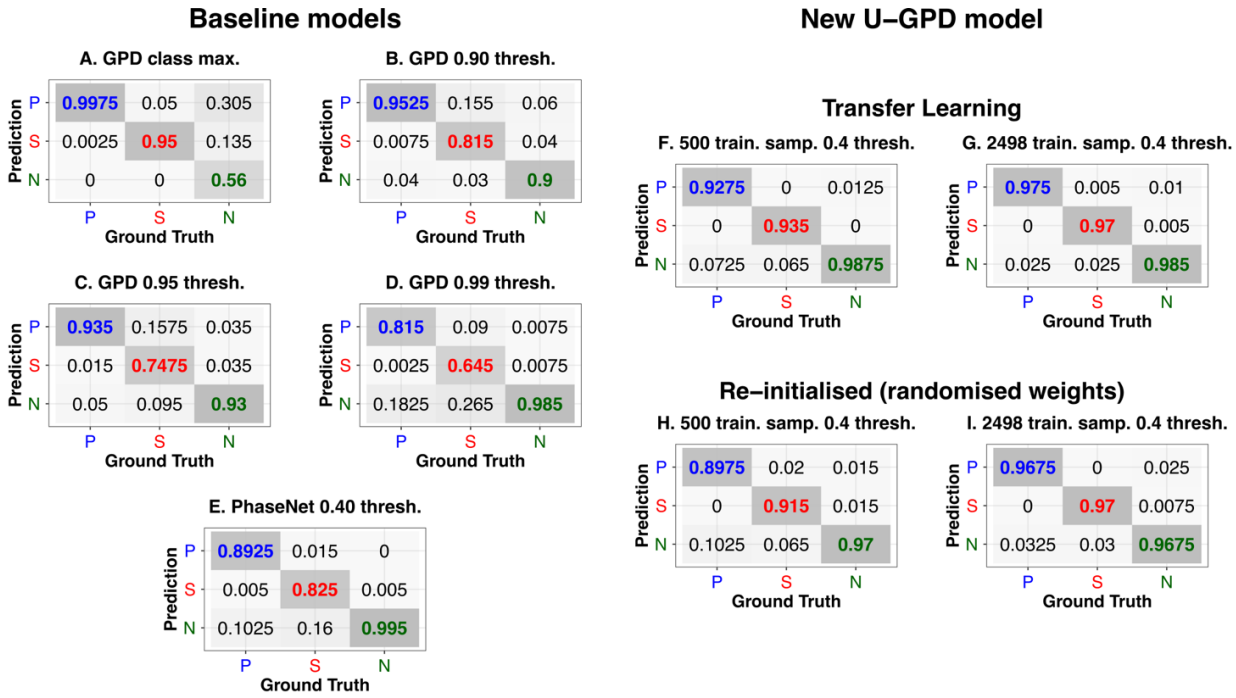


Figure 5. Confusion matrices for base GPD model (**a** – **d**), PhaseNet model (**e**), U-GPD transfer learning model (**f**, 500 training samples, and **g**, 2498 training samples) and re-initialized model (**h**, 500 training samples, and **i**, 2498 training samples). Values in matrices are proportion of ground truth phase arrivals assigned by each model to a given class (values of 1 along diagonal from top left to bottom right means all phase arrivals and sections of noise correctly identified).

When trained using a subset of just 500 training samples for each class (P/S/N) and evaluated using a prediction threshold value of 0.4, the transfer learning approach correctly detects ~ 93% and ~94% of P- and S-wave arrivals with very few false phase arrival detections in sections of noise (~ 1 %; Fig 5F), a clear improvement over our model trained with re-initialized weights and the same training subset (Fig 5H). When our full training dataset is used (2498 samples for each class), model performance converges between transfer learning (Fig 5G) and re-initialization (Fig 5I), with a similar number of correctly identified phase arrivals and false detections in noise, although the transfer learning model still performs marginally better, particularly on sections of noise. In essence, the transfer learning model strikes a better balance between high phase arrival detection rate (~ 97 – 98% for each phase arrival type; Fig 5G, top left and center squares) and low false detection rates in sections of noise (~ 1%; Fig 5G, bottom right square) on our test data from

Nabro volcano than any of the existing baseline models (Fig 5A – E) or training a model from scratch (Fig 5I).

Figure 6 shows the residuals for each model between their predicted phase arrival times and the original manual pick times for these test waveforms. Predicted phase arrival times were determined using a simple trigger algorithm (e.g., Withers et al., 1998) on each model's probability time series with the time series index that yields maximum predicted value chosen as the pick time for a given phase arrival type. The models that employ semantic segmentation (i.e., PhaseNet, our U-GPD transfer learning model and our re-initialized model; Fig 6B – F) show comparable pick time precision (root mean square deviation [RMSD] of 0.036, 0.038 and 0.044 seconds, respectively, for each model's P-wave predictions and RMSD of 0.053, 0.053 and 0.065 seconds, respectively, for each model's S-wave predictions), with no predicted arrival times more than 0.3 seconds before or after the manually determined pick time, regardless of training dataset size. The GPD model (Fig 6A), by comparison, has a more diffuse range of phase arrival pick times (RMSD of 0.217 seconds for P-waves and 0.188 seconds for S-waves), with some model picks made more than 1 second before or after the manually determined arrival time. This is almost certainly a result of its more ambiguous class labelling (Fig 1) and the broad phase arrival probability peaks it generates.

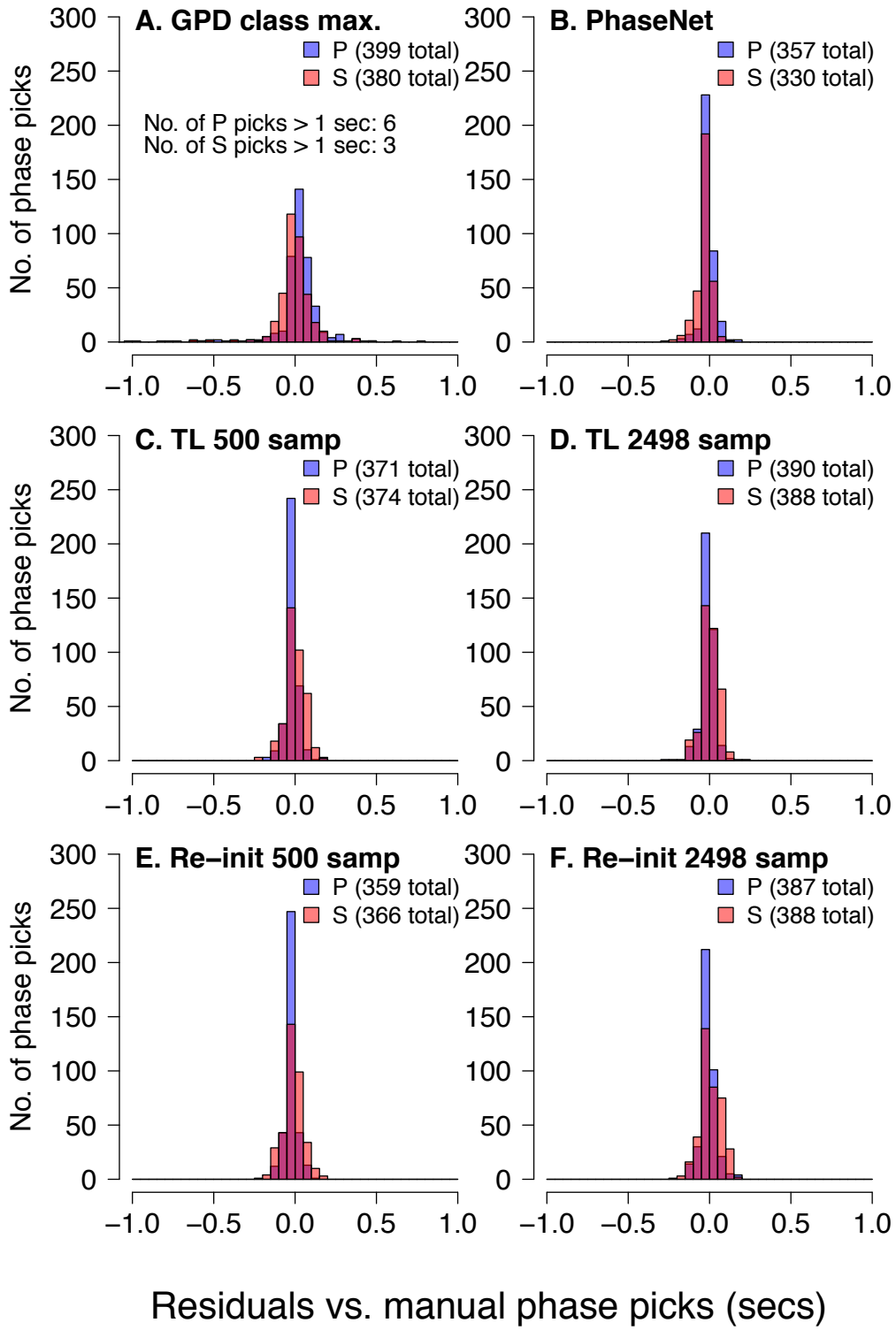


Figure 6. Model phase pick residuals vs. manual phase picks for base GPD model (**a**), PhaseNet model (**b**), U-GPD transfer learning model (**c**, 500 training samples, and **d**, 2498 training samples),

and reinitialized model (**e**, 500 training samples, and **f**, 2498 training samples). The models based on semantic segmentation (**b – f**) yield smaller phase pick residuals.

5.3 Full 14-Month Deployment (Unknown Arrival Times)

Whilst evaluating model performance on individual, manually scrutinized waveforms is useful for benchmarking and yielding estimates of model efficacy, the model's performance in a 'real-world' setting is ultimately of most importance to seismic analysts. Evaluating such performance is inherently more challenging, however, as the number of events in long sections of monitoring data and their respective phase arrival times are unknown, and other considerations, such as computational time and resources (e.g., memory requirements and availability of optimized hardware), affect model feasibility as a monitoring tool.

In this section, we present results of our best performing model in the prior section (U-GPD transfer learning model trained with full training dataset of 2498 samples of each class) and the original base GPD model when run over the full 14-month Nabro seismic deployment (Fig 7). As with the test dataset in Section 5.2, phase arrivals are detected at individual stations through a simple trigger algorithm, where an arrival is detected if the probability assigned to that class label (P or S) exceeds a given threshold (e.g., 0.4 for our U-GPD transfer learning model). The phase arrival time is determined as the waveform sample with the highest probability for that phase.

The U-GPD transfer learning model was applied to the data as a sliding window with 50 % overlap (i.e., applied at 'time shifts' of 200 samples) over 24-hour sections of data from each individual station. The model takes 5 seconds to process 24 hours of 3-component data at 100 Hz sample rate (or 3 seconds per day at 50 Hz sample rate) on a single graphics processing unit (GPU; NVIDIA GeForce RTX 2080 Ti), a rate many orders of magnitude faster than 'real-time' even when run on hundreds of stations. To avoid poor predictions due to window edge effects, only the middle 200 sample predictions out of 400 from each window are used to predict phase arrivals and are concatenated to produce one long continuous prediction trace without overlap or gaps and with the same sample rate as that of the input signal (i.e., 100 or 50 Hz). With all other processing steps (e.g., software initialization, data read/write, signal windowing, running trigger algorithm, etc.),

623 the U-GPD transfer learning model picks phase arrivals at all 7 available stations from the full 14-
624 month deployment in less than 4 hours using a single GPU (greatly reduced when parallelized over
625 multiple GPUs), indicating that it could easily be used within real-time monitoring constraints.
626
627 Conversely, as the GPD model produces only one class prediction per window (Fig 1A),
628 we apply this model with much greater overlap (97.5 %; every 10 samples of data) and with
629 varying threshold values (0.9, 0.95 and 0.99) for phase arrival detection triggering. This generates
630 a prediction trace with a much coarser sample rate than the original input signal (i.e., from 100 or
631 50 Hz to 10 or 5 Hz, respectively) and takes 26 seconds per 24 hours' 3-component data at 100 Hz
632 sample rate (or 15 seconds per day at 50 Hz sample rate) on the same NVIDIA GPU, approximately
633 a five-fold increase in computational time with a tenth of the temporal detail. With all other
634 processing steps, the GPD model took almost 50 hours to run over the full 14-month deployment
635 using a single GPU, more than a ten-fold increase in computational time over the transfer learning
636 model, due to more (pre-)processing required (e.g., more signal windows generated and
637 subsequent processing). Assuming a linear increase in computational time, running the model as a
638 sliding window over every sample of data would take ~ 260 seconds per 24 hours' 3-component
639 data at 100 Hz sample rate and ~ 500 hours (nearly 3 weeks) for the full 14-month deployment and
640 7 stations. While this is still faster than real-time, these timescales for a single or limited number
641 of station(s) could become limiting when applied at hundreds of stations, particularly without high
642 performance computing resources.
643

644 **5.3.1 Phase Association Method**

645
646 Both models detect P- and S-wave phase arrivals but do not associate them to the same
647 event. To assess the number of locatable events detected, we group P-wave phase arrival triggers
648 into 4-second bins and keep only bins with arrivals detected at four or more stations. This bin size
649 was chosen to encompass the maximum plausible travel time between any two stations. If multiple
650 arrivals were detected at the same station within a 4-second bin, the detection threshold was
651 increased for all arrivals in that particular bin to retain only the highest probability phase picks. If
652 any of these bins now had arrivals at less than four stations, as a result of removing lower

probability phase picks, they were discarded as there would be too few stations to constrain event location. If there were still multiple arrivals present at any given station, only the arrivals with highest probability for each station were kept. Finally, if phase arrival bins intersected (a subset of one bin was contained in another), the bin with highest mean probability was kept. This association method is clearly quite crude, and only works for small, local arrays, but allows a broad evaluation of model performance at detecting phase arrivals.

We associate S-wave arrivals to their corresponding P-wave arrivals by first locating events using NonLinLoc (e.g., Lomax et al., 2000), a widely used software package for probabilistic earthquake location, using the P-wave arrival bins outlined above and a simple 1D velocity model (Fig 7A). The difference between P-wave arrival and event origin times were used to predict which S-wave arrival detections should be associated with each P-wave arrival using a Vp/Vs ratio of 1.76 and S-wave travel time error of 0.25 (25%). S-wave arrival triggers that lay within this error bound for each detected P-wave arrival were associated to that event. S-wave arrivals at stations without a detected P-wave arrival were not included. All events were then located again in NonLinLoc using all included phase arrivals (Fig 7B).

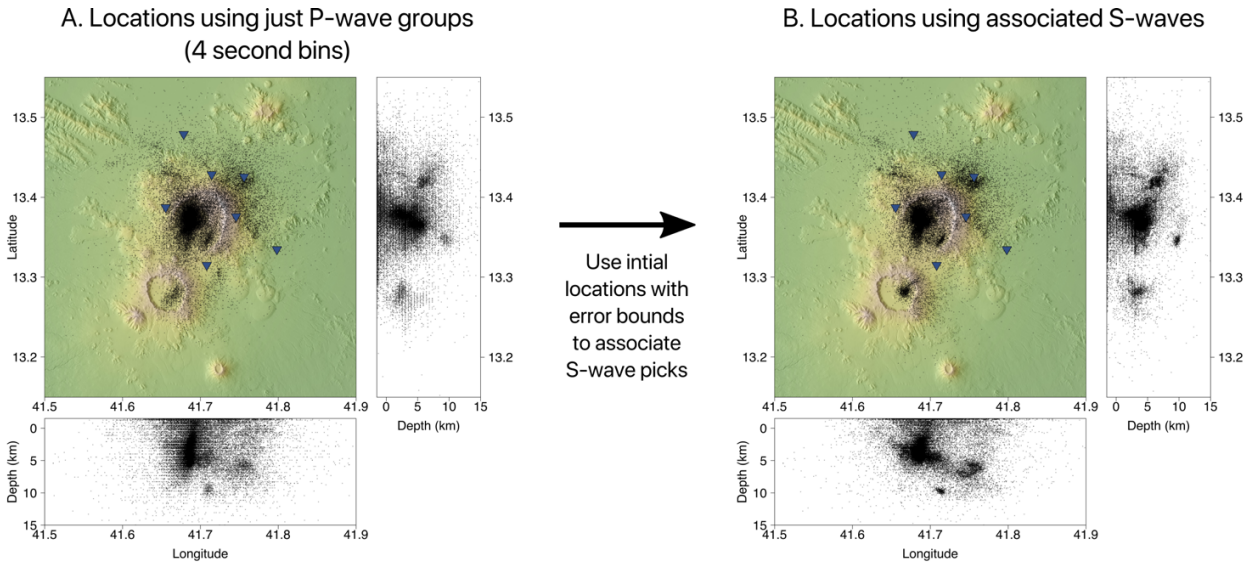


Figure 7. U-GPD transfer learning model event locations (total no. of events = 33,950) using automated phase association strategy. **a)** P-wave phase arrival triggers are grouped into 4 second

bins and these groupings are used to obtain initial event hypocenters and origin times. **b)** S-wave phase arrival triggers are associated to P-waves in (**a**) using initial origin times, a Vp/Vs ratio of 1.76 and a travel-time error of 25 %. Events are then located again using all included P-wave and S-wave arrivals.

5.3.2 Detected Events and Location Errors

Figure 8 shows the cumulative number of events detected by the U-GPD transfer learning model (threshold value of 0.4; black solid line) and the original GPD model (threshold values of 0.9, 0.95 and 0.99; grey lines). The cumulative number of events from an existing manual catalogue for this deployment (Goitom, 2017; Hamlyn et al., 2014), some of which provided the transfer learning model training data, is also given for reference. When only P-wave arrivals are used (Fig 8A), the GPD model with detection threshold of 0.9 appears to detect the most events (total no. of events detected by GPD model = 41,007; total no. of events detected by transfer learning model = 33,950). A threshold of 0.95 also detects more events than the transfer learning model until shortly after the switch in instrument sample rates from 100 Hz to 50 Hz. However, when we consider events with at least one associated S-wave arrival, the transfer learning model detects more events overall (Fig 8B; no. of events detected by transfer learning model = 31,387; no. of events detected by GPD model with 0.9 threshold = 26,808). This is consistent with the results from our test dataset in Section 5.2, with the proportion of S-wave arrivals accurately detected by the GPD model at these threshold values much lower than the proportion of P-wave arrivals detected (Fig 5B – D). Furthermore, 6 % of noise waveforms and 16% of S-wave arrivals from our test data were mislabeled by the GPD model (0.9 threshold value) as P-wave arrivals (Fig 5B), a higher rate of false detections or labels than the transfer learning model (1 % of noise sections and 0.5% of S-waves, respectively; Fig 5G). This means that a higher proportion of the P-wave groupings detected by this model with 0.9 threshold value are likely to include mislabeled S-waves or false arrivals.

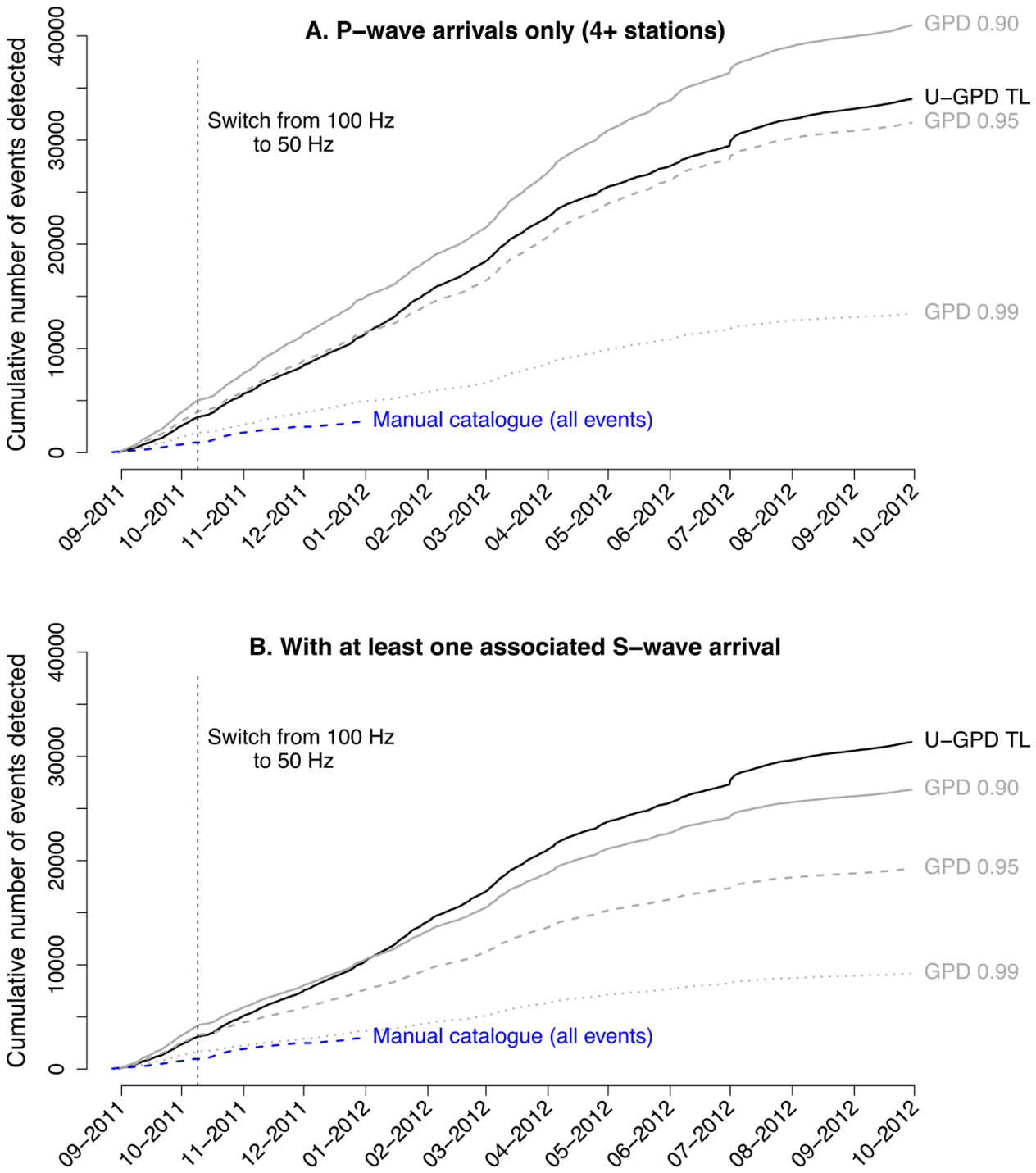


Figure 8. Cumulative number of events detected by GPD model (various thresholds, grey lines) and transfer learning model trained on full Nabro dataset (2498 samples of each class, 0.4 threshold, black line). Blue dashed line is existing manual catalogue (Goitom, 2017). All training / validation waveforms are from dates before switch in sample frequency (vertical dashed line). **a)**

708 Cumulative number of events detected using P-wave arrivals only (see main text for event binning
709 procedure). **b)** Cumulative number of events with at least one associated S-wave arrival.
710
711 To scrutinize these results further, we examine the number of stations with P- and S-wave
712 arrival detections per event (Fig 9A – B). In general, the events detected and picked by the U-GPD
713 transfer learning model include more stations and considerably more S-wave arrivals than those
714 picked by the GPD model, although the number detected by the GPD model may have been
715 reduced by using a coarser prediction trace (every 10 samples, a requirement to reduce model run
716 time to a reasonable timeframe). This increase in the number of stations and S-wave arrivals per
717 event will constrain event locations, as seen in the location errors derived from the models' phase
718 arrival picks (Fig 9C – D).
719
720 The horizontal errors (Fig 9C; standard deviation of estimated Gaussian error distributions)
721 for the locations produced using the transfer learning model pick times are comparable to the
722 existing manually picked events. Furthermore, vertical (depth) errors are much improved over the
723 manual catalogue (Fig 9D), likely reflecting more consistency in S-wave arrival picking than that
724 of a manual analyst. The GPD model, by comparison, produces a more diffuse range of horizontal
725 and vertical errors, which is likely to be a combination of coarser prediction trace, poorer pick
726 precision (Fig 6A), lack of S-wave arrivals (Fig 9B) and false/mislabeled P-wave arrival detections
727 (Fig 5B). This interpretation is further supported when we look at the number of event locations
728 lying within the array (i.e., event locations lying within the convex hull of station coordinates) for
729 each model: NonLinLoc locates more events within the array using the transfer learning picks (n
730 = 23,859) than using the GPD model with 0.9 threshold value (n = 22,826). While we expect many
731 events to occur outside of the array (e.g., at neighboring faults or volcanic centres), this metric
732 shows that a much larger proportion of event locations detected by the GPD model lie away from
733 the volcanic edifice, which may reflect poorer pick precision, false/mislabeled arrivals or coarser
734 prediction trace, but may also reflect the event types (i.e., regional tectonic) that the original model
735 was trained on.
736

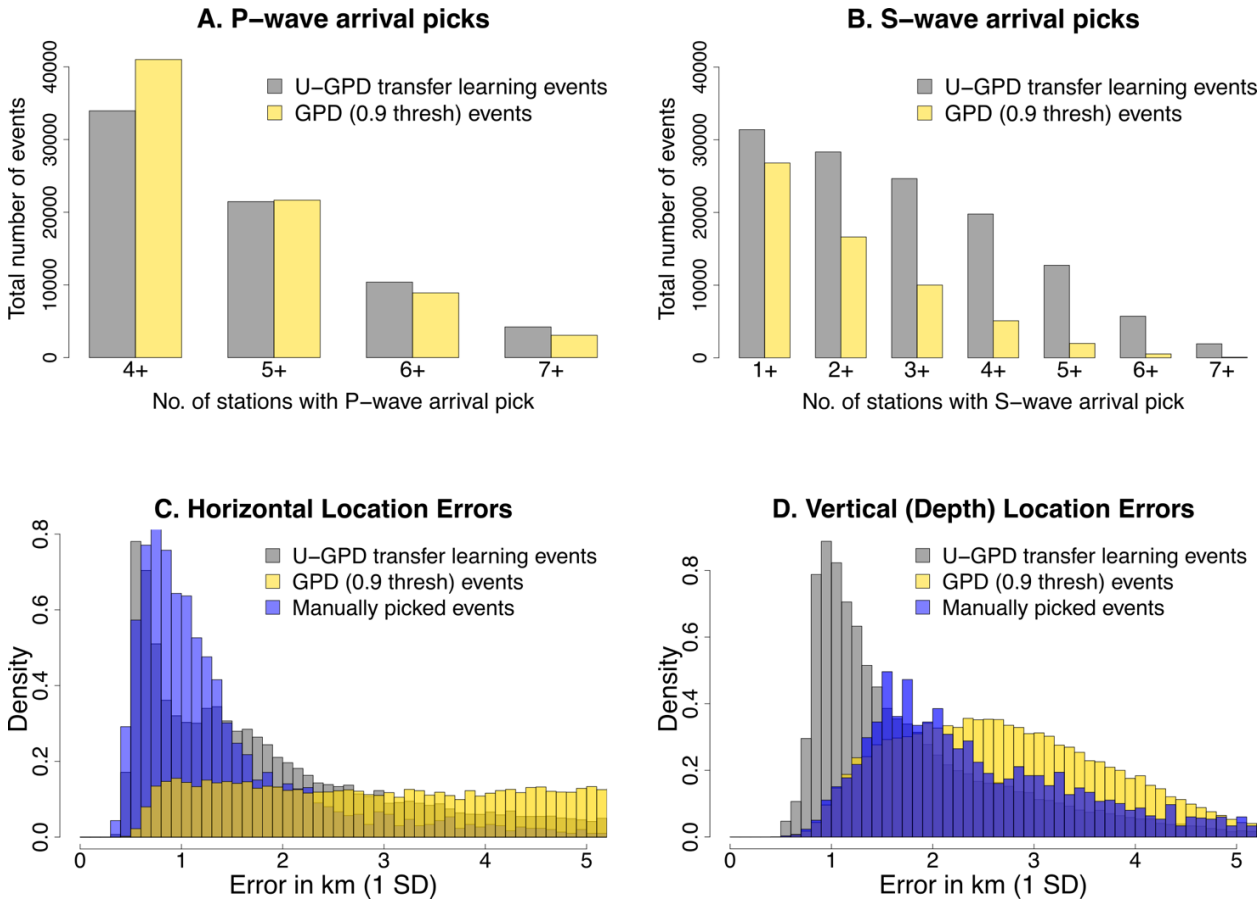


Figure 9. a) Number of P-wave arrival picks per event for transfer learning model (grey) and base GPD model (gold). **b)** Number of S-wave arrival picks per event. **c)** Histogram of Gaussian horizontal location errors (1 standard deviation) for events picked by transfer learning model (grey) and base GPD model (gold), and those in the existing manual catalogue (blue). **d)** Histogram of Gaussian vertical (depth) location errors (1 standard deviation).

6 Discussion

Transfer learning using existing seismological deep learning models can be a highly effective strategy to automate phase arrival picking in settings with little or no prior monitoring. We demonstrate that, with a limited number of hand-labelled waveforms (on the order of hundreds to low thousands) and a few minutes of training time, one can produce a consistent and effective

751 deep learning model for phase arrival detection that requires no other manual intervention or tuning
752 and can process years of data in a matter of hours.
753
754 For small training datasets, the use of pre-existing, generalized CNN filters greatly reduces
755 model overfitting (i.e., model parameters 'memorizing' the training data) when compared with
756 training a model from scratch (Fig 3) and yields a more stable relationship between maximizing
757 model accuracy and minimizing model error (Fig 4). Furthermore, when combined with a good
758 data augmentation strategy, transfer learning can also address the issue of processing data when
759 instrument sample rates differ from those used to train existing models. When applied to data from
760 Nabro volcano, augmenting our training set with decimated waveforms greatly improves model
761 performance on lower sample rate data (Supplementary Materials). As such, hand-labelled training
762 data from the first 35 days of the deployment (all 100 Hz sample rate) were sufficient to detect
763 phase arrivals throughout the duration of the deployment, even after instrument sample rates were
764 switched to 50 Hz (Fig 8). Without this data augmentation step, model performance on lower
765 sample rate data declines dramatically (Supplementary Materials). This shows that where sample
766 rates are altered or new instruments added during a seismic deployment, data augmentation can
767 overcome the cost of collecting further hand-labelled data and allow models to be adapted cheaply
768 and quickly throughout the deployment.
769
770 The introduction of new, task-specific data and the change in model task from one of
771 classification to one of segmentation also improves our U-GPD model pick time precision (Fig 6),
772 the number of stations per detected event (Fig 9A), the number of S-wave arrivals detected (Figs
773 5 and 9B) and computational efficiency over the original base GPD model, as well as potentially
774 reducing the number of false/mislabeled P-wave detections (Fig 5) and increasing the number of
775 identified events that relate directly to volcanic activity (evidenced by the increased number of
776 events located within the array). Without manual intervention or sophisticated phase association,
777 phase arrival picks from the U-GPD transfer learning model produce locations with smaller depth
778 errors than the base GPD model and even manually determined phase arrival times (Fig 9D). This
779 is likely a result of more consistent picking and labelling, particularly for S-wave arrivals, which
780 is difficult even for manual analysts to perform consistently, and suggests that very few of the
781 events detected are false.

Given the greatly improved computational time over the base GPD model, the small number of training events required and the use of a high-level, user-focused programming library (Keras), this approach is well within the reach of volcano observatories and research groups. Previous studies that analyze the pre-, syn- and post-eruptive periods at Nabro volcano have relied on manually-produced seismic catalogues comprising hundreds of events (e.g., Goitom et al., 2015; Hamlyn et al., 2014; the latter locating 658 events over 38 days, a rate of < 18 events per day). Our U-GPD transfer learning model yields a seismic catalogue that is order of magnitudes larger (33,950 events over 396 days, a rate of > 85 events per day; Figs 7 and 8), with smaller location errors (Fig 9), in a matter of hours. Furthermore, as the model processes 1D waveform data, as opposed to 2D spectrogram images in some other existing models (e.g., Dokht et al., 2019; Lara et al., 2020; Titos et al., 2020), it runs quickly on high resolution data without using a GPU optimized for deep learning frameworks (32 secs per 24 hours of 100 Hz data on an Intel Core i7 desktop CPU) and so could easily be deployed for real-time monitoring with limited computing resources or at much larger arrays. The methods and computational times in this paper have relied on standard, generic libraries (ObsPy, TensorFlow and Keras); the use of more optimized, compiled code or higher-performance / lower-level languages (e.g., Julia and C) could greatly improve computational times further.

Beyond phase arrival picking, the generalized waveform features extracted by existing, extensively trained models, such as the GPD model (Fig 1A), could serve as a useful feature extraction system for models designed for other waveform processing tasks. For example, information regarding frequency content and orientation of seismic energy extracted by the GPD model (Fig 1A inset) could reasonably provide useful features for a new model designed to automatically classify volcano seismic event types (e.g., Bueno et al., 2020; Hibert et al., 2017; Lara et al., 2020), particularly when available annotated datasets are small or unbalanced. However, with larger datasets, there is the potential for transfer learning to inhibit learning of new, useful features, particularly if the source and target tasks or data distributions differ considerably.

The number of seismological studies to date that employ transfer learning is relatively low (e.g., Bueno et al., 2020; Chai et al., 2020; El Zini et al., 2020; Huot et al., 2018; Titos et al., 2020).

This is undoubtedly, in part, due to the lack of extensively trained, well-documented, publicly available seismological models. However, the number is likely to grow as more extensive datasets and models are developed and released into the public domain. We credit the availability of the GPD model in the public domain and use of a popular, user-focused machine learning framework (Keras) as the foundation of the work presented in this paper. Such availability facilitates adaptation and experimentation; development of other publicly available models and extensive datasets would aid progress in the field of seismological machine learning.

Whilst the application of transfer learning can overcome the perception that deep learning models require a 'large upfront cost' in terms of data and computational resources, the development and benchmarking of large-scale, extensive models and datasets are still imperative to push the field of seismological machine learning forwards and extend applications to all aspects of seismic processing and inference. However, it is hoped that applications such as the one presented in this paper will motivate the initial investment in the development of such models so that the cost of producing effective task-specific models (e.g., through transfer learning) is progressively reduced.

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Data Availability Statement

All seismic data from the Nabro Urgency Array are publicly available through IRIS Data Services (http://service.iris.edu/fdnws/dataselect/1/). See http://www.fdsn.org/networks/detail/4H_2011/ for further details on data access and availability. Model training, validation and test sets / metadata are archived and available through Zenodo (Lapins et al., 2021; https://doi.org/10.5281/zenodo.4498549). Full code to reproduce our U-GPD transfer learning model, perform model training, run the U-GPD model over continuous sections of data and use model picks to locate events in NonLinLoc (Lomax et al., 2000) are available at https://github.com/sachalapins/U-GPD, with the release (v1.0.0) associated with this paper also archived and available through Zenodo (Lapins, 2021; https://doi.org/10.5281/zenodo.4558121).

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