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Eruption Forecasting Model for Copahue Volcano (Southern Andes) Using Seismic Data and Machine Learning: A Joint Interpretation with Geodetic Data (GNSS and InSAR)

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Abstract

Anticipating volcanic eruptions remains a challenge despite significant scientific advancements, leading to substantial human and economic losses. Traditional approaches, like volcano alert levels, provide current volcanic states but do not always include eruption forecasts. Machine learning (ML) emerges as a promising tool for eruption forecasting, offering data-driven insights. We propose an ML pipeline using volcano-seismic data, integrating precursor extraction, classification modeling, and decision-making for eruption alerts. Testing on six Copahue volcano eruptions demonstrates our model’s ability to identify precursors and issue advanced warnings pseudoprospectively. Our model provides alerts 5–75 hr before eruptions and achieving a high true negative rate, indicating

robust discriminatory power. Integrating short- and long-term data reveals seismic sensitivity, emphasizing the need for comprehensive volcanic monitoring. Our approach showcases ML’s potential to enhance eruption forecasting and risk mitigation. In addition, we analyze long-term geodetic data (Interferometric Synthetic Aperture Radar and Global Navigation Satellite System) to assess Copahue volcano deformation trends, in which we notice an absence of noteworthy deformation in the signals associated with the six small eruptions, aligning with their small magnitude.

Introduction

The capability to anticipate a volcanic eruption remains an elusive challenge in Earth science despite years of scientific research (Zobin, 2011; Acocella et al., 2023). This problem becomes especially important when devastating volcanic eruptions occur, which usually result in human and economic losses as well as environmental damage. Two examples of this are the 2008–2009 eruptive process of the Chaitén volcano (VEI 5; Major and Lara, 2013) in the southern Andes (Chile) and the 2019 eruption of the Whakaari volcano (VEI 2) in New Zealand (Dempsey et al., 2020). Although the former required the complete evacuation and subsequent relocation of the town of Chaitén, also affecting nearby forest vegetation and commercial air traffic, with a single casualty in the evacuation process, the latter fatally injured 22 of the 47 tourists and guides on the volcano. In the last 15 yr, more than 1000 people were killed in volcanic eruptions and the resulting hazards (Surono et al., 2012; Yamaoka et al., 2016; Brown et al., 2017; Naismith et al., 2019). Therefore, access to pre-eruption information linked to volcanic processes is essential for making informed decisions and implementing effective disaster mitigation strategies.

Traditionally, the information available on the status of a volcano (e.g., before an eruption) is summarized in its volcano alert level (VAL), which is based on the level of activity of the volcano (e.g., seismic activity, surface deformation, and/or emissions, thermal anomalies, among others; United Nations Disaster Relief Organisation [UNDRO], 1985; Fearnley et al., 2012). In the case of Chile, this classification consists of four levels (SERNAGEOMIN, 2018), ranging from green (no change in the volcano’s activity) to yellow, orange, and finally red (expected development of an eruptive event). VAL systems rarely provide an eruption forecast, which is generally undertaken as a separate activity, for example, by expert elicitation (Potter et al., 2014) or Bayesian Event Trees (Sobradelo

et al., 2014). Although these systems depend on quantitative input data, reaching a consensus among experts is essential for synthesizing observations and thus manually determining a threat level. This consensus often involves assessing data in comparison to pre-established geophysical thresholds. Therefore, the VAL serves as a description, reflecting an assessed condition such as unrest, eruption, or imminent and past hazards (Barberi et al., 2009; Suroño et al., 2012; Potter et al., 2014). This is distinct from a forecast, which entails predicting the probability of a volcanic eruption within a specific future timeframe (De la Cruz-Reyna and Reyes-Dávila, 2001; Tilling, 2008; Marzocchi and Bebbington, 2012; Poland and Anderson, 2020). Forecasting eruptions is challenging due to the complexity and seemingly individualistic nature of volcanoes (for a review, see Acocella et al., 2023). Moreover, published probabilities are subject to scrutiny after events (e.g., Dempsey et al., 2022), in which any missed eruptions or excessive false alarms can undermine public trust (Voight, 1990).

Forecasting typically relies on identifying anomalous patterns embedded within different types of data, such as Global Navigation Satellite System (GNSS; e.g., Lee et al., 2015), Interferometric Synthetic Aperture Radar (InSAR; e.g., Kobayashi et al., 2018), acoustic (e.g., Garcés et al., 1999), and/or seismic data (i.e., seismic precursors; Zobin, 2011), among others (for a review, see Acocella et al., 2023). In particular, given the high sampling rate that can be achieved with seismic data (e.g., 100 Hz) and the wide frequency spectrum that can be observed (e.g., 0.01–100 Hz, typically for broadband instruments), an important part of the research into volcanic eruption precursors has predominantly concentrated on volcanic tremors. Volcanic tremors are a continuous, long-period seismic signal typically within the frequency range of 1–10 Hz (Konstantinou and Schlindwein, 2003). These signals are thought to primarily originate from fluid-rock interactions in magmatic and hydrothermal systems, including the resonance of fluid-filled cracks and conduits (e.g., Rust et al., 2008) or gas dynamics (e.g., Girona et al., 2019). Given that the generation of tremors is often complex, and its wave field may be low-amplitude, long-lasting, and with a dynamic frequency content, seismic data are commonly analyzed in informative frequency ranges or by considering average measurements of the amplitude of the seismic signal in specific time windows. An example of this amplitude measurement is the real-time seismic amplitude measurement (RSAM; Endo and Murray, 1991), which can then be used for short-term prediction purposes (Chardot et al., 2015; Caudron et al., 2019; Dempsey et al., 2020; Ardid, Dempsey, Caudron, Cronin, Kennedy, et al.,

2023). However, to be useful for forecasting, eruption precursors should satisfy two criteria (Ardid et al., 2022): (1) they should reliably recur before most eruptions (i.e., a common pattern occurs before multiple events), and (2) they should be differentiable from noneruptive unrest or volcanic repose.

In this scenario, the use of machine learning (ML) techniques is an emerging tool for volcanic eruption forecasting (Carniel and Guzmán, 2021). In contrast to conventional methods that often rely on predefined rules or signals (e.g., volcano-tectonic [VT] tremors, long-period or very-long-period events), expert knowledge, and simpler models, ML techniques are characterized by their data-driven nature, adaptability, and ability to learn complex patterns. For example, using time-series feature engineering, Dempsey et al. (2020, 2022), Ardid et al. (2022), and Ardid, Dempsey, Caudron, Cronin, Miller, et al. (2023) were able to identify pre-eruptive patterns at different volcanoes from massive seismic data. In particular, under pseudoprospective testing conditions, Dempsey et al. (2022) were able to anticipate six out of seven eruptions at Whakaari (New Zealand) at the cost of 14 warning days each year. In a generalized way, Ardid, Dempsey, Caudron, Cronin, Kennedy, et al. (2023) trained ML models using waveform-derived features of 24 volcanoes around the world and found that numerous eruption precursors are applicable across various volcanoes, challenging the notion that volcanoes exhibit individualistic behavior. In addition, ML has been applied to analyze diverse forms of data, encompassing seismic (Rouet-Leduc et al., 2019; Manley et al., 2020; Ren et al., 2020; Majstorović et al., 2021; Mousavi and Beroza, 2023), GNSS (Costantino et al., 2023; Donoso et al., 2023; Xue and Freymueller, 2023), gas (Manley et al., 2021), and satellite data (Anantrasirichai et al., 2018; Biggs et al., 2022).

In this work, we use seismic data and the ML pipeline developed by Dempsey et al. (2020, 2022) for Whakaari (New Zealand) to both train and test an ML model in a different region in the Southern Andes. In addition, we assess the performance of the model in forecasting recurrent short-scale eruptions originating from the same volcanic source. To create our ML model, we use seismic data from the Copahue Volcano (Chile and Argentina, Fig. 1), which has been characterized by low-magnitude phreatic and phreatomagmatic eruptive pulses over the last two centuries (Caselli et al., 2016; Hantusch et al., 2021) and had six eruptive pulses between March 2020 and November 2021. We test our model under a cross-validation approach in which we leave one eruption out of the training dataset and test the model over the out-of-sample eruption (Fig. 1b). We then

116 use a receiver operating characteristic (ROC) curve as a metric to evaluate the performance of
117 the model when classifying pre-eruptive and noneruptive data. Finally, we analyze GNSS and
118 InSAR geodetic data from the volcano during the same period (this type of data is not used in the
119 construction of ML models due to its lower temporal resolution compared to seismic data). Our
120 results show that, in pseudoprospective, the model forecasts five of the six eruptions with different
121 alert times. This illustrates the variability of the pre-eruptive process even for the same volcano
122 and highlights the importance of carefully setting alert thresholds and determining appropriate alert
123 periods. In addition, our geodetic data results show long-term (years) signals likely associated
124 with cyclic inflation and deflation of the volcano without showing significant changes that allow
125 anticipating these eruptions, highlighting the need to integrate short- and long-term data to achieve
126 more integrated forecast models.

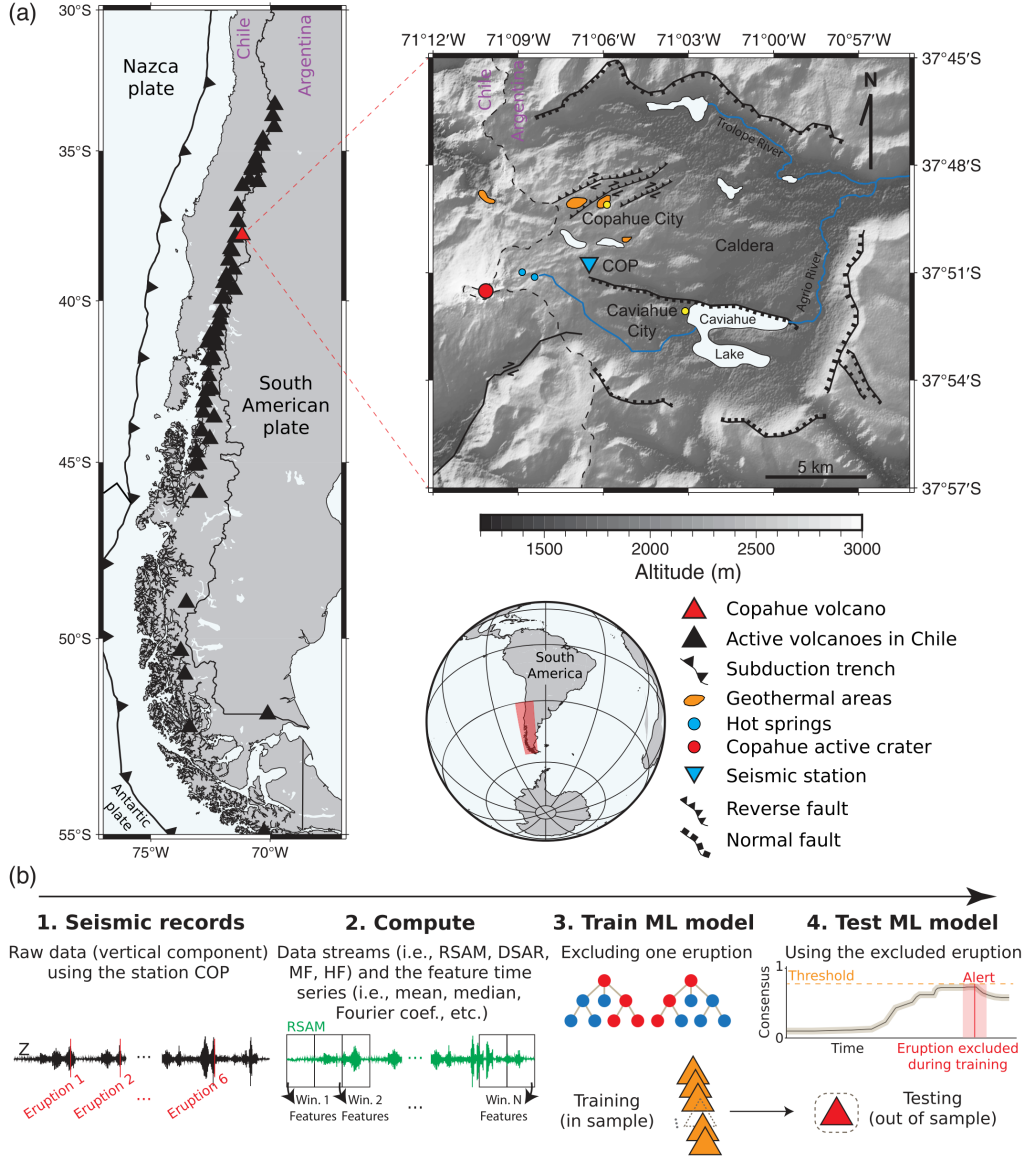


Figure 1. (a) Location map of the Copahue volcano (red triangle) and other active volcanoes in Chile (black triangles; SERNAGEOMIN, 2018). Inset: Location of the Copahue active crater (red dot), geothermal areas (orange marks), hot springs (blue dots), and the seismic station COP (light blue inverted triangle) used in this study. (b) The machine learning pipeline followed in this work (see the ML workflow section, for more detail).

Copahue Volcano

Copahue is an active stratovolcano that has had several eruptions of low-to-mid intensity in the past decades (VEI 1–2; Caselli et al., 2016) in the central part of the Southern Volcanic Zone (33–46° S) of the Andean arc (Fig. 1). The main vent is located at the western rim of the Agrio Caldera—a

rectangular intra-arc pull-apart basin of 300 km² (e.g., Folguera et al., 2016). Besides the Copahue volcano, the caldera has two main structures: a geothermal field with a production capacity >30 MWe (e.g., Barcelona et al., 2021) and an active fault system that constitutes vertical permeable pathways for magmatic fluid circulation (Lamberti et al., 2019; Montenegro et al., 2021). Several authors have conceptualized structurally controlled fluid circulation models for the Agrio Caldera (Tardani et al., 2021; Yagupsky et al., 2023) based on two magma sources (Lundgren et al., 2017): a shallower source located 2.5 km beneath Copahue’s vent and a deeper source located 7–10 km under the center of the caldera.

The crater of Copahue hosts an acid lake supplied by magmatic gas and meteoric waters (Agusto et al., 2017). Between 2012 and 2019, the eruptive activity showed a correlation with the charge–discharge cycles of the crater lake (Melchor et al., 2022). This activity is characterized by phreatic to phreatomagmatic explosions at the vent, high degassing rates of sulfur dioxide (SO₂; e.g., Tamburello et al., 2015), low-altitude ash, and vapor plumes that quickly bend to the volcanic edifice. Melchor et al. (2020) analyzed the seismicity recorded before and during phreatic explosions with ash emissions between June and August of 2020 (Table 1) and observed the presence of tremors in the band 1–3 Hz several hours before the surficial activity.

The eruptive activity of Copahue volcano is monitored jointly by the Observatorio Volcanológico de los Andes del Sur (OVDAS–SERNAGEOMIN) and the Volcanic Surveillance Observatory of Argentina (OAVV–SEGEMAR). The Global Volcanism Program chronologically summarizes the main eruptive activity based on reports from OVDAS, the Buenos Aires Volcanic Ash Advisory Center, and other remote-monitoring projects such as the Global Sulfur Dioxide Monitoring Group or the Middle InfraRed Observation of Volcanic Activity. Between June 2020 and September 2021, several phreatic-to-phreatomagmatic explosions (e.g., Hantusch et al., 2021) were reported by the OAVV and residents of Caviahue (Table 1)—an Argentinian village located ~10 km east from the vent (Fig. 1). These reported activities were identified within its normal activity with a VEI of 1–2 (Global Volcanism Program).

Given the phreatic–phreatomagmatic nature of the eruptive activity of the Copahue volcano, its forecasting poses an extra challenge (Barberi et al., 1992). Phreatic eruptions occur when water comes into contact with hot volcanic rocks, resulting in explosive steam-driven eruptions such as in Mt. Ruapehu (Christenson et al., 2010), Lascar (Gaete et al., 2019), or others (Barberi et al.,

1992). Unlike magmatic eruptions, phreatic events do not typically show clear precursory signs such as seismic activity or ground deformation. The mechanisms behind phreatic eruptions involve the sudden release of steam pressure generated from groundwater. Consequently, accurately forecasting these eruptions requires the detection of short-term (e.g., hours, days) anomalies.

Methodology

ML workflow

In this work, we employ the ML pipeline developed by Dempsey et al. (2020, 2022) and Ardid, Dempsey, Caudron, Cronin, Kennedy, et al. (2023), which is summarized in the following and schematically represented in Figure 1b.

Seismic data preprocessing. We use the continuous vertical component velocity data of the broadband station COP for the period 9 March 2020–19 November 2022. Following Dempsey et al. (2020), we adopt a singular component approach to maintain simplicity, which is particularly advantageous for potential real-time implementations in observatories. In addition, the vertical component is less prone to site effects. This station is part of the seismic network of the National University of Rio Negro (UNRN) and was deployed ~ 4.5 km away from the volcano crater (Fig. 1), recording (with a sampling rate of 100 Hz) the six eruptions indicated in Table 1.

TABLE 1

Dates of Phreatic Explosions Recorded between June 2020 and August 2021 (Global Volcanism Program, 2020, 2021)

Number of Eruption	Date (yyyy/mm/dd)
1	2020/06/16
2	2020/07/16
3	2020/08/06
4	2020/09/07
5	2021/07/02
6	2021/08/10

We remove the instrumental response and filter the records in four different frequency ranges (encompassing distinct aspects of the volcano-seismic signal) to produce four different data streams, each with a sampling rate of 10 min (Ardid et al., 2022; Dempsey et al., 2022). In addition to the physical processes related to each of the selected frequency bands (described in the following), these bands were also chosen considering the results of previous work at Whakari volcano using a methodology similar to ours (e.g., Dempsey et al., 2020, 2022) as well as previous results detecting fluid release episodes at Copahue and other volcanoes (e.g., Ardid, Dempsey, Caudron, Cronin, Miller, et al., 2023). In both cases, the same frequency bands were tested. The first frequency range is between 2 and 5 Hz, which focuses on volcanic tremor signals while excluding microseismic noise at low frequencies (e.g., Beroza and Ide, 2011). The filtered time series were divided into 10-minute windows without overlap, and the average absolute velocity for each window was calculated. Following Ardid et al. (2022) and Dempsey et al. (2022), we have termed this data stream RSAM, although we observe that RSAM is traditionally calculated using unfiltered data (Endo and Murray, 1991). We also calculate median- (MF) and high-frequency (HF) data streams using a similar approach as RSAM, with the distinction that we apply filtering within the 4.5–8 Hz range for MF and the 8–16 Hz range for HF. These two data streams are designed to examine the effects of signal attenuation occurring beyond the frequency range in which tremor energy is typically emitted (Caudron et al., 2019). The last data stream corresponds to the displacement seismic amplitude ratio (DSAR), which is calculated as the ratio of the integrals of the MF and HF data streams, as described in Caudron et al. (2019). High DSAR values have been associated with high gas levels in the edifice, indicating a potential decrease in fluid motion and/or trapping, leading to gas accumulation (Ardid et al., 2022; Ardid, Dempsey, Caudron, Cronin, Miller, et al., 2023).

We also removed earthquake signals such as regional earthquakes or VT earthquakes not associated with fluid dynamics because they disturb the temporal averaging of the data. For this, we applied the filter proposed by Dempsey et al. (2020) to the raw data before filtering. Specifically, we excised a 2-minute envelope from the raw velocity trace whenever its value exceeded five standard deviations above the mean of the data in the 10-minute window. Finally, linear interpolation was employed to fill in gaps in the data streams, and a subsequent down-sampling step minimizes their influence on the models because these gaps typically occur during noneruptive periods.

Feature calculation and labeling.

The four data time series generated in the previous step are segmented into windows spanning 48 hr each, in which each window contains 288 10-minute samples. We use this window based on previous work at Whakaari volcano (e.g., Dempsey et al., 2020, 2022; Ardid, Dempsey, Caudron, Cronin, Kennedy, et al., 2023) and the similarities between this volcano and Copahue volcano (e.g., both volcanoes have developed hydrothermal systems, with crater lakes and relatively small phreatic-style eruptions, VEI 1–2). For each of these windows in each data stream, we compute about 700 time-series features using the Python package tsfresh (Christ et al., 2018). Another advantage of computing features on RSAM, MF, HF, and DSAR windows over raw data is that the computational effort is reduced. Some examples of these features are distribution measures (mean, standard deviation, and number of peaks), linearity (slope and intercept of linear regression models), and correlation measures (Fourier coefficients and lags), among others (energy, entropy, and nonlinear scores). Each feature value is recorded in a matrix, with distinct columns denoting different features and rows indicating the end-time index for each window. It is important to observe that we use a 48-hour window because we focus on short-period fluctuations of the volcano (in addition, similar results for 24- and 72-hour windows are given in Fig. S1, available in the supplemental material to this article). On the other hand, Dempsey et al. (2020) explored a range of windows between 12 hr and 5 days at the Whakaari volcano (New Zealand) and found that the choice did not greatly impact the forecast accuracy. Similarly, but using template matching, Ardid et al. (2024) explored the use of different windows for different volcanoes (Copahue included) and found that some volcanoes are more responsive at some time scales than others. Further work to understand the sensitivity of window length at Copahue and other volcanoes may improve forecasts.

The next step in our workflow is labeling. Simply put, in this step, the windows are labeled as “pre-eruptive” or “noneruptive.” For this aim, we formulate a classification challenge that directs the algorithm’s focus to signals observed in the 48-hour time frame leading up to eruptions, denoted as the “look forward” window. All feature windows occurring within 48 hr or less before an eruption date receive a label of “1” (pre-eruptive), whereas the remaining windows are assigned a label of “0” (noneruptive). In the course of model training, we permit adjacent windows to overlap by 36 hr (equivalent to 75% of their length, i.e., 1968 windows). This approach enhances the probability of fully capturing a precursor pattern within at least one window, preventing its fragmentation by window boundaries. To address the imbalance between eruptive and noneruptive windows (i.e.,

eruptive windows likely represent a minority class compared to noneruptive windows), we implement a strategy of random removal of noneruptive “0” windows until a balanced dataset has been achieved. This is important to prevent bias toward the majority class (here, noneruptive windows) and ensure that the model can learn equally from all classes, leading to fairer predictions. This process is iterated multiple times to mitigate the impact of randomness on down-sampling. For more detailed information, refer to Dempsey et al. (2022).

Training and pseudoprospective forecasting. In the training phase of the model, we employ a cross-validation approach wherein we set aside data from one out of the six available eruptions. The model is then trained using the data from the remaining five eruptions and subsequently evaluated on the reserved eruption. This strategy is commonly referred to as leave-one-eruption-out cross-validation, as described in Ardid, Dempsey, Caudron, Cronin, Kennedy, et al. (2023).

By dividing the dataset into multiple subsets during training, we can assess how well the model performs on unseen data. This iterative process helps identify if the model is overfitting to the training data by evaluating its performance on various subsets. In addition, cross-validation provides more robustness to the model’s performance compared to approaches in which only a section of the data is used for training and another section for testing.

To address the classification task, we train a random forest algorithm. One key advantage of a random forest is its ability to estimate the importance of each feature in the classification process. This feature importance analysis can be valuable for understanding the relevance of different factors in predicting volcanic activity. Each model is constructed with a maximum of 200 distinct decision trees, individually trained on unique subsets of down-sampled windows. The implementation is carried out using the scikit-learn Python library (Pedregosa et al., 2011).

Testing is exclusively conducted on out-of-sample data reserved during the model training phase, simulating, though not precisely replicating, conditions encountered in future forecasting scenarios. This method, however, provides a more accurate evaluation of performance compared to a hindcast, in which test data are assimilated into the training set. The feature time series for the test data is generated by calculating them with overlapping windows of 48 hr, progressing at 10 min intervals, resulting in an overlap of 287 out of 288 samples. The intention behind this design is to mimic real-time volcano monitoring, in which data are interpreted as they are received. Features extracted from

each consecutive window are then fed into the trained random forest model. The binary outputs of individual decision trees are subsequently averaged to generate a value within the range of 0–1, denoted as the forecast model’s consensus (Fig. 1b). We then compare the consensus output with a predetermined threshold between 0 and 1 (see the next section, for more detail about the threshold estimation). If the consensus exceeds this threshold, an eruptive warning is created for the next 48 hr (the forecast’s look forward period).

Forecasting model assessment. The main scope of the model assessment is to evaluate the overall accuracy of out-of-sample datasets, encompassing the false positive rate (FPR; i.e., incorrect prediction that an eruption will occur) and the false negative (FN) rate (i.e., failure to predict an eruption). Accuracy can be assessed in both pseudoprospective and prospective scenarios, with the latter requiring real-time or future data to assess a fixed model (Dempsey et al., 2022).

To assess the model performance, we used cross-validation. This approach also allows for assessing the model’s ability to be generalized to new data or contexts. Leave-one-out cross-validation (LOOCV) involves training a model with all samples (e.g., eruptions) in a dataset except for a single one (Ardid, Dempsey, Caudron, Cronin, Kennedy, et al., 2023). The omitted sample is then used as a validation set to assess the model’s performance. This process is repeated for every sample in the dataset (six eruptions in our case), and the performance of all the models is combined to provide a comprehensive assessment of the model’s overall performance. Here, we applied LOOCV for every individual eruption. For the remaining noneruptive data, a single model was trained considering all the eruptions. Because of the under-sampling of noneruptive data for training, this model is considered approximately out of sample when applied to noneruptive data (Dempsey et al., 2020).

To measure the discriminability of the classification model, that is, its ability to correctly classify pre-eruptive and noneruptive data using different thresholds, we use the ROC curve (e.g., Dempsey et al., 2022; Ardid, Dempsey, Caudron, Cronin, Kennedy, et al., 2023). ROC curves plot the true positive rate (TPR; sensitivity) versus the FPR (1-specificity) at various threshold values. Consequently, they assess the forecast across a spectrum of threshold values. Thus, the trade-off between sensitivity and specificity helps identify an optimal threshold. The area under the curve (AUC) for the ROC curve serves as a unified metric for model performance across all thresholds, in which values approaching 1 indicate perfect performance.

We generated a ROC curve for our model as follows: (1) a threshold is selected (from 0 to 1); (2) the model consensus output over the whole period is evaluated against the threshold; (3) a true positive (TP) or true negative (TN) is scored in each window that the forecast agrees with the label: both “1” for TP or both “0” for TN; (4) a false positive (FP) occurs when the model predicts a “1,” but it does not match a corresponding “0” in the label vector; any other mismatches result in an FN; (5) the TPR and FPR are estimated as $TPR = TP / (TP + FN)$ and $FPR = FP / (FP + TN)$; (6) steps (1)–(5) are repeated by employing 100 uniformly distributed thresholds ranging from 0 to 1, and the resultant set of corresponding pairs constitutes the ROC curve; and finally, (7) AUC is calculated as the integral of the ROC curve.

Geodetic data and processing

GNSS. To characterize deformation, we use a set of four GNSS stations operated by the OVDAS, together with the GNSS network stations of the National Seismological Center of the University of Chile (see Data and Resources), data of which have been available since approximately 2014. All GNSS observations were processed in network arrays in a differential approach based on daily solutions (see Báez et al., 2018, for more details). For every station located around the volcanic area, we remove the tectonic effects using a set of stations closer to the study area (Novoa et al., 2019). As a result, we produced a time series that shows the deformation in the Copahue volcano area. The locations of the stations and examples of these time series are shown in Figure S1.

InSAR. We complement the seismic and GNSS observations with spaceborne InSAR data. InSAR provides observations of ground deformation with a high spatial resolution but low temporal resolution (6–12 days). In this study, we use Sentinel-1 C-band data (wavelength of ~ 5.5 cm) processed by the LiCSAR on the cloud processor by the Centre for the Observation and Modelling of Earthquakes, Volcanoes, and Tectonics (Lawrence et al., 2013; Wright et al., 2016; Lazecký et al., 2020; Morishita et al., 2023). The interferograms were automatically preprocessed using the GAMMA SAR software (Wegmüller et al., 2016) and then down-sampled to a pixel size of ~ 100 m. We used interferograms obtained from LiCSAR for descending track 83, frames 12832-131313 (083D_12832_131313), spanning February 2016 until the end of 2021.

We used the open-source package LiCSBAS to perform the InSAR time-series analysis (Morishita

et al., 2020). We apply corrections for tropospheric phase delays using the Generic Atmospheric
Correction Online Service data (Yu et al., 2017; Yu et al., 2018). Because the Copahue volcano is
prone to decorrelation in the winter (e.g., Fig. S3), we performed a manual quality analysis to discard
interferograms that have low coherence and are likely to contain phase unwrapping errors. LiCSBAS
uses a modified small baseline approach (López-Quiroz et al., 2009; Doin et al., 2011), in which the
displacement recorded by the individual interferograms was inverted with a least squares method to
reconstruct the cumulative displacement field. Afterward, the software carries out a pixel-by-pixel
linear inversion to retrieve the mean ground velocity (Morishita, 2021). The uncertainty in velocity
is estimated from the standard deviation using the bootstrap method (Efron and Tibshirani, 1986),
and finally, a spatiotemporal filter is performed to reduce the noise of the displacement time series. A
topographic correction was also applied, and a linear ramp was removed to reduce the residual long-
wavelength signals, which may be related to other tropospheric delays, ionospheric phases (Gomba et
al., 2016), orbital inaccuracies (Fattahi and Amelung, 2014), and any long-wavelength signal related
to subduction tectonics.

Results

Forecasting on Copahue eruptions

Figure 2 shows the temporal evolution of the out-of-sample consensus (see the Training and pseu-
doprospective forecasting section) 10 days before the six volcanic eruptions (Table 1). We observe
that for five out of the six eruptions, the consensus shows lower values (<0.5) at the beginning of
the time series, with subsequent increases (>0.5) in the last days before the eruptions. On the other
hand, the time series before eruption 4 shows the opposite behavior, with values around 0.8 until
two days before the eruption, in which a sharp drop to values close to 0.1 is observed (discussed
later in the Discussion section).

For illustrative purposes, Figure 2 shows a threshold of 0.7 (orange-dashed lines). This means
that an alert would be issued if the consensus exceeds the threshold and then rescinded when it
stays below the threshold for 48 hr. For this pseudoprospective test, we found that a threshold of
0.7 provides an advanced warning for five out of the six eruptions, not satisfying the criterion only
for eruption 4 (Fig. 2).

In the same way that the ability to anticipate an eruption is a fundamental part of the model performance so is the ability to correctly classify noneruptive periods as noneruptive. This avoids false alerts that lead to the loss of credibility for the forecaster. Figure 3 shows the temporal evolution of the consensus for the entire studied period and the occurrence of the six eruptions. The consensus consistently exhibits values below 0.5 for the majority of the time series, interspersed with intermittent episodes during which the consensus surpasses this value. The highest values (≥ 0.8) are in general observed in the vicinity of the eruption dates. In addition, the period between eruptions 3 and 4 stands out for having high consensus values close to 0.8 for a longer duration of time (~ 32 days; see also eruptive episode 4 in Fig. 2). This contrasts with the periods between eruptions 1 and 2 or 5 and 6, with similar durations but low consensus values close to 0.3. It is also interesting to observe that, in general, the behavior of the consensus is flat, except for what occurred after eruption 4 on 7 September 2020. For this period, a sustained decay is observed over time, lasting until approximately the beginning of 2021.

For real-time applications, the definition of an alert threshold is essential. One way to measure the model’s classification performance over a wide range of thresholds (i.e., 0–1 in our case) is using an ROC curve (Fig. 4; see the Forecasting model assessment section, for more detail), which can help identify an optimal threshold based on specific requirements and evaluate the performance of the model over the whole period. The AUC for our model is 0.88, indicative of its robust discriminability. A careful examination of the curve highlights that the best performance of the model is achieved with thresholds up to approximately 0.7, considering the data we have available.

Long-term geodetic data (InSAR and GNSS)

Here, we describe only the GNSS data for CPH and MLZS stations, which are the closest to the volcano (Fig. 5). Data recorded by the other stations (MHID and CAVH) are shown in Figure S2. Our analysis indicates that the GNSS time series projected onto the radar line-of-sight (LOS) agrees well with the InSAR time series. Therefore, both datasets record the same deformation process within their uncertainties and differences in spatiotemporal sampling (Fig. 5). From a long-term perspective, InSAR ground velocities calculated from time series show that Copahue volcano uplifted with a velocity of up to 6 mm/yr in the radar LOS between February 2016 and the end of 2021 (Fig. 5a). A close inspection of the GNSS time series (Fig. 5b,c and Fig. S2) shows that this

yearly average trend is composed of three distinct trends. These are (1) an episode of uplift with a total uplift of 3–4 cm lasting from September 2017 to March 2020; (2) an episode of subsidence of 2 cm from March 2020 until the end of the study period in late 2021; and (3) seasonal signals with peak-to-peak amplitudes of 1–2 cm. These trends are interpreted as a period of inflation and subsequent deflation on the volcano. None of the six eruptions that occurred during the period of this study were related to coeval ground deformation (i.e., deformation days before the eruptions) above the background level of noise in the data.

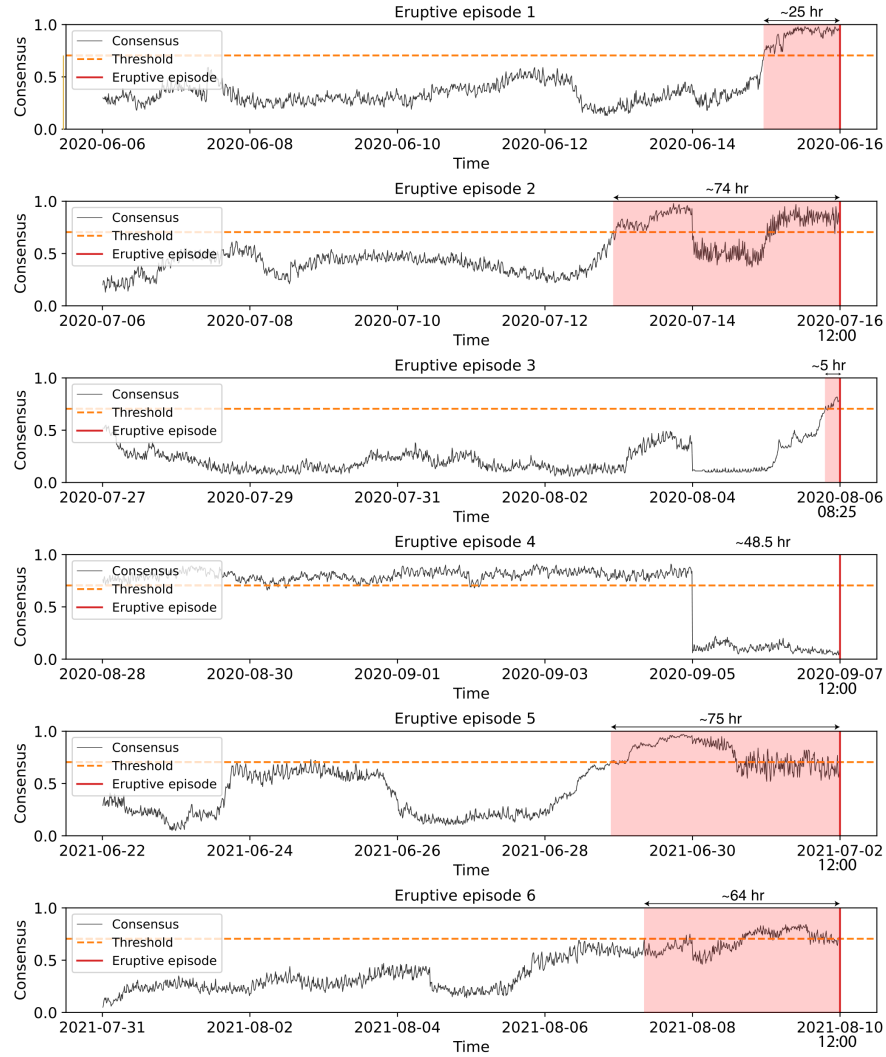


Figure 2. Temporal evolution of the consensus (black lines) 10 days before each volcanic eruption (red vertical lines). The consensus for each eruption is out of sample, that is, the estimated consensus with the model that does not see the corresponding eruption during training. For illustrative purposes, a threshold of 0.7 (orange dashed line) is plotted.

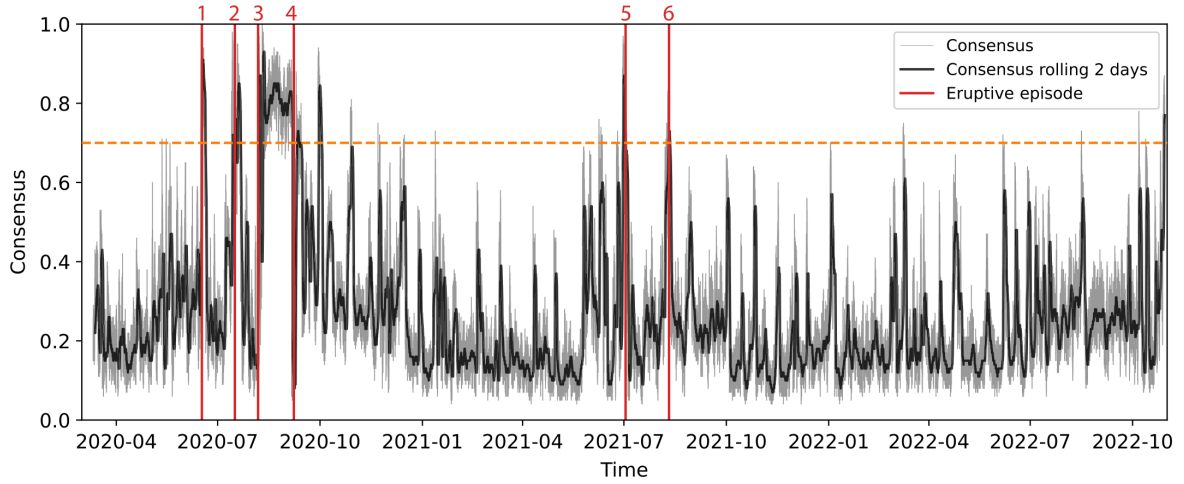


Figure 3. Temporal evolution of the consensus (gray line) over the analysis period. A rolling mean using a window of 48 hr is plotted in black to show a smoother representation of the general behavior of the consensus values. Volcanic eruptions are indicated by the vertical red lines. For illustrative purposes, a threshold of 0.7 (orange dashed line) is plotted.

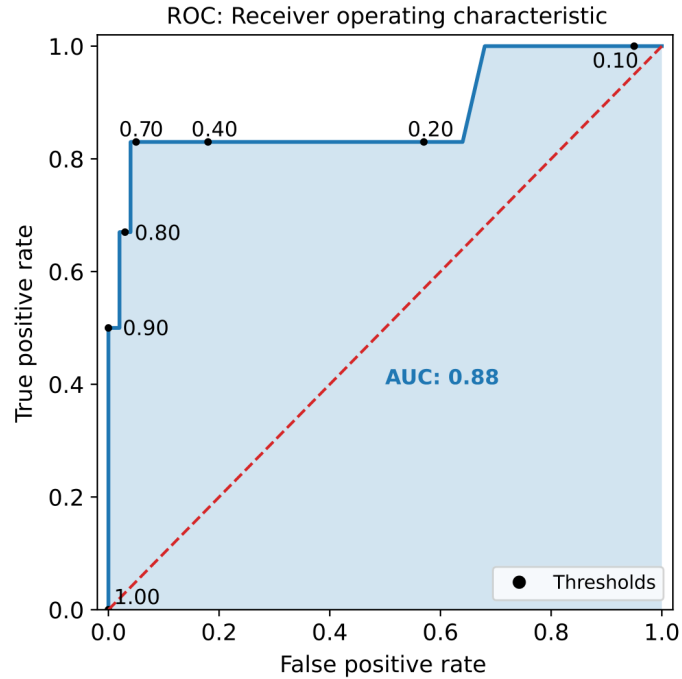


Figure 4. Receiver operating characteristic curve at different thresholds. The vertical axis represents the true positive rate (sensitivity), and the horizontal axis represents the false positive rate (1-specificity). The area under the curve is also estimated (0.88). The red dashed line represents the diagonal for illustrative purposes.

Discussions

Short-term forecasting model

Using a threshold of 0.7 for alert activation and a warning duration of 48 hr (Fig. 2), alerts are initiated within a range of 5 (eruption 3) to 75 hr (eruption 5) before the eruptions. This suggests that the pre-eruptive processes in the same volcano may not consistently manifest in the data with the same amount of time in advance or that they could manifest with different magnitudes, affecting the ability to detect them. This behavior is probably due to the variability of the processes (e.g., fluid transport, degassing) that might take place inside the volcano before each eruption (e.g., Acocella et al., 2023).

On the other hand, eruption 4 occurs outside the warning period, leading to an FN. We observe that this occurs because the consensus value drops drastically below 0.7, 48.5 hr before the occurrence of the eruption. This could indicate that there are statistical differences between the features 48 hr before eruption 4 and 48 hr before the remaining eruptions. Similarly, when testing this approach in Whakaari (New Zealand), the model obtained by Dempsey et al. (2022) missed an eruption out of seven. That outcome and the similar finding here are a caution for future automated forecasting systems that they cannot be relied on to anticipate all eruptions and that future eruptions may have different precursors to those previously studied.

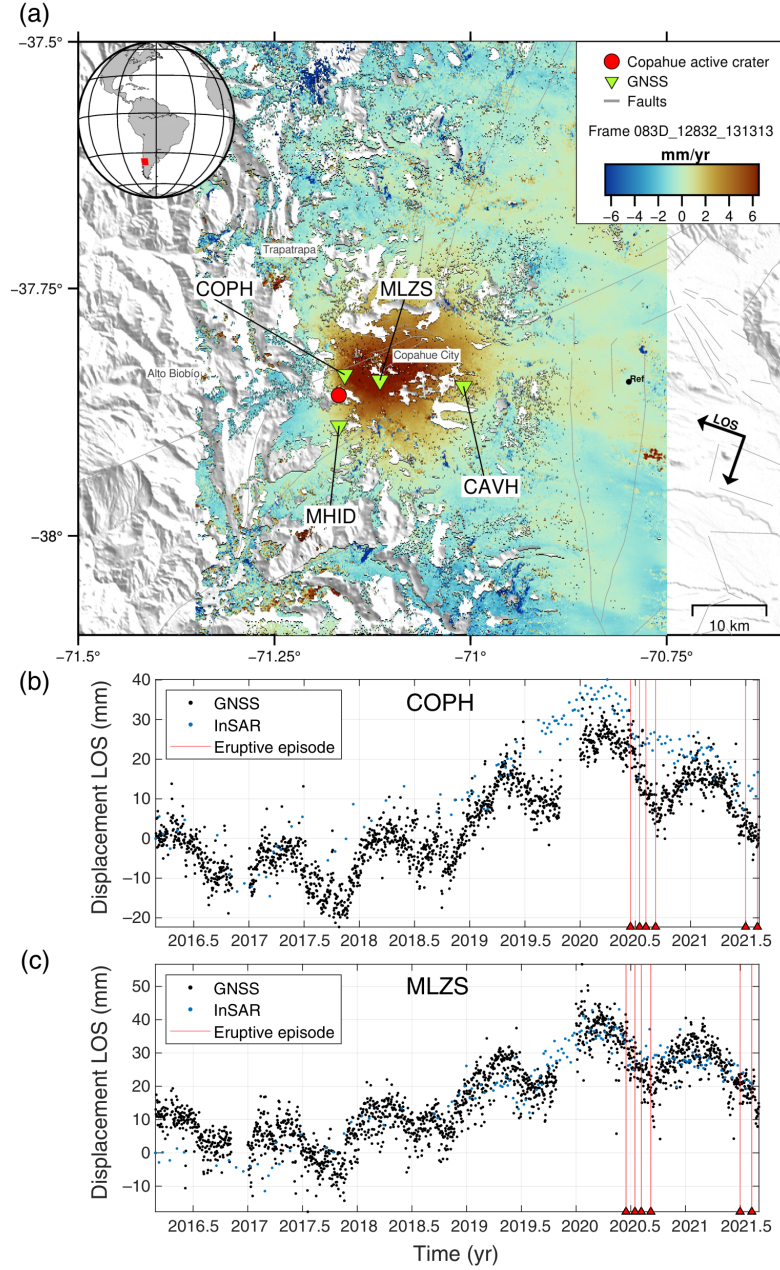


Figure 5. (a) Line-of-sight (LOS) velocity map of the Interferometric Synthetic Aperture Radar (InSAR) from the stack of Sentinel-1 interferograms between 2016 and 2021. The green inverted triangles denote the Global Navigation Satellite System (GNSS) stations, a red circle denotes the Copahue active crater, and a black point denotes the reference point (Ref) of the InSAR. (b,c) LOS displacement time series for the COPH and MLZS stations (blue dots) and GNSS observations projected with respect to LOS (black dots). The vertical red lines denote the Copahue eruptive episodes.

The unique case of eruption 4 is intriguing because it highlights the importance of not only accurately setting the alert threshold but also determining the appropriate duration of the warning

period for successful volcanic eruption forecasting. A minor modification in the time window could have led to a precise forecast of eruption 4. Nonetheless, such an adjustment might also pose the potential for false detections in other temporal contexts. It is also a hindsight assessment of the hypothetical warning model. Consequently, investigating the efficacy of diverse models employing both shorter and longer warning windows can contribute to a more comprehensive understanding of the required time window for identifying pre-eruptive phases. In this direction, Ardid et al. (2024) explore the use of different windows using template matching for feature time series.

An alternative explanation for eruption 4 occurring outside the warning window could be potential inaccuracies in the eruption date and/or a smaller magnitude of this event. Reports of eruption occurrence times depend largely on surface observations (e.g., cameras, ash emissions, deformation) and reports from the local population, which could introduce a time lag in the reported times in the case of low-visible manifestations or dominant subsurface processes. Eruption 4 occurred on 7 September 2020, and a little ash plume was reported by local people without further alert from the agencies. After that, there were no reports of eruptions at the volcano until 2021, which could indicate that there was a decrease in volcanic activity. Figure 3 shows that after eruption 4, the consensus starts to decay in time until the beginning of 2021. This correlates with SO_2 emissions measured by a differential optical absorption spectroscopy (DOAS) deployed by the OVDAS (Fig. S4), which show anomalous SO_2 values from June 2020 (date of eruption 1) until the end of 2020. Thus, knowing the exact times when volcanic eruptions occur for training short-scale models is crucial, and the integration of other parameters such as surface displacement from the high-rate Global Positioning System (e.g., Mattia et al., 2008) and tilt from near-field tiltmeters (e.g., Gambino et al., 2014) is essential for their correct constraint.

Limitations of the models

The six eruptions of the Copahue volcano used in this work are phreatic or phreatomagmatic type, low magnitude (VEI 1–2), and short duration. Therefore, our model is optimized for this type of eruption. Nevertheless, our model missed eruptive pulse 4, which reflects that models are not infallible and that the statistics of this event are different from the others. In this aspect, the integration of longer time series that include a greater number of eruptions as well as different types of eruptions would allow training models that consider a wide range of scenarios. Similarly, extensive

analyses considering the needs of the different observatories for frequency ranges, alert thresholds, and window durations will allow further optimization of these models, providing a complement to current efforts (which is beyond the scope of this work).

Many complex eruptive processes are composed of different phases, which can last from days to weeks or months (e.g., Llaima volcano; Ruth et al., 2016; Franco et al., 2019), making it difficult to define a single date as an “eruption.” In this context, the definition of thresholds that allow to establish a change in the state of a volcano, but in a data-driven way, represents a new opportunity. For this, one approach would be to use the extensive databases of volcano state changes based on observatory VAL systems (e.g., Volcanic Activity Bulletins in New Zealand or the Volcanic Activity Report in Chile). In this way, models could be trained to learn directly from the data when to change from one state to another, in addition to defining the respective thresholds quantitatively. The time lag associated with the time it takes to make the decision must be taken into account.

Integrating short- and long-term data

One advantage of seismic data is its high sampling rates (e.g., 100 Hz), which allow recording with high temporal resolution and across a broad frequency range (0.01–100 Hz, typically for broadband instruments). This capability facilitates the detection of short-term changes. In contrast, InSAR data and daily average positions from GNSS time series, while enabling the recovery of surface deformations at lower frequencies (10^{-6} – 10^{-5} Hz), in general, lack sensitivity to record signals from small eruptions, such as those exhibited by Copahue volcano (VEI of 1–2). In addition, these data sources have much lower sampling rates, with GNSS recording mainly daily or sub-daily (although high-rate GNSS also exists, i.e., samples every 1 or 15 s, for example) and InSAR capturing data every several days, depending on the SAR mission. In general, eruptions with a VEI of 1–2 ($1\text{--}10 \times 10^6 \text{ m}^3$) of highly compressible magma with a water-rich phase like that erupted at Copahue do not result in clear geodetic signals. This has been observed at other small-magnitude episodes of deformation at Copahue during 2011–2016 (Lundgren et al., 2017; Velez et al., 2016) and other Andean volcanoes like Cotopaxi (Morales Rivera et al., 2017), Sabancaya (MacQueen et al., 2020), Peteroa (Romero et al., 2020), Nevados de Chillan (Cardona et al., 2021; Astort et al., 2022), and Llaima, and Villarrica (Delgado et al., 2017). During the 2011–2016 episode of ground deformation at Copahue, the first eruptions occurred on 17 July 2012, and the largest eruption of the sequence

occurred on 22 December 2012 after more than one year of ground uplift (Velez et al., 2016; Caselli et al., 2016; Lundgren et al., 2017). These eruptions did not significantly reduce the source overpressure, and no co-eruptive deflation was observed. Therefore, the uplift continued at least until 2016. A similar situation was observed at Sabancaya volcano in southern Peru, where an episode of uplift with a LOS average rate of 4–5 cm/yr lasting between 2013 and at least 2019 resulted in several VEI 1–2 eruptions with a total erupted volume of less than $20 \times 10^6 \text{ m}^3$ (MacQueen et al., 2020; Fries et al., 2023).

To the first order, these sequences of eruptions in these two volcanoes follow the same mechanical behavior of the plumbing system—episodes of unrest that result in volcano uplift lasting several years, but no direct relation to the individual VEI 1–2 eruptions. However, a significant difference between Copahue 2020 with Copahue 2011–2016 and Sabancaya is that the eruptions analyzed in this study occur right after the whole edifice starts to deflate. The exact timing of deflation is difficult to assess without removing the seasonal signals recorded by the geodetic data. A more in-depth analysis is left for future studies. The lack of correlation with the eruptions does not rule out that deformation occurs near the vent in relation to shearing and/or pressurization of a gas slug inside the conduit before magma fragmentation. This is likely to be detected only with borehole tiltmeters located less than 1 km away from the vent (e.g., Ripepe et al., 2021). The lack of ground deformation during individual explosions can also be explained by the magma compressibility, in which gas-rich magmas accommodate pressure changes, resulting in little to no ground deformation (Mastin et al., 2008). Magma extracted from a storage region beneath a volcano is decompressed explosively, resulting in erupted volumes that are significantly larger than the inferred sources’ volume changes by a factor between 3 and 10 (e.g., Delgado et al., 2017). If we assume that magma erupted from a deep source located at a depth of 7 km imaged with InSAR by Lundgren et al. (2017) but with spherical geometry, then the maximum vertical deformation is 4.8–48 mm for source volume changes of $1\text{--}10 \times 10^6 \text{ m}^3$. If we scale this by a factor of 3–10 to take into account the magma compressibility, then the predicted ground deformation is within the noise in the geodetic time series. Indeed, none of our geodetic data show any clear deformation signal related to these eruptions. Volumes of erupted tephra derived from field isopachs are not available for direct comparison with these models. Therefore, the six eruptions can be interpreted as leakages to the surface of geodetically undetectable small volumes of magmatic fluids driven by an episode of reservoir pressurization during 2017–2020,

resulting in a lack of clear coeruptive source subsidence due to source deflation. In the future, the integration of high-resolution tiltmeters (e.g., <0.005 microradians; see Gambino et al., 2014, for a review) in the near field could improve the ability to detect low-amplitude geodetic signals.

The deformation during 2017–2020 is similar in spatial wavelength and location to the volcano-wide uplift that occurred between 2011 and 2016, but significantly slower in velocity with respect to the LOS rates of 12–15 cm/yr observed by Lundgren et al. (2017). This implies that both the episodes of uplift were likely produced by the same deformation sources—a near-vertical, elongated source at a depth of 2.5 km that represents a conduit and a plunging source at a depth of 7 km that likely corresponds to the uppermost fluid-rich layer of a crystal mush (Lundgren et al., 2017). Under the assumption of a linear elastic rheology, pressure changes are proportional to ground deformation. Therefore, if the deformation sources are the same for the 2011–2016 and 2017–2020 episodes of uplift, the change in deformation magnitude from 12–15 cm/yr to 6 mm/yr implies a change in source pressure of at least one order of magnitude between the two episodes. A detailed geophysical inversion of these deformation sources is beyond the scope of this study.

Because understanding what role (if any) long-term processes play in smaller-scale eruptions is critical to advance our understanding of volcanic processes, the integration of both types of data in the construction of these forecasting models offers promising future avenues. In this context, geodetic data (e.g., from GNSS, InSAR, and tiltmeters) or other types of data (e.g., SO_2 emissions, infrasound, seismicity rate, among others) could be integrated to assess whether the performance of the model improves. For example, Farias et al. (2023) proposed that variations in the behavior of the Copahue volcano would be related to variations in the b-value, which is derived from the seismicity rate in the region. Similarly, Hantusch et al. (2021) proposed that similar variations can be monitored from infrasound recording and ash characteristics. Thus, finding ways to integrate this type of data, as well as understanding the information it provides about the physics of the system, is a challenge that must be addressed.

Multiple volcano datasets

Recent studies by Dempsey et al. (2022) and Ardid, Dempsey, Caudron, Cronin, Kennedy, et al. (2023) have successfully demonstrated the applicability of our approach not only to Copahue volcano but also to other volcanoes worldwide. Expanding this methodology to incorporate data

from multiple volcanoes in the southern Andes offers a valuable opportunity to assess data-driven techniques based on ML. Active volcanoes such as Villarrica (Palma et al., 2008), Cordón Caulle (Basualto et al., 2023), Nevados de Chillán (Cardona et al., 2021), Lascar (Gaete et al., 2019), and others within the region have undergone eruptions in recent years, and these events have been meticulously recorded using seismic data.

In light of this, a transition toward a policy of open, real-time data by observatories becomes imperative. This shift presents a challenging yet crucial endeavor that requires attention. By embracing open data practices across multiple volcanic sites, observatories can facilitate the testing and implementation of data-driven ML methods for enhanced volcanic monitoring and early warning systems. The collective insights gained from diverse volcanic activities contribute to refining and advancing our understanding of volcanic processes and eruption prediction methodologies.

Conclusions

The short-term forecasting model presented in this study shows the potential for early eruption alerts at Copahue Volcano, located in the southern Andes, suggesting a broader application beyond New Zealand, where this approach was initially conceived (e.g., Dempsey et al., 2022). Our study reveals fluctuating alert times for recurrent eruptions from the same volcanic source, highlighting the challenges in consistently forecasting eruptions with a fixed alert duration, particularly evident in the case of eruption 4. Thus, our findings underscore the importance of carefully setting alert thresholds and determining appropriate alert periods, acknowledging that adjustments may not only lead to more accurate forecasts in specific cases but could also introduce the risk of false detections in others. Our study also highlights the need for caution in relying solely on automated forecasting systems, as demonstrated by missed eruptions in both the current research and previous studies. This underlines the complexity of volcanic processes and the variability of precursors, emphasizing the necessity of continued research and diverse model testing to enhance the reliability of volcanic eruption forecasting.

Furthermore, the integration of short- and long-term data emerges as a crucial aspect of advancing volcanic forecasting models. Although seismic data provide high temporal resolution for detecting short-term signals, combining it with geodetic data and/or others (e.g., SO₂ emissions,

tiltmeter measurements, infrasound) might offer a more comprehensive understanding of volcanic behavior, providing insights on processes that occur over longer time scales. For Copahue, geodetic observations do not provide insights on the scale of individual eruptions that last a few minutes to hours. For this aim, assessing the role of long-term processes in smaller eruptions (if any) becomes crucial.

Data and Resources

The seismic data used in this study was provided by the National University of Rio Negro (UNRN; <https://www.unrn.edu.ar/home>). Global Navigation Satellite System (GNSS) and SO₂ data are available through the Southern Andes Volcano Observatory (Observatorio Volcanológico de los Andes del Sur, OVDAS) together with the National Seismological Center (Centro Sismológico Nacional, CSN) of the Universidad de Chile (see <http://gnss.csn.uchile.cl>). Interferometric Synthetic Aperture Radar (InSAR) data are available on the COMET-LiCS Sentinel-1 InSAR portal (<https://comet.nerc.ac.uk/comet-lics-portal/>). All websites were last accessed in January 2024. The supplemental material to this article includes Figures S1–S4.

Declaration of Competing Interests

The author acknowledges that there are no conflicts of interest recorded.

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