Forecasting and Tracking Volcanic Explosions using Shannon Entropy at Volcán de Colima.

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Abstract

In this work we demonstrate that Shannon Entropy (SE) calculated on continuous seismic signals can be used efficiently in a volcanic monitoring system. We analysed three years of volcanic activity of Volcán de Colima, México, recorded between January 2015 and May 2017. This period includes two large explosions, with pyroclastic and lava flows, and intense activity of less energetic explosion, culminating with a period of quiescence. In order to confirm the success of our results, we used images of the Visual Monitoring system of Colima Volcano Observatory. Another of the objectives of this work is to show how the decrease in the SE values can be used to track minor explosive activity, helping Machine Learning algorithms to work more efficiently in the complex problem of distinguishing the explosion signals in the seismograms. We demonstrated the two big eruptions selected were forecasted successfully (6 and 2 days respectively) using the decay of the SE. We conclude that the SE could be used as a complementary tool in seismic volcano monitoring, showing its successful behaviour prior to energetic eruptions, giving time enough to alert the population and prepare for the consequences of an imminent and well predicted moment of the eruption.

Introduction

One of the great challengers of the Earth Sciences scientific community is studying the behaviour of volcanoes during eruptive episodes, in order to understand the underlying physical processes and to develop warning systems to minimize those risks **(Sparks et al., 2012; Manga et al., 2017; Caudron et al., 2020).** Volcanic eruptions involve highly energetic interactions between the inner fluid dynamic and the medium. Therefore, its understanding embrace the use of several disciplines such as geochemistry, geology or geophysics **(Brenguier et al., 2008; Pyle, 2015; Dempsey et al., 2020; Girona et al., 2021).** With this kind of studies, volcanologists are advancing successfully in the development of forecasting tools to predict eruptive episodes in the last decades. However, the high variety of volcanic scenarios and eruptive styles when an eruption could happen make forecasting a complex problem to solve in a unified way. Each volcano is a different system itself, with different source mechanisms and various eruptive dynamics. Therefore, at this time there is not a true universal way to board the pre-eruptive activity making the prediction of an eruption a difficult task. One of the most successful tools when forecasting an eruption is the Volcano Seismology **(Ibáñez et al., 2000; Chouet & Matoza, 2012; McNutt & Roman, 2015)**. Volcanic activity associated to magma movement or gas emission, generates seismicity that can be recorded through time as a seismic signal. Seismicity has been used in different ways for the development of early warning tools. Based on the type of signal, its frequency content, duration, energy, spatial position within the volcano and many other parameters, it is possible to make precursor eruption models, some with evident success **(McNutt & Roman, 2015; White & McCausland, 2016; Kilburn, 2018).** In general, the study of the energy released, and some models derived from it, has been one of the most widely used tools **(Power et al., 2013; Boué et al., 2015, 2016; Caudron et al., 2021; Ardid et al., 2022).**

The use of seismic catalogues to carry out volcanic forecasting has had great relevance in recent times from the use of Machine Learning (ML) techniques. These techniques allow better identification of events and greater completeness of databases **(Benítez et al., 2006; Ibáñez et al., 2009; Cortés et al., 2014; Manley et al., 2020).** However, even though these methods are widely adopted around volcanic observatories, there are several topics that still lack of a strong solution, as exportability to other volcanic systems (**Titos et al., 2018; Bueno et al., 2022a)**. Moreover, even the same volcano may erupt in different ways (closed vent or open vent, depth of the reservoir, energy accumulated, etc.) and different processes may occur at the same time **(Titos et al., 2019; Martínez et al., 2021; Manley et al., 2022).** Thus, the big amount of labelled database required usually obstructs the development of a simple, reliable and exportable system. Seismic records may exhibit increasements of the energy that scientists use to forecast eruptive episodes. Through both energy based methods and automatic earthquake classification systems, vulcanologist have achieved numerous forecasting successes. However, the uniqueness of every volcano and the variety of its type of eruptions makes of these methods non-universal tools.

Rey-Devesa et al. (2023) proposed a promising early-warning tool, tested in different volcanic systems (Bezymianny, Mt. Etna, Kilauea, Augustine and Mount St. Helens) and in different eruptive episodes of the same volcano. This approach applies advanced signal analysis techniques to extract a set of underlying parameters of the seismic signal and study their temporal evolution. These authors developed a short-term volcanic eruption forecasting tool working efficiently and successfully in these scenarios. They observed how the decrease in Shannon Entropy (SE) generated stable pre-eruptive signs from around 5 days prior to a large explosion, to tens of hours in the case of lava fountains.

In this work we will advance in this line showing the SE can be used routinely in a seismic monitoring system in a reliable way. We will study a long time period of seismic record in an active volcano with a wide variety of eruptive processes. We will analyse three years of intense volcanic activity of Volcán de Fuego de Colima, (2015-2017). This analysis includes at least two large volcanic explosions, two pyroclastic flows, an effusive period, less energetic explosions, and a period of quiescence that is lasting until at least the date of the present work **(Reyes-Dávila et al., 2016; Arámbula-Mendoza et al., 2018)**. The analysis of the quiescence stage is important because it can help us demonstrate that SE variations appear as one-to-one and stable indicators of a pre-eruptive alert. Therefore, its implementation in volcanic surveillance systems could be crucial to determining a possible reactivation of this volcanic system. The seismic analysis is complemented with the images of the Visual Monitoring system that the Colima Volcano Observatory has, obtaining confirmation of how the eruptive episode was. This double study is not always easy to perform. It is a fact that in many cases the presence of clouds or night does not facilitate this work. We were able to visually confirm the volcanic origin of more than 70% of the SE minima considered as potential eruptive episodes. In the remaining 30% of the potential false cases night and clouds affected to not being able to identify volcanic activity in the visual records, but it does not mean they did not occurred.

Another of the objectives of this work is to show how the decreases in the SE can also be used as a seismic alternative to track this minor explosive activity, and help ML algorithms. Some volcano-seismic event classification systems based on ML approaches used in forecasting involve a category associated with volcanic explosions, debris flow and effusive eruptions **(Whitehead & Bebbington, 2021)**. To improve the training of ML approaches with additional data of volcanic eruptions it crucial.

Volcanic framework and Data:

Volcán de Colima is an andesitic stratovolcano located in western Mexico (Figure 1) and represents one of the most studied volcanoes in the world due to its high activity, being considered as one of the most active of the North American continent. There are evidences of its very high explosive activity since the beginning of the 16th century when the first chronicles written by the Spanish conquerors appear **(Bretón, 2012)**. Recently **Bretón et al. (2022)** evidenced that this volcano is able to have very intense volcanic activity after period of tens of years of quite state including very energetic activity as the growing of El Volcancito lateral vent. In 1913 a Plinian eruption destroyed the summit of the volcano and generated various pyroclastic flows; a similar eruption nowadays would affect around half a million people **(Lesage et al., 2018)** turning Volcán de Colima into a very hazardous volcano. Volcán de Colima is being monitored since 1989, recording many periods of moderate effusive activity and processes like dome building and destruction, lava flows, pyroclastic flows, or vulcanian eruptions **(Zobin et al., 2002; Reyes-Dávila & De la Cruz-Reyna, 2002; Palo et al., 2009).** Volcanic activity is characterized by eruptive cycles between which the volcano does not show any type of activity, but its petrological characteristics explain the explosive nature of its main eruptions **(Luhr & Carmichel, 1990; Savov et al., 2008).** The reactivation of the volcanic system starts with phases of dome-growing at the summit zone **(Zobin et al., 2023)**; after that, lava and pyroclastic flows are emitted **(Carrara et al., 2019)**, followed by frequent explosions of variable intensity **(Luhr 2002; Zobin et al., 2005; Lamb et al., 2017)**. The cycle uses to end with a plinian eruption that destroys the summit region.

After signs of reactivation in January 2013, Volcán de Colima gradually increased its effusive and explosive activity, including the growing of a dome in the summit area. Among the different eruptive episodes, in this manuscript we will pay our attention in the analysis in detail of three different periods:

a. On July 10th – 11th, 2015 Volcán de Colima erupted producing 2 pyroclastic flows (named also Pyrocaltic Density Currents) and destroying the summit dome **(Capra et al., 2015; Reyes Dávila et al., 2016).** The episode was the most energetic since 1913 Plinian eruption. Prior to this eruptive episode, only few volcano-tectonic events, usually considered as an important precursor, where detected **(Arámbula-Mendoza et al., 2019).** This implies that a classic forecasting strategy based on the increasing number of earthquakes and their evolution from VTs to other events **(McNutt & Roman, 2015; White & McCausland, 2015)** does not fit for this type of eruptions. Therefore, this is the ideal scenario to test how reliable is our approach of forecasting using the SE. This eruption was preceded by an increasing number of rockfalls and degassing activity, with elevated fumarolic activity and SO_2 flux **(Reyes-Dávila et al., 2016).** On July 10th at 20:16 hours, the collapse of the dome produced a first pyroclastic flow that reached 9.1 km and lasted 52 min. Around 16 hours later a second event occurred, lasting 1 h and 47 min and reaching 10.3 km.

b. The second episode is an effusive volcanic activity occurred between 26 of September and 1 of October of 2016. This episode finalized with a moderate volcanic explosion but no important pre-eruptive seismicity was recorded.
c. Explosive stage during January-February 2017 with a set of moderate volcanic explosions culminating with a vulcanian explosion that reached up 5 km over the submit crater occurred the 3 of February of 2017, followed by minor eruptive episodes. After this moment no seismicity neither other external volcanic activity is measured in the volcano with the exception of moderate fumarolic emission and thermal anomalies.

We will analyse continuous seismic record of a set of seismic stations belonging to the Telemetric Seismic Network of Colima (RESCO). RESCO is a part of the Centre for Studies and Volcanological Research (CUEV) of the University of Colima, and manage the monitoring of the volcano. The seismic network used in this analysis has 4 short-period SS-1 Ranger vertical seismometers and 6 broadband Guralp CMG-40TD and CMG-6TD, with a sampling rate of 100 Hz **(Arámbula-Mendoza et al., 2018).** In this work we used data from the stations SOMA, WEST, INCA and EZV4 (Figure 1) recorded between January 2015 and March 2017. In this manuscript we will show results obtained for stations SOMA and INCA due to their temporal completeness. SOMA and INCA are the closest stations to the crater, located at less than 2 km.

In addition, to cross check our seismic results with evidences of the explosive episodes we used photos and videos of the volcanic activity. Volcán de Colima is video monitored in real time with a network of several stations that transmit images continuously to the observatory in the CUEV **(Zobin et al., 2015; Bretón-González et al., 2013).** We used images from cameras: Biblioteca, Cuauhtemoc, MAZE, Naranjal, Nevado 213 and Nevado 221.

Method

In this work we apply advanced signal analysis techniques to use the Shannon Entropy as a reliable tool as short term volcanic eruption forecasting for three purposes:

- First of all, we calculate SE and measure its temporal evolution prior to a set of energetic eruptions, determining the forecasting interval with time enough to alert the population and prepare for volcanic hazard.
- Secondly, is to test if this parameter is able to distinguish between high and low energy episodes and determine if the pre-eruptive interval is associated to the energy of the explosions.
- Finally, SE will be introduced to redefine the label associated with eruptions in classifications models.

SE is a statistical feature associated to the waveform and its frequency content. We take the vertical component of the raw seismic signal and use a bandpass filter to filter the signal between 1 Hz and 16 Hz. We selected this frequency band to avoid low and high frequency noise associated to climatic conditions like wind or storms. Then we create a moving window overlapped along the seismic temporal vector. The length of this window varies in function of the target of our search and the length of the period analysed. For the systematic analysis of the almost three years of seismic record, we used a window length of 10 minutes. For the study of the largest explosions, the window length was of 10 minutes. In the case of low energy eruptive episodes, the briefness of the changes lead us to use shorter windows of 1 minute. In all cases the used windows were overlapped a 50%. We calculated the SE in the frequency domain in every window and then we built a vector with the temporary evolution of the entropy. The Eq. 1 show the expression used to calculate the SE **(**Esmaili et al., 2004; **Malfante et al., 2018 a)**:

$$SE = -\sum_{i} P\left(S_i\right) log_2\left(P\left(S_i\right)\right)$$

1

where $P\left(S_i\right)$ is the probability density function of the seismic record, on the frequency domain.

According to Eq. (1), since the analysis is done in the frequency domain, SE is associated to the homogeneous frequency contains of the signal. When seismograms are composed by random signals (e.g., background or cultural noise), or by a set of non-homogeneous volcanic signals, then values of SE are high. In case of the occurrence of a continuous arrival of homogeneous signals with same or coherent frequency content, then SE must have lower values, since the probability to find similar signals moves toward 1, and log of 1 is zero. The main advantage of this parameter in confront to others is that this SE excursion to zero is independent of the type of recorded seismicity and its energy. For example, if the pre-eruptive seismicity is composed by VT earthquakes (dominated by high frequencies) the SE will move to zero since VTs dominate over the rest of seismicity and P(Si) will be moved toward 1. This behavior will be the same if the pre-eruptive signal is a volcanic tremor (dominated by low frequencies), or a mix of seismicity. The necessary condition for SE to move towards zero is that the seismic signal is homogeneous, in the frequency domain, over time. Therefore, the variation of SE is not dependent on the type of signal, but on the self-order of the frequency content of the seismic signal prior to eruptive processes. Our hypothesis is the majority of the elastic energy recorded in the seismogram is associated with this eruptive process and must be similar to itself. Otherwise, when there is no imminent eruptive process, the volcano can show different seismic signals that do not reflect homogeneity of the seismogram, and the values of SE are higher.

We developed a numerical rule to quantify when the SE begins to decrease in a regular value approaching zero. Through this type of measure we will establish an interval to determine when the volcanic system is in a pre-eruptive process. Rey-Devesa et al., (2023) proved the accuracy of the LTA/STA algorithm to implement this quantification. Following these authors, we define the LTA value by calculating the mean value of the SE using a period of two months previous to the STA window, SE_0. Then, we compare this value with the SE value in each window of the analysis, $\mathrm{SE}\left(\mathrm{i}\right)$, estimating a Decay Ratio using Eq. (2):

$$DecayRatio\left[\%\right] = 100 \cdot \left(1 - \frac{SE\left(i\right)}{SE_0}\right)$$

2

According to Rey-Devesa et al. (2023) a decay of the STA/LTA values over the 70% could be considered as indicator of potential eruptive episodes, avoiding potential false eruption alarms. Systematically we computed the SE decay (Eq. 2) obtaining its temporary evolution. Then, we identified those intervals where there are decays of the SE below the threshold and analysed the images recorded by the CUEV cameras system to confirm whether there is an eruptive event. In case of positive confirmation we evaluated the length of the pre-eruptive interval of each eruptive event.

Results And Discussion

Three years of seismic record.

The first step is to evaluate the robustness of the temporal evolution of the SE. We selected the eruptive stage occurring on Volcán de Colima between January 2015 and May 2017, analysing more than two years of data recorded at 4 different seismic stations. In Figure 2 we show the envelope of the SE evolution, calculated with the signal recorded at stations SOMA (blue) and INCA (green), selected for being near the crater (less than 2 km far) and for their complementary records throughout time. It is a normal and usual fact in volcanic seismic networks, the operability interruptions of seismic stations due to numerous causes: e.g. ash falls that make it impossible for solar panels to function and feed electronic equipment, impossibility of maintenance by volcanic risks or by bad climatology, or even damage caused by eruptions.

Noteworthy, SE evolves in a similar way in the two seismic stations, implying SE is directly associated with volcanic dynamics. It is well known that volcanic structures are very heterogeneous **(Sychev et al., 2019; Castro-Melgar et al., 2021; D'Auria et al., 2022)**. Therefore, although the two stations are at the same distance, but at different azimuths, they may be influenced by strong scattering and attenuation effects. However, it is observed that the SE is very similar between them, representing a robust and reliable value.

Notice, the temporal evolution of the SE plotted in Figure 2 starts from low values. As reported by **Carrara et al. (2019)**, the 28 of December 2014 Volcán de Colima had an intense eruptive episode dominated by lava flows. This eruptive episode was not included in our analysis since we focused our study in explosive episodes. It is noteworthy the SE is also sensible to any type of eruptive mechanism, as demonstrated by **Rey-Devesa et al., (2023)**. It is also interesting to observe how after the last volcanic explosion and the beginning of a rest period of Volcán de Colima, the SE has higher and more stable values. Finally, we highlight that the two main volcanic processes selected (11 July 2015 and 1 October 2016) show how SE reaches values very close to zero evidencing their high energy and the coherence of the seismic process prior to the eruptions.

The 11th of July 2015 volcanic explosion.

Prior to the high energy volcanic explosion of July 11th, SE trend was abruptly changed, dropping to minimum values close to zero (Figure 3). According to Figure 3a and 3b the pre-eruptive short term interval of this explosion was of 5 days (green area of figure 3a and red line of figure 3b). This interval corresponds to the stable decay of the SE below the 70% of threshold. Notice that when the two associated pyroclastic flows happened the SE has a decay value of 100%. Fitting the decay of the SE we could be able to determine in advance the timing of the first pyroclastic flow, demonstrating this parameter could be a powerful tool to determine the beginning of a volcanic eruption.

According to **Reyes-Dávila et al., 2016** and **Arámbula-Mendoza et al, 2019**, this explosion presented a low VT or LP level of seismicity on the base of the use of ML techniques as Hidden Markov Models **(Benítez et al., 2009)** lacking classical pre-eruptive precursors. This observation gives an added value to the use of the SE as short term volcanic precursor.

The 1st of October 2016 volcanic eruption.

The selected eruptive interval started with an effusive style finalizing with a Vulcanian explosion. As evidenced in Figure 2, the decay of the SE to values close to zero occurred just before the vulcanian explosion. Again, non-intense pre-eruptive VT or LP seismicity was reported **(Dávila et al., 2019).** However, the SE shows a pre-eruptive decay two days in advance. Notice as the pre-eruptive time is shorter than in the previous explosion that was more energetic than the present one (Figure 2). We realized the pre-eruptive interval determined by the decay of SE seems to be associated to the magnitude of the eruptive episode.

The intense explosive period of June 2015.

As reported by **Arámbula-Mendoza et al, (2019)**, the most leading precursory activity of 11 of July 2015 pyroclastic flows was the high number of small volcanic explosions occurred in June. In figure 4 we zoomed in detail this period in order to observe the temporal evolution of SE according to the less energetic explosions. This study corresponds to a re-analysis of this period using windows 1 minute long overlapped the 50%. We identified the excursions of SE towards lower values (local minima) and associated them with the corresponding images recorded by the visual monitoring system. As observed in figure 4, all local minima of the SE were associated to small volcanic explosions, whenever the weather conditions allowed getting these images. These variations towards the local minima take place in a short time and it is not possible to assign a potential forecasting interval, as observed in the two largest eruptive episodes analysed before.

The local minima associated to small volcanic explosions do not always are below the defined decay STA/LTA threshold. Since we have values of the SE after the volcano began the present quiescence period, we redone a re-estimation of the STA/LTA ratio changing the dynamical model for a static procedure. In the dynamic model, the LTA term was calculated within two months interval prior to the estimation of the STA. In the static approximation we estimated a fixed average value of the LTA for a period between March and May 2017, when the volcano was in quiescence. In this case, results of the decay indicate that all the local minima of the SE of the analysed period are below 70% of the threshold. This result can be interpreted as these periods of intense explosive activity of lower energy also present an ordering of the seismic energy to generate the explosions. We can affirm that the entire period can be considered a single eruptive state from the point of view of the SE.

Note we can use these local minima of SE as a tool to developing a more efficient and robust recognition system using ML of small explosions. It is well known that a seismic signal recognition training process using ML requires a high number of previously labelled events, but also with the certainty that these labels undoubtedly correspond to that type of seismic event. Moderate and small volcanic explosions have a signature that is not easy to generalize **(Palo et al., 2009)**. Thus, it is very common to confirm the existence of this type of event visually. But not all volcanoes have visual monitoring systems, nor is it always possible to observe these explosions due mainly to climatic conditions. Therefore, making a double check between the local minima of the SE in active volcanoes and the seismograms would permit: a) to confirm the existence of these explosions, and b) to improve seismic and eruptive catalogues. Thus, an added value to the use of the SE in seismic monitoring is that it can be used to improve the training processes of ML algorithms to be able to recognize volcanic explosions on seismograms.

The explosive sequence prior the quiescence volcanic stage.

After February 2017, the eruptive activity of Volcán de Colima ceased **(Arámbula-Mendoza et al., 2020)**. This is reflected in figure 2, where we can appreciate how SE started to grow reaching the maximum values of all the period studied between March and May 2017. We finalized our study analysing how SE evolves during the end of an eruptive period. **Arámbula-Mendoza et al. (2020)** identifies 10 volcanic explosions between January 7th and February 3rd, 2017, prior to the quiescence phase started after them (end of February 2017).

As observed in Figure 2, even if there are several volcanic explosions in the period selected in this study, the SE was in a trend to have higher values than in previous months. We can interpret this increase of the SE values due to the approaching of the end of the eruptive episode. However, we could identify relative minima of the SE and associated them with images of the visual monitoring network. In Figure 5 we associated the pictures of 8 of the 10 explosions reported by **Arámbula-Mendoza et al. (2020)** with the minima of the SE. The other 2 explosions (January 7th and 27th) were not recorded on camera due to high fog, but we can observe minima values for SE (Figure 5). Notice in the pictures that even the ash column is big, the white colour of the clouds leads us to think about a big phreatic component taking part of these explosions, identifying them as low energetic explosions **(Palo et al., 2009)**. As in the previous analysis, these minima presented STA/LTA values close above the 70% of threshold in a dynamic case but below the 70% in case of static analysis.

Remarks.

We remark the systematic analysis of the SE can be a very useful tool in the processes of monitoring and seismic surveillance of volcanoes. Analysing three years of seismic signals at Volcán de Colima SE presents high and stable values when the volcanic activity is low or the volcano is quiescent, while whenever the SE has local minima, or tends towards values close to zero, it is marking eruptive processes.

SE measures the uncertainty in probability distributions **(Malfante et al., 2018b),** associating maximum SE with maximum uncertainty (all possible outcomes have equal probabilities), and vice-versa coherent outcomes show high probabilities (minimum SE). On the other hand, the Entropy defined by the Statistical Physics establishes that the macroscopic state of a physical system is characterized by a distribution of microstates **(Posadas et al., 2021 and cites)**. A volcanic system is a set of different inner processes defined by a set of microstates defining the exchange of energy with the medium. The configuration of equilibrium of a volcanic system, for example a quiescence period, is associated with minimum exchange of energy and low values of Entropy. Seismic record associated to this state is characterized by a random low energetic composition of signals providing high SE values. In opposition, seismic signals with similar temporal and frequency patterns (same source) provide low SE values. In tectonic seismology high Entropy and low SE are associated to the arrival of large earthquakes with impulsive and energetic phases generated in the same source **(van Ruitenbeek et al., 2020).** In volcanic systems the increase of the Entropy is related to several microstates associated to the inner dynamic of the volcano. Particles of gas, magma, bubbles, solid material and other components existing in the interior of the volcano interact between them and with the limits of the volcanic structure, exchanging energy. When these microstates are coherently organized to generate a “volcanic macrostate”, i.e. oriented to produce a volcanic eruption, then the values of the SE is moved toward zero and the Entropy is maximum.

Conclusion

This study reveals SE is a very useful tool for volcano monitoring and provide in many cases evidences to be used as short-term volcanic eruption forecasting warnings. The temporal analysis of SE shows interesting behaviour whenever the volcanic activity changes to an eruptive state, in both cases for high and low energetic episodes. The volcanic system self-organises prior to an eruption. This self-organization is reflected through a homogeneous composition of the seismic signal. We can interpret this self-similarity as a way out of the trend that the volcanic activity was following, reflected as minimum values of SE. Moreover, they offer new information about the eruptive state of the volcano. Thus, when SE moves toward zero the most probable interpretation of this variation is an energetic eruptive episode of the volcano. This study makes an approach to a better understanding of the activity and the processes underlying in a volcanic system close to an eruption. Thus, when a high energy explosion is approaching, SE starts to decrease from days before in a homogeneous way until reaching absolute minimums when the volcanic eruption happens. Furthermore, we have observed that SE is as a reliable feature for the improvement of ML automatic classification systems and the identification of low energy explosions.

Finally in the case of Volcán de Colima we demonstrated the two big eruptions selected could be forecasted with a few days in advance (6 and 2 days respectively) using the homogeneous decay of the SE. We showed SE was sensible to another previous eruptive episode, occurred at the end of 2014 (very low SE values), and also to the end of the eruptive stage and beginning of a quiescence period (high and stable SE values).

We conclude that SE could be used as a complementary tool in seismic volcano monitoring. The SE has coherent decreasing behaviour prior to energetic eruptions, giving time enough to alert the population and prepare for the consequences of an imminent and well predicted moment of the eruption.

Declarations

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Author contributions:

P.R.D. code development, data analysis, figure construction and text writing. J.P. conceptualization and text revision. C.B. conceptualization, code development and text revision. M.B., I.P, Z.L, F.O., R.A.M. and L.G. data curation and text revision. J.I. project management, conceptualization and text writing.

Competing interests:

The authors declare no competing interests.

Data availability and Open Science.

The used software of this work (all programmes developed by us) are also publically accessible (link provided below) and are also presented with specific use examples to be able to independently reproduce all the results obtained in this work. The repository sites used are stable, publically accessible for free and recognized by the scientific community.

The seismic parameter analysis software, with illustrative examples to be able to reproduce our results, are available in the compressed folder "Software.Rar", located in the ZENODO repository at the following address and DOI.

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The seismic data used in this work are accessible in:

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Figures

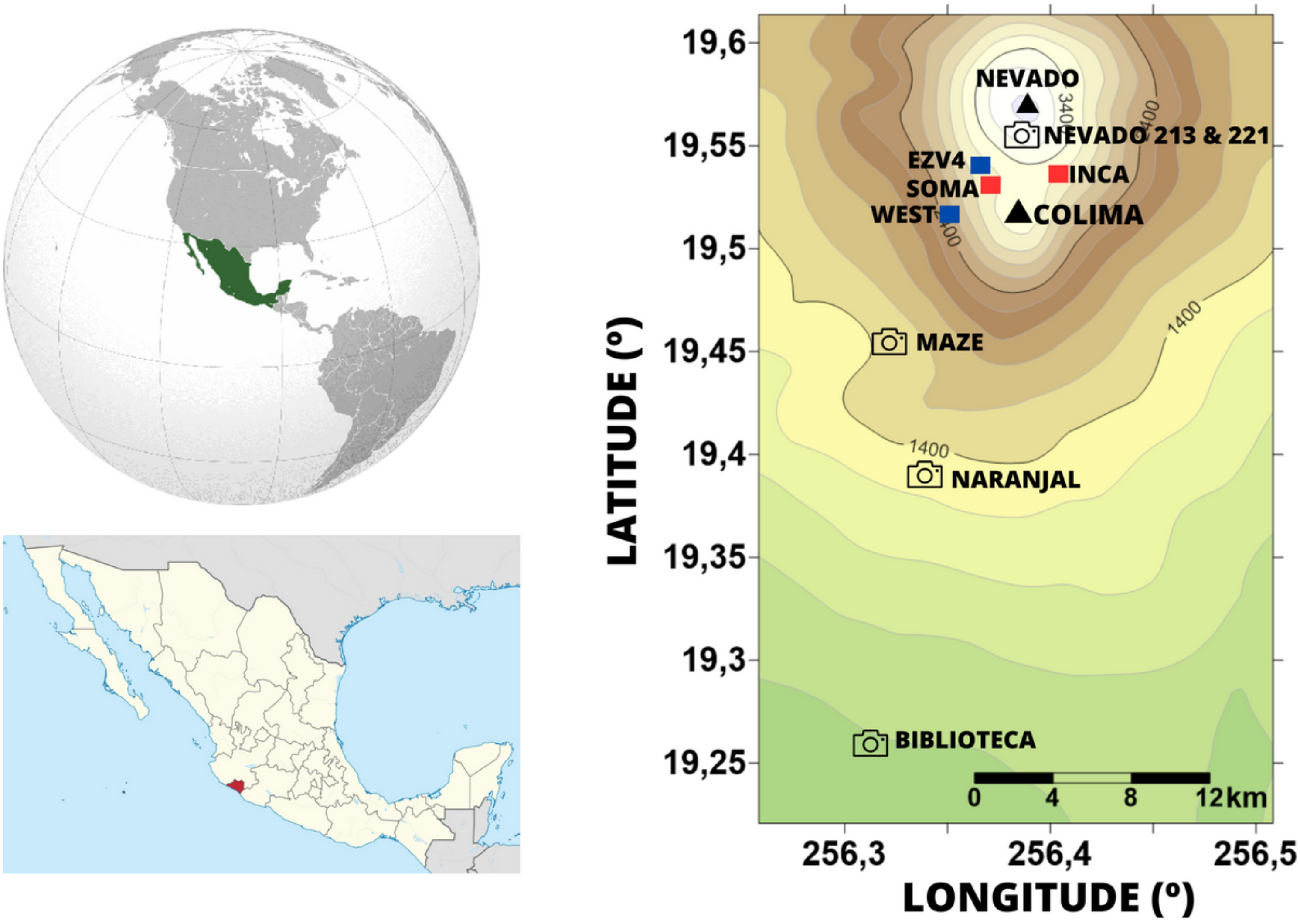

Figure 1

Map of the seismic stations (squares) and visual cameras (cameras) monitoring Volcán de Colima, Mexico. Black triangles show the old Nevado volcano and the active Volcán de Colima. Red squares are the representing seismic stations in this work.

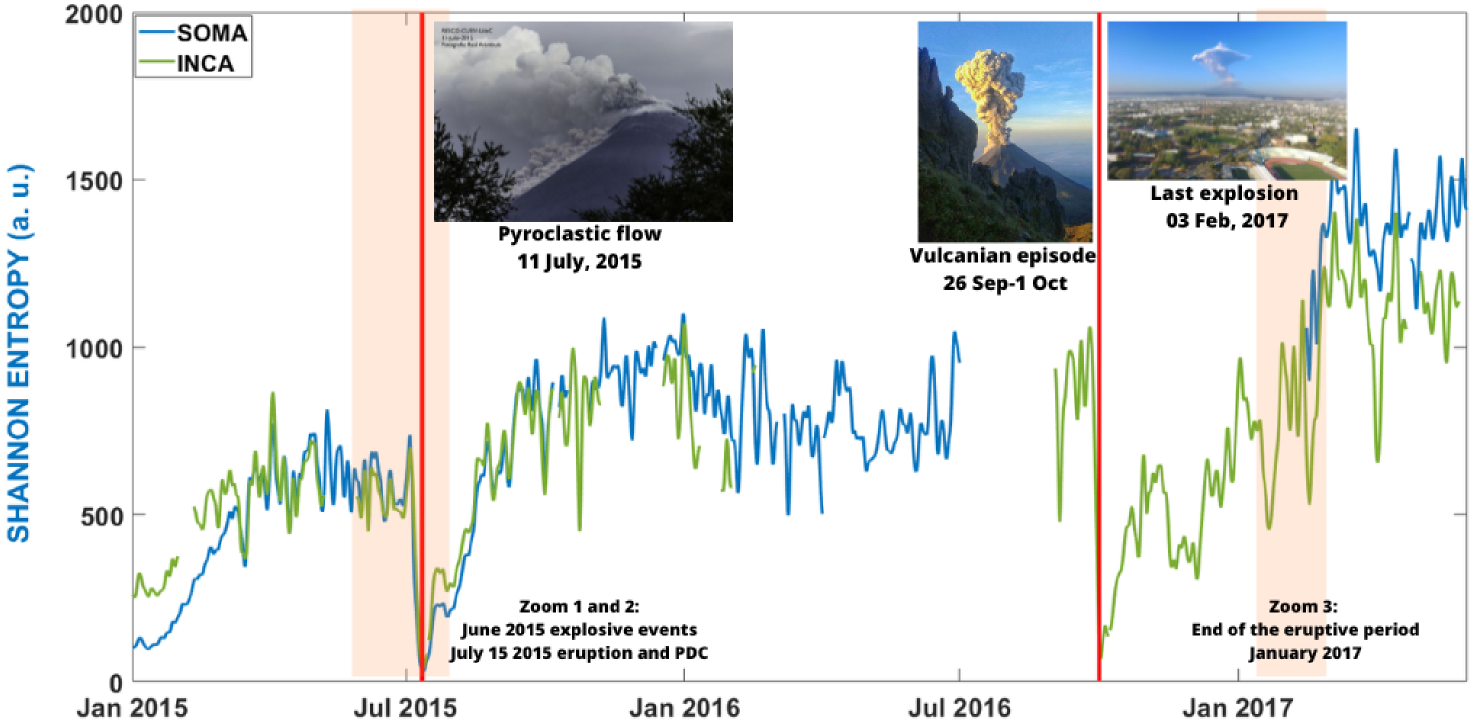

Figure 2

Temporal evolution of the SE between January 2015 and May 2017 analysed at SOMA (blue) and INCA (green) seismic stations using window lengths of 10 minutes overlaped 50%. We represented the envelope of the SE values. Vertical red line represents the two selected eruptive episodes occurred on July 11th 2015 and October 1st 2016. Shadow red areas represent the two intervals selected to analyzed smaller volcanic explosions. White spaces represent periods without data. Pictures from left to right show three explosive episodes recorded by the CUEV cameras occurred on 11 July 2015, 1 October 2016 and 3 February 2017 respectively.

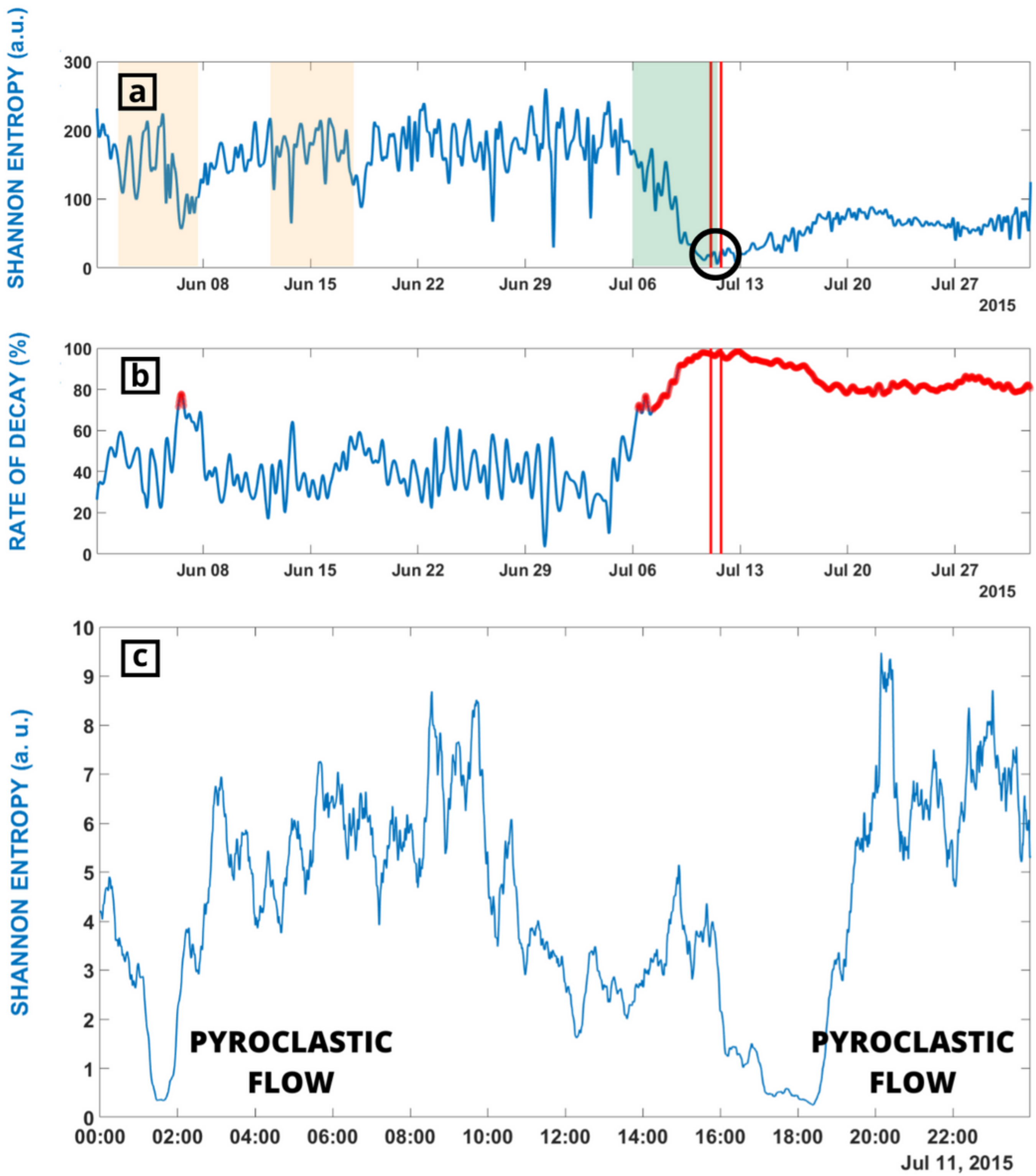

Figure 3

a) SE and its decay during June and July 2015. Red lines show the moment of the two pyroclastic flows occurred in July 11th. Red shadow areas are the periods used to evaluate how SE can be used to monitor volcanic explosions. Green area is the confirmed short term forecasting period (5 days) obtained from the decay of the SE. b) Plot of the STA/LTA ratio during June and July 2015. Period in which values are over

70% of decay are highlighted in red. c) Zoom of 11 of July showing as the SE reached zero when the pyroclastic flows happened.

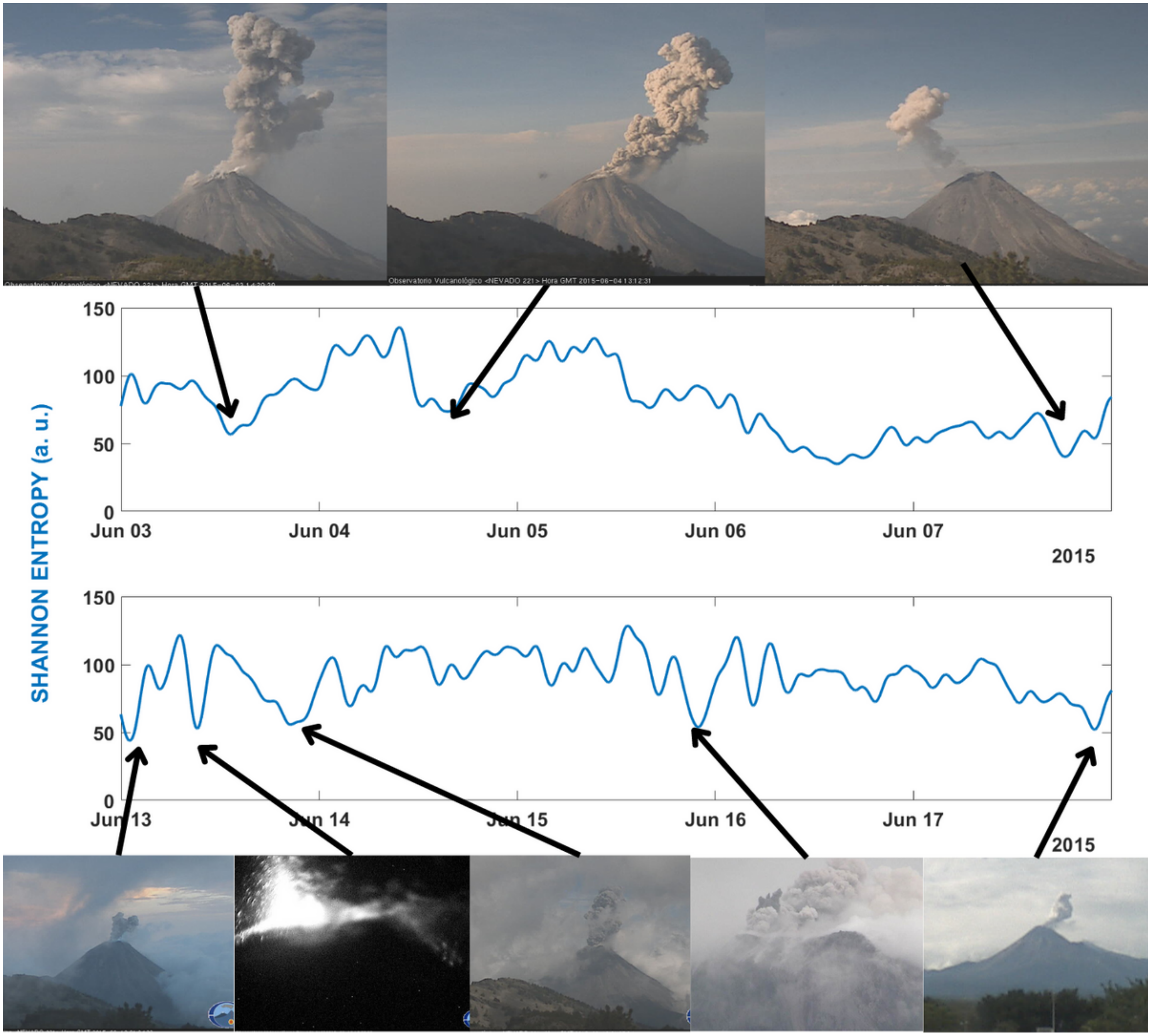

Figure 4

Temporal evolution of the SE values, obtained for the seismic station SOMA, associated to the high explosivity period of 3-20 June 2015. In this period we identified local minima and compared them (if available) with the images obtained by the visual monitoring Network. As observed all identified minima are linked low energy explosive activity.

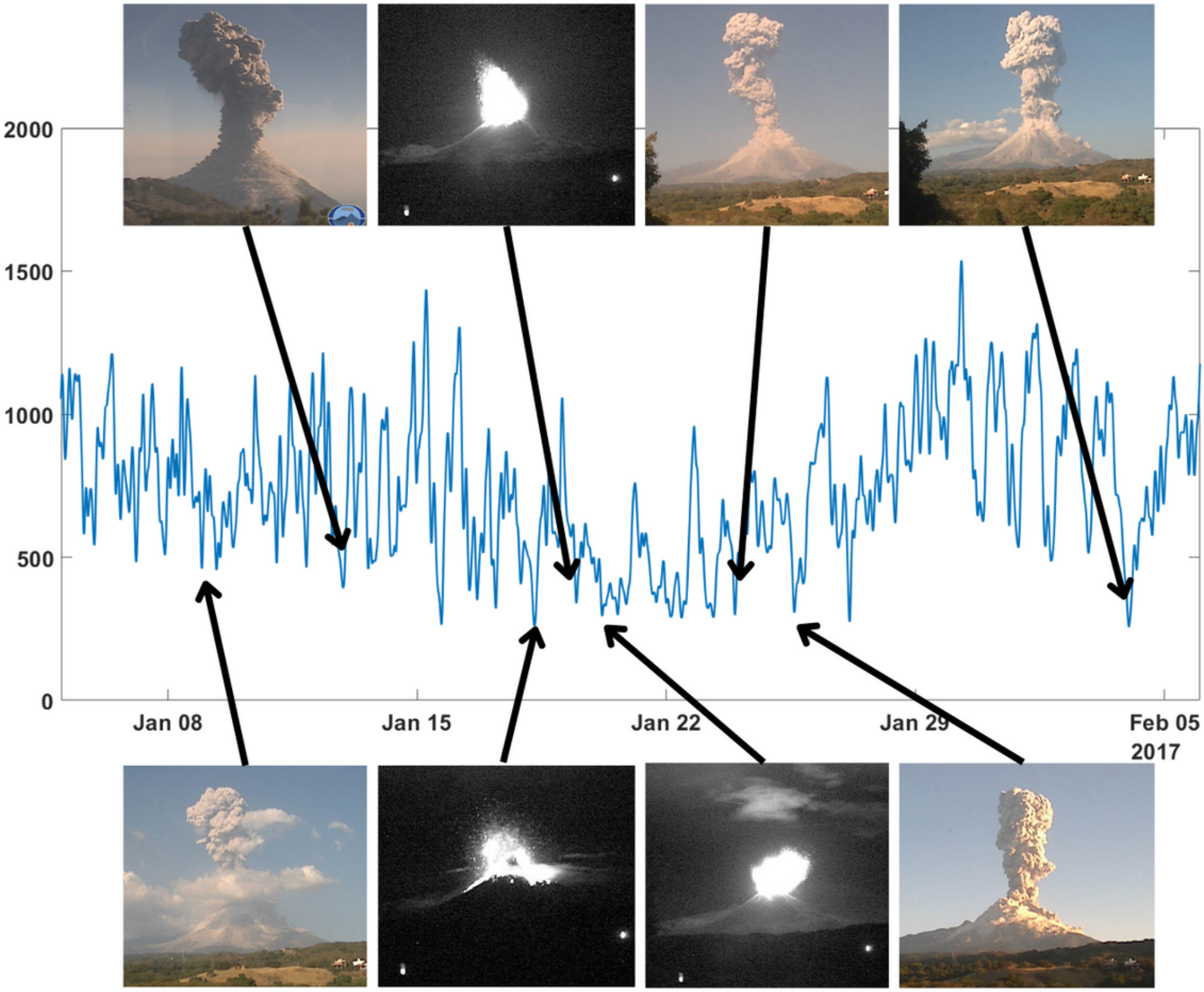

Figure 5

Temporal evolution of the SE values, obtained for the seismic station INCA, associated to period of 3 January-5 February 2015. In this with period we identified local minima and compared them (if available) with the images obtained by the visual monitoring Network. As observed all identified minima are linked to explosive activity.