International Journal of Disaster Risk Reduction 91 (2023) 103694

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Press media impact of the Cumbre Vieja volcano activity in the island of La Palma (Canary Islands): A machine learning and sentiment analysis of the news published during the volcanic eruption of 2021

J. Navarro [a], J. Urias Piña [b], F. Magdaleno Mas [d], R. Lahoz-Beltra [b,c,*]

[a] *Grupo Decisión Multicriterio Zaragoza (GDMZ), Departamento de Economía Aplicada, Facultad de Economía y Empresa, Universidad de Zaragoza, 50003, Zaragoza, Spain*
[b] *Department of Biodiversity, Ecology and Evolution (Biomathematics), Faculty of Biological Sciences, Complutense University of Madrid, 28040 Madrid, Spain*
[c] *Modeling, Data Analysis and Computational Tools for Biology Research Group, Complutense University of Madrid, 28040, Madrid, Spain*
[d] *Ministry for the Ecological Transition and the Demographic Challenge, And Technical University of Madrid, Spain*

ARTICLE INFO

Keywords:
Sentiment analysis
Machine learning
Volcanic eruption management
Disaster journalism analysis

ABSTRACT

In this work we have used as a source of information a large sample of the press articles published during 2021 about the eruption of the Cumbre Vieja volcano in the island of La Palma (Canary Islands). In contraposition, the scientific papers evaluating different facets of natural disasters have preferentially used social networks as a source of information. Herein we have shown how the emotions and sentiments expressed in press media can be efficiently analyzed via AI techniques to better assess the social impact of a disaster at the time it takes place. We have also gauged the usefulness of different classifiers combining sentiment analysis with multivariate statistical analysis and machine learning techniques. By applying this methodology, we were able to classify a newspaper article within a certain time frame of the eruption, and we observed significant differences between local news published in Spanish and those of foreign newspapers written in English. We also found different emotional trajectories of articles by applying the Fourier transform onto the inner "valence" progress along each article narrative time. In addition, there appeared a significant relationship between the surface area occupied by lava and the emotions and sentiments expressed in the articles—many other correlations and causalities could be explored too. The main findings of this research may constitute a helpful resource for a better understanding of the way press media react to volcanic activity, and may guide in public decision-making under different temporal horizons, including the design of improved strategies in the risk reduction domain.

1. Introduction

Cumbre Vieja volcano, the most active of the Canary Islands according to existing historical records, came into eruption on

* Corresponding author. Department of Biodiversity, Ecology and Evolution (Biomathematics), Faculty of Biological Sciences, Complutense University of Madrid, 28040 Madrid, Spain.
E-mail address: lahozraf@ucm.es (R. Lahoz-Beltra).

https://doi.org/10.1016/j.ijdrr.2023.103694
Received 16 November 2022; Received in revised form 23 March 2023; Accepted 12 April 2023
Available online 19 April 2023

September 19, 2021 (Fig. 1), following five decades of repose [1]. But Cumbre Vieja is not properly a volcano—it is a monogenetic volcanic field. Actually, in the geological records the erupting volcano has been called "Tajogaite", and it is a monogenetic volcano located inside the Cumbre Vieja volcanic field. But herein we maintain the popular name that has been used in press articles. Before the eruption, the Spanish Geographic Institute (IGN) and the Canarian Vulcanologic Institute (IVC) had detected from September 11, 2021, an intensified seismicity in the area, with thousands of seismic episodes of different magnitude, which began at a depth of over 20 km and progressively ascended towards the surface. The volcano eruption lasted 85 days and 8 h, originating damages estimated by the regional government of circa 900 million €. During that period, 2988 buildings were destroyed, from which 1345 had residential use, and 7000 people had to leave their houses [2]. Satellite information from EU Copernicus programme [3] showed that 1219 ha of land were covered by the volcanic lava, from which 370 corresponded to cropping areas—bananas mainly, also vineyards and avocado groves.

Cumbre Vieja had been studied for decades by different authors regarding its unrest signals [4], helium emission and concentration in its soils [5], its dynamics of diffuse carbon dioxide emissions [6], and the potential effects of such reactivation, such as near- and far-field tsunamis [7–9]. The interest of scientists and other segments of society for the governing processes and the predictable aftermaths of the volcano eruptions has kept going for many years, in the light of the aforementioned works and many others. Scientific and social awareness and attraction by Cumbre Vieja, and by volcanoes in general, is well-known. In fact, the term "volcanologist paradox" [1] was coined to explain the interpretive tension arising by the coexistence of specialists and the laymen fascination for eruptions, which also occurs in the evaluation of their consequences—in the human and monetary costs associated. Minimizing these conceptual tensions would imply working in the construction of a reinforced trust and collective involvement, particularly among expert teams and local people, including the press media too.

Social grieving for the damages created by the Cumbre Vieja eruption has been widely shown by local, national, and international media, and some authors have analyzed the relevance of adding new dimensions (mostly related to empathy and support) beyond the current vision of grief, by incorporating more adaptive and resilient processes within the personal and social sentiment of coping [10]. In this line, understanding natural events and their interaction with people's emotions and ways of life would oblige researchers and managers to study and interpret different environments: the closer physical environments of those more affected by the eruption, the affective environment (family, friends, neighborhood, school, etc.), and the communication environment as well. It would contribute to disseminate a more solid knowledge of the natural and human processes along the volcanic eruption [11]. In this respect, by analyzing how different media follow the natural dynamics and their immediate consequences, deeper insights for accurate communication of public policies and risk-taking decisions could be achieved.

1.1. On the coverage of different media

A thorough and systematic approach to the media impact of this volcanic eruption, and of other volcanoes, looks feasible and

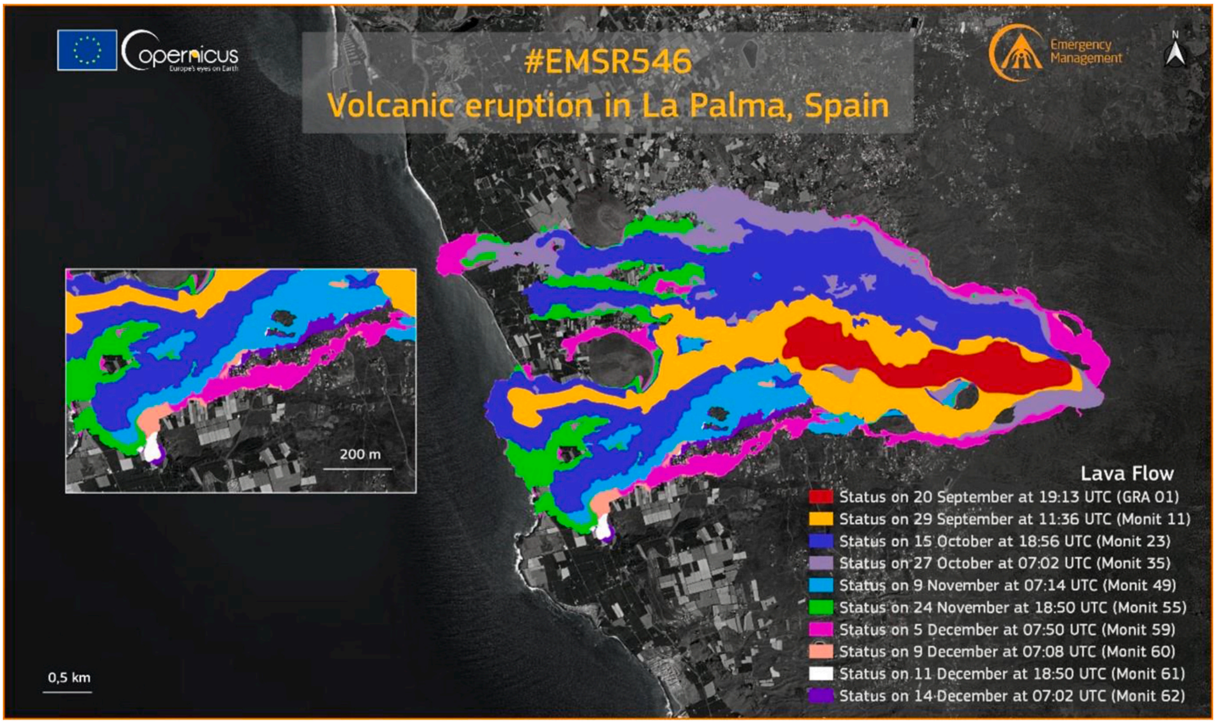

Fig. 1. Eruption of the Cumbre Vieja ("Tajogaite") volcano on the island of La Palma (Canary Islands) during 2021. Evolution of the lava flow from September 20 to December 14 (Source: Copernicus. https://www.copernicus.eu/en/news/news/observer-copernicus-eyes-la-palma-eruption).

helpful via the new sentiment analysis tools. In the construct of the social reality around an eruption in a complex semi-urban population, like in the Cumbre Vieja eruption, there were many participant voices – speeches of volcanologists, inhabitants of affected areas, vulnerable elders, and children, affected farmers, tourists, different administrations, etc. – which were largely reflected and reconfigured within the coverage of the different media. In this regard, the main difference between press media approaches (newspapers & news media) and social media approaches (social networks) is that there is a surplus of reflection and analytical thought inside the *curated* contributions of journalists, notwithstanding the ever-present temptation to sensationalize, in comparison with the immediacy and emotional spontaneity of social media contents.

So, thinking in terms of decision-making and preparedness for future risk reduction, the information distilled from press media would be, in Daniel Khaneman's terms of System 1 immediacy (S1) and System 2 reflexivity (S2) [12], halfway positioned in between these two systemic extremes. Thus, the S1 cascades of tweets or similar platforms and the S2 long-term commissioned reports, scientific articles, and meta-reviews, with the press media situated in between, would constitute an information continuum of social communication modalities. In this work we highlight potential advantages of press media for public decision bodies and risk management—including the necessity of getting rid of the vast misinformation campaigns that plague social media and social networks: fake news, trolls, bots, etc. This is an important concern when handling masses of tweets or from other platforms.

In the above sense, deceptive social bots—automated or semi-automated accounts designed to impersonate humans—have been effectively exploited for these kinds of abuse [13,14]. The spread of fake news and infodemic have increased dramatically worldwide in the last years, especially during the COVID-19 pandemic [15]. Such unverified and inaccurate information is generally referred as encompassing misinformation (false information created without any harmful intention), disinformation (false information deliberately created to harm an entity), or malinformation (information based on reality, created to inflict harm on an entity) [16]. Very often, during a disaster the confusion created leads to the publication of misinformation in social media [17]. During the Cumbre Vieja eruption, the volcanologist Dr Janine Krippner asked on Twitter to avoid the dissemination of tweets which respond to rumors related with the formation of tsunamis. In addition, the information published by social media users is subject to the ups and downs of events and mood changes in the affected community [18]. Thus, the fluctuations undergone by the information disseminated by social media can be useful in some cases, e.g., during Hurricane Dorian [18], but not for others. Furthermore, during the eruption of the Hunga Tonga-Hunga Ha'apai submarine volcano, the submarine cables were severely damaged cutting off Tonga (a Polynesian archipelago) communications with the outside world [19].

1.2. Social reactions to volcanic activity

Social perspectives about volcanoes in our times have been largely influenced by the way they have been portrayed in literature, films, and media [20]. It is also worth recalling that many cultures and civilizations which coexisted with volcanoes came into contact with them in pre-scientific ages, which contributed to the development of particular ways to explain their dynamics, usually involving mythological approaches that reflected fearful and even apocalyptic feelings towards eruptions [21]. Potentially, some ancient texts are susceptible of comparative analysis following our approach, particularly when different narratives have survived. In our times, the public reactions to volcanic activity are mostly based on its intensity and variability, on the risk of collateral destructive events (fires, earthquakes, tsunamis), and in the preparedness and potential vulnerability of neighboring populations [22]. The press information could efficiently contribute to bring these factors on the table and to discuss them more meaningfully. As argued, it can straightforwardly sidestep and minimize the risks of misinformation via fake news and media bots.

About the emotions and feelings displayed in volcanic eruptions, the perception of danger is essential. It generates the most powerful emotional reactions [23–25], gauged by the proximity to the danger area and other risk factors. These human emotional reactions have strong evolutionary roots [26]. They can be classified in fixed action patterns, flexible perception-action patterns, and superstructural perception-action patterns [27]. Depending on the level of danger, reactions may rapidly escalate towards the most basic or "fixed" emotions. In general, negative sentiments belong to the superstructural type, related to a combination of different personal, social and physical aspects, biased by income, demographic layers, livelihood type, level of education, culture, religion and perception, among other factors, which also include local and national governance responses. At any rate, the interactions between people and volcanic effects become multifaceted and complex, also comprising positive emotions about the associated risk hazards, which could suggest the necessity of applying an open-risk and multidimensional comprehension about such interactions [28–30], which additionally co-evolve following the natural patterns of perturbation.

Evaluating and monitoring sentiments about volcanic activity may thus be relevant to better understand such co-evolution and better prepare society for future volcanic risks. Sentiment analyses or opinion mining of different events and processes, including volcanic activity, have been increasingly explored [31]. Current opinion mining approaches are manifold, focused on the classification of positive/negative valences (polarity sentiment analysis [32]) and on the typification of the different levels of detail which may be applied to the analysis. By introducing more specifically oriented statistical methods, some common challenges in opinion mining may be overcome: (i) the conflict induced by the fact that an opinion word could be deemed as positive or negative according to specific situations; (ii) the probability that people could not transmit their opinions in the same way under different circumstances; (iii) the relative absence of sentiment analyses in languages different from English or Chinese [33], which are the dominant languages, up to this date, in these studies.

In essence, we are trying to answer the following question: Do the emotions and sentiments expressed by a journalist in a newspaper article reflect the date or period in which the article was written and chart the devastation effects caused by a catastrophe or natural disaster? We respond positively and provide robust analytical tools. By counting with the possibility of classifying press news within a certain episode or period of time during the development or evolution of a natural disaster, with the emerging differences between national and international clustering effects, and with the corresponding valence scrutiny via Fourier transform, new avenues may be open for the careful analysis of social impact, for better assessing the changing of social mood, and for the design of improved risk-reduction communication protocols. Anecdotally, the social impacts of an environmental disaster or natural catastrophe of the past might also be gauged many years after the catastrophe, based on the different narratives preserved.

2. Review of literature

Volcanic eruptions have been the subject of a number of studies. Each episode has generated specific approaches according to its own geophysical characteristics. For instance, the Fagradalsfjall eruption, in Iceland 2021, particularly affected atmospheric dynamics [34]; the Hunga Tonga-Hunga Ha'apai unleashed an enormous submarine eruption accompanied with important tsunamigenesis [35, 36]; the Anak Krakatu eruption in Indonesia 2018 generated a devastating tsunami [37]. Similarly, recent studies during the Tajogaite (Cumbre Vieja) eruption have covered geological/geophysical aspects [38], as well as the general impact of the eruption, its aftermath, and the long-term challenges [39].

Regarding sentiment analysis, it has been applied to the study of numerous crises and natural disasters, particularly during the pandemic caused by COVID-19, taking as the usual source of information micro-blogging services, i.e., Twitter [40–42]. In these cases, social networks allow a faster dissemination of the posted information, highlighting damages and help needed "in real time" [18]. The pros and cons of Twitter based approaches become evident. Subsequently, sentiment analysis techniques applied to social networks have been a useful tool in many quantitative analyses of crises and disasters [43]. See for instance text analysis for volcano monitoring [44], disaster response and recovery [45], Syrian chemical attack [17], COVID-19 pandemic [46,47], L'Aquila's earthquake [48], hazard crises responses [49], risk detection through crisis information [50], and hurricane Dorian social impact [18].

3. Methodology

The methodological approach was based on the combination of sentiment analysis with machine learning techniques and multivariate statistical models. The general protocol was similar to the approach used in previous studies in which these authors analyzed the conversations of a chat bot with other bots or with a human interlocutor [51] and about the effects of the COVID-19 pandemic [47, 52]. The chart in Fig. 2 shows the methodological procedure, which basically consisted of three steps. First, news were collected from press media sources, and their texts were normalized (depurated and cleaned); then, they were object of sentiment analysis; and finally, the results obtained were processed by means of multivariate statistical analysis and machine learning methods.

3.1. News collection and depuration

A total of 158 press items were collected and analyzed. The press articles were classified into two groups, one consisting of press articles written in Spanish ($n = 87$) and the other group of articles written in English ($n = 71$). The press articles were collected from the beginning of the volcano eruption (September 19, 2021) until the official date of the end of the eruption (December 13, 2021), with an extra period of about two weeks in order to compile a sufficient number suitable for statistical analysis. Thus, the articles were

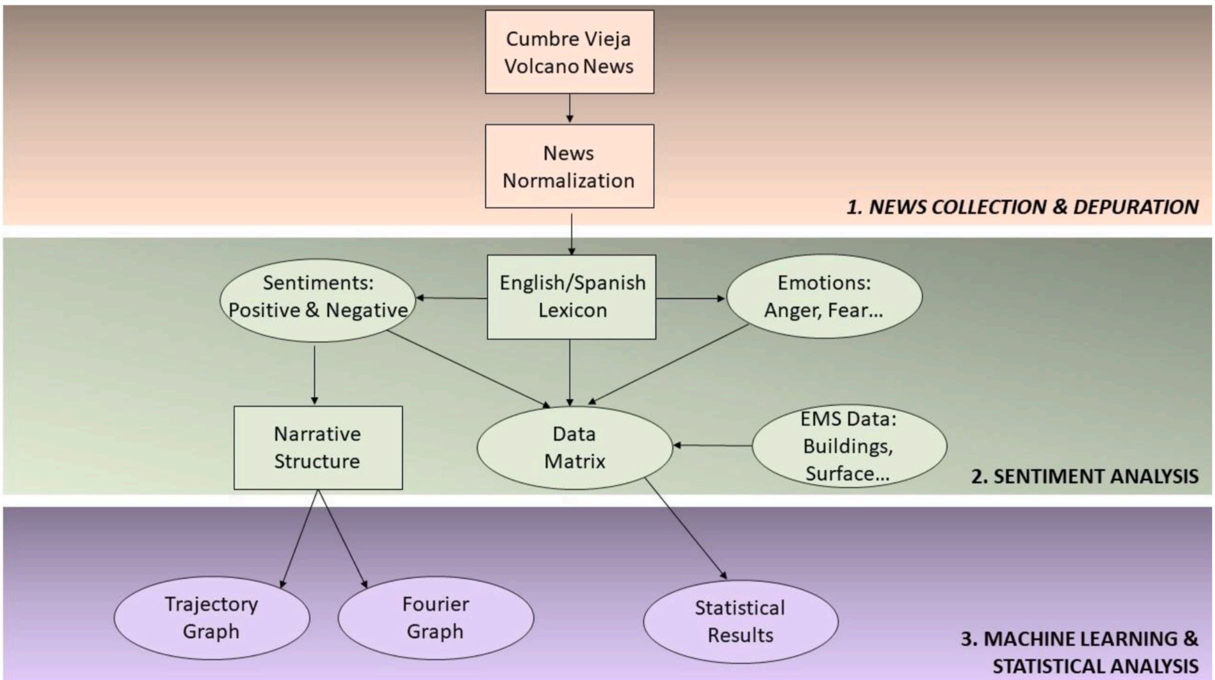

Fig. 2. Methodological flow diagram.

collected until December 26 and December 31 for the news written in Spanish and English, respectively. The final choice of 158 press articles, 87 articles published in the Spanish press and 71 published in foreign media, is statistically appropriate because sample sizes are both representative ($n > 30$) and close to each other, being a balanced design.

The sources of the articles were official web pages of reliable press media, newspapers, TV, and radio media. The Spanish and foreign press media were chosen on the basis of whether they were published in both print and online, as well as on their relevance. A similar criterion, relevance, was followed to choose radio and TV channels. Otherwise, sports newspapers, e.g. Marca, were selected because they reported the events in the local 'La Palma' on time, having more diffusion than the general press. The press articles in Spanish were extracted from the following information sources: As, Diario de Navarra, El Pais, La Vanguardia, El Mundo, RTVE, Telecinco, Cadena Ser, La Razon, Antena3, Marca, and El Confidencial. The sources from which we obtained the press releases published in English were: Reuters, Garda, BBC UK, BBC, Aljazeera, NY Times, The Guardian, CNN Reuters, The Local, Euronews, Euroweekly News, NBC Connecticut, New Indian Express, ITV News, Voanews, Volcano.si.edu, Surinenglish, UK Yahoo News, Accuweather, Earthsky, VolcanoDiscovery, Globalnews, CNN, Dailymail UK, Phys.org, CBS News, Earth observator. In this mix, which we think is also representative internationally of widely followed media, there is a small but significant presence of specialized sources (it may contribute to explain some of the risk appreciation differences found).

All the collected news were 'depurated'. Since their texts contained words in different tenses, plurals, or derived from other words, they were normalized transforming the words into their basic forms. Next, the texts were 'cleaned up', a process that included different tasks such as orthographic correction, elimination of punctuation marks and special characters, conversion of acronyms to regular expressions, conversion of capital letters to lower case, etc.

3.2. Sentiment analysis

The sentiment analysis was performed separately in two groups of press articles depending on the language used. The press articles were analyzed in different steps applying text mining by means of the Syuzhet 1.0.6 package [53] and RStudio 1.1.419, as shown in Fig. 2.

In both cases (English and Spanish), the procedure applied was similar. Once the text of a press article was normalized (depurated and cleaned), it was fragmented into smaller strings or sentences. The result of this preliminary analysis was a sentiment vector whose length, i.e., the number of elements, was the number of paragraphs that frame the text from each press article. Thereafter, each element of the vector was given the value that corresponded to the evaluation of the emotion and sentiment words in the analyzed item. The sentiment valence was calculated for each one of the sentences obtaining its value as the difference between the number of positive and negative words. In addition, it was also obtained the number of words associated with the basic emotions, calculating the percentage of words associated with each emotion expressed in the text. This sentiment analysis procedure was performed separately in the two groups of press articles depending on the language used.

The sentiment analysis was conducted with NRC Word-Emotion Association Lexicon Version 0.92 [54,55]. This lexicon is a list of English/Spanish words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). In total, the lexicon contains 14,182 unigrams (words) and more than 25,000 senses. The NRC lexicon can be explored deeply through an interactive visualization on the NRC website [56], where one can look for the number of words associated with each emotion, word-sentiments associations, and word-emotions associations. The Spanish version of the lexicon has already been used to assess mood evolution in the COVID-19 vaccination process in Spain [47].

Next, from the values of the sentiment vector– the valences of the sentences– we examined how emotions were distributed in the text, obtaining an overall statistical assessment of each press article. To this end, several univariate sample statistics were obtained: the minimum value (Min), the first quartile (Q_1), the median (Me), the mean ($\overline{x}$), the third quartile (Q_3), and the maximum value (Max). Another feature analyzed in the articles was the story narrated in the text and how the frequency of words expressing positive or negative sentiments changed over the course of the article. The result of this analysis was a trajectory graph—a plot of the variation of the emotional valence with respect to the narrative time.

Afterwards, to eliminate the extreme values of sentiments we applied the Fourier transform, converting the trajectory graph into another equivalent graph independent of the length of a press article [57]. Based on this graph, it was possible to find out which sentences of a particular article item expressed a positive or negative emotion, whether the narrative of a specific story evolved towards a happy or a sad ending, etc. In previous studies [51] these authors found that the graph of the Fourier transform, plotting the emotional variation of valence with respect to the narrative time, followed one of four possible elementary patterns (Positive, Negative, O_Negative, O_Positive), which are the Fourier terms describing the elementary 'arc' evolution of a narrative. Lastly, once the Fourier plot of each article was obtained, we analyzed with a chi-square test of independence whether there was a relationship between the number of Fourier plots of each class (Positive, Negative, O_Negative, O_Positive) and the month during the volcanic eruption in which the article was published (September, October, November, December).

3.3. Statistical and machine learning analysis

3.3.1. Statistical analysis

As a result of the sentiment analysis, a data matrix was obtained for the total of analyzed press articles. In this matrix, there were 16 columns or predictor variables whose values were six univariate sample statistics of the sentiment vector (Min, Q_1, Me, $\overline{x}$, Q_3, Max) as well as the total number of words associated with eight emotions (anger, fear, anticipation, trust, surprise, sadness, joy and disgust) and two sentiments (negative and positive). In this matrix, the units of analysis – the press articles – were placed in rows.

Once completed the previous stage, the data matrix was analyzed by applying multivariate statistical analysis and machine learning methods. The aim of these analyses was to answer a series of relevant questions. In a press article about a natural phenomenon that represents a disaster for the involved population, such as the volcanic eruption of Cumbre Vieja and based on the analysis of the sentiments expressed in the article, is it possible to estimate the time period of the eruption at which the article was published? Is there any difference in the sentiments expressed in a press article depending on whether the journalist or the news media are local or foreign? In a newspaper story, is there any stochastic relationship between the predictor variables resulting from the sentiment analysis and the variables related with the eruption effects, such as the surface area occupied by the lava?

In order to answer these questions, we performed a principal component analysis [58]. The goal was to simplify the information provided by the 16 predictor variables in the data matrix, so to choose a smaller number of predictors and to understand the data matrix in a simpler way, reducing the dimension space. For this purpose we obtained the eigenvalues—the proportion of variance explained by the new predictor variables or principal components.

Next, our goal was to study the suitability of differente classifiers in order to have a predictive model capable of classifying the press news in one of the four months in which the Cumbre Vieja volcanic eruption occurred. Classifiers are procedures or algorithms that classify the news in different classes or groups, in particular the period of time in which the article was published. If the classification of a given article was correct, then the classifier would have accurately detected the period in which the news item was published via the sentiments expressed in its text.

3.3.2. Combining statistical and machine learning models

In our study we chose the following classifiers for evaluation: discriminant analysis, perceptron neural network, and logistic regression classifiers; all of them are very common techniques in multivariate statistical analysis and machine learning. Moreover, at present these techniques are included in most of the current statistical packages.

- *Discriminant analysis*. It was conducted by constructing Fisher's linear discriminant functions [59] which maximize the separation of groups. The goal was to find two or more linear combinations of predictor variables, among the 16 variables resulting from the sentiment analysis, with which we could classify a press article in a particular group representing the months in which the Cumbre Vieja volcano eruption took place.
- *Perceptron neural networks*. Artificial neural networks are connectionist machine learning models inspired by the neural circuits of the brain [60] allowing the classification of objects. They consist of nodes representing neurons arranged in layers, with the networks usually comprising an input layer and an output layer, and including one or more intermediate or hidden layers. In the present work we have used a neural network known as a multilayer perceptron network (MLP). In a MLP neural network, the input layer would receive for a certain press item the values of the 16 prescriptor variables, it would internally process that information, and the output layer would obtain the network's response. The output of the network was in this case the month in which the notice about the volcanic eruption was published. Based on a subset of press articles from the data matrix, the MLP network was previously trained to recognize and classify news correctly by applying an algorithm known as backpropagation method [60]. By means of this algorithm, the weights of the connections between nodes were modified, following what is known as supervised learning. The topology of the network included an input layer with 16 neurons, a hidden layer formed by 2 or 3 neurons, and an output layer of 4 neurons corresponding to the months of September, October, November, and December. The 16 neurons in the input layer accounted for the 16 variables (anger, anticipation, disgust, fear, joy, sadness, surprise, trust, negative, positive, Min, Q_1, Me, $\bar{x}$, Q_3 and Max), thus with the number of words associated with the eight emotions, two sentiments, and the sample univariate statistics of the sentiment vector. The activation functions were the hyperbolic and sigmoid tangent for the hidden and output layers, respectively. The gradient slope algorithm was used with an initial learning rate equal to 0.4, and learning was evaluated with the sum of squares as an error function. We compared the appropriateness of the discriminant analysis and the perceptron neural network classifying a press article in a given period of time in two different scales. On the one hand, the articles were classified into one of the four months (September, October, November or December) in which the volcanic eruption took place. On the other hand, we decided to study the suitability of the classifiers sorting the press articles into two groups or clusters. One group '0' included the press articles published in the months of September and October, during the initial stage of the eruption. The other group '1' represented a final stage defined by the articles published during the months of November and December.
- *Logistic regression model*. Since in the latter case the output of the classifier was either 0 or 1, we included the study of other classifier, using the logistic regression model [61] as one of the procedures to classify press releases into each group. With this type of regression model it was possible to predict the outcome of a categorical variable, in our case 0 for the initial stage of the eruption (September, October) or 1 for the final stage (November or December), as a function of the independent or predictor variables.
- *Probabilistic neural network*. Further we studied the suitability of another classifier, a probabilistic neural network, in order to classify each news into one or another group according to the language in which it was written. We classified the articles by means of a probabilistic neural network classifier [62] because we found sentiment differences between the press articles depending on the language in which they were written. The procedure used to carry out the present non-parametric classification method [63] involved the estimation of a density function for each group of articles. The estimation was constructed using a Parzen window, a procedure that weights the observations of each group of articles according to the distance from their location. In this study the network comprised four layers of neurons, i.e. input, pattern, summation, and output layers, which were composed of 2, 10, 2, and 2 neurons respectively. The 2 neurons of the input layer were standing for the predictor variables, so in the present study only the positive and negative sentiments. The 10 neurons of the pattern layer calculated the contribution of the input variables to the density function of each news group. At last, the 2 neurons of the sum layer assigned each press article to one or the other news group, a decision which was obtained and displayed in the 2 neurons of the output layer.

Finally, since the language of the source of information affected the sentiment analysis outcomes, we evaluated the extent to which the emotions and sentiments expressed in the articles were different depending on the language in which they were written. We compared the medians of each emotion between the news written in English and those written in Spanish by means of a Mann-Whitney (Wilcoxon) test. The Wilcoxon test was also applied to compare the medians of positive and negative sentiments in the two groups of press articles.

3.3.3. *Statistical relationship between volcanic eruption and press emotions and sentiments*

Using Copernicus Emergency Management Service (EMS) as a source of information, we could systematically obtain data on the activity of the volcano during the months of the eruption. For each date, we compiled in a table the surface area (hectares) covered by lava, the number of earthquakes, and the number of buildings destroyed per day.

We studied whether there was a statistical relationship between the surface area covered by lava with the emotions and sentiments expressed in a press article. For this purpose, and due to the presence of multicollinearity among the predictor variables, we applied the multiple linear regression chain method. In this study, however, we only analyzed the surface area covered by the lava to illustrate the magnitude of the natural disaster; the number of earthquakes and the number of buildings destroyed per day could be subject to future research.

In all the above-mentioned works, the principal component analysis, discriminant analysis as well as the logistic regression model, the probabilistic neural network, and the multiple linear regression, their respective models were built by means of STATGRAPHICS Centurion 18 version 18.1.12. Using this statistical package, other statistical tests were also conducted, such as the Wilcoxon test and the multiple linear regression. In addition, the perceptron neural network model was performed with the IBM SPSS Statistics version 22 statistical package.

4. Results

In this Section we processed the data obtained from sentiment analysis. As we described in Fig. 2, there was a narrative structure, a series of variables related to the physical and urban impacts, and a data matrix summarizing all these variables together with sentiment analysis results. Obtaining the eigenvalues of the data matrix (via principal component analysis) appeared as the first step. It would determine whether further predictions based on the data obtained were feasible or not. We had to do that for the news in each language, first in English and then in Spanish.

4.1. *Analysis of the news written in English*

4.1.1. *Principal component analysis: space dimension reduction*

In this study we first performed a factorability test by obtaining the Kaiser-Meyer-Olkin measure (KMO) for ideal sampling, assessing whether it was worthwhile to extract reducing factors from a set of variables. Since KMO was equal to 0.835828 (must be at least 0.6) we concluded that in the present study a factorization was feasible. In consequence, a principal component analysis was conducted considering the classification of the press articles during the four months of the eruption. We extracted three principal components, since their eigenvalues (7.6324, 1.9262, 1.5446) were equal or higher than unity. Together the three principal components explained 69.396% of the variability in the original data, with the two principal components PC1 and PC2 (see Table 1) aptly summarizing most variables of the sentiment analysis in each article. The first principal component (PC1) collected the effect of the eight emotions and the two sentiments, their weights being very similar and of positive sign. The second principal component (PC2) aptly captured the effect of the sample statistics calculated from the sentiment vector. Finally, the third principal component (PC3) reflected the rank of the *valence* in a press article: Median, Max, Q1, and Min values of valence.

In Fig. 3 we show the biplot for these two principal components. It is interesting to note a correlation between positive emotions (*joy, trust, surprise, and anticipation*) and positive sentiment (*positive*), as well as between negative emotions (*fear, anger, disgust, and*

Table 1
Table of component weights (English press articles).

	PC1	PC2	PC3
	1	2	3
Anger	0.30906	−0.100829	−0.0888711
Anticipation	0.327952	0.0778098	0.0426475
Disgust	0.282448	−0.0405535	0.00487426
Fear	0.339326	−0.0776851	−0.0609463
Joy	0.303533	0.197328	0.072347
Sadness	0.300654	−0.0600962	−0.105506
Surprise	0.323247	0.0489104	−0.00663019
Trust	0.286234	0.109637	0.11191
Negative	0.330943	−0.146225	−0.0889564
Positive	0.338591	0.0822905	0.0215608
Min	−0.0569136	0.310579	0.309858
Q1	−0.0121977	0.250056	−0.566931
Me	−0.028023	0.418606	−0.524037
Mean	0.00747464	0.464483	0.266309
Q3	−0.0334614	0.478347	−0.127658
Max	0.0595891	0.33497	0.412284

sadness) and negative sentiment (*negative*).

4.1.2. Discriminant analysis classification of press articles

Fig. 4 shows how the impact of the volcanic eruption was reflected in the emotions and sentiments expressed in the articles published all through the months of September, October, November and December. The analysis of emotions combined with the discriminant analysis allowed us to classify each news in the month in which it was written, mirroring the course of the volcanic eruption.

Table 2 shows how the sentiments reflected in the news varied significantly during the four months of the eruption. See also Fig. 4. This was confirmed by a discriminant function statistically significant (*p-value* = 0.0005) that accounted for 76.64% of the variance. A high value of the canonical correlation (0.7295) indicated a strong relationship between the group membership (month in which a press article was published) and the discriminant function values. This was also specified by the eigenvalue ($\lambda = 1.1358$) with a proportion of 23.36% of the total variance (Wilk's Lambda) not explained by differences among months. In consequence, the discriminant function was taking different values in the different months, successfully discriminating among the articles published in each month. The classification table (Table 3) shows how the foreign press articles were correctly predicted in the classification, with an efficacy of 69.01% (weighted arithmetic mean).

Nevertheless, when the press items were only classified into two groups, the initial stage (September and October as group 0) and the final stage (November and December as group 1), then the success rate in the classification was increased. In this case the discriminant analysis correctly classified 76.06% of the articles in one of the two groups (0/1).

4.1.3. Multilayer perceptron network (MLP) classification of press articles

The perceptron neural network (Fig. 5) successfully classified 80% and 78% of the press articles into two groups (0/1) during the training and trying out stages, respectively. We could conclude that both classifiers, discriminant analysis, and perceptron had very similar performance in classifying an article into one of the two groups. It is important to note that the most important predictor variables for the perceptron (Fig. 6) were Q_3 (100%), that is, the third quartile of the valence, plus three emotions: trust (92%), joy (84%), and fear (80%). It was also found that the mean value of valence and the negative sentiments exhibited both equal relevance (74%). In conclusion, the press articles published in English were successfully classified by the perceptron into two groups 0/1, being the most relevant predictor variables fear and the negative sentiments expressed. However, at the same time, the articles written in English reflected 'confidence' (trust) and 'enjoyment' (joy) in the face of a spectacular natural phenomenon.

4.1.4. Logistic regression classification of press articles

In the logistic regression model, the press articles were again classified into the same two groups, obtaining in the chi-square goodness-of-fit test a *p*-value equal to 0.7929. Consequently, a relationship between the group or cluster 0/1 and the independent predictor variables was established by the following equation of the fitted model:

$$G_{English} = \frac{e^{x}}{1 + e^{x}}$$

with x being equal to:

$$x = -0.3326 + 0.0001\,disgust + 0.0004\,anger + 0.0006\,anticipation + 0.0007 fear$$
$$-0.0042\,joy - 0.0017 sadness - 0.0031\,trust + 0.0007\,negative + 0.0010\,positive$$

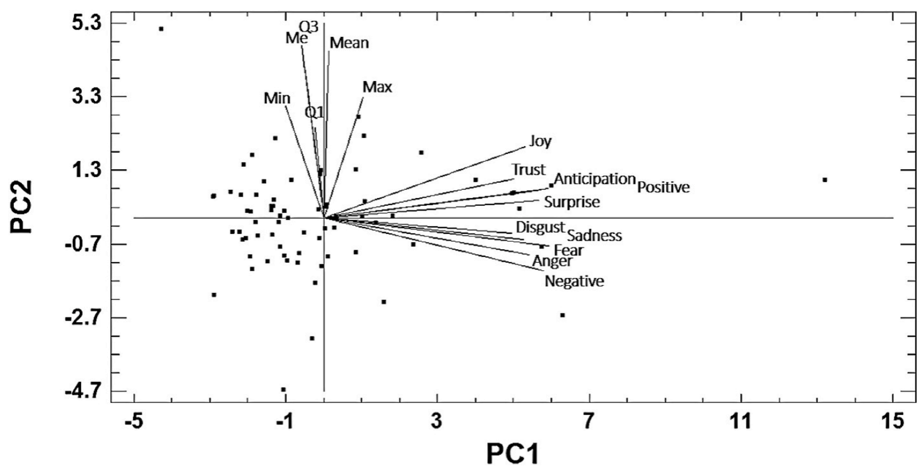

Fig. 3. Biplot of articles written in English showing press articles as a function of the first (PC1) and second (PC2) principal components. The figure shows emotions (joy, trust, anticipation, surprise, disgust, sadness, fear, anger), two sentiments (positive, negative), and sample statistics (Min, Q_1, Me, $\overline{x}$, Q_3 and Max).

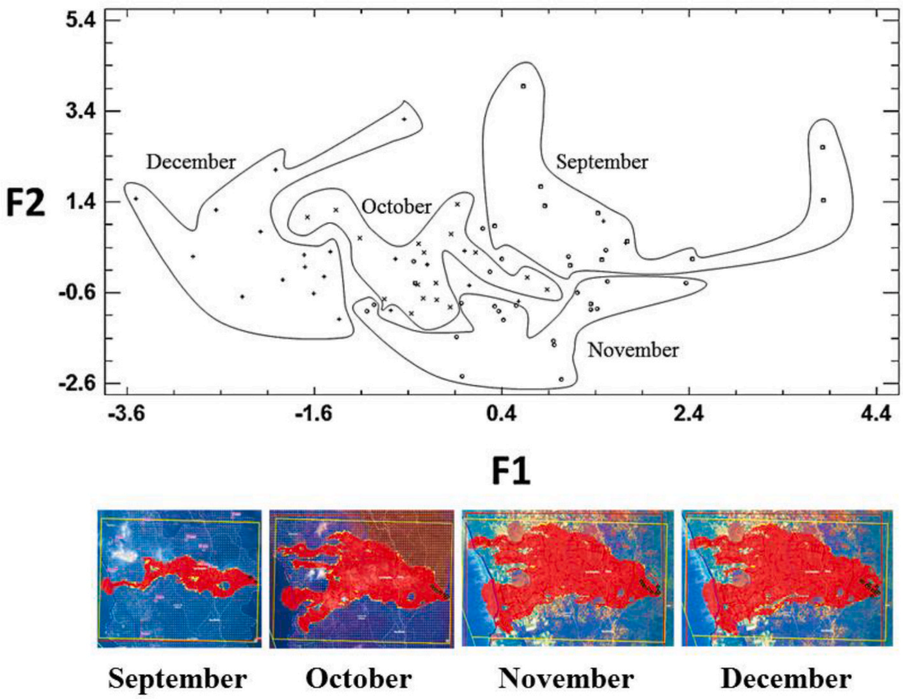

Fig. 4. Monthly classification of foreign press articles (written in English) based on discriminant analysis (F1 and F2 are classification functions). The bottom section of the figure shows the surface occupied by lava during the months of volcanic eruption.

Table 2
Discriminant analysis of English press articles.

Discriminant function	Eigenvalue	Relative percentage	Canonical correlation
1	1.13584	57.73	0.72925
2	0.430197	21.87	0.54845
3	0.40131	20.40	0.53515

Functions	Wilks' Lambda	Chi-squared	d.f.	p-value
1	0.233615	87.2448	48	0.0005
2	0.498965	41.7132	30	0.0757
3	0.713618	20.2445	14	0.1226

Table 3
Classification table of English press articles.

Actual month	Size	*Predicted month*			
		September	**October**	**November**	**December**
September	13	10 (76.92%)	2 (15.38%)	1 (7.69%)	0 (0.00%)
October	17	0 (0.00%)	11 (64.71%)	5 (29.41%)	1 (5.88%)
November	23	3 (13.04%)	3 (13.04%)	15 (65.22%)	2 (8.70%)
December	18	1 (5.56%)	2 (11.11%)	2 (11.11%)	13 (72.22%)

4.2. Analysis of the news written in Spanish

4.2.1. Principal component analysis: space dimension reduction

The principal component analysis with the KMO measure was equal to 0.8607, explaining a 75.46% of the variability. We also obtained the first two principal components, PC1 and PC2 (Fig. 7), showing that their modeling content was similar to the principal component analysis of the English-language news. However, we observed differences between the biplot obtained for the news written in English (Fig. 3) and the biplot for the news published in Spanish (Fig. 7). For the latter, the correlation among the univariate sample

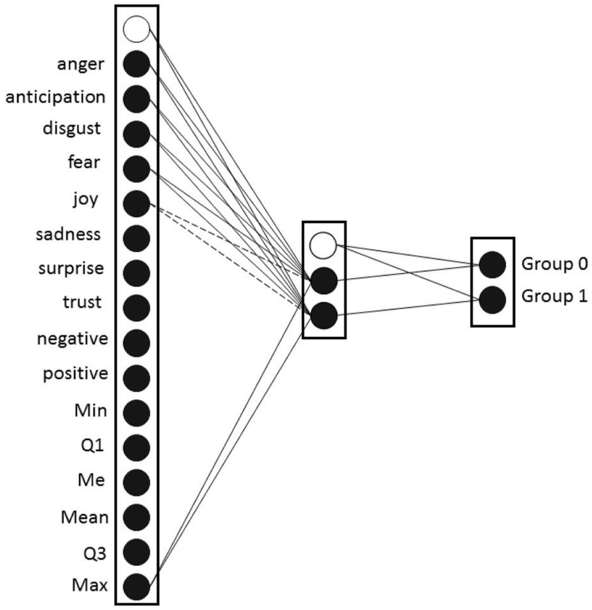

Fig. 5. Multilayer Perceptron Network (MLP) for the classification of news written in English. MLP depicts in the input layer the 16 neurons that receive the values of the prescriptor variables collected in the sentiment analysis step, plus an intermediate or hidden layer formed by 2 neurons, and the output layer with 2 neurons whose activation results in the classification of a news article in Group 0 (articles published in September and October) or in Group 1 (November and December). In the figure the white node represents the voltage or bias used to enhance MLP training via backpropagation, and the black nodes stand for the neurons.

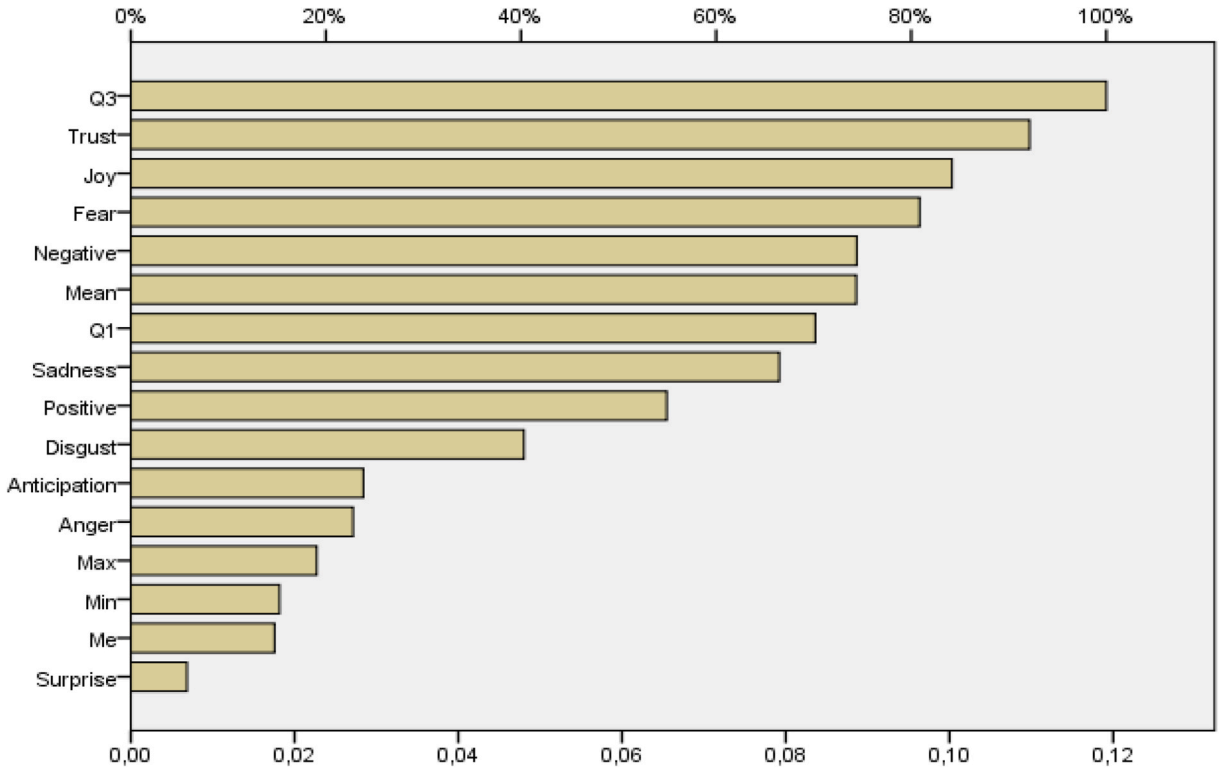

Fig. 6. Bar chart showing the relevance of the predictor variables in the perceptron neural network when classifying the news written in English into two Groups (0 and 1).

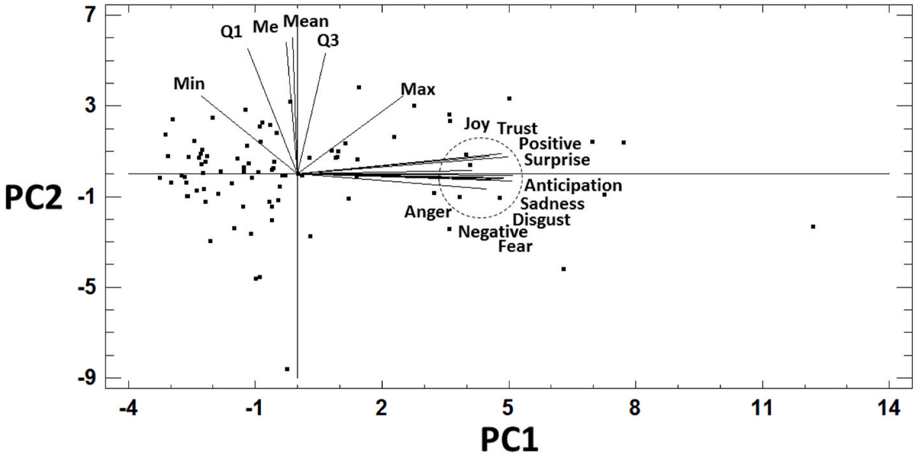

Fig. 7. Biplot of articles written in Spanish showing press articles as a function of the first (PC1) and second (PC2) principal components. The figure shows emotions (joy, trust, anticipation, surprise, disgust, sadness, fear, anger), two sentiments (positive, negative) and sample statistics (Min, Q_1, Me, $\bar{x}$, Q_3 and Max). The circle shows the area in which there is a correlation between emotions (anger, fear, anticipation, confidence, surprise, sadness, joy and disgust) and sentiments (negative and positive).

statistics (Min, Q_1, Me, $\bar{x}$, Q_3, Max) of the sentiment vector was lower than for articles written in English. Also, we found that for Spanish-language articles the correlation between emotions (anger, fear, anticipation, confidence, surprise, sadness, joy and disgust) and sentiments (negative and positive) was higher than for articles written in English.

4.2.2. Discriminant analysis and multilayer perceptron network (MLP) classification of press articles

One of the most surprising outcomes of this work relates to the discriminant analysis results. When we considered the classification of the press articles in Spanish into four groups – the months elapsed from September through December – then the percentage of correctly classified press articles releases dropped to 59.77%.

Similarly, the perceptron neural network (Fig. 8) was less successful in classifying the press articles into two groups or clusters, group 0 (September and October) and group 1 (November and December). In that case, the perceptron classified correctly 59.0% and 69.0% of the articles during the training and try out stages, respectively. However, the discriminant analysis (p-value = 0.0200) correctly classified 74.71% of the articles (Table 4). Thus, when we classified the articles into two groups (0/1) the discriminant

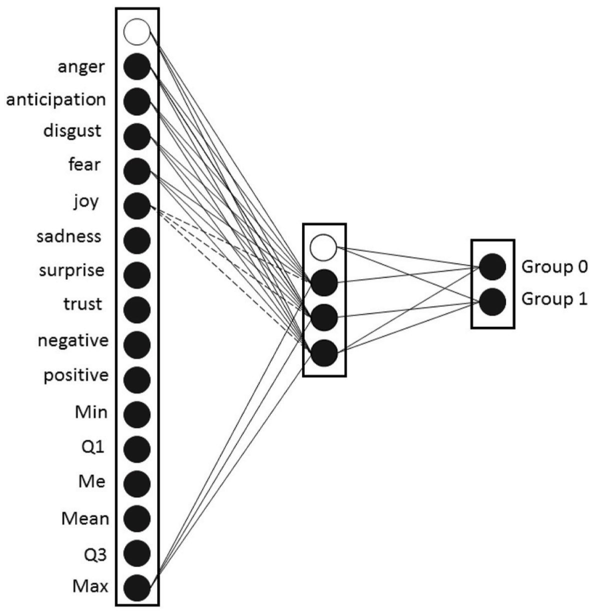

Fig. 8. Multilayer perceptron network (MLP) for the classification of news written in Spanish. MLP depicts in the input layer the 16 neurons that receive the values of the prescriptor variables collected in the sentiment analysis, an intermediate or hidden layer formed by 3 neurons, and the output layer with 2 neurons whose activation results in the classification of a news article in Group 0 (articles published in September and October) or in Group 1 (November and December). In the figure the white nodes represent the voltage or bias used to enhance MLP training via backpropagation, and the black nodes stand for the neurons.

analysis was more efficient than the perceptron neural network. But the percentage of Spanish articles classified correctly was lower than for the foreign press.

In contrast to the articles written in English, another interesting result was that the most important predictor variables in the perceptron classification (Fig. 9) were Max (100%), or the maximum value of the valence, and three negative emotions: sadness (77%, equaling the median Me of the valence), anger (73%), and fear (72%). In the Spanish press there was never during the course of the volcanic eruption a high confidence or 'trust' as there was in the foreign press (falling from a 92% for foreign articles to 39% for Spanish articles). This was also observed for the joy variable (falling from 84% for foreign articles to 25% for Spanish articles).

4.2.3. Logistic regression classification of press articles

Similarly, a logistic regression analysis was conducted with the Spanish articles by sorting them into group 0 (September and October) and group 1 (November and December). The chi-square goodness-of-fit test resulted in a p-value equal to 0.1870, which allowed us to conclude that with a confidence level of 95% the logistic function adequately fitted to the observed data. Therefore, the relationship between the predictor variables and the group was established by the following equation:

$$G_{Spanish} = \frac{e^{x}}{1 + e^{x}}$$

with x being equal to:

$$x = 0.1423 + 0.1072\ anger + 0.0325\ anticipation + 0.3783\ disgust - 0.3228\ fear + 0.3374\ joy + 0.6342\ sadness - 0.4459\ surprise - 0.0387\ trust - 0.1280\ negative - 0.0373\ positive + 1.5798\ Min + 0.4463\ Q_1 + 5.7468\ Me - 14.8267\ \overline{x} + 8.2243\ Q_3 + 3.2159\ Max$$

4.3. Analysis of the differences between articles written in English and Spanish with a probabilistic neural network

The differences in emotions and sentiments between the articles in the two languages may be appreciated in Table 5. Regarding the eight emotions analyzed, there were significant differences in the emotions expressed in the written stories, with the exception of trust. The median of anger, anticipation, disgust, fear, joy, sadness, and surprise was significantly higher for the articles in English than for those in Spanish. The Cumbre Vieja volcano eruption was experienced with a greater emotional content by foreign journalists than by Spanish journalists. Likewise, it was found that there were no significant differences in the medians of positive emotions between the two groups of articles. However, the medians of the negative sentiments differed significantly, with the medians of English articles higher than the medians of the Spanish articles.

The latter finding indicated that for the foreign journalists sentiments were more negative than for the Spanish journalists. Possible explanations will be discussed later. Fig. 10 illustrates the probabilistic neural network designed to classify the negative/positive news according to the language in which they were written. The percentage of correctly classified training cases was equal to 78.48%, showing in Fig. 11 the classification graph. Note how the region defined by the prescriptor variables was split into two areas where press articles written in Spanish and in English became classified.

4.4. Analysis of the Fourier patterns in the narrative plot

In our study there appeared several characteristic patterns in the temporal change of sentiments and emotions along the narrative plot. Fig. 12 shows examples of the different classes of Fourier plots. In Fig. 12a we may observe how an article starts the story reflecting positive emotions but concludes with words expressing negative emotions. In sentiment analysis parlance, the article has been written with a theatrical style typical of a 'tragedy'. In the present study, we have referred to this pattern as 'Positive'. On the other hand, in Fig. 12b the narrative style is the opposite. That is, a 'Negative' article starts expressing negative emotions but ends with positive emotions, which is typical in theatrical language of the 'comedy'. Likewise, there are articles (Fig. 12c and d) in which positive and negative emotions and sentiments alternate throughout the narrative time. In this case, and regardless of how the article ends, we have studied two kinds of patterns. In particular, we found press articles which begin by expressing negative emotions (Fig. 12c) and articles which start with a predominance of positive emotions (Fig. 12d); they were denominated as 'O_Negative' and 'O_Positive' respectively.

The chi-square statistical analysis of independence shows that there was a significant relationship between the four Fourier plot classes (Positive, Negative, O_Negative, O_Positive) regarding the variation of valence (see Fig. 12), as well as the narrative time and the month in which the article was published (Fig. 13). Thus, both in the articles written in English and those written in Spanish the test of independence allowed us to conclude that there was a dependence (p-value equal to 0.000) between these two factors, i.e. the article

Table 4
Classification table of Spanish press articles.

Actual month	Size	Predicted Group	
		Group 0	**Group 1**
Group 0	40	30 (75.00%)	10 (25.00%)
Group 1	47	12 (25.53%)	35 (74.47%)

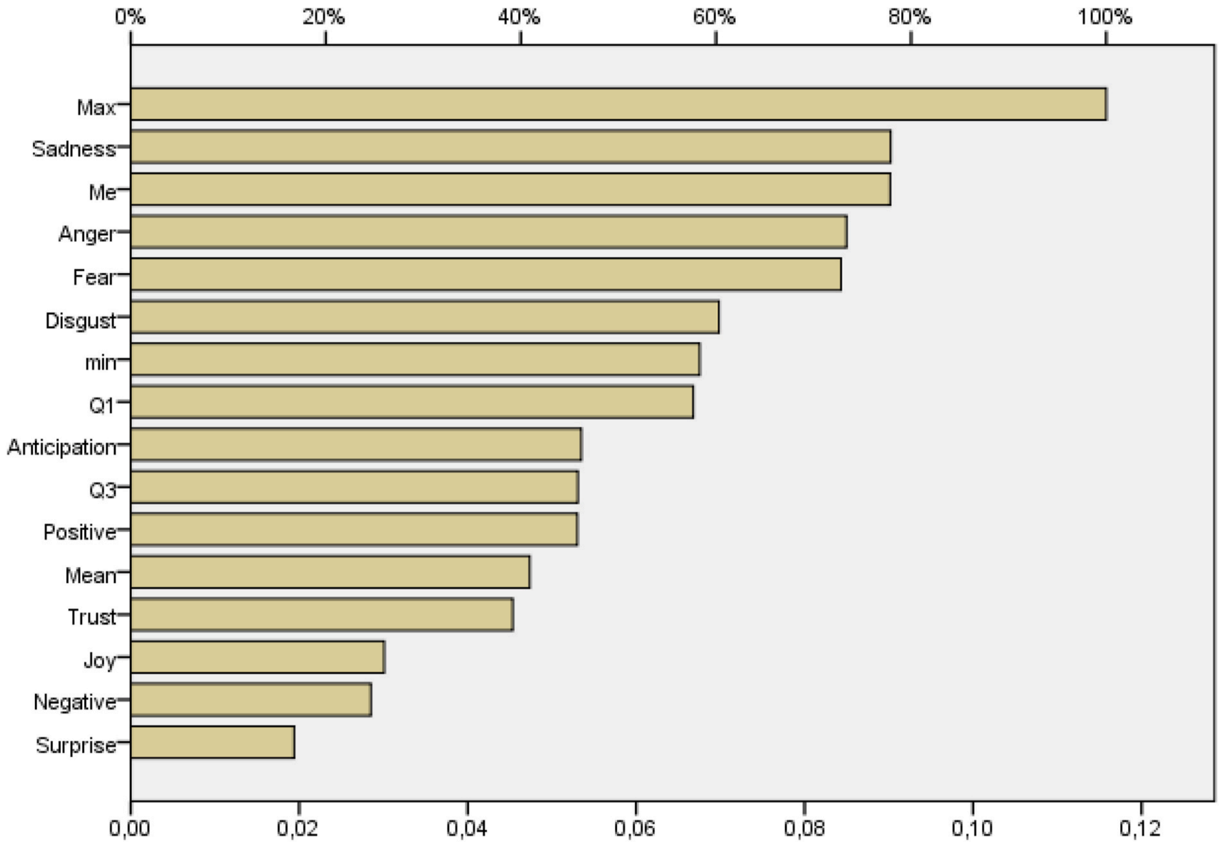

Fig. 9. Bar chart showing the relevance of the predictor variables in the perceptron neural network when classifying the news written in Spanish into two Groups (0 and 1).

Table 5
Contrast of medians between articles written in English and Spanish. Mann-Whitney (Wilcoxon) test.

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Positive	Negative
p-values	0.0000	0.0106	0.0000	0.0000	0.0020	0.0014	0.0000	0.8224	0.5553	0.0000

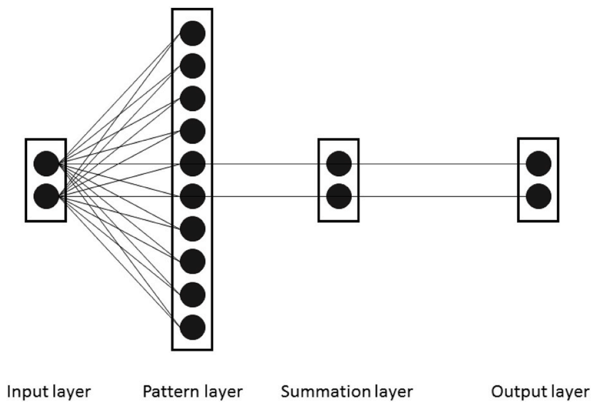

Fig. 10. Probabilistic neural network designed to classify the news in two clusters: 'English' for the foreign newspapers and 'Spanish' for the local press. The input layer has only 2 neurons that receive the value of positive and negative sentiments, being the only two descriptor variables coming from the sentiment analysis. The pattern layer is composed of 10 neurons which calculate the contribution of positive and negative sentiments to the density function of each language group (news written in English or in Spanish). The sum layer assigns a press article to a language group, sending the decision to the output layer.

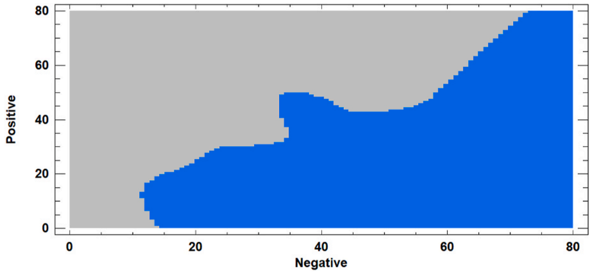

Fig. 11. Classification graph of the probabilistic neural network. The region defined by the prescriptor variables is split into two areas that turn out to be the classified samples: press articles written in Spanish (gray area) and in English (blue area).

month of publication and the Fourier plot pattern.

Fig. 13 shows the journal articles published each month with a given Fourier pattern along the volcanic eruption. In the articles written in English (Fig. 13 Left) the number of 'Positive' articles decreases with the passing months. Likewise, for the 'O_Negative' pattern those articles that begin with a negative paragraph and have an oscillating valence, we found an increase in the number of articles month by month, with a slight decrease at the end of the volcanic eruption. This trend was also observed in the news written in Spanish. Similarly, in the Spanish news (Fig. 13 Right) we observed an increasing number of articles with a negative pattern, the 'Negative' class, month by month. While in the press articles written in English the 'O_Positive' articles repeat the trend observed in the articles with the 'O_Negative' pattern, we have not observed this same trend in the news written in Spanish, more irregularly distributed.

4.5. Regression model between the area occupied by lava and the variables resulting from the sentiment analysis

The multiple linear regression method applied to the English article group allowed us to confirm, with an R^2 equal to 63.04%, the existence of a statistical relationship between the surface (hectares) occupied by the lava (*Lavaflow*) and the variables resulting from sentiment analysis:

$$\begin{aligned}&Lavaflow = 1086.15 - 35.26\ anger + 1.26\ anticipation - 53.05\ \ disgust + 32.28\ \ fear+\\&54.89\ \ joy + 18.47\ sadness - 35.24\ \ surprise + 15.59\ \ trust - 26.39\ \ negative+\\&8.06\ \ positive - 78.58\ \ \bar{x}\end{aligned}$$

However, when the Spanish local news data were fitted to this model, R^2 was reduced to 43.29%. In spite of this lower value, a similar regression model could also be built.

Lavaflow = 1045.27–29.43 anger +8.68 anticipation +46.37 disgust - 34.67 fear- 1.92 joy +26.66 sadness - 29.19 surprise +7.63 trust - 0.10 negative −7.60 positive +7.97 $\bar{x}$.

Obviously, the model should not be interpreted as a causal relationship, but as a statistical correlation between the area occupied by the lava flow and the predictor variables. Thus, given a date and an article published on such date, the model is able to predict from the predictor variables of sentiment analysis an estimate of the hectares occupied by lava.

5. Discussion

Our analytic work follows a growing trend. Currently the proliferation of programs and libraries on machine learning is such that the application of these techniques has become popular in many disciplines and practical situations, including disaster analysis and risk management [64]. Moreover, the fact that during the 21st century the number of natural disasters related to climate-change has almost doubled [65], and the alarming international events such as the COVID-19 pandemic [66], together have made these new techniques to be present in many studies. In previous papers [47,51,52] we have already successfully applied the combination of sentiment analysis techniques with multivariate analysis methods, e.g., cluster analysis, principal component analysis, and discriminant analysis. Indeed, this methodology is fairly oriented to data analysis when data themselves are texts.

In the results herein obtained, we have observed that the origin of the text, whether the journalist was foreign or domestic, decisively influences the results of sentiment analysis. That the foreign journalists' sentiments were more negative than those of the Spanish journalists demands further discussion. A possible explanation could be that local journalists were more knowing and familiar with the volcanic nature and geology of the Canary Islands and therefore more aware of the actual risk level. Or conversely, it may indicate a higher level of geological knowledge about the potential risks by foreign journalists (as some foreign news were coming from specialized sources), and a higher level of geological interest as well, or perhaps there was a higher proclivity to sensationalize. Since the current data do not allow us to discern between them, or to discard some other possible options, we leave this interesting aspect open for future guesses.

Another interesting result is that the classifiers were less efficient in classifying the news in Spanish than the news written in English. In particular, the discriminant analysis of the English articles reached a 69.01% (59.77% for the Spanish articles) and 76.06% (74.71% in the Spanish articles) depending on whether the periods in which the news were classified were four or two, respectively. Likewise, the perceptron neural network correctly classified in two groups a 78% of the English articles whereas for Spanish-language news the success rate was a 69.0%.

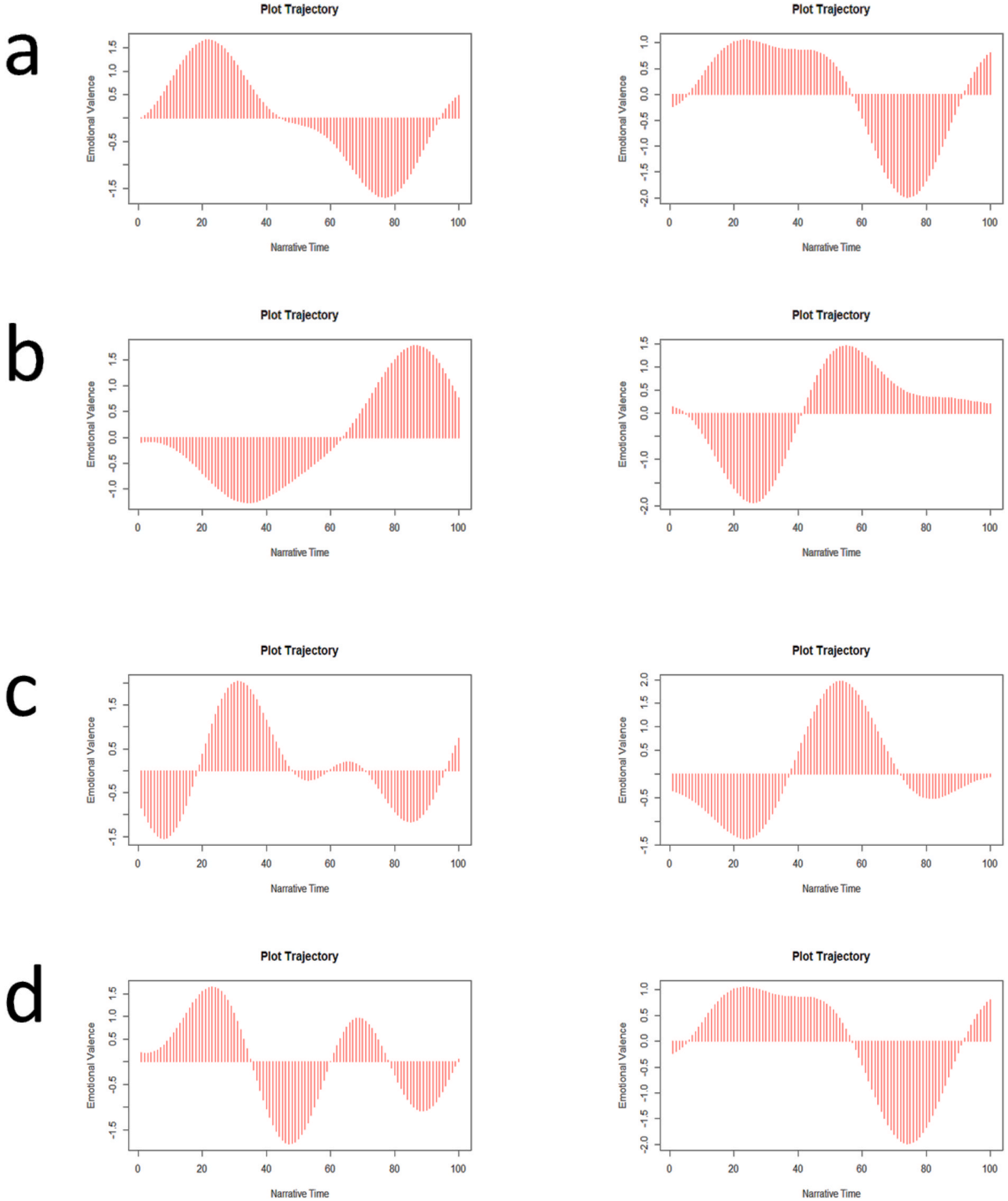

Fig. 12. The elementary Fourier plot patterns. (a) A 'Positive' pattern corresponds to a text that begins positively and ends negatively, as occurs in the theatrical genre of 'tragedy'. (b) A 'Negative' pattern exhibits a change of valences during the narrative time that is the reverse of (a). This pattern is typical of the theatrical genre of 'comedy'. (c) A 'O_Negative' pattern starts negatively and alternates the narrative style between negative-positive valence. (d) A 'O-Positive' pattern starts positively and alternates positive-negative valence.

Further, the medians of sentiments were significantly lower for Spanish journalists than for foreign journalists during the eruption. This would denote a lower predictive power of emotions expressed in the texts of articles written in Spanish by local and national journalists. This fact may explain why the classifiers were less successful with the articles published in Spanish.

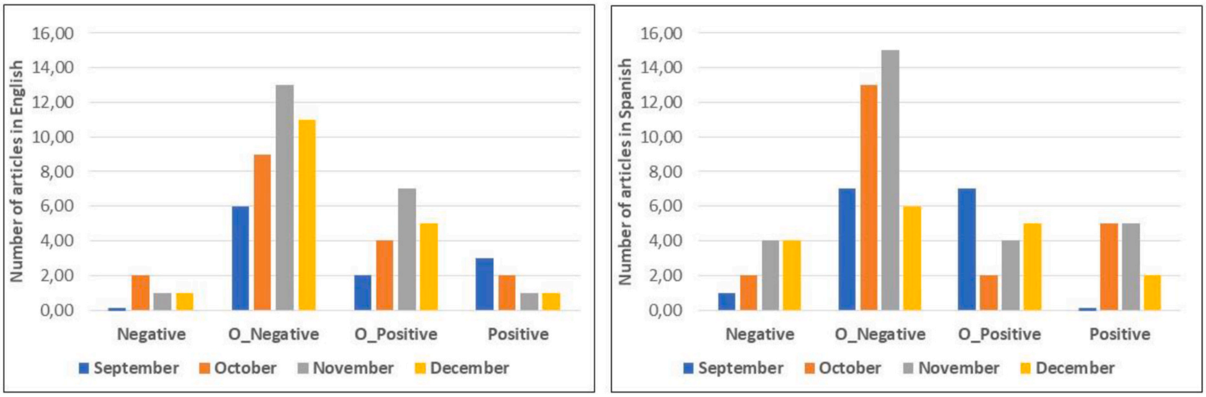

Fig. 13. Number of articles with a given Fourier pattern in the news published in English (Left plot) and Spanish (Right plot).

The fitting of the data to a logistic regression model was also sensitive to the findings discussed above. The fit of the news written in English is better than for news written in Spanish. This fact is not only remarkable because of a higher *p*-value for the news in English, but also if we consider the expression of x in the logistic function. That is, while for news in English x captures only seven emotions (disgust, anger, anticipation, fear, joy, sadness, trust) and the two sentiments (positive, negative), for the news written in Spanish x requires the sixteen variables (eight emotions, two sentiments, six sample statistics of the sentiment vector) resulting from the sentiment analysis.

It was also interesting the presence of a significant relationship between the month of publication of a press article and the type of Fourier plot pattern (variation of valence with respect to the narrative time). Thus, the pattern that the change in valence follows with respect to narrative time depends on the month in which an article was published. We also found that the values of the variables resulting from sentiment analysis could predict the surface area (hectares) occupied by lava. Obviously, this is a statistical or stochastic relationship, not a cause-effect relationship, which is reminiscent of the curious experiment where crickets are 'used' as thermometers [67], predicting the number of chirps the temperature. In any case, there is an interesting psychological analysis on how the different emotions and sentiments correlated with the advancement of lava flow.

In sum, we believe that the results obtained show how press articles can be useful as a source of information to evaluate the social and environmental consequences of a natural disaster or catastrophe. Moreover, the combination of sentiment analysis with multivariate analysis and machine learning techniques – a main originality of our approach – could improve the protocols oriented to the evaluation of the environmental, economic, and social impacts of a natural disaster or catastrophe. Likewise, the described methodology could also allow the evaluation from ancient texts, particularly if there were different sources of historical interest, searching for the impact and consequences of those catastrophes and disasters occurred long ago.

The manifold aftermaths of volcanic eruptions, assessed as natural phenomena occurring in complex socio-environmental frameworks, require integrated approaches to their spatial and temporal dynamics. It makes necessary the application of robust tools adequately coupled with the related social and individual emotional dynamics, in terms of components, connections, scale, and context, as well as the associated space-time frontiers [68]. Governance of catastrophic natural disasters may not leave behind the interpretation of people's sentiments. With that aim, additional research about natural language processing techniques would be necessary, by improving deep learning models, such as convolutional neural networks for local data extraction, recurrent models for dependence ordering in sequential data, or deep ensemble learning, among others [69].

6. Conclusions

The Cumbre Vieja ("Tajogaite") eruption is shown in this work as a valuable example about how the application of novel approaches and the combination of tools may provide new frameworks for understanding people's sentiments and needs under the frame of various types of disaster risks.

The results herein obtained allow us to conclude that sentiment analysis applied to press media is a useful technique that in combination with multivariate statistical methods and machine learning classifiers is able to classify an article into a series of groups or clusters and to establish useful correlations. Thus, the emotions and sentiments expressed in the text of a press article can be closely related to the stage or period in which the article was written during the course of a disaster. Indeed, the emotions and sentiments expressed in a text change over time in response to the direction of events and to the social impact generated. This approach would allow improved designs of tools to study the evolution of social and environmental impacts of a natural phenomenon and to assess how impacts change over time.

Another potentially important fact is the origin (local press *vs* foreign press)of the information source. There might be significant differences in the emotions and sentiments expressed in the text of a given article depending on whether the news analyzed were coming from a foreign or a local media. We have also found that there is a statistical relationship between the emotions and sentiments expressed in an article and the impact of a natural disaster. And we were able to gauge the valence inherent of each individual article across narrative time and in an aggregate cluster.

Essentially, we demonstrate the usefulness of the press media as a source of information complementing currently popular sources such as Twitter and other platforms. As we have argued, when a population is affected by a crisis or a natural disaster, it is important analyzing the three main layers of communication: immediacy and spontaneity (social media), curated press news in newspapers and online (press media), and in-depth reflections and reports (articles and reviews). These three modalities of communication have their own social function during a crisis or disaster, with their respective characteristics, advantages, and inconveniences.

Therefore, the main findings of this research may constitute a helpful resource for developing ameliorated insights into the way a society reacts to volcanic activity and may strengthen the foundations for decision-making under different temporal horizons, also considering that other eruptions may occur in the future.

So, this study's outcomes may contribute to fill in knowledge gaps related to potential information dissemination biases during crises and natural disasters, and to improve the analysis of the disaster risk-reduction strategies followed.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The authors acknowledge the excellent revision work performed by the anonymous reviewers. Their comments, suggestions, and criticisms have much contributed to improve the quality of this article. The authors are also very grateful to Pedro C. Marijuán for his comments and suggestions that were addressed into the revised version of the article.

References

[1] M.A. Longpré, Reactivation of cumbre vieja volcano, Science (1979), https://doi.org/10.1126/science.abm9423, 374 (2021.
[2] Comisión Mixta, Informe sobre las actuaciones y medidas emprendidas tras la erupción del volcán de Cumbre Vieja (La Palma), seis meses después del inicio de la emergencia, (n.d.) 17–20. https://www.mpr.gob.es/prencom/notas/Documents/2022/060622-informe_palma.pdf (accessed March 6, 2023).
[3] European Union, Copernicus. https://www.copernicus.eu/en.
[4] P.A. Torres-González, N. Luengo-Oroz, H. Lamolda, W. D'Alessandro, H. Albert, I. Iribarren, D. Moure-García, V. Soler, Unrest signals after 46 years of quiescence at cumbre vieja, La Palma, Canary Islands, J. Volcanol. Geoth. Res. 392 (2020), https://doi.org/10.1016/j.jvolgeores.2019.106757.
[5] E. Padrón, N.M. Pérez, P.A. Hernández, H. Sumino, G. Melián, J. Barrancos, D. Nolasco, G. Padilla, Helium emission at Cumbre Vieja volcano, La Palma, Canary Islands, Chem. Geol. (2012) 312–313, https://doi.org/10.1016/j.chemgeo.2012.04.018.
[6] E. Padrón, N.M. Pérez, F. Rodríguez, G. Melián, P.A. Hernández, H. Sumino, G. Padilla, J. Barrancos, S. Dionis, K. Notsu, D. Calvo, Dynamics of diffuse carbon dioxide emissions from Cumbre Vieja volcano, La Palma, Canary Islands, Bull. Volcanol. 77 (2015), https://doi.org/10.1007/s00445-015-0914-2.
[7] S.M. Abadie, J.C. Harris, S.T. Grilli, R. Fabre, Numerical modeling of tsunami waves generated by the flank collapse of the Cumbre Vieja volcano (La Palma, Canary Islands): tsunami source and near field effects, J Geophys Res Oceans 117 (2012), https://doi.org/10.1029/2011JC007646.
[8] J.C. Harris, S.T. Grilli, S. Abadie, T.T. Bakhsh, Near- and far-field tsunami hazard from the potential flank collapse of the Cumbre Vieja volcano, in: Proceedings of the International Offshore and Polar Engineering Conference, 2012.
[9] B. Tehranirad, J.C. Harris, A.R. Grilli, S.T. Grilli, S. Abadie, J.T. Kirby, F. Shi, Far-field tsunami impact in the north atlantic basin from large scale flank collapses of the Cumbre Vieja volcano, La Palma, Pure Appl. Geophys. 172 (2015), https://doi.org/10.1007/s00024-015-1135-5.
[10] A.M.G. Hernández, Refugiados en tierra propia. A Propósito de la situación de "duelo social" ocasionado por el volcán de la Cumbre Vieja en La Palma, Revista Ene de Enfermería. 15 (2021).
[11] A. Geyer, M. Aulinas, H. Albert, A.M. Álvarez-Valero, L'impacte del vulcanisme en la història de la humanitat, ATZAVARA 33 (2023) 11–26.
[12] D. Kahneman, Thinking, Fast and Slow, Farrar, Straus and Giroux, New York, 2011.
[13] K.C. Yang, O. Varol, C.A. Davis, E. Ferrara, A. Flammini, F. Menczer, Arming the public with artificial intelligence to counter social bots, Hum Behav Emerg Technol 1 (2019), https://doi.org/10.1002/hbe2.115.
[14] C. Zhang, Y. Yang, A. Mostafavi, Revealing Unfairness in social media contributors' attention to vulnerable urban areas during disasters, Int. J. Disaster Risk Reduc. 58 (2021), https://doi.org/10.1016/j.ijdrr.2021.102160.
[15] V. Balakrishnan, W.Z. Ng, M.C. Soo, G.J. Han, C.J. Lee, Infodemic and fake news – a comprehensive overview of its global magnitude during the COVID-19 pandemic in 2021: a scoping review, Int. J. Disaster Risk Reduc. 78 (2022), 103144, https://doi.org/10.1016/j.ijdrr.2022.103144.
[16] H. Allcott, M. Gentzkow, Social media and fake news in the 2016 election, J. Econ. Perspect. 31 (2017), https://doi.org/10.1257/jep.31.2.211.
[17] S. Bashir, S. Bano, S. Shueb, S. Gul, A.A. Mir, R. Ashraf, Shakeela, N. Noor, Twitter chirps for Syrian people: sentiment analysis of tweets related to Syria Chemical Attack, Int. J. Disaster Risk Reduc. 62 (2021), https://doi.org/10.1016/j.ijdrr.2021.102397.
[18] M.O. Badmus, When the storm is over: sentiments, communities and information flow in the aftermath of Hurricane Dorian, Int. J. Disaster Risk Reduc. 47 (2020), 101645, https://doi.org/10.1016/j.ijdrr.2020.101645.
[19] M. Cassidy, L. Mani, Huge volcanic eruptions: time to prepare, Nature 608 (2022) 469–471, https://doi.org/10.1038/d41586-022-02177-x.
[20] H. Sigurdsson, R.M.C. Lopes, Volcanoes in literature and film, in: The Encyclopedia of Volcanoes, 2015, https://doi.org/10.1016/b978-0-12-385938-9.00078-x.
[21] M. Nordvig, Volcanoes in Old Norse Mythology, Arc Humanities Press, 2021, https://doi.org/10.2307/j.ctv1k76ht8.
[22] J. Barclay, K. Haynes, B. Houghton, D. Johnston, Social processes and volcanic risk reduction, in: The Encyclopedia of Volcanoes, 2015, https://doi.org/10.1016/b978-0-12-385938-9.00069-9.
[23] L.F. Barrett, Solving the emotion paradox: categorization and the experience of emotion, Pers. Soc. Psychol. Rev. 10 (2006) 20–46, https://doi.org/10.1207/s15327957pspr1001_2.
[24] J.A. Russell, L.F. Barrett, Core affect, prototypical emotional episodes, and other things called emotion: dissecting the elephant, J. Pers. Soc. Psychol. 76 (1999) 805–819, https://doi.org/10.1037/0022-3514.76.5.805.
[25] P. Ekman, Basic emotions, in: T. Dalgleish, M. Power (Eds.), Handbook of Cognition and Emotion, John Wiley & Sons, Sussex (UK), 1999, pp. 45–60.
[26] J. Navarro, P.C. Marijuán, The natural, artificial, and social domains of intelligence: a triune approach, in: IS4SI 2021, MDPI, Basel Switzerland, 2022, p. 2, https://doi.org/10.3390/proceedings2022081002.
[27] V. Csany, Contribution of the genetical and neural memory to animal intelligence, in: H. Jerison, I. Jerison (Eds.), Intelligence and Evolutionary Biology, Ecological Sciences, Springer-Verlag, Berlin, 1988.

[28] M.R. Dove, Perception of volcanic eruption as agent of change on Merapi volcano, Central Java, J. Volcanol. Geoth. Res. 172 (2008), https://doi.org/10.1016/j.jvolgeores.2007.12.037.

[29] S. Bachri, J. Stötter, M. Monreal, J. Sartohadi, The calamity of eruptions, or an eruption of benefits? Mt. Bromo human-volcano system a case study of an open-risk perception, Nat. Hazards Earth Syst. Sci. 15 (2015), https://doi.org/10.5194/nhess-15-277-2015.

[30] J.C. Gomez-Zapata, C. Parrado, T. Frimberger, F. Barragán-Ochoa, F. Brill, K. Büche, M. Krautblatter, M. Langbein, M. Pittore, H. Rosero-Velásquez, E. Schoepfer, H. Spahn, C. Zapata-Tapia, Community perception and communication of volcanic risk from the cotopaxi volcano in Latacunga, Ecuador, Sustainability (2021) 13, https://doi.org/10.3390/su13041714.

[31] C. Clavel, Z. Callejas, Sentiment analysis: from opinion mining to human-agent interaction, IEEE Trans Affect Comput 7 (2016), https://doi.org/10.1109/TAFFC.2015.2444846.

[32] C.C. Chan, K.J. Liszka, Application of Rough Set Theory to Sentiment Analysis of Microblog Data, vol. 43, Intelligent Systems Reference Library, 2013, https://doi.org/10.1007/978-3-642-30341-8_10.

[33] G. Vinodhini, R. Chandrasekaran, Sentiment analysis and opinion mining : a survey international journal of advanced research in sentiment analysis and opinion mining : a, Int. J. Adv. Res. Comput. Sci. Software Eng. 2 (2012).

[34] E. Şentürk, M.A. Adil, M. Toker, M.C. Iban, Ö. Akyürek, Long-term ion hydration process and lithosphere-atmosphere coupling following the 2021 Fagradalsfjall volcanic eruption using remotely sensed data, Adv. Space Res. (2022), https://doi.org/10.1016/j.asr.2022.12.008.

[35] S. D'Arcangelo, A. Bonforte, A. de Santis, S.R. Maugeri, L. Perrone, M. Soldani, G. Arena, F. Brogi, M. Calcara, S.A. Campuzano, G. Cianchini, A. del Corpo, D. di Mauro, C. Fidani, A. Ippolito, S. Lepidi, D. Marchetti, A. Nardi, M. Orlando, A. Piscini, M. Regi, D. Sabbagh, Z. Zhima, R. Yan, A multi-parametric and multi-layer study to investigate the largest 2022 Hunga Tonga–Hunga Ha'apai eruptions, Rem. Sens. 14 (2022) 3649, https://doi.org/10.3390/rs14153649.

[36] P. Lynett, M. McCann, Z. Zhou, W. Renteria, J. Borrero, D. Greer, O. Fa'anunu, C. Bosserelle, B. Jaffe, S. la Selle, A. Ritchie, A. Snyder, B. Nasr, J. Bott, N. Graehl, C. Synolakis, B. Ebrahimi, G.E. Cinar, Diverse tsunamigenesis triggered by the Hunga Tonga-Hunga Ha'apai eruption, Nature 609 (2022) 728–733, https://doi.org/10.1038/s41586-022-05170-6.

[37] L. Ye, H. Kanamori, L. Rivera, T. Lay, Y. Zhou, D. Sianipar, K. Satake, The 22 December 2018 tsunami from flank collapse of Anak Krakatau volcano during eruption, Sci. Adv. 6 (2020), https://doi.org/10.1126/sciadv.aaz1377.

[38] J.C. Carracedo, V.R. Troll, J.M.D. Day, H. Geiger, M. Aulinas, V. Soler, F.M. Deegan, F.J. Perez-Torrado, G. Gisbert, E. Gazel, A. Rodriguez-Gonzalez, H. Albert, The 2021 eruption of the Cumbre Vieja volcanic ridge on La Palma, Canary Islands, Geol. Today 38 (2022) 94–107, https://doi.org/10.1111/gto.12388.

[39] P.J. González, Volcano-tectonic control of Cumbre Vieja, Science 375 (1979) 1348–1349, https://doi.org/10.1126/science.abn5148, 2022.

[40] F. Yuan, M. Li, R. Liu, Understanding the evolutions of public responses using social media: hurricane Matthew case study, Int. J. Disaster Risk Reduc. 51 (2020), 101798, https://doi.org/10.1016/j.ijdrr.2020.101798.

[41] V.K. Neppalli, C. Caragea, A. Squicciarini, A. Tapia, S. Stehle, Sentiment analysis during Hurricane Sandy in emergency response, Int. J. Disaster Risk Reduc. 21 (2017) 213–222, https://doi.org/10.1016/j.ijdrr.2016.12.011.

[42] S. Behl, A. Rao, S. Aggarwal, S. Chadha, H.S. Pannu, Twitter for disaster relief through sentiment analysis for COVID-19 and natural hazard crises, Int. J. Disaster Risk Reduc. 55 (2021), 102101, https://doi.org/10.1016/j.ijdrr.2021.102101.

[43] G. Bhullar, A. Khullar, A. Kumar, A. Sharma, H.S. Pannu, A. Malhi, Time series sentiment analysis (SA) of relief operations using social media (SM) platform for efficient resource management, Int. J. Disaster Risk Reduc. 75 (2022), 102979, https://doi.org/10.1016/j.ijdrr.2022.102979.

[44] M. Berardi, L. Santamaria Amato, F. Cigna, D. Tapete, M. Siciliani de Cumis, Text mining from free unstructured text: an experiment of time series retrieval for volcano monitoring, Appl. Sci. 12 (2022) 3503, https://doi.org/10.3390/app12073503.

[45] J.R. Ragini, P.M.R. Anand, V. Bhaskar, Big data analytics for disaster response and recovery through sentiment analysis, Int. J. Inf. Manag. 42 (2018) 13–24, https://doi.org/10.1016/j.ijinfomgt.2018.05.004.

[46] S. Jabalameli, Y. Xu, S. Shetty, Spatial and sentiment analysis of public opinion toward COVID-19 pandemic using twitter data: at the early stage of vaccination, Int. J. Disaster Risk Reduc. 80 (2022), 103204, https://doi.org/10.1016/j.ijdrr.2022.103204.

[47] A. Turón, A. Altuzarra, J.M. Moreno-Jiménez, J. Navarro, Evolution of social mood in Spain throughout the COVID-19 vaccination process: a machine learning approach to tweets analysis, Publ. Health 215 (2023) 83–90, https://doi.org/10.1016/j.puhe.2022.12.003.

[48] D. Contreras, S. Wilkinson, N. Balan, P. James, Assessing post-disaster recovery using sentiment analysis: The case of L'Aquila, Italy, Earthquake Spectra 38 (2022) 81–108, https://doi.org/10.1177/87552930211036486.

[49] S. Behl, A. Rao, S. Aggarwal, S. Chadha, H.S. Pannu, Twitter for disaster relief through sentiment analysis for COVID-19 and natural hazard crises, Int. J. Disaster Risk Reduc. 55 (2021), 102101, https://doi.org/10.1016/j.ijdrr.2021.102101.

[50] J. Rexiline Ragini, P.M. Rubesh Anand, V. Bhaskar, Mining crisis information: a strategic approach for detection of people at risk through social media analysis, Int. J. Disaster Risk Reduc. 27 (2018) 556–566, https://doi.org/10.1016/j.ijdrr.2017.12.002.

[51] R. Lahoz-Beltra, C.C. López, LENNA (Learning Emotions Neural Network Assisted): an empathic chatbot designed to study the simulation of emotions in a bot and their analysis in a conversation, Computers 10 (2021) 170, https://doi.org/10.3390/computers10120170.

[52] J. Navarro, A. Turón, A. Altuzarra, R. Lahoz-Beltra, Comparative sentiment analysis of COVID-19: a machine learning approach, in: 7th ICDSST 2021 (International Conference on Decision Support System Technology), Loughborough (Reino Unido), 2021.

[53] M.L. Jockers, Syuzhet Release 1.0.6. , (n.d.). https://Cran.r-Project.Org/Web/Packages/Syuzhet/Syuzhet.Pdf (accessed March 6, 2023).

[54] F. Bravo-Marquez, E. Frank, S.M. Mohammad, B. Pfahringer, IEEE/WIC/ACM International Conference on Web Intelligence (WI), in: Determining Word-Emotion Associations from Tweets by Multi-Label Classification, IEEE, 2016, pp. 536–539, https://doi.org/10.1109/WI.2016.0091, 2016.

[55] S.M. Mohammad, P.D. Turney, Crowdsourcing a word-emotion association lexicon, Comput. Intell. 29 (2013) 436–465, https://doi.org/10.1111/j.1467-8640.2012.00460.x.

[56] S. Mohammad. https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm. (Accessed 6 March 2023). https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm.

[57] M.L. Jockers, Revealing Sentiment and Plot Arcs with the Syuzhet Package, 2015. https://www.matthewjockers.net/2015/02/02/syuzhet/. (Accessed 6 March 2023).

[58] A.J. Izenman, Modern Multivariate Statistical Techniques, Springer New York, New York, NY, 2008, https://doi.org/10.1007/978-0-387-78189-1.

[59] R.A. Fisher, The use of multiple measurements in taxonomic problems, Ann Eugen 7 (1936) 179–188, https://doi.org/10.1111/j.1469-1809.1936.tb02137.x.

[60] R. Lahoz-Beltra, Bioinformática: Simulación, Vida Artificial e Inteligencia Artificial, Ediciones Díaz de Santos, Madrid, Spain, 2004.

[61] M.I. Hidayat Jati, Suroso, P.B. Santoso, Prediction of flood areas using the logistic regression method (case study of the provinces Banten, DKI Jakarta, and West Java), J Phys Conf Ser (2019), https://doi.org/10.1088/1742-6596/1367/1/012087.

[62] R. Muñoz-Mas, S. Fukuda, J. Pórtoles, F. Martínez-Capel, Revisiting probabilistic neural networks: a comparative study with support vector machines and the microhabitat suitability for the Eastern Iberian chub (Squalius valentinus), Ecol. Inf. 43 (2018), https://doi.org/10.1016/j.ecoinf.2017.10.008.

[63] B. Mohebali, A. Tahmassebi, A. Meyer-Baese, A.H. Gandomi, Probabilistic neural networks: a brief overview of theory, implementation, and application, in: P.D. T.B.S.C.R.C. Samui (Ed.), Handbook of Probabilistic Models, Butterworth-Heinemann, Oxford, UK, 2020, pp. 347–367.

[64] V. Linardos, M. Drakaki, P. Tzionas, Y.L. Karnavas, Machine learning in disaster management: recent developments in methods and applications, Mach Learn Knowl Extr 4 (2022) 446–473, https://doi.org/10.3390/make4020020.

[65] G. Alimonti, L. Mariani, On the Exponential Increase of Natural Disasters in the 20th Century. Science, climat et énergie, (n.d.). https://www.science-climat-energie.be/on-the-exponential-increase-of-natural-disasters-in-the-20th-century/(accessed March 6, 2023).

[66] World Health Organization, Coronavirus Disease (COVID-19) Pandemic, (n.d.). https://www.Who.Int/Emergencies/Diseases/Novel-Coronavirus-2019 (accessed March 6, 2023).

[67] A.E. Dolbear, The cricket as a thermometer, Am. Nat. 31 (1897), https://doi.org/10.1086/276739.
[68] S. Pulver, N. Ulibarri, K.L. Sobocinski, S.M. Alexander, M.L. Johnson, P.F. McCord, J. Dell'Angelo, Frontiers in socio-environmental research: components, connections, scale, and context, Ecol. Soc. 23 (2018), https://doi.org/10.5751/ES-10280-230323 art23.
[69] A. Mohammadi, A. Shaverizade, Ensemble deep learning for aspect-based sentiment analysis, Int. J. Nonlinear Anal. Appl. 12 (2021), https://doi.org/10.22075/IJNAA.2021.4769.