Probabilistic multi – hazard assessment at an active but under-monitored volcano: Ceboruco, Mexico

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Abstract

We conduct a probabilistic volcanic hazard assessment for Ceboruco volcano (Mexico) using PyBetVH, an e-tool based on the Bayesian event tree (BET) methodology. We use available information about the volcano, including eruptive history, numerical and theoretical models, to generate probability maps. Our hazard assessment accounts for the variability of eruption types expected at Ceboruco and the hazardous volcanic phenomena these eruptions generate. We create a generic event tree for Ceboruco to account for magmatic and amagmatic activity. For a magmatic eruption, we choose three scenarios: i) small (effusive), ii) medium (vulcanian/subPlinian) and iii) large (Plinian) based on the Holocene history of the volcano; with their related hazardous phenomena: ballistics, tephra fallout, pyroclastic density currents, lahars and lava flows. Despite numerous eruptions in the latest Holocene and efforts by several university and government groups to create and sustain a monitoring network, Ceboruco remains under-monitored, meaning that it is intermittently rather than continuously monitored by dedicated groups. With no consistent monitoring data available, we look at the geology and the eruptive history to inform our prior models. We estimate the probability of a magmatic eruption within the next time window (1 year) of ~ 0.002. We show how the BET creates higher probabilities in the absence of monitoring data. That is, there is a cost in terms of higher probabilities and higher uncertainties for having not yet developed a sustained volcano monitoring network. We present absolute probability maps (unconditional in terms of eruption size and vent location) for a magmatic eruption at Ceboruco volcano. With PyBetVH we estimate and visualize the uncertainties associated with each hazard map. Our intent is that hazard maps and uncertainties will be useful to local authorities who need to understand the hazard maps when considering the development of long-term urban and land-use planning and short-term crisis management strategies, and to the scientific community in their efforts to sustain monitoring of this active volcano.

Introduction

Recent volcanic eruptions have resulted in a significant number of fatalities, evacuations and economic loss (e.g., White Island, New Zealand in 2019 (Park et al. 2020; Cao et al. 2020); Fuego, Guatemala in 2018 (Charbonnier et al. 2019; De Angelis et al. 2018); Hawaii, U.S.A. in 2018 (Feng et al. 2020; Neal et al. 2019); Anak Krakatoa, Indonesia in 2018 (Heidarzadeh et al. 2020); Sinabung, Indonesia in 2014 (Chatfield et al. 2014); Ontake, Japan in 2014 (Maeno et al. 2016) and Eyjafjallajökull, Iceland in 2010 (Langmann et al. 2012)). It is estimated that >500 million people live in areas with some volcanic risk (Martí 2017; Auker et al. 2013) and large volcanic eruptions can affect our interconnected world in numerous ways. Depending on their size, volcanic eruptions create multiple hazardous phenomena (e.g., ballistics, pyroclastic density currents, tephra fallout) with impacts at different scales (e.g., local, regional and global), placing a premium on hazard assessments at various map scales (Chester et al. 2002).

A useful volcanic risk assessment, from local to global scales, relies heavily on probabilistic volcanic hazard analysis (PVHA). Any volcanic hazard assessment employs diverse techniques to generate different types of volcanic hazard maps. Calder et al. (2015) identified five main categories of hazard maps, usually generated by two main approaches: *i)deterministic* – based on distribution of deposits from past eruptions (often scenario based), and *ii) probabilistic* – which rely on numerical simulations of a hazardous volcanic phenomenon (Ang et al. 2020; Martí 2017; Loughlin et al. 2015; Connor et al. 2015; Calder et al. 2015; Marzocchi and Bebbington 2012) often tuned by the record of past activity, including the depositional record. From a practical standpoint, a deterministic analysis assumes that an eruption of some type and magnitude will occur in some specific period of time. A probabilistic analysis considers the likelihood of eruptions occurring and their likely characteristics.

PVHA e-tools have been developed to estimate and visualize the probabilities that an area will be affected by a volcanic event (Bertin et al. 2019; Bartolini et al. 2019; Sobradelo et al. 2013; Marzocchi et al. 2010). PVHA serves to bridge the volcanological and societal aspects of a volcanic crisis and to assist authorities in real-time decision-making (Bartolini et al. 2019). These tools are mostly based on Event Trees (ET) or Bayesian Belief Networks (BBN) structures. An ET is a directed graph (nodes and branches) (Fig. 1) of progressive events, from an initial state, through subsequent stages, to final outcomes (Newhall and Hoblitt 2002). The final outcomes are often referred to as contingencies, and the idea of the ET is to capture all possible contingencies, unless otherwise stated. This unidirectional structure allows probabilities for sequences of events in volcanic activity to be calculated and uses different sources of data, including eruptive history (past data) and theoretical or mathematical models (prior models), to update the probability of specific outcomes. Similar to ETs, Bayesian Belief Networks (BBN) are graphical structures representing different events related to volcanic activity. Unlike ETs, BBNs describe the complexity of this activity as uncertain variable nodes, which are interlinked by branches representing the causality between them (Christophersen et al. 2018; Hincks et al. 2014; Aspinall and Woo 2014; Aspinall et al. 2003). The estimation of probabilities at each node in the ET or BBN schemes is done by implementing a computer algorithm based on Bayes' rule, which allows update of the output as new information becomes available (Christophersen et al. 2018; Aspinall et al. 2003). Both ETs and BBNs have been tested successfully for several volcanoes: White Island, New Zealand (Christophersen et al. 2018); La Soufrière, Guadeloupe (Hincks et al. 2014); Galeras, Colombia (Aspinall et al. 2003); Santorini, Greece (Aspinall and Woo 2014); Etna and Vesuvius, Italy (Tierz et al. 2017; Cannavò et al. 2017); St. Helens, U.S.A (Newhall 1982); Soufrière Hills, Montserrat (Aspinall and Cooke 1998), and Pinatubo, Philippines (Punongbayan et al. 1996).

Two of the most commonly used e-tools in PVHA are HASSET (Hazard Assessment Event Tree) (Sobradelo et al. 2013) and BET_VH (Bayesian Event Tree for Volcanic Hazard) (Marzocchi et al. 2010). Both are software implementations of the volcano eruption ET structure (Marzocchi et al. 2004; Newhall and Hoblitt 2002). HASSET and BET_VH have been applied for hazard evaluation at different volcanoes (e.g. San Miguel, El Salvador (Jiménez et al. 2018); Okataina, New Zealand (Thompson et al. 2015); Deception Island, Antarctica (Bartolini et al. 2014); El Hierro, Canary Islands (Becerril et al. 2014); El Misti, Peru (Sandri et al. 2014); Vesuvius and Campi Flegrei, Italy (Selva et al. 2014; 2010); Auckland Volcanic Field, New Zealand (Sandri et al. 2012); Teide – Pico Viejo, Canary Islands (Martí et al. 2012; 2008).

Here, we use the PyBetVH software (Wild et al. 2019; Strehlow et al. 2017; Tonini et al. 2015), an updated version of BET_VH, to conduct a PVHA for Ceboruco volcano (Mexico). We define a generic ET, that is, not calibrated by current monitoring or related observations, for Ceboruco. This ET includes hazards related to both magmatic and amagmatic unrest. We describe how PyBetVH is used to produce probability maps for the magmatic branch by merging information from the geological record (i.e., past data), numerical simulations and expert-based weighting of the data (i.e., prior models).

An important reason to develop an ET for Ceboruco volcano is that the volcano has been quite active within the last ~1,000 yr, but has not erupted during the last century. Because of this hiatus in most recent activity, Ceboruco is less monitored than other active volcanoes in Mexico. We show through constructing the ET that this comparative under-monitoring increases uncertainty in probability of eruptions and probable eruption impacts. The resulting probability maps reflect this uncertainty. Consequently, in addition to estimating eruption probabilities, the Ceboruco ET can be used to consider the cost-benefit of additional monitoring efforts, and perhaps be used to help justify them. As this situation exists at many volcanoes globally, this uncertainty quantification can be useful for global efforts to prioritize volcano monitoring more systematically (Ewert et al. 2005).

Eruptive History And Hazard Assessment At Ceboruco

Eruptive history. Located at the western edge of the Trans-Mexican Volcanic Belt (TMVB), Ceboruco (2280 m.a.s.l.) (Fig. 2) is the only historically active stratovolcano among the ~28 monogenetic edifices of the San Pedro – Ceboruco half-graben (Sieron et al. 2019 a; Petrone 2010; Sieron and Siebe 2008). Its eruptive history includes diverse effusive and explosive activity (Sieron et al. 2019 a; Sieron and Siebe 2008; Gardner and Tait 2000). We refer the reader to Sieron et al. (2019 a), Sieron and Siebe (2008), Gardner and Tait (2000) and Nelson (1980) for detailed descriptions of Ceboruco's geology and eruptive history. In this section we summarize the activity of the past ~1000 years as this time span is the basis of our hazard assessment.

In the past ~1000 years Ceboruco had at least eight eruptions or eruptive episodes: - the Plinian (VEI 6) ~1060 BP Jala eruption, the subPlinian (VEI 3) AD 1870-75 eruption and several effusive events dominated by lava flows (LF) and/or dome growth episodes accompanied by small phreatomagmatic explosions (Sieron et al. 2019 a; Sieron and Siebe 2008; Nelson 1980). Stratigraphic evidence suggests that after a repose period of ~ 40 kyr, an effusive eruption preceded the caldera forming Jala event (VEI 6) that created the current summit caldera (~3.7 km diameter). The Jala event produced extensive tephra fallout (TF) and several pyroclastic density currents (PDC) with a total estimated eruption volume of 3-4 km^3 dense rock equivalent (DRE) (Sieron et al. 2019 a; Sieron and Siebe 2008; Gardner and Tait 2000; Nelson 1980). The PDC deposits exhibit both end members (i.e., concentrated flows and dilute surges). Syn-and-post eruptive lahar (LH) deposits are identified as far as 35 km from the vent. Ballistic (BA) bombs are found within a 5 km radius from the vent. Eruptive activity persisted for another ~150 years during which time several lava flows were emplaced (Boehnel et al. 2016). After a break of several hundred years, the most recent and documented eruption of AD 1870-'75 comprised alternating effusive and explosive activity that generated LF, TF and PDC. The total erupted volume of this eruption was estimated to be ~0.1 km^3 for pyroclastic deposits and ~1.14 km^3 for lava flows (Sieron et al. 2019 a; Sieron and Siebe 2008). Today, small urban centers, national freeways, railroads and agricultural land are constructed on these eruption deposits.

Deterministic Hazard Assessment. Ceboruco is ranked the third most hazardous volcano in Mexico (Sieron et al. 2019 a; Espinasa-Pereña 2018). Several urban centers (> 55,000 people), as well as important infrastructure lie within the area impacted by past activity (Sieron et al. 2019 a, b). Sieron et al. (2019 b) developed the first hazard maps for Ceboruco as part of a project funded by the Federal Electricity Commission that manages two hydropower plants in the area and the Tepic-Mazatlán sectorial power distribution station at the foothills of Ceboruco.

Based on the activity of the last ~1000 years, three possible eruption scenarios were defined. We refer to Sieron et al. (2019 a) for a full description of these scenarios. Summarizing:

Scenario 1 (S1) – this *high likelihood* scenario considers a *smallmagnitude* (e.g., VEI < 2) effusive eruption that will generate andesite LFs. Small explosions will likely produce BA and low ash plumes from a central or flank vents (Sieron et al. 2019 a, b).

Scenario 2 (S2) – is a *medium likelihood* event (e.g., VEI 2 -3). This *medium magnitude* scenario considers both explosive and effusive activity. The explosive activity is expected to produce BA and to be of vulcanian to sub-Plinian style with small to moderate transient plumes of dacitic composition, similar to the AD 1870-’75 eruption. Dome emplacement and LF are expected due to the high viscosity of the dacitic lava. TF is expected which might reach relatively large thickness near the vent (Sieron et al. 2019 a, b). PDC and LH are also expected.

Scenario 3 (S3) – a *low likelihoodlarge magnitude* eruption similar to the Jala Plinian event. This eruption is expected to produce BA (~3 km radius) and widespread TF and voluminous PDC. Syn-and-post eruptive LH are expected due to the availability of pyroclastic material and water during the rainy season (Sieron et al. 2019 a, b).

The hazard maps created by Sieron et al. (2019 b) used these three scenarios to simulate individual hazards. These computer models use various source parameters derived from previous research, field data and from analogue volcanoes (e.g., ballistics), to generate maps with the area impacted by each eruptive phenomenon. The resulting maps of each of these hazards were integrated into a single hazard map for each of the three scenarios (i.e., scenario-based hazard maps) (Figs. 8, 9 and 10 in Sieron et al. (2019 b). A generalized hazard map for Ceboruco was obtained by integrating the three scenario-based hazard maps into a single map showing the areas that could be affected by various volcanic phenomena associated with a future eruption (Fig. 11 in Sieron et al. (2019 b). In the following, we use the ET approach to assign probabilities to these eruptive scenarios.

The Event Tree For Pvha At Ceboruco

We design an ET to conduct a PVHA at Ceboruco volcano (Fig. 1) that considers three potential triggers for unrest:

1. *magmatic unrest* (m_u) – with a comparatively high rate of eruptive activity in the past ~1000 years, we consider that future unrest at Ceboruco may be triggered by magma migration to shallow depth, convective overturn in a long-lived magma chamber or by fresh magma entering the chamber from depth;
2. *seismic unrest* (s_u) – triggered by a large regional tectonic earthquake or a local seismic swarm. *i)* 'Sulphur-smelling' waters after two tectonic earthquakes in AD 1566 (Sieron and Siebe 2008; de Ciudad Real 1976) and AD 1567 (Sieron and Siebe 2008; Tello 1968) indicate changes in porosity and permeability that might have facilitated migration of magmatic gases (Sieron and Siebe 2008). *ii)* Núñez-Cornú et al. (2020), Rodríguez Uribe et al. (2013) and Sánchez et al. (2009) concluded that the seismic swarms at Ceboruco are dominated by volcano-tectonic (VT) and low-frequency (Lf) earthquakes and are associated with the faults in and around the edifice;
3. *increased degassing* (i_u) – infiltration of abundant meteoric water from a passing hurricane may lead to an increased degassing due to the residual heat from cooling magma. From the analysis of two seismic datasets, Rodríguez Uribe et al. (2013) and Sánchez et al. (2009) confirmed that the Lf events recorded at Ceboruco are associated with movement of pressurized fluids.

Several hazardous phenomena have been associated with non-magmatic unrest episodes (i.e., seismic and increased degassing) and are considered in our ET: rock slides, debris avalanches, debris flows, ballistics, ash fallout and increased fumarolic activity (Fig. 1). By including these events in the ET, we clarify that potentially hazardous phenomena may result from eruptive or noneruptive events and perhaps when there is no evidence of unrest at all. We emphasize that while these events represent contingencies in the ET, their probabilities vary.

If unrest of magmatic origin is detected at Ceboruco, we consider three potential outcomes: *i)* no eruption (i.e., activity subsides); *ii)* phreatic eruption or increased degassing activity (i.e., if large amounts of water infiltrate the volcanic system) and, *iii)* magmatic eruption (m_e). In contrast to the latter case, the hazards associated with the first two outcomes resemble the contingencies in the non-magmatic unrest case, especially for locations that are inhabited around the volcano complex. However, the occurrence of a magmatic eruption results in a series of destructive phenomena that will impact the region around Ceboruco at different scales. We focus on the magmatic unrest branch and its subsequent events (the highlighted branch in Fig. 1). The past eruptive cycles at Ceboruco included both explosive and effusive activity, therefore we model the most devastating phase of the past eruptions (e.g., Plinian explosion; sub-Plinian explosion; effusive eruption). We follow the three eruptive scenarios identified by Sieron et al. (2019 b) and described in the previous section.

Estimating The Probabilities In The Event Tree: The Calculation

The ET for Ceboruco becomes a Bayesian event tree (BET) because of the additional information we incorporate in the analysis. The ET and the BET have identical structure (Fig. 1), but the way in which probabilities are estimated is different. To estimate the probability at each node of the BET, PyBetVH relies on *observations of past volcanic activity* including the geological record and on *prior models* that are theoretical, statistical or numerical (Constantinescu et al. 2016; Tonini et al. 2015; Thompson et al. 2015; Sandri et al. 2014; Marzocchi et al. 2010). As seen in the following, prior models rely on other information, such as the state of activity derived from monitoring (Wright et al. 2019) or data from analog volcanoes (Ogburn et al., 2016) to refine probability estimates and that are based primarily on observations of past activity.

The background calculations that PyBetVH performs rely on specified data and parameters for each branch of the ET. Given that the first three nodes of the BET represent questions with binary answers the probability estimates are managed through a binomial distribution (e.g., Connor 2021; Marzocchi et al. 2006), which arises because (1) the volcano will enter into a period of unrest in the time window (e.g., τ = 1 yr.) or not, (2) the unrest will be associated with magma or not, (3) the magmatic unrest will result in an eruption, or not. Each of these nodes will be answered yes or no, with some probability. If the ET is not Bayesian, then the probability at each node only depends on the sample proportion (: the number of observations of an affirmative outcome in the past, *y*, divided by the number of time windows observed, *n*:

$$\mu_u = \frac{y}{n} \qquad (1)$$

Imagine a theoretical volcano has three of 100 time windows in which unrest is observed, then the sample proportion for the first node is 0.03. If two of these periods of unrest were observed to be magmatic, then the sample proportion for the second node is 0.67. If one of these two periods of magmatic unrest resulted in eruption then the sample proportion of the third node is 0.5. The product of these probabilities is the probability of eruption in a given time window, based only on likelihood, which in this example is 0.03 x 0.67 x 0.5 = 0.01. This result is easily checked, since one time window out of one hundred was observed to have an eruption.

In a BET, such as implemented in PyBetVH, additional information, called *prior models*, is used to improve the probability estimate by weighting the sample proportion. In practice, prior models are cast as a Beta distribution, which depends on parameters α and β that take on values between 0 and 1. The mean of the prior distribution (μ) at any binomial node is given by:

$$\mu = \frac{\alpha}{\alpha + \beta} \qquad (2)$$

and the posterior probability at any binomial node is:

$$E = \frac{\alpha + y}{\alpha + \beta + n} \quad (3)$$

The posterior probability deviates from the sample proportion depending on the values of these two parameters, α and β. If the value of α is large compared to β, the posterior probability will increase, as in the case of monitoring data that indicates increased unrest. Conversely, if monitoring data indicates that there is no unrest, then β is large compared to α and the posterior probability will be less than the sample proportion. For the case in which there are no monitoring data available to inform the values of α and β, then $\alpha = \beta = 1$, $\mu = 0.5$ and the Beta distribution is uniform random. This means that the posterior probability will tend toward 0.5.

Suppose that for our theoretical volcano we have no monitoring data, so the Beta distribution is uniform random between 0 and 1. For the first node, recall that three time windows had unrest out of one hundred observations, so with $\alpha = \beta = 1$ the posterior probability of node 1 is 4/102 = 0.039, which is slightly higher than the sample proportion (0.03) because $n >> \alpha, \beta$. For node 2, the posterior probability is 4/5 = 0.8 and for node three the posterior probability is 2/3 = 0.67, both considerably higher than the sample proportion for those nodes. Overall, the probability of eruption based on the BET in this example is 0.039 x 0.8 x 0.67 = 0.02. Using the BET, the probability of the volcano erupting in a given time window is approximately twice the probability calculated using a likelihood approach (0.01), which only depends on the sample proportions.

Subsequent nodes in the BET (Fig. 1) are not binomial but their probabilities are calculated in a similar way (Marzocchi et al. 2006, 2010). We refer the reader to Marzocchi et al. (2006, 2008 and 2010) and Tonini et al. (2015) for a detailed description of the software implementation of the calculations of the BET structure. An advantage of PyBetVH is that the posterior probability calculation includes the distribution for the probabilities, in addition to the expected values, providing a more complete view of the uncertainty in the probability estimate than is otherwise possible.

PyBetVH uses as input several text files in which the user specifies the values each parameter (e.g., y, n, α and β) is taken in order to estimate the sample proportions and the prior distributions. The software and a step-by-step tutorial for building the input files are freely available at https://vhub.org/resources/betvh (Tonini et al. 2016 b) or by request to the corresponding author. In the next section we describe the implementation of the BET for Ceboruco and the choice of model input data to estimate probabilities related to a magmatic eruption.

Pybetvh Set-up: The Implementation Of The Ceboruco Bet

Nodes 1-2-3: what is the probability of a magmatic eruption within the next time window?

The goal of a PVHA is to provide probability estimates for the occurrence of specific events in a given time window (Connor et al. 2015; Newhall and Hoblitt 2002). Typically, volcanic hazard assessment and eruption forecasting are conducted for short-term (days, weeks after the initiation of unrest), intermediate-term (months) and long-term (years) (Newhall and Hoblitt 2002). The long-term hazard assessment is useful for the local authorities and stakeholders to devise plans and strategies for responding to future potential activity. A commonly used time window (τ) for hazard assessment is one year (Thompson et al. 2015; Sandri et al. 2014; Marzocchi et al. 2008; Newhall and Hoblitt 2002). Altough we suggest that this time window can be extended when the hazard assessment is considered for very long-term development of infrasturcture projects.

At *Node 1 (N1),* we want to estimate the probability of entering a new unrest phase within the next time window. *Unrest* is a diverse and complex phenomenon described as a deviation from the background activity of a volcano or by anomalies in monitoring data (Gottsmann et al. 2019; Phillipson et al. 2013). Although subjective, this generalized definition cannot be readily applied to active volcanoes that are poorly monitored or that are not at all monitored. Ceboruco is under-monitored, therefore, we rely on geological information to define unrest, recognizing that this lack of reliable monitoring data limits our analysis to long-term PVHA. Geological field data suggests a long period of dormancy (~40 kyrs) at Ceboruco preceded the Plinian Jala event (~1060 BP) and its immediately precursory eruptions (i.e., the Destiladero lava flow; Nelson 1980; Sieron et al. 2019 a, b). Following the Jala eruption, this phase of activity continued for another ~150 years during which time six lava flows were erupted (Boehnel et al. 2016).

From AD 1142 until AD 1870 no magmatic eruptions were observed. This quiescent period was interrupted by two powerful tectonic earthquakes (AD 1566 and AD 1567; Sieron and Siebe 2008; de Ciudad Real 1976; Tello 1968). The aftermath of these events included changes in activity observed at the surface of the volcano (Sieron and Siebe 2008; Tello 1968) and no other activity was reported for another ~ 200 yrs. First signs of reactivation of the system appeared in AD 1783 and AD 1832 and included reported seismic activity (ground shaking), underground noise, and a water vapor plume at the summit. Decades later, this activity was followed by the AD 1870-'75 eruption. Post-AD 1875, fumarole activity persisted until ~AD 1894 (Sieron et al. 2019 a; Ordónez 1896) and since then decreased in intensity and the fumarole temperature declined with time.

Occasional surveys of the fumaroles show their composition is meteoric water vapor generated by the residual heat from the last eruption and that there is no magmatic component in fumarole gases or their condensates (Sieron et al. 2019 a; Ferrés et al. 2019; CENAPRED internal reports 2016). Sánchez et al. (2009) and Rodríguez Uribe et al. (2013) analyzed several years of seismic data (2003-2008) from one station and concluded that Lf events indicate the presence of pressurized fluids, in agreement with the presence of water vapor fumaroles and an active hydrothermal system. Occurrence of VT events indicate intra-crustal stress accommodation, either from a magmatic body or the regional tectonic setting (i.e., the half-graben within which the edifice is located). Recently, Núñez-Cornú et al. (2020) used data from four stations around Ceboruco (deployed 2012 – 2014) and concluded that most of the recorded events follow shallow structural lineaments and have shallow hypocenters (<10 km). Although insightful, these geophysical signals cannot serve as basis for a wider definition of background activity and therefore unrest, since the network was small and deployed temporarily. Sánchez et al. (2009) suggest Ceboruco might be in an intra-eruptive phase while Núñez-Cornú et al. (2020) suggest that the seismic activity indicates local tectonic stresses. No other observations that may indicate changes in Ceboruco's behavior have been recorded.

The past data describes our likelihood function (Marzocchi et al. 2008) and is estimated from geological information. We assume that the Jala eruptive period, ~AD 912 - 1142 (including the Jala Plinian eruption and pre-and-post Jala effusive activity) and the AD 1783 - 1894 period (including the AD 1870-'75 eruption) represent two long-lived unrest episodes. The long dormancy (quiescence) interval between the two episodes indicates an inter-eruptive period with no clear signs of magma intrusion but disturbed twice by large tectonic earthquakes that may have perturbed the magmatic system at Ceboruco. In total we count four episodes of unrest, magmatic or amagmatic including seismic, that began in time windows during the past ~1108 years. Therefore, the sample proportion, which is the mean of the likelihood function, is 4/1108.

The prior probability function is usually informed by monitoring data at volcanoes with a monitoring network. However, due to the lack of reliable and sustained geophysical data collection at Ceboruco, we consider there is no prior information about whether unrest will be initiated during the next time window and therefore set the mean prior probability at 0.5 (maximum ignorance), with an equivalent number of data parameter Λ = 1 in PyBetVH (indicating the large uncertainty associated with this choice) (Constantinescu et al. 2016; Sandri et al. 2014; Marzocchi et al. 2008). Because the mean prior probability is greater than the sample proportion, the posterior probability is greater than the sample proportion. That is, there is a penalty for lack of monitoring data.

Node 2 (N2) -Given unrest, what is the probability that magma is involved? An unrest episode may be magmatic or amagmatic (e.g., tectonic). Given its activity of the past ~1000 years and the relatively short time since its most recent eruption, it is reasonable that unrest could be associated with magma. Ceboruco, however, lies within a tectonically active area within which large-magnitude tectonic earthquakes are common, like the two earthquakes reported in the 16th century. Given the variability of both volcanic systems and tectonic regions we assume a prior probability distribution with Beta = 0.5 and Λ = 1, indicating maximum ignorance (i.e., equal chances of having magmatic or amagmatic unrest). The likelihood function is described by the past data according to which two of the four unrest episodes were clearly magmatic in origin. As the sample proportion, 2/4, is equal to the mean of the prior probability, 0.5, the posterior probability for this node is also 0.5, which is the probability that magma is involved, given unrest.

Node 3 – if magmatic unrest is due to magma, what is the probability a magmatic eruption will occur during the time window? In the absence of real-time monitoring data, the long-term probability of eruption is usually estimated from the volcano's eruptive history. The past data (likelihood) used at this node is informed by the two eruptive magmatic unrest episodes. We know that the only two episodes of magmatic unrest that we know of resulted in magmatic eruptions. The sample proportion is 2/2. We can update our posterior using a prior probability distribution based on theoretical models. Previous studies involving the use of a BET tool used as prior models at this node a Beta distribution with α = β = 1 (i.e., maximum ignorance; equal probability of eruption or no-eruption) (Constantinescu et al. 2016; Sandri et al. 2014, 2009) or data from Phillipson et al. (2013). According to the global volcanic unrest catalogue presented by Phillipson et al. (2013), 64% of magmatic unrest intervals at stratovolcanoes lead to eruption. We use the maximum ignorance as prior probability at this node (i.e., Beta = 0.5; Λ = 1) and update the posterior probability at this node with past data with two eruptive magmatic unrest episodes. That is, the sample proportion is 2/2 but this value is modified by the prior mean, 0.5, to yield a probability of magmatic eruption given magmatic unrest of 0.75, which is reasonably close to the Phillipson et al. (2013) value, given our high uncertainty.

Based on the assumptions made at the first three nodes from geological data and available models, we estimate the probability of a magmatic eruption at Ceboruco in the next year (time window) to be 0.002. A summary of the input data at the first three nodes is presented in Table 1.

Nodes 4 and 5: vent location and eruption type/size

We focus here on the activity at Ceboruco's cone and do not consider hazards related to the monogenetic field, because the past ~1000 years of activity at Ceboruco was concentrated within the summit caldera. Therefore, we assume the probability of monogenetic eruptions is much smaller than summit caldera eruptions. Several lava flows, both pre-and-post Jala, occurred closer to the present caldera rim or on the north flanks (e.g., Copales, El Norte, Coapan lava flows (Fig. 8 in Sieron et al. 2019 a)), however, most activity was restricted to the main edifice of Ceboruco. We therefore consider five possible sectors for a new eruption to occur: - the summit caldera and four flank locations (North, e.g., the Coapan lava eruption site; East, South, e.g., the Copales lava eruption site; and West flanks, e.g., the AD 1870- '75 lava eruption site). The probabilities for new vent opening were decided by project participants who weighted geologic evidence. We assume a 0.98 prior probability for the summit caldera location and 0.005 for each flank sectors. Based on the three eruption scenarios identified by Sieron et al. (2019 a) and discussed in the previous section, we assume that future activity at Ceboruco will likely include a: *S1* - small eruption (effusive / small explosive); *S2* – moderate eruption (vulcanian/sub-Plinian) and *S3* – large eruption (Plinian). The probabilities of these scenarios were assigned by a power-law, with small eruptions having a higher likelihood of occurrence than large events: *S1* – 0.6, *S2* – 0.3, *S3* – 0.1 (Sandri et al. 2014, Marzocchi et al. 2008, Newhall and Hoblitt 2002).

Nodes 6, 7 and 8: occurrence of hazardous phenomena and areas impacted

We consider: LF, BA, TF for Scenario 1; LF, BA, TF, PC, LH for Scenario 2 and BA, TF, PDC, LH for Scenario 3. The prior best-guesses of occurrences for each phenomena conditional to the eruption size were set using data from Newhall and Hoblitt (2002) (i.e., frequency of phenomena associated with eruption type) except BA that has a probability of 1. Further, we divide the area around Ceboruco in a grid of 500 m x 500 m cells and compute the probability of each cell to be invaded by a selected phenomenon. As past data we use the area covered by the deposits of past eruptions associated with each phenomena and eruption size. The modeling-based hazard assessment conducted by Sieron et al. (2019 b) serves as prior models in PyBetVH. We refer the reader to Sieron et al. (2019 b) for a detailed description of the methodology, the simulation tools utilized to model each selected phenomenon, and the output maps.

The past data and prior model files for Nodes 6, 7 and 8 are constructed by counting how many times a grid cell was affected by a hazard during past eruptions or in simulations, respectively (e.g., if a grid cell was affected by one simulation from a total of three, the prior probability of the grid cell will be 1/3).

In Table 2 we present a summary of the hazards considered for each scenario and the PyBetVH input data.

Results

The absolute probability maps were calculated from the Ceboruco ET (Figs. 3 and 4). These maps show the combined mean probabilities that an area is invaded by a volcanic phenomenon regardless of the eruption size and vent location (i.e., considering the occurrence of an eruption of any size from any vent) within a 1-year time window.

Ballistics. We use 540 simulations made with the Eject! code (Mastin 2001) and field measurements of distances travelled by the ballistics of the Jala eruption (i.e., S3) (Sieron et al. 2019 a) to estimate the posterior probabilities. The map (Fig. 3a) shows the highest probabilities (~1– 2 x 10^{-3}) around the summit caldera, decreasing with distance for approximately 5 km. The flanks of Ceboruco up to 5 km away from the vent are uninhabited and several crop fields lie at the base; however, the telecommunications towers located on the NE of the caldera rim will likely be affected by ballistics, with considerable impact on regional communications.

We considered *lava flows* in scenarios 1 and 2. Figure 3b shows the extent of the LF is comparable with the results from the numerical modeling in Sieron et al. (2019 b); the areas of higher probability (~8 x 10^{-4} – 1 x 10^{-3}) correspond to the areas inundated most often in simulations (i.e., ~5 -10 km to the north, north-east and south-west) and the valleys where past deposits were identified (i.e., north). Ahuacatlán and Jala have relatively high probabilities (~4 - 6 x 10^{-4}) of being affected by lava flows. Smaller communities to the South and West as well as important infrastructure (e.g., major roads) to the South and North (some already built on lava flows) have significant probabilities (~ 6.5x 10^{-4}) of being affected.

Pyroclastic density currents (Fig. 3c). We consider both end members of pyroclastic density currents (flows and surges) and use past data (from Jala eruption) and simulations (i.e., Titan2D; Patra et al. 2005) for flows and the Energy Cone module in LaharZ (Schilling 1998) for surges) to estimate posterior probabilities for these hazardous phenomena. The PDC map shows the highest probabilities (>5 x 10^{-4}) within 10 km of the vent. The valleys and some interfluves at >10 km from the vent have a lower probability of inundation attributed to the simulated surges and field data from past large magmatic eruptions. The cities of Ahuacatlán and Jala, both at ~10 km from the vent, along with several smaller communities, have relatively elevated probabilities (~ 1 – 3 x 10^{-4}) of being affected by PDC, along with existing infrastructure.

Tephra fallout hazard is evaluated for all three eruption sizes. Sieron et al. (2019 b) describe in detail the methodology used for simulations of tephra fallout that serve as prior models in our analysis. Figure 4a shows the average annual probability map for the accumulation of at least 10-cm-thick tephra layer. The distribution of the probabilities is strongly controlled by the spatial extent of tephra in the numerical models since we lack a good set of field data (only one set for Jala eruption, S3). The wide spread tephra deposit to the NE is associated with a large Plinian eruption and it is controlled by the prevailing winds at high altitudes (and illustrated by the numerical simulations). The higher probabilities closer to the volcano are associated with the sedimentation from lower transient plumes affected by the variable monthly wind field at lower altitudes. All communities to the East, South and West of Ceboruco will be impacted by tephra fallout and significant damage is expected to the agricultural lands and the infrastructure in the area.

Lahars (syn-and-post eruptive) are considered for both S2 and S3 eruption scenarios due to the availability of fresh pyroclastic material available with such events and the availability of water during the rainy season at Ceboruco or a passing tropical storm. Lahar deposits have been identified in the field and associated with the large Jala eruption (Sieron et al. 2019 a). We use the extent of past lahars and simulation with LaharZ as input data in PyBetVH. The average probability map of lahar inundation is shown in Figure 4b. Unlike Sieron et al. (2019 b) who considered lahar hazards as far north as Grande de Santiago river, we focus our assessment on Ceboruco and its main drainage network and tributaries to the Ahuacatlán river. The highest probabilities are within the drainage network of Ceboruco (>1.7 x 10^{-4}) and the cities of Jala and Ahuacatlán, as well as the nearby infrastructure. Marquezado, Uzeta, Tetitlan and the area of the drainage network flowing in the Ahuacatlán river to the SW have relatively high probabilities of being affected by lahars (>1.7 x 10^{-4}) as they are located within the drainage network that is flowing in the Ahuacatlán river to the SW.

In the Additional Material 1 we present the conditional probability maps for each considered phenomena (i.e., occurrence of hazards is conditional to the occurrence of a specific eruption size from the central vent).

Discussion

The event tree and the probability of eruption

Volcanoes, active or extinct, are sources of inherent hazards conditioned to the occurrence of a specific triggering event (e.g., a magmatic eruption triggers a PDC or a tectonic earthquake triggers slope failures and debris avalanches at extinct or long dormant volcanoes). Given the complexity and intrinsic variability of volcanic systems, a PVHA (Marzocchi et al. 2010; Marzocchi and Woo 2007) is preferred to a simple deterministic approach based on the extent of deposits of past eruptions. The event tree approach provides a useful way to visualize and estimate the probabilities of occurrence of various hazards at different time scales (Marzocchi et al. 2008; Newhall and Hoblitt 2002). To fully benefit from the use of event trees, these have to comprise a wide range of volcanic events, magmatic and amagmatic. Therefore, they can provide a clear and broad view of the possible hazards related to the volcanic system and how these hazardous phenomena may affect the area during a long-term period. This is of great interest to local authorities and stakeholders who often make decisions regarding long-term investments in the local community. Important infrastructure projects are developed to last for decades and the sites selected for their development must be considered carefully with respect to an acceptable level of hazard even if the probability of occurrence is very small (Connor 2011). The advantage of a probabilistic approach in hazard assessment is that it can account for all probable events, even if direct evidence of past specific eruptive phenomena is not identified in the field. Most volcanoes have very long periods of inactivity (dormancy) and are often considered extinct or less dangerous and their fertile slopes attract cultivation. To make matters worse, most active volcanoes are poorly monitored, or not monitored at all. With an ever-increasing population around active volcanoes, we have to look at a broad range of volcanic processes in order to consider all the ways a volcano might impact us. From birth until extinction, a volcano poses multiple threats, not only related to a magmatic eruption. Flank collapses, debris avalanches and rock slides can occur long after the volcano goes extinct. However, our human perspective forces us to consider the most dramatic events in our hazard assessments and those are more often than not related to a magmatic eruption. Here we have developed a generic event tree for Ceboruco volcano and try to account for all the possible outcomes regardless of the involvement of renewed magmatism.

In a typical ET, the first three nodes describe the short-term component of hazard assessment (i.e., unrest; origin of unrest; eruption) and start with the assumption the volcano is in repose (as opposed to unrest) (Newhall and Hoblitt 2002). However, the assumption of the volcano being ‘at rest’ at the beginning of an event tree is not universally applicable and is often associated with high uncertainty. What if the volcano is already in unrest but we do not have a monitoring network to help us differentiate between states of unrest and not unrest? Establishing unrest at a specific volcano is of paramount importance as this affects the subsequent probabilities in an ET. Geophysical data helps to define background activity and to identify transitions to unrest. Well-monitored volcanoes often also benefit from good constraints on geological data, helpful in determining more accurately the history of unrest and eruptive cycles. When geological data are not sufficient, a monitoring network becomes important as the posterior probability of eruption will be informed by the prior probabilities estimated from the geophysical data. Also, monitoring data reduces uncertainties and improves unrest and eruption forecast on very short time windows (e.g., days, weeks). Therefore, a successful PVHA relies on both geological and geophysical data, which are used jointly to establish the activity cycles at a volcano and inform the probabilities of each node in the ET.

We explore the effects of the likelihood and prior functions on the posterior probability estimates. A non-Bayesian hazard assessment is highly biased since it often relies on the interpretation of an incomplete geological record. Based on our interpretation of the recent eruptive history at Ceboruco the probability of eruption based only on the mean likelihood function is 0.0018. This probability decreases by half if we conservatively assume that after ~40 kyrs of quiescence Ceboruco entered unrest before the Jala eruption and continues today (Fig. 5a). Therefore, a hazard analysis based only on the geological record is highly biased and poorly informative.

We can refine these estimates by updating the posterior probabilities with a mean prior function. Ideally, the prior is informed by monitoring data and other numerical or theoretical models. When such data is missing, maximum ignorance is usually assumed to inform the mean prior functions (i.e., Beta = 0.5; equal chances for each binomial outcome to occur) yielding higher probability estimates associated with large uncertainties. If we add a prior function with maximum ignorance in the first three nodes at Ceboruco, we increase slightly the probability of eruption given magmatic unrest from 0.0018 to 0.00243. The uncertainties in these estimates can be reduced with more informed prior distributions. For example, by using Beta = 0.64 in node 3 (based on the Phillipson et al. 2013 catalogue) the final estimate for probability of eruption decreases slightly (dotted line in Fig. 5b).

The PVHA at Ceboruco is sensitive to the definition of unrest and the prior probability estimates, and both depend on geophysical monitoring. Without consistent data from a developed and continuous monitoring network to inform the hazard assessment, the final probability estimates are relatively higher. The uncertainties in both the prior and likelihood functions are propagated to the posterior probability estimates; the only solution to refine the PVHA and deal with the uncertainty is the development of a real-time and continuous monitoring network and to conduct more detailed field studies.

Limitations and advantages of using PyBetVH

The ability to combine multiple sources of information, as well as the possibility of exploring various combinations of eruptive scenarios leads to a better estimate of the uncertainty associated with different hazard maps. Probabilistic hazard maps are usually conducted for a single volcanic phenomenon by using different numerical simulation tools (Charbonnier et al. 2020; Gallant et al. 2018). PyBetVH can merge the outputs of different simulation tools with geological data and assess the uncertainty range associated with the average prior probability presented in each map. In Figure 6, we show an example of the uncertainty range (i.e., 10^{th}, 50^{th} and 90^{th} percentiles) in the conditional probability maps for PDC (conditional to the occurrence of a Plinian eruption (S3). These maps provide an easier way to evaluate our confidence in the hazard maps, a useful feature for decision makers (Thompson et al. 2015; Sandri et al. 2014; Lindsay et al. 2010).

PyBetVH has an easy-to-use graphical interface (Tonini et al. 2015) that allows the user to update the input files as soon as more information becomes available. The current version of PyBetVH was developed to analyze volcanic hazards associated to magmatic unrest only. However, recent efforts helped describe and recognize indicators for amagmatic unrest and related hazards (Rouwet et al. 2014). The implementation of an amagmatic branch in the ET is important for short-term forecasting applied to monitored volcanoes (Tonini et al. 2016 a).

Conclusions And Final Remarks

We conduct a PVHA for Ceboruco, a poorly monitored and active volcano on the western part of the TMVB. Based on the eruptive scenarios proposed by Sieron et al. (2019 b), we create a generic ET for Ceboruco to account for magmatic and amagmatic activity. For the magmatic eruption branch of the ET, we choose three scenarios: *i)* small (effusive*), ii)* moderate (vulcanian/sub-Plinian) and *iii)* large (Plinian); with their related hazardous phenomena: ballistics, tephra fallout, pyroclastic density currents, lahars, and lava flows. We use PyBetVH, an e-tool based on the Bayesian event tree methodology, to create probabilistic hazard maps for each of the selected eruption scenarios. Using geological data with outputs from other numerical and theoretical models in PyBetVH, we estimate the probability of a magmatic eruption at Ceboruco within the next time window (i.e., 1 year) of ~ 0.002. The resulting absolute probability maps show that the communities and infrastructure around Ceboruco have relatively high probabilities of being impacted by LF, PDC, TF, and LH. The BA will likely impact only the cone area. If the deterministic maps presented by Sieron et al. (2019 b) are easy to interpret for the general public and represent an asset in case of a volcanic emergency, the maps presented here are fundamentally different.

These maps assign a probability, hopefully making them a useful tool for authorities and stakeholders in the decision-making process. We suggest that decisionmakers will make a decision using probabilistic results if they are able to compare probabilities with other potential events in a community. This depends on the low population. For example, globally children are the people in communities least likely to die in a given year, with a probability of dying of around 1/10000 with higher rates among children in rural communities (Svenson 1996). A probability of 1/500 or 1/1000 of PDC inundation of their community (Fig 6) is a high probability for children in a community because it increases their probability of dying in a given year considerably. Of course, it is up to the community to decide which level of probabilities are unacceptable, but such comparisons can provide context and these comparisons rely on valid probabilistic hazard maps.

Our analysis indicates that PVHA at poorly monitored volcanoes relies mostly on the likelihood function (informed by geological data) and/or maximum ignorance for prior distribution functions, thus yielding high probabilities than are found using the likelihood function alone. These estimates are associated with high uncertainties which can only be reduced by refining the prior distribution functions with information from geophysical monitoring.

We recognize the numerous efforts by academic and government institutions, and we recommend the set-up of at least a minimal permanent monitoring network at Ceboruco with the capabilities to provide real-time geophysical data continuously. Another important consideration at Ceboruco is to extend the event tree presented here to include the surrounding monogenetic field.

Abbreviations

ET – Event tree

BET – Bayesian event tree

BBN – Bayesian Belief Networks

HASSET – Hazard Assessment Event tree

BET_VH – Bayesian Event Tree for Hazard Assessment

PyBetVH – python Bayesian Event Tree for Hazard Assessment

PVHA - probabilistic volcanic hazard assessment

TMVB – Trans-Mexican Volcanic Belt

VEI – Volcanic Explosivity Index

LF – lava flows

TF – tephra fallout

PDC – pyroclastic density currents

LH – lahars

BA – volcanic ballistics

DRE – Dense rock equivalent

m_u – magmatic unrest

t_u – tectonic unrest

id – increased degassing

Lf – low-frequency earthquakes

VT – volcano tectonic earthquakes

m_e – magmatic eruption

S1 – Scenario 1

S2 – Scenario 2

S3 – Scenario 3

N1 – Node 1

N2 – Node 2

N3 – Node 3

Kyrs – kiloyears

u – unrest

Declarations

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Authors' contributions. All authors contributed to the writing of the manuscript, the interpretation and discussions of the results. RC designed and conducted the implementation of the study. RC, CC and RT conducted the PyBetVH set-up and running of the code. KGZ and RC conducted the elaboration of the maps. RC, CC, DF, KS, CS, CB participated in the elicitation sessions for parameters set-up. KGZ and DF assisted with data analysis and conversion.

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Availability of data. The data set used for this study is published in Sieron et al. (2019 a, b). The PyBetVH files are available by request to the corresponding author.

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Tables

Table 1. Summary of the input data used in PyBetVH for the first three nodes.

Nodes	Input parameters (see text)
***τ** = 1 year (forecast time window)*	
Node 1 – *unrest/no unrest*	
Past data	4 unrest episodes (*u*) in 1108 years
Prior models	Beta = 0.5; *Λ* = 1
Node 2 – *origin of unrest*	
Past data	$m_u = 2$
Prior models	Beta = 0.5; *Λ* = 1
Node 3 – *eruption/no eruption*	
Past data	$m_e = 2$
Prior models	Beta = 0.5; *Λ* = 1

Table 2. Summary of the hazardous phenomena considered in our event tree for each of the three scenarios considered. For past data we have the number of times the selected phenomena occurred at past eruptions. Most past data are considered for Scenario 3, Plinian eruption due to the better preservation and mapping of the deposits of the Jala eruption. As prior models we used the maps created by various simulation tools used by Sieron et al. (2019 b) for each considered phenomena.

Hazardous phenomena	*Past data*			*Prior models* *
	Scenario 1	Scenario 2	Scenario 3	
Ballistics	0	0	1	540 simulations with *Eject! (M*astin 2001)
Tephra fallout	0	0	1	S1 and S2: 24 simulations with *HAZMAP* (Macedonio et al. 2005) S3: 1000 simulations with *Tephra2* (Bonadonna et al. 2005)
Pyroclastic density currents	-	0	1	66 simulations with *Titan2D* and *Energy Cone* (Patra et al. 2005, Schilling 1998)
Lahars	-	0	1	54 simulations with *LaharZ* (Schilling 1998)
Lava flows	1	1	-	539 simulations with *ELFM* (Damiani et al. 2006)