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# On the feasibility and usefulness of high-performance computing in probabilistic volcanic hazard assessment: An application to tephra hazard from Campi Flegrei

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For active volcanoes, knowledge about probabilities of eruption and impacted areas becomes valuable information for decision-makers to develop short- and long-term emergency plans, for which probabilistic volcanic hazard assessment (PVHA) is needed. High-resolution or spatially extended PVHA requires extreme-scale high-performance computing systems. Within the framework of ChEESE (Center of Excellence for Exascale in Solid Earth; www.cheese-coe.eu), an effort was made to generate exascale-suitable codes and workflows to collect and process in some hours the large amount of data that a quality PVHA requires. To this end, we created an optimized HPC-based workflow coined PVHA\_HPC-WF to develop PVHA for a volcano. This tool uses the Bayesian event tree methodology to calculate eruption probabilities, vent-opening location(s), and eruptive source parameters (ESPs) based on volcano history, monitoring system data, and meteorological conditions. Then, the tool interacts with the chosen hazard model, performing a simulation for each ESP set or volcanic scenario (VS). Finally, the resulting information is processed by proof-of-concept-subjected high-performance data analytics (HPDA) scripts, producing the hazard maps which describe the probability over time of exceeding critical thresholds at each location in the investigated geographical domain. Although PVHA\_HPC-WF can be adapted to other hazards, we focus here on tephra (i.e., lapilli and ash) transport and deposition. As an application, we performed PVHA for Campi Flegrei (CF), Italy, an active volcano located in one of the most densely inhabited areas in Europe and under busy air traffic routes. CF is currently in unrest, classified as being in an attention level by the Italian Civil Protection. We consider an approximate  $2,000 \times 2,000 \times 40$  km computational domain with 2 km grid resolution in the horizontal and 40 vertical levels, centered in CF. To explore the natural variability and uncertainty of the eruptive conditions, we consider a large number of VSs allowing us to include those of low probability but high impact, and simulations of tephra dispersal are performed for each of them using the FALL3D model. Results show the potential of HPC to timely execute a vast range of simulations of complex numerical models in large high-resolution computational domains and analyze great volumes of data to obtain quality hazard maps.

#### KEYWORDS

HPC, probabilistic volcanic hazard assessment, ash dispersal, exascale computing, Bayesian event tree, performance optimization and productivity, workflow manager, Campi Flegrei

# **1** Introduction

Volcanic eruptions can cause a wide variety of hazardous phenomena, with impacts ranging from proximal to global scales. For instance, during explosive eruptions (Newhall and Hoblitt, 2002; Jenkins et al., 2014), volcanoes can inject large volumes of fragmented pyroclasts (tephra), which disperse into the atmosphere under the effects of turbulence and prevailing winds, and deposit up to thousands of km from the volcano (Martin and Nemeth, 2007). Pyroclasts can range in size from several cm to a few µm. Depending upon their size, they can persist in the atmosphere for a few seconds or for several days and can represent a serious threat when an eruption occurs near inhabited areas or to air traffic routes in very distal regions. The finest fraction of tephra (i.e., PM10, with a diameter smaller than 10 µm) can be inhaled by humans and animals, and the fraction with a diameter smaller than 4 µm (called respirable) can be breathed into the alveolar region of the lung and has the greatest toxic potential (Horwell and Baxter, 2006). Exposure to high concentrations of fine tephra can have serious implications for human health and represents a serious hazard to consider in the presence of explosive volcanoes (Damby et al., 2013). Eventually, tephra fallout may affect a variety of infrastructures that are essential for our daily lives all over the world. Examples are the road network, where a few-mm thick tephra deposit can create dangerous driving conditions (Blake et al., 2017); power plants and powerline transmissions (Wilson et al., 2012); transportation systems in general (Guffanti et al., 2010); contamination of water (Ágústsdóttir, reservoirs and vegetation 2015); telecommunication networks (Wilson et al., 2012). The adverse effect of volcanic ash (i.e., tephra smaller than 2 mm in size) on aircraft gas turbine engines is well known (Prata and Tupper, 2009; Chen and Zhao, 2015) and recently described more quantitatively (Clarkson et al., 2016). Fine ash can travel for thousands of km, extending the potential impact of explosive eruptions beyond borders and continents.

The quantification of tephra hazard is particularly relevant for volcanoes located close to large urban centers and/or to air traffic routes; the Neapolitan area in Southern Italy is one of those. Field-based hazard maps obtained from the study of the deposits of past eruptions and the eruptive history of specific volcanoes represent important information to assess volcanic hazards (Lirer et al., 2001; Alberico et al., 2002; Orsi et al., 2004). However, since volcanic processes are complex, that is, governed by many degrees of freedom (the number of independent parameters that define their state), their outcome is intrinsically unpredictable in terms of temporal occurrence and eruption parameters. For this reason, a probabilistic approach, that is able to integrate the uncertainty due to intrinsic stochasticity (aleatory uncertainty) and due to our limited knowledge of chemical-physical processes and system conditions (epistemic uncertainty), is more suitable than a deterministic approach, where randomness or uncertainty are not considered (Budnitz et al., 1997; Bonadonna et al., 2005; Macedonio et al., 2008; Marti et al., 2008; Neri et al., 2008; Folch et al., 2009; Marzocchi et al., 2010; Biasse et al., 2014; Marzocchi and Jordan, 2014; Barsotti et al., 2018; Selva et al., 2018; Marzocchi et al., 2021). PVHA is indeed the main tool for hazard and risk mitigation plans, as well as the main input to quantitative risk assessment (Spence et al., 2004; Zuccaro, 2008; Jenkins et al., 2014). Depending on the application, PVHA may be performed in the long-term by forecasting the hazard over long time windows (e.g., 50 years) as well as in the short-term by forecasting the hazard over shorter time windows (e.g., few hours). Long-term PVHA is the primary tool for long-term mitigation actions like evacuation plans or regulatory aspects of buildings (Marzocchi et al., 2008, 2010), while short-term PVHA (Selva et al., 2014) is more suitable for actions such as evacuation or air traffic management (for example, airport closure and rerouting).

PVHA can be defined as the quantification of the potential impact of a volcanic hazardous phenomenon generated by any possible volcanic eruption, evaluated at specific geographical points around the volcano, and quantified by the exceedance probability of a selected set of thresholds (e.g., tephra load at the ground or ash concentration at flight levels in case of tephra hazard) in a given time window (hours/days for short-term analyses or years/tens-of-years for long-term analyses). This information allows estimation of, for instance, the probability that the tephra deposit accumulated during an eruption exceeds the critical condition that causes building collapse/failure, the probability that the ash cloud concentration exceeds the critical values for flight safety and with what persistence, or the probability that airports or important assets will be affected by the presence of ash (Sulpizio et al., 2012).

The performance of PVHA with physics-based fully resolved numerical models (e.g., FALL3D) is computationally expensive, as it ideally involves thousands to millions of simulation runs exploring the full natural variability of the source (eruption magnitude, intensity, vent position, etc.) and of the propagation conditions (wind distribution), also considering the epistemic uncertainty (alternative databases, alternative models, etc.). This problem has typically been solved by restricting the exploration of natural variability (e.g., with representative scenarios) or simplifying the modeling strategy (e.g., with analytical models or with restricted target grids), potentially introducing unwanted biases in the hazard estimates (Bonadonna et al., 2005; Sandri et al., 2016; Selva et al., 2018).

Advances at the computational level, particularly in highperformance computing (HPC) and high-performance data analytics (HPDA), already permit PVHA in a reasonable time (hours), with a sufficient level of detail to help civil protection officials and society for reliable risk ranking and assessment. Several works have been carried out in this direction. For instance, Folch and Sulpizio (2010) performed a long-term probabilistic assessment of volcanic ash hazard for Somma–Vesuvius (Italy) using a specific range of eruption parameters, and Titos et al. (2022) developed a long-term hazard assessment of ash dispersion at relevant flight levels for Jan Mayen (Norway) exploring a large set of possible combinations of eruptive parameters.

Herein, we present the probabilistic volcanic hazard assessment workflow (PVHA\_HPC-WF) developed within the ChEESE project (www.cheese-coe.eu), an optimized numerical tool for developing short-term to long-term PVHA for a specific volcano. We then apply it to the Campi Flegrei caldera (CFc), Italy, considering a wide number of VSs for demonstrating the feasibility and potential usefulness of PVHA\_HPC-WF to produce robust and unbiased tephra PVHA for end users such as civil protection agencies, aviation stakeholders, and other scientific institutions. To this end, first, the probabilistic methodology on which this study is based is outlined in Section 2. Section 3, then describes PVHA\_HPC-WF in which this methodology is accommodated and illustrates how the workflow manager system light (WMS-light) and the performance optimization and productivity (POP) process have helped to make optimized codes and workflows. The test cases at Campi Flegrei are discussed in Section 4. Finally, the results are discussed, and some conclusions are drawn in Section 5. Although we also briefly explore the volcanological background, this work focuses on the probabilistic and computational methodology.

# 2 Probabilistic volcanic hazard analysis

The chain of processes leading to a volcanic eruption is complex (Marzocchi et al., 2004, 2008), implying that there are substantial and non-negligible uncertainties, stemming both from the intrinsic natural variability of such processes (socalled aleatory variability) and from the limitations of our models and observations (epistemic uncertainty). Probabilistic volcanic hazard analysis defines a set of variables, called intensity measures *X*, that describe the intensity of a given hazardous phenomenon *h* and quantifies the so-called hazard curves  $\theta$ , which report the probability that *X* exceeds the interest intensity values (thresholds) *x* at a specific target point  $\vec{a} =$  (latitude, longitude, altitude) at least once in a period of time  $\Delta T$ :

$$\theta^{\left(h,\bar{a},\Delta T\right)}(x) = P^{\left(h,\bar{a},\Delta T\right)}(X \ge x).$$

Statistically, this exceedance probability curve is a survivor function, describing the natural variability of the phenomenon at the site, that is, the aleatory uncertainty.

With the total probability theorem, hazard curves can be evaluated considering the contribution of a set of volcanic scenarios, that is,

$$\theta^{\left(h,\vec{a},\Delta T\right)}(x) = P(\Delta T, E) \int_{\Omega} P(vs|E) \cdot P^{\left(h,\vec{a},\Delta T\right)}(X \ge x|vs) dvs$$
$$\approx P(\Delta T, E) \cdot \sum_{i}^{N} \left[ P(VS_{i}|E) \cdot P^{\left(h,\vec{a},\Delta T\right)}(X \ge x|VS_{i}) \right]$$
(1)

where  $P(\Delta T, E)$  represents the probability of the occurrence of a general event eruption E during the period of time  $\Delta T$ , and  $\Omega$  represents the infinite set of possible source (vs) (e.g., magnitude and location) combinations that can be approximated with a finite set of N specific volcanic scenarios. The factor  $P^{(h,\vec{a},\Delta T)}(X \ge x|VS_i)$  evaluates the potential impact at the site  $\vec{a}$  of each VS based on the model and thus is often called the propagation factor (in the insurance industry, this is normally known as the *footprint generator* because each realization of the model (propagator) generates a so-called *footprint*). As explained in the next section, the dependence of this factor on  $\Delta T$  is related to the fact that the evaluation of this probability may change for smaller/larger  $\Delta T$  (days vs. years). The other factors instead deal with the variability of the source, and they are thus collectively called source factors.

This representation is possible only if such scenarios represent a set of mutually exclusive and collectively exhaustive representations of the general event *E*, that is,

$$\sum_{i}^{N} P(VS_{i}|E) = 1,$$

which is approximately achieved by using as many randomly selected volcanic configurations as possible within the known ranges for each volcano. This formulation assumes that the

Node	Parameter	Value	Source
1—unrest	Prior probability	0.5	Selva et al. (2012a)
	Lambda	1	
	Past data suc./tot	7.4/306	
2—magmatic	Prior probability	0.5	Selva et al. (2012a)
	Lambda	1	
	Past data suc./tot	0/0	
3—eruption	Prior probability	0.33	Selva et al. (2012a)
	Lambda	1	
	Past data suc./tot	0/3.7	
4—vents	Number of vents	40	Selva et al. (2012b)
	Lambda	2	
	Prior probabilities	See Supplementary Material	
	Past data suc./tot	See Supplementary Material	

TABLE 1 Parameters of Gaussian functions used for Nodes 1 to 4 for the application of the PVHA\_HPC-WF in Campi Flegrei.

probability of observing more than one eruption in  $\Delta T$  is negligible and, under this condition, it holds for both longand short-term PVHA.

The hazard curves are often computed conditional on the event *E*, in which case only the summation in Eq. 1 is evaluated, neglecting the temporal component *P* ( $\Delta T$ , *E*). The obtained conditional volcanic hazard (cVH) curves have direct application to planning short-term risk mitigation actions during a volcanic crisis, such as the definition of evacuation areas.

In all cases, hazard curves are usually quantified on a set of points within the geographic area under study, and hazard/ probability maps are produced to show the exceeded thresholds/probability distribution by cutting at a probability/ critical-intensity value.

The evaluation of Eq. 1 involves studying the statistics (aleatory uncertainty) of the source (i.e., eruption scenarios) and the propagation of the hazard from the source to the target point (e.g., tephra dispersion). Multiple alternative models can be formulated, leading to alternative quantifications of  $\theta^{(h,\vec{a},\Delta T)}(x)$ . This uncertainty, named epistemic, is typically modeled by quantifying the variability of the hazard curves under a reasonable range of scientifically acceptable scientific models (Budnitz et al., 1997; Marzocchi and Jordan, 2014; Marzocchi et al., 2021).

# 2.1 Short-term and long-term probabilistic volcanic hazard assessment

PVHA can be focused on different scales for  $\Delta T$  depending on the time horizon in which significant variations are expected in the activity of the volcano under study and on the type of potentially risk-reducing actions. We focus here on two different time scales: the short-term (ST) PVHA and the long-term (LT) PVHA. ST PVHA refers to a time window ranging from hours to weeks and is useful for crisis management during volcanic unrest (Sandri et al., 2012; Selva et al., 2014). LT PVHA considers years to decades and is interesting, for example, in the case of a quiescent volcano for landuse planning (Marti et al., 2008; Neri et al., 2008; Selva et al., 2010; Titos et al., 2022). The methods adopted in ST/LT PVHA are inherently linked to different sources of information used to issue an eruption forecast or to model the hazard (Marzocchi et al., 2008). For LT assessments, PVHA mostly relies on the historical and/or geological records of the volcano under study (or from analog volcanoes) and on expert opinion (e.g., Aspinall, 2006), as well as on the statistics for propagation conditions of the hazard we are assessing. For ST assessment, PVHA considers the actual and updated information coming from the monitoring system and other short-term forecast systems (e.g., weather).

Also, the information used to constrain propagation conditions may change for ST and LT PVHA. In the case of tephra hazard, ST and LT PVHAs rely on different information for the wind data: for the former, the present wind forecast is used to run the tephra dispersion model; for the latter, the climatology of wind over tens of years is used instead. This impacts the quantification of  $p^{(h,a,\Delta T)}(X \ge x | V S_i)$ ) in Eq. 1, which in fact explicitly depends on  $\Delta T$ . Actually, the difference between ST and LT is the potential variability of the wind to be accounted for in the  $\Delta T$ . In the ST (few days), the possible meteorological scenarios (propagators) are strictly connected to wind forecasts, and only a rather small set of wind scenarios have practically non-zero probability, resulting in a smaller N. As  $\Delta T$  increases, their variability necessarily increases because we move from forecast to seasonal climatology and finally to annual averages, and N should increase accordingly.

# 2.2 Probabilistic volcanic hazard assessment through Bayesian event tree analysis

The Bayesian event tree (BET) method can be used to calculate the long- and short-term probabilities of any volcanic phenomena



(A) Graphical representation of the Bayesian event tree methodology (BET) used in this work [image from Selva et al. (2014)]. (B) Flow diagram of the PVHA\_HPC-WF.

(Eq. 1) by applying a Bayesian inference procedure (Newhall and Hoblitt, 2002; Marzocchi et al., 2004, 2008; Lindsay et al., 2010; Selva et al., 2010, 2014). Using a structured event tree, each volcanic event is represented by an individual branch which splits up into a set of possible subsequent events whose probabilities and uncertainties are estimated from prior information available from the volcanological information obtained from the history of a volcano, empirical and theoretical models, and monitoring observations.

Figure 1A shows a graphical representation of the BET used in this work (Selva et al., 2014). This event tree describes the possible evolution of an eruption in eight steps (nodes). Node 1 indicates the

probability of unrest or not unrest within the time interval  $\Delta T$ , Node 2 gives the probability that, in the case of unrest, it is due to magma or to other causes, and Node 3 provides the probability that, in the case of unrest due to magma, the magma will trigger an eruption or not. The final eruption probability, representing the eruptive forecasting (EF), will then be calculated by a combination of Nodes 1, 2, and 3. Nodes 4 and 5 handle the VSs, dealing with variability in potential vent positions and size, respectively. Node 6 expresses the probability of generating or not generating a specific hazardous phenomenon *h*, Node 7 expresses the probability to reach or not to reach a site  $\vec{a}$  by the hazardous phenomenon, and Node 8 provides the probability of

TABLE 2 PDFs and value ranges of the main eruptive parameters for CFc. Bounds on mass eruption rate (MER) values are a consequence of the sampling procedure for total erupted volume (TEV) and duration of the fallout phase described in this work. For the total grain size distribution (TGSD), we selected three different kinds of particles: juveniles, lithics, and crystals. To describe juvenile particle, we used a bi-Gaussian (in  $\Phi$ ) distribution where both  $\mu$  and  $\sigma$  were sampled from the distribution detail and whose degree of mixing is given by the TGSD probabilities of juveniles. Lithics and crystals were described using a Gaussian distribution.

Parameter	Eruption size	PDF type and ranges
TEV (kg <sup>a</sup> )	Low	Uniform on [10 <sup>10</sup> ;10 <sup>11</sup> ]
	Medium	Uniform on [10 <sup>11</sup> ;10 <sup>12</sup> ]
	High	Uniform on [10 <sup>12</sup> ;10 <sup>13</sup> ]
Duration of fallout (hours)	Low	Uniform on [3.48; 27.36]
	Medium	Uniform on [1.95; 3.48]
	High	Uniform on [1.92; 1.95]
MER (kg/s)	Low	Uniform on [1.5*10 <sup>6</sup> ;1.2*10 <sup>8</sup> ]
	Medium	Uniform on [1.2*108;2.1*109]
	High	Uniform on [2.1*10 <sup>9</sup> ;2.2*10 <sup>10</sup> ]
TGSD juveniles (Φ units)	All types	Beta on [2.7; 4] for $\mu 1$
		Beta on [4.9; 5.4] for $\mu 2$
		Beta on [0.9; 1.5] for $\sigma_1$
		Beta on [3.5; 5.5] for $\sigma_2$
CGSD probabilities of juveniles (%)	Low	Beta on [0.3; 0.5]
	Medium	Beta on [0.2; 0.4]
	High	Beta on [0; 0.3]
CGSD lithics (Φ units)	All types	Beta on [-2; -0.5] for $\mu$
		Beta on [1.4; 1.7] for $\sigma$
'GSD crystals (Φ units)	All types	Beta on $[0.1; 0.6]$ for $\mu$
		Beta on [0.7; 1.2] for $\sigma$
nitial density of juveniles $\rho_0$	All types	Beta on [500; 1,000]
faximum juvenile density (kg/m³)	All types	2,500
Density of juveniles (%)	Low	Beta on [1; 1.5] for $\alpha$
		Beta on [0.3; 0.6] for r
	Medium	Beta on [1.5; 2] for $\alpha$
		Beta on [0.4; 0.7] for r
	High	Beta on [2; 4.5] for $\alpha$
	-	Beta on $[0.5; 1]$ for r
Density of tephra particles (kg/m³)	All types	Lithics: 2,500
	· •	Crystals: 2,800
Particle proportion (kg/m <sup>3</sup> )	All types	Dirichlet on [2.01; 0.66; 0.33]
'ephra mass fraction (%)	All types	25
Density of particle aggregates (kg/m <sup>3</sup> )	All types	Accretionary lapilli: [1,000; 2,000]
7 1 00 0 × 0 7	7 A.	Other aggregates: [100; 600]
Diameter of particle aggregates ( $\Phi$ units)	All types	Accretionary lapilli: 2,000
	**	Other aggregates: 200
Particle proportion aggregates (%)	Low	Uniform on [10; 30]
1 1 1 1 1 1 00 0 m (V-)	Medium	Uniform on [30; 60]
	High	Uniform on [60; 90]
Particle proportion lapilli (%)	All types	Uniform on [0; 20]

exceeding a critical threshold x in the target site in the event of an eruption with a given VS. Nodes 6–8 deal with the impact of each VS, that is, collectively evaluate the propagation factor of Eq. 1, whose probability values are calculated by BET by analyzing the results of the propagation model (in our case, FALL3D) (Selva et al., 2010).

The event tree factorizes Eq. 1 into a set of conditional probabilities  $\theta_i$ , with *i* from 1 to 8. The probability at each node is evaluated with a Bayesian method, quantifying the epistemic uncertainty as a distribution for  $\theta_i$ , hereinafter indicated as  $[\theta_i]$ . In this way, Eq. 1 can be expressed as

$$\left[\theta^{\left(h\vec{a},\Delta T\right)}\left(X > x\right)\right] = \left[\theta_{123}^{\text{Eruption}}\right] \cdot \sum_{j \in J} \sum_{k \in K} \left[\left[\theta_{4}^{k}\right] \cdot \left[\theta_{5}^{k}\right] \cdot \left[\theta_{6}^{h}\right] \cdot \left[\theta_{7}^{h\vec{a}}\right] \left[\theta_{8}^{h\vec{a},X > x}\right]\right], \quad (2)$$

where

$$\begin{bmatrix} \theta_{123}^{\text{Eruption}\,(\Delta T)} \end{bmatrix} = \begin{bmatrix} \theta_1^{\text{Unrest}} \end{bmatrix} \cdot \begin{bmatrix} \theta_2^{\text{MagmalUnrest}} \end{bmatrix} \cdot \begin{bmatrix} \theta_3^{\text{Eruption}|\text{Magmatic unrest}} \end{bmatrix}$$

is the probability that an eruption occurs in the time window  $\Delta T$ , and *X* is the random variable that describes the intensity measure associated with the hazard *h* at the point  $\vec{a}$ . *J* is the set of potential vent-opening locations, and *K* is the set of possible VSs for each vent location in *J*.

A critical role in the definition of PVHA hazard curves through Eqs. 1 and 2 is played by the definition of volcanic scenarios (VSs). A VS is defined as an eruption of a given size in a given vent location. At Nodes 4 and 5, often a generic definition of VS is applied, defining a set of VS classes, each class often modeled with representative scenarios. However, Sandri et al. (2016) demonstrated the importance of modeling the intra-class variability (i.e., eruptive size difference within a class). To this end, it is important to create a consistent stratified sampling of the VSs in order to represent the entire variability of the eruptive source parameters (ESPs). To this end, a four-step procedure may be proposed. First, the possible eruptive size classes may be defined, for example, based on the volcanic explosivity index (VEI) (Newhall and Self, 1982) or preferably on eruption magnitude and intensity (Mason et al., 2004; Pyle, 2015). Each eruptive size class will be characterized by a series of ESPs such as the total erupted mass (TEM), the column height, and the duration of tephra fallout phases, as well as any known parameters that may influence the modeling of the volcanic hazard. The parameters used for the modeling of tephra dispersal by means of FALL3D in Campi Flegrei are listed in Table 2. Such size classes and ESPs will be in turn fully described by probability density functions (PDFs) fixed on the basis of the knowledge of the volcano. Next, within an eruptive size class, a value should be sampled from each ESP's PDF, characterizing this set as the ESPs of the VS. Then, the vent location has to be estimated from historical or monitoring data. Finally, the propagation conditions (e.g., wind distribution) have to be associated with the VS. For example, for an ST tephra PVHA, the sampled scenarios would be associated with the forecast meteorological conditions, while for an LT tephra PVHA, each scenario would have different weather conditions chosen randomly from the meteorological data of a period of time.

# 3 Probabilistic volcanic hazard assessment HPC workflow

To accommodate the methodology described in the previous section, we built the software package PVHA\_HPC-WF (Probabilistic Volcanic Hazard Assessment HPC Workflow) based on the prototype tool BET@OV (Perfetti et al., 2021). BET@OV was created by researchers at Istituto Nazionale di Geofisica e Vulcanologia (INGV, Italy) to compute eruption forecasting and probabilistic tephra fallout hazard assessment at CFc by combining the Bayesian event tree method and the FALL3D tephra dispersal model (Costa et al., 2006; Folch et al., 2009). In particular, BET@OV was designed to compute 1) the probability of eruption at CFc ( $[\theta_{1,2,3}^{Eruption(\Delta T)}]$ ) with  $\Delta T = 1, 2, 3$ days, 2) the conditional vent-opening probability map ( $[\theta_4]$ ), and 3) the probability  $[\theta^{(h, \vec{a}, \Delta T)}]$  by using three fixed VSs in terms of eruptive sizes, that is, low, medium, and high explosive according to Orsi et al. (2009). To achieve new goals, we increased the BET@OV modeling capabilities so that it can generate PVHA, overcoming current computational limitations in terms of time/ space domain size, resolution, and the number of representative VSs. In particular, to simulate tephra fallout and ash concentration at flight levels, PVHA\_HPC-WF interacts with the model FALL3D-8.0 (Folch et al., 2020; Prata et al., 2021).

#### 3.1 Workflow architecture

PVHA\_HPC-WF is made up of a set of Python modules (see Figure 1B) in charge of calculating each of the BET nodes described earlier in Subsection 2.2 as well as performing the post-processing and visualization of results. The workflow tasks are managed by the ChEESE workflow management system *WMS-light*, and to consolidate the data and keep history, the PostgreSQL LISTEN exchange is used. The next section describes how the workflow is managed by WMS-light and how the optimization has been carried out. A description of each of the Python modules can be found in the Supplementary Material.

#### 3.2 Workflow implementation

The PVHA\_HPC-WF is a classic workflow-based application, in which the data-interconnected components are executed in a synchronized order according to the application logic, as depicted in Figure 1B. Running such applications on IT infrastructures, including diverse HPC systems with their distributed computing and storage components or their respective different resource access and application execution strategies, is a challenging task. In practice, running application workflows on the on-demand parallel and distributed infrastructures often impose the following issues:

- Automation of distributed control flow. The workflow components that are running on different parts of the physically distributed infrastructure resources have to employ sophisticated synchronization strategies in order to be able to track the progress of the interdependency of tasks.
- Heterogeneous deployment configurations. Depending on the infrastructure availability and the application's non-



functional requirements, it might be necessary for application components to be executed on different infrastructure sites, which can change from one deployment (execution) to the next one. In such cases, the application will have to deal with different access policies (e.g., certificate-based authorization instead of the user's login and password), job execution strategies (different job managers like *PBS/Torque* or *SLURM*), organization of the storage, and many other site-specific settings that have zero or little relevance to the application itself.

• Distributed data access. The application components are interchained not only by the control but also by the data flow. The data dependencies can be implemented in several different ways, depending on the concrete (and, generally, deployment-specific) properties of the infrastructure resources that are hosting the components, such as with the classic *FTP* and *SCP*, but also with the throughput-optimized grid protocols such as *GridFTP*.

• Dynamic scaling of components. Depending on the availability of the infrastructure resources, the application components might need to scale up or down to saturate the maximal capacity of the assigned hardware in order to increase the performance and/or optimize non-functional properties. As the available resource size might be unknown at the time of the application workflow submission, the scaling has to be performed dynamically at the runtime of the application instance.

In order to address the abovementioned issues during the development and execution of the application workflow, the PVHA\_HPC-WF application employs workflow а management system WMS-light, which was developed in the context of the ChEESE project (see a basic introduction in Cheptsov and Beljaev, 2020). WMS-light is a lightweight middleware that supports developers of the application workflows that are to be run in distributed, parallel, and heterogeneous computing environments and have dynamic deployment properties. The WMS-light support generally includes the synchronized execution of components on distributed hosts (serial, parallel, HPC), the realization of data dependencies, and the tracking of execution properties (across several applications and/or their instances) and requires minimal to zero changes in the original application components' code due to a non-intrusive programming model of WMS-light. Nonintrusiveness is a key property of WMS-light and applies not only to the applications but also to the infrastructure. Unlike the majority of well-established workflow managers, WMS-light requires only a minimal set of software that has to be installed in the user's space and does not require any special administrative privileges. WMS-light is designed in a modular and highly transparent way (see Figure 2A). The core of WMS*light* is constituted by a set of Java components and service bash scripts, which makes it portable to almost any architecture, from a small edge-server to the largest HPC system. All data related to the execution of instances (runs) of the application workflows are stored in the intelligent data layer and made available to the users and system middleware components by means of a richfunctional RESTful web service interface. All specifications, including the workflow definition (see Figure 2Bi), are made in the flexible JSON format. WMS-light allows live-tracking of the workflow execution status for each of the submitted instances (Figure 2Bii).

### 3.3 Workflow performance optimization

Within the framework of the EU Performance Optimization and Productivity Center of Excellence in HPC (POP CoE), critical parts of the PVHA workflow were analyzed because of their initial poor performance. More specifically, the analysis of volcanic hazard probabilities from FALL3D capability simulations became a concerning bottleneck due to long capability workflow execution times (note that this optimization does not concern single FALL3D model instances, but the capability workflow resulting from the aggregation of many independent instances). Thus, we applied the POP's profiling and optimization cycle. First, we identified through a performance assessment what was causing such bad workflow performance. Second, we addressed with a proof-ofconcept (PoC) each individual problem.

#### 3.3.1 Workflow performance assessment

With a performance assessment, we discovered that the part of the code that was slowing down the workflow was the analysis of the many instances of FALL3D, and we figured out what factors were responsible. Using Extrae (Center, 2022), we traced the application in various strong scalability tests up to 1,024 ranks MPI (Message Passing Interface). Then, with Paraver (Pillet et al., 1995), we analyzed the traces and generated a set of metrics giving us insights into the application's efficiency. For example, Figure 3A displays a Paraver trace showing qualitatively what regions of the program are being run in one execution with 48 MPI ranks. In Figure 3B, we can see the quantitative results of one strong scalability test. Thanks to these POP performance metrics (POP, 2022) we could identify that PVHA\_HPC-WF suffered mainly from two problems. First, it suffered from load-balancing problems. For instance, with 192 MPI ranks (four compute nodes in this setup), the load balance is already below 80%. Second, it presented a low serial performance as indicated by the average IPC (instructions per cycle). With 4 MPI ranks, the average IPC is 0.98, which is already low since a good IPC would be 2-3 for an application. However, from here, it only gets worse until an average IPC of 0.36 with 1,024 MPI ranks.

Given the previous analysis, we identified why the workflow performed badly and the reasons for load imbalance and poor CPU (central processing unit) utilization. Indeed, we realized that the different processor performances between ranks and one non-parallel region were causing load balance problems. Regarding low IPC, we attributed it to poorly optimized Python code. In addition to all that, we also saw that MPI usage could be improved.

#### 3.3.2 Proof-of-concept

Once we discovered what could be improved, we started working on optimizations in a proof-of-concept. On one hand, we addressed load balance issues by equally mapping data to every processor, keeping NUMA (non-uniform memory access) awareness in mind and parallelizing a region of serial code. On the other hand, we improved the poor workflow serial performance by optimizing the main nested loops of the

	entsl0scenF	TyNone-48	.prv					
THREAD 1.1.1								
THREAD 1.8.1								
THREAD 1.13.1								
THREAD 1.18.1								
THREAD 1.23.1								
THREAD 1.28.1								
THREAD 1.33.1							Other	
THREAD 1.38.1							Initializati	on
THREAD 1.43.1							Scenarios	
THREAD 1.48.1							Main com	
0 us					3,50	05,136,997 us		
B								
MPI Ranks	4	16	24	32	48	192	576	1024
Nodes	1	1	1	1	1	4	12	22
Global efficiency	91	47	33	33	32	25	16	11
Global efficiency -Parallel efficiency	91 91	47 89	33 95	33 80	32 90	25 71		11 31
Global efficiency	91	47	33	33	32	25	16	11
Global efficiency -Parallel efficiency	91 91	47 89	33 95	33 80	32 90	25 71	16 46	11 31
Global efficiency  -Parallel efficiency  -Load Balance	91 91 93	47 89 93	33 95 95	33 80 86	32 90 91	25 71 71	16 46 46	11 31 32
Global efficiency     I       -Parallel efficiency     I       -Load Balance     I       -Communication efficiency     I	91 91 93 98	47 89 93 96	33 95 95 99	33 80 86 94	32 90 91 99	25 71 71 100	16 46 46 98	11 31 32 99
Global efficiency -Parallel efficiency -Load Balance -Communication efficiency -Serialization efficiency	91 91 93 93 98 100	47 89 93 96 100	33 95 95 99 100	33 80 86 94 100	32 90 91 99 100	25 71 71 100 100	16 46 46 98 100	11 31 32 99 100
Global efficiency -Parallel efficiency -Load Balance -Communication efficiency -Serialization efficiency -Transfer efficiency	91 91 93 98 100 98	47 89 93 96 100 96	33 95 95 99 100 100	33 80 86 94 100 94	32 90 91 99 100 99	25 71 100 100 100	16 46 46 98 100 98	11 31 32 99 100 99
Global efficiency     I       -Parallel efficiency     I       -Load Balance     I       -Communication efficiency     I       -Serialization efficiency     I       -Transfer efficiency     I       -Computational Scaling     I	91 91 93 93 98 100 98 98 100	47 89 93 96 100 96 53	33 95 95 99 100 100 35	33 80 86 94 100 94 94 41	32 90 91 99 100 99 35	25 71 71 100 100 35	16 46 98 100 98 35	11 31 32 99 100 99 35
Global efficiency     I       -Parallel efficiency     I       -Load Balance     I       -Communication efficiency     I       -Serialization efficiency     I       -Transfer efficiency     I       -Computational Scaling     I       -IPC Scaling     I	91 91 93 98 100 98 100 100	47 89 93 96 100 96 53 53	33 95 95 99 100 100 35 35	33 80 86 94 100 94 41 41	32 90 91 99 100 99 35 35	25 71 100 100 100 35 35	16 46 98 100 98 35 35	11 31 32 99 100 99 35 37
Global efficiency     I       -Parallel efficiency     I       -Load Balance     I       -Communication efficiency     I       -Serialization efficiency     I       -Transfer efficiency     I       -Computational Scaling     I       -IPC Scaling     I       -Instruction Scaling     I	91 91 93 98 100 98 100 100 100	47 89 93 96 100 96 53 53 53	33 95 99 100 100 35 35	33           80           86           94           100           94           41           41           100	32 90 91 99 100 99 35 35 35	25 71 71 100 100 100 35 35	16 46 98 100 98 35 35 35	11 31 32 99 100 99 35 37 96
Global efficiency     I       -Parallel efficiency     I       -Load Balance     I       -Communication efficiency     I       -Serialization efficiency     I       -Transfer efficiency     I       -Computational Scaling     I       -IPC Scaling     I       -Instruction Scaling     I       -CPU Frequency Scaling     I	91 91 93 98 100 98 100 100 100 100	47 89 93 96 100 96 96 53 8 53 100 100	33 95 99 100 100 35 35 100 100	33           80           86           94           100           94           41           100           100	32 90 91 99 100 99 35 35 35 100	25 71 71 100 100 100 35 35 35 100	16 46 98 100 98 35 35 99 99	11 31 32 99 100 99 35 37 96 98

#### FIGURE 3

(A) PVHA\_HPC-WF Paraver trace. The x-axis shows the program's execution time in microseconds, while the y-axis displays each one of the 48 parallel MPI ranks. Colors indicate what part of the application is being run at a time. (B) POP metrics table of a PVHA\_HPC-WF strong scalability test. Colored values are in percentage.

Python code. The outcome of these optimizations improved the workflow's time-to-solution by 588 times.

We first optimized the serial computation loops. After some experiments, we found that the best performance was achieved using Numpy vectorization. Thanks to Numpy we replaced all Python for-loops with calls to Numpy vector operations, which yielded a maximum speedup of 775 times in the execution of that part of the code compared to the original workflow version. Listings 1 and 2 show an example of a change made to the code, which is to replace matrix multiplication in plain Python with matrix multiplication using Numpy vectorization. We also fixed a memory access pattern that was not exploiting the spatial locality of cache memory well.

#### Listing 1. Matrix multiply in plain Python.

```
product = np.zeros ((n, m), dtype = `int')
for i in range (n):
for j in range (m):
for z in range (k):
product [i, j] += matrix1 [i, z] * matrix2 [z, j]
```

Listing 2. Matrix multiply using Numpy vectorization. import numpy as np

product = np.matmul (matrix1, matrix2)

After the first optimization, all processors had the same amount of data to compute and the same memory access latency, so one balancing problem was already gone. The second problem was a sequential workflow region that took 2/ 3 of the execution time. Therefore, we parallelized this part with MPI, which reduced the total execution time by 2.3 times. Figure 4A shows the result of this parallelization. In the window at the bottom, the master rank is doing useful computation (in blue) for the last 2/3 of the window, while all the other processors are idle (in black) waiting. In the window at the top, the master rank is spending 2.3 times less execution time running sequential code. It seems that there is still room for improvement, as the application presents large serial parts. However, those parts belong mostly to the I/O operations of pre and post processing.

The final results of this PoC are displayed in Figure 4B, where we compare the base version versus our PoC version running with different number of ranks. Thanks to our



at the bottom is the application with the expensive sequential region. The trace at the top is the same application but with that region parallelized. Ignore the color gradient, only notice that the execution at the bottom takes 44s to finish, while the execution at the top takes a bit less than half of the time. Black means threads are not running the program. (B) PVHA\_HPC-WF execution time comparison between the original code (in red color) and the proof-of-concept version (in blue color) for the FL050 case.

changes; we were able to reduce the application's runtime by up to 588 times on average. Usage of Numpy vectorization was the main source of this large improvement and after that the parallelization with MPI of the sequential region.

### 4 Test case: Tephra probabilistic volcanic hazard assessment for Campi Flegrei

The metropolitan area of Naples (more than three million inhabitants, www.cittametropolitana.na.it) is under the threat of three active and well-studied volcanoes: Somma-Vesuvius,

Campi Flegrei, and Ischia. The PVHA of these volcanoes is based on several multidisciplinary studies (Costa et al., 2009; Selva et al., 2010; Sandri et al., 2016; Macedonio and Costa, 2018; Selva et al., 2018, 2021). In this study, we focused on the Campi Flegrei volcanic system, although the presented methodology can be applied to other volcanoes as well. The Campi Flegrei caldera (CFc) resulted from at least two major collapses from the Campanian Ignimbrite (Ort et al., 2003) and the Neapolitan Yellow Tuff (Deino et al., 2004) eruptions, 37,000 and 12,000 years BP, respectively. More recent volcanism was concentrated in epochs of intense activity (i.e., eruptions occurred at time intervals of a few tens of years), alternating with periods of quiescence (Costa et al.,

2022). Subsection 4.2 provides information on eruption probabilities, styles, intensity, and vent locations in CF. CFc is located in one of the most densely populated areas in Europe, so an eruption would have a tremendous impact, not only on air traffic but also on people and infrastructure. INGV is the reference scientific institution for the Italian government in the field of volcanic monitoring and hazards and operates in close synergy with the Italian Civil Protection authorities at the national and local levels. The surveillance system of Osservatorio Vesuviano of INGV continuously monitors, among others, volcano seismicity, ground deformations, and gas emissions and performs tephra dispersion simulations driven by this information and the ARPA-SIM meteorological data for forecasting plume evolution in the Campania region. A short-term PVHA is currently run twice daily for tephra fallout and is based on three representative scenarios over a 250 km  $\times$  200 km geographic area at 1 km grid spacing due to the high computational cost of simulating the eruptive variability on local servers (Perfetti et al., 2021).

Herein, we improve the assessment of the tephra hazard associated with an eruption at Campi Flegrei in order to better answer important questions such as

- 1. In the short term, what are the probabilities of eruption and vent-opening locations?
- 2. In the short and long term, what is the probability, both absolute and conditional on the occurrence of an eruption, that the cumulative tephra deposit will exceed critical thresholds known to cause issues, such as building collapse/failure or traffic disruption after a certain number of hours from the eruption onset?
- 3. In the short and long term, what is the probability, both absolute and conditional on the occurrence of an eruption, that the ash cloud concentration will exceed critical conditions and hazardous temporal persistence known for safe flights within a certain number of hours since the beginning of the eruption, and which levels (FLs) are likely to be most predominantly affected?
- 4. In the short and long term, what is the expected time for ash concentration to reach a critical value at a specific geographical point and flight level?

The PVHA\_HPC-WF presented here allows us to answer these questions by conducting a hazard assessment related not only to tephra ground load but also to ash concentration at various FLs over a surveillance area large enough to track the evolution of ash clouds, and considering a large number of VSs, thus reducing the uncertainty in the eruptive parameters and meteorological conditions.

In this application case, we generated both LT and ST tephra PVHA for Campi Flegrei. For an LT assessment, we have considered 1,500 VSs for each of the three explosive eruption sizes at Campi Flegrei, that is, low (L), medium (M), high (H) size, and meteorological conditions during 20 years of reanalysis from Copernicus Climate Change Service ERA5. As examples of ST, we developed the PVHA for December 5, 6, and 7, 2019, when seismic activity was more energetic than usual with a magnitude 3.1 intracaldera earthquake: in the present example, we consider 180 VSs for each explosive eruption size and day and the monitoring data from the Osservatorio Vesuviano surveillance system recorder on those days. All the studies were carried out in a regional-scale domain of 2,000 km  $\times$ 2,000 km at a 2 km horizontal resolution, approximately, and a vertical resolution ranging from 0.5 to 1 km, considering eight flight levels from FL050 to FL400, 5,000 ft (1.5 km) to 40,000 ft (12.2 km) altitude, approximately. The simulations for each of the 6,120 VSs (1,500 VSs  $\times$  3 sizes +180 VSs  $\times$  3 sizes  $\times$  3 days) have been carried out by running the FALL3D-8.0 model on the French Joliot-Curie supercomputer, while the eruptive forecast (EF) has been calculated on the CENERI server of the Osservatorio Vesuviano of INGV, and the workflow manager system has been launched in the ADA cluster at INGV-Bologna.

An introduction to the monitoring system is given in the next Subsection 4.1. Subsection 4.2 describes the configuration of the model adopted for this test case and the parameters used to calculate each of the BET nodes, and a detailed explanation of the VS generation process is shown in Subsection 4.3. In Subsection 4.4, it is specified how the meteorological data have been obtained. Subsection 4.5 is dedicated to the specification of the computational resources and performance of the PVHA\_HPC-WF. Finally, the presentation of results and a sample of the graphs and maps obtained are shown in Subsection 4.6.

#### 4.1 Monitoring system

Monitoring data, necessary for ST assessment, are provided by the Osservatorio Vesuviano's surveillance system (Bianco et al., 2022). Seismic data are collected from the seismological database SERENADE (SEismic Restful ENAbled DatabasE), which was developed to manage multiple locations for each event in order to unify the data source for automatic, preliminary, and revised locations (Peluso, 2014). The PostgreSQL database server is the internal engine of SERENADE and allows requests to be made using standard HTTP commands. On the other hand, from the network of permanent GPS stations operating in the CFc, we obtained the deformation data for these studies (De Martino et al., 2021). Other data, such as anomalies in gas fluxes or compositions, can also be accounted for as user-specified parameters.

#### 4.2 Model setup

Here, we describe the parameters at each of the BET nodes and the computational domains used for this test case.

The BET\_EF settings used to calculate Nodes 1, 2, and 3 rely on the work of Selva et al. (2012a) and are reported in the first three

rows of Table 1 and in Figure 5A regarding the probability of unrest, magmatic unrest, and eruption, respectively. For the LT, a Poisson distribution over time has been assumed, and the results of which are compatible with the works of Sandri et al. (2018) and Bevilacqua et al. (2017).

The considered eruptive area for Node 4, based on the geodynamical structures and the position of past eruptive vents within the CF caldera (Selva et al., 2012b), consists of 40 potential vent-opening locations distributed equidistantly in a geographical area encompassed between 40.775°N and 40.875°N latitude and 14.05°E to 14.225°E longitude, whose locations and prior (LT) probabilities are indicated in Table 1 and displayed in Figure 5B. Short-term maps are built by integrating the position of observed anomalies, such as seismic activity and deformation, as in Marzocchi et al. (2008). Although part of the CFc is under the sea, since the most likely opening vent areas are in shallow waters and the effects are generally negligible at relatively large distances (Selva et al., 2018), we do not consider the effects of the sea on the formation of eruptive columns. The reader who wants to go deeper into the effects over sea water on the eruptions at CFc, including tsunamis, can consult, for example, Tonini et al. (2015), Selva et al. (2018), Paris et al. (2019), and Grezio et al. (2020).

Based on the eruptive record of Campi Flegrei (Orsi et al., 2009), we consider four eruption sizes: an effusive (E) size and three explosive ones, which are the low (L) (e.g., Averno 2), the medium (M) (e.g., Astroni 6), and the high (H) (e.g., Agnano-Monte Spina) sizes. The probabilities of occurrence for each size are defined in Table 1 and graphically represented in Figure 5C (Sandri et al., 2016). Then, as we already mentioned earlier, for each explosive size, we build 1,500 VSs for LT assessment, 180 VSs for ST, and for 5, 6, and 7 December 2019, totaling 6,120 VSs. In Subsection 4.3, we provide the details on the creation of the volcanic scenarios.

Regarding Node 6, we study tephra fallout hazard at ground and ash concentration hazard at eight flight levels (FL050–FL400) during the 24 and 48 h after the eruption by running FALL3D-8.0 for each VS in a computational domain spanning from 31°N to 50°N latitude and from 3°E to 28°E longitude at 0.025° resolution (2 km, approximately). Due to the flat topography of the CFc (that does not affect significantly the pattern of ash dispersal), to the proximity of the volcanic vents with respect to the size of the simulation grid, and to the resolution of the meteorological data, we do not repeat the tephra dispersion simulations for each of the vent locations but instead translate the output of simulations to each of the 40 vent positions (Selva et al., 2010).

For Node 7, we examined the target area from 34°N to 50°N latitude and 3°E to 28°E longitude (Figure 5D) at 0.025° resolution and the eight flight levels from FL050 to FL400. The reason this target area is slightly smaller than the FALL3D area is to have the same number of simulation outputs in each target area cell after translating the simulations over the 40 vent locations.

With respect to Node 8, we examine 23 critical thresholds, from 0.01 to 16.0 kPa, for the ground load hazard (Wilson et al., 2012) and

the thresholds of 0.2, 2, and  $4 \text{ mg/m}^3$  for the airborne ash concentration, as well as the temporal persistence of 1, 3, 6, 12, 18, and 24 h.

These input parameters are collected in a configuration file called BET.CFG, which is the input file to the PVHA\_HPC-WF (see Supplementary Material).

### 4.3 Generation of volcanic scenarios

As explained in previous sections, we adopt a probabilistic approach that merges the results of a large number of numerical simulations, each of them corresponding to a potential VS, to fully explore the natural variability associated with volcanic phenomena and to take into account the impact of low-probability but highconsequence events. The probabilistic approach adopted follows Sandri et al. (2016) based on the definition of three broad eruptive size classes (low-, medium-, and highexplosive, respectively): L, M, and H. Each eruptive explosive size is fully described by a set of ESPs sampled from PDFs previously defined. The PDF shape and parameters are defined on the basis of previously published articles in agreement with field observations (Sandri et al., 2016; Mele et al., 2020) and compiled in Table 2. The methodology followed to generate a potential eruptive scenario is reported in the Supplementary Material.

### 4.4 Meteorological data

To fully explore the natural variability of weather conditions, each VS was randomly assigned weather conditions corresponding to a time period between 1 January 1999 and 1 January 2019 for the tephra dispersal simulations for the long-term assessment. For the short-term assessment, the meteorological data corresponding to each of the days 5, 6, and 7 December 2019 have been used. All these data have been obtained from the Copernicus Climate Change Service ERA5 reanalysis with a temporal resolution of 3 h at a spatial resolution of 0.25°. Details for downloading and handling these data are attached in the Supplementary Material.

# 4.5 Computational resources and performance

The PVHA\_HPC-WF has been distributed into three clusters:

• ADA. HPC-MASTER-Computing Cluster, 140 cores × node, INGV Section of Bologna;

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#### FIGURE 5

CF model setup. (A) reports the probability of unrest (Node 1), magmatic unrest (Node 2), and eruption (Node 3) and the combination of the three nodes. (B) is the Campi Flegrei eruptive area where the 40 vent-opening locations considered in this study and their respective prior probabilities are indicated. (C) shows the probability density function for the size of the eruption at Campi Flegrei and the number of scenarios considered for each of them. (D) indicates the geographical area studied in this work (upper image) and the resolution and coordinates of the computational domain (lower table). (E) specifies the thresholds set for each hazard.

- CENERI. Debian GNU/Linux, Osservatorio Vesuviano in INGV Section of Naples;
- IRENE-SKYLAKE. Bi-processor with 24 cores per node, TGCC, France.

The workflow management system was installed and launched on ADA which interacted with CENERI, IRENE, and with itself. The BET\_EF and BET\_FETCH modules, in charge of interrogating the monitoring database and calculating the probabilities of eruption, were serially executed on the CENERI server, lasting less than 1 min. Also, the BET\_PRE\_VH was run in series on ADA, generating the set of VSs in a few seconds for the LT and the ST. The module

BET\_TEPHRA, responsible for executing the simulations of volcanic tephra transport and deposition via FALL3D-8.0 for each of the 6,120 VSs generated, was executed in parallel on IRENE using an average of 16 nodes and 3 h, approximately, of elapsed time for each simulation. The analysis of the FALL3D simulations, through the BET\_POST\_TEPHRA module, has been carried out in parallel in IRENE using 1 node and less than 20 min, approximately, for each set of simulations corresponding to each of the three eruptive sizes. Also in IRENE, the module BET\_VH was executed utilizing 12 nodes and 15 min, approximately, for each desired combination of altitude level/persistency/period of time. In total, approximately 11.106 h of CPU time was used in Irene for the

TABLE 3 Computational performance for PVHA at Campi Flegrei. Herein, we use the abbreviation PERS for temporal persistence and TP for period of time.

LT	Number of runs	Cluster	CPUs per run	Nodes per run	Average elapsed time per run
BET_EF	1	CENERI	Serial	-	< 1 min
BET_POST_EF	1	CENERI	Serial	-	< 1 min
BET_WEATHER	20	ADA	Serial	-	90 min
BET_PRE_VH	1	IRENE			
BET_TEPHRA	4,500	IRENE	768	16	3 h
BET_POST_TEPHRA					
Exceedance probability	6 (3 sizes $\times$ 2 TPs)	IRENE	48	1	20 min
Arrival time	3 (3 sizes)	IRENE	48	1	15 min
BET_VH	$(1 \times \text{GROUND}, 1 \times \text{FL} \times \text{PERS}) \times \text{TP}$	IRENE	576	12	15 min
BET_POST_VH					
Exceedance probability	$1 \times \text{GROUND} \times \text{TP}$	ADA	Serial	-	8 min
Exceedance probability	$1 \times FL \times PERS \times TP$	ADA	Serial	-	5 min
Arrival time	$1 \times FL \times size \times TP$	ADA	Serial	-	2 min
ST	Number of runs	Cluster	CPUs per run	Nodes per run	Average elapsed time per run
BET_FETCH	1	CENERI	Serial	-	< 1 min
BET_EF	1	CENERI	Serial	-	< 1 min
BET_POST_EF	1	CENERI	Serial	-	< 1 min
BET_WEATHER	$1 \times day$	ADA	Serial	-	30 min
BET_PRE_VH	1	IRENE			
BET_TEPHRA	1,620	IRENE	768	16	3 h
BET_POST_TEPHRA					
Exceedance probability	6 (3 sizes × 2 TPs)	IRENE	48	1	10 min
Arrival time	3 (3 sizes)	IRENE	48	1	15 min
BET_VH	$(1 \times \text{GROUND}, 1 \times \text{FLxPERS}) \times \text{TP}$	IRENE	576	12	15 min
BET_POST_VH					
			0.11		8 min
Exceedance probability	$1 \times \text{GROUND} \times \text{TP}$	ADA	Serial	-	8 11111
Exceedance probability Exceedance probability	$1 \times \text{GROUND} \times \text{TP}$ $1 \times \text{FL} \times \text{PERS} \times \text{TP}$	ADA ADA	Serial	-	5 min

LT, and 125-10<sup>4</sup> for each of the ST days. Finally, the final hazard curves and figures were generated serially in ADA by BET\_POST\_VH, requiring approximately 8 min. All this information is compiled in Table 3.

### 4.6 Results

A large portfolio of results from the workflow can be extracted and mapped. Herein, we show some of the results that may answer the questions posed in the second paragraph of Section 4, following the numbering of those questions.

For LT analysis, the workflow can provide:

- 1. probability maps with uncertainty showing the 50-year forecast absolute probability and the probability conditional on the occurrence of an eruption exceeding the previously defined critical tephra fallout thresholds after 24 and 48 h from the beginning of an eruption,
- 2. probability maps with uncertainty showing the 50-year forecast absolute probability and the probability conditional on the occurrence of an eruption exceeding the critical ash concentration thresholds of 0.2, 2, and 4 mg/m<sup>3</sup> for at least 1, 3, 6, 12, 18, and 24 of the hours after 24 and 48 h from the beginning of an eruption at eight flight levels from FL050 to FL400,
- 3. maps of the time required to exceed the ash concentration thresholds corresponding to each explosive eruption size.



persistence of 1, 6, 12, 18, and 24 h (left to right columns) during a period of time of 48 h in FL050, FL150, FL250, and FL350 (bottom to top columns). We can see that the probability for the next 50 years of exceeding 2 mg/m<sup>3</sup> for at least 1 of the 48 h observed is greater than 1% at all flight levels. FL050 would be the most affected where the critical threshold could be exceeded for at least 24 out of the 48 h studied. We can also observe that the spread pattern is toward the east and slightly south.

For ST analysis corresponding to each of December 5, 6, and 7, 2019, the workflow can provide:

- 1. eruption probabilities and vent-opening location maps,
- 2. probability maps with uncertainty showing the absolute probability and the probability conditional on the occurrence of an eruption exceeding the critical tephra fallout thresholds after 24 and 48 h from the beginning of an eruption,
- 3. probability maps with uncertainty showing the absolute probability and the probability conditional on the occurrence of an eruption exceeding the previously defined critical ash concentration thresholds for at least 1, 3, 6, 12, 18, and 24 of the hours after 24 and 48 h from the beginning of an eruption at eight flight levels from FL050 to FL400, and
- 4. maps showing the time required to exceed the ash concentration thresholds corresponding to each explosive eruption size.

We show here only a small sample of the large number of maps generated. Other maps can be found in the Supplementary Material, including those corresponding to each of the seasons of the year.

#### 4.6.1 Long-term analysis

As an example of probability maps, Figure 6 presents the 50-year forecast absolute probability that the ash concentration at FL050, FL150, FL250, and FL350 exceeds the critical concentration of 2 mg/m<sup>3</sup> with persistency of 1, 6, 12, 18, and 24 h in the 48 h following an eruption onset. We can observe that the probability for the next 50 years of exceeding 2 mg/m<sup>3</sup> for at least 1 of the 48 h observed is greater than 1% at all flight levels. FL050, especially interesting because it is the aircraft takeoff and landing flight level, would be the most affected where the critical threshold could be exceeded for at least 24 out of the 48 h



Long-term hazard maps relative to the 5% probability threshold conditional on an eruption event provide a graphical representation of epistemic uncertainty for tephra fallout (left column) and ash concentration at FL050 (right column). For each hazard intensity value (color bar label), the maps show the areas where that value will be exceeded with a probability greater than 0.05 in the event of an eruption within 48 h from eruption onset. We can see that in the case of an eruption, a large part of the Campania region would be affected for tephra load with a probability greater than 5%. Also, an eruption would affect air traffic with an exceedingly high ash concentration above 4 mg/m<sup>3</sup> throughout a large area with a spread pattern to the east and slightly south.

studied. As a sample of intensity hazard maps, Figure 7 shows the tephra ground load and the ash concentration at FL050 within 48 h from eruption onset, both the mean values and those corresponding to the 2.5 and 97.5 percentiles, relative to the 5% probability conditional on an eruption event. We can see that in the case of an eruption, a large part of the Campania region would be affected by tephra load above  $1 \text{ kg/m}^2$  with a probability greater than 5%, even exceeding thresholds above 300 kg/m<sup>2</sup> in the areas closest to the volcano. Also, an eruption would affect air traffic in extensive areas with exceedingly high ash concentrations above 4 mg/m<sup>3</sup>. Both Figures 6 and 7



#### FIGURE 8

Long-term arrival time maps. Left column shows, from top to bottom, the expected time in which the ash concentration at FL050 will reach the critical threshold of 2 mg/m<sup>3</sup> with a probability of 5% in the event of a low-, medium-, and high-sized eruption at Campi Flegrei, respectively. The right column shows the probabilities to reach 2 mg/m<sup>3</sup> at FL050 above some of the surrounding airports in each of the hours following the eruption.

show the trend of the ash to spread to the east and slightly to the south, following the most common wind patterns in that area. As for the arrival time maps, Figure 8 shows, for each eruption size, the expected time to reach the critical ash concentration threshold of  $2 \text{ mg/m}^3$  at FL050 with a probability of 5% in the event of an eruption and, for some of the airports around Campi Flegrei, arrival time values

versus their probability values. Most airports would be affected in less than 48 h in case of an explosive eruption with a probability of 5%. We can observe that the arrival time to exceed the critical threshold of ash concentration in the different airports is less the greater the size of the eruption. Examples for other flight levels and persistence can be found in the Supplementary Material.



temporal evolution of the mean values of the probability density function of unrest (blue circles), magmatic unrest (pink circles), and eruption (red circles) in the 3 days of application, where the occurrence of a magnitude 3.1 earthquake is marked by the red arrow.

# 4.6.2 Short-term analysis for days 5, 6, and 7 December 2019

Figure 9 is a compilation of the eruption forecasting (EF) for 5, 6, and 7 December 2019. As we have explained previously, EF is independent of the hazard we are

modeling, and it is based mainly on the information from the monitoring system. Regarding the location of the eruption, Figure 9A presents the temporal evolution of the mean conditional probability of the eruption occurring at each of the 40 potential vent locations. Figure 9B shows the



 $1 \text{ kg/m}^2$  tephra load, while rows from 1 to 3 show the probability of exceeding the 2 mg/m<sup>3</sup> ash concentration at FL300, FL150, and FL050, respectively, with the persistence of 1 h.

temporal evolution of the mean and the 16, 50, and 84 percentiles of the conditional probability density function (CDF) of unrest, magmatic unrest, and magmatic eruption (those percentiles are equal to two standard deviations  $(2\sigma)$ , that is, 68% confidence interval).

Figure 9C, left panel, displays the temporal evolution of the mean values of the probability density function of unrest, magmatic unrest, and eruption in the 3 days of application, where the occurrence of a magnitude 3.1 earthquake is marked by the red arrow on the left



observed time.

panel. The right panel shows the time trend in the probability of unrest, magmatic unrest, and eruption in the previous days, where shaded areas indicate the 10th–90th percentile confidence band. As a sample of ST probability maps, Figure 10 presents the mean absolute probability for each of the days of exceeding the tephra load of  $1 \text{ kg/m}^2$  at the ground and that of exceeding an ash concentration of  $2 \text{ mg/m}^3$  at FL050, FL150, and FL300, respectively, for at least 1 hour in the 48 h following the eruption onset. The most affected flight level would have been FL050, closely followed



by FL150, while at FL300, this critical threshold would have not been exceeded. Figure 11 shows ST hazard maps with tephra load and ash concentration at FL050 with a probability of 5%. Note, for example, that the day 6 eruption could have produced a tephra load beyond the Albanian coast. The arrival time of exceeding the threshold of  $1 \text{ kg/m}^2$  and  $2 \text{ mg/m}^3$  at the ground and at FL050, respectively, with a probability of 5% in the case of a medium-size eruption, is displayed in Figure 12. In all the images, the wind field pointed predominantly to the north on day 5, to the east on day 6, and to the southeast on day 7, which illustrated the influence of meteorological variability and the need to develop a daily evaluation of the tephra hazard in a wide geographical area.

# **5** Conclusion

This study highlights the feasibility and usefulness of HPCintegrated PVHA. In particular, we have shown that HPC integrated into PVHA can provide quantitative hazard results capable of answering some of the questions that decision-makers have to face in case of volcanic unrest possibly evolving toward an eruption (short-term) or in planning land use or air traffic development (long-term) over a large-scale and highresolution domain.

We have implemented the Probabilistic Volcanic Hazard Assessment HPC Workflow (PVHA\_HPC-WF) to calculate the short-term (ST) and the long-term (LT) probabilistic volcanic hazard assessment (PVHA) for a specific volcano based on the Bayesian event tree (BET) methodology and starting from the existing prototype tool BET@OV. We have subjected the code to a performance and productivity audit and have optimized it following a proof-of-concept process, thanks to which the execution time of some of the most critical parts of the workflow has been reduced by up to 588 times. Through the workflow manager system light (WMSlight), we have given the PVHA\_HPC-WF the ability to interact with different machines to distribute tasks and exchange data.

We have tested the LT PVHA\_HPC-WF by performing a long-term tephra hazard assessment of the Campi Flegrei (CF) volcanic caldera, Italy, on the ground and at eight flight levels in a geographic area of approximately 2,000 km × 2,000 km. To this end, we have used the FALL3D-8.0 model to perform ash dispersion simulations at a horizontal resolution of 0.025° (approximately 2 km) for 4,500 different volcanic scenarios (VS), also including those of low probability but high impact, and considering 20 years of meteorological data from ERA5. The workflow tasks have been distributed into three clusters, the ADA, HPC-MASTER Super Computing Cluster in the INGV Section of Bologna (Italy), the CENERI, Cluster at the Osservatorio Vesuviano in the INGV Section of Naples (Italy), and the IRENE-SKYLAKE, in the Computing Center TGCC (France), using approximately 576 h of CPU time in ADA, some minutes in CENERI, and 11·10<sup>6</sup> h of CPU time in IRENE, demonstrating that the entire process could be carried out in a real time within 4.5 h if resources are available to execute the independent tasks simultaneously.

We have also tested the ST PVHA\_HPC-WF by performing the short-term tephra hazard assessment of CF for December 5, 6, and 7, 2019, with the same model configuration used for LT but using, for each of the days, 540 VS and its corresponding meteorological data also from ERA5. For this, we have used approximately, for each date, 576 h of CPU time in ADA, some minutes in CENERI, and 125·10<sup>4</sup> h of CPU time in IRENE, showing that a daily process considering 540 VSs could run in 4.25 h if resources are available. We note that this time could be improved for real-time crisis management if specific location targets are provided (e.g., a specific FL).

### Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

### Author contributions

Conceptualization: LS, ACo, JS, GM, AF. Methodology: BMM,MTL, LS, ACo, JS, AF, GM, SB. Software: BMM, MTL, OR (Performance Optimization), ACh (development of WMS-light and adaptation to PVHA HPC-WF) Writing – original draft: BMM Writing – review and editing: BMM, MTL, LS, ACo, JS, AF, GM, SB, OR, and ACh. Supervision and coordination: ACo. Funding: ACo.

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# **Conflict of interest**

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2022. 941789/full#supplementary-material

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# Glossary

BET Bayesian event tree CDF conditional probability density function CF Campi Flegrei CFc Campi Flegrei caldera ChEESE Center of Excellence for Exascale in Solid Earth CPU central processing unit **E** effusive EF eruptive forecasting ESP eruptive source parameter ESPs eruptive source parameters FL flight level H high HPC high-performance computing HPDA high-performance data analytics INGV Istituto Nazionale di Geofisica e Vulcanologia IPC instructions per cycle L low LT long term

M medium MER mass eruption rate MPI Message Passing Interface NUMA non-uniform memory access PDF probability density function PoC proof of concept POP performance optimization and productivity POP CoE EU Performance Optimization and Productivity Center of Excellence in HPC PVHA probabilistic volcanic hazard assessment PVHA\_HPC-WF Probabilistic Volcanic Hazard Assessment Workflow SERENADE SEismic Restful ENAbled DatabasE ST short term TEM total erupted mass TEV total erupted volume TGSD total grain size distribution VEI volcanic explosivity index VS volcanic scenario WMS-light workflow manager system light.