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Review article

Exploring the role of model classification, complexity, and selection in volcanic hazard forecasting

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ABSTRACT

This review examines the current landscape of computational volcanic hazard models, focusing on their creation and application, for a diverse set of end-users' short-term and long-term forecasting requirements. We provide a comprehensive classification of volcanic hazard models, categorising them according to their theoretical foundations. This is central to understanding the diversity of hazard characterisation and simulation approaches, from empirical models to computationally demanding physics-based numerical models. The classification framework helps contextualise the strengths and limitations of different models and their suitability for specific forecasting demands. We discuss the fundamental principles behind model construction, considering factors such as input parameters, conceptual frameworks, and the incorporation of uncertainties. We also synthesise existing literature on model testing, covering aspects such as model verification, validation, calibration, and benchmarking, and provide a systematic and transparent framework for model selection, considering data availability, computational constraints, and specific forecasting needs. We explore the balance between model complexity, computational efficiency, and accuracy, addressing the uncertainties inherent in both input parameters and model processes. A key focus is the role of input parameters in forecasting and the need to select models that are detailed enough to capture essential hazard dynamics, yet simple enough to minimise error and computational costs.

Contents

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1. Introduction

Volcanoes are complex and unique systems governed by underlying non-linear dynamics (Cashman and Biggs, 2014), with potentially catastrophic eruptive hazards (Brown et al., 2017). Forecasting the spatial extent and intensity of these hazards, whether in the long-term, short-term, or near-real-time, currently relies on the use of computational models (Bayarri et al., 2009). Volcanic hazard models have to deal with both the aleatoric uncertainty (natural inherent variability), as well as the epistemic uncertainties that arise from data and knowledge limitations specific to a given volcano (Bayarri et al., 2009; Rougier and Beven, 2013). Together, these factors create substantial and often poorly constrained uncertainties in hazard and eruption forecasting (Sparks, 2003; Poland and Anderson, 2020).

Computational volcanic hazard models simulate the transport and deposition of potentially hazardous eruption products such as tephra (volcanic ash), debris flow/lahars, pyroclastic density currents (PDCs), lava flows, and volcanic ballistic projectiles (VBPs) e.g., Folch (2012), Kavanagh et al. (2018), Pardini et al. (2024). These models use empirical relationships and/or numerical physics-based equations to simplify inherently complex natural processes (Renschler, 2005). Models vary in complexity, balancing trade-offs between (e.g.) computational cost, data requirements, the level of physical detail incorporated, the knowledge available for a specific volcano, and time constraints. Additionally, the degree of uncertainty that can be tolerated by the end-user, shaped by the type of decision being made, such as short-term evacuation versus long-term land-use planning, as well as the specific purpose and context of use, can influence the choice of model (Loucks and van Beek, 2017; Crawford et al., 2018). While complex models are often assumed to provide more accurate forecasts than simpler models, there is little empirical evidence to support this assumption (Petropoulos et al., 2022). Green and Armstrong (2015) found that for economic models, model complexity may even harm forecast accuracy, particularly when data are limited, as complexity increases uncertainty.

Despite the increasing number of volcanic hazard models available, model selection is still highly subjective and often based purely on model familiarity or institutional preference (e.g., Hurst and Davis, 2017) rather than situational suitability (Jackson et al., 2000; Jakeman et al., 2006). This lack of clear guidance can result in the selection of models that may not be the most accurate for a given application. We evaluate how model characteristics influence forecasting performance across different timescales, from near-real-time operational contexts to long-term planning scenarios.

This review is intentionally focused on volcanic hazard simulation models — that is, models that are used once a hazard is assumed to occur. As such, the review inherently addresses conditional hazard modelling. A detailed discussion of temporal occurrence rates and hazard likelihood estimation methods is beyond the scope of the review, but the reader is directed to (e.g.,) Bebbington (2009), Marzocchi et al. (2010), Bebbington and Jenkins (2019).

This work delineates the volcanic hazard model space for end-users over five key themes. In Section 2, we provide an overview of model classifications and their theoretical/conceptual foundations. Section 3 examines how factors such as conceptual models, model structure, input parameters, and uncertainty influence model design. Model complexity is examined in Section 4 in relation to its impacts on output accuracy and forecasting capability within volcanic hazard models. As the reliability and accuracy of volcanic hazard models depend on rigorous testing, Section 5 examines model verification, validation, calibration, and benchmarking methodologies. In Section 6, we discuss model selection, considering practical criteria such as data availability, computational constraints, and end-user needs, intertwined with model complexity.

1.1. Definitions

Terminology varies across disciplines, including within volcanology. Thus, we define here key terms for clarity (Table 1).

The focus here is specifically on computational models. Any reference to the word 'model' is specifically referring to computational models unless otherwise specified.

2. Model classification

Models for simulating volcanic eruption phenomena originated in the 1950s, with theoretical works by Prandtl (1954) and Morton et al. (1956) looking at turbulent gravitational flows. These papers became the foundations of many flow models that were developed in the 1980s, e.g., Malin and Sheridan (1982), Sheridan and Malin (1983), Armienti and Pareschi (1987), Valentine and Wohletz (1989), which were primarily used to understand and reconstruct the spatial extents and dynamics of past eruptions. Around the same time, models for ashfall and lava flow also began to emerge, e.g., ash — numerical analysis by Suzuki (1983) and Sparks (1986); and lava flows — analytical and empirical analysis by Dragoni et al. (1986) and Young and Wadge (1990). In the 1990s and 2000s, advances in computational power and improved understanding of volcanic processes enabled the development of more complex and computationally intensive numerical models (Pitman et al., 2003; Costa et al., 2016b; Papale, 2021).

All volcanic hazard models are ultimately grounded in the fundamental laws of physics, including the conservation of mass, momentum, and energy (Kavanagh et al., 2018). These laws underpin the governing equations that define volcanic flow dynamics, atmospheric dispersion, particle settling, and other key processes, even when simplifications are applied due to model structure, computational demand, or data constraints.

Volcanic hazard models (Table 2) can broadly be defined into three categories based on the governing force for the phenomena being

Table 1
Key terms and their definitions.

Term	Definition	Reference
Accuracy	A measure of closeness between a model's output and the observed or actual value	This publication
Aleatoric uncertainty	The uncertainty in eruption phenomena, observations, and data that comes from the inherent variability of a natural system	Marzocchi et al. (2004)
Benchmarking	An exercise to compare the performance of many models when simulating a specific case with a known solution	Dietterich et al. (2017)
Calibration	The manipulation of model parameters to align with observations from a specific event or dataset	Oreskes et al. (1994)
Computational model	The use of computers to simulate volcanic systems	This publication
Conceptual framework	The definition of scope, key concepts, and theoretical foundations of a system, theory, or phenomenon	This publication
Conceptual model	A schematic or qualitative description of a system, theory, or phenomenon and its components or relationships	Thalheim (2011)
Deterministic model	A model that produces an individual point measure for an event	Manga et al. (2017)
Empirical model	A model developed from observational data (these may include statistical models)	This publication
Epistemic uncertainty	The uncertainty in eruption phenomena, observations, and data that comes from incomplete knowledge or conceptual limitations	Marzocchi et al. (2004)
Input parameter	Data provided to the model, used to drive model behaviour	This publication
Long-term forecast	An assessment of the eruption likelihood and related phenomena over the scale of years to decades	Marzocchi and Bebbington (2012)
Model	A computational representation of volcanic eruption phenomena	This publication
Near-real time forecast	An assessment of the eruption likelihood and related phenomena for the immediate future (also known as syn-eruptive forecasts)	This publication
Numerical model	A model that solves governing equations using numerical methods (these may include physical and analytical models)	Larson (2005)
Ontology	A formal, unambiguous description of domain-specific knowledge, providing standardised definitions for terminology within a given field	Hofmann et al. (2011), Masseroli (2019)
Output	Refers to the results produced by the model	This publication
Probabilistic model	A model that produces a range of possible outcomes, often expressed as distributions	Manga et al. (2017)
Short-term forecast	An assessment of the eruption likelihood and related phenomena over the scale of hours to months	Marzocchi and Bebbington (2012)
Simulation	The execution of a model within a computational environment	This publication
Validation	The demonstration that a system of equations and their numerical approximation reasonably represents the physical conceptual model for the real-world process it is intended to simulate	Esposti Ongaro et al. (2020)
Verification	The demonstration that a model implementation accurately represents the conceptual description and solution of the model	Oberkampf and Trucano (2002)

modelled: (1) Atmospheric/weather driven models for volcanic ash and gases, (2) Gravity-driven models for lava flows, pyroclastic density currents (including surges and block-and-ash flows), lahars (including debris flows), and debris avalanches, and (3) Momentum-driven models for projectile motions such as volcanic ballistic projectiles (VBPs).

2.1. Atmospheric dispersion and deposition models

Atmospheric dispersion and deposition models simulate how volcanic ash and gases are transported through and settle from the atmosphere. Their primary outputs are atmospheric particle concentrations and/or mass loading on the ground. Both tephra and volcanic gas dispersal are governed by the advection–diffusion–sedimentation (ADS) equation, which governs the movement of particles in the atmosphere (Tsunematsu et al., 2011). Dimensionality plays a key role in input parameter requirements, with higher-dimensional models typically requiring more detailed input parameter data (Cao et al., 2021).

Two-dimensional (2D) Eulerian models, such as Tephra2 and HAZMAP, apply a simplified Gaussian solution to the ADS equation. These models assume a constant diffusion rate and wind fields that may vary with height but are spatially uniform across the computational domain, which limits their accuracy for weak plumes, long-range dispersal, or changing meteorology (Pfeiffer et al., 2005; Folch, 2012; Bonadonna et al., 2015).

Three-dimensional (3D) models offer enhanced spatial resolution and the ability to simulate more complex atmospheric interactions compared to 2D models. Lagrangian models (e.g., PUFF, NAME) track particles individually via random-walk diffusion (Schwaiger et al., 2012), while Eulerian models (e.g., Fall3D, Ash3D) solve the full ADS equation on a fixed grid. These models can resolve detailed wind and turbulence interactions but are computationally intensive (Folch, 2012).

Output accuracy across all models depends heavily on the quality of eruption source parameters (ESPs) and meteorological input data (primarily wind direction and speed) (Bursik, 2001; Bonadonna and Costa, 2013). 2D models typically use static wind profiles, while 3D models use full meteorological datasets (e.g., Numerical Weather Prediction (Haupt et al., 2017) and observational reanalysis (Hersbach et al., 2020)). Atmospheric dispersion models always require ESPs such as plume height, total erupted mass, and grain size distribution, often estimated from deposit mapping (e.g., Longchamp et al., 2011; Bonadonna and Costa, 2012), remote sensing (both after the fact and in real-time) (e.g., Prata and Grant, 2001), or inversion techniques (e.g., Volentik et al., 2010; Mannen, 2014).

2.2. Flow models

Volcanic flows are gravity-driven and strongly influenced by topography (e.g., obstacles, breaks, surface roughness) (Branney and Kokelaar, 2002; Sulpizio and Dellino, 2008; Dietterich et al., 2015). 1D flow models simulate channelised flows constrained to a single downslope direction, typically to estimate runout distance. Simple 1D models use digital elevation models (DEMs), and sometimes volume, as input parameters (Schilling, 1998). These models range in complexity: some, such as DOWNFLOW, incorporate probabilistic input distributions to account for uncertainty, while others, such as FLOWGO, include detailed rheological properties such as cooling, viscosity changes, and crystallisation (Harris and Rowland, 2001).

2D models, particularly cellular automata models (e.g., MAGFLOW, SCIARA, MOLASSES), are widely used for probabilistic hazard assessments (Herault et al., 2009; Gallant, 2016). Cellular automata models use a simple set of rules (often not derived directly from physical laws) to distribute fluids from a central cell (i.e. a grid point) to a neighbouring one, depending on the cell's relative elevation and sometimes flow

Table 2
Examples list of different volcanic hazard models and their characteristics. Dimension: x = horizontal coordinate along east–west axis, y = horizontal coordinate in north–south axis, z = vertical coordinate (elevation or height in 3D space), t = time. Model type: E = Empirical, N = Numerical. Frame of reference: E = Eulerian, L = Lagrangian, H = Hybrid. Model Approach: D = Deterministic, P = Probabilistic.

Volcanic hazard model	Dimension	Model type	Frame of reference	Model approach	Volcanic phenomena
Atmospheric Dispersion and Deposition Models					
HYSPLIT (Draxler and Hess, 1997)	3D (x,y,z,t)	N	H	D	Tephra, Gas
PUFF (Searcy et al., 1998)	3D (x,y,z,t)	N	L	D	Tephra
HAZMAP (Macedonio et al., 2005)	2D (x,y,z)	N	E	D	Tephra
NAME III (Jones et al., 2007)	3D (x,y,z,t)	N	L	D	Tephra, Gas
Tephra2 (Connor et al., 2008)	2D (x,y,z)	N	E	D	Tephra
Fall3D (Folch et al., 2009)	3D (x,y,z,t)	N	E	D	Tephra, Gas
Ash3D (Schwaiger et al., 2012)	3D (x,y,z,t)	N	E	D	Tephra
Volcanic Flow Models					
Energy Cone (ΔH/L) (Malin and Sheridan, 1982)	1D (x,y)	E	E	D	Mass Flows
SCIARA (Crisci et al., 1986)	2D (x,y,z)	N	E	D	Lava
FLOW-3D (Kover, 1995)	3D (x,y,z,t)	N	E	D	Lava, Mass Flows
LaharZ (Schilling, 1998)	1D (x,y)	E	E	D	Mass Flows
FLOWGO (Harris and Rowland, 2001)	1D (x,y,z,t)	N	L	D	Lava
PDAC (Neri et al., 2003; Esposti Ongaro et al., 2007)	2D/3D (x,y,z,t)	N	E	D	Mass Flows
DOWNFLOW (Favalli et al., 2005)	1D (x,y)	N	E	P	Lava
Titan2D (Patra et al., 2005)	2D (x,y,z,t)	N	E	D	Mass Flows
MAGFLOW (Vicari et al., 2007)	2D (x,y,z)	N	E	D	Lava
VolcFlow (Kelfoun and Vargas, 2016)	2D (x,y,z,t)	N	E	D	Lava, Mass Flows
MOLASSES (Richardson, 2016)	2D (x,y,z)	N	E	D	Lava
MrLavaLoba (de'Michieli Vitturi and Tarquini, 2018)	2D (x,y,z)	E	L	P	Lava
IMEX_SfloW2D (de' Michieli Vitturi et al., 2019)	2D (x,y,z,t)	N	E	D	Mass Flows
EC_MapProb & Box_MapProb (Aravena et al., 2022)	1D (x,y)	N	E	P	Mass Flows
Volcanic Ballistic Projectile (VBP) Models					
Eject! (Mastin, 2001)	2D (x,y,)	N	L	D	VBP
LPAC (de'Michieli Vitturi et al., 2010)	2D (x,y,t)	N	L	D	VBP
Alatorre-Ibargüengoitia et al. (2012)	2D (x,y)	N	L	D	VBP
Ballista (Tsunematsu et al., 2014)	3D (x,y,z)	N	L	D	VBP
Great Balls of Fire (Biass et al., 2016)	2D (x,y,t)	N	L	D	VBP

viscosity and temperature, until all cells meet the criteria defined by the model (e.g., when the total volume defined by the user has been added to the flow) (Kavanagh et al., 2018; Hyman et al., 2022). They perform well on gentle terrain or in depressions, but lack vertical detail and mainly estimate deposit extent (Cordonnier et al., 2015).

Depth-averaged models approximate shallow water equations by averaging flow properties (energy, mass, momentum) over depth (e.g., Titan2D, VolcFlow) (Cordonnier et al., 2015; Hyman et al., 2022). These models are suited for simulating flow dynamics such as arrival times, especially for concentrated PDCs where flow properties remain relatively uniform, but are slower to run as they involve more detailed computations (Dufek, 2016; Hyman et al., 2022).

3D models are thermodynamically coupled models that use computational fluid dynamics (CFD) principles to simulate heat transfer and account for various viscous flow behaviours, incorporating the complex interactions between temperature, velocity, and viscosity (Neri et al., 2015b). These models have higher computational requirements but are particularly suitable for long-lived, cooling-limited lava flows (when the rate of cooling and solidification is the primary control of the flow's length) (Dietterich et al., 2017).

All volcanic flow models use DEMs, but for hindcasting, modern DEMs must be adjusted to represent pre-eruption terrain (Procter et al., 2010). This can be worked around, although impractically, by subtracting thicknesses of past flow deposits based on detailed stratigraphy of the deposit (e.g., Daag, 2003; Dietterich et al., 2021). For forecasting, using a DEM of the current landscape is generally more applicable. However, this approach becomes challenging during multi-flow events, where DEMs must be dynamically updated to improve simulation accuracy (e.g., De Beni et al., 2019). DEM resolution (both grid size and vertical accuracy) also significantly affects model simulations, especially for small-scale features that influence flow paths (Huggel et al., 2008; Joyce et al., 2009). For example, in simulations of mass flows at Nevado del Ruiz, Colombia, a 10 m DEM successfully constrained flows within steep valley walls (~70 m relief), whereas a coarser 30 m DEM resulted in unrealistic lateral spread due to its inability to resolve sharp topographic boundaries (Deng et al., 2019).

Typical model inputs include volume, effusion rate, viscosity, and density. Lava flow viscosity is a key factor in determining the shape and extent of the flow. Lava viscosity can be measured through laboratory measurements (e.g., Sehlke et al., 2014; Kolzenburg et al., 2016), estimated in the field (e.g., Chevrel et al., 2018, 2019), and/or inferred from empirical relationships based on temperature (e.g., Pinkerton and Norton, 1995; Ishihara et al., 1990; Giordano and Dingwell, 2003). PDCs and lahars have more complex, variable rheologies, which are harder to model. PDCs range from dense pyroclastic flows (which are topographically controlled) to dilute surges (which are capable of overriding obstacles) (Sparks, 1976; Burgisser and Bergantz, 2002). Their behaviour is poorly understood due to complexities in gas–particle interactions, flow mechanics, and generation processes (Lube et al., 2020; Jones et al., 2024). Lahars are water-saturated flows categorised by high densities and velocities. Their properties, such as particle concentration, temperature, and bulk rheology, vary significantly in space and time due to processes such as flow bulking (erosion and incorporation of debris) and debulking (Thouret et al., 2020). The rheological properties for both PDCs and lahar are derived from laboratory experiments (e.g., Roche et al., 2004; Lube et al., 2015; Jones et al., 2024), field-based depositional analyses (e.g., Sparks, 1976; Branney and Kokelaar, 2002; Dumaisnil et al., 2010; Bernard et al., 2014), and remote sensing techniques (e.g., Kumagai et al., 2009; Bosa et al., 2021; Macorps, 2021; Bosa et al., 2024), while direct studies on the rheology of propagating PDCs are sparse (Sulpizio et al., 2014; Delannay et al., 2017).

2.3. Volcanic ballistic projectile models

Volcanic ballistic projectiles (VBPs) range from a few centimetres to tens of metres in diameter and are large enough to follow ballistic trajectories through the atmosphere. Most VBP models are 2D and use simplified gravity and drag equations (e.g., Eject!, Great Balls of Fire, Alatorre-Ibargüengoitia et al., 2012) (Table 2). The LPAC VBP model differs by applying the Basset–Boussinesq–Ossen equation to calculate Lagrangian particle acceleration under set assumptions (e.g., constant drag coefficient, no lift forces) (Maxey and Riley, 1983; Crowe et al., 1998).

The Ballista model (Tsunematsu et al., 2016) is one of the few 3D VBP models, considering multiple particles and their collisions in 3D space (Tsunematsu et al., 2014). Ejected particles follow a parabolic trajectory until they reach the ground or collide with another airborne particle (Tsunematsu et al., 2014).

All VBP models require inputs for block properties (e.g., density, size) and ejection parameters (e.g., initial velocity, angle), which are either measured (e.g., Alatorre-Ibargüengoitia et al., 2012; Fitzgerald et al., 2014; Tsunematsu et al., 2016) or assumed (e.g., Chouet et al., 1974; Patrick et al., 2007; de'Michieli Vitturi et al., 2010; Kilgour et al., 2010). Because the travel distance of projectiles is primarily influenced by ejection parameters, these are often estimated using short-term exposure time (e.g., Chouet et al., 1974; Blackburn et al., 1976; Ripepe et al., 1993; Edwards et al., 2017) or thermal videos (e.g., Patrick et al., 2007; Capponi et al., 2016).

3. Model construction

Model construction has been well defined across various fields, including ecology (e.g., Jackson et al., 2000; Grimm et al., 2014) and hydrology (e.g., Gupta et al., 2008; Clark and Kavetski, 2010; Gupta et al., 2012; Anderson et al., 2015). In the context of volcanic hazards, Renschler (2005) highlights the importance of structuring model development to balance environmental processes, data limitations, and uncertainty. Here we apply the following five defining principles to volcanic hazard models: (1) identifying model purpose and scope, (2) building a conceptual model, (3) formulating model structure, (4) defining model input parameters, and (5) model documentation and evaluation, as outlined in previous studies.

3.1. Model purpose and scope

Volcanic phenomena models generally fall into two overlapping categories: (1) process-based models, that aim to improve understanding of the physical processes governing volcanic phenomena (e.g., plume dynamics, flow rheology) (e.g., Mastin, 2007; Piombo and Dragoni, 2009; Hoffman et al., 2023), and (2) hazard models, that aim to simulate the spatial extent and intensity of volcanic phenomena (e.g., ashfall distribution, lahar inundation, lava flow paths) (Table 2). While hazard models often incorporate simplified process-based components, their primary goal is to support forecasting and decision-making. For example, users can integrate the 1D model FPLUME (Folch et al., 2016), an eruption column model based on buoyant plume theory (BPT), to calculate the vertical distribution of mass within an eruption column, which can then be used to estimate the atmospheric or deposited mass of ash.

When defining a model's scope, developers must consider both the intended outputs and the target end-users (Renschler, 2005; Jakeman et al., 2006; Topcu and Mesmer, 2018). Process-based models typically produce outputs that contribute to advancing scientific knowledge (e.g., Mastin, 2007; Cerminara et al., 2016; Folch et al., 2016; Dioguardi and Mele, 2018), whereas hazard models generate outputs that inform decision-making, such as hazard assessments, mitigation strategies, and evacuations (Costa and Macedonio, 2005; Folch, 2012). In particular, developers must carefully consider the model's temporal and spatial scope, scale, and resolution, particularly for models designed to support decision-making (Jakeman et al., 2006).

Hazard model outputs can be communicated to decision-makers in ways that require minimal understanding of volcanic processes or the model itself, which can introduce significant risks (Barclay et al., 2008; Procter et al., 2021). Engaging end-users in the development process allows for valuable feedback on model assumptions and limitations, ultimately improving model reliability and usability (Jakeman et al., 2006; Robinson and Brooks, 2024).

3.2. Conceptual model

Once the scope and purpose of the model is defined, the system being modelled must be conceptualised (Banks, 1999; Seppelt, 2003; Thalheim, 2019). This includes the system's physical boundaries, such as computational domain limits (e.g., simulations will not run over areas larger than 100 km^2) and atmospheric boundaries (e.g., processes above 70 km may not be simulated), as well as physical and behavioural laws that must be obeyed (e.g., momentum, conservation of mass) (Seppelt, 2003; Gupta et al., 2008). The conceptual model allows developers to determine which variables should be included, the level of detail required, and the role of prior knowledge and assumptions about different processes (Section 3.3) (Butts et al., 2004; Jakeman et al., 2006; Robinson and Brooks, 2024). This process initially begins with qualitative questions such as: *what is known about the system? Are there available data, instrumentation, or monitoring that can be used to quantify aspects of the system?*

In volcanic hazard modelling, many computational models are built upon conceptual models developed in the late 20th century, such as those for eruption plume dynamics (Suzuki, 1983; Woods, 1988; Holasek et al., 1996), pyroclastic flow dynamics (Fisher, 1966; Sparks, 1976; Branney and Kokelaar, 1992), and lava flow dynamics (Walker, 1973; Dragoni et al., 1986). Conceptual models are continually updated as new data and understanding become available (Butts et al., 2004; Anderson et al., 2015), including during model calibration (Section 5.3) and sensitivity analysis.

3.3. Model structure

Developers must translate the features identified in the conceptual model into specific mathematical representations to build the model structure. This begins with selecting governing equations that represent the relevant process dynamics and their interactions (Gupta et al., 2012) - such as the ADS equation used in atmospheric dispersion and deposition models (Folch, 2012; Bonadonna et al., 2015), or the Navier–Stokes equations for flow models (Cordonnier et al., 2015). While these governing equations are typically dictated by the physical processes involved, model developers must make critical decisions about how to simplify, structure, or adapt these equations that balance accuracy, computational efficiency, and available data.

These decisions give rise to different model structures (e.g., empirical or numerical), each offering different levels of complexity (Section 4.2). Even within the same model family, structures may vary in detail, with more complex models incorporating additional mechanisms (e.g., particle aggregation in ash models Folch et al., 2010; Hoffman et al., 2023).

In practice, model structure is often influenced by factors beyond scientific rationale, including institutional preference, model familiarity, and established acceptance within the technical community (Jakeman et al., 2006; Jackson et al., 2000). Advances in high-performance computing and model optimisation are helping to reduce some of these limitations, enabling more complex models to be used in ensemble or probabilistic frameworks (e.g., Folch et al., 2022; Martinez Montesinos et al., 2022; Massaro et al., 2023; Hyman et al., 2024). However, careful structural choices remain essential, especially when short-term and near-real-time forecasts are generated quickly and with limited input parameter data.

3.4. Model inputs

Determining how model input parameters will be estimated occurs alongside the development of model structure (Jakeman et al., 2006). As the model structure is developed, it must be translated into a discretised form suitable for computer implementation. Discretisation not only affects model fidelity and computational demand, but also shapes which input parameters are required, how they are estimated, and what can be held constant or inferred from others (Seppelt, 2003; Jakeman et al., 2006).

In atmospheric dispersion and deposition models, for instance, ESPs such as plume height, duration, and particle characteristics (i.e., size, shape) define the initial conditions for simulations (Engwell et al., 2024). Other input parameters, such as the vertical mass distribution in the plume or diffusion coefficients, arise from how the governing equations (e.g., the ADS equation) are simplified and parameterised (Bonadonna et al., 2005; Macedonio et al., 2005; Pfeiffer et al., 2005; Schwaiger et al., 2012). Similarly, in flow models, discretised forms of the momentum equations require specification of parameters such as basal friction angle, which controls when and how a flow will begin to move downslope (Procter et al., 2010).

The process of estimating these parameters differs depending on the forecasting stage. After an event, observed deposits can be used to retrospectively calibrate or validate input parameters (Section 5.5). Before an event, the model relies on past eruptive data at a volcano (e.g., Barsotti et al., 2018; Spiller et al., 2020; Titos et al., 2022), analogous event/volcano data (e.g., Sheldrake, 2014; Clarke et al., 2020; Tennant et al., 2021) and/or expert elicitation/opinion (e.g., Tadini et al., 2021; Bernard et al., 2024). During an event, real-time data can constrain key input parameters (e.g., Vicari et al., 2011; Scollo et al., 2019; Hyman et al., 2022; Pardini et al., 2022;?).

3.5. Model uncertainty

Uncertainties in model development occur at every stage of model construction and should be explicitly acknowledged. A commonly adopted framework in volcanic hazard modelling is to classify these uncertainties into two broad types: epistemic and aleatoric. Epistemic uncertainty is often seen as reducible through better data or understanding, while aleatoric uncertainty is considered irreducible and should be managed in a fully structured, probabilistic manner (Marzocchi et al., 2004; Beven et al., 2018; Marzocchi et al., 2021). Some recent probabilistic hazard modelling approaches explicitly address both types of uncertainty using doubly stochastic frameworks (e.g., Neri et al., 2015a; Bevilacqua, 2016), where epistemic and aleatoric uncertainties are separately characterised and propagated.

However, this distinction has been criticised for oversimplifying the nature of uncertainty in complex natural systems. In practice, what is initially characterised as aleatoric may later be better understood and reclassified as epistemic, highlighting the limitations of a rigid dichotomy. As discussed by Marzocchi and Jordan (2014), Marzocchi et al. (2021), such classifications are model-dependent, and the reducibility of uncertainty often reflects the assumptions and scope of the model itself rather than any intrinsic property of the volcanic system. They further propose that a more robust framework includes a third category, ontological error, that accounts for the unknown unknowns: behaviours of the system that fall entirely outside of the model's representational assumptions.

A critical component of model development and evaluation, particularly in forecasting, is the quantification of uncertainty in both model structure and input parameters. This is especially important when forecasts are used to inform emergency management personnel responsible for interpreting hazard information (Renschler, 2005; Bayarri et al., 2009; Bonadonna et al., 2012; Folch, 2012). Model users, whether they are scientists, policymakers, or emergency managers, must be informed about the limitations and assumptions in both the model and its input parameters (Sparks et al., 2013). Failing to communicate these uncertainties can lead to inappropriate or ineffective decision-making (Renschler, 2005). For operational users in particular, understanding the order of magnitude of uncertainty is often more useful than knowing the precise value of a model output (Gupta et al., 2008; Crawford et al., 2018).

These uncertainties relate to both the model's accuracy in representing physical processes and its ability to forecast. For example, technical uncertainty (a subset of epistemic uncertainty) includes not only potential coding errors (Walker et al., 2003), but also unavoidable approximations and assumed relationships that may not always hold (e.g., grain size — magma viscosity relationships Costa et al., 2016a). These uncertainties can be further unpacked by identifying where they arise within the modelling process. In volcanic hazard modelling, key sources of uncertainty include:

- **Governing equations**: physical processes are often represented using idealised or simplified equations (Section 2), but the extent to which these fully capture the real behaviour of volcanic phenomena, especially under varying conditions, is uncertain.
- **Model resolution (spatial and temporal)**: models must be discretised in time and space for computational implementation, yet coarse resolutions may fail to capture key dynamics, while fine resolutions are computationally expensive and may still not guarantee accuracy (Section 2).
- **Input data**: key input parameters may be poorly constrained, especially for long- and short-term forecasting (Section 3.4). Epistemic uncertainty dominates when such input parameters are based on limited or past observations. Past data is often incomplete, as historic eruptions may be unobserved or misclassified (e.g., Wilson et al., 1995), pre-historic eruptions may not exist in the geologic record due to deposition and weathering processes (e.g., Kueppers et al., 2019), and small sized eruptions may be missed in the geologic record (Mead and Magill, 2014). The certainty of direct observations can also be affected by many factors, such as bad weather conditions, low frequency of satellite passages, poor vertical resolution (radar measurements), or hazardous conditions (e.g., Prejean and Brodsky, 2011; Oddsson et al., 2012; Dürig et al., 2018; Lube et al., 2020).
- **Input parameter relationships**: there are some key input parameter relationships, such as the linear relationship between plume height and total erupted mass/mass eruption rate (Mastin et al., 2009; Aubry et al., 2022), that are often incorporated into volcanic hazard modelling. These types of relationships are complicated by a variety of real-world factors, including but not limited to total grain size distribution, wind velocity, the plume water content, and aggregation (e.g., Degruyter and Bonadonna, 2012; Girault et al., 2014).
- **Volcano and eruption heterogeneity**: volcanic systems are heterogeneous, and model assumptions calibrated on one volcano or eruption may not apply to another volcano or eruption (Cashman and Biggs, 2014). Site-specific behaviours (e.g., unique conduit geometries, wind profiles, terrain) introduce both epistemic and aleatoric uncertainty, challenging generalisation, and transferability.
- **Plausible input parameter values**: while model developers often assume that users will input physically realistic values, some lack internal checks to prevent implausible values. For example, atmospheric dispersion and deposition model Tephra2 allows users to apply negative plume heights (intentionally or otherwise) without producing an explicit error. This introduces technical uncertainty as the model may proceed with invalid assumptions and generate misleading outputs.

3.6. Model documentation

A critical aspect of model construction is documentation, which should be maintained throughout every stage of development. Comprehensive documentation provides a clear rationale for model selection, including the chosen model family (e.g., empirical vs. numerical), structural features (e.g., governing equations), and input parameter data sources. This ensures that model assumptions and design choices are transparent to both current users and future developers.

Volcanic hazard models are typically well-documented, detailing their utility, assumptions, limitations, and areas for potential improvement (e.g., de'Michieli Vitturi et al., 2010; Mastin et al., 2013; Kelfoun and Vargas, 2016; Folch et al., 2020). In operational or decision-making contexts, it helps that users understand model constraints and do not misinterpret outputs.

The documentation process should continue during model testing (Section 5). This includes during recording test cases, software version upgrades, and any model refinements based on performance or expert review. Thorough documentation also supports the identification of the provenance of unexpected behaviours or errors, particularly when models are developed in open-source platforms such as GitHub (https://github.com/).

4. Model complexity

Research into model complexity is vast, yet no strict or unified definitions exist within or across different disciplines (Brooks and Tobias, 1996; Guthke, 2017; Höge et al., 2018; Baartman et al., 2020). Various recurring themes emerge in definitions of complexity, such as an increased number of mechanisms or processes (e.g., Bal and Rein, 2013; Larsen et al., 2016; Baatz et al., 2018; Getz et al., 2018), an increased number of input parameters (e.g., Rickles et al., 2007; Bal and Rein, 2013), and greater computational or data requirements (e.g., Zeigler et al., 2019).

In the context of forecasting, especially for volcanic hazards, understanding model complexity is crucial. While volcanic systems are inherently complex, this does not mean that models used to forecast hazardous behaviour must be equally complex. While it is often assumed that more complex models produce more accurate forecasts, evidence from environmental modelling suggests that increased complexity can reduce accuracy due to higher error and uncertainty (Oreskes et al., 1994; Snowling and Kramer, 2001; Srikrishnan and Keller, 2021). This can be partly explained by the bias–variance trade-off, a core issue in model development. Overly simplistic models are prone to high bias, defined as the difference between a model's average prediction and the true value, while overly complex models are prone to high variance, which captures the spread of predictions around the true value (Friedman, 1997).

A recurring challenge in forecasting is balancing model complexity with the inherent uncertainties in both input parameters and model processes. Ultimately, the primary outputs required for volcanic hazard forecasting are spatial extent and hazard intensity (e.g., ash density at a location, lahar inundation thickness). If both simple and complex models yield comparable outputs, and unless input parameters are well constrained (which is next to impossible), increasing complexity by adding more parameters does not provide a meaningful advantage for forecasting (Scollo et al., 2008a). However, complex models remain essential in research and hindcasting (Sparks and Aspinall, 2004). Achieving the right balance between simplicity and complexity is essential in volcanic hazard forecasting; however, this challenge is not unique to volcanology, as similar issues arise in weather and climate forecasting (Scher and Messori, 2019), hydrology (Doherty and Christensen, 2011), and ecology (Evans et al., 2013; Ward et al., 2014). Ultimately, selecting a model that is both reliable and appropriate for its intended use requires careful evaluation of complexity in terms of structure, data requirements, and usability (Höge et al., 2018).

The following sections explore how model complexity influences volcanic hazard modelling, both conceptually and practically, and highlight the trade-offs between realism, usability, and computational capacity.

4.1. Volcanic hazard model complexity

A recent study by Malmborg et al. (2024) presents a comprehensive framework for defining model complexity in ecological models, which serves as the basis for defining complexity in volcanic hazard models. Similarly to volcanic systems, ecological systems exhibit inherent complexity (Levin, 1998; May, 2019; Riva et al., 2023), yet the term "complex" remains inconsistently used across studies (Malmborg et al., 2024).

Following Malmborg et al. (2024), model complexity can be defined into four categories:

- **Model Class Complexity:** The mathematical framework that defines a model's structure and governs the interaction between its input parameters and outputs.
- **Input Parameter Complexity**: Compromises of several components of complexity, including the number of input parameters in a model and input parameter–parameter relationships.
- **Input Data Complexity**: Refers to the resolution, variability, and uncertainty of the data used to populate model input parameters. This includes how difficult the data are to obtain, process, or interpret.
- **Computational Complexity**: Includes concepts such as the computing resources required to run a model and the time required to complete a model simulation.

These categories together form a conceptual framework to facilitate a systematic assessment of a given model's outputs and complexities is applied here to volcanic hazard models (see Fig. 1).

For comparison, various descriptions of complex models found in volcanic hazard modelling studies are shown in Table 3.

4.2. Model class complexity

Different model classes involve inherent trade-offs between realism, generality, and precision (Jehn et al., 2019). In volcanic hazard modelling, primary model classes are defined as empirical and numerical (Section 1.1, Fig. 2).

Empirical models provide a comparatively simpler alternative to heavily parameterised numerical models. However, empirical models are not inherently less complex, as they encompass a wide range of phenomenological modelling techniques and inputs (e.g., volcanic flow models MrLavaLoba, LAHARZ). One of the most well-known empirical models in volcanic hazard modelling, the Energy Cone, simulates a flow using only the release height and run-out distance (the Heim coefficient) (Malin and Sheridan, 1982; Sheridan and Macías, 1995). In contrast, LAHARZ utilises an empirical relationship between volume and planimetric area of inundation derived from a scaling analysis of 27 documented lahar paths from nine volcanoes (Schilling, 1998).

Additionally, some modelling approaches blend in elements of both empirical and numerical models, forming 'hybrid' approaches. In volcanic hazard modelling, numerical models can be updated or calibrated using new information derived from empirical models. An example of this occurs in atmospheric dispersion and deposition model Fall3D, where the input parameter mass eruption rate (MER) can be determined through embedded empirical models (e.g., Mastin et al., 2009; Degruyter and Bonadonna, 2012; Woodhouse et al., 2013).

This demonstrates that complexity is not strictly tied to model class, as both empirical and numerical models can range from simple to complex, depending on their formulation, assumptions, and data requirements.

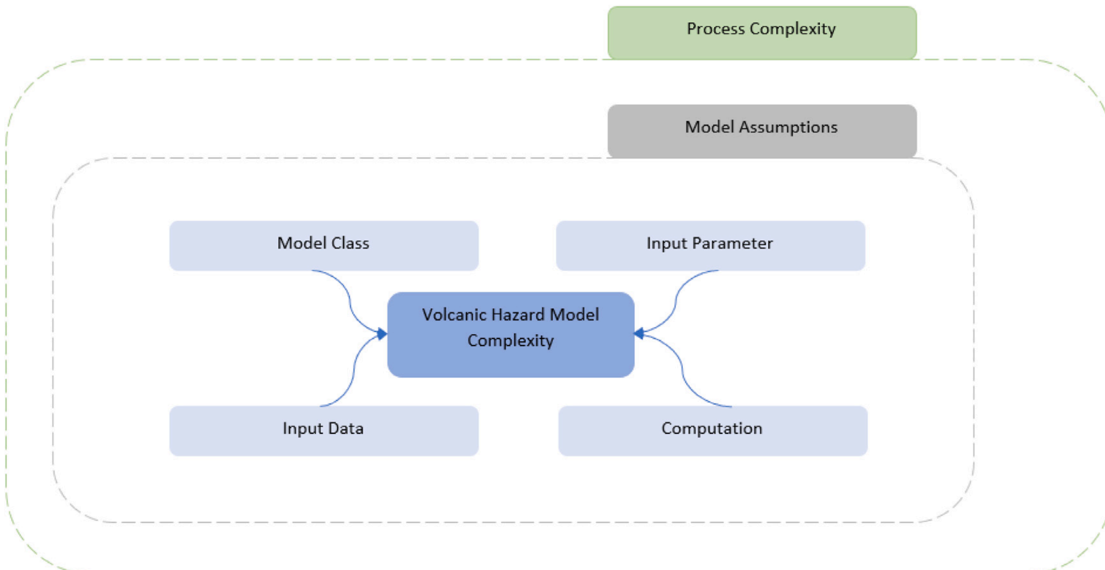


Fig. 1. Volcanic hazard model complexity can be decomposed into four primary categories: model class complexity, input parameter complexity, input data complexity, and computation complexity. Model assumptions influence the four facets of model complexity. Process complexity refers to the complexity of the volcanic hazard being modelled, which inherently defines and shapes the facets of model complexity.

Table 3
Different indicators of model complexity in volcanic hazard model literature.

What makes models complex?	Directly referenced	Indirectly referenced
Number of parameters	Volcanic ballistic projectile model[a]	Hazard mapping[b], General hazard modelling[c,d]
Variability each input parameter introduces	Volcanic ballistic projectile model[a]	
Dimensionality		Tephra dispersion and deposition models[e,f,g], Lava flow model[h], Mass flow model[i]
Run time		Lava flow model[h], Mass flow model[i], Hazard assessment[j], General hazard modelling[d]
Accounting for multiple physical process		Mass flow models[i,k,l,m]
Computational Requirements		Hazard mapping[b]

[a] Núñez Corrales and Brenes-André (2023).
[b] Felpeto et al. (2007).
[c] Sparks and Aspinall (2004).
[d] Douglas (2007).
[e] Scollo et al. (2008a).
[f] Poulidis and Iguchi (2021).
[g] Pardini et al. (2024).
[h] Harris (2013).
[i] Esposti Ongaro et al. (2020).
[j] Marzocchi et al. (2010).
[k] Neri and Macedonio (1996).
[l] Hooper and Mattioli (2001).
[m] Ogburn and Calder (2017).

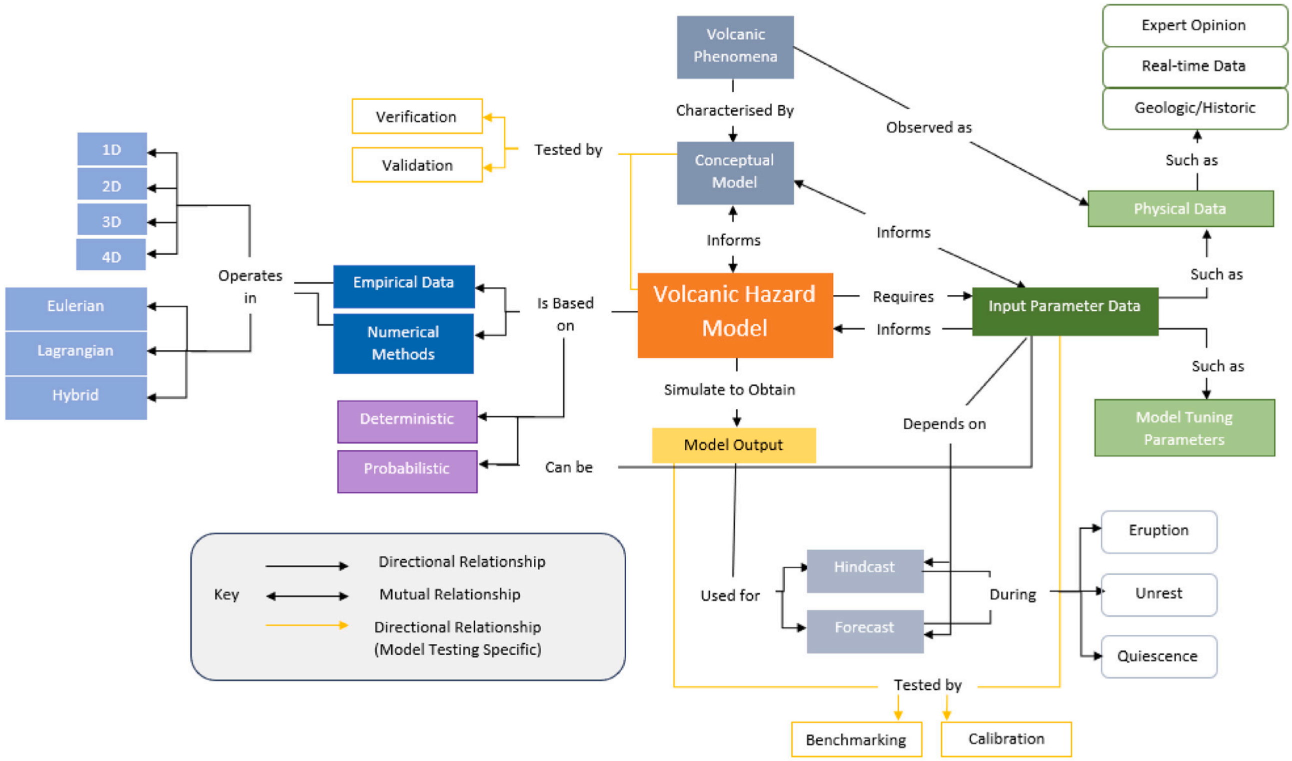
4.3. Input parameter complexity

Model complexity increases as additional parameters are introduced, whether by incorporating more covariates or accounting for interactions between them (Malmborg et al., 2024). While adding parameters can enhance model flexibility, it also introduces new challenges. A higher number of input parameters increases the dimensionality of the input space, which can make calibration more difficult and lead to greater uncertainty if those parameters are poorly constrained (Parry, 1996; Sparks and Aspinall, 2004; Felpeto et al., 2007). Additionally, complex models are generally more prone to overfitting, especially when data are limited.

Beyond the total number of input parameters, the nature and distribution of these input parameters also influence model complexity. For example, linear relationships are often easier to generalise and interpret, while non-linear forms (e.g., exponential or quadratic) increase a model's sensitivity to input variation, potentially amplifying forecast error. Similarly, the choice of which input parameters to actively estimate versus those held constant can alter the effective complexity. In the atmospheric dispersion and deposition model Fall3D, for instance, users may choose to enable particle aggregation. Doing so introduces up to seven additional parameters (Folch et al., 2022), expanding the model structure and increasing its sensitivity to those specific input parameter values.

4.4. Input data complexity

While input parameter complexity concerns the number and interactions of input parameters within a model, input data complexity relates to the characteristics of the data used to quantify those parameters — its resolution, availability, quality, and source. Due to the hazardous



Knowledge Needs per User					
Model Users	Conceptual Model	Model Type	Model Approach	Input Parameter Data	Model Output
Geologist	Relevant	Relevant	Somewhat Relevant	Relevant	Somewhat Relevant
Forecasters/ Modellers	Somewhat Relevant	Relevant	Relevant	Relevant	Relevant
Emergency Managers	Less Relevant	Less Relevant	Relevant	Less Relevant	Relevant

Fig. 2. Volcanic hazard model ontology. The table at the bottom of the figure shows the relative relevance of different aspects of volcanic hazard models to three user types: geologists, forecasters, and emergency managers. Relevant = Directly impacts the user's ability to use, trust, or interpret the model. Somewhat Relevant = Useful context but not essential for decision-making. Less Relevant = Not typically a focus for this user type.

nature of volcanic eruptions and their products, collecting certain data can be challenging due to physical limitations or the inherent complexity of the natural process being measured.

This issue is particularly emphasised in literature on PDCs (Lube et al., 2020), as PDCs are extremely hazardous, accounting for one-third of volcanic fatalities and injuries worldwide (Auker et al., 2013). The limited optical depths of PDCs prevent visual observations from capturing their internal dynamics (Dufek, 2016). Moreover, the intense forces within these flows can destroy structures and instruments deployed to study them (Valentine, 1998).

Given these challenges, estimating input parameter data may necessitate the use of proxies rather than direct measurement. Such proxies can include post-depositional field-based observation and sedimentation techniques (Bonadonna et al., 2015; Brown and Andrews, 2015) and analogue experiments (Holasek et al., 1996; Rowley et al., 2014; Poppe et al., 2022), or through theoretical modelling (Alatorre-Ibargüengoitia et al., 2010; Doronzo et al., 2011; Folch et al., 2016)?. However, due to the infrequent, complex, and hazardous nature of volcanic eruptions, it is challenging to gather high-resolution or repeatable observations across a wide range of eruption conditions. As a result, the statistical uncertainty associated with many key input parameters can be substantial (Parry, 1996).

The spatial and temporal resolution of input parameters also adds to model complexity by introducing greater heterogeneity in space and time. Higher resolution data requires more memory, computational power, and/or storage (see Section 4.5). As a result, processing and analysing larger volumes of data can take significantly more time. An example of this is the resolution of meteorological data used in atmospheric dispersion and deposition modelling. For modelling particle dispersion and deposition, a larger modelling area and higher resolution of both the meteorological data and the simulation grid will increase simulation and processing times (Parra, 2019; Poulidis et al., 2019; Poulidis and Iguchi, 2021). The same is true for digital elevation models and their resolution, used in volcanic flow models (Capra et al., 2011; Marquez et al., 2022).

Using these models for forecasting further increases the complexity of input data. Whether short- or long-term forecasting, in the absence of direct observations, the data needed to run these models is usually based on prior data, including past eruptions (e.g., Mastin et al., 2009; Aubry et al., 2021; Deligne, 2021) and expert judgement (Folch, 2012; Engwell et al., 2024). However, historic data is often incomplete, as historic eruptions may be unobserved or misclassified (e.g., Wilson et al., 1995), pre-historic eruptions may not exist in the geologic record due to deposition or weathering processes (e.g., Kueppers et al., 2019), and small sized eruptions may be missed in the geologic record (e.g., Mead and Magill, 2014; Damaschke et al., 2017). When models require many input parameters, uncertainty inevitably increases due to the number of assumptions that must be made about both eruptive behaviour and data quality. To account for this uncertainty, input parameters can be represented as probability distributions rather than single values (probabilistic models, Section 2), and (deterministic) models are run multiple times using a range of sampled values. This strategy helps capture the plausible range of outcomes, but also increases the computational demand (Section 4.5).

4.5. Computational complexity

Computational cost (e.g., run time, memory usage, energy consumption) is a critical factor when evaluating the complexities of different models. Numerical models, particularly high-dimensional ones, tend to have higher computational cost (Folch, 2012). Probabilistic hazard assessments, which rely on volcanic hazard model outputs, typically require hundreds to several thousands of simulations to capture the full range of natural variability in input parameters (e.g., n = 1000; Jenkins et al. (2012), Volentik and Houghton (2015), n = 10 000; Clarke et al. (2020), n = 19 200; Jenkins et al. (2015)). While restricting the input parameter space to representative scenarios can reduce this burden, such shortcuts risk introducing bias or underestimating uncertainty (Sandri et al., 2016; Selva et al., 2018). Ensemble modelling approaches help manage this challenge by combining outputs from multiple models or multiple runs of the same model under different conditions to better capture uncertainty (e.g., Holland et al., 2020; Plu et al., 2021; Folch et al., 2022; Hyman et al., 2022).

Model parallelisation is commonly employed to improve computational efficiency (e.g., Esposti Ongaro et al., 2007; D'Ambrosio et al., 2013; de la Cruz et al., 2016; Martínez-Sepúlveda et al., 2024), but this approach often requires the use of additional libraries (e.g., MPI, OpenMP), thereby increasing the overall complexity of the model. Importantly, computational efficiency also informs model selection, particularly in forecasting contexts. Simpler models, which require fewer input parameters and lower computational cost, can generate forecasts more efficiently, making them especially useful for time-sensitive operational forecasting where decision-makers must rapidly assess a wide range of hazardous outcomes (Bayarri et al., 2009; Folch, 2012; Dietterich et al., 2017; Ogburn and Calder, 2017).

Another important strategy for reducing computational cost is the use of statistical emulators, also known as surrogates. These are statistical models trained to approximate the outputs of more computationally expensive models (Bayarri et al., 2009, 2015). Once trained, emulators can generate rapid outputs, dramatically reducing the number of full model runs needed for probabilistic forecasting (e.g., Monte Carlo simulations, Rutarindwa et al., 2019; Yang et al., 2020; Mead et al., 2023).

Ultimately, appropriate model complexity should be determined by the specific forecasting or decision-making context rather than the level of detail alone. Overly complex models can become computationally impractical, and the tendency to equate detail with realism can undermine a model's usefulness (Salt, 2008). Effective models strike a balance between bias and variance, realism and interpretability, and theoretical accuracy and operational practicality. Model complexity is also inherently shaped by the quality and availability of input data, limiting the feasibility of high-detail approaches in many real-world scenarios. Crucially, probabilistic forecasting provides a framework to incorporate uncertainty regardless of model complexity.

5. Model testing

Model testing assesses the viability of a model for the purpose for which it was developed. Model testing is composed of model verification, validation, calibration, and benchmarking. Model testing is an integral part of making sure a model is scientifically robust - i.e., reproducible, replicable, and generalised with clear definitions (Larson, 2005; Bollen et al., 2015). However, the concept of model testing is not straightforward.

It has been argued that models cannot truly be verified or validated in an absolute sense. As Oreskes et al. (1994) states, "models can only be evaluated in relative terms, and their predictive value is always open to question". Even when model outputs match observations, this does not necessarily mean the model structure is correct; it could simply reflect compensating errors or coincidental agreement. Therefore, the primary value of models is often considered to be heuristic: they help improve understanding and support decision making, rather than offering definitive predictions.

These issues are particularly relevant when evaluating forecasts produced by probabilistic models or deterministic models applied probabilistically. In theory, probabilistic forecasts could be tested by comparing predicted and observed hazard phenomena over many repeated events. But in volcanology, where eruptions are infrequent and each event is unique, this is rarely possible. A Bayesian perspective offers an alternative, framing probabilities as expressions of belief that can be updated with new data or knowledge. Under this approach, probabilistic forecasts are not validated in the classical sense. Instead, they are assessed based on how well they incorporate existing knowledge, characterise uncertainty, and are compared to alternative models or expert judgement (Rougier and Beven, 2013).

Given these challenges, testing volcanic hazard models should be viewed as a multi-step, iterative process. Rather than seeking to "prove" a model is right or wrong, the goal should be to evaluate whether it is fit for purpose. This also requires transparency about assumptions, simplifications, and known limitations, and careful attention to how uncertainty is handled (Section 3.5).

The following subsections provide a practical overview of how model testing has been applied in volcanic hazard modelling.

5.1. Verification

Model verification is not often explicitly mentioned in volcanic hazard model literature, indicating that there is an assumption that if a model is validated, then it is also verified (Esposti Ongaro et al., 2020). A thorough literature search revealed only five examples of volcanic hazard models being explicitly verified: atmospheric dispersion and deposition models Tephra2 (Connor et al., 2011), Ash3D (Schwaiger et al., 2012), Fall3D (Folch et al., 2020; Prata et al., 2021), VBP model Eject! (Mastin, 2001), and mass flow model IMEX_SfloW2D (de' Michieli Vitturi et al., 2019). This pattern is not unique to volcanology; in many scientific modelling domains, verification is often conflated with validation (Augusiak et al., 2014). While model verification in volcanology rarely involves direct comparison to analytical solutions or theoretical benchmarks, because such solutions often do not exist for complex volcanic processes, verification is still possible by testing whether the model implementation behaves as intended, given the conceptual model (e.g., conserving mass, producing physically plausible transport behaviour).

5.2. Validation

Validation exercises for volcanic hazard models are primarily conducted using past eruptions (Table 4) (hindcasting, Section 5.5). Model validation is a continuous process — as the greater the number and diversity of validated eruptions, the more probable that the model's equations and conceptualisation are not flawed (Oreskes et al., 1994; Trucano et al., 2006; Esposti Ongaro et al., 2020).

However, it is technically infeasible to validate a model against future, unknown hazardous events. This is particularly challenging in long-term forecasting, where the rarity and unpredictability of eruptions limit opportunities for model validation (Mason et al., 2004; Sheldrake et al., 2017). Similar issues have been acknowledged in other hazard domains, such as earthquake forecasting, where efforts such as the Regional Earthquake Likelihood Models (RELM) project — that aims to produce and evaluate models of earthquake potential

Table 4
Examples of validation cases for different volcanic hazard models.

Volcanic Hazard Model	Validated Eruption(s)	Reference
Atmospheric Dispersion and Deposition Models		
HYSPLIT	2008 Kasatochi	Crawford et al. (2016)
PUFF	1992 Mount Spurr/Crater Peak, 1994 Klyuchevosky volcano, & 1994 Rabaul caldera	Searcy et al. (1998)
HAZMAP	79AD, 1631 & 1994 Vesuvius, 2002-03 Mount Etna	Andronico et al. (2008), Macedonio et al. (2008)
NAME III	2010 Eyjafjallajökull	Grant et al. (2012)
Tephra2	1992 Cerro Negro	Connor et al. (2011)
Fall3D	2008 Chaitén, 2010 Eyjafjallajökull, 2011 Puyehue-Cordon Caulle, & 2019 Raikoke (SO_2 cloud),	Folch et al. (2012), Osores et al. (2013), Prata et al. (2021)
Ash3D	1992 Mount Spurr/Crater Peak	Schwaiger et al. (2012)
Volcanic Flow Models		
Energy Cone (ΔH/L)	1980 Mount St. Helens	Malin and Sheridan (1982)
SCIARA	1991 & 2001 Mount Etna	Crisci et al. (2004)
FLOW-3D	1982 El Chichon	Macías et al. (2008)
LaharZ	1998 Sarno, 1997 & 2001 Popocatepetl	Dorta et al. (2007), Muñoz-Salinas et al. (2009)
FLOWGO	1984 Mauna Loa, 1997 Pu'u 'Ō'ō & 1998 Mount Etna	Harris and Rowland (2001)
PDAC	1997 Soufrière Hills	Clarke et al. (2002)
DOWNFLOW	1991–93 & 2001 Mount Etna	Favalli et al. (2005)
Titan2D	Soufrière Hills	Widiwijayanti et al. (2004)
MAGFLOW	2001 Mount Etna	Vicari et al. (2007)
VolcFlow	2006, 2010 Tungurahua	Kelfoun et al. (2009), Kelfoun and Vargas (2016)
MOLASSES	2012–13 Kamchatka	Richardson (2016), Kubanek et al. (2015)
MrLavaLoba	2021 Fagradalsfjall	Pedersen et al. (2022)
IMEX_SfloW2D	Synthetic eruption Vesuvius	de' Michieli Vitturi et al. (2019)
EC_MapProb & Box_MapProb	2008–09 Chaitén	Aravena et al. (2020)
Volcanic Ballistic Projectile Models		
Eject!	2016–2017 Bogoslof & 2022 Mount Etna	Waythomas and Mastin (2020), Costa et al. (2023)
LPAC	1997 Soufriere Hills	de'Michieli Vitturi et al. (2010)
Alatorre-Ibargüengoitia et al. (2012)	1998 & 2003 Popocatepetl	Alatorre-Ibargüengoitia et al. (2012)
Ballista	2014 Mount Ontake	Tsunematsu et al. (2016)
Great Balls of Fire	1888 - 90 La Fossa (Vulcano Island)	Biass et al. (2016)

for California, USA — have highlighted the difficulty of evaluating model performance on long timescales due to the scarcity of observed events (Schorlemmer et al., 2007, 2010).

Furthermore, the various components of volcanic hazard models (Section 7.1), along with model complexity (Section 4), can be explored to assess their influence on a model's ability to produce accurate forecasts.

5.3. Calibration

Table 5 provides examples of calibration efforts across various volcanic hazard models. In many volcanic hazard studies, the distinction between calibration and validation is blurred, and both are often conducted simultaneously (e.g., Bonadonna et al., 2005; Andronico et al., 2008; Wantim et al., 2013; Biass et al., 2016). For instance, input parameters may be adjusted iteratively until model outputs align with observations - a process that may serve both to calibrate uncertain model parameters and validate the model. This process is typically not about making extreme changes, but rather refining uncertain parameters based on observational constraints or expert judgement.

In some cases, such as in studies using the atmospheric transport and deposition model Ash3D, the term "calibration" is rarely used. Instead, the literature refers to "input parameter adjustment" or similar terminology (Mastin et al., 2016). For other models, such as the atmospheric transport and dispersion model HYSPLIT and VBP model Eject!, published studies often focus on calibrating observational tools (e.g., radar, thermal imagery, or camera measurements) while using the model outputs as a reference or validation target (e.g., Corradini et al., 2016; Pardini et al., 2020; Costa et al., 2023).

5.4. Benchmarking

In tephra modelling, a benchmarking exercise was carried out during the 2010 International Association of Volcanology and Chemistry of the Earth's Interior (IAVCEI) workshop on Ash Dispersal Forecast and Civil Aviation (Bonadonna et al., 2011, 2012). 12 atmospheric dispersion and deposition models were benchmarked against the Hekla 2000 eruption in Iceland Hoskuldsson et al. (2007). This exercise highlighted substantial variability in model outputs, primarily due to differences in model structure and model input parameters and assumptions, but did not identify a single best-performing model. These findings underscore that model performance is potentially eruption- or volcano-specific, and no single model can be universally applied across all scenarios.

For lava flows, Cordonnier et al. (2015) conducted five benchmarking exercises with seven flow models simulating (1) a dam-break flow, (2) inclined viscous isothermal spreading, (3) axisymmetric cooling and spreading, (4) a split flow experiment, and (5) a natural case. Dietterich et al. (2017) expanded this by incorporating additional experimental data and assessing both accuracy and CPU efficiency. They found that while most models performed similarly for short-duration, isoviscous flows, thermal processes became increasingly important for longer-lived, cooling-limited lava flows. This suggests that models incorporating thermal dynamics may offer improved performance for simulating longer-duration eruptions and cooling-limited lava flows.

For PDC, Esposti Ongaro et al. (2020) proposed — though did not implement — a set of experimental configurations to test PDC models, including: (1) large-scale, dilute, turbulent, polydisperse gravity current over an incline, (2) large-scale axisymmetric polydisperse gravity current from jet collapse, (3) concentrated, fluidised/non-fluidised granular current over an incline, (4) turbulent gas–particles flows

Table 5
Examples of calibration cases for different volcanic hazard models.

Volcanic Hazard Model	Eruption	Reference
Atmospheric Dispersion and Deposition Models		
HYSPLIT	N/A	N/A
PUFF	2018 & 2019 Sakurajima	Tanaka and Iguchi (2019), Tanaka et al. (2020)
HAZMAP	2002-03 Mount Etna	Andronico et al. (2008)
NAME III	Post 2010 Eyjafjallajökull	Beckett et al. (2017)
Tephra2	1315 Kaharoa (Mount Tarawera) & June 1996 Mount Ruapehu	Bonadonna et al. (2005)
Fall3D	2013 Mount Etna, 1980 Mount St. Helens, & 1992 Crater Peak	Folch et al. (2010), Prata et al. (2021)
Ash3D	N/A	N/A
Volcanic Flow Models		
Energy Cone (ΔH/L)	Tungurahua, Soufriere Hills & Arenal Volcano	Toyos et al. (2007), Aravena et al. (2024)
SCIARA	2001 & 2006 Mount Etna	D'Ambrosio et al. (2005), Spataro et al. (2015)
FLOW-3D	N/A	N/A
LaharZ	Original Calibration of Nine Volcanoes	Iverson et al. (1998)
FLOWGO	Mount Cameroon	Wantim et al. (2013)
PDAC	N/A	N/A
DOWNFLOW	1977 & 2002 Nyiragonga, Mount Etna, 2014–15 Fogo	Favalli et al. (2009), Tarquini and Favalli (2011), Richter et al. (2016)
Titan2D	2006 Merapi	Charbonnier and Gertisser (2012)
MAGFLOW	N/A	N/A
VolcFlow	2006 Merapi	Charbonnier and Gertisser (2012)
MOLASSES	N/A	N/A
MrLavaLoba	N/A	N/A
IMEX_SfloW2D	2022 Mount Etna	Zuccarello et al. (2025)
EC_MapProb & Box_MapProb	2070 cal yr BP El Misti	Aravena et al. (2022)
Volcanic Ballistic Projectile Models		
Eject!	N/A	N/A
LPAC	N/A	N/A
Alatorre-Ibargüengoitia and Delgado-Granados (2006)	1994 Popocatepetl	Alatorre-Ibargüengoitia and Delgado-Granados (2006)
Ballista	2012 Te Maari	Fitzgerald et al. (2014)
Great Balls of Fire (GBF)	La Fossa	Biass et al. (2016)

with buoyancy reversal, and (5) interaction of stratified gas–particle gravity currents with obstacles. In contrast, Gueugneau et al. (2021) conducted a benchmarking exercise focused on four concentrated PDC models, with five test scenarios that included flat slopes, bends, slope breaks, obstacles, and constriction, which highlighted the complexity of simulating PDC dynamics across varied terrain.

One study used laboratory experiments to evaluate the performance of VBP models, comparing analytical and numerical implementations under simplified conditions (e.g., no topography, consistent initial conditions across simulations) (Bertin, 2017). Although the authors referred to this as benchmarking, the exercise more closely resembled a sensitivity analysis, focused on internal comparisons of model behaviour rather than performance against other VBP models or real-world data.

Benchmarking is the least frequently conducted type of model testing for volcanic hazard models. However, benchmarking exercises are rare in volcanic hazard modelling.

5.5. Past event testing (Hindcasting)

Hindcasts, or retrospective forecasts, are constructed after an event has occurred. The advantage of running a model retrospectively is that input parameters are better constrained (to the best of the monitoring data and sampling techniques). Hindcasting is an integral part of model testing, as it can be used to see whether a model can correctly simulate a historical event. At all four stages of model testing — verification, validation, calibration, and benchmarking — hindcasts can, and are, used to test model accuracy (e.g., Widiwijayanti et al., 2004; Scollo et al., 2007; Procter et al., 2012; Dietterich et al., 2017). If a model can accurately simulate a past event, then the model is considered to be an accurate and credible representation of the phenomenon modelled. However, this is only the case if the observations used to evaluate the hindcast were not also used in calibrating the model, as this can lead to overfitting (e.g., Schorlemmer et al., 2018). Hindcasting can also be applied to simulate past behaviours at any volcano for applications such as reconstructing hazard records (e.g., Johnston et al., 2012; Jenkins et al., 2020; Tennant et al., 2021) and hazard assessment (e.g., hazard maps, Bonasia et al., 2011; Michaud-Dubuy et al., 2019).

However, even when using optimal or carefully calibrated input parameters, different models can produce different results when simulating the same eruption. Scollo et al. (2008a) ran a comparative parametric study of different atmospheric dispersion and deposition models (Fall3D, HAZMAP, and TEPHRA) for two plausible eruption scenarios from Mt. Etna, similar to the 2002–03 and 1990 eruptions, and found that there were differences in model outputs between all three models. The study found that each model responded differently to changes in key input parameters, such as erupted mass, column height, column model, bulk granulometry, particle shape, and settling velocity. These differences highlight how structural and technical variations between models can influence outcomes, even when input parameters are held constant or tuned to observed events.

Hindcasting also provides insights into a model's uncertainty — if a model output were accurate, there would exist a set of input parameters that could perfectly reproduce past observations. However, if a model exhibits large errors in hindcasting, its ability to accurately simulate future events becomes questionable.

5.6. Near-real-time forecast evaluation

Forecast testing evaluates a model's performance against future events and is an important component of model evaluation in domains with continuous or frequent data streams, such as weather forecasts (e.g., Thornes and Stephenson, 2001; Gilleland and Roux, 2015), economic market forecasting (e.g., Pyo et al., 2017; Iregui et al., 2021), and electricity price modelling (e.g., Yamin et al., 2004; Weron, 2014).

In these fields, routine forecasts are continuously updated, tested, and refined through near-immediate feedback from observations.

In contrast, forecast testing for volcanic hazard models remains extremely limited due to the infrequent and highly variable nature of eruptions. Moreover, not all eruptions produce the same hazard types, as some generate ash clouds but not lava flows, so evaluating a specific hazard model requires an eruption of the relevant style and magnitude. This lack of continuous observational feedback impedes systematic calibration and iterative correction of volcanic hazard models.

Despite these challenges, emerging efforts are attempting to evaluate model accuracy for near-real-time forecasts. For example, Folch et al. (2022) assessed the accuracy of ensemble-based deterministic and probabilistic simulations in the Fall3D model using post-event observations of SO_2 clouds (from the July 2018 Ambae eruption) and ash clouds and ashfall (from the April 2015 Calbuco eruption). While conducted retrospectively, this study highlights a promising direction towards more accurate near-real-time forecasts.

Forecast evaluation is also supported by a broad body of statistical literature that offers tools for assessing both deterministic and probabilistic forecasts. This includes the use of proper scoring rules, such as the continuous ranked probability score (CRPS), which evaluate the calibration and precision of probabilistic forecasts (e.g., Gneiting and Raftery, 2007; Gneiting, 2011; Gneiting and Katzfuss, 2014). These methods are widely used in fields such as weather and earthquake forecasting (e.g., Brehmer et al., 2024), and provide a theoretical framework for comparing volcanic hazard models against observed outcomes. While their direct application to volcanic hazard forecasting is still limited, these approaches offer useful guidance for future efforts to evaluate model performance, particularly as more observational data become available.

6. Model selection

In many scientific disciplines, including weather prediction and earthquake forecasting, the use of multi-model ensembles is becoming standard practice (e.g., Krishnamurti et al., 2000; Rhoades and Gerstenberger, 2009; Krishnamurti et al., 2016; Marzocchi et al., 2012; Llenos and Michael, 2019). These approaches combine outputs from multiple models to provide a more robust representation of uncertainty, often outperforming individual models (Herrmann and Marzocchi, 2023). Ensemble approaches offer a clear advantage in volcanic hazard forecasting as well, particularly in capturing uncertainty from the models, input parameters, and data. However, the strength of an ensemble depends on the quality and suitability of the individual models it includes. Poorly chosen or incompatible models can introduce biases and reduce forecast interpretability. Thus, whether adopting a single model or ensemble-based approach, selecting appropriate models remains a foundational step.

Selecting the most appropriate model or set of models for any given purpose is critical, even though, in theory, running all available models might yield the most accurate forecast. In practice, however, this is rarely feasible due to constraints on time, computational resources, and data availability. Traditional model selection techniques, such as F-tests, Bayesian model averaging, or Akaike's Information Criterion, are valuable tools for evaluating goodness-of-fit in contexts where observed outcomes are known (Ludden et al., 1994; Glatting et al., 2007; Steel, 2011). However, in forecasting applications, these approaches are often impractical because the true outcome is not yet available. Instead, model selection must also consider factors such as operational constraints and the feasibility of implementation for real-time or decision-making purposes. While formal validation techniques, such as comparing model outputs to observed data (Section 5.2), are essential for assessing model accuracy, they are use- and user-dependent and may not always be feasible, particularly for forecasting. The next steps in model selection should involve iterative testing to ensure the chosen model aligns with the intended application. Ultimately, model selection is shaped by its broader context — the who, why, when, and where — each of which influences what model is most suitable:

- **Who is using the model?** Scientists and modellers may prioritise detailed representations of volcanic phenomena; emergency managers may require simpler yet accurate outputs for risk communication and decision making; and policy makers may need technically accurate results that are useable and clear for long-term planning (Fig. 2) (Doyle et al., 2014; Thompson et al., 2015; Das et al., 2025). Additionally, some models require specialised datasets that may only be accessible through government agencies or research institutions, which are unlikely to be used in practical decision making (Renschler, 2005). These user needs influence which models are considered suitable candidates — whether for individual use or in a broader ensemble forecast.
- **Why is the model being used?** Long-term hazard assessments or hindcasting allow time for detailed modelling and data collection, whereas short-term and syn-eruptive forecasting necessitates models that can run quickly with limited data.
- **When will the model be used?** Similarly to above, short-term and syn-eruptive forecasting impose constraints on data availability, as well as computational efficiency. Conversely, long-term forecasting and hindcasting allow for more time for data collection (e.g., historical data on past eruptions) and model testing (hindcasting past events to refine model accuracy).
- **Where is the model being applied?** The model should be appropriate for both the volcano and the spatial scale of interest. Model users must define the target volcano, which dictates the level of knowledge available about its past activity and hazards. The spatial extent over which a user wants to simulate will also influence model selection. Some atmospheric dispersion and deposition models are designed for local-scale simulations (e.g., Tephra2), while others can simulate hazards at regional or global scales (e.g., Fall3D, Ash3D, HYSPLIT).

These considerations can be synthesised into a broader framework that links model selection to volcano type and modelling purpose. For example, Mount Etna (Italy) is a frequently active basaltic system where key volcanic phenomena include ashfall, lava flows, and VBP (Branca and Carlo, 2005; Andronico et al., 2021). Mount Etna benefits from a wealth of observational data for these phenomena (e.g., Barberi et al., 1993; Behncke et al., 2005; Andronico et al., 2009; Costa et al., 2023), enabling the use of more complex models with numerous input parameters. However, because these frequently active systems often require rapid, short-term forecasts, lower-CPU models that can deliver more timely outputs are often more practical in operational contexts.

In contrast, Taupō volcano (Aotearoa New Zealand) is a large rhyolitic caldera system with a history of widespread ashfall and PDCs (Wilson, 1985; Wilson et al., 2006). Taupō volcano erupts infrequently but with high impact, and has no observational eruption data and high epistemic uncertainty (Barker et al., 2020). In such cases, models with fewer input parameters may be preferred to minimise user assumptions, while higher-CPU models that simulate over larger spatial domains or include more detailed processes are feasible due to the longer timescales between unrest and eruption (Phillipson et al., 2013; Sandri et al., 2017).

7. Discussion

This review of computational volcanic hazard models situates volcanic hazard modelling within the broader context of environmental modelling, where challenges such as model complexity, input parameter uncertainty, and model selection are well recognised — particularly in fields such as hydrology (e.g., Butts et al., 2004; Li et al., 2015; Guthke, 2017; Paul et al., 2021) and ecology (e.g., Tredennick et al., 2021; Riva et al., 2023; Malmborg et al., 2024;?). Like these disciplines, volcanic hazard modelling often requires balancing physical realism with computational resources and limited data. To help address these challenges, this review introduces a volcanic hazard model ontology that captures key components of model structure, function, and application. This ontology is described in detail below (Section 7.1). This review also supports the application and future development of volcanic hazard models for a diverse set of end-users, across forecasting timescales — long-term, short-term and near-real-time.

7.1. Volcanic hazard model ontology

In the context of volcanic hazard modelling, ontologies enable consistency in model descriptors, which is essential for transparent comparison and evaluation of different models, as well as improving interpretability, comprehension, and ultimately, trust in modelling outcomes (Broniatowski, 2021). In other environmental disciplines, this is accomplished through model ontologies. These often consist of terminologies (nodes) connected through a semantic network (via relationship links). Top-level nodes represent fundamental processes and assumptions in the domain, while sub-level nodes capture more specialised entities and terms (Myer, 2018). Example model ontologies exist for systems biology (Lambrix, 2004), medicine (Haendel et al., 2018; Ong et al., 2020), tsunami research (Ramar and Mirnalinee, 2012; Babič et al., 2022), and landslide susceptibility (Jackson et al., 2008; Jung and Chung, 2015).

In volcanology, ontologies have been used to describe geologic features and processes (e.g., Mcguinness et al., 2006; Pulido et al., 2009; Fauziati and Watannabe, 2010; Myer, 2018), but existing frameworks do not yet incorporate components related to volcanic hazard models.

We present here a volcanic hazard model ontology (Fig. 2) that connects volcanic processes with modelling components, to facilitate effective model comparison and meaningful knowledge sharing.

This ontology was produced by systematically identifying and documenting key features across multiple volcanic hazard models and incorporates the key features from Sections Section 2,3,5. An example of how different model users may engage with this ontology is illustrated in the table within Fig. 2, which outlines the relative relevance of key model components, such as conceptual models, model type (i.e., empirical or numerical), model approach (i.e., deterministic or probabilistic), input parameter data, and model outputs, for geologists, forecasters/modellers, and emergency managers.

An example of model representation with this ontology is an atmospheric dispersal and deposition model, Tephra2, and a flow model, LAHARZ (Fig. 3). Tephra2 is a deterministic, Eulerian, two-dimensional model that employs numerical methods. The model requires tuning parameters, such as the number of column integration steps (i.e., the number of levels in the eruption plume) (Connor et al., 2008) - and physical data, such as ESPs (e.g., plume height, total grain size distribution, and particle density). These input parameters can inform the conceptual model, while the conceptual model, in turn, guides parameter selection. As discussed in Section 5, the Tephra2 conceptual and computational models have undergone verification and validation, while their input parameters and outputs have been calibrated (e.g., Table 4, 1992 Cerro Negro, Nicaragua; Connor et al., 2011) and benchmarked (e.g., 2000 Hekla, Iceland; Hoskuldsson et al., 2007).

In comparison, LAHARZ is a probabilistic, Eulerian, one-dimensional model that employs an empirical relationship. The model primarily requires physical data, including a digital elevation model, flow volume, and channel geometry (i.e., height and length). The LAHARZ conceptual and computational models have also undergone verification and validation, and their input parameters have been calibrated (Iverson et al., 1998; Oramas-Dorta et al., 2012). However, unlike Tephra2, LAHARZ has not been subject to benchmarking exercises.

7.2. Limitations

One key gap is the lack of benchmarking studies for volcanic hazard models. Among the different types of model evaluation identified in this review, benchmarking was the least frequently documented. Despite an exhaustive literature review, few studies directly compare model outputs under standardised conditions. Notably, there have been no benchmarking exercises for volcanic ballistic projectile models. Another limitation found in the literature is that some models have not been explicitly calibrated against observational data, making their reliability in forecasting contexts uncertain. For forecasting applications, particularly those involving atmospheric dispersion and tephra deposition, more benchmarking efforts are essential. This is because both eruptive and atmospheric conditions exhibit far greater variability than the relatively static terrain parameters involved in volcanic flow modelling.

In addressing model uncertainty, a proposed approach in forecasting is to constrain input parameter values using databases of ESPs from past eruptions (e.g., Mastin et al., 2009; Aubry et al., 2021; Deligne, 2021; Ogburn, 2025; Paine and Wadsworth, 2025). This method has been primarily applied in tephra dispersal and deposition modelling (e.g., Bonadonna et al., 2011, 2013). However, there are currently no open-source databases specifically designed for VBP, although initiatives such as the LaMEVE database have aimed to provide global eruption records that could support their future development (e.g., Crosweller et al., 2012). In theory, such databases could enhance forecast accuracy by offering historically informed input parameter estimates. However, it remains unclear whether this strategy meaningfully improves predictive capability, as volcanic eruptions are highly variable and may deviate significantly from a volcano's past behaviour (Whitehead and Bebbington, 2021). Testing is needed to evaluate whether database-informed input parameters actually improve forecasting accuracy.

Given these limitations and uncertainties, sensitivity analysis plays a crucial role in model selection and refinement. Sensitivity studies help identify which input parameters most influence model output variance, enabling users to focus efforts on characterising the most impactful sources of uncertainty (e.g., Stevens et al., 2003; Scollo et al., 2008b; Bilotta et al., 2012; Devenish et al., 2012; Osman et al., 2020; Scott et al., 2025). This information is particularly valuable in operational settings, where reducing the dimensionality of input parameter space without sacrificing accuracy can make probabilistic forecasting more computationally feasible and actionable.

8. Conclusion

By evaluating model construction principles and synthesising insights from existing model approaches, this research contributes to a more systematic and transparent approach to volcanic hazard modelling. This research explores the classification, development, testing, and complexity of volcanic hazard models, with a particular focus on their application in forecasting. It highlights the need to balance model complexity, computational efficiency, and accuracy while acknowledging the uncertainties inherent in both input parameters and model processes. Model construction and selection must consider not only data availability but also the intended application, whether for syn-eruptive forecasting or long-term hazard assessments.

This manuscript adopts a qualitative lens to discuss model complexity, reflecting the diverse ways complexity manifests in volcanic hazard models. While many quantitative metrics exist, such as spatio-temporal resolution, model dimensionality, and the number of input parameters, none fully capture the multifaceted nature of complexity. Future research should explore integrating these quantitative measures with qualitative insights to develop more comprehensive complexity assessments.

A key finding is the importance of models that are detailed enough to provide meaningful simulations yet simple enough to minimise error.

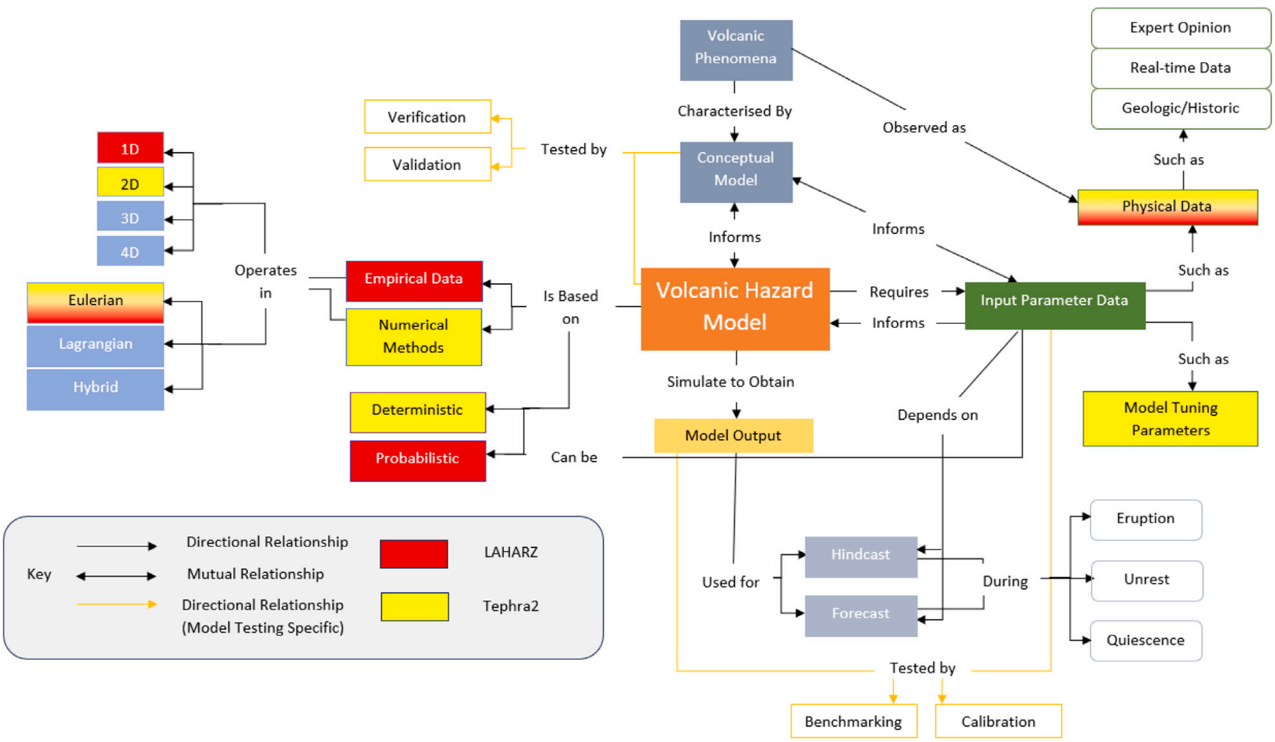


Fig. 3. Volcanic hazard model ontology with two volcanic hazard model examples — Tephra2 (highlighted yellow) and LAHARZ (red).

The structured framework for model selection proposed in this research enables an objective selection method, based on the suitability of volcanic hazard models for different objectives.

This review is limited to forward modelling. Other approaches, including inverse modelling and model falsification, fall outside the scope of this work. However, they offer valuable methods for improving model development and testing, and should be explored in future studies (e.g., Bevilacqua et al., 2019).

CRediT authorship contribution statement

Emmy Scott: Writing – original draft, Investigation, Conceptualization. **Melody Whitehead:** Writing – review & editing, Conceptualization. **Jonathan Procter:** Writing – review & editing, Conceptualization.

Computer code availability

No software/code was developed or used in this paper.

Declaration of competing interest

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

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Data availability

No data was used for the research described in the article.

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