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SIMULATION OF CATASTROPHIC VOLCANIC DEBRIS AVALANCHES FROM SOURCE TO IMPACT

A THESIS PRESENTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF
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Abstract

Volcanic debris avalanches are rapid, complex gravitational flows triggered by the collapse of unstable portions of volcanic edifices. Their significance as a major volcanic hazard was only fully recognised after the 1980 Mount St. Helens eruption, in which a cryptodome emplacement triggered a catastrophic flank collapse (2.5 km^3) and a large lateral blast. Real-time observations and eyewitness accounts from this event greatly advanced understanding of large-volume debris avalanche processes (Glicken, 1996). Subsequent research has focused on better characterising these processes and improving hazard predictions.

These collapses represent destructive phases within a volcano's lifecycle and depend on factors such as edifice morphology, eruptive activity, and external conditions, including rainfall or earthquakes. Some volcanoes, such as Mount Taranaki (New Zealand), show recurrent collapse behaviour (Zernack, 2021). Although their frequency varies, debris avalanches can be highly destructive, as they can exhibit very large volumes, extreme mobility, and high velocities. Such mobility is commonly enhanced by the incorporation of water and sediment, which alters the flow rheology from dry frictional to fluidised, as seen in the 1998 Casita collapse (Nicaragua), where a small volume ($200,000 \text{ m}^3$) failure rapidly transformed into a deadly lahar, resulting in 2,500 fatalities. Events of this magnitude occur worldwide every few years, underscoring their persistent threat to nearby populations and infrastructure (Siebert, 1992; McGuire, 1996).

Debris avalanches are inherently multi-stage phenomena, comprising pre-failure, failure, and post-failure phases (van Asch et al., 2007). Each stage involves distinct processes, from quasi-static deformation to fully dynamic flow, complicating robust hazard estimation. Most attempts to model debris avalanches (del Potro et al., 2013; Ball et al., 2018; Reid et al., 2010; Procter et al., 2021) focus on simulating a single stage, treating it independently from the others. Failure is usually assessed with slope-stability analyses, from limit-equilibrium methods (LEM) to continuum-mechanics approaches, based on material properties, pore pressures, and slope geometry (e.g., Gu et al., 2015; Acevedo et al., 2021; Ji et al., 2025). Post-failure dynamics is commonly modelled with depth-averaged approaches (e.g., Sheridan et al., 2010; Mead and Magill, 2017; Charbonnier et al., 2015; Ding et al., 2023; Wolff et al., 2025), ranging from single-phase models treating the avalanche as a homogeneous mass to multi-phase models capturing solid-fluid interactions. Attempts to couple these stages remain limited, and comprehensive physics-based simulations are rare, often relying on empirical simplifications or producing semi-quantitative outputs (e.g., Mergili et al., 2012; Horton et al., 2013).

The central hypothesis of this thesis is that accurate debris avalanche predictions require modelling of the entire multi-stage process, since assumptions made in one stage can strongly

influence subsequent stages. To address this, the thesis develops an integrated approach combining slope-stability analysis with depth-averaged flow modelling, aiming to improve the quantification of debris avalanche hazard, demonstrated and validated using the well-documented 2012 Te Maari debris avalanche in New Zealand.

Finite-element modelling of the pre-failure conditions at Te Maari indicates that hydrothermal alteration and elevated pore pressures are the primary drivers of the collapse. The interaction of these conditions also reveals the potential for progressive failure, involving two sliding blocks. Overall, the results show that failure predictions require detailed evaluation of pre-failure conditions, including well-constrained mechanical properties and groundwater distribution.

Post-failure flow dynamics are examined using the depth-averaged, two-phase model D-Claw to assess the influence of initial parameters on flow mobility. Assessing the post-failure stage is a crucial step in landslide risk analysis, as it helps delineate areas potentially impacted by the event. Simulations reveal that the internal permeability regime strongly controls runout through its effect on excess pore pressure build-up. The results also highlight the influence of topographic confinement on energy dissipation and flow behaviour, as well as the occurrence of equifinality, where different parameter combinations can produce similar inundation extents. For Te Maari, both low- and high-permeability combinations reproduced the observed runout, indicating that flow behaviour is not dominated by a single parameter but emerges from the complex interaction of multiple factors.

Building on these findings, a coupled, physically-based approach integrating LEM slope-stability analyses with depth-averaged flow modelling is developed and validated against observations from Te Maari to quantify spatial probabilities of flow inundation. Results show that the framework can effectively reproduce the complex, channelised Te Maari flow, with several simulations achieving high performance scores. A Factor of Safety (FOS)-based weighting function converts deterministic stability outputs into relative failure probabilities, accounting for uncertainty in the most likely slip surface. Exceedance maps derived from this approach better delineate observed hazard zones, demonstrating improved hazard prediction. The transferability of this approach is also demonstrated using the Ruapehu case study, illustrating its applicability to a distinct volcanic environment and over a larger spatial extent. By encompassing a broader range of potential failures and reducing dependence on past events, this application represents an important advance towards probabilistic volcanic debris avalanche hazard assessment.

Together, these results demonstrate that integrating pre-failure assessment, failure mechanics, and post-failure flow modelling provides a robust framework for understanding and predicting debris avalanche behaviour. The approach reproduces observed events with high fidelity and captures key uncertainties and interactions that govern avalanche dynamics. While the framework represents a major advance towards probabilistic volcanic landslide hazard assessment, several avenues remain for future research. These include exploring more parameter variability, implementing more sophisticated FOS-based weighting schemes, reducing computational demands for large-scale or multi-scenario assessments, and incorporating additional impact metrics such as flow velocity or dynamic pressure. Pursuing these directions will further enhance the predictive capability of the framework and its applicability for risk mitigation and planning in diverse volcanic contexts.

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Chapter 1

Introduction

This chapter provides an overview of the research field and its broader implications. It presents the hazards and impacts associated with debris avalanches, as well as the challenges involved in forecasting these events. By highlighting existing gaps, it clearly states the research motivations and presents the objectives and aims guiding this thesis. The chapter concludes with an outline of the content and structure of each subsequent chapter.

1.1 Introduction to volcanic debris avalanches

Volcanic debris avalanches are very rapid, complex mass movements triggered by the collapse of unstable sections of volcanic edifices. The volume associated with these events is usually on the order of km^3 , forming debris layers tens of metres thick (Siebert et al., 1987) across vast areas, such as the infamous Mount St. Helens debris avalanche in 1980 where 2.5 km^3 of material travelled up to 28 km from source (Glicken, 1996; Sousa and Voight, 1995). During transport, debris avalanches can fluidise and transition into debris flow through the incorporation of water and sediment. These transformations in flow behaviour significantly increase their mobility and runout distance (Hutter et al., 1994; Iverson, 1997). Consequently, debris avalanches pose a serious danger to populations and infrastructure both near and distal to volcanoes, due to their destructive capacity, large volume, and potential to evolve into more mobile flows.

1.2 Hazards and impacts of debris avalanches

Debris avalanches are a frequent hazard on stratovolcanoes, occurring as part of the natural lifecycle of volcanic edifices that includes periods of growth and catastrophic collapse (Roverato et al., 2021; Zernack, 2021). To date, nearly a thousand volcanic debris avalanches have been identified across approximately 600 volcanoes, each characterised by distinct failure types and emplacement styles (Siebert and Roverato, 2021). The frequency of these events varies significantly between volcanoes, influenced by factors such as their shape, eruptive activity and external conditions (e.g, rainfall, glaciers). For instance, Mount Taranaki in New Zealand has experienced an average of one debris avalanche every 5,000 years over the past 25,000 years (Zernack, 2021), while Mount St Augustine in the USA has seen one every 150-200 years over the past 2,000 years (Siebert and Roverato, 2021).

Despite the variability in occurrence, the consequences of debris avalanches can be severe and are difficult to forecast. Over the past five centuries, these events have claimed approximately 30,000 lives worldwide (Siebert and Roverato, 2021). The deadliest recorded event was the collapse of the Mayu-yama lava dome on Mount Unzen in 1792, which resulted in a 0.34 km^3 debris avalanche that slid into the sea, inducing a tsunami that swept through the most populated part of Shimabara City and Bay, killing more than 15,000 people (Sassa et al., 2016). Smaller, more frequent events can also have dramatic impacts, as demonstrated by the 1998 collapse at Casita Volcano in Nicaragua. During Hurricane Mitch, heavy rainfall triggered



Figure 1.1: Aerial photograph showing the lahar inundation zone from the 1998 collapse at Casita Volcano, Nicaragua, spanning 18 km north-south. Image courtesy of the USGS Open Sky Program.

the failure of a hydrothermally altered cliff, releasing around $200,000 \text{ m}^3$ of debris that rapidly transformed into a lahar. Flowing at approximately 40 m/s (Kerle and van Wyk de Vries, 2001), the lahars submerged the towns of El Porvenir and Rolando, killing nearly 2,500 people (Fig. 1.1). Events of this scale occur globally every few years, underscoring the persistent threat they pose to nearby populations and infrastructure (Siebert, 1992; McGuire, 1996).

The economic impact of these events can also be substantial; for example, the recent (2010) Mount Meager debris avalanche in Canada cost approximately CAD \$ 10 million (McDougall and Hungr, 2005). Given the frequency and potential severity of these events, advancing our understanding of their triggers, frequency, and flow dynamics is essential for mitigating future hazards.

1.3 Forecasting volcanic debris avalanche

This PhD research focuses on developing and applying numerical tools to forecast and mitigate future avalanche hazards. The mechanics of debris avalanches can be divided into three general stages (van Asch et al., 2007):

1. The pre-failure stage encompasses the progressive weakening and deformation of the edifice, driven by both volcanic and exogenous factors. Volcanic processes include hydrothermal activity, seismic events, and magmatic intrusions, while exogenous processes involve weathering, climate events, water saturation, and pore pressure changes.
2. The failure stage involves the detachment of a specific volume of material from the volcano, often developing a shear surface and resulting in geomorphic changes such as a scar.
3. The post-failure stage involves the flow of the failed mass down the slope, altering the landscape to its final point of impact.

Numerical modelling is a critical tool for investigating the physics and impacts of these stages (e.g., initiation, runout, and impacts). Most models addressing the failure stage rely on one of two deterministic approaches: the limit-equilibrium method (LEM) (Bishop, 1955; Morgenstern and Price, 1965; Spencer, 1967; Janbu, 1973) or finite element method (FEM) (Brown and King, 1966; Dunlop and Duncan, 1970; Wright et al., 1973; Giam and Donald, 1988; Huang and Yamasaki, 1993; Zou et al., 1995). Both approaches evaluate slope stability by quantifying the system resistance to failure (Reid, 2004). LEM provides a straightforward calculation under assumed rigid slope behaviour, but does not account for deformation or stress redistribution. In contrast, FEM discretises the slope into interconnected elements to capture stress-strain responses, progressive failure, and potential shear band development. FEM also enables dynamic analyses under seismic loading, incorporating ground motion data to simulate transient slope behaviour and identify potential failure surfaces. Both methods require accurate input parameters, including slope geometry, boundary conditions, material strength properties, and groundwater conditions (Duncan, 1996).

Material properties are particularly critical, as they determine the selection of the most suitable failure criterion, a key aspect since there is no universally applicable method to characterise the material response to stress and strain (Ahmed et al., 2022). The widely used Mohr-Coulomb criterion assumes linear elastic behaviour (Griffiths, 1990; Yu, 2002; Labuz and

Zang, 2012), but other criteria account for more complex behaviours. For instance, the Generalised Hoek-Brown (GHB) criterion considers macroscopic-scale discontinuities and surface conditions specific to rock masses, providing a more nuanced representation of stress-strain relationships in heterogeneous materials (Hoek and Brown, 1980; Hoek et al., 2002; Hoek, 2005). Groundwater parameters are also crucial for both the failure and post-failure stage, as pore pressure can reduce material strength, initiate fluidisation, and alter flow rheology (Voight and Elsworth, 2000; Ball et al., 2018). Accurate characterisation of these parameters is essential, as they strongly influence the initial pre-failure state and subsequent flow dynamics. The post-failure stage can be characterised through physical flow models (Denlinger and Iverson, 2001; Procter et al., 2021). Over the past two decades, numerous models (Pitman and Le, 2005; Pudasaini, 2012; Mergili et al., 2017; Iverson and George, 2014; Pudasaini and Mergili, 2019) have been developed, primarily based on hydrodynamic continuum mechanics. These models typically employ depth-averaged shallow flow equations that have been adapted to simulate gravitational flows (Savage and Hutter, 1989). Early models employed single-phase approaches based on the Mohr-Coulomb criterion (Salm, 1993; Pitman et al., 2003), while more recent models incorporate fluid-solid interactions (Pitman and Le, 2005; Pudasaini, 2012; Iverson and George, 2014; Mergili et al., 2017; Pudasaini and Mergili, 2019). Increasingly sophisticated flow models, such as D-Claw (Iverson and George, 2014), simulate complex flow behaviour by incorporating the dynamic evolution of apparent rheology, which is critical for explaining flow behaviour transitions.

In hazard assessments, these flow models provide reliable predictions of flow thickness, extent, and impact areas, thereby enhancing risk mitigation strategies.

1.4 Challenges in forecasting debris avalanches.

Despite advancements in numerical modelling techniques, especially in identifying many of the key variables and elementary mechanisms, significant challenges remain in accurately simulating debris avalanche dynamics. Limitations arise not only from uncertainties in input parameters but also from the inherent assumptions embedded within the models. Understanding these constraints is crucial for refining predictive capabilities and enhancing the reliability of hazard assessments. This section discusses the primary limitations and challenges associated with modelling debris avalanches:

(1) Complexity of modelling due to the multi-stage characteristic of a debris avalanche:

Developing an accurate mathematical model describing debris avalanches behaviour is challenging due to the complex, four-dimensional nature (space and time) of slope movements. The three stages of a debris avalanche occur over disparate timescales (Fig. 1.2, van Asch et al. 2007) and are driven by distinct physical processes, which make them difficult to combine. The majority of published models (Heinrich et al., 2001; Revellino et al., 2004; del Potro et al., 2013; Ball et al., 2018; Reid et al., 2010; Procter et al., 2021) concentrate on either the failure or post-failure stages of debris avalanches. This compartmentalised approach simplifies the modelling framework but neglects key interdependencies between stages, potentially leading to inaccuracies in the prediction of flow dynamics and runout distances.

The initiation or pre-failure stage is a critical component that is often under-represented in hazard assessment. This phase may span months to millennia, involving slow, progressive changes such as pore pressure build-up, gradual slope weakening, or structural degradation. Accurately capturing these temporal changes is essential, as they establish the initial conditions that drive subsequent failure dynamics. These changes influence the failure mode, source volume, and location of volcanic debris avalanches (i.e, landslide susceptibility). A comprehensive modelling approach would account for the evolution of the destabilising factors (e.g., pore pressure) during the pre-failure stage, linking them to the rapid acceleration observed at failure onset. The failure stage occurs over much shorter timescales, milliseconds to seconds. It is associated with a transient change (van Asch et al., 2007; Crozier, 1986; Leroueil, 2001) such as a change in pore pressure decreasing effective strength in the case of a rainfall-triggered landslide. If the pre-failure conditions are not adequately defined, the initial parameters for the failure stage may be unrealistic, leading to discrepancies in the simulated flow behaviour. Following failure, the post-failure movement can last minutes to weeks and concentrates most of the deformation and displacement of the mass (Fig. 1.2, van Asch et al. 2007). Models that simulate this phase typically employ rheological frameworks (e.g., Bingham fluid, Voellmy rheology) to capture flow behaviour. However, a model that isolates the post-failure phase without adequately accounting for initiation and failure dynamics may produce unrealistic deposition patterns, runout distances, or flow velocities (Reid et al., 2000). Many authors (Reid et al., 2001; Ball et al., 2018; Kereszturi et al., 2021) suggest approaches to couple the failure and

post-failure stages, but there are few attempts to simulate the entire process (Mergili et al., 2012; Horton et al., 2013; Mergili et al., 2019; Horton et al., 2024), and no published studies validating a combined physically-based modelling approach. Approaches attempting to integrate statistical susceptibility analyses with physically based runout modelling have emerged only recently (Horton et al., 2024), reflecting a growing interest in linking initiation and post-failure processes (e.g., Goetz et al., 2021; Mergili et al., 2019). For instance, Mergili et al. (2019) explored two different techniques to statistically couple release and runout components, each presenting challenges such as over-smoothing of susceptibility patterns and difficulties in deriving consistent spatial probabilities due to overlapping flow trajectories (Horton et al., 2024). Addressing these limitations presents a significant opportunity for further research, particularly in developing approaches that capture both transient and steady-state dynamics throughout the entire sequence of debris avalanche processes.

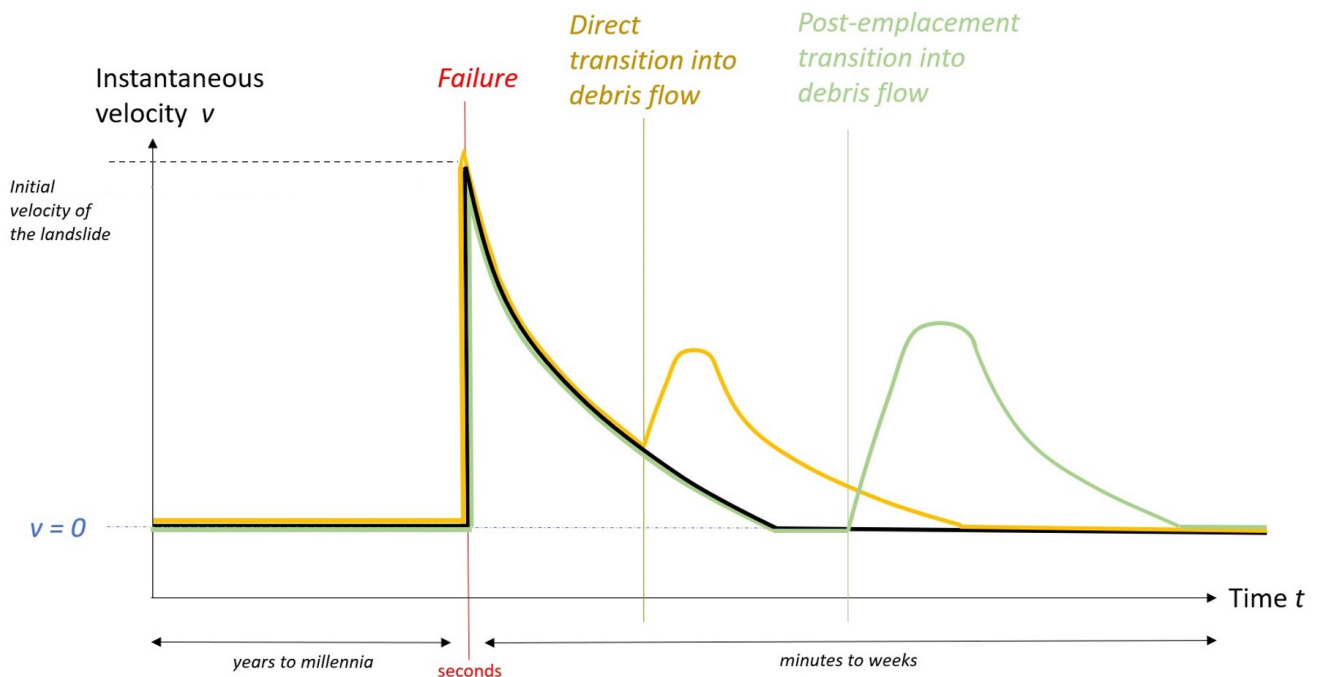


Figure 1.2: Graphical diagram of landslide velocity over time (after van Asch et al., 2007). Failure (red line) is instantaneous and initiates the mass movement. Black scenario: dry debris avalanche; Yellow scenario: debris avalanche transforming into a debris flow directly during emplacement; Green scenario: post-emplacement reworking of the deposit. Timescales of each phase are presented on the diagram: years to millennia for the pre-failure phase; seconds for the failure phase; minutes to weeks for the post-failure phase. Zero velocity is assumed for the pre-failure phase, but very small displacements may occur.

(2) Uncertainty of input parameters:

The accuracy of input parameters significantly conditions the viability of simulations for each phase of volcanic debris avalanche. However, the difficulty in determining these parameters presents uncertainties that can be categorised as epistemic (arising from incomplete knowledge) or aleatory (arising from natural variability). In the context of composite volcanoes, consisting of multiple layers of varying composition and properties (e.g., solidified lava, tephra, hydrothermally altered materials, and highly weathered deposits; Gonzales et al., 2014; Ball et al., 2018), accurately defining the mechanical behaviour of these materials complicates stability analysis.

For instance, the assumption of perfectly elastic behaviour may apply to solidified lavas but is less applicable to altered deposits that are more ductile due to the presence of clay minerals (Barden, 1972). In such cases, plastic behaviour must also be considered, allowing deformation within the rock mass before collapse (Heap et al., 2021). The rheological response of these heterogeneous materials can substantially affect flow initiation and its subsequent dynamics, with initial velocity and mobility being particularly sensitive to source material properties. The influence of material properties is notably evident at Mount Taranaki, where high clay content in the avalanche material has been linked to increased flow mobility and transformation into cohesive debris flows over travel distance (Neall, 1976; Parfitt et al., 1981; Alloway et al., 2005; Breien et al., 2008; Procter et al., 2009; Roverato et al., 2015). This is further exacerbated by water saturation, especially in humid climates (Carrasco-Núñez et al., 1993; Capra et al., 2002; Capra, 2006; Roverato et al., 2011, 2021). Additionally, the failure mechanics themselves introduce further uncertainty: while many models assume a single collapse event, the possibility of successive collapses has been observed, such as in the 1980 Mount St. Helens eruption (Glicken, 1996). This emphasises the critical role of rupture mechanics (single or multi-phase) in influencing flow dynamics, effectively accumulating multiple sources of uncertainty that propagate throughout the analysis.

(3) Variability in debris avalanche behaviour

The behaviour of debris avalanches is influenced by the nature of the source material, the failure triggers, and the interactions with external factors such as erosion, hydrology, and sediment entrainment. This variability complicates the prediction of avalanche motion and runout, as it prevents the establishment of universal constitutive laws governing the mechanical behaviour of such flows (Pastor and Crosta, 2012; McDougall, 2017).

Flow interactions with the surrounding environment, such as the incorporation of sediment

or water from lakes, rivers, or glaciers, can result in transitions to more mobile flows. Similarly, initiation conditions, such as water saturation (particularly in areas with high rainfall or hydrothermal systems), can promote initial liquefaction and rapid acceleration of the failed mass. These processes are complex to model, and many unknown remains regarding flow dynamics comprehension. Numerous theories have been proposed to explain these behaviours, such as the effect of pore pressure (Iverson, 1997; Hungr and Evans, 2004; Evans et al., 2007; Iverson et al., 2011), lubrication by snow or ice (Evans, 1988; Delaney and Evans, 2014), fluidisation by air, steam (Kent, 1966; Manzanal et al., 2016), or frictional weakening by rapid heating (Lucas et al., 2014).

While advanced flow models, such as *r.avaflow* (Mergili et al., 2017) or *D-Claw* (Iverson and George, 2014), are designed to capture some aspect of these flow transitions and complex processes, they also require an increased number of input parameters, effectively increasing epistemic uncertainty. Consequently, the accumulation of uncertainty in input parameters can propagate throughout the analysis, potentially offsetting any gains in predictive accuracy achieved through more sophisticated models (Mead et al., 2021).

1.5 Thesis aims and objectives

The aim of this thesis is to improve the accuracy of debris avalanche simulations and hazard assessment by accounting for the entire multi-stage process, as assumptions made in a preceding stage can greatly influence the subsequent stages. To achieve this, we develop a new modelling approach that assesses slope stability, identifies the failure mechanisms, and characterises the transition from static to dynamic states, while incorporating potential rheological changes during flow. This aim will be pursued through three specific research objectives, outlined as follows:

Objective 1: Influence of pre-failure conditions on the failure mechanics.

Pre-failure conditions set the stage for volcanic destabilisation, and together with triggering factors, govern the failure mechanics and timing. Understanding these initial conditions is therefore essential as they constitute the starting point of a debris avalanche sequence. This objective was assessed using the recent debris avalanche at Te Maari (Procter et al., 2014) as a case study to examine these processes in a hydrothermal setting. By parametrising key mechanical, groundwater, and seismic variables, we assess slope sensitivity through finite-element

slope stability analysis. This approach refines our understanding of the pre-failure and failure processes at Te Maari and provides broader insights into how complex hydrothermal and environmental interactions influence slope stability.

Objective 2: Impact of flow initiation on runout behaviour.

Debris avalanche mobility and runout are strongly influenced by dynamic transitions governed by factors such as material properties, slope geometry, entrainment, and water saturation. Advanced numerical models attempt to reproduce these transitions by introducing additional parameters, which can increase uncertainties (Mead et al., 2021). Understanding how initial flow parameters influence flow behaviour is therefore essential for improving simulation accuracy and model performance. This objective was assessed by building on the Te Maari case study, using the depth-averaged, multiphase numerical model D-Claw to examine the effect of key initial material properties (intrinsic permeability, compressibility, and dilatancy) on the mechanical response of the avalanche at initiation and throughout its transformation into a debris flow (Procter et al., 2014). This approach helps identify the optimal combination of initial parameters that best replicates the observed flow runout at Te Maari and determines which initial properties most significantly govern debris flow mobility in laterally confined settings.

Objective 3: Develop a probabilistic hazard assessment framework for debris avalanches that integrates both failure and post-failure processes.

Mass flow models offer a powerful framework for assessing debris avalanche hazards, as they can capture the spatial and temporal variations in avalanche intensity (e.g., depths, velocities) along the entire flow path (Dai et al., 2002; Hürlimann et al., 2008). However, the simulated runout behaviour is highly sensitive to the accuracy of input parameters, such as the initial volume and location of the mass (Mergili et al., 2018b). Defining the initial conditions is therefore a crucial step for debris-avalanche hazard assessment. This challenge can be addressed by coupling slope-failure models with post-failure models. We proposed a coupled approach combining limit-equilibrium slope stability analysis with depth-averaged flow simulations, propagating uncertainties in failure characteristics (e.g., location, volume, slip direction). By linking failure modelling with flow modelling, we aim to improve debris avalanche hazard assessment.

1.6 Thesis outline

This PhD thesis is divided into seven chapters as follows:

Chapter 1: Introduction

The thesis starts with this introductory chapter that outlines the research field and its associated challenges. It presents the motivations for the study and clearly defines the aims and objectives guiding the project.

Chapter 2: Literature Review

This chapter provides a comprehensive review of research on volcanic debris avalanches. It covers their historical context, sedimentary characteristics, and the key processes underlying the three-stage mechanics of debris avalanches. The chapter also discusses the main experimental and numerical approaches used to replicate debris avalanche behaviour.

Chapter 3: Methodological framework

This chapter presents the methodological framework used to investigate debris avalanche processes, with a detailed focus on numerical modelling approaches. It outlines the methods applied in this study and reviews the principal numerical approaches developed to simulate debris avalanche behaviour. Relevant examples from the literature are included to highlight the strengths, limitations, and applications of these methods, situating the present research within the broader methodological context.

Chapter 4: Simulation of the 2012 Te Maari debris avalanche: insight into the failure mechanics and the role of the hydrothermal system.

Chapter 4 (Vicente et al., 2025) addresses Objective 1 using the 2012 debris avalanche at Te Maari as a case study, where 700,000 m³ of hydrothermally altered material collapsed. The study develops a failure model that incorporates the hydrothermal influence at Te Maari, applying finite-element modelling to assess the slope's sensitivity to mechanical, groundwater, and seismic scenarios. The findings indicate that a modest pore pressure increase (~ 200 kPa), potentially driven by upward infiltration within hydrothermally altered rocks, was sufficient to destabilise the slope, triggering a multi-stage failure involving the sequential sliding of two

distinct blocks.

Chapter 5: Modelling the impact of initiation parameters on the dynamics of the 2012 Te Maari laterally-confined debris avalanche.

Chapter 5 (Vicente and Mead, 2025) continues with the Te Maari case study, addressing Objective 2 by employing the depth-averaged, multiphase model D-Claw to assess how intrinsic permeability, dilatancy, and compressibility influence flow mobility and runout distances. A linear regression analysis based on these flow simulations reveals that flow mobility is primarily controlled by intrinsic permeability, compressibility, and dilatancy, together driving excess pore pressure generation and persistence. The findings also show that distinct sets of initial parameters can produce similar mobility outcomes.

Chapter 6: Coupled limit equilibrium/depth-averaged approach for debris flow hazard assessment: the 2012 Te Maari avalanche

Chapter 6 addresses Objective 3 by integrating LEM-derived failure characteristics (e.g., geometry, volume of potential collapses) into depth-averaged flow modelling for probabilistic hazard assessment. Thirty source geometries were selected based on observations from the 2012 Te Maari debris avalanche. The coupled approach demonstrated strong ability to back-calculate complex, channelised mass flows, with several simulations achieving performances comparable to values reported in other studies, derived from post-event volumes. The ensemble of scenarios represent the uncertainty in predicting runout extent, largely driven by differences in source surface shape, volume, and alignment. Exceedance probability maps of flow depth (both unweighted and FOS-weighted) highlighted that incorporating the factor of safety (FOS) as a proxy for relative failure probability improves agreement with observed deposits and enhances the robustness of the probabilistic hazard framework.

Chapter 7: Exploring the transferability of the coupled modelling approach: application to Ruapehu

Chapter 7 presents an exploratory application of the coupled LEM/depth-averaged modelling framework to Ruapehu to assess its applicability beyond the 2012 Te Maari debris avalanche case study. The methodology was generalised and applied to 1,024 potential collapse scenarios derived from slope stability analyses of the edifice. The resulting ensemble simulations enabled

the generation of probabilistic exceedance maps at the scale of the entire volcano, providing insight into potential debris avalanche routing and hazard patterns across the southern and western flanks. Results showed that smaller-volume failures remained strongly channelised, whereas larger collapses produced more widespread hazard patterns extending onto the ring plain and downstream catchments. Although discrepancies between simulations and geological evidence highlighted important limitations related to poorly constrained pre-failure conditions and flow parameters, the study demonstrated the potential of the framework to be adapted to larger volcanic systems and emphasised the need for calibration against past events for future hazard assessment applications.

Chapter 8: General discussion and conclusions

In this final chapter, the main findings of the thesis are synthesised and the key challenges associated with physically based debris-avalanche modelling and hazard assessment are discussed. The chapter highlights how the integrated framework developed in this research links slope stability analyses with depth-averaged flow modelling to provide a more physically consistent and probabilistic representation of debris-avalanche hazards. Using the Te Maari case study and the exploratory Ruapehu application, the chapter also discusses the influence of uncertainties in pre-failure conditions and flow parameters on hazard predictions, as well as the limitations and transferability of the framework. Finally, future research directions are outlined to improve uncertainty quantification, calibration, and applicability to other volcanic settings.

Chapter 2

Literature Review

This chapter provides a detailed review of debris avalanche characteristics and the associated physical processes. It begins by outlining the historical context in which debris avalanches were recognised as a major hazard. It then describes their sedimentary features and the key physical processes underlying the three-stage mechanics of debris avalanches. The chapter concludes with an overview of the main experimental and numerical approaches used to simulate debris avalanche behaviour.

2.1 What is a volcanic debris avalanche?

Volcanic debris avalanches are rapid, flow-like landslides involving downslope movements (van Asch et al., 2007) of partially or fully saturated debris on steep volcanic slopes (Hungr and Evans, 2004). In the context of volcanic mass movements, the term ‘debris’ refers to a heterogeneous mixture of volcanoclastic debris, including pyroclastic deposits, tephra, scoria, and lava blocks. The material is texturally diverse, often comprising a mix of sand, gravel, and boulders within a variable matrix of silt and clay.

They are classified as gravitational granular flows, in which particle–particle interactions occur through frictional and/or collisional regimes (Hungr et al., 2014). Compared to other landslides, volcanic debris avalanches exhibit particularly long runouts and extremely high velocities (up to 150 m/s; Siebert et al., 1987; Scott, 2001). For example, video evidence from the 2011 debris avalanche in Seoul (South Korea), captured flow fronts travelling at speeds exceeding 20 m/s (Hungr et al., 2014).

Like other gravitational mass movements, they progress through phases of pre-failure deformation, sudden failure, and post-failure displacement (Skempton and Hutchinson, 1969; van Asch et al., 2007). As they move downslope, their flow characteristics often change. Near the source, motion generally resembles block sliding or dry granular flow, whereas further downslope, the flow becomes increasingly chaotic and fluidised. In distal areas, the entrainment of water and fine sediments can transform the avalanche into a more saturated debris flow, exhibiting complex transitional behaviours (Pierson and Costa, 1987; Scott, 2001). These transitions are strongly influenced by factors such as initial water content, water entrained during runout, and the presence of fine-grained, clay-rich materials (often introduced through hydrothermal alteration or fragmentation during transport). These factors are critical in shaping flow behaviour and determining runout distances (Palmer et al., 1991; Capra et al., 2002; Paguican et al., 2012; Roverato et al., 2015).

2.2 Historical perspective

Among the destructive processes of composite volcanoes, debris avalanches are the most catastrophic, as they can strongly modify the morphology of a volcano and affect the landscape for tens of kilometres beyond the cone itself (Zernack, 2021). The typically hummocky deposits left by such events, often located far from the volcanic source, were initially poorly understood.

Their origin was debated, with some attributing them to volcanic processes such as mudflows or blast deposits, while others linked them to non-volcanic origins like glacial activity (Siebert and Roverato, 2021). As a result, volcanic debris avalanches were only incorporated into volcanic hazard assessment relatively recently.

A pivotal moment in the recognition of these phenomena occurred following the 1980 eruption of Mount St. Helens. The event, observed in real-time and thoroughly documented, provided critical insights into the mechanisms behind lateral collapses and the generation of large-volume debris avalanches (Glicken, 1996). This led to a major shift in volcanology: previous interpretations of deposits around volcanoes were re-examined, revealing that many had been misclassified, often as volcanic mudflows (Roverato and Dufresne, 2021). In light of this understanding, many previous works (Park, 1926; Grange, 1931; Cotton, 1944; Bullard, 1976; Hoyt, 1978; Rampino et al., 1979; Neall, 1979; Cooke, 1981; Macdonald et al., 1983) were re-evaluated.

The 1888 collapse of Ritter Island volcano (Papua New Guinea), which is the largest flank collapse known in historical time, is a notable example of such re-evaluation. Before 13 March 1888, Ritter Island was a conical stratovolcano characterised by steep flanks rising 780 m above sea level. On 13 March 1888, the volcanic edifice underwent a sudden collapse, leaving an arcuate border rising only about 140 m above sea level. This collapse generated a tsunami that travelled over 500 km, with estimated casualties between 500 to 3,000 (Paris et al., 2014). At the time, this event was compared to the dramatic 1883 Krakatau eruption and tsunami. In the absence of clear evidence for a major explosive eruption, Cooke (1981) hypothesised the presence of an unbreached caldera. After a bathymetric survey conducted in 1985, Johnson (1987) recognised the presence of a breached caldera, which was interpreted as a massive collapse of the edifice leading to a subsequent catastrophic volcanic debris avalanche ($4\text{--}5\text{ km}^3$). More recent high-resolution studies have revised the collapse volume downward to $2.4 \pm 0.2\text{ km}^3$ (Watt et al., 2019; Karstens et al., 2019). Karstens et al. (2019) further proposed that the collapse was preconditioned by a combination of long-term deformation (gravitational spreading, see subsection 2.4) and magma intrusions, and likely triggered by a local tectonic or magmatic event.

The Mount St. Helens eruption also inspired comparisons with other volcanoes, such as Bezymianny in Kamchatka. The post-1956-eruption morphology of Bezymianny was closely similar to that of Mount St. Helens (Fig. 2.1), and later studies revealed that both eruptions

followed the same sequence: intrusion of a cryptodome, followed by a catastrophic flank collapse and debris avalanche, and then a lateral blast and Plinian eruption (Siebert and Roverato, 2021). However, before the 1980 event, the Bezymianny deposits were either considered as resulting from the lateral blast (Gorshkov, 1963) or ash flows (Bullard, 1976). Some have also characterised this eruption as Pelean (Macdonald et al., 1983), others as phreatic or steam-blast eruption (Williams and McBirney, 1979).

Similar re-interpretations took place in New Zealand. The western Taranaki conical mounds (Fig. 2.2) were previously considered as the result of volatile explosions within lava flows (Bossard, 1928), while the hummocky topography around Ruapehu was attributed to glacial processes (Park, 1926). Grange (1931) reinterpreted them as volcanic mudflows caused either by the drainage of a crater-lake, volcanic flank collapse, or by exogenous processes such as weathering. Later, Neall (1979) mapped several lahar deposits that were later identified as debris avalanches. He notably identified and described the Pungarehu Formation "as a huge lahar [...] characterised by thousands of mounds", which is now recognised as the largest debris avalanche (7.5 km^3) known at Taranaki.

These examples collectively illustrate the significant impact that the 1980 Mount St. Helens eruption had on the understanding of volcanic debris avalanches. It catalysed a comprehensive re-evaluation of similar deposits worldwide and solidified the role of debris avalanches as a critical component of volcanic hazard assessment.

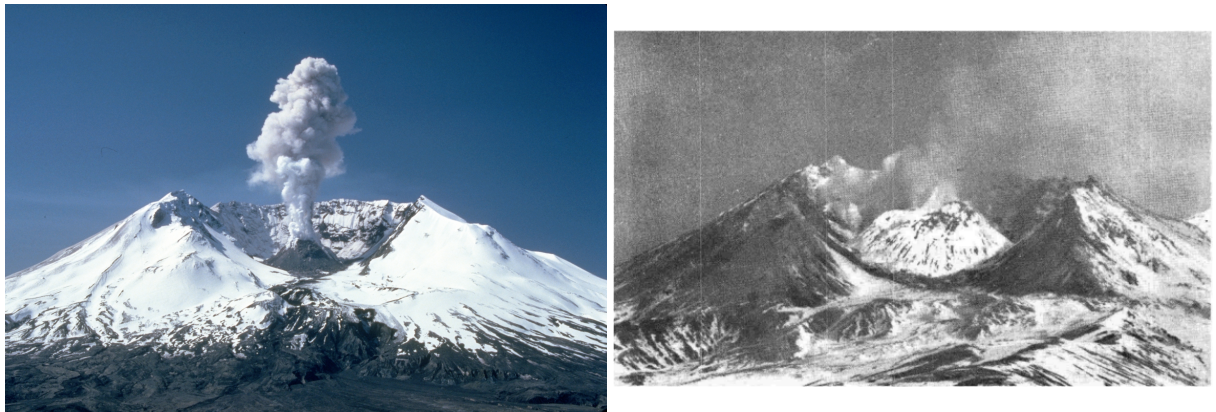


Figure 2.1: Mount St. Helens (May 1982, U.S. Geological Survey, public domain) and Bezymianny (August 1956, photograph by G.S. Gorshkov; from Girina 2013), showing similar horseshoe-shaped collapse scars with active domes. Reproduced with permission from Elsevier.



Figure 2.2: Southwest view of Mount Taranaki, showing hummocky terrain on the ring plain and Pouākai Volcano to the left (from Molloy 1998). Reproduced with permission of the NZSSS.

2.3 Sedimentary and geomorphic features

Because direct observations of volcanic debris avalanches are very rare, most insights into their triggering mechanisms, transport, and emplacement processes come from the sedimentary and geomorphic characteristics preserved in deposits from past events (Paguican et al., 2021; Dufresne et al., 2021).

These deposits can be characterised macroscopically according to their distance from the source. The source area typically features a large, horseshoe-shaped scar that forms a broad incision in the volcanic edifice (Voight et al., 1981; Ui, 1983; Siebert, 1984; Bernard et al., 2021). At the base of this scar and in proximal zones, deposits are characterised by the typical hummocky topography (Fig. 2.2) comprising conical mounds of variable size. In distal zones, these deposits become flatter and more laterally extensive (Ui, 1983; Bernard et al., 2021).

Volcanic debris avalanche deposits are typically unsorted and composed of particles spanning a wide range of sizes (Turnbull et al., 2015). Their internal structure generally includes three main components (Neall, 1979; Ui, 1983; Crandell et al., 1984; Palmer et al., 1991; Glicken, 1996; Alloway et al., 2005; Bernard et al., 2021; Dufresne et al., 2021):

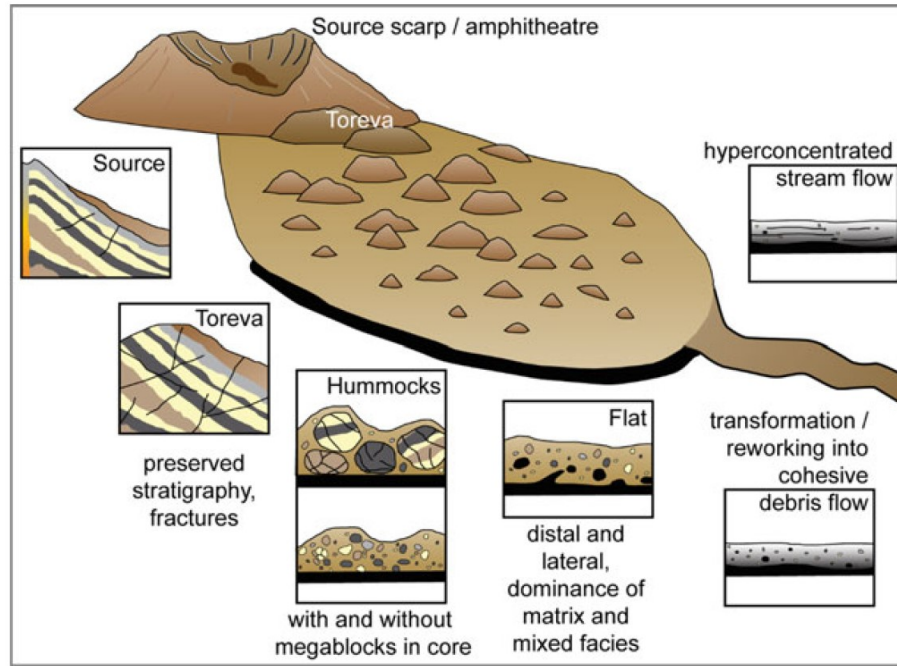


Figure 2.3: Schematic of a volcano and its debris avalanche deposits (from Dufresne et al. 2021). Near the toe of the scar, deposits are dominated by toreva blocks and hummocks, while further from the source they flatten and are mainly matrix- and mixed-facies. Reproduced with permission from Springer Nature.

- Megaclasts: fragments larger than 1 m, often displaying jigsaw cracks (Shreve, 1968; Ui, 1983; Ui et al., 2000), which indicate dilatation without disaggregation of the rock unit (Dufresne et al., 2021).
- Clasts: fragments smaller than 1 m, defined by Palmer et al. (1991) as "all components of the deposit between 2 mm and 1 m maximum size that are bounded by an outer surface and show an internal lithological homogeneity." (Dufresne et al., 2021).
- Matrix: a very fine-grain component consisting of particles ranging in size from clay to coarse sand (Alloway et al., 2005; Ui et al., 2000)

With distance from the source, the number and size of megaclasts decrease, segregating upward and laterally to form levees along the flow margins (Johnson et al., 2012; Iverson, 2014; Turnbull et al., 2015). In contrast, the matrix proportion increases (Ui, 1983; Palmer and Neall, 1991) in the distal flat portions generally considered to be debris flow deposits (Janda et al., 1981; Ui, 1983; Palmer et al., 1991; Scott, 2001; Zernack et al., 2009).

Source characteristics can be preserved in the deposits. In particular, slow-moving rotational blocks called torevas (Reiche, 1937; Voight et al., 1981, 1983; van Wyk De Vries et al., 2001), which mostly remain near the scar toe due to limited transport and disintegration, preserve the

initial stratigraphic state of the source (e.g., Mount St. Helens, Voight et al. 1983; Mt. Shasta, Crandell et al. 1984; Socompa, Wadge et al. 1995).

Deposits may also reflect the nature of the triggering mechanisms. For example, dry debris avalanches generated during magmatic eruptions (Siebert, 1984) often contain juvenile materials and are interlayered with blast and/or pyroclastic flow deposits (Belousov, 1996; Belousov et al., 1999). In contrast, debris avalanches caused by phreatomagmatic eruptions, or high initial water content due to hydrothermal alteration or heavy rainfall, are typically more cohesive. These cohesive deposits have a higher proportion of matrix, with few clasts and megaclasts, and more abundant rip-up clasts (Zernack et al., 2009).

Transport processes are also recorded in these deposits (Paguican et al., 2021). Evidence of entrainment processes, including strong shear features and the incorporation of substrate materials, can be preserved in the deposits, particularly at the basal contact between the deposits and the substrate (e.g., Belousov et al., 1999; Clavero et al., 2002; Keigler et al., 2011; Dufresne et al., 2010). Grain size analyses and microstructural studies can help distinguish between transport mechanisms and reveal how these evolve downslope. For example, the distal matrix-rich facies of the Mount St. Helens deposit reflects disaggregation of debris avalanche blocks and mixing with blast deposits during transport (Glicken, 1996).

One key challenge in hazard assessment is understanding the transition from debris avalanche to debris flow, as this greatly increases the runout potential (Scott et al., 1995; Vallance and Scott, 1997; Capra and Macias, 2000; Kerle and van Wyk de Vries, 2001; Kerle, 2002; Evans et al., 2007; Dufresne et al., 2021). This transition can occur directly during the flow due to high water or clay content (Neall, 1979; Palmer et al., 1991), or post-deposition via remobilisation (Dufresne et al., 2021). In New Zealand, debris avalanches generally transition directly into cohesive debris flows (Neall, 1979; Palmer and Neall, 1991; Palmer et al., 1991; Lecointre et al., 1998; Alloway et al., 2005; Zernack et al., 2009, 2011) due to the fine-grained nature of the source material (e.g., weathered tephra at Taranaki and hydrothermally altered rocks at Ruapehu and Tongariro). These cohesive flows are characterised by a clay-rich matrix (often allophane-rich) and a thin marginal facies, indicating their rapid transformation from avalanche to debris flow (Neall, 1979; Palmer et al., 1991; Zernack et al., 2009, 2011; Procter et al., 2009).

2.4 Stages of volcanic debris avalanche development

The mechanics of a debris avalanche can be broadly divided into three stages (Fig. 2.4, van Asch et al. 2007; Troncone et al. 2025):

1. The pre-failure phase involves the progressive weakening of the volcanic flank. Various factors related or not to volcanic activity (slope morphology, e.g., del Potro and Hürlimann 2008; hydrothermal systems, e.g., Reid et al. 2001; seismic activity, e.g., Rodgers et al. 2015; magmatic intrusion, e.g., Glicken 1996; climatic changes, e.g., Roverato et al. 2011; heavy rainfall, e.g. Kerle and van Wyk de Vries 2001; porosity/permeability, e.g., Ball et al. 2018; water saturation, e.g., Finn et al. 2018; etc.) can contribute to that weakening (Fig. 2.4a). These factors influence the depth and volume of the potential collapse.
2. The failure phase is initiated by a triggering factor (earthquake, volcanic eruption, pore-pressure increase, etc.) and marks the detachment of a mass from the volcanic flank (Fig. 2.4b). This detachment can also cause a rapid pressure drop on the volcanic system and may lead to an eruptive response.
3. The post-failure phase involves the transport and emplacement of the mobilised mass (Fig. 2.4c). It represents the most hazardous phase for surrounding populations and infrastructure.

2.4.1 Pre-failure stage

Volcanic edifice instability arises from a complex interplay of internal and external factors. The degree to which a volcano is affected depends on its structural characteristics, volcanic activity, and surrounding environmental conditions. While destabilisation generally occurs over tens to hundreds of thousands of years, it can also occur over a much shorter timescale. A well-known example of a very rapid destabilisation is the Mount St. Helens event in 1980, where the cryptodome emplacement occurred only a few months before the May 18 collapse (Glicken, 1996). This contrasts with slower, more progressive factors such as long-term hydrothermal alteration or gravitational loading. This section outlines the major factors that contribute to volcanic edifice instability and thus promote sector collapses. The factors described here are not triggers, but they do promote weakening.

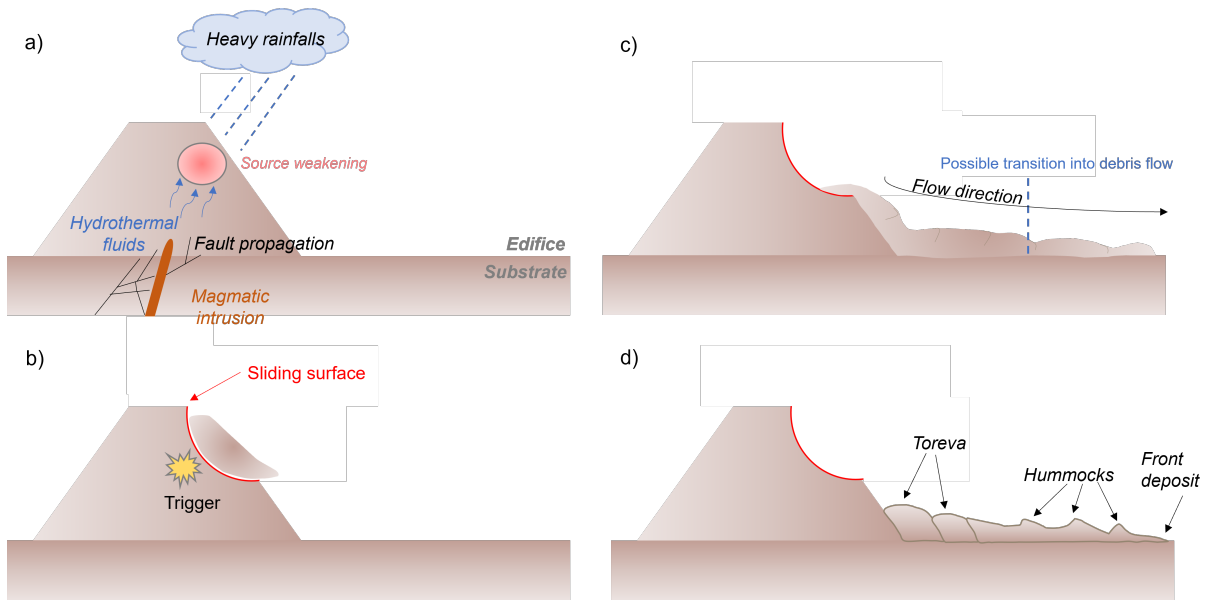


Figure 2.4: Diagram illustrating the mechanical phases of a volcanic debris avalanche. (a) Pre-failure: weakening factors leading to the development of the potential source. (b) Failure: collapse of a volume of material triggered by an event. (c) and (d) Post-failure: flow and deposition.

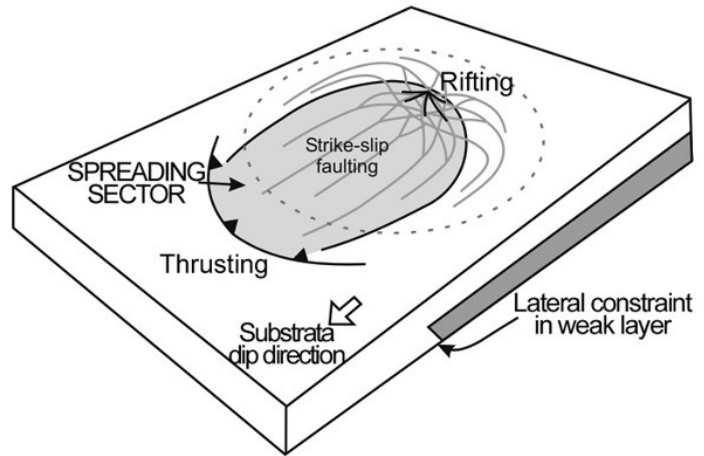
Faults and basement substratum

Volcanoes develop in tectonically active regions where dense fault networks (extensional or compressional) can propagate from the substratum into the edifice, forming complex structural patterns. These faults influence magma pathways and significantly impact edifice stability (Francis and Self, 1987; Carracedo, 1994; Tibaldi, 1995). Their geometry, kinematics, and orientation may define preferential directions for structural failure (Tibaldi et al., 2005).

The nature and structure of the basement rocks also play a crucial role. Many volcanoes are built atop sedimentary or igneous substrates that often appear tilted due to long-term tectonic deformation. This tilt introduces force anisotropy within the substrate, which can influence the direction of flank collapse, as observed in northern Chile, where westward-dipping sedimentary units beneath the Tumisa volcanic complex facilitate slope failure in that direction (Wooller et al., 2004). In areas with less topographic effects of the substratum, collapse directions are more variable, as for example, on Augustine Island in Alaska, where collapses propagate radially in all directions (Begét and Kienle, 1992).

In cases where the substratum consists of weak or ductile materials (e.g., clays, non-welded ignimbrites), volcanic loading may initiate gravitational spreading. This process transforms vertical stress into horizontal deformation, producing extensional faulting near the summit and compressional structures at the base (Fig. 2.5; Wooller et al., 2004; Roverato et al., 2021).

Figure 2.5: Sketch showing the volcano spreading downward, with deformation propagating in a weaker lateral discontinuity where a thrust fault forms. Reproduced from Wooller et al. (2004), copyright Geological Society of America (GSA).



Such deformation has been linked to large-scale sector collapses. For example, at Paríacota Volcano in northern Chile, the edifice is built atop soft, unconsolidated glacial and pyroclastic deposits that underwent gravitational spreading under volcanic loading. This ultimately led to a major flank collapse around 8,000 years ago, generating a 6 km³ debris avalanche (Clavero et al., 2002).

Such cases illustrate how the local tectonic forces and the substrate properties, by affecting the volcanic structure, strongly influence the direction and magnitude of destructive flank failures.

Magmatic intrusions and extrusions

Instabilities of volcanic edifices can also be promoted by magmatic activity, including intrusions, such as dykes, laccolith, or cryptodomes, and extrusions like summit and lateral domes. These structures can destabilise the flanks by causing mechanical overload, deformation, or changes in pore pressure associated with the movement of hot fluids (Elsworth et al., 1996; McGuire, 2003; Norini and Acocella, 2011). Pore pressure increases may result from shallow magma degassing (Thomas et al., 2004) or from the vaporisation of existing hydrothermal zones during magma emplacement (Reid, 2004). Additionally, intrusions can exert mechanical or thermal stress through expansion, which may cause uplift and trigger collapse of unstable sectors (Voight, 1995).

Historical examples show how shallow intrusions can lead to catastrophic collapses. At Bezymianny in 1956, and Mount St. Helens in 1980, the growth of a cryptodome within the edifice (Fig. 2.6) caused shallow seismicity, internal deformation, and flank bulging, ultimately triggering large-scale lateral collapses.

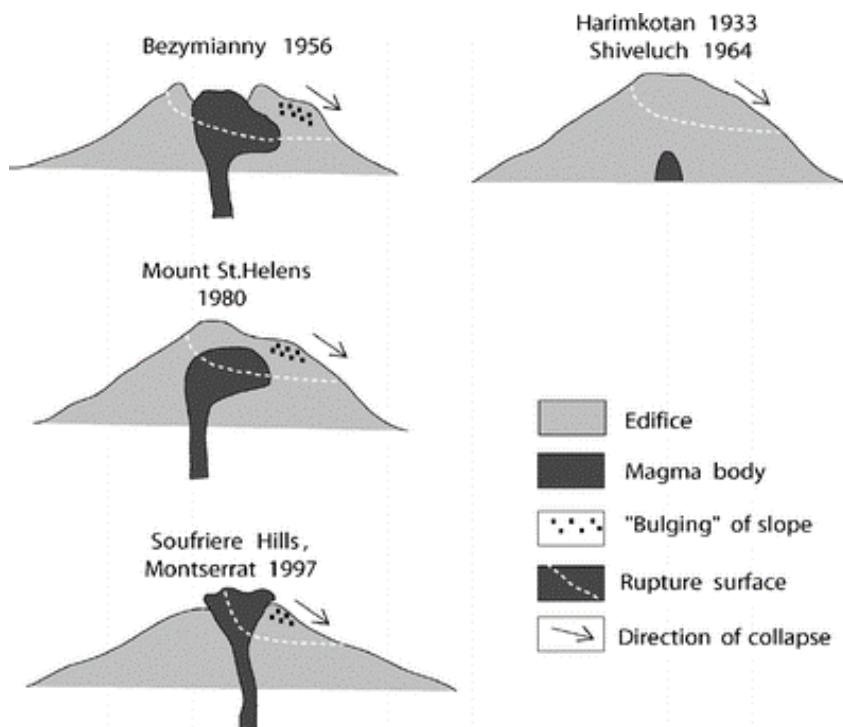


Figure 2.6: Sketches from Belousov et al. (2007) illustrating shallow magma intrusions within volcanic edifices that triggered collapse. Reproduced with permission from Springer Nature.

Extrusive features, particularly lava domes, can also lead to failure. For example, the partial collapse of the Mayu-yama dome at Mount Unzen in 1792 generated a 0.34 km^3 debris avalanche. More recently, at Shiveluch (Kamchatka) in 1964, a dome collapse produced a 1.5 km^3 debris avalanche and triggered a phreatic explosion, followed by a major eruption of juvenile pyroclastic material (Wallace et al., 2022). Older collapses have been attributed to similar processes, primarily based on deposit analysis. For example, at Ruapehu, New Zealand, deposits from the 9.5 ka BP Murimotu Formation revealed high-temperature dacite blocks, indicating the presence of an active dacite dome prior to collapse (McClelland and Erwin, 2003).

Hydrothermal alteration

Hydrothermal alteration in volcanic environments develops in response to several key factors, including the fluid-to-rock ratio, host rock chemistry, and the temperature, pH, and composition of circulating fluids (John et al., 2008; Kereszturi et al., 2020; Zimbelman et al., 2005). These processes commonly lead to the formation of argillic to advanced argillic alteration (Hedenquist and Arribas, 2022). As hydrothermal fluids percolate within the edifice, they drive chemical transformations such as the dissolution, replacement, and/or the precipitation of new minerals (Browne, 1978; Heap et al., 2017). This results in the formation of various secondary minerals:

mainly sulphides (pyrite, marcasite), sulfates (alunite, jarosite, barite, gypsum, anhydrite), oxides (silica polymorphs, magnetite, hematite, goethite, rutile), phyllosilicates (kaolin-, smectite-, mica- and chlorite-group minerals, montmorillonite), and native sulfur. These chemical changes inherently modify the physical properties of the host rocks (Pola et al., 2012; Wyering et al., 2014; Frovolá et al., 2014; Heap et al., 2015; Mayer et al., 2016; Heap et al., 2017; Mordensky et al., 2018a; Cant et al., 2018; Callahan et al., 2019; Heap et al., 2019), although the mechanical implications of such changes remain incompletely understood and are likely to vary between volcanic systems. For example, the replacement of primary minerals with “softer” and less-dense minerals, such as sulfates or phyllosilicates (del Potro and Hürlimann, 2009), results in a decrease in strength, whereas the precipitation of minerals like quartz polymorphs and adularia may increase strength through silica precipitation (Heap et al., 2020).

Besides mineralogical changes, hydrothermal alteration can affect pore pressure regimes. Clay-rich zones often reduce porosity and permeability, promoting localised water saturation and elevated pore pressures. These conditions affect the overall flank stability (Reid et al., 2001) and facilitate shallow landslides (Ball et al., 2018). These clay-rich zones are more prone to form in materials that have connected permeability via existing primary bubble-spaces or via fracturing. As a result, unconsolidated pyroclastic deposits, characterised by high porosity, are more prone to alteration than dense lavas (John et al., 2008; Mielke et al., 2015). Therefore, such argillic alteration can occur on the surface and at depth, often in discontinuous patches. On Tongariro and Ruapehu, similar alteration architectures have been described (Christenson and Wood, 1993; Miller and Williams-Jones, 2016; Kereszturi et al., 2020; Miller et al., 2020). Tongariro shows more widespread alteration (Fig. 2.7), while Ruapehu’s alteration is concentrated around and beneath the active Crater Lake (Jones et al., 2008; Miller et al., 2020; Kereszturi et al., 2020).

Hydrothermal systems, whether fed by magmatic fluids or by the circulation of meteoric water, can significantly weaken volcanic rocks by altering their mineralogy, porosity, and fluid pressure regimes. These changes play a critical role in destabilising volcanic flanks. As such, assessing volcanic stability requires not only identifying the presence of hydrothermal alteration, but also characterising its extent and properties (temperature, pH, fluid composition, fluid–rock ratios, etc).

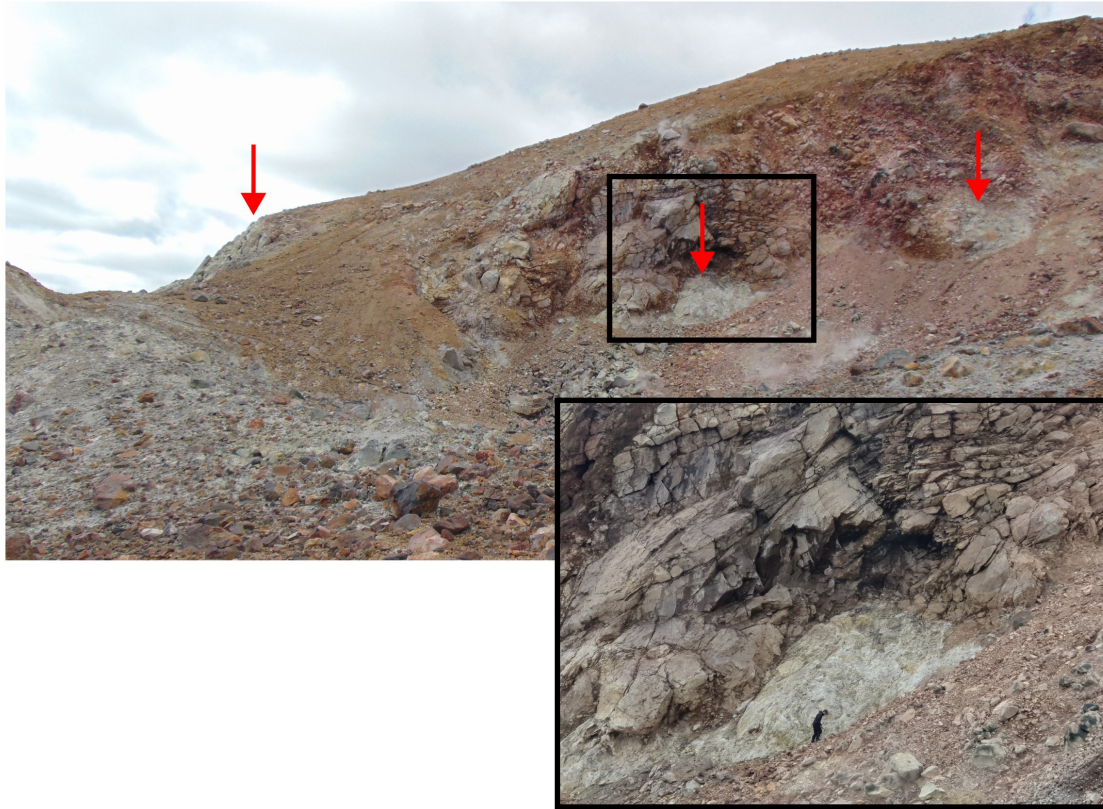


Figure 2.7: Highly altered material exposed within the Te Maari debris-avalanche scar (Tongariro, New Zealand). Red arrows indicate highly altered zones.

Climate influence

Climate and weather also exert a strong control on volcanic edifice stability. Short-term extreme events, such as intense storms or hurricanes, as well as longer-term climatic shifts, can promote the initiation of volcanic debris avalanches (Huggel et al., 2008). An example is the Casita debris avalanche of 1998, triggered by Hurricane Mitch and responsible for around 2,500 fatalities (van Wyk de Vries et al., 2000).

Deglaciation further enhances instability by accelerating volcanic activity (Capra et al., 2015) and weakening flanks (Capra et al., 2013). For example, Tormey (2010) showed that global ice retreat in the late Pleistocene caused a significant increase in volcanic lateral collapses and debris flows. Ice melt promotes failure through several mechanisms: meltwater-driven hydrothermal activity that raises pore pressure (Roverato et al., 2011; Roverato and Capra, 2013; Roberti et al., 2018), glacier abrasion of slopes (Capra et al., 2013), and ice infiltration into fractures (Glasser and Bennett, 2009). This water can also fluidise debris avalanches, enhancing their mobility and runout by transforming them into debris flows (Roverato et al.,

2011).

Climatic factors are therefore a major external driver of instability, and their role is particularly relevant in the context of global warming, where they increasingly contribute to conditions that may lead to volcanic flank failure.

2.4.2 Failure stage

While weakening processes reduce the strength of a volcanic edifice, collapse occurs only when internal stresses exceed the material resistance. These stresses, defined as forces exerted on surfaces (Jaeger et al., 2009), can be separated into two components: normal stress (σ_n), which acts perpendicular to a plane, and shear stress (τ), which acts tangentially and promotes sliding along that plane. The total stress refers to the overall force per unit area acting on the rock mass, including both solid and fluid components. In contrast, the effective stress is the portion of the total stress transmitted through the solid skeleton of the rock, reduced by the pore pressure u . Changes in pore pressure can significantly alter the effective stress, directly impacting the strength and deformation behaviour of the rock mass.

In volcanic settings, these stresses arise from overload, tectonic forces, or internal pressurisation (e.g., magma or hydrothermal fluids). To describe the resistive response of brittle materials to these stresses, the Mohr-Coulomb criterion (Coulomb, 1776) is commonly applied :

$$\tau_f = c + \sigma_n \tan \phi \quad (2.1)$$

Specifically, the shear strength τ_f consists of a cohesive component (c) and a frictional component (ϕ), both contributing to rock mass stability (Barton, 1976; Bieniawski, 1978; Bandis et al., 1983). Shear strength increases linearly with the normal stress σ_n .

When pore pressure u is affecting the considered material, the criterion must be modified to incorporate effective stress, as originally proposed by Terzaghi (1936):

$$\tau_f = c + (\sigma_n - u) \tan \phi \quad (2.2)$$

Here, $\sigma_n - u$ represents the effective normal stress, which governs the actual resistance to shear by accounting for the pressure exerted by fluids within the pore spaces. This reduction

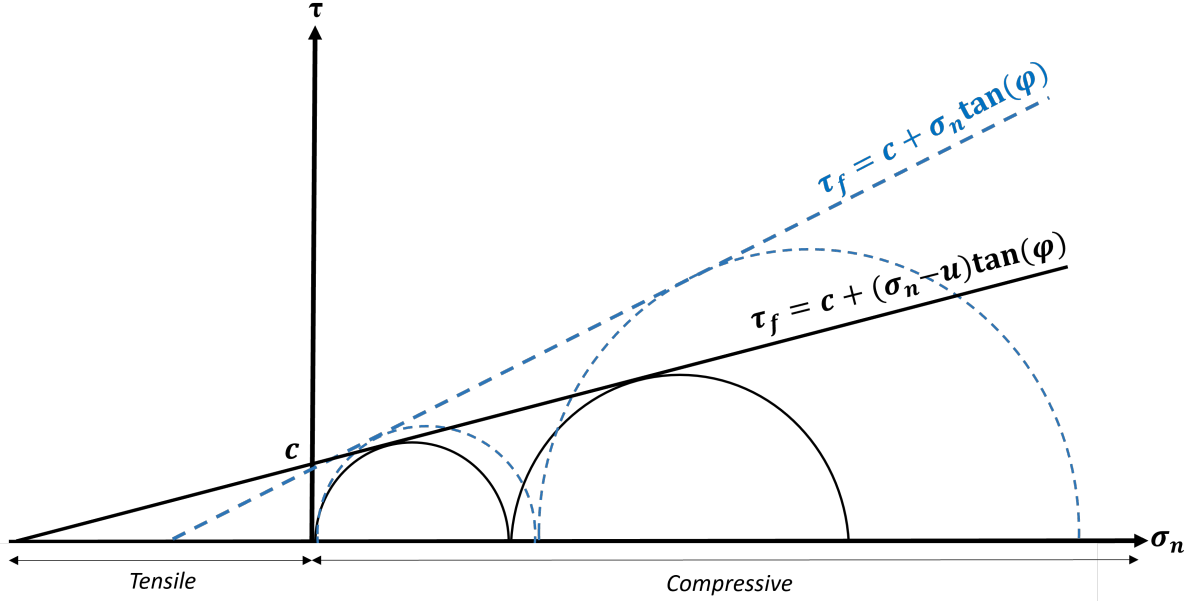


Figure 2.8: Failure envelopes according to the Mohr-Coulomb criterion. Effective stress envelope: $\tau_f = c + (\sigma_n - u)\tan\phi$; total stress envelope: $\tau_f = c + \sigma_n\tan\phi$.

in effective stress lowers the shear strength and can promote failure even under constant total stress conditions.

The stress state within a rock mass can be graphically represented by Mohr's circles, which depict the normal and shear stresses acting on planes in all possible directions through a point. This representation also identifies the principal stress axes, where no shear stress is exerted, and outlines the material failure envelope (Fig. 2.8), under which the rocks remain stable.

The Mohr-Coulomb criterion remains widely used because of its simplicity, the physical clarity of its parameters, and its agreement with experimental data (triaxial test) (Wojciechowski, 2018). However, this criterion has several limitations in accurately defining the strength threshold (Jiang and Xie, 2011; Wojciechowski, 2018). In particular, when applied to volcanic slopes, it tends to overestimate material strength because it is based on intact rock tests and does not account for macroscopic-scale discontinuities or surface conditions inherent to rock masses. This is an important consideration because soils and rocks can be significantly weakened by pre-existing discontinuities such as faults, foliations, and fractures (Abramson et al., 2001). Alternative failure criteria exist, such as the Generalised Hoek-Brown (GHB) criterion. The GHB criterion consists of a set of non-linear equations, developed from the work of Hoek (1968) on the brittle failure of intact rock and Brown (1970) on the behaviour of jointed rock mass. It introduces empirical constants (m_b , a , and s) that capture rock mass structural characteristics. These constants are calculated using the Geological Strength Index (GSI), a visual classification

system accounting for the structure and surface conditions of rock masses (Fig. 3.2)

In the context of volcanic flank failures, the initiation of failure occurs when the balance between driving and resistive forces is disrupted, causing shear stresses to exceed the strength threshold defined by the chosen failure criterion (e.g., Mohr-Coulomb, Generalised Hoek-Brown). Among the driving forces, gravity plays a dominant role. While the weight of the rock section (a combination of mass and gravity) can stabilise the rock mass by increasing the normal force, this normal force tends to transform into a shearing force on slopes, critically promoting instability. Failures are often initiated by transient factors (Crozier, 1986; Leroueil, 2001; van Asch et al., 2007) that temporarily intensify shear stresses and/or decrease the material shearing resistance (Duncan et al., 2014). These triggering factors include internal overpressures, such as those linked to pressurised magma (Schaefer et al., 2023), hydrothermal fluids (Reid, 2004), and/or gases (Voight and Elsworth, 2000); seismic activity (Sherburn et al., 1999; Calder et al., 2002; Mordensky et al., 2022); or exogenous processes such as heavy rainfall (Carn et al., 2004) or snow melting (Pierson et al., 1990). Among them, processes that lead to water saturation of the rock mass (e.g., from glacier meltwater infiltration, heavy rainfall, or hydrothermal fluids) are commonly encountered factors that influence volcanic slope stability. When coupled with the contraction of debris at the time of failure (Iverson and George, 2016), it can lead to transient pore pressures. These pore pressures reduce the effective stress, responsible for holding the rock mass together. As a result, compared to dry material, the rock mass under pore pressure is more vulnerable to shear and is more likely to collapse and turn into a flow (Eckersley, 1990; Iverson, 1997). This weakening effect is illustrated by a lowered Mohr-Coulomb failure envelope (Fig. 2.8).

2.4.3 Post-failure stage

After slope failure, the rock mass undergoes a transformation from a static to a dynamic state, forming a debris avalanche that flows down the volcano slope under gravity, usually following pre-existing topographic features (channels, valleys). Volcanic debris avalanches are especially notable for their potential to travel very long distances, a behaviour attributed to complex internal processes, such as fluidisation. Understanding these processes is key to assessing the potential hazard and runout behaviours.

Water content and pore pressure effects

Water plays a central role in modifying debris flow behaviour, both before and during motion. Fluidisation may occur along the flow path, from incorporation of surface water (e.g., from lakes or rivers), snow and ice melt, or saturated sediment. Alternatively, it may be preconditioned during the pre-failure phase by water saturation of the rock mass (e.g., from heavy rainfall or hydrothermal alteration). Such water can transform a dry debris avalanche into a debris flow, a two-phase mixture of solid particles suspended within a viscous or turbulent fluid. One of the key effects of water is the generation of elevated pore pressure, particularly in fine-grained material. When water becomes trapped within the pore spaces and drainage is limited, it can support a significant portion of the overlying load, lowering the effective stress and shear resistance. The spatial distribution of excess pore pressure within a debris flow plays a critical role in controlling its mobility (Iverson, 1997; Iverson and George, 2014, 2016).

Debris flows often exhibit a wave-like structure (Iverson and George, 2016), with a coarse, relatively dry front and margins showing near-zero pore pressures. In contrast, the body of the flow often approaches or surpasses the liquefaction threshold, where high pore pressure facilitates sustained motion (Iverson, 1997). Fluid drainage of the flow body is prevented by the low-permeability flow head and margins, maintaining high pore pressure over time (Iverson, 1997).

This internally variable pore pressure distribution, combined with the heterogeneous solid-fluid mixture, results in distinctive rheological behaviours that complicate debris flow dynamics. Unlike purely granular or Newtonian flows, debris flow exhibits complex non-Newtonian properties like yield strength (Iverson, 1997; Major and Pierson, 1992) or shear-thinning (Coussot and Meunier, 1996). These properties, by affecting both internal deformation and basal frictional resistance, can significantly influence flow runout. Consequently, no single constitutive law can fully describe flow behaviour. Several models have been proposed to describe debris flow rheology, including the Voellmy model (combining frictional and turbulent resistance), Bingham (which includes a yield stress), and Herschel-Bulkley (which allows for shear-thinning or thickening). Each model captures different aspects of the flow and may apply to different stages or zones depending on factors like grain size, water content, and shear rate. In reality, debris flows often exhibit multiple rheological behaviours throughout their motion.

Granular-scale dynamics and grain-size effects

At the granular scale, interactions between solid particles and interstitial fluid control the internal structure and dynamics of the flow. These interactions include grain collisions, inter-particle friction, or viscous fluid entrainment. A key control on these processes is grain size, which directly influences how particles are transported and suspended within the flow (Iverson, 1997; Kowalski and McElwaine, 2013; de Haas et al., 2015, 2016; Pudasaini and Fischer, 2020).

Very fine grains (clay-size particles) are often held in suspension by viscous forces due to their small size and long settling time (Fig. 2.9). They can enhance flow mobility by increasing buoyancy and enabling the suspension of coarser particles (Fig. 2.9; McArdell et al., 2007). However, these fine grains can also reduce mobility, as an increase in their concentration can raise the fluid-mixture effective viscosity (Thomas, 1965).

In contrast, coarse particles require sustained agitation, through turbulence or collisions, to remain suspended. When these interactions weaken, coarse grains tend to settle. The resulting internal structure often shows coarse material concentrated near the front or at the surface of the flow. This is frequently attributed to kinetic sieving, a sorting process where smaller grains percolate downward through voids created during deformation, forcing larger particles upward (Hutter and Rajagopal, 1994; Davies, 1990). An example of this behaviour is observed in the Te Whaiau (Tongariro) debris avalanche (Lecointre et al., 2002), where the unusual preservation of hummocks in the distal zones indicates that the clay-rich flow was able to transport large megaclasts over long distances. The high clay content in the distal matrix suggests a dense and viscous interstitial fluid, which enhanced the flow capacity to carry coarse material. During transport, coarse clasts may have "floated" on the surface of the flow and migrated toward the lateral and frontal margins due to segregation processes, such as percolation, which are favoured in fine-rich flows (Vallance, 1994).

A related concept is the granular temperature (Ogawa, 1978), which refers to the agitation or random motion of particles. Higher granular temperatures correlate with higher collision rates, lower bulk density and more fluid-like behaviour (Chapman and Cowling, 1970). However, granular temperature tends to dissipate over time due to friction and must be maintained by continuous energy input, such as shear forces.

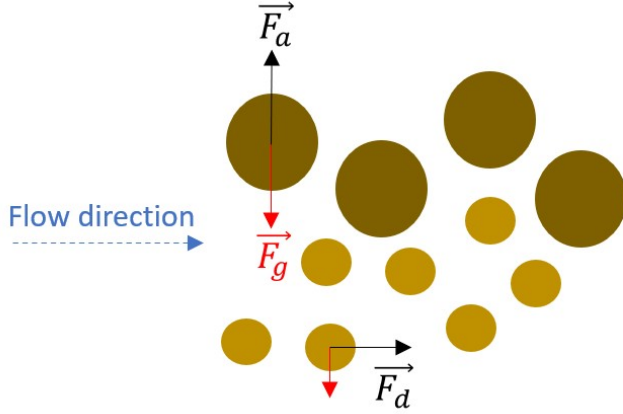


Figure 2.9: Diagram (adapted from Iverson 1997) showing the suspension mechanisms of different grain sizes. Fine grains remain suspended primarily due to viscous forces ($\vec{F}_d$, drag), while coarser grains are supported by buoyancy ($\vec{F}_a$) because of the interactions with finer grains. $\vec{F}_g$ represents the gravitational force.

Flow deceleration and deposition processes

Debris flow deposition occurs when all the potential energy has degraded into an irrecoverable form. A key indicator of flow deposition is the local dissipation of granular temperature, firstly in zones containing the largest clasts. These clasts typically accumulate to form the flow margins, where they act as a mechanical barrier, decelerating the more water-rich body that follows. As a result, marginal deposits tend to be relatively dry and stable, while the interior may still exhibit high pore pressure after deposition, remaining in a liquefied state (Major, 1996). The final transition from fluid to static deposit is governed by a gradual decrease in pore pressure and consolidation via grain sedimentation.

2.5 Study of debris avalanche behaviours

Observations of real volcanic debris avalanches are fundamental to advancing our understanding of these events and have considerably expanded current knowledge (e.g., Mount St. Helens event). However, such events remain very rare, which is why experimental and numerical approaches are essential for investigating debris-avalanche dynamics.

2.5.1 Experimental approaches to replicate debris avalanche behaviours

Experimental studies on debris flows complement field observations and numerical modelling by providing controlled environments to isolate specific variables and refining our understanding of debris flow processes. However, a key challenge lies in achieving dynamic similarity with real events through proper scaling (Turnbull et al., 2015; Iverson, 2015).

Field-scale experiments attempt to preserve the complexity and natural variability of real-world slopes (Iverson, 2015). Some studies have initiated slope failure through artificial water infiltration on natural hillsides (e.g., Ochiai et al. 2004; Springman et al. 2009), while others have released water-sediment mixtures onto natural terrain to simulate flow and deposition. A number of these experiments aim to replicate the full sequence of debris avalanche behaviour, from initiation to runout and deposition. For example, Ochiai et al. (2004) conducted large-scale rainfall-triggered landslides on a natural slope in Japan, successfully capturing both failure onset and post-failure debris flow behaviour. These large-scale field experiments minimise scaling issues and generally capture the complexity of natural processes.

Large-scale flume experiments provide an alternative by offering highly controlled environments to study the entire debris flow lifecycle. They allow researchers to vary slope geometry, sediment properties, and water content while recording flow behaviour in detail. These setups are ideal for exploring complex dynamics such as fluidisation, entrainment, and erosion, and for testing mitigation strategies like barriers or channel designs. Facilities such as the USGS 95-meter-long debris-flow flume (Fig. 2.10) have been central to studying debris flow processes. For example, Iverson et al. (2010) used the flume to investigate the role of fine sediment in sustaining pore pressures, showing that debris flows evolve with time-varying resistance rather than a fixed rheology. Similarly, Reid et al. (1997) triggered debris flows by saturating sediment in flume beds, monitoring pore pressures and deformation to examine the initiation phase in detail. Major (1996) and Major and Iverson (1999) used the flume to explore debris flow deposition processes, linking flow behaviour to deposition by measuring how pore-fluid pressures and friction affect flow deceleration and deposition. More recently, Iverson and George (2016) used the flume to explore run-up behaviour on adverse slopes, highlighting the flume’s utility in investigating specific flow phenomena.

In contrast, small-scale laboratory experiments idealise natural processes by maintaining a strong control over the boundary conditions and material properties. Compared to large-scale experiments, they provide additional advantages such as reduced cost, ease of reproducibility and the ability to conduct numerous tests across a wide range of parameters. However, scaling issues arise due to their smaller sizes, with most using small slope and small volumes ($\leq 2 \text{ m}^3$, e.g. Eckersley 1990, Manzella and Labiouse 2009, de Haas et al. 2015). Dimensional analysis can be performed to help determine how some physical processes vary with scale (Iverson, 2015). For laboratory experiments formalised through mathematical models and designed to



Figure 2.10: Photographs of a USGS flume experiment (U.S. Geological Survey, public domain), as presented in Iverson (2020), showing a debris flow entraining and interacting with wet bed sediment. Inset highlights the debris flow front and underlying sediment.

test specific hypotheses, model normalisation can be performed to ensure the experiment design accurately represents the full-scale phenomenon. Small-scale experiments have permitted considerable advancements by isolating key factors of debris flow dynamics and testing scaling effects. For instance, Iverson and Denlinger (2001) connected small-scale experiments to real-world phenomena, improving predictive models.

A more recent small-scale experimental approach is centrifuge modelling, which uses high-speed centrifuges to replicate the stress and deformation conditions of full-scale debris flows (Garnier et al., 2007). Although relatively few studies have applied this technique, it has proven valuable for investigating both initiation mechanisms and runout processes (Turnbull et al., 2015). By enabling the simulation of enhanced gravitational forces, centrifuge modelling allows for more realistic sediment behaviour, particularly in terms of entrainment and pore pressure dynamics. Drum centrifuges allow for the simulation of unconsolidated debris motion with longer runout distances (Kailey et al., 2011; Bowman et al., 2010), while beam centrifuges

are more suited to initiation studies within confined setups (Milne et al., 2012). However, centrifuge testing faces several challenges, particularly when simulating fluid-saturated debris flows. Issues such as the mismatch between fluid and particle scaling, the need for artificial adjustments like high-viscosity fluids, and dynamic effects introduced by rotation (e.g., Coriolis forces) can affect the realism of flow behaviour (Turnbull et al., 2015; Bowman et al., 2012). Despite these limitations, it remains a valuable method for isolating specific processes under controlled conditions.

Across all scales, recent experimental designs are increasingly focused on replicating the multi-stage sequence of debris avalanches. This includes work using rainfall or basal pressurisation to induce failure, followed by detailed measurements of internal stresses, fluid pressures, and deposition patterns (e.g., Major 1996; Reid et al. 1997; Ochiai et al. 2004; Iverson et al. 2010; Major and Iverson 1999). These experiments provide critical data to calibrate and validate depth-averaged multiphase models like D-Claw (Iverson and George, 2014), enhancing our ability to predict debris-flow initiation, evolution, and impact.

2.5.2 Numerical approaches to simulate debris avalanche behaviours

Numerical modelling provides a complementary tool to investigate debris avalanches, enabling the simulation of complex flow dynamics over realistic terrain under controlled and repeatable conditions (Trujillo-Vela et al., 2022). These approaches are particularly valuable for exploring processes that are difficult to capture experimentally, such as large-scale runout, fluid-solid interactions, or the sensitivity of flow behaviour to source geometry and material properties. They are also a valuable tool for hazard assessment by allowing scenario testing and probabilistic analysis (Dai et al., 2002). However, they rely on simplifying assumptions and often require empirical calibration, which can introduce uncertainty (McDougall, 2017).

Most physically based debris-flow models consist of partial differential equations that represent depth-averaged continuum mass and momentum conservation (Trujillo-Vela et al., 2022). Integrating these equations over the flow depth allows simplification of the 3-D problem to two dimensions, which greatly improves computational efficiency by neglecting the vertical component of velocity and pressure. This allows large-domain simulations and analyses based on many model runs to explore parameter uncertainty. However, the assumption that vertical momentum fluxes are negligible limits their ability to resolve internal flow structures and can lead to inaccuracies on very steep slopes (Trujillo-Vela et al., 2022).

These depth-averaged models can be coupled with digital elevation models (DEMs) to simulate flow routing, entrainment, and deposition over complex topography. They typically rely on empirical or semi-empirical rheologies, such as Coulomb, Voellmy, Bingham, or Herschel–Bulkley formulations, to represent bulk flow resistance (McDougall, 2017). Depth-averaged models range from single-phase approaches, which treat the avalanche as a homogeneous mass (e.g. Voellmy–Salm: Salm 1993; FLO-2D: O’Brien et al. 1993; DAN3D: McDougall 2006), to multi-phase approaches that explicitly account for interactions between solid and fluid phases (e.g., TITAN2D: Pitman and Le 2005; r.avaflow: Mergili et al. 2017; D-Claw: Iverson and George 2014). Multiphase models solve coupled mass and momentum equations for each phase and incorporate pore-pressure dynamics and interphase drag. They are particularly relevant for water-rich or saturated debris avalanches, where fluid-solid interactions strongly influence mobility (Trujillo-Vela et al., 2020). By explicitly representing pore pressure evolution, these models can simulate how entrainment, fluidisation, and mobility influence one another (e.g., Iverson and George, 2014), which single-phase depth-averaged models cannot do. However, they involve numerous parameters that are difficult to measure directly and often require extensive calibration using data from flume or field experiments. The large number of parameters can also introduce additional sources of uncertainty into the models (Mead et al., 2021).

To solve the governing equations, various numerical techniques to discretise space have been developed (Fig. 2.11). Mesh-based methods discretise space into fixed computational cells and can adopt either an Eulerian perspective (grid fixed in space, Fig. 2.11a) or a Lagrangian perspective (grid moves with the material, Fig. 2.11b). Common mesh-based techniques include the Finite Difference Method (FDM), Finite Element Method (FEM), and the Finite Volume Method (FVM). The FDM discretises derivatives at grid nodes, offering simplicity, low-computational cost and the ability to capture sharp fronts and shock structures (Savage and Hutter, 1989; Shieh et al., 1996; Pudasaini et al., 2005; Luna et al., 2012; Mergili et al., 2017, 2018b, 2020; Zhao et al., 2019; Shugar et al., 2021). The FEM uses Lagrangian polynomial to interpolate variables within each element and is particularly used for solid-mechanics or low deformation flows (Chen and Lee, 2000; Denlinger and Iverson, 2004; Quecedo et al., 2004; Naef et al., 2006; Rickenmann et al., 2006; Martinez et al., 2008). The FVM performs computations at the centre of discontinuous volumes and uses numerical fluxes functions to link them, and, as with FEM, facilitates the discretisation of space in complex geometries (LeVeque,

2002; Denlinger and Iverson, 2004; Blazek, 2015). More advanced high-order methods use n th-degree polynomials to interpolate variables within elements, combining features of FEM and FVM to achieve very high accuracy, but their high computational cost have limited their use in debris-flow modelling.

In contrast, the more recently developed mesh-free methods discretise space using particles or points instead of a fixed mesh (Liu and Liu, 2010). Each particle carries its properties and moves following a Lagrangian approach, dynamically updating its neighbours during motion (Fig. 2.11c and d). Two widely used mesh-free methods for debris-flow modelling are the Smooth Particle Hydrodynamics (SPH) and the Discrete Element Method (DEM). SPH represents the material as a continuum (Fig. 2.11c) and uses kernel functions within an influence radius to interpolate variables (Gingold and Monaghan, 1977). It has been applied to dry granular flows, two-phase debris flows, and more specific processes such as deposit segregation processes (e.g., Zhou et al., 2016) and impacts on rigid barriers (e.g., Shen et al., 2018). In contrast, DEM resolves the motion and contact forces of individual particles (Fig. 2.11d; Cundall and Strack, 1979; Galindo-Torres, 2013), particularly useful to investigate grain-scale processes such as dilatancy or fragmentation during failure and runout. Hybrid SPH–DEM models have also been developed to simulate fluid-solid interactions and their effects on structures (Trujillo-Vela et al., 2020; Liu et al., 2021). Despite their ability to handle large deformations and complex interactions, mesh-free methods have high computational costs and can exhibit, such as grid-based approaches, unphysical oscillations, which can be mitigated through correction strategies (Ma et al., 2009; Antuono et al., 2012; Ye et al., 2019).

Across all approaches, numerical modelling studies increasingly aim to replicate the full sequence of debris avalanche behaviour, from failure initiation to runout and deposition. Accurately representing the initiation phase is crucial, as it strongly influences the subsequent flow dynamics and mobility. Slope stability analyses are commonly used to simulate the onset of failure. Among the most used are the Limit Equilibrium Methods (LEM) (Bishop, 1955; Morgenstern and Price, 1965; Spencer, 1967; Janbu, 1973) and the Finite Element Method (FEM) (Brown and King, 1966; Dunlop and Duncan, 1970; Wright et al., 1973; Giam and Donald, 1988; Huang and Yamasaki, 1993; Zou et al., 1995). LEM evaluate potential failure surfaces by computing safety factors along predefined slip surfaces, providing a good estimate of failure location and volume, although they do not account for progressive deformations (Duncan, 1996). FEM solve the full stress-strain relationship within the slope, allowing deformation and pore

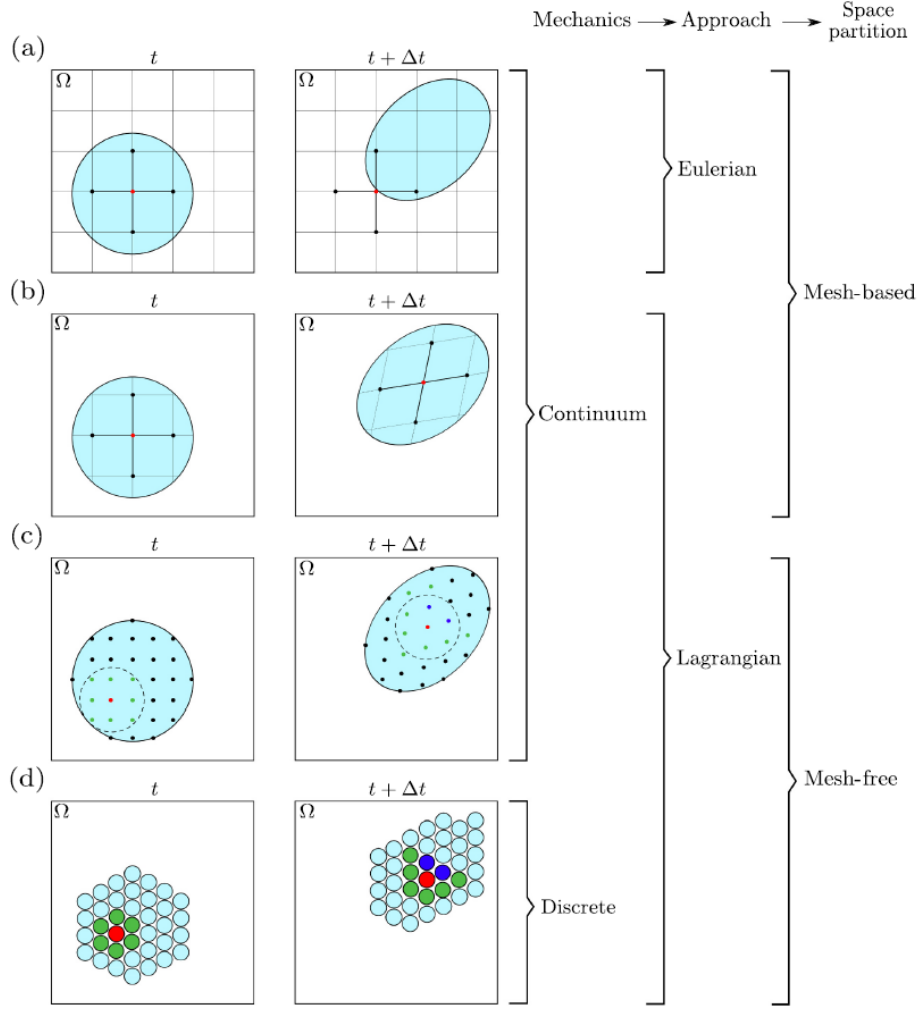


Figure 2.11: Illustration of fundamental spatial discretisation methods. Each row (a–d) corresponds to a different approach, with the hierarchy shown on the right. Left sketches represent the reference state at time t , and right sketches show the system state at $t + \Delta t$. Ω denotes the computational domain. In rows c and d, the point of interest (red) flows relative to neighbours (green), while newly involved neighbouring points are shown in blue. Reprinted from Trujillo-Vela et al. (2020), *Earth-Science Reviews*, with permission from Elsevier.

pressure evolution, and can simulate complex geometries, heterogeneous materials, and transient loading conditions such as seismic acceleration (Chang and Huang, 2005). These methods, coupled with high-resolution topography, help define the initial geometry, stress state, and volume of material that collapse into a debris avalanche, improving the accuracy of the subsequent flow simulations.

Experimental and field data are often used to calibrate and validate these models, constraining key parameters such as friction angles, pore-pressure dynamics, and entrainment rates. While these models are powerful tools for understanding debris avalanche dynamics and forecasting their hazards, their predictive capacity remains constrained by parameter uncertainty

and scaling assumptions. For this reason, recent studies increasingly combine multiple modelling approaches or perform ensemble simulations to quantify uncertainty in predicted runout patterns (e.g., Rossi et al., 2010; Aaron and McDougall, 2019; Liu et al., 2021).

While experimental approaches, outlined in the previous section, provide valuable insights into debris avalanche processes and have been instrumental in developing and calibrating numerical models, they are not applied in the present work. Instead, this thesis focuses exclusively on numerical modelling to investigate both the initiation and post-failure behaviour of debris avalanches. This work also aims to better connect failure initiation with post-failure dynamics, helping to make debris avalanche simulations more realistic and informative.

Chapter 3

Methodological framework

This chapter presents the methodological framework used to investigate debris avalanche processes, with a focus on numerical modelling approaches. In addition to outlining the methods applied in this study, it provides a thorough overview of the main numerical approaches developed to replicate or simulate debris avalanche behaviour. Simulating debris avalanches requires coupling models based on different physical principles to capture each stage of the process: failure initiation is typically modelled using concepts from rock and soil mechanics, while the subsequent flow is modelled using fluid dynamics and granular flow theories. Examples from the literature are included to illustrate the strengths, limitations, and applications of these various methods, situating the present research within the broader methodological landscape.

This chapter is organised so that the first two sections detail the methods for quantifying and modelling the failure and post-failure stages of debris avalanches. The following section focuses on hazard assessment and mapping, and the final section presents the selected approaches for this study, explaining their selection in relation to the research objectives. Detailed descriptions of the methods are provided in Chapters 4, 5, and 6, which are structured as publication-based chapters.

3.1 Quantifying and modelling the failure stage

To simulate the initiation of volcanic debris avalanches, slope stability analyses are commonly employed. These analyses help identify potential failure surfaces and estimate unstable volumes, providing insights into slope failure susceptibility. Among the most widely used deterministic approaches are the Limit Equilibrium Methods (LEM) (Bishop, 1955; Morgenstern and Price, 1965; Spencer, 1967; Janbu, 1973) and the Finite Element Method (FEM) (Brown and King, 1966; Dunlop and Duncan, 1970; Wright et al., 1973; Giam and Donald, 1988; Huang and Yamasaki, 1993; Zou et al., 1995). Both methods evaluate the mechanical stability of volcanic flanks by providing a quantitative measure of the system resistance to failure (Reid, 2004): the factor of safety (FOS) for LEM and the Shear Reduction Factor (SRF) for FEM.

3.1.1 Input parameters

Key inputs for these analyses include the slope geometry and boundary conditions, the material strength properties, and the groundwater conditions.

Slope geometries can be readily obtained using Digital Elevation Models (DEM), which are digital representations of topographic surfaces. They are used to determine terrain attributes such as elevation, slope and aspect, parameters that are critical for slope stability modelling. The accuracy and resolution of DEMs significantly influence the reliability of the analysis. For example, variations in resolution can alter computed slope angles and the geometry of potential failures, leading to substantial differences in the calculated FOS (Fuchs et al., 2014; Qiu et al., 2022).

Material strength properties such as cohesion (c), internal friction angle (ϕ), and Unconfined Compressive Strength (UCS) are typically determined through a combination of field studies and laboratory experiments. In the laboratory, uniaxial and triaxial compression tests are commonly performed on cylindrical rock samples to characterise the material failure envelope (Fig. 3.1). In an uniaxial test, the sample is subjected only to vertical axial stress (σ_1), and the maximum axial stress at failure defines the UCS, which is the highest stress the material can withstand under uniaxial loading. In contrast, a triaxial test applies both a vertical axial stress (σ_1) and a lateral confining pressure ($\sigma_2 = \sigma_3$), simulating more in-situ conditions, typically with $\sigma_1 > \sigma_2 = \sigma_3$. Triaxial tests provide additional information beyond UCS, including shear

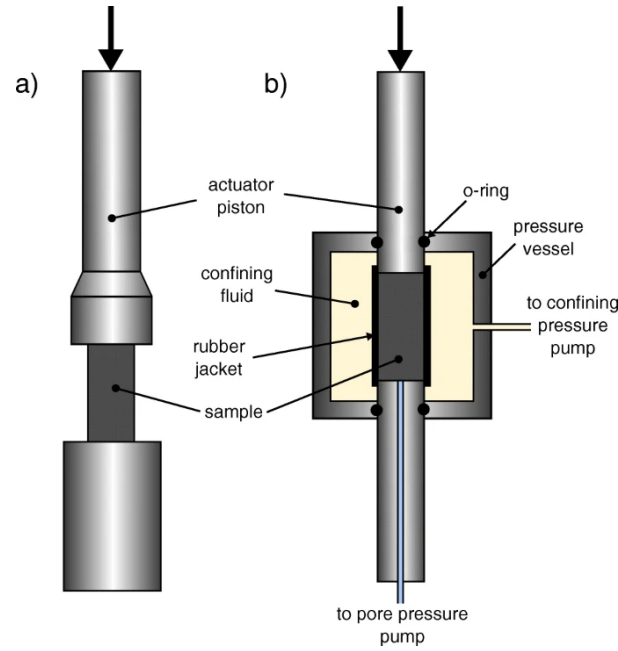


Figure 3.1: Schematic diagrams of typical setups for (a) uniaxial compressive strength and (b) triaxial deformation experiments, with arrows indicating piston movement. Reproduced from Heap and Violay (2021), licensed under CC BY 4.0.

strength parameters (c and ϕ), pore-pressure response, and stress-strain paths under different confinement levels. In addition to strength parameters, elastic properties such as Young's modulus (E) and Poisson's ratio (ν) are also obtained from stress-strain curves during these tests. These elastic parameters are especially important for use in finite element models, which account for material deformation under stress in slope stability analysis.

However, slope stability assessments require consideration at scales far beyond the 10-15 cm core samples used in lab tests. While these laboratory tests provide important strength parameters, they do not account for the natural heterogeneity of rock masses in the field. Rock masses typically contain numerous discontinuities, such as joints or fractures, that significantly weaken the material relative to intact rock. As a result, strength values derived from triaxial tests tend to overestimate the rock capacity to resist stress. To address this discrepancy, field investigations are carried out to characterise the in-situ strength of the rock units. A widely used approach is the Geological Strength Index (GSI) (Hoek and Brown, 1980; Hoek, 1994; Hoek et al., 1995) which provides a qualitative method to estimate rock mass strength, based on its structure and surface conditions (Fig. 3.2). It assumes that (1) the rock mass strength is controlled by its structure and joints and (2) the intact rock samples used in lab tests are homogeneous and free of discontinuities. GSI values ranges from 0 to 100, with lower values indicating greater degradation of rock mass strength relative to intact rock. This index is

employed in the Generalised Hoek-Brown (GHB) failure criterion to determine the empirical constants m_b , s , and a , accounting for the structural characteristics of the rock mass. With the intact rock UCS, these constants define a non-linear failure envelope, in contrast to the linear failure model of the Mohr-Coulomb criterion, which essentially relies on cohesion c and the friction angle ϕ .

In saturated materials, the total stress is composed of the effective stress transmitted through the solid matrix and the pore pressure exerted by the fluid within the pores (Fig. 2.8). To evaluate this partitioning, variations of the triaxial test are used, particularly the Consolidated Undrained (CU) test. This setup allows the measurement of both pore pressure and effective stress during loading. Triaxial tests can also be adjusted to measure additional parameters such as permeability and porosity, which are crucial for understanding fluid flow within rock masses. For example, in a study by Heap and Kennedy (2016), cylindrical andesite samples were tested under confining pressures to assess the evolution of permeability under mechanical loading, allowing for a detailed evaluation of how fractures affect fluid movement and the overall stability of the material under stress. Such tests are essential for assessing the influence of water on rock strength, particularly for volcanic slope stability analyses, as they are environments prone to heavy rainfall, snowmelt or hydrothermal activity.

For natural slopes, obtaining accurate data on pore pressure is crucial for understanding groundwater conditions and their impact on slope stability (Pirone et al., 2015). Pore pressure in the field can be measured using piezometers or pressure transducers, which are installed at various depths within the slope to monitor the pressure exerted by the groundwater (e.g., Rinaldi et al., 2004; Oya et al., 2024). These instruments provide real-time data on the pore pressure fluctuations due to rainfall, hydrothermal activity, or other hydrological processes. In addition, geophysical methods such as electrical resistivity tomography (e.g., Kereszturi et al., 2021) can be used to indirectly infer the distribution of pore pressure in the subsurface. Integrating these field measurements with numerical models helps in simulating the influence of pore pressure on slope stability and predicting failure mechanisms under varying groundwater conditions.

3.1.2 Limit equilibrium methods

Due to their simplicity and efficiency, limit-equilibrium methods (LEM) have been widely used for slope stability analysis. These methods assume that slope failure occurs instantaneously along the entire slip surface once a critical stress is reached (Duncan, 1996). This assumption

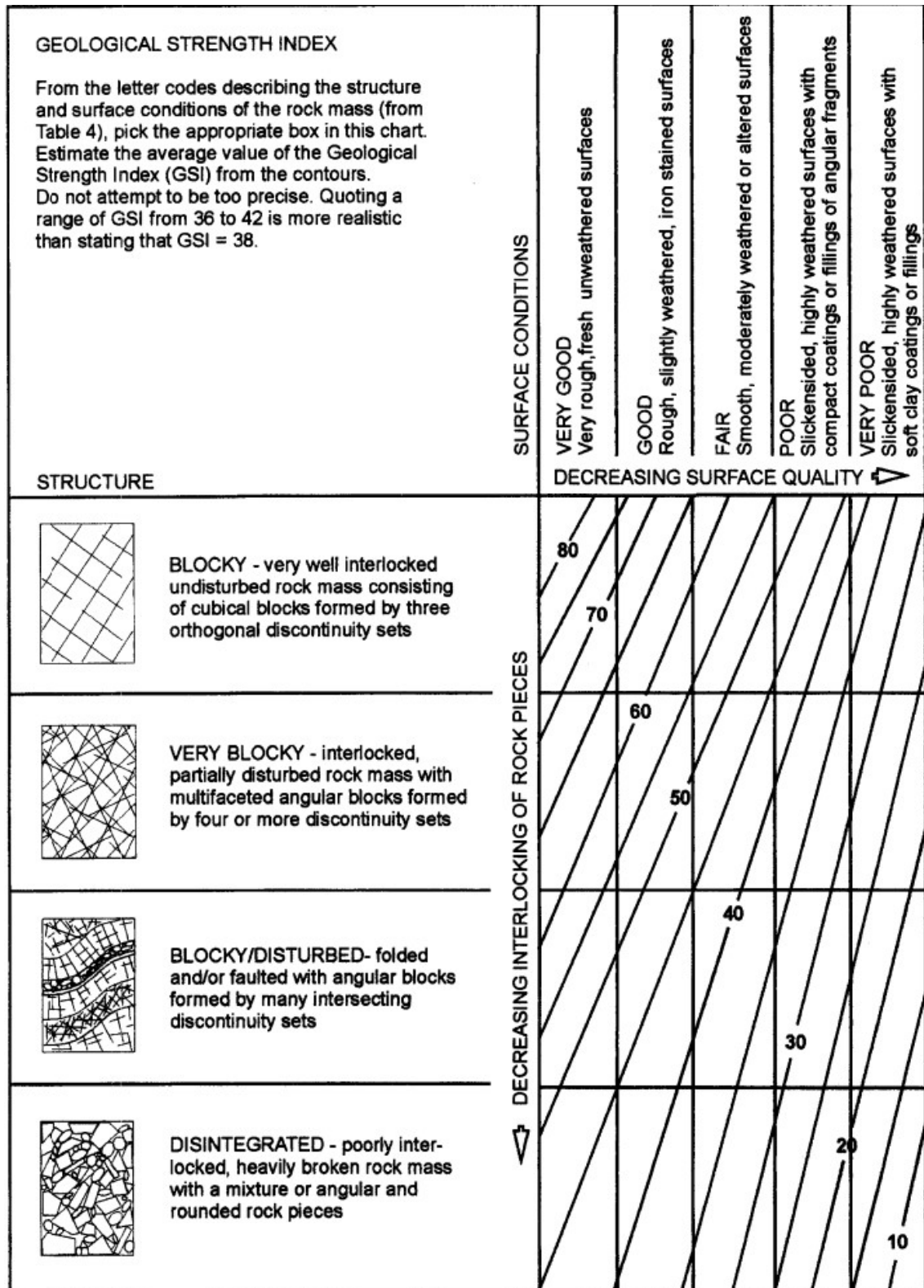


Figure 3.2: Geological Strength Index (GSI). Reprinted from Hoek and Brown (1997), International Journal of Rock Mechanics and Mining Sciences, with permission from Elsevier.

relies on the soil exhibiting ductile behaviour, i.e. the shear strength does not decrease after reaching a peak. A key limitation of LEM, associated with this assumption, is that it does not provide information on the magnitude or propagation of deformation along the sliding surface.

LEM typically employs the 3D ‘method of columns’, assessing the static equilibrium of a potential failure mass by dividing it into columns intersecting the predefined sliding surface (Fig. 3.3). The vertical force for each column is calculated from its weight, determined by volume and material unit weight. This vertical force contributes to the normal force acting on the base of the column. Equilibrium of forces and moments is then evaluated in two orthogonal directions (typically X and Y) to solve the normal and shear forces on the base of each column.

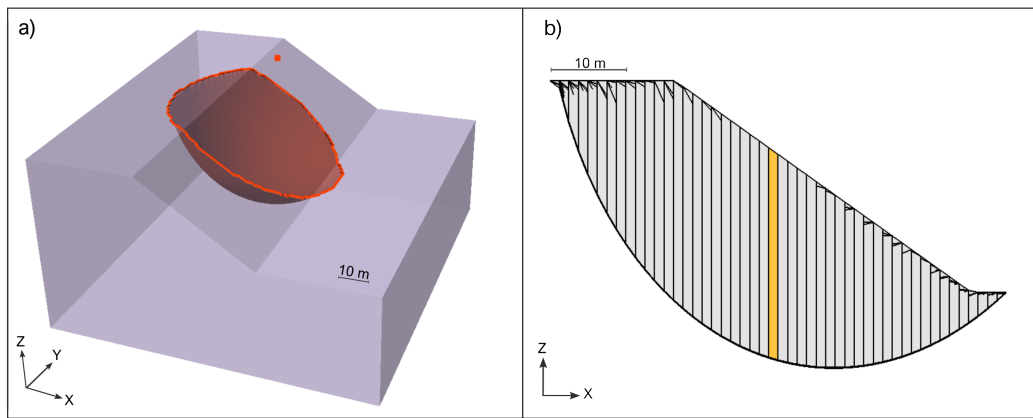


Figure 3.3: Limit Equilibrium Method (Bishop Simplified). (a) 3D visualisation of the potential slide surface (red), with the rotational centre marked by a red square. (b) 2D cross-section of the failing mass.

Several methods exist to evaluate forces on each column. The Bishop Simplified method (Bishop, 1955) assumes circular slip surfaces and only considers moment equilibrium, making it very efficient for preliminary assessment but less accurate for non-circular slip surfaces. It accounts only for interslice normal forces while neglecting interslice shear forces. The General Limit Equilibrium (GLE)/Morgenstern-Price method (Morgenstern and Price, 1965) extends the analysis to include both forces and moments equilibrium, accommodating complex slip geometries and both normal and shear interslice forces. The Janbu Simplified method (Janbu, 1955), suitable for non-circular slip surfaces, focuses only on force equilibrium and like the Bishop Simplified method, neglects interslice shear forces. The Spencer method (Spencer, 1967) is more rigorous, simultaneously satisfying both forces and moments equilibrium while assuming constant interslice shear angles, offering higher accuracy at greater computational cost.

To quantify stability with LEM, the factor of safety (FOS) is calculated for each predefined

failure surfaces. It is defined as the ratio between shear strength (resistance) and shear stress along a specified trial surface. Values of $FOS \leq 1$ indicate instability.

Advances in 3D slope stability analysis have been facilitated by specialised software, such as Scoops3D (Reid et al., 2015) and Slide3 (Rocscience Inc., 2025). These programs allow analyses under complex geological structures, varying pore pressure distributions, and external loads. Scoops3D relies on a grid of rotational centres, whereas Slide3 allows users to define specific slip surface geometries, including circular, planar, and compound surfaces.

3.1.3 Finite element methods

First introduced by Clough and Woodward (1967), the finite element method (FEM) enables a non-linear analysis of stress-strain relationships, allowing for more accurate calculations of stress distribution within slopes. Unlike LEM, FEM discretises the rock mass into smaller polygonal sections, calculating stress and strain at each node when subjected to external loads. Besides, it employs iterative techniques, simulating the problem as a series of linear events to determine the critical strength for failure (Duncan, 1996). This makes FEM particularly suitable for modelling slope stability in complex materials with varying physical properties over time, such as inhomogeneous, anisotropic soils. Furthermore, FEM is more appropriate than LEM for analysing progressive slope failures driven by deformation and time.

The method accuracy is closely tied to the initial stress state, as stress variations in each increment are added to the initial stresses. This cumulative effect makes the accurate definition of the initial stress state critical to obtain reliable results. The choice of stress-strain relationship in FEM is also directly influencing the accuracy of the analysis, particularly when dealing with complex materials and varying stress conditions. While a linear elastic model may be sufficient for small deformations and soils not approaching failure, more advanced models (e.g., hyperbolic, elastoplastic, elastoviscoplastic) are often necessary to capture the variability of soil modulus under different confining pressures (Duncan, 1996). This consideration is especially important when analysing undrained behaviour and pore pressure variations, conditions frequently encountered in volcanic and hydrothermal systems.

In FEM, the failure surface is not considered a single, distinct slip surface but rather a yield zone that extends from the base to the top of the slope (Matsui and San, 1992), a concept supported by laboratory tests (Roscoe, 1970). Consequently, FEM assumes that slope failure is associated with maximum shear strain (Fig. 3.4), resulting in a failure zone that spans the

entire slip surface rather than a unique slip surface (Chang and Huang, 2005). Any slip surface intersecting this yield zone will share the same factor of safety.

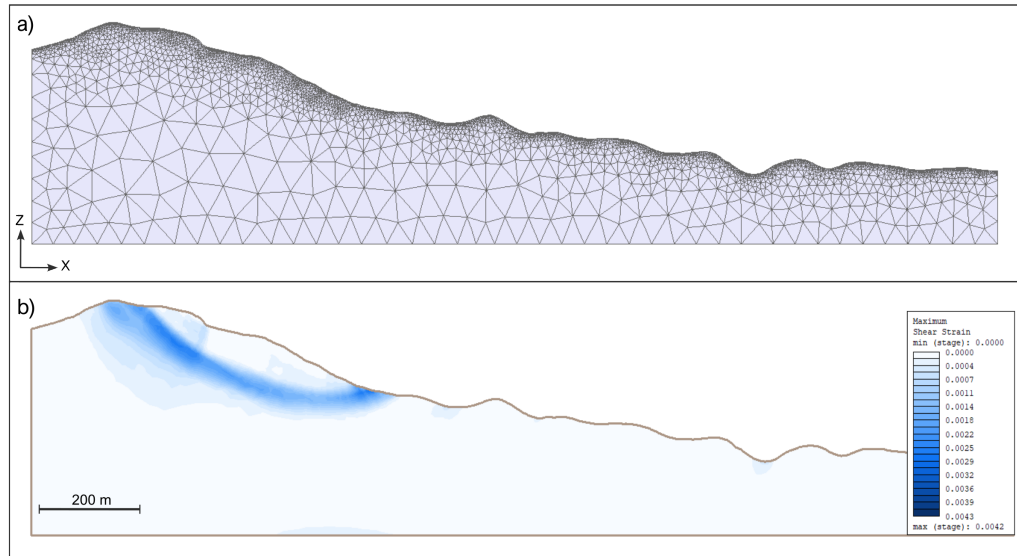


Figure 3.4: Finite Element Method (Shear Strength Reduction): (a) 2D cross-section of the Te Maari slope illustrating the finite element mesh. (b) Maximum shear strain distribution highlighting the potential slip surface.

To quantify stability with FEM, two primary procedures are typically employed (Chang and Huang, 2005). The first considers the stress state on the potential slip surface (Wright et al., 1973; Giam and Donald, 1988; Huang and Yamasaki, 1993) and adopts an analysis scheme very similar to that used in LEM, i.e. the search for several potential slip surfaces and the evaluation of the minimum factor of safety (also defined as the ratio of the available shear strength to the shear stress acting on the surface). This first procedure has the advantage over LEM in that it provides a more reliable estimate of soil stress state (Chang and Huang, 2005). The second procedure is the shear strength reduction technique (SSR) (Zienkiewicz et al., 1975; Matsui and San, 1992; Dawson et al., 1999; Zheng et al., 2006; Chang and Huang, 2005) which is based on the reduction of the soil strength parameters until the soil breaks (Duncan, 1996). For example, in the context of Mohr Coulomb failure criterion, the cohesion (c) and internal friction angle (ϕ) are progressively reduced until the model does not converge to a solution (Griffiths and Lane, 1999). At this point, the soil is considered to have collapsed. The factor of safety calculated by this method known as the strength reduction factor (SRF), is defined as the ratio of the initial strength parameters to the reduced strength parameters at failure. The reduced strength parameters, as determined under the Mohr-Coulomb criterion, are expressed as:

$$c_f = \frac{c}{SRF} \quad (3.1)$$

$$\phi_f = \tan^{-1} \frac{\tan \phi}{SRF} \quad (3.2)$$

where c_f and ϕ_f are the reduced cohesion and friction angle.

As for LEM, specialised computer programs have been designed to perform FEM slope stability analysis, such as the Rock and Soil 3-dimensional analysis program (RS3, Fig. 3.4).

A comparative overview of the strengths and weaknesses of FEM-SSR and LEM is provided in Table 3.1.

Feature	LEM	FEM-SSR
Failure surface	Requires predefined failure surface	Failure surface emerges naturally based on stress conditions
Interslice/inter-element forces	Assumptions needed about interslice shear forces	No assumptions required; full stress field is computed
Soil conditions	Limited in capturing discontinuities or heterogeneities	Well-suited for modelling heterogeneities, anisotropy, and pore pressure effects
Displacement and stress computation	Provides FOS but limited information on displacements or stresses	Provides detailed evaluation of displacements, stresses, and pore pressure variations
Computational effort	Low; suitable for quick and preliminary analyses	Higher; requires more input data and expertise
Interpretation	Simple and well-established in engineering practice	More complex, but provides richer insights
Accuracy of prediction	Conservative and simpler	Can overestimate deformations due to modelling assumptions and lab sample properties (Duncan, 1996)

Table 3.1: Comparison between Limit Equilibrium Method (LEM) and Finite Element Method with Shear Strength Reduction (FEM-SSR) for slope stability analysis.

3.2 Quantifying and modelling the post-failure stage

After collapse, the rock mass transitions into motion, evolving into a flow whose propagation depends on the underlying topography and the physical properties of the moving mass. Analysing landslide dynamics is a critical component of hazard assessment (Jakob, 2005; Hürlimann et al.,

2008), as it enables investigation of the impacts of such events (e.g, height, velocity, runout distance). Such analyses can be conducted a-posteriori, to reconstruct past events and refine simulation tools, or a-priori, to predict potential scenarios and support preventive measures in at-risk areas.

3.2.1 Empirical methods

Empirical relationships are widely used to estimate landslide runout distances by quantifying mobility through geometric ratios. For example, one of the best-known metrics is the reach angle α (also called 'Fahrböschung' angle, Heim 1932) which is expressed as the ratio between the vertical drop H_{max} , and the maximum horizontal travel distance L_{max} (Fig. 3.5). This angle provides a simple geometric measure of landslide mobility, with smaller reach angles indicating more mobile landslides that travel farther relative to their fall height. Numerous studies report an inverse correlation between landslide volume and reach angle, where larger volumes tend to have smaller reach angles and thus longer runouts (e.g., Corominas, 1996; Rickenmann, 1999). Other mobility indices focus on vertical-to-horizontal ratios, such as the ratio between the vertical and horizontal distances between the centres of mass of the landslide source and deposit, denoted as $\frac{H_{CM}}{L_{CM}}$ (Fig. 3.5), which holds more physical significance. This ratio acts as a proxy for the net effective basal friction coefficient, implicitly accounting for factors such as liquefaction and internal deformation (Legros, 2002; Iverson and George, 2016). Landslide spreading behaviour can be further characterised by relating the total planimetric area A of the deposit to landslide volume V . Statistical trends indicate that for high-speed landslides, $A \approx 20V^{\frac{2}{3}}$ (Griswold and Iverson, 2008).

These empirical indices, despite their simplicity, are powerful because they produce statistical results that can be used to establish confidence limits for predictions (Hung et al., 2005; Iverson, 2006; Schilling et al., 2008) and thus for quantitative risk assessment.

3.2.2 Numerical models

Numerical models provide detailed insights into debris-flow dynamics that go beyond what empirical methods can offer. They allow the simulation of flow depths, velocities, runout distances, and the spatial evolution of the moving mass (Fig. 3.6), which are critical for assessing debris-flow intensity and associated hazards (Hürlimann et al., 2008; McDougall, 2017). Numerical modelling is therefore essential for both reconstructing past events and generating predictive

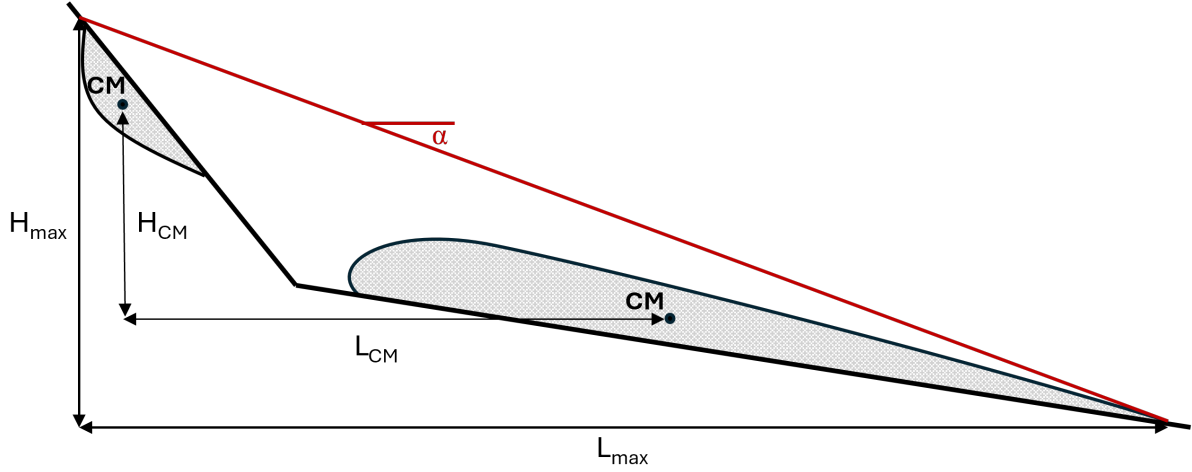


Figure 3.5: Sketch of a landslide cross-section showing the source and deposit areas, defining the horizontal and vertical distances: H_{max} , L_{max} , H_{CM} and L_{CM} . Here, CM denotes the centre of mass and α the angle of reach.

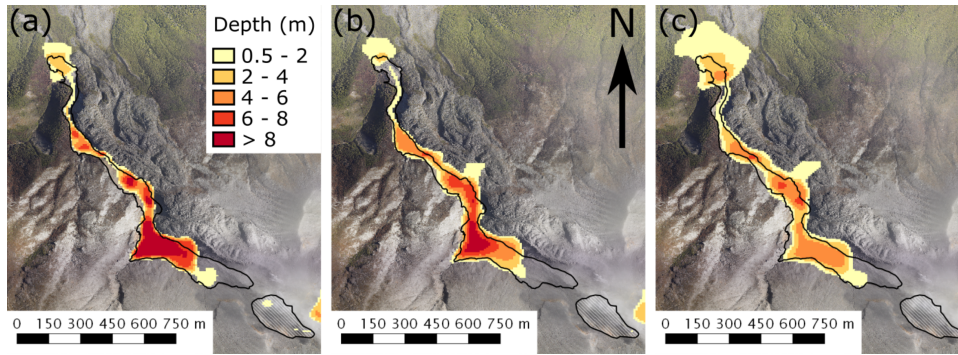


Figure 3.6: Example of numerical simulations at Te Maari, New Zealand, showing predicted deposit depths (m) using three different models: (a) Voellmy-Salm, (b) Pitman and Le (2005), and (c) Pudasaini (2012). The black line represents the observed deposit outline. Reproduced from Mead et al. (2021), licensed under CC BY 4.0.

hazard scenarios.

Over the past few decades, more than twenty 1D and 2D numerical codes have been developed to simulate debris flows dynamics (e.g., Savage and Hutter, 1989; Hungr, 1995; Iverson, 1997). Most are continuum models adapted from hydrodynamic concepts to represent landslide phenomena. They typically rely on depth-averaged shallow flow equations modified to simulate landslide motion (Savage and Hutter, 1989), under the assumption that granular flows behave as incompressible, shallow and finite volumes of Coulomb-like material (Hutter, 2005).

Numerical landslide models are often a combination of analytical and empirical approaches, because no universal constitutive laws exist for debris flows (Pastor and Crosta, 2012). This is

particularly evident in the choice of rheology, which varies widely across models, from single-phase approaches (e.g., Voellmy, Bingham, Herschel-Buckley) to more complex two-phase approaches (e.g., Iverson, 1997; Pudasaini, 2012). Rheological parameters are typically determined through back-analysis of similar events or calibration against laboratory flume experiments (Revellino et al., 2004; Hürlimann et al., 2008).

Rheology and flow mechanics

In 2D and 3D continuum models, the study domain is commonly discretised into slices and columns (representing continuum elements over which physical quantities are averaged), with each numerical element subjected to both driving and resisting forces. Gravity is typically the primary driving force, while resistance to motion is mainly provided by basal shear stress. This resistance can be reduced or counteracted by processes, that enhance mobility, enabling debris flows to travel long distances. Proposed mechanisms include elevated pore pressures (Iverson, 1997; Hungr and Evans, 2004; Evans et al., 2007; Iverson et al., 2011), lubrication by snow or ice (Evans, 1988; Delaney and Evans, 2014), fluidisation by air, steam (Kent, 1966; Manzanal et al., 2016), or frictional weakening by rapid heating (Lucas et al., 2014). However, these processes are difficult to quantify, as reproducing the complex physical conditions of debris flow in laboratory settings remains a significant challenge.

Transitions to highly mobile behaviour are very common in volcanic landslides and can occur either at the onset of the landslide motion or develop progressively in parts of the moving mass during runout (Iverson and George, 2016). Many models assume that the landslide fluidises directly after failure, but this often leads to overestimating flow spread during the early stages. To better represent this transition, some models include mechanisms to delay or control initial spreading. For example, Aaron and Hungr (2016) developed a modified version of DAN3D that allows the user to specify a distance before the flow begins to spread.

Simple, uniform rheological models have limitations in representing this evolving mobility. To address this, more advanced depth-averaged models have been designed to account for rheological changes during motion. For example, Pudasaini and Mergili (2019) proposed a multi-mechanical, multi-phase flow model comprising three distinct phases: (i) a coarse solid fraction (boulders, cobbles, gravels or ice blocks) with Mohr-Coulomb plastic rheology independent of shear rate; (ii) a fine solid fraction (sand to coarse silt) with Coulomb-viscoplastic behaviour

dependent on shear rate and pressure; and (iii) a fluid fraction (mixture of water and very fine particles such as clay and silt) behaving as a viscoplastic fluid dependent on shear rate. Rather than applying a single rheology to the entire flow, this framework considers each phase separately, with particular attention to the viscoplastic properties of the fluid phase. Similarly, Iverson and George (2014) developed the two-phase model, D-Claw, which simulates the coupled evolution of solid volume fraction and pore pressure during motion, representing a significant step towards more physically based modelling of debris flows.

Despite these advancements, significant challenges remain in debris-flow modelling. One particularly difficult process to capture is the progressive entrainment of material along the flow path. Entrainment can substantially alter the flow by increasing volume changes and transferring momentum from the moving mass to the stationary material in its path (McDougall, 2017). Various approaches have incorporated this effect, most commonly through empirical formulations (McDougall and Hungr, 2005; Chen et al., 2006). For example, the r.avaflow model (Mergili et al., 2017) defines entrainment as a dynamic function, recalculating entrainment and updating the topography at each computational step based on a user-defined entrainment coefficient. In D-Claw (Iverson and George, 2014), entrainment is modelled using user-defined entrainment rate and erosion thickness parameters, which influence the spatial evolution of the debris-flow solid volume fraction along the flow path. While such models can better represent certain aspects of flow physics, they require additional parameters, increasing uncertainty and making it unclear whether such models consistently improve predictive accuracy (Mead et al., 2021).

Another challenge lies in simulating where landslides leave their main channel and deflect in another direction, which is essential for hazard assessment. While models generally perform well in identifying run-up locations (Iverson et al., 2016), which can indicate potential overtopping sites, channel overflows can also occur when debris accumulates and blocks the flow. Modelling such blockages remains challenging, and is often approximated by manually altering the topography within the simulation domain.

Model evaluation and calibration

Evaluating model performance is fundamental to assessing flow simulations. A simple qualitative method involves visually comparing the simulated results with the actual field deposits

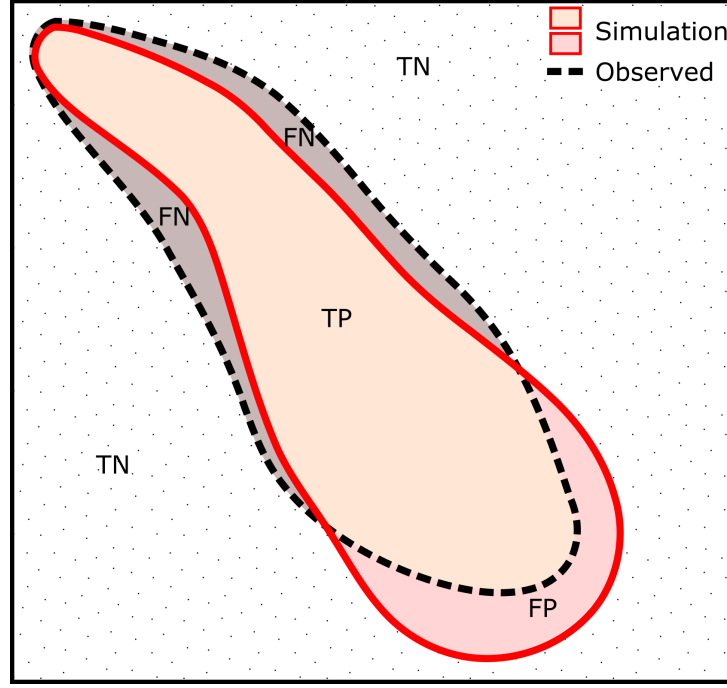


Figure 3.7: Map-cell classification scheme. TP: True Positives; FP: False Positives; TN: True Negatives; FN: False Negatives. The observed trimline is shown as a dashed black line and the simulated trimline as a solid red line. Reproduced from Mead et al. (2021), licensed under CC BY 4.0.

(McDougall, 2017). However, a more robust hazard assessment requires quantitative evaluation of model performance. The most common approach uses map-cell classification, which compares simulation outputs to observations on a cell-by-cell basis to determine true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). Various performance metrics derived from these classifications and analysed together provide a comprehensive evaluation of model performance. For example, the Sensitivity Index, defined as $\frac{TP}{TP+FN}$, measures the proportion of observed hazard correctly simulated by the model. This metric is critical for hazard assessment because a high sensitivity indicates the model effectively minimises missed hazard (FN). Conversely, the Positive Predictive Value (PPV), given by $\frac{TP}{TP+FP}$, measures the proportion of predicted hazard areas that were actually observed. A high PPV implies fewer false alarms (FP), which increases confidence in hazard alerts.

These evaluation metrics also facilitate systematic calibration by allowing model parameters (e.g., friction angle, turbulence term) to be adjusted in order to better fit field observations. Some models incorporate calibration tools; for example, the DAN3D model (McDougall, 2017) includes the PEST parameter estimation package, which uses a systematic inverse analysis algorithm to minimise the error variance between simulated outputs and observed data. Automated

calibration methods based on maximising the overlap ratio between simulated and observed flow outlines have also been developed (Galas et al., 2007; Mergili et al., 2017). Nonetheless, expert judgment remains very important in these approaches, as they can produce non-unique results depending on the choice of parameters and metrics.

3.3 Hazard assessment and mapping

Hazard assessment of debris avalanches is a stepwise process (Fig. 3.8; Dai et al., 2002; Hürlimann et al., 2006). The first step is to evaluate landslide susceptibility, defined as the spatial and temporal probability of failure (van Westen et al., 2006; Mead et al., 2016). The following stages focus on the behaviour of the failed mass (runout) and the integration of both susceptibility and runout into hazard zonation maps (Fig. 3.8).

3.3.1 Landslide susceptibility

Susceptibility represents the likelihood of occurrence of a landslide event and enables the identification of potential zones of debris avalanche initiation. It is influenced by both spatial probability and temporal probability (van Westen et al., 2006). According to van Westen et al. (2006), three essential datasets are required to evaluate the temporal and spatial probability of failure (Fig. 3.8):

1. Historical records, typically compiled in the form of landslide inventory maps (Hürlimann et al., 2006; Yong et al., 2022), provide estimates of frequency, location, type, and magnitude. These are seen as the most valuable source of information for evaluating the hazard, although compiling a complete database remains challenging, especially for smaller events that may not be preserved due to erosion.
2. Triggering factors, such as rainfall and earthquake records. They are critical for temporal probabilities. However, correlations between triggers and past events are often difficult to establish due to incomplete or imprecise dating.
3. Environmental factors (e.g., slope, lithology), which can help identify potential initiation zones by assuming that future events are likely to occur under similar conditions as previous events. They are used to determine spatial probabilities.

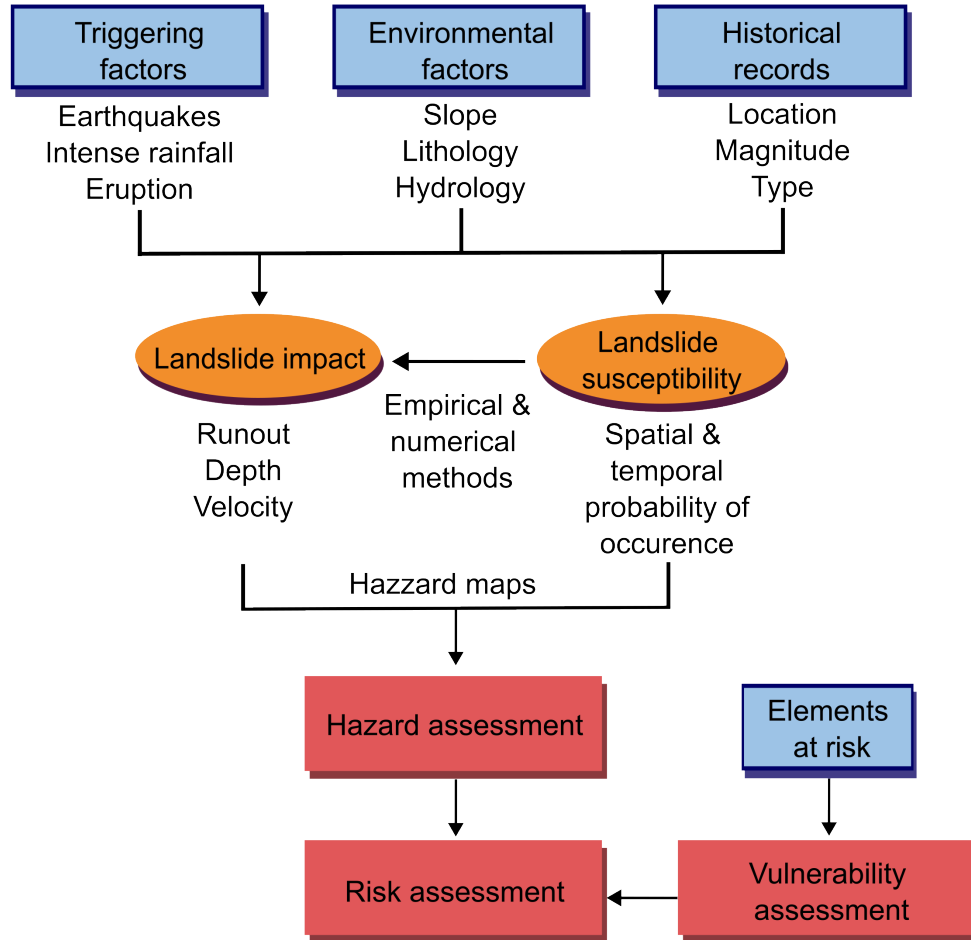


Figure 3.8: Methodological framework of landslide hazard and risk assessment. Blue boxes represent input data. Orange ovals indicate intermediate analyses while red boxes highlight the final assessment steps.

Several methods have been developed to assess susceptibility (e.g., inventory, statistical and deterministic).

A basic and widely adopted approach to assessing landslide susceptibility is through landslide inventories. These consist of databases documenting the characteristics of past landslides on a given area (Dai et al., 2002; Yong et al., 2022). Traditionally, such inventories are compiled from historical records and field investigations, and more recently, they have increasingly relied on remote sensing techniques (e.g., Bernat Gazibara et al., 2019; Osako, 2021; Zhou et al., 2022). They form the basis of most susceptibility maps, providing essential informations such as landslide locations, types of movement, estimated thickness of mobilised material, and the dates of know events (Dai et al., 2002). While inventory-based maps can offer realistic estimates of landslide probability in regions with a history of significant landslide activity, they cannot

identify areas susceptible to landsliding where no prior events have occurred (Dai et al., 2002).

In contrast, deterministic models (e.g., Terlien et al., 1995; Jelínek and Wagner, 2007) of susceptibility go a step further by explicitly modelling the physical processes controlling the slope stability to predict future failures. They are mostly based on slope stability analyses (e.g., LEM, FEM) and therefore require a large amount of input data, derived from laboratory tests or field measurements, such as slope properties, slope geometry, and pore pressure distribution. They are often related to external triggers such as rainfall or earthquakes. The analysis of shallow rainfall-induced landslides involve the coupling between dynamic hydrological models (i.e., spatial and temporal pore pressure distribution) and slope stability models quantifying the susceptibility by identifying critical pore pressure threshold (e.g., Terlien et al., 1995; Safaei et al., 2011; Wang et al., 2023). Dynamic effects, such as seismic acceleration, can be accounted in pseudo-static models. Stability is often calculated using an infinite slope model, where local equilibrium along a potential slip surface is considered (van Beek, 2002). Deterministic methods provide quantitative outputs such as the factor of safety (FOS) and allow incorporation of soil property variability. However, their applicability is limited by high data requirements, the need for simplifications, and the difficulty of obtaining all necessary input parameters, making them less practical for large or heterogeneous areas (Dai et al., 2002; van Westen et al., 2006).

Statistical analysis of susceptibility, in contrast, estimate landslide likelihood by analysing past event occurrences and identifying combinations of environmental variables associated with failure (Dai et al., 2002). The most common approaches involve multivariate techniques, such as multiple regression, which predicts probabilities, or discriminant analysis, which classifies into categories (e.g., Baeza and Corominas, 2001; Eiras et al., 2021). These methods, however, have limitations in handling categorical data (e.g., geology type) and binary outcomes. Logistic regression has been increasingly used to overcome these issues, as it allows the inclusion of both continuous and categorical variables and it is specifically designed to handle binary outcomes (e.g., Cemiloglu et al., 2023; Sujatha and Sridhar, 2021).

Most recently, machine learning algorithms, including Random Forest (RF) and Support Vector Machines (SVM), have been extensively applied, offering predictive accuracy and better handling non linear relationships among variables (Catani et al., 2013; Taalab et al., 2018; Liu et al., 2024). RF constructs multiple decision trees on random subsets of variables (Breiman, 2001), while SVM optimality separates landslide-prone and non-prone areas using kernel functions (Huang and Zhao, 2018). However, these methods still rely on pre-defined condition

factors, and cannot automatically identify the most representative features to further improve classification accuracy (Wang et al., 2019). To address uncertainties inherent to inventory-based datasets, deep learning approaches, such as Convolutional Neural Networks (CNNs), have recently been explored. CNNs automatically extract spatial features from raster datasets (e.g., DEM) to classify landslide-prone areas, offering high predictive performance but requiring large datasets and computational resources (Feng et al., 2025). In addition, ensemble and hybrid models are becoming common, as they combine the strengths of multiple algorithms to improve robustness and generalisation (e.g., Moghimi et al., 2024; Yan et al., 2025).

Overall, while these methods provide valuable insights into landslide initiation, each approach carries uncertainties related to input data, model assumptions, and simplifications. These uncertainties are particularly important because they propagate into runout modelling (van Westen et al., 2006). Consequently, understanding and quantifying susceptibility is a critical first step, as any errors or limitations in these models can compound overall uncertainty in hazard and risk assessments.

3.3.2 Landslide runout

Landslide runout describes the distance travelled by a landslide, defined by its initiation characteristics (e.g., location, mode of failure, volume). Assessing runout is essential in landslide risk analysis, as it helps delineate areas potentially affected by an event. Runout behaviour is characterised by both quantitative and qualitative spatially distributed parameters that reflects the destructive potential of a landslide (e.g., flow depth, velocity) (Hungr et al., 1999; Dai et al., 2002) and is influenced by several key factors:

- **Slope and downslope characteristics:** The geometry of the slope affects how the potential energy released at failure is redistributed into kinetic energy, internal deformation and frictional resistance (Dai et al., 2002; Wu et al., 2023). Downslope morphology and material properties strongly influence landslide mobility. Key parameters include slope gradient, potential for channelisation, and ground surface shear properties. Steeper slope promote rapid mass acceleration while gentler slopes tend to decelerate the landslide mass (Wu et al., 2023). Low-strength layers, such as snow or loose saturated sediments, can increase mobility by acting as lubricated basal surfaces (Aaron and McDougall, 2019).
- **Failure mechanisms:** The failure initiation process strongly governs how the mass is

mobilised (Dai et al., 2002). Loose, contractive soils may undergo static liquefaction when sheared under undrained conditions, generating rapid pore-pressure build-up and long-travel debris flow (Iverson and George, 2016). In contrast, dilatant soils expand during shearing and typically initiate as slower slides, with mobility controlled by rainfall intensity and soil permeability (Dai et al., 2002).

- **Volume and material properties:** The total volume and physical characteristics of the sliding mass are major controls on runout. Larger volumes carry more potential energy and tend to travel further (Legros, 2002; Cerbus et al., 2024; Santi et al., 2025). Material properties, including density, particle size distribution, cohesion, and internal friction angle, determine how the mass deforms and accelerates (Santi et al., 2025). Highly saturated or low-friction materials, such as clay-rich or water-lubricated debris, enhance mobility and promote long-runout flows (Hung et al., 2005).
- **External triggers and hydrological conditions:** Factors such as intense rainfall, rapid snowmelt, or seismic shaking can significantly influence runout by increasing the driving forces or reducing resistance along the path (Zou et al., 2017). Rainfall infiltration or water input from streams (when slopes align with hydrological pathways), can fluidise the mass, lowering effective friction and extending travel distances (Cuomo, 2020). Similarly, earthquakes can induce initial acceleration and partial liquefaction in sensitive soils, facilitating longer travel distances (Huang and Zhao, 2018; Sordo et al., 2025).

Methods for predicting landslide runout are described in Section 3.2. Empirical methods provide a robust preliminary assessment of landslide runout, offering rapid estimates and statistical predictions useful for risk evaluation. Numerical models, in contrast, simulate debris-flow dynamics in details, capturing flow depths, velocities, and spatial evolution that empirical approaches cannot resolve. Based on these assessments, landslide hazard maps can be produced to delimit the areas at risk (Fig. 3.9).

3.3.3 Hazard map

Landslide hazard mapping translates runout assessments and susceptibility analyses into spatial representations of potential risk. The probability of occurrence (i.e., susceptibility) and the process intensity (i.e., flow depth, discharge, velocity) are generally the two parameters correlated in a hazard matrix to construct a hazard map (Hürlimann et al., 2006). Hazard impact

probabilities can be expressed qualitatively (e.g., low-medium-high) or quantitatively (Fig. 3.9; van Westen et al., 2006; Calder et al., 2015). Qualitative assessments are the most widely used for hazard maps (Calder et al., 2015), due to their accessibility to decision-makers, though they allow broader interpretations. Quantitative numerical methods, in contrast, provide precise estimates of hazard intensity and spatial extent (Johnston et al., 1999; Gregg et al., 2004; Haynes et al., 2007).

Most hazard maps currently used by government institutions are geology-based, constructed from the distribution of past events (Calder et al., 2015). While these maps provide valuable information about volcanic capabilities, they do not capture all possible future scenarios. Increasingly, physically-based models of volcanic processes are used to complement the geological knowledge and estimate potential areas affected by future events.

Hazard maps delineate areas exposed to potential landslides and allow identification of elements at risk (e.g., population, buildings, economic activities, public services) and their vulnerability. However, this thesis only focuses on the quantitative hazard assessment (initiation and propagation of volcanic debris avalanches), and does not assess the consequences on the elements at risk.

3.4 Selected approaches

This thesis focuses on the 2012 Te Maari debris avalanche (Tongariro, New Zealand) as a case study to investigate the full sequence of processes from slope failure initiation to post-failure flow dynamics, and ultimately advancing toward hazard assessment. The research was therefore organised in three stages: slope stability assessment, flow modelling, and hazard assessment.

3.4.1 Te Maari case study

Te Maari craters are located on the northern flank of Tongariro, a multi-centre composite volcano covering approximately 65 km² (Leonard et al., 2021) at the southern boundary of the Taupo Volcanic Zone (TVZ). The craters are part of an active hydrothermal system, promoting alteration of the host rocks and thereby affecting mechanical strength and failure modes.

On 6 August 2012, a section of Upper Te Maari crater collapsed, triggering a channelised debris avalanche of nearly 7×10^5 m³ of material down the Mangatipua Stream (Procter et al., 2014). The avalanche progressively transformed into a cohesive, clay-rich debris flow

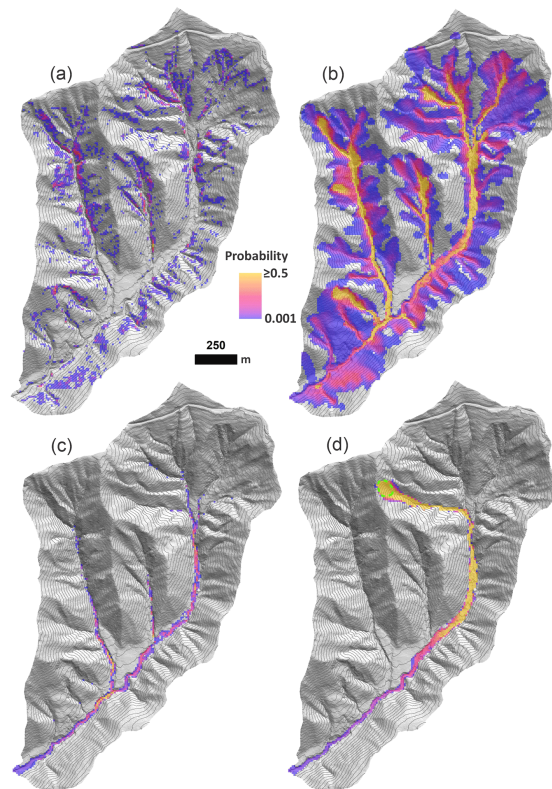


Figure 3.9: Example of quantitative landslide impact maps for the Olympic Mountains site. (a) Probability of landslide ($FOS \leq 1$). (b) Associated landslide runout probability. (c) Probability of deposit ≥ 1 m. (d) Runout probability for a potential scenario (source outlined with dashed green). Reproduced from Keck et al. (2024), licensed under CC BY 4.0.

over a 2 km path, covering $\approx 1.5 \times 10^5 \text{ m}^2$. Observations indicate that the matrix proportion increased from 40 vol % near the source to 60 vol % downstream, reflecting progressive disaggregation and mixing (Procter et al., 2014). This transformation was likely facilitated by high pore-water content and entrainment along the flow path (Procter et al., 2014), consistent with pore-pressure-induced fluidisation and reduced basal friction (Iverson et al., 2011).

We conducted several field studies in order to characterise the study area in term of rock strength and structural arrangement of the rock masses (Fig. 3.10). These studies revealed that the surface lithologies vary from fresh rocks at the base of the channel to more or less pervasive altered rocks in the scar, and that the debris avalanche deposits rest on a highly altered, clay-rich layer, interpreted as the sliding surface of the 2012 avalanche. The presence of this highly deformable layer supports the use of FEM in Chapter 4, as it allows the modelling of material deformations.

Rock masses exposed in the 2012 debris avalanche scar display distinct lithologies (Fig. 3.10), which were used to define rock units in the stability models of Chapter 4 and 6:

- Altered unit (outcropping in the western part of the scar): Composed of loose pyroclastic deposits, including highly porous scoriaceous material, this unit closely approximates the failed mass described by Procter et al. (2014) as ‘variably hydrothermally altered breccias, scoria, tuff and other coarse-grained diamictons’. It exhibits a disturbed to disintegrated structure with poorly interlocked angular to subrounded clasts, and surfaces showing strong alteration (sulfur stains, silica-filled cracks). A GSI of 20–30 was then assigned to this unit.
- Unaltered unit (outcropping in the eastern part of scar): Characterised by a blocky and imbricated structure of cubic blocks (0.5–1 m) separated by orthogonal fractures, this unit has generally good surface conditions with minor alteration near the scar (e.g., white precipitates, sulfur deposits). GSI was estimated at 55–65 for this unit.

3.4.2 Slope stability assessment

The first stage addressed the initiation of slope failure at Te Maari, where instability is hypothesised to have been driven by a progressive increase in pore pressure due to a pressurisation

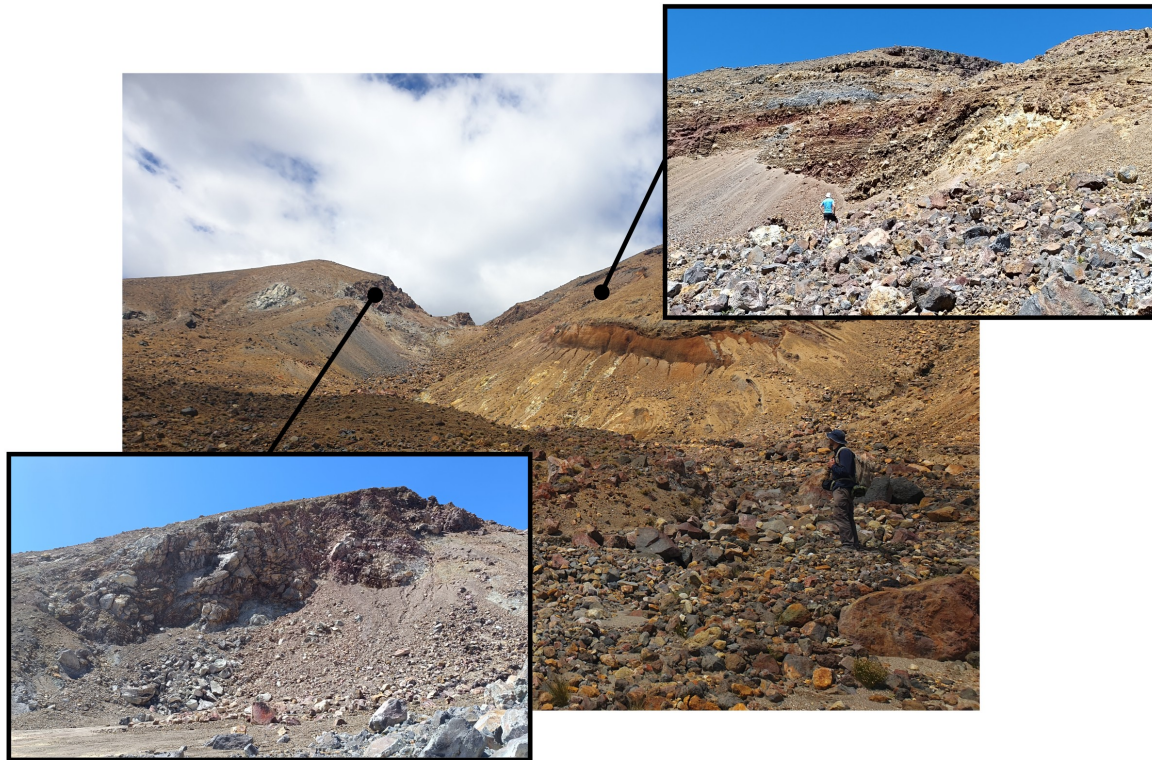


Figure 3.10: Field photographs of the 2012 Te Maari debris avalanche. Main image: view from the bottom of the channel looking up at the avalanche scar. Bottom inset: lava flow with altered surface on the eastern side of the scar. Top inset: altered pyroclastic deposits exposed on the western side of the scar.

of the hydrothermal system in response to a fluid infiltration. FEM and LEM were applied as complementary approaches.

In Chapter 4, FEM was used to replicate Te Maari debris avalanche instability and to explore the mechanisms that may have triggered failure (Fig. 3.11). A SSR analysis was performed with the Rock and Soil 3-Dimensional (RS3) finite-element programme, allowing for a detailed evaluation of stress redistribution, deformation, and pore pressure effects, factors considered the most likely drivers of slope collapse at Te Maari.

By contrast, in Chapter 6, a larger number of scenarios were required for hazard-oriented analyses. In this context, LEM was employed, implemented with Rocscience Slide3 (Simplified Bishop method). LEM's computational efficiency make it suitable for rapidly estimating slope stability across multiple potential slip surfaces. Importantly, insights gained from the detailed FEM analysis in Chapter 4 were used to inform and validate the LEM-based assessments. This complementary use of FEM and LEM ensured that the initiation stage was investigated both

in terms of causal mechanisms for a past event and as a practical tool for predictive hazard analysis.

3.4.3 Flow modelling

The second stage of the research focused on post-failure dynamics, again using the Te Maari case as a reference event. Flow behaviour was modelled using the recently developed two-phase D-Claw model (Iverson and George, 2014). In D-Claw, motion is triggered by gradual changes, such as an increase in basal pore-fluid pressure, which progressively reduces the effective frictional resistance of the slope (Iverson and George, 2016; George et al., 2022). This mechanism is particularly suitable for Te Maari, where slope failure is hypothesised to have been initiated by a pore-pressure rise (Vicente et al., 2025). Moreover, by coupling pore pressure evolution with changes in solid-volume fraction, D-Claw offers a more realistic representation of flow behaviour evolution, and is more likely to capture the transition from a solid-like mass to a mobile debris flow along the path, as hypothesised for Te Maari by Procter et al. (2014).

In Chapter 5, D-Claw was applied to systematically test how initiation parameters affect flow mobility, with a focus on runout distances. Simulations were initialised with the observed source geometry, ensuring that model performance could be evaluated against field evidence. Model performance was assessed using the Critical Success Index (CSI), which quantifies spatial overlap between simulated and observed deposits. This analysis allowed calibration of the flow parameters for the Te Maari debris avalanche (Fig. 3.11) and provided a robust understanding of the mechanisms controlling debris-flow behaviour, while also validating the model suitability for subsequent applications.

3.4.4 Hazard assessment

The final stage of this research, presented in Chapter 6, integrates the different methods into a comprehensive hazard assessment framework for Te Maari (Fig. 3.11).

In this chapter, environmental factors (e.g., DEM, rock density, strength parameters) and triggering factors (e.g., pore pressure increase) identified in Chapter 4 were used to inform a deterministic LEM slope stability analysis. This analysis generated multiple potential slip surfaces that captured uncertainties in slope initiation. The resulting scenarios, which varied in factors such as FOS, volume, depth, and slip direction, were then used as inputs for D-Claw

simulations of post-failure flow dynamics. Flow-related initiation parameters (e.g., permeability, basal friction angle) calibrated in Chapter 5 were held constant across simulations, so that uncertainties were only propagated through initiation geometries and magnitudes. By propagating these variations into the flow model, the outputs were synthesised into probabilistic hazard maps, showing the exceedance probability of flow height.

This combined use of deterministic and physics-based modelling with site-specific data produced robust probabilistic predictions, directly linking slope stability analysis with dynamic runout simulations and providing a practical tool for debris-flow hazard assessment.

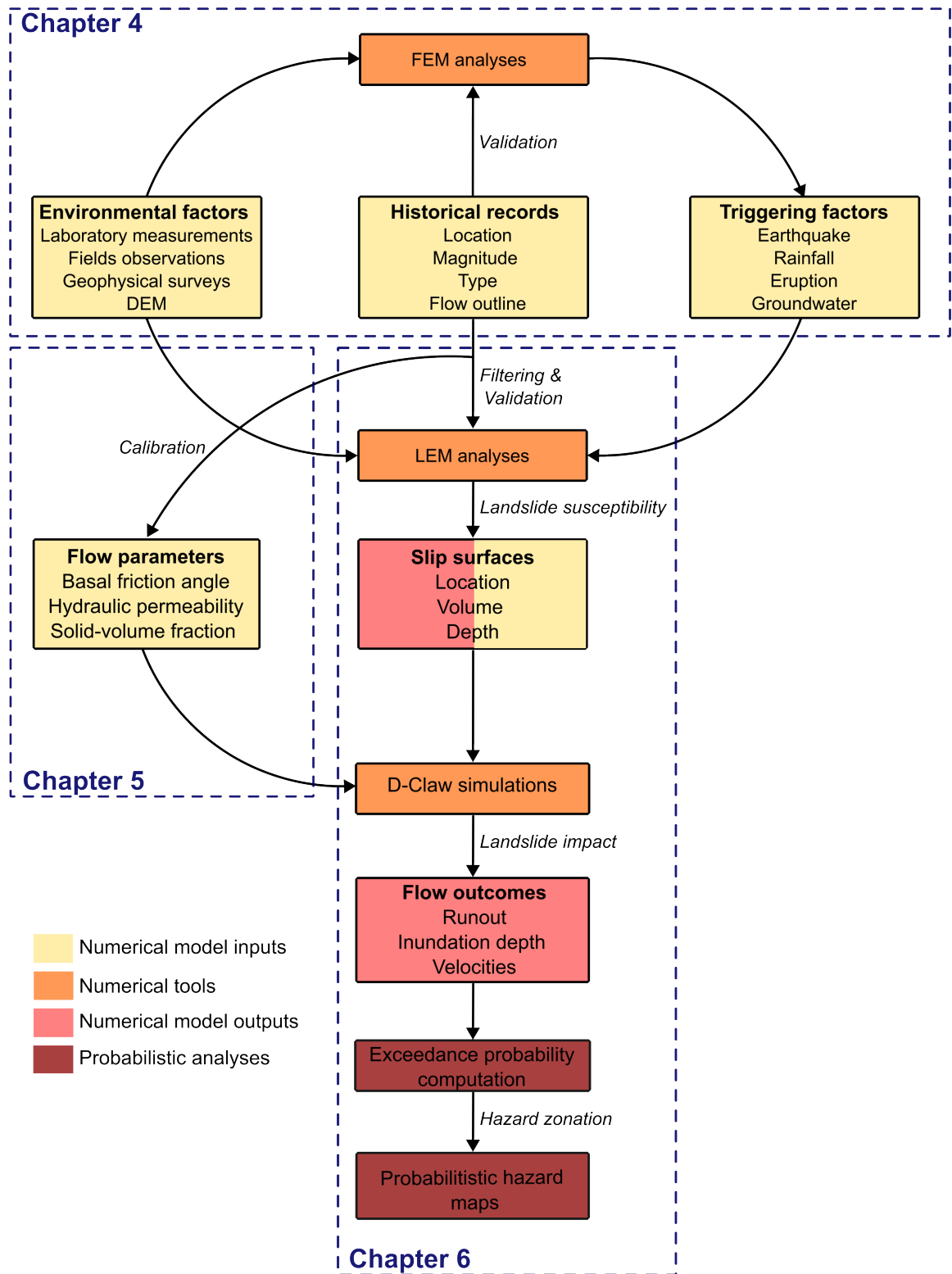


Figure 3.11: Methodological flowchart of the PhD. Box colours indicate the numerical tools, inputs, outputs, and probabilistic steps. Dark blue dashed lines delimit the sections of the framework applied in each chapter.

Chapter 4

Simulation of the 2012 Te Maari debris avalanche: insight into the failure mechanics and the role of the hydrothermal system.

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Contributions:

- **Juliette Vicente:** Conceptualisation, Methodology, Data Curation, Software analyses, Investigations, Interpretations, Writing – original draft, Reviews and Editing.
- **Stuart Mead:** Conceptualisation, Resources, Supervision, Methodology, Investigations, Interpretations, Writing – review and editing.
- **Gabor Kereszturi:** Resources, Supervision, Investigations, Field observations, Writing – review and editing.
- **Craig Miller:** Resources, Funding acquisition, Writing – review and editing.

4.1 Introduction

Volcanoes form complex structures through the accumulation of alternating layers of lava, pyroclastic material, and endogenous growth (Ball et al., 2018; Heap et al., 2021). The accumulation of these materials not only steepens the edifice’s slopes, but also results in physical and mechanical variability from one layer to another (Heap et al., 2021). This broad range of physical and mechanical characteristics (e.g. density, alteration potential, strength) favours the instability of volcanic flanks, leading to mass flow events such as lahars or volcanic debris avalanches. The latter are very frequent on the geological time scale, with approximately a thousand volcanic debris avalanches identified to date for 600 volcanoes, each exhibiting diverse failure types, modes of emplacement, and associated risks (Siebert and Roverato, 2021). Debris avalanche processes are time dependent phenomena (Flageollet, 1996; Qin et al., 2001; van Asch et al., 2007) that progress through distinct phases (pre-failure, failure, post-failure), each characterised by different timescales and controlling factors. The pre-failure phase, marked by gradual weakening of the edifice, often unfolds over extensive timescales, from years to millennia. This leads into the failure phase, a transient event lasting milliseconds to seconds, where a volume of material detaches from the volcano along a developing shear surface. The most significant risks arise during the post-failure phase, where the failed mass flows down the slope, a process that may last minutes to weeks (van Asch et al., 2007). If this flow is characterised by an extreme mobility, it can significantly impact nearby populations and infrastructures (Pudasaini and Miller, 2013). High mobility in volcanic debris avalanches results from fluidisation phenomena which can substantially increase runout distances, even for smaller-volume debris avalanches (Siebert and Roverato, 2021; McGuire, 1996; Hungr et al., 2008). Additionally, numerous volcanic flank collapses are associated with magmatic eruptions (Siebert et al., 2010; Heap et al., 2021), demonstrating their potential to trigger secondary catastrophic events, such as the 1980 Mount St Helens (Glicken, 1996) and the 1956 Bezimianny eruptions (Belousov et al., 2007). Both share similarities including a flank collapse that triggered an instantaneous pressure drop on the volcano, followed by a volcanic blast (Siebert et al., 1987; Sousa and Voight, 1995; Glicken, 1996; Belousov, 1996; Belousov et al., 2007; Siebert and Roverato, 2021).

Flow initiation and subsequent mechanics are strongly influenced by failure conditions. Volcanic slope instabilities are promoted by a combination of preparatory and triggering factors (van Asch et al., 2007), often related to volcanic activity. Preparatory factors are contingent on

the pre-failure phase, during which progressive structural changes occur, leading to the weakening of the slope. These changes may result from the cumulative effect of long-term factors, such as groundwater circulation and hydrothermal alteration (Mordensky et al., 2018b; Kennedy et al., 2020; Schaefer et al., 2023; Mordensky et al., 2022), as well as short-term influences such as climatic events and magmatic intrusions. Triggering factors of slope movements are transient (Crozier, 1986; Leroueil, 2001; van Asch et al., 2007) and are responsible for either decreasing the shearing resistance of the material and/or increasing the shear stress (Duncan et al., 2014). These triggering factors include internal overpressures linked to pressurised magma (Schaefer et al., 2023), hydrothermal fluids (Reid, 2004), and/or gases (Voight and Elsworth, 2000); seismic activity (Sherburn et al., 1999; Calder et al., 2002; Mordensky et al., 2022), or exogenous processes such as heavy rainfall (Carn et al., 2004) or snow melting (Pierson et al., 1990). Steep slopes (Siebert, 1984; Moon et al., 2005; Miller and Williams-Jones, 2016) and the presence of a hydrothermal system are often identified as significant contributors to volcano instability by promoting both preparatory factors (e.g. alteration of material properties; van Wyk de Vries et al. 2000, Reid et al. 2001, del Potro and Hürlimann 2009) and triggering factors (e.g. shallow seismicity, fluid redistribution, and pore pressure changes ; Reid 2004, Cecchi et al. 2004, Ball et al. 2018, Rosas-Carbajal et al. 2016, Heap et al. 2021). The presence of hydrothermally altered material has been demonstrated to weaken slopes by precipitating weaker secondary minerals, such as sulfates and phyllosilicates, thus promoting flank collapses (e.g., Reid et al. 2001, del Potro and Hürlimann 2009, Ball et al. 2015, Siratovich et al. 2016, Bouligand et al. 2016, Mordensky et al. 2019, Heap et al. 2021, Kereszturi et al. 2021). In addition to these mineralogical changes, hydrothermal alteration can also reduce porosity and permeability (e.g. by the precipitation of clays, silica polymorphs, sulfides and sulfates), leading to increased pore pressure and consequently promoting instabilities (Reid, 2004; Heap et al., 2019; Ball et al., 2018). Moreover, uncapping a pressurised hydrothermal system can lead to subsequent explosive behaviour (Siratovich et al., 2016; de Moor et al., 2019; Heap et al., 2021; Kennedy et al., 2020; Mick et al., 2021). Consequently, a thorough analysis of these pre-failure weakening factors and the failure mechanics is essential to assess the hazards associated with the subsequent post-failure movement.

Numerical modelling can be used as a tool for examining the physics and impacts of the different phases of debris avalanches. Slope stability models have been extensively used to investigate the mechanics of major collapse events and assess the slope response to changes in material

properties (Kereszturi et al., 2021; Schaefer et al., 2015; Wallace et al., 2022), groundwater conditions (Ball et al., 2018; Mordensky et al., 2022) or external loads (Iverson, 1995). Continuum numerical methods such as finite element method (FEM) have demonstrated their effectiveness in assessing failure modes by allowing the calculation of stress and strain distribution (Duncan, 1996; Hammah et al., 2005; Schaefer et al., 2023; Wallace et al., 2022) and accurately capturing the complex behaviour of slopes composed of heterogeneous and anisotropic materials (Duncan, 1996). FEM analysis enables a detailed visualisation of the development of failure mechanisms under various disturbance factors (Schaefer et al., 2023), without requiring assumptions about the type, shape, or location of sliding surfaces.

In this study, we develop a stability model using the FEM to investigate the mechanical and groundwater scenario involved in the failure that occurred at Te Maari, Tongariro (New Zealand) in 2012. The succession of events (section 4.2.2) suggests that the failure is linked to the presence of an active vapour-dominated shallow hydrothermal system (Miller et al., 2018) beneath the edifice (Walsh et al., 1998; Hill et al., 2015; Miller and Williams-Jones, 2016). The Te Maari case study, enriched with a multitude of various pre- and post-event geophysical data (e.g., topographic, gravimetric, magnetic, hyperspectral) provides well-constrained information and serves as an instructive case to thoroughly explore failure processes in hydrothermal systems over a complete timespan. Here, we tested the sensitivity of the slope to various groundwater, seismic, and mechanical scenarios, allowing for a better characterisation of the preparatory and triggering factors involved in the 2012 event. We then discuss the influence of these factors on the failure mechanics and highlight implications for future volcanic hazard assessments.

4.2 Tongariro and the 6th of August 2012 debris avalanche

Tongariro is a multi-centre composite volcano (Leonard et al., 2021) covering an area of approximately 65 km², located at the southern boundary of the Taupo Volcanic Zone (TVZ). Volcanism at Tongariro is characterised by frequent, low-volume (0.1-1 km³) eruptions with compositions ranging from basaltic andesite to dacite (Hobden et al., 1996; Nakagawa et al., 1998; Hobden et al., 2002; Shane et al., 2017). The volcanic complex consists of at least 15 overlapping vents that were formed during 6 episodes of major cone formation (Hobden et al., 1999). Since the first eruption c. 275 kyr ago in the Lower Tama Lake area (Hobden et al., 1996), the edifice has undergone many geomorphic changes, including glacial erosion (Topping,

1974; Cole et al., 2018; Leonard et al., 2021; Eaves and Brook, 2021) and later eruptions from new vents, making it difficult to identify old vents. Geomorphic changes due to volcanic mass flows (pyroclastic density currents, lahars, debris avalanches, etc.) are very rare in the history of Tongariro, compared to its neighbour, Ruapehu. However, 5 lahar-type deposits have been identified as resulting from the activity of the Tongariro volcanic complex between 26 and 11 kyr ago, in the northeast part of the massif (Cronin et al., 1997; Procter et al., 2014). These deposits are mainly preserved 10-30 km from the source and are attributed to the remobilisation of loose pyroclastic deposits. To the northwest, Lecointre et al. (2002) identified and mapped the Te Whaiu Formation, which consists of a large debris avalanche deposit (0.5 km^3) emplaced between 55 and 60 kyr ago, initiated as a wet debris avalanche that transformed downstream into a single cohesive debris flow. On the northern flanks, Topping (1974) mapped a series of proximal lahar deposits, the Mangatipua Formation, that are associated with the eruption of Te Maari craters in November 1892. The present morphology of the volcanic edifice is therefore the result of gravitational collapses, as well as the retreat of the glaciers, which greatly contributed to the generation of lahars by providing large quantities of water and exposing the loose, unconsolidated volcanic material in the valleys (Procter et al., 2014). Since the Mangatipua Formation, no debris flows, landslides, or lahars were observed on Tongariro until 2012.

4.2.1 Hydrothermal system of Tongariro

The hydrothermal system of Tongariro, identified as a large, deep demagnetised and low-density region by Miller and Williams-Jones (2016), extends from north of Ngauruhoe to Upper Te Maari, reaching the basement rocks at approximately 2 km depth. It is predominantly vapour-dominated (Miller et al., 2018) with localised condensate zones, as revealed by multiple electrical geophysical studies (Walsh et al., 1998; Hill et al., 2015; Miller et al., 2018; Heise et al., 2024). A low-resistivity layer at approximately 1000 m a.s.l. has been interpreted as a condensate layer several hundred metres thick, with Ketetahi Hot Springs acting as one of its major outflows (Walsh et al., 1998; Hill et al., 2015). However, a more recent groundwater study conducted by Miller et al. (2018) confirmed the presence of a binary hydrothermal system dominated by vapour and liquid zones but also revealed that the system is highly segmented, with irregularly distributed vapour and condensate regions. This complex distribution likely explains the spatially heterogeneous observations of surface unrest indicators prior to the 2012 Te Maari

eruption (Miller et al., 2018).

Due to the presence of this extensive, complex, active hydrothermal system, rocks constituting Tongariro’s edifice undergo significant physico-chemical alterations. The interaction between host rocks and hot acidic fluids results in the precipitation of secondary minerals, often with lower densities, such as sulfides (marcasite), phyllosilicates (kaolin-, smectite-, mica- and chlorite-group minerals, montmorillonite), sulfates (alunite, jarosite, barite, gypsum, anhydrite), silica polymorphs (opal, tridymite, cristobalite), and native sulfur. These alterations, affecting the physical characteristics of the rocks, significantly influence the mechanical response and failure mode (Reid et al., 2001; Heap et al., 2015). With the volume of hydrothermally altered rock within Tongariro edifice estimated at about 20 km³ (Miller and Williams-Jones, 2016), it is important to characterise hydrothermal zones for volcanic hazard assessment, as they could serve as sources for future debris avalanches.

4.2.2 The 6th of August 2012 debris avalanche and eruption

The most recent eruptions of Tongariro occurred on August 6, 2012, and November 21, 2012, at Upper Te Maari Crater (Procter et al., 2014; Jolly et al., 2014) and are linked to the presence of the hydrothermal system. The August 6 event featured a complex eruption sequence, including a small debris avalanche, a multiple-pulse phreatic eruption, and the formation of a chasm in a fissure-like form (Fig. 4.1) about 300 m from the main eruption vent (Jolly et al., 2014).

Unrest began on July 13, 2012, marked by volcano-tectonic and high-frequency repeating earthquakes occurring in three distinct swarms: July 12-13, July 17-20, and July 29-30, 2012 (Hurst et al., 2014). This unrest was also marked by an increase in long-period (LP) earthquakes, which are associated with a source mechanism typically ascribed to fluid resonance in the volcano conduit and fractures (Clarke et al., 2021). On 6 August 2012, two local earthquakes of approximately magnitude 1.8 M_L were recorded at 23:49:06 (UTC+12) and 23:49:21 (UTC+12). Jolly et al. (2014) located the first earthquake directly within the head wall of the debris avalanche scar (Fig. 4.1), suggesting it triggered the collapse of approximately 7×10^5 m³ of material from the northern flank of the volcano (Procter et al., 2014). This first earthquake was then interpreted as concomitant with the onset of the debris avalanche (Jolly et al., 2014). The second earthquake was followed by a low-amplitude persistent tremor for about two minutes, interpreted as the signature of the debris avalanche, increasing in amplitude and culminating in a series of explosive pulses beginning at 23:52:18 (UTC + 12), marking the onset of the phreatic

eruption (Jolly et al., 2014). The eruption is therefore presumed to result from depressurisation due to the unroofing of the hydrothermal system (Procter et al., 2014). The end of this eruption phase was marked by the generation of an eruptive column about 10 km high (Crouch et al., 2014). Intense degassing followed this eruption (Christenson et al., 2013) until November 21, when a smaller eruption that caused localised ash fallout and short-distance pyroclastic flows (Jolly et al., 2014) occurred.

The debris avalanche transformed into a cohesive debris flow that travelled more than 2 km from the source and covered an area of 151,000 m² (Fig. 4.1), following the existing topography of the Mangatipua Stream (Procter et al., 2014). Deposits are characterised by a mixture of hydrothermally altered clasts and agglutinated scoria in a fine clay-rich matrix.

4.3 Method

In this study, finite element slope stability simulations are performed using the 2D finite-element analysis (FEA) software RS2. These analyses examine the influence of the hydrothermal system on rock properties and pore pressure distribution within the edifice, offering insights into its impact on failure mechanics.

FEM discretises the rock mass into smaller polygonal sections, calculating stress and strain at each node when subjected to external loads. This approach allows for a more detailed representation of the internal stress distribution and deformation characteristics (Duncan, 1996), which is particularly useful in the Te Maari case study due to the slope's heterogeneous material properties, including highly deformable altered materials (Fig. 4.3). The failure surface in each scenario is determined through iterative techniques (Duncan, 1996), and corresponds to areas of the edifice where the shear strength is no longer able to maintain the shear stress applied (Wong, 1984). To calculate the critical shear strength of the material and therefore quantify the stability at Te Maari, we used the shear strength reduction (SSR) method (Zienkiewicz et al., 1975; Matsui and San, 1992; Dawson et al., 1999; Zheng et al., 2006; Chang and Huang, 2005). This method iteratively reduces strength parameters until the FEM model fails to converge, which is interpreted as failure (Duncan, 1996). The ratio of initial strength parameters to reduced strength parameters at failure is then determined, expressed as the critical shear reduction factor (SRF).

The general inputs required to conduct these FEM stability analyses are the geometry of the

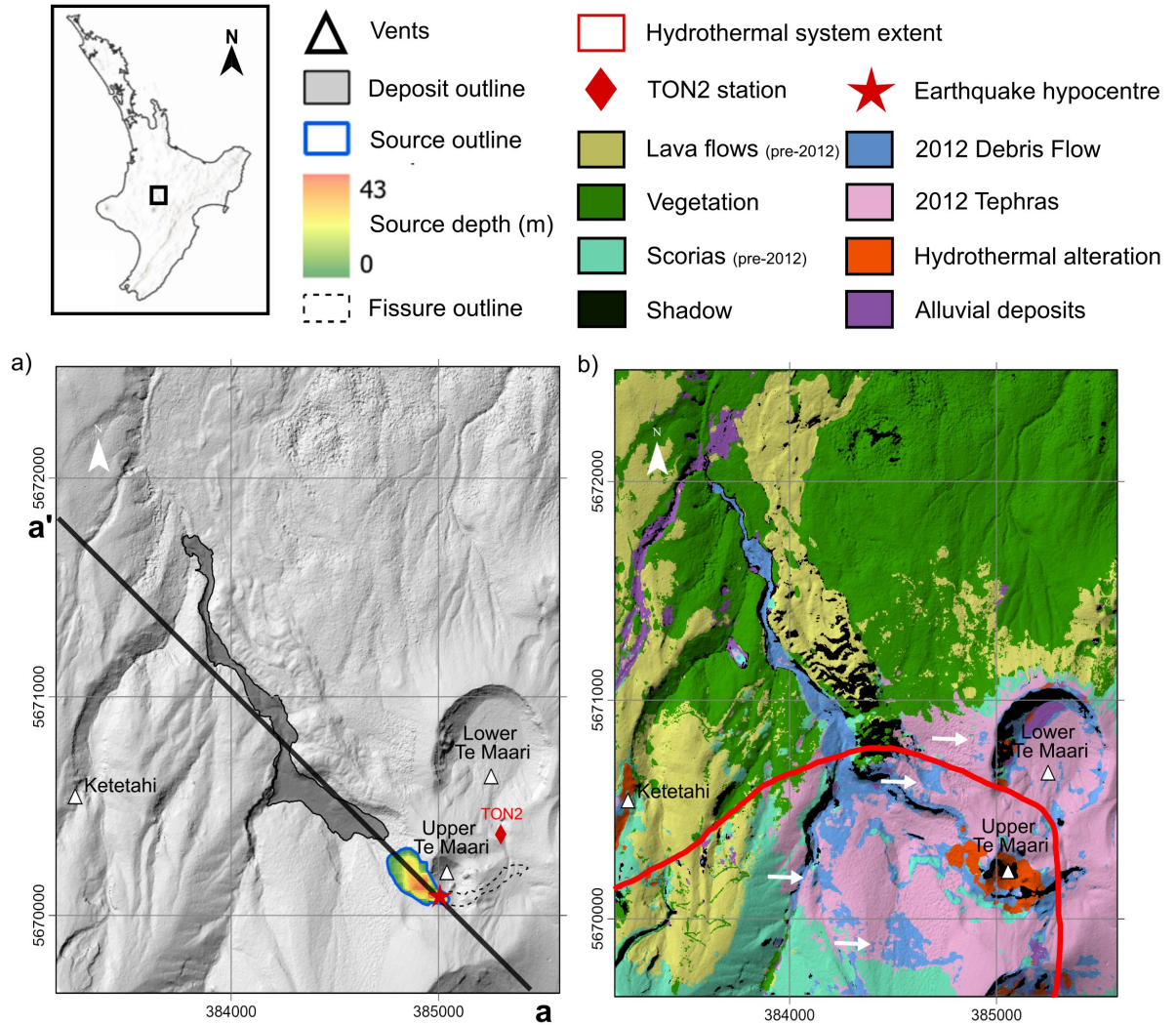


Figure 4.1: (a) Location of the source and deposits of the 2012 debris avalanche. The blue line outlines the source location and the failure depth for each pixel is represented. The dashed line outlines the phreatic eruption fissure. The red star represents the earthquake hypocentre from Jolly et al. (2014) (referred to as EQ (HF) 1 in their study), while the red diamond marks the location of the TON2 station. Profile aa' is used for 2D slope stability simulations. (b) Simplified geological map obtained from the hyperspectral-based image classification of Kereszturi et al. (2018) (overall accuracy of 85 %, misclassified areas are highlighted by white arrows). The red line outlines the extent of the hydrothermal system from Miller and Williams-Jones (2016).

edifice, the mechanical response of the materials (e.g., failure criterion, strength parameters), the groundwater conditions, and the external forces (e.g., seismic loading).

4.3.1 Model geometry

Detailed topographic and subsurface information about the Te Maari edifice are required as boundary conditions for the finite element analysis (FEA). Pre- and post-event DEM data are available, allowing a precise description of erosion processes and debris avalanche deposition (Procter et al., 2014). A difference map between these elevation models allowed the estimation of the debris avalanche source outline (Fig. 4.1) and initial volume, ranging from 6.83×10^5 to $7.74 \times 10^5 \text{ m}^3$ (Procter et al., 2014).

Topography for the FEA is based on a 10 m resolution pre-event DEM provided by GNS Science. This dataset was derived from 20 m contours of the New Zealand LINZ national database originally obtained through stereo photogrammetry in 1975 (Procter et al., 2014). The post-topography is derived from a 1 m resolution post-event DEM obtained through a LiDAR survey conducted in November 2012 (Procter et al., 2014).

Subsurface geometry of the rock units

While most of the groundwater studies (Walsh et al., 1998; Hill et al., 2015; Miller and Williams-Jones, 2016; Miller et al., 2018) encompassed the entire volcanic edifice, the 2012 debris avalanche, constituting a small and shallow event, is inherently very localised. Consequently, the resolution of these studies does not allow for an accurate identification of the heterogeneities within the shallowest layers of the edifice near Te Maari. As a result, the geometry of our model is guided by interpretations of these geophysical data, rather than direct adoption of the geophysical models.

Our approach first used the image classification of Kereszturi et al. (2018), which integrates data from several surveys, an airborne hyperspectral survey conducted in April 2016 (Kereszturi et al., 2018), and the LiDAR survey of November 2012 used to generate the 10 m post-event DEM. Field studies were also conducted in early 2017 (Kereszturi et al., 2018) to investigate the lithologies located around Te Maari craters. This classification effectively delineates the surface lithology, particularly highlighting hydrothermally altered rocks in situ at the surface. The area of interest for our study is the Upper Te Maari crater, wherein a highly localised zone of in situ alteration is observed (Fig. 4.1). The identification of surface alteration in this area

facilitates an initial estimation of sub-surface properties.

Gravity data collected by Miller and Williams-Jones (2016) were then used to estimate the three-dimensional extent of the altered material. Results revealed a local negative complete Bouguer Anomaly at Te Maari, indicating a low-density region and suggestive of the presence of hydrothermally altered rocks. This low-density region was delineated within a density isosurface of $2,250 \text{ kg/m}^3$ (Fig. 4.1, Miller and Williams-Jones 2016). Although this model can clarify the extent at depth of the hydrothermal system identified in Kereszturi et al. (2018), the surface alteration may not correspond to that found at depth. Miller and Williams-Jones (2016) suggest that the highly altered surface zones likely surround a core of less altered rocks that extends to depth. Additionally, the relatively coarse resolution of the model is sufficient to characterise the entire hydrothermal system across the volcanic complex but lacks the necessary resolution to fully define alteration at specific areas of the volcano.

The 2012 deposits originate from a shallow altered zone (Kereszturi et al., 2018) and do not exhibit significant differences in geomechanical properties (Procter et al., 2014). Therefore, the source of the debris avalanche can be assumed from a single altered unit. In that sense, and following other studies (e.g. Wallace et al. 2022), we simplified our FEA models into two geological units (Fig. 4.2) :

- The altered unit encompassing rocks exhibiting signs of hydrothermal alteration.
- The unaltered unit comprising rocks that are not or only slightly affected by alteration processes.

This assumption is sufficient to evaluate the general influence of altered geomechanical properties on the pre-event edifice stability.

We assume the 3D alteration extent as constrained on the surface using the hyperspectral classification of Kereszturi et al. (2018), and at depth using the low-density isosurface of Miller and Williams-Jones (2016). These surfaces were merged using a convex hull, creating the smallest convex volume enclosing all points from both surfaces. The resulting volume (Fig. 4.2b) was assigned to the altered unit, and the rest of the model to the unaltered unit. From this 3D geometry (Fig. 4.2b), we extracted a 2D profile, aa' (Fig. 4.2c), following the major axis of the observed failure, which is used for our numerical simulations.

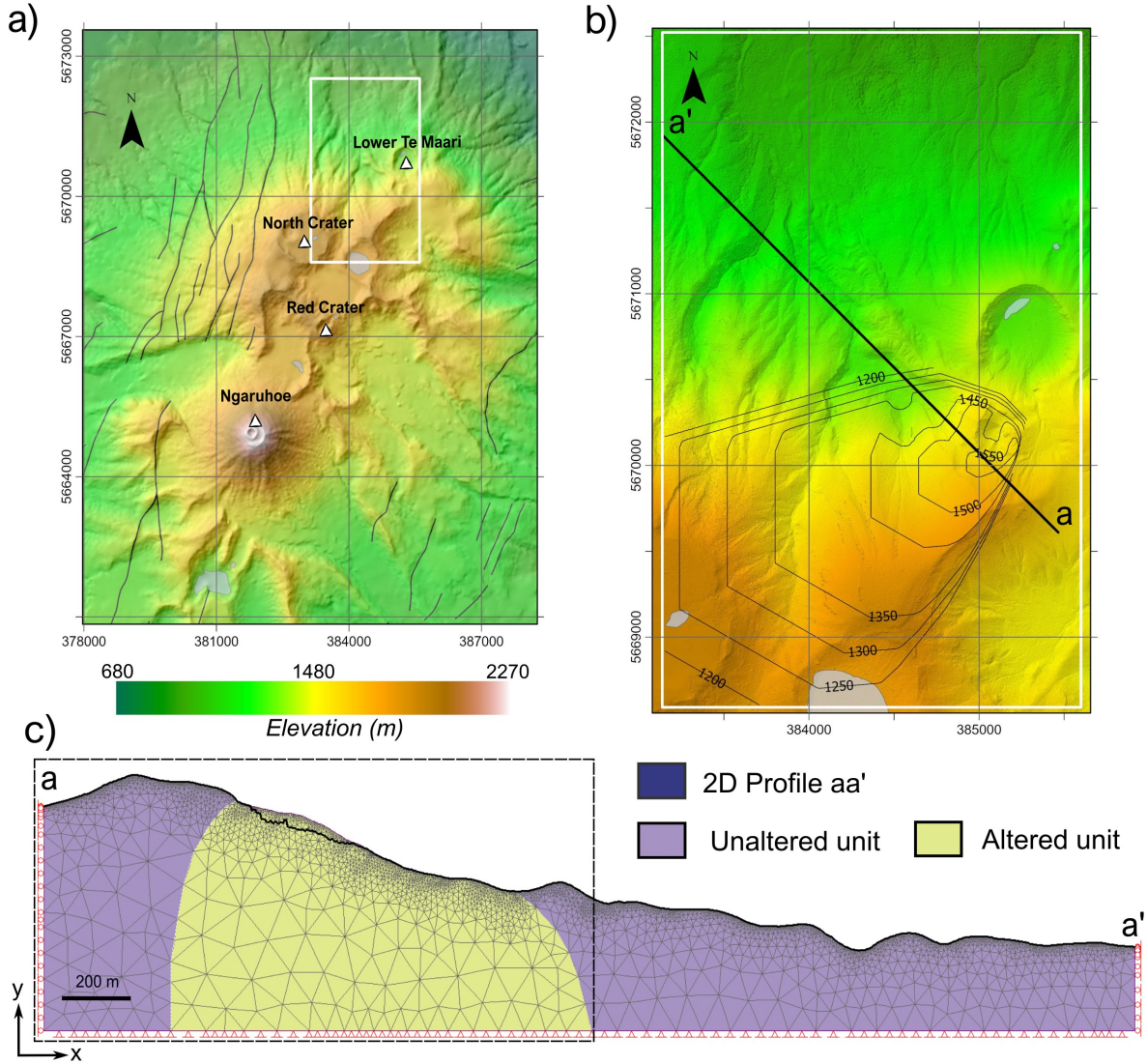


Figure 4.2: (a) Topographic map of Tongariro. The white box highlights the area of interest. (b) Close-up of the area of interest, with contour lines representing the elevation (in metres) of the 3D volume modelled as the altered unit, created by merging the data from Kereszturi et al. (2018) and Miller and Williams-Jones (2016). (c) 2D model geometry along the aa' profile (black profile on subfigure b). Unaltered rocks are shown in purple, altered rocks in yellow. The grey mesh represents a 6-Noded Triangles Graded Mesh. Red circles indicate restraints in the x-direction, red triangles represent restraints in all directions. The black line marks the post-topography of the observed source, and the black dashed box outlines the area for results interpretation in subsequent figures.

4.3.2 Material mechanical response

Generalised Hoek Brown criterion

To predict failure under triaxial stresses, our analyses employ the Generalised Hoek-Brown (GHB) criterion, which accounts for the discontinuities and surface conditions of the rock masses (Hoek and Brown, 1980; Hoek et al., 2002; Hoek, 2005).

This criterion comprises a set of non-linear equations, derived from a combination of the work by Hoek (1968) on the brittle failure of intact rock and Brown (1970) on the behaviour of jointed rock mass. The GHB criterion defines material strength in terms of principal stresses as:

$$\sigma_1 = \sigma_3 + \sigma_{ci} \left(m_b \frac{\sigma_3}{\sigma_{ci}} + s \right)^a \quad (4.1)$$

with σ_1 and σ_3 , the respective major and minor principal stresses; m_b , s , and a , the empirical rock mass constants of the criterion; and σ_{ci} , the unconfined compressive strength (also referred as UCS).

When applying the GHB criterion, SSR-FEM returns the following reduced shear strength envelope (Hammah et al., 2005) at failure:

$$\tau_f = \frac{\tau}{SRF} = (\sigma_1 - \sigma_3) \frac{\sqrt{1 + am_b(m_b \frac{\sigma_3}{\sigma_{ci}} + s)^{a-1}}}{2 + am_b(m_b \frac{\sigma_3}{\sigma_{ci}} + s)^{a-1}} \cdot \frac{1}{SRF} \quad (4.2)$$

τ represents the initial shear strength of the material. The reduced shear strength, denoted τ_f , corresponds to the strength at which the model fails to converge, indicating the onset of failure in the rock mass. The Strength Reduction Factor, denoted as SRF, is the scalar factor applied to incrementally reduce the material strength in SSR-FEM approach, until the system becomes unstable. A $SRF \leq 1$ indicates that the slope is unstable in its modelled form.

Models based on the GHB criterion require the following essential numerical parameters:

- Young's modulus (E), quantifies the material's capacity to deform under the effect of an applied load.
- Poisson's ratio (ν), characterises the relationship between transverse and longitudinal strains of the material when subjected to an applied load, giving crucial information on

how the material deforms.

- Unconfined Compressive Strength (UCS or σ_{ci}), corresponds to the highest stress that a rock can withstand when subjected to a unidirectional stress σ_1 , without any lateral support. UCS, based on intact rock properties, serves as a reference strength in the GHB criterion.
- Geological Strength Index (GSI), is a visual index used for calculating the Hoek-Brown empirical constants (m_b , s , and a) (Hoek, 1994; Hoek and Brown, 1997; Hoek, 2005), and providing qualitative analyses of the surface conditions and structure of the rock mass (Marinos and Hoek, 2000).
- m_i , m_b and s , are the Hoek-Brown empirical rock mass constants (Hoek and Brown, 1980). The disturbance factor D (Hoek et al., 2002), reflecting the impact of anthropogenic actions, is fixed to 0.

The geomechanical properties (porosity, UCS, Young’s modulus and Poisson’s ratio) were estimated for the Te Maari edifice through multiple field surveys (Fig. 4.3) and a literature-based dataset (Table 4.1) of rock strength based on altered and unaltered andesitic rocks from Tongariro [Kidd et al, unpublished data] and analogous rocks from Ruapehu (Mordensky et al., 2018b; Schaefer et al., 2023) and Whakaari (Heap et al., 2015). The chosen analogue volcanic rocks are mineralogically similar (both fresh and altered samples) and are assumed to have similar mechanical properties.

To understand the effect of slope mechanical properties, we run simulations with three different material property configurations (Table 4.2): (1) a homogeneous slope (configuration H), where the entire slope consists of a single rock unit, tested in both a medium-strength unaltered unit (Ha) and a medium-strength altered unit (Hb); (2) a heterogeneous slope (configuration M) with two rock units—one altered and one unaltered—both with medium strength; and (3) a heterogeneous slope (configuration W) where the altered unit has low strength, while the unaltered unit maintains medium strength. The strength of the unaltered unit (i.e., UCS) is considered as the median from the collected dataset of unaltered rocks (Table 4.2). The UCS of the altered unit is estimated either from the median (configuration M) or the lower quartile (configuration W) of the collected dataset of altered rocks (Table 4.2). Accounting for these various mechanical configurations allows us to examine the effect of material strength on edifice stability.

Unit	References (Number of samples)	Parameters	Lithology description
Altered Unit	Heap et al. (2015) (17)	UCS, ϕ	Hydrothermally altered ash tuff (Whaakari)
	Mordensky et al. (2018b) (33)	UCS, ϕ , E , ν	Altered brecciated margin lava (Ruapehu)
	Schaefer et al. (2023) (4)	UCS, ϕ , E	Autoclastic breccia showing surface weathering (Ruapehu)
	Kidd et al, unpublished data (29)	UCS, ϕ	Lava showing intermediate argillic alteration (Tongariro)
Unaltered Unit	Mordensky et al. (2018b) (47)	UCS, ϕ , E , ν	Unaltered dense coherent lava and unaltered intrusions (Ruapehu)
	Schaefer et al. (2023) (2)	UCS, ϕ , E	Unaltered lava (Ruapehu)
	Kidd et al, unpublished data (4)	UCS, ϕ	Unaltered lava (Ruapehu)

Table 4.1: Summary of the dataset used to determine the mechanical parameters of the altered and unaltered units.

The strength dataset (Table 4.1) is based on laboratory tests of intact rocks, and tends to overestimate the strength of the material. Therefore, field studies were undertaken to characterise the macroscopic-scale conditions of the rock masses involved in the collapse through the determination of the GSI. The GSI compares the strength of the rock mass with the laboratory-calculated strength of the intact rock, operating under the assumptions that the strength of the rock mass is controlled by its structure and joints, and that the intact rock samples are homogeneous without discontinuities (Hoek and Brown, 1997). Ranging from 0 to 100, the index represents a proportion of the laboratory-calculated stress. A lower GSI suggests that the total compressive force of the rock mass is a smaller fraction of the laboratory-calculated compressive force.

Field studies at Te Maari revealed that the debris avalanche deposits lie on a highly altered, clay-rich surface (Fig. 4.3c), which is suspected to be the sliding surface of the 2012 debris avalanche. This highly deformable layer supports our choice to use the FEM, which accounts for the plasticity of the materials. Field studies also revealed that rock masses outcropping in the 2012 debris avalanche scar have different lithologies:

- The western side of the scar, which is composed of successions of loose pyroclastic deposits, rich in highly porous scoriaceous deposits, can be assimilated to the altered unit (Fig. 4.3b). It is the closest approximation of the material that formed the failed mass, described by Procter et al. (2014) as mainly composed of ‘variably hydrothermally altered breccias, scoria, tuff and other coarse-grained diamictons’. This unit shows a disturbed

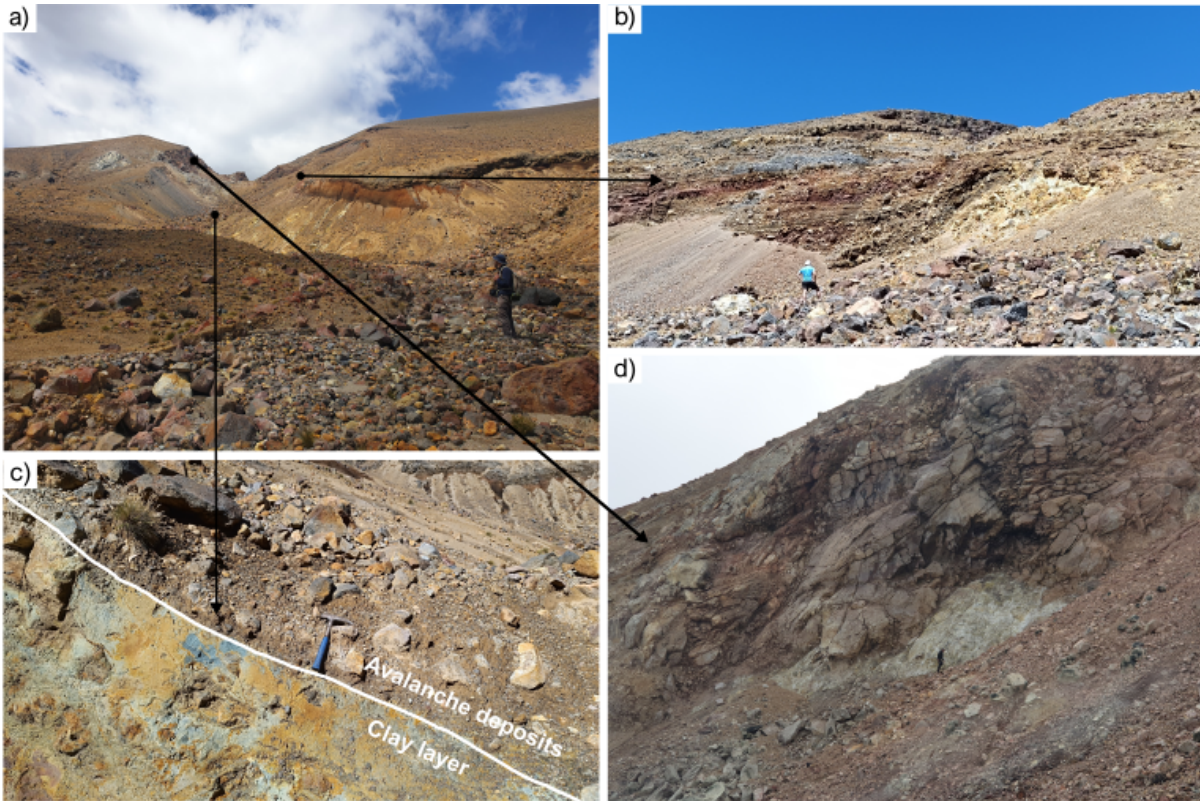


Figure 4.3: Field photographs. (a) Down view of the channel and the scar from the 2012 Te Maari debris avalanche. (b) Altered pyroclastic deposits exposed on the western side of the debris avalanche scar. (c) Clay-rich layer (suspected to be the sliding surface) with debris avalanche deposits on top. (d) Altered lava flow on the eastern side of the debris avalanche scar. The black arrows show the approximate locations of photographs b, c, and d on photograph a.

to disintegrated structure with poorly interlocked mixture of angular to subrounded rock pieces, and poor surface conditions showing high level of alteration (sulfur stains, silica filling cracks). Regarding these conditions, we attribute a GSI ranging from 20 to 30 to that unit, which is consistent with GSI values attributed to similar formations in other studies (e.g. Mordensky et al. 2018a).

- Rock masses constituting the unaltered unit, notably the lava flow forming the eastern part of the channel, show an imbricated and blocky structure made up of cubic blocks ranging from half a meter to a meter, separated by orthogonal fractures, and good surface conditions with slightly altered, iron-stained surfaces (Fig. 4.3d). Closer to the scar, this lava flow shows local pockets of alteration on the surface (e.g. white precipitation within the joints, sulfur deposition, etc). We estimate for this unit a GSI ranging from 55 to 65, which is consistent with typical ranges of GSI values found in the literature for fractured lavas (Moon et al., 2005; Heap et al., 2019).

Slope configuration	Number of units	Unit properties	Unit strength (UCS)	Initial Conditions	Stiffness		Strength				Hydraulics
				Unit weight (kN/m ³)	Poisson's ratio	Young's modulus (GPa)	UCS (MPa)	GSI	m_B	s	Porosity
Ha	1	Unaltered	Medium	26	0.25	35	160	60	6.66	0.012	0.03
Hb	1	Altered	Medium	18	0.2	12	25	25	1.15	0.002	0.2
M	2	Unaltered	Medium	26	0.25	35	160	60	6.66	0.012	0.03
		Altered	Medium	18	0.2	12	25	25	1.15	0.002	0.2
W	2	Unaltered	Medium	26	0.25	35	160	60	6.66	0.012	0.03
		Altered	Weak	18	0.2	12	5	25	1.15	0.002	0.2

Table 4.2: Summary of the input parameters for each mechanical property configuration. Except for the weak-strength altered unit UCS (in configuration W), which is a lower quartile, all parameters are median values derived from a literature-based dataset made of 53 samples for the unaltered unit and 83 samples for the altered unit (Table 4.1).

GSI and porosity values are then used to calculate the empirical constants m_i , m_b and s (through the Eberhardt (2012) equations), associated with the GHB criterion. The parameters used for each mechanical property configuration (Ha, Hb, M, and W) are presented in Table 4.2.

4.3.3 Groundwater and seismic acceleration conditions

Whether fed by magmatic or meteoric fluids, the fluid circulation strongly modifies pore pressure and causes strength changes in the edifice. The three months preceding the eruption show no significant increase in rainfall compared with the monthly average over the last 30 years. Based on data from the two nearest NIWA stations recording over this period (Mt Ruapehu Chateau Ews and Tongariro Hatchery), we find that the quarterly average rainfall for May-August 2012 (266.9 mm and 189.2 mm respectively) is very similar to the quarterly average recorded for the same period between 1991 and 2020 (268.6 mm and 182.9 mm respectively). Therefore, the correlation between the circulation of rainwater and instability is not demonstrated. Rainfall infiltration is therefore neglected in our simulations. However, the seismic record analysis suggests an injection of magmatic fluid prior to the event with small unlocatable micro-earthquakes at 23:46:50 (UTC +12), interpreted as increased flux of fluids from the shallow magma system (Jolly et al., 2014). This fluid injection could possibly have generated a rise in pore pressure throughout the hydrothermal system.

Accounting for this prior knowledge and the complexity of the hydrothermal system at Tongariro, we aim to better constrain the groundwater conditions beneath Te Maari, their effect on the pore pressure distribution, and the impact of these changes on slope stability. Hydrothermal activity and its effect on the stability at Te Maari is therefore modelled using

assumptions of hydrostatic pore pressure changes and seepage (e.g. Mordensky et al. 2022). We tested the sensitivity of volcanic flank stability to different groundwater conditions and seismic effects with the following hydrostatic (configurations 1, 2 and 4), pseudo-static (configurations 3 and 5) and seepage (configurations 6 and 7) assumptions:

1. no groundwater.
2. a wet edifice with an increase in pore pressure using a higher pore pressure ratio in the altered unit (for heterogeneous material property configurations).
3. a wet edifice with an increase in pore pressure in the altered unit and seismic acceleration (pseudo-static coefficients based on acceleration data).
4. a wet edifice with a high perched water table due to the impermeable clay layer.
5. a wet edifice with a high perched water table due to the impermeable clay layer and seismic acceleration.
6. no infiltration.
7. a range of infiltration rates (from $1 \times 10^{-9} \text{ m.s}^{-1}$ to $5 \times 10^{-6} \text{ m.s}^{-1}$), travelling upward from depth due to hydrothermal fluid circulation.

Physical and mechanical boundary conditions allow movement at the top surface, whereas movements are restrained in the horizontal direction for the lateral boundaries, and in all directions at the base surface (Fig. 4.2c). Pore pressure conditions for both hydrostatic and pseudo-static configurations were modelled as a single stage. Dynamic conditions for pseudo-static configurations are applied as pseudo-static loads to represent the earthquake ground motion during the event. For seepage configurations, a localised infiltration is applied at the base of the altered unit in a second model stage.

Hydrostatic and pseudo-static models

Configurations 2 and 3 assume an increase in pore pressure in the altered unit (Fig. 4.4a). In these cases, we establish a pore pressure ratio that evolves with depth as follows:

$$r_u = \frac{u}{\gamma z} \quad (4.3)$$

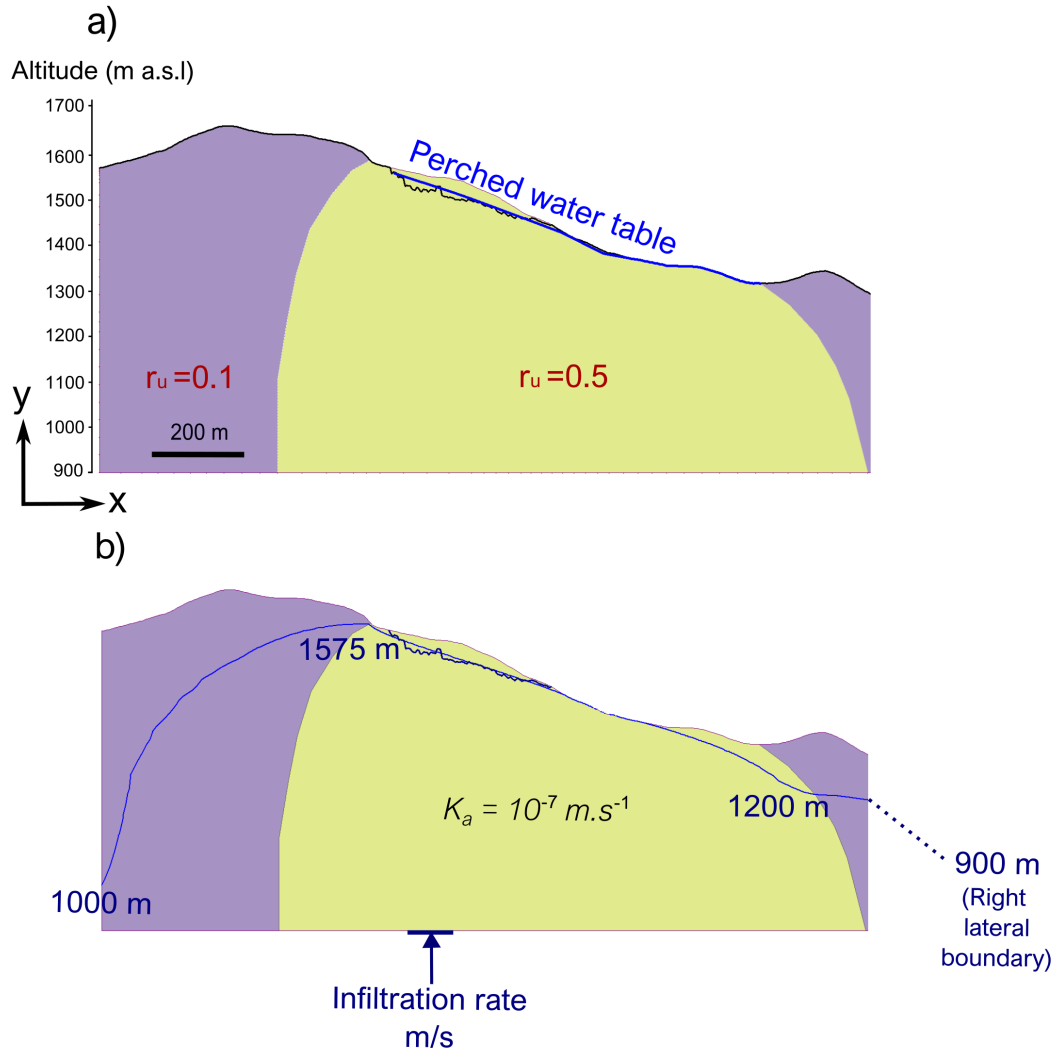


Figure 4.4: Groundwater boundary conditions. (a) Hydrostatic assumptions. R_u is the pore pressure ratio applied in each unit for configurations 2 and 3. Blue line represents the perched water table in configurations 4 and 5. (b) Seepage assumption. Blue line represents the total head (water table level). Depth of the total head (in metres) is indicated at each vertical boundary (both external and material). Upper external boundary is characterised by 0 flow or no groundwater. Lower boundary is characterised by infiltration. K_a is the hydraulic conductivity of the altered unit.

where u is the pore-water pressure, γ is the unit weight of the soil and z is the depth below ground. Considering a saturated edifice, the unaltered unit is attributed to $r_u = 0.1$, and the altered unit to $r_u = 0.5$. This pore pressure ratio approximates hydrostatic pressure in the altered unit and offers a reasonable, simplified, and conservative estimate for saturated initial conditions (e.g. del Potro et al. 2013).

Configurations 4 and 5 assume the presence of the clay-rich sliding surface identified in field studies (Fig. 4.3c). This layer is likely the result of intermediate argillic alteration of an initially highly porous layer (e.g., pyroclastic deposits, Ball et al. 2018), leading to the precipitation of phyllosilicates, significantly reducing its permeability and forming local saturated zones (Ball et al., 2018). When these impermeable layers perch on the slopes of the edifice, shallow pore pressure can increase, thereby promoting instability (Ball et al., 2018). Building our hypothesis on the potential of this clay-rich layer to act as a local impermeable barrier to groundwater flow, we simulate a perched water table elevated at the top of this layer (Fig. 4.4a).

Analysis of the eruptive sequence of the 2012 event by Jolly et al. 2014 identifies an earthquake of magnitude 1.8, located within the head wall of the debris avalanche (Fig. 4.1). The latter is associated with the onset of the debris avalanche, but its trigger role has not been demonstrated. Given the small magnitude of this specific event, we do not consider it sufficient to independently explain the destabilisation. However, previous studies have demonstrated that the combined effect of rising pore pressure and low-magnitude earthquakes can destabilise volcanic edifices (e.g. van Duong et al. 2023). In that sense, we assess its potential influence in conjunction with pore pressure rise in configurations 3 and 5. The pseudo-static method was used to simulate seismic acceleration, employing dimensionless seismic coefficients derived from the study of Peak Ground Acceleration (PGA). The PGA values of 0.003g east, 0.005g north, and 0.0013g vertical were calculated from velocity data recorded at the TON2 station (Fig. 4.1). Given that the station is very close to the hypocentre (≈ 350 m) and assuming that local conditions are not significantly affected by amplification or strong attenuation, we based the calculation of the pseudo-static seismic coefficients on these PGA values. Using Hynes-Griffin and Franklin (1984) method, a horizontal seismic coefficient of 0.020 (average of the x- and y-directions) and a vertical seismic coefficient of 0.0065 were vectorially added to the gravity force on each element of the mesh.

Seepage models

The hydrostatic pore pressure ratio approach (configurations 2 and 3) provides a useful preliminary assessment of slope stability without requiring detailed groundwater data. However, it can be considered more conservative (Mordensky et al., 2022) since it assumes that the edifice is completely saturated. On the other hand, the perched water table assumption (configurations 4 and 5) accounts for a partially saturated altered unit and an unsaturated unaltered unit, which is still a simplified assumption.

A second set of models (configurations 6 and 7), also based on profile aa' (Fig. 4.2), is conducted to simulate the seepage effects, providing a more accurate assessment of the dynamic effects of pore pressure distribution on slope stability. This approach better represents rock heterogeneities by simulating the groundwater level as a function of topography and accounting for the different hydraulic parameters of rock units (Mordensky et al., 2022). The rock mass hydraulic parameters were derived from Mordensky et al. (2022) based on the Pinnacle Ridge units at Ruapehu. We assigned a hydraulic conductivity, K_a of $1 \times 10^{-7} \text{ m.s}^{-1}$ to the altered unit and K_u of $6 \times 10^{-7} \text{ m.s}^{-1}$ to the unaltered unit. Investigations of the groundwater system at Te Maari indicate the presence of a gravitationally stable condensate layer at 1000 m a.s.l (Walsh et al., 1998; Hill et al., 2015; Miller et al., 2018), which serves as a base to fix the lateral hydraulic boundary conditions of the model with a total head fixed at 1000 m a.s.l on the left boundary and at 900 m a.s.l on the right boundary, representing the inclination of the water table (Fig. 4.4b). The seepage models assume an almost completely saturated altered unit with a total head fixed in the shallow layers.

Using the interpretation of the seismic record of the 2012 eruptive sequence by Jolly et al. (2014), we simulate a potential fluid infiltration by implementing a vertical infiltration rate at the base of the altered unit (Fig. 4.4b). The objectives, using seepage models, are to determine the impact of a vertical infiltration on pore pressure distribution and to identify the infiltration rates capable of replicating the 2012 failure.

In the following sections, we refer to our fourteen stability models using abbreviations that indicate both material properties and groundwater configurations (see Table 4.3). "H" represents homogeneous material, "M" indicates a medium-strength altered unit, and "W" stands for a weak-strength altered unit. Groundwater conditions are denoted by the corresponding number from the groundwater conditions list. For example, simulation M3 refers to a medium-strength altered unit under a pore pressure ratio (r_u) of 0.5.

4.4 Results

A total of 14 FEA simulations exhibiting different material, groundwater, and seismic conditions were performed (Table 4.3). The stability of each simulation was quantified by calculating the critical SRF through the SSR method (Zienkiewicz et al., 1975), presented for each simulation in Table 4.3. This is the ratio of the initial strength parameters to the reduced strength parameters at failure. A $\text{SRF} \leq 1$ indicates that the initial strength state of the material is unstable, making the slope more likely to fail. In homogeneous, dry edifice conditions, the SRF is significantly greater than 1. Generally, weaker materials ("W" configurations) yield a lower SRF, and higher pore pressures further reduce SRF values. Only two scenarios, simulations W3 and M7, result in SRF values below 1; both involve high pore pressure in the upper layers of the edifice.

In our study, we further investigate the potential zone of failure for each simulation using the maximum shear strain, which is defined as the largest angle of deformation within a material under an applied load and given as:

$$\gamma_{max} = \frac{\varepsilon_1 - \varepsilon_3}{2} \quad (4.4)$$

with γ_{max} , the maximum shear strain, ε_1 and ε_3 , the minimum and maximum principal strain.

Shown as coincident with the slip surface by several laboratory tests (e.g. Roscoe 1970), maximum shear strain is simple to use, because of its hyperbolic dependency with the shear strength (Duncan and Chang, 1970; Matsui and San, 1992). Using this technique, the failure surface is not unique but consists of a yield zone extending from the base to the top of the slope (Matsui and San, 1992). This yield zone allows an interpretation of the overall location and geometry of the failure surface.

4.4.1 Effect of material properties and discontinuities on failure

The post-topography surface outline (Procter et al., 2014) is used to compare our results with the observed failure. Simulation results are presented as the maximum shear strain distribution (Fig. 4.5) corresponding to one or two strength-reduction stages past the critical SRF, which allows for a better visualisation of the failure propagation.

The mode and extent of failure in dry homogeneous (H1) conditions are approximately the same regardless of material properties, only affecting the critical SRF, which reduces from $\text{SRF} = 9.17$ (Table 4.3) for unaltered homogeneous (H1a) to $\text{SRF} = 3.37$ (Table 4.3) for altered

	Conditions				Results	
	Simulation	Groundwater configuration	Seismic coefficients (H ; V)	Material configuration	Critical SRF	Max Pore Pressure (MPa)
Hydrostatic & Pseudo-static	H1a	Dry	-	Unaltered homogeneous	9.17	NA
	H1b	Dry	-	Altered homogeneous	3.37	NA
	M1	Dry	-	Medium unaltered (UU) and altered unit (AU)	3.46	NA
	W1	Dry	-	Medium UU and weak AU	2.02	NA
	M2	$R_u = 0.5$	-	Medium UU and AU	1.58	7.7
	W2	$R_u = 0.5$	-	Medium UU and weak AU	1	7.7
	M3	$R_u = 0.5$	0.020 ; 0.0065	Medium UU and AU	1.47	7.7
	W3	$R_u = 0.5$	0.020 ; 0.0065	Medium UU and weak AU	0.91	7.7
	M4	Perched water table	-	Medium UU and AU	2.07	6.4
	W4	Perched water table	-	Medium UU and weak AU	1.26	6.4
	M5	Perched water table	0.020 ; 0.0065	Medium UU and AU	1.94	6.4
	W5	Perched water table	0.020 ; 0.0065	Medium UU and weak AU	1.18	6.4
Seepage	M6	No infiltration	-	Medium UU and AU	2.16	6.7
	M7	Infiltration rate: $1.5 \times 10^{-6} \text{ m.s}^{-1}$	-	Medium UU and AU	0.97	8.7

Table 4.3: Summary of the main conditions and results for each simulation. H and V stands respectively for horizontal and vertical pseudo-static seismic coefficients.

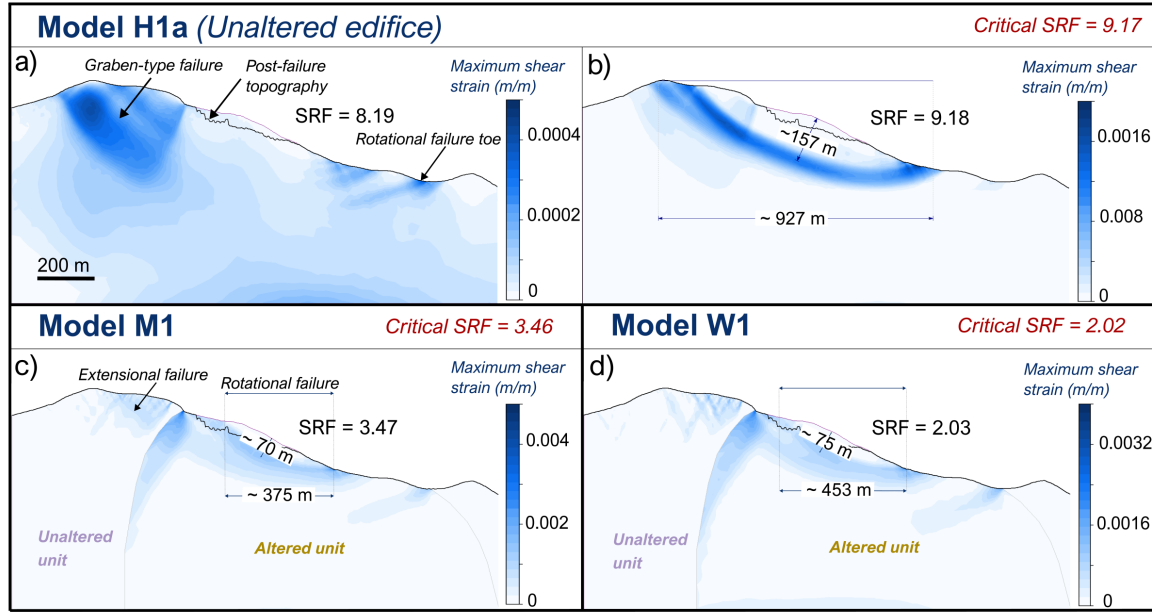


Figure 4.5: Te Maari shear strain results under dry conditions. (a) Simulation H1a at multiple strength-reduction stages before the critical SRF and (b) at one strength-reduction stage beyond the critical SRF for a homogeneous unaltered edifice. (c) Simulation M1 at one stage beyond the critical SRF for a heterogeneous edifice. (d) Simulation W1 at one stage beyond the critical SRF for a heterogeneous edifice. The black line outlines the post-failure topography built from Procter et al. (2014) difference map.

homogeneous configurations (H1b). Considering a dry, homogeneous edifice (H1) with unaltered (Fig. 4.5a and 4.5b) or altered material properties, strain is primarily concentrated in a graben-type extensional failure in the upper portion of the slope, with a deep-seated rotational failure toe (Fig. 4.5a). This progressively connects with the extensional failure at critical SRF to form a large rotational slip surface including the upper part of the slope (Fig. 4.5b). The strain concentration zone forms a slip surface of nearly 160 metres deep and 930 metres long (Fig. 4.5b) for both material property scenarios (H1a and H1b).

In comparison, M1 and W1, the dry heterogeneous configurations (Fig. 4.5c and 4.5d) show rotational strain concentration zones that are mainly confined to the altered unit. These zones do not extensively propagate into the upper portion of the slope, which is part of the unaltered unit (Fig. 4.5c and 4.5d). The disconnected extensional failure in the upper part of the slope is still observed. The resulting rotational failures are much narrower than the homogeneous simulations (H1), with collapse depths on average 50 % smaller. Adding the altered unit also has a significant impact on the overall stability of the slope with a decrease in SRF (62 %) for simulation M1 (Fig. 4.5c), which is more pronounced (78%) when the altered unit is weaker (simulation W1, Fig. 4.5d).

Therefore, considering an entirely homogeneous edifice (H1), the upper portion of the slope is always involved in a large, deep-seated rotational failure. In contrast, a heterogeneous edifice (M1 and W1) results in localised rotational failures that more closely represent the slope failure at Te Maari. Despite showing shallower and thinner potential collapses, the dry heterogeneous simulations still overestimate the magnitude of collapse (i.e., the volume of material involved) and produce extensional failures in the upper portion of the slope. Moreover, these configurations exhibit $\text{SRF} \geq 2$, indicating that the slope remains stable.

4.4.2 Effect of hydraulic properties on failure characteristics

Simulations using dry conditions (H1a, H1b, M1, and W1) cannot replicate the observed failure, thus other conditions (e.g., pore-water pressure) must be explored. Here, we explore the effect of groundwater parameters on stability to understand the impact of the hydrothermal system on the failure.

Hydrostatic assumptions

Both the pore pressure ratio models (configurations 2 and 3) and the perched water table models (configurations 4 and 5) exhibit similar pore pressure profiles, closely approximating the hydrostatic pressure (Fig. 4.6). However, slight differences between these profiles are observed, particularly at shallower depths. In the pore pressure ratio models, the vertical pore pressure profile is slightly higher in the first 300 metres compared to the perched water table configurations. The perched water table is approximately located at a depth of 30 metres, extending to the surface towards the northwestern boundary of the altered unit (Fig. 4.4a). Therefore, the pore pressure remains zero over the first 30 metres in these models (Fig. 4.6), indicating an unsaturated layer without matric suction effects.

Although the difference in pore pressure is small, it results in large variations in failure depths and extents (Fig. 4.7). In the perched water table models (Fig. 4.7c and 4.7d), the strain concentration zones reach maximum depths of approximately 110 metres for simulation M4 and 130 metres for simulation W4, both of which are significantly deeper than the observed failure depth. They also reveal a longer major axis, strongly controlled by the perched water table boundaries. Additionally, considering either a weak (W4) or medium strength altered unit (M4), the initial slope conditions remain stable with a critical $\text{SRF} \geq 1$. In contrast, the pore pressure ratio models (Fig. 4.7a and 4.7b) show strain concentration zones with substantially

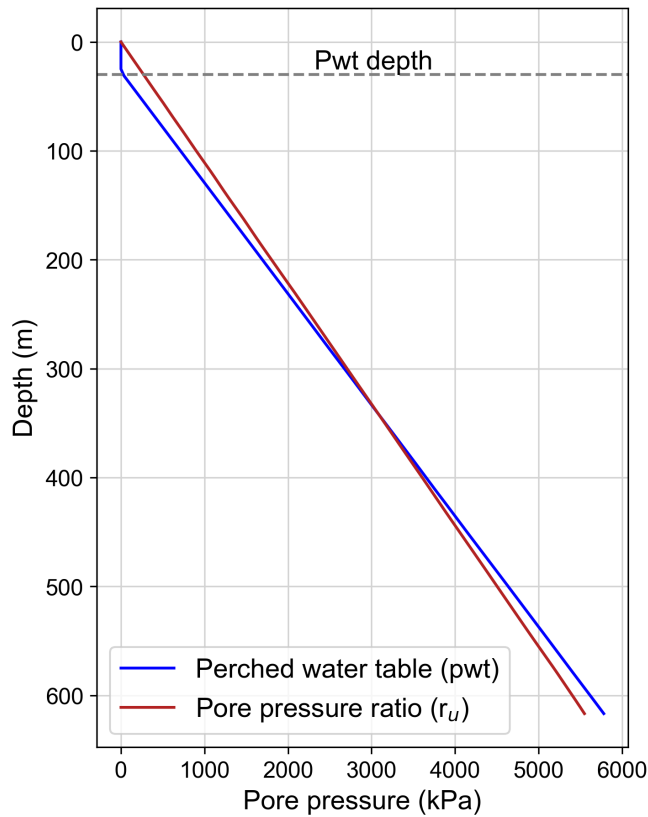


Figure 4.6: Pore pressure profiles with depth along the black vertical profile shown in Fig. 4.7a, for both hydrostatic groundwater configurations: perched water table (blue) and pore pressure ratio (red).

smaller maximum depths of approximately 55 m for simulation M2 and 65 m for simulation W2, as well as narrower extents. Simulation M2 presents a critical SRF of 1.58, whereas it reaches instability when considering a weak-strength altered unit (W2), with a critical SRF of 1. Despite a slightly deeper failure for simulation M2, both material property configurations show approximately the same failure geometry.

These results show that the pore pressure state of the upper layers significantly impacts the failure extent and depth. When the entire hydrothermal system is saturated and then subjected to high pore pressure (simulations M2 and W2), we observe shallower collapses, resulting in failure geometries similar to the observed failure. Therefore, we consider that the modelled pore pressure in these models is a reasonably simplified representation of the groundwater state during the event. The most notable difference between the observed and simulated results is the location of the failure, with the simulated failure shifted 80 metres to the northwest. Instability conditions are also achieved with a SRF of 1 when considering a weak-strength altered unit (W2).

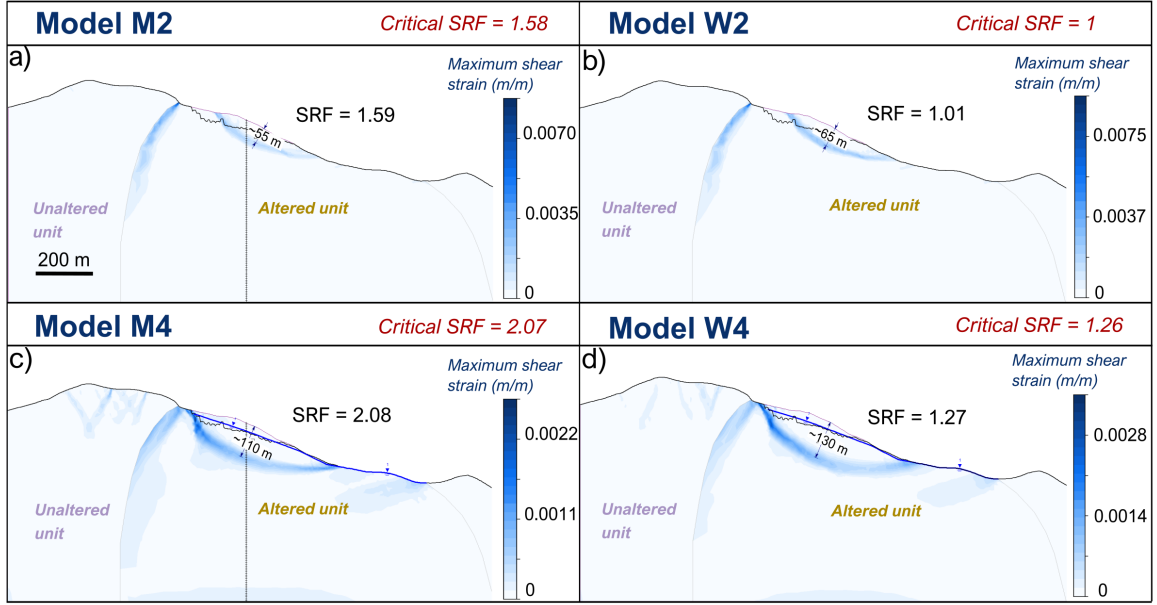


Figure 4.7: Te Maari shear strain results under hydrostatic groundwater configurations. (a) Simulations M2 and (b) W2 at one strength-reduction stage beyond the critical SRF. (c) Simulations M4 and (d) W4 at one strength-reduction stage beyond the critical SRF.

Seepage assumption

The results of infiltration rate simulations (Fig. 4.8) show very large potential failure depths (70-100 m) and low pore pressures at failure depth (P30) when the infiltration rates are lower than the hydraulic conductivity ($1 \times 10^{-7} \text{ m.s}^{-1}$). In contrast, the results show a linear increase in pore pressure (P30) and generally shallower failure depths (25-70m) when infiltration rates are higher than the hydraulic conductivity. Collapses ($\text{SRF} \leq 1$) occur with infiltration rates of at least 10^{-6} m.s^{-1} , corresponding to a pore pressure threshold of 200 kPa at failure depth. This infiltration rate corresponds to a maximum infiltration pressure of 8 MPa, which results in an excess pore pressure of $\approx 1.5 \text{ MPa}$ above hydrostatic at the infiltration site, indicating that even a relatively minor change in pore pressure is sufficient to promote instability.

We attribute the results in Fig. 4.8 to the development of a positive pore-pressure front due to infiltration at depth. As the infiltration rates exceed the hydraulic conductivity of the material, excess water rapidly accumulates due to limited drainage options. This leads to increased pore pressure around the infiltration point, which then progressively propagates throughout the system. The saturation front is then pushed through the initially unsaturated upper layers, leading to a build-up of shallow pore pressure (Fig. 4.8). Building pore pressure in the shallow layers tends to promote shallower failures (Ball et al., 2018). Conversely, if the

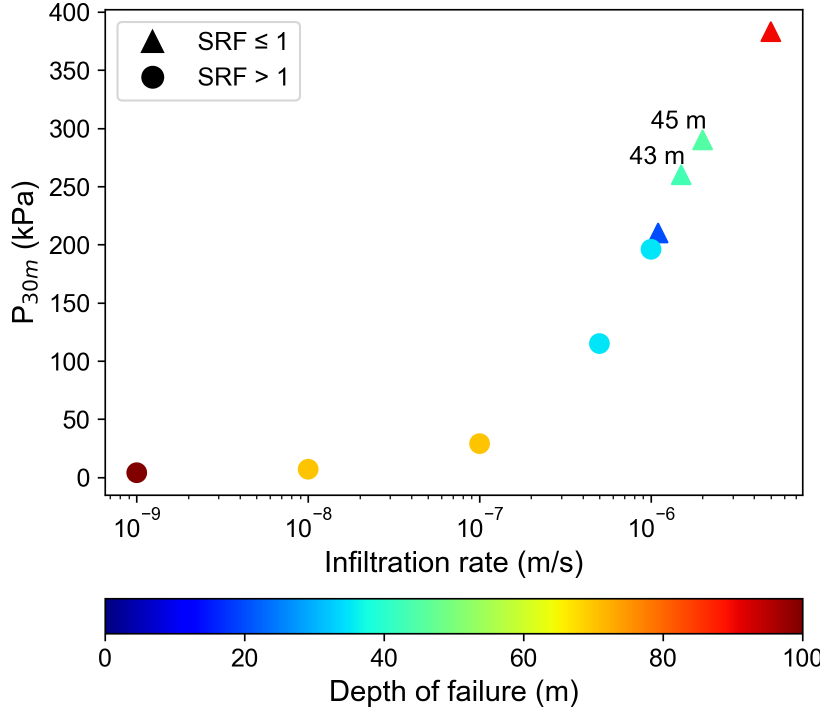


Figure 4.8: Infiltration rate values (m.s^{-1}) leading to instability (triangular markers, $\text{SRF} \leq 1$) and stability (circular markers, $\text{SRF} > 1$) as a function of the pore pressure at 30 metres depth. Colour scale displays the maximum depth of failure for each scenario.

infiltration rates are lower than the hydraulic conductivity, the infiltrated fluid does not impact the upper layers where the pore pressure remains zero, and the rocks remain stable (Fig. 4.8).

Among the unstable infiltration scenarios (Fig. 4.8), the two modelled combinations of infiltration rates of $1.5 \times 10^{-6} \text{ m.s}^{-1}$ (simulation M7, Fig. 4.9c), and $2 \times 10^{-6} \text{ m.s}^{-1}$, corresponding to 30-meter depth pore pressures of respectively $\approx 260 \text{ kPa}$ and $\approx 290 \text{ kPa}$, provide the most accurate representations of the observed failure depth and shape (Fig. 4.8 and 4.9c), despite a northward shift of approximately 150 metres. In contrast, the no infiltration scenario (simulation M6, Fig. 4.9b), with a water table level approximately aligning with the sliding surface, exhibits a wide and deep failure, reaching a depth of 110 metres, which closely resembles the results of the hydrostatic simulations M4 and W4 considering a perched water table (Fig. 4.7). Additionally, for simulation M7, considering an infiltration rate of $1.5 \times 10^{-6} \text{ m.s}^{-1}$, we note the development of multiple shear bands, tilted in the slope direction, propagating from the slope surface to the main slip surface, indicating the potential for a retrogressive failure (Fig. 4.9).

4.4.3 Effect of seismic ground acceleration on failure onset

Our pseudo-static models allow us to evaluate the combined destabilising effects of the low-magnitude earthquake located within the head wall of the debris avalanche (Jolly et al., 2014)

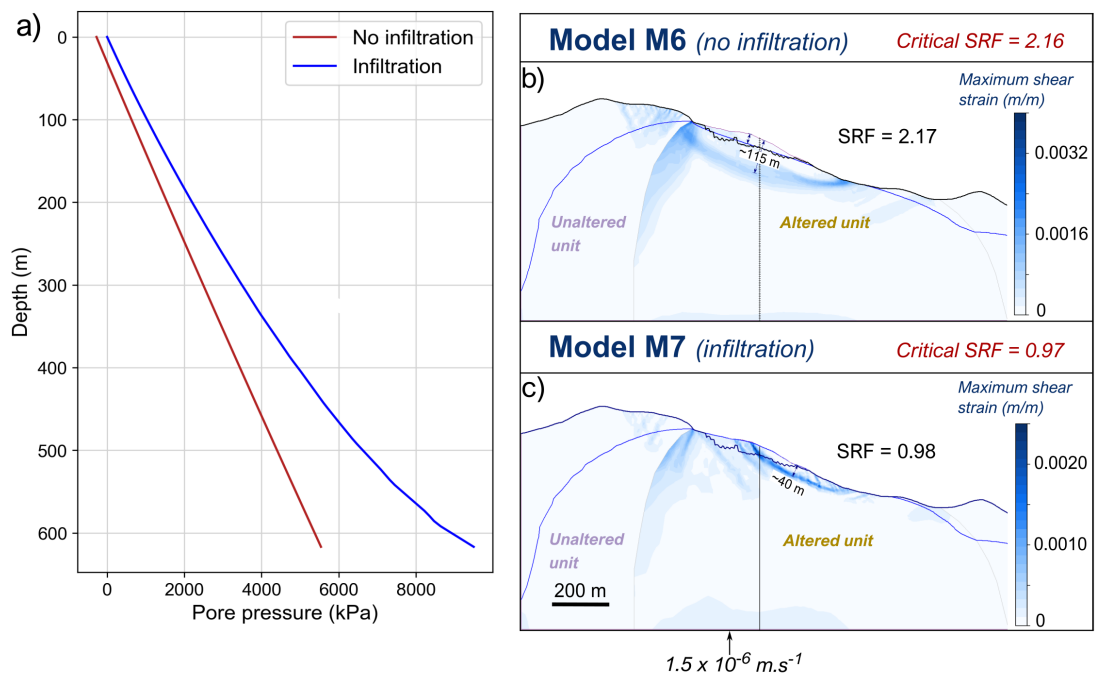


Figure 4.9: (a) Pore pressure profiles along the black vertical query for simulation M6, without infiltration (red) and for simulation M7, with infiltration (blue). (b) and (c) are Te Maari shear strain results under seepage groundwater configurations: without infiltration (b) and with an infiltration of $1.5 \times 10^{-6} \text{ m.s}^{-1}$ (c).

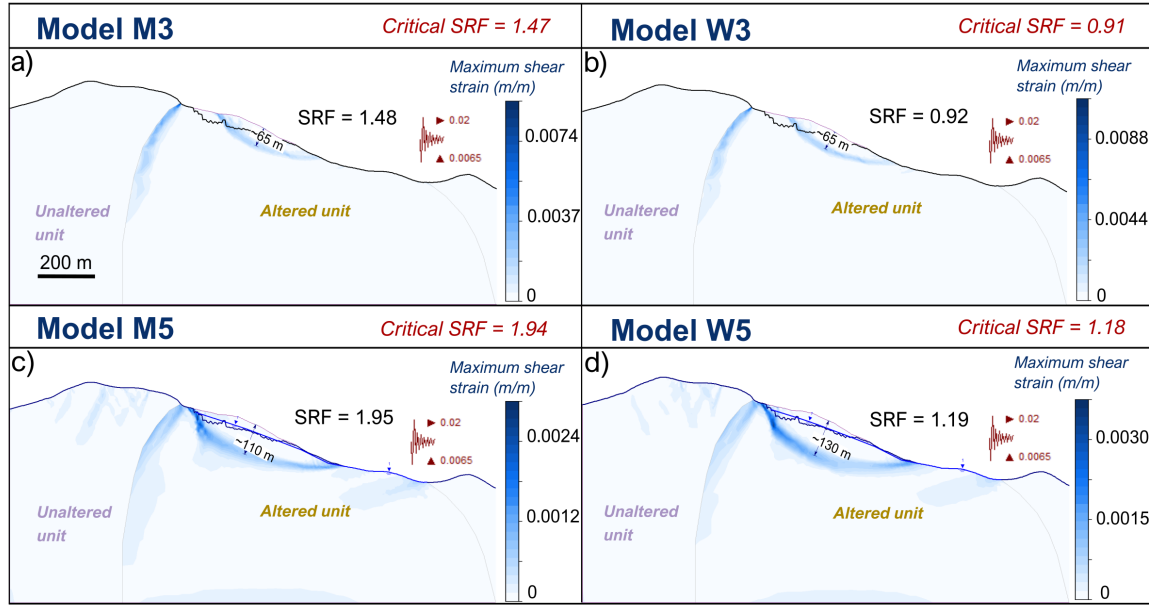


Figure 4.10: Te Maari shear strain results under hydrostatic groundwater configurations and pseudo-static seismic loading. (a) Simulations M3 and (b) W3 under pore pressure ratio assumption + seismic loading. (c) Simulations M5 and (d) W5 under perched water table assumption + seismic loading.

and the groundwater circulation.

Pseudo-static seismic loading reduces stability by approximately 6-9 % compared to simulations without seismic loading, which, in most cases, is insufficient to trigger collapse. Models considering a perched water table indicate that instability (critical $\text{SRF} \leq 1$) is not reached with (simulations M5 and W5, Fig. 4.10) or without ground acceleration (simulations M4 and W4, Fig. 4.7). Similarly, models accounting for a pore pressure ratio and a medium-strength altered unit show no instability (critical $\text{SRF} > 1$) with (simulation M3, Fig. 4.10) or without ground acceleration (simulations M2, Fig. 4.7). The only scenario in which the earthquake acts as a trigger is simulation W3, which considers a pore pressure ratio and a weak-strength altered unit. However, simulation W2 (without seismic loading) already indicates a critically unstable initial state (critical SRF of 1).

Therefore, for seismic ground acceleration to act as a trigger, the slope must already be substantially weakened by other preparatory factors (e.g., alteration, pore pressure increase). Compared to seismic loading, the destabilising effect of groundwater is much greater. For example, groundwater parameters alone lead to an average 40 % reduction in critical SRF compared to dry simulations (Fig. 4.5 and 4.7). Moreover, no significant changes in terms of failure geometry or magnitude are observed when adding the pseudo-static seismic coefficients.

4.5 Discussion

4.5.1 Pre-event conditions: pore pressure-driven failure.

Volcanic debris avalanches evolve in stages, and failure cannot be attributed to a single controlling factor, but is influenced by a combination of preparatory and triggering factors (van Asch et al., 2007). Focusing on the pre-failure and failure stages, our Te Maari FEM results enable us to describe the complex interplay between these preparatory and triggering factors (inputs) and the slope responses (outputs) at various pre-event scenarios tested under simplified assumptions.

Unlike homogeneous cases, where failure extent and depth are largely governed by slope geometry and gradient (Zhang et al., 2013; Sharma, 2013), composite volcanoes with hydrothermally altered rock masses experience more complex failures, influenced by multiple factors. These volcanoes are built by layered eruptive products, including lavas, pyroclastic and lahar deposits, each with distinct initial strengths and alteration potentials (John et al., 2008; Mielke et al., 2015; Ball et al., 2018). Such material discontinuities are particularly conducive to instability, as they accumulate the highest deformation rates. Our results highlight that in hydrothermally affected failures, the mechanical properties of the materials and their local geometry (e.g., layering, discontinuities) play a significant role in determining the probable failure extent. A simplified heterogeneous geometry (comprising an altered and unaltered unit) effectively captures the location of the failure surface in both area and depth.

Moreover, understanding hydrothermal fluid circulation is crucial, as it may induce thermomechanical fracturing and chemical alteration processes. It may also cause transient changes in pore pressure, a common trigger for shallow failures (van Asch et al., 2007; Ball et al., 2018) within hydrothermal systems. By reducing the effective stress, material strength is lowered, and the stability threshold can be overcome. Our simulations suggest that the 2012 failure was heavily influenced by the groundwater conditions within the edifice. Simulations neglecting pore pressure effects and focusing only on the mechanical properties of a dry edifice (H1a, H1b, M1, and W1, Fig. 4.5) result in significant overestimates of the stability and the volumes of potential collapses. The presence of water in the edifice reduces the SRF by 50-60 %, with significant changes in collapse volumes. Simulations incorporating positive pore pressures within the upper layers (simulations M2 and W2, Fig. 4.7; simulation M7, Fig. 4.9; simulations M3 and W3, Fig. 4.10) of the edifice were able to reproduce similar failure depths as the observed

failure. Simulations considering a perched water table approximately 30 to 40 metres deep (simulations M4 and W4, Fig. 4.7; simulation M6, Fig. 4.9; simulations M5 and W5, Fig. 4.10) result in more substantial failures, as there is no pore pressure reducing the effective stresses in the upper layers. Elevated pore pressure in the shallow regions of the edifice results in shallower failures and smaller collapse volumes (Ball et al., 2018), indicating its role in the small localised failure at Te Maari in 2012.

Consequently, we attribute instability at Te Maari to two mechanisms: strength reduction due to rock alteration and elevated pore pressures at shallow depths. The relationship between these mechanisms is not clearly demonstrated by our simulations. However, our simulations show that simply considering the presence of an impermeable layer (potentially formed by clay precipitation) does not replicate the magnitude of the observed failure. An increase in pore pressure in the shallow layers is necessary to replicate the observed instability. Our simulations also indicate that the likely trigger for this pore pressure increase is fluid infiltration from depth within the hydrothermal system (simulation M7, Fig. 4.9c), supporting the seismic interpretation of Jolly et al. (2014). This configuration can reproduce failure depths and shapes similar to those observed, but is less constrained than the hydrostatic model, which is better at locating the failure. Infiltration models carry more uncertainties, particularly regarding the location of the infiltration point, which significantly influences the failure’s position. Nevertheless, the hydrostatic model, assuming a uniform pore pressure ratio to represent elevated pore pressures in the altered unit, fails to capture the heterogeneous permeability structures characteristic of a composite volcano slope (del Potro et al., 2013; Ball et al., 2018). Moreover, the interplay between rock mechanics and groundwater circulation is complex, and other unexplored effects could contribute to instability (e.g., thermodynamic effects).

4.5.2 Failure mechanics over time

FEM enables an evaluation of displacements, stresses, and deformations across the entire edifice. This method proves particularly suitable for inferring progressive slope failure influenced by deformations and time.

Visual analysis of Te Maari post-event topography using the LiDAR survey carried out in November 2012 by Procter et al. (2014) reveals a circular failure with a failure plane angle of $\approx 20^\circ$. A discontinuity in the failure plane is observed, which we interpret as the limit between two ellipsoidal failures (approximated on Fig. 4.11): slide block 1 (SB1), with its top part

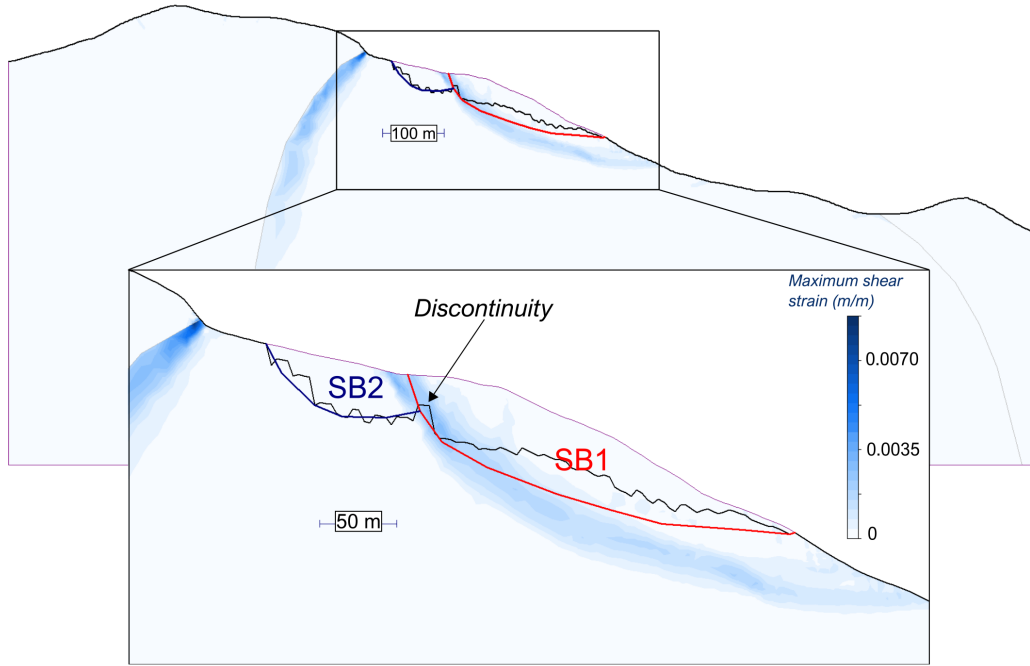


Figure 4.11: Te Maari shear strain simulation M2 at critical SRF. Post-event topography (black line) overprinted on the 2D profile. Red line indicates the approximate slip surface of SB1 based on the post-event topography (Procter et al., 2014). Blue line delineates the approximate slip surface of SB2 based on the post-event topography (Procter et al., 2014).

attributed to the discontinuity detected by LiDAR analysis and a failure plane angle of $\approx 23^\circ$; and slide block 2 (SB2), with its base attributed to the discontinuity location and a failure plane angle of $\approx 20^\circ$.

The topography of this slip surface (Fig. 4.11) suggests a two-stage progressive failure, characterised by the collapse of SB1 followed by SB2. This hypothesis is supported by our simulations, which were based on the closest result to the initial phase location (SB1) of the collapse (Fig. 4.11). Therefore, we used simulation M2 (Fig. 4.7) to delineate the SB1 outline (red outline in Fig. 4.12). Comparing this outline with the LiDAR visual analysis, we find that the modelled slip surface approximately aligns with the extent and position of the observed SB1 (Fig. 4.11). However, a slight northward shift (10 to 15 metres) of the failure base is noted, potentially due to model uncertainties (e.g., pre-event DEM uncertainty) or residual material within the scar.

We propose that the second phase of the failure is characterised by the collapse of SB2 in

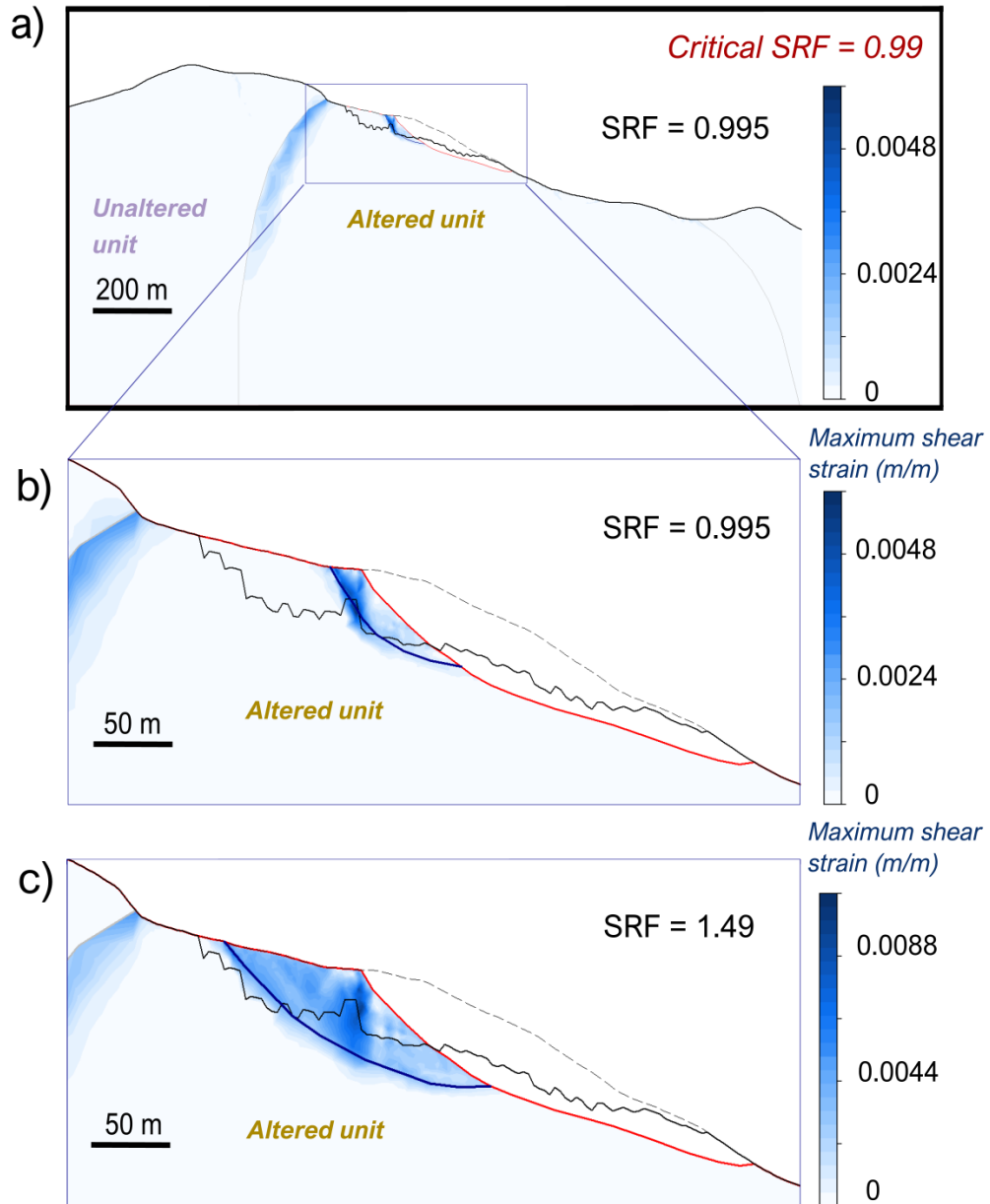


Figure 4.12: Progressive failure model. (a) Te Maari shear strain simulation at critical SRF, on post-event topography from simulation M2. (b) Zoom on failure location at critical SRF (c) Zoom on failure location at SRF = 1.49. Black dashed outline represents the pre-event topography. Red line delineates the modelled post-topography after the collapse of SB1. Blue line delineates the modelled post-topography after the collapse of SB2.

response to the destabilisation of SB1. To test this hypothesis, a 2D simulation (Fig. 4.12), built with the M2 post-SB1 collapse topography as the external boundary and the same strength and pore pressure parameters, was performed. With a critical SRF <1 , the material is unstable and therefore collapses. At the critical SRF, the extent of the simulated SB2, defined by the surface of maximum shear strain in Fig. 4.12b, is smaller than the SB2 observed by LiDAR analysis. However, examining several strength-reduction stages after the critical SRF (Fig. 4.12c) reveals that the failure propagation aligns with the observed slip surface of SB2 (Fig. 4.11).

Our 2D model (Fig. 4.12) then confirms that a second block collapses in response to the sliding of the first block. Confirming the progressive failure hypothesis through field measurements or satellite imagery can be challenging (Moretti et al., 2015). However, additional work can be carried out to determine the number and timing of each failure phase by analysing the forces inverted from the long-period seismograms (Favreau et al., 2010; Moretti et al., 2012, 2015; Mitchell et al., 2022).

4.5.3 Implication for future hazard assessment

Consistent with previous studies (e.g. Finn et al. 2018, Ball et al. 2018, Mordensky et al. 2022), our simulations highlight the influence of various parameters, especially alteration and groundwater parameters, on volcanic flank stability. Our results show that the presence of water-saturated altered rocks within the edifice significantly decreases the SRF with associated changes in collapse volumes. An increase in pore pressure in the shallow part of the edifice (e.g., through an elevated water table) tends to trigger shallow and minor collapses, as demonstrated by Ball et al. (2018). Seepage analysis results for Te Maari have shown that even a relatively deep infiltration can induce fluctuations in water-table elevations, thus modifying the pore pressure in the shallow layers of the edifice.

The outcomes of our simulations are primarily influenced by the accuracy of the hydrological parameters rather than the geomechanical parameters (Okunishi and Okimura, 1987; Haneberg, 1991; van Asch et al., 2007). Simulations that do not consider the fluid distribution within the edifice generally result in an overestimation of slope stability and potential collapse volumes compared to the Te Maari failure. However, the accuracy of our hydrological configurations is limited by the relatively low-resolution groundwater data. Therefore, to refine the three-dimensional distribution of pervasive alteration and shallow groundwater within New

Zealand’s volcanoes, more detailed geophysical surveys must be conducted, e.g., involving detection by electromagnetic data or induced polarisation (Finn et al., 2001, 2007; Miller and Williams-Jones, 2016; Revil et al., 2017; Finn et al., 2018). Low electrical resistivities characterise zones of hydrothermally altered volcanic rocks (due to their water and clay content) as well as groundwater of various salinities (Finizola et al., 2006; Finn et al., 2007). In addition to these geophysical analyses, regular monitoring of springs or wells located around the edifices can serve as a quick and cost-effective initial step in assessing the stability of active volcanoes (Ball et al., 2018).

Post-eruption field investigations and airborne hyperspectral imaging (Kereszturi et al., 2018) indicate that additional areas can substantially be affected by hydrothermal alteration, especially around Red Crater, Ketetahi Hot Springs, and Te Maari craters (Fig. 4.1). Our simulations show that considering an altered material strongly decreases edifice stability, primarily due to the weakening of rock strength caused by chemical replacement of primary minerals. Therefore, by considering hydrothermal alteration as first-order potential sources of debris flow, a scenario similar to the 2012 event may be repeated, and can pose a significant danger, especially to both infrastructure and hikers on the Tongariro Alpine Crossing.

4.6 Conclusions

The interaction between preparatory and triggering factors offers insight into the complex mechanics underlying the 2012 debris avalanche at Te Maari. Our simulations highlighted several aspects of this complexity.

Firstly, the magnitude and shape of the collapse are primarily controlled by the heterogeneous nature of the edifice and the circulation of hydrothermal fluids. Simulations indicating a relatively minor (≈ 250 kPa) change in pore pressure in the upper layers were able to replicate instabilities with geometries and magnitudes closely similar to the observed failure, confirming the failure was driven by a pore pressure change. This mechanism also accounts for its shallow depth (Ball et al., 2018), illustrating the significant potential impact of slight pore pressure variations on stability. The triggering effect of the small-magnitude earthquake, identified by Jolly et al. (2014), is only demonstrated for a specific set of parameters, which necessarily involves an increase in pore pressure in shallow layers and the presence of weak-strength altered materials. This set of parameters tends to underestimate material strength, suggesting that the

earthquake may just be a consequence of the groundwater circulation or the debris avalanche itself.

Secondly, our analysis of the observed post-failure topography reveals two ellipsoidal scars. Additional simulations on post-event topography suggested that the 2012 failure at Te Maari was progressive. Highlighting the dynamics of the failure at Te Maari, these simulations indicate a two-stage failure where the destabilisation of a first block led to the subsequent failure of the second block. The progressive nature of this failure would affect flow dynamics, increasing the complexity of the flow. Depending on the time interval between collapses, it can either cause deceleration, when phases act independently and material deposition obstructs the flow path, or acceleration, when phases act dependently, increasing momentum.

Thirdly, in terms of hazard assessment, the post-failure phase presents the main risk to nearby populations and infrastructure. Therefore, debris avalanche risk assessment requires a comprehensive understanding of flow dynamics, by the quantification of flow physical parameters such as runout distances, movement velocities, and inundation depths. These properties are largely influenced by the conditions at failure (preparatory and triggering factors). Our study shows that it is essential to better constrain these conditions, particularly the extent of the hydrothermal system and the groundwater distribution within the edifice, as it can significantly reduce stability and affect the magnitude and sequence of collapse. Additionally, the presence of water in the failed mass can affect the flow dynamics by causing fluidisation, thereby increasing the runout distance and potential impact area. On Te Maari, but also on other New Zealand stratovolcanoes (e.g. Ruapehu, Whakaari), significant areas of hydrothermally altered rock remain (Kereszturi et al., 2018, 2021), contributing to reduced stability. Consequently, a scenario similar to the 2012 event may be repeated, posing a significant risk to both infrastructure and populations in New Zealand.

Chapter 5

Modelling the impact of initiation parameters on the dynamics of the 2012 Te Maari laterally-confined debris avalanche.

This chapter has been submitted to *Journal of Geophysical Research: Solid Earth* under the same title, and is currently under peer-review.

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Contributions:

- **Juliette Vicente:** Conceptualisation, Methodology, Data Curation, Software analyses, Investigations, Interpretations, Writing – original draft, Reviews and Editing.
- **Stuart Mead:** Resources, Supervision, Methodology, Interpretations, Writing – review and editing.

5.1 Introduction

Volcanic debris avalanches are rapid, gravity-driven mass movements of fragmented volcanic material that flow downslope, typically channelised by pre-existing topographic features such as valleys. These avalanches can travel very long distances (Hutter et al., 1994; Iverson, 1997), a behaviour often attributed to fluidisation processes that modify the material’s rheology during motion (Iverson and LaHusen, 1993). Fluidisation may occur along the runout path through the incorporation of external water sources (e.g., glacier melt, lakes, rivers) or sediment entrainment. It may also be preconditioned at initiation by water saturation within the rock mass, driven by factors such as heavy rainfall or hydrothermal fluid circulation. In addition to promoting slope failure by reducing shear strength (Roverato et al., 2021), such water can transform a dry debris avalanche into a debris flow, significantly enhancing mobility and runout distances, even in smaller-volume debris avalanches (Siebert and Roverato, 2021; McGuire, 1996; Hungr et al., 2008).

Debris flows occupy a complex spectrum between sediment-laden water floods and dry rock avalanches (Iverson and George, 2024). Because of their water content, they exhibit hybrid behaviour reflecting both fluid and granular characteristics. Consequently, momentum transfer and energy dissipation in these flows are controlled by complex mechanical interactions between grains and the interstitial fluid, involving frictional, collisional, and viscous forces (Iverson, 1997; George et al., 2022; Iverson and George, 2024). These interactions are central to the evolution of debris flows, from their initiation to rapid flow and ultimately to the formation of nearly rigid deposits (Iverson, 1997, 2003; Iverson and George, 2024). Transitions to highly mobile behaviour have been attributed to complete or partial liquefaction of the landslide mass or underlying bed, often triggered by undrained compression and contractive shearing in one or both of these materials (e.g., Eckersley, 1990; Iverson, 1997; Iverson et al., 2000, 2011; Iverson and George, 2016; Hungr and Evans, 2004). All liquefying landslides undergo a significant reduction in frictional strength, which may occur at the onset of the landslide motion (and sometimes persists throughout the runout) or may develop progressively in parts of the landslide during the runout (Iverson and George, 2016). Because debris flows exhibit such complex and evolving behaviour, they are difficult to capture with simple rheological models that are only based on local stress state and strain rates (Iverson, 2003). Instead, realistic models of liquefying landslides must account for the dynamic evolution of the mixture’s apparent rheology in response

to its hydrological state (e.g., pore pressure, permeability). This includes the effects of granular properties (e.g., compressibility, dilatancy) on the intergranular fluid pressure (Iverson and George, 2024).

To investigate the conditions governing the onset of motion, as well as the evolving rheology and mobility of debris flows, we employ D-Claw, a depth-averaged, multiphase numerical model that captures the coupled evolution of dilatancy (i.e., changes in solid volume fraction during shear), pore-fluid pressure, flow thickness, and velocity (Iverson and George, 2014). We apply this model to the pore-pressure-driven debris avalanche that occurred on 6 August 2012 at Te Maari, Tongariro, New Zealand (Vicente et al., 2025), which transitioned into a debris flow along its runout path (Procter et al., 2014). Our modelling approach focuses on how key initial material properties, such as compressibility, permeability, and dilatancy, influence the mechanical response of the mass during failure and throughout its transformation into a debris flow. These properties critically affect how fluid-particle interactions promote or suppress flow mobility.

Previous modelling efforts have explored the influence of initial conditions (e.g., permeability and solid-volume fraction) on flow dynamics, such as the study by Iverson and George (2016) that focused on unconfined debris avalanches undergoing liquefaction at initiation (e.g., 2014 Oso landslide). However, these dynamics differ substantially from laterally confined systems (Hung et al., 2001; Cascini et al., 2014; Strom et al., 2019; Cuomo, 2020). In contrast, the Te Maari debris avalanche, which was laterally confined, shows no evidence of immediate liquefaction at the source but transitioned into a more cohesive debris flow further downslope (Procter et al., 2014). This makes Te Maari an ideal case for examining how initial properties govern both the initiation of motion and the evolution of debris flow behaviour in confined settings.

To explore these dynamics, we conducted a full factorial suite of numerical simulations, systematically varying key input parameters, to explore the sensitivity of flow mobility to initial material properties, such as compressibility, dilatancy, and hydraulic permeability. From this dataset, we developed a predictive model trained on the simulation outputs, using the Critical Success Index (CSI) as the response variable. Our objectives were to (1) identify the optimal combination of initial parameters that best reproduces the observed flow runout at Te Maari and (2) determine which initial material properties most strongly influence, and how they govern, debris flow mobility in laterally confined settings. As part of a broader quantitative hazard assessment effort, the performance metric CSI, by penalising both over- and under-predictions

of flow extent (Mead et al., 2021), allowed for a robust evaluation of the spatial accuracy of each simulation in replicating the observed landslide extent.

5.2 Geological setting

Tongariro’s most recent eruptions occurred at Upper Te Maari Crater on August 6, 2012, and November 21, 2012. The August 6 event featured a complex eruption sequence, including a small channelised debris avalanche, a multi-pulse phreatic eruption, and the formation of a chasm in a fissure-like form about 300 m from the main eruption vent (Jolly et al., 2014).

Estimation of the landslide source-area volume was performed by differencing pre- and post-DEM data (Procter et al., 2014), identifying between $6.83 \times 10^5 \text{ m}^3$ and $7.74 \times 10^5 \text{ m}^3$ of material that flowed down the Mangatipua Stream for over 2 km, covering an area of $1.51 \times 10^5 \text{ m}^2$ (Fig. 5.1). Procter et al. (2014) described the initial stage of the flow (first 0.7 km) as having landslide characteristics, transitioning into a more cohesive, clay-rich debris flow over the subsequent 0.7–2 km. This transformation was likely facilitated by the high internal clay content of the collapsing mass, enabling efficient mixing (Procter et al., 2014). The progressive disaggregation of the moving mass is evidenced by an increase in matrix proportion with distance, from 40 vol% in the upper deposit to 60 vol% downstream. Although this increase in matrix proportion indicates particle-particle interactions within the flow, analyses of the fine sand grains (Procter et al., 2014) did not reveal high-energy collision features (e.g., conchoidal fractures). This suggests that the initially saturated material, characterised by high pore water content, lacked excess pore-water pressure and began as a slow-moving mass dominated by deformation and sliding effects. Over time, the material disaggregated and evolved into a more homogeneous, clay-rich cohesive debris flow. Procter et al. (2014) hypothesised that the extended runout of the flow was largely due to material entrainment along its path, which may have caused fluidisation by pore pressure increase and/or reduced basal friction (Iverson et al., 2011).

5.3 Method

In this study, the influence of source conditions on debris flow mobility is evaluated using a depth-averaged numerical model (D-Claw - Iverson and George, 2014; George and Iverson, 2014), with model parameters constrained by results from a finite-element slope stability model for the Te Maari debris flow (Vicente et al., 2025). The influence of three key initial factors is

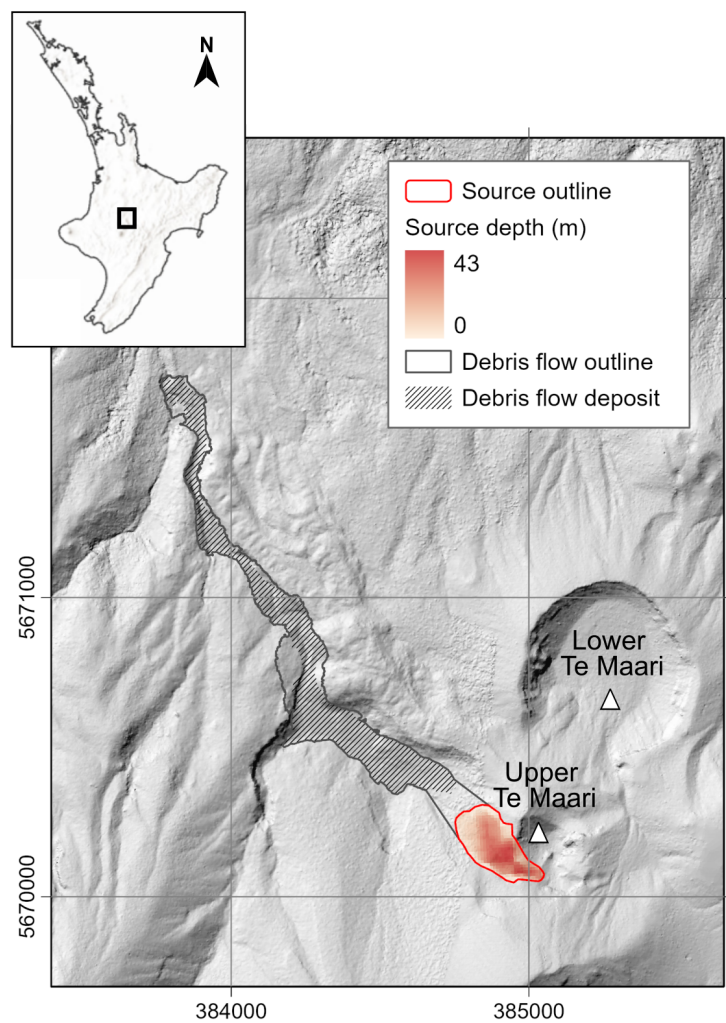


Figure 5.1: Location of the source and deposits of the 2012 Te Maari debris avalanche.

investigated: initial hydraulic permeability k_0 , dilatancy δ_m (defined as the difference between the initial and the critical solid-volume fractions, $m_0 - m_{crit}$) and the compressibility coefficient α . These variables are systematically varied, while other initial parameters are fixed from one simulation to another (e.g., basal friction, initial solid-volume fraction, internal friction, density of fluid and solid, effective mean stress). To systematically evaluate the influence of these parameters and to capture linear, quadratic, and interaction effects, we adopted a full factorial design and developed a second-order response surface model to assess the sensitivity of flow mobility to variations in these properties.

5.3.1 Depth-averaged modelling

We use a depth-averaged, shock-capturing, debris-flow model (D-Claw) that integrates principles from soil mechanics, granular flow mechanics, and fluid mechanics to simulate debris-flow behaviour from initiation to deposition (Iverson and George, 2014; George and Iverson, 2014). The model describes the coupled evolution of solid volume fraction m , flow thickness h , basal pore-fluid pressure p_b , and the depth-averaged flow velocities u and v . The physical and mathematical derivation of the model equations used in D-Claw computation are detailed by Iverson and George (2014), and the computational algorithms used to solve the model equations are described by George and Iverson (2014).

Similar to other depth averaged debris-flow models (Bozhinskiy and Nazarov, 2000; Iverson and Denlinger, 2001; Savage and Iverson, 2003; Pitman and Le, 2005; Pudasaini et al., 2005; Pelanti et al., 2008; Pudasaini, 2012; Kowalski and McElwaine, 2013; Mergili et al., 2017), D-Claw accounts for the effect of solid-fluid interactions. However, most of these debris-flow models treat rheology and debris-flow resistance as fixed properties. In contrast, D-Claw captures the spatial and temporal changes in macroscopic material behaviour by incorporating the coupled evolution of dilatancy effects, pore-fluid pressure, debris flow thickness and velocity (Iverson and George, 2014). It relies on the principle that the co-evolution of solid-volume fraction and excess pore-pressure along the flow can significantly modify the apparent rheology of the debris (e.g., effective frictional resistance), thereby influencing flow mobility.

5.3.2 Triggering the failure

D-Claw supports a statically balanced initial slope configuration, similar to 3D limit-equilibrium slope stability analyses that use the method of columns (e.g., Bishop, 1955). Motion is triggered

by gradual changes, such as an increase in basal pore-fluid pressure, progressively reducing the effective frictional resistance of the slope (Iverson and George, 2016; George et al., 2022). This process is more realistic for modelling natural landslides, often triggered by rainfall, snowmelt, or groundwater flow, which increase pore-water pressure at the slope’s base, compared to dam-break models (e.g., Hungr, 1995) that assume an instantaneous and finite initial force imbalance.

For our simulations, based on Vicente et al. (2025)’s assumption, initialisation of the motion is triggered by progressively and uniformly increasing $\frac{p_b}{\rho g z h}$ throughout the landslide source area until the weakest point starts to move. The numerical results are presented such that $t = 0$ corresponds to the time of the first detected motion.

5.3.3 Estimation of initial parameter ranges

The evolution of the solid-volume fraction m reflects how the granular skeleton contracts or dilates under shear, directly influencing pore pressure build-up or dissipation, and thereby affecting the overall mobility of the flow. The local dilatation rate of the solid phase relates to the variation of m over time through:

$$\nabla \cdot v_s = -\frac{1}{m} \frac{dm}{dt} \quad (5.1)$$

where a negative dilatation rate (i.e., $\frac{dm}{dt} \geq 0$) corresponds to a contraction, and a positive rate (i.e., $\frac{dm}{dt} \leq 0$), to a dilatation of the granular skeleton. In D-Claw, changes in m arise from two independent mechanisms: bulk compressibility and dilatancy. This leads to a decomposition of the total rate of change of m as follows (Iverson and George, 2014):

$$\frac{dm}{dt} = \frac{\partial m}{\partial \sigma_e} \frac{d\sigma_e}{dt} + \frac{\partial m}{\partial \gamma} \dot{\gamma} \quad (5.2)$$

where σ_e is the effective stress and γ is a scalar measure of shear strain.

Therefore, the evolution of m results from coupled physical processes, controlled by several key parameters, including the compressibility coefficient a which controls the sensitivity of m to changes in effective stress; the dilatancy δm which defines the maximum change in m during

shear deformation; and the initial permeability k_0 which initiates the rate of pore pressure diffusion within the mixture.

By systematically varying a , δm , and k_0 , we directly assess their respective roles in controlling flow dynamics. Other parameters remain fixed; for example, following the approach of Iverson and George (2016) in the Oso simulations, we fix the basal friction angle at $\phi = 21^\circ$, a value previously tested by Mead et al. (2021) as the best fit in other debris-flow models. The values of all parameters used in our simulations are summarised in Table 5.1.

Variable material property	Design Levels		
	Min (-1)	Mid (0)	Max (1)
Compressibility proportionality coefficient a	0.01	0.03	0.05
Hydraulic permeability k_0 (m ²)	1×10^{-9}	5.05×10^{-8}	1×10^{-7}
Dilatancy $\delta m = m_0 - m_{\text{crit}}$	0.02	0.04	0.06
Associated critical solid-volume fraction m_{crit}	0.78	0.76	0.74
Fixed material property			
Initial solid-volume fraction m_0	0.8		
Basal friction angle ϕ (°)	21		
Internal friction angle ϕ_{int} (°)	36		
Compressibility reference stress σ_0 (Pa)	1000		
Fluid density ρ_f (kg/m ³)	1000		
Solid density ρ_s (kg/m ³)	2500		
Fluid viscosity μ (Pa·s)	0.001		
Characteristic grain size δ (m)	0.01		

Table 5.1: Values of all parameters used in D-Claw simulations.

Compressibility coefficient, a

Bulk compressibility, a key driver in m evolution, describes how changes in effective mean stress σ_e modify pore volume and, therefore, regulate pore pressure build-up and dissipation. This effect is captured by the term $\frac{\partial m}{\partial \sigma_e} \frac{d\sigma_e}{dt}$ in equation 5.2. D-Claw uses the following constitutive relationship to quantify it:

$$\alpha = \frac{a}{m(\sigma_e + \sigma_0)} \quad (5.3)$$

where α is the bulk compressibility, and both a and σ_0 are user-defined material parameters. The reference stress, σ_0 , defines an upper bound for the debris compressibility α , when $\sigma_e \rightarrow 0$. Based on values reported for solid-fluid mixtures (Major, 1996; Iverson and George, 2014; George and Iverson, 2014), we fix $\sigma_0 = 1000$ Pa, which is typical for coarse-grained debris material. We are particularly interested in the proportionality coefficient a , as it directly governs the magnitude of compressibility. Typically, coarser-grained materials (e.g., sand or gravel) exhibit lower a values due to their higher resistance to compression, while finer-grained materials are more compressible and exhibit higher a values. Based on experimental studies (Major, 1996; Iverson and George, 2014; George and Iverson, 2014), we explore the full spectrum of plausible compressibility coefficients a , by varying it from 0.01 to 0.05. This range allows us to investigate the influence of bulk compressibility.

Initial solid-volume fraction, m_0

We treat the initial solid-volume fraction, m_0 , as fixed for our simulations, using a value of 0.8, consistent with prior work on Te Maari by Mead et al. (2021). To validate this choice, we use the compressibility relationship (Equation 5.3), as it establishes a direct relationship between the solid-volume fraction m and the effective mean stress σ_e . Specifically, we use the integrated form of equation 5.3 (Iverson and George, 2014) under simplified quasi-static conditions (i.e., zero shear rate $\dot{\gamma} = 0$ or zero dilatancy $\frac{\partial m}{\partial \gamma} = 0$), that satisfies $m = m_{min}$ when $\sigma_e = 0$:

$$m - m_{min} = a \ln\left(\frac{\sigma_e}{\sigma_0} + 1\right) \quad (5.4)$$

Here, m_{min} represents the minimum solid-volume fraction of the debris material under conditions where $\sigma_e = 0$, reflecting the loosest packing configuration. Experiments conducted by Major (1996) indicate that values of $0.58 \leq m_{min} \leq 0.62$ are suitable for debris flow mixtures composed of sand and gravel. We adopt an average value of $m_{min} = 0.60$ in our study.

To determine the initial solid-volume fraction m_0 at $t = 0$, we initialise the parameters in equation 5.4 as:

$$m_0 - m_{min} = a \ln\left(\frac{\sigma_{e0}}{\sigma_0} + 1\right) \quad (5.5)$$

The effective stress at failure σ_{e0} was averaged from the finite-element 2D section results of Vicente et al. (2025). Several vertical profiles were extracted between the ground surface and the slip surface, and the effective stress along these profiles was averaged to obtain a representative mean value of 350 kPa, which is used as the initial effective stress σ_{e0} in the model.

Using $\sigma_{e0} = 350$ kPa at failure, $m_{min} = 0.60$, $\sigma_0 = 1000$ Pa and $0.01 \leq a \leq 0.05$, equation 5.5 provides an initial estimate of $0.65 \leq m_0 \leq 0.85$. However, this estimate neglects dilative and deformation-driven effects typically observed at failure. Given that Te Maari deposits are dominated by coarse, dense materials (Procter et al., 2014), which tend to undergo dilatation during failure (Iverson et al., 2000), this approach may underestimate m_0 . The true value of m_0 at failure is expected to be closer to the upper end of the range, potentially exceeding 0.8 in some cases. We therefore refine the estimated range accordingly to $0.75 \leq m_0 \leq 0.85$, and conclude that $m_0 = 0.8$ is a suitable and physically realistic choice for the Te Maari case study.

Critical solid-volume fraction, m_{crit}

Dilatancy, another key driver in m evolution, describes how shear strain γ modifies pore volume and therefore regulates pore pressure. This effect is captured by the term $\frac{\partial m}{\partial \gamma} \dot{\gamma}$ in equation 5.2.

In D-Claw, this shear-induced change is governed by how far the current value of m deviates from a dynamically evolving equilibrium state m_{eq} . During flow, the ambient solid-volume fraction m relaxes gradually over time towards the equilibrium value m_{eq} , while m_{eq} changes instantaneously in response to local changes in the material. This equilibrium value acts as a 'target' value for m , and the dynamic difference $m - m_{eq}$ controls the dilatancy angle:

$$\tan \psi = m - m_{eq} \quad (5.6)$$

Based on annular shear cell experiments (Boyer et al., 2011), D-Claw describes the equilibrium state as:

$$m_{eq}(N) = \frac{m_{crit}}{1 + \sqrt{N}} \quad (5.7)$$

Here, m_{crit} represents the value of m_{eq} that applies under quasi-static lithostatic stress (i.e., shear rate $\dot{\gamma} = 0$). The dimensionless ratio N defines the local stress state of the granular-fluid mixture, balancing viscous shear stress against inertial stress and effective normal stress. When N approaches 1, the flow behaves more like a highly mobile viscous fluid, whereas when it approaches 0, it is more granular-dominated and less mobile.

Correctly defining m_{crit} is important as the difference $\delta_m = m_0 - m_{crit}$ strongly controls the flow initiation behaviour (Iverson and George, 2016). When $\delta_m < 0$, the material exhibits contractive failure, leading to pore pressure build-up and fluidisation. In contrast, $\delta_m > 0$ indicates dilative behaviour, initiating a solid-like flow. Based on prior knowledge (Procter et al., 2014), we apply $\delta_m > 0$ to represent dilative failure, consistent with the initial phase of the debris avalanche being described as a solid-like flow dominated by granular interactions. To explore the influence of this relaxation behaviour on the flow mobility, we examine a range of $0.02 \leq \delta_m \leq 0.06$.

Initial permeability k_0 .

Debris flow mobility is also largely influenced by the hydraulic permeability $k(m)$ (Iverson and George, 2014, 2016). This parameter is directly related to the excess pore pressure p_e through Darcy's law, which D-Claw employs to treat solid-fluid drag as a continuum phenomenon (Iverson and George, 2014):

$$q = \frac{-k(m)}{\mu} \nabla p_e \quad (5.8)$$

where q represents the apparent velocity of the fluid relative to the solid and μ is the fluid viscosity.

The excess pore pressure p_e is the non-hydrostatic component of the total pore-fluid pressure and evolves based on q , which is affected by debris dilatation and contraction (variations of m). This process is captured by the hydraulic permeability terms:

$$k(m) = k_0 \exp \left(\frac{0.6 - m}{0.04} \right) \quad (5.9)$$

where k_0 represents the initial hydraulic permeability when $m = m_0$.

For Te Maari, Procter et al. (2014) estimated saturated hydraulic conductivity K ranging from approximately $5.6 \times 10^{-9} \text{ m.s}^{-1}$ at the deposit margins to $2.4 \times 10^{-7} \text{ m.s}^{-1}$ at the deposit centre. These correspond to hydraulic permeabilities of approximately $5.6 \times 10^{-16} \text{ m}^2$ to $2.4 \times 10^{-14} \text{ m}^2$, typical of static gravel-sized materials. However, Iverson and George (2014) noted that values of k might be a few orders of magnitude larger for agitated granular flow. Therefore, in this study, following Iverson and George (2016)'s method, we adopt k_0 ranging from 10^{-9} to 10^{-7} m^2 .

5.3.4 Full factorial experimental design and prediction model

Given our interest in examining the linear, quadratic, and interaction effects of the factors, we use a 3-level full factorial design, which is a common sampling approach for such analyses (Tan et al., 2013). Each of the three factors is tested at three levels: the minimum (design level -1), the midpoint (design level 0), and the maximum (design level 1) of the established ranges. The real values and design levels of the input parameters are presented in Table 5.1. According to the defined ranges for input parameters, the factorial design suggested 27 D-Claw simulations, as shown in Table S1 (Supporting Information).

Following the simulations, a multiple linear regression prediction model for simulation performance was developed. Our approach uses a second-order model (Gunaraj and Murugan, 1999; Kwak, 2005; Aslan and Cebeci, 2007; Ozgen and Yildiz, 2010) defined as :

$$y = b_0 + \sum_{i=1}^k b_i x_i + \sum_{i=1}^k b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=2}^k b_{ij} x_i x_j + \epsilon \quad (5.10)$$

with y being the response variable, and $x_i = x_1, x_2, \dots, x_k$ being the input factors influencing this response. The unknown coefficients β_0 , β_i , β_{ii} , and β_{ij} are typically estimated using the least-squares method, where β_0 is the constant term, β_i represents the linear effect coefficients,

β_{ii} corresponds to the quadratic effect coefficients, and β_{ij} denotes the interaction effect coefficients. The term ϵ accounts for the model error. We used the residual standard error (RSE), as it provides an estimate of the standard deviation of the error term ϵ , reflecting the typical deviation of observed values from the fitted model.

The prediction model also uses scaled factor values to their coded level (-1, 0, and 1) instead of raw values to prevent scaling issues arising from differences in magnitude and units (e.g., Kostić et al., 2015). Scaling ensures that each factor has a normalised effect on the response variable, facilitating comparison. Without this adjustment, the model would suffer from severe numerical instabilities. The scaled factors are denoted by A , K_0 , M_0 , and Δ_m .

The response variable y was selected to evaluate model performance. Each simulation’s performance is quantitatively assessed based on its ability to delineate the debris flow inundation zone (e.g., Charbonnier et al., 2018; Mergili et al., 2017; Mead et al., 2021). In this study, we used the Critical Success Index (CSI, Formetta et al., 2016), a performance metric that evaluates model accuracy by comparing observed and simulated flow footprints using map-cell classification. Map-cell classification quantifies the proportion of true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). The CSI, calculated as $\frac{TP}{(TP+FP+FN)}$, quantifies the proportion of correctly simulated area (TP) over a combined simulated and observed inundation footprints (TP+FP+FN). CSI values approaching 1 indicate higher model accuracy, while CSI values < 0.5 suggest lower prediction accuracy, with more FP and FN than TP.

5.4 Results

5.4.1 Response surface model

Table A1 (see Appendices) presents the simulated CSI results for each configuration, obtained through the full factorial experimental design. The distribution of CSI values ranges from 0.48 to 0.673, with most observations concentrated within a narrow interquartile range (IQR) of 0.018 and clustering around the median of 0.615, despite a slight negative skew caused by a few lower values (Fig. 5.2).

An optimal regression model (Equation 5.11 and Table 5.2) was obtained following a backward elimination procedure (e.g., Koch and Fäh, 2002; Scherrer et al., 2004, see Supplementary

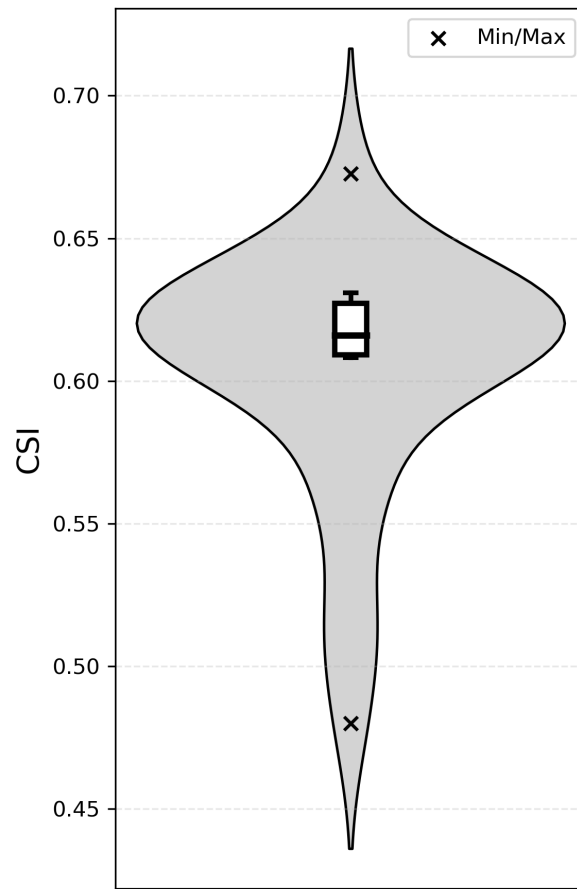


Figure 5.2: Distribution of the CSI across all simulations, highlighting data density, median, quartiles, and the minimum and maximum values.

Scaled model term	Coefficients for scaled factor	p-values	Standard error
Intercept	0.6214	1.00×10^{-28}	0.006
A	0.0137	4.00×10^{-3}	0.004
K_0	0.0254	9.00×10^{-6}	0.004
Δ_m	-0.0129	7.00×10^{-3}	0.004
K_0^2	-0.0265	2.00×10^{-3}	0.007
$A \times K_0$	-0.0243	2.00×10^{-4}	0.005
$K_0 \times \Delta_m$	0.0300	1.00×10^{-5}	0.005
R^2	0.858		
Adjusted R^2	0.816		
Significance of the model (p -value)	1.64×10^{-7}		

Table 5.2: Prediction model based on scaled values and its statistical significance.

Material 2 for details) to exclude the non-influential predictors. Six statistically significant predictors were identified, and CSI was expressed as a function of these input variables as follows (Table 5.2):

$$\begin{aligned}
CSI = & 0.6214 + 0.0137 \times A + 0.0254 \times K_0 \\
& + (-0.0129) \times \Delta_m + (-0.0265) \times K_0^2 + (-0.0243) \times A \times K_0 \\
& + 0.0300 \times K_0 \times \Delta_m \pm 0.0157 \quad (5.11)
\end{aligned}$$

The model accounts for 85.8 % of the variance in CSI ($R^2 = 0.858$) and is statistically significant (p-value < 0.05), suggesting a robust and well-specified model. The remaining unexplained variance (≈ 15 %) likely reflects the intrinsic complexity of natural systems and the exclusion of additional parameters known to affect flow mobility and CSI.

Equation 5.11 highlights the importance of the linear terms (A , K_0 , and Δ_m), the quadratic term (K_0^2), and two interaction terms ($A \times K_0$ and $K_0 \times \Delta_m$), all of which significantly influence the CSI. Among these, the scaled hydraulic permeability K_0 stands out as the dominant factor, particularly due to its interactions with the other predictors.

The strongest effect arises from the interaction between K_0 and Δ_m , which has a strong positive impact. This indicates that Δ_m contributes more significantly to CSI when K_0 is high. In contrast, the interaction between A and K_0 negatively impacts the CSI, suggesting that the CSI becomes less sensitive to A as K_0 increases. Individually, K_0 has a positive linear effect on CSI, though this is tempered at higher values by a negative quadratic term. Two additional terms, A and Δ_m , have smaller, but still notable, individual effects: increasing A tends to

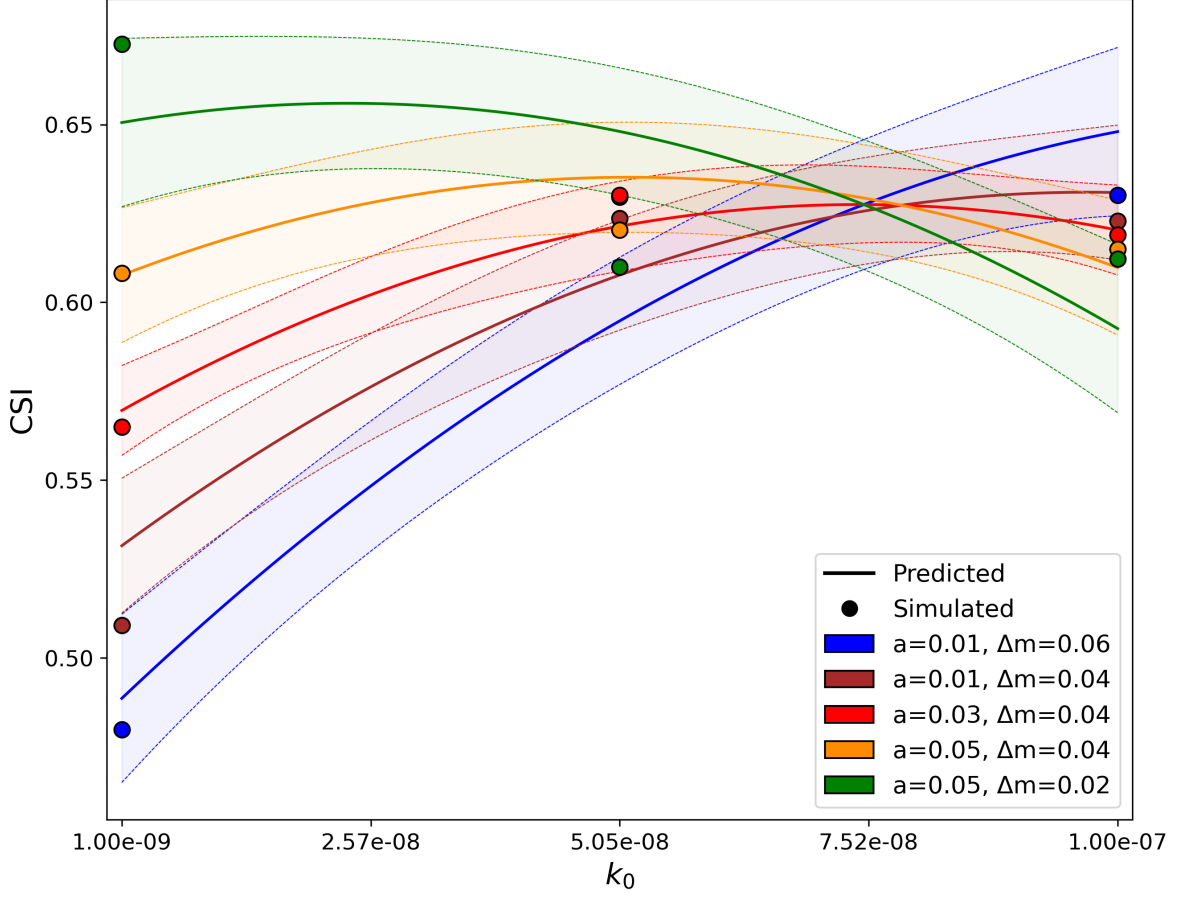


Figure 5.3: CSI values as a function of hydraulic permeability k_0 for different compressibility a and dilatancy δ_m configurations. Predicted values are shown as continuous lines, while simulated values are represented by points. Each predicted curve includes a shaded area indicating the 95 % confidence interval.

increase CSI, while increasing Δ_m tends to reduce CSI.

The results presented in Figure 5.3 show how the predicted CSI varies as a function of k_0 for different a and δ_m configurations. At low values of k_0 , CSI is significantly influenced by both parameters: increasing compressibility a leads to higher CSI values, while increasing dilatancy δ_m reduces CSI. For a hydraulic permeability of $k_0 = 1 \times 10^{-7} \text{ m}^2$, a combination of $a = 0.05$ and $\delta_m = 0.02$ results in a peak predicted CSI of approximately 0.65, which is the highest across all configurations. This highlights a first zone of high model performance associated with low-permeability (low k_0), highly compressible (high a) materials experiencing low dilatancy (low δ_m). However, in this low k_0 regime, comparison with simulation data reveals that the model underestimates the sensitivity of CSI to variations in a and δ_m . It tends to overpredict CSI values for configurations with high δ_m and low a , and underpredicts CSI for those with high a

and low δ_m .

As k_0 increases, the influence of a and δ_m diminishes, and all curves converge near $k_0 \approx 7.5 \times 10^{-8} \text{ m}^2$. This transition point, referred to as a bifurcation, marks a range where CSI becomes less sensitive to the variations in a and δ_m (Fig. 5.3), with all configurations showing nearly identical CSI values (≈ 0.625). Yet, simulation results suggest this transition is more gradual than the model implies. For example, nearly identical CSI values are observed in simulations for $k_0 = 5.05 \times 10^{-8} \text{ m}^2$ and $k_0 = 1 \times 10^{-7} \text{ m}^2$, indicating a plateau within this range of permeability. This points to a limitation in the model's ability to capture the nature of the transition, which may be overly sharp.

Beyond this point, the model-predicted curves begin to spread again, though the sensitivity to a and δ_m is significantly reduced at higher k_0 . In this high-permeability regime, the effects of a and δ_m reverse: higher a now slightly decreases CSI, while higher δ_m increases it. For a hydraulic permeability of $k_0 = 1 \times 10^{-7} \text{ m}^2$, a combination of $a = 0.01$ and $\delta_m = 0.06$ predicts a CSI of approximately 0.645. This highlights a second zone of high model performance associated with high-permeability (high k_0), slightly compressible (low a) materials experiencing high dilatancy (high δ_m). However, compared to simulation data, the model, despite accurately capturing the reduced sensitivity to a and δ_m , slightly overestimates the divergence between configurations in this high- k_0 regime, predicting a wider spread in CSI values (0.59 to 0.65) than is observed in the simulations (0.61 to 0.63).

Despite this limitation, both the model and simulation results suggest two high-CSI scenarios with contrasting material characteristics: one involves a low-permeability, highly compressible material with low dilatancy, while the other involves a high-permeability, slightly compressible material with high dilatancy. Despite these contrasting initial conditions, both scenarios exhibit very similar inundation areas and depth patterns (Fig. 5.4). In both cases, the classification maps reveal overpredicted spreading within the first 700 metres. However, the low-permeability simulation (simulation 3, Table A1 in Appendices) reaches a better CSI of 0.6727 (Fig. 5.4a), largely due to a lower rate of false positive predictions compared to the high-permeability scenario (simulation 25, Table A1 in Appendices), which yields a CSI of 0.6301 (Fig. 5.4b). The high-permeability simulation shows overtopping over the western lava flow, which increases the proportion of false positives (Fig. 5.4b). Additionally, the low-permeability scenario is better at predicting the distal deposit spreading.

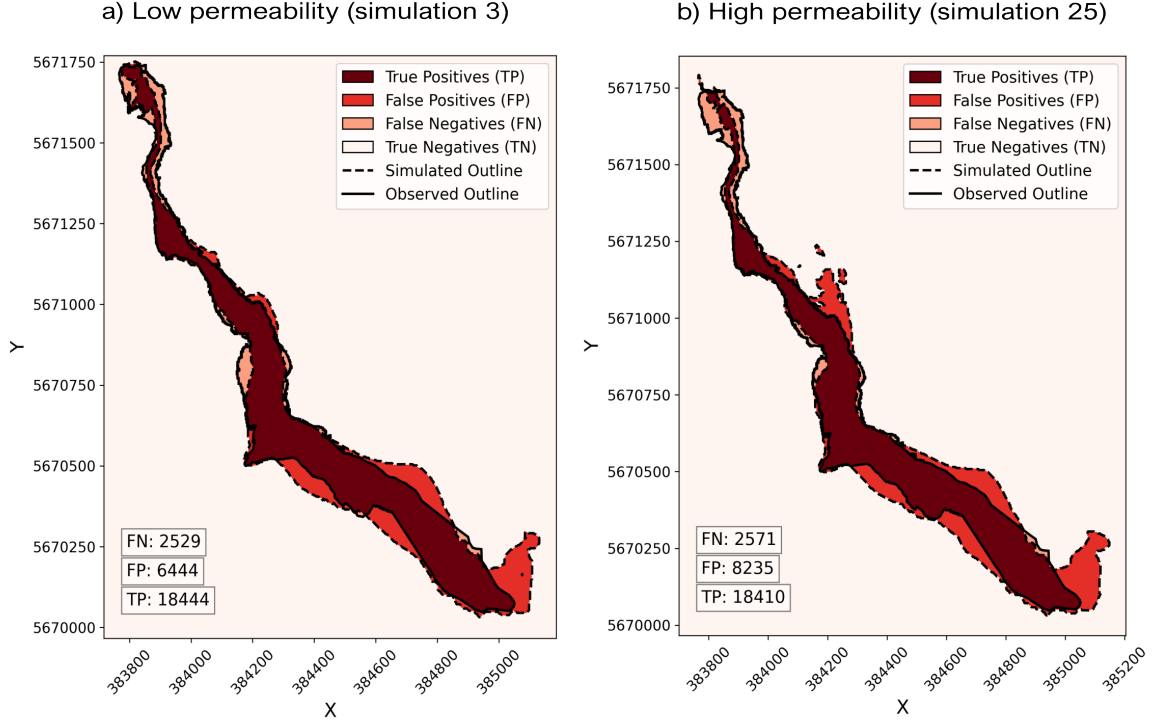


Figure 5.4: Classification maps based on the confusion matrix for (a) the high-CSI, low-permeability configuration (simulation 3; see Table A1 in Appendices) and (b) the high-CSI, high-permeability configuration (simulation 25; see Table A1 in Appendices).

5.4.2 Energy-based indices of landslide mobility

Landslide energy metrics were computed for both high-CSI scenarios (simulations 3 and 25, Table A1 in Appendices), as well as for alternative simulations with varying values of a and δ_m (simulations 1, 9, 19, and 27, Table A1 in Appendices) to provide context for the interpretation of the interaction between k_0 , a and δ_m . Simulations 1 and 9 represent variations of the low-permeability high-CSI scenario (simulation 3), differing from it by setting $a = 0.01$ for simulation 1 and $\delta_m = 0.06$ in simulation 9. Similarly, simulations 19 and 27 are variants of the high-permeability high-CSI scenario (simulation 25), with $\delta_m = 0.02$ in simulation 19 and $a = 0.05$ for simulation 27. The initial potential energy PE_0 of the landslide is calculated using a pre-collapse mass $M_0 = 1.58 \times 10^9$ kg (Procter et al., 2014), with the elevation datum set to the lowest centre-of-mass elevation. The modelled landslide has an initial potential energy PE_0 of $\approx 3.2 \times 10^{12}$ J, which progressively decreases as the mass loses elevation during motion. The total kinetic energy (KE) of the modelled landslide is computed as the sum of translational kinetic energy across all grid cells. Analysing the conversion of potential energy to kinetic energy provides insight into landslide mobility, as it reflects the efficiency of gravitational energy to transform into motion. Energy conversion is often described by the mobility index, $\frac{KE_{max}}{PE_0}$, with

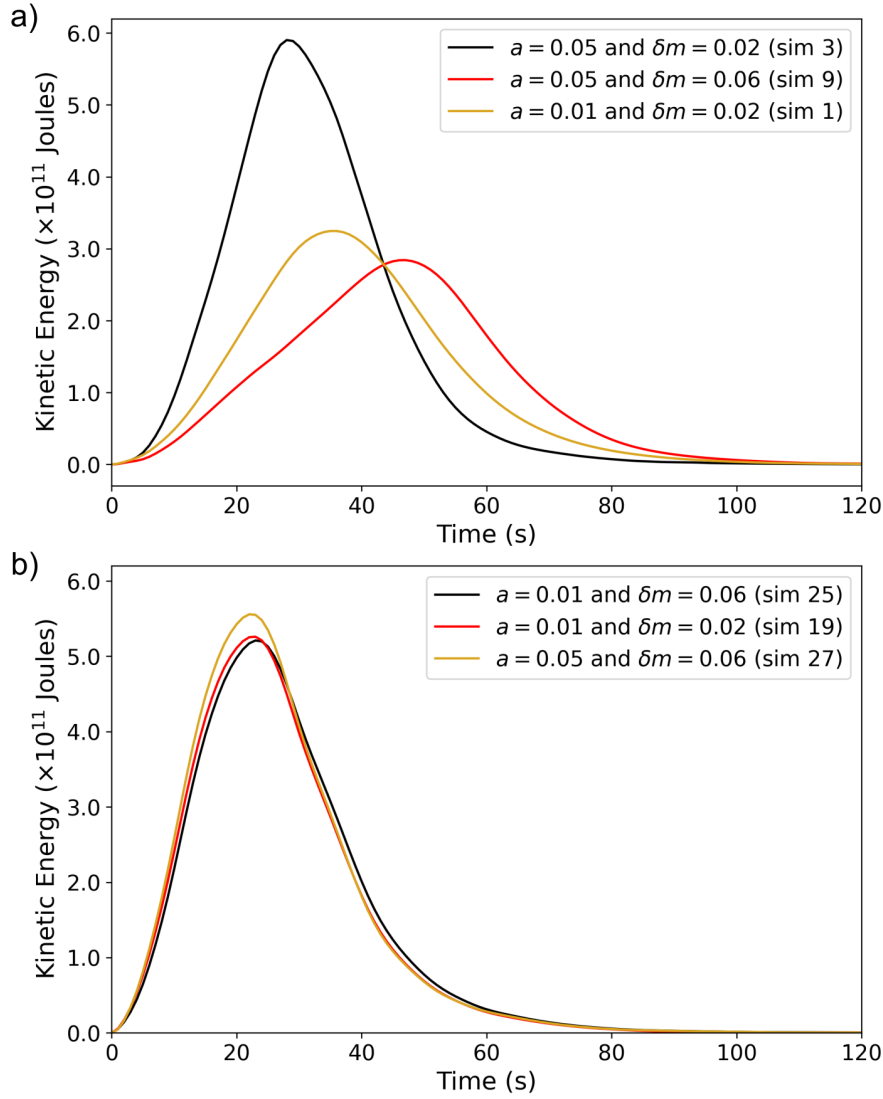


Figure 5.5: Evolution of kinetic energy during the simulated Te Maari landslide for (a) low-permeability and (b) high-permeability configurations.

KE_{max} being the total kinetic energy at peak.

At low-permeability, simulation 3 (Fig. 5.5a, black line) reaches a kinetic peak (KE_{max}) of 5.9×10^{11} J occurring at 28 seconds. This is followed by a rapid drop in KE, reflecting a high rate of mass deceleration. By 70 seconds, the energy level stabilised at a low value, indicating that the flow has mostly stopped or entered a quasi-equilibrium state. At its peak, 18.4 % of the initial potential energy is converted into motion, corresponding to a mobility index of $\frac{KE_{max}}{PE_0} \approx 0.184$. In comparison, increasing δm (simulation 9) and decreasing a (simulation 1) both lead to significantly lower KE_{max} (reduced by approximately 52 % and 45 % respectively) with maxima at 2.85×10^{11} J and 3.25×10^{11} J. This reduced efficiency of energy conversion is

reflected by shorter runout distances (Fig. 5.6a and c) relative to simulation 3, which assumes a lower dilatancy (δ_m) and greater compressibility (a). Reduced acceleration leads to a delayed peak in kinetic energy, around ≈ 35 s for simulation 1 and 47 s for simulation 9. As deceleration is also more gradual, the flow remains mobile for longer, with stabilisation occurring by 80 s in simulation 9 and 100 s in simulation 1.

In the high-permeability scenario, simulation 25 reaches a kinetic energy peak (KE_{max}) of 5.21×10^{11} J at 23 seconds (Fig. 5.5b), corresponding to a 16.3 % conversion of potential energy into motion ($\frac{KE_{max}}{PE_0} \approx 0.163$). As for simulation 3, KE declines rapidly, stabilising around 70 seconds. Both the high- and low-permeability high-CSI scenarios show similar overall dynamics; however, simulation 25 exhibits a slightly earlier and lower KE_{max} , along with a faster deceleration. These subtle distinctions suggest that simulation 3 may experience reduced internal resistance or enhanced material fluidisation compared to simulation 25. In contrast to the low-permeability scenarios, variations in δ_m (simulation 19) and a (simulation 27) do not result in significant changes in energy transfer or conversion efficiency relative to simulation 25 (Fig. 5.5b, black line). However, modifying these parameters does influence flow mobility. Specifically, increasing a leads to a noticeable reduction in runout: in simulation 19, the flow runout is shorter as it fails to pass through the narrowest downstream section of the channel (Fig. 5.6b).

Overall, the energy-based results indicate that, although both high-CSI scenarios exhibit similar energy dynamics, the high-permeability case reaches a slightly earlier and lower kinetic energy peak, followed by faster deceleration. This suggests that low-permeability conditions promote a slightly more efficient conversion of potential energy into motion and allow the flow to be sustained over a longer duration. Moreover, energy conversion and flow mobility appear significantly more sensitive to variations in δ_m and a under low-permeability conditions, with energy conversion efficiency decreasing by approximately 50 % (Fig. 5.5) and runout distances reduced by half (Fig. 5.6). This heightened sensitivity to a and δ_m under low-permeability conditions is consistent with the behaviour predicted by our model (Fig. 5.3).

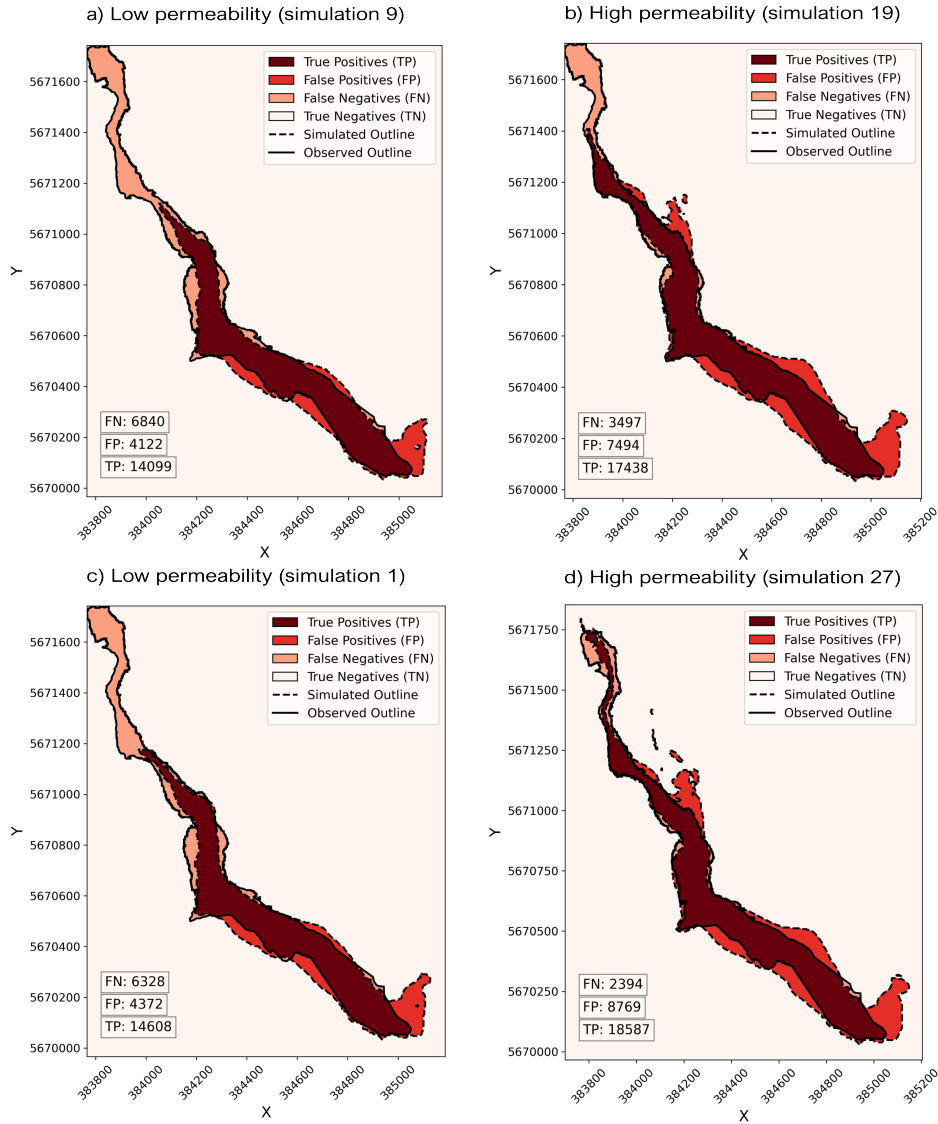


Figure 5.6: Classification maps derived from the confusion matrix for the alternative scenarios. Panels (a) and (c) correspond to the low-permeability configurations (simulation 9 and simulation 1, respectively; see Table A1 in Appendices), while panels (b) and (d) correspond to the high-permeability configurations (simulation 19 and simulation 27, respectively; see Table A1 in Appendices).

5.5 Discussion

5.5.1 Internal controls on laterally-confined landslide dynamics

Volcanic debris avalanche mobility is fundamentally influenced by the degree of lateral confinement they experience (Iverson, 1997). In our study, the Te Maari debris avalanche is a laterally confined, channelised flow, with a varying degree of confinement along its path. For the first 700 metres, the flow spreads within a broad, flat channel area, where confinement is relatively weak and allows some lateral expansion. Beyond this initial section, the flow becomes strongly channelised as it enters a narrower, more deeply incised valley that significantly reduces lateral spreading (Procter et al., 2014). Unlike unconfined flows that dissipate energy across a broader area through lateral spreading (Iverson and George, 2016), laterally channelised flows tend to retain kinetic energy more effectively, allowing them to travel longer longitudinal distances (de Haas et al., 2015; Strom et al., 2019; Jones et al., 2023). For example, Strom et al. (2019) showed that confined debris avalanches of similar volumes to Te Maari (i.e., $0.7 \times 10^6 \text{ m}^3$) can reach runout distances nearly twice as long as their unconfined counterparts. This suggests that, in laterally confined settings, even small-scale landslides can sustain significant momentum, as topographic confinement limits energy dissipation. We believe this confinement highlights the role of internal material properties, such as compressibility, dilatancy, and permeability, in governing overall flow mobility.

Our results support this interpretation: we observe that variations in permeability and its interaction with other parameters (e.g., δ_m , a) meaningfully affect flow mobility. This contrasts with the findings of Iverson and George (2016), whose simulations of the unconfined 2014 Oso landslide showed little to no influence of permeability k_0 and dilatancy δ_m in the dilative regime ($\delta_m \geq 0$). They demonstrated that dilation-induced negative pore pressure feedback inhibits fluidisation, maintaining high frictional resistance and causing rapid momentum loss (Iverson and George, 2016). As a result, changes in internal parameters such as k_0 and δ_m had minimal impact on mobility. In contractive regimes, however, their results showed that energy conversion and runout increased monotonically with $|\delta_m|$, and that lower k_0 values, by sustaining longer excess pore pressure, led to extended runouts (Iverson and George, 2016).

We propose that the contrasting outcomes between our study and Iverson and George (2016)’s findings result from differences in topographic confinement. In the unconfined Oso simulations, the combination of dilative behaviour and early energy loss through lateral spreading

may have masked the effects of internal properties. In our confined configuration, by contrast, the channelised geometry limits lateral dispersion and preserves flow coherence over longer distances. This allows the influence of internal properties to persist throughout the motion, even in the absence of initial liquefaction. The topographic confinement therefore plays a key role in modulating how material properties control landslide dynamics, revealing sensitivities that may remain hidden in unconfined settings.

5.5.2 Physical drivers of high-CSI scenarios

Despite originating from contrasting initial conditions, the two high-CSI scenarios (one characterised by low permeability and the other by high permeability) ultimately result in a similar extent of inundation. This convergence in runout area, despite divergent internal properties, highlights the complexity of landslide dynamics and suggests that different mechanical processes can compensate for one another to produce comparable mobility outcomes. In our case, we have shown that the influence of the material’s compressibility a or dilatancy δ_m differs significantly depending on the permeability regime. For the Te Maari topographic setting, we identified a transition in behaviour occurring around an observed threshold of approximately $k_0 = 5 \times 10^{-8} \text{ m}^2$ (Fig. 5.3). While the model predicts a bifurcation point at $k_0 = 7.5 \times 10^{-8} \text{ m}^2$ (Fig. 5.3), we interpret this as a modelling artefact. Below this transition, flow dynamics is highly sensitive to internal properties with increased mobility for higher compressibility a and lower dilatancy δ_m . Above this transition, the same variations in internal properties only produce minor changes in dynamics, with a slight increase in mobility observed for lower compressibility a and higher dilatancy δ_m . This suggests that for the permeability range tested, we have a shift in the dominant physical controls on mobility across this permeability threshold.

In the low-permeability scenario, matrix suction (i.e., negative pore pressure) develops at the onset of deformation (Fig. 5.7), temporarily increasing the resistance to failure and delaying flow initiation. Although this early-stage resistance slows the onset of motion, elevated pore pressures, once developed, are sustained for longer durations, thereby supporting prolonged flow activity (Fig. 5.5a). This effect is moderated by the initial dilatant response to deformation, as pore space expansion reduces the magnitude of pressure increase. Yet, when the material exhibits high compressibility (a) and low dilatancy (δ_m), this initial buffering is overcome (Fig. 5.5a). High compressibility allows greater deformation under effective stress, promoting pore

pressure accumulation, while low dilatancy restricts pore expansion under deformation, sustaining elevated pressures. Moreover, lateral confinement, by increasing the thickness of the flow and therefore its weight, promotes undrained loading (further amplified by high compressibility), thereby enhancing the development of excess pore pressure in channelised regions. This combination enables the flow to achieve peak velocities up to 25 m/s and to travel longer distances, comparable to those in high-permeability scenarios. Excess pore pressure is maintained along the flow, with spatial variability in the liquefaction ratio, reaching values close to 1 in parts of the flow (Fig. 5.7). This case shows that the model is able to capture transformations in flow behaviour. However, scenarios with low permeability combined with high dilatancy (Fig. 5.6a) or low compressibility (Fig. 5.6c) result in shorter flow distances. In these cases, the increase in pore space associated with high dilatancy or low compressibility inhibits the build-up of pore pressure, thereby reducing flow mobility.

The high-permeability scenario is characterised by rapid acceleration and pore pressure build-up (Fig. 5.5b), due to quick water infiltration and minimal early-stage resistance (no matrix suction). But in contrast to the low-permeability scenario, pore pressure dissipates rapidly, minimising its impact on flow dynamics. Here, the role of dilatancy becomes predominantly geometric rather than hydraulic. We believe that in this case, lower dilatancy results in a denser, more interlocked granular matrix that resists internal deformation and prevents disaggregation. This increased internal resistance may lead to earlier flow arrest, particularly in narrow gullies (Fig. 5.6c), despite having energy levels similar to the other configurations (Fig. 5.5b). As shown in Figure 5.7, the liquefaction ratio remains consistently close to its average value (≈ 0.5), with a very low and time-invariant standard deviation, indicating minimal pore pressure build-up and rapid dissipation throughout the flow path.

5.5.3 Implications for future hazard assessment

This study highlights that landslide dynamics are highly sensitive to initial conditions, even minor variations can lead to significantly different behavioural outcomes. Such sensitivity presents an important challenge for quantitative landslide hazard assessment, where accurate predictions of runout distances, velocities, and impact areas are critical. Our results demonstrate that the internal permeability regime plays a central role in controlling runout and mobility, influencing both the development of excess pore pressure and the timing of its release. However, in real-world events, permeability is difficult to predict, especially within a moving, multiphase mixture

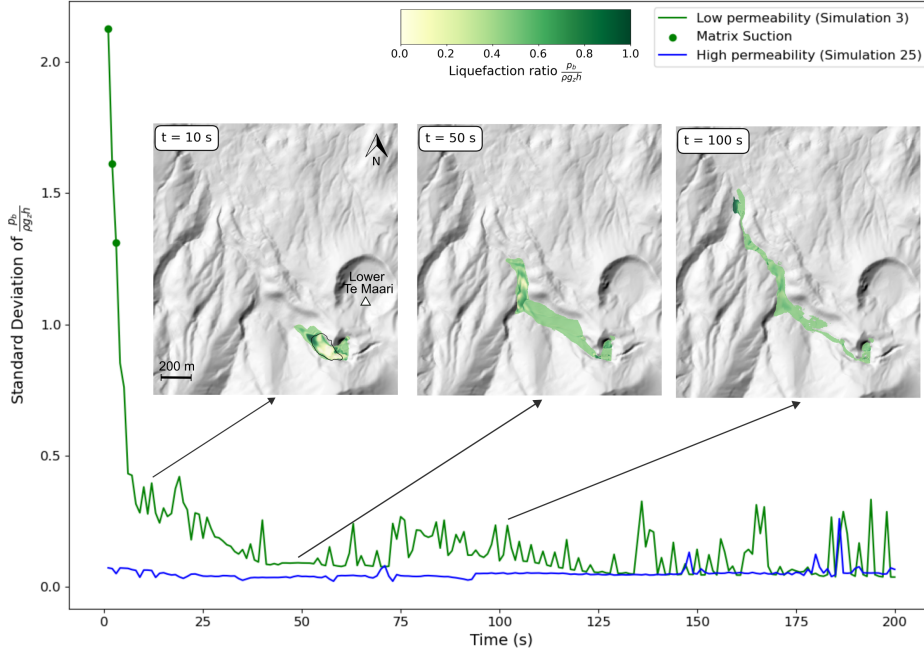


Figure 5.7: Standard deviation of the liquefaction ratio for the high-CSI, low-permeability configuration (simulation 3, in green) and the high-CSI, high-permeability configuration (simulation 25, in blue). Snapshots of the liquefaction ratio for simulation 3 at 10, 50, and 100 s are shown on the graph, with green shading indicating the degree of basal liquefaction. During the first 3 seconds of simulation 3, matrix suction occurs, followed by a progressive increase in the average liquefaction ratio, eventually reaching values comparable to those of simulation 25.

whose internal structure evolves dynamically during motion (Iverson and George, 2014). More specifically, our findings indicate that particular combinations of internal material properties can overcome the mobility-reducing effects associated with low permeability in dilative failures leading to channelised flows. For example, a combination of low-permeability, high compressibility, and low dilatancy enhances mobility, enabling flows to reach high peak velocities early and travel long distances, similar to high-permeability settings. This result emphasises that landslide behaviour is not governed by a single dominant parameter, but rather emerges from the complex interplay between multiple factors (e.g., initial saturation, solid fraction, compressibility, dilatancy, and permeability).

These insights reveal a need for more nuanced approaches to hazard modelling. Simplified or unconstrained initial assumptions about material properties may fail to capture transitions in landslide behaviour and may therefore lead to inaccurate predictions. Future efforts should prioritise the integration of the internal material variability and its effect on hydromechanical complexity into probabilistic hazard assessments, as this governs the development of pore pressure and ultimately dictates landslide mobility.

5.6 Conclusions

The dynamics of the 2012 Te Maari debris avalanche, investigated using depth-averaged, multi-phase numerical model D-Claw, demonstrate that two contrasting sets of initial conditions (i.e., a low-permeability and a high-permeability scenario) can both accurately reproduce the observed flow runout. Among the two, the low-permeability scenario offers a slightly better fit in terms of distal spreading and channel confinement, avoiding overtopping where super-elevations were observed.

This case study reveals how the interplay between internal material properties and topographic confinement strongly influences the mobility of channelised volcanic debris avalanches. While topographic confinement limits lateral spreading and preserves flow coherence, it simultaneously amplifies the effect of internal controls such as dilatancy, compressibility, and permeability in shaping flow behaviour.

Our results show that, in channelised debris avalanches, similar runout extents can emerge from distinct permeability regimes, each driven by different physical processes. In low-permeability conditions, flow dynamics is dominated by the development and sustained presence of excess pore pressure, particularly under high compressibility and low dilatancy. Conversely, high-permeability regimes allow for rapid pore pressure generation and dissipation. As a result, the flow dynamics is largely controlled by that initial rapid acceleration, after which it may become constrained by the material's internal structural coherence. These findings indicate that landslide mobility is the result of nonlinear interactions between internal properties and boundary conditions. Permeability, in particular, plays a key role through its interaction with other structural parameters, driving transitions in flow behaviour that are strongly shaped by the degree of confinement.

Future efforts should move toward probabilistic, physics-informed modelling frameworks that account for the dynamic evolution of internal properties during motion. In particular, better constraints on material characteristics and their spatial variability (paired with topographic context) will be key to improving forecasts of landslide runout and impact areas in confined terrain like Te Maari.

Chapter 6

Coupled limit equilibrium/depth-averaged approach for debris flow hazard assessment: the 2012 Te Maari avalanche

This chapter has been submitted to *Géotechnique* under the same title, and is currently under peer-review.

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Contributions:

- **Juliette Vicente:** Conceptualisation, Methodology, Data Curation, Software analyses, Investigations, Interpretations, Writing – original draft, Reviews and Editing.
- **Stuart Mead:** Resources, Supervision, Methodology, Interpretations, Writing – review and editing.

6.1 Introduction

Volcanic debris avalanches are among the most hazardous volcanic processes, responsible for an estimated 30,000 casualties worldwide over the past five centuries (Siebert and Roverato, 2021). While large-volume events are often catastrophic, even small avalanches can result in significant local impacts, particularly when conditions such as high saturation or water entrainment along the flow path enable rapid transformation into highly mobile debris flows capable of travelling long distances (McGuire, 1996; Capra et al., 2002; Hungr et al., 2008; Siebert and Roverato, 2021). A notable example is the 1998 Casita event in Nicaragua (Kerle and van Wyk de Vries, 2001). Triggered by heavy rainfall during Hurricane Mitch, the collapse of a hydrothermally-altered cliff released approximately 200,000 m³ of material, which rapidly transformed into a lahar. Flowing at speeds of up to 40 m/s, the lahar inundated the towns of El Porvenir and Rolando, claiming nearly 2,500 lives (Kerle and van Wyk de Vries, 2001).

The societal and economic consequences of such events underscore the critical need for reliable hazard assessments that can identify areas at risk and inform mitigation strategies. Central to these assignments is the ability to predict the spatial likelihood of failure (i.e., landslide susceptibility) and the potential runout of debris avalanches. Numerical models provide a powerful framework for investigating landslide susceptibility and runout behaviour, offering capacities that extend beyond empirical and analytical approaches. For runout analysis, they can capture the complete evolution of the hazard, predicting not only the total runout, but also the spatial and temporal distribution of key flow variables (e.g., depths, velocities) along the entire flow path (Dai et al., 2002; Hürlimann et al., 2008). However, most physically-based approaches remain highly sensitive to input parameters such as initial volume, material properties, and basal friction (Reid et al., 2000; Mergili et al., 2018a). Integrating failure characteristics and flow dynamics within a unified framework offers a pathway to reduce these uncertainties and better represent the complete landslide process. Some limited studies have attempted such integrated frameworks, aiming to improve hazard zonation for predictive purposes. These approaches, whether applied at regional or local scales, typically generate semi-quantitative outputs and generally do not employ fully physically-based simulations (e.g., depth-averaged models), instead using empirical rules and simplifying key dynamic processes (e.g., Mergili et al., 2012; Horton et al., 2013; Mergili et al., 2019). In cases where quantitative probabilities are generated, the methods often smooth out the spatial variability of source susceptibility (Mergili

et al., 2019) and miss crucial information such as initiation volumes (Horton et al., 2013; Mergili et al., 2019). Integrative quantitative methods that can properly estimate the probability of a given area being affected by a landslide (considering both failure and flow) are therefore still rare (Mergili et al., 2019). Yet, such approaches would likely provide a significant improvement in hazard delineation compared to methods that account for either the failure or the flow alone.

For models focusing on either the initiation or the flow phase alone, physically-based numerical simulations are commonly employed. In the context of initiation, slope stability analyses such as limit-equilibrium method (LEM) or more advanced continuum-mechanics approaches are used to evaluate the likelihood of failure based on soil and rock properties, pore pressures, and slope geometry (e.g., Gu et al., 2015; Acevedo et al., 2021; Ji et al., 2025). For the flow phase, depth-averaged models are commonly used (e.g., Sheridan et al., 2010; Mead and Magill, 2017; Charbonnier et al., 2015; Ding et al., 2023; Wolff et al., 2025), providing quantitative estimates of flow behaviour and deposition patterns. These models range from single-phase approaches, which treat the avalanche as a homogeneous mass, such as the Voellmy–Salm (Salm, 1993), FLO-2D (O’Brien et al., 1993), and DAN3D (McDougall, 2006) models, to multi-phase approaches that explicitly account for interactions between solids and fluids, such as TITAN2D (Pitman and Le, 2005), r.avaflow (Mergili et al., 2017), and D-Claw (Iverson and George, 2014). Despite the development of more complex modelling methodologies, the reliability of model predictions is fundamentally constrained by the accuracy of key input parameters (Mead et al., 2021), particularly the geometry and volume of the initial source, which govern the potential energy and runout behaviour of the avalanche.

To efficiently integrate the failure characteristics with the post-failure dynamics in hazard assessment, we develop a framework to integrate susceptibility with flow, explicitly propagating variability in LEM-derived source geometries into depth-averaged flow modelling for probabilistic debris flow hazard assessment. This approach couples landslide susceptibility obtained from LEM slope stability analyses with debris avalanche runout simulated using the depth-averaged, two-phase model D-Claw (Iverson and George, 2014), and is validated using the 2012 Te Maari debris avalanche.

Landslide susceptibility was first assessed deterministically using LEM, informed by material properties derived from laboratory testing, field observations, and geophysical surveys (Miller and Williams-Jones, 2016; Kereszturi et al., 2018; Vicente et al., 2025). Candidate slip surfaces were filtered based on the characteristics of the 2012 Te Maari debris avalanche, allowing for

a volume uncertainty of $\pm 300,000 \text{ m}^3$ relative to the observed event and a maximum depth uncertainty of $\pm 12 \text{ m}$ relative to the observed maximum depth. Surfaces with $0 \leq \text{Factor of Safety (FOS)} \leq 4$ were selected, and a weighting function was applied to the FOS values to estimate the relative probability of failure. The selected LEM surfaces were subsequently used as input for D-Claw flow simulations. Flow parameters were held constant across all simulations, ensuring that uncertainty in rheology or flow dynamics was not propagated. As a result, all variations in runout predictions can be attributed to differences in the geometry of the initial failure surface, including its location, volume, depth, shape, and slip direction. Each simulated runout was evaluated using quantitative performance metrics to assess the influence of key LEM characteristics on the predictive accuracy of our framework. Finally, all simulated runouts were aggregated into unweighted and FOS-weighted exceedance probability maps, providing quantitative predictions of inundation extent for small-volume scenarios originating at Te Maari and propagating along the Mangatipua Stream. The performance of these maps was then evaluated against observed data to assess how well the model can predict potential future events given the uncertainties in the LEM-derived source geometries.

6.2 Study area

The Lower and Upper Te Maari craters are located on the northern flank of Tongariro (New Zealand), a composite multi-vent volcanic complex south of the Taupo Volcanic Zone (TVZ). Over the past few thousand years, activity at Tongariro has been concentrated at vents in the northern part of the edifice, including Ngauruhoe, Red Crater, and the Te Maari craters (Miller and Williams-Jones, 2016; Leonard et al., 2021).

These vents are part of a large active hydrothermal system, expressed at the surface by condensate outflows at Ketetahi Hotsprings and fumaroles at Te Maari (Fig. 6.1). Geophysical imaging suggests these features are not part of a single large circulation system, but rather form discrete pockets of vapour and condensate regions (Miller et al., 2018; Leonard et al., 2021). At Te Maari, the circulation of hot and acidic hydrothermal fluids through the fractured volcanic deposits leads to the precipitation of low-density minerals such as kaolinite, smectite, or montmorillonite (Kereszturi et al., 2018). This argillic alteration changes the physical characteristics of the volcanic rocks and strongly influences their mechanical behaviour and failure modes (Reid et al., 2001; Heap et al., 2015). In addition, groundwater circulation from active

hydrothermal systems can increase pore pressure (van Wyk de Vries et al., 2000; Reid, 2004; Cecchi et al., 2004; Ball et al., 2018; Rosas-Carbajal et al., 2016), reducing the effective stress and the material resistance to failure. These alteration zones and their geotechnical properties are therefore important in evaluating landslide susceptibility, as they delineate likely initiation zones and constrain initial volumes of future landslides (Kereszturi et al., 2021).

Geological evidence for past mass flows at Tongariro is limited. Only five lahar-type deposits have been identified from 26–11 kyr ago (Cronin et al., 1997; Procter et al., 2014), mainly preserved 10–30 km from the source and attributed to remobilised pyroclastics. In addition, the Te Whaiau Formation (0.5 km³ debris avalanche, 55–60 kyr ago) was mapped to the northwest (Lecointre et al., 2002), and lahar deposits from the 1892 Te Maari eruption were documented on the northern flanks (Topping, 1974). The most recent gravitational collapse occurred on 6 August 2012 ($\approx$ 23:50:00 UTC+12) at Upper Te Maari and is part of a complex multi-hazard cascade. This small debris avalanche ($\approx 7 \times 10^5$ m³) followed a series of earthquake swarms in July (Hurst et al., 2014), and led to a multi-pulse phreatic eruption due to hydrothermal system unloading (Jolly et al., 2014; Procter et al., 2014). Despite being relatively small and superficial, the collapse generated secondary hazards. First, likely due to entrainment, it transformed into a cohesive, clay-rich debris flow that travelled approximately 2 km (Procter et al., 2014). Second, the debris-flow deposit formed a small ephemeral lake that impounded subsequent rainfall, which, on 13 October 2012 ($\approx$ 23:30:00 UTC+12), breached and released a breakout flow (Walsh et al., 2016). This secondary event produced a small hyperconcentrated flow that destroyed over 500 metres of the Tongariro Alpine Crossing track before spreading across State Highway 46 (Fig. 6.1; Procter et al., 2014). Fortunately, no casualties occurred, as both the initial debris avalanche and the subsequent lahars happened during the night, when no visitors were present on the tracks. If these events had occurred during the day, the consequences could have been much more severe.

At Te Maari, and across the entire edifice, zones of intense hydrothermal alteration remain (Fig. 6.1; Kereszturi et al., 2018), representing potential sources for future debris avalanches. The volume of hydrothermally altered rock within the edifice has been estimated at approximately 20 km³ (Miller and Williams-Jones, 2016). Therefore, for volcanic edifices affected by hydrothermal circulation and alteration, characterising these zones is particularly important for hazard assessment, as they strongly influence landslide susceptibility and may also promote saturated failures that rapidly liquefy into debris flows, thereby affecting runout behaviour.

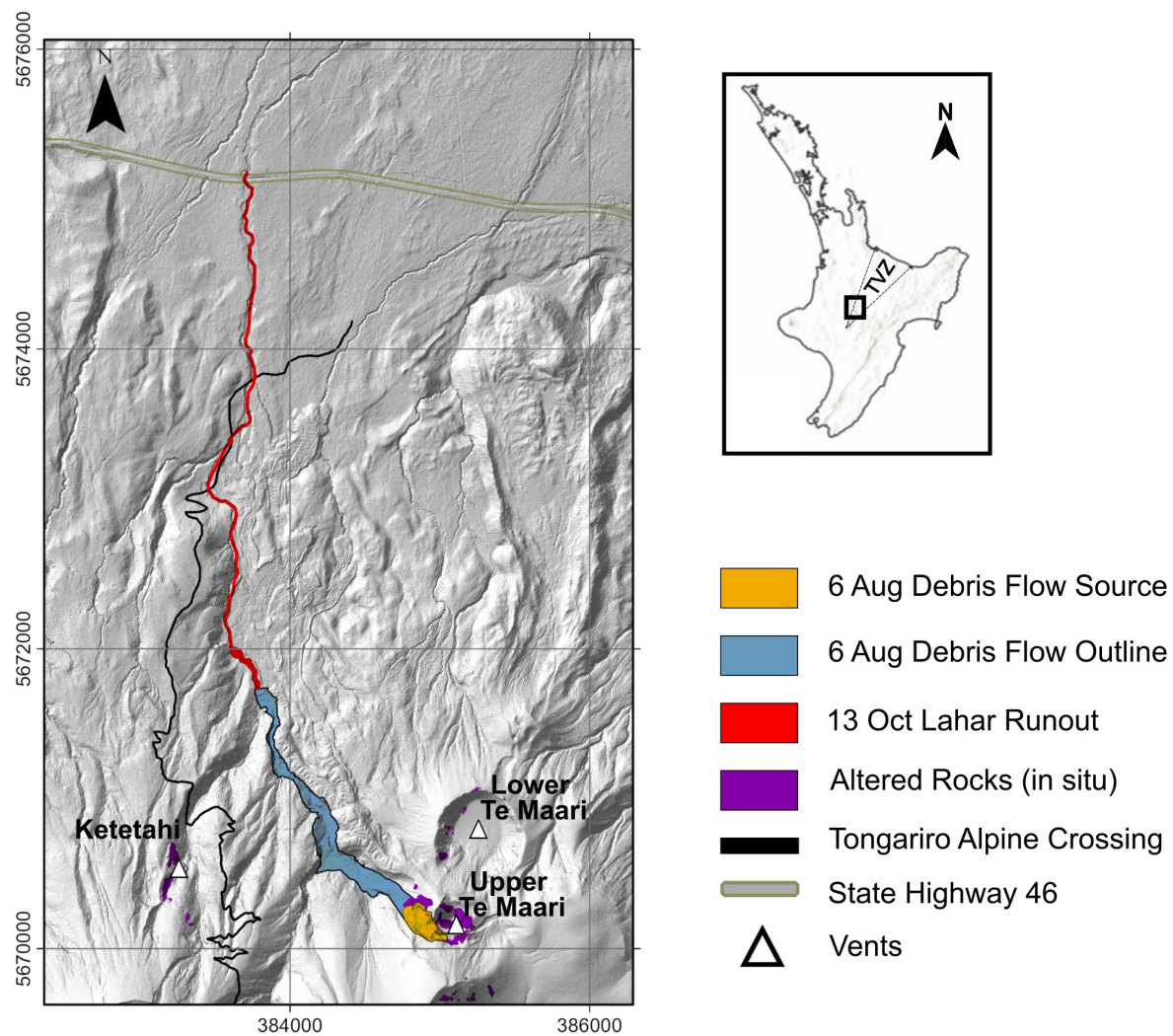


Figure 6.1: Study area map showing the 6 August debris-flow source (orange) and flow outline (blue), the 13 October lahar runout (red), and in-situ altered rock (purple, from Kereszturi et al., 2018)

6.3 Method

A three-step methodology is proposed for local-scale debris-flow hazard assessment, integrating both failure initiation and post-failure dynamics (Fig. 6.2).

In the first step, a deterministic analysis based on Limit Equilibrium Methods (LEM) is used to delineate potential failure zones. Informed by site-specific data from Vicente et al. (2025), the LEM directly provides quantitative outputs, such as the FOS, potential slip volume, and expected slip direction.

In the second step, these LEM-derived outputs are then used as initial conditions for process-based numerical simulations. Flow-related initiation parameters (e.g., permeability, basal friction angle) were calibrated by Vicente and Mead (2025) through optimisation of numerical simulations of the 2012 Te Maari debris avalanche to reproduce the observed flow extent. Using numerical models, we capture debris flow runout in detail, predicting variables such as flow depth and velocity, that are essential for evaluating debris-flow intensity and associated hazards.

In the third step, landslide hazard maps are generated from predicted deposit heights. These maps express the probability of exceeding a given deposit thickness, a commonly used measure of mass flow hazard because it is both easy to interpret and practical for delineating hazard zones (Mead and Magill, 2017).

6.3.1 LEM surfaces generation

LEM are widely used to analyse slope stability (Deng et al., 2015; Mebrahtu et al., 2022; Garo et al., 2024) due to their simplicity and low computational cost. These methods are based on assumptions regarding the geometry and the mode of failure. The sliding mass is discretised into vertical columns, and the forces acting on each column along the pre-defined failure plane are evaluated. For each potential slip surface, the factor of safety (FOS) is computed as the ratio of resisting forces (e.g., shear strength) to driving forces (e.g., applied shear stress). Failure is considered to occur when the mobilised shear strength equals the applied stress, corresponding to a condition of $\text{FOS} \leq 1$.

In this study, the Slide 3 software (Rocscience Inc., 2025) was used to assess the 3D stability of a set of pre-defined slip surfaces. The surface search was conducted using the Bishop Simplified method (Bishop, 1955) as it provides a robust and computationally efficient estimate of FOS for the slip surfaces considered. The method considers only interslice normal forces while

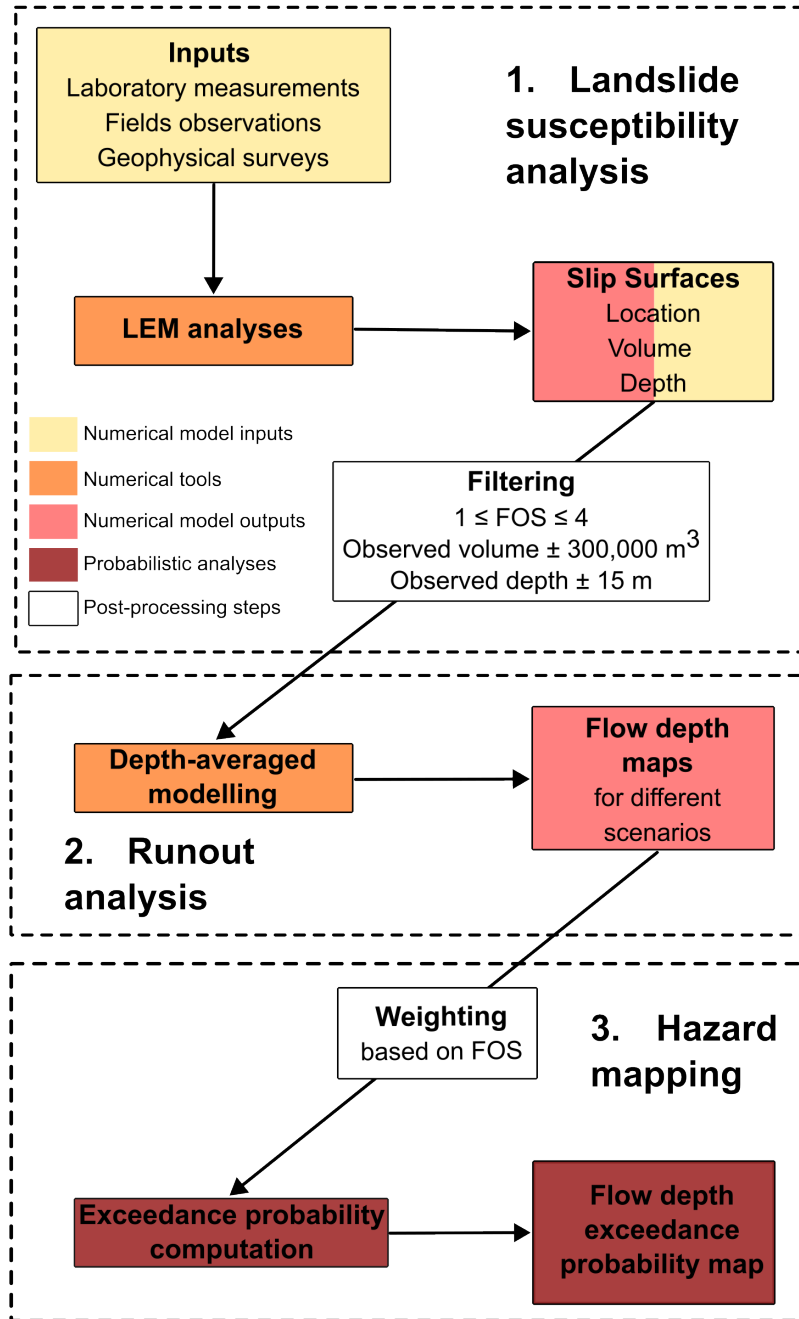


Figure 6.2: Flowchart illustrating the three-step methodological approach of this study. Box colours indicate inputs, numerical models, outputs, post-processing steps, and probabilistic components.

neglecting interslice shear forces. Its simplicity and efficiency make it widely adopted for both slope stability analyses and probabilistic hazard assessment (e.g., Reid et al., 2015; Ball et al., 2018; Arca and Lorenzo, 2018; Singh et al., 2020).

The inputs required for the LEM analysis include the slope geometry and boundary conditions, material strength properties, and groundwater conditions. These parameters were based on a thorough analysis by Vicente et al. (2025), who used 2D finite-element modelling (FEM) at Te Maari to evaluate slope stability and identify the preparatory and triggering mechanisms that led to the 2012 Te Maari collapse. Their study highlighted two primary mechanisms controlling slope failure: (i) strength reduction due to hydrothermal alteration, and (ii) elevated pore pressure caused by fluid infiltration within the altered unit.

Input parameters were chosen to replicate the Vicente et al. (2025) study, characterising the slope geometry and the variability of edifice mechanical characteristics. The slope geometry was derived from a 10-m pre-event DEM and divided into two rock units (altered and unaltered units), delineated using hyperspectral image classification (Kereszturi et al., 2018) and gravity data (Miller and Williams-Jones, 2016). The altered unit comprises hydrothermally altered rocks, while the unaltered unit includes rocks that are not, or only slightly, affected by alteration, with each unit defined by distinct mechanical parameters (see Table 6.1). Groundwater properties were simplified from the infiltration model of Vicente et al. (2025) by assuming a linear increase in pore pressure from the surface to depth in the altered unit. In this unit, pore pressure increases approximately linearly from 0 Pa at the surface to ≈ 8 MPa at 600 m depth, allowing the use of a pore-pressure ratio (r_u) approach, defined as:

$$r_u = \frac{u}{\gamma z} \quad (6.1)$$

where $\gamma = 18 \text{ kN/m}^3$ is the unit weight of the altered unit, $u = 8 \text{ MPa}$ is the pore pressure at depth $z = 600 \text{ m}$, giving $r_u \approx 0.75$.

As in Vicente et al. (2025), the Generalised Hoek-Brown (GHB) criterion was applied to characterise rock strength, accounting for rock mass structure and surface conditions (Hoek and Brown, 1980; Hoek et al., 2002; Hoek, 2005). This empirical, non-linear criterion relates peak shear stress to confining pressure (Eberhardt, 2012; Mebrahtu et al., 2022), and introduces the Geological Strength Index (GSI), a visual assessment of the rock mass. GSI is then used to calculate the empirical constants m_b , a , and s .

Table 6.1: Summary of the mechanical and groundwater parameters used in LEM analysis.

Unit properties	Unit weight (kN/m ³)	UCS (MPa)	GSI	m_b	s	a	r_u
Unaltered	26	160	60	6.66	0.012	0.5028	0.1
Altered	18	25	25	1.15	0.002	0.5312	0.75

The mechanical and groundwater parameters used in the LEM analysis are summarised in Table 6.1.

The LEM identified approximately 1000 slip surfaces across the Te Maari area. These were subsequently filtered to select candidate failures that align with characteristics observed at the source area, according to three criteria: $0 \leq \text{FOS} \leq 4$, volume ranging from 450,000 to 1,050,000 m³ ($\pm 300,000$ m³ relative to the observed volume), and a maximum depth ranging from 31 to 55 m (± 12 m relative to the observed maximum depth). Applying these historical constraints, 31 LEM slip surfaces were identified (Table B1).

6.3.2 Flow modelling

The 31 LEM-derived slip surfaces were used to define the initial volumes and geometries for flow simulations. We employed the depth-averaged multiphase model D-Claw (Iverson and George, 2014), which captures the evolving rheology of debris flows through the coupled evolution of solid-volume fraction and pore pressure along the flow path. One of the LEM slip surfaces, however, did not produce a runout and was therefore excluded from debris-flow outcomes, reducing the total number of simulations to 30.

For each simulation, following the assumptions of Vicente et al. (2025), D-Claw progressively increases the basal pressure (p_b) until the weakest point yields to the minimum it can sustain.

Flow initiation parameters for each simulation were based on Vicente and Mead (2025), who identified two contrasting sets representing different combinations of permeability, compressibility, and dilatancy. We selected the high-permeability set (see Table 6.2) because it showed less variability in model performance, helping to reduce the propagation of flow-related uncertainties.

Each scenario was simulated for 200 seconds, producing one output frame of flow height (in m) per second. These 201 frames (0-200 s) were then processed to extract the maximum flow height for each given scenario. The final runout of each scenario was then categorised based on its offset from the observed runout (≈ 2 km).

The performance of each simulation was assessed using quantitative metrics. Simulation

Table 6.2: Values of the D-Claw simulation input parameters.

Material property	Value
Hydraulic permeability k_0 (m ²)	1×10^{-7}
Compressibility proportionality coefficient a	0.01
Critical solid-volume fraction m_{crit}	0.74
Initial solid-volume fraction m_0	0.8
Basal friction angle ϕ (°)	21
Compressibility reference stress σ_0 (Pa)	1000
Fluid density ρ_f (kg/m ³)	1000
Solid density ρ_s (kg/m ³)	2500
Fluid viscosity μ (Pa·s)	0.001
Characteristic grain size δ (m)	0.01

maximum flow heights were compared to observations on a cell-by-cell basis, identifying true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). To comprehensively assess performance, we calculated several commonly used metrics (e.g., Mergili et al., 2017; Charbonnier et al., 2018; Mead et al., 2021): the Positive Predictive Value (PPV, $\frac{TP}{TP+FP}$); the Sensitivity Index ($\frac{TP}{TP+FN}$); and the Critical Success Index (CSI, $\frac{TP}{TP+FP+FN}$). PPV reflects the proportion of predicted hazard areas that were actually observed, Sensitivity measures the proportion of observed hazard correctly captured by the model, and CSI provides an overall measure of correspondence between simulated and observed hazard footprint.

6.3.3 Generation of probabilistic hazard maps

To produce probabilistic hazard maps, we estimated the probability of flow heights exceeding selected thresholds at each grid cell, based on the ensemble of 30 simulations. The unweighted exceedance probability for a given threshold h_t was calculated as the complementary form:

$$P(h > h_t) = 1 - p(h \leq h_t) \quad (6.2)$$

where $p(h \leq h_t)$ represents the probability that the maximum flow height does not exceed the threshold. This probability is determined empirically using the simulated heights across all scenarios:

$$p(h \leq h_t) = \frac{1}{N} \sum_{i=1}^N \mathbf{I}(h_{i,j} \leq h_t) \quad (6.3)$$

Here, j identifies the grid cell, i identifies the simulation, $h_{i,j}$ is the maximum flow height

at a cell j in simulation i , $\mathbf{I}$ is the indicator function (1 if $h_{i,j} \leq h_t$ and 0 otherwise), and $N = 30$ is the total number of simulations.

To account for the relative probability of failure of each potential slip surface, we also introduce a simple weighting function based on the FOS. Our focus is not on the detailed evolution of the probability of failure, but rather on the overall trend: the probability of failure decreases as FOS increases (Whitman, 1984; Silva et al., 2008; Javankhoshdel and Bathurst, 2014; Ford, 2020). To reflect this trend, we propose an inverse weighting function for each simulation:

$$w_i = \frac{1}{FOS_i} \quad (6.4)$$

After normalising the weights to $w_{i,\text{norm}} = \frac{w_i}{\sum_{i=1}^N w_i}$, the weighted exceedance probability at each cell is calculated as:

$$P_j(h > h_t) = 1 - \sum_{i=1}^N w_{i,\text{norm}} I(h_{i,j} \leq h_t). \quad (6.5)$$

A flow height threshold of $h_t = 0.5$ m was adopted to define hazardous areas. This value was chosen to ensure that the hazard maps capture significant hazards, preventing overestimation of areas with negligible risk. This choice is consistent with common practice in probabilistic hazard assessments (e.g., Mead and Magill, 2017; Nakamoto et al., 2025; Gao et al., 2025).

6.4 Results

Based on the predefined selection criteria ($0 \leq \text{FOS} \leq 4$; $450,000 \leq \text{volume} \leq 1,050,000 \text{ m}^3$; $31 \leq \text{maximum depth} \leq 55 \text{ m}$), the LEM analysis resulted in 30 distinct potential failure surfaces. The resulting candidates exhibit a wide range of stability conditions ($\text{FOS} = 0.75 - 3.82$), volumes ($453,000 - 1,048,000 \text{ m}^3$), and maximum depths ($31 - 52.7 \text{ m}$). Their overlap with the observed source area varies significantly ($0.5 - 92\%$), and their slip directions are mostly downslope ($109 - 154^\circ$) but include some notable deviations from the observed failure slip direction ($D_{\text{obs}} = 145^\circ$). Details on the failure characteristics of the LEM-generated surfaces, including FOS, maximum depths, volumes, and slip directions, can be found in Table B1. The simulated runouts show strong variability to initial failure geometry, from overestimations exceeding +480 m to underestimations greater than -570 m relative to the observed deposit,

highlighting the sensitivity of runout behaviour. Information on the simulated runouts and performance metrics for each scenario is provided in Table B2.

6.4.1 Validation of the coupled LEM/depth-averaged approach

Figure 6.3 compares the best-performing LEM-derived simulation ($\text{CSI} = 0.6271$) with the best-fit observed-source simulation ($\text{CSI} = 0.6301$, from Vicente and Mead, 2025). Both initial slip surfaces are broadly similar in geometry and location. The LEM-derived source has an ellipsoidal shape with a maximum depth of 36 m and a volume of $\approx 5.2 \times 10^5 \text{ m}^3$, of which $\approx 80\%$ overlaps with the observed source. In comparison, the observed source is larger, with a volume of $\approx 7 \times 10^5 \text{ m}^3$ and a maximum depth of 43 m, but exhibits a similar ellipsoidal shape. Both slip directions are aligned with the channel. When used as input in D-Claw, both sources generate simulations that effectively reproduce the overall landslide footprint, runout distance, and deposition zone. Minor differences are apparent: the LEM-derived source results in more FN at initiation due to its slight positional offset relative to the observed source and shows a marginally longer runout. However, the comparison demonstrates that the LEM-derived source closely captures the observed landslide impacts, with spatial agreement comparable to that obtained using the actual observed source (i.e., the best possible input, only available a posteriori).

6.4.2 Ensemble variability and controlling factors

Considering all 30 simulations, each simulated footprint exhibits distinct spatial characteristics, resulting in substantial variability in the performance metrics across the ensemble (Fig. 6.4). PPV has the highest variability across performance metrics, with higher PPV corresponding to higher CSI (Fig. 6.4), indicating that overall performance is strongly influenced by the presence of FP. A secondary, less pronounced effect of Sensitivity is also visible: for a given PPV, simulations with higher Sensitivity tend to achieve higher CSI (Fig. 6.4), reflecting improved capture of observed hazard areas. The relatively small variation in Sensitivity, which remains high across all simulations, reflects their consistent ability to minimise FN along the flow path, a feature facilitated by the channelisation of the flow. The variability in model performance can be attributed to differences in LEM-source characteristics.

Figure 6.5 shows the relationship between PPV, Sensitivity, and CSI for each simulation with initial failure geometry, grouped by alignment with the observed slip direction. The observed

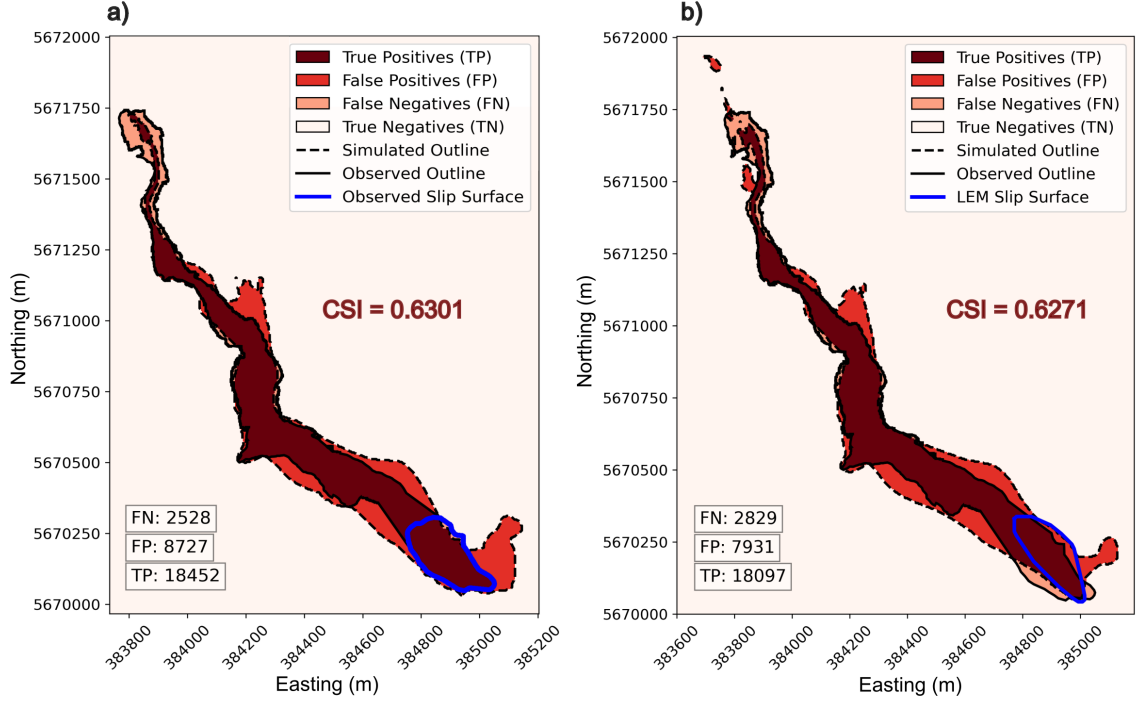


Figure 6.3: Classification maps derived from the confusion matrix for (a) the observed-source runout (Vicente and Mead, 2025) and (b) the LEM-source runout. Blue outlines indicate the source areas; dashed lines show simulated flow, and solid lines show observed flow.

slip direction is $D_{obs} = 145^\circ$, and simulations were classified as aligned if their direction fell within $D_{obs} \pm 10^\circ$. Each point is coloured according to source volume, with the observed volume approximated at $750,000 \text{ m}^3$. Three volume categories were defined: below observed ($< 650,000 \text{ m}^3$), close to observed ($650,000\text{--}850,000 \text{ m}^3$), and above observed ($> 850,000 \text{ m}^3$). Runout differences relative to the observed flow were also categorised: close to observed (-200 m to 200 m , round markers), short runout (-200 to -400 m , triangle markers), and very short runout ($< -400 \text{ m}$, square markers). Overall, simulated runouts tend to be under-predicted compared to the observed flow.

Alignment strongly affects Sensitivity, with misaligned sources producing shorter runouts, therefore generating more FN and lowering the Sensitivity, regardless of collapse volume (Fig. 6.5). Aligned sources generally yield lower Sensitivity for low-volume collapses because their limited runout generates a lot of FN. An exception is observed in two low-volume aligned simulations, which show longer runouts and high Sensitivity (> 0.85 , Fig. 6.5). These cases correspond to shallow, elongated, ellipsoidal slip surfaces oriented along the slope, which facilitate more complete mobilisation of material downslope.

In contrast, PPV appears largely insensitive to alignment but decreases with increasing

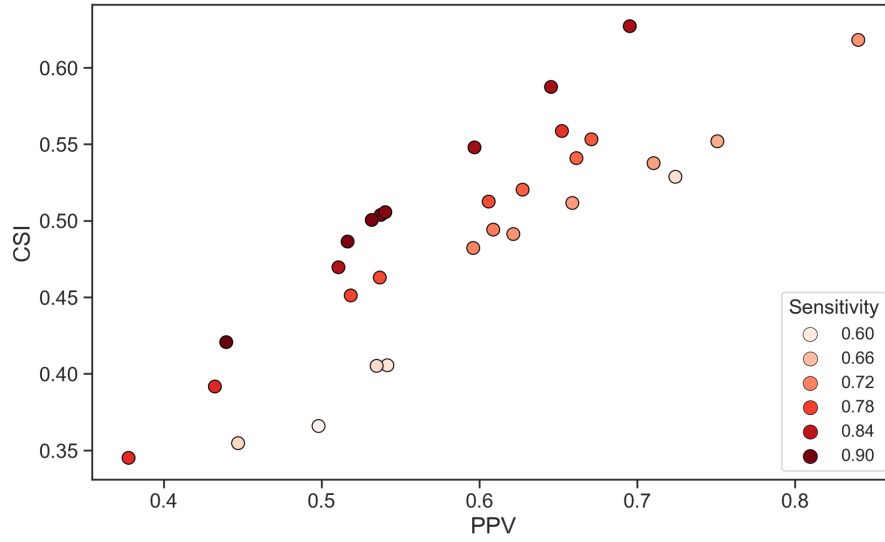


Figure 6.4: CSI evolution versus PPV and Sensitivity for the 30 simulations, calculated at a 0.5 m height threshold.

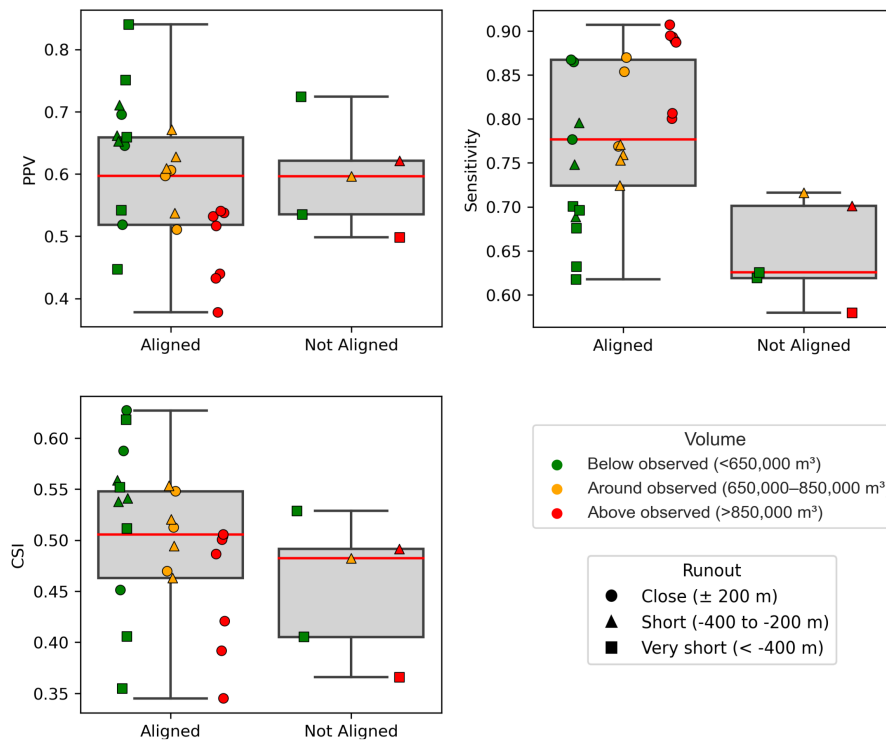


Figure 6.5: Box-plots of PPV, Sensitivity, and CSI, grouped by alignment. Individual simulations are overlaid, with colours indicating source volume and shapes indicating relative runout differences.

volume (Fig. 6.5). High-volume sources tend to produce longer runouts, increasing FP and reducing PPV, whereas low-volume sources often achieve higher PPV due to limited spread. Consequently, CSI is highest for aligned, low-volume sources, as they minimise FP. Yet, a few aligned, low-volume sources also exhibit reduced CSI (Fig. 6.5); these correspond to simulations with poor overlap with the observed source or elongated slip surfaces oriented $\approx 90^\circ$ from the observed major axis, both factors generating many FP at initiation and consequently lowering PPV. Misaligned simulations generally have lower CSI, as deviations from the channel direction increase initial lateral impacts and energy loss, increasing FN and therefore reducing Sensitivity. Overall, these results highlight the uncertainty associated with the location, shape, volume, and slip direction of the LEM surface, which can strongly influence flow outcomes.

6.4.3 Probabilistic hazard assessment

To evaluate the ability of this method to assess hazard likelihood, we aggregated the 30 simulations into exceedance probability maps (Fig. 6.6), where each cell indicates the proportion of simulations predicting inundation above a 0.5 m depth threshold. Both unweighted and weighted maps show the highest exceedance probabilities (> 0.8) concentrated along the main channel. They also both predict low probabilities in the mid-course region on the eastern lava flow adjacent to the channel, where overtopping was not observed. In contrast, distal debris-flow deposits are observed to exceed 0.5 m (Mead et al., 2021), yet the simulations predict a low probability (< 0.4) of exceeding this threshold in these areas. Subtle differences between the maps are apparent: in the weighted map, high-probability zones are slightly more focused along the initiation and central flow path, extending further along the channel (Fig. 6.6b). Low- to moderate-probability areas (0.2–0.6) are also more restricted, particularly near the initiation, indicating a reduced likelihood of flow exceeding 0.5 m toward the Lower Te Maari crater (Fig. 6.6b). When compared visually with the observed flow footprint (dashed line, Fig. 6.6), the weighted map better limits overestimation.

We quantitatively evaluated the performance of both the weighted and unweighted ensemble by analysing how CSI, PPV (precision), and Sensitivity (recall) vary as a function of the exceedance probability threshold (h_t) used to classify inundated cells (Fig. 6.7). Increasing the threshold leads to higher PPV but lower Sensitivity, reflecting the trade-off between reducing FP and retaining TP. CSI initially increases as FP are filtered out, then declines as more TP are excluded at higher thresholds (Fig. 6.7). To identify the threshold that best balances precision

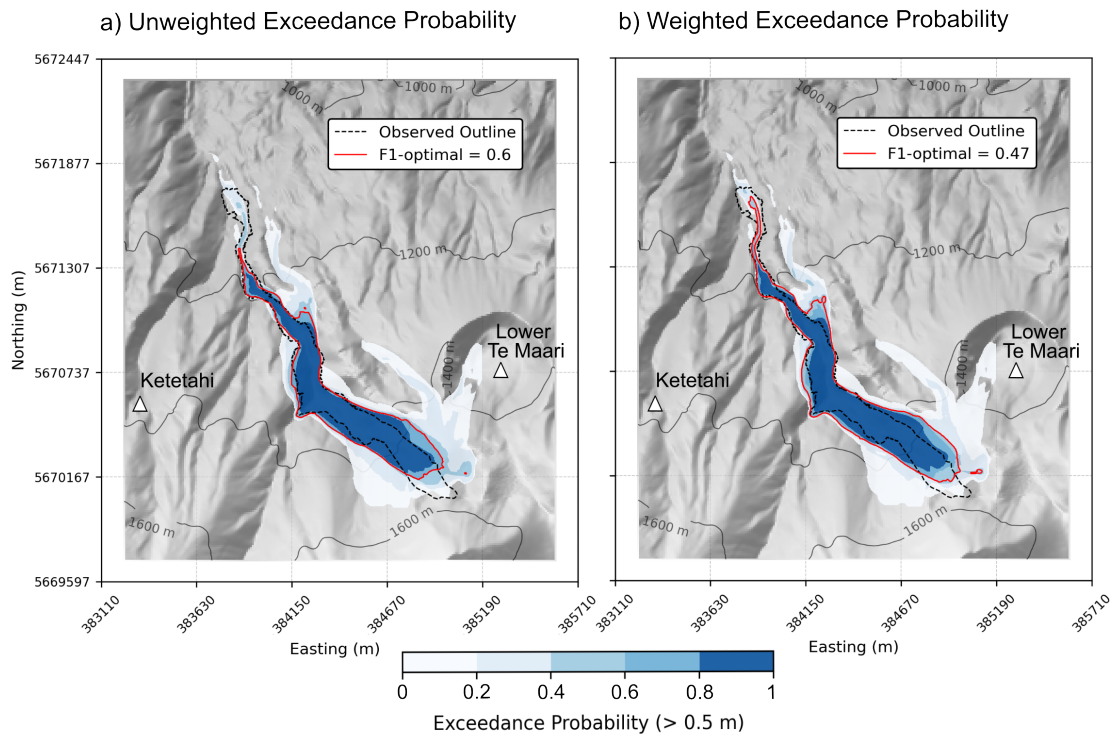


Figure 6.6: Exceedance probability maps for debris flows exceeding 0.5 m in height: (a) un-weighted and (b) FOS-weighted. The red outline shows the optimal threshold corresponding to the maximum F1-score.

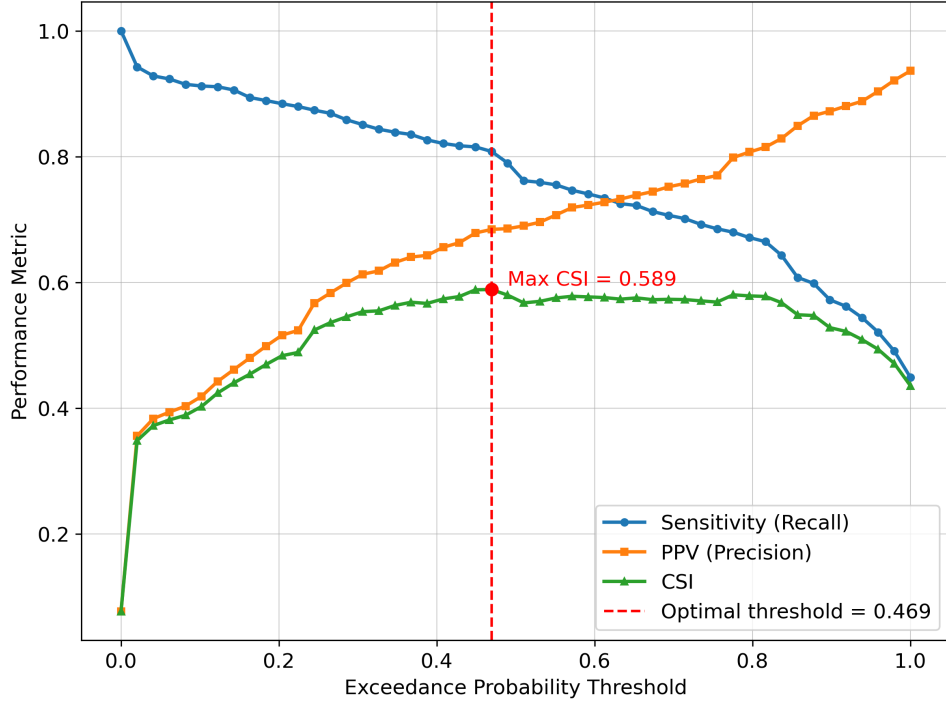


Figure 6.7: Evolution of CSI, PPV, and Sensitivity as a function of the exceedance probability threshold. The red dashed line indicates the optimal threshold.

and recall, we calculated the F1-score, defined as the harmonic mean of PPV and Sensitivity:

$$F1 = 2 \times \frac{PPV \times Sensitivity}{PPV + Sensitivity} \quad (6.6)$$

The F1-score for the weighted ensemble reaches a maximum of 0.743 at an exceedance probability threshold of 0.469, corresponding to the highest CSI of 0.589 (Fig. 6.7). At this threshold, it captures a higher proportion of observed hazardous cells (Sensitivity = 0.807) while maintaining reasonable control of false positives (PPV = 0.689). In comparison, the unweighted ensemble achieves a slightly lower maximum F1-score of 0.733 at a higher optimal threshold of 0.6, with a maximum CSI of 0.578 (Sensitivity = 0.736, PPV = 0.730).

The increase in recall in the weighted ensemble arises from the weighting scheme, which assigns greater influence to simulations with lower FOS, i.e., simulations that are more prone to failure. This approach boosts recall with minimal loss in precision, allowing a lower exceedance probability threshold to capture additional hazardous cells effectively. Overall, weighting by FOS offers an improvement in the balance between precision and recall.

6.5 Discussion

The ability of physically-based approaches to comprehensively assess spatial hazard intensity is critical for debris avalanche hazard assessment, as it allows the identification of areas at greatest risk and supports mitigation strategies. However, runout predictions are highly sensitive to input parameters, and uncertainties in these inputs propagate through the simulations, affecting the predicted flow extent (Reid et al., 2000; Mergili et al., 2018a). Accurate estimation of the initial conditions is therefore a critical step in debris avalanche hazard assessment. To address this challenge, the coupling of failure and flow models has been explored, allowing initial conditions to be fully integrated into the simulations. While such coupling remains technically challenging due to distinct physical processes and timescales involved (van Asch et al., 2007), this study successfully addressed some of these technical challenges by integrating LEM with depth-averaged modelling, thereby improving the reliability of hazard assessments.

The coupled LEM/D-Claw simulations presented in this study demonstrated the model ability to back-calculate complex, channelised mass flows. Our best-performing simulations achieve CSI values greater than 0.6 (Figs. 6.3 and 6.4), comparable to values reported in other studies. For instance, Mergili et al. (2018a) conducted a series of r-avaflow simulations for the 2012 Santa Cruz event (Peru), varying key parameters such as initial landslide volume and basal friction, and obtained a best CSI of 0.59. In another study, Mergili et al. (2018b) used r-avaflow to simulate two rock-ice falls observed on Nevado Huascarán (Peru), optimising key input parameters iteratively to achieve the best match with observations, resulting in CSI values of 0.61 and 0.62. Similarly, simulating flows initiated with the observed Te Maari source, Mead et al. (2021) obtained CSI values (with a 0.5 m depth cut-off) of 0.51 when using either the Voellmy–Salm or Pitman and Le (2005) models, and 0.59 when using the Pudasaini (2012) model. These results indicate that the coupled LEM/depth-averaged approach performs at least as well as other state-of-the-art models when using volumes and geometries predicted by the LEM, rather than post-event volumes. This demonstrates that the method can provide physically consistent predictions linking failure and flow stages, making it a useful tool for forecasting debris flows. The relatively high CSI values suggest that our best-fit simulations capture the observed deposition patterns with reasonable accuracy, despite the uncertainties in initial conditions and material properties.

Considering the full ensemble of simulations, CSI values span a wider range (0.35 - 0.63),

reflecting the inherent variability in the initial failure geometry. Part of the observed uncertainty arises from intrinsic limitations of the modelling approach. For example, the shape of the failure surface is predefined by the method chosen to perform the LEM analysis (e.g., Bishop Simplified, Janbu Simplified, Spencer), inherently limiting the range of possible geometries. However, it is possible to forecast failure geometry using LEM with minimal effect on simulation performance compared to using an observed (i.e., post-event) input (Fig. 6.3). This is despite the epistemic uncertainty in LEM, reflecting incomplete knowledge or measurement limitations, which could be reduced with more precise observations or improved data.

The variation in initial failure geometries (Table B1) reflects the uncertainty in failure forecasting. The consequences of this uncertainty on subsequent runout are demonstrated in Figure 6.5. In particular, variations in the slip surface shape, such as its elongation or orientation relative to the slope, can affect how efficiently material is mobilised; differences in volume influence the overall flow extent and deposition pattern; and misalignment with the natural flow path can reduce the accuracy of predicted runout. Together, these factors explain much of the observed variability in CSI across the ensemble. In the present study, we incorporated observational constraints from the 2012 Te Maari event to limit the range of initial conditions. Without such constraints, the number of plausible LEM-generated slip surfaces (and consequently the associated flow scenarios) would significantly increase, potentially involving thousands of scenarios. Fully exploring all of these possibilities would substantially increase the variability of runout predictions, and would be computationally challenging. Dimensional reduction and sampling procedures, such as clustering surfaces with similar characteristics, could be applied to efficiently reduce the set of potential failures (e.g., Kereszturi et al., 2021). Our analysis suggests that surface shape, volume, and alignment are particularly important factors to consider when defining representative scenarios. Since a full exploration was beyond the scope of our study, we focused on the limited, observationally informed ensemble, allowing us to investigate predictive outcomes in a way that balances physical consistency and computational efficiency, while still capturing the main uncertainties in the initial conditions.

Results from the aggregated hazard footprints (Fig. 6.6) show that, despite the uncertainties, this coupled approach can produce a forecast with comparable accuracy ($CSI = 0.5 - 0.59$) to simulations that are constrained with source volumes and areas that are only available post-event ($CSI = 0.6301$, Vicente and Mead, 2025). Critically, the optimal CSI value is near the middle of the probability distribution (0.6 for unweighted, 0.47 for weighted), indicating the

coupled workflow (Fig. 6.2) produces unbiased exceedance probabilities that represent the uncertainties in forecasting of slope failure and consequent runout. Furthermore, by weighting the simulated deposition patterns according to the corresponding FOS of each surface, the method captures a key form of epistemic uncertainty (the uncertainty in which surface will actually fail), thereby providing a more nuanced estimate of hazard intensity. Our results highlight that the FOS-weighted exceedance map provided a better agreement with the observed debris avalanche extent compared to the unweighted version. While preliminary, this method demonstrates the potential of linking FOS values to relative failure probability for hazard assessment, and more refined weighting functions should be explored in future work.

6.6 Conclusions

This study reveals the potential of coupling slope stability models with flow models to improve debris flow hazard assessment. By integrating LEM-derived failure surfaces with depth-averaged flow simulations, we were able to back-calculate the complex, channelised 2012 Te Maari event and evaluate the sensitivity of runout to uncertainty related to initial conditions. The results showed that this coupled approach was able to reproduce the observed deposition pattern with a level of accuracy similar to other debris avalanche simulations (Mergili et al., 2018a; Mead et al., 2021), while providing a physically consistent linkage between the failure and post-failure stages.

However, our ensemble of simulations reveals a significant variability in the predicted runouts, driven primarily by differences in geometry, shape, alignment, and volume of the initial slip surfaces. This highlights the importance of properly constraining the initial conditions, as even small differences result in highly different flow dynamics and deposition patterns.

We further demonstrated a simple weighting function that links the LEM-derived FOS to the relative probability of failure, allowing the exceedance probability map to incorporate epistemic uncertainty about which surfaces are more likely to fail. This method improved the agreement between predicted and observed flow extent, highlighting its potential as a step toward more robust hazard assessments.

This study has practical implications for landslide hazard assessment while highlighting important limitations of current predictive approaches. By linking slope stability analyses with flow simulations, our approach allows the generation of probabilistic hazard maps that account

for uncertainty in initial conditions related to the location and geometry of the failure surface. The FOS-weighted exceedance maps, in particular, provide a more nuanced estimate of areas at risk, which can support early-warning systems and targeted mitigation strategies. However, as in many previous studies, the predictive outcomes presented here are based on back-analysis of a past event. While this approach helps optimise parameters and ensures the simulations match the observations, it limits the exploration of the broader space of possible failures. To address this, future work should include the full diversity of possible failure scenarios. Developing efficient strategies to sample and cluster large sets of possible slip surfaces will be essential to make such full exploration computationally feasible. Combined with probabilistic representation of material strength, this would help detached from past events, and enhance the reliability and applicability of coupled failure-flow models as a tool for future hazard assessments.

Chapter 7

Exploring the transferability of the coupled modelling approach: application to Ruapehu

This chapter is an exploratory application intended to provide a preliminary assessment of the framework's applicability to a broader volcanic context and to explore its potential use for larger-scale hazard investigations. As such, the analyses presented here are used as a proof-of-concept application of the methodology rather than a fully validated hazard assessment, and are intended to highlight considerations for future research.

7.1 Introduction

The modelling framework developed and validated in Chapter 6 demonstrated that coupling slope stability analysis with physically based flow modelling can successfully reproduce the 2012 Te Maari debris avalanche and generate probabilistic hazard maps for a well-constrained volcanic collapse event. While this provided validation of the methodology under controlled conditions, the approach was calibrated and tested using a single observed case study, limiting assessment of its broader applicability to other volcanic settings and collapse scenarios.

To evaluate the transferability of the framework beyond the Te Maari case, this chapter applies the same coupled methodology to Ruapehu, New Zealand. In contrast to the Te Maari study, where simulations were constrained by observations of a known event, the Ruapehu application adopts a broader exploratory approach by considering a large ensemble of potential collapse scenarios across the edifice. This enables assessment of the framework under less constrained but realistic hazard conditions and allows investigation of its performance when applied to a larger volcanic system with different geomorphological and hydrothermal characteristics.

The objective of this chapter is therefore to explore the practical applicability and transferability of the modelling framework to a new volcanic context. In doing so, this chapter evaluates whether the integrated methodology can be extended to larger-scale instability problems and identifies the principal limitations and uncertainties associated with its application in data-limited environments.

7.1.1 Study area

Ruapehu was selected as a suitable test case for transferability assessment due to its larger edifice scale, documented history of sector collapses, and contrasting hydrothermal and structural characteristics relative to the Te Maari crater system. These characteristics reflect its long and complex geological evolution. Ruapehu, the largest stratovolcano of the Taupo Volcanic Zone (TVZ), was constructed through four main cone-building phases (Hackett and Houghton, 1989; Gamble et al., 2003; Price et al., 2012; Townsend et al., 2017): the Te Herenga Formation (200–150 ka), the Wahianoa Formation (160–180 ka), the Mangawhero Formation (50–15 ka), and the Whakapapa Formation (< 15 ka). The edifice experienced alternating periods of growth, characterised by intense lava effusion (Conway et al., 2016, 2018), and periods of destruction, marked by mass-wasting events (Palmer and Neall, 1989; Palmer et al., 1993; Conway et al.,

2016). These destructive phases produced large-scale debris avalanches and lahars. The oldest debris avalanche deposits, such as the Turakina (310–330 ka), Mataroa (218–223 ka), Lower Whangaehu (218–223 ka), Piriaka-A and B (180–200 ka), and Oreore (158–164 ka) Formations, outcrop in distal downstream catchments, 50–100 km south and east of the massif. More recent activity, often sourced from the Crater Lake region, mainly involved lahars and minor crater rim collapses. Notable events include the Murimotu Formation ($\approx$ 9,500 years ago), triggered by magma intrusion into the older cone (Palmer and Neall, 1989; McClelland and Erwin, 2003), and the Mangaio Formation ($\approx$ 4,600 years ago), associated with a vent shift near the Crater Lake (Donoghue and Neall, 2001). While some collapses may have been influenced by magmatic intrusions or climatic factors such as glacier unloading, mass-wasting events generally appear decoupled from the main cone-building phases (Tost et al., 2014; Kereszturi et al., 2020).

Unlike Tongariro, where hydrothermal activity is distributed across multiple shallow vents and expressed through abundant surface features such as fumaroles, hot springs, and condensate outflows, the current active hydrothermal system at Ruapehu is largely concentrated beneath and around the currently active Crater Lake (Miller and Williams-Jones, 2016; Miller et al., 2018; Kereszturi et al., 2020). This suggests that ongoing hydrothermal alteration is mostly confined to the summit crater and conduit. However, laboratory, airborne hyperspectral, and aeromagnetic data (e.g., Jones et al., 2008; Kereszturi et al., 2020, 2021; Miller et al., 2020) indicate that extensive alteration exists in the upper south and southeast flanks, either due to lateral fluid migration and/or remnants of older hydrothermal systems. These findings illustrate the complexity of hydrothermal activity at Ruapehu: surface hydrothermal alteration is limited and patchy, covering only $\approx$ 2.6 % of the edifice but scattered across the volcano (Kereszturi et al., 2020), and large zones of deeper alteration, such as beneath the Summit Plateau, have been identified and interpreted as relict hydrothermal systems (Jones et al., 2008; Townsend et al., 2017). Such altered zones can reduce rock permeability (for example, via clay precipitation into pores and fractures), leading to elevated pore pressures when saturated. Increased pore pressure typically decreases the rock strength and raises the likelihood of slope failures. Therefore, even without widespread surface hydrothermal features, Ruapehu contains mechanically vulnerable areas, widespread across the edifice, prone to sector collapse, and is a key focus for hazard assessment.

7.1.2 Method

To adopt a more probabilistic perspective and assess the transferability of the method to a different volcanic edifice, the methodology presented in Chapter 6 is generalised and applied to the entire edifice of Ruapehu. This chapter uses the same three-step workflow: (1) LEM-based slip surface generation; (2) flow modelling; and (3) generation of probabilistic hazard maps (Fig. 7.1).

The first step builds on the three-dimensional limit equilibrium analysis of Kereszturi et al. (2021), which characterises potential slip surfaces based on pre-failure conditions incorporating mineralogical, geomechanical, and geophysical data. Using Bishop’s Simplified method in Scoops3D, they obtained four different groupings of potential failures. All slip surfaces with a factor of safety (FOS) below 5 were grouped into characteristic failure clusters using K-Means clustering. This FOS threshold accounts for the possibility that very large perturbations on an initially stable edifice, such as magma injection or a major earthquake, may trigger flank collapse. The resulting clusters delineate zones of similar instability patterns on the southern and western flanks of the edifice. Clusters 1 and 2 correspond to relatively small and shallow failures around Girdlestone Peak and the Turoa skiffeld (Fig. 7.2), likely influenced by advanced to intermediate argillic alteration. In contrast, clusters 3 and 4 represent larger and deeper potential failures located between Turoa and Whakapapa skiffelds (Fig. 7.2), possibly associated with hydrothermal alteration or lithological heterogeneities (e.g., coherent lava vs. volcaniclastic deposits).

To ensure computational tractability, dimensionality reduction and sampling techniques, including Principal Components Analysis (PCA) and space-filling algorithms, were used to reduce the initial $\approx 12,000$ potential failures to 1,024 representative scenarios Kereszturi et al. (2021).

The second step involved simulating the flow of these 1,024 debris avalanches using the depth-averaged, two-phase model D-Claw, as described in Chapter 6. Flow initiation parameters were selected based on a contractive failure assumption (e.g., Iverson and George, 2016), reflecting the presence of weak, hydrothermally altered zones that can easily be saturated due to their low permeability. Such saturation increases the likelihood of liquefaction during the early stages of landslide motion. The initial contractive behaviour is determined by the choice of initial and critical solid-volume fractions, m_0 and m_{crit} , with $m_0 < m_{crit}$. For this initially stable edifice ($2 < \text{FOS} < 5$), motion must be triggered by a significant perturbation. Here,

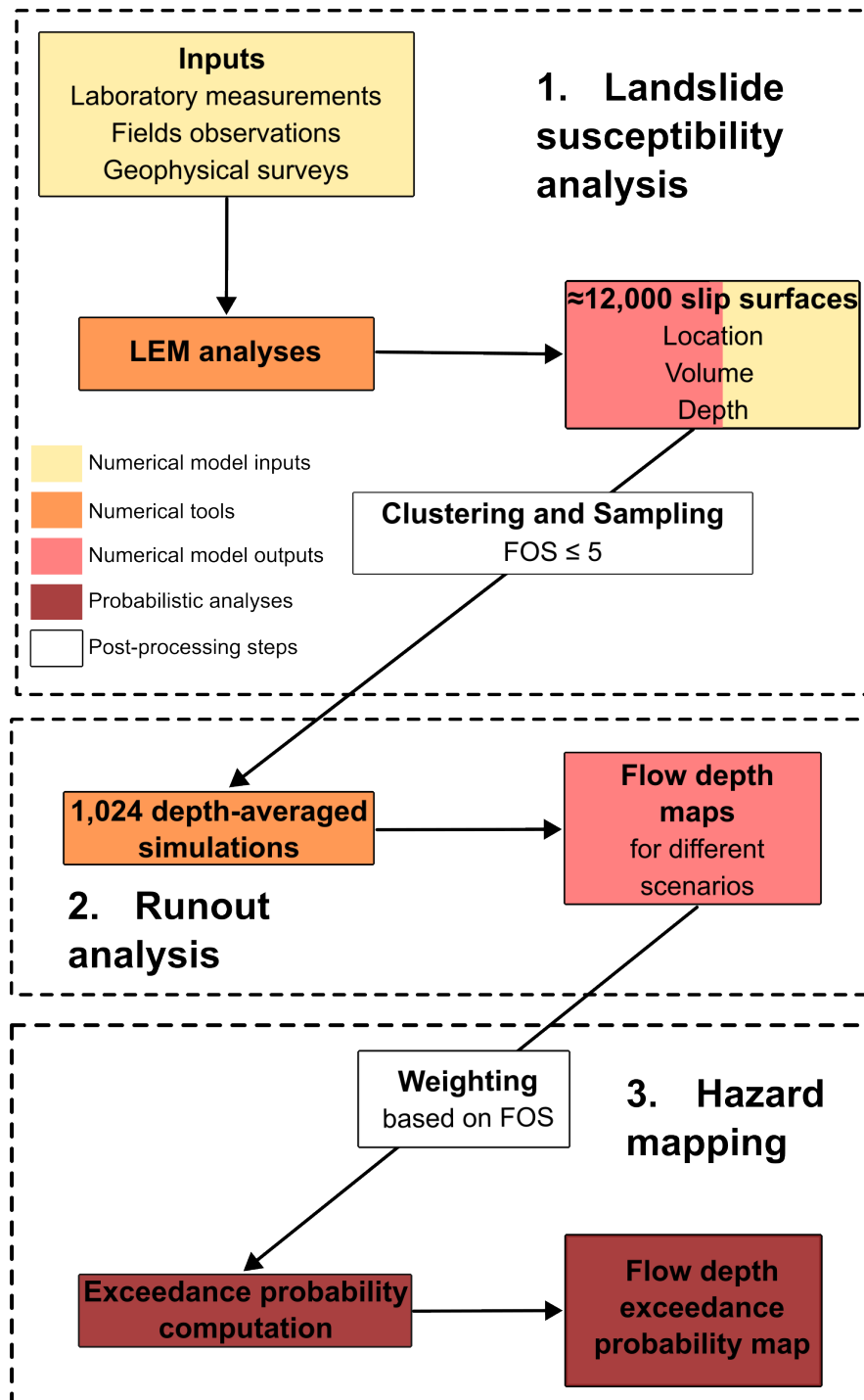


Figure 7.1: Methodological flowchart from Chapter 6, modified for the Ruapehu case study.

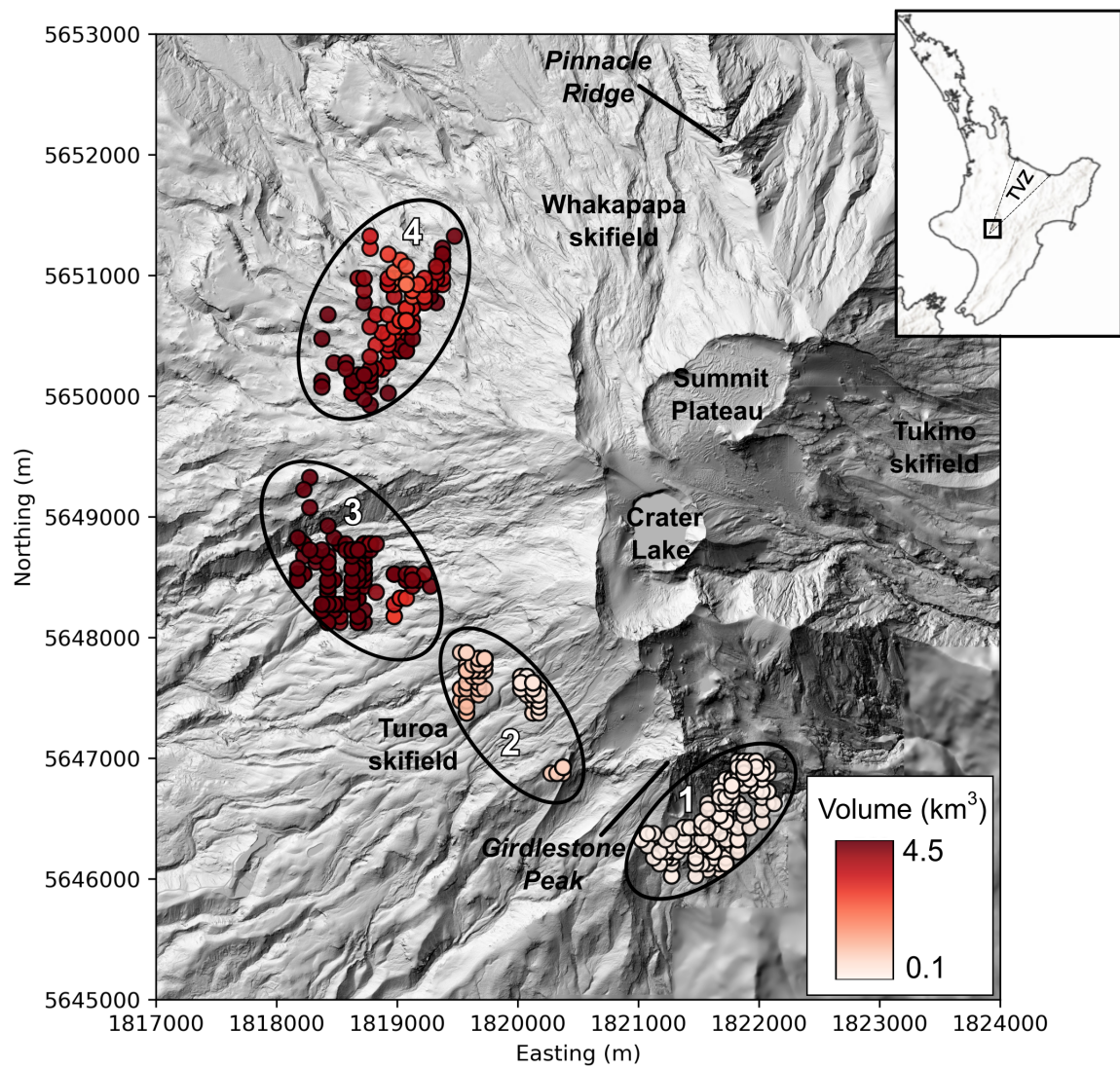


Figure 7.2: Centres of potential collapse slip surfaces, grouped by cluster (after Kereszturi et al. 2021).

we assume a progressive increase in basal pressure until motion initiates at the weakest point, which could, for example, result from melting snow or hydrothermal fluid circulation. The remaining flow parameters were adapted from the Chapter 6 Te Maari simulations (see Table 7.1).

Table 7.1: Values of the D-Claw simulation input parameters.

Material property	Value
Hydraulic permeability k_0 (m ²)	1×10^{-7}
Compressibility proportionality coefficient a	0.01
Critical solid-volume fraction m_{crit}	0.8
Initial solid-volume fraction m_0	0.74
Basal friction angle ϕ (°)	21
Compressibility reference stress σ_0 (Pa)	1000
Fluid density ρ_f (kg/m ³)	1000
Solid density ρ_s (kg/m ³)	2500
Fluid viscosity μ (Pa·s)	0.001
Characteristic grain size δ (m)	0.01

Each scenario was simulated for 1,800 seconds, after which the maximum flow height in each computational cell was recorded. This process generated a total of 1,024 raster files representing the peak flow height for every simulated avalanche scenario.

The final step involved producing probabilistic hazard maps for both the overall ensemble and for each cluster. These maps represent conditional exceedance probabilities, i.e., the probability that flow heights exceed a threshold of $h_t = 0.5$ m, given that a debris avalanche occurs, either for the full set of 1,024 simulations or for the subset of simulations within each cluster. Following the approach in Chapter 6, we accounted for the relative likelihood of failure of each potential slip surface by applying an inverse FOS-based weighting function. The exceedance probability at each cell j was then computed as:

$$P_j(h > h_t) = 1 - \sum_{i=1}^N w_{i,\text{norm}} I(h_{i,j} \leq h_t). \quad (7.1)$$

where $w_{i,\text{norm}}$ is the normalised weighting function:

$$w_{i,\text{norm}} = \frac{\frac{1}{FOS_i}}{\sum_{i=1}^N \frac{1}{FOS_i}}. \quad (7.2)$$

Here, i indexes the simulation, $h_{i,j}$ is the maximum flow height at cell j in simulation i , $\mathbf{I}$ is the indicator function (1 if $h_{i,j} \leq h_t$, 0 otherwise), and N is the total number of simulations.

This approach allows a preliminary evaluation of the framework’s transferability while explicitly acknowledging site-specific uncertainties and the limitations of parameter choices.

7.1.3 Results

The analysis of potential landslide scenarios on Ruapehu reveals distinct behaviours across the four clusters (Fig. 7.3). Clusters 1 and 2, corresponding to smaller-volume events (0.01–1.15 km³), mainly affect the southern flanks of the volcanic edifice. These debris avalanches have a low probability (< 0.2) of extending beyond the base of the edifice, and consequently, exert limited influence on the surrounding ring plain. Cluster 1 represents the smallest events (maximum 0.3 km³), shows high exceedance probabilities (> 0.8) concentrated along channels, indicating that most scenarios in this cluster are strongly channelised. This pattern suggests that smaller-volume failures tend to follow confined pathways, whereas larger-volume debris avalanches are more prone to spread, with runout less constrained by incised topography. This pronounced channelisation in Cluster 1 appears to produce longer runout distances compared with Cluster 2, where flows, although generally larger, exhibit shorter runout but wider spatial spreading. Such behaviour is consistent with previous observations that laterally confined flows tend to retain kinetic energy more effectively than unconfined flows, allowing them to travel longer longitudinal distances (Iverson and George, 2016; de Haas et al., 2015; Strom et al., 2019; Jones et al., 2023).

Clusters 3 and 4 involve larger failure volumes (2–4.5 km³) and produce more widespread hazard patterns. High-probability areas (> 0.8) encompass the entire western flank of Ruapehu and extend into parts of the ring plain, where channelisation guides the flow along defined paths. Even in downstream catchments, up to 10–15 km from the source, hazard probabilities remain moderate (0.5–0.7) for large-volume scenarios. This spatial extent aligns with geological evidence of preserved large-volume debris-avalanche deposits on the ring plain and in downstream catchments (Tost et al., 2014), such as the Mataroa Formation (2.9 km³) or the Lower Whangaehu Formation (2.4 km³).

When considering both unweighted and FOS-weighted overall exceedance maps encompassing all 1,024 simulated scenarios, the highest probabilities of flow occurrence (> 0.7) are concentrated along three main channels draining the southern and western flanks of the volcano, including the Mangaturuturu and Wahianoa catchments (Fig. 7.4). The concentration of high probabilities within these channels indicates their persistent role in controlling flow routing and

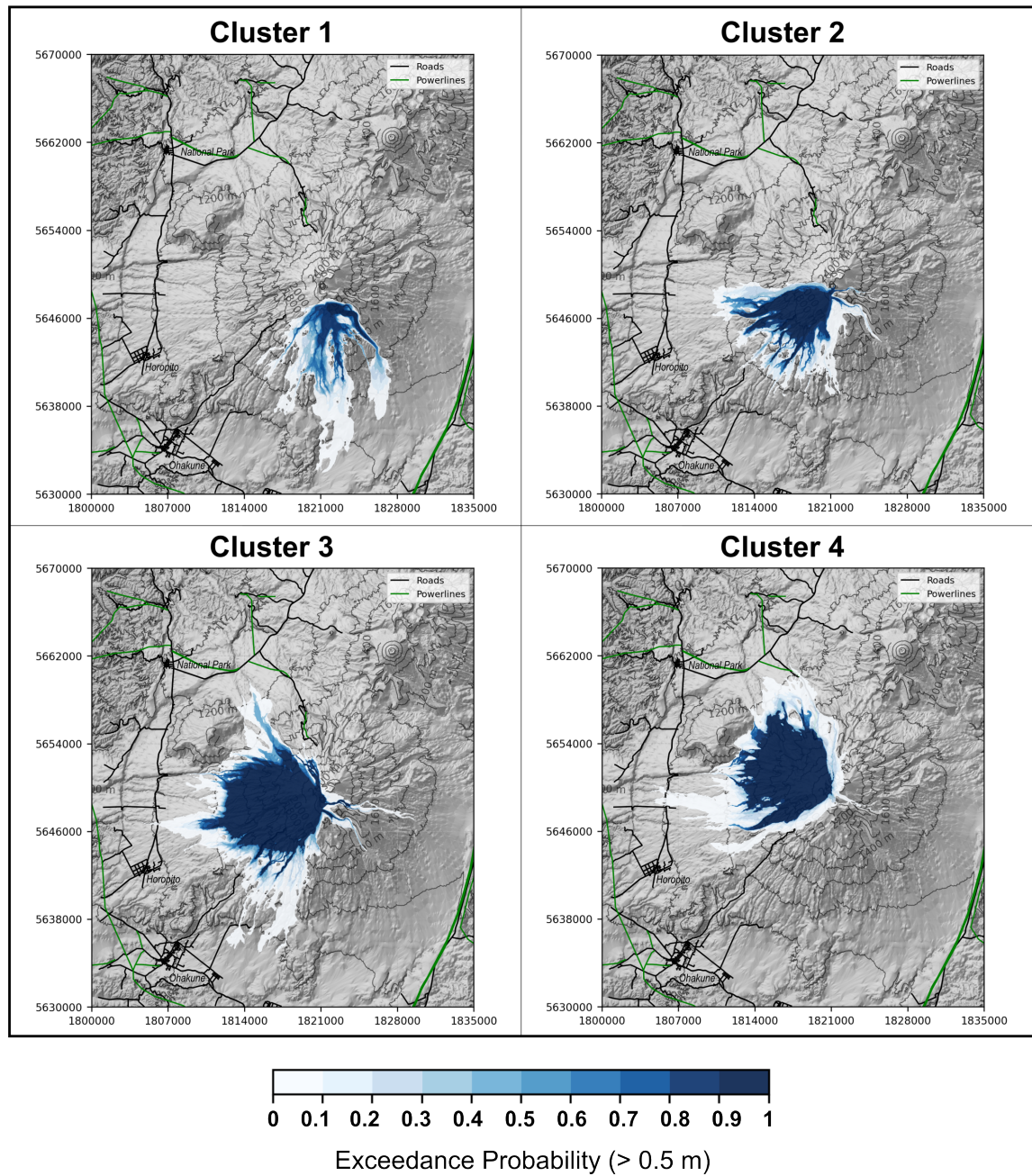


Figure 7.3: FOS-weighted exceedance probability maps of flow heights exceeding 0.5 m for each cluster

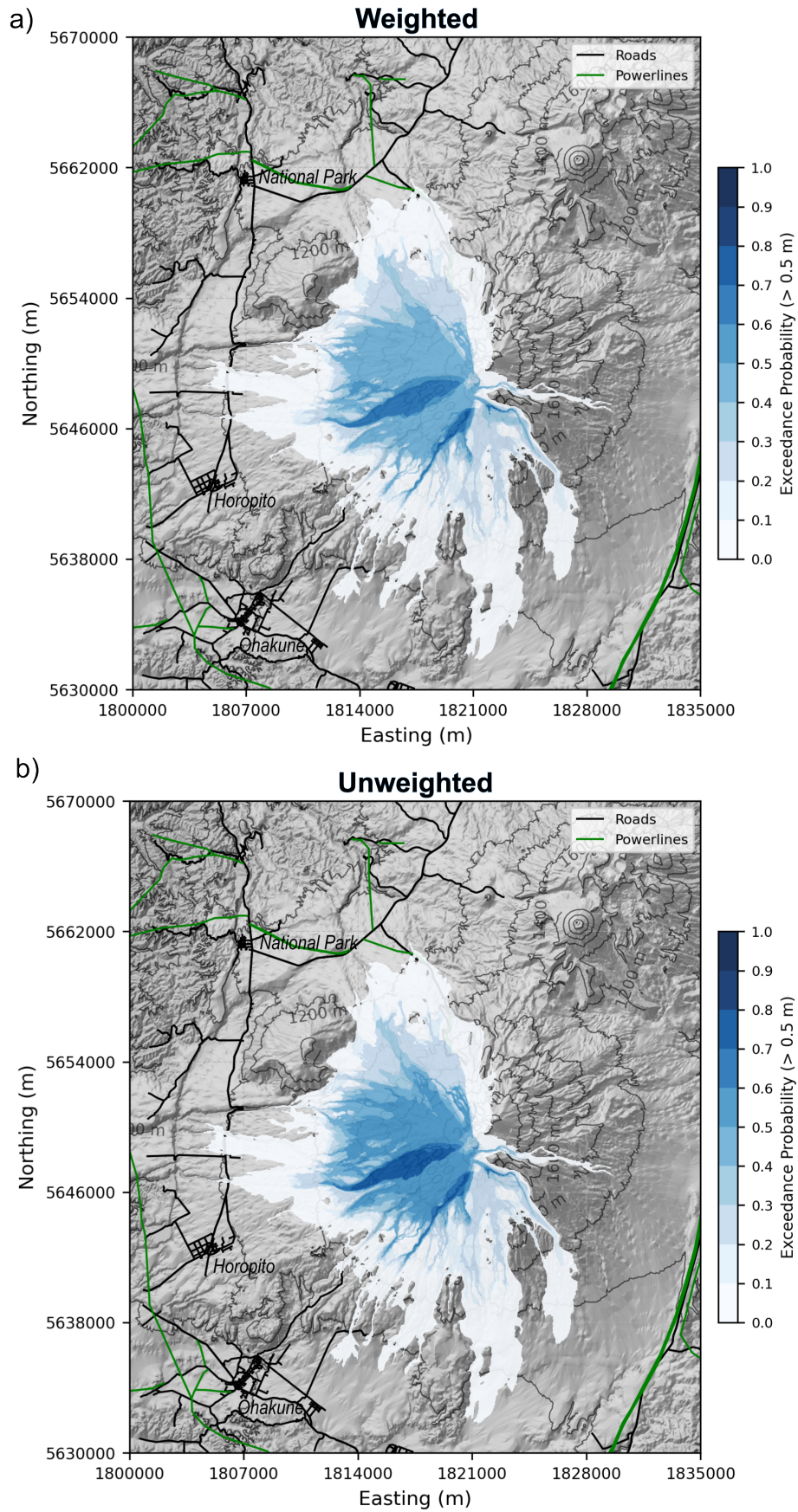


Figure 7.4: Overall exceedance probability map (> 0.5 m flow height) across all clusters: (a) FOS-weighted and (b) unweighted.

runout behaviour across different collapse scenarios. This suggests that future large-scale failures at Ruapehu are most likely to be funnelled into these established drainage systems, where confined flows could maintain higher mobility and impact distal areas. Comparing the two maps reveals subtle differences: in the unweighted map, central channel probabilities reach 0.8–0.9, while probabilities along ridges separating the channels are 0.5–0.6. Applying FOS weighting slightly narrows the spatial extent of high-probability zones, with ridge probabilities decreasing to 0.4–0.5 and the central Mangaturuturu channel dropping to 0.7–0.8. This demonstrates that incorporating FOS weighting sharpens the hazard patterns, focusing the highest probabilities along the most likely flow paths, according to the relative probability of failure of each scenario.

7.1.4 Discussion

This exploratory application represents a significant step forward from the Te Maari case study previously examined in this thesis. In the Te Maari application, the LEM-derived slip surfaces were filtered using characteristics of a single historical event (the 2012 debris avalanche), limiting the analysis to 30 simulations within a single catchment. In contrast, the Ruapehu case study expands the framework to a full-edifice scale, exploring 1,024 potential collapse scenarios across a broader range of failure volumes and initiation locations. Although the hazard assessment remains based on a dimensionally reduced and sampled subset of potential slip surfaces, it provides a more comprehensive perspective on debris avalanche behaviour and spatial hazard patterns across an entire volcanic edifice.

These results, however, must be interpreted with caution, as they remain highly dependent on the assumptions made throughout the modelling workflow. While the simulations provide useful first-order insights into potential debris avalanche routing and hazard patterns at Ruapehu, several aspects differ from interpretations proposed in the literature. For instance, previous studies suggest that the most likely initiation zones for large collapses may be concentrated around the Crater Lake region (Phillips, 2011; Schaefer et al., 2018), particularly along its eastern rim, which is the steepest sector and where active hydrothermal circulation and groundwater accumulation are focused (Kereszturi et al., 2020; Miller et al., 2018). This area was the source of the Mangaio debris avalanche involving the failure of a hydrothermally altered flank ($\approx 4,600$ years ago; Donoghue and Neall 2001). In contrast, the slip surfaces used in this study were derived from the dry-edifice slope stability analyses of Kereszturi et al. (2021), which

did not explicitly account for groundwater or pore pressure conditions, and are mainly concentrated on the southern and western flanks of Ruapehu (Fig. 7.2). Similarly, geological evidence indicates that many past Ruapehu debris avalanches remained strongly channelised across the ring plain and into distal catchments (Tost et al., 2014), whereas the present simulations show more lateral spreading once flows leave the edifice and reach lower-gradient terrain.

Nevertheless, despite these limitations, the present workflow extends beyond the approach previously applied by Kereszturi et al. (2021), who coupled slope stability analyses with TITAN2D flow simulations to explore potential collapse scenarios at Ruapehu. While that study provided valuable deterministic runout scenarios, it did not incorporate any estimation of the probability of occurrence. By integrating a FOS-based weighting scheme into the hazard assessment, the framework developed in this thesis introduces a probabilistic dimension that enables comparison between alternative collapse scenarios and identification of the most likely flow pathways. This represents an important step forward in moving from deterministic scenario modelling toward probabilistic hazard forecasting.

The discrepancies between the simulated results and geological evidence likely reflect limitations in the characterisation of each stage of the modelling chain. At the pre-failure stage, the distribution of hydrothermal alteration, groundwater, and pore-pressure conditions at Ruapehu remains poorly constrained, and the assumption of a dry edifice may lead to unrealistic FOS estimates and misrepresentation of likely collapse locations and geometries. This is particularly important given that water-rich conditions are considered a major contributing factor in the Ruapehu debris avalanches (Tost et al., 2014). At the failure stage, the model assumes collapse occurs only in mechanically weakened regions identified through static material properties, without accounting for transient triggering processes such as pore pressure increase, magmatic intrusion, seismic loading, or progressive weakening. At the post-failure stage, flow simulations adopt parameters calibrated from the Te Maari debris avalanche, despite likely rheological and mechanical differences between the two volcanic systems. Furthermore, key dynamic processes such as basal erosion, entrainment of volcanoclastic sediment and incorporation of stream water are not explicitly represented, although these processes are thought to strongly influence mobility and channelisation at Ruapehu (Tost et al., 2014).

Taken together, these limitations highlight that the predictive capability of the framework is strongly dependent on the reliability of the input assumptions at each modelling stage. The Ruapehu application therefore reinforces one of the key conclusions of this thesis: accurate

debris avalanche hazard assessment requires robust characterisation of pre-failure conditions, realistic representation of failure mechanisms, and careful calibration of post-failure flow parameters. Uncertainties introduced during the early stages of the modelling chain propagate through the workflow and can significantly influence final hazard predictions. Consequently, the integrated framework performs best when each component can be constrained and validated against geological, geotechnical, or historical observations.

A key next step for the application of the framework at Ruapehu is therefore the calibration and validation of the modelling chain against well-characterised past events. Reconstructing the source conditions and runout behaviour of known debris avalanches, such as the Mangaio Formation or the Murimotu Formation, would provide a basis for calibrating both failure and flow parameters and for assessing the geological realism of the simulations. Such an approach would allow the framework to move from exploratory scenario analysis toward more robust, site-specific hazard assessment.

7.1.5 Conclusions

The exploratory application of the coupled LEM/depth-averaged framework to Ruapehu demonstrates the potential of the methodology to be extended beyond the Te Maari case study and applied at a larger, edifice-wide scale. By expanding the analysis from a single well-constrained historical event to 1,024 potential collapse scenarios across an entire volcanic edifice, this study illustrates how the framework can be adapted to investigate a broader range of possible failure locations, volumes, and hazard outcomes.

The resulting ensemble of simulations represents an important step toward more probabilistic volcanic landslide hazard assessment, as it enables comparison of multiple potential collapse scenarios and estimation of exceedance probabilities across the volcano and surrounding ring plain. However, while the workflow adopts a probabilistic structure through the use of multiple scenarios and FOS-based weighting, it does not yet constitute a fully probabilistic framework, as uncertainties in other key parameters (e.g., material properties, pore-pressure conditions, and flow rheology) are not explicitly represented through probability density functions.

More broadly, the Ruapehu application highlights both the promise and the limitations of transferring the framework to other volcanic settings. While the workflow can be reproduced in contrasting geomorphological and structural environments, the reliability of the outputs remains strongly dependent on the quality of the geological, geotechnical, and hydrological constraints

available to inform each modelling stage. As demonstrated by the discrepancies between simulated behaviour and geological interpretations at Ruapehu, successful application to other volcanic edifices requires careful calibration and validation against independent geological evidence. The Ruapehu case study therefore, should be viewed as a proof of concept for broader applicability rather than a definitive demonstration of transferability, and it highlights the need for further validation before the framework can be confidently applied for operational hazard forecasting in new settings.

Chapter 8

General discussion and conclusions

This chapter first summarises the contribution of each chapter and its role in achieving the main objective of the thesis. It then provides a broader discussion of the key challenges associated with physically based debris avalanche modelling. Building on this, the chapter discusses the contribution of the proposed framework to hazard assessment and how it addresses some of these limitations. It then critically evaluates the validation, applicability, and limitations of the framework, including insights from the Te Maari case study and its transferability assessed through the exploratory Ruapehu application. Finally, it outlines future research directions and presents the main concluding remarks of the thesis.

8.1 Synthesis

The main objective of this thesis was to advance the quantification of debris avalanche hazard by developing a combined, physically-based modelling framework. As highlighted by this research, a key challenge in debris avalanche hazard modelling lies in the complex, multi-stage nature of these events, uncertainties in input parameters and variability in flow behaviour, all of which influence hazard predictions. To address these challenges, the research focused on a complex and well-documented case study, the Te Maari 2012 debris avalanche in New Zealand, which provided a rare opportunity to investigate the full sequence of a debris avalanche, from pre-failure conditions through failure initiation to post-failure dynamics. Each chapter in this thesis contributes specific tools or methods, which together support the common goal of creating an integrated approach that links failure and post-failure physically-based modelling, thereby enhancing the accuracy and reliability of debris avalanche hazard assessment.

8.1.1 Initiation processes and failure mechanics

The first component of this research focused on understanding the initiation mechanisms of volcanic debris avalanches and their influence on failure mechanics. Chapter 4 (Vicente et al., 2025) examines the interaction between pre-failure conditions and failure processes using finite-element modelling (FEM) to identify the preparatory and triggering factors that led to the 2012 Te Maari debris avalanche. The analyses identified pore-pressure increase due to infiltration as the primary short-term trigger and hydrothermal alteration as the main long-term preconditioning factor. The study also highlighted the potential for a progressive failure involving two distinct blocks. In volcanic settings, the distribution of alteration and groundwater, often controlled by hydrothermal circulation and permeability, plays a crucial role in influencing effective stresses and failure characteristics (Ball et al., 2018). However, the accuracy of such hydrological configurations remains limited by the available groundwater data, a common constraint across most volcanoes worldwide. More generally, these findings demonstrated that debris avalanche initiation is controlled by a complex interplay of various factors, strongly shaped by material heterogeneity and fluid circulation. Therefore, accurate estimates of failure mechanics and source characteristics require a detailed assessment of pre-failure conditions, as uncertainties in this stage can propagate throughout the entire debris avalanche sequence. Chapter 4 also showed that, despite their complexity, the infiltration effects can be moderately approximated

using a simplified pore-pressure ratio approach in slope stability analyses. This approach was subsequently applied in Chapter 6, in which limit-equilibrium (LEM) analyses, based on the same geological and hydrological settings as Chapter 4 (Vicente et al., 2025), produced a range of possible slip surfaces with varying geometries, volumes, and depths. When these surfaces were used as initial masses in flow simulations, they resulted in a spectrum of mobility outcomes, highlighting the sensitivity of debris-avalanche dynamics to source characteristics. This further reinforces that uncertainties in the initial stage can significantly affect the accuracy of predictive outcomes.

8.1.2 Variability in flow dynamics

The second component of this research focused on the post-failure dynamics of debris avalanches and the influence of initial flow parameters on mobility. Building on the hypothesis from Chapter 4 (Vicente et al., 2025) that the Te Maari debris avalanche was triggered by a significant increase in pore pressure, Chapter 5 applied the depth-averaged, two-phase D-Claw model. This model allows motion to initiate through a progressive increase in basal pore-pressure, enabling realistic simulation of the early stages of flow (Iverson and George, 2014). To only account for flow parameters variability, the observed source geometry was used as the initial collapsed mass. Simulations demonstrated that the internal permeability regime is central in controlling runout and mobility, as it influences the excess pore pressure build-up. However, in real-world events, permeability is difficult to estimate, particularly within a moving, multiphase mixture whose internal structure evolves dynamically (Iverson and George, 2014). The results also highlighted the influence of topographic confinement on energy dissipation and flow mobility, as well as the occurrence of equifinality: different initiation scenarios can yield similar inundation extents. For instance, in the Te Maari case, two distinct sets of parameters, one representing low-permeability conditions and another high-permeability conditions, were able to reproduce the observed runout at Te Maari. In the case of channelised dilative failures, we have shown that particular combinations of internal material properties can overcome the reduced mobility due to the low permeability. Specifically, a combination of low permeability, high compressibility, and low dilatancy enhances mobility by allowing flows to achieve early high peak velocities and travel long distances, comparable to high-permeability settings. This finding shows that flow behaviour is not governed by a single dominant parameter and is rather controlled by the complex interplay between multiple factors such as initial saturation, friction angle, solid fraction, compressibility,

dilatancy, and permeability. Consequently, this complexity presents significant challenges for predictive modelling based on optimised parameters, as realistic behaviour can result from diverse combinations of interacting variables.

8.1.3 Towards an integrated probabilistic hazard assessment

The central hypothesis of this thesis is that accurate prediction of both the failure and flow stages, when combined into a single workflow, can improve hazard predictions. Accordingly, the final stage of this research builds on insights from the failure analysis (Chapter 4) and post-failure dynamics (Chapter 5) to develop and validate an integrated framework for probabilistic debris-avalanche hazard assessment, using the Te Maari case study. In Chapter 6, landslide susceptibility derived from LEM slope stability analyses was coupled with D-Claw runout simulations to quantify the spatial probability of flow inundation. Thirty candidate source geometries were selected based on observations from the 2012 Te Maari debris avalanche. Results from this modelling workflow showed that the coupled approach could effectively reproduce the complex and channelised Te Maari flow, with several simulations achieving high performance scores. A FOS-based weighting function was introduced to translate deterministic stability outputs into relative failure probabilities, thereby accounting for uncertainty in which slip surface is most likely to fail. Exceedance maps derived from this weighted approach performed better in delineating the observed hazard zones, demonstrating its ability to improve hazard predictions. By directly combining slope stability analyses with dynamic flow simulations, this approach enables the generation of quantitative hazard maps, representing an improvement over most volcanic debris-avalanche assessments, which mostly address susceptibility and runout separately and rely on semi-quantitative outputs. Importantly, this combined workflow allows uncertainties in initial conditions, such as the location and geometry of potential failure surfaces, to be propagated through to the hazard predictions. The FOS-weighted exceedance maps, in particular, provide a more nuanced estimate of areas at risk, offering valuable information for early-warning systems and targeted risk-mitigation strategies.

8.1.4 Extension beyond the Te Maari case study

In addition to the publication-based case studies centred on the Te Maari 2012 debris avalanche, the integrated framework was also applied in an exploratory manner to the Ruapehu volcanic edifice in Chapter 7, to illustrate how the modelling chain behaves under different geological

conditions and data availability. The Ruapehu case provides a contrasting volcanic context in terms of edifice structure, potential failure mechanisms, and the level of available site-specific constraints. In this sense, it offers an opportunity to qualitatively assess the flexibility of the framework when applied beyond the well-constrained Te Maari case study, without the same level of calibration or detailed observational control. The results from this exploratory application indicate that the coupling between slope stability analysis and runout modelling can be implemented in a consistent manner in a different volcanic setting, and that the general structure of the framework remains applicable. However, they also highlight the increased sensitivity of the modelling outcomes to input assumptions when site-specific constraints are more limited, particularly with respect to the definition of potential source areas and failure conditions.

8.2 Modelling challenges in debris avalanche simulations

Debris avalanche modelling remains challenging due to the inherently complex, multi-stage nature of these events (van Asch et al., 2007), which involve interactions between slope failure, fragmentation, fluidisation, and other long-runout flow processes (e.g., entrainment). Although simpler modelling approaches, such as empirical methods (e.g., angle of reach, Heim ratio), are widely used and have proven effective for first-order hazard estimation (Hungr et al., 2005; Iverson, 2006; Schilling et al., 2008; Mitchell et al., 2020), they overlook important physical processes controlling mobility, particularly transitional behaviours that can significantly enhance runout and hazard extent. To address these limitations, more sophisticated physically based models have been developed to simulate the dynamic behaviour of debris avalanches (Dai et al., 2002; Pudasaini et al., 2005; Hürlimann et al., 2008; Iverson and George, 2014; Mergili et al., 2017). However, despite their greater physical realism, the predictive capability of such models remains strongly constrained by uncertainties in model parametrisation and input data (Prochaska et al., 2008; Mead et al., 2021).

In this thesis, the depth-averaged D-Claw model was employed because it improves upon conventional depth-averaged approaches by explicitly simulating evolving solid-volume fraction and pore pressure feedback mechanisms, thereby allowing representation of liquefying and transitional flow behaviour (Iverson and George, 2014; George and Iverson, 2014). However, this

increased process representation comes at the cost of substantially greater parameter complexity. Many of the required input parameters are difficult to constrain because they do not represent fixed material constants, but rather bulk properties of dynamically evolving multiphase mixtures. As a result, they cannot be directly measured from static deposit characteristics or laboratory samples, which may not accurately reflect in-motion flow conditions. For example, the reference initial permeability (k_0) defines the overall permeability regime of the flowing mass and strongly influences pore pressure dissipation throughout the simulation, yet available field measurements of deposit hydraulic conductivity do not directly translate to this dynamic parameter. Consequently, several D-Claw parameters had to be constrained through sensitivity analyses within physically realistic ranges derived from previous experimental and modelling studies (e.g., Major, 1996; Iverson and George, 2014; George and Iverson, 2014).

Beyond the difficulty of constraining individual parameters, an additional challenge in physically based debris avalanche modelling is the issue of equifinality (Beven, 1996; Mergili et al., 2018b), whereby multiple combinations of input parameters may produce similar model outputs despite representing different physical conditions. As demonstrated in Chapter 5, distinct parameter sets were able to reproduce the observed Te Maari runout with comparable performance, despite reflecting contrasting internal permeability regimes and flow initiation mechanisms. This creates a major limitation for model calibration, as agreement between simulated and observed inundation extent does not necessarily imply that the underlying physical processes are accurately represented. This limits confidence in inverse calibration approaches and complicates the use of historical events as direct templates for forecasting future collapses (Mergili et al., 2018b). Consequently, calibration against a single observed event may lead to non-unique parameter solutions, reducing the predictive robustness of the model when applied to unseen scenarios.

A further limitation of many debris avalanche hazard assessments is that the failure and post-failure stages are often modelled independently (e.g., Heinrich et al., 2001; Revellino et al., 2004; del Potro et al., 2013; Ball et al., 2018; Reid et al., 2010; Procter et al., 2021), with little consideration of the mechanical relationship between source conditions and subsequent flow behaviour. In many existing approaches, potential source volumes are predefined using simplified geometric assumptions or empirical estimates (e.g., George et al., 2022) and then directly imposed into runout models without explicit assessment of the failure processes that generated them. While this simplification reduces modelling complexity, it neglects the strong

control that source geometry, failure depth, and initiation mechanism exert on debris avalanche mobility and inundation patterns. As demonstrated throughout this thesis, uncertainties in the initial failure conditions can significantly alter simulated runout behaviour and therefore propagate directly into hazard predictions. Integrating slope stability and flow modelling provides a more physically consistent representation of the debris avalanche sequence, but also introduces additional complexity by linking uncertainties across multiple modelling stages. Errors or assumptions made during the pre-failure or failure stages are inherited by subsequent flow simulations, increasing the sensitivity of the overall hazard assessment to the reliability of upstream inputs.

Finally, the integration of physically based failure and flow models within a probabilistic framework introduces several computational challenges. Comprehensive hazard assessments ideally require exploration of the full range of uncertainty associated with slope stability conditions, source characteristics, and dynamic flow parameters. However, explicitly accounting for these uncertainties through probabilistic sampling or probability density functions can rapidly generate thousands of parameter combinations, making full uncertainty quantification computationally expensive and often impractical. This challenge becomes even greater when using complex physically based models such as D-Claw, for which each simulation may require significant computational time and resources. As a result, practical applications often rely on simplified approaches, such as reduced parameter sampling, representative scenario selection, or dimensionality reduction techniques, to maintain computational feasibility (Kereszturi et al., 2021). While these strategies improve efficiency, they may reduce the completeness of uncertainty representation and risk overlooking less probable but potentially high-impact scenarios. Balancing physical realism, uncertainty quantification, and computational feasibility, therefore, remains one of the principal challenges in developing debris avalanche hazard assessment frameworks.

8.3 Contribution of the framework to hazard assessment

Some widely used landslide hazard assessment approaches are based on single-stage modelling frameworks, where either slope failure susceptibility or runout behaviour is analysed independently (e.g. Gu et al., 2015; Acevedo et al., 2021; Ji et al., 2025; Sheridan et al., 2010; Mead and Magill, 2017; Charbonnier et al., 2015; Ding et al., 2023; Wolff et al., 2025). In these methods,

the initiation and propagation phases are not explicitly coupled, and hazard is typically assessed either through susceptibility mapping or through runout simulations conditioned on predefined source areas. Isolating propagation from initiation and failure dynamics may lead to unrealistic deposition patterns, runout distances, or flow velocities (Reid et al., 2000). This limitation has motivated many authors to suggest coupled approaches in order to improve the accuracy and physical consistency of hazard assessment (Reid et al., 2001; Ball et al., 2018; Kereszturi et al., 2021).

Building on this, some studies have proposed integrated frameworks aimed at improving hazard zonation and predictive capability. These approaches, applied at both regional and local scales, generally remain semi-quantitative and rely on empirical or simplified process representations rather than fully physically based simulations, for example, by using empirical runout rules or simplified flow descriptions instead of depth-averaged dynamics (Mergili et al., 2012; Horton et al., 2013; Mergili et al., 2019). As a result, key interactions between initiation, mobilisation, and propagation are only partially represented, limiting their ability to fully capture the cascading nature of landslide hazards. More recently, fully physically based integrative approaches have started to emerge. These frameworks aim to better couple hydrological processes, slope stability, and mass movement dynamics within a unified modelling chain. Among these, the study by Bout et al. (2018) is particularly relevant, as it builds upon the hydrological model OpenLISEM to simulate runoff generation, slope stability, and debris flow propagation within a single modelling environment. However, this approach relies on an infinite slope stability formulation, which is restricted to shallow translational failures and assumes a simplified force balance. In addition, the model remains deterministic and produces maps of maximum inundation depth, without providing probabilistic outputs. In particular, it does not explicitly quantify either the probability of slope failure or the resulting probability of inundation. Beyond this, even when probabilistic information is introduced in some existing frameworks, several limitations remain. Spatial variability in source susceptibility is often smoothed out (Mergili et al., 2019), and important information such as potential failure volumes is not always explicitly considered (Horton et al., 2013; Mergili et al., 2019). Consequently, truly quantitative approaches capable of consistently linking failure occurrence and flow impact in a probabilistic manner remain scarce.

In addition, modelling strategies used in real-time hazard assessment contexts highlight further limitations of approaches that do not explicitly account for failure processes. During the

Te Maari eruptive crisis, for example, flow hazard zones were delineated prior to the eruption using the Titan2D model (Leonard et al., 2014), which applies a depth-averaged Coulomb continuum formulation to simulate flow propagation. In this application, slope stability was not explicitly modelled, and potential source areas were defined a priori based on geomorphological interpretation and expert judgement. While such models are generally calibrated against well-documented past events, the historical record at Te Maari was poorly constrained, with limited information available on previous flow characteristics. As a result, parameters such as friction coefficients, initial volumes, and source locations were selected based on analogue reasoning and expert interpretation rather than direct calibration. While this strategy is well-suited to time-constrained emergency situations, it implies that both the location and magnitude of potential failures, as well as the governing flow properties, are not dynamically linked to the physical state of the system. Consequently, the modelling produces scenario-based inundation maps that depend strongly on user-defined inputs, without providing any estimate of failure likelihood or associated uncertainty. These outputs were used to delineate a broad flow hazard zone, with boundaries represented as gradational areas of decreasing transparency over several hundred metres to reflect a reduction in hazard away from the vent. However, this visual representation does not rely on probabilistic metrics and primarily reflects expected impact areas derived from a limited set of scenarios. Although some spatial patterns, such as preferential channelisation along valleys, are mentioned on the maps, they are not explicitly represented in the hazard delineation.

In contrast, the framework developed in this thesis explicitly addresses these limitations by fully coupling slope failure initiation and post-failure debris avalanche propagation within a physically based modelling chain. It adopts a limit-equilibrium approach for slope stability, allowing for more realistic failure geometries and enabling potential source areas to emerge from the model rather than being prescribed. In addition, it introduces a probabilistic formulation based on FOS-weighted failure relative likelihoods. Within this framework, the probability of inundation is derived from the relative probability of failure and propagated through the runout model, enabling a consistent representation of uncertainty from initiation to impact. The results presented in Chapter 6, based on the Te Maari case study, further demonstrate the practical added value of this approach for hazard zoning and risk mapping. In practice, translating these probabilistic outputs into hazard maps requires the definition of spatially distributed hazard metrics derived from the simulated flow properties. In the case of depth-averaged models, hazard

zones are typically delineated by aggregating quantities such as flow depth or velocity into spatial indicators that can be interpreted for risk assessment. The choice of hazard metric is strongly dependent on the intended application. Flow depth is commonly used, as it provides an intuitive and easily interpretable measure for decision-makers, particularly in emergency management contexts, whereas metrics such as dynamic pressure may offer a more physically meaningful representation of impact intensity but are generally more difficult to communicate in operational settings. A key challenge in this process is the definition of a meaningful hazard boundary, as hazard delineation inherently depends on the balance between minimising false alarms and capturing the full extent of potentially affected areas. The probabilistic formulation allows hazard zones to be defined using a user-defined exceedance probability threshold, providing a flexible means to control this trade-off depending on the objectives of the assessment. The analysis of the framework performance shows that an optimal balance can be achieved, with performance metrics comparable to or exceeding those obtained in studies relying on single-stage approaches (e.g. Mergili et al., 2018a; Mead et al., 2021). This performance is further enhanced by the FOS-based weighting scheme, which increases the influence of simulations closer to instability, improving recall while maintaining high precision and enabling lower exceedance probability thresholds to remain effective in capturing hazardous zones.

Overall, the proposed framework provides a more consistent and comprehensive basis for hazard assessment by integrating physically based modelling with probabilistic analysis. It enables not only the simulation of coupled failure and flow processes, but also the quantification and propagation of uncertainty, resulting in spatially distributed probabilistic hazard outputs rather than deterministic inundation maps.

8.4 Validation, applicability and limitations of the framework

The validation of the integrative approach relies primarily on the Te Maari case study, which provides a well-documented and relatively well-constrained reference event. This event is particularly relevant for hazard assessment, as it corresponds to a small-volume collapse, relatively more frequent on stratovolcanoes (Siebert and Roverato, 2021). In addition, it occurred within a hydrothermal system, where alteration processes are a primary driver of slope instability, and exhibits transitional behaviour between failure and flow propagation. These characteristics make it a suitable test case for evaluating an integrated modelling framework that aims to

capture both initiation and runout processes.

However, the reliance on a single case study also limits the generality to other types of volcanic instability. In particular, the framework is effectively validated for a specific type of initiation mechanism, a volcanic slope failure driven by pore pressure changes and hydrothermal alteration. Although LEM-based approaches have demonstrated their potential to simulate slope instability under various triggers (e.g., magmatic intrusion, Reid et al. 2015; pore-pressure changes, Ball et al. 2018), their application within the present framework has not been evaluated across the full spectrum of possible triggers.

While calibration against a historical event allows model parameters to be constrained within physically realistic ranges, thereby improving the robustness and interpretability of the results, it does not guarantee transferability to other contexts. As discussed in Section 8.2, equifinality remains a key issue, and multiple parameter combinations may reproduce similar runout patterns while representing different internal dynamics. Consequently, the framework’s predictive capability outside well-constrained conditions remains dependent on the representativeness of the calibration case.

In situations where no well-documented historical event is available, the definition of input parameters becomes significantly more uncertain. In such cases, parameter ranges must be expanded and described using probability density functions to account for the wider range of possible conditions. This leads to a substantial increase in the number of simulations required, resulting in higher computational costs. Moreover, the broader exploration of parameter space tends to produce more diffuse hazard patterns, reducing the spatial precision of predicted impact areas and complicating the delineation of hazard zones.

The transferability of the framework is further explored through its application to the Ruapehu case study presented in Chapter 7. This application highlights the inherently site-specific nature of the approach. A comprehensive assessment of environmental conditions and potential triggering factors is required, including topography, material properties, hydrological forcing, and the mechanisms controlling slope instability. As a result, the framework is relatively data-intensive, and the quality of the outputs is strongly dependent on the accuracy and resolution of the input data. In data-limited environments, uncertainties in these inputs may propagate through the modelling chain and affect the reliability of both failure and flow predictions.

Overall, while the proposed framework provides a physically consistent and probabilistic approach to hazard assessment, its applicability is constrained by data availability, computational

requirements, and the representativeness of calibration datasets. These limitations highlight the need for careful consideration of environmental context, triggering mechanisms, and input uncertainty when applying the framework to new sites.

8.5 Future research perspectives

The limitations identified in this study open the way to future research directions towards a fully probabilistic and physically consistent framework for debris avalanche hazard assessment. A central challenge lies in the characterisation of pre-failure conditions, which define the initial state of the system and strongly influence all subsequent stages of the modelling chain. In particular, uncertainties in the spatial distribution of material properties and hydrological conditions remain a major source of variability in slope stability analyses. Improving their representation is therefore essential to enhance the reliability of hazard predictions. In this context, recent advances in remote sensing, such as the use of hyperspectral data as a proxy for rock physical and mechanical properties (Kereszturi et al., 2023; Thiele et al., 2025), offer rapid, efficient, and scalable means of mapping large volcanic areas. Compared to field investigations or geophysical surveys, which are often time-consuming, logistically complex, and spatially limited, these approaches provide spatially extensive and increasingly accessible datasets, particularly suited to large and remote volcanic edifices. By delivering regular surface coverage, they enable the identification of mineralogical composition and alteration patterns that can be used to infer key physical and mechanical parameters. However, these methods remain primarily sensitive to surface conditions and therefore provide only indirect constraints on subsurface structures and processes, which are critical for accurately characterising slope stability. As such, remote sensing should be viewed as a powerful complement to in situ and geophysical investigations, rather than a replacement, with significant potential for reducing uncertainty.

Beyond the initial conditions, a major limitation of the current framework relates to the explicit treatment of uncertainty throughout the modelling chain. Fully probabilistic hazard assessment requires exploring a high-dimensional parameter space that encompasses slope stability inputs, source characteristics, and flow dynamics. However, the computational cost associated with such an approach remains a significant constraint, particularly when relying on physically based models. Addressing this challenge will require the development of more efficient strategies to explore parameter space, including the use of dimensionality reduction techniques,

surrogate models, or informed sampling approaches. The results obtained in this thesis suggest that incorporating physically meaningful initiation parameters, such as failure volume and slip direction, may help structure this exploration and improve the representation of variability while maintaining computational feasibility.

At the same time, the way hazard is quantified and communicated also deserves further attention. Although flow depth provides an intuitive and widely used metric for hazard mapping, it does not fully capture the destructive potential of debris avalanches. A more comprehensive representation of hazard would require integrating additional indicators, such as flow velocity or dynamic pressure, in order to better characterise impact intensity and improve the relevance of model outputs for risk assessment.

Another key aspect concerns the probabilistic representation of slope failure itself. In this study, the FOS was used as a proxy for relative likelihood of failure, allowing deterministic stability results to be incorporated into a probabilistic framework. While this approach provides a practical and effective way to account for variability in potential failure scenarios, the relationship between FOS and actual probability of failure remains poorly constrained (Ford, 2020). As such, the weighting scheme adopted here should be considered as a first-order approximation. Further work is needed to establish a more rigorous and quantitative relationship between these quantities, which would strengthen the theoretical basis of the framework and improve the consistency between failure modelling and probabilistic hazard assessment.

More broadly, extending the application of the framework beyond the Te Maari case study represents an important step for future research. Applying the approach to a wider range of volcanic settings, characterised by different triggering mechanisms, material properties, and scales of instability, would allow its robustness and transferability to be more thoroughly evaluated.

8.6 Conclusion

This thesis developed and evaluated an integrated, physically based and probabilistic framework for debris-avalanche hazard assessment, with the aim of improving the representation of both failure initiation and post-failure dynamics within a single modelling chain. The approach couples slope stability analysis, based on limit-equilibrium methods, with depth-averaged flow modelling using the D-Claw model, enabling a physically consistent linkage between pre-failure conditions, source characteristics, and runout behaviour.

A key outcome of this work is the demonstration that uncertainties in the initial stages of a debris avalanche, particularly those related to slope stability and failure geometry, exert a first-order control on the resulting flow dynamics and inundation patterns. By explicitly propagating these uncertainties through the modelling chain, the framework moves beyond deterministic scenario-based approaches and enables the generation of spatially distributed probabilistic hazard outputs. In particular, the introduction of a FOS-based weighting scheme provides a practical means of incorporating relative failure likelihood into hazard assessment, improving the representation of variability in potential source areas.

The results obtained for the Te Maari 2012 case study show that the coupled framework is able to reproduce the complex, channelised nature of the observed debris avalanche while also capturing the sensitivity of runout behaviour to variations in source geometry and material properties. Compared to conventional approaches that treat failure and flow processes independently, the integrated framework provides a more consistent representation of the full debris-avalanche sequence, from initiation to deposition, and improves the physical interpretability of hazard predictions.

Despite these advantages, several limitations remain. The framework is strongly dependent on the availability and quality of input data, particularly for pre-failure conditions, which are often poorly constrained in natural systems. In addition, the use of physically based models introduces significant computational demands, especially when uncertainty is explored through multiple simulations. Equifinality also remains an inherent challenge, as different parameter combinations can reproduce similar runout patterns while representing different internal dynamics. These limitations highlight that, while the framework improves physical consistency and uncertainty representation, it does not eliminate the intrinsic ambiguities associated with debris-avalanche modelling.

Overall, the proposed approach provides a step forward in the quantitative assessment of debris avalanche hazard by integrating failure mechanics, flow dynamics, and probabilistic analysis within a unified framework. It offers a more robust basis for hazard mapping than traditional single-stage or purely deterministic methods, while also making uncertainties explicit and traceable throughout the modelling chain. As such, it can support more informed hazard assessment and risk mitigation strategies, particularly in volcanic environments where both slope instability and rapid mass movements pose significant threats.

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Appendices

A Supplementary Table for Chapter 5

This appendix presents a summary table (Table A1) of the input parameters, including the compressibility coefficient (a), initial permeability (k_0) and dilatancy (Δ_m), along with the CSI results for all 27 D-Claw simulations of the full factorial design.

Table A1: Summary of simulated CSI values for each parameter combination.

Simulation	Design Levels	a	k_0	Δ_m	CSI
1	-1, -1, -1	0.01	1.00×10^{-9}	0.02	0.5772
2	0, -1, -1	0.03	1.00×10^{-9}	0.02	0.6309
3	1, -1, -1	0.05	1.00×10^{-9}	0.02	0.6727
4	-1, -1, 0	0.01	1.00×10^{-9}	0.04	0.5092
5	0, -1, 0	0.03	1.00×10^{-9}	0.04	0.5649
6	1, -1, 0	0.05	1.00×10^{-9}	0.04	0.6082
7	-1, -1, 1	0.01	1.00×10^{-9}	0.06	0.4799
8	0, -1, 1	0.03	1.00×10^{-9}	0.06	0.5207
9	1, -1, 1	0.05	1.00×10^{-9}	0.06	0.5626
10	-1, 0, -1	0.01	5.05×10^{-8}	0.02	0.6137
11	0, 0, -1	0.03	5.05×10^{-8}	0.02	0.6143
12	1, 0, -1	0.05	5.05×10^{-8}	0.02	0.6099
13	-1, 0, 0	0.01	5.05×10^{-8}	0.04	0.6236
14	0, 0, 0	0.03	5.05×10^{-8}	0.04	0.6302
15	1, 0, 0	0.05	5.05×10^{-8}	0.04	0.6204
16	-1, 0, 1	0.01	5.05×10^{-8}	0.06	0.6296
17	0, 0, 1	0.03	5.05×10^{-8}	0.06	0.6298
18	1, 0, 1	0.05	5.05×10^{-8}	0.06	0.6213
19	-1, 1, -1	0.01	1.00×10^{-7}	0.02	0.6134
20	0, 1, -1	0.03	1.00×10^{-7}	0.02	0.6160
21	1, 1, -1	0.05	1.00×10^{-7}	0.02	0.6122
22	-1, 1, 0	0.01	1.00×10^{-7}	0.04	0.6229
23	0, 1, 0	0.03	1.00×10^{-7}	0.04	0.6190
24	1, 1, 0	0.05	1.00×10^{-7}	0.04	0.6150
25	-1, 1, 1	0.01	1.00×10^{-7}	0.06	0.6301
26	0, 1, 1	0.03	1.00×10^{-7}	0.06	0.6295
27	1, 1, 1	0.05	1.00×10^{-7}	0.06	0.6248

B Supplementary Tables for Chapter 6

This appendix provides a comprehensive overview of the results from all 30 LEM-generated scenarios. Table B1 summarises the failure characteristics for each scenario, including the FOS, maximum depth, estimated volume, overlap with the observed source area, and the slip direction. Table B2 presents the corresponding model performance metrics, such as PPV, Sensitivity, CSI, and the differences in runout compared to observations. Together, these tables allow for a detailed comparison of initial conditions and the resulting flow predictions.

Table B1: Failure characteristics for each LEM scenario.

Surface	FOS	Max depth (m)	Volume (m ³)	Overlap (%)	Direction (°)
1	0.75	51.6	725 000	34	151
2	0.88	49	962 000	60	151
3	0.92	42.3	588 000	50	149
4	1.23	45	785 000	58	153
5	1.24	33.4	918 000	48	138
6	1.45	36.2	708 000	41	139
7	1.46	43.6	560 000	54	114
8	1.56	38.4	728 000	50	147
9	1.57	46.9	869 000	24	116
10	1.65	53	1 048 000	61	151
11	1.74	36.4	519 000	80	150
12	1.77	51.5	641 000	31	153
13	1.81	31	627 000	61	149
14	1.91	45.2	755 000	40	117
15	1.99	46.8	870 000	57	151
16	2.20	40.6	453 000	42	144
17	2.27	49.6	489 000	92	150
18	2.29	52.3	734 000	47	151
19	2.45	49.4	1 003 000	49	147
20	2.50	48	620 000	59	154
21	2.60	41	680 000	49	148
22	2.88	43.3	640 000	63	152
23	2.90	45.4	811 000	38	147
24	3.13	53	530 000	41	143
25	3.16	42.5	952 000	18	141
26	3.39	44.6	939 000	42	139
27	3.51	38.8	484 000	6	109
28	3.65	52.3	609 000	74	150
29	3.75	52.7	984 000	0.5	129
30	3.82	41.5	457 000	48	146

Table B2: Model performance metrics for each LEM scenario.

Surface	PPV	Sensitivity	CSI	Runout difference (m)
1	0.6059	0.7688	0.5125	+139
2	0.5375	0.8892	0.5038	+113
3	0.7104	0.6885	0.5376	-394
4	0.5969	0.8698	0.5479	+13
5	0.5165	0.8931	0.4864	+73
6	0.6088	0.7242	0.4942	-375
7	0.7242	0.6190	0.5287	-477
8	0.6710	0.7592	0.5532	-307
9	0.6215	0.7011	0.4913	-308
10	0.5318	0.8947	0.5005	+43
11	0.6953	0.8648	0.6271	+199
12	0.5185	0.7766	0.4512	+15
13	0.6454	0.8673	0.5874	+16
14	0.5961	0.7163	0.4822	-374
15	0.5404	0.8871	0.5056	+53
16	0.5417	0.6175	0.4056	-541
17	0.8401	0.7006	0.6181	+487
18	0.5369	0.7707	0.4629	-327
19	0.4396	0.9071	0.4207	+113
20	0.6615	0.7480	0.5409	-397
21	0.5107	0.8537	0.4696	+106
22	0.6523	0.7955	0.5586	-324
23	0.6274	0.7529	0.5203	-311
24	0.6589	0.6959	0.5116	-454
25	0.3777	0.8003	0.3451	+86
26	0.4324	0.8064	0.3917	-31
27	0.5349	0.6255	0.4052	-447
28	0.7508	0.6756	0.5519	-527
29	0.4981	0.5796	0.3659	-554
30	0.4471	0.6319	0.3547	-577