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Stay-or-relocate model (STORM): An agent-based population displacement simulator applied to a multi-phase volcanic eruption scenario

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A R T I C L E I N F O

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A B S T R A C T

Households are central to societal functionality and may be impacted directly or indirectly by natural hazard events, resulting in the displacement of residents. Emergency management practitioners and policy decision-makers require adaptable decision support tools capable of accounting for fine-scale variations in hazard exposure, vulnerability and demographics across the emergency response and recovery periods. Responding to this critical need, we present the newly developed agent-based Stay-or-Relocate Model (STORM) demonstrated through application to a multi-phase and multi-hazard volcanic eruption scenario affecting the Taranaki Region, Aotearoa-New Zealand. STORM evaluates resident decision-making whether to remain, relocate or return home given household characteristics and changing circumstances over time. Decision components include evacuations, building damage, electricity and water outages, loss of road access, school disruption and reduced community liveability. Incorporation of an empirical relocation module quantifies the displaced residents' selection of accommodation type, area of relocation, duration at location before return or further relocation, and accommodation payment support requirements. Modelling results indicate a peak of 32,000 individuals displaced following the first phase of volcanic activity (24.9% of the population of Taranaki Region), reducing to 16,400 (12.8%) as some residents return during a period of volcanic quiescence, and rising to a second peak of 47,000 (36.5%) following a second phase of volcanic activity. STORM is hazard agnostic and can be readily adjusted to suit the local context of application.

1. Introduction

Natural hazard events such as volcanic eruptions disrupt the functioning of society through increased risk to life, direct damage, and infrastructure service interruption. Populations directly or indirectly exposed to the impacts of events may be forced from their homes or choose to relocate if circumstances become intolerable. While the primary drivers of initial population displacement in rapid-

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Glossary

Displacement The voluntary or involuntary movement of people away from their habitual residence in response to an adverse impact of a disaster
Habitability The degree to which a residential dwelling is safe and healthy to occupy
Household impact Direct or indirect impacts to a household caused by a hazardous event, from the perspective of the residents
Liveability The ability of residents to go about their normal household routines in a location
Relocation The temporary or permanent movement of people from one accommodation to another

onset events are well-established [1–5], resident decision-making and relocation in the face of changing circumstances throughout the emergency response and recovery periods remains understudied and rarely accounted for in models [5–7].

Globally, a holistic view of societal functionality and risks are recognised as essential for reducing disaster impacts to communities [8,9], including consideration of the various drivers of population displacement [10–12]. Displacement is commonly defined as a forced or involuntary movement of people away from their habitual residence [5,13–15]. Yet, there is recognition of displacement as a complex phenomenon where pre-existing vulnerabilities, beliefs and attitudes contribute to residents' decisions whether to relocate given the impacts of an event [4,11,15–17]. In this study, displacement is considered as inclusive of those who are forced from their homes as well as those who decide to leave as an adaptation to the disruption caused by a disaster event. Relocation refers to the temporary or permanent movement of people from one accommodation to another.

Emergency management and policy decision-makers in Aotearoa-New Zealand (A-NZ) have expressed a critical need for improved decision support tools focused on societal impacts beyond life safety [18–22]. Related to this study, population displacement models have been developed in A-NZ and applied to tsunami [23] and earthquake [24,25] scenarios, and have been extensively used for emergency preparedness and response planning, including for emergency management exercises. Demand is increasing for decision support tools that are adaptable to a wide variety of contexts, and account for fine-scale variations in hazard exposure, vulnerability and demographics.

In this study, the newly developed agent-based Stay-or-Relocate Model (STORM) is presented. STORM evaluates resident decision-making whether to remain at home, relocate or return, given household characteristics and the direct and indirect impacts of natural hazard events over time. STORM is demonstrated through application to a credible multi-phase and multi-hazard volcanic eruption scenario affecting Taranaki Region, A-NZ, developed by Weir et al. [26]. The eruption scenario is complemented by studies in evacuation management [27], building damage and critical infrastructure disruption [28,29]. The eruption scenario and associated impact models were developed through partnerships between scientists, emergency management practitioners, and infrastructure providers. The suite of scenario models represents a large, robust body of work that form an ideal set of inputs for implementation within STORM.

This paper begins with a review to inform the development of STORM (Section 2), consisting of volcanic hazards and impacts, population displacement factors, and existing models. The STORM framework is presented in Section 3, followed by description of the context and scenario for model application (Section 4). The components of household decision-making are detailed in Section 5, followed by modelling results and sensitivity testing (Sections 6 & 7). Through the discussion and conclusions (Sections 8 & 9), we reflect on advancements offered by STORM for improving simulations of population displacement and the applicability to other contexts, alongside suggestions for future research into household decision-making during disruptive natural hazard events.

2. Background

2.1. Volcanic hazards and impacts

Volcanic eruptions can create a variety of hazards that may impact communities [30]. Volcanic ash may spread over a large area and can disrupt and/or damage electrical systems, contaminate water supplies, damage buildings (especially roofs and guttering), reduce the serviceability of roads and can accumulate on land, reducing productive potential [31]. Deposited volcanic material may be remobilised as lahars which can travel large distances, particularly along stream and river channels radiating out from slopes of a volcano, severely damaging structures within the lahar path [32]. Pyroclastic density currents (PDCs) may form as the eruption column collapses, sending heated gasses and volcanic material downslope at high speeds, representing a severe risk to life [33]. The warning time for volcanic hazards, based on observations, varies greatly [34], even for well-monitored volcanoes.

Further to the direct impacts from volcanic processes, disruption to the functionality of societal systems can extend beyond the zone of direct exposure. Network infrastructure is particularly susceptible including electricity, water supply and roads, depending on interdependencies and available redundancies [32]. Therefore, there is a high degree of spatial and temporal variation for direct and indirect impacts, combined with uncertainty regarding future volcanic activity. Households face a changeable set of circumstances influencing their decisions whether to remain, relocate elsewhere or return to their homes as the situation progresses [35,36].

2.2. Factors influencing population displacement

In most contexts, initial population displacements are largely driven by physical impacts and associated service disruptions, along with pre-emptive evacuations for life safety or to avoid societal impacts [1–5]. Housing damage is typically regarded as the strongest indicator of displacement potential and frequently used as a proxy to estimate displacement numbers [37,38]. However, while damage tends to be spatially correlated with the broader impacts of events and therefore may serve as a reasonable proxy, the extent to which it drives household relocations varies between contexts and events. Determining habitability loss based on damage estimates is not necessarily straightforward, except in cases of severe damage, because observed and modelled damage states are typically focused on loss or restoration requirements rather than habitability. Infrastructure service disruptions are common reasons for relocation, with loss of water generally perceived as less tolerable by residents than electricity outages, and intolerance increases over time [5,39–42]. Evaluating tolerance and likelihood of relocation is influenced by many factors e.g. service dependence, availability of alternatives, preparedness, expected restoration time, and type of dwelling [40,43–45]. Pre-emptive evacuations may be mandatory or voluntary, with compliance and willingness to relocate varying by context and influenced by risk perception and risk tolerance [46–49]. Wider community impacts are also linked with relocation decisions [50], such as loss of access to community services [51,52], disruption to places of work or education [51,53], and loss of social capital [54,55].

Several demographic, psychological and socioeconomic factors have been observed as associated with displacement, mostly tied to lower socioeconomic status. Those more likely to be displaced and face difficulties with recovery have lower incomes or education, are children or elderly, are women or minorities, rent their home, and have lower levels of community participation, social connections, or place attachment [1,3,4,56–67]. Those of lower socioeconomic status have fewer resources and options to cope with recovery and are more likely to permanently resettle elsewhere [51,65], for example renters tend to lack access to financial assistance that favours homeowners [68]. Recovery trajectories and the outcomes for displaced populations also depend on context-specific aspects such as disaster governance, insurance and economics.

Despite these factors being common across events globally, the relative influence of factors varies between contexts and is difficult to weight [1,40,61,64,69]. Throughout this paper, the relevant literature is discussed for each household decision point (e.g. evacuation compliance, infrastructure outage tolerance), considering how the factors and indicators should best be incorporated into modelling with respect to the case study context.

2.3. *Existing population displacement models*

There are several existing simulation models for estimating population displacement. Earlier models are typically designed to estimate the displacement of residents and emergency sheltering demand immediately following a hazard event, whereas more recent models are commonly focused on housing recovery. The earlier models include HAZUS-MH [70], SYNER-G [71–73], ERGO-EQ [74] and InaSAFE [75]. Building damage is the primary displacement driver considered in each model, with utility outage and demographics also incorporated in SYNER-G and ERGO-EQ. Within HAZUS-MH, demographics are a modifier for estimating emergency sheltering demand. None of these models estimates timeframe of population displacement, and demographics are included at an aggregate level (e.g. US Census tract). Vecere et al. [76] applied the HAZUS and ERGO-EQ models to a case study area representing the February 22, 2011 Christchurch earthquake, finding the models were challenging to apply and produced poor results for both the number of displaced residents and emergency sheltering needs. This was due to the models having been developed for a US-context and finding that the fragility functions and social vulnerability (income, ethnicity and age) parameters would require modification to reflect the local context. Vecere et al. [76] also considered the SYNER-G model for application to Christchurch, concluding the variables were too specific to the European context.

Addressing the lack of appropriate models for estimating household displacement in Aotearoa, in previous work related to the present study the HDS-T model was developed and applied to tsunami scenarios impacting Christchurch, A-NZ [23]. Data inputs to HDS-T include tsunami inundation layers, building damage, spatial and temporal infrastructure outage (water, electricity and access), and aggregated demographic data from the 2013 Census. A scoring system is used to assess dwelling habitability given building damage and outages, and demographics are used as a modifier to increase or decrease the likelihood of residents relocating (e.g. renters and low income residents are more likely to leave their homes) [23]. While the model is functional for the case study, there are major drawbacks to using aggregated demographic data because the specific circumstances of each household cannot be accounted for. Further, the conflation of damage, access and outages into a single measure of habitability via the scoring system limits the ability to model household decision-making for disruptive factors independently (e.g. an electricity outage only).

Several models have been developed that estimate population displacement with a focus on evaluating housing recovery over time. Burton et al. [77] used logistic regression functions incorporating physical impacts and demographics to evaluate displaced resident decision-making whether to repair, reoccupy, sell or abandon their property. Burton et al. [77] informed their model through survey data of Los Angeles, US residents, and discuss the requirement for regionally-specific surveys to apply their framework elsewhere. Costa et al. [7] created an agent-based framework applied to an earthquake scenario in Vancouver, Canada, conceptually based on Chang et al. [78]. An inventory of dwellings with vulnerability attributes and households with demographics was created at the neighbourhood level via random assignment from aggregated census data, and preparedness attributes were added through survey data. The factors included in Costa et al. [7] reflect those commonly identified in the literature, through components that evaluate perceived habitability, type of alternative accommodation for those displaced, and household capacity for dwelling repair. As for all population displacement models, judgement was required for developing the equations and thresholds of each component. Bhattacharya & Kato [79] developed a conceptual agent-based model for household decision-making whether to repair their dwelling or relocate permanently, incorporating impact and demographic factors to evaluate location attractiveness and household needs relative to the ability of the community to provide for those needs. The conceptual model is functional, but not applied to a real-world scenario, and is targeted towards policy-based strategies for housing recovery. Similar to reflections from other studies, Bhattacharya & Kato

[79] note that while the factors incorporated agree with the collective literature, further development is required for application to a real-world case study. These recent studies presenting models for estimating population displacement and housing recovery demonstrate a range of conceptual and functional approaches for incorporating factors relevant to the focus of each study. In all cases, context was identified by study authors as critical, reflecting the limitations in existing literature.

2.4. Summary of gaps and study methodology

The factors influencing initial population displacement have been established through the literature and are reflected in existing models, but substantial challenges remain. The strength and weighting of factors are highly uncertain, and approaches for incorporation into models vary significantly. Population displacement in models is usually driven primarily by the physical factors affecting habitability, and often demographics are only considered when assessing sheltering needs. No existing displacement models account for the changing strength of factors over time, for example an electricity outage may become less tolerable to households as time progresses [39,42–44]. The typical use of aggregated demographic data for representing populations limits the ability to account for heterogeneity in household decision-making given the specific circumstances of each household. Current literature and models are almost exclusively targeted towards urban environments and populations, neglecting the diversity across smaller communities including rural areas. Existing models tend to be specific to the context of their demonstrated application and the justification for factor strengths and weightings are limited, inhibiting transferability to other contexts and scenarios. Applications have been to scenarios where disruption occurs at the beginning of the simulation, without consideration of ongoing hazards or risks.

In this study, we build on the existing body of knowledge and develop a model framework capable of incorporating each of the factors identified above (Section 3). A multi-phase and multi-hazard volcanic eruption scenario affecting rural and urban communities is selected for model application due to the robustness of the scenario and availability of fine-scale spatial and temporal hazard, evacuation and impact data (Section 4). The components of household decision-making are developed and weighted based on available literature and expert judgment (Section 5).

3. Model framework

The impacts to households are assessed in STORM through an agent-based modelling (ABM) approach coded using the GAMA Platform [80]. Entities within the model are represented as species of agents, such as households and buildings, each with attributes, actions, and behaviours. Species of agents are the equivalent of classes in object-oriented programming. A global agent species initialises the simulation with parameters defining aspects such as the shape of the world and the time step for each cycle, and instantiates each of the other species. Finally, the experiment agent initiates the simulation as generates display of monitors and a spatial representation of agent species. While the actions and behaviours for each species are defined as a whole, the individual responses of each agent can vary depending on their specific attributes (e.g. the behaviour of a household could depend on its location and demographic characteristics). The agents within the simulation are listed and briefly described in Table 1, with further details in the following sections. Several agents utilise geographies from Stats NZ, namely Statistical Areas 1 and 2 (SA1, SA2) which represent areas typically populated by 100-200 and 1000-4000 residents respectively [81].

A simplified overview of the modelling process is shown in Fig. 1. STORM incorporates several externally developed model inputs. In this application, the external inputs are each informed by the volcanic eruption scenario [26] and include evacuation zones, building damage, water and electricity level of service, and road access. Within the STORM framework are disruption models that evaluate the external factors in household decision-making, household agents containing characteristics that influence their decisions for a given situation, and a relocation model where displaced residents select an accommodation type, area of relocation, duration at each alternative accommodation location, accommodation payment support requirements, and decide whether to return if conditions allow or permanently relocate.

The architecture of the simulation is primarily reflexive, where the behaviour of each agent is reactive to the conditions present during each cycle (time step). Additionally, decision-making within the household agents makes use of belief-desire-intention (BDI) architecture [85]. Beliefs are the agents' knowledge of the world (e.g. whether the household has water), desires are what the agent

Table 1
Agents within the simulation and input data source where applicable.

Agent	Description	Input data source
Global	Parameters for simulation, instantiates other agents, generates outputs	STORM (GAMA)
Household	Demographics, spatial relationships to buildings and infrastructure, decision-making given circumstances	Synthetic population model [82]
Building	Use category, damage state, recovery	Building inventory [29,83]
School	Type (primary or secondary), damage state and recovery	Building inventory [29,83]
Supermarket	Damage state and recovery	Building inventory [29,83]
Electricity	Functionality over time	Level of service by SA1 [29]
Water	Functionality over time	Level of service by SA1 [28,29]
Road	Access over time to local CBD and ability to travel within region	Access by SA1 [84]
Evacuation	Evacuation zones for specified time periods	Evacuation zone shapefiles [27]
Aggregation	Determines local community boundaries, also used for outputs	Stats NZ geographies (SA1, SA2)
Experiment	Creates a simulation, includes monitors and displays	STORM (GAMA)

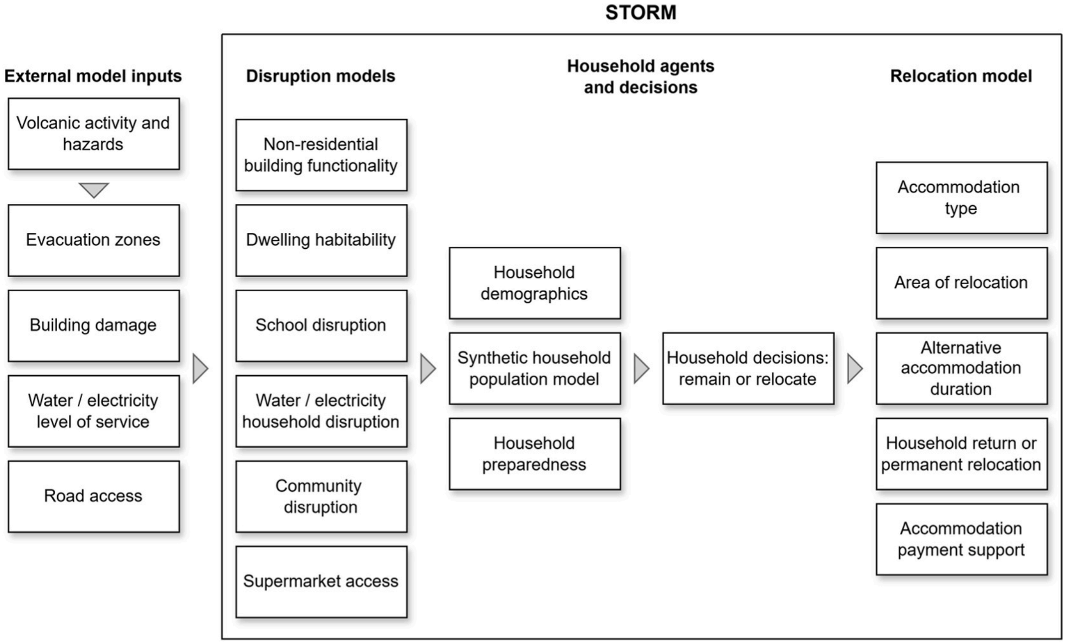

Fig. 1. Simplified overview of the modelling process, showing externally developed model inputs and the key components within STORM.

wants (e.g. to relocate to alternative shelter), and intentions are what the agent is currently doing to try to achieve their desire (e.g. exercising a plan on where to relocate to). BDI architecture is utilised in this model primarily for purposes of intuitive coding, communication and future extensibility [86–88].

Households are the primary agents within the simulation and make decisions about whether to remain, relocate or return based on their changing circumstances over time. The circumstances are considered as either external factors (beyond the control of residents) or household factors (characteristics of the household that may influence decision-making given external factors). Examples of external factors are mandatory evacuation orders, building damage, and infrastructure outages. Household factors represent the characteristics and needs of the household e.g. schooling for children, caring for domestic animals or livestock, obtaining emergency supplies. Household decision points, and the relevant external and household factors influencing the decision-making are shown in Fig. 2. Residents may be forced out of their homes or choose to leave if the disruption they experience exceeds their ability to meet their needs through adaptive behaviours. Each household decision is evaluated independently, although multiple sources of disruption will increase the overall probability of relocation. The simulation evaluates household decision-making each cycle, which is set at one day for the present case study.

The modelling presented in this study seeks to include the primary drivers of relocation decision-making identified through the literature, weight factors appropriately given their influence, and include factors that may be important but understudied. The following section describes the context and scenario of the case study. Section 5 describes the household agents and each of the six household decision points whether to remain or relocate including external and household factors, and the relocation model.

4. Context and scenario

Taranaki is a region on the western side of the North Island, consisting primarily of productive farmland, rural service towns and the city of New Plymouth (Fig. 3). The estimated population is 128,700 as of June 2023, with 117,561 residents recorded during the 2018 Census, the most recent data available at the time of this study. According to the 2018 Census, approximately 80% of the population reside in urban areas, 69% of households own their home, the mean household size is 2.5, 31% of households include at least one dependent child, and the median household income is $64,000. On average, rural households in Taranaki have higher incomes than urban households, are larger households with more dependent children, and have higher rates of home ownership. Ethnicities in Taranaki, as reported by individuals who can identify with more than one group, are approximately 85% New Zealand European, 20% Māori, 4.5% Asian, 2% Pacific Peoples, and 3% identify with other ethnic groups. Taranaki is a major source of dairy production and processing, and is the sole regional producer of oil and gas used across the country.

The dominant feature of the region is Taranaki Mounga (also known as Mt. Taranaki or Mt. Egmont), an active stratovolcano with multiple volcanic cones and forested flanks protected from development by a national park (Te Papakura o Taranaki). Hazards from volcanic activity on Taranaki Mounga include pyroclastic density currents, debris avalanches, tephra dispersal and lahars [89,90]. The

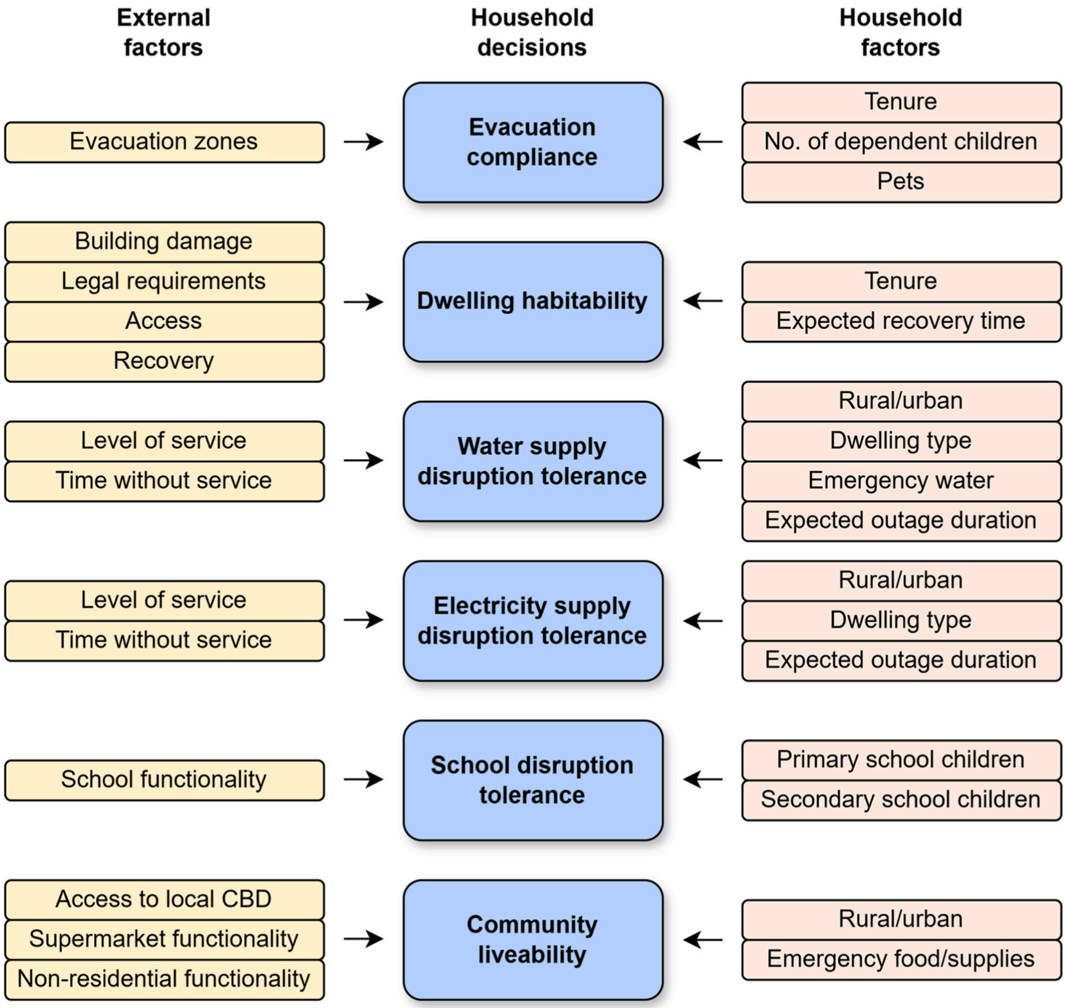

Fig. 2. Household decisions whether residents remain or relocate and the external and household factors that contribute to the decision-making.

estimated eruption probability is 33-42% within the next 50 years [91].

A suite of longitudinal, multi-phase eruption scenarios for Taranaki Mounga[1] were developed by Weir et al. [26] through a partnership between scientists and emergency management practitioners. The eruption scenarios vary in eruptive magnitude, style, duration and associated hazard frequency/magnitude. The eruption scenarios are complemented by longitudinal physical and systemic volcanic impact scenarios [84]. 'Scenario Large 1 (L1)' was selected for use in this study, as it is currently being used operationally for risk reduction and response planning by emergency management agencies. Additionally, Scenario L1 has been further developed for studies in evacuation management [27], building damage, infrastructure interdependency and service disruption [29]. The body of work developed around Scenario L1 has been extensively reviewed and the fine-scale spatial and temporal data produced by these studies are ideal model inputs for STORM.

Scenario L1, in this application, runs for 183 days and covers two major phases of volcanic activity across 143 days (directly from Weir et al. [26] and an additional 40 days of escalating 'volcanic unrest' preceding the first eruption [29]. The pre-eruption period consists of precursory volcanic activity (including seismicity and deformation, Days 25-40) and associated risk management actions, such as pre-emptive infrastructure shutdown, evacuation management and enhanced monitoring. The timeline of volcanic activity is shown in Fig. 4, additionally displaying periods of mandatory evacuation [27] that are further described in Section 5.2. The cumulative extents of ashfall and lahar deposits at the end of each eruptive phase are shown in Fig. 5.

The first eruptive phase begins with a major eruption on Day 40, followed by continuous minor eruptive activity through to Day 68, with ashfall deposited throughout the eruptive phase, primarily towards the east (Fig. 5). Lahars occur on Day 50 due to heavy rainfall remobilising volcanic material, covering extensive rural areas and impacting the towns of Stratford, Eltham, Inglewood, Midhirst and

[1] The term Mounga is the Māori language term for mountain, mount or peak, and is a local variation of the more commonly used Maunga.

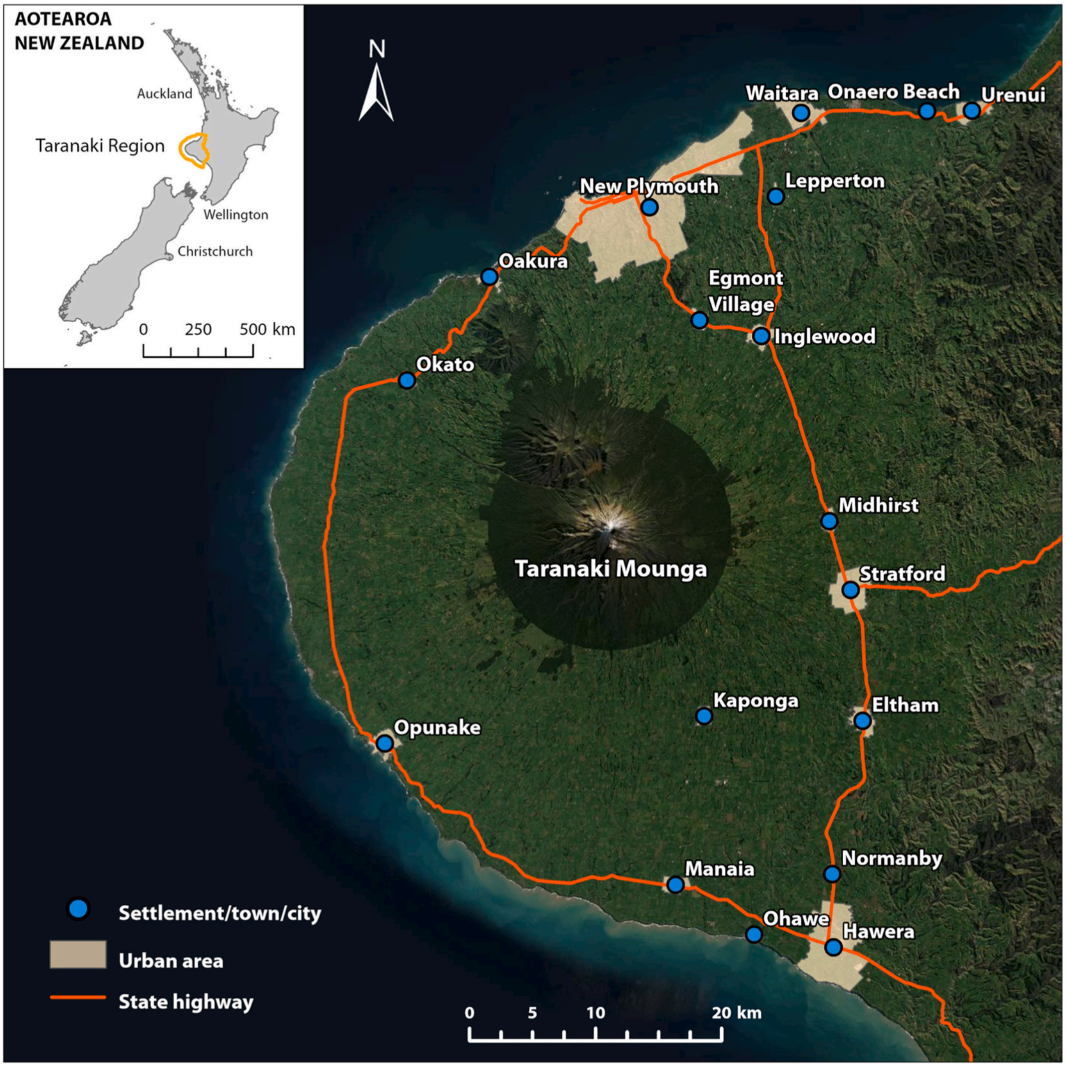

Fig. 3. The primary study area of the Taranaki Region with Taranaki Mounga summit at the centre, showing urban areas and the state highway network. Dark green areas around Taranaki Mounga represent the national park extent (Te Papakura o Taranaki).

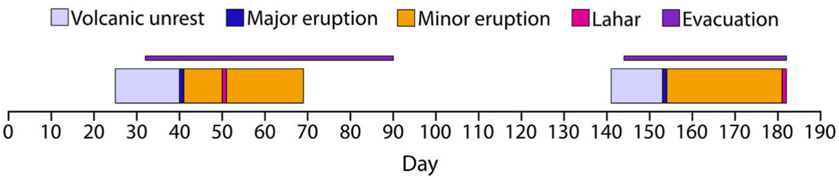

Fig. 4. Timeline of eruptive phases and evacuation of populated areas. Volcanic eruptive activity phases are from Weir et al. [26], precursory volcanic unrest from Weir et al. [29] and evacuation zones from Coultas [27].

Kaponga. A quiescent period begins on Day 69 until volcanic unrest resumes on Day 141, leading to the second eruptive phase beginning with a major eruption on Day 154. Continuous minor eruptive activity and ashfall continues through to Day 182, with ashfall primarily deposited towards the north-east. Lahars on Day 182 radiate downslope from Taranaki Mounga in many directions, inundating rural areas and reaching the towns of Ingelwood, Egmont Village, Okato and parts of the city of New Plymouth.

Ashfall and lahars constitute the main volcanic hazards impacting rural and urban areas beyond the national park (Fig. 5), and constitute the two hazards modelled for direct damage to infrastructure and buildings (Section 5). Additionally, pyroclastic density currents (PDCs) are associated with the two major eruptions, and block-and-ash pyroclastic flows occasionally occur throughout the periods of minor eruptive activity. The PDCs in Weir et al. [26] are constrained by the national park and therefore do not provoke

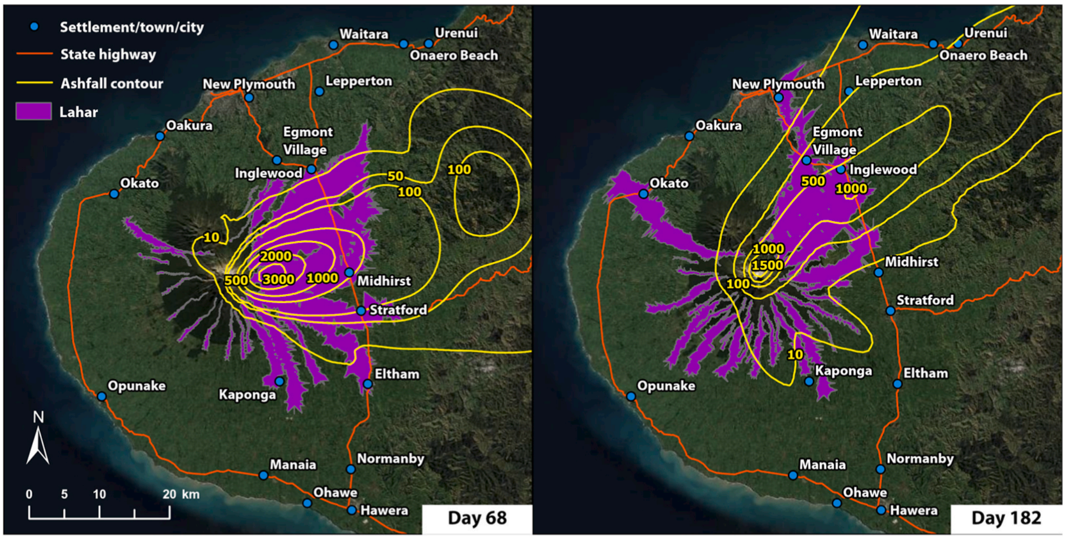

Fig. 5. Cumulative ashfall and lahar deposits on Day 68 (left) and Day 182 (right), representing the extent of hazards directly impacting populated areas for the two main phases of volcanic activity respectively (hazard data from Weir et al.

substantial direct impacts to communities and infrastructure [84]. However, indirect impacts (such as evacuation disruptions, national park closures and contribution to volcanic lahars) are significant. Debris avalanches are thought to coincide with the opening or closing phases of volcanism at Taranaki Mounga [92], yet current edifice conditions are thought to be stable [90]. As in Weir et al. [26], debris avalanches are not considered in Scenario L1, as they are unprecedented events that exceed regional capacity to respond.

The eruption scenario considered within this study is limited to the extent of Taranaki Region (Figs. 4 and 5) where the highest intensity of volcanic hazards occur, although ashfall is modelled to extend beyond the region [26] and societal impacts are also likely to be experienced nationwide, albeit mostly indirectly such as disruption to oil, gas and dairy supplies [84].

In this study, the following assumptions were made within the scenario. Areas impacted by lahars are rendered uninhabitable throughout the scenario timeframe and no building recovery takes place. In contrast, ashfall is cleaned up between the two main eruptive phases allowing building recovery to occur. Communications are assumed to be available throughout the scenario.

5. Household decision-making

5.1. Household agents

Households are the central agent within STORM for decision-making by considering external factors and household characteristics. Households are assumed to make decisions collectively, with all members remaining, relocating, or returning. This section describes the household attributes, with the following sections detailing the influence on decision-making.

A synthetic population model forms the household agents, consisting of households with attributes of composition, tenure, income, number of individuals and number of dependent children. The development of the population model is described in Scheele et al. [82], created using customised tables of 2018 Census data at SA2 level for households. The attributes are correlated, enabling the creation of a population model that reflects the number of households with each combination of attributes by SA2. The dependent children attribute was not available through the customised census data, and was subsequently estimated for household compositions that specify the presence of children by assigning the number of children based on the total number of individuals within a household (e.g. a household of five individuals specified as “couple with child(ren)” would have three dependent children). Households were randomly distributed to residential buildings within the building inventory [83] that are within the same SA2, and assigned based on the number of residential units within each building (e.g. single-family dwellings are one unit, whereas apartment buildings have multiple units). In A-NZ, there are not strong associations between household size and dwelling size, or income and dwelling structural vulnerability, are not strongly associated. Demographics are largely accurate at the SA2 level, although the specific locations of households are not possible to identify due to confidentiality requirements of the census.

Further to the attributes contained within the synthetic population model, additional attributes were added for the present case study (Table 2). Dependent children (aged under 18 years) were randomly assigned as either a primary or secondary school student (or neither) based on the proportions of school years for each group. Primary school designation includes the first eight years of schooling (ages approximately five through twelve), and secondary school designation is five years (ages approximately thirteen through

Table 2
Attributes of household agents within the ABM.

Household attribute	Source	Description
Composition	Population model	Composition e.g. couple with child(ren), single person living alone
Tenure	Population model	Home ownership or renting
Income	Population model	Total household income
Number of individuals	Population model	Total residents including children
Number of dependent children	Population model	Dependent children aged under 18 years
Primary/secondary school children	ABM (GAMA)	Dependent children assigned as primary or secondary school students, or neither.
Rural/urban	Stats NZ	Urban/rural geographic delineation
Municipal water connection	Weir [93]	Binary value indicating whether household has mains water supply or private water supply
Pets	Companion Animals NZ survey	Presence of pets within household
Emergency water	NEMA survey	Emergency water supply for 3 or 7 days
Emergency supplies	NEMA survey	Emergency supplies (e.g. food, batteries) for 3 or 7 days
Disability	NEMA survey	Presence of at least one household member with disability that may experience difficulty in a disaster

eighteen). A uniform distribution of individual age was assumed. The expected proportion of children under the age of five are not assigned to a school type.

Households are assigned as either rural or urban based on geographic location within Stats NZ 'Urban Rural 2023' boundaries.[2] Whether a household is connected to municipal water supply is based on water supply catchment areas for Taranaki developed by Weir [93], with households outside the catchment areas assumed to have their own private water supply (e.g. rainwater or groundwater bores). Whether a household has pets is randomly assigned based on weightings for household income as per a survey conducted by Companion Animals New Zealand [94], with higher income households more likely to have pets. Raw data from the 2023 National Emergency Management Agency (NEMA) annual preparedness survey was used to randomly assign whether a household has three days of emergency water or emergency supplies (e.g. food, batteries), or whether at least one member of the household has a disability which might affect their ability to get through a disaster (e.g. mobility difficulties, visual impairment, reliance on electricity for medical devices). Assignment is based on differing probabilities determined by whether a household is rural or urban, and renting or owning (Table 3). Rural or owned households are more likely to have emergency water and supplies than urban or renting households. The probability of disability within a household shows only minor variance. The NEMA survey questions ask if all members of the household have water or supplies sufficient for three days. Within the model, it is assumed that if a household has water or supplies for three days, there is a 0.5 probability of having water or supplies for seven days.

5.2. *Evacuation*

Evacuation zones aligned with Scenario L1 [26] were developed in partnership with Taranaki Emergency Management Office (TEMO) by Coultas [27]. The evacuation zones incorporate volcanic hazards and impacts to the built environment including critical infrastructure, and balance mitigating life safety risk while limiting societal disruption. The extent of the evacuation zones varies across the scenario (Fig. 6), beginning at Day 26 with the national park evacuated and pre-emptively responding to ashfall and lahar risks and impacts as they arise. The study by Coultas [27] only considers evacuation up until Day 135 of the scenario, therefore alternative evacuation zones were considered in consultation with Coultas. Evacuation zones approximating the hazard extent and timings of volcanic activity were reused for Days 136 – 178. The evacuation zone for Days 179 – 182 approximates the extent of the lahar deposit on Day 182 of the scenario (Fig. 5), and was developed through expert elicitation in partnership with TEMO as part of earlier, unpublished work related to the use of Scenario L1 [26] by TEMO.

Households within evacuation zones decide whether to comply with the evacuation order. Considerable variation in evacuation order compliance has been recorded through studies of previous natural hazard events, reflecting the complexity of factors for resident decision-making. The purpose of this model component is to capture the variation in evacuation compliance considering the most frequently cited household characteristics available within the model input data that influence decision-making whether to stay or go. Few studies have examined evacuation decision-making for volcanic events in developed country contexts, although many studies have examined evacuations during hurricanes in the US, an event type that shares similarities with volcanic activity due to the potential for a warning period prior to potential impacts. Two systematic review papers [46,48] were used to inform the household attributes influencing evacuation compliance within the current model. Across the multitude of variables examined in the reviews, the presence of children, pets, and home ownership were attributes available within the current model showing significant influence on evacuation compliance.

The base probability of evacuation compliance (*EC*) is assumed to be 0.85 based on expert judgment, with modifiers applied as follows:

[2] Sourced from the Stats NZ Geographic Data Service and licensed for reuse under the CC BY 4.0 licence.

Table 3
Probabilities of a household having three days of emergency water or emergency supplies, or a resident with a disability, based on demographics. Sourced from the 2023 NEMA annual preparedness survey.

Demographic	Has emergency water	Has emergency supplies	Disability in household
Rural & own home	0.47	0.79	0.18
Rural & renting	0.22	0.59	0.21
Urban & own home	0.34	0.73	0.16
Urban & renting	0.21	0.52	0.17

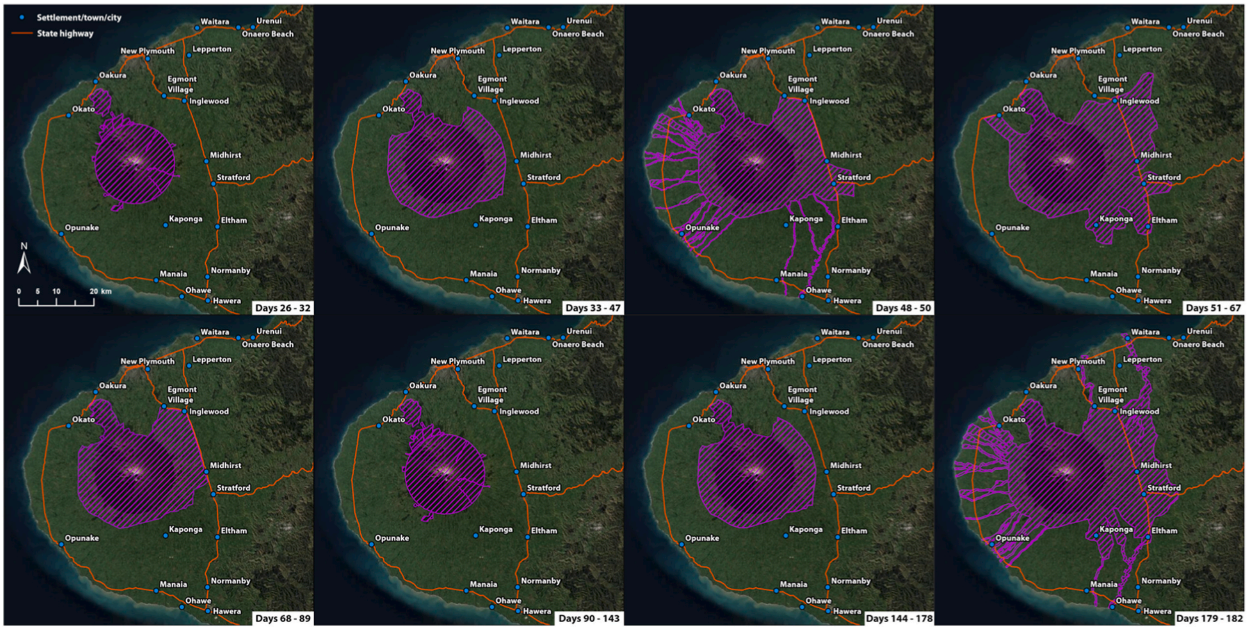

Fig. 6. Evacuation zones per time period (data from Coultas [27]).

$$P_{EC} = 0.85 + \begin{cases} 0.05 \; if > 0 \; children \\ 0.05 \; if > 2 \; children \\ -0.05 \; if \; own \; home \\ -0.05 \; if \; has \; pets \end{cases} \tag{1}$$

The presence of children in a household increases the probability of evacuation compliance, especially for larger families [48]. Home ownership [46,48] and the presence of pets [48] decreases the likelihood of choosing to leave during evacuation orders. Multiple modifiers may apply for a given household and are additive (including the modifiers relating to children). The strengths of the modifiers are assumed, due to a lack of specific detail available through the literature.

5.3. Building damage, habitability and functionality

Building agents are represented within the model as outlines containing essential attributes including construction type, age, use category, number of storeys and the number of residential and non-residential units. The data covers the majority of buildings within Taranaki Region and is sourced from a national building inventory dataset described in Scheele et al. [83]. Attributes are derived from point data aligned with addresses[1] originally collected for rating valuations, and assigned to building outlines[3] via a series of merging rules considering property parcel boundaries[1] and building outline shape area. Modifications to the national inventory were made for Taranaki to better identify residential dwellings in rural areas, where the source data are poor. Where the use category attribute was 'farm' and the number of residential units was one or more, property parcels containing one or more building outlines were identified and building outlines reclassified as residential given the number of residential units.

Supermarkets and schools are subspecies of the building agent, with the use category identified via the building outlines dataset directly, rather than the national building inventory. This method allows for collections of buildings (particularly common for schools) to be identified as a single facility, for use in household decision-making described in Sections 5.5 and 5.6.

[3] Sourced from the LINZ Data Service and licensed for reuse under the CC BY 4.0 licence.

Building impacts are analysed in the RiskScape modelling tool [95] using multi-phase, multi-hazard vulnerability functions [29] modified from Maqsood et al. [96]. The functions from Maqsood et al. [96] output a damage ratio (loss versus replacement cost), which was then matched to a damage state (*DS*) following the approach in Deligne et al. [97]. Lahars were assumed to induce a binary damage relationship, where lahar exposure results in complete damage (*DS* 5), and no exposure leaves the building entirely intact (*DS* 0; bar any impact from cumulative ashfall). Damage states were assessed for each eruptive phase of Scenario L1 [29].

Residential buildings, in which households reside, are assessed for the probability of structural uninhabitability (*UH*; unsafe to occupy) based on damage state:

$$P_{UH} = \begin{cases} 1.0 \ if \ DS \geq 4 \\ 0.65 \ if \ DS = 3 \\ 0.35 \ if \ DS = 2 \\ 0.0 \ if \ DS \leq 1 \end{cases} \tag{2}$$

The probabilities of uninhabitability for moderate (*DS* 2) or major (*DS* 3) damage states represent pragmatic assessments of habitability by residents, where some households would deem a dwelling habitable whereas others would not. This is in contrast to legal definitions where dwellings may be assessed by authorities as restricted access under the Building Act 2004 or the Civil Defence Emergency Management Act 2002 (if a state of emergency is declared). The effect of the stricter legal definition on residential dwellings on model outcomes is examined in Section 7. Non-residential buildings are assessed for functionality based on damage state assuming the legal definition, where $DS \geq 2$ represents a loss of functionality, which is a lower threshold than residential buildings due to heightened safety requirements for buildings the public may access. Lightly damaged buildings (*DS* 1) do not represent a loss of habitability or functionality.

Households within uninhabitable dwellings will relocate to alternative accommodation and potentially return once repairs are completed, following the decision-making process described in Section 5.7. Non-residential building functionality influences household decision-making regarding school functionality (Section 5.5) and community liveability (Section 5.6).

Recovery of habitability and functionality over time is evaluated for buildings in *DS* 2 or *DS* 3. Buildings that are $DS \geq 4$ are deemed unrepairable within the timeframe of the scenario, and are commonly within lahar-affected zones which represent an ongoing risk to life, indicating that repair or reconstruction may or may not occur in the future. Repair time (*RT*) is randomly selected between one day and a maximum, accounting for the different damage characteristics within each damage state. For all buildings except schools and supermarkets, the maximum *RT* is 90 days for *DS* 2 and 180 days for *DS* 3. Schools and supermarkets have maximum RT of 30 days for *DS* 2 and 90 days for *DS* 3. Although other important non-residential buildings would also be targeted for expedited repair (e.g., medical facilities, fire stations), these are not identified within the model and are therefore treated as standard non-residential buildings. The repair times presented here are assumptions given a lack of empirical data on building recovery for ashfall on the New Zealand building stock. The assumptions are partially based on reported and modelled ashfall clean-up times for communities affected by the 2015 eruption of Calbuco volcano, Chile [98], and account for variance in delays before repairs are undertaken.

Repair of buildings will only take place in locations where no mandatory evacuation is in place and where road access within the region is available. If a building is undergoing repair and access is lost, repair will be paused until allowable conditions are restored. Further, if subsequent hazard events result in an increased damage state, the repair time is reset.

5.4. Utility service outages

Direct impacts to critical infrastructure were modelled by Weir et al. [84], along with indirect disruptions to interdependent infrastructure sectors using a systemic vulnerability tool developed by Weir et al. [99]. Daily component and network functionality were estimated by applying recovery assumptions co-produced with infrastructure and emergency management sectors in the Taranaki Region [28,29]. The resultant level of service for electricity and potable water is binary (available or unavailable) and is evaluated each day per SA1.

Household tolerance to utility service outages varies over time [39,42], is affected by levels of preparedness and ability to adapt [41,100], and outages typically have different impacts for urban versus rural residents [101–103]. This model component is intended to capture the diverse circumstances experienced by households across the case study region. If a household decides either electricity or water service disruption is intolerable, the household will relocate. Specific adaptations other than emergency water supplies are not included in the model, but are implicitly accounted for through varying household tolerance over time and due to household characteristics. The components for evaluating household decision-making are shown in Fig. 7.

The probability of household intolerance to utility outages (*OT*) is calculated as:

$$P_{OT} = UH - ED - UR \tag{3}$$

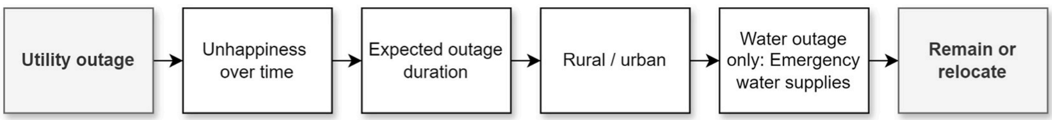

Fig. 7. Components of household decision-making whether to remain or relocate due to utility outages.

Where *UH* is the value for unhappiness, *ED* is the value for expected outage duration and *UR* is the value for rural characteristics. The values of each equation variable are shown in Table 4Error! Reference source not found. Unhappiness is the base value for the probability of a household deciding to relocate, with expected outage duration and rural characteristics as potential modifiers that reduce the probability. Unhappiness is based on the application of functions developed by Stock et al. [42] where the probability of a household being within a state of unhappiness (from happy to extremely unhappy) is evaluated each day. For each unhappiness state, an associated probability of deciding to relocate is applied, loosely based on the analysis by Abbou et al. [39] who observed that relocation is a potential adaptive behaviour for a utility outage, that the desire to relocate increases over time, and that households are more likely to relocate during water supply outages than electricity outages. Expected outage duration is taken as the number of days before service is restored, based on the assumption that a rough estimate of the length of outages would be known to households. Shorter expected outages reduce the probability that households will relocate.

Rural households are categorised as either 'lifestyle' (primarily residential properties smaller than a farm) or typical rural households where farming is the primary income source, as per the building inventory [83]. Lifestyle properties may or may not have their own water supply and residents tend to be more reliant on external assistance in disasters compared to farming households [104], although may have more adaptive capacity (e.g. alternative water supplies) than urban residents, and are therefore assumed to be less likely to relocate than urban residents. Rural farming households are assumed to remain regardless of electricity or water outages due to greater potential for adaptation and ties to their properties (e.g. to care for livestock).

Households in urban areas are on municipal water supplies, as are some rural areas of Taranaki. For water outages, the possession of emergency water supplies (for either three or seven days) is assumed to allow residents to remain until the supplies are exhausted, wherein the calculation of Equation (3) applies.

5.5. School disruption tolerance

For households with school-age children, the closure of school facilities may be a reason for the household to relocate due to the importance of maintaining continuity of education [105] and other household routines (e.g. parents able to go to work). This phenomenon was observed in Christchurch following the 2010-2011 Canterbury earthquake sequence, where some households moved to areas with functional schooling from areas with otherwise limited direct impacts to dwellings [106].

For households with primary and/or secondary school aged children, the nearest school of the respective type is checked for functionality each day of the simulation. If the respective school is non-functional, households with primary school aged children have a probability of 0.5 to relocate, and those with secondary school aged children a probability of 0.25. These values assume that secondary school students are better able to continue education than primary school students, at least temporarily (e.g. due to greater independence, and via online learning). While the importance of schooling to households and communities post-disaster is documented [105], detailed studies into school closures as a factor in household decision-making for relocation are unavailable.

5.6. Community disruption

The liveability of a household's local community refers to the ability of residents to maintain routines such as obtaining supplies, going to work, utilising services, maintaining social connections and so on. Community disruption (a reduction in liveability), sometimes referred to as neighbourhood damage, is often cited as a driver of displacement or return decisions [2,5,107–109]. This model component consists of road access, damage to non-residential buildings, supermarket access and emergency supplies, as combined indicators of community liveability. The local community is defined as the urban area where a household is located, therefore rural households are not evaluated for this model component due to the assumption of reduced reliance on localised services compared to urban residents.

First, a liveability score (*LS*) is calculated for each urban household as follows:

$$LS = 1.0 - AC - SM - NF \tag{4}$$

Where *AC* is given a value of 0.5 if the local CBD is inaccessible by road for a household (described below), *SM* is given a value of 0.1 if

Table 4
Variables for calculating the probability of household intolerance to electricity and water outages.

Variable	Electricity outage	Water outage
Happy	0	0
Slightly unhappy	0.025	0.05
Moderately unhappy	0.05	0.1
Very unhappy	0.125	0.25
Extremely unhappy	0.25	0.5
Expected outage $\leq$7 days	−0.2	−0.2
Expected outage >7 days & $\leq$ 14 days	−0.1	−0.1
Expected outage >14 days & $\leq$ 30 days	−0.05	−0.05
Lifestyle property on own water supply	−0.1	−0.2
Lifestyle property on municipal water supply	−0.1	−0.1
Rural non-lifestyle property on own water supply	−1	−1

no supermarkets within a 10 km radius of a household are functional and the household does not have any remaining emergency supplies, and *NF* is the proportion of non-functional non-residential buildings within the local urban area. Each household evaluates whether they perceive the local community to have disrupted liveability if a random number drawn between 0.0 and 1.0 exceeds *LS*. Finally, for households that perceive the community to have disrupted liveability, there is a 0.2 probability that the household will choose to relocate. These values are assumptions that are intended to reflect the magnitude of community disruption and relative levels of household intolerance, though specific values and thresholds were not available through the literature.

The level of service for road access given ashfall, lahar and evacuation zones was modelled using RiskScape [95], as described in Weir et al. [84]. One-kilometre segments of road are evaluated for level of service from full service through limited access (e.g. for evacuation or emergency services only) to full road closure. For the purposes of the present study, road level of service is considered binary as accessible or inaccessible for resident usage. Access for residents is evaluated utilising the network of road segments at SA1 level per day. Each SA1 is assigned the location of the local CBD (nearest urban population centre, see Fig. 3), and network analysis is used to determine if an unobstructed route is available to the local CBD. Loss of road access may also lead to household isolation, however it is assumed that residents who wish to leave are able to do so, by their own means or via assistance from authorities, as experienced in past A-NZ disasters [110,111].

5.7. Relocation

Households that decide to leave their homes will relocate to alternative accommodation, temporarily or permanently. Residents will make choices of accommodation type, duration and area of relocation depending on their circumstances and needs. Consistently across many previous natural hazard events, displaced residents initially prefer to stay with family or friends if possible or commercial accommodation if their financial situation allows, with a minority utilising emergency shelters if no other options are available [65,66,107,112]. Residents displaced for longer periods may transition to other forms of temporary housing such as rental properties, motorhomes or portable cabins. The majority of displaced residents relocate locally, preferring to remain close to their original residence, although some relocate further afield [2,113]. Displaced residents commonly move between multiple alternative accommodation types for various durations, before either returning to their original homes or relocating permanently [5,106,113–115]. Demographic determinants for accommodation choice vary across contexts, although common observations are that households with higher socio-economic status have broader options, renters are more likely than homeowners to require emergency sheltering and are less likely to return to their original address, and household composition (e.g. presence of children or elderly) is associated with accommodation choices [65,66,107,112].

The process for evaluating household relocation decisions is shown in Error! Reference source not found. Whether circumstances are intolerable for a household is determined through the six decision conditions visualised in Fig. 2 and described in Sections 5.2-5.6. Alternative accommodation choices, durations and transitions are determined through stochastic implementation of an empirical relocation model detailed in Scheele [116]. The methodology of implementation within this case study is provided in the Appendix.

Households will seek alternative accommodation for the duration of intolerable circumstances at their original address, potentially

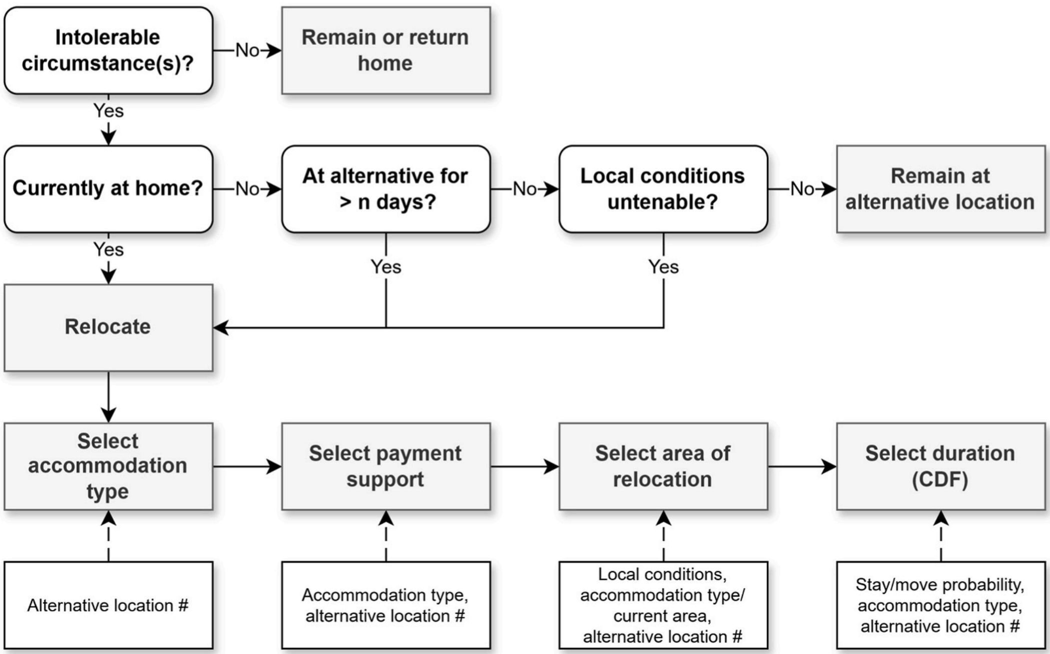

Fig. 8. Modelling process for evaluating household relocation decisions.

relocating multiple times during a period of displacement. If a household returns home after a period of displacement and intolerable circumstances resume, the household may be displaced a subsequent time, and the relocation process begins again. It is assumed that homeowners will seek to return to their homes once conditions allow, as will renters unless the dwelling is damaged with an expected repair time of greater than 60 days, in which case renters will permanently relocate as the tenancy may no longer be viable (tenancies may be legally ended by tenants or landlords in the situation of the property becoming uninhabitable; Residential Tenancies Act 1986). This assumption broadly reflects the general experience of renters compared to homeowners in past A-NZ events, including the 2010-2011 Canterbury earthquake sequence [116] and 2017 Edgecumbe flood [116,134], where renters were obliged to permanently relocate if a dwelling was significantly damaged and homeowners sought to return if conditions were tolerable.

5.8. Population scaling

Scaling of the population numbers in model outputs was applied to account for two main issues with the input data from the household population model. Firstly, approximately 7.5% of residents are missing who do not fit in 'households' as defined by Stats NZ, for example rest home residents, students in halls, or prison populations. Individuals who did not respond to the 2018 Census were counted via alternative administrative data but are not grouped within households. Secondly, the population of Taranaki grew by 7.2% from the 2018 Census to June 2023, which was the latest population estimate at SA2 geographies available from Stats NZ at the time of modelling. The aggregated ABM outputs are multiplied by the difference in population for the relevant SA2, averaging a 17.3% increase. Demographics of the missing residents are assumed to have the same proportions as existing households.

6. Results

The model outputs can be arranged and displayed in multiple ways depending on the intended purpose, with numerical outputs of either individuals or households as appropriate. The results presented here are a high-level regional overview. Detailed spatial and temporal outputs, including demographic information, are available from the online data repository.

The number of individuals displaced per day for each reason is shown in Fig. 9, along with the total number of displaced and the hazard phases for the scenario. Individuals may be displaced for multiple reasons. Displacement begins from Day 26 triggered by mandatory evacuation orders, rising from Day 40 as eruptive activity begins causing the first infrastructure outages and loss of dwelling habitability. Expansion of evacuation zones on Day 48 and the impacts from lahars on Day 50 cause a spike in displacement, rising to the first peak of 32,030 individuals displaced on Day 63 as intolerance to water and electricity outages grows. The progressive restoration of services in some areas, reduction of evacuation zones and cessation of eruptive activity contribute to residents returning to their homes, stabilising at approximately 16,440 individuals displaced during the middle period of volcanic quiescence (Days 69 – 140). The increased volcanic seismicity and deformation from Day 141 results in expanding evacuation zones and limits road access in some areas, causing some households to relocate. Further displacement occurs from Day 154 as a major eruption causes damage to the built environment and associated loss of services and access. Towards the end of the scenario, ongoing eruptive activity, evacuation zone expansion and lahars lead to a final peak displacement of 46,960 individuals. The number of people experiencing electricity and water outages shown in Fig. 10 relative to the individuals displaced due to outages in Fig. 9 demonstrates the tolerance of households to short outages, with displacement occurring as tolerance decreases over time. The relatively short period of volcanic quiescence and ongoing community disruption results in negligible recovery of uninhabitable dwellings before volcanic activity resumes.

The percentage of households displaced per day for each of the seven largest urban areas is shown in Fig. 11. Stratford, Inglewood and Eltham are on the eastern side of Taranaki Mounga and subject to direct hazard impacts, especially lahars, with the majority of households displaced beginning with the expanded evacuation zone on Day 48 and subsequent lahars on Day 50. Displacement in Hawera and Opunake is primarily driven by infrastructure outages during the first phase of volcanic activity, despite avoiding direct hazard impacts to the built environment. Household displacements in New Plymouth and Waitara are relatively modest as percentages of the populations of each urban area, and are driven by infrastructure outages. The percentage of displaced households is mapped by SA1 in Fig. 12 for Day 63, representing the first peak of displacement for the scenario. High percentages of household displacement are associated with the multiple disruptive aspects on the eastern side of Taranaki Mounga, whereas the moderate percentages of

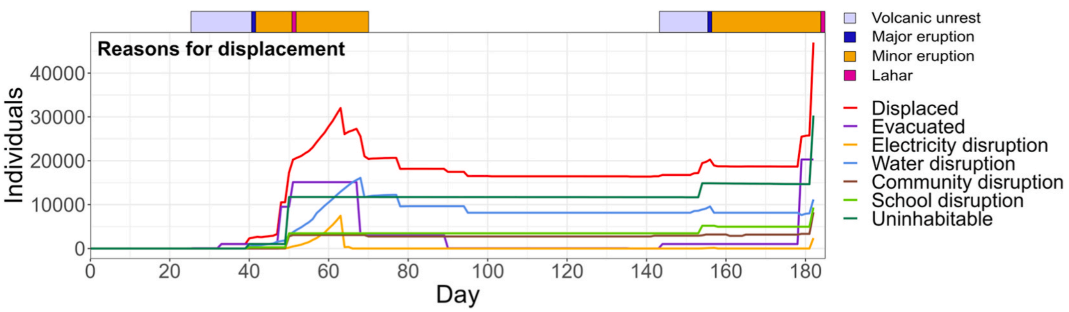

Fig. 9. The number of displaced individuals per day for each associated reason, including the total displaced (red line). Individuals may be displaced for multiple reasons. "Evacuated" refers to those displaced due to being within mandatory evacuation zones.

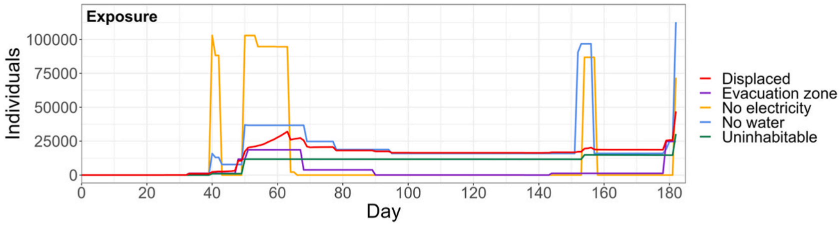

Fig. 10. The number of individuals per day within an evacuation zone, without electricity, without water, with uninhabitable homes, alongside the total displaced.

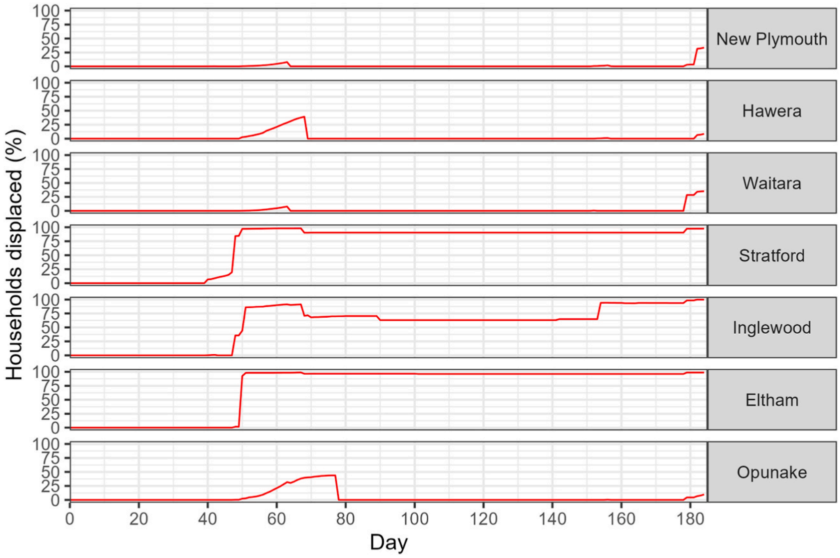

Fig. 11. The percentage of households displaced per day for the seven largest urban areas, in descending order.

displacement visible in western and southern coastal areas indicates the impact of infrastructure outages despite avoiding the direct effects of significant volcanic hazards.

The results of the relocation model for accommodation type and payment support requirements (Fig. 13), and area of relocation (Fig. 14), show the number of individuals in each category per day. Upon initial displacement, the majority of households relocate to friends or family, followed by commercial accommodation and emergency shelters. As displacement time progresses and some households move to other locations, increasing proportions secure rental properties, the number using commercial accommodation or temporary/portable accommodation becomes relatively stable, while the proportion staying with friends or family decreases over time but remains the largest group. The number of households requiring accommodation payment support approximately aligns with displacement numbers, although it is more common as displaced households transition beyond the initial alternative accommodation location. A high proportion of displaced residents move within the region, despite preferences to secure local accommodation close to their homes, due to many impacted communities lacking local accommodation options.

7. Model sensitivity

Sensitivity testing of numerical model parameters was undertaken to examine the relative influence of the assigned values. In general, these parameters determine the strength of household intolerance to adverse circumstances, or for expected outage times, the strength of mitigating circumstances. Each parameter is increased and decreased by 20% compared to the base value, as shown in Table 5. The conservative and strict habitability assessments represent alternatives to the default pragmatic habitability assessment of building damage, and therefore do not have an increase or decrease from the base. Similarly, the effect of using alternative preparedness data from the 2021 Stats NZ General Social Survey [117] is tested, with the probabilities of having 3 days of emergency water (*EW*) and 3 days of emergency supplies (*ES*) incorporated as per Equations (5) and (6) respectively. The results of the testing are shown via the tornado plot in Fig. 15, with the total number of displaced individuals as the response variable, averaged across all days in the scenario.

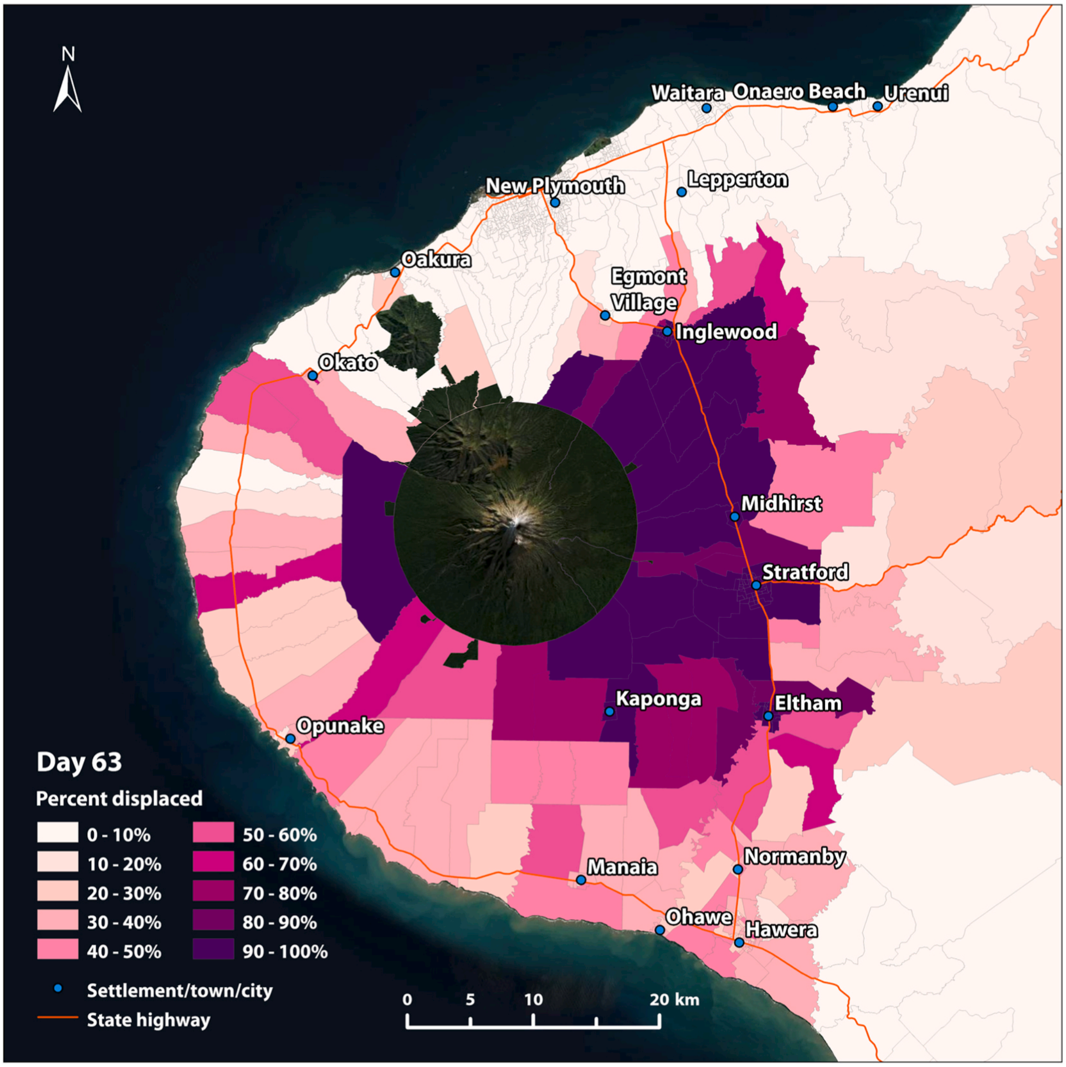

Fig. 12. Percentage of households displaced per SA1 on Day 63 of the scenario.

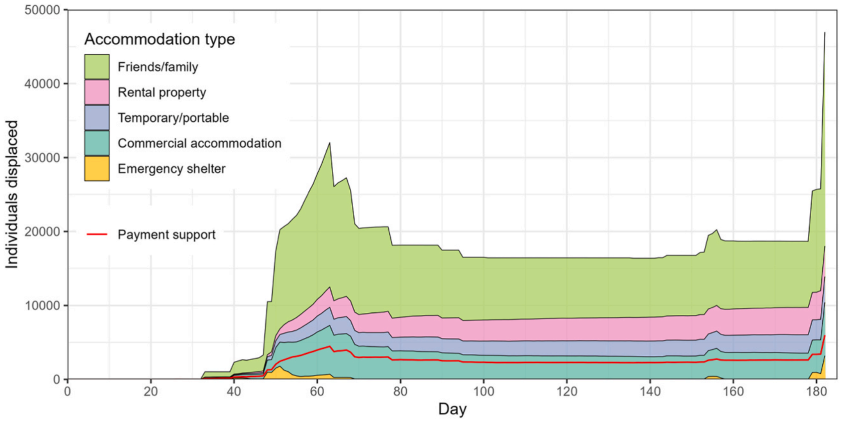

Fig. 13. Stacked chart of the number of individuals in each accommodation type per day, and the number requiring accommodation payment support (red line).

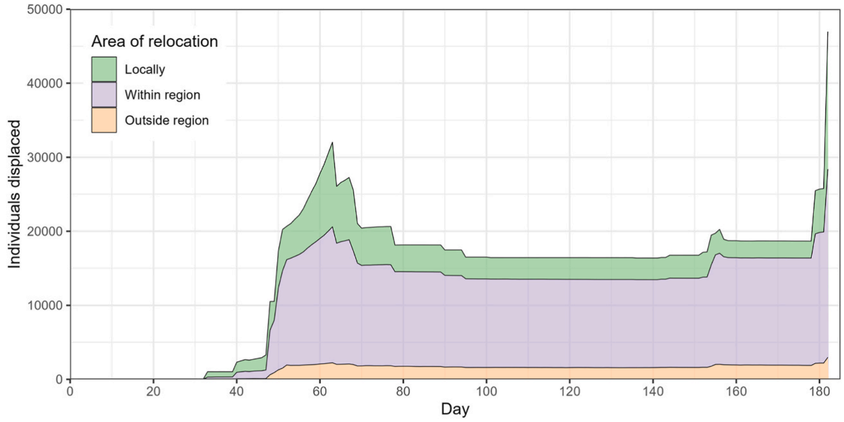

Fig. 14. Stacked chart of the number of individuals relocated locally, within the region, or outside the region per day.

Table 5
Numerical parameters of household intolerance to adverse circumstances or response to mitigating circumstances, showing the base value and decrease or increase by twenty percent. Conservative and strict habitability represent alternatives to pragmatic habitability intolerance.

Parameter		Decrease	Base	Increase
Evacuation compliance		0.68	0.85	1.02
Water outage intolerance	Extremely unhappy:	0.4	0.5	0.6
	Very unhappy:	0.2	0.25	0.3
	Moderately unhappy:	0.08	0.1	0.12
	Slightly unhappy:	0.04	0.05	0.06
Water expected outage time mitigation	≤7 days:	0.16	0.2	0.24
	≤14 days:	0.08	0.1	0.12
	≤30 days:	0.04	0.05	0.06
Electricity outage intolerance	Extremely unhappy:	0.2	0.25	0.3
	Very unhappy:	0.1	0.125	0.15
	Moderately unhappy:	0.04	0.05	0.06
	Slightly unhappy:	0.02	0.025	0.03
Electricity expected outage time mitigation	≤7 days:	0.16	0.2	0.24
	≤14 days:	0.08	0.1	0.12
	≤30 days:	0.04	0.05	0.06
Community disruption intolerance		0.16	0.2	0.24
Local CBD access disruption intolerance		0.4	0.5	0.6
School disruption intolerance	Primary:	0.4	0.5	0.6
	Secondary:	0.2	0.25	0.3
Pragmatic habitability intolerance (dwelling damage)	DS2:	0.28	0.35	0.42
	DS3:	0.52	0.65	0.78
Conservative habitability assessment intolerance	DS2:	-	0.5	-
	≥ DS3:		1	
Strict habitability assessment intolerance	≥ DS2:	-	1	-

$$P_{EW} = \begin{cases} 0.708 \text{ } \mathit{if} \text{ rural} \\ \mathit{else} \text{ } 0.516 \text{ } \mathit{if} \text{ own home} \\ \mathit{else} \text{ } 0.37 \end{cases} \tag{5}$$

$$P_{ES} = \begin{cases} 0.903 \text{ } \mathit{if} \text{ rural} \\ \mathit{else} \text{ } 0.872 \text{ } \mathit{if} \text{ own home} \\ \mathit{else} \text{ } 0.743 \end{cases} \tag{6}$$

The most sensitive parameter is water disruption intolerance, followed by evacuation compliance. Electricity, community and school disruption have a similar effect, slightly stronger for increases in intolerance parameters. Electricity and water expected outage time parameters have a minor effect, with the lower sensitivity for water indicative of the long outage times in some areas, beyond 30 days where the parameter is not employed. Alternative preparedness data [117] only results in a minor reduction in the mean number of individuals displaced, indicating that timeframes of disruption to water supply and access to supplies commonly exceed the household stores of emergency provisions. Habitability assessments are effectively only for ashfall impacts as dwellings exposed to lahar are always assumed to experience complete damage. Despite significant parameter differences between pragmatic, conservative and strict habitability assessments, the sensitivities are minor. The sensitivities of building damage recovery time parameters were tested, but are not plotted due to having negligible effects across the scenario, as repair times typically exceed the timeframe of

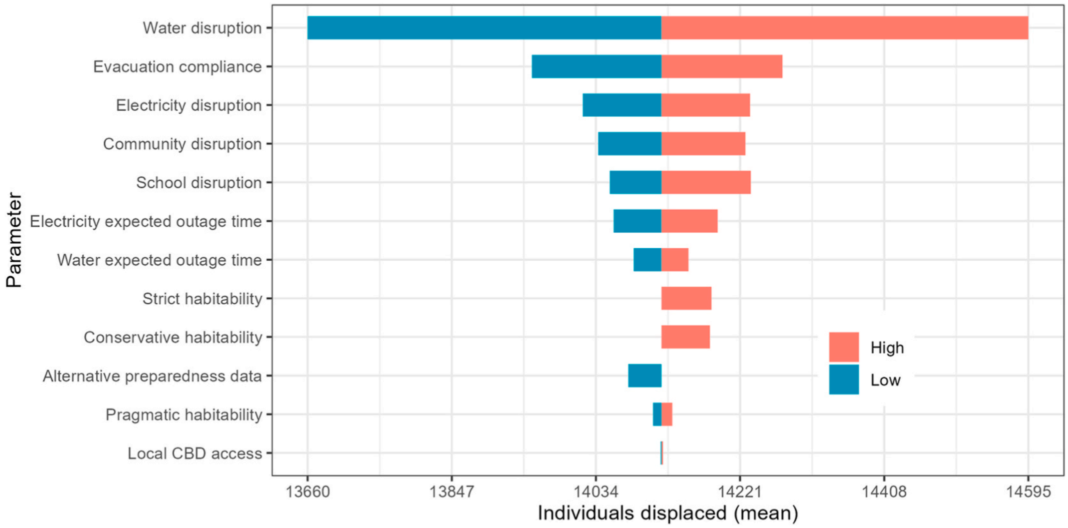

Fig. 15. Sensitivity testing of parameters with the mean number of individuals displaced across all days of the scenario as the response variable.

volcanic quiescence between eruptive activity and associated disruption. Notably, the sensitivity of each tested parameter reflects both the influence of the parameter itself and the characteristics of the scenario, with disruption from some aspects occurring across greater timespans or affecting a greater number of households.

8. Discussion

The agent-based model presented in this paper (STORM) unifies fine-scale spatial and temporal inputs to enable evaluation of household decision-making for individual household agents. Building on the established understanding of the primary factors influencing household displacement, each model component offers a new method for evaluating household decision-making given diverse circumstances, accounting for the adaptive capacity and tolerances of each household. The synthetic population model, coupled with the building inventory, is essential for representing the heterogeneity of individual household characteristics. It avoids the drawbacks of using aggregated data sources that do not properly account for the interdependent relationships between attributes, such as income, tenure, household composition, and dwelling location.

The model components incorporate logic intended to simulate the key drivers of household decision-making for each situation, informed by available literature and utilising influential attributes across the data inputs (e.g. demographics, building use category). Parameters of intolerance or mitigation (Table 5) are nevertheless based on expert judgment by the authors of this study, intended to be appropriately weighted relative to their importance in decision-making. The six household decision modules are largely independent, albeit with overlapping consideration of circumstances such as evacuation zones and building damage. The stochastic nature of each decision module means that each additional adverse situation affecting a household increases the probability of causing displacement. In reality, interdependencies between factors exist, such as workplace closure due to damage and loss of electricity impeding the ability to work from home as an alternative. Each model component could be further developed, although this would be best informed by further quantitative research into household decision-making given adverse circumstances. Of particular value are studies into resident adaptative behaviours during infrastructure outages, the points at which the adaptive capacity is exceeded causing displacement, and the overall impact of outages on societal functioning [39,41–43,100,118,119]. This is a nascent field of study [118] that is worthy of further investigation across multiple contexts and event types internationally.

In addition to new methods for assessing household decision-making for established drivers of displacement, STORM incorporates factors that are typically absent from population displacement models. Throughout this study, consideration of the differences between the responses of urban and rural households [101–103] is established in the modelling logic. These differences are important for regional scale case studies and should be given greater focus in future modelling efforts. School disruption may drive relocation, even where the household is otherwise minimally affected [106]. Where households relocate is important for understanding the socio-economic consequences of events and for estimating sheltering and housing demand, and impacts to the economy that can influence recovery policy. Implementation of the empirical relocation module [116] enables estimation of accommodation type, duration, payment support, and area of relocation of displaced residents, through the phases of emergency sheltering, temporary sheltering, temporary housing, and permanent housing [65,66,120]. Accommodation choice and area are coherent with studies from other natural hazard events causing population displacement [66,107,113,121], indicating the transferability of the developed functions to new contexts. The inclusion of duration at each alternative accommodation location throughout the period of displacement is the first known implementation of an empirical model explicitly considering this dynamic.

The six-month timeframe of the simulation explores the response and early recovery phases of a volcanic event with multiple hazards across time. Typically, previously published models have focused on quantifying the impacts of events with a single shock, such as for estimating emergency sheltering needs [76], or simulating the recovery period [122]. However, events can have prolonged phases of recurring hazards, including for volcanism of the style expected from Taranaki Mounga [26,30,89,123]. The consequences for households are evidenced by the Canterbury earthquake sequence where ongoing aftershocks represented a risk to life and the built environment, influencing population movement [106], raising risk perception of hazards [124,125] and delaying reconstruction efforts [126,127]. The model presented in this paper accounts for these aspects through the components of household decision-making across frequently changing circumstances.

Restoration of dwelling habitability and non-residential building functionality are incorporated into the model, but have a negligible effect on population displacement in the case study application, due to the ongoing disruption caused by volcanic activity that limits recovery of buildings. Evaluating the medium to long-term recovery trajectory of the Taranaki region would require further development of volcanic scenarios, along with modelling of economic and policy decision-making to frame the environment of housing recovery and population return. While beyond the scope of the current study, the agent-based model presented here is compatible with economic models such as MERIT [128], providing important inputs on housing impacts, community functionality and population movement to assist in evaluating long-term recovery.

Potentially influential decision-making factors that are not currently implemented in the model as explicit features include place attachment [129,130], workplace linkages [130], social connections [2,131], and risk perception [48,132]. Each of these factors are at least partially accounted for through the model components, for example place attachment is considered through demographics, workplace linkages and social connections are related to community liveability, and evacuation compliance may reflect risk perception. Further, households are assumed to make decisions collectively, whereas in some cases household members may remain or relocate separately. However, these factors are highly nuanced and require further research or input data. The modelling framework readily allows further component development, with the implementation of BDI architecture especially conducive to social interaction between agents [85,87].

Currently there is a lack of comprehensive empirical data and analysis on household decision-making during disruptive events sufficient for extensive model validation. Sensitivity testing allows for the influence of parameters to be assessed and adjusted if necessary. The model can be run through Monte Carlo simulation to determine the range of outcomes given the usage of stochastic variables. However, limited examination of several model runs showed variations in the total number of individuals displaced per day to be consistently constrained within two percent of the base values reported, likely explained by the large number of household agents substantially accounting for stochastic variations. Overall, estimating the impacts of future events is inherently uncertain, and ultimately the value of the model for emergency response and planning purposes is to highlight the heterogeneity of household and community responses that warrant tailored approaches for risk reduction and recovery.

While Māori communities are included within the modelling, specific consideration of Māori perspectives was beyond the scope of this study. The following quote from a Māori researcher expresses the need for future research. *"Whānau, hapū and iwi in Taranaki have long co-existed with eruptions of Taranaki Mounga, with pūrākau, waiata, and other forms of knowledge transmission describing adaptation and strategic relocation during events. There is also a long history of migrations of Māori communities in Taranaki driven by tribal warfare, land confiscation and broader colonial impacts offering important lessons for contemporary planning. While marae resilience initiatives are already underway, broader discussions around future relocation, evacuation, or migration—should these be required for some communities during future eruptions—as well as the processes by which such decisions might be made and enacted, are still emerging. Further Māori-led research is needed to explore these themes in ways that uphold tikanga in contemporary contexts and reflect the aspirations of whānau, hapū, and iwi"* (pers. comm., Kristie-Lee Thomas).

The results of the case study indicate that the societal impacts and population displacement in Scenario L1 would be a major challenge for emergency management and recovery. Electricity and water supply outages trigger a significant number of households to relocate during periods of volcanic activity, well in excess of those compelled to leave due to mandatory evacuation orders or direct damage. Prolonged displacement occurs due to direct building damage and water supply outages. Negligible restoration of damaged housing is possible within the period of volcanic quiescence, and parts of the water supply network are also unable to be restored within this timeframe [28,29]. While Scenario L1 only extends for six months, covering two phases of volcanic activity, Taranaki Mounga may remain intermittently active for years or decades [26]. In this situation, the societal structure of the region would be substantially altered.

9. Conclusions

The agent-based model presented in this paper (STORM) advances simulation of household decisions regarding whether to remain, relocate or return during and following disruptive natural hazard events. The benefits of fine-scale spatial and temporal inputs are demonstrated through application of the model to a robust multi-phase and multi-hazard volcanic eruption scenario affecting Taranaki Region, A-NZ, widely used preparedness and response planning by the emergency management sector. Household decisions are based on six evaluation components that consider mandatory evacuation zones, building damage, water supply outages, electricity outages, school disruption and community liveability. Incorporation of a synthetic population model coupled with a building inventory allows critical attributes to be combined at the household level, including demographics, dwelling type, and location. Therefore, the heterogeneity of household circumstances is accounted for and a nuanced view of the impacts to diverse communities is possible. Consideration is given to the differences between urban and rural households, with the latter typically lacking specific attention in previously published models simulating household displacement. The relocation module, simulating accommodation type, duration, and location based on empirical data provides estimates of the needs of displaced residents and indicates broad-scale population movement.

Utilising BDI modelling architecture enables the flexibility to modify or add components and provides an intuitive method for simulating household decision-making. With the STORM framework established, future work should focus on component development informed by quantitative research into household decision-making, such as through analysis of detailed empirical data on household behaviours gathered following natural hazard events.

The results of the modelling indicate that while direct damage and risk to life are primary drivers of household displacement, household impacts such as utility outages and community disruption are significant factors contributing to relocation. The ability to interrogate model outputs at the community level and through response and recovery periods improves the ability of decision-makers to plan and prepare for minimising societal impacts. This case study application of STORM provides a major contribution to global understanding of societal impacts and population displacement in regions exposed to volcanic hazards. The STORM framework can be readily adapted and applied to other scenarios internationally, with consideration of the local context of application.

CRediT authorship contribution statement

Finn Scheele: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Thomas Wilson:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Alana Weir:** Writing – review & editing, Methodology, Data curation. **Julia Becker:** Writing – review & editing, Supervision, Conceptualization. **Malcolm Campbell:** Writing – review & editing, Supervision, Conceptualization. **Nick Horspool:** Supervision, Methodology, Conceptualization. **Nam Bui:** Writing – review & editing, Methodology, Data curation.

Declaration of competing interest

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

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APPENDIX. EMPIRICAL RELOCATION MODEL

This section describes the implementation of an empirical relocation model developed by Scheele [116], linked with the framework for assessing household relocation (Fig. 8) introduced in Section 5.7. The relocation model was developed through analysis of survey data collected from households displaced following two flooding events in A-NZ (2017 Edgecumbe [134] and 2021 Westport [133] floods). The relocation model incorporates components of displacement outcomes that were similar between events and therefore may be generalisable to other scenarios, determined through statistical tests of variable association and strength of effect. The tests examined accommodation type, area of relocation, number of alternative accommodation locations, suitability, support requirements and duration against variables of household composition, household size, dependent children, ethnicity, tenure, household income, pets, insurance, mandatory evacuation, and inundation exposure. Demographics and the reasons for displacement (mandatory evacuation or inundation) were not found to have consistent associations with relocation outcomes. Significant associations were found for accommodation type and duration, accommodation type and payment support requirements, and area of relocation influenced the subsequent location following movement. The analysis results and relocation model broadly reflect observations across the international literature, except for the lack of evidence for demographic influence.

The relocation model accounts for the movement of displaced households between alternative accommodation locations, with different selection probabilities for each sequential location. At each location, displaced households either stay for the remainder of their displacement or move to a subsequent location after a period. The relocation model contains component selection probabilities for either three or four sequential locations, depending on the sample size of the empirical data informing each category. The probabilities for the last location are repeated for any subsequent relocations.

Households randomly select an accommodation type based on the probabilities in Table A.1. "Temporary/portable" represents miscellaneous accommodation types such as portable cabins, motorhomes, and garages. In the survey data informing the empirical relocation model, respondents who indicated they utilised emergency accommodation usually referred to short-term emergency shelters, or occasionally to other types of alternative accommodation (longer-term). As this distinction was not always clear within the survey data, the following logic has been applied for implementation of the empirical model in this study. If emergency accommodation is selected, within an initial displacement period of up to two weeks and when staying a location for seven days or less (see duration at location below), it is classified in STORM as "Emergency shelter". Households that stay in emergency accommodation for longer than one week are randomly assigned to "Commercial accommodation", "Rental property" or "Temporary/portable" based on the relative probabilities of these categories. These modifications reflect the survey data where specific durations and accommodation types (e.g. school halls, civil defence centres, motels) were specified by some respondents, in addition to ticking the category for emergency accommodation. No survey respondents indicated staying within a single emergency shelter for longer than seven days, although some moved between multiple shelters, utilising emergency shelters for a maximum duration of two weeks.

Table A.1
Probability of selecting each accommodation type by location.

Accommodation type	Location 1	Location 2	Location 3	Location 4+
Friends/family	0.706	0.468	0.316	0.25
Commercial accommodation	0.122	0.243	0.132	0.173
Emergency accommodation	0.133	0.081	0.184	0.212
Rental property	0.008	0.117	0.237	0.212
Temporary/portable	0.031	0.09	0.132	0.154

Households select whether accommodation payment support (government provided) is required via the probabilities listed in Table A.2, by accommodation type and location. Payment support excludes those staying in emergency shelters.

Table A.2
Probability of requiring payment support by accommodation type and location.

Accommodation type	Location 1	Location 2	Location 3+
Friends/family	0.12	0.122	0.182
Commercial accommodation	0.233	0.333	0.25
Emergency accommodation	0.92	0.556	0.571
Rental property	0	0.077	0
Temporary/portable	0	0	0.2

Area of relocation is selected based on accommodation type at the first location, and based on the current area for subsequent locations (Table A.3). Each cycle (day) in the simulation, a check is made whether local accommodation is a viable option. Within the local aggregation area (urban area or SA2), if $>$ 70% of households are evacuated or $>$ 70% are uninhabitable, it is assumed no alternative accommodation is available locally. Displaced households in this situation will relocate within or outside the region.

Table A.3
Probability of area of relocation by accommodation type for Location 1, and by current area for subsequent locations.

Location	Accommodation type/current area	Area of relocation		
		Locally	Within region	Outside region
Location 1	Friends/family	0.578	0.389	0.033
	Commercial accommodation	0.71	0.258	0.032
	Emergency accommodation	0.942	0.029	0.029
	Rental property	0.575	0.407	0.018
	Temporary/portable	0.819	0.078	0.103
Location 1 to Location 2	Locally	0.768	0.164	0.068
	Within region	0.229	0.742	0.029
	Outside region	0.631	0.342	0.027
Location 2 to Location 3	Locally	1.0	0.0	0.0
	Within region	0.181	0.712	0.108
	Outside region	0.611	0.236	0.153
Location 3+ to Location 4+	Locally	1.0	0.0	0.0
	Within region	0.0	0.9	0.1
	Outside region	0.184	0.806	0.01

The duration at each location is calculated in two steps. First, households decide whether to stay at a location until returning home, or move to a subsequent location after a period of time (Table A.4). For households that will move, the number of days before relocation is selected by random sampling of the cumulative distribution functions (CDFs) shown in Figures A.1-A.3. The CDFs are sampled by accommodation type preferentially, or “All types” if the selected accommodation type does not have a specific CDF for a given location (due to insufficient empirical data for some categories).

Table A.4
Probability of staying at a location until return or moving after a period of time, by location and accommodation type.

Accommodation type	Stay			Move		
	Location 1	Location 2	Location 3+	L1 - > L2	L2 - > L3	L3+ - > L4+
Friends/family	0.329	0.458	0.53	0.671	0.542	0.47
Commercial accommodation	0.429	0.312	0.31	0.571	0.688	0.69
Emergency accommodation	0.0	0.704	0.584	1.0	0.296	0.416
Rental property	1.0	0.727	0.811	0.0	0.273	0.189
Temporary/portable	0.418	0.892	0.685	0.582	0.108	0.315

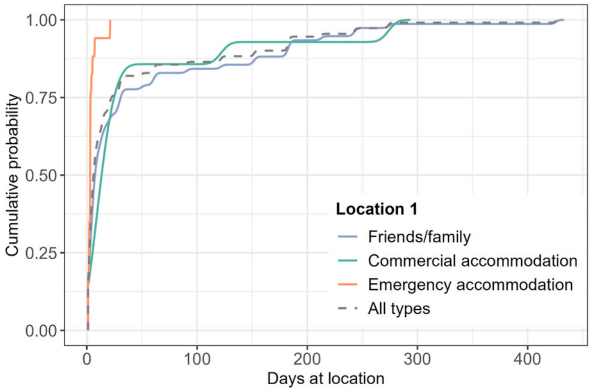

Fig. A.1. Cumulative probability of the number of days at Location 1 before relocation, by accommodation type.

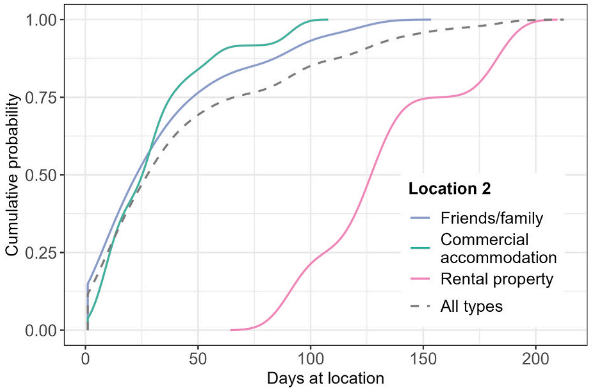

Fig. A.2. Cumulative probability of the number of days at Location 2 before relocation, by accommodation type.

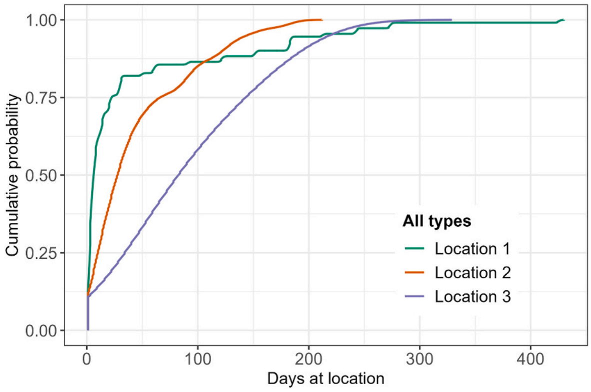

Fig. A.3. Cumulative probability of the number of days before relocation for all accommodation types (combined), at Locations 1-3.

Data availability

The model code and simulation output data are available from: https://data.mendeley.com/datasets/3gmfk8gmrs/1

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