A Spatial Agent-based Model for Volcanic Evacuation of Mt. Merapi

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The candidate confirms that the work submitted is his own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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Thesis by Alternative Format Rationale

This thesis is submitted as an alternative style of doctoral thesis including published material. This format is appropriate for the thesis because two out of the four chapters have already been published in peer-reviewed journals, one of them has been reviewed with invitation to be resubmitted and one article is in review. The four manuscripts are preceded by an introduction (Chapter 1), which includes a review of the literature to give context to the work, highlight the literature gaps, the objectives and the general methodology. A discussion and conclusion section follows the research articles in Chapter 6. This structure connects together the ideas of all four manuscripts, placing them in the context of the relevant literature and providing further critical analysis, and lastly conclude the overarching findings. The contributions of the research will also be highlighted here. This format adheres to the Faculty of Environment protocol for the format and presentation of an alternative style of doctoral thesis including published material.

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Abstract

Natural disasters, especially volcanic eruptions, are hazardous events that frequently happen in Indonesia. As a country within the “Ring of Fire”, Indonesia has hundreds of volcanoes and Mount Merapi is the most active. Historical studies of this volcano have revealed that there is potential for a major eruption in the future. Therefore, long-term disaster management is needed. To support the disaster management, physical and socially-based research has been carried out, but there is still a gap in the development of evacuation models. This modelling is necessary to evaluate the possibility of unexpected problems in the evacuation process since the hazard occurrences and the population behaviour are uncertain.

The aim of this research was to develop an agent-based model (ABM) of volcanic evacuation to improve the effectiveness of evacuation management in Merapi. Besides the potential use of the results locally in Merapi, the development process of this evacuation model contributes by advancing the knowledge of ABM development for large-scale evacuation simulation in other contexts. Its novelty lies in (1) integrating a hazard model derived from historical records of the spatial impact of eruptions, (2) formulating and validating an individual evacuation decision model in ABM based on various interrelated factors revealed from literature reviews and surveys that enable the modelling of reluctant people, (3) formulating the integration of multi-criteria evaluation (MCE) in ABM to model a spatio-temporal dynamic model of risk (STDMR) that enables representation of the changing of risk as a consequence of changing hazard level, hazard extent and movement of people, and (4) formulating an evacuation staging method based on MCE using geographic and demographic criteria.

The volcanic evacuation model represents the relationships between physical and human agents, consisting of the volcano, stakeholders, the population at risk and the environment. The experimentation of several evacuation scenarios in Merapi using the developed ABM of evacuation shows that simultaneous strategy is superior in reducing the risk, but the staged scenario is the most effective in minimising the potential of road traffic problems during evacuation events in Merapi. Staged evacuation can be a good option when there is enough time to evacuate. However, if the evacuation time is limited, the simultaneous strategy is better to be implemented. Appropriate traffic management should be prepared to avoid traffic problems when the second option is chosen.

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Chapter 1
Introduction

1.1 Background

Understanding volcanic risks is important in disaster risk reduction, because this is used to provide risk-oriented land use planning and ensure proper planning for disaster management (Zimmermann, 2005). Risk-oriented land use planning can be used efficiently to reduce volcanic risks by restricting hazardous living areas. However, particularly in Merapi, this is difficult in practice due to social, cultural and economic factors (Lavigne et al., 2008). In this area, people have been living for generations and so the Merapi environment is part of their life. The physical condition of the Merapi environment that is suitable for both farming and tourism, attracts people to live in this area, even though it is prone to volcanic disasters. More than 50,000 people have been identified as continuing to live in the dangerous zone of Merapi, even though they have experienced several eruptions (Mei et al., 2013). Moreover, many people have rejected the relocation policy, even though the volcanic eruption damaged their settlements in 2010 (Ayuningtyas, 2013; Nuzulia, 2014). Because applying land use planning is difficult in this case, stakeholders should provide the proper planning of disaster management to protect the lives of those at risk whenever disaster strikes. Evacuation is one important effort to save lives.

Establishing volcanic risk management is complicated. This is not only due to the complexity of the hazard but also the complexity of the population’s responses. The volcanic hazard model is difficult to develop precisely due to the complicated volcanic systems which are controlled by the interactions of many processes (Sparks, 2003). Meanwhile, the population’s responses are complex social processes that are influenced by the socio-economic characteristics of the population. The impacts vary because volcanoes commonly produce various form of hazardous material during eruptions, which is spread as ash, a pyroclastics density current (PDC), or lava flow (lahars) (Felpeto et al., 2007). It is also difficult to predict occurrences. Although the likelihood of events might be predicted based on the observation of physical phenomena, such as seismic activity, the exact event itself is commonly difficult to forecast accurately in terms of its timing, magnitude, the spatial extent of its impact, and who will be exposed to its effects.

In order to understand and minimise the risk, Merapi has been explored in extensive studies from various points of view and using different methods/approaches, but less attention has been paid to evacuation modelling to improve the plan. This research ranges across the physical and social/human elements of the case study area. Considering the activities, the lesson learnt from the 2010 event (Mei et al., 2013), and also the complexity of both volcanism and the social processes associated with the disaster in Merapi, it is clear that providing a model for evacuation planning is very important. It can be used to identify any weaknesses in the plan as well as evaluate the plan for improvement. As the goal of the plan is to save human lives from the volcanic impact, the effectiveness of the plan is evaluated by its ability to achieve this goal.

However, currently, there does not exist a method for measuring this effectiveness until the plan is tested by a real disaster. As a consequence, potential problems that might emerge during evacuation are difficult to detect – for instance, if there are insufficient transportation utilities to mobilize the population at risk. Losing time at this critical point might result in fatalities. There are many examples of emergency management failure due to unforeseen elements, such as in Merapi, Indonesia (Surono et al., 2012; Jenkins et al., 2013; Mei et al., 2013), El Chichón Volcano, Mexico (Tilling, 2009), and Kelut, Indonesia (De Bélizal et al., 2012). In 2010, the eruption magnitude of Merapi suddenly increased significantly compared to its level during the 20th century (Mei et al., 2013). Similarly, the unusual eruption behaviour of Kelut Volcano in 2007 caused misunderstandings between the authorities and the population during an emergency situation (De Bélizal et al., 2012) while, the eruption of El Chichón Volcano in Mexico in 1982 caused the deaths of about 2,000 people (Tilling, 2009).

Developing a computer simulation of the evacuation process is one approach that can help to evaluate an evacuation plan and potentially minimise such failures (De Silva and Eglese, 2000). In the case of volcanic evacuation, people can display highly variable and uncertain behaviour during emergency situations (Mas et al., 2012) that should be considered when developing simulations; therefore, this requires an appropriate model. On the other hand, the spatial dynamics of hazards need to be taken into account in the modelling. To do so, many related works on evacuation modelling and simulation successfully involve the spatial attributes that can be included in Geographic Information Systems (GIS), but pay less attention to human behaviour (Pidd et al., 1996; Cova and Church, 1997; Silva and Eglese, 2000; Church and Sexton, 2002; Uno and Kashiyama, 2008). The agent-based model (ABM) is considered an adequate approach not only for simulating the non-linearity of the social system but also for integrating the spatial variables into the simulation (Srbljinović and Škunca, 2003; Brown et al., 2005; Crooks and Castle, 2012; Malleson et al., 2014). The general aim of this thesis is to develop and evaluate an ABM of a volcanic evacuation to improve the effectiveness of evacuation management in Merapi.

1.2 Study Area

1.2.1 Overview of Merapi: Location and History

Mt. Merapi (Figure 1.1) is located at 110° 26.5' E, 7°32.5' S in Java Island, Indonesia. Merapi spans four regencies of two provinces including Sleman (Yogyakarta), Magelang, Boyolali and Klaten (Central Java). Those regencies are all densely inhabited, but Sleman is the most densely populated of all. Based on the latest data from Bureau of Statistics (BPS) the total population of Sleman is 1,180,479 (1,901 people/km^2), Magelang is 1,245,496 (1,123 people/km^2), Boyolali is 950,531 (912 people/km^2), and Klaten is 1,300,000 (1,768 people/km^2). Eruptive activities have been experienced by residents since Merapi was first settled.

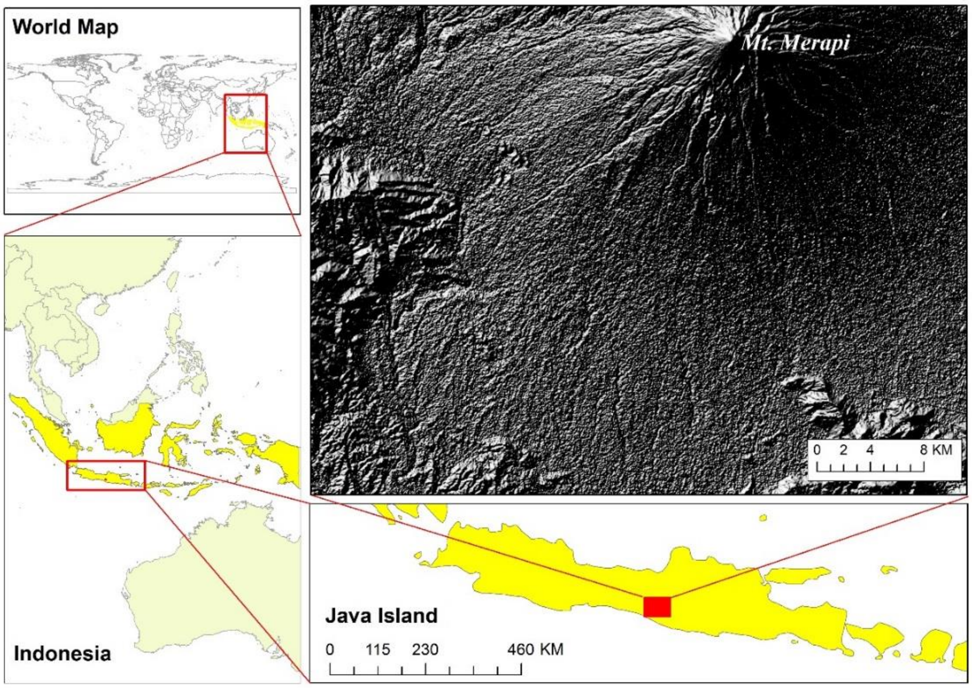

Figure 1.1 The location of Merapi volcano.

This volcano developed through several phases of geological processes. Newhall et al. (2000) explained the development phase of Mount Merapi from the formation and destruction of Proto-Merapi in detail. Merapi was formed from volcanic eruptions thousands of years ago with a peak shift following the initial development. The phases of development began with the establishment of *Gunung* (Mount/Hill) Gendol erosion located 20 km west-southwest of Merapi (Newhall et al., 2000) near *Gunung* Sari, *Gunung* Ukir and some other hills. Those hills were assessed by van Bemmelen (1949) as consisting of lava deposits from Old Merapi cone, collapsed into a hill due to gravity failure from the west side. Citing sources of archeology, van Bemmelen stated that the collapse of Merapi host occurred in 1006. However, more reliable evidence indicates that these hills are the eroded remnants of the pre-Merapi volcanic area.

The next phase was the formation of the Mountain and *Gunung* Turgo Plawangan which rose as high as 375 m above the pyroclastic deposits covering most of the south side of Merapi. The hills consist of variable weathered, mostly basaltic lava flows, and apparently a single mass that is now split by Kali Boyong. Some experts assume that these hills formed from the old Merapi. As an alternative interpretation, Newhall et al. (2000) suggest that these hills are the eroded remnants of the prominent initial cone of Merapi, referred to as "Proto-Merapi". The lava bedding direction is slightly to the north, toward modern Merapi, so that these hills may be a block that rotated slightly during the collapse due to gravity failure from the Proto-Merapi. The collapse of the Proto-Merapi due to gravity failure left steep slopes on both sides at the base of the structure. After that, Lava Batulawang, the deposits of an Old Merapi, was formed (van Bemmelen, 1949). Lava Batulawang, as lava of the top of Old Merapi, ranges from basalt to andesitic lava (Bahar, 1984). Lava forms most of the eastern and northern slopes of Merapi, also the Old Merapi. Another hill often referred to as part of the development of Merapi is *Gunung* Bibi: a small but conspicuous cone or dome-shaped hill, situated high on the northeast side of Old Merapi.

1.2.2 Eruptive Activities of Merapi

Merapi is one of the most active volcanoes in Indonesia with a long history of violent activities (Lavigne et al., 2000; Voight et al., 2000). The development of Merapi has been followed by a series of disasters as the human population in the vicinity of the volcano has grown. It is recorded that the eruption in 1006 AD had severe impacts on civilization of the Mataram Kingdom in Central Java (Newhall et al., 2000). The dangerous activities are likely to continue in the modern era as recorded in the following Table 1.1. This table shows that there are many casualties in most of the events, but the highest number of casualties was recorded for the 1930 eruption.

Moreover, Merapi has potential to erupt violently in the future; therefore, effective disaster management is needed. A study of two centuries of eruptive activities revealed that if the recurrence time of eruptions still applies in Merapi a large explosive event is possible in the future (Voight et al., 2000). As the population in the vicinity of Merapi is growing greatly, the recurrence of a big eruption can result in high casualties if not well managed. Therefore, it is important to provide an adequate disaster management plan to reduce destructive impacts. Evacuation management is part of the disaster management which is important in the emergency phase of a disaster. The research provided in this thesis can contribute to improving the evacuation management in Merapi.

Table 1.1 Records of eruption events of Merapi.

Eruption	Deaths	Injuries
1832	32	-
1872	200	-
1904	16	-
1920	35	-
1930	1369	-
1954	64	57
1961	6	-
1969	3	-
1976	29	2
1994	66	6
1997	-	-
1998	-	-
2001	-	-
2006	2	-
2010	354	240

Sources: (BNPB, 2010; BNPB, 2014).

1.2.3 2010 Eruption of Merapi

The most recent eruption (2010), recorded as the biggest eruption for a century, was surprisingly unpredicted (Surono et al., 2012). The eruptive activities at that time can be divided into five phases with respect to the dynamics of the hazard zone (Mei et al., 2013). The unusual activity of Merapi triggered the decision to increase the evacuation zone from a radius of 15 km to 20 km (Surono et al., 2011). The volcanic activities started to increase (low level) on 20 September 2010, reached the highest level between 25 October 2010 and 3 December 2010, peaking on 4 November (Figure 1.2), and decreased to a low level at 3 December 2010 (Mei et al., 2013).

Figure 1.2 The highest eruption on 4 November 2010 (source: tribunews.com).

This eruption not only resulted in extensive physical changes of Merapi but also a high number of casualties (Table 1.2). Physically, this eruption changed the geomorphological structure (Saepuloh et al., 2013) and geological character of Merapi (Gertisser et al., 2012) affecting the potential flow direction of pyroclastic or lahars flow (Figure 1.2). Consequently, this eruption has changed the spatial extent of the hazard map (compare Figure 1.2a and Figure 1.2b) (BNPB, 2008; BNPB, 2011). Therefore, it can be predicted that the southern flank of Merapi (area of Sleman) will experience more potential impact from the next eruption than was the case during previous events.

Table 1.2 Distribution of casualties and people at risk during eruption 2010.

No.	Location		Deaths			Injuries	Evacuee
			Burned	Not Burned	Total		
1	**Yogyakarta**		**190**	**62**	**252**	**98**	**34,113**
	1.1	Sleman	190	62	252	98	27,127
	1.2	KulonProgo					1,574
	1.3	KotaYogyakarta					1,142
	1.4	Bantul					1,961
	1.5	Gunungkidul					2,309
2	**Central Java**		**7**	**95**	**102**	**142**	**13,373**
	2.1	Klaten	7	29	36	30	3,909
	2.2	Boyolali		10	10	37	34
	2.3	MagelangRegency		56	56	75	8,971
	2.4	MagelangCity					28
	2.5	Temanggung					359
	2.6	SemarangRegency					72
		Total	**197**	**157**	**354**	**240**	**47,486**

Source: BNPB (BNPB, 2010)

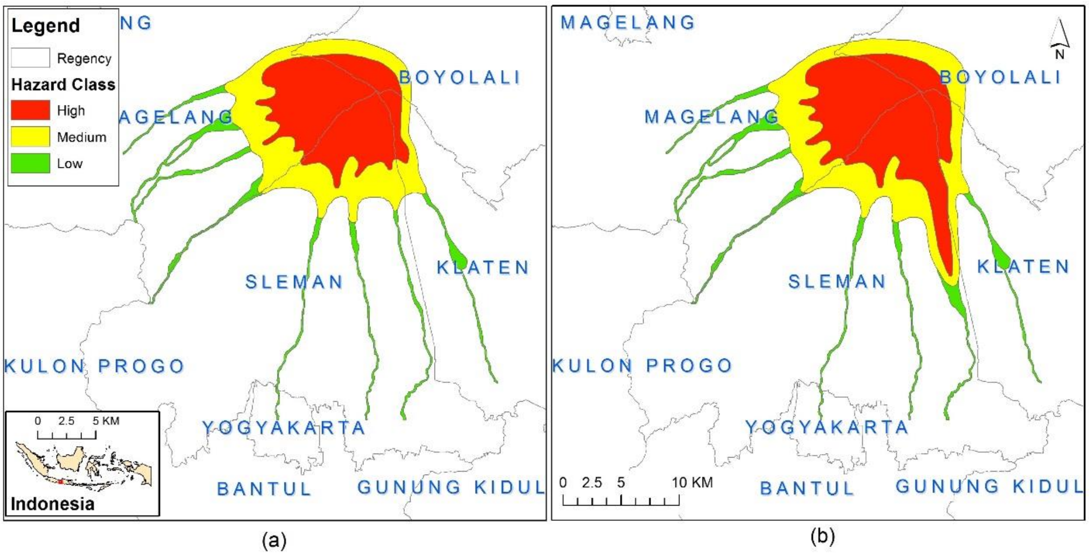

Figure 1.3 Hazard model. (a) Before 2010 eruption (updated 2002), (a) after 2010 eruption (updated 2011).

The eruption not only killed a high number of people but also destroyed the settlements in areas surrounding the volcano (Figure 1.4). It is estimated that 3,245 houses were damaged by the eruption (Juliani et al., 2011). The subsequent relocation strategy enacted by the government was needed both to replace these damaged settlement areas and to mitigate future volcanic disasters. The government built 2,132 houses to relocate people whose houses were destroyed by the eruption (Maly et al., 2015).

Figure 1.4 The example of remains of houses damaged by the 2010 eruption (source: author documentation).

1.2.4 Sleman Regency: Where the Population Meets the Hazardous Environment

This research will focus on the area of Sleman Regency which is located in the southern flank of Merapi (Figure 1.3) given this area's experience of the highest casualties in 2010 eruption (Table 1.2) and the likely potential direction of a future hazard. This area is administratively part of Yogyakarta Special Province, part of Java Island of Indonesia. Sleman is geographically located between 107° 15' 03'' and 107° 29' 30'' longitude, 7° 34' 51'' and 7° 47' 30'' latitude. Sleman covers 57,482 hectares or 574.82 km^2 or about

18% of Yogyakarta Province area. Administratively, this region consists of 17 districts, 86 villages and 1,212 hamlets with a total population of about 1,066,673 people in 2010 (BPS, 2015).

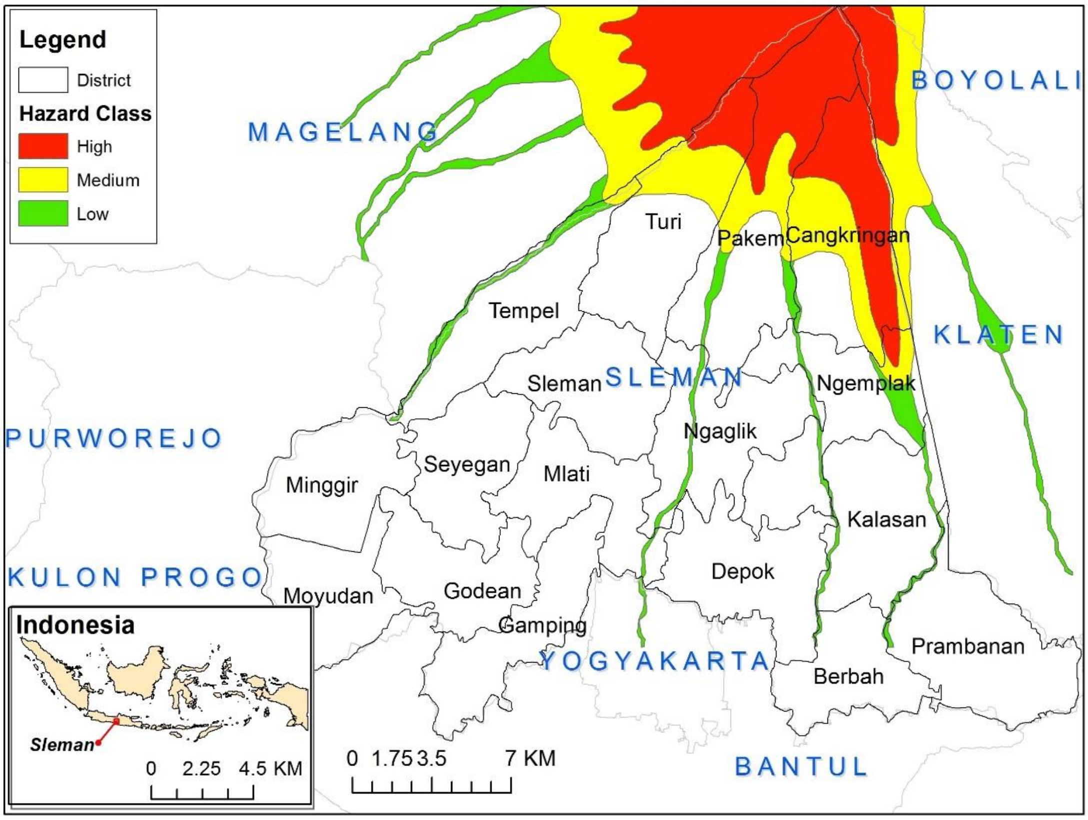

Figure 1.5 The area of Yogyakarta Special Province (DIY) superimposed with hazard map.

1.3 Literature Review

This section provides an overview of the background concept of the research and is organized as follows: the first part is a conceptual description of disaster management is presented to provide a broader perspective of these activities and position the roles related to evacuation in disaster management. Next comes a focus on evacuation planning and the possibility of integrating spatial data into ABM. It closes with a review of the related work on evacuation modelling using ABM.

1.3.1 Disaster Management and Evacuation Planning

The term “disaster management” derives from the term “management”. This is defined as a comprehensive approach to reducing the adverse impacts of particular disasters (natural or otherwise) that brings together into a disaster plan all of the actions that need to be taken before, during, immediately after, and well after the disaster has occurred (Park and Allaby, 2013). Management itself is defined as the process of dealing with or controlling things or people (Stevenson, 2010). Management consists of many activities, including planning and decision-making, organizing, leading and controlling resources to achieve certain goals (Griffin, 2012).

Coppola (2015) described comprehensive disaster management as being based upon four distinct components: mitigation, preparedness, response, and recovery. Although a range of terminology is often used to describe them, effective disaster management utilizes each component in the following procedures (Figure 1.4) (Cova, 1999): (1) *Mitigation*. Involves reducing or eliminating the likelihood and/or consequences of a hazard. Mitigation seeks to “treat” the hazard so that it impacts on society to a lesser degree. (2) *Preparedness*. Involves equipping people who may be impacted by a disaster, or who may be able to help those impacted, with the tools to increase their chance of survival and minimize their financial and other losses. (3) *Response*. Involves taking action to reduce or eliminate the impact of disasters that have occurred or are currently occurring, in order to prevent further suffering and/or financial loss. Relief, a term commonly used in international disaster management, is one component of response. (4) *Recovery*. Involves returning victims’ lives back to a normal state following the impact of a disaster. The recovery phase generally begins after the immediate response has ended, and can persist for months or years thereafter.

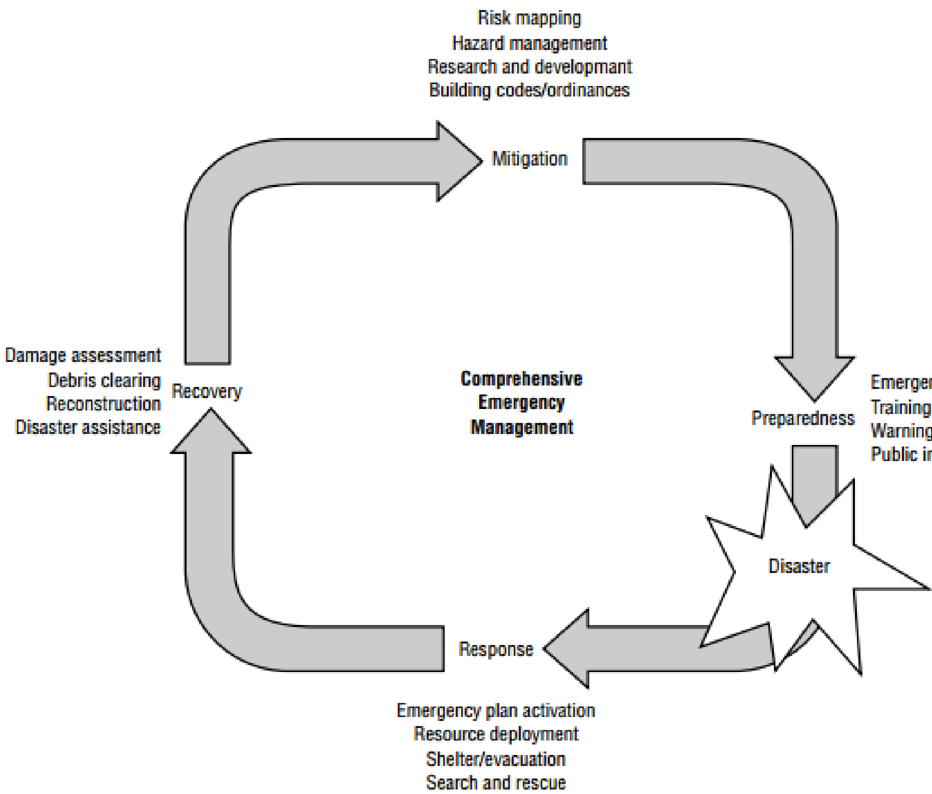

Figure 1.6 Disaster management cycle (Cova, 1999).

To understand disaster management, it is important to describe the concepts of hazard, vulnerability, disaster, and risk. Hazards refer to a potential harm which threatens our social, economic, and natural capital at a community, regional, or national scale. Hazards may refer to many types of natural, technological, or human-induced events (Pine, 2008). To analyze a hazard, one must determine exactly how that hazard came to exist within that specific community or country. Each hazard will be different in this respect, due to climate, geography, settlement patterns, and regional and local politics and stability, among many other factors. Disaster managers commonly create what is called a risk statement, which serves to summarize all of the necessary information into a succinct report for each identified hazard (Coppola, 2015).

Disasters are the inevitable consequence of hazards. Disasters of all kinds happen when hazards seriously affect communities and households and destroy, temporarily or for many years, the livelihood security of their members. A disaster results from a combination of hazard risk conditions, societal vulnerability, and the limited capacity of households or communities to reduce the potential adverse impacts of the hazard (Baas et al., 2008). Disaster risk is usually described as a function of the hazard and the vulnerability context, including the resilience (coping capacity) of the societal system under threat (Baas et al., 2008).

The concept of hazard has been widely described, while the concept of vulnerability remains debatable (Scaini et al., 2014). Blaikie et al., (2014) explained that vulnerability involves the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard. Other studies define vulnerability as the potential for exposed elements to be directly or indirectly damaged by a given hazard (Scaini et al., 2014). The definition offered by Blaikie et al. (2014) clearly describes the role characteristics of the population who are coping with disaster.

Both hazard and vulnerability are important factors in risk assessment. Risk Assessment is the process of making a decision and recommendation regarding whether the existing risks are tolerable and the present risk control measures are adequate and, if not, whether alternative risk control measures are justified or will be implemented. These activities form part of complex processes in disaster risk reduction (Figure 1.5). Risk assessment incorporates the risk analysis and risk evaluation phases (Kingma & van Westen, 2011). Furthermore, Kingma and van Westen note that risk assessment forms part of risk management, with the main purpose of providing information on risk reduction activities. The detailed processes of risk analysis and assessment are described in Figure 1.6 (UNISDR, 2002). The figure emphasizes the precise role of these risk factors. It consists of activities designed to identify both the hazard and the vulnerability of the elements at risk. Hazard identification is used to determine physical, social and geographic characteristics, intensity, and the probability of occurrence, while vulnerability/capacity identification is used to define susceptibility and capacity. Based on this information, an estimation of the level of risk can be provided. In both Figure 1.4 and 1.5, evacuation planning is an integral part of the preparedness in order to mitigate the consequences of hazard, thus reducing the level of risk.

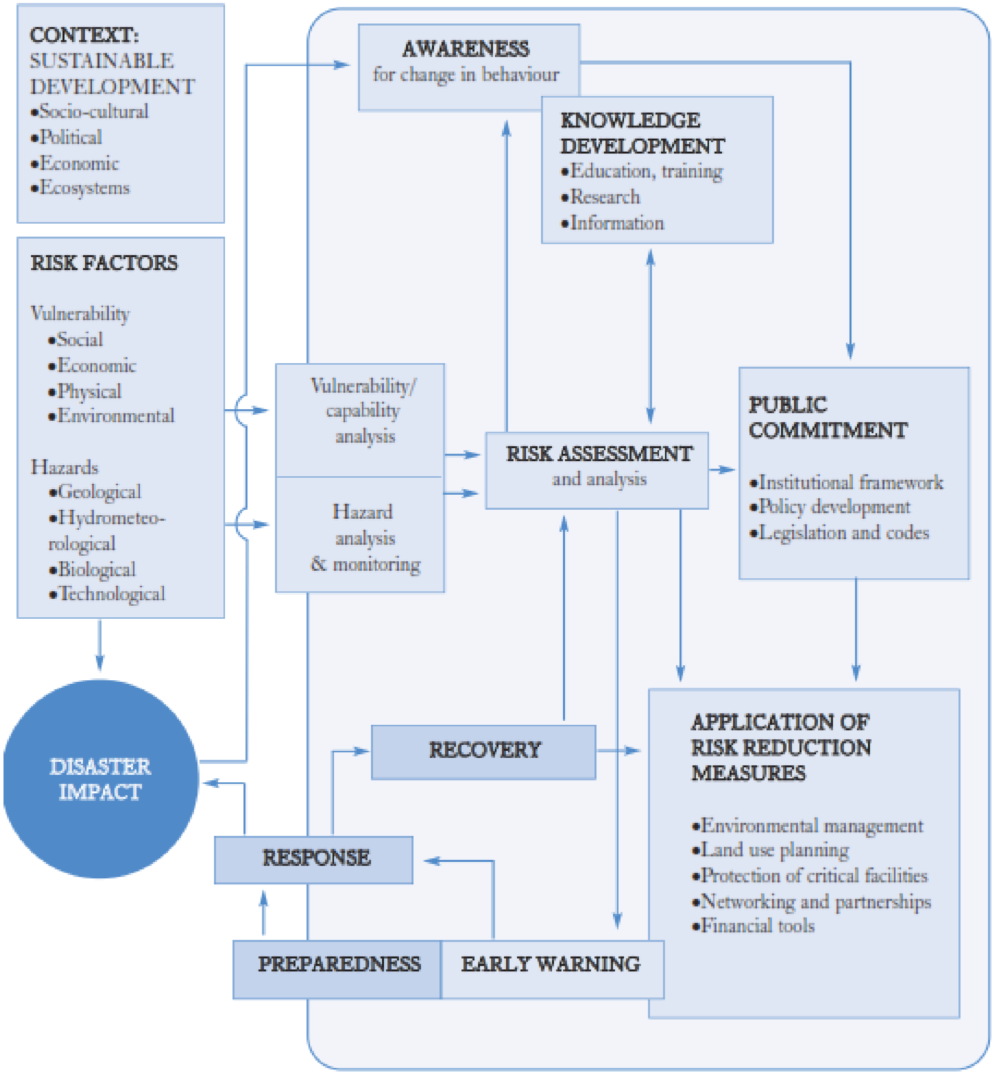

Figure 1.7 Framework for disaster risk reduction (UNISDR, 2002).

1.3.2 ABM for Evacuation Modelling and Planning

Evacuation planning is an important aspect of disaster management, so a reliable plan should be prepared, with the purpose of allocating resources and responsibilities effectively in order to evacuate populations at risk. Several components should be established to prepare for evacuation planning, namely: 1) a crisis condition that requires evacuation; 2) the populations at risk; 3) evacuation routes and destinations; and 4) the resources and time required to evacuate populations at risk (MCDEM, 2008).

However, Tomsen et al. (2014) explained that evacuations are typically complex, and so lead to uncertainty about which people wish to be evacuated and which wish to stay. This makes it difficult to estimate the duration of the evacuation process as well as the estimated resource allocation for this. The population's evacuation is a social process that is dependent on numerous variables, including the characteristics of the hazard, the geographical and environmental conditions, and the behaviour of people.

Since the social process is a non-linear, dynamic system, studies relating to this categorize it as a complex, adaptive system (Srbljinović and Škunca, 2003). It can be simulated using symbols manipulation using programming languages (Troitzsch, 1997). Many years ago, social scientists sought to understand a certain social process in a simulated environment (Gilbert, 2008). Simulation in this field means running a simplified social system that may occur in the real world. This simulation is important for several reasons, namely: (1) to obtain understanding, (2) to predict the result of particular social processes, (3) to substitute human capabilities, (4) training, (5) entertainment, and (6) to assist discovery and formalization (Gilbert and Troitzsch, 2005).

There are many techniques that are suitable for social process simulation, including cellular automata, artificial intelligence and agent-based modelling. However, ABM is the only one that can accommodate the high complexity of the system and instantiate interactions between agents at the same or different levels (Gilbert and Troitzsch, 2005). It can be used to model social entities, together with their behaviors, social attributes, and the properties that emerge from their interaction.

ABM is defined as a computational method that enables researchers to create, analyse, and experiment with models composed of agents that interact within an environment (Gilbert, 2008). This term is used interchangeably with ABS (Agent-based Systems) or IBM (Individual-based Modelling) (Macal and North, 2005). Macal and North (2005) recognised a complete term of modelling and simulation based on this technique with ABMS (Agent-based Modelling and Simulation). To provide a better understanding of the definition, it is important to explain each concept of ABMS. Agents (Figure 1.6) can be separate computer programs or take the common form of distinct parts of a program that are used to represent a social actor, which can be individual people, organizations such as firms, or bodies such as nation-states (Gilbert, 2008). Modelling is the act of creating a simplified representation of a system – an 'abstraction of reality' – for a particular purpose, such as to describe it, understand it, or derive some properties from it (Press, 2004; Demeritt and Wainwright, 2005) and a simulation is defined as the imitation of a system using a prototype of the system to find the flaws and problems inherent in the system and so rectify them (Bandyopadhyay and Bhattacharya, 2014).

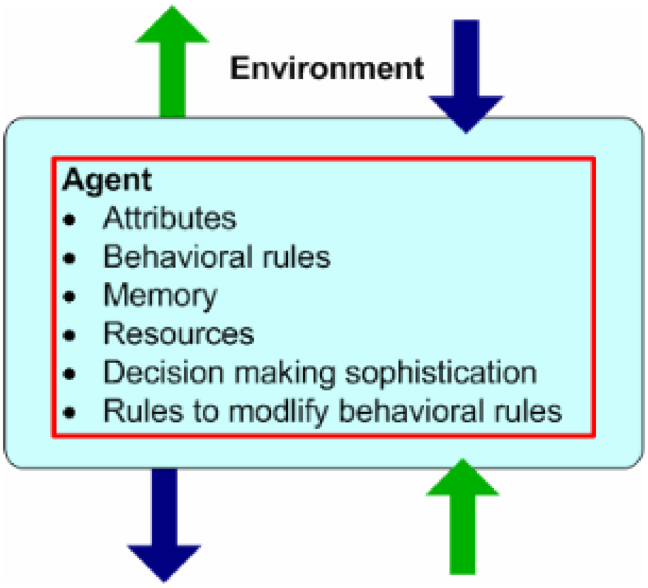

Figure 1.8 The agent (Macal and North, 2005).

1.3.3 Spatially Realistic ABM (Spatial ABM)

Providing a spatially realistic environment is required in most ABM, which integrates both social and environmental systems. Therefore, the integration of GIS into ABM is required (Brown et al., 2005). The integrated model is called spatial agent-based modelling (Brown and Xie, 2006) or a georeferenced agent-based model (Pons et al., 2014). The conceptual integration of both GIS and ABM is provided successfully by (Brown et al., 2005), where GIS is used as the spatial data model representation and ABM as the processes model. This approach can be used to model and simulate complex systems and present the results of the spatial processes in the form of spatiotemporal information.

Particularly in evacuation modelling, there are various types of spatial representation to choose from, with various considerations. The spatial environment/object can be modelled as vector data or raster data (Sugumaran and DeGroote, 2010). The vector data model represents the real world as a point, line, or polygon geometry while, in raster data, it can be represented as a regular two-dimensional grid with a specific spatial resolution.

These data models have advantages and disadvantages when visualizing the real world so, when choosing a model, it is important to ensure that it is appropriate for the specific application in mind. Moreover, each data model has a particular suitability for modelling geographical objects (Sugumaran and DeGroote, 2010). A vector is very suitable for representing discrete human objects, such as roads, buildings, and agricultural landscape. On the other hand, the raster is commonly used to model continuous phenomena with various values of data across space. Marrero et al. (2010) used a vector model to develop an evacuation model, where the road networks are represented as lines, the population as polygons and points, and the hazard zone as a polygon. Based on the above explanation, the population data, road networks and shelters can be appropriately represented as a vector. Meanwhile, the hazard zonation is suitable to be mapped as a raster to provide a better representation of the hazard level distribution.

1.3.4 ABM Development Process

There are various methods for developing ABM, and no one method has been recognised as the best approach (Gilbert and Terna, 2000). Macal and North (2010) explain that an ABM should contain three main elements: agents, relationships and environment. ABM can be developed by means of several steps (Macal and North, 2006): (1) identifying its purpose and the questions that are intended to be answered; (2) systematically analysing the system, identifying components and component interactions, relevant data sources and so on; (3) conducting the experiment; and (4) understanding the robustness of the model. Meanwhile, Salgado and Gilbert (2013) use three steps in developing ABM including specification-formalisation, modelling - verification - experimentation, calibration - validation. More simply, Crooks et al. (2018) formulate three steps in developing ABM including preparation and design, model implementation, evaluating the model.

Although the formulation of the development steps varies, they share similar tasks in their steps. The development steps by Crooks et al. (2018) can be used to describe the similarities of the method. The preparation and design step begins with formulating a research question which will be answered with the ABM and the purpose of building the ABM. The step one by Macal and North (2006) “identifying its purpose and the questions that are intended to be answered” is covered in this step which is also similar to the first step by Salgado and Gilbert (2013) “specification-formalisation”. Designing the abstraction of the model is also needed in the first step (Crooks et al., 2018).

In other words, the modeller should specify the agents with their attributes and behaviour rules that are involved in the model and the environment where the agents are living (Salgado and Gilbert, 2013).

The model implementation step translates the designed model into a computer program (Crooks et al., 2018). There is no generic model in ABM; therefore, as every ABM has a unique purpose and specification, the researcher should build their own model. There are various building toolkits that can help a modeller build their model and each one has a different capability and specification (Kravari and Bassiliades, 2015; Crooks et al., 2018). It is very common to make many errors when writing a complex computer program. Therefore, Salgado and Gilbert (2013) put the verification step together in the second step. Verification is the process of checking that the program works as it was planned or ensuring the model implementation corresponds to the model design (Salgado and Gilbert, 2013; Crooks et al., 2018). Crooks et al. (2018) put the verification process as part of the step of evaluating a model along with calibration and validation processes.

The last step of ABM development processes is model evaluation (Crooks et al., 2018). The model implementation and evaluation is an iterative process to make sure that the model runs as expected. There are three ways to evaluate the model including verification, calibration and validation (Crooks et al., 2018). The verification process has been explained previously, while calibration and validation are unseparated processes of the evaluation process. Calibration aims to adjust the parameters of the model in order to produce a valid outcome (Klügl, 2008) or reach the best fit to historical data (O’Sullivan, 2004). On the other hand, validation aims to demonstrate that the ABM is sufficiently accurate/good in modelling the real system (Salgado and Gilbert, 2013; Crooks et al., 2018). There are four techniques in conducting validation including face validation, retrodiction, prediction and docking (Hawe et al., 2012). Face validation is conducted by using human intuition (experts) to assess whether the ABM behaves reasonably (Hawe et al., 2012; Crooks et al., 2018). Face validation is a qualitative approach (Crooks et al., 2018), while the others tend to be quantitative. Retrodiction is conducted by testing the ABM prediction using historical datasets, whereas prediction is conducted by comparing the prediction with the real event or field experiment (Hawe et al., 2012). Meanwhile, docking is comparing the outcome from the ABM with another validated model that might include two different languages or different developers (Hawe et al., 2012; Crooks et al., 2018).

1.3.5 Behaviour of People in Evacuation and Modelling Approach

Evacuation simulation is important in supporting evacuation management (De Silva and Eglese, 2000). Simulation can range from 'pen and paper' to real-life exercises. However, real-life exercises can be expensive and therefore, *in silico* simulation is beneficial (Hawe et al., 2012). In addition to minimising the cost, simulation *in silico* can reproduce scenarios that may be impossible to conduct in real-life due to their high risk or because they are environmentally damaging. In evacuation management, computer simulation can be used to reproduce various emergency scenarios and evaluate the ability of particular plans to minimise the risks. For example, De Silva and Eglese (2000) show that evacuation simulation can be used to test scenarios involving contingency plans. This simulation integrates GIS and a simulation model to develop simulation-based spatial decision support for evacuation planning. Evacuation from various types of hazard has been modelled in various approaches based on the evacuees' behaviour (see Chapter 2 for more details). The modelling ranges from macroscopic to microscopic, depending on the evacuees' behaviour (see the model).

There are several approaches used to model evacuation on a microscopic scale, such as ABM (Mas et al., 2012; Wise, 2014; Ukkusuri et al., 2017), cellular automata (Zia and Ferscha, 2009; Wang et al., 2014), microsimulation (Chen, 2012), the Particle Swarm Optimisation algorithm (Yang et al., 2012), and game theory (Lo et al., 2006). However, based on the literature survey by Wang et al. (2016), which compared seven modelling approaches, ABM is more efficient at representing human behaviour. Macroscopic models do not take into account human behaviour or the interaction between the agents and are therefore unable to capture the variability within individuals' behaviour (Alaeddine et al., 2015; Yang et al., 2015). On the contrary, individual behaviour and interactions are considered in the microscopic model (Alaeddine et al., 2015; Yang et al., 2015). Between the two lies the mesoscopic model, which comprises both micro and macro output (Silva, 2001). This model is able to represent evacuees as individual entities/agents but unable to model their behaviour and interactions (Alaeddine et al., 2015). The evacuation model employed in this thesis used the microscopic approach, where evacuees are expressed as an individual entity together with their behaviour and interaction ability. ABM is one of the most powerful tools for developing the simulation of an evacuation in an emergency, based on the microscopic approach. ABM is applied to simulate emergency situations arising due to various hazards, as presented in Table 1.3. The table presents an overview of the application of ABM for evacuation simulation based on some points of view, including the modelling tool used, the agent's decision-making rules, the spatial scale, and the agent's population generation method.

There are a number of tools with a range of capabilities available for developing ABMs; for example, AGlobe, Cougaar, Repast, CybelePro, SESAM, AnyLogic, GAMA, and NetLogo (Kravari and Bassiliades, 2015). Abar et al. (2017) surveyed a large number of ABM platforms for developing ABMs with more comprehensive comparison criteria. Here, 85 agent-based toolkits were compared to help the user select the most appropriate for their needs. Based on the results from this survey, AnyLogic was selected and used in this thesis. It has a high degree of scalability and can be used across a wide range of applications. Importantly, this tool meets the current requirement to involve the spatial environment within the simulation.

Modelling based on agent decision rules can be categorised into either simple or complicated (Sun et al., 2016). Simple decision-making and behavioural rules can be represented with simple expressions; for example, “if-then” rules, or some straight-forward mathematic equations. Meanwhile, complicated rules offer more advanced approaches, such as linear programming, decision trees, multivariate regression, the threshold rule and Bayesian networks. An example of a simple decision rule is provided by Mas et al. (2012), where each agent is assigned a decision preference based on the probability distribution generated by the survey. Meanwhile, an a example of complicated rule application for evacuation simulation is provided by Wise (2014), who developed a simulation of an evacuation from wildfire, where a decision tree is used to develop the agent decision rule. The decision tree provides a mechanism for action selection when the agent faces an emergency condition. Crooks et al. (2018) categorise the approach on modelling human behaviour into two categories: a) the mathematical approach, for example including probabilistic and threshold models, and b) conceptual cognitive models, for example the Belief-Desire-Intention (BDI) model.

Based on spatial scale, the simulation of emergencies varies from buildings (e.g. fires (Shi et al., 2009)) to regions (e.g. earthquake (Bernardini et al., 2014), wildfire (Wise, 2014), hurricane (Zhang et al., 2009) and tsunami

(Mas et al., 2012)). Hawe et al. (2012) provide a comprehensive review of a large-scale emergency simulation using ABM. The term “large-scale” can refer to the number of agents or the size of the environment. In this thesis, the ABM applied “large-scale” in terms of the size of the area covered in the simulation.

ABMs commonly apply either random or synthetic population generation. A synthetic population can mimic the real population but only few of them use a synthetic population, such as a wildfire crisis (Wise, 2014), while most of them use a random agent to provide the population of agent (see Table 1.3). More complex agent populations simulated by these models should implement synthetic populations to imitate real world heterogeneity (Cajka et al., 2010; Malleson and Birkin, 2012; Namazi-Rad et al., 2014). Volcanic disasters impact on cities and regions, so a complex population composition should be involved. It is important to involve a synthetic population in the model utilised, with individual behaviour regarding making decisions and their interactions.

Table 1.3 Comparison of the existing evacuation models.

No	Model	Hazard	Spatial Scale	Population Generation	Hazard Modelling	Agents Evacuation Decision Modelling
1.	Agent-based emergency evacuation simulation with Individuals with disabilities in the population (Christensen and Sasaki, 2008)	Building damage-related hazard	Building	The population number is limited to the building occupiers. The population characteristics were based on real data.	There is no specified hazard modelling used	Decision of movement is using consecutive binomial choices (move or not move)
2.	Agent-based evacuation model of large public buildings under fire conditions (Shi et al., 2009)	Fire	Building	Random generation of building occupants	Fire dynamics simulator	Rule reasoning with numerical calculation of environmental factors using a weighted linear combination equation
3.	Agent-based modelling for household level hurricane evacuation (Zhang et al., 2009)	Hurricane	City/region	This is experimental research and no population mimicking,	No hazard modelling used	All agents assumed to evacuate
4.	Agent-based simulation of building evacuation: Combining human behaviour with predictable spatial accessibility in a fire emergency (Tan et al., 2015)	Fire	Building	Agent population is limited to the building occupier.	No hazard modelling	Evacuees chose exit door based on pre-defined knowledge level.

Table 1.3 Continued …

No	Model	Hazard	Spatial Scale	Population Generation	Hazard Modelling	Agents Evacuation Decision Modelling
5.	Agent-based simulation of the 2011 great east Japan earthquake/tsunami evacuation: An integrated model of tsunami inundation and evacuation (Mas et al., 2012)	Tsunami	Region	The population agents were divided into two groups (car passengers and pedestrian evacuees), synthetic pop not used in the model.	Numerical simulation was used to model the tsunami propagation.	Evacuation start time was generated from the survey.
6.	An agent-based model of a multimodal near-field tsunami evacuation: decision-making and life safety (Wang et al., 2016)	Tsunami	Region	The population was divided into two classes (resident and tourism) with different characteristic of evacuation decision based on the awareness.	Tsunami evacuation map was used.	Each agent was assigned a predefined rule to select the evacuation mode.
7.	Integrating decentralized indoor evacuation with information depositories in the Field (Zhao et al., 2017)	Building damage-related hazard	Building	A numbers of agents were generated randomly.	No hazard modelling used.	Agent decides to evacuate after the emergency alert, and delays for individuals or community purposes are not considered.

Table 1.3 Continued …

No	Model	Hazard	Spatial Scale	Population Generation	Hazard Modelling	Agents Evacuation Decision Modelling
8.	ABM for urban evacuation (Chen and Zhan, 2008)	Generic Hazard	City	Population generated in household units that were represented as vehicle units.	No hazard model used.	Each driver agent assigned with behavior in selecting the destination and route. All households are assumed to evacuate.
9.	ABM discrete events simulation of large-scale disaster evacuation (Na and Banerjee, 2014)	Generic Hazard	Region	Population generated as patient agents. There was no adequate explanation on how to generate this.	No hazard model used.	There is no clear explanation of the evacuation decision of the evacuees.
11.	Wildfire crisis (Wise, 2014)	Wildfire	Region	Synthetic population was used.	Fire propagation used to generate hazard.	Agent has the ability to decide whether and how to evacuate based on decision tree.

1.4 Aims and Objectives

The general aim of this thesis is to develop an ABM of volcanic evacuation to improve the effectiveness of evacuation management in Merapi. Several objectives were drawn up to achieve this overarching aim, including:

Objective 1: To design a framework volcanic evacuation model using spatial ABM simulation.

Objective 2: To develop and validate a spatial ABM of volcanic evacuation and explore the potential use of this model.

Objective 3: To use the spatial ABM of volcanic evacuation to experiment with improving the effectiveness of evacuation management in Merapi.

These objectives were reached by developing a conceptual framework of the evacuation model, followed by the development of an experiment to create a simultaneous and staged evacuation scenario. This application will provide both practical and theoretical outcomes. The practical outcome is reached by increasing the evacuation planning's effectiveness, whereas the theoretical outcome is expected to emerge after evaluating the results and discussing the existing model. Consequently, it can highlight the new conceptualization of knowledge of volcanic evacuation modelling using spatial ABM. The simulation of various scenarios will produce a population risk state which can be analysed using GIS. An exploration of the results as well as a comparison between scenarios will enrich the understanding of crisis management. Based on the above objectives, the following research questions were formulated:

1. How can ABM evacuation simulation be used to support evacuation management?
2. What are the requirements for developing an ABM of volcanic evacuation?
3. What are the factors influencing the evacuation decision of people?
4. Does ABM make it possible to model individuals' evacuation decisions?
5. What is individual risk and how can this be modelled in ABM?

6. How can ABM simulate the spatiotemporal dynamics of risk?
7. How can ABM evacuation simulation be used to improve evacuation management?
8. Does a staged evacuation produce a better outcome in terms of reducing risk compared with a simultaneous evacuation strategy?
9. Does a staged evacuation strategy produce a better outcome in terms of reducing road traffic congestion compared with a simultaneous evacuation strategy?
10. Which factors can be used to plan a staged evacuation?

1.5 General Methodology

This section presents an overview of the approach adopted to achieve the objectives. A general overview of the research is described followed by the operational framework, which presents the technical flow of the research design. The dataset required for the research design is also reviewed to complete the description. An overview of the simulation method is then provided to give a logical flow to the model.

1.5.1 Overview of the Method

The methodology of this research relies strongly on ABM simulation based on the literature review and empirical study complemented by GIS analysis for the preparation and output analysis. The simulation was based on the assumption that risk perception will influence the population's behaviour regarding decision-making during crises. This relates to the probability of people being impacted by the disaster. Behaviour is commonly influenced by the social and demographic characteristics of people. Moreover, spatial and environmental features, such as road networks, evacuation shelters' location and accessibility can also contribute to populations' capacity to cope with disaster.

The general concept of the ABM simulation is provided in Figure 1.9. In the ABM simulation, the synthetic population agents will be generated from census data, with a spatial distribution estimation using settlement areas drawn from a land use map. Regarding the evacuation decision-making processes, the spatial and environmental factors will be taken into consideration. A questionnaire survey with area sampling will be used to identify the household preferences regarding the decision-making processes during evacuation. The identified result in the statistical data can then be used to characterise the agents' behaviour during the simulation.

At the end of the simulation, the populations who remain in the hazard zones at the expected time of onset will be considered to be at-risk populations. The results are spatially visualized in GIS. Finally, the effectiveness of the disaster management plans is measured by the degree of the risk that can be reduced as well as the ability to reduce road traffic congestion during the evacuation process.

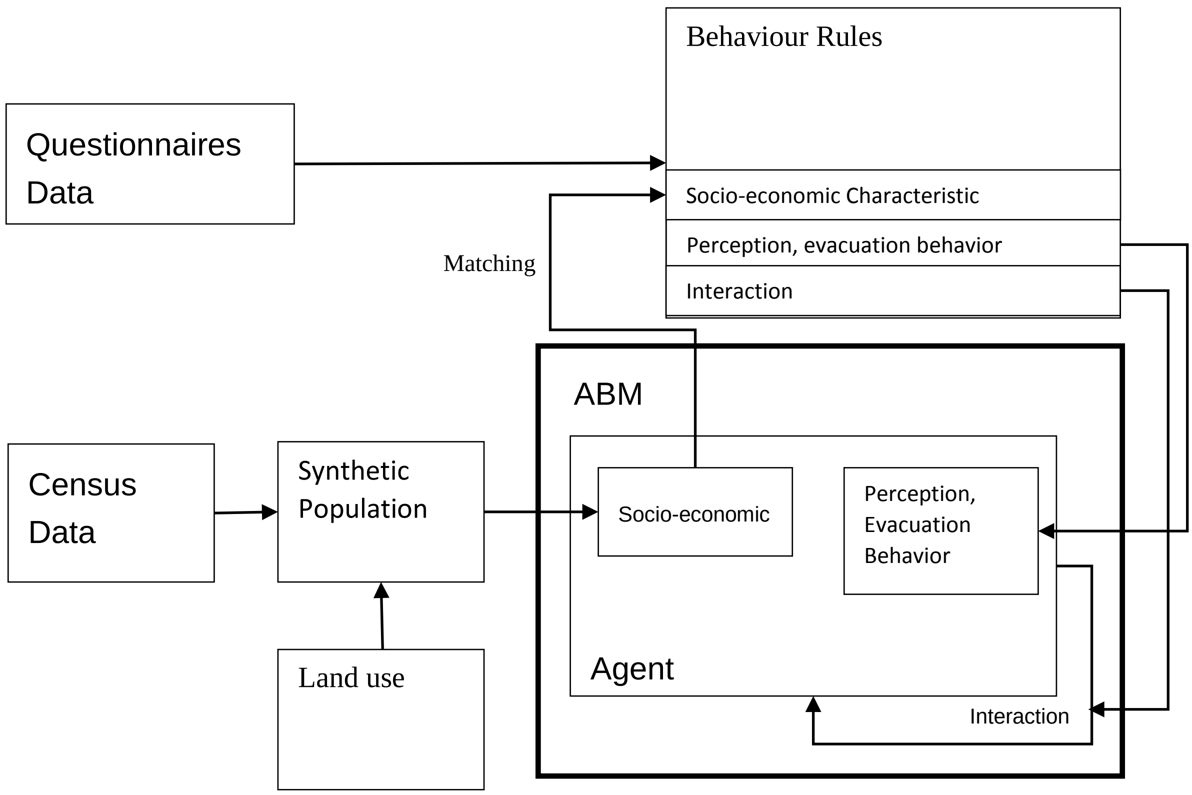

Figure 1.9 General concept of the involvement of the behaviour rule from the survey in ABM.

1.5.2 Overview of the Data Collection

Various data were involved in developing the model, both spatial and non-spatial, and also primary and secondary. A complete description of the dataset is provided in Chapter 3. Here, some additional information about the primary data collection (questionnaire survey) is elaborated.

The questionnaire was used to identify the variables that will be used in the simulation. There are five primary variables collected from the questionnaire surveys, namely: socio-demographic characteristics that express social vulnerability, perceptions of volcanic hazard, decision-making behavior, interaction during the crisis, and also past evacuation experience (see Appendix 1.1). These data (mainly the perception of volcanic hazard, decision-making behavior and interaction during the crisis) will be used to generate population agents for the ABM simulation (Figure 1.9). Stratified random sampling was applied to conduct the survey. A total of 120 household member samples, represented as building units, were selected randomly for each building block (*dusun*), with the distance from the volcano as the stratified value. This area segmentation is based on the consideration that each *dusun* will have one command (*Rukun Tangga*) and commonly, in rural areas of Indonesia, homogenous social characteristics. The following figure illustrates the sampling selection method.

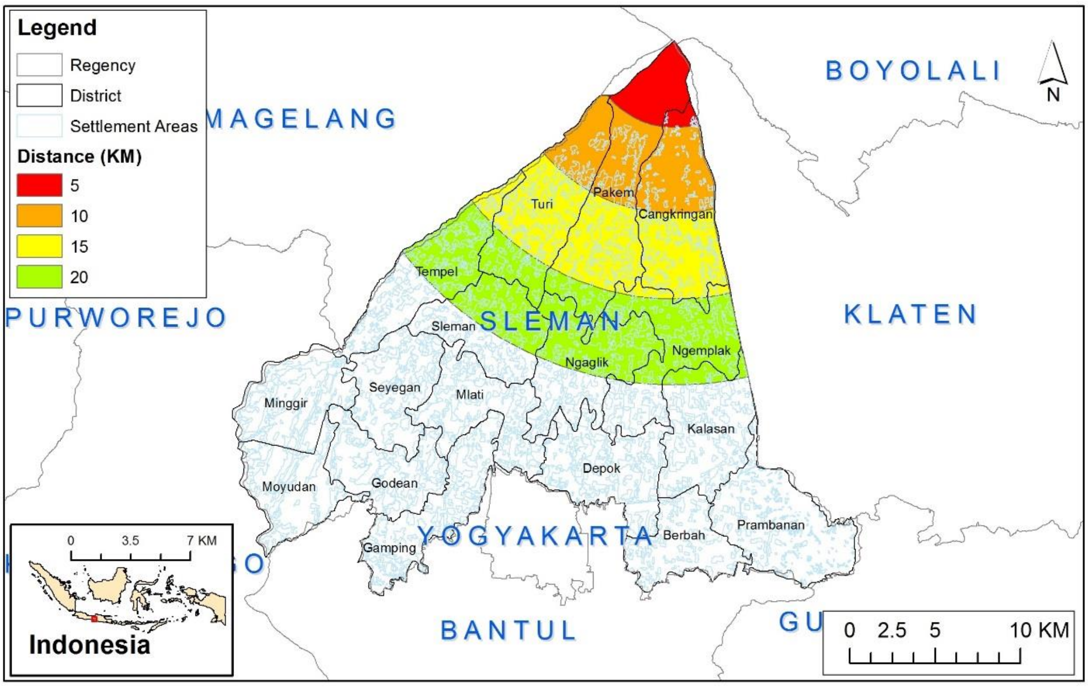

Figure 1.10 Example of sampling selection.

The participants were distributed proportionally across all zones (Figure 1.10). Each zone consists of three villages (*dusun*) as a sample, which was selected randomly using the randomise tool in Quantum GIS (see Figure 1.11). For the first 5km zone, three relocation areas were used, as the people within this area had been relocated. A settlement (the building footprint) from each village from the selection set was extracted using intersect analysis. Similar to the village selection process, the buildings group of each village was randomised to select 10 buildings which were used as samples. This random selection resulted in 120 buildings in total (Figure 1.12) (see Appendix 1.2 for the survey results). Finally, the selected buildings were exported to Keyhole Markup Langage (KML) to enable this to be imported into GPX Viewer (Android Application) for a field guide during the survey.

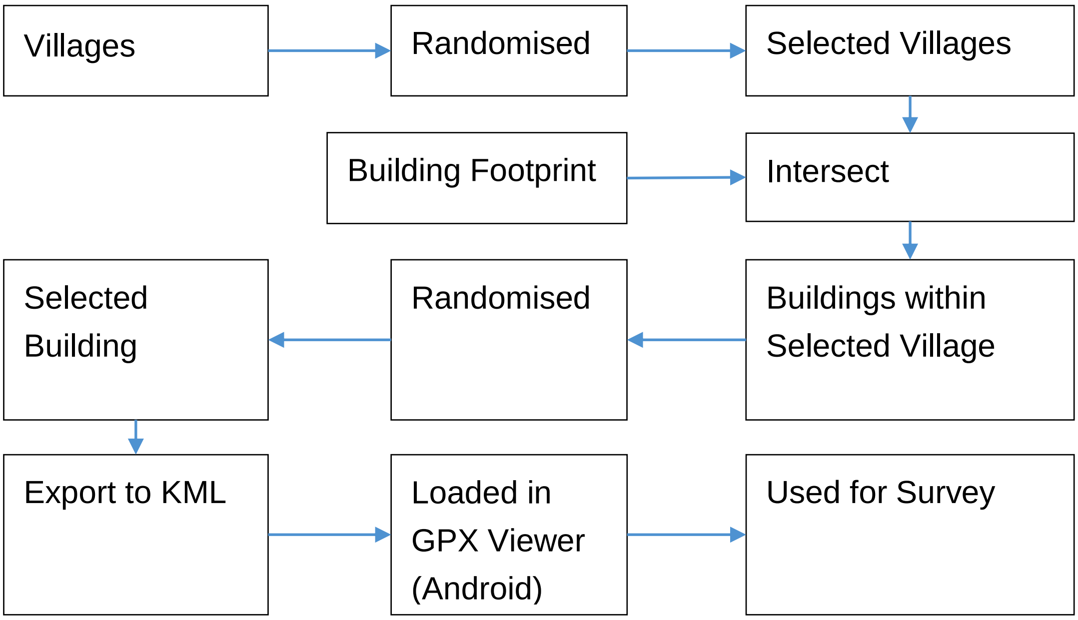

Figure 1.11 Household selection and field identification procedure.

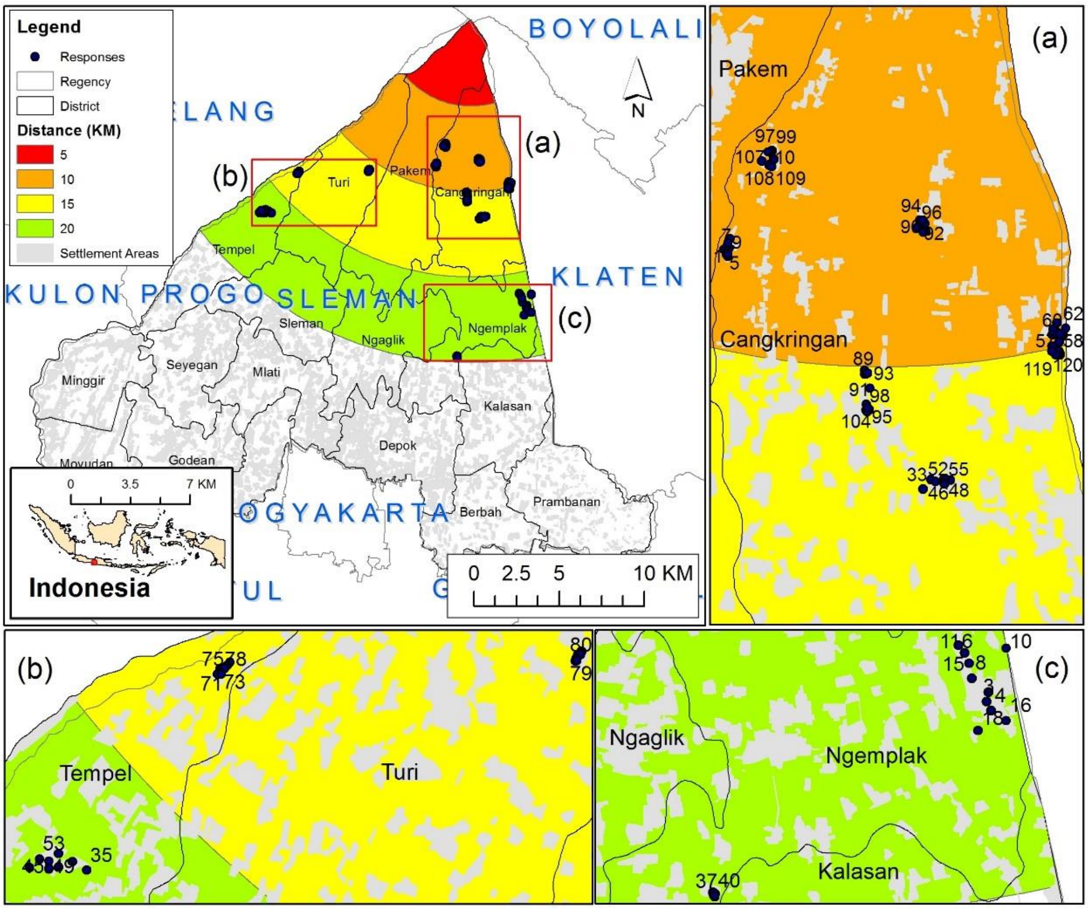

Figure 1.12 Distribution of the samples.

1.5.3 Overview of Model Development, Experiments and Output Analysis

Overall, the principle of this research follows the interaction of GIS (preparation) – ABM (simulation) – GIS (output analysis) (see Chapter 2). First of all, GIS is used to provide data for the simulation input. It is followed by the development of ABM and the simulations. The development process of the ABM was documented using the Overview, Design Concepts, and Details (ODD) approach (Grimm et al., 2006; Polhill, 2010). The general framework of the model was documented as a guide to implement the model in AnyLogic (Borshchev, 2013). The principal framework of ABM consists of three main agents, namely: volcano, stakeholder, and people (population), that interact within the geographical environment. The volcano acts as an agent, which initiates the hazardous situation and influences the environment as a potential threat to the surrounding population. The other agents in the interactions are the stakeholder and the population (people). The stakeholder, in this case the authorities (government), has a significant role in observing and analysing the activities of the volcano and in issuing warnings to the population, whereby the human agent (population) is assigned an evacuation decision rule (Chapter 3). All human agents are also characterised by an individual risk assessment rule that makes it possible to capture the spatiotemporal dynamics of risk-taking during crises (Chapter 4). Based on those models, two scenarios (namely, the simultaneous and staged strategies) are used to evaluate which is more effective in diminishing risk and reducing traffic congestion during evacuation processes. The whole simulation outcome can be exported to enable spatiotemporal analysis using GIS or statistical software. Various software packages were used to support the preparation, development and analysis, including ArcGIS, AnyLogic, R and R studio, Quantum GIS, Map Info Pro, Map Comparison Kit 3.2 (Visser and Nijs, 2006), and Origin Pro.

1.6 Thesis Outline

Following the introduction chapter at the beginning and preceding the discussion chapter at the end, the main part of this thesis is divided into three parts: (1) designing the concept and framework, (2) developing the model, (3) applying the model (Figure 1.9). The improvement part consists of two sub-parts: improvement with the individual decision-making model and improvement with the individual risk model. Each part of this work will be published as a paper (Chapters 2 to 5). This chapter provides an introduction to these parts, and the overarching outcome will be discussed in the last chapter (Chapter 6).

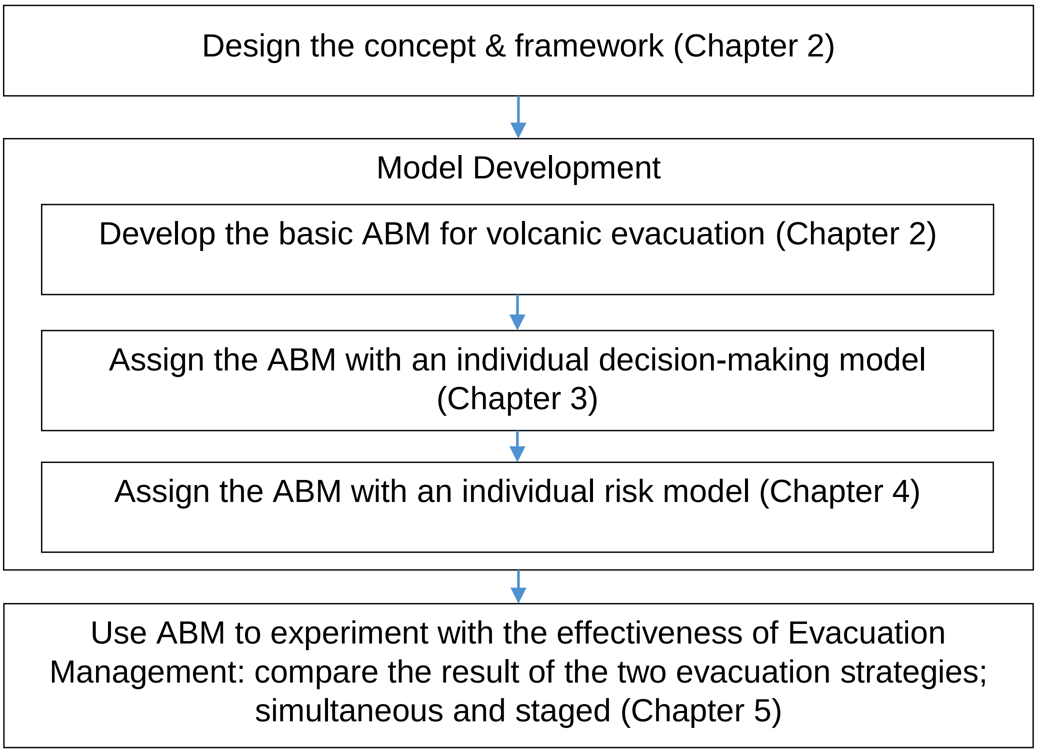

Figure 1.13 Thesis outline.

The introduction chapter (Chapter 1) provides a general overview of the importance of this research, introduces the study area, reviews the relevant literature, highlights the research gap, and presents the aim and objectives of the research. The introduction to the general method of this thesis is also provided in this chapter including the data collection and the model development and the experimentation.

Chapter 2 presents the framework and initial model of the ABM to address the first and second objectives and to answer the research question 1 – 2 at the same time. This chapter starts with the introduction of Merapi and the importance of developing an instrument to improve the evacuation plan followed by the reason for choosing ABM as an approach to the instrument development. Consequently, the concept and design of the spatio-temporal ABM of volcanic evacuation is introduced here. This is supported with the initial implementation of the model using AnyLogic. The early developed model was used to show the potential application of the model and was evaluated for further improvements that are provided in Chapters 3 and 4.

Chapter 3 provides improvements by utilizing the human agent with an evacuation decision mechanism and validates the outcome with real data to complement the achievement of the second objective as well as to answer research questions 3 - 5. The evacuation decision model was formulated from the literature review supported by empirical data from the survey. The decision model allows the human agent to evacuate or to stay during the crisis based on the evaluation of their social attributes and the environment. Spatio-temporal validation was conducted by comparing the outcome of the simulation with the real data from the 2010 evacuation.

Chapter 4 presented the concept and the implementation of spatio-temporal dynamics of risk in the evacuation model. This is complementing the achievement of the second objective and answering questions 6 – 7 at the same time. Here, the macro dynamic of risk is resulting from individual risk dynamics, whereas the dynamic of individual risk is a consequence of the dynamic hazardous environment and the agent’s movement. The individual risk uses multi-criteria evaluation (MCE) that is integrated into the ABM. The use of MCE in this model enables the Social Vulnerability Index (SoVI) of each individual to be derived and, in combination with the hazard level of individual environment, the risk to individual agents can be evaluated.

Chapter 5 is dedicated to achieving the third objective as well as answering questions 8 – 10 at the same time. This chapter introduces a novel approach to developing a staged evacuation plan and implements this in the ABM experiment. Several “what-if” scenarios of staged evacuation plan were created and examined in the experiments. Those results are compared with the result from a simultaneous evacuation plan to evaluate the relative effectiveness of staged evacuation. The comparisons among various staged evacuation scenarios are also provided and discussed.

The summary of all chapters is also provided in Chapter 6 in more detail. This is followed by the highlights of the contribution made by this study to the both methodology and the practice of risk reduction. It concludes with the lessons learn from the development, implementation, experimentation, and evaluation processes in this research.

1.7 Summary

The modelling of volcanic evacuation in Merapi is important in supporting the evaluation of the implementation of potential plans for reducing risk and providing more effective evacuation management. However, evacuation models specifically for volcanic hazards are absent from the literature. This thesis aims to develop an ABM of volcanic evacuation to improve the effectiveness of evacuation management in Merapi. The model is based on the interaction among the components within the volcanic hazard system, including volcano, people at risk, responsible stakeholders, and the environment. The development of the model is divided into three steps that are used to structure this thesis, namely: the development of a basic ABM for volcanic evacuation, assigning the model an individual decision-making rule and the individual risk model. Finally, the model was used to compare the effectiveness of a staged evacuation scenario with a simultaneous scenario. Each of these stages make novel contributions that are worthy of publication.

References

Abar, S., Theodoropoulos, G.K., Lemarinier, P. and O'Hare, G.M.P. 2017. Agent Based Modelling and Simulation tools: A review of the state-of-art software. *Computer Science Review*. **24**, pp.13–33.

Alaeddine, H., Serrhini, K., Maizia, M. and Néron, E. 2015. A spatiotemporal optimization model for the evacuation of the population exposed to flood hazard. *Nat. Hazards Earth Syst. Sci.* **15**(3), pp.687–701.

Ayuningtyas, D. and Gabriel, L. 2013. *Respon Masyarakat Terhadap Kebijakan Relokasi Pada Kawasan Rawan Bencana (KRB) (Studi Kasus: Relokasi Desa Glagaharjo)*.[Online] Universitas Gadjah Mada. [Accessed 19 March 2015]. Available from: http://etd.ugm.ac.id/index.php?mod=penelitian_detail&sub=PenelitianDetail&act=view&typ=html&buku_id=66995&obyek_id=4.

Baas, S., Ramasamy, S., DePryck, J.D. and Battista, F. 2008. *Disaster risk management systems analysis: A guide book* [Online]. Food and Agriculture Organization of the United Nations. [Accessed 25 March 2015]. Available from: http://library.wur.nl/WebQuery/clc/1889327.

Bandyopadhyay, S. and Bhattacharya, R. 2014. *Discrete and Continuous Simulation: Theory and Practice* [Online]. CRC Press. [Accessed 17 March 2015]. Available from: http://www.crcnetbase.com/doi/book/10.1201/b17127.

Bernardini, G., D'Orazio, M., Quagliarini, E. and Spalazzi, L. 2014. An Agent-based Model for Earthquake Pedestrians' Evacuation Simulation in Urban Scenarios. *Transportation Research Procedia*. **2**, pp.255–263.

Blaikie, P., Cannon, T., Davis, I. and Wisner, B. 2014. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. Routledge.

BNPB 2014. BNPB. [Accessed 26 November 2014]. Available from: http://dibi.bnpb.go.id/DesInventar/dashboard.jsp?countrycode=id&continue=y&lang=ID.

BNPB 2010. Laporan Harian Tanggap Darurat Gunung Merapi 5 Desember 2010.

BNPB 2008. Peta Kawasan Rawan Bencana Gunung Merapi. Available from: http://www.webcitation.org/6pimWt1Fc.

BNPB 2011. Peta Kawasan Rawan Bencana Merapi. [Accessed 9 October 2015]. Available from: http://geospasial.bnpb.go.id/wp-content/uploads/2011/05/2011-04-29_KRB_Area_Terdampak_Langsung_Merapi.pdf.

Borshchev, A. 2013. *The Big Book of Simulation Modeling: Multimethod Modeling with AnyLogic 6*. Lebanon, NJ, USA: AnyLogic North America.

BPS 2015. Sleman Dalam Angka 2011. [Accessed 14 September 2017]. Available from: http://www.webcitation.org/6tTCrkUPU.

Brown, D.G., Riolo, R., Robinson, D.T., North, M. and Rand, W. 2005. Spatial process and data models: Toward integration of agent-based models and GIS. *Journal of Geographical Systems*. **7**(1), pp.25–47.

Brown, D.G. and Xie, Y. 2006. Spatial agent-based modelling. *International Journal of Geographical Information Science*. **20**(9), pp.941–943.
Cajka, J.C., Cooley, P.C. and Wheaton, W.D. 2010. Attribute assignment to a synthetic population in support of agent-based disease modeling. *Methods report (RTI Press)*. **19**(1009), p.1.
Chen, X. 2012. Agent-based micro-simulation of staged evacuations. *International Journal of Advanced Intelligence Paradigms*. **4**(1), p.22.
Chen, X. and Zhan, F.B. 2008. Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. *The Journal of the Operational Research Society*. **59**(1), pp.25–33.
Chien, S.I. and Korikanthimath, V.V. 2007. Analysis and Modeling of Simultaneous and Staged Emergency Evacuations. *Journal of Transportation Engineering*. **133**(3), pp.190–197.
Christensen, K. and Sasaki, Y. 2008. Agent-Based Emergency Evacuation Simulation with Individuals with Disabilities in the Population. [Accessed 17 March 2015]. Available from: http://jasss.soc.surrey.ac.uk/11/3/9.html.
Church, R.L. and Sexton, R.M. 2002. *Modeling Small Area Evacuation: Can Existing Transportation Infrastructure Impede Public Safety?*
Coppola, D.P. 2015. *Introduction to International Disaster Management* 3rd ed. Burlington: Elsevier Science.
Cova, T.J. 1999. GIS in emergency management. *Geographical information systems*. **2**, pp.845–858.
Cova, T.J. and Church, R.L. 1997. Modelling community evacuation vulnerability using GIS. *International Journal of Geographical Information Science*. **11**(8), pp.763–784.
Crooks, A., Heppenstall, A. and Malleson, N. 2018. Agent-Based Modeling *In*: *Comprehensive Geographic Information Systems*. Oxford, UK: Elsevier.
Crooks, A., Malleson, N., Manley, E. and Heppenstall, A. 2019. *Agent-Based Modelling and Geographical Information Systems: A Practical Primer*. SAGE.
Crooks, A.T. and Castle, C.J. 2012. The integration of agent-based modelling and geographical information for geospatial simulation *In*: *Agent-based models of geographical systems* [Online]. Springer, pp.219–251. [Accessed 9 April 2015]. Available from: http://link.springer.com/chapter/10.1007/978-90-481-8927-4_12.
De Bélizal, É., Lavigne, F., Gaillard, J.C., Grancher, D., Pratomo, I. and Komorowski, J.-C. 2012. The 2007 eruption of Kelut volcano (East Java, Indonesia): Phenomenology, crisis management and social response. *Geomorphology*. **136**(1), pp.165–175.
De Silva, F.N. and Eglese, R.W. 2000. Integrating simulation modelling and GIS: spatial decision support systems for evacuation planning. *Journal of the Operational Research Society*. **51**(4), pp.423–430.
Demeritt, D. and Wainwright, J. 2005. Models, Modelling, and Geography *In*: *Questioning Geography: Fundamental Debates* [Online]. Oxford UK: Blackwell Publishing, p.206. [Accessed 7 April 2015]. Available from: http://sociology.sunimc.net/htmledit/uploadfile/system/20110602/20110602035853251.pdf.
Felpeto, A., Martí, J. and Ortiz, R. 2007. Automatic GIS-based system for volcanic hazard assessment. *Journal of Volcanology and Geothermal Research*. **166**(2), pp.106–116.
Gertisser, R., Charbonnier, S.J., Keller, J. and Quidelleur, X. 2012. The geological evolution of Merapi volcano, Central Java, Indonesia. *Bulletin of volcanology*. **74**(5), pp.1213–1233.
Gilbert, G.N. 2008. *Agent-Based Models*. London: SAGE.
Gilbert, N. and Terna, P. 2000. How to build and use agent-based models in social science. *Mind & Society*. **1**(1), pp.57–72.
Gilbert, N. and Troitzsch, K. 2005. *Simulation For The Social Scientist*. McGraw-Hill Education (UK).
Griffin, R. 2012. *Management*. Cengage Learning.
Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., Huth, A., Jepsen, J.U., Jørgensen, C., Mooij, W.M., Müller, B., Pe'er, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R.A., Vabø, R., Visser,

U. and DeAngelis, D.L. 2006. A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*. **198**(1–2), pp.115–126.

Hawe, G.I., Coates, G., Wilson, D.T. and Crouch, R.S. 2012. Agent-based simulation for large-scale emergency response: A survey of usage and implementation. *ACM Computing Surveys (CSUR)*. **45**(1), p.8.

Jenkins, S., Komorowski, J.-C., Baxter, P.J., Spence, R., Picquout, A., Lavigne, F. and Surono 2013. The Merapi 2010 eruption: An interdisciplinary impact assessment methodology for studying pyroclastic density current dynamics. *Journal of Volcanology and Geothermal Research*. **261**, pp.316–329.

Juliani, A., Brontowiyono, W., Ribut, L., Hamidin, H. and Evi, O. 2011. Rapid Assessment Terhadap Kerusakan Bangunan Akibat Erupsi Merapi Tahun 2010. *Jurnal Sains & Teknologi Lingkungan*. **3**(2), pp.115–124.

Klügl, F. 2008. A Validation Methodology for Agent-based Simulations *In*: *Proceedings of the 2008 ACM Symposium on Applied Computing* [Online]. SAC '08. New York, NY, USA: ACM, pp.39–43. [Accessed 30 April 2017]. Available from: http://doi.acm.org/10.1145/1363686.1363696.

Kravari, K. and Bassiliades, N. 2015. A Survey of Agent Platforms. *Journal of Artificial Societies and Social Simulation*. **18**(1), p.11.

Lavigne, F., De Coster, B., Juvin, N., Flohic, F., Gaillard, J.-C., Texier, P., Morin, J. and Sartohadi, J. 2008. People's behaviour in the face of volcanic hazards: Perspectives from Javanese communities, Indonesia. *Journal of Volcanology and Geothermal Research*. **172**(3–4), pp.273–287.

Lavigne, F., Thouret, J.C., Voight, B., Suwa, H. and Sumaryono, A. 2000. Lahars at Merapi volcano, Central Java: an overview. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.423–456.

Lo, S.M., Huang, H.C., Wang, P. and Yuen, K.K. 2006. A game theory based exit selection model for evacuation. *Fire Safety Journal*. **41**(5), pp.364–369.

Macal, C. and North, M. 2006. Tutorial on Agent-Based Modeling and Simulation PART 2: How to Model with Agents *In*: *Proceedings - Winter Simulation Conference*., pp.73–83.

Macal, C.M. and North, M.J. 2005. Tutorial on agent-based modeling and simulation *In*: *Proceedings of the 37th conference on Winter simulation* [Online]. Winter Simulation Conference, pp.2–15. [Accessed 7 April 2015]. Available from: http://dl.acm.org/citation.cfm?id=1162712.

Macal, C.M. and North, M.J. 2010. Tutorial on agent-based modelling and simulation. *Journal of Simulation*. **4**(3), pp.151–162.

Malleson, N. and Birkin, M. 2012. Analysis of crime patterns through the integration of an agent-based model and a population microsimulation. *Computers, Environment and Urban Systems*. **36**(6), pp.551–561.

Malleson, N., See, L., Evans, A. and Heppenstall, A. 2014. Optimising an Agent-Based Model to Explore the Behaviour of Simulated Burglars *In*: V. Dabbaghian and V. K. Mago, eds. *Theories and Simulations of Complex Social Systems* [Online]. Berlin, Heidelberg: Springer Berlin Heidelberg, pp.179–204. [Accessed 23 April 2015]. Available from: http://link.springer.com/10.1007/978-3-642-39149-1_12.

Maly, E., Iuchi, K. and Nareswari, A. 2015. Community-Based Housing Reconstruction and Relocation: REKOMPAK Program after the 2010 Eruption of Mt. Merapi, Indonesia. Indonesia Institute of Social Safety Science **27**, pp.205–214.

Marrero, J.M., García, A., Llinares, A., Rodríguez-Losada, J.A. and Ortiz, R. 2010. The Variable Scale Evacuation Model (VSEM): a new tool for simulating massive evacuation processes during volcanic crises. *Nat. Hazards Earth Syst. Sci.* **10**(4), pp.747–760.

Mas, E., Suppasri, A., Imamura, F. and Koshimura, S. 2012. Agent-based simulation of the 2011 great east japan earthquake/tsunami evacuation: An integrated model of tsunami inundation and evacuation. *Journal of Natural Disaster Science*. **34**(1), pp.41–57.

MCDEM 2008. *Mass evacuation planning: director's guidelines for civil defence emergency management (CDEM) groups, DGL 07/08* [Online]. Ministry of Civil Defence and Emergency Management. Available from:

http://www.civildefence.govt.nz/assets/Uploads/publications/dgl-07-08-mass-evacuation-planning.pdf.

Mei, E.T.W., Lavigne, F., Picquout, A., de Bélizal, E., Brunstein, D., Grancher, D., Sartohadi, J., Cholik, N. and Vidal, C. 2013. Lessons learned from the 2010 evacuations at Merapi volcano. *Journal of Volcanology and Geothermal Research*. **261**, pp.348–365.

Murray, A.T. 2010. Quantitative Geography. *Journal of Regional Science*. **50**(1), pp.143–163.

Na, H.S. and Banerjee, A. 2014. An agent-based discrete event simulation approach for modeling large-scale disaster evacuation network *In*: *Simulation Conference (WSC), 2014 Winter*., pp.1516–1526.

Namazi-Rad, M.-R., Huynh, N., Barthelemy, J. and Perez, P. 2014. Synthetic population initialization and evolution-agent-based modelling of population aging and household transitions *In*: *International Conference on Principles and Practice of Multi-Agent Systems* [Online]. Springer, pp.182–189. [Accessed 2 August 2017]. Available from: http://link.springer.com/chapter/10.1007/978-3-319-13191-7_15.

Newhall, C.G., Bronto, S., Alloway, B., Banks, N.G., Bahar, I., del Marmol, M.A., Hadisantono, R.D., Holcomb, R.T., McGeehin, J., Miksic, J.N., Rubin, M., Sayudi, S.D., Sukhyar, R., Andreastuti, S., Tilling, R.I., Torley, R., Trimble, D. and Wirakusumah, A.D. 2000. 10,000 Years of explosive eruptions of Merapi Volcano, Central Java: archaeological and modern implications. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.9–50.

Nuzulia, Y. and Sudibyakto, S. 2014. *kajian penolakan relokasi oleh warga terdampak erupsi merapi tahun 2010 (studi kasus di dusun kalitengah lor, DIYdan dusun Sambungrejo JawaTengah)*.[Online] Universitas Gadjah Mada. [Accessed 19 March 2015]. Available from: http://etd.ugm.ac.id/index.php?mod=penelitian_detail&sub=PenelitianDetail&act=view&typ=html&buku_id=66452&is_local=1.

O'Sullivan, D. 2004. Complexity science and human geography. *Transactions of the Institute of British Geographers*. **29**(3), pp.282–295.

Park, C. and Allaby, M. 2013. *A Dictionary of Environment and Conservation* [Online] 2nd ed. Oxford University Press. [Accessed 11 March 2015]. Available from: http://www.oxfordreference.com/view/10.1093/acref/9780199641666.001.0001/acref-9780199641666.

Pidd, M., de Silva, F.N. and Eglese, R.W. 1996. A simulation model for emergency evacuation. *European Journal of Operational Research*. **90**(3), pp.413–419.

Pine, J. 2008. *Natural hazards analysis: reducing the impact of disasters* [Online]. CRC Press. [Accessed 25 March 2015]. Available from: http://books.google.co.uk/books?hl=en&lr=&id=TU3k6MuE2BAC&oi=fnd&pg=PP1&dq=Natural+hazards+analysis+:+reducing+the+impact+of+disasters&ots=VOfYEqQfk5&sig=ZfVTY03Zp-gVkh4TUJWSloWgWtU.

Polhill, J.G. 2010. ODD Updated. *Journal of Artificial Societies and Social Simulation*. **13**(4), p.9.

Pons, M., Johnson, P.A., Rosas, M. and Jover, E. 2014. A georeferenced agent-based model to analyze the climate change impacts on ski tourism at a regional scale. *International Journal of Geographical Information Science*. **28**(12), pp.2474–2494.

Press, O.U. 2004. *A Dictionary of Computing*. Oxford University Press.

Saepuloh, A., Urai, M., Aisyah, N., Widiwijayanti, C., Jousset, P. and others 2013. Interpretation of ground surface changes prior to the 2010 large eruption of Merapi volcano using ALOS/PALSAR, ASTER TIR and gas emission data. *Journal of Volcanology and Geothermal Research*. **261**, pp.130–143.

Salgado, M. and Gilbert, N. 2013. Agent Based Modelling *In*: T. Teo, ed. *Handbook of Quantitative Methods for Educational Research* [Online]. SensePublishers, pp.247–265. [Accessed 21 March 2015]. Available from: http://link.springer.com/chapter/10.1007/978-94-6209-404-8_12.

Scaini, C., Felpeto, A., Martí, J. and Carniel, R. 2014. A GIS-based methodology for the estimation of potential volcanic damage and its application to Tenerife Island, Spain. *Journal of Volcanology and Geothermal Research*. **278**–**279**, pp.40–58.

Shi, J., Ren, A. and Chen, C. 2009. Agent-based evacuation model of large public buildings under fire conditions. *Automation in Construction*. **18**(3), pp.338–347.

Silva, F.N. de 2001. Providing spatial decision support for evacuation planning: a challenge in integrating technologies. *Disaster Prevention and Management; Bradford*. **10**(1), pp.11–20.

Silva, F.N. de and Eglese, R.W. 2000. Integrating Simulation Modelling and GIS: Spatial Decision Support Systems for Evacuation Planning. *The Journal of the Operational Research Society*. **51**(4), pp.423–430.

Sparks, R.S.J. 2003. Forecasting volcanic eruptions. *Earth and Planetary Science Letters*. **210**(1–2), pp.1–15.

Srbljinović, A. and Škunca, O. 2003. An Introduction to Agent Based Modelling and Simulation of Social Processes. *Interdisciplinary Description of Complex Systems*. **1**(1–2), pp.1–8.

Stevenson, A. 2010. *Oxford Dictionary of English*. Oxford University Press.

Sugumaran, R. and DeGroote, J. 2010. *Spatial Decision Support Systems Principles and Practices* [Online]. CRC Press. Available from: http://dx.doi.org/10.1201/b10322-4.

Sun, Z., Lorscheid, I., Millington, J.D., Lauf, S., Magliocca, N.R., Groeneveld, J., Balbi, S., Nolzen, H., Müller, B., Schulze, J. and Buchmann, C.M. 2016. Simple or complicated agent-based models? A complicated issue. *Environmental Modelling & Software*. **86**, pp.56–67.

Surono, Jousset, P., Pallister, J., Boichu, M., Buongiorno, M.F., Budisantoso, A., Costa, F., Andreastuti, S., Prata, F., Schneider, D., Clarisse, L., Humaida, H., Sumarti, S., Bignami, C., Griswold, J., Carn, S., Oppenheimer, C. and Lavigne, F. 2012. The 2010 explosive eruption of Java’s Merapi volcano—A ‘100-year’ event. *Journal of Volcanology and Geothermal Research*. **241**–**242**, pp.121–135.

Surono, S., Jousset, P. and Pallister, J. 2011. Crisis Management during the centennial 2010 eruption at Merapi volcano, Central Java, Indonesia *In*: *2011 International Union of Geodesy and Geophysics (IUGG) General Assembly* [Online]. Melbourne, Australia. [Accessed 21 November 2014]. Available from: https://hal-brgm.archives-ouvertes.fr/hal-00599184.

Tan, L., Hu, M. and Lin, H. 2015. Agent-based simulation of building evacuation: Combining human behavior with predictable spatial accessibility in a fire emergency. *Information Sciences*. **295**, pp.53–66.

Tilling, R.. 2009. El Chichón’s “surprise” eruption in 1982: Lessons for reducing volcano risk. *Geofísica Internaciona*. **48**(1), pp.3–19.

Tomsen, E., Lindsay, J.M., Gahegan, M., Wilson, T.M. and Blake, D.M. 2014. Evacuation planning in the Auckland Volcanic Field, New Zealand: a spatio-temporal approach for emergency management and transportation network decisions. *Journal of Applied Volcanology*. **3**(1), p.6.

Troitzsch, K.G. 1997. Social science simulation—origins, prospects, purposes *In*: *Simulating social phenomena* [Online]. Springer, pp.41–54. [Accessed 5 April 2015]. Available from: http://link.springer.com/chapter/10.1007/978-3-662-03366-1_3.

Ukkusuri, S.V., Hasan, S., Luong, B., Doan, K., Zhan, X., Murray-Tuite, P. and Yin, W. 2017. A-RESCUE: An Agent based regional evacuation simulator coupled with user enriched behavior. *Networks and Spatial Economics*. **17**(1), pp.197–223.

UNISDR 2002. *Living with risk: a global review of disaster reduction initiatives*. United Nations Publications.

Uno, K. and Kashiyama, K. 2008. Development of simulation system for the disaster evacuation based on multi-agent model using GIS. *Tsinghua Science & Technology*. **13**, pp.348–353.

Visser, H. and Nijs, T. 2006. The Map Comparison Kit. *Environmental Modelling & Software*., pp.346–358.

Voight, B., Constantine, E.K., Siswowidjoyo, S. and Torley, R. 2000. Historical eruptions of Merapi Volcano, Central Java, Indonesia, 1768–1998. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.69–138.

Wang, D.Q., Gong, Q.G. and Shen, X.F. 2014. An Improved Personnel Evacuation Cellular Automata Model Based on the Ant Colony Optimization Algorithm. *Applied Mechanics and Materials*. **513**–**517**, pp.3287–3291.

Wang, H., Mostafizi, A., Cramer, L.A., Cox, D. and Park, H. 2016. An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety. *Transportation Research Part C: Emerging Technologies*. **64**, pp.86–100.

Wise, S. 2014. *Using Social Media Content to Inform Agent-based Models for Humanitarian Crisis Response*.[Online] Ph.D. Thesis, Fairfax, VA, USA: George Mason University. [Accessed 20 May 2015]. Available from: http://digilib.gmu.edu:8080/jspui/handle/1920/8879.

Yang, B., Ren, B. and Wu, Y. 2012. The Research of Multi-Resolution Modeling and Simulation of the Emergency Evacuation. *Procedia Engineering*. **29**, pp.3110–3116.

Yang, L., Liu, Q., Yang, S.-H. and Yu, D. 2015. Evacuation Planning with Flood Inundation as Inputs *In*: *Proceedings of the ISCRAM 2015 Conference* [Online]. Kristiansand. [Accessed 27 May 2015]. Available from: http://iscram2015.uia.no/wp-content/uploads/2015/05/3-c.pdf.

Zhang, B., Chan, W.K. and Ukkusuri, S.V. 2009. Agent-based modeling for household level hurricane evacuation *In*: *Proceedings of the 2009 Winter Simulation Conference (WSC)*., pp.2778–2784.

Zhao, H., Winter, S. and Tomko, M. 2017. Integrating Decentralized Indoor Evacuation with Information Depositories in the Field. *ISPRS International Journal of Geo-Information*. **6**(7), p.213.

Zia, K. and Ferscha, A. 2009. A Simulation Study of Exit Choice Based on Effective Throughput of an Exit Area in a Multi-exit Evacuation Situation *In*: IEEE, pp.235–238. [Accessed 29 December 2014]. Available from: http://dl.acm.org/citation.cfm?id=1671362.

Zimmermann, M.N. 2005. The Risk Concept *In*: Kobe. Available from: http://www.unisdr.org/2005/wcdr/thematic-sessions/presentations/session1-8/swiss-mr-zimmermann.pdf.

Chapter 2
A Conceptual Design of Spatio-Temporal Agent-Based Model for Volcanic Evacuation

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This chapter presents the framework of the spatial agent-based model (ABM) of volcanic evacuation. This framework was applied and explored to identify the potential uses in improving the emergency evacuation management in Merapi, Indonesia.

Abstract: the understanding of evacuation processes is important for improving the effectiveness of evacuation plans in the event of volcanic disasters. In terms of social processes, the enactment of evacuations in volcanic crises depends on the variability of individual/household responses. This variability of population response is related to the uncertainty and unpredictability of the hazard characteristics of volcanoes—specifically, the exact moment at which the eruption occurs (temporal), the magnitude of the eruption and which locations are impacted (spatial). In order to provide enhanced evacuation planning, it is important to recognise the potential problems that emerge during evacuation processes due to such variability. Evacuation simulations are one approach to understanding these processes. However, experimenting with volcanic evacuations in the real world is risky and challenging, and so an agent-based model is proposed to simulate volcanic evacuation. This paper highlights the literature gap for this topic and provides the conceptual design for a simulation using an agent-based model. As an implementation, an initial evacuation model is presented for Mount Merapi in Indonesia, together with potential applications of the model for supporting volcanic evacuation management, discussion of the initial outcomes and suggestions for future work.

Keywords: agent-based model; evacuation model; risk perception; Mount Merapi.

2.1 Introduction

Mount Merapi is located near the densely populated city of Yogyakarta and is one of the most active volcanoes in Indonesia (Lavigne et al., 2000; Voight et al., 2000). Merapi has a centuries-long record of numerous violent eruptions (Newhall et al., 2000). These dangerous events are likely to continue in the modern era and the recurrence of large explosive events on Mount Merapi is likely in the future (Voight et al., 2000). The physical condition of Merapi's environment, which is suitable for farming and tourism, attracts people to live in and visit the area even though it is prone to volcanic disaster. It has been identified that there are more than 50,000 people living in the danger zone surrounding Merapi, even though they have themselves experienced several eruptions (Mei et al., 2013). Moreover, many people have refused to relocate, despite the 2010 volcanic eruption having damaged their settlements (Ayuningtyas and Gabriel, 2013; Nuzulia and Sudibyakto, 2014). It is therefore important to provide better evacuation planning, as this is the only way to reduce the risks for the nearby population.

An important means of reducing the risk presented by volcanic eruption is through the provision of effective evacuation plans. However, people do not always respond positively to evacuation orders in volcanic crises. Although it is believed that people are aware of the decision to evacuate following an order from the authorities during a crisis (Mei et al., 2011), based on the experiences of the 2006 and 2010 Mount Merapi crises (POSKO SET BAKORNAS PBP, 2006; Mei et al., 2013), it appears that people's slow evacuation response remained the major problem that led to fatalities. It was claimed that the response to the last eruption in 2010 was better planned than for previous eruptions; however, the casualties were higher than in 2006 due to the unanticipated changing of the intensity of the eruption.

Various study attempts relating to the reduction of physical and social aspects of the risks relating to Mount Merapi have been made (Table 2.1). The physical aspects considered mainly relate to the identification of hazards, based on historical events, seismicity, modelling/mapping, material sediment/deposit characteristics and ground-based/remotely sensed-based monitoring. The social aspects are related to disaster/risk management, decision-support systems, disaster impact, population responses and characteristics, and evacuation decisions/management. There is a lack of research, however, on evacuation simulation and its importance in supporting the provision of better evacuation plans (De Silva and Eglese, 2000; Handayani et al., 2016).

Table 2.1 Existing studies of Mount Merapi.

No.	Research Focus	References
1	Disaster/risk management	(Mei et al., 2011; Surono et al., 2011; Aman et al., 2012; Bachri et al., 2012; Bakkour et al., 2013; Ismayasti et al., 2014)
2	Decision support for disaster/crisis management	(Putra et al., 2011; Schneider et al., 2011; Setijadji, 2011; Jumadi et al., 2012)
3	Historical events	(Andreastuti et al., 2000; Newhall et al., 2000; Voight et al., 2000)
4	Sediment/deposit characteristics	(Gomez et al., 2008; Charbonnier and Gertisser, 2008; Charbonnier and Gertisser, 2011; Gertisser et al., 2012)
5	Hazard mapping/modelling	(Itoh et al., 2000; Takahashi and Tsujimoto, 2000; Schwarzkopf et al., 2005; Miyamoto et al., 2011; Charbonnier and Gertisser, 2012; Darmawan et al., 2014)
6	Impact of eruption	(Takahashi and Tsujimoto, 2000; S.J. Charbonnier et al., 2013; Yulianto et al., 2013)
7	Seismicity	(Ratdomopurbo and Poupinet, 1995; Ratdomopurbo and Poupinet, 2000)
8	Activity monitoring	(Beauducel et al., 2000; Voight, Young, et al., 2000; Pallister et al., 2013)
9	Population response, characteristics, perception and vulnerability	(Utami, 2008; Dove, 2008; Lavigne et al., 2008; Donovan, 2010; Christia, 2012; Donovan et al., 2012; Mei and Lavigne, 2012)
10	Factors influencing evacuation decision	(Sagala and Okada, 2009; Handayani et al., 2016)
11	Hazard characteristics	(S. Charbonnier et al., 2013; Damby et al., 2013; de Bélizal et al., 2013; Bignami et al., 2013)
12	Lessons from past evacuation management	(Mei and Lavigne, 2013; Mei et al., 2013)

Various aspects should be considered in order to provide modelling for volcanic evacuations, including socio-demographic attributes, behaviour, and spatial and temporal aspects. The population response is composed of the nonlinear mechanisms of social processes, and such responses are highly stochastic rather than deterministic. The model therefore needs to utilise an appropriate approach to accommodate this nonlinearity.

Nowadays, agent-based modelling (ABM) is considered an adequate model to simulate such nonlinear processes (Srbljinović and Škunca, 2003; Malleson et al., 2014). This approach, with the integration of geographic information systems (GIS) to model spatial aspects, is considered appropriate. The integration of GIS into ABM is known as spatial agent-based modelling (Brown and Xie, 2006), or georeferenced agent-based modelling (Pons et al., 2014). The conceptual integration of both GIS and ABM is provided successfully by Brown et al. (2005), in which GIS is used as the spatial data-model representation, and ABM is used as the model for the processes. This approach can be used to model and simulate complex systems and represent the results of the spatial processes as spatio-temporal information.

This article, which comprises a conference paper published by Jumadi et al. (2016a), highlights the lack of research available in the literature related to evacuation modelling for Mount Merapi, provides a conceptual design for the simulation using spatial ABM and explores its potential use in supporting evacuation management. This paper contributes to the development of ABM for large-scale evacuation simulation, which integrates the hazard model, an aspect that is absent from the literature, especially regarding volcanic hazards. For further explanation, Section 2.2 presents the background to agent-based simulation in support of the evacuation decisions modelled; Section 2.3 outlines the concept of the volcanic evacuation model; Section 2.4 presents the initial model design, implementation and its potential use in support of evacuation management; Section 2.5 specifies the future direction of research to validate this model, while Section 2.6 discusses the initial results and future work.

2.2 Spatial Agent-Based Modelling to Support Evacuation Management

Evacuation simulation is an important tool for the support of evacuation management (De Silva and Eglese, 2000). The example put forward by De Silva and Eglese (2000) shows that evacuation simulation can be used to test contingency plan scenarios. Their simulation integrates GIS and simulation models to develop simulation-based spatial decision support for evacuation planning. However, creating realistic evacuation scenarios is challenging because various factors need to be taken into consideration (Silva, 2001), especially the modelling of evacuee behaviour, which is very important in defining the evacuation outcome.

Evacuations from various types of hazard have been modelled through various approaches, based on the details of evacuee behaviour. Some examples of these, ranging from macroscopic to microscopic levels, depending on the evacuee behaviour detailed in the model, are presented in Table 2.2. A macroscopic model is unable to capture the level of variability of population behaviour that can be achieved through a microscopic model (Yang et al., 2015), whereas a mesoscopic model compromises both micro and macro outputs (Silva, 2001). Evacuation modelling uses varying methods such as GIS (Marrero et al., 2010; Ye et al., 2011; Yang et al., 2012; Marrero et al., 2013), ABM (Chen et al., 2006; Mas et al., 2012; Handford and Rogers, 2012; Nagarajan, 2014; Teo et al., 2015; Tan et al., 2015), numerical models (Pourrahmani et al., 2015; Pillac et al., 2015; Yang et al., 2015), cellular automata (Zia and Ferscha, 2009), linear programming (Dixit, 2008), game theory (Lo et al., 2006) and logit models (Sadri et al., 2015; Ng et al., 2015). Of these studies, only a few are concerned with volcanic evacuation, such as Marrero et al. (2010, 2013), but, in these, the behaviour of both volcanoes and population is inadequately considered in the models (macroscopic).

Table 2.2 Existing research on evacuation modelling.

Modelling Type and Method	Hazard
Macroscopic	
Agent-Based Model	Hurricane (Zou et al., 2005)
Geographic Information System	Volcanic (Kohsaka, 2000; Marrero et al., 2010; Marrero et al., 2013); Earthquake (Ye et al., 2011) Generic hazard (Brachman and Dragicevic, 2014)
Mathematical/numerical model	Earthquake (Pourrahmani et al., 2015); Generic hazard (Pillac et al., 2015);
Genetic algorithm	Generic hazard (Goerigk et al., 2014); Flood (Yang et al., 2015)
Discrete choice	Hurricane (Cheng et al., 2008)
Mesoscopic	

Table 2.2 Continued …

ABM and numerical simulation	Tsunami (Teo et al., 2015)
Linear programming	Hurricane (Dixit, 2008)
Microscopic	
Agent-Based Model	Fire/building-damage-related hazard (Christensen and Sasaki, 2008; Shi et al., 2009; Joo et al., 2013; Tan et al., 2015; Adam and Gaudou, 2017; Zhao et al., 2017); Generic hazard (Chen and Zhan, 2008; Zhang, 2012; Nagarajan, 2014); Tsunami (Mas et al., 2012; Wang et al., 2016; Usman et al., 2017); Hurricane (Chen et al., 2006; Zhang et al., 2009; Handford and Rogers, 2012; Yin et al., 2014; Ukkusuri et al., 2017); Earthquake (Bernardini et al., 2014; Cimellaro et al., 2017); Flood (Dawson et al., 2011; Medina et al., 2016) Wildfire (Wise, 2014)
Cellular automata	Generic hazard (Zia and Ferscha, 2009; Wang et al., 2014); Fire (Yuan and Tan, 2007)
Dijkstra's algorithm, virtual reality Visualisation	Flood (Uno and Kashiyama, 2008)
Particle swarm optimization algorithm	Generic hazard (Yang et al., 2012)
Game theory	Fire (Lo et al., 2006)
Micro-simulation	Generic hazard (Chen, 2012)
Mixed logit	Terror attack (Hsu and Peeta, 2013)

The involvement of the behaviour of people in the evacuation model is important since evacuations are composed of complex social processes. Social processes are nonlinear and dynamic, and the studies relating to them are categorised as investigating complex adaptive systems (Srbljinović and Škunca, 2003). For many years, social scientists have tried to understand particular social processes by means of simulation environments (Gilbert, 2008). In this field, simulation means running simplified versions of social systems that might occur in the real world. Such simulation is essential for several purposes: to obtain understanding; to predict the consequences of particular social processes; to substitute human capabilities; training; entertainment; and to assist in discovery and formalisation (Gilbert and Troitzsch, 2005). Although many techniques are suitable for social process simulations, including cellular automata, artificial intelligence and ABM, ABM is the only one that can accommodate the high level of complexity of a system and instantiate interaction between agents at the same or different levels (Gilbert and Troitzsch, 2005). It can be used to model social entities, their behaviours, social attributes, and properties that emerge from their interactions. Spatial data from GIS can be involved in the simulation environment, to match with particular geographic locations.

ABM is defined as a computational method that enables a researcher to create, analyse and experiment with models comprised of agents that interact within an environment (Gilbert, 2008). This term is used interchangeably with the terms ‘agent-based systems’ and ‘individual-based modelling’ (IBM) (Macal and North, 2005). Macal and North (2005) introduced a complete term for modelling and simulation based on this technique of agent-based modelling and simulation (ABM). Agents can be separate computer programs or can take the form of distinct parts of a program used to represent social actors such as individual people, organisations such as firms, or bodies such as nation states (Gilbert, 2008). Modelling is the act of creating a model of something for a particular purpose, such as to describe it, understand it, or derive certain properties (Press, 2004). A model is defined as a simplified representation or ‘abstraction of reality’ (Demeritt and Wainwright, 2005) and a simulation is defined as the imitation of a system through a prototype of the system, in order to find the flaws and problems inherent in it so as to rectify them (Bandyopadhyay and Bhattacharya, 2014). An agent can be represented in a spatially realistic environment involving a GIS. The integration of GIS and ABM has been discussed in numerous pieces of research and is known as spatial agent-based modelling (Brown and Xie, 2006) or georeferenced agent-based modelling (Pons et al., 2014).

ABM has advantages in modelling the complexity of interactions between social and physical environments (Heppenstall et al., 2016), which make it appropriate for modelling certain emergency conditions in silico to provide greater understanding of them (Hawe et al., 2012). It can model the dynamic changes of hazardous environments, as well as the behaviour of people in response to a disaster (Mas et al., 2012), so that the simulation outcomes can improve the understanding of evacuation processes and optimise evacuation plans (Silva, 2001). For a more realistic model, spatial data can be integrated in the model at various scales (Hawe et al., 2012) ranging from small areas (e.g., (Christensen and Sasaki, 2008; Shi et al., 2009; Joo et al., 2013; Tan et al., 2015; Zhao et al., 2017)) to large areas (e.g., (Chen et al., 2006; Zhang et al., 2009; Handford and Rogers, 2012; Yin et al., 2014)), depending on the type of hazard being modelled. For example, fire may only impact a building, while an earthquake or tsunami can destroy a city or region. Some simulations proposed for a specific hazard integrate the hazard model in the ABM simulation and can therefore provide a more realistic model of interactions between human and hazard—for example, the fire dynamics simulator (Shi et al., 2009), numerical simulation of tsunami propagation (Mas et al., 2012), the tsunami inundation model (Wang et al., 2016) and hydrodynamic simulation of a flood (Dawson et al., 2011). Meanwhile, the evacuation models proposed for generic hazards are developed without the integration of the hazard model (e.g., (Christensen and Sasaki, 2008; Zhang et al., 2009; Na and Banerjee, 2014; Tan et al., 2015; Zhao et al., 2017)). Given that the hazard is spatially dynamic, providing this dynamic mechanism is significant. The hydrodynamic-using numerical simulations for tsunami (Mas et al., 2012; Wang et al., 2016) and floods (Dawson et al., 2011) are examples of the integration of the hazard dynamic model in the simulation on a regional (large) scale. However, these examples are limited in involving historical events to express the spatial extent of hazard in the model. This limitation is addressed in this paper.

In addition, the composition of the population and its characteristics, behaviour and interactions can be modelled to complete the representation of the social environment. To do so, the synthetic population of agents utilises synthetic social networks, allowing synthetic daily activities to be generated based on real population data (Wise, 2014; van Dam et al., 2017). There are several techniques that can be used to generate a synthetic population, including deterministic reweighting, conditional probability (Monte Carlo simulation) and simulated annealing (Harland et al., 2012). Moreover, certain rules relating to how people respond to the hazardous event can be included, in order to specify the agent’s behaviour (Adam and Gaudou, 2017). The agents utilised in the model used in this paper have the ability to observe and measure the hazard level of their environment and make decisions based on this as well as on their interactions.

2.3 The Concept of the Volcanic Evacuation Model

It should be noted that no one method has been recognised as the best approach in the development of an ABM (Gilbert and Terna, 2000). However, it should contain three main elements: agents, relationships and environment (Macal and North, 2010). According to Macal and North (2006), ABM can be developed by means of several steps: (1) identifying its purpose and the questions that are intended to be answered; (2) systematically analysing the system, identifying components and component interactions, relevant data sources and so on; (3) conducting the experiment; and (4) understanding the robustness of the model. The purpose of the evacuation model presented in this paper is to provide a spatially realistic simulation of a volcanic evacuation. This model intends to answer questions related to spatial and temporal aspects of evacuation—for example, how different scenarios affect the disaster outcome and which route(s) might experience potentially high levels of congestion during the evacuation process.

Spatial data is essential for providing a spatially realistic evacuation simulation. Therefore, GIS is used for preparing spatial data as input into the ABM simulation (Figure 2.1). The spatial data in GIS can be modelled as vector data or raster data (Sugumaran and DeGroote, 2010). The vector data model represents the real world as point, line or polygon geometry, while, in raster data, representation can be as a regular two-dimensional grid with specific spatial resolution. These data models have advantages and disadvantages in visualising the real world, which should be noted when deciding which model is appropriate for certain applications. The choice of vector or raster model depends on the purpose and design of the simulation, in terms of how the data will be represented. There are a number of platforms that can be used to integrate GIS data into the ABM simulation—for example AGlobe, Cougaar, Repast, CybelePro, SESAM, AnyLogic, GAMA, and NetLogo (Crooks and Castle, 2012; Kravari and Bassiliades, 2015); however, their capabilities for supporting this type of GIS data vary. Repast, for example, is suitable for vector models, while AnyLogic, NetLogo and GAMA accommodate both vector and raster models (Crooks and Castle, 2012; Kravari and Bassiliades, 2015). In this present model, the GIS data of the population unit, hazard zones, road networks and shelters are represented as a vector. This data was prepared using GIS software and used to set up the environment where the agents are living or moving through (road networks).

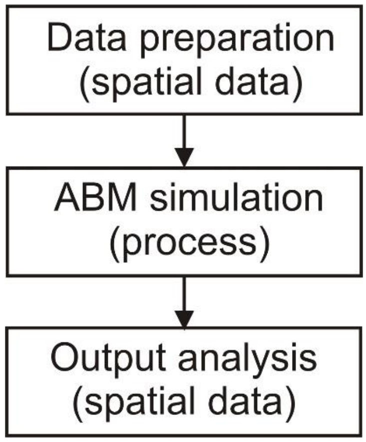


Figure 2.1 Geographic Information System (GIS) and Agent-Based Model (ABM) interaction concept.

Figure 2.1 shows the flow of the model from preparation and simulation to output. The output can be analysed using spatial analysis that is suitable for the purpose. Several of these outcomes are provided in Section 2.4.2 with the aim of answering evacuation-related problems. Therefore, it is important to utilise GIS in the analysis of the output. Additionally, there are some types of spatial analysis that can be used to analyse the output: point density analysis, for example, can be used to provide an analysis of the density map of the population that has been aggregated from the individual evacuees. It can also be used to analyse the road density map.

2.3.1 Data Input Requirements

Providing a spatially realistic model is important because the location of the crater and the population distribution are critical in defining the risk. Therefore, some spatial and non-spatial data were employed as inputs into this model. This data is predominantly comprised of:

1. Administrative boundaries (vector data): this is used to populate the agents within the population unit (district) (BPS Kab. Sleman, 2015) (see the data in the supplementary material).
2. Volcanic hazard zones (vector data): setting up the hazard scenarios and spatial distribution related to the eruption impact.
3. Land use (vector data): defining the mean centre of population distribution (Jumadi et al., 2016b). This data is used to make the distribution of agents spatially similar to the real data.
4. Census data: defining the number of agents within each population unit (BPS Kab. Sleman, 2015).

5. Road networks (vector data): this is used for evacuation routing of agent movement. Open Street Map data was used in PBF format for this purpose (GEOFABRIK, 2016). For the purpose of modelling movement, Dijkstra’s algorithm (Skiena, 1990) was utilised to find the shortest path from the origin location to the destination, as this algorithm is advantageous for analysing evacuation routing in a dynamic environment (Oyola et al., 2017).
6. Evacuation shelter data (vector data): the shelter is used to accommodate the evacuees. In the initial model, the shelters are placed randomly within the city and outside the hazard zone. It is assumed that people would go to the city, as it will provide much-needed public services. However, a few datasets have been listed that could be used to improve the model in this aspect in future work (BNPB, 2010c; BNPB, 2010a; BNPB, 2010d; BNPB, 2010b),(Budiyono, 2010).

2.3.2 Agents and Environment

The following list provides an overview of the agents as well as the environment components. Details of the agents and environment attributes are provided in Table 2.3. This table also details some attributes of the agents and environment that indicate geographic location e.g., district ID, latitude, and longitude. The determinations of both location (spatial) and attributes of the agents are based on the dataset provided in Section 2.3.1. The agents consist of volcano, stakeholders and people. The volcano has a specific coordinate based on its real location, while the human population is spatially distributed to mimic the real population (Section 2.3.3). The georeferenced environment where these agents live comprises population units, hazard zones, route networks and evacuation shelters.

Agents:

1. Volcano: this is a single agent that can produce activity and influence the hazard zone.
2. Stakeholders: represent the authority that has the role of observing the volcano and alerting people.
3. People: represent the people who live in the area surrounding the volcano. This agent has the ability to decide to move from the hazard zone to a safe area.

Environment:

1. Population unit: this is a fixed environment that is provided as a GIS region. The population unit is provided as the district boundary where the agent's population will be distributed within this region.
2. Hazard zones: the hazard zones are provided to express the hazardous environment that is dynamically changing as the volcanic activity is changing.
3. Route networks: the evacuation routes that are generated using OpenStreetMap (OSM) are a fixed environment that is used by agents to move along.
4. Evacuation shelters: this is a fixed environment that is distributed outside the hazard zones at GIS points.

Table 2.3 Overview of entities and attributes.

Entity	Attribute Name	Attribute Type	Description
Volcano	Latitude	Double	Latitude of the volcano location
	Longitude	Double	Longitude of the volcano location
	Activity length	Integer	The duration of crisis
	Activity level	Double	This represents the level of volcanic activity expressed qualitatively from low (1) to high (4)
	VEI		Volcanic Explosivity Index
	Activity Scenarios	List<double>	Contains the list of the scenarios of activity length of each level (low to high)
People	District ID	Integer	Number of districts where people live
	Latitude	Double	Latitude of current location
	Longitude	Double	Longitude of current location
	Home latitude	Double	Latitude of home location
	Home longitude	Double	Longitude of home location
	Movement speed	Double	Speed of movement (km/h)
	Hazard level	Integer	The hazard level of the agent location

Table 2.3 Continued …

	Destination	Shelter	The selected destination for evacuation
	Links	List<People>	List of people generated randomly to express agents' relationship
	Age	Integer	Age of person generated from custom distribution based on census data
	Education	Integer	Education level of person generated from custom distribution based on census data
	Sex	Integer	Gender (male = 1, female = 2) of person generated from custom distribution based on census data
Stakeholder	Alert level	Integer	Alert level as a result of volcanic activity observation
	Links	List<People>	List of random people who directly receive the alert
Environment	Districts	List<Polygon>	The boundaries of districts (polygon)
	Hazard zone	List<Polygon>	The hazard zones
	Shelters	List<Point>	Location of shelters as evacuation destinations
	Routes	List<Object>	Routes where people are moving loaded from OSM

2.3.3 Agent Population Generation

Developing a simulation in which the outcomes rely on individual behaviour needs a synthetic population of human agents in which the heterogeneity of the agents' characteristics is consistent with the aggregate of characteristics of the real population (van Dam et al., 2017). Especially for spatially realistic simulation purposes, these population characteristics should be similar to real conditions in terms of socio-demographic attributes as well as spatial distribution (Heppenstall et al., 2011). However, the available population microdata commonly lacks spatial representation detail for household location due to confidentiality requirements (Huang and Williamson, 2001). Therefore, synthetic population generation should not only characterise demographic character but also geographic location.

A synthetic population is a population built from anonymous survey data at the individual level (Heppenstall et al., 2011). There are several techniques used to generate synthetic populations, including deterministic reweighting, conditional probability (Monte Carlo simulation) and simulated annealing (Harland et al., 2012). Among these techniques, conditional probability has advantages for use in this model as it contains stochastic elements. This stochastic condition is needed because the exact data is unknown. This technique comprises three steps: data preparation, conditional probability simulation development and execution, and verification to fit the result, with development, execution and verification being iterative processes. If the verification process finds that deviation from the real data is high, then the process loops back to the development and execution process to fix possible bugs or logical errors.

In this model, the human agents are generated in individual units for each sub-district of Sleman that is located in the hazard zones. The number of agents within each district is proportionally minimized due to limitation of the agents in Anylogic Personal Learning Edition (PLE) (see supplementary data No. 4). The attributes were matched with the real data using census statistics represented as custom distribution in AnyLogic. The spatial distribution of the population was also randomly generated to match the real spatial distribution of the population agent using the centre of gravity model (Jumadi et al., 2016b), in which the agent population tends to be distributed randomly within the mean centre of residential areas**.** Furthermore, the outcome of the population generation model was verified using statistical and spatial distributions.

2.3.4 Agents and Environment Interaction

The ABM of the volcanic evacuation simulation is developed from the relationship between the volcano and the surrounding population (Figure 2.2). An active volcano such as Merapi is a potential threat to the surrounding population. Two other important agents in the interactions are the stakeholders and the population at risk. Stakeholders, in this case the authorities (government), have a significant role in observing and analysing the activities of the volcano and in issuing warnings to the population. In the ABM simulation, these three elements are represented as agents who interact with the environment. Each agent displays specific behaviour and mechanisms when interacting with the others, as well as with the environment. The environment is represented through spatial data with dynamic hazard properties. Meanwhile, the agents live in the environment within a specific geographic location. The volcano can be represented as a fixed agent that has the ability to influence the environment, although it has no ability to move, where its influence on the environment (hazard zone, see Figure 2.3) depends on its activity level and the intensity of the eruption (volcanic explosivity index (VEI)). When the volcano becomes active, the environment might change because of the material emitted from the volcano and thus become dangerous (Tables 2.4 and 2.5).

Table 2.4 Matrix of relationships of the hazard level with VEI and hazard zone (Source: (BNPB, 2011)).

Zone \ VEI	1	2	3	4
High	High	High	High	High
Medium	Medium	Medium	High	High
Low	Low	Low	Low	Low

Table 2.5 Matrix of relationships of the hazard level with hazard zone and volcanic activities (Source: (BNPB, 2011)).

Zone \ Activity	Low	Medium	High
Low	Low	Low	Low
Medium	Low	Medium	Medium
High	Low	Medium	High

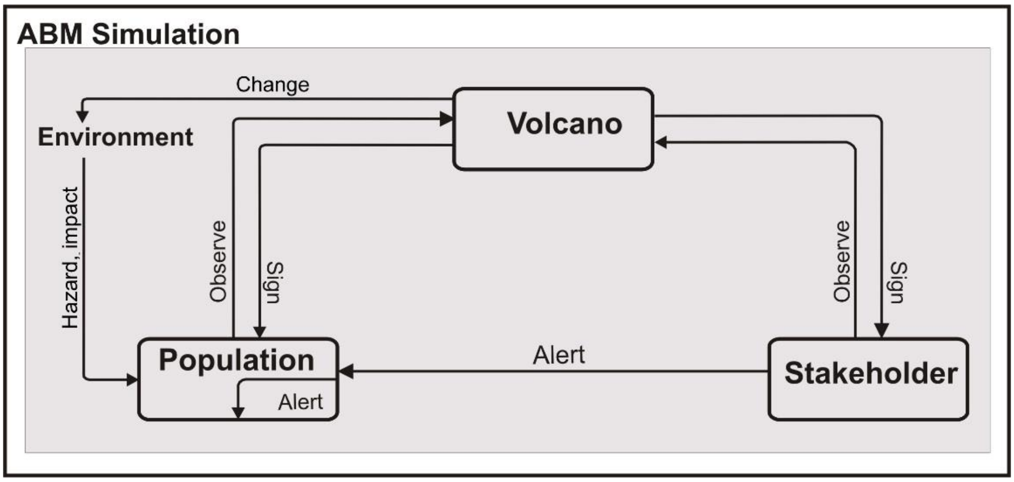


Figure 2.2 Conceptual framework of agent and environment interaction.

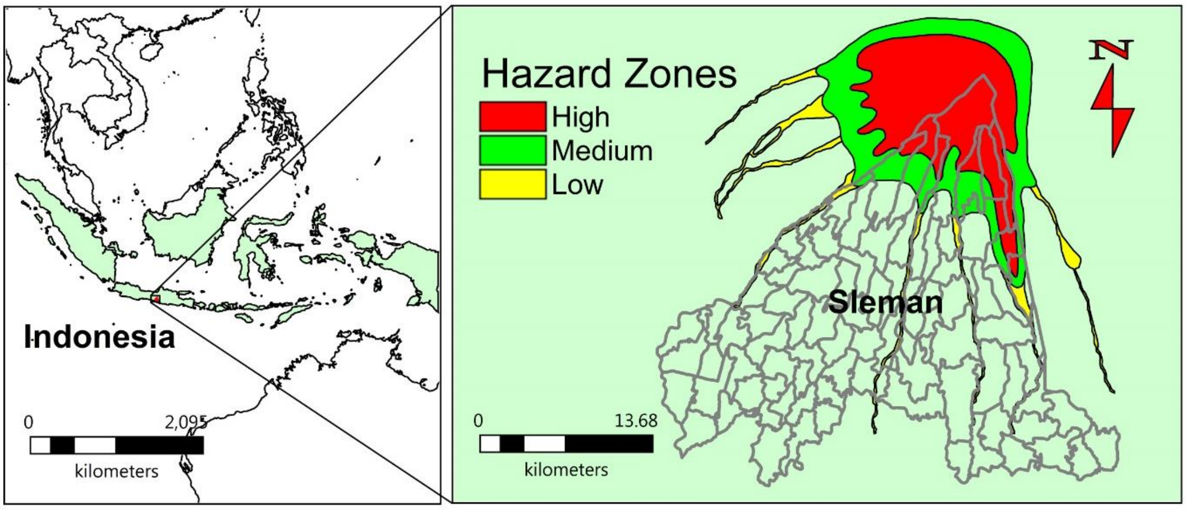


Figure 2.3 Hazard zonation for the area around Merapi (BNPB, 2011).

There are various types of hazards in one eruption event. The hazard originating from a volcano can be categorised into two types: (1) destructive: lava flows, nuées ardentes, and lahars; and (2) less destructive: heavy ash or pumice falls, deposition of toxic chemicals, pollution of surface or underground waters, etc. (d'Albe, 1979). Nuées ardentes and lahars are recognised as the most harmful events caused by eruptions of Merapi. Merapi produces specific nuées ardentes compared to other volcanoes (Bardintzeff, 1984). The distance of travel of deposits can be 3.5 km from only a few individual events (Abdurachman et al., 2000). Lahar-related disasters also have a high potential of occurring at Merapi (Lavigne et al., 2011). *Nue'esardentes* originate from coupling of volcanic gases and volcanic material as a specific hazard of Merapi that usually kill people

(Bardintzeff, 1984), while lahars are overbank pyroclastic flows coupled with rainwater that occur during the rainy season (Lavigne and Thouret, 2003; Charbonnier and Gertisser, 2008).

The hazard map (Figure 2.3) is developed based on historical records of eruptions together with deposit analysis (Andreastuti et al., 2000; Thouret et al., 2000; BNPB, 2011) that summarizes these events. The map expresses the spatial extent of hazard that relates to the location of the volcano. The hazard level of the area close to the summit is the highest, followed by the successive zones. The VEI influences the hazard level of each because this expresses the magnitude of the impact of eruptions quantitatively (Newhall and Self, 1982). A low VEI will produce a relatively low hazard level in relation to the zones. On the contrary, a high VEI will result in higher hazard levels (Table 2.4). Moreover, because the activity level of the volcano increases/decreases gradually (dynamically), the hazard level of each zone will also change based on this activity level (Table 2.5).

The matrix of the relationships of the hazard characteristics, volcanic activity level and the hazard level of each zone provided in Tables 2.4 and 2.5 can be used to provide rules for the spatio-temporal dynamic of the hazard. Based on the matrix in Tables 2.4 and 2.5, the changing of the hazard level within these zones can be simulated dynamically (Figure 2.4). In referring to the tables interpreted in the official hazard map (BNPB, 2011), the scenarios related to 3 and 4 in the VEI have a more severe impact than scenarios 1–2. Likewise, the changing of the volcanic activity level from low to high (Mei and Lavigne, 2012; Mei and Lavigne, 2013) affects the hazard level in each hazard zone.

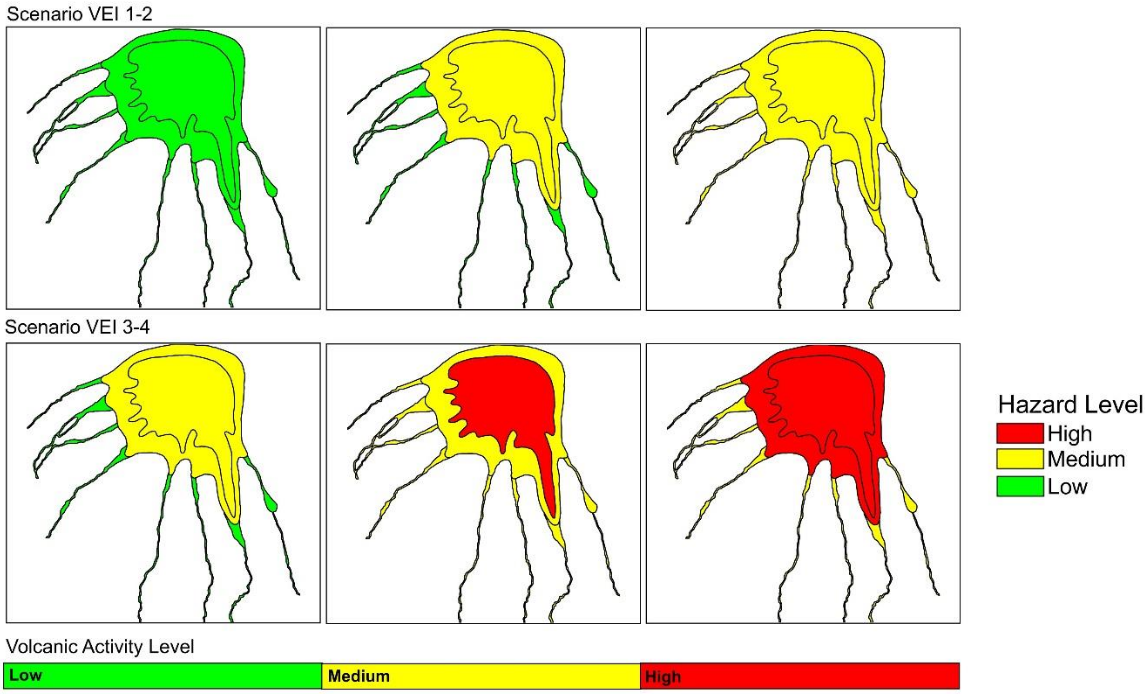


Figure 2.4 The dynamic changes of hazard level of the zones during the simulation in two different scenarios (BNPB, 2011).

2.3.5 Evacuation Decision

The evacuation decision made is an important aspect of an agent's (person's) behaviour. During the crisis, this defines whether the agent remains or evacuates the risk zone. Several factors influence evacuation decisions, including (Dash and Gladwin, 2007; Lim et al., 2015; Ahsan et al., 2016) risk communication and warnings, perceptions of risk, community and social network influences, disaster likelihood, environmental cues and natural signals. The mechanisms related to individual decision-making during an evacuation, based on the literature review, is provided in Figure 2.5. This figure provides an overview of the mechanisms of the above factors in their influencing of decisions made and their results, in terms of evacuating or remaining during the volcanic crisis. The following brief reviews provide an overview of how these factors affect the evacuation decision.

1. *Risk communications* deal with the dissemination of risk warning regarding the probability of disaster occurrence within a community. There are three models of interaction in emergency situations, namely vertical (top-down), peer to peer and horizontally broadcast (Linardi, 2016). Communication among people at risk (horizontal communication) is believed to be an effective way to increase the reach of a broadcast.

However, the delivering of risk warnings through social interaction also has the potential result of miscoordination (Linardi, 2016). This can lead to the occurrence of congestion and shadow evacuations (Lamb et al., 2011). A shadow evacuation is the voluntary evacuation of people from areas outside a declared evacuation area that can congest roadways and inhibit the egress of those evacuating from the area at risk (Weinisch and Brueckner, 2015).

2. *Community and social networks* also have an important role to play in influencing people in their responses to a disaster. People tend to follow their group's (community's) actions in their decisions in such situations (Khalid and Yusof, 2014). At the most basic community level, they will tend to stand together with their family when deciding to stay or to leave (Liu et al., 2014). It was found by Liu et al. (Liu et al., 2014) that people in crises will be more easily influenced when they interact with a group rather than with individuals. People may therefore decide to leave after seeing crowds of evacuees leaving their homes. Furthermore, social network contact is relatively more important in influencing evacuation decisions than warnings received from mass media (Ronald, 1983).
3. *Disaster likelihood and/or environmental cues and/or natural signals* also influence evacuation decisions (Ronald, 1983; Sagala and Okada, 2009). Studies of volcano and flood evacuation have identified that natural signals are the most important factors in evacuation decision (Ronald, 1983). Others state that risk perception is associated with environmental cues as well as with the characteristics of the hazard (Lim et al., 2015).
4. *Risk perception* is a critical aspect in understanding how individuals decide to evacuate or to stay (Dash and Gladwin, 2007). Risk perception is also responsible for influencing people in their decisions about when they should evacuate and when they should return home during and after a crisis (Siebeneck and Cova, 2012).

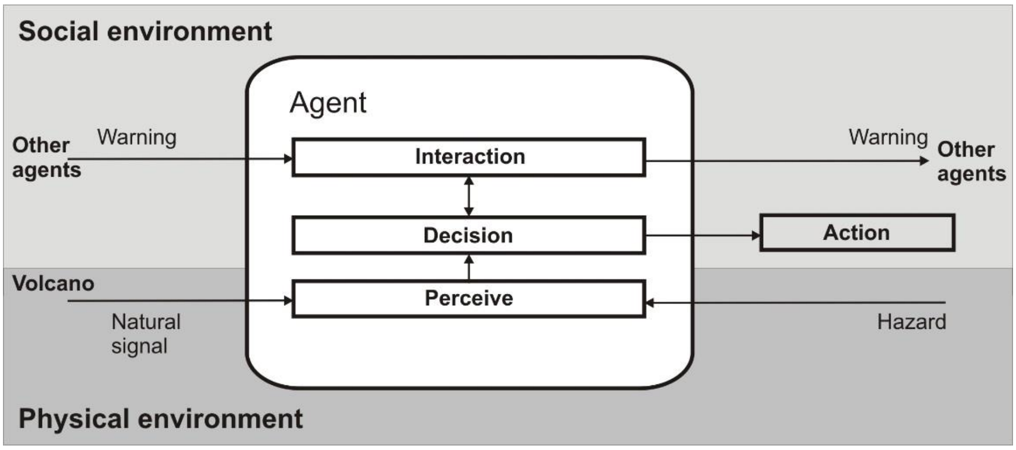


Figure 2.5 Main agent (people) characteristics.

The social and physical aspects of influencing factors in evacuation decisions that are presented in Figure 2.5 are involved in the model developed in this study. Generalisation and simplification were applied to make the modelling feasible. For the *risk communication* procedure, the model implements top-down as well as horizontal broadcasting as models for communicating the warning. This is to represent real conditions in which not all people directly receive alerts from government sources. The warning can be delivered through several layers of actors (Mei and Lavigne, 2012) as well as being broadcast among the population at risk. For this reason, agents are utilised in connection to other agents to express their *social network*. Some of them (1 in 100 people) are connected directly to the stakeholder, who represents the authority network delivering the evacuation command. When the volcano is active, it sends signals to all the other agents expressing cues for *disaster likelihood*. Meanwhile, the agents (people and stakeholders) perceive the risk by classifying the hazard level of their location based on the matrix presented in Section 2.3.4.

2.4 Initial Model Design and Implementation

2.4.1 Initial Design of the Model

Based on the above conceptual framework, the initial model is developed and implemented using AnyLogic. Then, the agents are developed, consisting of the volcano, stakeholders, and people living within a geographically explicit environment and with concurrent properties/attributes and rules (Figure 2.6) (see the detailed attributes in documentation included as supplementary material). The environment aspect contains a map of the boundary of the district in which the population is distributed, hazard zones to define hazard locations, and evacuation shelters as the evacuation destinations and routes for movements, as described in the previous section. Each agent has their own rules in responding to the occurring crisis, as well as in creating interactions.

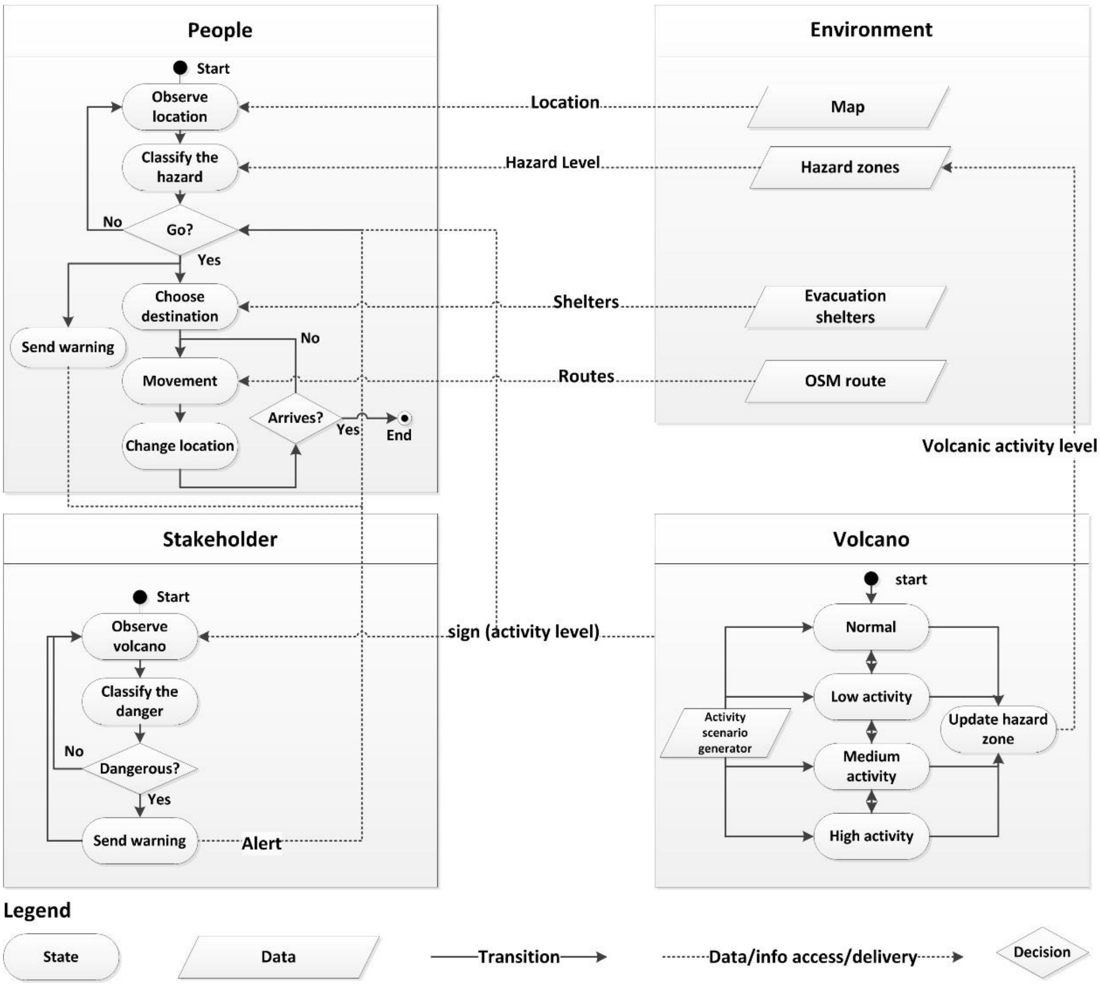


Figure 2.6 Agents—environment mechanism and interaction flowchart.

The response procedure to the crisis primarily consists of volcanic activity/hazard observation procedure (owned by people and stakeholders), warning/alerting (owned by people and stakeholders), evacuation decision (owned by people) and destination selection and movement (owned by people). There are also interactions between the agents and environment among the agents. The interaction between agents and the environment include updating the hazard level of the hazard zones as the volcanic activity level changes, and human agents (people) retrieving environment data where they are living, such as hazard existence, routes and evacuation shelter location. The interaction among agents consists of top-down interaction and horizontal interaction. Top-down interaction is the alerting procedure from the stakeholder agent to the human agents that consists of the disaster warning, whereas the horizontal interactions occur between human agents in communicating the disaster warning, their departure times and destinations.

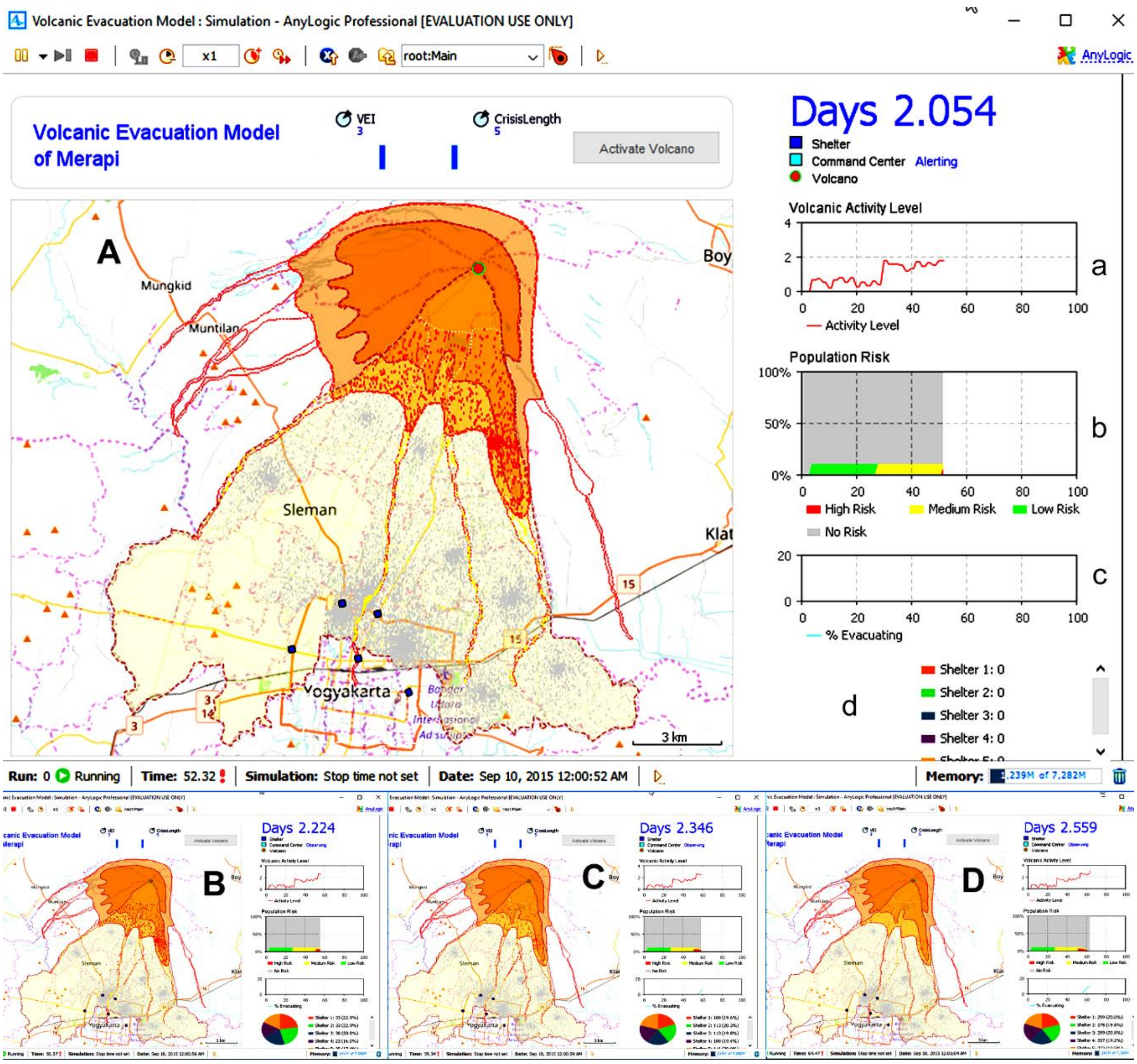


Figure 2.7 Screenshot of model implementation using AnyLogic. Red dots at (A) are the initial spatial distribution of people at risk. Grey dots are the people outside the danger zones. Subsequently, the people dots change to yellow with the increment of hazard levels at (B–D). The movements of people and the changing of the spatial distribution of individuals are displayed in (B–D). The monitor chart is (a) monitoring the simulated volcanic activity level, (b) monitoring the number of people at risk and (c) monitoring the percentage of people evacuating.

Based on the flow chart in Figure 2.6, rules are developed for each agent in the model. The rules for each agent are expressed as an activity state chart in AnyLogic. This consists of the alerting mechanism, the volcanic-activity-changing mechanism and the evacuation mechanism. Interaction is handled by sending a message to the other agents. Furthermore, an interface is developed that can be used to monitor the simulation spatially or statistically. The screenshot of the developed ABM simulation that can be run from the AnyLogic portal is provided in Figure 2.7 (see the supplementary materials). The movement and changing of the distribution of the population at risk are recorded as spatial data that can be used for further spatial analysis. Examples of the results and the potential analysis from the data are provided in the following sub-section.

2.4.2 Potential Use of the Model to Support Evacuation Management

Evacuation management requires decision support that can be generated from predominantly spatial information (Silva, 2001). Information that can be generated from this simulation includes (1) spatial distribution of human exposure that is valuable in analysing volcanic risk to people and providing effective evacuation strategy (Pareschi et al., 2000; Escobar Wolf, 2013; Zhang et al., 2013); (2) information related to the volcanic disaster outcome in various scenarios, which is valuable in providing adjustable evacuation planning for changing hazard scenarios (Jumadi et al., 2016b); (3) information on route density analysis that can be used in managing evacuation routes to avoid high congestion, which may hold up the evacuation processes (Dixit, 2008; Liu and Lim, 2016; Huang et al., 2016); (4) information about variation in evacuation destination preferences provided by the evacuee distribution model that might produce a range of distribution scenarios concerning evacuees, this being information helpful in supporting shelter provision, logistical support, services and commodity-needs planning (Yi and Özdamar, 2007); and finally, (5) clearance time analysis in various scenarios, which is a vital parameter in defining the effectiveness of evacuation processes and thus providing information essential for the decision maker (Mitchell and Radwan, 2006).

2.4.2.1 Spatio-Temporal Analysis of the People at Risk Distribution

This model can be used to simulate the changing of human exposure spatio-temporally. The human agents’ mobility can be recorded at every time step. Due to the movement of the evacuation processes, the spatial pattern and density of the population at risk changes over time. This approach allows the changing of spatial patterns of human exposure provided by GIS to be analysed. Figure 2.8 provides an example of spatial analysis using point density analysis of the human exposure within four different time steps, illustrating this spatial dynamic. The changing of the density from days 1.194 to 6.465 can be observed in this figure.

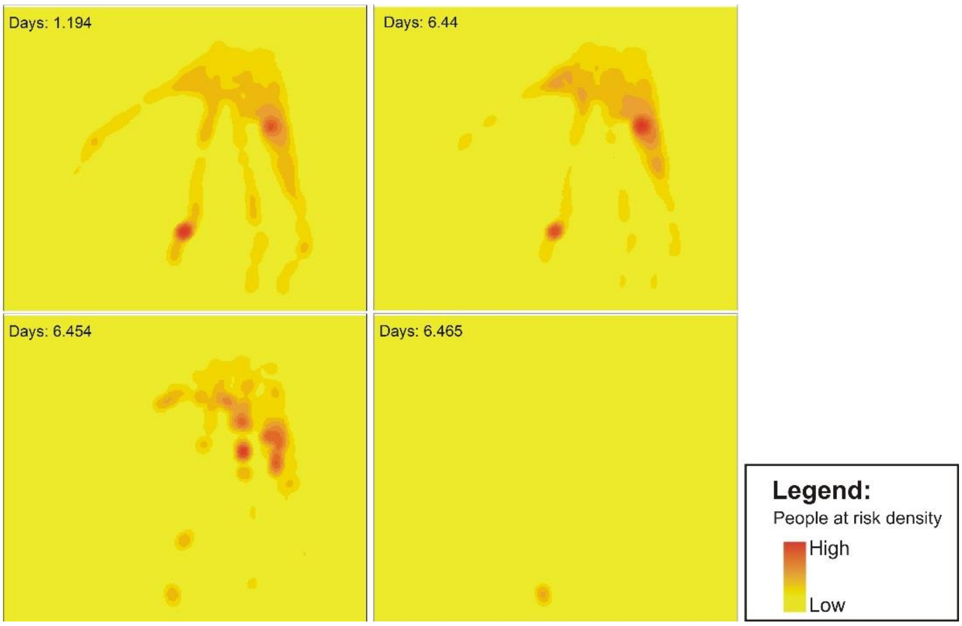


Figure 2.8 Example of result analysis of people at risk in different time steps using GIS.

2.4.2.2 Analysing the Evacuation Outcome in Different Scenarios

Knowing the possible evacuation outcome in various scenarios is important (Jumadi et al., 2016b), and so evacuation simulation should accommodate this requirement. The percentage of people at risk and the evacuating population in every time step of the simulation has been captured. The result of this information is the dynamic changing of human exposure (in medium- and high-level hazard zones) and evacuees temporally, as presented in Figure 2.9. This figure shows the variability of the human exposure percentage between scenarios 1 and 4 of the VEI. This variability results from the differences in the spatial extent of the impact (see Figure 2.4). Furthermore, the stochasticity of the model is also slightly affected by both the number of human exposures/evacuees and the evacuation rate, as shown by the curve. This stochasticity is shown in the variations in the chart, resulting from the randomness of the population distribution and the varying departure time decisions present in the simulations.

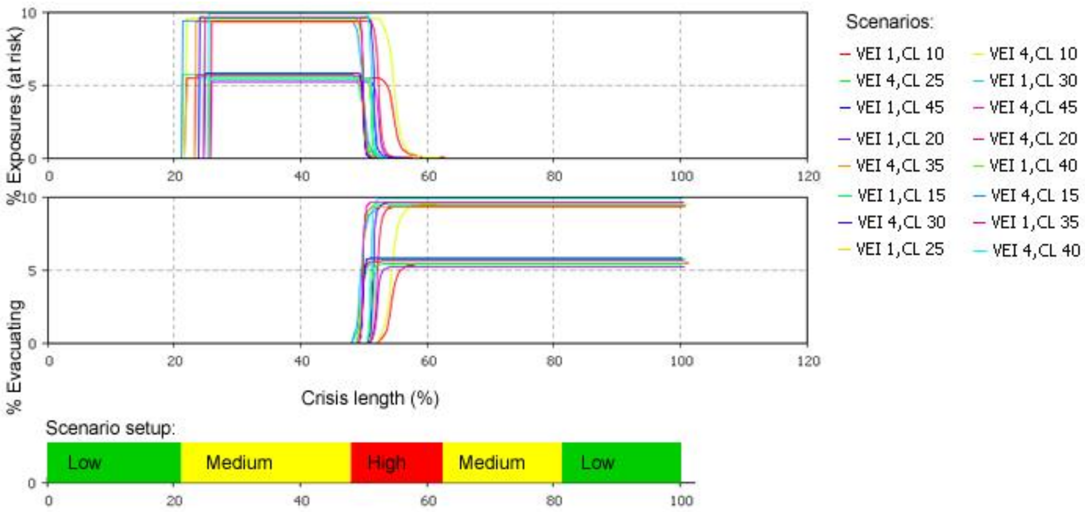


Figure 2.9 Example of the simulation outcomes of various scenarios. VEI: volcanic explosivity index, CL: crisis length (days). This can be adjusted based on the preferred scenario. The scenario setup shows the length of each activity phase, which can be adjusted to match with the real crisis situations. The top chart shows that the percentage of people at risk is continuously decreasing along with the increase in the percentage of people evacuating.

2.4.2.3 Route Density Analysis

Evacuation routing is another important aspect of evacuation modelling, especially for a large-scale evacuation that potentially produces congestion (Dixit, 2008; Liu and Lim, 2016; Huang et al., 2016). Here, 1000 human agents were selected randomly and their movements tracked consistently. The dataset resulting from this technique was analysed in GIS and produced the route density analysis presented in Figure 2.10. This figure reveals the relative density of the roads from the residential areas surrounding Merapi volcano to the five evacuation shelters that are placed randomly around the city. From this analysis, several major roads that may be crowded with evacuees are highlighted. Such information can help to support traffic management, in addition to examining potential congestion in relation to the shelters.

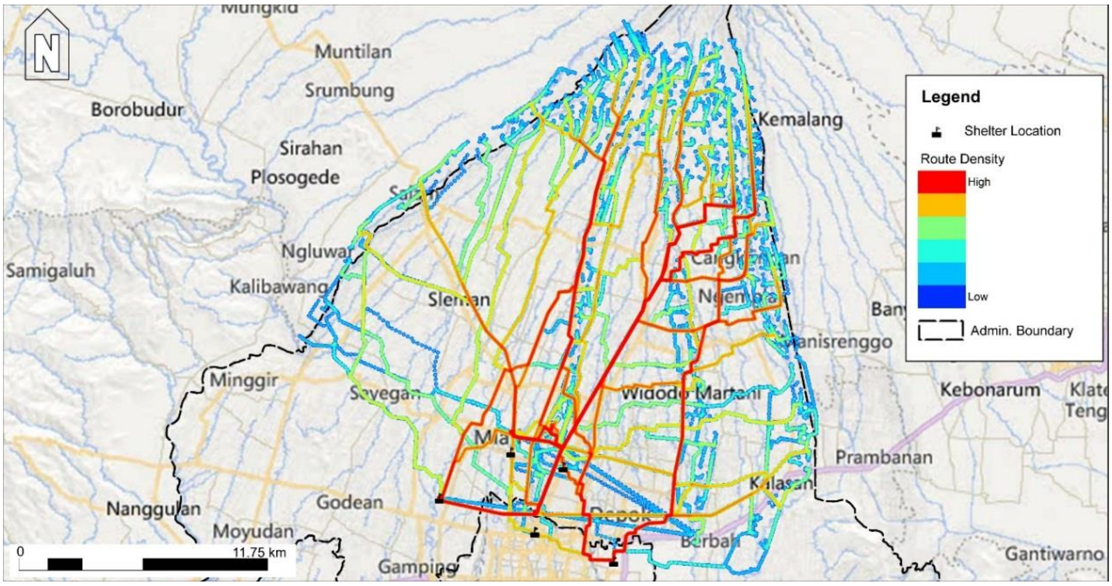
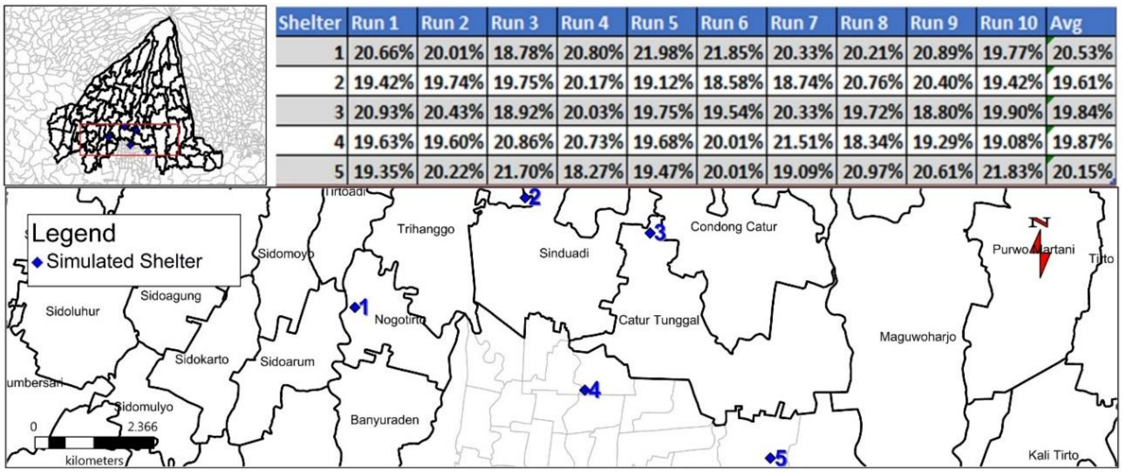


Figure 2.10 Example of the result of route density analysis.

2.4.2.4 Evacuee Distribution Analysis

Planning the distribution of services, logistical support and commodity needs for evacuees requires supporting data for the distribution of evacuees (Yi and Özdamar, 2007). This is especially significant in Merapi, where the evacuation shelters are mostly non-permanent and the community surrounding the hazard zone can better plan the voluntary building of emergency evacuation shelters (Mei et al., 2011) to simulate the possible distribution of evacuees. In this model, the distribution of evacuees was modelled based on the assumption that people will vary in selecting their destinations. The human agents are randomly categorised into three categories: those who prefer the nearest shelter, those who prefer to ask their relatives (other agents), and those who randomly select their destination. The real destination preference of people remains under investigation and will be included in a future model. The results of the simulation are presented in Figure 2.11, where the slight variations in the distribution of evacuees can be observed in the different runs.



Shelter	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10	Avg
1	20.66%	20.01%	18.78%	20.80%	21.98%	21.85%	20.33%	20.21%	20.89%	19.77%	20.53%
2	19.42%	19.74%	19.75%	20.17%	19.12%	18.58%	18.74%	20.76%	20.40%	19.42%	19.61%
3	20.93%	20.43%	18.92%	20.03%	19.75%	19.54%	20.33%	19.72%	18.80%	19.90%	19.84%
4	19.63%	19.60%	20.86%	20.73%	19.68%	20.01%	21.51%	18.34%	19.29%	19.08%	19.87%
5	19.35%	20.22%	21.70%	18.27%	19.47%	20.01%	19.09%	20.97%	20.61%	21.83%	20.15%

Figure 2.11 Example of the results of evacuee distribution simulations.

2.4.2.5 Clearance Time Analysis in Different Scenarios

Clearance time/evacuation time is an important parameter in demonstrating the effectiveness of performance evacuation planning. Therefore, this is used as an indicator in some evacuation simulations (Mitchell and Radwan, 2006; Tu et al., 2010; Marrero et al., 2010). In this model, the clearance time is simulated by calculating the time required between the dissemination of the warning to the clearance of the hazard zones (zero humans at risk). In this initial model, it is assumed that everyone would evacuate. Potential reluctance, as found by (Sagala, 2009; Lavigne et al., 2017), has not been considered. The human agents are characterised by random preparation time of up to 12 h. Such preparation time is needed in evacuation processes for activities such as protecting property (Donovan, 2010), gathering family members (Van Drimmelen, 2010; Liu et al., 2014) and evacuating livestock (Wilson et al., 2009). The result of the varying clearance time in different scenarios is presented in Figure 2.12. The real variability in departure time (see Figure 2.13) will be included in future work, with the aim of validating this result.

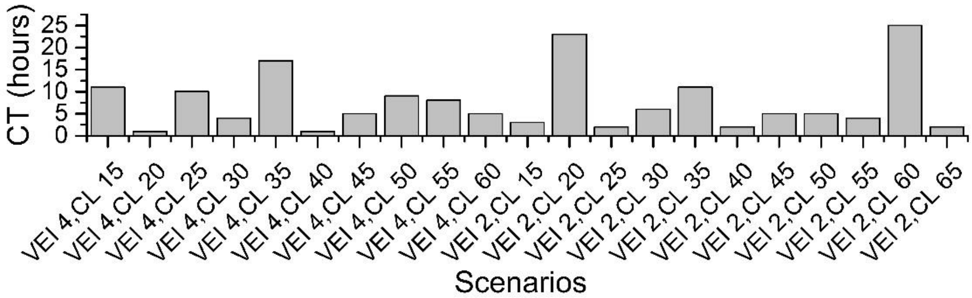


Figure 2.12 Clearance time for various scenarios.VEI: volcanic explosivity index, CL: crisis length (days).

2.5 Towards a Validation of the Model with Real Data

There are several procedures that can be used to validate the ABM simulation (Klügl, 2008). Dixit presents one of these appropriate procedures for a microscopic evacuation model (Dixit et al., 2011). This method is applied by making a comparison using a statistical approach between the simulation results and the real data. It is possible to make such a comparison of this model by setting up the spatio-temporal parameters of the disaster with data from a past event and comparing the results with the model. There are several records related to previous Merapi eruptions (Voight, et al., 2000; Siebert et al., 2011), but the last eruption in 2010 is relatively better documented than the others. This documentation includes a chronology of the eruption, evacuation data and the spatial distribution of the evacuees.

The Merapi eruption crisis of 2010 took place over 104 days (Mei et al., 2013). The chronological detail of this eruption is provided in (Mei and Lavigne, 2013). During the crisis, the volcano’s activity level changed over time. To make it more straightforward, this activity can be divided into four classes: normal (excluded from the volcanic crisis period), low, medium and high. Figure 2.13 presents the activity profile during the 2010 eruption, from rest conditions to the climax of activities to the return to normal conditions. The government issued several alerts during this crisis to anticipate the occurrence of the disaster (Figure 2.13). Alerts and warnings are part of the social capacity of the community in the event of a disaster. As the disaster warnings are produced from observation of the likelihood of disaster, these commonly include many uncertainties and limitations and so can result in false warnings and/or an unexpected eruption (Durage et al., 2016). The authorities in Merapi produce disaster warnings by means of observing the volcano’s activity, warnings being delivered through several layers of actors (Mei and Lavigne, 2012). The warning steps, referring to the actual warning procedures in Merapi, are provided by considering the volcanic activities occurring (Mei et al., 2013). Figure 2.13 also provides real data on the 2010 evacuation (Local Government of Sleman, 2010), demonstrating a major increase in the number of evacuees resulting from the evacuation process and a significant decrease resulting from the return-entry process (returning home after the crisis).

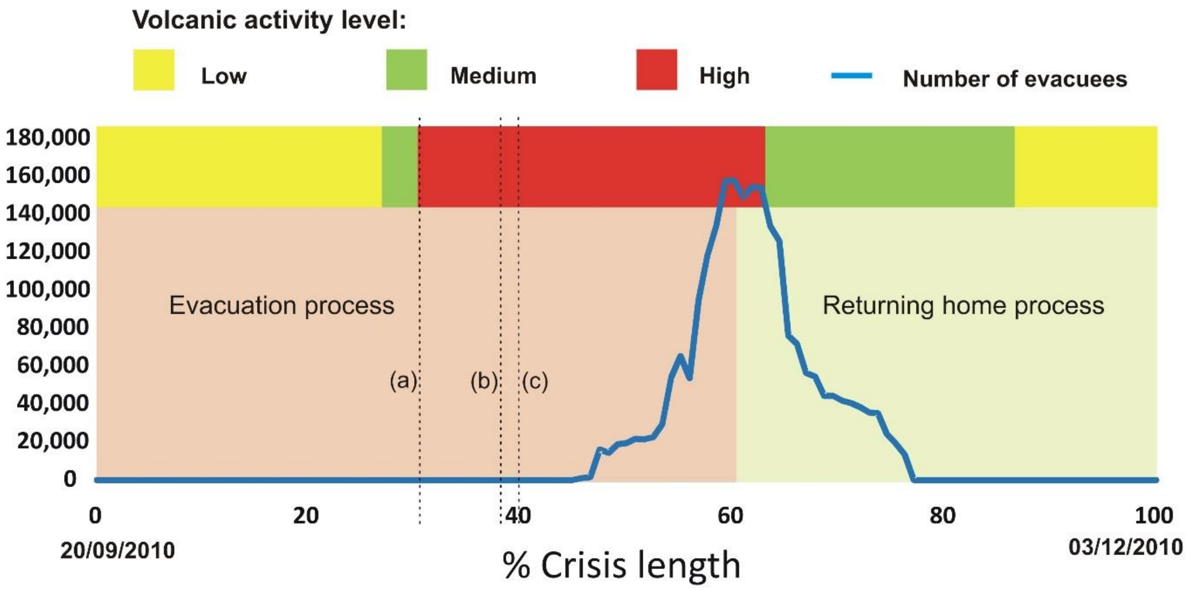


Figure 2.13 Temporal dynamic of evacuees through the crisis period in 2010.(a) the issuance of the first evacuation order on 3 November 2010, (b) the issuance of the second evacuation order on 3 November 2010, (c) the issuance of the third evacuation order on 5 November 2010 (Source: Volcanic Crisis Chronology (Mei et al., 2013) and Evacuation data (Local Government of Sleman, 2010)).

The data taken from the 2010 eruption records can be used to set up the evacuation simulation, as undertaken by Mas et al. (2012) for the 2004 tsunami. Subsequently, the outcome of the simulation using the real data is statistically and spatially compared. Comparison can be made in three ways. Firstly, comparing the emergence of people who are reluctant to evacuate with the real data that was observed by Lavigne et al. (2017) expresses the validity of the evacuation decision. Then, comparison of the accumulation of evacuation movement temporally can express the validity of the departure time as well as the number of people who decide to evacuate. Finally, the appropriateness of the destination decision choices can be evaluated by comparing the distribution of the evacuees within the shelter with the real evacuation distribution data (BNPB, 2010c; BNPB, 2010a; BNPB, 2010d; BNPB, 2010b),(Budiyono, 2010).

In this study, we used a comparison of the accumulation of evacuation movement temporally to evaluate the departure time and the percentage of evacuating people (Figure 2.14). This first comparison of the average of simulation results from ten runs with the real data of 2010 can be used for initial evaluation of this model. It shows that there are discrepancies between the simulation results and the real data. Currently, there is limited information about the reasons why people evacuate so late in reality compared to the simulated expectation. In terms of the difference between the percentage of people evacuating in 2010 and the simulation, the unpredicted nature of the 2010 eruption led to the unpreparedness of the stakeholder. The stakeholder used a simple delineation of a radius of 20 km from the summit as a limit for the evacuation order (Mei et al., 2013). This might have led to the occurrence of 'shadow evacuation'. This term describes the behaviour of those who perceive personal danger despite not being in an evacuation zone (Dash and Gladwin, 2007) and as a result decide to evacuate. The occurrence of shadow evacuation can be a result of social interaction and communication, with people deciding to leave after seeing crowds of evacuees leaving their homes. These occurrences potentially stimulate people in low-risk or even safe areas to leave their homes without coordination (Baker, 1991). This phenomenon can lead to a higher-than-expected number of evacuees (Lamb et al., 2011), which necessitate more evacuation resources.

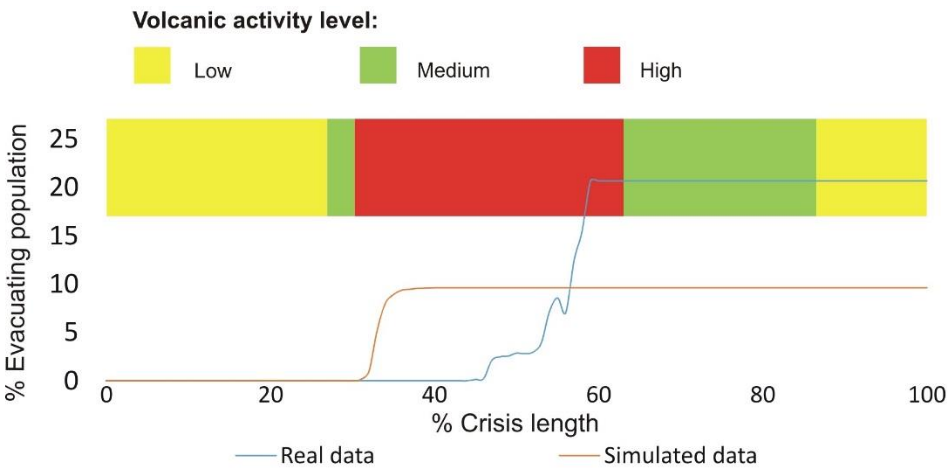


Figure 2.14 Comparison of the average simulation result (10 runs) with the real data for the 2010 evacuation. Note: the returning home process is excluded from this comparison.

2.6 Discussion and Future Work

The importance of developing a volcanic evacuation model is presented in this paper. This is followed by the formulation of a conceptual design and the initial implementation of the model using AnyLogic. This is used to illustrate the potential use of such a model to support the decision-making for evacuation management. Models can also potentially be used to simulate the evacuation processes in various scenarios, such as the integrated GIS and simulation model developed by (De Silva and Eglese, 2000); however, compared to that model, the implementation of the model in this study, using the new ABM approach and new technology (AnyLogic), provides a superior method of modelling population behaviour and interaction.

This initial model development provides a novel approach for integrating the hazard model into the simulation. The approach is different from the tsunami model (Mas et al., 2012; Wang et al., 2016) or the flood model (Dawson et al., 2011), which employ a hydrodynamic numerical process to generate the hazard. The hazard model in this simulation is expressed as zones. This was originated from historical records of eruptions (BNPB, 2011) and enabled the hazard zones to be adjusted to the simulation scenarios as well as to the level of volcanic activity. However, several improvements are required to validate this simulation model with the real data from previous evacuations and for further decision-support purposes. There are some aspects of the evacuation processes from the 2006 and 2010 data, for example, that could not be accommodated in this initial model and this will be improved in future work. These aspects include the decision-making of agents, synthetic population development, and the effect of social networks on agent (people) decisions.

Firstly, the evaluation of the decision-making mechanisms of agents needs to be improved. All people at risk were evacuating in the simulation (see Section 2.4.1), but the real data from the evacuations in 2006 and 2010 reveal that not everyone took part in the evacuation, meaning that some of the population disobeyed the evacuation order and preferred to stay at home during the crisis (Sagala, 2009; Lavigne et al., 2017). It was observed that, in the 2006 eruption, individuals in some areas of Merapi disobeyed the evacuation order and suffered the consequences of the eruption (Mei and Lavigne, 2012). The evacuation rate at this time was 0.63 (Sagala, 2009). A similar phenomenon occurred in 2010, in which there were large numbers of reluctant people although the scale of the disaster was larger (Lavigne et al., 2017). Some concepts of decision-making, such as those presented in (Lovreglio et al., 2015; Lovreglio et al., 2016), could be used as background to improve this evacuation model in the future.

Secondly, the synthetic population agents need to be improved for family aggregation characteristics. This model applied loosely distributed individual agents, whereas, in the real world, the agents are generally grouped in families. Although statistically and spatially the synthetic population in this model closely matched with the real-world situation, this drawback should be addressed in future work. Within the family/household situation where agents stay together or evacuate together, the outcome might be different from the individual decisions they might have made. The agents might also consider waiting with their families before evacuating (Van Drimmelen, 2010; Liu et al., 2014), leading to delays.

Thirdly, the effect of social influence and the probability of successful contact among people on the evacuation decision might be varying and this might affect the outcome. This model ignores these variables and assumed that all agents always successfully make contact with their connections and always follow the commands given. In addition, it is possible for people to ignore the evacuation order altogether (Lavigne et al., 2017). A good example of this is presented by Wise (2014), in which studying these variables is expressed as contact success probability and communication success probability; these concepts could be used to improve this model. The decision result as a response from interaction may vary among people, based on their perception of risk, and, because of such interactions, people at risk may socially aggregate in making decisions or/and in the evacuation process.

2.7 Conclusions

This article was developed based on four points of focus: (1) highlighting the importance of providing evacuation simulation for Merapi, (2) providing and introducing the initial design of ABM for volcanic evacuation simulation, (3) demonstrating the potential uses of the model to support evacuation decisions, and (4) evaluating the initial design and giving insights for further improvements. This paper contributes to the development of ABM for large-scale evacuation simulation by integrating the hazard model, especially regarding volcanic hazard, which is a topic absent from the literature.

The evacuation simulation of a volcanic crisis involving Mount Merapi is important for improving evacuation management as an element of disaster risk reduction. Therefore, we initially developed this model as the basis for further application purposes. The volcanic evacuation model represents the relationships between physical and human agents, consisting of the volcano, stakeholders, the population at risk and the environment. Some potential uses of this model to support decision-making were demonstrated—for instance, analysing route densities, evacuees’ distribution in shelters, and the evacuation outcome in various scenarios. The comparison of some simulation results with real data was provided with the aim of evaluating this model. We found that there are discrepancies between the simulation results and the real data. Based on this, we suggest improvements to several aspects of this model, including the decision-making of agents, synthetic population development and the effect of social networks on agent decisions.

Supplementary Materials

Appendix 2.1. Online Model: http://www.runthemodel.com/models/k-RgpNLa1oojYE1To31FJa/.

Appendix 2.2. Simulation Video: https://osf.io/qr65b/.

Appendix 2.3. Application documentation: https://osf.io/7yf3p/.

Appendix 2.4. Population unit and data: https://osf.io/k6d2n/.

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References

Abdurachman, E.K., Bourdier, J.-L. and Voight, B. 2000. Nuées ardentes of 22 November 1994 at Merapi volcano, Java, Indonesia. *Journal of Volcanology and Geothermal Research*. **100**(1), pp.345–361.

Adam, C. and Gaudou, B. 2017. Modelling Human Behaviours in Disasters from Interviews: Application to Melbourne Bushfires. *Journal of Artificial Societies and Social Simulation*. **20**(3), p.12.

Ahsan, M.N., Takeuchi, K., Vink, K. and Ohara, M. 2016. A Systematic Review of the Factors Affecting the Cyclone Evacuation Decision Process in Bangladesh. *Journal of Disaster Research Vol*. **11**(4), p.741.

d'Albe, E.M.F. 1979. Objectives of volcanic monitoring and prediction. *Journal of the Geological Society*. **136**(3), pp.321–326.

Aman, A., Bakhtiar, T., Hanum, F. and Supriyo, P.T. 2012. OR/MS Applications in Mt. Merapi Disaster Management. *Journal of Mathematics and Statistics*. **8**(2), pp.264–273.

Anderson, W.A. 1969. Disaster Warning and Communication Processes in Two Communities. *Journal of Communication*. **19**(2), pp.92–104.

Andreastuti, S.D., Alloway, B.V. and Smith, I.E.M. 2000. A detailed tephrostratigraphic framework at Merapi Volcano, Central Java, Indonesia: implications for eruption predictions and hazard assessment. *Journal of Volcanology and Geothermal Research*. **100**(1), pp.51–67.

Ayuningtyas, D. and Gabriel, L. 2013. *Respon Masyarakat Terhadap Kebijakan Relokasi Pada Kawasan Rawan Bencana (KRB) (Studi Kasus: Relokasi Desa Glagaharjo)*.[Online] Universitas Gadjah Mada. [Accessed 19 March 2015]. Available from: http://etd.ugm.ac.id/index.php?mod=penelitian_detail&sub=PenelitianDetail&act=view&typ=html&buku_id=66995&obyek_id=4.

Bachri, S., Stöetter, J., Sartohadi, J. and Setiawan, M.A. 2012. Evaluation of volcanic risk management in Merapi and Bromo Volcanoes *In*: *EGU General Assembly Conference Abstracts* [Online]., p.13111. [Accessed 21 November 2014]. Available from: http://adsabs.harvard.edu/abs/2012EGUGA..1413111B.

Baker, E.J. 1991. Hurricane evacuation behavior. *International Journal of Mass Emergencies and Disasters*. **9**(2), pp.287–310.

Bakkour, D., Enjorlas, G., Robert, K. and Thouret, J. 2013. The adaptive governance of natural disasters: Insights from the 2010 Mount Merapi Eruption in Indonesia. [Accessed 23 January 2015]. Available from: http://www.webcitation.org/6vD8LzkFg.

Bandyopadhyay, S. and Bhattacharya, R. 2014. *Discrete and Continuous Simulation: Theory and Practice* [Online]. CRC Press. [Accessed 17 March 2015]. Available from: http://www.crcnetbase.com/doi/book/10.1201/b17127.

Bardintzeff, J.M. 1984. Merapi volcano (Java, Indonesia) and Merapi-type nuée ardente. *Bulletin volcanologique*. **47**(3), pp.433–446.

Beauducel, F., Cornet, F.H., Suhanto, E., Duquesnoy, T. and Kasser, M. 2000. Constraints on magma flux from displacements data at Merapi volcano, Java, Indonesia. *Journal of geophysical research*. **105**(B4), pp.8193–8203.

de Bélizal, E., Lavigne, F., Hadmoko, D.S., Degeai, J.-P., Dipayana, G.A., Mutaqin, B.W., Marfai, M.A., Coquet, M., Le Mauff, B., Robin, A.-K. and others 2013. Rain-triggered lahars following the 2010 eruption of Merapi volcano, Indonesia: A major risk. *Journal of Volcanology and Geothermal Research*. **261**, pp.330–347.

Bernardini, G., D'Orazio, M., Quagliarini, E. and Spalazzi, L. 2014. An Agent-based Model for Earthquake Pedestrians' Evacuation Simulation in Urban Scenarios. *Transportation Research Procedia*. **2**, pp.255–263.

Bignami, C., Ruch, J., Chini, M., Neri, M., Buongiorno, M.F., Hidayati, S., Sayudi, D.S. and Surono 2013. Pyroclastic density current volume estimation after the 2010 Merapi volcano eruption using X-band SAR. *Journal of Volcanology and Geothermal Research*. **261**, pp.236–243.

BNPB 2011. Peta Kawasan Rawan Bencana Merapi. [Accessed 9 October 2015]. Available from: http://geospasial.bnpb.go.id/wp-content/uploads/2011/05/2011-04-29_KRB_Area_Terdampak_Langsung_Merapi.pdf.

BNPB 2010a. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Bantul (11 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6pikQru7D.

BNPB 2010b. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Kulon Progo (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6piskXxQF.

BNPB 2010c. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Sleman (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6piPoQCLs.

BNPB 2010d. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kota Yogyakarta (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6pilvuYiE.

BPS Kab. Sleman 2015. Statistik Daerah Sleman 2015. Available from: http://www.webcitation.org/6vD9mA8gE.

Brachman, M.L. and Dragicevic, S. 2014. A spatially explicit network science model for emergency evacuations in an urban context. *Computers, Environment and Urban Systems*. **44**, pp.15–26.

Brown, D.G., Riolo, R., Robinson, D.T., North, M. and Rand, W. 2005. Spatial process and data models: Toward integration of agent-based models and GIS. *Journal of Geographical Systems*. **7**(1), pp.25–47.

Brown, D.G. and Xie, Y. 2006. Spatial agent-based modelling. *International Journal of Geographical Information Science*. **20**(9), pp.941–943.

Budiyono, A.F. 2010. Informasi Posko Pengungsian Merapi DIY (Update 10 November 2010). [Accessed 6 April 2017]. Available from: http://www.webcitation.org/6pWJmis9R.

Charbonnier, S., Germa, A., Connor, C., Connor, L., Dixon, T., Komorowski, J.-C., Gertisser, R., Lavigne, F. and Preece, K. 2013. The 2010 Pyroclastic Density Currents of Merapi Volcano, Central Java, Indonesia *In*: *EGU General Assembly Conference Abstracts* [Online]., p.6629. [Accessed 11 July 2015]. Available from: http://adsabs.harvard.edu/abs/2013EGUGA..15.6629C.

Charbonnier, S.J., Germa, A., Connor, C.B., Gertisser, R., Preece, K., Komorowski, J.-C., Lavigne, F., Dixon, T. and Connor, L. 2013. Evaluation of the impact of the 2010 pyroclastic density currents at Merapi volcano from high-resolution satellite imagery, field investigations and numerical simulations. *Journal of Volcanology and Geothermal Research*. **261**, pp.295–315.

Charbonnier, S.J. and Gertisser, R. 2011. Deposit architecture and dynamics of the 2006 block-and-ash flows of Merapi Volcano, Java, Indonesia. *Sedimentology*. **58**(6), pp.1573–1612.

Charbonnier, S.J. and Gertisser, R. 2012. Evaluation of geophysical mass flow models using the 2006 block-and-ash flows of Merapi Volcano, Java, Indonesia: towards a short-term hazard assessment tool. *Journal of Volcanology and Geothermal Research*. **231**, pp.87–108.

Charbonnier, S.J. and Gertisser, R. 2008. Field observations and surface characteristics of pristine block-and-ash flow deposits from the 2006 eruption of Merapi Volcano, Java, Indonesia. *Journal of Volcanology and Geothermal Research*. **177**(4), pp.971–982.

Chen, X. 2012. Agent-based micro-simulation of staged evacuations. *International Journal of Advanced Intelligence Paradigms*. **4**(1), p.22.

Chen, X., Meaker, J.W. and Zhan, F.B. 2006. Agent-Based Modeling and Analysis of Hurricane Evacuation Procedures for the Florida Keys. *Natural Hazards*. **38**(3), pp.321–338.

Chen, X. and Zhan, F.B. 2008. Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. *The Journal of the Operational Research Society*. **59**(1), pp.25–33.

Cheng, G., Wilmot, C.G. and Baker, E.J. 2008. A destination choice model for hurricane evacuation *In*: *Proceedings of the 87th Annual Meeting Transportation Research Board, Washington, DC, USA* [Online]., pp.13–17. [Accessed 7 January 2017]. Available from: http://www.ltrc.lsu.edu/pdf/2008/08-0840.PDF.

Christensen, K. and Sasaki, Y. 2008. Agent-Based Emergency Evacuation Simulation with Individuals with Disabilities in the Population. [Accessed 17 March 2015]. Available from: http://jasss.soc.surrey.ac.uk/11/3/9.html.

Christia, M. 2012. *Experiences of people affected Merapi eruption in 2010: A qualitative study conducted in Krinjing village Indonesia*.[Online] Oslo, Norway: University of Oslo. [Accessed 10 March 2015]. Available from: https://www.duo.uio.no/handle/10852/30048.

Cimellaro, G.P., Ozzello, F., Vallero, A., Mahin, S. and Shao, B. 2017. Simulating earthquake evacuation using human behavior models. *Earthquake Engineering & Structural Dynamics*. **46**(6), pp.985–1002.

Crooks, A.T. and Castle, C.J. 2012. The integration of agent-based modelling and geographical information for geospatial simulation *In*: *Agent-based models of geographical systems* [Online]. Springer, pp.219–251. [Accessed 9 April 2015]. Available from: http://link.springer.com/chapter/10.1007/978-90-481-8927-4_12.

van Dam, K.H., Bustos-Turu, G. and Shah, N. 2017. A methodology for simulating synthetic populations for the analysis of socio-technical infrastructures *In*: *Advances in Social Simulation 2015* [Online]. Berlin, Germany: Springer, pp.429–434. [Accessed 2 August 2017]. Available from: http://link.springer.com/chapter/10.1007/978-3-319-47253-9_39.

Damby, D.E., Horwell, C.J., Baxter, P.J., Delmelle, P., Donaldson, K., Dunster, C., Fubini, B., Murphy, F.A., Nattrass, C., Sweeney, S. and others 2013. The respiratory health

hazard of tephra from the 2010 Centennial eruption of Merapi with implications for occupational mining of deposits. *Journal of Volcanology and Geothermal Research*. **261**, pp.376–387.
Darmawan, H., Wibowo, T., Suryanto, W. and Setiawan, M. 2014. Modeling of pyroclastic flows to predict pyroclastic hazard zone in Merapi volcano after 2010 eruption *In*: *EGU General Assembly Conference Abstracts* [Online]., p.1685. [Accessed 4 December 2014]. Available from: http://adsabs.harvard.edu/abs/2014EGUGA..16.1685D.
Dash, N. and Gladwin, H. 2007. Evacuation Decision Making and Behavioral Responses: Individual and Household. *Natural Hazards Review*. **8**(3), pp.69–77.
Dawson, R.J., Peppe, R. and Wang, M. 2011. An agent-based model for risk-based flood incident management. *Natural Hazards*. **59**(1), pp.167–189.
De Silva, F.N. and Eglese, R.W. 2000. Integrating simulation modelling and GIS: spatial decision support systems for evacuation planning. *Journal of the Operational Research Society*. **51**(4), pp.423–430.
Demeritt, D. and Wainwright, J. 2005. Models, Modelling, and Geography *In*: *Questioning Geography: Fundamental Debates* [Online]. Oxford UK: Blackwell Publishing, p.206. [Accessed 7 April 2015]. Available from: http://sociology.sunimc.net/htmledit/uploadfile/system/20110602/20110602035853251.pdf.
Dixit, V., Montz, T. and Wolshon, B. 2011. Validation techniques for region-level microscopic mass evacuation traffic simulations. *Transportation Research Record: Journal of the Transportation Research Board*. (2229), pp.66–74.
Dixit, V.V. 2008. Hurricane evacuation: origin, route, and destination. *Journal of Transportation Safety & Security*. **1**(1), pp.74–84.
Donovan, K. 2010. *Cultural responses to volcanic hazards on Mt Merapi, Indonesia*.[Online] Ph.D. Thesis, Plymouth, UK: University of Plymouth. [Accessed 19 March 2015]. Available from: http://core.kmi.open.ac.uk/download/pdf/10808180.pdf.
Donovan, K., Suryanto, A. and Utami, P. 2012. Mapping cultural vulnerability in volcanic regions: The practical application of social volcanology at Mt Merapi, Indonesia. *Environmental Hazards*. **11**(4), pp.303–323.
Dove, M.R. 2008. Perception of volcanic eruption as agent of change on Merapi volcano, Central Java. *Journal of Volcanology and Geothermal Research*. **172**(3–4), pp.329–337.
Durage, S.W., Wirasinghe, S.C. and Ruwanpura, J.Y. 2016. Decision Analysis for Tornado Warning and Evacuation. *Natural Hazards Review*. **17**(1), p.04015014.
Escobar Wolf, R.P. 2013. Volcanic processes and human exposure as elements to build a risk model for Volcan de Fuego, Guatemala. [Accessed 12 April 2017]. Available from: http://search.proquest.com/openview/e4ac0ac98a5fa2a6122db7d413cba2f9/1?pq-origsite=gscholar&cbl=18750&diss=y.
GEOFABRIK 2016. Download OpenStreetMap data for this region: Indonesia. [Accessed 26 August 2017]. Available from: http://www.webcitation.org/6t07rwZox.
Gertisser, R., Cassidy, N.J., Charbonnier, S.J., Nuzzo, L. and Preece, K. 2012. Overbank block-and-ash flow deposits and the impact of valley-derived, unconfined flows on populated areas at Merapi volcano, Java, Indonesia. *Natural hazards*. **60**(2), pp.623–648.
Gilbert, G.N. 2008. *Agent-Based Models*. London: SAGE.
Gilbert, N. and Terna, P. 2000. How to build and use agent-based models in social science. *Mind & Society*. **1**(1), pp.57–72.
Gilbert, N. and Troitzsch, K. 2005. *Simulation For The Social Scientist*. McGraw-Hill Education (UK).
Goerigk, M., Deghdak, K. and Heßler, P. 2014. A comprehensive evacuation planning model and genetic solution algorithm. *Transportation Research Part E: Logistics and Transportation Review*. **71**, pp.82–97.
Gomez, C., Lavigne, F., Lespinasse, N., Hadmoko, D.S. and Wassmer, P. 2008. Longitudinal structure of pyroclastic-flow deposits, revealed by GPR survey, at Merapi Volcano, Java, Indonesia. *Journal of Volcanology and Geothermal Research*. **176**(4), pp.439–447.

Handayani, D., Herliansyah, M.K., Hartono, B. and Sopha, B.M. 2016. Community behavior during the evacuation of Mount Merapi eruption disaster *In*: *2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*., pp.276–280.

Handford, D. and Rogers, A. 2012. An agent-based social forces model for driver evacuation behaviours. *Progress in Artificial Intelligence*. **1**(2), pp.173–181.

Harland, K., Heppenstall, A., Smith, D. and Birkin, M. 2012. Creating realistic synthetic populations at varying spatial scales: a comparative critique of population synthesis techniques. *Journal of Artifical Societies and Social Simulation*. **15**(1), pp.1–15.

Hawe, G.I., Coates, G., Wilson, D.T. and Crouch, R.S. 2012. Agent-based simulation for large-scale emergency response: A survey of usage and implementation. *ACM Computing Surveys (CSUR)*. **45**(1), p.8.

Heppenstall, A., Malleson, N. and Crooks, A. 2016. “Space, the Final Frontier”: How Good are Agent-Based Models at Simulating Individuals and Space in Cities? *Systems*. **4**(1), p.9.

Heppenstall, A.J., Harland, K., Smith, D.M. and Birkin, M.H. 2011. Creating realistic synthetic populations at varying spatial scales: a comparative critique of population synthesis techniques *In*: *Geocomputation 2011 Conference Proceedings, UCL, London* [Online]., pp.1–8. [Accessed 1 December 2016]. Available from: http://www.geocomputation.org/2011/papers/heppenstall.pdf.

Hsu, Y.-T. and Peeta, S. 2013. An aggregate approach to model evacuee behavior for no-notice evacuation operations. *Transportation*. **40**(3), pp.671–696.

Huang, Z. and Williamson, P. 2001. A comparison of synthetic reconstruction and combinatorial optimisation approaches to the creation of small-area microdata. *Department of Geography, University of Liverpool*. [Online]. [Accessed 2 August 2017]. Available from: http://pcwww.liv.ac.uk/~william/Microdata/Pop91/Methodology/workingpapers/hw_wp_2001_2.pdf.

Huang, Z., Zheng, P., Ren, G., Cheng, Y. and Ran, B. 2016. Simultaneous optimization of evacuation route and departure time based on link-congestion mitigation. *Natural Hazards*. **83**(1), pp.575–599.

Ismayasti, R., Bakema, M. and Sagala, S. 2014. Integrating Disaster Management and Sustainable Development: Finding the Role of NGOs in the Post-Eruption Merapi 2010. *Jurnal Perencanaan Wilayah dan Kota 2 SAPPK*. [Online]. **3**(2). [Accessed 19 March 2015]. Available from: http://sappk.itb.ac.id/jpwk2/wp-content/uploads/2014/12/Ratri-Ismayasti.pdf.

Itoh, H., Takahama, J., Takahashi, M. and Miyamoto, K. 2000. Hazard estimation of the possible pyroclastic flow disasters using numerical simulation related to the 1994 activity at Merapi Volcano. *Journal of volcanology and geothermal research*. **100**(1), pp.503–516.

Joo, J., Kim, N., Wysk, R.A., Rothrock, L., Son, Y.-J., Oh, Y. and Lee, S. 2013. Agent-based simulation of affordance-based human behaviors in emergency evacuation. *Simulation Modelling Practice and Theory*. **32**, pp.99–115.

Jumadi, Carver, S. and Quincey, D. 2017. A Conceptual Design of Spatio-Temporal Agent-Based Model for Volcanic Evacuation. *Systems*. **5**(4), p.53.

Jumadi, Carver, S. and Quincey, D. 2016a. A conceptual framework of volcanic evacuation simulation of Merapi using agent-based model and GIS. *Procedia - Social and Behavioral Sciences*. **227**, pp.402–409.

Jumadi, Carver, S. and Quincey, D. 2016b. ABM and GIS-based multi-scenarios volcanic evacuation modelling of Merapi *In*: *AIP Conference Proceedings* [Online]. AIP Publishing, p.050005. [Accessed 9 May 2016]. Available from: http://scitation.aip.org/content/aip/proceeding/aipcp/10.1063/1.4947401.

Jumadi, J., Suharyadi, R. and Tuladhar, A.M. 2012. Web-Based Spatial Information System To Support Collaborative Lahars Disaster Management. *Indonesian Journal of Geography*. [Online]. **44**(1). [Accessed 18 December 2014]. Available from: http://jurnal.ugm.ac.id/ijg/article/view/2392.

Khalid, M.N.A. and Yusof, U.K. 2014. A Crowd Modelling Considering Group Cohesion in the Emergency Route Planning Problems. [Accessed 25 May 2015]. Available from: http://ajbasweb.com/old/ajbas/2014/IPN%20JAKARTA/33-39.pdf.

Klügl, F. 2008. A Validation Methodology for Agent-based Simulations *In*: *Proceedings of the 2008 ACM Symposium on Applied Computing* [Online]. SAC '08. New York, NY, USA: ACM, pp.39–43. [Accessed 30 April 2017]. Available from: http://doi.acm.org/10.1145/1363686.1363696.

Kohsaka, H. 2000. Risk prediction and evacuation-rescue plans for pyroclastic flow using GIS: A case study of the southern slope of Asama Volcano, Japan. *Geographical Review of Japan, Series A*. **73**(6), pp.483–497.

Kravari, K. and Bassiliades, N. 2015. A Survey of Agent Platforms. *Journal of Artificial Societies and Social Simulation*. **18**(1), p.11.

Lamb, S., Walton, D., Mora, K. and Thomas, J. 2011. Effect of authoritative information and message characteristics on evacuation and shadow evacuation in a simulated flood event. *Natural hazards review*. **13**(4), pp.272–282.

Lavigne, F., de Bélizal, E., Cholik, N., Aisyah, N., Picquout, A. and Mei, E.T.W. 2011. Lahar hazards and risks following the 2010 eruption of Merapi volcano, Indonesia. *EGU General Assembly*. [Online]. **13**(EGU2011-4400). [Accessed 25 January 2015]. Available from: http://meetingorganizer.copernicus.org/EGU2011/EGU2011-4400.pdf.

Lavigne, F., De Coster, B., Juvin, N., Flohic, F., Gaillard, J.-C., Texier, P., Morin, J. and Sartohadi, J. 2008. People's behaviour in the face of volcanic hazards: Perspectives from Javanese communities, Indonesia. *Journal of Volcanology and Geothermal Research*. **172**(3–4), pp.273–287.

Lavigne, F., Morin, J., Mei, E.T.W., Calder, E.S., Usamah, M. and Nugroho, U. 2017. Mapping Hazard Zones, Rapid Warning Communication and Understanding Communities: Primary Ways to Mitigate Pyroclastic Flow Hazard *In*: *SpringerLink* [Online]. Advances in Volcanology. Springer, Berlin, Heidelberg, pp.1–13. [Accessed 12 August 2017]. Available from: https://link.springer.com/chapter/10.1007/11157_2016_34.

Lavigne, F. and Thouret, J.-C. 2003. Sediment transportation and deposition by rain-triggered lahars at Merapi Volcano, Central Java, Indonesia. *Geomorphology*. **49**(1–2), pp.45–69.

Lavigne, F., Thouret, J.C., Voight, B., Suwa, H. and Sumaryono, A. 2000. Lahars at Merapi volcano, Central Java: an overview. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.423–456.

Lim, M.B.B., Jr, H.R.L., Piantanakulchai, M. and Uy, F.A. 2015. A household-level flood evacuation decision model in Quezon City, Philippines. *Natural Hazards*. **80**(3), pp.1539–1561.

Linardi, S. 2016. Peer coordination and communication following disaster warnings: An experimental framework. *Safety Science*. [Online]. [Accessed 18 August 2016]. Available from: http://www.sciencedirect.com/science/article/pii/S0925753516300236.

Liu, S., Murray-Tuite, P. and Schweitzer, L. 2014. Incorporating Household Gathering and Mode Decisions in Large-Scale No-Notice Evacuation Modeling. *Computer-Aided Civil and Infrastructure Engineering*. **29**(2), pp.107–122.

Liu, X. and Lim, S. 2016. Integration of spatial analysis and an agent-based model into evacuation management for shelter assignment and routing. *Journal of Spatial Science*., pp.1–16.

Lo, S.M., Huang, H.C., Wang, P. and Yuen, K.K. 2006. A game theory based exit selection model for evacuation. *Fire Safety Journal*. **41**(5), pp.364–369.

Local Government of Sleman 2010. Pemerintah Kabupaten Sleman » Update Data Pengungsi Bencana Merapi 2010. [Accessed 31 March 2017]. Available from: http://www.webcitation.org/6pNWR8K4a.

Lovreglio, R., Borri, D., Ronchi, E., Fonzone, A. and dell'Olio, L. 2015. The need of latent variables for modelling decision-making in evacuation simulations *In*: *In Proceedings of the IX International Workshop on Planning and Evaluation* [Online]. Bari, Italy. [Accessed 21 May 2015]. Available from: http://www.researchgate.net/profile/Ruggiero_Lovreglio/publication/273697043_The_need_of_latent_variables_for_modelling_decision-making_in_evacuation_simulations/links/552e5b440cf22d43716e1614.pdf.

Lovreglio, R., Ronchi, E. and Nilsson, D. 2016. An Evacuation Decision Model based on perceived risk, social influence and behavioural uncertainty. *Simulation Modelling Practice and Theory*. [Online]. [Accessed 21 May 2016]. Available from: http://www.sciencedirect.com/science/article/pii/S1569190X15302768.

Macal, C. and North, M. 2006. Tutorial on Agent-Based Modeling and Simulation PART 2: How to Model with Agents *In*: *Proceedings - Winter Simulation Conference*., pp.73–83.

Macal, C.M. and North, M.J. 2005. Tutorial on agent-based modeling and simulation *In*: *Proceedings of the 37th conference on Winter simulation* [Online]. Winter Simulation Conference, pp.2–15. [Accessed 7 April 2015]. Available from: http://dl.acm.org/citation.cfm?id=1162712.

Macal, C.M. and North, M.J. 2010. Tutorial on agent-based modelling and simulation. *Journal of Simulation*. **4**(3), pp.151–162.

Malleson, N., See, L., Evans, A. and Heppenstall, A. 2014. Optimising an Agent-Based Model to Explore the Behaviour of Simulated Burglars *In*: V. Dabbaghian and V. K. Mago, eds. *Theories and Simulations of Complex Social Systems* [Online]. Berlin, Heidelberg: Springer Berlin Heidelberg, pp.179–204. [Accessed 23 April 2015]. Available from: http://link.springer.com/10.1007/978-3-642-39149-1_12.

Marrero, J.M., García, A., Llinares, A., De la Cruz-Reyna, S., Ramos, S. and Ortiz, R. 2013. Virtual tools for volcanic crisis management, and evacuation decision support: applications to El Chichón volcano (Chiapas, México). *Natural Hazards*. **68**(2), pp.955–980.

Marrero, J.M., García, A., Llinares, A., Rodríguez-Losada, J.A. and Ortiz, R. 2010. The Variable Scale Evacuation Model (VSEM): a new tool for simulating massive evacuation processes during volcanic crises. *Nat. Hazards Earth Syst. Sci.* **10**(4), pp.747–760.

Mas, E., Suppasri, A., Imamura, F. and Koshimura, S. 2012. Agent-based simulation of the 2011 great east japan earthquake/tsunami evacuation: An integrated model of tsunami inundation and evacuation. *Journal of Natural Disaster Science*. **34**(1), pp.41–57.

Medina, N., Sanchez, A. and Vojinovic, Z. 2016. The Potential of Agent Based Models for Testing City Evacuation Strategies Under a Flood Event. *Procedia Engineering*. **154**, pp.765–772.

Mei, E.T.W. and Lavigne, F. 2012. Influence of the institutional and socio-economic context for responding to disasters: case study of the 1994 and 2006 eruptions of the Merapi Volcano, Indonesia. *Geological Society, London, Special Publications*. **361**(1), pp.171–186.

Mei, E.T.W. and Lavigne, F. 2013. Mass evacuation of the 2010 Merapi eruption. *International Journal of Emergency Management*. **9**(4), pp.298–311.

Mei, E.T.W., Lavigne, F., Picquout, A., de Bélizal, E., Brunstein, D., Grancher, D., Sartohadi, J., Cholik, N. and Vidal, C. 2013. Lessons learned from the 2010 evacuations at Merapi volcano. *Journal of Volcanology and Geothermal Research*. **261**, pp.348–365.

Mei, E.T.W., Lavigne, F., Picquout, A. and Grancher, D. 2011. Crisis Management During the 2010 Eruption of Merapi Volcano *In*: *Regional Geographic Conference–International Geographical Union, Santiago, Chile* [Online]., pp.15–19. [Accessed 10 March 2015]. Available from: http://www.acreditacion.fisa.cl/ugi/archivo_presentacion/201109050300_20112211wvgz7h_archivo_presentacion.pdf.

Mitchell, S. and Radwan, E. 2006. Heuristic Priority Ranking of Emergency Evacuation Staging to Reduce Clearance Time. *Transportation Research Record: Journal of the Transportation Research Board*. **1964**, pp.219–228.

Miyamoto, K., Gonda, Y., Yamashita, S. and Matsuyoshi, H. 2011. Hazard estimation of the possible pyroclastic flow disasters using numerical simulation related to the 2010 activity at Merapi Volcano, Indonesia. [Accessed 11 July 2015]. Available from: http://presentations.copernicus.org/EGU2011-12984_presentation.pdf.

Na, H.S. and Banerjee, A. 2014. An agent-based discrete event simulation approach for modeling large-scale disaster evacuation network *In*: *Simulation Conference (WSC), 2014 Winter*., pp.1516–1526.

Nagarajan, M. 2014. *An operational research-based integrated approach for mass evacuation planning of a city*.[Online] Aston University. [Accessed 21 May 2015]. Available from: http://eprints.aston.ac.uk/22198/.

Newhall, C.G., Bronto, S., Alloway, B., Banks, N.G., Bahar, I., del Marmol, M.A., Hadisantono, R.D., Holcomb, R.T., McGeehin, J., Miksic, J.N., Rubin, M., Sayudi, S.D., Sukhyar, R., Andreastuti, S., Tilling, R.I., Torley, R., Trimble, D. and Wirakusumah, A.D. 2000. 10,000 Years of explosive eruptions of Merapi Volcano, Central Java: archaeological and modern implications. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.9–50.

Newhall, C.G. and Self, S. 1982. The volcanic explosivity index (VEI) an estimate of explosive magnitude for historical volcanism. *Journal of Geophysical Research*. **87**(C2), p.1231.

Ng, M., Diaz, R. and Behr, J. 2015. Departure time choice behavior for hurricane evacuation planning: The case of the understudied medically fragile population. *Transportation Research Part E: Logistics and Transportation Review*. **77**, pp.215–226.

Nuzulia, Y. and Sudibyakto, S. 2014. *kajian penolakan relokasi oleh warga terdampak erupsi merapi tahun 2010 (studi kasus di dusun kalitengah lor, DIYdan dusun Sambungrejo JawaTengah)*.[Online] Universitas Gadjah Mada. [Accessed 19 March 2015]. Available from: http://etd.ugm.ac.id/index.php?mod=penelitian_detail&sub=PenelitianDetail&act=view&typ=html&buku_id=66452&is_local=1.

Oyola, A., Romero, D.G. and Vintimilla, B.X. 2017. A Dijkstra-Based Algorithm for Selecting the Shortest-Safe Evacuation Routes in Dynamic Environments (SSER) *In*: *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems* [Online]. Springer, pp.131–135. [Accessed 1 October 2017]. Available from: http://link.springer.com/chapter/10.1007/978-3-319-60042-0_15.

Pallister, J.S., Schneider, D.J., Griswold, J.P., Keeler, R.H., Burton, W.C., Noyles, C., Newhall, C.G. and Ratdomopurbo, A. 2013. Merapi 2010 eruption—Chronology and extrusion rates monitored with satellite radar and used in eruption forecasting. *Journal of Volcanology and Geothermal Research*. **261**, pp.144–152.

Pareschi, M.T., Cavarra, L., Favalli, M., Giannini, F. and Meriggi, A. 2000. GIS and volcanic risk management. *Natural hazards*., pp.361–379.

Pillac, V., Cebrian, M. and Hentenryck, P.V. 2015. A column-generation approach for joint mobilization and evacuation planning. *Constraints*. **20**(3), pp.285–303.

Pons, M., Johnson, P.A., Rosas, M. and Jover, E. 2014. A georeferenced agent-based model to analyze the climate change impacts on ski tourism at a regional scale. *International Journal of Geographical Information Science*. **28**(12), pp.2474–2494.

POSKO SET BAKORNAS PBP 2006. Penanganan Gunung Merapi: Laporan Posko, 16 Juni 2006. [Accessed 19 March 2015]. Available from: http://118.97.53.73/userfiles/file/buletin/Buletin%20Merapi16.pdf.

Pourrahmani, E., Delavar, M.R., Pahlavani, P. and Mostafavi, M.A. 2015. Dynamic Evacuation Routing Plan after an Earthquake. *Natural Hazards Review*., p.04015006.

Press, O.U. 2004. *A Dictionary of Computing*. Oxford University Press.

Putra, T.Y.D., Trias, A. and de Vries, W. 2011. A Local Spatial Data Infrastructure to Support the Merapi Volcanic Risk Management: A Case Study at Sleman Regency, Indonesia. *Indonesian Journal of Geography*. [Online]. **43**(1). [Accessed 11 July 2015]. Available from: http://journal.ugm.ac.id/index.php/ijg/article/viewFile/2294/2060.

Ratdomopurbo, A. and Poupinet, G. 2000. An overview of the seismicity of Merapi volcano (Java, Indonesia), 1983–1994. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.193–214.

Ratdomopurbo, A. and Poupinet, G. 1995. Monitoring a temporal change of seismic velocity in a volcano: Application to the 1992 eruption of Mt. Merapi (Indonesia). *Geophysical research letters*. **22**(7), pp.775–778.

Ronald, W. 1983. Population Evacuation In Volcanic Eruptions, Floods, and Nuclear Power Plant Accidents: Some Elementary Comparisons. *Journal of Community Pschology*. [Online]. **2**. [Accessed 6 January 2017]. Available from:

https://www.researchgate.net/profile/Ronald_Perry3/publication/229580397_Population_evacuation_in_volcanic_eruptions_floods_and_nuclear_power_plant_accidents_Some_elementary_comparisons/links/53f243a10cf2f2c3e7fcdf90.pdf.

Sadri, A.M., Murray-Tuite, P., Gladwin, H. and others 2015. Hurricane Evacuation Routing Strategy from Miami Beach: Choice of Major Bridges *In*: *Transportation Research Board 94th Annual Meeting* [Online]. [Accessed 21 May 2015]. Available from: http://docs.trb.org/prp/15-4340.pdf.

Sagala, S. and Okada, N. 2009. F-2 Statistical analysis of correlation between hazard-related factors and households' evacuation decisions in Mt. Merapi. *Proceedings of the annual conference of the Institute of Social Safety Science*. **AA12381938**(24), pp.61–64.

Sagala, S.A.H. 2009. *System Analysis of Social Resilience against Volcanic Risks Case Studies of Merapi, Indonesia and Mt. Sakurajima, Japan*.[Online] Ph.D. Thesis, Kyoto, Japan: Kyoto University. [Accessed 5 April 2017]. Available from: http://repository.kulib.kyoto-u.ac.jp/dspace/handle/2433/88040.

Schneider, D.J., Pallister, J.S., Griswold, J. and Wessels, R.L. 2011. Use of satellite remote sensing to support crisis response to the 2010 eruption of Merapi Volcano, Indonesia. *AGU Fall Meeting Abstracts*. **52**, p.02.

Schwarzkopf, L.M., Schmincke, H.-U. and Cronin, S.J. 2005. A conceptual model for block-and-ash flow basal avalanche transport and deposition, based on deposit architecture of 1998 and 1994 Merapi flows. *Journal of Volcanology and Geothermal Research*. **139**(1), pp.117–134.

Setijadji, L.D. 2011. Towards an Effective Decision Support System for Merapi Volcano (Yogyakarta Region, Indonesia) *In*: *AGU Fall Meeting Abstracts* [Online]. San Francisco, California, USA: American Geophysical Union, p.1271. [Accessed 7 February 2015]. Available from: http://adsabs.harvard.edu/abs/2011AGUFMIN11A1271S.

Shi, J., Ren, A. and Chen, C. 2009. Agent-based evacuation model of large public buildings under fire conditions. *Automation in Construction*. **18**(3), pp.338–347.

Siebeneck, L.K. and Cova, T.J. 2012. Spatial and temporal variation in evacuee risk perception throughout the evacuation and return-entry process. *Risk analysis*. **32**(9), pp.1468–1480.

Siebert, L., Simkin, T. and Kimberly, P. 2011. *Volcanoes of the World* [Online]. Berkeley, CA, USA: Univ of California Press. [Accessed 31 May 2017]. Available from: https://books.google.co.uk/books?hl=en&lr=&id=0DZrfpL9_DMC&oi=fnd&pg=PP2&dq=Volcanoes+of+the+World.+3rd+edition&ots=DnfhJ6he8N&sig=qxytaoNhd9_c2o-6q0CBprkDmfQ.

Silva, F.N. de 2001. Providing spatial decision support for evacuation planning: a challenge in integrating technologies. *Disaster Prevention and Management; Bradford*. **10**(1), pp.11–20.

Skiena, S. 1990. Dijkstra's algorithm. *Implementing Discrete Mathematics: Combinatorics and Graph Theory with Mathematica, Reading, MA: Addison-Wesley*., pp.225–227.

Srbljinović, A. and Škunca, O. 2003. An Introduction to Agent Based Modelling and Simulation of Social Processes. *Interdisciplinary Description of Complex Systems*. **1**(1–2), pp.1–8.

Sugumaran, R. and DeGroote, J. 2010. *Spatial Decision Support Systems Principles and Practices* [Online]. CRC Press. Available from: http://dx.doi.org/10.1201/b10322-4.

Surono, S., Jousset, P. and Pallister, J. 2011. Crisis Management during the centennial 2010 eruption at Merapi volcano, Central Java, Indonesia *In*: *2011 International Union of Geodesy and Geophysics (IUGG) General Assembly* [Online]. Melbourne, Australia. [Accessed 21 November 2014]. Available from: https://hal-brgm.archives-ouvertes.fr/hal-00599184.

Takahashi, T. and Tsujimoto, H. 2000. A mechanical model for Merapi-type pyroclastic flow. *Journal of Volcanology and Geothermal Research*. **98**(1), pp.91–115.

Tan, L., Hu, M. and Lin, H. 2015. Agent-based simulation of building evacuation: Combining human behavior with predictable spatial accessibility in a fire emergency. *Information Sciences*. **295**, pp.53–66.

Teo, J.S., Schmöcker, J.-D., Leon, F., Li, J.Y., Ji, J., Atanasiu, G. and Taniguchi, E. 2015. An Agent-based Evacuation Model Considering Field Effects and Government

Advice *In*: *Transportation Research Board 94th Annual Meeting* [Online]. [Accessed 21 May 2015]. Available from: http://docs.trb.org/prp/15-2724.pdf.

Thouret, J.-C., Lavigne, F., Kelfoun, K. and Bronto, S. 2000. Toward a revised hazard assessment at Merapi volcano, Central Java. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.479–502.

Tu, H., Tamminga, G., Drolenga, H., de Wit, J. and van der Berg, W. 2010. Evacuation plan of the city of almere: simulating the impact of driving behavior on evacuation clearance time. *Procedia Engineering*. **3**, pp.67–75.

Ukkusuri, S.V., Hasan, S., Luong, B., Doan, K., Zhan, X., Murray-Tuite, P. and Yin, W. 2017. A-RESCUE: An Agent based regional evacuation simulator coupled with user enriched behavior. *Networks and Spatial Economics*. **17**(1), pp.197–223.

Uno, K. and Kashiyama, K. 2008. Development of simulation system for the disaster evacuation based on multi-agent model using GIS. *Tsinghua Science & Technology*. **13**, pp.348–353.

Usman, F., Murakami, K., Wicaksono, A.D. and Setiawan, E. 2017. Application of Agent-Based Model Simulation for Tsunami Evacuation in Pacitan, Indonesia. *MATEC Web of Conferences*. **97**, p.01064.

Utami, P. 2008. *Measuring Social Vulnerability in Volcanic Hazards: The Case Study of Merapi Volcano, Indonesia, Earth Sciences*. MSc thesis, University of Bristol, Bristol.

Van Drimmelen, M.N. 2010. *Family gathering in evacuations: A case-study of the 2007 Angora Fire*.[Online] The University of Utah. [Accessed 26 May 2015]. Available from: http://content.lib.utah.edu/utils/getfile/collection/etd2/id/176/filename/2076.pdf.

Voight, B., Constantine, E.K., Siswowidjoyo, S. and Torley, R. 2000. Historical eruptions of Merapi Volcano, Central Java, Indonesia, 1768–1998. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.69–138.

Voight, B., Young, K.D., Hidayat, D., Purbawinata, M.A., Ratdomopurbo, A., Sayudi, D.S., LaHusen, R., Marso, J., Murray, T.L. and Dejean, M. 2000. Deformation and seismic precursors to dome-collapse and fountain-collapse nuées ardentes at Merapi Volcano, Java, Indonesia, 1994–1998. *Journal of volcanology and geothermal research*. **100**(1), pp.261–287.

Wang, D.Q., Gong, Q.G. and Shen, X.F. 2014. An Improved Personnel Evacuation Cellular Automata Model Based on the Ant Colony Optimization Algorithm. *Applied Mechanics and Materials*. **513**–**517**, pp.3287–3291.

Wang, H., Mostafizi, A., Cramer, L.A., Cox, D. and Park, H. 2016. An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety. *Transportation Research Part C: Emerging Technologies*. **64**, pp.86–100.

Weinisch, K. and Brueckner, P. 2015. The impact of shadow evacuation on evacuation time estimates for nuclear power plants. *Journal of Emergency Management (Weston, Mass.)*. **13**(2), pp.145–158.

Wilson, T., Dantas, A. and Cole, J. 2009. Livestock Evacuation Or Not: An Emergency Response Assessment Of Natural Disasters. *Proceedings of the Eastern Asia Society for Transportation Studies*. **2009**, pp.8–8.

Wise, S. 2014. *Using Social Media Content to Inform Agent-based Models for Humanitarian Crisis Response*.[Online] Ph.D. Thesis, Fairfax, VA, USA: George Mason University. [Accessed 20 May 2015]. Available from: http://digilib.gmu.edu:8080/jspui/handle/1920/8879.

Yang, B., Ren, B. and Wu, Y. 2012. The Research of Multi-Resolution Modeling and Simulation of the Emergency Evacuation. *Procedia Engineering*. **29**, pp.3110–3116.

Yang, L., Liu, Q., Yang, S.-H. and Yu, D. 2015. Evacuation Planning with Flood Inundation as Inputs *In*: *Proceedings of the ISCRAM 2015 Conference* [Online]. Kristiansand. [Accessed 27 May 2015]. Available from: http://iscram2015.uia.no/wp-content/uploads/2015/05/3-c.pdf.

Ye, M., Wang, J., Huang, J., Xu, S. and Chen, Z. 2011. Methodology and its application for community-scale evacuation planning against earthquake disaster. *Natural Hazards*. **61**(3), pp.881–892.

Yi, W. and Özdamar, L. 2007. A dynamic logistics coordination model for evacuation and support in disaster response activities. *European Journal of Operational Research*. **179**(3), pp.1177–1193.

Yin, W., Murray-Tuite, P., Ukkusuri, S.V. and Gladwin, H. 2014. An agent-based modeling system for travel demand simulation for hurricane evacuation. *Transportation Research Part C: Emerging Technologies*. **42**, pp.44–59.

Yuan, W. and Tan, K.H. 2007. An evacuation model using cellular automata. *Physica A: Statistical Mechanics and its Applications*. **384**(2), pp.549–566.

Yulianto, F., Sofan, P., Khomarudin, M.R. and Haidar, M. 2013. Extracting the damaging effects of the 2010 eruption of Merapi volcano in Central Java, Indonesia. *Natural Hazards*. **66**(2), pp.229–247.

Zhang, B. 2012. *Agent-based discrete-event simulation and optimization of regional transportation evacuation*.[Online] Ph.D., United States -- New York: Rensselaer Polytechnic Institute. [Accessed 10 March 2015]. Available from: http://0-search.proquest.com.wam.leeds.ac.uk/docview/1095407400/abstract/1E0C650410564115PQ/1?accountid=14664.

Zhang, B., Chan, W.K. and Ukkusuri, S.V. 2009. Agent-based modeling for household level hurricane evacuation *In*: *Proceedings of the 2009 Winter Simulation Conference (WSC)*., pp.2778–2784.

Zhang, N., Huang, H., Su, B. and Zhang, H. 2013. Population evacuation analysis: considering dynamic population vulnerability distribution and disaster information dissemination. *Natural hazards*. **69**(3), pp.1629–1646.

Zhao, H., Winter, S. and Tomko, M. 2017. Integrating Decentralized Indoor Evacuation with Information Depositories in the Field. *ISPRS International Journal of Geo-Information*. **6**(7), p.213.

Zia, K. and Ferscha, A. 2009. A Simulation Study of Exit Choice Based on Effective Throughput of an Exit Area in a Multi-exit Evacuation Situation *In*: IEEE, pp.235–238. [Accessed 29 December 2014]. Available from: http://dl.acm.org/citation.cfm?id=1671362.

Zou, N., Yeh, S.-T., Chang, G.-L., Marquess, A. and Zezeski, M. 2005. Simulation-Based Emergency Evacuation System for Ocean City, Maryland, During Hurricanes. *Transportation Research Record: Journal of the Transportation Research Board*. **1922**, pp.138–148.

Chapter 3
Modelling Individual Evacuation Decisions during Natural Disasters: A Case Study of Volcanic Crisis in Merapi, Indonesia

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This chapter improves the spatial ABM of volcanic evacuation that has been presented in Chapter 2. There are some improvements of the model presented in this chapter including the involvement of the individual decision in the model, employment of the synthetic population based on census microdata, validation of the output of the model based on the real data, and the use of real data to parameterise the model. Evaluation of several scenarios of the decision and hazard model is also presented and discussed in this chapter.

Abstract: As the size of human populations increases, so does the severity of the impacts of natural disasters. This is partly because more people are now occupying areas which are susceptible to hazardous natural events, hence evacuation is needed when such events occur. Evacuation can be the most important action to minimise the impact of any disaster, but in many cases there are always people who are reluctant to leave. This paper describes an Agent-based Model (ABM) of evacuation decisions, focusing on the emergence of reluctant people in times of crisis and using Merapi, Indonesia as a case study. The individual evacuation decision model is influenced by several factors formulated from a literature review and survey. We categorised the factors influencing evacuation decisions into two opposing forces, namely the driving factors to leave (evacuate) versus those to stay, to formulate the model. The evacuation decision (to stay/leave) of an agent is based on an evaluation of the strength of these driving factors using threshold-based rules. This ABM was utilised with a synthetic population from census microdata, in which everyone is characterised by the decision rule. Three scenarios with varying parameters are examined to calibrate the model. Validations were conducted using a retrodictive approach by performing spatial and temporal comparisons between the outputs of simulation and the real data. We present the results of the simulations and discuss the outcomes to conclude with the most plausible scenario.

Keywords: Agent-based model, evacuation model, evacuation decision, risk perception model, volcanic hazard, synthetic population, Merapi.

3.1 Introduction

Geophysical events such as earthquakes, volcanic eruptions, landslides and flooding have been occurring on the planet long before the advent of humans, but these events are transformed into natural disasters when they threaten human life (Alcántara-Ayala, 2002). The occurrence of natural disasters has increased over the last decades in line with the increase in the human population, because more people are now occupying those areas which are susceptible to such events (Beck, 2009). While disasters occur worldwide, they have the greatest impact in developing countries due to the prevailing physical (i.e. geographic and geologic) and social conditions (Alcántara-Ayala, 2002). During the last decade, the number of affected people increased greatly in 2015 compared to the period 2005 to 2014, with the highest percentage in Asia (CRED, 2016). In that year, Indonesia was the fourth most frequently affected Asian country (Guha-Sapir et al., 2016). Among the various natural hazards, volcanic eruptions pose a significant threat to Indonesia, as it is located within the “Ring of Fire” (Siagian et al., 2013). Merapi is the most active volcano in Indonesia, and the 2010 eruption was ranked third in the world since 2005 in terms of impact (Guha-Sapir et al., 2016). Being in such susceptible areas, people living close to Merapi should, therefore, develop their awareness and preparedness to evacuate when a hazard occurs.

Evacuation is an important life-saving action in any disaster (Makinoshima et al., 2017), with a history as old as human history in saving lives (Quarantelli, 1990). It takes place by moving people from a hazardous area to a safer place in a very limited time (Saadatseresht et al., 2009). This time limit depends on the speed of the onset of the hazard. Some hazards occur rapidly, with others more slowly (Alcántara-Ayala, 2002; Cutter et al., 2008). For example, hurricanes or earthquakes happen very quickly, while global temperature variations, rises in sea level, drought, and disease affect society more slowly (Cutter et al., 2008). For fast-onset hazards, immediate responses leading to evacuation are needed, because being at the wrong place at the wrong time will quickly lead to fatalities. Volcanic eruptions can happen several days after the initial signs of instability, but it is also possible for them to happen several weeks later (Voight et al., 2000). Therefore, immediate responses from the surrounding population are needed, but there are often cases of people who refuse or are reluctant to evacuate from hazardous areas (Quarantelli, 1990). For example, in two crises in Merapi (2006 and 2010), it was recorded that some people stayed even after official evacuation orders from the local authorities. In the 2006 eruption, individuals in some areas of Merapi disobeyed the evacuation order and suffered the consequences of the eruption (Mei and Lavigne, 2012). Likewise, reluctance was one of the main issues in the volcanic crisis management of the 2010 eruption (Lavigne et al., 2017).

This phenomenon can hamper evacuation processes, but has received surprisingly little attention in studies on evacuation modelling (e.g. (Chen and Zhan, 2008; Zhang et al., 2009; Mas et al., 2012; Jumadi et al., 2017)). Modelling the emergence of reluctant people during a crisis might help in improving evacuation plans; that is, to what extent the number of reluctant people can be reduced to save more lives. This paper aims to model the individual decision-making processes of evacuation (evacuate/stay) during a volcanic crisis using an agent-based model (ABM). The model uses several interacting factors (Sagala, 2009; Donovan, 2010a; Wilson et al., 2012; Chandan et al., 2013) that drive people to leave (forced to evacuate) versus the driving factors to stay (forced to stay). Mt Merapi in Indonesia was used as a case study, with records from the 2010 eruption and associated documentation used as empirical data to validate the model. In the paper, Section 3.2 will present the background literature within this field. Section 3.3 presents the methodology of the research and also gives an introduction to the study area, the synthetic population generation technique, and data on past eruptions. A description of the ABM using Overview, Design concepts and Details (ODD) protocol (Grimm et al., 2006; Polhill, 2010), and the calibration and validation techniques are also included in this section. Section 3.4 presents the results and discussion, followed by the conclusion in Section 3.5.

3.2 Background

The decision to evacuate is not only complex, but also dynamic. Therefore, developing a model can be intricate and needs an appropriate approach. Evacuation is a complex social process, resulting from many interrelating physical and social factors. Studies have identified that evacuation decisions are influenced by several factors (Dash and Gladwin, 2007; Lim et al., 2015; Ahsan et al., 2016) including: (1) risk communication and warning; (2) perception of risk; (3) community and social network influence; and (4) disaster likelihood, environmental cues and natural signals. As a social process, it will be dynamically changed nonlinearly as the above factors also change.

Risk communications deal with the dissemination of risk warnings regarding the probability of a disaster occurring within the community. There are three types of interaction models in emergency situations, namely vertical (top-down), peer to peer, and horizontally broadcast (Linardi, 2016). On the other hand, risk perception is a critical aspect of understanding how individuals decide to evacuate or to stay put (Dash and Gladwin, 2007). Risk perception is also responsible for influencing people's decisions on when they should evacuate, and when they should return home during a crisis (Siebeneck and Cova, 2012). Perception, from the geographer's point of view, describes how things that are related to the surrounding environment are remembered and recalled by people (Golledge, 1997), whereas risk perception is the way people interpret the likelihood of danger, with those who believe that they are not at risk (perceive themselves as safe) tending to feel that evacuation is not essential (Ronald, 1983). Several factors influence risk perception, including social and cultural factors, gender, and experience (Dash and Gladwin, 2007). Another study by Botzen et al. (2009) has stated that some demographic aspects, namely location, experience, knowledge and socioeconomic status, contribute to the perception of the population toward risk. The perceptions of people who live on and around the volcano commonly vary, and this affects the warning-response outcome (Rianto, 2009; Bird et al., 2011). Community and social networks also play an important role in influencing how people respond to a disaster. People tend to keep within their group (community) in their decision response in such situations (Khalid and Yusof, 2014), so they will stand together with their family when deciding to stay or to leave (Liu et al., 2014). Moreover, in crises people are more easily influenced when they interact with a group rather than with individuals. Therefore, people may decide to leave themselves after seeing crowds of evacuees leaving their homes. Lastly, disaster likelihood, environmental cues or natural signals, also affect evacuation decisions (Ronald, 1983; Sagala and Okada, 2009). Some studies on volcano and flood evacuation have identified that natural signals are the most critical factor in evacuation decisions (Ronald, 1983), while others state that risk perception is associated with environmental cues, as well as with the characteristics of the hazard (Lim et al., 2015).

These aspects should all be considered when modelling evacuation decisions in order to better understand how willingness and reluctance emerge. Several studies highlight that traditional beliefs, culture/inherited local knowledge, and economic aspects are found to be the common reasons for refusing to follow evacuation orders (Tayag et al., 1996; Lavigne et al., 2008; Sagala, 2009; Donovan, 2010b; Bird et al., 2011). Although the economic aspect has no influence in the case of evacuation decisions in Merapi (Sagala, 2009), it does encourage people to return home to protect their property or to feed cattle during the evacuation period (Donovan, 2010a). Some modelling studies show how social processes affect evacuation decisions. An example of a communication model among agents within a group, and from one group to different groups, has been presented by Canessa and Riolo (2003). Agent interaction, specifically the mechanisms of how actions and messages from other agents motivate individuals, can be represented using an agent-based model (Marsella et al., 2004). The aggregation behaviour of people was successfully presented by Qiu and Hu (2010). However, models of the decision-making mechanisms as a result of these factors are limited. The evacuation decision model (EDM) developed in this paper is different from another recent model based on perceived risk by Reneke (2013) and improved by Lovreglio et al. (2016). These models (Reneke, 2013; Lovreglio et al., 2016) disregard the social characteristics of agents in defining risk perception. However, based on other research, risk perception does not stand alone, but depends on other factors (Rosenbaum and Culshaw, 2003; Dash and Gladwin, 2007; Botzen et al., 2009). Therefore, this paper attempts to address this problem by involving risk perception and some of the other aforementioned factors in evacuation decision making. For this purpose, Agent-based modelling (ABM) was employed to simulate the decision making mechanism during an emergency situation.

ABM, which in some literature is called ABS (agent-based systems) or IBM (individual-based modelling) (Macal and North, 2005), is defined as a computational method that enables a researcher to create, analyse, and experiment with models comprising agents that interact within an environment (Macal, 2005; Gilbert, 2008). These agents can be separate computer programs, or in the common form, distinct parts of a program that are used to represent social actors, which can be individual people, organisations such as firms, or bodies such as nation-states (Gilbert, 2008). The agent can also be represented in a spatially realistic environment involving a Geographic Information System (GIS), which is called spatial agent-based modelling (Brown and Xie, 2006) or georeferenced agent-based model (Pons et al., 2014). The conceptual integration of both GIS and ABM is achieved successfully by Brown et al. (Brown et al., 2005), where GIS is used as the spatial data model representation, and ABM as the processes model. Such a model is suitable for developing an emergency evacuation model, considering the spatial aspects of both hazard and population.

In addition to ABM, there are several other computer simulation techniques for emergency simulation and evacuation, namely system dynamics, stochastic modelling, queuing networks, lattice gas models, social force models, fluid-dynamic models, and game theoretic models (Zheng et al., 2009; Hawe et al., 2012). GIS and cellular automata (CA) are also used by some models for the same purposes (Cole et al., 2005; Yuan and Tan, 2007; Marrero et al., 2010; Ye et al., 2014; Wang et al., 2014). However, ABM has more benefits in modelling individuals in emergencies, including the possibility to capture emergent phenomena, to naturally describe the system, and flexibility (Bonabeau, 2002; Hawe et al., 2012). ABM and CA share some similar characteristics, but ABM is superior since CA is less able to represent the heterogeneity of agents within a population (Reynolds, 1999; Zheng et al., 2009). With particular reference to evacuation modelling, Zheng et al. (2009) compared seven methodologies for simulating crowd evacuation, including CA and ABM. Their study highlighted that only simulation using ABM has the capability to model heterogeneous agents at a microscopic scale; this ability is important to model evacuation with varying population characteristics.

Although the development of ABM is intricate, such as being a complicated development process, being difficult to understand, challenging to collect the required data, difficult to validate, commonly needing very large runs due to the randomness; and complex in analysing the output, it provides a promising approach to simulating human-natural system interaction (Gilbert, 1993; Grimm et al., 2006; Klügl, 2008; An, 2012; Lee et al., 2015; Robinson and Rai, 2015; Heppenstall et al., 2016; Chapuis et al., 2018). Its advantages enable ABM to be better at representing human behaviour in decision-making (Wang et al., 2016), especially when dealing with disaster events. This approach has been applied to a range of hazards; for instance, fire and building damage-related hazards (Christensen and Sasaki, 2008; Shi et al., 2009; Tan et al., 2015; Zhao et al., 2017), hurricanes (Zhang et al., 2009), and tsunami (Mas et al., 2012; Wang et al., 2016). These models vary in terms of the spatial extent of the simulated areas, the population mimicking method, integration of the hazard model, and the evacuation decision of agents. Fire and building damage-related hazards apply to a smaller spatial extent than hurricanes and tsunami, which use regions/cities as simulation areas.

Wider areas imply more complexity in the agent population and evacuation routes. Small area evacuation, such as in fire evacuation models, use only a small number of evacuees, making their characteristics less complex. These models commonly generate a number of agents randomly as building occupiers in the simulations (Shi et al., 2009; Tan et al., 2015). More complex agent populations simulated in models should implement synthetic populations to imitate real world heterogeneity (Cajka et al., 2010; Malleson and Birkin, 2012; Namazi-Rad et al., 2014). However, few of the evacuation models have used this approach in generating the population of agents. This approach might not be important for a model intended for experimental purposes only (Zhang et al., 2009), but it should be applied to a model that uses real data with heterogeneous population characteristics. The emergence of a new library for synthetic population generation, such as Gen* (Chapuis et al., 2018), is promising for future enhancement of this aspect.

3.3 Materials and Methods

3.3.1 Study Area

Mt. Merapi (110^{o} 26.5' E, 7^{o}32.5' S) in central Java is one of the most active volcanoes in Indonesia (Sadono et al., 2017). More than 1 million people live in the vicinity, with 400,000 people at especially high risk (Mei et al., 2011; Mei et al., 2013); the city of Yogyakarta (population 4 million) lies only 28 km to the south. There is a record of dangerous eruptions going back many hundreds of years, with an average interval between eruptions of 1-6 years (Voight et al., 2000; Siebert et al., 2011). More than 74 eruptions have been recorded since 1548 AD, most of them around VEI 2 (Newhall and Self, 1982) but larger events (VEI >3) occurred in 1672, 1822, 1846, 1849, 1872, 1930-31 and 1961 (Voight et al., 2000; Siebert et al., 2011; Gertisser et al., 2012). Eruptions in the 20th century have caused many deaths, including those of 1930 (1400 deaths), 1954 (54 deaths), 1961 (6 deaths), and 1994 (69 deaths) (Thouret et al., 2000; Wilson et al., 2007), while the VEI 4 (Newhall and Self, 1982) eruption in 2010 was the largest in over a century, ejecting 30-60 million m^3 of pyroclastic material (Surono et al., 2012) and resulting in 332 deaths and 1,705 injuries (Marfai et al., 2012). As an active volcano, further large explosive eruptions of Merapi should be anticipated by studying its characteristics from historical events (Voight et al., 2000).

The historical activity of Merapi is dominated by the episodic growth and collapse of andesitic lava domes at the summit (2978 m a.s.l prior to the 2010 eruption). Less frequently, the summit dome complex is destroyed by more massive explosive eruptions. Lava dome collapse triggers a range of pyroclastic density currents (PDCs), a general term applied to fast-moving ground-hugging mixtures of hot gas, rock fragments and ash, which have both dilute, turbulent (surge) and dense pyroclastic flow (PF) end-members (Branney and Kokelaar, 2002). At Merapi these include: (1) high energy dilute, turbulent pyroclastic surges; (2) valley-confined, relatively dense block-and-ash flows (BAF), comprising juvenile volcanic blocks in an ash matrix, sometimes referred to as Merapi-type *nués ardentes* (Bardintzeff, 1984; Charbonnier and Gertisser, 2008), which travelled as far as 16.5 km during the 2010 eruption (Solikhin et al., 2015); (3) unconfined and overbank pyroclastic flows; and (4) dilute ash cloud surges elutriated and decoupled from the denser flows (Kelfoun et al., 2000; Thouret et al., 2000).

Rain-triggered *lahars* are a serious additional hazard at Merapi, both during and after eruptions, when heavy rainfall remobilises fresh pyroclastic deposits (Pierson and Major, 2014). The word *lahar* is an Indonesian term referring to a sediment-laden flow of water from a volcano, other than the normal stream flow (Smith and Fritz, 1989). At Merapi, lahars, including both debris- and hyper-concentrated flow types (Smith and Lowe, 1991), can travel at 5-7 m/s at elevations above 1000 m a.s.l and reach as far as 30-40 km from the summit along each of the several rivers that drain the mountain, inundating extensive areas of the ring plain below 600 m a.s.l and aggrading channels (Lavigne et al., 2000; Thouret et al., 2000; Lavigne and Thouret, 2003; Lavigne et al., 2011; de Bélizal et al., 2013; Gob et al., 2016). In comparison with the PDC and lahar hazards, distal ashfall is a relatively minor phenomenon at Merapi (Damby et al., 2013).

Geographically, Merapi spans four regencies of two provinces, i.e. Sleman (Yogyakarta), Magelang, Boyolali and Klaten (Central Java). This study focuses on the Sleman regency, lying on the southern flank of Merapi (Figure 3.1) between 107° 15 '03" to 107° 29 '30" E and 7° 34' 51" to 7° 47' 30" S. The area covers 57,482 hectares (574.82 km^2), or about 18% of the Yogyakarta metropolitan area. Administratively, the region contains 17 sub-districts, 86 villages and 1,212 hamlets. The area was selected because it is located on the southwest flank of Merapi, which is prone to disaster (Lavigne et al., 2007), and also due to the significant geomorphic (Saepuloh et al., 2013) and geological changes (Gertisser et al., 2012) produced by the 2010 eruption, which have potentially changed the likely run-out direction of the pyroclastic and lahar flows, impacting the accuracy of existing hazard maps (see Figure 3.1) (BNPB, 2008; BNPB, 2011).

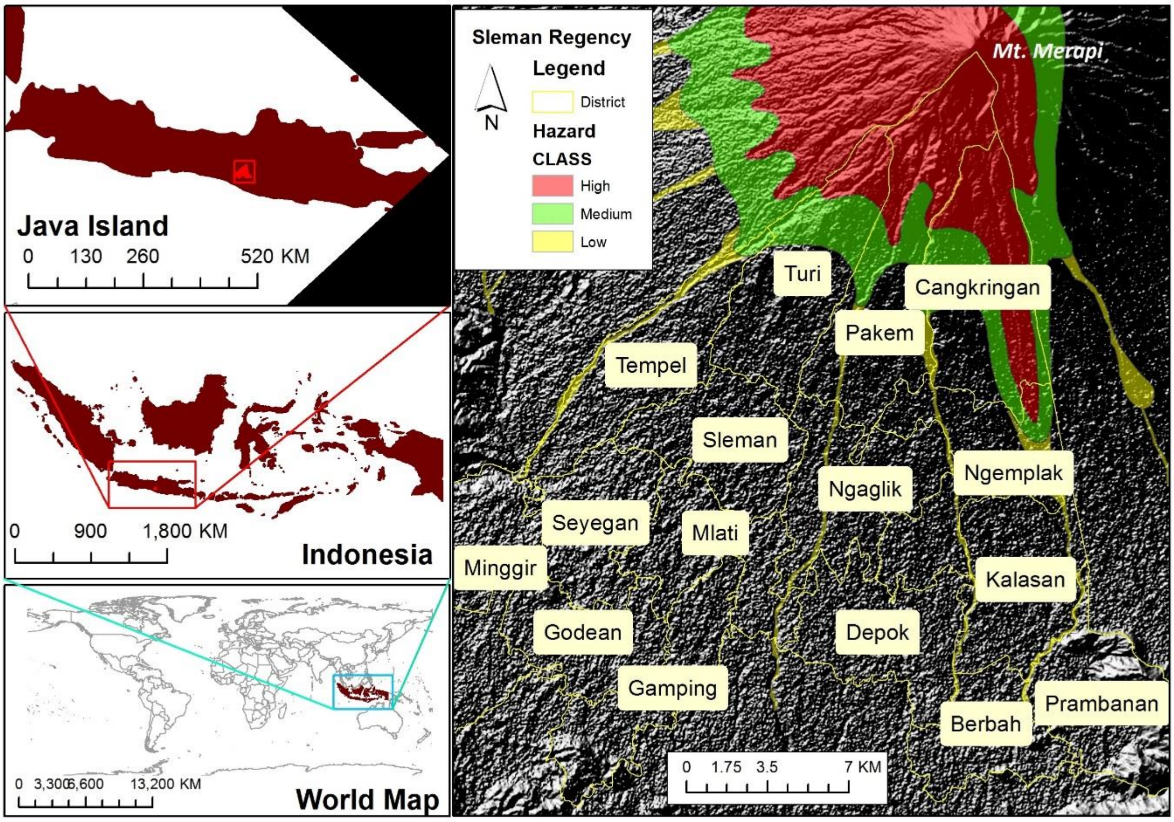

Figure 3.1 Study area and hazard zones.

3.3.2 General Framework

The framework to develop the model (Figure 3.2) mainly comprises preparation, model development and simulation, calibration and validation. The purpose of the preparation step is to collect and analyse the dataset that is used to generate the variables and formulate the rules in the simulation (see Section 3.3.3). The simulation step includes the development of the ABM application and experimentation based on the formulated rules. Calibration and verification steps are needed when the output of the model is unacceptable (see Section 3.3.6.2). The aim of the calibration was to adjust the variables used in the model, whereas verification aimed to improve/revise the rules and the ABM application. When the revision/improvement was complete, re-simulation and re-validation were then needed iteratively. Two adjustments were made to the hazard model, while the decision model was adjusted three times, resulting in three simulation scenarios. Finally, the validation step compared the simulation output of both the spatial and temporal data (see Section 3.3.6.3).

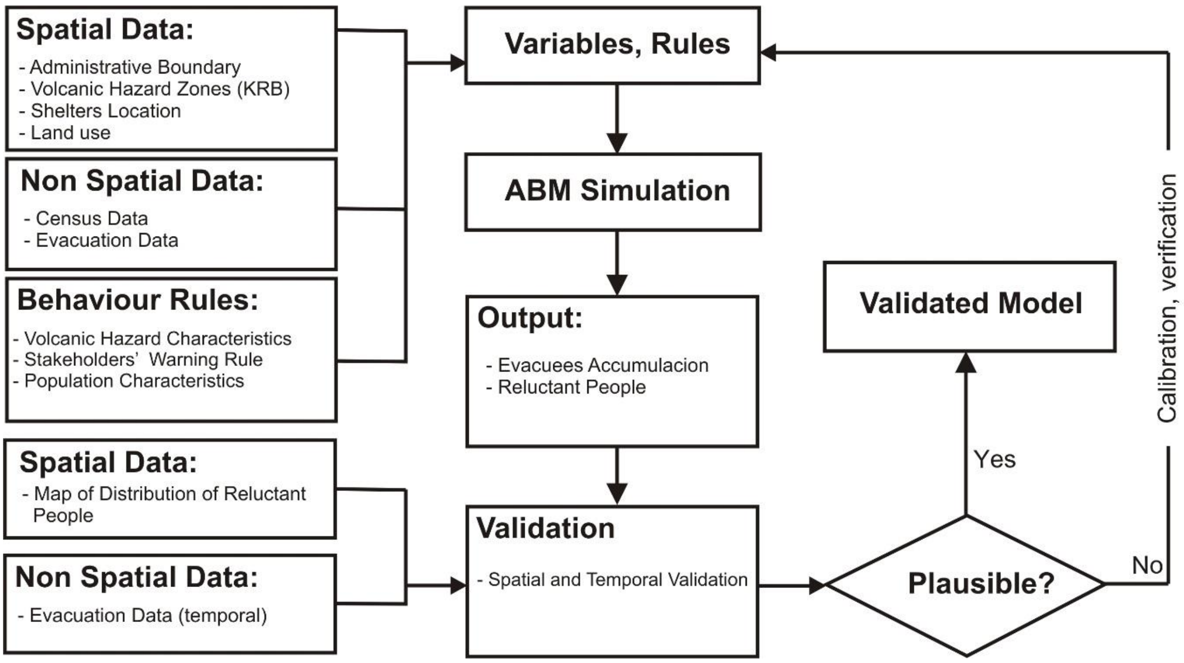

Figure 3.2 General framework.

3.3.3 Input Data

3.3.3.1 Data Requirement and Sources

Several types of spatial and non-spatial data from Merapi were collected and used to generate the agent and environment (Table 3.1). The spatial data mainly comprises the administrative boundaries of Sleman, the volcanic hazard zone, land use, and road network. The non-spatial data comprises microdata from the Indonesian Census of 2010 from IPUMS (Minnesota Population Center, 2015), demography, and population characteristics developed from the survey.

Table 3.1 Dataset list for the model.

Data	Source	Use
ABM development		
Administrative boundary	Indonesian Geospatial Agency (BIG)	This data is used to distribute the human agents within the boundary.
Volcanic hazard zones	(1) National Agency for Disaster Management (BNPB), (2) Based on the evacuation order hazard zones in 2010 (Mei et al., 2013)	Setting up the hazard scenarios and spatial distribution of the eruption impact.
Shelter location	Geospatial BNPB (BNPB, 2010c; BNPB, 2010a; BNPB, 2010d; BNPB, 2010b), DYMDIS GEGAMA (Budiyono, 2010)	Defining evacuation destination.
Land use	Indonesian Geospatial Agency (BIG)	Defining the mean centre of population distribution (synthetic population generation).
Census microdata	Microdata of the Census of Indonesia 2010 from IPUMS (Minnesota Population Center, 2015)	Defining the sociodemographic characteristic distribution (synthetic population generation).
Road networks	OSM PBF File (GEOFABRIK, 2016)	Evacuation routing
Survey data	Survey	Formulating the decision making.
Validation		
Map of distribution of reluctant people	Evacuation refusal map (Lavigne et al., 2017)	Spatial validation.
Series of daily records of evacuees in 2010 eruption	Local Government of Sleman (Slemankab, 2010)	Temporal validation.

3.3.3.2 Survey: Design and Data Analysis

1. Questionnaire Development

The questionnaire was developed to gather information regarding the mechanisms used in decision-making and the interaction of people during eruption crises in the Mt. Merapi region. A literature review was conducted to explore the variables that influence decision-making and interaction. Five primary variables were assessed in the questionnaire survey; namely, socio-demographic characteristics, perception of volcanic hazard, decision-making behaviour, interaction during a crisis, and willingness to accept and act on an alert. The question list is developed based on these variables.

The demographic characteristics are used in this research to characterize the agent as well as identify the social vulnerability of the agent. Social vulnerability is defined as "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard" (Blaikie et al., 2014). Vulnerability is multidimensional, and so consists of many variables (Lummen and Yamada, 2014). Cutter et al. (2003) recognized that the social vulnerability index comprises several indicators: socioeconomic status (income, political power, prestige), gender, race and ethnicity, age, commercial and industrial development, unemployment, rural/urban status, residential property type, infrastructure and lifelines, renter, occupation, family structure, education, population growth, availability of medical services, social dependence, and special needs populations. Alcorn et al. (2013) listed the social vulnerability factors, consisting of ethnicity, age, class, wealth, wealth/extractive employment, poverty/unemployment, race, and gender. Letsie (2015) summarized the social vulnerability factors from various studies, mainly comprising income, gender, race/ethnicity, age, unemployment, housing condition, infrastructure, family structure, education, culture, place, population growth, special need, commercial and industrial development, and built environment. Holand et al. (2011) classified the vulnerability indicators as socioeconomic vulnerability and built environment vulnerability. More specific to the evacuation assistant needs, Chakraborty et al. (2005) developed Social Vulnerability for Evacuation Assistance Need (SVEAI), with ten variables from three social characteristics; namely, population and structure, differential access to resources, and population with special evacuation needs. According to Holand et al. (2011), the questionnaire needs to measure socioeconomic vulnerability. Meanwhile, the built environment vulnerability is observed from spatial data. Several relevant indicators from Letsie (2015) and Chakraborty et al. (2005) are used: income, gender, race/ethnicity, age, unemployment, family structure, education, culture, special need, communication access, and transportation access. The questionnaire is thus used to capture the full range of demographic characteristics of the people.

Perception, on the other hand, relates to the way in which individuals or communities respond to natural disasters (Rianto, 2009). Risk perception is the estimated probability at which people perceive that hazards will affect them (Lavigne et al., 2008). Perception of risk is developed from several factors: exposure, familiarity, preventability and dread (Rosenbaum and Culshaw, 2003). Exposure, preventability and dread are actually quite complex in nature. They are related to the nature of hazard events and the element at risk. Therefore, to measure the perception of the population, familiarity with the likelihood of an eruption will be used. Table 3.2 lists the questions used to assess the perception of people regarding the risk, based on natural cues. The expected answer to each question (the real risk level) is provided in Table 3.3. The perception (how accurately people perceive the risk) is measured based on how the answer compares to the real risk level (Table 3.4), where the overall score is the average.

Table 3.2 Question list to assess people's perception of volcanic risk.

Volcanic Activity	1 **No Risk** It is safe for me to stay	2 **Slight Danger** but I prefer to stay	3 **Moderate Danger** May still be safe for me to stay	3 **Severe Danger** I have to evacuate	4 **Extreme Danger** I should not be here
You see gas rising from the crater	☐	☐	☐	☐	☐
You feel tremors	☐	☐	☐	☐	☐
You hear/see explosion	☐	☐	☐	☐	☐
Your environment is full of ash	☐	☐	☐	☐	☐
You see material in your village collapsing	☐	☐	☐	☐	☐

Table 3.3 Expected answers to the questions in Table 3.2.

Volcanic Activity	Risk level (Real)
You see gas emitted from the crater	1
You feel tremors	2
You hear/watch explosion	3
Your environment fulfilled by ashes	4
You see material collapse to your village	5

Table 3.4 Matrix for evaluating the accuracy of people's perceptions.

Perceived (P) – Real (R)	R1	R2	R3	R4	R5
P1	5	4	3	2	1
P2	4	5	4	3	2
P3	3	4	5	4	3
P4	2	3	4	5	4
P5	1	2	3	4	5

Meanwhile, the decision-making process describes when people start to evacuate. It explores the variability of the population in terms of making decisions during a crisis. The main indicator of this behaviour is the start time, related to the onset of enhanced activity of the volcano. Based on Golledge (1997), decision-making can be classified as disaggregate or aggregate. Aggregate decision-making occurs when the decision is made by a single unit of the population i.e. an individual or household. Meanwhile, an aggregate decision is made by a group within the population i.e. the community. This questionnaire explores the decision-making process on the basis of the household (disaggregate) level. The questionnaire explores the factors that might motivate or demotivate people in making the decision whether to evacuate.

Interaction during a crisis can take the form of word-of-mouth (WOM) via various media. Word-of-mouth can be analyzed based on the probability that people will forward information to others (Allsop et al., 2007). In this case, data on the probability that people will forward their information about alerts and the impact of this on people's decisions people is needed. Mathbor (2016) highlighted that social organizations play an important role in reducing vulnerability. It mainly consists of the social coping mechanism of the family, group or community: resilience, unity and solidarity. Such interaction can be an advantage in an emergency situation. This information was identified from the questionnaire survey. These data are used to estimate the probability that people will pass their information on to others. The interaction behaviour is expressed as a social concern variable in the questionnaire.

2. Field Survey

In order to collect these variables, stratified random sampling was applied. Household member samples, represented as building units, were selected randomly for each building block (*dusun*). This area segmentation is based on the consideration that each *dusun* has one village chief who mobilizes people (*Rukun Tangga*) and, commonly, in the rural areas of Indonesia, has homogenous social characteristics. Twelve villages were selected within a radius of 20km. Several ring buffers with distance ranges of 5 km were created to define the sampling areas, with three villages selected from each range. Furthermore, 10 participants from each village were selected randomly, resulting in 120 participants in total.

3. Data Analysis

The results of the survey were statistically analysed to develop the evacuation decision model (see Supplementary Material–Appendix 3.1). The data from the survey were tabulated and analysed using SPSS. Linear regression was used to analyse the data to generate a formulation of the variable value based on the demographic characteristics (Figure 3.3). The result of the regression analysis is used to develop the driving forces governing the decision to evacuate and to stay. These were also partially used to characterize the agents (the majority of agent characteristics were taken from census microdata).

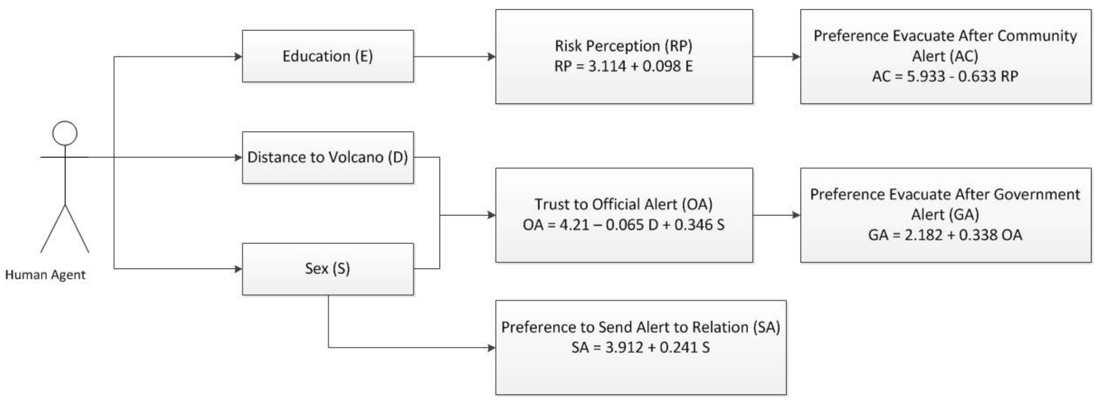

Figure 3.3 Formulation of the variable values based on the regression.

4. Limitation of the Survey

This survey has limitations regarding uncertainty of participant selection and the possible changes in the perceptions of people regarding the risk. The survey expected to meet the head of the household as a participant. However, in some cases, the head of household was away for work or other purposes because the survey was conducted during the daytime. In those cases, a member of the household who had the ability to answer the questions was selected to represent the head of the household. On the other hand, people may also change their perceptions regarding the volcanic risk due to the time lag between the last eruption (2010) and the survey (2016).

3.3.4 Model Design

3.3.4.1 Overview

Purpose

The purpose of the simulation was to model individual decisions in the volcanic evacuation which led to reluctance and to validate the output with real data. The validation is based on temporal and spatial data from the evacuation of 2010. The temporal data is the evacuation dataset (see Supplementary Material–Appendix 3.2) that was provided on a daily basis during the crisis, whereas the spatial data is the emergence of reluctant people (see Supplementary Material–Appendix 3.3).

Entities, State Variables, Scales and Environment

The ABM is based on a model from Jumadi et al. (2017) that mainly consists of three agent types, namely the volcano, people, and stakeholder. Additionally, there are safe shelters, which are objects assigned as properties of the environment, together with districts, hazard zones and routes. A detailed description of the entities and the corresponding attributes is provided in a previous article (Jumadi et al., 2017), with some improvements in the people agent provided in Table 3.5. The following is a brief description of each element:

1. Volcano: this agent represents Mt. Merapi, which has the rule to produce activity and trigger a change in the environment.

People: this agent type represents people, generated based on the census data as synthetic population agents (see Section 3.5 for details of the synthetic population generation).

2. Stakeholder: this is an agent who acts as stakeholder, with the role to alert people to evacuate.

3. Environment: this is represented as a spatial environment where the agents live. It consists of: (1) the population unit, which is a fixed environment provided as a GIS region; (2) the administrative boundary of the district where the agent's population will be distributed within the region; (3) hazard zones to model the hazardous environment that dynamically changes following the volcanic activity; (4) the route networks that are used by agents to move; and (5) evacuation shelters, which are distributed outside the hazard zones as GIS points.

Table 3.5 Overview of main attributes additional to the previous model (Jumadi et al., 2017).

Entity	Attribute	Type	Description
People	Disability	Integer	Expresses whether the agent has a disability or not.
	Experience	Integer	Expresses whether the agent has experienced a previous eruption or not.
	Income	Integer	Income class of agent.
	PersonalIntension (PI)	Integer	The degree to which people are motivated to evacuate by themselves (taken from the survey).

Table 3.5 Continued …

	ProtectProperty (PP)	Integer	The degree to which are people motivated to stay to protect their property (taken from the survey).
	SeeTheExplosion (SE)	Boolean	Whether the agent has seen the volcanic eruptionor not.
	Perception	Integer	This value describes how well the agent perceives the hazard.
	CulturalBelief (CB)	Integer	The degree to which people are motivated to stay by their beliefs (estimated from the literature; this is only assigned to aged and poorly educated people).
	GovernmentAlert (GA)	Integer	The degree to which people are motivated to evacuate when they receive an alert from the stakeholder (taken from the survey).
	FeelingDanger (FD)	Integer	Quantification of feeling in danger.
	FeelingSafe (FS)	Integer	Quantification of feeling safe. This will be deduced when FD increases.
	NotKnowingTheDestinatio n (ND)	Integer	The degree to which people are motivated to stay because they do not know where to go (taken from the survey).
	TransportConcern (TC)	Integer	The degree to which people are motivated to stay because they have a problem with transportation (taken from the survey).
	SocialInfluence (SI)	Integer	The degree to which people are motivated to evacuate by their social relation decisions (taken from the survey).

Process Overview and Scheduling

The model comprises several processes: (1) volcanic activity generation, (2) the stakeholder's alerting procedures, and (3) people's individual decision-making. The volcanic activity will change over the time of the simulation. The length of crisis can be either predefined at the simulation start or randomly generated by the simulation, while the stakeholder is observing this activity during simulation. When the activity changes, it will be analysed against the alerting rules. The alert will be sent to the population if the condition fulfils the requirements of evacuation order issuance. Otherwise, the stakeholder will continue to observe the volcano. The population can observe the volcanic activity and the environment, as well as receiving commands from the stakeholder. People will evacuate when the conditions meet the criteria. Details of the procedures are provided in Section 3.3.4.3.

3.3.4.2 Design Concepts

The following concepts will be used in the model:

Emergence: by simulating the evacuation decision in a spatiotemporal dynamic model, the potential problems for evacuation may emerge, especially the emergence of reluctant people.

Sensing: the stakeholder can sense the change in volcanic activity level by reading the signal (message) from the volcano. Human agents can sense their location, and whether they are located in a danger zone or not.

Interaction: the stakeholder interacts with the human agents regarding the alert issuance. Human agents interact with each other to convey their decision to evacuate.

Stochasticity: the socio-demographics and location of the human agents are generated randomly. The socio-demographics are generated using custom distribution based on census microdata, whereas the location of agents is generated based on the settlement distribution generated from land use data (Jumadi et al., 2016).

Observation: the output can be monitored directly during the simulation from the map, as well as the monitoring charts. Some indicators are observed during the simulation, including the percentage of people at risk (low, medium, high), the percentage of evacuating people, occupancy of the evacuation shelters, and the level of volcanic activity. This output is also recorded as a CSV file that can be spatiotemporally analysed using GIS, or Excel for other purposes.

3.3.4.3 Details

Initialisation and Input

The initialisation of the model relies on the input data previously provided in Section 3.3.3, complemented with data from the literature and author estimation of missing data. The volcano attribute initiation values are mostly based on data from the literature. In addition, the population attributes are mostly from the statistical data derived from the census microdata and the survey. We developed custom distribution based on these statistics to initiate the value of the demographic attributes. Custom distribution is a feature in AnyLogic 8.2 (The AnyLogic Company, Oakbrook Terrace, IL, USA), developed based on frequency from the observed samples (Borshchev, 2013). Meanwhile, the stakeholder has simple attributes taken from the literature. The overall parameterisation of agents in the model is provided in Table 3.6. In this initial condition, the environment is assigned with safe or low hazard, depending on the hazard zone.

Table 3.6 Overview of the initialisation of the primary attributes.

Entity	Attribute	Initial Value	Unit	Changing Mechanism	Source
Volcano	Latitude	-7.541	Degree	Fixed	(BNPB, 2011)
	Longitude	110.446	Degree	Fixed	(BNPB, 2011)
	ActivityLength	104	Days		(Mei et al., 2013)
	ActivityLevel	0	-		(Mei et al., 2013)
	VEI	4	-	Fixed	(BNPB, 2011)
Stakeholder	AlertLevel	1	-	Changed by changing ActivityLevel	(Mei et al., 2013)
People	Age	Based on custom probability	Years	Fixed	Dataset (Minnesota Population Center, 2015)
	Disability	Based on custom probability	-	Fixed	Dataset (Minnesota Population Center, 2015)

Table 3.6 Continued …

Education	Based on custom probability	-	Fixed	Dataset (Minnesota Population Center, 2015)	Education
Experience	Based on custom probability	-	Fixed	Survey Data	Experience
HouseHoldID	From Simulation	-	Fixed	Simulation	HouseHoldID
	Income	Based on custom probability	-	Fixed	Dataset (Minnesota Population Center, 2015)
	DistrictID	From simulation	-	Fixed	Simulation
	Sex	Based on custom probability	-	Fixed	Dataset (Minnesota Population Center, 2015)
	Latitude	From simulation	Degree	Changed by movement	Simulation
	Longitude	From simulation	Degree	Changed by movement	Simulation
	HomeLatitude	From simulation	Degree	Fixed	Simulation
	HomeLongitude	From simulation	Degree	Fixed	Simulation
	MovementSpeed	30 – 40	km/h	Fixed	(Muhammad, 2015)
	PersonalIntension (PI)	1 – 5		Fixed	
	ProtectProperty (PP)	1 – 5	-	Fixed	Simulation
	SeeTheExplosion (SE)	0	-	Changed by the volcano activity	Simulation
	Perception	1 – 5	-	Fixed	Simulation
	CulturalBelief (CB)	0 – 5	-	Fixed	Simulation
	GovernmentAlert (GA)	0	-	Changed when alert received	Simulation
	FeelingDanger (FD)	0	-	Changed by the volcano activity and the hazard zone	Simulation

Table 3.6 Continued …

	FeelingSafe (FS)	5	-	Changed when FD changes	Simulation
	NotKnowTheDestination (ND)	1 – 5	-	Fixed	Simulation
	TransportConcern (TC)	1 – 5	-	Fixed	Simulation
	SocialInfluence (SI)	0	-	Changed when receiving alert by social network	Simulation

Sub-models

1. Volcanic Activity

During a period of crisis, the activity level of the volcano (VAL) changes over time. This activity can be divided into four classes: normal (out of the volcanic crisis period), low, medium and high. For instance, the data from two crisis records (2006 and 2010) show how the relative length of each level varies randomly (Mei and Lavigne, 2012; Mei and Lavigne, 2013) for chronological details). Temporally, the VAL changes over time, typically from low to medium to high to medium to low. This spatially affects the changes in the hazardous environment in the model. Similarly, the variability of the Volcanic Explosivity Index (VEI) also affects the variability of the spatial extent of the impact. The impact will be much wider when the intensity is higher. VEI is a semi-quantitative index used to describe the magnitude or the destructiveness of an eruption (Newhall and Self, 1982), ranging from 0 (least destructive) to 8 (most destructive) (Newhall and Self, 1982). Based on historical records, the VEI of Merapi eruptions ranges from 1 – 4 (Surono et al., 2012). The rule in this model on how VAL and VEI influence the hazard zone is provided in Table 3.7 (a more detailed illustration is provided in Figure 3.7 of a previous paper (Jumadi et al., 2017)).

Table 3.7 Matrix Relationship between the Volcanic Explosivity Index (VEI), VAL and the hazard level within Hazard Zones (adapted from (Jumadi et al., 2017)).

VEI	1			2			3			4		
Hazard Zone / VAL	L	M	H	L	M	H	L	M	H	L	M	H
III (H)	L	M	M	L	M	M	M	H	H	M	H	H
II (M)	L	M	M	L	M	M	M	M	H	M	M	H
I (L)	L	L	M	L	L	M	L	M	M	L	M	M

Notes: L: Low, M: Medium, H: High

2. Official Warning Models

Alerts and warnings are part of the social capacity of the community in a disaster. Disaster warning is a communicative process comprising interrelated activities and procedures (Anderson, 1969). As this is produced from observation of the likelihood of disaster, it is commonly included with many uncertainties and limitations that can fall to the false warning and missed event (Durage et al., 2016). The sources of warnings can be authorities, peers, friends or family members, and media (Thompson et al., 2017). The authorities issue disaster warnings in Merapi from the observation of activity levels. Subsequently, warnings are delivered to all agents; the warning level is derived from the VAL. The warning steps, referring to the actual warning procedure in Merapi, are provided in Table 3.8 (Mei et al., 2013).

Table 3.8 Alert rules in Merapi.

VAL	Definition	Volcanic Activity	Evacuation Alert
I	Normal activity	No indication of activity change, either visual likelihood or seismicity level.	No Evacuation alert
II (Low)	On guard	Indications of activity are increasing, either from visual likelihood on the crater, or seismicity level.	No Evacuation alert
III (Medium)	Prepare	Seismic activity is increasing intensely, with obvious visual changes on the crater.	Prepare to Evacuate
IV (High)	Beware	About to erupt.	Evacuate

Adapted from Mei et al. (2013).

3. Evacuation Decision Model of People

The human agents in the ABM are utilised with the ability to decide to evacuate or to stay, based on the threshold rule (Robinson et al., 2011; Kennedy, 2012) and evacuation states model of Lovreglio et al. (2016). The decision is made by evaluating social and physical factor variables (Figure 3.4). These factors are quantified, weighted and classified into two main categories: driving factors to evacuate (EF) or driving factors to stay (SF) (Figure 3.4a). A detailed description and quantification of EF and SF are provided in the supplementary material (Appendices 3.4 – 6), where the weight of the factors varies based on the scenario setting (see section 3.7.2). Both EF and SF are used in Equation (3.1) to define the strength of the evacuation decision (ED). Agents use threshold-based rules (Robinson et al., 2011; Kennedy, 2012) to evaluate the ED (Figure 3.4b). The change in ED triggers the transition between the states of Normal-Investigating-Evacuating. When the agents have enough EF, i.e. they exceed the threshold, they will evacuate, otherwise they will continue to stay. An overview of the states is provided as follows (a detailed state chart diagram is provided in the Supplementary Material–Appendix 3.7):

`Normal`: initial state of agent when there is no sign of hazard.

`Investigating`: the agent observes the volcano and their environment (social, physical) as the activity of the volcano increases.

`Evacuating`: the agent decides to evacuate. In this state, the agent warns their family as well as their relations to evacuate.

ED = EF – SF ……………………………………………………………………….. (3.1)

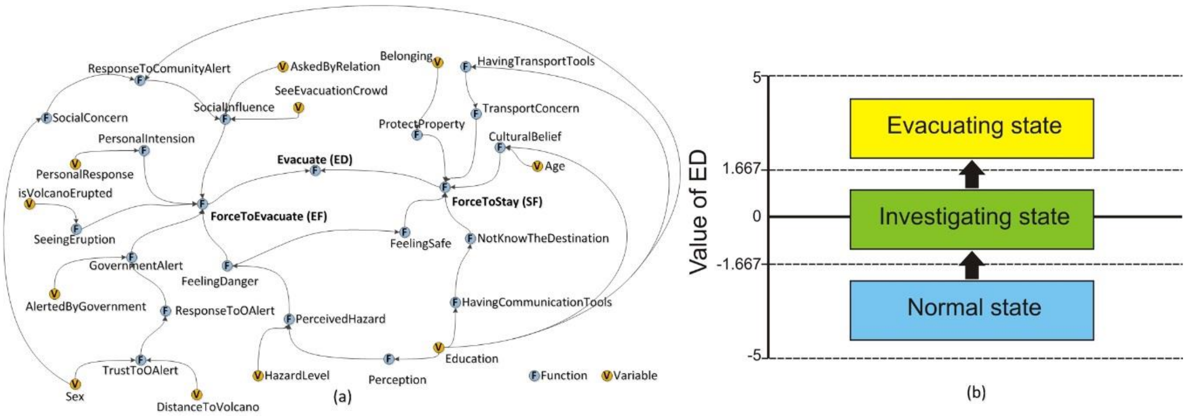

Figure 3.4 Threshold-based decision rule based on the Normal-Investigating-Evacuating state model. (a) The interrelating variables and functions define the value of the evacuation decision (ED); and (b) the transition between states in the evacuation decision as result of changing ED based on the threshold model. Descriptions of the variables and functions are provided in the supplementary materials (Supplementary Material—Appendices 3.5–7).

3.3.5 Population and Synthetic Population Generation

Spatially realistic ABM requires the utilisation of realistic agent attributes and localisation (spatial distribution) (Chapuis et al., 2018). However, population microdata is commonly lacking in the spatial representation details of household location due to confidentiality issues (Huang and Williamson, 2001). Moreover, the aggregate characteristics of human agents need to be consistent with the aggregate characteristics of the real population (van Dam et al., 2017). This population characteristic should be similar to the real situation regarding socio-demographic attributes as well as spatial distribution (Heppenstall et al., 2011). Therefore, the synthetic population generation characterizes not only the demographic character, but also the geographic location, to fulfil this requirement.

The synthetic population is a population built from anonymous survey data at the individual level (Heppenstall et al., 2011). In this model, the individuals will be grouped into households to represent reality. There are several techniques to generate a synthetic population, including deterministic reweighting, conditional probability (Monte Carlo simulation) and simulated annealing (Harland et al., 2012). Among these techniques, conditional probability has advantages for use in this model as it contains stochastic elements. This stochastic condition is needed because the exact location is unknown. The general technique for generating the synthetic population in this model is provided in Figure 3.5. The technique comprises three steps: data preparation; conditional probability simulation development and execution; and verification to fit the result. Development, execution and verification are iterative processes. If the verification finds high deviation between the real data, it then loops back to the development and execution process to fix possible bugs or logical errors.

The details of Monte Carlo simulation to generate the synthetic population model are based on a method by Moeckel et al. (2003). In this model, human agents are generated for each sub-district of Sleman in individual units grouped as households. The attributes are matched with the real data using census data statistics and field data from questionnaires. The spatial distribution of the population is also randomly generated to be matched with the real spatial distribution of the population using the centre of gravity model (Jumadi et al., 2016). Due to software and computer resource limitations, the simulated population was minimised proportionally (Table 3.9).

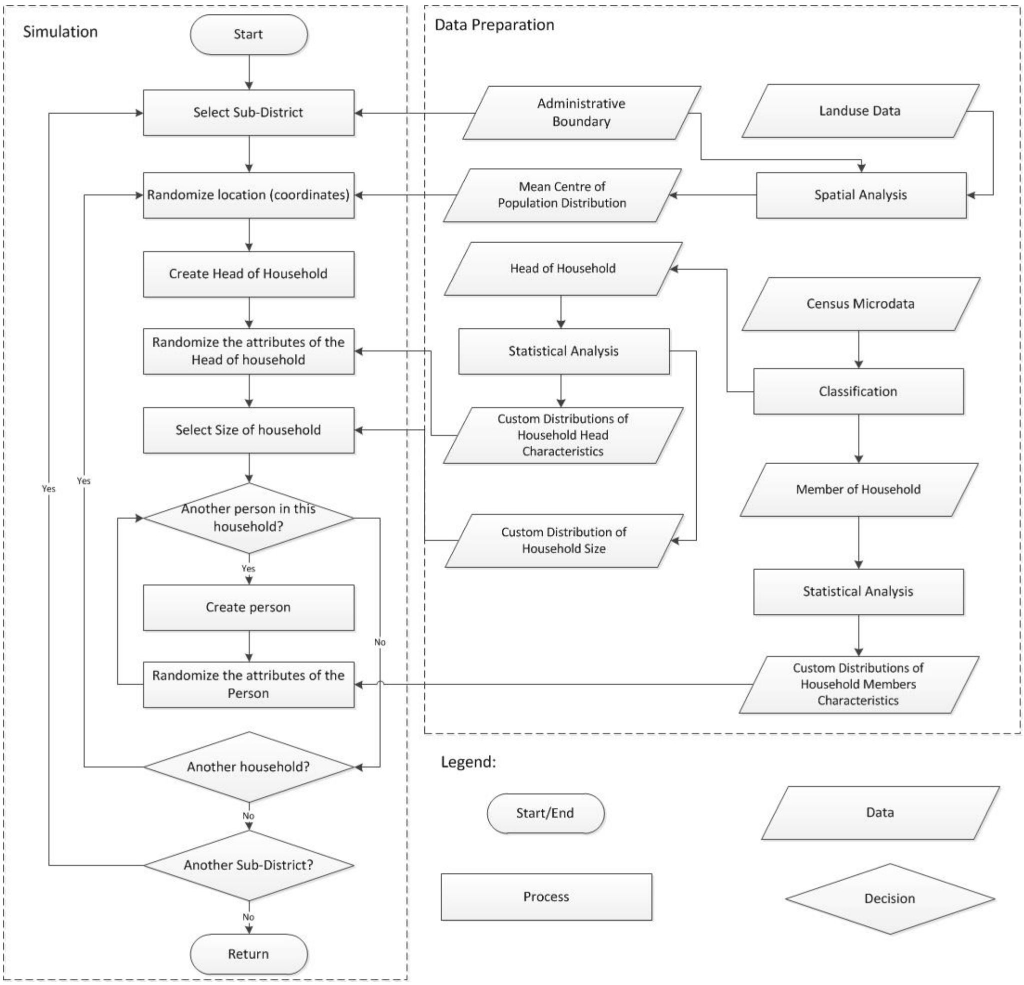

Figure 3.5 Synthetic population generation.

Table 3.9 Real population level (2010) and simulated agents.

District	Population Mean Centre		Number of Households	Number of Simulated Households	Estimated Level of Simulated Populatio n
	Longitude	Latitude			
Berbah	110.448997	-7.802559	18,927	473	1,892
Cangkringan	110.456001	-7.649149	9,187	230	920
Depok	110.400001	-7.773849	47,228	1,181	4,724
Gamping	110.334999	-7.78209	31,724	793	3,172
Godean	110.301002	-7.77015	24,619	615	2,460
Kalasan	110.467002	-7.74484	25,277	632	2,528
Minggir	110.238998	-7.73681	13,432	336	1,344
Mlati	110.361	-7.75394	34,703	868	3,472
Moyudan	110.239997	-7.772729	11,677	292	1,168
Ngaglik	110.378997	-7.743549	39,991	1,000	4,000
Ngemplak	110.430999	-7.71747	20,906	523	2,092
Pakem	110.410003	-7.653709	12,585	315	1,260
Prambanan	110.496002	-7.787529	28,141	704	2,816
Seyegan	110.299003	-7.72833	17,278	432	1,728
Sleman	110.347999	-7.70054	23,814	595	2,380
Tempel	110.317001	-7.670989	19,977	499	1,996
Turi	110.376998	-7.63426	1164	29	116
			380,630	9517	38,068

Source: BPS (2015) and spatial analysis of land use data.

This model is also utilised with a synthetic social network, which represents the human relations and spread of risk warning. The social network for the spread of risk warning does not always require physical contact, as in modelling for the spread of disease (Adiga et al., 2015), but can be through non-physical contact, e.g. using the medium of social media (Wise, 2014). Each agent is assigned with links with other agents in order to mimic social network reality. The number of linked agents is generated differently to accommodate the varying social interactions between people. There are several types of connections among agents: household member connections; friendship connections; and connections with the stakeholder.

3.3.6 Calibration and Validation

In implementing the model structure discussed above, we need to verify that the model works in line with the concept, as well as fitting the real world. We used the retrodiction approach from the various other validation techniques

(Hawe et al., 2012) to measure the validity of the model. This approach focuses on measuring the replicative validity, i.e. the ability of the resulting output from the simulation to match the real data (Troitzsch, 2004). Two outputs were compared with the real data to establish that the model was plausible: the spatial pattern of reluctant people; and the temporal accumulation of evacuees. If any output was unreasonably different from the real data, we manually adjusted the parameter or the rules of the model to produce reasonable outputs (calibration). Graphical monitor and statechart inspection were used to verify that the implemented model worked corresponding to the model design (visualisation approach) (Hawe et al., 2012). Calibration and fitting of some parameter values or data was conducted to achieve output similarity (Section 3.3.6.2). To quantitatively measure the similarity between the modelling output and the real data (Section 3.3.6.1), we used temporal and spatial validation (Section 3.3.6.3)(Robinson and Rai, 2015).

3.3.6.1 Empirical Data for Comparison

We used several data to measure the validity of the model, including the spatial distribution of reluctant people and the temporal accumulation of evacuees. All these data were provided by the 2010 evacuation records (see Section 3.3). The data on reluctance is provided in Figure 3.6. Such reluctance always occurs in Merapi based on past eruption records. It also occurred in the 2006 eruption, as identified by Sagala and Okada (2009). Reluctance to evacuate potentially leads to fatalities in disasters; therefore, we considered that validating the model based on this output was important. These data were derived from a map provided by Lavigne et al. (2017), which consists of the distribution of villages in which at least one person refused to evacuate in 2010 based on reports from the village chiefs (Lavigne et al., 2017). We selected relevance areas from the original map (Lavigne et al., 2017), extracted the centroid of the areas and created the density map (Figure 3.6) using kernel density analysis in ArcGIS to make comparison possible with the output of the model (Robinson and Rai, 2015). In addition, when people start evacuating (the temporal aspect) is also significant, as late evacuation can also increase risk. Therefore, we also used this issue to measure the validity of the model, where the temporal aspect is expressed as the temporal accumulation of evacuees (Figure 3.7). This data was from the daily records of evacuees during the eruption of 2010. These records are documented on the government website (Local

Government of Sleman, 2010). These data were copied to Excel and are provided in the supplementary material (Supplementary Material–Appendix 3.2).

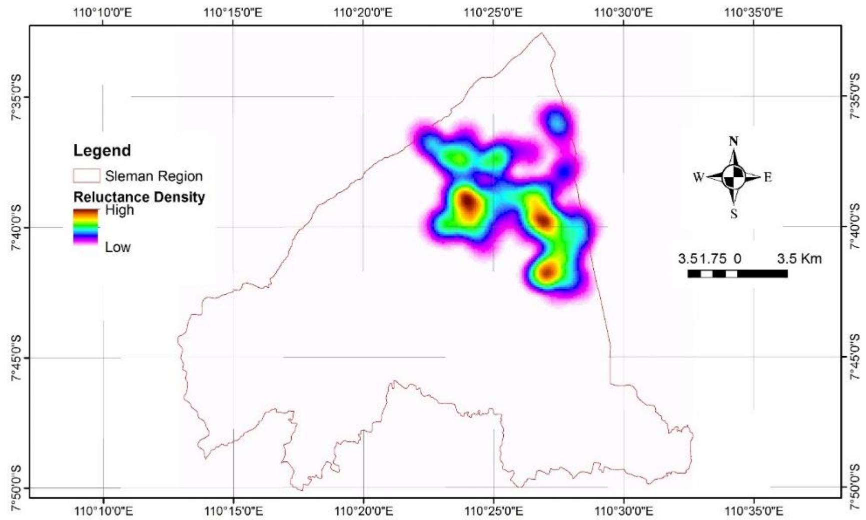

Figure 3.6 Distribution of reluctant evacuees during the 2010 evacuation (adapted from (Lavigne et al., 2017)).

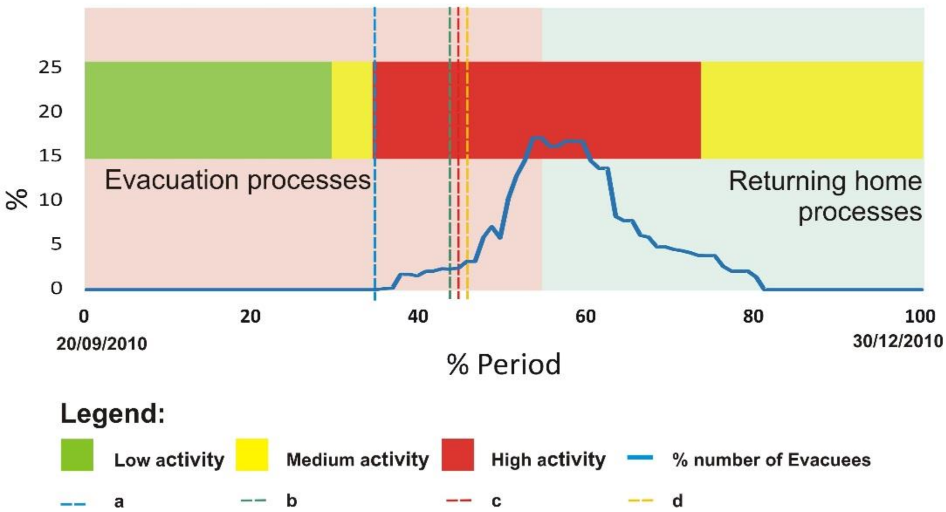

Figure 3.7 Temporal accumulation of evacuees during the crisis period in 2010. (a) Issuance of first evacuation order on 25 October 2010; (b) issuance of second evacuation order on 3 November 2010; (c) major eruption on 4 November 2010; (d) issuance of third evacuation order on 5 November 2010 (Adapted from [15,76]). Excel data: see Supplementary Material—Appendix 3.2.

3.3.6.2 Calibration

We conducted several calibrations to fit the model, as the initial evaluation indicated that there were discrepancies between the simulation results and the real data (Jumadi et al., 2017). The differences were mainly in the comparison of the percentage of the evacuating population, the temporal accumulation of evacuees, and the emergence of reluctant people, which could not be captured in the first model. We assumed that the differences in both the percentage of the evacuating population and the temporal accumulation of evacuees were because of the different hazard scenarios used to make evacuation decisions. The evacuation order in 2010 was based on radius distance, i.e. 20 km from the summit (Mei et al., 2013). The population within this radius (Figure 3.8b) is higher compared to that within the actual hazard zone (Figure 3.8a), which possibly results in the differences. Based on this assumption, we first calibrated the model by fitting the hazard scenario. We used both hazard zones scenarios (Figure 3.8) in the simulation and made a comparison of the results. Meanwhile, we addressed the drawback of the first model, which was unable to capture the emergence of reluctance (to evacuate) behaviour, by assigning the evacuation decision (Section 3.4.3), which is the main focus of the paper.

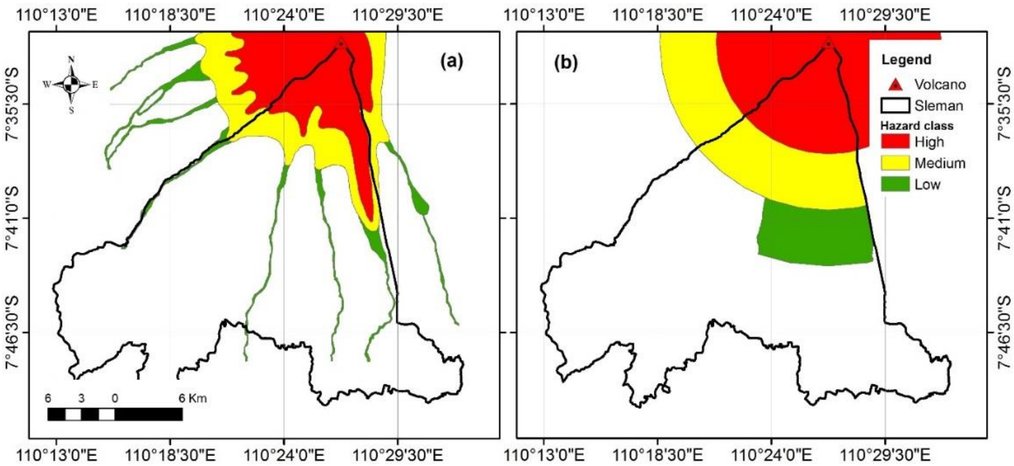

Figure 3.8 Hazard scenarios setting: (a) based on actual hazard map (BNPB, 2011), (b) based on hazard map used for evacuation order in 2010 eruption (Mei et al., 2013).

The simulations were divided into three scenarios with varying parameters. The variation in the settings of these scenarios is provided in Table 3.8. Scenario 1 uses hazard model a (Figure 3.8a) to set the hazard zone of the ABM environment. The evacuation decision of this scenario is based on evaluation of the force to evacuate versus the force to stay (Section 3.3.4.3). However, SE was disregarded in this scenario. Meanwhile, scenario 2 uses hazard model b (Figure 3.8b) to set the hazardous environment with regard to the SE factor for the decision model. We assumed that this factor was important since the evacuation records from 2010 show that people continued to stay at home after receiving two evacuation alerts from the government, but did evacuate after the major explosion occurred (Figure 3.10). The scenario uses the same hazard map setting, as well as the same evacuation decision factors, as the second scenario, but different weighting was applied to SI for this scenario.

Table 3.10 Simulation scenarios.

Scenario	Hazard Model	Weight of Driving Factors to Evacuate (EF)					Weight of Driving Factors to Stay (SF)				
		FD	PI	GA	SI	SE	PP	ND	TC	FS	CB
1	a	1	1	1	1	-	1	1	1	1	1
2	b	1	1	1	1	1	1	1	1	1	1
3	b	1	1	1	1	1.5	1	1	1	1	1

3.3.6.3 Validation

The validation approach was to make comparisons between the temporal and spatial aspects of the output and the real data. The aim was to assess how well the model predicted the outcome under the same parameters compared to the real event (see Section 3.3.3 for the data used and Section 3.3.4.3 for the parameter value setup). We adapted approaches used by Robinson and Rai (2015) for the spatial and temporal validation techniques. The spatial validation was conducted to establish the ability of the model to predict the spatial distribution of the reluctant people. Fuzzy similarity (K^*) and a wavelet correlation coefficient (r^w) were used to measure the similarity between the simulation output and the real data (Hagen-Zanker, 2006; Robinson and Rai, 2015). We used Map Comparison Kit 3.2 of Visser and Nijs (2006) to perform this analysis. Moreover, temporal validation was conducted to establish the ability of the model to represent the time when people start to evacuate. We compared the temporal accumulation of evacuees of both the real and simulation output data. Root Mean Square Error (RMSE) was used to measure the plausibility of this output. We used the rmse library in R (Bigiarini, n.d.) to calculate this error for all periods (n=100) of the simulated crisis (see Figure 3.6). The returning home process was excluded in this comparison, since the model only regards the evacuation process (Jumadi et al., 2017). When the outputs appeared very different, some parameters/data and rules were calibrated/fitted to obtain the most similar output with the real data. Lastly, we concluded with the most plausible scenario with the indicators being the highest value of K^* and r^w, and the lowest value of RMSE.

3.4 Results and Discussion

3.4.1 Results of the Simulation Scenarios

Once the model design (Section 3.4) was applied in the previous model (Jumadi et al., 2017), we performed several simulations to verify that the developed model corresponded to the design and that there was no error in the code (Crooks et al., 2018). After the verification had been conducted and the program ran as intended, we ran the simulation 30 times for each scenario (Section 3.6.2) to provide enough samples for statistical analysis (Haneberg, 2004; Ghasemi and Zahediasl, 2012). The outputs of the scenarios were analysed and presented both as spatial and temporal distributions. The indicators of the plausibility of the model are presented alongside the results. The results for scenarios 1, 2, and 3 are shown below.

3.4.1.1. Scenario 1

The first scenario is the basic model of the evacuation decision used in this ABM. Spatial and temporal comparison between the real data (empirical) and the simulation results of scenario 1 are provided in Figures 3.9 and 3.10. The results indicate that the model is able to represent the emergence of reluctant people, as shown in Figure 3.9. However, the evacuees departed too quickly compared to the empirical data (Figure 3.10).

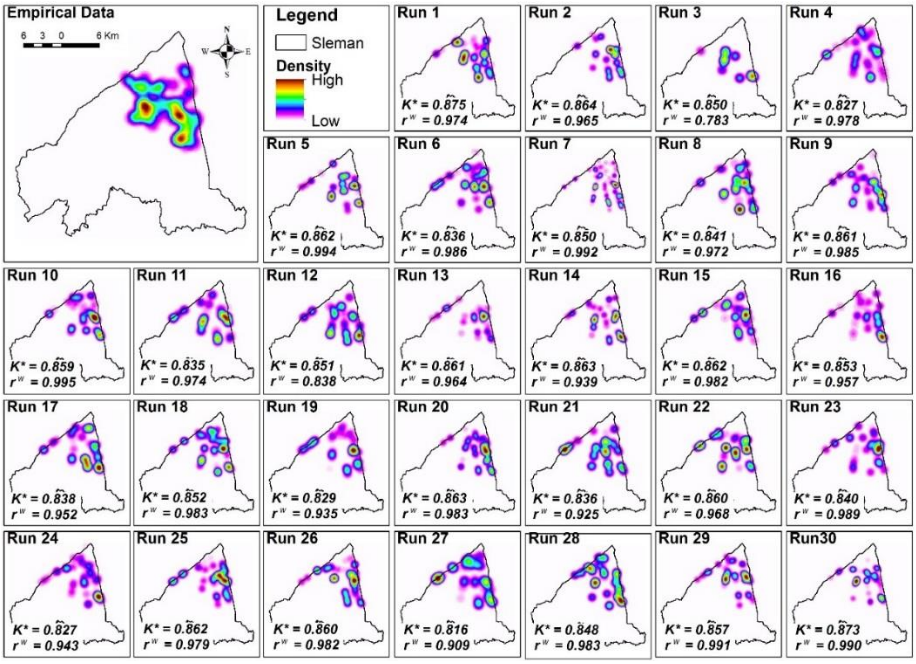

Figure 3.9 Spatial comparison of simulated and observed reluctance distribution based on scenario 1. The raster data is provided in the supplementary material (Supplementary Material–Appendix 3.8).

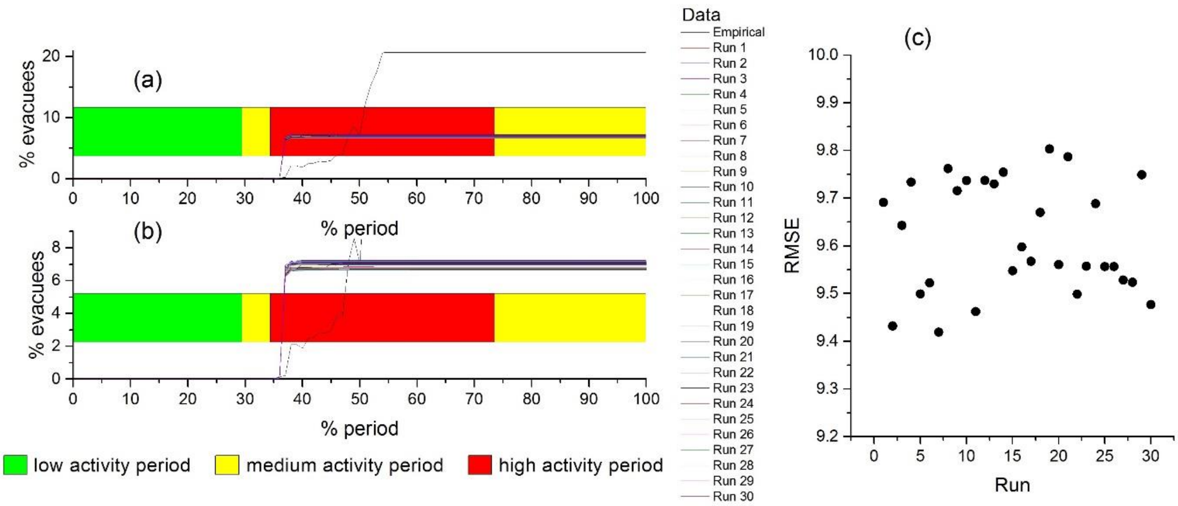

Figure 3.10 Temporal comparison of simulated and observed evacuee accumulation based on scenario 1: (a) overall comparison; (b) zoomed to the simulation outputs; and (c) RMSEs.

3.4.1.2. Scenario 2

The second scenario is the improved model, in which both the hazard model and the evacuation decision factors have been adjusted (Section 3.3.4.3). Spatial and temporal comparison between the real data (empirical) and the simulation results of this scenario are provided in Figures 3.10 and 3.11. The results of this scenario also indicate that the model is able to represent the emergence of reluctant people, as shown in Figure 3.11. The evacuees' departure in this scenario can be classified into two different times: first, roughly half the evacuees departed once the volcanic activity had reached its highest level; second, the remainder departed after the timestep reached the major explosion time (Figure 3.12). This also shows discrepancy with the empirical data.

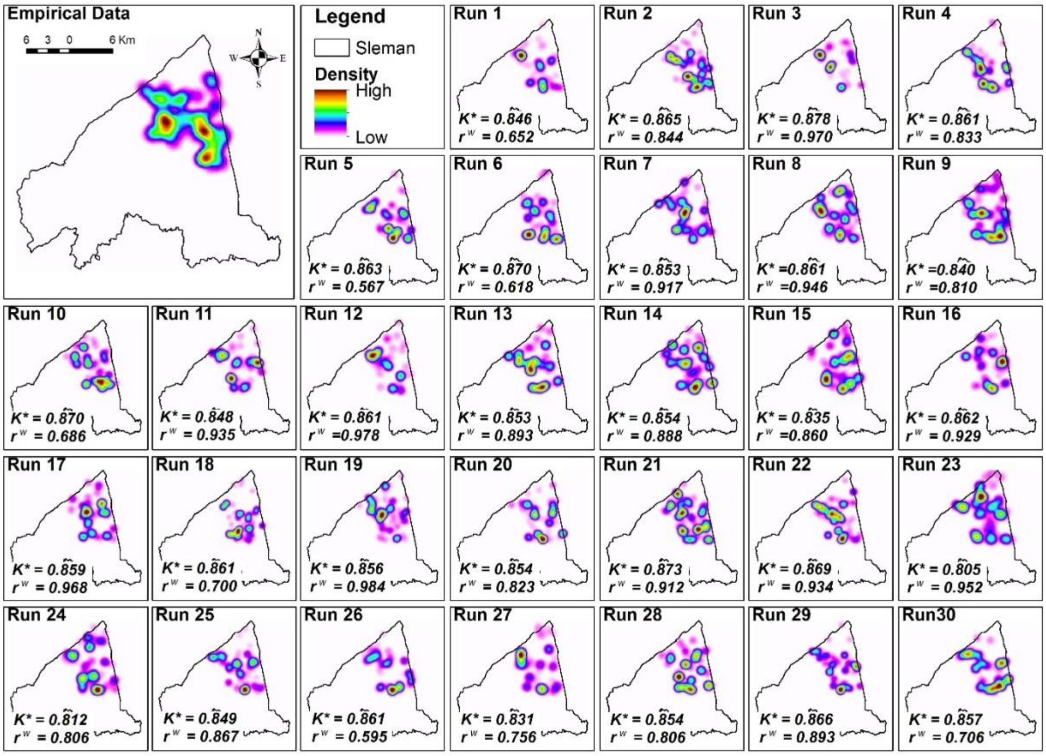

Figure 3.3 Spatial comparison of simulated and observed reluctance distribution based on scenario 2. The raster data is provided in the supplementary material (Supplementary Material–Appendix 3.9).

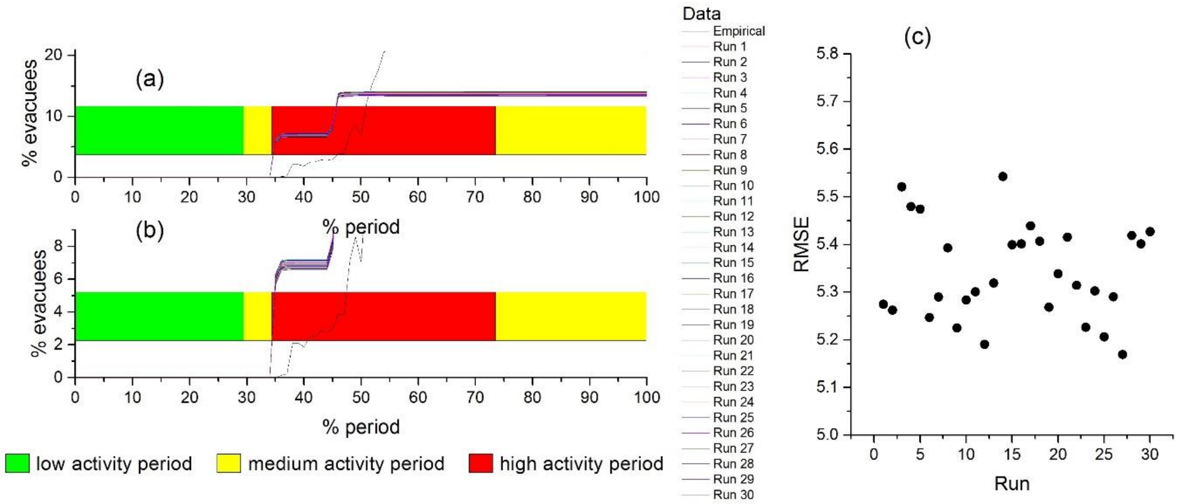

Figure 3.4 Temporal comparison of simulated and observed evacuee accumulation based on scenario 2: (a) overall comparison, (b) zoomed to the simulation outputs, (c) RMSEs.

3.4.1.3 Scenario 3

The third scenario uses a similar hazard and evacuation decision model, but this one has been improved with a weighting strategy for observing the explosion factors (Section 3.3.4.3). Spatial and temporal comparison between the real data (empirical) and the simulation results of this scenario are provided in Figures 3.13 and 3.14. Similarly, the results of this scenario also indicate that the model is able to represent the emergence of reluctant people, as shown in Figure 3.13. However, the temporal data shows a different result, that all the evacuees departed after the time-step reached the major explosion time (Figure 3.14). This shows a discrepancy with the empirical data, but appears better than the results of scenarios 1 and 2. Detailed discussion of the comparison between all the scenario results is provided in Section 3.4.2.

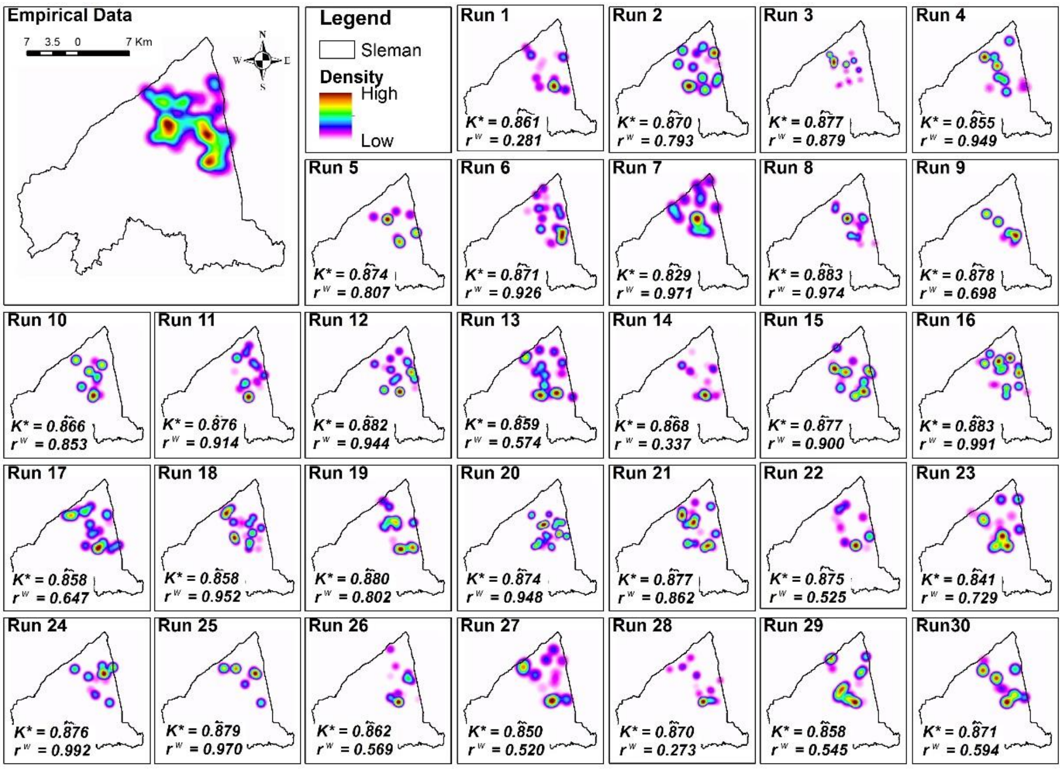

Figure 3.5 Spatial comparison of simulated and observed reluctance distribution based on scenario 3. The raster data is provided in the supplementary material (Supplementary Material–Appendix 3.10).

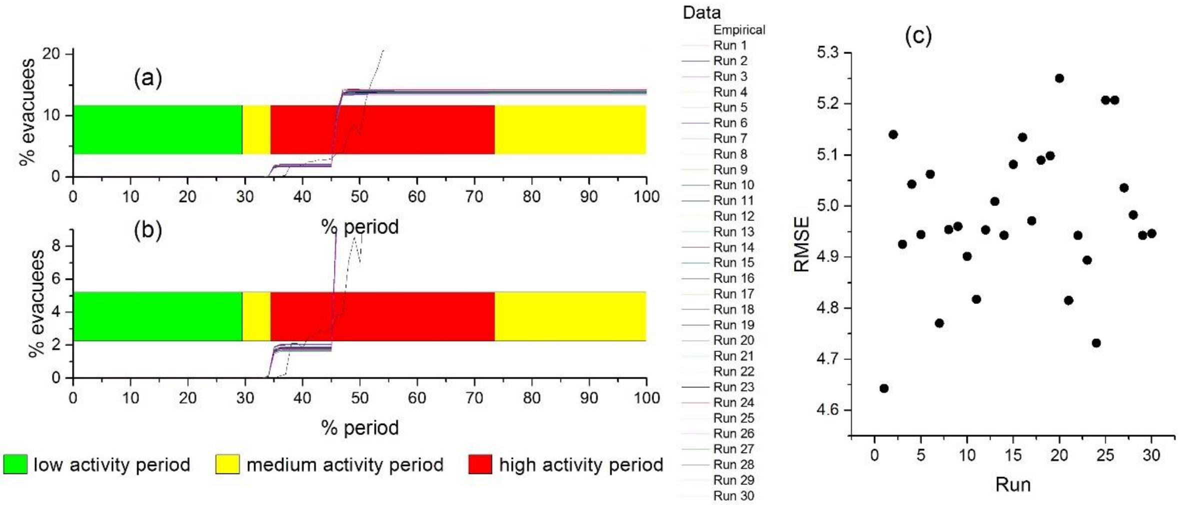

Figure 3.6 Temporal comparison of simulated and observed evacuee accumulation based on scenario 3: (a) overall comparison, (b) zoomed to the simulation outputs, (c) RMSEs.

3.4.2 Discussion and Future Research

An evacuation decision model based on both physical and social factors with three scenarios to fit the model with reality is presented in this paper. The outcome of the research addresses a drawback that was found in the previous model, which was unable to capture the emergence of reluctant people (Jumadi et al., 2017). It also improves on other similar models of evacuation, which give less consideration to this phenomenon (e.g. Zhang et al. (2009); Mas et al. (2012); Wise (2014); Wang et al. (2016); Adam and Gaudou, (2017)). Additionally, the model has been evaluated through a spatial and temporal validation approach to evaluate its plausibility. The spatial validation is based on evaluation of K^* and r^w (Hagen-Zanker, 2006; Robinson and Rai, 2015) in the simulated and real spatial distribution of reluctant people. Meanwhile, the temporal validation is based on evaluation of the RMSE (Robinson and Rai, 2015) of simulated and real temporal accumulation of evacuees (the returning home process is excluded).

There are some studies which help understand these measures (e.g. Briggs and Levine (1997); Hagen (2003); Hagen-Zanker et al. (2005); Hagen-Zanker (2006); Rai and Robinson (2015); Robinson and Rai (2015); Bigiarini (n.d.)). Fuzzy similarity (K^*) measures the similarity of cells in the same location of one map with their counterparts by taking into account the directly neighbouring cells (local similarity) of the counterpart map based on Fuzzy Kappa (Hagen, 2003; Hagen-Zanker, 2006; Rai and Robinson, 2015), where the degree of similarity is assigned as 0 (different) or 1 (similar). This means that the higher the value, the more similar the maps. In interpreting the results, a higher value means that the output is more similar to the real data. Meanwhile, the wavelet correlation coefficient (r^w) compares two maps, which are decomposed using a discrete wavelet transform, by RMSE (quantity), r (pattern), and ER (energy) (Hagen-Zanker, 2006). This paper focuses on pattern comparison, therefore an r coefficient is used for the measurement. Similar to K^*, the degree of similarity of this is also assigned as 0 or 1, in which a higher correlation means the greater the similarity of the pattern. Both K^* and r^w measure the degree of similarity based on the equivalency of the structures of the maps, where the individual values may not exactly be the same (Rai and Robinson, 2015). r^w is used together with K^* to measure the robustness of the results; if the r^w value is consistent with K^* this means that the similarity of the simulation output with the real data is robust (Rai and Robinson, 2015). On the other hand, the RMSE that is used to measure temporal validity measures the deviation of the output of the simulation from the real data (Rai and Robinson, 2015). A smaller value means better mimicry of the real data.

Based on the evaluations and measurements, all the scenarios presented here are able to simulate the emergence of reluctant people, which is the main objective of this paper. The first scenario is the most robust of all, with the value of K^* consistent with r^w. However, the third scenario is the most plausible, based on the evaluation of both the spatial and temporal validation results. However, this is not the best scenario as evaluated from one aspect, i.e. spatial validation. Based on the visual inspection of Figure 3.15 to provide a qualitative comparison (Crooks and Hailegiorgis, 2014), this indicates that the second model is the most appropriate, but the statistical analysis shows differences. The statistical analysis of K^* and r^w shown in Figure 3.15a indicate that the first scenario gives the best outcome. This is indicated not only from the values of both K^* and r^w, but also from the ranges of the values; their values in this scenario are relatively higher than those in the other scenarios. In addition, these have the smallest of all the ranges (minimum variation). Moreover, both values in this scenario are the most consistent compared to the others; the outcomes from the other scenarios show variance between K^* and r^w. However, the temporal validation (Figure 3.16b) indicates that the first scenario results in the highest error (RMSE), while the third scenario give the best results based on both the values and the range from the simulation results. Based on this, and its spatial validation results which are still reasonable compared to the others, the third scenario can better represent real evacuation.

We found from this model evaluation that the occurrence of disaster can be a major factor to evacuate. This is proved in this model, as the results more closely fit reality after this aspect (explosion occurrence) was weighted (Scenario 3) in the case study (see Figures 3.7 and 3.14). People are likely to disobey the evacuation command, but are motivated to evacuate after the real explosion has occurred (Figure 3.7). Such difficulties in ordering people to evacuate is a common phenomenon (Tobin and Whiteford, 2002). It occurs not only in the case of volcanic eruption, but also in the other hazards, such as Hurricane Katrina (Elder et al., 2007). Therefore, a strong evacuation command is needed to ensure the evacuation processes (Riad et al., 1999); for example, military force, as in the evacuation from Tungurahua, Ecuador in 1999 (Tobin and Whiteford, 2002). Nevertheless, although this evaluation indicates that explosion (occurrence of disaster) is the major motivation to evacuate, we still lack information on why there is a delay between the major explosion and the evacuation, as indicated in Figure 3.7. This missing information makes it impossible to model this delay in the current design.

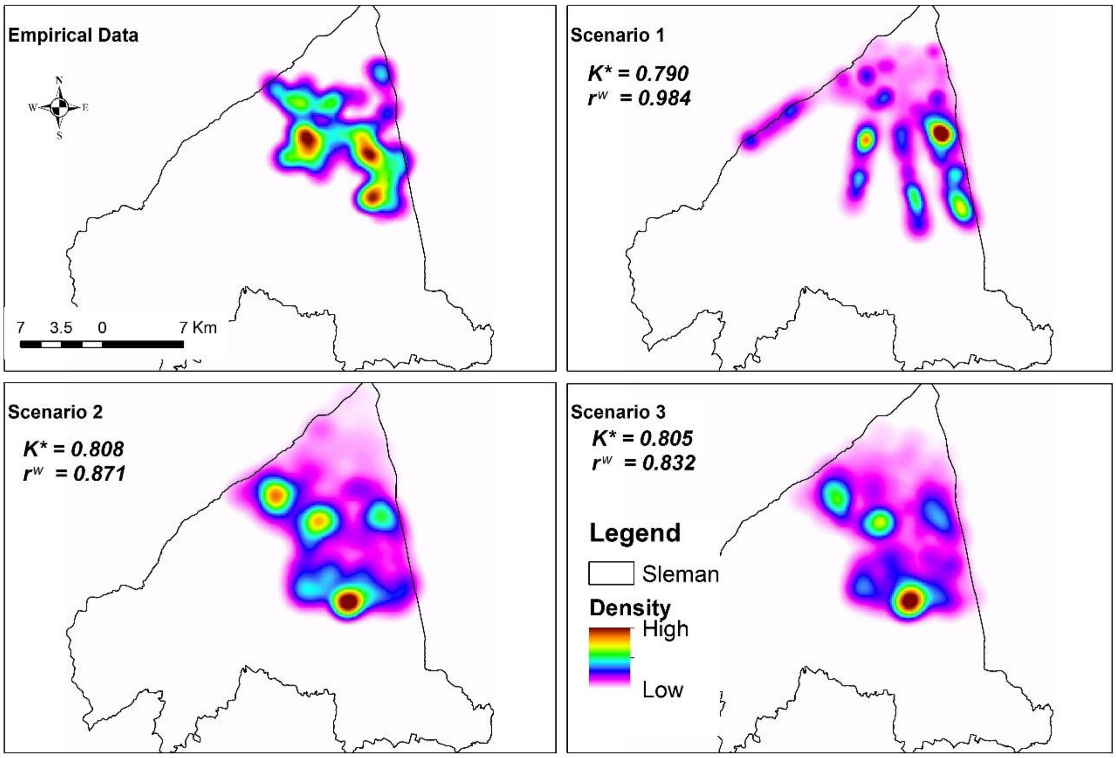

Figure 3.7 Overall comparison of spatial distribution of reluctant people. The scenario output was averaged.

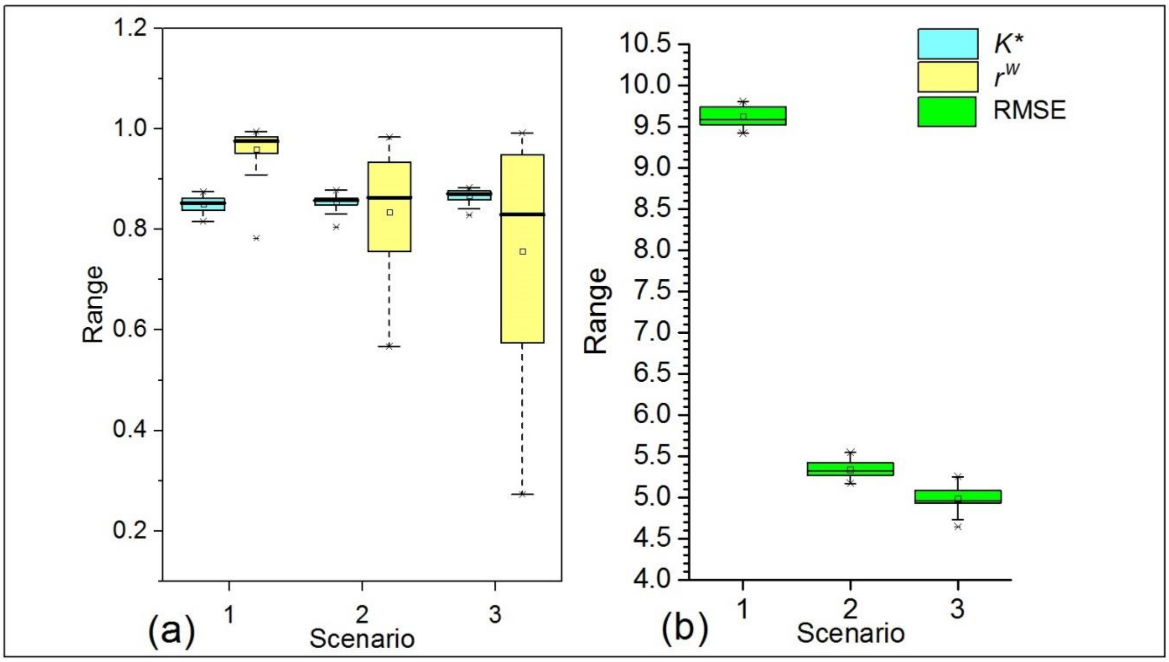

Figure 3.8 Comparison of both spatial and temporal measures of validity for all scenarios. (a) Spatial validity evaluation based on K^* and r^w, (b) temporal validity evaluation based on RMSE.

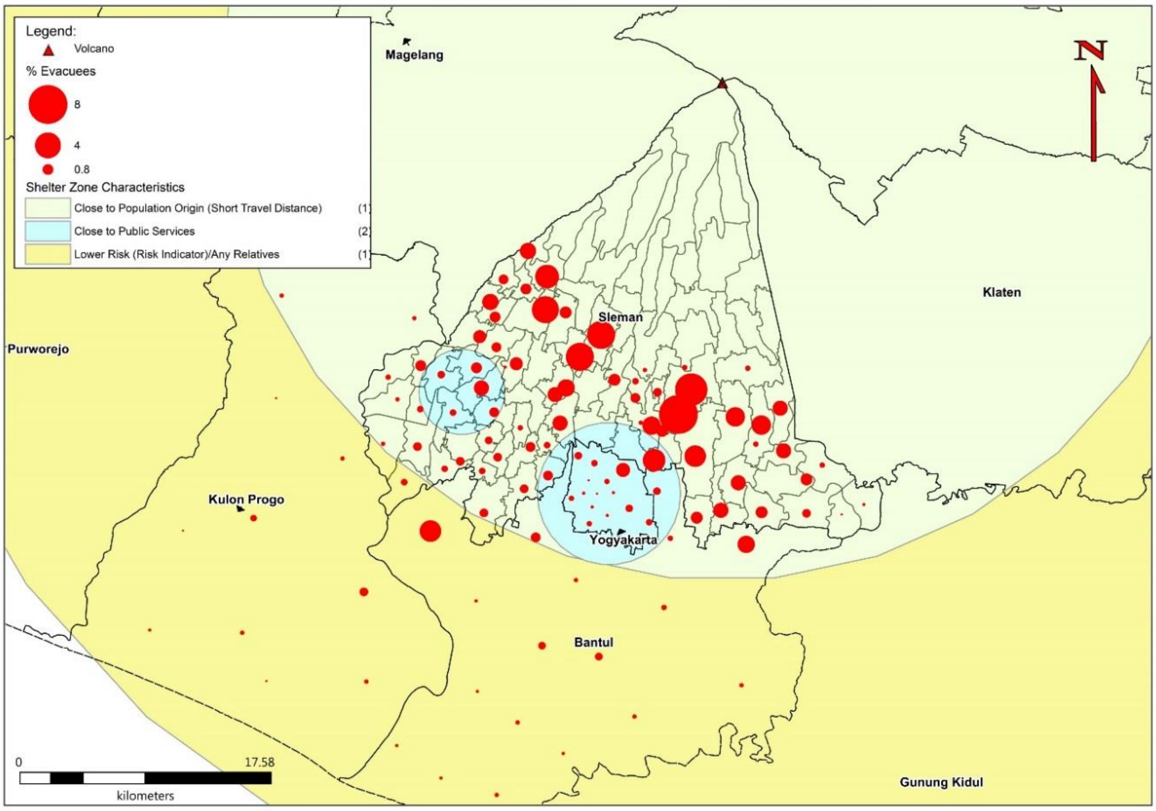

Figure 3.9 Distribution of evacuees from Sleman in the 2010 Merapi crisis . Source: Geospatial BNPB (BNPB, 2010c; BNPB, 2010a; BNPB, 2010d; BNPB, 2010b), DYMDIS GEGAMA (Budiyono, 2010). The shapefile is provided in Supplementary Material–Appendix 3.11.

Furthermore, a thorough evacuation decision should also include a decision on destination choice. This has also been assigned in this model, but has yet to be calibrated or validated. It is important to compare the distribution of evacuees with the real data as this expresses the validity of the destination choice rule of the agent. In 2010, the population within the danger zone in Merapi evacuated to temporary shelters (evacuation centres) distributed outside the danger zone (Figure 3.17). These shelters were commonly public facilities, such as stadiums, schools, mosques/churches, etc. Analysing the distribution of evacuees in Figure 3.17, it can be assumed that the majority from Merapi selected the nearest shelter as their destination (travel distance). This is proven by the fact that the percentage occupancy of the shelters in the surroundings of the restricted zone were relatively high compared to more distant ones. Some people chose shelters close to public services. Interestingly, few people chose quite remote spots as their destination. Commonly, evacuees chose this kind of shelter because they had relatives in the destination area (Joglosemar, 2010; JPNN, 2010) or they were looking for a safer place (Ramdan, 2010), which is relevant to the finding by Cheng et al. (2008). In Merapi, based on the shelter zoning analysis of Figure 3.16, 80.3% of evacuees preferred to select the shortest distance, 12.4% preferred to select destinations close to public services zones, and the rest (7.2%) either used relatives or risk indicators as preferences. Addressing this issue, together with involving the delay factors as mentioned earlier, would be a good way to improve this model.

3.5 Conclusion

The paper presented an individual evacuation decision model in ABM with Mt. Merapi, Indonesia as a case study. The model was based on various interrelating factors developed from the literature review and survey. These factors were categorized into driving forces to evacuate or driving forces to stay. The threshold-based approach was used to evaluate the differences in both values and to define whether agents would evacuate or stay. This decision model can be used to simulate two important aspects of evacuation, namely the dynamic of evacuation departure, and the emergence of reluctant people. Both of these aspects are important in defining the effectiveness of evacuation because a high emergence of reluctant people or evacuation which is too late will increase the risk. Calibration was conducted by setting up the parameters based on three scenarios. We validated the model by a retrodiction approach which consisted of spatial and temporal validation. K^* and r^w were used to measure the validity of the spatial distribution of the simulated reluctant people against the real data. Meanwhile, RMSE was used to measure the validity of the temporal accumulation of evacuees. Analysis of the simulation outputs shows that scenario 3, which weighted the occurrence of an explosion as the most important motivation for evacuation (four times more important than the other aspects), was the most plausible model in mimicking the real volcanic disaster events in Mt. Merapi. This plausibility was indicated by both the spatial and temporal similarity of the output with the real data being relatively high (high K^*, r^w and low RMSE) compared to the other scenarios.

Supplementary Materials

(1) Appendix 3.1. Statistical Analysis of Survey Data (https://osf.io/a8zew/); (2) Appendix 3.2. Evacuation dataset (https://osf.io/4kujy/); (3) Appendix 3.3. Reluctance raster map (https://osf.io/gy8ew/); (4) Appendix 3.4. Functions Overview of Evacuation Decision for Scenario 1 (https://osf.io/pqmv3/); (5) Appendix 3.5. Functions Overview of Evacuation Decision for Scenario 2

(https://osf.io/tkanc/); (6) Appendix 3.6. Functions Overview of Evacuation Decision for Scenario 3 (https://osf.io/rcqb3/); (7) Appendix 3.7. Main statechart diagram of the evacuation decision (https://osf.io/wftx7/); (8) Appendix 3.8. Raster data for Figure 3.9 (https://osf.io/chgdy/); (9) Appendix 3.9. Raster data for Figure 3.11 (https://osf.io/cygmp/); (10) Appendix 3.10. Raster data for Figure 3.13 (https://osf.io/3jvhb/); (11) Appendix 3.11. Shapefile for Figure 3.16 (https://osf.io/4upe9/).

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References

Adam, C. and Gaudou, B. 2017. Modelling Human Behaviours in Disasters from Interviews: Application to Melbourne Bushfires. *Journal of Artificial Societies and Social Simulation*. **20**(3), p.12.

Adiga, A., Beckman, R., Bisset, K., Chen, J., Chungbaek, Y., Eubank, S., Marathe, H.S., Nordberg, E., Rivers, C., Stretz, P. and others 2015. Synthetic populations for epidemic modeling *In*: *Proceedings of the International Conference on Computation and Social Sciences (ICCSS)* [Online]. [Accessed 2 August 2017]. Available from: http://staff.vbi.vt.edu/abhijin/papers/ic2s215_synthetic.pdf.

Ahsan, M.N., Takeuchi, K., Vink, K. and Ohara, M. 2016. A Systematic Review of the Factors Affecting the Cyclone Evacuation Decision Process in Bangladesh. *Journal of Disaster Research Vol*. **11**(4), p.741.

Alcántara-Ayala, I. 2002. Geomorphology, natural hazards, vulnerability and prevention of natural disasters in developing countries. *Geomorphology*. **47**(2–4), pp.107–124.

Alcorn, R., Panter, K.S. and Gorsevski, P.V. 2013. A GIS-based volcanic hazard and risk assessment of eruptions sourced within Valles Caldera, New Mexico. *Journal of Volcanology and Geothermal Research*. **267**, pp.1–14.

Allsop, D.T., Bassett, B.R. and Hoskins, J.A. 2007. Word-of-mouth research: principles and applications. *Journal of Advertising Research*. **47**(4), p.398.

An, L. 2012. Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling*. **229**, pp.25–36.

Anderson, W.A. 1969. Disaster Warning and Communication Processes in Two Communities. *Journal of Communication*. **19**(2), pp.92–104.

Bardintzeff, J.M. 1984. Merapi volcano (Java, Indonesia) and Merapi-type nuée ardente. *Bulletin volcanologique*. **47**(3), pp.433–446.

Beck, U. 2009. *World at risk*. Cambridge, UK: Polity.

de Bélizal, E., Lavigne, F., Hadmoko, D.S., Degeai, J.-P., Dipayana, G.A., Mutaqin, B.W., Marfai, M.A., Coquet, M., Le Mauff, B., Robin, A.-K. and others 2013. Rain-triggered lahars following the 2010 eruption of Merapi volcano, Indonesia: A major risk. *Journal of Volcanology and Geothermal Research*. **261**, pp.330–347.

Bigiarini, M.Z. n.d. Root Mean Square Error. [Accessed 6 February 2018]. Available from: http://www.webcitation.org/6x2E7KY2O.

Bird, D.K., Gísladóttir, G. and Dominey-Howes, D. 2011. Different communities, different perspectives: issues affecting residents' response to a volcanic eruption in southern Iceland. *Bulletin of volcanology*. **73**(9), pp.1209–1227.

Blaikie, P., Cannon, T., Davis, I. and Wisner, B. 2014. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. Routledge.

BNPB 2008. Peta Kawasan Rawan Bencana Gunung Merapi. Available from: http://www.webcitation.org/6pimWt1Fc.

BNPB 2011. Peta Kawasan Rawan Bencana Merapi. [Accessed 9 October 2015]. Available from: http://geospasial.bnpb.go.id/wp-content/uploads/2011/05/2011-04-29_KRB_Area_Terdampak_Langsung_Merapi.pdf.

BNPB 2010a. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Bantul (11 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6pikQru7D.

BNPB 2010b. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Kulon Progo (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6piskXxQF.

BNPB 2010c. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Sleman (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6piPoQCLs.

BNPB 2010d. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kota Yogyakarta (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6pilvuYiE.

Bonabeau, E. 2002. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*. **99**(suppl 3), pp.7280–7287.

Borshchev, A. 2013. *The Big Book of Simulation Modeling: Multimethod Modeling with AnyLogic 6*. Lebanon, NJ, USA: AnyLogic North America.

Botzen, W.J.W., Aerts, J.C.J.H., Bergh, V.D. and M, J.C.J. 2009. Dependence of flood risk perceptions on socioeconomic and objective risk factors. *Water Resources Research*. **45**(10).

BPS 2015. Sleman Dalam Angka 2011. [Accessed 14 September 2017]. Available from: http://www.webcitation.org/6tTCrkUPU.

Branney, M. and Kokelaar, B.P. 2002. Sedimentation of ignimbrites from pyroclastic density currents. *Memoir of the Geological Society of London*. **27**, p.150.

Briggs, W.M. and Levine, R.A. 1997. Wavelets and Field Forecast Verification. *Monthly Weather Review*. **125**(6), pp.1329–1341.

Brown, D.G., Riolo, R., Robinson, D.T., North, M. and Rand, W. 2005. Spatial process and data models: Toward integration of agent-based models and GIS. *Journal of Geographical Systems*. **7**(1), pp.25–47.

Brown, D.G. and Xie, Y. 2006. Spatial agent-based modelling. *International Journal of Geographical Information Science*. **20**(9), pp.941–943.

Budiyono, A.F. 2010. Informasi Posko Pengungsian Merapi DIY (Update 10 November 2010). [Accessed 6 April 2017]. Available from: http://www.webcitation.org/6pWJmis9R.

Cajka, J.C., Cooley, P.C. and Wheaton, W.D. 2010. Attribute assignment to a synthetic population in support of agent-based disease modeling. *Methods report (RTI Press)*. **19**(1009), p.1.

Canessa, E. and Riolo, R.L. 2003. The effect of organizational communication media on organizational culture and performance: an agent-based simulation model. *Computational & Mathematical Organization Theory*. **9**(2), pp.147–176.

Chakraborty, J., Tobin, G.A. and Montz, B.E. 2005. Population Evacuation: Assessing Spatial Variability in Geophysical Risk and Social Vulnerability to Natural Hazards. *Natural Hazards Review*.

Chandan, S., Saha, S., Barrett, C., Eubank, S., Marathe, A., Marathe, M., Swarup, S. and Vullikanti, A.K.S. 2013. Modeling the interaction between emergency communications and behavior in the aftermath of a disaster *In*: *International Conference on Social Computing, Behavioral-Cultural Modeling, and Prediction* [Online]. Berlin, Germany: Springer, pp.476–485. [Accessed 19 August 2016]. Available from: http://link.springer.com/chapter/10.1007/978-3-642-37210-0_52.

Chapuis, K., Taillandier, P., Renaud, M. and Drogoul, A. 2018. Gen*: a generic toolkit to generate spatially explicit synthetic populations. *International Journal of Geographical Information Science*. **32**(6), pp.1194–1210.

Charbonnier, S.J. and Gertisser, R. 2008. Field observations and surface characteristics of pristine block-and-ash flow deposits from the 2006 eruption of Merapi Volcano, Java, Indonesia. *Journal of Volcanology and Geothermal Research*. **177**(4), pp.971–982.

Chen, X. and Zhan, F.B. 2008. Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. *The Journal of the Operational Research Society*. **59**(1), pp.25–33.

Cheng, G., Wilmot, C.G. and Baker, E.J. 2008. A destination choice model for hurricane evacuation *In*: *Proceedings of the 87th Annual Meeting Transportation Research Board, Washington, DC, USA* [Online]., pp.13–17. [Accessed 7 January 2017]. Available from: http://www.ltrc.lsu.edu/pdf/2008/08-0840.PDF.

Christensen, K. and Sasaki, Y. 2008. Agent-Based Emergency Evacuation Simulation with Individuals with Disabilities in the Population. [Accessed 17 March 2015]. Available from: http://jasss.soc.surrey.ac.uk/11/3/9.html.

Cole, J.W., Sabel, C.E., Blumenthal, E., Finnis, K., Dantas, A., Barnard, S. and Johnston, D.M. 2005. GIS-based emergency and evacuation planning for volcanic hazards in New Zealand. *http://www.nzsee.org.nz*.

CRED 2016. *2015 Disasters in Numbers* [Online]. Brussels, Belgium: CRED. Available from: http://www.emdat.be/publications.

Crooks, A., Heppenstall, A. and Malleson, N. 2018. Agent-Based Modeling *In*: *Comprehensive Geographic Information Systems*. Oxford, UK: Elsevier.

Crooks, A.T. and Hailegiorgis, A.B. 2014. An agent-based modeling approach applied to the spread of cholera. *Environmental Modelling & Software*. **62**, pp.164–177.

Cutter, S.L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E. and Webb, J. 2008. A place-based model for understanding community resilience to natural disasters. *Global environmental change*. **18**(4), pp.598–606.

Cutter, S.L., Boruff, B.J. and Shirley, W.L. 2003. Social Vulnerability to Environmental Hazards*. *Social Science Quarterly*. **84**(2), pp.242–261.

van Dam, K.H., Bustos-Turu, G. and Shah, N. 2017. A methodology for simulating synthetic populations for the analysis of socio-technical infrastructures *In*: *Advances in Social Simulation 2015* [Online]. Berlin, Germany: Springer, pp.429–434. [Accessed 2 August 2017]. Available from: http://link.springer.com/chapter/10.1007/978-3-319-47253-9_39.

Damby, D.E., Horwell, C.J., Baxter, P.J., Delmelle, P., Donaldson, K., Dunster, C., Fubini, B., Murphy, F.A., Nattrass, C., Sweeney, S. and others 2013. The respiratory health hazard of tephra from the 2010 Centennial eruption of Merapi with implications for occupational mining of deposits. *Journal of Volcanology and Geothermal Research*. **261**, pp.376–387.

Dash, N. and Gladwin, H. 2007. Evacuation Decision Making and Behavioral Responses: Individual and Household. *Natural Hazards Review*. **8**(3), pp.69–77.

Donovan, K. 2010a. *Cultural responses to volcanic hazards on Mt Merapi, Indonesia*.[Online] Ph.D. Thesis, Plymouth, UK: University of Plymouth. [Accessed 19 March 2015]. Available from: http://core.kmi.open.ac.uk/download/pdf/10808180.pdf.

Donovan, K. 2010b. Doing social volcanology: exploring volcanic culture in Indonesia. *Area*. **42**(1), pp.117–126.

Durage, S.W., Wirasinghe, S.C. and Ruwanpura, J.Y. 2016. Decision Analysis for Tornado Warning and Evacuation. *Natural Hazards Review*. **17**(1), p.04015014.

Elder, K., Xirasagar, S., Miller, N., Bowen, S.A., Glover, S. and Piper, C. 2007. African Americans’ Decisions Not to Evacuate New Orleans Before Hurricane Katrina: A Qualitative Study. *American Journal of Public Health*. **97**(Supplement_1), pp.S124–S129.

GEOFABRIK 2016. Download OpenStreetMap data for this region: Indonesia. [Accessed 26 August 2017]. Available from: http://www.webcitation.org/6t07rwZox.

Gertisser, R., Charbonnier, S.J., Keller, J. and Quidelleur, X. 2012. The geological evolution of Merapi volcano, Central Java, Indonesia. *Bulletin of volcanology*. **74**(5), pp.1213–1233.

Ghasemi, A. and Zahediasl, S. 2012. Normality Tests for Statistical Analysis: A Guide for Non-Statisticians. *International Journal of Endocrinology and Metabolism*. **10**(2), pp.486–489.

Gilbert, G.N. 2008. *Agent-Based Models*. London: SAGE.

Gilbert, N. 1993. Computer simulation of social processes. *Social research update*. **6**, p.1993.

Gob, F., Gautier, E., Virmoux, C., Grancher, D., Tamisier, V., Primanda, K.W., Wibowo, S.B., Sarrazin, C., de Belizal, E., Ville, A. and others 2016. River responses to the 2010 major eruption of the Merapi volcano, central Java, Indonesia. *Geomorphology*. **273**, pp.244–257.

Golledge, R.G. 1997. *Spatial behavior: A geographic perspective* [Online]. Guilford Press. [Accessed 16 December 2015]. Available from: https://www.google.com/books?hl=en&lr=&id=2JPMvpMbLrMC&oi=fnd&pg=PR7&dq=Spatial++Behavior:+A+Geographic+Perspective&ots=55GMUtHdn4&sig=357rctB9z-gRoVaPAISc7B_6BGI.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., Huth, A., Jepsen, J.U., Jørgensen, C., Mooij, W.M., Müller, B., Pe'er, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R.A., Vabø, R., Visser, U. and DeAngelis, D.L. 2006. A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*. **198**(1–2), pp.115–126.

Guha-Sapir, D., Hoyois, P. and Below, R. 2016. *Annual Disaster Statistical Review 2015* [Online]. Brussels, Belgium: CRED. Available from: http://cred.be/sites/default/files/ADSR_2015.pdf.

Hagen, A. 2003. Fuzzy set approach to assessing similarity of categorical maps. *International Journal of Geographical Information Science*. **17**(3), pp.235–249.

Hagen-Zanker, A. 2006. Comparing continuous valued raster data: a cross disciplinary literature scan. [Accessed 24 January 2018]. Available from: http://epubs.surrey.ac.uk/790371/.

Hagen-Zanker, A., Straatman, B. and Uljee, I. 2005. Further developments of a fuzzy set map comparison approach. *International Journal of Geographical Information Science*. **19**(7), pp.769–785.

Haneberg, W. 2004. *Computational Geosciences with Mathematica*. Berlin, Germany: Springer Science & Business Media.

Harland, K., Heppenstall, A., Smith, D. and Birkin, M. 2012. Creating realistic synthetic populations at varying spatial scales: a comparative critique of population synthesis techniques. *Journal of Artifical Societies and Social Simulation*. **15**(1), pp.1–15.

Hawe, G.I., Coates, G., Wilson, D.T. and Crouch, R.S. 2012. Agent-based simulation for large-scale emergency response: A survey of usage and implementation. *ACM Computing Surveys (CSUR)*. **45**(1), p.8.

Heppenstall, A., Malleson, N. and Crooks, A. 2016. "Space, the Final Frontier": How Good are Agent-Based Models at Simulating Individuals and Space in Cities? *Systems*. **4**(1), p.9.

Heppenstall, A.J., Harland, K., Smith, D.M. and Birkin, M.H. 2011. Creating realistic synthetic populations at varying spatial scales: a comparative critique of population synthesis techniques *In*: *Geocomputation 2011 Conference Proceedings, UCL, London* [Online]., pp.1–8. [Accessed 1 December 2016]. Available from: http://www.geocomputation.org/2011/papers/heppenstall.pdf.

Holand, I.S., Lujala, P. and Rød, J.K. 2011. Social vulnerability assessment for Norway: a quantitative approach. *Norsk Geografisk Tidsskrift-Norwegian Journal of Geography*. **65**(1), pp.1–17.

Huang, Z. and Williamson, P. 2001. A comparison of synthetic reconstruction and combinatorial optimisation approaches to the creation of small-area microdata. *Department of Geography, University of Liverpool*.

Joglosemar 2010. Pengungsi Meningkat 10 Kali Lipat. [Accessed 16 April 2017]. Available from: http://www.webcitation.org/6plZ8aDi7.

JPNN 2010. Pengungsi Merapi Lari Ke Gunungkidul. *www.jpnn.com*. [Online]. [Accessed 16 April 2017]. Available from: http://www.webcitation.org/6plXZgtDJ.

Jumadi, Carver, S. and Quincey, D. 2017. A Conceptual Design of Spatio-Temporal Agent-Based Model for Volcanic Evacuation. *Systems*. **5**(4), p.53.

Jumadi, Carver, S. and Quincey, D. 2016. ABM and GIS-based multi-scenarios volcanic evacuation modelling of Merapi *In*: *AIP Conference Proceedings* [Online]. AIP Publishing, p.050005. [Accessed 9 May 2016]. Available from: http://scitation.aip.org/content/aip/proceeding/aipcp/10.1063/1.4947401.

Kelfoun, K., Legros, F. and Gourgaud, A. 2000. A statistical study of trees damaged by the 22 November 1994 eruption of Merapi volcano (Java, Indonesia): relationships between ash-cloud surges and block-and-ash flows. *Journal of Volcanology and Geothermal Research*. **100**(1), pp.379–393.

Kennedy, W.G. 2012. Modelling human behaviour in agent-based models *In*: *Agent-based models of geographical systems* [Online]. Berlin, Germany: Springer, pp.167–179. [Accessed 12 April 2017]. Available from: http://link.springer.com/chapter/10.1007/978-90-481-8927-4_9.

Khalid, M.N.A. and Yusof, U.K. 2014. A Crowd Modelling Considering Group Cohesion in the Emergency Route Planning Problems.

Klügl, F. 2008. A Validation Methodology for Agent-based Simulations *In*: *Proceedings of the 2008 ACM Symposium on Applied Computing* [Online]. SAC '08. New York, NY, USA: ACM, pp.39–43. [Accessed 30 April 2017]. Available from: http://doi.acm.org/10.1145/1363686.1363696.

Lavigne, F., de Bélizal, E., Cholik, N., Aisyah, N., Picquout, A. and Mei, E.T.W. 2011. Lahar hazards and risks following the 2010 eruption of Merapi volcano, Indonesia. *EGU General Assembly*. **13**(EGU2011-4400).

Lavigne, F., De Coster, B., Juvin, N., Flohic, F., Gaillard, J.-C., Texier, P., Morin, J. and Sartohadi, J. 2008. People's behaviour in the face of volcanic hazards: Perspectives from Javanese communities, Indonesia. *Journal of Volcanology and Geothermal Research*. **172**(3–4), pp.273–287.

Lavigne, F., Morin, J., Mei, E.T.W., Calder, E.S., Usamah, M. and Nugroho, U. 2017. Mapping Hazard Zones, Rapid Warning Communication and Understanding Communities: Primary Ways to Mitigate Pyroclastic Flow Hazard *In*: *SpringerLink* [Online]. Advances in Volcanology. Springer, Berlin, Heidelberg, pp.1–13. [Accessed 12 August 2017]. Available from: https://link.springer.com/chapter/10.1007/11157_2016_34.

Lavigne, F. and Thouret, J.-C. 2003. Sediment transportation and deposition by rain-triggered lahars at Merapi Volcano, Central Java, Indonesia. *Geomorphology*. **49**(1–2), pp.45–69.

Lavigne, F., Thouret, J.-C., Hadmoko, D.S. and Sukatja, B. 2007. Lahars in Java: initiations, dynamics, hazard assessment and deposition processes. *Forum Geografi*. **21**.

Lavigne, F., Thouret, J.C., Voight, B., Suwa, H. and Sumaryono, A. 2000. Lahars at Merapi volcano, Central Java: an overview. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.423–456.

Lee, J.-S., Filatova, T., Ligmann-Zielinska, A., Hassani-Mahmooei, B., Stonedahl, F., Lorscheid, I., Voinov, A., Polhill, J.G., Sun, Z. and Parker, D.C. 2015. The Complexities of Agent-Based Modeling Output Analysis. *Journal of Artificial Societies and Social Simulation*. **18**(4), p.4.

Letsie, M.M.A. 2015. *An assessment of place vulnerability to natural hazard in south-western Lesotho (Quthing and Mohale's Hoek districts)*.[Online] Thesis. [Accessed 1 December 2015]. Available from: http://wiredspace.wits.ac.za/handle/10539/17650.

Lim, M.B.B., Jr, H.R.L., Piantanakulchai, M. and Uy, F.A. 2015. A household-level flood evacuation decision model in Quezon City, Philippines. *Natural Hazards*. **80**(3), pp.1539–1561.

Linardi, S. 2016. Peer coordination and communication following disaster warnings: An experimental framework. *Safety Science*.

Liu, S., Murray-Tuite, P. and Schweitzer, L. 2014. Incorporating Household Gathering and Mode Decisions in Large-Scale No-Notice Evacuation Modeling. *Computer-Aided Civil and Infrastructure Engineering*. **29**(2), pp.107–122.

Local Government of Sleman 2010. Pemerintah Kabupaten Sleman » Update Data Pengungsi Bencana Merapi 2010. [Accessed 31 March 2017]. Available from: http://www.webcitation.org/6pNWR8K4a.

Lovreglio, R., Ronchi, E. and Nilsson, D. 2016. An Evacuation Decision Model based on perceived risk, social influence and behavioural uncertainty. *Simulation Modelling Practice and Theory*.

Lummen, N.S. and Yamada, F. 2014. Implementation of an integrated vulnerability and risk assessment model. *Natural Hazards*. **73**(2), pp.1085–1117.

Macal, C.M. 2005. Model verification and validation *In*: *Workshop on" Threat Anticipation: Social Science Methods and Models* [Online]. Chicago, IL, USA. [Accessed 21 April 2017]. Available from: https://pdfs.semanticscholar.org/2b44/3950272309c0e3b05f901b6e8f607a75d8a6.pdf.

Macal, C.M. and North, M.J. 2005. Tutorial on agent-based modeling and simulation *In*: *Proceedings of the 37th conference on Winter simulation* [Online]. Winter Simulation Conference, pp.2–15. [Accessed 7 April 2015]. Available from: http://dl.acm.org/citation.cfm?id=1162712.

Makinoshima, F., Abe, Y., Imamura, F., Machida, G. and Takeshita, Y. 2017. Possible Factors Promoting Car Evacuation in the 2011 Tohoku Tsunami Revealed by Analysing a Large-Scale Questionnaire Survey in Kesennuma City. *Geosciences*. **7**(4), p.112.

Malleson, N. and Birkin, M. 2012. Analysis of crime patterns through the integration of an agent-based model and a population microsimulation. *Computers, Environment and Urban Systems*. **36**(6), pp.551–561.

Marfai, M.A., Cahyadi, A., Hadmoko, D.S. and Sekaranom, A.B. 2012. Sejarah Letusan Gunung Merapi Berdasarkan Fasies Gunungapi di Daerah Aliran Sungai Bedog, Daerah Istimewa Yogyakarta. *Jurnal RISET Geologi dan Pertambangan*. **22**(2), pp.73–80.

Marrero, J.M., García, A., Llinares, A., Rodríguez-Losada, J.A. and Ortiz, R. 2010. The Variable Scale Evacuation Model (VSEM): a new tool for simulating massive evacuation processes during volcanic crises. *Nat. Hazards Earth Syst. Sci.* **10**(4), pp.747–760.

Marsella, S.C., Pynadath, D.V. and Read, S.J. 2004. PsychSim: Agent-based modeling of social interactions and influence *In*: *Proceedings of the international conference on cognitive modeling* [Online]. Citeseer, pp.243–248. [Accessed 17 October 2016]. Available from: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.126.9185&rep=rep1&type=pdf.

Mas, E., Suppasri, A., Imamura, F. and Koshimura, S. 2012. Agent-based simulation of the 2011 great east japan earthquake/tsunami evacuation: An integrated model of tsunami inundation and evacuation. *Journal of Natural Disaster Science*. **34**(1), pp.41–57.

Mathbor, G.M. 2016. Local Capacity Building in Humanitarian Crises: An Effective Dealing Strategy for Bangladesh.

Mei, E.T.W. and Lavigne, F. 2012. Influence of the institutional and socio-economic context for responding to disasters: case study of the 1994 and 2006 eruptions of the Merapi Volcano, Indonesia. *Geological Society, London, Special Publications*. **361**(1), pp.171–186.

Mei, E.T.W. and Lavigne, F. 2013. Mass evacuation of the 2010 Merapi eruption. *International Journal of Emergency Management*. **9**(4), pp.298–311.

Mei, E.T.W., Lavigne, F., Picquout, A., de Bélizal, E., Brunstein, D., Grancher, D., Sartohadi, J., Cholik, N. and Vidal, C. 2013. Lessons learned from the 2010 evacuations at Merapi volcano. *Journal of Volcanology and Geothermal Research*. **261**, pp.348–365.

Mei, E.T.W., Lavigne, F., Picquout, A. and Grancher, D. 2011. Crisis Management During the 2010 Eruption of Merapi Volcano *In*: *Regional Geographic Conference–*

International Geographical Union, Santiago, Chile [Online]., pp.15–19. [Accessed 10 March 2015]. Available from: http://www.acreditacion.fisa.cl/ugi/archivo_presentacion/201109050300_20112211wvgz7h_archivo_presentacion.pdf.

Minnesota Population Center 2015. Integrated Public Use Microdata Series, International: Version 6.4 [dataset].

Moeckel, R., Spiekermann, K. and Wegener, M. 2003. Creating a synthetic population *In*: *Proceedings of the 8th International Conference on Computers in Urban Planning and Urban Management (CUPUM)* [Online]., pp.1–18. [Accessed 27 February 2017]. Available from: http://www.spiekermann-wegener.com/pub/pdf/CUPUM_2003_Synpop.pdf.

Muhammad, A. 2015. Kemenhub Sosialisasikan Batas Kecepatan Kendaraan Di Jalan Raya. [Accessed 16 September 2017]. Available from: http://www.webcitation.org/6tWdf8s7A.

Namazi-Rad, M.-R., Huynh, N., Barthelemy, J. and Perez, P. 2014. Synthetic population initialization and evolution-agent-based modelling of population aging and household transitions *In*: *International Conference on Principles and Practice of Multi-Agent Systems* [Online]. Springer, pp.182–189. [Accessed 2 August 2017]. Available from: http://link.springer.com/chapter/10.1007/978-3-319-13191-7_15.

Newhall, C.G. and Self, S. 1982. The volcanic explosivity index (VEI) an estimate of explosive magnitude for historical volcanism. *Journal of Geophysical Research*. **87**(C2), p.1231.

Pierson, T.C. and Major, J.J. 2014. Hydrogeomorphic effects of explosive volcanic eruptions on drainage basins. *Annual Review of Earth and Planetary Sciences*. **42**, pp.469–507.

Polhill, J.G. 2010. ODD Updated. *Journal of Artificial Societies and Social Simulation*. **13**(4), p.9.

Pons, M., Johnson, P.A., Rosas, M. and Jover, E. 2014. A georeferenced agent-based model to analyze the climate change impacts on ski tourism at a regional scale. *International Journal of Geographical Information Science*. **28**(12), pp.2474–2494.

Qiu, F. and Hu, X. 2010. Modeling group structures in pedestrian crowd simulation. *Simulation Modelling Practice and Theory*. **18**(2), pp.190–205.

Quarantelli, E.L. 1990. *The Warning Process And Evacuation Behavior: The Research Evidence* [Online]. Newark, Delaware: Disaster Research Center. [Accessed 19 August 2016]. Available from: http://udspace.udel.edu/handle/19716/520.

Rai, V. and Robinson, S.A. 2015. Agent-based modeling of energy technology adoption: empirical integration of social, behavioral, economic, and environmental factors. *Environmental Modelling & Software*. **70**, pp.163–177.

Ramdan, D.M. 2010. Pengungsi Sudah Masuk Bantul Sampai Gunung Kidul. *news.okezone.com*. [Online]. [Accessed 16 April 2017]. Available from: http://www.webcitation.org/6plYQ7im5.

Reneke, P.A. 2013. *Evacuation decision model* [Online]. Washington, DC, USA: US Department of Commerce, National Institute of Standards and Technology. [Accessed 6 January 2017]. Available from: http://nvlpubs.nist.gov/nistpubs/ir/2013/NIST.IR.7914.pdf.

Reynolds, C. 1999. Individual-based models. *Retrieved November*. **25**, p.2003.

Riad, J.K., Norris, F.H. and Ruback, R.B. 1999. Predicting Evacuation in Two Major Disasters: Risk Perception, Social Influence, and Access to Resources. *Journal of Applied Social Psychology*. **29**(5), pp.918–934.

Rianto, T. 2009. *Spatial analysis of volcanic risk perception Case study in local community at Merapi volcano dangerous zones*.[Online] Master's Thesis, Enschede, Netherlands: ITC, University of Twente. [Accessed 6 March 2015]. Available from: http://www.itc.nl/library/papers_2009/msc/aes/rianto.pdf.

Robinson, E.J.H., Franks, N.R., Ellis, S., Okuda, S. and Marshall, J.A.R. 2011. A Simple Threshold Rule Is Sufficient to Explain Sophisticated Collective Decision-Making. *PLOS ONE*. **6**(5), p.e19981.

Robinson, S.A. and Rai, V. 2015. Determinants of spatio-temporal patterns of energy technology adoption: An agent-based modeling approach. *Applied Energy*. **151**, pp.273–284.

Ronald, W. 1983. Population Evacuation In Volcanic Eruptions, Floods, and Nuclear Power Plant Accidents: Some Elementary Comparisons. *Journal of Community Pschology*. **2**.

Rosenbaum, M.S. and Culshaw, M.G. 2003. Communicating the Risks Arising from Geohazards. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*. **166**(2), pp.261–270.

Saadatseresht, M., Mansourian, A. and Taleai, M. 2009. Evacuation planning using multiobjective evolutionary optimization approach. *European Journal of Operational Research*. **198**(1), pp.305–314.

Sadono, R., Hartono, H., Machfoedz, M.M. and Setiaji, S. 2017. Monitoring Land Cover Changes in the Disaster-Prone Area: A Case Study of Cangkringan Sub-District, the Flanks of Mount Merapi, Indonesia. *Forum Geografi*. **31**(2).

Saepuloh, A., Urai, M., Aisyah, N., Widiwijayanti, C., Jousset, P. and others 2013. Interpretation of ground surface changes prior to the 2010 large eruption of Merapi volcano using ALOS/PALSAR, ASTER TIR and gas emission data. *Journal of Volcanology and Geothermal Research*. **261**, pp.130–143.

Sagala, S. and Okada, N. 2009. F-2 Statistical analysis of correlation between hazard-related factors and households' evacuation decisions in Mt. Merapi. *Proceedings of the annual conference of the Institute of Social Safety Science*. **AA12381938**(24), pp.61–64.

Sagala, S.A.H. 2009. *System Analysis of Social Resilience against Volcanic Risks Case Studies of Merapi, Indonesia and Mt. Sakurajima, Japan*.[Online] Ph.D. Thesis, Kyoto, Japan: Kyoto University. [Accessed 5 April 2017]. Available from: http://repository.kulib.kyoto-u.ac.jp/dspace/handle/2433/88040.

Shi, J., Ren, A. and Chen, C. 2009. Agent-based evacuation model of large public buildings under fire conditions. *Automation in Construction*. **18**(3), pp.338–347.

Siagian, T.H., Purhadi, P., Suhartono, S. and Ritonga, H. 2013. Social vulnerability to natural hazards in Indonesia: driving factors and policy implications. *Natural Hazards*. **70**(2), pp.1603–1617.

Siebeneck, L.K. and Cova, T.J. 2012. Spatial and temporal variation in evacuee risk perception throughout the evacuation and return-entry process. *Risk analysis*. **32**(9), pp.1468–1480.

Siebert, L., Simkin, T. and Kimberly, P. 2011. *Volcanoes of the World* [Online]. Berkeley, CA, USA: Univ of California Press. [Accessed 31 May 2017]. Available from: https://books.google.co.uk/books?hl=en&lr=&id=0DZrfpL9_DMC&oi=fnd&pg=PP2&dq=Volcanoes+of+the+World.+3rd+edition&ots=DnfhJ6he8N&sig=qxytaoNhd9_c2o-6q0CBprkDmfQ.

Slemankab 2010. Update Data Korban Bencana Erupsi Gunung Merapi 2010. [Accessed 6 March 2018]. Available from: http://www.webcitation.org/6xi7fofUK.

Smith, G.A. and Fritz, W.J. 1989. Volcanic influences on terrestrial sedimentation. *Geology*. **17**(4), pp.375–376.

Smith, G.A. and Lowe, D.R. 1991. Lahars: Volcano Hydrologic-Events and Deposition in the Debris Flow—Hyperconcentrated Flow Continuum *In*: *Sedimentation in Volcanic Settings* [Online]. Tulsa, OK, USA: Society for Sedimentary Geology. [Accessed 1 June 2017]. Available from: http://archives.datapages.com/data/sepm_sp/SP45/Lahars_Volcano_Hydrologic_Events.pdf.

Solikhin, A., Pinel, V., Vandemeulebrouck, J., Thouret, J.-C. and Hendrasto, M. 2015. Mapping the 2010 Merapi pyroclastic deposits using dual-polarization Synthetic Aperture Radar (SAR) data. *Remote Sensing of Environment*. **158**, pp.180–192.

Surono, Jousset, P., Pallister, J., Boichu, M., Buongiorno, M.F., Budisantoso, A., Costa, F., Andreastuti, S., Prata, F., Schneider, D., Clarisse, L., Humaida, H., Sumarti, S., Bignami, C., Griswold, J., Carn, S., Oppenheimer, C. and Lavigne, F. 2012. The 2010 explosive eruption of Java's Merapi volcano—A '100-year' event. *Journal of Volcanology and Geothermal Research*. **241**–**242**, pp.121–135.

Tan, L., Hu, M. and Lin, H. 2015. Agent-based simulation of building evacuation: Combining human behavior with predictable spatial accessibility in a fire emergency. *Information Sciences*. **295**, pp.53–66.

Tayag, J., Insauriga, S., Ringor, A. and Belo, M. 1996. People's response to eruption warning: the Pinatubo experience, 1991-1992 *In*: *Fire and mud. Eruptions and Lahars of Mount Pinatubo, Philippines, University of Washington Press* [Online]. Seattle, WC, USA: University of Washington Press. [Accessed 27 July 2017]. Available from: https://pubs.usgs.gov/pinatubo/tayag/.

Thompson, R.R., Garfin, D.R. and Silver, R.C. 2017. Evacuation from Natural Disasters: A Systematic Review of the Literature. *Risk Analysis*., n/a-n/a.

Thouret, J.-C., Lavigne, F., Kelfoun, K. and Bronto, S. 2000. Toward a revised hazard assessment at Merapi volcano, Central Java. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.479–502.

Tobin, G.A. and Whiteford, L.M. 2002. Community Resilience and Volcano Hazard: The Eruption of Tungurahua and Evacuation of the Faldas in Ecuador. *Disasters*. **26**(1), pp.28–48.

Troitzsch, K.G. 2004. Validating simulation models *In*: *Proceedings of the 18th European Simulation Multiconference*. Erlagen, Germany: SCS, pp.98–106.

Visser, H. and Nijs, T. 2006. The Map Comparison Kit. *Environmental Modelling & Software*., pp.346–358.

Voight, B., Constantine, E.K., Siswowidjoyo, S. and Torley, R. 2000. Historical eruptions of Merapi Volcano, Central Java, Indonesia, 1768–1998. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.69–138.

Wang, D.Q., Gong, Q.G. and Shen, X.F. 2014. An Improved Personnel Evacuation Cellular Automata Model Based on the Ant Colony Optimization Algorithm. *Applied Mechanics and Materials*. **513**–**517**, pp.3287–3291.

Wang, H., Mostafizi, A., Cramer, L.A., Cox, D. and Park, H. 2016. An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety. *Transportation Research Part C: Emerging Technologies*. **64**, pp.86–100.

Wilson, T., Cole, J., Johnston, D., Cronin, S., Stewart, C. and Dantas, A. 2012. Short- and long-term evacuation of people and livestock during a volcanic crisis: lessons from the 1991 eruption of Volcán Hudson, Chile. *Journal of Applied Volcanology*. **1**(1), p.2.

Wilson, T., Kaye, G., Stewart, C. and Cole, J. 2007. *Impacts of the 2006 eruption of Merapi volcano, Indonesia, on agriculture and infrastructure* [Online]. Lower Hutt, New Zealand: Institute of Geological and Nuclear Sciences Limited. [Accessed 25 January 2015]. Available from: http://ir.canterbury.ac.nz/handle/10092/760.

Wise, S. 2014. *Using Social Media Content to Inform Agent-based Models for Humanitarian Crisis Response*.[Online] Ph.D. Thesis, Fairfax, VA, USA: George Mason University. [Accessed 20 May 2015]. Available from: http://digilib.gmu.edu:8080/jspui/handle/1920/8879.

Ye, Z., Yin, Y., Zong, X. and Wang, M. 2014. An Optimization Model for Evacuation Based on Cellular Automata and Ant Colony Algorithm *In*: *Computational Intelligence and Design (ISCID), 2014 Seventh International Symposium on* [Online]. IEEE, pp.7–10. [Accessed 21 May 2015]. Available from: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=7064066.

Yuan, W. and Tan, K.H. 2007. An evacuation model using cellular automata. *Physica A: Statistical Mechanics and its Applications*. **384**(2), pp.549–566.

Zhang, B., Chan, W.K. and Ukkusuri, S.V. 2009. Agent-based modeling for household level hurricane evacuation *In*: *Proceedings of the 2009 Winter Simulation Conference (WSC)*., pp.2778–2784.

Zhao, H., Winter, S. and Tomko, M. 2017. Integrating Decentralized Indoor Evacuation with Information Depositories in the Field. *ISPRS International Journal of Geo-Information*. **6**(7), p.213.

Zheng, X., Zhong, T. and Liu, M. 2009. Modeling crowd evacuation of a building based on seven methodological approaches. *Building and Environment*. **44**(3), pp.437–445.

Chapter 4
An Agent-based Spatio-temporal Dynamics Model of Risk in Merapi

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This chapter proposes an individual risk model based on multi-criteria evaluation (MCE) and implements this to simulate the spatio-temporal dynamics of risk using the ABM from Chapter 3. As in Chapter 3, the results suggest that the real and perceived hazard might different, dual hazard model is implemented to the ABM (real and perceived). The real model is used in assessing individual risk, while the perceived model is used in defining the individual evacuation decision. The spatial distribution of risk (risk hotspots) as aggregated from individuals risk is presented and discussed in this chapter.

Abstract: Managing disasters caused by natural events, especially volcanic crises, requires a range of techniques including risk modelling and analysis. Risk modelling is commonly conducted at community/regional scales using GIS. However, such an approach cannot properly capture the dynamic of risk due to limitations in accommodating object movement over time and space. The development of individual modelling, specifically Agent-based Modelling (ABM), allows modelling of risks at individual scale over space and time to address this limitation. We propose a new approach of Spatio-temporal Dynamics Model of Risk (STDMR) by integrating multi-criteria evaluation (MCE) within a georeferenced ABM with Mt. Merapi, Indonesia as a case study. Using this model it was possible to simulate the spatio-temporal dynamic of people at risk during a volcanic crisis. The model captures dynamic risk as a function of hazard and vulnerability, where the intensity of the hazard varies over time and space. Here, vulnerability is defined using a social vulnerability index (SoVI) as aggregated in the MCE from several attributes of individual agents. We generate a synthetic population to assign attributes to the individual agents using probability

distribution of the population characteristics sourced from primary and secondary data. Importantly, individual vulnerability is heterogeneous and depends on the characteristics of the individuals concerned. The risk to individual people dynamically changes along with the changing hazard dynamics and the location of people (movement). The model can be used to simulate the risk dynamics within the crisis and potentially improve the decision making process of evacuation.

Keywords: ABM, volcanic crisis, risk dynamics, spatio-temporal risk model, MCE.

4.1 Introduction

When natural disasters occur, hazard levels vary over space and time depending on various factors. During a volcanic eruption, for example, the spatial extent of the impact relates to the contrasting nature of the volcanic sources, the type and magnitude of explosive eruptions and the topography (Lirer et al., 2010) while the level of hazard can vary over space and time during such crises. Likewise, in the case of floods, the spatio-temporal hazard can vary depending on a range of hydro-meteorological and topographical factors (Merz et al., 2006; Yan et al., 2015). Such spatio-temporal variability of hazards means that the associated risk varies over time and space. Especially during volcanic crises, time and location are critical in defining the risk to human populations: fatalities can result from people being located in the wrong place at the wrong time. Therefore, under certain conditions, residents in the vicinity of a volcano need to evacuate quickly from hazardous areas. Evacuation is often the only way to reduce the risk from volcanic impact because it is almost impossible to survive the hazardous material emitted during an eruption such as pyroclastic flows and toxic gases (d’Albe, 1979).

The combination of the mobile nature of people with the spatio-temporal variability of hazard means that the risk changes dynamically. More thorough spatio-temporal modelling is required to figure out the dynamic rather than static risk map, such as that produced by Alcorn and colleagues (Alcorn et al., 2013). Risk modelling plays an important part in improving understanding of the potential impact of certain hazards and for informing disaster management. This is traditionally conducted at community/regional scale using GIS. For example, Biass et al. (2012) successfully analysed risk focusing on the impact of tephra fallout from the Cotopaxi volcano and produced several thematic maps that included social risk level.

Meanwhile, Alcorn et al. (2013) more comprehensively analysed the volcanic risk of Valles Caldera, New Mexico, focusing on testing and demonstrating a GIS-based Multi-Criteria Evaluation (MCE) for risk assessment. Both hazard and vulnerability were aggregated from several criteria using MCE. Similarly, Scaini (2014) used spatial overlay analysis of the hazard and vulnerability map in GIS to generate the risk in Tenerife Island, Spain. Although both the Alcorn and Scaini studies present more comprehensive analyses regarding the hazards than does the Biass approach, they share a similar limitation with respect to accounting for the dynamic risk posed to mobile individuals.

Such GIS-based overlay analysis can provide spatial risk information that is suitable for the risk to fixed elements such as buildings, infrastructure and economic units but is less appropriate for modelling the risk to people who have the ability to move during an emergency in response to unfolding volcanic activity. Therefore, a model that can represent the dynamics of individual risk over time and space is required. Agent-based Models (ABMs) provide a new approach to risk analysis that focuses on the individuals who are ultimately at risk (Clarke, 2014), but the concept and model of individual risk is less developed, whereas MCE has advantages for modelling individual risk involving multiple attributes.

ABM has been shown to be effective in simulating agent behaviour in non-linear systems (Malleson et al., 2014; Srbljinović and Škunca, 2003). In an ABM, people are represented as agents who have heterogeneous characteristics and behaviour (Crooks and Heppenstall, 2012). They are able to navigate their environment and interact with other agents and the model therefore reflects individual variations in vulnerability and mobility. The coupling of ABM with a dynamic hazard model is therefore an ideal framework within which to represent the dynamic risk to individuals during a volcanic emergency.

In this paper, we propose a new approach of Spatio-temporal Dynamics Model of Risk (STDMR) and provide a case study using a pre-developed agent-based evacuation model of Mt. Merapi (Jumadi et al., 2018, 2017). This approach first creates an individual-level population (synthetic population) of agents who live in the area surrounding a volcano. Each agent has a unique vulnerability and since vulnerability comprises several factors (Cutter et al., 2003), MCE is used to create a single social vulnerability index for each individual. This is coupled with a dynamic hazard model to capture the dynamics of risk. The model is able to highlight a small number of high-risk spatio-temporal positions where, due to the behaviour of individuals evacuating the volcano and the dynamics of the hazard itself, the overall risk in those times and places is extremely high. The outcomes are interesting and extremely relevant for stakeholders and the work of combining an ABM and a MCE with a dynamic volcanic hazard is novel.

The paper is organised as follows: in Section 4.2 we describe the background concept of the approach; Section 4.3 then presents the method of the application of the model and the case study; Section 4.4 provides the results of the experimentation and the spatio-temporal analysis of the results and discusses the outcomes; and lastly, Section 4.5 provides overall conclusions.

4.2 The concept of Individual Risk using MCE in ABM

Previously we have discussed the importance of incorporating the spatio-temporal dynamic of a hazard into the modelling of human risk. This section provides the background concept to the approach through the integration of Multi-Criteria Evaluation (MCE) into an ABM. MCE was originally a technique to make a decision from multiple criteria and conflicting priorities (Voogd, 1982). This concept has since been widely used to analyse problems or to assess values that consist of multiple criteria or attributes (Abella and Westen, 2007; Armaș and Gavriș, 2013; Labadie and Prodhon, 2014). The vulnerability of people to a volcanic hazard is multi-faceted, so MCE is a useful technique that can be used to quantify this value (Armaș and Gavriș, 2013). Meanwhile, ABM is used here to account for the nature of the social processes in an emergency situation which are complex (Dash and Gladwin, 2007). Representing human behaviour in such situations is extremely challenging due to the difficulties in modelling human behaviour. Specifically, the responses and behaviour of people during a disaster will vary according to their socio-economic and demographic characteristics (Christia, 2012; Donovan, 2010; Dove, 2008; Lavigne et al., 2008; Rianto, 2009). Integrating the two approaches enables spatio-temporal modelling of the dynamics of human risk in relation to natural hazards.

The risk is considered here to be the probability of harmful consequences or expected losses that result from the interactions between hazards and vulnerable people or objects (Blaikie et al., 2014; UNISDR, 2004). Risk is estimated as a function of hazard and vulnerability using Equation 4.1 (Sar et al., 2015; UNISDR, 2004). Consequently, when the value of the hazard changes, risk changes as well. For example, consider a population with a degree of vulnerability arising from living in the certain hazard zone (Figure 4.1). During a volcanic emergency, the magnitude and intensity of hazards vary with respect to the proximity to the summit, as well as the topographic conditions that determine the direction of the flow of volcanic material. As the population may be moving during the crisis, their hazard level will vary with time (t_1 to t_2). Simultaneously, the hazard will vary due to the changing of the intensity of the volcanic activity. Therefore, the degree of risks varies in both cases. The mentioned concept of risks with regards to the mobility of people and the dynamics of hazard can be used to formulate the spatio-temporal risk model on an individual basis.

$$Risk = Hazard * Vulnerability \qquad (4.1)$$

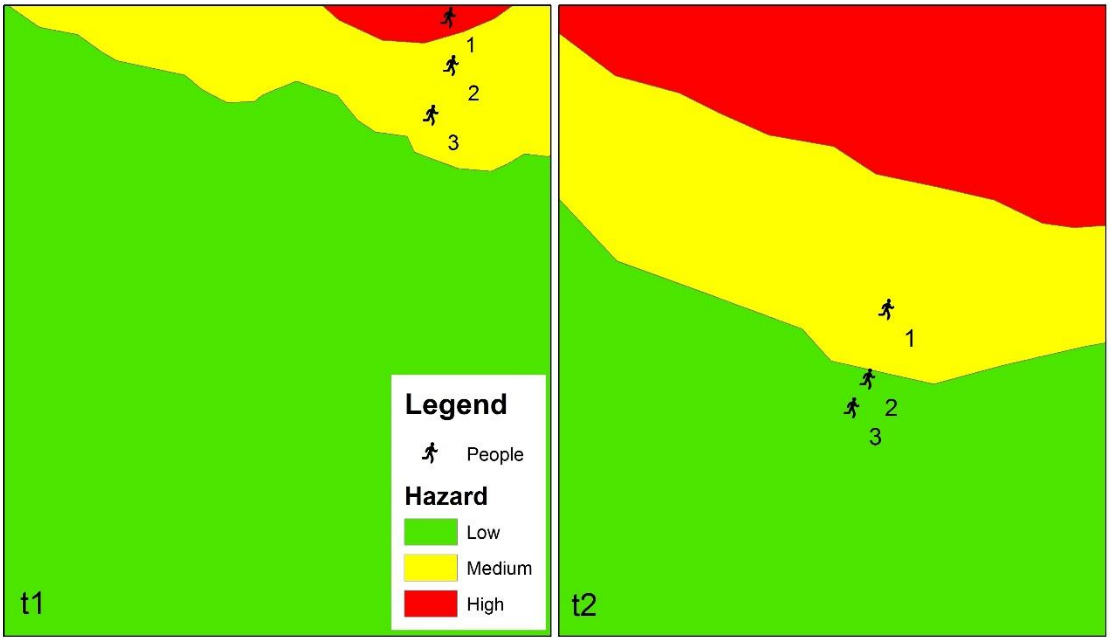

Figure 4.1 Illustration of moving people and the dynamic of hazard within time and space.

Individual risk (Newhall and Hoblitt, 2001) is the probability that a particular individual, at known co-ordinates, will be killed or injured by the volcano within a specified period. In this research, we specify the hazard as a potentially damaging eruption that may cause loss of life or injury and social disruption (UNISDR, 2004). A map of the hazard can be composed of several elements. Specifically, in the case of volcanic hazards, the elements include the types of hazardous material that are emitted during eruption such as Pyroclastic Density Current (PDC), lava flow and tephra fallout (Alcorn et al., 2013). In the study area, the hazard map has been compiled from the historical record to be a single hazard map (BNPB, 2011). Meanwhile, we describe vulnerability as the characteristics of a person or group that influence their capacity to anticipate, cope with, resist and recover from the consequences of a natural hazard (Blaikie et al., 2014). Vulnerability is multidimensional and can be measured using a combination of many variables (Lummen and Yamada, 2014). Here, we quantify vulnerability using the Social Vulnerability Index (SoVI) (Cutter et al., 2003). This index has been developed based on several attributes: socio-economic status (income, political power, prestige), gender, race and ethnicity, age, commercial and industrial development, employment loss, rural/urban, residential property tenure, infrastructure and lifelines, occupation, family structure, education, population growth, medical services, social dependence, special needs populations (Cutter et al., 2003). The index has been widely used to measure social vulnerability toward environmental hazards in various regions (Armaș and Gavriș, 2013; Chakraborty et al., 2005; Garbutt et al., 2015; Letsie and Grab, 2015; Schmidtlein et al., 2008; Tapsell et al., 2010; Yoon, 2012).

The individual risk assessment has different criteria compared with the risk assessment for a community/region which uses criteria based on the characteristics of the community and the region where the population lives. There is no relevant literature in this field that addresses risk assessment on an individual basis. Therefore, in this research, we define several characteristics of individual people (or ‘agents’) to generate the SoVI and degree of hazard that any agent is exposed to in any specific location at any particular time. The concept used here to define individual risk consists of three parts: defining the socio-economic parameters for individual vulnerability; defining hazard at the individual location; and measuring the risk. Several socio-economic parameters are used in the vulnerability assessment through the application of a MCE. Meanwhile, the hazard is assessed based on the location of a person within the given hazard zone. The risk is defined based on the measured vulnerability and the hazard level (Figure 4.2).

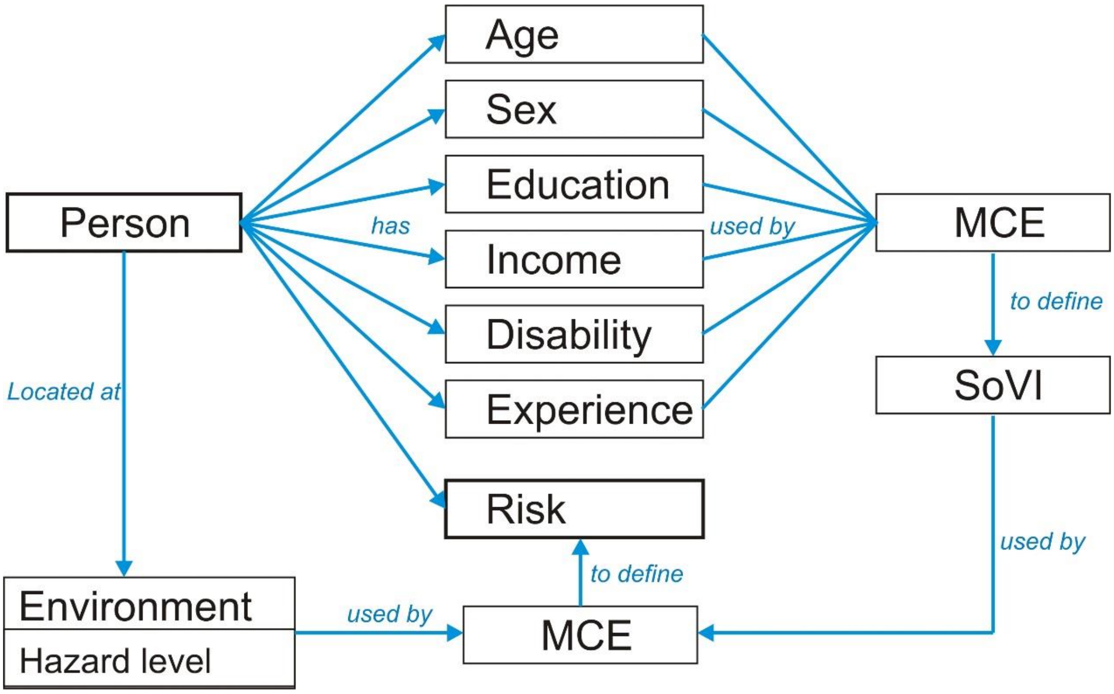

Figure 4.2 Individual risk concept using Multi-Criteria Evaluation (MCE) using physical (hazard) and social (person attribute) variables.

MCE plays a major role in defining the individual risk. In the individual risk model, MCE is used to evaluate both SoVI and the risk as a final result, based on the criteria provided. MCE, also called Multi-Criteria Analysis (MCA), was initially conceptualised in the early 1970s. MCE is often used to analyse a compromise between choice alternatives, while GIS enables analysis of complex spatial problems from several layers of spatial data. MCE analysis starts with the construction of an evaluation matrix containing elements that reflect the characteristics of the set of alternatives based on a specific set of criteria. Each element can be weighted based on its contribution to the goal using several techniques: ranking, rating, pairwise comparison (AHP) and trade-off (Malczewski, 1999). Commonly there are two techniques to aggregate this element so that the final result can be achieved through a weighted linear combination (WLC) and Boolean overlay (Eastman, 1999; Malczewski, 2000).

Finally, those concepts need to be implemented in ABM to simulate the dynamics. Although potentially powerful and successfully integrated into GIS (Carver, 1991), the integration of MCE and ABM is rare. They have been used for decision-making simulations of various expert groups (Bishop et al., 2009) and for recreational fishing management (Gao and Hailu, 2012). Bishop et al. (2009) discussed the potential use of MCE to explore the various outcomes of decision-making processes with different preferences of human agent, while Gao and Hailu (2012) applied MCE in an Agent-based Simulation as a Decision Support System (DSS) to select fisheries management strategies. However, we found no articles using such an approach for disaster risk modelling. ABM has emerged as a valuable alternative to traditional aggregate mathematical modelling as it can accommodate the complexity of a system through its ability to capture the interactions between agents at the same or different scales (Gilbert and Troitzsch, 2005). An ABM consists of discrete 'agents' that can interact within an environment (Gilbert, 2008). It can incorporate complex and multiple attributes of individuals but lacks the capacity to evaluate those attributes into single decisions/values. Integrating MCE into the model, however, is promising for solving this problem.

4.3 Application and the Case Study

The basic concepts of integrating MCE into ABM for the STDMR have been theoretically discussed in the previous section. In this section, we provide an overview of the application of STDMR. It starts with the introduction to the study area, an outline of the process of collecting data for use in the model and the integration of STDMR into the ABM of evacuation. This ABM is developed based on the spatio-temporal volcanic evacuation model framework (Jumadi et al., 2017) that has been improved with the addition of the individual evacuation decision model and underwent validation with the real data (Jumadi et al., 2018).

4.3.1 Study Area

Merapi Volcano, located on Java Island, Indonesia, can be a potential hazard to the surrounding communities. Recent work suggests that the potential for eruptions from Merapi is much higher now than has was the case historically (Andreastuti et al., 2000; Camus et al., 2000). These risks were confirmed by the last event in 2010. The eruption style tends to be either Sub-Plinian or Plinian. In disaster studies, a volcanic explosivity index (VEI) is often used to describe the destructiveness of an eruption with a range from 0 (least destructive) to 8 (most destructive) (Newhall and Self, 1982). The VEI of Merapi eruptions is generally within the range 1– 3 but it unexpectedly increased to 4 in 2010 (Surono et al., 2012). As a consequence of this event, the area surrounding Merapi suffered the worst disaster impact for a century.

Merapi eruptions commonly produce diverse hazardous events: *nuées ardentes* (fast-moving clouds of hot gas and ash produced by gravitational dome collapse) (Bardintzeff, 1984) and lahars (the overbank flows of pyroclastic material coupled with rainwater) (Lavigne and Thouret, 2003) are two particular hazards that are harmful to the communities living close to explosions (Thouret et al., 2000). Ash fall also has an impact (Damby et al., 2013). The effect of *nuées ardentes* depend on topographic character (Kelfoun et al., 2000) and can travel up to 3.5 km from only a few individual events (Abdurachman et al., 2000). Lahar events are usually initiated by high rainfall intensity (Lavigne and Thouret, 2003). These are considered the most dangerous part of the material flow system in Merapi (Charbonnier and Gertisser, 2008). The direction of this flow is strongly influenced by the initial flow direction and the topography subsequently affects the spatial extent of the hazard (Itoh et al., 2000).

Previous eruptions have strongly affected the geomorphological structure (Saepuloh et al., 2013) and geological character (Gertisser et al., 2012) of Merapi with implications for the spatial extent of the hazard map (BNPB, 2011, 2008). Also, eruption history has changed the potential direction of pyroclastic or lahar flows. It can be foreseen that the southern flank of Merapi will be the most likely area to be impacted by the next eruption (Figure 4.4). Based on this prediction, we use the Sleman Regency, a region that is located on the southern flank of Merapi, as a case study. Sleman (Figure 4.3) is geographically located between 107° 15 '03 "and 107° 29 '30" east longitude, 7° 34' 51" and 7° 47' 30" South latitude. Sleman covers 57,482 hectares or 574.82 km^2 or about 18% of Yogyakarta Province area. Administratively, this region consists of 17 districts, 86 villages and 1,212 hamlets.

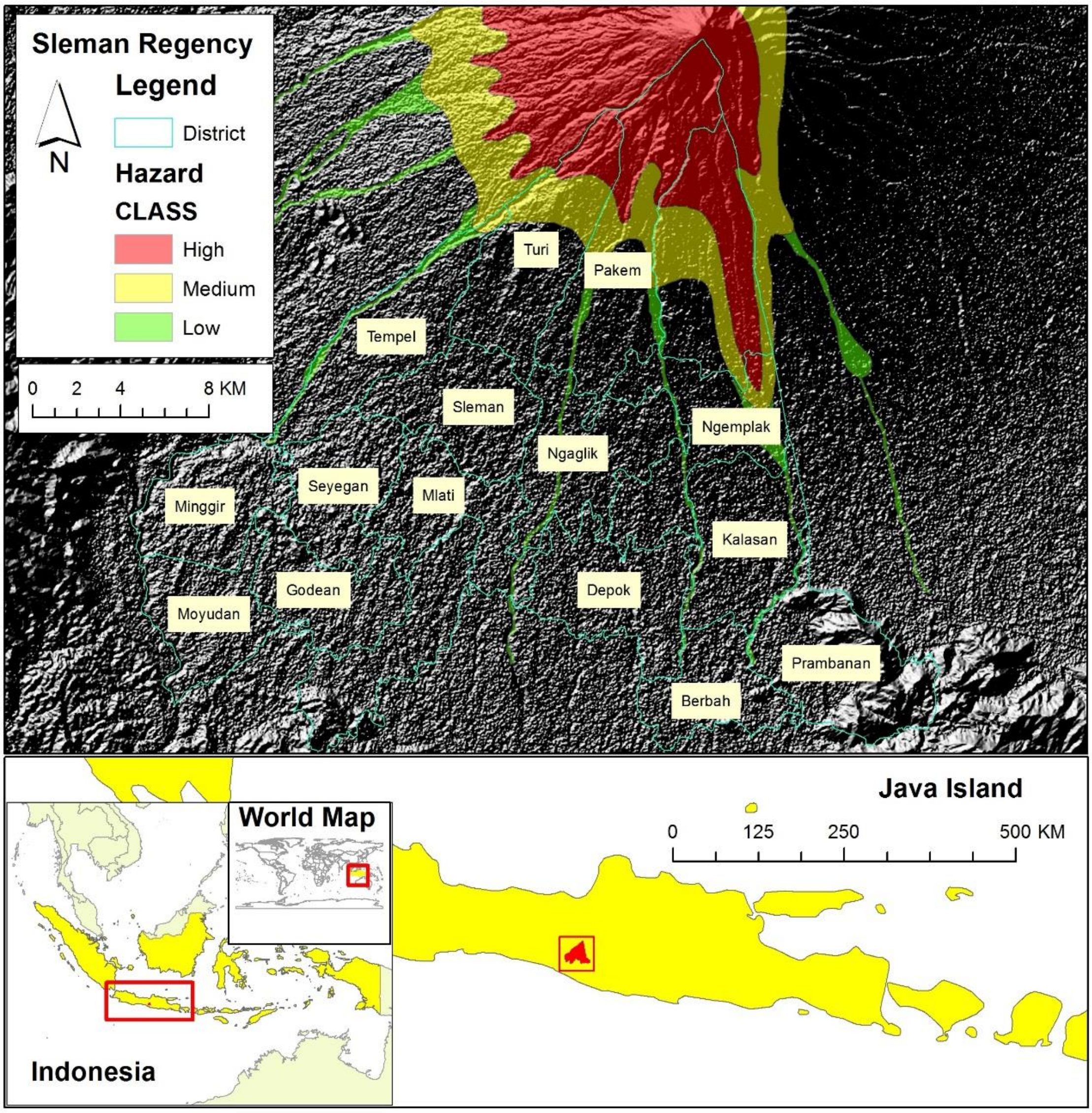

Figure 4.3 Study area.

4.3.2 Data Collection

The data used here are collected from secondary and primary sources. The secondary data consist of administrative boundary, volcanic hazard zones, the location of shelters, land use, census microdata and road networks. The primary data from an extensive questionnaire survey undertaken in 2016 were used to complete the variables of census microdata (Minnesota Population Center, 2015) to create the population of people agents as well as developing the evacuation decision model (Jumadi et al., 2018). This survey used 12 villages within a radius of 20km. We created several ring buffers with distance ranges of 5km to define the sampling areas. Three villages were selected from each area. Furthermore, 10 participants from each village were selected randomly, resulting in 120 participants in total. The detailed information on the data is elsewere (Jumadi et al., 2018).

4.3.3 Agent-based STDMR of Volcanic Evacuation

4.3.3.1 General Framework

The ABM of the volcanic evacuation simulation was developed based on the relationship between the volcano and the surrounding population. The basic model and its complete documentation was provided in the previous publication (Jumadi et al., 2017). This model marries the physical environment and social interactions to generate the value of risk (Cova, 1999; Pons et al., 2014; Sengupta and Bennett, 2003) as presented in Figure 4.4. The physical variables were generated from the characteristics of the volcano and its hazard zone. These include VEI, activity length, activity level and the spatial extent of the hazard (Figure 4.4). The VEI can also be used to estimate the spatial extent of the impact and was generated from the eruption record of the volcano. The probability distribution of the VEI was used to define the VEI in the simulation. Eruption records can also be used to estimate the length of the crisis (activity length). As volcanic activity fluctuates within a period of crisis, the activity level from the rest condition to the climax of the events can be estimated. This activity level is also related to the hazard.

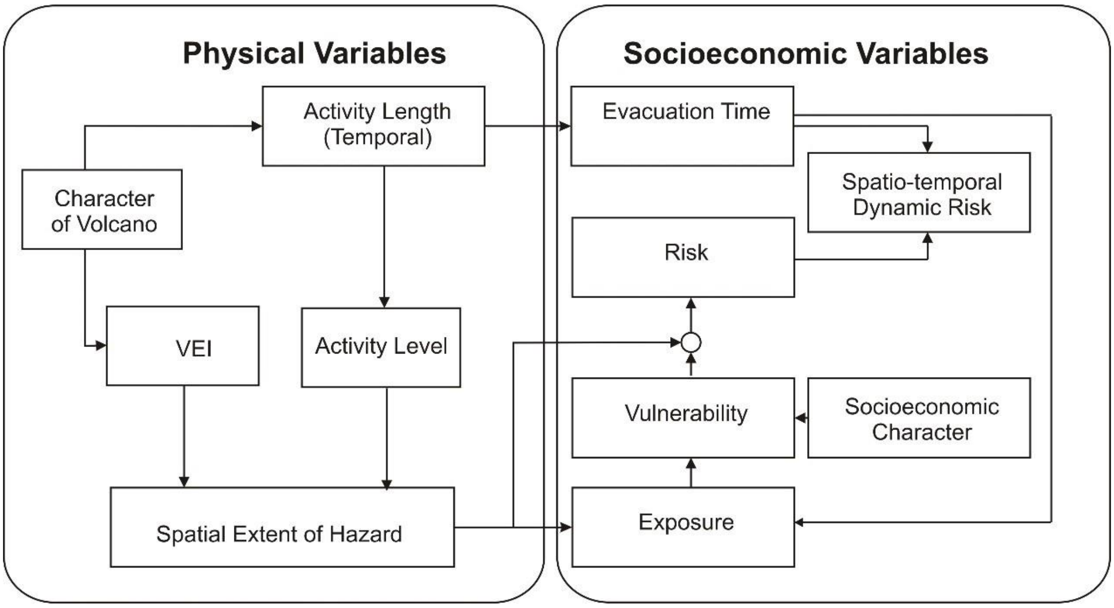

Figure 4.4 General framework of ABM. The left box (Physical Variables) illustrates how the VEI and activity level are used to estimate the spatial extent of the volcanic hazard. The VEI and the length of the activity are the physical characteristics of the volcano as recorded in literature. These feed into the socio-economic variables (right box) that are attributes of the people agents and are used to assess the overall risk. The hazard (which varies spatially and temporally) is used to estimate exposure to the population and subsequently the overall risk. Activity length is used to estimate the evacuation time (the period in which the risk changes dynamically as a result of the movement of people) and subsequently the spatiotemporal risk dynamic which quantifies the risk at every time period (t).

4.3.3.2 Synthetic Population Generation

To create human agents, data from the census microdata (Minnesota Population Center, 2015) and a separate survey of 120 households are used. We used conditional probability (Monte Carlo Simulation) to generate the synthetic population of agents (Heppenstall et al., 2011; Moeckel et al., 2003), where the complete description of this generation is provided elsewhere (Jumadi et al., 2018). In this model, the human agents are generated for each sub-district of Sleman with individual units grouped as a household. It would be advantageous to create an agent to represent every person, but the AnyLogic PLE limits the total number of agents to 50,000. Therefore approximately 50,000 representative agents were created. The characteristics of the people are used in order to calculate the SoVI variables; they, together with the other variables, influence the decisions of the agents. This is discussed in more detail in (Jumadi et al., 2018). Each agent is initialised with characteristics that are randomly drawn from probability distributions generated from the census microdata and survey data.

4.3.3.3 Overview of the Agents and Their Behaviour

The model consists of three main agents: volcano, stakeholder and people (population) that interact within the geographic environment (Jumadi et al., 2017). The volcano acts as an agent which initiates the hazardous situation and influences the environment as a potential threat to the surrounding population. The other agents in the interactions are the stakeholder and the population (people). The stakeholder, in this case the authorities (government), plays a significant role in observing and analysing the activities of the volcano and in issuing warnings to the population. In the ABM simulation, each agent displays specific behaviour and mechanisms when interacting with the others, as well as with the environment. The environment is represented through spatial data with dynamic hazard properties.

People in this model are the most important agents and form the main focus of the simulation observation. Each agent can be expected to act to save themselves from danger in crisis. Therefore, the human agent is utilized with a decision mechanism that allows them to make the decision to evacuate in circumstances of danger. This evacution decision is based on the Normal – Investigating – Evacuating state model that is provided in the other paper (Jumadi et al., 2018). Conceptually, this evacuation decision is influenced by several factors including (Ahsan et al., 2016; Dash and Gladwin, 2007; Lim et al., 2015): (1) risk communication and warning; (2) perception of risk; (3) community and social network influence and (4) disaster likelihood, environmental cues, and natural signals. The mechanism of the individual decision in evacuation based on the literature review is provided in Figure 4.5. The transition between states is based on threshold-based rules (Kennedy, 2012; Robinson et al., 2011) that evaluate the strength of force to evacuate based on various factors.

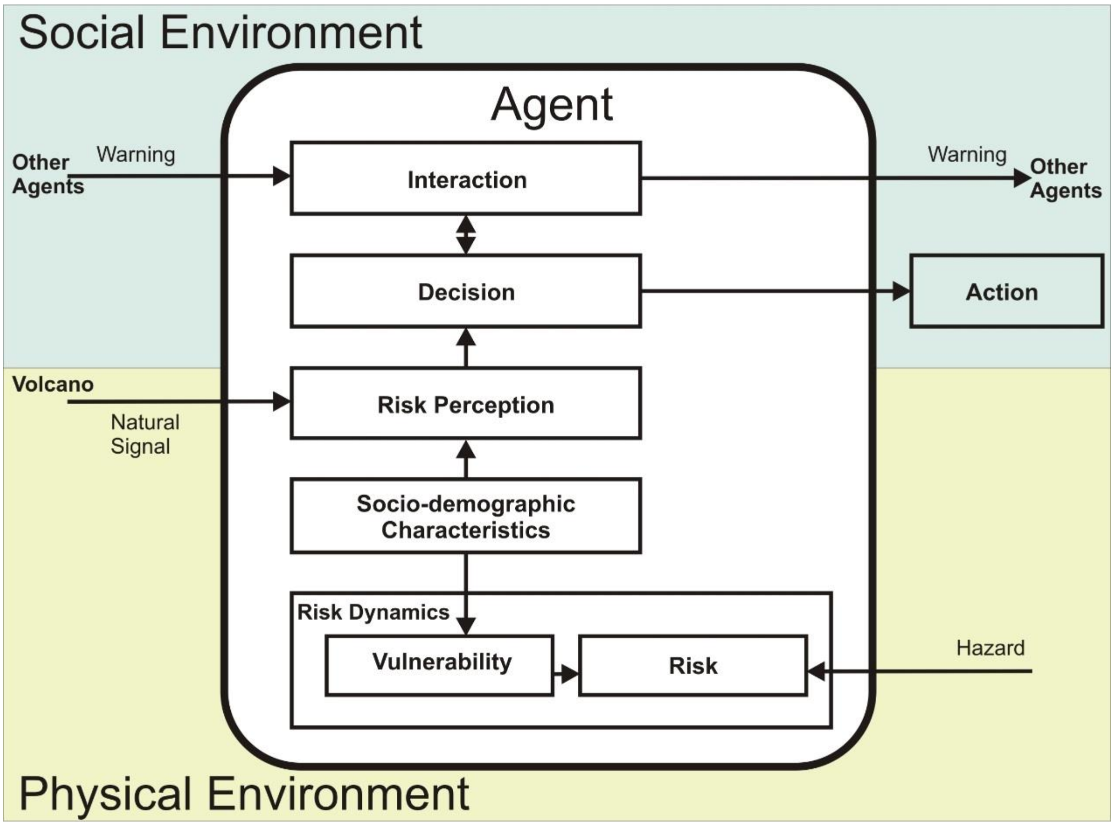

Figure 4.5 Main agent (people) characteristics.

The risk to each individual is evaluated based on the hazard and vulnerability variables. The hazard level is measured from the environmental properties at the agent location whereas the vulnerability of each individual is based on SoVI that is evaluated based on socio-demographic character. The following sub-section (Section 4.3.3.4) elaborates this risk model in detail. The risk to the individual might change after the decision and subsequent movement because this results in a change of location with a different hazard profile: the level of risk is dynamic over time for a mobile individual.

4.3.3.4 Implementation of Individual Risk Model in the ABM

The concept of individual risk set out in Section 4.2 states that risk comprises two main components: hazard and vulnerability. We provide a calculation procedure based on MCE to integrate this into the ABM of evacuation. Consequently, Java functions are designed based on this concept and integrated into the previous model (Jumadi et al., 2018).

1. Hazard

The hazard is classified into three zones (Figure 4.2). The hazard level of each zone is dynamically changed over the duration of the simulation to reflect the changing volcanic activity. The rule of hazard level changing, based on a function of several variables of the volcano including Volcanic Explosivity Index (VEI) and Volcanic Activity Level (VAL), is provided in Table 4.1 (Jumadi et al., 2017). An illustration of the changing of the hazard level within those zones is provided in Figure 4.6. Finally, the hazard level in the agent location (based on the co-ordinates) is classified and scored based on Table 4.2. The value is used in the risk calculation.

Table 4.1 Matrix relation of VEI, VAL and hazard level within hazard zones.

VEI	1			2			3			4		
Zone VAL / Hazard	L	M	H	L	M	H	L	M	H	L	M	H
III (H)	L	M	M	L	M	M	M	H	H	M	H	H
II (M)	L	M	M	L	M	M	M	M	H	M	M	H
I (L)	L	L	M	L	L	M	L	M	M	L	M	M

Notes: L: Low hazard level, M: Medium hazard level, H: High hazard level

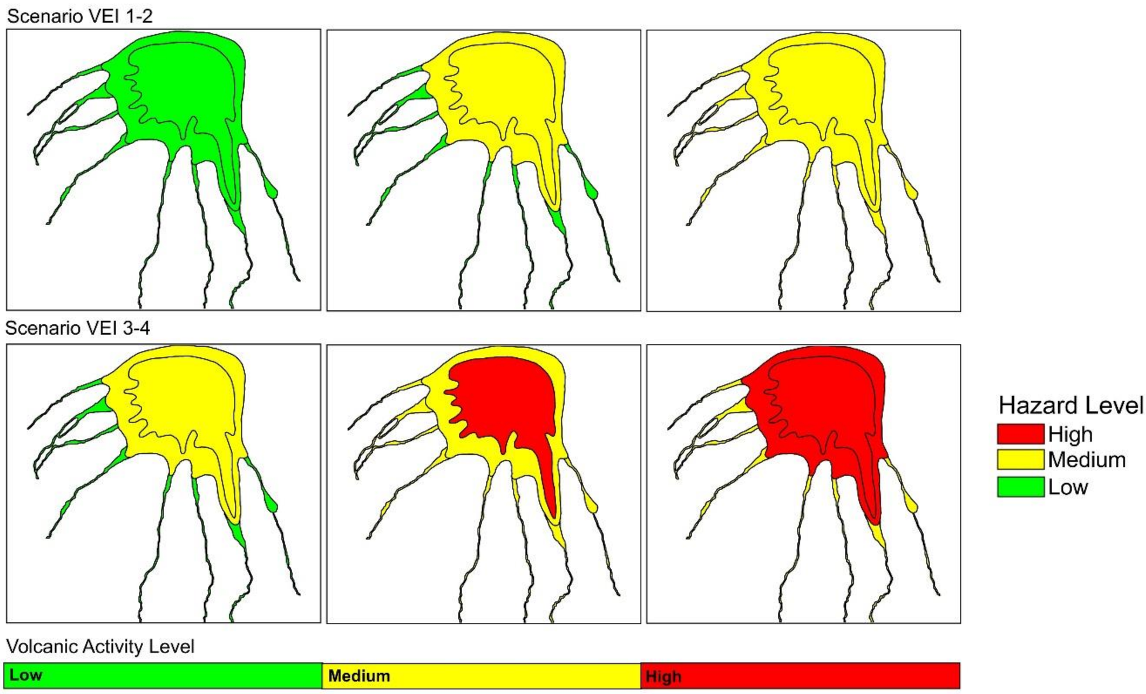

Figure 4.6 Hazard dynamics scenarios.

Table 4.2 Hazard level classification and scoring.

Criteria	Theme of attributes	Description	Pairwise comparison index (H)
Hazard level	High	Highly hazardous	0.723
	Medium	Hazardous	0.216
	Low	less Hazardous	0.061

2. Vulnerability

The vulnerability index used in the model is based on SoVI (Cutter et al., 2003) with some attributes of each agent (person) given scores that are then used to generate the SoVI. The score of each attribute is defined based on pairwise comparison weighting (Saaty, 2008). Each theme of the attribute is ranked based on the vulnerability level (Cutter et al., 2003). The result of the pairwise comparison analysis is shown in Table 4.3. Finally, we aggregate the social attributes using Equation 4.2 to calculate the SoVI (Chakraborty et al., 2005). The variables for SoVI are provided in Table 4.3.

$$SoVI = \frac{\sum_{i=1}^{n} I_i}{n} \qquad (4.2)$$

Table 4.3 Variables classification and scoring to determine social vulnerability index (SoVI).

Criteria	Theme of attributes	Description	Pairwise comparison index (*I*)
Age	Elderly and Child (>75 years and <14 years)	Vulnerable	0.75
	Adult (15 - 75 year)	Less Vulnerable	0.25
Sex	Female	Vulnerable	0.75
	Male	Less Vulnerable	0.25

Table 4.3 Continued ...

Education	Basic Education	Vulnerable	0.75
	High Education	Less Vulnerable	0.25
Income	Live in Poverty	Vulnerable	0.75
	Standard Living	Less Vulnerable	0.25
Disability	Disable	Vulnerable	0.75
	Non-Disable	Less Vulnerable	0.25
Experience	No Experiences	Vulnerable	0.75
	Experienced with Previous Eruption	Less Vulnerable	0.25

3. Risk

The calculation of the individual risk is based on the risk concept explained in Section 4.2 (Sar et al., 2015; UNISDR, 2004). We express the individual risk as a certain quantification that can be classified. The formula to provide the value is presented in Equation 4.3. This equation generates the risk to each individual as a risk index value (*Ri*) using a weighted linear combination (WLC) (Malczewski, 2000). Once the index is obtained, it is classified into one of three categories (Table 4.5).

Table 4.4 Weight of hazard and SoVI in defining risk.

Classification	Description	Weight (*w*)
Hazard (*h*)	Important	0.75
SoVI (*v*)	Less important	0.25

$$Ri = (h\, w_h)(SoVI\, w_v) \qquad (4.3)$$

Table 4.5 Risk classification rule.

Ri Range	Classification	Description
0.18 <	Low	Less Risky
0.18 - 0.33	Medium	Slightly Less Risky
> 0.33	High	Risky

4.3.3.5 Dual Hazard Model Implementation: Real and Perceived

We implemented a dual hazard model in setting up the environment of the agent-based evacuation model (Figure 4.7). The first hazard model (a) is the actual spatial extent of hazard in Merapi based on several historical records of eruptions including the eruption in 2010 (actual hazard) (BNPB, 2011). The distribution of hazard on this map is strongly based on the physical distribution of volcanic material deposit. While, the second hazard model (b) is the hazard map used by government to alert the population at risk in 2010 (perceived hazard) (Mei et al., 2013). This hazard model is a rough estimation based on the distance from the volcano as well as being closely related to the administrative boundaries. This makes it easier to translate the model into an evacuation command. For example, it will be easier for people to remember that “people within a distance of up to 10 km are in danger” (hazard model b) rather than “people within the medium hazard zone are in danger” (hazard model a). The first hazard model will be used for defining the individual risk, while the second hazard model is used for the decision making of evacuation. This is based on the experiment that using the second hazard model will result in a smaller error compared with the first hazard model (Jumadi et al., 2018), while the second hazard model does not directly represent the hazard, so it is not appropriate for assessing the risk. Therefore, we implement dual hazard models to get a better outcome of evacuation decision while retaining a more precise appreciation of risk.

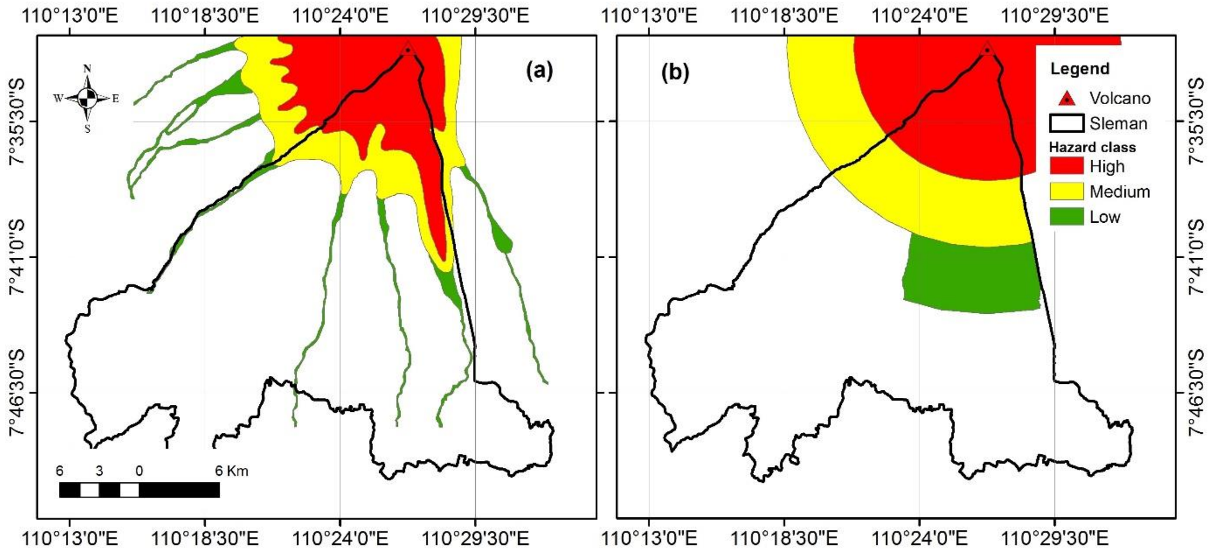

Figure 4.7 Dual hazard model implementation. (a) actual hazard map (BNPB, 2011), (b) perceived hazard map based on a hazard map used for evacuation order in 2010 eruption (Mei et al., 2013).

4.3.4 Implementation, Experimentation and Analysis of STDMR

The model is implemented by using AnyLogic, a multimethod (Agent-based, System Dynamics, and Discrete Event) simulation modelling tool developed by The AnyLogic Company (Borshchev, 2013). The overview of agents' statechart to express the behaviour rules of agents is provided in Figure 4.8. A statechart is a graphical representation of transition between states of an agent. The detail of the documentation of the ABM application is provided at https://goo.gl/Xp44iH. These statecharts represent the implementation of the model in AnyLogic (Jumadi et al., 2017). Statechart is typically a state transition diagram used to define event- and time-driven behaviour in AnyLogic (Grigoriev, 2015). There are three main statecharts for people agents (Figure 4.8a) including observing hazard, evacuation decision and alerting community. The observing hazard statechart enables the human agents to sense the hazard at their location and classify the level based on Table 4.1. The 'evacuation decision' statechart is used by the agents to decide whether they need to evacuate (see Section 4.3.3.3 and the other paper (Jumadi et al., 2018) for the detail of the evacuation decision model). When the human agent feels in danger the 'alerting community' statechart is used to decide whether they will alert their relations or not. Meanwhile, the volcano and stakeholder agent have only one statechart each. The volcano agent is utilised with the statechart of the volcanic activity generator, while the stakeholder agent is able to make a decision based on the volcanic activity. The stakeholder will alert people when the volcano shows a high level of activity.

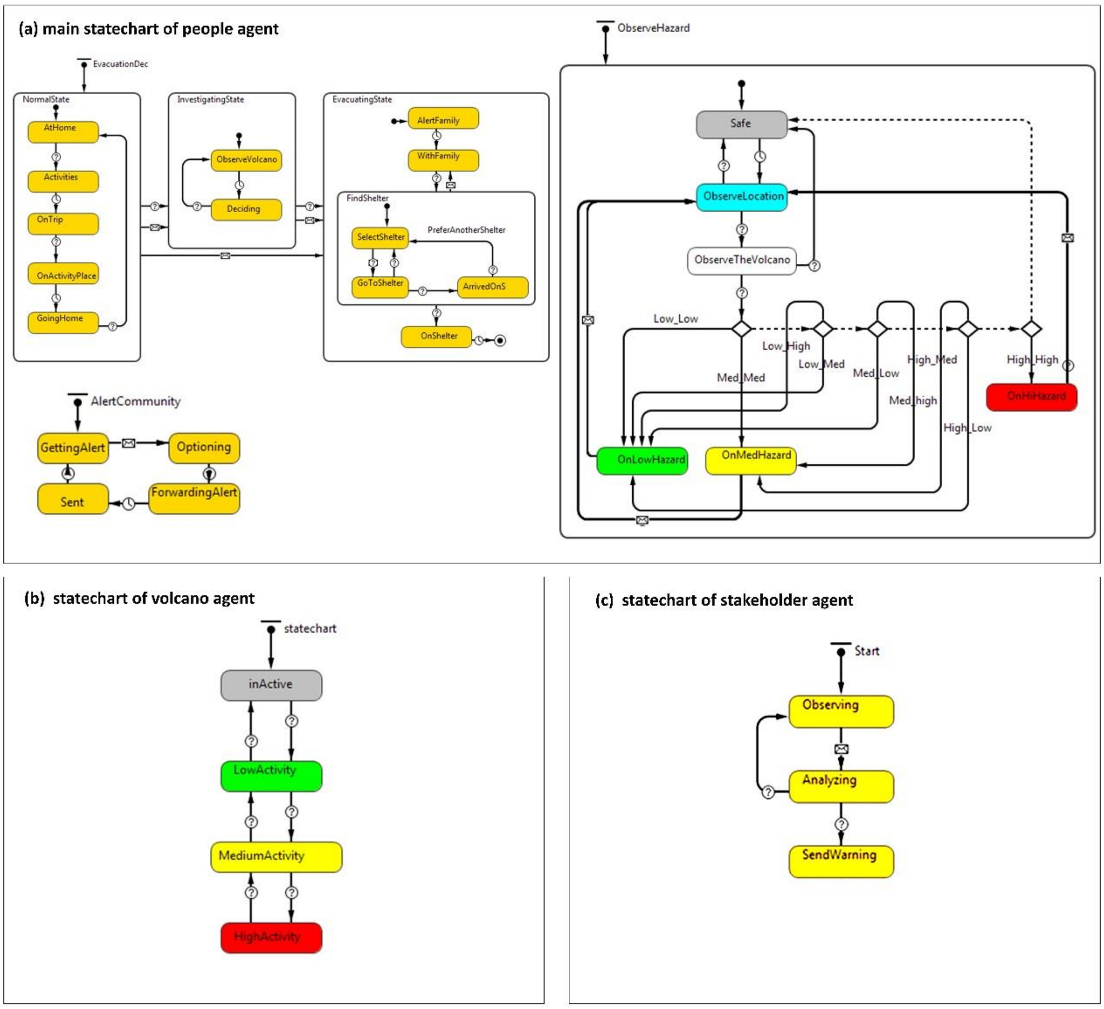

Figure 4.8 Overview of agents' statecharts expressing the agents' behaviour.

Using the developed model, experiments can demonstrate how the spatio-temporal dynamics of risk vary with the magnitude of the hazard (VEI) and the crisis length. Here, we explore the eruptive activity using a scenario with VEI 4 and Crisis Length 102 days to mimic the past eruption in 2010 (Mei et al., 2013; Surono et al., 2012). The results, consisting of the combination of people and their risk level, are then analysed using kernel density analysis to identify the risk hotspots in ArcGIS. Kernel density was used to provide the spatial density of risk to which people are exposed since it is a popular geostatistical-based method that has been widely used in analysing risk hotspots (Lin et al., 2010; Thakali et al., 2015). To produce the final risk hotspots, we ran the model 30 times to provide enough samples for statistical analysis based on the central limit theorem (Ghasemi and Zahediasl, 2012; Haneberg, 2004) and spatially averaged the results.

4.4 Experimentation Results and Discussion

Section 4.3 provided a technical overview of the model; we now describe the simulation experiments, the spatio-temporal analysis of the results and discuss the outcome with reference to related works, highlighting potential implementation in supporting emergency management.

4.4.1 The STDMR

The purpose of the experiment is to highlight the validity of the approach (coupling an ABM with a physical hazard model and a MCE to determine individual vulnerability and, consequently, the individual risk) and to show that the overall outcomes are potentially extremely valuable for practical emergency management. The outcome of the experiment can be saved for further analysis as well as directly overviewed during the simulation (e.g. Figure 4.9). Figure 4.9 shows the result by illustrating the spatial distribution of the people at risk as well as the dynamic of risk level. Subfigures a–d illustrate the changing level of risk as the emergency develops. Initially (a) most individuals are at low (or negligible) risk. However, as the hazard spreads the risks become much greater (b and c). Then, few people at risk are remaining in Figure 4.9d due to the massive evacuations. Most people are moving away from the hazard zone during the high level of volcanic activity. The remaining people are considered as the reluctant people as a consequence of the variability of the individuals' decisions (Jumadi et al., 2018).

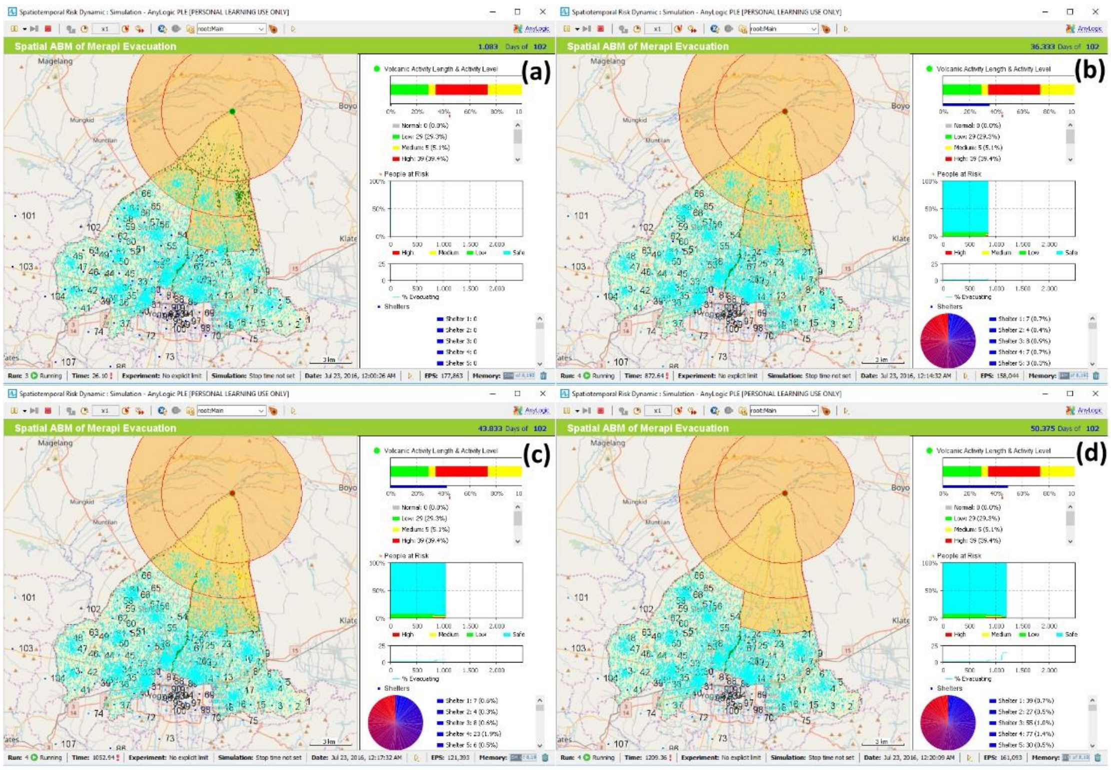

Figure 4.9 Spatio-temporal risk dynamic simulation. (a) Shows the initial condition before the volcanic activity start: most individuals are at low or negligible risk. (b) illustrates the increasing individual risk level due to the increasing volcanic activity. (c) shows numbers of people moving after the alert from the government. (d) shows the reluctant people that remain in the hazard zone during the crisis. There are four graphs in the interface: these show, from the top to the bottom respectively, the volcanic activity level and show the progress of the simulation, the risk composition of the individuals, percentage of evacuees, and the distribution of evacuation in shelters. See the animated image at https://goo.gl/QYqihw.

The saved outputs of the simulations are used to provide spatio-temporal densities of people at risk to show the dynamic. The densities provide a better approximation of the spatial distribution of people at risk, rather than the points distribution (Figure 4.9), because the agent population members were distributed randomly using the Monte Carlo approach (Section 4.3.3.2). Using the point distribution of people at risk directly to understand the risk can be misleading. We used GIS (see Section 4.3.4) to explore the dynamic risk over time by analysing the locations and attributes of the people (risk level attribute). Figure 4.10 presents these results of varying density (calculated using kernel density analysis) of the individuals who are at risk at various time points in the simulation. From these results we can see that risks of the hazard toward humans can change dynamically. The risk values not only depend on the level of hazard but also the number of people. This model can show the direct impact of evacuation processes on reducing disaster risk, confirming the importance of considering risks through a dynamic rather than static model.

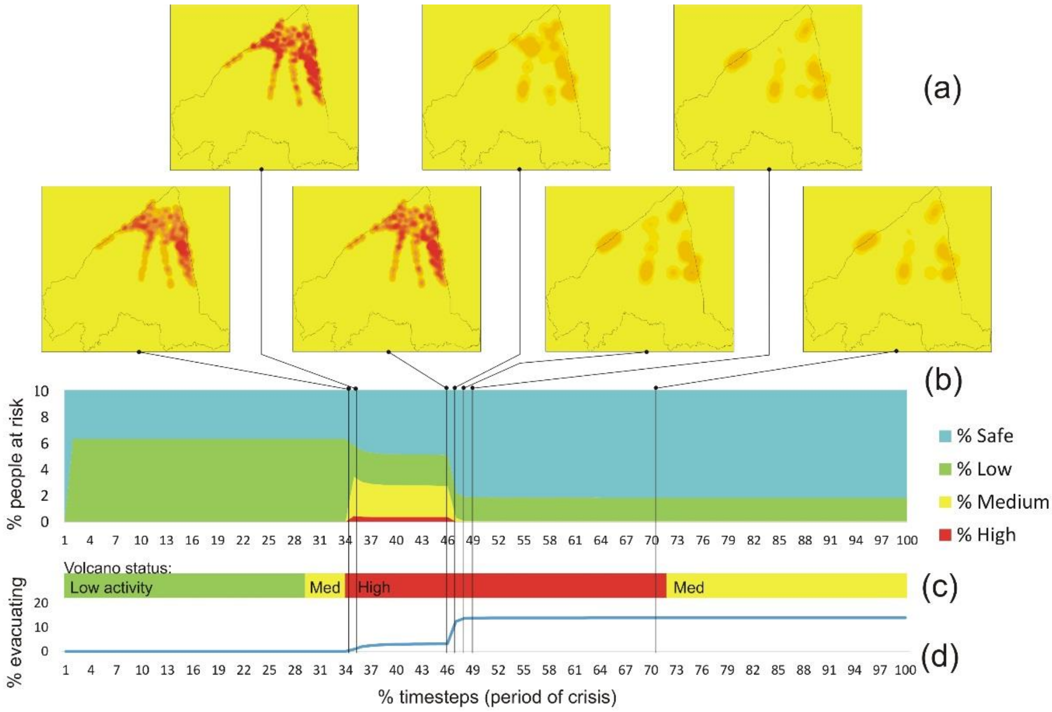

Figure 4.10 The STDRM analysis. The densities of people at risk (a) are fitted with the people at risk distribution graph (b), the simulated temporal volcanic activities graph (c) and the temporal curve of percentage of evacuees accumulation (d).

4.4.2 The Risk Hotspots

In this study, we use the term ‘Risk Hotspots’ to indicate the geographic locations of people at risk who are reluctant to evacuate during the simulated crisis. Hotspots are defined as relatively high-risk locations (Thakali et al., 2015). To create the hotspot, we analyse the density of the individuals (using kernel density analysis) who are at risk when the volcanic activity becomes high. A risk hotspot is, therefore, a place with a substantial concentration of people who are at risk and reluctant to leave at a time when the activity of the volcano is high. We captured the distribution of individuals who remain in their location until the end of the high-activity period of the volcano (see Figure 4.10). The Risk Hotspots are provided in Figure 4.11. To produce the hotspots below, the scenario was executed 30 times and the results were averaged. From the figure, it becomes clear that the risk hotspots are mainly located in three areas. The first is in Cangkringan District, the second is around Ngaglik District and the third is around Temple District. The Cangkringan District is in the high and medium hazard zone, where individuals are at risk of direct volcanic events such as toxic gases, *nuées ardentes* and PDC.

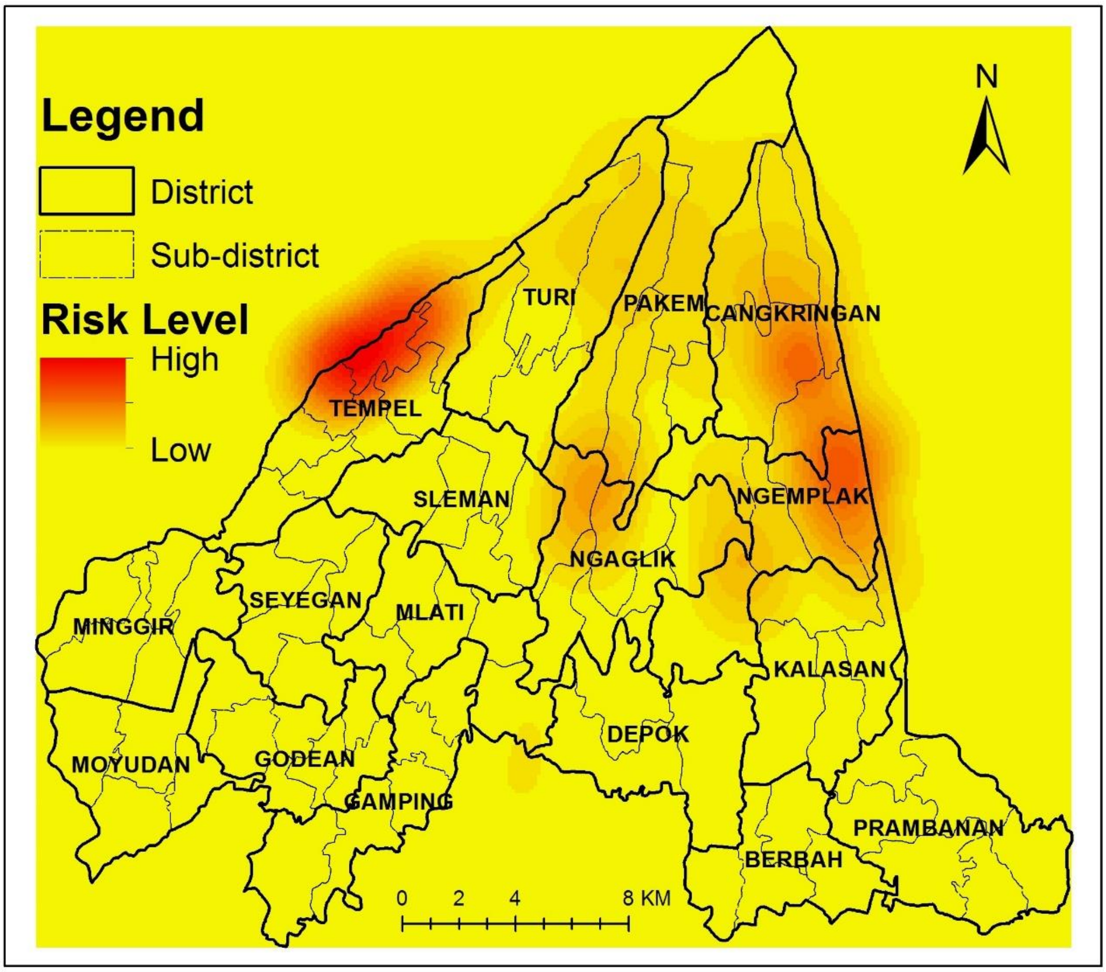

Figure 4.11 The risk hotspots.

4.4.3 Discussion

The STDMR of this experiment, that integrates the MCE-based individual risk model into ABM simulation, can show the impact of improved evacuation processes for reducing the impact of disasters. The most striking result of the simulation is that we can highlight the risk hotspots as an emerging result of the evacuation decisions of people during a crisis. This mapping can improve the decisions of disaster managers in focusing resources to mobilise and facilitate evacuation processes in the hotspot areas. The patterns are closely related to the real casualties distribution data provided by local government of Sleman (Pemkab Sleman, 2010) (Figure 4.12). The distribution of casualties map also shows relatively high percentage of casualties in Cangkringan District; however, there are discrepancies in Pakem, and Turi District.

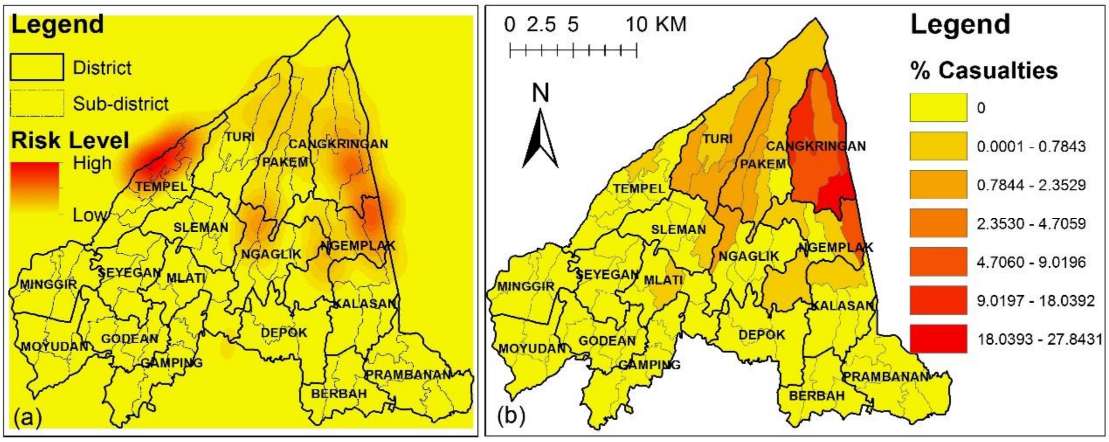

Figure 4.12 The risk hotspots (a) and distribution of casualties in 2010 eruption (b). Source: (a) Simulations, (b) Casualties Data (Pemkab Sleman, 2010).

Moreover, this approach can improve the existing static GIS-based risk analyses that are commonly conducted at area/regional level (Alcorn et al., 2013; Martins et al., 2012) by providing a more detailed pattern of the people who are at risk in two ways. Firstly, enabling the population at risk to move during the crisis creates a considerably more realistic spatial distribution of the population. Secondly, by accounting for the individual risk to people as well as the dynamic volcanic activity, the resulting pattern of the risk is much more realistic. This model can provide individual levels of risk that can be used to build a more detail spatial pattern of risk compared with less detailed regional-level risk analysis (Alcorn et al., 2013; Martins et al., 2012).

4.5 Conclusion

The integration of MCE-ABM for STDMR has been successfully presented in this paper to show the dynamic change of volcanic risk across an area and through time. The ability of the model to show how evacuation processes affect the risk reduction outcome has potential to be used to measure the effectiveness of various evacuation plans to reduce risk. Moreover, from the simulation, we present the risk hotspots that emphasise the concentration of people at risk at particular sites as the outcome of the evacuation decision of individuals. This simulation can potentially be used to improve the decision-making processes of evacuation. Knowing the hotspots can help the decision maker allocate more resources to manage and mobilise these areas.

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References

Abdurachman, E.K., Bourdier, J.-L. and Voight, B. 2000. Nuées ardentes of 22 November 1994 at Merapi volcano, Java, Indonesia. *Journal of Volcanology and Geothermal Research*. **100**(1), pp.345–361.

Abella, E.A.C. and Westen, C.J. 2007. Generation of a landslide risk index map for Cuba using spatial multi-criteria evaluation. *Landslides*. **4**(4), pp.311–325.

Ahsan, M.N., Takeuchi, K., Vink, K. and Ohara, M. 2016. A Systematic Review of the Factors Affecting the Cyclone Evacuation Decision Process in Bangladesh. *Journal of Disaster Research Vol*. **11**(4), p.741.

d'Albe, E.M.F. 1979. Objectives of volcanic monitoring and prediction. *Journal of the Geological Society*. **136**(3), pp.321–326.

Alcorn, R., Panter, K.S. and Gorsevski, P.V. 2013. A GIS-based volcanic hazard and risk assessment of eruptions sourced within Valles Caldera, New Mexico. *Journal of Volcanology and Geothermal Research*. **267**, pp.1–14.

Andreastuti, S.D., Alloway, B.V. and Smith, I.E.M. 2000. A detailed tephrostratigraphic framework at Merapi Volcano, Central Java, Indonesia: implications for eruption predictions and hazard assessment. *Journal of Volcanology and Geothermal Research*. **100**(1), pp.51–67.

Armaș, I. and Gavriș, A. 2013. Social vulnerability assessment using spatial multi-criteria analysis (SEVI model) and the Social Vulnerability Index (SoVI model) – a case study for Bucharest, Romania. *Natural Hazards and Earth System Science*. **13**(6), pp.1481–1499.

Bardintzeff, J.M. 1984. Merapi volcano (Java, Indonesia) and Merapi-type nuée ardente. *Bulletin volcanologique*. **47**(3), pp.433–446.

Biass, S., Frischknecht, C. and Bonadonna, C. 2012. A fast GIS-based risk assessment for tephra fallout: the example of Cotopaxi volcano, Ecuador-Part II: vulnerability and risk assessment. *Natural Hazards*. **64**(1), pp.615–639.

Bishop, I.D., Stock, C. and Williams, K.J. 2009. Using virtual environments and agent models in multi-criteria decision-making. *Land Use Policy*. **26**(1), pp.87–94.

Blaikie, P., Cannon, T., Davis, I. and Wisner, B. 2014. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. Routledge.

BNPB 2008. Peta Kawasan Rawan Bencana Gunung Merapi. Available from: http://www.webcitation.org/6pimWt1Fc.

BNPB 2011. Peta Kawasan Rawan Bencana Merapi. [Accessed 9 October 2015]. Available from: http://geospasial.bnpb.go.id/wp-content/uploads/2011/05/2011-04-29_KRB_Area_Terdampak_Langsung_Merapi.pdf.

Borshchev, A. 2013. *The Big Book of Simulation Modeling: Multimethod Modeling with AnyLogic 6*. Lebanon, NJ, USA: AnyLogic North America.

Camus, G., Gourgaud, A., Mossand-Berthommier, P.-C. and Vincent, P.-M. 2000. Merapi (Central Java, Indonesia): An outline of the structural and magmatological evolution, with a special emphasis to the major pyroclastic events. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.139–163.

Carver, S.J. 1991. Integrating multi-criteria evaluation with geographical information systems. *International journal of geographical information systems*. **5**(3), pp.321–339.

Chakraborty, J., Tobin, G.A. and Montz, B.E. 2005. Population Evacuation: Assessing Spatial Variability in Geophysical Risk and Social Vulnerability to Natural Hazards. *Natural Hazards Review*.

Charbonnier, S.J. and Gertisser, R. 2008. Field observations and surface characteristics of pristine block-and-ash flow deposits from the 2006 eruption of Merapi Volcano, Java, Indonesia. *Journal of Volcanology and Geothermal Research*. **177**(4), pp.971–982.

Chen, X. 2012. Agent-based micro-simulation of staged evacuations. *International Journal of Advanced Intelligence Paradigms*. **4**(1), p.22.

Chen, X. and Zhan, F.B. 2008. Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. *The Journal of the Operational Research Society*. **59**(1), pp.25–33.

Christia, M. 2012. *Experiences of people affected Merapi eruption in 2010: A qualitative study conducted in Krinjing village Indonesia*.[Online] Oslo, Norway: University of Oslo. [Accessed 10 March 2015]. Available from: https://www.duo.uio.no/handle/10852/30048.

Clarke, K.C. 2014. Cellular Automata and Agent-Based Models *In*: M. M. Fischer and P. Nijkamp, eds. *Handbook of Regional Science* [Online]. Springer Berlin Heidelberg, pp.1217–1233. [Accessed 26 April 2016]. Available from: http://link.springer.com/referenceworkentry/10.1007/978-3-642-23430-9_63.

Cova, T.J. 1999. GIS in emergency management. *Geographical information systems*. **2**, pp.845–858.

Crooks, A.T. and Heppenstall, A.J. 2012. Introduction to agent-based modelling *In*: *Agent-based models of geographical systems* [Online]. Springer, pp.85–105. [Accessed 30 October 2016]. Available from: http://link.springer.com/chapter/10.1007/978-90-481-8927-4_5.

Cutter, S.L., Boruff, B.J. and Shirley, W.L. 2003. Social Vulnerability to Environmental Hazards*. *Social Science Quarterly*. **84**(2), pp.242–261.

Damby, D.E., Horwell, C.J., Baxter, P.J., Delmelle, P., Donaldson, K., Dunster, C., Fubini, B., Murphy, F.A., Nattrass, C., Sweeney, S. and others 2013. The respiratory health hazard of tephra from the 2010 Centennial eruption of Merapi with implications for occupational mining of deposits. *Journal of Volcanology and Geothermal Research*. **261**, pp.376–387.

Dash, N. and Gladwin, H. 2007. Evacuation Decision Making and Behavioral Responses: Individual and Household. *Natural Hazards Review*. **8**(3), pp.69–77.

Donovan, K. 2010. Doing social volcanology: exploring volcanic culture in Indonesia. *Area*. **42**(1), pp.117–126.

Dove, M.R. 2008. Perception of volcanic eruption as agent of change on Merapi volcano, Central Java. *Journal of Volcanology and Geothermal Research*. **172**(3–4), pp.329–337.

Eastman, J.R. 1999. Multi-criteria evaluation and GIS. *Geographical information systems*. **1**, pp.493–502.

Gao, L. and Hailu, A. 2012. Ranking management strategies with complex outcomes: An AHP-fuzzy evaluation of recreational fishing using an integrated agent-based model of a coral reef ecosystem. *Environmental Modelling & Software*. **31**, pp.3–18.

Garbutt, K., Ellul, C. and Fujiyama, T. 2015. Assessment of social vulnerability under three flood scenarios using an open source vulnerability index *In*: Leeds, UK. [Accessed 1 December 2015]. Available from: http://leeds.gisruk.org/abstracts/GISRUK2015_submission_70.pdf.

Gertisser, R., Charbonnier, S.J., Keller, J. and Quidelleur, X. 2012. The geological evolution of Merapi volcano, Central Java, Indonesia. *Bulletin of volcanology*. **74**(5), pp.1213–1233.

Ghasemi, A. and Zahediasl, S. 2012. Normality Tests for Statistical Analysis: A Guide for Non-Statisticians. *International Journal of Endocrinology and Metabolism*. **10**(2), pp.486–489.

Gilbert, G.N. 2008. *Agent-Based Models*. London: SAGE.

Gilbert, N. and Troitzsch, K. 2005. *Simulation For The Social Scientist*. McGraw-Hill Education (UK).

Grigoriev, I. 2015. *AnyLogic 7 in Three Days* [Online] 2nd ed. anylogic.com. Available from: http://www.anylogic.com/free-simulation-book-and-modeling-tutorials.

Haneberg, W. 2004. *Computational Geosciences with Mathematica*. Berlin, Germany: Springer Science & Business Media.

Heppenstall, A.J., Harland, K., Smith, D.M. and Birkin, M.H. 2011. Creating realistic synthetic populations at varying spatial scales: a comparative critique of population synthesis techniques *In*: *Geocomputation 2011 Conference Proceedings, UCL, London* [Online]., pp.1–8. [Accessed 1 December 2016]. Available from: http://www.geocomputation.org/2011/papers/heppenstall.pdf.

Itoh, H., Takahama, J., Takahashi, M. and Miyamoto, K. 2000. Hazard estimation of the possible pyroclastic flow disasters using numerical simulation related to the 1994 activity at Merapi Volcano. *Journal of volcanology and geothermal research*. **100**(1), pp.503–516.

Jumadi, Carver, S. and Quincey, D. 2017. A Conceptual Design of Spatio-Temporal Agent-Based Model for Volcanic Evacuation. *Systems*. **5**(4), p.53.

Jumadi, Heppenstall, A.J., Malleson, N.S., Carver, S.J., Quincey, D.J. and Manville, V.R. 2018. Modelling Individual Evacuation Decisions during Natural Disasters: A Case Study of Volcanic Crisis in Merapi, Indonesia. *Geosciences*. **8**(6), p.196.

Kelfoun, K., Legros, F. and Gourgaud, A. 2000. A statistical study of trees damaged by the 22 November 1994 eruption of Merapi volcano (Java, Indonesia): relationships between ash-cloud surges and block-and-ash flows. *Journal of Volcanology and Geothermal Research*. **100**(1), pp.379–393.

Kennedy, W.G. 2012. Modelling human behaviour in agent-based models *In*: *Agent-based models of geographical systems* [Online]. Berlin, Germany: Springer, pp.167–179. [Accessed 12 April 2017]. Available from: http://link.springer.com/chapter/10.1007/978-90-481-8927-4_9.

Labadie, N. and Prodhon, C. 2014. A Survey on Multi-criteria Analysis in Logistics: Focus on Vehicle Routing Problems *In*: *Applications of Multi-Criteria and Game Theory Approaches* [Online]. Springer, pp.3–29. [Accessed 20 May 2015]. Available from: http://link.springer.com/chapter/10.1007/978-1-4471-5295-8_1.

Lavigne, F., De Coster, B., Juvin, N., Flohic, F., Gaillard, J.-C., Texier, P., Morin, J. and Sartohadi, J. 2008. People’s behaviour in the face of volcanic hazards: Perspectives from Javanese communities, Indonesia. *Journal of Volcanology and Geothermal Research*. **172**(3–4), pp.273–287.

Lavigne, F. and Thouret, J.-C. 2003. Sediment transportation and deposition by rain-triggered lahars at Merapi Volcano, Central Java, Indonesia. *Geomorphology*. **49**(1–2), pp.45–69.

Letsie, M.M. and Grab, S.W. 2015. Assessment of Social Vulnerability to Natural Hazards in the Mountain Kingdom of Lesotho. *Mountain Research and Development*. **35**(2), pp.115–125.

Lim, M.B.B., Jr, H.R.L., Piantanakulchai, M. and Uy, F.A. 2015. A household-level flood evacuation decision model in Quezon City, Philippines. *Natural Hazards*. **80**(3), pp.1539–1561.

Lin, Y.-P., Chu, H.-J., Wu, C.-F., Chang, T.-K. and Chen, C.-Y. 2010. Hotspot Analysis of Spatial Environmental Pollutants Using Kernel Density Estimation and Geostatistical Techniques. *International Journal of Environmental Research and Public Health*. **8**(1), pp.75–88.

Lirer, L., Petrosino, P. and Alberico, I. 2010. Hazard and risk assessment in a complex multi-source volcanic area: the example of the Campania Region, Italy. *Bulletin of Volcanology*. **72**(4), pp.411–429.

Lummen, N.S. and Yamada, F. 2014. Implementation of an integrated vulnerability and risk assessment model. *Natural Hazards*. **73**(2), pp.1085–1117.

Malczewski, J. 1999. *GIS and multicriteria decision analysis*. John Wiley & Sons.

Malczewski, J. 2000. On the Use of Weighted Linear Combination Method in GIS: Common and Best Practice Approaches. *Transactions in GIS*. **4**(1), pp.5–22.
Malleson, N., See, L., Evans, A. and Heppenstall, A. 2014. Optimising an Agent-Based Model to Explore the Behaviour of Simulated Burglars *In*: V. Dabbaghian and V. K. Mago, eds. *Theories and Simulations of Complex Social Systems* [Online]. Berlin, Heidelberg: Springer Berlin Heidelberg, pp.179–204. [Accessed 23 April 2015]. Available from: http://link.springer.com/10.1007/978-3-642-39149-1_12.
Martins, V.N., Silva, D.S. e and Cabral, P. 2012. Social vulnerability assessment to seismic risk using multicriteria analysis: the case study of Vila Franca do Campo (São Miguel Island, Azores, Portugal). *Natural Hazards*. **62**(2), pp.385–404.
Mei, E.T.W., Lavigne, F., Picquout, A., de Bélizal, E., Brunstein, D., Grancher, D., Sartohadi, J., Cholik, N. and Vidal, C. 2013. Lessons learned from the 2010 evacuations at Merapi volcano. *Journal of Volcanology and Geothermal Research*. **261**, pp.348–365.
Merz, R., Blöschl, G. and Parajka, J. 2006. Spatio-temporal variability of event runoff coefficients. *Journal of Hydrology*. **331**(3), pp.591–604.
Minnesota Population Center 2015. Integrated Public Use Microdata Series, International: Version 6.4 [dataset].
Moeckel, R., Spiekermann, K. and Wegener, M. 2003. Creating a synthetic population *In*: *Proceedings of the 8th International Conference on Computers in Urban Planning and Urban Management (CUPUM)* [Online]., pp.1–18. [Accessed 27 February 2017]. Available from: http://www.spiekermann-wegener.com/pub/pdf/CUPUM_2003_Synpop.pdf.
Newhall, C. and Hoblitt, R. 2001. Constructing event trees for volcanic crises. *Bulletin of Volcanology*. **64**(1), pp.3–20.
Newhall, C.G. and Self, S. 1982. The volcanic explosivity index (VEI) an estimate of explosive magnitude for historical volcanism. *Journal of Geophysical Research*. **87**(C2), p.1231.
Pemkab Sleman 2010. Jumlah Korban Meninggal Bencana Erupsi Merapi per Tanggal 25 November 2010 mencapai 270 orang. [Accessed 1 July 2018]. Available from: http://www.webcitation.org/70aRtPVrc.
Pons, M., Johnson, P.A., Rosas, M. and Jover, E. 2014. A georeferenced agent-based model to analyze the climate change impacts on ski tourism at a regional scale. *International Journal of Geographical Information Science*. **28**(12), pp.2474–2494.
Rianto, T. 2009. *Spatial analysis of volcanic risk perception Case study in local community at Merapi volcano dangerous zones*.[Online] Master's Thesis, Enschede, Netherlands: ITC, University of Twente. [Accessed 6 March 2015]. Available from: http://www.itc.nl/library/papers_2009/msc/aes/rianto.pdf.
Robinson, E.J.H., Franks, N.R., Ellis, S., Okuda, S. and Marshall, J.A.R. 2011. A Simple Threshold Rule Is Sufficient to Explain Sophisticated Collective Decision-Making. *PLOS ONE*. **6**(5), p.e19981.
Saaty, T.L. 2008. Decision making with the analytic hierarchy process. *International journal of services sciences*. **1**(1), pp.83–98.
Saepuloh, A., Urai, M., Aisyah, N., Widiwijayanti, C., Jousset, P. and others 2013. Interpretation of ground surface changes prior to the 2010 large eruption of Merapi volcano using ALOS/PALSAR, ASTER TIR and gas emission data. *Journal of Volcanology and Geothermal Research*. **261**, pp.130–143.
Sar, N., Chatterjee, S. and Adhikari, M.D. 2015. Integrated remote sensing and GIS based spatial modelling through analytical hierarchy process (AHP) for water logging hazard, vulnerability and risk assessment in Keleghai river basin, India. *Modeling Earth Systems and Environment*. **1**(4), pp.1–21.
Scaini, C., Felpeto, A., Martí, J. and Carniel, R. 2014. A GIS-based methodology for the estimation of potential volcanic damage and its application to Tenerife Island, Spain. *Journal of Volcanology and Geothermal Research*. **278**–**279**, pp.40–58.
Schmidtlein, M.C., Deutsch, R.C., Piegorsch, W.W. and Cutter, S.L. 2008. A Sensitivity Analysis of the Social Vulnerability Index. *Risk Analysis*. **28**(4), pp.1099–1114.
Sengupta, R.R. and Bennett, D.A. 2003. Agent-based modelling environment for spatial decision support. *International Journal of Geographical Information Science*. **17**(2), pp.157–180.

Srbljinović, A. and Škunca, O. 2003. An Introduction to Agent Based Modelling and Simulation of Social Processes. *Interdisciplinary Description of Complex Systems*. **1**(1–2), pp.1–8.

Surono, Jousset, P., Pallister, J., Boichu, M., Buongiorno, M.F., Budisantoso, A., Costa, F., Andreastuti, S., Prata, F., Schneider, D., Clarisse, L., Humaida, H., Sumarti, S., Bignami, C., Griswold, J., Carn, S., Oppenheimer, C. and Lavigne, F. 2012. The 2010 explosive eruption of Java's Merapi volcano—A '100-year' event. *Journal of Volcanology and Geothermal Research*. **241**–**242**, pp.121–135.

Tapsell, S., McCarthy, S., Faulkner, H. and Alexander, M. 2010. Social vulnerability to natural hazards. *State of the art report from CapHaz-Net's WP4. London*.

Thakali, L., Kwon, T.J. and Fu, L. 2015. Identification of crash hotspots using kernel density estimation and kriging methods: a comparison. *Journal of Modern Transportation*. **23**(2), pp.93–106.

Thouret, J.-C., Lavigne, F., Kelfoun, K. and Bronto, S. 2000. Toward a revised hazard assessment at Merapi volcano, Central Java. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.479–502.

UNISDR 2004. *Living with risk: A global review of disaster reduction initiatives*. United Nations International Strategy for disaster Reduction, Geneva, Switzerland.

Voogd, J.H. 1982. Multicriteria evaluation for urban and regional planning.

Yan, K., Di Baldassarre, G., Solomatine, D.P. and Schumann, G.J.-P. 2015. A review of low-cost space-borne data for flood modelling: topography, flood extent and water level: A Review of Low-Cost Space-Borne Data for Flood Modelling. *Hydrological Processes*. **29**(15), pp.3368–3387.

Yoon, D.K. 2012. Assessment of social vulnerability to natural disasters: a comparative study. *Natural Hazards*. **63**(2), pp.823–843.

Chapter 5
An agent-based Evaluation of Varying Evacuation Scenarios in Merapi: Simultaneous and Staged

Submitted to Computers, Environment and Urban Systems: Jumadi, Carver, S., and Quincey, D. An agent-based evaluation of varying evacuation scenarios in Merapi: simultaneous and staged.

This chapter used the ABM from Chapter 4 to evaluate the relative effectiveness of two evacuation strategies namely simultaneous and staged. The simultaneous strategy model assumes that all populations are commanded to evacuate at the same time, while staged strategy model assumes that the populations are clustered into several zones and commanded sequentially based on certain priority. A method of prioritisation (staging) is proposed and implemented in this chapter. The results of both strategies are then evaluated and compared based on the ability to minimise the traffic congestion and the ability to reduce the risk.

Abstract: Mass evacuation should be conducted when a disaster threatens within a regional scale. It is reported that 400,000 people were evacuated during the last eruption of Mt. Merapi in 2010. Such a large-scale evacuation can lead to chaos or congestion, unless well managed. Staged evacuation has been investigated as a solution to reducing the degree of chaos during evacuation processes. However, there is a limited conception of how the stages should be ordered in terms of which group should move first and which group should follow. This paper proposes to develop evacuation stage ordering based on the geographical character of the people at risk and examine the ordering scenarios through an agent-based model of evacuation. We use several geographical features, such as proximity to the hazard, road network conditions (accessibility), size of the population and demographics as the parameters for ranking the order of each population unit in GIS. From this concept, we produced several scenarios of ranking based on different weightings of the parameters. We applied the scenarios in an agent-based model of volcanic evacuation experiment to observe the results. Afterwards, the results were evaluated based on the ability to reduce the risk and spatio-temporal traffic density along road networks compared to the result of simultaneous evacuation to establish the relative effectiveness of the outcome. The results show that the staged scenario has a better ability to reduce the potential traffic congestion during the peak time of the evacuation compared to the simultaneous strategy. However, the simulations of simultaneous strategy has better performance regarding the speed of reducing the risk. An evaluation of the relative performance of the four varying staged scenarios is also presented and discussed in this paper.

Keywords: Agent-based Model, GIS, Merapi, staged evacuation, simultaneous evacuation, evacuation management, simulation.

5.1 Introduction

The human population growth and distribution changes on earth increase the occurance of natural disasters over time (Shahabi and Wilson, 2018). Natural disasters occur worldwide but have a greater impact on developing countries, especially Indonesia. These disasters occur when geophysical events, such as earthquakes, volcanic eruptions, landslides and floods, threaten human life (Alcántara-Ayala, 2002). The impact of natural disasters is increasing in present years due to the increasing size of the population in the hazard-prone areas (Beck, 2009). Indonesia is one of the countries that is prone to suffering natural hazards, especially volcanic eruptions (Siagian et al., 2013). Indonesia is also one of the most volcanically active countries, with over 130 volcanoes and some of the most densely populated areas in the world (Voight, Sukhyar, et al., 2000; Thouret et al., 2000; Mehta et al., 2015). This combination of both physical and social factors has led to Indonesia suffering the greatest number of fatalities due to eruptions (Alcántara-Ayala, 2002; GVP, 2017). Merapi, in central Java, is one of the most dangerous volcanoes in Indonesia because of its frequent activity, location in a densely populated area, and proximity to the city of Yogyakarta (Mei et al., 2011; Mei et al., 2013; Sadono et al., 2017). More than a million people live in this city, and 400,000 people are at particular risk (Mei et al., 2011; Mei et al., 2013).

Mass evacuations should be conducted when a volcanic crisis threatens the surrounding areas and demands effective management. Over 400,000 people were evacuated in the last eruption of 2010. Various problems arose following this mass mobilisation, and it can lead particularly to congestion and excessive delays unless well managed (Sbayti and Mahmassani, 2006). These conditions not only decrease the effectiveness of evacuations in minimising the risk but also lead to secondary fatalities, such as fatal accidents (Rizvi et al., 2007). Providing a well-tested evacuation plan is one of the ways to increase the effectiveness of evacuations in terms of saving lives (Pidd et al., 1996). It is necessary to evaluate the evacuation plan based on the population's behavior, in order to test the plan. As the goal of the plan is to save human lives from the volcano's impact, the effectiveness of the plan is measured by its ability to achieve this goal.

Two major evacuation plans are commonly applied; namely, staged and simultaneous evacuation (Chien and Korikanthimath, 2007). In simultaneous plans, all of the residents on the affected area are evacuated simultaneously, while a staged strategy divides the affected area into zones and organizes the evacuation of residents in each zone in a sequence (Chen and Zhan, 2008). The simultaneous strategy has been applied widely but examples of the staged strategy remain limited. A well-documented staged evacuation was that in New Orleans in response to Hurricane Katrina in 2005 (Wolshon, 2006). Staged evacuation has been investigated as a potential solution to reducing the time required for evacuation processes when the road network is incapacitated (Chen and Zhan, 2008).

Studies exist on developing methods for a staged evacuation strategy, including scheduling the start time for the evacuation of each group using a mathematical approach (Li et al., 2012), defining the evacuation time and delay time using a mathematical approach (Chien and Korikanthimath, 2007), identifying the priority ranking using a heuristic approach (Mitchell and Radwan, 2006), and defining the evacuation zones using a clustering approach (Lim et al., 2016). However, there exists limited knowledge regarding how the sequential ordering of the evacuation measures should be managed, i.e. how to prioritise which zone should be evacuated first and which should follow. Moreover, evaluation of the effect of evacuation staging on reducing disaster risk is absent from the literature.

This paper proposed to develop evacuation stage ordering based on the geographical character of the people at risk and examine the scenarios within the agent-based model of evacuation. We use several parameters modified from Mitchell and Radwan (2006), such as proximity to the hazard, the accessibility of shelters, and population density as the parameters for ranking the order of each population unit in GIS. Based on this concept, we produced several ranking scenarios based on different weightings of the parameters. We use the scenarios in the agent-based model of volcanic evacuation experiment to observe the results. Afterwards, the results were evaluated based on the ability to reduce risk and spatio-temporal traffic density along road networks compared to the result of simultaneous evacuation in providing the relative effectiveness of the outcome. The details about the method are provided in the following section. Subsequently, the results and discussion are provided in the third section and, finally, the conclusion is presented in the fourth section.

5.2 Materials and Method

We used an agent-based experiment to examine the “what if” scenarios of evacuation staging produced by Spatial Multi-criteria Evaluation (SMCE) in GIS (Figure 5.1). The results of these scenarios were compared against simultaneous scenarios to evaluate: (1) whether staged evacuation is more effective than simultaneous evacuation, and (2) the importance of the ranking of the criteria in planning the zonal order. Pairwise comparison analysis (AHP) (Saaty, 2008) was used to rank the criteria. Afterwards, a weighted linear combination (WLC) (Eastman, 1999; Malczewski, 2000) was used to analyse the population unit spatially to produce the evacuation sequence in GIS, where the sequence results are used to set the agent-based model (ABM) that was previously developed (Jumadi et al., 2017; Jumadi et al., 2018; Jumadi et al., n.d.), whereby a detailed framework is provided in (Jumadi et al., 2017), the individual evacuation decision concept in (Jumadi et al., 2018), and the spatio-temporal dynamics of the risk model in (Jumadi et al., n.d.). For the experimentation, we used Merapi as a case study of evacuation during a volcanic crisis. This section provides (1) an overview of the study area, (2) a technique for developing the zonal ranking to short the evacuation sequence in the staged evacuation scenario, (3) the agent-based model used to evaluate the scenarios, (4) the implementation of the scenarios in the ABM experiment to examine them, and (5) an approach to evaluating the effectiveness of each scenario.

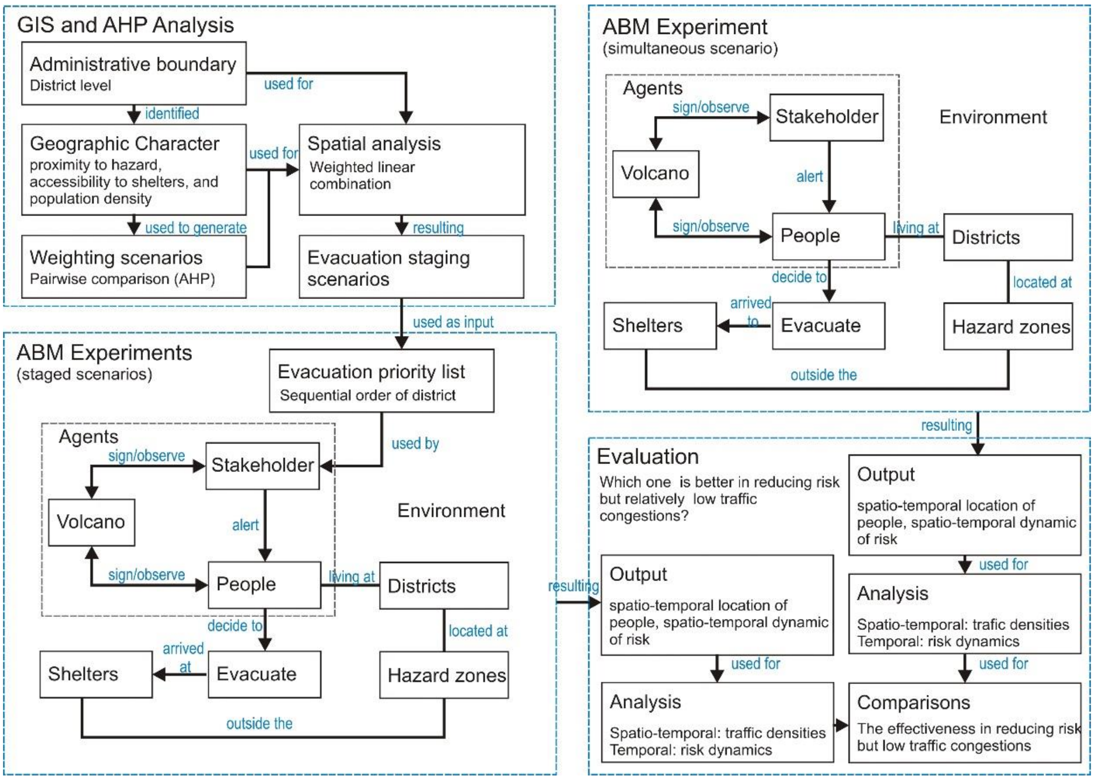

Figure 5.1 The general framework.

5.2.1 Study Area

Merapi Volcano is located in Indonesia, in the central part of Java Island. Geographically, Merapi is located across four districts of two provinces namely Sleman (Yogyakarta), Magelang, Boyolali and Klaten district (Central Java). More precisely, it is located at 7° 32' 30" latitude and 110° 26' 30" longitude. In this study, we only use the Sleman area, that is located on the southern flank of Merapi (Figure 5.2). It is geographically located between 107° 15 '03 "and 107° 29 '30" longitude, 7° 34' 51" and 7° 47' 30" latitude. Sleman covers 57,482 hectares or 574.82 km^2 (about 18% of Yogyakarta Province). Administratively, this region consists of 17 districts, 86 villages and 1,212 hamlets.

The latest eruption occurred in 2010 and was said by the authorities to have been the largest since the 1870s. The eruption began in late October 2010 and continued into November 2010. During this period, the activity of Merapi culminated in numerous pyroclastic flows down to the populated area on the lower slope. Almost 50,000 people were located in the high risk area. Moreover, 367 of these people lost their life, 277 were injured, and 410,388 were displaced (Surono et al., 2012). After the eruption, Merapi lahars can remain a potential threat to the surrounding communities for at least three years. This threat not only damaged hundreds of settlements but also bridges, tourism sites, irrigation channels and agricultural land. Accordingly, the National Agency for Disaster Management (BNPB) published a map of the vulnerable area of Merapi due to the neighbouring volcano (Figure 5.2). It can be seen that the vulnerable area spread down from the summit into the settlement areas.

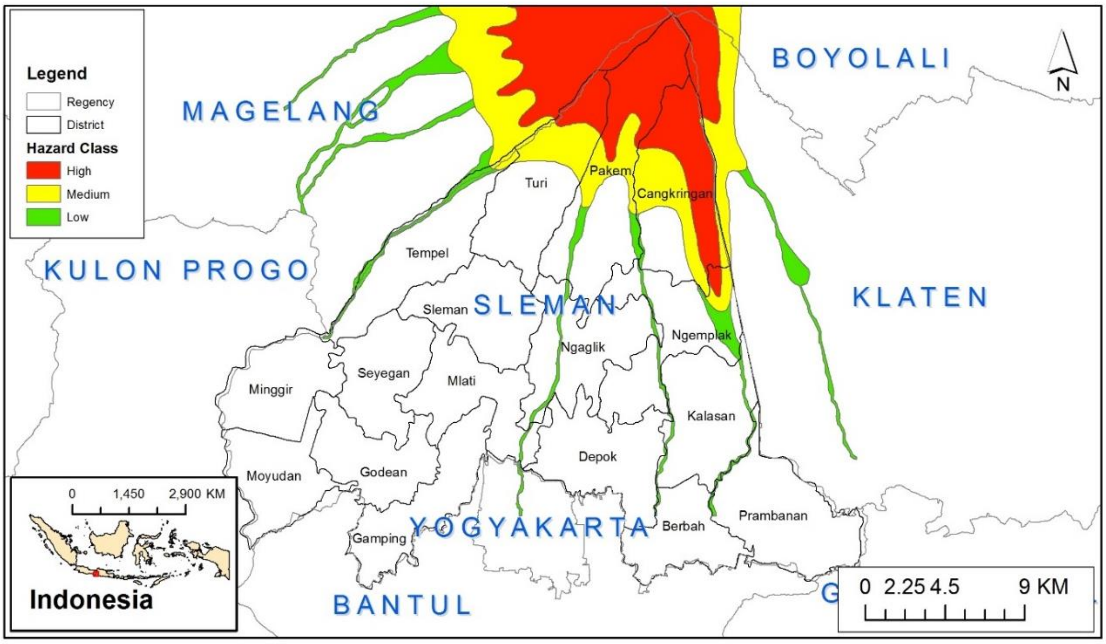

Figure 5.2 The hazard zones of Merapi volcano and Sleman area. Source: BNPB, 2011.

There are two potential hazards, namely *nuées ardentes* and lahars, that usually kill people. *Nuées ardentes* are produced by occasional gravitational collapses (Voight et al., 2000), and deposits can travel up to 3.5 km from only a few individual events (Abdurachman et al., 2000). They can be triggered by gravitational dome collapse, the extent of the impacts of which are commonly controlled by topographical factors (Kelfoun et al., 2000). On the other hand, lahars are usually initiated by intense rainfall (Lavigne and Thouret, 2003). Lahars are an overbank pyroclastic coupled with rainwater flow, which is considered the most dangerous part of the material flow system in Merapi (Charbonnier and Gertisser, 2008). The direction of this flow is strongly influenced by the initial flow direction and the topography that affect the spatial extent of the hazard afterwards (Itoh et al., 2000). This kind of disaster is prone to occur in Merapi (Lavigne et al., 2011) and potentially posed the major risk after the 2010 eruption (de Bélizal et al., 2013). In particular, the abundance of pyroclastic deposits on the slope lead to occurrences of lahars flooding during rainstorms.

5.2.2 Zones Ranking for Evacuation Staging

A staged evacuation strategy needs scenarios of leaving sequences among the evacuation zones. The sequence for which zone should be evacuated first and which later requires careful prioritisation. There are some aspects to consider when setting these priorities. Mitchell and Radwan (2006) used population density, roadway exit capacity, distance to safety or shelter, distance to major evacuation routes, and number of other regions or level of population density to transit. Conversely, Lim et al. (2012) used the distance of regions from the hazard, the hazard extent and the population density, while Alaeddine et al. (2015) used similar factors to Lim et al. (2012), with the additional factor of the age of the population. Based on the previous studies, we developed a method for building a sequence of evacuation staging using a spatial approach. We used this approach since evacuation is a geographically-related problem; therefore, decisions based on spatial data will provide better results. We used a pairwise comparison to rank and order the evacuation zones into a sequence in GIS. Several aspects were used to develop the priority ranking, modified from Lim et al. (2012) and Alaeddine et al. (2015). Here, we used three slightly different factors; namely, distance of the region from the hazard (the volcano’s crater), population density, accessibility to shelter and the proportion of those of vulnerable age. The various evacuation staging scenarios that which will be evaluated using an agent-based experiment are provided in Section 5.2.3.

5.2.2.1 Evacuation Zones and Spatial Characteristics

The administrative boundary of the district level (Figure 5.2) will be used as the unit of the zones of the group since the evacuation command will be organized mainly by the local government (Mei and Lavigne, 2012). There are five districts located in the main hazard zones of Merapi – Tempel, Turi, Pakem, Cangkringan and Ngempak (see Figure 5.2) – while districts at minor risk were excluded from the plan. The characteristics of each zone were identified to map the criteria used to design the staging. The data used to obtain the criteria included administrative boundaries, hazard zones (BNPB, 2011), 2010 evacuation distribution data (BNPB, 2010c; BNPB, 2010a; BNPB, 2010d; BNPB, 2010b) and population data (each age category) (Local Government of DIY, n.d.). All of the data were analysed and mapped to each zone (district) to establish the criteria.

The criteria used to analyse the zones’ ranking consisted of four spatial datasets (Figure 5.3), including: (1) Proximity to the hazard (PH), provided by calculating the distance between the centroid of each zone and the volcano (summit); (2) Population density (PD), provided by dividing the area of the zone by the population size within the zone; (3) Accessibility to shelter (AS), analysed using the Hansen Index (Hansen, 1959; Morris et al., 1979) provided in Equation 5.1, where A_i is the accessibility index for zone *i* to shelters (*S*), *Sj* is the capacity of shelter *j*, T_{ij} is the distance from zone *i* to shelter *j* (see https://goo.gl/RhKaSa for a detailed calculation); and (4) the proportion of population of vulnerable age (VA), based on the proportion of children (<15) and elderly people (>75).

$$A_i = \sum_{j=1}^{n} \frac{S_j}{T_{ij}} \quad \text{.......} \quad (5.1)$$

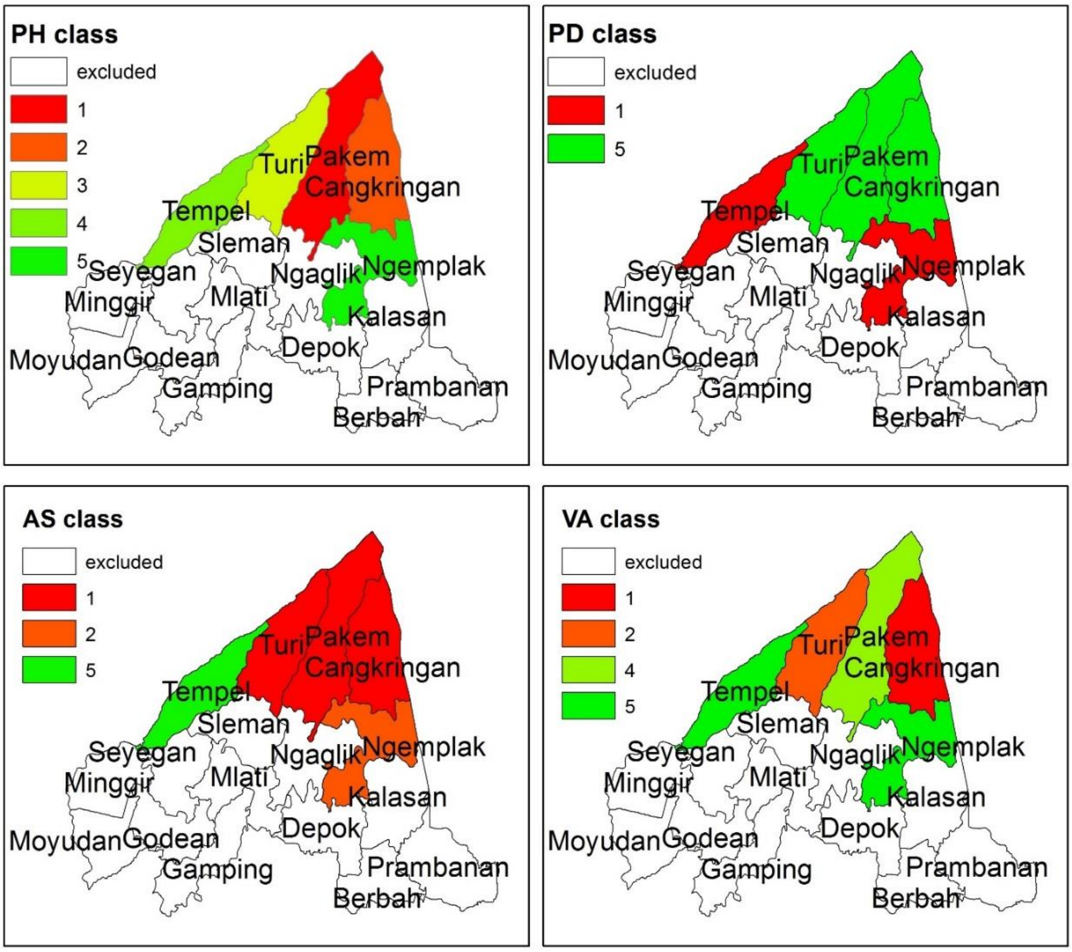

Figure 5.3 Spatial data for the zone ranking.

5.2.2.2 "What if" Scenarios Development using Pairwise Comparison Analysis

All of the datasets provided above (Section 5.2.2.1) were then analysed to design the staging scenarios using pairwise comparison analysis (Table 5.1 and 5.2). Since there has been little research on which factors are more important than others when designing the ordering, we used what if scenarios to examine all possible scenarios and select the most effective composition. Each scenario varied due to assigning the weight of each criterion depending on the importance scale (Table 5.2). The scenarios were designed to give all of the criterion a chance to be the most, medium or least. The final score for each district is calculated using WLC (Equation 5.2), after which the results are ordered to obtain the ranking.

Table 5.1 Criteria and attributes value for the priority design.

Criterion	Class	Description	Priority	I
PH	Very high	Very high priority to evacuate	1	0.503
	High	High priority to evacuate	2	0.260
	Medium	Moderate priority to evacuate	3	0.134
	Low	Slightly less priority to evacuate	4	0.068
	Very low	Less priority to evacuate	5	0.035
PD	Very high	Very high priority to evacuate	1	0.503
	High	High priority to evacuate	2	0.260
	Medium	Moderate priority to evacuate	3	0.134
	Low	Slightly less priority to evacuate	4	0.068
	Very low	Less priority to evacuate	5	0.035
AS	Very low	Very high priority to evacuate	1	0.503
	Low	High priority to evacuate	2	0.260
	Medium	Moderate priority to evacuate	3	0.134
	High	Slightly less priority to evacuate	4	0.068
	Very high	Less priority to evacuate	5	0.035

Table 5.1 Continued …

	Very low	Very high priority to evacuate	1	0.503
	Low	High priority to evacuate	2	0.260
VA	Medium	Moderate priority to evacuate	3	0.134
	High	Slightly less priority to evacuate	4	0.068
	Very high	Less priority to evacuate	5	0.035

Remark: I = priority index (see the complete calculation of the index: https://goo.gl/vZnLFm)

Table 5.2 "What if" weighting scenarios' criteria.

Criterion	Staged 1		Staged 2		Staged 3		Staged 4	
	R	**W**	**R**	**W**	**R**	**W**	**R**	**W**
PH	1	0.558	4	0.057	3	0.122	2	0.263
PD	2	0.263	1	0.558	4	0.057	3	0.122
AS	3	0.122	2	0.263	1	0.558	4	0.057
VA	4	0.057	3	0.122	2	0.263	1	0.558

Remarks: R = importance rank, W = weight (see the complete calculation: https://goo.gl/euDcNA)

$$Score = \sum_{i=1}^{n} I_i * W_i \quad (5.2)$$

5.2.2.3 Staging Scenarios

A staging strategy is needed during a mass evacuation when the transportation network is unable to accommodate the whole population at the same time (Alaeddine et al., 2015). Therefore, a priority list is required to establish an affective evacuation staging scheme when scheduling the evacuation (Mitchell and Radwan, 2006). We provide the staging scenarios based on the scoring approach of the zone characteristics (Section 5.2.2.2). Based on an analysis of the datasets using WLC, a distinct sequential order for each scenario was created, based on the degree of priority (Table 4 and Figure 4). The prioritisation result shows that each zone is assigned a different priority rating for each scenario. Only one of the scenarios has the full five stages, while three have four stages, since two zones have the same score.

Table 5.3 Staging scenarios calculation and ranking.

District	Staged 1		Staged 2		Staged 3		Staged 4	
	Score	**Priority rank**	**Score**	**Priority rank**	**Score**	**Priority rank**	**Score**	**Priority rank**
Ngemplak	0.30	1	0.07	5	0.11	3	0.16	2
Tempel	0.30	1	0.08	4	0.09	4	0.16	2
Pakem	0.22	2	0.42	1	0.33	2	0.14	3
Turi	0.12	4	0.23	3	0.33	2	0.13	4
Cangkringan	0.18	3	0.34	2	0.43	1	0.35	1

The attributes data are provided at https://goo.gl/Ek9aWS.

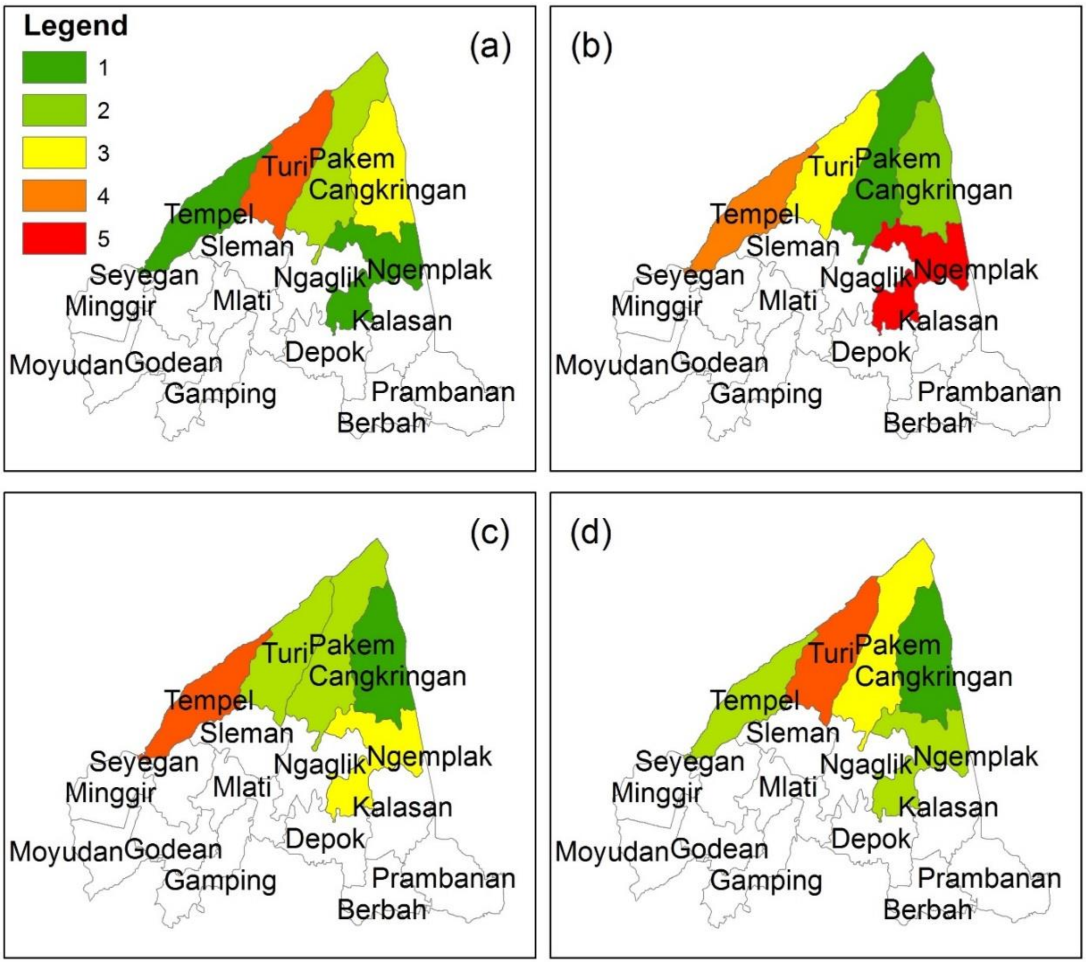

Figure 5.4 Staging scenarios map. (a) scenario 1, (b) scenario 2, (c) scenario 3, (d) scenario 4.

5.2.2.4 Time Interval between the Stages

The time interval is required to be set at the optimum value. This should be as low as possible but sufficient for the population within a zone to reach a major road network. It is assumed that, after reaching the major road, the traffic can run smoothly. To provide the values for the time intervals, we analysed the average time that people required to reach the major exit points using Google Maps Distance Matrix API. To provide the averages, we used the centroid of the population areas (districts) and found the minimum travel times from the grids to the exit points (Figure 5.5). The average of all of the travel times from the districts to reach the surrounding major exit points was used as the time interval between the stages (Table 5.5).

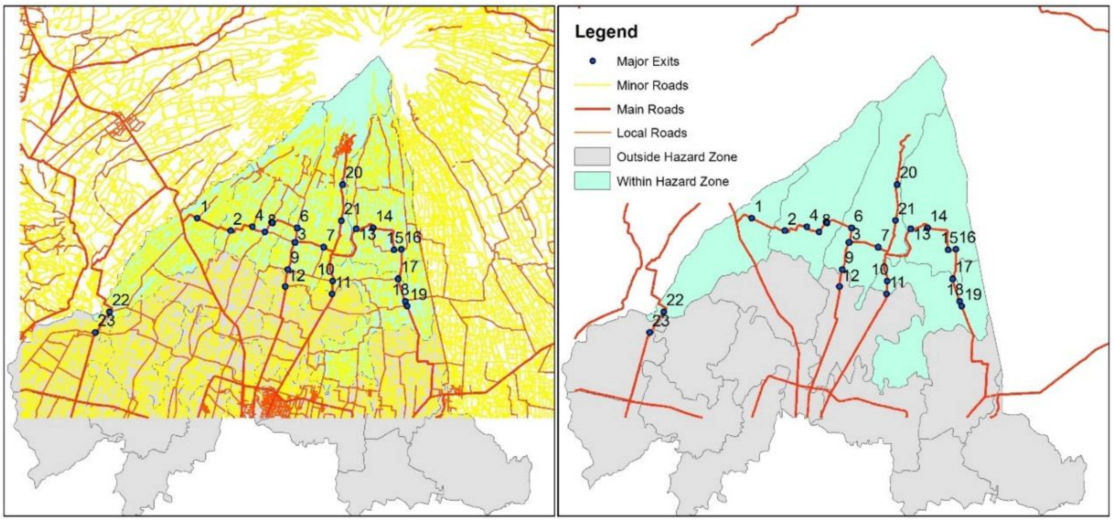

Figure 5.5 Population at risk's origin and the major exits for calculating the average travel time to reach the major evacuation routes.

Table 5.4 Time intervals between the stages.

No	District	Average travel time to reach a major road (in minutes)	Source
1.	Cangkringan	23.5	https://goo.gl/UWbZnY
2.	Ngemplak	24.5	https://goo.gl/M7RQe6
3.	Pakem	21.9	https://goo.gl/qqDvyL
4.	Tempel	28.2	https://goo.gl/59Xnb9
5.	Turi	20.9	https://goo.gl/BHppxA
Average (time interval)		23.8	

5.2.3 The Agent-based Volcanic Evacuation Model

The simulation used an agent-based volcanic evacuation model that was provided elsewhere (Jumadi et al., 2017; Jumadi et al., 2018; Jumadi et al., n.d.). Overall, the framework of this model consists of three main agents; namely, the volcano, stakeholders, and people (population) who interact within the geographical environment (Jumadi et al., 2017). The volcano acts as an agent which initiates the hazardous situation and influences the environment by posing a potential threat to the surrounding population. The other agents in the interactions are the stakeholders and the population (people). The stakeholders, in this case, the authorities (government), play a significant role in observing and analysing the activities of the volcano and issuing warnings to the population, where the human agent (population) is assigned an evacuation decision rule.This evacution decision is based on the Normal – Investigating – Evacuating state model, that is provided elsewhere (Jumadi et al., 2018). In the ABM simulation, each agent displays a specific behaviour and mechanisms when interacting with others as well as with the environment. The environment is represented through spatial data with dynamic hazard properties. Meanwhile, the risk to individuals, that is used as the main evaluation of evacuation effectiveness in this paper, is evaluated based on the hazard and vulnerability variables (Jumadi et al., n.d.). The hazard level is measured by the environment properties at the agent’s location, whereas the vulnerability of individuals is based on SoVI, that is calculated according to socio-demographic factors. The following sub-section describes this risk model in detail. The risk of the individual might change after the decision and movement are made, as his/her location changes. When people make a movement due to the evacuation process, the level of hazard of their environment changes, as does their degree of risk. Therefore, the value of their risk is dynamic over time as an individual moves.

5.2.4 Applying the Staging Strategy in the Agent-based Experiment

The previously developed agent-based evacuation model (Jumadi et al., n.d.) was used to design the experiment. There is no significant change with regard to the simultaneous scenario (Figure 6a). While the alerting rule of the stakeholder agent was modified for the staged scenario (Figure 6b), iterative alerting was used to alert the population agents in the districts on the list sequentially based on the provided order (Section 5.2.2.4). The interval between the alerts is based on the optimal value provided by the sensitivity analysis (Section 5.2.5).

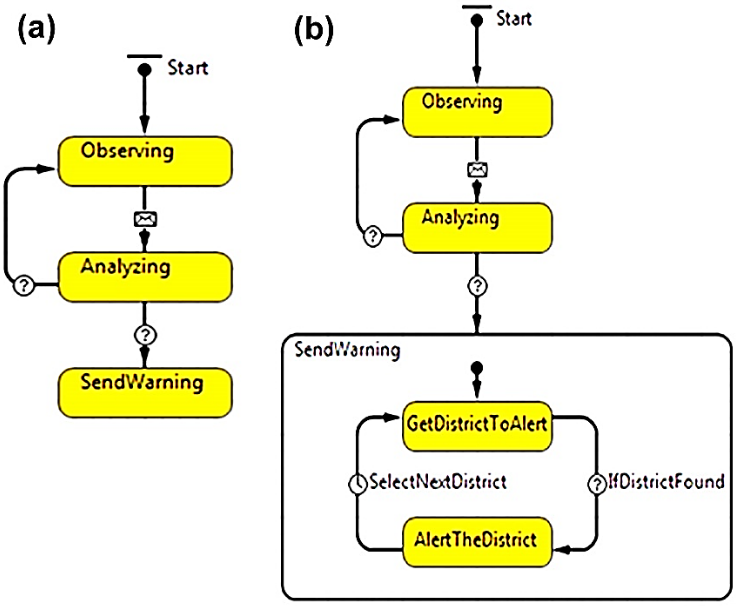

Figure 5.6 Alerting rule, (a) simultaneous scenarios, (b) staged scenarios.

5.2.5 Effectiveness Measures, Analysis, Comparison, and Evaluation

Three measurements were used to make comparisons between the scenarios, including the temporal and spatial distribution of evacuees on the road and the effectiveness in reducing the risk. The temporal distribution was expressed as a percentage of the evacuees on the road (evacuating) over time. The peak time of the evacuation, where the percentage was at a maximum, was used to compare all of the scenarios. Meanwhile, the spatial distribution was based on the relative density of the evacuees on the road. Figure 7 provides a flowchart of the spatial analysis to illustrate the relative density. The relative density at the peak time of evacuation, as identified by the percentage, is used to compare the outcome of all scenarios. To promote the effectiveness of the risk reduction, the graph showing the temporal distribution of the people at risk is used for the comparison. We focus on the high and medium-risk group for this comparison. The risk reduction ability is measured based on the time needed to clear people at risk (Jumadi et al., n.d.). The comparison is not only between a simultaneous and a staged strategy but also among staged-scenarios' output to select the most effective staging scenarios.

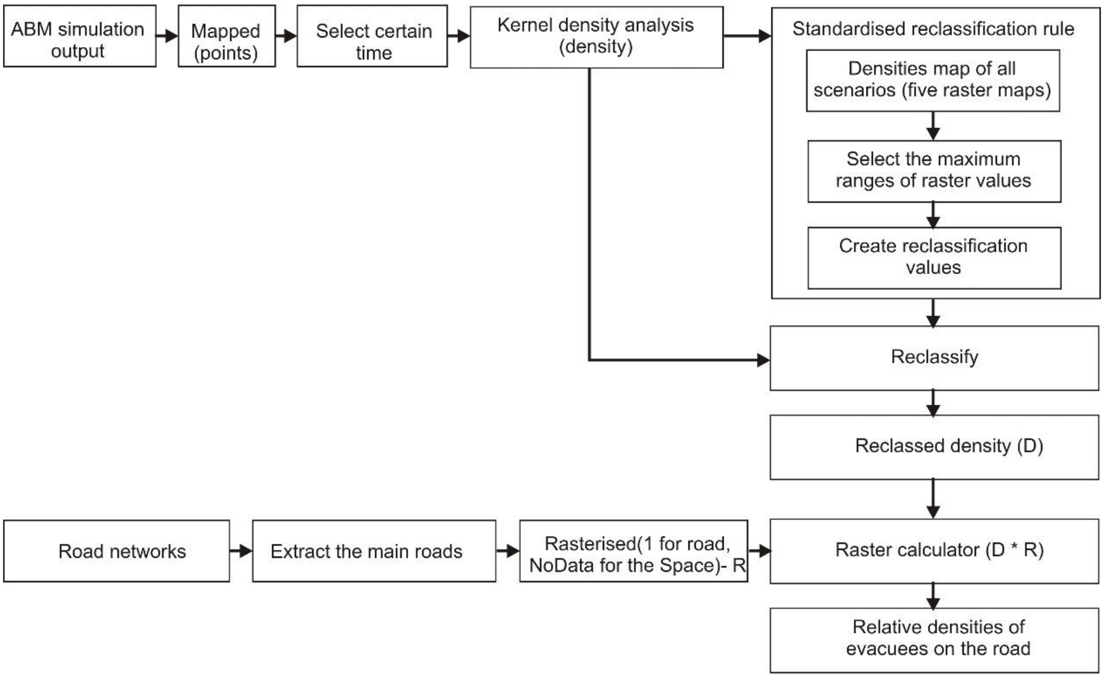

Figure 5.7 Relative density analysis of the evacuees' traffic.

5.3 Results and Discussion

5.3.1 Overview of the Simulations Run

The simulations were run over 102 days of a volcanic crisis length of VEI (volcanic explosivity index) 4 and the activities phases following the 2010 eruption. These parameters affected the spatio-temporal configuration of the simulation (Jumadi et al., 2017; Jumadi et al., 2018). A brief overview of the simulations run for all scenarios is provided in Figure 5.8. This figure shows that the evacuation peak times occurred between 30% and 35% of the crisis length, when the volcanic activity reaches a peak. A small percentage of evacuees were evacuated during the early and medium level of volcanic activity (before the peak evacuation time) and also at the explosion time (after the peak of the evacuation time). The maximum percentage of the evacuees on the road (Figure 5.8b) exceeded 27% at the peak evacuation time under the simultaneous evacuation strategy. The result of each scenario presented in this paper is averaged from several results of simulation runs.

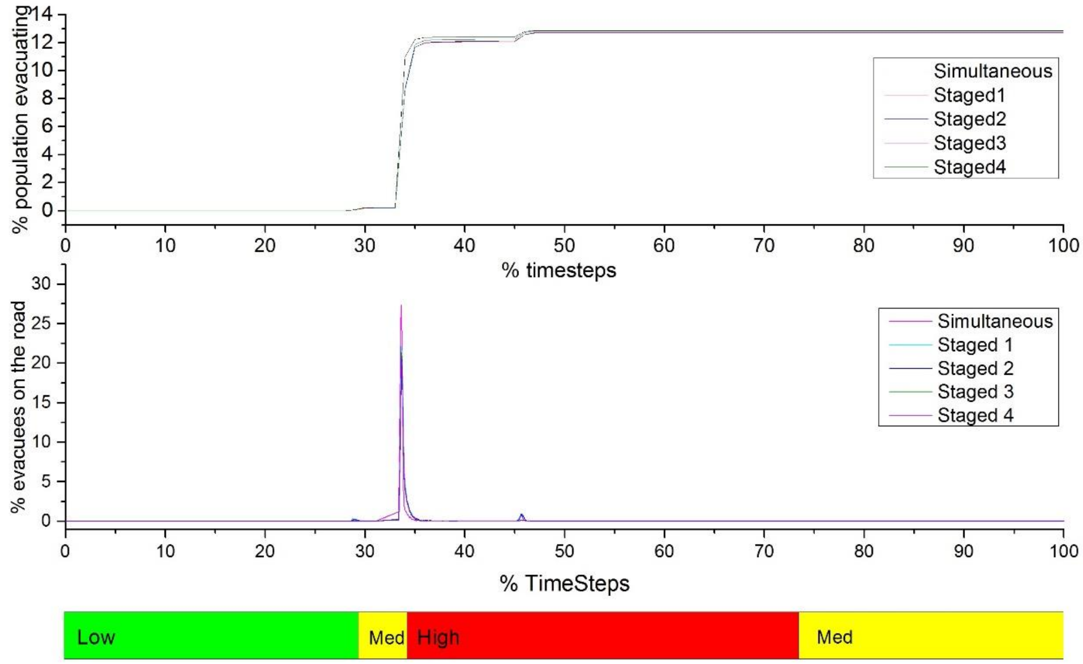

Figure 5.8 Overview of the simulations run for all scenarios. (a) the temporal accumulation of the evacuees (% of population), (b) the temporal distribution of the evacuees on the road (% of evacuees), (c) volcanic crisis phases setup.

5.3.2 Spatial and Temporal Distribution of Evacuees on the Road

Agent-based model may be used in simulating the spatial distribution of traffic as a result of human behaviour (Manley and Cheng, 2018). This ability is employed in this research to evaluate the effectiveness of implementation of the staged evacuation strategy. The evaluation is not only based on the spatial distribution but also based on the percentage of evacuees distributed on the road at the peak time of evacuation. Based on the simulation results as presented in Figure 5.8, we highlighted the peak time of the evacuation (Figure 5.9). It is clear that there are different percentages of evacuees on the road at the peak time of the evacuation in the simultaneous scenario and staged scenario, respectively. The staged scenario has about 23% fewer evacuees at the peak time of evacuation compared to the simultaneous scenario. This relative effectiveness of the staged scenario in reducing evacuee traffic compared to the simultaneous scenario is also proved by the spatial density distribution of evacuees at the peak time (Figure 5.10). Figure 5.10 shows that the simultaneous scenario produces relatively higher traffic density at two major roads; namely, Kaliurang Road and Palagan Tentara Pelajar Road (Figure 5.10a). On the other hand, the staged scenario highlighted that mainly Kaliurang Road is congested, but has a smaller density compared to the simultaneous scenario (Figure 5.10b – e).

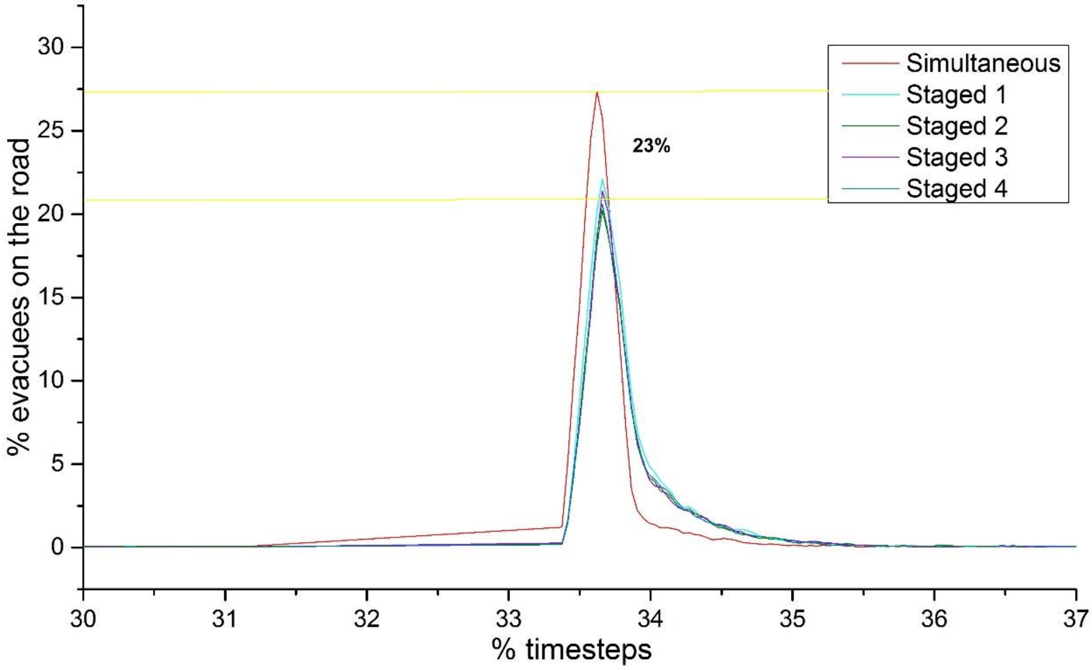

Figure 5.9 Comparison of the percentage of evacuees on the road during the peak evacuation time.

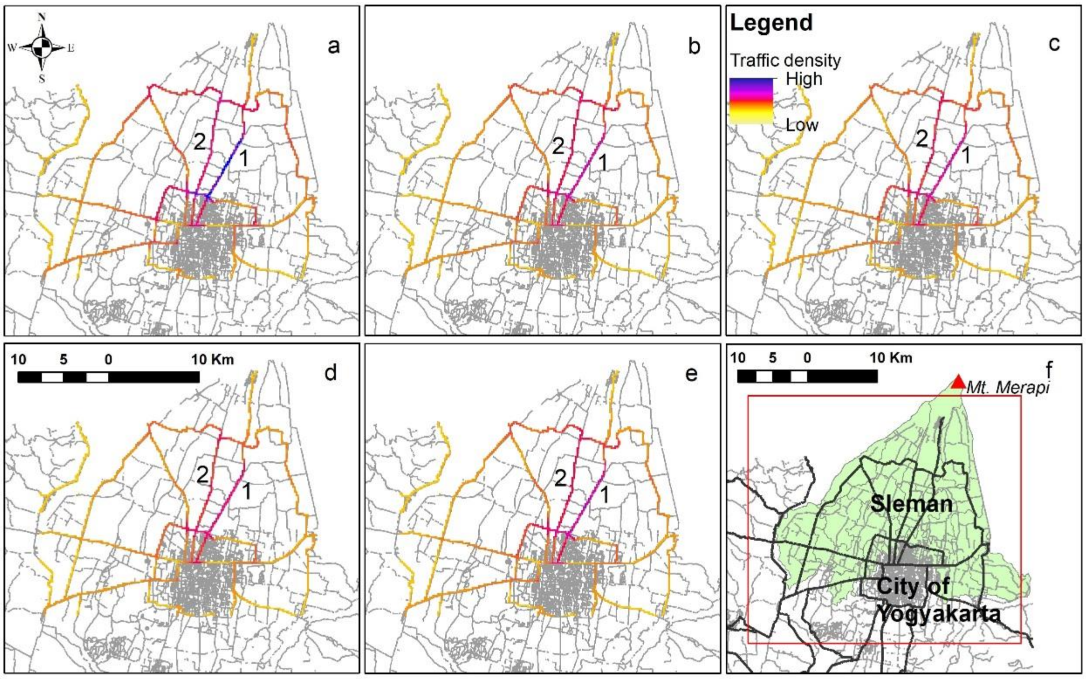

Figure 5.10 Relative densities of evacuee traffic on the road at the peak evacuation time. (a) simultaneous, (b) staged 1, (c) staged 2, (d) staged 3, (e) staged 4 scenario, and (f) inset map. Road name: (1) Kaliurang road, (2) Palagan tentara pelajar road.

5.3.3 Efficiency in Reducing the Risk

Figure 5.11 presents graphs showing how the evacuation reduces the number of people at risk (%) temporally. The variation in the percentages of the at risk group (high-risk and medium-risk group) in these graphs is caused by the random nature of the ABM. These graphs show that there is no significant difference between the speed of reducing the risk among the staged scenarios (Figure 5.11b – e), but the simultaneous strategy (Figure 5.11a) has the best performance of all. The percentage of risk group of both high and medium groups never reaches the same number with the staged strategy, because the population within the hazard zone is evacuating directly at the same time.

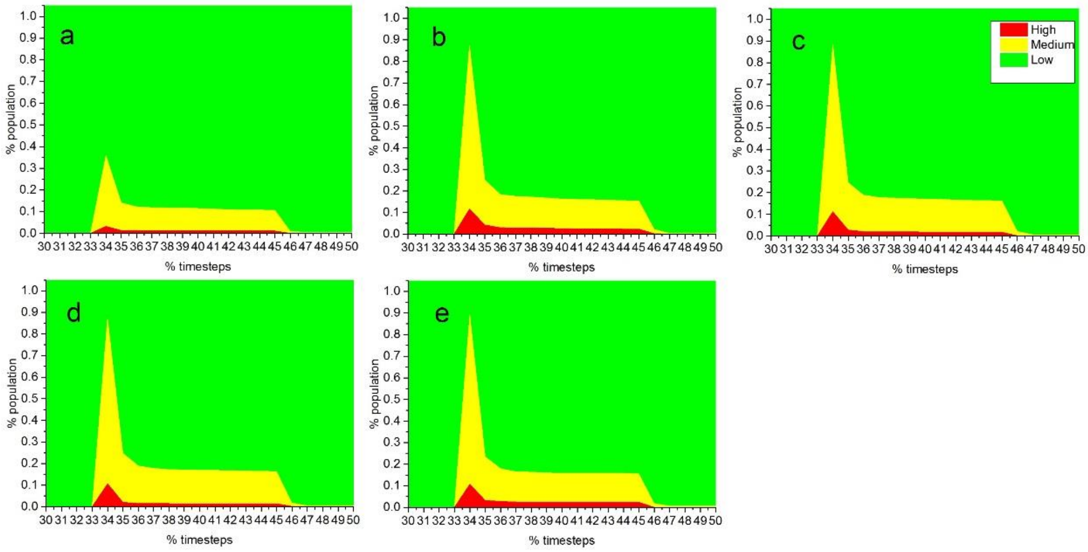

Figure 5.11 Risk reduction comparison. (a) simultaneous, (b) staged 1, (c) staged 2, (d) staged 3, (e) staged 4 scenarios.

5.3.4 Evaluating the Performance of the Staged Scenarios

Among the four scenarios for staged evacuation (see Section 5.2.2.4), the second scenario (Staged 2) performs best in reducing the percentage of evacuees (potential traffic congestion) on the road during the peak time of the evacuation (Figure 5.12). This scenario sets the population density (PD) as the most important criterion in developing the prioritisation, followed by accessibility to shelter (AS), proportion of people of vulnerable age (VA), and proximity to the hazard (PH), respectively. However, in terms of the evacuees distribution on the road at that time, the third staged scenario, which places accessibility to shelter (AS) as the most important criterion, followed by the proportion of people of vulnerable age (VA), population density (PD), and proximity to the hazard (PH), performs best in terms of reducing traffic density, as identified from the spatial distribution of the traffic density (see Figure 5.10d). Meanwhile, the first staged scenario (Staged 1) performs worst in terms of reducing the potential for traffic congestion.

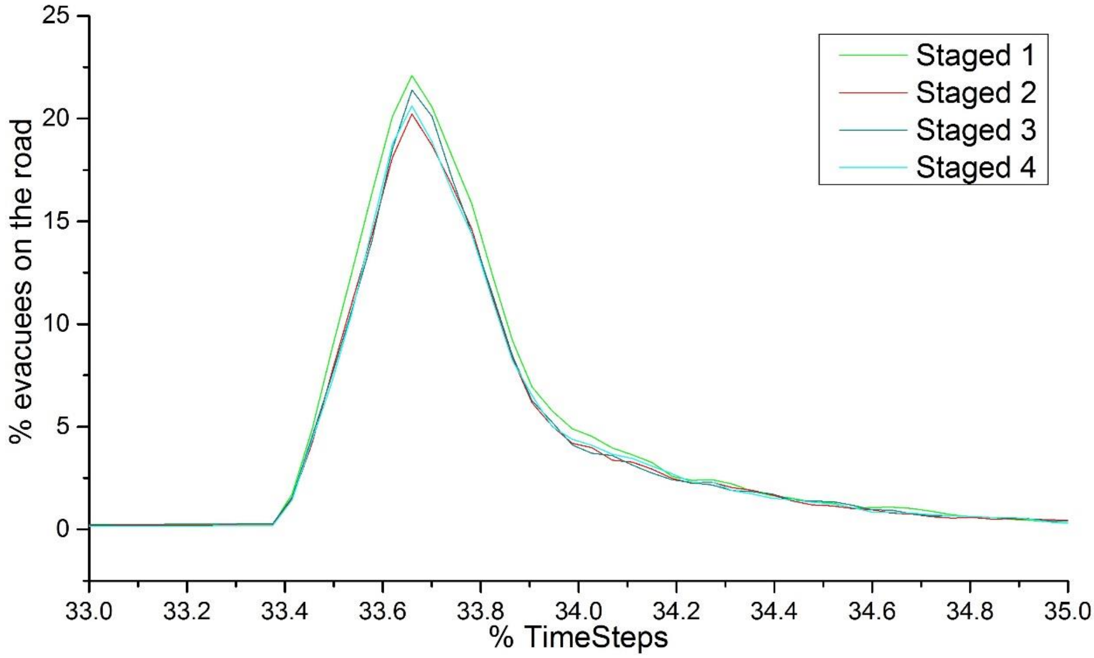

Figure 5.12 Performance comparison among the four staged scenarios.

5.3.5 Discussion

5.3.5.1 Supporting the Evacuation Management with Simulation

There are four important contributions and findings that can be highlighted from this research: (1) a novel approach of zones prioritising a staged evacuation strategy, based on the demographic and geographical characteristics of the zones using SMCE, was developed and examined, (2) the experiments and analysis confirm that staged evacuation is more effective in reducing the potential traffic congestion at the peak time of the evacuation, (3) the problem regarding potential traffic congestion under the simultaneous evacuation strategy was identified and proved using actual evacuation data (2010 evacuation), and (4) the optimum formulation of the prioritising criteria was found.

The staging technique used in this research offers a more geographical approach than the existing methods, such as (Mitchell and Radwan, 2006; Li et al., 2012). Both Mitchell and Radwan (2006) and Li et al. (2012) implement numerical modelling to provide a staging technique which pays less consideration to the geographical aspect of the evacuation zones. Meanwhile, the ABM experiment and the evaluation, that demonstrate the ability of a staged evacuation scenario to reduce the potential traffic congestion during the peak time of the evacuation, complemented the research by (Chien and Korikanthimath, 2007; Chen and Zhan, 2008). Both Chen and Zhan (2008) and Chien and Korikanthimath (2007) focus on the effect of adding a staging strategy to the evacuation duration. They commonly agree that a staged evacuation strategy, under certain conditions, is effective in reducing the overall evacuation duration. Meanwhile, the simulation presented in this paper focuses on the effect of implementing a staged evacuation in reducing traffic congestion.

The simulation identified that two major roads were mainly likely to become crowded during the simultaneous evacuation process; namely, Kaliurang Road and Palagan Tentara Pelajar Road. This result is proved by a report of the evacuation in 2010 by national mass media "*The movement of citizens simultaneously made Kaliurang Road full and jammed. A number of accidents occurred in the evacuation process"* (translated from Indonesian) (Liputan6.com, 2010). Kaliurang Road remains the most densely crowded road during the implementation of the staged evacuation strategy but to a lesser extent than during a simultaneous evacuation strategy (see Section 5.3.2). Therefore, the application of a staged strategy will potentially reduce the chaos and congestion that occurred during the 2010 evacuation process (Liputan6.com, 2010).

Among the staged scenarios examined by the ABM, the first one performed best in terms of reducing traffic density, as identified from the spatial aspect. This scenario ranks proximity to hazard (PH) as the most important criterion when developing the prioritisation, followed by population density (PD), accessibility to shelter (AS), and the proportion of people of vulnerable age (VA).

5.3.5.2 Limitation of the Study

The results presented above show that ABMs can be used to test various scenarios of evacuation and evaluate the effect of factors such as the road traffic density. Although the experiment noted important findings on managing evacuations in Merapi - and more generally provides a method for developing prioritisation in evacuation staging that is applicable for many other hazards and locations - the limitations of this model should be considered when developing future works or, for more practical purposes, deriving policy implication based on these findings.

First of all, the current model used in these experiments disregards the possible effect of road traffic congestion on the movement of agents, and therefore it is unable to simulate the dynamic interaction between evacuees and road/traffic conditions. Batty et al. (2003) explains that the interaction of people over different scales implies different dynamics, purpose, and goals. Where interactions take place over very small spatial scales (i.e. less than tens of square metres), the dynamics of movement are dominated by density considerations such as overcrowding. On the other hand, over wider areas, movement is more likely to be characterised by cost and purpose. In reality, congestion affects the dynamic of traffic movement by limiting the movement of people and vehicles at “bottle-necks” (Rao and Rao, 2012) and can possibly trigger re-routing of the movement via alternative roads (Bazzan and Klügl, 2014). Although the potential of high crowd of movement of evacuees can be identified from the current model, the impact of the congestion is still hard to identify. Such dynamic and behavioural effects can affect spatiotemporal traffic density in ways that might produce different results. As Dixit and Wolshon (2014) explain, speed movement is inversely proportional to traffic density, therefore, the lower the speed, the higher the density of traffic will be produced. Moreover, re-routing behaviour in congestion affects the dynamic of spatial distribution of evacuees which in turn affects their density. It should be noted that approaches do exist to model such re-routing behaviour, for example ant-colony optimisation (Bedi et al., 2007) or swarm-intelligence (Tatomir and Rothkrantz, 2006).

Secondly, road capacity is an important aspect in modelling evacuation traffic (Dixit and Wolshon, 2014). This has not been considered in the model. Road capacity is defined as the flow of traffic which moves at the minimum acceptable average speed (Wardrop, 1954). Congestion commonly occurs when the volume of traffic is too close to the maximum capacity of the road (Goodwin, 2004). Therefore, the result of the model might different when this factor is applied, and this will depend on the road capacity and the number of evacuees conducting the evacuation.

Thirdly, the behaviour of people in choosing their evacuation destination is also important in defining the traffic (Charnkol et al., 2007; Cheng et al., 2008; Mesa-Arango et al., 2012). Yet this aspect is not fully validated in the current model. Besides the stay-or-leave behaviour, the people behaviour in selecting their destination is another complex decision in modelling evacuations. The behaviour in selecting the destination depends on the preference and socio-economic character of the people Charnkol et al.

(2007). In Merapi, the outcome of the destination choice decision has been investigated. Based on the shelter zoning analysis by Jumadi et al. (2018), 80.3% of evacuees preferred to select the shortest distance, 12.4% preferred to select destinations close to public services zones, and the rest (7.2%) either used relatives or risk indicators as preferences. However, what and how such socio-economic factors affect the decision is still unknown, and therefore further study is needed to apply this aspect in the model.

Based on the limitations mentioned above, there are three aspects that can be improved to make this model more accurate. (1) Involvement of the interaction model of people on the road that leads to congestion and the interactions on speed dynamic and re-routing behaviour. (2) Assigning road capacity on the road network so that the congestion caused by this aspect can be modelled. (3) Assigning the decision model of destination choice to the agents so that the dynamic of the shelter choice that affects traffic distribution can be captured.

5.5 Conclusions

A novel approach to staged scenario design using spatial multi-criteria analysis to create the prioritisation is presented and examined in this paper. The prioritisation was applied in ABM to evaluate the relative comparison between simultaneous and staged evacuation, and among various staged scenarios based on different criteria weightings. The evaluation is based on the ability to reduce the potential road congestion during evacuation processes, which includes the percentage of evacuees on the road and the spatial distribution of relative traffic density, as well as the ability (fastness) to reduce the number of the population at risk. The result shows that the staged scenario was more effective in reducing the potential traffic congestion during the peak time of the evacuation compared to the simultaneous strategy. However, simultaneous evacuation strategy has better performance in reducing the risk compare to staged strategy. Among the four staged evacuation scenarios, there is no significant difference between them with regard to the speed at which the risk is reduced. Among the staged scenarios, the second one performed best in terms of reducing traffic density, as identified from the percentage of evacuees on the road during the peak time of evacuation.

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References

Abdurachman, E.K., Bourdier, J.-L. Voight, B. 2000. Nuées ardentes of 22 November 1994 at Merapi volcano, Java, Indonesia. *Journal of Volcanology and Geothermal Research*. **100**(1), pp.345–361.

Alaeddine, H., Serrhini, K., Maizia, M. and Néron, E. 2015. A spatiotemporal optimization model for the evacuation of the population exposed to flood hazard. *Nat. Hazards Earth Syst. Sci.* **15**(3), pp.687–701.

Alcántara-Ayala, I. 2002. Geomorphology, natural hazards, vulnerability and prevention of natural disasters in developing countries. *Geomorphology*. **47**(2–4), pp.107–124.

Batty, M., Desyllas, J. and Duxbury, E. 2003. The discrete dynamics of small-scale spatial events: agent-based models of mobility in carnivals and street parades. *International Journal of Geographical Information Science*. **17**(7), pp.673–697.

Bazzan, A.L. and Klügl, F. 2014. A review on agent-based technology for traffic and transportation. *The Knowledge Engineering Review*. **29**(3), pp.375–403.

Beck, U. 2009. *World at risk*. Cambridge, UK: Polity.

Bedi, P., Mediratta, N., Dhand, S., Sharma, R. and Singhal, A. 2007. Avoiding traffic jam using ant colony optimization-a novel approach *In*: *International Conference on Computational Intelligence and Multimedia Applications (ICCIMA 2007)*. IEEE, pp.61–67.

de Bélizal, E., Lavigne, F., Hadmoko, D.S., Degeai, J.-P., Dipayana, G.A., Mutaqin, B.W., Marfai, M.A., Coquet, M., Le Mauff, B., Robin, A.-K. and others 2013. Rain-triggered lahars following the 2010 eruption of Merapi volcano, Indonesia: A major risk. *Journal of Volcanology and Geothermal Research*. **261**, pp.330–347.

BNPB 2011. Peta Kawasan Rawan Bencana Merapi. [Accessed 9 October 2015]. Available from: http://geospasial.bnpb.go.id/wp-content/uploads/2011/05/2011-04-29_KRB_Area_Terdampak_Langsung_Merapi.pdf.

BNPB 2010a. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Bantul (11 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6pikQru7D.

BNPB 2010b. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Kulon Progo (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6piskXxQF.

BNPB 2010c. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kab. Sleman (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6piPoQCLs.

BNPB 2010d. Peta Lokasi dan Jumlah Pengungsi Letusan G.Api Merapi di Wilayah Kota Yogyakarta (15 nov). [Accessed 14 April 2017]. Available from: http://www.webcitation.org/6pilvuYiE.

Charbonnier, S.J. and Gertisser, R. 2008. Field observations and surface characteristics of pristine block-and-ash flow deposits from the 2006 eruption of Merapi Volcano, Java, Indonesia. *Journal of Volcanology and Geothermal Research*. **177**(4), pp.971–982.

Charnkol, T., Hanaoka, S. and Tanaboriboon, Y. 2007. Emergency trip destination of evacuation as shelter anslysis for tsunami disaster: a case study in Phuket, Thailand *In*: *Proceedings of the Eastern Asia Society for Transportation Studies The 7th International Conference of Eastern Asia Society for Transportation Studies, 2007* [Online]. Eastern Asia Society for Transportation Studies, pp.119–119. [Accessed 15 April 2017]. Available from: https://www.jstage.jst.go.jp/article/eastpro/2007/0/2007_0_119/_article/-char/ja/.

Chen, X. and Zhan, F.B. 2008. Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. *The Journal of the Operational Research Society*. **59**(1), pp.25–33.

Cheng, G., Wilmot, C.G. and Baker, E.J. 2008. A destination choice model for hurricane evacuation *In*: *Proceedings of the 87th Annual Meeting Transportation Research Board, Washington, DC, USA* [Online]., pp.13–17. [Accessed 7 January 2017]. Available from: http://www.ltrc.lsu.edu/pdf/2008/08-0840.PDF.

Chien, S.I. and Korikanthimath, V.V. 2007. Analysis and Modeling of Simultaneous and Staged Emergency Evacuations. *Journal of Transportation Engineering*. **133**(3), pp.190–197.

Dixit, V. and Wolshon, B. 2014. Evacuation traffic dynamics. *Transportation Research Part C: Emerging Technologies*. **49**, pp.114–125.

Eastman, J.R. 1999. Multi-criteria evaluation and GIS. *Geographical information systems*. **1**, pp.493–502.

Goodwin, P. 2004. The economic costs of road traffic congestion.

GVP 2017. Global Volcanism Program, Smithsonian Institution, Museum of Natural History. [Accessed 31 May 2017]. Available from: http://www.webcitation.org/6qsJbuRFi.

Hansen, W.G. 1959. How Accessibility Shapes Land Use. *Journal of the American Institute of Planners*. **25**(2), pp.73–76.

Itoh, H., Takahama, J., Takahashi, M. and Miyamoto, K. 2000. Hazard estimation of the possible pyroclastic flow disasters using numerical simulation related to the 1994 activity at Merapi Volcano. *Journal of volcanology and geothermal research*. **100**(1), pp.503–516.

Jumadi, Carver, S. and Quincey, D. 2017. A Conceptual Design of Spatio-Temporal Agent-Based Model for Volcanic Evacuation. *Systems*. **5**(4), p.53.

Jumadi, Heppenstall, A.J., Malleson, N.S., Carver, S.J., Quincey, D.J. and Manville, V.R. 2018. Modelling Individual Evacuation Decisions during Natural Disasters: A Case Study of Volcanic Crisis in Merapi, Indonesia. *Geosciences*. **8**(6), p.196.

Jumadi, J., Malleson, N., Carver, S. and Quincey, D. n.d. An Agent-based Approach for Spatio-temporal Dynamics of Risk Modelling in Merapi. *Submitted to JASSS*.

Kelfoun, K., Legros, F. and Gourgaud, A. 2000. A statistical study of trees damaged by the 22 November 1994 eruption of Merapi volcano (Java, Indonesia): relationships between ash-cloud surges and block-and-ash flows. *Journal of Volcanology and Geothermal Research*. **100**(1), pp.379–393.

Lavigne, F., de Bélizal, E., Cholik, N., Aisyah, N., Picquout, A. and Mei, E.T.W. 2011. Lahar hazards and risks following the 2010 eruption of Merapi volcano, Indonesia. *EGU General Assembly*. **13**(EGU2011-4400).

Lavigne, F. and Thouret, J.-C. 2003. Sediment transportation and deposition by rain-triggered lahars at Merapi Volcano, Central Java, Indonesia. *Geomorphology*. **49**(1–2), pp.45–69.

Li, X., Huang, B., Liu, Z., Zhang, X. and Sun, J. 2012. A novel method for planning a staged evacuation. *Journal of Systems Science and Complexity*. **25**(6), pp.1093–1107.

Lim, G.J., Zangeneh, S. and Kim, S.J. 2016. Clustering approach for defining hurricane evacuation zones. *Journal of Urban Planning and Development*. **142**(4), p.04016008.

Lim, G.J., Zangeneh, S., Reza Baharnemati, M. and Assavapokee, T. 2012. A capacitated network flow optimization approach for short notice evacuation planning. *European Journal of Operational Research*. **223**(1), pp.234–245.

Liputan6.com 2010. Kesaksian Korban Merapi. [Accessed 28 July 2018]. Available from: http://www.webcitation.org/71FT3eKkI.

Local Government of DIY n.d. Informasi Jumlah Penduduk D.I. Yogyakarta. [Accessed 17 April 2018]. Available from: http://kependudukan.jogjaprov.go.id/.

Malczewski, J. 2000. On the Use of Weighted Linear Combination Method in GIS: Common and Best Practice Approaches. *Transactions in GIS*. **4**(1), pp.5–22.

Mehta, M., Kumar, V., Singh, S., Singh, R. and Singh, A. 2015. Spatial and temporal changes of aerosol optical depth in three most populated countries of Asia over the last decade *In*: *2015 1st International Conference on Next Generation Computing Technologies (NGCT)*., pp.523–526.

Mei, E.T.W. and Lavigne, F. 2012. Influence of the institutional and socio-economic context for responding to disasters: case study of the 1994 and 2006 eruptions of the Merapi Volcano, Indonesia. *Geological Society, London, Special Publications*. **361**(1), pp.171–186.

Mei, E.T.W., Lavigne, F., Picquout, A., de Bélizal, E., Brunstein, D., Grancher, D., Sartohadi, J., Cholik, N. and Vidal, C. 2013. Lessons learned from the 2010 evacuations at Merapi volcano. *Journal of Volcanology and Geothermal Research*. **261**, pp.348–365.

Mei, E.T.W., Lavigne, F., Picquout, A. and Grancher, D. 2011. Crisis Management During the 2010 Eruption of Merapi Volcano *In*: *Regional Geographic Conference–International Geographical Union, Santiago, Chile* [Online]., pp.15–19. [Accessed 10 March 2015]. Available from: http://www.acreditacion.fisa.cl/ugi/archivo_presentacion/201109050300_20112211wvgz7h_archivo_presentacion.pdf.

Mesa-Arango, R., Hasan, S., Ukkusuri, S.V. and Murray-Tuite, P. 2012. Household-level model for hurricane evacuation destination type choice using hurricane Ivan data. *Natural hazards review*. **14**(1), pp.11–20.

Mitchell, S. and Radwan, E. 2006. Heuristic Priority Ranking of Emergency Evacuation Staging to Reduce Clearance Time. *Transportation Research Record: Journal of the Transportation Research Board*. **1964**, pp.219–228.

Morris, J.M., Dumble, P.L. and Wigan, M.R. 1979. Accessibility indicators for transport planning. *Transportation Research Part A: General*. **13**(2), pp.91–109.

Pidd, M., de Silva, F.N. and Eglese, R.W. 1996. A simulation model for emergency evacuation. *European Journal of Operational Research*. **90**(3), pp.413–419.

Rao, A.M. and Rao, K.R. 2012. Measuring urban traffic congestion-a review. *International Journal for Traffic & Transport Engineering*. **2**(4).

Rizvi, S.R., Olariu, S., Weigle, M.C. and Rizvi, M.E. 2007. A Novel Approach to Reduce Traffic Chaos in Emergency and Evacuation Scenarios. *In*: *VTC Fall* [Online]., pp.1937–1941. [Accessed 19 September 2016]. Available from: https://pdfs.semanticscholar.org/be49/c16ebc164d74c7098b197c5a7d6578e39ce3.pdf.

Saaty, T.L. 2008. Decision making with the analytic hierarchy process. *International journal of services sciences*. **1**(1), pp.83–98.

Sadono, R., Hartono, H., Machfoedz, M.M. and Setiaji, S. 2017. Monitoring Land Cover Changes in the Disaster-Prone Area: A Case Study of Cangkringan Sub-District, the Flanks of Mount Merapi, Indonesia. *Forum Geografi*. **31**(2).

Sbayti, H. and Mahmassani, H.S. 2006. Optimal scheduling of evacuation operations. *Network Modeling 2006*.

Shahabi, K. and Wilson, J.P. 2018. Scalable evacuation routing in a dynamic environment. *Computers, Environment and Urban Systems*. **67**, pp.29–40.

Siagian, T.H., Purhadi, P., Suhartono, S. and Ritonga, H. 2013. Social vulnerability to natural hazards in Indonesia: driving factors and policy implications. *Natural Hazards*. **70**(2), pp.1603–1617.

Surono, Jousset, P., Pallister, J., Boichu, M., Buongiorno, M.F., Budisantoso, A., Costa, F., Andreastuti, S., Prata, F., Schneider, D., Clarisse, L., Humaida, H., Sumarti, S., Bignami, C., Griswold, J., Carn, S., Oppenheimer, C. and Lavigne, F. 2012. The 2010 explosive eruption of Java's Merapi volcano—A '100-year' event. *Journal of Volcanology and Geothermal Research*. **241–242**, pp.121–135.

Tatomir, B. and Rothkrantz, L. 2006. Hierarchical routing in traffic using swarm-intelligence *In*: *2006 IEEE Intelligent Transportation Systems Conference*. IEEE, pp.230–235.

Thouret, J.-C., Lavigne, F., Kelfoun, K. and Bronto, S. 2000. Toward a revised hazard assessment at Merapi volcano, Central Java. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.479–502.

Voight, B., Constantine, E.K., Siswowidjoyo, S. and Torley, R. 2000. Historical eruptions of Merapi Volcano, Central Java, Indonesia, 1768–1998. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.69–138.

Voight, B., Sukhyar, R. and Wirakusumah, A.D. 2000. Introduction to the special issue on Merapi Volcano. *Journal of Volcanology and Geothermal Research*. **100**(1–4), pp.1–8.

Wardrop, J.G. 1954. The Capacity of Roads. *OR*. **5**(1), pp.14–24.

Wolshon, B., Catarella-Michel, A. and Lambert, L. 2006. Louisiana Highway Evacuation Plan for Hurricane Katrina: Proactive Management of a Regional Evacuation. *Journal of Transportation Engineering*. **132**(1), pp.1–10.

Chapter 6
Discussion and Conclusions

6.1 Overview

This thesis represents an advance step toward utilisation of spatial ABM to simulate emergency evcuation in volcanic areas in order to find alternative scenarios in improving the effectiveness of evacuation plans. The thesis highlighted how statistical data, from both survey (primary) and secondary sources, can be used to parameterise spatial ABMs and develop the evacuation decision rule of the agents, as well as how different scenarios of evacuation can impact the effectiveness of evacuation. The insight derived from this research fills a gap in knowledge relating to the methodology of how to evaluate certain scenarios of evacuation in volcanic areas. The methodology presented here, includes the development of evacuation decisions based on questionnaire surveys, a method for designing the spatiotemporal dynamics of a hazardous environment, and a method for designing staged-evacuation strategies based on geographical variables.

The structure of the thesis represents the development processes of the spatial ABM of volcanic evacuation. The main development steps are elaborated in three chapters (Chapter 2-4) and followed by the use of the model in improving evacuation management (Chapter 5). This chapter (the final chapter) collates all the foregoing chapters, discusses and evaluates the findings in relation to the broader literature, points out limitations and concludes with the overarching findings.

The development of the ABM started with designing the framework and initial model as presented in Chapter 2. Briefly, this chapter developed based on four points of focus: (1) highlighting the importance of providing evacuation simulation for Merapi, (2) providing and introducing the initial design of ABM for volcanic evacuation simulation, (3) demonstrating the potential uses of the model to support evacuation decisions, and (4) evaluating the initial design and giving insights for further improvements. The initial volcanic evacuation model development was presented in this chapter as the basis for further application purposes. The volcanic evacuation model represents the relationships between physical and human agents, consisting of the volcano, stakeholders, the population at risk and the environment. The spatio-temporal dynamic of hazard following the volcanic activity level is also formulated in this chapter. Afterwards, some potential uses of this model to support decision-making were demonstrated – for instance, analysing route densities, evacuees' distribution in shelters, and the evacuation outcome in various scenarios. The comparison of some simulation results with real data was provided with the aim of evaluating this model. Drawbacks in the model were identified: in the decision-making of agents, synthetic population development and the effect of social networks on agent decisions.

The model was improved in the next phase to address those drawbacks. Chapter 3 presented an individual evacuation decision model in ABM with Mt. Merapi, Indonesia as a case study. In this version, the model was utilised with an individual decision-making rule, a synthetic population and social network interaction. The individual decision-making rule was based on various interrelating factors developed from the literature review and survey. These factors were categorised into driving forces to evacuate or influences tending to make people stay put. The threshold-based approach was used to evaluate the differences in both values and to define whether agents would evacuate or stay. This decision model can be used to simulate two important aspects of evacuation, namely the dynamic of evacuation departure, and the emergence of reluctant people. Both of these features are important in defining the effectiveness of evacuation because a high incidence of reluctant people or evacuation which is too late will increase the risk. Calibration was conducted by setting up the parameters based on three scenarios. The model was validated by a retrodiction approach which consisted of spatial and temporal validation. K^* and r^w were used to measure the validity of the spatial distribution of the simulated reluctant people against the real data. Meanwhile, RMSE was used to measure the validity of the temporal accumulation of evacuees. Analysis of the simulation outputs shows that scenario 3, which weighted the occurrence of an explosion as the most important motivation for evacuation (four times more important than the other aspects), was the most plausible model in mimicking the real volcanic disaster events in Mt. Merapi. This plausibility was indicated by both the spatial and temporal similarity of the output with the real data being relatively high (high K^*, r^w and low RMSE) compared with the other scenarios.

The speed in reducing risk is an important indicator of the success of evacuation. The overall risk is aggregated from the individual risk. Therefore, the concept of individual risk is formulated and demonstrated in Chapter 4 which presented the integration of MCE-ABM for STDMR to show the dynamic spatio-temporal change of volcanic risk. The model captures dynamic risk as a function of hazard and vulnerability, where the hazard varies over time and space. Here, vulnerability is defined using a social vulnerability index (SoVI) as aggregated in the MCE from several attributes of the individual agent. From the simulation, the risk hotspots were identified: particular sites of concentration of people at risk over time. This simulation can potentially be used to enhance the decision-making processes of evacuation. Knowing the hotspots can help the decision maker to allocate more resource to manage and mobilise these areas.

So far, the model was utilised with spatio-temporal dynamic of hazard, individual decision-making of evacuation, synthetic population, social network interaction, and individual risk modelling which is spatio-temporally dynamic. The verification, calibration, and validation effort was also presented in Chapter 3. The next phase uses the model to experiment with some scenarios of evacuation to evaluate the outcome as presented in Chapter 5. Firstly, this chapter provides the development of evacuation stage ordering based on the geographic character of people at risk and then examines the ordering scenarios in an agent-based model of evacuation. Several geographic characters such as proximity to hazard, road network condition (accessibility), number of population, and demographics as parameters were used to rank the order of each population unit in GIS. From this concept, several scenarios of ranking based on different weightings of the parameters were created and examined. Afterwards, the results were evaluated to assess the effectiveness in reducing risk and spatio-temporal traffic density along road networks compared with carrying out simultaneous evacuation. The results show that the staged scenario has the best potential to reduce traffic congestion during the peak time of the evacuation compared with the simultaneous strategy. However, simultaneous evacuation strategy has the best performance in the speed of reducing the risk.

6.2 Research Contributions

This thesis was developed based on several contributions that imply knowledge development and potential for practical application. Besides the potential to be used locally in Merapi, especially by experimenting with several scenarios and suggesting the most effective evacuation plan, the development processes of this evacuation model contribute to the development of ABM for large-scale evacuation simulation by (1) integrating the hazard model that is derived from historical records of spatial impact of eruptions, (2) formulating and validating an individual evacuation decision model in ABM based on various interrelating factors revealed from the literature review and survey, (3) formulating the integration of multi-criteria evaluation (MCE) in ABM to model spatio-temporal dynamic model of risk (STDMR) that enables representation of the changing risk as a consequence of changing hazard levels; hazard extent; and movement of people, (4) formulating an evacuation staging method based on MCE using geographic and demographic criteria.

6.2.1 Contributions in Local Context

Evaluation of evacuation scenarios through simulation is important for arranging further improvement of the evacuation plan. Merapi, with high uncertainty of both the hazard (physical) and the responses of people (social), needs an adaptable plan that is valid for any hazard scenario. Modelling of the volcanic evacuation in Merapi is important to support the evaluation of the implementation of potential plans for reducing risk and providing more effective evacuation management. However, although various aspects of Merapi have been researched (Jumadi et al., 2017), less attention has been paid to evacuation modelling. Some research has been conducted, such as Handayani et al. (2016, 2017), but those studies are still in the early phase of model development, i.e. formulating the behaviour rule of people in the evacuation processes.

This thesis has made a novel contribution by developing an agent-based model that allows simulation of the evacuation processes in Merapi. This can potentially be used to support the evaluation and improvement of evacuation management in Merapi as presented in Chapter 2 and Chapter 5. Moreover, the agent-based model of volcanic evacuation developed in this thesis enables evaluation of the potential problems of the existing scenario (simultaneous evacuation strategy) – the evacuation plan as practised in 2010 evacuation. This evacuation strategy produced some traffic problems during the movement as reported by national mass media (Liputan6.com, 2010). Such problems were also identified by the results of the simulation as presented in Chapter 5, where there are some high traffic densities on the roads at the peak time of evacuation. It is mainly at Kaliurang Road that was also reported in the real evacuation processes in 2010 (Liputan6.com, 2010).

This thesis suggests a more effective scenario as presented in Chapter 5, i.e. a staged evacuation strategy. Based on the simulation, traffic density at the peak time of evacuation could be reduced by up to 23% compared with the simultaneous strategy. A staged evacuation scenario was also proved more effective for evacuation from Hurricane Katrina (Wolshon, 2006). Also, based on the relative comparison, this strategy is better in reducing clearance time under certain road network conditions (Chen and Zhan, 2008).

6.2.2 General Contributions to Evacuation Modelling

6.2.2.1 The Spatial Dynamic of Hazard Model

Simulating a disaster event, especially a volcanic eruption, needs a spatio-temporally dynamic hazard model since the hazard is naturally changing in spatial extent and magnitude over the period of crisis. Some efforts in integrating the hazard dynamics have been made in developing models of evacuation, for example hydrodynamic numerical simulations for tsunami evacuation (Mas et al., 2012; Wang et al., 2016) and floods (Dawson et al., 2011). However, the implementation of spatio-temporal hazard dynamics that involves real data from previous events has only been considered in a limited way. This approach to modelling is further developed in this thesis, as presented in Chapter 2. It is based on the changing of physical parameters of the volcano. The hazardous environment is divided into several zones based on the impact records from the previous events. The changing volcanic eruption parameters – magnitude (VEI), and especially the volcanic activity level (VAL) – change the hazard level within each zone.

6.2.2.2 Individual Evacuation Decision Model

The reluctances phenomenon can hamper evacuation processes, but has received surprisingly little attention in studies on evacuation modelling (e.g. (Chen and Zhan, 2008; Zhang et al., 2009; Mas et al., 2012; Jumadi et al., 2017)). Modelling the phenomenon of reluctant people during a crisis might help in improving evacuation plans; that is, to what extent the number of reluctant people can be reduced to save more lives. The model of individual decision-making processes of evacuation (evacuate/stay) during a volcanic crisis using an agent-based model (ABM) is provided in Chapter 3. The model uses several interacting factors (Sagala, 2009; Donovan, 2010a; Wilson et al., 2012; Chandan et al., 2013) that drive people to leave (forced to evacuate) versus the factors tending to hold people back (forced to stay).

The evacuation decision model is based on a threshold model where the interacting factors are quantified and evaluated against the threshold. The change of values of the factors, when exceeding the threshold, triggers the transition state from Normal – Investigating – Evacuating (Lovreglio et al., 2016). Normal conditions mean there is no impulse to evacuate. The state moves to Investigating (people increase their level of awareness) when the urge to evacuate increases but does not yet exceed the tendency to stay. This rule can model the emergence of people who are reluctant to evacuate during the volcanic disaster.

6.2.2.3 Spatio-temporal Dynamics Model of Risk

Risk modelling from certain hazards is traditionally presented as a static map with the region as the mapping unit. Nowadays, the emergence of ABM as an approach to individual modelling allows risk modelling on an individual scale. ABM can accommodate this requirement (Clarke, 2014), and has been shown to be effective in simulating agent behaviour in non-linear systems (Srbljinović and Škunca, 2003; Malleson et al., 2014). In an ABM, people are represented as agents who have heterogeneous characteristics and behaviour (Crooks and Heppenstall, 2012). They are able to navigate their environment and interact with other agents. Furthermore, heterogeneity can be introduced into the population of agents which allows for modelling individual variations in vulnerability and mobility. The coupling of ABM with a dynamic hazard model is, therefore, an ideal framework with which to represent the dynamic risk to individuals during a volcanic emergency.

In this thesis (Chapter 4), a new approach of Spatio-temporal Dynamics Model of Risk (STDMR) was proposed and a case study using a pre-developed agent-based evacuation model of Mt. Merapi was provided (Jumadi et al., 2017; Jumadi et al., 2018). This approach first creates an individual-level population (synthetic population) of agents who live in the area surrounding a volcano. Each agent has a unique vulnerability and since vulnerability comprises several factors (Cutter et al., 2003), MCE is used to create a single social vulnerability index for each individual. This is coupled with a dynamic hazard model to capture the dynamics of risk. The model is able to highlight a small number of high-risk spatio-temporal positions where, due to the behaviour of individuals evacuating the volcano and the dynamics of the hazard itself, the overall risk in those times and places is extremely high. Nevertheless, the outcomes are interesting and extremely relevant for stakeholders, and the work of coupling an ABM, MCE, and dynamic volcanic hazard, is novel.

6.2.2.4 Evacuation Priority List Design and Staged Evacuation Evaluation

Staged evacuation has been put forward as an effective solution to reduce chaotic conditions during evacuation processes. However, there is limited grasp of how the stages can be ordered to manage which evacuees can leave earlier and which ones can follow later. An example of the design of priority ranking using a heuristic approach was presented by Mitchell and Radwan (2006), but less consideration was given to a spatial element. In this thesis (Chapter 5), the development of evacuation stage ordering based on the geographic character of people at risk was presented and examined. Several geographic characters such as proximity to hazard, road network condition (accessibility), number of population, and demographics as parameters were used to rank the order of each population unit in GIS. Four scenarios of ranking based on the different weight of the parameters were produced and examined.

6.2.2.5 Identifying Potential Problem on Evacuation

Identifying potential problems from an evacuation scenario is an important aspect of evacuation simulations. This was demonstrated in Chapter 5. In this chapter, a potential problem, especially traffic congestion during the peak time of evacuation, was identified by analysing the traffic density at that time. The traffic densities from simultaneous and staged evacuation strategies were compared. The results showed that the simultaneous strategy results in the highest potential traffic problem because most people start to evacuate at the same time so traffic is concentrated on particular roads/junctions at the peak time. In contrast, in the staged strategy, people start to evacuate gradually so traffic is more distributed, road congestion is less severe.

6.3 Evaluations of the Model

6.3.1 The Aspects of the Model that Worked Well

In order to represent the process of volcanic crisis occurrence and, followed by, the evacuation; this model involved various aspect including the environmental (physical) and social. There is some aspect of that representation that is work well, as expected. From the physical aspect, the model has been able to represent the spatiotemporal dynamic of hazard as effect of the changing of the volcanic activity. The volcanic activity matrix as a rule to drive this aspect can be used for this purpose. On the other hand, from the social aspects, there are some components that worked to comply with the model design such as the use of threshold-based rule that successfully trigger people to leave or stay based on the emerging value of driving forces to leave and driving forces to stay. Moreover, from the methodological perspective, the method of population synthesis as well as the development of evacuation stage prioritisation worked well. The success of the population synthesis can be seen from the spatial distribution as well as structure of agents of population that are generated. Nearest Neighbour analysis was used to compare the spatial distribution that is all simulation samples shows similarity of the pattern to the real data (clustered). While to analyse the structure similarity, descriptive statistics were used. Figure 5.1 shows the comparisons of the structure, based on the socio-economic attributes, between the real (census microdata) with the agents population.

Table 6.1 Spatial comparison based on Nearest Neighbour.

Data	Observed Mean Distance	Expected Mean Distance	NN Index	Number of Points	Spatial Pattern
Real Data	11.986	25.537	0.469	297659	Clustered
Simulation 1	91.326	136.972	0.667	13733	Clustered
Simulation 2	90.092	135.649	0.664	13733	Clustered
Simulation 3	90.246	135.275	0.667	13733	Clustered
Simulation 4	90.988	136.746	0.665	13733	Clustered
Simulation 5	91.098	135.352	0.673	13733	Clustered
Simulation 6	90.987	135.355	0.672	13733	Clustered
Simulation 7	90.327	137.019	0.659	13733	Clustered
Simulation 8	91.933	135.396	0.678	13733	Clustered
Simulation 9	91.558	136.018	0.673	13733	Clustered
Simulation 10	91.200	135.876	0.671	13733	Clustered

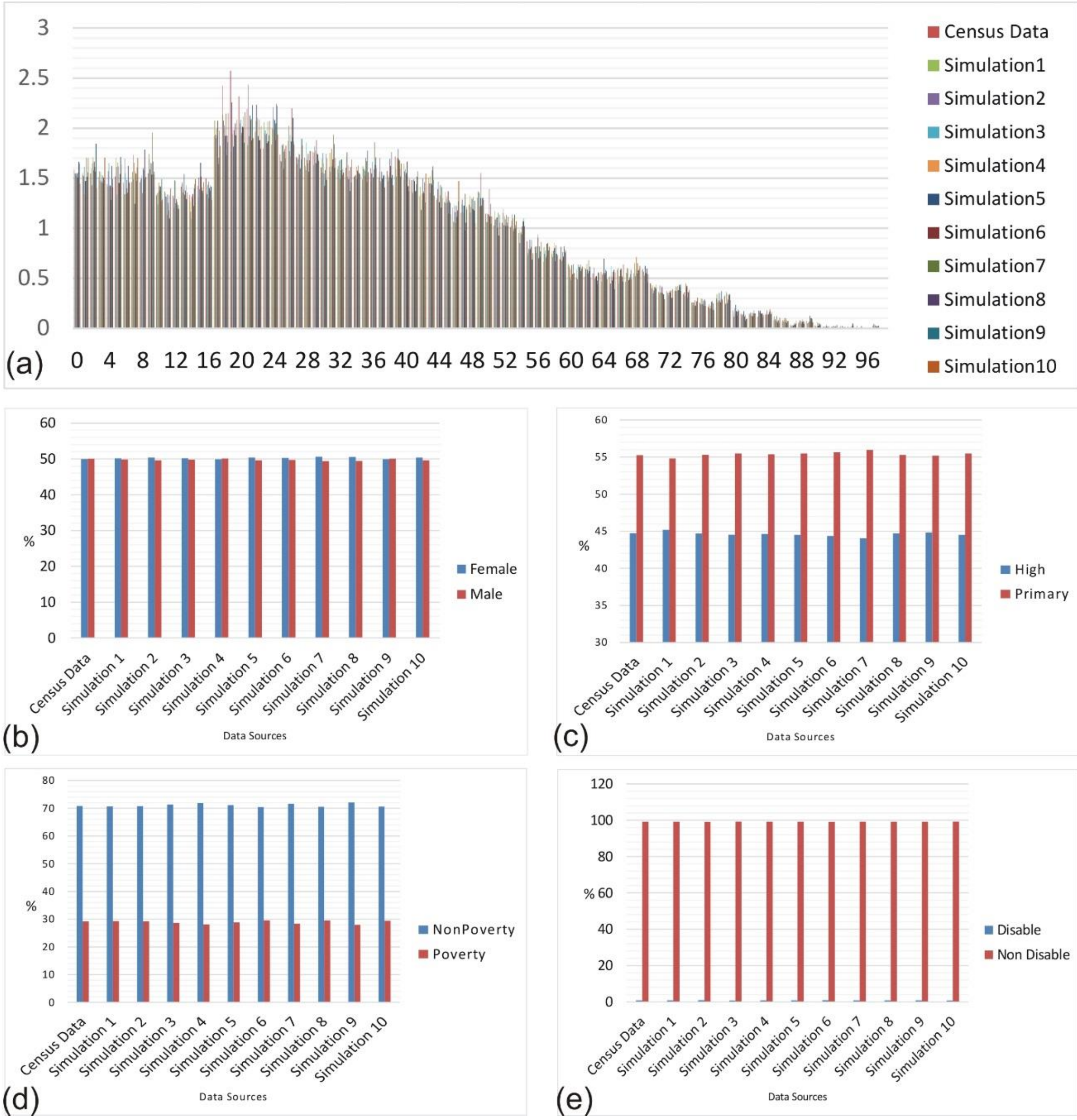

Figure 6.1 Structure of agents population – examples from ten simulation run. Note: (a) age structure, (b) sex structure, (c) education structure, (d) family income structure, (e) structure of disabilities.

6.3.2 The Aspects of the Model that Worked Less Well

Although the model has been able to model the emergence of reluctances, there are still discrepancies in the spatial distribution between the simulation output with the real data. The statistical analysis of this confirmed that these results are plausible and robust because the comparisons rely on the pattern (neighbourhood) rather than pixel to pixel. If we take a look at the map resulting from the simulations (Figure 5.2), we can see some spots that are different. This aspect should be taken into consideration when conducting further improvements, besides some limitations that will be presented in Section 6.4.

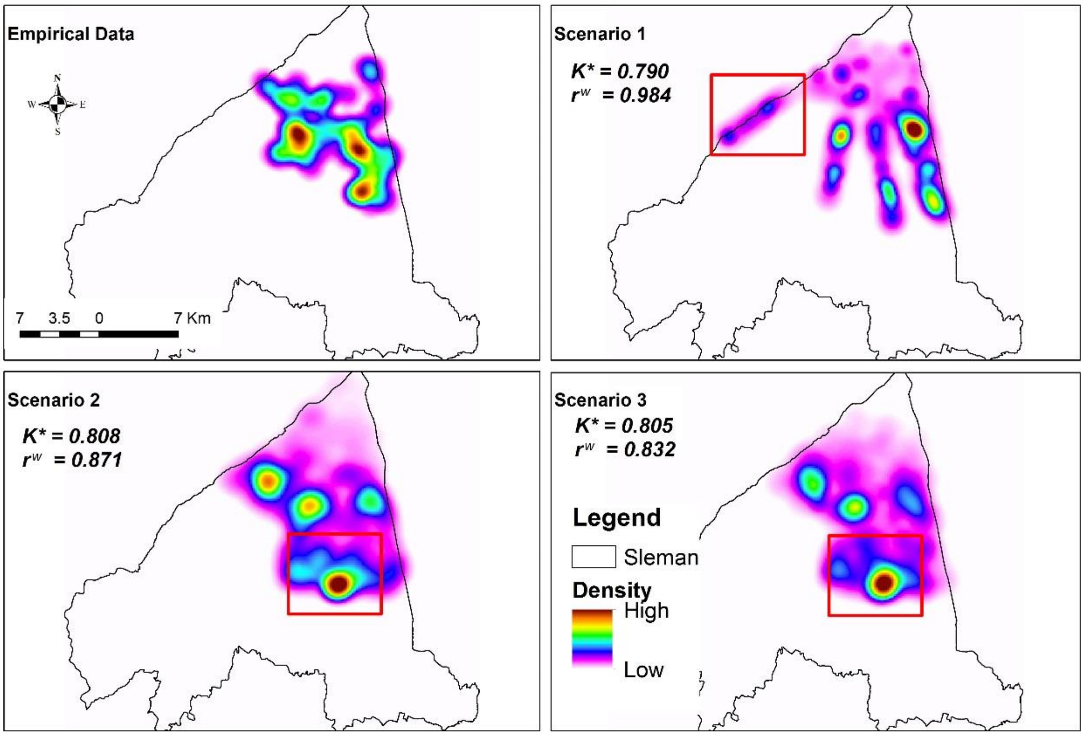

Figure 6.2 Spatial discrepancies between real and simulated data.

6.3.3 The Complicatedness of the Model

There is still academic debate on how complicated an ABM should be . Edmonds and Moss (2004) argue that ABM have the ability to model complexity in detail and suggest starting with a complex model and simplifying it provided the outputs continue to 'capture' real-world complexity. However, as yet, there is no consensus on whether to start with a simple model and make it more complicated or vice versa. Compared to a similar model, the ABM of wildfire (Wise, 2014) for example, the model developed in this thesis is more complex in terms of its parameterisation and decision rules. The wildfire model used decision a tree that relies on probability, while this thesis used threshold-based rules that need some parameters to generate the value. That is the reason why the there are so many parameters used in this thesis. In further improvement, following the guidance from Edmonds and Moss (2004), it is possible to simplify the model while attempting to retain the existing model behaviours.6.4 Limitations

This model has the potential to support the evacuation management in Merapi. However, there are several limitations that are possible to improve in the future. Based on the evaluation of both the model and the output, there are some limitations on the decision rules, the probability of interaction of people and the involvement of the road congestion effect on the agent speed.

Firstly, there is a key limitation regarding the decision rule of the agent. The destination choice rule should be improved since this is out of the scope of this research. The ABM has been utilised with the destination choice model when the agent decides to evacuate but is yet to be calibrated and validated. The distribution of evacuees is important to compare with the real data as it expresses the validity of the destination choice rule of the agent. In 2010, the populations within the danger zone in Merapi evacuated to temporary shelters (evacuation centres) distributed outside the danger zone. These shelters are commonly public facilities such as stadiums, schools, mosques/churches, etc.

Secondly, the effect of social influence and the probability of successful contact among people on the evacuation decision might be varying and this might affect the outcome. The model presented here ignores these variables and assumes that all agents always successfully make contact with their connections and always follow the commands given. In addition, it is possible for people to ignore the evacuation order altogether. The decision result as a response from interaction may vary among people, based on their perception of risk, and, because of such interactions, people at risk may socially aggregate in making decisions or/and in the evacuation process.

Thirdly, the result of traffic evaluation based on various scenarios of evacuation may be improved as there is an absence of involvement of congestion effect, road capacity variablility, and variability in the decision of destination choices. The current model used in the experiment disregards the possible effects of congestion to the movement of agents, therefore, it is unable to simulate the dynamics of evacuees following the interaction on the road. The congestions commonly occur when the volume of traffic is too close to the maximum capacity of the road (Goodwin, 2004). Therefore, the result of the model might be different when this factor is applied; but that depends on the value of road capacity and the number of evacuees conducting the evacuation. The distribution of evacuees is also defined by the variability of destination choice of evacuees since this affects their route selection.

6.5 The Road Map: from Modelling to Policy

Gilbert et al. (2018) suggest that there are seven aspects should be taken into account when bringing the model into public policy. (1) The appropriateness of the process means that the plausibility of the model is not merely measured from the output, but also the correctness of the process. It is needed to convince that the model is designed as a representation of the process in the real world. (2) The appropriateness of the level of model abstraction means the model should represent the real world in appropriate detail. All model requires a generalisation of the real system to simplify and make it easy to understand and validate. Therefore, the level of generalisation should consider the purpose of modelling (Edmonds and Moss, 2004). (3) By recognising the data and validation challenge, the future data collection and validation requirements can be identified for improvement, because modelling for policy is continuous processes (Gilbert et al., 2018). (4) Collaborative processes of model development and use are needed to ensure the model is focused on the purpose and to provide more effective peer review and scrutiny of the modelling processes (Gilbert et al., 2018). (5) Consideration of ethical issues is also important because policy will affect to human life. At least, it will involve human participants in developing the model. Likewise, the questionnaire survey that was conducted to develop the model in this thesis has undergone ethical review. (6) Communicating the modelling processes with stakeholder as well as the user who involved in the policy development is also important to be taken into account. (7) Lastly, the model also needs to be maintained regarding the evaluation of the policy implementation as well as the progress of technology.

It is considering the above successful keys of developing a model to support policymaker, this important to plan a roadmap to make sure that this volcanic evacuation model is implementable. The roadmap of the integration of the model to policy is presented in Figure 5.2. The roadmap consists of several steps that are including improvement of the model as well as stakeholder engagement. The improvement is that in order to consider, as well as to address the limitations that are presented previously in section 6.4. Therefore, because it should involve some additional rules, e.g. destination choice model, it should be undergone some further validations and data improvements whereas the stakeholder engagement is started by communicating the model with the stakeholder who responded to the evacuation management.

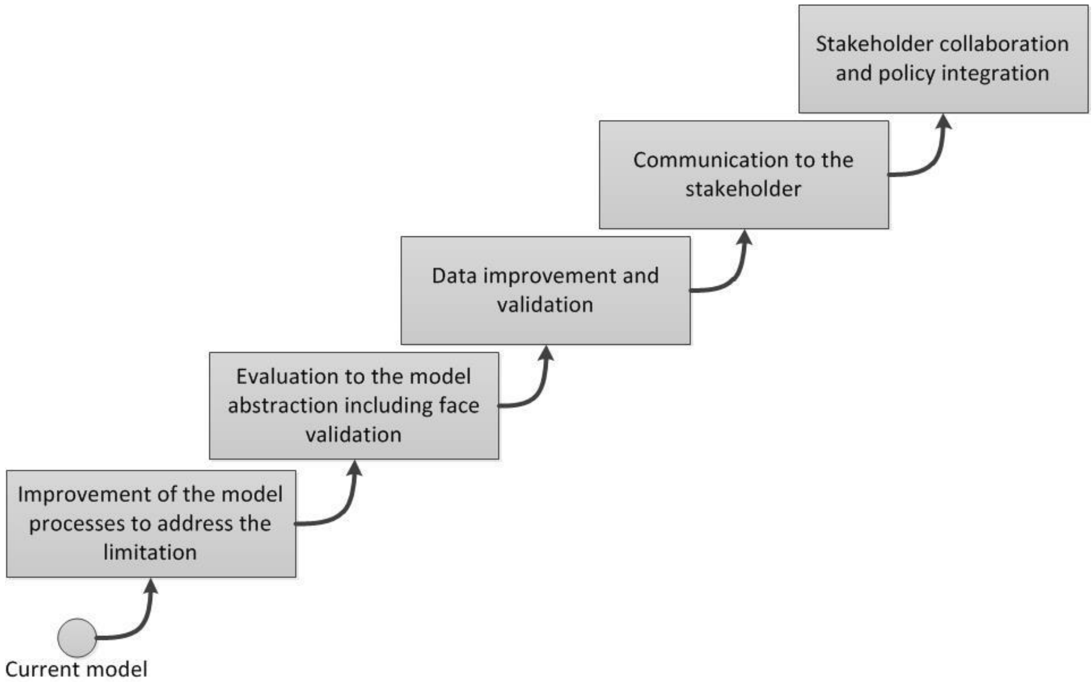

Figure 6.3 Road map of model implementation – leading to policy integration.

The integration of the model is then presented in Figure 5.2. The evacuation management procedure involves various parties of stakeholders including scientists (volcanologists), local government, and emergency response team that is some of the members are volunteers (Figure 5.2a) (Mei and Lavigne, 2012) whereas the model is attached to the procedure as a tool to support the local government in generating policy regarding the evacuation command issuance (Figure 5.2b). For example, the scenarios of the hazard following the result of the observation is then used to parameterise the simulation. The result of the simulation such as the evacuees density distribution along road networks is used to distribute police officer to anticipate bottlenecks or congestions.

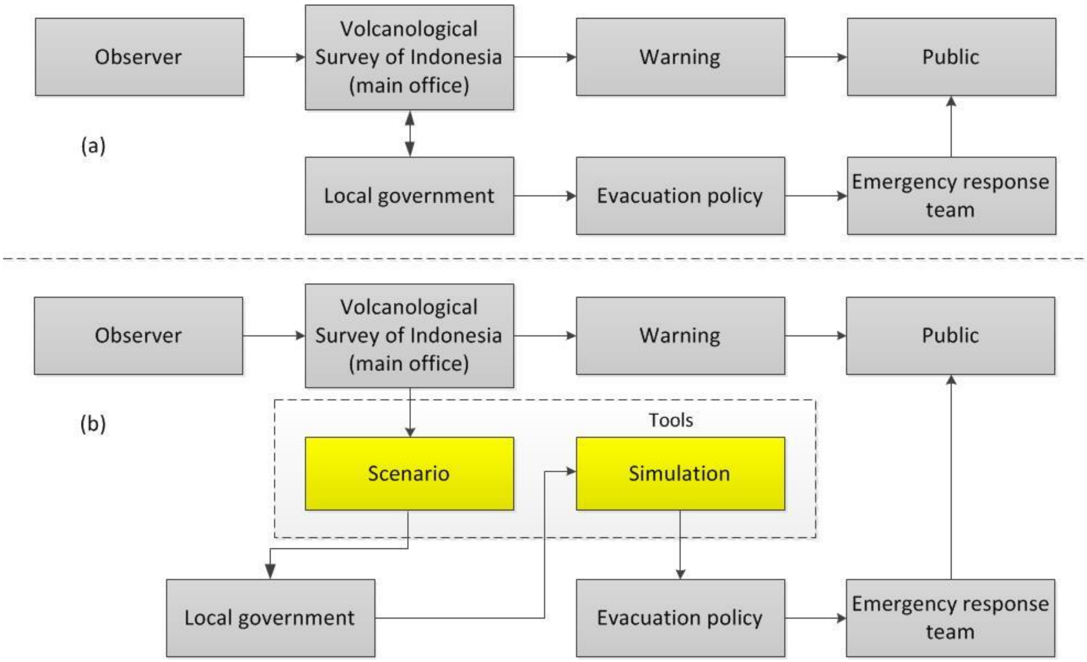

Figure 6.4 Attachment of the model to evacuation decision process (modified from Mei and Lavigne, 2012). (a) Current procedure of evacuation management process, (b) the evacuation procedure supported by the model.

6.6 Future Works

Considering the limitations mentioned above, there are some future works to improve the model as follows: (1) utilise the agent decision rule with a valid destination choice model derived from survey. This is important because developing an evacuation plan where the potential impact is uncertain needs several scenarios that might be possible to happen. One of the important aspects to consider in the plan is the distribution of evacuees. Research shows that destination choices are influenced by some factors. There are several relevant criteria for this model including travel distance, risk indicator, proximity to public services area, and the existence of family relatives (Cheng et al., 2008). Moreover, shelter capacity is also relevant in choosing evacuees' destination (Xu et al., 2014).This aspect is important in order to plan the services and logistics during the evacuation period. To do this, an extensive survey regarding the preference of people should be conducted. The result can be used to develop the agent's destination choice rule. (2) Utilise the model with synthetic social networks that mimic social networks derived from survey. (3) Utilise the model with a measure of agent friction during periods of congestion that impact the agent movement.

6.7 Concluding Remarks

The work presented in this thesis consists of developments in the processes of ABM and application of the techniques in order to achieve insights about how a spatial agent-based simulation can be used to improve volcanic evacuation management. The findings can be applied both to improvement of evacuation modelling and the practice of evacuation. This section discusses those aspects of Chapters 2 to 5 which advance not only the theory and practice of modelling but also the improvement of evacuation management in the specific case of Merapi.

This thesis offers improvements in a range of areas especially disaster management. The improvements to evacuation modelling are conducted by integrating spatio-temporal dynamics of the hazard into the model, utilising spatially realistic synthetic populations from microdata, formulating individual evacuation decision rules based on a survey, and using an individual risk model based on MCE. Improvements to evacuation management are provided by (1) new design of evacuation staging strategy, (2) anticipating reluctant people by identifying risk hotspots, (3) anticipating congestion by identifying potentially congested roads during the peak of evacuation time.

In this thesis, the use of geographical characteristics of an area to design evacuation prioritisation contributes to the application of geography for disaster management. This approach is applicable not only to manage evacuation from a volcanic hazard, but also from the other hazards where road networks and time constraints influence outcomes. The design of evacuation staging used in this thesis can easily be applied in other contexts by incorporating geographical characteristics of an evacuation zone to develop prioritisation. This spatial approach can be implemented in GIS by employing MCE.

To sum up, this thesis presents the development of a spatial agent-based model of volcanic evacuation in Mt. Merapi. This is an important effort due to lack of research in evacuation modelling conducted in Merapi. This can potentially be used to improve the effectiveness of evacuation plans by offering a less congested evacuation scenario and highlighting potential problems related to traffic management. Besides the potential for using these techniques locally in Merapi, the development processes of this evacuation model contribute in advancing the knowledge of ABM development for large-scale evacuation simulation by (1) integrating the hazard model that is derived from the historical record of spatial impacts of eruptions, (2) formulating and validating an individual evacuation decision model in ABM based on various interrelating factors revealed from the literature review and survey that enable modelling of the phenomenon of reluctant people, (3) formulating the integration of multi-criteria evaluation (MCE) in ABM to create a spatio-temporal dynamic model of risk (STDMR) that enables representation of changing risk as a consequence of changing of hazard level; hazard extent; and movement of people, (4) formulating an evacuation staging method based on MCE using geographic and demographic criteria.

References

Chen, X. and Zhan, F.B. 2008. Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. *The Journal of the Operational Research Society*. **59**(1), pp.25–33.

Cheng, G., Wilmot, C.G. and Baker, E.J. 2008. A destination choice model for hurricane evacuation *In*: *Proceedings of the 87th Annual Meeting Transportation Research Board, Washington, DC, USA* [Online]., pp.13–17. [Accessed 7 January 2017]. Available from: http://www.ltrc.lsu.edu/pdf/2008/08-0840.PDF.

Clarke, K.C. 2014. Cellular Automata and Agent-Based Models *In*: M. M. Fischer and P. Nijkamp, eds. *Handbook of Regional Science* [Online]. Springer Berlin Heidelberg, pp.1217–1233. [Accessed 26 April 2016]. Available from: http://link.springer.com/referenceworkentry/10.1007/978-3-642-23430-9_63.

Crooks, A.T. and Heppenstall, A.J. 2012. Introduction to agent-based modelling *In*: *Agent-based models of geographical systems* [Online]. Springer, pp.85–105. [Accessed 30 October 2016]. Available from: http://link.springer.com/chapter/10.1007/978-90-481-8927-4_5.

Cutter, S.L., Boruff, B.J. and Shirley, W.L. 2003. Social Vulnerability to Environmental Hazards*. *Social Science Quarterly*. **84**(2), pp.242–261.

Edmonds, B. and Moss, S. 2004. From KISS to KIDS–an 'anti-simplistic'modelling approach *In*: *International workshop on multi-agent systems and agent-based simulation*. Springer, pp.130–144.

Gilbert, N., Ahrweiler, P., Barbrook-Johnson, P., Narasimhan, K. and Wilkinson, H. 2018. Computational Modelling of Public Policy: Reflections on Practice. *Journal of Artificial Societies and Social Simulation*. **21**, pp.1–14.

Goodwin, P. 2004. The economic costs of road traffic congestion.

Handayani, D., Herliansyah, M.K., Hartono, B. and Sopha, B.M. 2016. Community behavior during the evacuation of Mount Merapi eruption disaster *In*: *2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*., pp.276–280.

Handayani, D., Sopha, B.M., Hartono, B. and Herliansyah, M.K. 2017. The Behavioural Rules of People During Disaster Emergency Evacuation: A Case Study of Mount Merapi Eruption in Indonesia. *Journal of Engineering and Applied Sciences*. **12**(21), pp.5443–5451.

Jumadi, Carver, S. and Quincey, D. 2017. A Conceptual Design of Spatio-Temporal Agent-Based Model for Volcanic Evacuation. *Systems*. **5**(4), p.53.

Jumadi, Heppenstall, A.J., Malleson, N.S., Carver, S.J., Quincey, D.J. and Manville, V.R. 2018. Modelling Individual Evacuation Decisions during Natural Disasters: A Case Study of Volcanic Crisis in Merapi, Indonesia. *Geosciences*. **8**(6), p.196.

Liputan6.com 2010. Kesaksian Korban Merapi. [Accessed 28 July 2018]. Available from: http://www.webcitation.org/71FT3eKkI.

Lovreglio, R., Ronchi, E. and Nilsson, D. 2016. An Evacuation Decision Model based on perceived risk, social influence and behavioural uncertainty. *Simulation Modelling Practice and Theory*.

Malleson, N., See, L., Evans, A. and Heppenstall, A. 2014. Optimising an Agent-Based Model to Explore the Behaviour of Simulated Burglars *In*: V. Dabbaghian and V. K. Mago, eds. *Theories and Simulations of Complex Social Systems* [Online]. Berlin, Heidelberg: Springer Berlin Heidelberg, pp.179–204. [Accessed 23 April 2015]. Available from: http://link.springer.com/10.1007/978-3-642-39149-1_12.

Mei, E.T.W. and Lavigne, F. 2012. Influence of the institutional and socio-economic context for responding to disasters: case study of the 1994 and 2006 eruptions of the Merapi Volcano, Indonesia. *Geological Society, London, Special Publications*. **361**(1), pp.171–186.

Mitchell, S. and Radwan, E. 2006. Heuristic Priority Ranking of Emergency Evacuation Staging to Reduce Clearance Time. *Transportation Research Record: Journal of the Transportation Research Board*. **1964**, pp.219–228.

Srbljinović, A. and Škunca, O. 2003. An Introduction to Agent Based Modelling and Simulation of Social Processes. *Interdisciplinary Description of Complex Systems*. **1**(1–2), pp.1–8.

Wise, S. 2014. *Using Social Media Content to Inform Agent-based Models for Humanitarian Crisis Response*.[Online] Ph.D. Thesis, Fairfax, VA, USA: George Mason University. [Accessed 20 May 2015]. Available from: http://digilib.gmu.edu:8080/jspui/handle/1920/8879.

Wolshon, B. 2002. Planning for the evacuation of New Orleans. *Institute of Transportation Engineers. ITE Journal*. **72**(2), pp.44–49.

Xu, W., Li, Y., Okada, N., Takeuchi, Y., Kajitani, Y. and Shi, P. 2014. Collaborative modelling-based shelter planning analysis: a case study of the Nagata Elementary School Community in Kobe City, Japan. *Disasters*. **38**(1), pp.125–147.

Appendices

All appendices below are provided soft file in the attached memory stick (except Appendix 2.1):

Appendix 1.1 The questionnaire survey.

Appendix 1.2 The survey results.

Appendix 2.1. Online Model: http://www.runthemodel.com/models/k-RgpNLa1oojYE1To31FJa/.

Appendix 2.2. Simulation Video: https://osf.io/qr65b/.

Appendix 2.3. Application documentation: https://osf.io/7yf3p/.

Appendix 2.4. Population unit and data: https://osf.io/k6d2n/.

Appendix 3.1. Statistical Analysis of Survey Data (https://osf.io/a8zew/)

Appendix 3.2. Evacuation dataset (https://osf.io/4kujy/);

Appendix 3.3. Reluctance raster map (https://osf.io/gy8ew/);

Appendix 3.4. Functions Overview of Evacuation Decision for Scenario 1 (https://osf.io/pqmv3/);

Appendix 3.5. Functions Overview of Evacuation Decision for Scenario 2 (https://osf.io/tkanc/);

Appendix 3.6. Functions Overview of Evacuation Decision for Scenario 3 (https://osf.io/rcqb3/);

Appendix 3.7. Main statechart diagram of the evacuation decision (https://osf.io/wftx7/);

Appendix 3.8. Raster data for Figure 3.9 (https://osf.io/chgdy/);

Appendix 3.9. Raster data for Figure 3.11 (https://osf.io/cygmp/);

Appendix 3.10. Raster data for Figure 3.13 (https://osf.io/3jvhb/);

Appendix 3.11. Shapefile for Figure 3.16 (https://osf.io/4upe9/).

Appendix 4.1. Documentation of the ABM application.

Appendix 4.2. ODD.

Appendix 4.3. The animated image of STDMR.

Appendix 5.1. Criteria weight calculation for Table 5.1 (https://goo.gl/vZnLFm).

Appendix 5.2. Criteria weight calculation for Table 5.2 (https://goo.gl/euDcNA).

Appendix 5.3. Data for Table 5.3 (https://goo.gl/Ek9aWS).

Appendix 5.4. Data time interval calculation for Table 5.4.

Appendix 5.5. Temporal output data and analysis.

Appendix 5.6. Spatial output data and analysis.