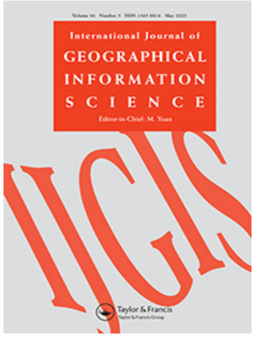

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RESEARCH ARTICLE

Exploring multi-modal evacuation strategies for a landlocked population using large-scale agent-based simulations

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ABSTRACT
At a time when the impacts of climate change and increasing urbanization are making risk management more complex, there is an urgent need for tools to better support risk managers. One approach increasingly used in crisis management is preventive mass evacuation. However, to implement and evaluate the effectiveness of such strategy can be complex, especially in large urban areas. Modeling approaches, and in particular agent-based models, are used to support implementation and to explore a large range of evacuation strategies, which is impossible through drills. One major limitation with simulation of traffic based on individual mobility models is their capacity to reproduce a context of mixed traffic. In this paper, we propose an agent-based model with the capacity to overcome this limitation. We simulated and compared different spatio-temporal evacuation strategies in the flood-prone landlocked area of the Phúc Xá district in Hanoi. We demonstrate that the interaction between distribution of transport modalities and evacuation strategies greatly impact evacuation outcomes. More precisely, we identified staged strategies based on the proximity to exit points that make it possible to reduce time spent on road and overall evacuation time. In addition, we simulated improved evacuation outcomes through selected modification of the road network.

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KEYWORDS
Agent-based simulation; evacuation policy; risk context; traffic model; urban area

1. Introduction

The Sixth IPCC assessment report shows (IPCC 2021) that extreme events such as heavy precipitation and tropical cyclones will increase in the coming decades. Those weather and climate extreme will increase the vulnerabilities of the most densely populated territories and unplanned areas, which makes risk and disaster management very complex. When structural solutions (reinforcement of habitats or construction of

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dams) have not been considered or are insufficient, the rapid and massive evacuation of populations facing the threat of imminent danger is a solution considered in many countries. However, evacuating large numbers of people is always an at risk strategy: people (including officials) may not make the most appropriate decisions, emerging congestion during the evacuation may make it difficult to get evacuees to appropriate shelters at the right time, and globally this whole complex procedure is subject to many unplanned circumstances, phenomenon obviously amplified for large populations. All this can increase exposition of evacuees to hazard and the occurrence of incidents. For example, the 55 deaths which occurred during Hurricane Rita in Texas were a consequence of the evacuation process rather than the storm itself (Knabb *et al.* 2006). In such complex and uncertain situations, local governments must therefore prepare systematic evacuation plans that can take into account many factors: number of people to be evacuated, number of buses available to evacuate non-autonomous people, relief routes in the event of disturbed traffic, identification of roads potentially blocked by floods … However, evaluating these plans outside a crisis context is, if not impossible, then very difficult. Indeed, while it is essential to prepare populations and organizations to deal with such events through exercises or educational programs, many aspects cannot be anticipated: secondary effects—also known as cascading disasters (Alexander and Pescaroli 2019)—coming from the primary disaster event such as traffic light shutdown, car accidents or landslides caused by flood may prevent people from leaving the area or communicating; on the same line, individual and collective behaviors such as refusal to evacuate, mass panic or antisocial actions cannot be easily predicted (Vorst 2010) but should be considered key aspects of any evacuation plan.

In this context, as in many other complex social phenomena, computer simulation appears to be an interesting tool to test how the system behaves for a variety of scenarios, provided of course that it allows to consider the impact of individual choices on global dynamics. Among the existing approaches, agent-based modeling (ABM) appears to be particularly well adapted to the study of such phenomena, as it allows representing the way in which the heterogeneity of individual behaviors and mobility choices will influence the dynamics of an evacuation.

In recent years, many agent-based models have been proposed to simulate the evacuation of populations in risky contexts. Some of these models have focused on pedestrian mobility, others on vehicle mobility. However, very few of them have taken into account the mixed and non-normative traffic that can be observed in many countries where people use a wide range of mobility modes while having a fairly relaxed relationship to legal traffic rules (Dang-Huu *et al.* 2020). To address this limitation, we propose a new model, part of the ESCAPE framework (Daudé *et al.* 2019), which incorporates a traffic sub-model suitable for representing mixed and non-normative traffic. This model is calibrated through a case study of the Phúc Xá district in Hanoi, Vietnam. This urban district is built in a flood zone and has a very high population density. Enclosed by a system of dikes supposed to protect it, the population of this district has only a few exit points if a breach were to occur. This case study is then very interesting to show how spatial constraints can be overcome by crisis response and evacuation planing. It gives us the opportunity to present how our model can be used to evaluate the effectiveness of different strategies in terms of population evacuation time.

In a first section, we will present the case study of the Phúc Xá district. Then, in a second section, we review the state of the art regarding agent-based modeling and evacuation in an urban context to highlight some shortcomings of existing works. Then, we will present our model and its application for the Phúc Xá district. The results of the simulations with different scenarios will be presented and discussed. Finally, we will conclude and discuss future perspectives for this work.

2. Evacuation of the Phúc Xá District, Hanoi, Vietnam

Phúc Xá is a district of Hanoi (Vietnam) of about 1 km^2 located in the flood-prone area, highlighted in Figure 1. Despite the fact that this district is declared unbuildable because it is included in the flood area of the river, its density (17,000 $inhabitants/km^2$) is one of the most important of Hanoi (the mean population density of Hanoi is around 9300 $inhabitants/km^2$). The Red River, which runs alongside the district, is known for its violent floods. The flow of the river has significant seasonal fluctuations. It can drop to 430 m^3/s during the dry season but reach 30,000 m^3/s during the monsoon season. Since the 1970s, a number of dams have been built to harness the river and produce electricity in China (Yunnan Province) and Vietnam. Among these structures, two present important risks for the districts of Hanoi close to the river, in particular in the case of rupture or sudden discharge: the Hòa Bình dam and the Thác Bà dam (Chapuis *et al.* 2021).

Figure 1. Map of the Phúc Xá District (OSM data). The red line shows the district border.

One of the specificities of this district is that it is enclosed: to the south, the district is blocked by the Long Biên bridge, to the east by the Red River, to the west by a dike, and it communicates to the north with another landlocked district. Thus, in case of flooding, the" exit doors" are limited. In practice, only few roads can be used to exit the flood zone. Figures 2 and 3 show these different exits, and for each building respectively the closest exit and the distance to it (using the road network). Apart from these main evacuation routes, a few metal ladders and staircases pass over the dikes and could allow for pedestrian flow, but these are too few and narrow to use for a planned evacuation.

The road data comes from OpenStreetMap and the Building data were digitalized from the cadastral maps provided by the Vietnamese authorities. A comparison with satellite data (Google) allowed us to validate these layers.

While there is no recent study on mobility in Hanoi, a 2017 study gives this breakdown on mobilities in Ho Chi Minh City (Hee and Dunn 2017) (second-biggest city in Vietnam): 74% of daily travel is done by motorcycle, 19% by bicycle and 1% by car, 4% by bus, and 2% by Taxi. If mobility has changed since then, with a consequent

Figure 2. Sectorization of buildings according to the nearest evacuation point using the road network. The spheres represent the exit points, the color associates a building with the nearest exit.

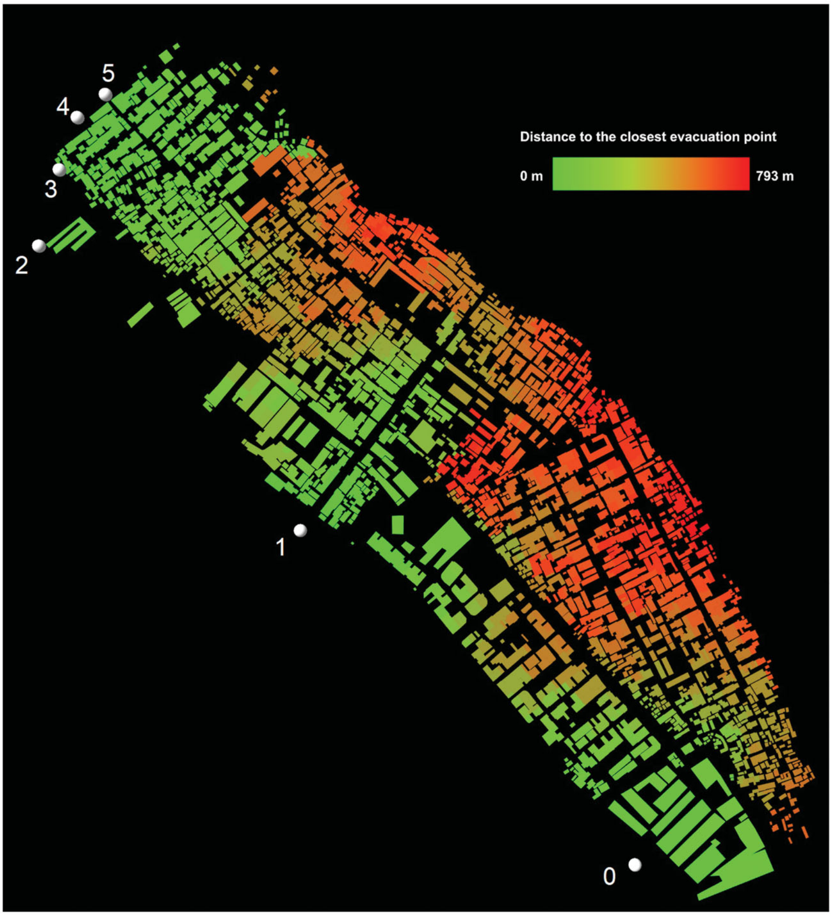

Figure 3. Distance (using the road) between the building and the evacuation points. The greener the building, the closer it is to an evacuation point. The redder it is, the farther it is. The white spheres represent the evacuation points.

increase in the use of the car, we can assume this distribution to reflect today's mobility pattern, notably with a significant predominance of the motorcycle. These data disregard displacement on foot, while (Labbé *et al.* 2019) stated that this is not true: in fact, when it comes to go to a nearby place (in the article concerned, to a park) or to take a bus or cab, Vietnamese people mostly go by walk. In a small district like Phúc Xá where the bus must be taken outside the district (the nearest bus stations are located on the main road behind the dike in the west), a significant part of the population which does not have a motorcycle, bicycle or car (difficult to park in the district) moves on foot. A characteristic of most roads in Vietnam and all roads in Phúc Xá is that there are no sidewalks and when there are, they are rarely usable by pedestrians because they are obstructed by motorcycles or other things. Therefore, pedestrians must walk on the road with other vehicles.

Regarding crisis management, there is no specific plan for this district (nor for any district in Hanoi), nor any awareness of the risks by the inhabitants, except a habit of regular flooding caused by heavy rainfall in Hanoi.

3. Related works

Agent-based simulation, because of its ability to represent individual behaviors, is particularly well suited to address mass evacuations, which explains the large number of models developed on this topic. To analyze these models, we propose in this section a review of the most recent researches in the domain. To do so, we followed a classical methodology based on the search of articles related to our theme in online databases and the selection of relevant articles. Concerning the database search, we used the keywords" *Agent based model evacuation urban*"gent based model evacuation urban its ability to represent individual behaviors, is particularly well suited to addes, (ii) written in English, (iii) from 2017 or newer – indeed, we consider that these articles already take advantage of older works. This last eligibility criteria have been chosen to stress recent advancements and challenges related to the design of ABM for mass evacuation. These criteria made it possible to reduce the number of articles to 36. Of these articles, 9 were removed because they did not present an agent-based model or did not provide enough information about the model (short articles).

Tables A1–A4 present the list of selected articles and the corresponding references. To classify them, we defined several categories: *evacuation* for articles presenting an evacuation model; *mobility model* for articles presenting a new mobility model or an improvement of an existing model (typically, a new social force model); *behavioral model* for articles focusing on peopleobility model or an improvement of an existing model (typically, a new socia*large-scale model* for articles presenting new methods for evacuation of large populations. An article may belong to more than one category: for example, Makinoshima *et al.* (2018) presents an evacuation model, but much of the article is devoted to presenting and testing a parallelization strategy for the calculation. For each article, we also noted the hazard involved (if any), whether its dynamics are simulated or only used as input or context, the territory involved, the number of agents simulated (when multiple experiments are performed, we just noted the highest value), the way mobility is modeled, and the type of strategies or scenarios tested.

3.1. Mobility model

These papers present an innovation in terms of mobility modeling. Two papers in this category (Prédhumeau *et al.* 2021, Hesham and Wainer 2021) deal with pedestrian mobility: their objective is to propose an improved model to simulate pedestrian behavior. A third paper, i.e. Haghpanah *et al.* (2021), which proposes a real application for evacuation, but focuses on the comparison of mobility models. From the perspective of the proposed review, too few models tackle the issue of mixed mobility modes in the context of mass evacuation.

3.2. Behavior model

These articles focus on the behavior of people in the face of the crisis: evacuation is usually one of the possible strategies, but the model also proposes other behaviors (e.g. staying at home, informing others, etc.). Taillandier *et al.* (2021) is a good example of a model where the focus is more on the behavior of people in a flood context: the behavior is modeled using a BDI architecture with many actions that people can undertake among which evacuation. Another example is Bernardini *et al.* (2017) which focuses on video analysis to extract a behavioral model. In Yang *et al.* (2018), the agents representing the household do not move, the model focuses only on their behaviors. Other works like Battegazzorre *et al.* (2021) and Parikh *et al.* (2017) propose different actions for the agents, but focus more on the movement of the population. In this case, they belong to both categories (*evacuation model* and *behavioral model*). Recent researches in the domain either focus on behavioral response to crisis situation or on the decision-making of individuals during the evacuation. There is a need for integrative models, that is to say, models that include both behavioral responses and evacuation mechanics: models that make it possible to combine crisis behavior with an in-depth representation of the complex evacuation decision-making process, at both individual and collective levels.

3.3. Large-scale model

These articles propose methods to allow large-scale simulation. Both the proposed method (coupling of models/parallelization) and the number of simulated agents differ (from 25,869 to 10 million). Thus, some of these articles propose to couple a macro/meso model with a micro model (agent-based model) to be able to carry out scenarios with a large population. Other works like Makinoshima *et al.* (2018), Battegazzorre *et al.* (2021), Wijerathne *et al.* (2018) use parallel computing. Finally, Parikh *et al.* (2017) uses a simple routing model to be able to simulate a large population. One of the major drawback of realistic evacuation ABM is the computational power required. From what we had extracted from recent attempts, allowing models to run complex processes while simulating hundreds of thousands of agents is still an issue in the domain.

3.4. Evacuation model

The largest category is that of articles that present an actual evacuation model (22 articles). An important first observation is that most of the models propose to incorporate only one mode of travel: no less than 13 of these articles focus on walking trips and 5 on driving trips. Note that one paper focuses on evacuation using urban air mobility systems, and human mobility is not considered (West and Sherry 2020). Therefore, only 3 models in this category propose to simulate both car and pedestrian mobility. Thus, Aguilar *et al.* (2019) propose to represent both pedestrian and car traffic using a model based on the calculation of a collision-free velocity along a graph. Few details are given about the precise calculation of this velocity and the model used. Haghpanah *et al.* (2021) uses two different models for cars and pedestrians: for cars, a simple version of the car tracking model is used; for pedestrians, two bug navigation algorithms coming from robotics are tested. Two types of interactions are considered between pedestrians and cars: at intersections without traffic lights, pedestrians have the right to cross streets before vehicles; in addition, if sidewalks are crowded, pedestrians can use the road and cars must stop to let pedestrians pass.

Daudé *et al.* (2019) also proposes to use two mobility models: a social force model for pedestrians and a model derived from the intelligent driver model for cars (and buses). However, no information is given about the interaction between the car and the pedestrian.

Regarding pedestrian models, several types of mobility models are used, but most of the works relies on social force models, cellular automata models, optimal reciprocal collision avoidance models, or on a simple calculation of the agent's speed as a function of its characteristics or density. As far as car traffic is concerned, apart from simple models, most of the works are based on classical traffic models (Transim, Sumo, Matisse, etc.). Another remark is that the hazard is rarely modeled, except for flooding. Sometimes, the impact of the hazard (area affected, impact on the building) is taken as input. Concerning the type of scenarios and strategies tested with the model, they can be of different types: hazard scenarios (Battegazzorre *et al.* 2021, Veeraswamy *et al.* 2018), different parameters for the population—e.g. density/number (Li *et al.* 2019, Wang *et al.* 2020, Nakasaka *et al.* 2020), psychological/physical characteristics (Yamazaki *et al.* 2017, Wang *et al.* 2020, West and Sherry 2020), knowledge of the shelters (Sun *et al.* 2021), information/communication (Parikh *et al.* 2017), car use (Aguilar *et al.* 2019, Kim and Cho 2020), group composition (Pan *et al.* 2021) or evaluation of different policies (Kim *et al.* 2017, Yin *et al.* 2020, Bianchin and Pasqualetti 2020, Oh *et al.* 2021, Al-Zinati and Zalila-Wenkstern 2018). Regarding the latter type, Bianchin and Pasqualetti (2020) proposes to optimize the duration of traffic lights to minimize congestion. Yin *et al.* (2020) are interested in the optimization of the evacuation plan: how to minimize the evacuation time by assigning a specific exit to each agent. Oh *et al.* (2021) study the impact of staged evacuation by introducing a delay between the evacuation processes of different areas. Al-Zinati and Zalila-Wenkstern (2018) are also interested in zoning strategies, but test as well the impact of a route reversal. Finally, Yin *et al.* (2020), whose main contribution concerns the use of cell phone data to improve the efficiency of evacuation model exploration, tests different scenarios among which different departure time, phasing and road policies.

In summary, while many models exist, few are able to consider the reality of a massive population evacuation that will involve travel on foot, by two-wheeler, by private car and by public transportation. The study of evacuation in Hanoi requires the ability to consider different types of mobility (at least cars, motorbikes and pedestrians) and their interaction. Moreover, as in many places in Vietnam, there are no sidewalks: pedestrians, cars and motorcycles use the same space. Finally, the way people drive in Vietnam is very different from most developed countries: while people tend to respect driving on the right, many other driving rules like the notion of priority, passing on the left or to respect driving speed limitations are more loosely followed. If the population's size, about 20,000 people, requires attention to the model chosen to simulate mobility, it does not require a very specific large-scale modeling strategy. Since our goal is to focus on the spatio-temporal impacts of evacuation's strategies rather than investigating the impact of people's behavior in the face of flooding, we choose to make different simplifications in the crisis scenario and in the behaviors of individuals: when the alert signal is triggered, people leave without having to think about the relevance of evacuating; the dynamics of the flood is not considered as we simulate a preventive evacuation. As for tested strategies, we can draw on the strategies tested previously regarding zoning, i.e. introducing a delay in the evacuation order between the different zones.

Our model takes advantage of an existing framework (Daudé *et al.* 2019). ESCAPE integrates several mobility models, and in particular a lane-based traffic model – each vehicle moves on one lane of a road and can change lane at any time (Tranouez *et al.* 2010, Taillandier 2014). One of the strengths of this mobility model, in addition to being adapted to large-scale simulations with tens of thousands of vehicles, is that it can consider non-normative driving: drivers may or may not respect traffic rules, e.g. they may decide not to stop at a red light, not to respect right/left priorities, to overtake using left/right lanes, etc. However, in the previous version of ESCAPE, it does not model vehicles of different widths, and it is based on simple ad hoc acceleration and lane change models. An ESCAPE application for the Phúc Xá district had already been proposed (Chapuis *et al.* 2021), but this one mainly focused in the coupling between a flooding software (HEC-RAS) and a simple mobility model (with pedestrians and motorbikes). In this work, we used ESCAPE and more precisely its abstractions (road, building, moving agent) and its mobility model, but we enriched it to adapt it to our context. ESCAPE, and thus our model, is implemented with the GAMA open-source agent-based simulation platform (Taillandier *et al.* 2019). This platform provides a complete modeling and simulation development environment for building agent-based simulations. Many models dedicated to evacuation have already been implemented using this platform (e.g. Valette *et al.* (2018), Le *et al.* (2017), Anh *et al.* (2011)). The model and all data used for the experiments have been made available (see section 6).

4. Model proposed

4.1. Hypotheses

To design the evacuation model, we defined a set of hypothesis that allowed us to frame our simulation around the impact of mixed mobility modes and optimization of overall evacuation time. Those hypotheses seek at limiting the complexity of the model to achieve our purpose but have not been based on statistical data, even if most of them are based on common sens and empirical observations. The following hypotheses are posed on the evacuation model:

1. people evacuate as soon as they receive the order to evacuate;
2. people are familiar with the district in which they live and therefore know all the possible routes and paths as well as all the exits from the area, which for us correspond to evacuation points;
3. people use the same means of transport as usual, and may be several in a car or on a motorcycle. Since there is no bus station in the district and ordering a cab takes time, people who usually use the bus or cab walk to the exit of the district;
4. pedestrians do not use sidewalks, but walk on the road with other vehicles;
5. people evacuate by the nearest exit (by the roads);

6. to go to this exit, people use the shortest route (minimization of the distance by the roads);
7. at the crossroads, people can see if the road is congested and possibly choose a new exit and/or a new path. Whether people choose to question their path depends on how close they are to the exit they are trying to reach: the closer a person is to the exit, the less likely she/he will question her/his path;
8. if an inextricable traffic jam appears, it is the most mobile people who will try to unblock it (by stepping back).

In the following sections we describe the model following the summary form of the ODD protocol (Grimm *et al.* 2020). A complete, detailed model description, following the ODD protocol is provided in Appendix B.

4.2. Summary ODD

The overall purpose of our model is to test the impact of a spatio-temporal evacuation strategy on the evacuation time at the scale of a district (several thousand agents) in a context of mixed mobility modes (car, motorcycle, bicycle, pedestrian). Specifically, we address the following questions: What is the impact of the mobility mix on evacuation times, and how to minimize evacuation times and average time spent on the roads? To consider our model realistic enough for its purpose, we use the following patterns: when a large population seeks to evacuate, it will generate traffic jams that will slow down the evacuation; not evacuating everyone at the same time greatly limits traffic jams and therefore the time spent on the roads by people; evacuation times are highly dependent on the type of mobility.

The model includes the following entities: moving agents, buildings, roads, intersections and evacuation points.

The moving agents are the main agents of the model. All attributes of these agents are described in Table 1. The model includes 4 subtypes of moving agents: cars, motorcycles, bicycles and pedestrians. These 4 subtypes share the same attributes, but different values for these attributes (see Appendix C for the values of the attributes retained for our case study).

The buildings, intersections and evacuation points are only characterized by their geometry (georeferenced in the environment).

In addition to their geometry, the roads are also characterized by a speed limitation and a number of lanes. Each road is linked to each of its ends to an intersection. In this model, a bidirectional road is considered as two roads of opposite direction, each one linked to the other (called" reverse" road): a moving agent will be able to use this reverse road to overtake another moving agent.

A time step represents 0.5 s and the model aim at representing the complete evacuation; thus the temporal extent goes up to several hours. The spatial extent is that of a city district (around $1km^2$).

The most important processes of the model, which are repeated every time step, are the choice of an evacuation point and a path to reach it by the moving agents,

Table 1. State variables of the moving agents.

Attribute name	Type	Description
Location	Coordinate	Coordinate (point) of the location of the agent – dynamic
Acceleration	Float	Current acceleration of the agent – dynamic
Current road	Road	Current road on which the agent is located – dynamic
Current lane	Integer	Current lane on the current road – dynamic
Known traffic jam	List of roads	List of known congested roads – dynamic
Home	Building	Home and initial location of the agent – static
Leaving time	Float	Departure time for the agent (to evacuate) – static
Leaving time	Float	Departure time for the agent (to evacuate) – static
Length	Float	Length of the agent – static
Number of lanes occupied	Integer	Width of the agent in terms of number of lanes occupied – static
Max speed	Float	Maximal speed of the agent – static
Speed coefficient	Float	Tendency to drive under or below the road speed limitation (for vehicles) – static
Max acceleration	Float	Maximal acceleration of the agent – static
Min spacing	Float	Minimum distance to the leading moving agent that the current agent must maintain – static
Max deceleration	Float	Comfortable braking deceleration of the agent – static
Time headway	Float	Minimum time difference accepted between the agent and the leading agent when they pass a given point – static
Politeness factor	Float	Attention to others when changing lanes – static
Acceleration gain threshold	Float	Minimum acceleration gain for the agent to change lanes – static
Maximum safe deceleration	Float	Maximum deceleration of the new follower induced by lane changing accepted – static
Proba reverse road	Float	Probability for the agent to consider to use the linked road (if there is one) – static
Reverse road lane limit	Float	Maximum number of lanes on the linked road that the agent considers to use – static
Time before parking	Float	If stuck, time before parking and letting agents coming from opposite direction to pass – static
Traffic jam density threshold	Float	The minimal density on the road for the agent to consider it as congested – static
Tendency to recalculate path	Float	Tendency of the agent to recompute its path if there is traffic jam – static

their movement and the reconsideration of their evacuation point and of the path if necessary, especially in case of blockage in a traffic jam.

The most important design concepts of the model are the emergence of traffic jams from the interaction of moving agents and the capacity of the moving agents to adapt their behaviors to these traffic jams. This adaptation is stochastic and depend on each agent.

Important outputs of the simulation are the time needed for the complete evacuation of the area and the time spent on the road.

The model is initialized from 3 types of geographical data: the roads (linear geometries), the buildings (polygonal geometries) and the evacuation points (point geometries). Once the roads, buildings and evacuation points created from these data, the moving agents are created and located on the buildings. The type of agent created (car, motorbike, bicycle, pedestrian) depends on the mobility mode probabilities.

5. Experiments

The model was applied to the Phúc Xá district using the geographical data described in Section 2. All the parameter and attributes values are described in Appendix C

(Tables C1–C4). The choice of parameters resulted in the generation of 123 car agents, 7427 motorbike agents, 1997 bicycle agents and 609 pedestrian agents.

The first series of experiments carried out is dedicated to the stochasticity analysis of the model to define a relevant number of replications for the following experiments. A hypothesis of this work is that it is important to represent the diversity of actual types of mobility modes to better assess evacuation strategies. To validate this hypothesis, we propose in a second set of experiments to test the impact of mobility type on the evacuation. The third set of experiments evaluates drivers capacity to question their evacuation point and path. What is the impact of drivers behavior facing traffic jam on the evacuation?

We then focus on the impact of the implementation of a spatio-temporal evacuation strategy through two series of experiments: what is the efficiency of an evacuation strategy per proximity to the exits, compared to a zonal evacuation. Finally, we study the impact on the evacuation process of small enhancements applied to the road network: is it possible to improve the evacuation's efficiency by a minimal modification of the road network?

For all these experiments, we will analyze 2 main outputs: the evacuation time, which stands for the time between the first evacuation order and the last agent to leave the area, and the average time spent on the roads, which is the average time between the order to evacuate and actual exit of the agents.

5.1. Stochasticity study of the model

In the first experiment, we analyze the impact of simulations randomness on the results and in particular on evacuation time and on the average time spent on roads. The main objective is to find a threshold value of replications beyond which an increased number of replication would not imply a significant change in-between results. To do so, we compare the evacuation time and the average time spent on roads between repetitions of the simulation. We run 100 repetitions of such a simulation and compare the variability of the results for the first 10, 25, 50 and 100 repetitions. The number of 100 was chosen empirically considering the simulation time and the impact of stochasticity on the model (see below).

The departure time of each agent is randomly set (uniform distribution) between 0 and 1 *h*. The goal is to choose parameter values that lessens as much as possible the impact of stochasticity on simulations results (in most of the other experiments conducted, agentbjective is to find a threshold value of repo be sure of the robustness of the results for the other experiments. A simulation (complete evacuation) takes about 10 minutes using a single core on an Intel Core i7-7700HQ CPU (2.80 GHz).

First, Figure 4 shows the evolution of the number of agents left to evacuate along the time over all the repetitions. The red line is the median value. The curves follow a constant decrease throughout time highlighting the capacity limitation of the evacuation points. After a certain time (around 60 minutes), as it is possible to see on Figure 5 which presents an example of results of simulations, only some exits are still in use (mainly exit 0 but also exit 1), the remaining agents being stuck in traffic jams and waiting for their turn to evacuate, which explains the bending of the evacuation

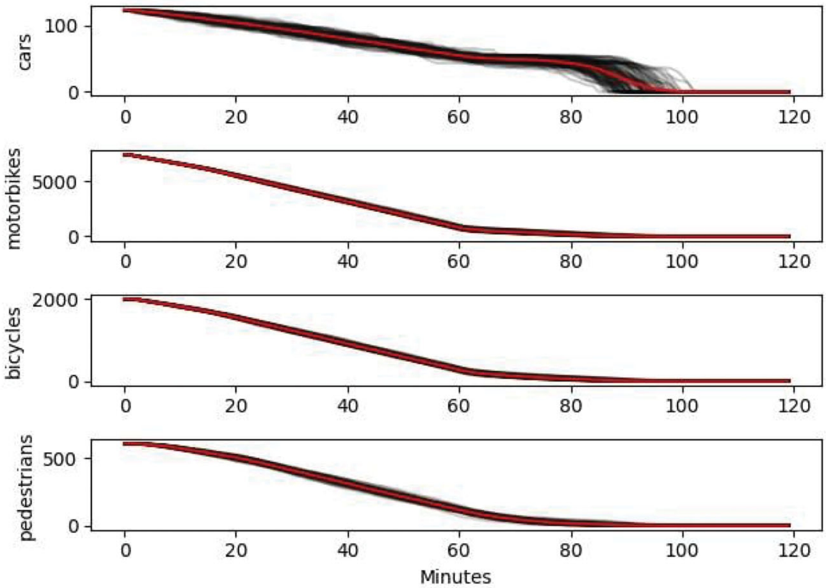

Figure 4. Number of agents who have not yet evacuated by mode of travel along the time. In red, the median values.

curves. We also can see that cars have more difficulty to evacuate being more easily blocked in traffic jams (particularly visible at exit 1).

Regarding the impact of stochasticity, Figure 6 shows the standard error obtained with different number of replicates on the evacuation time and on the average time spent on roads. Figure 7 shows the impact of the number of replication on the evacuation time and on the average time spent on roads: black lines are the median, boxes show the second and third quartiles (IQR), whiskers show the minimum and maximum excluding outliers (simulation results which differ from the median by more than 1.5 times the IQR). We can observe that with 10 replicates not only is the standard error is very high, but also significant differences can be observed from the 100 replicates. With 25 replicates, the difference is small enough to ensure sufficient robustness of the results. Thus, the experiment suggests that increasing the number of replicates beyond 25 does not have an important impact on the aggregate trend of the simulated evacuation.

For the study of the scenario presented in the next section, we decided to set the number of replicas to 25 in order to minimize the required computational time while trying to adequately represent the dispersion of possible simulation outputs.

5.2. Impact of agents mobility mode

A strong statement of this work is that it is important to consider the different modes of transport to evaluate large-scale evacuation policies. To validate this statement, we therefore propose to compare an evacuation considering only certain modes of transport: what would be the impact if all inhabitants of Phuc Xa evacuate using only car, motorcycle, bicycle or on foot compared to a realistic traffic mix?

Figure 5. Example of a mixed traffic simulation results at different time step. In cyan, cars; in magenta, motorcycle; in yellow, bicycle; in green pedestrian. This example shows the main traffic jam area near exit number 1.

We thus tested five scenarios:

- Mixed traffic: 74% of motorcycles, 19% of bicycles, 6% of pedestrians and 1% of cars.
- Traffic composed only of cars.
- Traffic composed only of motorcycles.
- Traffic composed only of bicycles.
- Traffic composed only of pedestrian.

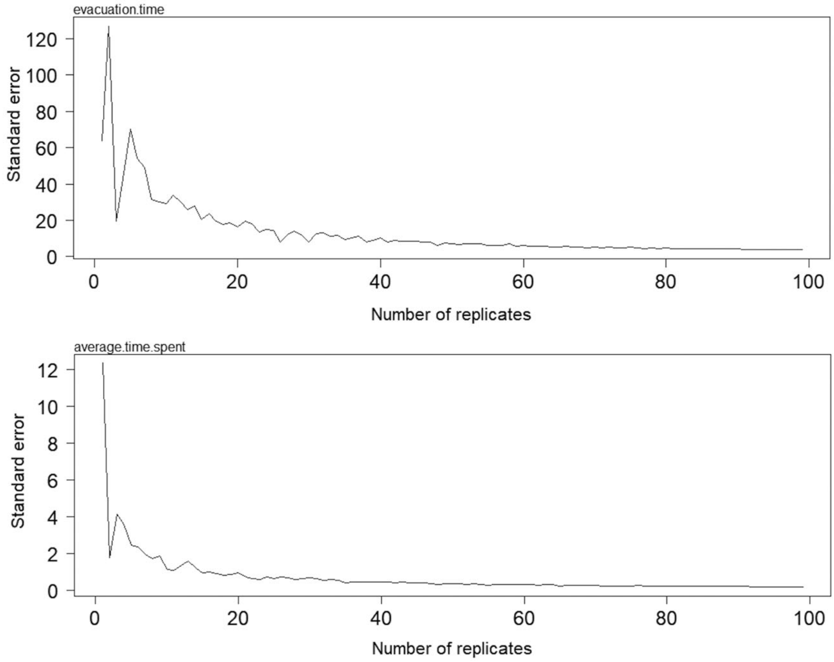

Figure 6. Comparison of the standard error on the evacuation time (in seconds) and of the average time spent on roads (in seconds) for the different number of replicates of a mixed traffic simulation.

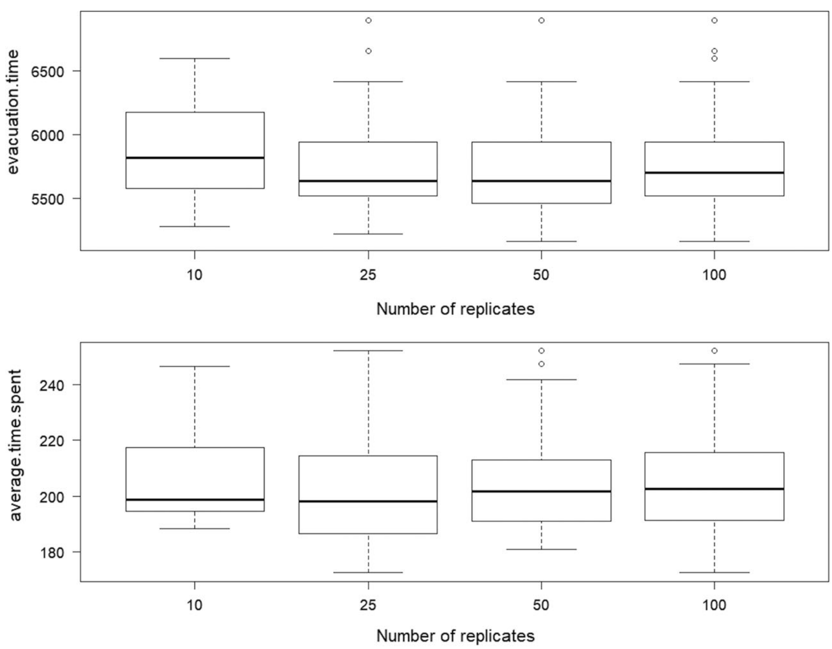

Figure 7. Whiskers plot of the evacuation time (in seconds) and average time spent on roads (in seconds) for the different number of replications. Black lines represent the median values; boxes represent the interquartile range (IQR), whiskers represent the minimum/maximum excluding 1.5 IQR outliers. Points are outliers beyond that distance.

The departure time of each agent has been set to 0, i.e. we consider that all agents left at the same time – at the beginning of the simulation. An important point is the number of people per vehicle: in the case of car-only mobility, the number of agents will be much lower than in the case of pedestrian mobility. One of the assumptions of this work, in line with practices in Vietnam, is that there can be several people in a car or on a motorcycle. More details on the number of people per vehicle are given in Section B.3.1.

Figure 8 shows the evolution of the number of agents left to evacuate along the time and Table 2 the results obtained in terms of evacuation time and time spent on roads for the five scenarios.

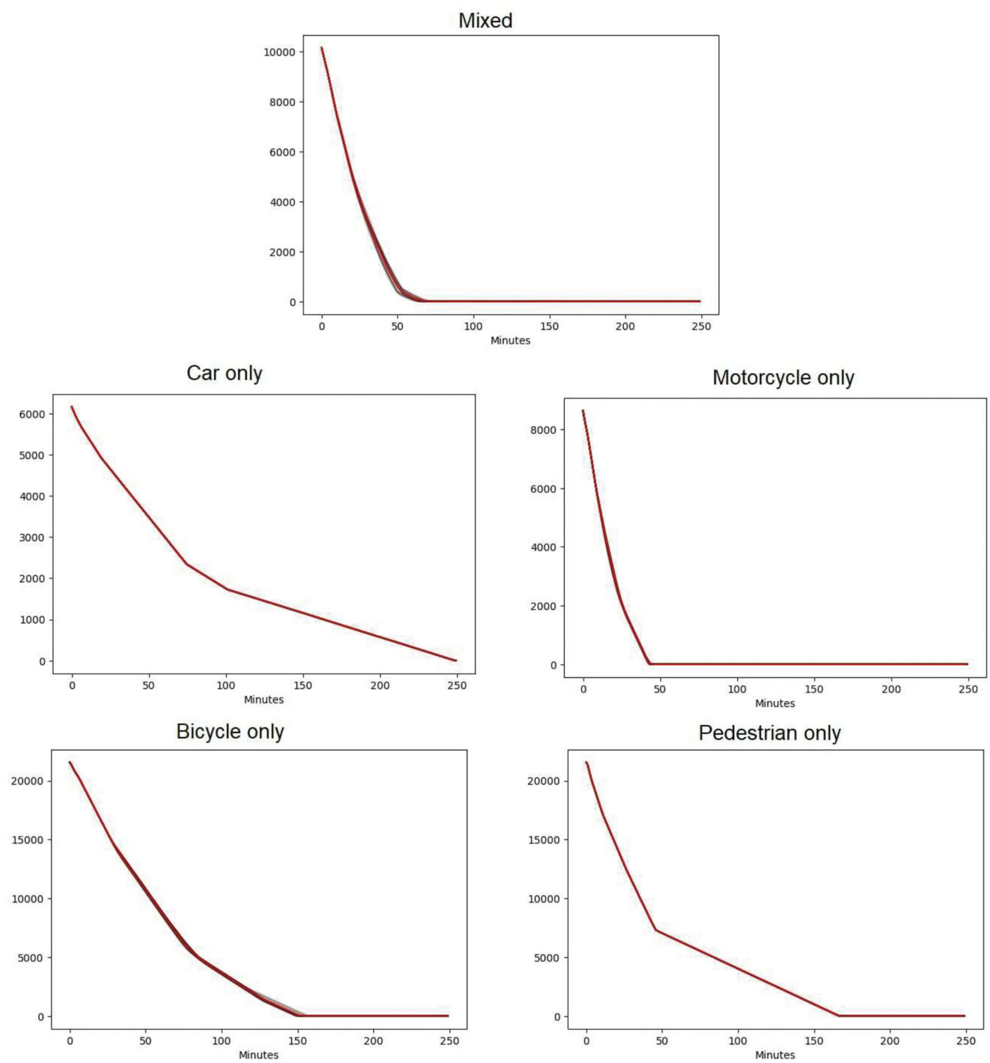

Figure 8. Number of agents not yet evacuated along the time for the different scenarios based on the means of transport used by the population. In red, the median values.

Table 2. Evacuation time (time elapse between evacuation order to last agent evacuated) and time spent on roads in seconds (average duration of the evacuation path over all the agents) with standard deviation for different mobility modes and averaged over replications.

Mobility mode	evacuation time (in s)	Time spent on the roads (in s)
Mixed	4686 (±624)	1372 (±31)
Only cars	14,937 (±12)	2502 (±689)
Only motorcycles	2638 (±32)	502 (±5)
Only bicycles	9204 (±141)	1757 (±408)
Only pedestrians	10,034 (±26)	1491 (±2)

A first finding, which corroborates our hypothesis on the importance of considering the different modes of mobility as they exist in Hanoi, is the difference in the results obtained with the five scenarios: in the case of mobility only by motorcycle, evacuation is much faster whereas it takes much longer in the case of mobility only by car, bicycle or on foot. Motorcycles indeed allow moving several people (they are often used in Vietnam to move families) with a limited rate of encumbrance and a significant speed. While cars have higher top speeds and can carry more people, their size on the road and their limited ability to maneuver lead to a sharp increase in traffic jam, and consequently the worst evacuation time of all scenario. In this regard, it is worth noting that the infrastructure of the studied area, i.e. made of small roads and many crossings, is particularly detrimental to the car modality. Regarding evacuation on foot, the high evacuation time is largely attributable to the speed limit of individuals. Indeed, this problem of travel speed is particularly visible on the time spent on the road. Compared to bicycle only mobility, the average time spent on the road is lower, which means that the majority of people evacuate faster. However, some agents, who have to travel a longer distance (e.g. because they decide to change their evacuation point), will take a long time to reach their destination. As for bicycles, if they allow moving faster than on foot, their greater size and the fact that they do not allow to move more than one person, makes the evacuation far from being as fast as for motorcycles.

Concerning the mix of mobility modes which corresponds to that of Hanoi, with a significant dominance of the motorcycle, the result is between the mobility by motorcycle only and the other one transportation mode scenarios, as could be expected, considering the proportions in the mix.

5.3. Impact of agents behavior

The purpose of this experiment is to evaluate the impact of the agentsi, with a significant dominance of the motorcycle,path in case of congestion. More precisely, we tested the impact of the variation of the attributes" Traffic jam density threshold" over the variation of" Tendency to recalculate the evacuation point/path" on the evacuation times and on the average time spent on roads. As in the previous experiment, the departure time of each agent has been set to 0. We tested 4 values for each attribute:

- Traffic jam density threshold (tj_a): 0.25, 0.5, 0.75 and 1.0
- Tendency to recalculate the evacuation point/path (k_a): 0.1, 0.01, 0.001 and 0.0001

Table 3. Evacuation time and standard deviation in seconds for different values of tj_a (Traffic jam density threshold) and k_a (Tendency to recalculate the evacuation point/path) averaged over replications.

	k_a			
tj_a	0.1	0.01	0.001	0.0001
0.25	4539 (±408.33)	4068 (±318.85)	8983 (±411.0)	9510 (±157.8)
0.5	4260 (±568.38)	4127 (±448.29)	8724 (±336.0)	9710 (±574.37)
0.75	4534 (±720.82)	4464 (±527.73)	8555 (±209.94)	9526 (±245.5)
1.0	9368 (±153.54)	9468 (±105.33)	9480 (±129.24)	9442 (±44.51)

Table 4. Time spent on the roads and standard deviation in seconds for different values of tj_a (Traffic jam density threshold) and k_a (Tendency to recalculate the evacuation point/path averaged over replications).

	k_a			
tj_a	0.1	0.01	0.001	0.0001
0.25	1254 (±27.57)	1172 (±25.39)	2498 (±23.95)	2733 (±14.85)
0.5	1218 (±28.99)	1232 (±24.57)	2493 (±66.09)	2739 (±14.25)
0.75	1363 (±28.0)	1363 (±31.12)	2484 (±50.65)	2737 (±16.67)
1.0	2714 (±48.58)	2743 (±30.86)	2743 (±9.74)	2740 (±10.26)

Table 3 shows the results obtained in terms of evacuation time, and Table 4 shows the results obtained in terms of time spent on the roads. A first observation is that the introduction of a path recalculation behavior has a strong impact on the result. In the case where there is almost no path recalculation ($tj_a = 1.0$ or $k_a > 0.001$), the average evacuation time (and the time spent on the road) is much longer (more than twice higher). For the other cases, we can observe a better evacuation time when the tj_a is at 0.25 and k_a at 0.01 which seems to be a good compromise between persisting in the path and changing it when there are too many people.

Note that in reality, people rarely follow an optimal behavior. Thus, for the other experiments, we chose to take an arbitrary value of 0.75 for tj_a and of 0.01 for k_a, which seemed to deliver a coherent behavior in terms of re-routing: agents change their route following a trade-off between escaping from congestion and keeping on the same densely populated road when an exit is close.

5.4. Impact of proximity/time

The goal of this experiment is to test the effectiveness of an evacuation strategy based on proximity to the exit and to compare such approach to a random strategy (no spatial rules on evacuation priority). We defined two parameters to define the departure time of agents:

- α: this is a parameter between 0.0 and 1.0 which allows weighting the strategy consisting in preferentially warning peoples closest to an exit to evacuate them first. If α is 0.0, the evacuation order is given randomly following a uniform law over the whole area. If α is 1.0, it will warn -gradually- people closest to one of the exits who are ordered to evacuate. In this case, peoples closest to the exits will be warned first.

- β: this is a parameter which allows controlling the speed (in people notified per second) at which evacuation orders are given. If β is 0.0, the speed is infinite in the sense that the order is given to all individuals at the beginning of the evacuation. If β is at 1.0, the speed will be of *N/MaxDuration* which makes it possible to send the order of evacuation to *N* individuals in the *MaxDuration*.

The departure time of an agent *a* is defined as follows:

$$leavingTime(a) = TIME\_MAX \times \beta \times \left((\alpha \times rnd(1.0)) + (1-\alpha) \times \frac{distance_a}{distance_{max}} \right) \quad (1)$$

with *TIME_MAX*, the maximum time to start evacuating; $rnd(1.0)$, a function that returns a random number between 0.0 and 1.0 following a uniform distribution; $distance_a$ the distance between *a* and its nearest evacuation point (using the road network) and *distance_max* the maximum distance between the agents and their nearest evacuation point (using the road network). In our case, *TIME_MAX* was set to a constant value of 1 *h*—which is enough time for every agent to evacuate according to our exploratory analysis—and we tested 6 values for α and β (0.0, 0.2, 0.4, 0.6, 0.8, 1.0).

Table 5 shows the mean evacuation time and Table 6 the mean time on roads. The results may seem counterintuitive in several regards. First, on the evacuation time: the simulation shows that it is more efficient to evacuate everyone at the same time ($\beta = 0$) than to try to integrate a delay for the departure of some agents ($\beta > 0$). The longer the delay is, the worse is the result in terms of evacuation time. In fact, we are typically in a case with a bottleneck which is the access to the evacuation points, in particular those of the west center (exit 1) and the South (exit 0) which constitutes

Table 5. Mean evacuation time (in seconds) and standard deviation for different values of α (warning people regarding their distance to the exit) and β (speed of dissemination of the alert to the population).

	β					
α	0.0	0.2	0.4	0.6	0.8	1.0
0.0	4491 (±567)	4541 (±508)	5035 (±448)	5250 (±538)	5443 (±492)	5798 (±334)
0.2	4503 (±562)	4603 (±433)	4774 (±284)	5256 (±754)	5398 (±374)	5785 (±495)
0.4	4210 (±344)	4670 (±501)	4837 (±506)	4998 (±536)	5520 (±674)	5833 (±593)
0.6	4242 (±350)	4721 (±602)	4808 (±517)	5094 (±416)	5433 (±492)	5676 (±397)
0.8	4342 (±371)	4724 (±377)	4642 (±374)	4912 (±420)	5209 (±358)	5763 (±350)
1.0	4373 (±494)	4452 (±472)	4612 (±433)	4766 (±425)	5302 (±453)	5815 (±431)

Table 6. Mean time spent on the roads (in seconds) and standard deviation for different values of α (warning people regarding their distance to the exit) and β (speed of dissemination of the alert to the population).

	β					
α	0.0	0.2	0.4	0.6	0.8	1.0
0.0	1365 (±43)	1141 (±43)	958 (±33)	778 (±33)	611 (±37)	522 (±23)
0.2	1368 (±40)	1132 (±32)	948 (±34)	779 (±33)	632 (±26)	538 (±38)
0.4	1365 (±36)	1143 (±27)	943 (±31)	785 (±29)	661 (±24)	569 (±30)
0.6	1365 (±35)	1117 (±41)	918 (±31)	758 (±35)	630 (±36)	527 (±33)
0.8	1376 (±33)	1120 (±43)	853 (±28)	696 (±49)	539 (±32)	436 (±36)
1.0	1365 (±33)	1066 (±34)	810 (±34)	590 (±46)	446 (±35)	410 (±31)

two strongly engorged points. We can note that the complete evacuation time is more than 2h30 in all cases, underlying that some traffic jams will last long after the maximal delay (1 h). The fact that everyone is leaving at the same time will just create traffic jams more quickly, so more people will decide to change their route and thus participate less in the traffic jam.

However, we observe an expected result: when we increase the delay time (β), the time spent on the roads decreases. Indeed, the traffic jams have already started to disappear when the last agents arrive, so their time spent on the roads is lower. Nevertheless, and this is an interesting result, making the closest agents to the evacuation points leave first have a negative effect ($\alpha = 0.0$). On the contrary, it is in the case of a purely random departure ($\alpha = 1.0$) that we obtain the best results in terms of time spent on the roads: it allows fewer agents coming from the same area to leave at the same time and therefore to get stuck in a congestion. Even if the agent is farther away from its exit point, it will go faster than another agent supposedly closer because it has a lower chance to cross by any traffic jams.

5.5. Optimal scheduling of zones

We saw in the last experiment how evacuation time is impacted by a scheduling tailored on proximity to the evacuation points. However, in addition to not being efficient, such a strategy is difficult to implement as it require giving to all people a precise time of departure and expect them to respect this time constraint. A simpler strategy is to make evacuations by zone, i.e. dedicate to each exit point a population area. We propose in this experimentation to divide the Phúc Xá district in several areas and to evacuate the population zone by zone. The challenge is then to determine when and to which evacuation points evacuating the agents from each zone to minimize the evacuation time and the average time spent on the roads.

Concerning the zones construction, we made the choice to define them according to buildings nearest road. We have thus defined a group of buildings (and thus of *Moving agents*) by road. We then fused the closest contiguous groups until we obtained groups gathering at least 1000 agents.

The 10 zones obtained are presented in Figure 9. We defined thus 10 parameters T_z ranging from 0.0 to 1.0 corresponding to these 10 zones. The departure time of each agent a leaving in the zone $z(a)$ was defined as follows:

$$leavingTime(a) = TIME\_MAX \times T_{z(a)} \quad (2)$$

with $TIME\_MAX$, the maximum time to start evacuating. Like in the previous experiment, it was set to 1 h.

We used a Genetic algorithm to search for the parameter set that minimizes the evacuation time. We were able to test about 461 different parameters sets. Figure 10 shows the results obtained with the different parameter sets.

The best solution found resulted in an average evacuation time (over 25 replications) of 3887 s (standard deviation: 323 s) and an average time spent on the roads of 690 s (standard deviation: 16 s). Figure 11 shows the best solutions over the whole explored space: the target defined for each zone and their departure time.

Figure 9. Zoning defined by grouping buildings per closest roads and according to a limit of inhabitants per zone.

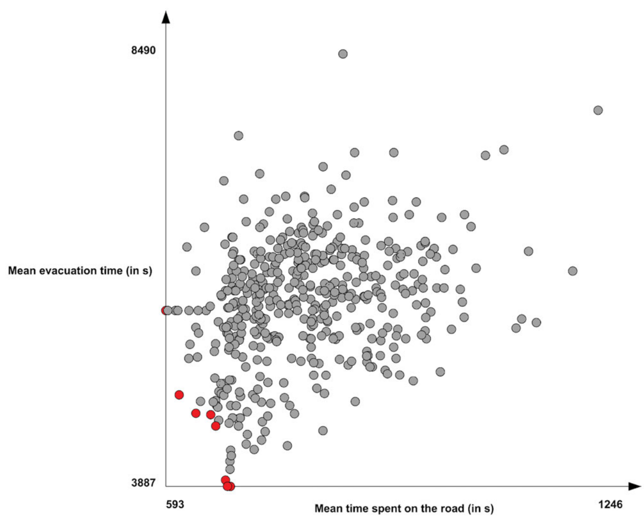

Figure 10. Distribution of the solutions explored according to the evacuation time and the mean time spent on the roads. The red circles are the solution on the Pareto front.

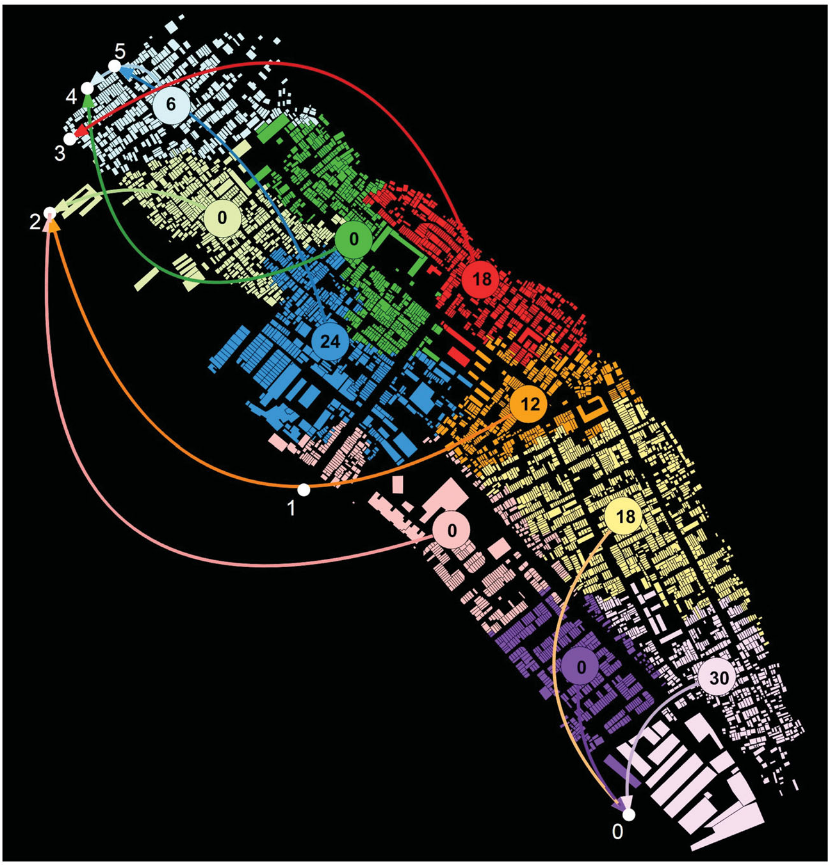

Figure 11. Best solution find: the arc represents the chosen evacuation point and the number in the circle the departure time (in minutes).

An interesting point with this solution is that it allowed to obtain both a good result on the evacuation time (better than all those obtained whatever the values of α and β) and the time spent on the roads (close to the best results obtained at this level with a very high level of beta and therefore a very long evacuation time). Another interesting element is that the west center evacuation point (exit 1) is not used even though it is the closest exit for many agents. Even though no zone has defined this evacuation point as a reference point, this does not mean that no agent will use it: the process of questioning the path may lead to changing the evacuation point and therefore choosing this particular evacuation point. The access road to this evacuation point is very narrow, which often leads to the generation of major congestion and can explain why this exit is not used. Thus, it is also interesting to look at the road network to see if some minor modifications can improve the evacuation efficiency.

5.6. Impact of infrastructure modification

We have already seen that good spatio-temporal evacuation strategies, designed by simulation, can improve the efficiency of the evacuation process. A last question is

Figure 12. Road network displaying the shortest path between a building, and its closest evacuation point. The width of the road is proportional to its number of lanes. The spheres represent the evacuation points. The color of roads depends on the number of times they have been part of a shortest path to an exit point: the more it is red, the more it supposed to be used by the agents to evacuate the area.

whether a minor modification of the road network could lead to a major improvement in the efficiency of the evacuation process. Figure 12 shows the most used roads by the shortest paths from each building to its closest exit. It is possible to see that some roads are particularly critical, especially those that connect the district to the main road west (linked to exit points 0 and 1).

We, therefore, tried to increase the number of lanes on the most used roads. More precisely, starting by the most used one, we added a lane to roads until we reach a cumulative lane addition threshold (sum of the perimeters of the roads on which a lane has been added). The district of Phúc Xá includes 50,849 m of road. So, we elicit these value for the road perimeter threshold: 0 m, 100 m, 500 m, 1 km and 5 km. We can think of this as resources that would be available to improve the transportation network: few resources (100 more meters of road), many resources (5000 more meters

Figure 13. Roads (in magenta) that have been widened (an additional lane) according to their importance in the transport graph and the available resources (perimeter threshold). With a target of 100 meters, only the main section leading to exit number 1 is impacted. With more resources (5000 m), the number of impacted roads increases, which allows covering almost the whole area.

Table 7 Mean evacuation time (in second) and time spent on roads (in second) with standard deviation for different values of the road perimeter threshold.

Road perimeter threshold (in m)	Evacuation time (in s)	Time spent on the roads (in s)
0	4686 (±624)	1372 (±31)
100	3736 (±550)	1196 (±22)
500	3643 (±417)	1178 (±22)
1000	3307 (±292)	1132 (±22)
5000	3383 (±392)	1090 (±14)

of road). Figure 13 shows in magenta roads for which we added a lane according to these different values of the road perimeter threshold. As the most used roads are the ones linked to the exit 1, it is these roads that are improved in priority: from a threshold value of 100 m, we can see that it is almost exclusively the roads leading to this exit for which a lane has been added. From a threshold of 500 m, several roads leading to exit 0 are also improved. At last, from a threshold of 1000 m roads leading to exit 5 are improved.

Table 7 shows the simulation results obtained for each values of the perimeter threshold.

As shown by the results, adding a lane to the most heavily used roads resulted in substantial improvements in the evacuation time and in the average time spent on the roads. While adding lanes on more roads still improves the evacuation result, this improvement is more negligible as the number of roads increases. There is no significant difference between 1 km of roads and 5 km.

To conclude this part, it is indeed interesting to work on the improvement of the road network to ease evacuations, and, even, avoid traffic jams in general. Even minor modifications, if concentrated on the right road, can have a significant impact on evacuation, especially in a case like this one, with an enclave with limited exits. It should be noted that Vietnamese major cities are now undergoing major changes on the road network with the widening of many roads, the construction of urban bridges, etc. If the district of Phúc Xá, built in a flood-prone area, was not yet concerned, it is likely that in the future this district will also undergo deep change.

6. Conclusion

6.1. Summary

In this paper we explored a model dedicated to the evaluation of spatio-temporal mass-evacuation strategies applied to a landlocked area in a context of mixed traffic. An application for the evacuation of the Phúc Xá district, in Hanoi, Vietnam, was presented. One major outcome of our experiment is the crucial determinant of mobility modes on evacuation time and strategies. Indeed, while most of the simulation models only focus on one mode of transportation, we demonstrate that mixed traffic display very contrasting results in terms of evacuation outcome. In particular, we highlight the detrimental impacts of an increasing proportion of cars in the mobility modes distribution, as it is a concern in Vietnam and other south-east Asian countries. Furthermore, the experiments showed the impact of individual behaviors on questioning followed paths and the interest of setting up evacuation policies by zones. When agents constantly switch from one target exit to another one due to congestion, time spent on road and evacuating can be twice as required compare to the case where everyone follows evacuation plans with areas attached to staged departure time. This finding stresses the needs for a clear crisis communication strategy, one thing often missing for large urban areas in many southern countries like Vietnam. We also showed that even minor modifications of the road network could have a significant impact on the evacuation process. More precisely, we demonstrate that a one lane enlargement of the road leading to the main exit reduced overall evacuation time by 20% (from 1h18 to 1h02).

This contribution emphasis the necessity to explore several evacuation management strategies according to the spatial specificity and modes of transport of the area at risks: for our case study, we developed simulation experiments to study the impact of spatially defined staged evacuation with the addition of infrastructure changes and mixed traffic, to explore the best options to optimize the time to evacuate, and the average time spent evacuating per agent. Both strategies, i.e. the management of evacuation orders and new infrastructure planning, have been tested in realistic settings, in terms of geographical data but also with a specific focus on non-normative and mixed traffic related evacuation behaviors.

6.2. Discussion

The proposed model calls for a broader development of agent based simulation models in GIS science, in particular to tackle the process of mass-evacuation where spatial and behavioral aspects heavily impinge the outcome (Hemmati *et al.* 2021). To do so, we propose an application of the Escape framework and urge modelers to rely on such re-usable tools to enlarge the theoretical and practical scope of ABM to support spatially explicit processes. In a recent publication, Manson *et al.* (2020) calls for such an improvement of spatially based ABM, especially through the creation of reusable modules, methodological framework and tools. Our proposal takes advantages of the Gama (GIS Agent-based Modeling Architecture) platform (Taillandier *et al.* 2019) that makes it possible to easily build spatially explicit ABM, and exposes a use case of the Escape framework (Daudé *et al.* 2019), hence providing re-usable code and method to foster ABM use in GIS science. Transferability of models to other scenarios, locations or disasters can only be achieved with the use of generic methods. This research is an example of applying the ESCAPE (Daudé *et al.* 2019) framework to a particular risk and place, therefor participating in the spread of re-usable tools. We hope this contribution can support more research along the same generic model, to enhance knowledge sharing, replicability of simulation findings and applicability to other evacuation issues.

6.3. Limitations

Our proposal suffers from several limitations due to practical and methodological constraints. The first limitation comes from the limited scope of agent behaviors in the model: except when it comes to micro/meso traffic related decision-making, our agents do not behave proactively (e.g. each agent escapes as soon as they have been told to), nor emotionally (e.g. agents aren't concerned about danger); which are two important behavioral determinants of the evacuation process (Bangate *et al.* 2017). On a methodological side, we have been limited by the availability of data, in particular to simulate realistic scenarios.

For our case study, official data about infrastructure and evacuation plan were largely missing, either because they were not available or not accessible. In this context, it is difficult to propose simulation experiment to validate our model against real data. However, exploring simulations model using counterfactual scenario, as we did, can offer local authorities new insights and gain interest in this kind of tool, consequently providing more accurate data. Another limitation concerns the multi-modality of individual trips. Indeed, if we model different modes of transport globally, an agent can only use one mode of transport during a simulation. Thus, an agent who uses its car to evacuate will not be able to abandon or park his vehicle in case of a traffic jam to continue his evacuation on foot for example.

6.4. Future work

We plan several enhancements to this model in the future. Indeed, in this proposal we focused mainly on travel behavior without considering other types of behavior. However, many studies have highlighted the effects of panic, non-rational behavior or just poor knowledge of the instructions that could exist (Fenet and Daudé 2020). Thus, it would be interesting to enrich the model with more complex behaviors. The fact that our model is based on the ESCAPE framework may allow, as it has been done in (Taillandier *et al.* 2021), to use the BEN (Behavior with Emotions and Norms) architecture which allows the integration of cognitive, emotional, social and normative dimensions in the behaviors (Bourgais *et al.* 2020). Another point of improvement concerns the population of agents created: we limited ourselves here to create a realistic number of agents from the population data and the mobility data in Vietnam. It would have been interesting to go further, especially if we wanted to go towards a more realistic model by integrating a real population generation process taking advantage of every available data. In this regard, ESCAPE already integrates the Gen* framework which allows generating a spatialized and socially structured population (Chapuis *et al.* 2018, 2019).

We also plan to work on the validation of the model. Actually, a recurrent problem with evacuation simulations concerns their validation: it is very rare to see models confronted with real data (only a few articles presented in the state-of-the-art section resort to this). At best, some patterns emerging from simulations are confronted with real observations. A problem for our case study is that although there are real risks for the Phúc Xá district, there has never been a massive evacuation of this district or even exercises performed. Moreover, as previously said, our paper focuses only on the movements of people in an ideal world where everyone follows the evacuation instructions, which is unlikely to happen in reality. Nevertheless, we have undertaken a validation of the mobility model used. If this one is based on very classical sub-models and already validated on many case-studies (IDM and MOBIL), the general model proposed and the parameter values used, even if they are coming as much as possible from field data, would deserve to be validated. In this regard, we have started a data collection to compare traffic observations with simulations.

Note

1. Which is actually a length given that *Roads* are represented as lines.

Author contributions

Kevin Chapuis: Conception and development of the original model and case study. Writing of the article and the documentation. Pham Minh-Duc: Development of the agent-based traffic model. Arthur Brugière: Development of the case study, model exploration and result mining. Jean-Daniel Zucker: Supervise model development and writing. Alexis Drogoul: Supervise model development. Pierrick Tranouez: Initial agent-based traffic model development and supervision. Éric Daudé: Conceptual development of the model. Patrick Taillandier: Development of the model, conception of the exploration and analysis, writing of the article.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Pham Minh-Duc earned a bachelorvelopment of the original model and case study. Writing of the article and the documentationexploratanoi, and is now studying Data Science at EURECOM. He worked at IRD as an engineer to implement agent-based traffic meta-models which are better suited for traffic simulation in Vietnam.

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Data and codes availability statement

The data and codes that support the findings of this study are available at figshare following this doi (https://doi.org/10.6084/m9.figshare.16622437.v1). The packaged model can be run using the Gama platform, see https://gama-platform.org to download the proper version. A complete readme file has been added to the repository to ease the reproducibility of model results and figures presented in this proposal.

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Appendix A. Data on ABM for evacuation in urban area

Table A1. Synthesis on ABM for evacuation in urban area.

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	Number of agents
Al-Zinati and Zalila-Wenkstern (2018)	Evacuation	Any – not modeled	abstract	car: MATISSE (Al-Zinati and Zalila-Wenkstern 2015)	Road reversal and zoning	3500
Nakasaka *et al.* (2020)	Evacuation	Flood – not modeled (input)	Umeda area, Osaka, Japan	Pedestrian: speed according to density	Variation of the number of agents	20,000
Prédhumeau *et al.* (2021)	Mobility model	–	Abstract	Pedestrian: Social Force Model	–	240
Hesham and Wainer (2021)	Mobility model	–	Abstract	Pedestrian: Centroidal particle dynamics (variant of SFM)	–	900
Pan *et al.* (2021)	Evacuation	Any – not modeled	Maglev Transit Lines, China	Pedestrian: Pathfinder (Thornton *et al.* 2011)	Variation of the proportion of small groups in passenger crowd, of the gathering status of small groups and on the width evacuation walkway.	1032
West and Sherry (2020)	Evacuation	Any – not modeled	abstract	Urban Air Mobility System: simple rules	Variation of the proportion of non-compliant agents	1093
Wang *et al.* (2020)	Evacuation	Flood – not modeled	Abstract	Pedestrian: speed according to density	Density of people; risk tolerance; vulnerable people	1800
Haghpanah *et al.* (2021)	Evacuation and mobility model	Tsunami – not modeled	City of Iquique, Chile	Car: simplified car following algorithm; pedestrian: path planning and maximum density for collision avoidance	2 Models tested for path planning and collision avoidance	34,000 people and 2000 cars

Table A2. Synthesis on ABM for evacuation in urban area.

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	Number of agents
Taillandier et al. (2021)	Behavior model	Flood – modeled	La Ciotat, France	Pedestrians and cars: simple move on a network (speed depending on density for car)	Proportion of informed people and maintenance of the river and canal	6145
Yang et al. (2018)	Behavior model	Flood – modeled	Ng Tung River basin, Hong Kong	Household: no movement	Different rainfall scenarios	3294
Oh et al. (2021)	Evacuation	Flood – not modeled	abstract	Car: simplified version of a cellular automaton traffic model (Nagel and	Comparison between simultaneous evacuation and staged evacuation plan (range of time	1500

(*continued*)

Table A2. Continued.

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	Number of agents
				Schreckenberg 1992)	delays between the evacuation processes of the different zones)	
Makinoshima et al. (2018)	evacuation – Large Scale model	Tsunami – not modeled	Kesennuma City, Japan	Pedestrian: Social force model	–	25,869
Daudé et al. (2019)	Evacuation	Any – possibility to model it	Diverse case-studies	Pedestrian: Social force model; car: model derived from the Intelligent Driver Model	–	several thousands
Li et al. (2019)	Evacuation	Flood – modeled	Niaodao Island	Pedestrian: cellular automata model	Different numbers of agents	Up to 34,853
Bernardini et al. (2017)	Behavior model	Flood – not modeled	Abstract	Pedestrian: Social Force Model	–	–
Bianchin and Pasqualetti (2020)	Evacuation	–	Manhattan, USA	car: SUMO (Behrisch et al. 2011)	Optimization of the duration of green lights at intersections	4000

Table A3. Synthesis on ABM for evacuation in urban area.

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	Number of agents
Battegazzorre et al. (2021)	Evacuation – behavior model – Large scale model	Earthquake – impact modeled	Turin, Italy	Pedestrian: speed according to debris and health / characteristics of the agents	Location and characteristics of the earthquake, number of ambulances	Up to 900,000
Yin et al. (2020)	Evacuation	Any – not modeled	Huaqiangbei business district in Shenzhen, China	Pedestrian: model based on the Reciprocal velocity obstacles (Van den Berg et al. 2008)	Optimization of the evacuation plan	50
Kim and Cho (2020)	Evacuation	Chemical accident – spatial extent computed by the model	Ulsan, Korea	Vehicles: use of TRANSIMS (Smith et al. 1995)	Sensitivity of the proportion of private vehicles, of evacuation departure time period, of phasing policies, and of lane policies	223,083
Parikh et al. (2017)	Evacuation – behavior model – Large scale model	Detonation of a nuclear device – not modeled	Washington DC, USA	Agent: simple routing model	Variation of information and communication	730,833
Chooramun et al. (2019)	Evacuation	Fire – not modeled	abstract	Pedestrian (micro one): based on a steering model (Reynolds et al. 1999)	–	50,000
Aguilar et al. (2019)	Evacuation	Any, case study for Tsunami and earthquake – not modeled (only the damaged)	Japan	Pedestrian and car: based on the computation of a collision-free velocity along a path	Variation in the use of cars	57,000

Table A4. Synthesis on ABM for evacuation in urban area.

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	Number of agents
Wijerathne et al. (2018)	Evacuation – Large scale model	Any – not modeled	Kochi, Japan	Pedestrian: based on Optimal Reciprocal Collision Avoidance Van den Berg et al. (2008)	–	10 millions
Sun et al. (2021)	Evacuation	Earthquake – not modeled	Huaping community, Xiangzhou District, Zhuhai, China	Pedestrian: movement based on a continuum model (with forces and different factors)	variation of the proportion of opportunity exit familiarity of pedestrians	19,948
Veeraswamy et al. (2018)	Evacuation	Forest fire – not modeled (input of the model)	Swinley forest (southeast England)	Pedestrian (micro one): based on a steering model (Reynolds et al. 1999)	Scenarios with different routes and critical locations	1220
Yamazaki et al. (2017)	Evacuation – behavior model	Any – not modeled	abstract	Pedestrian: speed defined according to the agent characteristics	Variation of different psychology parameters for the population	5000
Len et al. (2020)	Evacuation	Tsunami – not modeled	Via del Mar, Chile	Pedestrian (micro) : based on Optimal Reciprocal Collision Avoidance Van den Berg et al. (2008)	–	22,846

Appendix B. ODD protocol

In this appendix, we describe the model following the form of the ODD protocol Grimm et al. (2020).

B.1. Overview

B.1.1. Purpose and patterns

The objective of the model is to test the impact of spatio-temporal evacuation policy on the evacuation time at the scale of a district (several thousand agents). This allows considering the different types of mobility that can be found in Vietnam (car, motorcycle, bicycle, pedestrian) as well as the rules of the road in this country. We evaluate our model by its ability to reproduce three patterns.

Pattern 1: generation of traffic jams – when a large population seeks to evacuate, it will generate traffic jams that will slow down the evacuation.
Pattern 2: interest of the evacuation by zone – anot evacuating everyone at the same time greatly limits traffic jams and therefore the time spent on the roads by people, which is particularly important because the roads are often areas at risk for the populations.
Pattern 3: impact of mobility mode – aevacuation times are highly dependent on the type of mobility, with some mobility modes generating more congestion (car) or being slower (walking).

B.1.2. Entities, state variables, and scales

Figure 14 presents the UML class diagram of the model. The model is composed of several types of entities. Concerning the environment, this one is composed of *Roads*, *Buildings* and *Evacuation points*. Each *Road* is characterized by linear oriented geometries (polyline) with a number of lanes and speed limitation. Each *Road* is linked to each of its ends by an *Intersection*. A *Road* can be linked to a reverse *Road* (i.e. with reversed geometries). If a reverse *Road* is

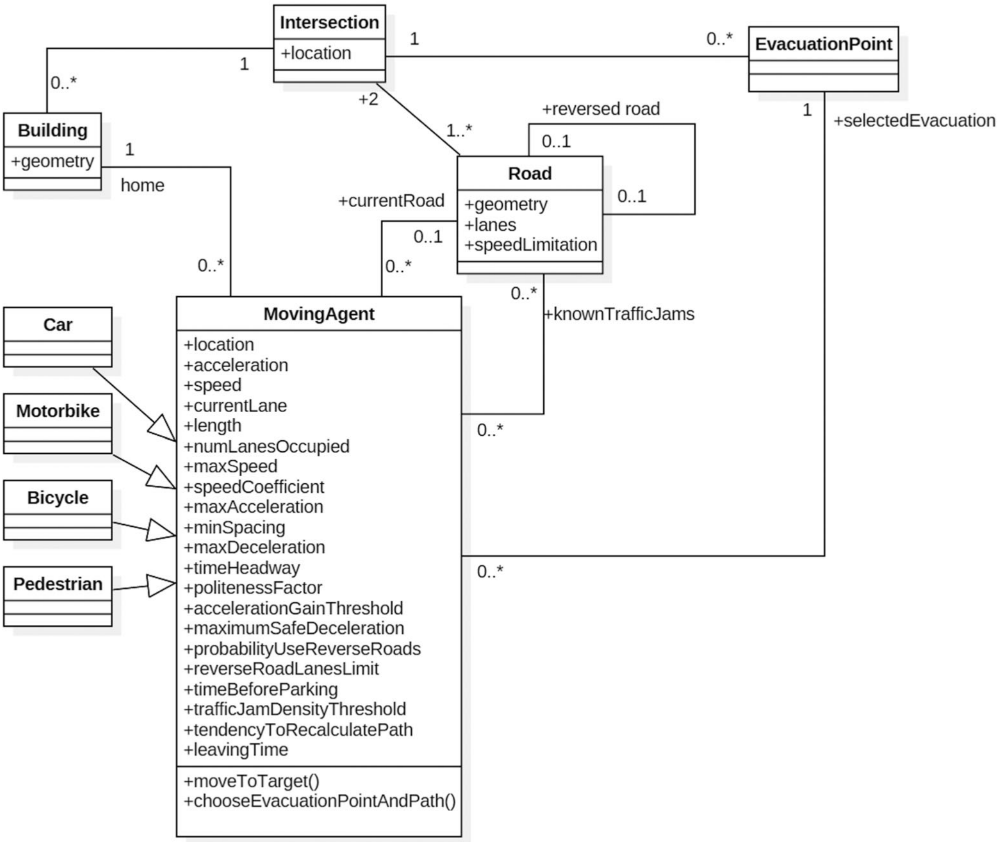

Figure 14. UML class diagram of the model.

defined, it means that a *Moving agent* can use it to overtake another *Moving agent*. Each *Building* is located in the environment with a given geometry (polygon) and is linked to an *Intersection* (the closest *Intersection*). Finally, each *Evacuation point* is located in the environment and linked to an *Intersection* (the closest *Intersection*).

The main active agents are *Moving agents* which represents an abstract class of agents. There are four types of them: *Cars*, *Motorbike*, *Bicycles* and *Pedestrians*. These agents share the same attributes. First, a *Moving agent* has a home (a *Building*), a preferred evacuation point and a departure time. They are also characterized by physical attributes: a length, a maximal speed, a maximal acceleration, and a number of lanes occupied. Indeed, our mobility model is based on extending the usual notion of lane: each *Moving agent* will occupy one or more lanes according to its width. This means that a car will occupy more lanes than a motorcycle or a pedestrian The width of a lane is based on the average width of a pedestrian. *Moving agents* are also characterized by several attributes linked to the way they are driving and moving, and linked to two sub-models we are using to compute the vehicle speed (Intelligent Driver Model—IRM Treiber *et al.* (2000)—and lane-change (Minimizing Overall Braking deceleration Induced by Lane changes—MOBIL Kesting *et al.* (2007)). First, the *Moving agents* have a speed coefficient that defines if they tend to move above or below the speed limit (a value of 1.0 means that the desired speed is the speed limit, if the max speed of the agent allows it). Concerning the IDM model, 3 additional attributes are defined: the maximal deceleration, the minimum spacing, i.e. the minimal distance from the car in the front, and the desired headway time, i.e. the minimum possible time to the vehicle in front. For the MOBIL model, 3 additional attributes are defined: the politeness factor (0.0, a purely selfish behavior; 1.0 a very polite behavior), the maximum safe deceleration, and a minimal acceleration gain threshold to avoid lane-change triggered by marginal advantages. Two last attributes characterizing *Moving Agents* are their propensity to use reverse *Roads* if necessary: a probability to use these and a maximum number of lanes that the agent will be able to use on it. In addition to these static attributes, *Moving agents* have some dynamic attributes: they are characterized by a location in the space (x-y coordinate), they can be located on a specific lane of a road, and have a speed and an acceleration. Finally, they can memorize a list of congested roads so that they will be able to change their path according to this knowledge.

Concerning the timescale, a simulation step represent 0.5 s, which is the most suitable simulation step for the IDM model (Treiber *et al.* 2000) following the magnitude of the model parameters. Furthermore, micro-traffic simulations often need to be as precise as possible due to the very sensitive nature of the modeled phenomenon, like collision avoidance or stop-and-go traffic jam.

B.1.3. Process overview and scheduling

The only acting agents are the *Moving agents*, i.e. *Cars*, *Motorbikes*, *Bicycles* and *Pedestrians*. At each simulation step, they will carry out 3 main behaviors:

1. Once the departure time is reached, i.e. equal to current time, the agent chooses an evacuation point and a path to reach it.
2. if the agent has computed a path, it progresses along it.
3. if the agent is stuck upon (or before taking) a high road density (i.e. traffic jam), the evacuation point (and the path to it) might be reconsidered.

For the first behavior, the agent will choose the closest evacuation point to its current position using the road network. To compute the distance and the shortest path, the agent considers the traffic jams it knows: it will favor roads without traffic jams if possible. More precisely, to compute the shortest path, the agent uses a directed weighted graph representation of the road network: each road represents an arc. The weight of each arc corresponds to the perimeter of the road. If the agent has the belief that there is a traffic jam on the road, it multiplies the weight of the arc by a penalty factor. This factor corresponds to the maximum possible length of a path, arbitrarily chosen so to exclude it from a potential evacuation track.

The agentirst behavior, the agent will choose the closest evacuation point to its current position using the road network. To compute the distance and the shortest path, the agent considers the traffic jams it knows: it ersection: for all roads connected to this intersection, the agent will update whether the road is congested or not depending on the density of vehicles on the road. If the density is higher than a certain threshold tj_a specific to each agent, it is considered as congested. The density of vehicles on the road r is computed following Equation (B1) below:

$$density(r) = \frac{\sum_{a \in r_a} l_a}{p_r \times n_r} \tag{B1}$$

with r_a represents the list of *Moving agents* on the road r; l_a the length of the *Moving agent a*; p_r the perimeter[1] of road r and n_r the number of lanes of road r. The NBA* algorithm is used to compute the shortest path (Pijls and Post 2009). NBA* is a generalized version of bidirectional A*, which is particularly efficient in a context where each agent makes shortest-path calculations based on its own weights. This feature is particularly important in our context because agents elicit the shortest path during simulation updating their knowledge (weight) on road congestion.

Concerning the second behavior, the agent moves toward the evacuation point, by following the path defined. On a microscopic scale, the agent first calculates a desired speed which depends on the speed limit on the road, its speed coefficient and its maximum speed. From this desired speed, it defines, using the MOBIL and IDM models, a lane to move on and a speed/acceleration on this lane according to other *Moving agents*. These two models are based on the notion of leading and backward agents. The calculation of these agents includes the number of lanes occupied by the vehicles (attribute num_l_a of agent a): for example, a car can be the leading vehicle for 2 motorcycles on 2 different lanes. More information about the IDM and MOBIL models are given in the Details section B.3.

When an agent arrives at an intersection, it first updates its knowledge about traffic jams (see previous paragraph), then it defines whether it wants to continue on its path or not. The third behavior is akin to the agent recognition of overcrowded roads, and triggers the re-evaluation of target and path: recalculating an evacuation point and its path depends on the distance to the evacuation point and to a random draw. More precisely, the probability for an agent a to recalculate its evacuation point and path is:

$$proba_{recalculate}(a) = k_a \times d(a, a_{ep}) \tag{B2}$$

with $d(a, a_{ep})$ the distance between agent a and its current selected evacuation point a_{ep} and k_a the tendency for agent a to recalculate the path. An agent who recalculates its evacuation point will recalculate the distance to all evacuation points thinking about its knowledge about traffic jams and choose the fastest way. This process may well lead to keeping the same evacuation point or even the same path if no other path is better.

Finally, after moving, the *Moving agents* can, if necessary, make a specific maneuver to let another vehicle pass to avoid complete blockages. More precisely, we integrated the following rule: if a vehicle is blocked (speed of zero) on a reverse road and if the vehicle in front of it (which is in the opposite direction) has the same size or a bigger size, then after a certain time (defined by the attribute $time\_p_a$ of the agent a), the agent will park, i.e. it does everything it can to go back on the normal road (not the reverse one) even if this violates the minimum distances to other agents – this corresponds to the classic maneuver in Vietnam where motorcycles will stick together to let a car pass.

B.2. Design concepts

B.2.1. Emergence

Due to the capacity limits of the roads and the interactions between the moving agents, traffic jams will emerge from the simulation. This is a classical result, well described by the fundamental diagram of two-phase traffic (Geroliminis and Daganzo 2008). When the number of vehicles on a road is very small, interaction between these vehicles is close to zero. Each agent can therefore ride at the maximum speed it wants, without being disturbed by the presence of other vehicles. As the number of cars increases, the interaction between vehicles also increases, which has the effect of reducing the speed of the vehicles. As a result, the average speed on the road decreases regarding the number of vehicles.

B.2.2. Adaptation

There are several levels of adaptation. The first level concerns microscopic traffic movement: the speed of the *Moving agents* is adapted to the speed of other *Moving agents* and to the road infrastructure. The second level concerns the mesoscopic scale of path selection and change: agents are able, if they perceive traffic jams, to question their destination and the path followed. The third is that an agent may temporarily use a reverse traffic lane to avoid or escape a blockage on the regular lane he is following.

B.2.3. Sensing

Moving agents have perception capabilities: they can perceive the *Moving agents* on the same road as them to define their speed of travel. Also, when they arrive at intersections, they can perceive traffic jams and thus adapt their behavior.

B.2.4. *Stochasticity*

The model is stochastic in several aspects. The allocation of the starting time can, depending on the scenario, depend on a random draw. The scheduling of the agents also has a random part: the closer a road is to an evacuation point, the more the *Moving agents* on it will be activated in priority. When two roads are at the same distance from evacuation points, the choice from the agents will be made randomly between the two roads. Finally, when the *Moving agents* perceive a traffic jam, whether they recalculate or not the current route will depend on a random draw.

B.2.5. *Observable outputs*

Important outputs of the simulation are the time needed for the complete evacuation of the area and the time spent on the road. They are thematically relevant as many tragic events have shown that spending too much time on the road can be dangerous. As mentioned in the introduction, the 55 deaths during Hurricane Rita in Texas were associated with the evacuation process. Being able to limit as much as possible this time spent on the road is thus critical.

B.3. *Details*

B.3.1. *Initialization*

The initialization of the simulation is based on several pre-computation steps that are done once. The model takes as input 3 types of geographical data:

- roads – linear geometries
- buildings – polygonal geometries
- evacuation points – point geometries

Roads must be oriented and have three attributes: the number of lanes, the speed limit and whether it is a one-way road or not. In the case where the road is not one-way, the model considers two roads in opposite directions (reverse roads) with the same characteristics (number of lanes and speed limit). For the creation of the population, the process is as follows: while there are still inhabitants to place, choose a random building, then create *Moving agent* on this building according to the mobility mode probabilities. Depending on the type of agent created (*car*, *motorbike*, *bicycle* or *pedestrian*), a specific number of agents will be removed from the population. Indeed, we consider that there can be several people in a car or on a motorcycle. This number of people is defined uniformly according to the type of transport and the acceptable maximum values (e.g. no more than 3 people on a 2 wheels vehicle). This initialization process therefore requires, in addition to the geographic data, to define the following parameters:

- total population
- probability of use of each mode of transport
- maximum number of people per mode of transport

B.3.2. *Input data*

The model does not use any input data to represent time-varying processes.

B.3.3. *Sub-models*

B.3.3.1. *Intelligent driver model (IDM)*

We use the classic Intelligent Driver Model to compute *Moving agent*'oving agentlassic Intelligent Driver Model to compute -varying processes., we consider that there can be several people in a car or on a motorcyc*a* be an agent characterized by *f* its leading agent (front agent), max_acc_a its maximum acceleration, v_a its current speed, $v_a^0(r)$ its desired speed on road *r*, i.e.

the speed the vehicle would drive in free traffic, s_a^0, its minimum desired spacing, i.e. minimum desired distance from its leading vehicle, s_a, the actual distance between agent a and its leading vehicle, T_a its desired time headway, i.e. minimum possible time to reach its leading agent, and b_a its comfortable braking deceleration. The actual acceleration of *Moving agent a*, denoted acc_a, is computed following equation $acc(a)$ below:

$$acc(a) = \frac{d_{acc_a}}{d_t} = max\_acc_a \times \left[1 - \left(\frac{v_a}{v_a^0}\right)^4 - \left(\frac{s^*(v_a, v_f)}{s_a}\right)^2\right], \tag{B3}$$

With:

$$s^*(v_a, v_f) = s_a^0 + \max\left[0, \left(v_a \times T_a + \frac{v_a \times (v_a - v_f)}{2\sqrt{max\_acc_a \times b_a}}\right)\right]. \tag{B4}$$

The desired speed of an agent a on a road r is defined by:

$$v_a^0(r) = \min(max\_v_a, cv_a * v_r) \tag{B5}$$

with max_v_a the agentd by:ed of an agenv_r the road speed limit, and cv_a the agentspeed limit, and nt on tion. The actual acceleration of leading agent, and that there c

B.3.3.2. Minimizing overall braking deceleration induced by lane changes (MOBIL)

The MOBIL model is used to define whether the agent will change its lane or not. It is based on the IDM model to evaluate the relevance of the different possible lanes. Regarding the tested lanes, we consider in this model that the agent can use all the possible lanes of the road. In addition to that, it will have a certain probability (p_r_a for agent a) to also test the lanes on the reverse roadside. The number of lanes the agent can use on this side is defined by an attribute (rl_l_a for agent a).

The MOBIL model provides two criteria to define whether the agent should change lanes for another given lane: the safety criterion (is it safe for the closest agent behind on the targeted lane?) and the incentive criterion (is the new lane more interesting?).

Let a be an agent who wants to change from lane l to a new lane l'. We note b the back agent of the agent a on lane l, and b' the agent who would be behind a if the agent changes its lane to the targeted one l'. We also note acc_a the current acceleration of the agent a, acc_b the current acceleration of the agent b, and acc'_b the current acceleration of the agent b'. $\tilde{acc}_{a'}$ denotes the acceleration of a if the agent has really changed lane for lane l' (calculated with equation B3). Similarly, $\tilde{acc}_b$ is the acceleration of agent b if agent a changed lane to lane l', and $\tilde{acc}_{b'}$ is the acceleration of agent b' if agent a' changes lane to lane l'.

The safety criterion, which ensures the lane change does not cause the new follower to brake too hard, is stated as:

$$\tilde{acc}_{b'} > -b_{b'}^{save}, \tag{B6}$$

with $b_{b'}^{save}$ the maximum safe deceleration of agent b'. The incentive criterion is stated as follows:

$$\tilde{acc}_{a'} - acc_a > p_a \times (acc_b + acc_{b'} - \tilde{acc}_b - \tilde{acc}_{b'}) + thr_a \tag{B7}$$

with p_a the politeness factor of agent a. A politeness factor higher than 1.0 means a very altruistic behavior and a value of 0.0 is a purely selfish behavior. thr_a is a threshold for agent a which has for goal to avoid frenetic lane change by limiting the fact of changing lane for a marginal advantage. Note that the decision to change lane is only considered when the first component of the Equation (B7) is positive, meaning that current acceleration is lower than expected acceleration in the target lane. In other words, *Moving agents* consider moving to another lane only when they face an obstacle that forces them to decelerate on their current lane. Finally, if the agent has multiple lanes to choose from, the one with the highest raw incentive (Equation (B8)) will be chosen.

For example, let.to another lane only when a) who has the choice between 2 other lanes (lanes 0 and 2) in addition to the lane it is currently on (lane 1). Letne imagine that there will be an agent (called b_0) in lane 0 and another one (called b_2) behind a if a changes respectively to lane 0 and to lane 2. Agent a first tests for these two new lanes the first criterion. We then compute using *IDM* the acceleration that the agents b_0 and b_2 would have if a changes lanes for respectively lanes 0 and 2. Letterion. We then compute using ne it b_0 will be $-5m/s^2$ and of b_2 will be $-2m/s^2$ (negative values mean that agents b_0 and b_2 will have to break if a changes lanes to theirs). If we take a value of *maximum safe deceleration* of $4m/s^2$, the 0 lane will not be considered among the possible lanes for a. This would leave only the 2 lane to be tested. To know if it is interesting for agent a to go on this lane, it will use the second criterion: is the gain of acceleration it will gain by going on this lane compared to if it stays on its current lane sufficient. Lethe one with the highest raw incentive$0.1m/s^2$ by staying on its lane and accelerate to $2.5m/s^2$ by going to the lane 2. We will calculate for the agent behind it (called b_1) its acceleration if a stays in its lane or if a changes to lane 2: letf We will calculate$a$ stays in its lane, b_1 will have an acceleration of $-0.5m/s^2$, but if a changes to lane 2, that b_1 can then accelerate to $0.3m/s^2$. Similarly, we calculate for an agent b_2 the acceleration it would have if a stays in its lane (imagine, $0m/s^2$) and the acceleration b_2 would have if a moves to lane 2 ($-2m/s^2$). If the agent a has an *acceleration gain threshold* of $2m/s^2$ and a politeness factor of 0.25, this will give an acceleration gain of $2.4m/s^2$ for lane 2 which will be compared to $(0.3 + 0.5) - 0.25 times(-0.5 + 0 - 0.3 - (-2)) + 2 = 2.5m/s^2$. Since $2.4m/s^2$ is less than $2.5m/s^2$, the gain will not be considered sufficient. Note that if the politeness factor were lower (e.g. 0.0), in this case, this criterion would be verified and the agent a would indeed switch to the lane 2.

$$\tilde{acc}_{a'} - acc_a + p_a \times (acc_{b'} - \tilde{acc}_{b'}) \tag{B8}$$

Appendix C. Parameter and attribute values

Table C1. Parameter of the simulations.

Attribute name	Value	Commentaries
Total population	21,559	Data coming from the General Statistics Office of Vietnam
Probability to use car	0.01	Taken by (Hee and Dunn 2017), see Section 2 for more details.
Probability to use motorbike	0.74	Taken from (Hee and Dunn 2017), see Section 2 for more details.
Probability to use bicycle	0.19	Taken from (Hee and Dunn 2017), see Section 2 for more details.
Probability to walk	0.06	Taken from (Hee and Dunn 2017), see Section 2 for more details.
Maximal people per car	6	Empirical data (observation in Hanoi).
Maximal people per motorbike	4	Empirical data (observation in Hanoi). Corresponds to the classic use of a motorcycle in Vietnam with a family composed of 2 children.
Maximal people per bicycle	1	Empirical data (observation in Hanoi).

Table C2. Attributes of agent *a*.

Attribute name	Pedestrian	Bicycle	Motorbike	Car	Commentaries
length (l_a)	$0.28m$	$1.71m$	$1.9m$ m	3.8 m	Sources for pedestrians (Buchmueller and Weidmann 2006), for bicycles (Jin et al. 2015) and for cars and motorbikes Dang-Huu et al. (2020)
Max speed (max_{v_a})	Gaussian draw with mean of $1.34m/s$ and standard deviation of $0.26m/s$	Gaussian draw with mean of $13.48km/h$ and standard deviation of $4km/h$	$70km/h$	$160km/h$	Sources for pedestrians (Bosina and Weidmann 2017) and for bicycles (Jin et al. 2015); for cars and motorcycles, we have taken realistic values for the fleet installed in Vietnam.
Speed coefficient (cv_a)	1.0	1.0	Uniform draw between 0.375 and 0.725	Uniform draw between 0.9 and 1.0 s	Pedestrians and bicycles are not influenced by the road speed limitation; for motorbikes data adapted from (Tong et al. 2011) and for car adapted from Dang-Huu et al. (2020)
Number of lanes occupied (num_{l_a}	1	1	1	2	The typical width for pedestrian is $0.5m$, for bicycle is $0.6m$, for motorbike is $0.7m$ and for car is 1.7 m (Buchmueller and Weidmann 2006, Dang-Huu et al. 2020, Jin et al. 2015). To simplify the model, and considering personal space, we consider that a pedestrian, a bicycle and a motorcycle take 1 lane and a car 2 lanes.
Max acceleration ($max_a cc_a$)	Uniform draw from $1.1m/s^2$ to $1.6m/s^2$	Uniform draw from $0.8m/s^2$ to $1.2m/s^2$	Uniform draw from $2.8m/s^2$ to $5m/s^2$	Uniform draw from $3m/s^2$ to $5m/s^2$	Source for pedestrian (Zebala et al. 2012), for bicycle (Parkin and Rotheram 2010), for motorbike (Ngo et al. 2010)

Table C3. Attributes of agent *a*.

Attribute name	Pedestrian	Bicycle	Motorbike	Car	Commentaries
Min safety distance (s_a^0	0.2 m	0.2 m	0.2 m	0.5 m	In the peak periods, Vietnamese are willing to accept to be close to the others. So, we have defined low values. Cars are the only ones to keep a minimum distance more important in general.
Time Headway (T_a)	Gaussian draw with a mean of $0.5s$ and a standard deviation of $0.1s$	Gaussian draw with a mean of $0.75s$ and an standard deviation of $0.4s$	Gaussian draw with a mean of $1.09s$ and a standard deviation of $0.5s$	Gaussian draw with a mean of $1.25s$ and a standard deviation of $0.5s$	Source for motorbikes (Minh et al. 2005). As we do not have data for the other types of agents, we have taken the values for my motorcycles considering that the more maneuverable the agent is, the lower this value is.
Politeness factor (p_a)	0.0	0.05	0.1	0.25 s	Lane changes in Vietnam are often abrupt. Few drivers look in their mirror before changing lanes. We have therefore set low politeness values – the smaller the agent the less likely he will pay attention to other agents (typical value: between 0.0 and 0.5)

(*continued*)

Table C3. Continued.

Attribute name	Pedestrian	Bicycle	Motorbike	Car	Commentaries
Acceleration gain threshold (thr_a)	0.01	0.05	0.1	0.2	This attribute in the MOBIL model is used to avoid frantic lane change, but frantic lane change is part of the driving in Vietnam (except for cars), so we set low values for this attribute (typical value: 0.2)
Maximum safe deceleration (b_a^{save})	$2m/s^2$	$2m/s^2$	$3m/s^2$	$4m/s^2$	use of the typical value for cars of the MOBIL model. We adapted it for other types of agents

Table C4. Attributes of agent *a*.

Attribute name	Pedestrian	Bicycle	Motorbike	Car	Commentaries
Probability use reverse roads (p_{r_a})	1.0	1.0	1.0	0.0	We consider that cars to avoid maneuvering and getting stuck will not use the reverse road. The other agents can use it if necessary.
Reverse road lane limit (rl_{l_a})	1	1	1	0	We consider that the agents (except for the cars that will not use the reverse roads) will only use one lane of this reverse road once, to let the oncoming vehicles pass.
Time before parking ($time_{p_a}$	Uniform draw between 5 s and 10 s	Uniform draw between 10 s and 20	Uniform draw between 10 s and 30 s	∞	The idea is that the bigger an agent is, the less easily it will let others through. Thus, cars will never try to make a maneuver to let others pass while pedestrians will be the first to do so.
Traffic jam density threshold (tj_a)	0.75	0.75	0.75	∞	As maneuvering in the narrow roads of Phúc Xá is difficult for cars, we consider that they will never recalculate their evacuations points and path.
Tendency to recalculate the evacuation point/path (k_a)	0.01	0.01	0.01	0.0	As maneuvering in the narrow roads of Phúc Xá is difficult for cars, we consider that they will never recalculate their evacuations points and path.