Coupling agent-based simulation with optimization to enhance population sheltering

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ABSTRACT

Population sheltering is a recurrent problem in crisis management that requires addressing two aspects: evacuating vulnerable people using emergency vehicles and regulating movements of pedestrians and individual vehicles towards shelters. While these aspects have received considerable attention in modeling and simulation literature, very few approaches consider them simultaneously. In this paper, we argue that Agent-Based Modeling and Simulation (ABMS) and Optimization are two complementary approaches that can address the problem of sheltering globally and efficiently and be the basis of coherent frameworks for decision- and policy-making. Optimization can build efficient sheltering plans, and ABMS can explore what-if scenarios and use geospatial data to display results within a realistic environment. To illustrate the benefits of a framework based on this coupling approach, we simulate actual flash flood scenarios using real-world data from the city of Trèbes in South France. Local authorities may use the developed tools to plan and decide on sheltering strategies, notably, when and how to evacuate depending on available time and resources.

Keywords

Sheltering, Simulation, Agent-Based Modeling, Optimization, Vehicle Routing Problem, Coupling, Flood Evacuation.

INTRODUCTION

Earth's climate is rapidly changing due to the growing detrimental human activity. This fact threatens the environmental equilibrium and causes an increase in natural hazards such as fast floods and forest fires. Decision-makers and crisis management units need to respond efficiently before, during, and after the disaster to reduce the impact of similar events, particularly human casualties. One of the major issues is to anticipate evacuating populations from risk areas. This process has to consider individuals who can self-shelter and those who need assistance to flee the risk, namely disabled and older people. Hence, authorities must not only control local population movements but also deploy emergency vehicles to evacuate vulnerable populations (populations located in risk areas and who cannot self-shelter).

Today, advanced research and new technologies propose several techniques to help rescue services improve the sheltering process, notably optimization and simulation. Optimization can build efficient evacuation plans,

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and simulation can explore what-if scenarios and use geospatial data to visualize dynamics and display useful metrics within a realistic environment. Therefore, it is crucial to couple optimization and simulation in crisis management tools while considering their reusability to different disaster contexts and their possible use to support decision-making (Anuar et al. 2021; Gruler et al. 2019). In the optimization domain, Vehicle Routing Problem (VRP) algorithms allow optimizing resources and finding optimal routes to evacuate people from risk areas towards evacuation centers (Dubois et al. 2019). In the simulation domain, Agent-Based Modeling and Simulation (ABMS) can describe and simulate heterogeneous interacting entities within a complex environment (Macal 2016) and provide aggregate indicators from different simulations. Hence, combining these two techniques with Geographical Information Systems (GIS) allows developing practical tools to ease decision-making in crisis management.

Current architectures implementing simulation with optimization are usually ad-hoc (Azimi et al. 2018) or merge the code of the two functionalities (Oh et al. 2018) and are therefore difficult to reuse in other contexts or improve each component separately (Peres and Castelli 2021). Moreover, most models combining ABMS and VRP solvers have been designed for transport and logistics case studies, and their specificity prevents generalizing them to other domains such as risk management (Barbati et al. 2012). This specificity is due to the fact that VRP dynamics and constraints are usually problem- or domain-specific. Besides, implemented models do not fully use agent-based features to abstract the complexity of crisis phenomena or use limited optimization algorithms that do not include sufficient real-world constraints such as disruptions and unpredictable events (Gruler et al. 2019; Chica et al. 2017). Finally, proposed models dealing with crisis management generally address only one aspect of sheltering (self-sheltering or evacuation by emergency vehicles). These limitations restrict the applicability of existing architectures implementing ABMS with VRPs and establish the need for more hybrid and combined approaches (Anuar et al. 2021; Gruler et al. 2019).

In this work, we address some of the previous limitations, namely specificity, non-modularity, and the limitation to one aspect of the problem, through the following contributions:

- A generic conceptual metamodel that describes the invariant concepts of sheltering and their relationships. To demonstrate this generic approach, we define two instances of this metamodel. The first one supports the regulation of movements of the population, and the second one handles the evacuation of vulnerable people.
- An agent-based simulator that implements the previous models with geospatial data to simulate sheltering populations in risk areas. The simulation includes regulating population movements towards shelters and evacuating people from critical locations.
- A coupling architecture of two software components: the previous ABM simulator and a VRP optimizer that computes optimal routes for emergency vehicles using graph-based data produced by the simulator. This tool simulates a crisis phenomenon and optimizes the related evacuation process. The modular design separates the functional aspect of the simulator (simulation of the phenomenon) and the external component performing a specific service (optimization of the evacuation plan). This architecture allows updating the two elements independently to adapt the tool to different case studies and ease the implementation of new functionalities.
- A case study of a flooding scenario in the south of France. This experimentation demonstrates the use of the developed tools to support decision-making on sheltering strategies during the anticipation and response phases of a flooding event. The tool allows estimating the total time required for a population to self-shelter when police officers regulate their movements, the resources and the time needed to evacuate vulnerable people, and the optimal distribution of resources in the city.

The remainder of this paper is as follows. The following section contextualizes this study and presents related research. The third section introduces the conceptual model and describes the ABMs and the coupling architecture. The fourth section illustrates the application of the tool to flood evacuation in the south of France. The fifth section discusses the application results. Finally, we conclude with some perspectives of this research.

BACKGROUND AND RELATED WORK

Current literature highlights the lack of advanced digital tools and computer simulations to support and improve the decision-making process in crisis management (Anuar et al. 2021). In France, most crisis management systems still operate using traditional ways that do not take advantage of new technologies. For example, crisis management units anticipate floods using two tools: meteorological vigilance provided by Météo-France[1], and flood vigilance

[1]The French national meteorological service.

(potential inundation zones) provided by flood forecasting services (Belin and Moulin 2016). These tools use static maps and forecasted indicators to provide information about the predicted evolution of flooding events. Besides, the various solutions used by different units lack interoperability (Truptil et al. 2010). Therefore, using the information they produce is complicated and time-consuming for decision-makers to decide on sheltering and evacuation strategies. In conclusion, it becomes of paramount importance to provide decision-makers with interactive and interoperable tools to ease their understanding of the crisis, help them build sheltering scenarios, and support their decision-making on which strategy to adopt based on relevant indicators.

Several works have investigated the coupling of simulation with optimization tools; however, most of them are in logistics and transportation, and very few have used this combination in crisis management (Barbati et al. 2012). For example, Azimi et al. (2018) use an agent-based simulation to optimize the routes of ambulances and manage the allocation of medical assistance to victims after a disaster. Their model executes the optimization process whenever a blocked road affects rescue operations. Fikar et al. (2016) present an agent-based simulation to optimize the distribution of relief goods with trucks and drones after a disaster. They used the simulation to conduct experiments about the impact of coordination and fleet configuration on the efficiency of relief strategies. Shafiee and Berglund (2016) present an approach to model the dissemination of warning and critical information during disaster events by optimizing the routes of emergency vehicles. Their simulation includes several dynamics of hazards, populations, and transports. Oh et al. (2018) is the closest work to ours and uses interactions between emergency vehicles and rescue demands to improve evacuation planning by updating task lists of the involved vehicles. Their model implements a complex agent-based algorithm based on heuristics to optimize the routes between different disaster sites. The main limitations of the previous works are their restriction to the vehicle routing problem, weak connection to GIS, and the lack of modularity in their design. Regarding the VRP aspect, they do not fully consider the heterogeneity of emergency vehicles (capacity, speed) and the priority and deadlines of rescue demands.

Regarding the sheltering of populations moving as pedestrians or using individual cars, we can distinguish two types of works, with or without regulator agents (e.g., police officers) (Daudé et al. 2019). In systems without regulation, Takabatake et al. (2020) present an agent-based simulation to study the movements of pedestrians and individual vehicles towards shelters during a tsunami. They use optimization for cars, and their results highlight the impact of the localization of sheltering centers and the percentage of vehicle usage on mortality rates. Anh et al. (2011) manage the evacuation of pedestrians by simulating individual decisions and behaviors on a road network depending on the importance of the area. Similarly, Le et al. (2021) investigates the role of risk awareness of pedestrians in the sheltering strategies during a tsunami. Their model simulates two levels of awareness and highlights the importance of the information on the mitigation of damage.

In systems with regulation, involving regulator agents plays a significant role in controlling crowds, limiting unnecessary and unsafe movements, and improving population awareness. Dulam et al. (2012) simulate the role of police officers in reducing mass evacuations time by encouraging people to evacuate. Their experiments confirmed the positive effect of officials on reducing pre-evacuation time and fatalities in large risk areas. (He et al. 2015) develop a network-based algorithm and an optimization model to manage the allocation of police officers to principal roads in a city. The presence of police officers improves the efficiency of emergency evacuation and prevents accidents and congestion. In this work, we adopt a similar approach based on three types of agents: regulator agents (police officers), individual vehicles, and pedestrians. All three agents can disseminate awareness.

In conclusion, none of the previous works addresses both aspects of sheltering: emergency vehicle routing optimization and regulation of population and individual cars. Furthermore, most optimization solutions use limited VRP constraints, do not integrate GIS, and provide no modular and reusable solutions.

COUPLING ABMS WITH VRP FOR SHELTERING POPULATIONS

In this work, we present an ABMS approach addressing the sheltering of populations in crises. This approach associates two models. The first one manages population movements and self-sheltering with the assistance of police officers, while the second one optimizes the routes of rescue vehicles. These two models are complementary as they simulate two different aspects that crisis management units need to carry out to anticipate and respond to disaster events. Moreover, they are compliant with the same metamodel guaranteeing their coherence.

The first model manages the self-sheltering behaviors through the control of population movements and the dissemination of information and risk awareness. The self-sheltering strategy is crucial and can replace or facilitate other disaster relief measures such as assisted evacuation (Haynes et al. 2009). This model includes the role of police officers in charge of traffic and pedestrian movements regulation proven to be efficient in sheltering scenarios (Bonkiewicz and Ruback 2012; Lamb et al. 2012). The second model studies the evacuation of vulnerable people using emergency vehicles and uses an optimization algorithm to minimize the evacuation time and the number of required resources. These two models share various concepts and roles related to risk management in the context of sheltering and evacuation. They include human agents, material resources, and geographical locations. The metamodel depicted in Figure 1 summarizes these concepts and draws their inter-relationships. This metamodel differs from existing metamodels (Bénaben et al. 2008) covering more general aspects of crisis management with no focus on sheltering and evacuation.

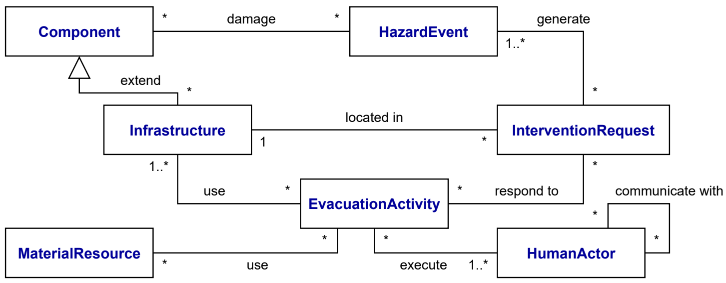


Figure 1. A UML metamodel of evacuation in crisis context

In this metamodel, classes (rectangles) represent the different concepts needed to model the response to disaster events. A *HazardEvent* is an entity representing a natural or human-made disaster such as a flood or a fire. When a hazard event occurs, it causes damage to the study area and creates rescue and evacuation demands that the model has to respond to. A *Component* is any object composing the environment (buildings, bridges, . . .), including *Infrastructure* objects, which are the active components used by the evacuation process, and their damage has an impact on the response. For example, a base transceiver station is considered as an infrastructure component if the response process involves wireless communications; otherwise, it is a simple component that, when damaged, does not affect the system. The hazard creates a set of *InterventionRequest* (*e.g.*, rescue demands) representing people, animals, or materials to evacuate out of risk areas. An *EvacuationActivity* consists in a basic task or a plan (set of basic tasks) to be performed to respond to an *InterventionRequest* (*e.g.*, blocking a road, an emergency vehicle trip, . . .). A *HumanActor* represents a role (*e.g.*, fire-fighter, police-officer, . . .) that may perform an activity. A *MaterialResource* is an object (*e.g.*, car, helicopter, . . .) that may be necessary to carry out an evacuation activity.

Agent-based model of self-sheltering and crowd management

The purpose of this model is to evaluate the impact of the spatial distribution of police officers on self-sheltering (pedestrians and people using individual cars). We can use the model to assess and visualize different configurations by choosing various distributions of police officers. The model produces three principal indicators: a) the total time required for a population to shelter at home or in designated shelters; b) the best starting time of the sheltering process; and c) the optimal spatial distribution of police officers, i.e., the one that minimizes the total sheltering time.

Structure of the self-sheltering model

Figure 2 depicts the structure of this model in the context of flooding management. This model is an instance of the metamodel of Figure 1 and specifies the relevant concepts involved in the self-sheltering process in our case study. We detail these concepts in the following paragraphs.

- **Building** represents a geographical location that may host people when the building is residential. A building is an infrastructure of the study area that the hazard event may damage. In this example, residents need to shelter away when the flood reaches their houses.
- **RescueCenter** represents a public safe place (a shelter located out of risk areas). Pedestrians and individual cars move to rescue centers to escape the risk.
- **RoadSegment** is a portion of a road. It can be damaged by a hazard, blocked by police officers to regulate movements, and potentially used by pedestrians or individual cars. A maximum speed limit is associated with each road segment. This limit may change according to the number of vehicles using the corresponding road segment. When the speed limit reaches 0, temporary traffic congestion blocks vehicles.
- **FloodSituation** is the flooded area at a particular moment. It starts at a predefined time and impacts the infrastructures of a determined area. A flood event is the aggregation of several flood situations.

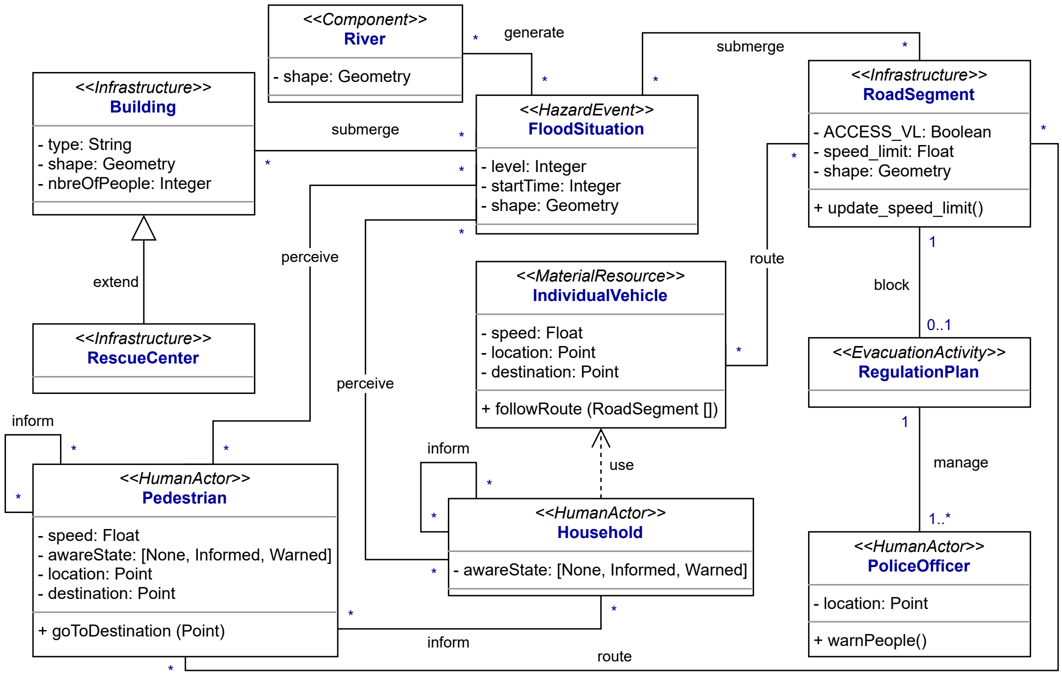


Figure 2. The UML model of self-sheltering with the assistance of police officers

- **River** represents the starting geographical point of floods but does not have any activity and is used mainly for visualization purposes of the map.
- **IndividualVehicle** is a resource that individuals may use if they decide to shelter by individual cars; otherwise, they move to shelters as pedestrians. Each vehicle transports one household and moves within the speed limit of its current road segment.
- **Household** is a group of people that shelter together in a vehicle. Each household has an awareness state impacting its decisions of sheltering. Households can transmit information on the risk level to other people.
- **Pedestrian** represents an individual who shelters by walking instead of taking a vehicle. The decision to shelter is determined according to the awareness state. A pedestrian can inform other people about the risk level.
- **PoliceOfficer** regulates traffic, blocks a road, and informs about flood risks and potential traffic congestions. The police warnings allow pedestrians and vehicles to avoid the risk and arrive rapidly at shelters.
- **RegulationPlan** represents the evacuation activity put in place by police officers to respond to the hazard event. It consists in blocking roads and warning the population.

Dynamics of the self-sheltering model

The simulation reproduces the daily activities of a population before the hazard occurrence. When individuals become aware of the risk either by information exchange, direct perception, or police warning, they start sheltering. Police officers control traffic and regulate the movements of pedestrians and individual cars toward shelters.

At initialization, the model generates individuals, households, and vehicles based on real-world data. The population is dispatched to residential buildings, and each moving pedestrian/vehicle gets a random destination corresponding to a building. A percentage of the population starts moving (corresponds to people who work, study, or perform their activities of daily living). Initially, the population has no risk awareness, and the state of individuals is "*not informed*". Moving people (pedestrians and households in vehicles) move towards their destinations and may: (i) get informed by other people and acquire the state "*informed*"; or get warned by police officers or perceive the risk directly, and change their awareness state to "*warned*". Informed and warned people may decide to shelter or not. Figure 3 shows how individuals shelter depending on whether or not their sheltering decision is regulated by police officers. The three principal activities of agents (sheltering decision, information exchange, and risk perception) depend on their awareness state and the following model parameters:

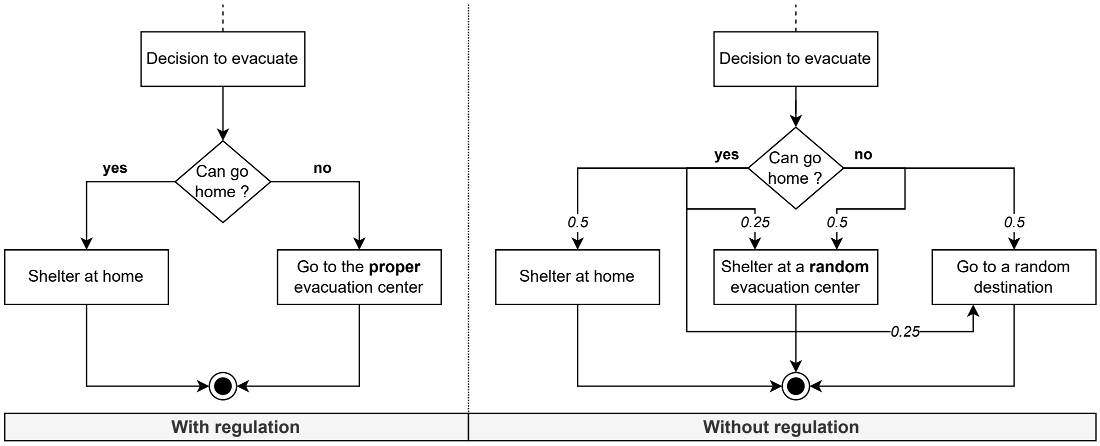


Figure 3. The UML activity diagram of self-sheltering decision with and without the assistance of police officers

- $\text{Transmit}_{informed}$: is the probability of an informed pedestrian/household to transmit the information and risk awareness to non-informed people.
- Transmit_{warned}: is the probability of a warned pedestrian/household to transmit the information. This probability is higher than the previous one to simulate the veracity and the higher impact of information emanating from direct perception or police warning (Bonkiewicz and Ruback 2012; Lamb et al. 2012).
- $\text{Transmit}_{\text{radius}}$: is the scope distance of information transmission between individuals. Each informed or warned pedestrian/household can impact the awareness level of its non-informed neighbors within this radius.
- $\text{Warn}_{\text{radius}}$: is the scope distance of the warning transmission from police officers. Once warned, individuals and households get the "*warned*" state and change their destination.
- $\text{Perceive}_{\text{radius}}$: is the distance from which pedestrians and vehicles can perceive the risk (a flooded area) and get warned. Some warned agents might choose to continue their route and get exposed to high risk.
- $\text{Shelter}_{informed}$: is the probability of an informed individual/household to decide to shelter.
- Shelter_{warned}: is the probability of a warned individual/household to decide to shelter. The sheltering decision follows the diagram of Figure 3 depending on the presence or not of police regulation.

Agent-based model of optimized evacuation with emergency vehicles

This model aims to simulate the evacuation of vulnerable people using emergency vehicles. The model couples an agent-based model to an optimization algorithm called Capacitated Vehicle Routing Problem under Deadlines (CVRPD) (Dubois et al. 2019). The objective is to simulate a fixed fleet of heterogeneous vehicles (several categories with different capacities and speeds) that have to evacuate rescue demands by repetitively (multiple trips) visiting heterogeneous nodes with the possibility of splitting pickups.

As input data, the optimizer takes a graph where nodes represent rescue demands and arcs represent the shortest available paths between nodes. A rescue demand is defined by a geographical location, the number of persons to evacuate, the category of vehicles that can evacuate it, a priority, and a deadline. Also, the optimizer requires a list of available emergency vehicles to use. The algorithm output consists of a set of routes for each vehicle. Indeed, when an emergency vehicle reaches its capacity, it goes to the evacuation center to drop off evacuated people and starts a new turn, if any.

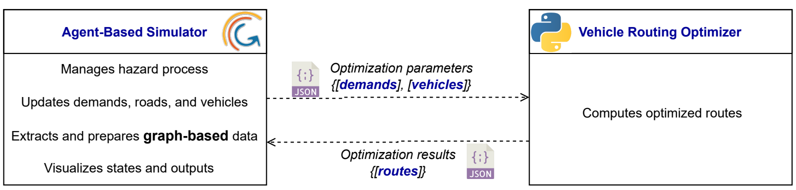


Figure 4. Software architecture: coupling the agent-based simulator with the optimization component

The agent-based simulator uses the geospatial map of the study area to visualize the evolving state of different components: rescue demands, roads, flood events, and circulation of vehicles. After a submersion, an emergency vehicle can interrupt its route and wait for another routing plan that the simulator requests from the optimizer. From an interaction point of view, the ABM simulator is responsible for gathering and providing input data to the optimizer. On the other side, the VRP optimizer computes and provides the simulator with the different routes associated with each vehicle. The two components use JSON files to communicate and exchange data (Figure 4).

Structure of the evacuation model

To allow monitoring the environment and including the optimization process in the context of flood management, the UML class diagram of the ABM (Figure 5) is composed of the following entities:

- **Building** represents geographical locations where rescue demands are located. The types of buildings determine the priorities of rescue demands. For example, a school has a higher priority than administrative buildings and individual houses.
- **RoadSegment** is the infrastructure that emergency vehicles use to travel between different locations. Depending on the hazard level, a category of vehicles may not travel on impacted roads. Only roads accessible to emergency vehicles are considered.
- **RescueCenter** represents a specific shelter-building that receives people evacuated from rescue demands.
- **RescueDemand** represents a location where vulnerable people wait to be evacuated. During the initialization, and depending on the geospatial configuration, each rescue demand is associated with a specific evacuation center.
- **FloodSituation** has the same meaning as in the previous model but differs from a behavioral point of view. At each new flood situation, deadlines and categories of rescue demands are updated.
- **River** *idem* as in the first model.
- **EmergencyVehicle** is a resource located initially in a given evacuation center where it is supposed to drop off evacuated people. An emergency vehicle may perform several trips considering its limited capacity.
- **EvacuationTrip** is an ordered list of rescue demands. It represents one round trip that starts and ends at the evacuation center. The optimization algorithm may compute several evacuation trips for each vehicle.

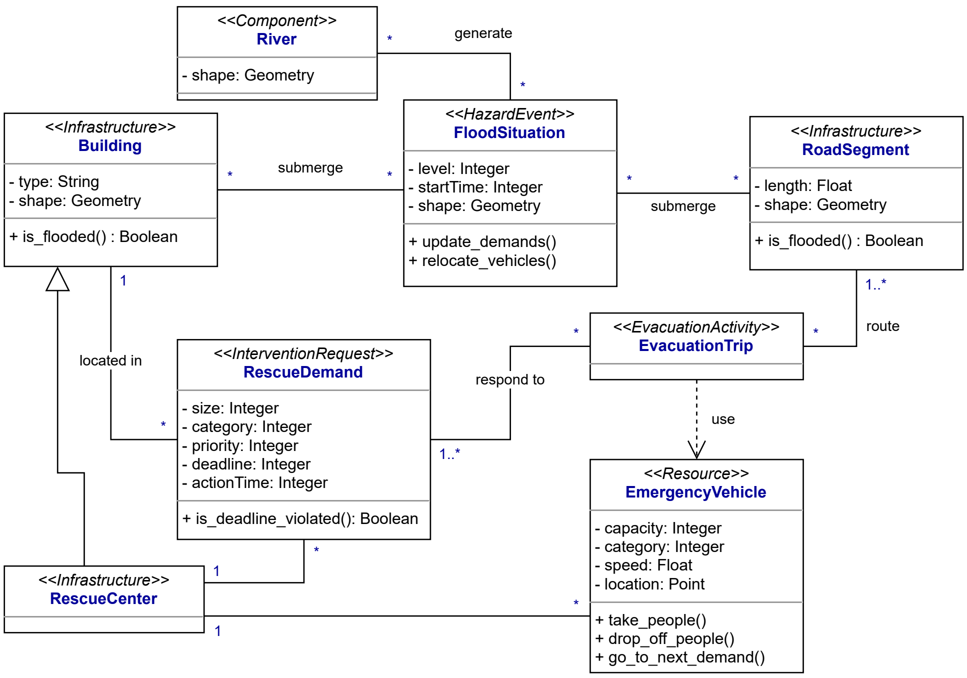


Figure 5. The UML class diagram of evacuation with emergency vehicles

Dynamics of the evacuation model

At initialization, and depending on the geospatial configuration of the study area, an allocation process associate each rescue demand to the closest evacuation center. Each evacuation center contains a set of emergency vehicles defined in simulation parameters. The optimization algorithm computes an initial routing plan, and the emergency vehicles start operating their trips. When a new hazard event affects the accessibility of some roads, the model updates the category of each impacted rescue demand (the type of vehicles that can reach it). The simulation gathers the updated data of the current environment state (number of people and categories of rescue demands; positions and passengers of vehicles) and requests the optimizer for a new routing plan.

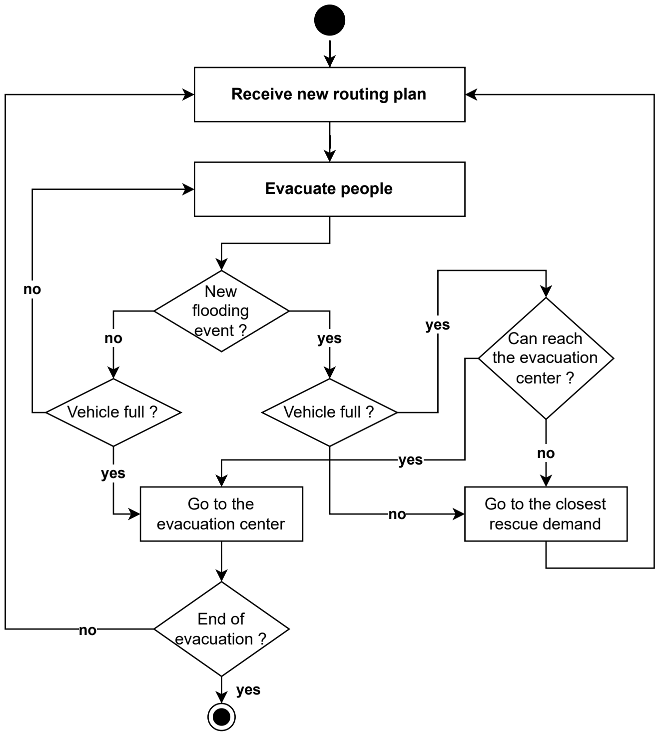


Figure 6. The UML activity diagram describing the behavior of a vehicle

After each submersion, the behavior of vehicles changes according to the situation of the environment. An emergency vehicle with full capacity returns to its evacuation center if a route is available; otherwise, it joins an emergency shelter (the closest accessible rescue demand) through the shortest available path. An incomplete vehicle goes directly to the nearest accessible rescue demand that updates its size to include the current passengers of the hosted vehicle. The new data are supplied to the optimizer to compute a new routing plan. Figure 6 summarizes the behavior of an emergency vehicle in this model.

Implementing simulations with GAMA platform

GAMA (Taillandier et al. 2019) is a spatially explicit platform for building large-scale agent-based models to implement ABM simulations. GAMA loads data from GIS sources to create different components of the study area: geospatial polygons of buildings and flood levels, graphical networks of roads and rivers, and geospatial points of police officers and rescue demands. Additional parameters of vehicles and dynamics are loaded from textual configuration files.

The first simulator (Figure 7) represents the self-sheltering model where pedestrians (represented by triangles) and vehicles move in the city and adapt their behaviors to the propagation of the hazard event and the risk information. Colors indicate the awareness level: non-informed (red), informed (yellow), and warned (green). Inputs window allows specifying simulation parameters such as anticipation time, movements regulation, and different action probabilities (informing and evacuating). The first output graph shows percentages of people in the risk area (400m around the flooded area), people at risk of death (people in flooded areas), and people who arrived at shelters. The second graph shows the percentages of moving people according to the purpose of their movements (moving towards a shelter or not). The last graph displays the evolution of risk awareness (the percentages of informed and warned people).

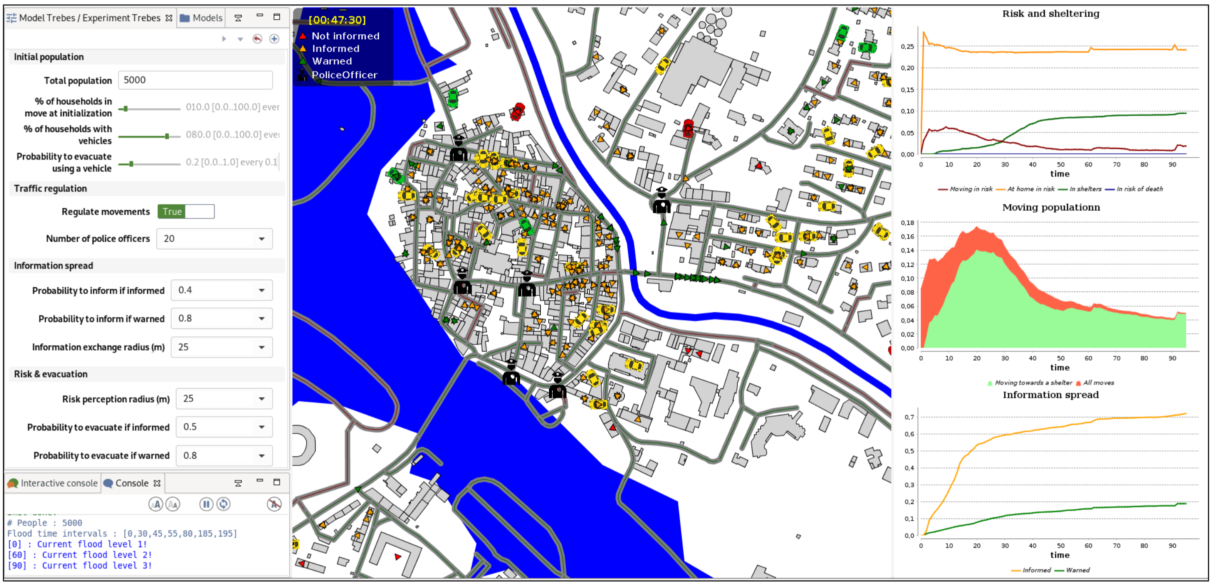


Figure 7. The graphical interface of the self-sheltering simulator under the GAMA platform with input parameters (top-left), real-time outputs and charts (right), and the map of the study area with the simulated agents (vehicles, pedestrians, police officers)

The second simulator (Figure 8) calls the optimization algorithm and visualizes the dynamics of flooding, routing, and evacuation of rescue demands towards evacuation centers. Simulator interfaces offer a dynamic environment to follow the sheltering and evacuation processes in real-time. Inputs window allows specifying different simulation parameters such as anticipation time and available resources in each evacuation center. Output charts and indicators can be displayed in real-time and their data saved to files for further analysis. Graphs of Figure 8 show, for example, the evolution of the evacuated people by evacuation priority and the evolution of the total traveled distance by each type of vehicle.

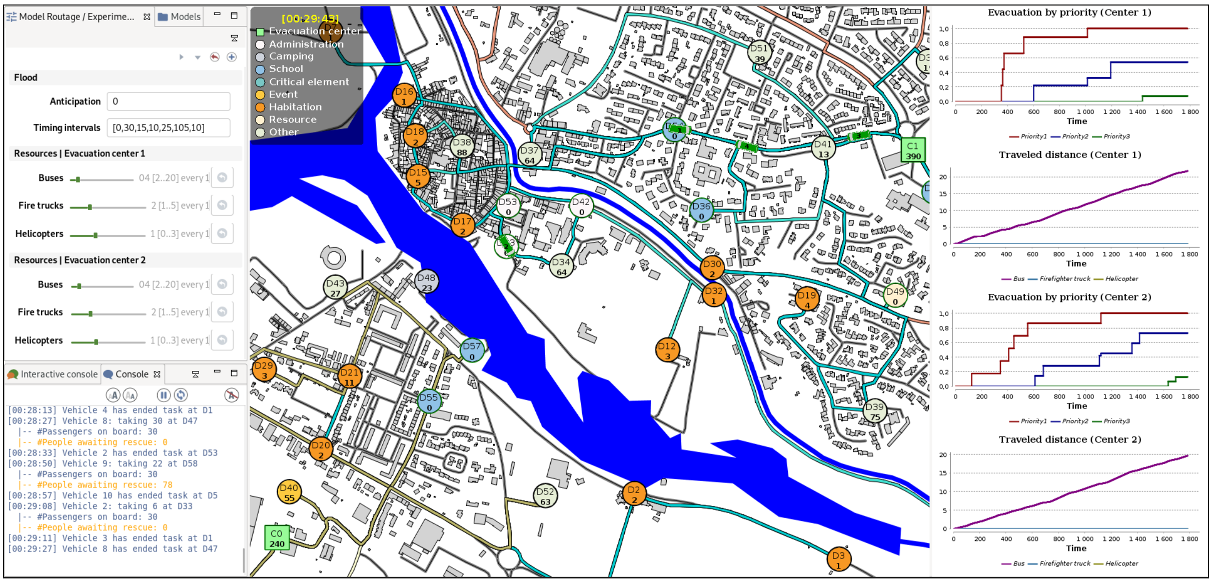


Figure 8. The graphical interface of the evacuation simulator under the GAMA platform with input parameters (top-left), log of evacuation activities (bottom-left), real-time outputs and charts (right), and the map of the study area with the simulated agents (emergency vehicles, rescue demands)

GAMA platform offers an in-built feature called *batch experiment* to execute multiple simulations in parallel, with different combinations of parameters (populations, hazard event, anticipation time, resources). This feature allows automatic testing of several scenarios to simulate various sheltering and evacuation strategies.

APPLICATION TO FLOODING CRISIS MANAGEMENT IN TRÈBES

Trèbes is a district of the Aude department in the Occitanie region in southern France. Located on an important river crossing, Trèbes is subject to Mediterranean rains that cause regular flooding, as was the case in October 2018. Six people have died during this episode of floods in Trèbes alone (14 in the department), with significant material damage of tens of millions of euros (269 M€ overall the Aude department)[2]. During flooding events, rivers split the city into two blocks, and authorities arrange two evacuation centers, one on each side. In this application, we propose an instance of our models that considers this constraint, and we launch simulations with the 2018 submersion parameters to assess strategies of sheltering and evacuation.

Simulation Data and Parameters

Developed simulations use geospatial data of the study area to simulate realistic scenarios and provide relevant results. Used real-world data concern spatial representation, population, and submersion event (Figure 9).

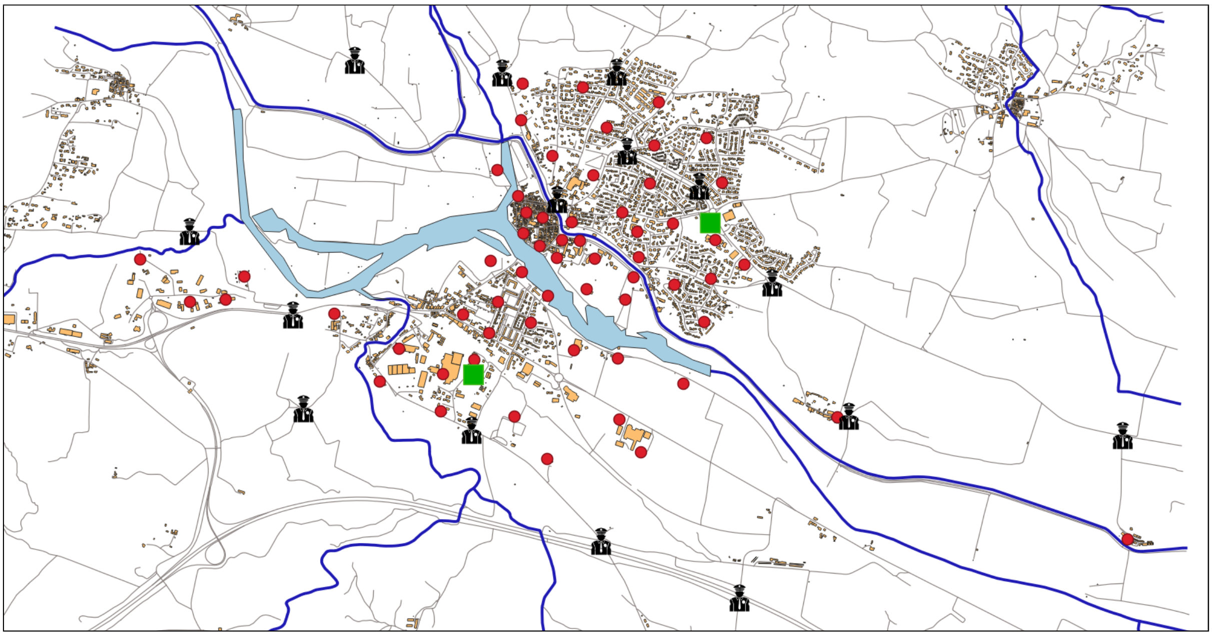


Figure 9. The map of Trèbes with buildings, roads, rivers, locations of police officers, and rescue demands (red circles). The green rectangles represent shelters/evacuation centers. The blue polygon is the first submersion level

The IGN (National Institute of Geographical Information) BD TOPO® database provides GIS data representing different aspects of the study area (buildings, roads, and rivers). Both models use the following three shapefiles: BUILDINGS to locate the population of residential buildings and the rescue demands; ROADS to create the graph network where agents move (pedestrians and vehicles if the road is physically accessible); and RIVERS to display additional details on the map. Seven flood files (Table 1) provided by the project case study are based on the flood vigilance maps to represent flood propagation. Each submersion level represents a flood situation with a water height above the Aude River and a time interval representing the time recorded between two successive flood levels.

Table 1. Water heights and time intervals of submersion levels during the 2018's flooding event

Submersion	*Level 1*	*Level 2*	*Level 3*	*Level 4*	*Level 5*	*Level 6*	*Level 7*
Water height	3.75m	4.55m	5.00m	5.45m	6.30m	7.60m	7.70m
Time interval	-	30min	15min	10min	25min	1h45min	10min

Self-sheltering model

The model uses the spatial distribution of police officers depicted in Figure 9 to simulate the impact of the presence of police officers. The simulation uses a shapefile of geometric points to include this configuration. Hence, 15

[2]Retour d'expérience des inondations du 14 au 17 octobre 2018 dans l'Aude. Rapport CGEDD n° 012561-01, IGA n° 18105-RP.

officers based at the main crossroads of the city intercept movements, control crowds and traffic, and spread information and awareness. The population is generated based on data of Trèbes provided by the national statistics bureau of France INSEE (National Institute of Statistics and Economic Studies): total population (5566), household mean size (2.15), and the percentage of households with vehicles (83.6%).

In this example, we consider that authorities do not order the sheltering of the population until the beginning of the flooding event. Hence, we start simulations with the first submersion level without considering any anticipation time. We execute five simulations to consider randomness in population generation and dispatching in residential buildings. We fix other parameters as follows: the probability of moving at initialization = 0.1; the probability of using the vehicle to move = 0.2; $Transmit_{informed}$ = 0.4; $Transmit_{warned}$ = 0.8; $Transmit_{\text{radius}}$ = 25m; $Warn_{\text{radius}}$ = 25m; $Perceive_{\text{radius}}$ = 30m; $Shelter_{informed}$ = 0.3; $Shelter_{warned}$ = 0.9;

Evacuation model

In the evacuation and routing optimization model, rescue demand locations are provided by the project case study. In this work, the number of potential people to evacuate is randomly estimated depending on the demand type (school, commercial center, hospital, etc.). Rivers crossing Trèbes isolate evacuation centers; hence, we consider them independent. Therefore, emergency vehicles evacuate rescue demands to the center on the same riverside. Figure 9 depicts the spatial distribution of rescue demands in this case study. The number of rescue demands and people to evacuate for each evacuation center is given in Table 2.

Table 2. Rescue demands, people to evacuate, and vehicles related to each evacuation center

Evacuation center	Related demands	Number of people	Available resources
Center 1 (south bank)	24	674	[2,12] (bus), 2 (truck), 1 (helicopter)
Center 2 (north bank)	33	859	[2,12] (bus), 2 (truck), 1 (helicopter)

Evacuation resources are also related to each center (Table 2). The initial location and number of resources depend on the simulated scenario. Three types of vehicles are considered in this work: buses, firefighter trucks, and helicopters (Table 3). Each vehicle type has a capacity representing the maximum number of people to evacuate at a time; a fixed speed of the vehicle as we omit all constraints that may affect this parameter (congestion, roads state); and the maximum flood level that the vehicle can cross. When a submersion makes a rescue demand unreachable for buses, the algorithm assigns it to a firefighter truck. Likewise, helicopters take demands that become inaccessible to trucks. For this work, we simulate 11 scenarios for each evacuation center and each anticipation time by varying the number of buses from 2 to 12. Two trucks and one helicopter are always present at each evacuation center (Table 2).

Table 3. Vehicles used to simulate flood evacuation in Trèbes

Vehicle	Capacity	Speed (km/h)	Maximum flood level
Bus	30	20	1
Firefighter truck	10	10	5
Helicopter	5	100	-

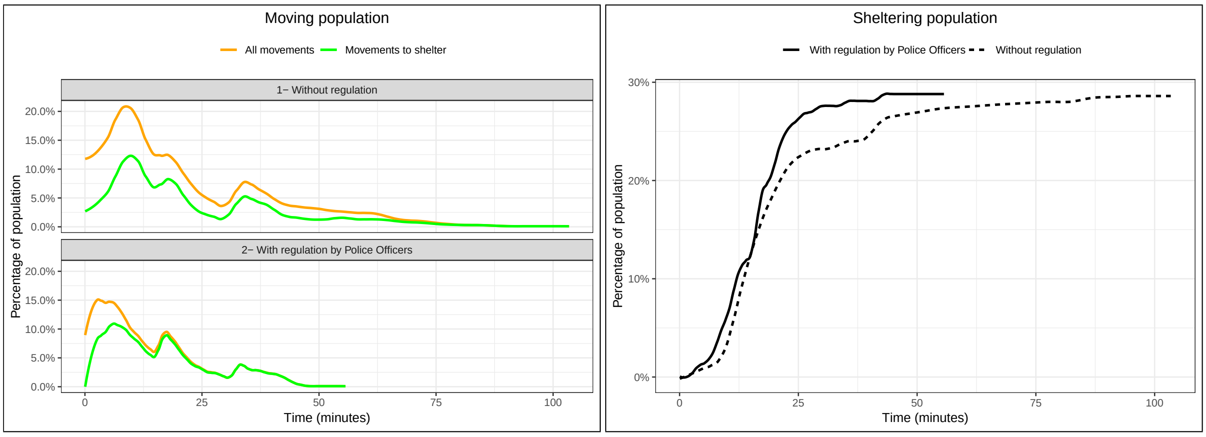
Simulation results

Self-sheltering of the population with the assistance of police officers

The purpose of this first simulation is to help decision-makers decide on the impact of installing police officers to control population movements and raise people's awareness during a flooding event. Figure 10 shows the simulation results in the case of Trèbes when the simulation starts at the same time as the first submersion level.

Figure 10a shows the percentage of moving population in the two simulated scenarios: without the assistance of police officers and with their assistance according to the previous spatial configuration (Figure 9). The orange curve represents the total percentage of the population that moves towards a destination (people on the street). The green curve represents people who move exclusively for the purpose of sheltering (at home or in evacuation centers). We notice that population movements decrease quickly with the presence of officers, and the majority of these movements are for the objective of sheltering.

Therefore, as depicted in Figure 10b, the presence of police officers allows people inhabiting risk areas to arrive rapidly at shelters. The proposed spatial distribution of 15 police officers helps reduce the sheltering time by



(a) **(b)**

Figure 10. Evolution of moving and sheltering populations, with and without regulation

approximately 50% (from 105 to 55 minutes) compared to the case where the population self-shelter without the assistance of police officers. This duration depends on the input parameters, namely the number and the spatial position of police officers. Our simulations confirm that the impact of police officers is influenced by both their number and their spatial configuration, as one police officer at a principal crossroad is more efficient than multiple officers on secondary and uncrowded roads.

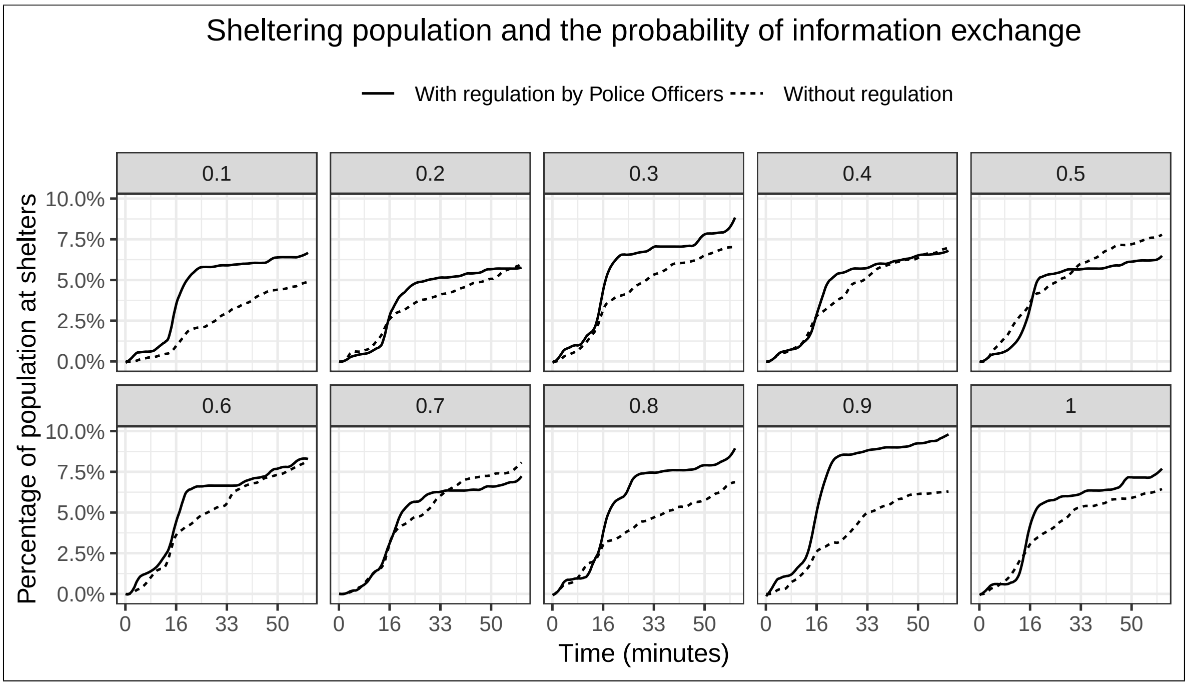


Figure 11. Evolution of sheltering populations according to the probability of information exchange

Concerning the two other principal parameters of this model, namely the probability of risk information exchange and the probability of deciding to evacuate, Figures 11 and 12 shows the impact of varying (from 0.1 to 1.0) these two inputs in scenarios with and without movements regulation. The results show that the positive effect of police officers on population sheltering is more significant in simulation scenarios with a low probability of deciding to evacuate (Figure 12). The presence of officers balances risk unawareness and people's reluctance (refusal to evacuate) and pushes them to avoid risk areas. The impact of regulation is insignificant in scenarios where people already have high tendencies to flee the flooding risk. Figure 11 shows approximately the same pattern overall simulated scenarios since the presence of officers contributes positively to spreading information.

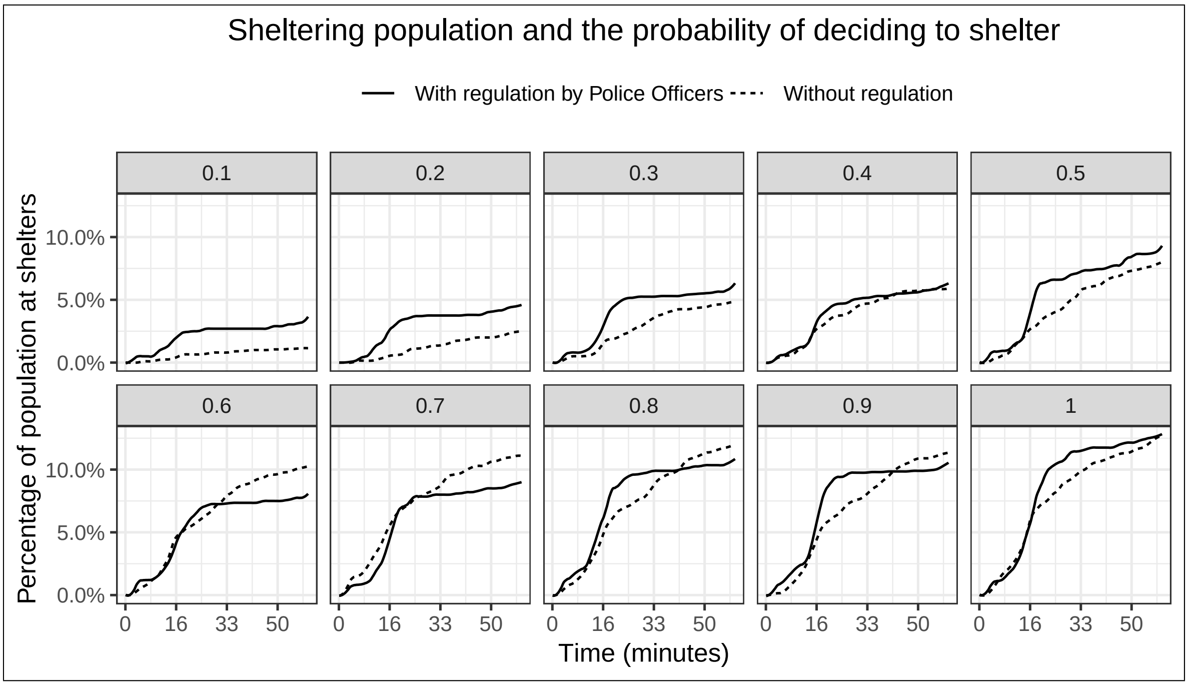


Figure 12. Evolution of sheltering populations according to the probability of deciding to shelter

Optimization of the evacuation of rescue demands by emergency vehicles

The purpose of this second simulation is to help decision-makers in the anticipation phase to decide on the time and resources needed to evacuate all vulnerable people in potential flood areas. Another objective is to evacuate all rescue demands without using particular and risky means, namely firefighter trucks and helicopters. These resources are difficult to deploy and need more logistic preparation than buses. In addition, using firefighter trucks and helicopters reveals a delay in the evacuation and may put evacuees and rescue teams in danger. Hence, it is practical to determine the number of required buses and their initial location to avoid using particular means. This required configuration of buses varies depending on available time and the forecasted flood levels.

The simulation estimates the number of buses and the total time required to evacuate rescue demands safely. Several anticipations (time before the first submersion level) are simulated to determine, for each scenario, the required configuration of resources. Figures 13 and 14 depict simulation results in the case of Trèbes with the flooding scenario of 2018. The X-axis of the graphs represents the number of available buses. The left Y-axis gives the number of rescued people using firefighter trucks and helicopters represented by the colored bars. The red line gives the total evacuation time represented on the right Y-axis. In all scenarios, the simulation evacuates all rescue demands.

Figure 13 shows results for the first evacuation center (south bank). Depending on the number of available buses, rescue teams may or may not need firefighter trucks and helicopters. With no anticipation and three buses, particular means are needed to evacuate 47 people. With six buses, evacuation of all rescue demands can be accomplished without using trucks or helicopters. If evacuation starts 30 minutes before the first submersion level, only five buses are needed to evacuate safely. With two hours of anticipation, all rescue demands can be evacuated with only two buses, but evacuation would take more than three hours.

Figure 14 shows simulation results for the second evacuation center (north bank). If the evacuation starts with the first submersion level (no anticipation), five buses need to be available in this evacuation center to evacuate all rescue demands without using particular means. The operations would take 1h35. When anticipating 30 or 60 minutes before the first flood level, four buses are needed to accomplish evacuation safely within approximately two hours. If evacuation is anticipated by two hours, no particular resource is needed to evacuate even with two buses; however, the evacuation would take more than three hours (3h15). The simulation shows that firefighter trucks are not necessary to rescue demands related to this evacuation center. Therefore, a good decision could be to locate all available trucks in the first center where they may serve to evacuate until one hour before the first submersion level.

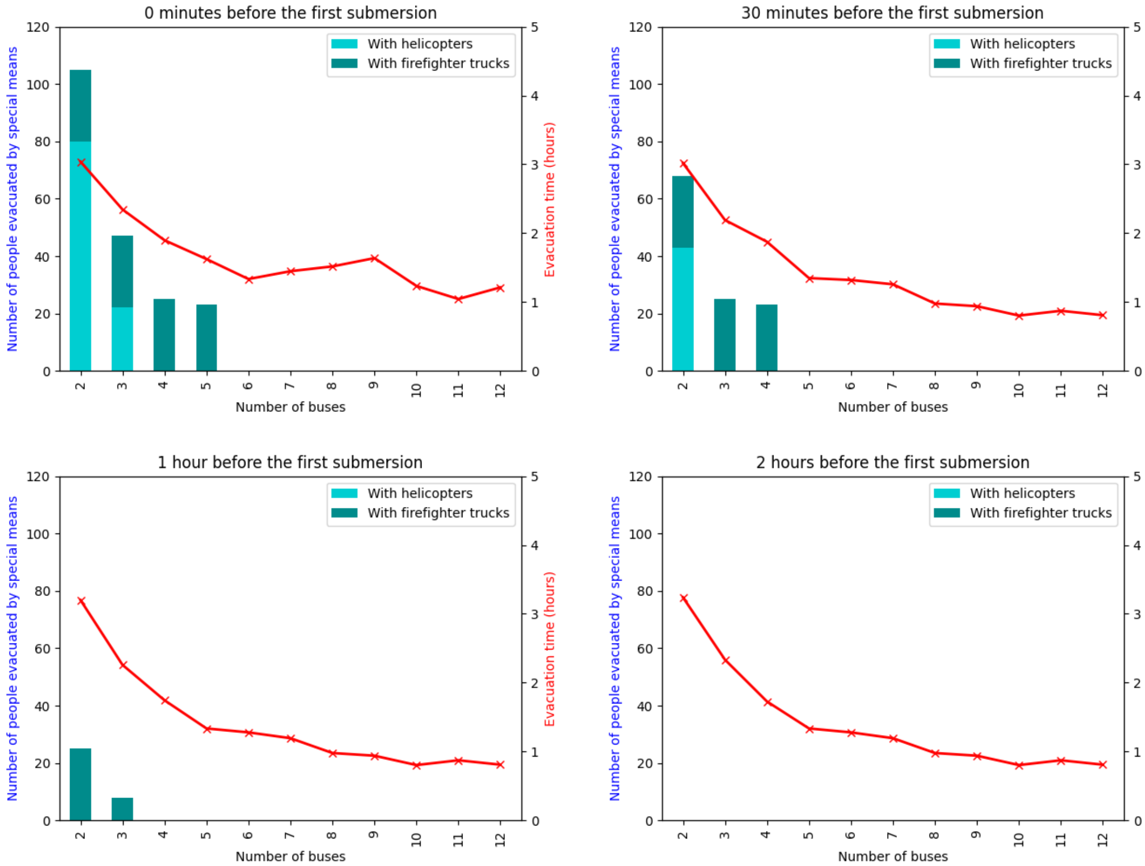


Figure 13. Evacuation center 1 (south bank): evacuation process depending on start time and available buses

DISCUSSION

Advantages of the coupling architecture

The coupling model designed and implemented in this work allows the coherent use of efficient optimization methods in a dynamic and stochastic environment to explore different what-if scenarios. From a software engineering point of view, the modular architecture of this solution allows the reusability of components. Implementing new optimization algorithms does not affect the ABM simulator when the new VRP optimizer has inputs and outputs that comply with our metamodel. We used agent-based simulations with geospatial and real-world data to produce realistic visualizations and relevant indicators. We believe that these outputs could be of great interest to decision-makers.

Usefulness in the French context

This work is a part of the CRIZ'INNOV research project that aims at implementing a portfolio of digital solutions according to the needs of crisis management units in France. The current flood management procedures encounter several difficulties, notably the complexity of information provided by forecasting tools (Belin and Moulin 2016). The solutions developed in this work contribute to addressing this problem by exploiting risk information of vigilance maps (potential flood areas) and available resources to simulate sheltering and evacuation strategies.

In the case study of Trèbes, we showed through simulated scenarios how the developed tools help in the decision-making process to respond to a flooding hazard. Models can simulate different management strategies with various flooding scenarios to anticipate or respond to the need of sheltering and evacuating exposed populations. Using simulations with new data and parameters can reproduce different scenarios in various contexts of crisis management.

Usefulness in crisis decision-making

The following subsections summarize how developed models can answer three main questions to help enhance decision-making in crisis management.

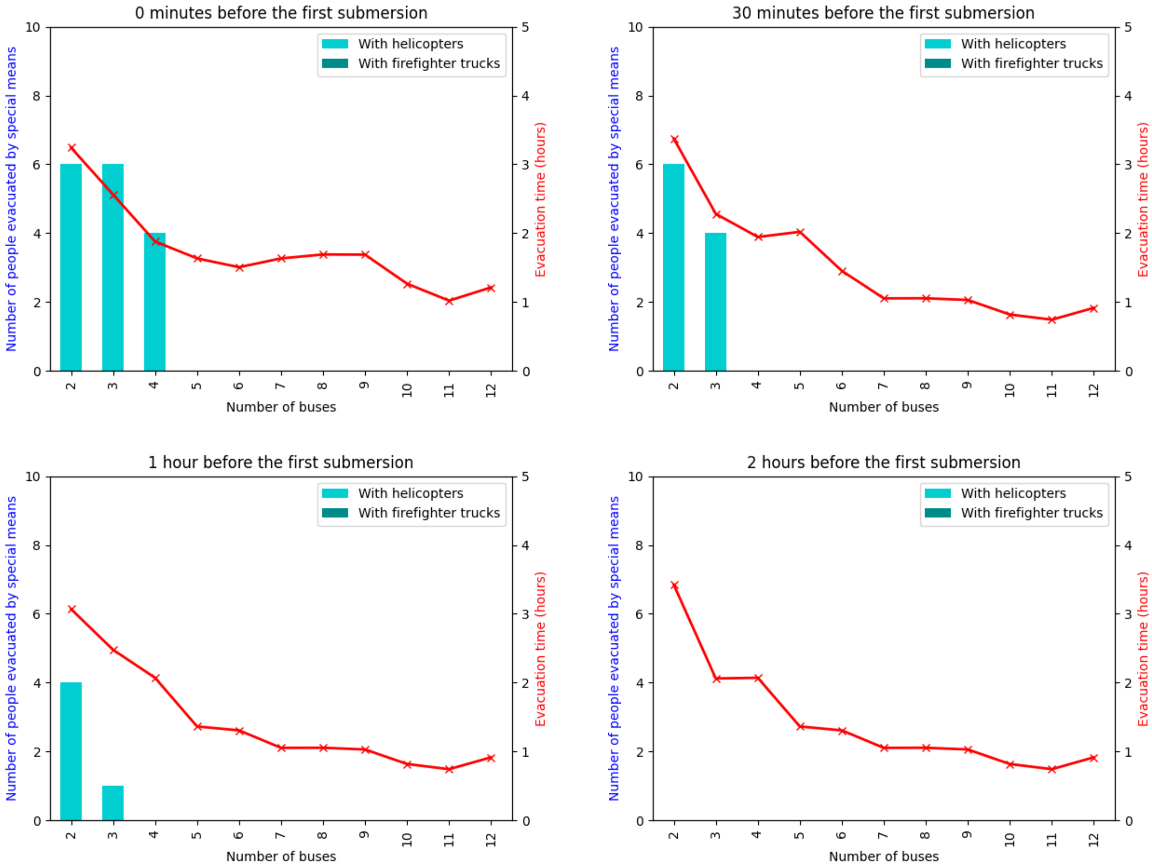


Figure 14. Evacuation center 2 (north bank): evacuation process depending on start time and available buses

Is it necessary to anticipate the hazard?

Decision-makers tend to avoid precocious and unnecessary evacuations that might be unjustified when a hazard event does not induce a significant risk (Huang et al. 2012). The tools proposed in this work contribute to addressing this problem by simulating a crisis to determine the best time to start sheltering and evacuation and whether it is necessary to anticipate the hazard event. The starting time can be adjusted depending on the available resources, the predicted evolution of the hazard, and the estimated total time required to accomplish sheltering and evacuation.

How much time is needed to evacuate populations in risk areas?

Depending on the input data and parameters, simulations estimate the required time for exposed populations to self-shelter and emergency vehicles to evacuate all rescue demands. These two indicators may help prevent the self-sheltering population from congesting roads and impeding emergency vehicles (Takabatake et al. 2020; Lim Jr et al. 2013). Besides, the estimated total time needed for sheltering and evacuation help estimate the required anticipation time and resources, and consequently, the crisis management unit may decide to call for reinforcements.

What is the best allocation of resources?

The self-sheltering simulation help explore different sheltering scenarios to decide on the best distribution of police officers that efficiently regulate movements of pedestrians and individual cars and limit crowd panic. The non-regulation of population movements may lead to *shadow evacuations* (evacuation of people from areas outside a declared evacuation area) (Lamb et al. 2012) or complicate applying alternative strategies such as *shelter-in-place* (staying indoors rather than evacuating the area) (Haynes et al. 2009). As demonstrated in the case of Trèbes, a good distribution of police resources can improve the awareness spread and accelerate the self-sheltering process. Also, this regulation can equilibrate the distribution of populations in shelters and avoid their overload.

Regarding the optimization of evacuation, simulations allow to determine the best distribution of vehicles between evacuation centers. These simulations can be extended to other objectives, such as determining the best geographical location for evacuation centers.

CONCLUSION

In this paper, we presented the design and the implementation of a solution combining agent-based modeling and simulation with optimization algorithms to anticipate sheltering populations in crises. The developed tool combines two models. The first one simulates the impact of the distribution of police officers on the efficiency of self-sheltering of the population. The second model simulates the evacuation of vulnerable people by emergency vehicles. These two models share the same metamodel easing their combination in a comprehensive and coherent sheltering approach. Such a solution can give decision-makers a practical tool to evaluate different sheltering strategies depending on available time and resources. Several simulations integrating real-world data were used to validate this work. The software architecture cleanly separates optimization and simulation, and the metamodel allows reusing this solution to simulate sheltering in other crisis contexts (forest fires, earthquakes, . . .).

In future works, we plan to improve the self-sheltering model by providing agents (pedestrians, households in vehicles, and police officers) with more autonomous behaviors using a BDI (Belief–Desire–Intention) architecture. This improvement would make agent behaviors closer to actual human reasoning and endow simulation outputs with more realism. At a collective level, we will implement crowd-sourcing protocols to regulate the spread of awareness among different stakeholders (police officers, citizens, . . .) and then measure the influence of this awareness on the efficiency of the sheltering process. Regarding the VRP optimizer, we will couple our agent-based simulator with a new dynamic algorithm that adjusts the routes of emergency vehicles locally instead of recomputing the whole routing plan after each flood event.

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