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Generating crime data using agent-based simulation

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ABSTRACT

Policing plays an important role in combating street crime. Though policing actions have a dissuasive impact on criminal behavior, they can also have unpredictable and even undesirable effects such as displacement of crime hot-spots. This paper presents an agent-based simulation model that generates artificial street-crime data which can be used to test different policing strategies in a virtual environment. The model can thus evaluate the strategies' effectiveness and collateral effects before putting them into practice and provide support for the policing decision-making process. Based on this model, a crime simulator was implemented in Repast Simphony and a series of test simulations on fictitious and real cities were carried out. The proposed formulation was successfully validated, confirming its potential as a powerful tool for the study of street crime.

1. Introduction

Research in the field of criminology covers a wide range of topics related to criminal activity, many of which focus on robbery and theft in urban environments (Brantingham & Brantingham, 1981a). Criminological studies may be divided into two main tendencies: those focussing on the environment in which crime occurs, and those concentrating on criminal behavior. It is generally accepted in the literature that the environmental component of crime is extremely important to an understanding of the complete phenomenon. For example, one aspect of the physical environment that plays an important role in crime is the structure of a city (Brantingham & Brantingham, 1981b). A different approach involves describing the areas where offences occur. Brantingham and Brantingham (1995) define four types of urban areas: crime generators, crime attractors, crime-neutral areas, and fear generators. We do not take into consideration the latter type since our focus in this paper is on crime rather than on fear of crime, which has been studied in more detail, e.g. in Doran and Burgess (2012). The other three types are relevant for our models as will be shown below. *Crime-neutral areas* tend to experience occasional crimes by local insiders, as is the case e.g. in some residential areas. *Crime generators* are areas that attract large numbers of people for reasons unrelated to crime, but which create opportunities for people with sufficient levels of criminal motivation who, though it was not their original intention, take advantage of the occasion to commit criminal acts. *Crime attractors*, on the other hand, are areas whose characteristics attract people strongly motivated to commit offences because they offer good opportunities for such activity. This approach is used by Brantingham and Brantingham (2003), who present a conceptual model to anticipate crime displacement in which criminals who shift from one location to another to evade crime prevention interventions do so in a predictable manner. The authors apply the principles of environmental criminology to determine the magnitude and most likely direction of these crime displacements depending on the characteristics of the intervened location, the street network, and the type of crime. One of the main concepts emerging from these works is that of the "crime hot-spot", which denotes a place with high concentrations of criminal activity.

The use of mathematical and computer models in many different application areas has grown considerably in recent decades. This is due mainly to the great increases in computational capacity on the one hand and sophisticated quantitative models on the other. Successful applications have been reported e.g. in the health sector (Chetouanea, Barkerb, & Oropezac, 2012), among others. Recently, more and more quantitative models are being used to study crime-related phenomena and made it possible to uncover dynamic crime patterns that could not have been detected 20 years ago.

In most countries, police forces patrol the streets of cities and towns in order to reduce the number of crimes committed. But efforts to reduce offences in any particular area will not necessarily translate into a general decline as criminals who would otherwise be active there may either shift to another area, wait until the police patrol has moved on, or apply any other of the six displacement forms (temporal, spatial, target, method, crime type, perpetrator) as described by Eck (1993). A review of situational crime prevention (Guerette & Bowers, 2009) found that the interplay between individual decisions by criminals as a reaction to police patrols is very complex, but results in many cases in a reduction of crime. To deal with these and other dynamics of street crime, authorities responsible for law enforcement would greatly

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benefit from a method for determining the real effects of their presence on street criminals' behavior. In particular, with a simulator that could represent such behavior in a given locality it would be possible to study the effectiveness of crime prediction models by analyzing the impacts of decisions proposed by such models.

In this paper we present a tool that tries to replicate the behavior of agents related to street crime (citizens, police, and criminals) emulating e.g. the reactions of criminals to policing actions and other crime-prevention policies, with a view to strengthening the bases of law enforcement decision-making. The paradigm chosen for this task is agent-based modeling and simulation (ABMS), which is ideal for modeling social systems (Axelrod, 1997) because of its ability to generate global patterns from individual behavioral rules observed in real persons. According to Malleson (2010), agent-based modeling is a promising technique in that it shifts the focus of criminology from aggregate approaches towards the level of the individual. It also gets around the unreported crime problem, that is, the discrepancy between reported and actual crime numbers, by simulating the occurrence of actual offences once the respective model has been calibrated accordingly.

Section 2 provides a brief overview on agent-based modeling and simulation. The agent-based simulation model proposed in this paper is introduced in Section 3. The results from applying this model to various fictitious as well as existing cities are presented in Section 4. Model validation is performed in Section 5 whereas sensitivity analysis and extreme conditions testing can be found in Section 6. Section 7 concludes this paper and hints at future work.

2. Agent-based modeling (ABM) and simulation

An agent-based model represents a system as a collection of autonomous decision-making entities called *agents*, each of which individually evaluates its situation and makes decisions based on a set of rules (Bonabeau, 2002).

In cases where there are many individuals making decisions and interacting, adopting an *individual* instead of an *aggregate* approach may lead to more realistic conclusions about the respective system's behavior given that the former would reproduce the observed system in a way it occurs in reality. According to Bonabeau, "*In many cases, ABM is most natural for describing and simulating a system composed of "behavioral" entities. Whether one is attempting to describe a traffic jam, the stock market, voters, or how an organization works, ABM makes the model seem closer to reality.*" (Bonabeau, 2002). ABM is thus both plausible and promising as a technique for studying such phenomena.

An ABM typically consists of three basic elements (Macal & North, 2010):

1. A set of agents.
2. A set of agent relationships.
3. An environment in which the agents live.

The main characteristics of an agent are as follows (Macal & North, 2010):

Self-contained:
It is a discrete, identifiable individual with a set of characteristics, rules of behavior and decision-making capabilities.

Autonomous:
It can function independently, that is, based only on its own rules of behavior and its observation of the environment.

Social:
It has behavior protocols that govern its interaction with other agents.

ABM and simulation (Axelrod, 2003) allows researchers to replicate interactions, whether among agents or between them and their environment, and thereby emulate large-scale social phenomena. Known in the literature as bottom-up simulation (Miller & Page, 2007), this methodology can be used to simulate the adaptive behavior of its agents, and can capture emerging processes in the simulated system. In so doing it affords a better understanding of how these relatively simple behaviors translate into large-scale phenomena of great complexity.

The use of Agent-Based Models and Simulation (ABMS) in the study of crime is a relatively recent phenomenon. An early example is that of Winoto (2003), who develops an agent-based model that applies a choice-theoretic approach in which agents decide whether or not to commit a crime according to their perception of the costs and benefits.

Another simulation model is that of Short et al. (2008). They study the dynamic properties of criminal hot-spots using a model that simulates residential burglary on a grid whose cells represent house locations with varying degrees of attractiveness to the criminal. The attractiveness of any cell is given by an intrinsic component plus a dynamic one based on the crime rate in the immediate area and incorporating the so-called "broken window effect" which suggests that neighborhoods that have already been burgled have a greater likelihood of being burgled again (Wilson & Kelling, 1986). Malleson, Heppenstall, and See (2009) and Malleson and Birkin (2012) also intend to replicate residential burglaries from a real city in a computer model applying, in their case, an agent-based model to simulate human and environmental factors. Based on this model an individual-based approach of burglary using the PECS framework (Physical Conditions, Emotional State, Cognitive Capabilities, and Social Status) has been presented (see Malleson, See, Evans, & Heppenstall, 2012) which considers "*the daily routines of criminals, their drivers, and the opportunities presented by their environment*".

Birks, Townsley, and Stewart (2012) present another ABM variant of residential burglary. Different to Malleson et al. they study the impact several theoretical propositions (routine activity approach, rational choice perspective, and crime pattern theory) have on offending patterns by a series of simulated experiments. They found that these propositions provide a generative explanation for several independent characteristics of crime.

Liu et al. turned their attention to street robbery and developed a crime simulation model based on the routine activities theory (Cohen & Felson, 1979) where "*offenders, targets, and crime places ... are modeled as individual agents*" (Liu, Wang, Eck, & Liang, 2005). Similar work has been done by Groff (2007) who using crime simulation strongly supported the basic premise of routine activity theory, i.e. that street crime will increase as individuals spend more time away from home. In the same context Melo, Belchior, and Furtado (2005) develop a model that simulates agents' physical reorganization, in which police patrol routes are the analyzed variable. Their results suggest that regularly changing the routes helps reduce the number of offences. However, they take no account of the costs and travel times involved, which could render it impractical to make route changes more often than, say, once a day.

Regarding the spatial representation of crime Elffers and van Baal (2008) argue that a realistic spatial backcloth for simulation of street crime is not that important. While we agree with their opinion that for an understanding of basic crime mechanisms an almost real background is not necessary, we follow the arguments provided by Ratcliffe (2010) who, among others, pleads for more sophisticated crime mapping techniques that could lead to improved decision-making processes by, e.g. policy makers. The ABM that will be presented in the following section builds upon these reflections.

3. An agent-based simulation model for the study of crime

In this section we present an agent-based simulation model for replicating street crime. This requires that we identify and model the *environment*, its *agents*, and their *rules of behavior* as determined by the characteristics of the city we intend to simulate. These three elements will be described in the following three subsections. In Section 3.4 we exhibit different scenarios that will be analyzed with the proposed model.

3.1. The model environment

The model environment consists basically of the following two elements that will be described afterwards.

- The elements that constitute a city's composition.
- The particular cities that will be analyzed.

3.1.1. Composition of cities

The proposed model is designed to be executed on a representation of a city, whether fictitious or real. This representation is a two-dimensional grid in which each cell is a section of the city's land area. The dimensions of a section may vary from model to model, but for a given case each one will be the same size. The model also classes the city land area into two main types: public spaces and private spaces. The principal difference between them is that model agents can freely use or pass through the former but not the latter. Public spaces include streets, pedestrian-only zones, parks and squares, while private spaces are made up of homes, buildings, businesses, educational establishments, etc. This design forces agents to move only through the public spaces, as with people in real cities. This ensures the model will generate true-to-life patterns, some of which impact crime-related agent decisions. To give the agents' movements a meaningful context, the city also contains various points of interest. They are represented in the model by the following six types of "facilities" that make up the private spaces.

Residences:
Places where agents live or stay. They include houses, apartment buildings, hotels, etc.

Retail businesses:
Places where agents carry out retail transactions such as shops, supermarkets, department stores, street markets, and shopping malls.

Banks:
Classed separately from other businesses because of their importance as crime attractors (Brantingham & Brantingham, 1995). For present purposes they include banks, insurance companies, and various other financial services where automated teller machines are installed and cash transactions are carried out thus affecting street crime.

Offices:
Places of work, including not only office buildings in the strict sense but also hospitals, government buildings, etc.

Educational establishments:
Include schools, universities, and any other type of educational institution.

Public transit accesses:
Bus stops, metro entrances and exits, bus terminals, train stations, etc.

To represent the entry and exit of persons to and from private spaces, each one of these structures in the model has the ability to generate and attract agents. *Agent generation* is determined by a particular parameter for each agent class (citizen, police, and criminals; see Section 3.2), by the type of structure, the day of week, and the time period of day as is exemplarily shown in Table 1 for the case of Central Santiago which is one of the analyzed cities; see Section 3.1.2. This parameter indicates the number of agents that enter the model per time step which is 1 min in our simulation.

Agent attraction is defined by the attractiveness each structure has for each agent type. As an example agents are generated in public transit accesses during the morning hours, whereas offices and banks attract agents during working hours.

As with real cities, those in the model have places where agent traffic is greater than others due to the presence of places of interest, public transit accesses and high concentrations of retail businesses and places of work. The model incorporates this phenomenon through an attractiveness metric that assigns a monetary attractiveness value to each place in the city. This value will depend on the surrounding facilities and reflect the perceptions of the criminals. The indirect result is that some areas of the city have more agent traffic than others, either because their intrinsic attractiveness values are higher or because they lead to areas with higher values.

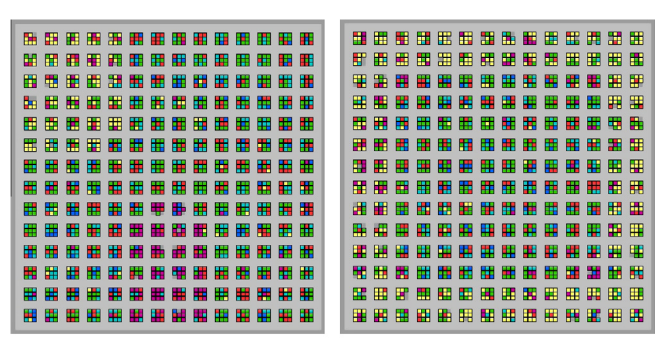
3.1.2. Cities

A key phenomenon we set out to analyze was the influence of the geographical environment on criminal behavior. To this end the model was tested on three cities with differing configurations and characteristics: "Gridville" (a fictitious city), Central Santiago (Chile), and Vancouver (Canada).

Gridville:
A simplified city with a grid-pattern layout in which all the streets are parallel or perpendicular and equidistant from one another. Four versions of the city were defined, differing only in the spatial configurations of their constituent districts, of which there are four

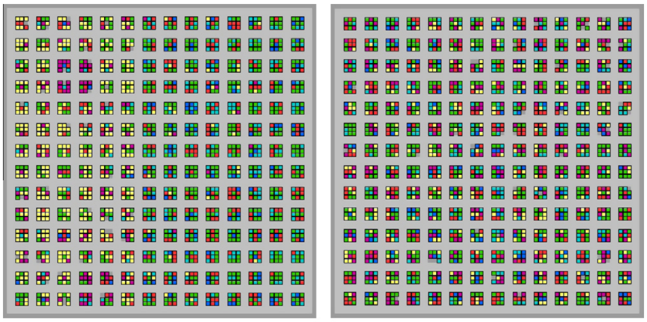
Table 1
Time periods of day.

Period	Hours
Early morning	00:00–05:59
Morning rush hour	06:00–08:59
Morning	09:00–11:59
Noon	12:00–14:59
Afternoon	15:00–17:59
Afternoon rush hour	18:00–20:59
Night	21:00–23:59



(a) Gridville 1 (b) Gridville 2

Fig. 1. Different configurations of Gridville.

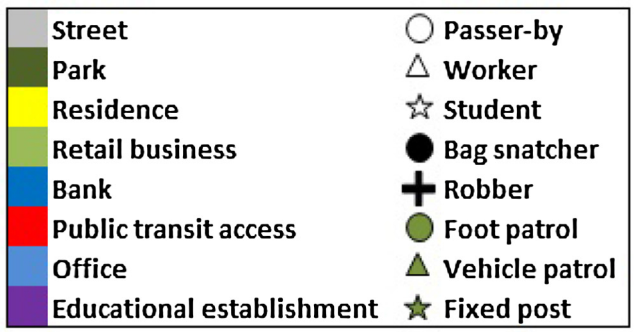


(a) Gridville 3 (b) Gridville 4

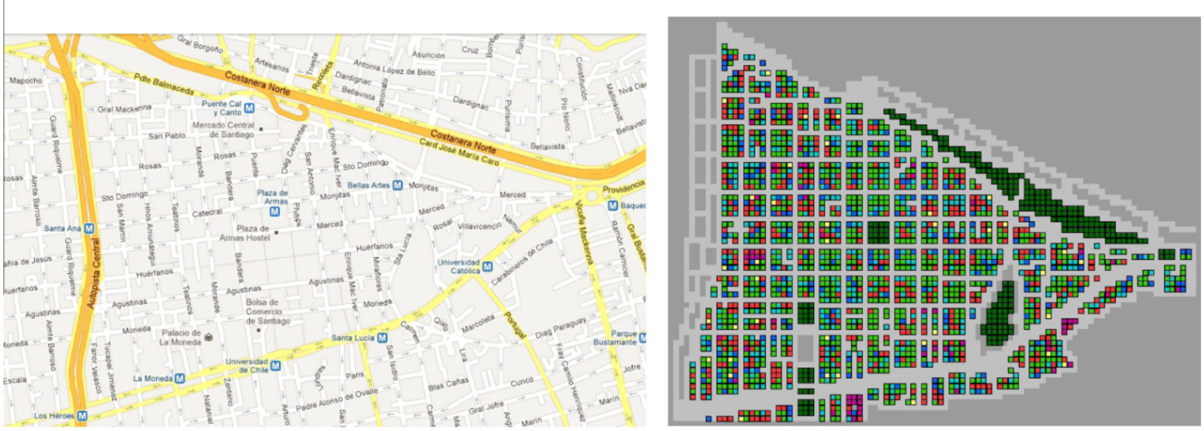
Fig. 2. Different configurations of Gridville.

types: residential, educational, commercial, and super-commercial. These district configurations are shown in Figs. 1 and 2. Gridville 1 has a clearly identifiable residential as well as an educational area. In the case of Gridville 2 the residential areas are organized "around" educational and commercial districts. Gridville 3 is characterized by two main areas, commercial mainly on the right and residential mainly on the left which has two small educational districts inserted. Gridville 4 has a completely random assignment of facilities.

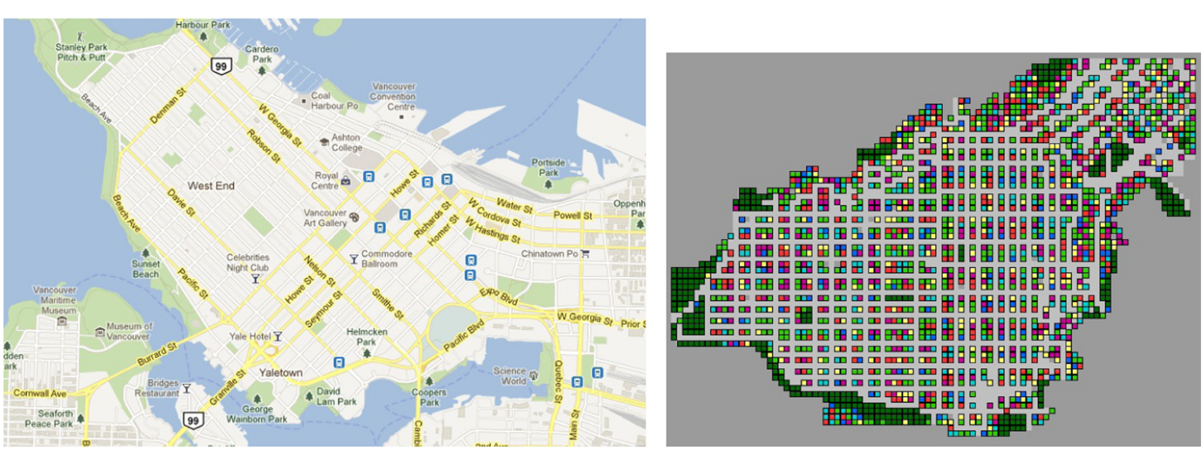
Central Santiago:
The central area of Greater Santiago. It is the responsibility of a single police station and has the highest pedestrian flows in the city



(a) Legend



(b) Santiago Center



(c) Downtown Vancouver

Fig. 3. Real versus modeled cities.

attracted by the dense concentration of commercial, work, and tourism-related activities. Fig. 3b shows the area as modeled next to a real map of the same area which is approximately 2 km $\times$ 1.5 km.

Downtown Vancouver:
This area of the city has a high level of commercial and tourism-related activity. A sector in the northern part of the area is considered a super-commercial district. The entire area as modeled is approximately 3 km $\times$ 2 km and is shown next to a real map of it in Fig. 3c .

We visited the respective areas in Santiago as well as in Vancouver and modeled their established land use (street networks, facilities, etc.) and the observed travel patterns as closely to reality as possible.

3.2. The agents

The proposed model has three main *classes of agents* representing the principal actors in the crime phenomenon: citizens, criminals (also called offenders), and police. We must ascertain the conduct of these agents at a disaggregated level as will be described in the following subsections.

3.2.1. Citizens

Citizens are ordinary honest persons who inhabit the city and never commit criminal acts. In our model, they play the role of potential crime victims, traveling the city along a pre-defined route. Within this class three *types of citizens* are modeled: passers-by, workers, and students. Below, in Section 3.3 we define with more detail their rules of behavior.

3.2.2. Criminals

Criminals are the class of agents that potentially commit street crimes. Two *types of criminals* are modeled: bag snatchers (including pickpockets) and robbers (i.e. thieves using or threatening with violence) since these two types turned out to be the most relevant in a database with real crime data we analyzed; see Section 5.1.

3.2.3. Police

Police are agents responsible for preventing crime. They patrol public places and attempt to cover as much territory as possible given that their presence has a partially dissuasive effect on criminals. Their actions in the model are strictly limited to prevention, thus excluding the capture of criminals. Three *types of police* are modeled as described next.

Foot patrol (FOOT):
Foot patrol officers get around by walking. Their travel speed is therefore the same as that of the other two classes of agents and their radius of action is relatively focussed, avoiding long distances between points along their route. The lengths of their routes are between two and three kilometers on a real scale.

Vehicle patrol (VEHI):
Vehicle patrol police get around in a motor vehicle and are thus able to patrol wider areas at greater speeds than foot patrol police. The lengths of a vehicle patrol route are between eight and ten kilometers on a real scale.

Fixed post (FIX):
Fixed post police are comparable to security guards, staying at their post or position and providing strong protection to a specific zone.

All (ALL):
Not a police type as such but rather a combination of all three acting simultaneously. Scenarios with this combination are simulated to evaluate whether it has a greater preventive effect on crime than using only one type.

3.3. Rules of behavior

Having described both the simulation environment and its agents, we now define how the latter interact and the behavioral rules they follow.

The decisions made by the agents depend exclusively on their attributes and their immediate environment. In other words, their respective decisions are affected only by what happens within a certain radius of their individual positions. Each agent has three main attributes: route, radius of vision, and travel speed.

A **route** is defined as an ordered set of facilities an agent visits. During a simulation, agents in movement proceed towards the next destination on their route unless they become involved in an action linked to a crime such as pursuing a victim, or fleeing a criminal or a police officer.

Radius of vision is the distance within which an agent can detect the presence of another agent. This value plays a fundamental role in agent decision-making, which depends on the immediate environment.

Travel speed is determined by the distance an agent travels in each iteration of the simulation and is given by a uniform random distribution. The only agents with a relatively high travel speed are the vehicle patrol police, all other agents being assumed to get around on foot.

Each agent class also has its own behavioral rules while the different agent types within a single class are all governed by the same rules but have different parameters.

Citizens have the simplest decision process as they travel their pre-defined routes, e.g. from their home to the university. We allow, however, random deviations according to the attractiveness of buildings close to these pre-defined routes, e.g. if on the daily way from his/her home to the university some agent wants to buy something in a nearby shop. This characteristic represents an observable phenomenon in real cities, where some zones attract large flows of people due to the high concentration of places of interest. Those zones are typically considered as crime generators; see Section 1. Once a citizen arrives at the pre-defined destination, he/she exits the model. The one exception to this rule is that if they are a victim of a crime, they exit the model immediately.

Police behave similarly to citizens in that they also travel pre-defined routes, but with the important difference that theirs are patrol routes which are determined by a set of places that must be visited such that each route terminates in its starting point from where police starts over again. Between the places to be visited, these routes are random within a certain radius of action, i.e. similar to the case of citizens, police can deviate randomly from the shortest paths between two points.

Criminals behave most of the time similar to non-criminals according to findings based on Routine Activity Theory (Cohen & Felson, 1979). This might change, however, in absence of a guardian to prevent crimes from happening and if at the same time a suitable target is present. They have the most complex decision process in the model given that it involves various different situations which may arise in a real scenario. In addition to choosing a location, they must make a number of decisions relating to a possible crime such as following a potential victim, fleeing from a police officer, and finally, whether or not to commit the offence. Choosing a location depends on the route initially assigned while the other decisions depend on the criminal's immediate environment. The decision to commit a crime is taken with a certain probability which differs for the above introduced types of bag-snatchers and robbers as shown in Table 2 and depends on the numbers of police (p) and citizens (c) close to a delinquent.

Table 2
Probability functions.

Function	Prob. of bag snatching	Prob. of robbery
Bold	$prob_L = \begin{cases} \frac{c}{30} & \text{if } p = 0 \\ \left[\frac{c}{30\cdot(p+1)}\right]^{\frac{3}{2}} & \text{if } p \geqslant 1 \end{cases}$	$prob_A = \frac{0.1}{(p+1)^3 \cdot c^3}$
Normal	$prob_L = \begin{cases} \frac{c}{20} & \text{if } p = 0 \\ \left[\frac{c}{20\cdot(p+1)}\right]^{\frac{3}{2}} & \text{if } p \geqslant 1 \end{cases}$	$prob_A = \frac{0.1}{(p+1)^3 \cdot c^2}$
Cautious	$prob_L = \begin{cases} \frac{c}{10} & \text{if } p = 0 \\ \left[\frac{c}{10\cdot(p+1)}\right]^{\frac{3}{2}} & \text{if } p \geqslant 1 \end{cases}$	$prob_A = \frac{0.1}{(p+1)^2 \cdot c}$
Factor	$f_L \sim U[0.9; 1.1]$	$f_A \sim U[0.8; 1.2]$

To these probabilities we add a noise factor as indicated in the table in order to have delinquents with varying behavior.

Unlike the routes of other agent classes, those assigned to criminals allow them to remain in the immediate area of a destination and commit crimes. Once they have committed a certain number depending on the type of criminal, they travel to the next destination and repeat the procedure. Criminals are thus represented in the simulation as changing location after committing a set of crimes in order to reduce the risk of being recognized and/or caught.

Criminals choose their routes at random taking into account **crime generators**, which are locations with high attractiveness for citizens.

Criminals are cautious in the presence of police and will tend in such situations to be less likely to engage in criminal activity and possibly move to another zone. The actual decision to commit an offence is therefore subject to a probability that depends on the number of police nearby but also on the number of citizens. Obviously, as the number of police increases the probability decreases, while the effect of greater numbers of citizens depends on the type of criminal. Table 2 displays the respective probability distributions.

We decided to run the model for one week, since literature (e.g. Liu & Brown, 2003) as well as policing experience coincide with this time unit regarding crime pattern recognition and – as a consequence – policing decisions, such as e.g. shift assignment. As has been said above, agent generation and attraction depends on the time of day leading to a high number of agents during the day and less during nights. Additionally offenders leave the model when they get trapped by police which occurs when they commit crime within the visibility radius of police.

3.4. Scenarios

Having developed the model as just described, we now analyze its behavior in various simulations using a set of defined scenarios that differ in the number, type, and distribution of police. The details of each of these three variables are set out in what follows.

3.4.1. Number of police

The number of police patrolling an area directly influences the commission of crimes. To analyze this variable we used various values, both fixed and varying.

Fixed number:
Scenarios were simulated using values for the number of police that remained fixed during the entire simulation. The actual values used are shown in Table 3.

Varying number (VAR):
Although the model was developed on the assumption of a fixed number of police, we also investigated the results obtained when the number was varied by time of day.

Table 3
Number of police used in the simulations.

Number of police									
0	5	15	30	50	75	100	250	500	VAR

3.4.2. Type of police

The different characteristics of the three police types (foot patrol, vehicle patrol, and fixed post) were applied to determine how they compare in terms of effectiveness in reducing crime. Various experiments were conducted using either a single police type or a combination of all three.

3.4.3. Police distribution strategies

Also of interest is the use of different distributions of police officers. The following distribution strategies were defined and analyzed:

Uniform distribution (UNI):
The police are distributed uniformly across the city, ensuring that each location has a similar level of protection and none are left unprotected.

Random distribution (RAN):
The police patrol city locations randomly, with the result that some locations have greater protection than others and some may be left unprotected.

Hot-spot distribution (HOT):
All police are assigned to the locations that were found, in simulated scenarios with no police (described below), to have the highest crime rates, thus providing greater protection to these so-called hot-spots.

Mixed strategy distribution (MIX):
Half of the total number of police patrol hot-spots while the other half patrol the rest of the city uniformly.

4. Results

The proposed model was programmed and executed using Repast Simphony, a free and open-source toolkit widely used for creating agent-based models (North, Tatara, Collier, & Ozik, 2007).

The following subsection presents as a base case for each one of the modeled cities (Gridville, Central Santiago (Chile), and Vancouver (Canada)) the situation without any police. In the subsequent three subsections we derive results varying the number of police, type of police, and distribution strategy, respectively.

For each model we assume as radius of vision one block in the case of Gridville and 100 m for Santiago and Vancouver.

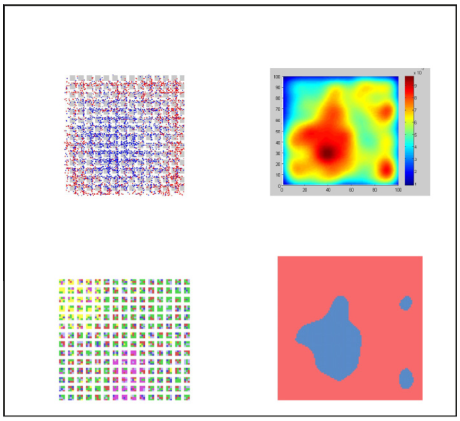
Table 4
Base case results by city.

City	Crimes	Type of crime	
		Bag snatchings	Robberies
Santiago	1732	1462	270
Vancouver	964	757	206
Gridville 1	1026	585	441
Gridville 2	856	510	346
Gridville 3	905	464	441
Gridville 4	896	510	386

4.1. Results with no police

A series of base cases with no police presence were simulated for the three cities to serve as a standard of comparison for the analyses with police. Key data were thus generated for each city such as the existence of natural hotspots and the number of crimes committed at each one. These results are summarized in Table 4.

The aggregated results of all the base case simulations were used to define the spatial distributions set out in Fig. 4. For each city the figure shows a vectorial map (upper left), the corresponding raster map (upper right), the city's division into districts (lower left), and the zones identified as hotspots (lower right). For the purpose of our simulations we defined hotspots as locations where crime is more than one standard deviation above the mean level used to generate the raster map.



(a) Gridville 1: vectorial map (upper left), raster map (upper right), districts (lower left), hotspots (lower right).

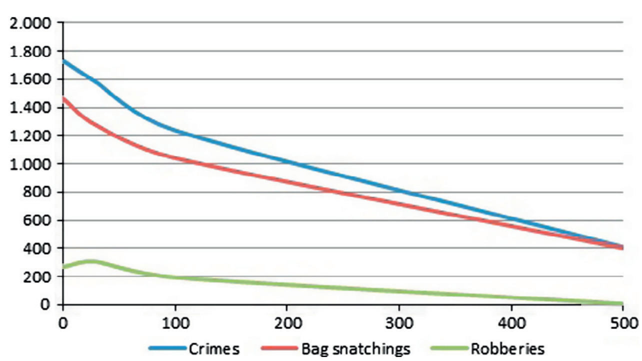
Fig. 4. Crime distribution in base cases and hotspots.

4.2. Results by number of police

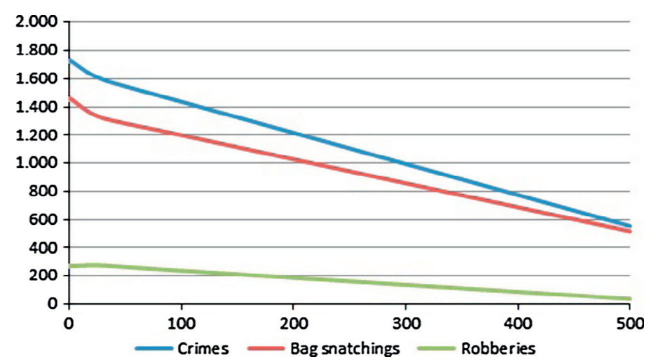
The number of crimes in Santiago as a function of the number of police under the four police distribution strategies (see Section 3.4.3) with police type "fixed post" is shown in Fig. 5. As can be seen, the number of crimes declines as the number of police rises under all four strategies, a result consistent with the decrease in the probability a criminal will commit an offence if police are nearby. On the other hand, since the curve is convex the marginal contribution of each police officer is also falling, especially under the hotspot strategy (Fig. 5c).

4.3. Results by police type

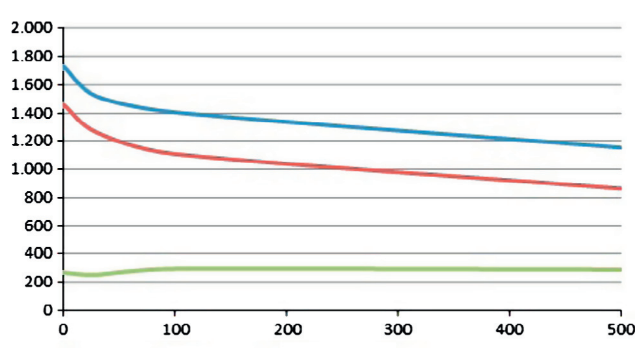
The effectiveness of each police type in terms of numbers of crimes committed was found to depend on both the distribution strategy and the number of police. Thus, the relative effectiveness



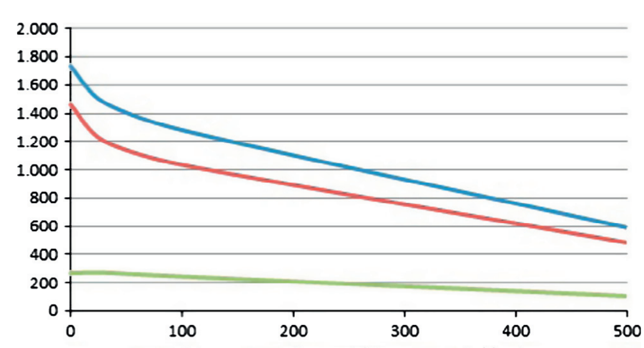
(a) Scenarios: Santiago with fixed post police under the uniform strategy by number of police.



(b) Scenarios: Santiago with fixed post police under the random strategy by number of police.

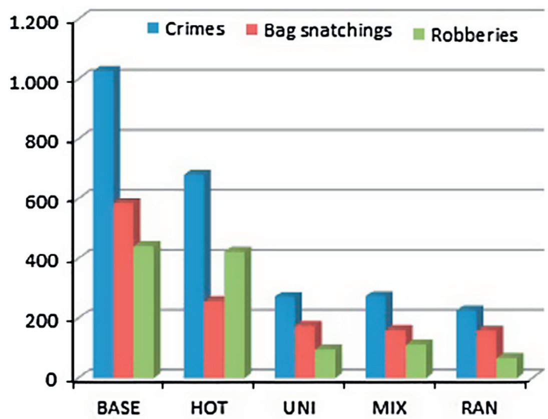


(c) Scenarios: Santiago with fixed post police under the hotspot strategy by number of police.

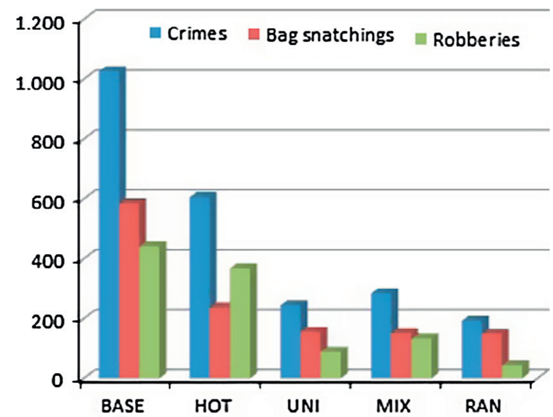


(d) Scenarios: Santiago with fixed post police under the mixed strategy by number of police.

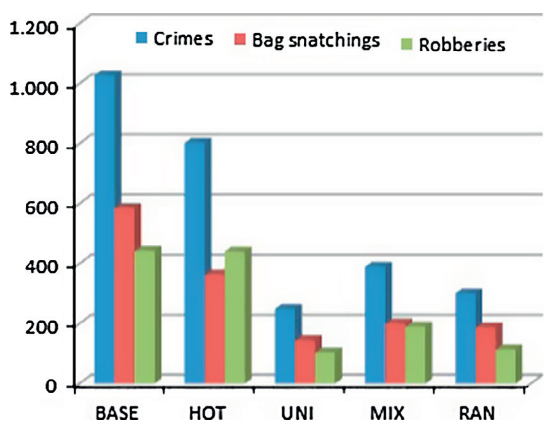
Fig. 5. Number of crimes by number of police under the different distribution strategies with fixed post police.



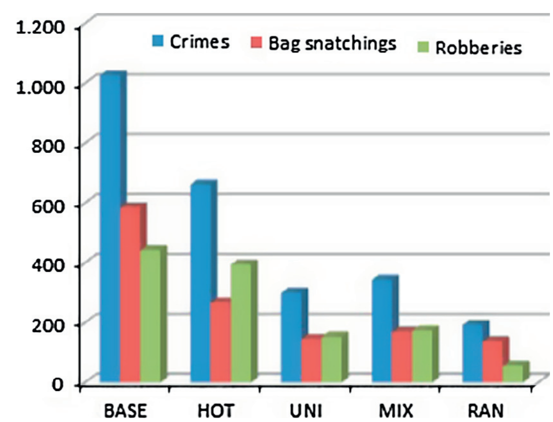
(a) Scenarios: Gridville with 30 police applying police type "foot patrol" by distribution strategies



(b) Scenarios: Gridville with 30 police applying police type "vehicle patrol" by distribution strategies



(c) Scenarios: Gridville with 30 police applying police type "fixed post" by distribution strategies



(d) Scenarios: Gridville with 30 police applying all three police types by distribution strategies

Fig. 6. Number of crimes by distribution strategies applying different police types (with 30 police).

of each police type can only be determined in terms of a specific situation.

The results for scenarios with 30 police officers in Gridville under the different *distribution strategies* and for different *police types* are shown in Fig. 6. As can be appreciated, the differences in police type effectiveness were relatively small and thus do not justify categorical conclusions. There is nevertheless a slight tendency for fixed post police to be the least effective given that they are not mobile and therefore cannot fully cover the whole city. With higher numbers of police, however, this is no longer the case. Also, using all police types yields better results given that under this scenario the fixed post officers are supported by mobile police on short and long patrols, thus providing better city coverage.

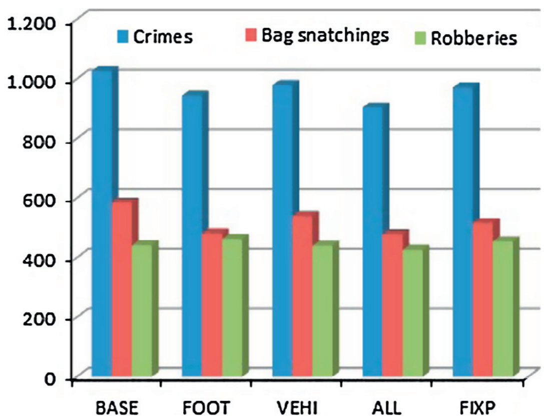
4.4. Results by distribution strategy

For 30 police officers in Gridville under the different *distribution strategies*, the results are shown in Fig. 7. As is evident, the uniform and random distributions perform best in every case. The hotspot distribution is the least effective strategy, for by concentrating all police personnel at the highest crime locations it displaces criminal activity towards the rest of the city which is completely unprotected. The mixed strategy shows a similar weakness, though on a lesser scale since only half of the police are assigned to hotspots while the other half are freed up to prevent the displaced activity.

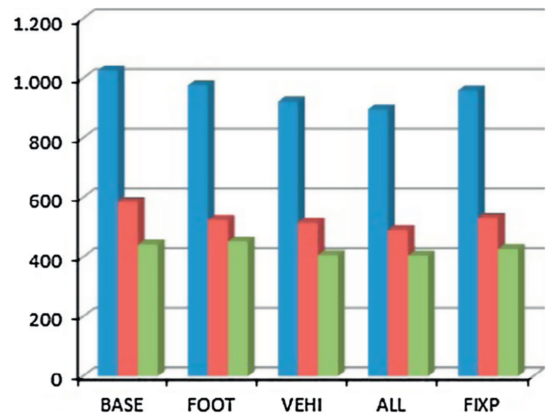
5. Model validation

Validating a simulation model is of particular importance since the artificially generated data are not necessarily representative of the real phenomena they are intended to reflect. Model validation has been defined as the *"substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model"* (Schlesinger, 1979). In other words, it is a process of demonstrating that the model results are valid. This process will typically consist of a series of tests performed on the data to determine their degree of accuracy and thus the model's validity. Sargent (1996) describes three different approaches to validating a model:

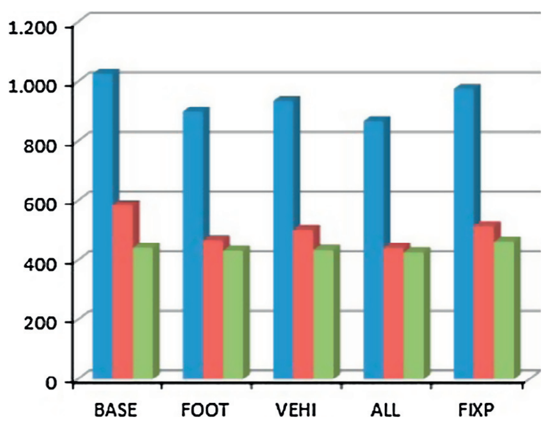
1. The model developers decide whether it is valid based on the results of various tests conducted on the data obtained.
2. A third party independent of both the developers and the users of the model is asked to decide whether it is valid. This is known as the independent verification and validation (IV & V) approach (Robinson & Brooks, 2010).
3. A points-based model is used to assign subjective weights to various aspects of the validation process and then derive a total score for the model being tested. This score is compared with a pre-defined qualifying level to determine validity.



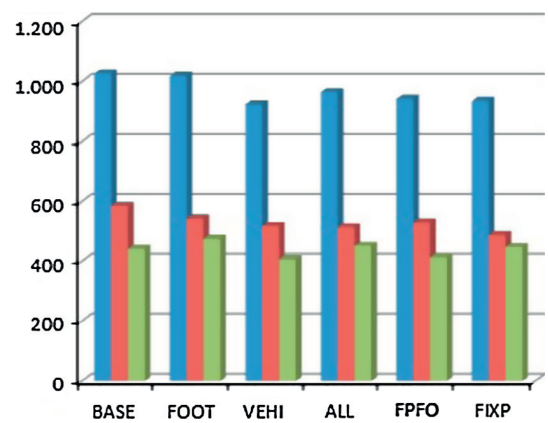
(a) Scenarios: Gridville with 30 police under the “uniform strategy” (UNI) by police type.



(b) Scenarios: Gridville with 30 police under the “random strategy ” (RAN) by police type.



(c) Scenarios: Gridville with 30 police under the “hotspot strategy” (HOT) by police type.



(d) Scenarios: Gridville with 30 police under the “mixed strategy” (MIX) by police type.

Fig. 7. Number of crimes by police type under different distribution strategies (with 30 police).

For the model developed here, the first approach is fundamental given that it is essential the data obtained be tested and compared with real crime statistics to determine whether they are a faithful reflection of reality. Techniques that belong to this approach and that are applicable for our purposes are reviewed below; see also (Balci, 2010).

5.1. Validation with historical data

If a database with historical data is available a portion of its data can be used to construct the model, leaving another portion for model validation. In general, historical data on crime do exist, although in most cases there are difficulties in collecting and consolidating them.

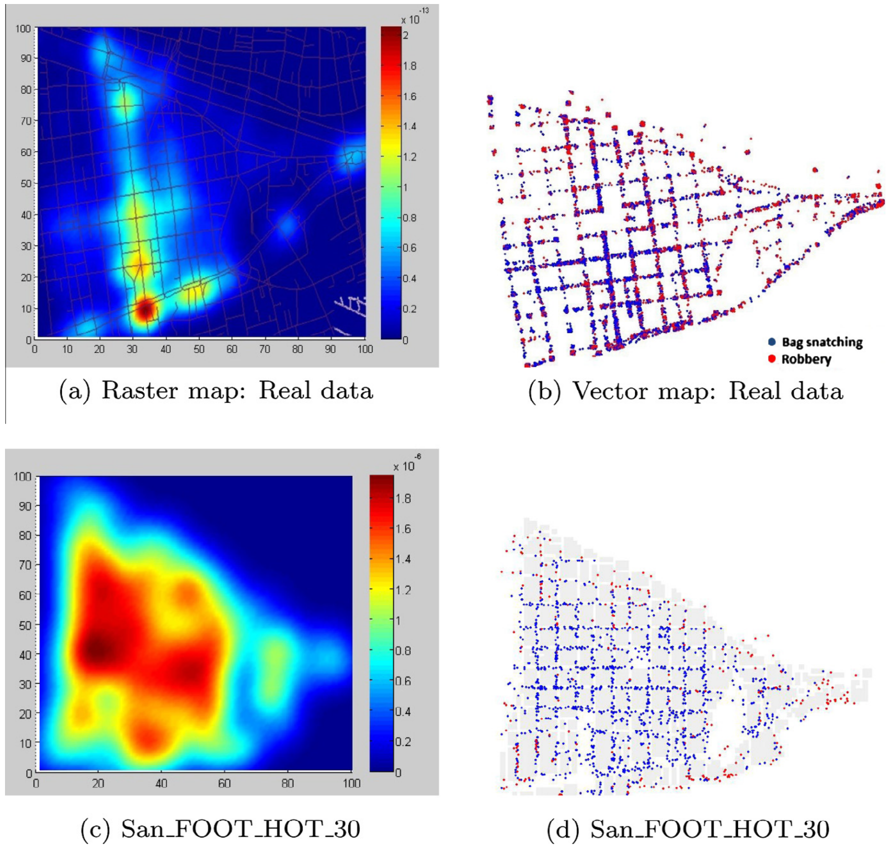
For Central Santiago, we used a database with reported crime covering the years 2001–2004 provided by the police station responsible for that area. The spatial distribution of the crimes captured by the mentioned database is shown in Fig. 8 while the temporal distribution is given in Fig. 9. Since the proposed model tries to replicate the conceptual patterns of crime numbers, both, the spatial as well as the temporal distributions need to be validated.

Having simulated data for a single week only, we compared certain patterns with real data on reported crime. One of these patterns is the time-of-day distribution of crimes, which is shown in Fig. 9. Panel (a) of the figure presents this distribution for the real Santiago data while panel (c) displays the corresponding results for the Santiago simulation with 30 uniformly distributed foot patrol police.[1] Both graphs clearly indicate that the number of crimes is low before dawn and picks up considerably once daylight arrives, with a major peak during lunchtime (in Chile typically 1 pm-3 pm or so) and a smaller one during the evening rush hour when workers are on their way home. While for various reasons we do not aim at replicating real crime numbers, a sufficient conceptual match between simulated and real pattern can be recognized.

Another important comparison is the day-of-the-week crime distribution, displayed in panel (b) for the real data and panel (d) for the simulations. As can be seen, considerably more crimes are reported on weekdays than on weekends, the largest number of offences registered on Fridays. A possible explanation for this general trend is that fewer people frequent Central Santiago on weekends, considerably reducing opportunities for crime there.

While in this example there are still differences between historical data from the period 2001 to 2004 and data generated with a particular configuration of our model, a match of the general pattern can be recognized. This match is considered to be sufficient for the purpose of the present model.

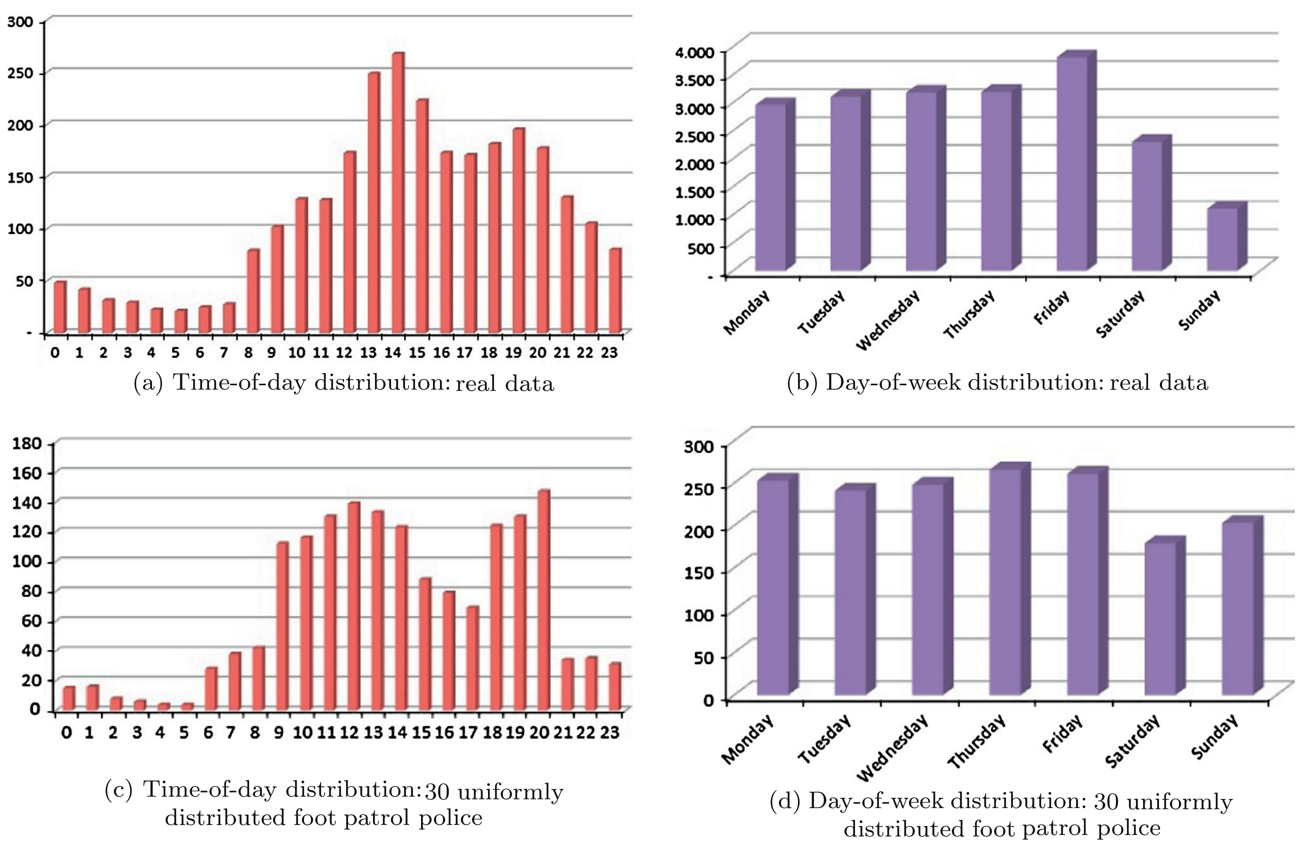
[1] Notice that this patrol scheme most probably differs from the scheme that had been applied during the observation period.



(a) Raster map: Real data (b) Vector map: Real data

(c) San_FOOT_HOT_30 (d) San_FOOT_HOT_30

Fig. 8. Comparison of spatial distribution.



(a) Time-of-day distribution: real data (b) Day-of-week distribution: real data

(c) Time-of-day distribution: 30 uniformly distributed foot patrol police (d) Day-of-week distribution: 30 uniformly distributed foot patrol police

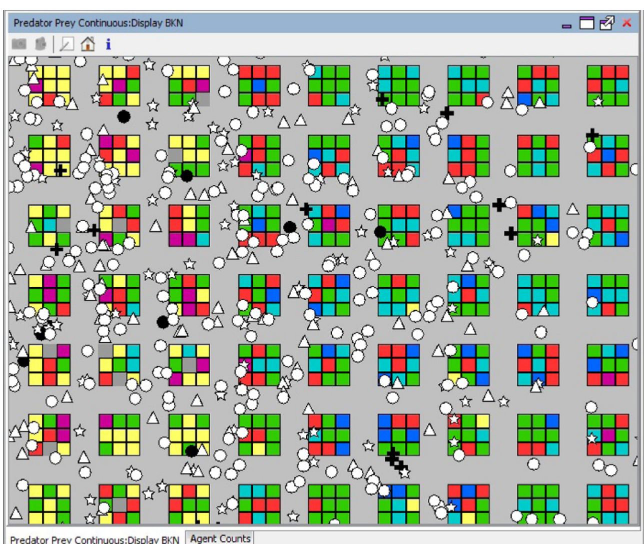
Fig. 9. Temporal distribution of real and simulated data.

Another issue in validation with historical data is unreported crime. Even if unreported crime clusters near to reported crime (Chainey & Ratcliffe, 2005), the aim cannot be to get as close as possible to reported crime data. This fact also limits the power of validation with historical data in our case and makes it necessary to employ also the following approaches.

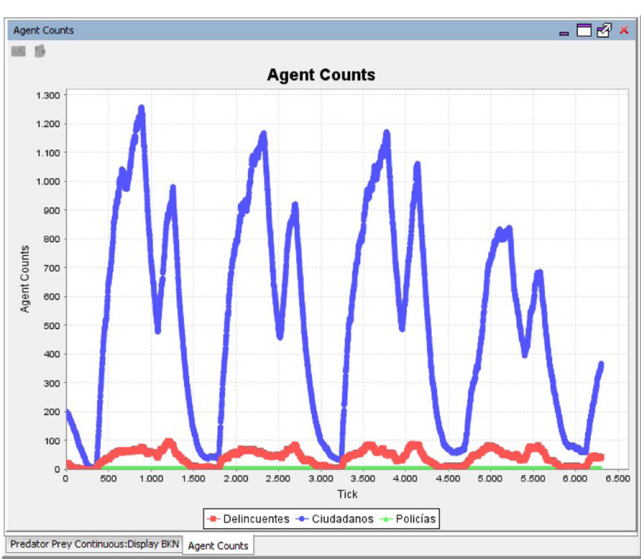
5.2. Model animation

The graphic interface included with the Repast Simphony simulation tool is employed to visualize the simulations as they are executed. This allows the user to monitor the process step by step, following the movements of the agents, the crimes, and other events as they occur. The user can thus ensure that the model is generating a faithful representation of the system being simulated, which also greatly reduces the chances that major coding errors will go undetected. A moment in the simulation of Gridville 3 is displayed in Fig. 10a.

The animations produced by the simulator clearly revealed that there is a tendency for citizens to flow from residential to commercial and educational districts. Also observable is that agents tend to concentrate between the city center and the commercial district and that the outlying sectors are usually the least frequented. The police distribution strategy is another characteristic of each scenario that can be clearly followed during the animation, which displays their initial assignments and their movements. Both were found to be consistent in every case with the distribution strategy defined for the scenario.



(a) Model animation



(b) Operating graphic

Fig. 10. Animation and operating graphic in Repast Simphony.

5.3. Operating graphics

Another complementary validation approach is to display operating graphics which present key indicators during the simulation. This has a similar purpose as model animation (see Section 5.2) which is to allow the user to visually monitor the simulation process, but in this case the emphasis is on numerical indicators.

An important characteristic of the simulations is the number of each type of agent at different times of day given that there exist known patterns for numbers of persons in the streets at different hours. It is therefore included among the indicators that can be displayed, as can be seen in Fig. 10b which shows the agent counts in a simulated scenario with no police from Wednesday through Saturday. The numbers of ordinary citizens (in blue/dark gray) and of criminals (in red/ light gray) vary depending on the time of day, the peak counts being recorded during lunchtime with a secondary peak during the evening rush hour.

5.4. Internal validation

An internal validation of the model was conducted by running it various times under the same conditions to determine its variability. High variability would suggest the model was inconsistent while low variability would justify a certain confidence in the reliability of its results.

The internal validation was carried out using a number of scenarios that were chosen for their representativeness in the sense that their characteristics were used in the rest of the simulations. Given the key role of the base cases in making comparisons, they were also included in the validation to ensure their consistency. Due to the models' complexity computational times of the simulation runs were critical. Given the low deviations as reported next, we decided therefore not to perform more than 5 runs for each scenario.

The results of the validation are summarized in Table 5, showing the scenarios tested, the average number of crimes ($\bar{x}$), the standard deviation (σ), and the latter as proportion ($\frac{\sigma}{\bar{x}}$). As can be seen, the variability of the scenarios is relatively low, indicating that the model did not have inconsistency problems.

Table 5
Variability of scenarios used for internal validation.

Model	Av. crimes ($\bar{x}$)	Std. dev. (σ)	%
SAN_BASE_0	1.732	46	3%
VAN_BASE_0	964	30	3%
GRI1_BASE_0	1026	26	3%
GRI2_BASE_0	856	44	5%
GRI3_BASE_0	905	36	4%
GRI4_BASE_0	896	37	4%
GRI1_FOOT_UNI_100	748	32	4%
GRI1_VEHI_RAN_5	1015	51	5%
GRI1_ALL_UNI_500	299	12	4%
GRI1_ALL_RAN_50	884	19	2%
GRI1_VEHI_RAN_30	959	29	3%
GRI3_VEHI_HOT_30	796	30	4%
GRI4_VEHI_UNI_100	557	39	7%

6. Sensitivity analysis and extreme conditions testing

In this section we present a sensitivity analysis of certain key model parameters and the results of tests conducted with extreme constellations of parameter values.

6.1. Sensitivity analysis of parameters

Three global parameters that could potentially have a major influence on the simulation results were varied to determine the effects of the corresponding variables on the model's behavior and its output. These effects must be predictable. The three parameters were:

- The agents' radius of vision, which indicates the maximum distance at which they can perceive the presence of other agents.
- The probability of committing a crime for a criminal who has identified a potential victim.
- The agent generation rates of the city's facilities at each time of day.

The value categories used for each of the three parameters are shown in Table 6 and will be detailed subsequently.

Table 6
Value categories of parameters.

Parameter	Values		
Radius of vision	Short	Medium	Long
Probability of committing crime	Cautious	Normal	Bold
Agent generation rate	Low	Normal	High

1. Radius of vision
An agent's radius of vision is defined by the maximum distance at which the presence of another agent can be detected. A short radius creates the impression that fewer police or other agents are present and is thus conducive to more robberies while a longer radius will tend to deter them. The effects on bag snatchers are a priori indeterminate. In all scenarios analyzed in the different versions of "Gridville" the "medium" radius of vision was one city block; whereas "short" was assumed to be 0.5 city blocks and "long" 1.5 city blocks. For the cities of Santiago and Vancouver we used 50 m, 100 m, and 150 m for "short", "medium", and "long" radii of vision, respectively.
The results of the tests for this parameter found that in every case, the number of robberies fell drastically for the longer radii. This is similar to the effect of improving public street lighting, which also creates the impression of being more visible to others. By contrast, with longer radii the number of bag snatchings rose, suggesting that the impression of a bigger crowd outweighs that of more police presence. The total effect on crime numbers will thus depend on the relative sizes of the separate effects on bag snatchings and robberies and cannot be predicted independently.
2. Probability of committing a crime
The model assumes that a criminal's decision whether or not to commit a crime in a given situation is expressed by a probability function that depends on the number of citizens and police in the immediate area. The function also differs by type of criminal (robber or bag snatcher). For the sensitivity analysis, two probability function parameters in addition to the normal case were defined: "cautious" and "bold". The former describes a criminal who is very careful, committing offences only when the perfect opportunity arises, and produces a relatively low crime rate. The

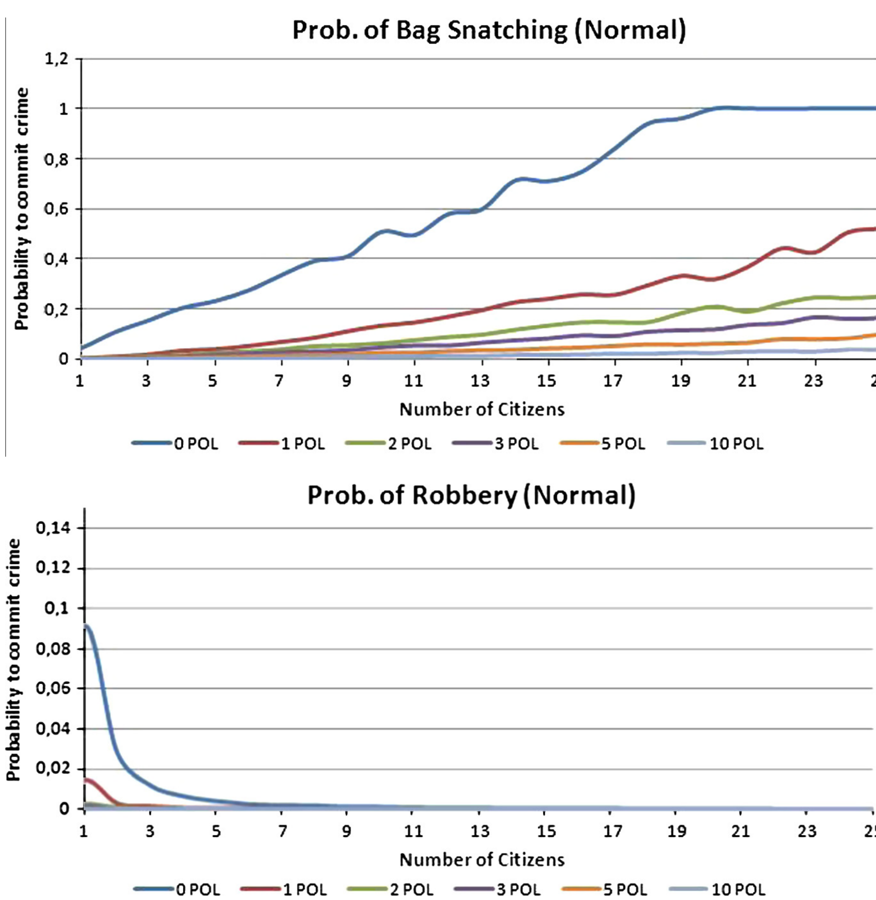


Fig. 11. Probabilities for bag snatching (above) and robberies (below), both for the case "normal".

latter, on the other hand, refers to a more audacious criminal who takes more risks, and translates into a higher crime rate. Two types of criminals (robber or bag snatcher) times three cases (cautious, normal, and bold) result in six probability functions that are displayed in Table 2. For illustration purposes we display two of these probability functions – one for bag snatching and one for robberies – in Fig. 11.
The results of the tests with the three parameter values show that among bolder criminals both robberies and bag snatchings were higher than the normal case, implying that the total number of crimes would also be higher. With cautious criminals, offences were fewer than the normal case. Finally, the difference between bold and normal in crimes committed was considerably greater than that between normal and cautious.

3. Agent generation rate
The sensitivity analysis of the agent generation rate attempts to determine whether the number of agents influences the number of crimes committed. On the one hand, a higher number of agents increases the likelihood of encounters between criminals and potential victims and facilitates bag snatchings, but on the other hand, robberies decrease because encountering an agent who is relatively isolated is less likely.
Two rates were defined for purposes of comparison with the normal rates used in the original simulations: a "low" rate at 50% below normal, and a "high" rate at 50% above normal.
The tests found that there does in fact exist a certain relationship between the number of agents and the number of crimes committed, which was very pronounced for bag snatchings but relatively attenuated for robberies. The latter result may be explained as the net effect of the greater number of agents, which results in more chances of finding a suitable victim but fewer chances of finding one who is relatively isolated. In other words, the first factor outweighs the second by a margin large enough to produce a weak increase.

From the above sensitivity analyses it can be concluded that variations of the studied model parameters lead to realistic output variations which confirms the model's robustness.

6.2. Extreme conditions testing

Experiments were carried out on the model using extreme or unlikely parameter values to check whether the results match those that would be expected if such conditions were to occur in reality. Four extreme conditions whose results could be easily predicted were chosen for testing and are described below.

- no police
- many police
- constant attractiveness
- uniform city (no district variations)

1. No police
To analyze this case we used the base simulation for each city, which was performed with no police in order to determine the natural hotspots (see Subsection 4.1). As might be expected, the numbers of crimes in these conditions were among the highest obtained for each city, but only for Gridville 3 and Gridville 4 were they the very highest.
Table 7 shows the five highest-crime scenarios for Santiago, in which the base case (no police) scenario is the second highest in number of offences. The fact that it is not the one with the most crimes is due to the variability in our simulation runs where almost no difference between very few and no police was detected for some assignments.

Table 7
Highest-crime scenarios in Santiago.

Pos.	Scenario	Crimes	Bag snatchings	Robberies
1°	SAN_TODOS_RAN_30	1.738	1.453	285
2°	**SAN_BASE_0**	**1.732**	**1.462**	**270**
3°	SAN_FOOT RAN_VAR	1.713	1.416	297
4°	SAN_FIX HOT_VAR	1.691	1.380	311
5°	SAN_FOOT_RAN_30	1.686	1.429	257

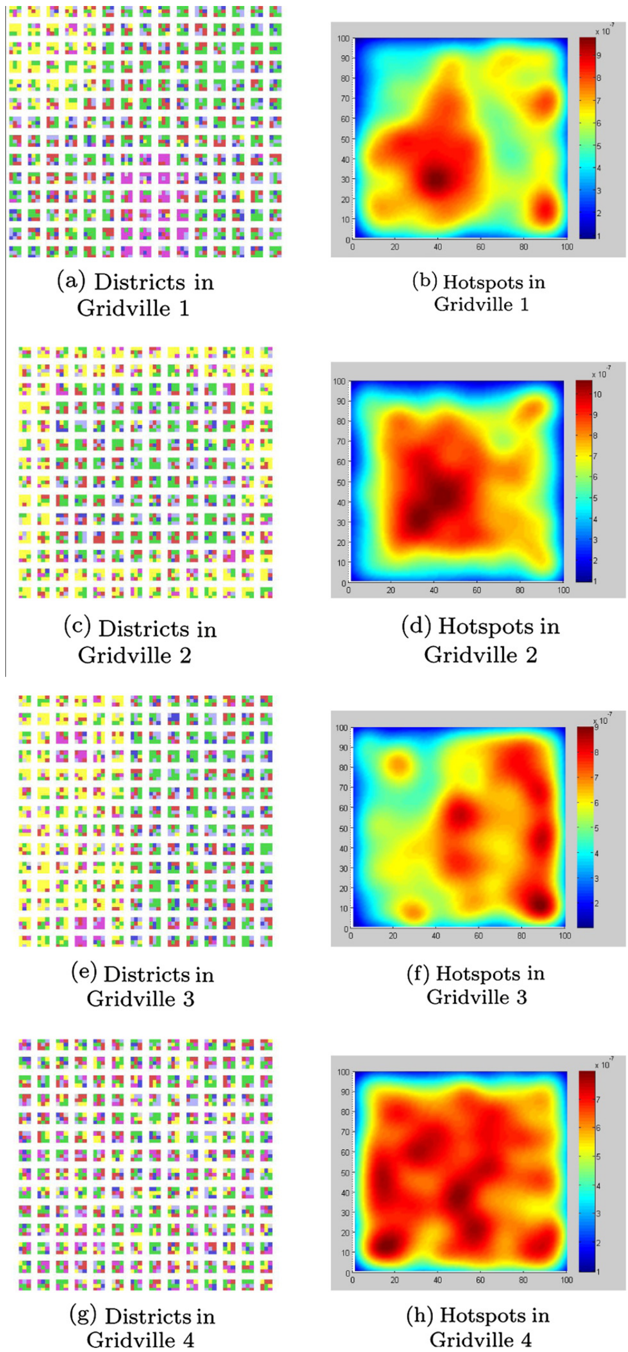
Table 8
Scenarios with fewest crimes in Vancouver.

Pos.	Scenario	Crimes	Bag snatchings	Robberies
1°	VAN_ALL_HOT_500	185	172	13
2°	VAN_FIX_HOT_500	186	183	3
3°	VAN_FIX_RAN_500	192	172	20
4°	VAN_VEHI_LOC_500	214	191	23
5°	VAN_VEHI_RAN_500	257	214	43
6°	VAN_ALL_RAN_500	258	229	29
7°	VAN_FOOT_RAN_500	274	227	47
8°	VAN_FOOT_MIX_500	280	208	72
9°	VAN_FOOT_LOC_500	311	266	45
10°	VAN_FIFO_MIX_500	350	259	91

2. Many police
Various scenarios were simulated for 500 police, with all police types and distribution strategies. The results show that in all of the cities, the number of crimes committed were fewer than for any smaller number of police. Even so, crime was not totally eradicated, demonstrating that criminals still found opportunities at times and places when police protection was not sufficient. Table 8 shows exemplarily the ten lowest-crime scenarios for Vancouver.
3. Constant attractiveness
For this analysis the attractiveness variable was set at zero for all city locations both for ordinary citizens and for criminals. The idea was to observe the influence of this factor on the appearance of hotspots. At constant attractiveness, the circulation of agents through the city should be relatively even and so, therefore, should be the degree of criminality. This fact has been confirmed in our experiments.
4. Uniform city
Gridville 4 is defined as a completely uniform city without definable districts where the probability of encountering each type of facility (residential, educational, commercial) is constant throughout the city area. The analysis compares this city to the other three Gridvilles in order to determine whether or not the type of district has an impact on the emergence of hotspots. The results are displayed in Fig. 12, which compares the district and hotspot distributions of the four Gridville versions. As can be seen, the distribution of districts does strongly affect the generation of natural hotspots. In Gridville 4 (Figs. 12g and 12h) there are no zones where crime rates are significantly higher than others whereas in the other Gridvilles with specific districts, such differences are observed. There is a clear tendency for crimes to be more concentrated in commercial and super-commercial districts (indicated in green), while residential districts (in yellow) are relatively crime-free. Districts with high concentration of educational establishments (in purple) also have considerable criminal activity, as is apparent in Fig. 12f where the two small Gridville 3 educational districts appear as light hotspots.

7. Conclusions and future work

The proposed agent-based models have shown enormous potential for simulating criminal activity. These models enable crime to be studied from an individual instead of aggregate perspective. This paper proposed an agent-based model and simulator whose



(a) Districts in Gridville 1
(b) Hotspots in Gridville 1
(c) Districts in Gridville 2
(d) Hotspots in Gridville 2
(e) Districts in Gridville 3
(f) Hotspots in Gridville 3
(g) Districts in Gridville 4
(h) Hotspots in Gridville 4

Fig. 12. Distribution of districts and hotspots in Gridvilles; see Section 3.1.2 for a more detailed explanation of cities.

main contribution is the ability to formulate criminal behavior in the context of different policing strategies.

7.1. Results of the study

A total of 335 different scenarios were simulated during the course of this study. The results obtained afford a first approximation of the potential of the proposed simulator to generate soundly based quality data and readily produce a series of different scenarios designed for analyzing variables.

As regards the number of police variable, the simulator output indicated a reduction in crimes committed as police numbers increased. The rates of marginal police effectiveness declined in all but a few scenarios where they rose over a limited range while total numbers were low. These results are consistent with what would be expected in reality. At low numbers of police, marginal effectiveness is relatively high, but once numbers reach a certain point, adding more would result in duplication and marginal contributions would begin to fall.

The simulated data also revealed that the police type variable has no considerable effect on the amount of crime. Differences were observed in the performance of some police types under certain combinations of police numbers and distribution strategies, but it cannot be said with certainty that any of the police types in the study are more effective than any other, including the combination of all three types. This is logical given that the differences between them lie only in the way they move and the speed they move at, not the degree of dissuasion they exert, so criminals do not distinguish between them when deciding whether or not to commit a crime.

The four police distribution strategies tested in the study performed similarly with low numbers of police, but as the numbers increased the hotspot strategy was found to be less effective than the others. This tendency was accentuated when using only fixed post police, which assigned static officers to high-crime spots while leaving the rest of the city unprotected. The mixed strategy, which placed half of the officers at hotspots and spread the other half over the rest of the city, showed a similar weakness albeit to a lesser degree. This was due to the displacement of criminals away from the relatively well-protected hotspots to areas with reduced coverage. The random and uniform strategies do not exhibit these weaknesses when police numbers are high given that they provide more complete coverage of the city, but with smaller numbers they are unable to provide the necessary protection and thus perform worse than the mixed and hotspot strategies.

7.2. Future research

To our knowledge, few previous studies have incorporated in an agent-based model the three main actors in street crime: the criminal, the victim, and the police. The proposed formulation could be improved, however, by adding variables that would explain phenomena not captured in the current version such as the existence of pedestrian streets, which according to Jofré (2011) have an important accentuating effect on the number of crimes.

It should also be emphasized that to apply the proposed model and simulator to a given city, they must be calibrated using local information. For example, in the version presented here the travel patterns of local residents at different times of the day had to be determined so that the agents' movements could be defined to approximate that reality. Similarly, to implement the model the distribution of activities within the city must be known. This information is more likely to be available given that the data are static and land use models already exist for many places. Information on the effectiveness of different police types is also required in order to model their impact on offences occurring in the immediate vicinity. This should be available from local police authorities.

The model can also be used to test the effectiveness of crime reduction initiatives. This is an important feature of the model since it would enable law enforcement authorities to test strategies before applying them in real situations and observe the effects of crime prevention measures such as displacement of hotspots. The proposed tool has the potential to emulate the interaction between delinquents and police, e.g. in cases where policing strategies have to be adapted dynamically to emerging or disappearing hotspots. The model can also make qualitative estimates of the benefits and costs of these measures to determine whether they are worth implementing. Furthermore, simulated data are not hampered by the unreported crime problem that afflict real-world crime figures. Finally, this study should open the door to the simulation of other types of crime such as e.g. shoplifting in airports or shopping malls where we have already first results.

The ABM for Gridville-1 will be available to interested readers. Please contact the corresponding author.

Acknowledgements

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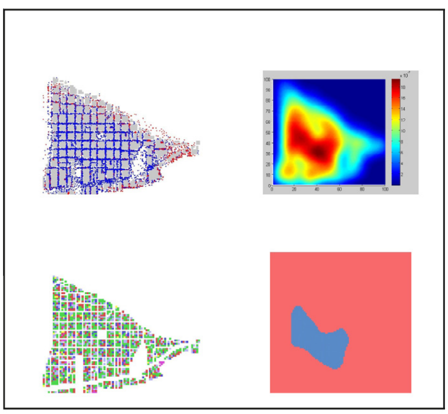
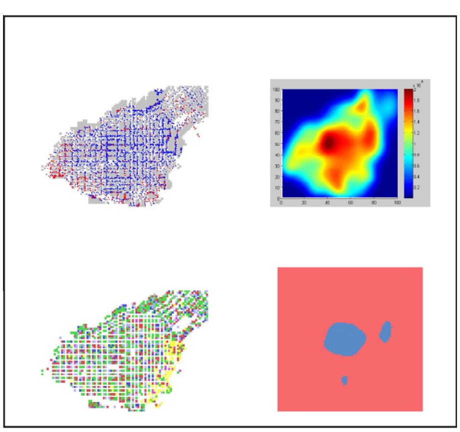
Appendix A. Spatial distribution of simulated crime

Figs. A.13, A.14, and A.15.



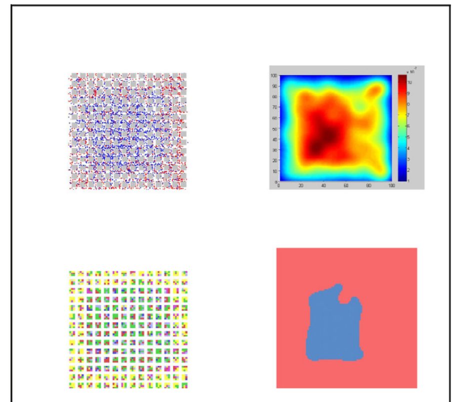
(a) Santiago: vectorial map (upper left), raster map (upper right), districts (lower left), hotspots (lower right).

Fig. A.13. Crime distribution in base cases and hotspots.

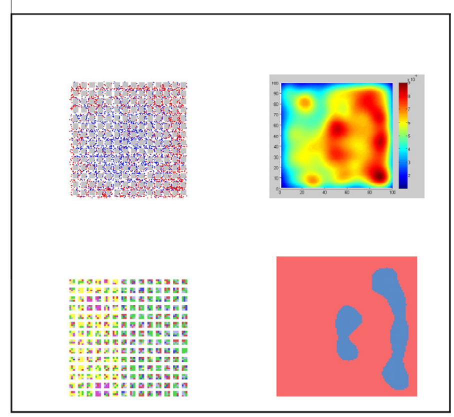


(a) Vancouver: vectorial map (upper left), raster map (upper right), districts (lower left), hotspots (lower right).

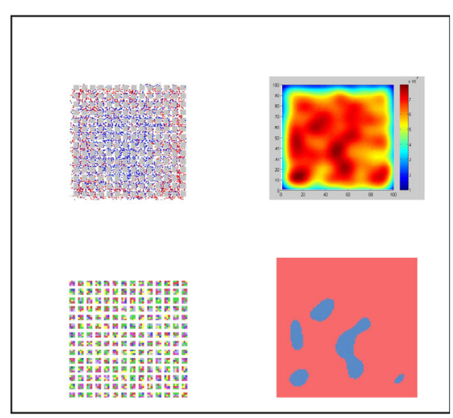
Fig. A.14. Crime distribution in base cases and hotspots.



(a) Gridville 2: vectorial map (upper left), raster map (upper right), districts (lower left), hotspots (lower right).



(a) Gridville 3: vectorial map (upper left), raster map (upper right), districts (lower left), hotspots (lower right).



(a) Gridville 4: vectorial map (upper left), raster map (upper right), districts (lower left), hotspots (lower right).

Fig. A.15. Crime distribution in base cases and hotspots.

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