IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 24 May 2023, accepted 18 June 2023, date of publication 22 June 2023, date of current version 7 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3288528

RESEARCH ARTICLE

An Agent-Based Model for Public Security Strategies by Predicting Crime Patterns

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ABSTRACT In recent years, statistical methods have been applied to the study of crime patterns. However, these schemes have several drawbacks that prevent accurate modeling of complex behaviors. Agent-based models (ABM) allow the modeling of human behavior by employing simple rules that consider each agent's neighborhood. In this paper, a new agent-based model is proposed to emulate crime patterns produced by the interaction of different urban actors, such as offenders (criminals), citizens, and defenders (police officers). Using this approach, the simulation results provide escape trajectories and robbery frequencies that can be used to create or improve public security strategies. Although our scheme can be generically applied, we validated the model by considering different scenarios for the case of Guadalajara, Mexico. Experimental results show that the proposed scheme creates realistic offender behaviors that efficiently predict criminal patterns and provides essential data that allow the creation and improvement of public security strategies to reduce the number of crimes.

INDEX TERMS Agent-based model (ABM), crime simulations, crime patterns, routine activity, computer simulation.

I. INTRODUCTION

Crime is a complex issue that has a strong impact on society, as it affects not only the population but also the environment in which each individual lives. From material losses to homicides, criminal activity is a recurrent problem worldwide. Despite the various security strategies used to reduce this problem, some have not been effective in predicting criminal patterns to prevent crimes. Identifying and analyzing the main characteristics of crime has been an important task in urban areas to identify the most significant behaviors and patterns for creating new security strategies or improving existing ones. Owing to the large number of interactions, patterns, and actors involved, crime phenomena in a city can be considered a complex system.

Owing to complex systems consisting of several components that interact with the environment, different social phenomena can be understood as complex systems [1], [2], [3]. The analysis of complex systems requires an understanding of the interactions of the connected components at the micro and macro levels. Several modeling techniques can be implemented in complex systems, one of the most important being Equation-Based Modeling (EBM). In the EBM, the variables that describe the system are identified using several equations to obtain the main characteristics. EBMs have been applied in different areas, such as engineering [4], biology [5], and economy [6], [7]. Nevertheless, EBMs approaches have several complications in modeling complex systems because of their inability to represent micro-level interactions [8], [9].

Agent-based modeling (ABM) [11], [12] is a computational modeling paradigm that emulates the behavior of complex systems through the interactions of individual agents, each with its own set of rules and decision-making processes. The agents can represent individuals, groups, or even institutions and can interact with each other and their environment according to specified rules. The main difference between ABM and EBM techniques is that ABM focuses on the

The associate editor coordinating the review of this manuscript and approving it for publication was Stavros Souravlas.

behavior of individual agents and their interactions, while EBM approaches often assume homogeneity in the system being modeled and represent it as a set of mathematical equations. EBM models typically assume that the behavior of the system can be understood by analyzing its aggregate properties, while ABM takes a more bottom-up approach, emphasizing the importance of individual-level behavior and the resulting emergent properties of the system. ABM is particularly well-suited for Modeling systems where the interactions between its elements are important and can have significant impacts on the behavior of the system as a whole. In such systems, the behavior of individual agents can have a cascading effect on the behavior of other agents, leading to emergent behavior that is difficult to predict using traditional modeling techniques. The interesting modeling abilities of ABMs have provoked they have been used in different fields, such as medicine [13], [14], [15], [16], sociology [17], [18], agronomy [19], and ecology [20], [21].

Routine activity theory is a criminological theory that suggests that the occurrence of a crime is related to the convergence of three key elements: a motivated offender, a suitable target, and the absence of capable guardians or defenders to prevent the crime. The theory suggests that crime is not caused by individual pathology or social disorganization but rather is the result of the convergence of these three elements in space and time. Crime pattern theory indicates that these elements are distributed unevenly in space and time, and this distribution influences the occurrence of crime events. Specifically, crime pattern theory argues that crime events are more likely to occur in areas and at times where there is a high density of potential offenders and suitable targets, and a low presence of capable defenders.

Modeling crime patterns [22] refers to the use of mathematical, statistical, and computational methods to analyze patterns of criminal activity in a particular area or population. This also involves the use of computational schemes to identify correlations and trends in crime data, as well as developing predictive models to forecast future crime patterns. The goal of modeling crime patterns [23] is to better understand the underlying factors that contribute to criminal activity, and to develop strategies and interventions that can help prevent or reduce crime in a given area. By identifying patterns and trends in crime data, law enforcement agencies and other organizations can develop more effective strategies for preventing crime and improving public safety.

Likewise, a valuable idea has been developed in "An Intelligent Clustering Routing Approach for UAV Ad Hoc Networks (ICRA)" [24]. This approach aims to optimize network performance by considering factors such as network density, node mobility, and link quality. It leverages intelligent decision-making algorithms to adaptively select optimal routes for data transmission, considering variables like node energy levels, congestion, and link stability. By combining intelligent clustering and routing techniques, the proposed approach offers a promising solution for UAV ad hoc networks, enhancing their efficiency, scalability, and reliability. This research contributes to the field of UAV communication systems by effectively addressing the distinct challenges associated with ad hoc networks and proposing an intelligent methodology to overcome them.

Another interesting research is discussed in The Privacy-Preserving Trust Management Scheme (PPTM) [25]. This paper establishes a secure and trustworthy communication framework for emergency situations. By incorporating privacy preservation and trust management, it addresses the concerns of unauthorized access, message tampering, and identity exposure. This paper contributes to the field of space-air-ground integrated vehicular networks by proposing an effective solution that protects user privacy, fosters trust among network participants, and facilitates efficient emergency message dissemination in critical scenarios. The PPTM scheme leverages advanced cryptographic techniques and trusts management mechanisms to ensure the confidentiality, integrity, and authenticity of emergency messages by employing privacy-preserving protocols. It enables the anonymous transmission of messages, safeguarding the identities of senders and receivers. Additionally, the trust management component assesses the reputation and reliability of vehicles participating in the network, ensuring that only trusted vehicles are responsible for relaying emergency messages.

On the other hand, the modeling of criminal patterns has also been addressed using AMB methods. Several studies have implemented ABMs to characterize criminal patterns [26], [27], [28], [29], [30], [31] and to understand different crime theories [31], [32], [33], [34], [35], [36], [37], [38]. In [39] ABM research was conducted by Diviak in 2023. His work examines the resilience and recovery of a criminal network following a disruption. Through simulation-based analysis, it highlights the importance of network structure in influencing the network's ability to recover and adapt after an intervention, providing valuable insights into strategies for disrupting and controlling criminal networks. However, in the developed approach the behavior of the citizens and police officers which have a significant impact on the improvement or design of public security strategies are not considered. Zhu et al. [40] developed an ABM to simulate urban crimes in the city of Baton Rouge, Louisiana. The proposed method integrates an improvement in daily routines to create more realistic human behavior. Furthermore, a priority system for agents was implemented. Nevertheless, the model did not consider the position of the defender in the simulation. The scheme developed by Dirksen et al. [41] in 2022 explores the application of ethnographic social simulation in the field of crime research. Moreover, the effectiveness of this approach in studying and understanding complex social dynamics, agent behaviors, and their impact on crime patterns, offering valuable insights for developing effective crime prevention strategies. Despite the good performance of the methodology, the authors do not consider the creation of computational ABM rules. Another interesting work was proposed by Malleson et al. [42], in which an ABM of burglary was implemented to reduce crime in the city of Leeds in the U.K. In this approach, the ability to experiment with different criminal theories and the reduction of defenders in the simulation are the most attractive elements. However, this method lacks a routine agent. Raquel Rosés et al. [43] proposed an ABM to simulate the offender's mobility in simulated urban structures, where several routines are created for agents with different types of distances such as static distance, uniformly distributed distance, and Levy flight distance. In addition, an interesting methodology was presented to generate different roads and avenues for urban structures. However, this approach does not consider sufficient criminal environmental data to generate or improve security strategies. Considering the defender's position, the agent's routines, and the environment data allows interactions between the agents and a robust simulation, thus obtaining more realistic behaviors and patterns. A robust simulation would allow the identification and prediction of crime patterns to develop crime-prevention strategies.

In this paper, a novel agent-based model is proposed to emulate criminal patterns produced by the interaction of different urban actors, such as offenders (criminals), citizens, and defenders (police officers), when they are located in a particular section of the city. The proposed method analyzes the offender's behavior by providing escape trajectories and theft frequencies that can be used to predict criminal patterns and identify conflictive regions of the city where security can be improved. Furthermore, a defender's position and crime factor are generated by considering environmental data to identify the best defender's positions to avoid crimes. This proposal can be implemented in any city under study. Nevertheless, to evaluate the performance of our method, the developed ABM was applied to the study of crime in Guadalajara, Mexico.

The rest of this paper is organized as follows: Section II presents an introduction to agent-based modeling. In Section III, the relevant characteristics of the crime in the simulation are reviewed. The proposed model is described in section IV. Section V presents a series of numerical experiments and the results of the proposed model. Finally, in Section 6, a brief conclusion and discussion of the proposed approach and future work are presented.

II. AGENT-BASED MODELING

Agent-based modeling is a new methodology for characterizing systems. This technique can be used to model complex systems in order to understand and explain the main behavior of the system. ABMs represent each entity of a complex system, their interactions with each other, and the environment. The interactions between the entities have an impact on the environment, and the relationship between the elements and the environment influences the interaction between the entities [1], [2]. The ABM can be successfully applied in systems where the synergy of the entities has a significant impact on their analysis.

Each entity is considered an agent that can represent any entity with several properties or characteristics [3]. Under the ABM methodology, agents interact based on several rules, which can represent simple decisions such as yes or no actions or complex decisions such as spatial movements. These rules influence the cooperation and competition of the agents, creating different patterns that allow us to understand the micro- and macro-level interactions of the complex system.

Agent-based models implement simple rules instead of difficult architectures or behaviors during model construction. These simple rules represent several complex global behaviors that allow the modeling of the main characteristics of the system given by the interaction of the agents. Global behaviors are composed of several micro-interactions, such as identifiable distributions or spatial and behavioral structures.

Agent-based modeling can be described as follows. First, a predefined number of agents (P) are initialized $\{a_1, a_2 \ldots a_P\}$, and several characteristics that determine their position, state, or rules to follow are randomly assigned to each agent. Each agent can then be selected randomly in a predefined order. The selected agent $a_i (i \in 1, \ldots, P)$ will follow the established rules to create an interaction that allows changing its state, position, or relation with other agents. These rules are created by considering the principal agents, their neighboring agents, and the environment. Finally, a stop criterion is established to stop the process once it is reached.

III. THE PROPOSED AGENT-BASED MODEL

This section discusses the proposed agent-based model for producing crime patterns in an urban city. The proposed methodology was developed to model the effects of interactions between citizens, defenders, and offenders in urban cities. The proposed model captures the heterogeneity of individuals (citizens, defenders, and offenders) and the complexity of their interactions. By representing each agent as a unique individual with its own characteristics and behavior, ABMs can emulate more realistic crime patterns than any other traditional model. The proposed model allows the analysis of global patterns of a complex system through several agent interactions that model micro-level interactions. Crime is composed of different factors, such as the number of citizens or offenders interacting in a specific place in the city, the different roads that have been available for the offenders to escape, and the position of the defenders in the city. This section is divided into two parts: (A) the model description and (B) the computational procedure.

A. MODEL DESCRIPTION

In our agent-based model, the agents are capable of interacting with each other through the same environment. In the proposed model three different agents' AC (citizen), A.O. (offender), and AD (defender) are defined. This can create complex and dynamic interactions that can lead to criminal events if certain conditions are met. Specifically, a criminal event can happen when there is a combination of a motivated offender, a suitable target, and the absence of capable guardians or defenders to prevent the crime. The way in which all agents behave before and after the crime event is regulated by a set of rules that govern their behavior. After the crime has been committed, the offender will often use the trajectories produced by their own decision-making process to escape the scene of the crime. This can involve choosing a route that is less likely to be monitored by security personnel or avoiding areas where there is a high risk of detection. By analyzing the trajectories produced by the agents before and after the crime event, security professionals can identify potential risks and develop strategies to prevent or mitigate future criminal events. For example, they may identify areas with a high risk of crime and deploy additional security personnel or surveillance equipment to deter offenders. They may also identify areas where the presence of capable guardians or defenders can reduce the risk of crime, such as well-lit public spaces or areas with a high level of foot traffic.

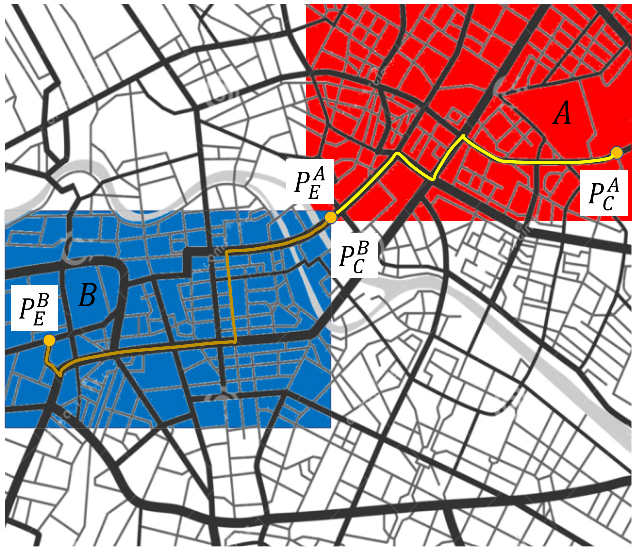


FIGURE 1. Illustration of two episodes (A and B) conducted by an agent.

1) ROUTINE

Our model considers two important elements in the simulation: Routine and episode. The routine involves all the possible activities executed by an agent during the simulation. On the other hand, episodes refer to the regular patterns of behavior that agents engage in as they go about their daily lives. These patterns can include commuting to work or school, running errands, engaging in leisure activities, and socializing with friends and family. Episodes are important in the context of geographic research because they influence the distribution of people and resources in space and time. For example, the location of schools, shopping centers, and other amenities can influence where people live and work, and the times when they are most likely to be present in particular locations. Episodes also influence the opportunities for crime and other types of deviant behavior to occur. Crime may be more likely to occur when there are opportunities for motivated offenders to come into contact with suitable targets in the absence of defenders. Therefore, understanding the episodes of agents and the spatial and temporal patterns of these episodes can provide insight into the distribution of crime and other types of deviance.

In our approach, episode A represents the movement experienced by an agent from its current position P_C^A to another randomly selected point P_E^A within a defined space or map. Once defined P_E^A, the agent is moved within the map until it reaches P_E^A, ending the execution of the episode A. In our model, when an agent reaches the end of the current episode, a new episode is randomly assigned, which allows for the maintenance of constant movement. For ease, in our model, the routine consists of only six episodes. Through the distribution of these episodes, it is possible to provide more interactions between agents and the environment.

As agents carry out their episodes, they follow paths and trajectories along established routes that connect different locations. For example, a person may follow a particular route to commute to work or school, or they may have a regular route for running errands or visiting friends and family. Movement trajectories are important because they can provide insights into the spatial and temporal patterns of behavior, as well as the social and economic processes that shape the distribution of people and resources in space. Agent-based models (ABMs) are computational models that simulate the behavior and interactions of individual agents in a system. In ABMs, agents are typically programmed to have different characteristics and behaviors that reflect the heterogeneity of real-world populations. As a result of this heterogeneity, the trajectories produced by ABMs are different for each agent. This means that each agent in the model will follow a unique path over time, based on its individual characteristics and interactions with other agents and the environment. Figure 2 presents an illustration of two episodes (A and B) conducted by an agent. In episode A, the agent moves from its current position P_C^A to its final location P_E^A. Once the agent reached the final position P_E^A, the new episode B starts. In the new episode B, the agent is displaced from its current position P_C^B (that is the end position P_E^A of episode A) to its final location P_E^B. This process is repeated for the other four episodes that complete the whole routine.

2) CREATION OF THE ENVIRONMENT

In agent-based models, a map is often used to provide a spatial context for the simulations. The map defines the space of the simulated environment and provides a framework for the placement of agents and other objects. The coordinates inside the map are used to determine the location of each agent in each episode of the simulation. For example, an agent might be located at coordinate (x,y) at the start of an episode, and then move to the end position based on their decision-making process. All the routines and crime events take place within this map. The agents move within the space of the map and interact with each other and their environment according to a set of rules. Crime events also take place within the map. A criminal might target a specific location within the map based on factors such as the presence of valuable objects or a lack of security. The crime event itself would take place within the space of the map, and the offender would then use the map to plan their escape route. To represent the environment where the agents interact, an image of the map of the city is acquired by implementing the Mapping Toolbox of MATLAB®software, then the map is binarized to obtain the roads and avenues.

3) INITIALIZATION

In the proposed model three different agents $AC(citizen)$, $AO(ofender)$, and $AD(defender)$ are defined. A predefined number of agents (P) and (K) are initialized as $\{AC_1, AC_2 \ldots AC_P\}$ and $\{AD_1, AD_2 \ldots AD_K\}$. The model begins defining the position of each agent AC_i and $AD_j(i \in 1, \ldots, P; j = 1, \ldots, K)$, these agents are initialized in random positions across the two-dimensional space of the map $(AC_i(i) = \left\{AC_{i,x}(s), AC_{i,y}(s)\right\}, AD_j(s) = \left\{AD_{j,x}(s), AD_{j,y}(s)\right\})$ where s indicates the actual iteration. The coordinates $AC_{i,b}$ and $AD_{j,b}(b \in [x, y])$ are numerical values uniformly defined between the upper (U_b) and lower (L_b) bounds as we can observe in equations (1-2).

$$AC_{i,b} = L_b + rand(0, 1) \cdot (U_b - L_b) \tag{1}$$

$$AD_{i,b} = L_b + rand(0, 1) \cdot (U_b - L_b) \tag{2}$$

The function $rand(0, 1)$ gives a random number within [0, 1] uniformly distributed. Furthermore, the position of each agent is validated to guarantee that the agent is positioned on any road or avenue on the map. For each agent its first episode is selected. The agent AC can be transformed to an agent AO creating a set of (I) offender agents $\{AO_1, AO_2 \ldots AO_I\}$.

4) BEHAVIORAL RULES

To emulate crime events and criminal trajectories in an urban map, agents' A.C., A.O., and A.D. follow certain behaviors that are defined by predefined rules. These rules allow for the correct interaction of the agents and their environment and help to produce realistic simulations of criminal activity. Our approach consists of four rules. Rule I is essential for simulating the movement of the agents. It provides the capacity to move from one point to another and emulates the decisions that agents make in order to reach a specific destination. This rule takes into account factors such as distance, accessibility, and the presence of obstacles in the environment. Rule II ensures that the agents can move from one episode to another without getting stuck due to the restrictions of the map. This rule ensures that the agents only move through valid roads and pathways. Rule III corresponds to the identification that a crime event has occurred. This rule is triggered when a combination of a motivated offender, a suitable target, and the absence of capable guardians or defenders are present. When this happens, a crime event is simulated within the space of the map. Finally, Rule IV represents the decisions of the A.C. and A.O. agents in an active crime event. The A.O. may decide to commit a crime, while the A.C. may decide to intervene or report the crime to the authorities. These decisions are based on a set of elements that take into account factors such as the presence of witnesses, the likelihood of getting caught, and the potential consequences of the crime.

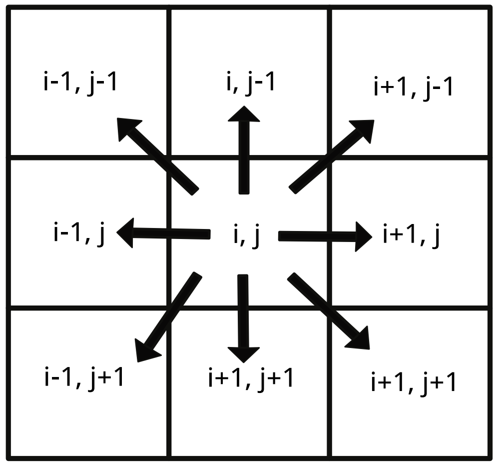


FIGURE 2. Moore neighborhood for agent movement.

a: RULE I–MOVEMENT

In Rule I, or the movement rule, the AC and AO agents determine the next cell (position) and the best direction to reach the goal of their episode in a certain neighborhood. In the proposed model, we assume that the agents move in a Moore neighborhood, which indicates that the agents can move vertically, horizontally, or diagonally, as shown in Fig. 2.

All agents tend to choose the minor Euclidean distance values of the neighboring cells. The rule procedure begins with the validation of the Moore neighborhood of the active agent. If the goal of the episode is identified in the neighborhood, the active agent is randomly assigned to another episode. If the target of the actual episode is not in the neighborhood, the Euclidean distance of the neighboring cells is compared to evaluate, which has a minor value to determine the direction of the agent. However, the cells that had an agent were not considered in the comparison. If a minor Euclidean distance value is not found, the agents wait in the current position (i, j), and a stuck identifier is assigned to it (stagnationid). Once the next step is defined, the agent leaves the actual cell to occupy the new position nearest to the target of the episode. Under such conditions, the new position $pos(AC)^{i+1}$ of an agent AC is determined through the following rule:

$$\begin{aligned} &\boldsymbol{IF} pos\,(AC)^i\ \boldsymbol{THEN}\ pos(AC)^{i+1} \\ &\quad = min(Moore\_neigborhood(pos\,(AC)^i)) \end{aligned} \tag{3}$$

b: RULE II–STAGNATION

The stagnation rule, or rule II, is activated when the active agent has a stagnation identifier (stagnation id). To eliminate this obstacle and allow the agent to continue its trajectory, a behavior based on a reinforcement learning algorithm [44] is applied. The behavior consists of penalizing the current cell (i, j) by adding a determined element (3) to the actual Euclidean distance value with the aim of providing the possibility of choosing another position in the next iteration; if the penalization does not offer a new scenario in which a new route can be chosen, the agent will wait in the position with the stagnation identifier until the new route emerges. This rule not only affects the active agent but also affects the behavior of the subsequent agents owing to the change in the distance map of the episode. These changes allow agents to avoid positions in which they can become stagnant. This behavior can be modeled by the following rule:

$$\boldsymbol{IF}\ stagnation\ id\ (i,j) == True\ \boldsymbol{THEN}\ \{(i,j)+3\} \quad (4)$$

c: RULE III—STAGNATION

The crime event is emulated by rule III or the crime rule, which evaluates the Moore neighborhood of the actual agent and obtains the crime factor of the geographic urban area where the agent is positioned, which determines the number of AO needed to activate the crime. A crime event is not activated if one or more AD are positioned in the current neighborhood. First, if the actual agent is a citizen and no defender is in the neighborhood, the number of offender agents in the neighborhood is calculated. If the crime factor is greater than 0.1, then only one offender is required to begin the crime event. Nevertheless, if the crime factor is less than 0.1, two or more offenders are required to start the crime. Finally, if a crime is activated, a marker is established on the map, and the AC and AO proceed to execute rule IV. This rule can be modeled using the following formulation:

$$\begin{aligned} &\boldsymbol{IF}\ CrimeFact \geq 0.1\ \boldsymbol{THEN}\ \{number\ of\ AO = 1\} \\ &\quad \boldsymbol{ELSE}\ number\ of\ AO = 2ormore\ \boldsymbol{End\ IF} \end{aligned} \quad (5)$$

d: RULE IV—POST-CRIME

Once a crime event is activated the behaviors of each agent AC_i and AO_j are defined by the rule IV or post-crime rule. This behavior can be considered to be the most complex because of the necessity of applying rules I and II. Under this rule, the endpoints $P_E^{AC_i}$ and $P_E^{AO_j}$ of a new episode for a citizen AC_i and an offender AO_j, respectively, are determined. First, the nearest agent AD_n is selected. Then, the end position $P_E^{AC_i}$ of the agent AC_i in a new episode is set to the position of AD_n. In contrast, to define the end position $P_E^{AO_j}$ for agent AO_j, the following process is considered. Initially, one of the ten most dangerous locations, PD, on the urban map was selected. Low-security neighborhoods often lack proper law enforcement, security infrastructure, and community support systems. Criminals may see these areas as shelters and take advantage of the vulnerable populations living there. This position PD is considered the end position $P_E^{AO_j}$ of agent AO_j. This behavior can be modeled using the following rule:

$$\begin{aligned} &\boldsymbol{IF}\ Crime\ is\ activated == True \\ &\quad \boldsymbol{THEN}\ \left\{P_E^{AC_i} = Position\,(AD_n)\,,\, P_E^{AO_j} = PD\right\} \end{aligned} \quad (6)$$

B. COMPUTATIONAL PROCEDURE

The proposed model has been implemented as an iterative approach. In Table 1, we observe the main operations of the entire model, allowing us to understand the sequence of their different sections. The methodology requires the urban map (Dat), the targets of the episodes (T), the number of episodes (E), the number of citizen agents (P) and defender agents (K), the upper (U_x, U_y) and lower (L_x, L_y) bounds, and the maximum number of iterations ($maxIter$) as input data. Probability (p) is defined as the number of episodes.

The algorithm begins with the creation of the environment (lines 1-2), here the dataset of the city (Dat) is implemented using the Mapping Toolbox of MATLAB®software to obtain the plot of the map and the ten most dangerous positions in the city (Dp). Furthermore, the map is transformed into an image that is converted to a grayscale image and then binarized (Ib) to obtain only roads and avenues. In line 2, the position map (PM) and distance map (DM) are generated for each episode. The initialization process (lines 3-4) initialize the citizen and defender agents in the position map of each episode, and the two agents in the same episode cannot remain in an equal position. Then, the offender agents are created by the citizen population; these agents have the same behavior as citizens; nevertheless, they can activate a crime event under certain conditions

Rule I (lines 8-16) starts evaluating the Moore neighborhood ($Mneighborhood$) of the active agent (AA); if the target of the actual episode is found in the neighborhood, then a random episode is assigned to the active agent to continue with their routine. On the other hand, if the target of the actual episode is not detected, then the distance map of the neighborhood is evaluated to determine the next position, which needs to have a minor Euclidean value than the actual and be available (do not have an agent). Furthermore, if the agent cannot move to another position, a stagnation identifier is assigned to the active agent to apply rule II in the next iteration. Rule II (lines 18-20) penalties the position of the distance map where the agent gets stuck, allowing the agent to continue its trajectory properly.

Rule III (lines 21-25) evaluate the neighborhood of the active agent to determine the number of defender agents; then, the necessary number of offender agents is calculated as if the actual position is in a dangerous region (DU). If the neighborhood has a defender, the crime event is not activated. On the other hand, if any defender agent is located in the neighborhood and the number of offenders is equal to or greater than the necessary number ($OfenderN$), then the crime event is activated and rule IV is applied. In rule IV (lines 26-29), agents involved in the crime proceed to change their episodes. A citizen agent (AA) changes its trajectory to the nearest defender on the map, and the offender agents go to a randomly dangerous location. While these episodes are active, these agents cannot have been involved in other crime events until they regroup with the whole population. Rules I and II have been implemented to complete their trajectories.

IV. EXPERIMENTAL RESULTS

To illustrate the capacities of the proposed agent-based model, five different experiments are conducted. They represent different hypothetical scenarios. The developed model can test in different scenarios due to its flexibility and adaptability. One of the significant advantages of agent-based modeling is that it allows researchers to simulate real-world scenarios without the necessity of conducting experiments in reality. This is particularly useful when the scenario being investigated is difficult or impossible to recreate in the real world.

The basic performance of the model was evaluated in the first experiment. In the second computational experiment, the proposed approach was tested to evaluate the repercussions of crime events and identify the main roads or avenues that represent a possible escape route for offender agents. In the third test, the model was oriented to visualize a scenario in which all defenders were deployed only in the dangerous regions of the urban map. In the fourth hypothetical scenario, the positions of the defenders changed throughout the iterations. This experiment allowed us to emulate the behavior of shift change during the day. In this simulation, three shifts were implemented to identify the central regions of the map where more criminal activities were detected. Finally, the fifth hypothetical scenario tested the model considering four different scenarios. First, 200 defending agents were set in the simulation process. In the second method, 600 defending agents are used. The third is 2000 defending agents, and the last is 10 000 defending agents. The proposed model was tested on Guadalajara, Jalisco, Mexico, an urban map obtained from [45]. In fig. 3, an urban map of Guadalajara, Jalisco, Mexico, is shown.

A. BASIC PERFORMANCE

In the first experiment, the performance of the model is exemplified by considering a population of 1000 agents, from this population, the numbers of citizens, offenders, and defender individuals are established. Furthermore, the test was conducted with the following dimensions: 505 × 470 ($L_x = 0, U_x = 540, L_y = 0, U_y = 470$). According to [46], the probability that an agent can be a criminal is set at 0.5; nevertheless, a stochastic behavior is applied and implemented as a random number that defines whether the agent will be a criminal or not. From the data obtained in [47], the most dangerous neighborhoods in the city were identified to establish the optimal criminal conditions for creating a crime event. Six episodes were created to emulate the correct dispersion of the agents along the urban map, which allows for a correct interaction between the agents. In the initialization phase, the agents are assigned to a specific episode and a new episode is assigned at the end of the episode to continue with

TABLE 1. Pseudo-code of the proposed model.

Input: $Dat, T, AC, AD, AO, P, K, [U_x, U_y, L_x, L_y], E, p, maxIter$	
$Ib, Dp \leftarrow$ ***ImageAdqBin***(Dat)	Creation Of the environment
$DM, PM \leftarrow$ ***SetupEnv***(Ib, T, E)	
$AC(P), AD(K) \leftarrow$ **InitializaPopulation**$(AC, AD, P, K, [U_x, U_y, L_x, L_y])$	Initialization
$AO(I) \leftarrow$ ***ProbabilisticSelec***(AC, p)	
While Iter $\leq$ maxIter **do**	
While $IterP \leq Pop$ ***do***	
For each $AC_P \in$ $\boldsymbol{AC}(iterP)$ and $AO_I \in$ $\boldsymbol{AO}(iterP)$	
$Mneighbor, AA \leftarrow$ ***ValTargNeighbor***$(AC(iterP)$ *or* $AO(iterP), PM)$	Rule I
If $Mneighbor == 1$ ***then***	
$AA, DM, PM \leftarrow$ ***NewEpisode***(AA, DM, PM)	
else	
$AA, PM \leftarrow$ ***ValDistNeighbor***(AA, DM, PM)	
end if	
If $actualPosition == nextPosition$ ***then***	
$StagnationIdentifier(AA) = 1$	
end if	
if $StagnationIdentifier(AA) == 1$ ***then***	Rule II
$DM \leftarrow$ ***PenaltyProc***(AA, DM)	
end if	
$Cneighbor, NOA, NDA \leftarrow$ ***ValOfenderNeighbor***(AA, PM)	
if $NDA == 0$ ***then***	Rule III
$OfenderN \leftarrow$ ***ValDangerUbication***(DU)	
if $Cneighbor \geq OfenderN$ ***then***	
$AA, Crime \leftarrow$ ***CNewEpiCit***(AA, DM, PM)	
end if	
end if	
if *Crime is activated* ***then***	Rule IV
$AA \leftarrow$ ***CNewEpCit***(AA, DM, PM)	
$NOA \leftarrow$ ***CNewEpOfe***(NOA, DM, PM)	
end if	
end for	
end while	
end while	

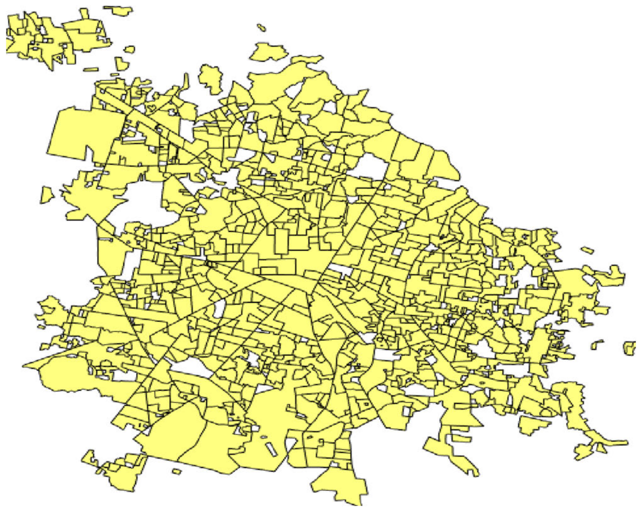


FIGURE 3. Illustration of two episodes (A and B) conducted by an agent.

the simulation. The complete simulation was executed over 1000 iterations (*maxIter*).

Fig. 4 shows the simulation process in four different iterations with the respective interactions of the agents. To obtain a better interpretation and visualization of the process, the size of the map was amplified. In the figure, each agent explores the map according to their current episode, which allows the generation of several criminal events along the urban map. At the beginning of the simulation, when crime events first start to occur, they typically appear in low numbers. This means that it is not always clear to establish a relationship between the crime event and spatial information, such as the location where the crime occurred. At this stage, it is difficult to discern patterns in crime behavior, and the factors that contribute to the occurrence of crime may not be readily apparent. However, as the number of crime events increases, patterns in criminal behavior may start to emerge. In Figure 4, red points or zones represent locations where a crime event has happened. It may become evident that crime events are occurring in higher density in certain areas, such as main avenues or places with a high density of potential offenders and suitable targets, and a low presence of capable defenders. This may be due to a number of factors, including the availability of potential targets and the level of surveillance or guardianship in a particular area. For example, if a particular area has a high concentration of shops or homes with valuable items, it may be more likely to attract potential offenders. Similarly, if an area is poorly lit or has few visible security measures, it may be more vulnerable to criminal activity.

B. CRIMINAL ESCAPE TRAJECTORY

The second experiment aims to evaluate the impact of crime events and identify the main roads or avenues.

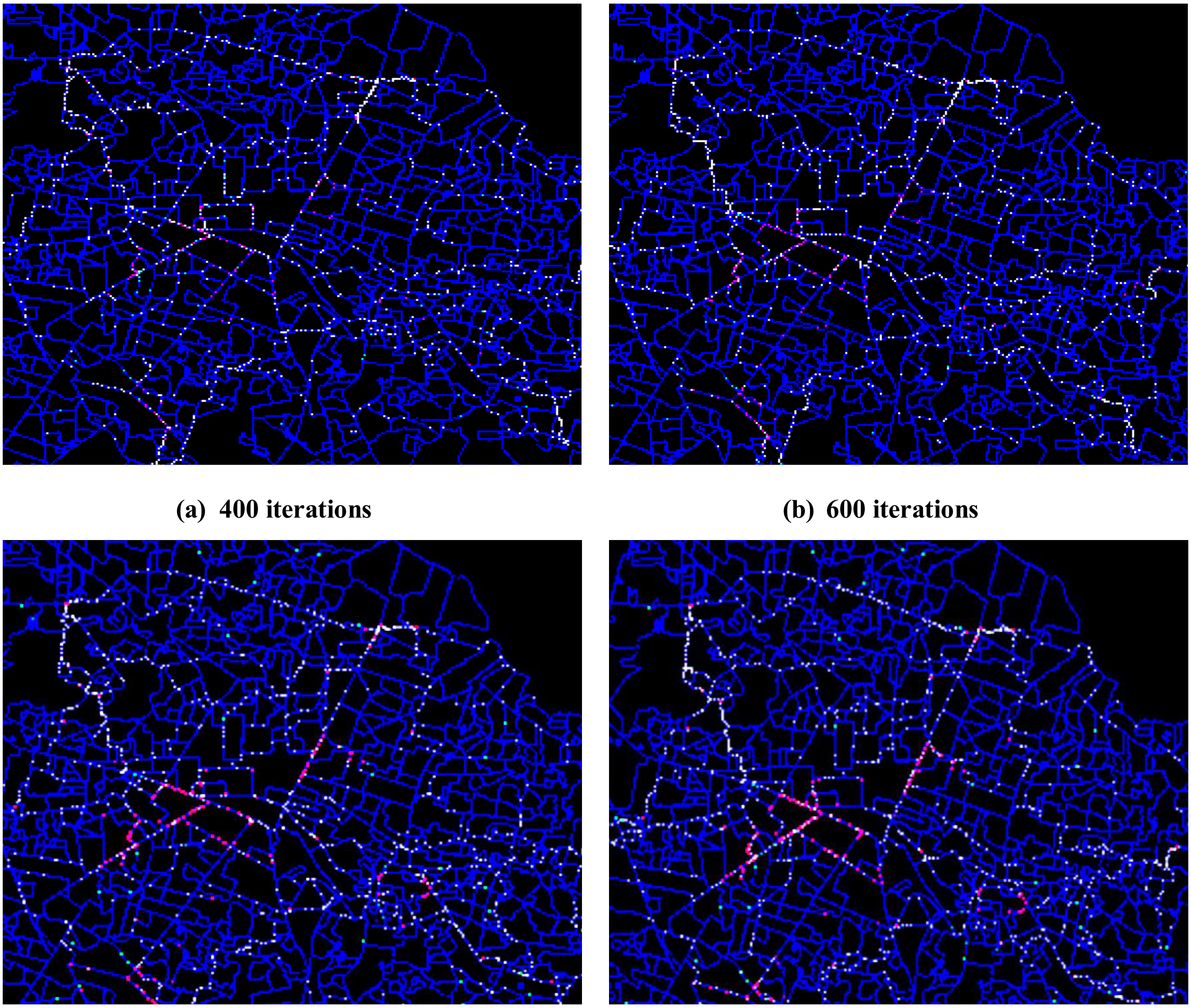
The simulations for this experiment have the same configuration as the basic performance section, but the probability of a citizen agent being a criminal agent is set at 0.8. This value has been selected to increase the probability of crime events happening.

Our agent-based model is a powerful tool that helps simulate real-world scenarios and predict several outcomes. Our model is able to produce the trajectories that offenders use to flee the crime scene. During the execution of the model, the trajectories of multiple offenders are generated and recorded. This data is then used to create maps that show the escape routes taken by each offender, including the streets and avenues they use. Figure 5(a) illustrates the roads and avenues with more densities. As can be seen, the identified escape routes include the main avenues and streets of the city that maintain more density of movements achieved by citizens. These areas have a high density of potential offenders and suitable targets, with a low presence of capable defenders.

The identified crime densities allow the development of specific strategies according to the location of the cluster in a region of interest. A correct interpretation of the affected location can provide a better perspective of the situation, allowing the creation of new security strategies that prevent criminal behaviors. Furthermore, the identification of the escape trajectories can help to set defender agents in strategic positions to catch the criminal agents and enforce the security of the dangerous neighborhoods.

Figure 5(b) provides a histogram that illustrates the frequency of crime events that occur along the routes. By analyzing this data, investigators can identify the most high-risk points and take proactive measures to prevent crime from proliferating. One approach is to identify the main intersections among these routes and assign a fixed patrol to monitor these locations. By using this strategy, law enforcement agencies can effectively reduce the frequency of crime events and improve public safety. Figure 5(c) provides important information about the most significant intersections where special security measures can be put in place. We have detected 20 main intersections. Another possible strategy is to set up surveillance cameras at these key intersections. These cameras can be used to monitor the activities of potential criminals, track their movements, and gather valuable evidence that can be used in criminal investigations.

The flexibility of the model enables the change of different parameters to observe the trajectory and the specific location of the criminals in certain areas. This capability allows the correct deployment of police officers to tackle crime activities effectively. In summary, the second experiment demonstrates the capability of the proposed approach to evaluate the impact of crime events and identify the main escape routes of the offender agents. The approach can assist in developing specific strategies for different regions of interest and improve the security of neighborhoods by setting defender agents in strategic positions to catch criminal agents. The flexibility of the model allows the adjustment of different parameters to observe the trajectory and specific location of the criminals in certain areas, enabling the effective deployment of police officers.



(a) 400 iterations (b) 600 iterations (c) 800 iterations (d) 1000 iterations

FIGURE 4. Results in different iterations of the simulation process. a, b, c and d are an amplified perspective of the center of the map.

C. RELOCATING DEFENDERS' POSITIONS IN DANGEROUS ZONES

In this experiment, the behavior of crime events is examined when a concentration of police officers (defenders) is placed in regions of the city where a high density of crimes has been detected previously. The aim of this experiment is to determine whether a concentration of defenders in high-crime areas can effectively reduce crime rates.

To begin the experiment, the basic agent-based model is executed (as it has been seen in subsection IV-B). The results of the model show that crime events are concentrated in different areas of the city. These areas correspond to parts of the city with high-traffic citizens, as a consequence of well-structured avenues, a great number of shops and commercial activities. This suggests that the presence of potential targets and offenders, coupled with a low presence of defenders, contributes to the occurrence of crime in these areas. Criminal events tend to be concentrated in zones because of the potential for criminal gain. For instance, areas with a high concentration of wealth or valuable assets may be targeted by criminals. Additionally, certain types of crimes tend to be associated with certain locations. Environmental factors such as good avenues, streets or connections can also contribute to high crime rates in certain areas. Criminals may be attracted to these areas because they offer concealment and easy escape routes.

Figure 6(a) shows the clusters that have been formed from the analysis of crime event data. These clusters correspond to five different clusters located in zones with high commercial activity and good escape routes. This suggests that these areas may be more vulnerable to criminal activity due to the high concentration of potential targets and offenders, as well as

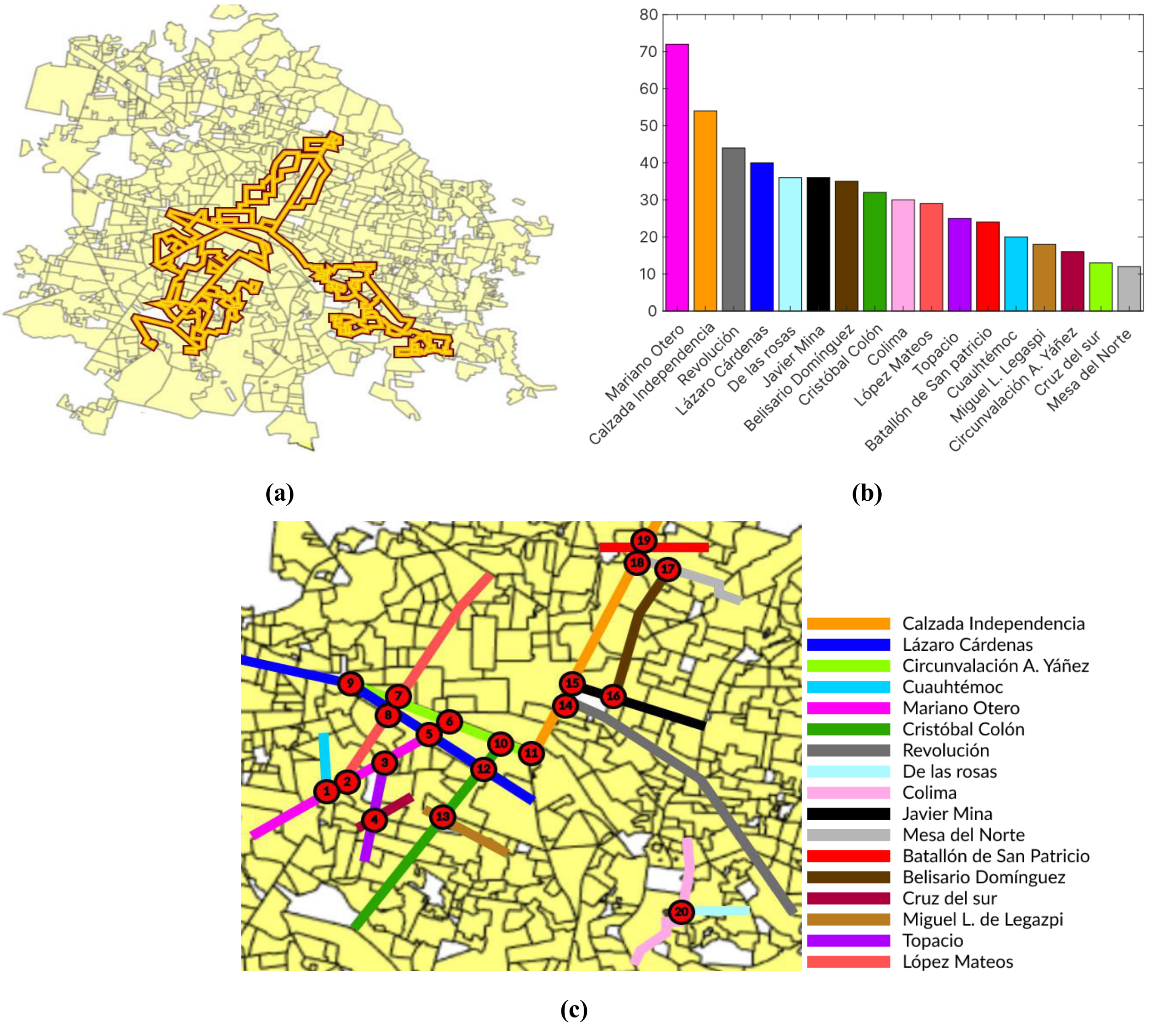


FIGURE 5. Results in different iterations of the simulation process. a, b, c and d are an amplified perspective of the center of the map.

the ease of escape from these areas. Figure 6 provides an example of a part of a city where a high number of crimes have been concentrated. The figure shows several points plotted on a map, with each point representing either a crime event, a normal citizen, or a defender/police officer. The red points on the map represent crime events that have occurred in the area. The white points on the map represent normal citizens who transit in the area. Finally, the green points on the map represent defenders or police officers who are working to protect the area and prevent further crime. Crime pattern theory suggests that these elements are distributed unevenly in space and time, and this distribution influences the occurrence of crime events. Specifically, crime events are more likely to occur in areas and at times where there is a high density of potential offenders and suitable targets, and a low presence of capable defenders. This is clearly demonstrated in Figure 6(a), where the crime events are occurring in areas with a high concentration of potential targets and offenders, and a low presence of capable defenders. Understanding the distribution of potential targets, offenders, and defenders in space and time is critical for developing effective strategies for preventing and reducing crime in different areas of the city. By identifying areas where there is a high concentration of potential targets and offenders, as well as a low presence of capable defenders, it may be possible to deploy defenders strategically to deter criminal activity in those areas.

In this experiment, we have relocated the position of defenders (police officers) in order to cover the regions with high criminal activity. The defenders have been located in the areas where the cluster of Figure 6(a) has been formed. The objective is to observe the behavior of the crime events in such zones if these positions are protected by a higher number of defenders.

Figure 7(b) shows a zoom of a part of the city that reflects this strategy. The area contains several defenders or police officers (in comparison to Figure 7(a)) that discourage the possibility of committing a robbery. As a result of this strategy, crime events have been displaced to other regions of the city. Figure 6(b) shows the new cluster that represents the density of crime in other parts of the city.

Reallocating police officers in zones with high rates of crime events provokes crime events to be committed in other zones because criminals tend to be opportunistic and adaptable. When police officers are deployed in high-crime areas, they create a higher risk for criminals, making it more difficult for them to carry out their criminal activities. This can lead criminals to shift their focus to other areas where police presence is lower, making those areas more vulnerable to criminal activities.

In addition, criminals may also be more likely to commit crimes in other areas due to a perception of lower risk. If they observe that police resources are concentrated in certain areas, they may assume that those areas are being closely monitored and opt to commit their crimes in other locations where the risk of being caught is lower. Furthermore, the new areas with a high crime density represent alternative zones that require further investigation to understand the underlying factors contributing to criminal activity in those areas. By analyzing the distribution of potential targets, offenders, and defenders in these alternative zones, it may be possible to develop new strategies for preventing and reducing crime in those areas.

From this computational experiment, it is clear that reallocating police officers to high-crime areas may help to reduce crime rates in those specific areas, but it does not address the underlying issues that contribute to the occurrence of crime.

Furthermore, deploying more police officers to high-crime areas can sometimes lead to negative consequences. Criminals are often strategic and will seek out areas with lower levels of surveillance and enforcement to avoid being caught. If several police officers are concentrated in certain areas, criminals may assume that other areas of the city are less heavily patrolled and may move their activities to those areas instead. In addition, reallocating police officers to high-crime areas can create a perception of over-policing or targeting certain communities. This can lead to a breakdown in trust and cooperation between the community and law enforcement, making it more difficult to prevent crime in the long term. As a result, criminals may feel emboldened to continue their activities in other areas of the city, believing that law enforcement will be less effective or less present in those areas.

D. THE IMPACT OF SHIFT IN CRIME EVENT PATTERNS

To accurately model the impact of shift changes on crime concentrations in an agent-based model, it is important to incorporate realistic patterns of police behavior, such as the timing and duration of shifts, as well as the number and distribution of police officers on the streets during each shift. By incorporating these factors into our model, it is possible to observe important behaviors in crime patterns.

In our agent-based model, the behavior of police officers is an important factor in understanding crime patterns. One factor that can significantly affect crime concentrations is the change of shift of police officers.

In our model, we are considering that police officers work three different shifts: the morning shift, the evening shift, and the night shift. These shifts are commonly used by law enforcement agencies around the world to ensure that there is adequate coverage throughout the day and night. However, one important factor to consider is that the night shift typically has the lowest number of defenders compared to the morning and evening shifts.

This is due to a number of reasons, including the fact that many officers prefer to work during the day or evening, and the fact that there may be fewer people on the streets during the night shift.

In the context of our scenario, we are examining in this computational experiment how crime patterns behave during the night shift when the number of defenders, such as police officers or security personnel, decreases, and the number of citizens in the streets also decreases. This situation can create a unique set of challenges for law enforcement agencies and increase the risk of criminal activity in certain areas.

One key factor to consider is the potential for criminals to take advantage of the reduced police presence during the night shift. With fewer defenders on duty, criminals may feel emboldened to engage in more brazen criminal activity or target areas that are normally considered to be more secure. This can include areas with lower levels of lighting, fewer surveillance cameras, or less foot traffic. Another important factor is the reduced number of citizens on the streets during the night shift. With fewer people out and about, criminals may have fewer potential targets for theft, robbery, or other crimes. However, this can also make it more difficult for defenders to identify criminal activity or respond quickly to incidents as they arise.

Figure 8 provides an overview of how crime events are distributed throughout the city. The figure includes two different types of points to differentiate between crime events that occur during the morning or evening shift, represented by blue points, and those that occur during the night shift, represented by black points. According to the Figure, it is not entirely accurate to say that crime events do not increase in frequency during the night shift, but it is true that criminal activity tends to distribute differently during this period compared to other shifts. During the night shift, there are fewer people out and about in public spaces, and certain types of crimes, such as theft or burglary, are more prevalent in residential areas or other locations than in the zones with higher commercial activities. An analysis of Figure 8 shows that the crime events in the night shift are concentrated not in the center of the city (where there is more traffic of citizens

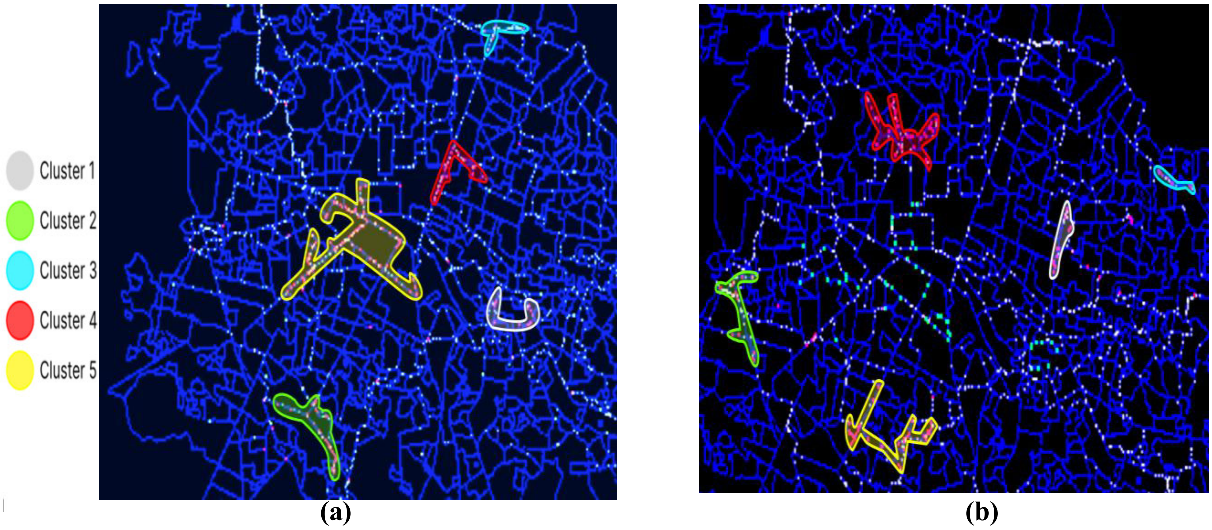


FIGURE 6. Concentration of the crime events. (a) from the basic experiment and (b) after reallocating police officers to high-crime areas.

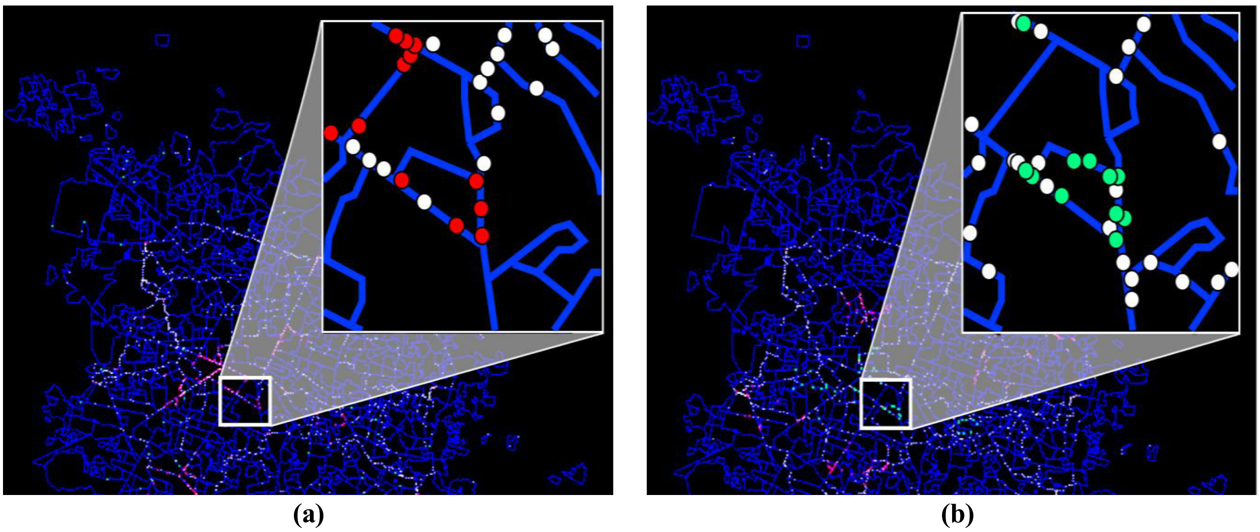


FIGURE 7. Example of a part of a city where (a) a high number of crimes have been concentrated or (b) a high number of defenders have been reallocated.

during the morning and evening). Most of these crime events happen in residential areas.

At the same time, criminal activity may also shift to the suburbs during the night shift, as criminals may see these areas as more vulnerable or less well-protected compared to urban centers or areas with higher police presence. This can be especially true in areas where there are lower levels of street lighting or other factors that may make it easier for criminals to avoid detection.

In the context of our simulation model, Figure 8 presents an interesting phenomenon that is worth exploring. It is observed that crime events in the morning and evening shifts are distributed across the city, while on the night shift, they are concentrated in certain residential areas. This behavior can be explained by the drastic reduction in the number of citizens moving around the city during the night shift. Crime events are more likely to occur in areas and at times where

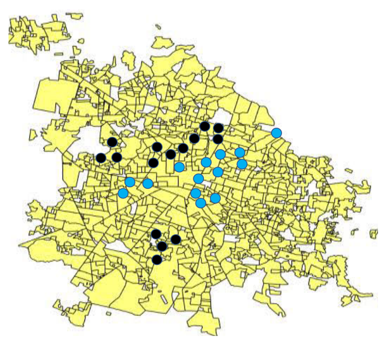
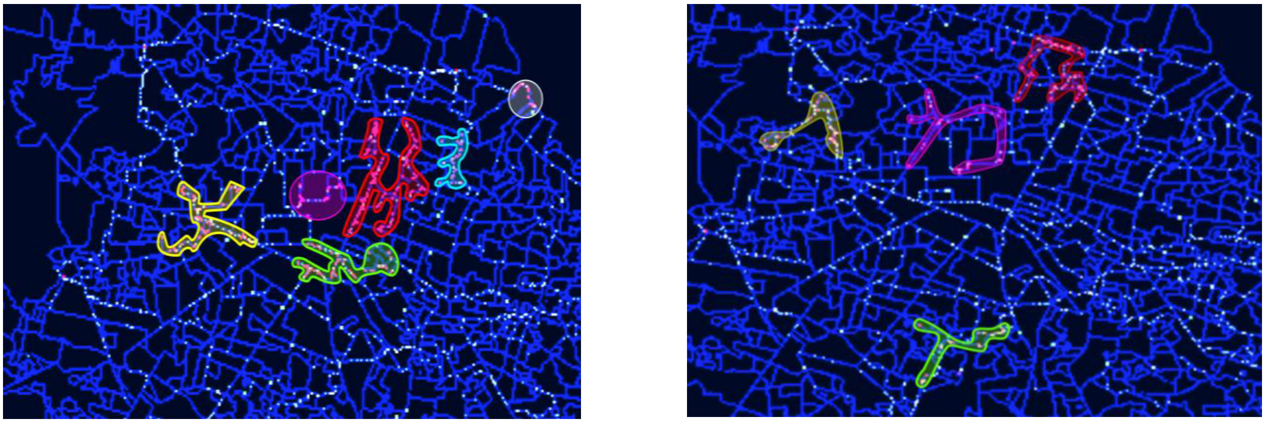


FIGURE 8. Overview of how crime events are distributed throughout the city depending on the shift. Blue points correspond to the morning shift, whereas the black elements represent the night shift.

there is a high density of potential offenders and suitable targets, and a low presence of capable defenders. During



(a) (b)

FIGURE 9. More detailed visualization of the crime events in (a) the morning and (b) night shifts.

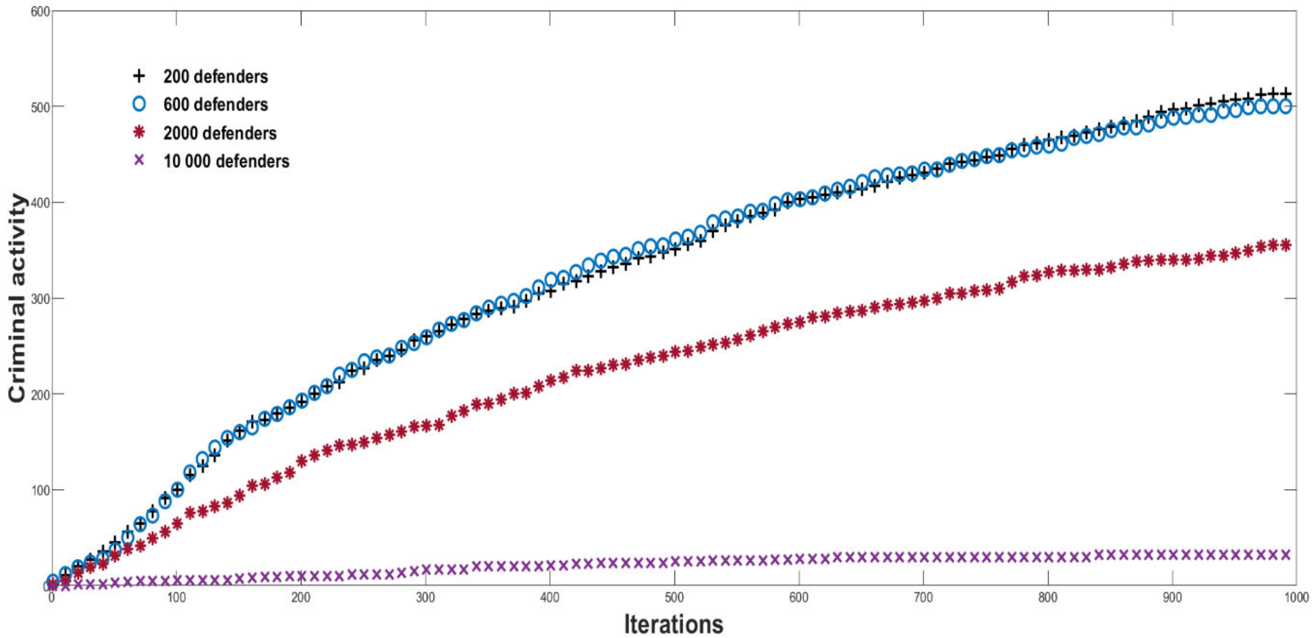


FIGURE 10. Results of the fifth experiment, where the impact of the number of defending agents on the occurrence of crime events is analyzed.

the night shift, there is a low density of citizens moving around the city, which leads to a low presence of capable defenders. Moreover, as the number of citizens in residential areas decreases, there is a higher concentration of potential offenders in those areas. Therefore, in our simulation model, the concentration of crime events in certain residential areas during the night shift can be attributed to the combination of a low presence of capable defenders and a low presence of normal citizens.

In Figure 9, we can see a more detailed visualization of the crime events in the morning and night shifts. The map highlights the specific avenues and zones where crime events occur and groups them into clusters to better understand their location. It is clear that in the morning shift, there are clusters of crime events along main avenues and important streets. These routes could serve as possible escape routes for the offenders. In contrast, in the night shift, the clusters of crime events are not along main avenues, but rather on unimportant streets. This suggests that the offenders are not concerned about escaping after committing the robbery. The low presence of police officers on the night shift makes them more confident that they will not be caught. It is important to note that the clustering of crime events allows for a better understanding of the patterns and locations of criminal activity. This information can be used to develop more effective strategies for preventing and addressing crime in specific regions. By analyzing these clusters, law enforcement can better allocate resources and personnel to combat criminal activity and protect citizens.

E. SCALABILITY IN THE NUMBER OF DEFENDERS

Crime pattern theory is a well-established theoretical framework that suggests that crime events are not random and instead are influenced by the distribution of citizens, offenders, and defenders in space and time. According to this theory, crime events are more likely to occur in areas and at times where there is a high concentration of potential offenders and suitable targets, and a low presence of capable defenders. Based on this theory, it is expected that increasing the number of defending agents in a simulation would lead to a reduction in the number of crime events. This is because a larger number of defenders would increase the probability of deterring offenders or apprehending them before they can commit a crime. In other words, a higher presence of capable defenders would create a less favorable environment for potential offenders and therefore discourage criminal activity.

In the fifth experiment of the simulation model, the focus is on understanding the impact of the number of defending agents on the reduction of crime events. This experiment aims to identify how many defending agents are required to minimize the frequency of crime events in the city. To test this, the model considers four different scenarios with varying numbers of defending agents: 200, 600, 2000, and 10,000. The simulation process for each scenario is the same as the basic performance experiment, with the probability that a citizen agent could become a criminal agent set to 0.2.

Figure 10 presents the results of the fifth experiment, where the impact of the number of defending agents on the occurrence of crime events is analyzed. The simulation results show that when the number of defending agents is less than 2000, the number of crime events remains constant, which indicates that the police force is insufficient to cover the city and prevent crime effectively. This situation allows offenders to take advantage of the low presence of capable defenders and commit crimes. However, when the number of defending agents increases to 2000 or more, the number of crime events decreases significantly. This suggests that a sufficient number of police officers can cover the city and reduce the occurrence of crime events. In other words, when there is a higher presence of capable defenders, offenders are less likely to commit crimes due to the increased risk of being caught. Furthermore, when the number of defending agents is more than 10,000, the number of crime events decreases even more. This implies that a high number of police officers can effectively cover the city and significantly reduce the occurrence of crime events. Overall, the results of the simulation experiment confirm the Crime pattern theory, which indicates that crime events are more likely to occur in areas and at times where there is a high density of potential offenders and suitable targets, and a low presence of capable defenders. The results also suggest that increasing the number of police officers can be an effective strategy to reduce crime events and improve public safety.

V. CONCLUSION

This paper proposes a novel agent-based model to emulate crime patterns produced by the interaction of different urban actors, such as offenders (criminals), citizens, and defenders (police), when they are in a given section of the city. The proposed method analyzes offender behavior by providing escape trajectories and robbery frequencies that can be used to predict crime patterns and to identify promising regions of the city where security can be improved. In addition, defender positions and crime factors were generated by considering environmental data to identify the best defender positions to prevent crime. This proposal can be implemented in any city. However, to evaluate the performance of our method, the developed ABM was applied to a study of crime in Guadalajara, Mexico.

Five different scenarios are implemented in the experimental section to test the proposed model. In the first scenario, the performance of the model is exemplified in its basic form to show the behavior of citizens, offenders, and defenders. The second computational experiment aimed to evaluate the impact of crime events and identify the main roads or avenues that represent a possible escape route for offender agents. In the third experiment, the behavior of crime events was examined when a concentration of police officers (defenders) was placed in regions of the city where a high density of crimes had been previously detected. The aim of this experiment was to determine whether the concentration of defenders in high-crime areas can effectively reduce crime rates. In the fourth scenario, we examine how crime patterns behave during the night shift when the number of defenders, such as police officers or security personnel, decreases and the number of citizens in the streets also decreases. This situation can create a unique set of challenges for law enforcement agencies and increase the risk of criminal activity in certain areas. In the fifth experiment of the simulation model, the focus was on understanding the impact of the number of defending agents on the reduction of crime events. This experiment aimed to identify the number of defending agents required to minimize the frequency of crime events in the city.

The results of this study suggest several elements. Crime is not evenly distributed across places but tends to cluster in certain hot spots. Therefore, police officers should be allocated according to the level of crime risk in different areas. Police officers can deter crime by being visible and present in high-risk areas. However, if they are concentrated too much in one area, they may create displacement effects, where criminals move to other areas with less police presence. Police officers can respond faster and more effectively to crimes if they are distributed according to the demand for service. If they are concentrated too much in one area, they may neglect other areas that also need their attention. Under all these results, it is clear that the distribution of police officers is more important than their number or concentration in determined areas in order to reduce crime.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding this work.

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