Journal of Computational Science 2 (2011) 238–246

Contents lists available at ScienceDirect

Journal of Computational Science

journal homepage: www.elsevier.com/locate/jocs

The social impact in a high-risk community: A cellular automata model

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ARTICLE INFO

Article history:
Received 15 November 2010
Received in revised form 14 May 2011
Accepted 28 May 2011
Available online 15 June 2011

Keywords:
Cellular automata
Social influence
High-risk community
Criminal behavior
Drug use

ABSTRACT

This research examines the spread of criminal behavior and hard drug consumption using a mathematical approach called cellular automata (CA). This CA model is based on two behavioral concepts. Firstly, peer association impacts criminal involvement. Secondly, addiction can heighten criminal activity. The model incorporates four types of actors who interact in a high-risk social community and one intervention method. The actors exert a social influence on each other by encouraging or discouraging drug use and criminal behavior. The intervention method called *Incapacitation* has a probabilistic impact on the individuals in the model. The results identify the threshold where positive influences on a population reduce the number of high-rate offenders in the community. These results are discussed to further the knowledge about the social influences in a high-risk community and how these influences can effect decisions on offender management.

1. Introduction

The impact of prolific criminal offending has become a matter of serious concern in modern societies. Many of these offenders enter into a heightened cycle of offending in order to support an expensive drug habit [4,10,11,18]. Policy makers are searching for relevant strategies to effectively control drug addiction as well as the associated medical and criminal repercussions [4,15,19]. In many cities, drug and community courts are aimed at providing offenders who are often suffering from an addiction with the appropriate services to help them stabilize and cease their criminal offending [17]. The purpose of this paper is not to analyze the dynamic nature of addiction, but rather to look at a certain form of addiction as it relates to criminal offending [4,20].

The spread of hard drug use (cocaine and heroin) is of particular concern because these addictions can lead to high-risk practices such as needle sharing, crack cocaine pipe sharing and drug related criminal activities [16]. These are also the drug types most often referred to when looking at the link between drug use and criminality. A study of 677 illicit opiate users from five Canadian cities found that increased use of crack, heroin and cocaine lead to a heightened likelihood of property crime offending [6]. As well, individuals using these types of drugs will find other ways to support their habit including participating in the drug market. For instance, some people involved in the market acted a brokers between the user and the dealer and that brokers engaged in this activity to consistently access drugs for personal consumption [13].

In this paper, a high-risk community is defined as a social place where individuals can easily access these hard drugs and participate in criminal activity to support their habit. Social relations within a group impacts individual decision making [6]. These social interactions in a high-risk community play an important role in spreading social behaviors especially those pertaining to crime, drug acquisition and use [3]. Indeed, access to the illicit drug market is often achieve through those who are entrenched in the drug subculture and new participants will receive social influences from those they interact with [3].

Modelling that uses cellular automata (CA) as the mathematical basis can effectively analyze the non-linear qualities in the transmission of infectious disease, drug use and criminal behavior [7,29]. This type of modelling is rarely used in the field of criminology, yet this method of analyzing complex and dynamic situations is extremely applicable to this field of study [1,2,12,17,30]. The dynamic social behaviors associated with crime and drug use can be successfully represented in a CA model and improve our understanding of the social and related processes tied to the aetiology of disease transmission, drug addiction patterns and behavior modification among the individuals in a high-risk population [1,31].

In this model, the four players are conceptual entities designed for this experiment. The *Stayer* is a person who does not commit crime or use drugs under any circumstances. This is a stable person who provides support to other individuals in this high-risk social community. The *Susceptible Person* (SP) does not currently use drugs or commit crime, but may be incited to do so depending on their interactions with others in the high-risk community. The *Low-Risk Person* (LRP) is an individual who is periodically using hard drugs and may commit crime, but their criminality is not associated with drug use. The *High-Risk Person* (HRP) is an individual

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doi:10.1016/j.jocs.2011.05.008

who is physiologically and psychologically addicted to hard drugs and their criminal behavior is primarily motivated by drug acquisition. The HRP will engage in criminal behavior to sustain their addiction. The single intervention incorporated in this model is *Incapacitation* which impacts the probability of a HRP of changing states based on their temporary removal from the community, and possible rehabilitation.

Some of the actors discourage (α) other individuals in the community from using drugs or committing crime. For example, the *Stayer* always discourages the other actors in the model from participating in the high-risk community. This individual could be conceptualized as a community nurse or a drug counsellor. Other actors encourage (β) others in the model to use drugs and commit crime. The HRP, for instance, is entrenched in the high-risk community and will encourage all the actors in the community to participate except the *Stayer*. Through social interaction the HRP will encourage both the LRP and SP to become involved in the high-risk community by committing crime and using drugs.

In this model, α and β are conceptual parameters that capture a multitude of influences present in the environment. These influences can be social ones such as someone physically offering another individual access to drugs. At the same, these influences can be environmental, for instance, an individual may be triggered to use drugs by the mere presence of drugs in their environment. As well, an individual well-established in the high-risk community may show a newcomer how to become involved in the drug market and how to commit crimes that provide direct access to drugs. Accessibility to drugs is also captured in α and β as these parameters can represent the competing influences on the drug market. For instances, police enforcement is represented by α if this results in reducing access to drugs.

As the model goes through numerous sequences called time steps, the individuals transition through different states. These state transitions result from dynamic social influences that occur when individuals interact in a high-risk social community. Each cell in the CA model represents an individual and has an associated *Social Influence Count* (SIC). The SIC for each cell goes up or down depending on the relative influence exerted on that cell. The SIC value is carried forward into the next time step so that this counter increases and decreases overtime, thus enabling the change of state once the counter has reached a certain value. For example, when the SP is repeatedly exposed to HRPs they will transition to a LRP. The only individuals who can transition to a state of *Incapacitation* are the HRPs. Upon release from incapacitation these individuals are subjected to a probabilistic influence (P) and can become a SP, a LRP or a HRP depending on this probability.

This CA model merges together the various complex social interactions existing in a high-risk community in order to identify the point at which the influences represented by α saturate the community enough to significantly reduce the HRP population. In order to attain these results, this CA model amalgamates social influences into two competing parameters α and β. This synthesis is necessary in a first instance to reveal the threshold for positive social influences on a high-risk community. Further iterations of this model can delve into the relative impact of various factors such as police enforcement on the drug market, drug treatment options or other interventions on this community.

2. Theoretical framework

The goal of this model is to look at the impact of social influences in a high-risk community. There are two main assumptions in this model:

1. Peer associations positively or negatively influence drug usage patterns.
2. Heightened drug consumption is correlated with increased criminal involvement.

2.1. Peer association and drug usage patterns

Within a high-risk community there can be several different types of individuals with different drug using and criminal offending patterns. Research in the area of network and cluster analysis has revealed variance in the drug using subtypes [24]. Other research has used ethnographic methods to establish what are the different stages of psycho-stimulant use [21]. In communities centred on the consumption of illicit drugs, high and low-risk behavioral drug consumption patterns can be spread because of tight social connections within these communities. The transmission of HIV through needle sharing serves as a primary example of these social connections where disease transmission can occur as a result of social interactions between users in a community [1,31].

Although it is not the purpose here to provide a comprehensive list of social influences on the peer network, some serve to illustrate the larger social concepts described in the following model. For instance, certain intervention techniques such as needle exchange or safe injection sites provide individuals who are in these high-risk communities with access to positive social influences through their contact with drug counsellors or health personnel [15]. Other occurrences like the introduction of a new drug such as crack cocaine into these communities has a rippling effect which can alter drug usage patterns [9]. On a more global perspective, the fluctuation in the drug market due to police enforcement, the Criminal Justice System, availability of drugs, or other factors can adversely or positively impact peer associations in a high-risk community [8,25].

2.2. High rate drug usage patterns and criminality

The high cost of consuming cocaine or heroin on a daily basis often causes people to turn to crime as a means to support their habit. Since frequency of crime is strongly correlated with incapacitation, high-rate drug users are more likely to be incapacitated through incarceration [26,27]. Research on persistent offenders has shown that higher criminality is associated with high-rate drug use [4,6,11,19]. As well, drug use can bring young adolescents who would normally desist in their criminality, into a drug subculture which fosters antisocial relationships [20].

These criminal and drug associations prolong the criminal career by subjecting individuals to an environment lacking in pro-social influences [10,23]. Once the cycle of addiction, antisocial peer association and incapacitation is activated qualitative fluctuations in this cycle can trigger both escalation and de-escalation in the cycle [18]. Thus a high-rate drug user who is exposed to drug treatment while incapacitated and then provided follow-through after release may be more likely to cease their addictive cycle [30]. On the other hand, another individual who received no treatment is more likely to exit incapacitation with a higher likelihood of re-engaging in a high-risk community.

3. Cellular automata modelling

In a CA model, a population can be represented in a two dimensional square grid where each cell represents an individual in the population [7]. The state of each cell can vary depending on pre-determined rules. These rules are derived from an existing theoretical framework describing a particular phenomenon and are used to model what is happening in the real world. A CA model can effectively capture social interactions that happen over time [1]. Since each cell has the capability of holding the information pertaining to that cell, changes can be recorded. In general, CA models measure time discretely, in other words, progress through time is represented as a series of time steps. The cells capture the information at each time step and their states can alter through successive time steps [14].

In order to simplify the complexity of human behavior, CA modelling must make assumptions which are supported by research. In this CA model the underlying premise is that individuals are socially influenced in a high-risk community where crime is used as a means to access more drugs. While each cell in a CA model can potentially be influenced by surrounding cells, this model accounts for only four neighbors, north, south, east and west. The assumption here is that individuals are not impacted by everyone that physically surrounds them, but only those people they have social contact with. This type of neighborhood is called the von Neumann neighborhood.

In this CA model the social interactions progress through time steps. Each cell holds information pertaining to that cell and changes are recorded. The cells capture the information at each time step and alter their state through successive time steps. These updates happen simultaneously following the pre-determined transition rules. There are four types of individuals and a single state of *Incapacitation*. In other words, a cell can transition from one individual to the next (e.g., SP to LRP) or from an individual to a state of *Incapacitation* (i.e., HRP to *Incapacitation*). While it is possible in reality for a SP, LRP or HRP to experience incapacitation, in this model only the HRP can experience this state. In future iterations of the model other probabilistic values can be introduced for the SP and LRP. We assume this model to have a constant population even though there are processes of births, deaths, immigrations and emigrations in any population.

4. The model

This model represents a high-risk social community that extend beyond the physical boundaries of a specific geographical area. This community consists of four types of individuals and one type of intervention.

- A *Stayer* is an individual who does not participate in criminal activities and does not consume illicit drugs, but is present in the high-risk community and provides support to the individuals who are in this community.
- A *Susceptible Person* (SP) is an individual who is not currently involved in criminal activity, but prone to become involved for a variety of reasons.
- A *Low-Risk Person* (LRP) is an individual who commits crime from time to time and may use drugs occasionally, but they do not support their drug use through crime.
- A *High-Risk Person* (HRP) is an individual who commits crime to support a drug habit.
- The single intervention is *Incapacitation* which can impact the HRP through a temporary removal from the high-risk community.

An individual can only play a single role at a time. Over time individuals can transition from one state to the next based on predetermined rules. For example, a HRP can become incapacitated, then upon release they are now a LRP. The purpose of this study is to analyze the evolution of a fixed population in a high-risk community according to rules that dictate their interaction as they evolve through time.

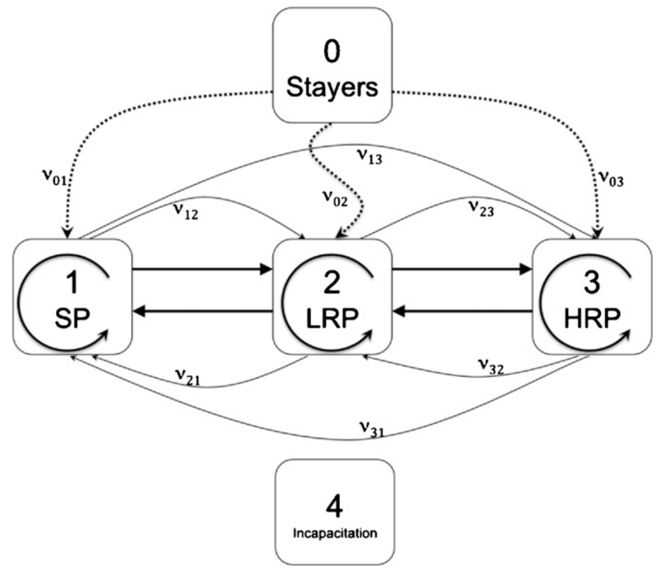


Fig. 1. The deterministic transitions processes in the model.

4.1. Model design

This CA model integrates social influences and transition rules. The cells in the grid interact as individuals would in a high-risk community. The cells change over time as they receive and give social influence to their neighbors. After each iteration, the grid is updated to reflect the modifications. Since this is a scenario-based model, the variables can be set according to input data and adjusted to reflect possible changes in the community.

Although the cells are stationary, the state of the cell can vary. This reflects the change in social state individuals may experience during their life course. These changes occur as a result of social influences experiences in the high-risk community. We selected the von Neumann neighborhood because the average of the surrounding cells as a means to describe these social interactions. As such, at any given time only four of the eight cells exert social influence on a cell.

4.2. Social influences

The act of encouraging criminality and drug use is represented by (β) while discouraging criminality and drug use is represented by (α). A *Stayer* is an individual who never commits crime or uses drugs and always discourages their neighbor from participating in the high-risk community (dotted curves in Fig. 1). A *Stayer* cannot be influenced by any type of person as this is the stable nature of a *Stayer*. The *Stayer* is meant to represent the individuals in a high-risk community that are actively attempting to mitigate the harmful effects associated to criminality and illicit drug use.

An SP discourages both the LRP and HRP from participating in the high-risk community because the SP exposes the LRP and the HRP to pro-social situations where crime and drug use are not the primary focus. A LRP can encourage the SP to further participate in the high-risk community, while HRP has this influence on both the SP and the LRP (solid line in Fig. 1). The SP always discourages another SP from engaging in the high-risk community. Depending on the scenario an LRP would either encourage or discourage another LRP as would an HRP on another HRP. Since both the HRP and the LRP vary in their intensity, the relative intensity between two neighbors of the same type dictates whether they are encouraged or discouraged. This type of influence is represented by the circular arrow in the SP, LRP and HRP box.

In Fig. 1, the *Stayers*, SP, LRP, HRP and *Incapacitation* are represented by 0, 1, 2, 3, 4, respectively. In the model, v_{ij} represents the influence an individual of type i has on an individual of type j, for $i = 0, 1, 2, 3$ and $j = 1, 2, 3$ (see Fig. 1). This is a number ranging from −1 to 1. v_{ij} is negative (positive) when an individual of type i is encouraging (discouraging) an individual of type j to participate in the high-risk community. Therefore, the value $|v_{ij}|$ represents the probability that the behavior of individual of type j changes and that they become a type i. Finally, individuals of type 4, people in *Incapacitation*, cannot influence their neighbors.

4.3. State transitions rule

A person changes their type and state based on rules called transition rules. There are two types of transitions in the model.

1. Deterministic transition – transitions between SP, LRP and HRP.
2. Probabilistic transition – incarceration or release from *Incapacitation*.

4.3.1. Deterministic transitions – transitions between SP, LRP and HRP

A person has four neighbors which have influence on them. This collective influence has a net impact on this person. Each net impact is recorded and over time accumulates to form an overall influence. We will call this net impact the *Social Influence Count* (SIC). A person will change based on this count. After each time step the counter is updated with the current count which is carried through to the next time step.

Definition 1. The SIC of a person is the net impact of social influences accumulating at each time step. The SIC of a person is represented by $C_j(t)$. Mathematically the SIC of a person of type j at time t is defined in the following manner:

$$C_j(t) = C_j(t-1) + \sum_{i=0}^{3} R_i v_{ij} \quad j = 1, \quad 2, \quad 3$$

where R_i is the number of neighbors of type i and v_{ij} is the value of influence of the individual i on the individual j.

The *Stayers* (type 0) do not receive influence or change state and incapacitated persons (type 4) cannot receive or provide any kind of influences, these two types do not have a SIC. The transitions $1 \to 2$, $2 \to 1$, $2 \to 3$, and $3 \to 2$ are based on the SIC. We call these transitions deterministic because these are based on a pre-determined count built into the SIC (see Fig. 1).

4.3.1.1. Transition rules. In order to transition, an individual must follow the transition rules. Let $X(t) \in \{1, 2, 3, 4\}$ represent the state of an individual at time t and suppose $X(t) = j$ then at a later time t',

$$X(t') = \begin{cases} j+1, & C_j(t') < -1 \quad \text{for } j = 1, 2 \\ j-1, & C_j(t') > 1 \quad \text{for } j = 2, 3 \end{cases}$$

For example, a person of type 2 would change to type 3 if at any time his/her SIC becomes greater than 1 and to type 1 if it becomes less than −1.

4.3.2. Probabilistic transitions – release from Incapacitation

Since a HRP is involved in a high-risk cycle where crime is linked to a drug habit, there is a probability associated with them being sent to incapacitation. The transition $3 \to 4$ is based on this probability which is represented by P_{34} in the model. A person in incapacitation when released can become a SP, a LRP or a HRP. We can associate probabilities with these transitions ($4 \to 1$, $4 \to 2$ and $4 \to 3$) which are represented by P_{41}, P_{42} and P_{43}, respectively (see Fig. 2).

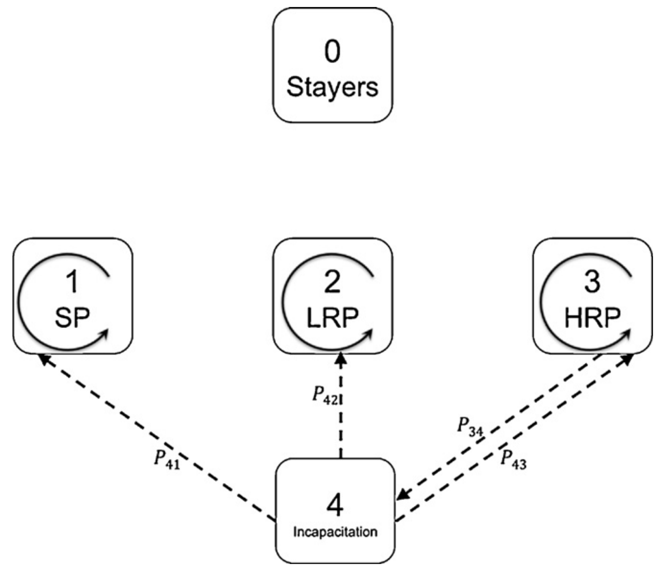


Fig. 2. The probabilistic transitions processes in the model.

4.3.2.1. Transition rules. P_{41}, P_{42} and P_{43} are the probabilities of becoming respectively a SP, a LRP or a HRP upon release from incapacitation. P_{34} is the probability of a HRP going into incapacitation. These are scenario-based values that can be derived from real data. These variables can also be changed to reflect social changes. For instance, with increase police enforcement on the drug market, improved drug treatment and intervention, or increase transition housing, the probability of becoming a HRP upon release could be reduced.

4.4. Positive and negative social influences

Modelling can be used to test out theories, but in order to do so it is best to use simplified concepts. While we accept that discouraging (positive) and encouraging (negative) influences for the *Stayer*, SP, LRP and HRP may be different types of influences, for the purpose of this simulation these influences are generalized. The value α is used to express the positive influence and the value β is used to express the negative influence (see Fig. 3).

5. Simulations and results

For simulation of this CA model, a two dimensional 40 by 40 cell-array is used by the numerical computing environment called MATLAB.[1] This grid size was selected as it is small enough for rapid computation, but this size does not affect the results. To remove the boundary conditions we consider this model as toroidal shape where each cell has an identical neighborhood. Each element of the cell array is a vector storing type, current SIC and time spent in *Incapacitation*. These vector elements were updated at each time step, following the transition rules. The model was run for 1000 iterations. Two population distributions were simulated.

5.1. Parameters and initial conditions

In this simulation, an iteration of the model represents one month of real time. We have chosen a population distribution

[1] MATLAB is a numerical computing environment used to simulated CA models http://www.mathworks.com/products/matlab/.

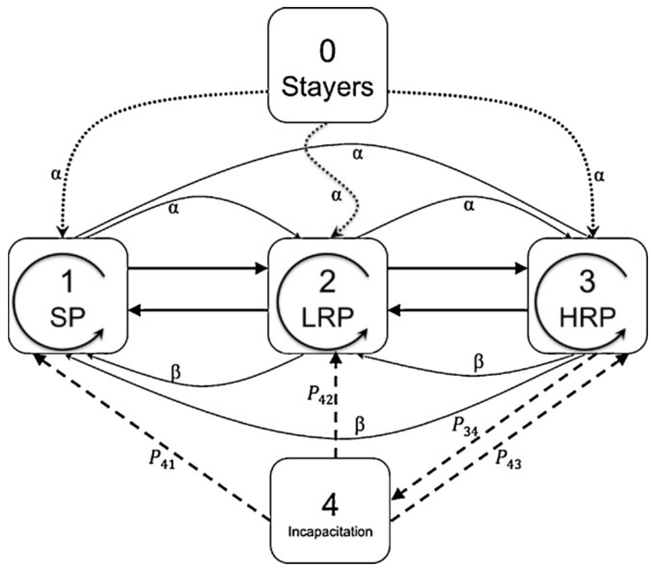


Fig. 3. The model with two social influences α and β.

which could represent a high-risk community. These values can be modified to reflect a variety of distributions and to model real data. The probabilities used for *Incapacitation* (P_{34}) and for becoming a SP (P_{41}), LRP (P_{42}), or HRP (P_{43}) upon release were chosen in order to reflect a realistic scenario. These values could also be modified in order to replicate a given situation within the criminal justice system.

There are no reliable estimates available for the population of *Stayers*, SPs, LRPs and HRPs and for this simulation we chose the following initial populations: 5%, 55%, 20%, and 20%, respectively. This distribution was selected as a scenario to describe a high-risk community. Since specific data on such a community was not available. This scenario explores a community which contains a higher concentration of SPs. We took 0% as the initial population for persons in *Incapacitation*. Furthermore, the probabilities for P_{41}, P_{42}, and P_{43} were 0.3, 0.3 and 0.4, respectively. The probability of *Incapacitation* P_{34} was set at 0.02 per month. This value was derived from a study where the author found the probability for incapacitation for committing for grand larceny is 0.02 which is a common offending pattern for individuals who are supporting a drug habit through crime [22].

6. Results

The results comparing α values and incapacitation periods are shown in Table 1. Four simulations are conducted with β fixed. In a first instance, α is set at 0.01 and then it is raised to 0.02. In the table, the configuration of the cellular automata is shown at different times for the α and β values for 6 and 24 months of incapacitation. The colors change from light-grey to black and represent the *Stayer* (lightest grey), SP (light grey), LRP (medium grey), HRP (dark grey) and person in *Incapacitation* (black). The first and second rows or third and fourth rows of Table 1 can be compared to see the impact of the positive influence α.

In order to study the evolution of a population over time, a proportion of individuals in each state were plotted for values of α, β and incapacitation periods as shown in Table 1. As depicted in Figs. 5–8, after a sufficient number of iterations the proportion of persons in each state stabilizes. In other words, the population reaches a stable configuration. For example, approximately 50% of the total population becomes HRPs when α is set at 0.01, β is set at 0.03 and the incapacitation is 24 months (see Fig. 4).

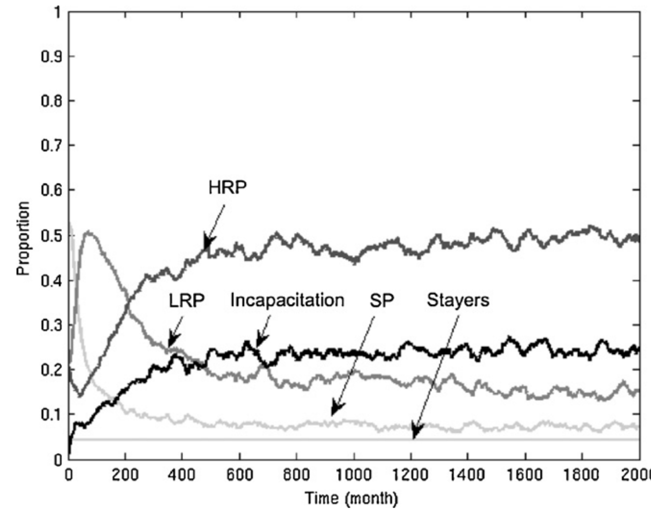


Fig. 4. A community with 24 months incapacitation and a low α value (α = 0.01).

The HRP population remains high because the influence of α is not strong enough to overcome the influence of β. When α is increased to 0.02 a different scenario occurs (see Fig. 5). Here the SPs constitute 95% of the total population while there are no LRPs or HRPs in the population.

The impact of an incapacitation period can be further analyzed. As depicted in the time plots, for both the incapacitation periods, the population reaches a stable configuration after a sufficient number of time steps. However, for the lesser values of 6 months, the stable configuration is attained faster. The other important difference between these two incapacitation periods is the different proportion of HRPs and incapacitated persons when α = 0.01. In the case of the 6 months incapacitation period, approximately 65% of the population are HRPs and 10% are incapacitation (see Fig. 6). Whereas in the case of 24 months of incapacitation, approximately 50% of the population are HRPs and 25% are incapacitated (see Fig. 4).

7. Phase diagram

A phase diagram can be used to view the behavior of a total system and can to illustrate the how changed values impacts the whole system. To understand the global behavior of the model and

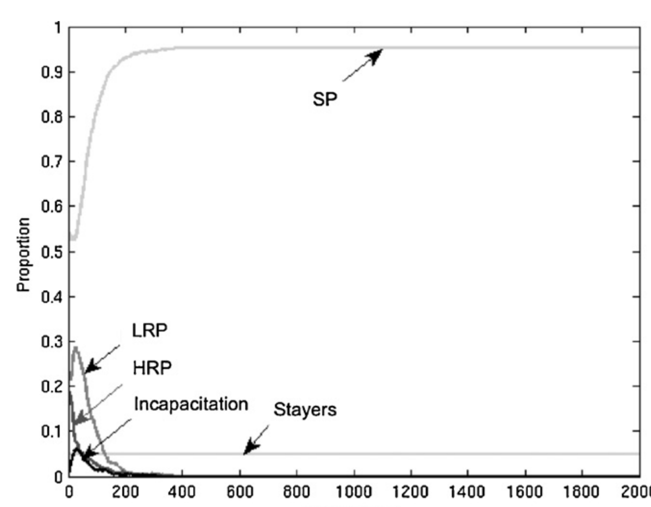
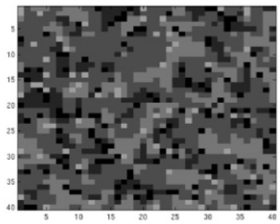
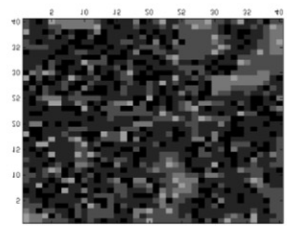
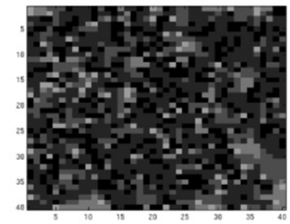
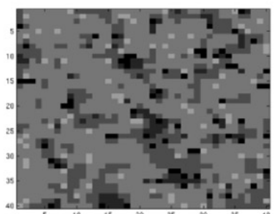
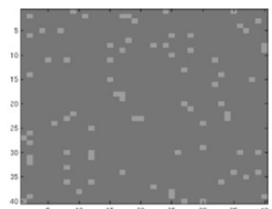
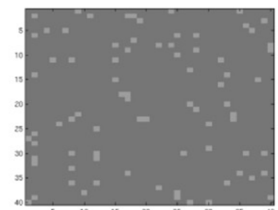
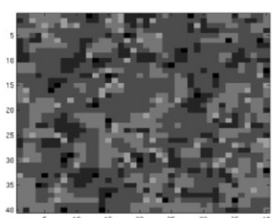
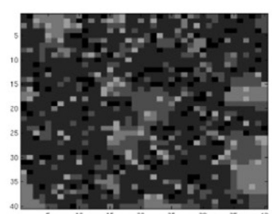
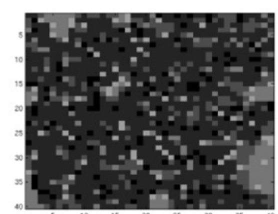
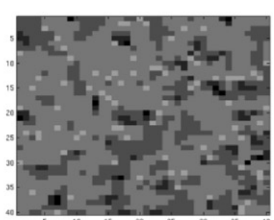
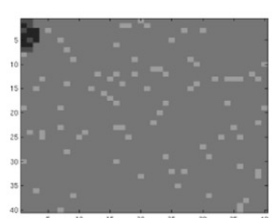


Fig. 5. A community with 24 months incapacitation and a higher α value (α = 0.02).

Table 1
Comparing two incapacitation periods (6 and 24 months).

	t = 50	t = 400	t = 1000
24 months	 α = 0.01, β= 0.03	 α = 0.01, β= 0.03	 α = 0.01, β= 0.03
24 months	 α = 0.02, β= 0.03	 α = 0.02, β= 0.03	 α = 0.02, β= 0.03
6 months	 α = 0.01, β= 0.03	 α = 0.01, β= 0.03	 α = 0.01, β= 0.03
6 months	 α = 0.02, β= 0.03	 α = 0.02, β= 0.03	 α = 0.02, β= 0.03

the impact of both α and β, we constructed a phase diagram for ranges of α and β (see Fig. 8). The phase diagram presented in Fig. 8 provides an overview of the model where on the right side of the line the population is mostly from the SPs and the left side of the line the population is mostly from the HRPs. For every α value there is a β value which makes all the HRPs disappear. For example, the scenario represented in Fig. 6 (α = 0.01) which is illustrated in the left area of the phase diagram. Whereas the scenario represented in Fig. 7 (α = 0.02) is illustrated in the right are of the phase diagram.

On the left side of the threshold line, the value of α is such that HRPs form 50% of the population in the scenario of 24 months of incapacitation, and 65% for 6 months of incapacitation. Whereas on the right side of the threshold line, the value of α is such that HRPs are 0% of the population.

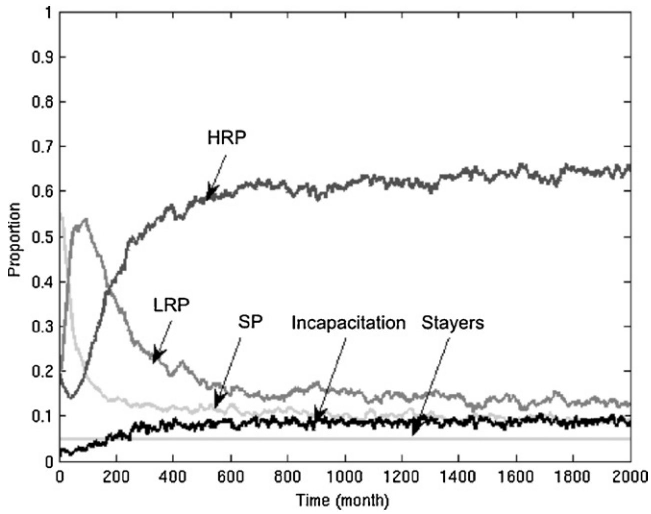


Fig. 6. A community with 6 months incapacitation and a low α value ($\alpha = 0.01$).

Simulations were carried out to compare a 6 month to a 24 month incarceration time. This phase diagram shows a small difference when HRPs are incarcerated for 24 months.

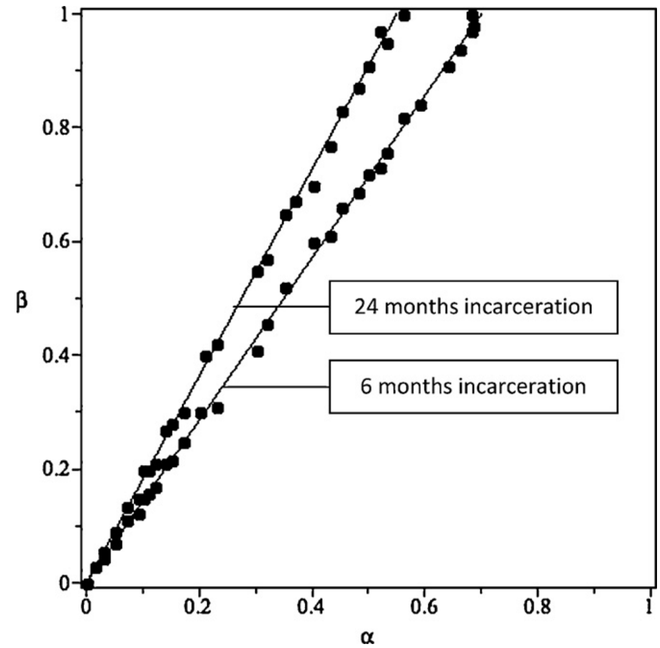


Fig. 8. 6 months incapacitation versus 24 months.

8. Discussion: model dependence on parameters

The model was simulated for different values of α and β, which interestingly resulted in only these two types of plots: one where there is a prevalence of HRPs (Figs. 4 and 6) and the other where HRPs are eliminated (Figs. 5 and 7). A better way to understand these results is to suppose that α is fixed and vary β, thus there is a transition value of β, say β_0 is such that for all the values of $\beta \geq \beta_0$ there is prevalence of HRPs and for $\beta < \beta_0$ there is a prevalence of SPs. This suggests that the model does not depend on the values of α and β explicitly, but rather it depends on the relative difference of these values.

A phase diagram for the model with α and β as axis shows a curve which divides the range space of α and β ($[0,1] \times [0,1]$) into two parts, one being HRPs prevalence and the other being non-prevalence. The phase diagram shows the threshold where for a given β there exist and point where α is such that the HRP population goes from 50% to 0%. This means there always exists a point when the positive influences on the high-risk population eliminates the presence of HRPs in the community.

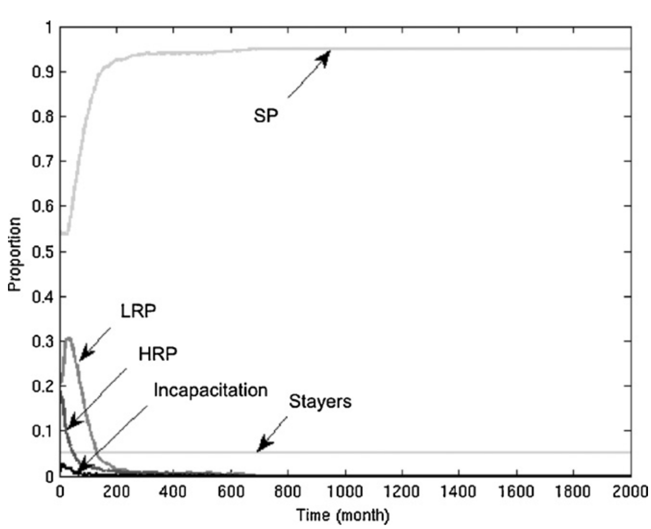


Fig. 7. A community with 6 months incapacitation and a higher α value ($\alpha = 0.02$).

The simulation was completed for different values of these parameters to study the role of other parameters (initial population, months spent in *Incapacitation* P_{34}, P_{41}, P_{42} and P_{43}) and interestingly the simulations reveal that the results are not dependent on these parameters. There were always only two kind of plots, one being prevalence and the other being non-prevalence of HRPs. The only difference among these plots was the final approximate proportion of HRPs which varied by approximately 5%. The conclusion derived from this simulation is that this model depends on the relative difference of positive (α) and negative (β) influences.

The model shows that when the negative influence (β) is fixed, increasing positive influence (α) to a certain threshold eliminates the HRP population. This model in its current state is theoretical and abstract. However, exploring scenarios in this model derived from real data could provide policy makers with a better understanding of the social processes in these types of communities. Additionally, since α is constructed as a conceptual parameter it is important to consider the relative importance present in the confluence of positive influences. These positive influences could be varied with some having more influence over others. The value α represents a combination of positive influences not limited to: police enforcement, drug policies, or fluctuations in the drug market. In future research, this model needs to be expanded to explore how these various positive influences interact in this type of community. Rather than introducing a single intervention strategy, positive influences need to take into account the dynamic nature of this community.

The length of incapacitation does not change the population significantly, it only shifts the process. The simulation was completed for two incapacitation periods and this did not impact on the distribution of HRPs. The probability of incapacitation would need to be increased significantly so that more HRPs are in this state, and then the negative influence would change the outcome of the total system. In future iterations of this model, the limit of this probability could be explored to see what percentage of HRPs would need to be removed in order to effect a change in the model behavior. This model further shows that increasing positive influences on the high-risk community has the most impacting result. Furthermore the phase diagram shows that for any value of β there exists an α value where HRPs are eliminated.

9. Conclusion

The CA model presented here exposes the role of social interactions in the spread of high-risk activities in a high-risk social community. Increased interactions with LRPs or HRPs tend to change the behavior of a SP to be a LRP first and then a HRP. The results from this model suggest that positive influences play a stronger role than negative ones. This CA model used the von Neumann neighborhood and in future iterations of the model other neighborhoods can be introduced to further explore how CA models can describe and analyze social interactions.

The incapacitation period does not change the population. This would appear counterintuitive since removing HRPs would seem to naturally reduce their influence. However, incapacitation in this model does not impact population distribution because the probability of a HRP moving from this state to incapacitation is set at 2%. Thus removing 2% of HRPs is not sufficient enough to cause a major shift in the distribution of the population or reduce their negative influence in the high-risk community.

The results presented here should encourage policy makers to continue in their efforts to exert positive influences on high-risk communities where drug habits fuel criminal offending. Further research in this area could focus on the relative impact of these various influences to assist agencies in improving their services. In this model, α is a generalized concept and in further iterations of the model this value will be broken down to compare positive influences and their impact on a high-risk community. Available data on drug populations is difficult to access, especially when the focus is on those individuals who are committing crime to support their habit. We are currently working to attain this type of data on a high-risk community in Vancouver, British Columbia. Once we have collected this data we will validate the model with this information.

Acknowledgements

The project was supported in part by the SFU CTEF MoCSSy Program. We are also grateful for the technical support from the IRMACS Centre, Simon Fraser University.

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