Modeling Sexual Violence within the Homelessness Population through an Agent-Based Approach

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Abstract - Sexual violence is an unfortunate crime of opportunity, requiring an offender and a victim. We develop a model that simulates the occurrence of sexually violent events in an urban environment. Here, we take the victims to be homeless individuals since studies find that sexual violence is increasing in homeless communities. We modify an agent-based model for residential burglaries to incorporate non-stationary victims. The residential burglary simulations evolve by having the target house attractiveness increase when nearby residences were burgled, modeling the 'broken window effect'. In the case of sexual violence, the victim is non-stationary, yet both offenders and victims visit locations, such as homeless shelters, based on their own perceptions of attractiveness. The attractiveness level of a location is affected by previous events, however, victims and offenders will consider an event differently. We allow for different victim behaviors, such as a risky lifestyle or being at the wrong place at the wrong time. We compare the resulting simulations to the events in San Francisco, CA. The simulated results agree with the expected behavior for the different types of victim behaviors. Moreover, the results show that simulated events are concentrated in regions near homeless shelters. We then tested the model with an increase in the generation of victim agents, observing the outcome for an increase in the number of homeless individuals. Initial increases in the victim generation rate substantially increase the overall amount of crime. However, after a certain level, increasing the number of victims does not increase the crime rates.

Keywords : agent-based modeling; hot spots; sexual victimization; homelessness

Mathematics Subject Classification (2010) **:** 69U20; 91D10

1 Introduction

An estimated one out of every six women become a victim of sexual violence in their lifetime [1]. Of those victims, approximately 15 percent have experienced a completed rape and approximately 3 percent have experienced an attempted rape. Men also experience sexual violence at an estimated rate of 1 out of 10 men [1]. Moreover, sexual victimization within the homelessness community suffer even higher rates of sexual violence. Approximately 32 percent of women, 27 percent of men, and 38 percent of trans-genders reported to have experienced sexual or physical violence [9]. Women in the homeless community are also often forced into prostitution or into an escort business [9].

Studies show that homeless women are the most prone to becoming victims of sexual and physical abuse [11]. The most crucial factor of a victim experiencing sexual violence is housing status. Homeless people either live in a shelter that lacks protection against danger and crime or have no protective shelter at all. Individuals who are homeless are more inclined to using drugs, share needles or other tools to inject drugs, have unprotected sex, and use sex as a survival mechanism [10]. These individuals are exposed at all times to unhealthy and hazardous behavior and are more likely to engage in these behaviors themselves [11].

Individuals who are often exposed to high crime environments are more vulnerable in becoming potential victims [6]. Low self-control tendencies and risky routines influence individuals to put themselves at greater risk for violent victimization [6]. Potential offenders first see whether or not the victim is a suitable target. This depends on many variables, to include the absence of guardians and witnesses, time, and location. However, the victim's behavioral routines are the more risky factors because they provide an exposure with the potential offender [6]. According to the lifestyle theory, it is not the potential victim leaving home that exposes the victim to violence, but the activities engaged in outside of the victim's home [6]. For instance, an individual going to a party may not be risky, but drinking past the limit will increase the likelihood of victimization.

We focus on sexual violence within the homelessness community since these groups of individuals are often subject to victimization. We consider the Short et al. model that simulates residential burglaries [3]. This model considers burglar agents moving about an environment, committing criminal acts. One main difference between residential burglaries and sexual violence is that the victims for the residential burglary case are stationary. For our model, we work with non-stationary victims, requiring a new framework. We modify the Short et al. model to accommodate these non-stationary victims. We also allow the non-stationary victims to adopt one of three behaviors, namely, victims who live a 'risky' lifestyle, victims who happen to be at the wrong place at the wrong time, and victims who are better educated and aware of past sexual violence occurrences. We then apply the model to sexual violence to see if patterns observed are consistent with simulated results. We use the San Francisco police department data for sexually violent occurrences reported during the years 2010 to 2014.

2 Previous Works

Here, we discuss some of the studies of individuals in the homeless community and sexual victimization, as well as mathematical models in criminology. We then describe the Short et al. model, the preliminary framework from which we build our model.

2.1 Victimization in the Homeless Community

The homeless community suffers from physical and sexual violence more than any other community [11]. A recent study from the University of California, San Francisco examined sexual and physical victimization within the homeless community. In this research study, 2577 homeless and marginally housed persons in San Francisco were interviewed about their recent history of physical and sexual violence [11]. According to the article

"No Locked Doors," there are many studies that suggest that homeless women are more prone to sexual victimization [11]. This study interviews women, men, and trans-gender persons with characteristics that include housing status, substance abuse, mental illness, education, and sex work. According to their multivariate model's predictions, physical and sexual assault are instigated by substance abuse, poor health, and illegal activities [11]. Another study focuses on the correlation between psychological well-being of homeless women and victimization experiences [15]. They examine sexual victimization and other stressors such as criminal victimization and sexual harassment [15]. These stressors can have a major effect on a person's mental health, and it is important to understand the measures of these stressors to know how to help these victims. Moreover, it is important to note that housing status is also a stressor due to the insecurity of safety and basic necessities [15].

2.2 Mathematical Models in Crime

Various mathematical approaches, such as statistical models, differential equation models, and agent-based simulations, have been applied to criminal behavior and policing. For example, predictive policing is a technique used by mathematicians and criminologists in efforts to predict crime [14]. Predictive policing takes data, analyzes that data, and uses the results to predict future crime to be able to prevent and respond effectively. This mathematical technique is not meant to change or replace any police techniques, but aids in strategy.

Agent-based modeling and simulation is an approach to modeling systems of interacting agents [13]. This approach has been used by mathematicians to simulate several different crimes and social behaviors [5]. Agent-based models are useful because they allow for complicated dynamics to discover any behaviors and patterns. In agent-based modeling, agents make decisions based on a set of rules. The model uses simple behavioral rules, so that an agent's behavior will depend on the agent's environment. This modeling approach has been used to show hot spot pattern formation in residential burglaries [3], test policing strategies [16], and gang formation [17].

Mathematical modeling has also been used to simulate gang rivalries [4, 21, 20]. According to a study based on gang violence in Los Angeles, mathematical models may aid in understanding and predicting the region's frequent gang crime and violence. An agent-based approach is utilized to understand the behavior and movement of gang members [4]. Another approach for gang rivalries uses agent-based modeling to model the long term gang rivalry structure and gang member mobility, incorporating simple behavioral rules and geographical factors [21]. The agents will move according to their gang location and interact with agents associated with other gangs. Another model uses a system of differential equations to examine the territorial nature of gangs and their behavior geographically [12]. Self-exciting point processes have been used to model the retaliatory nature of violence among gangs [20].

2.3 Short et al. Model for Residential Burglaries

Our proposed model builds on the framework created by Short et al. [3]. Their model simulates residential burglaries through an agent-based approach, which incorporates previous burglaries to nearby locations into an agent's decision making. A burglar's perception of attractiveness of a home and the location of the home dictate the burglar's movement patterns and decision of whether to burgle. Additionally, the Short et al. model incorporates the 'broken window effect,' a phenomenon where a state of disorder encourages more disorder. In terms of residential burglaries, if a house is burgled, houses within a short distance of it have an increased likelihood of being burgled within two weeks [19]. The model has several parameters, which are listed in Table 1.

Parameter Name	Meaning
l	Grid spacing
δ_t	Time step
ω	Decay rate of attractiveness
η	Measures neighborhood effects
θ	Increase in attractiveness due to one burglary event
A_s^0	Intrinsic attractiveness of site s
Γ	Rate of burglar generation

Table 1: Short et al. Model Parameters and their Meanings [3].

The burglars perceive the attractiveness of a site s (voxel location on a grid) based on an intrinsic value, A_s^0. This gives a baseline level for the attractiveness of site s. Additionally, burglars' interest in a region will increase if previous burglaries were successful at a given location. The component $B_s(t)$ provides this increase in attractiveness for this region, demonstrating the phenomenon of repeat and near repeat victimization. The final attractiveness for the site s adds these terms to obtain

$$A_s(t) = A_s^0 + B_s(t). \tag{1}$$

The B_s is updated at each time step by events in the current time step by

$$B_s(t+\delta_t) = \left[B_s(t) + \frac{\eta l^2}{z}\Delta B_s(t)\right](1-\omega\delta_t) + \theta E_s(t), \tag{2}$$

where $\Delta B_s(t)$ is the discrete Laplacian of $B_s(t)$, given by

$$\Delta B_s(t) = \frac{1}{l^2}\left(\sum_{r\sim s} B_r(t) - zB_s(t)\right). \tag{3}$$

The summation $\sum\limits_{r\sim s} B_r(t)$ adds the value of B at the locations r adjacent to s. The parameter z indicates the number of adjacent locations to site s.

In Equations 2, $E_s(t)$ represents the total number of successful events completed at site s on the interval $[t, t+\delta_t)$. The parameter θ determines the amount of increase in attractiveness due to a prior event. Since previous events do not elevate the attractiveness of a site indefinitely, a decay factor ω allows for the dynamic attractiveness term to decrease in the absence of new events. The parameter η indicates how much the neighborhood is affected by an event. Larger values of η result in a larger influence of an event to surrounding sites. This is better seen with a simplification of Equation 2,

$$B_s(t+\delta_t) \;=\; \left[(1-\eta)B_s(t) + \frac{\eta}{z}\sum_{r\sim s} B_r(t)\right](1-\omega\delta_t) + \theta E_s(t). \tag{4}$$

The η gives a balance between the $B_s(t)$ at the current site and the average of the $B_r(t)$ at neighboring sites.

The probability of a burglary at site s on the interval $[t, t+\delta_t)$ is

$$p_s(t) = 1 - e^{-A_s(t)\delta_t}. \tag{5}$$

If a home is burglarized, the criminal agent is removed from the simulation. This represents the criminal either returning home after a successful score, leaving the scene to avoid arrest, or being caught. If the home was not burglarized, then the criminal will move to a new location. The decision of where to move depends on the attractiveness of the surrounding locations. The probability of moving to the neighboring site n from site s is given by

$$q_{s\to n}(t) = \frac{A_n(t)}{\sum\limits_{s'\sim s} A_{s'}(t)}. \tag{6}$$

The denominator denotes the sum of attractiveness of the neighboring sites, making the probability depend on the relative attractiveness for each site. We include all of these features into our model, but we allow for non-stationary victims.

3 Methodology

We modify the Short et al. model to simulate sexually violent events [3]. Though residential houses are stationary, our model considers victims who are non-stationary. We consider three components: the location of the sexually violent event, the victim involved in the event, and the offender who intends to commit the sexual offense. To consider these components we introduce the following quantities: A_s^{victim} and $A_s^{offender}$ to represent the victims' and offenders' attractiveness to site s, respectively, and B_s^{victim} and $B_s^{offender}$ to represent the dynamic attractiveness of site s that depends on previous events at s and its neighbors.

For our model we focus on three victim behaviors: those who make 'risky' life choices (RLV), those who were just in the wrong place at the wrong time (WPWT), and victims who are better educated on the locations of previous events, avoiding risky locations (ILV). If a victim and offender meet, the offender will decide to assault or not assault, depending on victim conditions. If no assault occurred, the agents will move to new locations.

3.1 Initialization

We initialize a grid consisting of randomly placed victims and offenders. The intrinsic attractiveness of site s for offenders is represented by $A_s^{offender}(0)$. This is initialized to be the same value throughout the grid. For the victims, $A_s^{victim}(0)$ represents the intrinsic attractiveness of site s. There is a baseline level for the whole grid, $A_{baseline}^0$. Additionally, the victims will have a higher intrinsic value for locations where the homeless population tend to gravitate towards. These locations can be homeless shelters or a place where they are not forced to leave. The attraction for sites with homeless shelters will increase to a high rate of $A_{increase}^0$.

3.2 Characteristics of the Homeless Population

We add characteristics to the victims based on the odds of an offender encountering a victim. We consider the victim's housing status, α_1. The homeless population, more specifically homeless women, have a higher risk of sexual and physical assault [11]. The housing status of the victim does matter: long-term homeless, short term homeless, or marginally housed [11]. A marginally housed person lives in a low-budget hotel. Marginally housed people are least likely of the housing statuses to be victimized since they have some type of secure shelter. We also consider if the victim has taken any illegal substances or consumed any alcohol, α_2. Intoxicated Victims may not be capable of making reasonable decisions and judgments while under the influence [2]. When a person is intoxicated, that individual may fail to perceive risky situations and therefore may delay the defense response and increase the likelihood for assault [2]. We also consider the mental health of the victim, α_3. The victim's mental health may determine whether or not the victim is capable of making good judgments and decisions based on the individual's own mental state [15]. The odds ratio values used for our model are represented in Table 2, coming from the source [11]. The lower the number, the lower the odds are for sexual victimization.

Victim Conditions		Odds Ratio Value
Housing Status, α_1	Long-Term Homeless	3.8
	Short-Term Homeless	3.2
	Marginally Housed	1
Substance Abuse, α_2	Not Intoxicated	1
	Intoxicated	1.8
Health, α_3	Fair	1
	Poor	1.3

Table 2: Victim Conditions and their Corresponding Odds Ratio Value [11].

We modify Equation 5 to include the odds ratio value from Table 2, giving the new probability of an event,

$$p_s(t) = \left(1 - e^{-A_s(t)\delta_t}\right) \cdot \frac{\alpha_1\ \alpha_2\ \alpha_3}{(3.8)(1.8)(1.3)}. \tag{7}$$

Thus, victim agents with larger odds ratios will have a higher probability of being victimized. The division by (3.8)(1.8)(1.3) ensures the probability is at most one.

During the simulation, each victim agent is randomly assigned victim conditions, with the proportion of victims in each category taken from the source [11]. This allows for different agents to have different conditions during a simulation.

3.3 Movement Rules

After a victim and offender encounter one another, it is determined whether or not the offender decides to commit an offense. If the offender does not offend, both the victim and the offender move. We determine this movement by Equation 6 from the Short et al. model. This gives the probability of moving from site s to site n for offenders as

$$q_{s\to n}^{offender}(t) = \frac{A_n^{offender}(t)}{\sum\limits_{r\sim s} A_r^{offender}(t)}, \tag{8}$$

and for victims as

$$q_{s\to n}^{victim}(t) = \frac{A_n^{victim}(t)}{\sum\limits_{r\sim s} A_r^{victim}(t)}. \tag{9}$$

The victim and offender are moved randomly throughout the grid, and the attractiveness is updated for both the victims and offenders.

Agents are not allowed to move off the grid, giving no-flux boundary conditions. If they are at a location on the boundary, they can only move to adjacent locations either on the boundary or the interior of the grid. The value of z depends on the number of adjacent locations to site s. If the site is on the interior of the grid, then $z = 4$. If it is at a corner on the boundary, $z = 2$. If it is on the boundary and not at a corner, then $z = 3$.

3.4 Update in Attractiveness for Offenders

We update the level of attractiveness for the offenders similar to that of Short et al. In particular,

$$A_s^{offender}(t) = A_s^{offender}(0) + B_s^{offender}(t),$$

where the term $A_s^{offender}(0)$ is equivalent to A_s^0 from the Short et al. model. The level of attractiveness of the site may rise for offenders due to success of sexually violent events at that site or nearby sites. Therefore, the $B_s^{offender}(t)$ dynamic attractiveness is updated the same as the burglars in the Short et al. model,

$$B_s^{offender}(t+\delta t) = \left[B_s^{offender}(t) + \frac{\eta}{z}\Delta B_s^{offender}(t)\right](1-\omega\delta_t) + \theta E_s(t),$$

where we have taken the grid spacing to be $l = 1$.

3.5 Update in Attractiveness for Victims

The attractiveness for a site s for victims will depend on the lifestyle choice for each victim. Victims are attracted to homeless shelters and other locations, which are represented in the intrinsic attractiveness of a site, $A_s^{victim}(0)$.

Case 1: Risky Lifestyle Victims (RLV)

Victims behave similar to offenders by being attracted to risky locations. Thus, B_s will be the same for both victims and offenders, giving

$$B_s^{victim}(t+\delta t) = \left[B_s^{victim}(t) + \frac{\eta}{z}\Delta B_s^{victim}(t) \right](1-\omega\delta_t) + \theta E_s(t),$$

and

$$A_s^{victim}(t) = A_s^{victim}(0) + B_s^{victim}(t).$$

Case 2: Wrong Place Wrong Time Victims (WPWT)

Victims are not biased towards any location other than shelters, giving

$$A_s^{victim}(t) = A_s^{victim}(0).$$

We consider this to be appropriate for the WPWT victims because the baseline attraction of locations will be constant, eliminating bias towards a specific location that is not a shelter. These victims can either be passing through a dangerous area without a choice in route to their destination or may be uneducated in the previous events of the location.

Case 3: Informative Lifestyle Victims (ILV)

Informative lifestyle victims adjust their movement due to knowledge of previous events. Therefore,

$$B_s^{victim}(t+\delta t) = \left[B_s^{victim}(t) + \frac{\eta}{z}\Delta B_s^{victim}(t) \right](1-\omega\delta t) - \theta_{victim} E_s(t).$$

We decrease B_s^{victim} at locations of prior events because these victims are more educated and aware of 'risky' locations. The number of sexually violent events of site s will decrease the attractiveness for these individuals, giving

$$A_s^{victim}(t) = \max\left(A_s^{victim}(0) + B_s^{victim}(t), 0 \right).$$

The maximization is to prevent the attractiveness from being negative. If $A_s(t) < 0$, then $p_s(t) < 0$ in Equation 7, giving a negative probability.

3.6 Adding New Victims and Offenders

After updating the attractiveness for all sites, we add new victims and offenders. The rates of victim and offender generation are Γ_{victim} and $\Gamma_{offender}$, respectively. For each location on the grid, a random number $u \sim U([0,1])$ is sampled. If $u \leq \Gamma$, then an agent is added to that location.

After the victim and offender agents are added to the grid, a cycle of the simulation is complete. The full simulation will repeat each cycle until the desired number of iterations have been completed.

4 Results

For each of the victim behaviors we use values that will produce tangible results. Table 3 displays the values used for each of the victim behavior cases.

	Meaning	Parameter Value
δt	Time step	0.01
ω	Decay of attractiveness	0.05
η	Measures neighborhood effects	0.7
θ_{victim}	Decrease in attractiveness due to one event (ILV)	0.01
θ	Increase in attractiveness due to one event	10
$A_s^{offender}(0)$	Offender Intrinsic attractiveness	0.01
Γ_{victim}	Rate of victim generation of site s	0.001
$\Gamma_{offender}$	Rate of offender generation of site s	0.0001
$A^0_{baseline}$	Victim baseline attractiveness	0.125
$A^0_{increase}$	Victim attractiveness increase for shelters	60

Table 3: Table of Parameter Values. θ_{victim} is only used for Informative Lifestyle Victims.

In order to test the modeling assumptions, we compare the simulation results to the crime data from San Francisco, CA. We first give the initialization for the simulations and then provide metric comparisons for the different victim behaviors.

4.1 Application to San Francisco

We gathered data on the locations of shelters for the homelessness communities in San Francisco. These coordinates will be used for the initialization of the $A_s^{victim}(0)$ grid for the San Francisco simulations. We created a kernel density estimate (heat map) of reported sexual violence from the years 2010–2014 in San Francisco to compare with the model simulations. We note that the locations for the homeless shelters (obtained in 2015) and the sexual violence crimes are concentrated in Downtown San Francisco. These plots are provided in Figure 1.

Other attractive locations could also be chosen for the homeless community. In particular, public spaces, encampments, inexpensive motels, and areas that allow for overnight car or RV parking. Since we do not have this data, we keep our attractive locations to be the homeless shelters.

4.2 Model Simulation Results

For each of the victim behaviors, simulations were run for 1,826 days, or 5 years. This is to match the length of time for the data for the five year period from San Francisco. At the end of the simulation, the $B_s^{offender}$ grid gives the overall indication of the amount and location of violence. For each of the behaviors, Figure 2 shows the final $B_s^{offender}$ grid.

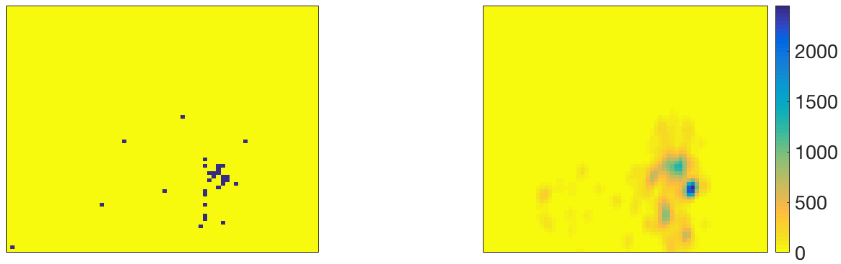
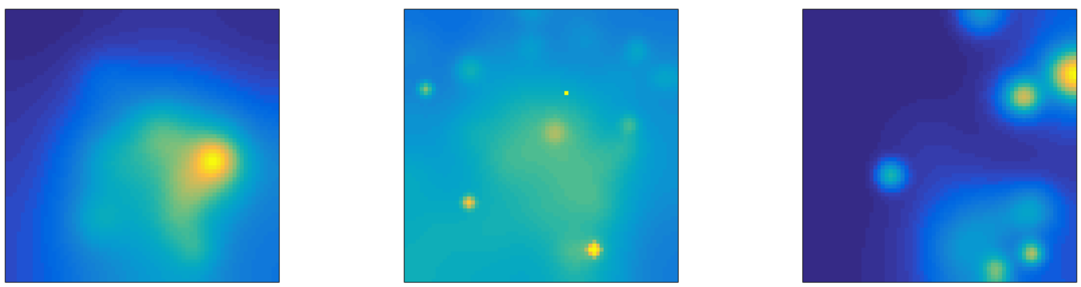


Figure 1: (Left) The $A_s^{victim}(0)$ grid based on the locations of homeless shelters in San Francisco in 2015. (Right) The kernel density estimate of the reported sexual assault cases in San Francisco from 2010–2014.



(a) RLV (b) WPWT (c) ILV

Figure 2: $B_s^{offender}$ grid from the model simulations with victim behaviors: (a) Risky Lifestyle Victims (RLV), (b) Wrong Place Wrong Time Victims (WPWT), and (c) Informative Lifestyle Victims (ILV). Lighter colors indicate regions with more crime.

4.2.1 Risky Lifestyle Victims (RLV)

The attraction for risky locations for risky lifestyle victims is similar to the offenders. For the simulations for this behavior (refer to Figure 2), there are hot spots in the graph that match the shape of the $A_s^{victim}(0)$ grid (refer to Figure 1). Here, we see that the greater crime hot spots are concentrated where the homeless shelters are located.

4.2.2 Wrong Place, Wrong Time Victims (WPWT)

The wrong place, wrong time victims have random movement with no bias in direction other than to homeless shelters. However, the offenders are biased toward the locations where there have been successful crimes. For this case, the simulation gives a few small hot spots, but a large dispersion of crime. The majority of the crime from the simulation is centered where most of the actual crime was reported.

4.2.3 Informative Lifestyle Victims (ILV)

The informative lifestyle victims move opposite from the victims with risky behavior. These victims avoid risky locations, showing more events in regions away from downtown San Francisco (refer to Figure 2). Many events have been displaced to areas adjacent to the shelters. We note that this case has the fewest number of events from all the other cases.

4.3 Comparison Between Data and Model Simulations

To quantify the differences between the model simulations and the data, we use the Kullback-Leibler divergence method [7]. The optimal value of zero would indicate the simulation and the kernel density estimate were identical. Since the simulations vary for each run, we performed 100 runs of each simulation with the varying behaviors. We include the average and standard deviation of the Kullback-Leibler divergence in Table 4.

Victim Movement Behavior	Average KLD	Standard Deviation
Risky Lifestyle	1.96	0.053
Wrong Place, Wrong Time	1.93	0.052
Informative Lifestyle	2.69	0.42

Table 4: Kullback-Leibler Divergence (KLD) Comparison between the Data and Model for the various behaviors. Each method was run 100 times, and the average and standard deviation for the runs are included here.

Based on the metric comparison values (Table 4), the Wrong Place, Wrong Time Victims have the lowest value from all other cases and the Informative Lifestyle Victims have the highest value. The Risky Lifestyle Victims have a value very close to the WPWT victims. This is likely due to both types of victims being attracted to the locations of the shelters and not being repulsed by previous events.

A smaller value indicates the simulation is a closer match to the data. According to the values in Table 4, the Wrong Place, Wrong Time simulations are the ones most closely related to Figure 1 and the Informative Lifestyle Victim simulations are the least closely related. Theoretically, this makes sense since the ILV victims stay away from the locations where there are high crime levels. If no victim agents are present, then the offenders would not be able to commit crimes.

5 Discussion

By varying the attractiveness for the victims, the simulations produce results as expected for the different victim behaviors. One benefit of using agent-based models is the flexibility in testing changing environments. Using the results obtained above, we can use this as a baseline for seeing how crime would change if certain parameters were increased. One particular parameter, Γ_{victim}, gives the rate at which victims are added into the model. For our simulations, this means new homeless individuals are being added as potential victims. This scenario is particularly relevant due to the lack of affordable housing.

The major causes of homelessness are lack of low cost housing, high poverty rates, poor economic conditions and few facilities that care for mental health [8]. The inability to afford housing and other necessities increases the chance of becoming homeless or living in poverty [8]. The cost of rent in the 1970s was on average 108 US dollars a month and rose to 315 US dollars by the 1980s, a 192 percent increase [8]. Currently, the average cost of renting is approximately 1,700 US dollars. This is a drastic increase of housing cost in the span of 50 years and continues to increase. San Francisco has one of the most expensive housing and cost of living rates in the world. It is currently ranked number one in the United States as the most expensive city to live. A study from Zillow estimated an average of 60% of the income goes to rent in San Francisco, compared to 28% nationally [22]. Since January 2017, the unsheltered population is approximately 58 percent of the homeless population [18].

To see if there would be more crime, we increase the victim generation. We will leave the offender generation fixed at $\Gamma_{offender} = 0.0001$, indicating that despite the increase in potential victims, the number of offenders will remain unchanged. We vary Γ_{victim} to test whether significant increases in the number of victims will lead to great amounts of sexual violence events. Due to the stochastic nature of the model, we run each model 20 times for a particular value of Γ_{victim} ranging from 0.0005 to 0.01, a 20 fold increase. From each run, the sum of the $B_s^{offender}$ grid will indicate the amount of crime at the end of the simulation. Larger values are indicative of more crime. These values are displayed in Figure 3.

According to Figure 3, when increasing the number of victims in the simulation, RLV and WPWT had only a slight in crime. However, the informative lifestyle victims had a dramatic increase in crime. By increasing the victim generation rate 10-fold from 0.0005 to 0.005, the crime increased more than 100-fold. Victim generation level increases above approximately 0.005 did not result in more crime for any of the victim behaviors. This suggests an upper limit for the amount of crime given a set offender generation rate. This is likely due to having enough victims in the simulation that an offender does not have to travel far to offend and be removed from the grid.

6 Conclusion

Though the Short et al. model produced tangible results for stationary victims, such as residential burglaries, it is not applicable for crimes with non-stationary victims, such as sexual violence. We built on the Short et al. model by creating a framework that allows for non-stationary victims. We applied our model to the homeless community, where individuals are free to roam about the region, but often have locations they frequent, such as homeless shelters. We incorporated different characteristics for the victims, such as housing status, substance abuse, and mental health. We further allowed for victims to have different behaviors, such as having a risky lifestyle or an informed lifestyle. We

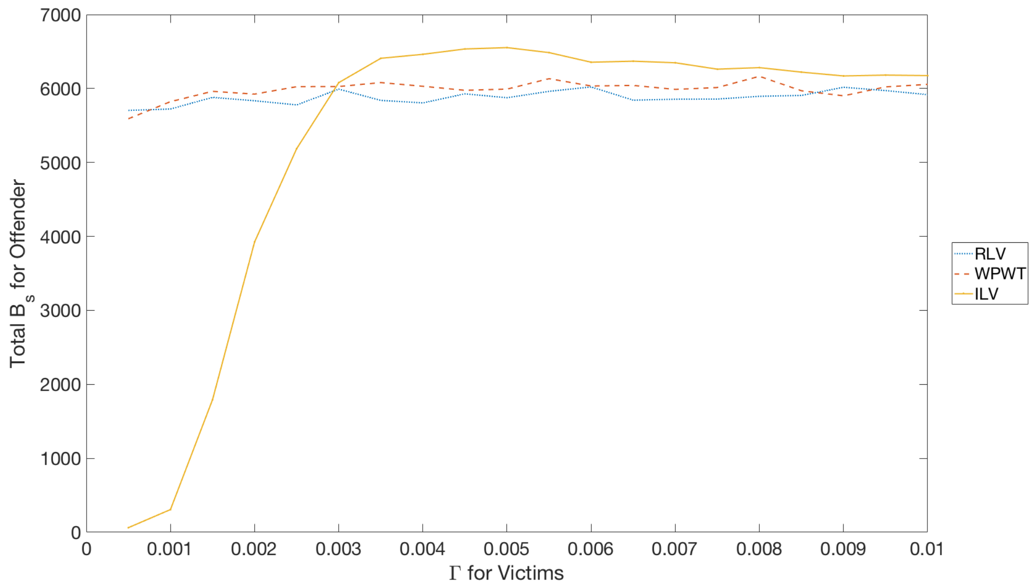


Figure 3: Varying Γ_{victim} for all Victim cases. The vertical axis gives the average of the $B_s^{offender}$ grid sum, giving an overall indication about the amount of crime at the end of the simulation. The curve for the ILV victims is fairly close to zero.

also consider the case where the victim is in the wrong place at the wrong time. These behaviors were seen in the final results of the simulations, showing that there were more concentrated events in hot spots for the risky lifestyle victims and more spread out events for the wrong place at the wrong time victims. Additionally, the informed lifestyle victims had crimes displaced to areas adjacent to homeless shelters, but fewer events overall. These simulations indicate the model produces reasonable results for the assumptions made about victim and offender behavior.

Of the three victim behaviors, the WPWT lifestyle generated the most crime, while the ILV lifestyle generated the least for lower values of Γ_{victim}. This suggests that social workers or police could help to reduce sexual violence by informing the homeless community about locations of previous events.

To compare the final results to real world data, we use the sexual violence data from San Francisco, CA. The two types of victim behaviors that were the closest match to the data were the risky lifestyles and the wrong place at the wrong time. We note that the data from San Francisco consisted of all sexual violence events, regardless of whether the victim was homeless or not. If available, data on sexual violence within the homeless community would be a better comparison for results. However, if reported these events are a subset of the entire data set used for evaluation of the model.

Given this framework, we can test different changes to the environment. One relevant factor is the increase in homeless individuals. With the lack of affordable housing, the homelessness community has grown in recent years. With our model, we tested the impact of an increasing population on sexual violence crimes. Initial increases in the victim generation rate substantially increase the overall amount of crime only for the informative lifestyle victims. However, after a certain level, increasing the number of victims does not increase the crime rates for all victim types. We note that since sexual violence is an opportunistic crime, having more victims present could possibly increase the number of offenders. However, the rate of increase is unclear. More information is needed to identify this relationship.

Overall, this model provides a framework for crimes with non-stationary victims and gives a method for understanding the patterns of sexual victimization in urban areas. Further extensions of the model could include applications to other non-stationary crimes, such as burglary from motor vehicles or robbery.

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