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Power of Criminal Attractors: Modeling the Pull of Activity Nodes

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Abstract

The spatial distribution of crime has been a long-standing interest in the field of criminology. Research in this area has shown that activity nodes and travel paths are key components that help to define patterns of offending. Little research, however, has considered the influence of activity nodes on the spatial distribution of crimes in crime neutral areas - those where crimes are more haphazardly dispersed. Further, a review of the literature has revealed a lack of research in determining the relative strength of attraction that different types of activity nodes possess based on characteristics of criminal events in their immediate surrounds. In this paper we use offenders' home locations and the locations of their crimes to define directional and distance parameters. Using these parameters we apply mathematical structures to define rules by which different models may behave to investigate the influence of activity nodes on the spatial distribution of crimes in crime neutral areas. The findings suggest an increasing likelihood of crime as a function of geometric angle and distance from an offender's home location to the site of the criminal event. Implications of the results are discussed.

Keywords: Crime Attractor, Directionality of Crime, Mathematical Modeling, Computational Criminology

Introduction

1.1 Investigating the spatial distribution of crime across geographic areas has been a long-standing interest of scholars, sociologists, and criminologists over the past two centuries (Burgess 1925). More recently, criminologists have advanced our knowledge in this area by demonstrating that crime is not randomly distributed, rather it exhibits clear spatial patterns. Specifically, the geometric theory of crime informs us that activity nodes and travel paths are key components that help to define such patterns (Brantingham and Brantingham 1981). Nodes and paths shape the activity and awareness spaces of individuals which contribute to the target selection behaviour of potential offenders and ultimately determine where crimes may occur. With this research, the role of activity nodes (in this case suburban regional shopping centres) on criminal activity is investigated.

1.2 The concentration of crime at place has been well established in criminological literature. For example, a sizable body of research has shown that crimes tend to cluster at certain geographic locations (see for example, Sherman et al. (1989)). Crime generators and crime attractors (Brantingham and Brantingham 1995) are two types of areas where crimes tend to concentrate. Crime generators draw masses of people who without any predetermined criminal motivation stumble upon an opportunity too good to pass up. Crime attractors lure motivated offenders because of known criminal opportunities. Only a relatively small amount of research, however, has considered the influence of activity nodes on the spatial patterning of crime neutral areas (Brantingham and Brantingham 1995) - those where crimes are more sporadically distributed with few clusters or concentrations. Despite the seemingly haphazard spread of crimes in these areas, the tenets of Crime Pattern Theory suggest that an underlying pattern should be present. Since the target selection behaviours of criminals are influenced by their awareness spaces which are largely defined by nodes and paths in their daily travel routines, it is expected that crimes will be committed along the routes between offenders' homes and activity node locations (Brantingham and Brantingham 1993). In order to understand the attraction of activity nodes and uncover the systematic distribution of crimes in the crime neutral areas around them, a mathematical structure is needed to model components that contribute to patterns of crime.

Patterns of Human Activity

2.1 Many factors influence how an individual navigates in an urban area, including their personal mobility, transportation options, and the physical form of the city. Geographic theories are used to describe the patterns of activity of urban residents including those from behaviourial geography which examines, at its core, the connections between spatial decision-making, human cognition, and human movements in the environment (see Argent and Walmsley (2009) and Golledge et al. (2001)). Lynch's seminal work (1960), *The Image of the City*, was one of the first to examine an individual's perception of space as applied to navigation through urban areas. The author argued that individuals understand and therefore navigate through their surroundings in predictable ways. They do this by using 'mental maps' with five basic elements: paths (roads, transit lines), edges (walls, boundaries, shorelines), districts (defined areas, neighbourhoods), nodes (urban focal points such as railway stations, intersections, or plazas), and landmarks (physical structure unique in its environs). A person maneuvering their way through an urban area utilizes their knowledge of these spatial elements in order to successfully carry out all of their daily activities such as shopping, recreation, or the daily commute back and forth from work.

2.2 Individuals interact with their surrounding environments in predictable ways. *Activity space* is a key concept in human-environment interaction studies, defined as the set of locations that an individual has direct contact with as a result of the execution of their daily activities (Golledge and Stimson 1997). Core geographic principles are at the heart of the activity space idea, including distance decay, referring to the decreasing likelihood of interaction as a function of distance, and directional bias, an agent's predisposition to move in a particular direction at the expense of other directions (Rai et al. 2007). These concepts help to describe the differential likelihood of people interacting with other individuals or environments. The characteristics (size, shape) of a person's activity space are likely to be determined by home residence location (urban, suburban, rural), socio-economic status (SES) (Morency et al. 2009), age and gender (see Matthews (1980) and Mercado and Pimez (2009)), and personal mobility (Kopec 1995) in addition to many other potential determinants. The activity space concept has been widely applied, owing to its utility and flexibility for modeling the socio-spatial context of diverse urban phenomena. It has been utilized for this purpose in a variety of disciplines including geography, public health, transportation studies, and criminology (see for example, Mason and Korpela (2009)).

2.3 It is likely that a person has knowledge of environments beyond their usual activity space. All places that an individual has some knowledge of constitutes their *awareness space* (Brown et al. 1977). Knowledge of places outside of one's activity space is likely to exist according to the principle of distance decay, wherein a person will have greater awareness of places geographically proximal to their activity space. For an example, see Figure 1.

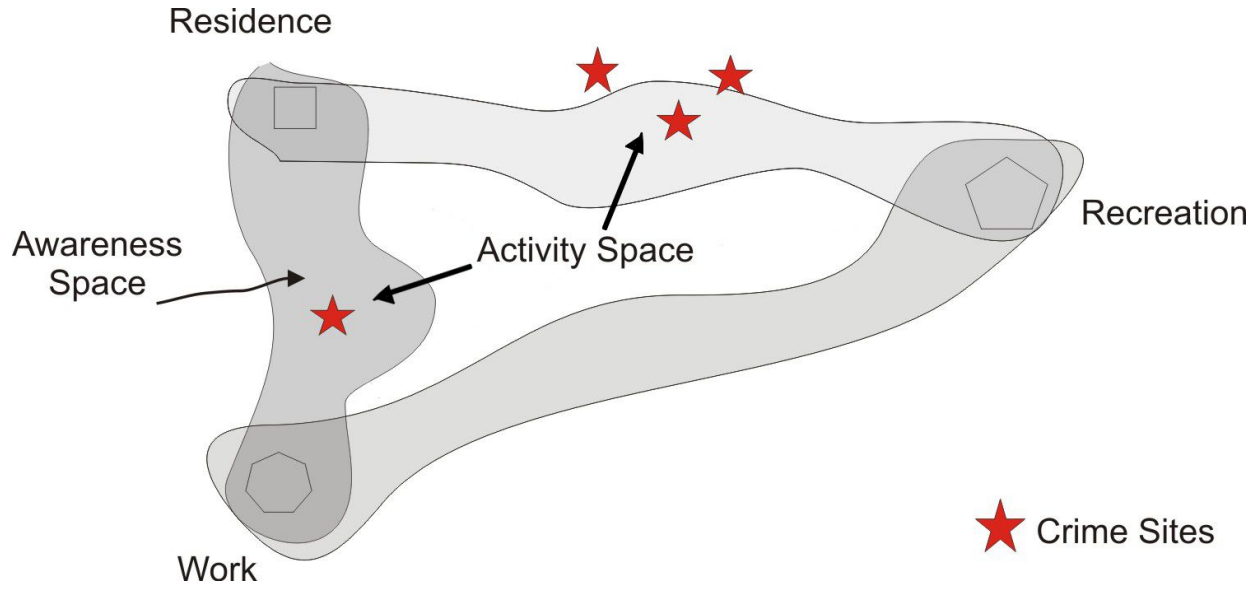


Figure 1: The Awareness and Activity Spaces of Criminals

Patterns of Crime

3.1 The criminological sub-field of environmental criminology uses the concepts discussed above to understand criminal activity in the context of urban environments. The target selection behaviour of offenders is one area of research within this sub-field that has generated considerable interest. A variety of factors including the attractiveness and accessibility of an area, and the opportunities available within an area have been found to influence where offenders commit crimes (Bernasco and Luykx 2003). These patterns even exist for different age-groups (Groff 2005). The theoretical foundation that informs the design of the proposed model is the geometric theory of crime (Brantingham and Brantingham 1981). The central idea divulged from this framework is that crime locations are largely dependent upon where potential offenders reside and what their awareness spaces consist of, and where potential targets are located and whether they are located within an offender's awareness space[3]. In short, while the target selection behaviour of offenders has been shown to be influenced by a variety of factors related to the characteristics of areas, criminal event locations are ultimately bound by the activity and awareness spaces of potential offenders.

3.2 There are several factors that contribute to defining a person's activity and awareness spaces. Nodes and paths are two concepts that are of greatest concern for the purposes of the current discussion. In general, people move from one activity to the next, spending time at several locations throughout the day. Home, work, school, shopping centres, entertainment venues and recreation sites are common activity nodes that consume the majority of our daily lives. Since some activity nodes draw larger masses of people (e.g., shopping centres and sports stadiums), they are said to have a greater pull or attraction. In contrast, some activity nodes draw fewer people (e.g., single family dwellings

and stand-alone commercial properties) and are said to have a reduced pull or attraction. Several criminological studies have demonstrated the pull of specific types of activity nodes based on their concentrations of crime and the spatial-temporal transitions of certain crime types (see Kinney et al. (2008) and Bromley and Nelson (2002)). In Bromley and Nelson (2002), for example, the authors found that hot spots of alcohol related crimes in Worcester exhibited clear spatial-temporal transitions. Pubs and clubs attracted high concentrations of alcohol related crime around midnight but this type of crime shifted after the alcohol outlets closed. In the early morning hours alcohol related crimes concentrated closer to residential areas.

Overview of Journey to Crime Research

3.3 Paths are the spaces used to navigate between activity nodes. Roadways and walkways are two examples of paths that connect us from one place to the next. Since individuals develop routine travel patterns to and from their destinations, paths contribute to the activity and awareness spaces that define an offender's target search area. The importance of travel paths has also been demonstrated in criminological literature (see Bromley and Nelson (2002) and Alston (1994)). In Alston's (1994) study of target selection patterns of serial rapists, for example, initial contact with victims was repeatedly found to be near routine travel paths. Related to the target selection behaviours of potential offenders are components of an offender's journey to crime. Three elements that constitute an offender's journey to crime include a starting location (usually an offender's home location), the direction of travel, and the distance from starting point to crime location (Rengert 2004). To date, journey to crime research has largely been dominated by investigations into the distance factor. Generally, it has been found that most crimes occur short distances from offenders' home locations and follow a distance decay pattern (Wiles and Costello 2000).

3.4 According to literature (Brantingham and Brantingham 1995), crimes can be separated into two general categories, probably should read "those against a specific property, which are usually tied to a location, or those against a person, which are usually not tied to fixed locations. In this paper the focus is on those crimes where the location plays a central role, hence the application of the model is restricted in this paper to only property-crimes.

Extending Journey to Crime to Directionality

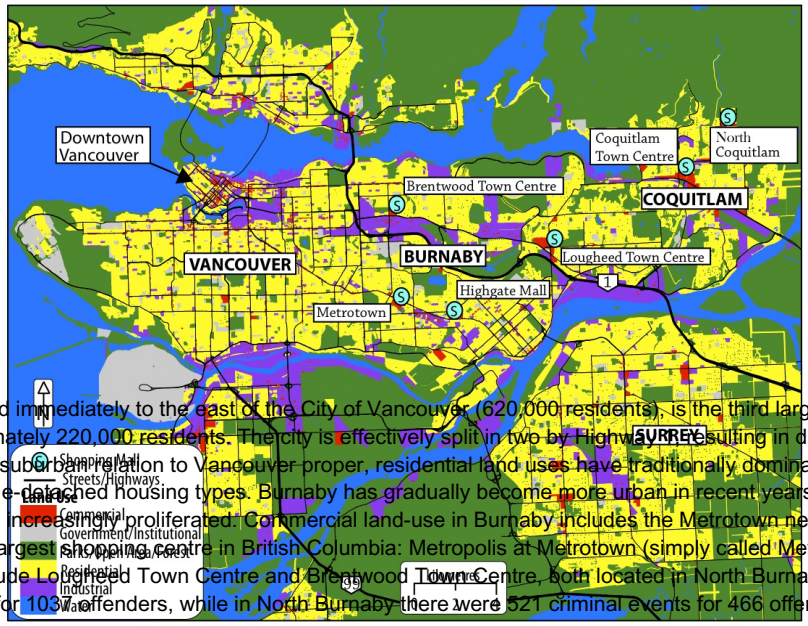
3.5 The directionality component of an offender's journey to crime is largely determined by the configuration of their activity nodes and travel paths. If most of their activities fall along a single trajectory, directionality should be strong. While research on this topic is quite sparse, there is some evidence that suggests activity nodes do influence the directionality of crimes because of their general forces of attraction. In Rengert and Wasilchick (1985) for example, the authors investigated offenders' directional preferences in burglary offences. They found a strong directional preference towards offenders' places of employment. In fact, most of the offences were located just past the offenders' work locations or along the travel paths between home and work. Public transport systems are also influential in the development of offenders' awareness spaces. Transit systems in urban areas transport people across great distances along a limited number of paths and to a limited number of transit hubs. As a result, awareness spaces can become tightly clustered (Brantingham et al. 1991).

3.6 There are still many questions about the influence of activity nodes that remain unanswered. It is unknown, for example, whether the spatial patterning of crimes in crime-neutral areas can be described by the relationship between the directionality of offenders' movements and activity nodes. We are also unaware of any research that has investigated the relative strength of attraction that different types of activity nodes possess based on characteristics of criminal events in their immediate surrounds.

3.7 Mathematical modeling has been applied in several social science research initiatives. Recent applications in the field of criminology have included agent based, cellular automata, process, and system dynamics models (see for example, Brantingham and Tita (2008), Dabbaghian et al. (2010), Li (2008), Alimadad et. al. (2008), Gerritsen (2010) and Malleson and Brantingham (2008)). These types of models focus on the actual movement of agents (offenders), their interaction with the environment, and the development of patterns while assuming an underlying set of rules for the model. The current project differs from these previous approaches by applying mathematical structures to define the actual rules by which the above mentioned models may behave. Using directional and distance parameters defined by offenders' home locations and the locations of their crimes, the influence of activity nodes on the spatial distribution of crimes in crime neutral areas is investigated.

Study Area

4.1 The sites of investigation for this study were Burnaby and Coquitlam; two fast-growing suburban cities in the Metro Vancouver region located in the extreme south-west of British Columbia, Canada. This urban region consists of 22 municipalities with a total population of 2,275,000 (BCStats 2009), see Figure 2.



4.2 The City of Burnaby, located immediately to the east of the City of Vancouver (620,000 residents), is the third largest of the 22 municipalities by population with approximately 220,000 residents. The city is effectively split in two by Highway 1, resulting in distinct north and south areas of the city. Due to its suburban relation to Vancouver proper, residential land uses have traditionally dominated in Burnaby, including a mix of apartments and single-detached housing types. Burnaby has gradually become more urban in recent years however, as industrial and commercial land-uses have increasingly proliferated. Commercial land-use in Burnaby includes the Metrotown neighbourhood in South Burnaby which boasts the largest shopping centre in British Columbia: Metropolis at Metrotown (simply called Metrotown hereafter). Other large shopping centres include Lougheed Town Centre and Brentwood Town Centre, both located in North Burnaby. In South Burnaby there were 1250 criminal events for 1037 offenders, while in North Burnaby there were 521 criminal events for 466 offenders.

4.3 The City of Coquitlam—with a residential population of approximately 125,000—is located to the east of Burnaby in the Metro Vancouver region. Land-use in Coquitlam is primarily single-family residential, as it primarily functions as a bedroom community for Vancouver and surrounding areas. There is some industrial and commercial activity in Coquitlam, less however than in neighbouring Burnaby. The main commercial area in Coquitlam is Coquitlam Town Centre, a centrally-located retail destination that also includes a high-rise residential neighbourhood. Average family income in 2005 was $74,413 for Burnaby and $82,934 for Coquitlam, both below the metropolitan area average of $87,788 (BCStats 2006). In Coquitlam, for this study, there were 20493 criminal offenses for 16920 offenders.

4.4 As a result of collaboration between the Institute of Canadian Urban Research Studies (ICURS) research center at the School of Criminology at SFU and the Royal Canadian Mounted Police (RCMP), five years of real-world crime data was made available for research purposes at ICURS. This data was retrieved from the RCMP's Police Information Retrieval System (PIRS). PIRS contains the type of calls for service for the entire division of RCMP in British Columbia (BC) between August 1, 2001 and August 1, 2006. It records all calls, and contains data about the subjects (people), as well as vehicles and businesses involved in the event and what their involvement was. All property crime and offender home locations for the cities which are analyzed in this paper were extracted from this dataset. For those offenders with a valid home or crime location, the locations were geocoded onto the road-network to get longitudes and latitudes. The home location is kept in its original form as it was reported by the offender to the police at the time of the offense (which could be a friend's house, home or shelter). The crime location was where the crime event actually occurred. The data geocoded at a rate of 90%, which exceeds the minimum standard of 85% identified by Ratcliffe (2004). If any location did not geocode, it was discarded. From the remaining locations, crime vectors were constructed to show which direction the offenders moved when they committed crimes, this is shown in Figures 3, 4 and 5. Although the data contains other types of crimes, and even unfounded calls-for-complaints, only the set of events with a known offender were used.

4.5 For the models proposed in this paper, we assume that malls are the major attractors in the region due to the concentration of stores, restaurants and major transit hubs in their immediate surrounds. We further assume that, due to extensive work and entertainment opportunities, many people in the neighbouring municipalities would define downtown Vancouver as a major activity node in their activity space. Thus, for North Burnaby we have two malls defined as attractors. Brentwood Town Centre is located in the north-west area of the city and Lougheed Town Centre is located in the north-east part of the city. Finally, downtown Vancouver makes up the third attractor for this study area. For South Burnaby, Metrotown (located towards the south-west of the city) and Highgate Mall (located towards the south-east) are defined as two attractors, in addition to downtown Vancouver.

4.6 For Coquitlam we defined Coquitlam Town Centre, the central shopping mall, as an attractor. We also defined Lougheed Town Centre as an attractor for this model because it is located just outside the city limits of Coquitlam. Although Lougheed Town Centre is located in Burnaby, it is immediately on the border of the City of Coquitlam, and for all intents and purposes that area cannot be divided (it is in fact called Burquitlam). For visualization purposes, downtown Vancouver will not be shown on the images as it would skew the images too greatly.

4.7 For visualization purposes, we colour-coded all of the attractors on the images that display the results for each of the models. The summary of colours used to identify each attractor is shown in Table 1.

Table 1: The colours and corresponding names of attractors

Name of Attractor	Colour
Downtown	Blue
Lougheed Town Centre	Red
Brentwood Town Centre	Green
Coquitlam Town Centre	Yellow
Metrotown	Cyan

Highgate Mall	Magenta
North Coquitlam	Black

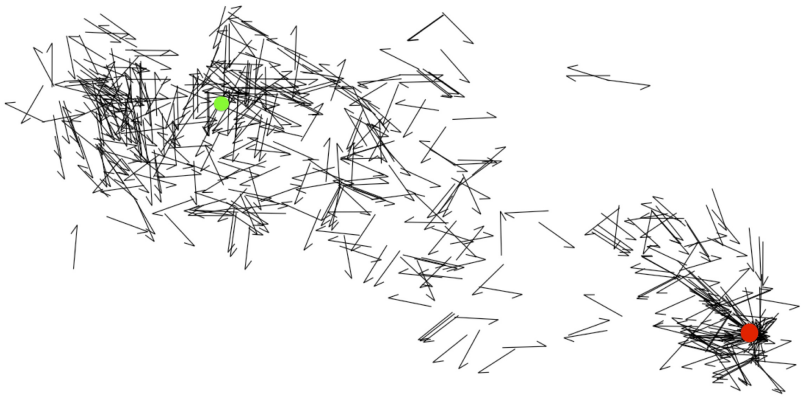


Figure 3: Crime Vectors of North Burnaby

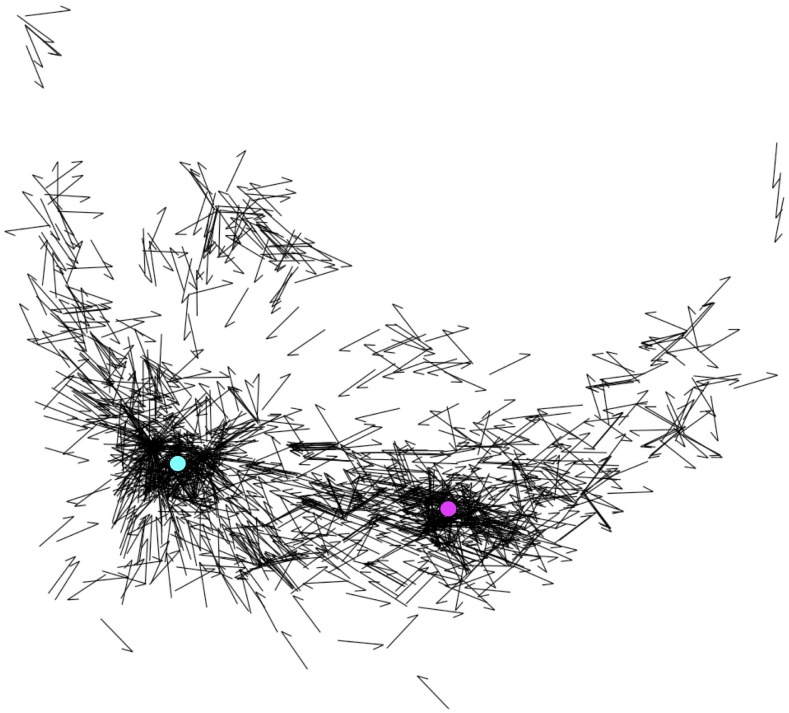


Figure 4: Crime Vectors of South Burnaby

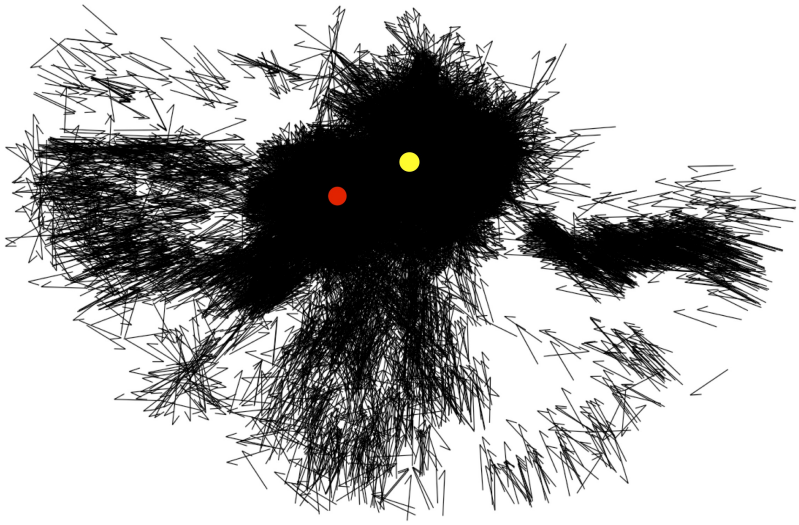


Figure 5: Crime Vectors of Coquitlam

Model 1: Home Location and Distance

5.1 The goal of this paper was to model Crime Locations and the likely Attractor that influenced the spatial location where the crime occurred, with respect to the offender's home. The vector connecting the home and crime locations we refer to as the Crime Vector. There are several types of locations in any given area which act as attractors to offenders (e.g., shopping malls). We would like to see the behaviour of Crime Vectors around these locations.

5.2 In line with research in environmental criminology, our initial model consists of just location and distance, and we incrementally improve our model to include all the aspects which we are interested in. Instead of analyzing the relationship between Home Location and distance, like in van Koppen and de Keijser (2006) , we are interested in what *attracted* the offender to offend at that specific location based on the distance between the Crime Location and Attractor. By considering components of the offenders' journeys to crime, we model the attraction of regional shopping centres in two urban municipalities in British Columbia: Burnaby and Coquitlam.

5.3 Let us first define the components of the model. There are two sets of locations which are important with respect to the offenders' activities. The first is the set of all Crime Locations $C_{i,j}$, denoting offender i 's crime j . There are specific locations, such as shopping malls, that attract offenders to commit crimes. These are known as Criminal Attractors, or simply Attractors, where Attractor n is denoted as A_n . In reality these locations are polygon shapes, but for now we consider them as points, where the point is at the center of the locations. To determine which is the primary Attractor, we calculate the distance $d(C_{i,j}, A_n)$ from Crime Location $C_{i,j}$ to Attractor A_n . Each Attractor n has a Magnitude Of Attraction, denoted M_n , which encompasses the area that A_n attracts; the larger the value of M_n , the stronger the pull to A_n . For the first model, this magnitude of attraction is fixed. The distance $d(C_{i,j}, A_n)$, combined with the Magnitude of Attraction M_n for Attractor A_n , determines which Attractor offender i was moving towards when they committed crime j . This is shown in Figure 6.

5.4 First, in order to mimic the techniques provided by most criminal researchers studying the Journey to Crime, we define the rules by which our model will behave. We then construct the model and apply it to real data. Finally we comment on how well the result describes the real world environment.

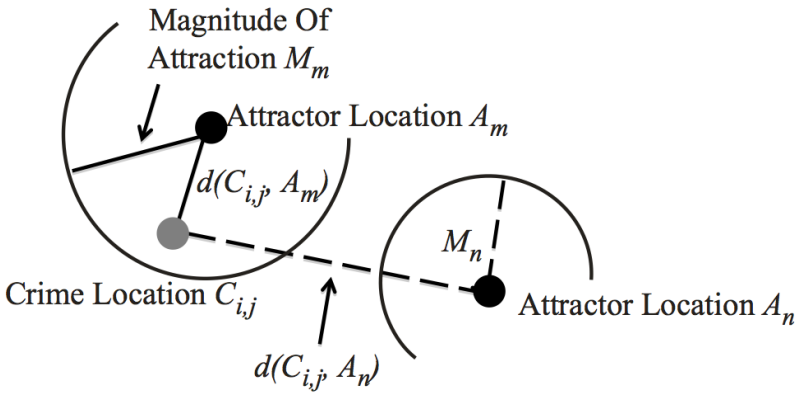
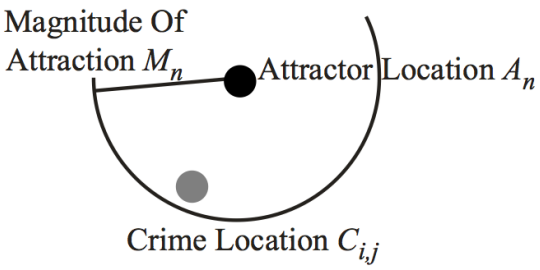


Figure 6: Terminology for Model 1

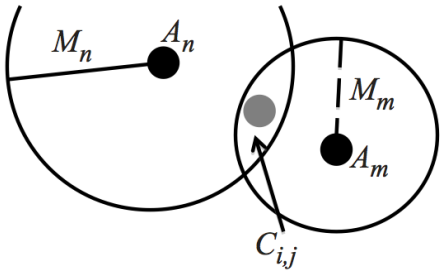
Rules of the Model

5.5 Given a Crime Location $C_{i,j}$ we try to find the Attractor this offender was attracted to. We use distances between Crime Locations and Attractors to determine the Magnitude Of Attraction and to define some rules for finding the Attractor for each crime.

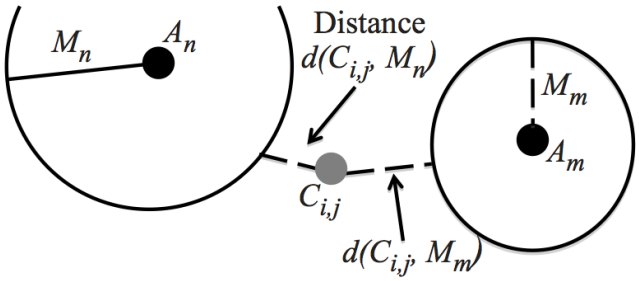
1. Rule 1: If $C_{i,j}$ is inside the Magnitude Of Attraction M_n for a single Attractor A_n , i.e., $M_n > d(C_{i,j}, A_n)$, then the offender is attracted to this Attractor (Figure 7a).
2. Rule 2: If $C_{i,j}$ is inside the intersection area of the Magnitudes Of Attraction for several Attractors in A , i.e., $M_n > d(C_{i,j}, A_n)$ for multiple n , then the offender is attracted to the Attractor with the greatest Magnitude Of Attraction M_n (Figure 7b).
3. Rule 3: If $C_{i,j}$ is outside all the Magnitudes Of Attractions, i.e., $M_n < d(C_{i,j}, A_n)$ for all $A_n \in A$, then the offender is attracted to the Attractor whose Magnitude of Attraction is closest to the Crime Location, i.e. A_n for which $d(C_{i,j}, M_n)$ is minimal. (Figure 7c).



a) Rule 1



b) Rule 2



c) Rule 3

Figure 7: The rules of Model 1

```
Function AssignAttractor(CrimeLocation C_{i,j}, HomeLocation H_i, AttractorLocations A(),
                         AttractorMagnitudes M())
    //Evaluate RULE 1: Calculate the distance to each attractor
    AttractorCandidate= {}
    For each Attractor n in A()
        d(C_{i,j}, A_n) = sqrt((C(x) - A_n(x))^2 + (C(y) - A_n(y))^2)
        if M_n >= d(C_{i,j}, A_n) then
            AttractorCandidate() = AttractorCandidate() + A_n
        //Keep track of the smallest distance
        if d' > d(C_{i,j}, A_n) then
            d' = d(C_{i,j}, A_n)
    if |AttractorCandidate()|= 1 then
        AssignAttractor = AttractorCandidate()
        EXIT FUNCTION
    //Evaluate RULE 2: Calculate the angle to each attractor
    AttractorCandidate() = {}
    For each Attractor n in A()
        ∠(C_{i,j} H_i A_n) = cos^{-1}( H_iC_{i,j} · H_iA_n / (|H_iC_{i,j}| × |H_iA_n|) )
        if θ_n > ∠(C_i H_i A_n) then
            AttractorCandidate() = AttractorCandidate() + A_n
        //keep track of the minimum such angle
        if ∠(CHA)' > ∠(C_{i,j} H_i A_n) then
            ∠(CHA)' = ∠(C_{i,j} H_i A_n)
    if |AttractorCandidate()|= 1 then
        AssignAttractor = AttractorCandidate()
        EXIT FUNCTION
    else //Evaluate RULE 3: Find attractor with minimal directionality
        AttractorCandidate = {}
        For each Attractor n in A()
            if ∠(CHA)' = ∠(C_i H_i A_n) then
                AttractorCandidate() = AttractorCandidate() + A_n
        if |AttractorCandidate()|= 1 then
            AssignAttractor = AttractorCandidate()
            EXIT FUNCTION
        else //Evaluate RULE 4: Find attractor with minimal distance
            AttractorCandidate = {}
            For each Attractor n in A()
                if d' = d(C_{i,j}, A_n) then
                    AttractorCandidate() = AttractorCandidate() + A_n
            AssignAttractor = AttractorCandidate()
```

5.6 The model presented above uses only the distance to each attractor to determine which location is the likely Attractor for the offender. The pseudo-code to calculate this is presented in Figure 8. Note that ' denotes optimality.

Results

5.7 Figures 9 to 11 shows the results of Model 1 applied to our 3 datasets with M_n fixed to 100. The locations of the attractors can clearly be identified by the focal points at which most of the vectors are directed toward. Assigning the Attractors in this fashion simply results in each Crime Vector being associated to the closest Attractor. Although possible in real life, it is probably a bit too naive. The critical component missing is the inclusion of directionality.

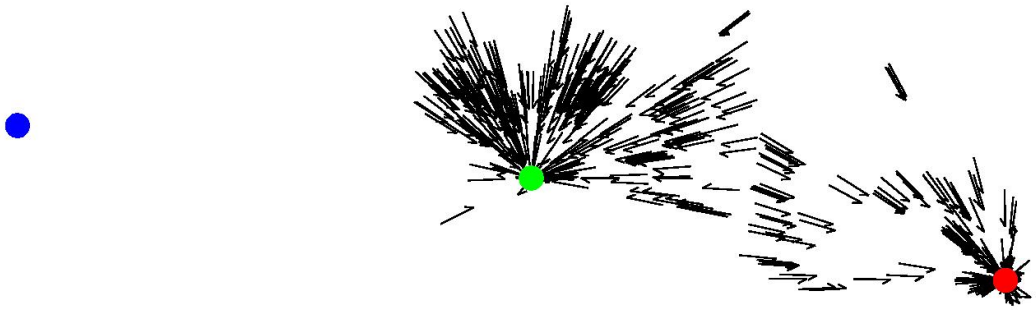
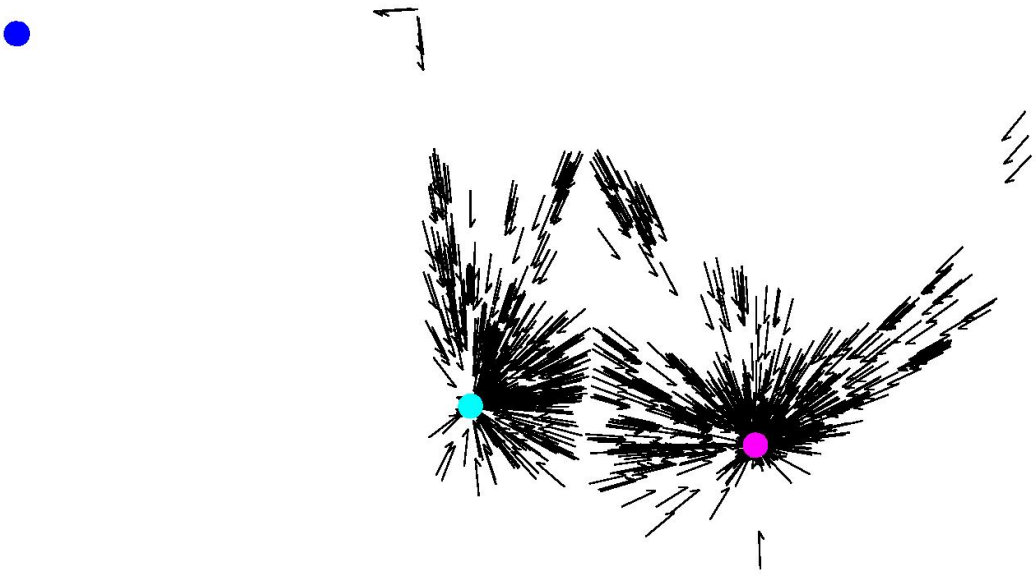


Figure 9: Crime Vectors of North Burnaby according to Model 1



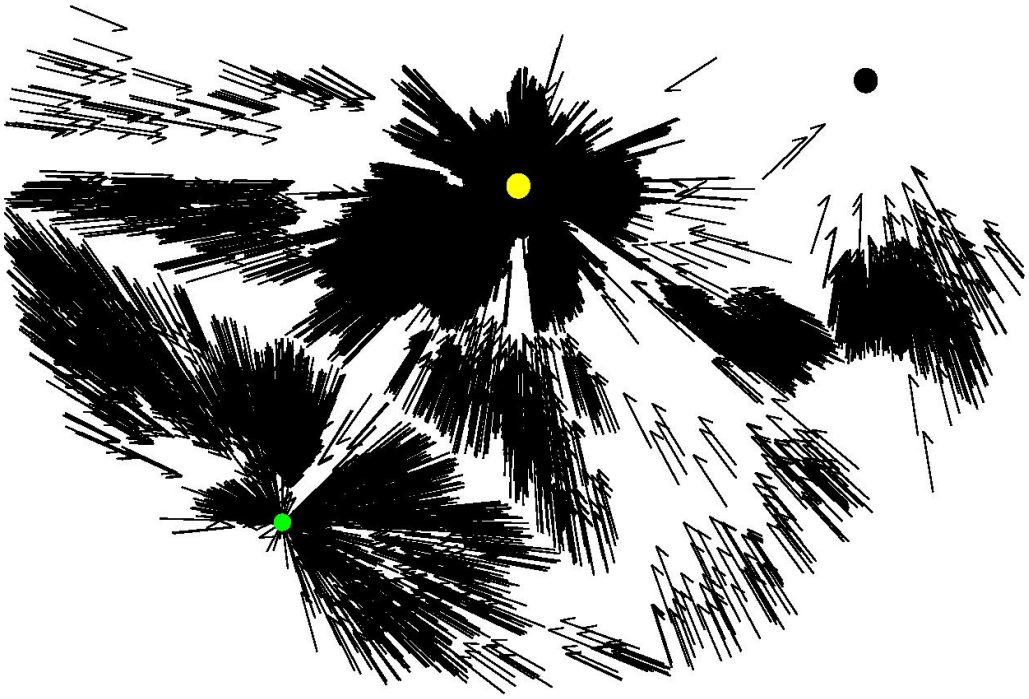


Figure 11: Crime Vectors of Coquitlam according to Model 1

Model 2: The Full Journey to Crime

6.1 This model includes all of the components of the Journey to Crime by incorporating directionality into the previous model. In order to do this, we need to add the Home Location of all offenders, which we denote with H, where offender i resides at H_i. From H_i, two vectors are of importance. First, the Crime Vector, denoted as $\overrightarrow{H_iC_{i,j}}$ is the vector directed from H_i towards $C_{i,j}$ and denotes the direction from an offender's Home to the place they committed the crime. Second, the Attractor Vector $\overrightarrow{H_iA_n}$ is the vector directed from H_i towards A_n and denotes the direction an Attractor is with respect to the Home of the offender. Third, the Tangential Cone is the cone projected from H to the circumference of the Attractor's Magnitude Of Attraction. Thus, the size of the Tangential Cone from H_i to A_n is given by $\theta_{i,n} = \sin^{-1} \frac{M_n}{d(C_{i,j},A_n)}$ and is used to denote the relative directional proximity of H_i to A_n. The larger the Tangential Cone, the closer the directional proximity is H_i with respect to A_n, given a constant M_n. The final component is the Crime Angle $\measuredangle(C_{i,j}H_iA_n)$, which is the angle between $\overrightarrow{H_iC_{i,j}}$ and $\overrightarrow{H_iA_n}$ and is given by

$$\cos^{-1}\left(\frac{\overrightarrow{H_iC_{i,j}} \cdot \overrightarrow{H_iA_n}}{\left|\overrightarrow{H_iC_{i,j}}\right| \times \left|\overrightarrow{H_iA_n}\right|}\right) = \tan^{-1}\frac{H_i(y) - C_{i,j}(y)}{H_i(x) - C_{i,j}(x)} - \tan^{-1}\frac{H_i(y) - A_m(y)}{H_i(x) - A_m(x)}.$$

These are illustrated in Figure 12.

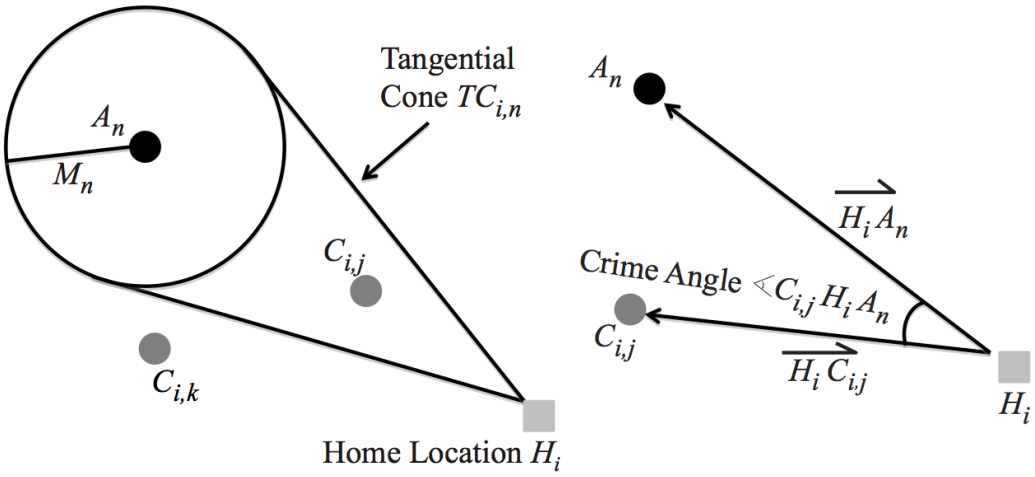
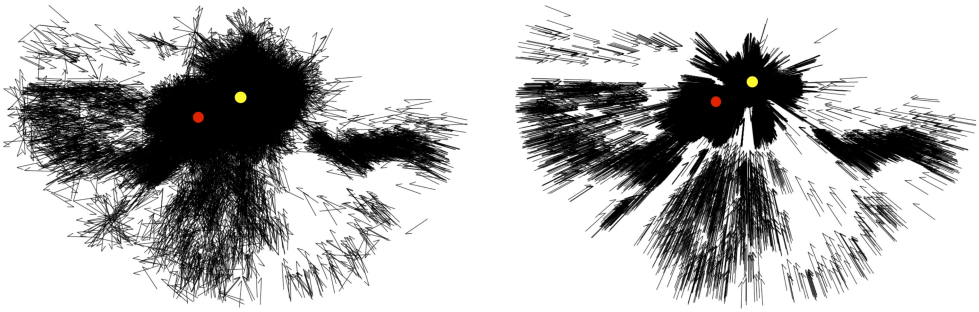


Figure 12: Terminology for Model 2

6.2 We develop an algorithm to model this. This algorithm gives priority to the direction along which the crime occurred rather than the distance between Crime Location and Criminal Attractor.

Rules of the Model

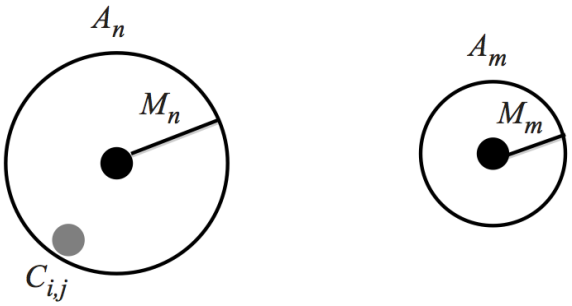
6.3 Rules are needed to determine which crimes are attracted to which Attractors. Thus, we define rules to relate the distances between the Crime Location and Attractor to the Magnitude Of Attraction. We would say an offender is attracted towards a given criminal Attractor if the corresponding crime was committed within close directionality (as opposed to proximity) to the Attractor. That is, if $\measuredangle(C_{i,j}H_iA_n) \leq \beta$, where β is a user specified parameter. As an example, all the crime vectors for the City of Coquitlam are shown in Figure 13a, while the subset of crime vectors where $\measuredangle(C_{i,j}H_iA_n) \leq 5$ are shown in Figure 13b.



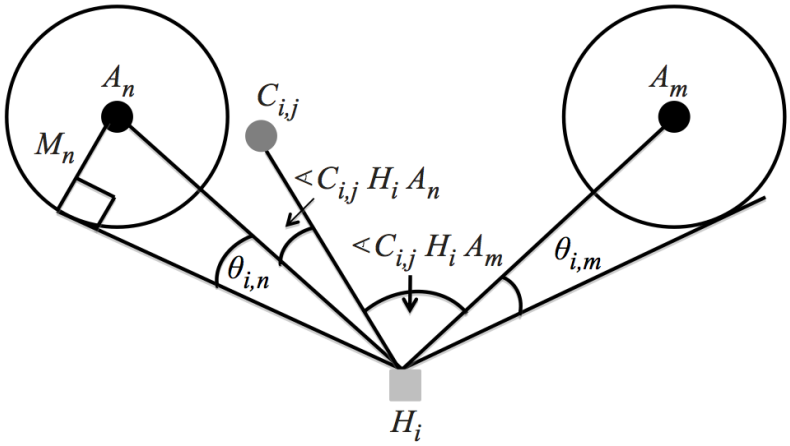
a) Coquitlam crime vectors

b) Coquitlam City Center as criminal attractor

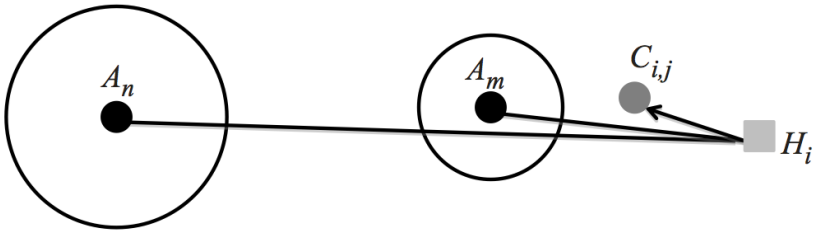
Figure 13: Crime vectors of Coquitlam and the criminal attractor



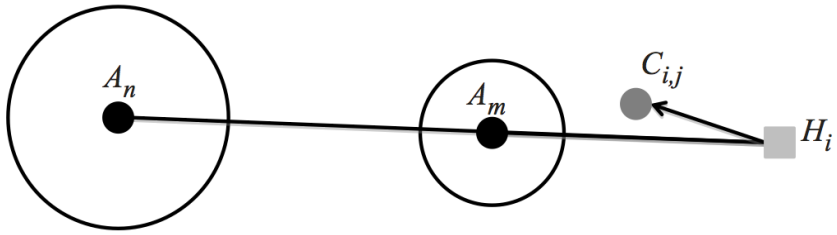
a) Rule 1



b) Rule 2



c) Rule 3



d) Rule 4

Figure 14: The rules of Model 2

6.4 We give the following rules to find the criminal attractor corresponding to a crime vector. It is easy to understand these rules visually so we provide Figure 14.

1. Rule 1: If the Crime Location is inside the Magnitude of Attraction for a single Attractor, i.e., $M_n > d(C_{i,j}, A_n)$ for a single A_n, then the offender is attracted to this Attractor (Figure 14a).
2. Rule 2: If the Crime Vector is outside the Magnitude of Attractions for all A, then the Crime Vector is attracted to the attractor with smallest $|\angle(C_{i,j}H_iA_n) - \theta_{i,n}|$, say A_n. For example in Figure 14b the Crime Vector is closer to the Tangential Cone of Attractor A_n as $\angle(C_{i,j}H_iA_n) < \angle(C_{i,j}H_iA_m)$.
3. Rule 3: If the Crime Vector is inside the Tangential Cones of multiple Attractors in A then we look strictly at the Crime Angle and assign the Crime Vector to the Attractor with minimal $\angle(C_{i,j}H_iA_n)$. For example, in Figure 14c the Crime Vector is inside the Tangential Cones of both Attractors but we observe that $\angle(C_{i,j}H_iA_m) < \angle(C_{i,j}H_iA_n)$, hence the Crime Vector is assigned to A_m.
4. Rule 4: If the Crime Vector is inside the Tangential Cones of multiple Attractors in A and multiple Attractors have the same minimum Crime Angle, then we look at the distance to the attractor and pick the closest Attractor. For example, in Figure 14d the Crime Vector is inside both Tangential Cones and the Crime Angles are same but the Crime Location is closer to the perimeter of A_m hence the Crime Vector is attracted to A_m.

6.5 Although Rules 2 and 3 are similar in meaning, there is a key difference between them. It is possible that a Crime Location is close to a weak Attractor, say A_m, but is not in the Tangential Cone of A_m in which case it would be ignored.

6.6 The pseudo-code for this algorithm is presented in Figure 15. Note that ' denotes optimality.

Function `AssignAttractor`(CrimeLocation $C_{i,j}$, HomeLocation H_i, AttractorLocations $A()$,
AttractorMagnitudes $M()$)

//Evaluate RULE 1: Calculate the distance to each attractor

`AttractorCandidate`= {}

For each Attractor n in $A()$

$d(C_{i,j}, A_n) = \sqrt{(C(x) - A_n(x))^2 + (C(y) - A_n(y))^2}$

if $M_n \geq d(C_{i,j}, A_n)$ then

`AttractorCandidate`() = `AttractorCandidate`() + A_n

//Keep track of the smallest distance

if $d' > d(C_{i,j}, A_n)$ then

$d' = d(C_{i,j}, A_n)$

//Keep track of the largest attractor

if $M' > M_n$ then

$M' = M_n$

if |`AttractorCandidate`()| = 1 then

EXIT FUNCTION

elseif |`AttractorCandidate`()| > 1 then

//Evaluate RULE 2: Assign to strongest attractor

For each Attractor n in A_n

if $M' = M_n$ then

`AssignAttractorCandidate`() = `AssignAttractorCandidate`() + M_n

EXIT FUNCTION

elseif |`AssignAttractorCandidate`()| = 0 then

//Evaluate RULE 3: Assign to closest Magnitude of Attraction

For each Attractor n in $A()$

//Calculate distance to Magnitude

if $D' \geq d(C_{i,j}, A_n) - M_n$ then

$D' = d(C_{i,j}, A_n) - M_n$

`ActualAttractorCandidate`() = {}

if $D' = d(C_{i,j}, A_n) - M_n$ then

`AttractorCandidate`() = `AttractorCandidate`() + A_n

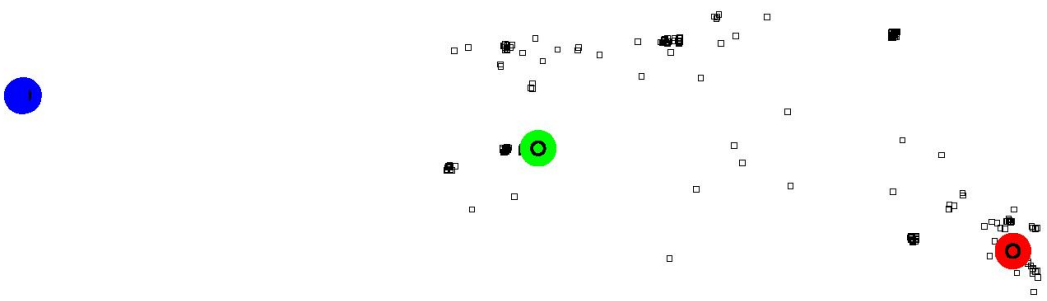
Results

6.7 In order to maintain clarity in the images, visualizations were changed from using arrows to using squares and diamonds. We can see that Model 2 provides some expected results. In North Burnaby there is a small cluster of crimes formed around the mall towards the east edge of the city (Figure 16a). Similarly, the mall towards the west of the city (represented by a green point) has a cluster of crimes that are attracted to that Attractor (Figure 16b). Based on the rules defined for the model, not all crimes are attracted to that mall. Some (those shown as diamonds) are actually attracted to the Attractor (downtown Vancouver, Figure 16c) located far to the west.

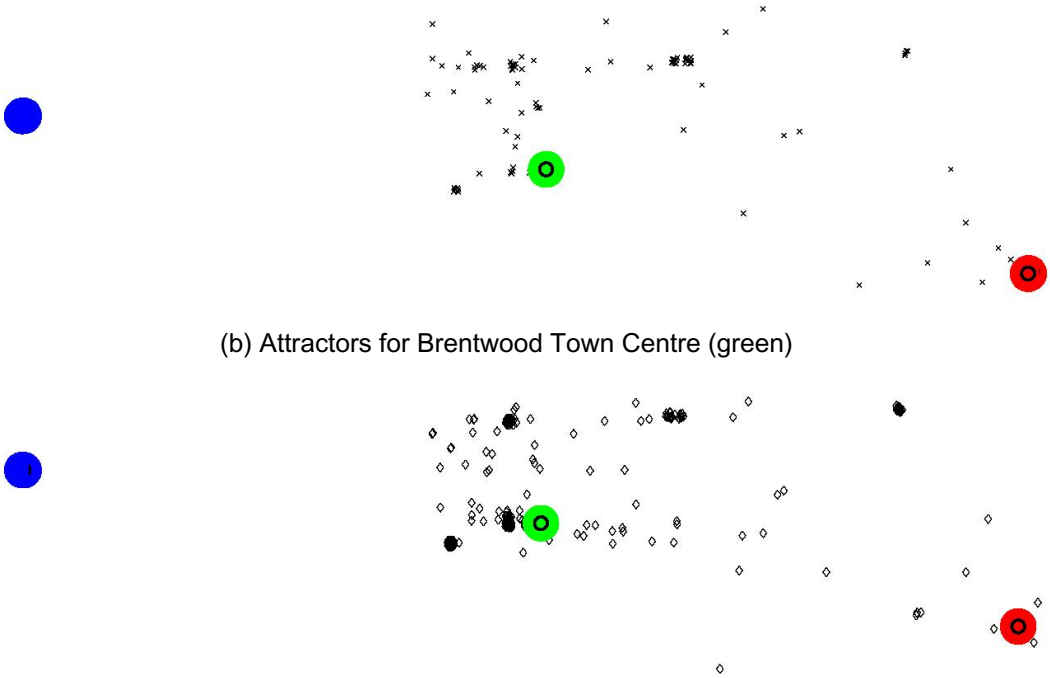
6.8 In South Burnaby we see a somewhat equal distribution of crimes attracted to each of the attractors. This is expected in this model because the two malls are assumed to have the same initial level of attractiveness (Figure 17a-b). They are also separated by about 5 minutes of travel-time so people can travel to either one quite easily. Some but not a lot of the offenders are attracted towards downtown Vancouver (Figure 17c).

6.9 Finally, Coquitlam is dominated by Coquitlam Town Centre, and our model shows the majority of the offenders (shown by diamonds in Figure 18b) being attracted to it. The other crimes are relatively evenly spread out to the other two attractors (Figure 18a and b).

6.10 What this Model does not deal with is the different strength of attractiveness, and treats each location identically, hence M_n was again fixed to 100. However, if a lot of criminals commit crimes on the way to A_1, but a trivial amount towards A_2, this should be reflected in the size of attractiveness and A_1 should be much larger than A_2. This is what we call the Magnitude of the Attractor, and is dealt with in Model 3.



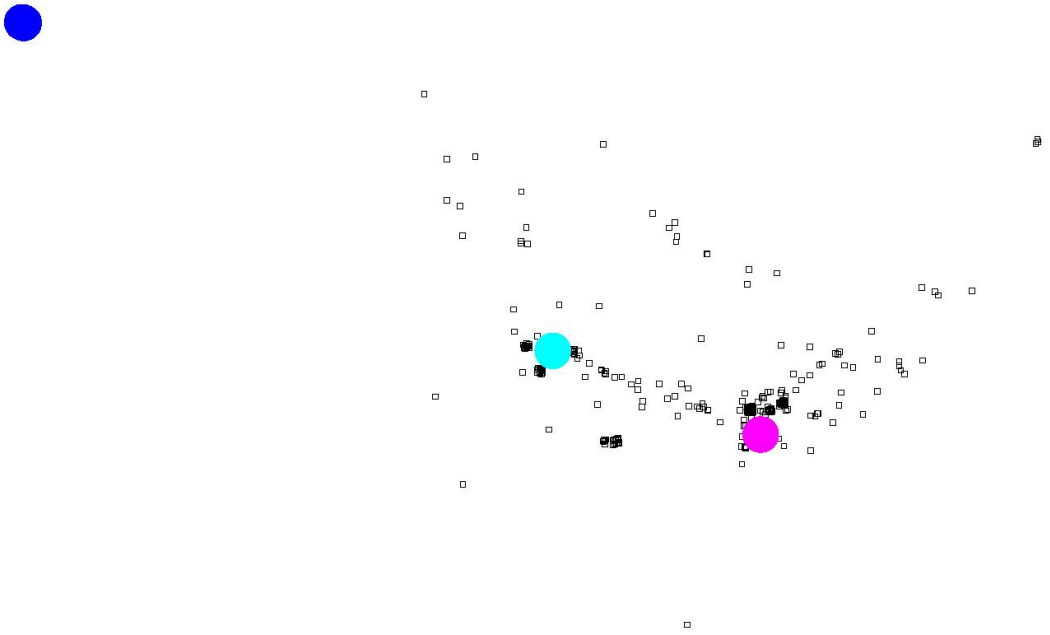
(a) Attractors for Lougheed Town Centre (red)



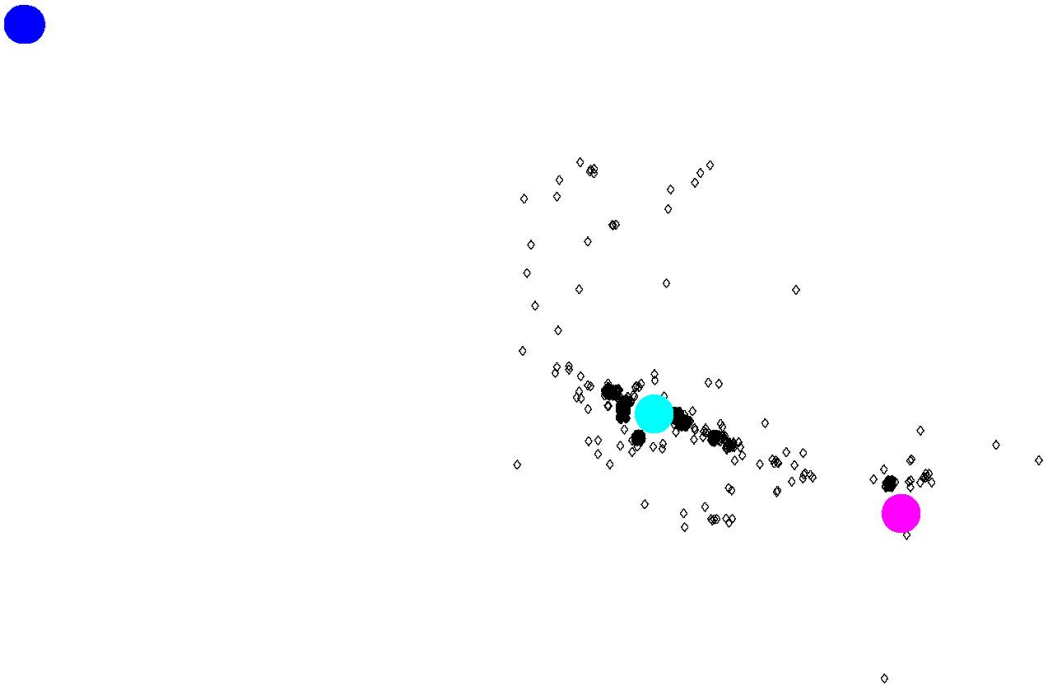
(b) Attractors for Brentwood Town Centre (green)

(c) Attractors for Downtown Vancouver (blue)

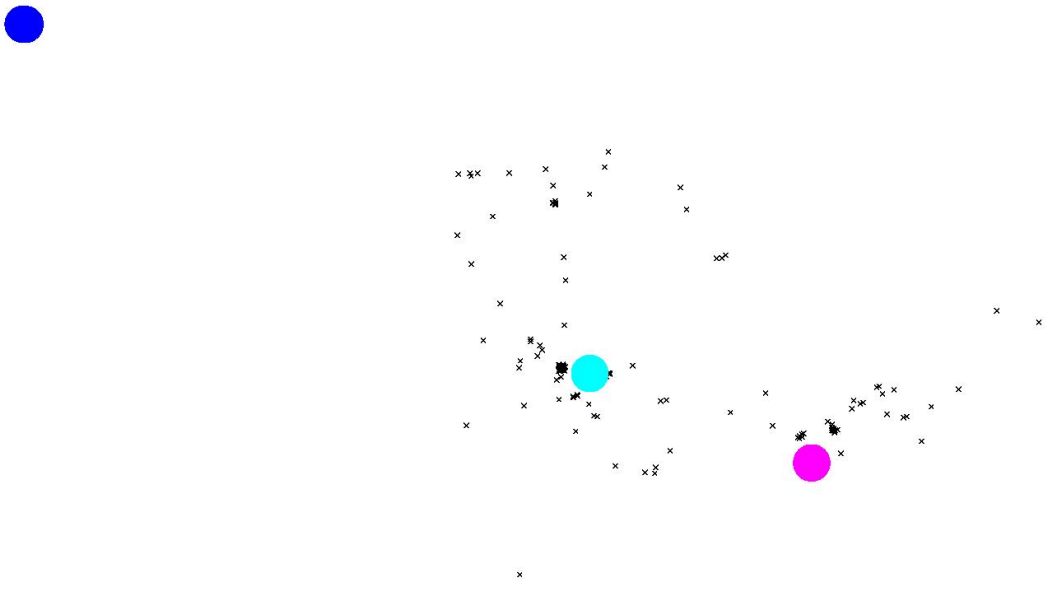
Figure 16: Results of North Burnaby using Model 2



(a) Attractors for Highgate Mall (magenta)

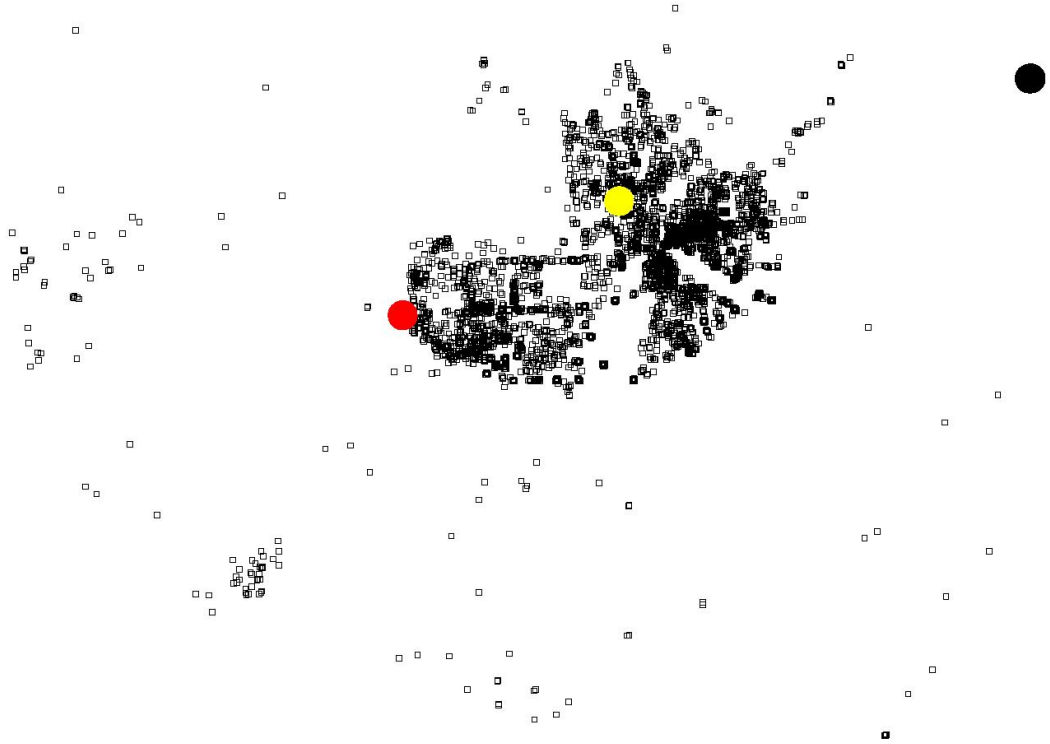


(b) Attractors for Metrotown (cyan)

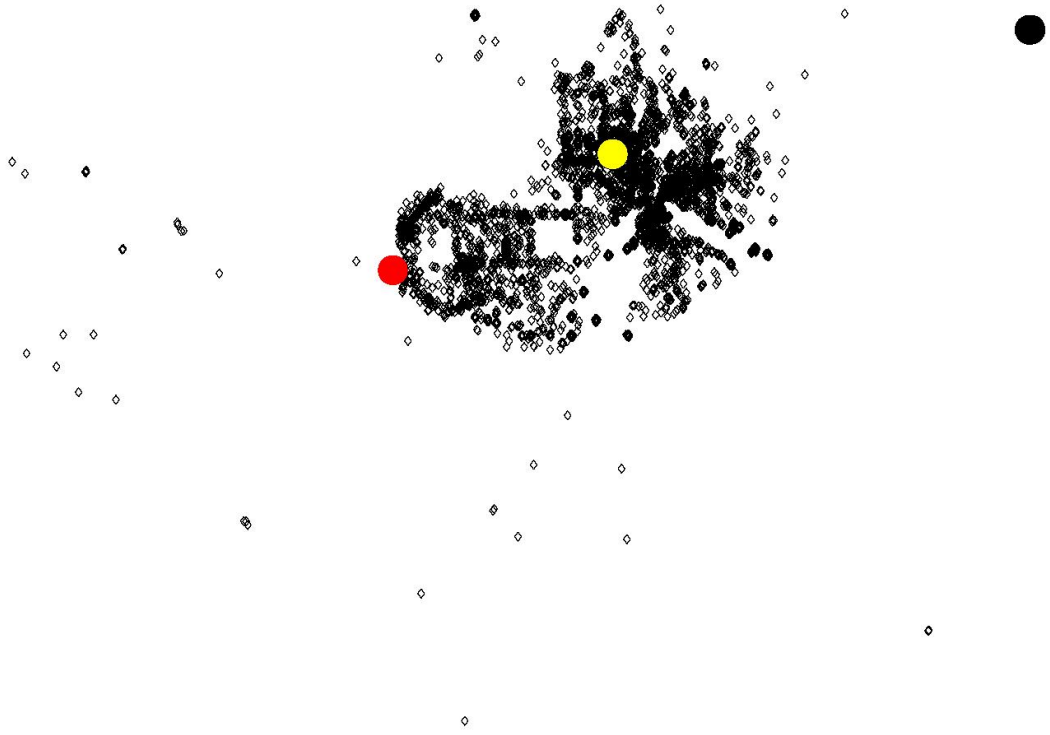


(c) Attractors for Downtown Vancouver (blue)

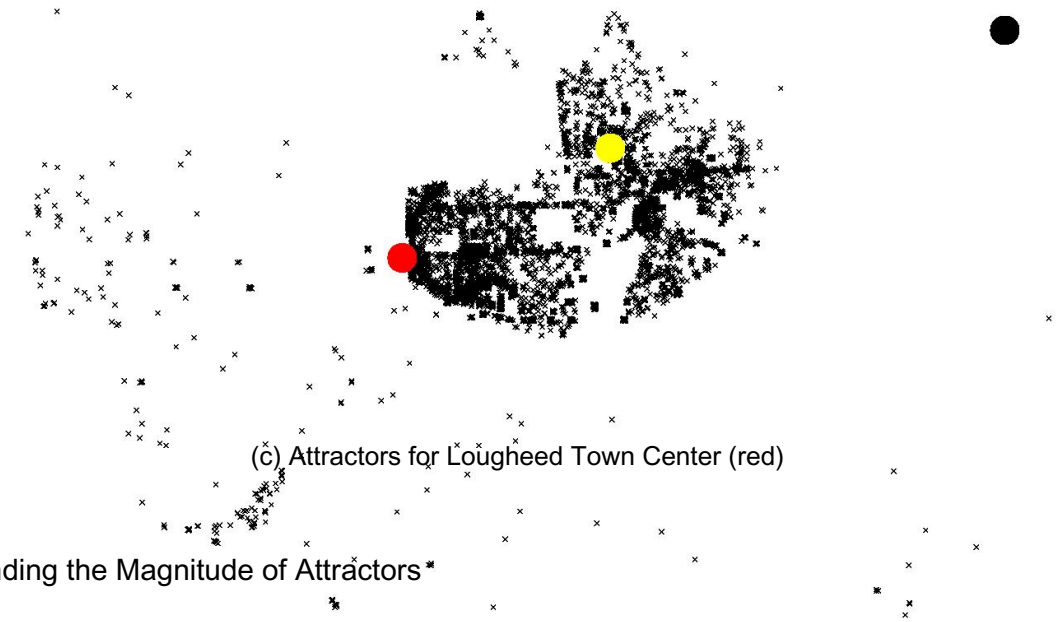
Figure 17: Results of South Burnaby using Model 2



(a) Attractors for Coquitlam Town Centre (yellow)



(b) Attractors for North Coquitlam (black)



(c) Attractors for Lougheed Town Center (red)

Model 3: Finding the Magnitude of Attractors *

7.1 Until now we assumed that the level of attraction among Attractors is the same. In Model 3, the initial level of attraction remains the same among the Attractors but is updated during each iteration of the algorithm. The algorithm takes these magnitudes as the initial input values and updates them during each iteration in proportion to the number of crimes attracted to each Attractor during that iteration. It terminates if there are no changes from time t to $t + 1$.

7.2 Suppose the Magnitude of Attraction at time t for Attractor A_n is $M_n(t)$, and the number of criminals attracted to it is $q_n(t)$. For example, the number of criminals attracted to Attractor A_n at time $t = 0$, the initial state, is $q_n(0)$. Knowing that at the beginning of $t = 0$ the Magnitude of the Attractor was $M_n(0)$, and during that iteration $q_n(0)$ criminals were attracted to it, we can calculate $M_n(1)$ as

$$M_n(1) - M_n(0) \propto q_n(0).$$

7.3 In general, if $M_n(t)$ and $M_n(t + 1)$ are the levels of attraction at t and $t + 1$ respectively, and $q_n(t)$ is the number of crimes attracted to A_n at time t then

$$M_n(t + 1) - M_n(t) \propto q_n(t)$$

or,

$$M_n(t + 1) - M_n(t) = c \times q_n(t)$$

Hence

$$M_n(t + 1) = M_n(t) + c \times q_n(t)$$

where c is some proportionality constant.

7.4 We note the iterative nature of the formula so once we know $q_n()$ for all t , set some value for the proportionality constant c and initial level of attraction we can find the level of attraction for each Attractor. The pseudo-code for this algorithm is shown in Figure 19. ' denotes optimality.

Function `FindAttractorMagnitude`(CrimeLocations $C()$, HomeLocations $H()$, CrimeDates $D()$,
AttractorLocations $A()$, AttractorMagnitudes $M()$)

For each Attractor n in $A()$

$M_n = 100$ //set to some initial value.

$D'() =$ chronologically sort $D()$

For $i = D'_1$ to $D'_{|D()|}$ in $D'()$

//Assign the attractor(s).

`BestAttractor`() = `AssignAttractor`(C_i, H_i, $A()$, $M()$)

$M'_n = M_n$ //the new model is the same as the old model

For each n in `BestAttractor`()

$M'_n = M'_n + 1$ //increase attractiveness

//The model has changed. Recalculate the model.

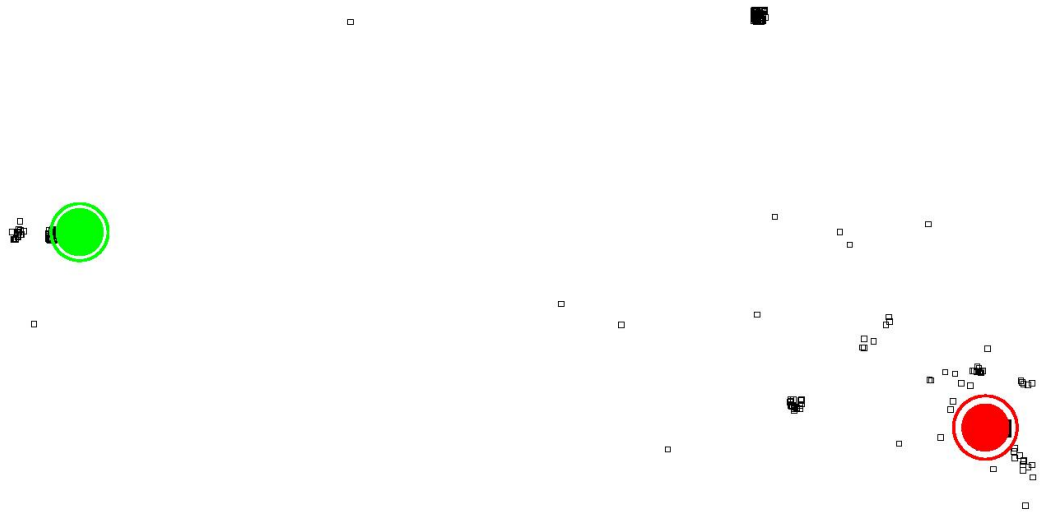
For $i = D'_1$ to D'_i in $D'()$

`BestAttractor`() = `AssignAttractor`(C_i, H_i, $A()$, $M()$) //calculate using old model

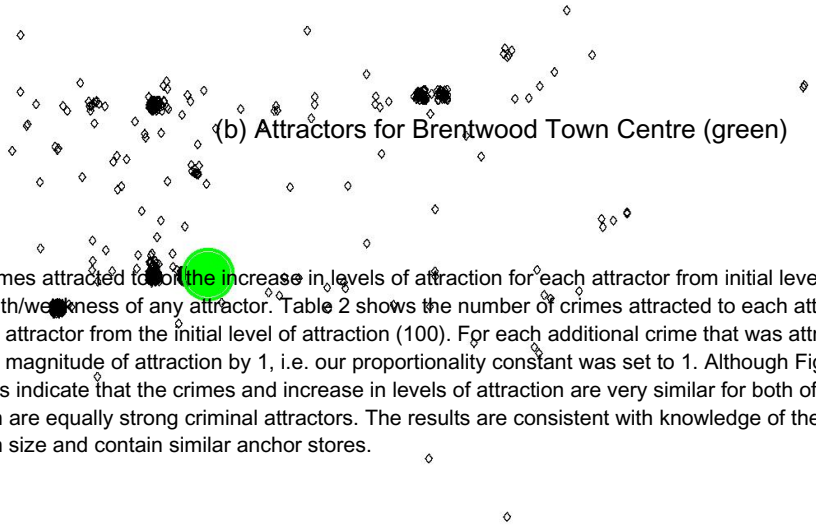
7.5 We simulated the algorithm using real crime locations for North Burnaby, South Burnaby and Coquitlam. The algorithm was simulated for two and three attractors.

Model 3 with two Attractors

7.6 We considered the two largest shopping malls of North Burnaby (Lougheed Town Centre and Brentwood Town Centre) for the simulation. Figure 20 shows Lougheed Town Centre and Brentwood Town Centre as the two attractors, with two concentric circles denoting their location. The radii of smaller circles represents the initial level of attraction which we defined to be 100. The larger circles are the output of the algorithm, radii of which represent the desired level of attraction for each attractor. We have shown the crime locations with symbols. The squares are the crime locations which are attracted to Lougheed Town Centre while the diamonds are the crime locations which are attracted to Brentwood Town Centre.



(a) Attractors for Lougheed Town Centre (red)



(b) Attractors for Brentwood Town Centre (green)

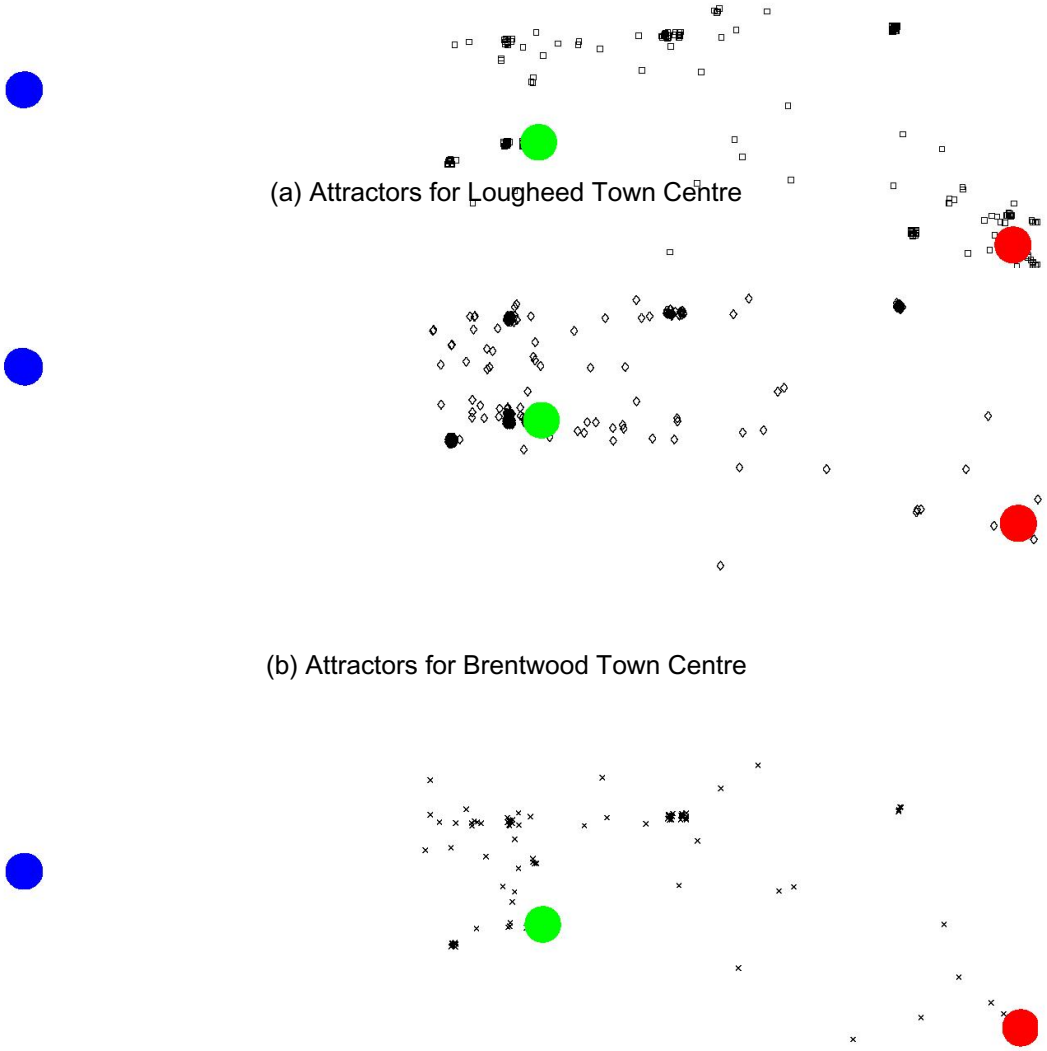
7.7 The number of crimes attracted to and the increase in levels of attraction for each attractor from initial level of attraction (100), can be a measure of strength/weakness of any attractor. Table 2 shows the number of crimes attracted to each attractor and the increase in levels of attraction for each attractor from the initial level of attraction (100). For each additional crime that was attracted to an attractor, we increment the corresponding magnitude of attraction by 1, i.e. our proportionality constant was set to 1. Although Figure 20 seems to show otherwise, the actual numbers indicate that the crimes and increase in levels of attraction are very similar for both of the attractors. From this, we can conclude that both are equally strong criminal attractors. The results are consistent with knowledge of the area, since both malls are relatively similar in size and contain similar anchor stores.

Table 2: Number of crimes and levels of attraction for each attractor

City	Number of Attractors	Attractor	Number of crimes	Increase in Magnitude of Attraction
North Burnaby	2	Lougheed Town Centre	924	161
North Burnaby	2	Brentwood Town Centre	779	134
North Burnaby	3	Lougheed Town Centre	963	265
North Burnaby	3	Brentwood Town Centre	646	211
North Burnaby	3	Downtown Vancouver	94	118
South Burnaby	2	Highgate Mall	300	181
South Burnaby	2	Metrotown	2710	856
South Burnaby	3	Highgate Mall	268	174
South Burnaby	3	Metrotown	2644	837
South Burnaby	3	Downtown Vancouver	98	126
Coquitlam	2	Coquitlam Center	19778	5930
Coquitlam	2	Lougheed Town Centre	713	1734
Coquitlam	3	Coquitlam Center	9272	3688
Coquitlam	3	Lougheed Town Centre	6973	2458
Coquitlam	3	North Coquitlam	4246	1528

Model 3 with three Attractors

7.8 Further, we introduce one more attractor in the model, Downtown Vancouver. Although we do not include crime data for the City of Vancouver in the current model, it is a suitable Attractor to include since offenders do not necessarily commit their offences within the boundaries of their residential municipality. Furthermore, the work opportunities, shopping and entertainment districts of Downtown Vancouver attract people from a variety of municipalities in Vancouver's lower mainland. In Figure 21 the level of attraction of Lougheed Town Centre (red), Brentwood Town Centre (green) and Downtown Vancouver (blue) can be seen. Similar to the previous model, we initialized the level of attraction with a value of 100 for each attractor. The squares are the crime locations which are attracted to Lougheed Town Centre, diamonds correspond to Brentwood Town Centre and crosses correspond to Downtown Vancouver.



(a) Attractors for Lougheed Town Centre

(b) Attractors for Brentwood Town Centre

(c) Attractors for Downtown Vancouver

Figure 21: North Burnaby property crimes with three attractors

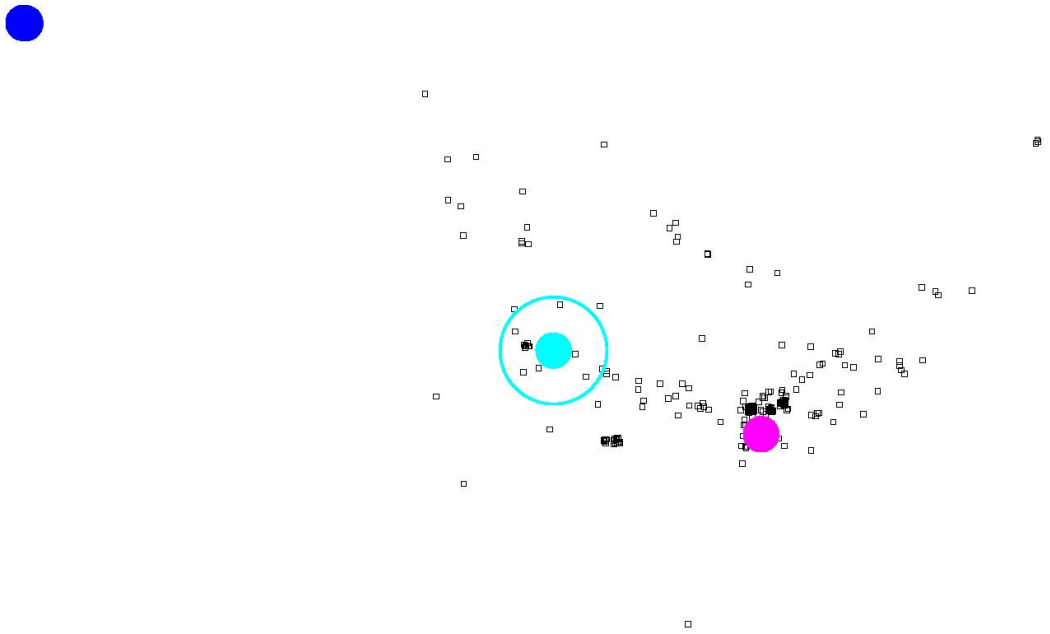
Model 3 comparing two and three Attractors

7.9 Table 2 shows our results for all of the datasets used for experiments. Figure 21- 23 show the results pictorially.

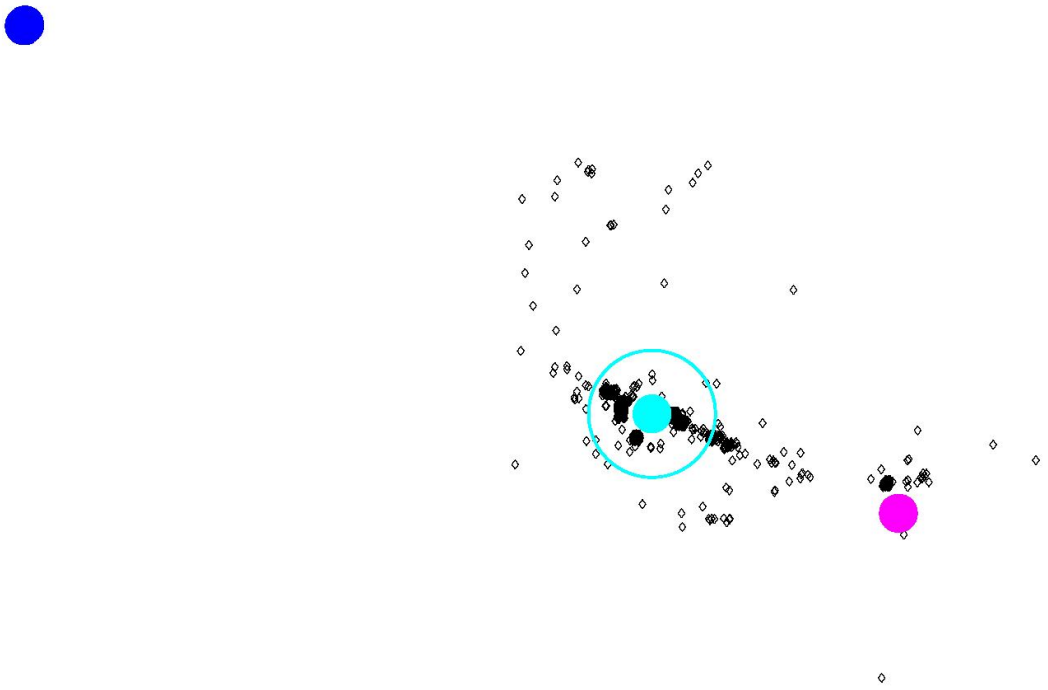
7.10 In North Burnaby, Figure 21, we see that both Lougheed Town Centre and Brentwood Town Centre are similar in attractiveness as the amount of crimes attracted to their location is similar. When downtown Vancouver is introduced as an attractor, Lougheed Town Centre actually becomes a stronger attractor (39 more crimes are associated to it), while Brentwood Town Centre becomes weaker (133 crimes are lost). Downtown Vancouver receives only 94 crimes, which is about a 10th the size of Lougheed Town Centre. While the two local malls were initially equal, the introduction of a third attractor shows us that Lougheed Town Centre is more important of a crime attractor than Brentwood Town Centre is. This could possibly be explained due to the distant location of Lougheed Town Center from downtown Vancouver. If offenders living in Burnaby wish to travel East, they will most likely head towards Lougheed Town Center, while offenders traveling West will now have a choice between Brentwood Town Center and Downtown Vancouver.

7.11 In Figure 22, the two malls, Highgate and Metrotown, are clearly not of similar scope. Metrotown is *the largest* mall in British Columbia, and our results are consistent with this. Highgate Mall is only a fraction of the size of Metrotown, and correspondingly its strength as an attractor is also only a fraction of Metrotown. The introduction of downtown Vancouver decreases the attractiveness of both malls, as it takes crimes from both locations equally. Proportionally however, downtown Vancouver only takes 1% of the crimes from Metrotown, and 11% of the crimes from Highgate Mall.

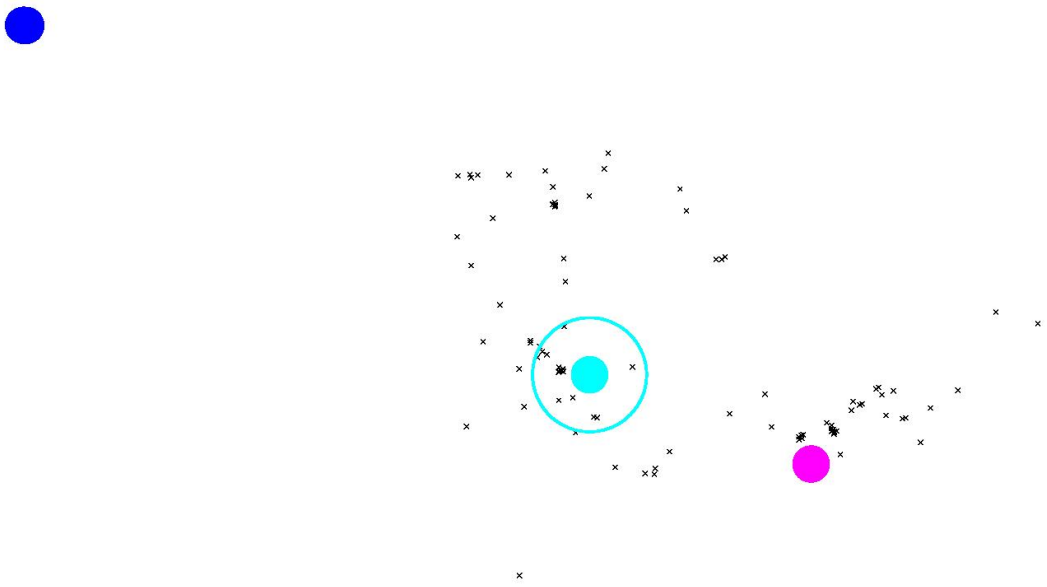
7.12 Coquitlam, Figure 23, is very interesting. It is very different from the two portions of Burnaby. Coquitlam Center simply dominates in both instances, when there are two attractors and when there are three. When there are only two attractors, compared to Lougheed Town Centre, Coquitlam Center is a factor of 25 greater of an attractor. When a third attractor is introduced, the attractiveness of Coquitlam Center is halved, and this allows Lougheed Town Centre to retain a lot of attractiveness. What happens in the two-attractor scenario is as follows. The magnitude of Coquitlam Center is simply so large, that it swallows up the other attractor. When attractors near Lougheed Town Centre are evaluated, the magnitude of Coquitlam Center is so large that, according to our rules, the offender is attracted to it, rather than Lougheed Town Centre. This is reasonable. If a location is attractive to criminals, more criminals will likely go there, increasing its attractiveness further.



(a) Attractors for Highgate Mall

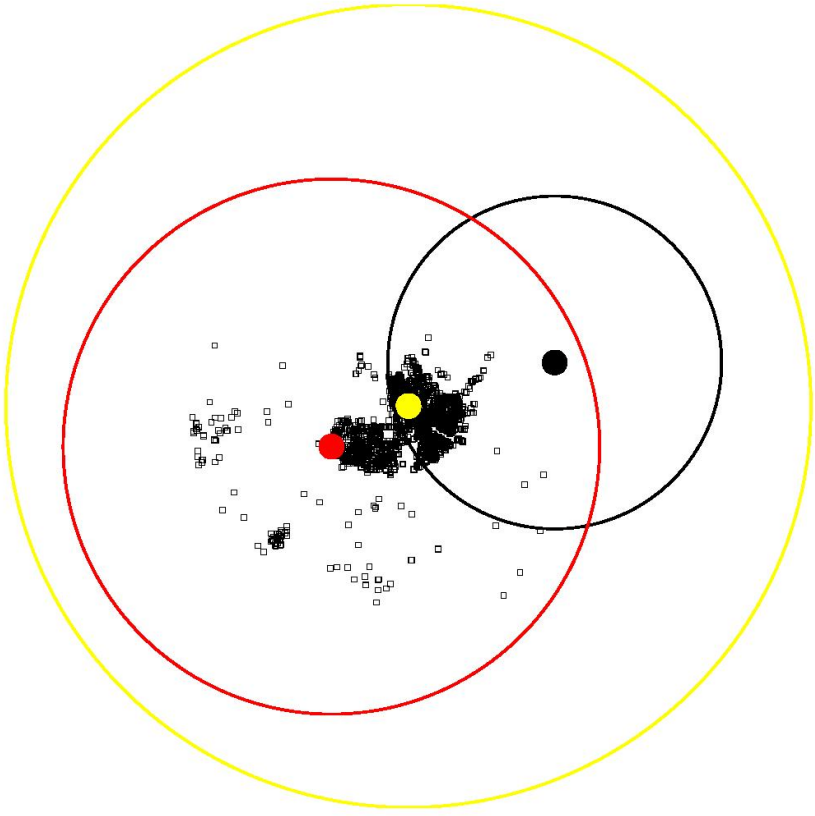


(b) Attractors for Metrotown

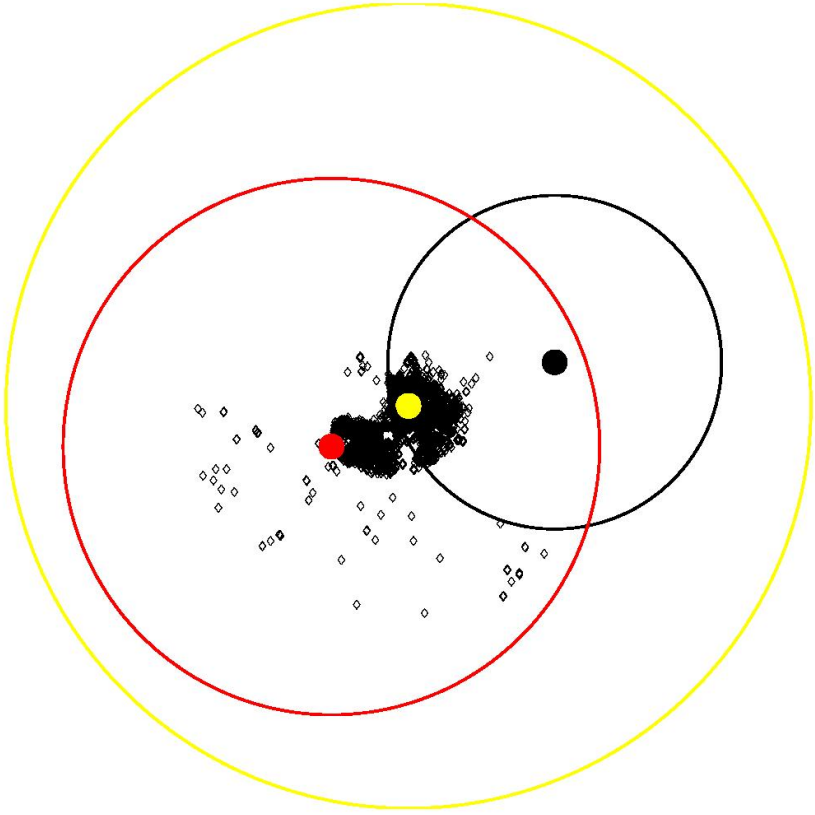


(c) Attractors for Downtown Vancouver

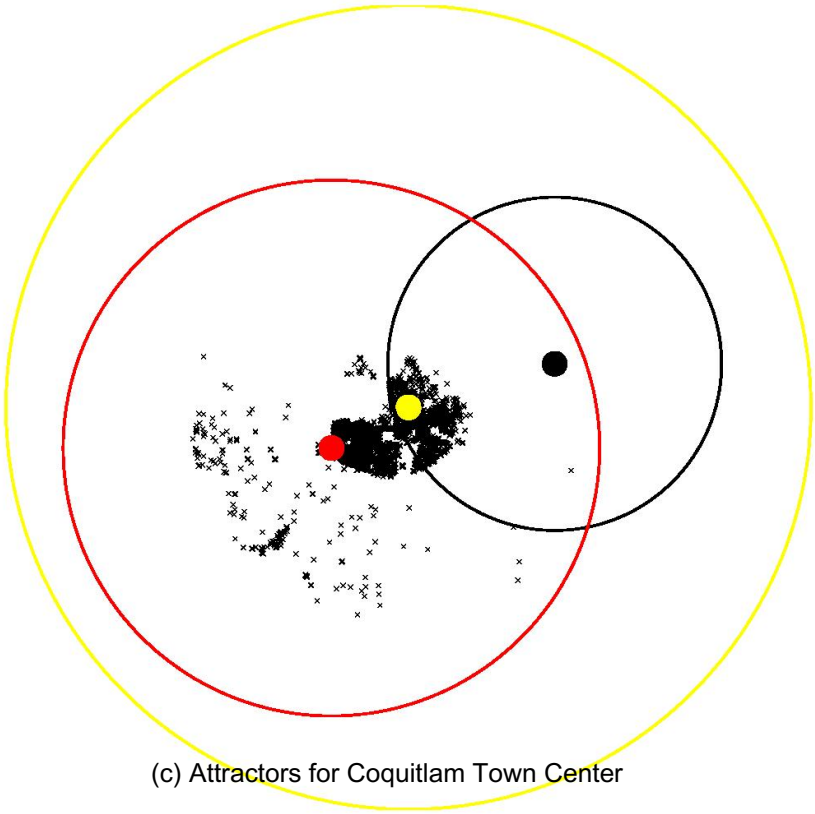
Figure 22: Results of South Burnaby using Model 3



(a) Attractors for Lougheed Town Center



(b) Attractors for North Coquitlam



(c) Attractors for Coquitlam Town Center

Discussion

8.1 These results point to the role of activity nodes, in this case suburban regional shopping centres, on criminal activity. The findings suggest an increasing likelihood of crime as a function of geometric angle and distance from an offender's home location to the site of the criminal event. This was highlighted, in particular, when Model 3 was applied to the City of Coquitlam, which resulted in an overwhelming attractor at Coquitlam Town Centre. This strongly supports Crime Pattern Theory (Brantingham and Brantingham 1993) which suggests an underlying pattern to the offense locations should be present. Our results confirm this.

8.2 The model and its findings may have relevance for real-world issues. Forecasting crime in urban areas is an obvious point of interest for police and city planners, and, given that criminal activity is likely to reduce the success of commercial enterprises in an area, so too for citizens and business owners. The techniques described in this paper may be useful for predicting crime levels in urban areas given the introduction of a new shopping centre, or perhaps other forms of activity nodes. The ability to forecast crime is an invaluable tool that could lead to the prevention of crime. Law-enforcement organizations could use information from criminal activity models such as the one described in this paper to design locally specific crime prevention strategies. This type of proactive policing is gaining favour as decision-makers look for novel crime-reduction and safety promotion strategies. The information provided by this type of modeling research can also be fed into urban land-use policy making. City land-use zoning and policy should consider future consequences of crime when probable criminal attractors are being developed.

Conclusions

9.1 In this paper, a model was developed to explore the geometric and geographic determinants of criminal activity in space through an exploration of crime activity vectors. Offenders' home locations and the site of their property crimes were extracted from police records to examine hypotheses of human criminal behaviour. Making use of Journey to Crime and Activity Space theories used in environmental criminology, we modeled the relationship between location of shopping centres, offenders' home location, and the location of property crimes in two suburban cities, Coquitlam and Burnaby in British Columbia, Canada. A key advancement of this model to the environmental criminology literature was the focus on geometric directionality as a potential determinant of criminal activity locations.

9.2 There is growing interest in modeling criminal activity patterns, as police, policy makers, and government look for new methods to better understand crime patterns which could ultimately lead to crime reduction. The model described in this paper represents a starting point for future research. Plans are being made to extend the directionality model described herein in order to deal with changes to the system, such as the addition or removal of an activity node, or changes to the urban infrastructure. This will be particularly useful for examining future consequences of urban policy decisions. Similar to this idea, we would like to see if the model can pick up seasonal or annual trends, or simply changes in the attractors as time progresses. In the existing models the Attractors were given to the model. We are searching for ways of determining the locations of those Attractors based on the real world crime data. Once locations are determined, the model presented above can be applied to determine its strength.

9.3 The road-network is an important consideration when analyzing patterns in urban areas. In the future, the theories presented in this paper will be modified to deal with the complexities introduced by the road-network. One such complexity is the varying directionality present as a road winds from one point to another. In extreme cases, it is possible that the shortest path between a source and target actually initially leads away from the target.

9.4 Finally, in order to validate the model in a more complete fashion, but without waiting for future events to occur, the next task will be to

validate this model using cross-validation where the dataset available is split into *n* portions, where *n-1* are used to build the model with the remaining portion used for validation (repeating *n* times, each time leaving a different portion for validation). This way the predicted magnitude of strength can be considered against each result from the dataset.

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Notes

3 This simple summary of the factors that determine the spatial patterning of crimes does not account for more complex target selection behaviour that is found with multiple (co-) offenders (see Brantingham and Brantingham (1981) for a more detailed discussion of the target selection behaviour of criminals).

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