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Social Network and Distance Correlates of Criminal Associates Involved in Illicit Drug Production

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This research examines the relationship between demographic, social network, and criminal history variables, and the distance between the home and locations of individuals (associates) involved in an illicit drug production network. The authors integrate principals from environmental criminology and routine activities theories, journey to crime research, and social network analysis in order to explore the geographic and social space of criminal associates. The results show that the distance between individuals in the drug production criminal network and their associates vary systematically with network characteristics (centrality measures) but not with demographics or criminal history variables.
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Introduction

Research has shown that the per capita rate of marijuana grow operations known to the police in the province of British Columbia had risen dramatically since the mid-1990s (Malm, 2006). Law enforcement personnel and policy makers alike also fear that organized crime is becoming progressively more involved in these cultivation operations (Gordon and Kinney, 2006). From both a theoretical and policing policy standpoint, it is important to better understand the nature (and structure) of criminal groups, or associations, involved in the illicit production of controlled substances, especially as most of these production efforts take place in residential communities where hazardous materials, and unsafe practices appear to be the norm (Malm, 2006). This paper examines the nature of this purported "organized crime" involvement by utilizing a combination of social network and spatial analysis techniques to explore the connections between criminal associates taking part in marijuana growing operations in social and geographic space. Specifically, the authors set out to isolate what variables are correlated with various distance measures within the criminal network while offering a fruitful combination of social network analysis (SNA) and spatial analysis of crime. To this end, our strategy is three-fold. Initially, the criminal network is described. Next, several social network and spatial analysis techniques are combined to study the distances travelled from associate to associate within the network. Finally, the results are presented and prospects for supporting intelligence-led policing policy are discussed. Given that this paper represents the first attempt to study the issue of "journey to associates", it is particularly important to move with caution from the latest thinking and research regarding organized crime, the journey to crime, and principles from environmental criminology, such as rational choice, routine activities and pattern theories.

The topic of organized crime has challenged academics and criminal justice practitioners alike for many years. Published research on organized crime replicates the anecdotal reports of police investigators, which characterize many organizations as inherently complex (von Lampe, 2006). Tracking (and prosecuting) members of organized crime groups may be made more difficult due to the lack of concrete linkages between suspected associates, known associates, and the key individuals who are thought to "broker" relations between constellations of other criminal networks or subgroups. Linkage analysis – the linear tracking of associates – whether in an informal set of hardcopy investigator files or notes, or in a structured, electronic suspect database, is currently the most common mode of information gathering and management. However, linkage databases are limited by their inability to efficiently capture the inherent qualities (nature) of these links; typically, all that can be noted in such a system is the fact that objects (suspects) are linked in some way. Formal SNA databases, on the other hand, capture the specifics of the relationship itself as the primary unit of analysis. The research presented in this study makes use of the latter technique. While it is often preferable to capture data that would eventually support a complete SNA whenever possible, the simplicity and resource economy of linkage analysis should not be overlooked. Furthermore, linkage data can often be expanded – although most likely not without significant effort – into more fully rounded social network data.

The organized crime literature has a rich history, especially over the past 30 years, but more recent work suggests a reconsideration of what it meant to be "organized", and that groups of criminals may not be as closely regimented as first thought (von Lampe 2006). Following Kleemans and Van de Bunt (1999), this research focuses on criminal associations rather than criminal organizations, and is more directly concerned with relationships between individuals than the organization of those individuals. Focusing on the attributes of known associations has the added benefit of highlighting possible interactions with other variables suggested by the geographic study of crime events.

The analytic techniques used in this paper rely on several underlying theories and bodies of research. The "journey to associates" analysis is guided by the principles of a stream of research on the spatio-temporal ordering of crime events, a research orientation known generally as environmental criminology. Routine activities and crime pattern theories – two influential aspects of this approach – also offer theoretical insights into the typical spatial relationships between each associate, and a set of empirical methods for measuring their effects. Such techniques include calculating various measures of spatial proximity (such as Manhattan or simple Euclidean distances) and computational methods to model, simulate, or in some cases, predict likely travel paths between key offender activity nodes. We consider the suspect's place of residence, offence location, or the residence of known associates to comprise key activity nodes for this study. While it is not possible with the present data, comprised of police incident files, to consider the reliability of these nodes as genuine stops or meeting places of associates, we argue that this assumption is no less stable than the use of last known address, or place of employment, in other research contexts such as the journey (or trips) to and from crime. Journey to crime research has generally confirmed the early predictions, that, all else being equal, offenders tend to exploit nearer targets more readily than those farther away from his (or her) residence, node, or assumed starting point. This literature further outlines an expectation that there will be a characteristic buffer zone of relative inactivity for the area immediately surrounding the offender's residence.

Before moving forward, it is helpful to pause quickly to consider the layout of our discussion. While many readers of the *Journal* are likely familiar with what is broadly referred to as Environmental Criminology, many may not be as familiar with the core aspects of SNA, and as such, we provide brief orientation for the non-specialist. We begin this first section with a brief review of the journey to crime and crime-event literature before linking it to our formulation of the journey to associates. In the second section, we set out to analyse the theoretical and empirical links between spatial and social distance between known criminal associates in our marijuana grow operations network. The third section describes the data and results of the spatial and SNA, while the fourth and final section considers these findings with a mind to making recommendations for an improved set of data collection standards to further exploit this technique to understand and eventually disrupt illicit enterprises and associations.

From journey to crime to journey to associates

Crime trips are patterned

Interest in the journey to crime arose from a general interest in the geography of crime literature (Harries 1971, 1974; Brantingham and Brantingham, 1978; Rengert, 1992), and their efforts to connect criminal events within the context of people's regular movements in urban social and physical settings. Key among the objectives of these and others (Cornish and Clarke, 1986) was the process of how crime events take place at specific locations and times based on opportunity (Ekblom and Tilley, 2000), with particular attention paid to the offender's movements to and from the offence site Felson, 1986). According to this perspective, offender movements are dictated by his/her personal awareness space, which is formed primarily during non-criminally intending trips to and from primary activity nodes, such as those that might be linked to employment, shopping, or visiting friends or relatives (Brantingham and Brantingham, 1993). In combining the assessment of how offenders are thought to evaluate possible criminal opportunities (or what fits his or her offending template), with an understanding (or at least an estimation of) the routine activities that brought that location/opportunity to the attention of the offender in the first place, theorists argue that it is possible to forecast crime placement and likely distributions of crime across time and space (Brantingham and Brantingham, 1978; Rengert, 1992; Eck and Weisburd, 1995; Xue and Brown, 2003; Felson, 2006). Journey to crime research, along with related efforts regarding offender path and target selection simulations, purport to develop this predictive capability even further (Brantingham *et al.*, 2005). This in turn has led to set of pragmatic research applications for law enforcement, such as the ability to spatially profile an offender's residence or similar anchor point by using crime event, or incident, data (Canter and Larkin, 1993; Rossmo, 1999; Rengert and Wasilchick, 2000).

Rational choice theory asserts that offenders will embark upon criminally intending trips through a structured decision-making process, which seeks opportunities to both maximize benefits while minimizing risks and or costs. In this way, offenders are seen as active in this decision-making process, and will use environmental, social, and cognitive cues at their disposal to aid in their decision making. While the decision to offend is considered a rational choice, it is, nevertheless, constrained by a number of situational, physical, and individual dimensions: time, activities, the structural environment, and social situations – all in addition to the agent's ability to "process" this information into a series of decisions about what activities to pursue. Therefore, analysis of offending must take into account this rational decision-making process at each step along the path to offending, through the continuance of the offence (Cornish and Clarke, 1986; Cornish, 1993). The routine activity approach primarily focuses on the elements of the criminal event that are necessary for that event to occur – namely, the well-known "precursors" of crime: the presence of a motivated offender, a suitable target, and the absence of capable guardians against the offence (Cohen and Felson, 1979), and, as well, a need to follow its aftermath (Felson, 2006) . This approach argues that anything that makes crime harder to commit, reduces the prospects for gain or reward, also makes it less likely to occur (Felson, 1986, 2006), which echoes the view of rational choice and self-control theories in stating that these limits on opportunity are "costs" that reduce the "expected utility" of crime, and make it immediately and ultimately less gratifying (Cornish and Clarke, 1986; Gottfredson and Hirschi, 1990; Cornish, 1993). Pattern theory complements both rational choice theory and routine activities theory by focusing on how crime happens in specific locations and at specific points in time, paying special attention to positioning the offender and victim in social and legal context, or "environmental backcloth" (Brantingham and Brantingham, 1991).

The next section considers the way that such travel patterns to and from activity nodes can help us predict not only the likely origin of such trips (Rossmo, 1999), but also to infer the distance between any offenders/suspects that are linked to one-another in police incident reports.

Crimes cluster around the home or key anchor point

The proposition that the majority of crime trips are relatively short is well documented in the literature (Brantingham and Brantingham, 1991; Rengert, 1992; Eck and Weisburd, 1995; Warren *et al.*, 1998; Fritzon, 2000; Wiles and Costello, 2000; Sorenson, 2005). This proposition is based on the distance decay model, which asserts that individual's interactions with other people and places decrease as the distance between them increases. This model predicts that it is more likely to see a clustering of offending around a particular offender's home than a random distribution across a vast distance (Brantingham and Brantingham, 1991). The development of this awareness space is also highly dependent upon the perceived distance, type of street, mode, and ease with which one can travel between any given nodes, but especially anchor points (Brantingham *et al.*, 1991, 2005). It is reasonable, we argue, to expect that co-offenders of marijuana production facilities, or "grow ops", will also be relatively short in most cases. Simple economic and logistical considerations would put limits on how far one would be prepared to travel in developing one's network. Obviously, this distance-to-associate will increase if persons connected to one marijuana grow at *Time 1* are no longer actively associated by the time one or more are identified as at another grow at *Time 2*. However, we would suggest once again that the least energy and the awareness space principles will still result in this new location being close by.

This is based primarily on the social psychology approach, which posits that the human preference for the familiar, and is also supported by the distance decay model (Brantingham and Brantingham, 1991; Rhodes and Conly, 1991). Presumably, areas near the home, or any other key activity node, would be more familiar than those further away. If familiarity with an area promotes its use for mundane, every day trips to and from activity nodes, it would also be reasonable to expect that these areas would be at risk for criminally intending persons to notice and exploit criminal opportunities, including observing and exploiting opportunities to set up a marijuana grow. Felson's "chemistry of crime" alerts us to the need to think about what are the necessary elements for certain crime types, and for grows this might mean proximity to an easily exploited power supply (to steal electric power to maintain the costly lighting characteristic of hydroponic grows), areas with poor surveillance (to allow post-harvest processing), proximity to the actual drug market, and so on. Additionally, research suggests that offenders are less willing to commit offences in areas in which they are unfamiliar (Sorenson, 2005; Ratcliffe, 2006). This negative pressure is likely due to the rational decision-making process involved in the determination of good (or "CRAVED") targets, which would often be dependent upon an intimate knowledge of the area (Felson, 2006).

Expectation of a buffer zone

A further structural limitation can still be added: that of the "buffer zone". The buffer zone concept is a theoretical expectation posited by Brantingham and Brantingham (1974, 1984) for crime patterns proximal to an offender's residence, and later updated to include other key nodes (e.g. Rossmo, 1999). While insiders may be more knowledgeable about an area and, all else being equal, more likely to offend therein, we argue that individuals will most often avoid offending in the immediate vicinity of primary activity nodes, forming a "buffer zone" in order to avoid being identified should they be seen. Therefore, the distance decay model is typically modified to include this proposed "dip" or decrease in activities in the immediate area surrounding the offender's home (Brantingham and Brantingham, 1984). There are, of course, exceptions. Offences like domestic assaults and workplace-related theft would not follow this theoretical expectation (Kent *et al.*, 2006). Although little empirical evidence has been found to support the theory of a buffer zone (Santtila *et al.*, 2003; Levine, 2004), the majority of offences were still found in close proximity to the offender's home (Canter and Larkin, 1993; Rossmo, 1995, 1999; Rengert *et al.*, 1999).

In addition to crime type, travel distance also varies with the age and gender of the offender (Brantingham and Brantingham, 1978; Rhodes and Conly, 1991). The age relationship often equates to a finding that older offenders tend to travel farther than younger offenders to commit offences (Nichols, 1980). However, more recent research has refined this trend to recognize that the age–journey relationship may in fact be more akin to an inverted U-curve, where the very young and very old offenders travel shorter distances than youth and adults (Fritzon, 2000; Sorenson, 2005).

Anchor points can include work, home or school (Rengert, 1992). An offender's choice of anchor point may also vary according to his/ her age and understanding of the opportunities embedded within that activity space. For instance, in keeping with the notion that offending occurs primarily during discretionary times, school-age children may use their school or friend's house as a anchor points for offending during breaks at school, or before their guardians expect them home after the school day is completed. In a similar vein, opportunity structures may also determine the length of the journey, as neighbourhoods with limited viable opportunities for offending will likely see their resident offenders travelling farther to neighbourhoods where the opportunities are more plentiful (Hesseling, 1992).

Although research has considered the differences in offending patterns when anchor points other than the home are considered (Canter and Larkin, 1993), most journey to crime estimates are based on the offender's home location. Research has cautioned that this may run the risk of underestimating distances due to an increased likelihood of those offending near the home being caught (Eck and Weisburd, 1995). Errors in measuring distances can also be introduced if researchers are not aware of alternate anchor points. It is possible that such errors are likely to result in overestimations as offenders may actually use the home address of a friend or associate as a more common anchor point for criminal journeys than their official home address (Wiles and Costello, 2000). Journey to crime estimates should concede that alternate anchor points may produce different journey distances. In the case of illicit drug production, the offence location is often the place of residence and as such, social connections between associates are likely to involve visits to each other's home location, although errors in using last known address would still apply, as is the case with geographic profiling or journey to crime research that relies on this as one of the nodes (Rossmo, 1999).

Given that the qualities of the built environment have been found to impact the distribution of crime in time and space, it follows that the nature of the social network should also interact with many of the tenets of journey to crime. The following section describes in greater detail what the study of social networks has to add to environmental criminology and journey to crime/associate research.

Social networks and journey to associates

SNA has much to offer the field of environmental criminology and journey to crime research because it explores an element of crime that traditional spatial analysis does not – the associations between interdependent individuals. This linking of individuals to one another in social and geographic space adds another layer to the backcloth of environmental criminology. The concepts of nodes, edges, and paths are arguably the most central to network analysis and must be defined at the outset. Network analysis uses the term *nodes* to denote subjects or sample elements. Nodes are not independent from one another, as subjects or sample elements may be, regardless of how they are sampled. *Egos* are the nodes whom the connections/ties in your network are based upon, and *alters* are the nodes whom the egos are connected/tied to. *Edges* are the relationships or ties between nodes. Edges/connections between nodes can be directed or undirected. Directed connections allow for information to travel in one direction, rather than freely between both nodes. Undirected connections involve symmetry, meaning that information (or whatever variable you are interested in) is assumed to travel freely between both nodes. Connections can also be weighted or unweighted. In weighted edges, the connection includes a measure of strength (Hanneman, and Riddle, 2005; Wasserman and Faust, 1994). SNA elements that are added to traditional journey to crime and environmental criminology research in this paper include the homophily hypothesis, centrality measures, and density and power of a network.

One of the most common observations in SNA is that demographically similar individuals are more likely to form social ties. This phenomenon, termed the *homophily hypothesis*, tests these observations by positing that in a network with different types of actors, the density (number of actual ties/number of possible ties) of ties will be greater within each group than between groups. In other words, Vietnamese are more likely to be connected to other Vietnamese than to individuals of Caucasian or Indo-Canadian descent. Applying the homophily hypothesis to a criminal network is important when considering spatial distance because of the principle of least effort. This principle states that, all else being equal, people travel the least distance necessary to achieve their goals. However, if people are more likely to associate with demographically similar individuals, then the opportunity surface for building ties between individuals has been changed. If the homophily hypothesis holds, then people would theoretically be willing to travel further to build ties with someone of a similar ethnicity.

Centrality and power are concepts very important to criminal network analysis. Network analysis has taught us much about power in social settings. Most importantly, it emphasizes that power is relational – one node's power is reflected in another node's dependence (Hanneman and Riddle, 2005). It can be argued that individuals high in centrality can exude more influence on their associates and on the entire network as a whole than those with lower scores. However, the power of this influence depends on the density of the network. Network density is defined as the total number of ties between individuals present divided by the total number of ties possible. If a network has a high density, indicating more group cohesion, then more power can be exuded. Power in a social network is associated with position. The concept of centrality is particularly important when discussing position and power in a social network (Ruhnau, 2000; Costenbader and Valente, 2003; Hanneman and Riddle, 2005).

There are four different forms of network centrality correlated with geographic distance between associates in this paper. *Degree centrality* (Freeman, 1979) measures the amount of connections each node has within the network. The node with the most connections has the highest degree centrality. *Closeness centrality* (Freeman, 1979) focuses on the geodesic distance of the connections between nodes. The geodesic distance is the shortest path between two nodes in a network, not to be confused with geographic distance. *Betweenness centrality* (Freeman, 1979) measures the amount of time a node is between another node's connections. In the context of information transfer, the individual who has to rely on the least amount of other individuals to pass information through has the highest betweenness centrality and the highest degree of power in the network. *Eigenvector centrality* (Bonacich, 1972) is the degree to which an individual is connected to other highly connected individuals.

SNA informs police investigations when combined with the finding from journey to crime research that travel distances seem to vary with certain demographic variables such as age and gender. SNA can also be used to identify "new" information embedded within existing files, and allow police organizations to allocate precious resources more effectively on the key people within the illicit drugs production network. Generating the information to support requests for surveillance, specialized investigation, or warrants approvals often involve a significant draw on total officer time and departmental costs. Prioritizing key people (or "players") for investigative efforts can help target and maximize specific crime or harm reduction outcomes. This is especially true if the key players turn out to have fewer police contacts than other associates – something that a simple linkage analysis may miss, especially if researchers or analysts are primarily concerned to identify the most active, or prolific, among their files.

Unique aspects of SNA

SNA involves studying the associations between interdependent individuals, or other variables, recognizing that each actor is influenced by their associates. This is different from classic quantitative methods because the unit of analysis is not an individual, but rather a group of individuals and the number and type of connections between them. As such, network analysis cannot rely on independent random sampling, or popular statistical techniques based on independent samples, such as multivariate regression, because most populations in network analysis are dependent on one another by definition. Network analysts often choose to work out precise probability distributions using simulation instead of using inferential statistics. In this paper, we employ these permutation-based statistics to compare distances between associates to demographic, criminal history, and social network variables.

While the use of experiential knowledge of law enforcement personnel to inform criminal associations has been used in gang (Braga *et al.*, 2001; Tita *et al.*, 2003; McGloin, 2005), and organized crime research (Morselli, 2006), there are many threats to validity and reliability associated with this form of data collection that need to be addressed. The first issue is that of missing data. It is impossible to collect all of the possible nodes (individuals) and edges (ties between individuals) in a network without surveying the individuals involved. However, the hidden, illicit nature of criminal networks makes surveying participants difficult. The participants are unlikely to be forthcoming about the nature and frequency of their associations since revealing this information could have personal and business ramifications. The second issue deals with fuzzy network boundaries. When collecting data for SNA, it is important to know what your network boundaries are. Owing to the same issues mentioned above, it is impossible to ascertain accurate network boundaries in criminal networks. The researcher must make a decision as to where to set the network boundaries.

Key points thus far

We see an importance in understanding not only the spatial patterning of illicit drug production facilities, but more particularly, their placement in social network space. Principles drawn from environmental criminology theory have provided a base from which to consider the parallels observed between the geographic journey to crime and social journey to criminal associates. Key among these insights are that, all things being equal, we would expect to find that distances to associates will, on average, conform to similar patterns as found in the journey to crime literature. Further, the least energy principle should work equally well for associates, in that linked offenders will generally seek proximal rather than distal associates, but, not – if the theoretical expectation of a buffer zone is supported – so near that their association is noticeable as something possibly criminal. Based on an expectation that "organized" crime may no longer be so systematically connected, we do not expect to see our associate network to be dense, but we do expect to find some evidence of within-group clusters, as found in related studies of networks of street gangs. SNA in other contexts suggests that demographic variables should promote connections along demographic groups, such as young grouping with young, and more within-ethnicity connections than without. The next section takes on the setup and analysis of these issues. We conclude with our findings and a brief discussion of the SNA and the future of "organized" crime group research.

Data

Data on 376 individuals involved in an illicit drug production network in Vancouver, British Columbia were collected (see Figure 1). The data were collected from the case files generated by the Vancouver Drug Unit, which identified both suspects and their associates who were known to operate multiple marijuana grow operations in the jurisdiction between 1997 and 2003. The primary members of the criminal network were identified as co-offenders in illicit marijuana production. In addition to capturing primary members of the drug

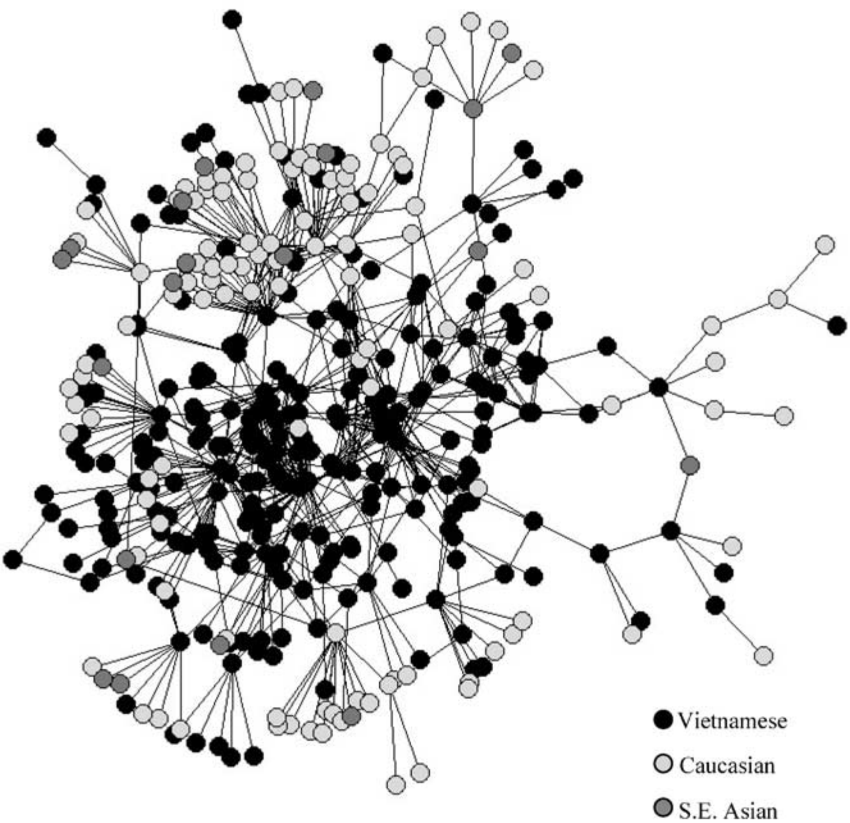

Figure 1. Drug production criminal network.

production network, their associates were identified. In order to be classified as a criminal associate of a primary member, the individuals must have co-offended together, be relatives, or be deemed criminally connected through source-based intelligence (wires, surveillance), or some combination of the categories. It is important to mention that not all co-offenders or family members are included in these data, but only those positively linked in the course of their involvement in the production of marijuana. The ties between individuals are symmetrical and undirected. In other words, the relationships are reciprocal – individuals co-offend with one another and/or they are family members with one another.

The incident, demographic, geographic, and criminal history data were collected from a police records management system. If the individual was a suspect in a drug production file, as the majority of our primary members were, then the information on that incident was coded using a 32-item coding sheet. Variables collected include size, location, and hazards of the operation. Demographic and criminal history information on each individual was collected from the police database. Demographic information collected included age, ethnicity, gender, citizenship, place of employment, and last known home location. The criminal history variables included number, type, location and date of prior offence(s).

The spatial data were generated using ArcGIS and CrimeStat software packages. The last known address and incident location (if known) for each of the individuals in the network were geocoded in ArcGIS. Out of the 376 individuals, 318 had last known addresses that were geocodable. The geocoded addresses were then imported into CrimeStat III software and a point to point distance matrix was created. This matrix contains the Euclidean distance between the last known address of the 318 individuals. The distance matrix was then imported into UCInet and using elementwise multiplication, the distance matrix was combined with the criminal network matrix. The result was a distance matrix between every individual tied within the network. The distance matrix was then transformed into spreadsheet format. This geographical database was then integrated with the incident, demographic, and criminal history database and analysed with statistical software.

Analysis and results

Network descriptives

Prior to examining distance correlates, general aspects of the network must be described. The network is composed of 65 per cent Vietnamese, 30 per cent Caucasian, and 5 per cent Southeast Asian individuals. The social clustering of ethnicities is illustrated in Figure 1. The network is also 75 per cent male. The criminal associates network in this research did not conform to the homophily hypothesis across either ethnicity or gender. In other words, individuals of similar ethnicity and gender are not more likely to form ties in the drug production network. A possible explanation for this is that the predominant ethnicity, Vietnamese who also happen to be the actual producers/growers, most likely have to make ties to other ethnicities, who represent other criminal associate units, in order to traffic the drug. The less prevalent associate ethnicities, Caucasians and South Asians, are scattered throughout the network, and presumably, must form ties with the Vietnamese in order to obtain access to the product.

The density of a network is one indicator of group cohesion. The criminal network involved in marijuana production has 17,672 observations and the proportion of possible ties present, or the density of the network, is 0.01. In other words, the probability that there is a tie between two random actors is 1 per cent. This is a very low density, but is similar to other studies conducted on incomplete criminal networks/gangs (see McGloin, 2005). This density coefficient suggests that the criminal network involved in marijuana production is not tightly organized.

While the overall network is not tightly organized, there are, nonetheless, cohesive subgroups embedded within. Gang researchers have identified cliques of core members within larger networks that "essentially shape the nature, purpose, and activities of the larger group" (Spergel *et al*., 1994; McGloin, 2005). The cliques in the drug production network from this research range in size from three to 12 persons.

Integrating social network and geographic analysis

At the outset, 31 per cent of the ties between associates had zero distances. In other words, 31 per cent of the individuals who were criminally associated were living with one another. These distances were excluded from the analysis for the following reasons: (1) their inclusion would dramatically underestimate average distances and (2) this analysis focuses on examining the distribution and correlates of the distances involved in the *journey to associates*. If associates live together there is no travel distance *per se*, and thus, no *journey*. An additional five individuals were removed from the spatial data analysis as they involved addresses outside of the Vancouver Police jurisdiction. It was determined that due to problems inherent with jurisdictionally based police data systems it was not pragmatic to extend the analytic framework to include long distance, inter-jurisdictional travel patterns. This left 95 egos with associations living within the local jurisdiction and outside of their last known residence. The 95 egos account for 531 edges.

Following journey to crime research, three distance variables were computed: mean, closest, and farthest distance. As described by Warren *et al.* (1998), the closest distance is the distance from the ego to their closest associate and correspondingly, the farthest distance represents the longest distance between ego and alter. These distances are important as they provide the range and some description pertaining to the skew of the distribution (Table 1).

This portion of the analysis mathematically describes the distances between associates in the criminal network to explore the role of distance decay in journey to associates. In order to standardize the distribution, each of the distances between associates was binned in 0.25

Table 1 Distances travelled to criminal associates involved in drug production

Distance measure	*Mean*	*SD*	*Range*
Closest distance	1.49	1.00	0.01–5.56
Mean distance	3.96	5.13	0.61–36.13
Farthest distance	8.06	8.06	0.61–40.11

N=95.

mile containers and then the mid-point of each container is used to represent the data point of that bin. For instance, a distance of 1.09 miles would be binned to 1.00–1.25 miles and then the data point used would be 1.13 (the midpoint between 1.00 and 1.25 miles). Figure 2 shows the standardized distribution of distance travelled to criminal associates involved in drug production.

Inferential statistical techniques were used to examine the correlates between distance to associates and demographic, criminal history, and social network variables within the data. Statistics are especially appropriate for large networks like the drug production network presented in this research, where reliability issues are a concern (Wasserman and Faust, 1994; Hanneman and Riddle, 2005). Standard statistical tools used to describe differences and associations are appropriate for network analysis; however, standard statistics cannot be used for inferential questions where the observations are not independent (Wasserman and Faust, 1994; Hanneman and Riddle, 2005). To clarify what is meant by dependent observations, consider the following: persons A and B are related, or connected; while in a second relationship, person A is observed as tied to person C, while still another relationship sees B and C as connected. These are not independent observations because individuals may have more than one relationship; A's relation to C is necessarily impacted via their shared connection to B. Instead of standard inferential techniques, the interdependent observations seen in network analysis necessitate specialized statistics using "boot-strapping" or random permutation to generate accurate standard errors.

The relationship between distance to associates was statistically compared with several demographic, criminal history, and social network variables (using permutation-based statistics described above). See Table 2 for a list of variables that were examined. Interestingly,

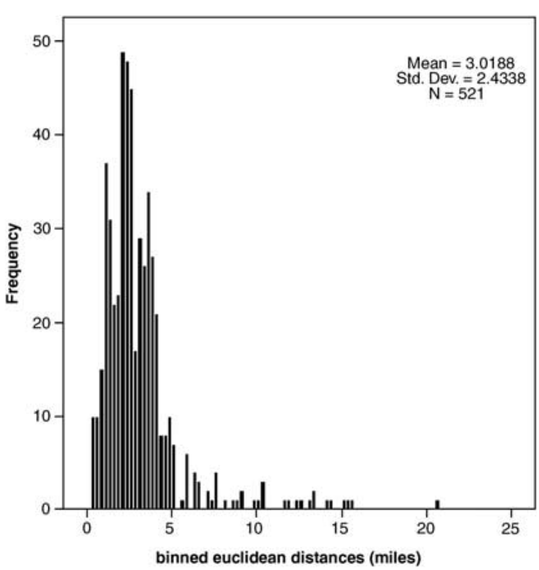

Figure 2. Histogram of distance travelled to criminal associates involved in drug production.

Table 2 Variables correlated with distance between associates

Demographic variables	*Criminal history variables*	*Social network variables*
Age	# of convictions	Degree centrality
Gender	# of violent convictions	Betweenness centrality
Ethnicity	# of property convictions	Eigenvector centrality
Citizenship	# of Drug Convictions	Closeness centrality
Interprovincial mobility (# of previous provinces on record)	# of non-compliance offences	
Intraprovincial mobility (# of jurisdictions within BC)	Age at first conviction	
Employed/unemployed		

Table 3 Distance correlation matrix

	Avg. distance	*Betweenness*	*Degree*	*Eigenvector*	*Closeness*
Average distance	1.000	0.302**	0.451**	0.323**	0.336**
Betweenness		1.000	0.625**	0.579**	0.122*
Degree			1.000	0.657**	0.115*
Eigenvector				1.000	0.228**
Closeness					1.000

*$p<0.05$.
**$p<0.01$.

the only variables that were found to be significantly correlated with distance to associates were the centrality measures of degree, closeness, betweenness, and eigenvector centrality.

In order to assess the relative importance of the centrality variables, a regression using randomization tests was performed. A correlation matrix (see Table 3) revealed no substantial problems of multicollinearity in the data. The highest correlation was 0.657 (degree centrality with eigenvector centrality), which is marginally below the standard 0.700 benchmark for exclusion set by Tabachnik and Fidell (1989).

Table 4 shows that the most predictive model is obtained using average distance as the dependent variable, and the model constructed for far distance is the least predictive. While the model for average distance only accounts for 15 per cent of the variance, this, in addition to the absence of theoretical evidence to the contrary, is enough to suggest that average distance is the most appropriate distance measure for associates. The centrality measure that explains the most variance in average distance travelled to associates is betweenness. Associates who have a high betweenness centrality travel further to their associates. Closeness centrality also has a positive regression coefficient indicating that individuals who have a high graph theoretical distance, or are closer in the social network, travel further to their associates. Degree centrality has a moderate negative regression coefficient, indicating that associates with a high degree centrality travel a shorter distance to their associates.

Table 4 Multiple regression of distance between associates and network centrality measures

Independent variable	*Close distance*	*Average distance*	*Far distance*
Betweenness	−0.056	0.347	0.114
Degree	−0.443	−0.208	0.191
Eigenvector	0.043	0.002	−0.060
Closeness	0.256	0.251	0.115
R^2	0.118	0.150	0.097
F value	3.015	3.980	2.427

Interestingly, the direction of the correlation between average distance and degree centrality changes once the variable is combined in a regression with betweenness centrality.

Discussion

The results of this research add a new dimension to the journey to crime literature – the journey to associates. The distance between associates in a criminal network is, on average, 3.96 miles. The average closest distance between associates is 1.49 miles, and the average farthest distance is 8.06 miles. This suggests that the criminal network involved in drug production is spatially constrained.

In connecting the current research on social networks to the distance decay model of offending and the concept of the buffer zone and, it appears that there is a 0.5 mile buffer zone around the homes of the individuals where associates are less likely to live. The distance to associates peaks around 2.5 miles and then loosely follows a distance decay model. These findings suggest that other than in-house associations, individuals involved in a criminal network do not live in extremely close proximity to one another, but they still typically live close enough to the same neighbourhood as their associates. This finding is consistent with the least effort principle in that criminal associates – all else being equal – tend to live closer rather than farther away, while still "observing" the buffer zone principle of "not too close". However, it is important to remember that this only applies to individuals who do not live at the same home address. If in-house associations were included, then the buffer zone would not exist. This research also shows that drug production locations tied to the criminal network may be anchors that keep people, and thus the criminal network, tied to a particular geographic area, and thus lends support to the central tenets of routine activities theory and pattern theory. Knowing that marijuana cultivation appears to be patterned in both geographic and social space is valuable to law enforcement. Associates tend to be localized rather than dispersed, although in network terms, associates are not as "organized" or as linked as the traditional organized crime models would expect. Observations from our network of offenders suggest that individuals within the network are unlikely to know more than a small subset of all persons in the network.

The authors find that the distance between individuals in the drug production criminal network and their associates vary systematically with network characteristics (centrality measures) but not with demographics or criminal history variables. This is an important finding in that it is at odds with the generally accepted journey to crime expectation of the differential mobility within each socio-economic stratum. In other words, young males do not appear to be located more distally than other population segments, as we have come to expect from the journey to crime corpus.

In terms of policy and practice, it is recommended that police agencies keep, at a minimum, at least some form of linkage data as a baseline, and should further inquiry prove warranted, then additional efforts can be made to develop more extensive data sets for special purposes. Tracking criminal organizations is one such purpose, and one that lends itself particularly well to the study of marijuana production.

Police policy and investigators will find it interesting that the central figures in the network, that is the individuals scoring high in betweenness, degree, and closeness centrality measures, tend to travel the farthest to associates and place themselves on the geographic periphery of the *network habitat*. There are two possible reasons for this. First, central figures in a criminal network are more likely to profit economically and have more to lose if the police discover the criminal network's activities (i.e. a grow operation location). It follows, we argue, that these central figures will distance themselves geographically in order to better protect themselves from police detection; or at a minimum, this concern for insulation from their own growing operations forms at least part of their selection process for a home location. Nevertheless, the central figures still need to be close enough to the network habitat in order to manage routine logistical concerns, not unlike legitimate business managers. Second, central figures who have more economic means would rather live in a more affluent neighbourhood than the typical area in which grow operations are found, all things being equal. The less central figures in a network who deal with the day-to-day running of a drug production facility, it can be argued, are less likely to be able to afford to live in affluent areas. Presumably, property values also would influence the decision of where to "set up" a marijuana grow operation. Therefore, the core of the network tends to be concentrated in a low to mid-income range area, and the central figures in the network extend the periphery of the *network habitat* to more affluent regions. From a surveillance perspective, or for other law enforcement tactics, it is valuable to know that the most central persons within the network are not typically those that are encountered at the production site, or even those persons that "turn up" in police investigations with the most frequency.

The results presented in this paper must be qualified with the statement that the network is incomplete and contains fuzzy boundaries. Individuals who have criminal histories are more likely to be included in the network (node inclusion) and have more ties known to the police (edge inclusion) than individuals who have managed to avoid being charged with a crime. While the incomplete network is a serious consideration for the validity and generalizability of results, particularly in reference to centrality measures (Borgatti *et al.*, 2006), it is an unavoidable issue in the study of hidden criminal networks.

Future research and directions

The results presented in this paper, like most other research efforts, lead to a host of new questions, and opportunities for theory-building. Obviously, better, more complete and objective data would help isolate more meaningful nodes and activity space information than simple police incident logs. An example of such a bounty is wire-tap recordings of actual associate discussions. Data that might result would likely include the locations of key nodes, and hints or even direct evidence of the nature of the relationships themselves, such owner of the crop to a distributor, to his preferred "pickers" (those whose task it is to convert the harvested plant into saleable product). Further, it would be helpful to track the location of specific key players and determine whether their location is indeed in more affluent areas on the periphery of their "investment" properties. Still another issue is that of the prominence of Vietnamese in the British Columbian marijuana industry; this begs further investigation as to whether or not grow operations "track" or follow concentrations of this population in the study area over time.

The type of results presented in this article can inform intelligence-led policing policies in a number of ways. First, identifying individuals central to a criminal organization, often termed "key players", will help police managers target surveillance efforts. Rarely are police fiscally able to surveil an entire network, so it becomes essential to target individuals who are central to the network. Second, isolating a criminal *network habitat*, or the geographic setting in which associates offend, allows police managers to target surveillance and community-based crime prevention/reduction initiatives geographically until better network intelligence can be gathered.

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