VISUALISING THE SPATIO-TEMPORAL PATTERNS OF MOTOR VEHICLE THEFT IN ADELAIDE, SOUTH AUSTRALIA

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Abstract

Motor Vehicle Theft (MVT) in Australia is as a serious problem with high social and economic costs. MVT is neither unique nor random, but rather tends to be unevenly distributed and has a spatial-temporal pattern. This study assesses and explains the spatio-temporal distribution of MVT within metropolitan Adelaide based on MVT incidences that occurred in 1999. In this exploratory spatial data analysis of MVT we identify vehicle theft *hotspots* based on point pattern analysis, determine the changes in spatial distribution of MVT during the day, day of week and time of the year, and investigate the relationship between the location and theft and recovery of motor vehicles in the study area. This study uses Crime Pattern Analysis (CPA) techniques including Kernel Density Estimation and Linkage Analysis to identify patterns in point-based MVT data and discusses the results in terms of crime place theories. Advanced spatial data visualisation techniques such as 3D images and spatio-temporal animation are employed to assist interpretation of crime patterns.

Introduction

Motor Vehicle Theft (MVT) in Australia is an escalating problem. It has been described as the "most common crime faced every day" (Atkey 2000) and as "one of the country's favourite larcenies". Internationally, Australia was ranked second highest of all countries behind the United Kingdom, in terms of its car theft rates per population (Haran 2000, Johnson 1999; Merriman 2000). MVT in South Australia increased substantially in 1998 compared to 1997, a reversal of the trend of the last 7 years where there was a steady 50% decline. However the 1998 figure was still lower than those recorded between 1985 and 1995 (Zeman *et al*. 1999). There are three main types of theft of motor vehicles. ***Casual*** or ***Opportunistic*** theft is primarily for personal use such as transportation, to commit another crime, and joyriding. ***Professional*** theft is usually by organised gangs for financial gains from resale after *re-birthing*. Vehicles may also be stolen for the purpose of ***insurance fraud***.

The costs of MVT borne by the community are high. Approximately A$1 billion a year in direct and indirect costs of MVT is borne by the Australian community (Higgins 1997). Nationally, the direct cost (based on average insurance payouts) was about A$700 million while in South Australia it was about A$53 million (Zeman *et al*. 1999). Indirect costs are costs incurred by police, courts and victims who experience inconvenience, loss of earnings (average of at least one working day) and higher insurance premiums (Higgins 1997). Strategies are required to counter MVT and reduce the cost to the community. Current measures to counter MVT in Australia have not utilised the spatial information contained in databases such as the CARS database to its full potential. This information usually contained in the address field identifying where a vehicle was stolen from or recovered can provide vital intelligence about the nature of vehicle theft.

Crime pattern analysis (CPA) attempts to quantify the spatio-temporal distribution of crime. Crime place theories suggest reasons offenders commit crimes where and when they do. In other words, they attempt to explain why crime incidences exhibit a particular spatio-temporal distribution.

Currently, the Office of Crime Statistics of the Attorney General's Department in South Australia conducts crime pattern analysis to determine the spatial distributions of MVT. This analysis involves the aggregation of MVT incidences to the census collection district in which the offence occurred. However, studies have shown that crime is concentrated at specific places even within neighbourhoods that have high crime rates (Eck and Weisburd 1995). Consequently, information on the precise location of crime is lost and the spatial distribution is distorted by the artificial boundaries of census districts.

In this study we conduct a crime pattern analysis of motor vehicle theft (MVT) in metropolitan Adelaide during 1999. The spatio-temporal distribution of crime is located precisely and MVT density surfaces are created and visualised using Geographic Information System (GIS). Crime Place theories suggest that MVT activity varies in space and time according the spatio-temporal interactions of motivated offenders and their targets. CPA is used to describe the spatio-temporal distribution of MVT and crime theories are used to explain it.

Aims and Objectives

This study aims to conduct an exploratory spatial data analysis study of the patterns of MVT theft in Adelaide, South Australia, using a database of theft records for 1999.

The objectives of the study are to:

- Geocode the spatial location of MVT incidents using address matching;
- Determine overall MVT *hotspots* by density analysis of the point pattern of MVT;
- Visualise the spatio-temporal distribution of MVT according to the time of day, day of the week, and time of the year;
- Assess trends in the location of where vehicles were stolen compared to where they were recovered using Linkage Analysis.

Crime Place Theories

Crime is a complex, multi-dimensional event that occurs when the law, offender and target (refers to a person in personal crimes and an object in property crimes) converge in time and place (such as a street corner, address, building or street segment) (Brantingham and Jefffery 1981). Theories on crime that seek to explain this non-random spatio-temporal distribution can be classified as n*eighbourhood* theories and *crime place* theories. Neighbourhood theories focus on the motivation of the offender and use socio-economic factors to explain the distribution of crime. Crime place theories focus on the location of crime and its characteristics, the movement paths that bring the offenders and victims together at the location, and the offender's perceptions of crime locations that make it attractive or unattractive (Brantingham and Jefffery 1981). Three crime place theories are described below and their relevance to MVT is discussed.

The Rational Choice Perspective

Within the rational choice perspective offenders are seen as rational decision-makers - making tradeoffs and choosing targets that fulfil their goals. The offender's choice of the place and time to offend is based on the attractiveness of the place for such crimes which includes such factors as the presence or absence of security personnel, the convenience of public transport to the place and the presence of car types that satisfy the required goals). Based on this perspective, MVT incidents will tend to cluster spatially if offenders behave consistently in their choices.

Routine Activity Approach

As people perform their routine activities, crime opportunities present themselves to motivated offenders who are able to steal the desired vehicles in the absence of capable guardians (e.g. parents) or place managers (e.g. security guards) whose presence might have prevented the crime from happening. Thus, the spatial distribution of MVT depends on the distribution of targets, offenders and capable place managers (Felson and Clarke 1998).

Crime Pattern Theory

As offenders move through routine activities of home, school, work, entertainment (shopping and recreation) they develop knowledge of the paths to their routine activities as well as areas around routine activities (personal awareness spaces). Different offenders may have different awareness spaces which may overlap. Generally, motivated offenders will discover potentially good target areas which offer a good choice of targets and low risk within their awareness space, although some will seek out uncharted areas (Figure 1). Consequently areas within the general urban space that are part of most individuals selective target areas will have the most numerous crimes (Brantingham and Jefffery 1981).

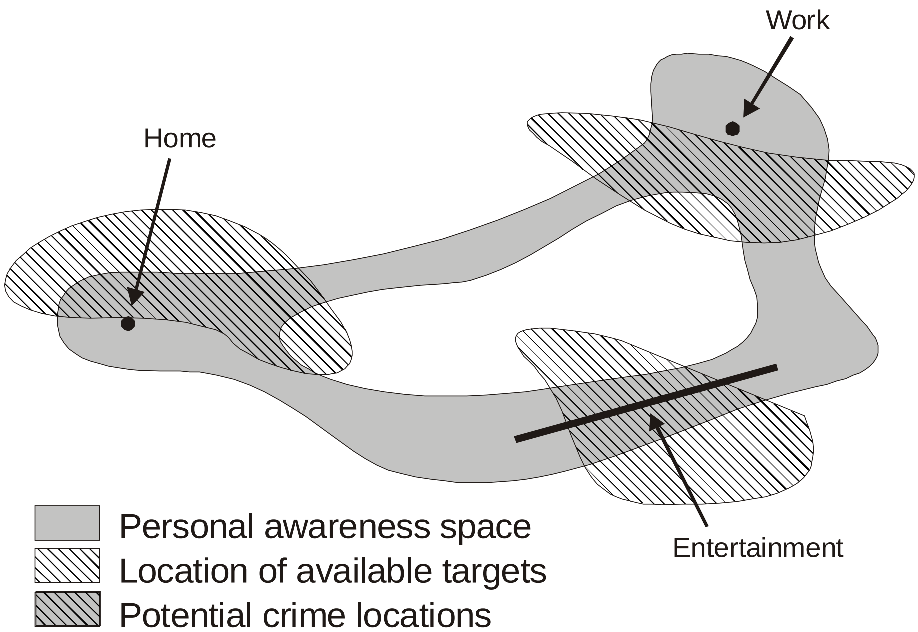

Figure 1 - Selective crime occurrence area for individual offender (after Brantingham and Jefffery 1981, p. 43)

Crime Place Theories and Analysis of MVT in Adelaide

The non-random spatio-temporal distribution of crime suggests the existence of clusters or *hotspots* of crime in space and time (see also Sorban 2000). Sherman *et al*. (1989; Sherman 1995) found that in Minneapolis of 323,000 service calls to police in 1986, found that a small number of hotspots produced most of the crime in the city (50% of the calls came from only 3% of the locations).

Opportunities for MVT tend to shift by the hour of the day and day of the week as changes in the risk of offending and the availability of attractive targets (Felson and Clarke 1998). The day of the week dictates the set of routine activities undertaken. For example, on weekdays people engage in a limited number of routine activities by following routine paths to routine locations, while on weekends people have a different set of movements as the weekend (even vacation or holidays) represents a break from the weekday routine (LeBeau and Langworthy 1986). According to the routine activities theory, this change in routines may affect the spatio-temporal distribution of MVT as offenders and targets flux based on trips to work, school and leisure settings. In addition, crime has also been found to vary with the time of the year (Cheatwood 1994; Farrell and Pease 1994).

In this study, hotspot analysis is conducted to investigate the spatio-temporal distribution of MVT in Adelaide. Variation in MVT is assessed for the time of the day, day of the week, and time of the year to investigate the possible influence of routine activities theory.

Automated Crime Mapping

Analysis of the spatial dimensions of crime has had a long history and has traditionally taken the form of pin maps of crime locations, traffic accidents and other police events (Lee and Egan 1972; Ekblom 1988; Phillips 1972). Automated crime mapping refers to the mapping and spatial analysis of crime using computer-based GIS - computer-based and geographically referenced systems for storing, manipulating, modelling and visualising spatial data (Alexander and Xiang 1994). Automated crime mapping has a much shorter history but has been common since the mid-1970s (McEwen and Taxman 1995). The primary users of crime mapping have been medium to large police departments with computer aided despatch (CAD) and records management systems; community organisations partnering law enforcement agencies as part of community policing to understand neighbourhood crime, infrastructure and social problems; and multi-agency crime control task forces (Rich 1995).

Automated crime mapping applications are classifiable into *Crime Analysis of Patterns* (CAP) and *Crime Pattern Analysis* (CPA) which have quite different objectives and meet different operational requirements (Hirschfield *et al*. 1995). CAP applications are used mainly in tactical analysis, to show the occurrence of crimes in certain areas such as police beats. The search of patterns is manual, through the structuring of spatial queries and the inspection of pin maps. CPA applications use spatial tools such as GIS to analyse crime distributions for significant patterns that transcend administrative boundaries and require minimum user intervention. Some of the types of CPA include hotspot analysis and geographic profiling – a technique used to determine the likely home base of a serial offender based on the spatial behaviour of offenders (Grescoe 1996). This study is an example of a crime pattern analysis and spatial data visualisation techniques to identify patterns in motor vehicle theft in Adelaide, South Australia.

Methods

The study focuses on MVT that occurred in metropolitan Adelaide (Figure 2) during 1999 and is based on South Australia's Comprehensive Auto Theft Research System (CARS database).

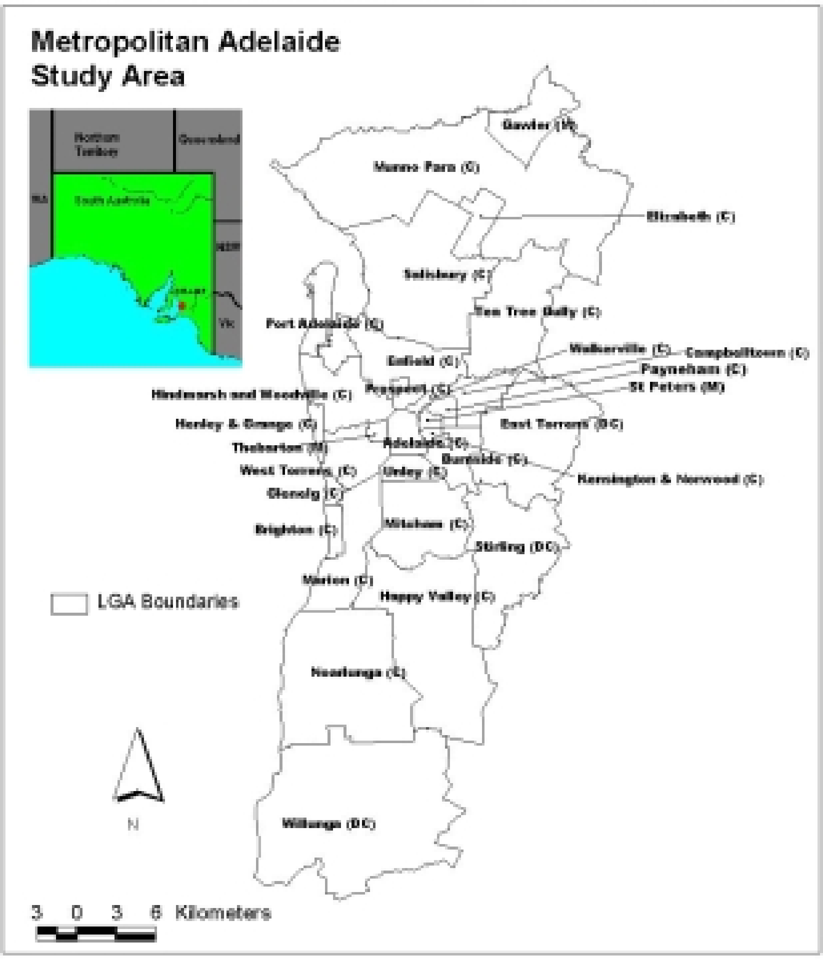

Figure 2 – Location of the Adelaide metropolitan study area.

CARS has been in operation since 1995 and is owned and maintained by the Office of Crime Statistics, Attorney General's Department. The database contains police data, insurance policy and claim data, registration information about the stolen vehicle and more relevant to this study, the street address, date and time of theft. The database is mainly used to produce statistics on motor vehicle thefts for police, crime prevention practitioners and policy makers (see Hackett 1995; Merriman 1998; McGarry 1999).

The CARS database is a reliable source of MVT information for South Australia with a level of reporting of 95% of all incidents. Higgins (1997) notes that generally, reported crime statistics on MVT are reliable indicators of the actual numbers of vehicles stolen, as it is requirement that thefts are reported to the police first for insurance purposes. Incidents may go unreported when the stolen vehicle is uninsured due to age or low value. The MVT incident data used in this study was extracted from this database.

The types of vehicle thefts considered were those classified as joyriding, used to commit another crime, unclassified and reselling. Incidents classified as *not stolen* were excluded as these were reported as stolen only because the owner had forgotten where the vehicle was parked or was unaware that a relation had borrowed it.

Geocoding

Before spatial analyses could be performed on the CARS data the MVT records had to be *geocoded* using a process of address matching. In other words, the address information attached to records in the CARS database had to be converted to point locations in a GIS database. All theft locations were geocoded interactively using the MapInfo GIS. However, only about half of the MVT incidences had exact locations (a street number, name and suburb), while the remainder had only street name and suburb. Street numbers may not have been recorded either because car thefts occurred at imprecise locations (such as sports grounds, shopping centres) where only the street name and suburb where the car was parked is known, or police simply omitted to record it (Craglia *et al*. 2000). Consequently the street numbers of the incidences were not used during geocoding. Rather MapInfo was customised to assign the closest address numbers. In addition to the street name, suburb information was used to ensure that incidences were geocoded to a point of the street segment occurring within the suburb. The recovery locations geocoded for *Linkage Analysis* were those stolen from Adelaide and Oaklands Park.

Analysis

Vehicle Theft Hotspots

A Kernel Estimation (KE) method was used within the Spatial Analyst extension in the ArcView GIS to calculate the density of MVT incidents across the study area based on the point pattern. Density is calculated for each cell in a raster grid. A 3D floating function visits every cell in the grid and distances are measured from the center of the grid cell to each observation that falls within the user-specified search radius. Each observation contributes to the density value of the grid cell based on its distance to the center. Hence, nearby incidences have more influence in the density calculation than those further away (ESRI 1999). The density at each location reflects the concentration of the points in the surrounding areas (Williamson *et al*. 1999). The output is a density surface where the values are measured in incidences per unit area and change continuously over space.

KE was chosen to identify hotspots for a number of reasons. The output is interval scaled allowing analysis of magnitude and quantitative comparison (Levine 2000). The smooth surface output lends itself to visualisation as a 3D surface. Unlike other crime clustering algorithms, KE density analysis does not require hotspots to be circles or ellipses as hotspots are often irregular in shape unless the crime distribution is uniform (Williamson *et al*. 1999). The technique also facilitates pattern identification unlike the electronic pin map where with many points, many may overlap, visibility is obscured and pattern detection becomes difficult.

The MVT density surface was created using the point pattern of MVT in the study area with a grid cell size of 20m and a search radius of 1000m. The output density surface was clipped to the study area and then viewed as a 3D surface with shading and enhanced resolution.

Daily, Weekly and Yearly Patterns of MVT

The exact time the MVT incident occurred is unlikely to be known. The period during which the theft occurred is captured in the CARS database as the *date and time the vehicle was last seen and the date and time the vehicle was noticed missing.* The incident could have occurred at anytime between these two values. For the purposes of this study the precise time of the incident was calculated as the midpoint of the *date and time the vehicle was last seen and the date and time the vehicle was noticed missing* values using functions in Microsoft Access (cf. Ratcliffe and McCullagh 1998).

To determine the daily spatio-temporal patterns of MVT the frequency of incidences at each hour of the day was graphed which revealed three distinct periods of MVT (12am – 8am, 8am – 6pm and 6pm – 12am). A density surface was produced from points for three time periods within the study boundary and visualised using a 3D surface.

To determine the weekly spatio-temporal distribution of MVT the total number of MVT incidences for each day of the week was graphed. The density surface of MVT for each day of the week was also visualised as a 3D surface. The daily surfaces were included in an online animation which enables visualisation of the spatio-temporal variation in MVT through the week.

Yearly spatio-temporal variation in the pattern of MVT was calculated by graphing MVT incidences according to the month of the year. A snapshot approach was used to calculate the changes between the selected months (Ratcliffe and McCullagh 1998). A density surface was produced from points for the two selected months of the year – August (highest MVT) and December (lower MVT). The August density surface was subtracted from the December surface, thereby producing a surface with the differences between the highest and lowest monthly MVT incidences.

Linkage Analysis

Linkage analysis was performed for several locations to assess the relationship between the location of vehicle theft and recovery (Nulph *et.al* 1997). Vehicles stolen from Oaklands Park were linked to their recovery locations. The percentage of cars recovered at various distances from the theft site was also determined. Conversely, vehicles recovered within the Adelaide LGA were linked to the location of theft.

To establish links between theft and recovery locations separate coverages were created for theft and recovery locations with each vehicle identified by a serial number. The Avenue script used within the ArcView GIS for Linkage Analysis creates a line theme which links the locations for each vehicle between the theft and recovery locations. The distance between the recovered and stolen location is stored in the line theme.

Results & Discussion

The results of this exploratory spatial data analysis reveal that the distribution of MVT in Adelaide for 1999 is not uniform but displays distinct patterns in space and over time. This distribution is presented and discussed below.

Vehicle Theft Hotspots

Density analysis using the KE method illustrated significant spatial variation in MVT in metropolitan Adelaide (Figure 3) with the density of incidences ranging from 0 to 308 incidences/km^2. The density patterns of MVT illustrates that some areas were more prone to theft than others and had higher risks.

MVT hotspots were found in the central business district (Adelaide LGA) as well as in the suburbs. Adelaide LGA displayed a very high concentration of MVT. Adelaide CBD had the highest densities, the peak of which reached 308 incidences/km^2, tailing off to moderate levels of around 68 to 34 incidences/km^2. Some suburbs also exhibited MVT hotspots, particularly Oaklands Park within Marion LGA and Modbury within Tea Tree Gully LGA were the worst areas, with theft density up to 171 incidences/km^2. Glenelg LGA, Kilkenny and Woodville in the Hindmarsh and Woodville LGA, Salisbury LGA, Elizabeth LGA and Noarlunga also exhibited hot spots up to 103 incidences/km^2 (Figure 3).

This pattern illustrates that the density of thefts was highest near major commercial and entertainment centres (e.g. business district, retail and recreational areas). Crime place theories suggest that these areas attract more people, thereby resulting in a greater number and concentration of potential targets and motivated offenders. Motivated offenders are presented with great opportunities. There is a high concentration, diversity and visibility of vehicles all in one place. There is minimal risk, as shopping centre car parks and surrounding streets have low security. A low nocturnal residential population, especially in the CBD, offers minimal physical barriers. Offenders find it easier to blend in with the people traffic and do not appear *out of place* in such high traffic areas. The locations are also easily accessible, being located on or near main roads, with many entrances and exits.

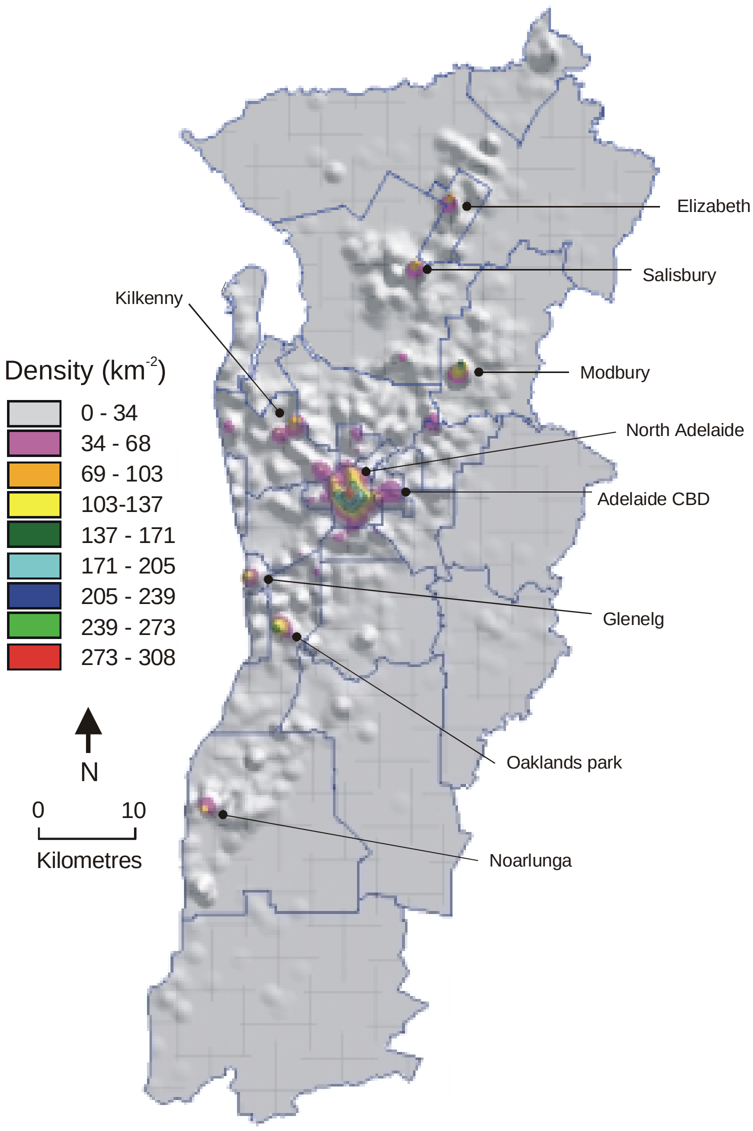

Figure 3 – Density of MVT in the Adelaide study area.

Spatio-temporal Distribution of MVT in Adelaide

Spatial Distribution During The Day

Three distinct periods of MVT were identified: between 12am and 8am, between 8am and 6pm; and between 6pm and 12am (Figure 4). Between 12am and 8am there were higher numbers of MVT, which peaked around 1am and 3am. Between 8am and 6pm, MVT peaked around 12pm and 2pm. Between 6pm and 12am, MVT peaked around 7pm and 9pm (Figure 4).

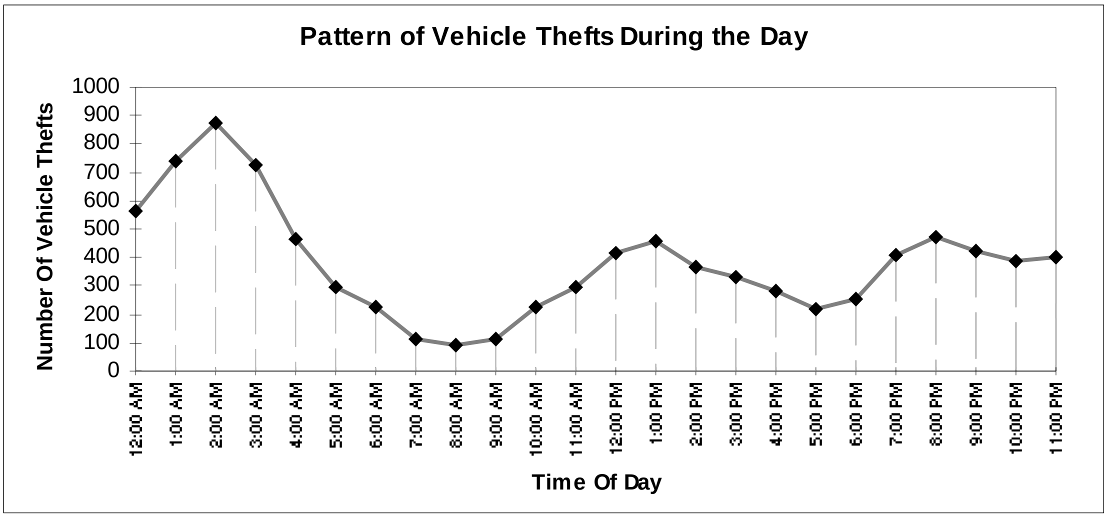

Figure 4 – Frequency of MVT incidences during the day.

Distinct spatial variation is evident when the density of MVT is visualised for these three time periods (Figure 5). Between 12am to 8am a higher number of incidences occurred throughout the metropolitan area with hotspots occurring in the Salisbury, Port Adelaide, Noarlunga, and Tea Tree Gully LGAs. The Adelaide CBD hotspot reached its peak of 118 incidences/km^2. The density of thefts in the suburbs was lower.

Between 8am and 6pm MVT was moderately high (Figure 4). Densities remained very high in the CBD (103 incidences/km^2). However, suburban hotspots were comparatively higher than the previous time period. Modbury showed the highest density of up to 116 incidences/km^2, Oaklands Park had the second highest rate up to 90 incidences/km^2 and most of the suburban retail areas such as Elizabeth, Salisbury, Noarlunga and Kilkenny also displayed high densities (Figure 5).

Between 6pm and 12am the suburban shopping areas displayed lower densities of MVT. Density at Modbury was 47 incidences/km^2 while Oaklands Park was 59 incidences/km^2 (Figure 5).

In summary, the spatial distribution of MVT varied with the time of the day, especially in the suburban hotspots. The suburbs were worst between 8am to 6pm and though the density reduced thereafter, there was always some activity even between 12am and 8am. The Adelaide CBD showed consistently high concentrations of MVT during the three periods.

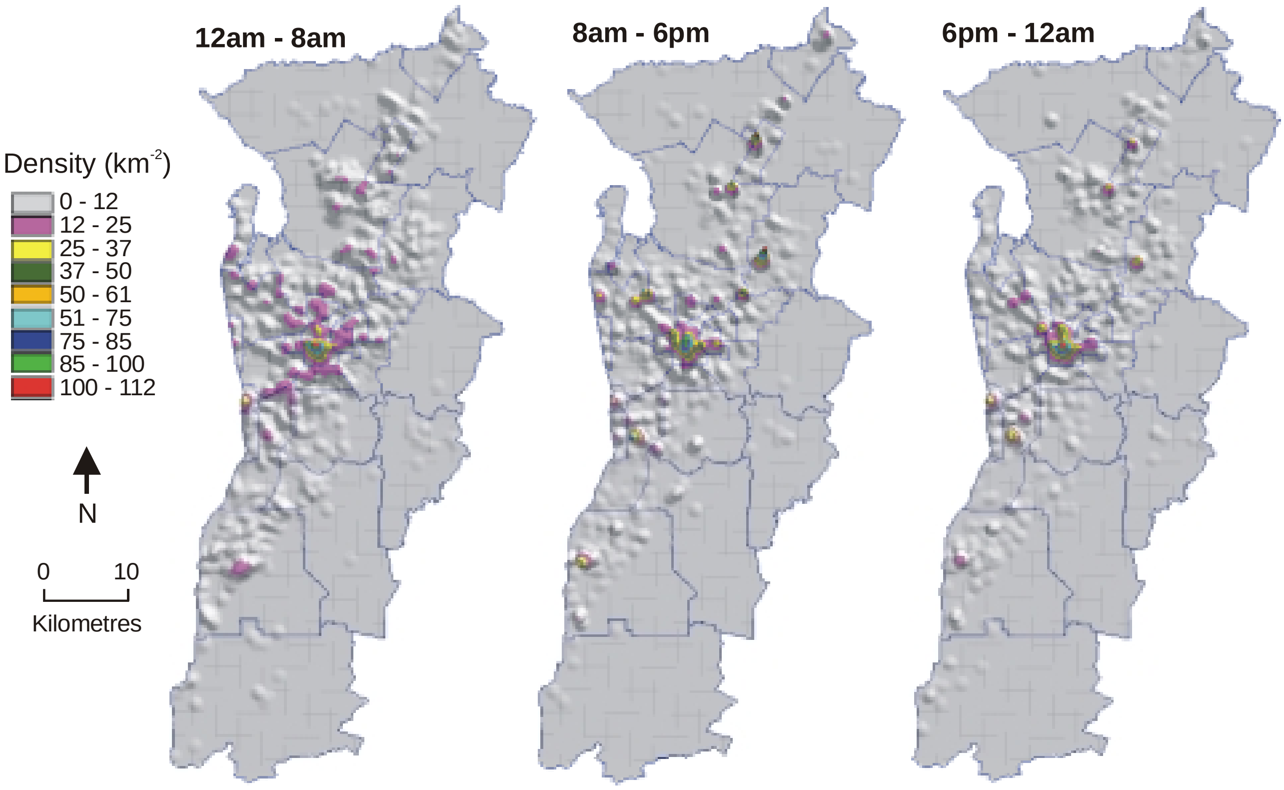

Figure 5 – Density of MVT in Adelaide for three different time periods 12am – 8am, 8am – 6pm and 6pm – 12am.

Spatial Distribution During The Week

Analysis of the distribution of MVT for each day of the week revealed that higher numbers occurred on Friday and Saturday while less occurred on Tuesday and Wednesday (Figure 6). Theft was more common during the weekend. This pattern may be a manifestation of the routine activity theory. Monday through Thursday reflects the pursuit of weekday activities (school, work and home), while Friday and Sunday are transitional days as Friday marks the start of weekend activities and Sunday marks the preparation for routine weekday activities (LeBeau and Langworthy 1986).

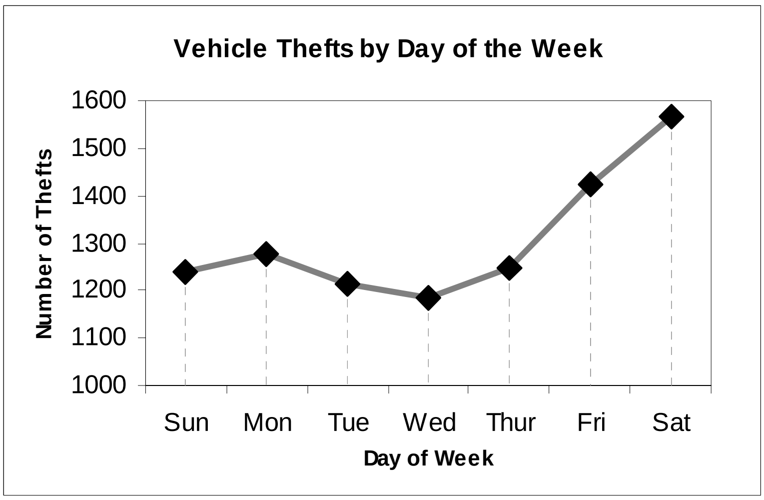

Figure 6 – Frequency of MVT for different days of the week.

The spatial distribution of MVT also displays distinct patterns (Figure 7). Changes in the spatio-temporal pattern of MVT are readily apparent when this information is presented as an animation (http://www.gisca.adelaide.edu.au/~lhenry/ dayofweek.html).

From Monday through Wednesday, MVT was relatively moderate in suburban hotspots such as Modbury and Oaklands Park, and in the CBD with up to 30 incidences/km^2. On Thursday, MVT was primarily concentrated around suburban hotspots. The Modbury hotspot peaked at a high 80 incidences/km^2. The density was generally lower in Adelaide LGA, Adelaide CBD peaking at only 30 incidences/km^2 and North Adelaide up to 10 incidences/km^2. On Friday, there was a shift of MVT to Adelaide LGA, with a peak of 60 incidences/km^2 in the Adelaide CBD and 25 incidences/km^2 in North Adelaide. Generally, the density for the Adelaide LGA was high and spread outwards into Hindmarsh and Kensington & Norwood. The density in suburban hotspots, such as Modbury and Oaklands, was moderate at 30 cases. The MVT pattern on Saturday was similar to Friday. However, density in Adelaide CBD increased to 80 incidences/km^2. The Glenelg LGA also increased to 25 incidences/km^2. On Sunday, the density of MVT in Adelaide CBD was still high at 60 incidences/km^2. Suburban hotspots displayed reduced activity of up to 10 incidences/km^2 (Figure 7).

In summary, the spatial distribution of MVT varied with the day of the week. The Adelaide CBD hotspot was most intense from Friday through to Sunday. Throughout the rest of the week it remained moderate at about 30 incidences/km^2. The suburban hotspots were most intense on Thursdays with late night shopping, but moderate on other days and on Sundays were relatively low.

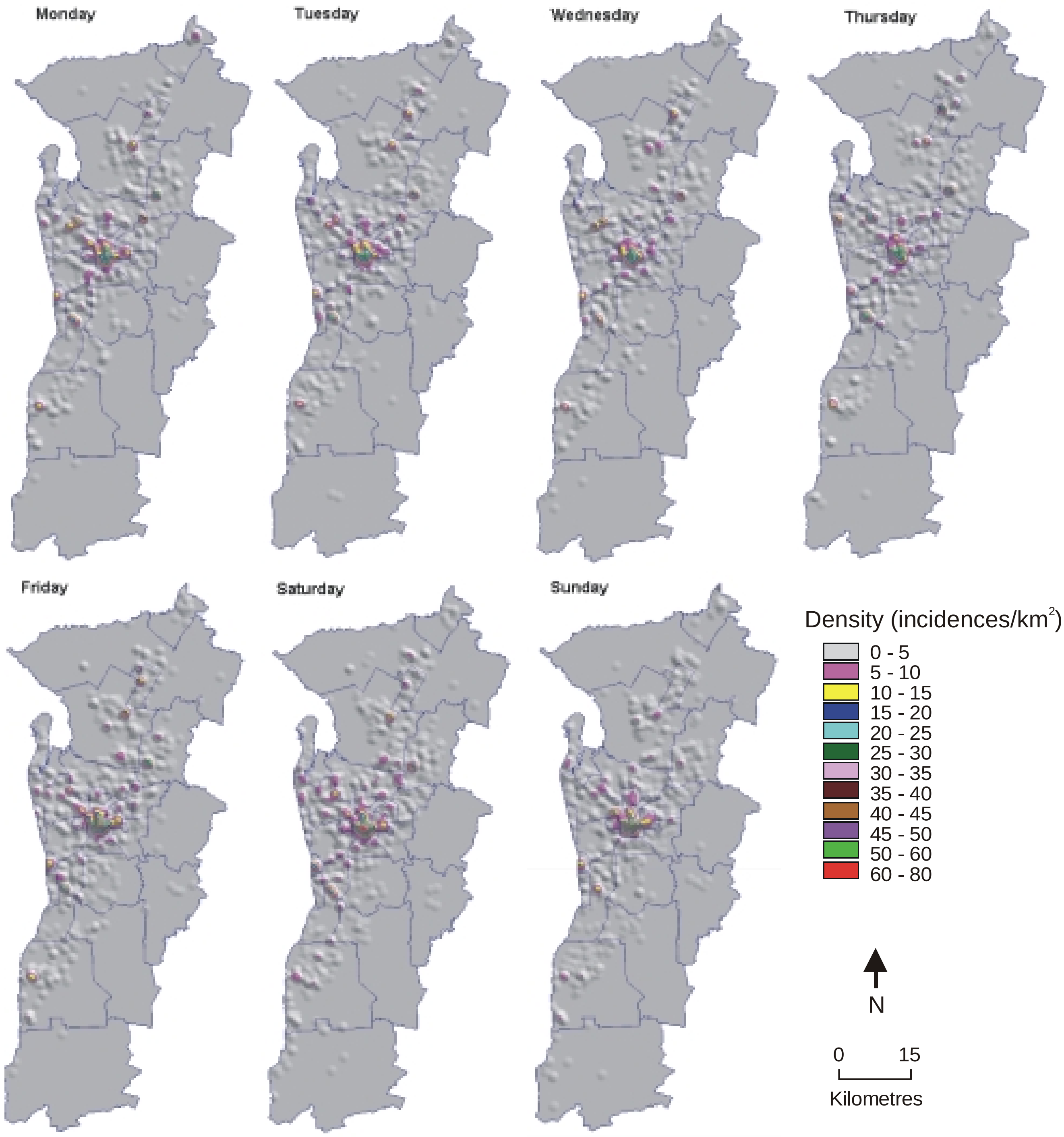

Figure 7 – Spatial distribution of the density of MVT for each day of the week.

Spatial Distribution During the Year

There was limited variation in MVT for different months of the year. August and December were the months selected for the analysis of changes. August had the highest number of incidences whilst MVT was lower in December (Figure 8).

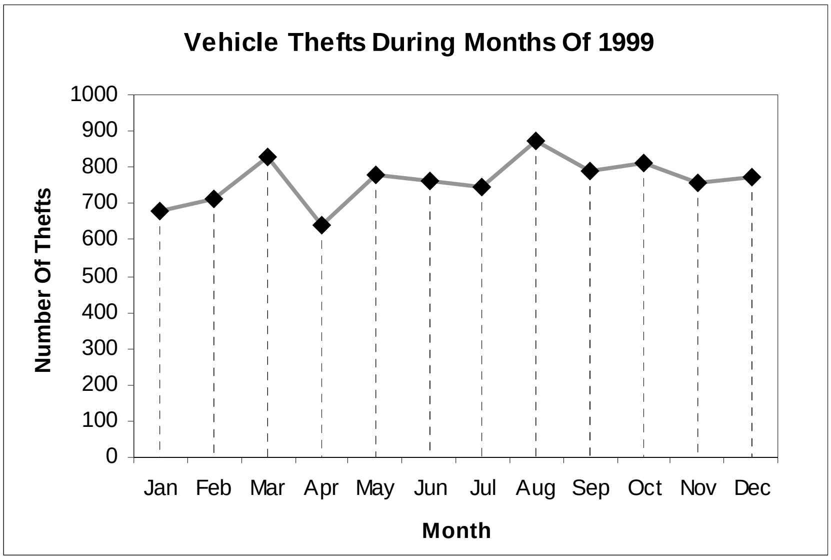

Figure 8 – Frequency of MVT during the months of 1999.

Calculation of the difference in MVT density between August and December revealed substantial decrease in the Adelaide CBD, where there was a reduction of 1 to 16 incidences/km^2. Suburban hotspots that showed significant increases were Oaklands Park with increases from 1 to 21 incidences/km^2. Glenelg also showed an increase of 1 to 5 incidences/km^2 (Figure 9). The increases in Glenelg and Oaklands Park could be due to changes in routine activities as a result of school holidays and Christmas shopping activities.

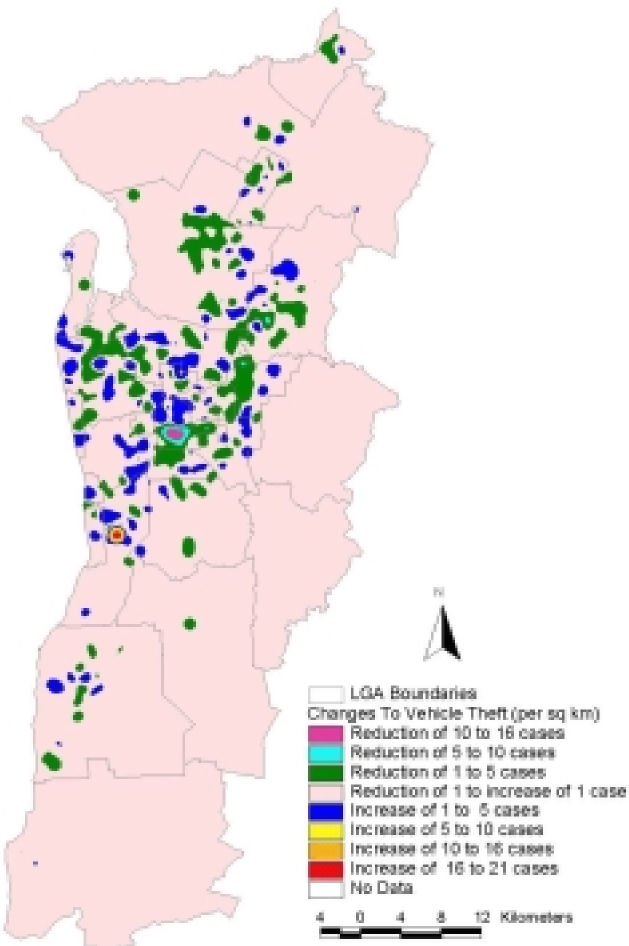

Figure 9 – Differences in MVT between August and December, 1999.

Linkage Analysis

Within the Oaklands Park suburb, 49.5% the stolen vehicles were recovered within 5km, 20.3% were recovered within 10km, 14% were recovered within 15km, 8.1% were recovered within 20km and 8.1% recovered beyond 20km (Figure 10). The finding that vehicles tend to be recovered relatively close to where they were stolen is supported by Zeman *et.al*. (1999).

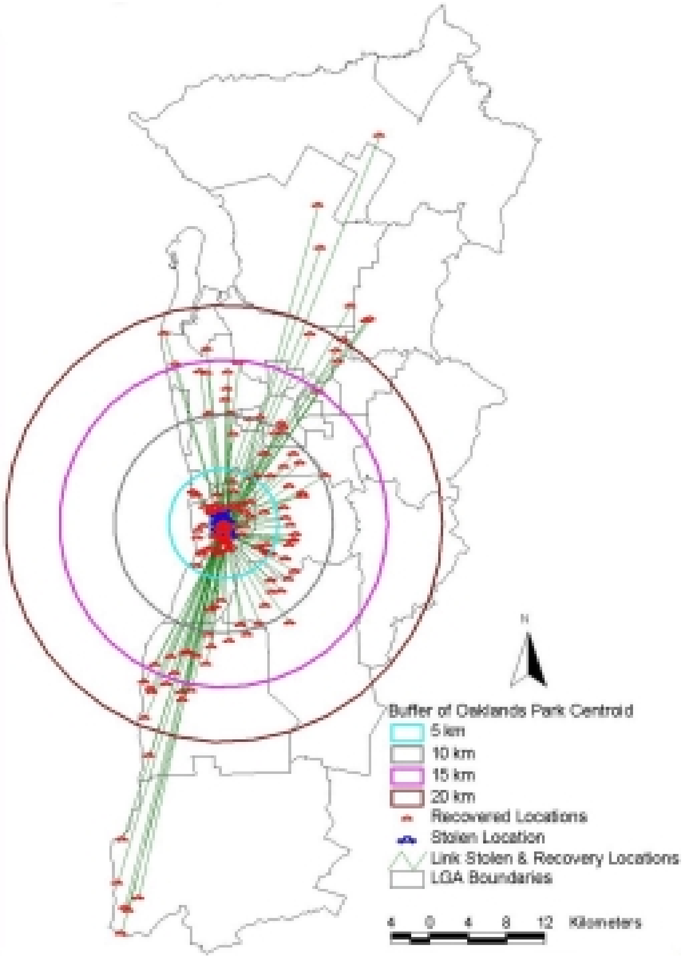

Figure 10 – Linkage analysis of recovery locations of vehicles stolen from Oaklands Park.

Within the Adelaide LGA, 73.7% of the thefts happened within 5 km of the centre of the recovery site, while 14.2% occurred within 10km, 7.1% within 15km, 2.9% within 20km, and 2.1% were located outside 20km (Figure 11). The high proportion of thefts occurring within 5 km of the recovered area, suggest that thefts within the city were mainly joy riders and those seeking transport to nearby locations. It is likely that thefts in the outer suburbs were primarily for transportation to the city itself.

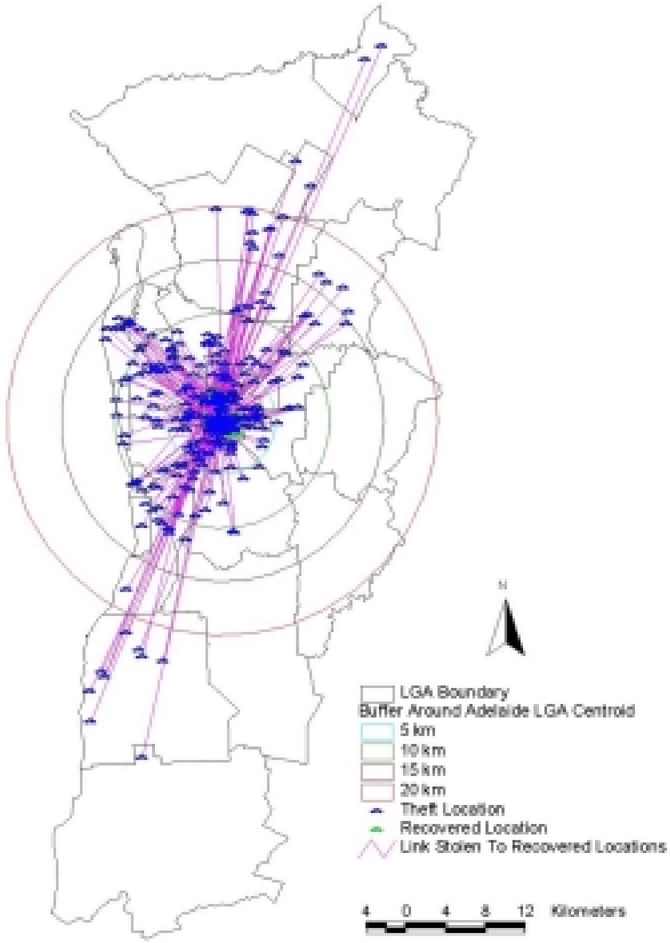

Figure 11 – Linkage analysis of theft locations of vehicles recovered in the Adelaide LGA.

Implications for CPA and Crime Place Theories

This study represents a successful application of crime pattern analysis. The Kernel Estimate density calculation technique was successful in revealing patterns in the point pattern of MVT incidences and in the identification of MVT hotspots. The visualisation of the spatial distribution of MVT density as 3 dimensional surfaces with shadowing provided an effective means of communicating the results of crime pattern analysis. The 3D surface enabled substantial intra-class variation to become apparent as the texture provides information about surface values within the uniform shading of the class symbol.

The use of the precise location of MVT incidences through geocoding the unit record data in the CARS database provides increased accuracy over previous crime pattern analysis conducted by the Office of Crime Statistics. The use of density surfaces for the representation of MVT is sensitive to fine-scale spatial variation in density that may be generalised by the use of census collection districts as the smallest spatial unit of analysis. At the same time, privacy of the individual records in the database is maintained.

The spatio-temporal variation of MVT in Adelaide is readily explained by established crime place theories. Of particular importance is the temporal variation in MVT at various times of the day and the spatial variation between the CBD and the suburbs of Adelaide at various times of the week. Elements of each of the three theories discussed above can be used to explain this variation. Firstly, offenders make rational choices about their actions. MVT in Adelaide seems to be mostly dominated by joy riders and opportunistic theft. Much of the theft occurs on the weekend, which signifies a break in the routine activities of offenders and victims. Thirdly, as crime pattern theory suggests, thefts occur when the awareness spaces of offenders coincide with high availability of targets such as on Thursday nights in large shopping centre carparks or on the weekend in the CBD, an entertainment hotspot.

Limitations of Study

One possible source of spatial error could have occurred during the geocoding process when the geocoding software was customised to assign the closest street number as more than half of the incidences did not possess a street number but only a street name and suburb. Also there were some data entry errors in street names and suburbs. Increased accuracy in police data entry could minimise these sources of error. Some ways this could be achieved is by referencing the location of vehicle theft to the nearest postal address or known fixed point, officers mapping directly onto digitised maps and using up-to-date street and suburb coverages (Craglia *et.al* 2000)

The hotspots were not tested for statistical significance. Feedback from the Office of Crime Statistics was obtained about the location of the hotspots, based on their experience with vehicle theft patterns. Thus, despite these sources of probable error, the Kernel Density Method provided reliable surfaces of MVT in Adelaide.

Benefits for Crime Prevention

Knowledge of the spatio-temporal distribution of MVT in the study area and its explanation through crime place theories can provide valuable intelligence about the nature of MVT. Crime prevention officers can use this information to target valuable resources at MVT hotspots in space and time, and to understand the social milieu that sustains the hotspots. These locations are *hot* as a result of their characteristics, the concentration and distribution of targets and offenders, and the movement paths that bring the offenders and victims together at the location and people's perceptions of crime locations (Brantingham and Jeffery 1981). For example, in Adelaide, different crime prevention strategies need to target the major suburban shopping centres during shopping hours, especially Thursday nights, and the CBD area on weekends.

Future Research

This study focused on one year of motor vehicle theft only. Future research should provide similar assessments for previous years to test the representativeness of the 1999 data. Nonetheless, this study has highlighted criminological research areas that need attention. Crime pattern analysis of recovered vehicles may reveal the location of common dumping grounds as well as operation of nearby vehicle *chop shops*. A wider array of point pattern analysis tools could be used to further quantify and understand the spatial and temporal patterns of MVT. Predictive techniques such as multiple regression or artificial neural networks could also be used to predict when and where MVT incidences are likely to occur and include independent variables such as weather.

Conclusions

Crime pattern analysis revealed that MVT did not occur randomly over space but rather was concentrated in hotspots in the Adelaide CBD and in the suburbs containing major shopping centres. MVT also displayed variation in time, being higher between 12am and 8am than at other times of the day and concentrated in the suburbs and the CBD during the week and in the CBD on the weekends. Recovered vehicles tended to be found within close distance to the location of theft. These findings support the hypotheses made by crime place theories that offenders make rational choices regarding the decision to steal a motor vehicle, thefts are influenced by changes in the routine activities of people, and theft is determined by the interaction of motivated offenders and targets in time and space.

The GIS-based techniques used in the crime pattern analysis in this study provide significant advantages over previous analyses insofar as fine-scale spatial variation can be visualised without compromising the privacy of individuals within the database. The 3-dimensional surface visualisation techniques employed enable the communication of more detailed intra-class information about the density of MVT. GIS has proven to provide insights into the spatio-temporal distribution of MVT through crime pattern analysis.

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