Document Title:	**Motor Vehicle Theft: Crime and Spatial Analysis in a Non-Urban Region**
Author(s):	**Deborah Lamm Weisel ; William R. Smith ; G. David Garson ; Alexi Pavlichev ; Julie Wartell**
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EXECUTIVE SUMMARY
Crime and Spatial Analysis of Vehicle Theft in a Non-Urban Region

Motor vehicle theft in non-urban areas does not reveal the well-recognized hot spots often associated with crime in urban areas. These findings resulted from a study of 2003 vehicle thefts in a four-county region of western North Carolina comprised primarily of small towns and unincorporated areas.

While the study suggested that point maps have limited value for areas with low volume and geographically-dispersed crime, the steps necessary to create regional maps – including collecting and validating crime locations with Global Positioning System (GPS) coordinates – created a reliable dataset that permitted more in-depth analysis. This in-depth analysis was inherently more valuable and identified distinctive crime patterns in the region. These patterns included:

- Vehicle thefts were widely dispersed – 95% of census block groups (235 of 248) in the region had at least one of 633 thefts during the year.

- The risk of vehicle theft was significantly higher in areas with higher concentrations of rental housing *and* in areas with manufacturing or industrial land use.

- In contrast to vehicle theft in urban areas, business premises were common theft locations in the region; "risky facilities" such as car dealerships and repair shops were prominent among these theft locations.

- An unusually high number of vehicles other than cars and trucks were stolen. These "hot products" included ATVs and mopeds.

In contrast to point maps, these findings about the nature of stolen vehicles pointed law enforcement towards highly specific crime prevention strategies. It is unlikely that such patterns – and the suggested responses – would have emerged without aggregate regional data about vehicle theft.

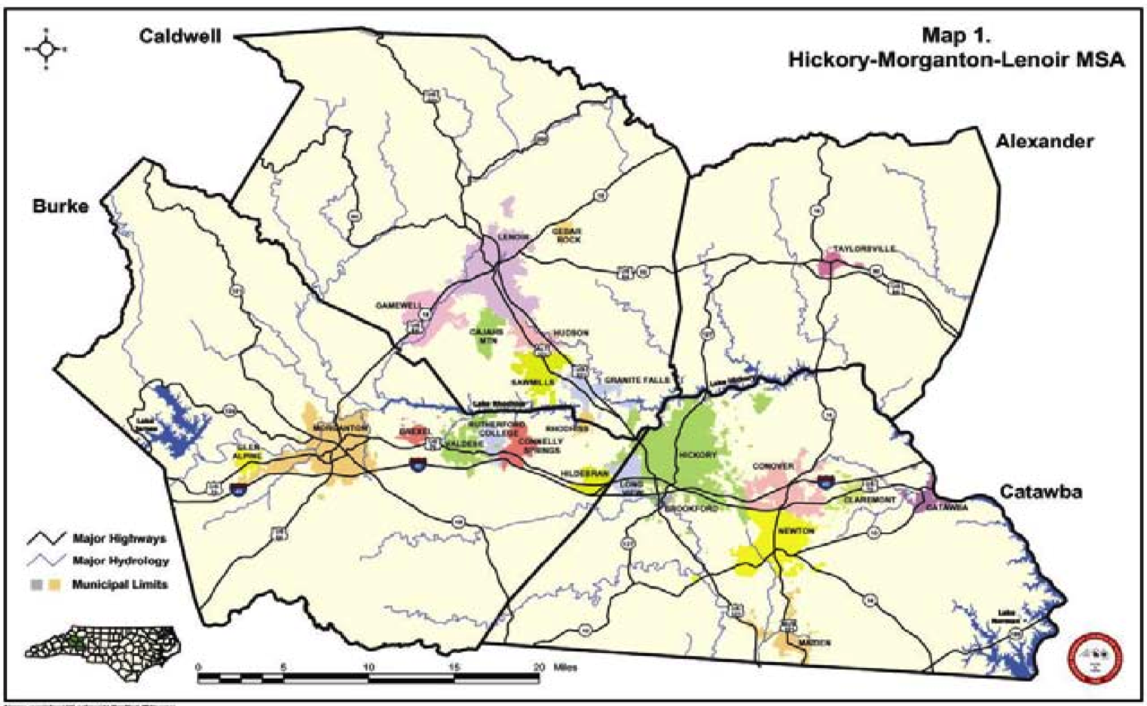
While the study revealed that address data were initially weak for spatial analysis, there are relatively simple ways to improve data quality; the usefulness of findings suggest efforts to improve data quality would yield important benefits in terms of crime prevention.

Research Approach

It is well-established that both the volume of crime *and* crime rates are much lower in rural areas. Little is known, however, about the nature of crime in rural areas or its geographic concentration. The dearth is particularly true for vehicle theft; while the crime is oft-studied in urban locales, there is no research on vehicle theft in non-urban areas. Not only is little known about *where* vehicle theft occurs in non-urban areas – a phenomenon that could be redressed with point maps, but virtually nothing is known about the descriptive nature of vehicle thefts – such as the prevalence of joyriding or the types of vehicles stolen.

To assess the accuracy and usefulness of crime and spatial analysis for vehicle theft, incident reports for 2003 were collected from 11 law enforcement agencies – four sheriffs' departments and seven municipal police agencies that serve the Western Piedmont region of North Carolina – an SMSA of nearly a half-million population. The agencies had been experiencing problems with an increasing number of stolen vehicles, while recoveries were declining. Regional data were necessary to ensure a sufficient volume for statistical analysis.

The Western Piedmont is an area known for furniture manufacturing and is comprised primarily of small towns. Hickory, the largest municipality, has a population of 37,000; the town is sited at the junction of the four counties and centered along a major East-West Interstate Highway (See Map 1). The jurisdictions in this area have a common economic base and a strong history of cooperation.



Mapping Crime Locations

A total of 633 vehicle thefts were recorded by police in 2003 and many of the thefts, about one-third, occurred in Hickory. Crime reports contain information about location, including a specific address for the theft. To create maps, addresses must minimally include a street name and a number or intersecting street. In non-urban areas, incident locations for stolen vehicles might be expected to lack street numbers such as for offenses occurring on private streets; other offenses might be expected to occur on large land parcels, where a street number is imprecise.

At the outset of the study, addresses of offenses were presumed to be of poor quality for geocoding and this was true; while every incident report contained *some* type of information about the offense location, many of the addresses were deficient for geocoding. Of 633 theft locations, 51 lacked *any* address information. Many of these cases consisted of address fields that contained only descriptive information, such as the following:

Interstate 40 Area rest area, Catawba, NC
1st House on left Walsh Rd., Off Hwy 268
1st chicken house on left, Winterhaven
White House across from 4 Truckers, Morganton
Shed on Trails End

Numerous reports were missing street numbers, such as the following:

Hwy 268
I-40 at Exit 125

Other reports included the names of businesses but no street name or street number within the address field. Such addresses including the following:

Winn Dixie Parking lot
Mount Herman United Methodist Church
Lowman's Motel #2
Hickory Drilling on R from Haway Rd I-40 Access Rd.
Hildebran Texaco
West Side Metal, Calico Road

Initial geocoding of theft addresses produced a match rate of only 49%, with geocoded scores at 80% or better, while another 27% of addresses were geocoded with scores less than 80%. Thus, a total of 76% of addresses were initially geocoded. Manual cleaning – particularly the addition of theft addresses recorded at commercial premises – increased the overall geocoding to 85%, with 75% of addresses scored at 80-100%.

Improving Address Quality with GPS

Address quality could not be improved beyond the 85% match without additional data collection efforts. To improve address data, the narratives of crime reports were reviewed and information was recorded about the locations of offenses, including the precise location of thefts on residential parcels and even within large parking lots.

Using descriptive information from the crime reports, all offense locations were visited by a researcher and GPS equipment was used to establish x-y coordinates via satellite.

The precise physical location of most offenses was often easy to detect visually. In many cases, the stolen vehicle – now recovered – was parked in the very location described on the offense report. Even for thefts of vehicles such as mopeds or All-Terrain Vehicles (ATVs), location information was often precise – mopeds were often recorded as being stolen from a back porch or patio, while an ATV was under a carport or next to a shed. In many cases, victims or others at the location provided precise theft information. In one case, a neighbor at a residence was able to point to a very specific theft location – the precise parking stall in the lot of an eight unit multi-family building. In some cases, the researcher called the victim to gather additional information about the theft location.

The precision continued at commercial theft locations. At one large factory parking lot, the researcher pulled up to the loading dock and asked workers where a certain vehicle had been stolen months before. Although the victim was absent from work that day, several co-workers immediately chimed in agreement and pointed to the precise parking spot where the victim's car had been parked.

Of course, there were some thefts for which precise information was not available. For example, at one second-hand car lot, the manager could not recall the precise location of the theft but pointed to four parking stalls where that type of vehicle would have been parked. X-y coordinates were recorded for the mid-point of the location.

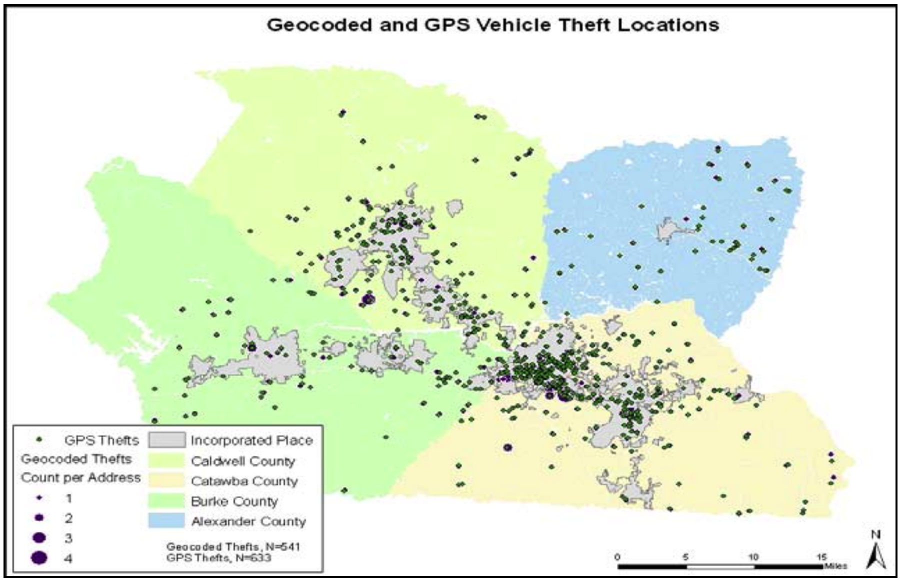
Accuracy of Geocoding

Once GPS coordinates for theft locations were recorded, these were integrated into the Geographic Information System (GIS). A map was produced that added GPS coordinates to complete the missing data from geocoding, thus combining both data sources (see Map 2). The comparison of geocoded maps with GPS maps revealed three types of error in the geocoded maps – missing data, geocoding error, and other data errors. While missing data were anticipated, the latter two types of error would have been undetected without the use of GPS.

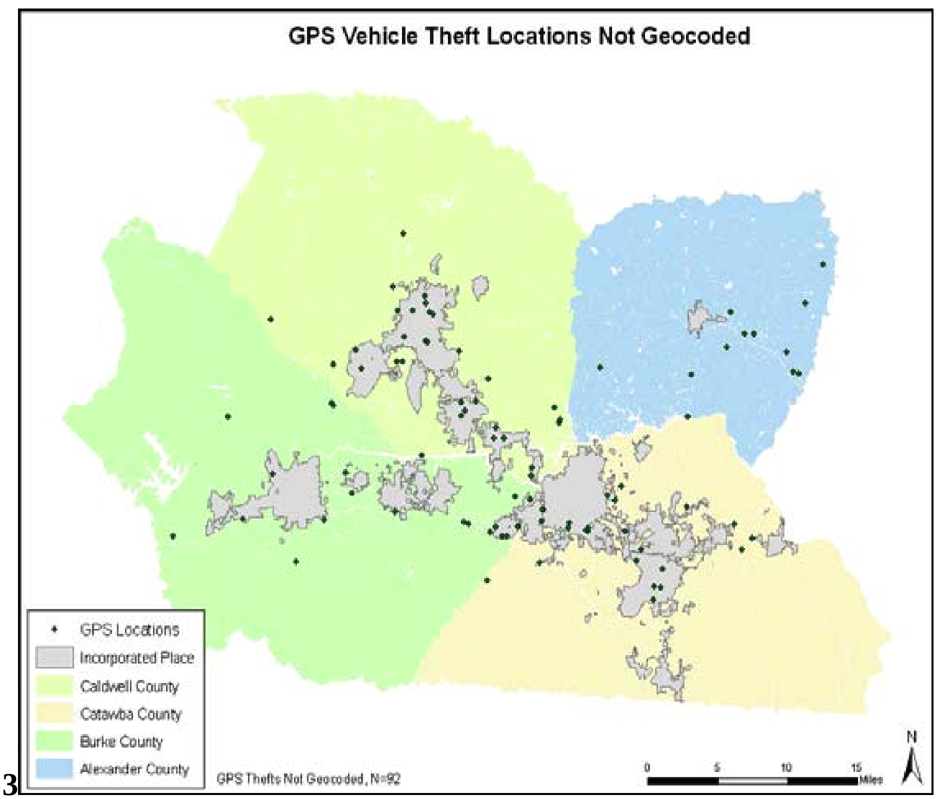
Missing Data

Retrospective collection of x-y coordinates improved the "match" of offense locations from 85% to 100%. In other words, GPS put 92 more points on a point map than did geocoding alone; relying upon a geocoded map would have resulted in a substantial loss of data. Although we anticipated that the majority of the missing data would be associated with unincorporated jurisdictions, this was not the case. The missing data were about equally split between municipalities and unincorporated areas (see Map 3).

Map 1


Geocoded and GPS Vehicle Theft Locations
GPS Thefts
Geocoded Thefts
Count per Address
1
2
3
4
Incorporated Place
Caldwell County
Catawba County
Burke County
Alexander County
Geocoded Thefts, N=541
GPS Thefts, N=633
N
0
5
10
15
Miles

Map 3


GPS Vehicle Theft Locations Not Geocoded
GPS Locations
Incorporated Place
Caldwell County
Catawba County
Burke County
Alexander County
GPS Thefts Not Geocoded, N=92
N
0
5
10
15
Miles

3

Geocoding Errors

Missing data were not the only problem with address data. Recording s-y coordinates through GPS also identified numerous geocoding errors that otherwise would have been undetected. Geocoding errors occurred when automatic geocoding placed a theft in the wrong location within a jurisdiction. Many of these errors placed points down the street or in other nearby locations; some were more distant. The accuracy of geocoding is related to the quality of the street file used for geocoding. The street files used in this study were obtained and integrated from four different counties, and this included two towns that spanned county boundaries. At a low threshold, geocode settings may result in incorrect matches, and these will be undetected unless there is a method to validate the accuracy of the geocoding. In this study, the collection of GPS points provided a method to assess the accuracy of geocoding. The geocoding scores showed that some matches were very weak; initially, only 49% of theft locations could be geocoded with scores of 80% or more. GPS provided a way to detect the frequency and magnitude of geocoding errors.

Data Entry Errors

In addition to missing data and geocoding error, the comparison of the two spatial datasets identified other errors that can be classified as data entry errors. (Data entry error also explains some errors that resulted in geocoding errors.) For example, a street direction mistakenly entered as 100 South Main Street SW when it should have been recorded as 100 South Main Street *NW* will result in an apparent geocoding error. In validating the address, it is found that 100 South Main Street *SW* does not exist or reflects a different location from the one recorded on the offense report. For example, the recorded offense may be related to a street address reported as a residence, while the visual observation reveals that a business is located at the recorded address.

When data entry errors were identified, information in the report narrative of the offense report often permitted errors to be corrected. Thus, the physical collection of x-y coordinates via GPS served as another iteration of data cleaning – data entry errors were corrected when offense locations were matched to the description on the offense report.

Alternate Methods of Geographic Data Collection

The reliability of crime locations could be improved in different ways. First, greater attention to accurately recording information in reports might substantially improve address information. However, it is well-established that accurately-recorded addresses are often problems in crime reports, regardless of attention to report quality.

Electronic entry of crime reports into a Records Management System (RMS) that uses up-to-date street files in drop-down lists for data entry will reduce errors in recording addresses of crimes. In such a system, an address cannot be entered unless there is a corresponding address in the street file. While this does not guarantee that an address will be entered correctly, the method limits many data entry errors.

Electronic data entry however will not resolve problems related to thefts that occur at locations without addresses – the ditches, barns, parking lots, unpaved lanes, and other locations that were common in the unincorporated areas of the Western Piedmont. It also will not resolve problems with precision at crime locations that are large parcels of lands such as parks or wooded areas.

One way to increase data quality and address precision is to employ contemporaneous collection of GPS coordinates at the time of the offense. Through such a method, police would collect satellite coordinates through hand-held or portable GPS systems while collecting information for the crime report. These coordinates could be downloaded later for incorporating into the GIS.

If GPS equipment were not available to officers, electronic orthophotographic maps loaded onto mobile computers in police vehicles or stored in hand-held palm pilots. In using such devices, police can visually locate a crime location on a satellite photo and record these coordinates for the crime report. If necessary due to weather or darkness, such a procedure could occur after the incident is completed.

Recording crime addresses through GPS or orthophotographs, or both, will reduce data error, and will reduce dependence on street files – files that may not be up to date in developing areas, and improve mapping precision over using standard offsets regardless of parcel size.

Major Crime Patterns

Much effort in this study was invested to improve the quality of location data, and get points on a map. The resultant point maps revealed no distinctive geographic clusters of thefts in the region, and hot spot analysis revealed the absence of hot spots. Indeed, thefts were evenly distributed in the region, occurring in 95% of census block groups in the region.

Since GPS increased data volume by 15%, more rigorous spatial analysis of vehicle thefts in the region identified concentrations of thefts in two specific types of census tracts – those with large concentrations of rental housing and those with industrial manufacturing land use. These patterns could not have been detected from a point map.

The greater concentration of vehicle thefts in areas with much rental property likely reflects easier access to vehicles, such as those parked on public streets or in accessible parking lots. In other words, the increased access and reduced guardianship of common parking locations makes vehicle theft more likely in these areas – and makes vehicle theft more similar to urban patterns of theft. Also *rates* of vehicle ownership are likely lower in rental areas, creating relatively fewer targets and relatively greater need by offenders.

In addition to higher theft rates in rental areas, theft rates were also higher in census tracts with manufacturing and industry land use. Vehicles in such areas likely face increased risk because of their concentration at predictable times. Just as vehicles parked in long-term commuter lots have been found to be more vulnerable to theft, vehicles in large parking lots at factories may share a similar lack of guardianship creating a greater concentration of targets for motivated offenders.

Spatial analysis of regional data permitted detection of these geographic patterns by incorporating variables – such as demographics and land use – not typically used in crime analysis by law enforcement.

Hot Products

Most studies of vehicle theft show that automobiles comprise the majority – 73% or more – of all stolen vehicles. In the Western Piedmont, only 52% of stolen vehicles were autos; a noteworthy 26% of stolen vehicles were “other,” contrasting dramatically with 9% nationally based on the FBI’s Uniform Crime Reports (UCR) for 2004. The classification of “other” is used by the UCR to record thefts of motorcycles, All-Terrain Vehicles (ATVs), mopeds, scooters, riding lawn mowers and other self-propelled motorized vehicles. In the Western Piedmont, “other” vehicles were not only common targets of theft, but these vehicles were less likely than any other type of vehicle to be recovered.

The prevalence of ATVs, mopeds and the like among stolen vehicles suggests these vehicles can be considered “hot products” because of their accessibility, and the ease in which they may be both transported from a theft location and then concealed.

Seasonal and Regional Patterns

Theft of “other” vehicles demonstrated a strong seasonal and regional pattern; ATVs were most often stolen during the late summer and fall within the unincorporated areas, while mopeds and scooters were most often stolen during late spring and summer within municipalities. This pattern reflects the local culture where mopeds are used to move around within the towns, while ATVs are more commonly used for recreation, especially hunting during autumn in the more rural regions.

The seasonal patterns and urban-rural distinction between vehicle type was not identified in the spatial analysis using gecoded data. The thefts of “other” were overrepresented in the crime locations that did not geocode and thus initial spatial analysis did not reveal this distinctive pattern.

Risky Facilities

National data shows that vehicles are usually stolen at night, on streets, and close to residential properties with less than 20% stolen from business locations. In the Western Piedmont region, nearly 40% of vehicle thefts were at business premises. This pattern was strongest in the municipalities – 60% of all thefts in towns occurred at business premises while only 19% of all thefts in the counties occurred at businesses.

There was a distinctive pattern among vehicles stolen at business premises as a substantial number of vehicles were stolen at locations that were classified in this analysis as car dealerships, both new and second-hand lots, and businesses involving car repairs, auto parts or rentals; at least 26% of vehicles stolen at businesses (64) occurred at these types of locations.

As with the other distinctive patterns, regional data were necessary to detect the prevalence of the types of business premises where vehicles were stolen. Every agency reported at least one theft at a car-related business, but the 64 thefts were spread across the 11 agencies in the study and it is unlikely that the prominence of these "risky facilities" would have been identified within a single jurisdiction over a shorter period of time.

Implications of Crime Patterns for Law Enforcement

Because the volume of crime is relatively low in non-urban jurisdictions, regional data are critical for analysis of crime. Further, distinctive crime patterns are not short-term, and a sufficiently long time period – such as a year– is necessary to detect distinctive patterns. Even with long-term data, there are no hot spots or distinctive spatial clusters of vehicle thefts the Western Piedmont.

In urban areas, police use hot spot analysis to justify the use of short-term and resource-intensive enforcement tactics, such as bait cars and surveillance. In a non-urban area, the *absence* of hot spots necessitates a deeper level of crme and spatial analysis. Only through the process of "digging deeper" into data can findings emerge that are highly crime and place specific, and suggest specific crime prevention strategies. Findings from the Western Piedmont area suggest that the following preventive strategies are likely to be highly effective:

- Limiting access and/or increasing security at specific types of locations, such as car dealerships and industrial sites, including holding owners accountable for increasing security of vehicles and preventing thefts. In some cases, these strategies will be as simple as requiring test drivers to be accompanied by an employee to prevent thieves from copying keys to be used later in stealing the vehicle.

- Increasing security of vehicles in areas with high concentration of rental housing, such as securing parking lots or increasing natural or formal surveillance. In such area, devices as the "club" may be advisable. In the long term, increasing home ownership may reduce other crimes such as vehicle theft.

- Increasing security of vehicles in areas with industry and manufacturing businesses. Such steps are likely to include limiting access to parking lots adopting other strategies such as those employed at commuter parking lots.

- Given the increasing ownership of vehicles such as ATVs and mopeds, extensive public education efforts should be developed to improve the efforts of vehicle owners to properly secure their vehicles. Such security steps may be quite simple, such as placing ATVs in sheds or using security devices. Systematically recording serial numbers for “other” vehicles” such as ATVs at retail outlets or etching property with identification may assist law enforcement in returning recovered vehicles to their owners if recovered.

Further, the findings suggest that in the long term, efforts to increase home ownership in areas may substantially reduce the risk of victimization.

ABSTRACT

Motor Vehicle Theft: Crime and Spatial Analysis in a Non-Urban Region

Little is known about crime nor its spatial distribution in rural areas of the United States. The low volume of crime in these areas, and problems with address reliability have likely dampened applications of crime and spatial analysis in non-urban areas. To redress that dearth, N.C. State University, in collaboration with the Western Piedmont Council of Governments and 11 county and municipal law enforcement agencies in western North Carolina, examined motor vehicle thefts using 2003 incident reports to analyze and map offenses across a four-county region.

Using regional data provided a sufficient quantity of incidents to examine the spatial distribution of thefts. The study also collected Global Positioning System (GPS) coordinates to specify precise locations of offenses. This technique was useful even when parcel addresses were available, but the technology was critical when addresses consisted only of general descriptions such as “Highway 268.”

Because GPS was able to associate locations with 100% of vehicle thefts, the technique substantially improved the 85% match rate resulting from geocoding. In other words, GPS put nearly an additional 15% of points on a map than otherwise would have been possible. In addition, GPS identified numerous geocoding errors that would otherwise have been undetected.

By improving address quality, the study was able to examine the relationship of vehicle thefts to contextual features in the region, including proximity to major roadways, home ownership and proximity to industrial areas. Further descriptive analyses of motor vehicle theft shed light on noteworthy patterns of crimes, such as trends in types of vehicles stolen, recovery patterns and common theft locations.

Motor Vehicle Theft: Crime and Spatial Analysis in a Non-Urban Region

Final Report to the National Institute of Justice

Mapping and Analysis for Public Safety

By
Deborah Lamm Weisel
William R. Smith
G. David Garson
Alexei Pavlichev
Julie Wartell

May 2006

Acknowledgements

This report could not have been completed without the valuable assistance of the 11 police and sheriffs' agencies who participated in this study. Taking the time to extract electronic data (or to manually pull reports as was necessary in some agencies) placed a burden when local resources were strained. Unfailingly, however, police have been accessible and interested in this study, and have offered important insights into the nature of a common crime problem. Their insights have aided the authors in "getting the story straight" and assessing the practical implications of findings that might otherwise be considered by police as interesting but not inherently useful. For the Western Piedmont region, our hope is that the findings from this study spearhead an on-going regional crime analysis. This has the potential to greatly increase the usefulness of crime and spatial analysis, and guide agencies to evaluate effectiveness and implement longer-term solutions that might otherwise be overlooked.

Equally valuable was the assistance of the Western Piedmont Council of Governments (WPCOG). Doug Taylor, WPCOG executive director, has a strong vision about regional coordination, and could see the value of regional crime analysis. Scott Miller, WPCOG GIS Director, has strong technical skills of GIS, the unique knowledge of different jurisdictions, and exhibited a commitment to see the research to its conclusion. During the course of the project, Scott hired a recent college graduate and area native, Stephen Fox, to collect the GPS data. Stephen exhibited the ingenuity and commitment to quality field research that made the data extremely reliable. His knowledge of the region and his interpersonal skills enabled him to identify, access and collect x-y coordinates in a wide range of locations and conditions.

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CHAPTER I: INTRODUCTION AND NEED FOR RESEARCH

Much is known about crime in America, and advancements in the last decade in crime analysis, mapping and problem solving have increased the ability of police to respond more effectively to crime problems, often resolving long standing problems. Today, police can draw upon a large body of scientific knowledge and applied research and employ widely-available technology such as Geographic Information Systems (GIS) to focus resources where crime problems are most concentrated (Sherman et al., 1998; Bayley, 1998; Zhao, Scheider and Thurman, 2002; Sherman and Eck, 2001; O'Shea and Nicholls, 2003; Reaves and Hickman, 2005; Hickman, 2001).

Knowledge and understanding of crime and policing in America are primarily drawn from studies of crime in urban areas. Although there is a substantial amount of crime in rural areas, the greater concentration of crime in urban areas – usually referred to as the higher crime rate – has formed the basis for the vast majority of empirical research on crime. Historically, higher rates of victimization in urban areas have created a sense of urgency to focus on improving police responses. These needs have attracted funding and supported improved automation of data, data collection tasks and enhanced statistical analyses necessary for valid research. Further, technological and operational resources are often more available in urban areas. These include electronic databases and crime analysis units which have made research on urban crime problems easier to undertake and thus more prevalent in the published academic and applied literature. Similarly, a review of innovations in policing – award winning problem-solving efforts (Scott, 2001; Sampson and Scott, 2000) reflect a strong urban bias. Popular strategies, such as CompStat (McDonald, 2002) and GIS (Hickman, 2001; Chamard, 2004;

Garson and Vann, 2001; Paulsen, 2001), have emerged primarily from larger police agencies in urban environments rather than those of small or rural jurisdictions.

Although research findings about crime and policing are widely generalized, Weisheit and Donnermeyer (2000) suggest that there are important distinctions in rural areas and small towns. These differences have important implications for crime analysis, including the relevance of mapping and problem solving. Urban areas, for example, often have problems with "data overload" – too much data or too many points on a map. The corollary in rural areas is that there are often too few crimes for routine point mapping.

While it may seem evident that crime analysis practices, and thus the usefulness of crime analysis and mapping, will vary across and within places, there is little evidence that this axiom has been carefully examined among the wide range of crime problems and numerous law enforcement agencies across the United States.

Applications of Crime Analysis and Mapping

In practice, crime analysis and crime mapping are closely related. GAO (2005) and Rosenthal et al. (2000) distinguished crime analysis as a distinctive category of policing practices related to community policing and problem solving; GAO (2005: 27) further distinguished crime analysis as "including the use of tools such as geographic information systems to identify crime patterns.

The technology of mapping has emerged as an indispensable tool with a wide array of applications within the criminal justice field and has made a major contribution to both crime analysis and problem-solving efforts (Weisburd and McEwen, 1998; LaVigne and Wartell, 1998, 1999a, 1999b). The widespread availability of GIS has enhanced problem-solving by police

(LaVigne and Wartell, 1998b; Rich, 1999; Weisburd and McEwen, 1998; Sampson and Scott, 2000) and GIS provides a powerful and accessible tool to illuminate the spatial distribution of crime. The display of information is an important function in addition to data input, storage, and analysis (Clarke, 1997). Maps offer an effective and powerful communication tool for the dissemination of information to the map user. Indeed, many resources are devoted to the topic of designing effective maps and enhancing the communication of information through maps (MacEachren, 1995; Robinson et. al., 1995; Dent 1993). Further, researchers have shown that differing types of maps can be constructed to relate to the specific ways people acquire and use information about the spatial environment (Lloyd, 1997). Thus, maps are not only useful to display and convey descriptive information, but can also provide findings that are useful to end users such as police (Ratcliffe, 2004; Eck, 2005) although Paulsen (2004) cautions that police cannot effectively use maps without training. In many police agencies, mapping provides a powerful tool for identifying the presence of problems at particular places or times. It also contributes to problem solving by allowing users to collect and then analyze a range and combination of data sources from the police, community and environment. And, importantly, mapping provides a powerful mechanism for assessing the impact of criminal justice initiatives (LaVigne and Wartell, 1999b).

National studies show that crime and spatial analysis have been used primarily to focus on detecting offenders and identifying crime hot spots (O’Shea and Nicholls, 2003). Among the best known uses of GIS in criminal justice are applications that have successfully resolved crime series, such as leading to the apprehension of serial offenders. In a recent book on the subject, the president of the International Association of Crime Analysts (IACA) touted the success of crime analysis in resolving two series in his city — the “Ski Mask Bandit” and the “Baskin Robbins

Bandit" (Bruce et al., 2004). Geographic profiling is another predictive technique that uses GIS to predict where a specific offender lives.

Identifying hot spots is a common use of GIS in policing (Eck, 2005; Ratcliffe, 2004; Harries, 1999; Sherman, 1995). While the detection of crime hot spots may lead to more efficient deployment of human resources, some research suggests that much crime and spatial analysis are primarily short-term, and the resultant responses usually tactical and temporary. Used this way, crime and spatial analysis may lack the in-depth inquiry necessary to lead to lasting improvements in public safety problems (O'Shea and Nicholls, 2003; Boba, 2003, 2000; Clarke and Eck, 2005; Ryan, 2004).

GIS has been used to examine crime and environmental features such as street lighting (Harries, 1999), proximity to roadways (Wood, 1998; Smith, Frazee and Davidson, 2000; Rice and Smith, 2002), and traffic volume (Brantingham and Brantingham, 1982; Beavon et al., 1994). Given the well-established relationship between crimes and their context (Felson, 1998; Brantingham and Brantingham, 1982; Sampson, Raudenbush and Earls, 1997; Smith, Frazee and Davidson, 2000) – that is, environmental and social features – there is a critical need to systematically incorporate non-crime data into GIS for problem solving to elaborate the relationships between crime and environment (Poulson and Kennedy, 2004; Block et al., 1997; Rich, 1999).

While GIS has been used as a tool in problem-solving, its potential uses have not been realized (Ryan, 2004; O'Shea and Nicholls, 2003; LaVigne, 1999; Taxman and McEwen, 1994). One of the most powerful uses of a GIS is data integration from multiple sources to examine social and ecological contributions to crime (Mollenkopf and Goldsmith, 1997; Rich, 1999). In a survey of crime mapping utilization, only half of the departments using this technology integrated data from non-crime sources (Mamalian et. al., 1999).

Crime Analysis in Small Jurisdictions and Rural Areas

There is little doubt that crime analysis functions in policing agencies have become more prevalent and well-established during the last decade (O'Shea and Nicholls, 2003; Reaves and Hickman, 2005), and American police are making increasing use of GIS for mapping and analyzing crime. In a survey conducted in 1997 researchers found that 13% of police departments were using computerized crime mapping, while another 20% planned to purchase mapping software within the year (Mamalian et al., 1999). By 2000, a survey showed that 75% of large law enforcement agencies (100 officers or more) were engaged in crime analysis, and most of these agencies used crime mapping (O'Shea and Nicholls, 2003).

The increasing prevalence of crime mapping is consistent with national attention to the method; nearly a decade ago, the National Institute of Justice's (NIJ) Mapping and Analysis for Public Safety Program (MAPS) was formed.[1] MAPS has disseminated information on crime mapping and continues to conduct an annual conference that attracts hundreds of police practitioners and researchers. Strong support by the NIJ was also demonstrated through a major investment in the Strategic Approaches to Community Safety Initiative (SACSI) and Computer Mapping, Planning and Analysis of Safety Strategies (COMPASS); the Office of Community Oriented Policing Services (COPS) has also supported the Crime Mapping Laboratory at the Police Foundation.

Despite its rising prevalence in law enforcement, crime analysis and GIS are not well-established in small law enforcement agencies (Chamard, 2004; Rich, 1995; Hickman, 2001;

[1] MAPS was called the Crime Mapping Research Center (CMRC) when it was created in 1997.

Garson and Vann, 2001; Paulsen, 2001). There are distinct differences in the prevalence of crime analysis by the size of the jurisdiction, and the type of agency. As shown in Table I, the larger the agency, the more likely it is to have a crime analysis unit (JRSA, 2005; Rosenthal et al., 2000).

Virtually all the largest police law enforcement agencies in the nation have a crime analysis unit (95%); about two-thirds of mid-sized agencies have a unit (71%) while only 44% of agencies serving populations of 25,000-50,000 have such a unit. [2]

The *size* of an agency's jurisdiction is also closely related with the *size* of its crime analysis unit; the smaller the jurisdiction, the more likely that the unit consists of a single person. While the largest law enforcement agencies have a crime analysis unit, 90% are comprised of more than a single analyst. In contrast, among the smallest jurisdictions (25,000-50,000 population) with crime analysis units, the large majority of units are comprised of a single employee.

Table I: Crime Analysis in Law Enforcement Agencies

Population	Crime Analysis Unit	One Person Unit
More than 250,000	95%	12%
100,000-250,000	96%	40%
50,000-100,000	71%	71%
25,000-50,0000	44%	86%
Less than 25,000	10%	100%

There are also distinctions between crime analysis and the type of law enforcement agency. Municipal agencies are much more likely to use crime analysis and mapping than sheriffs' agencies. The national surveys by the Bureau of Justice Statistics (Law Enforcement Management and Administrative Statistics or LEMAS) suggest that the large majority of

[2] Rosenthal et al. (2000) found that only 23% of agencies with fewer than 25 sworn personnel had a centralized crime analysis unit, while 85% of agencies with 500 or more sworn officers had such a unit.

municipal police agencies (from 86 - 90%) use automated crime analysis, and about two-thirds of these agencies also geocode and map crime incidents (Reaves and Hickman, 2004; Reaves and Hart, 2000; Reaves and Goldberg, 1999; Reaves and Smith, 1995). (See Table II).

Table II: Crime Analysis and Mapping
In Law Enforcement Agencies
1993 to 2000

	Agency Type	**Computerized Crime Analysis**	**Map Crime**
2000	Municipal	86%	71%
	Sheriff	66%	45%
1999	Municipal	90%	67%
	Sheriff	83%	54%
1997	Municipal	--	53%
	Sheriff	--	35%
1993	Municipal	90%	--
	Sheriff	75%	--

The data in Table II suggest a decline in crime analysis units in recent years; e.g., from 90% in 1993 to 85% in 2000 for municipal agencies, and 83% to 66% for sheriffs' agencies.[3] Further, findings reported by Rosenthal et al. (2000) suggest that the number of crime analysis units among law enforcement agencies of all sizes did not increase significantly from 1993 to 1999, but remained relatively constant. While these data and varied methodological approaches are subject to interpretation, it appears that the increasing prevalence or growth of crime analysis has stabilized.

It is not surprising that smaller law enforcement agencies and more rural jurisdictions typically served by sheriffs' agencies are less likely to have crime analysis units; the most common types of crime analysis and mapping described previously – hot spots, geographic

[3] The declines in crime analysis units reflected in the table are modest and may reflect changes in the survey population; it appears that respondents increasingly reflected a larger number of smaller agencies. The LEMAS survey for 1993 included 146 sheriffs' agencies with 100 or more sworn officers, while the 2000 survey included 222 respondents in this category – a 52% increase. Since these survey newcomers are more likely at the smaller range of the population group, their inclusion is likely to dilute the more widespread prevalence of crime analysis units among larger agencies.

profiling, series detection – are unlikely to have many applications in such areas as the low volume of crime in these jurisdictions reduces the utility of GIS. Further, successful mapping requires that crimes are recorded at specific locations that include a street name and number. In very rural areas, this specificity may not be routine.

Although crime analysis and mapping functions are not well-established in non-urban areas, crime in these areas has been on the rise in recent years. Some researchers anticipate this trend will continue because offenders increasingly have greater access to rural areas via improved roadways and transportation systems. There is also evidence that offenders increasingly perceive rural businesses and residents as less risky targets than those in urban locations (Weisheit and Donnermeyer, 2000; Wesheit and Wells, 1998; Weisheit, Falcone and Wells, 1994).

Motor Vehicle Theft

Motor vehicle theft is a major problem in the United States with an estimated $8.6 billion lost to vehicle theft in the year 2003, and more than 1.26 million vehicles stolen (FBI, 2004:55). The volume of vehicle theft rose from the mid-1980s to the early 1990s and then began to rather steadily decline (Newman, 2004). But vehicle theft began to rise again in 1999 in the United States, climbing nearly 10% from 1,147,305 thefts in 1999 to 1,260,471 in 2003 (FBI, 1999; FBI, 2003). Nationally, vehicle theft comprises about 11% of all Part I offenses recorded by the FBI in the Uniform Crime Reports (UCR) (See FBI, 2000-2004).

The decline in vehicle theft throughout the 1990s was largely attributed to improvements in vehicle security at the point of manufacture; however there is little discussion of the reasons for the subsequent rise in thefts. The period of increasing security for motor vehicles has been well documented. Newman (2004) described the introduction of steering column locks and ignition keys in the mid-1960s that prevented hot wiring. The addition of the Vehicle Identification Number (VIN) on all "road-going" motor vehicles was required by the Federal Motor Vehicle Standard in 1969 and later expanded (1984) to engines and other body parts of high theft autos.

A national centralized registry of stolen vehicles was created in 1966 (National Crime Information Center or NCIC); this aided in the recovery and return of motor vehicles to their lawful owners. Additional security devices were introduced in the last decade of the century. By 1989, immobilizers had become standard features on many vehicles and the mid-1980s, Lojack devices were widely being installed to deter theft and, failing that, to increase the likelihood of recovery. Transponder keys were introduced in the 1990s, and keyless entry and vehicle tracking systems have become more common.

Despite improvements in vehicle security, vehicle theft remains prevalent and a major concern to law enforcement. Although it is a common and serious offense, law enforcement agencies fare poorly in resolving vehicle theft through arrest.

Although many motor vehicles are recovered[4], most thefts do not result in arrest; nationally, 13% of thefts are cleared by arrest or exception (FBI, 2004) but the clearance rate has been declining nationally, dropping from the 1999 average clearance rate of 15% (FBI, 2000).

Given the prevalence of vehicle theft, its steady rise since 1999, its 11% contribution to Part I offenses, combined with low and declining clearances averaging a mere 13%, there is an amazing dearth of published research on the offense (Maxfield, 2004; Clarke and Harris, 1992; Rice and Smith, 2002; Herzog, 2002). This dearth is particularly acute in non-urban areas.

[4] Slightly more than half of stolen motor vehicles are recovered; a 54% recovery rate is reported in the National Incident Based Reporting System (NIBRS) (2000) and a 51% recovery rate reported by NCIC (2000). In 2002, 63% of the value of stolen vehicles was recovered (FBI, 2003).

Urban-Rural Distinctions in Vehicle Theft

The vehicle theft studies that have been undertaken have focused on urban locations, and these include studies in London (Chainey, 2005), Newark (Maxfield, 2004), Philadelphia (Rengert, 1996), Reno NV (Decker and Bynum, 2003), Vancouver (Barclay et al., 1995) and Chula Vista, CA (Plouffe and Sampson, 2004). An important distinction between urban and non-urban vehicle theft studies is a matter of volume or quantity of data. For example, Chainey's study of vehicle crime in one London borough (2005) during three months was comprised of 1,747 offenses.[5] Maxfield's study of Newark (2004) was based on 5,538 thefts in 2002; Reno, NV had 626 vehicle thefts in nine months of 2000 (Decker and Bynum, 2003); and Vancouver, where a single lot had 192 thefts in a single year (Barclay et al., 1995). The least populous of these jurisdictions – Chula Vista, CA with a population of about 200,000 – had 1,700 vehicle thefts in 2001; this included one parking lot with 42 vehicle thefts (Plouffe and Sampson, 2004). The volume of thefts within these urban jurisdiction dwarfs the number of vehicle thefts that occur in non-urban areas.

Clarke and Harris (1992) emphasize that vehicle theft is predominately an urban problem, and the differences between rural and urban areas are not simply a matter of volume. Instead, it is the *rate* of vehicle theft by households or population that is much higher in urban areas — vehicle theft rates are as much as six times higher in urban areas than in rural areas.

The 2003 National Crime Victimization Survey (NCVS) suggests that households in urban areas have rates of vehicle theft that are more than three times the rate of vehicle thefts in rural areas; vehicle theft victimization rates are 13 per 1,000 urban households and 4 per 1,000 for rural households (BJS, 2004). The differences in vehicle theft victimization rates between

[5] Chainey (2005) included theft from motor vehicles in addition to theft of motor vehicles.

urban and rural regions contrast sharply with the urban-rural differences of other Part I offenses; for example, burglary victimization is 38.7 per 1,000 urban households and 30.5 per 1,000 rural households.

The distinctions between vehicle theft rates by the type of jurisdiction are also echoed in the size of the jurisdiction. Vehicle theft rates in large cities are approximately four times the rate of vehicle theft in smaller towns — see Table III (FBI, 2004, 2003, 2002). Similarly, the vehicle theft rate in 2003 in large metropolitan counties was 491 per 100,000 while non-metropolitan counties experienced 129 per 100,000 – again, the rate in the larger metropolitan jurisdiction was nearly quadruple the rate of the rural counties.

Table III: Vehicle Theft Rates per 100,000 Population

	2003	**2002**	**2001**
Largest cities (> 250,000)	910.9	927.8	942.5
Smallest cities (< 10,000)	230.0	229.9	228.8

Unfortunately, victimization rates are calculated using population or households as the denominator. This is appropriate for some offenses such as residential burglary but victimization risks for vehicle theft could be compared more reliably by using the number of registered vehicles as the denominator. Indeed, Clarke and Harris (1992)suggest that vehicle theft rates relate to the density of vehicle ownership. The rate of vehicle ownership is higher in rural areas, reflecting a practical reality; where there is no mass transit system and places are located far from one another, persons cannot get to school, work or shopping without a motor vehicle; thus, the rate of vehicle ownership in rural areas is likely higher.[6]

[6] We find no studies of vehicle theft that have examined differences based upon ownership rates.

It seems reasonable that the higher rates of vehicle ownership in rural areas serves to moderate the vehicle theft rates in these areas. While more targets often increase crime, understanding the primary types of vehicle theft provides a rationale for why this does not occur in rural areas. The most common type of vehicle theft is for short-term transportation, when persons have greater lawful access to vehicles, they are probably less likely to steal a vehicle for this purpose. Although the ownership-rate rationale seem reasonable to explain sharp differences in vehicle theft rates, they are untested. Indeed, Weisheit and Donnermeyer (2000) suggest there are other distinctive characteristics of rural areas that explain lower vehicle theft rates; the authors suggest that overlapping social networks, higher rates of acquaintanceship and a tendency toward reliance on informal social control may result in fewer crimes, and may produce lower reporting rates in rural areas.

Nationally, most vehicles are stolen in urban areas (93% of all vehicle theft is recorded in counties classified as MSA or Metropolitan Statistical Areas) and most research about vehicle theft is drawn from urban areas of the United States. But non-urban law enforcement agencies dominate the population of law enforcement agencies in the nation. Only 4% of all law enforcement agencies in the nation employ 100 or more sworn officers while the remaining 15,000 law enforcement agencies have fewer than 100 sworn employees, with an average of 21 sworn employees (Reaves and Hickman, 2002). While vehicle theft rates are lower in non-urban jurisdictions, the prevalence of non-urban law enforcement agencies in the nation causes concern about increasing vehicle thefts. For example, in rural counties, the vehicle theft rate has risen dramatically in recent decades, from 61:100,000 in 1960 to the 144:100,000 in 1997 (Weisheit and Donnermeyer, 2000).

Nationally, vehicle theft rose 1.4% from 2001 to 2002 but the number of offenses rose 7% in suburban counties and 3% in rural counties compared to the 0.2% increase in the nation's largest cities. In North Carolina, vehicle theft in rural areas constitutes a substantial proportion of all reported vehicle thefts – approximately 13% of all vehicular thefts in North Carolina in 2000 occurred in rural areas (FBI, 2000: 67).

In addition to urban-rural distinctions in volume and rate of vehicle theft, there are also important urban-rural distinctions in clearances and recoveries of stolen vehicles. For vehicle theft, consistent with other index crimes, the proportion of reported offenses cleared by arrest are substantially higher in rural counties – 29.3% – than in other types of jurisdictions. In contrast, the clearance rate in cities with populations of over 1 million is 9.9%. Small cities clear more offenses; in 2003, cities with populations less than 10,000 cleared 24% of vehicle thefts (down from 26% in 2002) while the nation's largest cities cleared 10% (compared to 10.1% in 2002). Similarly, non-metropolitan counties cleared 27% in 2003 while metropolitan counties cleared 16%, similar rates to the preceding year (FBI, 2004).

Most stolen vehicles are recovered – nationally, nearly 67% of vehicles, based on value, are recovered but recovery rates are substantially higher in rural counties than in urban. Divergent clearance and recovery rates for urban-rural areas for motor vehicle theft suggest there are some substantive differences between the types of motor vehicle theft occurring.

Motor vehicle theft is a unique offense in many ways. While many crimes are inherently local, motor vehicle theft has demonstrated a regional dimension; vehicles stolen in one jurisdiction are often recovered in another (Maxfield, 2004); vehicle theft offenders also appear to travel further in order to steal vehicles (Wiles and Costello, 2000). The regional nature of motor vehicle theft has important implications for small jurisdictions, as law enforcement personnel may be unaware of a theft or recovery in a nearby jurisdiction.

Key Characteristics of Vehicle Theft

Although vehicle theft research is sparse, we have a basic understanding of vehicle theft and national trends of this crime problem based on historic data collected by the FBI through the UCR and NIBRS, victimization data collected via NCVS and thefts recorded by NCIC. These sources, combined with a handful of local studies, have contributed to a broad outline of the crime problem.

Types of Motor Vehicle Theft

It is widely acknowledged that there are different *types* of motor vehicle theft. Three primary types of motor vehicle theft are based upon the differing motivations of offenders. These include: profit motivated theft in which stolen motor vehicles are exported, or disassembled for spare parts, and fraud; theft for transportation for short-term or prolonged use, which may be used to commit another crime; and recreational theft, often know as joyriding and typically involving youths.

Joyriding or short-term transportation is considered the most common type of motor vehicle theft, although the prevalence of this type is difficult to distinguish; “joyriding” and other types of motor vehicle theft do not constitute a UCR code or subcategory, and cannot be deduced based on incident data. Thefts associated with joyriding, however, are associated with a higher recovery rate (Clarke and Harris, 1992) and often a quicker recovery.

Vehicle Type

There are two important dimensions of vehicles that relate to vehicle theft – the type of vehicle stolen, and descriptive characteristics of the types of vehicles stolen.

Automobiles comprise the vast majority – nearly 73% – of all vehicle theft, and many studies approach vehicle theft as if it is comprised solely of automobiles. Many studies of vehicle theft employ the term *car* theft or *auto* theft although presumably their analysis is of *all* vehicle thefts (Rice and Smith, 2002; Clarke and Harris, 1992; Tremblay et al., 1994; Decker and Bynum, 2003). In addition to automobiles, vehicle theft includes two other categories of vehicles: first, trucks and buses, and second, "other" motor vehicles. "Other" is a UCR classification that includes motorcycles, All-Terrain Vehicles (ATVs), mopeds, scooters, riding lawn mowers and other self-propelled motorized vehicles. Other is not inconsequential; nationally, trucks comprise 18% of vehicle theft and "other" vehicle theft is 9% (FBI, 2005).

While autos are the most common vehicle stolen, the proportion of vehicle type stolen varies substantially across the nation. For example, theft of "other" vehicles ranges from 6% in the West and Northeast to 11.5% in the Southern region of the nation (FBI, 2005). Since the South is the largest reporting region and reports the most vehicle theft in the nation, the South's contribution to "other" drives the 8.7% of "other" reported nationally. Similarly, the South and Western region (the latter reports 34% of the nation's vehicle theft) dominate theft of trucks in the nation. In the Western region of the nation, 22% of stolen vehicles are trucks compared to 5% in the Northeast region of the nation.

Burns (2000) describes how specific types of vehicles, such as trucks, become ingrained in local culture, and how understanding such cultures can point to effective crime prevention strategies. This is evident in a study in Arizona (2004) that showed sport utility vehicles (SUVs) and large pick-up trucks were common targets of theft, primarily for use in smuggling across the Mexican border. (Arizona Criminal Justice Commission, 2004).[7] In Chula Vista, CA, trucks were 43% of stolen vehicles compared to 34-42% in nearby jurisdictions.

National data show that cars are a declining portion of vehicles stolen in the United States. In 1989, automobiles comprised 79% of vehicle theft nationally but the proportion has steadily declined to the current 73%. In contrast, "other" has been on the rise, particularly in the South. In 1995, 5% of vehicles stolen in the South were "other'; this rose to 7.5% in 1999, 10% in 2002 and 10.8% by 2003.

The changing composition of types of vehicles stolen is not as sharp in other regions of the country, but even in the Northeast, where thefts of automobiles are the most prevalent, automobiles have declined from 92% of all stolen vehicles in 1996 to 89% in 2003. The decline of cars among vehicles stolen appears steady. It is tempting to assume that the decline of cars stolen reflects the changing composition of vehicle targets as ownership of Sport Utility Vehicles (SUVs) has exploded in recent decades; however, the vast majority of SUVs are classified as cars as they are primarily used for personal transportation of passengers rather than commercial or business purposes based on definition of vehicle type in the UCR reporting guidelines.

As the proportion of stolen autos has declined, "other" has taken on increasing importance. We can find, however, no statistics or studies on the composition of "other." The NICB (n.d.) reported that 44,000 motorcycles were stolen in 2001, which would comprise 4% of all vehicle theft that year (FBI, 2002).

The contribution of *type* vehicle theft is important for analysis because vehicle type is closely related to recoveries of vehicles and, presumably, clearances.

[7] These vehicles dominated the "Top 10 Vehicles Stolen" list in two major theft cities, Phoenix-Mesa and Tucson. There was no statistical analysis of theft types.

Although there have been little examination of differences between vehicle types, evidence suggests that recoveries of motorcycles are substantially lower than that of autos and trucks. NICB (n.d.) reports that only 25-30% of motorcycles are recovered; in the U.K., 32% of motorcycles are recovered, compared to 65% for autos (Braun, 2003).

In the United States, there are no specific data on the proportion of recoveries by different type of vehicles but the correlation between theft type and clearance can be examined. In the Southern region, which reports 35% of the nation's vehicle thefts, vehicle theft clearances have declined as the volume of "other" vehicles stolen has increased; 17% of vehicle thefts were cleared when "other" comprised 5% of thefts in 1995, clearances dropped to 14.9% by 2003 when other comprised 10.8% of vehicle theft.

The difference in recovery rates holds true for trucks. In Chula Vista (2004), trucks were stolen more often than other vehicles and they were also recovered less frequently (43%) than autos were recovered (69%). Even within Chula Vista, some locations had higher recovery rates, including thefts of motor vehicles from high schools and colleges.[8]

A few case studies of vehicle theft in the U.S. offer some insight into "other." Rienick et al. (1999) report that 41% of vehicle theft in Santee, CA, was autos; 53%, trucks; and 6%, recreational vehicles and motorcycles (3% each). In Reno, NV, Decker and Bynum (2003), autos comprised 54% of vehicle theft; trucks, 20%; and "other" vehicles, 26%.

Some Internet sites suggest that thefts of motorcycles in the U.S. have risen in recent years. Further, motorcycles were 2% of vehicle theft in Reno (Decker and Bynum, 2003), and 3% in Santee, CA (Rienick et al., 1999). Some sources report that thefts of All-Terrain Vehicles

[8] Chula Vista and other cities along the U.S. border typically have low recovery rates reflecting the prevalence of stolen vehicles being taken into Mexico.

(ATVs) have also increased; rising 27% in one year, in Texas, from 1,923 in 2001 from 1,515 in 2000 (Texas Department of Public Safety, 2002).

Vehicle Model, Age and Value

Descriptive characteristics of stolen vehicles are commonly made public, presumbably to alert owners of high-risk vehicles to take greater security precautions. NICB publishes lists of the vehicles at highest risk of theft. For 2003, the 2000 Honda Civic was the most often stolen vehicle. Following, in descending order were 1989 Toyota Camry, 1991 Honda Accord, 1994 Chevrolet 1500 Pickup, 1994 Dodge Caravan, 1997 Ford F 150 Series, 1986 Toyota Pickup, 1995 Acura Integra, 1987 Nissan Sentra and 1986 Oldsmobile Cutlass. All of the models are among the highest volume cars sold in the U.S., so their inclusion on the “Top 10” list is as much a factor of prevalence as risk.

Most of the vehicles in the NICB’s “Top 10” list are not new models. The newest, the 2000 Honda Civic, was three years old during the base theft year of 2003; the oldest vehicles stolen, the Toyota pickup and the Oldsmobile Cutlass, were 16 years old when stolen. While many metropolitan areas and states generate these “Top 10” lists, there appears to be much variation between high-risk models stolen in different jurisdictions, including neighboring cities. Such variation likely reflects local ownership trends and prevalence.

In contrast to variations in make and model of stolen vehicles, age of stolen vehicles is a key and consistent factor when examining vehicle theft. Although much vehicle theft is characterized as focusing upon high performance vehicles, older vehicles are consistently more often the targets of vehicle theft (Laycock, 2004; Brown, 2004; Fleming, Brantingham and Brantingham, 1995; Clarke and Harris, 1992; Sallybanks and Brown, 1999; Herzog, 2002), primarily because of less security on these vehicles. More numerous thefts of these older vehicles also relates to their being more plentiful. In the U.K., cars that are 11 years old or older face the highest risk of theft (Sallybanks and Brown, 1999).

In recent years, thefts of new vehicles have declined in the United States, reflecting increased security on new vehicles. Steering column locks were introduced in the 1970s and electronic immobilizers and other security devices in the mid-1990s (Newman, 2004). To some extent, the decline in thefts of newer vehicles has been displaced to older cars, which are stolen primarily for temporary use, and are more often recovered (Fleming et al., 1995; Herzog, 2002). While newer cars are still stolen, however, their theft is often through the use of keys, and their recovery unlikely – both hallmarks of professional theft. Since older vehicles are the primary vehicles stolen, the average value of stolen vehicles is often lower than commonly believed. The average value of a vehicle stolen in the U.S. in 2003 was $6,797 (FBI, 2004).

Theft Locations

Most research on vehicle theft examines the location of the offense, classifying locations into at least two types of premises – residential or business. Vehicle theft locations are further distinguished by place of occurrence of the theft – on the public streets or roadways; in parking lots, which may be public or semi-private; carports, garages and driveways on private property.

The distinctions between residential and business premises are consistent with the UCR; while the distinctions between public and private property, are consistent with the British Crime Survey (BCS). The residential-business distinction relates to American attention to concentrations of crimes by type of business (such as robberies of convenience stores) while the public-private distinction in the BCS relates to assumptions that property is at greater risk in locations that are easily and lawfully accessible to the public, while offenders may be reluctant to venture onto private property to steal vehicles. In this vein, the BCS further distinguishes between thefts of motor vehicles that occur in public parking lots, thefts on streets, and thefts on an owner's property.[9]

Residential Premises

Although differing data sources require inferences about the precise proportions, it is generally well-established that many if not most vehicle thefts occur at residential locations. In the U.S., incident data from 1999 showed that 47% of all vehicle theft occurred at a residence (FBI, 2000b).[10]

Victimization data are consistent with the incident data. Based on NCVS (2003), nearly half of all vehicle theft (47%) occurred at residences or on streets near residences (30% and 16.5% respectively for the two types of locations).[11] The proximity of vehicle theft to residences is further confirmed by the distance of theft from the victim's residence: 62% of vehicle theft occurred within a mile of the victim's residence (BJS, 2004). Findings about the prominence of vehicle theft at residences are echoed in the British Crime Survey; 60% of vehicle thefts occur on streets outside the owner's home (Sallybanks and Brown, 1999) and this is consistent with a study in British Columbia which found that 63% vehicle theft occurred at the owner's residence (Fleming et al., 1995). In contrast, however, two studies in the U.S. show much less vehicle theft

[9] Note that the BCS excludes residential parking lots from this classification, considering such lots as "semi-private" and thus counts only parking lots that are public or commercial. This distinction is not made in the U.S.
[10] The data on vehicle theft location are weak for reliably classifying theft location. Based on incident data (FBI 2000b), 35% of vehicle thefts occurred at residences, 12% occurred at business locations, 7% were unknown locations while 5% were "other" locations. The remaining 41% of vehicle theft occurred in parking lots/garages or on streets. It seems likely that these categories are not mutually exclusive; for example, many of the parking lots might be associated with either residential or business locations.
[11] Again, as Biderman and Lynch (1991) note, commercial vehicles comprise 17% of vehicle thefts and these are not represented in victimization surveys.

at residential locations: in Santee, CA, 39% of vehicle theft occurred at residences (Rienick et al., 1999) and in Reno, NV, 41% of vehicle thefts were at residences (Decker and Bynum, 2003).

Location and distance of vehicle theft from residences may vary by dwelling type. In many locations, residents of a single-family dwelling may park on the land parcel that contains their premise. Indeed, the rates of vehicle theft are lower for single-family dwellings at 8:1000 compared to multi-family dwellings; vehicle theft rates for multi-family premises range from 11:1000 to 14:1000, depending upon the number of units in the structure. Residents of multi-family units may often park in common parking lots or garages. It seems reasonable that some portion of vehicle theft at or near residences, particularly those related to multi-family premises, may also occur in parking lots or garages; 35% of all vehicle thefts occurred in this type of parking location (BJS, 2004).

Business Premises

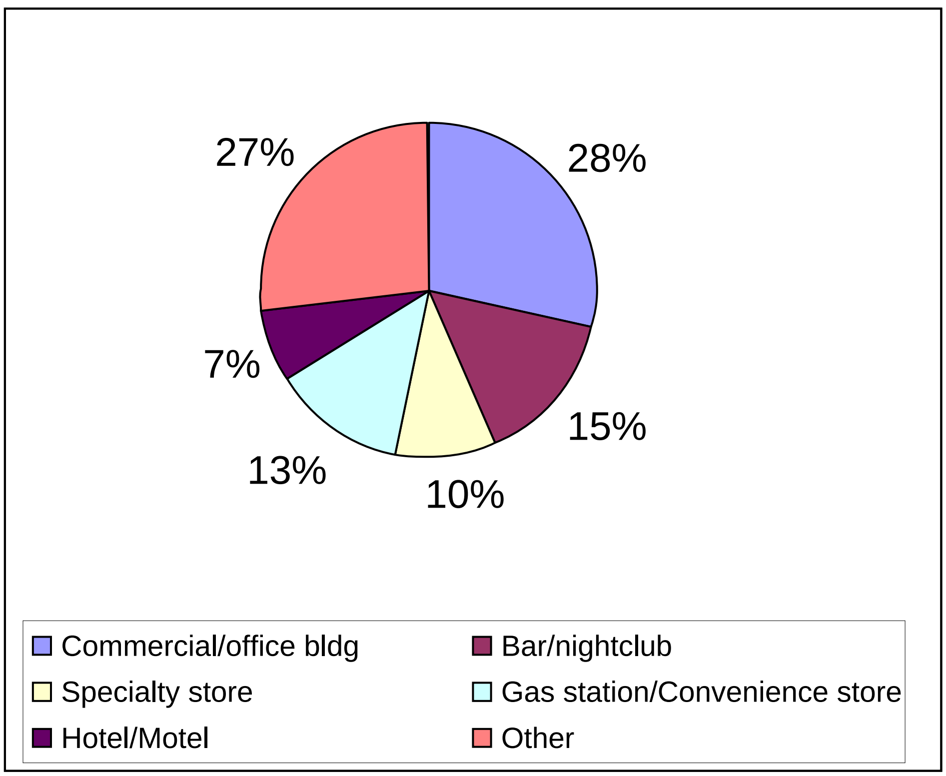
While data are weak for definitively attributing thefts to either residential or business locations, some portion of vehicle theft can be reliably associated with business premises. Based on NIBRS data (FBI, 2000b), 17% of vehicle thefts in the U.S. in 1999 occurred at locations *other* than at residences, on streets or in parking lots.[12] Again, the studies from two cities – Santee, CA, and Reno, NV – differ. In Santee, CA, 42% of vehicle theft occurred at business locations and specifically in the parking lots of businesses (Rienick et al., 1999), and theft data from Reno paralleled this proportion (Decker and Bynum, 2003).

Since 17% of vehicle thefts recorded in NIBRS are recorded as *not* having occurred at residences, in streets or parking lots, we presume that most of these are business locations and

[12] The classification scheme used in FBI (2000b) for offense locations offers little insight into vehicle theft at businesses. It seems likely that some portion of vehicle thefts from parking lots were at businesses.

many are classified by the type of commercial premise where the theft occurred. Some types of businesses appear to be more prevalent in vehicle theft than others (See Figure I). While 28% of the vehicle thefts at business premises occurred at offices or commercial properties, a substantial amount of vehicle theft occurred at bars/nightclubs (15%), motels (7%), and service stations/convenience stores (13%)[13]. The reader should note that 27% of vehicle theft at business premises were "other" types of businesses, suggesting that there is much variation between the types of commercial premises associated with vehicle theft.

Figure I: Vehicle Thefts at Business Locations
Calculated from FBI, 2002a



[13] Vehicle thefts are reported separately by the FBI for convenience stores and gas and service stations. We find few distinctions between these premises and thus have combined the two types of businesses in this graph.

Parking Lots

Although vehicle thefts may be more prevalent at residential premises, they are often more concentrated in parking lots.

In the U.S., 23% of vehicle thefts were classified as occurring in parking lots/garages (FBI, 2000b) and the NCVS showed that 35% of vehicle theft in these locations (BJS, 2004).[14] Much of the 17% of vehicle theft recorded at business premises (FBI, 2000b) likely occurred in parking lots; it seems reasonable to assume that many businesses such as motels and convenience stores will routinely have a parking lot for customers.[15] In the U.K., 15% of all vehicle theft occurred in commercial or public parking lots (Mayhew and Braun, 2004).[16] In Canada, most vehicle thefts are from parking lots (Linden and Chaturvedi, 2005). In Reno, 60% of vehicles were stolen from parking lots; the British Columbia study showed that large parking lots (100 stalls or more), including residential and commercial lots, accounted for 40% of all vehicle theft (Fleming et al., 1995).

While most vehicles are stolen from residences and streets, Clarke (2002) points out that the risk of theft – i.e., the likelihood of theft per hour parked – are much higher for vehicles while they are in parking lots, such as those located at factories, shopping areas, schools, or transportation hubs, because risk is computed based upon the length of time the vehicle is parked. Victimization surveys in the U.K. show that vehicles are at highest *risk* of theft while parked in public parking lots, and at lowest risk while parked in a garage or driveway at a

[14] These two data sources vary in important ways; FBI data are comprised of crime reports made to police while the NCVS data are drawn from victimization surveys.
[15] UCR reporting guidelines instruct law enforcement officers to be as specific as possible in recording the location of an offense. Given the nature of vehicle theft, it seems unlikely that a vehicle would be stolen from within a convenience store but more probable that the theft occurred in the parking lot or on the street adjacent to the store. Since the UCR premise classifications combine types of premise with types of parking structures, the data are not reliable.
[16] These data are drawn from the 2002/2003 British Crime Survey. Parking lots in this survey consist only of public or commercial parking lots, such as those at office buildings. Residential lots are specifically excluded.

residence. Vehicles parked in the street, including streets near home or work, have risks between the two other types of locations (Mirlees-Black, Mayhew and Perry, 1996; Clarke and Mayhew, 1995). Similar risk statistics for vehicle theft are not available in the U.S. as incident locations are drawn from crime reports, recorded in UCR or NIBRS, rather than established through victimization surveys such as the BCS. Because of the higher risks of vehicle theft in parking lots, Clarke (2002) focused his seminal guide for police *only* on thefts of motor vehicles that occurred in lots.

Hot Spots and Risky Facilities

Since much vehicle theft occurs in parking lots, we expect vehicle theft to demonstrate some concentration or to cluster geographically, just as other crimes cluster. Indeed, Rice and Smith (2002) found that urban vehicle theft was higher in areas close to pools of motivated offenders, where social control mechanisms (such as two-parent families) were lacking, and where there were suitable targets such as bars, gas stations, motels, and other types of businesses. Such locations attract more cars, attract cars at particular times of day, and attract more expensive vehicles than might typically be observed in areas with low social control. Yet, there are distinctions between geographic areas with more vehicle theft and actual hot spots of vehicle theft.

Several studies of vehicle theft have identified hot spots (Plouffe and Sampson, 2004; Rengert, 1996; Fleming, 1995; Barclay et al., 1995). A study in Chula Vista, CA, identified ten hot spots that accounted for 23% of the city's 1,714 vehicle thefts in 2001.[17] The hot spot parking lots included two types of lots: first, long-term parking lots serving commuters and second, retail shopping centers lots, including both strip centers and malls.

[17] Of note, the hot spots were not fleeting but enduring across 2000 to 2001

In general, hot spots of vehicle theft will always be locations where numerous vehicles can park, although such lots may be businesses or multi-family residential premises. Such locations may best be considered as "repeat victims," since most maps geocode the point to a single street address, and parking lots will have only one street number. Hot spots of vehicle theft may also potentially be comprised of a number of parking lots in proximity to one another, or a street segment with multiple thefts.

Studies of vehicle theft routinely identify describe the characteristics of non-residential locations of vehicle theft.[18] These include parking lots close to interstate highways, and especially those in close proximity to Mexico (Plouffe and Sampson, 2004), areas with high traffic volume (Rice and Smith, 2002) and areas near schools (Kennedy, Poulson and Hodgson, n.d.). Among parking lots, common theft locations include large parking lots such as those with 100 or more spaces (Fleming et al., 1995) and long-term parking lots that serve commuters or transit passengers (Plouffe and Sampson, 2004; Kennedy, Poulsen and Hodgson, n.d.; Barclay et al., 1995). Some of the specific uses of these parking lots include:

- Commuter or transit passenger lots (Plouffe and Sampson, 2004; Kennedy, Poulsen and Hodgson, n.d.; Barclay et al., 1995) and employee parking lots (Arizona Criminal Justice Commission, 2005).

- Shopping centers and mall parking lots (Plouffe and Sampson, 2004; Smith, 1996; Barclay et al., 1995; Henry and Bryan, 2000; Arizona Criminal Justice Commission, 2005). In particular, offenders in Fleming et al. (1995) described malls as an easy spot to find vehicles to steal and the Arizona Criminal Justice Commission (2005) found that vehicle thefts at shopping centers were trice as common during the day than at night.

- Parking lots of "Big Box" retail stores (Plouffe and Sampson, 2004). vehicle theft concentrations were found at K-Mart, Target, Wal-Mart and Costco. An analysis of vehicle theft at Home Depot stores showed that 60% of vehicle thefts occurred at 30% (5) of the chain's 17 stores in the county. Trucks in these locations comprised 82% of all vehicle theft.

[18] Note, the descriptions of common theft locations are primarily anecdotal, derived from mentions of such locations in larger research studies.

- Entertainment venues, such as movie theatres, restaurants and bars (Plouffe and Sampson, 2004; Smith and Rice, 2002; Rengert, 1996; Henry and Bryan, 2000; Arizona Criminal Justice Commission, 2005).
- Motel parking lots (Rice and Smith, 2002; Plouffe and Sampson, 2004).
- Gas stations (Smith and Rice, 2002).
- Auto repair shops (Maxfield, 2004).
- Car dealerships (Rengert, 1996; Saville and Murdie, 1988; Fleming et al., 1995). In the Fleming et al. (1995) study, 22% of offenders mentioned car dealerships as easy targets.
- Schools and universities (Arizona Criminal Justice Commission, 2005).

Temporal Patterns

Many analyses of temporal patterns of vehicle theft examine time of day, day of week or season of year. Rengert (1996) noted that temporal patterns relate to land use: thefts that occur on streets near residences primarily occur at night while owners are asleep and their vehicles unattended. These observations are supported by the NCVS: 68% of thefts occur at night, between 6 p.m. and 6 a.m., 47% at or near the victim’s home, and 49% while the victim was sleeping (NCVS, 2004). In the U.K., 56% of vehicle theft occurs at night (Sallybanks and Brown, 1999) while Fleming et al. (1995) found that 70% of vehicle theft occurred at night (70%).

Theft patterns are distinctly different for thefts at commercial properties, but the variation relates to the type of property. Although Plouffe and Sampson (2004) do not discuss temporal patterns, the majority of thefts at the 10 hot spots in Chula Vista likely occurred during the day or early evening since the lots were at retail stores and commuter lots, and the authors note that victims parked on average more than one hour before the theft was identified, and many victims parked for three hours or more.

Rengert (1996) points out that temporal patterns are inherently local: thefts of vehicles near bars and restaurants will occur in the early evening; thefts at motels will mirror those of residential properties, while vehicle theft will occur during the day near schools, in commuter lots and retail stores. Auto repair shops and car dealerships will be late night thefts.

National data show that most vehicles are reported stolen on Saturday (14.2%), Friday (14.9%) or Monday (14.9%). The fewest vehicles are stolen on Sunday, but at 13.55% of thefts on Sunday, the differences between days of the week are slight (FBI, 2000). Since many thefts occur during the night, offenses may often be committed on one day but reported the following day when the owner awakens to find the vehicle missing.

Thefts at commercial properties are likely to be consistent with the volume of customers in parking lots. Commuter lots will have thefts on weekdays. Thefts at malls and other shopping venues will necessarily relate to business hours.

Delayed reporting of vehicle theft is not uncommon. Vehicles stolen from residential premises during the day are detected when the owner arrives home from work, finds a vehicle missing from the property and calls the police. While these thefts are likely reported on the same day that the theft occurred, the report may be delayed by hours.

Based on 1999 NCIC vehicle theft, most vehicle thefts occur in November (9.3%) and fewest occur in February (6.6%) (FBI, 2000). But the seasonal pattern of vehicle theft varies from year to year; in 1998, the most vehicle theft (9.1%) occurred in January; in 2000, the most thefts occurred in August (9.0); while in 2002, the most thefts occurred in July (FBI, 2002). While seasonal variation exists in vehicle theft, such variations are more likely to be observed at the local level.

Unsuccessful Thefts

An enduring feature of vehicle theft many stolen vehicles are recovered, and a good portion of vehicle thefts are attempts and not completed thefts.

Historically about half of stolen vehicles are recovered, and are recovered quickly. In the U.S., 51% of vehicles are recovered (based on NCIC data); 53% are recovered based on NIBRS data (FBI, 2000); while the UCR reports that 63% of the *value* of vehicles stolen in 2002 was recovered (FBI, 2003). Most vehicles are recovered within a short period of time – 42% are recovered within a week of the theft while another 5% are recovered in the next two weeks (FBI, 2000). Research on vehicle theft often distinguishes between temporary and permanent theft. Temporary thefts are those in which vehicles are recovered, usually within a short period of time. Permanent thefts are those in which the vehicle is not recovered (Maxfield, 2004).

Recovery rates appear to vary substantially between jurisdictions and by type of vehicle. In Reno, 81% of stolen vehicles were recovered (Decker and Bynum, 2003); Chula Vista, less than half were recovered (Plouffe and Sampson, 2004). The low recovery rate in Southern California is related to proximity to Mexico where many stolen vehicles are taken.

While Brown and Clarke distinguished a declining recovery rate of a particular make of vehicle, Plouffe and Sampson (2004) identified that some *types* of vehicles are stolen more often than others, and the recovery rates of vehicle type vary between jurisdictions. Older vehicles are more likely to be recovered (see below), and thus often characterized as temporary theft. In general, permanent theft is considered as professional theft and is characterized by vehicles not being recovered (Tremblay et al., 1994). Vehicles characterized as "professional theft" may be newer, high performance vehicles that are stolen for export, resale or parts (Laycock, 2004) although such vehicles are seldom stolen in some locales (Fleming, Brantingham and

Brantingham, 1995). Older vehicles that are not recovered may also reflect professional theft, as some studies have suggested that older models that are not recovered are usually exported for resale in third world countries such as Mexico (Plouffe and Sampson, 2004).

In addition to vehicle age, condition of recovered vehicles is an important component of vehicle theft. Older vehicles that are recovered intact, or crashed, are presumed to be associated with non-professional theft; such thefts are often classified as temporary, joy-riding, short-term transportation or personal use. Many recovered vehicles are damaged:

- In Reno, 94% of recovered vehicles were damaged (Decker and Bynum, 2003).
- In British Columbia, 90% of recovered vehicles were damaged (Fleming et al., 1995).
- In Santee, CA, 52% of vehicle theft victims rated the condition of their recovered vehicle as good or very good (Rienick et al., 1999).

Vehicles of any age that are recovered but stripped for parts are associated with professional theft. Vehicles that are recovered burned or flooded are associated with fraud, and recoveries that occur more than 30 days after the theft also fall into this category.

Since older cars are usually the target of vehicle theft, and are usually recovered, vehicles that are newer and of higher value are less often recovered and more often associated with professional theft. Some studies suggest that keys are often used in such thefts to overcome better security on newer vehicles.

Numerous studies suggest that vehicle theft offenders had keys to the stolen vehicles:

- In the U.K., 12% of vehicles stolen were taken with the owner’s keys; a figure reported by Randerson (2004) as double that of the previous year.
- In Santee, CA (Rienick et al., 1999), 15% of vehicle theft victims reported that their vehicles were stolen because the offender had keys.
- In British Columbia (Fleming et al., 1995), 20% of vehicles were stolen with owner keys.

- In Reno, when the method of entry was known, 82% of vehicles were stolen with keys. Further, although many vehicles were recovered, the ignition in only few had been tampered with (Decker and Bynum, 2003).

- In Arizona, 28% of vehicle thefts were attributed to the use of a key that was on or in the vehicle; and keys were stolen in another 7% of thefts. In a further 20% of thefts, the method of theft was unknown and keys may have been involved in some of these (Arizona Criminal Justice Commission, 2004).

Another enduring feature of recovered vehicles is that location information is often poor. One reason for missing recovery information is that many recovered vehicles are not recovered by law enforcement. In Santee, CA, 13% of recoveries were made by the victim, while 11% were made by another citizen. An additional 4% of vehicles were impounded or recovered by an insurance company (Rienick et al., 1999). Even among vehicles recovered by law enforcement, many of these recoveries occurred outside the jurisdiction in which the theft occurred (Maxfield, 2004).

Just as many stolen vehicles are recovered, in many thefts, the vehicle is not actually stolen. On average, attempts comprise 20% of all vehicle theft recorded by police (Farrington et al., 2004) and even *attempted* vehicle thefts are well-reported although victims are somewhat less likely to report attempted than completed vehicle thefts. About 35% of vehicle thefts are not reported to police because the offenses were not completed (Farrington et al., 2004; Biderman and Lynch, 1991). Note that the UCR classification of vehicle theft includes attempts, thus recovery rates of stolen vehicles will include those vehicles that were never actually stolen. A jurisdiction with a higher proportion of attempted thefts may thus tend to report a higher percentage of recoveries.

Some research suggests that the ratio of attempts to completed thefts does vary by the type of vehicle. For example, attempts are more prevalent among motorcycles; while Clarke and Harris (1992) suggest attempts of motorcycle theft are more likely because they are not well secured, the opposite is more likely. While poorly secured vehicles are more likely to be successfully stolen, motorcycles face much higher risk rates than passenger vehicles, and are much less likely to be recovered when stolen (Braun, 2003). Such risk and reward surely play a role in an offender's choice of targets.

Monitoring the ratio of attempted to completed thefts over time provides an indicator of the effectiveness of crime prevention strategies. As the number of thefts stays constant, an increase in attempts suggests that crime prevention strategies are deterring more offenders.

The ratio of attempted to completed vehicle theft does appear to vary across the U.S. by region, and also by the type of premise and parking location. Overall, 74% of vehicle thefts were completed in 2003 (BJS, 2004). For the 30% of vehicle theft that occurred "near home," 42% of thefts were completed and 58% were not.[19] The sharply higher proportion of attempts at residential locations suggests that vehicle thefts may be more likely to be interrupted or thwarted at residential locations. In contrast, the 35% of vehicle theft that occurred in parking lots or garages were equally likely to be attempted or completed.

There are also sharp distinctions between the ratio of attempted and completed vehicle theft by the size of the jurisdiction. In urban and suburban jurisdictions, 73% of vehicle thefts are completed, while 80% of all vehicle theft are completed in rural areas (BJS, 2004: Table 58). Since rural areas have substantially lower volume and rates of vehicle theft, the attempted or completed distinction appears to suggest that most vehicle thefts in rural areas are successful, and few offenders are thwarted from the offense; however, reporting of attempted vehicle theft may also vary by urban-rural locations.

[19] These proportions are calculated on the 28% and 38%, respectively, of completed and attempted thefts that occurred at these locations.

Regional Dimensions of Vehicle Theft

In contrast to many other crimes, vehicle theft has more than one geographic dimension. Since most stolen vehicles are recovered, the recovery location provides an important cue about the offense and the offender. Most offenses include only the offense location but vehicles may be recovered either nearby or at a distance, within the jurisdiction or outside its boundaries.

Jurisdiction Boundaries

Few studies of vehicle theft are regional, and recovery data are often incomplete or missing. Based on research in Newark, Maxfield (2004) described vehicle theft as a regional problem, finding that at least 55% of vehicle thefts in the city crossed jurisdictional boundaries as evidenced in recovery data. Of 5,538 vehicle thefts in 2002, 25% (1,382) were recovered outside Newark and 52% (2,880) were recovered within Newark. A total of 23% of vehicles (1,276) were not recovered at all. But, a further 3,891 vehicles were recovered in Newark that were stolen in other jurisdictions. In other words, substantially more vehicles were *recovered* within Newark (2,880 + 3,891=6,771) than were actually stolen in the city.

Studies that employ vehicle theft recovery data suggest location data are poor; that is, locations for recovered vehicles are not routinely available. For example, LaVigne et al. (2000) were able to construct a dataset of 4,000 vehicle theft offenses for which both theft and recovery addresses within Baltimore County were available. The authors were able to construct this dataset by using seven years of vehicle theft data. While the authors do not state the number of vehicle thefts in the large jurisdiction or the recovery rate, there appear to have been at least 35,000 vehicle thefts in seven years.[20] The rate of within-county recovery addresses relative to the number of stolen vehicles would thus be about 11% percent (4,000 recovery addresses

[20] Computed from the Baltimore County Police Department website.

divided by 35,000 vehicle thefts). Although this rate is well below the 52% within-jurisdiction recovery rate reported in Newark by Maxfield (2004), it is consistent with findings from Reno, where Decker and Bynum (2003) found address information was recorded for only 10% of vehicle theft recoveries.

Pattern Detection and Low Volume

Brown and Clarke (2004) noted that small increases in theft, or even declines in recoveries, within individual police jurisdictions may seem just that – small; but small increases across numerous jurisdictions may comprise much larger regional or even national trends. The masking of such trends is particularly problematic for emerging trends that may otherwise go unnoticed.

In the Brown and Clarke study, the number of Nissan Cabstar trucks stolen and not recovered was initially about 44 per month nationally during 1999 but sharply increased in 2000, particularly in one region of the U.K. comprised of seven police agencies. The number of unrecovered Cabstars nationally and in that area climbed throughout 2000, peaking at 100 per month in the region.

The Brown and Clarke study highlights that theft patterns that are spread across numerous jurisdictions may be difficult to detect; each jurisdiction in that region initially experienced 5 or 6 unrecovered thefts per month. Even when the pattern increased, each jurisdiction experienced only 14 thefts per month. The authors do not report the overall number of thefts within these jurisdictions but it is likely that the rise in Cabstar thefts within each jurisdiction was further obscured by a variety of other stolen vehicles.

The Brown and Clarke study demonstrated that regional data are necessary and multiple years of data may be needed for pattern detection. Three full years of theft data were employed to detect the distinctive regional pattern of Cabstars and determine its contribution to the more modest national trend. The final year was key to monitoring the decline of unrecovered Cabstars.[21]

The Brown and Clarke study also demonstrated the need to monitor the number of thefts and the rate of recoveries *relative* to those of other jurisdictions and aggregate numbers. In the U.K., 41% of trucks similar to the Cabstar were recovered while only 15% of Cabstars were recovered. The sharp difference between the recovery of similar vehicles highlighted the Cabstar pattern, however, the difference in any single jurisdiction would have been difficult to detect.

While it is unusual that a particular type and make of vehicle is consistently the target of theft, the Cabstar theft-for-export problem – a distinctive theft pattern – highlights the critical need of regional data for vehicle theft. If vehicle thefts of particular models rise, their numbers will be diluted across multiple jurisdictions, and thus patterns difficult if not impossible to detect.

Critical Need for Vehicle Theft Analysis in Non-Urban Areas

The growth of crime analysis in the 1990s and 2000s seemed promising for learning more about vehicle theft – particularly vehicle theft at the local level, including non-urban areas to which much vehicle theft research cannot be generalized. Specific vehicle theft analyses could be used to develop effective police and crime prevention practices, and to evaluate the impact of efforts to reduce vehicle theft.

Despite the prevalence of vehicle theft, there are few published reports on crime analysis employed for motor vehicle theft. There are only a few problem solving case studies of vehicle

[21] These thefts were part of an international export operation by organized crime.

theft, such as Plouffe and Sampson (2004) and Santiago (1998). And, with some exceptions[22], there are few examples where GIS has been used for in-depth analysis of vehicle theft. Among the excellent examples of crime mapping in LaVigne and Wartell (1998, 2000), there is only one case study of vehicle theft (Santiago, 1998). In their compendium of public safety problem solving efforts, Sampson and Scott (2000) feature no case studies of vehicle theft. In 2003, the California Highway Patrol won a national problem solving award (the Goldstein award) for a vehicle theft project, but there is no suggestion that spatial analysis was used at all. Even a detailed study of vehicle theft and problem-solving in Reno, NV, makes no mention of spatial analysis (Decker and Bynum, 2003); Maxfield (2004) provided important findings about regional patterns of vehicle theft in Newark, but the scope of the study was descriptive and quite limited. Other than the current study, the 8th Annual Crime Mapping Research Conference in Savannah (GA) in 2005 featured only one presentation on vehicle theft (Luongo, 2005).

Canter (1998) has suggested that crime analysis incorporating GIS has been used more so for burglary and robbery than for other offenses, presumably including vehicle theft. This is primarily because burglary and robbery are perceived as more amenable to police tactics such as directed patrol and surveillance. It also seems likely that problems with address quality for vehicle theft – since vehicles may be stolen from places without specific addresses – and the resultant difficulty in geocoding vehicle theft, has likely dampened GIS applications. For example, Potchak et al. (2002) were able to geocode only 88% of a small sample of theft locations in Newark, NJ, while Henry and Bryan (2000) were able to obtain complete addresses for only 50% of vehicle thefts in Adelaide, AU. These authors thus used street segments, rather than addresses, as their unit of spatial analysis.

[22] See, for example, LaVigne et al., 2000; Potchak et al., 2002; Henry and Bryan, 2000; Thomas, 2000; and Saville and Murdie, 1988.

Although there is also much potential to map locations of vehicle theft recoveries, data quality – that is, missing location data described previously – has likely been a key factor dampening GIS applications for vehicle theft.

The crime analyses of vehicle theft that can be identified suggest that most analyses have focused on the following:

- Identifying temporal patterns, such as day of week, time of day or month of year.
- Identifying most frequently stolen vehicles by make and model, generating "top 10 lists" of frequently stolen vehicles. Other analysis has focused on identifying vehicle characteristics, such as make, model and color
- Monitoring the proportion of vehicle recoveries relative to thefts, to distinguish joyriding from professional theft. Also monitoring clearances and vehicle condition upon recovery to detect professional theft.
- Identifying common theft locations, such as hot spots or repeat locations. Some localities publicize "top 10" theft locations.

In this vein, vehicle theft analyses appear to rely almost exclusively upon information contained on initial incident reports completed by uniformed officers at the scene of thefts. Such crime analysis can be used to detect patterns involving hot spots and "hot vehicles" so that enforcement efforts such as increased patrols, bait cars or undercover operations can be deployed to apprehend specific or general offenders. We find no systematic evaluations examining the effectiveness of such strategies; however, it seems likely that the success of the strategy would depend upon the specific type of vehicle theft experienced within a jurisdiction.

As a crime type, vehicle theft is highly amenable to research and analysis. Police incident reports of vehicle theft have a high rate of validity since, in contrast to many other reported offenses, the crime is well-reported, at least partly for purposes of insurance claims.

Based on comparisons with victimization surveys, nearly 95% of motor vehicle theft is reported to police (Skogan, 1974). Comparisons of police reports and victimization surveys over 19 years (1981-1999) showed that:

- 91% of completed vehicle thefts were reported to police (the proportion reported ranged from 86% - 95%) (Farrington et al., 2004).
- 95% of vehicle thefts reported to police were also recorded by police, and this proportion has ranged from 84% to 100%, and the ratio of reported to recorded vehicle theft has remained steady over time (Farrington et al., 2004). [23]

Police-recorded vehicle thefts may be even more reliable than victimization surveys; 17% of vehicles stolen in the U.S. are of commercial vehicles and thus not represented in victimization surveys (Biderman and Lynch, 1991). If that were not sufficient to ensure confidence about its validity, the data are also corroborated through an additional data source; NCIC basically serves as verification for vehicle thefts reported by local law enforcement agencies. These sources validate the use of police reports of motor vehicle thefts, mitigating concerns about using official crime statistics for analysis of this crime.

Since motor vehicle theft is both prevalent and well-reported, it is a problem amenable to crime prevention even in non-urban areas because there are sufficient numbers of thefts to permit statistical analyses. Police are also highly motivated to examine vehicle theft because of its prevalence and low clearance rates; although Santiago (1998) noted that vehicle theft remains "a hard nut to crack" (p. 53). In addition, since many stolen vehicles are recovered, data about recovery locations provide important insights into the crime, including potential avenues for follow-up investigation that would not normally be associated with an offense without witnesses.

[23] The reader should note that Farrington et al. (2004) defined vehicle theft as the unlawful taking of a self-propelled road vehicle, including automobiles, trucks and motorcycles, theft of commercial vehicles and attempts. In sharp contrast to the UCR definition, these authors also included "unauthorized use of a vehicle (joyriding) as a vehicle theft. UCR defines motor vehicle theft as specifically excluding "the taking of a motor vehicle for temporary use by persons having lawful access" (FBI, 2002). This contrasting definition does not reduce the reliability of vehicle theft data recorded by police.

CHAPTER II: RESEARCH CHALLENGES IN NON-URBAN AREAS

There are unique challenges, if not barriers, in applying crime and spatial analysis to vehicle theft in non-urban areas. A lower volume of crime, lower crime rates and generally higher clearance rates in rural areas have not created a compelling need for crime analysis. Further, to be most useful, crime analysis (including spatial analysis and problem analysis) in rural areas must address four specific issues: address quality, scale, data sufficiency, and political boundaries.

- **Address quality.** In non-urban areas, many offense addresses are not specific and cannot be geocoded. These become "missing data" on rural maps. Other offenses are addressed but the addresses relate to large land parcels; this affects decisions about offsets used in mapping, and raises issues of data precision for spatial analysis.

- **Scale.** Geography (distance) and large denominators (population) dilute hot spots or otherwise mask patterns.

- **Data Sufficiency.** A small "n" or number of incidents tends to characterize crime in rural areas, making pattern detection difficult.

- **Political Boundaries.** Jurisdiction boundaries in rural areas are highly politicized, often representing areas served by elected sheriffs. Willingness or the ability to share data across such boundaries may be constrained by technological or resource limitations, and differences in reporting practices between jurisdictions.

These issues are not mutually exclusive, but relate closely to one another, and must be disentangled to improve the practice of crime analysis in rural areas.

Missing Data: Geocodability

In spatial analysis of crime, geographic address is generally used as the primary unit of analysis. Most law enforcement data systems (both Records Management Systems (RMS) and Computer Aided Dispatch (CAD) are address-based. Crime analysts report "match rates," the proportion of addresses that can be geocoded and thus corresponding points placed on a map.

Geocodable addresses typically include a specific street number, street name and street suffix and, for reliable geocoding, addresses may also need a street direction. Street intersections and hundred-block numbers (e.g., Main Street and Jones Street, or 100 W. Main Street) can also be geocoded and mapped albeit with less precision.

Although there are many options for mapping crime and non-crime data, police agencies most commonly produce point or pin maps to identify problem areas (Harries, 1999; Hendrix, 2000; Mamalian and LaVigne, 1999). Pin maps are perhaps the easiest type of map to produce and for police to understand. On pin maps, each unique event is represented by one dot on a map; the point may be at a specific address (e.g., 315 W. Main Street), an intersection, or otherwise placed on a map by decisions about geocoding – such as to the parcel. The most common use of point maps is to identify hot spots. Hot spot or cluster maps present data in a simple, descriptive fashion, revealing patterns of the mapped variable. These maps can be crafted with ease, and used to detect what appear to be concentrations of some type of activity.

There are complexities that underlie basic assumptions used when creating a cluster map. For example, there is no standardized definition of a "hot spot" of crime (Eck, 2005; Harries, 1999) and point clusters will vary depending upon the time period selected, the size of the geographic area, and the designated number of incidents. The type of software utilized can also result in the variability of clusters (Jefferis, 1999) but there are ways to standardize the procedures for creating hot spot maps (Chainey, 2005; Chainey and Reid, 1999).

Data Precision: Parcel Size

Point maps may not be the most useful for rural areas because of the lack of specificity about offense locations. This issue is important for making maps useful in rural areas. Clarke

(2002) notes that points within places have features such as "blind spots and nooks" where property cannot easily be seen, and thus protected. Although Clarke is describing places within parking lots, his finding suggest that knowing the *precise* location of offenses within a geocoded address will most effectively point out ways to prevent subsequent offenses. This would include the parking place within the parking lot, the specific location on a 100-acre farm or large recreational area such as a park or lake, and so forth.

Discerning the relevance of spatial patterns, however, can present a challenge because of the large amount of information included on maps. In urban areas, crimes are often clustered and closely related to socioeconomic patterns and traffic volume; both create well-defined areas of crime. In rural areas, crimes may only loosely cluster and reflect another pattern. For example, crime is diffused in a somewhat linear pattern along major roadways in rural areas, creating a somewhat linear pattern of less density rather than the more familiar hot spot. Of course, even this loose concentration of incidents is an artifact of using point maps with geocoded addresses based on an arbitrarily selected offset, or distance from the roadway. In the rural Illinois study, Wood (1998) concluded that most offenses occurred within a mile of major roadways and many were proximal to cemeteries. Of course, the incident data were geocoded to the county's street centerline file, requiring a standardized offset to select a point for an incident that may have occurred anywhere on a large tract of land.

Similarly, the Rogers County, OK (COPS Problem Solving Partnership) project is of particular note because thefts appeared to have occurred on large plots of land in which a geocoded address would not have provided enough specificity about the place of occurrence.

Scale and Concentration: Data Sufficiency

In rural jurisdictions, crime incidents are less numerous and the concentration and similarities of offenses are diluted by the large geographic areas. For example, in the Rogers County, OK project, 37 trailers were stolen over a period of eight months. Although the recovery rate was quite low and financial losses were high, the number of incidents may appear trivial to many. Nonetheless, the problem had been increasing and the community was concerned about the problem. In the Illinois study described, Wood (1998) used 60 incidents aggregated from a three-year period: a very small population for making inferences. Wood employed the technique of increasing the time period for data in the study to ensure a sufficient number of incidents. While this technique increases the amount of data, it does not insure that discrete events are related. In contrast, a problem solving study of motor vehicle theft in Newark analyzed 182 thefts of vehicles that occurred during a two-week period (Santiago, 1998).

Maltz (1994) has cogently warned of the risks of increasing the time period or the data range for incidents in order to obtain a sufficient number for statistical analyses, noting that such aggregation techniques introduce greater heterogeneity into data, thus masking important characteristics of a more homogeneous albeit smaller sample. In other words, the researcher may have to relax statistical significance in favor of practical significance.

The relatively lower prevalence of incidents in rural areas makes the detection and classification of incidents as problems more difficult. While GIS is of great benefit to problem solving by pointing to geographic clusters of incidents and enhancing analysis of contextual factors relating to incidents, further collection of primary data and additional analysis is almost always necessary to distinguish proximal causes of problems (Weisel, 2003) and develop effective interventions.

Political Boundaries and Boundary Clustering

A wide spatial distribution of crime incidents, including dispersion across boundaries of small jurisdictions or across large rural areas, masks the similarities among incidents necessary to recognize a group of incidents as a problem. While a single or small group of incidents may merit a substantial case investigation, the detection of a recurring pattern is more difficult in jurisdictions with small populations or large geographic areas. Eck (2002) notes that this is one of the major advantages that might be anticipated with regional analysis – the early detection of such patterns that straddle political boundaries.

Research Strategies

Literature and experience suggest that, with rare exceptions, crime analysis in rural areas cannot focus predominately on identifying patterns that will lead to apprehending an offender. Unless there are very distinctive or repetitive offense characteristics, there are simply too few events to detect such patterns. In order to maximize the benefits of crime and spatial analysis in non-urban areas, the following approaches must be incorporated into analyses:

- The volume of data for analysis must be increased by aggregating regional data for sufficient time periods.
- Data quality should be rigorously assessed and enhanced to reduce error associated with missing data.
- Analysis should focus on in-depth longer-term patterns, including the relationship between crime and environmental and other offense characteristics.

The following section of this chapter describes these strategies in greater depth, forming the rationale for the research approach undertaken in this study.

Aggregating Regional Data

Research and crime analysis have increasingly recognized that political boundaries – such as city limits or county boundaries – are not natural breakpoints for the spatial distribution of crime (Eck, 2002; LaVigne and Wartell, 2001). More than 20 years ago, Brantingham and Brantingham (1982) found that crimes often occur at boundaries of areas. Thus, jurisdiction boundaries will tend to mask crime patterns. Where two jurisdictions share boundaries, pattern detection may be an issue of communication. The involvement of multiple jurisdictions may further mask crime patterns, particularly those such as motor vehicle theft that are less local.

Based on research in rural areas, this problem is not just theoretical. Crime rates in rural counties are closely related to the crime rates of neighboring counties (Barnett and Mencken, 2002), reinforcing the notion that political boundaries are abstract and of little importance to offenders. Crime will be more clustered by common transportation corridors and diffused by other boundaries, such as rivers or topography, than political boundaries. While there have been an increasing number of regional crime analysis and mapping efforts in recent years, such as the SACSI and COMPASS, there seem to be little evidence of success in these efforts.

Improving Data Quality through GPS

Address quality can be improved in rural areas through the use of global positioning systems (GPS). The technology of GPS allows users to employ devices to read signals transmitted by a network of satellites and calculate precise spatial coordinates based on distance from each satellite. The GPS assigns a latitude/longitude or x,y coordinates. Since GPS provides exact spatial coordinates for incidents, there are no missing data, or data errors that may occur through standard geocoding of addresses. In addition, GPS coordinates can be integrated into a GIS, including other data and land use features, thus providing a way to make the context for crime much more specific. Using a GPS is an efficient mechanism for creating an inventory of highly reliable data.

GPS data are not associated with a street address, which is the case with the more traditional method of geocoding using a street centerline. In other words, GPS data are much more accurate than address-matched data. Such accuracy is valuable for examining areas such as large parks, wooded tracts, rural roads, parcels of commercial land such as farms, parking lots, alleys and paths – areas which typically lack sufficient address information to point to specific locations within the larger area.

GIS maps that include GPS data have not been widely used in crime and spatial analysis, although the technology is inexpensive and the training needed to collect coordinates quite modest. Harries (1999) and Sorenson (1997) suggest police could easily incorporate GPS into operations, improving police response to calls and officer safety as well as providing more reliable crime maps. While there have been some applications of GPS in crime mapping for specialized environments – public housing (Hayes and Ludlow, 1999), university campuses (Henderson and Lowell, 1999), for mapping of graffiti locations (Egilmez, 2004) and collisions on highways (Hughes, 2004), the primary uses of GPS in public safety have been related to monitoring offenders under community supervision (Reza, 2004) or undercover operations, such as monitoring and tracking bait cars (Mertens, 2003; Khanna, 2004).

Similar to public housing and college campuses, there are inherent limitations to GIS for rural settings as many offenses occur in open areas without precise addresses. Such problems will often result in missing data, as a responding officer may include only a building name, a single street name or other generic description of the location. Since address precision in such settings is low, GPS-based maps have great promise for rural areas. By developing standardized and easy-to-use GPS-based reference points, police may initially respond to offenses with greater precision. Once established, GPS-based maps provide a more complete and more accurate database for spatial analysis and more detailed, and thus useful, examinations of the relationship between offenses and ecological features.

CHAPTER III: COMPARING GPS WITH GEOCODED POINTS

This study was carried out in a four-county region in the foothills of North Carolina. Using the UCR offense of motor vehicle theft, the study sought to develop a regional crime map for motor vehicle theft, examining the spatial distribution of offenses that would otherwise be obscured by politically-established boundaries separating the jurisdictions. The maps were developed to provide practical assistance to law enforcement agencies in identifying and understanding area-level problems.

The research study was designed to address a set of specific research questions. In brief, the study sought to determine:

- Spatial distribution of motor vehicle theft in a non-urban region, comprised of small towns and unincorporated areas.
- The relationship of recovery locations to theft locations.[24]
- Contextual features related to spatial distribution of offenses.
- Analyze descriptive characteristics of vehicle theft and compare these with national data and other jurisdictions

In addition, the study sought to determine the:

- Empirical difference between address-based maps and GPS-referenced maps of motor vehicle theft
- Perceived value of regional maps to area law enforcement personnel

To answer these questions, the research team:

- Examined the spatial distribution of motor vehicle theft in a regional area, identifying edge occurrences and other spatial distributions.

24 The original research proposed to examine the relationship of recovery locations to addresses of offenders. However, less than half of vehicles were recovered, and addresses were not available for many of these recoveries – some being outside of the region and even outside the state. Even fewer offenses were cleared by arrest, and suspect information such as address was often missing.

- Used non-crime data to analyze the contribution of contextual, environmental and temporal features to motor vehicle theft, thus assisting with problem analysis .

- Conducted focus group-type discussions with law enforcement to determine their mental map of respective jurisdictions and identify common offense points in places for which GPS coordinates will be recorded and entered into a GIS.

- Generated differing map formats and had law enforcement personnel evaluate the utility of different maps.

- Conducted descriptive analysis of theft characteristics.

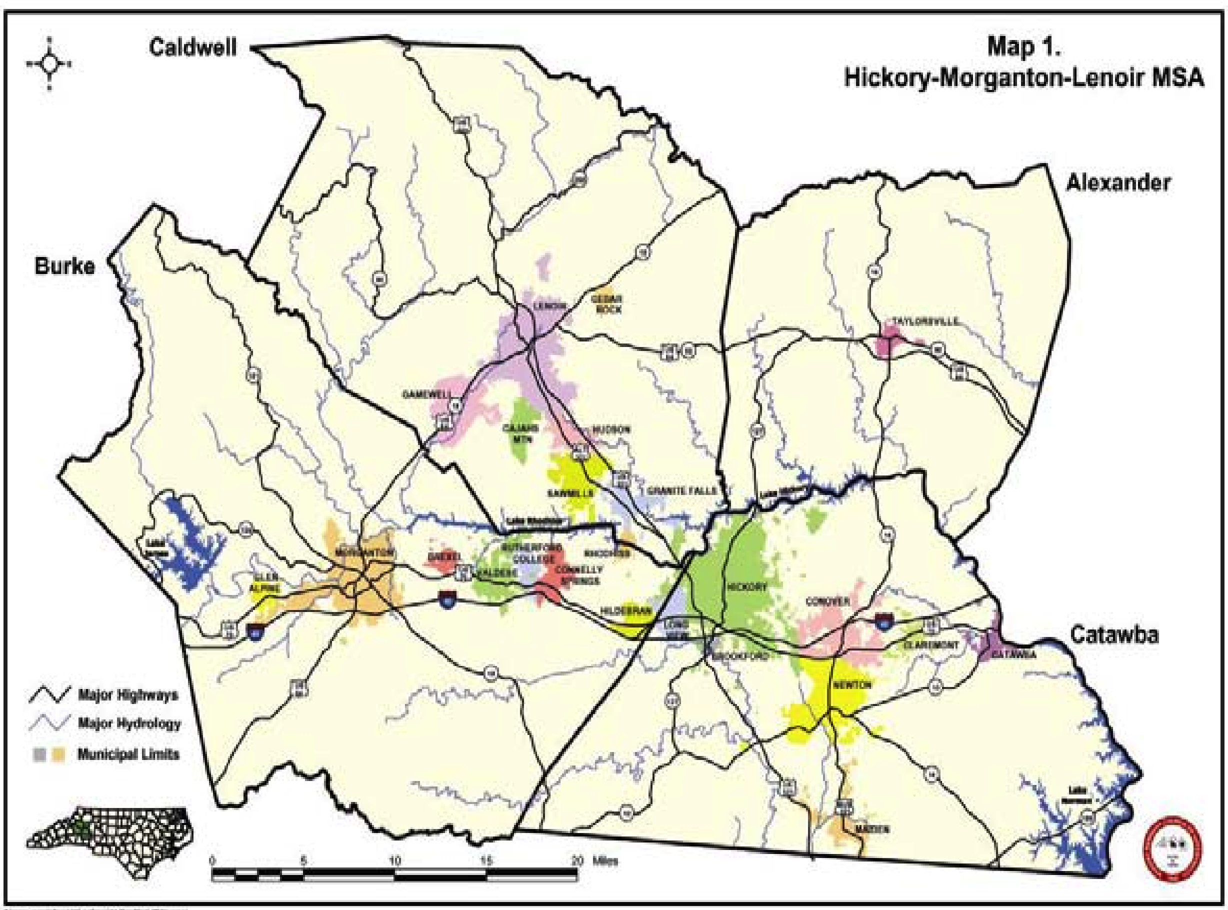
Research Sites and Partnership

This research study was conducted in a four-county area of North Carolina. The area is predominately rural and includes 24 municipalities and townships within those four counties. The four largest municipalities have a total population of 60,000 while the area, known as Western Piedmont or Unifour, constitutes an MSA with a population of 360,000.

The definition of rural is not well-established; however, some studies define rural counties as those that contain no municipality or township of 2,500 or more population. Small non-metropolitan counties are those which have no towns with 20,000 or more population while larger non-metropolitan counties are those with one or more towns of 20,000 population or greater. Using this classification scheme, the four county region consists of one rural county (Alexander), two small non-metropolitan counties (Burke and Caldwell), and one larger non-metropolitan county (Catawba), the latter of which contains the region's largest city, Hickory, with a population of 35,000. This classification at the county level is consistent with each county's overall population: Catawba, Burke, Caldwell, and Alexander with respectively, populations, of 141,685; 89,148; 77,415; and 33,603.

The large non-metro county (Catawba) is roughly twice as large as the two small non-metro counties (Burke and Caldwell), while the two small non-metro counties are more than double the population of the rural county (Alexander). The relative populations of, and the size of municipalities within, the four counties is thus consistent with widely used classifications of rural. Weisheit and Wells (1998), however, note that small jurisdictions are often located within larger metropolitan areas. While the four counties in this study comprise an MSA, each is in close proximity to the region's largest city, Hickory, which is physically located at the intersection of the four counties on the major Interstate highway that traverses all four counties (See Map 1 provided courtesy of the Western Piedmont Council of Governments). [25]

Map 1: Western Piedmont Region



[25] In the FBI's UCR, Catawba County and the three adjacent counties are considered metropolitan counties as they have a high degree of economic and social integration with the principal city (Hickory) and Catawba, the county in which Hickory is located. This definition of a Metropolitan Statistical Area (MSA) follows the definition established by the Office of Management and Budget.

The Western Piedmont region has a rich history of interagency cooperation. The four counties are arrayed around Hickory, the largest municipality with a population of 32,000; this city experienced a population growth of 31% from 1990 to 2000. The counties share the Catawba River, and have cooperated in many regional endeavors including sharing the water supply and effluence and sewage treatment. The region shares an economic base consisting of furniture, textiles and fiber options, and comprises an MSA.

The counties, municipalities and townships in this area are member agencies of the Western Piedmont Council of Government (WPCOG), based in Hickory. The staff of 50 at WPCOG administers an annual budget of $11.5 million, including an administrative budget of $3.4 million. WPCOG operates a GIS program and currently provides mapping services for Hickory, Lenoir and Alexander County. At the outset of the research, WPCOG already had base maps for the counties and street center line files for its member jurisdictions. While WPCOG does not map crime data, the organization is a rich source of secondary data, serving as the area's Census depository, and, as the center for transportation planning, maintains all zoning maps.

Participating law enforcement agencies included four sheriffs' agencies: Alexander, Burke, Caldwell and Catawba, and seven municipal agencies: the police departments of Conover, Granite Falls, Hickory, Lenoir, Long View, Morganton and Newton. In terms of sworn officers, Catawba County Sheriffs' Agency and Hickory Police Department are the largest agencies, with just over 100 officers each. Five of the agencies have 50 or fewer sworn – Granite Falls, Lenoir, Conover, Long View, Newton and Alexander County.

Consistent with its relatively rural composition, crime is relatively modest in the area and has been quite stable. During 1999, there were a total of 624 motor vehicle thefts in the four-county region, a rate of 191:100,000 residents in the region. In terms of crime, Hickory has the largest crime volume in the four-county area. Hickory has about three times the volume of crime as the next two largest towns, Lenoir and Morganton; but Hickory has only twice the population of those two towns. The higher crime volume reflects primarily the economic centrality of the town; commuting patterns show that many residents of the other three counties and their townships commute into Hickory for work.

Table IV: Western Piedmont Law Enforcement Agencies

Law Enforcement Agency	Service Population	Sworn Personnel
Alexander County Sheriffs' Office	33,603	26
Burke County Sheriffs' Office	89,148	79
Caldwell County Sheriffs' Office	77,415	65
Catawba County Sheriffs' Office	141,685	105
Conover Police Dept.	6,604	24
Granite Falls Police Dept.	4,612	12
Hickory Police Dept.	40,014	106
Lenoir Police Dept.	18,238	54
Long View Police Dept.	4,722	15
Morganton Police Dept.	17,536	60
Newton Police Dept.	12,884	36
Total	**446,461**	**582**

At least two agencies in the region use crime data for analysis and mapping. Hickory Police Department has a full-time crime analyst, and routinely reviews crime data as part of its management similar to CompStat. Conover Police Department is small but technologically-advanced agency that analyzes crime and has also experimented with using GPS to map traffic collisions. Many of the other agencies appear to have few resources and have not engaged in crime analysis.

The research effort was a product of a partnership between N.C. State University (NCSU), WPCOG, and area law enforcement agencies. While NCSU was responsible for the overall direction and administration of the research, the effort required the coordination of tasks and communication with geographically diverse sites.

The research team believed that law enforcement personnel should have a direct role in clarifying the context of crime analysis, and sought to informally examine practitioner-generated hypotheses arising from their professional experience. At an initial meeting with law enforcement personnel, officers were asked to identify patterns that might be detected among vehicle theft in the region. Police perceived that some vehicle theft might be related to an increase of Hmong immigrants living in the region, and increasing unemployment associated with the decline of the furniture manufacturing industry in the area. Since the area features a very low education level, other employment opportunities were perceived as limited, and police believed that “hard times” might increase the amount of vehicle theft.

Police articulated no other patterns but expressed interest in learning about common makes and models of vehicles stolen, times of occurrence, recurring locations, recovery rates and time course, recovery value and locations. In many ways, police seemed skeptical of the value of crime analysis for vehicle theft, inferring low expectations for the clearance of offenses and low expectations for crime reductions. Consistent with other offenses such as burglary, the absence of physical evidence and witnesses reduce the potential for police success in apprehending offenders, and police verbalized few expectations for crime prevention, a perception consistent with the sparse volume of crime in the region.

Incident Data and Management Tasks

While crime is modest in the Western Piedmont region, there were a sufficient number of cases of vehicle theft for analysis, yet the data were manageable for cleaning, recoding, further data collection and analysis. The initial data for this study consisted of incident reports obtained from law enforcement agencies in the region. Additional non-crime data including land use, census and roadway data were incorporated into an archive for analysis, and GPS coordinates were collected. Each of these sources is described.

Full incident reports for motor vehicle thefts occurring in 2003 were obtained from 11 law enforcement agencies – all four county agencies and the seven largest townships. These reports included report narrative, supplemental reports including arrests, and recovery information.

Table V: 2003 Vehicle Thefts by Jurisdiction[26]

	Frequency	% of vehicle theft	Vehicle theft per 1,000 population
Alexander Co SO	42	6.6	1.25
Burke Co. SO	65	10.4	.73
Caldwell Co SO	115	18.1	1.48
Catawba Co. SO	88	13.9	.621
Conover PD	22	3.5	3.33
Granite Falls PD	9	1.4	1.95
Hickory PD	190	30.0	5.1
Lenoir PD	39	6.2	2.32
Long View PD	14	2.2	2.96
Morganton PD	8	1.4	.52
Newton PD	41	6.3	3.18
Total	**633**	**100.0**	**1.43**

A total of 633 vehicle thefts were recorded in the four-county area (See Table V). Many of the thefts in the region – about one-third – occurred in Hickory. The number of thefts varied

[26] The number of thefts reported in this table reflect the number of incidents used for analysis in this study. The reports were collected from participating agencies. Cases that reflected unauthorized use were eliminated from analysis.

from one jurisdiction to another, and the rate of vehicle theft also varied. The highest theft rate at 5.1:1,000 was in Hickory while Conover, a small town adjacent to Hickory, suffered a theft rate of 3.3: 1,000.

Prior to the research study, the agencies were asked if crime data were stored in an electronic Records Management System (RMS). While all did, they were only able to extract data on individual reports, and not compile the data across records.[27] Paper reports were also requested of agencies initially for purposes of verification and further data extraction, as needed. It was anticipated initially that much descriptive information about the nature of the theft would be contained in the report narrative. Experience has shown that rich offense details are often included in officers' reports but not captured in electronic databases. As none of the law enforcement agencies were able to extract offense data sufficient for analysis, the paper reports became the sole data sources.

Data elements from the incident reports including the narrative were entered into a database. This manual data entry was time consuming, particularly as numerous offense reports were hand-written, but permitted the researchers to standardize data elements and identify any data gaps or inconsistencies. Once data entry was complete, incidents were geocoded and mapped.

Initial Data Errors

The data entry process revealed many errors on the incident reports, and also revealed the informal nature of recording of crime by law enforcement in the region. Street names were often misspelled and street numbers were often omitted. When thefts occurred in a location that could

[27] Two agencies, Conover and Hickory PDs, use electronic data for mapping but can only extract a handful of report variables.

not be attributed to a specific building address, sometimes the entire address field was left blank. Sometimes, a text entry, such as National Guard Armory, was included. Since none of the agencies except Hickory Police Department use data for mapping or other analyses, it is unlikely that address data quality has ever been an issue.

In addition to poor address data, there were other problems with variables contained in the offense reports. In particular, variables regarding the value of vehicle at the time of theft, and the value of the vehicle upon recovery were inconsistent, and often missing. In numerous cases, the recovery value exceeded the value of the stolen vehicle. In other cases, the recovery value was listed as the same as the stolen value, although the report narrative indicated that the vehicle had been crashed or otherwise damaged. The data were thus inconsistent with the Uniform Crime Reporting Handbook (2004), which notes that: “Often the condition of property is different at recovery than it was when stolen. The market value at the time of recovery must be used even if it is less than the value reported at the time of the theft.” Of note, UCR reporting guidelines also require that agencies reporting thefts also report the recovery value of property (on Supplement to Return A), even when the property is recovered by another jurisdiction. In our data, we found that many of the vehicles recovered in other jurisdictions were simply returned to their owner, and no evaluation of the vehicle’s value or condition could be made.

Data Quality and Geocoding

At the outset of the study, addresses of offenses and recoveries were presumed to be of poor quality for geocoding. In non-urban areas, incident locations for vehicle theft might be expected to lack street numbers such as on public or private streets; other offenses might be expected to occur on large land parcels, where a street number is imprecise. As predicted, address information contained on the reports was often of poor quality. While every incident report contained *some* type of address, many of the addresses were deficient for geocoding.

Initially, 51 of the 633 offenses lacked *any* address information. Many of the cases consisted of address fields that contained only descriptive information, such as the following:

Interstate 40 Area rest area, Catawba, NC
1st House on left Walsh Rd., Off Hwy 268
1st chicken house on left, Winterhaven
White House across from 4 Truckers, Morganton
Shed on Trails End

Numerous reports were missing street numbers, and recorded addresses such as the following:

Hwy 268
Spartan Dr.
Mission Road
I-40 at Exit 125

Other reports included the names of businesses but no street name or street number within the address field. Such addresses including the following:

Winn Dixie Parking lot
Mount Herman United Methodist Church
Lowman's Motel #2
Hickory Drilling on R from Haway Rd I-40 Access Rd.
Hildebran Texaco
West Side Metal, Calico Road

An initial cleaning of the 633 theft incidents produced 610 addresses and 578 had sufficient information to be geocodable. Geocoding of these 578 addresses resulted in a match rate of 76% —only 49% of the addresses resulted in geocoded scores at a threshold of 80% or higher while 27% of the addresses were geocoded with lower scores.

Table VI: Geocoding Results

Final Geocoding Score		**Initial Geocoding Score**	
Burke Co			
Matched with score 80-100:	48	Matched with score 80-100:	41
Matched with score <80:	3	Matched with score <80:	9
Unmatched:	30	Unmatched:	31
Total Matched	51	Total Matched	50
Caldwell Co			
Matched with score 80-100:	99	Matched with score 80-100:	81
Matched with score <80:	31	Matched with score <80:	42
Unmatched:	38	Unmatched:	45
Total Matched	130	Total Matched	123
Catawba Co			
Matched with score 80-100:	128	Matched with score 80-100:	85
Matched with score <80:	6	Matched with score <80:	26
Unmatched:	20	Unmatched:	43
Total Matched	134	Total Matched	111
Hickory - Burke Co			
Matched with score 80-100:	0	Matched with score 80-100:	0
Matched with score <80:	0	Matched with score <80:	0
Unmatched:	193	Unmatched:	193
Total Matched	0	Total Matched	0
Hickory - Caldwell Co			
Matched with score 80-100:	0	Matched with score 80-100:	0
Matched with score <80:	0	Matched with score <80:	0
Unmatched:	193	Unmatched:	193
Total Matched	0	Total Matched	0
Hickory - Catawba Co			
Matched with score 80-100:	150	Matched with score 80-100:	72
Matched with score <80:	10	Matched with score <80:	76
Unmatched:	33	Unmatched:	45
Total Matched	160	Total Matched	148
Long View - Burke Co			
Matched with score 80-100:	0	Matched with score 80-100:	0
Matched with score <80:	0	Matched with score <80:	0
Unmatched:	14	Unmatched:	14
Total Matched	0	Total Matched	0
Long View - Catawba Co			
Matched with score 80-100:	7	Matched with score 80-100:	3
Matched with score <80:	0	Matched with score <80:	4
Unmatched:	7	Unmatched:	7
Total Matched	7	Total Matched	7
ADDRESSES TOTAL:	610	ADDRESSES TOTAL:	610
GEOCODABLE:	578	GEOCODABLE:	578
TOTAL GEOCODED:		TOTAL GEOCODED:	
Score 80-100:	432 (75%)	Score 80-100:	282 (49%)
Score <80:	50 (7%)	Score <80:	157 (27%)
TOTAL:	482 (82%)	TOTAL:	439 (76%)

Another iteration of manually cleaning the data corrected errors in street numbers, names, prefixes, and suffixes, and this increased the geocoding match to 82%, with 75% of addresses scored at 80% or higher. Address quality could not be improved beyond the 82% match without additional data collection efforts. (See

Table VI for detailed geocoding scores by jurisdiction.)

GPS Data Collection

Based on the crime reports, the research team developed a list of vehicle theft addresses and this list with descriptive information about the precise location of the theft. These addresses formed a list to guide collection of GPS data; providing practical information about locations. Many of the reports included precise information describing where vehicles were taken from the parcel, for example, noting that the vehicle was stolen from under the carport of the dwelling, or occurred in the street. This information permitted the GPS candidate list to be annotated with landmarks to guide the recording of GPS coordinates.

The research grant did not permit the use of funds for purchasing equipment. The grantee was able to borrow GPS units from NCSU's Department of Forestry Sciences, and WPCOG also provided GPS units for data collection. Using a mobile GPS unit, the researcher followed a map of theft locations, supplemented with information from offense reports. The list included the address of the offense, with the type of premise or name of business when available, the victim's name and phone number; date and time of theft; make, model and color of vehicle; and descriptive information about the site, such as whether the theft occurred in the driveway, beside the barn or in the back yard. The researcher than traveled to designated locations to secure satellite coordinates at each theft location.

GPS technology enabled the researcher to pinpoint the actual physical location in which an offense occurred. The GPS units that were used established incident locations with a minimum of 5-meter accuracy—precisely pinpointing the location of the incidents. Since GPS-established locations did not exist in existing data, reliable recoding procedures were developed.

Then, offense data were entered into the GIS using GPS coordinates. To clarify locations, victims were sometimes contacted by the researcher to clarify specific points within places.

The precise physical location of most offenses was easy to detect visually. In many cases, the stolen vehicle – now recovered – was parked in the very location described on the offense report. Even for thefts of vehicles such as mopeds or All-Terrain Vehicles (ATVs), location information was often precise – mopeds were often recorded as being stolen from a back porch or patio, while an ATV was under a carport or next to a shed. In many cases, victims or others at the location provided precise theft information. In one case, a neighbor at a residential theft location was able to point to a very specific theft location point – the precise parking stall in the lot of an eight unit multi-family building. In some cases, the researcher called the victim to gather additional information about the theft location.[28]

The precision continued at commercial theft locations. At one large factory parking lot, the researcher pulled up to the loading dock and asked workers where a certain vehicle had been stolen months before. Although the victim was absent from work that day, several co-workers immediately chimed in agreement, noting the distinctive color of the vehicle, and pointed to the precise parking spot where the victim's car had been parked that day as it was parked every day.

There were some thefts for which precise information was not available. For example, at one second-hand car lot, the manager could not recall the precise location of the theft but pointed to four parking stalls where that type of vehicle would have been parked. GPS coordinates were recorded for the mid-point of the location. Once x-y coordinates for theft locations were established, these were recorded and integrated into the Geographic Information System (GIS).[29]

28 The success in reaching victims was indicative of the unique nature of a non-urban area as most still resided at the recorded residence.

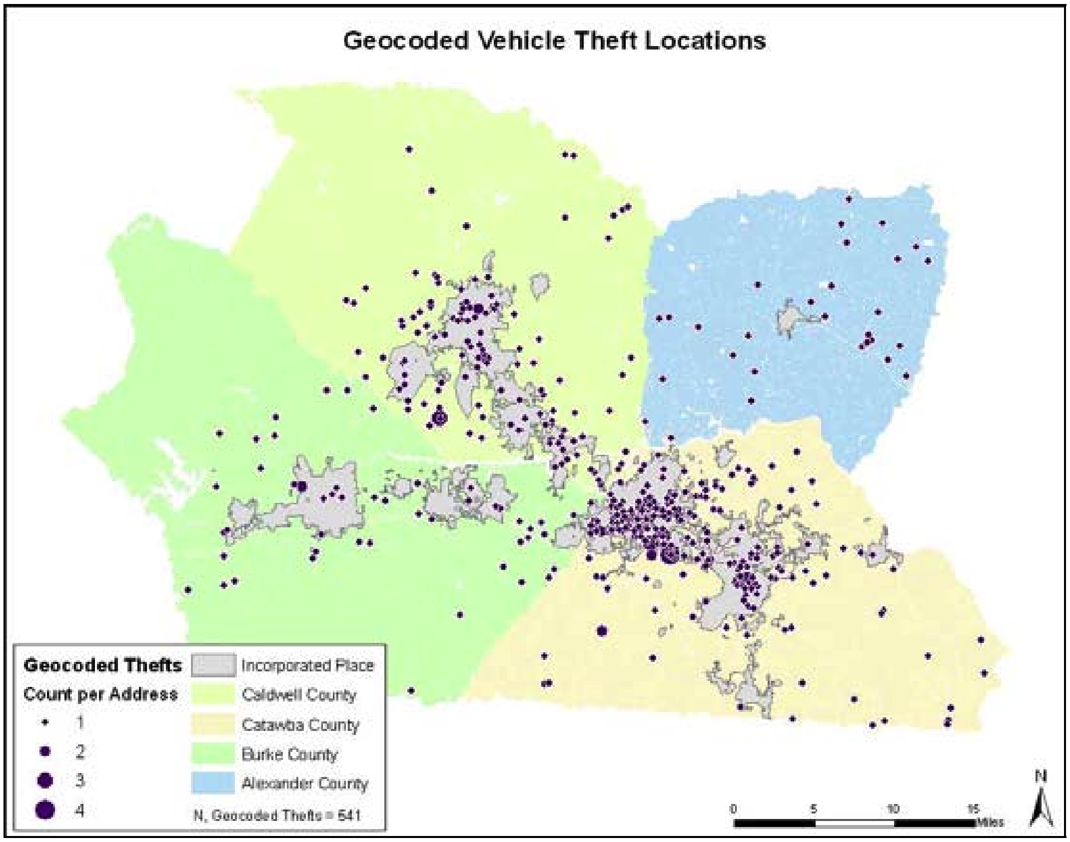
[29] It should be noted that the success of collecting coordinates for recovery locations did not match that attained for theft locations.

Collecting data retroactively invariably reduces the precision that might be associated with on-scene data collection; in some cases, data collection was encumbered by fencing or other barriers to the parcel. IN some cases, the researcher recorded coordinates for the center of a parking lot when there was no information available. In all cases, current data collection at the scene of a crime seems likely to reduce, if not eliminate, error associated with incomplete information or other problems such as victim recall.

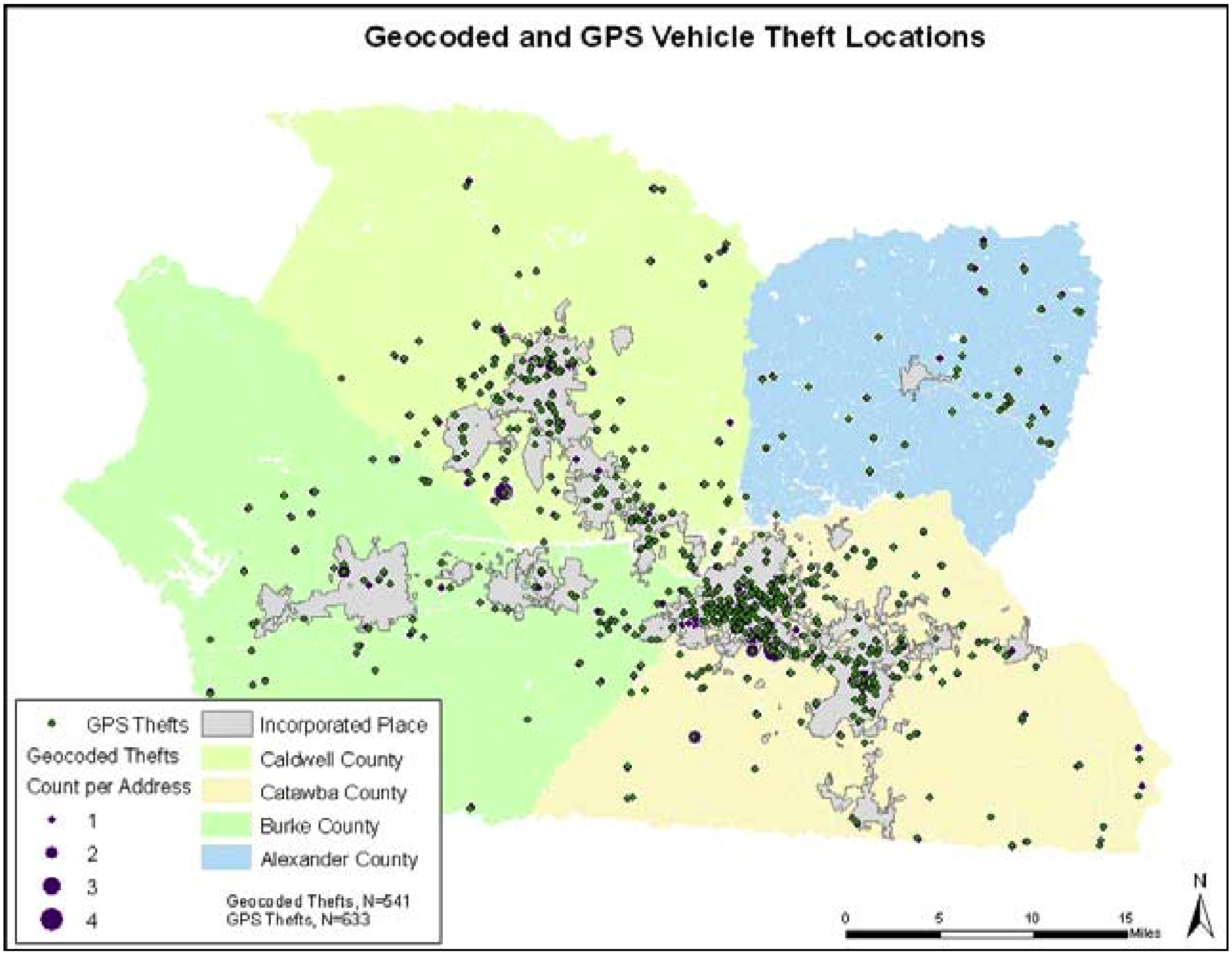
Comparing Geocoded and GPS Maps

Using the two geographic sources of vehicle theft data, incidents were mapped in two ways. First, a point map was created using address locations of vehicle theft incidents (See Map 2). The theft locations were geocoded using the specific address recorded on the police incident report. Second, another map was created using x-y coordinates established through the retrospective collection of GPS coordinates at the offense locations. The incident locations identified by GPS are illustrated on Map 3. For purposes of this report, the first type of map is referred to as the “geocoded map” while the latter is referred to as the “GPS map.” The comparison of address-geocoded maps with GPS-generated maps revealed three types of errors associated with geocoded maps: missing data, geocoding error, and other data errors.

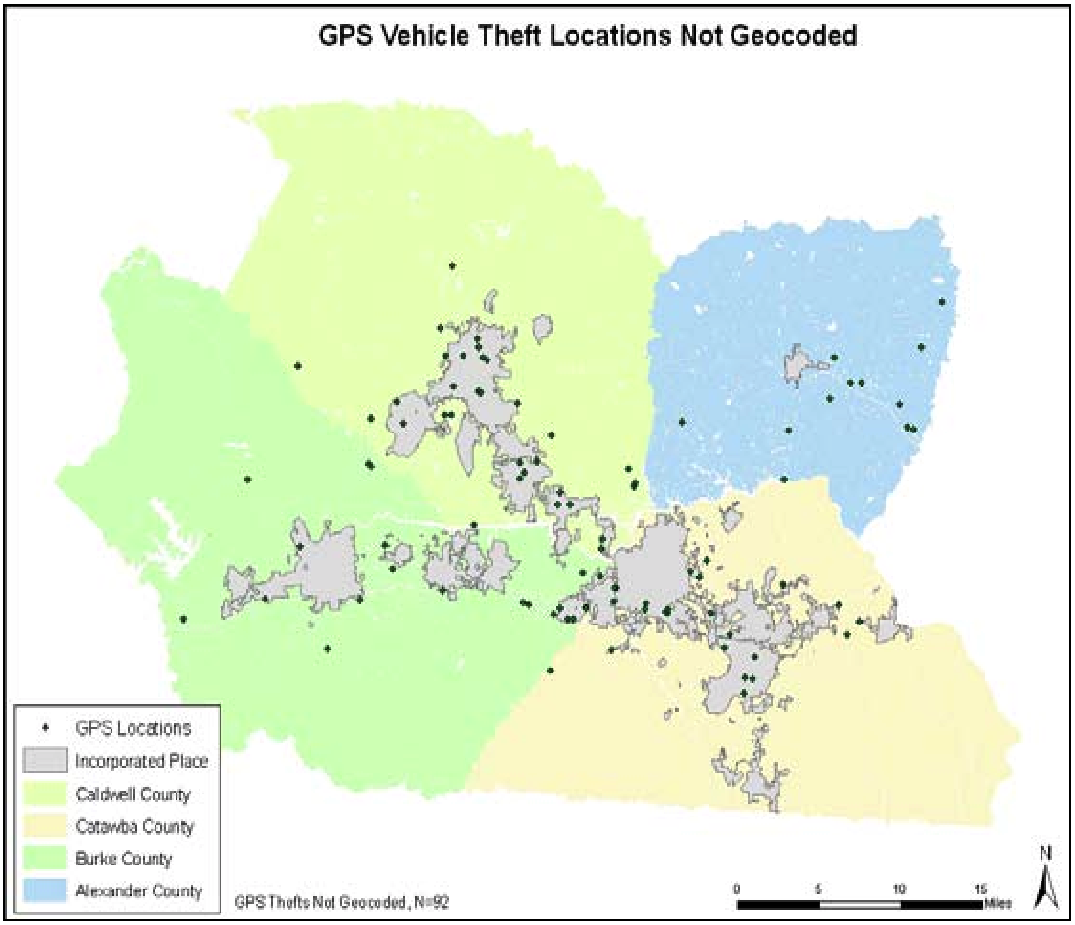
Map 2: Geocoded Vehicle Theft Locations



Map 3: Geocoded and GPS Vehicle Theft Locations



Map 4: GPS Vehicle Theft Locations Not Geocoded



Identification of Missing Data

Using GPS to map vehicle theft locations provided important benefits beyond mapping the geocoded address locations. GPS lead to significant improvement in the completeness of mapping the crime locations. By using x-y coordinates established through GPS, it was possible to map all theft locations recorded by police, producing a match rate of 100% (633). In contrast, the geocoding of addresses resulted in an 85% success rate (541). Retrospective collection of x-y coordinates improved the "match" of offense locations by putting 92 more points on the map than did geocoding alone.

While we anticipated that the added data would be disproportionately within the unincorporated areas of the region, this was not so. Of the 92 GPS points, 44 were in incorporated towns, and 48 were not. This represented 14% of the 323 thefts within towns, and 16% of the thefts in the counties.

Comparing geocoded thefts with the additional cases added by GPS, 6.5% of the geocoding group consisted of cases that contained no town; 31.3% of the GPS-added cases were of this category. Of the geocoded cases, 40.4% were in Hickory, the largest municipality, but only 16.2% of the GPS-added cases were in Hickory. These rates were similar for Lenoir (14.2% geocoded, 13.1% GPS added), and for Morganton, the GPS-added set contained 10.1% of cases from that municipality whereas the geocoded percentage was 4.5%.

In general, GPS added somewhat more points for areas outside municipalities. Map 4 shows the location of the 92 additional points identified by GPS that were not identified through geocoding alone.

The value-added of GPS in this study can be empirically examined by comparing the distance between GPS and geocoded points for 541 pairs of such points – addresses that were both geocodable and for which x-y coordinates were established. The average distance between GPS and geocoded points was 1,979 feet, but the average is skewed by outliers, including one pair that resulted in a 20 mile difference between GPS and geocoded point.

The data distributions between incorporated and unincorporated areas revealed other distinctions, as shown in Table VII. .Thefts within incorporated townships featured a higher proportion of automobiles (49.5% v. 44.3%), a higher rate of truck thefts (17.9% v. 16.7%), a higher rate of SUV thefts (8.5% v. 7.8%), and a higher rate for commercial vehicles and equipment (4.9% v. 1.5%) than for thefts overall in the four-county area. In contrast, thefts within incorporated places featured a lower proportion of thefts of ATV/4-wheelers (1.9% v. 7.2%), farm equipment (0% v .2%), and mowers (.3% v. .6%), and mopeds/dirt bikes/motorcycles (8.0% v.11.2%).

Table VII: Selected Variables by Incorporated vs. Unincorporated Areas

Variable	Incorporated Areas	Unincorporated
Victim Age	37.46	39.93
Victim, % White	59.6%	86.6%
Vehicle Year, Modal Case	1995	1995
Vehicle Make, Modal Case	Ford	Honda
Car Type, Percent	49.5%	37.9%
Truck Type, Percent	17.9%	15.2%
SUV Type, Percent	8.5%	6.9%
Motorcycle Type, Percent	4.7%	8.3%
Stolen Value	$6,990	$5,329
Not Recovered	57.4%	49.3%
Block Group % White	76.9%	90.4%
Block Group % 15-24	13.8%	12.1%
Block Group, Median Age	49.7	36.5
Block Group, Vacant	7.6%	8.7%

Geocoding Errors and Precision

Most spatial analysis uses automated geocoding of addresses with GIS software. Crime locations are attributed to intersections or specific addresses, and sometimes addresses are associated with large land parcels. Since much vehicle theft occurs in parking lots, for example, geocoded addresses are not very precise. The theft may have occurred in an area of the parking lot with poor sight lines or little lighting; a theft may have occurred close to an entrance or an exit, or to pedestrian traffic patterns. In contrast, GPS permits mapping of the precise vehicle theft location, regardless of the size of the land parcel.

Similarly, much vehicle theft occurs on streets or open areas without street numbers or intersecting roads. In these cases, it is not possible to map theft locations at all using geocoding utility of the GIS software. In essence, such points become missing data in spatial analysis, and introduce some amount of error for subsequent analysis.

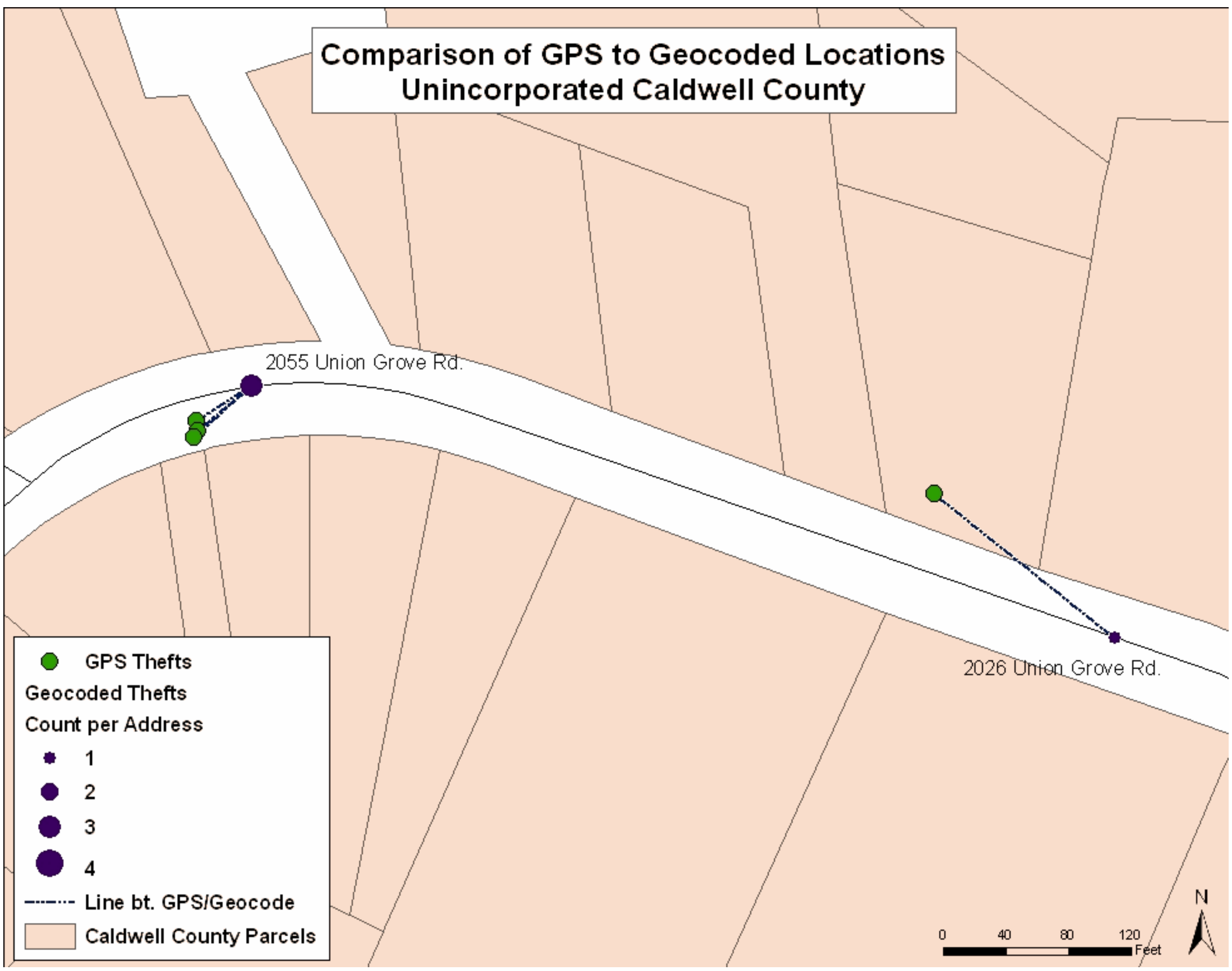
Even when geocoding is relatively straightforward – such as a residential land parcel within a municipality, there are questions about the accuracy of geocoding. Some municipalities develop rapidly. When such development occurs, new streets appear, old streets cease to exist, while the names of other streets are changed and new street numbers may be created. Since there is often a delay before street layers used in the geocoding process are updated, it is often impossible to geocode vehicle theft locations in new areas. Address data on crime reports are often poor because of data entry errors, missing data, or erroneous information recorded by a responding officer or data entry clerk. Each of these address problems results in errors, that prevent accurate geocoding of data. While it is often possible to clean, check and recode data – sometimes at great time and expense, it is usually not possible to detect errors that may be associated with geocoding.

While GPS corrected for missing data, GPS also detected, and thus corrected, numerous geocoding errors that otherwise would have been undetected. Geocoding errors occurred when automatic geocoding placed a theft in the wrong location within a jurisdiction. Many of these errors placed points down the street or in other nearby locations. And this likely reflected the geocoding default settings for data inconsistencies which were set at a threshold of 80% (See Map 5, Map 6 and Map 7).

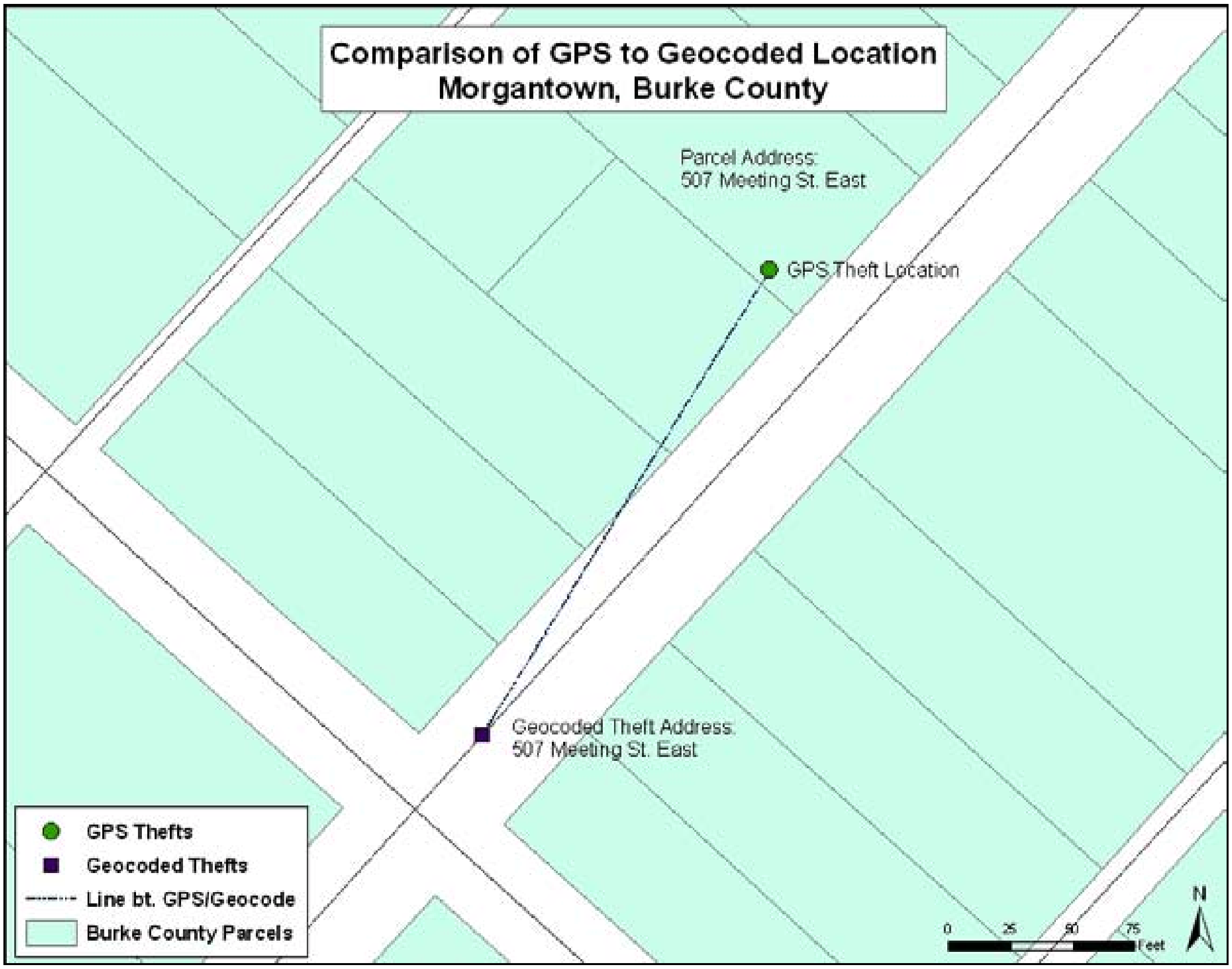
Using GPS put more points on a map, and GPS reliably put points on the map in the exact locations of the land parcels in which events actually occurred while geocoding of addresses associated with small parcels of land resulted in error of varying degrees.

While geocoding of addresses associated with large parcels of land was more accurate because the points went into the correct parcels, they did not go into the correct place on the parcel, and address information was often insufficient to permit further precision of geocoding. For example, in areas comprised of smaller parcels, such as the single family residences common in Hickory, geocoded points were often inaccurate although usually nearby. (See Map 7).

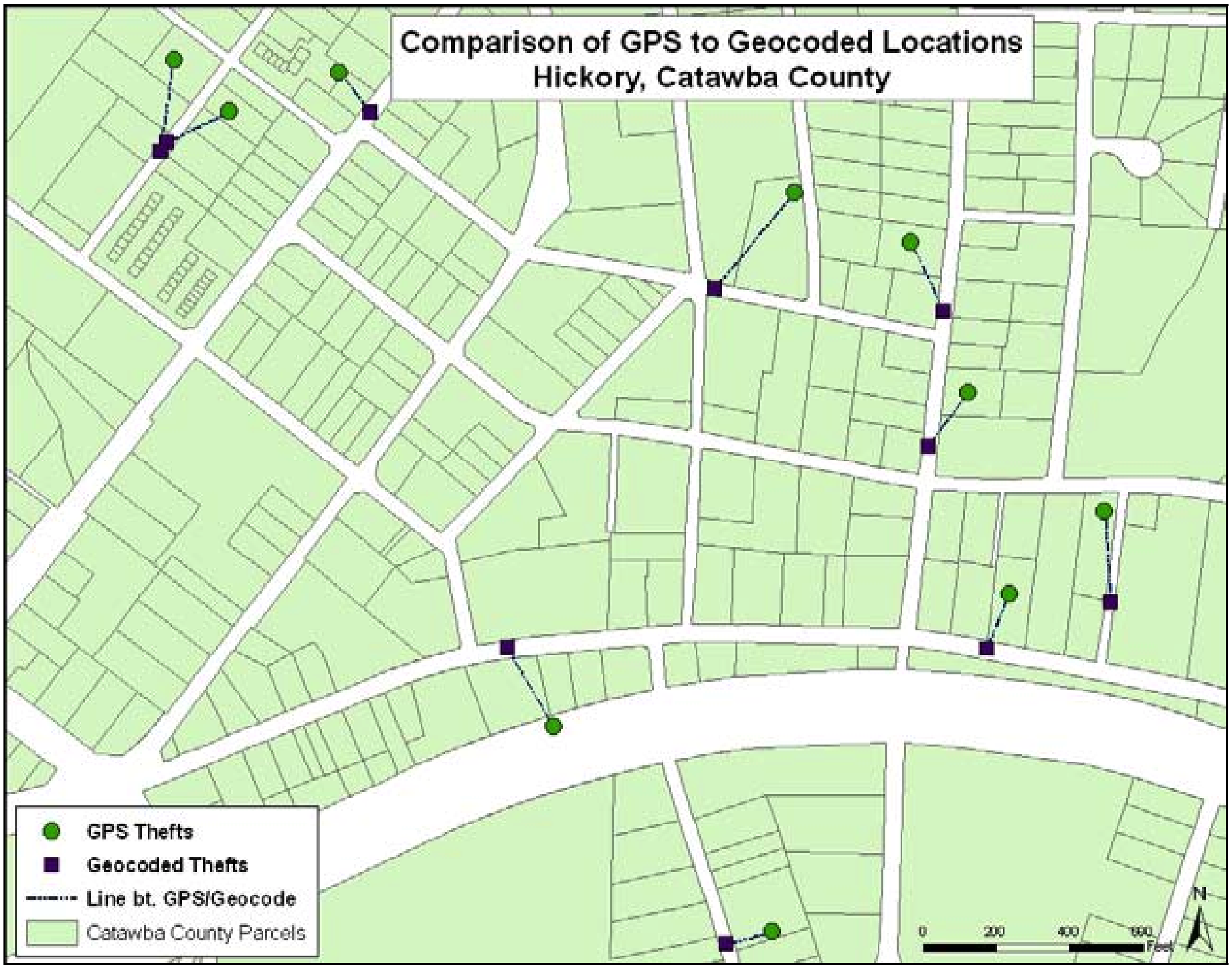
Map 5: Comparison of GPS to Geocoded Locations: Unincorporated Caldwell County



Map 6: Comparison of GPS to Geocoded Locations: Morganton, Burke County



Map 7: Comparison of GPS to Geocoded Locations: Hickory, Catawba County



Detection of Data Errors

Some errors that might have been attributed to geocoding error actually reflected data entry errors. For example, a street direction mistakenly entered as SW (such as 100 South Main Street SW) when it should have been recorded as NW (such as 100 South Main Street *NW*) will result in an apparent geocoding error. In seeking the original address, the researcher finds that 100 South Main Street *SW* does not exist.

Data collection strategies permitted visual verification of the actual offense location and thus corrected for geocoding errors that would have been undetected. Thus, the physical collection of x-y coordinates via GPS served as another iteration of data cleaning – data entry errors were necessarily corrected as the researcher visually matched the offense location to the description on the offense report. When a reported address could not be located by the researcher, an obvious alternative address (such as the nearby 100 South Main Street *NW*) was sought or the victim was called to correct what was usually erroneous address information.

Data completeness could be improved with better quality reports and contemporaneous collection of GPS coordinates at the time of the police report. If GPS were not available, police could use orthophotographic maps, loaded onto the mobile computers in police vehicles or hand-held palm pilots to collect x-y coordinates.

Importance of Spatial Precision

Utilizing GPS rather than relying on address geocoding alone improved the match rate from 85% to 100% for the vehicle theft data studied. While an 85% geocoding rate would be considered quite acceptable by many, these data demonstrate that the additional matches provided by GPS significantly changed mean and modal values of important variables.

All spatial analysis was conducted using ArcGIS 9, which provides a scalable framework for implementing a geographic information system (GIS). The ArcInfo level was used, due to its comprehensive GIS functionality, including rich geoprocessing tools such as geocoding, data visualization, query, analysis, and integration capabilities along with the ability to create and edit geographic data. This software was selected because it is the industry standard and as such enjoys the widest range of support services and is available at reduced cost pricing to government jurisdictions.

Hot spot analysis was conducted using the Spatial Statistics module of ArcGIS, measuring and averaging the distance between adjacent centroids. The average distance in this analysis was .51, reflecting less than 1% likelihood that the pattern of dispersion was random.

ArcGIS High/Low Clustering (Getis-Ord Gi*) was also used to analyze hot spots, using offenses and a distance of 1,320 feet (one quarter mile). The default algorithm type was used to reflect inverse distances, so that points closer to the centroid would count more than points on the periphery. For these parameters, the hot spot z score was .684 —well below the 1.96 score that would indicate statistically significant concentrations. Repeating the analysis at the one-eighth and half-mile cluster distances produced z scores of .307 and .312, respectively. These scores also indicated that there were no statistically significant hot spots as the .05 significance level.

In general, decisions about the completeness, accuracy and precision necessary in maps should be related to their relevance in decision-making. In Sydney, Australia, Ratcliffe (2001) found that using a 10 meter offset (32.8 feet) resulted in the following:

- 10% of the points fell into the correct parcel
- 26% were in the wrong parcel
- 74% did not land in any parcel for an address

- 7.5% were in the wrong census tract

Based on some experimentation, Ratcliffe (2001) established that an inset of 15 meters (about 50 feet) and an offset of 25 meters (about 82 feet) worked the best for an urban area such as Sydney. With these changes, 47% of the points were placed in the correct parcel and only 5.0% addresses were placed in the wrong census tract.

One alternative is to use parcel center geocoding for large land parcels, and centerline offsets for jurisdictions with smaller parcels, or some combination of both techniques. Establishing the appropriate offset for the road centerline may vary, based upon the housing and parking patterns within the area. In areas where residents routinely park on streets or very close to streets (such as in the Newark study carried out by Potchak et al., 2002), the standard offset might be quite small. In areas where residents typically park off street, securing vehicles behind their dwelling units, a larger offset might be used, such as 50 feet. In areas where residences are placed well off the roadway – perhaps as a requirement of a subdivision – an alternative, but rationalized offset might be employed rather than an arbitrarily selected offset.

We were unable to think of a practical reason why precision or accuracy of point maps is absolutely critical for a non-urban area. While the accuracy of mapping in the region was not determined to be of practical value despite improvements through the use of GPS, the use of GPS substantially improved data quality by redressing missing data, thus permitting point maps to be generated. In most cases, it will be more critical to get dots onto a map rather than invest exhaustive effort in getting the dots into very precise locations on a map.

Even with substantial data-cleaning efforts, only 85% of theft locations could be geocoded, and there were important differences between geocoded and non-geocoded addresses. With GPS, x-y coordinates were obtained for 100% of theft locations.

The clear benefits of contemporaneous GPS are as follows:

- Events on large parcels can be mapped with precision, while events on small parcels can be mapped correctly.
- Time-consuming data cleaning efforts will not be necessary to make maps.
- Errors related to geocoding, missing data, poor data, and data entry error will be eliminated and 100% of events can be mapped.

The maximum benefit of using GPS would be achieved when the technology is used during the initial response to the victim's report about the theft, with the GPS location recorded during an officer's report taking, based on information provided by the victim, witnesses or physical evidence on the scene.[30] Equipping officers with GPS units to record events in real-time. Another alternative is to use orthophotographs of areas at the crime scene, or refer to these soon after the incident, and establish x-y coordinates from a visual identification of a location on the photographs which could be loaded onto an officer's in-car computer or hand-held PDA.

Despite the increased accuracy of mapping crime using GPS coordinates, there are difficulties. In areas with dense overhead foliage or during bad weather, it can be difficult to get a satellite reading. Further, sometimes it may not be possible for an officer to remain on the scene sufficiently long to record GPS coordinates, or the victim may not be able to determine the precise location of an incident. It should not be difficult to establish standard practices to deal with both situations.

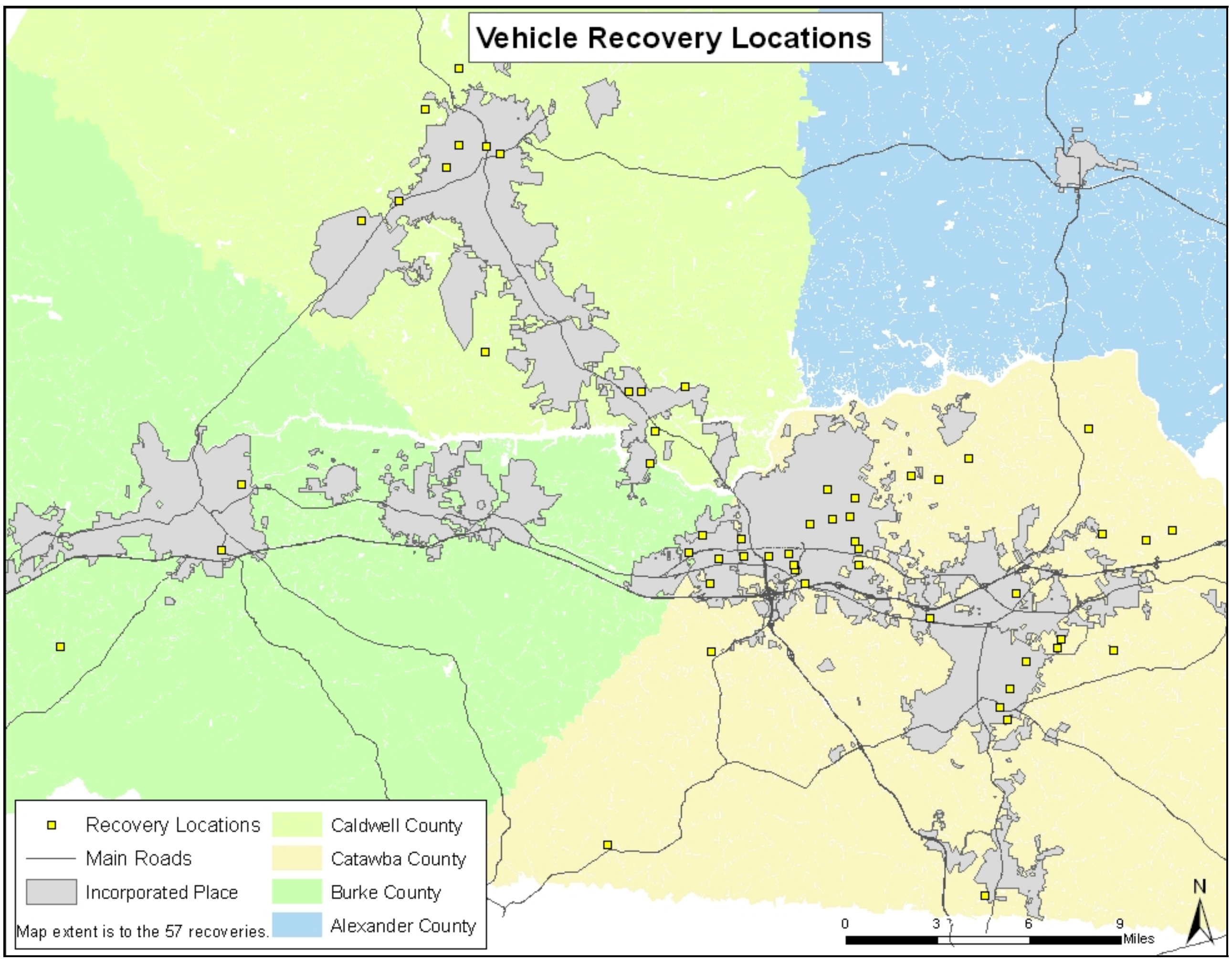
While recording GPS coordinates accurately will take training of officers, GPS equipment is increasingly available and affordable as well as user friendly. In addition to improving data quality, GPS can also be used to improve officer safety, such as providing back up for officers responding to calls for service in remote or unaddressed areas.

30 There are some cases in which the precise theft location within a parcel was unknown or could not be recalled by the victim, particularly for vehicles such as mopeds or ATVs left in open areas, and even automobiles parked in large parking lots. However, the narrative contained on incident reports and our experience in speaking with victims during the collection of GPS coordinates suggests that victim estimations are probably quite accurate.

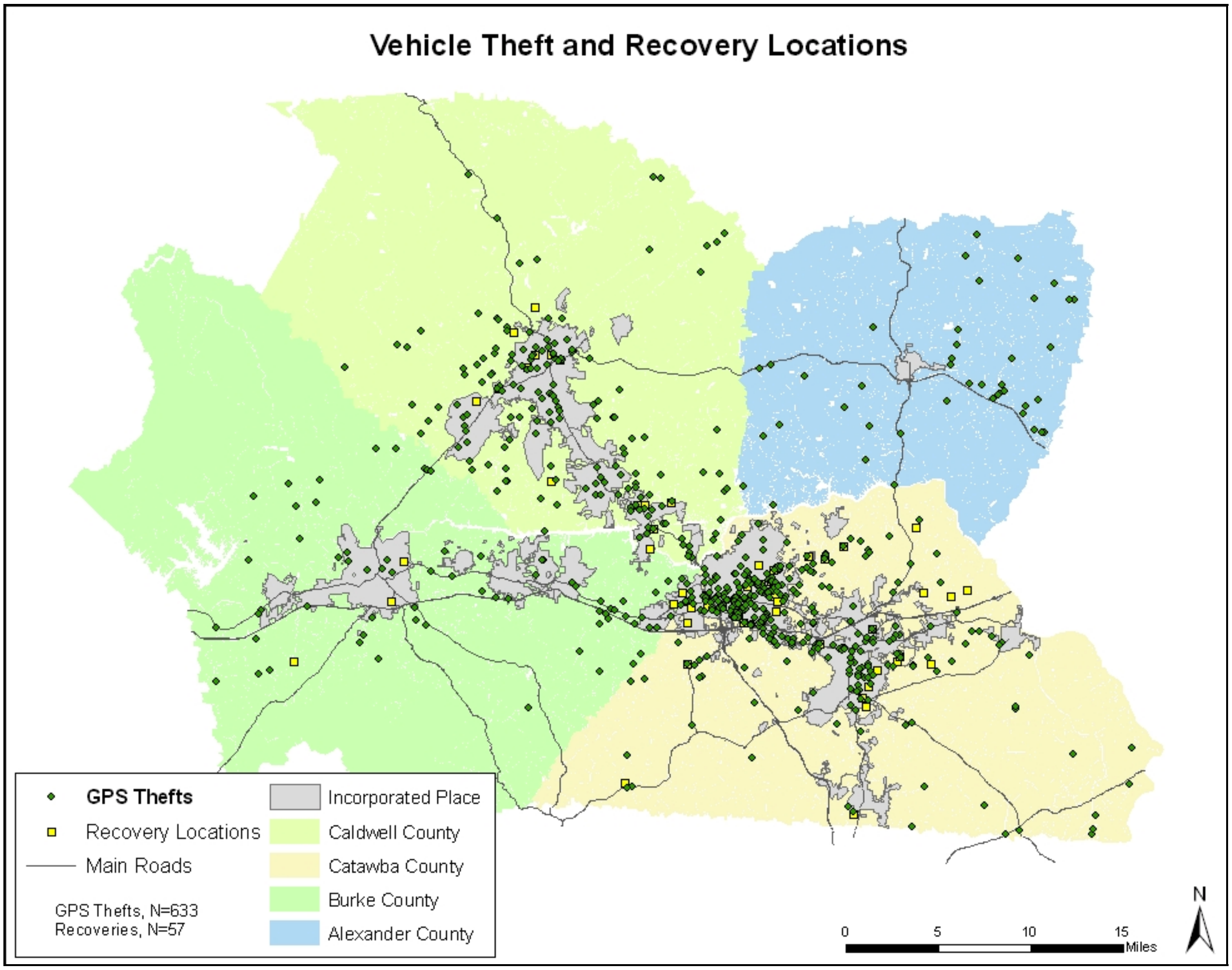
Relationship between Theft and Recovery Locations

A particular benefit anticipated with mapping vehicle theft locations is examining the relationship between the locations of vehicle theft and the locations of recovered vehicles. Unfortunately, recovery data were often missing from incident reports in this study and only 57 recovery locations could be mapped. (See Map 8.) Although this is disappointing, 9% is consistent with the LaVigne et al. (2000) study mentioned earlier. The recovery locations were predominately within incorporated areas.

Map 8: Vehicle Recovery Locations



Map 9: Vehicle Theft and Recovery Locations



CHAPTER IV: SPATIAL ANALYSIS OF VEHICLE THEFT

This report has thus far described the collection of data about locations of stolen vehicles. It would be useful to be able to predict vehicle theft at the individual level, that is, to know what attributes of individual vehicle ownership are associated with the risk of vehicle theft. Unfortunately, we lack information on the individuals at risk of such theft. So, in this section of the report, we take up the question of how well vehicle theft can be predicted by examining data collected at the aggregate level. The data collected on the location of vehicle theft were geocoded and located on electronic maps and associated with available data (e.g., census and tax assessor data), which supply us with an array of variables measuring concepts of the more general theories of the ecological causes of crime and of vehicle theft specifically. Analysis using such variables was conducted with the realization that it is also important to find predictor variables that point toward practical steps to prevent – or at least limit – the extent of vehicle theft. That is, we not only examined variables because they are found in some of the predominant theories of vehicle theft – theories such as social disorganization theory and routine activity theory – but also if they are predictive, theoretically grounded and point toward possible policy implications.

We will present the analysis in stages. In the first stage we will present models of the number of vehicle thefts in each census block group (enumeration group) – areas with approximately 1,000 residents (although there is considerable variation across block groups in their geographic size). In the four county area of our study (Catawba, Alexander, Caldwell and Burke), there are 248 census block groups (235 that had incidents of vehicular theft), with a median population size of 1,338 and a range from 69 to 3,634 residents. The initial analysis correlated characteristics measured in the year 2000 census with the reported vehicle thefts for which we gathered police records in 2003. In the second stage of the analysis we incorporated prevalence of certain "land parcel uses" into the analysis (general types of property uses such as commercial, residential). The division is due to the fact that it took many months to get the land use data in useable format. In the meantime we developed the models using the available census data. Thus, while the order of presentation is somewhat artificial, we argue that it is methodologically instructive.

Stage One Analysis: Vehicle Thefts Relative to Census Measures

In this section of the report, results are presented for the analysis of the number of vehicular thefts in a census block group (enumeration group). The unit of analysis is chosen because previous research had shown that it is a useful one for aggregate level crime analysis and analysis with a goal of providing useful information to police departments (Smith et al., 2000). Previous research has demonstrated that various measures derived from the US. Census can be useful for predicting the occurrence of crimes, including vehicle theft. We employ various measures derived from the census of 2000 (listed in detail in Appendix A) as discussed below.[31]

The census variables are divided into several categories. One category consists of **basic** demographic variables, such as the population size, average number of persons per household, age, race, ethnicity and gender of the residents. These are measured specifically with the following variables: Number of residents, average number of persons per household, percent of residents who are ages 15 to 19, percent of residents ages 20 to 35, median age, number of

[31] Because the data for the independent variables were collected in 2000 and the vehicle theft data are 2003, there may have been changes in the local areas between these dates that is not accounted for in the analysis. Research done elsewhere, however, suggests that such a "lag" in time may not introduce substantial measurement error (Rice and Smith, 1992). We believe that in the current analysis, the 2000 census is an adequate source of information for modeling vehicle theft in 2003.

Hispanics, number of African Americans, the racial mix (proportion white multiplied times proportion African American), and average household size.

A second type of variable from the census we argue to be related are measures of social disorder and social disorganization. That is, we look at measures of social disorder such as the level of deterioration in the neighborhood (number of vacant buildings, percent of buildings vacant), and measures of social disorganization that have been associated with community or social control (percent of males 15 and over who are unmarried, percent of families with single parent, percent living in an urban setting – where there is greater anonymity and thus less control – and number of owner-occupied homes).

Additional types of measures include various measures of poverty – percent below 1.5 times the poverty level, percent below the poverty level, and median income. Also a measure of education was included: percent of males with some college or higher levels of educational attainment. In addition we introduced the size or area of the census block group as a variable. These variables are tested as there are previous research studies to suggest that they are predictive of crime in general or vehicle theft specifically (Rice and Smith 2002; Smith et al., 2000; Messner and Blau, 1987; McCaghy et al., 1977).

Before discussing the analysis itself, it should be pointed out that there is little agreement in the field of social ecological research as to what is the best way to handle the multitude of possible measures that are available. For example, how exactly should poverty be measured? Some researchers argue that it is more useful to combine the multiple measures of concepts such as "poverty" into a smaller number of "factors" and proceed using these factors as the independent variables. Other researchers prefer to use the individual items (the specific variables, e.g., each measure of poverty), but then researchers typically have to deal with the issues associated with high intercorrelations among individual variables (sometimes prohibiting fair tests of specific variables due to their high correlation with other variables). Because there is no agreed upon way to handle the dilemma of using factors or individual variables, we present the results of the factor analysis (in Appendix A) and the results of the regression using individual items. Thus, the analysis is presented using two different modalities. In one modality, the variables are reduced through combination with other variables, using factor analysis. The factors (combinations of specific independent variables) are subsequently used as independent variables in regression analysis. In the second modality, select individual variables are tested. Details of these two approaches are described in Appendix A, along with a regression analysis conducted using factors derived from factor analysis. In brief, the results of the factor analysis shows that the prevalence of youth, urbanness and population size predict the number of vehicle thefts in an area. As discussed in Appendix A, these are not surprising correlates of vehicle theft since young people are known to be more active criminally than older people, and one would expect more vehicles to be stolen where more such vehicles are present – where there are more people or a higher density of people. As such, the factor analysis results do not help us appreciably in achieving information useful for policy to reduce vehicle theft.

As discussed in Appendix A, an alternative approach to the use of factor scores is to examine the prediction of vehicle thefts using individual variables rather than the factors derived from factor analysis. The advantage of this alternate approach is that the individual items measure more specific attributes of the census block groups, and such characteristics might point to promising practical directions. The primary disadvantage is that there will tend to be issues of multicollinearity that we will have to address (high correlations among the independent variables). We take up this discussion next.

The problem of "multicollinearity" stems from high intercorrelations among variables. As a result, it is difficult to test for the statistical significance of variables involved in high intercorrelations with other independent variables. Factor analysis generally solves the problem by combining measures into more general measures of phenomena (as we did in Appendix A), but the generality of those measures makes it very ambiguous as to what the causal mechanisms are. The individual items arguably are less ambiguous, but there are not entirely satisfactory solutions to the problems of using the individual items as predictors because available measures are often highly intercorrelated. We argue here that a "forward entry" regression method helps us deal efficiently with the multicollinearity issues. Essentially, all the variables are tested and the one with the highest correlation is allowed entry first. Then, estimates are made again, and the variable with the highest partial correlation, having controlled statistically for the first variable entered, entered next into the equation. With two predictor variables in the equation, a test is made of the next highest partial correlation, and the variable associated with that variable is then entered. This "survival of the fittest" strategy is used until all of the variables that are statistically significant predictors have entered the equation. We check various multi-collinearity statistics along the way to be sure that the variables entered have sufficient unique variation such that the standard errors are not artificially "inflated" (Gordon, 1968). Also, any strong correlate of vehicle theft that does not survive the tests for inclusion will be analyzed separately to see how it might contribute to our understanding of vehicle theft.

Table VIII shows the results of an analysis using individual variables (not factors). A model is presented in which only three variables were found to be statistically significant in a "forward entry" solution. That is, when all the variables are entered one at a time, with the variable with the largest partial correlation (net the effects of the other variables) entered first, partial correlations re-estimated, and the next highest entered (and so on), only three variables enter the equation: the number of Hispanic residents, the percent of the household that are owner-occupied, and the resident population (again as a statistical control variable).

Table VIII: Number Vehicle Thefts Regressed on Individual Variables

	Unstandardized Coefficients		Standardized Coefficients		t	Sig.	Collinearity Statistics	
R^2 = 23.4%	B	Std. Error	Beta	IQR Effect			Tolerance	VIF
(Constant)	6.089	1.033			5.892	.000		
N Hispanic	.006	.003	.166	.342	2.145	.033	.547	1.829
Percent Owner Occupied	-.071	.015	-.344	-1.361	-4.822	.000	.643	1.555
Pop. (divided by 1000)	1.036	.335	.222	1.886	3.092	.002	.634	1.577

a Dependent Variable: N_auto_thefts

As such, these findings arguably have more policy implications than the findings from the analysis in Appendix A involving factors as independent variables. Using the individual items as independent variables, we see from the analysis that that there seems to be a prevalence of vehicular thefts in Hispanic neighborhoods, as well as in neighborhoods where there are simply more people and therefore (presumably) more drivers and vehicles to steal. In fact we treat the population size variable as a statistical control variable – since there is variation in population size across areas, it is necessary to control for the population size. The logic here is that, all else being equal, we would expect more vehicle theft where there are more vehicles, and there are likely to be more vehicles where there are more people present.

More important for policy is the effect of percent owner-occupied. The higher the percent of households that are owner-occupied (households with the owner living in the household vs. households with renters), the fewer are the vehicular thefts. Each percentage increase in owner-occupied households results in .07 fewer vehicle thefts in a year. Relative to the other two variables in the model, the percent owner occupied has the largest effect or the second largest effect, depending on whether one compares the Betas (standardized regression coefficients) or the inter-quartile range effects (defined and discussed below).

Comparing the Betas, it can be seen that a one standard score increase in the percent owner occupied results in a reduction of -.344 in the standard score of vehicular thefts. This compares favorably to (i.e., it is larger than) the .166 Beta for number of Hispanic residents, and .222 for population size. The Beta effect for population size is larger than that of the percent owner occupied variable. However, if interquartile range (IQR) effects are compared, the effect of percent owner-occupied is not as large as the effect of population. An IZR effect is the effect of the change in the dependent variable with a change in the independent variable from an average "low" value (the 25^{th} percentile) to an average "high" value (the 75^{th} percentile). Each thousand residents account for one more vehicle theft per year (1.036). Increasing the population by one IQR (1.82) results in 1.886 more vehicles stolen (1.82 x 1.036), whereas increasing the percent owner occupied by one IQR (19.17) results in 1.361 fewer vehicle thefts. (The IQR for the Hispanic variable is .57). Some researchers argue that the IQR effect is more stable across samples than the Betas, and that if additional samples were to be drawn, the IQR effects would be more similar across samples than would be the Betas (essentially because the IQRs are more stable across samples than are the standard deviations of the variables).

The fact that the percent owner occupied is associated with lower vehicle theft rates is interesting from a policy point of view because the variable is often used by urban planners as a measure of the overall "health" of a neighborhood. The goal of many city/regional planning and public housing organizations is often to achieve higher percentages of owner occupied housing in an area (Galster and Quercia, 2000). If one sets as an objective to put into place policies so as to achieve a predominance of owner-occupied housing, such as 60% (i.e., planning is approved or proposed that works toward the achievement of a 60% goal of owner-occupied households), one may be solving a host of community problems, including crime problems. Interestingly, in an analysis of the present vehicle theft data, we find that 60% marks the optimal ratio of vehicle theft differential compared with other percentages. Thus, we find a ratio of 2.17 between the number of vehicle thefts in areas with less than 60% owner occupied compared with areas that have 60% or more owner occupied. Stated another way, there are twice as many automobile thefts in areas with less than 60% owner occupied than in areas with 60% or more owner occupied households. In terms of policy ramifications, the activities of local planners and developers may be important to limiting vehicular theft.

The effect of percent owner occupied is quite robust statistically. For example, it might be argued that the percent owner occupied effect is compromised by the fact that it is a type of "social class" measure (presumably to own a home, one has to have a steady income above the "poverty line"). One might argue that the percent owner occupied is correlated negatively with poverty, and that poverty should be controlled for statistically. However, we find that adding to the equation all of the poverty measures – or any one poverty measure – makes no difference to the results. The percent owner occupied remains a strong predictor variable in such equations (results not presented here). Some also might argue that percent owner occupied is correlated with other variables, such as the prevalence of single parent families. However, again, controlling for single parent families, the percent owner occupied remains just as strong a predictor of vehicle thefts.

Also of note in

Table VIII is the tolerance and Variance Inflation Factor (VIF) of the variables. The tolerance is simply the unexplained variance in the variable if it were regressed on the other independent variables in the equation. It represents the "uniqueness" of the variable relative to the other independent variables, and should generally have a value of .25 or higher. The VIF is simply the inverse of the tolerance and should be less than approximately 4.0 (following recommendations suggested by Belsley, 1991).

Although tolerances are well within the limits of acceptability for making reliable estimates of the regression coefficients, there are still moderately high correlations among the three independent variables in the equation. Some of the variables did not enter the equation because they did not reach statistical significance when tested because another variable already entered in the equation essentially kept it out. Three such variables with low tolerances (and high VIFs) are: number of males, number of single head of households, and number of owner occupied (i.e., not percents but counts of owner occupied households). They are of interest because they have been somewhat arbitrarily omitted from the equation in Table VIII – we say "arbitrarily" because these variables happen to correlate rather highly with some or all of the three variables represented in that model.

Of these three omitted variables, the omission of the number of males does not concern us because it correlates .99 with the number of people, and is thus fully redundant with a variable we already have in the model. The number owner occupied correlates moderately highly with the percent owner occupied (.502) and with the population size (.919), so it too is largely redundant with what is already in the equation and brings us little that is theoretically new to the equation since we already have a measure of percent owner occupied. The single-head of households count, however, is arguably tapping a component of the neighborhoods that is similar conceptually to that of percent owner occupied: community control. Several researchers have indicated that the prevalence of single parent households is a measure of the social control in an area – specifically lack of social control over youth, since, all else being equal, one-parent families can monitor children less effectively than two-parent families (Sampson and Groves, 1989; Smith et al., 2000). Also, the prevalence of one-parent families implies that there are fewer "eyes on the street" – at least adult eyes – than in areas with a prevalence of two-parent families. The prevalence of single heads of households is also correlated with other variables in the model, specifically the population size (.710) and more weakly (-.321) with percent owner occupied (partly supporting the claim of single head of household as a social control measure).

We tested an alternative model in which we dropped the percent owner-occupied variable and also entered the population size variable first in the step-wise process. The results are presented in Table IX. The Hispanic variable again enters the equation, but now the percent single parent enters the equation with a Beta of .212 (IQR effect of .671). Thus, interestingly, the percent single parent variables essentially "replaces" the percent owner occupied variable in the equation (although obviously the effects are reversed), and also supports a community control interpretation.

Table IX: Alternative Model Using Individual Variable Predictors

	Unstandardized Coefficients		Standardized Coefficients		t	Sig.	Collinearity Statistics	
R^2 = 19.3%	B	Std. Error	Beta	IQR Effect			Tolerance	VIF
(Constant)	-.099	.671			-.147	.883		
pop_by1000	.529	.313	.113	.434	1.689	.093	.764	1.308
N Hispanic	.010	.003	.281	.570	3.904	.000	.668	1.498
Percent_single parent	.125	.038	.212	.671	3.259	.001	.817	1.223

a Dependent Variable: N_auto_thefts

In addition to the above tests, we also tested for interaction effects among the following sets of variables: 1) percent owner occupied with population size, percent single parent, number of Hispanics, and percent ages 20 to 35; 2) percent single parent with population size, number of Hispanics, and percent ages 20 to 35. None of them were found to be statistically significant. However, several of the product terms were highly inter-correlated with other variables (especially the "main effect" variable, e.g., the product term "percent owner occupied times population size" was collinear with "percent owner occupied"). In such situations it is not likely that two highly correlated variables both would be statistically significant in a regression equation.

Stage Two Analyses: Adding Land Use Variables to the Model

Gathering together the land parcel data from the tax assessment databases in the four counties required considerable time, and thus we completed the models with the census independent variables first (having obtained those data early in the process). It was not until the summer of 2005 that we were able to put together the tax assessor data for the seven variables (discussed below) that were comparably measured across three of the four counties. Data from Alexander County on land use were missing (consisting of only 24 census block groups). However, we include the observations from Alexander County as we have census and vehicle theft data for that county. We use "mean substitution" for the missing values on the independent variables for Alexander County and include a dummy variable to represent the fact that such data have had the mean substituted for the missing values (a procedure recommended for handling missing data by Cohen and Cohen, 1983).

The seven independent variables from the land parcel data bases are: mean assessed property value, number of land parcels in the bottom 10% of land values (calculated using the decile value for each county), the number of land parcels in the top 10% of land values (again, calculated relative to the 90th percentile value for each county), the number of commercial land parcels, the number of residential land parcels, number of manufacturing or industrial land parcels, and number of office land parcels. (We also tested parcel value per acre, but it was not found to be statistically significant in the subsequent models, nor did it influence the effects of other variables in the model, so we dropped it from further discussion.) In general we would expect that the number of vehicular thefts would be positively correlated with the variables just mentioned. The higher the assessed property value, the more likely that the vehicles in the area will be "attractive" to those planning or tempted to steal a vehicle (later models, more expensive models, etc.). Also, some previous literature has suggested that in poor areas there are more vehicle thefts, so here we measure the number of land parcels with assessed value in the bottom ten percent of values (judged according to the decile value in each county rather than all four counties combined). Also, arguably in those more expensive or upscale areas, some of the most attractive vehicles to steal would be located. As for the other measures, the number of residences, number of commercial, number of manufacturing or industrial land parcels, or the number of office parcels, we would expect more vehicle thefts.

We include the variables from the earlier analysis presented in Table IX and the results of including the land use measures are presented in Table X. It can be seen that the population and percent owner occupied remain statistically significant, but the number of Hispanics is no longer statistically significant. The results indicate that property value is an important predictor of vehicular theft with a Beta value of .143. The number of parcels in the bottom decile is unrelated to the number of vehicle thefts, but the number of parcels in the top decile of values is found to be important. Somewhat surprisingly, the effect is negative. Perhaps vehicles in such areas are less accessible (as in more remote suburban areas, or simply they are more likely to be parked inside of garages). The only other variable statistically significant at the .05 level is the number of industrial or manufacturing parcels in a block group, with a Beta of .404, the largest Beta that we observe in the equations. Two other variables are marginally significant, number of resident land parcels and number of commercial land parcels. (Note that we also tested to see if any of the non-significant independent variables from the earlier "census" analysis were now significant, and we found that none were. Also, we tested for two-way interaction effects among all of the predictor variables in the equation for Table X. None were found to be significant, but there were multi-collinearity issues with several of the product terms relative to their "main effects." (Results are not presented here).

Table X: Vehicle Thefts: Model with Land Use Variables Added
(n=247 CBG)

Model With Land Uses / R^2=.468	B	Std. Error	Beta	T value	Prob.	Tolerance	VIF
1 (Constant)	1.844	1.051		1.754	.081		
Population/1000	1.100	.309	.236	3.565	.000	.492	2.034
Percent Owner Occupied	-.032	.014	-.155	-2.311	.022	.482	2.077
Hispanic	.001	.003	.040	.589	.556	.469	2.130
Property Average Value /10000	.057	.023	.143	2.443	.015	.624	1.603
N Parcels in bottom 10% in value	.000	.001	-.019	-.391	.696	.895	1.117
N Parcels in top 10% in value	-.003	.001	-.152	-2.148	.033	.430	2.327
N of commercial Parcels	.032	.017	.137	1.888	.060	.406	2.461
N Residential Parcels	.001	.001	.128	1.838	.067	.441	2.267
N Manufacturing Parcels	.109	.017	.404	6.546	.000	.565	1.771
N Office Parcels	-.014	.026	-.036	-.532	.595	.470	2.128
Alexander Co Parcel	-.626	.472	-.063	-1.328	.185	.967	1.034

a Dependent Variable: N_auto_thefts

In Table XI, the "trimmed model" is presented (i.e., only statistically significant variables retained in the equation). We keep in the model all of the variables from Table X, including the "marginally significant" ones. (Note also that we include a dummy variable for Alexander County because we are missing information on the land parcel variables. Also included in Table XI are the IQR effects, and these will be focused on here. The IQR effects will be discussed in terms of the largest effects first. In general the IQR effects are not large, indicating the rarity of vehicle theft, and to some extent the weakness in our prediction of it (although the explained variance in vehicle theft is a respectable 47%). With a change in population across census block groups of 819 people (the IQR for population, here the coefficient represents that amount divided by 1000), there are approximately .962 more vehicular thefts (in a year's time period), or roughly one vehicular theft for every 819 more people in a census block group.

The second largest effect is the presence of manufacturing or industrial land parcels, with an average change across block groups of 7.75 (the change from the lowest quartile to the highest quartile); there is .860 more vehicular thefts (just less than one vehicle in a year). This is a somewhat surprising finding relative to research done in more urban contexts (Rice and Smith, 2002). Perhaps the industrial areas are where more vehicles are parked in relative unguarded lots (the "company" parking lot), or it may be that the workers in industrial settings are more often the target of – and perhaps even the perpetrators of – vehicle theft.

The variable with the third largest effect is the percent owner occupied variable with a -.670 IQR effect. Thus, a change in the percent owner occupied of 19 percentage points results in a net reduction of about two-thirds of a vehicle theft. More importantly, the findings of a reductive effect of percent owner occupied remains in place even after controlling for the land use variables modeled here.

Somewhat more difficult to interpret are the findings for the number of parcels in the top ten percent of assessed value parcels. This variable has the fourth largest IQR effect, and it is negative (-.522), indicating that the more highly valued property the less vehicle theft by about a half a vehicle a year. The statistical mechanism that would produce this result is not clear. The variable correlates .434 with median income levels across census block groups, so perhaps those with more income are better able to protect their vehicles. However, we found earlier in our analysis that income is not a predictor of vehicle theft. There may be a spatial aspect or geographic component to the explanation of why there are relatively few vehicle thefts where there are the most valuable properties: accessibility. More suburban and "well off" homes may be far removed from the routine activities of auto thieves. That is, the "spatial awareness" of auto thieves may not include the areas with the most expensive properties and vehicles. Further, residents of more expensive properties are simply more likely to use a garage, and park a vehicle on private property further from the street and thus

The next largest IQR effect that we observe is for the number of residential land parcels, with every 365 residential land parcels resulting in about a third (.365) of a vehicle theft. This effect we interpret to simply mean that the vehicles are more likely to be stolen in block groups with more residential land uses. However, it may also be useful to think of this as a kind of "dispersal" measure, since most residences are single family houses, the vehicles are – relative to the concentration at industrial or commercial land uses – "scattered" across a geographic area. The scattering of the vehicles implies that many of the locations will be relatively "unguarded" by the populace of an area.

Whereas the most expensive land/building values are associated with lower numbers of vehicle thefts, the same cannot be said in general for areas that are more "well off" but closer to the mean of assessed values. The IQR for average value is 5.53 or $55,300 (since the metric is measured in units of $10,000) and such an increase in assessed value leads to just under a third (.310) more vehicle thefts (in a year). We interpret this to mean that the availability of "desirable" vehicles goes up with assessed property values in the middle range.

Finally, the number of commercial land uses is associated with .308 more vehicle thefts with an increase of 11 commercial places across census block groups. We are somewhat surprised that the number of commercial parcels has the smallest IQR effect, as such land parcels were among the stronger determinants of vehicle theft in some previous research (Rice and Smith, 2002).

Note that we controlled for Alexander County census block groups, due to missing data on the land parcel variables. Although the coefficient was not statistically significant, keeping the variable in the equation controls somewhat for any bias that may be attributed to using the mean as an estimate for missing values (mean substitution was used for these missing values – the results look very similar with these cases dropped in a "listwise deletion" regression – results not presented here).

It is also interesting to note what variables explain more of the variance when the variables are entered in the order of the strongest predictor first, followed by the next strongest, and so forth. In such an analysis we see that the number of manufacturing or industrial land uses explains on its own .367 of the variance in the number of vehicle thefts. (Recall that the most variance that we explain using all of the variables is .473). The second variable to enter is the population size, which adds .040 to the explained variance and then percent owner occupied, which adds .046. None of the other variables add much (.01 or less) to the explained variance once these three variables are controlled for. Thus, these three variables are not only having the largest effects in terms if IQR effects, but also in terms of contribution to explained variance.[32]

Table XI: Number of Thefts by Census and Land Parcel Variables: "Trimmed" Model

R^2 = .473		B	Std. Error	Beta	IQR Effect	t	Prob.	Tolerance	VIF
1	(Constant)	1.981	.982			2.017	.045		
	Population /1000	1.175	.256	.252	.962	4.583	.000	.706	1.417

[32] Also, models were run with a logged version of the dependent variable. The results were very similar to those presented in Table 6 in that the variables with the largest Beta values were the same, and all of the variables statistically significant in the unlogged version were also in the logged version.

Percent Owner Occupied	-.035	.012	-.169	-.670	-2.838	.005	.599	1.669
Average Parcel Value /10000	.056	.023	.140	.310	2.452	.015	.656	1.525
N Residential Land Parcels	.001	.001	.133	.365	1.931	.055	.452	2.211
N of Commercial Parcels	.028	.014	.117	.308	1.933	.054	.580	1.723
N of Parcels in Top Decile of Assessed Value	-.003	.001	-.162	-.522	-2.326	.021	.442	2.263
N of Manufacturing/ Industrial	.111	.016	.414	.860	6.913	.000	.596	1.679
Alexander	-.632	.469	-.063	-.632	-1.347	.179	.969	1.032

Recall the discussion earlier of the correlation between percent owner occupied and the percent single head of family. Essentially, allowing the former in the equation precludes the predictive success of the latter. In a model with percent owner occupied omitted and percent single parent entered, the results look quite similar with an R^2 of .468 (slightly lower than the .473 reported in Table XI) and a Beta of .127 (compared to the Beta of -.169 for percent owner occupied in Table XI). The other coefficients in the model are similar to those reported here (model for percent single parent not presented here). Thus, as earlier, the percent single parent could substitute for percent owner occupied in the analysis. Again, we argue that a community control interpretation for either of these variables seems appropriate. That is, there is less vehicular theft in block groups where there are more owner-occupied or where there are fewer single-parent head of households.

Summary and Direction for Future Research

The data analysis at the block group level has shown what are some of the predictors of vehicle theft. While the population size of an area is an important correlate, we conceptualize it here as a “statistical control” variable because we would assume that there would be more vehicles stolen from areas with more population. That is what we found. More interesting is the contribution of other variables in the models, especially the variable measuring the frequency of land uses pertaining to manufacturing or industry. Other than the control variable of population, this variable (the count of such land uses in a census block group) is the best predictor of vehicle theft. From the aggregate data used here, we do not know if the vehicles are actually being stolen from the industrial or manufacturing parking lots or if it is simply that the block groups with a prevalence of such land uses where vehicle theft is prevalent. The descriptive data earlier in this report suggest that it is the lots, and the volume of vehicles in these lots, as much as the block group. This suggests that the security in parking lots associated with industry or manufacturing is poor, or that car dealerships or repair shops are also prevalent in such areas.

More importantly, perhaps, for policy purposes, is the finding that the levels of community control in an area may be among the most important factors influencing the level of vehicle theft. Community control here is measured indirectly through two measures, the percent owner occupied and the percent of single head of households. Previous research has demonstrated that these are possible “proxy” measures for the ability of a community to control unwanted behaviors (Smith et al., 2000; Rice and Smith 2002). (Since the two variables are intercorrelated, only one or the other proves predictive when both are entered into the model.) In general such factors have been identified as measures of “collective efficacy” (Sampson et al., 1997). Collective efficacy theorists maintain that a community that is well organized, with citizens motivated to keep crime problems out of their community, can be successful compared to communities where there is less value consensus and thus less capability to bring about desired community ends. This finding is reinforced somewhat by the finding that the areas with the more expensive properties have lower vehicle theft levels. This too make reflect an attribute of community control although we initially included the variable as a control for "target attractiveness" as we initially hypothesized that the more highly assessed properties may have more valuable vehicles to steal.[33]

In addition the results indicate that vehicle theft is more likely in areas with commercial land uses and where there are more residential land uses. Neither of these findings is surprising, as, everything else being equal, one would expect more vehicle thefts where there are more vehicles. Both the number of residences and the number of commercial establishments would presumably be measuring the availability of vehicles for possible theft.

Finally, the fact that our results indicate that assessed property values are positively associated with the number of vehicle thefts (except at the high end of assessed property value), indicates that it is probably a "target attractiveness" measure. Presumably the better quality vehicles are to be found near the more expensive properties, and thus there may be some "target seeking" on the part of some thieves.

In conclusion, the analysis of census and land use data has provided us with some information as to the contexts in which vehicle thefts occur. Not only are vehicle thefts more likely to occur where there are more people (including more residences or more commercial properties), but vehicle theft is more likely where there are more renters or more single head of households. These latter measures have been associated in previous research with levels of community control (Sampson and Groves, 1989; Smith et al., 2000). Thus, if there were more community control in an area, vehicle theft could be reduced. As important as this result, perhaps, is the finding that the land uses of manufacturing or industry add to vehicle thefts.

[33] We are somewhat surprised by the strength of the effect (-.522 IQR effect) for parcels in the top decile of assessed value, compared to some other variables. As mentioned, a possible aspect of this effect may be "accessibility" – the more expensive residential properties, for example, are more likely to have a garage, and thus it is less likely that a vehicle will be stolen from such a property.

Unfortunately, we are not sure what is the likely mechanism here that is bringing about vehicle theft, but the finding can lead further investigation as to where the thefts occur, and possibly why. The results regarding assessed value are also intriguing, as the most highly assessed properties have low vehicle theft rates, but among those properties below the most valuable, vehicle thefts increase with assessed value. Thus, it may be that target attractiveness is the mechanism (more attractive vehicles to steal with the higher assessed property values) that accounts for vehicular theft. In summary, community control as well as target attractiveness and accessibility may be accounting for vehicle theft patterns across the four-county area.

At a general theoretical level, we have found further support for the two predominant social ecological perspectives, social disorganization theory and routine activity theory. Whereas social organization theory posits that the level of social organization in the community will be crucial in determining the volume of crime, routine activity theory points toward the importance of “rational choice” factors such as the accessibility and “target attractiveness” in influencing whether an area has a high or low vehicle theft rate.

Although the data are somewhat limited because they are aggregate data, the results are generally promising for future research on the problem of vehicle theft. Toward that goal, we suggest that further study should be made of the risk of vehicle theft. Particularly helpful would be more complete data from the tax assessor databases, including more specific land uses, such as fast food restaurants, gas stations, etc. Although two of the counties studied here have such information, they each use a different classification schema, so it is difficult to combine them into one schema. More detailed information would presumably provide us with the level of detail such as that used in studies in more urban areas (Rice and Smith, 2002).

Another possibly useful approach would be to combine surveys of the public in select areas of the four-county district so as to know more about the nature of the neighborhoods in each county. By interviewing roughly 30 citizens in every block group, for example, more detailed information could be gathered about the characteristics of those areas and of the citizens who are the victims of vehicle theft (assuming the sample is selected with overrepresentation of vehicle theft victims).

Finally, it would be useful to conduct "configurational" analysis of the location of vehicle theft relative to the street structure and accessibility of specific addresses to the grid of streets and road in the area (Hillier and Hanson, 1984; Penn et al., 1998). Vehicle thieves may take into consideration "escape" routes from where they steal cars, such as accessibility to major thoroughfares, in making decisions as to what car to steal or from where to steal a car. A configurational analysis could give a mathematical evaluation of how connected and accessible a given location is, and thus help determine how important these factors are.

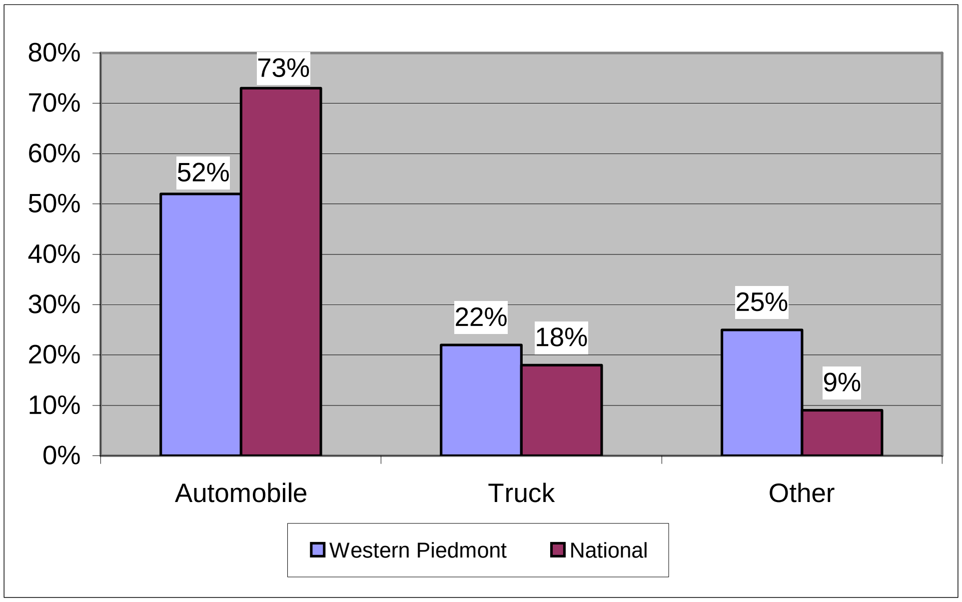
CHAPTER V: VEHICLE THEFT IN THE WESTERN PIEDMONT

Aggregating vehicle thefts from data provided by 11 law enforcement agencies provided a sufficient basis for analysis, and permitted us to develop a comprehensive description of vehicle theft across the region – findings that would not be possible given the low volume of vehicle thefts within any single agency. In many cases, we can compare and contrast these findings between the Western Piedmont and findings from other more urban studies of vehicle theft, we can compare the Western Piedmont with national and regional data; and we can compare the unincorporated areas of the region with the municipalities. In this way, descriptive findings revealed distinctive patterns in the Western Piedmont related to the types of vehicles stolen, theft locations, seasonal patterns, and the regional nature of theft and recoveries.

Types of Vehicles Stolen

In the Western Piedmont area of North Carolina, passenger vehicles (automobiles, SUVs and other passenger vehicles) comprised 52% of all vehicle theft (compared to the 73% nationally) while trucks comprised 22%, similar to the 18% reported nationally (FBI, 2005). In contrast with national figures, however, 26% of vehicles stolen in the Western Piedmont region were vehicles classified as “other.” (See Figure II.) Nationally, “other” vehicles comprise 9% of vehicle theft, and this UCR reporting classification includes motorcycles, motor scooters, snowmobiles and other vehicles in this broad classification. In the Western Piedmont, “other” vehicles comprised a large portion of vehicle theft, and they were less likely than any other type of vehicle to be recovered.

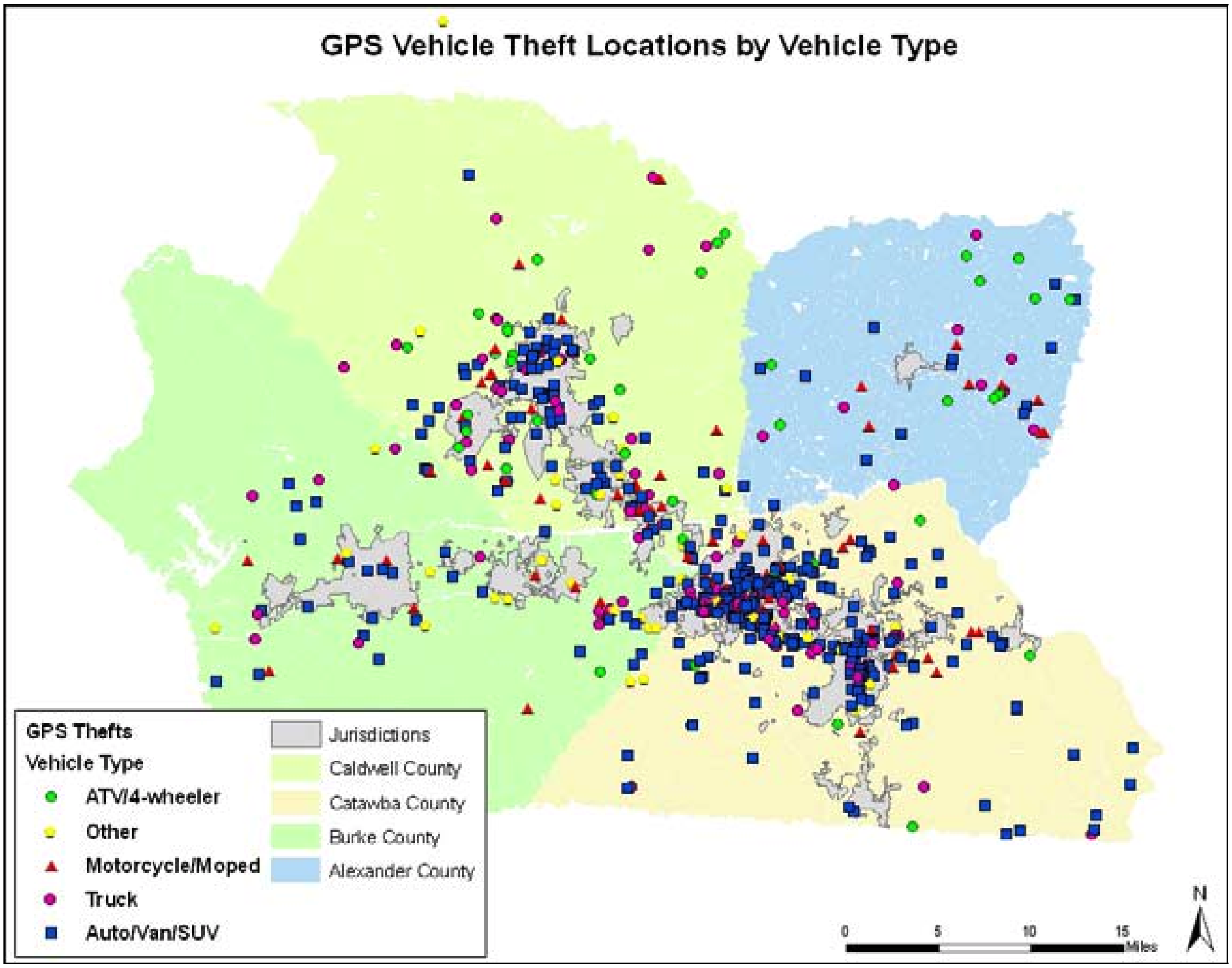
Figure II: Type of Vehicles Stolen



Given the volume of “other” vehicles stolen, additional analysis was undertaken to determine the precise types of vehicles being stolen. Many of the “other” vehicles – 7% of all vehicle theft – were four-wheeled All-Terrain Vehicles (ATVs), recreational vehicles that are often used in the region for hunting. An additional 5% were of mopeds or scooters, 6% were of motorcycles and 7% were a range of vehicles, from trailers to riding lawn mowers.

Thefts of “other” vehicles were evenly distributed among the four counties and townships in the study, except for thefts of ATVs. Of the ATV thefts, 96% occurred in the four county jurisdictions. Most of these thefts were concentrated in the three more rural counties – Alexander, Burke and Caldwell. In Catawba County, 15% of vehicle theft was “other” while in Alexander, 45% of vehicle theft was “other,” 40% in Caldwell; and 42% in Burke. Thefts of mopeds, motorcycles and other vehicles were more evenly distributed among all jurisdictions. Some towns, such as Long View and Lenoir, reported only thefts of automobiles and trucks and no “other” (See Map 10.)

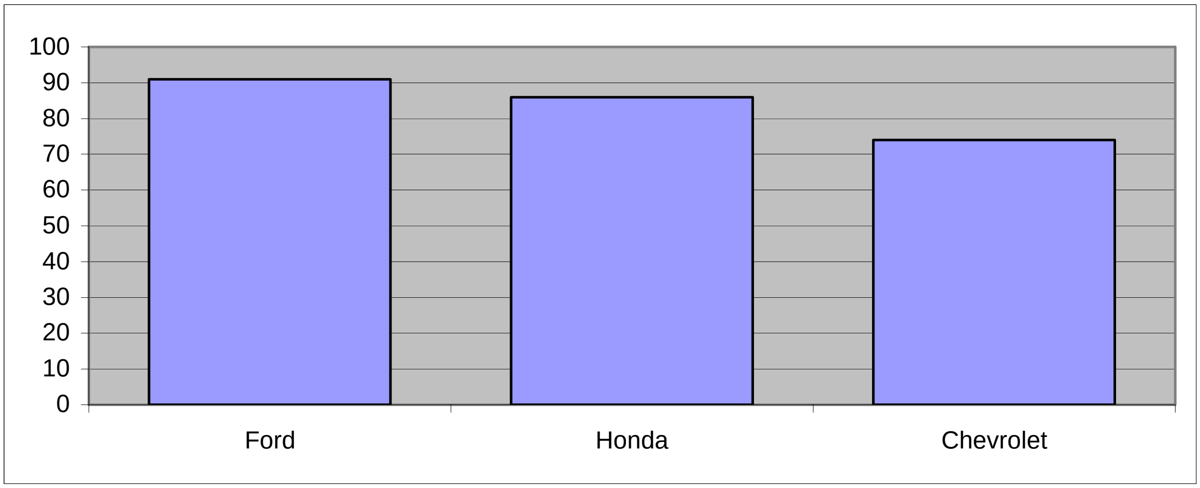
Map 10: GPS Vehicle Theft Locations by Vehicle Type



Vehicle Characteristics

Crime analysts often examine vehicle make, model and color – presumably to identify common targets of vehicle theft by offenders. Among all makes of vehicles stolen, Fords (91 or 14%) were the most frequently stolen; however, Honda and Chevrolet were a close second with 86 (14%) and 75 (12%) respectively. These three manufacturers accounted for 40% of all vehicle theft (See Figure III).

Figure III: Make of Vehicle Stolen



Comprising 17% of vehicle theft (104), white was the color of vehicles most frequently stolen; however, red vehicles were a close second with 14% (89) and blue at 13% (79), black 13% (83), and green 12% (72).[34] Although law enforcement often express interest in the color and make of vehicles, the patterns of manufacturer and color were not significant, and likely reflect the distribution of makes and colors among vehicles in the area.

Stolen vehicles ranged in value from $50 to $50,000, with an average value of $6,095. Half the vehicles stolen were worth more than $4,000 while only 25% were worth more than $8,000 (See

Figure IV). As expected, the average value of vehicles such as mopeds and ATVs was substantially less than that of autos and trucks (See Table XII), and the prevalence of these types of vehicle diluted the average value of vehicles.

[34] Interviews with vehicle theft offenders in Santee, CA (Rienick et al., 1999) revealed that offenders prefer to steal vehicles of neutral color.

Figure IV: Value of Vehicles Stolen

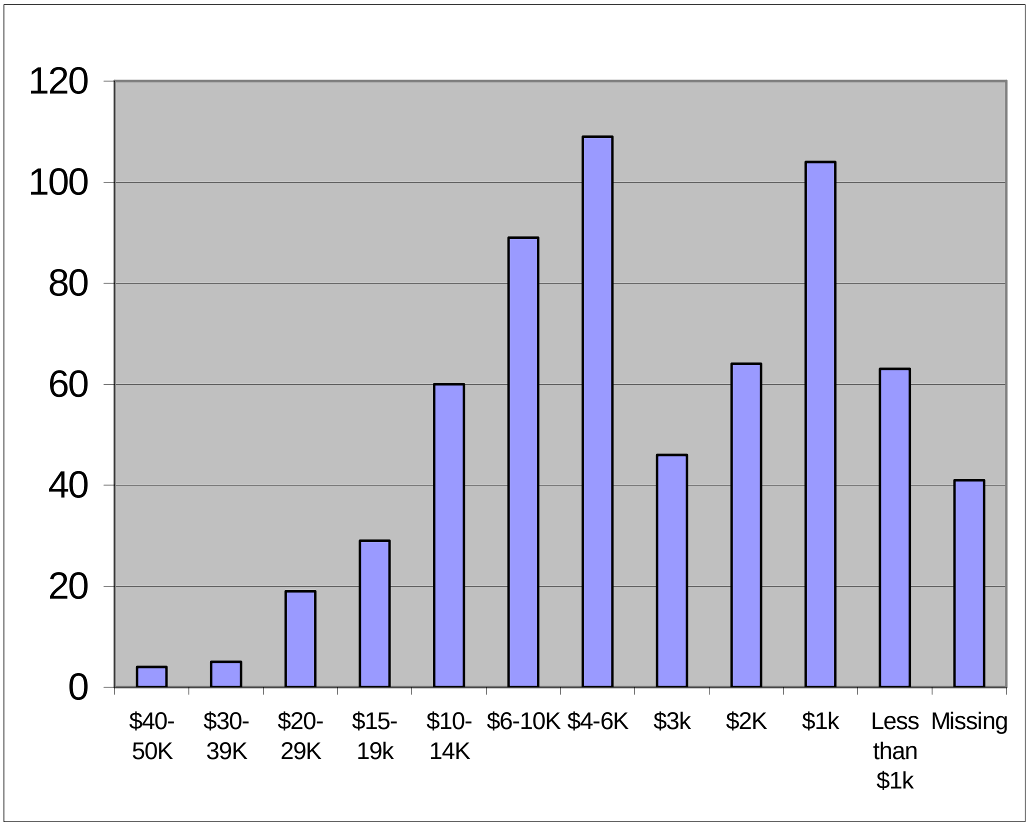


Table XII: Average Value of Vehicles Stolen
(Value recorded for 592 vehicles)

Type Vehicle	Number Stolen	Average Value
Mopeds	32	$1,166
ATVs	43	$3,573
Motorcycles	39	$5,677
Other	39	$5,558
Autos	309	$6,331
Trucks	130	$7,789
Total[35]	592	$6,100

35 Among 592 vehicles with a value reported.

The value of stolen vehicles was also moderated by the prevalence of older vehicles. Stolen vehicles stolen ranged in age from 2003 to 1958. The average age of stolen vehicles was 1993 and 50% of vehicles stolen were 1995 or older, suggesting that newer vehicles are not the target of theft (See Figure V). Of note, 9% of vehicle theft (57) had no date for the stolen vehicle. Most of the vehicles without dates were ATVs and mopeds.

Figure V: Age of All Vehicles Stolen

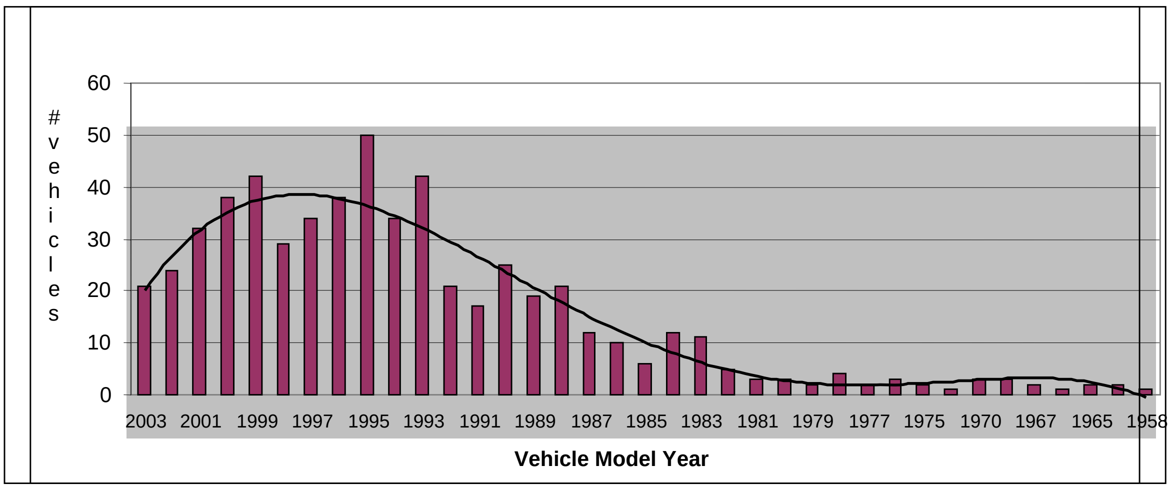
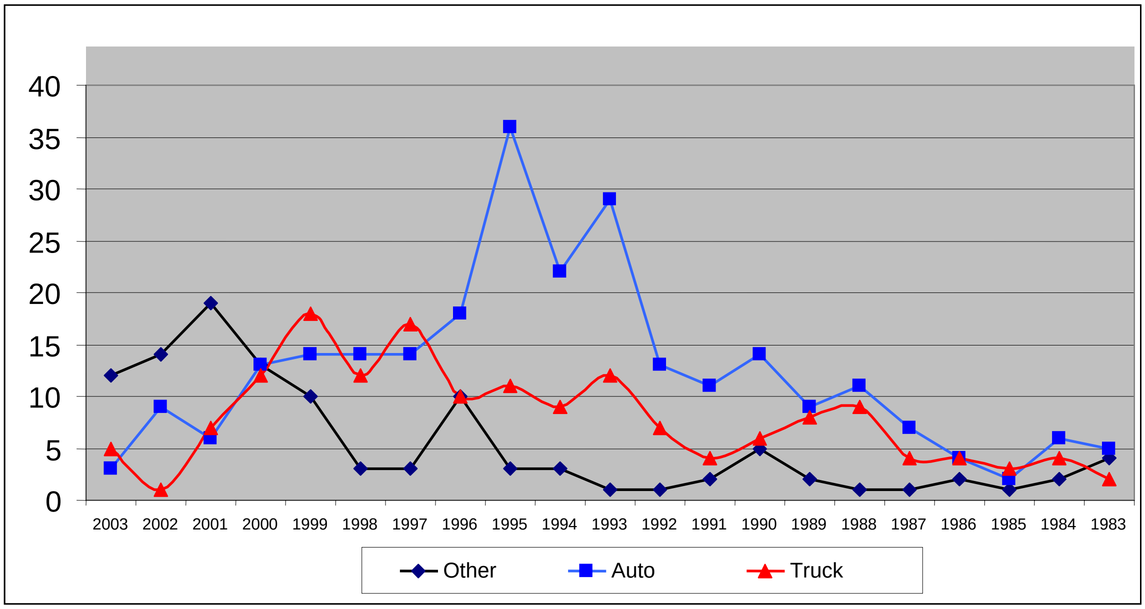


Figure VI: Age by Type of Vehicles Stolen



The average age of stolen vehicles is also moderated by the prevalence of ATVs among stolen vehicles (See Figure VI). Most vehicles that were classified as "other" were newer vehicles, manufactured in 1999 or later. A more distinctive preference for older vehicles is observed among autos where the modal year was 1995.

Theft Locations

Locations of vehicle theft vary by the type of land use – primarily business or residential property, but also public locations such as along streets and by the type of parking structure such as parking lot or driveway.

Business v. Residential Premises

To use spatial analysis for crime prevention, it is critical to examine locations of vehicle theft. Much of the research on vehicle theft has focused on the prevalence of parking lots as these locations are more amenable to crime prevention strategies than locations that are public, such as streets.

Table XIII: Location Type of Stolen Vehicles

Location Type	Frequency	Percent
Open Area	5	.8
Road/Street/Hwy	13	2.1
Residence	89	14.1
Business	247	39.1
Home of Victim	272	43.0
Missing	7	1.0
Total	633	100.0

In our study, 57% (361) of vehicle thefts occurred at residential locations while 39% (247) occurred at business locations (See Table XIII). The prevalence of residences among theft locations is consistent with findings from Reno, NV, and Arizona. In Reno, 41% of vehicle thefts were at residences (Decker and Bynum, 2003); in Arizona, 72% of thefts were at residences (Arizona Criminal Justice Commission, 2004).

Residential Locations

Among the 361 vehicle thefts at residential locations, the large majority was at premises classified as single-family residences; 82% of vehicle thefts at residences (297) occurred at premises classified as single-family (297).

Among the thefts at residential locations, most occurred at the home of the victim (75%); most thefts at victims' residences (84%) occurred at properties that were classified as single-family premises (229 of 272). (Based on the report narrative, at least 119 of the vehicles were parked in the driveway, in a garage or in the yard of the residence and not in the street. While this information was also gathered for use in recording x-y coordinates, the specific type of location was not recorded at this stage of data collection.)

While some would anticipate that vehicle theft at residential properties would occur at multi-family premises such as apartments, this was not the case. (The prevalence of single-family residences at theft locations was also identified in Arizona, where apartments had 1/3 the volume of vehicle thefts as non-apartment residences, according to the Arizona Criminal Justice Commission, 2005.) Instead, nearly all of thefts at residences were at single-family premises. The absence of multi-family premises among vehicle theft reflects housing patterns in the region, in which single-family premises predominate.

From the spatial analysis in Chapter IV, we know that neighborhoods with high concentrations of rental housing experienced significantly more vehicle thefts. However, from crime reports, we do not know whether the residential premises of thefts were rental property or owner-occupied as the incident report includes only a check-off block indicating if a dwelling was single-family or multi-family dwelling.

Among vehicle thefts at residential locations, “other” vehicles such as ATVs, mopeds and motorcycles were common targets. Among all “other” vehicles, 87% were stolen from residential locations. This contrasted with 56% of autos and 47% of trucks were stolen from residential locations. The distribution suggests that these “other” vehicles are primarily left unattended while on the residential premises; in contrast, autos and trucks are commonly parked at residential *or* commercial locations, making their risk more evenly distributed across these types to premises.

Business Premises and Risky Facilities

Vehicle theft at business premises in the region demonstrated a strong county-town bias as thefts at business locations were most prominent within the municipalities. Overall, about half of vehicle thefts were reported by the four sheriffs' offices (310), and 323 were reported by the seven municipal agencies.

- Of the 247 vehicles stolen at business premises; 77% (189) of these occurred in the towns and 23 % (58) occurred in the counties.
- Within towns, such as Hickory and Lenoir, 59% of all vehicle thefts occurred at businesses (189 of 316).
- Within counties, 19% of vehicle thefts (58 of 299) occurred at business premises.

Among vehicle thefts at business premises (247), the type of business could be identified in 210 cases. We anticipated that there would be many common offense locations, such as parking lots of shopping centers, in the data. Neither discussions with law enforcement officers nor manual review of incident reports identified any of these common locations.

But the locations of vehicle theft among businesses (see did not appear to vary randomly.

- Nearly one-third (31%) of vehicle thefts occurred at locations involving car repairs, rentals, or sales (66 of 210).
- Other common theft locations were business premises including retail centers, shopping malls, and specific "big box" retail centers, such as Wal-Mart and Home Depot. (27)
- Bars and restaurants (26)

In contrast to other studies, there were no hot spots at specific parking lots or other unique locations; however, entertainment venues such as movie theatres and bowling alleys; retail shopping centers; and bars/restaurants were common locations of thefts.[36] In the Western

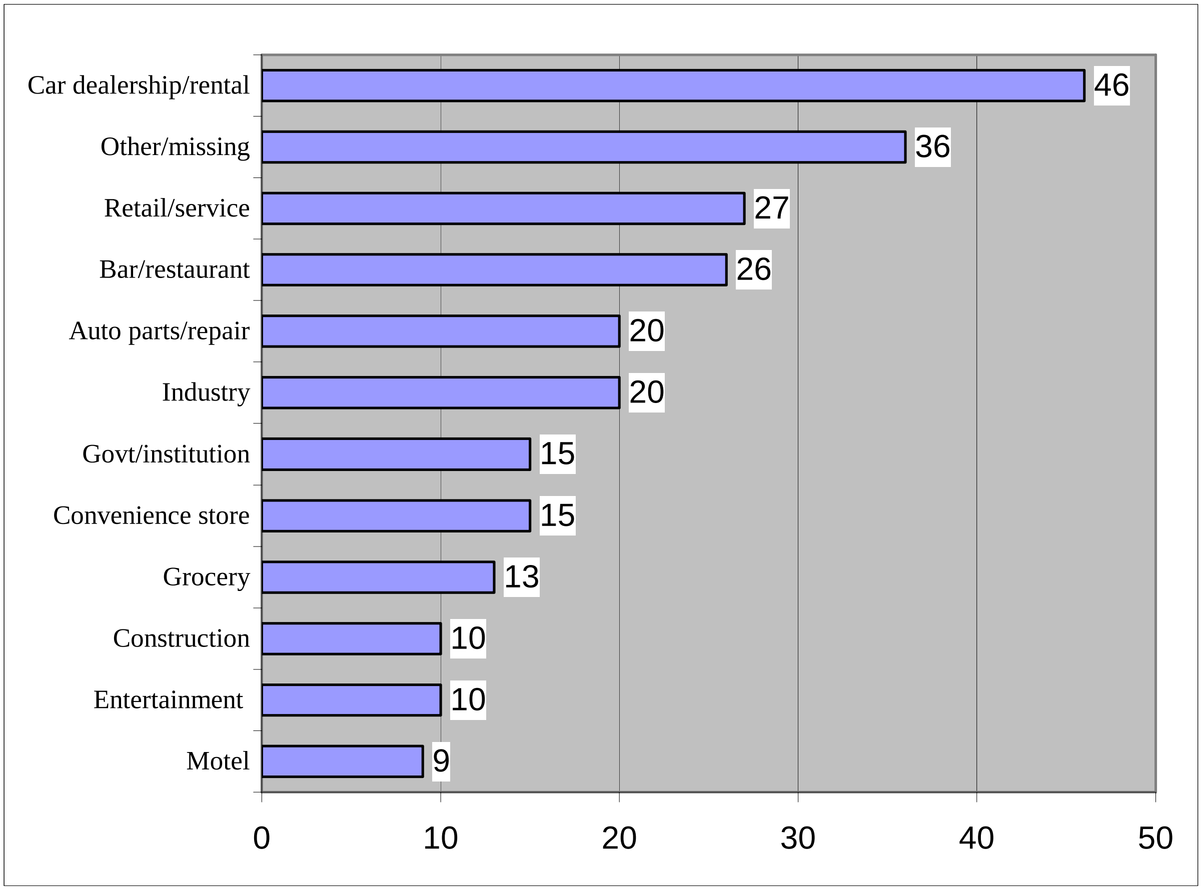
36 The classification of businesses includes but does not follow the UCR premise classifications displayed in Figure I. Instead, efforts were made to reduce the size of the "other" classification and enumerate location types that have been identified in other studies.

Piedmont region, these locations were not clustered geographically, although they were more numerous closer to the population centers, and distributed across the region.

Rather than a spatial pattern, the finding suggests a more distinctive pattern related to the characteristics of car repair shops and dealerships. It seems likely that the concentration reflects the greater availability of vehicles – potential targets – at these locations; however, it is also likely that management practices at such businesses are not effective in preventing theft. Clarke and Eck (2005) call this distinctive pattern one of “risky facilities”; it is not a spatial pattern but nonetheless a distinctive pattern that offers clear opportunities for crime prevention strategies.

Given the dispersion of these thefts across multiple jurisdictions, this pattern would be undetectable in a single jurisdiction. Each of the 10 law enforcement agencies reported at least one vehicle theft at a car dealership. For example, Caldwell County reported four thefts at car lots, and Catawba County five thefts, and Conover, three.

Figure VII: Theft Location by Type of Business



There were only a handful of repeat vehicle theft victims during 12 months. The vast majority of addresses were victimized only once during the calendar year; 94% of addresses (560) suffered only one theft and generated 88% of thefts, while 32 addresses suffered 73 thefts (See Table XIV); 5% of theft locations accounted for 12% of vehicle theft. These repeat locations were primarily at business locations, including four thefts at each of three locations: Mike Johnson Toyota and Carmike Theatres in Hickory and Club Senorial in Newton. (Note that these business types are all represented in Figure VII.) Other repeat offenses occurred at apartment complexes.

Table XIV: Locations with Multiple Thefts

Number thefts	Number locations	Total # thefts
One only	560 (94%)	560 (88%)
2	26 (4%)	52 (8%)
3	3 (.05%)	9 (1%)
4	3 (.05%)	12 (2%)
	592	633

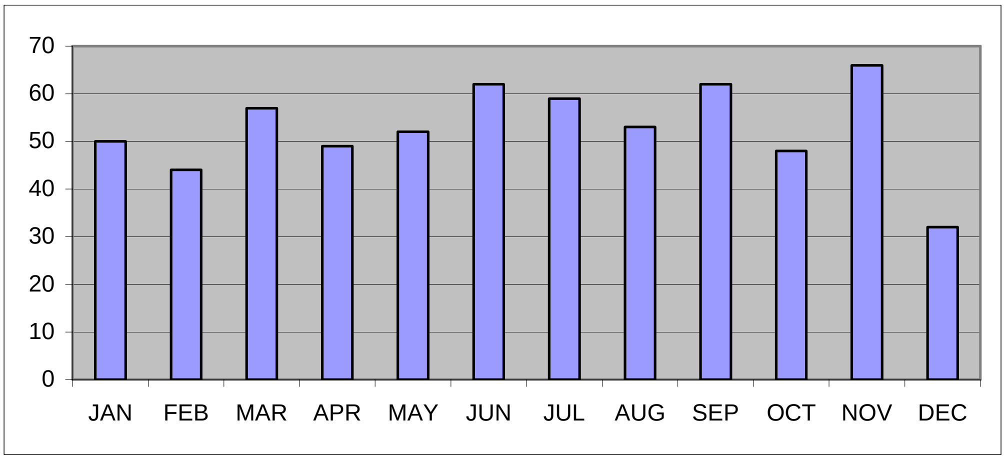
Temporal Patterns

Analysis of temporal patterns typically relates to identifying the largest concentrations of offenses by month, by day of week, and time of day. Distinctive seasonal patterns for vehicle theft in the Western Piedmont region were initially obscured by data heterogeneity. An initial analysis of regional thefts by month revealed no apparent seasonal pattern over a year. The region averaged 53 thefts per month, while thefts ranged from a low of 44 in February to a high of 66 in November (See Figure VIII). Similarly, an analysis of vehicle theft by week of the year showed the region averaged 12 thefts per week over the year, with some variation from week to week—23 in the highest week and 4 thefts in the lowest week (See

Figure IX). These data also initially suggested that there were no distinctive seasonal patterns in vehicle theft.

The low number of offenses in the region, however, tends to mask more important seasonal trends reflected in subcategories of vehicle types stolen. For example, few ATVs and mopeds were stolen in the region during any month. However, aggregating offenses on a 28-day period, and graphing these data by week reveals a strong seasonal pattern associated with these thefts.[37]

Figure VIII: Vehicles Stolen by Month



In contrast to Figure VIII and Figure IX. Figure X shows an increase in thefts from weeks 20 to 40 – approximately June 1 to October 1. The two periods appear to reflect increases during the summer and fall months. Even these are two different trends – summer thefts may be associated with juveniles out of school, while fall thefts mirror hunting season, when hunters commonly use ATVs to reach remote hunting locations and for transporting heavy carcasses, such as deer, away from kill areas.

[37] This technique is known as a "moving window" rather than the more commonly used statistical technique of moving average. A "moving window" simply presents a period of summed data, increasing the amount of data while maintaining the homogeneity of the data and the number of time points.

Figure IX: Vehicles Stolen by Week

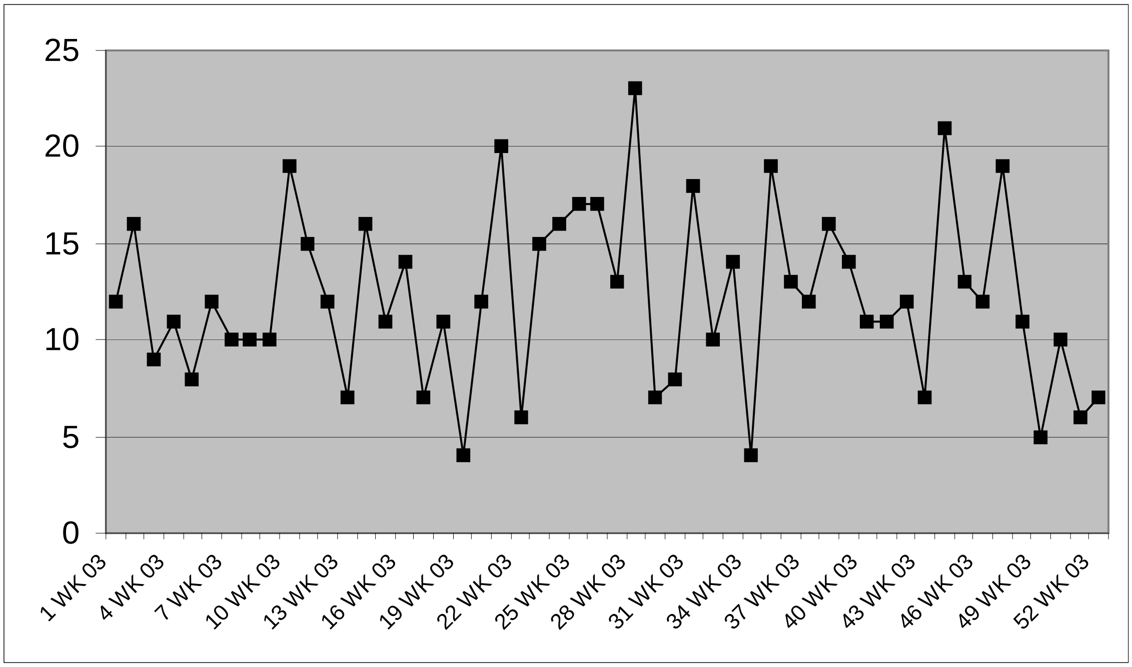
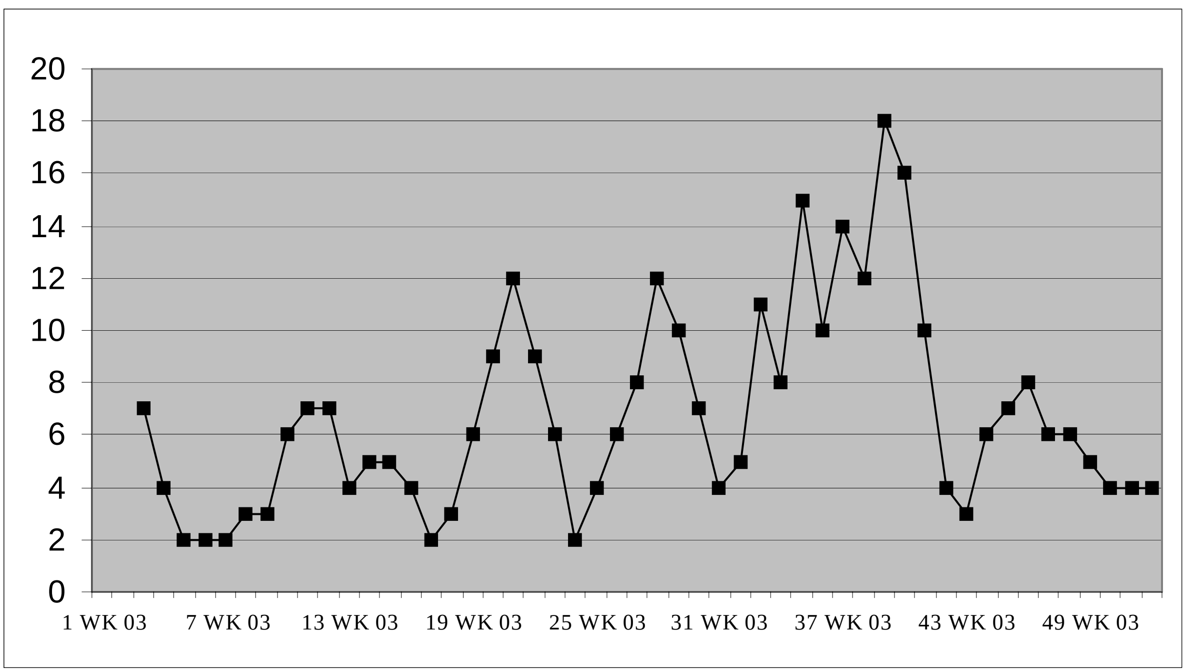


Figure X: "Moving Window" of Vehicles Stolen by Week



Attempted Thefts and Recovered Vehicles

An important analysis task to shed light on the nature of vehicle theft is to examine the ratio of attempted thefts to completed thefts, and the ratio of recovered to unrecovered vehicles within jurisdictions and overall in the region.

Attempted Thefts

Law enforcement agencies recorded only 16 vehicle thefts as attempts. (There were other vehicles that might have been considered "not stolen;" this included eight vehicles that were repossessed or towed, four false reports and two vehicles that had been "misplaced" by their owners while parked in a large parking lot. These were not included as attempts for our analysis. See Appendix C.)

With only 16 attempts, 97% of vehicle thefts were completed (617 of 633). This ratio of attempt to completed thefts is a sharp contrast to the 20% of vehicle theft nationally that are recorded as attempts in police data (Biderman and Lynch, 1991). Why the ratio of is attempted to completed vehicle theft in the Western Piedmont so low? There are two possible explanations:

- Vehicle thieves are more successful in the region. That is, a theft undertaken is not interrupted or otherwise aborted but more likely to be successfully concluded by an offender.

- Attempted thefts are less likely to be reported in the region. Victims may know the offender, or take matters into their own hands.

Regardless of the explanation, the low ratio of attempted to completed vehicle thefts is an important finding about the distinction between urban and non-urban vehicle thefts and one that merits further examination.

Recovered Vehicles

Overall, 311 or 48% of the stolen vehicles were reported as recovered but it appeared that recovery data were incomplete. For example, data from the jurisdiction with the most thefts, Hickory, reflected recovery of only 23% of vehicles stolen, thus missing data are presumed and analyses are not reliable. Only 209 of the reports contained some information about the recovery location, such as a town, county or even a state. Only 62 of the recoveries contained a recovery address that included a street number, street name and town, and only 57 addresses could be mapped using the GPS coordinates. The reasons for the missing data seemed practical. Many of the incident reports noted that the suspect had returned the vehicle or the victim found the vehicle.

While the addresses on recoveries were poor, we found that a sizeable portion of vehicles were stolen within one jurisdiction and recovered in another jurisdiction with the Western Piedmont. Among the 311 recovered vehicles, 93 vehicles were recovered within the region. Thus, for 93 vehicles we know both the theft and recovery jurisdiction. Of these 93 pairs, only 29 vehicles (31%) were recovered within the jurisdiction from which the vehicle was stolen.[38] This low within-jurisdiction recovery low is much higher than the 11% within-jurisdiction recovery rate associated with LaVigne et al.. (2000) for Baltimore County but less than the 52% reported by Maxfield (2004) for Newark, NJ.

Computing the within-jurisdiction recovery rate suggests that the large majority of stolen vehicles in the Western Piedmont cross jurisdictional boundaries but many remain within the

[38] It is probably more accurate to state that only 9 percent of recovered vehicles were recovered within the same jurisdiction as the theft (29 of 311) but missing data about recovery locations make us cautious about making such a claim.

region. As an example, each theft and recovery incident can be considered as a vehicle theft incident. In Newton:

- Six vehicles were stolen in Newton and recovered elsewhere in the region (6 events).
- Four vehicles were stolen in Newton and recovered in Newton (8 events).
- Ten vehicles (in addition to the four above) were recovered in Newton that had been stolen elsewhere in the region (10 events).

Thus, of 24 vehicle theft incidents in Newton, only eight or 33% of the incidents can be considered as within-jurisdiction. Of course, this suggests that at least 67% of vehicle theft incidents cross jurisdictional boundaries within the region. Since we are only including the 93 vehicles stolen and 93 vehicles recovered within the region, the true rate of vehicle theft crossing jurisdictional boundaries is much higher.

The pattern is true in other jurisdictions, such as Conover:

- Four vehicles were stolen in Conover and recovered elsewhere in the region (4 events).
- Three vehicles were stolen in Conover and recovered in Conover (6 events).
- Four vehicles (in addition to the three above) were recovered in Conover that had been stolen elsewhere in the region (4 events).
- Thus, of 14 vehicle theft incidents in Conover, we can determine that 43% (6 of 14) were within-jurisdiction, while 57% of incidents (8 of 14) crossed jurisdictional boundaries within the region.

Although the volume of vehicle thefts in any jurisdiction is low, the cross-jurisdictional pattern between thefts and recoveries suggests the importance of gathering precise address information for recovered vehicles, and examining the relationship between these variables.

We anticipated few thefts in the most rural areas; in general, offenders need a way to get to a rural location. In contrast, offenders from outlying areas might be more likely to come to towns, such as Hickory, to steal vehicles and these vehicles would be likely to be recovered elsewhere. While the recovery data in this study are too weak to arrive at that conclusion, the data seem suggestive that thefts in one jurisdiction are often linked to recoveries in another. Since Hickory reported the highest rate of vehicle theft, this hypothesis merits further investigation, and law enforcement should invest additional effort invested in recording both the jurisdiction of the recovery, and the specific location including address whenever possible.

Vehicle Age

It can be misleading to examine vehicle age with aggregate data. In this study, older vehicles were consistently more likely to be stolen (see Figure V), but this pattern was most distinct for automobiles and less distinctive for trucks (See Figure VI). The declining age of stolen vehicles is inverse for “other” vehicles; “other” vehicles stolen are more often newer models – likely because of their relative newness and increasing prevalence in the area, as well as lower levels of security. Incident reports about thefts of “other” vehicles however, were often missing the vehicle age. Owners of these vehicles often lack ownership information, as there is no registration such as that required by the state for trucks and automobiles. The lowest recovery rates (25-31%) were associated with newer vehicles, aged 2001 – 2003. Recovery rates climb after that, averaging around 50% of all vehicles.

Recovery Condition and Value

Recovery condition is an important indicator of the type of theft that occurred and provides important cues for developing police responses. Among recovered vehicles in this study, 36 were reported as damaged, including stripped, burned, flooded or crashed but the data quality of the recovery value of vehicles was poor.

- 94% (596 of 633) stolen vehicles contained some valuation in dollars for the stolen vehicle.
- 49% (311 of 633) of all stolen vehicles were recorded as recovered.
- 54% (167 of 311) of recovered vehicles included some recovery value.

The recorded vehicle condition and recovery value however were often inconsistent with the value of the vehicle when stolen. For example, 36 of the recovered vehicles were damaged upon recovery – burned, crashed, damaged or stripped. While five of the recovered vehicles were classified as stripped, three of those vehicles were valued the same amount at recovery as the value at theft. Eight recovered vehicles were classified as wrecked but their recovery value was identical to the theft value. In 152 cases, the recovery value and the theft value were identical, and there was no indication of damage to the vehicle.

Summary

The analysis in this chapter and Chapter IV identified distinctive patterns of vehicle theft that contrast markedly with national patterns and those documented in urban areas. These patterns included the following:

- Vehicles other than cars and trucks comprised a large and increasing share of vehicle thefts – a share much higher than the national average. Thefts of ATVs and similar vehicles demonstrate a seasonal pattern, rising in the summer and fall months. In contrast to automobiles and trucks, ATVs and similar vehicles, have a very low recovery rate.
- Vehicle theft shows a strong regional trend in the four counties, as vehicles stolen in one jurisdiction are routinely recovered in another. The interjurisdictional pattern illustrates the economic interdependence among the four counties and their townships.
- In contrast to other studies, the most common locations of vehicle thefts – especially autos and trucks – were business rather than residential locations; and car repair shops and car dealerships dominated theft locations.

- Despite identifying common types of theft locations, there were no identifiable hot spots in the region. Only a few addresses had more than one theft, and these were too few in number to comprise a hot spot. Patterns of spatial dispersion were diffused over time.

- With 3% of thefts recorded as attempts, the region demonstrates a markedly higher proportion of completed thefts (97%) than nationally (80%). Although attempts may be substantially underreported, we might expect to find a lower recovery rate for stolen vehicles, as attempted thefts are virtually always recovered vehicles. Unfortunately, missing recovery data prevented us from drawing such conclusion.

CHAPTER VI: CRIME AND SPATIAL ANALYSIS IN NON-URBAN AREAS

Crime is a low-volume phenomenon in non-urban areas and consequently little academic research – which requires sufficient volume for statistical analyses – has focused on offenses in these jurisdictions. Similarly, crime analysis and mapping have emerged as valuable tools for police in urban areas in the last decade, but non-urban jurisdictions have largely been ignored in advances and applications. While non-urban law enforcement agencies comprise a majority of agencies in the nation, there are clear challenges in crime analysis and mapping in these jurisdictions; in addition to the low volume of crime, missing data compromise mapping applications as a map with a mere handful of points is not particularly useful for police or others.

The research in this study resulted in a comprehensive map of motor vehicle theft in the Western Piedmont region area of North Carolina. Regional data aggregated over time – one year for this study – resulted in more robust maps and revealed important patterns amenable to intervention. The comprehensive map, however, resulted only from additional data collection; x-y coordinates were collected with GPS for offense locations that could not be geocoded. As a result of the data collection, 15% more theft locations were placed on a point map than otherwise would have been possible, increasing the data from 541 to 633 points. While it took substantial effort to map crime in this non-urban region, the benefits of doing so were not readily apparent as there were no identifiable hot spots or other geographic clusters.

But there were important analytic benefits arising from data collection and mapping. The data collection process provided a method to undertake further spatial and descriptive analyses of vehicle theft in the region. The findings, discussed in chapters IV and V, revealed important and distinctive patterns that contrasted with national patterns and those in urban areas. The findings have important implications for crime prevention and demonstrate the need for crime and spatial analysis to be tailored to the local context to guide adoption of the most promising crime prevention efforts. This chapter describes how spatial and crime analysis findings in the Western Piedmont relate to our understanding of vehicle theft, common and emerging crime prevention efforts, and reflect on the usefulness of crime and spatial analysis.

Local Characteristics of Vehicle Theft

As described in Chapter I, both the volume and rate of vehicle theft are much lower in non-urban areas, even when adjusting for differences in population. While the reasons for the exponentially lower rates have been generally attributed to differences in vehicle ownership rates and social networks, this study also revealed contextual features that dampened vehicle theft risk as the rural areas and small towns in this study were largely absent the crime magnets associated with thefts in urban locations:

- Few large parking lots, and no transit or commuting lots.
- Little pedestrian traffic along public roadways.
- No transit systems to deliver likely offenders to theft locations.
- Little parking on streets as most overnight residential parking occurs on the land parcel, in driveways, under carports, and in front and back yards.
- High levels of natural surveillance in many areas, including clear sight lines onto properties.
- High levels of acquaintanceship, observed during data collection when researchers encountered neighbors or co-workers of victims who were very familiar with the vehicle and routine parking habits of victims.
- Dog ownership appeared prevalent at many residences, particularly in less dense areas, and dogs on residential parcels were not typically confined but roamed free as watch dogs.

Despite these protective features against vehicle theft in the area, some features suggest vulnerability to more thefts in the future:

- Vehicle ownership appeared to include older vehicles (autos and trucks) that have fewer security features, and are thus easier to steal.

- Census tracts with industrial and commercial land use were most highly correlated with vehicle theft, suggesting that such areas – more so than residential areas – provide the most numerous targets for theft. So, too, factory workers may more routinely drive older vehicles that face higher risk of theft. At larger factories, vehicles in parking lots featured very little security, and researchers found easy access to all areas.

- Business practices were often informal such as when car dealerships allowed would-be buyers to test drive vehicles unaccompanied by an employee. While vehicles were not stolen during the test drive, these unsupervised drives provided an opportunity to duplicate vehicle keys, facilitating later thefts.

- Non-urban areas appeared to have a high level of ownership of ATVs, readily used for hunting or recreation opportunities that would be scarce in more urbanized areas. Such vehicles – similar to motorcycles – are often not secured, easy to steal, easy to conceal, and seldom recovered. Owners are often missing serial numbers for these vehicles making recoveries difficult.

- Simple crime prevention strategies, such as locking vehicles, are not well utilized in non-urban areas with low crime. Many rural residents routinely leave keys in vehicles. Such residents may also routinely fail to secure property, such as ATVs, on residential parcels.

While there are some features of non-urban areas that might attract vehicle theft, the protective characteristics of non-urban areas appear to outweigh risk factors in these areas.

Common Vehicle Theft Prevention Strategies

Motor vehicle theft is a common and serious crime problem for police, and one that features low clearance rates. To respond to vehicle thefts, a wide range of strategies have been employed by law enforcement agencies in many countries, including:

- Using bait cars, or tracking devices on high-risk vehicles at high-risk locations (Eisler, 2004; Sallybanks, 2002; Arizona Criminal Justice Commission, 2004).

- Deploying bike patrols, conducting directed patrols or increasing surveillance of hot spots (Barclay et al., 1995; Webb, 1994; Sallybanks and Brown, 1999; Rengert, 1996; Clarke, 2002).

- Establishing "Watch Your Car" programs so law enforcement can identify stolen vehicles during certain hours (Curtin et al., 2005) and circulating "hot sheets" to keep police alert to stolen vehicles (Decker and Bynum, 2003).

- Increasing collection of forensic investigation from recovered vehicles (Chatterton and Frenz, 1993; Sallybanks and Brown, 1999; Decker and Bynum, 2003).

Are these strategies promising in the Western Piedmont region? Sallybanks and Brown (1999) advise that effective vehicle theft reduction strategies must focus on crime prevention and must not be generic but should focus on strategies that are locally relevant. But local relevance can only be determined through examination of local problems.

Virtually all of the vehicle theft tactics listed above relate to apprehending offenders, primarily through short-term tactical operations in "hot spot" locations. For example, circulating hot sheets may be promising if stolen vehicles remain in the jurisdiction; data from this study (and others such as Maxfield, 2004) suggest they do not. Similarly, collecting forensic evidence is promising if there are no suspects and thieves have a criminal record; such physical evidence is much less useful if thefts reflect joyriding.

Rather than tactics related to apprehending offenders, findings from the Western Piedmont suggest longer-term strategies focused on reducing opportunities for vehicle theft. These include:

- Controlling vehicular access, limiting pedestrian access and increasing surveillance of parking lots, including use of CCTV (Barclay et al., 1995; Webb, 1994; Sallybanks and Brown, 1999; Rengert, 1996; Clarke, 2002).

- Changing management practices to limit access to large parking lots through gates or other techniques (Barclay et al., 1995; Webb, 1994; Sallybanks and Brown, 1999; Rengert, 1996; Clarke, 2002).

- Holding business owners accountable for preventing thefts at specific types of locations, such as manufacturing and auto repair shops or dealerships.

- Conducting public education efforts to increase security for ATVs, scooters and other vehicles, including placing them out of public view in secured storage, recording serial numbers or registration for ATVs at point of sale and/or property marking, and publicizing these efforts to deter offenders.

- Targeting community improvement efforts to increase home ownership as this appears to increase protective characteristics related to social networks and acquaintanceships.

There are additional prevention strategies that may be relevant to the Western Piedmont but for which sufficient data were not available in this study. These include:

- Developing public education efforts to reduce risks if thefts are characterized by keys left in vehicles, such as at residential premises.

- Holding business owners accountable for thefts where keys to vehicles are easily accessible, such as at auto repair shops.

- Systematically recording recovery date, location, condition and vehicle value on crime reports to provide important information about types of theft, and a basis to evaluate the effectiveness of preventive efforts.

Making Crime Analysis More Useful

In Chapter I, we discussed that crime and spatial analysis are not well established in non-urban and smaller law enforcement agencies, and the low volume and wide spatial dispersion of crime are key reasons for this. Even in urban police agencies, crime analysis and mapping are most often used to identify hot spots or other geographic concentrations of crime, and these findings invariably suggest tactical responses. For example, the Arizona Criminal Justice Commission (2004) analyzed vehicle theft across the state, generating lists of “Top 10” vehicles stolen and “Top 10” theft locations. If these are the only findings arising analysis, bait vehicles and surveillance operations will be the natural response. But these are short-term resource intensive and focus only on apprehending offenders; as such, they are unlikely to have lasting effects. Moreover, these analyses and the related responses have little relevance for non-urban areas that are absent the "Top 10." To be useful, crime analysis and mapping in rural areas must make some important changes to adapt to the local context of crime. These adaptations include:

Increase Time Frame

Police inevitably want real-time data; thus, much urban crime and spatial analysis has focused on identifying short-term or emerging crime patterns, usually those relating to repeat offenders or hot spots. There is no evidence of such short-term patterns or prolific offenders in non-urban areas and relying on short-term data will mask more important long-term trends. Useful crime analysis and maps in non-urban areas should lengthen the time frame for analysis and emphasize periods such as three, six or 12 months rather than weekly, bi-weekly or monthly data commonly used in more populous jurisdictions.

Increase Data Volume

Relative to urban jurisdictions, there are few thefts in non-urban areas. Even the largest jurisdiction in this region averaged only 16 vehicle thefts per month; other jurisdictions in the study averaged as few as one or two vehicle thefts per month. Crime analysis within a single jurisdiction is unlikely to be useful because there are simply too few events for meaningful analysis. The number of crime incidents can be increased by lengthening the time period as discussed above; the number of crime incidents can also be increased by aggregating thefts across jurisdictions. In this study, aggregating thefts resulted in about 50 thefts per month, a number of events more compatible with more robust and useful analyses.

Improve Data Validity and Reliability

If crime mapping is to be useful in a non-urban area, data quality must be improved; this study identified much missing data and many data errors relating to crime locations. For reliable and valid analysis, consistent and reliable data collection and recording practices must be integrated into law enforcement operations. At relatively low cost, law enforcement personnel could be equipped with GPS units to record crime locations for incident reports.

Maps are necessary to demonstrate the cross-jurisdictional patterns of theft and recovery in the Western Piedmont but maps require that all thefts be addressed (even if to the nearest intersection) and recording recovery locations has the potential to reveal even stronger cross-jurisdictional patterns. Thefts and recoveries of vehicles in the Western Piedmont routinely crossed jurisdictional boundaries. While this pattern was not as distinctive as in urban jurisdictions (see Maxfield, 2004), vehicle theft is clearly a regional problem.

Employ Strategic Approach

While citizens look to police to reduce crime, the analysis in this study showed that others may be better positioned to address vehicle thefts; these include managers of car dealerships and manufacturing plants, and individual owners of ATVs and similar vehicles. Recent evidence has shown that effective policing for vehicle theft and other crimes increasingly involves identifying the owners of problems, and shifting responsibility from police to those owners (Scott and Goldstein, 2005; Clarke, 2002; Plouffe and Sampson, 2004). Because shifting responsibility to others may involve local politics, a regional approach arising from analysis creates a powerful evidence for coordinated regional responses. Regional efforts can also be more easily evaluated, lending empirical support to practical crime prevention policies. Further, such coordinated approaches are inherently more efficient, as they conserve scarce law enforcement resources by minimizing tactical deployment. Regional efforts in improving crime data can also conserve resources as economies of scale may be realized through investments in shared Records Management Systems, substantially reducing costs of data entry, cleaning and archiving while improving data reliability; and reducing costs associated with training of in-house GIS or crime analysis personnel by sharing expertise across jurisdictions.

Conclusion

Since both the *volume* and the *rate* of vehicle theft are much higher in urban areas, the advantages to police of using crime and spatial analysis in non-urban locales are not immediately apparent. This study has demonstrated that there are no hot spots or series patterns that make “real time” crime analysis critical for non-urban areas.

But the research in this study has demonstrated that crime and spatial analysis *could* be used strategically to identify, analyze and coordinate responses to vehicle theft in a non-urban area; it is likely, however, that such benefits could only be realized through a regional approach. Regional systems to analyze crime can be difficult to develop (see Wernicke, 2005), but the benefits of regional crime analysis are high (LaVigne and Wartell, 2001; Eck, 2002; Rich, 1999; Faggiani et al., 2001).On a regional basis, routine analyses could be used to:

- Assist with detection and analysis of public safety problems by providing a larger database from which to detect crime patterns, and identify both impact and displacement associated with police efforts.

- Pioneer a region-wide GPS-based incident database to more accurately identify locations of offenses which often lack sufficient addresses for mapping – locations such as those on roadways, in parking lots, in parks or on open farmland.

- Use maps as a standardized way to monitor public safety problems, share information between agencies and with the public and evaluate the effectiveness of law enforcement efforts.

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APPENDICES

Appendix A: *Ecological Analysis*

Theories, Ambiguity, Redundancy and Causal Mechanisms

Social ecological research since its origins in the 19th century has been characterized by methodological issues and debates, for which there has not often been definitive – or satisfactory – conclusions (Elmer, 1933; Robinson, 1950). For example, much of social ecological research has been conducted at one level of measurement, the aggregate level (e.g., cities, counties, census tracts or census enumeration groups – the latter was used for the current research project), although in recent years multi-level analysis has risen in popularity (Bryk and Raudenbush, 1992). In aggregate data analysis at one level (e.g., census tract or enumeration group, as employed in the current analysis) there are two general problems confounding interpretations of research findings. One, when the dependent variable is an aggregation of individual behaviors (as in counts or rates of crime behaviors or health conditions) there is no direct measure available to the researcher of who it is who is criminal or ill. Rather the researcher only knows the rate of crime or illness and, thus, any correlation at the aggregate level is inherently ambiguous as to who committed the crime or suffered the illness. When correlated with factors thought to affect these rates or counts – for example, poverty – one cannot be sure that, despite a moderately high positive correlation at the aggregate level, that it is actually the poor who are the ones who are criminal/sick, or others. This is not a trivial observation since – in the case of poverty levels and crime rates, for example – the predominant theory in the field of the social ecology of crime, "social disorganization" theory, posits that anyone in a poor neighbourhood, regardless of his/her own poverty, is more likely to commit crime because the poverty is actually an indicator of the degree of heterogeneity in value orientations in a geographic area (Kobrin, 1971). Heterogeneity in value orientations implies weakness in a community's ability to exercise control over criminal and delinquent behaviors. Such areas are more likely to foster crime regardless of the individual's own poverty. In summary, the lack of a direct measure of whom it is who is delinquent or diseased makes the interpretation of findings an inherently ambiguous enterprise.

The second major problem that characterizes aggregate-level social ecological analysis is that of redundancy in measurement. The same geographic areas often have a variety of social conditions and problems such that there are often somewhat high correlations among the so-called independent variables in the often-used regression models across a wide variety of social outcomes (Land, McCall and Cohen, 1990). This is sometimes called the collinearity problem and is defined as an excessively high among independent variables (defined more formally as excessive correlation among independent variables to the extent that effects cannot be estimated reliably). Some refer to it as "redundancy of measurement" (measures of differing concepts "overlap" empirically to an excessive degree).

Collinearity or redundancy leads to two general strategies on the part of researchers. One is to reduce the field of independent variables by using "data reduction" techniques, such as factor analysis, to combine individual variables into "factors", and then to use such factors as the independent variables in regression models of outcomes, such as a crime count or rate. Such an approach generally leads to rather abstractly defined factors, as the researcher must find a concept (or name) to "cover" the individual variables that have been combined into a single factor. Oftentimes the abstractly defined concept (defined ex post facto) lacks the specificity desired relative to research questions about what it being studied and fails to address important issues in existing substantive theories (theories of crime, health, etc.). Thus, for example, those who use the factor approach for explaining crime often conclude that poverty or "deprivation/

affluence" is an important cause of crime (Land et al., 1990: 952), but there are several mechanisms by which such a "cause" could have an effect on the crime rate or level (e.g., relative deprivation, low social integration to educational or occupational institutions, or exposure to crime tolerant subcultures). The latter mechanisms are invoked by several different substantive theories and the general measure cannot offer any help in differentiating which theory is better.

A second approach to handling the collinearity problem is to use individual variables (or combinations of a few variables with "face" validity) of more specific theoretical concepts, and to carefully select the variables for inclusion in a model based on specific theoretical grounds coupled with a recognition that some omitted variables correlate with the included variables. Such analysis runs the risk that not every researcher would agree as to what variables are important – and therefore should be included in the models – and which should be dropped from the equation because of collinearity and relative theoretical vacuity. In general, this latter approach is more likely to be used if there are practical or applied consequence to the research, as there is a clearer idea of what it is that might be manipulated to achieve desired policy goals.

The combination of the two problems just outlined above – no "direct tie" between the independent variables and the outcome, and collinearity – are perhaps responsible for the marginalization of social ecological analysis across a variety of subfields of the social sciences (arguably since the time of Robinson's famous article on the ecological fallacy in 1950). In recent years, however, ecological analysis has come back in a large fashion with the widespread availability of multi-level "hierarchical models" (HM) as in the work of Bryk and Raudenbush (1992). These models typically include measurement at the individual level (thus addressing the problem of a lack of a direct measure of who it is with the characteristics of the dependent variable, e.g., who is criminal or not), and at one or more aggregate levels (such as "neighbourhood area" or census tract – see Rountree et al., 1994 for analysis at all three of these levels). While the problems associated with collinearity at the aggregated units of measurement remain, it is often the case that the HM approach, given that the right data are available, allow for simultaneous statistical control for variables that seem very similar at both the individual and aggregate level (e.g., poverty of the person and poverty of the census tract). By having "conceptually similar measurement" at the individual and aggregate level, HM approaches allow for less ambiguous interpretations of the aggregate level variables in question. Thus, in the case of poverty and crime, finding an effect at the aggregate level when controlling for poverty and crime at the individual level in an HM analysis would lend support for an "emerging property" interpretation of the aggregate poverty effect. That is, something other than the poverty of the individual is the mechanism by which crime is generated. Poverty at the aggregate level is measuring an "emergent property" at the aggregate level. This property is unspecified, but because of the inclusion of the poverty measure at the individual level, we can exclude a "compositional" interpretation: the effect at the aggregate level is not due to the poverty of the individual per se.

Below we present an analysis of the census predictor variables, using the count of the number vehicle thefts as a dependent variable. Table A1 displays the results of the factor analysis itself, (using the statistical program SPSS, "promax," the pattern matrix is displayed). Down the left hand column are the individual variables. Across the top are the seven factors, which have been named in accordance with the principle that the variables with the highest "loadings" as the name seems to best represent the factor.

Table A1. Factor Analysis Results (Pattern Matrix)

Pattern Matrix(a)

	Factor						
	1. Population Size	2. Poverty	3. Urban-ness	4. Racial Hetero-geneity	5. Prevalence of Young Adults	6. Ave. Household Size	7. Prevalence of Teens
Population (divided by 1000	.991	.028	.014	-.030	.009	.094	.016
Household size	.070	-.021	-.084	.047	.064	.943	-.022
Percent teens	.026	.002	-.032	.010	-.125	-.044	1.030
Percent 20-35	-.047	-.086	-.017	-.013	1.066	-.035	-.191
median_age	-.008	-.051	-.134	.025	-.664	-.332	-.308
N Black	.117	.011	-.187	1.014	.009	.034	-.001
N Hispanic	.353	-.061	.325	.198	.304	.039	-.078
Racial Heterogeneity of Blacks and Whites	-.163	-.021	-.004	.959	-.040	.049	-.003
N Males	.953	-.005	-.067	.010	.062	.049	.083
Percent Single Parent	-.004	.491	.583	.078	-.011	.195	-.048
N Single Head of Household	.789	.029	.258	.015	.028	-.349	-.032
Percent_Urban	.074	-.088	.743	-.111	-.043	-.102	-.026
Percen of males15 of over who are Unmarried	-.044	.163	.214	.306	.083	-.278	.141
Percetn Owner Occupied	.123	-.171	-.737	.056	-.111	.241	.039
N Owner_Occupied	.937	.009	-.135	-.128	-.136	.187	-.028
Percent Males with College or Higher Education	.035	-.733	.430	.047	-.240	-.156	.079
Percent below 1.49 of Poverty Level	.021	.761	-.018	.056	-.044	-.041	-.044
Percent below Poverty	.042	.829	.100	-.018	-.131	-.010	-.030
Percent on Public Assistance	3.912E-05	.669	.130	.054	-.203	.181	.046
Median Head of Household lest than 25 Years Old	.120	-.118	-.314	-.001	.228	-.145	.096
Median White Income	-.025	-.761	.258	.091	-.115	.357	-.112
Median Black Income	.169	-.176	.241	.077	-.084	.081	.018
N Vacant Houses	.321	.079	-.301	.152	-.130	-.140	-.106
Area Size	.079	.180	-.614	.054	-.042	-.044	-.035

Extraction Method: Maximum Likelihood. Rotation Method: Promax with Kaiser Normalization.
a Rotation converged in 8 iterations.

Table A2. Regression of Number of Vehicular Thefts on Factor Scores (Trimmed Model).

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2=22.6	B	Std. Error	Beta			Tolerance	VIF
(Constant)	2.783	.175		15.935	.000		
Urbanness	1.104	.196	.350	5.618	.000	.850	1.176
Popopulation Size	.616	.178	.202	3.465	.001	.969	1.032
Prevalence of	.454	.193	.149	2.361	.019	.828	1.208

Young Adults

a Dependent Variable: N_vehicular_thefts

In the regression analysis (See Table A2) in which the number of vehicle thefts is the dependent variable, only three of the seven factors were found to be statistically significant predictors (using forward selection for inclusion of variables): urbanness, population, and young adult prevalence.[39] Approximately 22.6% of the variance across census block groups was accounted for using this simple model with three independent variables. Thus, the vast majority of the variance in vehicular theft remains unexplained by the model (77.4%). The other four factors make no unique contribution to the explained variance in the number of vehicle thefts. Thus, neither the poverty, racial mix, average household size, nor prevalence of teenagers has an independent effect on the count of vehicular thefts.

One of the primary issues that we have with the model in Table A2 is that it does not tell us much with regard to policy actions that might be taken to combat vehicular theft. The effect of population size simply tells us that, all else being equal, there are more vehicles stolen in block groups where there are more residents and presumably more vehicles to steal. (In fact, as will be seen, we statistically control for population in all of the equations discussed below to "standardize" the analysis for availability of vehicles.) The effect of "urbanness," independent of population size, may be due to the possibility that we are measuring the relative "anonymity" of people in a block group (the more urban, the less likely that someone will be recognized, and less at risk of being reported for vehicular theft), or it may be a measure of some other

39 Using counts of the number of vehicle thefts rather than rates is the preferred way to treat the measurement of the dependent variable. We control for population in the regression equation to control for differences in the "size" of the pool of vehicles at risk in each census block area.

characteristic of the environment such as prevalence of parking lots or proximity to specific types of land uses such as bars or restaurants – essentially land uses more common in an urban environment. Finally, the prevalence of young adults (ages 20 to 35), as opposed to teenagers or older adults, implies that vehicles tend to be stolen where there are more people of an age when they are most actively involved in using vehicles. Presumably most of those stealing the vehicles are of this same age group (in our sample of vehicular thefts, the median victim's age is 32 and median offender's age is 26– although only 6.4% of the thefts have a known perpetrator with age information). In short, the factor analysis results are not very "informative" relative to what we knew before conducting the analysis.

Appendix B

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Date : 12-21-2004          CensusCD 2000 Long Form
Time : 14:10
                                Summary Report


P001    TOTAL POPULATION
 Universe: Total population
001 Total.................................................
341,851

P005    URBAN AND RURAL
 Universe: Total population
001 Total: population.....................................         341,851
002 Urban:................................................         194,025
005 Rural:................................................         147,826

P006    RACE
 Universe: Total population
001 Total: population.....................................         341,851
002 White alone...........................................         299,055
003 Black alone...........................................          23,951

P007    HISPANIC BY RACE
 Universe: Total population
010 Hispanic:.............................................          13,308

P008    SEX BY AGE
 Universe: Total population
002 Male:.................................................         169,555
041 Female:...............................................         172,296

P018    SEX BY MARITAL STATUS POP 15+
 Universe: Population 15+
001 Total: Population 15+.................................         272,860
002 Male:.................................................         133,984
003 Male Never married....................................          33,759
004 Male Now married:.....................................          84,929
005 Male Married, spouse present..........................          77,126
006 Male Married, spouse absent:..........................           7,803
007 Male Separated........................................           3,647
008 Male Other............................................           4,156
009 Male Widowed..........................................           3,150
010 Male Divorced.........................................          12,146

P037    SEX BY EDUCATIONAL ATNMNT POP 25+
 Universe: Population 25+
001 Total: Population 25+.................................         230,937
002 Male:.................................................         111,344
003 Male No schooling completed...........................           1,752
004 Male Nursery-4th grade................................           1,110
005 Male 5th and 6th grade................................           2,677
006 Male 7th and 8th grade................................           7,729
007 Male 9th grade........................................           6,081
008 Male 10th grade.......................................           6,711
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009 Male 11th grade.......................................          4,648
010 Male 12th grade, no diploma...........................          4,182
011 Male High school grad (inc equivalency)...............         34,676
012 Male Some college, under 1 year.......................          6,861
013 Male Some college, 1+ years, no degree................         13,003
014 Male Associate degree.................................          6,353
015 Male Bachelor's degree................................         10,742
016 Male Master's degree..................................          3,027
017 Male Professional school degree.......................          1,418
018 Male Doctorate degree.................................            374

P038    ARMED FORCES STATUS BY SCHOOL ENROLL BY EDUC ATNMNT BY
 Universe: Population 16-19 years
001 Total: Population 16-19 years.........................         16,846
002 In Armed Forces:......................................              0
003 Enrolled in school:...................................              0

P053    MEDIAN HH INCOME($)
 Universe: HH
001 Median HH income......................................         38,713

P056    MEDIAN HH INCOME($) BY AGE OF HHLDR
 Universe: HH
001 Total.................................................         38,713
002 HHldr under 25 years..................................         28,359

P062    SOCIAL SECURITY INCOME FOR HH
 Universe: HH
001 Total: HH.............................................        134,105
002 With Social Security income...........................         35,857

P064    PUBLIC ASSISTANCE INCOME FOR HH
 Universe: HH
001 Total: HH.............................................        134,105
002 With public assistance income.........................          3,283

P077    MEDIAN FAMILY INCOME($)
 Universe: Families
001 Median family income..................................         45,214

P080    MEDIAN NONFAMILY HH INCOME($)
 Universe: Nonfamily HH
001 Median nonfamily HH income............................         22,277

P085    MEDIAN EARNINGS($) BY SEX POP 16+ WITH EARNINGS
 Universe: Population 16+ with earnings
001 Total.................................................         22,399
002 Male .................................................         26,573
003 Female................................................         18,777

P087    POVERTY STATUS BY AGE
 Universe: Population, poverty stat checked
001 Total: Population, poverty stat checked...............        334,747
002 Income below poverty:.................................         32,802

P088    RATIO OF INCOME TO POVERTY LEVEL
 Universe: Population, poverty stat checked
003 50-.74................................................          8,203
004 75-.99................................................         11,368
005 1.00-1.24.............................................         13,306
006 1.25-1.49.............................................         16,727
007 1.50-1.74.............................................         16,148
008 1.75-1.84.............................................          7,385
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009 1.85-1.99	9,740
010 2.00 and over	238,639

P089 POVERTY STATUS BY AGE BY HH TYPE
Universe: Population, poverty stat checked

001 Total: Population, poverty stat checked	334,747
002 Income below poverty:	32,802
003 0-55 years:	28,073
006 Male HHldr, no wife present	2,722
007 Female HHldr, no husband present	10,155

P150A SEX BY EMPLOYMENT STATUS POP 16+ (WHITE ALONE)
Universe: White alone pop 16+

001 Total: White alone pop 16+	238,730
002 Male:	115,820
003 Male In labor force:	88,057
004 Male In Armed Forces	117
005 Male Civilian:	87,940
006 Male Employed	85,408
007 Male Unemployed	2,532
008 Male Not in labor force	27,763

P152A MEDIAN HH INCOME($) (WHITE ALONE HHLDR)
Universe: HH with HHldr White alone

001 Median HH income	39,243

P152B MEDIAN HH INCOME($) (BLACK ALONE HHLDR)
Universe: HH with HHldr Black alone

001 Median HH income	24,902

Appendix C: Police Reporting Practices

This study has suggested that there are inconsistencies with the way thefts of motor vehicles are classified in the 11 law enforcement agencies. Some offenses that may appear as stolen vehicles may be alternatively be classified as fraud, or as unauthorized use, and this judgment is usually made by the responding officer. The offense "unauthorized use of a motor vehicle," a Part II offense, is appropriate when motor vehicles are taken by persons with lawful access to vehicles; however, these offenses may rise to the felony motor vehicle theft classification when the vehicles are taken with the intent to permanently deprive the owner of the vehicle. In this study, law enforcement personnel suggested that vehicles that are not recovered within 30-45 days are often viewed as meeting the condition of "permanent" and thus may be reclassified from unauthorized use to vehicle theft.

In this study, we found that many stolen vehicle reports appeared to reflect elements of unauthorized use. Law enforcement personnel later agreed that a portion of offenses recorded as vehicle thefts include vehicles which:

- Arose out of domestic conflict
- Occurred at car lots in which lot managers fail to secure proper identification for prospective buyers taking "test drives"
- Arose from "drug swaps," where a vehicle owner may swap his or her motor vehicle for a crack rock or other illegal drug
- Reflected repossession of vehicles or insurance fraud

Some police may have a traditional approach in recording offenses and thus tend to over-classify offenses. For example, labeling an unauthorized use of a motor vehicle as a vehicle theft is a traditional practice, and such caution may reflect the discretion of individual officers or prevailing police practices. This thinking relates to a presumption that the vehicle will be returned, but the officer classifies the offense as vehicle theft in case the vehicle is *not* returned. In other law enforcement agencies, particularly agencies concerned about increases in Part I offenses, officers may tend to be more conservative in recording offenses and thus tend to under classify offenses. In such an agency, a vehicle theft arising from a drug swap may be seen as clearly a case of unauthorized use rather than a Part I vehicle theft. Agencies that are conservative in reporting Part I offenses will tend to have fewer vehicle thefts and this may be reflected in lower recovery rates; agencies that are traditional in classifying vehicle theft may tend to have more thefts and higher recovery rates of vehicles.

Similarly, there were numerous vehicle thefts that might have been classified as unauthorized use, because of the nature of the relationship between victim and offender. For example, some thefts appeared to arise out of domestic conflict. In one case, the theft victim was a man who reported the theft after being released from jail for violating a protective order. Arriving home, the victim found three vehicles and his spouse missing. Despite our observations, we have relied on the classification used by the reporting agency although we note that law enforcement officers are conservative in completing offense reports, and probably tend to err on the side of reporting a vehicle as stolen (a Part I offense), when it may be the less serious Part II classification. In some cases, we were told that police relied on the suspect's intent to "permanently deprive the owner of the vehicle" rather the suspect's lawful access to the vehicle.