Casual Factors Influence Repeat Violent Criminal Offenses in a GIS Spatial Context

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Abstract

This research focused on whether or not demographic characteristics influence repeat violent offenses. Discussions occurred regarding the potential of the correlation between demographic values in census block groups of the City of Madison, Wisconsin and repeat violent offenses from January 2000 to November 2007. Statistical analysis, Geographic Information Systems (GIS), and repeat violent offender profiles were created using demographic values from census block groups. In the process of creating these profiles, the use of a bivariate correlation matrix helped compare common themes with offense data and to find correlations between demographics and repeat violent offenses. Examination of the demographics showed statistically significant relationships between repeat violent offenses and 33 census demographic variables. Seven demographic variables were determined to be statistically significant.

Introduction

Crime and Demographics

Crime analysis consists of systematic processes that aim to identify patterns and correlations between crime data and other related information sources that help support decisions that could affect agency allocations (Chainey and Ratcliffe, 2005). Preventing crime, predicting crime, and finding crime trends and hotspots are just a few areas GIS is used for in Criminal Justice. GIS modeling can be tied to knowledge of the real world and can help define spatial relationships within socio–economic characteristics.

"Crime mapping is not just about mapping crime, but also mapping the underlying drivers that potentially contribute to crime – features of the physical and socio-economic world that might be the 'root cause' of crime" (Chainey and Ratcliffe, 2005).

When observing demographics and the location of an offense, it is sometimes difficult to understand any correlation between the two – if in fact, there is any correlation. Use of linear regression analysis and a bivariate correlation matrix helped understand influential underlying demographic factors.

It is important to examine the underlying factors of offenses and the location those offenses took place. Numerous researchers in criminal justice have tried to understand the underlying influence may it be low-income, tenure, education, age or any other socio-economic factors to understand criminal

activity (Chainey and Ratcliffe, 2005). In trying to understand certain neighborhoods, researchers have identified one main theme – neighborhoods in poverty tend to have extremely high crime rates (Simpson, 2000).

According to Shaw and McKay's (1929) social disorganization theory, high rates of crime and delinquency in a neighborhood are influenced by declining social values, rules of behavior, and economic deprivation due to the fact that certain neighborhoods appeared not stable (Simpson, 2000). Repeat violent offenses have been an issue in many metropolitan cities, where neighborhoods consisting of specific socio-demographic characteristics experience increased criminal activity. By examining these underlying factors, it can be determined if demographic factors influence or correlate with violent repeat offenders. Andre-Michel Guerry and Lamert-Adolphe Quetelet mapped violent and property offenses and examined their spatial relationship to poverty on a national basis, a relationship known as Social Disorganization Theory (Rossmo, 2000). Based on findings from bivariate matrices, profiles created can help determine demographics correlation with repeat violent offenses. Many offenders choose their location of offense based on socio-economic factors (Rossmo, 2000).

Offense Types

Under Chapter 940: Crime Against Life and Bodily Security of the Wisconsin State Statute (Wisconsin State Statute) contains the classification of all repeat violent offenses used throughout this study. The more commonly occurring offenses are homicides, homicide by neglect, operation of vehicle, abortion, battery (simple and aggravated), and sexual assault.

Some lesser-known violent offenses are false imprisonment and intimidation of witness. According to Wisconsin State Statute 940.30, "false imprisonment is intentionally confining or restraining another without the person's consent and with knowledge that he or she has no lawful authority to do so and therefore is guilty of a Class H felony. Intimidation of witnesses is knowingly and maliciously preventing or dissuading, or who attempting to so prevent or dissuade any witness from attending or giving testimony at any trial, proceeding or inquiry authorized by law."

Data

Gathering repeat violent offense data and demographic data consisted of the initial steps before statistical and spatial analysis processes could occur. In the initial stage, three main tasks occurred: first, collecting all data; second, spatially referencing (geocoding) all repeat violent offenses; third, creating tables of data for analyzing.

Data Collection

Offense Data

The violent offense data of Madison, WI collected from the City of Madison Police Criminal Intelligence Department occurred from January 2000 through November 2007.

The queried violent offense data records database, contained case number, offense type, address of location of offense, name of offender, court status, gender, birthday, race,

home address of offender, driver's license number, and social security number. Omitting personal identification data was done to protect the identification of any individuals. Lastly, extraction (after geocoding) of repeat violent offenses occurred before further analysis.

City Feature Data

Street line features, geographic address points, parcels, a lake polygon layer, police sectors, and census block group polygons were all collected.

Some of these layers were collected for geographic reference and as visual aids. Census block group data were used to help understand demographic character of the study area.

No altering or manipulation of city feature data took place during this study. The streets layer and geographic address point layer were important for geocoding the offense data.

Census Demographic Data

The U.S. Census of Population and Housing, also known as the decennial census, is regarded as one of the most important sources of GIS data for studying communities. Census data provides the most reliable, detailed, and consistent demographic information for describing local areas (Myint et al., 2007).

The City of Madison Police Criminal Intelligence Department possessed the census demographics used in the project. The demographic data consisted of the summary file 3 (SF3), which was collected in 2000.

Income, education attainment, house tenure, family structure, race, income, poverty, and income assistance

were the demographic characteristics examined in this study. Use of the SF3 data was chosen over the SF1 data because SF3 contains the most complete statistical data originating from 1 out of 6 households in the United States (U.S. Census Bureau, 2002).

SF3 (Summary File 3) Data

Demographic data consisted of house tenure, households with public assistance, education attained by individuals over 25 years of age, race of total population, employment of population over 16 years of age, family structure, and poverty. All of the data sets used consisted of subcategories. Some of the subcategories were omitted because they were not relevant to the research.

Block Group Data

The smallest geographic entity for SF3 data are census block groups. The use of census block groups instead of census tracts was used because of the smaller geographic area and the values achieved within smaller areas.

With census data, it is important to identify what the goal is before gathering the data. The geographic hierarchy for census 2000 (Figure 1) was evaluated to help determine the level of geographic organization that would best represent the most important data.

Geocoding Offense Data

The following formula was used for geocoding according to Ordnance Survey 2005, "Distance along the street segment = (the house's numerical position in the range – 1) x A, where A= length of street segment/ (Number of

houses along one side of the street – 1) (i.e. A = 112 / (14 – 1) = 8.615)" (Chainey and Ratcliffe, 2005).

The offense data consisted of 17,011 offenses in the City of Madison area. Offenses were initially geocoded to the city street layer, and then to the geographic address point. Of all offense data, 16,524 out of 17,011 (97 %) offenses were successfully spatially referenced (Figure 2).

Elimination of the 487 offenses that did not geocode were important because those offenses could have skewed spatial analyses.
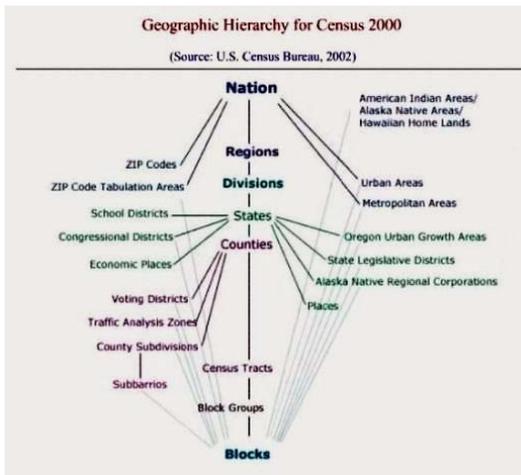

Figure 1. Representation of the geographic hierarchy for Census 2000 (U.S. Census Bureau, 2002).

The geocoding process consisted of creating an address locator by using a one street style using the street layer and one address style using the geographic address point using ArcGIS 9.2. Geocoding to the street layer was the first procedure, and all addresses that did not geocode the first time were geocoded again to the geographic address point.

Census Data

Block groups generally contain between 300 and 3,000 people with the most ideal size being 1,500 people (U.S. Census Bureau, 2002). There was no alteration in demographic values at any point during this research. The list below contains all the demographic variables used in this study. The rationale for selecting these variables is discussed in subsequent sections.
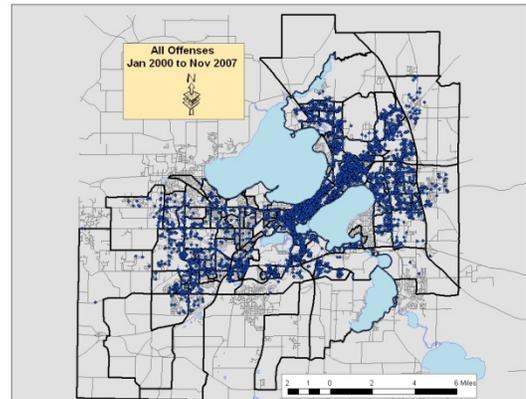

Figure 2. Geocoded offenses represented in the City of Madison, Wisconsin. The black lines represent census block group boundaries, while blue dots represent offense locations.

1) House tenure: Number of houses that were renter occupied and owner-occupied.

2) Public assistance: Total population of households that receive public income assistance. This also contains total population that does not receive public assistance.

3) Education: Education attainment by the total population of individuals ages 25 and older as of the year 2000. All of the categories were of males or females that never completed high school. All categories were combined into three common categories: first, males without high school diploma; second, females without a high school diploma; third, all population without a high school diploma.

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4) Race: Race breakdown for the total population. The subcategory consisted of African American, American Indian, Asian, Hawaiian / Native Pacific, and White Caucasian.

5) Employment: Total population of individuals over the age of 16 either employed or unemployed. Subcategories consisted of in labor force but unemployed, in labor force civilian, and not in labor force unemployed for both male and females.

6) Family Structure: Total populations that were married with or without own children, no wife present with or without own children, and no husband with or without own children.

7) Poverty: Total population for whom poverty status was determined above or below in the year 1999.

8) Income: Households' total income contained data for households with less than $10,000 to over $200,000 income. Sixteen different subcategories were combined into three that fit the economical value and structure of the area. The first category was less than $10,000 to $39,999, the second category was $40,000 to $99,999, and the third category was $100,000 and above.

Methods

Discussions throughout this section explain processes of selecting repeat violent offense data and demographic data.

Offense Data Selection

After geocoding all offenses, attribute data were exported into a geodatabase where it could be opened in Microsoft Access to query all repeat violent offenses and used to create a new shapefile.

The process to separate all single and repeat offenses included reviewing the suspect's name, suspect's date of birth, personal identification number, reviewing the case file number, and then comparing the date of the offenses. Many suspects had case files that consisted of more than one charge. Due to the fact that hard copy reports were not available during this research, there were duplicate reports that had to be eliminated because they occurred on the same data and time. After evaluating the data, multiple shapefiles were created. The different shapefiles consisted of suspects that committed 2 offenses, 3 offenses, 4 offenses, and 5 or more offenses (Table 1).

Table 1. Breakdown of offenses per shapefile.

Total 2 Offenses	2914
Total 3 Offenses	1452
Total 4 Offenses	776
Total 5 & More Offenses	661
Total Offenses	**5803**

After creating each repeat violent offense shapefile, a point count was determined within each census block group. Hawth's Analysis Tools were used to capture the point count of all repeat violent offenses in each census block group. Hawth's point in poly tool that counts all points in a polygon and places values into a new attribute field that was added to the census block group shapefile for each repeat violent offense shapefile.

Demographic Selection

The chosen demographics used for this analysis were chosen based on previous research. Researchers, "…have to rely on indirect measures that provide an indication of possible precursors of social disorganization" (Chainey and Ratcliffe, 2005).

Prior research studies have used demographic characteristics consisting of family structure, poverty, ethnicity, and income. This project evaluated similar characteristics including house tenure, education of individuals over the age of 25, employment of individuals over the age of 16, and public assistance.

The chosen demographics in this research can help crime analysts better understand different social demographic variables and the correlation between repeat violent offenses and social demographics.

Analysis

Two different analysis procedures were utilized. Spatial analyses were first conducted to obtain a visual representation of the data. In addition, spatial analysis has potential of showing spatial correlation between the offense data and the social demographics. After spatial representation of the data was complete, statistical analyses were performed to create profiles that were used to further analyze the data.

Spatial Analysis

Crime mapping is effective because it visually and spatially displays the nature of crime (Boba, 2005). Spatial analysis helped with examining locations, attributes, and relationships of features in the repeat violent offense data sets. The spatial analysis process utilized CrimeStats, a crime analysis program

and density tool of the spatial analysis extension in ESRI ArcMap 9.2.

The CrimeStats program created a K-Means cluster polygon that represented areas where points are similar and in close proximity to each other by using each individual repeat violent offense to create the K-Means clusters to represent the areas of clustering points (Figure 3). Areas represented in yellow contain 462 offense locations, areas represented in orange contain 462 to 624 offense locations, and red areas contain 624 to 826 offense locations. All of these areas consist of individuals who have committed a second violent offense. By only creating three clusters per violent offense shapefile, the distributions of the offenses were spatially consistent through the number of repeated violent offenses.
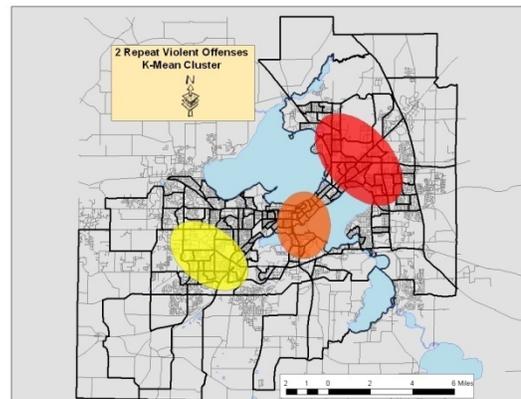

Figure 3. A visual display of three cluster areas of the repeat violent offense data. The thick black lines represent census block groups, the thin lines represent streets, and the blue polygons represent lakes. The red, orange, and yellow represent cluster areas.

"K-means represents an attempt to define an optimal number of *K* locations where the sums of the distance from every point to each of the K centers are minimized" (Levine, 1999). While examining the cluster shapefiles of the

repeat violent offenses, it appears that they are spatially distributed in close proximity of each other.

While working with the repeat offense shapefiles in ArcMap 9.2, the density tool helped spatially examine repeat violent offense data. Use of the density tool generated a surface layer that represented concentrated areas of the repeat violent offense shapefile (Figure 4).
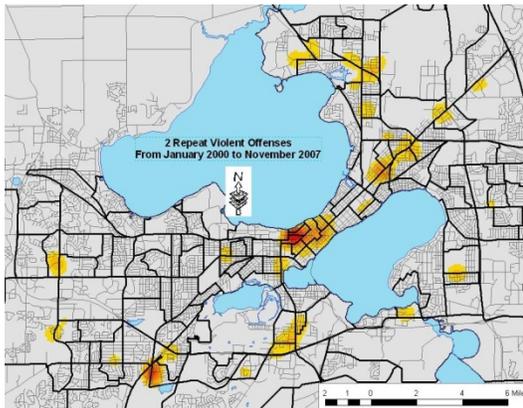

Figure 4. A representation of the repeat violent offense density layer. The red areas represent higher occurrences of violent offenses.

By examining the density layer and K-Means cluster layer, the repeat violent offenses appear spatially distributed throughout the city of Madison, WI. To understand the underlying factors and the correlation between the repeat violent offenses and social demographics, the use of bivariate correlation and linear regression analysis was used.

Statistical Analysis

Statistical Package for the Social Sciences (SPSS) is computer software that finds statistical correlation between variables in social science contexts. Results from the data analysis allow for smarter decisions by uncovering key facts, patterns, and trends.

The use of bivariate correlation in the initial stage of statistically analyzing demographics and the repeat violent offense data sets helped to understand the data. "The bivariate correlations procedure computes Pearson's correlation coefficient and significance levels. Correlations measure how variables or rank orders are related. Pearson's correlation coefficient is a measure of linear association" (SPSS, 2007). The use of the bivariate correlation was chosen because a matrix of each variable and their correlation values with another single variable helped determine relationship values between the variables.

The variables chosen consisted of renter occupied, owner occupied, with and without public assistance, income below poverty, income above poverty level, male and female unemployment, total unemployment, male and females, without high school diploma, total without high school diploma, no wife in household with own kids, no husband in household with own kids, married with own kids, income less than $40,000, $40,000 to $99,999, $100,000 and above, African American, American Indian, Asian, Hawaiian/Native Pacific, White Caucasian, single offense, male and female single offense, repeat offense, male and female repeat offenses, two offenses, three offenses, four offenses, and more than four offenses (Table 2).

Once the bivariate correlation matrix was completed, the results were examined to find non-significant variables that returned Pearson's correlation values of .200 or lower when correlated with individual repeat violent offense variables; those variables were eliminated before further analysis took place.

Table 2. Results of demographics correlation values using SPSS. PC is the Pearson Correlation value. Sig represents the significant level and N is the number of variables used.

	Renter	With Assistance	Below Poverty	Total Unemployed	Total No Education	No Husband W/ Own Kids	Income Less than $40000	African American	American Indian	Asian	Hawaiian / Native Pacific	White Caucasian
Offense2	0.427	0.468	0.344	0.289	0.547	0.387	0.425	0.597	0.277	0.218	0.017	0.184
Significant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.007	0.832	0.024
Variables	151	151	151	151	151	151	151	151	151	151	151	151
Offense3	0.400	0.428	0.317	0.302	0.553	0.422	0.401	0.630	0.285	0.215	-0.039	0.128
Significant	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000	0.008	0.630	0.117
Variables	151	151	151	151	151	151	151	151	151	151	151	151
Offense4	0.326	0.423	0.280	0.228	0.520	0.327	0.343	0.567	0.244	0.181	-0.008	0.086
Significant	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.003	0.027	0.925	0.296
Variables	151	151	151	151	151	151	151	151	151	151	151	151
Offense 5 or More	0.335	0.431	0.24	0.241	0.526	0.392	0.344	0.595	0.289	0.165	0.024	0.085
Significant	0.000	0.000	0.003	0.003	0.000	0.000	0.000	0.000	0.000	0.043	0.769	0.300
Variables	151	151	151	151	151	151	151	151	151	151	151	151

No wife with own kids, income $40,000 to $99,999, $100,000 and above, without public assistance, and owner occupied were the variables eliminated before using a linear regression analysis. After elimination of non-significant variables, creations of five profiles with the demographic variables were created (Figures 5 – 9).

Profiles

The five profiles consisted of renter occupied, with public assistance, below poverty, unemployed, no high school diploma, no husband in household, income less than $40,000 and the changing variable in each profile was ethnicity. The five different ethnicities used were; African American criminal profile (Profile 1 (P1)) Figure 5),

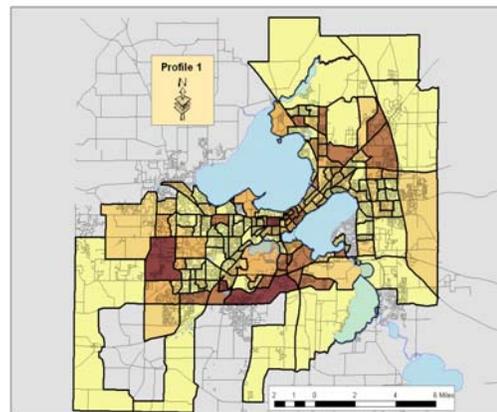American Indian criminal profile (Profile 2 (P2)) (Figure 6),

Figure 5. Dark brown represents common area of criminal profile P1 (African American) where light brown represents lower values of.

Asian criminal profile (Profile 3 (P3)) (Figure 7), Hawaiian/Native Pacific

criminal profile (Profile 4 (P4)) (Figure 8), and White Caucasian criminal profile (Profile 5 (P5)) (Figure 9).

After creating and evaluating the profiles, the profiles revealed minimal qualitative difference. With the profile independent variable measured against the offense data dependent variable, linear correlation was undertaken to quantify relationships.
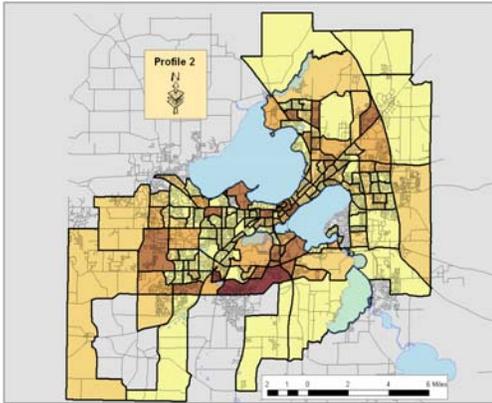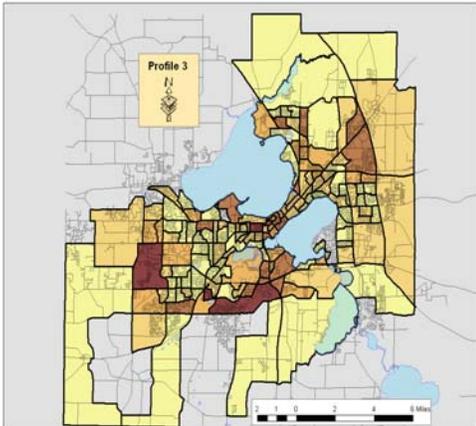

Figure 6. Dark brown represents common area of criminal profile P2 (American Indian) where light brown represents lower values of.

Figure 7. Dark brown represents common area of criminal profile P3 (Asian) where light brown represents lower values of.

Results from the linear correlation analysis (Table 2) reveal a highly significant correlation between demographics (underlying factors) and repeat violent offenses.
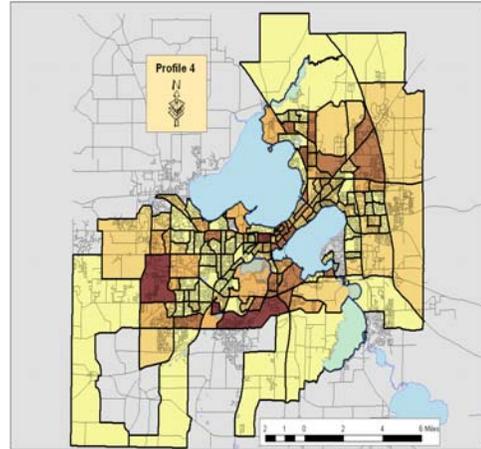

Figure 8. Dark brown represents common area of criminal profile P4 (Hawaiian/Native Pacific) where light brown represents lower values of.
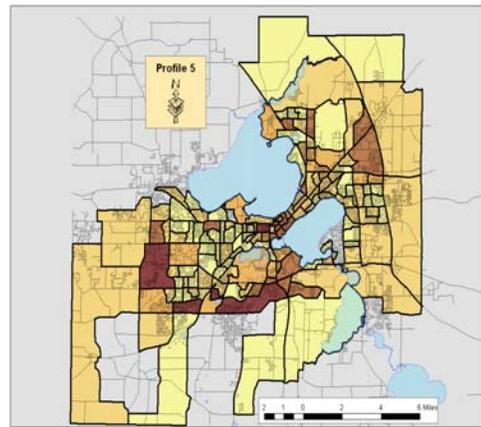

Figure 9. Dark brown represents common area of criminal profile P5 (White Caucasian) where light brown represents lower values of.

Results

GIS and statistical results show that a correlation exists between demographic characteristics and repeat violent offenses. By creating profiles, significance between repeat violent offenses and social demographics can be determined.

Spatial Analysis

Spatial analysis processes consisted of creating layers for K-Means clusters of

repeat violent offenses as well as density layers of demographic profiles. By converting the demographic vector layers into raster layers and adding each layer together to represent each profile, spatial correlation between the profiles and the repeat violent offenses created a suitability layer where repeat offenses were most likely to occur.
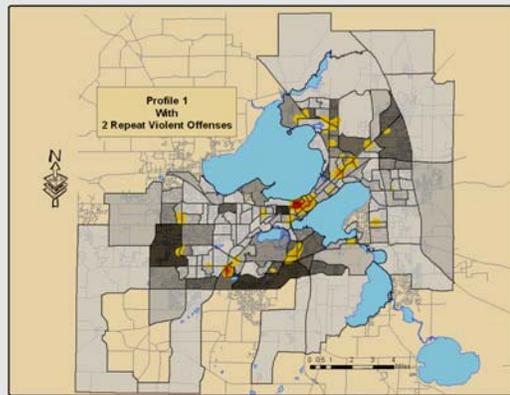

Figure 10. Dark gray represents high areas of the African American criminal profile (P1) where light gray represents lower values. The dark red to yellow represents the case of two repeat violent offenses.
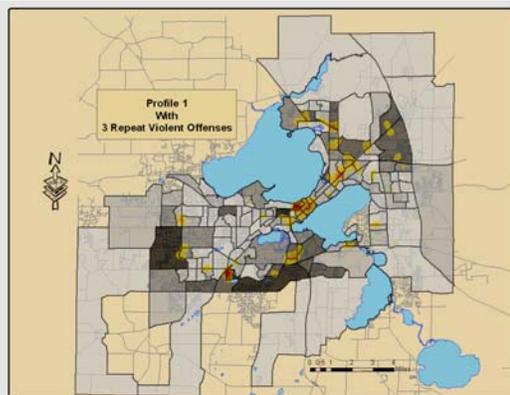

Figure 11. Dark gray represents high areas of the African American criminal profile (P1) where light gray represents lower values. The dark red to yellow represents the case of three repeat violent offenses.

When examining the African American criminal profile (P1) with the repeat violent offense layers, the areas of high occurrences of repeat offenses appear to be largely occur in similar areas (Figures 10 – 13).

For spatial perspective to visualize location, the criminal profile/repeat offense information is overlain on census block group boundaries. Visually, one can see that where there are high occurrences of the African American criminal profile (P1), there also exists a high level of repeat offenses.
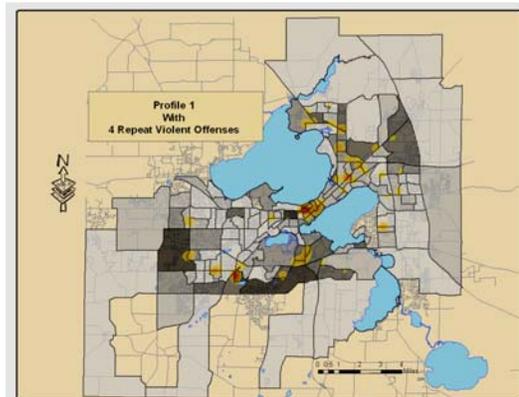

Figure 12. Dark gray represents high areas of the African American criminal profile (P1) where light gray represents lower values. The dark red to yellow represents the case of four repeat violent offenses.
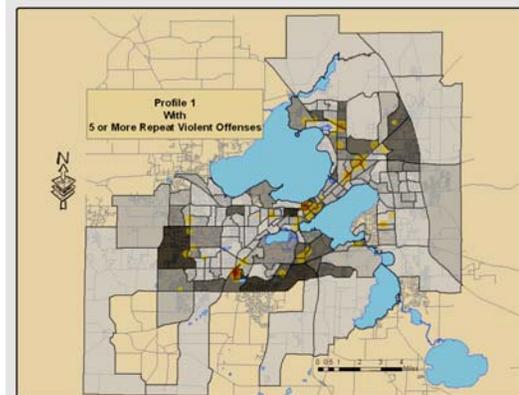

Figure 13. Dark gray represents high areas of the African American criminal profile (P1) where light gray represents lower values. The dark red to yellow represents the case of five or more repeat violent offenses.

Findings reveal that repeat offenses occur in areas where there is

low income, rental units, and no husband in the household. When examining repeat violent offenses (2 repeat, 3 repeat, 4 repeat, and 5 or more), the location of offenses become more evident with the African American criminal profile (P1). The same observations hold true for the other four profiles examined in this study as well.

Statistical Analysis

Linear correlation revealed a significant relationship between profiles and repeat violent offenders.

It is important to note that no one variable causes repeat violent offenses, but that there is some association between variables. The seven common demographics variables include the following: renter occupied, with public assistance, below poverty, total unemployment, total no high school diploma, no husband with own kids, and income less than $40,000 as well as ethnicity. The five ethnicities were the changing variable between profiles.

The repeat violent offense data were the dependent variables, and there were four of these including two repeated violent offenses, three repeated violent offenses, four repeated violent offenses, and five and more repeated violent offenses. Using SPSS, linear correlation was used to quantify the relationships.

Correlation values (r-values) were quite consistent and ranged from .645 to .671 (Tables 3-7). Higher the r-value indicates stronger relationships between variables. The r square statistics is the Coefficient of Determination. An r square value of 1 indicates that the independent variable explains 100% of the variation noted in the dependent variable.

In this study, the correlation analysis regularly explained about 40% of the variation noted. As a whole, while the r square was not perfect, it did indicate that the demographic signature of this study did a good job of explaining much of the variability noted in the repeat violent offense data.

Table 3. Correlation values for the African American criminal profile (P1).

African American Criminal Profile	
TEST	VALUES
R Value	0.671
R Square	0.450
Adjusted R Square	0.419

Table 4. Linear Correlation values for the American Indian criminal profile (P2).

American Indian Criminal Profile	
TEST	VALUES
R Value	0.645
R Square	0.416
Adjusted R Square	0.383

Table 5. Correlation values for the Asian criminal profile (P3).

Asian Criminal Profile	
TEST	VALUES
R Value	0.646
R Square	0.417
Adjusted R Square	0.384

Table 6. Correlation values for the Hawaiian/Native Pacific criminal profile (P4).

Hawaiian/Native Pacific Criminal Profile	
TEST	VALUES
R Value	0.465
R Square	0.416
Adjusted R Square	0.383

Table 7. Correlation values for the White Caucasian criminal profile (P5).

White Caucasian Criminal Profile	
TEST	VALUES
R Value	0.645
R Square	0.416
Adjusted R Square	0.383

Other factors undoubtedly have an impact on the repeat violent offense occurrence too, but linear correlation demonstrates that there is a relationship between demographics and repeat violent offenses.

When using all five profiles and the four different repeat violent offense data sets, the African American criminal (P1) had the highest correlation values and the American Indian criminal (P2) and the Hawaiian/Native Pacific criminal profile (P4) had the lowest correlations, but all were statistically significant (Table 8).

Table 8. The table displays regression between the repeat violent offense variables and profiles.

	2 O	3 O	4 O	>= 5 O
African American	.671	.679	.623	.630
American Indian	.645	.587	.578	.640
Asian	.646	.640	.578	.586
Hawaiian / Pacific	.645	.640	.578	.587
White Caucasian	.645	.647	.579	.591

By classifying the African American profile (P1) with the highest correlation as the most significant profile with repeat violent offenses, it indicates the underlying demographics characteristics have influence in the underlying cause of repeat violent offenses. The most significant correlations through all repeat violent offenses were for the African American criminal profile (P1) and the White Caucasian criminal profile (P5). It is apparent that higher incidences of repeat

violent offenses occurred in neighborhoods that have low income (less than $40,000), no completion of school, poverty, no husband in household, unemployed, and rental units.

By combining the results from the spatial analysis and the statistical analysis, there is strong suggestion that social disorganization factors such as low-income, house tenure, education, employment, assisted living, and race, among others, have influence on repeat violent offenses.

Discussion

During the course of this study, there were problems that were encountered. Querying selection of repeat violent offenses was one of the problems. After individuals and violent offense data were joined into one table, queries for repeat offenses were created. Initially this query caused problems due to fact that some offenses were listed more than once for the same case file. It was also important to make sure the suspect name and date of birth were the same for the repeat offenders. Further, in order to successfully geocode the offense data, records needed to contain addresses within the City of Madison. In some instances, street name spelling and street suffix created difficulties.

Conclusion

When studying crime, there are not many different ways to examine the offense location and the underlying contributing causes. In general, by studying crime, one can infer that crime occurs in neighborhoods that have a society status consisting of low-income/troublesome areas. Many other researchers have found that crime occurs

where opportunity and rewards are highest.

In order to decrease the likelihood of crime, it is beneficial to develop programs such as cop shops where people of the area become active with law enforcement to help prevent crime. The cop shops will also build relationships between law enforcement and residents. Areas identified in this study include: the area around Carling Street - Allied Drive, areas around and including State Street, Washington Ave – Commercial – Hauk, Northport – Browning, and between Badger – North/Bram as these areas are high in repeat violent offenses.

These crime-rich areas might also benefit from social services' programs. In addition, care and maintenance of area curb appeal could have a positive impact on and deter repeat violent offenses. With area improvement, it could bring more business, homes, parks, city growth, and improved expectations of citizenry and value of surrounding neighborhoods. Other suggestions for these areas might include neighborhood-sponsored events, such as neighborhood education activities and neighborhood watch, which would get the community involved and could instantiate change around these areas.

Suggestions for Future Research

When scoping this study, there were many directions that could have been explored. There were 67,966 total violent offense records identified; this study only evaluated 5,803 of these. Others could be evaluated to learn more about criminal behavior in the Madison area.

Additionally, in this study only limited suite social-demographics characteristics were used. Thus, this project serves as beginning of analysis and exploration. Suggestions for future analysis could be to analyze crime by the breakdown of ethnicity, sex, how many cases have been cleared by arrest, open-case status, age of the offenders, day of the week the offense took place, and what offenses were most common.

Home addresses were included in the offense data and it would be interesting to see if travel distance was involved. If there was, was the location of where the offense occurred on a known path of the offender? By also considering the home address, did the offender travel to a neighborhood that had similar characteristics as his or her own, or is it different? If so, in what ways are the locations of the offense and home the same or different?

Acknowledgements

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