Using geographical information systems to effectively organize police patrol routes by grouping hot spots of crash and crime data

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ABSTRACT

Applying Data-Driven Approaches to Crime and Traffic Safety (DDACTS) can help police departments allocate limited resources more efficiently. By focusing on hazardous areas, highly visible traffic law enforcement can reduce crime and crashes simultaneously. Most studies have focused on the reduction of crime and crashes after applying new patrol routes, but few have documented how to improve or change police dispatch time. The objective of this study was to compare the police dispatch time between two conditions: (1) Police patrol routes with organized hotspots; and (2) Police patrol route patterns without focusing on hotspots. A secondary objective consisted of developing a procedure describes the calculation of the change in dispatch time.

This study used data obtained from the College Station Police Department. Crime and crash data were collected between January 2005 and September 2010, which included 65,461 offense reports and 14,712 crash reports. The proposed study procedure included four steps: (1) Geocoding data, (2) defining hotspots, (3) organizing the best patrol routes, and (4) estimating the effectiveness. ArcGIS was used for the data analysis. The results indicated that using DDACTS principles can potentially reduce police dispatch time by 13% and 17% when the top 5 and top 10 hotspot routes are included in the analysis, respectively. The procedure can be used by law enforcement agencies to estimate whether or not the DDACTS protocols can be an effective tool for reducing law enforcement dispatch times when crash and crime data are analyzed simultaneously.

Keyword: Kernel Density, DDACTS, HotSpots, Cluster pattern, Crash and Crime

1. Introduction

Traffic crashes and crime events are known threats to public safety. According to statistics obtained from the National Highway Traffic Safety Administration (NHTSA) and the Federal Bureau of Investigation (FBI), there are about 32,000 to 35,000 traffic crash fatalities, 2.2 million crash-related injuries, and 1.3 million violent crimes reported annually. As documented in Naumann et al. (2010) and FBI statistics (FBI, 2012), motor-vehicle crashes and crimes have significant social costs.

Law-enforcement officers play a very important role in improving traffic safety and reducing crime rates. For the former, law enforcement officers can provide a proactive approach by conducting an effective police patrolling (e.g., identifying and pulling over driving-while-intoxicated (DWI) drivers before they are involve in crash), while engineers
can devote more efforts on other critical issues, such as detection of hotspots. For example, Yannis et al. (2007) has shown that there is a significant inverse spatial dependence between crashes and enforcement, and the intensification of police presence can reduce crashes related to the human element, such as speeding or impaired driving. However, some police departments face significant challenges in providing effective enforcement strategies because of increasing police-service demands, growing operational costs, and shrinking budgets. Additionally, many police departments focus their staffing workload productivity on production instead of concentrating solely on traffic safety aimed at reducing collisions. As a result of this trend, officers tend to choose enforcement locations where they can write a greater volume of citations instead of patrolling locations where their actions could more effectively reduce motor vehicle crashes (Weiss and Morckel, 2007).

The purpose of this study is to describe the development of an optimal police patrol route concentrating enforcement efforts in areas characterized by high crime rates and crash risks. By adopting this optimization scheme, law enforcement agencies can allocate limited resources to more efficiently and collectively address public safety. The two primary reasons law enforcement agencies should consider addressing crime and crash data together are: (1) highly visible traffic enforcement can simultaneously reduce the crime rate and traffic crash rate, and (2) dispatch times can be reduced and managed more efficiently.

2. Literature Review

2.1 Related Programs

The idea of combining crime and crash data for law enforcement departments is not new. Data-Driven Approaches to Crime and Traffic Safety (DDACTS) is a national initiative developed by the National Highway Traffic Safety Administration (NHTSA), the Bureau of Justice Assistance (BJA), and the National Institute of Justice (NIJ). Presently, six cities in the United States are using DDACTS protocols, and have generally resulted in positive results and public praise. In optimal conditions, crime rates have been found to decrease by about 41%, while motor-vehicle crashes have been observed to be reduced by 31% (Hardy, 2010). With the help of a geographical software program, such as ArcGIS, CrimeStat, or CrimeView 9 for hotspot analysis, law enforcement agencies are able to effectively target criminal activities and traffic crashes in an effort to proactively address community issues (Hardy, 2010). Table 1 provides an illustration of how DDACTS has impacted crime rates and traffic safety in six different implementation sites around the United States.
### Table 1
The DDACTS results from six demonstration sites.

<table>
<thead>
<tr>
<th>Demonstration Site</th>
<th>Results</th>
<th>Software</th>
</tr>
</thead>
</table>
| Baltimore, Maryland        | 1. Crime: Burglaries decreased by 16.6%, robberies decreased by 33.5%, vehicle thefts decreased by 40.9%  
2. Crash: Crash-related injuries decreased by 0.2%, total crashes decreased by 1.2% | ArcGIS, CrimeStat |
| Nashville, Tennessee       | 1. Crime data: Uniform Crime Reporting (UCR) Part 1 crime decreased by 13.9%, and DUI arrests increased by 72.3%  
2. Crash: Crash-related injuries decreased by 30.8%, fatal crashes decreased by 15.6% | ArcGIS7, CrimeView9 |
| Rochester, New York        | 1. Crime: Homicides decreased by 36% and the rate of vehicle theft was the lowest.  
2. Crash: Crashes reduced by 6% (374 crashes). | ArcGIS (Spatial Analyst) |
| Reno, Nevada               | 1. Crime: Burglaries decreased by 21%; vehicle thefts decreased by 8%; assaults decreased by 6%  
2. Crash: The observed crash number was too small to analyze. | unknown |
| Lafourche Parish, Louisiana| 1. Crime: DDACT area saw a lower crime rate (1.6%) than in the other adjusted area (2.3%).  
2. Crash: Crash-related injuries decreased by 11% ~14.7% in subarea. | unknown |
| St. Albans, Vermont        | 1. Crime: vandalism decreased by 27%, fraud decreased by 29%, assaults decreased by 37%, and burglaries decreased by 38%.  
2. Crash: Crash-related injuries and fatalities decreased by 19 %, and crash-related incidences of property damage only (PDO) decreased by 21% | unknown |

Source: (Hardy, 2010)

While DDACTS principles appear to provide impressive results, the authors found that use of both exaggerated study areas and a Naïve Before-After evaluation method in the program may lead to a bias estimate regarding its true effectiveness as described below.

- **Exaggerated Study Area:** In some community sites, crime and crash data are summarized at the city or county level instead of using actual DDACTS data ranges. Exaggerated study areas may bias the estimation of the DDACTS program effectiveness because of the reduced effect of treatment outside of the applied treatment areas. For example, if the study area is close to the DDACTS application area, a true estimation of the effectiveness of DDACTS should be close to the real value. However, if the city boundary is chosen as a data collection range in comparison with the DDACTS application area, the effectiveness value may be skewed.

- **Using a Naïve Before-After Method:** The six study reports all used a Naïve Before-After evaluation method. This method compares the crash frequency between the before and after periods only, and it may overestimate the effectiveness of a treatment because of
site-selection bias (Hauer, 1997; Lord and Kuo, 2012). A more robust method for estimating the effectiveness of DDACTS as a public safety countermeasure would be to use the Empirical Bayesian (EB) method or a Control Group (CG) method to analyze crash data. In addition, using a Naïve Before-After method can only be examined using the Wilcoxon test, which makes limited quantitative statements about the differences between two non-normal distribution populations. In other words, the Wilcoxon test cannot show the effective size difference and there is no confidence interval for the estimated difference.

Results from current case study studies appear to be positive; however, their estimations of DDACTS’s effectiveness are limited because of the exaggerated study areas and inappropriate before-after evaluation methods. Care should be taken when interpreting previous study results as the reference values. Consequently, sensitivity analyses should be used to estimate the possible benefit of using DDACTS as a means of reducing crime and vehicular crashes.

2.2 Place-Based Theorem

Wilson (2010) noted that the B.F. Skinner’s theory of learning explains why crimes and crashes may occur in the same neighborhood even if there is no causal link between these two kinds of events themselves. According to the DDACTS guidelines, law-enforcement agencies should perform high-visibility traffic enforcement in their patrol routes with the objective of simultaneously reducing crimes and crashes. High-visibility traffic enforcement functions because of a general deterrent effect, which reduces driving-speed in enforcement areas due to the threat of legal consequence. Most people who fear arrest or detection are expected to drive more slowly and carefully. Due to the increased visible presence of traffic enforcement, criminals may also avoid illegal activity within these zones.

Locations where crashes and crimes occur in close proximity to each other show the highest effectiveness of DDACTS methods in reducing both crime rate and crash frequency. When crashes and crimes are distributed randomly or the hotspots are farther from each other, DDACTS methods are not as effective.

2.3 Reducing Dispatch Time

The DDACTS reduces dispatch time by lowering crashes and crime rates. Figure 1 provides an illustration of dispatch time and the influence of DDACTS. If police patrol patterns prevent some crashes and crimes such as those at points 3, 4, 5, and 6 in Figure 1, this reduces total dispatch time from $T_{\text{before}}$ to $T_{\text{after}}$. In short, DDACTS patrol patterns are economically feasible with regards to time when the police patrol time ($T_{\text{patrol}}$) is shorter than the savings linked to the dispatch time ($T_3 + T_4 + T_5 + T_6$).
2.4 Hotspots

Numerous studies exist with regards to how to define hotspots of crashes and crime individually; however, few have combined crash and criminal data together. This study focused on a disaggregated data analysis methodology because of the necessary accuracy needed to define police patrol routes. Studies that define hotspots using aggregated data, such as zip code area, city, county, and state, are not discussed here.

2.4.1 Identifying Crash Hotspots

Before commercial GIS software programs were available, traffic safety analysts tended to use traditional statistical tests to define hotspots that experienced significantly higher crash rates. The use of traditional statistical methods are inconvenient and inefficient, because traffic engineers must separate road networks into multiple segments with equal lengths (if possible), record crashes for each segment length, apply the statistical methods such as Chi-square test or the equivalent property-damage-only method (see WRA, 2003) to define hotspots, and show results via tabulated data. In addition, using traditional statistical methods will not show a geographical relationship between crashes and other environmental variables.

GIS software programs simplify this procedure and minimize the above problems by providing graphical data points that can be used for mapping. They have remained one of the most popular tools for visualization of crash data and hotspot analysis (Harkey, 1999; Petch and Henson, 2000; Loo, 2006; Li et al., 2007). Schneider et al. (2004) provided an excellent review of the methods, findings, and problems related to using GIS for traffic-safety analyses. Previously, some crash datasets were recorded in textual or tabular formats. These datasets required transformation into geographic data before applying GIS software programs.
Traditional Numerical Methods and GIS Spatial Methods

Repeatability analysis is a common procedure in numerical methods, while the Kernel Density Analysis and other spatial-autocorrelation analyses (e.g., Getis-Ord analysis (Gi*)) are commonly used in GIS spatial methods (Black and Thomas, 1998; Flahaut et al., 2003; O’Sullivan and Unwin, 2003; Schneider et al., 2004; Pulugurtha, et al. 2007; Erdogan et al., 2008; Gundogdu, 2010; Steenberghen et al., 2010; Kingham, et al., 2011). In repeated analyses, hotspots are commonly defined as the locations where the top 5% or 1% of the number of crashes occurred. Crashes for each site are assumed to follow a Poisson distribution with mean crash rate $\lambda$, which is estimated by dividing the total number of crashes in a given study area by the segment number. The probability of each site having $x$ number of crashes $P(x)$, can be shown as follows,

$$P(x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

(1)

In other words, if a site has more than $x_{95\%}$ or $x_{99\%}$ crashes, the site is labeled as a hotspot.

With the Kernel Density method, it is easy to calculate the risk density for each crash instead of showing the actual location for a given crash. For a site to be considered a hotspot, it needs to show a crash rate higher than a chosen threshold value. For instance, Erdogan et al. (2008) used a threshold where the number of crashes was five times larger than the crash mean).

Erdogan et al. (2008) compared the above methods with regards to their ability to define crash hotspots in Afyonkarahisar, Turkey. Their results suggested that the repeatability analysis identified more hotspots than did the Kernel Density, but they did not provide a reason for the difference. In a recent study, Gundogdu (2010) combined traditional numerical methods and Gi* analysis to examine hotspots in Konya, Turkey. Hotspots were defined as those sites having either the highest 5% crash frequency or Gi* value. They showed that using two comparative methods can improve the accuracy of identifying hotspots.

Initial Settings for the Kernel Density Estimation (KDE) Method

Compared to simple evaluation methods, the KDE method is an advanced analysis tool because it determines the expansion of crash risk, and an arbitrary spatial unit can be defined for the whole study area. However, two factors, bandwidth and cell size, may affect the outcome of the KDE. Anderson (2009) provided details for setting up the initial settings when the KDE is used to identify crash hotspots and their cluster patterns. The bandwidth
size range is subjective, and the value of the bandwidth and cell size may be adjusted using other conditions, such as the study area or data characteristics.

2.4.2 Crime Hotspots

The theoretical work for defining hotspots in criminal activity is more complex than the methods used for traffic study areas, and crime-analysis software applications have been previously developed. Besides ArcGIS, common software packages for crime-data collection include CrimeStat, Spatial Analysis, HotSpot Detective, Vertical Mapper, Crime View, and SpaceStat (Schneider et al., 2004; Eck et al., 2005; Erdogan et al., 2008;). Most geographical-profiling software packages are used for analyzing serious crimes committed or for analyzing several crime locations linked by similar criminal characteristics. While crime and crash incidents are committed by different people, we decided to use ArcGIS software for conducting the analyses. In addition, the KDE is one of the most common hotspot mapping methods because of its consistency in predicting crime data and better visualizing output (Chainey et al., 2005; Chainey et al., 2008).

2.5 Summary

While the majority of DDACTS studies focus on the reduction of crime and crash rates after application of modified patrol routes, this study focuses on the change and/or improvement of police dispatch time. There is no step-by-step procedure in the literature that can currently calculate the change in dispatch times. Since there are no appropriate study results that can be used as a baseline of effectiveness for DDACTS, a sensitivity analysis was used. Traditional methods (frequency analysis) and geographical methods (KDE and Gi*) were also utilized for identifying hotspots. It was anticipated that combining the above methods would provide more accurate results (Flahaut et al. 2003; Schneider et al., 2004, Gundogdu, 2010). The Average Nearest Neighbor (ANN) and Gi* were used for further evaluating clustered patterns since locations where crashes and crimes occur need to be in close proximity, as discussed above. All the analyses were conducted in ArcGIS.

3. Material and Method

The study area was limited by the service area of the College Station Police Department. College Station is a mid-sized college town located in Central Texas, with a population of about 100,000. Data were collected for the time period between January 2005 and September 2010. All crime and crash data were provided by the College Station Police Department (CSPD). There were 65,461 crime offense reports and 14,712 crash reports spanning
The road-shape file, “All line Data,” was downloaded from the Census Bureau's MAF/TIGER database website. The road network in College Station is relatively simple, with the major arterial road network following a grid pattern. There are no complex interchanges located inside the city limits. Figure 2 shows a detailed roadmap of the city. The Coordination System used was the GCS North America 1983.

The procedure can be separated into four steps: (1) Geocoding data, (2) identifying hotspots, (3) defining optimal best patrol routes, and (4) estimating effectiveness. The steps are described in detail below.

![Map of College Station, TX](http://maps.google.com/)

**Fig. 2.** Map of College Station, TX. Retrieved on Oct 14, 2012 from website http://maps.google.com/

**3.1 Data Geocoding**

The first step, geocoding, consists of transferring information on crash and crime data from a tabular format to a geographic format based on address information. The initial matching rate for the crime and crash data was only 70%, because the datasets included abbreviations and alternative street names (e.g., some intersections have three or more street names or segments are known under different names). Hence, the authors had to change
abbreviations to full street names and add the alternative street names in the address locator. The rematch rates for the crime and crash data subsequently increased to 90%.

3.2 Defining Hot Spots

The second stage determined the location of the hotspots based on the crime and crash data. This study used three steps to define hotspots more accurately. The first step involved examining whether the data were clustered or not. If crimes and crashes occurred randomly, then high-visibility traffic enforcement may not work, since there would be no hotspots to focus on. We then summarized the frequency of each crime and crash event to remove data-point overlap. The actual frequency can be used for further statistical analysis. Finally, drawing the kernel density surface shows the continuous possibility of crimes and crashes in the study area. Hotspots could then be easily identified by the colored areas with high KDE values.

3.2.1 Cluster Index

The Average Nearest Neighbor (ANN) and the Gi* are the two main methods used for checking whether crimes and crashes are clustered or not. The difference between these two methods is that the ANN returns an overall value that represents the concentration ratio of all points, while the Gi* can be used to define the actual locations where hotspots or coldspots were clustered together (as defined by various colors). The following sections introduce the theory and equations to apply those methods.

- Average Nearest Neighbor (ANN)

The ANN is a nearest neighbor index based on the average distance from each point to its nearest neighboring point. Equation (2) shows the calculation for the ANN.

\[
ANN = \frac{\bar{d}}{\bar{\delta}} = \frac{\bar{d}}{0.5 \times \sqrt{A/n}}
\]

Where,
- \(\bar{d}\): The average nearest neighbor distance,
- \(\bar{\delta}\): The average random distance,
- \(A\): The area of the study region and,
- \(n\): The number of points.

If the ANN is less than 1, the data contain a clustered point. However, the ANN value can only be interpreted when the Z-score is significant. If the Z-score is not significant, the ANN value means nothing because it might occur by random chance.
• Getis-Ord (Gi*)

The Getis-Ord (Gi*) can measure the concentration ratio of high or low values for the study area. Large Z-values (positive, such as +100) mean hotspots are clustered together, while low Z-values (negative, such as -100) indicate coldspots are clustered together. Equations (3) to (5) show the calculation for the Gi* and Z values.

\[
Gi^*(d) = \frac{\sum_{j} W_{ij}(d)X_j - \bar{X} \sum_{j} W_{ij}(d)}{S \sqrt{\left[N \sum_{j=1}^{N} W_{ij}^2 - \left( \sum_{j=1}^{N} W_{ij} \right)^2 \right] / N - 1}}
\]

\[
\bar{X} = \frac{\sum_{j=1}^{N} X_j}{N}
\]

\[
S = \sqrt{\frac{\sum_{j=1}^{N} X_j^2}{N} - \left( \bar{X} \right)^2}
\]

Where,

- \( Gi^*(d) \): The Gi* value of distance \( d \),
- \( W_{ij}(d) \): One, when \( d \) is less than the threshold value, otherwise is zero,
- \( X_j \): The frequency at location \( j \), and
- \( N \): The number of the points.

This study used only the Getis-Ord index to show the cluster patterns for crime and crash data, but further studies could use the Gi* to compare different types of crime (e.g., robbery, DWI, gun-related), different time periods (e.g., day and night, weekday and weekend), or different levels of severity of crashes.

3.2.2 Calculating Frequency

The problem of point overlap causes difficulties in recognizing hotspots when observing point maps, especially for the high-point-density areas. For solving this overlap problem, the authors used the “Collect Event” function to calculate the frequency for each cell. The results were used to generate new maps that have points with different radii. Points with large radii represent higher frequencies of events.
3.2.3 Kernel Density

Kernel Density mapping is one of the most common methods for defining hotspots for crime and crash data, because it details a smooth and continuous surface map of risk targets in the study area (Chainey et al., 2002; Plug et al., 2011). The Kernel Density calculates the density of events around each point, scaled by the distance from the point to each event. The basic principle of the Kernel density is to calculate the density around each point instead of showing the actual location of each point. This method is resilient to uncertainty in event location, so is more appropriate when the location of the points (crash data) have a level of uncertainty when they are recorded on a map (usually 0.1 mile). The density of events is highest when the distance from the point is zero and the density decreases when the distance increases. The detailed calculation of the Quartic Kernel Density function is (Silverman, 1986):

$$K(u) = \sum_{d<\tau} \frac{3}{\pi \tau^2} \left(1 - \frac{d^2}{\tau^2}\right)^2$$  \hspace{1cm} (6)

Where,

- $K$: Kernel density value,
- $d$: The distance from event and,
- $\tau$: Bandwidth.

3.3 Optimum Route

For organizing the optimal patrol route, another ArcGIS extension, “Network analysis,” was used to connect hotspots via the shortest distance. Detailed street data were used to build the network database, and then the top 5 and top 10 hotspots were assigned as the necessary stops for two patrol routes. We defined the hotspots as coincident, high-event density areas in the frequency, KDE, and Gi* maps.

3.4 Estimating the Effectiveness

The effectiveness of applying a new police patrol route was estimated by calculating the difference between the dispatch time in the before and after time periods (see Equation 7). However, two assumptions were made for ease of calculation and limitations in the data:

- Based on a neutral assumption, crime and crash rates are reduced by 50% in the effect area (within a patrol route of 500 feet) in the after period. Since current studies cannot
provide precise estimations as to the effectiveness and the effect area, a sensitivity analysis needs to be performed to better estimate different scenarios. The effectiveness varied between a reduction of 25% to 75%, and the effect area was changed between 250 and 1,000 feet.

● The average dispatch time to each event point in the before period and in the after period is the same. Hence, the calculation using Equation (7) depends on the frequency of crimes and crashes. This assumption was based on two important factors. The first is attributed to data limitations. In practice, law-enforcement officers are usually on stand-by inside their own coverage zones rather than located solely at the police station during their shift. Unfortunately, the actual stand-by locations and work-shift periods are not known or available to the public for security reasons. Without this information, the average dispatch time was assumed to be the same between the before and after periods since the distance between the patrol route and stand-by locations of individual patrol areas are unknown. The second reason is to minimize the convergence of optimization time. If one assumes that all officers are on stand-by at the police station and calculates the actual dispatch time for all available points, the convergence time will be increased significantly due to the large dataset. However, since the objective of this study is to develop an easy-to-use procedure, the law enforcement agencies should be able to get better estimates of the effectiveness by including the exact stand-by location of their police officers in their jurisdictions. Based on these assumptions, the estimated effectiveness is given by

\[
\theta (\%) = \frac{\sum_{i=1}^{n} T_{i, after} - m \times \frac{\sum_{i=1}^{m} T_{i, before}}{m}}{\sum_{i=1}^{n} T_{i, before}} = \frac{n \times \bar{T}_{i, after} - m \times \bar{T}_{i, before}}{m \times \bar{T}_{i, before}} = \frac{n-m}{m} (\because \bar{T}_{i, after} = \bar{T}_{i, before}) \quad (7)
\]

Where,

\( \theta \) : The effectiveness of new police patrol route,

\( T_{i, before}, T_{i, after} \) : The dispatch time to point i in the before and after periods,

M: The number of events in the before period and,

n: The number of events in the after period.

It should be noted that previous studies assumed the same effectiveness for the entire study area; however, in this study, it was hypothesized that a police patrol route only works in the effect area. In other words, the crime and crash rate will not change outside the effect area because the visibility of law enforcement decreases with distance.
4. Application, Results and Discussion

The first step is for the geographic crime and crash data to be geocoded. Figure 3 (a) shows the point map of crimes in College Station, while Figure 3 (b) shows a magnified section of the map. It is difficult to judge which regions should be called hotspots, due to overlap between data points. The crash data suffered from the same limitation. As such, the frequency and KDE maps are necessary for defining hotspots. The next step is to define the cluster pattern for crime and crash data using the ANN. Table 2 shows the ANN values and the Z-scores. The data are clustered when the ANN value is less than one, and when the Z-score is used to evaluate its statistical significance. The results also show that the two types of data are both clustered, with crimes being more concentrated than crashes.

Fig. 3. (a) Crime map in College Station and (b) a magnified section of the map.

<table>
<thead>
<tr>
<th></th>
<th>ANN (NRR, Z)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crash</td>
<td>Cluster (0.08, -198.5)</td>
</tr>
<tr>
<td>Crime</td>
<td>Cluster (0.05, -455.8)</td>
</tr>
</tbody>
</table>

Figures 4 (a) and (b) show the frequency maps for the crime and crash data. The points with a larger radii represent higher incidences of crashes or crimes in that cell. Similarly to the discussion documented in the Methodology Section above, this function solved the overlap problem, but it was still difficult to determine true hotspots. Consequently, we created Kernel Density maps for the crash and crime data individually (Figure 5). From these two figures, it is easy to define their hotspots using different colors. Cold colors (i.e., purple and blue) in the crash map and warm colors (i.e., red and yellow) in the crime map represent
the hotspots. Also, the locations of these hotspots are in close proximity to each other. In other words, the crashes and crimes are not only clustered together, but they also have a spatial relationship between each other. Furthermore, the results from the Gi* analysis support this finding (Figure 6). Warm colors represent where the hotspots are clustered, while cold colors represent where the cold areas are clustered. Because of this, crime and crash data were combined together into one database, the Kernel Density and Gi* maps redrawn, and the frequency layer was then added. The weight of two types of points are equal because the dispatch time for crimes and crashes for same distance is identical. Further research can be used to change the weight based on study objectives used by the law enforcement agency. The results show that hotspots with a higher event frequency and hotspots from the Kernel Density and Gi* maps coincide. These points are marked with red circles and are defined as the final hotspots.

**Fig. 4.** Frequency maps of crimes and crashes in College Station.
Fig. 5. Kernel density maps of crashes and crimes (all data).
Fig. 6. Gi* (P-value) Maps of crashes, crimes, and all data.
The top 5 hotspots and top 10 hotspots were designated as the necessary stops in police Patrol Routes 1 and 2. The street file was downloaded from the College Station GIS Department and was used for building the network database. Network Analyst, another ArcGIS extension, was used to organize the optimal patrol routes based on the shortest travel distance, since the shortest travel time could not be used due to a lack of data regarding speed limits and traffic delays. Since this work was performed, more advanced route-choice toolkits are now offered, such as the route-choice analysis developed by Papinski and Scott (2011). Rural police departments lacking detailed road GIS files or that do not hold extra funding to purchase the ArcGIS extension Network Analyst, could potentially use free online resources such as Google Maps to organize the optimal patrol routes. Figures 7 and 8 show the ArcGIS and Google Maps results; it is interesting to note that Google Maps suggests the same routes as does ArcGIS. When real traffic conditions were considered, the travel time estimated from Google Maps was used. Also, CrimeStat, a free crime analysis package, provides several spatial analysis functions and may be a suitable choice for some police departments (see http://www.icpsr.umich.edu/CrimeStat/).

![Fig. 7. Optimal patrol routes developed from ArcGIS.](image-url)
Fig. 8. Optimal patrol routes suggested by Google Maps.

According to Equation (7), the total dispatch time may be reduced by 13% and 17%, respectively, for Patrol Routes 1 and 2 for the average conditions. For optimistic conditions (i.e., the largest effectiveness and widest effect area), the total dispatch time may be reduced by 36% and 44%, respectively, for Routes 1 and 2. Under pessimistic conditions (i.e., the lowest effectiveness and narrowest effect area), the total dispatch time may be reduced by 6% and 7%, respectively, for the same two routes (see Table 3 for detailed results). The patrol travel times are estimated to be equal to 21 minutes and 33 minutes using Google Maps. However, in this study, the patrol travel time to estimate the effectiveness was not used since the actual dispatch time for all points would have prohibitively lengthened computation time. A better approach for applying the procedure described above is to compare the patrol travel time and the decreases in dispatch time. For example, the total dispatch time of all police officers in CSPD was assumed to be 5 hours per day, but by applying Route 1 the dispatch time was reduced by 39 minutes (=5*60*13%) for average conditions. Hence, it would be beneficial to apply this new patrol route to reduce total dispatch time.

Table 3
Sensitivity analysis of the dispatch time-reducing ratio.

<table>
<thead>
<tr>
<th>distance (ft)</th>
<th>effectiveness</th>
<th>effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route 1 (p=5)</td>
<td>25% 50% 100%</td>
<td>Route 2 (p=10)</td>
</tr>
<tr>
<td>250</td>
<td>6% 11% 22%</td>
<td>250</td>
</tr>
<tr>
<td>500</td>
<td>6% 13% 26%</td>
<td>500</td>
</tr>
<tr>
<td>1000</td>
<td>9% 18% 36%</td>
<td>1000</td>
</tr>
</tbody>
</table>

5. Conclusions and Suggestions

While most DDACTS studies have focused on reducing crime and crash rates, this study focused on reducing police dispatch times. In this regard, this study described important problems with existing DDACT studies: using exaggerated study areas and a Naïve before-
after evaluation method. To overcome these problems, a sensitivity analysis was used. Consequently, this study documented a step-by-step procedure that shows how to calculate a change in dispatch times by determining optimal patrol routes based on crime and crash rate densities. For police departments that face important enforcement challenges (e.g., budget restraints), this procedure can be used to estimate whether or not the DDACTS is an effective tool for reducing law-enforcement dispatch times. If law-enforcement officers adopt effective police patrol routes to reduce the number and severity of certain categories motor-vehicle crashes, then traffic engineers and other stakeholders can concentrate their effort in other areas where crashes can be reduced (e.g., new signal timing, application of roadway countermeasures).

This study showed that crashes and crimes in College Station, TX are clustered data, and that their hotspots lie in close proximity to each other. These results are consistent with those documented in previous studies (Wilson, 2010; Hardy, 2010). Applying two police patrol routes based on the location of the top 5 and top 10 hotspots for crimes and crashes can reduce police dispatch time by 13% and 17%, with the patrol travel times equal to 21 minutes and 33 minutes, respectively. For optimistic conditions, that is, the largest effectiveness and widest effect area, the total dispatch time may be reduced by 36% and 44%, respectively, for Routes 1 and 2. For pessimistic conditions, that is, the lowest effectiveness and narrowest effect area, the total dispatch time may be reduced by 6% and 7%, respectively, for Routes 1 and 2. However, in this study, the average dispatch times to each point in the before period and in the after periods were assumed to be the same for convenience purposes. Future research should take note of that particular limitation of this study. Another limitation for identifying hotspots of crash data is network restrictions, since crashes are limited to the road network, but other data (e.g., crimes) may happen anywhere, including areas without any direct road access. Future research may apply the methods proposed by Steenberghen et al. (2010), Xie and Yan (2008), and Yamada and Thill (2004) to examine the difference between hotspots identified with or without network restrictions.

In order to show the complete procedure for calculating dispatch times, this study assumed several parameter values, such as the effectiveness of the patrol route, effect area, and patrol speed, among others. Additionally, default values of bandwidth in the KDE maps and cell size in the frequency maps were used. Other researchers might obtain different results if these parameters or default values are changed.

Spatial-time distributions to locate and designate hotspots are beyond the scope of the present work, as it is still unclear how different time distributions of crashes and crimes may change the effectiveness of DDACT. If crashes and crime are time-concentrated, such as DWI crashes related to alcohol and DWI violations, DDACT might function more accurately than the estimation method discussed herein. Otherwise, for time-diffuse data, installing a closed-circuit television (CCTV) camera or street lights may provide more effective solutions.
(Chainey and Ratcliffe, 2005). In addition, studying individual activities (drivers and criminals’ behaviors) might provide more information about the spatial-temporal characteristics of crashes and crime. Interested readers may refer to Shaw and Yu (2009) and McCullagh (2006) for the details about a proposed space-time GIS design tool. Future research topics might also include studying the relationships between specific crash and crime types and clustered hot spots to examine possible factors that influence these spots.

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Reference


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