Effectiveness of the Data-Driven Approach to Crime and Traffic Safety (DDACTS): A Cross-National Study

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Abstract

Data-Driven Approaches to Crime and Traffic Safety (DDACTS) integrate crash and crime data to design more efficient patrol routes for high visibility traffic enforcement. These new policies allow police to more effectively allocate their limited resources. Although the DDACTS model seems to work well in the United States, it is necessary to thoroughly study its effects before applying it in other parts of the world. Factors influencing crime, crashes, and police patrol systems in the United States may differ significantly from those in Asia. We have chosen Taiwan as our first area of study because of its open data policy.

Our research focused on two differences between the United States and Taiwan: (1) the cluster distributions of crash and crime events, and (2) the possible effectiveness of DDACTS in these two areas. ArcGIS was used to calculate point cluster patterns and identify hotspots.

The results showed that although the cluster patterns for crimes and crashes varied greatly between Texas and Taiwan, DDACTS may still be effective for improving patrol efficiency in this country. In the future, researchers in other countries will be able to use our results to revise and adjust their current DDACTS patrol plans.

Keywords: DDACTS, Hotspots, Police Patrol Route, Crash and Crime

1. Introduction

From the social harm perspective, crimes and traffic crashes are major threats to public safety. According to WHO statistics, approximately 1.25 million people die each year because of traffic crashes, and an additional 20 to 50 million are injured (WHO, 2009). Crime is also a universal social safety issue. For example, violent crime is responsible for 1.6 million deaths worldwide (WHO, 2002). Together, traffic crashes and crime are the leading causes of death among the young. Hence, it is crucial for police to develop an effective method of reducing these hazards. Previous studies have shown that the Data-Driven Approaches to Crime and Traffic Safety (DDACTS) method could simultaneously reduce both crash and crime rates if police officers engaged in highly visible traffic
enforcement and hotspots policing into their patrol plan. As a result, departments would be better able to allocate their limited resources so that officers could be at the right place, at the right time.

Although the DDACTS model has yielded positive results in the United States, it is necessary to verify its effectiveness before applying this approach in other countries. The characteristics of crimes, crashes, and police patrol systems in the United States may differ significantly from those in other countries, especially in Asia. For example, the traffic in most Asian countries is not primarily passenger cars but rather a mix of motorcycles, passenger cars, taxis, buses, bicycles, and pedestrians. Hence, the types of transportation modes involved in crashes, ratios of motor vehicle theft types, and corresponding crime and crash prevention policies may vary substantially. Taiwan was chosen as our test country, due to its open data policy; it was ranked number one in the Global Open Data Index by the Open Knowledge Foundation in 2016 (OKF, 2016). Scholars are able to access anonymized crash and crime datasets via an application; other Asian countries are more conservative about the data they release and related privacy issues.

This study illustrates the difference between using the DDACTS model in the United States and employing it in Taiwan. Although the cluster patterns of crime and crashes are different, DDACTS may still be useful for improving patrol effectiveness and reducing police dispatch times. There were three main goals of this study: 1) use local crash and crime data to examine the spatial distributions of these types of incidents in Taiwan; 2) determine if the relationship between crashes and crimes is similar (positively related) in Taiwan to what it is in the U.S.; and 3) determine if the DDACTS method would be as effective in Taiwan as it has been in the U.S.

2. Literature Review

2.1. DDACTS and Related Programs

DDACTS is a relatively new law enforcement model used in America. This innovative system utilizes a combination of crime and crash data with a focus on high risk areas to help officers design corresponding patrol routes for deterrence-based high visibility enforcement (Hardy, 2010). This model was developed by the National Highway Traffic
Safety Administration (NHTSA) first, and then NHTSA cooperated with the National Institute of Justice (NIJ) and Bureau of Justice Assistance (BJA) to support and promote DDACTS model nationwide.

Compared to traditional enforcement methods, DDACTS is more effective because it offers two key advantages: location-focused patrolling and diverse approaches to multiple operations systems (Weisburd & Eck, 2004). In traditional enforcement systems, police officers must react when they receive a service call. They rely on their forensic skills to collect evidence that is then used to solve crimes. However, this passive and event-reactive means of enforcement is both inefficient and cumbersome. A more advanced enforcement model, the Computer Statistics (Compstat), focuses on allocating limited enforcement resources to crime hotspots, which are determined via an analysis of crime data from recent years. In addition to focusing on hotspots, Weisburd and Eck (2004) also claim that if law enforcement officials embrace such a model, it will allow them to be more proactive and comprehensive; they will be able to cooperate directly with multiple authorities such as prisons, social welfare institutions, and departments regulating transportation.

DDACTS has already been used in several cities in the United States. Hardy’s study shows 41% reduction in crime and 31% reduction in crash by applying DDACTS program under optimal conditions (Hardy, 2010). Over 250 police agencies across the U.S. have participated in DDACTS training (NIJ, 2012). However, most DDACTS-related studies have been conducted by local law enforcement officers themselves; these practitioners have primarily focused on the implementation of detailed enforcement plans. In other words, their studies had a practical, results-oriented emphasis and were not focused on the generation of academic theories (NHTSA, 2014). Also, many DDACTS scholars have addressed the benefit of reducing traffic crashes and crime after adding new patrol routes; however, few have discussed the potential benefits of this system or conducted more advanced statistical analyses. Only Fell (2013) estimated the effects of increasing traffic enforcement on other types of crimes; his results showed a 17% reduction in drunk-driving, 32% reduction in burglary, and 29% reduction in car theft. Kuo et al. (2013) compared police dispatch times in two different scenarios: (1) when police officers patrol around hotspots, and (2) when they patrol randomly. The results show that hotspot policing focus on top ten hotspots could reduce police dispatch times up to 17%.
Although relatively few DDACTS studies have been published, a large body of work has been devoted to hotspot monitoring programs. The Compstat model, which originated in New York in 1993, is one of the most famous crime reduction programs in use. The idea came from a subway policeman who used pins to denote crimes on an office map, which he then analyzed to predict future crime locations and determine his daily patrol route. The New York Police Department noticed this targeted enforcement plan and promoted it statewide. Compstat went on to be adopted in more than 60 stations throughout the U.S. (Weisburd et al., 2003). A similar monitoring program in Memphis also had very positive results. By cooperating with the University of Memphis and IBM, the Memphis police developed the Criminal Reduction Utilizing Statistical History system (or Blue CRUSH) to analyze and predict crimes. In January of 2010, the Memphis police declared that Blue CRUSH had helped them arrest more than 50 drug dealers, reducing the local crime rate by 36.8% (IBM, 2011).

In the traffic safety field, the Crash Analysis Reduction Strategy (CARS), which originated in Cincinnati, Ohio in 2006, is another excellent example of problem-oriented patrol. CARS was developed based on the crime prevention theory of Problem-Oriented Policing (POP) and intelligence-led patrolling (Gerard et al., 2012). Thanks to a highly visible patrol pattern and consistent enforcement, fatal traffic crashes were reduced by 47% (as compared to 2005).

2.2. Place-Based and Routine Activity Theorems

When a police department utilizes the DDACT method, officers treat crashes as unintentional crimes caused by human factors, such as various dangerous driving behaviors (speeding, running a red light, drunk driving, etc.). This information is then applied to institute high-visibility enforcement around crash and crime hotspots. Hotspot patrols and DDACTS are based on three environmental criminology theories: the place-based and learning theorems and activity theory (Wilson, 2010). The key concepts of all three are listed below. First, if police officers adequately maintain and monitor communities, further serious crimes can be prevented. The “broken windows” analogy provides a useful example. When a car is parked along a roadside, people tend not to damage it. However, if
this same car’s window is broken, people tend to believe that the car is abandoned, and thus they can do whatever they want to it (such as spray paint graffiti all over it, steal the tires, or otherwise cause damage). In other words, people test the commitment of the police force according to perceived levels of enforcement and patrol frequency.

Second, scholars have utilized a learning theorem to explain this behavior. People learn from their own experiences and reactions from others. The above theorem is supported by real world cases such as the rapid increase in crime after Detroit declared bankruptcy, and upswings in crime after natural and man-made disasters. As discussed in Kuo et al. (2012), they found that crime hotspots and traffic crash hotspots are often spatial clustered. Based on the Deterrence Theorem, the DDACTS program can simultaneously reduce crimes and crashes. For more specifically, the targeted traffic enforcement discourages unsafe driving behaviors, such as speeding, red-light-running, and DWI; hence, the crashes caused by behavior factor instead of environmental factor could be reduced. Potential criminals are also likely to avoid illegal activity within such heavily patrolled zones.

Third, the routine activity theory can also be used to explain why some lifestyle and environmental factors (such as the presence of nightclubs, casinos, and bars) are associated with high crime and crash rates. In other words, people’s daily routine activities and their crime/crash rates coincide with one another. This theory assumes that when potential offenders and victims meet in the same place, the risk of criminal events increases if there is also the absence of a capable guardian. However, DDACTS provides capable guardians at the right times and in the right places. In other words, this method is a community-focused and place-based law enforcement mechanism used to help officers address current issues of social harm and the safety concerns of citizens in a manner that is more efficient than traditional policing strategies.

2.3. Differences in Crashes and Crimes Between Taiwan and the United States

Current DDACTS researchers have viewed this method in a positive light; however, their results are questionable because of methodological issues in data collection and before-after evaluation. For example, their crime and crash data are secondary data which is collected by existing resources (by the census unit instead of patrol ranges). Failing to
define the affected area may have biased estimations of the benefit of DDACTS because the treatment may have no effect outside of the area to which it was applied (Kuo et al., 2013).

Another major restriction is that the characteristics of crashes and crimes are different in Taiwan than in the United States, especially in terms of offender characteristics, event probabilities, and the distribution of occurrence points. There are two main perspectives on this problem. With regards to the generation of crashes and crimes, land-use laws in the U.S. are simpler than in Taiwan (business and residential areas are usually separated in the U.S., while land uses in Taiwan are usually mixed). It is worth considering if the different land-use patterns might affect the efficiency of DDACTS. Also, other important factors such as lifestyle, culture, or even economic conditions might have an impact on this method’s effectiveness. For example, it is known that drunk driving and street crimes cluster around alcohol retailers and bar areas on Friday nights in the U.S (Gorman et al., 2013; Levine, 2017). However, alcohol-related crashes and crimes might be clustered in different locations (e.g., homes or workplaces) and at different time periods in Taiwan because laws controlling the sale of alcohol and the toleration of drinking are different.

In addition, DDACTS tends to be more effective for certain specific crimes (such as street crime), and we are not sure if these types of crimes are also common in Taiwan. Table 1 shows that the rates for various types of crime in Taiwan and the U.S. are very different. First, the crime rate of the United States is approximately two times higher than that of Taiwan (2.09=4123.97/1976.69). The most common offense in Taiwan is larceny. The rates of other types of offenses, especially hate crimes, are much higher in the U.S. The ratio of crime rates in the United States to those in Taiwan for murder, rape, assault, robbery, and burglary are approximately 6, 4, 8, 12, and 4 to 1, respectively. The robbery ratio differs the most, while the vehicle theft rate is much closer. One possible reason for the difference in crime rates is that access to guns is more restricted in Taiwan. Another contributing factor between the two countries can be attributed to the differences in reporting rates to authorities. As for the crash, fatality, and injury rates, as well as crash frequency, rates in Taiwan are much higher than in the U.S. The reason is that the mixed traffic flow result in more conflict points, higher speed variance and higher crash risk in
Taiwan. Based on these results, it could be concluded that DDACTS may not reduce as many types of crimes in Taiwan as in the United States. However, it may still have a positive effect overall, because the crash rate in Taiwan is higher than in the United States. Also, the most common offense in both countries is theft. DDACTS can reduce most crimes of this type through deterrence.

Table 1. Crime Rate per 100,000 Inhabitants in Taiwan and the U.S. (NPA, 2002)

<table>
<thead>
<tr>
<th>Type</th>
<th>Taiwan</th>
<th>%</th>
<th>U.S.</th>
<th>%</th>
<th>Ratio (U.S./Taiwan)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crime</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Murder</td>
<td>0.9</td>
<td>0.05%</td>
<td>5.51</td>
<td>0.13%</td>
<td>6.12</td>
</tr>
<tr>
<td>Rape</td>
<td>7.79</td>
<td>0.39%</td>
<td>32.05</td>
<td>0.78%</td>
<td>4.11</td>
</tr>
<tr>
<td>Assault</td>
<td>40.33</td>
<td>2.04%</td>
<td>323.62</td>
<td>7.85%</td>
<td>8.02</td>
</tr>
<tr>
<td>Larceny-Theft</td>
<td>1,411.09</td>
<td>71.39%</td>
<td>2,477.30</td>
<td>60.07%</td>
<td>1.76</td>
</tr>
<tr>
<td>Robbery</td>
<td>11.64</td>
<td>0.59%</td>
<td>144.92</td>
<td>3.51%</td>
<td>12.45</td>
</tr>
<tr>
<td>Burglary</td>
<td>193.06</td>
<td>9.77%</td>
<td>728.42</td>
<td>17.66%</td>
<td>3.77</td>
</tr>
<tr>
<td>Vehicle Theft</td>
<td>215.24</td>
<td>10.89%</td>
<td>414.17</td>
<td>10.04%</td>
<td>1.92</td>
</tr>
<tr>
<td>All</td>
<td>1,976.69</td>
<td>100.00%</td>
<td>4,123.97</td>
<td>100.00%</td>
<td>2.09</td>
</tr>
<tr>
<td>Crash</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fatality rate</td>
<td>8.25(24 hrs.)</td>
<td></td>
<td>10.30(30 days)</td>
<td></td>
<td>0.78</td>
</tr>
<tr>
<td>Injury rate</td>
<td>1598.25</td>
<td></td>
<td>727.88</td>
<td></td>
<td>0.46</td>
</tr>
<tr>
<td>Crash rate</td>
<td>1191.04</td>
<td></td>
<td>510.11</td>
<td></td>
<td>0.43</td>
</tr>
</tbody>
</table>

2.4. Hotspot Identification Methods

The main purpose of the DDACTS method is to combine crime and crash data, and then determine the best patrol routes by connecting these high risk areas by the shortest possible distances. Scholars have traditionally separated their analysis of hotspots for crimes from those of hotspots for crashes. Consequently, combining crime and crash data for interdisciplinary issues is relatively new.

The theorem to define crime hotspot is more complex than that which deals strictly with traffic issues; however, certain analysis software applications can be useful for both aspects, such as ArcGIS. Readers are referred to several crime hotspot studies for other common software or package, such as CrimeStat, and SpaceStat (Eck et al., 2005; Levine, 2015). Also, Bernasco and Elffers (2010) study includes reviews of historical research on how criminologists have used GIS techniques to analyze data, as well as a discussion of the
types of crimes suitable for spatial analyses and a comparison between the most common analytical methods.

Ripley’s K function, Morans’ I, Local Indicators of Spatial Associations (LISA), and Gi* have all been used to calculate point cluster patterns. Point mapping, spatial ellipses, grid thematics, and KDE maps can also be used to identify hotspots on maps. Chainey et al. (2008) compared these common hotspot mapping techniques and systematically listed their advantages and limitations. Unlike previous studies that only considered ease of use when evaluating hotspot mapping techniques, Chainey used accuracy as the main criterion. A new index, PAI, which combines hit rate and target area, has also been used to assess the performances of hotspot identification methods. The results showed that KDE was more accurate than the other methods. Also, property crimes, such as burglary can more consistently be predicted than other types of crime. Although numerous scholars have attempted to individually define the hotspots related to crashes and crimes, few have combined these two types of data together.

2.5. Patrol Systems in Taiwan

From an enforcement perspective, DDACTS should be adjusted according to current patrol plans. For example, the detailed settings of kernel density maps (such as cell size and bandwidth) are primarily based on the size of the patrol block or beat. Using U.S. settings as our default values would have biased our results and rendered ineffective any patrol plans that were generated. We also needed to consider how the responsibilities of officers and expectations of police departments differ between the U.S. and Taiwan. In Taiwan, it is common for the same police officers to be in charge of investigating both crimes and traffic collisions. Only a very few large-scale departments with a wealth of manpower can afford to handle crimes and crashes separately.

It must be noted that Japan has a strong influence on Taiwan’s police patrol system, which can be seen in its use of the “koban” system for determining current police patrol areas (Alarid & Wang, 2000). In Taiwan, police officers are in uniform when they patrol their fixed routes, which have several stops and checkpoints that officers visit in the same order, at the same time every day. Only investigation teams from the criminal investigation
division and juvenile affairs officers wear street clothes. Police officers spend most of their working hours at the police station or patrolling their precinct. They may patrol by motorcycle or automobile, adapt their patrol routes, or change the above rules if they feel it is necessary to do so. Patrol duty usually occupies 50% to 70% of an officer’s shift.

The time spent on patrol continues to increase for two key reasons. The first is that people tend to call 110 (emergency call for police, similar to 911 in the United States) for all kinds of requests, not only emergencies. During off hours, people call 110 simply because they cannot contact other government authorities. Unrelated service calls and extra workloads occupy much of the already limited police resources and leave less time for the primary tasks of reducing crime and improving public safety. The second reason is that people tend to evaluate the performance of their local police department based on increased patrols and police visibility. In other words, when the public sees police officers out on patrol, their satisfaction with public safety increases and their fear of crime is reduced. Consequently, the current police work schedule is actually a rotation system that encompasses all hours of the day. Together, these two elements have created a vicious circle for police departments. Resources allocated to law enforcement activities are frequently insufficient for responding to service calls, dealing with threats to public safety, and staffing the rotation system (Kao et al., 2013).

Due to these and other issues, it is necessary to verify the transferability of the DDACTS model to Taiwan and then modify its implementation plan. Although this model has been shown to be valuable in Western countries, it is necessary to determine if it would be as effective in Taiwan. The causes and specific characteristics of the crimes and crashes in Western countries versus those in Taiwan could be very different. Variations in land uses, lifestyles, cultures, and economic conditions might all cause crime and crash patterns and criminal/offender constructions to differ dramatically, which could then impact the effectiveness of DDACTS. However, what is clear is that law enforcement authorities need more effective and efficient patrolling techniques, due to the increasing demand for their services; it is our hope that DDACTS will help to satisfy this need.

The issues discussed above are the reasons we chose to pursue this research, which has three specific objectives:

(1) We will utilize local crash and crime data to examine if DDACTS is effective in
Taiwan.

(2) Advanced statistical methods will be used to estimate the effectiveness of the model, and we will determine whether or not these methods are suitable for this approach.

(3) We will determine how differences in cultures, lifestyles, land uses, and crash and crime factors between the U.S. and Taiwan impact the effectiveness of the DDACTS model.

3. Study Data and Methodology

3.1. Research Framework and Methodology

The project research framework includes six steps: (1) mapping the DDACT data, (2) identifying the hotspots, (3) examining the coincidence of the hotspots, (4) estimating possible correlations between crashes and crimes, (5) designing the shortest patrol routes, and (6) evaluating the effectiveness of the DDACTS method.

3.2. Data Sources

Based on the literature review, we used two to three years of crash and crime data to establish accurate hotspot maps; this was done to retain data consistency and remove high variance effects (NHTSA, 2014; Hauer, 1997). In this study, we used local data to determine if DDACTS would be more effective, have a similar level of effectiveness, or be less effective in Taiwan than in the United States. Currently, the National Police Agency (NPA) is in charge of collecting, storing, and managing all crash and crime reports in Taiwan.

In our two study areas, crashes and crimes posed serious safety problems on the national level. In the United States, there are over 32,000 traffic crash fatalities, 2.2 million crash-related injuries, and 1.31 million violent crimes annually ((Naumann et al.,2010; FBI, 2012). In Taiwan, according to statistics obtained from the Ministry of the Interior, there were 278,387 vehicle crashes in 2013, which caused approximately 2,500 fatalities and 380,000 injuries. There were 298,967 crime events in 2013 (NPA, 2014). Undoubtedly, the corresponding costs to society are substantial for both countries.
However, because the population and area of the United States are much larger than in Taiwan, these two countries are not comparable at the national level. For this reason, we were forced to limit the data to the regional level in order to review our treatment and control sites.

In other words, a crash and crime dataset from a city in the United States was used as a baseline to compare the levels of effectiveness of the DDACTS models for Taiwan and the United States, as well as the distributions of hotspot crime scenes, including coincidental hotspots. For the comparison convenience, we used the same datasets from a 2013 research study conducted by the lead author. In other words, College Station, Texas, was our control group. Then, we chose the Zhong-shan district of Taipei as our study area because it has a similar population density and size to that of College Station, Texas. In this district, the number of crashes was 29,576 and the number of crimes was 7,021 (a ratio of 4:1).

3.3. Hotspot Identification and Coincidence Estimation Framework

We utilized the GIS software to map the crash and crime data. Then, we combined this information with other socioeconomic datasets by overlaying the various map files. The GIS technique was crucial because most of its crash and crime data came with location information. It should be noted that before we could locate any hotspots, we needed to estimate the overall cluster pattern; otherwise, the so-called “hotspots” or “cold-spots” could simply have been random occurrences. The section below includes a brief discussion of each cluster pattern and hotspot identification method.

- **Average Nearest Neighbor (ANN)** is an index to define the general cluster pattern of our observed points via the equation below, Eq. (1).

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

(1)

where \(d\) is the mean distance between each incident point and its nearest neighbour, \(\delta\) is the mean distance of points distributed randomly, \(A\) is our study area, and \(n\) correspond to the number of points (incident location). When the ANN value is less than 1 and its Z-
score is significant, our dataset contains clustered points.

- Ripley's K-Function is also called Multi-Distance Spatial Cluster Analysis in ArcGIS. This method can define the spatial patterns of data points (clustered or feature-dispersed) over a range of distances. If the observed K value is larger than its expected value for a particular distance, then the point pattern is clustered instead of randomly distributed. The K value is calculated via Eq. (2). When the observed K value is outside the 95% CI, the data points’ distribution is significantly different from a random distribution at distance $d$.

$$K(d) = \sqrt{\frac{A(\sum_i \sum_j (K_{ij})/(\pi \times n(n-1))}{}}$$

where $d$ is the distance between the points $i$ and $j$, $n$ is the total number of points, $A$ is the area of the region containing all points, and $K_{ij}$ is the weight. For example, the value of $k_{ij}$ would be 1 for the adjusted area; otherwise, $k_{ij}$ would be zero.

- Kernel density mapping is a common hotspot mapping methods because of its accuracy and consistency in prediction as well as its superior visual component (Chainey et al., 2008). The main purpose of the KDE is to calculate the risk surrounding each point. The risk density of an event is highest when the distance is zero; the K value decreases with increased distance. The detailed calculation of the quartic kernel density function is shown below in Eq. (3):

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

where $K$ is the kernel density value, $d$ is the distance from the incident, and $s$ is the search bandwidth (Silverman, 1986).
3.4. Organizing Patrol Routes to Estimate Their Effectiveness

The application of highly visible traffic enforcement is a proven and effective countermeasure to address both crashes and crimes, whether they occur simultaneously or independently in terms of time and/or location. Providing solutions and estimating their corresponding effectiveness are both important. With help from GIS, establishing the most effective patrol route is easier than ever before because ArcGIS can locate hotspots and determine the shortest distances among them based on built-in network information. If speed and turn information is also available, GIS can help establish another effective patrol route founded on the shortest driving time. In order to compare the effectiveness of the DDACTS method in Taiwan to its use in the United States, we used the same estimation formula of effectiveness (θ) to determine the difference adjustment as what was used in Kuo et al. (2013). The effectiveness is calculated via Eq. (4). The treatment’s effectiveness is higher if a new patrol route can reduce more dispatch time.

$$\theta (\%) = \frac{\sum_{i=1}^{n} T_{i, after} - \sum_{i=1}^{m} T_{i, before}}{\sum_{i=1}^{m} T_{i, before}} = \frac{n \times T_{i, after} - m \times T_{i, before}}{m \times T_{i, before}} = \frac{n-m}{m} \cdot \left( \bar{T}_{i, after} - \bar{T}_{i, before} \right)$$ (4)

where,

θ : the effectiveness of hotspot patrol plan;

$T_{i, before}$, and $T_{i, after}$ : the required time to dispatch police officer to incident i in the before and after periods, respectively;

M: the number of incident in the before period; and,

n: the number of incident in the after period.

4. Results

The first step in our analysis was to define the point patterns for the crime and crash data using ANN. As mentioned above, before defining any hotspots on maps, we needed to estimate the overall cluster ratio; otherwise, the so-called “hotspots” could have been random occurrences. In the rest of the study area, most of the points were dispersed. We used Eq. (1) to estimate the ANN values and Z scores of the 2012 to 2014 crash and crime...
data (see Table 1). If the ANN value was less than one, the data were more likely clustered. Z-scores are standard deviations that were used to evaluate the statistical significance of the above-mentioned ANN values. Very low (negative) Z scores meant that we could reject the null hypothesis; the point spatial pattern was not random. As we expected, the results showed that both types of data (crime and crash) were clustered. However, the crash data were more concentrated than the crime data. This result was contrary to previous findings in studies of data from the United States (Kuo et al., 2013). There are several possible reasons for this outcome. First, in our current study area, the crash frequency was much higher than the crime frequency. In the Zhong-shan district of Taipei, the number of crashes (29,576) far exceeded the number of crimes (7,021), to a ratio of 4:1. However, in College Station, Texas, the number of crashes was 14,712 and the number of crimes was 65,461 (a ratio of 1:4). Second, due to data limitations, we did not include all of the various types of crime data in our study. Some were unavailable due to the Personal Data Protection Law, and were removed by the Taipei City Police Station. Third, there are significant differences between Western and Asian countries in terms of environment (such as land-use, road design, and lifestyle), law enforcement procedures, and ratios of vehicle types (e.g., the number of motorcycles and types of public transportation). For example, the motorcycle, which has a much higher risk of involvement in severe crashes than other types of vehicles, is a major mode of transportation in Taiwan.

The order of the cluster ratios of the four types of crime mentioned above was burglary, motorcycle theft, vehicle theft, and robbery. These results aligned with our expectations. The crime of burglary is most concentrated in Taipei because of overcrowding, high land cost, and many tall, modern buildings. Also, the public roads and arcades near people’s homes are jammed with motorcycles; hence, the cluster pattern of motorcycle theft is similar to that of burglary. Interestingly, the point pattern for vehicle theft showed fewer clusters because the Taiwanese tend to park their cars in public parking lots, which lack security systems and are usually located far from their homes. The ANN value for robbery was the lowest of the four types of crime, because robberies occur much less often than other crimes. In addition, robberies seldom occur more than once in the same location. It should be noted that the average size of a city block is shorter in Taiwan than in the West. In other words, traffic density in Taiwan tends to be higher than in the United States.
Table 2. ANN Values for Crashes and Crimes

<table>
<thead>
<tr>
<th>Events</th>
<th>Number</th>
<th>ANN</th>
<th>Z</th>
<th>Number</th>
<th>ANN</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhong-Shan District, Taiwan</td>
<td></td>
<td></td>
<td></td>
<td>College Station, Texas</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crashes</td>
<td>29,576</td>
<td>0.002</td>
<td>-328.47</td>
<td>5,554</td>
<td>0.129</td>
<td>-124.19</td>
</tr>
<tr>
<td>Crimes - all</td>
<td>7,021</td>
<td>0.476</td>
<td>-40.13</td>
<td>27,416</td>
<td>0.062</td>
<td>-297.02</td>
</tr>
<tr>
<td>Burglary</td>
<td>4,093</td>
<td>0.395</td>
<td>-73.99</td>
<td>3,275</td>
<td>0.180</td>
<td>-89.75</td>
</tr>
<tr>
<td>Moto. theft</td>
<td>2,451</td>
<td>0.405</td>
<td>-56.38</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car theft</td>
<td>319</td>
<td>0.564</td>
<td>-14.64</td>
<td>2,852</td>
<td>0.194</td>
<td>-82.40</td>
</tr>
<tr>
<td>Robbery</td>
<td>158</td>
<td>0.730</td>
<td>-6.48</td>
<td>50</td>
<td>0.612</td>
<td>-5.25</td>
</tr>
</tbody>
</table>

The second method, Ripley’s K function, provides a means of summarizing spatial patterns and creating models to fit described arrangements. The results can also be used to compare the cluster patterns of various events (such as the crashes and crimes in our study). Figures 1(a) and 1(b) show that the observed data (indicated by the red line) is significantly different from the expected data (the blue line), and is outside of the 95% CI (the dashed line). In other words, the crash and crime points are both clustered. However, it is difficult to distinguish the difference between the cluster patterns when we compare the Ripley’s K function values in Figures 1(a) and 1(b). We also utilized this function to measure the occurrences of different crime types, and found that the results were very similar to those above. Hence, we decided not to include all of the K function figures here.

![Figure 1. Ripley’s K function of crimes (a), and crashes (b).](image-url)
We employed a kernel density map to define the hotspots of crashes and crimes. There are two common methods for achieving this. The first is to set the threshold and crash or crime risk to over 95% or higher than the mean plus two standard deviations. This location would be counted as a hotspot. The second method is to define the classes by natural breaks that maximize the differences between the groups and minimize the differences within groups. For example, when the risk distribution is significantly skewed, using the equal interval class method will cause the researcher to place too many observations in the same subgroup and too few in the groups with higher values. Here, since our data distribution was right-skewed, we used the latter method to define these areas.

Fig. 2 shows the KDE maps for the four types of crime. Based on these maps, it was easy to identify the hotspots and differentiate them by color. The cold colors (i.e., blue) in the KDE maps represent cold spots, while the warm colors (i.e., red) represent hot spots. The KDE hotspots corresponding to the above-mentioned four crime types were all close to one another, except for those representing vehicle thefts. The major hotspots were located on Linsen North Road (the circle in Figures 2(a), 2(b), and 2(d)), which is an area famous for its many bars, pubs, and other nightlife entertainment. Also, the buildings in this area tend to be old, have fewer than five floors, and do not have security personnel or alarm systems. The major hotspot for vehicle theft was close to a parking lot, ramp, and large public park (the circle in Figure 2(c)). Many vehicles park here because of the convenience and low cost, but there are very few pedestrians because it is not well lit at night. Another hotspot was near a local shopping center in the northern part of the Zhong-shan district. There are several large department stores, hotels, and one university in this area. This result was consistent with the findings from the United States, where crime hotspots tend to occur in areas close to shopping centers and bars, and crash hotspots are usually located on major roads with high levels of traffic flow (Kuo et al., 2013). Based on this information, we borrowed the routine activity theorem from the field of criminology to explain why this area in Taiwan tends to attract more crime than other places.
Figure 2. Hotspots for the four types of crime.

(a) Burglary

(b) Motorcycle theft

(c) Vehicle theft

(d) Robbery
As mentioned above, the hotspots for crime and crashes appeared close to one another in previous studies conducted in the United States, even when the offenders were not the same (according to the environmental criminology theorem). We used Taiwan’s local crash and crime data to test the above hypothesis. Table 3 shows the distances between the crash and adjusted crime hotspots in both Taipei and College Station.

*Table 3. Distances between the Centers of Crash and Crime Hotspots*

<table>
<thead>
<tr>
<th>Hotspot Center Distance</th>
<th>Taipei</th>
<th>College Station</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crash #A to Crime #A’</td>
<td>108.91</td>
<td>75.01</td>
</tr>
<tr>
<td>Crash #B to Crime #B’</td>
<td>284.55</td>
<td>291.75</td>
</tr>
</tbody>
</table>

The Taipei crash dataset incorporated all severity levels of accidents, including A1, A2, and A3 level (fatal, serious injury, and PDO) crashes. These crashes were usually close to highways with heavy traffic flow and ramps with high speed limits, but the College Station crash dataset included only severe crashes with injuries. We found that crash hot zones were clustered along all types of roads. The distance between the hotspots in College Station ranged from 75.01 to 291.75 meters, while the average distances between hotspots in Taipei ranged from 108.91 meters to 284.55 meters. The distances were relatively close, especially considering that the recorded distance bias was approximately 100 meters. Our results proved the above-mentioned hypothesis: hotspots of crashes and crime are relatively close together. Another interesting finding is that the distances between crash and crime hotspots in Taipei were slightly longer than in the United States. A possible reason is that in College Station, business and residential areas are separated, and only two crime attractors exist (bars and shopping malls), which means adjusted hotspots tend to be close by.
Figure 3. Hotspots for crash and crime events.
As mentioned above, the parameters should be carefully set because they may significantly affect the KDE results. Originally, the search bandwidth for our kernel maps was set to 500 meters, based on the findings of previous local studies (e.g., Chen et al., 2010). However, since our study site was different from those of the earlier studies, we attempted 250 and 1,000 meters as search bandwidths to test the KDE outputs and their visual performances (see Figure 4). Once we evaluated whether or not our maps would remain balanced and retain the local and global point patterns, we finally set the parameter to 500 meters. However, police departments could easily change the parameter setting (instead of using the default value in the ArcGIS software), based on their specific needs. For example, defining hotspots for police officers on foot patrol would require a greater level of specificity and accuracy. According to the KDE maps shown in Figure 4, the primary and secondary hotspots remained in the same places, even when we shortened the search bandwidth from 1,000 meters to 500 and even 250 meters. Only a few new hotspots appeared in the area (circled in red). The kernel maps use different colors to symbolize the different hotspot climates.

This finding was consistent with the findings of previous studies. Figs. 4(c) and 4(d) show the KDE maps for the crime and traffic crashes. Again, the hotspots of crime are located in the same place as the hotspots of crashes. In other words, the crash generator and crime generator seems clustered together, and we may apply DDACT in these places to improve it.
Figure 4. Hotspots resulting from different search bandwidths.
In this study, we examined the effectiveness of applying DDACTS patrol routes in Taiwan. In other words, we used data for all crime and crash types to design police patrol routes; we then gave the same weight to all crash and crime events, and calculated how much dispatch time could be reduced by applying the new patrol routes. For consistency, we employed the same procedures and hotspot maps used in our previous research on this topic (Kuo et al., 2013). After redrawing the kernel density maps, we added a frequency layer. We found that the hotspots with higher event frequencies (aggregated for each community) and those from the kernel density maps were almost identical. These points (marked with numbers) were chosen as our hotspots. The above weights could be changed based on the specific study objectives. If the traffic enforcement is effective for deterring certain types of incidents (such as DWIs), we suggest that police give higher weight for these points and design their patrol routes accordingly.

We constructed the optimum police patrol route by linking together the top five and top ten hotspots as New Patrol Route #1 and New Patrol Route #2 respectively. The road GIS file was provided by the Transportation Research Center. We utilized Network
Analyst (an ArcGIS package) to design the shortest patrol route. Future researchers may build optimal patrol route with the shortest travel time if detailed traffic data is available, such as speed limits, traffic turn, and possible traffic delays. The total length of the new patrol route was 3,845.62 meters. There were 3,982 crimes and crashes located within 50 meters of our patrol route area, 5,553 within 100 meters, and 8,331 within 200 meters.

According to Eq. (3), Patrol Route 1 could reduce the total dispatch time by 8.9%. Under more favorable conditions (i.e., the highest level of effectiveness and the widest area), Route 1 could reduce the total dispatch time by as much as 26.7%. Under less favorable conditions (i.e., the lowest level of effectiveness and narrowest area), the route could still reduce the total dispatch time by 3.2%, as shown in Table 4. By comparing this level of effectiveness (under neutral conditions) with the routes in College Station, we were able to determine that DDACTS was slightly less effective in Taiwan. However, if the effect area was extended to 200 meters, the effectiveness of the new police patrol route in Taipei was slightly higher than in College Station. One possible reason is that there were more crash and crime hotspots near the patrol route (major roads within 200 meters) in Taipei.

Table 4. Sensitivity Analysis of Dispatch Time-Reducing Ratio

<table>
<thead>
<tr>
<th>Distance</th>
<th>Effectiveness (Taipei)</th>
<th>Effectiveness (College Station)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25%</td>
<td>50%</td>
</tr>
<tr>
<td>50 m</td>
<td>3.2%</td>
<td>6.4%</td>
</tr>
<tr>
<td>100 m</td>
<td>4.5%</td>
<td>8.9%</td>
</tr>
<tr>
<td>200 m</td>
<td>6.7%</td>
<td>13.4%</td>
</tr>
</tbody>
</table>

5. Conclusions

Though a great deal of attention has been paid to deploying DDACTS programs in Western countries, in this study, we examined the possibility of applying this approach in Taiwan. The results could also be applicable to other Asian countries, such as China, Japan, and Singapore because their land uses, population distributions, crash and crime patterns,
and lifestyles tend to be similar. This research focused on comparing the point patterns and incidences of crime and crash events to determine if DDACTS would be useful outside the United States. In addition, we used a buffer area along the patrol route to evaluate this method’s effectiveness. In other words, we defined the actual area of effect instead of using units such as city or county. Finally, we used a sensitivity analysis to resolve any lingering questions regarding DDACTS’s efficacy. The departments employing DDACTS would be able to control the possible impacts, benefits, and costs in all probable scenarios.

The study results showed that crashes and crimes in an Asia City (Taipei, Taiwan), also tended to be clustered. We compared the KDE maps and calculated the straight-line distance between every pair of crash and crime hotspots. As we expected, these hotspots were in close proximity to one another (Hardy, 2010; Kuo et al., 2013). However, we found some interesting differences in the cluster order of crimes and crashes, as well as various types of crime. For example, crashes were more clustered than crimes. Also, the hotspots of burglary and motorcycle theft were very similar.

The practical contribution made by this work is it provides an evaluation procedure for Taipei police departments to use to determine if they should apply DDACTS in the Zhong-Shian district. Based on the sensitivity analysis, applying our new police patrol routes incorporating the top five hotspots would spend 21 minutes to patrol but can reduce police dispatch times by 8.9% (as calculated by Google maps). The results under the best and worst conditions were also estimated in this study, in order to provide our readers with a performance reference. Based on the results, we suggest that DDACTS be applied in the Zhong-Shian district. According to Fell (2013), DDACTS’s actual effectiveness could be higher than we expected, because traffic enforcement can reduce non-traffic crimes such as drunk-driving and drug abuse. However, verifying this would require information about other types of crime (such as DWIs and assault), as well as suitable enforcement methods.

There are a few limitations to this study. We utilized 100 and 500 meter bandwidths and cell sizes for the KDE maps. However, reasonable bandwidths may vary for different events (crime versus crash events, different types of crimes, etc.). Future research should verify the effectiveness of the KDE maps by employing various search bandwidths for different crimes, and overlap these maps in the final product. Also, the cell size has been shown to affect the accuracy of hotspot repeats, and different types of patrols may require different
cell sizes. Future researchers will need to determine the best default values for these key parameters. Also, if scholars wish to test the accuracy of our hotspot maps, they should collect extra data over an extended study time to further validate our model.

References


National Police Agency (2002).

National Police Agency (2014).
http://www.npa.gov.tw/NPAGip/wSite/ct?xItem=41406&ctNode=11395&mp=1


