A Promising Example of Smart Policing: A Cross-national Study of the Effectiveness of a Data-Driven Approach to Crime and Traffic Safety

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Abstract

Smart policing emphasizes the combination of existing interdisciplinary datasets, improvement in analysis procedures, and design of more efficient policing strategies. One promising example, the Data-Driven Approach to Crime and Traffic Safety (DDACTS), integrates traffic crash and crime data into the design of more efficient patrol routes, ensuring higher visibility traffic enforcement. This new method allows the police to more effectively allocate their limited resources. Although the DDACTS model has significantly reduced crime and crash rates in the United States, it is necessary to thoroughly study its effects before applying it in other parts of the world; the factors that influence crime, crashes, and police patrol systems in the United States may differ significantly from those in, for instance, Asia. In the present research, Taiwan was chosen as an initial area of study because of the nation’s open data policy and good quality of the data available. This study focused on two key differences between the United States and Taiwan: (1) the cluster distributions of crash and crime events, and (2) possible effectiveness of DDACTS in these two regions. ArcGIS was used to calculate point cluster patterns and identify hotspots. Although the point patterns for crimes and crashes varied greatly between Texas and Taiwan, all pairs of crash and crime hotspots were in close proximity to one another. Thus, DDACTS may be effective for improving patrol efficiency in Taiwan, despite the nation’s significant socioeconomic differences with the United States. Consequently, the results show that DDACTS may be efficient in various regions with different socioeconomic structures than the United States, such as countries in Asia. In the future, researchers from other nations may be able to use these results to revise and adjust their own DDACTS patrol plans.

Keywords: DDACTS, Hotspot, Traffic Enforcement, 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 World Health Organization (WHO) statistics, approximately 1.25 million people are killed each year because of traffic crashes, and an additional 20 to 50
million are injured (WHO, 2009). Crime is another 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 young people (i.e., individuals less than 24 years old) (WHO, 2014). Hence, it is crucial for the authorities (i.e., the police) to develop effective methods for reducing these hazards. Luckily, some smart policing programs have already provided solutions to these problems, helping the authorities to design evidence-based, data-driven law enforcement strategies and efficiently distribute their limited resources. One example of this type of program is called the Data-Driven Approach to Crime and Traffic Safety (DDACTS). Previous studies have shown that the DDACTS method could be used to simultaneously reduce both crash and crime rates if police officers integrate highly visible traffic enforcement with hotspot policing into their patrol plans (Hardy, 2010; Weiss, 2013; Kuo et al., 2013). Such a practice makes law enforcement departments, the only authority that can patrol and serve as a visible deterrent to both crashes and crimes, better able to allocate their limited resources, placing officers at the right place at the right time.

Even though many jurisdictions use different police units to attend crimes and crashes, it is the visibility of the police as a whole that serves to deter these events. Previous studies have shown that crime and crash event hotspots often overlap, making improvements to patrol routes important to the department as a whole (Hardy, 2010). Some may argue that crashes only happen on roadways, while crimes happen anywhere (moving beyond latitude and longitude to height, such as on the 3rd floor, 13th floor, 23rd floor, etc.). However, criminals still require transportation when approaching and leaving crime scenes (including when on foot), so increasing patrols and general traffic enforcement may still serve as a deterrent. Such officers can also be called to intercept offenders. In most countries, the police department is the first authority to deal directly with both crime and crash events. Hence, more efficiently allocating its resources to hotspots, rather than wasting human power on long dispatch times, shuttling back and forth between crime/crash hotspots and police stations, will save staffing budget while simultaneously decreasing crash and crime events (Weiss, 2013).

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 differ significantly from those in other countries, especially in Asia. For example, the traffic in most Asian countries is not primarily comprised of 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 (Tiwari, 2000). Taiwan was chosen as our test region in Asia, due to its open data policy; the nation was ranked first on 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 (Hogge, 2015). The main variables found in the Taiwanese crash and crime datasets include location information (e.g., address or coordinates) and time and type of event (e.g., burglary, car theft, or robbery for crimes and fatal or injury for crash type). In other words, the data quality, accuracy, and accessibility in Taiwan is relatively closer to that of the United States than to other Asian countries.

Also, the differences in traffic characteristics and laws in Taiwan and the United States are significant enough to make for interesting comparisons. For example, the traffic flow in Taiwan is considered mixed (e.g., motorcycles, passenger cars, buses), while the traffic flow in the United States consists mainly of passenger cars, as discussed above. In addition, gun ownership in Taiwan is very limited (only 0.02% of citizens are legal private handgun owners, and most of those are hunters), while gun control polices in the United States are much more permissive. We found two comparable study areas in Taiwan and the United States and controlled for population, area, and other important environmental factors (as discussed in Section 3.2).

The present study examined the effectiveness of DDACTS in Taiwan and compared it to DDACTS studies conducted in Texas in the United States. Other Asian countries could use the results documented herein as a reference for promoting DDACTS in their own countries, especially if the study area more closely resembles their home country’s socioeconomic distribution than might Western countries. Moreover, if in the future, other Asian countries open their crime and crash data to academia or the public, the methods and framework presented here will be useful in formulating studies of those datasets.
This research illustrates the differences between using the DDACTS program for the United States and Taiwan. The hypothesis is that 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 events in Taiwan, 2) determine if the relationship between crashes and crimes is similar (i.e., positively related) in Taiwan to what was found for the United States, and 3) determine if the DDACTS program would be as effective in Taiwan as it has been in the US.

2 LITERATURE REVIEW

2.1 DDACTS and Related Programs

DDACTS is a relatively new traffic 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 program was first developed by the National Highway Traffic Safety Administration (NHTSA). The NHTSA then cooperated with the National Institute of Justice (NIJ) and Bureau of Justice Assistance (BJA) to support and promote the DDACTS program nationwide.

Compared to traditional enforcement methods, DDACTS is more effective because it offers three key advantages: proactive prevention, 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, which 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 such as DDACTS or 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 claimed that if law enforcement officials were to embrace such a model, it would allow them to be more proactive and comprehensive; they would 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 showed a 41% reduction in crime and 31% reduction in crashes from applying DDACTS programs under optimal conditions (Hardy, 2010). Over 250 police agencies across the US 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). For example, their crime and crash data were secondary data collected from existing resources (by census unit instead of patrol range). Failing to define the affected area may have biased their estimations of the benefit of DDACTS because the treatment may have no effect outside the area to which it was applied (Kuo et al., 2013). It may also miss the diffusion of benefits because the treatment benefits may extend beyond the treatment (Clarke & Weisburd, 1994). There is no substantive reason for choosing this study unit, and in fact a poor choice of this parameter may produce data with ecological fallacies or modifiable areal unit problems (MAUP). For example, a spatial pattern that appears using an aerial unit of one scale may disappear if a smaller or larger scale is used, so this could prevent DDACTS results from being generalizable outside of the initial conditions. A well-chosen scale, however, can avoid this problem.

Many DDACTS scholars have addressed the benefits of reduced traffic crash and crime rates 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 for two different scenarios: (1) when police officers patrolled hotspots, and (2) when they patrolled randomly. The results showed that hotspot policing focusing on the top ten hotspots could reduce police dispatch times by up to 17%. In a recent study, Drawve et al. (2018) applied two more spatial analysis techniques, risk terrain modeling (RTM) and conjunctive analysis of case configurations (CACC), to the DDACTS framework, and then defined risk factors and high-risk locations for law enforcement.
Although relatively few DDACTS studies have been published, a large body of work has been devoted to crime hotspot monitoring programs. The Compstat program, 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 improved this targeted enforcement plan and promoted it statewide. Compstat went on to be adopted in more than 60 stations throughout the United States (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). However, this impressive outcome may not be true everywhere since it is based on a single case study.

In the traffic safety field, the Crash Analysis Reduction Strategy (CARS), which originated in Cincinnati, Ohio in 2006, is another excellent example of a 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). Although the above location-based patrol programs only focused on hotspots for one specific problem (i.e., crime or crashes) instead of both (as is the case with DDACTS), their positive results are still valuable for use as references to evaluate DDACTS program performance.

2.2 Place-Based Learning and Routine Activity Theorems

Hotspot patrols and DDACTS programs are based on environmental criminology theories (Wilson, 2010). Police officers treat crashes as unintentional crimes caused by human factors such as various dangerous driving behaviors (e.g., speeding, running a red light, drunk driving, texting while driving, etc.). The key concepts of environmental criminology theory include place-based learning theorems and activity theory (Wortley & Mazerolle, 2008). A primary tenet of place-based policing theory is that if police officers adequately
maintain and monitor a specific place such as a particular community, further serious crimes can be prevented there. The “broken windows” analogy provides a useful example (Wilson & Kelling, 1982). 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 on 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 (Wilson & Kelling, 1982).

Numerous researchers (see Wilson & Kelling, 1982; Cohen & Felson, 1979; Brantingham & Brantingham, 2008) have utilized a learning theorem to explain this behavior. People learn from their own experiences and the reactions of others. As discussed in Kuo et al. (2013), crime and traffic crash hotspots are often spatially clustered. Based on the deterrence theorem, the DDACTS program can simultaneously reduce crimes and crashes. More specifically, targeted traffic enforcement discourages unsafe driving behaviors such as speeding, the running of red lights, and driving while intoxicated (DWI). Hence, crashes caused by behavioral instead of environmental factors could be reduced, and potential criminals made more likely to avoid illegal activity within such heavily patrolled zones. In other words, traffic enforcement such as traffic stops may also help police officers find illegal drugs, alcohol, or weapons in offenders’ cars, preventing the corresponding crimes (such as those related to the drug trade) and crashes (such as DWI-related accidents) from happening.

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. Daily routine activities and crime/crash rates often coincide with one another. The main idea of routine activity theory is that the spatial-temporal distribution of people is defined by their daily activities (Wortley & Mazerolle, 2008). This theory assumes that when potential offenders and victims meet in the same place because of certain activities, the risk of criminal events increases, especially if there is also the absence of a capable guardian (Wortley & Mazerolle, 2008). However, DDACTS provides capable guardians at the right times and in the right places. Take DWI crashes, for example. DDACTS can deter potential offenders (such as drunk drivers) and protect possible victims
(such as drunk passengers) around bar areas on weekends and late at night. Thus, 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. It should be mentioned that some criminologists, such as Drawve et al. (2018), not only used criminology theories, but have also applied several common crime analysis tools such as RTM and CACC to the DDACTS model to define risk factors and hotspots for crashes and enact crime-prevention laws.

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

Current DDACTS researchers have viewed the DDACTS method in a positive light; however, a major restriction to promoting it in Taiwan is that the characteristics of crashes and crimes are different there than in the US, especially in terms of offender characteristics, event probabilities, and the distribution of occurrence points. Beside the differences in traffic flow characteristics and firearm policy measures mentioned above, there are two main problems. Land-use laws in the US are simpler than in Taiwan. In America, business and residential areas are usually separated, while land uses in Taiwan are usually mixed. It is worth considering that different land-use patterns might affect the efficiency of DDACTS if event probabilities are tied to that factor. Also, other important elements such as lifestyle, culture, and economic conditions may impact 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 US (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 toleration of drinking are different.

The DDACTS method tends to be more effective for specific crimes such as street crime; it is unknown if these types of crimes are as common and clustered in Taiwan as in the US. Table 1 shows that the rates of various types of crime in the two countries are very different. First, the overall (reported) crime rate in the United States is approximately two times higher than that of Taiwan (2.09 = 4123.97/1976.69). The two most common offenses in Taiwan are burglary and larceny. The rates for other types of offenses, especially hate crimes, are much higher in the US. 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 2 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 firearms is more restricted in Taiwan. Another contributing factor could be differences in reporting rates and crime definitions. The values for crash, fatality, and injury rates, as well as crash frequency, are much higher in Taiwan than in the US. The reason is that the mixed traffic flow in Taiwan results in more conflict points, higher speed variance, and an overall higher crash risk in Taiwan. Yet the overall crash rate being higher in Taiwan suggests that DDACTS could have an even greater effect on crash prevention. Furthermore, the most common offense in both regions is theft (about 90% among all crimes), and DDACTS can reduce most crimes of this type through visible deterrence. Finally, property crimes such as burglary can be predicted more consistently than can other types of crime (Chainey et al., 2008).

**Table 1**

Crime and Crash Rates per 100,000 Inhabitants in Taiwan and the US (National Police Agency, 2002).

<table>
<thead>
<tr>
<th>Type</th>
<th>Rate in Taiwan ($R_T$)</th>
<th>Percentage (%)</th>
<th>Rate in US ($R_{USA}$)</th>
<th>Percentage (%)</th>
<th>Rate Ratio ($R_{USA}/R_T$)</th>
</tr>
</thead>
<tbody>
<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>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 &amp; Larceny</td>
<td>1,604.15</td>
<td>81%</td>
<td>3,205.72</td>
<td>78%</td>
<td>2.00</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>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></td>
<td>13.23 (30 days)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Injury Rate</td>
<td>1,598.25</td>
<td></td>
<td>727.88</td>
<td></td>
<td>0.46</td>
</tr>
<tr>
<td>Crash Rate</td>
<td>1,191.04</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 DDAC TS method is to simultaneously use crime and crash data to improve the efficiency of traffic enforcement patrols and reduce crimes and crashes by determining the shortest and most effective patrol routes. Scholars have traditionally separated their analyses of hotspots for crimes from those of hotspots for crashes, and creating this combination of crime and crash data for interdisciplinary study is relatively new.

The theorem for defining crime hotspots is more complex than that which deals strictly with traffic issues; however, certain software applications can be useful when analyzing both aspects. One example is ArcGIS, which provides various hotspot identification tools (i.e., kernel maps and network kernels). Readers are referred to several crime hotspot studies for other common software packages, such as CrimeStat and SpaceStat (Eck et al., 2005; Levine, 2015). Also, Bernasco and Elffers’s (2010) study included 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 of the most common analytical methods. Several researchers also found that certain crime types have a higher likelihood of repeating or near-repeating in hotspots; one example is residence burglary, which tends to be more concentrated than vehicle theft (Piza & Carter, 2018; Youstin et al., 2011). In other words, vehicle theft offenders are willing to travel further to search for suitable victims than are other types of offenders (Wiles & Costello, 2000).

Among the above studies, most popular hotspot identification methods, such as Ripley’s K function, Morans’ I, Gi*, and local indicators of spatial associations (LISA) have all been used to calculate point cluster patterns and spatial heterogeneity. In order to solve the MAUP problem, recent research has also applied spatial ellipses, grid thematics, and KDE maps to identify hotspots (Kuo et al., 2013; Erdogan et al., 2008). Chainey et al. (2008) used a new tool to assess the accuracy of hotspot identification methods, the prediction accuracy index (PAI), which combines hit rate and target area. The results showed that KDE was more accurate in crime prediction than other available methods. Also, according to Wortley and Townsley’s work (2016) on environmental criminology and crime analysis, KDE could be one solution for MAUP because it calculates the risk for each point instead of aggregating them for each zone. The results solve the MAUP problem, since it is an
aggregation bias. Although numerous researchers have attempted to individually define hotspots related to crashes and crimes, few have combined these two types of data. Interested readers are referred to Kuo et al. (2013) for more detail. Thus, there is a gap in the current research that will be filled by our defining multiple event (i.e., both crashes and crime) hotspots and using that information to design police patrol routes.

3 Study Data and Methodology

3.1 Research Framework and Methodology

This project’s research framework included six steps: (1) mapping the DDACTS data, (2) identifying the hotspots, (3) examining the coincidence of the hotspots, (4) estimating possible spatial correlations between crashes and crimes, (5) designing the shortest patrol routes, and (6) evaluating the effectiveness of the DDACTS program. It should be noted that temporal correlations between crashes and crimes were not included in this study because the time records for crimes in our dataset usually reflected the report time rather than the time of occurrence.

3.2 Data Sources

In our two study regions, both crashes and crimes posed serious safety problems at 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, and 298,967 crime events (NPA, 2014). Undoubtedly, the corresponding costs to society are substantial for both regions. However, because the population and area of the United States are much larger than those of Taiwan, these two regions are not comparable on a national level. For this reason, we were forced to limit our data to the city and district levels in order to review our treatment and control sites.

In this study, 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 crime scene hotspots, including coincidental hotspots. For convenience, this work employed the same datasets as a 2013 research study conducted by the lead author, which used College Station, Texas as the control group (Kuo
et al., 2013). However, we re-ran the analyses to adapt it for the present work. The Zhongshan district of Taipei City was chosen as a study area because it has a similar population density, land use, and area size to that of College Station, Texas. For example, the Zhongshan district and College Station both have a large shopping center, university campus, and areas with high concentrations of establishments serving alcohol. In addition, the Zhongshan district being in the middle of Taipei City minimizes boundary condition issues. Therefore, the Zhong-shan district was the most appropriate and similar to College Station according the authors’ knowledge. Based on the literature review, two to three years of crash and crime data (2012–2014) were used to establish accurate hotspot maps; this was done to retain data consistency and remove the effects of a high level of variance (NHTSA, 2014; Hauer, 1997).

3.3 Hotspot Identification and Coincidence Estimation Framework

ArcGIS software (ESRI, 2012) was utilized to map the crash and crime data. Before any hotspots could be located, 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:

- The average nearest neighbor (ANN) is an index used to define the general cluster pattern of our observed points, using Eq. (1), below:

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

  where \(d\) is the mean distance between each incident point and its nearest neighbour, \(\delta\) is the mean distance of the points distributed randomly, \(A\) is our study area, and \(n\) is the number of points (i.e., incident locations). When the ANN value was less than 1 and its Z-score significant, our dataset contained clustered points. If the ANN value was larger than 1 and its Z-score significant, our dataset points were dispersed. Otherwise, the observed points were randomly distributed.
The Ripley's K function is also called multi-distance spatial cluster analysis in ArcGIS. This method defines the spatial patterns of data points (i.e., either clustered or feature-dispersed) over a range of distances. The Ripley's K values were calculated using Eq. (2). If the observed K value was larger than its expected K value for a particular distance ($d$), then the point pattern was clustered instead of randomly distributed. When the observed K value was outside the 95% CI, the distribution of the data points was significantly different from a random distribution at distance $d$ (see Figure 1 as an example).

$$K(d) = \sqrt{\frac{A(\sum_i \sum_j (K_{ij})/\pi \times n(n-1))}{n}}$$  \hspace{1cm} (2)

**Fig. 1.** Illustration of Ripley's K function (Scott & Janikas, 2010).

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.

The kernel density estimation (KDE) map is a commonly used hotspot mapping method because of its accuracy and consistency in prediction, as well as its superior visual component (Chainey et al., 2005; 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 kernel density value decreases with increased distance. The detailed calculation of the quartic kernel density function is shown below in Eq. (3):

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

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 their times and locations are the same or independent. It is important to both provide solutions and estimate the corresponding effectiveness. With the help of 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 based on the shortest driving times. In order to compare the effectiveness of the DDACETS model in Taiwan to its use in the United States, the same estimation equation of effectiveness ($\theta$) was used for determining the difference adjustment as was used in Kuo et al. (2013). The effectiveness was calculated using Eq. (4). The treatment’s effectiveness was considered to be improved if a new patrol route could reduce the dispatch time.

$$\theta (\%) = \frac{\sum_{j=1}^n T_{i, \text{after}} - \sum_{i=1}^m T_{i, \text{before}}}{\sum_{i=1}^m T_{i, \text{before}}} = \frac{n \times T_{i, \text{after}} - m \times T_{i, \text{before}}}{m \times T_{i, \text{before}}} = \frac{n-m}{m} \left(\cdot T_{i, \text{after}} = T_{i, \text{before}}\right) \hspace{1cm} (4)$$

In Eq. (4), the effectiveness of a hotspot patrol plan ($\theta$) is the percentage of the dispatch time reduced in the period after, as compared to the period before the implementation of the route. In other words, $T_{i, \text{before}}$ and $T_{i, \text{after}}$ are the times required to dispatch police officers to incident $i$ in the before and after periods, respectively. It was assumed that the average dispatch time to point $i$ in the before and after periods were the same, and the number of incidents in the before period ($m$) and after period ($n$) were equal.

### 4 RESULTS AND DISCUSSION

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The first step in this analysis was to use ANN to define the point patterns for the crime and crash data. As mentioned above, before defining any hotspots on maps, it was necessary to estimate the overall cluster ratio to ensure that the identified hotspots were significant and not just random occurrences. Eq. (1) was used to estimate the ANN values and Z scores of the 2012 to 2014 crash and crime data (see Table 1). As expected, the results showed that both types of data (i.e., crimes and crashes) were clustered, with ANN values significantly lower than one. However, in Zhong-shan, the crash data were more concentrated than the crime data. This was contrary to the results for College Station, where the crime data were more concentrated than the crash data. There are several possible reasons for this outcome. First, as mentioned above, the crash frequency was much higher than the crime frequency in the study area. 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 65,461 (a ratio of 1:4). Thus, there was a 16X difference between the two ratios. Second, there are significant differences between Western and Asian countries in terms of the 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 do other types of vehicles, is a major mode of transportation in Taiwan.

The ANN (i.e., cluster ratio) order for the four types of crimes in Zhong-shan was: burglary, motorcycle/scooter theft, vehicle theft, and robbery. These data are summarized in Table 2. The results align with our expectations and the conclusions drawn from the literature review (see Section 2.4). The crime of burglary was the most concentrated in the southwest of the Zhong-shan district because of overcrowding, high land cost, and the presence of many tall, modern buildings. Furthermore, the public roads and arcades near homes feature a high density of moving and parked motorcycles, causing the cluster pattern of motorcycle theft to be 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 that 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 occurred much less often than other crimes. In addition, robberies seldom occurred 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>Event</th>
<th>Number</th>
<th>ANN</th>
<th>Z</th>
<th>Event</th>
<th>Number</th>
<th>ANN</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhong-Shan District, Taiwan</td>
<td>29,576</td>
<td>0.002</td>
<td>-328.47</td>
<td>College Station, Texas</td>
<td>5,554</td>
<td>0.129</td>
<td>-124.19</td>
</tr>
<tr>
<td>Crashes</td>
<td>7,021</td>
<td>0.476</td>
<td>-40.13</td>
<td>All Crimes</td>
<td>27,416</td>
<td>0.062</td>
<td>-297.02</td>
</tr>
<tr>
<td>Burglaries</td>
<td>4,093</td>
<td>0.395</td>
<td>-73.99</td>
<td>Robberies</td>
<td>158</td>
<td>0.730</td>
<td>-6.48</td>
</tr>
<tr>
<td>Moto Thefts</td>
<td>2,451</td>
<td>0.405</td>
<td>-56.38</td>
<td>Car Thefts</td>
<td>319</td>
<td>0.564</td>
<td>-14.64</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></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 for different distances. The results can also be used to compare the cluster patterns of various events (such as crashes and crimes, in our study). Figures 1(b) and 2(a) show that the observed data (indicated by the red line) is significantly different from the expected data (the blue line) and outside of the 95% CI (the dashed line). Because our sample size was large, the 95% CI was very narrow (very close to the blue line). In other words, the crash and crime points were both clustered. However, it is difficult to distinguish the difference between the cluster patterns when comparing the Ripley’s K function values in Figures 2(a) and 2(b). This function was also utilized to measure the occurrences of different crime types (such as burglary and vehicle theft); the results were very similar to those above. Hence, not all of the K function figures were used here.
Fig. 2. Ripley’s K function for (a) crimes and (b) crashes.

As with the previous method, a kernel density map was used to define the hotspots of crashes and crimes. There are two common methods for achieving this. The first is to set the threshold of crash or crime risk to over 95% (or higher than the mean plus two standard deviations in the normal distribution). Such locations are considered hotspots. The second method is to define the classes by natural breaks that maximize the differences among 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 the data distribution was right-skewed, the latter method was used to define these areas. In order to keep the color consistent, nine groups and the same symbology were used throughout this research.

Fig. 3 shows the KDE maps for burglary, motorcycle/scooter theft, vehicle theft, and robbery. 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 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 circles in Figures 2(b), 2(d), and 3(a)), which is an area famous for its many bars, pubs, and other nightlife. 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/garden (the circle in Figure 3(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 Zhongshan district. There are several large department stores, hotels, and one university in this area. This result is 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; Piza & Carter, 2018). Based on this information, the routine activity theorem was borrowed from the field of criminology to explain why this area in Taiwan (with specific crime-attracting business types) tends to attract more crime than other places.
Fig. 3. Hotspots for the four types of crime in Zhong-shan.

(a) Burglary

(b) Motorcycle theft

(c) Vehicle theft

(d) Robbery
As mentioned above (see Section 2.2), the hotspots for crimes and crashes appeared close to one another in previous studies conducted in the United States, even when the offenders were not the same, which is consistent with the environmental criminology theorem. Taiwan’s local crash and crime data were used to test the above hypothesis. Table 3 shows the distances between the crash and adjusted crime hotspots in both Zhong-shan and College Station. The distances were measured by ArcGIS from the center point of Crash Hotspot (A) to its adjusted Crime Hotspots (A’). See Figure 5 for more details.

Table 3.
Distances Between the Centers of Crash and Crime Hotspots

<table>
<thead>
<tr>
<th>Hotspot Center Distance</th>
<th>Zhong-shan, 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>

unit: meter

According to the data in Fig. 4, the Zhong-shan crash hotspots were close to highways with heavy traffic flow and ramps with high speed limits, while the College Station crash hotspots were clustered along all types of roads. It is believed that this was due to the spatial distribution of urban traffic flow in Taipei and high under-reporting in general in Taiwan (generally, only severe and fatal crashes on major roads are reported to the police).

The researchers found that in all cases, the hotspots for crashes and crime were relatively close together. The distances between the hotspots in College Station ranged from 75.01 to 291.75 meters, while the average distances between hotspots in Zhong-shan ranged from 108.91 meters to 284.55 meters. The distances between crash and crime hotspots were relatively close, especially considering that in our dataset the recorded distance bias was approximately 100 meters. Another interesting finding is that the distances between crash and crime hotspots in Zhong-shan were slightly longer than in College Station. One possible reason is that in College Station, business and residential areas are separated, and only two crime attractors exist (i.e., bars and shopping malls), which means adjusted hotspots tend to be close by.
Fig. 4. Hotspots for (a, c) crashes and (b, d) crime events.
Finally, the effectiveness of applying DDACTS patrol routes was examined in Zhongshan (i.e., Taipei), and the data for all crime and crash types were used to design police patrol routes. All crash and crime events were weighted the same, and how much the dispatch time could be reduced was calculated by applying the new patrol routes. For the sake of consistency, the same procedures and hotspot maps used in previous studies were employed here (Kuo et al., 2013). After redrawing the kernel density maps, a frequency layer was added. The results show that the hotspots with higher event frequencies (as aggregated for each intersection or segmentation) and those from the kernel density maps were almost identical. These points (marked with numbers in the maps) were identified as hotspots. These weights can be changed based on the specific study objectives. If traffic enforcement is found to be effective for deterring certain types of incidents (such as DWIs), it is suggested that police give higher weights to these points and design their patrol routes accordingly.

The optimum police patrol routes were constructed 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. Since the algorithm for generating the optimal route is not the focus here, an existing tool, Network Analyst (an ArcGIS software package), was utilized to design the shortest patrol route. Future researchers could build optimal patrol routes with optimized travel times if detailed traffic data such as speed limits, traffic turns, and possible traffic delays are available. 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), New Patrol Route #1 could reduce the total dispatch time by 8.9% under neutral conditions. Under more favorable conditions (i.e., the highest level of effectiveness and widest effective area), New Patrol 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%. These estimates are summarized in Table 4. By comparing this level of effectiveness (under neutral conditions) with the routes in College Station, it was determined that DDACTS was slightly less effective in Zhong-shan. However, if the effect area was extended to 200 meters, the effectiveness of the new police patrol route in Zhong-shan was slightly higher than what was developed for College Station. One possible reason is that there were more crash and crime hotspots near the patrol route (i.e., major roads within 200 meters) in Zhong-shan.

Table 4.

Sensitivity Analysis of the Dispatch Time-Reducing Ratio

<table>
<thead>
<tr>
<th>Area (Buffer Distance)</th>
<th>Effectiveness (Zhong-shan)</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

A great deal of attention has been paid to deploying DDACTS programs in Western countries; in this study, the possibility of applying this approach to an area of Taiwan was examined in order to determine if DDACTS would be useful outside of the United States. The results may 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 to the region studied here (Kenworthy & Laube, 1996).

Based on both the calculated ANN and Ripley’s K test values, the results show that crashes and crimes in Zhong-shan (i.e., Taipei, Taiwan) tended to be clustered. The KDE maps were compared and straight-line distances between every pair of crash and crime hotspots calculated. As expected, these hotspots were in close proximity to one another (Hardy, 2010; Kuo et al., 2013). Also, hotspot locations near shopping centers and bars were found to be consistent between Zhong-shan and College Station, and the same was found with regards to crash data for major roads with high levels of traffic. However, some interesting differences in the cluster order of crimes and crashes, as well as between various types of crimes, were found. For example, crashes were more clustered than crimes in Zhong-shan. This may reflect the fact that the main social safety problems in the United States are more crime related, while the primary challenges for Taiwan’s police officers are more crash related. Also, the results show that the hotspots for burglary and motorcycle theft in Zhong-shan were closely co-located; this is because Taiwanese people tend to park their motorcycles close to their homes. However, the hotspots for vehicle theft were located in large parking lots in rural areas because this is where most cars are parked in Taipei. There are very high parking fees for parking in the city’s downtown area.

The practical contribution made by this work is that it provides an evaluation procedure for Taipei and other Asian police departments to use in determining if they should apply DDACTS to their local beat/management districts. Based on the sensitivity analysis, applying new police patrol routes by incorporating the top five hotspots would add 21 minutes to patrol but could reduce police dispatch times by 8.9% (as calculated by Google maps). The results were also estimated in this study under the best and worst conditions, in order to provide our readers with a performance reference. Based on these results, it was
concluded that DDACTS would be useful if applied in the Zhong-shan district. Moreover, according to Fell (2013), DDACTS’s actual effectiveness could be even higher than expected, because traffic enforcement can reduce other traffic violation crimes such as drunk driving and illegal drug use. In addition, real crime data are likely to be higher than the study data used here, because several types of crime data are not released (i.e., are removed by the Taipei City Police Station) due to the Personal Data Protection Law. 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 associated with this study. In this work, 100- and 500-meter bandwidths were utilized as cell sizes for the KDE maps in order to offer the best visual results. However, reasonable bandwidths may vary for different events (e.g., 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. In addition, cell size has been shown to affect the accuracy of hotspot repeats, and different types of patrols may require different cell sizes. Foot and bicycle patrols require more accurate hotspots. Future researchers will need to determine the best default values for these key parameters. Also, in order to test the future accuracy of the hotspot maps documented in this research, extra data should be collected over an extended study time to further validate the proposed model. Future research could also combine crash and crime hotspot information with other socioeconomic datasets by overlaying the various map files, and then building a spatial model to explain the possible impacts caused by the related factors. Interested readers should refer to Drawve et al. (2018) for specific examples related to defining risk factors.

It is believed that the GIS technique and spatial analysis will become more useful in the future because most of the current crash and crime data comes with location information, and as showed here, calculating routes incorporating DDACTS methods can provide reductions in crashes, crimes, traffic violations (e.g., DWI), and patrol times in cities in both the United States and Taiwan. Future research on DDACTS as an enforcement strategy should include citation and traffic rule violation data as a key direct performance index to measure the impact of DDACTS. These violations could also be used as a surrogate index for further crash analyses.
References


Hardy, E. (2010). Data-driven policing: How geographic analysis can reduce social harm. 
*Geography Public Safety*, 2(3), 1-2.


National Police Agency (NPA), (2002). 
=15

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


