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Early Warning System for Crime Hot Spots

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Running Head: Early Warning System for Crime Hot Spots

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Abstract

Objectives Using violent crime data from Pittsburgh, Pennsylvania we investigate the performance of an “early warning system” (EWS) for starting/stopping police deployments to hot spots for crime prevention. We show that (1) even the hottest chronic hot spots are dynamic with months “on” and “off” and (2) temporary hot spots are also targets for prevention. We compare the performance of EWS to constant deployment at chronic hot spots.

Methods We estimate chronic hot spots using kernel density smoothing. We use simple methods for implementing EWS rules for detecting flare-ups, predicting persistence of flare-ups, and stopping deployments. Using 2000–2010 data we run computational experiments varying size of hot spots and rule thresholds to tune EWS.

Results Tradeoff curves with crimes exposed to prevention efforts versus area of the city under prevention workload show that static and dynamic deployments have nearly the same efficiency. Different, however, is land-use distribution. While chronic hot spots tend to be in or adjacent to commercial areas, dynamic hot spots have significantly more and widely-scattered residential locations. We argue that dynamic hot spots thus have higher potential for reducing fear of crime and providing responsive police services to neighborhoods.

Conclusions Even though police resources are “wasted” during “off” months by constant deployment to chronic hot spots, a dynamic system of deployment with simple methods cannot improve the efficiency of crime prevention. EWS comparably “wastes” resources because of false positives for hot-spot persistence and waiting to confirm hot-spot extinguishment. Nevertheless, EWS is more responsive to residential crime.

Keywords Hot spots · Crime prevention · Police deployment · Early warning system
1. Introduction

Sherman (1995) defined crime hot spots as "small places in which the occurrence of crime is so frequent that it is highly predictable, at least over a one-year period." There are several other, similar definitions of crime hot spots (e.g., Grubesic 2006; Braga and Weisburd 2010; Braga et al. 2012). In regard to duration, Weisburd et al. (2004) used trajectory analysis (Nagin 1999) with annual data to show that crime hot spots in Seattle made up of block-long street segments can persist for many years, even more than a decade. These can be termed “chronic hot spots.” The practical implication for police decision-making is that chronic hot spots are constant and therefore good targets for crime prevention efforts. All that is needed is to determine the street segments or boundaries of chronic hot spots and then assign prevention resources to them over the long term. Wilcox and Eck’s (2011) “iron law of troublesome places” assures a constant series of potential crimes in such places.

This paper, however, provides evidence from a recent ten-year period in Pittsburgh, Pennsylvania using monthly data that chronic hot spots even for the hottest one percent of Pittsburgh’s area are only “on” on the average 8.5 out of 12 months per year. The criterion for a chronic hot spot remaining on after being identified was minimal, requiring only one or more crimes per month. In addition to chronic hot spots this paper identifies “temporary” hot spots along a continuum defined by hot spot duration. Temporary hot spots, which may occur only once or may reoccur, are also potential targets for police prevention work. We suggest that decision making by police in such a dynamic setting might benefit from dynamic decision rules, starting and stopping police prevention workload at hot spots, chronic and temporary, so as to get maximum exposure of potential crimes to prevention efforts without wasting limited police resources when hot spots are “off.”

The goal of this paper is thus to investigate the efficiency and feasibility of a dynamic, rule-based, early warning system (EWS) in comparison to static deployments at chronic hot spots for crime prevention management. By “early warning system” we mean an approach that detects hot spots as soon as possible that have a good chance of persisting into the future given no additional police prevention efforts. The system therefore includes rules with thresholds for (1) detecting the start or flare-up of a hot spot, (2) predicting persistence of crimes after detection (for triggering deployment of police for prevention work at a hot spot), and (3) stopping prevention
work after the hot spot is (temporarily if not permanently) extinguished. The underlying methods used in this paper for EWS are simple and therefore the current research provides a benchmark for more sophisticated approaches.

We use kernel density smoothing for estimating chronic hot spots (Chainey et al. 2002; McGuire and Williamson 1999; Gorr and Lee 2012) and grid systems with grid cells serving as potential hot spots for EWS (Chainey and Ratcliffe 2005). Computational experiments using offense-report data on part 1 violent (P1V) crimes (homicide, rape, robbery, and aggravated assault) from Pittsburgh, Pennsylvania during 2000–2010 are used to optimize hot-spot grid size and rule thresholds in a computational experiment over ranges of values for grid sizes and thresholds. The result of each run is a point on a graph of percentage of total P1V crimes exposed to prevention measures (and thus possibly prevented) versus average percentage area of the city under prevention workload (which is directly related to prevention resources expended). The frontier of all points (on the high side of percentage crimes exposed to prevention) from the experiment is the optimal tradeoff curve.

Given a tradeoff curve, police managers can determine the level of effort feasible and desired to estimate expected exposure of crimes to prevention measures. For example, simple calculations based on number of patrol units, call for service levels, policy on how much time to spend in a hot spot, etc. indicate that at most randomized patrol several times per day at hot spots could be made for only a few percent of Pittsburgh’s area (Brackney 2013), therefore we use three percent of area as a benchmark in this paper. At this resource expenditure level, about 30 percent of the total P1V crimes in Pittsburgh could be exposed to prevention, as seen later in this paper. Field experiments, or the literature on field experiments, estimating size effect of prevention measures can then be used to estimate the expected reduction in crimes. For example, if the size effect were 50 percent reduction in crimes, then the total reduction in P1V crimes expected would be 15 percent from the EWS.

An additional criterion for selecting hot spots is their composition in terms of residential versus commercial land uses. The literature suggests that fear of crime is much amplified by crimes in residential areas as compared to in commercial areas, therefore it is desirable to have increased crime prevention in residential areas. Only 5.5 percent of Pittsburgh is commercial while 48.2 percent is residential; nevertheless, chronic hot spots covering three percent of Pittsburgh’s area
are disproportionally in commercial areas: 36 percent commercial and 49 percent residential (with the balance in other land-use areas). Furthermore the residential areas of chronic hot spots tend to be adjacent to commercial areas: 94 percent of chronic hot spots comprising three percent of Pittsburgh are in or within 500 feet of commercial areas, while the comparable figure for EWS hot spots of the same size is 80 percent. Clearly crime concentration is highest in commercial areas and both chronic and EWS hot spots will include commercial areas, but EWS hot spots tend to include more residential areas and more widely-scattered residential areas, providing police services responsively when and where needed.

Section 2 reviews relevant literatures, Section 3 describes the Pittsburgh crime data used for testing alternative hot spot strategies. Section 4 describes the proposed EWS and Section 5 provides the results of computational experiments. Section 6 discusses the results further and future work, and Section 7 concludes the paper.

2. Literature Review

This section reviews the literature on crime hot spots, temporary hot spots, fear of crime, and crime detection and prediction methods.

2.1 Crime Hot Spots

Many scholars have suggested crime hot spots as excellent targets for crime prevention by police because of their high crime density and stability over long periods of time. Sherman and his colleagues (1989a) found that about three percent of street addresses produced over 50 percent of service calls to police officers in Minneapolis. Spelman (1995) found a large number of police service calls concentrated on high risk places such as high schools, subway stations, and parks in Boston for a relatively long period. Weisburd et al. (2004) found that five percent of block-long street segments accounted for 50 percent of crime in Seattle and the hottest hot spots chronically persisted longer than a decade. Recently, Braga and his colleagues (2010) found that about five percent of street units (e.g., street-segments and cross-streets) accounted for 74 percent of gun crimes in Boston from 1980 through 2008. Additionally Braga et al. (2011) found that only one percent of street units generated about 50 percent of commercial robberies during a 29-year (1980–2008) study period. Wilcox and Eck (2011) coined a term for the concentration of crime in a very few bad places as “The Iron Law of Troublesome Places.”
One criticism of police interventions in crime hot spots has been the possibility that criminals and their crimes merely displace to other locations, often nearby. There is a mixed literature on crime displacement (Repetto 1976; Miethe 1991; Scherdin 1992; Braga et al. 1999; Clarke and Weisburd 1994; Hesseling 1995; Ratcliffe et al. 2011). More recently, Weisburd et al. (2006) found that certain crimes, illegal drug dealing and prostitution, do not readily displace and thus benefit from prevention efforts. Recently, Braga et al. (2012) concluded that policing hot spots not only have a moderate size effect in reducing crime, but also a diffusion of benefits (crime reduction) in contiguous areas rather than crime displacement. To the extent that displacement of crime exist, EWS would be responsive to it while chronic hot spots would not. Both crime prevention at chronic and EWS hot spots could enjoy diffusion of benefits.

Another important finding from Braga et al. (2012) was on the impact of police hot spot programs on community members. Regardless the early critiques on police misconduct and force abuse in New York City (Greene 1999), the skepticism on the effectiveness of hot spot policing tactics (Tonry 2011), as well as the disagreement between the police and residents when assessing and prioritizing neighborhood problems (Rosenbaum, 2006), Braga et al. found that community members in residential areas expressed positive reactions to hot spot policing. We believe a key policy of any hot spot program should be that field police build positive relationships with citizens—being responsive to crimes that have occurred and attempting to prevent future crimes.

Paralleling the development of hot spot policing has been development of methods for automatically estimating hot spot boundaries, including point mapping (Jefferis 1999), spatial ellipses (Block 1995; Levine 2013), thematic mapping (Harries 1999), grid-system maps (Chainey and Ratcliffe 2005), and surface smoothing methods (Chainey et al. 2002; McGuire and Williamson 1999; Gorr and Lee 2012). In addition, Weisburd et al. (2004) simply tabulate counts of crimes by block-long street segments and presumably use a threshold count to define hot spots. One of the commonly-used surface smoothing methods is kernel density smoothing (KDS) which is a non-parametric method that estimates crime density (crimes per unit area) from point data. Crime hot spots are defined as peak crime density areas by choosing a crime density threshold, and areas above the threshold are considered crime hot spots.
Chainey et al. (2008) compared different types of hot spot methods in regard to persistence of crime in the same hot spots in the following month. The study generated hot spots from the previous three months’ crime data using different hot spot methods, controlling total hot spot area in each method to be three percent of the study area in Central/North London. Though the percentage of crime persisting in crime hot spots in the following month varied only from eight to 20 percent, KDS outperformed other hot spot methods.

### 2.2 Temporary Crime Hot Spots

Gorr and Lee (2012) defined temporary hot spots as small areas with crime densities (crimes per unit area per time period, estimated using KDS) that are comparable to chronic hot spots but typically persist for periods of time less than a year, generally months. Temporary hot spots flare up, persist, extinguish, and can reoccur. Gorr and Lee found chronic hot spots to be relatively few in number and concentrated in commercial and poverty-stricken areas of Pittsburgh while temporary hot spots are smaller in area, greater in number, and widely dispersed across the city. Temporary hot spots can be potential targets in addition to chronic hot spots for police if they can be forecasted or persist long enough after initial detection for police to prevent crimes.

Chronic to temporary hot spots defines a spectrum of cases from always hot, to mostly hot, and to sometimes hot. Depending on where the line is drawn to define chronic hot spots, some designated chronic hot spots or their parts exhibit the on-and-off behavior of temporary hot spots and thus could benefit from a dynamic pattern of police resource allocation for prevention. This section reviews four theories for temporary hot spots: near repeat crimes, routine activity theory, broken windows theory, and relocation of poor populations.

**Near Repeat Crimes:** Morgan (2001), Townsley et al. (2003), Johnson and Bowers (2004a, 2004b) found “near repeat” burglaries in their studies; namely, that residences nearby an initial burglary were more likely to be targeted for burglaries later in the month than otherwise expected. Also, near-repeat burglaries are more prevalent than repeat burglaries at the same location. Similar to the crime preventive benefit of focusing on repeat victims (Pease, 1998), focusing on particular dwellings at or nearby the initial burglary could also predict and prevent future crimes. Johnson and Bowers (2004a) found that properties within 400 meters on an initial
burglary suffered from the elevated risk of burglaries for two months after the initial burglary. Near-repeat crime areas thus are one form of temporary hot spot.

Townsley et al. (2003) considered near-repeat burglaries as a social disease, namely that infectious phenomena occur more repeatedly nearby in homogenous housing areas. If the second burglary crime occurs within relatively a short time period, a temporary crime hot spot exists and police could have been in place to prevent it with some degree of success.

Ratcliffe and Rengert (2008) studied near repeat patterns of shootings. Their study showed that near-repeat shootings typically occurred within 400 feet from an initial shooting within a few weeks. Their reasoning was that the near-repeat shootings were retaliation between offenders and victims. In addition, Mohler et al. (2011) found that robberies as well as burglaries are predictable as near repeats.

Also, disputes amid illegal activities such as illegal drug dealing can cause near repeats. In this case, shootings may be the most certain and swiftest means to punish another given that criminals cannot report crimes they suffer to the police. If legitimate means, such as a law enforcement were available, offenders would not have to retaliate. Another possibility is retaliation gang shootings. For example, initial shootings between the rival gangs trigger not only serial shootings, but also other types of violent acts. Repeat victimization theories (Jacobs et al., 2000) and near-repeat phenomena in regard to location can explain this case.

In sum, near-repeat criminal behavior is one theory that leads to temporary crime hot spots. This theory appears, however, to only pertain to limited crime types: burglary, robbery, and shootings. It may be able to be extended to other crime types, for example, aggravated assault and homicide, as the result of shootings. It also may pertain to the certain types of criminals, for example, gang members who seek revenge from recent acts of violence.

**Routine activity theory:** According to routine activity theory (Cohen and Felson 1979; Felson 1986, 1987; Sherman et al. 1989b; Eck 1994, 1997), any situational change among the three necessary elements—potential victim (suitable target), motivated offender, and capable guardianship—can either deter or provoke crime. If a motivated offender finds a suitable target without any situational barrier that increases the risk of being arrested, the likelihood of the offender committing crimes will increase. Crime-prone places provide potential offenders with
higher opportunity to be involved in criminal acts due to the lack of guardianship and existence of potential victims.

Thus, by eliminating the opportunity that a crime-prone location offers to motivated offenders, police can reduce the likelihood of crime before it happens or reduce the opportunity of repeated occurrence of crime (Weisburd and Braga 2006; Sherman et al. 1989b). Proactive policing could achieve this goal by increasing the presence of police officers or increasing the frequency of police patrol in crime-prone locations. Once, however, special police resources are removed from such locations, crimes can start up again after criminals perceive the changed circumstances (e.g., Cohen et al. 2003).

Thus on and off behavior of crime hot spots can be caused by police, location managers, and other involved persons affecting the target/offender/guardianship situations of locations.

**Broken windows theory:** Broken windows theory provides a basis for predicting crime flare-ups and temporary hot spots. The parable of the broken window describes the association between social disorder and crime (Kelling and Coles 1997; Wilson and Kelling 1982). If a window in a house is broken and left unfixed without any care, other windows are more likely to be broken sooner and eventually signal an environment suitable for crimes. Likewise, if a misconduct or disorderly behavior is neither regulated nor enforced, it might be a potential signal that guardianship is low in an area, leading to serious crimes.

Cohen et al. (2007) and Gorr (2009) developed a leading-indicator model to forecast serious property and violent crimes based on broken windows theory. They found that increases in particular soft crimes and police calls for service often precede increases in serious violent crimes. Empirical research in Pittsburgh provided evidence on the degree of success by the leading-indicator model for predicting P1V crime flare-ups.

**Displacement of poor populations:** Reports on the moving to opportunity for fair housing demonstration program conducted by the U.S. Department of Housing and Urban Development (e.g., Popkin et al. 2002; Kling et al. 2007; Sanbonmatsu et al. 2011) found that displacing poor people may result in poverty displacement and, in turn, displacement of crime places. After 10 to 15 years of experiments, the researchers found that there was no significant difference in serious forms of anti-social or criminal behavior between treatment and control groups. These findings
indicated that movement of poor and high-risk people to other places may cause displacement of crime, resulting in a hot spot displacement.

As a case study, public housing developments in Pittsburgh were demolished from the mid-1990s to the early 2000s with former inhabitants scattered throughout poor areas of the city. Prior to that, gangs tended to form by housing development and in relation to surrounding neighborhoods leading to established territories, boundaries, and crime hot spots. When relocated and scattered, members of rival gangs no longer had established territories and thus had increased chance encounters, with temporary sequences of violent crimes resulting (Garland 2012). For example, aggravated assaults increased substantially in poor areas of Pittsburgh as relocation progressed.

So local government policy on housing can have an adverse effect on crime, causing increased levels of serious violent crimes and temporary hot spots.

2.3 Fear of Crime

Those who live in communities with crime hot spots nearby are more likely to experience emotional unstableness as well as continuous fear of crime (Grohe 2007). Citizens in such areas are more likely to devote large amounts of effort to protect themselves from crime or stay indoors rather than enjoying outdoor activities (Moor and Trojanowicz 1988). Crimes have a multiplier effect in residential neighborhoods because social networks spread second-hand information on crimes widely (Skogan 1986). For example, Skogan and Maxfield (1981) reported that 48 percent of the interviewees knew about robberies in a neighborhood, while only five percent of the neighborhood population had been victimized at the same time. Due to the second-hand information effect, a community may gradually lose its neighborhood cohesiveness as fear of crime elevates (Nasar et al. 1993).

Fear of crime is amplified for the old (Box et al. 1988), females (Keane 1998), and the poor (Taylor and Hale 1986). These groups are more vulnerable to crime due to potential psychological, physical, and economic weaknesses, so they are less likely to cope with the fear of crime as well as crime itself. Also, the propensity for fear of crime is higher among residential communities than urban settings. Citizens in urban areas may accept crime as a part of their life while those in residential areas do not (Grohe 2007). Persons can take safeguards in regard to
when and how visiting commercial areas, but avoiding crime risks is much more difficult where persons live and their children play.

Box et al. (1998) found police as a crucial means for reducing the fear of crime among citizens and Braga et al. (2012) found residents favorable to hot-spot crime prevention. A strong relationship between citizens and police significantly reduces the fear of crime in community. No doubt, the same is true for police and shop keepers in commercial areas. When police are assigned to targeted patrol in hot spot areas, they should include positive interactions with residents as part of patrol, to collect crime prevention information as well as to build relationships.

2.4 Detection and Forecasting of Temporary Crime Hot Spots

Forecasting the on-and-off behavior of temporary crime hot spots, when they start and end, is necessary for efficient and effective prevention of their crimes by police. There are, however, no corresponding direct models and methods in the time series literature. Nevertheless, this section reviews concepts and methods from that literature that are related to this paper’s EWS.

The great majority of demand forecasting methods use space and time series data with fixed service or product categories (crime types in this case), fixed time increments (e.g., days, weeks, months, quarters, years), and fixed spatial units (e.g., service or sales territories, census tracts, etc.). A disadvantage of such data, relative to temporary hot spots, is that some crimes can occur across boundaries of fixed units and therefore be missed. For example, a crime flare up might be split between adjacent grid cells and while not detected as tabulated, would be detected in a new, custom areal unit that combines affected portions of areas from the adjacent cells. The same problem is possible for a flare up split across sequential time intervals.

Some methods exist that build custom areal units, such as Corcoran et al. (2003) and the spatial scan statistic (Neill and Gorr 2007). The latter assembles the best set of custom areal units from small, “atom” units, such as blocks, searching over all possible subsets of atom units. Recent results make the spatial scan statistic feasible computationally for many applications (Neill 2009). Nevertheless, the problem is that each time new data is available, the analyst is confronted with having to create new custom observation units and the computational burden is large.
The space and time series data of temporary hot spots is best characterized as “intermittent.” Intermittent time series data have very low demand (such as demand for spare aircraft parts) or are tabulated at such a fine-grained level, to the point that there are many zeros in the time series data with occasional positive demand points (which are often clustered in time) (Croston 1972; Regattieri et al. 2005). The intermittent time series forecasting literature, however, is exclusively devoted to inventory management policies and estimation of optimal safety stocks in order quantities to minimize inventory holding costs. The objective is to have enough stock on hand to meet demand with a fairly high probability, given a run with positive demand, as well as to not have excessive stocks. Thus while the models in this area include estimation of separate parameters for arrival time and demand levels distributions, they are not concerned with precise timings of demands nor durations of runs. All that is needed is enough stock on hand to meet demand, and that’s assured at a high probability by optimizing the safety stock. The temporary crime hot spot problem, however, is concerned with precise timing—start up and stopping time points—so that police resources for crime prevention are not wasted. So intermittent forecast methods in the literature are not applicable to temporary hot spots.

The great majority of time series models and methods are for regular (non-intermittent) data, meaning that almost every observation has positive magnitude. The greatest number of time series forecasting papers are on extrapolative methods that merely extend experienced time trends and seasonal adjustments into the future. The temporary hot spot/intermittent forecast problem is not solved by extrapolation. Before positive demand forecasts are biased low (zero) and after a demand point they biased high (positive when the demand is again 0).

A smaller time series literature is devoted to models that are “causal” in the sense that they are multivariate with independent variables. Causal forecast models using lesser crimes as leading indicators of serious crimes have had some success (Cohen et al. 2007; Gorr 2009). If leading indicator events/crimes (e.g., shots fired 911 calls, drug 911 calls, simple assaults) have recently had a large step increase in an areal unit (or neighboring areal units), then serious violent crimes (homicide, rape, robbery, and aggravated assault) will likely have a near-term future increase in the areal unit. While these models are much better than chance decisions, they have high false positive rates. A further limitation of such models is that they require relatively large areal units (e.g., census tracts or larger) in order to have sufficiently-accurate estimates of model
coefficients, while crime hot spots are much smaller, on the order of blocks. Given a leading-indicator forecast of a crime flare up, crime analysts must then use expertise, crime mapping, field intelligence, etc. to determine where exactly and if to intervene within the larger area flagged.

Time series monitoring methods (Brown 1959, 1963; Trigg 1964; McClain 1988; Cohen et al. 2009) provide an alternative to time series forecasting. These methods have the objective of detecting an unexpected, large change in time series data as soon as possible. They are based on decision rules analogous to hypothesis testing where the test statistic is based on departures from extrapolative forecasts. A large, one-step-ahead forecast error (or series of errors of the same sign) provides evidence of a departure from “business as usual.” Generally time series monitoring is more accurate than time series forecasting (having higher true positive rates for given false positive rates) but at the cost that initially-detected crimes can have no prevention exposure, by definition. In contrast, if it were possible to accurately forecast a temporary hot spot, then the initial crime or crimes could also be exposed to prevention. Also, as with leading indicator forecasts, the crime analyst must use additional information and expertise to pinpoint locations within larger areal units monitored. Nevertheless, time series monitoring is promising as an approach to detecting temporary hot spots. For example, CrimeStat IV (Levine 2013) implements time series monitoring for crime space and time series data, based on Cohen et al. (2009).

In summary, none of the existing time series models and methods meets the needs of temporary hot spot management by police for crime prevention. In our judgment, an approach that is based on detection is the most promising at this time, but then must add predictions of hot spot persistence of crimes after detection given no prevention, and finally must have rules for stopping prevention work at hot spots. Future studies should consider a system that includes both forecasting and detection. Crime flare ups missed by forecasting could then be detected.

3. Data

Altogether this study had available two months less than 21 years of crime offense reports from the Pittsburgh Bureau of Police—January 1990 through October 2010. These are official, hierarchy offense reports listing the highest UCR offence for each crime incident. We chose to
analyze part 1 violent (P1V) crimes in aggregate (murder/manslaughter, forcible rape, robbery, and aggravated assault), which are the highest priority of police. We did not filter these crimes to eliminate those not amenable to street-level prevention measures such as domestic crimes; all P1V crimes were used. Future work with field experimentation should include such screening, then accuracy performance should improve.

We decided to use the 1990–1999 data only for exploration work because conditions in the city of Pittsburgh and police bureau changed significantly by the year 2000. The city accomplished much in terms of redevelopment of several crime-prone neighborhoods and had demolished the majority of its public housing developments. Also, by the early 2000s crime mapping was available citywide to both field officers and police management on a real-time basis, and the police department had instituted a CompStat process that included reviewing crime patterns. High-density crime areas became recognized and good targets for police. The volume of crime in chronic hot spots was 50 percent less in the 2000s than it had been in the 1990s while temporary hot spots increased (Gorr and Lee 2012). Table I provides descriptive statistics on P1V crimes for the study period.

Nevertheless, these data are appropriate for computational experiments in regard to crime prevention by modern police forces because there were no formal chronic nor dynamic hot spot prevention programs in effect. There simply was regular policing informed by crime maps and other normal sources of information. So crimes that occurred after prevention workforces are deployed in computational experiments (in simulation mode) are a good representation of crimes that could have been prevented by random targeted patrol and other measures.

We geocoded offense report data using ArcMap 10, TIGER street centerlines projected to State Plane coordinates as spatial reference data, and an ArcMap locator using default settings. The match rate was 84 percent, close to the minimum of 85 percent prescribed by Ratcliffe (2004). We used the Grid Index Feature tool of ArcToolbox to create three grids of polygons with square grid cells, all with the same arbitrary origin, with cell sizes 500, 750, and 1,000 feet on a side. Spatial overlay of grids on geocoded crime locations allowed aggregation to monthly time series by grid cell.
4. Rule-Based Early Warning System and Experimental Design

Too often complex and sophisticated methods are no more accurate than simple methods in the realm of prediction and forecasting (e.g., Makridakis et al. 1982), so simple methods should always be considered. The EWS of this paper is simple, has positive results, is readily implementable by police departments, and provides a baseline for comparison with more sophisticated methods in future work. It uses the following components for dynamic management of both chronic and temporary P1V crimes.

4.1 Grid System

For simplicity of data analysis and implementation by police, we decided to aggregate data by fixed grid cell, rather than spatial buffers of flare-up crime points as is done for near-repeat crimes. While feasible and perhaps desirable in practice, buffering adds routine geoprocessing steps as well as additional communication requirements for field police. It is an empirical question as to whether buffering provides additional performance over fixed grids to justify its additional effort, and we leave that to future work.

The key question of grid design is the size or scale of hot spot to be considered. Weisburd et al. (2004, 2012) established that chronic hot spots are composed of micro areas on the order of one-block long street segments. Gorr and Lee (2012) showed that Pittsburgh’s chronic hot spots are indeed micro areas, but generally include several adjacent street segments along linear

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**Table I. Annual part 1 violent crime statistics: Pittsburgh, 2000–2010**

<table>
<thead>
<tr>
<th></th>
<th>Murder-Manslaughter</th>
<th>Forcible Rape</th>
<th>Robbery</th>
<th>Aggravated Assault</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage Among P1V</td>
<td>1.5%</td>
<td>4.4%</td>
<td>48.6%</td>
<td>45.5%</td>
</tr>
<tr>
<td>Mean</td>
<td>38</td>
<td>111</td>
<td>1,220</td>
<td>1,142</td>
</tr>
<tr>
<td>Median</td>
<td>36</td>
<td>99</td>
<td>1,114</td>
<td>1,055</td>
</tr>
<tr>
<td>Min</td>
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<td>54</td>
<td>928</td>
<td>655</td>
</tr>
<tr>
<td>Max</td>
<td>48</td>
<td>155</td>
<td>1,269</td>
<td>1,188</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>8</td>
<td>35</td>
<td>107</td>
<td>158</td>
</tr>
</tbody>
</table>
commercial corridors or several contiguous blocks of major commercial areas such as the central business district. Furthermore, exploratory data analysis using Pittsburgh P1V crimes from 1990 through 1999 showed that temporary crime hot spots cluster spatially and temporally but over multiple but small numbers of blocks. Hence this paper experiments with three alternative square grid systems with cells of sizes 500 feet on a side (approximately four blocks in area), 750 feet on a side (nine blocks in area), and 1,000 feet on a side (16 blocks in area). There is a single, arbitrary origin for all grid systems that has not been varied. We expect that there will be many cases where two or more adjacent cells are hot spots, especially for the smaller cell sizes and in chronic hot spot areas.

4.2 Monthly Data

Another simplification of this paper is to use monthly time series data instead of real-time occurrences of crimes. A hot spot is “on” after detection if it has one or more P1V crimes within a month and “off” if none occurred. Below in this section we explain that monthly data biases the percentage of crimes exposed to prevention measures on the low side but does not bias workload estimates. Otherwise there are no considerable errors in using monthly data. Nevertheless, future work should consider real-time time series data.

4.3 Stopping Rule

Gorr and Lee (2012) also used monthly data but custom hot spot boundaries estimated via kernel density smoothing (KDS), rather than fixed cells, to study temporary hot spots. Their results showed that temporary hot spots exist for only one or two months if no time gaps are permitted with “off” months in between “on” months. Further exploration of 1990–1999 P1V crime data in Pittsburgh suggested that it is common to have a gap of one or more months but then crimes resume in the area before going “off” for long periods of time. So it seemed worthwhile to allow gaps and to experiment with their size.

This paper therefore allows time gaps of “off” months with stopping-rule alternatives of 1, 2, and 3 months in a hot spot cell. For example, supposed that after detection of a hot spot cell and prevention resources are deployed, a gap of one month allows a temporary hot spot to continue. Then the stopping rule is two months: workload continues until there are two months in a row that are off with no additional P1V crimes. For a specific example, suppose that “1” stands for an
“on” month, “0” stands for an “off” month, and subscripts are month sequence numbers in the following example for a cell:

010213140516071809010

Suppose that rules declare the third month to be the start of a temporary hot spot. The hot spot exists for 6 months (3–8), prevention work starts in month 4 and stops after month 10. The workload length is 7 months (4–10), and 3 months have their crimes exposed to prevention measures (months 4, 6, and 8). If month 4 had one crime, month 6 two crimes, and month 8 one crime, there are four crimes exposed to prevention. The flare-up or initiation crimes of month 3 are not exposed to prevention. In a real-time system, prevention could start immediately after the first crime detected, so if there were two crimes in the detection month, 3, the second crime could be exposed to prevention. Computational experiments in this paper, however, assume that prevention does not start until month 4 for the example and thus bias then number of crimes exposed to prevention on the low side. For an optimal EWS that has an average 3 percent of Pittsburgh under workload, 86 percent of hot spot flare ups have a single P1V crime in the flare-up month, while 12 percent have two P1V crimes, and 2 percent have three.

The simplification of using monthly data instead of real-time occurrences of crime to trigger decisions does not bias workload estimates in regard to a real-time system. While monthly data delays the start of workload by a half month on the average, it also delays stopping by a half month on the average, cancelling out errors.

4.4 Detection Rule

While several time series monitoring methods exist to signal changes in time series data (e.g., Brown 1959, 1963; Trigg 1964), this paper uses a simple rule with threshold based on P1V crime count within a month for each cell. At first, thresholds of 1, 2, 3, etc. were considered, but monthly crime counts of two or higher are infrequent (14 percent of the time) in micro-scale locations such as the cells used in this paper. So while we initially considered a flare up to be two or more crimes within close distance and short period, we use a threshold of one. This decision is justified using near-repeat crime theory.
4.5 Prediction Rule

While the detection rule has the advantage of being highly reactive, by itself it produces too many false positives. It makes sense to deploy prevention resources only if additional crimes are expected to occur within the cell in the near term so that they can be exposed to prevention measures. Hence we add a rule predicting persistence of a flare up to become a temporary hot spot with additional crimes. A simple rule is to use the history of P1V crime occurrence within the cell, so we use the number of months with one or more P1V crimes within the preceding 12 months and thresholds of 1, 2, … , 5 months. There are many additional and more sophisticated methods for predicting persistence, for example, using univariate time series methods, multivariate forecasts based on leading indicator crimes (Cohen et al. 2007), near-repeat forecasts (Bowers et al. 2004; Mohler et al. 2011), or a spatial scan statistic (Neill 2009).

4.6 Resource Deployment Rule

If both the detection and prediction/persistence rules “fire” or attain thresholds, then police are deployed for prevention work in the cell. If a particular police zone or precinct does not have sufficient resources for deployment in all hot spot cells for consideration, the prediction rule magnitudes (number of “on” months in the previous 12 months in this paper) can serve as a score for ranking cells and resource allocation decisions.

4.7 Performance Measures

Over a period of computational experiments across the police jurisdiction, the benefit of a hot spot management system is represented by percentage of total P1V crimes exposed to prevention measures while cost is the average percentage area of a police jurisdiction under workload. We assume that all potential hot spot cells receive prevention treatment in tabulating costs and benefits. Also considered is the make-up of hot spots, in regard to commercial and residential land uses. While crime concentrations are highest in commercial areas, it is beneficial to provide crime prevention services in widely-scattered residential areas as well to build police/citizenship relations and reduce fear of crime.
4.8 Summary of Experiment

We used all Pittsburgh P1V crime data from 2000 through October 2010 to evaluate alternative grid sizes and rule thresholds in a full factorial design for EWS. Grid sizes were 500, 750, and 1,000 feet on a side. Thresholds were as follows: detection rule threshold = 1; prediction rule thresholds = 1, 2, 3, 4, 5; and stopping rule thresholds = 1, 2, 3.

Included in the study is the alternative method of a chronic-hot-spot-only system, characteristic of current crime hot spot methods. We use the kernel density smoothing (KDS) method of Gorr and Lee (2012) that estimates a crime density surface with search radius of 250 feet corresponding for Pittsburgh to the street-segment scale of Weisburd et al. (2004). We vary the threshold crime density to define a range of hot spot sizes in terms of percentage area of the city that are hot spots and assume that prevention resources are constantly allocated to those areas.

We estimate chronic hot spots using three years’ historical data. For example, for year 2000 chronic hot spots we make a KDS estimate using 1997–1999 data, select a threshold density which if exceeded defines a hot spot, and then predict that the resulting hot spots persist throughout 2000. Three years’ data seemed sufficiently long for estimating chronic hot spots while also being somewhat reactive to underlying changes in crime patterns. For instance, given the economic redevelopment of some of Pittsburgh’s most crime-ridden areas in the latter part of the 1990s and early 2000s, it makes no sense to use all available data (1990–2010) to estimate current chronic hot spots.

We then produce a tradeoff curve of percentage of total P1V crimes exposed to prevention versus percentage area of the city under prevention workload by varying the threshold density that defines a chronic hot spot. Tradeoff curves will have marginally decreasing returns because to increase area of a hot spots one must add locations with lower crime density.

5. Results

This section presents results of the two alternative approaches described in the previous section of this paper for prevention of serious violent crimes. First is chronic hot spots, followed by EWS.
5.1 Chronic Hot Spots

Figure 1 is the trade-off curve obtained from plotting percentage of total P1V crimes that could have been exposed to prevention measures versus average percentage of Pittsburgh area classified as chronic hot spots over the period 2000 through 2010. As expected, the curve shows marginally decreasing returns from increasing the size of hot spot areas. In addition to Figure 1 is the land-use composition of hot spots as their area increases; namely, that the percentage of hot-spot area that is zoned commercial decreases while percentage of residential area increases. For example, for one-percent-area chronic hot spots 44 percent is commercial while 41 percent is residential (and the balance has other land uses) while for three-percent-area hot spots 36 percent is commercial while 49 percent is residential. Clearly commercial areas have the highest crime densities and are taken first, so when expanding crime hot spots, residential areas enter later.

Suppose that for discussion purposes, that at the start of 2010 police decision makers decided to allocate prevention resources for three percent of Pittsburgh’s area. Figure 2 displays the resulting 39 chronic hot spots for 2010, accounting for 35 percent of total P1V crimes that could be exposed to prevention efforts. (Over the entire study period of 2000 through October 2010, chronic hot spots of the same size area accounted for fewer crimes, an average of 31 percent of P1V crimes.) Also shown in Figure 2 are commercially-zoned areas of Pittsburgh and the boundaries of poverty areas (estimated using kernel density smoothing of an index of four poverty measures). Chronic hot spots tend to be in commercial and poor areas of Pittsburgh.

5.2 EWS Hot Spots

As indicated earlier, chronic hot spots are not always “on;” for example, very hot chronic hot spots that comprise one percent of Pittsburgh’s area on only eight and a half out of twelve months per year. Moreover, parts of chronic hot spots may be “on” and other parts “off” in any month. So there are potential benefits of applying EWS to all crimes without any areas designated as chronic. Dynamic resource allocation may reduce use of police resources in what had been designated chronic hot spot areas while still providing a comparable level of chronic-area crimes exposed to prevention and making additional resources available for other, more widely-dispersed areas.
Figures 3 and 4 illustrate this potential for July 2010. Figure 3 overlays the three-percent-area chronic versus three-percent-area rule-based hot spots with “on” cells (having at least one P1V crime in July 2010) displayed for that month. Only parts of some chronic hot spots are on while others are off completely, indicating that the chronic hot spot areas are themselves dynamic.

Figure 4 shows all workload hot spot cells as well as areas zoned residential in Pittsburgh. The additional cells (shown in black) in Figure 4 over Figure 3 are locations in Pittsburgh that would have had prevention efforts assigned but no P1V crimes occurred (i.e., are false positives for that month). Here you can see that the majority of prevention work is in residential areas. Over the entire study period of 2000 through October 2010 for the three-percent-area case, 64 percent of rule-based workloads that would have exposed crimes to prevention measures (true positives) were located in residential areas, while only 21 percent were in commercial areas and 15 percent were in other land-use areas. The commercial-area cells tend to be concentrated and on with much higher frequency than the residential cells which are scattered.
Figure 5 is the tradeoff curve for the rule-based system. Black point markers are non-dominated, frontier points from the experiment making up the tradeoff curve, while the gray points are dominated. Shown in parentheses for frontier points are their cell sizes in feet, percentage of the previous 12 months that had one or more P1V crimes in the hot spot cell (persistence prediction rule), and number of months prevention is maintained without additional P1V crimes before stopping prevention workload at the cell. The three-percent-area tradeoff point has about 30 percent prevention exposure, which is comparable to the three-percent-area chronic hot spots.

Fig 2. Map of part 1 violent crime chronic hot spots (3 percent area) with commercial zone and poverty lines: Pittsburgh, 2010
(with 31 percent prevention exposure). Overall performance is similar (e.g., not significantly different for the three-percent-area case, \( p\text{-value} < 0.01 \)) to those of chronic crime hot spots.

Surprising in the pattern of decision rule thresholds as percentage area increases in Figure 5 is that the one-month stopping rule is optimal only for the most conservative point, less than one percent area. Then a two month stopping rule is optimal for one percent area and after that all optimal points have the three month stopping rule. We thought that the one month stopping

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3 We used a difference of means test on monthly data to determine whether the mean number of P1V crimes that could be exposed to prevention effort are significantly different between three-percent-area chronic and EWS hot spots. The result has 0.147 as the t-statistic (\( p\text{-value} = 0.884 \) in two tail test) which leads us to fail to reject the null hypothesis of equal means.
rule would be optimal for a larger range of areas, with resulting smaller month gaps between successive P1V crimes under workload and fewer false positives. Also interesting is that the smallest cell size considered, 500 feet, is optimal all the all up to over five percent area, then the 750 foot areas become optimal. A conservative pattern exists for predicting persistence of hot spots, with four of the previous 12 months (33 percent) up to one percent area and then alternating three and two months on.

**Fig 4.** Map of part 1 violent crime rule-based workload cells (3 percent area) with residential zone: Pittsburgh, July 2010. Note: rule-based hot spots are based on 3 month stopping rule with 17 percent persistence prediction rule and 500 foot grid cells.
Figure 6 shows the distribution of workload durations of the three-percent-area optimal solution (500 foot cells, two months persistence rule, and three month stopping rule). The spike at three months with 70 percent frequency corresponds to false positives where workload was triggered, terminated after three months, because no additional P1V crimes occurred.

EWS increases the percentage of hot spots in residential areas by 24 percent, to 61 percent from the 49 percent of the chronic hot spots. Moreover, by examining Figures 3 and 4 you can see that residential areas of chronic hot spots tend to be adjacent to commercial areas while those of the rule-based approach are more spread out and not adjacent to commercial areas. As stated in the introduction, 94 percent of chronic hot spots comprising three percent of Pittsburgh are in or within 500 feet of commercial areas, while the comparable figure for EWS hot spots of the same size is 80 percent.
6. Discussion

The ESW has the needed components for dynamic decision making on crime hot spots and its underlying methods are simple and easy to implement. There are, however, more sophisticated detection and prediction models and methods available than those used in this paper. For example, detection can use time series monitoring methods instead of occurrence of a crime as used in this paper and the spatial scan statistic is a prime candidate for making improvements in detection. Also, additional data about the nature of detected crimes (e.g., has gang involvement, involved illegal drug dealing) might better predict persistence of a temporary hot spot than the rule used in the paper based only on historical frequency of on months in a cell. The potential to improve chronic hot spots, however, appears to be less. Methods to identify chronic hot spots are all very simple and it is difficult to imagine any ways to make improvements. So while the
current results show that chronic and dynamic hot spot methods perform the same in terms of crimes exposed to prevention for effort expended, it is possible that dynamic hot spot accuracy could improve substantially in the future.

As discussed earlier, field experiments should use real-time deployment or prevention resources after detection/persistence prediction instead of monthly decisions. A rough estimate is that this would improve the percentage exposure of P1V crimes to prevention from 30 to 32 percent for the three-percent-area case. Likewise, stopping rules should be operated in real-time.

Besides the chronic and dynamic approaches to crime prevention at hot spots, a hybrid method is possible using the hot spot decomposition of Gorr and Lee (2012), crimes = chronic hot spot crimes + temporary hot spot crimes + random crimes, with sequential estimation. First we estimate very hot chronic hot spot crimes (to minimize “off“months) using KDS, then remove chronic hot spot crimes from the data, and apply the rule base to the balance of data. While not reported in this paper, we used a chronic hot spot threshold corresponding to less than one percent area for workload and then conducted the full factorial design on the balance of crimes. The tradeoff curve (using combined percentage area and crimes exposed to prevention from chronic and dynamic hot spots) were similar to those in Figures 1 and 5. Also the percentage area in hot spots that is residential was in between that of the chronic and dynamic hot spots. The benefit of the hybrid approach is that the chronic part has the simplicity of constant prevention workload, while the dynamic part can readily track changing conditions and temporary hot spots.

7. Conclusion

This paper provides evidence that most crime hot spots are dynamic (temporary) with “on” months during which targeted crimes occur and “off” months when they do not occur. Given a crime density threshold per unit time if exceeded that identifies crime hot spots, there is a continuum of hot spots defined by duration from “on” constantly, to on much of the time, and on some of the time. For example, chronic hot spots even for the hottest one percent of Pittsburgh’s area are only “hot” (i.e., have at least one crime per month) on the average only 8.5 out of 12 months per year. So a static, constant deployment of police to chronic hot spots even in this extreme case wastes prevention resources 3.5 months per year on the average. The larger the
percentage area designated as chronic hot spots, the larger proportionally the waste because there are marginally decreasing returns to adding area.

The question then becomes “Is there an efficient decision-making system that can allocate prevention dynamically, on and off, matching hot spot behavior?” If there were, then police could overall be more efficient with their limited resources. A dynamic approach of crime hot spot management by police, an early warning system (EWS) as proposed in this paper, has decision rules for: (1) early detection of a crime flare up in a small grid cell, (2) prediction of persistence given no police prevention efforts, and (3) stopping after evidence of hot spot extinguishment. The dynamic system, however, also wastes prevention resources because of waiting to confirm that hot spots are extinguished (stopping rule) and false positives for predicted persistence after detection (cells that have crime flare ups that do not persist even without police prevention work). So, it is an empirical question as to which approach is more efficient (maximizing crime exposed to prevention work given a fixed total level of prevention effort).

The results comparing static versus EWS in Pittsburgh is that the efficiency of each is almost identical comparing chronic hot spots (kernel density smoothing with block-long search radius, Gorr and Lee 2012) versus the simple detection and prediction methods used for the dynamic method. Using fear of crime as an additional criterion, however, favors EWS which tends to have more residential hot spots. Fear of crime in residential areas is amplified due to the multiplier effect of neighborhood social networks—knowledge of victimization and fear spreads widely in residential neighborhoods. Clearly citizens and city fathers want safe commercial areas as well, but crime near home is much more fearful and less avoidable. For hot spots covering three percent of Pittsburgh’s area, EWS has 24 percent more residential hot spots than do chronic hot spots. Also, while the residential area of chronic hot spots tends to be adjacent to commercial areas (and are fixed), the residential areas of EWS hot spots are widely scattered and therefore responsive to neighborhood crime.

Also, if underlying crime patterns change over time, besides normally being dynamic in terms of on and off behavior, the dynamic system has the advantage of tracking changes quickly and closely. Of course, chronic hot spots have the advantage of being easy to manage: simply identify them and assign prevention resources to them over the long term. Gorr and Lee (2012)
suggest using a rolling window of three year’s data to estimate chronic hot spots to make them adaptive to changes in underlying crime patterns.

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