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Early Warning System for Temporary Crime Hot Spots

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Abstract
Objectives We investigate the potential for preventing crimes at temporary hot spots in addition to chronic hot spots. Using data on serious violent crimes from Pittsburgh, Pennsylvania, we investigate an early warning system (EWS) for starting/stopping police deployments at temporary hot spots in coordination with constant prevention work at chronic hot spots.
Methods We estimate chronic hot spots using kernel density smoothing. We use simple rules for detecting flare-ups of temporary hot spots, predicting their persistence, deploying police, and stopping deployments. We also consider a combination program including the hottest chronic hot spots, with EWS applied to remaining areas. Using 2000–2010 data, we run computational experiments varying the size of chronic hot spots and varying rule thresholds to tune the EWS. Tradeoff curves with percentage of crimes exposed to prevention versus percentage area of the city with crime prevention workload provide tools for coordinating chronic and temporary hot spot programs.
Results The combination program is the most efficient, equitable, and responsive program. After first allocating police prevention resources to the hottest chronic hot spots, the marginal benefits of adding more chronic hot spot area is not as high as adding temporary hot spots. Chronic hot spots are limited to large commercial and adjoining residential areas. Temporary hot spots are widely scattered throughout Pittsburgh.
Conclusions Temporary hot spots exist outside of chronic hot spots and are targets for prevention as supplements to chronic hot spots. A combination program targeting both chronic and temporary hot spots is recommended.

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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 to assign prevention resources to them over the long term. Wilcox and Eck's (2011) "iron law of troublesome places" assures a constant series of crimes in such places.

This paper investigates *temporary* hot spots as targets for crime prevention in addition to chronic hot spots. Temporary hot spots, like chronic hot spots, have high crime density but persist only for months instead of years and thus require a dynamic approach for allocating crime prevention resources. We therefore propose and investigate a hot spot early warning system (EWS) for managing temporary hot spots that includes rules for (1) detecting the start or flare-up of a temporary hot spot, (2) predicting persistence of crimes after detection given no prevention work beyond existing policing efforts, (3) deploying police for prevention work at a temporary hot spot, and (4) stopping prevention work after the hot spot is extinguished temporarily if not permanently.

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 calibrate, investigate, and compare the performance of chronic, EWS, and combined chronic and EWS hot spot programs. Pittsburgh is an ideal test bed because while it has used modern crime mapping and CompStat approaches for tactical deployment of police, putting "cops on the dots," it has not had either sustained or centralized hot spot programs during the study period.[1] Thus the empirical work in this paper assesses the potential for preventing crimes beyond current good policing practices. Indeed the results show that 33.3 % of Pittsburgh's P1V crimes (with 95 % confidence interval [32.6, 33.9]) could have been exposed to hot spot prevention efforts with only an average of 3 % of Pittsburgh's area under prevention workload using the combination hot spot program as described below.

[1] The status of hot spot policing in Pittsburgh over 2000–2010 was confirmed by reading annual reports of the Pittsburgh Police Bureau and from interviews of commanders of the two zones with the highest violent crime rates. Authority to use hot spot programs rests with the six zone commanders, and they used saturation patrols in only two locations for short periods. A 2012 master's student project in the Heinz College of Carnegie Mellon University designed chronic hot spots using the methods provided in this paper for one of the commanders, who has since implemented the design. In the early 1990s, one Pittsburgh neighborhood, Homewood, famously had intensive hot spot policing for an entire summer, supported by a DMAP crime mapping project (Olligschlaeger 1998) but that kind of effort was not repeated in the study period.

We use grid cells as potential temporary hot spots (Chainey and Ratcliffe 2005) for computational convenience as well as a practical way for police to implement EWS. We optimize temporary hot-spot grid size and rule thresholds in the computational experiment over sets of values for grid sizes and rule thresholds. The result of each experimental run is plotted as benefits versus costs represented by percentage of city-wide P1V crimes exposed to prevention measures (and thus possibly prevented) versus average percentage area of the city under prevention workload. The frontier of all points from the experiment is the optimal EWS tradeoff curve.

We use kernel density smoothing (KDS), a non-parametric spatial smoothing method, for estimating chronic hot spots (Chainey et al. 2002; McGuire and Williamson 1999; Gorr and Lee 2012). KDS estimates crime density maps (crimes per unit area). KDS places a kernel, generally a three-dimensional Gaussian density centered over each mapped crime point (as is the case in this paper), and sums all kernels to yield the density surface. Crime densities above a selected crime density threshold for KDS maps estimated over a multiple-year period define chronic hot spot boundaries. The KDS map has the appearance of topography with hills and the threshold is a plane whose intersection with hilltops defines the chronic hot spot boundaries. This method of defining chronic hot spots has the advantage of allowing us to vary the crime density threshold and estimate performance for a range chronic hot spots of increasing size. We create tradeoff curves for chronic hot spots, with the same dimensions as those for temporary hot spots, by varying the KDS threshold.

The combined hot spot program first allocates resources to chronic hot spots up to a maximum size in area and then applies the EWS to remaining areas outside of the chronic hotspots, optimizing over grid sizes and rule thresholds. The combined tradeoff curve uses the chronic hot spot curve up to the maximum size and then uses the optimal EWS tradeoff curve for additional areas added to the end point of the chronic curve. The rationale for the combined program is based on two observations. First, an analysis of chronic hot spots shows their crime densities are steeply peaked so that crime densities fall off exponentially as chronic hot spot areas are increased. For example, the hottest chronic hot spots in Pittsburgh covering roughly 1 % of Pittsburgh's area have a crime density of 738 P1V crimes per square mile over a year while the additional ring of chronic hot spot area from roughly 1–2 % has a density of 372 and that for 2–3 % has a density of 214. Thus chronic hot spots in Pittsburgh degrade quickly to behaving more like temporary hot spots as sizes are increased. Second, the feasible areas for chronic hot spots are a subset of feasible areas for temporary hot spots, so that after the hottest areas are assigned to chronic hot spots there may exist better or simply more of the best temporary hot spots such as adjacent to the hottest chronic hot spots.

The results demonstrate comparative advantages of chronic and temporary hot spot programs, with the combination program capturing the best of both, providing overall the best efficiency as well as more equitable and responsive allocations of police prevention resources. We provide evidence that (1) chronic hot spots, with constant deployment of prevention resources, are the most efficient means for crime prevention, but only for the very hottest (highest crime density) areas; (2) temporary hot spots are more efficient than relatively large chronic hot spots for crime prevention as supplements to hottest hot spots of the same total area under prevention workload; (3) chronic hot spots tend to occur in large commercial areas of impoverished neighborhoods; and (4) temporary hot spots provide crime prevention services more equitably across the urban landscape where needed and especially in widely-scattered residential and small commercial areas.

Section 2 reviews relevant literatures. Section 3 describes the Pittsburgh crime data used for testing alternative hot spot strategies. Section 4 describes the proposed hot spot

EWS, and Sect. 5 provides the results of computational experiments. Section 6 discusses the results further and suggests future work, and Sect. 7 summarizes the paper.

Literature Review

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

Crime Hot Spots

Many scholars have suggested crime hot spots as targets for crime prevention by police because of their high crime density and stability over long periods of time. Sherman et al. (1989a) found that about 3 % of street addresses produced over 50 % of service calls to police officers in Minneapolis. Spelman (1995) found a large number of police service calls concentrated in high risk places such as high schools, subway stations, and parks in Boston for a relatively long period. Weisburd et al. (2004) found that 5 % of block-long street segments accounted for 50 % of crime in Seattle and the hottest hot spots chronically persisted longer than a decade. Recently, Braga et al. (2010) found that about 5 % of street units (e.g., street-segments and cross-streets) accounted for 74 % of gun crimes in Boston from 1980 through 2008. Additionally Braga et al. (2011) found that only 1 % of street units generated about 50 % 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 had been a mixed literature on crime displacement (Reppetto 1976; Miethe 1991; Scherdin 1986; Braga et al. 1999; Clarke and Weisburd 1994; Hesseling 1995; Ratcliffe et al. 2011). More recently, however, Weisburd et al. (2006) found that certain crimes, illegal drug dealing and prostitution, do not readily displace and thus benefit from prevention efforts. Moreover, Braga et al. (2012) concluded that policing hot spots not only has a moderate effect size 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 exists, 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 of the early critiques on police misconduct and force abuse in New York City (Greene 1999), the skepticism surrounding 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 recommend that a key policy of any hot spot program should be that field officers build positive relationships with citizens—being responsive to crimes that have occurred and working 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). One of the commonly-used surface smoothing methods is kernel density smoothing (KDS) which is a simple non-parametric method that estimates crime density (crimes per unit area) from point data (Haining 2012).

Chainey et al. (2008) generated hot spots using alternative mapping techniques and compared them based on persistence of crimes in the next month after estimation. Controlling total hot spot area in each hot spot mapping technique to be 3 % of the study area in Central/North London, the study generated hot spots using the previous 3 months' crime data. Though the percentage of crimes persisting varied by types of crime from only 8 to 20 %, KDS outperformed other commonly-used hotspot mapping techniques: standard deviational ellipses, thematic mapping of boundary areas, and grid thematic mapping.

Temporary Crime Hot Spots

Mohler et al. (2011) provide a methodology that models and simultaneously estimates both short-term and long-term crime hot spots using a marked point process. Their model, however does not identify or distinguish chronic hot spots versus temporary hot spots. Instead they compute a total crime density for grid cells, summing long-term average and short-term flare up contributions. They recommend ranking all grid cells daily and allocating the top x % for police prevention work depending on available resources.

Gorr and Lee (2012) defined temporary hot spots as 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. Craglia et al. (2000) pointed out the importance of different crime prevention responses in accordance with differences in neighborhood characteristics as well as offender, victimization and incident rates across neighborhoods. For example, an urban area with high offense rates requires long-term policing tactics to reduce crime, while a residential area with low offense rate but relatively high victimization needs more sophisticated approaches such as dynamic proactive policing. In this vein, temporary hot spots can be potential targets, in addition to chronic hot spots, for police if the temporary hot spots persist long enough after initial detection for police to prevent crimes or can be forecasted in advance. This paper shows that early detection is promising. Forecasting crime flare-ups is more challenging.

Chronic to temporary hot spots define a spectrum of cases from always hot, to mostly hot, to sometimes hot. The empirical work in this paper provides evidence that, depending on where the line is drawn to define chronic hot spots, some designated chronic hot spots or their parts may exhibit the on-and-off behavior of temporary hot spots and thus may 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, hardening of soft crimes, and relocation of poor populations.

Near Repeat Crimes Morgan (2001), Townsley et al. (2003), Johnson and Bowers (2004a, b) found "near repeat" burglaries in their studies; namely, that residences nearby an initial burglary were more likely to be targeted for burglaries soon afterwards 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 m on an initial burglary suffered from the elevated risk of burglaries for

2 months after the initial burglary. For burglaries in a portion of Los Angeles, Mohler et al. (2011) estimated areas of elevated risk to be 50–100 m.

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.

Also, disputes arising from illegal activities such as 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 (Cohen and Tita 1999; Tita and Ridgeway 2007). 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, gang-related violence, 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 special police resources are removed from such locations, however, 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.

Soft crimes harden Theoretical reasoning on certain criminal behaviors suggests that an increase in certain lesser crimes in a small geographic area may lead to an increase in serious crimes later in that area. Empirical research has borne this possibility out, giving rise to an additional theory for temporary hot spots.

Contributing to this development is that criminals tend to be generalists, committing a wide range of disorder and crime types (e.g., Blumstein et al. 1988; Piquero 2000; DeLisi 2001). Additionally, criminals generally do not travel far from their residences to commit crimes (e.g., Rengert et al. 1999). So if there is a new criminal element in a neighborhood, say due to new gang activity or release of a prisoner from jail, we expect to have a variety of crime types occurring in a relatively small area. Disorderly behavior and lesser crimes are much more prevalent than serious violent crimes; hence, by chance alone one would expect to experience lesser crimes first and serious violent crimes later by a specific group of criminals. Broken windows theory suggests that crime hardens over time as neighborhoods decay, and can occur over a variety of time scales including short time intervals (Doran and Burgess 2012, p 13).

A test of this theory is to determine if large increases in soft crime in small areas lead to large increases in hard crimes in the same areas. Cohen et al. (2007) and Gorr (2009) developed and tested a leading-indicator forecast model to forecast serious property and violent crimes from time-lagged soft crimes. They found that increases in particular soft crimes and police calls for service often precede increases in serious violent crimes in small areas. For example, approximately 25 % of all large increases in serious P1V crimes were forecasted one month ahead of occurrence with a false positive rate of 15 %, whereas a chance mechanism would forecast 15 % of such P1V crimes increases at the 15 % false positive rate. Cohen et al. (2009) in analyzing Pittsburgh Police crime analysts' preferences found a 15 % false positive rate to be optimal in the tradeoff between signaling P1V crime increases for prevention versus cost of false positives.

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 10–15 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 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 in isolated housing developments 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 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.

Therefore local government policy on housing can have an adverse effect on crime, causing increased levels of serious violent crimes in previously low-crime areas, and because housing relocations are scattered as opposed to concentrated, the result can be temporary hot spots.

Fear of Crime

While this paper uses potential reductions in crime counts as a measure of performance, it is also worthwhile to consider potential reductions in fear of crime, especially in residential areas where crime prevention workload at temporary hot spots has the potential to be effective. Fear of crime is considered by some researchers to be more important than crime itself, with fear exceeding actual crime rates (Doran and Burgess 2012, p 24). Crimes have a multiplier effect in residential neighborhoods because interpersonal social networks spread second-hand information on crimes widely (Skogan 1986). For example, Skogan and Maxfield (1981) reported that 48 % of interviewees knew about robberies in a neighborhood in which only 5 % of the neighborhood population had been victimized. Due to the second-hand information effect, a community may gradually lose its neighborhood cohesiveness as fear of crime elevates (Nasar et al. 1993).

Those who live in communities with crime hot spots nearby are more likely to experience emotional instability 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 in-doors rather than enjoying out-door activities (Moore and Trojanowicz 1988). 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. 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). People can take safeguards when visiting commercial areas, but avoiding crime risks is much more difficult where they live and their children play.

At the present time, there is little evidence suggesting that police can reduce fear of crime through hot spot enforcement (Braga et al. 2012), although if done properly there is the possibility that it may. Police need to engage in crime prevention proactively with problem- and community-oriented policing in partnership with communities (Doran and Burgess 2012, p 51). If, however, policing tactics become overly aggressive such as with zero tolerance, then community relations suffer and fear of crime may increase (Rosenbaum 2006; Tonry 2011). Also, unexplained increased police presence may increase fear of crime as an indication or reminder of nearby dangers of crime (Hinkle and Weisburd 2008). Nevertheless, Box et al. (1988) found police presence a crucial means for reducing the fear of crime among citizens. Weisburd et al. (2011) did not find evidence of negative impacts on community perceptions of police by hot spot enforcement while Braga et al. (2012) found residents favorable to hot-spot crime enforcement. If community members are aware that police presence has the purpose of preventing crimes, then perhaps fear of crime can be reduced.

Detection and Forecasting of Temporary Crime Hot Spots

Forecasting the on-and-off behavior of temporary crime hot spots, when they start and end, would be highly desirable for efficient prevention of crimes by police. So far forecasting the timing of changes in time series has not been addressed adequately in the literature although there is a small literature on detecting and forecasting the start of crime flare ups.

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, etc.), 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 area unit that combines affected portions of areas from the adjacent cells. The same is possible for a flare up split across sequential time intervals.

Some methods exist that build custom spatial 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 computationally feasible for many applications (Neill 2009). Nevertheless, each time new data is available, the analyst is confronted with having to create new custom observation units to communicate to field officers, the computational burden is large, and as yet there is no empirical validation that such methods are accurate enough for crime prevention work.

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, that there are many zeros in the time series data with occasional positive demand points, 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, while at the same time not to have excessive stocks. Thus while the models in this area include estimation of separate parameters for arrival time and demand-level distributions, they are not concerned with precise timings of demands or durations of runs. All that is needed is enough stock on hand to meet demand, and that is 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 cannot be forecasted 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 a spatial 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 spatial unit. While these models are much better than chance decisions, they have relatively high false positive rates. A further limitation of such models is that they require relatively large spatial units (e.g., census tracts) in order to have accurate estimates of model coefficients, while crime hot spots generally 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 using a test statistic 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 because of their relatively high true positive rates for given false positive rates (compared to forecasting). 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. At this time, detection appears to be the only feasible approach to managing temporary hot spots in a EWS at the spatial scale of multiple blocks.

Data

Altogether this study had available 2 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) because they 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, thereby improving accuracy.

We decided to use the 1990–1999 data for exploration work only 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. Overall violent crime decreased in Pittsburgh after the peak in 1993 due to the decline of the crack cocaine epidemic. Also, by the early 2000's 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 share of crime in chronic hot spots was 50 % less in the 2000's than it had been in the 1990's while the percentage of crime in temporary hot spots increased (Gorr and Lee 2012).

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 for 2000–2010 data was 86 % which meets to the minimum of 85 % 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.

Table 1 provides average counts for P1V crimes for Pittsburgh for the 2000–2010 study period with residential and commercial area crimes broken out. Only 5.5 % of Pittsburgh is commercial while 48.2 % is residential. The balance of Pittsburgh in addition to commercial and residential areas is not broken out but includes institutional and industrial land use areas along with large areas that are not inhabited such as steep hillsides, parks, and cemeteries. With this makeup of Pittsburgh, from Table 1 we calculate that the average P1V crime density for commercial areas is 128 crimes per percent land area while that of residential areas is 31. So while there are twice as many residential P1V crimes as commercial, commercial crimes are four times dense than residential crimes. To impact total

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

	Residential areas of Pittsburgh		Commercial areas of Pittsburgh		All of Pittsburgh	
	Annual average	Percentage residential (%)	Annual average	Percentage commercial (%)	Annual average	Percentage total (%)
Murder-Manslaughter	28	2	7	1	39	2
Rape	68	5	19	3	107	4
Robbery	654	44	458	65	1,302	50
Aggravated assault	741	50	223	32	1,140	44
Part 1 violent crime	1,491	100	707	100	2,588	100

P1V crimes with prevention, it is very desirable, while challenging, to find ways to impact residential areas.

Ninety-four percent of the P1V crime aggregate is made up of robberies and aggravated assaults in Pittsburgh as well as its residential areas; however, the percentage of robbery is higher in the former while the percentage of aggravated assault is higher in the latter, as might be expected. Furthermore, 58 % of all P1V crimes occur in residential areas, including 72 % of murder-manslaughter and the majority of rapes and aggravated assaults.

Rule-Based Early Warning System and Experimental Design

The Law of Parsimony suggests simple explanations. Along this line, too often sophisticated methods are no more accurate than simple methods in the realm of prediction and forecasting (e.g., Makridakis et al. 1982; Makridakis and Hibon 2000), therefore 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 temporary hot spots.

Grid System

For simplicity of data analysis and ease of 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 or KDS maps. While feasible and perhaps desirable in practice, buffering or KDS adds geoprocessing steps as well as additional communication requirements with field police as boundaries change. It is an empirical question as to whether dynamic boundaries for temporary hot spots provide additional performance over fixed grids to justify additional effort, and we leave that to future work. The use of fixed grid cells in this paper provides a proof of concept for temporary hot spots as targets for crime prevention.

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. Ratcliffe (2012), using change point regression, found elevated densities of violent crimes within 85 feet of bars in Philadelphia. Gorr and Lee (2012) showed that Pittsburgh's chronic hot spots are indeed micro areas, but generally include several adjacent street segments along linear commercial corridors or several contiguous blocks of major commercial areas such as the central business district. We imagine that temporary hot spots are smaller in size than chronic hot spots. Exploratory data analysis using Pittsburgh P1V crimes from 1990 through 1999 showed that temporary crime hot spots cluster both spatially and temporally but over small numbers of blocks as opposed to a single street segment or block. The near-repeat crime literature (e.g., Johnson and Bowers 2004a; Ratcliffe and Rengert 2008; Mohler et al. 2011) finds areas of elevated risk from initial crimes in the range of 150–1,200 feet.

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), and 1,000 feet on a side (16 blocks). We expected that there would be many cases where two or more adjacent cells are temporary hot spots, especially for the smaller cell sizes. If we had chosen to use buffers of initial or flare-up crimes instead of fixed grid cells, we would have chosen a size less than 500 feet for the smallest grid size. To increase the chance of capturing an entire or most of a near-repeat cluster with a grid cell, it is necessary to have grid cells larger than the clusters.

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 reason that monthly data biases the percentage of crimes exposed to prevention measures on the low side but does not bias workload estimates on the average. Otherwise there are no considerable errors in using monthly data. Nevertheless, future work should consider weekly and real-time time series data with the potential of improving crime-prevention efficiency.

Stopping Rule

Gorr and Lee (2012) also used monthly data but for custom hot spot boundaries estimated via KDS, rather than fixed cells, to study temporary hot spots. Their results showed that temporary hot spots exist for only 1 or 2 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. It therefore seemed worthwhile to allow gaps and to experiment with their size.

As a result, this paper allows time gaps of “off” months with stopping-rule alternatives of 1, 2, and 3 months in a hot spot cell. For example, suppose 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 2 months: workload continues until there are 2 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:

$$0_1 0_2 1_3 1_4 0_5 1_6 0_7 1_8 0_9 0_{10}$$

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. Estimates show this bias to be on the order of 10 % low.

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 in aggregate statistics.

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 thresholds 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 2 or higher are infrequent (occurring only 14 % of the time) in micro-scale locations such as the cells used in this paper. Therefore 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 based on near-repeat crime theory.

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; Gorr 2009), near-repeat forecasts (Bowers et al. 2004; Mohler et al. 2011), or a spatial scan statistic (Neill 2009).

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) can serve as a score for ranking cells and resource allocation decisions.

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. Also considered is the make-up of hot spots, in regard to commercial and residential land uses. While crime concentrations are highest in large commercial areas, it is beneficial to provide crime prevention services in widely-scattered residential and small commercial areas as well to build police/citizenship relations and reduce fear of crime.

Summary of Experiment

We used all Pittsburgh P1V crime data from 2000 through October 2010, plus 1997 through 1999 data for initial chronic hot spot boundary forecasts, to evaluate coordinated chronic and temporary hot spot programs.

We estimate chronic hot spots with a set of threshold crime concentrations leading to a tradeoff curve for hot spot sizes over the range from 0 to 5 % of Pittsburgh. We use the KDS method of Gorr and Lee (2012) for chronic hot spots 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). Given the economic redevelopment of some of Pittsburgh's most crime-ridden areas in the latter part of the 1990's and early 2000's, it is not sensible to use all available data (starting in 1990) to estimate current chronic hot spots. Therefore, we estimate chronic hot spots using 3 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 forecast that the resulting hot spots persist throughout 2000. For 2001, we advance the time window one year and repeat the process, etc. Three years' data in a moving time window proved sufficiently long for estimating chronic hot spots while also being somewhat responsive to underlying changes in crime patterns.

We estimate temporary hot spots over the same range of areas, 0–5 %, using alternative grid sizes and rule thresholds in all possible combinations for EWS. Grid sizes were 500, 750, and 1,000 feet on a side. Thresholds were as follows: detection rule threshold = 1 P1V crime; prediction rule thresholds = 1, 2, 3, 4, and 5 months; and stopping rule thresholds = 1, 2, and 3 months. The frontier of experimental points plotted as percentage P1V crime exposed to prevention versus percentage of Pittsburgh under prevention workload is the optimal tradeoff curve. For the combination hot spot program, we estimate chronic hot spots covering one percent of Pittsburgh's area and then apply the rule-based EWS to remaining crimes outside of chronic hot spots, using the same experimental variations as in the previous paragraph. We assume that prevention resources are constantly allocated to those chronic areas, but that resources are dynamically allocated to temporary hot spots according to EWS rules.

Results

From the computational experiments described in the previous section, we first provide estimates of the maximum-size hot spot programs feasible in Pittsburgh given current resources. Then we present tradeoff curves for the three hot spot programs considered. Finally we present sample maps of hot spots along with some resulting statistics.

Estimates of Feasible Workload Area

Using a simple Excel spread sheet model, we estimate that currently the Pittsburgh Police could have a hot spot program of 12–16 random patrols per day per hot spot (chronic and/

or EWS) in the range of about 2–3 % of Pittsburgh's area (workload). While these are at best rough estimates, using the most favorable end points of parameter ranges, we find that 5 % workload is infeasible.

The model incorporates the number of patrol units (36–42); average time per shift available for patrolling hot spots (only a half hour to one hour due to reduced numbers of sworn officers in Pittsburgh due to budget limitations and resulting high 911 call loads per officer[2]); average patrol speed including stops for traffic signals (5–15 miles per hour); size and shape of temporary hot spots made up of 500 foot cells (isolated, linear, and compact multiple-cell areas); and efficient looping drive patterns in square, equal-size blocks with two-way streets that first loop consecutively through north–south streets or east–west streets and then loop through the remaining streets in the other orientation. In addition, according to Pittsburgh Police policy, patrols must "park and walk" at least a half hour per shift and this resource would also be available for hot spots.

Tradeoff Curves

Figure 1 shows the three tradeoff curves for the chronic, EWS, and combined chronic and EWS programs. All three programs have decreasing marginal benefits as expected, and the combination program has the best overall efficiency, equaling that of the chronic curve up to 1 % workload and then exceeding both the chronic and EWS curves thereafter. Figure 1 estimates that the combination program could provide 27 % exposure of total P1V crimes in Pittsburgh to prevention for 2 % workload and 33 % exposure for 3 % workload. A chronic hot spot program would be close, with 26 % exposure at 2 % workload and 31 % exposure at 3 %, and the EWS would be somewhat worse at 23 % exposure at 2 % workload and 29 % at 3 %. As noted in the data section of this paper, these estimates of prevention exposure are in addition to the good policing practices already used by the Pittsburgh Police Bureau.

To use a tradeoff curve for implementation, one must tabulate a "reverse function" when building the curve for looking up the threshold crime density corresponding to a point on the curve. For EWS hot spots one must be able to look up the optimal grid size and decision rule thresholds. Of note is the EWS reverse function. Table 2 has a sample of points for the combination program's EWS. For 2 % total workload (1 % chronic and 1 % EWS), the optimal grid size is 500 feet on a side, 3 of the previous 12 months of a cell have to have at least 1 P1V crime each, and workload persists until a gap of more than 2 months occurs before stopping. For 2.7 % total workload, the only change is the more liberal persistence rule of 2 instead of 3 months with 1 or more P1V crimes. The grid size of 750 feet does not enter until 7.6 % workload and 1,000 feet does not enter 10 % for the tradeoff curve.

Hot Spot Maps

Figures 2 and 3 are maps of P1V crime hot spots. Figure 2 compares two hot spot programs, chronic and EWS, each covering 3 % of Pittsburgh's area for 2009 (the last full year of data available). The chronic hot spot areas are constant throughout 2009 while the

[2] This estimate was provided by Commander Brackney of the Pittsburgh Police Bureau through personal communication. In contrast, one estimate in the literature (Famega et al. 2005) is that up to 75 % of patrol officers' time is not spent answering calls, so other cities may have higher average times available for hot spot patrol than Pittsburgh.

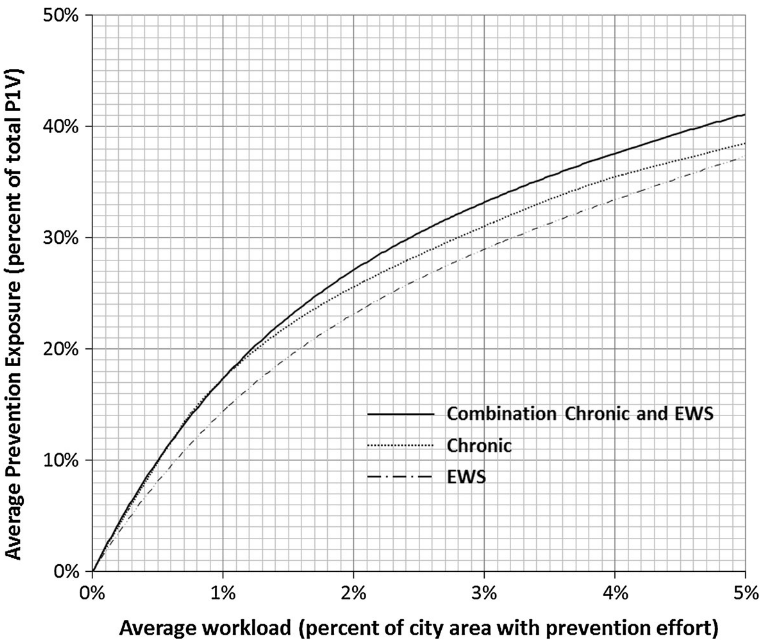

Fig. 1 Tradeoff *curves* for chronic, EWS, and combination program hot spots: 2000–2010

Table 2 Optimal grid sizes and rule thresholds for the EWS of the combination hot spot program: 2000–2010

Workload (percentage area of Pittsburgh)	Grid size (length of side, feet)	Prediction rule (months)	Stopping rule (months)
1.0	Substituted by chronic hot spots system		
1.3	500	4	1
1.6	500	4	2
1.8	500	4	3
2.0	500	3	2
2.4	500	3	3
2.7	500	2	2
3.4	500	2	3
5.0	500	1	3
7.6	750	2	3
10.3	750	1	3

EWS hot spots change each month. Shown are July 2009 EWS hot spots. All cells in Pittsburgh with one or more P1V crimes in July 2009 are shown as solid circles (these are positives). A cell that had prevention workload in July 2009 (and perhaps could have been prevented) is shown as a solid circle with the square boundary of the cell (true positives). A solid circle without a square boundary around it is a false negative. Cells without solid circles but square boundary shown had workload but no P1V crimes (false positives). Also shown on the map are separate boundaries of commercial and poverty areas of Pittsburgh. Note that because of the computational experiments behind these figures in which there

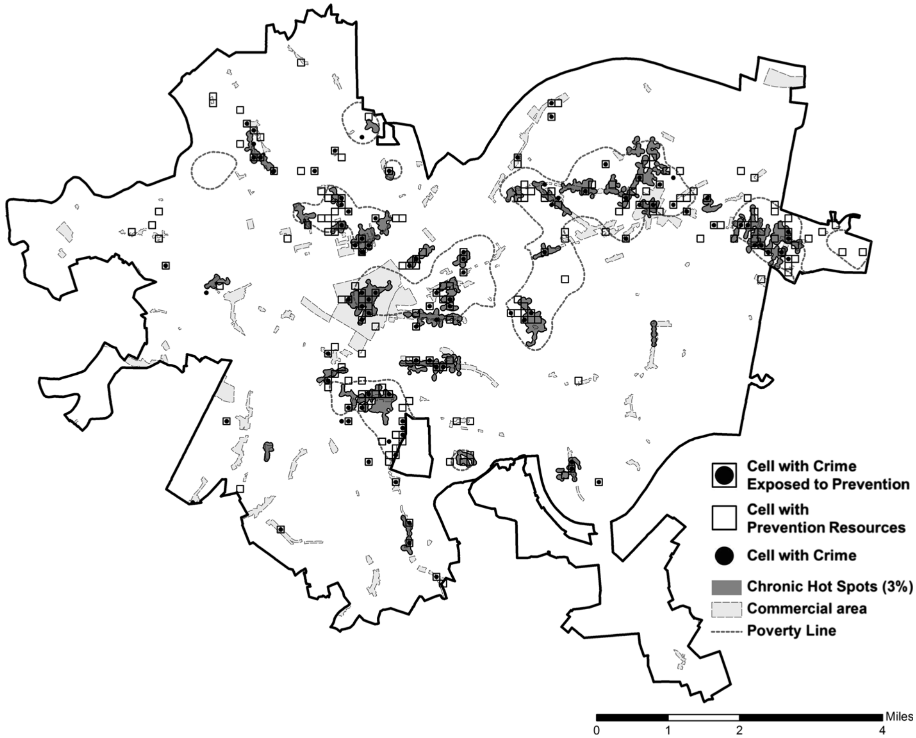

Fig. 2 Map comparing 3 % area chronic hot spots (2009) with 3 % EWS hot spots (July 2009): part 1 violent crimes

was no hot spot policing in effect, it is possible to identify all the cases listed above. In practice with hot spot policing, however, crimes that occurred as true positives may be prevented and then show up incorrectly as false positives.

There are several observations from this map. First, there are clear overlaps of chronic hot spots and EWS workload cells and there are numerous workload cells outside of chronic hot spots. Second, chronic hot spots tend to have one or more positive cells, but many areas (represented as cells) in chronic hot spots did not have crimes (perhaps due to "cops on the dots" already preventing crimes). Third, chronic hot spots tend to be in large commercial areas and/or poverty areas. Fourth, EWS workload areas outside of chronic hot spots are widely-scattered and tend to be in small commercial or non-commercial areas (another map, not included in this paper, shows the non-commercial areas to be largely residential). Of course, maps of other months have some of the same and many different workload cells due to the dynamics of the EWS.

Figure 3 is a map of the combination program with 1 % chronic hot spots supplemented with 2 % EWS hot spots. Not shown are crimes within chronic hot spots, but only shown are cells with one or more P1V crimes outside of chronic hot spots. In comparing this map to that of Fig. 2 with 3 % chronic hot spots, one can see that some chronic hot spots have disappeared and all are smaller in size, shedding lower crime density areas. In the place of removed chronic hot spot area are EWS workload cells. Also there are a great many EWS workload cells scattered throughout the city.

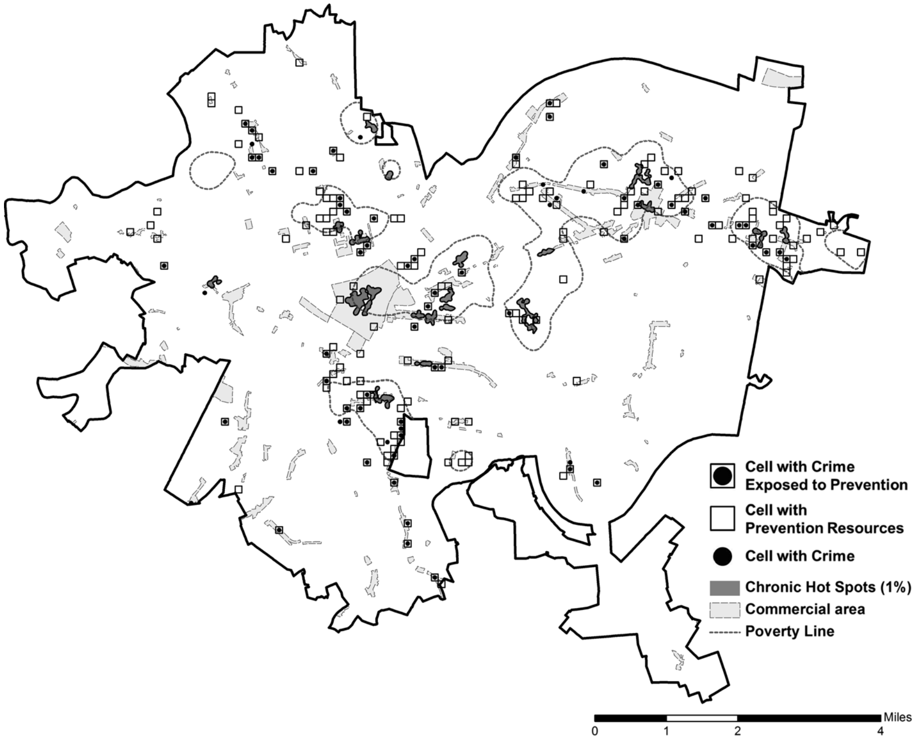

Fig. 3 Map for the combination hot spot program with total 3 % area workload (1 % chronic with 2 % EWS): part 1 violent crimes

Table 3 Commercial and residential land uses for alternative hot spot programs with 3 % area workload: 2000–2010

Hot spots combination	Residential (%)	Commercial (%)	Balance (%)
Chronic	49	36	15
EWS	56	22	22
Combination	56	24	20

Lastly, Table 3 has the 3 % total workload areas of each hot spot program broken out by residential, commercial, and balance of Pittsburgh areas. Here you can see that chronic hot spots have the largest share of commercial areas (36 vs 22 and 24 % for the EWS and combination programs) while the EWS and combination programs have the largest residential share (56 vs 49 % for chronic hot spots). Overall the EWS has 22 % more residential and non-commercial hot spots than do chronic hot spots, and combination hot spots have 19 % more residential and non-commercial hot spots.

Discussion

One implication of this paper's findings is that hot-spot size potentially could have dramatic impacts on performance in hot-spot field experiments. As noted earlier in this paper, Pittsburgh's chronic hot spots, estimated via KDS, are steeply peaked so that after hot spots covering the 1 % hottest areas, crime density falls off exponentially with additional chronic hot spot area. Perhaps studies such as reported in Braga et al. (2012) had a variety of hot spot sizes so that corresponding crime densities could account for a significant variation in crime reduction.

The EWS 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 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. The spatial scan statistic, based on city blocks, is a prime candidate for making improvements in detection. Perhaps LISA and Gi* statistics of spatial association could improve identification of spatial clusters. 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. Additional computational experiments, before field research, may improve efficiency of the EWS.

The existing literature has field research results for chronic hot spots. The first step for empirical research on the EWS is to estimate effect size of crime prevention for temporary hot spots. It would be straightforward to design and run a controlled experiment for this purpose because the relatively wide separation of temporary hot spots allows for treatments that do not contaminate controls.

Summary

This paper developed and conducted preliminary computational experiments on an EWS for crime prevention at temporary hot spots as a supplement to chronic hot spots using part 1 violent (P1V) crime data from Pittsburgh, Pennsylvania (2000–2010). Chronic hot spots have high crime densities continuously over long periods, years, and merit constant police resource allocations for crime prevention. Temporary hot spots also have high crime densities but only for durations of time on the order of months and generally over smaller areas than chronic hot spots. While chronic hot spots are relatively simple to identify and manage, temporary hot spots require a dynamic decision-making system, an EWS, for early detection of crime flare-ups, predicting persistence of crimes after detection, deploying prevention resources, and stopping deployments after a temporary hot spot is extinguished. This paper provided a simple rule-based EWS.

The Pittsburgh Police Bureau has used crime mapping (putting "cops on the dots"), CrimeStat management, and other modern policing practices, such as "park and walk," since the early 2000s but has not conducted centralized or sustained hot spot programs during the study period. Thus Pittsburgh provided an ideal test bed for estimating the effectiveness of hot spot programs for additional crime prevention above that provided by modern policing practices.

The empirical study compared the efficiency of chronic, EWS, and combination chronic and EWS programs via tradeoff curves of benefits versus costs represented by percentage of P1V crime that could have been exposed to prevention efforts and percentage area of Pittsburgh under prevention workload by police. A second criterion, assessed by GIS analysis, is the distribution of hot spots and allocation of police prevention resources across the city. A program that allocates resources equitably and responsively to prevent crimes and reduce fear of crime is desirable.

We forecasted chronic hot spot boundaries one year ahead using kernel density smoothing (KDS) applied to a three-year moving window of data and obtained a chronic hot spot tradeoff curve by varying the threshold concentration defining hot spot boundaries. We defined temporary hot spots using grid cells of alternate sizes and varied decision rule thresholds for predicting hot spot persistence and stopping. The frontier of all experimental points, plotted as benefits versus costs, provided the EWS tradeoff curve. The combined hot spot program uses chronic hot spots up to 1 % area of Pittsburgh under prevention workload and then adds temporary hot spots for areas outside of chronic hot spots, again producing a tradeoff curve. The rationale for this program was that crime density declines exponentially as percentage area workload increases for chronic hot spots so that additional area after about 1 % has behavior closer to temporary hot spots. Also, feasible areas for chronic hot spots are a subset of feasible areas for temporary hot spots so that after the hottest areas are assigned to chronic hot spots, there may exist better or simply more of the best temporary hot spots such as adjacent to the hottest chronic hot spots.

The research included a simple spreadsheet simulation to roughly estimate the maximum percentage area of Pittsburgh that the Pittsburgh Police Bureau could cover with 12–16 random patrols per day with existing resources. Varying the many parameters, we concluded that the range is from about 2–3 % but certainly not as high as 5 %. We thus provided tradeoff curves over the range from 0 to 5 % area. They show the combination hot spot program to be the most efficient, exposing 33 % of Pittsburgh's P1V crimes to prevention at 3 % area, but not by a great deal over the chronic hot spot program. The EWS program is dominated by the other two programs, but again, not by much.

Chronic hot spots tend to exist in large commercial areas, or in residential areas adjacent to large commercial areas, and in poverty areas. Of course, they are fixed in location over long periods of time. Temporary hot spots change from month to month and are widely scattered across the city, including smaller commercial areas and more residential areas. Hence temporary hot spots managed via the EWS are more equitable and responsive to changing crime patterns than chronic hot spots. Indeed the EWS can be the basis of a positive relationship between police and neighborhoods to prevent and reduce fear of crime. The combination hot spot program has the best of both chronic and temporary hot spots, with the highest-efficiency crime prevention overall plus dynamic and widespread crime prevention across a city, providing more responsive and equitable allocations of police prevention resources than a solely-chronic hot spot program.

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