The Next Step: A Spatiotemporal Statistical Model of the Birth and Death of Crime Hotspots[*]

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September 20, 2016

The *Criminology of Place* is an important book. It brings together more than two decades of research by Weisburd and colleagues on the question of why it is that one street corner or block face can be in the 99th percentile of calls for service while an adjacent location is virtually crime free. The concentration of crime and disorder at discrete locations is one of the most striking empirical regularities in criminology not only because of its important implications for the strategic use of police to prevent crime but also for its implications for understanding the causes of crime. On its face the highly disproportionate concentration of crime at discrete locations is at odds with, or at least, is inexplicable with sociologically-based theories of the causes of crime that emphasize the role of community-level factors such social disorganization or collective efficacy or even higher level macro-structural forces such as inequality of opportunity. Similarly, economics-based theories of crime with their emphasis on the role of incentives such as sanction risk and legal alternatives to crime are silent on the phenomenon of crime hot spots. Weisburd, Groff, and Yang offer the most thorough currently available exploration of the capacity of extant theory to explain the hot spots phenomenon.

Two of their conclusions are particularly germane to our commentary. One concerns spatiotemporal heterogeneity in crime hot spots. They observe: "Our analysis suggests overall that there is tremendous street-by-street variability in developmental patterns of crime..." (p. 88). The second is that even with such heterogeneity, larger community-level influences remain relevant. Here they observe: "But it would be a mistake to draw from our analyses the conclusion that larger area forces have no influence... We found significant spatial clustering at distances of a mile for many of the trajectory patterns." (p. 88).

[*]This is a pre-copyedited, author-produced version of an article accepted for publication in the *Jerusalem Review of Legal Studies*. The version of record is Reinhart and Nagin (2017), *Jerusalem Review of Legal Studies* **15** 1, pp. 55–60, doi:10.1093/jrls/jlx007

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We return to these observations below but before that we briefly summarize a parallel literature that focuses on predicting crime hot spots. This literature emerged to serve a very practical purpose—creating predictive tools intended to aid police departments in identify places where crime was or might soon be flaring with aim of their taking proactive action to prevent the flare or respond to a flare that has already emerged. This literature is distinctly different from the literature which tries to explain the reasons for hot spots not only because of it purpose but in the methods that are used. Because of the prediction objective, the methods used focus on accounting for and modeling stochastic variability, an issue that is left in the background in analyses of the causes of hot spots like those reported in *Criminology of Place*.

Stochastic variability comes in two forms. There is variability over time and over place. At risk of over-simplifying, the hot spot prediction literature tends to focus on one of these dimensions. On the temporal dimension hotspots can be chronic, lasting for years or decades, or temporary, appearing only for a few weeks or months.[1] They may be detected by spatial kernel density estimates, choropleth maps, standard deviational ellipses, scan statistics, or clustering methods;[2] these methods identify hotspots but do not predict crime rates within them or otherwise quantify the risk of crime. Police then choose the top hotspots for intensive patrol or other interventions, such as problem-oriented policing.[3]

Predictive studies that focus on the spatial dimension aim to identify readily measurable characteristics of the specific location or nearby location that predict crime. An example is Risk Terrain Modeling (RTM),[4] which attempts to identify spatial features that may predict crime: gang territories, bars, dance clubs, residences of recent parolees, foreclosed homes, schools, and so on. This type of analysis can provide local governments with important information to target law enforcement, social programs, and public works to reduce factors that may lead to crime.

These approaches to prediction have provided valuable service to police departments and local governments. Notwithstanding, they suffer from several important limitations. No available approach combines the spatial and

[1]Wilpen L. Gorr & YongJei Lee, *Early Warning System for Temporary Crime Hot Spots*, 31 J. Quant. Criminol 25 (2015).

[2]Spencer Chainey, Lisa Tompson & Sebastian Uhlig, *The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime*, 21 Security J. 4 (2008); Ned Levine, *The "Hottest" Part of a Hotspot: Comments on "The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime"*, 21 Security J. 295 (2008).

[3]Bruce Taylor, Christopher S. Koper & Daniel J. Woods, *A randomized controlled trial of different policing strategies at hot spots of violent crime*, 7 J. Exp. Criminol 149 (2011).

[4]Leslie W. Kennedy, Joel M. Caplan & Eric L. Piza, *Risk Clusters, Hotspots, and Spatial Intelligence: Risk Terrain Modeling as an Algorithm for Police Resource Allocation Strategies*, 27 J. Quant. Criminol 339 (2010); Leslie W. Kennedy, Joel M. Caplan, Eric L. Piza & Henri Buccine-Schraeder, *Vulnerability and Exposure to Crime: Applying Risk Terrain Modeling to the Study of Assault in Chicago*, 9 Appl. Spatial Analysis 529 (2016).

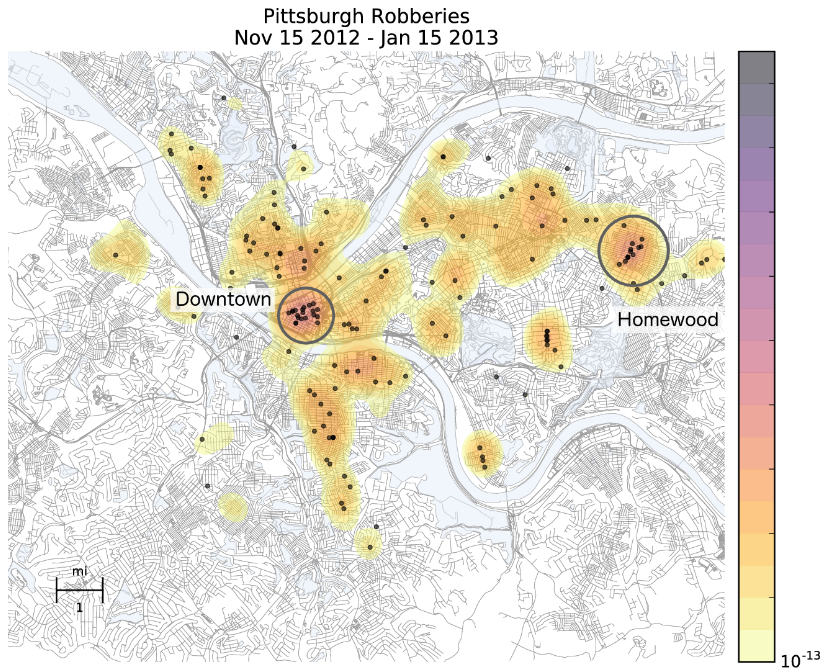

Figure 1

temporal dimensions of the prediction problem and also provides the capacity to conduct statistical tests about and/or calculate confidence intervals for model parameters. Such a capacities would not only improve upon predictive accuracy but also serve to advance the line of research pioneered by Weisburd and colleagues. The next step in advancing both the prediction and explanation lines of research requires a model that predicts persistent temporal and spatial heterogeneity in crime hot spots, on one hand, and on the other hand, their clustering in specific communities. In addition, the model should also have the capacity to capture the birth and death of hot spots because, as Gorr and Lee emphasize, some hotspots are not enduring.

One of us (Reinhart) is developing just such a model. It is a generalization of what is called a Self-Exciting Point Process Model.[5] The resultant model is analogous to a topographic map that evolves overtime, for example, a topographic map measured over millions of years of the build-up and eventual erosion of the Himalaya mountain range. Figure 1 is an illustrative application of the model for robberies in Pittsburgh, PA (USA) over the period November 15, 2012 to January 15, 2013. Overlaid on a map of Pittsburgh are the locations in form of black dots of all reported robberies over this period. The shaded areas are the product of model's parameter estimates—the spatial distribution of predicted "crime intensity" with the deeper the orange color-

[5]George O. Mohler, *Marked point process hotspot maps for homicide and gun crime prediction in Chicago*, 30 INT. J. FORECASTING 491 (2014).

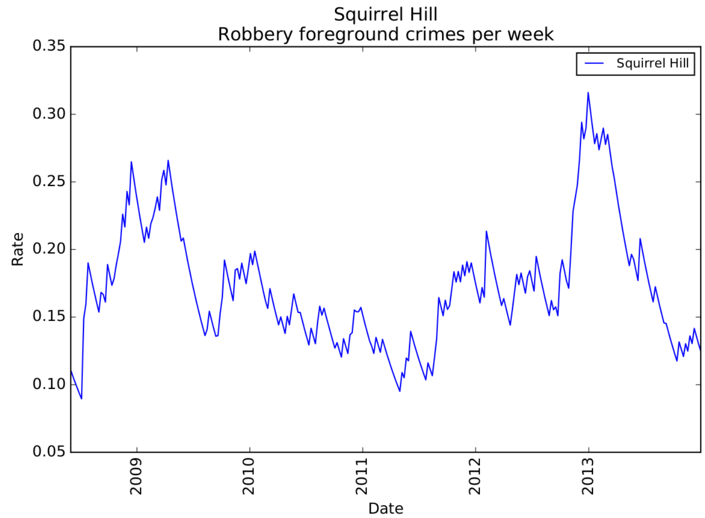

Figure 2

ing the higher the predicted crime intensity. Not surprisingly the highest intensity places correspond to locations with the most robberies. The crime intensity contours also correspond to the two key conclusions of Weisburd et al. There is large spatial heterogeneity in high intensity locations. Two examples are circled. One is downtown Pittsburgh, located at the confluence of the Allegheny and Monongahela Rivers, which is the city's commercial center. Another is Homewood, which a poor, largely African-American neighborhood. Even so intensities do tend cluster in larger geographic areas. For example, just east of downtown is another high intensity cluster which corresponds to still another disadvantaged neighborhood in Pittsburgh.

Figure 1 is snapshot at one point in time. The model also has a temporal dimension that allow for estimation of a spatiotemporal model. The following link `https://www.refsmmat.com/files/robbery.mp4` shows an animation of the changing robbery intensities across Pittsburgh over the period 1/1/2012 to 12/30/2013. Figure 2 reports the weekly robbery rate for the Squirrel Hill neighborhood over the period 2008 to 2014. While Squirrel Hill is one of Pittsburgh's lower crime rate neighborhoods, Figure 2 shows that even here there is considerable temporal stochastic variability. Figure 3 reports two snapshots of the model's intensity maps, centered in Squirrel Hill, one corresponding to the temporal spike at the beginning of 2013 and the other corresponding to a dip in early 2011. Note that the former has deeper orange contours than the later. We also, note that during the robbery spike from 11/15/2012 to 1/15/2013 that these robberies cluster at a hot spot in the Squirrel Hill commercial center which is surrounded by one of Pittsburgh's more affluent neighborhoods.

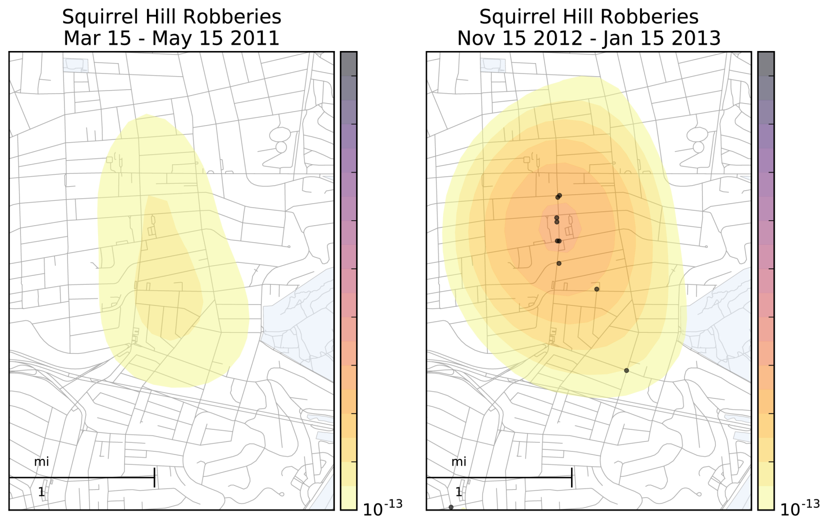

Figure 3

As noted, one of the model's most important features is that it provides the basis making statistical inferences about the model's underlying parameters. As an illustration, Figure 4 identifies the location of all bus stops in Pittsburgh. Their location was entered as a potential predictor of assaults over the period January 2008 to January 2014. Each bus stop was estimated to contribute on average 0.44 assaults over this period with a 95% confidence interval for this estimate of 0.425 to 0.45. While this does not prove causation, and does not account for confounding factors such as population density (though these can, in principle, be added as further inputs to the model), it demonstrates the ability of the model to account for both spatial and temporal stochastic variability. When fully developed, the model will be useful for testing various hypotheses about the causes and behavior of crime hotspots.

As stated at the outset the *Criminology of Place* is an important book. The next step forward is built on its findings with the development and statistical testing of models of the spatiotemporal birth and death of crime hotspots.

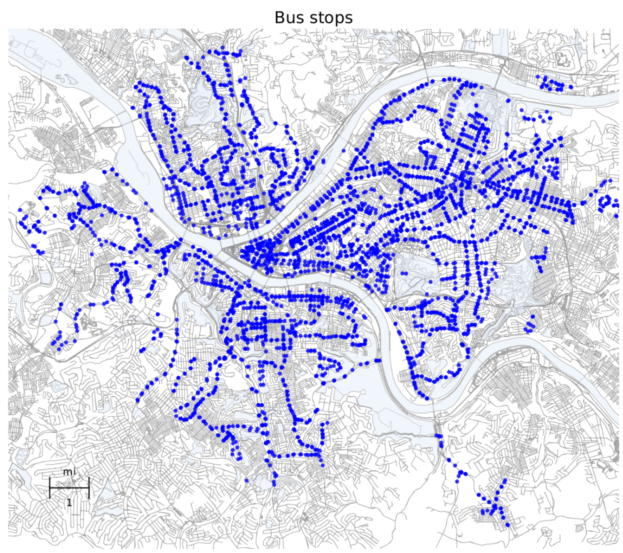

Figure 4