Intraurban Spatial Fluctuations in Crime by Season and the Temperate Sacramento Climate

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Abstract

Geographic and climatic modeling has garnered recent attention among criminologists, but few have combined these techniques to form a single model of crime. Among limited intraurban spatial-climatic models, each explores municipalities with wide-ranging seasonal variation. While not yet tested, there is reason to believe that climatically temperate cities would show little seasonal fluctuation in the spatial distribution of crime. Using Sacramento, California, as our spatial unit, we first explore monthly fluctuations in crime, followed by a test of spatial distribution in crime by month. We find no meaningful seasonal fluctuation in crime; raster density maps show no discernible seasonal fluctuation in the spatial distribution of crime; and spatial correlations reaffirm a lack of seasonal patterning. Our methodology and findings address the lack of intraurban modeling on climatically temperate municipalities and call for the requisite inclusion of a spatial component in all criminological research on climate, seasons, and weather.

Key words: crime, climate, seasonal, weather, intraurban, spatial

Introduction

In a recent survey of the American Society of Criminology (ASC), members were asked to identify the sources of a potential paradigm shift in the discipline (Cooper, Walsh, and Ellis 2010). Conspicuous in its absence was any mention of spatial or climatic predictors. Yet advancements in technology have led to a modern renaissance in the spatial analysis of crime (Althausen and Mieczkowski 2001). And growing concern over climate change has spurred an interest in criminological research on climatic, seasonal, and weather influences (Agnew 2011). The real neglect involves the dearth of criminological research that combines climatic and spatial data into one model. What makes this important is the ubiquity with which research finds spatial variability in climate and climate change, in-

cluding subsequent geographic variations and changes in seasonal and weather patterns (IPCC 2007, 2013).

In this paper we review contemporary research on spatial and climatic variations in crime. We then outline recent attempts at spatial-climatic crime modeling, focusing on the lack of intraurban modeling in more-temperate climates. Using five years (2005–2009) of Sacramento, California, crime data, we test for seasonal fluctuations in two forms of crime: one personal, and one property. This is followed by an exploration of spatial patterning in personal and property crime by season. In doing so, we parallel extant research in that we do not provide a test involving climate *per se*, but rather, seasonal (and spatial) variations within a particular climate. Nevertheless, our model addresses the need for intraurban tests on more climatically temperate municipalities (such as Sacramento) when exploring spatial fluctuations in crime by season. Given the well-documented spatial variations in climate and subsequent season and related weather parameters, we argue for the requisite inclusion of spatial methodologies in all criminological research on climate/seasons/weather and crime.

Spatial, Climate, and Crime

Despite the longstanding inattention, spatial and climatic analyses stand as two of the earliest empirical observations on crime. Befittingly, these observations were made by Lambert Adolphe Jacques Quetelet (1796–1874), arguably the most neglected figure in criminology (Bierne 1987; Sylvester 1984). Using three years of data (1827–1829) on France and the Low Countries, Quetelet (1831, 1842) rendered separate, personal and property, shaded choropleth crime maps and fleshed out spatial variations for both types of crime. Quetelet also found that the greatest number of personal crimes and fewest number of property crimes occurred during the summer months, and vice versa for the winter months.

Spatial Analyses of Crime

Quetelet's (1831) spatial observations of crime quickly stagnated until resurfacing with social ecology and the Chicago School at the turn of the 20th century, then stagnated again until recent advances in spatial software. Geography is now included in Criminal Justice curriculum (Althausen and Mieczkowski 2001); several textbooks have since been dedicated to the geography of crime (Brunsdon, Corcoran, Higgs, and Ware 2009); and an increasing number of police departments now utilize spatial maps (Markovic and Scalisi 2011). In 1997 the National Institute of Justice (NIJ) established the Crime Mapping Research Center (currently known as Mapping and Analysis for Public Safety—MAPS); and in 2008 the NIJ released *Geography & Public Safety*, a quarterly bulletin dedicated to crime mapping.

Current spatial analyses of crime typically center on municipal units of analysis and spatial variations within. This is expected, given the use of crime mapping to pinpoint and devote resources to crime clusters (Markovic and Scalisi 2011). Vector modeling is largely employed in such intraurban analyses and generally finds crime clusters in areas marked by impoverished socio-demographics (see McCord and Ratcliffe 2007; Suresh and Vito 2007; Fornango 2010; and Andresen 2011). Limited raster models report similar findings (see Caplan, Kennedy, and Miller 2011). Regardless of modeling, most studies explore the spatial distribution of personal crime, though property crime also displays intraurban spatial patterning.

Seasonal Analyses of Crime

Since Quetelet, seasonal and weather analyses of crime halted until spurred by the broader concerns of climate change. With each successive Intergovernmental Panel on Climate Change (IPCC) report, the anthropogenic sources of climate change are concluded with increasing confidence (Goodman, Boykoff, and Evered 2008); the most recent (Fifth) IPCC Assessment Report (2013) concluded that anthropogenic warming of the planet is certain. The current interest in crime and climate is essentially a byproduct of the empirical confirmation of climate change in general. Nonetheless, when it comes to climatic and other environmental influences, the current criminological paradigm remains well behind other social science disciplines (Lynch and Stretesky 2001; Simon 2000). But as noted by Agnew, "there is good reason to believe that climate change will become one of the major forces driving crime as the century progresses" (2011:21).

Despite climate concern, extant criminological research essentially centers on seasonal and/or weather parameter variation rather than the broader spatial and temporal elements of climate or climate change *per se*. Nevertheless, geographic variations in climate beget seasonal and weather differences, and climate change is known to alter seasonal and weather patterns (Mann 2012; IPCC 2013). Most studies find seasonal fluctuations in crime and that weather parameters (particularly temperature) influence crime. Recent stud-

ies comparing seasons and weather find that seasonal influences wash out the effects of temperature and other weather parameters (Brunsdon, Corcoran, Higgs, and Ware 2009; McDowall, Loftin, and Pate 2012). Either way, the influence of season and/or weather is better supported for personal crime than property crime.

Spatial-Climatic Modeling of Crime

It is not surprising that Quetelet neglected the potential for a crime model that combines seasons and geography. Climate change was not an issue in the days of Quetelet, and spatial technology was limited to shaded choropleth mapping. But spatial technology is now formidable, and climatic influence on crime is an emerging concern. We argue that a combined model is not only possible; it is requisite due to the known geographical variation in climate and climate change. Climate warming is known to vary by latitude (IPCC 2007, 2013). Changes in surface temperature are found to vary regionally (Christy, Norris, Redmond, and Gallo 2006). Research finds that differences in urban design generate microclimate variations in temperature (Stone 2012). With all geographic variations in climate come related variations in seasons and weather (Mann 2012).

Recent studies have addressed the viability of a combined model, focusing largely on intraurban methodologies. Harries, Stadler, and Zdorkowski (1984) tested for intraurban differences in assault by month in Dallas, 1980, using neighborhood vectors. They found that low-status neighborhoods displayed more distinct summer peaks in assault. Twenty-five years later, Brunsdon, Corcoran, Higgs, and Ware (2009) used raster modeling to test weather and seasonal influences on disorder and disturbances in an urban area of the United Kingdom. The authors found that high temperature and humidity increased incidents outside (but not inside) the city center during the summer and winter quarters. More recently, Sorg and Taylor (2011) examined community-level connections between temperature and street robbery in Philadelphia, 2007–2009. Intraurban raster modeling indicated that higher temperatures increased robbery in lower SES communities. Using 2001 Vancouver, Canada, data, Andresen and Malleson (2013) used vector modeling to compare quarterly fluctuations in various personal and property crimes. They found that most crimes fluctuated by season. In turn, crimes with the least seasonal fluctuation displayed little, if any, spatial patterning by season.

At least two studies exist that test seasonal fluctuations on larger (than intraurban) spatial units. Hipp, Bauer, Curran, and Bollen (2004) tested for bi-monthly fluctuations in crime at the state level. Using Uniform Crime Reports (UCR) data, they found seasonal oscillations in both personal and property crime for all states under study; however, states with more-temperate climates displayed less seasonal variation, with California revealing the least fluctuation. In a comparison of eighty-eight U.S. cities, McDowall, Loftin, and Pate (2011) used 2000 Census and UCR data to explore monthly variation in personal and property crimes. The authors found that cities with more-temperate climates displayed little seasonal fluctuation in crime, with several California cities displaying the least in seasonal variation.

In sum, research shows that states and municipalities located in temperate climates reveal fewer seasonal fluctuations in crime. Intraurban modeling by season suggests that when crime fluctuates little by season, there is little spatial patterning by season. In combination, temperate cities lack seasonal fluctuations in crime; subsequently, temperate cities are unlikely to display spatial patterning in crime by season. Yet there are currently no intraurban spatial analyses in crime by season on climatically temperate municipalities exhibiting little seasonal variation. This study explores intraurban spatial variations by season on a temperate California city.

Method

We chose Sacramento, California, for two reasons. One, previous research shows that California has a "temperate Mediterranean climate," making it one of the "states with the least seasonal variation" (Hipp, Bauer, Curran, and Bollen 2004:1361–1362). This is particularly true of California's Central Valley, where Sacramento is located. The coolest average temperature in our study is a relatively comfortable forty-two degrees, and Sacramento is dry in the summer, negating the interaction between high temperature and humidity (a.k.a. heat index). Two, Sacramento police data is publicly available and includes spatial location [(X,Y) coordinates]. Using Sacramento as a geographic unit, our analyses begin with exploring seasonal variations in personal and property crime. We then test for seasonal variation in the intraurban spatial distribution of each crime. Based on previous research, we hypothesize that (1) crime varies little, if any, by season in temperate Sacramento; and, as a consequence, (2) the intraurban spatial distribution of crime does

not differ by season. Moreover, extant intraurban crime analyses tend to employ vector modeling; but crime patterns tend to form in hot spots, making raster models more ideal since they allow hot spots to form in natural patterns over a continuous space (Filbert 2008; McLafferty, Williamson, and McGuire 2000; Vann and Garson 2001). Therefore, we choose raster mapping for our intraurban spatial analysis by season.

Data

Data for the years 2005–2009 was retrieved from the Sacramento Police Department website (City of Sacramento 2014). We chose these five years of data due to the consistent Uniform Crime Reports (UCR) coding during this period; data for 2004 and 2010 was omitted because of changes in the interdepartmental data coding system during each of these years, making them incompatible with the five chosen years. From this data, we used battery civilian (UCR code 1313-8) as the representative personal crime, and petty theft (UCR code 2399-2) as the representative property crime. These two crimes have the largest number of reported incidences (corresponding to personal and property crime) in the Sacramento data. All other crimes were excluded from this analysis.

Design and Findings

To test for seasonal fluctuations in crime, the five years of data are summated by month for each crime; incidences per month are then compared as a test of seasonal fluctuation (Table 1). High incidences of personal and property crime appear more common during the warmer months, with low incidences more common during the winter months—but this interpretation is provided with caution. For personal crime, the four lowest incidences per month are in the winter (December, November, February, and January, respectively), which suggests the potential for seasonal patterning; however, the remaining months show no overt seasonal pattern. For property crime, three of the four highest months are in the summer (June, July, and August, respectively), yet December reveals the third-highest incidence, and no overt pattern emerges among the remaining months. Overall, there seems little to suggest a clear seasonal fluctuation in crime based on monthly comparisons.

Turning to the spatial analysis by month, a series of spatial map layers was uploaded to GIS. Spatial map layers included the Sacramento city map layer and the Sacramento city coordinate system to identify geographic locations based on (X, Y) coordinates. Two steps are required in our test of seasonal fluctuations in the monthly distribution of crime. The first step is the creation of overall raster-density spatial maps for personal and property crime. To do this, the five years of battery civilian and petty theft were uploaded as separate point layers, with each individual point representing an incidence of personal and property crime, respectively. These point layers were used to create separate raster-density map layers via the ArcMap kernel density tool. Due to the geometric spatial distribution of both personal and property crime data, we employed the geometrical interval method to create five density classes.

Table 1: Monthly Fluctuations in Crime.

Month	Personal	Property
January	442	486
February	409	412
March	475	525
April	478	485
May	516	529
June	480	562
July	478	543
August	458	533
September	488	467
October	460	510
November	405	484
December	356	535
Total	5,455	6,371

For the second step, these two spatial maps are used to create monthly density maps. To do so, the five years of data were summated by month for personal and property crime, and spatial point layers were used to create concentric density maps for each of the twelve months. To calculate monthly spatial density classes, manual breaks were formed by dividing the original geometrical intervals by twelve. Doing so achieves the equivalent parameters necessary for direct comparisons (see Bolstad 2008; Caplan, Kennedy, and Miller 2011). In line with our overall breaks (and for the sake of visibility), monthly maps were classified according to five densities. These classes are represented by five shades (red, orange, green, light blue,

and dark blue) that center on crime hot spots and corresponding lesser densities, respectively (Figures 1 and 2).

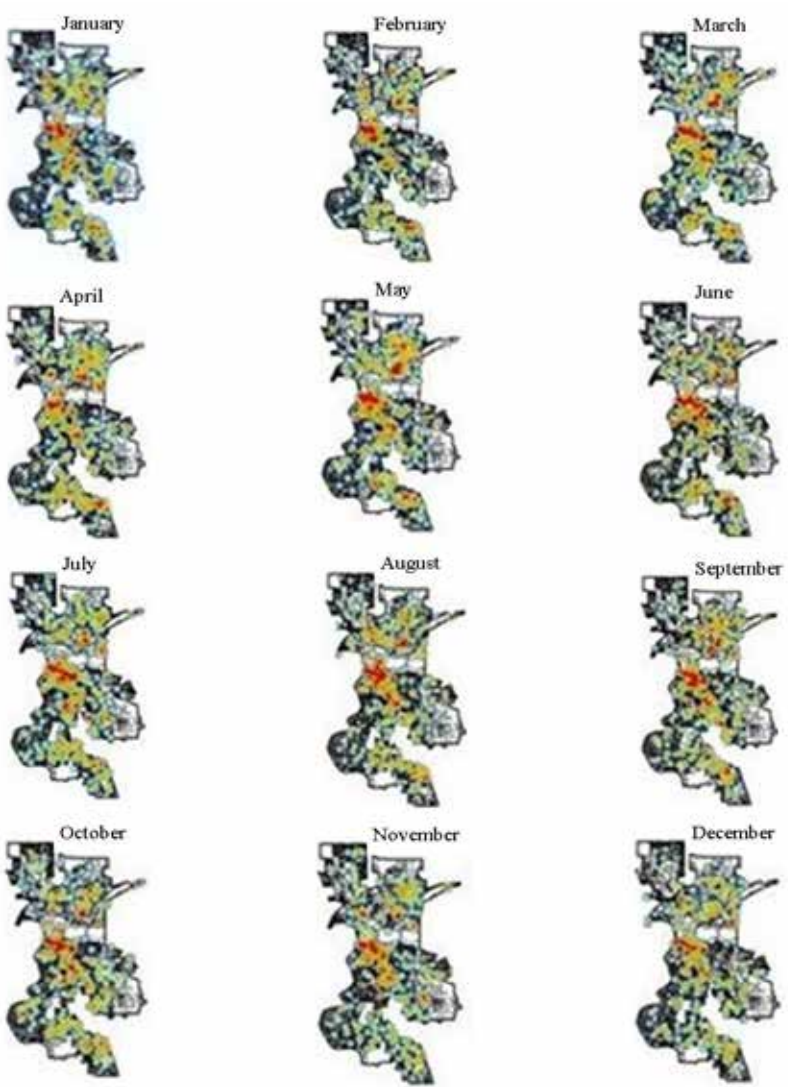

Figure 1.—Monthly Density Maps, Personal Crime.

Figure 2.—Monthly Density Maps, Property Crime.

When comparing the two crimes by density classification, three basic visuals emerge. One, crime hot spots are in the same areas for both personal and property crime. Two, property crime displays clearly larger hot spots (red) as well as greater expanses of least crime (dark blue). Three, there is no discernible variation by month for either personal or property crime. The spatial variations are trivial at best, with hot spots remaining within the same, heavily concentrated ar-

eas regardless of month or crime type, and the same is true for areas with least crime. Even if subtle differences can be detected, there is nothing to suggest a seasonal pattern in the spatial distribution of either crime. This is not surprising, given the general lack of seasonal fluctuations in crime by month presented in Table 1.

The final analysis involves monthly comparisons of bivariate spatial correlations (Table 2). Based on the aforementioned density classification in Figures 1 and 2, coefficients reflect spatial correlations between months and were calculated using an ArcGIS Spatial Analyst Multivariate tool, Band Collection Statistics. A seasonal impact on crime density would be reflected by stronger correlations between seasonally similar months and weaker correlations between months of dissimilar season. Our spatial correlations indicate three things. One, all coefficients are of the moderate to strong variety, with inter-month spatial correlations being somewhat stronger for personal crime. Two, little monthly variation exists among spatial correlation within either type of crime. Three, most importantly, no clear seasonal pattern emerges among spatial correlations by month for either personal or property crime. At times, winter months are most strongly correlated with other winter months; at other times, with summer months. The same is true for spring and fall months. If nothing else, the inability to distinguish the coefficients from one another is evidence of no apparent density variation by season. The coefficients essentially confirm the spatial maps, suggesting that season has little or no patterned effect on the spatial distribution of crime in Sacramento.

Discussion and Conclusion

As expected, we find little, if any, seasonal patterning for personal or property crime with the Sacramento data. This appears to translate into a lack of spatial patterning by season. For both personal and property crime, our findings support our hypothesis: there is little, if any, seasonal patterning in crime; as a consequence, the spatial distribution of crime does not differ by season. This is not surprising, since Sacramento is a climatically temperate municipality, which lacks meaningful variations in season. The lack of seasons are believed to account for the stability in personal and property crime by month and the subsequent stability in monthly density maps and spatial coefficients.

If anything, the temperate climate and subsequent tempered results signal a need for additional intraurban research on the spatial mod-

Table 2: Bivariate Spatial Correlations.*

	J	F	M	A	M	J	J	A	S	O	N	D
Jan		.677	.674	.662	.659	.642	.676	.661	.624	.672	.674	.624
Feb	.865		.679	.701	.664	.657	.668	.666	.640	.640	.649	.601
Mar	.890	.884		.735	.750	.717	.714	.707	.675	.727	.710	.660
Apr	.804	.810	.830		.699	.654	.683	.659	.578	.667	.680	.584
May	.784	.779	.806	.795		.626	.678	.691	.656	.692	.644	.592
Jun	.844	.818	.853	.787	.788		.680	.649	.585	.635	.659	.605
Jul	.856	.835	.867	.819	.812	.846		.663	.673	.680	.682	.621
Aug	.775	.790	.777	.777	.796	.781	.818		.636	.678	.669	.618
Sep	.850	.826	.840	.797	.818	.820	.845	.803		.641	.593	.612
Oct	.796	.803	.803	.780	.784	.810	.840	.801	.820		.668	.627
Nov	.841	.826	.845	.819	.820	.811	.855	.772	.826	.816		.618
Dec	.893	.863	.903	.794	.795	.849	.868	.764	.856	.820	.854	

**Personal Crime Above Diagonal; Property Crime Below Diagonal*

eling of crime by season, including a wide variety of climatically different municipalities. Spatial units could follow vector explorations of climate, seasons, weather, and crime, as well as more-sophisticated techniques in extant research. By knowing intraurban patterning by season, crime can be seasonally identified using hot-spot analysis to better utilize limited resources. This not only includes police resources, but resources dedicated to urban design as it relates to climate and climate change. Seasonally driven spatial analyses of crime can also continue on broader geographic units such as state and regional tests, though given the policy emphasis on intraurban crime, intraurban analysis by season seems most appropriate.

A wider shortcoming of our particular test mirrors the shortcoming in climate and crime models in a changing climate; we do not directly test the influence of climate or climate change *per se*. Nevertheless, we see value in a seasonal model that includes spatial variation. Seasons and weather are known to shift with a shifting climate. This being the case, seasonal analysis remains valuable as the climate continues to change. Moreover, our particular model can be extended to explore monthly (and other seasonal) increments longitudinally, over a period of time necessary to address climate change.

We agree with Agnew's (2011) assessment that climate change will become a focal point of criminology in the near future, but we add that the future of climate and crime research must address geographic variation. In the end, spatial-climatic models are limited by neglect, not opportunity. Our methodology and chosen municipality is but one example of the seemingly innumerable spatial-climatic combinations. Bottom line: climate and anthropogenic climate change are known to vary spatially, requiring spatial analyses of crime on a variety of climates.

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