

Chapter 15

Modelling Pedestrian Movement to Measure On–Street Crime Risk

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ABSTRACT

This chapter presents results for the first large-scale analysis of street crime rates that utilizes accurate on-street pedestrian population estimates. Pedestrian counts were generated at the street segment level for an area in central London (UK) using a modeling process that utilized key indicators of pedestrian movement and sample observations. Geocoded street crime positioned on street segments then allowed for street crime rates to be calculated for the entire central London study area's street network. These street crime rate measures were then compared against street crime volume patterns (e.g., hotspot maps of street crime density) and street crime rate statistics and maps that were generated from using the residential population as the denominator. The research demonstrates the utility of pedestrian modeling for generating better and more realistic measures for street crime rates, suggesting that if the residential population is used as a denominator for local level street crime analysis it may only misinform and mislead the interpretation and understanding of on- to pedestrians. The research also highlights the importance of crime rate analysis for understanding and explaining crime patterns, and suggests that with accurate analysis of crime rates, policing, and crime prevention initiatives can be improved.

INTRODUCTION

Measures and approaches for analysing patterns of street crime (i.e., robbery from the person and thefts from persons) are typically performed using volume statistics presented in tables and graphs, and as hotspot maps to identify the volumetric density patterns of street crime. With the proliferation of geographical information systems (GIS) into police and crime reduction agencies, hotspot analysis is seen as a crucial first step in developing intelligence to help identify and explain crime problems (Chainey & Ratcliffe, 2005; Eck, Chainey, Cameron, Leitner, & Wilson, 2005; Home Office, 2005). This analysis can then help inform the focused targeting of patrol and crime reduction resources to specific areas to help tackle the identified crime issues.

Hotspot maps certainly have a purpose, but can hide the relative levels of risk from being a victim of crime that people may experience. For example, hotspot maps show areas where crime is high but may purely be a product of the volume of people that frequent (or targets that exist in) the areas of high crime concentration. Geographic analysis that considers the spatial distribution of crime rates can provide added value to hotspot maps by considering some underlying population. This type of analysis may also make it easier to identify certain underlying causes of crime by classifying differences between hotspots (Clarke & Eck, 2003).

The analysis of crime rates alongside crime volume is regularly applied to burglary patterns (for examples see Chainey & Ratcliffe, 2005; Harries, 1999; Home Office, 2001a). Hotspot maps showing high concentrations of burglary may only reveal where there is a large amount of housing stock, hence the calculation of burglary rates against the underlying distribution of housing stock can provide an added dimension to the geographical analysis of burglary patterns by revealing where residents are at most risk of being a victim of this type of crime. Burglary rate

maps are straight-forward to construct because most developed countries possess census data at fine geographic resolution that describe the number of residential households in each census geographic unit, although, the choice and source of other denominators for other crime types is not as straight-forward (Chainey & Ratcliffe, 2005).

Rate maps and statistics calculated for crime rates for other crime types often make use of the resident population. For example, in England and Wales, published crime statistics include crime rates for vehicle crime and robbery to the person by using the resident population as a denominator. As a general-purpose measure to compare differences between areas it does have utility, however, in some cases it can greatly mislead (Chainey & Ratcliffe, 2005). Table 1 lists UK Home Office published robbery statistics for April 2002 to March 2003 for a sample of seven police force command areas (Home Office, 2003). The table also shows that the average robbery rate in England and Wales was 2.1 crimes per 1000 population per annum.

Table 1 demonstrates the large variation in robbery rates between areas in England and Wales. This can partly be explained due to the genuine differences in robbery between these areas. For example, inner city areas such as Lambeth in central London do tend to experience more problems with robbery than a provincial town such as Stratford-upon-Avon. These differences being explained due to the different socioeconomic and demographic characteristics between the two areas. There is though a large variation in the resident population between these six areas. The robbery rate statistics suggest that the likelihood of being a victim of robbery in the City of London is three times that of Newcastle, but half of that when compared to the neighbouring London borough of Lambeth. This may be useful as a general relative measure between areas, but may also be inherently inaccurate, as it does not consider the daytime population that frequent these areas. For example, the City of London is the financial

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