

1. Introduction

The Swedish newspaper *Dagens Nyheter* reported the case of a young woman raped in one of the most popular public garden's in the centre of Stockholm. At about the same time, another young woman was sexually attacked, but in that incident, the assault happened on the city's outskirts¹. About two-thirds of rape cases reported to the police in Sweden happen indoors committed by someone the woman knows; only about 30 per cent take place outdoors, in public places. But, outdoor rape is a distinctive form of this crime. First, in the case of outdoor rape, the rapist is usually someone unknown to the woman. Second, this type of sexual violence often takes place in interstitial public spaces such as back streets and hidden places and its occurrence depends, in part at least, on local environmental circumstances (Author). Third, outdoor rape has an impact on the community and may affect local levels of fear of crime. Fourth, unlike domestic rape, improvements in city planning and changes in policing methods might prevent, or at least greatly reduce, the numbers of cases of outdoor rape.

What characterizes the environments where rape takes place? Might a better understanding of the kinds of places where rape occurs be helpful in preventing it? We argue that place matters for our understanding of where the crime of rape happens in two senses. First, place matters in the sense of a specific, highly localised, micro-scale setting such as the existence of a secluded area in a park or badly lit alleyway where the criminal act takes place. Second, place matters in the sense of a more broadly defined meso-scale environment or geographical context such as a neighbourhood or small area of a town or city within which the crime is situated. In the past where an attack happened was regarded as a marginal aspect of the rape act (see for example Belknap, 1987) but more recent work has shown evidence of the importance of these settings (for a review, see Beauregard, Proulx, and Rossmo 2005 and Hewitt and Beauregard, 2014).

This article reports the results of modelling police recorded rape cases in Stockholm, Sweden by small areas (*basområde*) complementing earlier work that focused on the micro-places where individual rape incidents took place (Author). *Basområde* have, on average, a population of 2,200 individuals. In focusing on what we will term the meso-scale of analysis, the purpose is to emphasize the ecological characteristics of places, their land use, demographic

¹ Dagens Nyheter, 6 May, 2016, , <http://www.dn.se/nyheter/varlden/ung-man-gripen-for-valdtakt-utanfor-stockholm/>; <http://www.dn.se/sthlm/kvinna-overfallen-och-valdtagen-i-centrala-stockholm>.

composition and socio-economic characteristics, and their association with varying numbers of cases. Ecological models assess the statistical significance and substantive importance of different small area characteristics to our understanding of the geography of crime. However, in undertaking analysis at this scale and particularly with a predatory crime such as rape that involves very direct and immediate contact between offender and target, it is also necessary to recognize that small area (meso-scale) counts will be influenced by how many suitable “micro-scale spaces” exist within each area. These are areas offering adequate opportunity as well as anonymity to the attacker. This presents a challenge for ecological modelling but one that is not unique to the study of the crime of rape (see for example, Sherman et al, 2006 and Weisburd et al., 2012).

Data analysis involves two phases of modelling (Author 2). First, a hierarchical regression model is fitted the estimates from which show how each risk factor modifies the “whole map” or “global” crime risk with all other factors held constant. The second phase of analysis uses profile regression (Molitor et al. 2010) to reveal the association with “local” ecological characteristics. The combination of these two modelling techniques offers a better understanding of risk factor effects, by estimating the *whole map* effects associated with each individual risk factor and also identifying how these risk factors impact *at the local level*.

Both modelling phases adopt a Bayesian methodology. Bayesian hierarchical regression modelling separates the regression model into three linked models – a data model, a process model and one or more parameter models.² Regression modelling applied to spatial data raises a number of particularly complex challenges including the presence of spatial dependence in data and spatial heterogeneity (e.g. parameters varying spatially). Because spatial units can be small and cases of rape relatively uncommon, the data are often sparse (small numbers of cases per spatial unit; often many spatial units with no cases). Finally, uncertainty is endemic - uncertainty in respect of the data (e.g. unreported cases, the small number problem), the model (e.g. contested theories or explanations of where rapes are most likely to occur) and the model’s parameters (e.g. the unknown regression coefficients). Such complexity requires a flexible modelling framework that enables us to address all these challenges. Hierarchical modelling provides flexibility and the Bayesian approach to hierarchical modelling, unlike the frequentist

² The standard regression model, by contrast, combines the data model and the process model whilst parameters are constants estimated from the data. The Bayesian form of the standard regression model also includes models for the unknown parameters.

approach, allows us to jointly incorporate uncertainty *at all three model levels*. Spiegelhalter et al. (2004) argue that, compared to frequentist methods, the Bayesian approach is more flexible in adapting to each unique situation; more efficient in using all the available evidence and more useful in providing relevant quantitative summaries.

Profile regression produces a classification of areas not only based on their risk factor (covariate) values but also uses regression to associate these groups to the risk of rape. Other clustering methods classify areas based only on the former. The Bayesian aspect of this clustering process has some further advantages over traditional clustering approaches: it allows the number of groups to vary; it reveals groups (of areas) and examines the risk factor pattern and its association with the risk of rape within each group; the risk of rape in an area, in addition to its covariate values, influences the assignment of the area to the groups.

Bayesian inference is more relevant to observational (non-experimental) science than frequentist inference. Bayesian inference updates our prior beliefs (however vague or non-informative they might be) given a new set of data. Frequentist inference, by contrast, is founded on the idea of “infinite hypothetical replications of the situation under consideration” (Wakefield, 2013 p.23).

2. Literature review and hypotheses

2.1 The definition of outdoor rape

The legal definition of rape has varied over time, by country and even within national borders. In the United States the Justice Department defines rape as “forced sexual intercourse, including vaginal, anal, or oral penetration. Penetration may be by a body part or an object. Sexual assault is unwanted sexual contact that stops short of rape or attempted rape. This includes sexual touching and fondling” (RAINN 2014).

In European countries, rape may involve a wide spectrum of behaviours (for a comparative country review, see Lovett and Kelly (2009)). In Sweden, marital rape was criminalised in 1965 (in the 1970s in the USA and in the 1980s in the UK). The definition of rape was extended to include any sexual act committed by a stranger, an acquaintance, a partner or a family member of the woman. Rape is not confined to the penetrative act, but comprises “all sexual behaviour comparable in nature to violation having regard for the prevailing conditions. Having intercourse with a person who is unconscious, sleeping, intoxicated, handicapped or in a

similarly helpless state shall be regarded as equivalent to rape by threat or violence” (Chapter 6x1, Ministry of Justice, 1999). The maximum penalty is six years in prison, or 10 years in the case of ‘gross rape’ determined by the level of violence involved and whether more than one person assaulted the woman. In 1984, the definition of rape became gender-neutral, incorporating both male rape and assaults by women against men. The Swedish definition of rape is close to what some states in the USA (for example, the states of New York) define as ‘predatory sexual assault’. A person is guilty of predatory sexual assault when he or she commits the crime of rape, a criminal sexual act, or aggravated sexual abuse. In this case, rape is not confined to the penetrative act as previously mentioned and may also have a premeditated dimension to it (DCJS, 2014; NYSCASA, 2007).

‘Rape’ in this article refers to all police recorded cases of complete (sexual intercourse) and incomplete rape (attempted sexual intercourse and other types of sexual behaviour as defined by law) that happen outdoors (such as, for example, in streets, parks or transportation settings). In most cases, the offender was someone who was unknown to the victim. See Appendix A for crime codes and for details see BRÅ (2012).

2.2 An overview of socio-spatial research into the geography of rape

In common with other ecological studies into crime patterns (see, e.g. Bernasco and Luykx, 2003), the starting point for our analysis is to conceptualise where an act of rape takes place as the outcome of a two-stage rational choice process on the part of the offender. At the first stage, whilst the act may be primarily impulsive or opportunistic, we start from the position that the rapist will be rational to the extent that they will only be willing to take the risk in certain areas or neighbourhoods. At the second stage, the offender selects a specific target within the chosen neighbourhood. Rationality at this second stage involves assessing perceived target vulnerability and whether the time and location offers to the offender an acceptable level of risk.

At the first stage, neighbourhoods are chosen from within the offenders activity field (Brantingham and Brantingham, 1984) or awareness space which from experience or instinct offer opportunity with a low “subjective probability of detection” in committing rape (Hechter and Kanazawa, 1997, p.201). The activity field or awareness space of an individual comprises their anchor points in the urban landscape, such as place of residence, place of work, public meeting places including bars and frequently used subway stations and the lines of travel

connecting these anchor points. Most importantly, because the offender knows these areas they will be familiar with escape routes from the crime scene. *Accessibility* in the sense of getting to, and knowing, the crime scene and being able to flee it quickly forms an essential part of the decision process. Previous research into the geography of serial rape has found that offenders tend to use repeatedly the same geographic space (e.g., Pyle, 1974, Rhodes and Conly, 1981, Le Beau, 1985).

Other area characteristics are also important. Of necessity, the neighbourhood must offer *opportunities* for rape, that is the presence of women, perceived as vulnerable, who either live in the neighbourhood or travel through it on their way to home or work or leisure. Recent research shows that place factors affect the offender's behaviour more than offense timing (Hewitt and Beauregard, 2014). Finally, the neighbourhood must also provide sufficient *anonymity* for the criminal act as we now discuss.

Acts of rape tend to occur on isolated streets, interstitial spaces, parks, fields, places with footpaths with many sites for concealment and with building and street layouts with poor lighting and offering poor natural surveillance (Belknap, 1987; Canter & Larkin, 1993; Pyle, 1974; Rhodes & Conly, 1981; Rosay & Langworthy, 2003). Such spaces provide *micro-scale* anonymity for the motivated offender (Newman, 1972; Zelinka & Brennan, 2001). (Author) studied 76 cases of rape in Stockholm municipality during the period 2012-2013. (S)he concluded that the "micro-spaces" of rape share three commonalities. First, they are at or very close to areas with vegetation such as parks, forested areas or interstitial places that are easy to hide in. Second, they offer an easy escape route from the crime scene, because they are located close to public transportation such as bus stops or underground/train stations. Third, they tend to be secluded for example tunnels, ditches or stairs. The study did not answer the question of why other similar types of spaces in the city that share these commonalities reported no cases of rape during that period. Part of the answer to this question might lie in examining the types of neighbourhoods where these micro-places are located, that is placing micro-scale spaces in their meso-scale context.

Neighbourhoods where people have a high fear of crime or where there are few pedestrians on the streets provide what we term *meso-scale* anonymity for the offender. Opportunities for rape are greatest in neighbourhoods where social control is weakest, where individuals (both men and women) have become reluctant to go out (Gray, Jackson, & Farrall, 2011, Foster and Giles-

Corti, 2008). Evidence shows that socially disorganized neighbourhoods have disproportionately more crimes, including cases of rape (e.g. Amir 1971; Pyle et al. 1974; Maume 1989; Tewksbury and Mustaine 2006). Social Disorganization Theory (Shaw and MacKay, 1942 and later by Kornhauser 1978, Bursik and Grasmick, 1993, and Sampson and Groves, 1989) provides a significant part of the theoretical underpinning for many studies that focus on the impact of area and neighbourhood characteristics on crime. Shaw and McKay (1942) linked neighbourhood social disorganization to delinquency and crime. The mechanisms linking socially disorganized neighbourhoods and crime relate to people's inability to exercise social control in their neighbourhoods and solve jointly experienced problems. In neighbourhoods with high population turnover, guardianship is often low thereby further enhancing the ecological conditions associated with rape. Other neighbourhood characteristics are important to an understanding of the geography of rape including population overcrowding (Maume, 1989); the number of bars in an area (Rosay and Langworth, 2003); the number of vacant dwelling units and expressways cutting the neighbourhood (Pyle et al. 1974).

Person-environment interactions are central to our understanding of where crimes take place at the small area level, including, we argue, the crime of rape - a crime that necessarily involves direct contact between an offender and their victim. The ecological characteristics found in a place define the area level risk of rape occurring in that place. Given the above review we define such places in terms of three constructs. First *accessibility*, the ease of getting to and away from the crime scene for the offender because of familiarity, but also bringing potential victims into an area. Second *opportunity*, the potential of an area to provide suitable, vulnerable, targets. Third *meso- and micro-scale anonymity*, the potential of an area, at the meso-scale, to reduce the risks an offender faces and, at the micro-scale, provide cover and concealment for the actual criminal act. We shall use these three conceptual categories in our model.

2.3 Hypotheses of study

Two-stage rational choice theory provides a conceptual basis for separating the ecological level (numbers of cases of rape by small area) from the collection of individual criminal acts. It provides an argument to support the value of studying rape as counts of cases at the small area level. Here we test the following hypotheses at the small area (*basområde*) scale:

- (1) High counts of rape are associated with areas offering *opportunity* to the offender. These are areas with a relatively large number of vulnerable female targets either

frequenting or just passing through perhaps associated with their place of residence or with the locations of particular institutions or amenities. (e.g., Pyle et al. 1974; Hewitt and Beauregard, 2014; Author) (*Opportunity hypothesis*.)

- (2) High counts of rape are associated with areas with poor surveillance and/or poor social control where residents have a high fear of crime. Such areas may provide anonymity for the offender at the meso-scale (Maume 1989; Canter & Larkin, 1993; Tewksbury and Mustaine 2006). Neighbourhoods with buildings and street layouts providing areas for concealment, perhaps because of inadequate lighting or quiet alleyways, may provide a number of suitable “micro-spaces” for the offence to be committed thereby providing anonymity at the micro-scale (e.g., Pyle et al. 1974; Rosay and Langworth, 2003) (*Meso- and micro-scale anonymity hypothesis*).
- (3) High counts of rape are associated with areas that have good accessibility because they bring potential targets into an area and offer a quick and easy escape route from the crime scene for the offender. An offender is likely to be familiar with at least a subset of such areas because the more accessible a place is the more likely it is to form part of their awareness space. (e.g., Rhodes & Conly, 1981; Le Beau, 1985; Rosay & Langworthy, 2003). (*Accessibility hypothesis*).

We defer discussion of the variables used to test these hypotheses until section 3.2.

3. The Stockholm rape study

This case study is limited to the Stockholm municipality (population 880,000 in 2012), which means the inner-city area and those suburbs that administratively belong to the city of Stockholm. The municipality is an archipelago well connected by bridges, roads and an efficient public transport system consisting of subways, trams, commuting trains and busses. It is in the inner city area that the main public transport junction is located, concentrating a large number of people daily in the city’s centre. Stockholm’s inner city comprises residences where citizens enjoy a good quality of life. Housing, which may be rented, privately owned or occupied under a co-operative agreement, is of a high standard. Residents in these areas, on average, report a 30% higher annual income than those residing in the ten peripheral areas (USKAB 2012). The mass-produced blocks of flats built in the 1960s and 1970s do not all perform equally well: low prices are often linked to poor architecture, lack of amenities and social problems.

3.1 Data on rape cases

Stockholm's Police Headquarters provided records for the years 2008 and 2009. They contained crime code, day and hour of the crime and the geo-coordinates of where the rape happened. The records showed 555 cases of outdoor rape (including attempted rape) in this period. Outdoor locations are places where police surveillance and police patrols can limit or discourage acts of crime and disorder. Outdoor locations include: streets, transit environments; areas and premises adjacent to railways; metro and traffic terminals the public has access to; other facilities for public events that have the character of an outdoor facility such as an open-air sports ground (BRÅ, 2012). Of the 555 cases, 415 of these took place in Stockholm County and 237 cases in Stockholm municipality (e.g., 140 cases took place elsewhere in the country or abroad). This analysis includes 237 cases in Stockholm municipality (Figure 1).

Figure 1 – about here.

A Geographical Information System (GIS) was used to map rape cases and then aggregate to the *basområde* level. This is the smallest spatial unit of analysis giving access to demographic, social and economic statistics in Sweden. Note that of the 407 *basområdes* in the Stockholm municipality, 63% have no reported cases. We discuss the implications of this for modelling in section 3.3.

3.2 Area risk factors

We describe the covariates used to measure small area level accessibility, meso- and micro-scale anonymity and opportunity. Table 1 summarises the 11 area level covariates by category and detail as to data sources is provided in Appendix A. Eleven covariates are used – two measuring aspects of accessibility; five measuring meso-scale anonymity and one measuring micro-scale anonymity; three measuring opportunity.

We argue that areas exhibiting high levels of *opportunity* are those with large numbers of females (targets) and those with institutions, such as schools, or amenities, such as alcohol outlets, that may be associated with the presence in the area of particularly young, vulnerable targets. Females may be putting themselves at additional risk if they visit bars, they may be at additional risk by merely passing through areas with bars where males gather to drink (i.e. where there may be more potential perpetrators). Areas of Stockholm meeting these criteria

will include high-density residential neighbourhoods near the city centre and some suburban neighbourhoods.

We identify areas exhibiting high levels of *meso-scale anonymity* as those neighbourhoods with poor social control. We identify areas with poor social control using data on the percentage of people who fear crime and levels of population turnover. High values of these variables are indicators of poor social control. Neighbourhoods where the fear of crime is high tend to lack informal surveillance (“eyes on the street”) as people may be reluctant to spend leisure time out of their homes. High turnover is often associated with neighbourhoods that are less affluent, less desirable and less safe. Young males with no family and lacking steady employment may comprise a significant element of the resident population. We include average income as an indicator of affluence. Areas of low average income may show poor social control. Finally, we also define industrial and forested areas as exhibiting *meso-scale anonymity*. Such places, particularly at certain times of the day can be lonely and isolated with little or no surveillance.

We identify areas with good public transportation or which are located in the city centre of Stockholm as areas that enjoy good *accessibility*. Such areas are likely to form part of a would-be offender’s awareness space. We use access to subway stations, rather than say the bus network, as our measure of accessibility as previous work by (author) has drawn attention to the role of the subway system in providing targets for would-be perpetrators and providing a rapid means of escape from the crime scene. The city centre is arguably the most accessible area in any large city but its role in any study of rape victimization clearly overlaps other categories including, at certain times of the day, meso-scale anonymity and opportunity as we have defined them.

Table 1 – about here

We have argued above that anonymity needs to be defined at two scales but we have no direct data on the number of “micro-spaces” in each *basområde* that offer sites which give the attacker anonymity in the act of rape (*micro-scale anonymity*). There are clear challenges to providing a measure of the number of such spaces. In this study we have used a surrogate measure, the number of cases of street robbery because many forms of street robbery also require micro-scale anonymity for carrying out the criminal act. It is not, of course, ideal. Cases of street robbery also occur in places with many people, which offer opportunities for stealthy, distracted, rapid, offender-on-victim interactions. We suggest that future research should look

into constructing a more “direct” measure of micro-scale anonymity at the *basområde* scale. Perhaps remotely sensed imagery of Stockholm’s land use (forestry, industry, built form) by day and luminosity by night might provide a useful resource.

3.3 Statistical models

An ecological analysis of rape aims to assess how risk factors *individually as well as jointly* affect the risk of outdoor rape. To achieve this, we describe an approach that encompasses two statistical techniques: a Bayesian Hierarchical Poisson regression model for a “whole map” analysis and a Bayesian profile regression (BPR) model (Molitor et al. 2010) for a “local” analysis. Often employed in ecological crime studies (e.g. Matthews et al. 2010 and Congdon 2013), a Bayesian Poisson regression model estimates the “whole map” effect of individual covariates. Li et al. (2013) discusses the benefits of adapting the Bayesian approach in modelling small area crime data. In this paper, we perform a further localised analysis using BPR to understand how the covariates *jointly* affect the area-level risk. The combination of the results from both methods provides a better understanding of the ecology of outdoor rape. Because of its novelty to crime analysis, we will first highlight the benefits of employing BPR in the present study then provide the technical details of the two methods in 3.3.1 and 3.3.2.

BPR is a Bayesian clustering method that seeks to cluster or group areas based not only on the similarity of rape occurrence but also on the similarity of the *risk factor profile*. This modelling approach offers several advantages. First, by using risk factor profiles, BPR considers all risk factors *jointly* when assessing similarity. For example, two areas have similar risk factor profiles if they have similar levels of population turnover, income and female resident population. This clustering of risk factor profiles places no restriction on the correlation structure amongst the covariates, hence resolving the multicollinearity problem that is often encountered when fitting a standard regression model. Moreover, by using risk factor profiles, BPR does not require the specification of an explicit covariates-outcome relationship (as required when fitting a standard regression model), hence allowing for potential interactions *amongst* the covariates.

Second, BPR clusters areas based on their risk factor profiles **and** their risk levels, allowing us to differentiate, for example, two groups of high-risk areas, one group having a set of distinctly different *local characteristics* to the other. Third, the “local-focus” of BPR enables us to deal with spatially heterogeneous covariate effects. For example, a small female population may not

always be associated with a low risk of rape. While there are other methods to allow for such heterogeneous covariate effects (e.g. geographically weighted regression (Fotheringham et al. 2002) and Bayesian spatially varying coefficient models (Gelfand et al. 2003)), these methods may suffer from the multicollinearity issue (Wheeler and Tiefelsdorf, 2005).

Lastly, to model the observed rape cases, BPR allows the inclusion of random effects, which are often used to deal with the so-called overdispersion problem, whereby the variability in the observed count data exceeds that from a Poisson distribution. Often encountered in analysing small area crime data, overdispersion can be a result of effects arising from unmeasured/unobserved risk factors. Standard clustering methods do not include random effects and thus fail to account for such an important source of uncertainty in modelling small area crime data. Finally, placed in the Bayesian framework, BPR allows the number of clusters to be estimated from the data and this uncertainty is fully accounted for in estimating other parameters in the model. Non-Bayesian clustering methods fix the cluster number - such uncertainty is ignored.

3.3.1 A “whole-map” analysis using Poisson regression

In this part of the analysis, we use Poisson regression (McCullagh and Nelder, 1989, Osgood, 2000) to estimate the overall effects of the risk factors on the number of cases of outdoor rape.

Denoting O_i the number of outdoor rape cases in *basområde* i ($i = 1, \dots, 407$), a Poisson regression models O_i using a Poisson distribution (the data model), i.e. $O_i \sim \text{Poisson}(\mu_i)$. In Eq. (1), the Poisson mean μ_i (the process model) is expressed as a function of area-level risk factors and random effects, where the latter are included to account for effects that arise from unobserved/unmeasured covariates.

$$\log(\mu_i) = \alpha + \sum_{l=1}^{11} \beta_l X_{li} + u_i + v_i \quad (1)$$

The expected cases μ_i are log transformed to ensure that they are non-negative. The parameter α is the (log) overall expected number of cases in Stockholm municipality; $\sum_{l=1}^{11} \beta_l X_{li}$ represents the effects arising from the risk factors (see section 3.2) and u_i and v_i are the random effect terms. The regression coefficient β_l ($l = 1, \dots, 11$) quantifies the impact of the risk factor X_{li} on rape occurrence. For the random effects, u_i is modelled as a set of spatially-structured

random effects, representing a set of unobserved risk factors whose joint effects on the occurrence of rape display spatial structure and v_i is modelled as a set of spatially-unstructured random effects, representing the unobserved risk factors whose effects on the occurrence of rape do not display spatial structure. To impose spatial structure, the intrinsic conditional autoregressive (ICAR) model is applied to u_i such that neighbouring areas have similar values of u_i (Besag et al. 1991). This models spatial dependence in the Poisson mean.³ For v_i , independent normal distributions, $N(0, \sigma_v^2)$, are assigned. Incorporating the two random effect terms helps account for variability that is not explained by the 11 covariates that are already included in the model. In the present dataset, a source of such extra variability comes from a large proportion of areas with 0 cases and the two random terms help deal with these 0. Note that, compared to the modelling approach discussed in Osgood (2000), an offset term is not included for two reasons. First, it is difficult to define the “at risk” population for outdoor rape. Second, using female residential population as an offset implies a smaller female population is associated with a lower risk of rape. However, this assumption is not true for some of the *basområdes* (as results will show). Therefore, we directly modelled the underlying expected counts as opposed to modelling the rates but included the female population as a covariate, whose effect on risk is then estimated from the data.

Under the Bayesian approach, prior distributions are assigned to all model parameters (the parameter model). Here, non-informative priors were used so that the testing of the hypotheses discussed in 2.3 is minimally affected by the prior choice. This reflects the small amount of prior evidence we have from which to start the current modelling. Specifically, for both the intercept and the regression coefficients, a Normal prior $N(0, 10000)$ was used. To σ_v and σ_u , the standard deviations of the two sets of random effects, a Normal prior $N(0,1)$ is assigned; to ensure that a standard deviation parameter is non-negative, this normal prior is truncated so that it only takes non-negative values (Gelman 2006). Parameter estimation was carried out in WinBUGS (Lunn et al. 2000) via iterative Markov chain Monte Carlo (MCMC) methods and the WinBUGS code is provided in Appendix B.

³ Modelling correlated Poisson counts through the data likelihood raises severe computational challenges. Modelling spatial dependence in the process model, so that the Poisson counts are treated as independent given the process, is one of the major advantages of hierarchical modelling over standard forms of regression modelling when dealing with spatial count data.

3.3.2 A “local” analysis using Bayesian profile regression

This part of the analysis employs Bayesian profile regression to understand the local environments where outdoor rapes occur. BPR allocates *basområdes* into clusters (or groups⁴) so that *basområdes* within each cluster tend to have similar risks of rape *and* similar risk factor profiles. Specifically, the risk factor profile of an area is simply a list of the observed risk factor values for the area. Given a cluster formation, the risk factor profile for each cluster is estimated based on the observed risk factor profiles of its member areas. In our study, the risk factors are both continuous- and discrete-valued (binary and categorical). Within a cluster, the continuous-valued risk factors are modelled using a multivariate Normal distribution and the binary and categorical risk factors are modelled respectively using a vector of independent binary and categorical random variables. Independent of the cluster allocation, we also included two sets of random effects, spatially-structured and spatially-unstructured, to account for unmeasured/unobserved risk factors as well as dealing with the many areas with 0 cases. The specification of these two sets of random effects are the same as those in the Poisson regression model. The BPR model was fitted using the R package PReMiuM, which provides a simple platform to fit the BPR model using MCMC algorithms (see Liverani et al. 2015 for more detail).

It is important to note that BPR performs cluster allocation probabilistically, meaning that the number of clusters and the composition of each cluster (which areas are included in any cluster) may differ from one MCMC iteration to the next. This probabilistic way of clustering can be thought of as exploring different ways of grouping the areas and reflecting the uncertainty associated with the number of clusters and their composition. However, the challenge is to summarise the rich MCMC outputs and, ultimately, decide on the number of clusters and, their composition. To post-process these MCMC outputs, we follow the three steps suggested in Molitor et al. 2010. Briefly, the first step constructs the posterior similarity matrix \mathbf{S} that summarises different partitions of areas over all MCMC iterations. Each off-diagonal entry in \mathbf{S} , s_{ij} (for $i \neq j$), quantifies how likely it is for two *basområdes* i and j to be grouped together over all MCMC iterations. The second step finds a representative partition that has the shortest distance to the similarity matrix \mathbf{S} . Using all MCMC iterations the third step then produces the

⁴ The term cluster in profile regression refers to groups of areas that are classified together. Spatial contiguity is not a criterion for this classification.

estimates for the risk and risk factor profile associated with each of the clusters within the representative partition. The results presented in 3.4 are from the representative partition.

Note also that because BPR models the continuous-valued risk factors using multivariate normal distributions, each continuous-valued risk factor was transformed to be approximately normally distributed (see Appendix A). The two discrete-valued covariates, numbers of alcohol outlets and robbery cases, were converted into categorical covariates (as defined in Table 1) because no suitable normality transformation was found for the highly positively-skewed distributions. For the whole map analysis, the Poisson regression was fitted based on the untransformed continuous-valued risk factors with alcohol outlets and robbery cases being either in categorical form (model 1) or in count form (model 2) (see Table 1).

3.4 Results

3.4.1 “Whole map” associations for the risk factors

The estimated effects of the 11 risk factors from the Poisson regression are summarised in Table 1. Here $\exp(\beta_l)$ represents the relative risk due to a one-unit change in the risk factor X_l (or compared to the reference category for binary/categorical risk factors) while keeping all other risk factors fixed.⁵

The presence of a subway station in a *basområde* generally increases the risk of outdoor rape in an area by over 50%, perhaps because of the opportunities they offer for escape. An alternative explanation is that public transportation sites are the places where motivated offenders encounter the women that they will follow and assault. Figure 2 displays, in raster form, data on the density of stations as continuous colour gradations. Overlaying the cases of rape suggests an association between the locations of underground stations and the locations of rape cases. In addition to the effect of subway stations, the risk of rape is nearly doubled in the ‘city centre’. The importance of both these two risk factors provides evidence supporting the *accessibility hypothesis*.

Figure 2 here

⁵ The relative risk measures indicate how much the expected number of rape cases would increase/decrease if a particular risk factor were to be increased by one unit and all other risk factors remained constant. This quantity $\exp(\beta_l)$ is not an odds-ratio (as in a logistic regression) since the Poisson regression model here deals directly with event occurrence, not probability.

A *basområde* with a high level of population turnover tends to have an increased risk of rape (posterior mean of 2.06 with 95% CI: 1.16-3.53). The results also show some, albeit weak,⁶ evidence of an increased risk of rape associated with a falling level of average income (posterior mean of 0.98 with 95% CI: 0.97-1.00), suggesting a reduction of SEK 10,000 (equivalent to US\$ 1,175) leads to a 2% (95% CI: 0%-3%) increase in risk. By contrast the other three meso-scale anonymity risk factors (people's fear of crime and presence of forested or industrial areas) do not appear to be associated with the risk of rape. These results suggest that *meso-scale anonymity*, in the sense of poorer areas with high population turnover, does contribute to explaining variation in the number of rape cases. The covariate on street robbery counts, used as a surrogate measure of the *micro-scale anonymity*, is found to be positively associated with the risk of rape. Under Model 2, an increase in robbery count is found to be associated with an increase in the risk of rape (posterior mean of 1.05 with 95% CI: 1.02-1.07), indicating that one additional robbery case leads to a 5% (with 95% CI: 2%-7%) increase in risk of rape. Such a linear trend is also seen when the covariate is included as a categorical variable in Model 1, although the effect is only significant when the number of street robberies is 5 or more, suggesting that the relationship is strongest where micro-scale anonymity is greatest. These results, taken together, indicate that both forms of anonymity contribute to our understanding of small area variation in the number of cases of rape.

We have been unable to confirm the importance of the three risk factors we have associated directly with the *opportunity hypothesis*, i.e. the size of the female population, the number of alcohol outlets and the presence of educational establishments. The first two risk factors are significant in Model 2 but not under Model 1. However, it is worth noting the clear increasing trend between number of alcohol outlets in an area and the risk of outdoor rape, suggesting that risk in an area does increase when a larger number of alcohol outlets are present. Also, in section 3.2, we remarked that the city centre can be associated with the opportunity hypothesis and as noted above this covariate is significant.

3.4.2 “Local” associations for the risk factors

BPR was applied to reveal the localised characteristics of places where rape took place. Over the 200,000 MCMC iterations, about 99.7% of them consist of 7 clusters with 0.3% having 8

⁶ This is only weak evidence of an income effect because the upper bound of the 95% CI is on the borderline of 1, the value that indicates no effect.

clusters, showing some variability (or uncertainty) in determining the cluster number. To summarise different clustering options of the areas, the representative partition of the *basområdes* was produced following the steps outlined in 3.3.2. Figure 3 shows the seven clusters in the representative partition. There are three low-risk clusters (Clusters 1-3, all with the 95% CI for relative risk below and excluding 1). There are two medium risk clusters (Clusters 4 and 5, with relative risks of 0.71 (95% CI: 0.40-1.27) and 0.98 (95% CI: 0.78-1.22) respectively. Finally, there are two high-risk clusters (Clusters 6 and 7, both with the 95% CI for relative risk above and excluding 1).

Figure 3 here

Figure 4 describes the estimated cluster-specific risk factor profiles. For the two high-risk clusters, Cluster 6 represents areas mainly in the city centre with high population turnover, small female residential populations and small numbers of schools. There are also large numbers of alcohol outlets (a high proportion of *basområdes* are in category 4) and large numbers of street robbery cases in this cluster. The characteristics of this cluster illustrates that it is inappropriate to use the female population as an offset. Cluster 7, on the other hand, represents relatively deprived suburban areas with large numbers of subway stations and schools, relatively low income, high levels of fear of crime. The relatively large female residential populations in these areas present the would-be offenders with a large number of potential targets. All factors combined contribute towards the high risks of rape in these areas. Similar to Cluster 6, relatively large numbers of alcohol outlets and street robbery cases are found in these areas. The finding of these two groups of high-risk areas, each with distinctly different local characteristics, provides a better description of the clusters, illustrating a benefit of the Bayesian profile regression approach.

Figure 4 here

There are two medium risk clusters, Clusters 4 and 5. Cluster 5 consists of areas mainly on the outskirts of the city centre (Figure 3). These areas tend to have a relatively large female residential population with more schools and a generally low fear of crime amongst residents and good subway connections. There are large numbers of alcohol outlets present in these areas but numbers of robbery cases are relatively low, compared to the levels in the two high-risk clusters. Cluster 4, the other medium risk cluster, consists of 22 *basområdes*. These *basområdes* contain airports and shopping malls that have 0-values for income, population turnover and size of the female residential population (Appendix A). While the above three risk factors are all

zero, areas within this cluster are mainly industrial areas with schools present in only a few of these areas.

Clusters 1 to 3 are the three low risk clusters. Cluster 2 represents primarily industrial areas whilst Clusters 1 and 3 are the affluent suburban areas with few alcohol outlets and few robbery cases suggesting few micro-sites offering anonymity for the criminal act.

4. Discussion of the results

We hypothesized that small area variation in the number of cases of rape can be understood by reference to three theoretical constructs: accessibility, opportunity and (meso- and micro-scale) anonymity. To discuss the risk factors identified by the “whole map” Poisson regression modelling, we consider both models (1 and 2) reported in Table 1. We observe that all the theoretical constructs are significantly associated with small area variation although not with the same degree of empirical support. The two covariates measuring accessibility (city centre; presence of a subway stop) are significant in both sets of results. Two of the five covariates measuring meso-scale anonymity are also significant in both sets of results: population turnover and average income which taken together suggest that poor areas with low levels of social control (Maume, 1989) present the highest risk. The covariate measuring micro-scale anonymity, the number of street robberies, was significant in both sets of results with the results of the two analyses taken together suggesting that the association is most pronounced in areas with the largest numbers of street robberies. Not all street robberies necessarily depend on high levels of micro-scale anonymity, but those areas with high numbers of cases are likely to be the areas offering the largest number of suitable sites. On the other hand, the evidence for the importance of opportunity (as defined by the internal characteristics of a *basområde*) is less compelling. The presence of schools is not significant and the size of the resident female population and the number of alcohol outlets in the *basområde* are only significant when the alcohol covariate is measured as a continuous covariate. Here it is important to recall that *basområdes* represent artificial partitions of the urban space. The effects of some attributes may be felt “at a distance” from their actual location, that is when women are on the move. This was noted by Author (X, p.103) who observed that whilst more than half of the rape cases (s)he analysed occurred within 1 km of the women's residence, many of these as well as the other cases beyond 1 km might be recorded in *basområdes* other than where the women lived. The same is likely to be true in the case of attacks linked to alcohol outlets.

It is also interesting to note the risk factors that were not significant: *basområdes* where industry or forest was present and areas where fear of crime was high. We linked these covariates to the meso-scale anonymity hypothesis. The location of parks and forested areas may be associated with where *some* rapes occur (Author), but such areas seem not, in general, to be associated with a significant increase in area level risk. This may be because other characteristics need to be present in order to constitute a “whole map” risk factor. In the case of fear of crime, it is high levels of violent and property crimes that lie at the core of many people’s fear of crime (Author). People in better off areas may declare high levels of anxiety about crime and express concerns for their personal safety (Lewakowski, 2012), but they may have the resources to provide themselves with protection that lowers risk including the risk of sexual assault.

Profile regression reveals the localised characteristics of places where rapes occur and in particular the role of risk factor interactions in determining local area risk. Risk factors that do not emerge as significant in a whole map analysis may emerge in this form of regression modelling because of local context. Two types of areas stood out where risks were high. Cluster 6 represents areas in the city centre with high population turnover, large numbers of alcohol outlets and large numbers of cases of street robbery. This is not surprising. Cluster 7 represents relatively deprived suburban areas with large numbers of subway stations and schools, relatively low income levels, high levels of fear of crime and relatively large female residential populations. Relatively large numbers of robbery cases occur in these areas where there are also many alcohol outlets. In the case of the areas in cluster 7, two covariates emerge as important risk factors locally but not in the “whole map” analysis. These are areas with high levels of fear of crime and areas where many schools are located. This observation highlights the importance of understanding the effect of a risk factor within the local context, one of the original motivations for this study (see section 2.2), and jointly within the setting provided by other risk factors.

We conclude this discussion of findings by acknowledging that police data on rape is far from problem free. A general estimate from the National Council of Crime Prevention shows that only between 10 and 15 percent of all sexual crimes are reported to the police (BRÅ, 2014). From the cases that do go to trial, a quarter of them result in acquittal. Rapes that happen in public places committed by a stranger fit the ‘stereotypes of rape and rapists’ and constitute the majority of cases that reach court. If a reported case happened in an open or forested area or in

a place unknown to the raped woman, then the precise location of the rape usually cannot be determined.

5. Conclusions

This article has reported findings from an analysis of the geographical distribution of cases of rape in Stockholm 2008-9 at the small area (*basområde*) scale. Theories from urban criminology provided the basis for testing three hypotheses based on opportunity, accessibility and anonymity using land use, demographic and socio-economic characteristics of the small area units. Bayesian regression methods and Geographical Information Systems (GIS) technology underpin the work in this study. The main contribution of this study is that it indicates the areas that present the highest risk of rape. Previous research on an individual case by case basis in Stockholm (Author) drew attention to certain environmental commonalities relating to anonymity but was unable to explain why other areas, despite offering similar levels and forms of anonymity for example did not report any rape cases. The implication is that certain classes of risk factor, especially land use and service outlet variables may be highly place or context specific. This study sheds light on this contextual effect and the need to consider contextual effects when crime prevention initiatives are put into practice.

Findings from the “whole map” analysis has confirmed the importance of the accessibility dimension to an understanding of the geography of rape. Both of the accessibility risk factors (presence of subway stations; proximity to the city centre) are significant in both models 1 and 2. The importance of the opportunity dimension is captured by the presence of alcohol outlets and particularly where there are large numbers of such outlets. The number of women resident in an area is also significant in one form of the model. This is consistent with the earlier finding that it is women who are perceived as vulnerable as a result of alcohol consumption who are most at risk. There is support too for the importance of both forms of anonymity. Population turnover is significant in both forms of the model as is the number of cases of street robbery. Our findings with respect to micro-scale anonymity must be qualified by our dependence on surrogate data. However, notwithstanding these reservations there is clear evidence that areas experiencing the highest levels of street robbery are also the areas experiencing the highest risk of rape – a finding with clear crime prevention implications.

Findings from the local analysis in this study reveals two types of high-risk area within Stockholm. The first of these are the parts of the city centre where there are large numbers of

alcohol outlets, high residential population turnover and high counts of robbery. The second type of high-risk area comprises poor suburban areas with schools, where subway stops are located, and where a large proportion of the population express fears about crime sufficient to make them avoid going out in the neighbourhood. So in a local context, fear of crime is a risk factor. Finally, it is interesting to note those risk factors at the *basområde* level that were not significant in either form of the whole map model or the local regression model namely the presence of industrial or forested areas perhaps because only small numbers of women venture into such areas.

Finally, we turn to policy issues. Area-focused crime prevention strategies particularly those designed for large urban areas should draw on findings from both individual and aggregate level research. Whilst focusing on individual incidents will provide detailed insights into particular cases or groups of cases, small area research is better placed to make inferences about the environments within which particular crimes occur and the importance of local context. Local analyses can be used to tailor crime prevention measures to the locally significant risk factors. This study (combining the “whole map” effects of risk factors on the risk of rape and the local characteristics of areas at different risk levels using profile regression) clearly shows the need of using a two-stage analysis approach when the goal is to provide evidence for prevention of sexual violence in outdoor environments.

In the case of rapes, one way forward is to reflect upon the roles that transport nodes and the maintenance of public spaces around them have on the incidence of outdoor rapes (Author). The transportation system is one of the most important situational elements for outdoor rapes in Stockholm. These findings confirm trends in perceived safety by passengers. Safety surveys in Stockholm show that individuals often feel safe in the carriage, the bus and in the station’s environment, but their perceived safety levels decrease as they walk from the station to home, and vice-versa (City of Stockholm, 2011). This means that authorities should tackle safety by adopting a door-to-door strategy or the so-called ‘whole journey approach’ although, as suggested above, it is likely that strategies will need to be tailored to local circumstances.

Some cases of rape happen just after women leave the bus stop or subway station. As the subway system closes down overnight on weekdays, special attention should be given to busses, as they may become the only way to return home using public transportation. For the offender, transportation environments function both as a place where women can be identified

and a means to escape from the crime scene. The design, location and management of public facilities at entrances or close to stations and transport nodes may be enough to discourage offenders, and diminishes opportunities for rape in the immediate surroundings of the stations. In more peripheral stations, adding CCTV cameras particularly at exits and entrances, can support the work of ‘place managers’, ‘handlers’ and ‘guardians’, such as subway personnel, guards, safety hosts or parking lot attendants (Felson, 1995). The role of place managers and support systems and their potential to exercise guardianship needs to be examined in relation to the way public spaces are used by different communities in the city. ICT technology (particularly mobile phones and social media) has a role to play in reducing sexual attacks.

Phumzile Mlambo-Ngucka, Executive Director of UN Women, wrote: “we have to work with communities to change harmful social norms and attitudes, and social institutions that discriminate and tolerate violence against women.” (UN Women, 2014). **What this research draws attention to are the types of environmental or contextual circumstances that increase the risk of a rape occurring in an area.** This study has contributed to this knowledge base by assessing the importance of the contextual circumstances surrounding the crime of rape. Interventions are needed that include but also go beyond ‘quick fixes’ of the local environment at the scale of specific places (better lighting, greater physical openness of urban parks, perhaps closure of certain paths and passageways). Preventive measures to try to reduce rape need also to take account of specific geographical-ecological contexts. That means reflecting not only on how to address “harmful social norms and attitudes” raised by Phumzile Mlambo-Ngucka but also environmental design issues at different scales and identified for specific places. This may involve adjustments in the way cities are built and policed, but also changes in urban functions that create micro and meso spaces that allow a sense of ownership and control access. These findings call for a whole journey perspective to women’s safety. Since many rapes take place while women are on the move (on the way to or from home; to or from work or leisure), understanding the dynamics of rape calls for, data permitting, a space-time analysis of women’s levels of risk across the urban landscape.

Acknowledgements (funding support to be added)

6. References

(Author)

(Author 2)

Amir, A. (1971) *Patterns in forcible rape*. Chicago: University of Chicago Press.

Beauregard, E., Proulx, J., and Rossmo, D. K. (2005) Spatial patterns of sex offenders: Theoretical, empirical and practical issues. *Aggression and violent behaviour*, 10:579-603.

Beauregard, E., Proulx, J., and Rossmo, D.K. (2007) A descriptive model of the hunting process of serial sex offenders: a rational choice perspective. *Journal of family violence*, 22: 449-463.

Belknap, J. (1987) Routine activity theory and the risk of rape: Analyzing ten years of National Crime Survey Data. *Criminal Justice Policy Review*, 2:337-356.

Bernasco, W. and Luykx, F. (2003). Effects of attractiveness, opportunity and accessibility to burglars on residential burglary rates of urban neighbourhoods. *Criminology*, 41(3), 981-1002.

Besag, J., York, J. and Mollié, A. (1991) Bayesian image restoration, with two applications in spatial statistics. *Ann Inst Stat Math*, 43(1), 1-20.

Brantingham, P., and Brantingham, P. (1984) *Patterns in Crime*. New York: Macmillan.

BRÅ - The Swedish National Council of Crime Prevention (2005) *Våldtäkt: En kartläggning av polisanmälda våldtäkter*, 7.

BRÅ - The Swedish National Council of Crime Prevention (2012) *Kodning av brott: anvisningar och regler*. Version 11.0, Stockholm. (Available at http://www.bra.se/download/18.22a7170813a0d141d21800050764/Brottskodningslistan-2012+v11_3.pdf)

BRÅ - The Swedish National Council of Crime Prevention (2014) *Rape and sexual offences*. <http://www.bra.se/bra/bra-in-english/home/crime-and-statistics/rape-and-sex-offences.html>

Bursik, R. J., and Grasmick, H. G. (1993) *Neighbourhoods and Crime*. New York: Lexington.

Canter, D., and Larkin, P. (1993) The environmental range of serial rapists. *Journal of Environmental Psychology*, 13:63-69.

City of Stockholm. (2011) *Trygg i Stockholm? 2011 En stadsövergripande trygghetsmätning*. Stockholm: City of Stockholm, The Social Development Unit.

City of Stockholm (2014) Trygghet i Stockholmstad. Stockholms stadsövergripande trygghetsmätning. Stockholm city, Stockholm. Accessed 24th April 2016, <http://www.stockholm.se/trygghetsmatningen>

Congdon, P. (2013) A Model for Spatially Varying Crime Rates in English Districts: The Effects of Social Capital, Fragmentation, Deprivation and Urbanicity, *International Journal of Criminology and Sociology*, 2, 138-152

Dagens Nyheter (2016) Ung man gripen for valdtakt utanfor Stockholm (A young man arrested for rape in Stockholm outskirts). Available 6 May, 2016 /<http://www.dn.se/nyheter/varlden/ung-man-gripen-for-valdtakt-utanfor-stockholm>

Dagens Nyheter (2013) *Kvinna överfallen och våldtagen i centrala Stockholm*. (Woman attacked and raped in central Stockholm). Available 23th January, 2013, <http://www.dn.se/sthlm/kvinna-overfallen-och-valdtagen-i-centrala-stockholm>

DCJS - Division of Criminal Justice Services (2014) *Predatory sexual assault*. 2014, from http://www.criminaljustice.ny.gov/legalservices/ch107_predatorysexualassault.htm

Felson, M. (1995) Those who desincourage crime. In J. E. Eck & D. Weisburd (Eds.), *Crime and Place*, 53-66, Monsey, NY: Criminal Justice Press.

Foster, S., and Giles-Corti, B. (2008) The built environment, neighborhood crime and constrained physical activity: An exploration of inconsistent findings. *Preventive Medicine*, 47:241-251.

Fotheringham, A. S., Brunson, C., and Charlton, M. E. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Wiley, Chichester (2002).

Gelfand, A.E., Kim, H., Sirmans, C.F. and Banerjee, S. (2003) Spatial modelling with spatially varying coefficient processes. *Journal of the American Statistical Association*, 98, 387–396.

Gelman, A. (2006) Prior distributions for variance parameters in hierarchical models. *Bayesian analysis*, 1(3): 515-533.

- Gray, E., Jackson, J., and Farrall, S. (2011) Feelings and Functions in the Fear of Crime: Applying a New Approach to Victimisation Insecurity. *British Journal of Criminology*, 51: 75-94.
- Hechter, M. and Kanazawa, S. (1997) Sociological Rational Choice Theory. *Annual Review of Sociology*, 23:191-214.
- Hewitt, A, and Beauregard, E. (2014) Sexual crime and place: The impact of the environmental context on sexual assault outcomes. *Journal of Criminal Justice*, 42: 5, 375-383.
- Kornhauser, R. (1978) *Social Sources of Delinquency*. Chicago, IL: University of Chicago Press.
- Lewakowski, B. (2012). *Half locked? assessing the distribution of household safety protection in Stockholm*. (Master Thesis), Royal Institute of Technology, Stockholm.
- Li, G., Haining, R., Richardson, S. and Best, N., (2013). Evaluating the No Cold Calling zones in Peterborough, England: application of a novel statistical method for evaluating neighbourhood policing policies, *Environment and Planning A*, 45(8): 2012-2026.
- Liverani, S., Hastie, D. I., Azizi, L., Papathomas, M. and Richardson, S. (2015) PReMiuM: An R package for Profile Regression Mixture Models using Dirichlet Processes. *Journal of Statistical Software*, 64, 7 (2015): 1-30.
- Lovett, J., and Kelly, L. (2009) *Different systems, similar outcomes? Tracking attrition in reported rape cases across Europe*. Child and Women Abuse Studies Unit, London Metropolitan University, London.
- Lunn, D., Thomas, A., Best, N. and Spiegelhalter, D. (2000) WinBUGS – a Bayesian modelling framework: concept, structure, and extensibility. *Statistics and Computing*, 10:325-337.
- Matthews, S., Yang, T., Hayslett-McCall, K., and Ruback, R. (2010) Built environment and Property Crime in Seattle, 1998–2000: A Bayesian Analysis, *Environ Plan A*. 42(6): 1403–1420.
- Maume, D. J. (1989). Inequality and metropolitan rape rates: A routine activity approach. *Justice quarterly*, 6:513-527.

McCullagh, P. and Nelder, J. (1989) Generalized linear models, 2nd Ed. Chapman & Hall.

Ministry of Justice (1999) The penal code (pp. 179). Stockholm: Ministry of Justice. Accessed 29th April 2016, <http://www.regeringen.se/rattsdokument/departementsserien-och-promemorior/1999/01/ds-199936/>.

Molitor J, Papathomas M, Jerrett M, Richardson S. (2010). Bayesian profile regression with an application to the National Survey Of Children's Health. *Biostatistics* 11:484-498.

Newman, O. (1972) *Defensible space – Crime prevention through urban design*. New York: Collier Books.

NYSCASA - New York state coalition against sexual assault (2007) A Summary of New York State Penal Code 130 Sex Offenses as of 2008. Albany, NY NYSCASA.

O'Brien, R. (2007) A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity* 41:673–690.

Osgood, D. (2000) Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology*, 16: 21-43.

Pyle, G. (1974) *The spatial dynamic of crime*. Chicago, USA: Department of Geography, University of Chicago.

RAINN- Rape, abuse, incest national network. (2014). *Was I raped?* Retrieved 15th May, 2014, from <http://www.rainn.org/>

Regeringen. (1999) *Ändring av fridskränkingsbrotten*. Stockholm: Regeringen Retrieved from <http://www.regeringen.se/content/1/c4/11/27/5eab27a7.pdf>.

Rhodes, W., & Conly, C. (1981) Crime and mobility: An empirical study. In P. B. a. B. P. (Ed.), *Environmental Criminology*, 167-188. Beverly Hills; Canada: Sage.

Rosay, A., & Langworthy, R. (2003) *Descriptive analysis of sexual assaults in Anchorage, Alaska*, 107, 39. Anchorage: Bureau of Justice Statistics.

Sampson, R. J. and Groves, W. B. (1989) Community structures and crime: testing social disorganisation theory, *American Journal of Sociology*, 97, pp. 774 – 802.

Shaw, C. R., and McKay, H. D. (1942) *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.

Sherman, L., Gartin, P. and Buerger, M. (2006) *Hotspots of predatory crime: routine activities and the criminology of place*. New York, Wiley.

Spiegelhalter, D.J., Abrams, K.R. and Myles, J.P. (2004). *Bayesian Approaches to Clinical Trials and Health-Care Evaluation*. New York: Wiley.

Stockholm's Police Headquarters (2011) Police recorded cases of rape by coordinates. Stockholm, Stockholm's Police Authority.

Tewksbury, R., and Mustaine, E.E. (2006) Where to find sex offenders: an examination of residential locations and neighbourhood conditions. *Criminal Justice Studies*, 19: 61-75.

UN Women (2014) Safe cities global initiatives. United Nations, 2, Available at www.unwomen.org, 12 October 2014.

USKAB (2012) Statistics in English. Statistik om Stockholm. Retrieved February 28, 2012, from <http://www.uskab.se/index.php/statistics-in-english.html>

Wakefield, J. (2013). *Bayesian and Frequentist Regression Methods*. New York: Springer.

Weisburd, D., Goff, E. Yang, S. (2012). *The criminology of place: street segments and our understanding of the crime problem*. Oxford, Oxford University Press.

Wheeler, D. and Tiefelsdorf, M. (2005) Multicollinearity and correlation among local regression coefficients in geographically weighted regression. *Journal of Geographical Systems* 7, 161–187

Wikström, P.-O., Ceccato, V., Hardie, B. and Treiber, K. (2010) Activity Fields and the Dynamics of Crime. *Journal of Quantitative Criminology*, 26, 55-87.

Zelinka, A., and Brennan, D. (2001) *Safescape: creating safer, more liveable communities through planning and design*. Washington: Planners Press.