Crime and Poverty as a Predictor of Domestic Violence

Donald L Maruta

School of Geography and Environmental Sciences, University of Ulster, Cromore Road, Coleraine, Northern Ireland, BT52 1SA, United Kingdom.

Abstract

Domestic violence has been an increasing problem within Northern Ireland with rising rates since the start of centralised records in 2005. Domestic violence is defined as "Any incident of controlling, coercive, threatening behaviour, violence or abuse between those aged 16 or over who are, or have been intimate partners or family members regardless of gender or sexuality.” This study utilised Geographic Information Systems (GIS) as well as statistical analysis in the form of Ordinary Least Squares Regression and Geographic Weighted Regression in order explore statistical relationships between poverty, associated crimes and domestic violence. The results shown support the known link between domestic violence and poverty but also prove a link between domestic violence and other types of crime.

Keywords:

Domestic Violence, Domestic Abuse, Family Violence, Geographic Information Systems, Crime, Poverty, Regression, Ordinary Least Squares, Geographically Weighted Regression.

Introduction

Domestic violence (DV), also referred to as domestic abuse (DA) or Intimate Partner Violence (IPV) or Family Violence, is one of the most under reported type of crimes, but also one of the most destructive, with the short-term and long-term consequences having a lifetime effect on the victims (Bates et al, 2004; Browne and Bassuk, 1997). The scale of the problem is world-wide with lifetime prevalence rates ranging from 24.6% in the Western Pacific to 37.7% to South-East Asia (2013 WHO report) among ever-partnered women. When this data is broken down further, the majority of countries have a population, whom suffer from DV, with a lifetime long severe physical violence rate ranging from the highest of 49% reported in Peruvian provinces to 4% in Japanese cities (Garcia-Moreno et al, 2006). These figures are similar in nature to those reported in the 2002 World Report on Violence and Health with the percentage of females ever physically assaulted by a partner being at a high with 69% in parts of Nicaragua to the lowest percentage being found in Peru with a value of 10%.

Domestic violence is defined as "Any incident of controlling, coercive, threatening behaviour, violence or abuse between those aged 16 or over who are, or have been intimate partners or family members regardless of gender or sexuality." (Domestic Violence London, 2018). It should be noted that this definition is not restricted to intimate partners but to all members of the family. DV is categorised into four different categories: physical, sexual, psychological and stalking (Intimate Partner Violence in the United States, 2010). Psychological actions do not often come to the attention of civil authorities, while stalking is often covered by a different criminal act. The majority of DV cases being reported to the police are mostly physical with a smaller part being sexual. Common effects of DV on victims include physical injuries, mental health problems, substance misuse, chronic medical conditions, and in severe cases, death through murder or suicide (World Report on Violence and Health, 2002; Garcia-Moreno et al, 2013).

Khalifeh et al (2013) demonstrated that the rate of DV increased with greater economic deprivation. This was specifically shown with high rates of social housing inhabitation, the lowest quintile of household incomes, and the lowest social class all having the highest rate of DV within their relative groupings. This was further highlighted by the study by Gracia et Merlo (2016), who highlighted in their paper that IPV is now more widely spoken about and admitted by victims, than it was in previous years. In addition, Alsaker et al (2018) stated that the reluctance to speak about IPV within relationships has changed over recent years and this may occur even quicker due to the MeToo campaign.

The link between poverty and domestic violence was also examined in 2010 by Modie-Moroka in Botswana. Due to a lack of financial resources, many victims were unable to leave or escape from the perpetrators of DV, as they were reliant upon them for financial support. Most victims were reported to either being unemployed, and therefore entirely dependent upon their abuser for financial support, or else in low income employment, and unable to acquire the funds required to break free from the cycle of abuse. This study was validated by the findings of Gilroy et al (2018), who stated that DV victims often had to make themselves financially stable before deciding to leave a violent partner.

Cunradi et al (2000) also showed that there was a clear link between poverty and domestic violence with the strength of this relationship between these two variables changing dependant on the ethnicity of the individuals involved. This study was one of the few studies which differentiated between Male to Female Partner Violence (MFPV) and Female to Male Partner Violence (FMPV), where FMPV was higher than MFPV for white couples living in impoverished neighbourhoods. This was contrasted with black couples where it was found that both MFPV and FMPV were both equally strongly associated with living in impoverished areas.

Kiss et al refuted in their paper of 2012 that there was a significant link between IPV and extreme poverty, with the majority of IPV incidents being reported in the middle range of the socio-economic scale. However, the author did state that in other studies such as Jewkes et al (2002) that couples at the extreme lower end of the socio-economic spectrum may be less likely to experience IPV due to fewer conflicts over household finances especially if those finances are coming from an outside source. Gilroy et al (2018) however stated that women with a lower income are at a higher risk of violence, which was substantiated by Ali et al (2011).

This difference between Khalifeh et al (2013) and Kiss et al (2012) may be explained by factors such as a willingness by victims to admit that they were victims of DV. Other sources have provided a variety of explanations why people do not report DV such as fear of the partner, fear of retribution from the partner and a belief that the violence suffered wasn't enough to warrant police attention (Hayden, 2010).

Within the context of the United Kingdom, Gilchrist et al (2017), Kirby et al (2014), Richardson et al (2002) and Khalifeh et al (2013) have carried out a number of foremost studies with only Richardson et al and Khalifeh et al concentrating on a wide range of demographic influences to assess any correlations between DV and socio-economic factors.

Within Northern Ireland, research on this topic has been undertaken by several authors, including McWilliams and Ni Aolain, 2013; McWilliams and Kiernan, 1993; Taylor, 1995; Dorahy et al, 2007; McClennan et al, 1994. None of these studies had a country wide analysis of the DV rates as they had only begun to be collected centrally by the PSNI in 2005, but did give context to the recent history of DV within NI. Individuals from some parts of society were unwilling to report their partners to the Royal Ulster Constabulary (RUC), forerunner of the PSNI, as there was a lack of trust generally towards to the police and victims didn't wish to be seen as police informers or colluding with the state officials (McWilliams and Ni Aolain, 2013).

There is a research gap generally with very few studies covering an entire country, and none within any of the countries making up the UK. The majority of studies relating to domestic violence concentrate on a specific area of a country, most typically a city or a city and its environs, or else a sample of the population where questionnaires or interviews of a number of people which then are used to represent an entire city or country. Only a small number of nationwide studies have been carried out within Europe with none of the studies having been used for an entirety of a country such as Northern Ireland with a population of approximately 1.8 million.

A second research gap concerns possible correlations between domestic violence and other types of crimes. While there is a known correlation between crime and poverty (Flango and Sherbenou, 1976; Patterson, 1991; Hooghe et al, 2011) and also a known correlation between poverty and domestic abuse (Gilroy et al, 2018; Kiss et al, 2012; Modie-Moroka, 2010), there does not seem to be a large amount of research regarding a correlation between domestic violence with other types of crime in addition to poverty.

A third research gap can be described as a temporal research gap. This project will analyse an identical area of interest over different time periods using the most contemporary measurements for domestic abuse and crime. This study will attempt to overcome this issue by examining the data from three distinct but contiguous time periods. Most studies are based on a single snapshot in time and not gathered during a prolonged duration.

This study aims to identify which crime types and socio-economic factors are associated with DV within Northern Ireland. This research will allow authorities to target areas which are likely to be more susceptible to incidents of DV. It would also allow the police to allocate more resources relating to DV for regions assessed to be at a higher risk. Additionally, the economic impact of DV, as shown by Cadilhac et al (2015), is notable with approximately 926,000 working days lost due to DV and the potential gains being AUD 371 million. This study will look at Ward level data and examine the level of influence the differing crime types and socio-economic factors have on the rate of DV. It will also examine the data on a temporal basis and to ascertain which influences either are increased or decreased during this period. This analysis will be accomplished using primarily bivariate analysis, before progression onto Ordinary Least Squares regression and then Geographic Weighted Regression.

Methodology

This study will concentrate on DV in Northern Ireland and concentrate on any possible links between DV and crime as well as any links between DV and poverty. The study will incorporate the entirety of Northern Ireland.

Northern Ireland (NI) is a first world country located in western Europe, with Northern Ireland being part of the United Kingdom. Northern Ireland shares a land border to the south and west with the Republic of Ireland (RoI) with whom it shares close cultural links and historical links. The largest population centre in Northern Ireland is the capital Belfast with 286,000 inhabitants, followed Lisburn with 126,000 inhabitants and Derry-Londonderry with the third highest population of 110,000 (NINIS 2019).

A number of the datasets were supplied in Ward1993 format, where the whole of Northern Ireland is broken down into 582 wards as per the District Electoral Areas (Northern Ireland) Order 1993, which was revoked in 2014. The remainder of the datasets were supplied in Ward2014 format, which re-organised the wards within Northern Ireland to 462 wards by the District Electoral Areas (Northern Ireland) Order 2014, DV Data

There is one publically available dataset which covers Domestic Abuse for the whole of Northern Ireland (NINIS, 2018), which is named Incidents and Crimes with a Domestic Abuse Motivation. This dataset covers the years 2005 – 2017, giving a large temporal base for any future analyses. The dataset covers the whole of Northern Ireland, but only to Ward2014 level.

Crime Data

A dataset which broke down all crimes across Northern Ireland from the years 2001 to 2017 was obtained from NINIS and its lowest common denominational area available was Ward2014 level. This dataset incorporates the following crime categories: - All offences, burglary, theft, criminal damage, drug offences, and violence/sex/robbery.

Northern Ireland Multiple Deprivation Measure (NIMDM)

NIMDM has been defined as "measures that describe the spatial distribution of deprivation or disadvantage" (NISRA, 2018), which is made up of the following individual measures: - Income, Employment, Health and Disability, Education, Skills and Training, Proximity to Services, Living Environment, and Crime and Disorder. Multiple Deprivation data has been used by Khalifeh et al (2013) as well as Saunders & Naidoo (2018) as part of their published studies into poverty and DV.

NIMDM data was downloaded from the NISRA website, collected in 2005, 2010 and 2017, and available in the Ward1993 and Ward2014 data formats, dependant on the year. It should be noted that while all of the datasets contained ranked values while other datasets only contained ranked scores. The ranked values were classified from 1 to 462 with 1 being the most deprived area and 462 being the least deprived area. The ranked scores were a calculated score, with a range of 0 for the least deprived area to 100 for the most deprived area, which was constructed by combining the seven individual measures for poverty. As such, a ranked value for a region can be compared to another region and have a higher or lower value, but it cannot precisely describe the difference of how much a region is more deprived than another, which a ranked score would be able to do. For meaningful comparison with the three time periods, it was decided to use only the ranked values.

Census Data

Another method of measuring poverty is to use census data which was downloaded from NINIS for 2001 and 2011. The majority of studies use census data as it is recorded on a regular basis and is available on a free and ready to use format.

Measurements of Poverty

There are a number of statistics which have been used previously as a measurement of poverty including vehicle ownership (Richardson et al, 2002), poverty level (Caetano et al, 2010), consumer goods ownership (Jewkes et al, 2002), current social support (Bassuk et al, 2006), employment (Coker et al, 2000; Cunradi et al, 2000; Dutton et al, 2005; Ford-GIlboe et al, 2015; Jewkes et al, 2002; Maziak & Asfar, 2010; Naeem et al, 2008; Richardson et al, 2002; Saunders & Naidoo, 2018 and Vest et al, 2002), household income (Cunradi et al, 2000; Khalifeh et al, 2013; Naeem et al, 2008 and Rennison and Planty, 2003), housing ownership (Khalifeh et al, 2013; Richardson et al, 2002; Saunders & Naidoo, 2018; Williams et al, 2018) and income (Bassuk et al, 2006; Beyer et al, 2015; Kiss et al, 2012; Vest et al, 2002 and Williams et al, 2018). For this project, the following five measures of poverty was used which were available from the 2001 and 2011 censuses: -

- Number of persons who lived in households with more than 1.5 persons per room.
- Number of persons with no qualifications above the age of 16.
- Number of persons living in social housing.
- Number of persons who had never worked above the age of 16.

- Number of households with no vehicles.

Data Conversion – Ward1993 and Ward2014

The datasets were available either as Ward1993 or Ward2014, which can be seen in Table 1 below.

Ward1993 Data Format	Ward2014 Data Format
NIMDM 2005	NIMDM 2017
NIMDM 2010	Domestic Abuse (2005 – 2017)
Census 2001 – Persons Per Room	All Offences (2005 – 2017)
Census 2001 – Qualifications	Thefts (2005 – 2017)
Census 2001 – Type of Tenure	Racist Crimes (2005 – 2017)
Census 2001 – Last Year of Employment	Homophobic Crimes (2005 – 2017)
Census 2001 – Number of Vehicles Owned	Sectarian Crimes (2005 – 2017)
Census 2011 – Persons Per Room	Sex, Robbery and Violent Crimes (2005 – 2017)
Census 2011 – Qualifications	Drug Crimes (2005 – 2017)
Census 2011 – Type of Tenure	Criminal Damage (2005 – 2017)
Census 2011 – Last Year of Employment	All other offences (2005 – 2017)
Census 2011 – Number of Vehicles Owned	

Table 1: Datasets used.

Data Conversion

The datasets available for this project were either in the Ward1993 and Ward2014 data formats. While a small number of features (25) were identical in both datasets, the remainder of the features were different to each other. This can be seen in Figure 1 below.

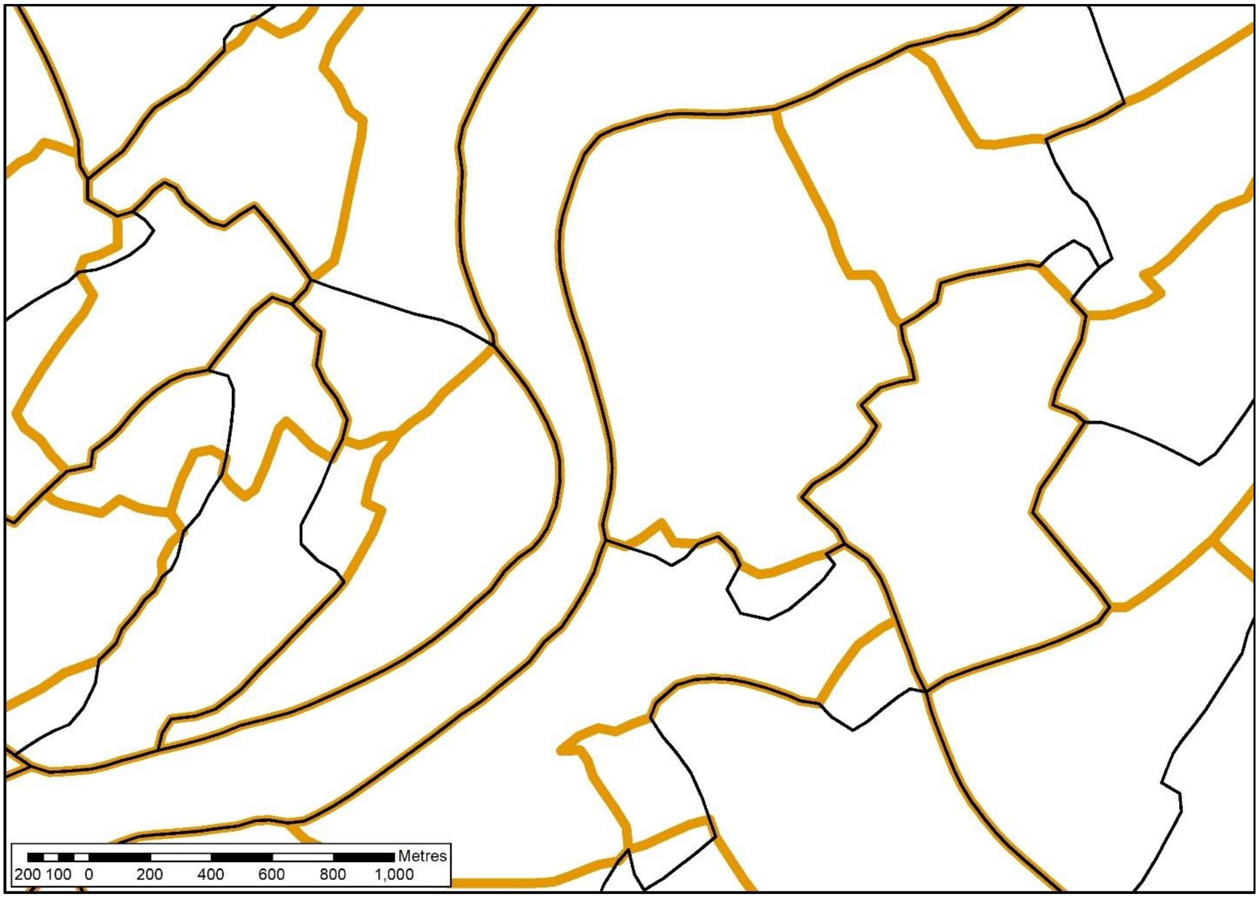

Figure 1. Comparison of Ward1993 (yellow) and Ward2014 (black) datasets – Central Derry-Londonderry.

A primary issue was found with the data created on or after 2014 being in the Ward2014 data format, while all the data created prior to 2014 was in the Ward1993 data format. As shown in Figure 1 above, the two datasets have no correlation and are not coincident to each other. A conversion matrix was completed using a method called Areal Conversion as detailed by Sadahiro, 1999 and Lam, 1983. A number of other methods were examined; however, the Areal Conversion method was deemed the most suitable for this project, as there was no additional information regarding how the data within the datasets was distribution.

Sadahiro (1999) demonstrated a number of other methods for areal interpolation, as did Lam (1983), with the following methods:

- Point in polygon method. This method *"sums up all the counts allocated to representative points that are included in the target zone".* None of the data collected was in point format; all points had already been collated into polygon areas, due to the requirement for data anonymisation under the Data Protection Act 1998 and 2018.
- Kernel method. This method *"treats the representative point as a 'high information point'",* and assumes that all points would be clustered around the representative point. This method again required the information to be in point format, which was not available.
- Intelligent method. This method uses *"supplementary data such as satellite images or landuse data in areal interpolation to improve estimation accuracy".* This data would then allow different mathematical operations to be used dependant on the landuse category. This method was not used in this dissertation as it was deemed to be too computationally expensive for this project.

Lam (1983) verified a number of methods for spatial interpolation but a large number of these were dependent on point data which, as stated previously, was not available. The other two methods shown by Lam were the areal interpolation method, which was ultimately used, and the pycnophylactic interpolation method. The weakness of the areal interpolation method is that it assumes that the data is evenly distributed within each polygon of the data. The pycnophylactic method counters this by applying a smooth density function which takes into account of neighbouring source zones, although it has been stated that this method also does not always apply to real world cases.

The Ward2014 dataset was intersected with the Northern Ireland outline, in order to remove all large areas of water. The resulting dataset was then intersected with the Ward1993 dataset to give a composite dataset of both Ward1993 and Ward2014 data.

For each newly intersected polygon, two new values were created, based on the percentage area of the intersected polygon of its two source polygons. This is demonstrated further by Figure 2 below.

Figure 2 – Diagram demonstrating Areal Conversion method.

In Figure 2 above, Ward1993 data is represented by red and Ward2014 data is represented by blue. Green represents the intersected area. Two new fields were created which represented the following two formulae: -

- Total Area Z / Total Area X = Ward1993 (decimal value between 0 and 1).
- Total Area Z / Total Area Y = Ward2014 (decimal value between 0 and 1).

This gave a value, which could then be used to convert data values from Ward1993 to Ward2014 and vice versa.

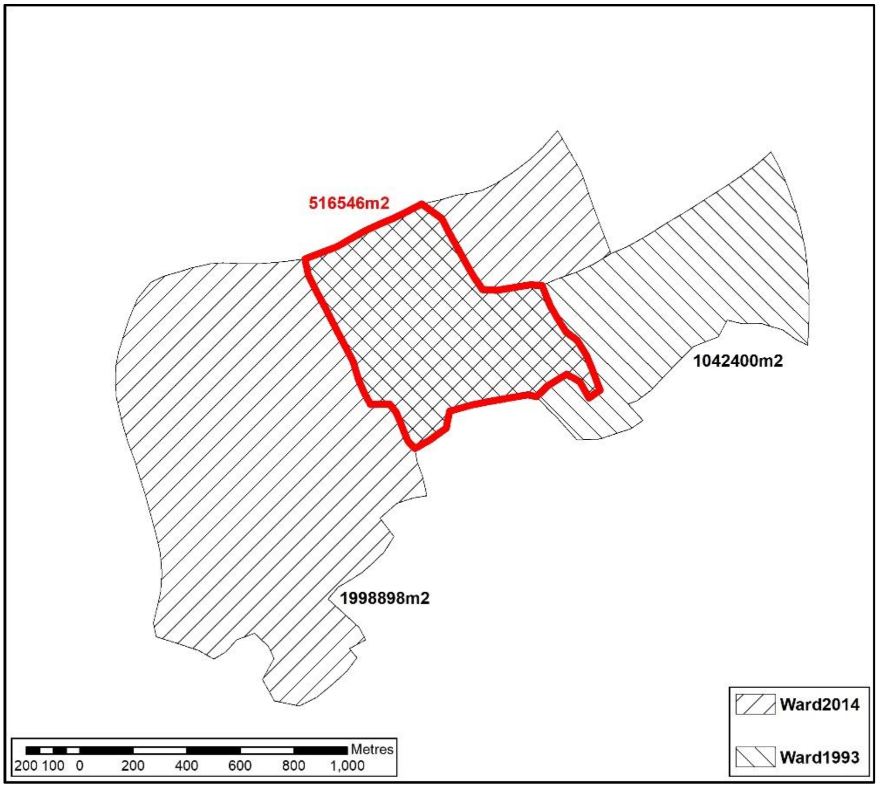

Figure 3 – Diagram showing composite areas.

In Figure 3 above, the red highlighted area represents one polygon which is a composite of both a Ward1993 polygon and a Ward2014 polygon.

- To calculate the value for Ward2014, the following formula would be used: -

Composite Area (510546m2) / Ward2014 Area (1998898m2) = 0.255.

- To calculate the value for Ward1993, the following formula would be used: -

Composite Area (510546m2) / Ward1993 Area (1042400m2) = 0.489.

Once the areal interpolation value had been calculated, it would then be multiplied by the required count value e.g. Domestic Violence in order to create a new figure for the new composite area. After the figures have been calculated, the feature class would then be dissolved to the required dataset format, either Ward1994 or Ward2014.

Data Analysis

GIS analysis was carried out using the ESRI ArcGIS software version (v 10.5.1) while statistical analysis was carried out using Statistical Package for the Social Sciences (SPSS v 25).

Owing to the wide range of the data, it was necessary to group the data into the following years using the following datasets to carry out analysis on a more manageable scale, as shown in Table 2 below: -

Time Period	Crime Factors	Deprivation	Socio-economic	Data Format
2005 - 2009	DV & Crime	NIMDM 2005	Census 2001	Ward1993
2010 - 2013	DV & Crime	NIMDM 2010	Census 2011	Ward1993
2014 - 2017	DV & Crime	NIMDM 2017	Census 2011	Ward2014

Table 2. Data analysis groupings.

Bivariate Analysis

Bivariate analysis was carried out using the count values of the various datasets with DV being the dependant variable and each of the remaining crime types and socio-economic values being the independent variable. Bivariate analysis was shown to be effective by Kiss et al (2012) to assess which factors were significantly associated with DV and which factors were not.

Ordinary Least Squares Multivariate Regression

Ordinary Least Squares (OLS) is a global regression model which allows a line of best fit to be attributed to any data correlations. However, one condition of its use is that is assumes any dependent variables will follow a normal distribution. OLS has been used by several authors investigating DV but Snowden (2016) experimented with its use using a number of mathematical operators between alcohol outlets and DV. OLS was used with DV being the dependant variable and the extra crime types and socio-economic factors were the independent variables. All crime variables were examined using their count values, their rate values (incidents per thousand) and their log values, which ensured that the distributions for each of these types will follow a normal distribution.

Geographically Weighted Regression

Geographically Weighted Regression is a local regression model which usually gives a better fit than OLS as it models each individual feature within the dataset as opposed to globally modelling all the data. It has been used by Saefuddin et al (2011) in their analysis of Indonesian poverty data as well as Amegbor and Rosenberg (2019). GWR was used with DV being the dependant variable and the additional crime types and socio-economic factors were the independent variables. In order to avoid multi-collinearity, which would ensure that any models created would be inaccurate, the model started with the variables with the lowest (Variance Inflation Factor) VIF value, and then extra variables were added. If the VIF value is too high (the literature normally states above 7.5 (ESRI, 2019)), then this demonstrates that there is a large amount of multi-collinearity. This would make any models with a large VIF value unreliable, as this would show that two or more variables are very closely related. If any explanatory variables are above 7.5, then they should be removed from the model, one by one, until the highest VIF is below 7.5 (ESRI, 2019).

Bayesian Methodology

Traditionally Bayesian spatial modelling has been used for disease and epidemiology mapping, although in more recent years, it has started to be used for crime analysis as it offers a new method of examination, as well as allowing a spatial and temporal element to be added to the analysis.

Bayesian modelling has been shown to be more advantageous than other methods due to "enhanced model flexibility and an ability to increase the formality of measuring prediction uncertainty" (Law and Quick (2013). Bayesian modelling has been proven to cope with less well-defined variables, where a variable may be defined as a random variable with a probability distribution instead of a fixed value. In addition, Bayesian modelling works well for locations which may have a low or zero count on different variables, by using a borrow of strength from neighbouring areas to stabilise the model (Law et al, 2014). Random effects can also be added to a model in order to better adapt it to deal with spatial autocorrelation (Law and Chan, 2012).

Although Bayesian spatial modelling was initially scoped for this project and showed a lot of promise, due to the time constraints and difficulty in using the software, which is not user friendly for those inexperienced with Bayesian modelling, it was deemed not to be feasible for this project.

Results

The DV data was mapped and correlated with the other crime types and socio-economic data listed earlier.

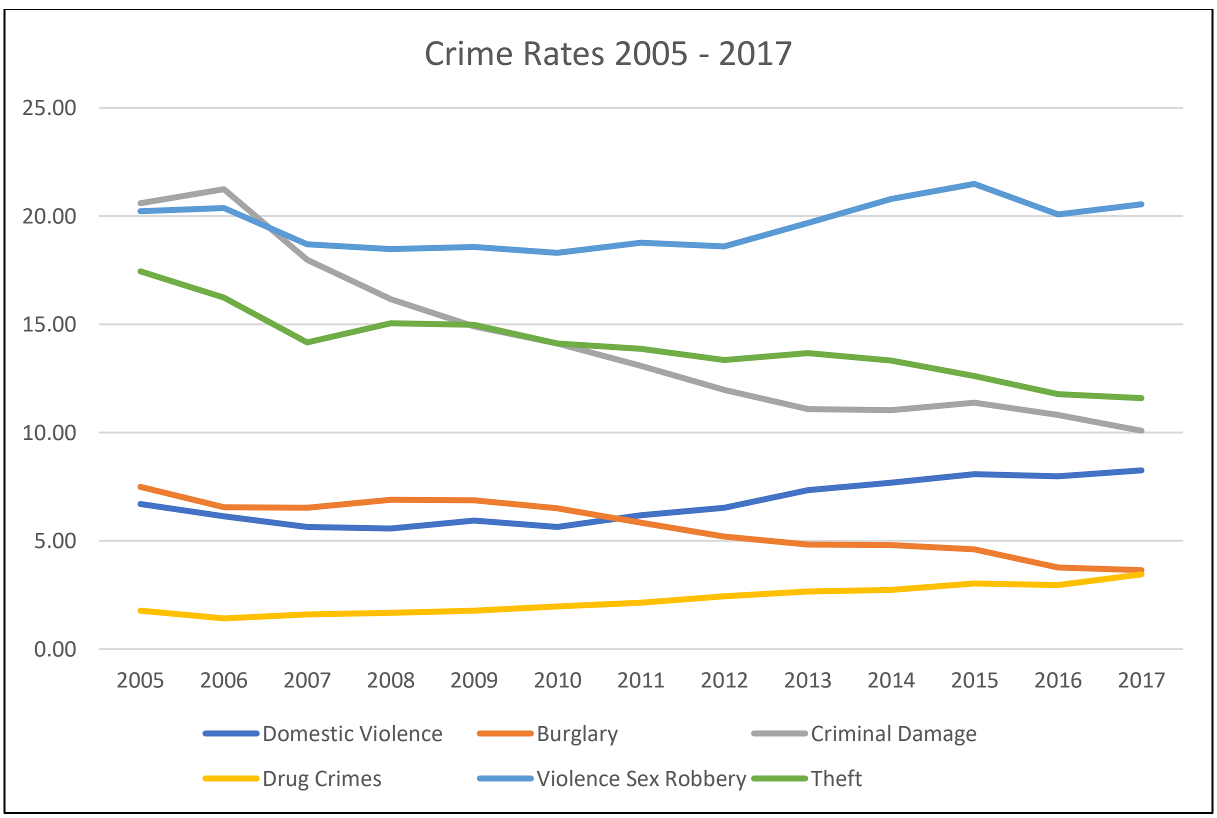

Figure 4 – Graph showing varying crime rates.

As seen above, some of the crime rates have varied enormously during the intervening years, with criminal damage showing a decrease of 50% during this period. Domestic violence has increased slightly after a dip mid-way through the time interval, but there has since been an uninterrupted increase since 2009. This may be due to a variety of factors such as an increased willingness to report DV, and also a change to the Sexual Offences (Northern Ireland) Order 2008, which altered the definition of sexual offences, some of which would be covered under the Domestic Violence statistics.

397 out of the 462 wards within Northern Ireland have experienced a rise in DV between 2005 and 2017.

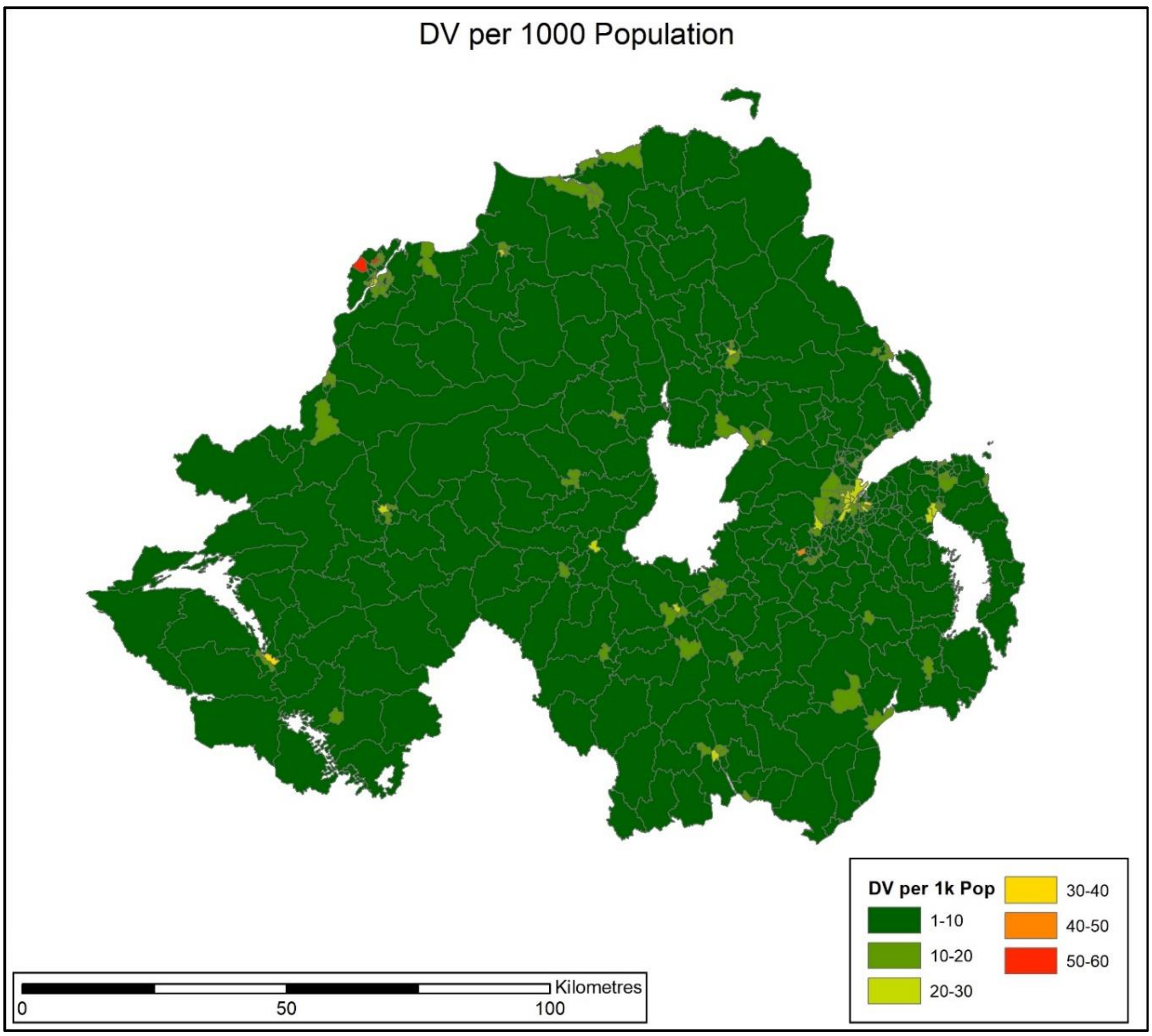

Figure 5 – Map showing DV per 1000 population.

Bivariate Analysis

Bivariate analysis (Pearson's) was carried out for each of the three distinct time periods using DV as the primary statistic.

Count (DV)	2005-2009	2010-2013	2014-2017
Population	0.558	0.578	0.355
Burglary	0.692	0.718	0.680
All Offences	0.754	0.767	0.769
Criminal Damage	0.853	0.871	0.873
Drugs	0.683	0.748	0.720
Theft	0.588	0.622	0.658
Violence Sex Robbery	0.782	0.786	0.798
No vehicles	0.742	0.792	0.857
Never worked	0.570	0.692	0.574
Social rented	0.714	0.763	0.784
No qualifications	0.707	0.756	0.599
Over 1.5 persons per room	0.452	0.563	0.565

Table 3: Bivariate analysis correlations from count values.

Overall there is a strong pattern of correlations between DV and other crimes and socio-economic factors with no negative correlations, and only two correlations below 0.5. The highest correlation is found with criminal damage and the second highest is found with all offences. The correlation between all offences and DV is not unexpected as DV crimes would make up part of all offences. The base data for the over-crowding per room for both 2010-2013 and 2014-2017 were both derived from the Census 2011 dataset which may explain the increase from 2005-2009, which used the Census 2001 dataset. In contrast the population dataset was gathered on an annual basis, which has shown a steady increase of approximately 10,000 inhabitants per year, with no notable deviations.

The correlation between DV and burglary appears to have remained steady with a small amount of deviation in the correlation of the results gathered. It should be unsurprising that there is a strong correlation between all offences and DV crimes, as the figured for the DV crimes would be included as part of the figures for all offences. Criminal damage has the highest correlation within this table overall and this may be a side effect of some DV crimes also including damage to property occurring within the same incident. It may also be symptomatic of poverty or general crime within the area. Social renting and no vehicles are shown to be both strong correlations with DV. The two serials with the lowest correlations are over 1.5 persons per room and population.

<u>Ordinary Least Squares Multivariate Analysis</u>

OLS multivariate analysis was carried out for each of the three distinct time periods using DV as the primary statistic. The following formula is used to assess the amount of correlation with the key factors: -

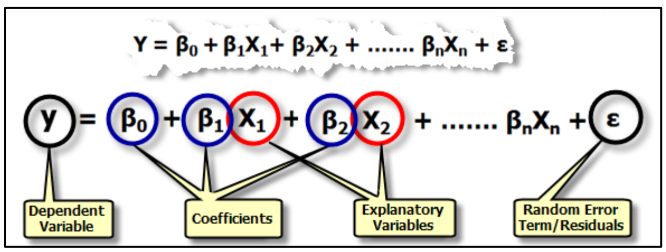

Figure 6. Formula for OLS regression (ESRI, 2019).

Year	Dependant Variable	Explanatory Variables	Adjusted R Squared	AIC	Highest VIF
2005-2009	DV_Log	Population & Log Burglary & Log Drugs & Log Criminal Damage & Log Over 1.5 Persons & Log Never Worked & Log No Qualifications & Log Social Rent & Log No Vehicle	0.854	430	5.66
2010-2013	DV_Log	Population & Log Burglary & Log Theft & Log Drugs & Log Over 1.5 Persons & Log Never Worked & Log No Qualifications & Log Social Rent & Log No Vehicle	0.793	581	5.82
2014-2017	DV_Log	Population & Log Burglary & Log VSR & Log Theft & Log Drugs & Log Over 1.5 Persons & Log Never Worked & Log No Qualifications & Log Social Rent	0.863	74	6.95

Table 4: Results for OLS with maximum adjusted R squared values and lowest AIC.

The table shows above which formula were used for all three distinct time periods. It should be noted that the 2014-2017 time period as a significantly lower AIC that the other two time periods. There may be several reasons for this, but it should be noted that the DV data had to be converted from Ward2014 regions to Ward1993 regions for the first two time periods. The Adjusted R Square shows that all three models are well defined by the explanatory variables with values ranging from 0.793 to 0.863.

The Adjusted R Square value is a decimal value ranging from 0 to 1, where the value explains how much of the explanatory (or independent) variables contribute to the dependent variable. A value close to zero would show that none of the explanatory variables contribute to the dependent variable, while a value close to one would show that the majority of the explanatory variables contribute to the dependent variable. It should be noted that a value of 1 is, in all likelihood, an indicator that a dependant variable has been included as an explanatory variable and that the model may be suffering from collinearity.

The Akaike Information Criterion (AIC) is used as a method of comparing one model to another and is a measure of model performance. Generally, it is accepted that the lower the AIC value, the better fit is provided to the observed data. It is a useful method of comparing different models, providing that they all apply to the same dependant variable.

The Variance Inflation Factor (VIF) is a method of measuring redundancy within all of the explanatory variables. If the VIF is above 7.5 for a model, then the explanatory variable with the highest VIF value should be removed, and the model run again. This process will be repeated until the VIF is below 7.5. If the VIF is high, then this proves that there may be multi-collinearity in the model.

Log transformation was carried out on the data in order to give the data a normal distribution, as prior to the log transformation, the data was skewed to the left as shown below in Figure 7.

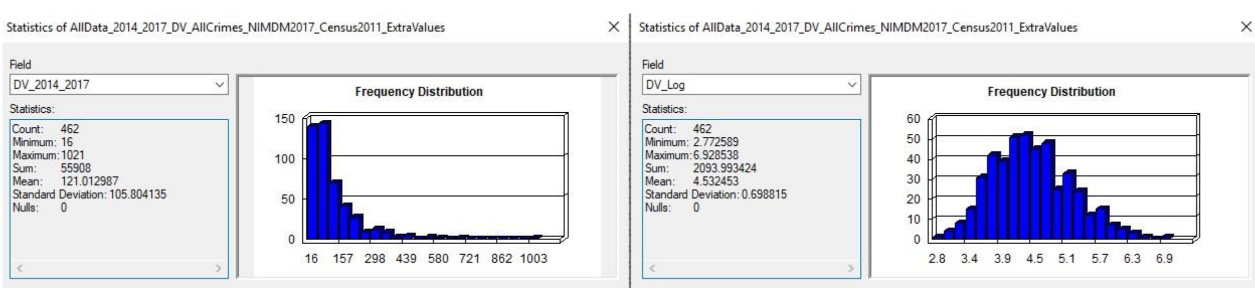

Figure 7. Comparison of DV count 2014-2017 before and after log transformation.

Dep Variable	Indep Variable 1	Indep Variable 2	Adjusted R Squared	AIC	Highest VIF	Comments
DV_Log	Burg_1k	N/A	0.316	1323	N/A	
DV_Log	AllOffences_1k	N/A	0.355	1289	N/A	
DV_Log	CrimDamage_1k	N/A	0.401	1246	N/A	
DV_Log	Drugs_1k	N/A	0.179	1430	N/A	
DV_Log	Theft_1k	N/A	0.23	1392	N/A	
DV_Log	VSR_1k	N/A	0.347	1297	N/A	
DV_Log	Burglary	Pop	0.338	1306	1.538	
DV_Log	AllOffences	Pop	0.392	1256	1.296	
DV_Log	Criminal Damage	Pop	0.491	1153	1.359	
DV_Log	Drugs	Pop	0.393	1255	1.114	
DV_Log	Theft	Pop	0.301	1337	1.206	
DV_Log	VSR	Pop	0.427	1222	1.241	
DV	Burglary	Pop	0.51	6268	1.538	
DV	AllOffences	Pop	0.617	6125	1.296	
DV	Criminal Damage	Pop	0.745	5888	1.359	
DV	Drugs	Pop	0.593	6160	1.114	
DV	Theft	Pop	0.463	6322	1.206	
DV	VSR	Pop	0.667	6044	1.241	
DV_Log	Burglary_Log	N/A	0.607	1000	N/A	
DV_Log	AllOffences_Log	N/A	0.811	575	N/A	
DV_Log	Criminal Damage_Log	N/A	0.817	555	N/A	
DV_Log	Drugs_Log	N/A	0.554	1074	N/A	
DV_Log	Theft_Log	N/A	0.649	935	N/A	
DV_Log	VSR_Log	N/A	0.852	430	N/A	
DV_Log	All Crimes 1k		0.433	1219	1000	Highest VIF - All Offences
DV_Log	All Crimes 1k	Less All Offences	0.434	1217	12	Highest VIF - VSR
DV_Log	All Crimes 1k	Less All Offences & VSR	0.42	1230	4.35	Highest VIF - Criminal Damage
DV_Log	All Crimes	Pop	0.595	1024	1000	Highest VIF - All Offences
DV_Log	All Crimes	Pop Less All Offences	0.591	1030	17.94	Highest VIF - VSR
DV_Log	All Crimes	Pop Less All Offences & VSR	0.575	1050	9.05	Highest VIF - Burglary
DV_Log	All Crimes	Pop Less All Offences & VSR & Burglary	0.576	1048	5.61	Highest VIF - Criminal Damage
DV	All Crimes	Pop	0.856	5558	1000	Highest VIF - All Offences
DV	All Crimes	Pop Less All Offences	0.836	5635	17.94	Highest VIF - VSR
DV	All Crimes	Pop Less All Offences & VSR	0.812	5714	9.05	Highest VIF - Burglary

DV	All Crimes	Pop Less All Offences & VSR & Burglary	0.812	5712	5.61	Highest VIF - Criminal Damage
DV_Log	All Crimes Log		0.87	360	266	Highest VIF - All Offences
DV_Log	All Crimes Log	Less All Offences	0.87	361	17.76	Highest VIF - VSR
DV_Log	All Crimes Log	Pop Less All Offences & VSR	0.821	546	8.43	Highest VIF - Theft
DV_Log	All Crimes Log	Pop Less All Offences & VSR & Theft	0.82	547	4.44	Highest VIF - Criminal Damage
DV_Log	All Crimes Log	NIMDM	0.871	356	279.65	Highest VIF - All Offences
DV_Log	All Crimes Log	NIMDM Less All Offences	0.871	356	19.4	Highest VIF - VSR
DV_Log	All Crimes Log	NIMDM Less All Offences & VSR	0.831	513	8.44	Highest VIF - Theft
DV_Log	All Crimes Log	NIMDM Less All Offences & VSR & Theft	0.831	513	4.88	Highest VIF - Criminal Damage
DV_1k	All Crimes 1k		0.786	2387	1000	Highest VIF - All Offences
DV_1k	All Crimes 1k	Less All Offences	0.766	2435	12	Highest VIF - VSR
DV_1k	All Crimes 1k	Pop Less All Offences & VSR	0.752	2470	4.35	Highest VIF - Criminal Damage
DV_Log	All Crimes Log	NIMDM & Census Max Values	0.882	313	292	Highest VIF - All Offences
DV_Log	All Crimes Log	NIMDM & Census Max Values Less All Offences	0.881	315	19	Highest VIF - VSR
DV_Log	All Crimes Log	NIMDM & Census Max Values Less All Offences & VSR	0.845	468	8.78	Highest VIF - Theft
DV_Log	All Crimes Log	NIMDM & Census Max Values Less All Offences & VSR & Theft	0.845	467	6.48	Highest VIF - NIMDM
DV_Log	All Crimes Log	NIMDM & Census Min Values	0.88	321	293.89	Highest VIF - All Offences
DV_Log	All Crimes Log	NIMDM & Census Min Values Less All Offences	0.879	323	19.65	Highest VIF - VSR
DV_Log	All Crimes Log	NIMDM & Census Min Values Less All Offences & VSR	0.839	490	8.89	Highest VIF - Theft
DV_Log	All Crimes Log	NIMDM & Census Min Values Less All Offences & VSR & Theft	0.839	489	6.51	Highest VIF - No Vehicle
DV_Log	All Crimes Log	Census Max Values	0.882	312	292	Highest VIF - All Offences
DV_Log	All Crimes Log	Census Max Values Less All Offences	0.881	313	19.51	Highest VIF - VSR
DV_Log	All Crimes Log	Census Max Values Less All Offences & VSR	0.845	466	8.77	Highest VIF - Theft
DV_Log	All Crimes Log	Census Max Values Less All Offences & VSR & Theft	0.845	465	5.86	Highest VIF - Criminal Damage
DV_Log	All Crimes Log	Census Min Values Log	0.888	281	298	Highest VIF - All Offences
DV_Log	All Crimes Log	Census Min Values Log Less All Offences	0.888	280	19.35	Highest VIF - VSR
DV_Log	All Crimes Log	Census Min Values Log Less All Offences & VSR	0.853	434	8.64	Highest VIF - Theft
DV_Log	All Crimes Log	Census Min Values Log Less All Offences & VSR & Theft	0.854	432	5.64	Highest VIF - Criminal Damage

DV_Log	All Crimes Log	Pop & Census Min Values Log	0.887	283	297	Highest VIF - All Offences
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences	0.887	282	19.79	Highest VIF - VSR
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences & VSR	0.854	431	8.64	Highest VIF - Theft
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences & VSR & Theft	0.854	430	5.66	Highest VIF - Criminal Damage

Table 5: 2005 – 2009 Results for OLS.

Dep Variable	Indep Variable 1	Indep Variable 2	Adjusted R Squared	AIC	Highest VIF	Comments
DV_Log	Burg_1k	N/A	0.323	1262	N/A	
DV_Log	AllOffences_1k	N/A	0.364	1226	N/A	
DV_Log	CrimDamage_1k	N/A	0.416	1176	N/A	
DV_Log	Drugs_1k	N/A	0.271	1305	N/A	
DV_Log	Theft_1k	N/A	0.249	1322	N/A	
DV_Log	VSR_1k	N/A	0.332	1255	N/A	
DV_Log	Burglary	Pop	0.354	1236	1.544	
DV_Log	AllOffences	Pop	0.396	1197	1.287	
DV_Log	Criminal Damage	Pop	0.491	1098	1.338	
DV_Log	Drugs	Pop	0.418	1175	1.214	
DV_Log	Theft	Pop	0.315	1270	1.206	
DV_Log	VSR	Pop	0.43	1163	1.238	
DV	Burglary	Pop	0.548	6080	1.544	
DV	AllOffences	Pop	0.647	5937	1.287	
DV	Criminal Damage	Pop	0.784	5649	1.338	
DV	Drugs	Pop	0.641	5945	1.214	
DV	Theft	Pop	0.509	6129	1.206	
DV	VSR	Pop	0.683	5873	1.238	
DV_Log	Burglary_Log	N/A	0.615	933	N/A	
DV_Log	AllOffences_Log	N/A	0.834	443	N/A	
DV_Log	Criminal Damage_Log	N/A	0.848	390	N/A	
DV_Log	Drugs_Log	N/A	0.639	896	N/A	
DV_Log	Theft_Log	N/A	0.685	817	N/A	
DV_Log	VSR_Log	N/A	0.848	391	N/A	
DV_Log	All Crimes 1k		0.439	1157	1000	Highest VIF - All Offences
DV_Log	All Crimes 1k	Less All Offences	0.438	1158	7.78	Highest VIF - VSR
DV_Log	All Crimes 1k	Less All Offences & VSR	0.436	1159	4.72	Highest VIF - Criminal Damage
DV_Log	All Crimes Log		0.877	274	321	Highest VIF - All Offences
DV_Log	All Crimes Log	Less All Offences	0.875	281	14.48	Highest VIF - VSR

DV_Log	All Crimes Log	Less All Offences & VSR	0.853	375	6.76	Highest VIF - Theft
DV_Log	All Crimes Log	Census Min Values Log	0.895	185	332	Highest VIF - All Offences
DV_Log	All Crimes Log	Census Min Values Log Less All Offences	0.894	192	14.75	Highest VIF - VSR
DV_Log	All Crimes Log	Census Min Values Log Less All Offences & VSR	0.876	279	7.57	Highest VIF - Criminal Damage
DV_Log	All Crimes Log	Census Min Values Log Less All Offences & VSR & Criminal Damage	0.789	590	5.8	Highest VIF - Theft
DV_Log	All Crimes Log	Pop & Census Min Values Log	0.895	187	332	Highest VIF - All Offences
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences	0.894	194	15	Highest VIF - VSR
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences & VSR	0.877	279	7.71	Highest VIF - Criminal Damage
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences & VSR & Criminal Damage	0.793	581	5.82	Highest VIF - Theft

Table 6: 2010 – 2013 Results for OLS.

Dep Variable	Indep Variable 1	Indep Variable 2	Adjusted R Squared	AIC	Highest VIF	Comments
DV_Log	Burg_1k	N/A	0.326	802	N/A	
DV_Log	AllOffences_1k	N/A	0.481	681	N/A	
DV_Log	CrimDamage_1k	N/A	0.489	674	N/A	
DV_Log	Drugs_1k	N/A	0.312	812	N/A	
DV_Log	Theft_1k	N/A	0.335	796	N/A	
DV_Log	VSR_1k	N/A	0.474	687	N/A	
DV_Log	Burglary	Pop	0.225	867	1.32	
DV_Log	AllOffences	Pop	0.299	821	1.2	
DV_Log	Criminal Damage	Pop	0.463	698	1.171	
DV_Log	Drugs	Pop	0.262	845	1.17	
DV_Log	Theft	Pop	0.185	891	1.197	
DV_Log	VSR	Pop	0.345	790	1.171	
DV	Burglary	Pop	0.46	5339	1.321	
DV	AllOffences	Pop	0.591	5210	1.12	
DV	Criminal Damage	Pop	0.76	4963	1.171	
DV	Drugs	Pop	0.523	5282	1.17	
DV	Theft	Pop	0.439	5356	1.197	
DV	VSR	Pop	0.638	5153	N/A	
DV_Log	Burglary_Log	N/A	0.464	696	N/A	
DV_Log	AllOffences_Log	N/A	0.781	281	N/A	
DV_Log	Criminal Damage_Log	N/A	0.827	172	N/A	
DV_Log	Drugs_Log	N/A	0.556	609	N/A	
DV_Log	Theft_Log	N/A	0.555	610	N/A	

DV_Log	VSR_Log	N/A	0.832	160	N/A	This is the most significant for DV Log and Crimes Log
DV_Log	All Crimes 1k		0.533	637	1000	Highest VIF - All Offenses
DV_Log	All Crimes 1k	Less All Offences	0.516	653	10.73	Highest VIF - VSR
DV_Log	All Crimes 1k	Less All Offences & VSR	0.498	669	3.84	Highest VIF - Criminal Damage
DV_Log	All Crimes Log		0.862	72	325	Highest VIF - All Offenses
DV_Log	All Crimes Log	Less All Offences	0.861	75	12	Highest VIF - VSR
DV_Log	All Crimes Log	Less All Offences & VSR	0.827	176	4.52	Highest VIF - Theft
DV_Log	All Crimes Log	Census Min Values Log	0.875	31.63	340	Highest VIF - All Offenses
DV_Log	All Crimes Log	Census Min Values Log Less All Offences	0.875	31	12.43	Highest VIF - VSR
DV_Log	All Crimes Log	Census Min Values Log Less All Offences & VSR	0.846	127	8.74	Highest VIF - No Vehicles
DV_Log	All Crimes Log	Census Min Values Log Less All Offences & VSR & No Vehicles	0.846	127	5.97	Highest VIF - Criminal Damage
DV_Log	All Crimes Log	Pop & Census Min Values Log	0.876	32.26	340	Highest VIF - All Offenses
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences	0.875	32.43	12.62	Highest VIF - Criminal Damage
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences & Criminal Damage	0.863	74.32	8.9	Highest VIF - No Vehicles
DV_Log	All Crimes Log	Pop & Census Min Values Log Less All Offences & Criminal Damage & No Vehicles	0.573	73.57	6.95	Highest VIF - VSR

Table 7: 2014 – 2017 Results for OLS.

2005 - 2009		2010 - 2013		2014 - 2017	
Variable	Coefficient [a]	Variable	Coefficient [a]	Variable	Coefficient [a]
Intercept	-3.733292	Intercept	-2.760200	Intercept	0.180209
POP 2005 2009	-0.000009	POP 2010 2013	-0.000017	POP 2014 2017	-0.000008
BURGLARY(LOG)	0.059721	BURGLARY(LOG)	0.259747	BURGLARY(LOG)	0.064899
DRUGS(LOG)	0.068260	THEFT(LOG)	0.261383	VSR(LOG)	0.726781
CRIMINALDAMAGE(LOG)	0.722569	DRUGS(LOG)	0.203591	THEFT(LOG)	-0.070513
OVER1.5PERS_ROOM(LOG)	0.004297	OVER1.5PERS_ROOM(LOG)	-0.039941	DRUGS(LOG)	-0.059985
NEVERWORKED(LOG)	0.019293	NEVERWORKED(LOG)	0.015236	OVER1.5PERS_ROOM(LOG)	0.029828
NOQUALIFICATIONS(LOG)	0.646496	NOQUALIFICATIONS(LOG)	0.593355	NEVERWORKED(LOG)	-0.007525
SOCIALRENTED(LOG)	0.068558	SOCIALRENTED(LOG)	0.064003	NOQUALIFICATIONS(LOG)	-0.041895
NOVEHICLES(LOG)	-0.197311	NOVEHICLES(LOG)	0.001387	SOCIALRENTED(LOG)	0.167508

Table 8: Co-efficient scores for OLS analysis.

Table 8 shows the co-efficients for the optimum solution as highlighted in Tables 5, 6 and 7. As the table above shows, the main intercept value is significantly different for 2014-2017 than it is for the other two time periods. As stated previously, this may be an unintended side effect of converting the data from Ward2014 to Ward1993. In addition, 2014-2017 is the only time period to include Violence/Sex/Robbery Crimes, which provides the highest co-efficient for that time period. The first two time periods also include the data for no vehicles, which was not used in the final model for 2014-2017, as well as the first two time periods being almost identical in the different crime and socio-economic types used for the final model.

Moran's I Spatial Autocorrelation measures spatial correlation in order to ascertain whether features are spatially dispersed, clustered or random. This process was run on all 3 time periods for the highest R Squared Value. Spatially clustering was discovered with a Z-score of 11 and 12 for 2005-2009 and 2010-2014 respectively. The value for 2014-2017 was 0.562, which may be evidence of proof that the data conversion caused higher AIC values and increased the clustering within the models.

The OLS for 2005-2009 showed three distinct areas with a greater than -2.5 SD from the expected values. However, upon closer examination these three regions all had an extremely low count of DV crimes and a relatively high population, which would explain this value. There appeared to be a small amount of spatial clustering of the Standardised Residuals, but no clustering for values which would greater than +- 2.5 SDs.

The OLS analysis for 2014-2017 was spread with the standard residuals above the SD located in the east of Northern Ireland with the standard residuals below the SD located on the north west coast and east of Lough Neagh.

Geographic Weighted Regression

Geographic Weighted Regression (GWR) was undertaken for each of the three time periods. The following formulae were completed successfully. Multiple analyses were carried out in order to avoid multi-collinearity and to ensure the highest R squares adjusted value was derived with the lowest AIC.

The results can be seen in the tables below: -

Dependant Variable	Explanatory Variables	Adjusted R Squared	AIC
DV_Log	Log Over 1.5 Persons	0.359	1336
DV_Log	Log Over 1.5 Persons & Log Drugs	0.709	910
DV_Log	Log Over 1.5 Persons & Log Drugs & Pop	0.706	902
DV_Log	Log Over 1.5 Persons & Log Drugs & Pop & Log Socially Rented	0.709	888
DV_Log	Log Over 1.5 Persons & Log Drugs & Pop & Log Socially Rented & Log Burglaries	0.763	715
DV_Log	Log Over 1.5 Persons & Log Drugs & Log Socially Rented	0.709	898
DV_Log	Log Over 1.5 Persons & Log Drugs & Log Socially Rented & Log Burglaries	0.775	688

Table 9. Co-efficient scores for GWR analysis – 2005-2009.

Dependant Variable	Explanatory Variables	Adjusted R Squared	AIC
DV_Log	Log Over 1.5 Persons	0.392	1247
DV_Log	Log Over 1.5 Persons & Pop	0.413	1230
DV_Log	Log Over 1.5 Persons & Pop & Log Drugs	0.755	743
DV_Log	Log Over 1.5 Persons & Pop & Log Drugs & Log Social Rent	0.747	736
DV_Log	Log Over 1.5 Persons & Pop & Log Drugs & Log Social Rent & Log Burglary	0.791	590

Table 10. Co-efficient scores for GWR analysis – 2010-2014.

Dependant Variable	Explanatory Variables	Adjusted R Squared	AIC
DV_Log	Log No Quals	0.348	810
DV_Log	Log No Quals & Log Over 1.5 Pers	0.348	798
DV_Log	Log No Quals & Log Over 1.5 Pers & Pop	0.322	813
DV_Log	Log No Quals & Log Over 1.5 Pers & Pop & Log Social Rent	0.584	587
DV_Log	Log No Quals & Log Over 1.5 Pers & Pop & Log Social Rent & Log Drugs	0.72	403

Table 11. Co-efficient scores for GWR analysis – 2014-2017.

The results for 2014-2017 have both the lowest adjusted R squared value but also the lowest AIC out of the three datasets. This related back to the OLS analysis where the same time period also had the lowest AIC. Interestingly it also has a lower R adjusted score in the GWR analysis than the OLS analysis. This dataset possesses less crime data in its final output and is mainly made up of socio-economic variables, which may have influenced the adjusted R squared score.

The first two time periods have very similar adjusted R squared values to each other, but a different AIC of over 1000 difference. They also used less socio-economic variables and more crime variables than the last time period.

When a Moran's I analysis was run, the final time period had a Z-Score of 3, while the other two time periods had scores of 11, which once again reflects the results found for the Moran's I analysis under the OLS regression methods. The majority of the analyses, when examined using Moran's I Spatial Statistics showed an over tendency for clustering, which suggests that the model is not correct. However, examination of the data does not show any apparent or obvious reason for this clustering, with high z-values (approximately between 8 to 12) being found in every dataset. It is possible that the clustering is a side effect of the method used to convert the DV data from Ward2014 to Ward1993 and vice versa.

If the datasets were to be re-modelled in future, then all time periods should use Ward2014 data and not Ward1993 data which 2005-2009 and 2010-2014 used. This would provide additional evidence that may be able to prove or disprove that that different geographic regions were having an effect on the final model outputs and their associated values. Additionally, if it were possible to have population data available for each year broken down by both Ward2014 polygons and Ward1993 polygons, then it would be possible to create a far more accurate translation matrix for the conversion of data from Ward2014 to Ward1993 and vice versa.

Discussion

A large number of previous studies have demonstrated a relationship between DV and poverty. It has been stated that there was a strong correlation between DV and social housing which has been shown by the results in the previous section. It should be noted that a large number of DV crimes occurred in areas of Belfast, Derry-Londonderry and Lurgan where there is also a high amount of social housing.

There was also a strong correlation between DV and the absence of vehicles within a household. While vehicle ownership has long been associated with poverty, there are almost no studies which have proven the link between vehicle ownership and DV. Vehicle ownership can be lower in areas with excellent transport links, such as city centres, although it should be much higher in rural areas with poor or infrequent transport links. Central and west Belfast have the highest regions with no vehicles, followed by Derry-Londonderry. The low number of vehicles could either be due to poverty or no requirement for vehicles due to excellent transport links.

There was a much weaker correlation between households with over 1.5 persons per room and DV. It has been stated that stress and over-crowding can be a predictor of DV (Caetano et al, 2010). There is no information regarding the familial composition of these homes, so there is no way to confirm or deny these findings, which stated that a larger number of young children within a household is a predictor of DV. There are several wards located sporadically within Northern Ireland which have a large amount of over-crowding but a lower amount of DV incidents. There is also no way to ascertain how over-crowded a home may be as the census statistics only have figures for 1.5 persons per room or more, so it is possible that the highest rate of DV crimes are associated with far more over-crowding than is covered in the statistics. Also, the statistics cover whole regions and not individual houses, and as such can only provide correlations for regions and not on a house by house basis.

There are also some correlations between DV and other crime types with the strongest correlation being between criminal damage and DV. This may be an effect of the Broken Windows crime theory, where areas of high crime are also more susceptible to other types of crime (Wilson and Kelling, 2018). Criminal damage is defined as "the intentional and malicious damage to the home, other property or vehicles and includes graffiti". The highest area of criminal damage was found in central Belfast, which while having a large number of households, it also contains a large majority of Belfast's infrastructure such as City Hall and the drinking establishment which is also associated with a high amount of social disorder and criminal damage.

The correlation between drug crimes and DV crimes starts off weak, but slowly increases in the second and third time periods. Drug crime has been associated with poverty and the highest region for drug crime is central Belfast, which may be due to a higher rate of drug crime or a higher police presence resulting in more crimes being detected.

A medium to strong correlation was also found between theft and DV. A link was found between poorer neighbourhoods and associated crimes as well as poorer neighbourhoods and poverty. Multiple reasons have been stipulated for this causation such as high crime areas, which may be more susceptible to people living in those areas to experience stress and be more likely to commit crime. DV has also been linked to poverty and that victims of DV may be forced to steal or enticed to take necessary items as their financial situation does not allow them to legitimately purchase food and necessary good.

Burglary may be a pre-cursor to DV again due to the link between DV and poor living conditions.

Belfast and Derry-Londonderry had consistently the highest values for over 1.5 persons per room, no qualifications, amount of socially rented housing and no vehicles. A lack of vehicles may not be significant due to the transport links which are more readily available in city centres, than they would be in rural areas. A lack of vehicles in rural areas would be a far more accurate correlation of poverty than a lack of vehicles in heavily urbanised modern cities.

The dataset covering the years 2010-2014 showed little signs of data clustering although there were more signs of over-prediction in the north west and more signs of under prediction in the south to south east areas. Similarly, to the previous time period, Lissan had a relatively high DV rate outside of Belfast. Curiously enough, it did not have high values for any of the five socio-economic factors which were collected for this analysis, although it did score highly for the other types of crime factors included in this analysis.

Conclusions

Domestic violence will always be present in society, but it may be possible for resources to be allocated with greater efficiency if it were possible to highlight which regions were at a higher risk.

While a large number of studies have concentrated on proving a correlation between DV and poverty, very few studies have concentrated on a correlation between DV and other crime types.

Limitations

There were several limitations, which had to be considered during this project.

The DV data used was collated on an annual basis, with no further temporal refinement available. Additional information such as date or time of day would have provided useful insight and enabled further and improved temporal analysis.

Certain types of crime are traditionally under reported for a variety of reasons. The total number of DV incidents recorded by the PSNI may not be an accurate reflection of the true picture. Traditionally in Northern Ireland, according to McWilliams and Ni Aolain, 2013, some crimes were not reported to the RUC, as it was believed by some people that the RUC were biased and some crimes were resolved internally by prominent members of the community.

For future studies, it may be beneficial to collate DV incidents from other sources such as DV charities, medical centres or anonymous questionnaires, either in online format or face to face interviews.

The DV data was originally collated in Ward2014 geographic data format. This newer format was not directly compatible with some of the other datasets which had been collated in the Ward1993 geographic data format. A method of translating the data from one format to another was utilised which resulted in small inaccuracies being introduced. The DV data was also not available for any smaller geographic areas such as OA or SOA, which would have produced a higher resolution of the data and giving a high granularity of the data.

Dark and Bram (2007) stated that “Of particular importance to the study of large-scale phenomena in physical geography is the modifiable areal unit problem (MAUP)”. Any project of this size and amount of GIS analysis must always contend with the MAUP. In essence it relates to the aggregation of geographic areas which can have a discernible effect on any geostatistical analysis. The scale of the data collected and how it is aggregated will have an effect on mean values of the statistics as well as the standard deviation, even though the original base data values are the same.

References

Ali, T.S., Asad, N., Mogren, I., and Krantz, G., (2011). Intimate partner violence in urban Pakistan: prevalence, frequency, and risk factors, *International Journal of Women's Health,* 3, 105–115.

Alsaker, K., Moen, B.E., Morken, T., and Baste, V., (2018). Intimate partner violence associated with low quality of life - a cross-sectional study, *BMC Women's Health,* 18(148), 1-7.

Amegbor, P.M., and Rosenberg, M.W., (2019). What geography can tell us? Effect of higher education on intimate partner violence against women in Uganda, *Applied Geography*, 106, 71-81.

Bassuk, E., Dawson, R., and Huntington, N., (2006). Intimate Partner Violence in Extremely Poor Women: Longitudinal Patterns and Risk Markers, *Journal of Family Violence,* 21, 387–399.

Bates, L.M., Schuler, S.R., Islam, F., and Islam, M.K., (2004). Socioeconomic Factors and Processes Associated with Domestic Violence in Rural Bangladesh, *International Family Planning Perspectives,* 30(4), 190-199.

Beyer, K., Wallis, A.B., and Hamberger, L.K., (2015). Neighborhood Environment and Intimate Partner Violence: A Systematic Review, *Trauma, Violence, and Abuse,* 16(1), 16-47.

Browne, A., and Bassuk, S.S., (1997). Intimate Violence in The Lives of Homeless and Poor Housed Women: Prevalence and Patterns in an Ethnically Diverse Sample*, American Journal of Orthopsychiatry,* 67(2), 261-278.

Cadilhac, D.A., Sheppard, L., Cumming, T.B., Thayabaranathan, T., Pearce, D.C., Carter, R., and Magnus, A. (2015). The health and economic benefits of reducing intimate partner violence: an Australian example. *BMC public health*, 15, 625.

Caetano, R., Ramisetty-Mikler, S., and Harris, T.R., (2010). Neighborhood Characteristics as Predictors of Male to Female and Female to Male Partner Violence, *Journal of Interpersonal Violence,* 25(11), 1986–2009.

Capaldi, D.M., Knoble, N.B., Shortt, J.W., and Kim, H.K., (2012). A Systematic Review of Risk Factors for Intimate Partner Violence, *Partner Abuse,* 3(2), 231-280.

Coker, A.L., Smith, P.H., McKeown, R.E., and King, M.J., (2000). Frequency and Correlates of Intimate Partner Violence by Type: Physical, Sexual, and Psychological Battering, *American Journal of Public Health*, 90, 553–559.

Cunradi, C.B., Caetano, R., Clark, C., and Schafer, J., (2000). Neighborhood Poverty as a Predictor of Intimate Partner Violence Among White, Black, and Hispanic Couples in the United States: A Multilevel Analysis, *Annals of Epidemiology,* 10(5), 297-308.

Dark, S.J., & Bram, D., (2007). The modifiable areal unit problem (MAUP) in physical geography, *Progress in Physical Geography,* 31(5), 471–479.

Domestic Violence London (2018). *What is Domestic Violence Definition:* Available at: http://www.domesticviolencelondon.nhs.uk/1-what-is-domestic-violence-/1-definition.html [Accessed 29 Oct 19].

Dorahy, M.J., Lewis, C.A., and Wolfe, F.A.M., (2007). Psychological Distress Associated with Domestic Violence in Northern Ireland, *Current Psychology, Developmental, Learning, Personality, Social,* 25(4), 295-305.

Dutton, M.A., Kaltman, S., Goodman, L.A., Weinfurt, K., and Vankos, N., (2005). Patterns of Intimate Partner Violence: Correlates and Outcomes, *Violence and Victims,* 20(5), 483-497.

Earth Sciences Research Institute (2019). *How Spatial Autocorrelation (Global Moran's I) works.* Available at: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/h-how-spatial-autocorrelation-moran-s-i-spatial-st.htm [Accessed 31 Mar 19]

Earth Sciences Research Institute (2019). *Interpreting GWR results.* Available at: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/interpreting-gwr-results.htm [Accessed 31 Mar 19]

Earth Sciences Research Institute (2019). *Interpreting OLS results.* Available at: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/interpreting-ols-results.htm [Accessed 31 Mar 19]

Earth Sciences Research Institute (2019). *Regression analysis basics.* Available at: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/regression-analysis-basics.htm [Accessed 31 Mar 19]

Eicher, C.L., and Brewer, C.A., (2001). Dasymetric Mapping and Areal Interpolation: Implementation and Evaluation, *Cartography and Geographic Information Science,* 28(2), 125-138.

Fisher, P.F., and Langford, M., (1995). Modelling the errors in areal interpolation between zonal systems by Monte Carlo simulation, *Environment and Planning,* 27, 211-224.

Flango, V.E., and Sherbenou, E.L., (1976). Poverty, urbanization, and crime, *Criminology,* 14(3), 331-346.

Ford-Gilboe, M., Varcoe, C., Noh, M., Wuest, J., Hammerton, J., Alhalal, E., and Burnett, C., (2015). Patterns and Predictors of Service Use Among Women Who Have Separated from an Abusive Partner, *Journal of Family Violence,* 30, 419–431.

Garcia-Moreno, C., Jansen, H.A.F.M., Ellsberg, M., Heise, L., and Watts, C.H. (2006). Prevalence of intimate partner violence: findings from the WHO multi-country study on women's health and domestic violence, *Lancet,* 368, 1260–1269.

Garcia-Moreno, C., Pallitto, C., Devries, K., Stockl, H., Watts, C., and Abrahams, N., (2013). *Global and regional estimates of violence against women: prevalence and health effects of intimate partner violence and non-partner sexual violence,* World Health Organisation.

Gilchrist, E.A., Ireland, L., Forsyth, A., Godwin, J., and Laxton, T., (2017). Alcohol use, alcohol-related aggression and intimate partner abuse: A cross-sectional survey of convicted versus general population men in Scotland, *Drug and Alcohol Review,* 36, 20-23.

Gilroy, H., McFarlane, J., Fredland, N., Cesario, S., Nava, A., and Maddoux, J., (2018). Using a Model of Economic Solvency to Understand the Connection between Economic Factors and Intimate Partner Violence, *Journal of International Women's Studies,* 19(6), 305-325.

Goodchild, M.F., Anselin, L., and Deichmann, U., (1993). *A framework for the areal interpolation of socioeconomic data,* Environment and planning, 25(3), 383-397.

Gracia, E., and Merlo, J., (2016). Intimate partner violence against women and the Nordic paradox, *Social Science & Medicine,* 157, 27-30.

Gregory, I.N., (2002). The accuracy of areal interpolation techniques: standardising 19th and 20th century census data to allow long-term comparisons, *Computers, environment and urban systems,* 26(4), 293-314.

Hayden, A., (2010). Why Rock the Boat? Non-Reporting of Intimate Partner Violence, *Institute of Public Policy Faculty of Applied Humanities.*

Hooghe, M., Vanhoutte, B., Hardyns, W. and Bircan, T., (2010). Unemployment, inequality, poverty and crime: spatial distribution patterns of criminal acts in Belgium, 2001–06, *The British Journal of Criminology,* 51(1), 1-20.

Intimate Partner Violence in the United States, *National Intimate Partner and Sexual Violence Survey,* (2010).

Jewkes, R., Levin, J., and Penn-Kekana, L., (2002). Risk factors for domestic violence: findings from a South African cross-sectional study, *Social Science and Medicine,* 55, 1603–1617.

Khalifeh, H., Hargreaves, J., Howard, L.M., and Birdthistle, I., (2013). Intimate Partner Violence and Socioeconomic Deprivation in England: Findings From a National Cross-Sectional Survey, *American Journal of Public Health,* 103(3), 462-472.

Kiss, L., Schraiber, L.B., Heise, L., Zimmerman, C., Gouveia, H., and Watts, C., (2012). Gender-based violence and socioeconomic inequalities: Does living in more deprived neighbourhoods increase women's risk of intimate partner violence?, *Social Science and Medicine,* 74, 1172-1179.

Krug, E.G., Dahlberg, L.L., Mercy, J.A., Zwi, A.B., and Lozano, R., (2002). *World report on violence and health,* World Health Organisation.

Lam, N.S.N., (1983). Spatial interpolation methods: a review, *The American Cartographer,* 10(2), 129-150.

Law, J., and Chan, P.W., (2012). Bayesian spatial random effect modelling for analysing burglary risks controlling for offender, socioeconomic, and unknown risk factors, *Applied Spatial Analysis and Policy*, *5*(1), 73-96.

Law, J. and Quick, M., (2013). Exploring links between juvenile offenders and social disorganization at a large map scale: a Bayesian spatial modeling approach, *Journal of Geographical Systems,* 15(1), 89-113.

Law, J., Quick, M., and Chan, P., (2014). Bayesian spatio-temporal modelling for analysing local patterns of crime over time at the small-area level, *Journal of quantitative criminology*, *30*(1), 57-78.

Legislation.gov.uk (1998). *Data Protection Act 1998.* Available at: https://www.legislation.gov.uk/ukpga/1998/29/contents [Accessed 31 Mar 19].

Legislation.gov.uk (2018). *Data Protection Act 2018.* Available at: http://www.legislation.gov.uk/ukpga/2018/12/contents/enacted [Accessed 31 Mar 19].

Legislation.gov.uk (2008). *The Sexual Offences (Northern Ireland) Order 2008.* Available at: https://www.legislation.gov.uk/nisi/2008/1769/contents [Accessed 31 Mar 19].

Martin, D., (2000). Towards the geographies of the 2001 UK Census of Population, *Transactions of the Institute of British Geographers,* 25(3), 321-332.

Maziak, W., and Asfar, T., (2003). Physical Abuse on Low-Income Women in Aleppo, Syria, *Health Care for Women International,* 24(4), 313-326.

McClennan, H., Joseph, S., and Lewis, C.A. (1994). Causal attributions for marital violence and emotional reactions in women seeking refuge, *Psychological Reports,* 75, 272-274.

McWilliams, M., and Northern Ireland Aolain, F.D. (2013). 'There is a War Going on You Know': Addressing the Complexity of Violence Against Women in Conflicted and Post Conflict Societies, *Transitional Justice Review,* 1(2), 4-44.

McWilliams, M. and McKiernan, J., (1993). *Bringing It Out in the Open: Domestic Violence in Northern Ireland: A Study Commissioned by the Department of Health and Social Services (Northern Ireland).* HM Stationery Office.

Mennis. J., and Hultgren, T., (2006). Intelligent Dasymetric Mapping and Its Application to Areal Interpolation, *Cartography and Geographic Information Science*, 33:3, 179-194.

Modie-Moroka, T., (2010). Intimate Partner Violence and Poverty in the Context of Botswana*, Journal of Psychology in Africa,* 20(2), 185–192.

Mrozinski, R.D., and Cromley, R.G., (1999). Singly-and doubly-constrained methods of areal interpolation for vector-based GIS, *Transactions in GIS,* 3(3), 285-301.

Naeem, F., Irfan, M., Zaida, Q.A., Kingdon, D., and Ayub M., (2008). Angry Wives, Abusive Husbands: Relationship Between Domestic Violence and Psychosocial Variables, *Women's Health Issues,* 18, 453-462.

Northern Ireland Neighbourhood Information Service, 2019. *Population Statistics.* Available at: https://www.ninis2.nisra.gov.uk/public/Theme.aspx?themeNumber=74&themeName=Population [Accessed 05 Jan 19].

Northern Ireland Statistics and Research Agency, 2019. *Deprivation.* Available at: https://www.nisra.gov.uk/statistics/deprivation [Accessed 05 Jan 19].

Office for National Statistics (2018). *Reasons for not reporting incidents of crime to the police, year ending March 2017 CSEW*. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/adhocs/007750reasonsfornotreportingcrimetothepolice2016to2017crimesurveyforenglandandwales [Accessed 29 Oct 19].

Patterson, E.B., (1991). Poverty, income inequality, and community crime rates, *Criminology,* 29(4), 755-776.

Reibel, M., and Agrawal, A., (2007). Areal interpolation of population counts using pre-classified land cover data, *Population Research and Policy Review,* 26(5-6), 619-633.

Rennison, C., and Planty, M., (2003). Nonlethal Intimate Partner Violence: Examining Race, Gender, and Income Patterns, *Violence and Victims,* 18(4), 433-443.

Richardson, J., Coid, J., Petruckevitch, A., Chung, W.S., Moorey, S., and Feder, G., (2002). Identifying domestic violence: cross sectional study in primary care, *British Medical Journal,* 324, 1-6.

Sadahiro, Y., (1999). Accuracy of areal interpolation: A comparison of alternative methods, *Journal of Geographical Systems,* 1(4), 323-346.

Saefuddin, A., Setiabudi, N. A., and Achsani, N. A., (2011). Comparison between Ordinary Linear Regression and Geographically Weighted Regression: With Application to Indonesian Poverty Data, *European Journal of Scientific Research,* 57(2), 275-285.

Sanz-Barbero, B., Linares, C., Vives-Cases, C., González, J.L., López-Ossorio, J.J., and Díaz, J., (2018). Intimate partner violence in Madrid: a time series analysis (2008-2016), *Annals of Epidemiology,* 28, 635-640.

Saunders, P., and Naidoo, Y., (2018). Mapping the Australian Poverty Profile: A Multidimensional Deprivation Approach, *The Australian Economic Review,* 51(3), 336-350.

Snowden, A.J., (2016). Alcohol Outlet Density and Intimate Partner Violence in a Nonmetropolitan College Town: Accounting for Neighborhood Characteristics and Alcohol Outlet Types, *Violence and Victims,* 31(1), 111-123.

Tapp, A.F., (2010). Areal Interpolation and Dasymetric Mapping Methods Using Local Ancillary Data Sources, *Cartography and Geographic Information Science*, 37(3), 215–228.

Taylor, C. (1995). Northern Ireland: The policing of domestic violence in nationalist communities, *Wisconsin Women's Law Journal,* 10, 307.

Vest, J.R., Catlin, T.K., Chen, J.J., and Brownson, R.C., (2002). Multistate Analysis of Factors Associated with Intimate Partner Violence, *American Journal of Preventive Medicine,* 22(3), 156–164.

Williams, J., Petersen, N., and Stoler J., (2018). Characterizing the spatial mismatch between intimate partner violence related healthcare services and arrests in Miami-Dade County, Florida, *BMC Public Health,* 18(1085), 1-10.

Wilson, J.Q. and Kelling, G.L., (1982). Broken windows, *Atlantic monthly,* 249(3), 29-38.