Spatial Statistics 41 (2021) 100485

Contents lists available at ScienceDirect

Spatial Statistics

journal homepage: www.elsevier.com/locate/spasta

Demography and Crime: A Spatial analysis of geographical patterns and risk factors of Crimes in Nigeria

Rasheed A. Adeyemi [a,*], James Mayaki [a], Temesgen T. Zewotir [b], Shaun Ramroop [c]

[a] Department of Statistics, Federal University of Technology, PMB 65, Minna, Nigeria
[b] School of Mathematics, Statistics and Computer Science, University of KwaZulu-Natal, Durban, South Africa
[c] School of Mathematics, Statistics and Computer Science, University of KwaZulu-Natal, Pietermaritzburg Campus, Scottsville 3209, South Africa

ARTICLE INFO

Article history:
Received 25 June 2020
Received in revised form 4 November 2020
Accepted 25 November 2020
Available online 10 December 2020

Keywords:
Spatial geography
High crime areas
Conditional autoregressive (CAR) model
Poisson mixed model

ABSTRACT

This paper explores the spatial distribution of crime incidences in Nigeria and evaluates the association between the geographical variations and the socio-demographic determinants of crimes. The analyses are based on 2017 reported crime Statistics obtained from the Nigeria's National Bureau of Statistics. This paper analysed the spatial patterns of four types of crimes (armed robbery, theft, rape and kidnapping) in relation to their geographical distributions across states in Nigeria. In contrast to the traditional regression analysis, a Poisson mixed model was formulated to incorporate the spatial dependence effects (clustering) and the specific state-level heterogeneity effects of crimes. The study modelled six explanatory variables (unemployment rate, population density, education index, Gross National Income (GNI), percentage males population (PMP), age 18–35 years and policing structure) as the determinants of crimes in Nigeria. A full Bayesian approach via Markov Chain Monte Carlo simulation was used to estimate the model parameters. The results show that the unemployment rate was positively associated with rape, kidnapping and armed robbery, but negatively associated with theft. The results further reveal that GNI and PMP show positive correlation with all the crimes. In addition to the

* Corresponding author.
E-mail addresses: rashid.adeyemi@futminna.edu.ng (R.A. Adeyemi), j.mayaki@futminna.edu.ng (J. Mayaki), zewotir@ukzn.ac.za (T.T. Zewotir).

https://doi.org/10.1016/j.spasta.2020.100485

risk factors of the crimes, the proportion variation attributed to clustering effect of the total variation was explained by 29.27 % in armed robbery incidents, 31.30% for theft (stealing), 27.07% for kidnapping and 41.40% in rape cases occurrence. Our approach also produces spatial predictive maps that identified areas of high crime concentration, which can assist the relevant agencies in crimes prevention, effective policing and areas needed urgent attention.

1. Background

Both criminology and demography share a complex and reciprocal relation (South and Messner, 2000) and demonstrate a neighbourhood propensity as the primary determinants of criminal behaviours. Over the years, crime incidences and the degree of violence have exacerbated tremendously in a number of African cities, Nigeria is not an exception. Crime and violence increasingly accompany economic deprivation in many developing economies as noted by Kessides (2007). In recent years, the direct effects of insecurity on people, crime and insecurity have hampered new foreign direct investment and expansion of existing business (Hove et al., 2013). In other words, for African nations to be able to attract new investment, to address rising unemployment and retain existing businesses, it is imperative that crime be combated, and overall safety and public security be restored.

In social disorganization theory, studies of social demography (e.g. the propensity to marry, decisions to move, family formation, socioeconomic stratification, ethnic community composition, sexual activity, and fertility) suggests that individual and family characteristics are independently related to neighbourhood characteristics and exert an important influence on crime patterns (South and Deane, 1993; Morenoff and Sampson, 1997; Xie and McDowall, 2010; Arnio and Baumer, 2012). Other studies have demonstrated that other demographic features such as age, sex, race and ethnicity, immigrant concentration, marriage, family structure, and residential mobility) have been linked to variation in criminal behaviour among individuals (Laub et al., 1998; King et al., 2007; King and South, 2011) and differences in crime rates across time and space (Zimmerman and Messner, 2011; Hipp, 2010; Sampson et al., 2002). The empirical results from the complex interplay between crime and key demographic context (e.g. the distribution of people by income, race, and ethnicity, economic deprivation, immigration and racial difference have been highlighted in previous studies South and Messner (2000), Hirschman and Tolnay (2005) and Barbosa (2019). Recently, the research interest has expanded to the geographic distribution and the determinant factors of crimes, which are of great importance for criminologists, sociologists, geographers and law enforcement agencies. A sizeable number of studies have used non-spatial regression models in crime analysis failing to account for the spatial dependence in crime data. For instance, Omotor (2009) adopts error correction model to investigate socio-economic determinants of crime in Nigeria and found that unemployment is the most important determinant factors of crime in Nigeria, while (Oguntunde et al., 2018) use a linear correlation method to investigate the trend

pattern of some selected crimes in Nigeria. In other regions, Craglia et al. (2001) employ a standard logistic regression model to determine the relationship between socioeconomic characteristics and high-intensity crime areas. Of recent, Lobonţ et al. (2017) adopt a co-integration approach to investigate the time series data on crime rates and socioeconomic factors in Romania. They found that the income disparity showed significant relationship with rising crime. Other studies have complemented the ordinary least squares (OLS) regression analysis with Moral I statistics to compensate for the presence of spatial error in crime data, see Charron (2009) for further readings. Brunsdon et al. (1996) analyse the relation between social factors and unemployment rate in UK using geographically-weighted regression model, where the regression coefficients are allowed to vary at different points in space.

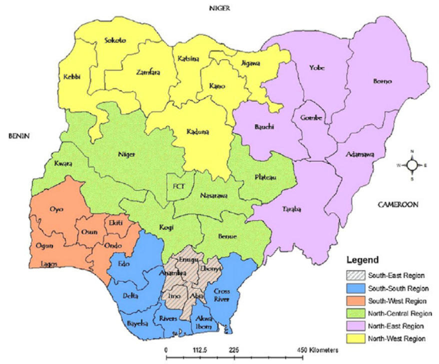
In social ecology, the popular theory is based on the assumption that the geographic variations in social activities are related to patterns of crimes. The pioneering work by Shaw and McKay (1942) recognized spatial disparities in juvenile delinquency in the city of Chicago. This indicates that criminal activities often demonstrate disparities in geographical distribution over space or time. Previous studies have established that the occurrence of crimes often concentrates in particular neighbourhoods and are related to socioeconomic activities and population demography. More importantly studies have showed that social disorganization exerts a strong association between economic deprivation and the number of crimes committed by the residents of a particular neighbourhood (Brantingham and Brantingham, 2013; Marco et al., 2017). A number of empirical studies have used other alternative measures such as location quotients of crime to investigate the crime rates and the social disorganization theory (Brantingham and Brantingham, 1995; Carcach and Muscat, 2002) and crime density (Harries and Powell, 1994; McCord and Ratcliffe, 2009).

Nowadays, spatial analysis of crime data has not only provided a visual representation of areas of concentrated crimes, but helped to identify neighbourhood characteristics in relation to severity level of crime. As mentioned in Charron (2009), crime mapping is useful as a vital tool for the development and implementation of crime reduction strategies. A good number of studies have explored mapping techniques to investigate the ecological perspective of crimes as regards the theories of social disorganization and routine activities, or opportunities for crimes (Fitzgerald et al., 2004; Andresen and Brantingham, 2007; Charron, 2009). For example, a study conducted in Canadan by Andresen and Brantingham (2007) examined the spatial distribution of crime in the relation with the neighbourhood characteristics such as low-income and economic activity. They found that crime was not randomly distributed in cities, but was concentrated in certain neighbourhoods.

In the present context, we explore spatial analysis by recognizing that crimes are committed on their victims (i.e. persons or their property) and those victims have definite geographic coordinates at any given moment. The crime activities are then recorded as geo-referenced data (geocoding), which are commonly measured over two-dimensional study area. The data observations of such crime activities can often be affected by the properties of the location in which they occur as noted in Charron (2009). The data observations recorded from the neighbouring regions or adjacent states would often be affected by the close location properties, as such the observations recorded from close location may be similar and they are not independently distributed. This spatial heterogeneity property (including spatial autocorrelation) comes to play and somehow violates the assumption of OLS regression model and must be accounted for in the data analysis to produce reliable and unbiased estimates. To account for spatial heterogeneity, empirical studies have adopted different version of mixture based approaches for modelling observed count data (Fernández and Green, 2002; Green, 2019), mapping of disease incidence (Knorr-Held and Raßer, 2000; Green and Richardson, 2002), and spatial data with overdispersion (Gschlößl and Czado, 2008). The above literature have motivated the present study. This study therefore proposes a unified model framework that combines the usual fixed effects and spatial structures. The spatial component is decomposed into two parts to capture the effects of the neighbourhood (autocorrelation) structure and specific-area level (uncorrelated) effect on the crime.

As a matter of fact, no previous studies have assessed the neighbourhood effects in the distribution of crimes in Nigeria context — the knowledge that is crucial for guiding priority setting for resource allocation by the policy makers, criminologists and policing. This study examines sub-national spatial variations in crime rates and their relation to key variables related to socio-demographics in the incidence year of 2017, a period during which Nigeria saw slightly increase in crime of all types over 2016. The present study analyzed four crimes from two major crime types: offence against persons and property. The present work extends the spatial distribution on personal crime (rape and kidnapping) to bringing researchers and practitioners to a similar level of understanding as is already available in respect of property crime (armed robbery and theft).

This paper is structured into five sections. The first section provides an introduction and the justification for spatial analysis of crime data in Nigeria context. In the second section, the study design and crime data in Nigeria are presented along with the geographical maps of Nigeria in relation to adjacent states. The third section discusses the analytic models for crime rates. In the fourth section, the results of risk estimates and spatial maps of crime rates in Nigeria are presented, along with the goodness of fit in relation to their neighbourhood characteristics. The fifth section contains the discussion and the conclusion.



ID	State	Adjacent Neighbours	ID	State	Adjacent Neighbours
1	Abia	3,4, 9, 11, 14, 17, 33,	19	Kaduna	5, 15, 20, 21, 26, 27, 32, 37,
2	Adamawa	8, 16, 35,	20	Kano	5, 18, 19, 21,
3	Akwa-Ibom	1 ,9, 33,	21	Katsina	18, 19, 20, 37,
4	Anambra	1, 10, 12, 14,17, 23, 33,	22	Kebbi	27, 34,37,
5	Bauchi	16, 18, 19,20, 32,35, 36,	23	Kogi	4, 7, 12, 13, 14,15, 24, 26, 27, 29,
6	Bayelsa	10,33,	24	Kwara	13, 23, 27, 30, 31,
7	Benue	9, 11, 14, 23, 26, 35,	25	Lagos	28,
8	Borno	2, 16, 36,	26	Nasarawa	7, 15, 19, 23, 32, 35,
9	Cross river	1, 3, 7, 11,	27	Niger	15, 19, 22, 23, 24, 37,
10	Delta	4, 6, 12, 29, 33,	28	Ogun	25, 29, 30, 31,
11	Ebonyi	1, 7, 9, 14,	29	Ondo	10, 12, 13, 23, 28, 30,
12	Edo	4, 10, 23, 29,	30	Osun	13, 24, 28, 29, 31,
13	Ekiti	23, 24, 29, 30,	31	Oyo	24, 28, 30,
14	Enugu	1, 4, 7, 11, 23,	32	Plateau	5 ,19, 26, 35,
15	FCT-Abuja	19, 23, 26, 27,	33	Rivers	1, 3, 4, 6, 10, 17
16	Gombe	2, 5, 8, 35, 36,	34	Sokoto	22, 37,
17	Imo	1, 4, 33,	35	Taraba	2, 5, 7, 16, 26, 32,
18	Jigawa	5, 20, 21, 36,	36	Yobe	5, 8, 16, 18,
			37	Zamfara	19, 21, 22, 27, 34

Fig. 1. Map of Nigeria showing 37 districts (36 states and Federal Capital Territory, Abuja) and the adjacent neighbours to each state.

2. Study area and data

Nigeria is located in the tropical zone of West Africa between latitudes 4° N and 14° N and longitudes 2°2′ E and 14°30′ E and has a total area of 923 770 km^2. The country extends to north–south by about 1 050 km and its maximum east–west extent is about 1 150 km. Nigeria is bordered to the west by Benin, to the northwest and north by Niger, to the northeast by Chad and to the east by Cameroon, while the Atlantic Ocean forms the southern limits of Nigerian territory. Land cover ranges from thick mangrove forests and dense rain forests in the south to a near-desert condition in the northeastern corner of the country. The detailed description of geographical distribution, agro-forestry zones, landmass and climatic distribution can be found in Frenken (2005).

For the purpose of the present study, Fig. 1 shows the geographical map of Nigeria showing 36 states (districts) and Federal Capital Territory, Abuja. The population groupings within the geopolitical regions and states are relatively homogeneous. Also, the people's cultural beliefs, demographic characteristics, arid environment and socioeconomic status are considered similar within the geopolitical zones and states. The table accompanying the geographical map of Nigeria indicates the state code and the adjacent neighbouring states as used in the WinBUGs programming. The WinBUGs code is provided as the supplementary material.

The study employs data from the reported cases of crime by Nigerian Police Force and available at system of National Bureau of Statistics (2017). The study analysed all cases of theft, armed robbery, rape and kidnapping for the incidence year 2017 (see Table 1).

Demographic covariates. Several indicators of crime were collected for projected population by states of Nigeria for year 2017. In line with previous studies, the indicators of social deprivation, social fragmentation and population density are assessed as suggested in empirical studies of Sparks (2011) and Law et al. (2014). The variables extracted from the Labour Force Statistics and Youth Survey (NBS) data and included in the model are: the projected population census 2017 by state (viz-a-viz computed population density), total work force population, unemployment rate, number of divisional police headquarters (HQ) and young adult male population (18–35 years).

Socio-economic covariates. From the Nigeria's National Human Development Index 2018 report, Annex 1, two economic components, namely the gross national income (GNI) and education index (EI) were selected and used in the model. The details have been reported elsewhere (UNDP, 2018). This study has included a novel variable, education index as an important factor for social disorganization. Because, life in many parts of the North East of Nigeria has been severely endangered on all basic human development infrastructure, and the long-term psycho-social impacts of insurgency on the destruction of education and health facilities.

The crime types, explanatory variables and the relevant covariates are defined and basic description is given in Table 1.

Table 1
Description of variables used in the model.

Variables	Description/Definition
Response variables[a]	
Armed Robbery	A crime of theft by force or by threat of force.
Theft or stealing	Taking someone else's property without such person's permission.
Rape	Sexual assault involving rape and indecent assault.
Kidnapping	Unlawful carrying away and confinement of a person against his or her will sometimes for ransoms.
Covariates	
Population density	Population density is computed as number of persons per square kilometres given by total population of a state divided by landmass area of the state (km^2).
Unemployment rate [b]	Unemployment rate is calculated as the total number of unemployed residents in each state between ages 18–60 divided by the available labour force population in the state.
Percentage male population (PMP)	PMP is calculated by the young adult male population between ages 18 and 35 years residents in each state divided by the total population in the state.
Policing	Number of divisional police HQ is used as a proxy for quantifying the number of policemen per state within the community policing infrastructure. That is policing staffing strength which includes state security services, police inspectors, assistant inspectors (AIG) and other ranks and files.
Education index (EI) [d]	EI is calculated using Mean Years of Schooling and Expected Years of Schooling. Data in the tables are those available to the HDI 2018.
Gross National Income (GNI)[d]	GNI per capita (formerly GNP per capita) is the Income (GNI) gross national income, converted to U.S. dollars using the World Bank Atlas method, divided by the midyear population. This is used as a proxy for measuring the level of economic activities per state.

a National Bureau of Statistics (NBS), Crime Statistics, 2017.
b — National Population Commission & NBS, 2017.
c — NBS, Labour Force Statistics, QUARTER 4, 2017.
d — UNDP report-Gross National Income per capita, data from World Bank economy Indicator and HDI https://data.worldbank.org/indicator/NY.GNP.PCAP.PP.CD?locations=NG.

3. Material and methods

The Bayesian generalized linear mixed models (GLMMs) via Markov chain Monte Carlo (MCMC) are commonly used to model relative risk (RR) and prevalence across regions. It was postulated that a GLMM version can be formulated as a Bayesian hierarchical model with Binomial and Poisson likelihoods, known as the BYM-model (Besag-York-Mollier model) (Chen, 2013; Best et al., 2005). This study adopts Poisson GLMMs. The BYM Poisson model using conditional autoregressive (CAR) priors for correlated random effect as described by Besag et al. (1991).

3.1. The model formulation

Suppose the variable of interest (dependent) was the number of crimes by types, and assume to follow a Poisson distribution:

$$Y_i \sim Pos(\lambda_{ik}) = Pos(E_{ik}\theta_{ik}) \quad k = 1, 2, 3, 4 \tag{1}$$

where k refers to the type of crime, Y_{ik} is the observed number of crimes of the type k in neighbourhood (state) i, λ_{ik} is the expected value for the Poisson distribution, E_{ik} denotes the expected number of crime type, k in state i, and θ_{ik} represents the relative risk of crime associated with state, i, which is state-specific and crime type, k-specific risk.

The logarithm of relative risk with the link function takes the following form:

$$\begin{aligned}\log(\lambda_{ik}) &= \log(E_{ik}) + \log(\theta_i) \quad i = 1, \ldots, 37 \\ &= \log(E_{ik}) + \beta_{0k} + \sum_{k=1}^{6} \beta_k X_i k + \Phi_i\end{aligned} \tag{2}$$

with an *offset* $= \log(E_{ik})$ and multiplicative impacts on the model-based expected observation counts. The β_{0k} is a fixed intercept, so $\exp(\beta_{0k})$ is the corresponding global mean for crime k, $\boldsymbol{\beta}_k = (\beta_1, \ldots, \beta_6)$ denotes the vector of unknown regression parameters, X_i is vector of covariates observable at state i. The parameter Φ_i represents unobservable random effect, which is split into $\Phi_i = U_i + V_i$, where V_i is the uncorrelated error and U_i is the correlated error is modelled with an intrinsic conditional autoregressive (ICAR) prior for spatial structure. The combination of the two-random spatial errors in a model is sometimes known as convolution model or BYM model.

The correlated random effect, U_i in area (state, i) is conditionally distributed given its neighbouring areas, j, which assumes ICAR prior as defined by Besag et al. (1991) and given as

$$U_i | U_j = u_j, j \neq i \sim \mathrm{N}\left(\frac{\sum_{j=1}^{m_i} u_j}{m_i}, \frac{\sigma_u^2}{m_i}\right) \tag{3}$$

where U_i assumes a Normal (N) distribution with mean, $\bar{u}_i = \frac{\sum_{j=1}^{m_i} u_j}{m_i}$ and variance $\frac{\sigma_u^2}{m_i}$, $\bar{u}_i$ is the weighted average for the adjacent neighbours of area i, m_i is the total number of all adjacent neighbours, and σ_u^2 is the conditional variance of U. The model specification in Eq. (2) with random effect, Φ is commonly called the convolution model according to Knorr-Held and Raßer (2000) for a log-linear link function.

The spatially unstructured effect, V_i assumes independent Gaussian distribution prior and it is given as $v_i \sim N(0, \sigma_v^2 I)$. The variation of the CAR effect, U is controlled by the variance parameter σ_u^2 or its corresponding variance precision, $\tau_u = 1/\sigma_u^2$. The variance component parameters ${\sigma_u}^2$ and ${\sigma_v}^2$ control the variation of u_i and v_i respectively. For further readings, see Besag and Kooperberg (1995), Best et al. (2005) and Lawson et al. (2003).

In addition, the study is also interested in the relative variation in the crime risk that is spatially correlated (clustering) effects against total random variation. The proportion of variation attributable to spatially structured variation is calculated using the ratio of random effect standard deviations and the total variation given as:

$$\phi = \frac{sd(u)}{sd(u) + sd(v)} \tag{4}$$

where $sd(v)$ is the standard deviation of the spatially unstructured(uncorrelated) random effects and $sd(u)$ is the standard deviation of the spatially structured(correlated) random effects.

3.2. The prior specification

In Bayesian framework, the unknown parameters are important components in making statistical inference and they are assigned appropriate prior specification as the required posterior distributions of parameters are derived by combining prior knowledge and data. The overall intercept, β_{0k}, is assigned a uniform prior due to a sum-to-zero constraint on the random effects as suggested by Spiegelhalter et al. (1996)

$$\beta_{0k} \sim dflat(), \quad k = 1, 2, 3, 4 \tag{5}$$

β_{ik}, the regression coefficients of the fixed effect predictors, are specified to follow a non-informative normal prior distribution with a zero mean and a variance 10^5 i.e $\beta_{ik} \sim N(0, 10^5)$ $k = 1, 2, 3, 4, j = 1, 2, \ldots, 6$.

As mentioned in Section 3.1, the spatially correlated (structured) components, U and uncorrelated heterogeneity, V are modelled by the CAR prior and independent Gaussian distribution respectively. The hyper-parameter prior, σ_{uk}^2 and σ_{vk}^2, are associated variance component parameters and they assumed Gamma distribution prior (Wakefield et al., 2000), which take the form:

$$\sigma_{uk}^{2\ -1} \sim \text{Gamma}(0.01, 0.01), \quad k = 1, 2, 3, 4 \tag{6}$$

$$\sigma_{vk}^{2\ -1} \sim \text{Gamma}(0.01, 0.01), \quad k = 1, 2, 3, 4 \tag{7}$$

All model parameters were estimated in GeoBUGS (Thomas et al., 2004). The WinBUGS code for the implementation of the univariate model can be found in the Supplementary Materials.

For the count data regression models on crime, the statistical inference on the underlying spatial structure and parameter uncertainty is performed in Bayesian framework as discussed in Section 3.1. MCMC was used for parameter estimation. More readings on Bayesian data analysis and MCMC methods can be found in Gilks et al. (1996) and Gelman et al. (2004).

The model performance was evaluated using deviance information criterion (DIC) as suggested in Spiegelhalter et al. (2002) for a Bayesian inference. Given the likelihood function for the observed data as $L(\text{data}|\boldsymbol{\theta})$ and $\boldsymbol{\theta}$ as the vector of model parameters, the deviance information criterion is given by

$$DIC = \bar{D} + pD \tag{8}$$

where $\bar{D}$ is the posterior mean of the deviance given as $\bar{D} = E_{\boldsymbol{\theta}|\mathbf{y}}(D)$, which measures the goodness of fit defined as $D(\bar{\theta}) - 2\log L(\text{data}|\boldsymbol{\theta})$. The pD is the effective number of model parameters and it is computed as the difference between the deviance posterior mean and the parameters posterior mean evaluated by $pD = E_{\theta|y}(D) - D(E_{\theta|y}(\boldsymbol{\theta}))$, which represents a measure of model complexity and penalizes over-fitting. For model comparison, the model with the lowest DIC, $\bar{D}$ is considered the best model among competing models and lower value of pD indicates a parsimonious model.

4. Data analysis and results

This section consists of two parts: descriptive summary of the variables considered in the model and the results of the model analysis. The model analysis comprises of two parts: the table of the risk factors for the covariates and the posterior means of the spatial residual effects.

4.1. Descriptive analysis

Descriptive statistics for the variables considered in this study is presented in Table 2. The summary statistics include minimum, maximum, mean and standard deviation (SD) of the dependent and independent variables at the state level are shown in the Table.

A total of 134 663 crime incidents were reported in 2017, of which 53 641 offences were crimes committed against persons, 68 579 incidents were the total property crimes and the remaining offences are committed against lawful authority. The total armed robber incidents committed across the 36 states and FCT-Abuja were 3 525, stealing was 32 330, kidnapping (1133) and 2 278 rape cases were reported. Observing the dependent variables (crime counts), it shows that the standard deviation (or variance) is greater than the mean, this is a data problem of over-dispersion in statistical theory. The problem may arise as a result of varying population sizes, which is common occurrence in small area estimation. Our model approach is re-parameterized to account for spatial dependence and over-dispersion in the crime data.

Descriptive Statistics Table 3 is followed by Table 2 of Pearson correlation analysis and the associated p-values, used for testing of significance. The analysis shows that the correlation coefficients between armed robbery are significant ($p < 0.05$) and positively correlated with stealing and kidnapping at 5% probability level, but insignificant ($p > 0.05$) with rape. However, rape incidence indicates significant positive correlations with kidnapping and stealing crimes.

In addition, rape occurrence was positively correlated with unemployment rate, population density, EI and GNI, but negatively correlated with the percentage of young males. Other crimes (armed robbery, stealing and kidnapping) are positively correlated with percentage of young male population per state, but has negative correlation with rape. This shows that the rape incidents per

Table 2
Summary statistics of the variables recorded per state and used in the models.

Variable	N	Mean	Std. Dev	Sum	Minimum	Maximum
ROB	37	95.27	121.77	3525	1	564
THEFT	36	898.06	2096.00	32 330	20	12 724
KIDN	36	31.47	29.43	1133	2	104
RAPE	36	63.28	79.17	2278	2	441
POL	37	46.76	20.21	1730	18	112
UEMP	37	9.98	3.57	369.18	3.87	17.24
POD	37	1078	1475	39 887	139.50	8752
EDU	37	0.72	0.20	26.52	0.33	1.01
GNI	37	1655	1689	61250	400	8174
PMP (%)	37	12.90	2.50	4.766	7.60	19.40

N = number of observation data, Std. Dev = standard deviation, ROB = armed robbery, THEFT = theft or stealing, KIDN = kidnapping, RAPE = rape,
POL = number of divisional police Head Quarters, UEMP = unemployment rate,
POD = population density, EDU = education index (EI) per state, GNI = gross national income (per capita),
PMP = percentage of young adult males.

Table 3
Pearson Correlation Coefficients and associated p-values in the parenthesis among the variables.

	ROB	THEFT	KIDN	RAPE	POL	UNEP	POPD	EDU	GNI	PMP
ROB	1.000	0.448 0.006	0.649 < .0001	0.319 0.058	0.364 0.027	0.097 0.569	0.421 0.010	0.297 0.075	0.596 < .0001	0.189 0.262
THEFT		1.000	0.434 0.009	0.865 < .0001	0.533 0.001	0.010 0.955	0.861 < .0001	0.264 0.119	0.714 < .0001	0.013 0.940
KIDN			1.000	0.410 0.013	0.324 0.054	0.043 0.802	0.495 0.002	0.367 0.028	0.360 0.031	0.110 0.524
RAPE				1.000	0.492 0.002	0.215 0.209	0.797 < .0001	0.183 0.285	0.638 < .0001	−0.083 0.632
POL					1.000	0.034 0.842	0.606 < .0001	0.325 0.050	0.364 0.027	0.013 0.939
UNEP						1.000	0.053 0.755	0.061 0.722	0.180 0.285	0.194 0.251
POPD							1.000	0.452 0.005	0.611 < .0001	0.114 0.500
EDU								1.000	0.455 0.005	0.513 0.001
GNI									1.000	0.191 0.258
PMP										1.000

state are not determined by the proportion of young adult male population in each state, though there is no strong evidence of significant relation. This shows that the proportion of young males in a state (region) is inversely associated with the rape incidents. The analysis further shows that armed robbery, stealing and kidnapping are not significantly correlated with unemployment rate and state level of education, but all crimes show significantly positive correlation with gross national income (GNI) as a measure of level of economic activities in each state.

4.2. Posterior estimates of risk factors of crimes and model parameters

Results presented in Table 4 are the posterior mean for each fixed effect β parameter value, along with the 95% Bayesian credible interval. The model results comprise of three results: fixed effect covariates, spatial random effects and model fit parameters.

Table 4
Posterior Estimates of risk factors of covariates and model fit parameters.

Parameters	Theft (stealing)	armed robbery	rape	kidnapping
Fixed effects	Post. mean (95% CI)	Post. mean (95% CI)	Post. mean (95% CI)	Post.r mean (95% CI)
β_0	−0.346 (−0.597, −0.116)	0.134 (−0.205 0.453)	0.215 (−0.056, 0.454)	0.247 (−0.127, 0.651)
β_1	−0.352 (−0.753, 0.034)	−0.114 (−0.689 0.580)	−0.512 (−1.015, −0.052)	−0.124 (−0.775, 0.590)
β_2	−0.311 (−0.636, −0.028)	0.095 (−0.384 0.515)	0.383 (0.017, 0.758)	0.013 (−0.444, 0.458)
β_3	0.334 (−0.131, 0.859)	−0.596 (−1.377 0.254)	−0.481 (−0.986, 0.065)	−0.804 (−1.575, −0.024)
β_4	−0.292 (−0.726, 0.043)	−0.173 (−0.803 0.338)	−0.407 (−1.067, 0.069)	0.018 (−0.676, 0.773)
β_5	0.191 (−0.210, 0.538)	0.227 (−0.236 0.898)	0.311 (−0.109, 0.752)	0.188 (−0.339, 0.768)
β_6	0.122 (−0.399, 0.596)	0.101 (−0.529 0.646)	0.463 (−0.004, 0.941)	0.561 (−0.156, 1.371)
Random effects				
ϕ	0.226 (0.059, 0.466)	0.272 (0.052, 0.597)	0.421 (0.064, 0.826)	0.271 (0.039, 0.728)
sd_u	0.248 (0.052, 0.640)	0.424 (0.062, 1.050)	0.505 (0.056, 1.190)	0.448 (0.050, 1.270)
sd_v	0.809 (0.635, 0.986)	1.039 (0.698, 1.290)	0.626 (0.197, 0.951)	1.089 (0.467, 1.460)
σ_u^2	0.395 (0.089, 0.990)	0.679 (0.099 1.950)	0.829 (0.093, 1.829)	0.732 (0.081, 2.373)
σ_v^2	0.829 (0.601, 1.120)	1.060 (0.686 1.459)	0.621 (0.205, 1.027)	1.112 (0.464, 1.624)
Model fit				
$\bar{D}$	323	256.2	236.8	209.6
pD	−3119	−645.4	−1136	−104.9
DIC	−2796	−389.2	−899.5	104.7

β_0 = overall base risk (intercept), β_1 = number of divisional police HQ, β_2 = unemployment rate,
β_3 = population density, β_4 = education index, β_5 = gross national income (GNI) per capita,
β_6 = young adult male population (age 18–35).

Model fit. Considering the goodness of fit of the models as presented in Table 4, the resultant measure of model fit is given by deviance information criteria (DIC) are: DIC = −2796 (theft), −389.2 (robbery), −899.5 (rape) and 104.7 (kidnapping) with their corresponding measures of goodness of fit (pD): $pD = -3119, -645.4, -1136$ and -104.9 respectively, which measure the number of effective parameters in the model. The model deviance are: $D(\theta) = 323$ for theft, 256.2 (robbery), 236.8 (rape) and 209.6 (kidnapping), which are used to measure the model deviations.

Fixed effect of risk factors of the crime. Using the generic model equation (1), the model can be explicitly expressed as

$$\lambda(j) = e^{\beta_0+\sum_{j=1}^{6} X_j\beta_j} \tag{9}$$

The model base intensity is therefore computed by

$$\begin{aligned} \text{Theft} &: \lambda(i) = e^{(-0.3461)} = 0.7074417 \\ \text{Armed robbery} &: \lambda(i) = e^{(0.1342)} = 1.1436215 \\ \text{Rape} &: \lambda(i) = e^{(0.2471)} = 1.2803071 \\ \text{Kidnapping} &: \lambda(i) = e^{(0.215)} = 1.2398619 \end{aligned}$$

The model results presented in Table 4 are based on the 2017 reported crime data in Nigeria. Keeping all the risk factors constant, the results are interpreted as the overall risk of theft (stealing) will be reduced by about (1 − 0.7074 = 0.2926), approximately 30%, while the overall relative risk of armed robbery increases by 14.4%, rape increases by 28.0% and kidnapping will increase by approximately 24%.

The result further reveals that the presence of police structure, β_1 shows a negative relationship with all the crimes, indicating that the presence of policing infrastructure within the community will lead to reduction in crimes of types in the neighbourhoods. In fact, the presence of police infrastructure indicates a significantly negative association with rape incidents. The policing staffing capacity (number of police posts) did not show a strong evidence of significant association with other crimes understudy.

Furthermore, the population density coefficient β_3, showed a negative association with three of the crimes, except armed robbery, although the effect was not significant for any crime. In our case with a Poisson model and for easy interpretation, by exponentiating the coefficient of population density for stealing crime as exp(−0.596) =0.551; which can be interpreted as one unit increase in population density will lead to about 45% reduction in stealing cases, keeping other covariates constant. Similarly, one unit increase population density resulted in a 38.2% reduction in rape incidents and 55.2% reduction in kidnapping cases.

The analysis further reveals that the unemployment rate would significantly reduce theft occurrence as an indication of negative coefficient value. However, unemployment rate shows positive association with other crimes except stealing. This means that the unemployment factor would raise the risk of armed robbery by *exp*(0.095)= 1.099659, by approximately 10% rise in armed robbery, increase rape occurrence by 46.7% and 1.3% for kidnapping, but significant decrease of 26.7% in theft. On the contrary, an improvement in the education level of the populace would lead to reduction in crimes of all types, except rape as observed from the analysis results of coefficients, β_4.

Gross national income (GNI) per capita, which was used as a proxy for measuring the economic activities per state would induce a relative increase in risk of all the crimes, though the evidence does not show a strong significant association. Similarly, the percentage male population (PMP) demonstrates a trend effect similar to GNI, one unit percentage rise in PMP would lead to about 13% rise in theft incidents, 10.6% rise in armed robbery, about 59% rise in rape incidents and 75% rise in kidnapping cases, though the PMP effect was insignificant at 5% probability level.

Spatial heterogeneity of random effects. We fitted separate BYM model for the four crimes and the results of the analysis presented in Table 4. From the model (2) described above, the geographical variation is captured by two components: correlated, U and uncorrelated, V. The variation due to clustering (neighbourhood effect) is estimated as 0.226 (refer to Table 4). For instance, the theft incidents is estimated as 22.6%, indicates the proportion of variation attributed to spatial correlated random (neighbourhood) effect and the remaining $1 - \phi = 77.4\%$ contribution is attributed to heterogeneity (uncorrelated) random effect. The conditional variance parameters due to CAR component, for theft is estimated as σ_u^2= 0.395 95% CI (0.089, 0.990). This indicates that the variation in theft crime committed across the states exhibits more disparities (spatial random heterogeneity effect) in their geographical occurrence than clustering in Nigeria.

The results further reveal that the variations of the CAR components in other crimes: for armed robbery: 0.272 (0.052, 0.597); rape: 0.421 (0.064, 0.826) and kidnapping: 0.271 (0.039, 0.728). Their corresponding variance parameters due heterogeneity parts are estimated as: σ_v^2: robbery:0.679 (0.099 1.950); rape: 0.829 (0.093, 1.829) and kidnapping: 0.732 (0.081, 2.373). The analysis therefore reveals that the variations in the geographical distribution of crimes are not significant for robbery rape and kidnapping, because the credible intervals contain one. The geographic pattern of variation of these crimes can be attributed to more heterogeneity (uncorrelated) random effect than clustering in their geographical distribution. Perhaps, the reason may be adduced to the exposure to local environmental factors, underlying ecological indices such as severity in poverty at local-community level.

4.3. Spatial mapping the relative risk (RR) of crimes

The posterior means of relative risk of the crimes are mapped and displayed in Figs. 2 to 5 for armed robbery, theft, rape and kidnapping respectively along with their associated dot plots. The spatial residual effects are categorized into colour intervals of five quantiles (classes) based on overall RR of the crimes ranging from green (low) to red (high).

Armed robbery. The spatial variation for armed robbery incidence ranges between 0.075 and 9.906, as mapped in Fig. 2a. It is apparently evidenced that the predicted probability maps show disparities in the geographical variation of the crimes across the states in the country. From the map in Fig. 2(a), it indicates that significantly high incidence of armed robbery occurred in 16 states and FCT-Abuja as high risk regions (red colour) and low risk (green colour) incident occurred in 15 other states. On the corresponding dot-plot displayed in Fig. 2(b), a horizontal line was marked on "1', is used to segment the low risk areas (states) from high risk states. States having relative risk (RR) < 1 are classified as significantly low risk , RR $= 1$, it indicates not significant and (RR) > 1, it signifies a

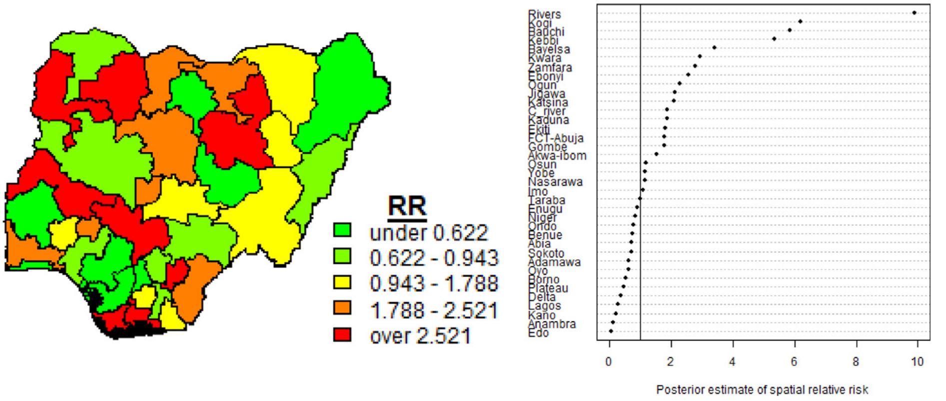


Fig. 2. The oosterior mean of spatial effects of armed robbery and a corresponding dot-plot of relative risk values of armed robbery crime for each state in Nigeria. Colour Quintile intervals for grouping the relative risk of crime from green (lowest risk) to red (highest risk)

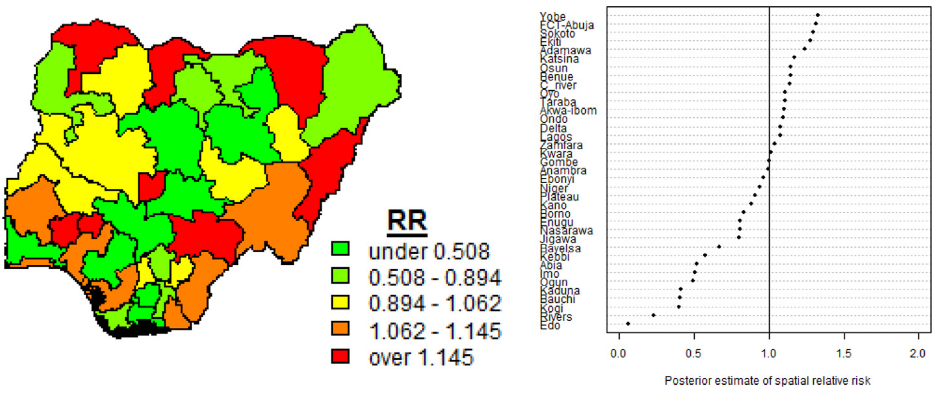


Fig. 3. The posterior mean of spatial effects of stealing (theft) and associated dot-plots of relative risk value of theft crime for each state in Nigeria. Colour Quintile intervals for grouping the relative risk of crime from green (lowest risk) to red (highest risk)

significant high risk. Using quintile colour classification, the states (areas) indicated on the map with (red coloured areas) show significantly high risk of robbery incidents are identified in Akwa-ibom, Gombe, Ekiti, Kaduna, Cross river, Katsina, Jigawa, Ogun, Ebonyi, Zamfara, Kwara, Bayelsa, Kebbi, Bauchi, Kogi, Rivers and FCT-Abuja.

Stealing. The spatial variation of stealing ranges between 0.065 and 1.325 as mapped in Fig. 3 a and an associated dot plot of the relative risk is displayed as Fig. 3 b. In Fig. 3 b, a horizontal line was marked on "1', is used to segment the low risk areas (states) from high risk states. States with RR value greater than one indicate significantly high risk area, while below one ($RR < 1$) are significantly low risk states. There is no evidence of any consistent in the geographical patterns of variation for theft or stealing incidence. The plot in Fig. 3(b) shows that there are significantly high risk of stealing are detected in 16 states (FCT-Abuja inclusive), while a relatively low stealing incident was found in 15 states. A careful inspection of the map, one can identify a trend pattern of stealing (theft) among the states along the eastern borders. Perhaps, the high incidence of stealing incidents could be attributed to civil unrest, herdsmen-farmers classes, and proliferation IDP camps as a result of Boko Haram terrorist activities in North East and North central political zones of

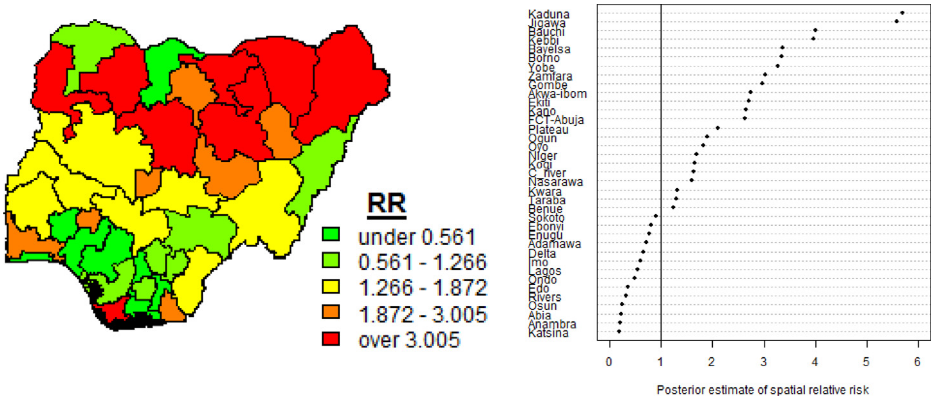


Fig. 4. Posterior mean of spatial effects of rape and associated dot-plots of relative risk value of rape crime for each state in Nigeria. Colour Quintile intervals for grouping the relative risk of crime from green (lowest risk) to red (highest risk)

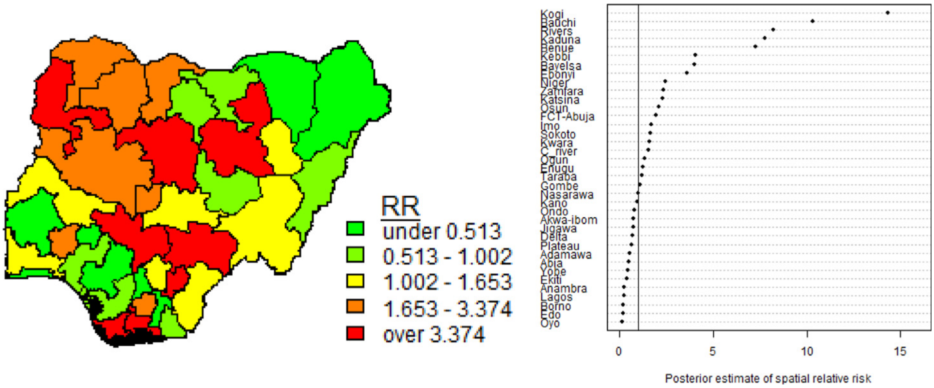


Fig. 5. The posterior mean of spatial effects of kidnapping and associated dot-plots of relative risk values of kidnapping crime for each state in Nigeria. Colour Quintile intervals for grouping the relative risk of crime from green (lowest risk) to red (highest risk)

Nigeria. Other contributory factors to rising theft incidents could be frequent communal clashes in the south-east zone and the inflows of migrants (refugee camps) in Cross Rives state due to political crisis in the neighbouring country.

Rape. The spatial variation of rape occurrence ranges from 0.1937 to 5.698 as displayed in Fig. 4(a) and a corresponding dot plot of RR value of rape crime displayed as Fig. 4(b). The predicted map in Fig. 4a depicts a significantly high incidence of rape in 17 states and majorly clustered in the northern parts (north central and north east regions) of the country, while a relatively low incidence occurred in the southern parts of the country. Using the 95% credible intervals for significance level, the map (c) indicates a significantly high incidence of rape crime in the states: Niger, Oyo, Ogun, Plateau, Kano, Ekiti, Akwa-ibom, Gombe, Zamfara, Yobe, Borno, Bayelsa, Kebbi, Bauchi, Jigawa, Kaduna and FCT-Abuja.

Kidnapping. The spatial variation of kidnapping occurrence was between 0.1623 and 14.35 as mapped in Fig. 5a. The spatial predictive map displayed in Fig. 5(a) indicates that a strong clustered tendency of occurrence exists among states of in the north-west, north-central, south-east and south-south zones of the country. A significant high risk was experienced in states such as Bauchi, Katsina, Kogi, Niger, Kebbi, Benue, Kaduna, Sokoto, Zamfara, Ebonyi, Bayelsa, Rivers, Imo, Osun, and FCT-Abuja, while a relative low risk of kidnapping incidents occurred in the north-east and south west zones of the country.

It is worth noting that despite the volume of commercial activities and high population density in Lagos state, significantly low risk of kidnapping was recorded in Lagos state, but a high risk of kidnapping crime was induced in its neighbouring state of Ogun State. Similarly, the socio-economic and demographic characteristics of Kano state in northern part of the country can influence the crime rates on neighbouring states of Kaduna, Katsina, Bauchi, Jigawa and Zamfara. A different scenario can be used to illustrate the neighbourhood pattern of robbery around Kano state. For example, armed robbery occurrence is relatively low in Kano, but Kano is bordered by the neighbouring states with high robbery incidents, whereas map displayed in Fig. 5(a) indicates low theft (stealing) in Kano, but surrounded by states with low theft incidence, except Katsina. The Fig. 5(b) is the corresponding dotplots, which consolidates the spatial map (a) with a vertical line mark on "1" segmenting the relative low risk states from high risk states of theft. The spatial model approach was able to detect clusters in the map, where Lagos and Kano states are found on the low risk side ($RR < 1$) and their state border these are found with high crime side (i.e. $RR > 1$). In general, the geographical patterns in the distribution of these crimes understudy demonstrate more spatial disparities across the states rather than the presence of strong neighbourhood characteristics (clustering).

5. Discussion

This study explores a Poisson version of generalized mixed models. Other studies on personal crimes have explored a multilevel negative binomial regression with extra variation (Tseloni, 2000; Goldstein, 1996) and in community policing Robinson (2003). Sparks (2011) adopts a spatial epidemiology model and observed that the determinants of crime depend on the model specification, where the author has investigated environmental factors and neighbourhood socioeconomic characteristics. They found that violent crimes in San Antonio were majorly associated with environmental characteristics, such as vacant housing and land use diversity.

This study reveals that population density leads to reduction in crimes. That is, a high population density will lead to reduced crime rates in the neighbourhoods as the criminal acts can be prevented by the fear of close and easier street monitoring by people in a densely populated street or community. However, our result on population density was not in complete agreement with the results from a similar study conducted using 2006 Nigeria data by Kunnuji (2016). Though Kunnuji (2016) used a simple ordinary regression analysis without spatial components in the model and they concluded that population density was found to be a good predictor of the volume of crime, but not the crime rates. Our finding is in tandem with similar empirical studies in other regions. Previous studies have demonstrated that the association between population density and crimes are found to be inversely related, which means that a high residential density can lower crime rates (Zhang and Peterson, 2007; Faria et al., 2013). For example, a study conducted in Brazil by Faria et al. (2013) found that higher overall crime rates in the Plano Piloto are related to the high concentration of commercial activities, lower density and greater population size, while lower burglary rates are related to areas with vertical housing designs. Conversely, a few other studies have hypothesized that high population densities create a high potential for crime because people and property are crowded in small spaces (Harries, 1995).

Mixed findings have been reported in other studies. The present analysis showed that the number of police posts is positively correlated with population density, but showed negative association with the crimes in our model. These findings indicate that the presence of police posts in the neighbourhood or within the community would lead to reduction in criminal activities of all types. In advanced jurisdiction, policing is usually measured by the number of community policing and monitoring rooms in each neighbourhood per 10 000 people. Other studies have found that the density of community police units and population density are positively correlated with crime. Evidence has shown that a larger population would induce the higher number of crimes in the surrounding neighbourhoods (Hipp and Kane, 2017; Ilijazi et al., 2019) and a population density is also related to increased police presence.

The analysis further revealed that unemployment and percentage young male population are positively associated with the crime rates (both personal and property crimes) in the country. This finding was consistent with previous studies. For instance, a empirical study conducted in Sweden found that there was a statistically and economically significant effect of youth unemployment on the incidence of burglary, auto theft, and drug possession (Öster and Agell, 2007). Altindag (2012) recently adopted a two-stage least squares (2SLS) estimation method and found that unemployment has a positive influence on property crimes, whereas Mocan and Rees (2005) earlier used ordinary regression analysis to investigate juvenile crime among high school children in the U.S and they concluded that a 1% increase in unemployment led to a 3% increase in the probability of committing a robbery crime. In other words, a 2% decrease in unemployment would lead to a reduction in juvenile crimes by 0.6% as reported by Mocan and Rees (2005). Several other studies have shown that young males are hugely over-represented among those engaged in criminal activities (Ackerman, 1998; Hannon, 2002; Liu and Zhu, 2017).

Results also demonstrated that improvement in quality of education can lead to reduction in crimes. Education is viewed as a process that teaches individuals to be more patient (Becker and Mulligan, 1997). This would discourage forward-looking persons to engage in crime, since such individuals place greater weight on any expected future punishment associated with their criminal activities (Lochner, 2020). In his earlier work, Lochner (2004) emphasizes the role of education as a human capita investment that increases future legitimate work opportunities, which discourages participation in crime. Thus, an investment in education of the youth and policies that promotes schooling would reduce most types of street crimes among adults. However, Lochner (2004) further argued that certain types of white collar crime such as embezzlement, fraud and corruption may increase with higher education attainment as if they sufficiently reward skills learned in school.

Other previous studies have established numerous and complex determinant factors and social disorganization. A good example typically involves a mix of mental health issues, addiction, peer associations, family disruptions, socioeconomic status, residential mobility, educational and employment opportunities, and poverty, among many other social, economic, and political issues (Andrews and Bontà, 1994; Andresen, 2006; Jacob, 2006; Dawson and Cuppleditch, 2007). A study conducted by Andresen and Brantingham (2007) found that high crime in the neighbourhoods is related to higher population residents, more single people, fewer immigrants and visible minorities, higher unemployment, lower family income, and more renters in the City of Vancouver in Canada.

6. Conclusion

This study expands the methodological strategy by linking the existing criminology literature and spatial modelling approach in a unified manner. In contrast to the conventional regression model, the Bayesian spatial model has not only taken into account borrowing information from neighbouring states, but also evaluated the relation between the socio-demographic determinant factors of the crimes. Bayesian models can easily accommodate unobserved variables such as an individual state risk level in the presence of diagnostic error. The use of prior probability distributions provides a powerful mechanism for incorporating information from previous studies or expert knowledge and for controlling confounding factors. The Bayesian analysis basically utilizes posterior probabilities for easy interpretable alternatives to p-values. The objective of the present analysis is to examine how demographic and the socio-economic characteristics at the sub-national level influences the crime patterns in Nigeria. This study adds to the literature on the topic of violent crime by using recent detailed spatial data on violent crimes (personal and property crime) and by controlling of other confounding factors. This contribution is also significant because of the use of the Bayesian statistical framework for parameter estimation and for model inference, and the use of disease mapping methods to visualize the locations of high crime risk areas.

This research study was not without limitations. First, the data came from only 2017 reported cases of Crime by Nigeria Police Force and the mid 2017's projected population census was used. A more temporal depth in the last one decade (2010–2019) could reveal different patterns in the crime risk. Secondly, the analysis has discussed the associations between the ecological characteristics and the characteristics of the individual crimes, which cannot be controlled and nothing is known of the victims or the profile of perpetrators of these crimes. Most importantly, the nature of data reported on crimes might impact the spatial effect underlying the observed spatial patterns of the crimes. In real situations, there is under-reporting of crime cases due to variability of case reporting at the local level thereby producing biased estimations for count models in the true underlying pattern of the crimes.

Notwithstanding the limitations, the main purpose of the present study is to illustrate the use of a Bayesian spatial model as commonly applied in disease mapping models (Lawson, 2013) for crime mapping and for investigating the geographic patterns of crimes in Nigeria.

CRediT authorship contribution statement

Rasheed A. Adeyemi: Designed and conceptualized the study, Developed the model u wrote the WinBUGS code, Performed the statistical analyses, Drafted the original manuscript, Wrote Latex type-setting, Edited the draft and implemented the final correction of the manuscript. **James Mayaki:** Designed and conceptualized the study, Drafted the original manuscript, Edited the draft and implemented the final correction of the manuscript. **Temesgen T. Zewotir:** Designed and conceptualized the study, Advised on the proposed models, Commented on the first draft. **Shaun Ramroop:** Designed and conceptualized the study, Advised on the proposed models, Commented on the first draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data associated with this article can be found in the online version at Nigeria's National Bureau of Statistics.

Acknowledgements

The authors would like to thank the Nigeria's National Bureau of Statistics for the data. The authors also thank the anonymous referees and Editor of the journal for their encouragement and insightful comments. All authors read and approved the final manuscript.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.spasta.2020.100485.

References

Ackerman, W.V., 1998. Socioeconomic correlates of increasing crime rates in smaller communities. Prof. Geogr. 50 (3), 372–387.
Altindag, D.T., 2012. Crime and unemployment: Evidence from europe. Int. Rev. Law Econom. 32 (1), 145–157.
Andresen, M.A., 2006. A spatial analysis of crime in vancouver, british columbia: A synthesis of social disorganization and routine activity theory. Can. Geogr./Géogr. Can. 50 (4), 487–502.
Andresen, M.A., Brantingham, P.J., 2007. Hot Spots of Crime in Vancouver and their Relationship with Population Characteristics. Department of Justice Canada, Ottawa.
Andrews, D.A., Bontà, J., 1994. The Psychology of Criminal Conduct, second ed.

Arnio, A.N., Baumer, E.P., 2012. Demography, foreclosure, and crime: Assessing spatial heterogeneity in contemporary models of neighborhood crime rates. Demograph. Res. 26, 449–486.
Barbosa, G.Y., 2019. Immigrant residential segregation. In: The Wiley Blackwell Encyclopedia of Urban and Regional Studies. pp. 1–9. http://dx.doi.org/10.1007/s13524-012-0177-x.
Becker, G.S., Mulligan, C.B., 1997. The endogenous determination of time preference. Q. J. Econ. 112 (3), 729–758.
Besag, J., Kooperberg, C., 1995. On conditional and intrinsic autoregressions. Biometrika 82 (4), 733–746.
Besag, J., York, J., Mollié, A., 1991. Bayesian image restoration, with two applications in spatial statistics. Ann. Inst. Statist. Math 43 (1), 1–20.
Best, N., Richardson, S., Thomson, A., 2005. A comparison of bayesian spatial models for disease mapping. Stat. Methods Med. Res. 14 (1), 35–59.
Brantingham, P.L., Brantingham, P.J., 1995. Location quotients and crime hot spots in the city. In: Crime Analysis Through Computer Mapping. Executive Research Forum, Washington, DC, pp. 129–149.
Brantingham, P., Brantingham, P., 2013. Crime pattern theory. In: Criminology and Crime Analysis. Willan, pp. 100–116.
Brunsdon, C., Fotheringham, A.S., Charlton, M.E., 1996. Geographically weighted regression: a method for exploring spatial nonstationarity. Geogr. Anal. 28 (4), 281–298.
Carcach, C., Muscat, G., 2002. Location quotients of crime and their use in the study of area crime careers and regional crime structures. Crime Prev. Commun. Saf. 4 (1), 27–46.
Charron, M., 2009. Neighbourhood Characteristics and the Distribution of Police-Reported Crime in the City of Toronto. Statistics Canada Ottawa.
Chen, J.T., 2013. 11 multilevel and hierarchical models for disease mapping. In: Geographic Health Data: Fundamental Techniques for Analysis. p. 183.
Craglia, M., Haining, R., Signoretta, P., 2001. Modelling high-intensity crime areas in english cities. Urban Stud. 38 (11), 1921–1941.
Dawson, P., Cuppleditch, L., 2007. An Impact Assessment of the Prolific and Other Priority Offender Programme. Home Office London.
Faria, J.R., Ogura, L.M., Sachsida, A., 2013. Crime in a planned city: The case of brasília. Cities 32, 80–87.
Fernández, C., Green, P.J., 2002. Modelling spatially correlated data via mixtures: a bayesian approach. J. R. Stat. Soc. Ser. B Stat. Methodol. 64 (4), 805–826.
Fitzgerald, R., Wisener, M., Savoie, J., 2004. Neighbourhood Characteristics and the Distribution of Crime in Winnipeg. Statistics Canada.
Frenken, K.E., 2005. Irrigation in africa in figures:. AQUASTAT Survey. p. 29.
Gelman, A., Carlin, J.B., Stern, H.S., Rubin, D.B., 2004. Bayesian Data Analysis. Chapman & Hall/CRC. Inc., New York.
Gilks, W., Richardson, S., Spiegelhalter, D., 1996. Markov Chain Monte Carlo in Practice. Chapman & Hall, London.
Goldstein, H., 1996. Consistent estimators for multilevel generalised linear models using an iterated bootstrap. Multilevel Modell. Newslett. 8 (1), 3–6.
Green, P.J., 2019. Introduction to finite mixtures. In: Handbook of Mixture Analysis. Chapman and Hall/CRC, pp. 3–20.
Green, P.J., Richardson, S., 2002. Hidden markov models and disease mapping. J. Amer. Statist. Assoc. 97 (460), 1055–1070.
Gschlößl, S., Czado, C., 2008. Modelling count data with overdispersion and spatial effects. Statist. Papers 49 (3), 531.
Hannon, L., 2002. Criminal opportunity theory and the relationship between poverty and property crime. Sociol. Spectrum 22 (3), 363–381.
Harries, K.D., 1995. Mapping Crime: Principle and Practice. US Department of Justice. Office of Justice Programs, National Institute of ….
Harries, K., Powell, A., 1994. Juvenile gun crime and social stress: Baltimore, 1980–1990. Urban Geogr. 15 (1), 45–63.
Hipp, J.R., 2010. Micro-structure in micro-neighborhoods: a new social distance measure, and its effect on individual and aggregated perceptions of crime and disorder. Social Networks 32 (2), 148–159.
Hipp, J.R., Kane, K., 2017. Cities and the larger context: What explains changing levels of crime? J. Crim. Justice 49, 32–44.
Hirschman, C., Tolnay, S.E., 2005. Social demography. In: Handbook of Population. Springer, pp. 419–449.
Hove, M., Ngwerume, E.T., Muchemwa, C., 2013. The urban crisis in sub-saharan africa: A threat to human security and sustainable development.
Ilijazi, V., Milic, N., Milidragovic, D., Popovic, B., 2019. An assessment of police officers' perception of hotspots: What can be done to improve officer's situational awareness? ISPRS Int. J. Geo-Inf. 8 (6), 260.
Jacob, J., 2006. Male and female youth crime in canadian communities: Assessing the applicability of social disorganization theory. Can. J. Criminol. Crim. Justice 48 (1), 31–60.
Kessides, C., 2007. The urban transition in sub-saharan africa: challenges and opportunities. Environ. Plan. C: Gov. Policy 25 (4), 466–485.
King, R.D., Massoglia, M., MacMillan, R., 2007. The context of marriage and crime: Gender, the propensity to marry, and offending in early adulthood. Criminology 45 (1), 33–65.
King, R.D., South, S.J., 2011. Crime, race, and the transition to marriage. J. Family Issues 32 (1), 99–126.
Knorr-Held, L., Raßer, G., 2000. Bayesian detection of clusters and discontinuities in disease maps. Biometrics 56 (1), 13–21.
Kunnuji, M.O., 2016. Population density and armed robbery in nigeria: an analysis of variation across states. Afr. J. Criminol. Justice Stud. 9 (1), 62–73.
Laub, J.H., Nagin, D.S., Sampson, R.J., 1998. Trajectories of change in criminal offending: Good marriages and the desistance process. Amer. Sociol. Rev. 225–238.
Law, J., Quick, M., Chan, P., 2014. Bayesian spatio-temporal modeling for analysing local patterns of crime over time at the small-area level. J. Quant. Criminol. 30 (1), 57–78.

Lawson, A.B., 2013. Bayesian Disease Mapping: Hierarchical Modeling in Spatial Epidemiology. CRC Press.
Lawson, A.B., Browne, W.J., Rodeiro, C.L.V., 2003. Disease Mapping with WinBUGS and MLwiN, Vol. 11. John Wiley & Sons.
Liu, H., Zhu, X., 2017. Joint modeling of multiple crimes: A bayesian spatial approach. ISPRS Int. J. Geo-Inf. 6 (1), 16.
Lobonţ, O.R., Nicolescu, A.C., Moldovan, N.C., Kuloğlu, A., 2017. The effect of socioeconomic factors on crime rates in romania: a macro-level analysis. Econ. Res.-Ekonomska Istraživanja 30 (1), 91–111.
Lochner, L., 2004. Education, work, and crime: A human capital approach. Internat. Econom. Rev. 45 (3), 811–843.
Lochner, L., 2020. Education and crime. In: The Economics of Education. Elsevier, pp. 109–117.
Marco, M., Gracia, E., López-Quílez, A., 2017. Linking neighborhood characteristics and drug-related police interventions: A Bayesian spatial analysis. ISPRS Int. J. Geo-Inf. 6 (3), 65.
McCord, E.S., Ratcliffe, J.H., 2009. Intensity value analysis and the criminogenic effects of land use features on local crime patterns. Crime Patterns Anal. 2 (1), 17–30.
Mocan, H.N., Rees, D.I., 2005. Economic conditions, deterrence and juvenile crime: Evidence from micro data. Amer. Law Econom. Rev. 7 (2), 319–349.
Morenoff, J.D., Sampson, R.J., 1997. Violent crime and the spatial dynamics of neighborhood transition: Chicago, 1970–1990. Soc. Forces 76 (1), 31–64.
National Bureau of Statistics, 2017. Crimestatistics: Reported offences by type and states. Data can be downloaded at: wwwnigerianstatgovng.
Oguntunde, P.E., Ojo, O.O., Okagbue, H.I., Oguntunde, O.A., 2018. Analysis of selected crime data in nigeria. Data Brief 19, 1242–1249.
Omotor, D.G., 2009. Socio-economic determinants of crime in nigeria. Pakistan J. Soc. Sci. 6 (2), 54–59.
Öster, A., Agell, J., 2007. Crime and unemployment in turbulent times. J. Eur. Econom. Assoc. 5 (4), 752–775.
Robinson, A.L., 2003. The impact of police social capital on officer performance of community policing. Policing: Int. J. Police Strateg. Manage.
Sampson, R.J., Morenoff, J.D., Gannon-Rowley, T., 2002. Assessing "neighborhood effects": Social processes and new directions in research. Ann. Rev. Sociol. 28 (1), 443–478.
Shaw, C.R., McKay, H.D., 1942. Juvenile delinquency and urban areas.
South, S.J., Deane, G.D., 1993. Race and residential mobility: Individual determinants and structural constraints. Soc. Forces 72 (1), 147–167. http://dx.doi.org/10.1093/sf/72.1.147.
South, S.J., Messner, S.F., 2000. Crime and demography: Multiple linkages, reciprocal relations. Ann. Rev. Sociol. 26 (1), 83–106. http://dx.doi.org/10.1146/annurev.soc.26.1.83.
Sparks, C.S., 2011. Violent crime in san antonio, texas: An application of spatial epidemiological methods. Spat. Spat.-Temporal Epidemiol. 2 (4), 301–309.
Spiegelhalter, D.J., Best, N.G., Carlin, B.P., Van Der Linde, A., 2002. Bayesian measures of model complexity and fit. J. R. Stat. Soc. Ser. B Stat. Methodol. 64 (4), 583–639.
Spiegelhalter, D.J., Thomas, A., Best, N.G., Gilks, W., Lunn, D., 1996. Bugs: Bayesian inference using gibbs sampling. Version 05, (version ii). p. 19, http://wwwmrc-bsucamacuk/bugs.
Thomas, A., Best, N., Lunn, D., Arnold, R., Spiegelhalter, D., 2004. Geobugs User Manual. Medical Research Council Biostatistics Unit, Cambridge.
Tseloni, A., 2000. Personal criminal victimization in the united states: Fixed and random effects of individual and household characteristics. J. Quant. Criminol. 16 (4), 415–442.
UNDP, 2018. Human development indices and indicators: 2018 statistical update: Briefing note for countries on the 2018 statistical update–nigeria.
Wakefield, J., Best, N., Waller, L., 2000. Bayesian approaches to disease mapping. In: Spatial Epidemiology: Methods and Applications. pp. 104–107.
Xie, M., McDowall, D., 2010. The reproduction of racial inequality: How crime affects housing turnover. Criminology 48 (3), 865–896.
Zhang, H., Peterson, M.P., 2007. A spatial analysis of neighborhood crime in omaha, nebraska using alternative measures of crime rates. Internet J. Criminol. 31, 1–31.
Zimmerman, G.M., Messner, S.F., 2011. Neighborhood context and nonlinear peer effects on adolescent violent crime. Criminology 49 (3), 873–903.