Spatial Heterogeneity Modeling of the Neighborhood Effects and Socio-economic Factors on Burglary Crimes in Nigeria

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ABSTRACT

This paper examined the geographical patterns of distribution in burglary crimes (residential and nonresidential) in Nigeria for the incidence year 2017. The study used a novel approach that integrates spatial structures into the traditional regression framework and evaluates the spatial disparities in neighborhood effects and the socio-economic characteristics of burglary crimes at sub-national levels. The study proposed four spatially varying models to demonstrate the importance of incorporating spatial dependence components in the models. The determinant factors included in the model are; unemployment, education, and poverty indices, alongside demographic variables, to understand crime patterns. The determinant factors included in the model are; the unemployment rate, education index, population density, percent economic deprivation, multidimensional poverty index (MPI), and proportion of young adult males resident in the state. A Bayesian analysis was performed via Markov chain Monte Carlo simulations to estimate the model parameters. The analysis revealed that the proportional contribution due to the neighborhood (clustering) effect was estimated as 24.7% for the house-breaking and the estimated neighborhood contribution as 29.0% for the store-breaking occurrence. This approach demonstrates superiority in model performance, as indicated by the lowest Deviance Information Criterion (DIC). Findings reveal negative associations between burglary and multidimensional poverty, while young male adults show a positive relationship with store-breaking incidents. Hot spot areas and spatial variations in crime patterns are identified, offering insights for criminologists and informing policing strategies for effective crime prevention.

Keywords

Spatial Geography, Crime Hotspots, Crime Mapping, Poisson Count Data, Spatial Regression Models, Mixed Effect Models

1. INTRODUCTION

The issue of crime is a multifaceted and complex social phenomenon that has profound effects on individuals, communities, and societies worldwide [27]. One type of crime that has significant ramifications is burglary, which involves unlawful entry into a building or structure with the intent to commit theft or another felony [10, 17]. Burglary is a major concern for individuals, researchers, law enforcement agencies, and policymakers, particularly in developing countries such as Nigeria, where it is a pervasive problem with high rates reported in urban and suburban areas [37, 25, 2].

In addition to having an adverse effect on the physical, social, and economic well-being of a community, burglaries also incur substantial financial costs for individuals, corporations, and governments in the form of insurance premiums, security precautions, and law enforcement resources [27]. To develop successful crime prevention and intervention methods, it is crucial to understand the spatial trends of theft and its fundamental causes.

Criminologists, law enforcement officers, and decision-makers have long been interested in the study of patterns and trends in crime. Over the years, numerous theories and models have been developed to explain the reasons behind crime and to forecast when it will occur. The routine activity theory, the crime pattern theory, and the rational choice theory are just a few of the theories and methods covered by [42] when attempting to explain the spatial and temporal patterns of domestic burglary. Different techniques, such as geographic information systems (GIS), spatial regression models, and hot spot analysis, have been used to examine the geographical and temporal trends of home burglary. In criminology, spatial modeling methods are frequently employed to investigate spatial trends of crime and pinpoint its causes [11, 12, 42]. To create focused interventions and find crime hotspots, spatial models offer a paradigm for examining the connection between crime and its spatial environment [41, 27, 35].

Numerous studies have investigated the spatial patterns of burglary across various regions of the world. [28] conducted a study in the United Kingdom and found that areas with a high proportion of rented properties, low levels of social cohesion, and high levels of deprivation had a greater incidence of burglary. In China City, [50] discovered that burglary rates were higher in areas with a high density of commercial properties and population density and, that the spatial distribution of these incidents varies over time.
Additionally, [40] investigated the connection between income inequality and the geographic distribution of residential burglaries in Campinas, Brazil, and discovered a statistically significant positive correlation between the two. This finding suggests that neighborhoods with higher income inequality are more likely to experience burglaries. [39] utilized crime pattern theory in conjunction with a statistical heterogeneous spatial point process model to analyze crime data from the Metropolitan Police Service and environmental data from various sources in London. They discovered that burglary was not randomly distributed throughout the city but rather, there were hot spots of burglary activities in specific areas. Factors such as social deprivation, proximity to transport links, and proximity to commercial areas were significant predictors of burglary. Thus, spatial point process models can offer a better understanding of crime patterns and inform policy decisions aimed at reducing crime in urban areas.
Recent research has highlighted the importance of neighborhood characteristics and spatial structure in shaping crime rates. Specifically, neighborhood characteristics, such as poverty, social cohesion, and physical disorder, can interact with the spatial structure of neighborhoods, resulting in spatial autocorrelation, which is the tendency for crime to cluster in space [16, 39, 1, 8].
In Nigeria, burglary represents a significant and persistent problem that causes a considerable number of victims each year. The 2017 Nigerian Police Force Crime Statistics (Nigeria, 2017) revealed that burglary accounted for 17.3% of all reported crimes in the country. Previous studies have investigated the factors that contribute to burglary in different states of Nigeria and identified poverty, unemployment, ineffective law enforcement or crime control, and poor urban planning as significant determinants of burglary crime[20, 1, 35]. Given the persistent problem of burglary in Nigeria, more research is needed to better understand the complex interplay between neighborhood characteristics and spatial structure in mapping hot spots of burglary crime rates and to estimate determinant factors for effective prevention strategies.
The remainder of this paper is structured as follows. Section 2, discusses analytic models for crime rates. Section 3, presents the findings, including risk estimates and spatial crime rate maps, and evaluates the model fit in light of neighborhood characteristics. Section 4, provides a general discussion of the findings. The conclusive insights are contained in the final section.

1.1 Study Design and Data

Nigeria is made up of a federation of thirty-six states and one Federal Capital Territory Abuja, which are regarded as a second-tier administrative level. The states are divided into 774 Local Government Areas (LGAs) in total. These 774 local government areas (LGAs), are each administered by a local government council consisting of a chairman, who is the chief executive, and other elected members, who are referred to as councillors. Each LGA is further subdivided into a minimum of ten and a maximum of twenty wards. The country is located in the tropical zone of West Africa between latitudes 4° N and 14° N and longitudes $2^\circ 2'$ E and $14^\circ 30'$ E and has a total area of 923 770 km^2. The detailed description of geographical distribution, agroforestry zones, landmass, and climatic distribution have been reported elsewhere in [18]. For the present study and the spatial model approach, these sub-nationals would be regarded as 37 districts (36 states and FCT, Abuja), and the geographical map is shown in Figure 1

Data. Data on burglaries (residential and non-residential) cases came from the Nigeria Crime Statistics on cases reported in 2017 managed and stored by the Nigeria Bureau of Statistics. The reporting system is the primary source of official crime information in Nigeria, as the public reports crimes to the Nigeria Police Force through emergency phone lines. A total of 3212 residential burglaries and 1872 non-residential (store breaking) incidents occurred in the study region from 1 January 2017 to 31 December 2017, respectively. Both types of incidents were unevenly distributed among neighborhoods (states) and the summary statistics of the state-level covariates are presented in Table 1. These incident data are used as dependent variables.

Fig. 1. **Map of Nigeria showing 37 districts (36 states and Federal Capital Territory (FCT)- Abuja**

Primary Outcome. This study analyzed data on Crime Statistics records as officially reported by Nigeria Police Force and stored in the database archive of the [38]. The crime data involved two types of burglary cases (that is, residential housebreaking and non-residential; store or warehouse breaking as indicated by Nigeria Police Force) for the incidence year 2017 are used as dependent variables in the models. Burglary is generally described as an illegal entry of a building with intent to commit a crime, especially theft during the night or day time. Housebreaking is the act of using physical force to gain access to and enter a house(dwelling homes) with the intent to commit a felony inside the house at any time of the day or night.
Store Breaking is an act of using physical force to gain access to, and enter a store (*non-residence*) with the intent to commit a felony inside during the day or night.

Table 1. **Descriptive Statistics of the variables in the model**

Variables	No. of observations	Minimum	Maximum	Mean	SD
Dependent Variables					
Residential (House breaking)	36	1	668	139.95	89.22
Non-residential(Store breaking)	33	1	417	94.28	56.73
Independent Variables					
MPI	37	0.02	0.59	0.18	0.23
School Attendance index (SEI)	37	1.01	69.12	22.27	22.12
% Economic deprivation	37	37.83	67	8.95	48.52
Unemployment rate	37	3.87	17.24	9.98	3.57
Young Male population	37	295058	1706146	663482	294566.15
Population density	37	139.50	8752.28	1078.04	1475.20

*MPI-Multi-dimensional Poverty index

Other variables. Population-level characteristics were measured to assess the influence of key sociodemographic and behavioral risk factors on crime outcomes across Nigeria and they are used as independent variables or measurable predictors. The Nigeria Population size used in this study is the projected population census for 2017 as computed by the National Population Commission based on the 2006 census.

In similar crime studies such as [34], population density is sometimes used as an alternative to population size and computed as the number of persons per square kilometers given by the total population of a state divided by the landmass area of the state in square kilometer). The unemployment rate is calculated as the total number of unemployed residents in each state between ages 18-60 divided by the available labor force population in the state. The young male population (YMP) 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 extracted from Youth Survey (NBS) published [38].

Percentage Population economic deprivation is defined as the intensity of deprivation among the poor economically deprived persons residents in a state and the computation was based on the Nigeria Demographic and Health (NDHS) survey 2018 as reported in [3]. Multidimensional poverty index (MPI) is described as the global multidimensional poverty index (MPI)=$H * A$ and defined in [3]. The computation is based on average % weighted deprivations from NDHS 2018, where H="Headcount ratio and A="Intensity of deprivation among the poor ". School attendance index (SAI) is calculated using Mean Years of Schooling and Expected Years of Schooling as extracted from data in the tables are those available to the Human Development Index 2018 according to [3].

The demographic and socio-economic covariates adopted in this study have been identified as dominant factors in social deprivation, social fragmentation, and population density as the underlying factors of crimes [44, 30]. This study also included a novel variable education index as an important factor in social disorganization [43].

Data observations visualization. The cases of house-breaking crimes (that is, residential burglary) and the specific area observations are mapped per state to illustrate the data visualization for the complex model as displayed in Figure 2. Map(a) shows the observed counts of residential burglary. Lagos and Abia districts had the highest number of reported cases as indicated in green color areas (upper legend), while other states observed lower incidences. The white area indicates a case where the data is not available (missing value). The map (g) displays the store-breaking cases for the incidence year 2017 with cases ranging between 1 to 417 and missing values in 4 states indicated in white areas. High store-breaking cases were recorded in Lagos and Delta states as seen in the green areas.

Map(b) illustrates the proportion of the population education index, which shows that a low level of education is prevalent among the population living in the Northern parts of the country compared to Southern Nigeria. Conversely, map(c) illustrates the pattern distribution in the severe poverty index indicating that a large percentage of the population living in the northern parts of the country experience higher multidimensional poverty as seen in the upper part of the legend with green color. The map(d)displays the population size by states (in thousands). It can be observed that Lagos and Kano states have the largest population of residents as indicated in the green regions. Map (e) is the unemployment rate for the fourth Quarter of 2017 and it shows the spatial variation in unemployment across states and regions in Nigeria. The proportion of economically deprived people living in each state is displayed in the map (f) and it shows that a large percentage of the population living in the Northern parts of the country are economically disadvantaged as shown in the green regions. The proportion of young adult males (18-35 years) residents in a state is also included in the model. These factors have been considered important in the previous studies shown that young male adults and economically deprived people are found to be dominantly involved in criminal activities in their neighborhoods as reported in previous studies [26, 4, 29, 23].

2. THE STATISTICAL METHOD

The 36 states and FCT-Abuja are treated as 37 districts in Nigeria, partitioned into non-overlapping areas, denoted as A_i, with the partition usually defined by available data, $i = 1, 2, \ldots, n$. Confounders likely to influence the analysis are identified as *a priori*. Assuming there are J confounders strata (that is, crime type). For a specific crime, Y_{ij} and N_{ij} denote, respectively, the number of incident cases and the total crime (or population in case of disease), in state i, stratum j, $i = 1, \ldots, n,\ j = 1, \ldots, J$. Demographic confounders are defined as crime type and young adult males, with additional control applied for the incidence year. See Best [6] for more readings. Populations used are available from the 2017 projected population by the National Population Commission (NPC) and the National Bureau of Statistics (NBS), Abuja.

Spatially structured models are employed to analyze the variation in the occurrence of burglary crimes in the Nigerian context. Bayesian hierarchical model allows the incorporation of sources

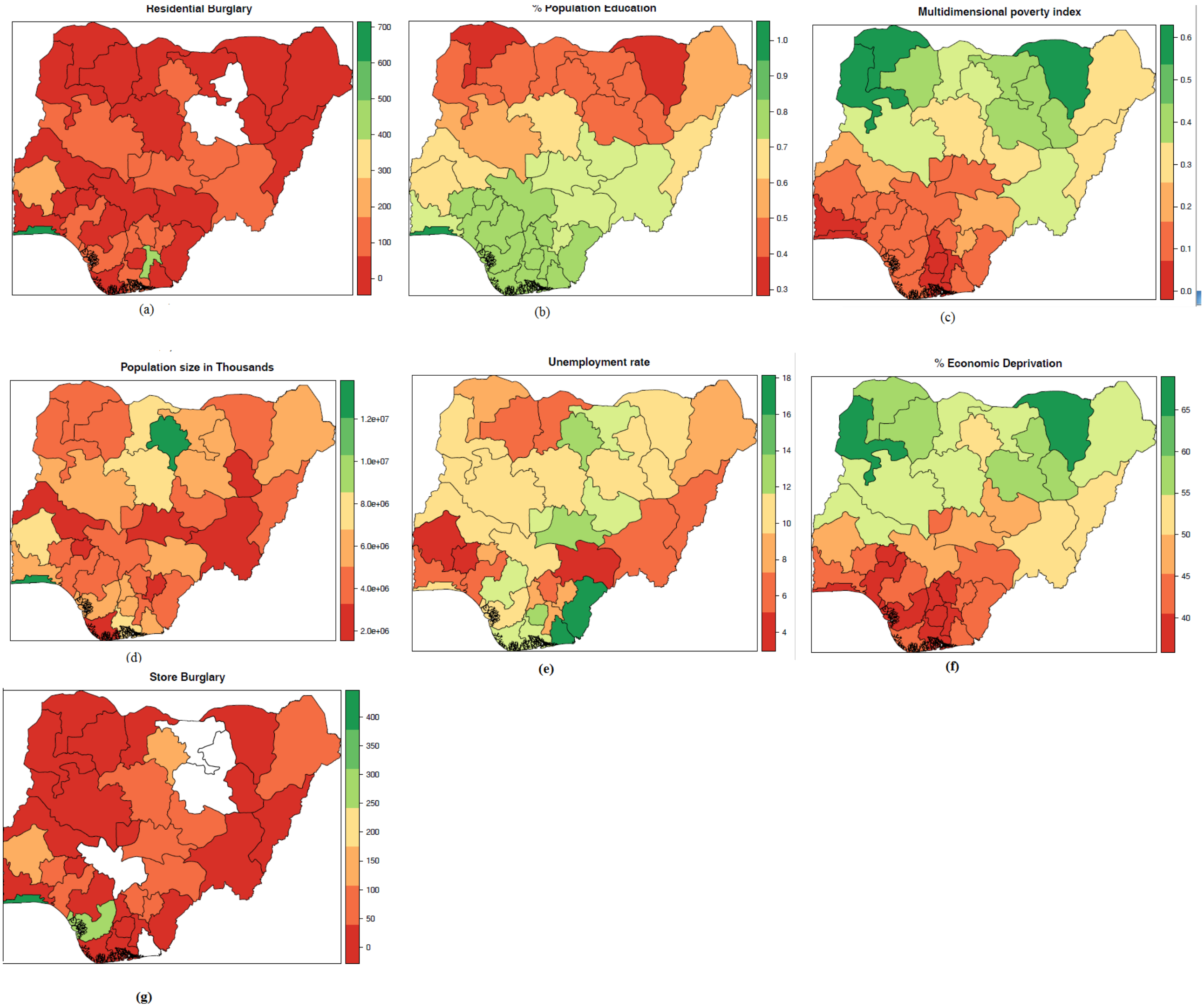

Fig. 2. **Geographical Maps of the Observed Crimes Counts of the Incidence Year 2017 and the Spatial Covariates Across 36 States and the FCT-Abuja**

of variability and unobserved uncertainty. The modeling approach adopted in this study is relevant to the historical epidemiology model, in which the major goal is to investigate the geographical distribution of disease mapping as described in [49] and [31]. Bayesian hierarchical models are usually formulated as Binomial or Poisson likelihoods. A Poisson GLMM is adopted in the present study.

Let counts, Y_i, denote the observed number of residential burglary crimes committed in state i, which assumes to follow a Poisson distribution. That is, $Y_i \sim Poisson(\mu_i = E_i\theta)$ in this case, μ is the average burglary case over the study period and the θ is the term representing different components (observed and unobserved) in the model. The expected number of burglary cases, E_i is calculated as

$$E_i = n_i \left(\frac{\sum_{i=1}^{37} Y_i}{\sum_{i=1}^{37} n_i} \right) \quad (1)$$

In equation ee, the E_i represents the expected number of residential burglary crimes in the state, $i(i = 1, \ldots, n)$. These expected numbers are commonly calculated based on the demographic characteristics or population size of victims at risk in state i as defined in [33].

Model 1: General Poisson model

Model 1 (M1) represents the General Poisson Regression model, which can be described as a baseline model, and it entails linear fixed effects covariates/predictors with no spatial components commonly used in social and environmental sciences. The General Poisson model is a static model, which consists of the spatial covariates only, and linear predictors are expressed as: $\log(\mu_i) =$

$\log(E_i) + \log(\theta)$
$= \log(E_i) + \alpha + \sum_{k=1}^{6} \beta_k x_k$. where α is the overall relative risk (intercept), $\log(E)$ represents the offset, β's are the regression parameters to be estimated, and X are spatial covariates observed in each state. In equation 2, $\log(\theta)$ comprises purely fixed effect covariates (or usually linear factors). Within each state the following variables are observed components and incorporated in the model: multidimensional poverty index (X_1), population size or density (X_2), percent population with education (X_3), unemployment rate (X_4), percent economic deprivation (X_5), and population of male adult (age 18-35 years) (X_6). Additionally, three spatially varying models are proposed later as extensions of the model in equation 2

Model 2: Poisson Normal Model

Model 2 (M2) extends the General Poisson model (M1) by incorporating an area-specific random effect term, v_i, modeled as an independent normal probability distribution. This term captures the unique influence of each state on crime incidence rates. The model introduces state-specific random effects, also referred to as spatially unstructured random effects, v_i, along with the overall relative risk, θ, to account for heterogeneity across states and enhance the precision of the estimated crime incidence rates.
The Poisson-Log-Normal model is another simple model that offers analytic tractability, which has been widely used in disease mapping in epidemiology and it was first proposed by [14].
From equation eq:1 above, the Poisson normal model and the log-linear link function are expressed as
$\log(\mu_i) = \log(E) + \log(\theta) + v_i$
$= \log(E_i) + \alpha + \sum_{k=1}^{6} \beta_k x_k + v_i$
$v_i \sim N(0, \sigma_v^2)$ where, v_i is the state-specific random effects (spatially unstructured) modeled by the normal prior distribution with a zero mean Gaussian prior distribution and its variance, σ_v^2.

Model 3: Conditional Autoregressive (CAR) Model

Model 3 (M3) builds upon the General Poisson model (M1) by integrating a spatial component term, u_i, which captures the spatial dependence effects of neighboring states. The inclusion of the spatial term, u_i enables the model to capture and quantify the spatial dependency structure, reflecting the influence of neighboring regions on observed variations. This approach improves the model's capacity to address spatial autocorrelation and enhances the understanding of regional dynamics [5]. This model has been widely used for the analysis of spatial data in different studies, such as demography, geography, and spatial epidemiology. For further readings see [49], [7],[31] and [50].
From equation eq:1 above, the CAR model and its log-linear link function is given as
$\log(\mu_i) = \log(E_i) + \log(\theta) + v_i$
$= \log(E) + \alpha + \sum_{k=1}^{6} \beta_k x_k + u_i$
$u_i | u_j, j \neq i, {\sigma_u}^2 \ \sim N\left(\sum_{j \neq i} \frac{w_i u_j}{w_{ij}}, \frac{{\sigma_u}^2}{w_{ij}}\right)$ where $i \sim j$ signify the adjacency between neighboring regions with $w_{ij} = 1$ and zero if they are not neighbors, the variance, σ_u^2 represents spatial variability of crimes between regions and X is a vector of different covariates as defined earlier.

Model 4: Convolution Model

Model 4 (M4) combines the features of Model 2 (M2) and Model 3 (M3). The convolution model is introduced to capture the state-specific heterogeneity effects, v_i, and spatial dependence, u_i. The convolution model is known as the Baseg, York, and Mollie (BYM) model named after [5], further readings can be found in [7, 13]. The BYM model facilitates the splitting of random effects into two components: spatially random and heterogeneous components. [15] emphasized the the importance of including a spatially-correlated term u_i in ecological analysis to allow for unobserved variation.
The equation eq:1 above is formulated as BYM model, which the log-linear link function becomes
$\log(\mu_i) = \log(E) + \log(\theta) + v_i + u_i$
$= \log(E_i) + \alpha + \sum_{k=1}^{6} \beta_k x_k + v_i + u_i$
$v_i \sim N(0, \sigma_v^2)$
$u_i | u_j, j \neq i, {\sigma_u}^2 \ \sim N\left(\sum_{j \neq i} \frac{w_i u_j}{w_{ij}}, \frac{{\sigma_u}^2}{w_{ij}}\right)$
where $i \sim j$ signifies the adjacency between neighboring regions with $w_{ij} = 1$ and zero if they are not neighbors, the variance, σ_u^2 represents spatial variability of crimes between regions, and X is a vector of different covariates as defined earlier. The variance component parameters ${\sigma_u}^2$ and ${\sigma_v}^2$ control the variability of u_i and v_i respectively as stated in [32]. In a full Bayesian analysis, prior distributions are specified for the parameters. The variance components are assigned gamma prior distributions as suggested in [32].
Furthermore, the study also evaluates the contribution of the neighborhood to the variation in residential burglary crime, which is quantified by the proportion of variation in spatial correlation or clustering effects to the total random variation. The attributable variation due to spatially structured term is calculated using the ratio of spatial (structured) standard deviation and the total variation given as:

$$\phi = \frac{\sigma_u}{\sigma_u + \sigma_v} \tag{2}$$

where $\sigma_(v)$ is the standard deviation of the spatially unstructured(uncorrelated) random effects and σ_u is the standard deviation of the spatially structured(correlated) random effects.

2.1 The Model Comparison

The model performance was evaluated using the deviance information criterion (DIC) as suggested in [45] for a Bayesian inference. Given the likelihood function for the observed data as $L(data|\boldsymbol{\theta})$ and $\boldsymbol{\theta}$ as the vector of model parameters, then the deviance information criterion is given by

$$DIC = \bar{D} + pD \tag{3}$$

where $\bar{D}$ is the posterior mean of the deviance given as $\bar{D} = E_{\boldsymbol{\theta}|\boldsymbol{y}}(D)$, which measures the goodness of fit defined as $D(\bar{\theta}) - 2\log L(data|\boldsymbol{\theta})$. 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 a lower value of pD indicates a parsimonious model.

2.2 The Prior Specification and Analysis

In making Bayesian inference, all unknown model parameters are assigned appropriate prior specifications. The posterior distributions of parameters are derived by combining prior distribution and data via the Bayesian theorem. All model parameters were estimated via Markov chain Monte Carlo (McMC) simulations in

GeoBUGS [47]. The WinBUGS code for the implementation of the univariate model can be found in the Supplementary Materials or on request from the authors.
The model intercept, α is assigned a uniform prior due to a sum-to-zero constraint on the random effects as suggested by [46]
The regression parameters, $\beta_{ik}, k = 1, \ldots 6$ are the fixed effect predictors and are specified with 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 2.1 above, the spatially correlated (structured) components, u, and uncorrelated heterogeneity, v are modeled by the CAR prior and independent Gaussian distribution respectively. The hyper-parameter prior, σ^2_{uk} and σ^2_{vk}, are associated variance component parameters and the Gamma distribution prior [49], which take the form: ${\sigma^2_{uk}}^{-1} \sim Gamma(0.01, 0.01),\;\; k = 1, 2$
${\sigma^2_{vk}}^{-1} \sim Gamma(0.01, 0.01),\;\; k = 1, 2.$
For more readings on Bayesian data analysis and McMC methods can be found in [21] and [19].

3. DATA ANALYSIS AND RESULTS

This section first presents the mapping of co-variables as observed in each state (district) in Nigeria, which were incorporated in the models. The results of the model analysis are later presented.

3.1 Exploratory analysis

A total of 134,663 crime incidents were reported in 2017. Of which 53,641 offenses were crimes committed against persons, 68,579 incidents were total property crimes and the remaining offenses were committed against lawful authority. Of the total property crimes committed across the 36 states and FCT-Abuja, 3,212 cases were housing-breaking incidences constituting about 4.7% and 1,873(2.7%) store-breaking cases were reported in the incidence year. Observing the occurrence of crime counts over the state (a defined geographical region called an administrative unit), shows that the variability in the data observation is expected to be greater than the expected value (i.e. averaging over the regions). This is an inherent data problem of over-dispersion in statistical theory. The problem may arise as a result of varying population sizes, which is a common occurrence in small-area estimation. For further readings on spatial modeling and over-dispersion, see [24] and [36].

3.2 Model Selection and Goodness of fit

Table (3.2) shows the goodness of fit for various models fitted to both types of burglaries (house and store breaking). The resultant measure of model fit is given by deviance information criteria (DIC).
With different combinations of covariates and spatial components, M4 has the lowest DIC values for both crimes with 62.5 for house burglary and 213.4(store), and M4 is considered the best model to capture the spatial variations of the burglary crimes in Nigeria for the study year. The baseline model M1 has the highest DIC (i.e. worse model) with DIC values of 1,751.2 and 976.2 for house and store burglary respectively. M4 results are considered the best model for both crime cases and the detailed components results of the model are reported for each crime.

3.3 Parameter Estimates of Fixed Covariates on the Burglary Crimes

Table (3.3) presents the estimated posterior mean of the covariates (fixed effect) and the 95% credible intervals(CI) as well as spatially structured effects for model M4. The overall relative risk effect of the model (M4) is $\beta_0 = 0.220$ (95% CI=(-0.108, 0.561)) for house burglary(henceforth HB) and $\beta_0 = -0.077$ (95% CI=(-1.169, -0.471)) for store breaking(henceforth SB). This overall risk effect is significantly difference from zero and negative for SB, but not significantly different from zero and positive for HB. The model results indicate that overall SB risk would be decreasing keeping all determinant factors of SB constant, while increasing for HB crime. The results further reveal that the variable, percent population of severely poor is significant and negative for SB, -1.424, 95%CI (-2.638, -0.133), but negative and not significant for HB crime with -0.344, 95%CI(-1.903, 1.254). Whereas the economic deprivation variable is positive and not statistically significant for both HB and SB crimes. This indicates that the more people are being deprived of their economic survival (i.e. the means of likelihood) would lead to increased burglary risk in the community. The results show that the percentage of economic deprivation among the resident population is majorly involved in perpetrating these burglary crimes.
The proportional contrition due to neighborhood effect is 24.7% for the HB crimes and 29.0% for the SB crimes. These translate to over a quarter $(1/4)$ of the burglary crimes could be attributed to neighboring influence with associated variability of 0.520 (0.079, 1.827) in clustering for HB and cluster variability 0.352 (0.072, 1.012) in SB. It is noteworthiness that these burglaries might be facilitated by criminals or spies who lived in the neighborhoods, and these criminals and their victims lived together within the communities.
Furthermore, the population density coefficient β_4, showed a negative association for both crimes and was not significant for HB crimes, but significant for SB crimes at 95% credible intervals. In our case with a Poisson model and for easy interpretation, by exponentiation the coefficient of population density for HB crime as (i.e.$\exp(-0.074) = 0.960$) yielding the relative risk(RR) of 0.960, 95% CI (0.569, 1.559) and 0.636, 95% CI (0.369 0.985). These can be interpreted as one unit increase in population size would lead to about 4.0% reduction in HB cases, keeping other covariates constant. Similarly, a unit increase in population size would reduce the relative risk of SB crimes by 37%. Conversely, the percentage young male population (PMP) demonstrates a positive and insignificant effect on SB cases, but a negative and insignificant on HB. In other words, one unit PMP would raise the relative risk of HB occurrences by 31.6% and would increase RR SB crimes by 57% keeping other covariates constant although the PMP effect was insignificant at 5% probability level.
The analysis further reveals that the unemployment rate had a negative and insignificant effect on SB crimes, indicating that unemployment reduces the RR of store-breaking crimes by about 6% while raising the RR of HB by 2% as an indication of a positive coefficient value. However, state population residents' percent education index, β_3 shows a positive association with SB crimes, but a negative for HB cases. This means that the education factor would raise the RR of store breaking by 1.473, 95% CI(0.402, 3.793), indicating that the education index increases the RR of SB incidences by 47%, but reduces the RR of HB occurrence by about 4.0% although not significant for both burglary crimes.

Table 2. Deviance Information Criteria (DIC) for four 4 fitted models

Model	Description	Specification	House burglary DIC	Store burglary DIC
M1	Non spatial	$No\ area\ effects$	1751.2	976.2
M2	Non spatial	v_i	1001.5	640.0
M3	Spatial	u_i	302.5	345.1
M4	Spatial	$u_i + v_i$	62.5	213.4

Table 3. Estimated Coefficients of Covariates in Model 4

Variables	Parameters	House Breaking	Store Breaking
	Parameter	Post. mean (95% CI)	Post. mean (95% CI)
Overall intercept	β_0	0.220 (-0.1083, 0.561)	-0.819 (-1.169, -0.471)
% Multi-dimensional poverty Index	β_1	-0.344 (-1.903, 1.254)	-1.424 (-2.638, -0.133)
% Population economic deprivation	β_2	0.077 (-1.541, 1.616)	1.220 (-0.146, 2.243)
% Population Education Index	β_3	-0.031 (-1.179, 1.101)	0.236 (-0.910, 1.333)
Population size	β_4	-0.074 (-0.5647, 0.444)	-0.486 (-0.996, -0.015)
Unemployment rate	β_5	0.005 (-0.3376, 0.342)	-0.077 (-0.429, 0.305)
% Male population (18- 35)	β_6	-0.054 (-0.478, 0.360)	0.430 (0.029, 0.850)
Random effects			
Neighborhood Effect	ϕ	0.247 (0.049, 0.699)	0.290 (0.048, 0.784)
CAR variance	σ_u^2	0.520 (0.079, 1.827)	0.352 (0.072, 1.012)
Precision variance	τ_u^2	3.695 (0.230, 159.7)	27.38 (0.3183, 168.6)
Heterogeneity variance	σ_v^2	0.873 (0.423, 1.223)	0.911 (0.690, 1.208)
Precision variance(area)	τ_v^2	1.313 (0.669, 5.594)	1.652 (0.670, 5.049)

3.4 Mapping Spatial Random Effects on House and Store Burglary Crimes

The geographic pattern of variations 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 inherent socio-demographic factors such as multi-dimensional poverty MPI) particularly among rural population residents compared to urban poor. Also, MPI may vary from state to state and it may even vary within states between local government areas. The posterior means of overall relative risk (RR) of the burglary crimes are mapped and displayed in Figures 3 for model 4 with covariates. The spatial residual effects are categorized into color intervals of five quantiles (classes) based on the overall RR of the crime ranging from green(low) to red(high). The spatial variation for house-breaking incidence ranges between 0.3031 to 7.832, as mapped in Figure 3 (a). It can be seen that the predicted probability maps show spatial inequality in the geographical variation of the cases across the states in the country. The maps significantly highest RR of HB in 8 states and moderately higher in 7 states. While Figure 3 (b) revealed a significantly high RR of store breaking in 8 states(Benue, Kogi, Delta, Nasarawa, Kaduna, Ogun, Osun, and Oyo) as indicated in red areas, insignificant in 7 states and significantly low RR in 21 states including FCT-Abuja.

Figure 4 (a) displayed the maps showing the residuals of spatial dependence structured effects of common house burglary. It apparently shows that there are clustering patterns, displaying ”borrowing strengthen from neighboring” areas. There were scenarios of large clustering comprised of about 8 states transverse the northwest to central and northeastern regions in high RR house burglary and smaller clustering of 2-4 states of low risk of residential burglary incidences. The states (areas) with a high concentration on the map (red colored areas) showing significantly high risk of HS incidence are identified in Adamawa, Bauchi, Gombe, Yobe, Taraba, Kaduna, Kano Jigawa, Nasarawa, Zamfara and Niger. Figure 4 (b) shows similarity in patterns of clustering for store breaking but with less virulence like housebreaking.

The residual maps of spate-specific effect (uncorrelated heterogeneity) effect of variations for house and store breaking crimes are shown in Figure 5 (a) and (b) respectively. It is apparently shown that there are spatial inequalities across the states in the variations of the geographical patterns for both burglary crime incidences.

4. 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 [48, 22] and in policing of crime hot spots [9]. Sparks [44] adopts a spatial epidemiology model and observes that crime determinants depend on the model specification, where they have investigated environmental factors and neighborhood socioeconomic characteristics. They found that violent crimes in San Antonio were majorly associated with environmental characteristics, such as vacant housing and land use diversity.

The current study found that burglary crimes in Nigeria exhibit significant variation between all states and certain regions exhibit higher risks than others. The best-fitting model (M4) incorporated spatial components to account for spatial dependence and spatial heterogeneity component over-dispersion in the crime data. This

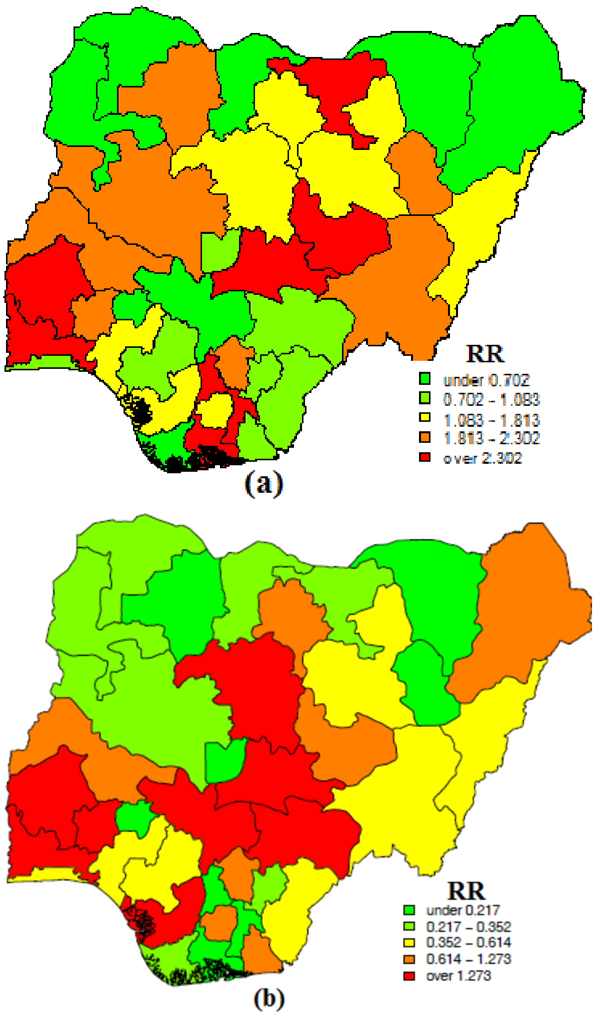

Fig. 3. Maps Showing Relative Risk (RR) of Model 4 (with Covariates) on (a) House Burglary (b) Store Burglary.

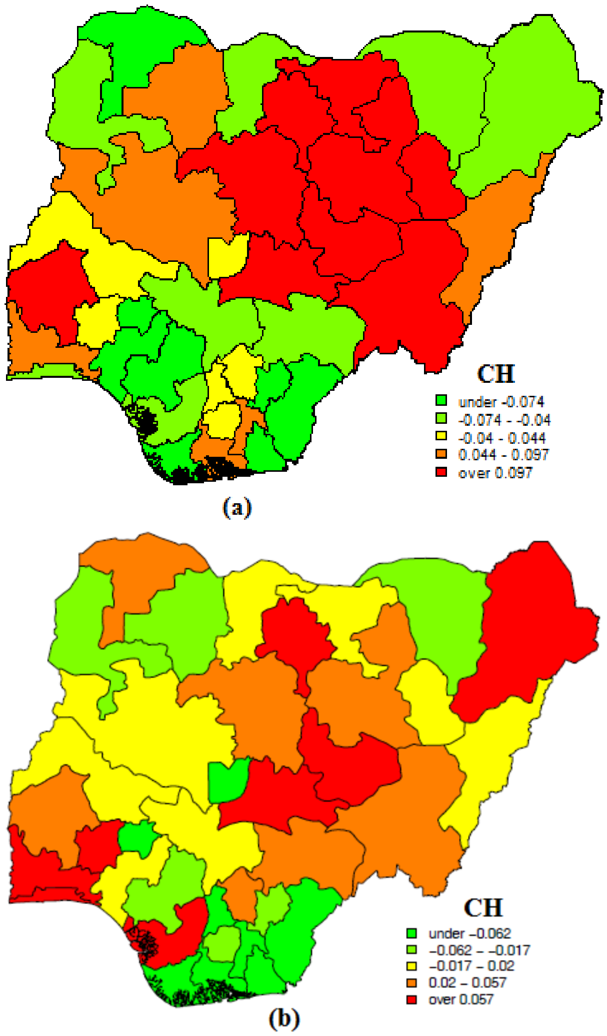

Fig. 4. Maps Showing Posterior Mean of Spatial Structured Effect (u) Components of Model 4 (without Covariates) on (a) House burglary (b) Store burglary.

model provides a more comprehensive understanding of the burglary patterns. The spatial analysis emphasized geographical disparities in burglary occurrences, with certain states exhibiting significantly higher relative risks. Other studies have reported similar spatial variations; [28, 39] reported that crime incidents are not randomly distributed but tend to cluster in specific geographical areas. Also, the finding that neighborhood effects accounted for a substantial portion of burglary incidents, suggests that neighboring influence played a significant role in shaping crime patterns, which can aid the police in early crime detection and prevention.

Furthermore, the analysis revealed that the overall risk effect was significantly positive on house burglary and the factors such as economically deprived population and the unemployment rate showed a positive relation with house burglary. In contrast, store-breaking occurrence had an overall significantly negative risk effect. still, it has a positive correlation with factors such as the young male population, economic deprivation, and the state population education index. The percentage of the severely poor population (measured by multidimensional poverty) was negatively associated with store breaking, indicating higher risks in areas with lower severe poverty rates. However, economic deprivation positively influenced both house and store burglary risks. In other words, the results revealed that the economically deprived population had a higher propensity to commit burglary crimes. This result agrees with the study of [28] that high levels of economic disadvantage and social disorganization are more prone to criminal activities,[40], also submitted that there is a positive relationship between economic deprivation and burglary risks and alluded that areas with a larger proportion of economically deprived residents may have limited access to legitimate economic opportunities, leading to increased involvement in illegal activities such as burglary. Additionally, population density showed a negative association with both crime types, indicating that higher population density led to reduced burglary risks. This contradicts the augment of [50] that says a positive correlation exists between population density and burglary risks. In densely populated areas, there are more potential targets and opportunities for burglaries due to the presence of valuable assets and a higher concentration of people.

This study benefits from a comprehensive model selection that

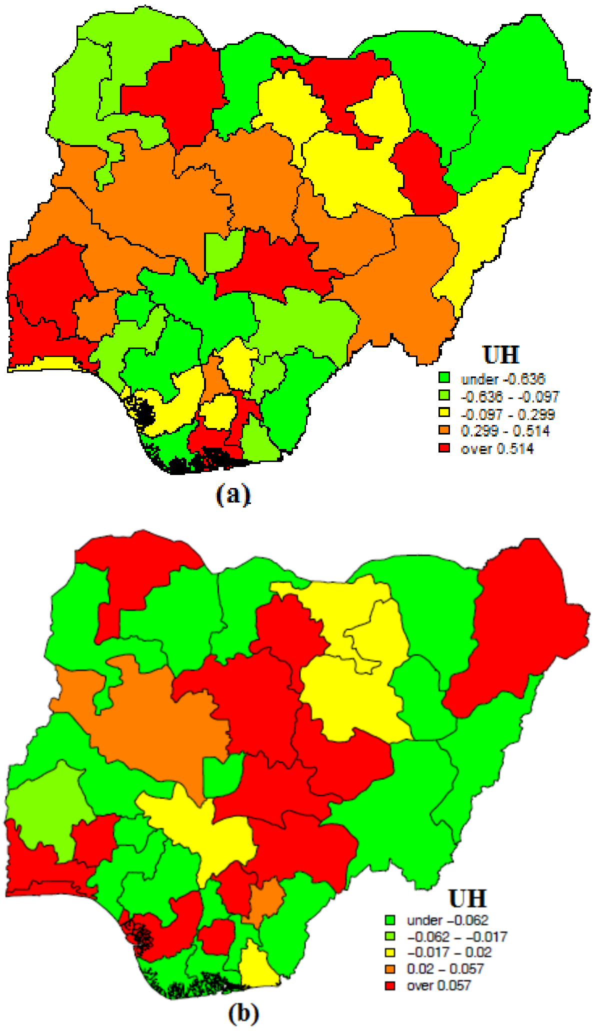

Fig. 5. Maps Showing the Posterior Mean of Unstructured Heterogeneity Effect (Area Specific) v Components of Model 4 (without Covariates) on (a) House burglary (b) Store burglary.

incorporates spatial components to account for spatial dependence and overdispersion in crime data. Moreover, the study's inclusion of spatial components to account for spatial dependence and overdispersion in the crime data further enhances the validity of the findings, as it considers the geographical distribution of crime incidents and their relationships. Additionally, the research demonstrates a nuanced analysis of different types of personal crimes, namely; house burglary and store breaking, revealing distinct risk patterns associated with each crime type. The model results also identified areas of uncommon clusters and high prevalence of burglary crimes, which can assist in policing the community and assist in the strategic allocation of resources to enhance crime detection and prevention.

However, despite these strengths, some limitations must be acknowledged. One limitation is the reliance on secondary data sources, which may have incomplete or inconsistent information on crime incidents. While efforts were made to ensure data quality, the study's accuracy is still dependent on the reliability of the underlying data. Secondly, the absence of an extensive temporal analysis in this study is a limitation when comparing it to previous studies. Understanding the temporal trends and changes in burglary patterns over time is essential for developing effective crime prevention strategies. Future research could incorporate a more comprehensive temporal analysis to enhance the understanding of burglary dynamics in Nigeria.

5. CONCLUDING REMARKS

In conclusion, the findings of this study have significant implications for policymakers in their efforts to address personal crimes effectively. Firstly, the identification of specific risk factors associated with personal crimes, such as unemployment, substance abuse, and low educational attainment, highlights the importance of targeted interventions to address these underlying issues. Policymakers should focus on implementing social welfare programs that provide support and opportunities for individuals at risk of engaging in criminal activities. Investing in education and job training programs could help break the cycle of crime by offering alternative paths to those vulnerable to criminal behavior. Secondly, the study's emphasis on the role of neighborhood characteristics in shaping personal crime rates calls for community-focused strategies. Policymakers should prioritize the implementation of community policing initiatives, where law enforcement agencies collaborate closely with local communities to address crime concerns.
By fostering trust and cooperation between residents and law enforcement, community policing can lead to more effective crime prevention and resolution. Furthermore, the study's spatial analysis indicates that personal crime rates vary across different regions, suggesting a need for geographically targeted or area-based approaches. Policymakers should consider tailoring crime prevention strategies to the specific needs and challenges of different neighborhoods. Implementing place-based policies that address the unique socioeconomic and environmental conditions of high-crime areas could lead to more efficient and impactful crime reduction outcomes. Finally, the finding that personal crimes are more prevalent in urban areas highlights the importance of urban planning and design in crime prevention. Policymakers should work with urban planners and architects to create safer and more secure environments. Improved street lighting, surveillance systems, and the establishment of community spaces can enhance the safety of urban areas and deter criminal activities.

Conflict of interest

The author declares that there is no conflict of interest.

Author's contributions

Conceptualization: RAA and JSO designed and conceptualized the study.
Data Curation : RAA proposed the models
Formal analysis: RAA wrote the WinBUGS code for the statistical analyses.
Original Draft: RAA and JSO drafted the original manuscript.
Methodological Review JSO & AI reviewed the proposed models and commented on the first draft
Type setting: RAA & JSO wrote Latex type-setting.
Writing – Review & Editing: RAA, JSO, and AI edited the draft and implemented the final correction of the manuscript. All authors read and approved the final manuscript.

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Data Availability

Data associated with this article can be found in the online version at Nigeria's National Bureau of Statistics (http://nigerianstat.gov.ng/elibrary).

Supplementary materials

The WinBUGs code can be made available on request by emailing the authors.

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