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Spatial Analysis of Distribution of Inmates in Nigeria Prisons

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Abstract

The number of prison facilities available in Nigeria differs from state to state as well as across the regions. Hence the distribution of the inmates across these correctional facilities differs. This study investigates the distribution of the inmates across Nigeria correctional facilities (prisons) and the likely factors that may influence the distribution considering the spatial effect of the distribution. The considered factors are; year, month, state, region, gender and state population. Ordinary Least Square (OLS) was used to obtain the multiple regression model and Moran's I test of spatial autocorrelation showed that there is presence of spatial autocorrelation in the distribution of inmates across Nigeria prisons. The Spatial Autocorrelation Regression Model (SARM) was therefore adopted to fit the regression model. While OLS approach indicated that all factors are significant except state, the SARM approach found both state and region not to be significant among the factors considered in the model. The SARM did not only give good compact spatial distribution of the inmates across Nigeria prisons it also gave a better predicted (forecast) values of inmates' distribution than the OLS approach.

Keyword: Autocorrelation, Inmates, Prison, Spatial Regression.

1. Introduction

Prison is a societal gathering and complex form of punishment designed which comprises a mixture of personalities, active habits, background stories, ways of thinking, and motivated by the common desire to be free (Pollock, 2005; Galtung, 1958). Prison is an environment with open and closed areas in which individuals are forcibly confined.

The western form of prison facility was introduced in Nigeria in 1876. All over the world, a prison is supposed to be a correctional facility. It is no wonder that the Federal Government of Nigeria renamed the Nigerian Prison services as the Nigeria Correctional Services through the correction service Act 2019.

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The number of prison facilities available in the thirty-six (36) states and Federal Capital Territory, FCT, of Nigeria differs from state to state and these numbers are not always dependent on the population or crime rates in the states. The current distribution (2021) of correctional facilities, according to the geo-political zones of the country, is as given below: North East - 70, North West - 67, North Central – 34, South West - 23, South East - 27 and South South - 27.

As of April 2021, there are 65,283 inmates as against the official capacity of 50,153 (National Prison Administration 2021), hence the problem of over population. The process of administration of justice in the country is slow and therefore there are many inmates who are not supposed to be in prison. These include awaiting trials, remand prisoners and those who were wrongfully, detained. Over population in the prisons has also resulted into inadequate health care and spread of disease/deaths and poor quality of food. In addition, the state of the prisons also affects the inmates. Most of the prisons were built a long time ago without regular or any renovations since they were built. As a result, they have become so dilapidated, and they now house more inmates than were originally intended.

In contrast with Nigeria, in the last two decades, the rate at which United States of American spends on prisons is six times higher than the rate spends on education (Jealous, 2011). Over half of African American men with less than a high school degree go to prison at some time in their lives (Pettit and Western, 2004).

According to Crnič (2012), prison architecture reflects the bonds between typology, function, and content through spatial elements and characteristics. The identification of crime hot spots was feasibly a watershed in changing attention on spatial features of crime (Sherman, Gartin, and Buerger, 1989*)*. Good prison architecture allows for the development of good relationship between staff and prisoners, provides space and opportunity for a full range of activities, and offers decent working and living conditions (Bosworth, 2002).

In Nigeria, the criteria for placement of inmates in various correctional facilities (Prisons) include; the inmate's background, inmate's risk status, needs and terms to serve. Consideration is rarely given to inmate's and visitor's freedom of movement. Due to congestion in most facilities across the country, it is not often easy to make intra/inter facilities transfer of inmates. This study therefore examines the distribution of inmates in the Nigerian correctional facilities (prisons) using spatial analysis with the intention of coming up with factors that may positively influence the distribution of inmates across the country.

2. Materials and Methods

2.1 Ordinary Linear Regression Model

In multiple ordinary linear regression using least square approach, a dependent variable Y is believed to have linear relationship with two or more independent variables. The independent variables $(X_1, X_2, X_3, , \; , \; , X_k)$ can be a mixture of continuous and non-continuous variables but the dependent variable Y must be a continuous variable. The model is given as;

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_1 X_{2i} + . \; . \; . + \beta_p X_{pi} + e_i, \quad (1)$$

Y is the dependent variable or the value we are trying to predict,

β_0 is the intercept or the point the straight line crosses the y-axis,

β_i is the slope coefficient or the gradient on the i^{th} independent variable,

e_i is the stochastic error term.

Some of the assumptions of linear regression model include; linearity in the independent variables and in relation with dependent variables, absence of outlying points, normality of error terms and uncorrelated error terms among others (Alanamu and Oyeyemi, 2018).

2.2 Spatial Autoregressive Model

Spatial data differs from time series data or other forms of data as a result of putting the site of the data into consideration rather than the time. Spatial data analysis depends on organizing data in neighboring clusters, these neighbors are believed to be homogeneous within and heterogeneous between with respect to some variables. Thus, the assumptions of ordinary least squares regression are violated, especially, the assumptions of homogeneity and of independence of error terms (Higazi et al, 2013).

Spatial data is characterized by having location or Spatial effects, where there are Spatial heterogeneity between and spatial homogeneity within neighboring clusters; thus spatial dependence is exhibited among these clusters. When these characteristics are ignored using Ordinary Least Squares (OLS) in linear regression analysis, for example, the resulting parameter estimates are biased, inconsistent and the R^2 values is not an accurate fitness of fit measure, since the assumption of independent error terms is violated since spatial dependence and spatial autocorrelation exist in the data.

When conducting regression analyses with data aggregated to geographic areas such as counties (an irregular lattice), it is common to find spatially auto-correlated residuals. Residuals usually are spatially positively auto-correlated such that high residuals tend to cluster in space and low-valued residuals similarly tend to show geographic clustering (Voss et al , 2006).

Spatial lag dependency in a regression setting can be modeled similar to an autoregressive process in time series. The model is formally given as;

$$y = \rho W y + X\beta + \epsilon. \tag{2}$$

The presence of the term Wy induces a nonzero correlation with the error term, similar to the presence of an endogenous variable, but different from time series context. Contrary to time series autoregressive model, Wy is always correlated with ϵ irrespective of the structure of the errors. This implies that Ordinary Least Square (OLS) estimates in the spatial model will be biased and inconsistent (Anselin and Bera, 1998).

2.3 Spatial Autocorrelation Model

Another way to model spatial data is spatial autocorrelation in a regression model by specifying the autoregressive process in the error term. Given a linear regression model as;

$$y = X\beta + \epsilon, \tag{3}$$

where $\epsilon = \lambda W \epsilon + u$.

Durbin-Watson test is frequently used to examine the presence of serial correlation between the error terms however, the test is only suitable for ordered time or spatial series data and not effective for cross sectional data coming from spatial random sampling because the test procedure depends on sequence of data points (Chen, 2016, Haining 2003). There are many procedures for testing the presence of spatial autocorrelation but the more appealing test is the Moran's I test of spatial autocorrelation (Chen, 2013).

2.4 Moran's I Test

Moran's I test was originally developed as a two-dimensional analog of Durbin-Watson's test given as:

$$I = \frac{e'We}{e'e}, \tag{4}$$

where $e = y - X\beta$ is a vector of OLS residuals, $\beta = (X'X)^{-1}X'y$ and W is the standardized spatial weights matrix (Anselin, 2006; Anselin and Bera, 1998).

Moran I is interpreted as Pearson's Product moment correlation coefficient. The spatial autocorrelation for neighboring units is called Local Moran I, it takes the weights of unit i and unit j within the same cluster into consideration. When significant spatial autocorrelation, (spatial dependence) exists either, spatial heterogeneity exists (Lesage 1998) and accordingly non- constant errors. There are several diagnostic tests that could be used to test the significance of spatial effects, such as examining residuals from OLS to reveal heterogeneity of variances. However, this requires special software programs that depend on maps to determine the locations of units. Spatial effects are tested using Breusch Pagan test (Breusch and Pagan, 1979) for testing homogeneity assumption, Moran test, Lagrange Multiplier (LM) lag test and LM-error tests for testing spatial autocorrelation (Haining, 2003).

3. Data Presentation and Analysis

3.1 Data Presentation

The data used in the study is a secondary data extracted from Nigerian Prison Annual Report publications from 2012 to 2018. The variables considered include; Number of inmates, State, Region (Zone), Gender, Year, Month, Population per state as well as their Latitude and Longitude.

The data were in two formats as presented in Tables 1 and 2. Table 1 presents the total number of prison inmates by Year, Month, State, Region and Gender, Population as well as Latitude and Longitude of the state while data in Table 2 is the compressed or summarized version of data in Table 1. It contains the number of inmates by Region, State with their Population sizes as well as Longitude and Latitude. The data in Table 1 was used to obtain graphical (spatial) distribution of inmates across the states for each year as well as the whole period (2012 – 2018) and also to fit a multiple regression model in determining the significant factors that may affect the distribution of inmates across the state.

The data in Table 2 was used to test for presence of spatial autocorrelation, that is, if there is need for fitting spatial regression for the total number of inmates across the states or if ordinary linear regression suffices.

Table 1: Total number inmates by year, month, gender, state, region, population, Latitude and Longitude.

Year	Month	State	Region	State	Gender	Inmate	Pop	Lat	Long
2012	1	1	1	Abia	1	112	3175953	5.532	7.486
2012	2	2	2	Adamawa	2	7	3588322	10.270	13.270
2018	11	36	5	Yola	1	13	2417915	11.749	11.966
2018	12	37	6	Zamfara	2	1	3798642	12.170	6.660

Region: 1 (North Central); 2 (North East); 3 (North West); 4 (South East); 5 (South South); and 6 (South West).

Table 2: Total number of inmates by state, region with state population, latitude and longitude.

State_1	State	Region	Pop	Inmate	Latitude	Longitude
Abia	1	4	3175953	15129	5.532	7.486
Adamawa	2	2	3588322	41859	10.270	13.270
Yola	36	2	2417915	16726	11.749	11.966
Zamfara	37	3	3798642	20300	12.170	6.666

3.2 Data Analysis

The data in Table 1 was used to map the total number of prison inmates across the states for each year between 2012 and 2018. The distributions are as shown in Figures 1 through 7, while Figure 8 showed the combine 7 years distribution of total number of inmates in the country. The Figures 1 to 7 show a consistent pattern in distribution of prison inmates across geopolitical zones (regions) in the country. The region seems to be more significant than state in the distribution of the prison inmates across the country.

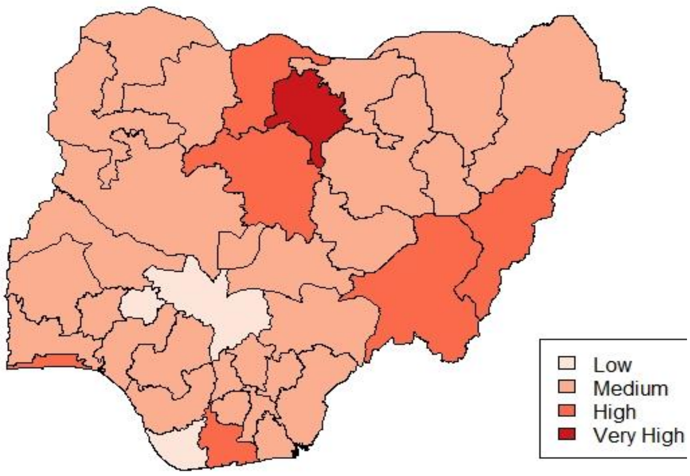

Figure 1: Distribution of number of inmates for 2012.

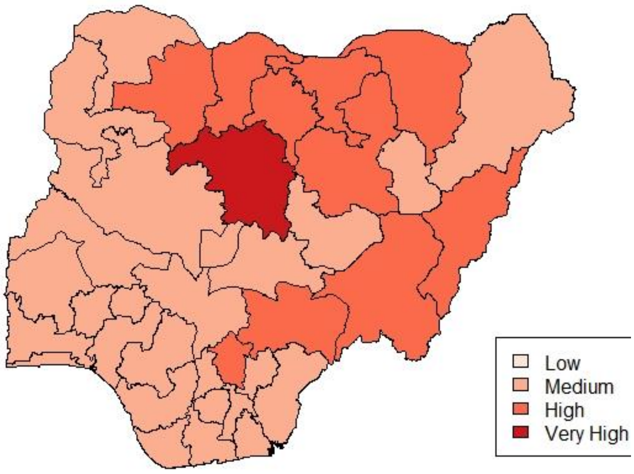

Figure 2: Distribution of number of inmates for 2013.

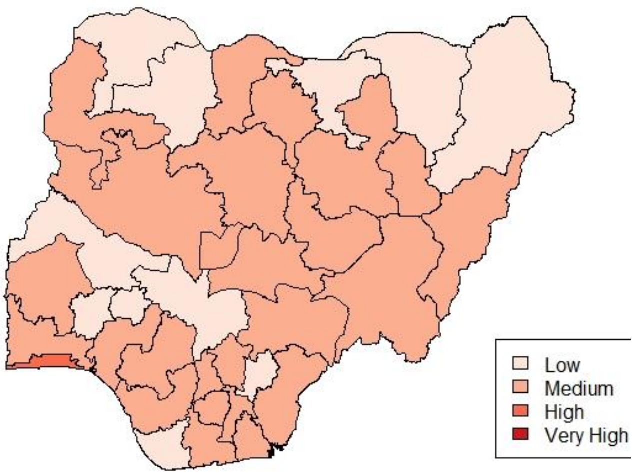

Figure 3: Distribution of number of inmates for 2014.

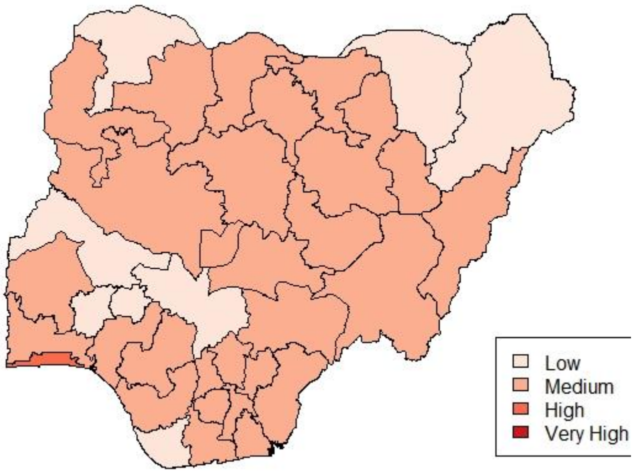

Figure 4: Distribution of number of inmates for 2015.

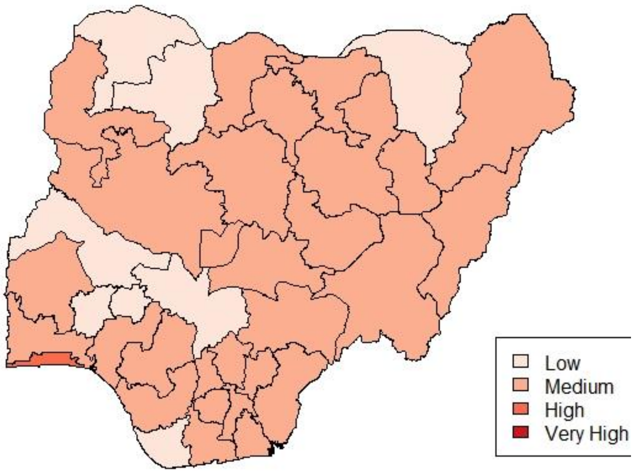

Figure 5: Distribution of number of inmates for 2016

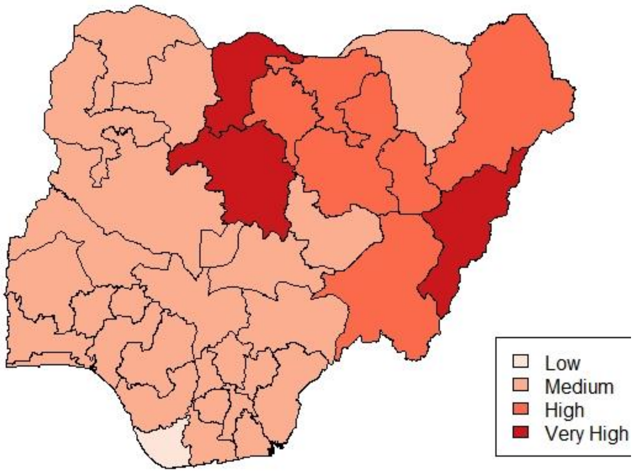

Figure 6: Distribution of number of inmates for 2017.

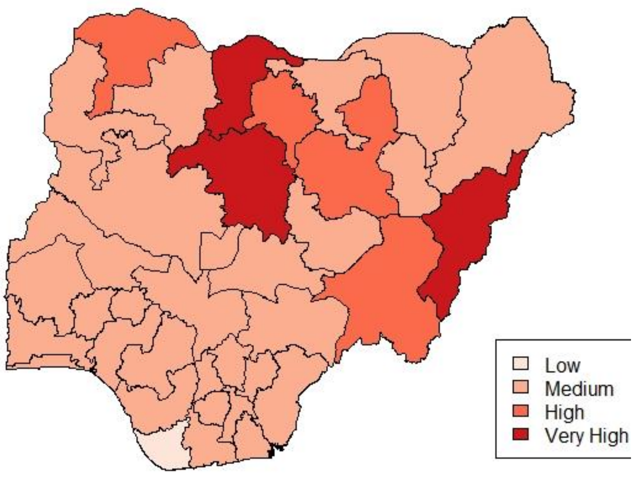

Figure 7: Distribution of number of inmates for 2018.

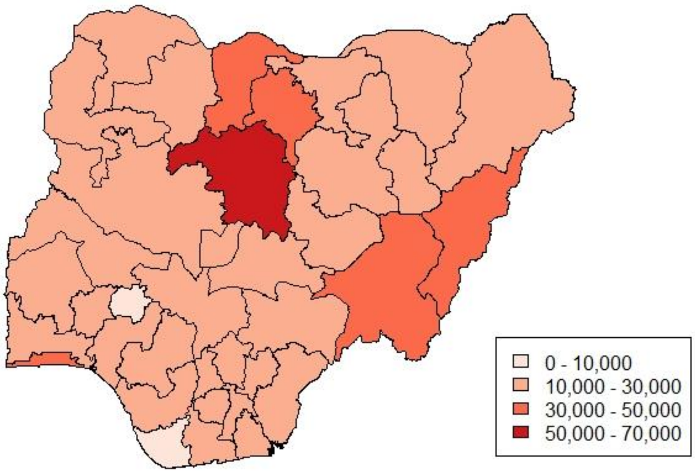

Figure 8: Distribution of number of inmates between 2012 and 2018.

In order to determine factors that affect the total number of inmates in the country, a linear multiple regression model of number of inmates is obtained using year, month, state, region and gender of the inmate as the independent variables. The results of the fitted model were as shown in Table 3.

Table 3: Coefficients of Multiple Linear Regression with t- and F- statistics.

Coefficient	Estimate	Std. Error	t-value	p-value
Constant	-11610.000	3105.000	-3.738	0.000
Year	6.098	1.541	3.957	0.000
Month	-5.066	1.138	-4.451	0.000
State	-0.496	0.370	-1.339	0.180
Region	-25.430	2.344	-10.849	0.000
Gender	-325.100	7.858	-41.372	0.000
Population	0.000026	0.0000017	15.163	0.000
RSE = 234.200				
R^2 = 0.364;	**Adjusted R^2 = 0.363**			
$F_{(6; 3545)}$ = 338.500;	**p-value = 0.000**			

$$Inmate = \hat{\beta}_0 + \hat{\beta}_1 Year + \hat{\beta}_2 Month + \hat{\beta}_3 State + \hat{\beta}_4 Region + \hat{\beta}_5 Gender + \hat{\beta}_5 Pop \quad (5)$$

The results as shown in Table 3 revealed that the fitted model is significant and all the factors considered are significant at 0.05 level of significance (p-value < 0.05) except the state. The significant of the fitted model is not a guarantee that the model is a good representation of the reality. Therefore, it is important to consider the spatial component of the data as ordinary least square (OLS) model assumes that what happens in area or state, s_i, is not in any way related (independent) of what happens in area or state s_j ($i \neq j$). But naturally, if two areas or states are adjacent in geographical space, it is obvious that there is a good chance that this assumption of spatial independence may be violated. The problem with ignoring the spatial structure of the data implies that the OLS estimates in the non-spatial model may be biased, inconsistent or inefficient, depending on what is the true underlying dependence (Anselin and Bera, 1998).

Before carrying out a formal test for spatial autocorrelation, graphical check for spatial autocorrelation is explored using regression residuals. The residuals obtained from the fitted model were standardized, that is, expressed in terms of standard deviations away from their mean. The standardized residuals were used in place of total number of inmates to obtain the distribution map as shown in Figure 9.

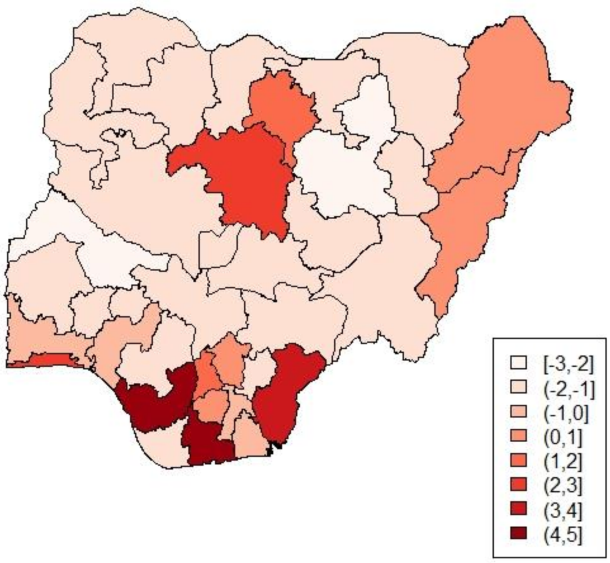

Figure 9: Standardized residual map to check for spatial autocorrelation.

It can be seen from Figure 9 that slight evidence of spatial autocorrelation exists as there is a clear pattern in the plotted standardized residuals. Areas or states sharing boundaries have the same colour except in isolated cases of Kwara, Bauchi and Lagos states.

3.3 Moran's Test of Spatial Autocorrelation

The data in Table 2 is used to test for the presence or otherwise of spatial autocorrelation in the distribution of total number of inmates across Nigeria prisons. The data in the Table has both Latitude and Longitude of each of the 36 states and the Federal Capital Territory. The Latitude and Longitude were used in generating a matrix of inverse distance weights. The matrix is obtained such that the entries for pairs of states that are close together are higher than pairs of points that are far apart (Kelejian and Prucha, 2001). The inverse distance weight matrix is a pre-requisite factor in conducting Moran's test of spatial autocorrelation without which the test cannot be conducted.

The results of the spatial autocorrelation test are presented in Table 4

Table 4: Moran's Spatial Autocorrelation Test.

	Computed Moran I	Expected value I	Std deviation of I	p-value
Statistic	0.097	-0.028	0.029	0.000

From Table 4, with the p-value of 0.000, the null hypothesis that there is zero spatial autocorrelation in the distribution of inmates across Nigeria prisons is rejected at $\alpha = 0.05$ (p-value < 0.05)

3.4 Spatial Autocorrelation Model

Having established the fact that there is spatial effect on the number of prison inmates across the country (Nigeria), a spatial regression model is therefore fitted on the data. The Spatial Autocorrelation is adopted, and the results of the fitted model are as presented in Table 5. All the variables considered are significant at $\alpha = 0.05$ (p-value < 0.05) except state and region. Interestingly, region was found to be significant when linear regression model was used.

Table 5: Coefficients obtained from Spatial Autocorrelation Model.

Coefficient	Estimate	Std. Error	t-value	p-value
Constant	-1161.000	2900.000	-4.004	0.000
Year	6.098	1.439	4.237	0.000
Month	-5.066	1.063	-4.767	0.000
State	0.047	1.173	0.402	0.184
Region	-9.225	10.030	-0.919	0.131
Gender	-0.033	7.338	-44.302	0.000
Population	-0.000012	0.0000046	2.631	0.006
Log-likelihood = -24222.29				

As a way of comparing the two methods (Models), numbers of inmates for each of the states and Federal Capital Territory were predicted for year 2019 using the two models; Linear Regression Model and Spatial Autocorrelation Regression Model. The estimates of number of inmates obtained from each of the models are used to obtain the spatial plots/maps of number of inmates. The summary statistics for both predictions are presented in Table 5 while the resulting maps are shown in Figures 10 and 11 for ordinary linear regression and spatial autocorrelation regression models respectively.

Table 5: Descriptive statistics of predicted number of inmates using OLS and SARM.

Model	Min	Q1	Median	Mean	Std. Error	Q3	Max
SARM	34981	66626	73906	78289	4205.202	90866	157289
OLS	27566	56362	66760	78289	6621.959	78068	222856

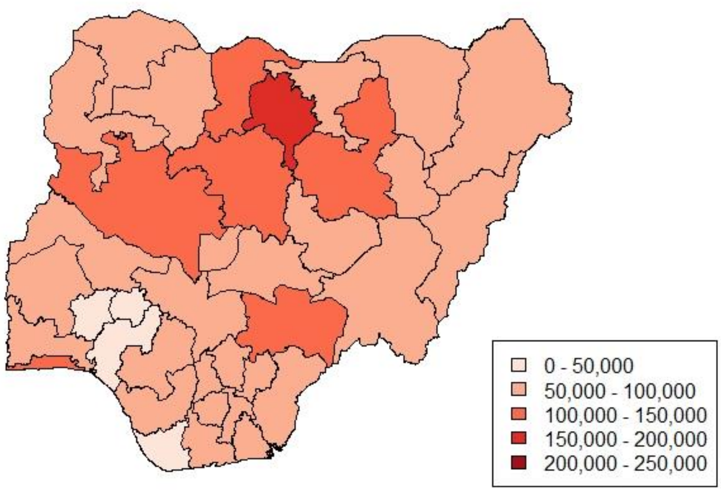

Figure 10: Map of predicted number of prison inmates for 2019 using OLS.

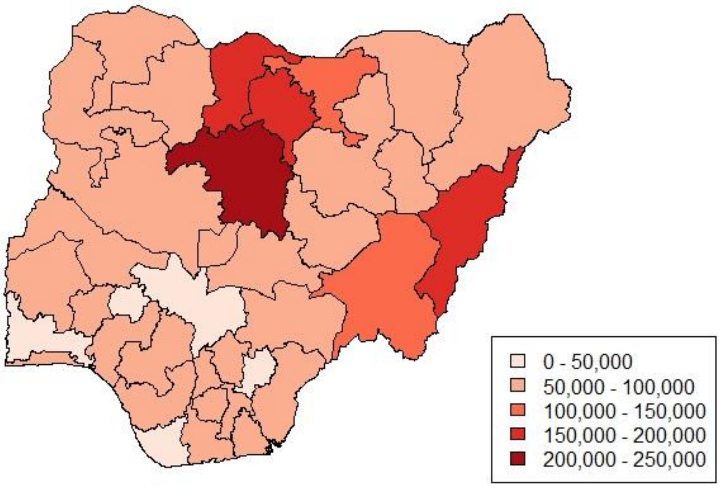

Figure 11: Map of predicted number of prison inmates for 2019 using SARM.

4. Summary and Conclusion

The result of spatial effect on the number of prison inmates across the country in Figures 1-8 showed that there is a consistent pattern in the distribution across geopolitical zones in Nigeria but the regions show a more consistent pattern than state irrespective of the gender.

Based on the factors that determined the number of inmates in the country using OLS model; the year, month, region, gender, and population contribute significantly to the model (p-value<0.001) except State. Considering the spatial Autocorrelation regression model, the result showed that the year, month, gender, and population are significantly to the model except State and Region.

This shows neither state nor region determine the number of inmates in Nigeria. The result also showed that spatial autocorrelation model performs better than OLS. In summary, the distribution of inmates in Nigeria Prisons is mainly affected by year, month, gender, and population of the state.

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