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SPATIAL ANALYSIS OF NIGERIA'S PRESIDENTIAL ELECTION BASED ON GEOGRAPHICALLY WEIGHTED REGRESSION

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ABSTRACT: *Geographically weighted regression (GWR) is a linear regression technique used to fit a regression equation to every observation in a dataset. In this study, both the global regression (multiple linear regression) and the GWR were calibrated for the 2019 Nigeria presidential election dataset, and diagnostics of each model were computed and compared. Experiments and analyses in the study were implemented in the R-environment, R-4.1.2. The GWR model outperforms the global regression model with an R^2 value of 0.776 exceeding that of the global regression of 0.513. The superiority of the GWR model is also confirmed by its much smaller RSS and AICc values (173.362 and 1372.8555 respectively), compared to those of the global regression (377.103 and 1662.316 respectively). The GWR model better fits the election dataset; it explains spatial variations in the dependent variable better than the global regression model does.*

KEYWORDS: Calibration, Election, Geographically Weighted Regression, Global Regression, Spatial Analysis

INTRODUCTION

The importance of space has been recognised in various scientific disciplines involving theoretical domains and applied domains; hence, the need for the understanding of spatial data analysis, including spatial modelling. The distinct contribution of spatial analysis in this overall framework is that it provides the means to explicitly recognise, assess and incorporate the importance of location in statistical data analysis and modelling (Anselin, 1999; Li *et al*., 2019; Fotheringham, *et al*., 2021).

Spatial regression models are typically "global". That is, all available data are used simultaneously to fit a single model. It can sometimes make sense to fit more flexible "local" models. In a spatial context 'local' refers to a location. Rather than fitting a single regression model [global linear regression, such as multiple linear regression whose parameters are estimated by the ordinary least squares technique (OLS)], it is possible to fit several models, one for each location (out of possibly very many) (Paez *et al*., 2011; Srinivasan, 2017). Local models allow model parameters to vary from location to location, unlike global models where model parameters are constant over the space.

The two main spatial effects that spatial data bring to data analysis are spatial autocorrelation and spatial non-stationarity. Spatial autocorrelation refers to the correlation among the values of a single variable measured at different locations in a geographical space, while spatial nonstationarity refers to the variation in processes and relationships over space. Addressing these two effects has been the main task of spatial analysis. The traditional non-spatial regression methods are often insufficient in addressing these effects and in analysing spatial data generally, due to various assumptions in non-spatial regression that are violated in spatial modelling. Take, for instance, global standard models such as those calibrated by OLS regression, assuming that the processes that generate the data observed are the same across spaces. This is not so in spatial modelling; in spatial modelling, processes that generate observed data could vary over space (Fotheringham *et al*., 2002). This study's main focuses are to estimate the local parameters of the GWR model and compare the performances of the GWR and the global regression models.

The GWR is appropriate if the process being modelled is spatially nonstationary; that is, the relation between the variables being investigated is not constant over space. A single model, although representing the overall relation, would miss important local variations. The GWR method is used to analyse the 2019 Nigeria presidential election. The election dataset helps in understanding the processes by which the various contributing covariates of the dataset affect the response factor; the spatial analysis also helps in understanding the spatial variations in the response factor. The software package *GWmodel* (Lu *et al*., 2021), in the R-environment, is used for model calibration in the study. Finally, the results of the GWR method for the spatial analysis and modelling of geographically-referenced data are compared with those of the global linear regression method.

LITERATURE REVIEW

Some of the spatial regression techniques that have been developed for the treatment of spatial data include the Spatial Expansion Model (SEM), Multilevel Modelling (MM), Spatial Filtering Model (SFM), Moving Window Regression (MWR) and Geographically Weighted

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Regression (GWR). Of these techniques, the GWR is considered the most important in the treatment of the two main spatial effects of spatial data analysis; namely, spatial autocorrelation and spatial non-stationarity. Only the GWR accounts explicitly for spatial non-stationarity. The technique takes nonstationary variables such as temperature, climate, demographic factors, physical environment characteristics, etc. into consideration in modelling the local relationships between these independent variables and an outcome of interest (Fotheringham *et al.*, 2002, 2017, 2021). The GWR allows regression parameters to vary spatially; thus, relaxing the traditional or global regression assumption. That is to say, the relationships being examined through the parameters of the model are constant over space.

The GWR was developed by Brunsdon *et al.* (1996) as an extension of linear or generalised linear regression. It investigates how the relationship between a dependent variable (Y) and one or more independent variables (the X's) vary geographically. Instead of assuming that a single model can be fitted to the entire study region, GWR looks for geographical differences. Local regression is performed at different geographical locations so that at each location a set of localised parameters is estimated. The GWR does this by calibrating a separate regression model at each location by borrowing data from nearby locations and weighting these data by distance from the regression point such that data from locations nearer to the regression point are weighted more than data from more distant locations (Yu *et al.*, 2019). Data at the local regression point are given a weight of one, and data borrowed from nearby locations are given a discounted weight of less than one depending on their distance away from the local regression point. The weighting is controlled by a kernel function, such as Gaussian, Bi-square, and Tri-cube, among other potential functional forms that contain a continuous measure of distance decay. The bandwidth, which is a parameter of the kernel function (i.e., standardisation of the function) is used to control the width of the kernel, and hence the amount of distance-decay in each local regression (Li, 2020).

Fotheringham *et al.* (2002) give the form of a global linear regression model as in Equation (1):

$$y_i = \beta_0 + \sum_{k=1}^{m} \beta_k x_{ik} + \varepsilon_i, \;\; for\ i = 1,2,\dots,n \qquad (1)$$

where y_i is the response (dependent) variable measured at location (observation point) i, $x_{ik}(k = 1,2,\dots,m)$ is the k^{th} independent variable at observation point i, β_k is the parameter for x_{ik} describing the relationship between y_i and x_{ik}. β_0 is the intercept and ε_i is the error term, which is independent and identically distributed. The authors stated that when the error terms meet the condition of being independently and identically drawn from a Normal distribution with mean zero and common variance σ^2, the regression parameters β_0 and β_k can be estimated by ordinary least squares (OLS), in which the value of $\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$ is minimised over the *n* observations in the dataset, where $\hat{y}_i$ represents the predicted values.

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Lu *et al*. (2014) state the basic form of geographically weighted regression as in Equation (2):

$$y_i = \beta_{i0}(u_i, v_i) + \sum_{k=1}^{m} \beta_{ik}(u_i, v_i)x_{ik} + \varepsilon_i, \qquad i = 1,2, \dots, n \qquad (2)$$

where y_i is the dependent variable at location i (here, i also indicates that there is a set of coefficients estimated for every observation in our dataset); x_{ik} is the value of the k^{th} independent variable at location *i*; *m* is the number of independent variables; (u_i, v_i) represents the two-dimensional geographical coordinates of the i^{th} observation; $\beta_{i0}(u_i, v_i)$ is the intercept parameter at location *i*; $\beta_{ik}(u_i, v_i)$ are parameters describing the relationships around location (u_i, v_i); β_{ik} is the local regression coefficient for the k^{th} independent variable at location *i*; and ε_i is the random error at location *i*. The authors also stated that a key assumption in this basic (and related forms of) GWR is that the local coefficients vary at the same scale and rate across space (depending on the particular kernel weighting function that is specified).

METHODOLOGY

The 2019 Nigerian presidential election dataset used in this study was compiled and computed by the researchers. The main source of the compilation is the document on the Report of the 2019 General Election (INEC, 2020), which was retrieved from the website of Nigeria's Independent National Electoral Commission (INEC) (https://www.inecnigeria.org). The postal code, latitude and longitudinal values of each of the 774 local government areas used were compiled from the website of World Postal Code: https://www.worldpostalcode.com/nigeria. Two other websites were used in compiling the population projection of each local government area- those of City Population (https://www.citypopulation.de/php/nigeria-admin.php) and National Population Commission (NPC) (https://www.nationalpopulation.gov.ng). The population projection assumes the same rate of growth for all local government areas within a State. Other sources used for the compilation and computation of the dataset included relevant publications of the National Bureau of Statistics (NBS) on Unemployment and Literacy Statistics, retrieved from https://nigerianstat.gov.ng. The unemployment and literacy statistics assume the same rate for all local government areas within a State. The compiled dataset was converted to an excel data file (.xlsx) format for compatibility with the *GWmodel* package. The empirical dataset was studied utilizing appropriate *GWmodel* functions to find the GWR, its summary statistics, regression fits and diagnostics, associated Monte Carlo significance tests for nonstationarity, and the optimal bandwidths for the covariates.

The dataset consists of the final results of the election in 774 Local Government Areas (LGA) $(n = 774)$ spread across 36 States and the Federal Capital Territory (FCT). Here, the empirical study entails using the GWR modelling techniques to examine spatial variations in the influences of local government-level socioeconomic factors on voter preference during the election. The people's voting preferences are considered linked with geographical location, varying from place to place, and operating at local, regional, and national scales.

From the literature, certain socio-demographic and ethnoreligious variables such as religion, ethnicity, and region are generally considered to have a direct impact on voting preferences in Nigeria (Sule, 2019; INEC, 2020). The results of the 2019 Nigeria presidential election show

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that the APC candidate secured massive votes from the Northeast and Northwest regions to emerge victorious, while the PDP candidate secured his major votes from the Southeast and Southsouth. The remaining two regions of Northcentral and Southwest were shared between these two major contenders (INEC, 2020). These locational variables are factored out as covariates in this study. Special interest is given to investigating local determinants of voter preference in these regions, which played vital roles in influencing the outcome of the 2019 presidential election. Variables also factored out in the GWR modelling of the election data include the literacy and unemployment rate in the States where each local government is located.

The dependent variable ($TotApcV$) is defined as the total share of the vote that went to the All Progressives Congress (APC) out of the total valid votes that went to the APC or the Peoples Democratic Party (PDP), or other parties, in each of the nation's contiguous 774 local government areas (36 States and the FCT). The descriptions of 13 variables used are described in Table 1. These are the key variables considered to have a direct impact on voting preferences in Nigeria.

Table 1: Variables of the 2019 Nigeria Presidential Election Dataset

Variable Name	**Variable Description**
Idnumb	Nigerian Postal Service (NIPOST) code for Nigeria's 774 LGAs
Latitude	The latitude of the local government headquarter
Longitude	The longitude of the local government headquarter
PopLg19	Projected population of the local government in 2019
TotApcV	Total share of APC vote in the local government, in the 2019 election
PctApcVR	Percentage of APC vote in the region where the local government is located
PctPdpVR	Percentage of PDP vote in the region where the local government is located
PctLitS	Percentage literacy in the State where the local government is located
PctUempS	Percentage unemployment rate in the State the local government is located
TotEVS	Total eligible voters in the State where the local government is located
PctVTS	Percentage voter turnout in the State where the local government is located
PctApcVS	Percentage APC vote in the State where the local government is located
PctPdpVS	Percentage PDP vote in the State where the local government is located

Source: Formulated by the Researchers

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The nine covariates used in the study are: PopLg19, PctApcVR, PctPdpVR, PctLitS, PctUempS, TotEVS, PctVTS, PctApcVS, and PctPdpVS. The selection of the covariates was influenced by the discussion of the 2019 Nigeria presidential election in both the academic literature and the media (print, broadcast, and the new media). The choice was also guided by statistical testing for multicollinearity using variance inflation factors; the tests identified no problems. Concerning spatial heteroscedasticity, residuals from geographically weighted regression are generally much lower and are not spatially autocorrelated; this removes the need for spatial regression modelling of the residuals (Rossiter, 2019, 2022; Yu *et al.*, 2019; Fotheringham *et al.*, 2021).

The GWR model for the 2019 Nigeria presidential election dataset is given by Equation (3) as:

$$\begin{aligned} TotApcV_i = \ & \beta_{i0}(X_i,Y_i) + \beta_{i1}(X_i,Y_i)\ PopLg19_{i1} + \beta_{i2}(X_i,Y_i)\ PctApcVR_{i2} \\ & + \beta_{i3}(X_i,Y_i)\ PctPdpVR_{i3} + \beta_{i4}(X_i,Y_i)\ PctLitS_{i4} + \beta_{i5}(X_i,Y_i)\ PctUempS_{i5} \\ & + \beta_{i6}(X_i,Y_i)\ TotEVS_{i6} + \beta_{i7}(X_i,Y_i)\ PctVTS_{i7} + \beta_{i8}(X_i,Y_i)\ PctApcVS_{i8} \\ & + \beta_{i9}(X_i,Y_i)\ PctPdpVS_{i9} + \varepsilon_i \ \} \qquad (3) \end{aligned}$$

where X_i and Y_i are the projected x-y coordinates, and $TotApcV_i$, the dependent variable, is the total APC vote for local government i, β_{im} is the parameter for the m^{th} covariate for local government i, and ε_i is the random error for local government i, which is the classic independent and identically distributed error term. β_{i0} is the intercept parameter.

RESULTS AND DISCUSSION

Global Regression

The results of the global regression model for the Nigeria election data, calibrated by the OLS technique, are shown in Table 2.

Table 2: Global OLS Calibration Results for the Nigeria Election Data

Covariate (Variable)	Estimated Parameter	Standard Error	*t*-value (Est/SE)	*p*-value
(Intercept)	0.000	0.025	0.000	1.000
PopLg19	0.426*	0.027	15.804	0.000
PctApcVR	0.029	0.255	0.115	0.908
PctPdpVR	-0.275*	0.255	-1.080	0.280
PctLitS	-0.185*	0.038	-4.889	0.000
PctUempS	0.018	0.026	0.681	0.496
TotEVS	0.045	0.029	1.542	0.123
PctVTS	0.151*	0.037	4.123	0.000

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PctApcVS	-0.323*	0.209	-1.542	0.123
PctPdpVS	-0.286*	0.209	-1.367	0.172
Residual sum of squares:				377.103
Log-likelihood:				-819.985
AIC:				1659.970
AICc:				1662.316
R^2:				0.513
Adj. R^2:				0.507
n:				774

* *Significant at 95 per cent level*

The AICc for this model is 1662.316 and the adjusted R-squared value is 0.507. The model performs fairly well in replicating 50.7 per cent of the variance in the percentage APC vote and many variables are statistically significant at the 5 per cent level of significance. Because the variables are unit normalised, the estimate of the intercept is zero and the absolute magnitude of the remaining parameter estimates can be used as an indicator of effect strength.

The results of the parameter estimates indicate that higher proportions of the vote that went to the All Progressives Congress (TotApcV) are associated with local government areas having higher populations (PopLg19) and higher proportions of voter turnout in States (PctVTS), as well as a lower proportion of All Progressives Congress vote in States where local governments are located (PctApcVS), a lower proportion of Peoples Democratic Party vote in States where local governments are located (PctPdpVS), lower proportions of PDP vote in geographical regions where local governments are located (PctPdpVR), and lower proportions of literate voters in States where local governments are located (PctLitS).

The population of local government (PopLg19) and percentage voter turnout (PctVTS) are the most positive variables, indicating that voting at the local government level for the All Progressives Congress increases as the population of residents and the percentage of voter turnout increases in a local government. Other consistent positive relationships with the All Progressives Party votes are the proportion of unemployed residents (PctUempS) in local governments as well as that of APC vote in geographical regions where local governments are located (PctApcVR), and total eligible voters in States where local governments are located (TotEVS). They are all marginally significant; they all have a little positive impact on the proportion of the vote garnered by APC.

On the other hand, the percentage of APC vote in the State where local government is located (PctApcVS) has the most negative association with the All Progressives Congress votes, followed by the percentage of PDP vote in the State where local government is located, the percentage of PDP vote in the region where the local government is located, and the percentage

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literacy level in State where local government is located (PctLitS). This simply indicates that increasing these four variables is associated with decreasing the proportion of votes for APC.

These parameter estimate results are corroborated by the *p*-value results. The covariates PopLg19, PctVTS, and PctLitS have the lowest *p*-value of 0.000 (which is smaller than 0.05). This shows that these three covariates are the most statistically significant test variables exhibiting local variation (that is, they show the most significant impacts on the total proportion of votes garnered by APC in local government areas). Also, the *p*-value for the intercept (1.000) and that for PctApcVR (0.908, which is higher than 0.5 and very close to the maximum of 1) indicates that the intercept and the covariate PctApcVR exhibit no significant local variation on the dependent variable.

Geographically Weighted Regression (GWR)

The results of the geographically weighted regression model, calibrated by the Weighted Least Squares (WLS) approach, are shown in Tables 4, 5, 6, and 7. The results in Table 3 indicate that the optimal bandwidth is 110; the confidence interval for the selected bandwidth is (106.0, 115.0).

Table 3: Optimal Bandwidth Selection for the Nigeria Election Data

Coordinates type:	Spherical
Spatial kernel:	Adaptive bisquare
Criterion for optimal bandwidth:	AICc
Bandwidth used:	110.000
Bandwidth confidence interval (95%):	(106.0, 115.0)

Table 4 gives the diagnostic information of the fitted GWR model. It shows that the AICc value (i.e., 1372.855) is smaller than that of the global regression model (i.e., 1662.316). Also, the adjusted R^2 value of 0.728 is higher than that of global regression (0.507).

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Table 4: Diagnostic Information of the Fitted GWR Model for the Election Data

Residual sum of squares:	173.362
Effective number of parameters (trace(S)):	136.317
Degree of freedom (n - trace(S)):	637.683
Sigma estimate:	0.521
Log-likelihood:	-519.233
Degree of Dependency (DoD):	0.607
AIC:	1313.099
AICc:	1372.855
BIC:	1951.836
R^2:	0.776
Adj. R^2:	0.728
Adj. alpha (95%):	0.004
Adj. critical t value (95%):	2.914

The Monte Carlo spatial variability significance test is given in Table 5 while the summary statistics of the estimated coefficients of local terms in the GWR model are given in Table 6.

Table 5: Monte Carlo Test for Spatial Variability of the Fitted GWR Model

Covariate	*p*-value
(Intercept)	0.000
PopLg19	0.000
PctApcVR	0.000
PctPdpVR	0.000
PctLitS	0.000
PctUempS	0.000

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TotEVS	0.000
PctVTS	0.000
PctApcVS	0.002
PctPdpVS	0.002

Table 6: Summary Statistics for GWR Parameter Estimates for the Election Data

Variable	Mean	STD	Min	Median	Max
(Intercept)	-0.271	0.544	-2.661	-0.263	2.558
PopLg19	0.544	0.387	0.014	0.492	1.522
PctApcVR	0.147	0.988	-4.510	0.165	3.423
PctPdpVR	-0.053	0.951	-3.928	-0.003	3.554
PctLitS	-0.014	0.380	-1.473	-0.008	1.242
PctUempS	0.166	0.315	-0.718	0.040	1.713
TotEVS	-0.176	0.458	-1.669	-0.066	0.992
PctVTS	0.262	0.296	-0.340	0.184	1.235
PctApcVS	-0.376	0.796	-5.114	-0.130	0.976
PctPdpVS	-0.301	0.760	-4.523	-0.096	1.055

Comparison of the Global and GWR Models for the Nigeria Election Data

Two forms of regression models- global regression and GWR - have been calibrated on the Nigeria election dataset with nine selected independent variables. The overall performances of the two models in terms of Residual Sum of Squares (RSS), Akaike Information Criterion (AIC), and R-squared values are listed in Table 7.

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Table 7: Comparison of Overall Model Performances

Performance Indicators	Global Regression	GWR
RSS	377.103	173.362
AIC	1659.97	1313.099
AICc	1662.316	1372.855
R^2	0.513	0.776
Adjusted R^2	0.507	0.728

The global regression model has the higher RSS and the higher AIC/AICc values. This suggests that the global model performs worse in fitting the Nigeria election dataset and results in more information loss in representing the true process than the GWR model. It further suggests that it is not appropriate to assume globally constant relationships between the independent variables and the total vote garnered by APC in the local government (TotApcV) and that local regression is necessary to reveal local effects and to guide further detailed studies. The GWR model yields lower RSS and lower AIC/AICc values, suggesting that it is the better fit for the dataset.

The R^2 tells the proportion of spatial variability in the dataset that is explained by the model. The accepted model is that having the higher R^2 value. The adjusted R^2 is an estimate of how well the model would fit different datasets from the same population; the adjusted R^2 value is always smaller than the value of R^2. The adjusted R^2 is commonly used as the best measure of a model's goodness of fit. The R^2 values of the GWR model are very high, and the higher of the two models. This indicates that apart from explaining very well the spatial variations in the dependent variable (total vote garnered by APC in local governments), the GWR model explains the spatial variations better than the global regression model does.

CONCLUSION

The study showed that the GWR model performs better, compared to the global regression model (OLS), in fitting the empirical datasets. The GWR model revealed more non-stationarity in local parameter estimates, therefore, serving as a guide for further local variable studies. The GWR model performed well in capturing the spatially varying relationships between the dependent variable and the independent variables; that is, relationships between voter preference and various local government-level socioeconomic characteristics.

There are significant spatial variations in the determinants of the dependent variable in the dataset. Location plays a vital role in shaping voters' preferences; political, economic, and social relationships are not uniform over space. For instance, the analyses in the study suggest

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that individual characteristics are not sufficient to fully explain voting preferences, there exists a certain amount of dependency between voting behaviour and location; and that electoral behaviour is shaped by localised political and social processes. Thus, it is important to consider spatial structures when conducting statistical analysis of voting patterns. What motivates and influences an individual to cast a particular vote is the aftermath of a wide range of processes that may vary over space and operate at different geographic scales.

The GWR model outperforms the global regression model with an R^2 value of 0.776 exceeding that of the global regression 0.513. The superiority of the GWR model is also confirmed by its much smaller RSS and AICc values (173.362 and 1372.8555 respectively), compared to those of the global regression (377.103 and 1662.316 respectively). The GWR model is the better fit for the election dataset; it explains spatial variations in the dependent variable better than the global regression model does. The GWR model appropriately examines geographically-referenced data, and in particular, it adequately describes the factors that influence the winning of a presidential election by a political party in Nigeria.

RECOMMENDATION

In view of the appropriateness and effectiveness of the geographically weighted regression to the election data used in this study, the technique is recommended for the study of geographically referenced data.

FUTURE RESEARCH

One of the main ongoing issues in statistical spatial analysis and modelling is that of spatial prediction. Even though geographically weighted regression is not meant for prediction (Rossiter, 2019; Rossiter, 2022), a possible way of predicting with GWR is by out-of-sample prediction, like interpolation methods. This is one important area that gives room for future research, i.e., being able to use the GWR technique/modelling to predict election results.

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