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Modelling Municipal Solid Waste Generation Using Geographically Weighted Regression: A Case Study of Nigeria

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Abstract

This study is aimed at developing a spatial model for municipal solid waste (MSW) generation rate based on socio-economic, demographic and climatic variables for Nigeria. The outcome is targeted at effective forecasting and management of MSW in the country. Secondary data sources were used to obtain the variables, then screened and linked to the administrative boundaries of the 36 States and the Federal Capital Territory (Abuja). Geographically Weighted Regression (GWR) tool in ArcGIS 10.0® was used to analyse the data. The analysis gives an acceptable condition number of 16.63, while local R^2 ranges from 0.54 to 0.90. The model also explains 65 per cent of the total variation in the dependent variables. The findings of this study revealed that nearer States tend to have similar coefficients than the distant ones and that dependent variables vary among States. In addition, the β coefficient estimates of unemployment rate, employment in crop farming, literate adults above 15 years, per-capita average household expenditure on food and non-food items, and excess proceeds of crude oil to local government areas exhibit positive relationship with MSW throughout the country. Whereas, only rainfall variable exhibited positive and negative relationship in northern and southern part of the country, respectively. The paper contributed towards improving the understanding of factors affecting MSW generation rate in Nigeria.

Keywords: Municipal solid waste, factors of municipal solid waste, geographically weighted regression, GIS, Nigeria.

Introduction

Municipal solid waste (MSW) generation and disposal has become a serious problem in many developing countries, Nigeria inclusive. MSW problems are more common in urban areas of large and rapidly growing cities. The increasing volume and variety of MSW generation are attributed to accelerated urbanization, high population growth, increase in per-capita incomes and technological development[1,2]. In Nigeria for instance, very large accumulations of MSW could be seen within towns and cities. This awkward situation often led to blockage of roads/streets and drainages with associated environmental problems[3,4] and diseases[5].

There are several factors that influence the generation of MSW. These factors vary geographically and can be categorized into social, economic, and environmental factors. Understanding how these factors affect MSW generation is important as it enables policy-makers to take more informed decisions about where and when to implement a particular policy. However, availability and quality of data on MSW generation is poor and even non-existent in Nigeria. The need for such data are important. Thus, an accurate measurement of current MSW generation is needed to determine and allocate resources required for waste management and also to estimate future requirements[6].

Several methods of solid waste generation rates are notable. These include a time series analysis[7], simple correlations[8], bivariate linear regression[9, 10], multi-variate linear regression[11], Autoregressive Integrated Moving Average (ARIMA) stochastic model[12]. All the authors mentioned above had established relationships between demographic factors with solid waste and have also isolated statistical determinants of solid waste generation sufficiently. While these methods are useful in the analysis of explanatory variables for MSW generation, they remain insufficient for satisfying the requirements of this paper, in this case, given the peculiarity of the problems of MSW in Nigeria, for two reasons. First, the ambition of the Federal Government of Nigeria (FGN) is to achieve at least 80% reduction in the volume of MSW generated at all levels. This statement is contained in a report submitted to the UN Commission on sustainable development[13]. According to Nigeria's report, this was to be achieved through strategies including, development and implementation of a national guidance and blue print for integrated management. Furthermore, to review and strengthen existing laws and regulations for sound environmental management of MSW disposal and recycling, amongst other strategies. Second, a nation-wide approach to MSW management is feasible to be tackled at the national level because it is the Federal government that had both the commitment and resources to do so. That is because the FGN holds an ecological fund which at the latest consists of 30% of all derivation allocations from the Federation accounts. The purpose for setting up the fund includes waste management and general environmental hazards[14].

The relevance of geographically weighted regression (GWR) application is to address the problems of MSW analysis not on the basis of identifying factors alone. GWR goes beyond ordinary statistical analysis and provides a spatial view of performance of determinants of MSW across the country. This appraisal provides the tools for policy intervention in the context of Nigerian government's mission, strategy and determination of where resources should be allocated.

Although, several studies have been conducted on solid waste problems in Nigeria using different methods; limited evidence exists for using modern techniques of spatial analysis such as GWR on data related to solid waste, especially in Nigeria. Recent studies have revealed the analytical utility of GWR for investigating a variety of topical issues, for instance, urban growth[15], intellectual disability[16], terrorism[17], climatology[18], rural economic development[19], environmental justice[20], and the ecological inference problem[21]. Hence, GWR can be applied in many areas to assess the spatial variability of relationships between the dependent and independent variables. This study, therefore aims at developing a spatial model of MSW generation based on socio-economic, demographic and climatic variables for Nigeria using GWR for effective management of solid waste in the country.

Material and Methods

Study Area: The study was conducted in Nigeria, which comprises of thirty six States and the Federal capital territory (FCT). Nigeria is situated in West Africa on Longitude 3° and 14° East and Latitude 4° and 14° North (figure-1) with an area of 923,769 km^2. It shares boundary with Niger and Benin Republics to the west; Cameroun Republic to the east. To the north are Niger and Chad Republics; while to the south is the Atlantic Ocean[22]. Nigeria is the Africa's most populous nation (168.8 million inhabitants) estimated as at 2012[23] and comprises over 250 socio-linguistic groups.

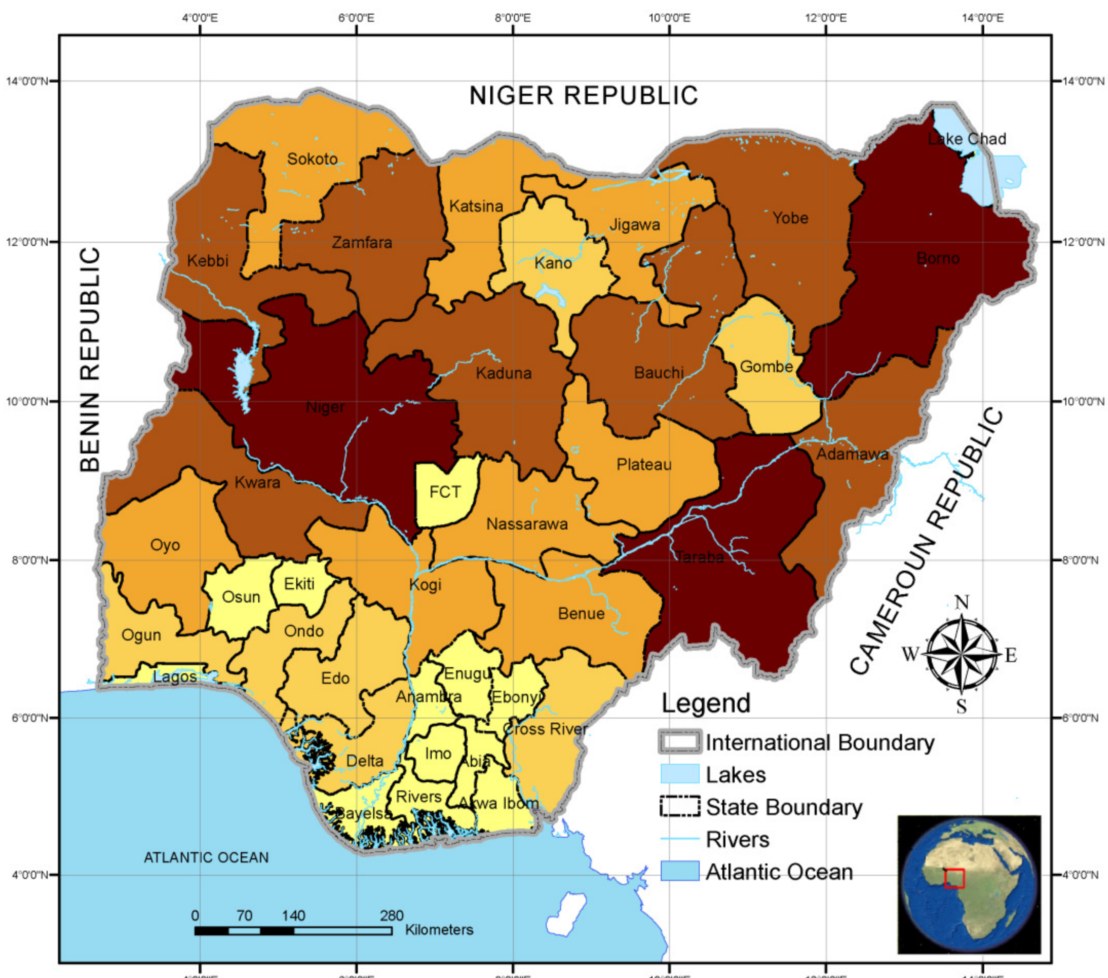

Figure-1
The study area showing the 36 States and FCT

Data and Software: Secondary data comprises of socio-economic, demographic and climatic variables were obtained from the National Bureau of Statistics[24, 22]. Whereas, the amount of MSW generated by each State and the FCT was estimated using a MSW rate of 1.2 kg/capita/day[25] and the 2006 population census. The 2006 data was chosen because it comprises of both population census and housing survey. MSW is considered as dependent variable while the explanatory variables comprises of socio-economic, demographic and climatic variables. In all, there are 22 explanatory variables (table-1). In addition, administrative boundaries of all the 36 States and FCT in Nigeria were obtained as shape file format from DIVA GIS[26] and then projected to Minna datum, UTM zone 31N in ArcGIS 10.0®. All the variables (dependent and explanatory) were then compiled in Microsoft Excel 2013. Multi-collinearity on explanatory variables was removed in order to eliminate problems of result interpretation. It was eliminated by executing OLS in SPSS v21. Explanatory variables with variance inflation factor (VIF) above 7.5[27, 28] were eliminated. Thus, only the explanatory variables that have VIF below 7.5 are considered for further analysis. These variables and the dependent variable (MSW) were joined as attributes data to the 36 States and FCT (administrative boundaries) shape file layer in Arc GIS 10.0®.

Methods: Global Spatial Autocorrelation Coefficient: Spatial autocorrelation is the degree to which attributes at some location on the surface of the earth are similar to attributes of nearby locations[29]. Thus, it is the correlation of a single variable between pairs of neighbouring observations. Positive spatial autocorrelation occurs when neighbouring values tend to be similar (data are spatially dependent), whereas, negative spatial autocorrelation occur when the values tend to be dissimilar[30]. This concept corresponds to the *first law of geography* which states that "*everything is related, but near things are more related than distant things*"[31]. Spatial autocorrelation has significant implications for the use of statistical techniques in analysing spatial data. For most classical statistics, including regression models, the main assumption is that sample observations are randomly selected and therefore independent of each other. However, analysing spatial data using these classical methods often violates the independence assumption due to existence of certain degree of spatial autocorrelation[32,33].

Therefore, the result of such statistical analysis will be incorrect if spatial autocorrelation is not recognized. In cases where data values are not spatially dependent, many forms of spatial analysis are irrelevant[30]. There are several spatial statistics used to assess levels of spatial autocorrelation in spatial data. In this study, the *Moran's I* is applied because it is easier to interpret considering its similarities to the Pearson correlation coefficient[34, 35]. According to Moran[36] the principles of *Moran's I* is that similarity of attribute values is defined as the difference between each value and the mean of all attribute values in question. The index is calculated as;

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sigma^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \qquad (1)$$

Where x_i is the value of variable in areal units (States) $i, x_j,$ is the value of variable in neighbouring areal units (States) j, σ^2 is the population variance, $\sigma^2 = \sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 / n, w_{ij}$ is spatial weight between locations i and j.

Table-1
Summary statistics of the demographic, socio-economic and environmental factors investigated for potential association with MSW

Variables	Definition	Unit	Minimum	Maximum	Mean	Std. Deviation
Dependent variable						
*MSW	Municipal solid waste	Kg/person/yr	615,932,682.00	4,117,764,144.00	1,662,408,757.30	754,904,465.13
Explanatory variables						
Demographic Factors						
POPDEN	Population density	Person/sq.km	40.77	2,482.59	304.45	419.89
MALR	Male ratio	%	0.50	3.40	1.34	0.63
FEMR	Female ratio	%	0.50	3.30	1.35	0.61
HOU_NO	Households number	Number	303,592.00	2,993,811.00	824,896.84	516,704.48
AVHSIZ	Average household size	Person	2.60	6.40	4.65	0.96

Variables	Definition	Unit	Minimum	Maximum	Mean	Std. Deviation
CBR	Crude birth rate	%	4.57	25.24	12.66	4.68
CDR	Crude death rate	%	0.00	5.42	1.50	1.23
Socio-conomic Factors						
UEMPR	Unemployment rate	%	2.30	50.80	13.84	8.75
YTRAI	Unemployed youths trained under annual training profile	Number	500.00	1,020.00	675.68	169.12
EMPCROF	Employment in crop farming	Number	27,000.00	3,921,000.00	1,186,864.86	938,078.45
LITAD	Literate adults 15 years +	%	16.82	94.43	58.62	21.67
FEDRD	Length of Federal roads by state	Kilometres	167.80	2,207.00	928.14	465.46
PEF	Per-capita average household expenditure on food and non-food items	Naira	42,137.59	176,069.92	95,264.10	33,812.89
NSS	Net statutory allocation to State	Billion Naira	10,375,832,301.26	117,557,051,645.86	26,536,815,899.87	23,581,333,745.49
CRS	Excess proceeds of crude oil to States	Billion Naira	2,647,043,171.40	31,449,469,134.70	6,950,109,425.94	6,430,242,843.86
VTS	Value added tax allocation to State	Billion Naira	1,362,946,933.52	16,392,693,283.48	3,011,892,868.59	2,342,568,333.17
NSL	Net statutory allocation to LGAs	Billion Naira	3,787,435,968.73	31,162,511,945.82	14,389,736,465.36	5,078,126,944.43
CRL	Excess proceeds of crude oil to LGAs	Billion Naira	288,806,424.14	7,271,635,771.14	3,233,336,384.91	1,344,371,891.90
VTL	Value added tax allocation to LGAs	Billion Naira	927,927,484.57	10,103,102,905.86	2,107,624,307.86	1,502,767,465.76
Environmental Factors						
A_MMTEM	Annual mean maximum temperature	^{o}C	28.00	36.10	32.88	1.92
A_RFL	Annual mean Rainfall	Mm	88.70	4,000.00	1,362.04	879.23
A_RHUM	Annual mean relative humidity at 0900 GMT	%	27.80	85.00	53.28	16.03

Source: National Bureau of Statistics[24, 22]. * Estimated using the 2006 population and MSW rate of 1.2 kg/capita/day Naira (Nigerian Currency)

The *Moran's I* values ranges from -1 for negative spatial autocorrelation to +1 for positive spatial autocorrelation. Thus, if a *Moran's I* value is 0, this indicate random pattern, whereas, negative and positive values are considered as disperse and cluster patterns respectively. If there is no indication of spatial autocorrelation, then the *Moran's I* value is;

$$E_i = \frac{1}{(n-1)}, \quad (2)$$

Before running the *Morans I*, distance band from neighbour count was computed by appying the Calculate Distance Band from *"Neighbour Count Tool"* in ArcGIS 10.0®. Using a distance threshold of 237,596, and inverse distance (a method of defining spatial relationships), Spatial Weight Matrix was generated. Then, *spatial autocorrelation (Moran's I)* from the *"Spatial Statistic Tools"* in ArcGIS 10.0® for all the variables in table-2 was computed. The Spatial Weight Matrix file and inverse distance method was specified. Detection of spatial autocorrelation indicates that locality is an essential point in describing and explaining the MSW generation rate. Thus, variables that do not indicate the presence of spatial autocorrelation were eliminated.

Table-2
Collinearity Analysis

Variables	Collinearity Statistics	
	Tolerance	VIF
HOU_NO	0.565	1.770
AVHSIZ	0.270	3.708
CBR	0.646	1.549
CDR	0.398	2.510
UEMPR	0.698	1.432
YTRAI	0.630	1.588
EMPCROF	0.523	1.913
LITAD	0.373	2.680
FEDRD	0.666	1.501
PEF	0.400	2.503
CRL	0.469	2.131
A_MMTEM	0.649	1.541
A_RFL	0.662	1.510

Geographically Weighted Regression: The main problem with conventional regression technique when applied to spatial data is that the processes under investigation are assumed to be constant over space, that is, one model fits all locations or areal units. On the contrary, GWR is a spatial statistical technique that uses both geographic and attributes information and allows the modelling of processes that vary and cluster across space[37]. The β coefficients estimated by GWR are local coefficients and therefore specific to each location or areal unit (in this case, administrative areal units) in the data set of this present study. GWR reveals these local coefficients by moving a spatial kernel over the study area. In other words, the relation of the dependent variable to the explanatory variables varies across the study area. In this way, Charlton[37] noted that GWR provides vital information on the nature of the processes under investigation and supersedes the conventional global types of regression model. Moreover, GWR model takes the spatial dependency into consideration satisfying the latter condition. In this regard, this study used the GWR to develop a spatial model of MSW rate for Nigeria. The GWR equation is;

$$Y_i = \beta_{0i} + \beta_{1i}X_{1i} + \beta_{2i}X_{2i} + ... + + \beta_{ni}X_{ni} + \varepsilon_i \quad (3)$$

Where: Y_i represents the value of the dependent (MSW) variable observed at the location i, X_{ji}, (j from 1 to n) is the values of the independent (socio-economic, demographic, climatic) variables observed at $i$included in the model, $\beta_{0i}, \beta_{1i}, ...\beta_{ni}$ are parameters to be estimated, and ε_i is the residual, all at location i .

This analysis was implemented in ArcGIS 10.0® using the *GWR Model (Spatial Statistic Tools)*. Dependent variable and independent variables (table-2) that shows the presence of spatial autocorrelation were supplied to the model simultaneously, and then followed by specification of other parameters of the model. To account for differences in the density of administrative boundaries across the study area, adaptive kernel method was chosen because changes in bandwidth of the kernel depend on the density of data. Thus, represents the spatial heterogeneity degree better than fixed kernel and ensures certain number of nearest neighbours as local samples[38,39]. Equation-4 shows the general form of kernel method:

$$\bar{\lambda}(s) = \sum_{i=1}^{n} \frac{1}{\tau^2} k\left(\frac{s - s_i}{\tau}\right) \quad (4)$$

Where k is the kernel, τ is the bandwidth, and the adaptive bandwidth is taken as:

$$\tau(s_i) = \tau_0 \left(\frac{\bar{\lambda}_g}{\tau(s_i)}\right)^{\alpha} \quad (5)$$

Where $0 \le \alpha \le 1$ is the sensitivity parameter, and $\bar{\lambda}_g$ is the geometric mean of the pilot estimates $\bar{\lambda}(s_i)$ at each s_i .

Akaike's Information Criterion (AIC) was applied in specifying how the extent of the kernel is been determined. After the first run, the model was unable to be computed due to severe model design problems. This means that there exist either severe global or local multi-collinearity. Finding local multi-collinearity is a difficult task. However, in this study, thematic maps were created for each of the explanatory variables with a view to identify areas with little or no variation in values. After analysing the thematic maps, three variables (AVHSIZ, A_MMTEM, CDR) which shows evidence of lack of variations were removed, then, the GWR model was run again successfully. The coefficients obtained from the results of GWR model was mapped using choropleth maps based on natural break (Jenk's) optimization classification scheme to explore the varying relationships between the dependent and independent variables. The fit of GWR was assessed by *AIC,* R^2 and *Adjusted* R^2.

Results and Discussion

Moran's *I*: The results of *Moran's I* test revealed that HOU_NO, CBR, YTRAI, and FEDRD shows random pattern throughout Nigeria. This means that their values for respective States do not show particular pattern. In other words, these variables do not exhibit spatial autocorrelation. On the other hand, the *Moran's I* of AVHSIZ, CDR, UEMPR, EMPCROF, LITAD, PEF, CRL, A_RFL, A_MMTEM shows statistically significant global positive spatial autocorrelation (clustering) with >99% confidence interval level. The *Moran's I* ranges from 0.13 to 0.72, meaning that adjacent or nearby States show similar characteristics. In addition, the *p*-values of these variables ranges from 0.000 to 0.8403 (table-3). The HOU_NO, CBR, YTRAI, and FEDRD variables were not considered for subsequent analysis since they do not show the presence of spatial autocorrelation.

GWR: The diagnostic information of the computed GWR model is shown in table-4. The information include the number of nearest neighbours to be included in the bi-square kernel, residual sum of squares and effective number of parameters which a measures the model complexity. Whereas, *Sigma* is the square root of the normalised residual sum of squares. The result revealed that the GWR explains 65 per cent (R^2 *Adjusted*) of the variation in the dependent variables with *AICc* of 1,605.12 and therefore acceptable.

From figure-2a, it can be observed that Akwa Ibom State exhibit over-prediction (-2.0 and above standardised residual) while Plateau and Lagos States display under-prediction (+2.0 and above standardised residual). This indicates that 91.89% of the prediction is good. On the other hand, figure-2b suggests that the result of this study is reliable since the largest condition number is 16.63, which is less than 30. Furthermore, the result of our study showed that the local regression (GWR) model fits observed y-values very well throughout the country (figure-2c). States comprises of Bauchi, Borno, Gombe, Jigawa, Kaduna, Kano, Katsina, Sokoto, Yobe and Zamfara exhibit the highest *local* R^2 (0.84 - 0.90), whereas Abia, Anambra, Akwa Ibom, Bayelsa, Cross River, Delta, Ebonyi, Enugu, Imo, and Rivers States has the moderate values (0.54 - 0.58).

The results of this study also indicate that the GWR coefficients vary over the study area. Even the sign of the coefficient changes for some of the variables meaning that the effect of the dependent variables on MSW generation rate differ from one location (State) to the other.

Table-3
Calculated Moran's *I* and determination of spatial pattern

S/N	Variables	Global Moran's *I*	Expected Index	Variance	z-score	p-value	Spatial Distribution
1.	HOU_NO	-0.0098	-0.0278	0.0079	0.2015	0.8403	Random
2.	AVHSIZ	0.7166	-0.0278	0.0107	7.1998	0.0000*	Cluster
3.	CBR	0.0162	-0.0278	0.0105	0.4295	0.6676	Random
4.	CDR	0.2590	-0.0278	0.0101	2.8473	0.0044	Cluster
5.	UEMPR	0.1282	-0.0278	0.0082	1.7184	0.0857	Cluster
6.	YTRAI	0.0329	-0.0278	0.0104	0.5950	0.5519	Random
7.	EMPCROF	0.4158	-0.0278	0.0099	4.4542	0.0000*	Cluster
8.	LITAD	0.6087	-0.0278	0.0107	6.1527	0.0000*	Cluster
9.	FEDRD	0.0451	-0.0278	0.0100	0.7278	0.4668	Random
10.	PEF	0.5339	-0.0278	0.0105	5.4712	0.0000*	Cluster
11.	CRL	0.1507	-0.0278	0.0099	1.7874	0.0739	Cluster
12.	A_MMTEM	0.1558	-0.0278	0.0103	1.8119	0.0699	Cluster
13.	A_RFL	0.4313	-0.0278	0.0102	4.5537	0.0000*	Cluster

*Significant

Table-4
GWR diagnostic information

Parameter	Values
Neigbours	37
Residual Squares	4.337637e+018
Effective Number	15.23
Sigma	446337727.22
AICc	1,605.12
R^2	0.79
R^2 Adjusted	0.65

Keser[40] noted that increase in unemployment leads to decrease in both buying and consumption power. Hence, solid waste generation per capita will experience a decline. Therefore, higher unemployment rate is expected to affect MSW generation rate significantly and negatively. Surprisingly, the result of this study did not support that notion. From figure-3a, it can be observed that β coefficient estimates of unemployment rate are positive throughout the country. The reason for this may be attributed to culture in this part of the world in which family members support their relations that are less privileged. In addition, the result suggests that the percentage of unemployed persons in the country is not high to an extend that will affect MSW rate negatively.

Employment in crop farming coefficient estimates are positive throughout the country. This means that there is a positive relationship between this variable and MSW generation rate in Nigeria. However, Adamawa, Bauchi, Borno, Gombe, Jigawa, Kaduna, Kano, Katsina, Plateau and Yobe States have the highest values ranging from 372.83 to 448.04. In general, States in the northern part of the country has higher values than those in the southern part (figure-3b). In other words, the effect of this variable can be seen in States that are agrarian except Kaduna and Kano States. Crop farming is generally prevalent in this part of the country both dry and wet seasons. In this regard, government should provide training and grants for composting of waste for manure and to convert waste to domestic gas production. Thus, organic farming strategy should be encouraged.

Literate adults above 15 years show a positive relationship with MSW throughout Nigeria as expected. Sokoto and Kebbi States have the highest coefficients, whereas Kaduna, Nassarawa, Plateau and Taraba States have the least values (figure-3c). Though, high positive relationships could be seen in Southern and North Western parts of Nigeria. Literacy, especially western education indicates more taste for consumer products that generate waste. These areas are also highly urbanised and industrial. In contrast, education does not have much impact in North East and parts of Middle belt with respect to MSW generated. The policy implication of this result is that government can use the vast number of non-literate population as a cheap source of labour for solid waste collection and recycling for employment.

The per-capita average household expenditure on food and non-food items by State and sector exhibit positive relationship with MSW rate generation throughout Nigeria (figure-3d). However, Lagos, Ogun, Oyo, Ekiti, Ondo, Osun, Edo, Delta, Bayelsa and Rivers States exhibit the highest coefficients (4574.36 - 5166.56). This indicates that States in the Southern Nigeria has higher income with more household purchasing power. The concentration of MSW in this part of the country is as a result of urbanisation, modern consumption, industrial production in oil and domestic sectors. Therefore, since households are more likely middle and high income class, there is need for government to sensitise and charge for MSW waste collection. More so, to provide incentive to public private partnership in solid waste collection.

Crude oil proceeds excess to LGAs is also positively related to MSW generation throughout the country as expected (figure-3e). This means that the monies allocated to LGAs from crude oil proceeds has gone a long way in improving the lives of people and infrastructure development. However, the effect of this variable is more pronounced in the following States: Lagos, Ogun, Ondo, Oyo, Osun, Ekiti, Kwara, Niger, and Kebbi.

The effects of rainfall variable are expected in raining season due to warm temperatures and high precipitation. This leads to increase in quantity of waste generation. The result of this study revealed that the significant β coefficient estimates of rainfall value are positive mostly in the Northern part of the country while the negative values are observed in the Southern States (figure-3f).

The possible explanation for this result is that States in the southern part of Nigeria are more urbanized that their northern counterparts. Thus, houses in the Southern parts tend to generate less wastes because they have small yards or not at all. Another possible explanation is that rainfall in those Northern states is less and more variable therefore, giving a significant difference in MSW generation between the wet and the dry seasons, respectively. The policy implication of this result is that since agriculture is critical in the North, some pollution must be avoided. The use of plastic bags should be banned while government provides grants entrepreneurs for establishment of bio-gradable plastic industry and packaging.

Conclusion

The paper contributed towards improving the understanding of factors affecting MSW generation rate in Nigeria. GWR generate a local model of the variable or process we want to understand and predict by fitting a regression equation to every feature in the dataset. The study shows that the method is powerful and is a reliable spatial statistics for examining and estimating linear relationships. The municipalities should pay necessary attention and cooperate with the relevant institutions to determine waste generation rates and trends, and to create a reliable database. One of the ways of achieving this is to relate the MSW generation rates to socio-economic and other factors. The results of this study which offers a valid model for Nigeria considering socio-economic, demographic and climatic differences between States may be a supporting tool. The versatility of the study in terms of variables may result in comprehensive projections. This model is also important in that it presents the determinants of solid waste generation in Nigeria which is very useful in supporting decisions in action plans for solid waste reduction. More so, the study has demonstrated the suitability of GWR in planning applications in Nigeria in three ways: i. that policy action could be taken along geographical or regional areas in respect to the thematic map outputs of models, ii. GWR identified priority action areas at the macro-level, where FGN needs to direct resources for MSW management, iii. that the same GWR could be used within any region for further intervention in MSW management and allocation of resources and strategies at a more precise problem or location identified.

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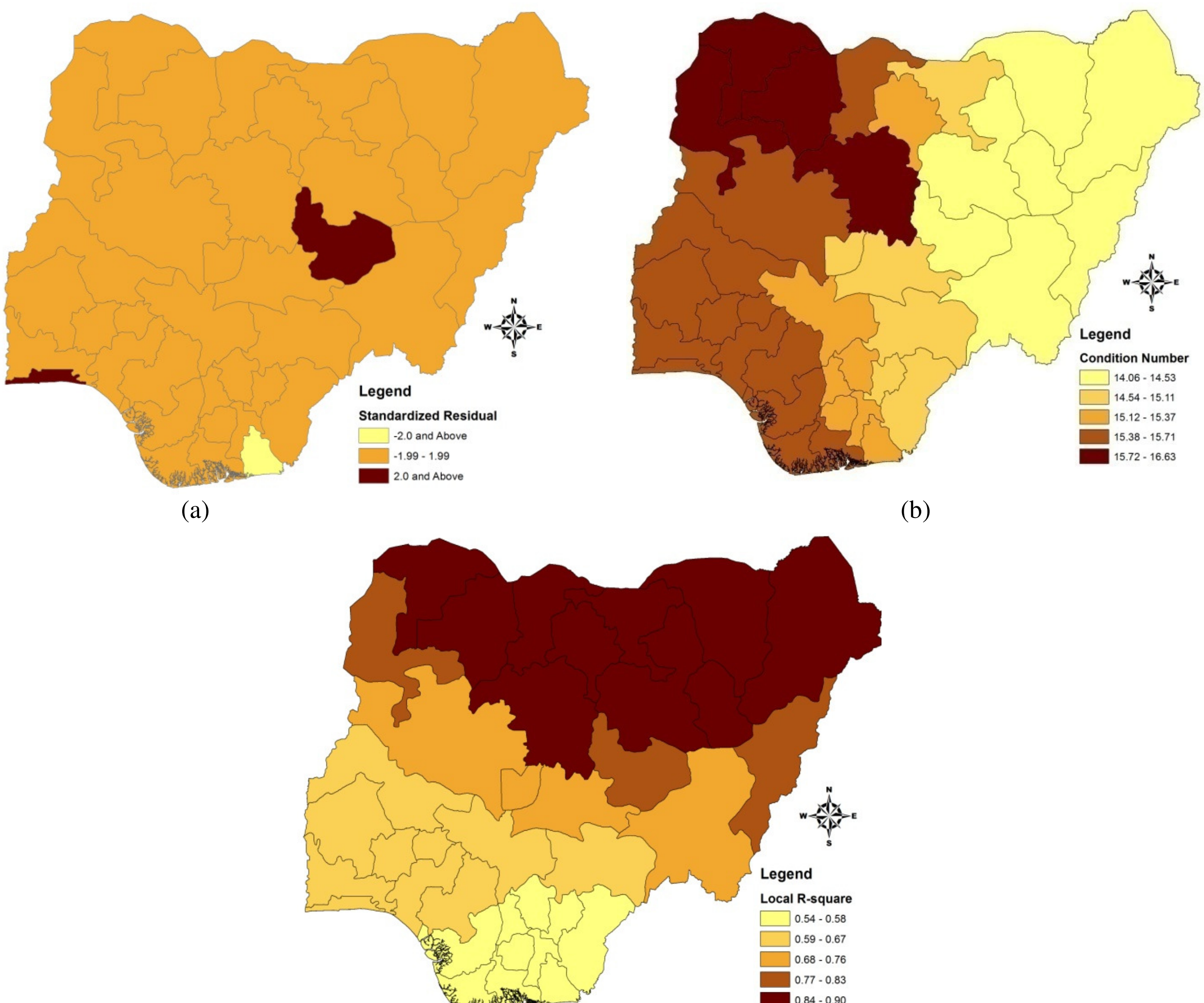

(a) (b) (c)

Figure-2
(a) Standardized Residual (b) Assessment of Local Multi-collinearity (c) Spatial variation of Local R^2

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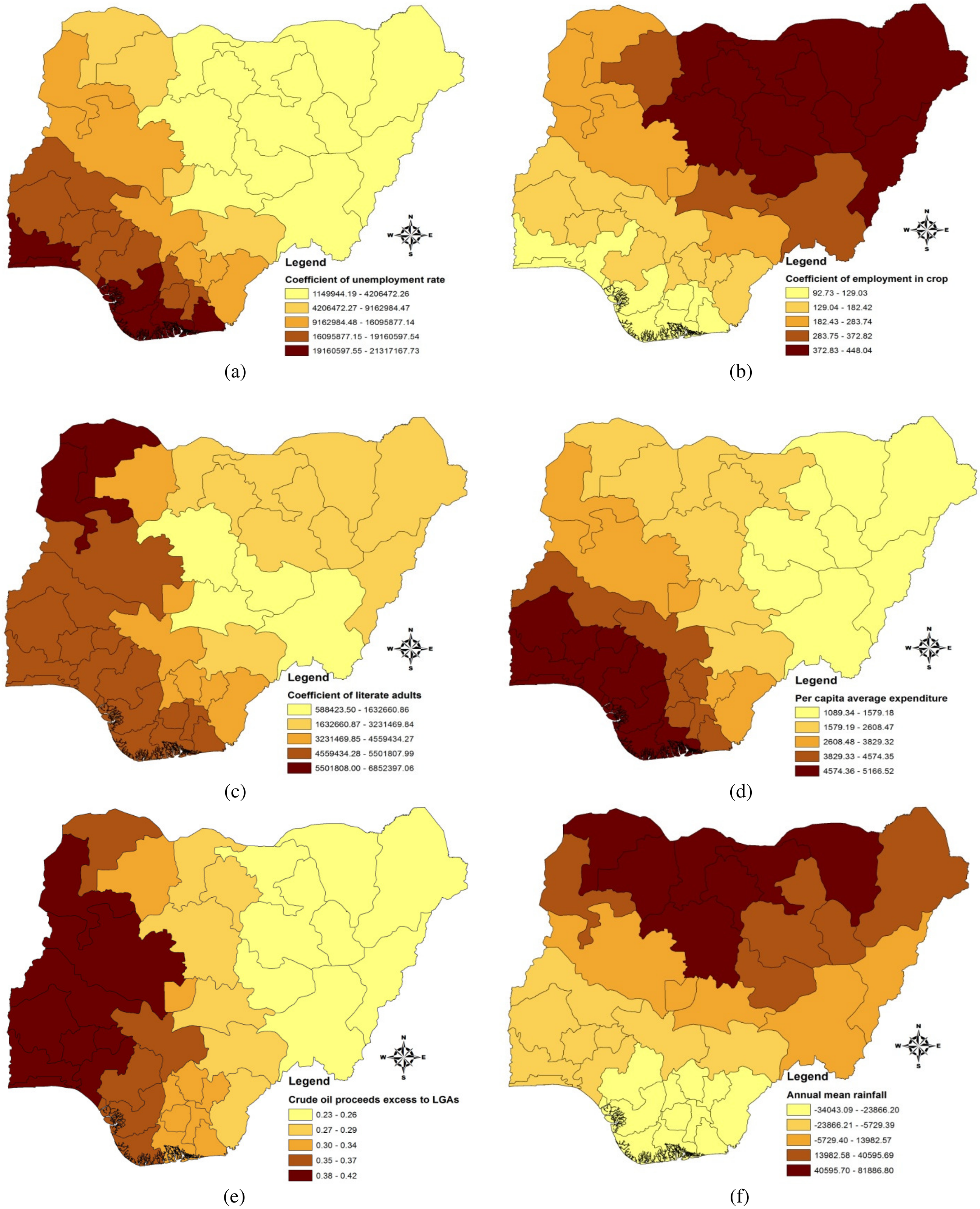

Figure-3

(a) Unemployment rate coefficient (b) Employment in crop farming coefficient (c) Coefficient literate adults above 15 years (d) Coefficient of per capita average household expenditure on food and non-food items by state and sector (e) Crude oil proceeds excess to LGAs coefficient (f) Annual mean rainfall coefficient

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