MODELING SLUM AND INFORMAL HOUSING DEVELOPMENT IN AKURE, NIGERIA (1986-2019)

ADEDEJI A. A.[1], JUNAID A. M.[2], SANNI L.M [3].
Department of Urban and Regional Planning, Federal University of Technology, Minna, Nigeria

Abstract:
Slums and informal housing developments in Akure are growing at an unprecedented rate. It was on this basis that this work assessed the indices of slum and informal housing development in Akure, Ondo State, Nigeria. A stratified sampling method was used in selecting the corridors, and a simple random sampling technique was used in selecting the residents in the corridors. Primary data was collected using a questionnaire administered to 600 respondents with the aid of trained enumerators. Descriptive statistics, spatial analysis, and logistic regression models were used for the analysis. The study concluded that between 16.3% and 40.8% of the variance in predicting whether there is or is not development of slum and informal housing in Akure were explained by the following predictors: housing shortage, lack of affordable housing, high incidences of urban poverty, lack of planning and development plans, inadequate development control by planning agencies, inadequate provision of sites and services, tenure insecurity, inadequate neighbourhood facilities and services, and inadequate sanitation, with significance values of 0.000, 0.035, 0.000, 0.045, 0.005, 0.021, 0.030, 0.024, and 0.000, respectively. Each of these values were less than 0.05. The study recommended that the state government should upgrade earth roads to gravel and construct distribution roads with drainage, especially in areas like Igoba, Ijoka, and Orita-Obele in Akure.

Keywords: Modeling, Slum and Informal, Housing Development, Logistic Regression

Introduction

Rapid urbanization with its attendant socio-economic problems poses challenges to the human race. Urbanization is associated with the problems of unemployment, poor sanitation, slums, informal housing, environmental degradation, and health hazards, especially in the developing countries of the world (Oyinloye *et al.,* 2017). Urbanization is characterized by the movement of people from rural areas that tend to be sparsely populated to cities that occupy more compact spaces and provide more densely populated living opportunities (United Nations Population Funds (UNFPA), 2007)

Nigeria has been experiencing a rapid rate of urbanization. According to the United Nations Conference on Sustainable Development (1997), in 1952, 10% of the population lived in urban centres with a population of 20,000 people or above. In 1970 and 1993, respectively, in Nigeria, this increased to 20% and 38%. By the year 2050, it is estimated that 69.6% of Nigeria's population will live in cities, compared to 50.6% in 2010. The growth in the size of cities has been equally rapid. In 1960, Lagos and Ibadan were the only two cities with more than 500,000 people. Presently, within multiple cities having populations exceeding one million, Nigeria is one of the most populous countries in the world. Its biggest city, Lagos, now contributes 9 million residents to the total population, while there are also 79 cities with a minimum population of 100,000 and 249 cities with populations that surpass 10,000. This is expected to rise substantially by 2050 (World Population Review, 2018).

Akure, the capital city of Ondo State is experiencing growth in an unplanned and uncontrolled way. This has resulted in the overstretching the existing urban infrastructure such as electricity, water supply, and growing environmental problem such as polluted waterways, insufficient clean water supply, air pollution, lack of sewage collection, piles of uncollected and rotting garbage, bad roads, loss of forest and green space, etc. The cumulative effect of these environmental problems is acutely damaging not only the health of the people but also the ability of the cities to support economic growth. Slums and informal housing development in Akure are growing at an unprecedented rate. Logistic Regression Model (LRM) has been proven to be a suitable approach for urban growth modeling in such kind of fast growing cities (Huang *et al.,* 2009). Logistic Regression technique, one of the empirical statistical methods can make a vital contribution in urban growth modelling studies (Pullar and Pettit, 2003; Lesschen *et al.,* 2005).

LRM has shown its high capability to capture the probability of new urban developments that will take place in the future using less computer resources (Hu and Lo, 2007; Hu, 2004). LRM has a strong capability to not only incorporate biophysical influence (slope, land use/cover, transport, zoning) but also demographic and social variables to better understand human forces' ability in urban growth pattern (Hu and Lo, 2007). Nong and Du (2011) assured that by less computation resources, LRM calibration can allow multi-scale (different moving window sizes) simulations. LRM is simple to interpret Field (2013); Moore. *et al.* (2009), suitable approach to evaluate critical areas for future urban development (informal settlement proliferation or urban growth; i.e. areas that will be highly urbanized and not) Dubovyk *et al.* (2011); Duwal (2013) and to assess the impact of macro-level changes (e.g major roads, built-up areas, etc.) (Lesschen *et al.,* 2005). The aim of the current study is to develop a predictive model for explaining slum and informal housing development in the Akure.

Methodology

Logistic regression modelling was used to model indices responsible for slum development so as to predict its future expansion. Three land cover maps in the periods of 1986, 2002, and 2019 were used and defined as 1 for informal settlement and 0 for formal settlement. Field (2013) defines LRM as either binary or multinomial. Binary LRM is being used to predict membership of only two categorical outcomes, and multinomial logistic regression when you want to predict membership of more than two categories used in the model (Field, 2013; Hu and Lo, 2007). Binary LRM is a type of regression analysis where the outcome variable is a dummy variable (coded 0, 1) means Yes or No or informal and formal settlement in the context of the present study (Field, 2013; Nong and Du, 2011). The general form of LRM is shown by the below equation (Cheng, 2003; Field, 2013; Hu and Lo, 2007; Padmavathi, (2012); Rogerson, 2015):

$$P\,(Y) = \frac{1}{1+e^{-(b0+b1\times 1i\times b2\times 1i+\cdots bn\times n)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

where P (Y) is the probability of Y occurring, e is the base of natural logarithms, b0 represents the overall occurrence (the overall incidence of slum and informal settlement in this study); the variable b1 represents the fraction by which the likelihood is altered by a unit change in x1; b2 is the fraction by which the likelihood is altered by a unit change in x2… and so on. The estimated probability values lie between 0 and 1, where a value close to 0 means that Y is very unlikely to have occurred, whereas a value close to 1 means that Y is very likely to have occurred. As the y value increases, the probability P increases as well.

Two dependent variables were used to explain slum and informal settlement development and densification. The dependent variable expansion has two categories: the presence of slums and informal settlements was (denoted by 1) and the absence of slums and informal settlements was (denoted by 0). Independent variables which are the indices responsible for slum and informal settlement development, were grouped into four categories: socio-economic, institutional, political and environmental indices. Twenty- four indices (as listed in Table 1) were incorporated into the model. As suggested by Cheng, (2003); Dubovyk et al., (2011); Hu and Lo, (2007); Hu, (2004); Huang *et al.,* (2009); and Munshi *et al.,* (2014), it is very important to test the correlation between independent variables to be included in the LRM. Multicollineality is a statistical analysis for the correlation detection among independent variables. When independent variables are correlated among themselves, multicollineality is said to exist (Cheng, 2003). There are some key problems that typically arise when these variables are highly correlated among themselves. Adding or deleting explanatory variables changes the regression coefficient significantly, and the estimated standard deviations of the regression coefficients become larger (Field, 2013; Moore et al., 2009).

Furthermore, it makes some variables statistically insignificant while they are significant. A test of multicollinearity was performed for all independent variables and the Variance Inflation Factor (VIF) was calculated. VIF is a measure of how much variance the estimated regression coefficient increases if the explanatory variables are correlated.

$$\mathrm{VIFj} = \frac{1}{1-R_j^2}, \qquad j = 1,2,\ldots.K \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

Where:
R^2 = is the coefficient of determination of the regression of the
j = independent variable on the remaining k-1 independent variables.
The higher the value of VIF the greater is the degree of collinearity. Some authors suggest that if the VIF is less than 10, there is strong evidence that collinearity is affecting the regression coefficients. During analysis, the variables with the VIF higher than 10 was removed from the model.

Findings and Discussion

Collinearity diagnostic test for independent variables

A test for collinearity was carried out by checking the "tolerance" and "VIF" values of theslum and informal housing variables. Collinearity usually occurs when there are two or more independent variables that are highly correlated with each other. That is where one of the independent variables can be linearly predicted from the others with a substantial degree of accuracy. Twenty-four variables were captured in the collinearity test (Table 1). These include housing shortage, lack of affordable housing, high incidences of urban poverty, high incidences of rural or urban-urban migration, economic recession, low income per capita, unemployment, unaffordable and high price of land, low access or non-availability of mortgage finance, poor enforcement of planning law, unclear regulation, and long procedures for building plan approvals, lackadaisical attitude of government towards the development of acquired public land, low capacity (human and technical), lack of planning or development plan , inadequate development control by planning agencies inadequate provision of site and services, tenure insecurity eviction, and poor resettlement programme by the government social conflict and population displacement disaster and population displacement , poor tenure, eviction, and poor, social conflict and population displacement, low capacity, social conflict, disaster, and disaster and population displacement, low-sized and The twenty-four variables that were captured in this model were each less than the reference value of 10. This means that there is no interaction between the independent variables. Thus, all the independent variables are fit to be used for modelling the indices of slum and informal housing development in Akure.
As shown in Table 2, the logistic model for all the variable was obtained as follows:
Log it (p(y=1) = 0.184 − 0.663 Housing shortage + 0.305 Insufficient affordable housing − 0.406 High incidences of urban poverty − 0.187 High incidences of Rural or Urban-Urban Migration + 0.292 Economic recession + 0.056 Low income per capital − 0.245 Unemployment + 0.063 Unaffordable and high price of land − 0.064 Low access or non-availability of mortgage finance + 0.202 Poor enforcement of planning law + 0.151 Unclear regulation and long procedures for building plan approvals + 0.000 Lackadaisical attitude of government towards the development of acquired public land − 0.002 Low capacity (human

and technical) − 0.367 Lack of planning /development plan + 0.323 Inadequate development control by planning agencies + 0.340 Inadequate provision of site and services + 0.352 Tenure insecurity − 0.237 Eviction and poor resettlement programme by the government − 0.312 Social conflicts and population displacement − 0.111 Disaster and population displacement − 0.179 Poor physical location (hill slope, water legged area, etc) − 0.004 High density of development and overcrowding – 0.417 Inadequate neighbourhood facilities and services + 0.812 Inadequate sanitation ....(1)

Table 1: Collinearity Diagnostic Test

Model	Collinearity Statistics	
	Tolerance	VIF
Housing shortage	.376	2.659
Insufficient affordable housing	.427	2.343
High incidences of urban poverty	.326	3.063
High incidences of Rural or Urban– Urban Migration	.484	2.067
Economic recession	.466	2.146
Low income per capital	.492	2.031
Unemployment	.657	1.521
Unaffordable and high price of land	.539	1.854
Low access or non-availability of mortgage finance	.454	2.204
Poor enforcement of planning law	.413	2.419
Unclear regulation and long procedures for building plan approvals	.393	2.542
Lackadaisical attitude of government towards the development of acquired public land	.308	3.245
Low capacity (human and technical)	.344	2.911
Lack of planning /development plan	.343	2.916
Inadequate development control by planning agencies	.569	1.757
Inadequate provision of site and services	.291	3.438
Tenure insecurity	.559	1.789
Eviction and poor resettlement programme by the government	.413	2.421
Social conflicts and population displacement	.351	2.852
Disaster and population displacement	.373	2.682
Poor physical location (hill slope, water legged area, etc)	.444	2.254
High density of development and overcrowding	.389	2.569
Inadequate neighbourhood facilities and services	.380	2.634
Inadequate sanitation	.417	2.399

Source: Author's Field work, (2022).

Logistic regression predicting the likelihood of slum and informal development

The decision on which logit coefficient is significant to the model is one of the challenges faced in logistic regression model building. This decision is made by comparing the p-value to the significance level (5%), or by using the Wald test or the log likelihood (2logL). If the p-value is less than 0.05, significance is established. For the purposes of the analysis, the significance level was set at 0.05 and as shown in Table 2, the final logistic model was obtained as follows:

Log it (p(y=1)) = 0.184 - 0.663 housing shortage + 0.305 lack of affordable housing – 0.460 high incidences of urban poverty – 0.367 lack of planning /development plan + 0.323 inadequate development control by planning agencies + 0.340 inadequate provision of site and services + 0.352 tenure insecurity – 0.417 inadequate neighborhood facilities and services + 0.812 inadequate sanitation…………………………………………………………… (2)

(1) Explanation of variables in the model

It can be noted from Table 2 that the predictors: housing shortage, lack of affordable housing, high incidences of urban poverty, lack of planning or development plans, inadequate development control by planning agencies, inadequate provision of sites and services, tenure insecurity, inadequate neighbourhood facilities and services, and inadequate sanitation have significance values of 0.000, 0.035, 0.000, 0.045, 0.005, 0.021, 0.030, 0.024, and 0.000, respectively, that are each less than 0.05. This means that each of these predictors is important enough to be included in the final model 2. Against this backdrop, there is enough basis to conclude that these predictors are relevant predictors for predicting slum and informal housing development in Akure from 1986–2019.

(2) Interpretation of the odds ratios

As in Table 2, the strongest predictor of the outcome of slum and informal housing development was inadequate sanitation (EI24), recording an odds ratio of 2.252 (95% C.I. = 1.571–3.228). This indicated that inadequate sanitation in the study area is twice as likely to estimate slum and informal development in the study area, controlling for all other factors in the model. The odds ratio for tenure insecurity (PI17) is 1.422 (95% confidence interval = 0.985–2.054), implying that there will be more emergences of slums and informal settlements as a result of the inability to secure approval and formalise the title deed for some government acquisitions sold by indigenes. The odds ratio for unemployment (SEI5) was 1.382 (95% confidence interval = 1.103–1.731), indicating that as the percentage of unemployed and underemployed people in Akure increases, so will the emergence of slums and informal housing. Also, the odds ratio with respect to inadequate development control by planning agencies (PI15) was 1.356 (95% CI = 1.021–1.801), which implies that slum and informal housing will emerge due to the failure of the planning agencies to effectively control and manage development in Akure.

(3) Explanation of variables not in the model

Table 2 revealed that the high incidences of rural or urban-rural migration, economic recession, low income per capita, unemployment, unaffordable and high price of land, low access or non-availability of mortgage finance, poor enforcement of planning law, unclear regulation, and long procedures for building plan approvals, lackadaisical attitude of the government towards the development of acquired public land, low capacity (human and technical), eviction and poor resettlement programme by the government social conflicts an population displacement , disaster and population displacement , poor physical location (hill slope, water legged area, etc.), high density of development and overcrowding were dropped from the mode Since the p-values of the variables (0.175, 0.123, 0.744, 0.234, 0.569, 0.658, 0.149, 0.419, 0.998, 0.990, 0.201, 0.113, 0.352, 0.173, 0.978) were each greater than 0.05, there is sufficient evidence to indicate that each of the predictors is equal to zero. This shows that these predictors were not important enough to be included in the model, and they were dropped from model 1 to arrive at model 2.

Table 2: Logistic Regression Predicting the Likelihood of Slum and Informal Development

Variables	B	S.E.	Wald	Sig.	Exp(B)	95% C.I.for EXP(B)	
						Lower	**Upper**
SEI1	-.663	.126	27.727	.000	.515	.402	.659
SEI2	.305	.145	4.432	.035	1.339	0.924	1.941
SEI3	-.460	.121	14.373	.000	.631	.498	.801
SEI4	-.187	.138	1.843	.175	.829	.633	1.086
SEI5	.292	.189	2.374	.123	1.382	1.103	1.731
SEI6	.056	.172	.106	.744	1.058	.755	1.483
SEI7	-.245	.206	1.419	.234	.783	.523	1.171
SEI8	.063	.110	.325	.569	1.065	.858	1.320
SEI9	-.064	.145	.196	.658	.938	.705	1.247
II10	.202	.140	2.087	.149	1.224	.931	1.609
II11	.151	.187	.653	.419	1.163	.806	1.679
II12	.000	.148	.000	.998	1.000	.748	1.337
II13	-.002	.169	.000	.990	.998	.716	1.391
II14	-.367	.183	4.013	.045	.693	.484	.992
II15	.323	.115	7.913	.005	1.356	1.021	1.801
PI16	.340	.147	5.349	.021	1.405	1.053	1.874
PI17	.352	.188	3.526	.030	1.422	.985	2.054
PI18	-.237	.186	1.634	.201	.789	.548	1.135
PI19	-.312	.197	2.507	.113	.732	.498	1.077
EI20	-.111	.119	.865	.352	.895	.709	1.131

EI21	-.179	.131	1.859	.173	.836	.646	1.082
EI22	.004	.154	.001	.978	1.004	.743	1.357
EI23	-.417	.184	5.105	.024	.659	.459	.946
EI24	.812	.184	19.510	.000	2.252	1.571	3.228
Constant	.184	.735	.063	.802	1.202		

Source: Author's Field work, (2022).

Key:

SEI= Socio-Economic Indices

II= Institutional Indices

PI= Political Indices

EI=Environmental Indices

Assessing Model Fit by Hosmer and Lemeshow Test

Goodness-of-fit statistics were used to determine whether the model adequately described the data. In order to achieve this, the following hypotheses were formulated

H_0: Factors of slum and informal housing development in Akure are not significantly different from those predicted by model 2

H_1: Factors of slum and informal housing development in Akure are significantly different from those predicted by model 2

The results of the Hosmer-Lemeshow statistic as shown in Table 3 is $p = 0.167$. The Hosmer-Lemeshow statistic indicates a poor fit if the significance value is less than 0.05.

Since the p-value, 0.167 is greater than the significance level of 0.05, we fail to reject the null hypothesis (H_0) and conclude that there is enough evidence to show that the hypothesised model fits the data set used in predicting slum and informal housing development. Hence, this indicates that the factors responsible for the development of slum and informal housing in Akure are not significantly different from those predicted by the model and that the overall model fit is good.

Table 3: Assessing Model Fit by Hosmer and Lemeshow Test

Chi-square	Df	Sig.
36.182	8	.167

Source: Author's Field work, (2022).

Omnibus Tests of Model Coefficients

The Omnibus Tests of Model Coefficients table shows us the results of a chi-square test. The hypothesis test examines whether or not there is a statistically significant impact of the indices on the prediction of slum and informal housing development. In order to accept that the indices of slum and informal housing have a statistically significant influence on the development of slums and informal housing in the study area, the p-value must be less than 0.05. It can be observed from Table 4 that the indices have a statistically significant influence on the development of slums and informal housing since p (0.000) < 0.05.

Table 4: Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	106.477	24	.000
	Block	106.477	24	.000
	Model	106.477	24	.000

Source: Author's Field work, (2022).

Model Summary

It is worth noting from Table 4 that between 16.3% and 40.8% of the variance in predicting whether there is or is not development of slum and informal housing in Akure was explained by the predictors: housing shortage, lack of affordable housing, high incidences of urban poverty, lack of planning or development plans, inadequate development control by planning agencies, inadequate provision of sites and services, tenure insecurity, inadequate neighbourhood facilities and services, and inadequate sanitation. The Cox & Snell r^2 statistic calculated in the Model Summary output as shown in Table 4 is used to gauge how much of the variation in the development of slums and informal housing is explained by this model and, therefore, how well our model fits our data. The r^2 is very low, at 0.163. This shows that only 16.3% of the variation in the development of slums and informal housing in Akure town is explained by the indices.

Table 4: Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
626.560[a]	.163	.408

Source: Author's Field work, (2022).

Classification Accuracy

This represents the level of predictive accuracy achieved by the fitted model. It can be observed from the classification in Table 5 that the fitted model predicted an overall percentage of 75.0% correctly. That is, 85.0% of the outcomes (yes) predicted the presence of slums and informal housing, whereas 15.0% did not. Coupled with the statistically based measures of model fit, the model is deemed acceptable in terms of both statistical and practical significance.

Table 5: Classification Table

	Observed	Predicted	
		Presence of slum and informal	Percentage Correct

			Yes	No	
Step 1	Presence of slum and informal	Yes	390	30	85.0
		No	120	60	15.0
	Overall Percentage				75.0
a. The cut value is .500					

Source: Author's Field work, (2022).

Conclusion

The findings revealed that all twenty-four variables that were captured in this model were each less than the reference value of 10. This means that there is no interaction between the independent variables. Thus, all the independent variables are fit to be used for modelling the indices of slum and informal housing development in Akure from 1986–2019. The key variables of interest are: whether or not slum and informal housing developments exist in the identified neighborhoods. Twenty-four explanatory variables were also captured, which are the indices for the number of slum and informal housing developments in the study area. The results of the probability of the presence of slums and informal housing in the block model shows that 75.0% of the neighbourhoods were correctly classified, so the model is 75.0% accurate.

The omnibus tests of the Model Co-Efficient Table give the result of the likelihood ratio (LR) test, which indicates whether the inclusion of this block of variables contributes significantly to model fit. A p-value (sig) of less than 0.05 for each block means that the slum and informal housing index has a statistically significant influence on the development of slums and informal housing in the study area. The p-value must be less than 0.05. The Cox & Snell r^2 statistic calculated in the Model Summary output is used to gauge how much of the variation in the development of slums and informal housing is explained by this model and, therefore, how well our model fits our data. The r2 is very low, at 0.163. This shows that only 16.3% of the variation in the development of slums and informal housing in Akure town is explained by the indices. The study recommended that the state government should upgrade earth roads to gravel and construct distribution roads with drainage, especially in areas like Igoba, Ijoka, and Orita-Obele in Akure.

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