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APPLICATION OF GIS-BASED ORDINARY LEAST SQUARES AND GEOGRAPHICALLY WEIGHTED REGRESSION TO LAND USE CHANGE MODELING: A CASE OF LAGOS, NIGERIA

Onuwa Okwuashi^{al}, Etim Eyo^b & Aniekan Eyo^c (Onuwaokwashi@yahoo.com, etim.eyo@newcastle.ac.uk, & ani eyo@yahoo.com)

Department of Geoinformatics & Surveying, Faculty of Environmental Studies, University of Uyo, Nigeria Department of Geomatics University of Newcastle, Newcastle, United Kingdom

ABSTRACT .

This research explored the processes of land use change in Lagos, Nigeria using the geographic information systems based ordinary least squares and geographically weighted regression models, based on three epochs: 19631978, 1978-1984, and 1984-2000. ArcGIS and MATLAB software were used for the modelling. Only two of the five tested statistical assumptions of linear

regression modelling were met. Multicollinearity and autocorrelation criteria were met while normality, linearity, and homoscedasticity criteria were not met. Nonetheless, the geographically weighted regression predicted maps for Lagos indicated substantial agreement with the reference data based on the computed Kappa statistic. The results of the modelling on one hand elucidated the tremen¹¹⁰us explanatory properties of linear regression models; on another hand the results showed that the nature of land use data makes their use for urban change modelling inconsistent with traditional statistical assumptions; therefore the trade-off for deriving highly accurate results from linear regression models is the inevitable violation of traditional statistical assumptions.

INTRODUCTION

Changing land use globally is a topical issue of discussion. Urbanisation may be the benchmark for measuring economic growth and development, however in the case of sprawling cities of developing countries it has been accompanied by poverty, unemployment, environmental degradation, decaying infrastructure, and uncontrollable growth of informal settlements (Angotti, 1993). Urban sprawl in Lagos has put profound pressure on housing, infrastructure, and the environment (Braimoh & Onishi, 2007), and is generally viewed by most Nigerians as an intractable problem (Abiodun, 1974; Gandy, 2006). This research therefore explores the use of the Geographic Information Systems (GIS) based Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models for modelling the processes of urban change in Lagos, Nigeria.

Conventional land use change modelling is implemented in the ArcGIS environment using the Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models. The GWR (Fotheringham et al., 2002) is the local equivalent of

$$y_i = \beta_0(u_i, v_i) + \sum_q \beta_q(u_i, v_i) x_{iq} + \varepsilon_i$$

where β_0 denotes the intercept, β_q represents the slope coefficients for the variable q, x_{iq} denotes the value for a qth variable for i number of observations, \mathcal{E}_i represents the error parameter, and

the global OLS. OLS and GWR are both linear regression models. The global OLS model can be expressed mathematically as,

$$y_i = \beta_0 + \sum_p \beta_p x_{ip} + \varepsilon_i$$
(1)

where y_i are the dependent variables, β_0 denotes the intercept, β_p are the slope coefficients for the p variable, x_{ip} denotes the value for a p th variable for i number of observations, and \mathcal{E}_i represents the error parameter.

Unlike the GWR model, OLS assumes that β_p is stationary or homoscedastic. This is a major difference between the OLS and the GWR (Fotheringham et al., 2002; Mennis, 2006). The GWR model can be expressed mathematically as,

 (u_i, v_i) stands for the coordinates of the *i*th location for an *i* observations.

GWR takes the effect of spatial dependency into consideration and assumes that β_q is non-stationary or heteroscedastic. The non-stationarity of β_q means that the solutions of β_q vary across the globe for the same values of x_{iq} . The solution of β_q is affected

by the locations (u_i, v_i) where x_{iq} were actually observed (Fotheringham et al., 2002).

In spite of the merits of the GWR model over the OLS model, it is still subject to fundamental statistical assumptions (just like the OLS), that there is: (i) a normal distribution; (ii) a linear relationship between the dependent and independent variables; (iii) no multicollinearity between the independent variables; (iv) no spatial autocorrelation; and (v) homoscedasticity (Leung et al., 2000; Fotheringham

Twelve salient land use drivers were selected for Lagos. The selected land use drivers influencing land use change in Lagos are: water, residential structures, industrial and commercial centres, major roads, railway, Lagos Island, international airport, international seaport, University of Lagos, Lagos State University, income potential, and population potential.

The land use data of Lagos consist of two remotely sensed Landsat Thematic Mapper images, acquired in 1984 and 2000 respectively; and two analogue base maps acquired in 1963 and 1978. The analogue base maps were sourced from the Lagos State Ministry of Lands.

The Landsat images acquired in 1984 and 2000 were classified with the k-means algorithm using MATLAB software. The analogue base maps acquired in 1963 and 1978 were scanned and digitised using ArcGIS. The analogue and remote sensing data were geo-referenced to ensure both data were in the same coordinate system. Digitising analogue maps reduces their accuracy. It is therefore important to enhance the accuracies of the analogue data to ensure they approximate those of the satellite data. The enhancement of the analogue base maps was done in MATLAB, by first obtaining n-classifications of the satellite data and overlaying the resulting classified satellite data with the digitised base maps. A digital editing procedure was then used to remove errors from the digitised maps.

The land use independent variables (Table 1) are grouped into two categories: (i) proximity variables, and (ii) weighted variables. The proximity variables were extracted with the GIS while the weighted variables were extracted in MATLAB.

The proximity variables were extracted by calculating the Euclidean distances from the proximity variables to all cells. For the weighted variables, income potential was estimated by ranking major towns in Lagos, using a ranking r_i of a production/service centre c_i . The ranking was normalized to weight w_i using the formula (Braimoh & Onishi, 2007),

et al., 2002; Wheeler & Tiefelsdorf, 2005; Farber & Páez, 2007).

Methodology

The study area for this experiment is Lagos, Nigeria (Figure 1). Lagos is a littoral environment, has a relatively flat terrain, an area of about 2910km², and lies between latitudes 6° 26′ and 6° 50′ N, and between longitudes 3° 09′ and 3° 46′ E (Braimoh & Onishi, 2007). Substantial land use change has occurred in Lagos between 1963 and 2000 (Figure 2).

$$w_i = \frac{r_i}{\sum_{c_i=1}^n r_i}$$

3)

Therefore the weighted inverse distance formula for calculating the income potential i_S of a location S is given as (Braimoh & Onishi, 2007),

$$i_{s} = \frac{\sum_{x=1}^{n} \frac{1}{\left|S - S_{x}\right|^{2}} w_{i}}{\sum_{x=1}^{n} \frac{1}{\left|S - S_{x}\right|^{2}}}.$$

(4)

where x = 1, 2, ..., n are settlements in the study area.

The final ranking was based on government documents, interviews, and personal knowledge of the author. The population estimate was obtained using the formula (Braimoh & Onishi, 2007),

$$P_{p} = \frac{P_{r}}{e^{r(Y_{r} - Y_{p})}}$$
(5)

where, r = intercensal population growth rate, P_p = previous population, P_r = present population, Y_r = recent year, and Y_p = previous year.

An inverse distance weighting formula for calculating an unknown population potential $p_{\mathcal{S}}$, at a given location \mathcal{S} , is given as (Braimoh & Onishi, 2007).

$$p_{s} = \frac{\sum_{x=1}^{n} \frac{1}{|S - S_{x}|^{2}} P(S_{x})}{\sum_{x=1}^{n} \frac{1}{|S - S_{x}|^{2}}}$$
(6)

where $P(S_x)$ is the population of a settlement located at S; x=1,2,...,n are settlements in the study area.

The original land use maps (in 1963, 1978, 1984, and 2000) had a cell size of 100m x 100m before they were gridded to increase their cell size to 500m x 500m (see the overlaid gridded maps in Figure 2). The essence of increasing the cell size of the maps is to reduce the matrix size of the maps for modelling convenience.

The GIS-based GWR and OLS models do not need to train the data before the data is used for prediction. The observed data in 1963 were used to predict the 1978 land use; 1978 data were used to predict the 1984 land use; and the 1984 data were used to predict the 2000 land use. The present year is furnished by the independent variables, while the target year is furnished by the dependent variables. Empirical measurements are only done on the present year. The dependent variables are represented with discrete variables. The present year and target year maps were overlaid to determine the changed regions between the present and target years. The results of the overlay are three categories of land use of the target year: (i) undeveloped region; (ii) change region; and (iii) developed region. The resulting overlaid maps form the data for the dependent variable. The dependent

variable was represented as follows: undeveloped region=1; changed region=2; and developed region=3.

The original values of the independent variables were scaled to [0, 1] using the transformation formula (Gong, 1996; Li & Yeh, 2002),

$$x_i' = (x_i - \min) / (\max - \min)$$
(7)

where x_i' is the scaled land use variable; min is the lowest value in the land use vector; max is the highest value in the land use vector; and x_i represents the land use variables.

This scaling technique is effective in ensuring that all the independent variables are equally weighted (Gong, 1996; Li & Yeh, 2002).

Equations 8-10 and equations 11-13 are the OLS and GWR equations for periods 1963-1978, 1978-1984, and 1984-2000 respectively;

 $LUC_1963-1978_i\,, LUC_1978-1984_i\,, \text{ and } \\ LUC_1984-200Q \text{ represent Land Use Change} \\ \text{(LUC) from 1963-1978, 1978-1984, and 1984-2000} \\ \text{respectively:} \\$

$$LUC_{1963-1978} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + e_i$$
 (8)

$$LUC_{1978-1984} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + e_i$$
 (9)

$$LUC_{19842000} = \beta_{0} + \beta_{1}x_{1} + \beta_{2}x_{2} + \beta_{3}x_{3} + \beta_{4}x_{4} + \beta_{5}x_{5} + \beta_{6}x_{6} + \beta_{7}x_{7} + \beta_{8}x_{8} + \beta_{5}x_{9} + \beta_{10}x_{10} + \beta_{1}x_{11} + \beta_{2}x_{12} + e_{i}$$
(10)

$$LUC_{1963-1978} = \beta_{0} + \beta_{1}x_{1}(u_{1}, v_{1}) + \beta_{2}x_{2}(u_{2}, v_{2}) + \beta_{3}x_{3}(u_{3}, v_{3}) + \beta_{4}x_{4}(u_{4}, v_{4}) + \beta_{5}x_{5}(u_{5}, v_{5}) + \beta_{6}x_{6}(u_{6}, v_{6}) + \beta_{7}x_{7}(u_{7}, v_{7}) + \beta_{8}x_{8}(u_{8}, v_{8}) + \beta_{9}x_{9}(u_{9}, v_{9}) + \beta_{10}x_{10}(u_{10}, v_{10}) + e_{i}$$

$$(11)$$

$$LUC_{1978-1984} = \beta_{0} + \beta_{1}x_{1}(u_{1}, v_{1}) + \beta_{2}x_{2}(u_{2}, v_{2}) + \beta_{3}x_{3}(u_{3}, v_{3}) + \beta_{4}x_{4}(u_{4}, v_{4}) + \beta_{5}x_{5}(u_{5}, v_{5}) + \beta_{6}x_{6}(u_{6}, v_{6}) + \beta_{7}x_{7}(u_{7}, v_{7}) + \beta_{8}x_{8}(u_{8}, v_{8}) + \beta_{9}x_{9}(u_{9}, v_{9}) + \beta_{10}x_{10}(u_{10}, v_{10}) + e_{i}$$

$$(12)$$

$$LUC_{1984-2000} = \beta_{0} + \beta_{1}x_{1}(u_{1}, v_{1}) + \beta_{2}x_{2}(u_{2}, v_{2}) + \beta_{3}x_{3}(u_{3}, v_{3}) + \beta_{4}x_{4}(u_{4}, v_{4}) + \beta_{5}x_{5}(u_{5}, v_{5}) + \beta_{6}x_{6}(u_{6}, v_{6}) + \beta_{7}x_{7}(u_{7}, v_{7}) + \beta_{8}x_{8}(u_{8}, v_{8}) + \beta_{9}x_{9}(u_{9}, v_{9}) + \beta_{10}x_{10}(u_{10}, v_{10}) + \beta_{11}x_{11}(u_{11}, v_{11}) + \beta_{12}x_{12}(u_{12}, v_{12}) + e_{i}.$$

$$(13)$$

The meaning of the explanatory variables $(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12})$ are given in Table 1. From equations 8-13, β_0 is the intercept; $\beta_1, \dots, \beta_{12}$ are the coefficients of the independent variables; u, v are the horizontal coordinates; and e_i

is the error term. The data were prepared in MATLAB, and thereafter imported into ArcGIS for modelling. The dependent variables must be shapefiles consisting of discrete variables. The attribute tables of the dependent variables (to be predicted) must contain: unique or primary keys, all the attributes of the independent variables (explanatory variables), and discrete variables of the

be represented with continuous variables because the types: undeveloped, change, and developed.

Results

The OLS model was used to explore the significance of each explanatory variable (see Tables 2-4). The calculated multiple R2 values for periods 1963-1978, 1978-1984, and 1984-2000 were 0.318959, 0.360174, and 0.381849 respectively; while the calculated

adjusted R2 values for periods 1963-1978, 1978-1984, and 1984-2000 were: 0.317984, 0.359258, and 0.380787 respectively. The hypothesis for assessing the significance of each explanatory variable can be

H₀: the coefficients are zero at the 95% CL

 H_1 : the coefficients are not zero (reject H_0 if p-value <5%)

Let us now assess OLS model with respect to some fundamental traditional statistical assumptions. We can now assess how the GIS-based OLS modelling results meet the following traditional statistical criteria: multicollinearity; linearity; normality; spatial autocorrelation; and homoscedasticity or stationarity.

For the multicollinearity test, the Variance Inflation Factor (VIF) (see the last columns of Tables 2-4) assesses the effect of multicollinearity in the spatial model. Explanatory variables with VIF >7.5 are considered redundant, and should be excluded from the model. The calculated VIF values for all the explanatory variables in the three experiments (1963-1978, 1978-1984, and 1984-2000) were <7.5 (see the last columns of Tables 2-4). This implies that all the variables were important in the prediction, and should be retained in the model.

For the linearity test, the scatter plot in Figure 3a depicts a typical relationship between a dependent and an independent variable in linear regression modelling. Based on empirical land use change data, Figure 3b is the plot of a dependent variable (1963-1978) against an independent variable (distance to water 1963-1978). Figure 3b shows that land use change data do not conform to a typical linear regression relationship between a dependent and an independent variable shown in Figure 3a. Figure 3b shows that the relationship between the land use dependent variable (y-axis) and the independent variable (x-axis) is nonlinear as expected. Using discrete variables to represent the dependent variable will definitely produce a nonlinear relationship between the dependent and explanatory variables, as in the case of Figure 3b. Therefore the land use change data do not meet the linearity condition expected of all linear regression modelling.

For normality test, the Jarque-Bera Statistic test (Table 5) is used to test whether the model residuals are normal:

 H_0 : the residuals are normally distributed at the 95% CL H_1 : the residuals are not normally distributed (reject H_0 if p-value <0.05)

All the calculated p-values for 1963-1978, 1978-1984, and 1984-2000 were <0.05; which indicates that the residuals deviate from the normal distribution as expected.

For autocorrelation test, the Moran's I Tool was used, Moran I values close to +1 indicate positive spatial autocorrelation; values close to -1 indicate negative spatial autocorrelation; while values close to zero indicate that the model residuals are random. The Moran's I tests (see Table 6) for 1963-1978, 1978-1984, and 1984-2000 yielded values close to zero. These results indicate that the model residuals were not spatially autocorrelated.

All the three results for periods 1963-1978, 1978-1984, and 1984-2000 indicate significant non-stationarity. This implies that the model is not homoscedastic and therefore violates traditional statistical requirements that expect OLS models to be homoscedastic. In ArcGIS, the GWR model becomes a veritable option for the prediction when the OLS results indicate significant non-stationarity.

The R^2 was used to assess the goodness-of-fit for predicting land use change in the three periods (1963-1978, 1978-1984, and 1984-2000). The resulting high R^2 and R^2 adjusted values (Table 8) show that the GWR predictions for the three periods (1963-1978, 1978-1984, and 1984-2000) were highly accurate.

This result is an indication that the GWR model was able to mitigate the effects of non-stationarity and autocorrelation that usually compromise the goodness-of-fit of the dependent variable as in the case of the OLS model.

The GWR model predicted maps for 1963-1978, 1978-1984, and 1984-2000 and their computed Kappa statistic are given in Figure 4 and Table 9 respectively.

It is desired that the standard residuals (that is under and over prediction) be randomly distributed. The standard residuals for the three periods shown in Figure 5 indicate that the residuals were random. This is an indication that no key independent variable was omitted from the model (Thapa & Murayama, 2009). High local R² values (Figure 5) indicate areas on the map where the GWR model predicted well while low local R² values indicate areas on the map that were less well predicted by the GWR model. Cond denotes condition number. Cond assesses local collinearity in the model. The results from cells with Cond values greater than 30 may not be reliable. All the predicted Cond maps for periods 1963-1978, 1978-1984, and 1984-2000 (Figure 6) yielded Cond values below 30. This indicates that the results from this prediction can be trusted.

4. Conclusion

The result of this research showed that only some of the linear regression assumptions were met. Often times, traditional statistics has questioned the validity of any modelling result that is inconsistent with traditional statistical assumptions governing linear regression models. Nonetheless, spatial statistics tends to undermine the relevance of traditional statistics in spatial modelling. In recent times, researchers have proposed the adoption of nonparametric models as a way-out of the controversy between traditional statistics and spatial statistics. The result of this work will assist urban planners in Lagos to: (i) understand how each land use driver affects the process of urban change and, (ii) forecast urban change between epochs.

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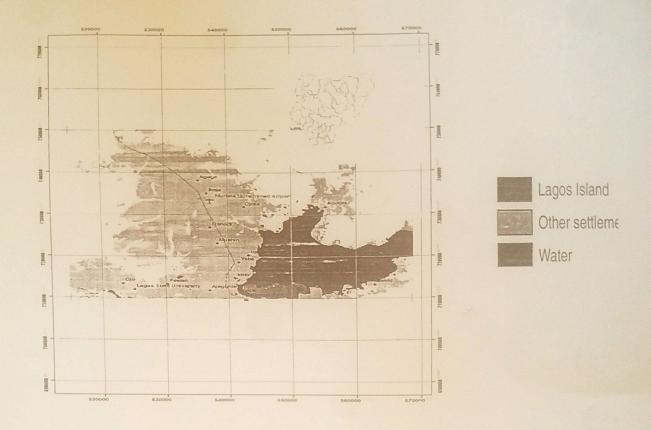


Table 1 Extracted land use variables

Proximity variables	X_1 : distance to water
,,	x_2 : distance to residential structures
,,	x_3 : distance to industrial and commercial centres
,,	x_4 : distance to major roads
,,	x_5 : distance to railway
,,	x_6 : distance to Lagos Island
,,	x_7 : distance to international airport (1984-2000 only)
,,	x_8 : distance to international seaport
,,	x_9 : distance to University of Lagos
,,	x_{10} : distance to Lagos State University (1984-2000 only)
Weighted variables	x_{11} : income potential
,,	x_{12} : population potential

Figure 1 Lagos in relation to Nigeria



Figure 2 Gridded land use map of Lagos between 1963 and 2000

Table 2 Statistical results for assessing the significance of each independent variable in the model for 1963-1978 (*significant at p<0.05 or t>1.96)

Variable	Coefficient	Std Error	t-statistic	P-value	VIF[1]
Intercept	0.847101	0.018673	45.363946	0.000000*	
Distance to water	-0.117348	0.055944	2.097593	0.035964*	1 500747
Distance to residential	-1.124156	0.050378	22.314590	0.000000*	1.509747
Distance to industrial and commercial	-0.806965	0.045379	17.782810	0.000000*	1.159984 1.342798
Distance to major roads	-0.421015	0.047971	8.776518	0.000000*	1.271059
Distance to railway Distance to Lagos	-0.716223 -0.397699	0.042507 0.042050	16.849342	0.000000*	1.194308
Island	0.557055	0.042030	9.457734	0.000000*	1.325239
Distance to international seaport	-0.174235	0.039471	4.414274	0.000013*	1.254065
Distance to University of Lagos	-0.062781	0.041584	1.509759	0.131166	1.274922
Income potential	0.520350	0.043490	11.964778		
Population potential	0.230385	0.035664	6.459927	0.000000*	1.141347

Table 3 Statistical results for assessing the significance of each independent variable in the model for 1978-1984 (*significant at p < 0.05 or t > 1.96)

Variable	Coefficient	Std Error	t-statistic	P-value	VIII
Intercept Distance to water Distance to residential Distance to industrial and commercial	1.092893 -0.208187 -1.919315 -1.010004	0.022225 0.065870 0.062447 0.059138	49.173422 3.160574 30.735343 17.078679	0.000000* 0.001597* 0.000000* 0.000000*	VIF [1] 1.440754 1.244771 1.410719
Distance to major roads Distance to railway Distance to Lagos Island Distance to international seaport	-0.927202 -0.655001 -0.308435 -0.140088	0.074672 0.052848 0.050105 0.047237	12.417024 12.393995 6.155783 2.965640	0.000000* 0.000000* 0.003041*	1.086095 1.270764 1.321559 1.236370

Distance to University of Lagos	0.137918	0.049860	2.766108	0.005689*	1.261713
Income potential Population potential	0.746732 0.339526	0.054971 0.057042	13.584038	0.000000*	1.178389

Table 4 Statistical results for assessing the significance of each independent variable in the model for 1984-2000 (*significant at p<0.05 or t>1.96)

Variable	Coefficient	Std Error	t-statistic	P-value	VIF[1]
Intercept	-2.290807	0.023219	98.658942	0.000000*	
Distance to water	-0.222466	0.075164	2.959756		1.176389
Distance to residential	-2.606189	0.077746		0.003099*	
Distance to industrial and	-2.113546		33.522009	0.0000000*	1.104094
commercial	-2.113340	0.092167	22.931596	0.0000000*	1.137527
Distance to major roads	-1.486506	0.106271	10.00.100.6		
Distance to railway		0.106371	13.974726	0.000000*	1.063784
Distance to Lagos Island	-0.910023	0.058224	15.629605	0.000000*	1.050858
Distance to international	-0.339675	0.056222	6.041727	0.000000*	1.093061
airport	-0.035236	0.054862	0.642261	0.520725	1.102546
Distance to international	0.100015				
seaport	-0.189215	0.062306	3.036886	0.002412*	1.093976
Distance to University of	0.147504				
Lagos	0.147534	0.060228	2.449619	0.014312*	1.104240
Distance to Lagos State	0.710727	0.070070			
University	-0.719737	0.058858	12.228258	0.000000*	1.052826
Income potential	0.721885	0.002262	11 00001		
Population potential		0.063363	11.392814	0.000000*	1.154016
	0.414852	0.048891	8.485296	*0000000	1.153289

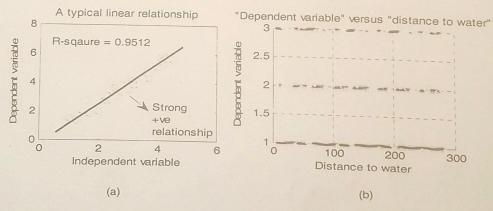


Figure 3 (a) A typical linear regression relationship between a dependent and an independent variable; (b) dependent variable plotted against distance to water

Table 5 Jarque-Bera Statistic test for 1963-1978, 1978-1984, and 1984-2000 (*significant at p<0.05)

Periods	Jarque-Bera Statistic	Degrees of freedom	P-value
1963-1978 1978-1984	706.116841 392.961529	10	0.000000*

1984-2000

318.762167

12 0.000000*

Table 6 OLS modelling: Spatial autocorrelation test for 1963-1978, 1978-1984, and 1984-2000 using ArcGIS Moran's I tool

Periods	Moran's I index for OLS
1963-1978	0.081073
1978-1984	0.073943
1984-2000	0.069293

For non-stationarity test, the Koenker (BP) Statistic test (Table 8) was used:

H₀: the model is stationary at the 95% CL H_1 : the model is non-stationary (reject H_0 if p-value <0.05)

Table 7 Koenker (BP) Statistic for 1963-1978, 1978-1984, and 1984-2000 (*significant at p<0.05)

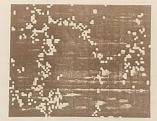
Periods	Koener (BP) Statistic	Degrees of freedom	P-value
1963-1978	1237.735416	10	0.000000*
1978-1984	532.003124	10	0.000000*
1984-2000	74.834390	12	0.000000*

Table 8 GWR modelling: calculated R² values for 1963-1978, 1978-1984, and 1984-2000

Periods	\mathbb{R}^2	R ² Adjusted
1963-1978	0.843159	0.792102
1978-1984	0.846021	0.805692
1984-2000	0.853782	0.799722



Predicted 1978



Predicted 1984



Predicted 2000

Figure 4 Predicted GWR maps for 1963-1978, 1978-1984, and 1984-2000 (TN=True negative; FP=False Positive; FN=False Negative; TP=True Positive)

Table 9 Calculated Kappa star

1984, and 1984-2000

Periods	Kappa statistic
1963-1978	0.8858

TN

FP

FN TP

1978-1984 1984-2000 0.8366 0.8812



1963-1978 StdResid <-2.5 Std. Dev.

-2.5 - -1.5 Std. Dev. -1.5 - -0.5 Std. Dev. -0.5 - 0.5 Std. Dev. 0.5 - 1.5 Std. Dev. 1.5 - 2.5 Std. Dev. > 2.5 Std. Dev.



1963-1978

LocalR2

0.000000 - 0.051997 0.051998 - 0.136320 0.136321 - 0.221902 0.221903 - 0.317179 0.317180 - 0.437439

0.437440 - 0.581147 0.581148 - 0.760945



1978-1984 StdResid

< -2.5 Std. Dev.

-2.5 - -1.5 Std. Dev.

-0.5 - 0.5 Std. Dev.

1.5 - 2.5 Std. Dev.

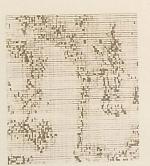


1978-1984

LocalR2

0.000000 - 0.071405 0.071406 - 0.152905 0.152906 - 0.243233 0.243234 - 0.349957 0.349958 - 0.468067

0.572241 - 0.711029



1984-2000 StdResid

< -2.5 Std. Dev.

-2.5 - -1.5 Std. Dev.

-0.5 - 0.5 Std. Dev.

0.5 - 1.5 Std. Dev.

> 2.5 Std. Dev.



1984-2000

LocalR2

0.000000 - 0.077658

0.077659 - 0.162827

0.162828 - 0.253379

0.253380 - 0.349259

0.349260 - 0.454171

0.0 10200 0.10111

0.454172 - 0.569116

0.569117 - 0.734357

Figure 5 Estimated GWR standard residuals and local R2 for 1963-1978, 1978-1984, and 1984-2000



1963-1978

Cond

9.603290 - 11.805569

11.805570 - 13.205946 13.205947 - 14.399716

14.399717 - 15.514525

15.514526 - 16.722243

16.722244 - 18.150355

18 150356 - 22 964431



1978-1984

Cond

8.282103 - 10.7568

10.756598 - 12.400

12.400197 - 13.72€

13.726618 - 14.971 14.971082 - 16.257

16.257462 - 17.816

17.816252 - 22.183

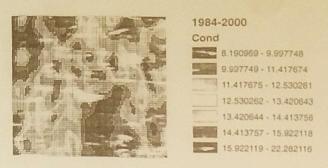


Figure 6 Estimated GWR model condition numbers for 1963-1978, 1978-1984, and 1984-2000