EVALUATING LAND USE CHANGE IN RAPIDLY URBANIZING NIGERIA: CASE STUDY OF YOLA, ADAMAWA STATE

Abdurrahman Belel, ISMAILA

Department of Geodetic & Geographic Information Technologies, Graduate School of Natural & Applied Sciences, Middle East Technical University, İnönü Blv., 06531, Ankara, Turkey

Department of Urban & Regional Planning, School of Environmental Sciences, Modibbo Adama University of Technology, P.M.B. 2076, Yola, Nigeria

belelismaila@yahoo.com

Abstract

This paper examines the land use change pattern of rapidly developing city of Yola, Nigeria with a view of finding the explanatory variables for the changes. To achieve this objective, two basic steps are followed: i) land use change detection analysis was performed using Landsat image of 1987 and 2005, ii) a model of land use change pattern was developed using Geographically Weighted Regression (GWR) to estimate the strength of the relationship between land use change and its associated factors. The classification accuracy and kappa statistics of the images are satisfactory. For the 1987 image, the overall classification accuracy of 87.07% and a kappa statistic of 83.37% are observed, whereas, 92.26% (overall accuracy) and 90.41% (kappa statistic) for 2005 were reported. In order to develop the GWR model, several candidate explanatory variables were identified and assessed. The result shows that population, administrative wards, population density, and new layouts are the most important variables that explain the changes. The GWR model result gives a strong Adjusted-R^2 of 0.967. While, the Local R^2 values varied spatially ranging from 0.26 to 0.96. The Akaike's Information Criterion (AIC) is (111.14); a smaller value of AICs is fine on local modelling. The spatial patterns of residuals showed some under prediction and over prediction. However, the model exhibits no spatial autocorrelation as evidenced by Moran's-I (0.02); this means that the residuals are randomly distributed. The coefficient surface maps indicate how the relationship of each explanatory variable varies across space. Areas with large coefficients indicate the locations where that particular explanatory variable is most important in explaining the depended variable.

Keywords: GIS, RS, Geographically Weighted Regression, Developing city

INTRODUCTION

Urban areas are not only the engines of global economic growth but also magnets for new residents flooding in from rural areas (Knox, McCarthy, 2005; Yang, 2007). Over the past decades, world-wide urban areas have experienced rapid changes and growth in both population and area size (Yang, 2007). For instance, in Nigeria, urban population over the last three decades has been growing at a faster rate close to about 5.8% per annum and projections indicate that more than 60% of Nigerians will live in urban areas by the year 2025 (Alkali, 2005). Due to this rapid urbanization, scientists, urban planners and engineers are facing many challenges, including the loss of forest lands, shortage of utilities and resources, aggravated traffic congestion, environmental problems, and ultimately an alteration to the land use patterns (Wu, 2007). These problems certainly pose greatest sustainable development challenges for Nigeria's urban Centres by progressively complicating and exacerbating interrelated problems of human settlements and the environment.

Yola, just like many other cities in Nigeria is not an exception. It has witnessed a remarkable expansion, growth and development including; buildings, roads, deforestation and many other anthropogenic activities since its inception in 1976 as the State capital of the former Gongola State and later as the capital of Adamawa State in 1991. Over this period, no detailed and comprehensive attempt has been made to evaluate the rate of these changes and understand the relationship with its associated factors. However, understanding and monitoring urban systems requires both reliable data sources and robust analytical methods (Yang, 2003; Wu, 2007). Traditionally, surveying and mapping methods have been the major approaches for obtaining urban information. These methods, however, are labour-intensive and cannot provide timely information (Wu, 2007). In comparison, Geographic Information System (GIS) and Remote Sensing (RS) technology plays a vital role in providing accurate and reliable information with cost effective and lesser time.

Therefore, this study aims to examine the changes in land use pattern of Yola from 1987 to 2005 using GIS and RS technologies, and then develop a Geographically Weighted Regression (GWR) model to estimate the strength of the relationship between land use change and its associated factors.

Geographically Weighted Regression

GWR is a local spatial statistical technique used to analyse spatial nonstationarity, defined as when the measurement of relationships among variables differs from location to location (Fotheringham et al., 2002). Unlike conventional model such as Ordinary Least Squares (OLS) which conveys only a single set of parameter estimates assuming to apply equally to all parts of the region (eq. 1), which produces a single regression equation to summarize global relationships among the explanatory and dependent variables, GWR generates spatial data that express the spatial variation in the relationships among variables. Maps generated from these data play a key role in exploring and interpreting spatial nonstationarity.

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \quad (1)$$

where y_i is the estimated value of the dependent variable for observation i, β_0 is the intercept, β_k is the parameter estimate for variable k, x_{ik} the value for the kth variable for observation i and ε_i is the error term.

In OLS, the parameter estimates β_k are assumed to be spatially stationary. But in reality, there will be intrinsic differences in relationships over space, which may be a non - stationary character. The non-stationary problem can be measured using GWR (Fotheringham et al., 2002; Platt, 2004). Conceptually, the GWR permits the parameter estimates of a multiple linear regression model to vary locally (eq. 2).

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad (2)$$

where (u_i, v_i) denotes the coordinates of the ith location of the observation i (Fotheringham et al., 2002).

MATERIALS AND METHODS

Study area

Yola is the administrative capital of Adamawa State of Nigeria. It is a twin settlement consisting of Jimeta - administrative and commercial center, and Yola Town - the traditional settlement. Yola is located on latitude 9°14″ N and longitude 12°28′ E (Fig. 1). It has total land coverage of 662.47 square kilometers and a population of 395,871 persons (National Bureau of Statistics, 2006). 2012 projection gives the population as 410,598 persons. The study area comprises of twenty two (22) administrative wards from three (3) local government areas (Yola North, Yola South, and Girei).

Yola has a tropical climate marked by rainy and dry seasons. The maximum temperature can reach 40^{o} C particularly in April, while minimum temperature can be as low as 18^{o} C between December and January. The mean annual rainfall is less than 1,000 mm (Adebayo, Tukur, 1999).

Materials

The key issues to be analysed in this study and the corresponding research methods are illustrated by the flowchart in Fig. 2. First, the temporal and spatial characteristics of land use change in the past two decades are investigated. Second, the driving forces of urban area growth and spatial distribution are examined. Table 1 present all the data used in this study, including socioeconomic data since 1987, two Landsat remote sensing images for 1987, and 2005, Digital Elevation Model (DEM) data, road network map for 2005, Yola administrative boundary, political ward boundary, etc., collected from various sources.

Software

Several sets of software were used in this study. ArcMap® 9.3 was utilized for georeferencing, creation of map layers, databases, OLS and GWR. Stitch Map® 2.0 was used to extract Google earth image for the purpose of updating a base map of Yola. TNTmips® 6.4 was utilized for image processing of satellite images. Lastly, Microsoft excel was used for descriptive analysis.

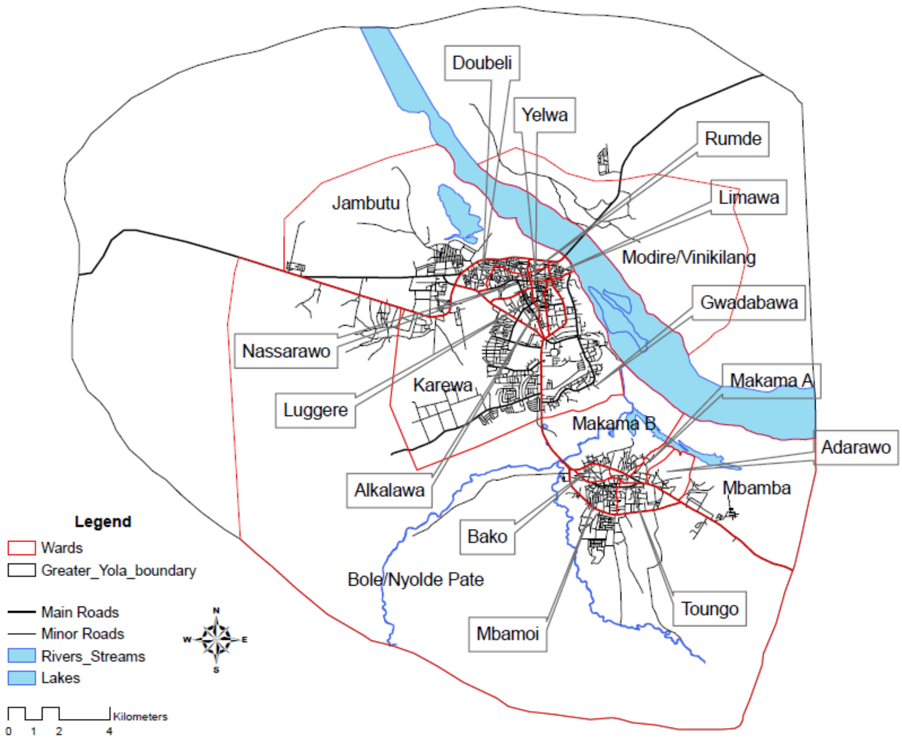


Fig. 1. Study area.

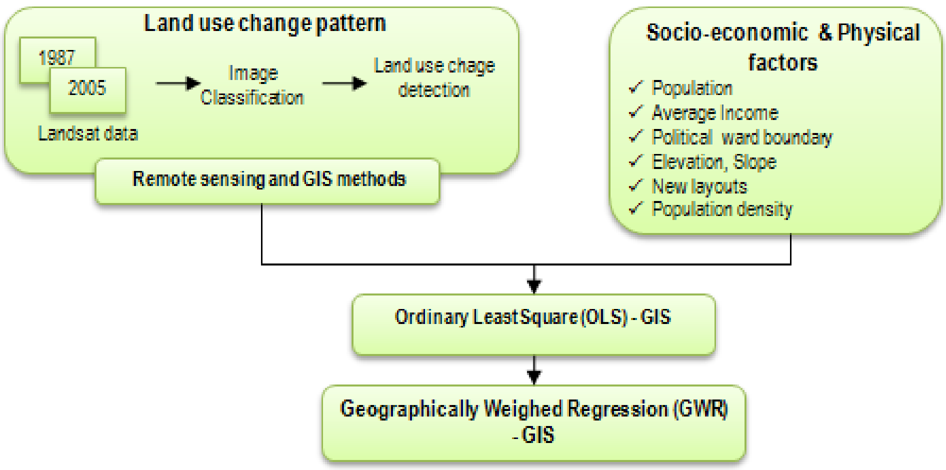


Fig. 2. Flowchart of this study.

Methods

Conversion of analogue data to digital format

The analogue maps were scanned and georeferenced to UTM zone 32N and datum “Minna-Nigeria” using GPS coordinates as ground control points (GCP), and then digitized into: road network, political ward boundary, and Yola administrative boundary vector layers. The road network was further updated using the Google earth image.

Table 1. Data used in the study.

Data Type	Year	Description	Source
Landsat TM image	1987/11/07	Resolution 30 x 30 m	[1]
Landsat ETM+ image	2005/11/08	Resolution 30 x 30 m	[1]
Google Earth image	2005		[2]
ASTER DEM	2008	30 meters	[3]
Road network map	2005	Major and Minor roads	Digitized from Google Earth image
Greater Yola administrative boundary		1:50,000	[4]
Political Ward boundary		1:50,000	[4]
Ground Truth	2005		Google Earth image, existing maps, prior knowledge of the study area, and field survey
GPS Coordinates	2006	Road Junctions coordinate	(Husain, Ismaila, 2006)
Population	2005	Projected using 1991 Census data using 3% growth rate	(Anderson, 1977)
Average Income	2002	Based on political ward basis	UNDP (2002)
Housing Finance	2002	Based on political ward basis	UNDP (2002)
Slope, Elevation		Derived from ASTER DEM	ASTER DEM
Distance Airport Noise contour		Derived	
Layouts	2005	Land subdivision	[4]
Area	2005	Ward basis	
Population density	2005		Generated from available data

* Layouts refers to the land use subdivision e.g., residential, commercial, etc.

* Ground truth is the reference data related to various land uses, e.g., water bodies, forest, agricultural, built-up, etc. collected from the field or ancillary data.

* Housing finance is the financial support received from Mortgage Banks, local and international bodies for the purpose of housing construction.

Image processing

The two Landsat (TM and ETM+) satellite images were processed using the TNTmips® 6.4 software. However, before classification, the images were re-projected to UTM zone 32 and an attempt was made to superimpose them properly with the existing vector layers, and then study area extracted using a vector layer of Yola administrative boundary. Images enhanced using histogram equalization and principal component analysis (PCA) which synthesized the signal from all individual channels into a group of main principal components (PC) (Jensen, 2005) was applied so as to reduce the amount of channels to be classified.

The first two PCs account for 94.48% and 95.03% for TM and ETM+ respectively. Whereas, the correlation matrix result of both images shows that bands (3, 4, and 5) might include almost as much as the entire channels considered. Therefore, these three bands were used in the classification process. Based on (Anderson, 1976; Anderson, 1977) land use classification method, a supervised classification based on the maximum likelihood approach was performed using the ground truth data to derive spectral signatures for seven land use classes of interest (water bodies, forest, agricultural, built-up, rock outcrop, vacant area, and vegetation). Since, the result of a supervised classification usually has some percentage of misclassification due to noise and unknown pixels, it is therefore necessary to test the accuracy of the classification by using field knowledge and other ancillary data (Jensen, 1996). As such, while performing the classification, accuracy assessment in terms of classification error and separability of the land use classes has been checked. These assessments were performed by providing the ground truth data in a raster format and output in the form of: error/confusion matrix consisting of percentages of individual land use class accuracy, overall accuracy, kappa statistics/coefficient (K_{hat}), and the co-occurrence matrix was generated automatically by the software. The K_{hat} is a measure of overall accuracy of image classification and individual category accuracy as a means of actual agreement between classification and observation (Ismail, Jusoff, 2008). It lies typically on a scale between 0 and 1, where the latter indicates complete agreement, and is often multiplied by 100 to give a percentage measure of classification accuracy, Kappa values are characterized into 3 groups: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement, whereas, a minimum of 85% overall accuracy is required (Anderson, 1976; Ismail, Jusoff, 2008). The K_{hat} (Congalton, 1991) is defined by

$$K_{hat} = \frac{p_0 - p_1}{1 - p_1} \tag{3}$$

where p_0 is the overall accuracy of classification given by sum over the diagonal matrix elements:

$$p_0 = \frac{1}{N}\sum_i X_{ii} \tag{4}$$

From this number the fraction p_1 of pixels that could have been accidentally correctly has to be subtracted:

$$p_1 = \frac{1}{N^2}\sum_i \left(\sum_j X_{ij} \cdot \sum_j X_{ji} \right) \tag{5}$$

The co-occurrence procedure analyses the spatial associations of pairs of classes. It determines the frequency with which cells of each class pair occur adjacent to each other in the image. These values allow one to judge which classes are spatially associated. A positive value in the co-occurrence matrix indicates that two classes are adjacent to each other more often than random chance would predict. A negative value indicates that two classes tend not to occur together (Smith, 2001). Having come-up with the land use maps for the two different dates, then areas occupy by each land use was computed, changes determined, and final maps generated using TNTmips®, ArcMap® while Microsoft Excel was used for descriptive analysis.

Variables selection and GWR

The change in land use detected from the classification analysis is considered as the dependent variable for the GWR model. Therefore, in order to develop the GWR model, several candidate explanatory variables that may explain these changes were identified and assessed. These variables include; population of Yola in 2005, population density, average monthly income, political ward area in hectares, elevation, and slope. Finally, the variables were analysed using the scatter - plot (ArcMap® graph function), OLS, and spatial autocorrelation analysis (ArcMap® Spatial Statistic tool).

RESULTS AND DISCUSSIONS

Land use map of 1987

Table 2 shows the accuracy (error/confusion matrix) of land use classification for 1987. The result indicates an overall classification accuracy of about 87.07% and a kappa statistic of agreement of 83.37%. Therefore, it is clear that the classification result met the minimum 85% for overall accuracy and 80% for kappa statistic stipulated by (Anderson, 1976; Rahman, 2004). On the other hand, a large separability value and negative co-occurrence values are observed in the co-occurrence matrix (Table 3) which indicates that two classes tend not to occur together. The percentage of land use for this period indicates that forest accounts for 29.76%, agricultural (22.71%), vacant area (21.98%), rock outcrop (13.78%), built-up (7.07%), vegetation (2.44%), and water bodies covers 2.26% (Figs. 3 and 4).

Land use map of 2005

The accuracy assessment of land use classification map of 2005 indicates an overall accuracy of about 92.26% and a kappa statistic of 90.41% (Table 4). (Anderson, 1976; Rahman et al., 2004) minimum accuracy assessment was satisfied and even stronger than the result obtained in 1987 case. This can be attributed to the fact that the researcher has a better knowledge of the study area during this period. However, in respect to co-occurrence analysis a similar result to 1987 is observed, i.e., large separability values and negative co-occurrence values (Table 5) which indicates that two classes tend not to occur together. Fig. 5 shows that agricultural use (44.97%) constitutes the highest percentage, forest accounts for 13.91%, rock outcrop (17.08%), vacant land (12.40%), built-up (6.67%), water bodies (3.36%), and vegetation (1.61%) has the least area coverage. The 2005 land use classification map is shown in (Fig. 6).

Table 2. Accuracy assessment of 1987 classification map.

	Ground Truth Data									
	Name	Water bodies	Forest	Agricultural	Built-up area	Rock outcrop	Vacant land	Vegetation cover	**Total**	**Accuracy**
Classification	Water bodies	**1762**	0	0	0	42	0	0	1804	97.67%
	Forest	0	**11044**	1	33	2750	0	0	13828	79.87%
	Grass/Farm land	13	0	**3920**	5	197	0	0	4135	94.80%
	Built-up area	7	0	43	**2718**	0	172	0	2940	92.45%
	Rock outcrop	0	0	134	11	**6907**	10	0	7062	97.81%
	Vacant land	5	25	462	313	296	**3490**	0	4591	76.02%
	Vegetation cover	20	0	0	0	0	0	**717**	737	97.29%
	Total	1807	11069	4560	3080	10192	3672	717	35097	
	Accuracy	97.51%	99.77%	85.96%	88.25%	67.77%	95.04%	100.00%		
Overall Accuracy = 87.07% **Khat Statistic** = 83.37%										

Table 3. Co-occurrence analysis of 1987 classification map.

	Water bodies (2.86%)	Forest (36.49%)	Agricultural (13.38%)	Built-up area (6.39%)	Rock outcrop (10.43%)	Vacant land (27.98%)	Vegetation cover (2.46%)
Water bodies (2.86%)	**1414.422**	-140.956 103.766	-95.296 130.300	-67.155 153.925	-100.691 114.689	-130.790 148.489	-40.071 85.216
Forest (36.49%)	-140.956 103.766	**549.774**	-316.124 43.186	-213.684 78.891	-267.246 21.587	-507.338 59.402	-125.849 48.787
Grass/Farmland (13.38%)	-95.296 130.300	-316.124 43.186	**917.853**	-153.665 38.259	-190.529 23.491	-276.200 19.277	-83.979 89.617
Built-up area (6.39%)	-67.155 153.925	-213.684 78.891	-153.665 38.259	**1192.393**	-141.431 57.951	-186.258 27.807	-74.373 121.219
Rock outcrop (10.43%)	-100.691 114.689	-267.246 21.587	-190.529 23.491	-141.431 57.951	**1008.398**	-242.457 39.558	-89.507 67.143
Vacant land (27.98%)	-130.790 148.489	-507.338 59.402	-276.200 19.277	-186.258 27.807	-242.457 39.558	**642.028**	-118.981 105.370
Vegetation cover cover (2.46%)	-40.071 85.216	-125.849 48.787	-83.979 89.617	-74.373 121.219	-89.507 67.143	-118.981 105.370	**1417.963**

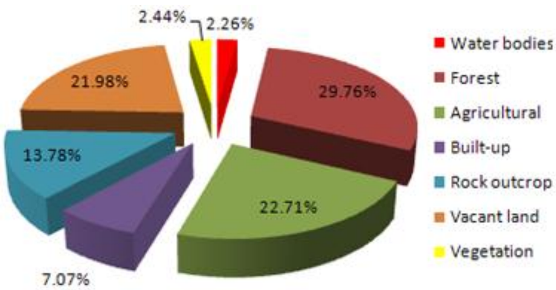


Fig. 3. Percentage cover comparison of land use classes 1987.

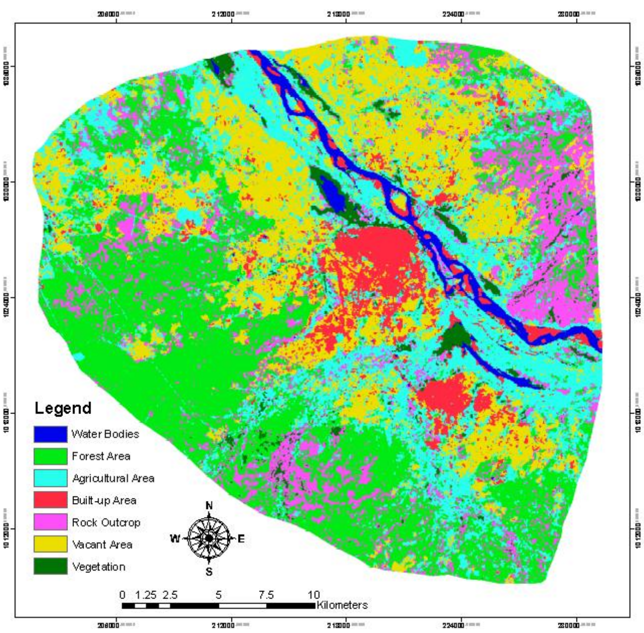


Fig. 4. Land use map of 1987.

Table 4. Accuracy assessment of 2005 classification map.

		Ground Truth Data								
	Name	Water bodies	Forest	Agricultural	Built-up area	Rock outcrop	Vacant land	Vegetation cover	**Total**	**Accuracy**
Classification	Water bodies	**2237**	0	0	0	0	0	0	2237	100.00%
	Forest	0	**2844**	0	0	327	0	0	3171	89.69%
	Grass/Farm land	1	0	**3394**	33	55	45	0	3528	96.20%
	Built-up area	21	0	90	**4776**	0	0	0	4887	97.73%
	Rock outcrop	0	11	421	0	**5321**	0	0	5753	92.49%
	Vacant land	0	0	316	286	0	**344**	0	946	36.36%
	Vegetation cover	41	0	0	0	0	0	**724**	765	94.64%
	Total	2300	2855	4221	5095	5703	389	724	21287	
	Accuracy	97.26%	99.61%	80.41%	93.74%	93.30%	88.43%	100.00%		
Overall Accuracy = 92.26% **Khat Statistic** = 90.41%										

Table 5. Co-occurrence analysis of 2005 classification map.

	Water bodies (3.36%)	Forest (13.91%)	Farm land (44.97%)	Built-up area (6.67%)	Rock outcrop (17.08%)	Vacant land (12.40%)	Vegetation cover (1.61%)
Water bodies (3.36%)	**1307.582**	-115.396 84.530	-140.656 97.935	-78.273 98.553	-118.680 77.108	-111.592 119.941	-34.331 76.100
Forest (13.91%)	-115.396 84.530	**860.518**	-320.120 31.151	-159.186 62.642	-214.186 8.030	-206.423 62.640	-80.252 36.970
Grass/Farmland (44.97%)	-140.656 97.935	-320.120 31.151	**432.502**	-208.600 36.481	-368.861 36.521	-289.235 31.827	-93.548 63.543
Built-up area (6.67%)	-78.273 98.553	-159.186 62.642	-208.600 36.481	**1129.253**	-169.217 64.986	-141.613 28.941	-57.138 88.565
Rock outcrop (17.08%)	-118.680 77.108	-214.186 8.030	-368.861 36.521	-169.217 64.986	**788.530**	-223.295 67.897	-80.739 32.919
Vacant land (12.40%)	-111.592 119.941	-206.423 62.640	-289.235 31.827	-141.613 28.941	-223.295 67.897	**903.896**	-78.403 94.333
Vegetation cover cover (1.61%)	-34.331 76.100	-80.252 36.970	-93.548 63.543	-57.138 88.565	-80.739 32.919	-78.403 94.333	**1422.393**

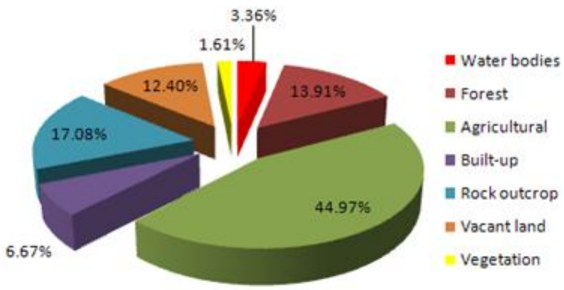


Fig. 5. Percentage cover comparison of land use classes 2005.

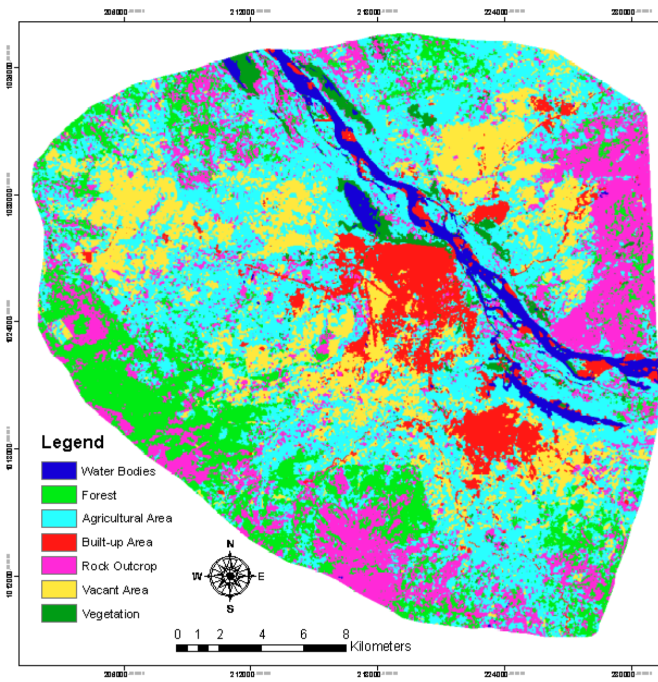


Fig. 6. Land use map of 2005.

Change detection analysis

The areas covered by each land use type for the two periods were compared. Then the directions of the changes (positive or negative) in each land use type 1987 and 2005 were determined (Figs. 7 and 8, and Table 6). Positive change indicates an increase whereas negative change means a decrease.

Remotely sensed images are vital in land use change detection as it provides spatial and temporal information about the land use condition of an area. In this study, an 18 year time span (1987 - 2005) which is moderately enough in showing long history of land use, is considered. These time periods were chosen based on the availability of satellite image and other ancillary data.

The most commonly used land change detection methods includes i) image overlay ii) classification comparisons of land use statistics iii) change vector analysis iv) principal component analysis and v) image rationing and vi) the differencing of normalized difference vegetation index (NDVI) (Duadze, 2004). However, the method used in this study was post-classification comparison and multi-date composite image change detection (Singh, 1989). This method is widely used and easy to understand. The advantage of this method includes the detailed from-to information that can be extracted. Change detection was carried out in order to obtain from-to information about changes in land use and especially to observe the trend of land use pattern which have a great contribution in preparing future planning proposals.

From Fig. 7 and Table 6, it can be observed that forest, vacant land, vegetation has been changed by -9,991.38, -4,136.70, and -200.16 hectares respectively. Whereas, water bodies (569.19 ha), agricultural land (10,181.80 ha), built-up (204.99 ha), and rock outcrop (3,371.90 ha) have increased. From this, it can be concluded that the forest areas is decreasing very drastically. The main reason for the reduction is severe deforestation due to encroachment and improper cutting down of trees for firewood, farming, and construction purposes. This reason is also applicable to the decreased observed in vegetated areas. On the other hand, agricultural land and the exposure of rock outcrop have increased dramatically. Built-up areas have also increased. These changes have great implications on global warming and the sustainability of the city of Yola and its environs.

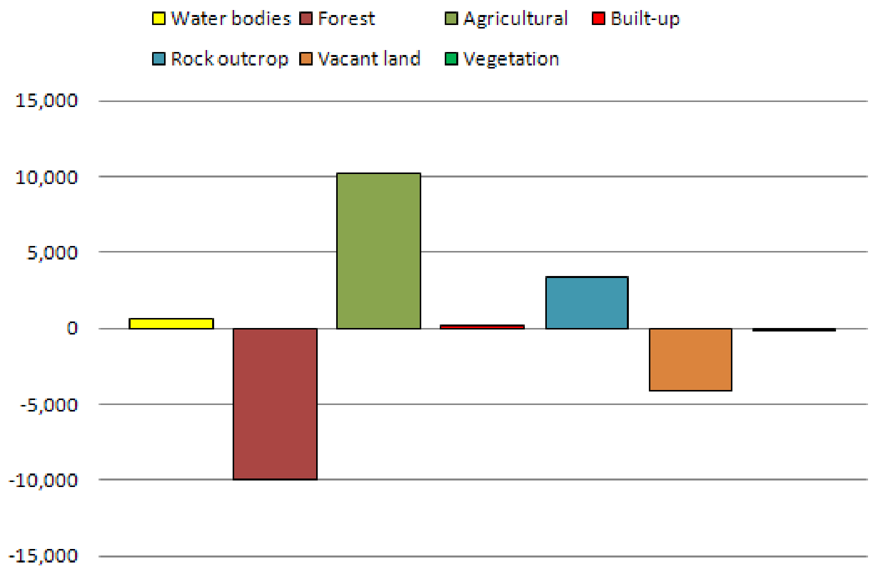


Fig. 7. Land use change between 1987 and 2005.

Table 6. Summary of land use classes for the two periods with their area coverage.

Land use Type	**1987**		**2005**		**Change between 1987 and 2005**	**Average change between 1987 and 2005**
	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(Ha/yr)
Water bodies	1,493.97	2.26	2,063.16	3.36	569.19	31.62167
Forest	19,716.60	29.76	9,725.22	13.91	**-9,991.38**	-555.077
Agricultural	15,042.60	22.71	25,224.40	44.97	10,181.80	565.6556
Built-up	4,683.27	7.07	4,888.26	6.67	204.99	11.38833
Rock outcrop	9,130.50	13.78	12,502.40	17.08	3,371.90	187.3278
Vacant land	14,562.40	21.98	10,425.70	12.40	**-4,136.70**	-229.817
Vegetation	1,617.84	2.44	1,417.68	1.61	**-200.16**	-11.12
Total	**66,247.18**	**100.00**	**66,246.82**	**100.00**	**-**	**-**

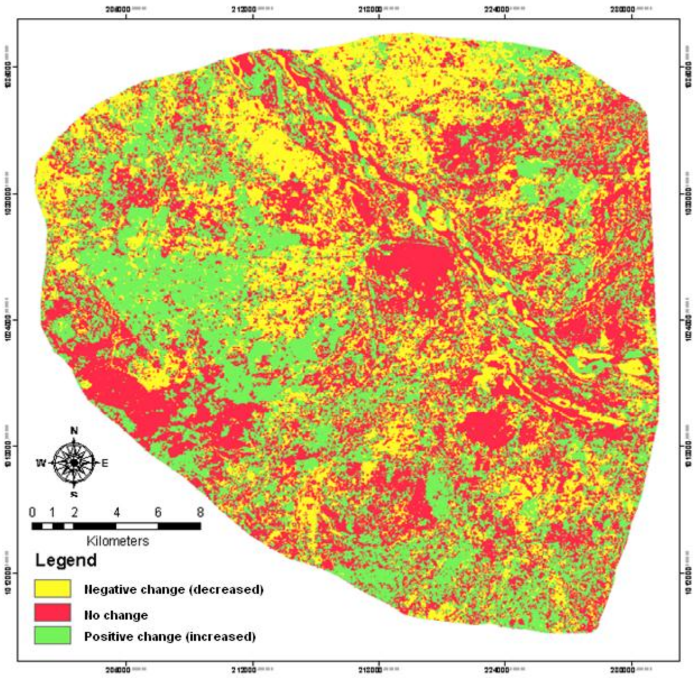


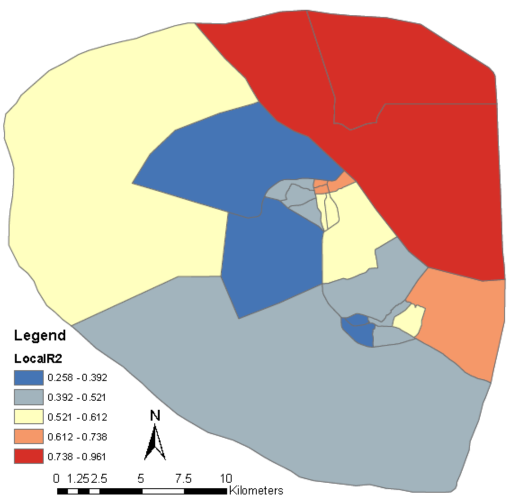
Fig. 8. Land use change map between 1987 and 2005.

Geographically Weighted Regression model

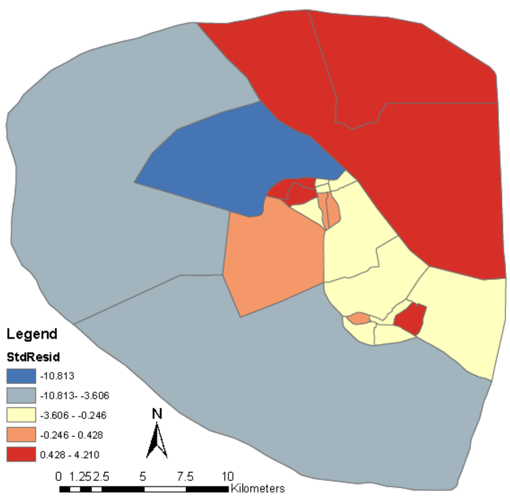
The statistics: Adjusted R^2, Akaike's Information Criterion (AIC), Variance Inflation Factor (VIF), p-value, robust probability, and Moran's I, etc., reported from the analyses were used in identifying the contribution of each explanatory variable. The result shows that population of Yola in 2005, political ward area in hectares, population density, and new layouts are the most important variables that explain the changes. Finally, the GWR analysis was performed.

The GWR model result gives a strong Adjusted-R^2 of 0.967. However, the Local R^2 values varied spatially ranging from 0.26 to 0.96 (Fig. 10a). The AICs (111.14); a smaller value of AICs is fine on local modelling (Fotheringham et al., 2002). The spatial patterns of residuals in fig. 10 (b) show some under prediction and over prediction. However the model exhibits no spatial autocorrelation as evidenced by Moran's-I (0.02), which means the residuals of the over and under predictions are randomly distributed. Figs. 10 (c) – (f) shows the coefficient surface maps which indicate how the relationship of each explanatory variable varies across space. Areas with large coefficients indicate the locations where that particular explanatory variable is most important in explaining the depended variable.

a.



b.



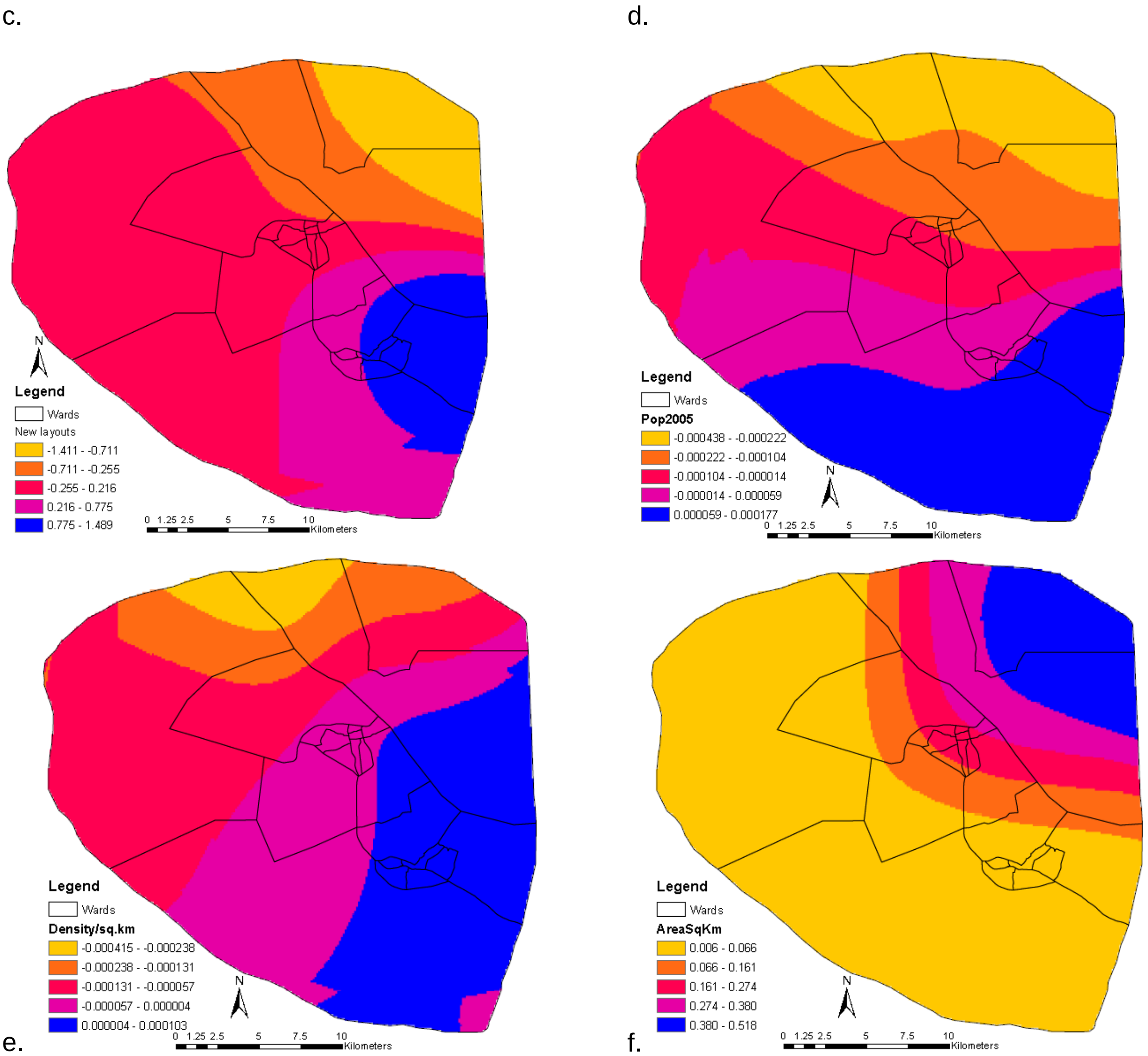


Fig. 10. Parameter estimates of GWR: (a) Local R^2 (b) Std. Residuals (c) New_layouts (d) Pop2005, (e) DensitySqKm (f) AreaSqKm

CONCLUSION

The use of satellite imagery and its integration into a GIS can provide a timely and appropriate tool for studying land use change of urban areas. The thematic maps obtained at relatively low cost and in a short time compare favourably with traditional methods of investigation. This study has looked at land use change in Yola during the past two decades and highlighted a comprehensive analysis of the driving forces behind urban expansion. The causes are examined using GWR approach. Land use change in Yola is influenced by available land area, layouts, population increase, and population density. However, the degree of influence of each variable varied at different location. The GWR model explained considerably more variation in the relationship of the explanatory factors when compared to conventional OLS models. The random distribution of standard residuals confirmed that the probability of missing variables to explain land use change in the study area is very low, which further strengthen the model. The localized regression estimates exhibited the relationships between the dependent and explanatory variables varied spatially.

ACKNOWLEDGMENTS

I wish to express my sincere appreciation to The Scientific and Technological Research Council of Turkey (TÜBİTAK) for the support received in the course of my Ph.D. program.

REFERENCES

Adebayo A., Tukur, A. L. (1999) Adamawa State in Maps. Paraclete Publishers, Yola, pp. 20-26.

Alkali, J.L.S. (2005) Planning sustainable urban growth in Nigeria: Challenges and strategies. Presented at conference on planning sustainable urban growth and sustainable architecture, held at the ECOSOC Chambers, United Nations Headquarters, New York, on 6th June 2005.

Anderson, J.R. Haardy, E.E., Roach, J.T., Witmer, R.E. (1976) A land use and land-cover classification for use with remote sensor data (USGS professional paper 964), Washington, DC: U.S. Government Printing Office, 18 pp.

Anderson, J.R. (1977) Land use and land cover changes: A framework for monitoring. Journal of Research, 5(3), 143-153.

Congalton, R. (1991) A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37, 35-46.

Duadze S.E.K. (2004) Land-use and land-cover study of the Savannah ecosystem in the Upper West region (Ghana) using remote sensing, ZEF Bonn, University of Bonn, Germany.

Fotheringham, S.A., Brunsdon, C., Charlton. M. (2002) Geographically weighted regression: the analysis of spatially varying relationships. John Wiley & Sons, Chichester, UK.

Husain, M.A., Ismaila, A.B. (2006) The routines and requirements for the creation of a Geographical Information System (GIS): the case of GIS database for the water board corporation, Yola. ENVIRON: Journal of Environmental Studies, 2(6), 47-56.

Ismail, M.H. and Jusoff, K. (2008) Satellite data classification accuracy assessment based from reference dataset. International Journal of Computer and Information Engineering, 2(6), 386- 392.

Jensen, J.R. (1996) Introductory Digital Image Processing, 2nd edition, Prentice Hall, London.

Jensen, J.R. (2005) Introductory Digital Image Processing: A Remote Sensing Perspective. Prentice-Hall, New Jersey, USA.

Knox, P.L., McCarthy, L. (2005) Urbanization: An Introduction to Urban Geography, 2nd edition, Prentice-Hall: Upper Saddle, NJ, USA.

National Bureau of Statistics (2006) Annual Abstract of Statistics 2006. Federal Republic of Nigeria.

Platt, R. V. (2004) Global and local analysis of fragmentation in a mountain region of Colorado. Agriculture, Ecosystem and Environment, 101, 207-218.

Rahman, M.M, Csaolovics,E., Koch, B., Kohl, M. (2004) Interpretation of Tropical Vegetation Using Landsat ETM+ Imagery, URL: http://www.isprs.org/congresses/ istanbul2004/yf/papers/951.pdf, Accessed on 31/12/2009.

Singh, A. (1989) Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing, 10, 989-1003.

Smith, R.B. (2001) Getting Started: Image Classification, URL: http://www.microimages.com, Accessed on 25/01/2010.

Wu, C. (2007) Remote sensing applications in urban socio-economic analysis. In: Mesev, V. (Ed) Integration of GIS and Remote Sensing. John Willey & Sons, West Sussex, England, pp. 150-172.

Yang, X. (2003) Remote sensing and GIS for urban analysis: an introduction, Photogrametric Engineering and Remote Sensing, 69, 1003-1010.

Yang, X. (2007) Integrating Remote Sensing, GIS and Spatial Modelling for Sustainable Urban Growth Management: In Integration of GIS and Remote Sensing, edited by Mesev, V., John Willey & Sons, West Sussex, England; pp. 173-197.

UNDP (2002) A gender disaggregated baseline survey on urban and housing conditions in Ganye, Michika and Yola, Adamawa State, Conducted by 3D Consult for UNDP.

[1] Global Land Cover Facility. URL: http://glcfapp.umiacs.umd.edu:8080/esdi/index.jsp. Accessed 29/01/2012.

[2] Google Earth Software 4.0.2722

[3] United State Geological Survey. URL: http://earthexplorer.usgs.gov/. Accessed on 10/02/2012.

[4] Ministry of Land and Survey, Yola, Adamawa State, Nigeria.