Modeling urban change using cellular automata: the case study of Johannesburg, South Africa

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Abstract: Urbanization is one of the most evident human-induced global changes. Despite its economic importance, urban growth has a considerable impact on the surrounding environment. The most hazardous impacts caused by the informal and sometimes poorly planned developments are: the destruction of green spaces, increase in traffic, air pollution, congestion with crowding and lack of significant contribution to national income. Remote sensing provides an excellent source of data, from which updated land use/land cover information and changes can be extracted, analyzed, and simulated efficiently. Recent advances in computer models, GIS and remote sensing tools enable researchers to model and predict urban growth effectively. Cellular automata models have better performance in simulating urban development than conventional mathematical models. Johannesburg is the economic powerhouse of South Africa and it is the most populous metropolitan area. The city has experienced a significant growth in informal settlements. This growth has led to the loss of vast expanses of land, thus reducing the land available for other land uses, and contributing to a series of environmental problems. This paper quantified, mapped, and analyzed, the urban growth of Johannesburg from 1995 to 2010 using Landsat TM & ETM$^+$ data. Cellular automata techniques were implemented for modeling the urban growth of the city of Johannesburg up to 2030. The model predicted future urban changes within and at the periphery of the city. The forecasted urban land cover change would prove useful for future urban planning and management of space in Johannesburg.

Introduction

The spatial dynamics of urban growth is an important area of analysis in urban studies. Several studies have addressed issues of urban growth and dealt with a diverse range of subjects, e.g. urban environment, urban development, urban change detection, and management (Cihlar, 2000; Wang, *et al*., 2003; Páez and Scott, 2004; Zhu, *et al*., 2006; Geymen and Baz, 2008; Hedblom and Soderstrom, 2008).

Urban areas are characterized by high levels of spatial dynamics where their sizes are increasing dramatically. The expansion of a city beyond its periphery requires population growth spatially distributed. Population growth contributes to urban change by absolute growth, which increases urban areas, and changes the dynamics of urban demography. This increases the number of people residing in small cities at a high rate, and consequently decreases the household sizes and increases the number of the housing units (Qiu, *et al*., 2003).

In South Africa urbanization levels approached 56% in 2001, resulting in a 4.3% increase from 1996 to 2001 (Kok and Collinson, 2006). Urban growth is influenced by a number of factors including geographic, demographic, economic, social, environmental, and cultural ones. Hence, modeling such a dynamic system is an analytical challenge (Kashem, 2008).

Remote sensing (RS) and Geographic Information Systems (GIS) techniques are useful geospatial tools widely used to assess natural resources and monitor spatial changes. Land Use/Land Cover (LULC) change dynamics can be analyzed using time series remotely sensed data and linking it with socio-economic or biophysical data in a GIS (Moeller, 2004; Reveshty, 2011). The integration of RS and GIS enables researchers to analyze environmental changes, this includes land cover mapping and change detection, monitoring and identifying land use attributes, and change hot spots. With the advancement in technology, reduction in data cost, availability of historical spatial-temporal data and high resolution satellite images, GIS and RS techniques are now useful research tools in spatial change and modeling (Feng, 2009; Bayes and Raquib, 2012).

Advances in satellite-based land surface mapping are contributing to the creation of considerably more detailed urban maps, offering planners a much better and deeper understanding of urban growth dynamics, as well as associated matters relating to territorial management (NASA, 2001). In terms of analyzing urban growth, (Batty and Howes, 2001) reported that, remote sensing technology provides a unique perspective on growth and land-use change processes. Data sets obtained through remote sensing are consistent over great areas, time, and can provide information at different geographic scales. Remote sensing-derived information is very useful in describing and modeling the urban development process. This leads to better understanding, management and planning (Banister, *et al*., 1997; Longley and Mesev, 2000; Longley, *et al*., 2001; Yikalo and Cabral, 2010).

Remote sensing data helps to understand how an urban landscape is changing through time. This understanding includes: (1) urban growth rate, (2) spatial pattern of the growth, (3) difference between the observed and forecasted growth, (4) spatial or temporal variance in growth, and (5) if growth is sprawling or not.

Urban growth modeling is getting more attention as an emerging research area. This is due to the recent dramatic increase in urban populations that increase the pressure on infrastructure services. Among all developed urban growth models, cellular automata (CA) models have better performance in simulating urban development than conventional mathematical models (Batty and Xie, 1994).

During the past 15-20 years a new generation models have been developed, based on the assumption that an understanding of the details can explain the whole – i.e. a bottom-up approach. One of these models is cellular automata (CA). CA has been shown to be successful in capturing complexity with simple rules. One of the most important parts in making CA more realistic is to find the transition rules which represent the real pushing and pulling forces.

Cellular Automata is based on a defined neighborhood, where every entity (in two dimensions represented by a cell) is interacting with the surrounding cells only. Thus, CA has been considered most suitable for processes where the immediate surroundings have an influence on the cell, such as diffusion processes. This includes processes of ecological dynamics (Parker, *et al*., 2003).

The essential component of a CA is: a grid (raster) consisting of cells cell states (1 and 0), a neighborhood within which transition rules can apply, and a temporal space or time-step interval (Torrens, 2000).

Despite all the achievements in CA urban growth modeling, the selection of the CA transition rules remains a research topic (Batty, 1998). CA models are usually designed based on individual preference and application requirements with transition rules being defined in an *ad hoc* manner (Li and Yeh, 2003). Furthermore, calibration of CA models is still a challenge. Most of the developed CA models need intensive computation to select the best parameter values for accurate modeling.

The purpose of this study is to apply an integrated approach incorporating GIS, RS, and modeling to identify and analyze patterns of urban changes within the study area of Johannesburg between the years 1995 and 2010. The study also aims to determine the probable future developed areas in 2030 to enable the anticipation of planning policies that aim to preserve the natural characteristics of the study area.

Material and methods

Study area

Johannesburg is South Africa's economic powerhouse and it's most populous metropolitan area. It is a rapidly growing city, with a population in excess of 3.2 million. The growth rate is 3-4% per year resulting from natural increase as well as migration from surrounding areas within and outside the country. Johannesburg configures 7.37% of the country's population, the population density of Johannesburg is 2231 person per km^2 (Lynelle, 2012).

The study area covers 3,657 Km^2 (51 x 71 km) and includes the entire area of Johannesburg and some other areas from the surrounding cities as shown in the following figure (1).

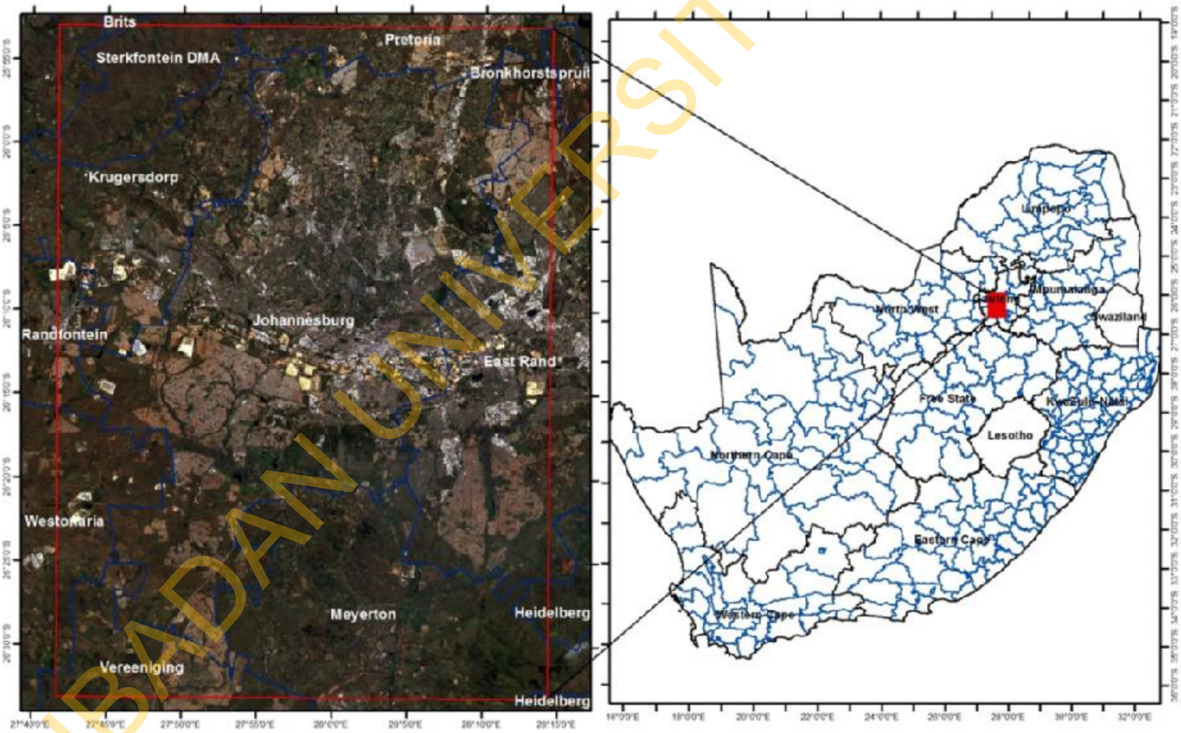

Figure 1: Study area.

The topography of study area is made up of diverse topographical features Mountainous ranges on the middle and western sides surround Johannesburg; the eastern side of the area is much flatter in comparison with the western part. The northern part is the lowest area (1230 m). Elevation of the area ranges between 1230m to 1930m above sea level.

Data analysis and processing

Two Landsat images were downloaded from the USGS web site. The first was a Landsat 5 TM image acquired in August 1995 while the second was a Landsat 7 ETM^+ captured in May 2010 (figure 2). Due to the Landsat Scan Line Corrector (SLC-off) failure the second image was gap filled using another Landsat image captured on March 2010. Other auxiliary data were collected as listed below:

- Road network layer was collected from Gauteng City-Region Observatory (GCRO) in vector file format.
- 2.5 m LULC data set obtained from GCRO in raster format was used for accuracy assessment for 2010 LULC map
- Twelve topographic sheets of 1:50,000 that covers the study area were used for accuracy assessment for 1995 LULC map.
- Five meter contour line data set for extracting the digital elevation model for the study area.

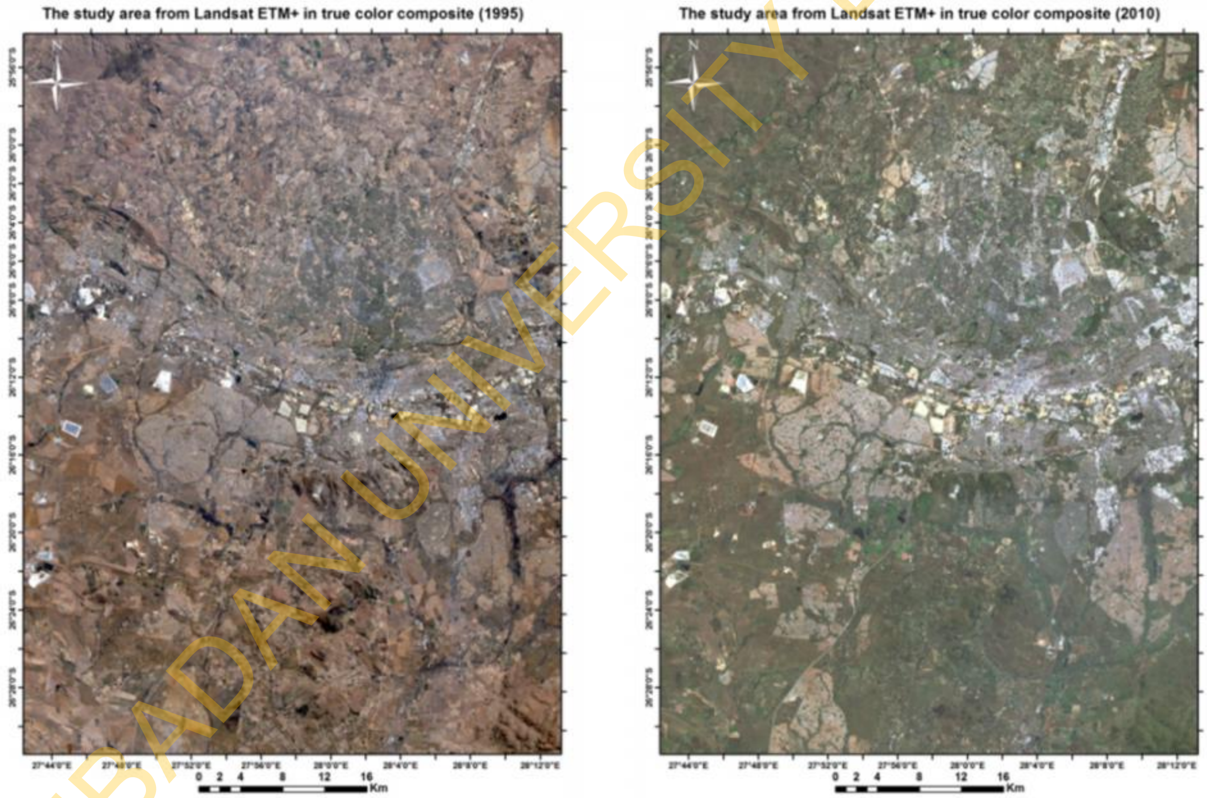

Figure 2: Landsat natural look for the study area.

Two bands local histogram match gap filling was done using Landsat gap fill module embedded in ENVI 5 software (ENVI, 2012). Layer stack was carried out to get multi-band file. The study area was clipped from the entire scene. Figure (3) summarizes the different steps applied to get the study results.

Minimum distance supervised classification was done using IDRISI Selva software (Eastman, 2012). The study area was classified into 10 different classes that were merged to 5 classes: Water and wet land, Crop land and Natural vegetation, Urban and Industry, Mines and Quarry, and bare soil and Rock. Accuracy assessment was carried out for the two classified images using 341 random points for 1995 and 315 points for 2010. The ground truth points was collected using the 2.5m LULC obtained from GCRO for the 2010 image while for 1995 image ground trothing points were collected from the topographic maps in combination with the satellite image itself. The Land Change Modeler module embedded in IDRISI was used for LULC change analysis and modeling future development of the study area.

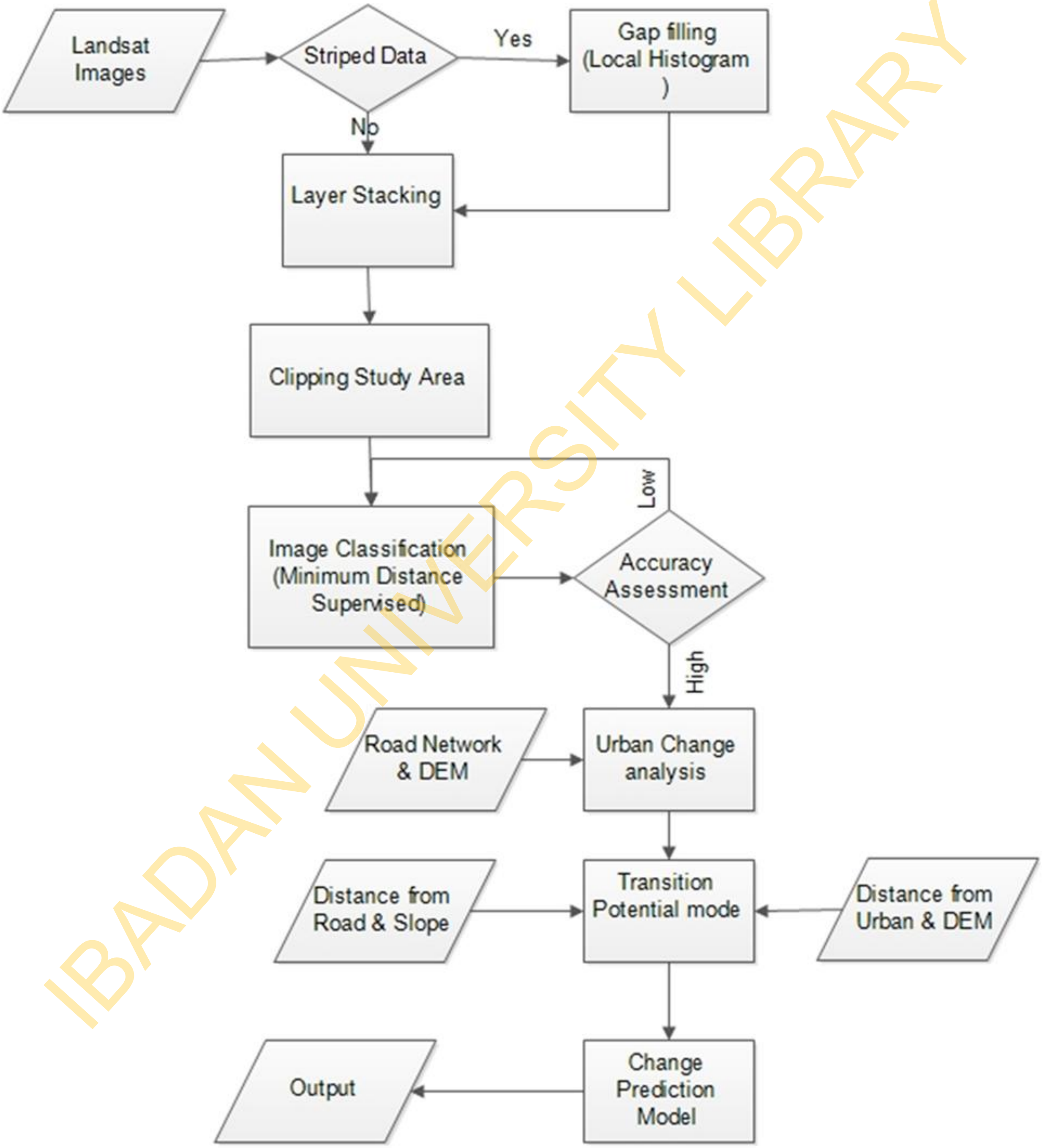

Figure 3: Flow chart for the applied methodology.

Results and discussion

Accuracy assessment

Table (1) summarizes the results for accuracy assessment for the year 1995. A total number of 341 points were chosen randomly. For the water and wet land class 52 points were selected with accuracy of 86 %. For the crop land and natural vegetation 62 points were selected. The final accuracy for that class is 96%. Urban class final accuracy is 84% with 90 points representing it. The major interference is due the industry, mines and quarry class which interfere with the urban class by more than 30%. For the bare soil and rock class the total of 63 points selected to represent that class. It interferes with crop land and natural vegetation class by 11% and this is resulting in a class accuracy of 84%. This reduces the total accuracy for the classification to 79%.

Table 1: Accuracy assessment for 1995.

1995	Water & Wet Land	Crop Land & Natural Vegetation	Urban	Industry, Mines & Quarry	Bare Soil & Rock	Total	Accuracy
Water & Wet Land	46	2	0	2	1	51	0.86
Crop Land & Natural Vegetation	3	60	2	0	7	72	0.96
Urban	0	0	80	24	0	104	0.84
Industry, Mines & Quarry	0	0	0	44	0	44	0.53
Bare Soil & Rock	3	0	8	4	55	70	0.84
Total	52	62	90	74	63	341	0.79

Accuracy assessment result for 2010 image represented in table (2). A total number of 315 points were selected for the assessment. Water and wet land class 39 points were selected. The final accuracy for the water and wet land class is 91 %. For the crop land and natural vegetation 58 points were selected. The final accuracy for that class is 89%. Urban class final accuracy is 93% with 92 points representing it. The industry, mines and quarry class final accuracy is 82%. For the bare soil and rock class the total of 64 points selected to represent that class. It interferes with crop land and natural vegetation class and the Urban class which reducing the class accuracy of 65%. This reduces the total accuracy for the classification to 84%.

Image classification

Figure (4) represents the classified images for the study area for the two investigated dates. Generally; for the year 1995 the area of the urban area was 988 km^2 and increased to 1582 km^2 in the year 2010 with change rate of 39.6 km^2 per year. New development areas have emerged during the investigated 15 years as well as the expansion of the existing ones. The highlighted areas by circles (1, 2, and 4) are examples for urban expansion in the study area. There is a big difference in the density of urban inside each circle. Circle 3 representing an example of new developed area over the 15 years investigated.

Table 2: Accuracy assessment for 2010.

2010	Water & Wet Land	Crop Land & Natural Vegetation	Urban	Industry, Mines & Quarry	Bare Soil & Rock	Total	Accuracy
Water & Wet Land	36	1	0	0	0	37	0.91
Crop Land & Natural Vegetation	0	53	0	0	6	59	0.89
Urban	1	2	88	9	13	113	0.93
Industry, Mines & Quarry	1	0	3	53	0	57	0.82
Bare Soil & Rock	1	2	1	0	45	49	0.65
Total	39	58	92	62	64	315	0.84

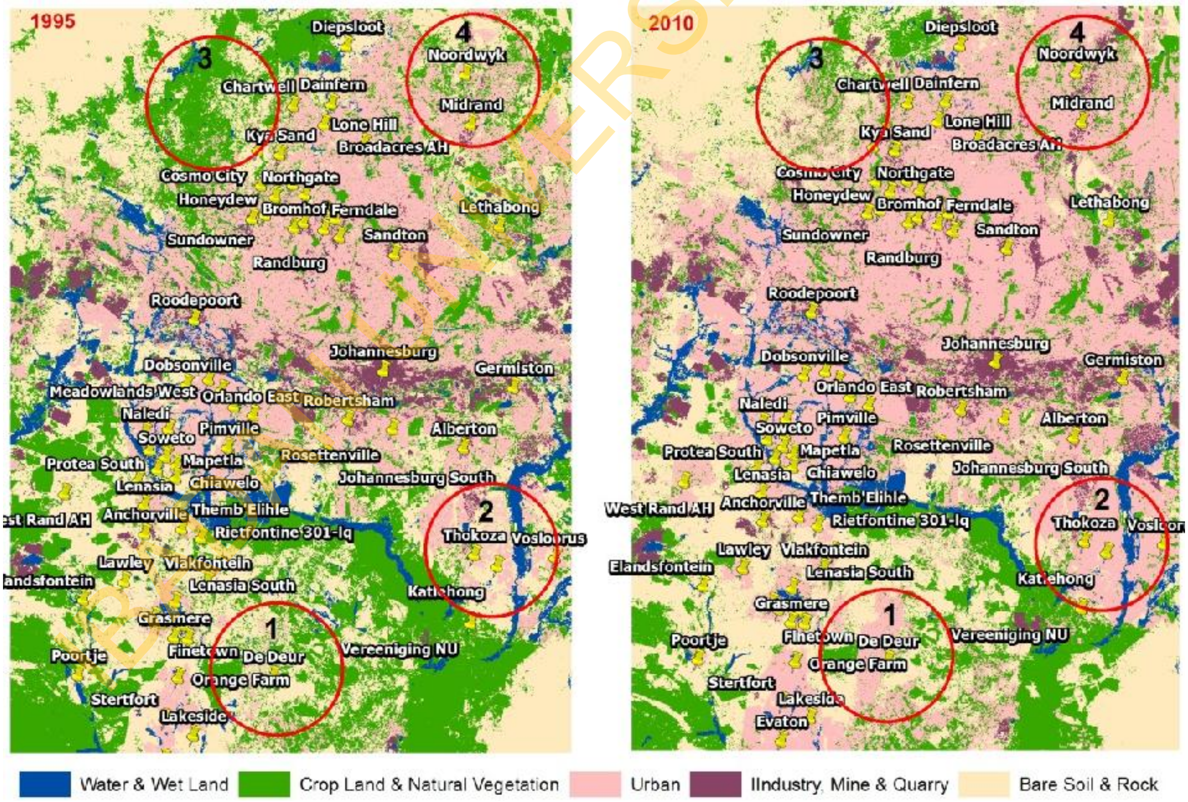

Figure 4: LULC maps for the study area for the two investigated dates.

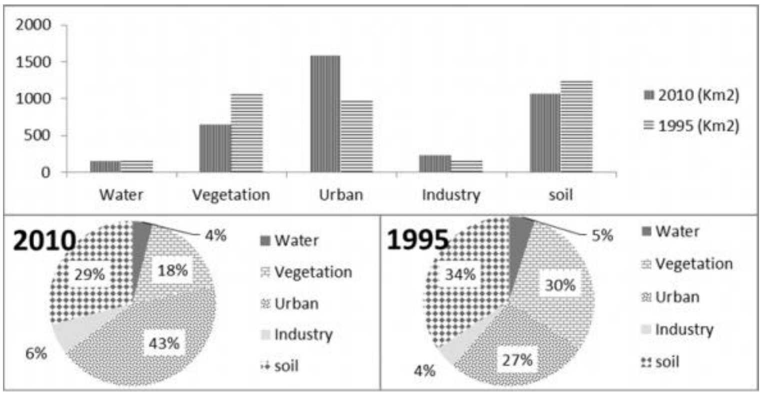

Figure 5: LULC changes between 1995 and 2010.

Change analysis

Table (3) and figure (5) summarizes the changes between the two investigated dates (1995 and 2010). Water and wet lands decreased by 19%, crop land and vegetation decreased by 40%, bare soil class decreased by15% all of these in comparison to 1995 areas. Urban and industry, mines and quarry increased by 60% and 40%, respectively compared to their areal extents in 1995.

Table 3: Class areas and the differences between 1995 and 2010 images.

Class	2010 (Km^2)	1995 (Km^2)	Differences (Km^2)	%
Water	145	179	-34	-19.1
Vegetation	644	1075	-431	-40.1
Urban	1582	988	594	60.1
Industry	224	158	66	42.0
Bare soil	1062	1257	-195	-15.5
Total	3657	3657	0	0.0

Figure (6) explore the gains and losses in areal extents of the different classes. It is clear that the urban class has gained the most with no significant loss in areal extent (597, -2.89 km^2). Industrial areas also gained but lost some of their extent (66, -0.2 km^2). The bare soil and rock class has also lost and gained a substantial extent. (278, -473 km^2). This could attributed to the difference in seasonality between the two images, hence the 1995 image captured in winter which is a dry season in Johannesburg and the study area, meanwhile the 2010 one captured in summer which has a lot of rains. The crop land and natural vegetation class decreased (-431 km^2) due to the transformation to urban and industrial areas.

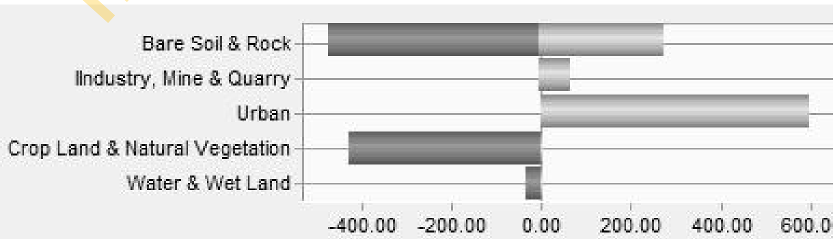

Figure 6: Gains and losses between 1995 and 2010.

In an attempt to understand the expansion of urban area, figure (7) shows the contribution of each of the classes to urban expansion that occurred during the 15 year period. It is obvious that; bare soil and vegetation classes are the main contributors to that expansion: 430 and 152 km^2 respectively. The Water and wet land class contributed to that expansion by only 12 km^2.

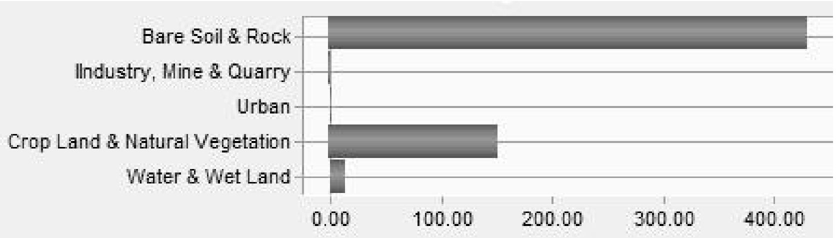

Figure 7: Contribution to net change in urban areas.

Figure (8a, b) shows the trend of urban expansion in the study area, and the spatial distribution of the occurred changes. Figure (8a) shows that the urban expansion in the eastern parts (Midrand and Noordwyk) of the study area is very rapid and also the south-western part area around Soweto (De Deur, Finetwon, Protea South and Lenasia). Figure (8b) maps the spatial distribution for the transformation accrued between different classes. The transformation of bare soils to urban areas is mainly concentrated on the periphery of the study area where the land is cheaper and the facilities are limited, meanwhile the transformation from vegetation to urban much noticed inside the urban communities and it is in small patches compared with the bare soil.

Modeling urban expansion

For modeling urban expansion the first step was to produce transition probability maps based on the detected changes and trend. In producing these maps the distance from roads, existing urban areas, the DEM and slope were taken into consideration. From the change analysis results; it was evident that two main significant changes have occurred in the study area i.e. the transformations of vegetated areas and bare soil to urban forms. Therefore in the prediction process; only these two transitions were taken into consideration.

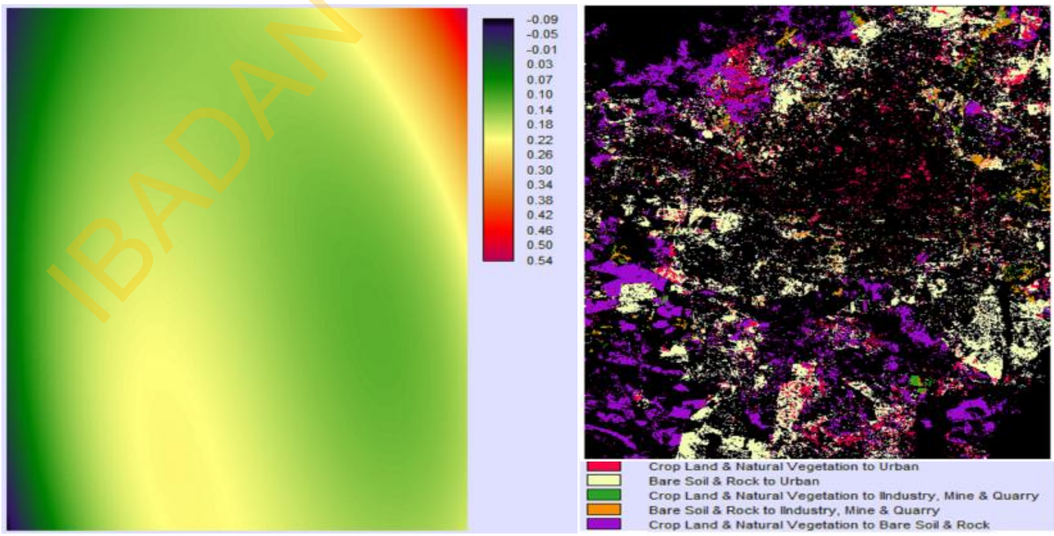

Figure 8: a) urban trend in the study area, b) main changes between 1995 and 2010 in the study area.

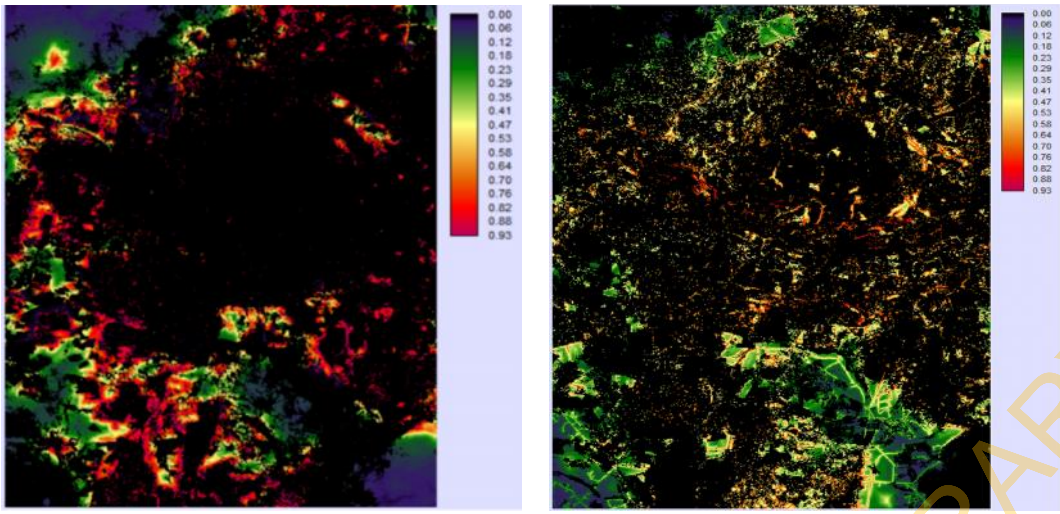

Figure 9: Probability transition (a) bare soil to urban, b) vegetation to urban.

Figure (9a, b) illustrates the probability of transition for the two modeled transitions in the study area. The probability of transition of bare soil is higher than that of vegetation and this may be attributed to vicinity to the roads and existing urban areas.

Change prediction results

Cellular automata model embedded in IDRISI software was applied to predict the urban expansion based on the produced transition probabilities. Figure (10) represents the forecasted land cover of 2030. The urban area will be increased by 600 Km^2 in 2030. Bare soil contributes to that change by 450 km^2 whereas 150 km2 will be contributed by vegetated areas. Figure (11) shows the spatial distribution of the changed areas from bare soil and vegetation to urban.

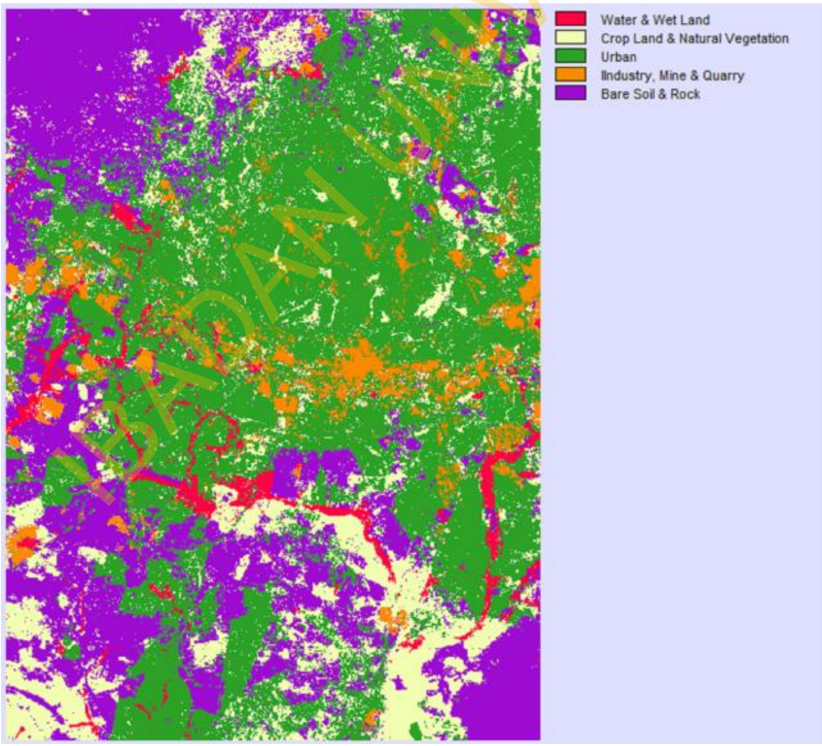

Figure 10: predicted land cover for 2030.

Although model validation was not carried out for the year 2030, the same model (i.e. same transition probability maps) was run for the year 2013 and the resultant land cover was compared with a 2013 Landsat 8 image. The model produced accurate results in forecasting the new areas within the urban area itself. . However, the model produced less accurate results for the new development areas.

Conclusion

This study assessed and modeled the trend of urban land cover changes in the study area using an integrated approach including GIS, RS, and modeling tools. The area experienced extensive conversion to urban land cover over the 15 year period (1995-2010). The results indicate that urban growth may continue to expand further into the future (2030), and might have certain impact on land resources, unless some careful planning and management are implemented.

For the transformation of vegetation to urban it was noticed that it occurs inside the urban communities. It comes on the share of the green area inside the urban area which has a hazardous impact on the environment and health of the habitants in these areas. In addition to that it overloads the facility exist in the area.

Cellular automata have been shown to be successful in capturing complexity with simple rules. However, there are many uncertainties with the technique and more research is required for adapting it better to an urban context. Future work should consider model validation and apply an advanced modeling approach that would allow for long-term accurate simulation.

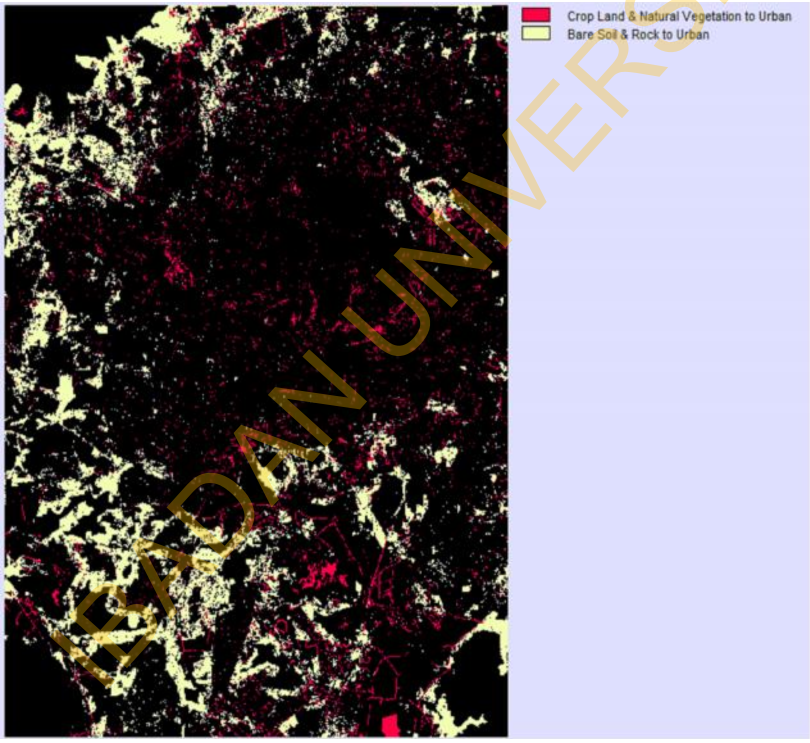

Figure 11: Spatial distribution from bare soil and vegetation to urban.

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