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## **Land Use Land Cover Change in the fringe of eThekweni Municipality: Implications for urban green spaces using remote sensing**

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### **Abstract**

*Concerns on urban environmental quality, increasing knowledge on impacts of climate change and pursuit for sustainable development have increased the need for past, current and future knowledge on the transformation of remnant urban fringe green ecosystems. Using land-cover change modeler and a Markov chain analysis on multi-temporal SPOT imagery, this study sought to determine a twenty two-year past and future land use and land cover trend and its implication on green spaces in an eThekweni Municipal Area's peripheral settlement. Results show a consistent pattern of decline in land use and land cover types associated with green spaces and an increase in impervious surfaces. The study confirms recent urban bio-physical transformation and anticipated increased pressure on peripheral urban green spaces in eThekweni Municipality. These changes can be attributed to natural urban growth and government led efforts like the Reconstruction and Development Programme. Findings in the study highlight the challenges faced by eThekweni Municipality, and indeed other South Africa's urban areas in maintaining urban green spaces and mitigating related implications like those associated with climate change. This study further demonstrates the value of multi-temporal remotely sensed datasets in planning, optimization and sustainable management of urban landscapes.*

### **1. Introduction**

Global population has increased significantly since mid-20<sup>th</sup> century. Accompanying this growth has been increased urbanization. By the end of the last decade for instance, the world's urban population had reached 2.9 billion or 40% of the world's 6.1 billion people (Van Zyl *et al.*, 1997; Martindale, 2008). In sub-Saharan Africa, this population is expected to double to more than 4.9 billion, an equivalent of 52-60% by 2030 (Keiser, *et al.*, 2004;

Odindi *et al.*, 2012). The rapid urban population growth has led to significant urban landscape transformation mainly through conversion of green environment to impervious and built-up surfaces (Palmer & Ainslie, 2005; Jensen, 1996; Odindi *et al.*, 2012). Such green environments are increasingly becoming valuable due to emerging concerns on urban environmental quality, climate change and increasing quest for sustainable urban living.

Urban environmental planning and designing mitigation measures require knowledge of past, current and future Land-Use-Land-Cover (LULC) transformations. Traditionally, this information has been derived from field surveys and aerial photo interpretation. The use of these techniques is however often time consuming, labour-intensive and costly (Peerbhay *et al.*, 2013; Wu *et al.*, 2013), consequently, these techniques are not considered ideal for quantification and analysis of the often highly dynamic urban LULC processes (Liverman 1998; Coppin *et al.*, 2004; Kavzoglu & Colkesen 2009).

Currently, there is a large body of valuable literature on urban LULC change and its implication on green spaces (see; Abbott & Douglas, 2003; Mundia & Aniya, 2005; Deng *et al.*, 2009 among others). Whereas existing literature has commonly focused entire urban landscapes, typically, the highest rate of urban LULC transformation occurs at the urban fringes.

According to Small and Miller (1999), urban landscapes, particularly the transformation of urban greenery, significantly influence earth systems within and beyond their geographical boundaries. In this regard growth and densification of urban fringes and consequent loss of green spaces has made monitoring of sub-urban areas increasingly important for understanding the landscape characteristics as a basis for sustainable urban landscape management. In this study we determine and predict the influence of LULC transformation on green spaces in a location within the Ethekwini Municipal Area (EMA) fringe using multi-temporal imagery and Markov prediction model.

## **2. The study area**

This study was conducted within the jurisdiction of Ward 7 of the EMA, KwaZulu-Natal Province, South Africa (Figure 1). The wider municipal area is characterised as urban and is the second largest manufacturing area in the country. The EMA is made up of Durban, the third largest city in South Africa and adjacent smaller towns and accommodates 33% and 7% of the province and country's population respectively (Ethekwini Municipality, 2013). Based on the 2011 population survey, the municipality has 3.5 million people and covers 2,292 km<sup>2</sup>

at 1513 people/km<sup>2</sup> (Board, 2008; Statistics, 2012). According to the Ethekewini Municipality (2013), EMA's central urban core in the Durban city is the most densely populated and accommodates 35% of the area's population.

As a result of increasing urbanization, most of the terrestrial habitat within the EMA has been significantly transformed (Ethekewini Municipality, 2013). The transformation of the existing green spaces has further been compounded by invasive plant species, pollution and impacts associated with climate change. Despite these threats, active conservation measures mainly by EMA's Durban Metropolitan Open Space System (D'MOSS) and other stakeholders, portions of the areas greenery are under active conservation and remain in good ecological condition.

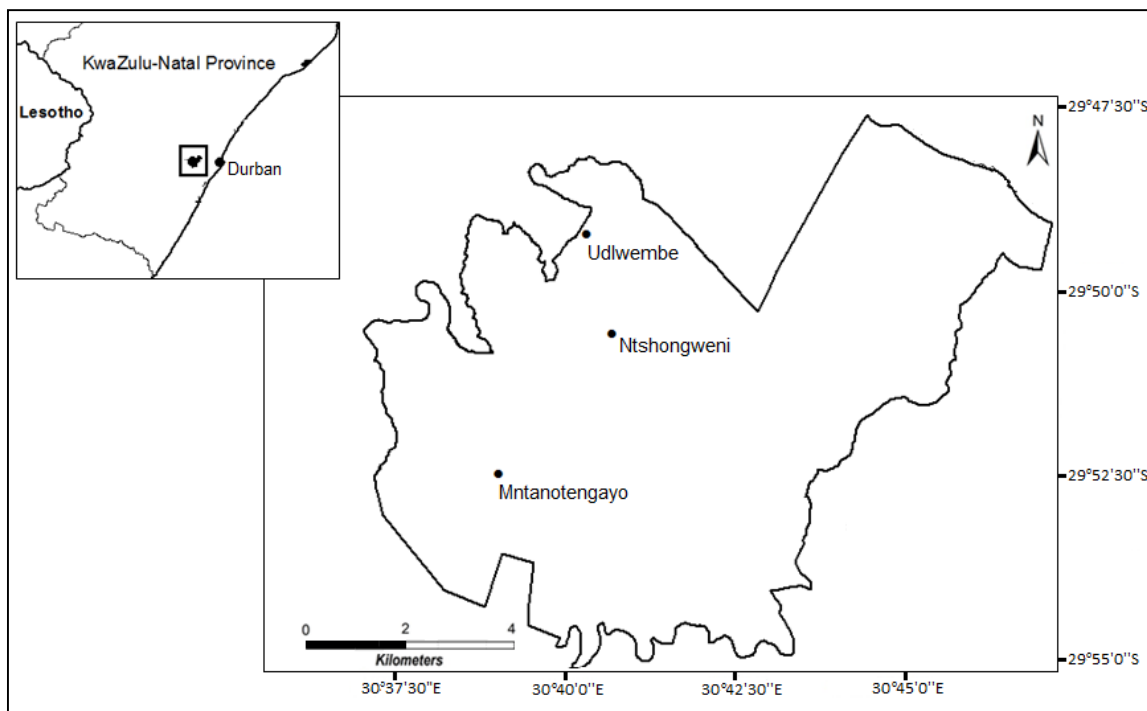


Figure 1: Location of the study area.

### 3. Material and methods

Three sets of multi-temporal SPOT-4 imagery acquired in 2000, 2006 and 2011 detailed in Table 1 were used for this study. The choice of relevant images was determined by their availability in the supplier's archives, amount of cloud cover and centennial or near centennial acquisition. Furthermore, unlike lower spatial resolution imagery like Landsat and ASTER, SPOT's higher spatial resolution was considered more suitable for mapping the small spatial extent. According to El Hajj *et al.* (2008) and Davranche *et al.* (2010), the

image's 10meter spatial resolution makes it ideal for temporal and multi-temporal LULC mapping, change detection and standing green biomass estimation. Whereas a uniform multi-temporal difference between the image datasets could have been ideal, the 2000-2006 and 2006-2011 year difference were used because a 2012 image was unavailable. In addition to the satellite imagery, Ground Control Points (GCPs), field observations, expert knowledge, existing land cover maps and associated aerial photographs were used for analysis and ground validation.

Table 1: Image acquisition dates and characteristics.

Image	Path/Row	Image centre	Resolution			
			Date	Time	Spatial	Spectral
2000	141/409	-29°43'12"/30°58'12"	14-Mar	07:49:06	10 m	4 bands
2006	141/408	-29°57'36"/31°01'48"	07-Mar	07:48:18	10 m	4 bands
2011	141/410	-29°57'36"/30°54'00"	29-Mar	07:23:28	10 m	4 bands

### 3.1 Image registration and pre-processing

Image pre-processing allow for conformity between multi-temporal imagery necessary for quantification and spatial comparisons (El Hajj *et al.*, 2008). Spatial and radiometric image pre-processing ensures that mis-calculations that may arise from image brightness are reduced. In this study, the three sets of images were geo-rectified and radiometrically corrected. The 2000 and 2006 images were co-registered to the 2011 SPOT-4 image to less than half a pixel Root Mean Squares Error (RMSE). To ensure comparability of the multi-temporal imagery, atmospheric normalisation using the relative dark object subtraction (DOS) approach was adopted as described by Furby & Campbell (2001), Du *et al.* (2002) and El Hajj *et al.* (2008). In this study, tarred roads, with average Digital Number (DN) values of 12, 7 and 9 for the 2000, 2006 and 2011 respectively were regarded as darkest. Consequently, the 2006 image was used for atmospheric normalisation.

Weng (2002) and Xiuwan (2002) note that a hybrid approach that combines unsupervised and supervised classification techniques is commonly adopted to improve the accuracy of LULC classes. Consequently this approach was adopted for in study. Firstly, an iterative self-organizing cluster analysis (ISOCCLUS) unsupervised classification scheme was performed on the image datasets to provide a multi-temporal overview of the different clusters in the

study area. This approach is reliant on an aggregation of image pixels based on naturally associated clusters (IDRISI, 2006).

Based on the multi-temporal imagery and associated ortho-rectified 0.3m spatial resolution aerial photographs, the 2000 provincial LULC map and on-site verification on the non-transformed LULC types, five general LULC types; Built-up, Degraded grassland, Forest, Grassland and Thicket were identified and labelled. For each of the LULC types, points from the associated aerial photos were generated using a stratified random sampling scheme. As described by Beyer (2004) and Mutanga *et al.* (2012), the generated points were split into training and validation datasets using the Hawth's analysis tool. A confusion matrix was then generated to determine the classification accuracy of LULC types.

To achieve the aforementioned objectives, a 'from-to' post-classification comparison change detection procedure using Land Change Modeller (LCM) and Markov chain process were employed. This techniques rely on separate multi-temporal image classification and subsequent image comparison (Deng *et al.*, 2008; Odindi *et al.*, 2012). According to Eastman (2006) and Bangamwabo (2010), the LCM is suited for analysis and prediction of LULC types and evaluation of implications of the changes on the entire ecosystem. Based on a landscape prediction tool, the LCM can be used to detail spatial increase and loss, net change, net change drivers, tendencies of change and landscape prediction (IDRISI, 2006; Mhangara, 2011).

The Markov chain projection model was implemented on the three classified LULC maps. This model is a randomised stochastic process that relies on probabilities rather than certainties (Lambin, 1994). According to Iacono *et al.* (2012), the model is based on the assumption that a future state ( $t_2$ ) can be determined by its current state ( $t_1$ ). In LULC modelling, the process determines the  $t_1$  to  $t_2$  LULC distribution using a transition matrix. This can be expressed as;

$$vt_2 = M \times vt_1 \quad [1]$$

Where  $vt_1$  is the LULC proportion vector input,  $vt_2$  is the LULC proportional vector output and  $M$  is the  $m \times m$  transition matrix for the time difference  $\Delta t = t_2 - t_1$ .

In LULC prediction, change based on  $\Delta t$  shows the quantity of land that is expected to transform from one class to another over a specified time period while the matrix indicates the probability of inter-class transitions among different LULC types (Veldkamp & Lambin, 2001; Eastman, 2006; IDRISI, 2006). Lambin *et al.* (1999) and Petit *et al.* (2001), note that

LULC change is considered to be temporally persistent over 10-15 year intervals, thus an eleven year period (2011-2022) illustrated in this study was deemed to be within the required range. In this study predictions were based on the state of LULC in 2000, 2006, and 2011.

According to Mubea *et al.* (2011) and Petit *et al.* (20010), Markov models have several advantages that include scientific compactness and easy execution with empirical LULC data and generation of simple transition summaries valuable in change analysis seldom achieved by other types of models. However, whereas the use of Markov model has become popular, its value is constrained by two major limitations. Firstly, the elimination of stationery supposition in first-order chains, while possible in theory, is difficult to analyse and computationally process. Secondly, the validation of Markov models depends on forecast of transformation over time, consequently, until the transformations occurs, the validation process may be unattainable (Mundia *et al.*, 2011).

#### **4. Results**

Based on the hybrid classification using supervised and unsupervised classification, field visits and LULC types identified from the 2000 South African national LULC classification scheme, five major LULC's (Forest, Thicket, Grassland, Degraded grassland and Built-up) were generated. Reliable overall classification accuracies of over 86% were achieved on all the datasets. These accuracies meet the minimum threshold of 85% stipulated by the United States Geological Survey classification scheme (Anderson *et al.*, 1976; Congalton & Green, 1999).

During the study period, higher transformations were experienced in Grassland, Degraded Grassland and Built-up areas while lower transformations were experienced in Forest and Thicket (Figure 2). Built-up areas, Forest and Degraded grassland had the least covers in 2000, 2006 and 2011 respectively. The highest net decline in LULC types were experienced in 2000-2006 (Grassland) and 2006-2011 (Degraded grassland) (Figure 2).

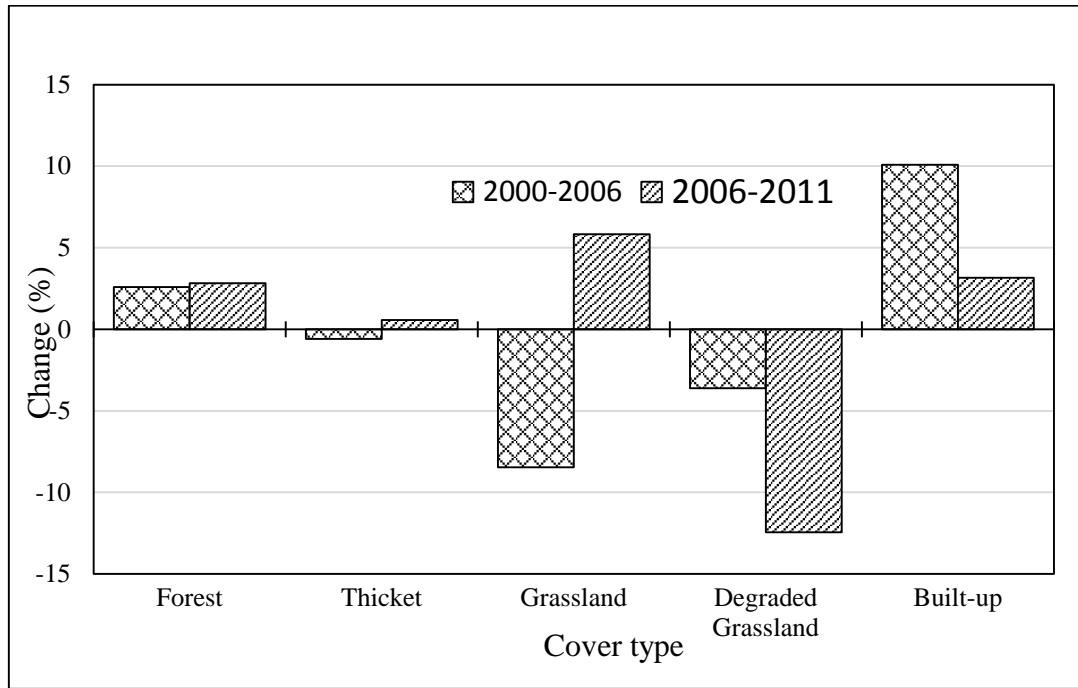


Figure 2: Multi-temporal LULC transformations.

Based on the Multi-temporal LULC transitions using the LCM, between 2000-2006, Grassland, Thicket, Degraded grassland and Grassland had the highest contribution to Built-up, Grassland, Thicket, Forest and Degraded grassland respectively (Table 2). During the 2006-2011 period, Forest had the highest contribution to Built-up and Grassland areas while areas covered by Degraded grassland had the highest contribution to Thicket, Forest and Grassland (Table 2).

Table 2: Multi-temporal LULC transition area.

<b>From LULC</b>	<b>To LULC</b>	<b>2000 to 2006 Area (ha.)</b>	<b>2006 to 2011 Area (ha.)</b>	<b>2000 to 2011 Area (ha.)</b>
Grassland	Built-up	744.56	433.24	565.32
Thicket	Built-up	381.68	645.32	638.2
Forest	Built-up	405.08	960.64	372.52
Degraded grassland	Built-up	447.12	333.16	818.24
Built-up	Grassland	75.88	172.8	197.36
Thicket	Grassland	456.48	553.8	614
Forest	Grassland	329.68	688.16	399.08
Degraded grassland	Grassland	784.4	249.88	957.08
Built-up	Thicket	268.96	412.84	295.16
Grassland	Thicket	556.4	287.92	687.16
Forest	Thicket	313.72	210.4	334.08
Degraded grassland	Thicket	630.52	824.48	573.76
Built-up	Forest	143.76	820.72	303.08
Grassland	Forest	391.56	176	780.84
Thicket	Forest	498.76	316.72	394.48
Degraded grassland	Forest	711.8	936.92	489.64
Built-up	Degraded grassland	355.36	611.24	109.44
Grassland	Degraded grassland	906.28	112.52	431.6
Thicket	Degraded grassland	498.84	145.6	235.44
Forest	Degraded grassland	405.48	74.48	253.76

Analysis based on the Markov transition probability matrix showed a general higher chance for transformation in Built up/Degraded grassland, Grassland/Degraded grassland and Grassland/Built-up in 2011 (Table 3). In 2016, there was an anticipated higher transformation for Degraded grassland/Grassland, Thicket/Built-up and Thicket/Grassland while in 2022, higher transformations were expected for the Forest/Built-up, Degrade/Forest and Grassland/Grassland (Table 3).



Table 3: Markov transition probability matrix 2011, 2016 and 2022 generated from LULC maps of 2000-2006, 2006-2011 and 2000-2011.

<b>Given</b>	<b>Probability of changing to: in 2011</b>				
<b>2000-2006</b>	<b>Built-up</b>	<b>Degraded grassland</b>	<b>Forest</b>	<b>Grassland</b>	<b>Thicket</b>
Built-up	0.2073	0.3338	0.1350	0.0710	0.2526
Degraded grassland	0.1473	0.1522	0.2345	0.2584	0.2077
Forest	0.2419	0.2422	0.1317	0.1969	0.1874
Grassland	0.2564	0.3121	0.1349	0.105	0.1916
Thicket	0.1713	0.2239	0.2238	0.2049	0.1761
<b>2006-2011</b>	<b>Probability of changing to: in 2016</b>				
Built-up	0.1608	0.1015	0.2810	0.1830	0.2726
Degraded grassland	0.2651	0.0804	0.1586	0.3100	0.1859
Forest	0.2251	0.1534	0.1784	0.2412	0.2019
Grassland	0.1965	0.1500	0.2714	0.1433	0.2388
Thicket	0.2851	0.1052	0.1762	0.2743	0.1591
<b>2000-2011</b>	<b>Probability of changing to: in 2022</b>				
Built-up	0.0880	0.2763	0.3711	0.0781	0.1866
Degraded grassland	0.1252	0.1194	0.3519	0.0939	0.3097
Forest	0.4803	0.0372	0.0333	0.3440	0.1052
Grassland	0.2473	0.0642	0.1005	0.4236	0.1644
Thicket	0.3021	0.0682	0.1483	0.2593	0.2222

The LULC in the 2000 and 2006 LULC classes were used to determine the expected transitions in 2011, the 2006 and 2011 were used to determine the expected transformation in 2016 and the 2000 and 2011 were used to determine the expected 2022 transformation (Figure 3, 4 and 5). In 2011, 2016 and 2022, the expected transformation in Built-up and Grassland areas showed consistent increase while areas covered by Degraded grassland classes showed a consistent decline (Table 4). There was inconsistency in areas covered by Forest and Thicket LULCs (Table 4). This can be attributed to the different rates of settlement and the reforestation initiatives during the study periods. Based on the determined and projected LULC types, green spaces (Forest, Grassland and Thicket) and non-green areas (Built-up and Degraded grassland) were grouped as Boolean classes (Figure 3 and 4).

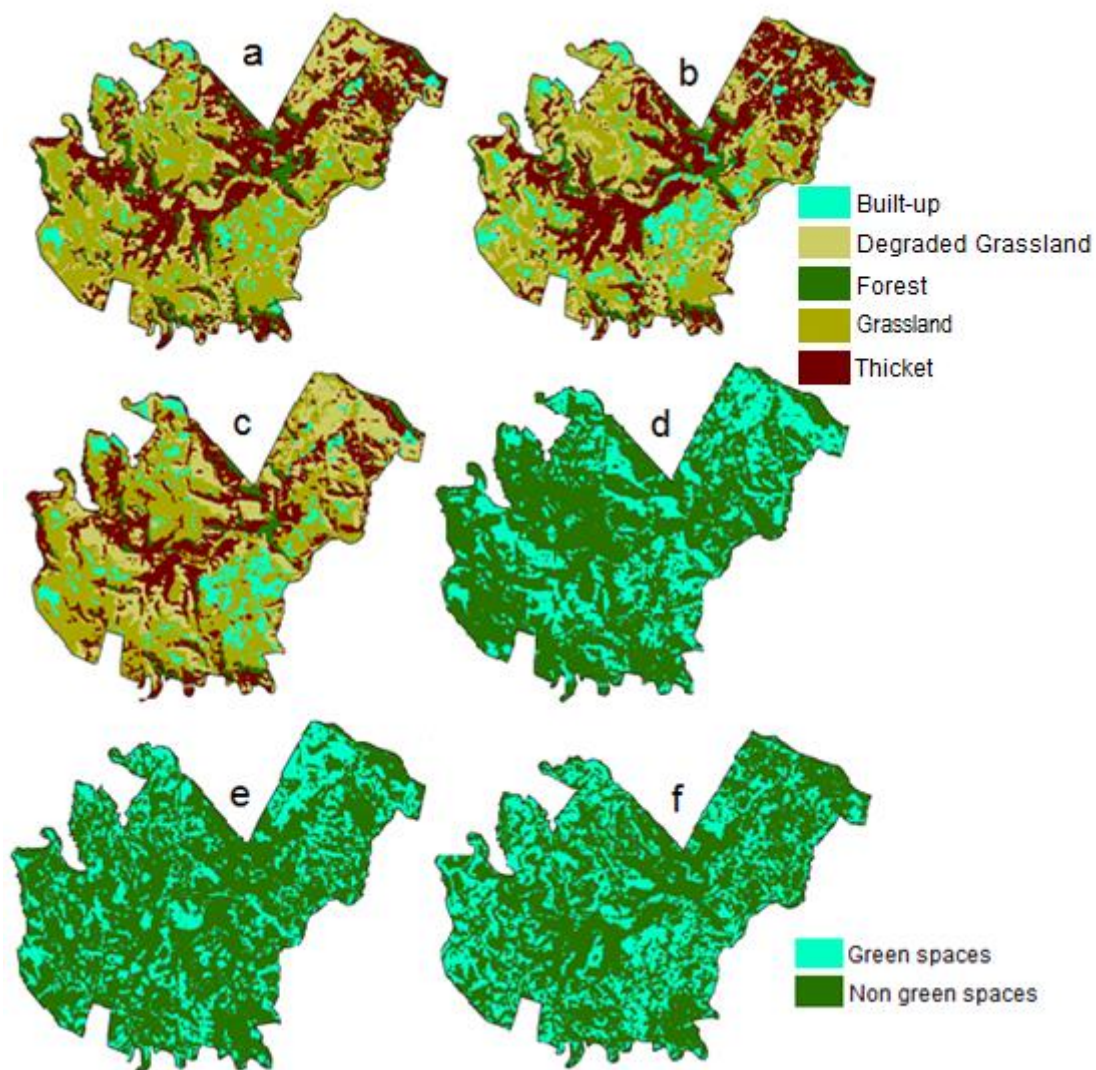


Figure 3: Spatial LULC for 2000 (a), 2006 (b), 2011 (c) and Boolean green spaces cover for 2000 (d), 2006 (e) and 2011 (f).

Table 4: Expected LULC transitions pixels in Markov transition probability matrix generated from LULC maps of 2000 and 2006, 2006 and 2011.

All cells in:		Expected transition to: in 2011			
2000-2006	Built-up	Degraded grassland	Forest	Grassland	Thicket
	56413	48334	5734	49583	69637
2006-2011		Expected transition to: in 2016			
	Built-up	Degraded grassland	Forest	Grassland	Thicket
	62042	34321	62289	61742	60919
2000-2011		Expected transition to: in 2022			
	Built-up	Degraded grassland	Forest	Grassland	Thicket
	71895	32368	53089	71521	52421

The projected multi-temporal LULC showed a general increase in the area covered by built-up and degraded grasslands (Figure 4 a-c). Since the rest of the LULC types constitute a form of green spaces, it can be concluded that multi-temporal increase in Built-up areas seen in Figure 4 a-c has led to decline in green spaces.

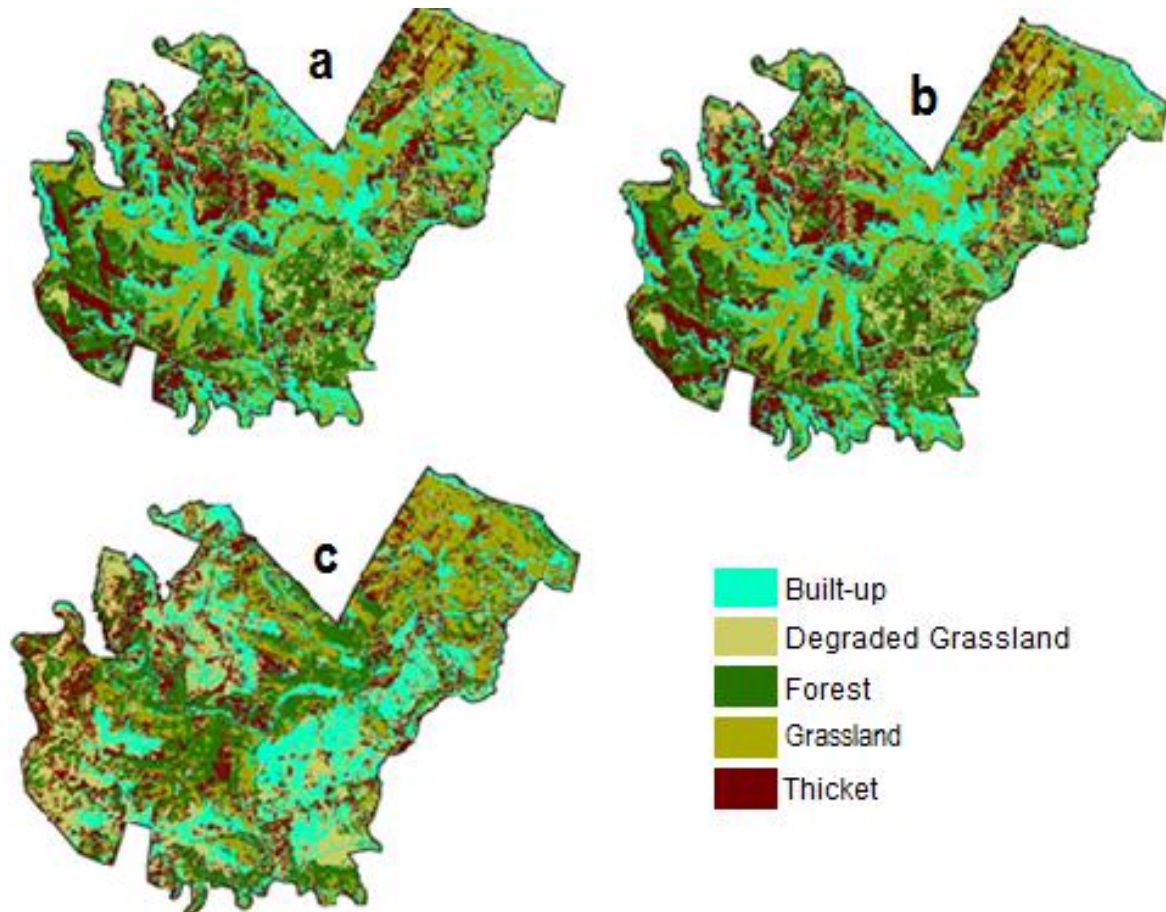


Figure 4: Projected LULCs for 2011 (a), 2016 (b) and 2022 (c).

To show the projected implication of settlements on the study area's green spaces, a Boolean image of non green spaces (Built-up and Degraded Grassland) and green spaces (Forest, grassland and Thicket) was generated (Figure 5). In the Boolean image, there was a projected increase in non green spaces and decline green spaces (Figure 5).

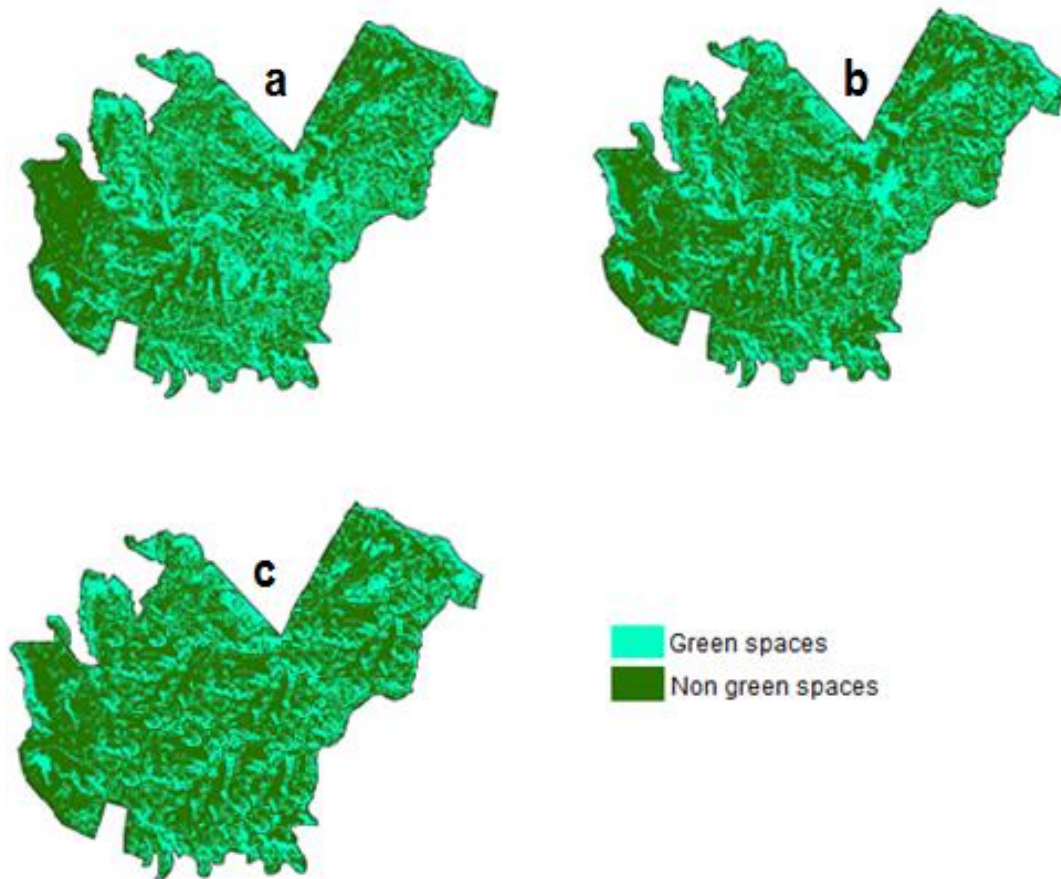


Figure 5: Boolean classes green spaces projections in 2011 (d), 2016 (e) and 2022 (f).

## 5. Discussion

Up-to-date knowledge on urban landscape transformation and its implication on urban greenery, particularly at the most vulnerable urban fringes is critical for informed socio-economic and environmental decision making (Naveh, 1995). Results in this study show a steady decline in the peripheral urban greenery within the EMA. These results are consistent with Florgård (2004) who note a more rapid decline in the area's peripheral natural landscape. In most of South Africa's urban areas, increased transformation of peripheral urban landscapes can be directly linked to post 1994 government efforts to formalize informal settlements through Reconstruction and Development Programme (RDP) initiatives and associated physical infrastructural development (Christopher, 2001; Collinson *et al.* 2007; Pillay & Sebake, 2008).

Based on the LULC categories identified in the study area, there were apparent changes LULC in the study area. The expansion of Built-up areas and reduction in Degraded grassland and Grassland LULCs (Table 2) are consistent with literature on South Africa'

urban growth and loss of natural landscapes on urban periphery within the EMA (Ethekewini Municipality, 2003; SANBI, 2009; Pillay, 2010), and other South African metropolitan areas Sihlongonyane (2003) and Odindi *et al.* (2012).

The Markov chain prediction model was used to compute LULC transition probabilities from the multi-temporal LULC maps. As shown in Tables 3 and 4, the probabilities of LULC associated with green spaces changing to other LULC categories in 2016 and 2022 was higher, indicating a further decline to that experienced between 2000-2011. The high chance of future green spaces transformation results from the losses to Built-up and Degraded grassland and indicates a continuous transformation of these critical greeneries. From 2000-2006 probability matrix, it is evident that the chance of Grassland remaining unchanged is lower than the likelihood of this category changing to other LULCs, this represents instability in the green spaces. This finding is consistent with the SANBI biodiversity survey report that projected future decline in Ethekewini's greenery (Ethekewini Municipality, 2003; SANBI, 2009).

In this study it is assumed that an increase in population and consequent increase in Built-up density leads to a decline in urban greenery. Firstly, green areas are cleared for establishment of physical structures and secondly, lower income settlements may lead to destruction of adjacent greenery through among others fuel wood extraction and grazing.

Due to the value of urban greenery, the transformation experienced in this study highlights the challenges faced by the EMA in maintaining urban greenery and therefore mitigating socio-ecological challenges including those associated with climate change. In addition to determining and projecting peripheral urban transformation, this study highlights the value of remotely sensed data set in concert with GIS applications in understanding the transformation of urban landscapes. With an increasing understanding of the a nexus between urbanization, LULC and ecosystem and environmental processes, understanding past, current and future patterns is increasingly becoming important (Gillanders *et al.*, 2008). According to Turner (1987), analysis based on remotely sensed datasets represents an emergence of contemporary methods valuable in understanding and quantifying the implications of urban landscape evolution.

Whereas remotely sensed data provides rapid generation of LULC maps, the accuracy of the LULC maps generated is still often compromised by the spatial and spectral resolution of commonly used imagery. In urban landscapes, often characterized by complex landscape heterogeneity, new generation imagery like WorldView and RapidEye would be ideal.

However, these images are costly and therefore commonly not cost effective in routine urban LULC mapping.

## **6. Conclusion**

This study successfully determined multi-temporal and projected LULC trends in EMA's Ward 7. The findings show that there has been a persistent reduction of the green areas in EMA's periphery. Based on this findings, it can be concluded that most of the greeneries are lost due to the built-ups that characterise urban area's peripheral growth. Although not investigated in this study, the existing and predicted loss of green spaces can be attributed to the municipality's densification of the urban core and the spillage of new settlements to the urban periphery. Such spillage is often accompanied by requisite physical infrastructure like road and retail services that lead to further decline in urban greenery. This study has further demonstrated the value of remotely sensed datasets and techniques in determining historical and future LULC trends and their implication on urban greenery. These tools offer a viable alternative for fast mapping of urban landscapes with reliable accuracy. Such up-to-date LULC maps are particularly critical for designing economically and environmentally sustainable urban systems.

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