African Journal of Agricultural and Resource Economics Volume 10 Number 2 pages 103-116

Assessing the built-up footprint in an agricultural system using multi-temporal remotely sensed data

Zibusiso Dlamini
School of Environmental Sciences, University of KwaZulu-Natal, P/Bag X01, Scottsville, Pietermaritzburg, South Africa. E-mail: mrszndlamini@gmail.com

Clement Adjorlolo
South Africa National Space Agency (SANSA) - Earth Observation, PO Box 484, Silverton, 0127 Pretoria. E-mail: cadjorlolo@sansa.org.za

John Odindi*
School of Environmental Sciences, University of KwaZulu-Natal, P/Bag X01, Scottsville, Pietermaritzburg, South Africa. E-mail: Odindi@ukzn.ac.za

*Corresponding author

Abstract

The advent of the new political dispensation in South Africa has seen an exponential growth in the rate of land transformation and encroachment by other land uses into valuable agro-ecological zones. Due to the socio-economic value of the often limited high-potential agricultural land in the country, a reliable determination of encroachment and transformation is necessary for effective monitoring and management of such agro-ecological resources. Using the robust support vector machine classification algorithm, this study adopted multi-temporal, remotely sensed datasets to assess the extent to which the physical development footprint in the uMngeni Local Municipality affected the existing agro-ecological zones from 1993 to 2003 and from 2003 to 2013. The results show a steady increase in built-up areas during the period under investigation. The study demonstrates the value of multi-temporal, remotely sensed datasets and techniques in mapping the vulnerability of existing agricultural land to urbanisation in the study area.

Key words: land-use change; built up; agricultural land; remote sensing; encroachment

1. Introduction

Knowledge of land-use and land-cover dynamics and causative factors is fundamental for landscape planning and management (Johnson & Maxwell 2001). Commonly, landscape transformation is influenced by a number of drivers, which could be categorised broadly as economic, policy and institutional, social and cultural, environmental and biophysical drivers (Shrestha *et al*. 2012). In rural and peri-urban areas, landscape transformation is often caused by growth in urban settlement and the associated infrastructural development (Gersh 1996; Long *et al*. 2007; Shalaby & Tateishi 2007). Typically, the settlement sprawl that characterises the urbanisation process consumes formerly productive agricultural land and open spaces (Heimlich & Anderson 2001; Konagaya *et al*. 2001; Wu *et al*. 2013). According to Johnson and Maxwell (2001) and Heimlich and Anderson (2001), residential and commercial developments in agricultural areas are often accompanied by detrimental impacts on agro-ecological functions, which further act as pull factors for additional amenities, more population and more degradation.

Globally, the evolving pattern of urban growth and development is driven by large profits to be made from converting agricultural land to non-farm uses in rural and urban fringes (Singh & Mohan 2001). Generally, residential developments on agricultural land have both a direct and an indirect effect on land values. When the demand for developable land is sufficiently high, the price of land in a developed state will inevitably exceed the value with which it is associated as an agricultural entity. Pressure by developers can lead to high rates of growth in land values, which in turn influences the conversion of more farmland to developed uses. Invariably, when faced with an option to either pursue or exit farming as a result of increased property prices, farmers may prefer the increase in farmland values and opt out of active agricultural production (Heimlich & Anderson 2001).

According to Plantinga *et al.* (2001), land prices reflect not only its current uses, but also its potential uses. In a competitive market, the price of land will equal the discounted sum of expected net returns obtained by allocating the land to its most profitable use. Without public intervention, the market will allocate land to the use that optimises economic returns, thus, in the process of urban growth the owners are expected to convert agricultural land to non-agricultural use, as land suitable for other development is more valuable (Plantinga *et al.* 2001; Singh & Mohan 2001; Phuc *et al.* 2014). Generally, Britz *et al.* (2011) and Gibreel *et al.* (2014) note that the conversion of cultivated land to non-farm uses such as housing poses a serious threat to agro-ecological sustainability and current and future food security.

Prime agricultural land is a scarce, finite and exhaustible natural resource (Tanrivermis 2003). In South Africa, with 13.8 million people vulnerable to food insecurity, the impacts of agricultural land transformation cannot be over accentuated (Niroula & Thapa 2005). The relationship between land and people is profound, with people's standard of living, wealth, social status and aspirations all closely linked to land (Niroula & Thapa 2005). Recently, South Africa published a policy framework on Food and Nutrition Security. In particular, the policy highlights the value of conserving scarce agricultural land resources to secure the nation's food supply at the household and national levels (Department of Agriculture, Forestry and Fisheries 2014). Furthermore, Chandrasena (2001) notes that the conversion of agricultural land could undermine rural livelihoods and economies, especially rural employment, as most farm workers are unskilled and will find it difficult to become assimilated into urbanised economies.

In full appreciation that land use is not static, but a dynamic, interacting system, there is increasing recognition that decisions with the potential to have an impact on agro-ecological systems require comprehensive and careful consideration to ensure sustainable development (Fazal 2001). Uncoordinated development can lead to inefficient and undesirable environmental, social and economic outcomes; hence a number of countries require local jurisdictions to prepare comprehensive plans outlining land use and whether specific types of land use should be encouraged or discouraged in specific areas (Andersson & Gabrielsson 2012). Against this background, it is desirable to implement mechanisms to ensure long-term monitoring and assessment of the trends in human settlement and other infrastructural development within the agricultural system at local administrative scales. To achieve this it is important to monitor changes in agricultural land use/land cover in order to maintain a healthy balance between man-induced land uses and ecosystem services, and to help establish rational land-use policy in favour of sustainable agricultural development (Shalaby & Tateishi 2007). Such decisions require an understanding of land use/land cover trends.

Traditionally, conventional methods that involve ground surveys have been used for mapping changes in agro-ecological landscapes. These methods commonly rely on the collection of field data and are often labour intensive, time consuming and lack temporal consistency, particularly at extended spatial scales. Remotely sensed data and tools have emerged as appropriate and cost effective means for mapping changes in agro-ecological systems (Shalaby *et al.* 2011). For instance, change detection, based on remotely sensed data that involves feature extraction techniques to compare differences or ratios, and decision function operations to create change vs. no-change maps, has emerged as a valuable technique. Machine learning techniques like decision trees, neural networks and support vector machines iteratively determine land use/land cover class boundaries (Mountrakis *et al*. 2011). Such approaches, in concert with post-classification feature extraction, have been known to perform better than traditional classification techniques like maximum likelihood and minimum distance to mean (Zhu & Blumberg 2002; Mountrakis *et al*. 2011). Therefore, using a robust machine learning classification algorithm and post-classification feature extraction, this study sought to assess the extent to which increased settlement and associated physical infrastructural development have affected agricultural land categories/zones in uMngeni Local Municipality, KwaZulu-Natal, South Africa.

2. Materials and methods

2.1 Study area

The study area (uMngeni Local Municipality) is located in uMgungundlovu District, KwaZulu-Natal Province, South Africa, approximately 90 kilometres from the coastline (Figure 1). The municipality is predominantly rural, with a variety of agricultural and tourism-related activities. Predominant agricultural activities include horticultural cash crops, agronomic crops (potatoes, soya beans, maize, etc.), timber plantations and livestock (poultry, dairy and beef).

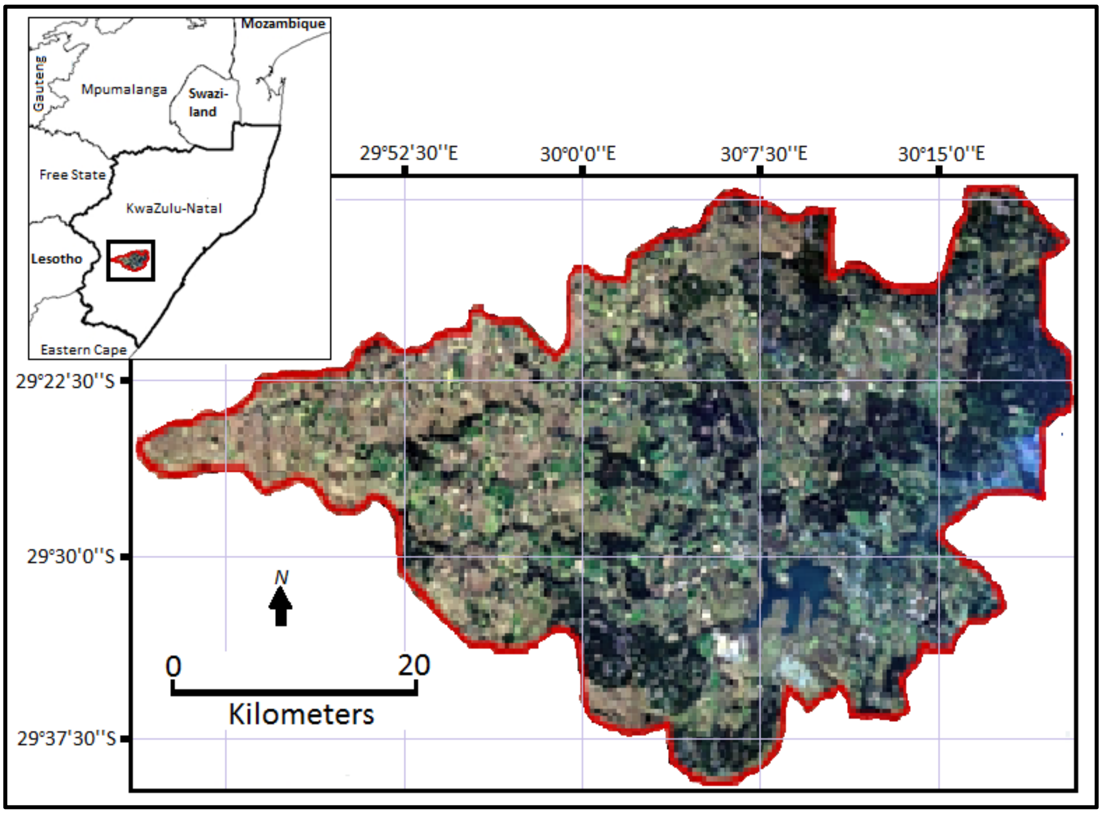

Figure 0: Landsat 8 true colour composite showing the location of uMngeni Local Municipality.

2.2 Data acquisition and pre-processing

The Worldwide Reference System path 80, row 81 Landsat 5, 7 and 8 images, captured on 5 April 1993, 7 April 2003 and 8 April 2013 respectively, were used in the study. All the multi-temporal datasets were collected at the closest possible dates to reduce scene-to-scene variation that may arise from differences in instrument calibration, geometric and atmospheric conditions, and natural vegetation phenological differences. The images had been orthorectified at delivery by the Earth Observation Directorate of the South African National Space Agency (SANSA) to a mean 0.19 error of the 30 m Landsat pixel ground sampling distance. Consequently, further orthorectification was deemed unnecessary.

The nature of optical remote sensing requires that radiation from the sun passes through the atmosphere before it is intercepted by a remote-sensing instrument. Thus, remotely sensed images include information about both the atmosphere and the earth's surface. For application focusing on the quantitative analysis of surface radiance or reflectance, removing the influence of the atmosphere is a critical pre-processing step. In order to compensate for atmospheric effects, properties such as the amount of water vapour, distribution of aerosols and scene visibility (including surface topography) must be known or inferred. In this study, the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) atmospheric correction method was adopted to reduce haze, water vapour and other atmospheric influences. The model was applied to the data of each geo-referenced and rectified Landsat image. The digital numbers were then converted to surface radiance data using the absolute radiometric calibration factors and effective bandwidths for specific Landsat bands in the Environment for Visualising Images (ENVI) 5.1 routine. A higher spatial resolution land use/land cover map (developed from 2008 SPOT5 imagery) was used as a reference dataset and ground-truth pixels representing six land use/land cover types in the study area were collected. The resultant data was used to derive a point distribution map of the land use/land cover types considered in this study.

Separability measurement relates to the extent to which patterns can be correctly in association with their target land cover classes using statistical methods. In this study, six classes were determined (Built-up land – buildings and other man-made infrastructure such as roads, Grassland, Cropland, Plantation forest, Water body and Bare land, including undefined features). The separability of the training data for all class pairs was assessed using the Jeffries Matusita (J–M) distance index (Sousa *et al.* 2003). The J–M measures the average distance between two class density functions. These values range from 0 to 2.0 and indicate how well the selected pairs can be separated statistically. In this study, a J–M distance greater than 1.90 ($\geq$ 95% of 2) was used as a threshold of spectral separability between group pairs.

2.3 Classification procedure and accuracy assessment

For the classification of targeted land cover types (i.e. Built up, Grassland, Cropland, Plantation forest, Water body and Bare land), it was necessary to develop and validate the classification algorithm, and to calculate a change map of the distribution of Built-up infrastructure in the area. A supervised learning algorithm, the Support Vector Machines (SVM), was implemented in the ENVI 5.1 environment. The SVM is a non-parametric method that makes no assumption about the underlying data distribution in classifying the multi-date Landsat images (Vapnik 1998). It identifies the class associated with each pixel and employs optimisation algorithms to locate the optimal boundaries between classes (Zhang & Ma 2008). The algorithm can be applied to stacked multi-temporal images to detect change and no-change in a binary classification problem. In this regard, the algorithm learns from training data and automatically finds threshold values from the spectral features for classifying change from no-change (Vural *et al.* 2008). The SVM is known to provide more superior classification results than traditional classification techniques such as the maximum likelihood classifier (Szuster *et al*. 2011). In this study, SVM was used to perform classification analysis independently on each of the multi-date Landsat images acquired for the study area.

It is a rule of thumb in remote sensing that the entire classification dataset be separated into 70% of data points for classification – also referred to as training data – and 30% data points for accuracy assessment – also referred to as validation data (Knorn *et al*. 2009; Adam *et al*. 2014). Therefore, in this study, about 30% of the ground truth pixel data was reserved for the validation of the accuracy or performance of the SVM classification algorithm. A simple random sampling method was used to subset the ground truth pixels across each of the input Landsat images with the aid of higher spatial resolution SPOT images and aerial photographs covering the study area. A confusion matrix for SVM classifications was then computed using the validation ground-truth samples. Overall classification accuracy, producers' and user's accuracies were calculated for each classification. In addition, the Cohen's kappa statistic was calculated for each matrix. According to Yang and Chinchilli (2009), the kappa (KHAT) measures the agreement between the classified map and mutually exclusive categories of the ground truth values, and is expressed as:

$$\widehat{K} = \frac{N\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(xi+*x+i)}{N^2 - \sum_{i=1}^{r}(xi+*x+i)} \quad (1)$$

where $\widehat{K}$ = is the KHAT statistic, xii is the number of diagonal entries in row i and column I, xi+ is the sum of the row I, x+i is the sum of column I, N is the total number of observations and r is the size of the matrix.

2.4 Post-classification feature extraction and comparison

This stage involved two major steps, namely independently extracting Built-up features from the multi-date images, and then comparing the extracted Built-up land class pixels for binary pairs of input classification images. The total number of extracted pixels/area from the pairs is calculated to quantify changes in Built-up land class between different time intervals. In this study, only the Built-up classes were specified in order to achieve the set objective of estimating the impact of the developmental footprint within the agricultural land categories in the study area using multi-date image analysis. Figure 2 provides a summary of the image data, pre-processing and analysis.

2.5 Agro-ecological zones (AEZs)

To determine the vulnerability of different agricultural zones to settlement, Built-up areas were overlaid on the agro-ecological zones (AEZs) of KwaZulu-Natal (KZN) province. The KZN Department of Agriculture and Rural Development (KZNDARD) uses the Food and Agricultural Organization of the United Nations (FAO) principle of zoning (IIASA/FAO, 2012) to classify the province into different AEZs. The zones consist of areas that have similar characteristics in relation to land suitability, production potential as well as environmental impacts, and are considered valuable for agricultural land-use planning. According to Collett and Mitchell (2012), the development of AEZs in the study region is motivated by the need to protect valuable agricultural landscapes across varying and diverse natural resources, rather than isolated land parcels.

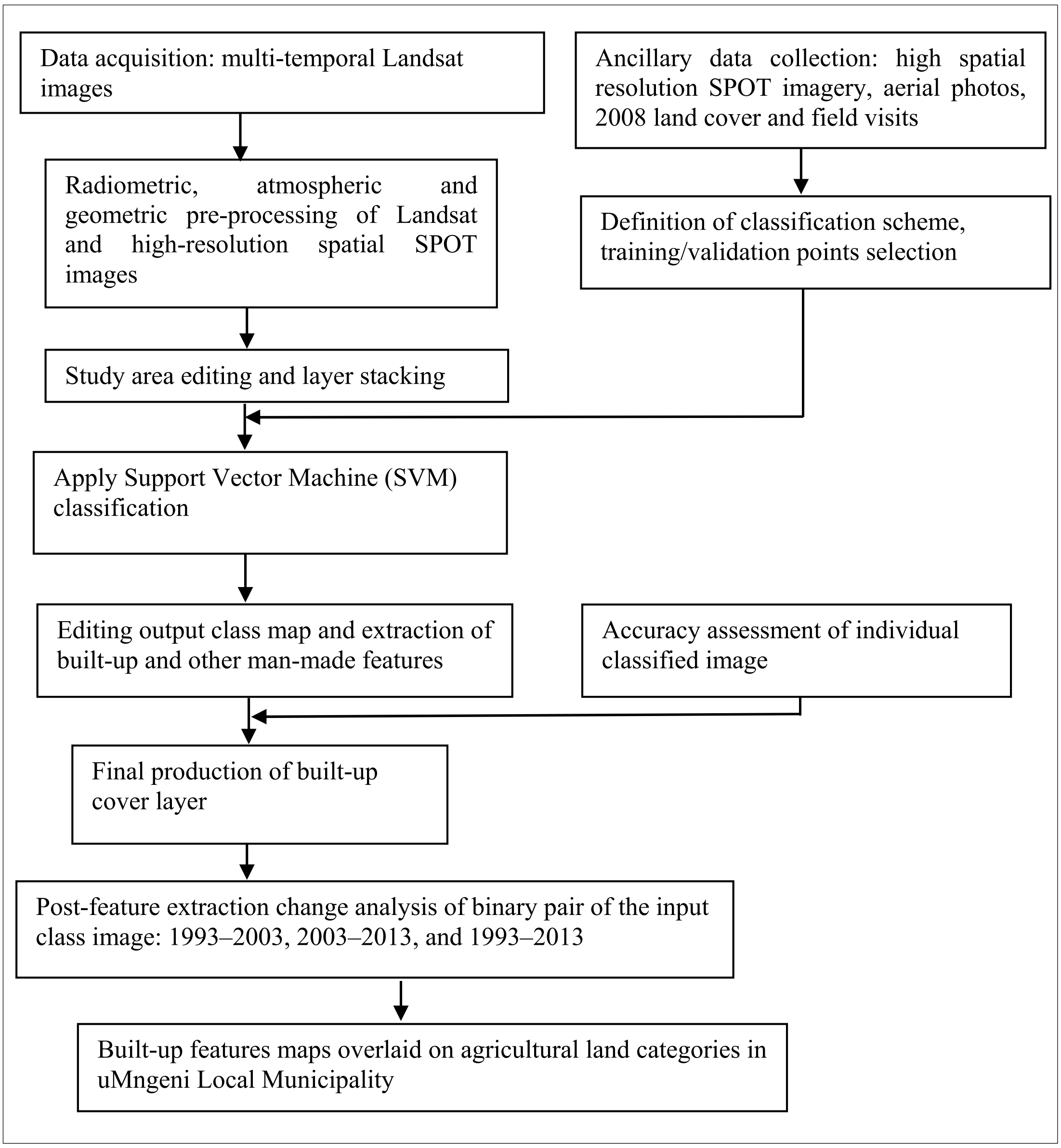

Figure 2: Data, image pre-processing and analysis.

3. Results

The confusion matrices based on the validation datasets for the multi-temporal Landsat 8, 7 and 5 data are shown in Table 2a, b and c respectively. As shown in the tables, high overall classification accuracies were achieved. All the producers' and users' accuracies were high, particularly the users' accuracies for the Built-up land use/land cover classes. Figure 3, a, b, c and d summarise the SVM classification results for the Landsat 8 (2013), 7 (2003) and 5 (1993) images respectively. The figure shows land use/land cover trends during the study period. The overall percentage of classification accuracy (OA) and the respective Cohen's kappa statistic (kappa) obtained for Landsat 8 (2013) was OA = 83.67% with kappa = 0.82; Landsat 7 (2003) was OA = 84.18% with kappa = 0.81, and Landsat 5 (1993) was OA = 83.33% with kappa = 0.81.

Table 2a: Error matrix for SVM classification results of Landsat 8, April 2013 input image. Overall accuracy = 83.67; kappa = 0.82.

Predicted class	Built up	Grassland	Cropland	Bare land	Plantation	Water body	Reference pixels
Built up	116	5	0	13	0	0	134
Grassland	12	112	4	2	5	0	135
Cropland	6	8	96	7	6	0	123
Bare land	3	2	9	77	7	0	98
Plantation	7	0	0	0	65	0	72
Water body	0	0	2	0	0	36	38
Sum of estimation	144	127	111	99	83	36	600
Producer accuracy (%)	80.56	88.19	86.49	77.78	78.31	100	
User accuracy (%)	86.57	82.96	78.05	78.57	90.28	94.74	

Table 2b: Error matrix for SVM classification results of Landsat 7, April 2003 input image. Overall accuracy = 84.18; kappa = 0.81.

Predicted class	Built up	Grassland	Cropland	Bare land	Plantation	Water body	Reference pixels
Built up	66	5	2	7	0	0	80
Grassland	8	54	8	6	3	0	79
Cropland	5	11	111	11	9	0	147
Bare-land	5	6	6	124	0	0	141
Plantation	3	0	0	0	119	0	122
Water body	0	2	0	0	0	42	44
Sum of estimation	87	78	127	148	131	42	613
Producer accuracy (%)	75.86	69.23	87.40	83.78	90.84	100	
User accuracy (%)	82.50	68.35	75.51	87.94	97.54	95.45	

Table 2c: Error matrix for SVM classification results of Landsat 5, April 1993 input image. Overall accuracy = 83.33; kappa = 0.81.

Predicted class	Built up	Grassland	Cropland	Bare land	Plantation	Water body	Reference pixels
Built up	64	9	2	9	0	0	84
Grassland	9	61	6	6	3	6	91
Cropland	2	3	102	4	9	0	120
Bare land	4	7	12	94	0	0	117
Plantation	0	2	4	0	110	0	116
Water body	0	0	0	4	0	74	78
Sum of estimation	79	82	126	117	122	80	606
Producer accuracy (%)	81.01	74.39	80.95	80.34	90.16	92.50	
User accuracy (%)	76.19	67.03	85.00	80.34	94.83	94.87	

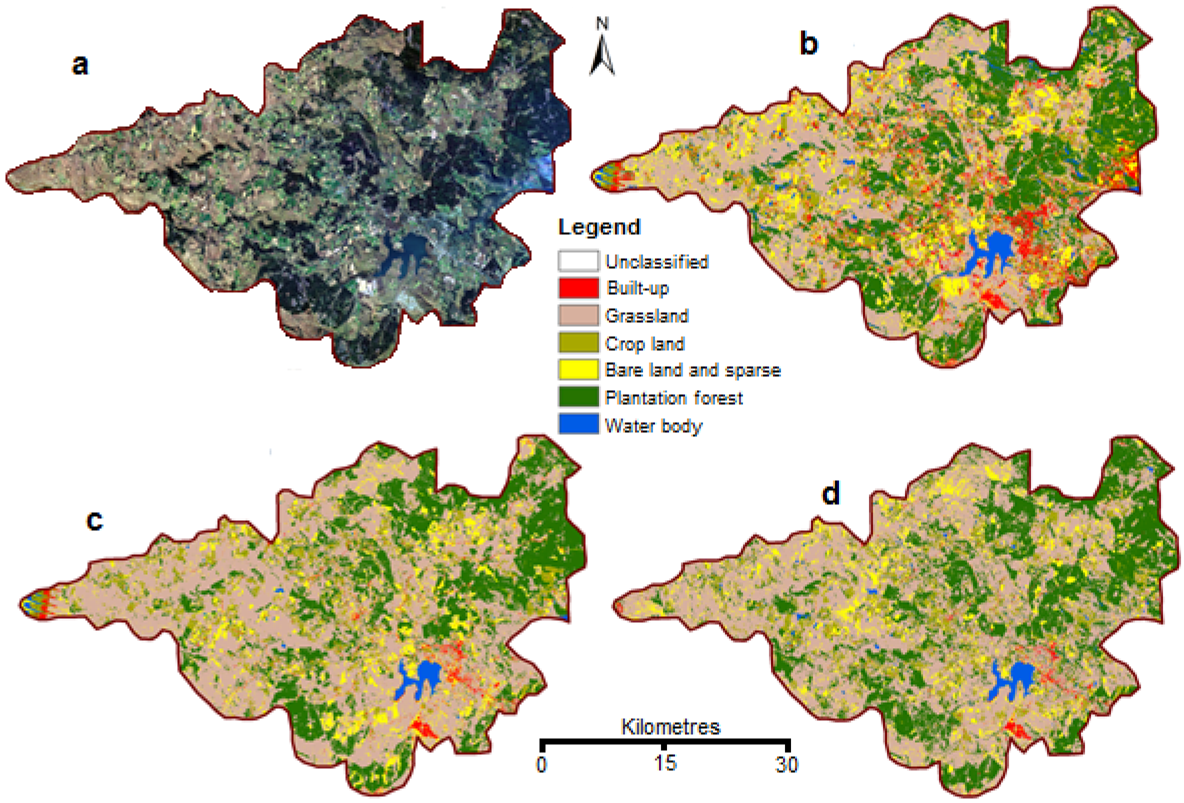

Figure 3: SVM classification results of input Landsat image data: a – Landsat 8 true colour composite; b – Landsat 8 (2013); c – Landsat 7 (2003); d – Landsat 5 (1993) classification outputs.

Figure 4 shows a comparison of the classified Built-up land use/land cover estimates derived from the multi-date Landsat using the SVM algorithm. The figure shows major agricultural zones, value and vulnerability. Overall, the average change between the 1993 and 2013 land use/land cover predictions was 38.92%. For the Built-up class only, the percentage change was 13.07%, 38.37%, and 32.03% for the period 1993 to 2003, 2003 to 2013 and 1993 to 2013 respectively (Table 3).

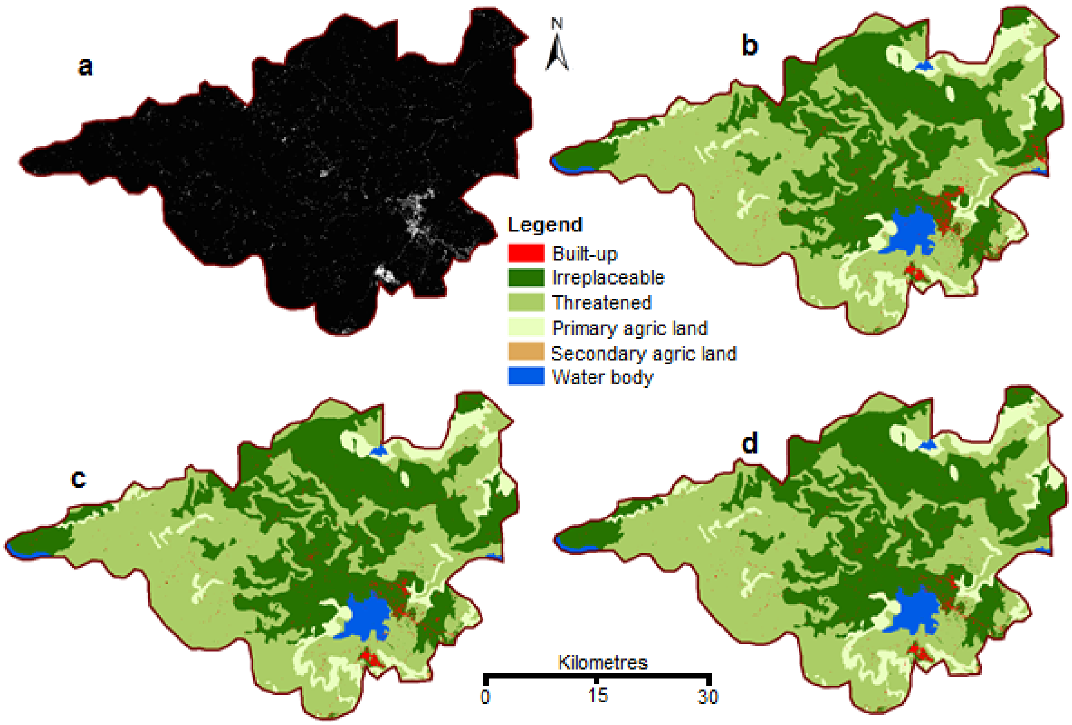

Figure 4: Built-up land use/land cover class within agricultural land categories in uMngeni: a – Built-up (white pixels) extracted from high-resolution (2.5 m) SPOT5 image; b – Built-up (red pixels) layer extracted from Landsat 8 (2013); c – Landsat 7; d – Landsat 5 images overlaid on the AEZs.

Table 3: Multi-temporal land use/land cover change

Class changes	1993–2003 (%)	2003–2013 (%)	1993–2013 (%)
Unclassified	0	0	0
Built up	13.07	38.37	32.03
Grassland	19.06	15.18	9.98
Cropland	2.18	2.83	1.76
Bare land/sparse veg.	42.70	35.96	49.85
Plantation	18.87	4.51	3.47
Water body	4.52	3.15	2.87
Class Total	100	100	100
Class Changes	25.34	47.63	38.92

Figure 5 shows an example of high-value agricultural land threatened by increasing settlement. The red areas show increasing growth in built-up areas between 1993 and 2013.

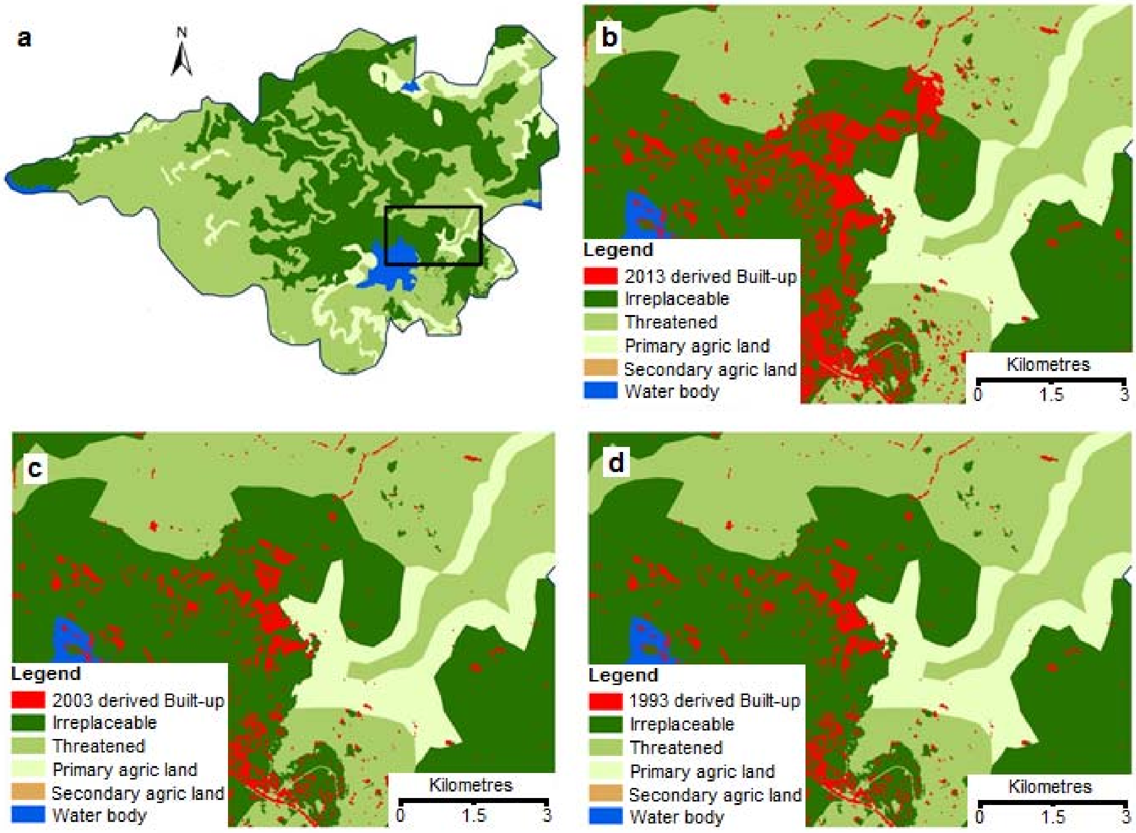

Figure 5: An illustration of increases in Built-up land use/land cover with high value agricultural land.

Note: a – Agricultural land categories; b – Built-up extracted from 2013 Landsat 8 image; c – Built-up extracted from 2003 Landsat 7 image; d – Built-up extracted from 1993 Landsat 5 image.

4. Discussion

Whereas large-scale regional determination of land use/land cover transformation remains critical, localised administrative land use/land cover change detection provides valuable insights for both short- and long-term monitoring and protection of high-value AEZs. Moreover, multi-temporal analysis of settlement offers insight into past, current and future agricultural potential. In this regard, increasing availability and accessibility of remotely sensed datasets and associated technologies provide better opportunities for understanding urban/agricultural landscape dynamics.

Anthropogenic landscape transformation is a major cause of cumulative change in agro-ecological systems. Commonly, public and private policy makers require accurate and up-to-date information to determine the implications of anthropogenic activities on agro-ecological systems. Whereas private and public policy makers seem to disagree on the best means to determine the economic costs and benefits of mapping AEZs, Bingham *et al*. (1995) note that there is general agreement on the need to improve the availability and adoption of information on AEZs to optimise decision making. According to Turner *et al*. (1994), extents and complexity within landscapes impede reliable determination and prediction of the agro-ecological process arising from anthropogenic drivers. However, in the last few decades, remotely sensed datasets have emerged as valuable tools in understanding land use/land cover transformation and the associated drivers. According to Lins (1994), the most common reason for the adoption of remotely sensed datasets and techniques is the high cost of field data collection. Smit *et al*. (1999) note that, due to often limited budgetary allocation, remotely sensed datasets offer a viable option to the often costly, tedious and time-consuming ground surveys.

To fully account for agro-ecological transformation, it often is necessary to value ecosystems within a historical context (Bingham *et al.* 1995). Archival data, which is available from commonly used sensors using objective and standardised analytical processes, provide valuable past, current and future agro-ecological trends. These, in concert with mainstream geographic information systems, offer additional value like digital storage, distribution and re-analysis, which often are difficult to achieve using other mapping techniques. Whereas fine spatial resolution mapping has for a long time been regarded as a major advantage of surveys over remotely sensed data, improvements in the spatial and spectral characteristics of the imagery has reduced the need for survey-oriented ground points. This provides a further economic advantage, as it eliminates the need for complementing remotely sensed and survey datasets for validation.

As a result of the additional costs required for higher classification accuracies, what is regarded as adequate is commonly determined by the minimum cost for datasets, characteristics, processing and analysis for a specific purpose. Consequently, due to the high multiplicity of interest groups and stakeholders interested or involved in determining the transformation of agro-ecological systems, it often is desirable that users of remotely sensed products determine their own minimum thresholds and the most cost-effective means of achieving the desired thresholds. Smit *et al*. (1999) provide an example of the provision of agro-ecological subsidies to European farmers based on the mapping errors of commission and omission. They note that an error of mapping omission will lead to underestimation, hence farmer losses, while an error of mapping commission may lead to overestimation and therefore government losses through over-subsidisation.

South Africa has limited high-potential agricultural land available for long-term sustainable agriculture, estimated at less than 4% of available agricultural land (ARC-ISCW 2005). Much of this land, however, has already been lost to non-agricultural land uses such as residential, industrial and mining, or is under severe pressure from other non-agricultural development (Collett 2013). The use of high-potential agricultural rural and peri-urban land must be viewed against the need to utilise it for production to achieve national food security versus providing for the necessary urbanisation process. This requires careful consideration to determine optimal and sustainable land-use options. Commonly, due to a lack of short- and long-term multi-temporal information on land use/land cover patterns, optimal and sustainable decisions often are a challenge. In this study, the integration of the SVM learning algorithm and multi-date Landsat data yielded important information for the time periods investigated. The results obtained in the study identified changes in Built-up land use/land cover that occurred from 1993 to 2003, 2003 to 2013, and 1993 to 2013 in the uMngeni Local Municipality. Generally, increased Built-up surfaces in the study area can be related to known land use/land cover changes, or the conversion of agricultural land to other uses (Collett & Mitchell 2012). Using multi-temporal datasets from different missions, the accuracy of the land use/land cover classification analyses was realistic and the mapping procedure was repeatable.

Generally, the transformation of valuable agricultural land into land uses associated with settlement is influenced by a range of factors that include economic, policy and institutional, social and cultural, environmental and biophysical considerations. Notwithstanding the circumscription of the study to assess the extent to which they contribute to the transformation of agricultural land to other land uses, economic factors, driven by urbanisation, are generally considered to be the strongest influence in the transformation of the rural and peri-urban landscape.

In some instances, the implementation of a new policy serves as an unintended impetus to rural and peri-urban land transformation. Following decades of segregated spatial development, the South African government promulgated the Development Facilitation Act No. 67 of 1995 as an instrument for the advancement of the Reconstruction and Development Programme (RDP). The significant change (approximately 38%) in Built-up area during the period 2003 to 2013 seen in this study therefore could be attributed to the use of this legislation to promote development in the uMngeni Municipality.

Globally, population is expected to continue to rise. However, population growth remains both an opportunity to increase food production and a threat to agricultural land in favour of development for human settlement. The transformation of agricultural land therefore should be considered within the context of sustainable development without neglecting other development imperatives. In this respect, this study advocates a holistic approach to land development without prejudice to specific types of land use.

5. Conclusions

Multi-temporal change in Built-up cover indicates that some agricultural land has been converted to settlement and associated infrastructure in the uMngeni Municipality. The rate of increase in Built-up land use/land cover often relates to a number of factors that include the subdivision of agricultural land for alternative uses, socio-economic development and legislation. Based on the study findings, it is concluded that the adoption of remotely sensed datasets offers a superior and cost-effective means to determine the transformation of AEZs. The results of this study offer valuable insights into the influence of settlement trends on the area's AEZs. Furthermore, the findings of this study hold great promise in providing an understanding of landscape transformation resulting from the presence or absence of policy guidelines for agricultural productivity and urbanisation.

References

Adam E, Mutanga O, Odindi J & Abdel-Rahman E, 2014. Land use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: Evaluating the performance of random forest and support vector machines classifiers. International Journal of Remote Sensing 35: 3440–58.

Andersson E & Gabrielsson S, 2012. Because of poverty, we had to come together: Collective action for improved food security in rural Kenya and Uganda. International Journal of Agricultural Sustainability 10: 245–62.

ARC-ISCW, 2005. Overview of the agricultural natural resources of South Africa. ARC-ISCW Report No. GW/A/2004/13. Pretoria: ARC Institute for Soil, Climate and Water.

Bingham G, Bishop R, Brody M, Bromley D, Clark E, Cooper W, Costanza R, Hale T, Hayden G, Kellert S, Norgaard R, Norton B, Payne J, Russell C & Suter G, 1995. Issues in ecosystem valuation: Improving information for decision making. Ecological Economics 14: 73–90.

Britz W, Verburg PH & Leip A, 2011. Modelling of land cover and agricultural change in Europe: Combining the CLUE and CAPRI-Spat approaches. Agriculture Ecosystems and Environment 142: 40–50.

Chandrasena UA, 2001. Land use changes and related issues in the suburban environment in Colombo metropolitan region of Sri Lanka. In Singh RB, Fox J & Himiyama Y (eds.), Land use and cover change. Plymouth: Science Publishers.

Collett A, 2013. The impact of effective (geo-spatial) planning on the agricultural sector. SASGI Proceedings 2013 – Stream 1. Durban: South African Geomatics Institute (SAGI).

Collett A & Mitchell FJ, 2012. KwaZulu-Natal Agricultural Land Potential Categories Internal Report N/A/2012/14. Cedara: KwaZulu-Natal Department of Agriculture and Environmental Affairs.

Department of Agriculture, Forestry and Fisheries, 2014. National Policy on Food and Nutrition Security for the Republic of South Africa. Government Gazette 37915 of 22, Pretoria.

Fazal S, 2001. The need for preserving farmland: A case study from a predominantly agrarian economy (India). Landscape and Urban Planning 55: 1–13.

Gersh J, 1996. Subdivide and conquer. Amicus Journal 18:14–23.

Gibreel TM, Herrmann S, Berkhoff K, Nuppenau EA & Rinn A, 2014. Farm types as an interface between an agroeconomical model and CLUE-Naban land change model: Application for scenario modelling. Ecological Indicators 36: 766–78.

Heimlich RE & Anderson WD, 2001. Development at the urban fringe and beyond: Impacts on agriculture and rural land. Washington DC: US Department of Agriculture, Economic Research Service.

IIASA/FAO, 2012. Global agro-ecological zones (GAEZ v 3.0). Laxenburg, Austria: IIASA; Rome, Italy: FAO.

Johnson J & Maxwell B, 2001. The role of the Conservation Reserve Program in controlling rural residential development. Journal of Rural Studies 17:323–32.

Knorn J, Rabe A, Radeloff VC, Kuemmerle T, Kozak J & Hostert P, 2009. Land cover mapping of large areas using chain classification of neighbouring Landsat satellite images. Remote Sensing of Environment 113: 957–64.

Konagaya K, Morita H & Otsubo K, 2001. Chinese land use predicted by GTR-model. In Singh RB, Fox J & Himiyama Y (eds.), Land use and cover change. Enfield; Plymouth: Science Publishers.

Lins K, 1994. Requirements analysis results for land cover and land use data. Reston VA: US Geological Survey.

Long H, Tang G, Li X & Heilig GK, 2007. Socio-economic driving forces of land-use change in Kunshan, the Yangtze River Delta economic area of China. Journal of Environmental Management 83: 351–64.

Mountrakis G, Im J & Ogole C, 2011. Support vector machines in remote sensing: A review. Journal of Photogrammetry and Remote Sensing 66: 247–59.

Niroula GS & Thapa GB, 2005. Impacts and causes of land fragmentation, and lessons learned from land consolidation in South Asia. Land Use Policy 22: 358–72.

Phuc NQ, Westen ACM & Zoomers A, 2014. Agricultural land for urban development: The process of land conversion in Central Vietnam. Habitat International 41: 1–7.

Plantinga AJ, Alig R & Cheng H, 2001. The supply of land for conservation uses: Evidence from the conservation reserve program. Resources Conservation and Recycling 31: 199–215.

Shalaby A & Tateishi R, 2007. Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt. Applied Geography 27: 28–41.

Shalaby A, Ali RR & Gad A, 2011. Urban sprawl impact assessment on the agricultural land in Egypt using remote sensing and GIS: A case study, Qalubiya Governorate. Journal of Land Use Science 7: 261–73.

Shrestha MK, York AM, Boone CG & Zhang S, 2012. Land fragmentation due to rapid urbanization in the Phoenix Metropolitan Area: Analyzing the spatiotemporal patterns and drivers. Applied Geography 32:522–31.

Singh RB & Mohan J, 2001. Diversification of rural agricultural land due to urban intrusion: A case-study of the metropolitan periphery of Delhi, India. In Singh RB, Fox J & Himiyama Y (eds.), Land use and cover change. Enfield; Plymouth: Science Publishers.

Smit PC, Dellepiane SG & Schowengerdt RA, 1999. Quality assessment of image classification algorithms for land-cover mapping: A review and a proposal for a cost based approach. International Journal of Remote Sensing 20: 1461–86.

Sousa AMO, Pereira JMC & Silva JMN, 2003. Evaluating the performance of multitemporal image compositing algorithms for burned area analysis. International Journal of Remote Sensing 24: 1219–36.

Szuster BW, Chen Q & Borger M, 2011. A comparison of classification techniques to support land cover and land use analysis in tropical coastal zones. Applied Geography 31: 525–32.

Tanrivermis H, 2003. Agricultural land use change and sustainable use of land resources in the Mediterranean region of Turkey. Journal of Arid Environments 54: 553–64.

Turner BL, Meyer WB & Skole DL 1994. Global land-use/land-cover change: Towards an integrated study. Ambio 23(1): 91–5.

Vapnik VN, 1998. Statistical learning theory. New York: John Wiley and Sons Inc.

Vural V, Fung G, Dy JG & Rao B, 2008. Fast semi-supervised SVM classifiers using a priori metric information. Optimization Methods and Software 23: 521–32.

Wu K, Ye X, Qi Z & Zhang H, 2013 Impacts of land use/land cover change and socioeconomic development on regional ecosystem services: The case of fast-growing Hangzhou metropolitan area, China. Cities 31: 276–84.

Yang J & Chinchilli VM, 2009. Fixed-effects modeling of Cohen's kappa for bivariate multinomial data. Communications in Statistics 38: 3634–53.

Zhang R & Ma J, 2008. An improved SVM method P-SVM for classification of remotely sensed data. International Journal of Remote Sensing 29: 6029–36.

Zhu G & Blumberg DG, 2002. Classification using ASTER data and SVM algorithms: The case study of Beer Sheva, Israel. Remote Sensing of Environment 80: 233–40.