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Research Paper

Spatial assessment of urban sprawl in Arua Municipality, Uganda

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ABSTRACT

Arua Municipality is one of the regional municipalities that has been earmarked for transformation to city status. Its population has been growing at rate of 3% per annum 1% higher than the capital, Kampala. Urbanisation provides economic opportunities. However, it also lead to emergence of unplanned urban settlements and urban sprawl. This paper applied remote sensing and geographical information system techniques to map land cover changes from 2001 to 2016, quantify urban sprawl within the period and estimate the urban growth pattern up to 2031. TerrSet's Land Change Modeller has been used to model the urbanisation and Markov Chain matrices used to predict future changes in the urban composition. Land cover classification accuracy of 85% in 2001, 84% in 2010 and 89.2% in 2016 were obtained. From 2001 to 2016, the four land cover types considered, contributed a total of 11.5% to the composition of built-up area with agricultural land cover type contributing the most at 7.4%. Results of urbanisation analyses indicated that in 2001, 18.2% of the total area were built-up. This increased to 28.8% in 2010 and 40.9% in 2016. Urbanisation is predicted to increase to 57.4% by the year 2031. This prediction indicates that agricultural land cover will be most negatively affected at −10% loss rate while built-up areas will increase by 6%. While urbanisation continues to increase at this rate, the municipal authority must implement sustainable measures to protect agricultural lands and ecosystems against the land consuming urbanisation.

1. Introduction

Arua Municipality is a growing urban centre and one of the 14 pioneer municipalities earmarked by Uganda Government's Vision 2040 to attain regional city status (Makau et al., 2012; Kiggundu, 2014). The administrative boundary will be increased from current two divisions to four divisions covering 10 sub-counties (Table 1). Population census of 2014 (UBOS, 2014) reported, the municipality's population grew at an annual rate of 3% faster than the 2% growth of the capital – Kampala over 12-year period. This steady population growth can be traced back 15 years after the signing of peace accord between the Uganda National Rescue Front II (UNRF-II) and Uganda government in 2002 (Bogner and Neubert, 2013). Following this accord, the region gained political stability and the municipality became the main business centre. This has led to continued high demands for housing, healthcare, roads and related infrastructures.

Government of Uganda (GoU) directly and through private-public partnerships such as with ACTogether and Uganda Slum Dwellers Federation in 2010, collected information about slum dwellers in the municipality so that the challenges of the urban poor living in these slum settlements are brought to the forefront in planning and development (Sdinet, 2010). GoU is also implementing a World Bank supported programme to enhance institutional performance of 14 pioneer municipalities so as to improve service delivery in the municipalities (World Bank, 2017). The Programme targets road sectors, urban transport, waste management, local economic infrastructure, water and sewerage. The implementation of this Programme coupled with other projects from governmental and non-governmental organisations have contributed to rapid physical and infrastructural development of the municipality.

Urban sprawl leads to horizontal enlargement of urban centres and portrays attributes such as scattered neighbourhoods, daily commuting to and from work and/or business in the inner urban centres. This daily need for commuting leads to urban dwellers

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Table 1
Proposed city structure.

City division	Former sub-counties	Population (2014 Census)
Arua Central	River Oli, Arua Hill	62,657
Arua South	Vurra	47,799
Arua East	Manibe, Dadamu, Oluko	108,590
Arua West	Pajulu, Adumi, Ayivuni, Aroi	137,606
Total		356,652

Source; UBOS, 2014.

preferring private cars and motorcycles as compared to previous use of buses and walk-trips thereby increasing urban traffic and air pollution of the urban areas (Dadi et al., 2016). Polidoro, et al (2012) enumerates the negative effects accrued from unmonitored and uncontrolled urban sprawl such as urban traffic congestion, air pollution, increases in urban temperatures, encroachment on different land uses, and destruction of urban environmental and ecological habitats.

Space-borne remote sensors have the capability to monitor and map the structural form of expanding conurbations by providing continuous information at intervals on urban expansion. Land cover maps extracted from satellite imagery represent patterns of developed and undeveloped areas and are used regularly for monitoring urban form. Most times measuring the social and spatial structures of cities helps in understanding urban sprawl (Lowry, 2010) and effectively planning and managing the needs associated with growth of urban areas. This study is the first of its kind conducted in the study area incorporating GIS and Remote Sensing for urban sprawl assessment. However, the approaches used are drawn from related international studies such as in Rustenburg, South Africa (Mudau et al., 2014); Surat, India (Kantakumar et al., 2016), Addis Ababa, Ethiopia (Kassa, 2014); Asmara, Eritrea (Tewolde & Cabral, 2011) and Ile-Ife, Nigeria (Oloukoi, et al., 2014), and local studies such as conducted in the capital, Kampala (Vermeiren et al., 2012) and in Mbarara municipality, south-western region of Uganda (Bwanika, 2016).

2. Study area

Arua Municipality (Fig. 1) is located in Arua District, West Nile region of Uganda. Arua District shares international borders with Democratic Republic of Congo (DRC) to the West. The Municipality is approximately 440 km from Kampala, 470 km from Juba, South Sudan and 20 km from the International border between DRC and Uganda; all distances measured on car access roads. Subsistence agriculture is the major source of livelihood alongside whole sale and retail businesses. The climate is tropical with annual temperature ranging 20–30 °C. The annual rainfall averages 1404 mm (Monaghan, et al. 2012).

3. Methods

3.1. Introduction

Fig. 2 provides diagrammatic representation of the different stages and processes employed in the study. Major activities included; generation of land cover maps, quantification of urban land cover changes, and determination of urban sprawl and prediction of future sprawling patterns.

3.2. Datasets

Table 2 shows the different datasets used and their sources. Datasets were cleaned, imported and stored in ArcGIS's geodatabase clipped to study area. Spatial consistency was attained by processing all data to a spatial resolution of 30 m and WGS84-UTM zone 36N projection. For Landsat ETM+ 2010 imagery, Scan Line Corrector-off (SLC) effects were corrected using the technique developed by Scaramuzza, et al. (2004). The technique is based on local histogram matching between two imagery with same co-registration. We radiometrically and atmospherically corrected Landsat 7 ETM+ imagery of 02 and 18 January 2010 and applied the ENVI's Landsat Gapfill plugin to correct the

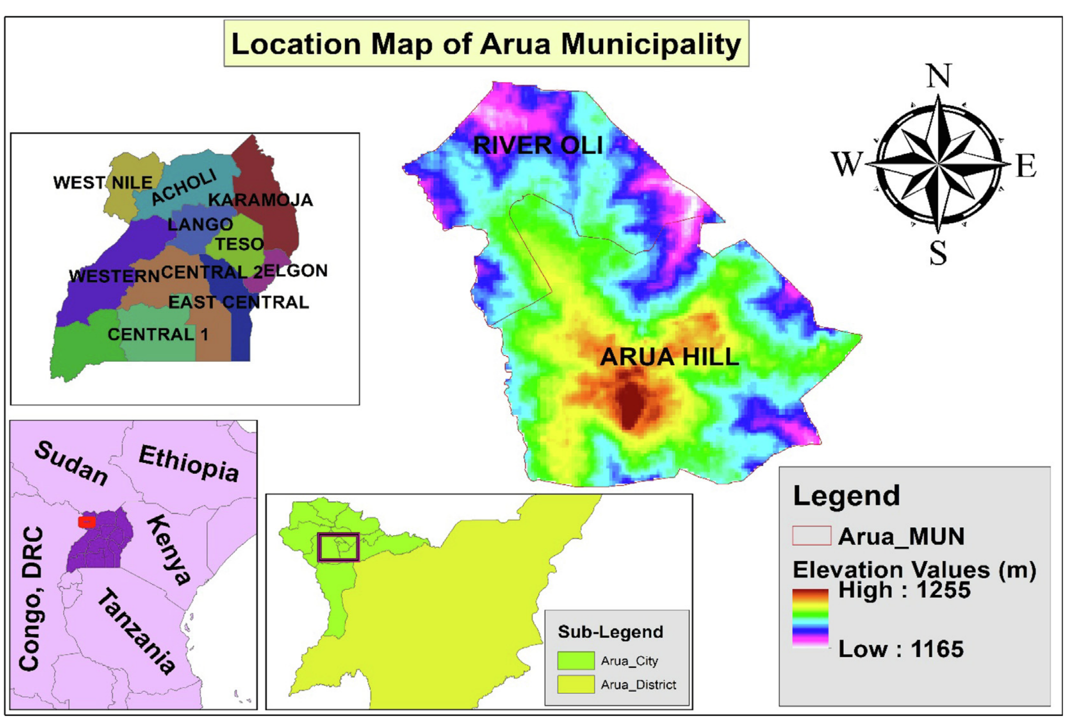

Fig. 1. Location of Arua Municipality, Uganda.

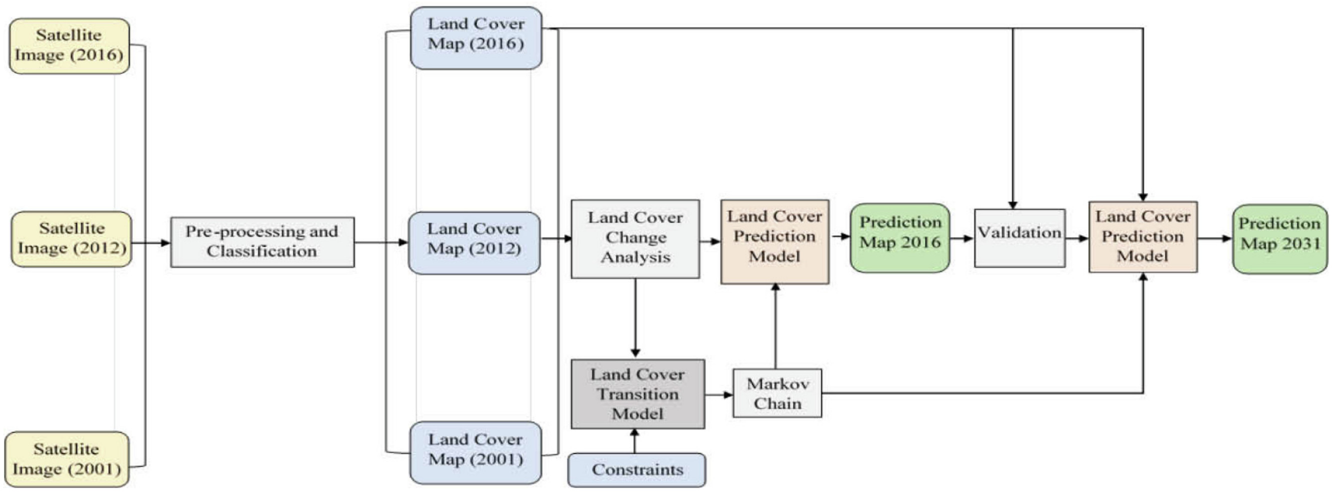

Fig. 2. Implementation Methodology Diagram.

Table 2
Datasets used in the study.

Data	Scale	Date	Data source
Landsat 8 OLI/TIRS	30 m	29 Jan 2016	US Geological Survey (USGS)
Landsat 7 ETM+	30 m	02 & 18 Jan 2010	US Geological Survey (USGS)
Landsat 7 ETM+	30 m	09 Jan 2001	US Geological Survey (USGS)
Digital Globe Imagery	2.4 m	14 Jan 2012	DigitalGlobe Foundation
DEM	30 m	2016	Shuttle Radar Topography Mission (SRTM)
Slope	30 m	2016	Derived from SRTM
Land cover	30 m	2001 & 2016	Derived from USGS
Land cover	30 m	2014 & 2015	Previous studies
Population	30 m	2014	Uganda National Bureau of Statistics
Road Network	1:60,000	2012	Created during the study
Settlement centres	1:60,000	2012	Created during the study
Boundary	1:60,000	2014	Ministry of Local Government

Table 3
Classes used in the land cover classification.

S/N	Class name	Description
1	Tree/Forest Cover	Includes natural and artificial tree covers
2	Open/Bare Land	Bare soil, barren land, rock cover and cleared construction sites
3	Built-up Areas	Buildings, weathered roads and human settlements of any size
4	Agriculture/Grass Land	Cropped land, fields, range-land, pasture land and agro-forestry systems falling below the thresholds used for the Tree/Forest cover

SLC-off effects. The master image was the 18 January 2010 imagery.

3.3. Characterisation of land cover properties

Land cover classification was performed using maximum likelihood supervised classification method (MAXLIK). Four land cover classes (Table 3) were used. The choice of classes and their definition were influenced by local knowledge of the study area and two previous related studies in the country conducted in 2014 (RCMRD, 2014) and 2015 (Abudu and Williams, 2015). As indicated in Lia, et al. (2015), the ability of MAXLIK in minimising misclassification errors by allowing variable weight specifications during the classification process and use of training data made it a suitable method for this study.

3.3.1. Accuracy assessment

An error matrix was used to assess the accuracy of the classification by comparing the pixel of the classified land cover maps with those obtained from the reference data. The reference data comprised of the 2.4 m spatial resolution DigitalGlobe imagery, Google Earth and ground visits of the study area. DigitalGlobe imagery were used as the main reference imagery. Google Earth's imagery provided visual time-series support and reference pixel points for training purposes. 1000 pixels were randomly selected for each of the years 2001, 2010 and 2016. A minimum of 250 pixels were considered stratified by each land cover type. Relatively stable features such as road intersections and landmarks were used for the sampling of control pixels. The results of this accuracy assessment are presented in Table 4. This method as presented in literatures (Abudu & Williams, 2015; Stehman & Wickham, 2011; Wickham et al., 2010), is a conventional procedure which evades difficulties arising from the use of supplementary spatial support units. Kappa analysis has been considered a credible method for analysing both single and multiple error matrices as well as comparing the difference between them (Congalton, 1991). The methodology for computing overall accuracy, producer's accuracy, user's accuracy and kappa statistic is documented in the literature (Lia et al., 2015; Allouche et al., 2006).

3.4. Measurement of urban sprawl development in Arua municipality

According to Afify (2011), the most accurate technique to quantify land cover change is the post-classification change detection technique where the resultant classified images are compared on a pixel by pixel basis in order to determine the similarities and differences of each of the pixel values. This comparison also helps in understanding the changes that occurred over time in a particular area (Setiawan and Yoshino, 2012). However, when it comes to quantifying urban sprawl, post-classification techniques produces limited results due to its inability to measure the degree of spatial dispersion and concentration in a given area (Sun et al., 2007). In this study, post classification method was used to quantify land cover changes (Fig. 3) and Shannon Entropy spatial-based algorithm (Mosammam et al., 2017; Effat & Shobaky, 2015; Bhatta,

Table 4
Accuracy assessment for the land cover classification 2001 and 2016.

Year	User's accuracy (%)				Producer's accuracy (%)				Overall accuracy (%)	Kappa statistic
	Tree/Forest	Open/Bare	Built-up	Agric/Grassland	Tree/Forest	Open/Bare	Built-up	Agric/Grassland		
2001	86.17	83.40	84.03	86.58	87.20	84.40	88.40	80.00	85.00	0.997
2010	90.95	81.99	80.32	83.33	84.40	85.60	80.00	86.00	84.00	0.996
2016	92.18	91.59	88.30	85.34	89.60	82.80	93.60	90.80	89.20	0.996

Note: Avg. Omission Error: (2001 = 12.00%; 2016 = 8.64%) & Avg. Commission Error: (2001 = 11.96%; 2016 = 8.52%).

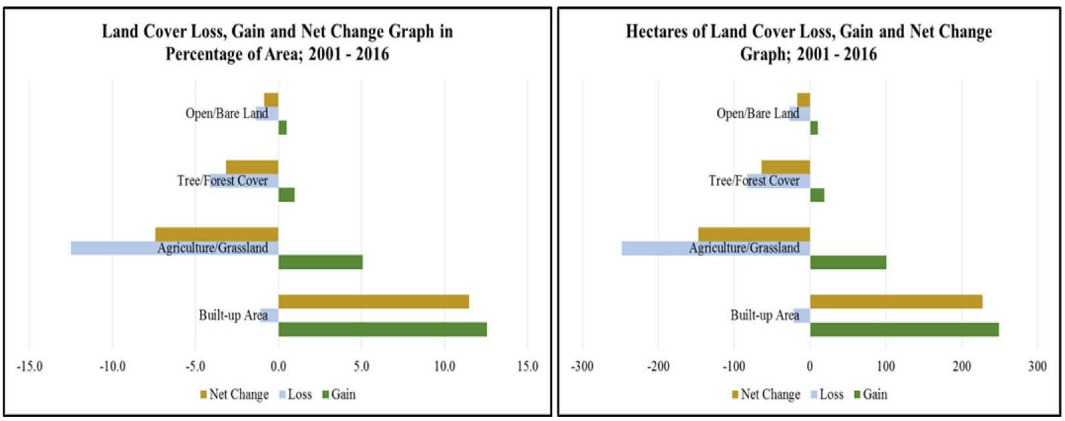

Fig. 3. Gain, Loss and Net Change per land cover class from 2001 to 2016.

et al., 2010) used to measure the degree of urban sprawl. Analysis of the land cover changes from 2001 and 2016 (Section 4.1) were performed in TerrSet's Land Change Modeller (Nahib and Suryanta, 2017), a package of the Terrset's software for land change modelling and prediction.

Land cover maps for 2010 in addition to 2001 and 2016 were used in the Shannon Entropy computation in order to determine the degree of sprawl over shorter time period (Sun et al., 2007). The maps were reclassified into two classes (Built-up and non-built-up), then concentric buffer zones of 200 m drawn from the municipality's centre in order to calculate the amount of built-up areas for use in the Shannon Entropy (SE_n) formula (Eqs. (1) and (2)). Shannon's Entropy spatial-based algorithm uses entropy values ranging from 0 to 1; with 0 indicating maximal concentration of built-up areas and the value 1 indicating uneven dispersion of the built-up areas (urban sprawl). The range 0–1 indicates the dispersion of high concentration of built-up areas in central urban centres to less concentration in the peripheries.

$$pi = xi \div \left(\sum_{i}^{n}(xi)\right) \tag{1}$$

$$SE_n = \sum_{i}^{n} pi\left(\frac{\log\left(\frac{1}{pi}\right)}{\log(n)}\right) \tag{2}$$

where; *pi*: Probability value,*xi*: [(Quantity of built-up area in *i*th of n buffer zones) ÷ (total quantity of land)].

3.5. Urban sprawl trend analysis and future prediction

The four land cover classes were analysed to determine their trends of change from one class to another and to a dominant class. A 9th polynomial Land Change Modeller trend analysis (Nahib and Suryanta, 2017) was implemented to identify the spatial trend of land cover changes within 2001 and 2016. The polynomial works on the basis of the levels of the input factor. When they are evenly spaced, and sample sizes are equal, trend analysis is accomplished as a sequence of contrast hypothesis tests, using specially chosen linear weights. Prediction of the future state of each class in the next 15 years (up to 2031) was accomplished using Markov Chain Analysis.

3.5.1. Markov chain analysis

According to Arsanjani, et al. (2013) and Guan, et al. (2011), random processes that evolves with time in a probabilistic manner is a stochastic process. Markov Chain is a stochastic processes if the conditional probability of any future event given any past event and the present state, is independent of the past event and depends only upon the present state. For any given duration (n), the probability of change from one land cover class to another land cover in the new period, is computed using a transition probability matrix (Eq. (4)) calculated from Markov Chain Model (Eq. (3)). TerrSet's Land Change Modeller was used to determine corresponding pixel values of the raster grids within the classified land cover maps and used in generation and computation of the matrix.

$$P(X_{t+n} = x_{t+n}|X_t = x_t) = P(X_n = x_{t+1}|X_0 = x_t); n = 0, 1, 2, \ldots \tag{3}$$

where; P is the Markov Chain transition probability or matrix; X, the sequence of length; n, the prediction duration; t and x, the new state of X after a specific length/time, t.

$$P(n)\begin{pmatrix} P_{00}^{n} & P_{01}^{n} & \ldots & P_{0M}^{n} \\ P_{10}^{n} & P_{11}^{n} & \ldots & P_{1M}^{n} \\ . & . & \ldots & . \\ . & . & \ldots & . \\ P_{M0}^{n} & P_{M1}^{n} & \ldots & P_{MM}^{n} \end{pmatrix} \tag{4}$$

4. Results and discussion

4.1. Land cover changes in Arua Municipality

Fig. 4 shows the obtained land cover map for the periods; 2001 to 2031. Examining the maps along with statistical representations in Fig. 3, built-up areas made a net gain of 11.5% of the total area from 2001 to 2016. The other three land cover types made net losses with agriculture/grass land most affected losing 7.4%; tree/forest cover losing 3.2% and open/bare land losing 0.9% of the total area. This confirms and indicates the extent at which urban sprawl is eating up the agricultural land and transforming them into built-up areas. These transitions as supported by Fan et al. (2007), are attributed to settlement patterns as well as farming activities where residents encroach on other land cover types to compensate for the lost one.

4.1.1. Accuracy of the land cover classification

The overall classification accuracy has been tested using error matrix for the three years considered in the study yielding an accuracy of 85.0% in 2001, 84.0% in 2010 and 89.2% in 2016 with a kappa coefficient of 0.997, 0.996 and 0.996 respectively (Table 4).

4.2. Measurement of the urban sprawl

The results of applying Shannon's Entropy spatial-based algorithm on the land cover maps of 2001, 2010 and 2016 are 0.2, 0.3 and 0.5 respectively. This shows that the rate of urban dispersion from concentrated centres were lower between 2001 and 2010 and almost doubled from 2010 to 2016. Fig. 5 shows the urbanisation pattern of built-up areas in the above time periods and as expected, the sprawling effect such as fragmented built-up areas are observed spreading south of the study area. Table 5 summaries the composition of built-up and non-built-up areas in the municipality. 22.7% built-up areal increase was observed from 2001 to 2010 which gradually reduced to 16.5% from 2010 to 2016 suggesting urbanisation saturation. An urban boom is also observed over the 2010–2016 period which suggests that the infrastructural development programmes (Section 1; paragraph 2) is contributing to increase in built-up areas. The prediction model did not account for re-urbanisation and urban regrowth factors.

4.3. Factors responsible for urban sprawl development in Arua Municipality

Similar urbans sprawl studies in Rustenburg, South Africa (Mudau et al., 2014); Surat, India (Kantakumar et al., 2016), Addis Ababa, Ethiopia (Kassa, 2014); Asmara, Eritrea (Tewolde and Cabral, 2011) and Ile-Ife, Nigeria (Oloukoi et al., 2014) reported migration, population and economic growth as prominent factors causing urban sprawl. Examining the population data from 1991 to 2014 (Table 6), a consistent population rise is observed, with an average annual population increment of 1685 persons. This increment is attributed to natural factors such as fertility as well as refugee influx due to political instabilities in neighbouring DRC and South Sudan.

Additionally, Fig. 4 shows that as much as built-up areas increased from 2001 to 2016, there are observably spotted built-up areas across the study area such as in the south. These spotted, unplanned built-up areas lead to urban sprawl as residents follow new infrastructures such as new roads, schools, water and the opportunities it provide.

4.4. Validation of the change prediction models

Land cover changes from 2001 to 2016 was validated to ascertain the accuracy and functionality of the change prediction model.

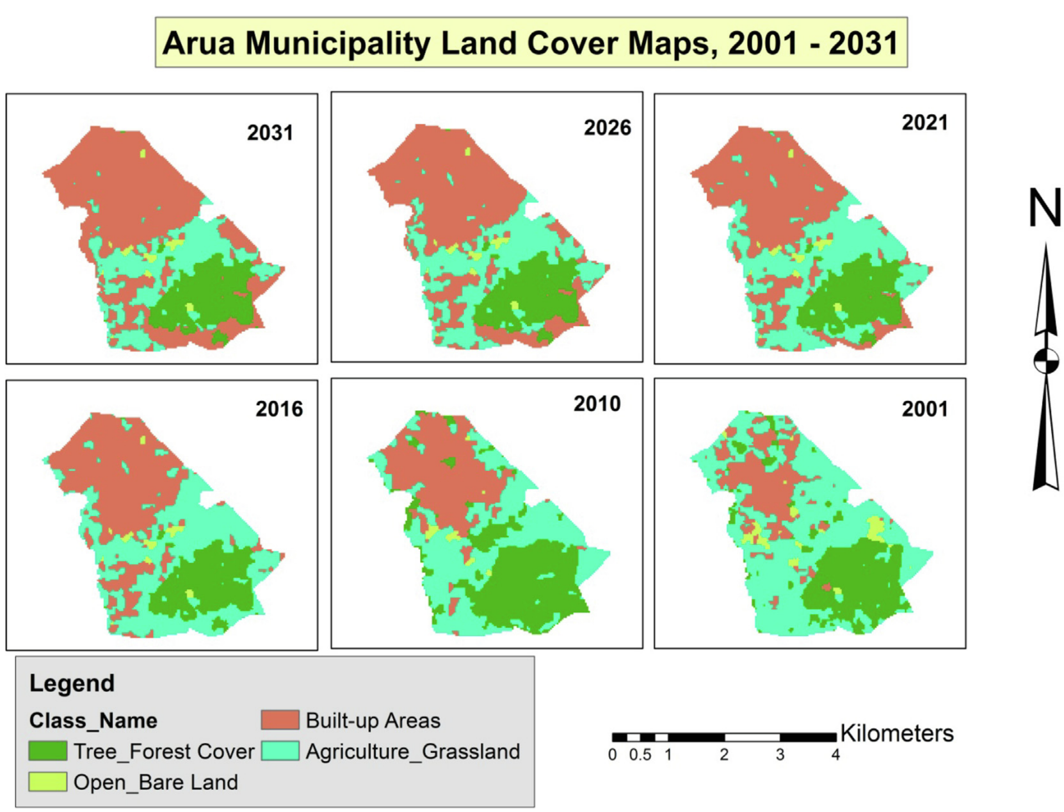

Fig. 4. Land cover maps for the study area from 2001 to 2031.

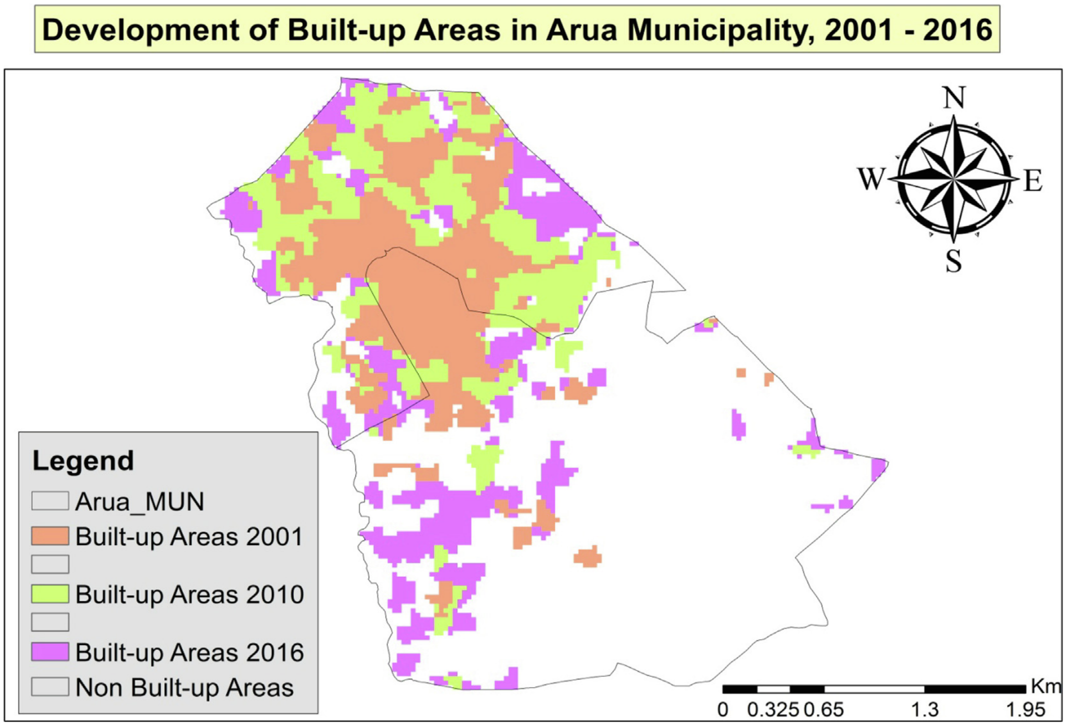

Fig. 5. Temporal map showing urbanisation of the study area from 2001 to 2016.

Table 5
Composition of built-up and non built-up areas between 2001 and 2016.

	2001		2010		2016		2031	
	Sq. Km	Area (%)	Sq. Km	Area (%)	Sq. Km	Area (%)	Sq. Km	Area (%)
Built-up	1.8	18.2	2.9	28.8	4.1	40.9	5.7	57.4
Non Built-up	8.2	81.8	7.1	71.2	5.9	59.1	4.3	42.6
Total	10	100	10	10.01	10	100	10	100

Table 6
Population changes of Arua Municipality 1991–2014.

Municipality divisions	1991 census	2002 census	2014 census
Arua Hill	–	14,979	18,935
River Oli	–	28,950	43,722
Total	22,217*	43,929	62,657

Source; UBOS, 2014. *Census data for 1991 reported block figure per municipality.

The VALIDATE model of TerrSet software was used to compare the predicted land cover map with control land cover map. In addition to previous land cover maps of 2014 and 2015 (RCMRD, 2014; Abudu and Williams, 2015), the 2012 high spatial resolution DigitalGloble satellite imagery was classified using MAXLIK supervised method using the same land cover classes (Table 3). The resulting classified land cover map was then used for validation. The 2012 data yielded better results compared to previous land cover maps. As supported by literature (Langely et al., 2001; Mandreka, 2011), acceptable kappa values ($K_n = 87\%$, $K_l = 84\%$ and $K_q = 83\%$) were obtained. The study was therefore, able to make future predictions shown in Fig. 4 with the required level of confidence.

4.5. Prediction of urbanisation of the study area in the next 15 years

The results in Fig. 4 predicts that over 90% of the northern part of the municipality will be built-up by 2031, enormously encroaching on the agricultural/grass land areas. However, little effect is observed on the tree/forest covering south-eastern parts of the study area. Built-up areas will have a net gain of 10% of the total area while agricultural land will lose 6% (Fig. 6).

The tree/forest covers have made the least gain in the 15 year period at 2.1% suggesting continuation of the current encroachment by urban dwellers to compensate for the lost agricultural lands and/or building new settlements away from urban centres. Recreational facilities such as parks will be maintained in the urban cores up to 2031 as confirmed by the existence of agriculture/grass land patches within the densely built-up areas in the north. Similarly, existence of open/bare areas in the north-eastern part of the study area suggests continued infrastructural developments such as road development, repairs and buildings up to 2031.

Arua Municipality as expected will continue to develop new infrastructures, expand social services and attract private and public sector opportunities and workers. However, as noted by Sahely, et al. (2003), while the Municipality grows, there is need for a sustainable balance to effectively manage infrastructural development, population growth and environmental conservation. The generated Markov Chain transition matrix can be used to predict any future land cover changes of Arua Municipality and aid in data-driven planning (see Table 7.)

4.6. The environmental impacts of urbanisation of Arua Municipality

Urbanisation is an essential activity that drives socio-economic development of a community. However, it does not come without

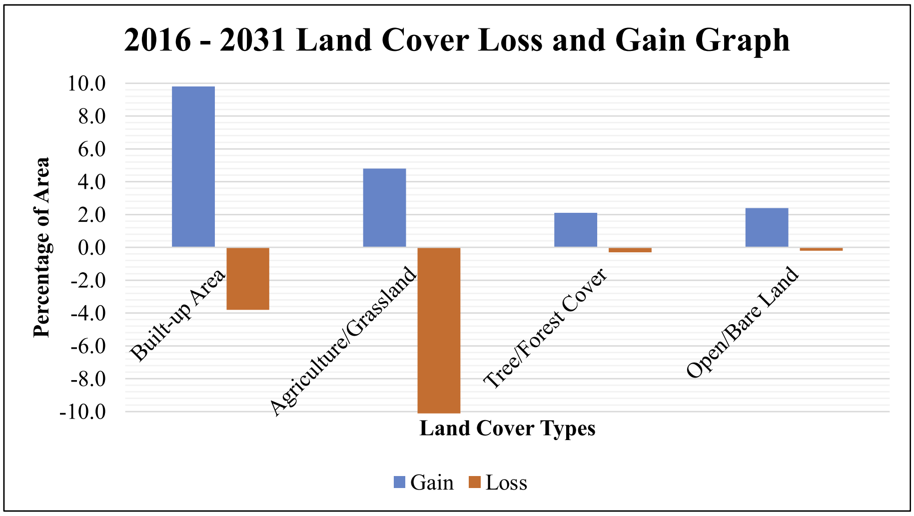

Fig. 6. Predictive loss and gain values for the different land cover types between 2016 and 2031.

Table 7
Markov Chain Probabilities of Change for each Land Cover Class.

		Percentage Predictability of Change into			
		Built-up Area	Agriculture/Grassland	Tree/Forest Cover	Open /Bare Land
Given	Built-up Area	88.2	8.3	1.0	2.5
	Agriculture/Grassland	41.4	54.5	3.2	0.9
	Tree/Forest Cover	5.1	28.9	65.9	0.2
	Open/Bare Land	34.4	49.6	0.6	15.5

costs especially on the land cover as seen in Section 4.1. Conversion of other land cover types such as agricultural land, bare land and forest cover to built-up areas destroys valuable habitat that are essential for many wildlife species. For instance, observed conversion of forest covers in the study area is a climatic threat to the environment. Forests are critical in regulating the amount of carbon dioxide in the atmosphere by absorbing it. Higher concentrations of carbon dioxide in the atmosphere is known to have adverse effects to local, regional and global climatic conditions resulting into global warming effects (Marland et al., 2003). It also intercept rainfall and acts as wind barrier, reducing the risks of soil erosion and flooding.

In social context, urbanisation in some cities such as Kampala, has provided important opportunities to farmers such as, the emergence of a new customer base for food crops and vegetables. Further study is required to investigate the trend in this study area. However, there has been reported cases of conflicts with non-farming neighbours, eviction of households and destruction of crops. Farmers are also not properly compensated whenever their land are converted to infrastructural developments. Usually when urban development projects are implemented, most economic costs are factored into land use decisions however, social costs are often under looked (Dannenberg et al., 2003). For example, a farmer uses a farm to produce both agricultural commodities and open space. During compensation, farmers are paid for the farmland and commodities that are on the land however, they are not compensated for the open space they provide. This is a social value that is not factored in the compensation hence resulting to reduced market prices for the farm land.

5. Conclusion

This paper demonstrated the capability of GIS and Remote Sensing techniques in assessing urban sprawl developments. Urban sprawl is existent in Arua Municipality and has led to many economic and social benefits but at a substantial cost to environment and society. Sustainable land cover and land use policies must be implemented by the municipal planners to strike a balance between societal interests and urban development. Conservation of land and ecosystems are critical to a sustainable development and long term economic growth. It is, therefore, recommended that the spiralling rate of built-up areas within the municipality be regulated with strict policy instruments with the aim of protecting the municipality's ecosystems as well as achieving the desired infrastructures. Similarly, high concentration of built-up areas in the northern part of the study area suggests the need to assess the level of urban heat islands and its effects. There is also need to investigate the socioeconomic causes, re-urbanisation and urban regrowth factors influencing urbanisation within the municipality.

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