A remote sensing-based approach to investigate changes in land use and land cover in the lower uMfolozi floodplain system, South Africa

Mandla Dlamini[1,2*], Elhadi Adam[1], George Chirima[3,4] & Hamisai Hamandawana[5]

[1] School of Geography, Archaeology and Environmental Studies, University of the Witwatersrand, 1 Jan Smuts Avenue Johannesburg, 2000,

[2] Institute for Water Studies, Department of Earth Science, University of the Western Cape, Robert Sobukwe Road, Bellville, Cape Town, 7535, South Africa,

[3] Agricultural Research Council: Institute for Soil, Climate and Water, Geoinformation Science Division, 600 Belvedere Street, Pretoria, 0083, South Africa,

[4] Centre for Geoinformation Science, Department of Geography, Geoinformatics and Meteorology, University of Pretoria, Pretoria, South Africa,

[5] Bindura University of Science Education, 741 Chimurenga Road Off Trojan Road, Bindura, Zimbabwe

*Author for correspondence: E-mail: mdlamini@uwc.ac.za

ABSTRACT

The goal of this study was to understand land use and land cover (LULC) changes within the lower uMfolozi floodplain system, South Africa, and relate those changes to wetland loss. Changes in LULC were assessed using a geographic object-based image analysis (GEOBIA) algorithm to classify multi-date Landsat images into eight cover types over a period of 20 years, between 1997 and 2017. Post-classification accuracy assessment of all map-outputs was conducted by compiling confusion matrixes and calculating producer, user, and global accuracies and kappa coefficients (K) for each map-output. Levels of accuracy for all map-outputs were within acceptable limits, ranging between 79% and 88% (K = 0.76 and 0.86, respectively). Thereafter, paired t-tests were applied to determine whether the changes in LULC over the study period were significant. Results of this investigation showed a significant (*p*-value, < 0.01) conversion of wetland to cultivation, by 14%. This finding is important because it demonstrates that in this environment, human agency is one of the major drivers of a persistent decrease in the wetland ecosystem. The major insight from this observation is that there is an urgent need to formulate and implement objectively informed interventions to enhance the sustainability of the uMfolozi floodplain system and that of others elsewhere.

Keywords: subsistence cultivation; wetland conversion; supervised classification; Landsat

1. INTRODUCTION

Wetlands provide a variety of ecosystem services that include water quality improvement, flood attenuation and protection, groundwater recharge and agricultural production (Bhatta *et al*., 2016). Despite the provision of these services, wetlands are widely threatened at regional, sub-regional and global scales by human activities that include hydrologic modifications, contamination by anthropogenic pollutants, eutrophication and conversion to a wide range of uses, notably agriculture and human settlement. These adverse effects are aggravated by changes in climate (Winter, 2000) that have far-reaching implications for the sustainability of these vital ecosystems. Evidence of these changes comes in the form of an extensive decrease in the wetland area, and persistent loss of vegetation (Xu *et* *al*., 2018). These adverse effects are a major cause of concern because of their established tendency to reinforce each other in inducing irreversible impairment of the natural balance in the functioning of these ecosystems (Banadda *et al*., 2009). This asseveration is supported by the reported decrease in the world's wetlands by 64–71% since 1900, largely because of encroachment by agriculture and other human land-use activities (Davidson, 2014).

Encroachment by human activities is now so widespread that it has come to be recognised not only as one of the major drivers of wetland degradation but also as a catalytic agent that amplifies the adverse effects of climate change. Human agency and climate change are further reinforced by a lack of routine monitoring, meaning the information needed to guide the formulation of environmentally friendly interventions is scarce (Driver *et al*., 2012). Information scarcity has far-reaching implications because it entails concomitant inaction. In South Africa, for example, only 15% of the country's varied wetland types remain in their near-natural ecological state, with floodplain wetlands recorded as presently having less than 5% of their total area under near-natural conditions (Isimangaliso Wetland Park Authority, 2016; Skowno *et al*., 2018). This situation is bound to deteriorate unless concerted efforts are taken to reverse the rate at which wetlands are being degraded by the combined effects of human agency and climate change.

Although wetlands continue to be degraded as a result of a conspicuous lack of interest in their sustainability, they still provide vital ecosystem goods and services that are essential for sizeable human populations whose livelihoods depend on what these shrinking resource niches provide. The range of provisions they offer is so wide that it should be obvious they must be safeguarded at all cost and without reservation. They support numerous ecological processes such as nutrient dynamics, energy flow, and movement of organisms and materials (Foley *et al*., 2005; Kareiva *et al*., 2007). They also serve as natural sinks for nutrients from terrestrial sources and provide (1) fresh water for multiple uses, (2) a wide variety of plants used for various purposes, (3) fall-back grazing during the dry seasons of all years, (4) nesting grounds and habitats for birds, (5) habitats and spawning grounds for multiple freshwater fish species and (6) aesthetically appealing environments in which to live and undertake non-extractive recreational activities (Hamandawana *et al*., 2020). The list is endless but, unfortunately, wetlands continue to be robbed and degraded by extractive and unsustainable human resource use practices.

These exploitive uses are often aggravated by competing demands for wetlands' finite resources, which are continuously increasing, in tandem with similar changes in human populations. One source of these problematic demands is agriculture, which accounts for most of the observed loss in wetland area through the conversion of wetlands for crop production. Equally problematic are industrial and urban development, which add their share of the pressure by converting what is available to meet their requirements (Kingsford *et al*., 2006, Kingsford, 2015) and degrading most of these natural systems due to a lack of proper monitoring and enforcement of conservation regulations. As human-induced pressures increase, climate change exacerbates this build-up by imposing externalities that are beyond the natural coping capacities of these ecosystems (Bate *et al*., 2016).

Although the situation may appear irremediable, there is in fact tremendous room to respond appropriately by providing the information mentioned above, which is conspicuously lacking. Obtaining this information requires innovative techniques that are not only cost-effective but also capable of offering what is required at appropriate temporal and spatial scales. As explained in subsequent sections, remote sensing provides a viable means of bridging this information gap in ways that are potentially capable of providing lasting solutions to the information scarcity problem.

An explanation is helpful here in demonstrating why the present study considers information critical in attempting to enhance the sustainability of our wetlands. Information is critical because apart from providing a reliable inventory of how wetland resources are being exploited and replenished, it is also the backbone of policy formulation, management decision-making and implementation of informed interventions. Inventory assessments are vital because they provide a reliable basis for monitoring what is happening and tracking disruptions that require immediate attention. Without this information, it is difficult to deploy conservation policies to protect wetlands, hence this example illustrates the usefulness of remote sensing because of its demonstrated capabilities to outperform conventional techniques by offering spatially explicit information at costs within the reach of many stakeholders.

Because of the dynamic nature of processes that occur in wetland ecosystems, long-term profiling is needed to discriminate periodic reversible changes from those that may end up being irreversible. Reversibility is crucial because it determines whether interventions will be successful by imposing limits beyond which corrective interventions cannot reverse the undesirable effects of degradation. Although wetland monitoring has for a long time relied on traditional methods, that include visual interpretation of maps and aerial photographs, and instrumental ground-based measurements, these methods are prohibitively costly, time consuming and incapable of providing consistent information that is representative of large areas at multiple temporal scales (Hoshino *et al*., 2012; Melton *et al*., 2013; Gilbertson *et al*., 2017). Besides the reliance on these methods, unevenly distributed observations render most of the information they provide of little use at the operational level; areas for which information cannot be provided are often superficially covered by poorly representative averages. These challenges can be addressed by fully exploiting what remote sensing offers.

Over the last few decades, remote sensing has become widely accepted as a viable means to provide usable information timeously. Some reasons for this recognition are: (1) the increasing availability of freely accessible images from the Landsat archives; (2) the long temporal coverage provided by the continuous Landsat data sets (48 years, from 1972 to the present), which makes it ideal for the investigation and detection of long-term change; (3) optimised spatial resolutions for reliable characterisation of informative land use and land cover (LULC) types (30 m for most bands); (4) immediate download access of required images from the United States Geological Surveys USGS data portal; and (5) dedicated and planned commitment to continue providing images into the future (Zhu *et al*., 2019). This scenario provides a convincing demonstration of the fact that for LULC monitoring at scales required for wetlands monitoring, access to raw data is indeed no longer one of the major obstacles confronting the policy–planning interface. What is lacking is an organised and collective effort by the scientific community to exploit fully the rich data sets that have become readily accessible. Although remote sensing has increasingly been used in many wetland research areas, notably LULC monitoring (Schmidt and Skidmore, 2003; Wang *et al*., 2004; Giri *et al*., 2011), vegetation quality and quantity assessment, and other areas that include hydrological processes (S.-N. Li *et al*., 2009), its full potential remains to be meaningfully exploited. While Landsat images have the above outlined potentials to bridge information gaps, radar data products could broaden the scope of investigative analysis because of their insensitivity to variable weather conditions and cloud cover. Unfortunately, however, their use is constrained by several limitations.

First, there is a price tag on most of these images, which makes them inaccessible to most potential users, with this same limitation affecting other image types provided by most platforms. Second, their acquisition involves high energy utilisation on satellite platforms, which makes it difficult to provide optimum time series data sets for many regions of the world (Woodhouse, 2006). These limitations make Landsat images the mainstay of pixel-based LULC characterisation at multiple temporal and spatial scales (Grundling *et al*., 2013; Jia *et al*., 2014b; T. Liu and Yang, 2015; Kumar and Acharya, 2016). This does not, however, imply that Landsat images do not have their own limitations. It is well known that Landsat images are incapable of supporting detailed discrimination of different vegetation species because of their coarse spatial resolutions (Gallant, 2015; Gómez *et al*., 2016). This limitation is noted by Adam *et al*. (2010), who report that Landsat's spatial and spectral resolutions are too coarse for reliable discrimination of wetland vegetation species.

While these limitations have been specifically raised as examples, these images are further affected by constraints similar to those associated with what other platforms provide. First, their utilisation is confounded by reliance on pixel-based classifications that are dependent on feature-based brightness values (Blaschke *et al*., 2014). This brightness dependence entails its own limitations that arise from the elimination of effective exploration and utilisation of the robust spatial concepts of a neighbourhood, proximity and homogeneity analysis (Burnett and Blaschke, 2003). Added to this is their narrow spectral resolutions (McIver and Friedl, 2002) that render them incapable of discriminating heterogeneously distributed vegetation species with low inter-class spectral separability (Bourgeau-Chavez *et al*., 2009; Gallant, 2015; Amani *et al*., 2017). Second, these limitations have substantial implications for biodiversity studies where the abundance of different species is considered to be a critical determinant of the stability and health of wetland ecosystems (Elliott *et al*., 2020). This valuation is premised on the fact that greater species richness is an uncompromisable characteristic of heathy wetland systems (Brose, 2008; Elliott *et al*., 2020). The implication of this connection is that although high-resolution data sets are expensive, they are essential for the species-level characterisation of different vegetation types. Hence, the information they can provide is indispensable because it is the backbone of conservation-oriented interventions (Tockner *et al*., 1999). Although difficult to implement due to a lack of suitable information, the success of these interventions determines the availability of functional wetland systems for present and future generations. To achieve this functionality, there is a need to explore innovative techniques of using what is available and readily accessible in order to secure the ability of these ecosystems to sustainably provide their valued goods and services (Tscharntke *et al*., 2005). With science at a crossroads because accessible data sets lack the required discrimination skills, while those with the requisite skills are not affordable, attempts to improve classification outputs from coarse resolution images by adding different vegetation indices have been explored by many (Peña-Barragán *et al*., 2011; Sahebjalal and Dashtekian, 2013).

The emergence of this new thinking is demonstrated by pioneer initiatives to use the geographic object-based image analysis (GEOBIA) approach, which has many advantages compared to pixel-based classification. This approach is a category of digital remote sensing image analysis that segregates geographic entities by discretising image objects as fundamental primitives (Blaschke, 2010). Known advantages of this novel technique include its ability to extract sub-pixel information at higher levels of classification accuracy by using the spatial, and textural properties of individual objects as additional information to their reflectance characteristics (D. Liu and Xia, 2010). Although GEOBIA has been largely applied to high-resolution images, the algorithms on which it is based can be adapted to classify readily accessible medium-resolution images such as Landsat images. This avenue promises better change detection by providing tremendous scope to refine conventional pixel-based classification techniques (Lu *et al*., 2014). The feasibility of the technique is demonstrated by recent studies (Ai *et al*., 2020) that used GEOBIA-based methods and medium-resolution remote sensing data to monitor continuous LULC changes in heterogeneous environments.

What this breakthrough suggests is that GEOBIA can be used in synergy with different spectral indices to extract the unused information contained in Landsat's pixelised images. The spectral indices worth exploring include but are not limited to (1) the normalised difference vegetation index (NDVI); (2) the green normalised vegetation index (GNDVI); (3) the soil adjusted vegetation index (SAVI); and (4) the ratio vegetation index (RVI). It is possible to use these indices because they can deliver improved LULC classifications using the red, green and near-infrared bands of the electromagnetic spectrum (Dronova, 2015).

Their usefulness can be illustrated by SAVI, whose capability to discriminate soil types on the basis of differences in brightness has been used to improve classifications of different vegetation types by fusing it with other vegetation indices (Xue and Su, 2017; X. Chen e*t al*., 2019). This technique has also been found to be capable of improving mapping accuracy in heterogeneous landscapes like wetlands (Y. Chen e*t al*., 2018), and improving land cover discrimination in high-density vegetation landscapes (Xue and Su, 2017). Although useful, as outlined above, indices like RVI and NDVI have compromised capabilities because of their sensitivity to soil brightness in sparsely vegetated areas (Xue and Su, 2017). This limitation can, however, be addressed by using various machine learning classification algorithms, for example support vector machine (SVM), which so far has been successfully implemented in GEOBIA (Mountrakis *et al*., 2011). SVM functions by using a decision surface (optimal hyperplane) that maximises separation margins between different information classes (Cortes and Vapnik, 1995; Veenman *et al*., 2002). This permutation enables it and the other vegetation-based indices to produce higher accuracies compared to what is achievable using the pioneer conventional classifiers (Lin *et al*., 2013; Salehi *et al*., 2015).

The challenges outlined above argue for tireless efforts to embrace responsible stewardship by routinely monitoring the remaining wetlands at our disposal. Given the difficulties confronting broad-based coverage of all systems, a bottom-up approach, in which the local informs the regional, promises to offer a viable compromise approach. This reasoning explains why we decided to focus on the uMfolozi floodplain system (UFS). Located in uMkhanyakude District Municipality, the UFS was also judged to be suitable for this investigation because it is found in one of the poorest and most underdeveloped local authorities in South Africa (Hansen *et al*., 2015).

This unfavourable positioning is aggravated by persistent degradation induced by the ever-growing demands of human populations that have rapidly increased from the recent historical past to the present (McCracken, 2008), with approximately 60% of wetland area being converted to unsustainable agricultural activities in less than two decades, by the early 1980s (Begg, 1988; Vivier *et al*., 2010). Considering that most people in this area are unemployed standing residents whose livelihoods are largely dependent on subsistence crop cultivation (Nustad 2015), it is apparent that there is an urgent need to focus attention on how this wetland can be conserved. Although research appears to be only distantly interested in this system, this wetland is clearly under siege because of conflicts between local communities and policy. While local communities consider free access to the UFS and its resources to be their birth right, official policy views subsistence cultivation and other extractive uses as unsustainable intrusions. As a result, the concept of a shared landscape is collapsing.

Given the complex nature of the UFS, an innovative monitoring technique is needed to provide up-to-date information that can be used to guide the formulation and implementation of effective interventions. We attempt to approach the realisation of this objective by using the GEOBIA algorithm along with purposefully selected vegetation indices comprising NDVI, GNDVI, SAVI and RVI to quantify long-term LULC changes in this system. The goal of this initiative was to better understand the major drivers of the aforementioned changes in this environment to provide objectively informed recommendations on adoptable interventions that are potentially capable of enhancing the sustainability of this threatened ecosystem.

2. MATERIALS AND METHODS

2. 1 Study area

The UFS is a floodplain wetland (Garden, 2008) situated in the small town of St Lucia (28°22'S, 32°25E'), in the uMkhanyakude District Municipality of South Africa (Figure 1). This municipality is well known for being one of the country's poorest and most underdeveloped local authorities (Hansen *et al*., 2015). In terms of physiography, the floodplain is bound inland by deeply incised meanders of the Mfolozi River, which cuts its way through rhyolite rock formations of the Lebombo Mountains. After these mountains, it meanders downstream towards the Indian Ocean, within the confines of elevated landscapes in the southern and northern peripheries of Zululand and Maputaland (Garden, 2008). With an evolution dating back to ~18 000 yrs BP, the UFS originated from a dramatic loss of the river's confinement from a marginal width of ~950 m to > 6 km in less than 1.5 km before it enters the ocean (Garden, 2008). The surface geology of Maputaland, in which most of our study sites are situated, consists of conglomerates, limestone, calcareous rocks and clayey sands.

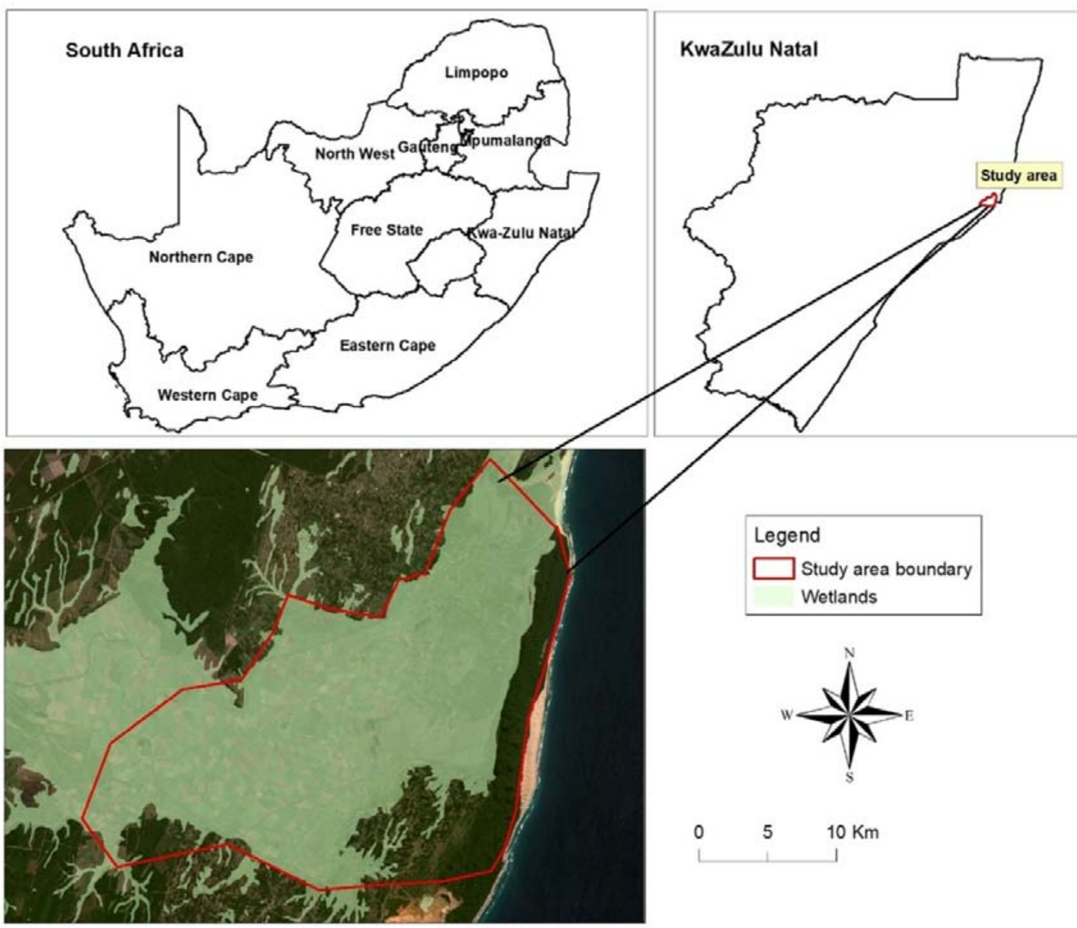

Figure 1. Geographical location of the study area.

Rainfall in this area is predominantly seasonal. Localities distant from the Indian Ocean experience a subtropical climate, with large seasonal variations in precipitation, which ranges between 671 mm/a and 1002 mm/a (Morgenthal *et al*., 2006). The coastal floodplain areas receive similar but less variable amounts, ranging between 645 and 1090 mm/a along a precipitation gradient in which the lowest amounts are confined to localities in the upper river's upper catchment areas. Throughout the entire area, however, most of the rainfall is confined to the summer months between October and March, with the highest amounts occurring between January and March (Morgenthal *et al*., 2006). This rainfall regime translates into seasonal inundation of the floodplain and evapotranspiration rates approximating 1805mm/a (Schulze, 1997).

Surface hydrology is dominated by (1) two main rivers – the Mfolozi River in the north and the Msunduze River in the south – that converge into a common mouth that marks their terminal entry into the Indian Ocean; and (2) shallow floodplain lakes, the largest of which are Lake Teza and Lake Futululu. Flow in these rivers is highly variable (Garden, 2008), and characterised by low base-flows and isolated occurrences of short-duration peak floods that mimic the seasonal distribution of rainfall. Although they are mostly short-lived, these flash floods have a profound influence on the floodplain's morphological characteristics (Grenfell and Ellery, 2009) that are characterised by repeated landform construction and destruction. The major vegetation types in this wetland include *Cyperus papyrus*, *Phragmites mauritianus*, *Phragmites australis* and *Ficus trichopoda* (Garden, 2008).

About 39% of people in this area are unemployed, depending on subsistence cultivation of *Ipomoea batatas*, *Musa acuminata* and *Colocasia esculenta* and small-scale production of vegetables (cabbage, spinach, carrots, etc.) that provide supplementary livelihoods. Although the UFS is an extensive wetland system covering approximately 19 000 hectares (Ellery *et al*., 2009), most of it has been converted to small-scale commercial sugarcane production and commercial forestry that date back to 1911 (Keddy, 2010). Since then, conversion has progressively increased, to the extent that by as early as 1960, more than 50% of the floodplain had already been modified by sugarcane farming and canalisation of the uMfolozi River to supply irrigation water to the sugarcane plantations (Vivier *et al*., 2010, Hansen *et al*., 2015). These exploitive and extractive uses have imposed severe strain on the wetland's functional capacities.

2.2 Landsat data and field data collection

The data sets that were used include like-season Landsat 5 Thematic Mapper (TM) images from 1997, 2001, 2004 and 2008; a Landsat Enhanced Thematic Mapper (ETM) image from 2012; and a Landsat Operational Land Imager (OLI) image from 2017. Table 1 describes the temporal sequencing and characteristics of these images. These images were purposefully selected to provide cloud-free footprint coverage of the study area. Landsat images were preferred for this investigation because of (1) the demonstrated capability of their 30 m spatial resolution for land-cover characterisation, (2) their accessibility and the fact that they are free of charge, and (3) their long-term temporal coverage. Table 1 describes the temporal sequencing and characteristics of the Landsat images that were used.

Table 1. Temporal sequencing and characteristics of the images that were used in the study.

Acquisition date	Scene product ID	Path/row	Cloud cover (%)	Spatial resolution (m)	Quality rating
11/10/1997	LT51670801997284JSA00	167/080	25	30	*9
16/06/2001	LT51670802001167JSA00	167/080	0.00	30	9
21/04/2004	LT51670802004112JSA00	167/080	0.00	30	9
07/09/2008	LT51670802008251JSA00	167/080	0.00	30	9
21/05/2012	LE71670802012142ASN00	167/080	0.00	30	9
19/01/2017	LC81670802017019LGN01	167/080	0.01	30	9

Note: Image quality as rated by the United States Geological Survey (USGS): 9 = excellent, 7–8 = good, 5–6 = fair,1–2 = extremely poor. * This image was assigned a quality rating of 9 because the recorded 25% cloud cover did not obscure any part of the study area. Source: https://earthexplorer.usgs.gov/

Fieldwork was conducted during the wet-season months of February and March 2017, after a pilot survey in the same months of the previous year. The compilation of ground truth was guided by a thematic map that was prepared from the unsupervised classification of a footprint coverage of the study area, obtained by clipping the 2017 Landsat image. The number of thematic classes in this map was purposefully set at 18, with this upper limit being preferred because, it was reasoned, this number was large enough to be capable of accommodating most of the different vegetation and non-vegetation cover types in the area due to limited heterogeneity in their distributions. Three sample sites were systematically selected for each of the 18 thematic classes, whose exact locations were identified with a Garmin geographical positioning system (GPS) with a rated absolute positional accuracy of ± 4 m.

Ground truth was compiled by characterising different cover types on the basis of spatial distributions in (1) different vegetation, (2) land use types and (3) natural features that were observed. Thereafter, this information was summarised to produce eight land-cover types: (1) bare land and harvested fields, (2) forest, (3) grassland, (4) plantations, (5) subsistence farms, (6) sugarcane plantations, (7) water and (8) wetland. Although different woody and herbaceous species were present in different areas of the floodplain, species-level classification was not possible because of heterogeneous distributions and the inability of Landsat imagery's coarse 30-m spatial resolution (C-res) to discriminate sub-pixel-sized cover types. C-res misclassification occurs when a single pixel represents an integration of many smaller image objects that do not correspond to their real-world appearance. To overcome this limitation, broad information classes were created by merging field-observed features with close resemblance into contiguous cover types. For example, tree-size specimens of *Ficus sycomorus* (sycamore fig), *Hibiscus tilliaceus* (lagoon hibiscus), and other woody species that are common in floodplain wetland areas (Van Deventer *et al*., 2017) were combined into a forest. This information was then segregated into two classes with 2/3 of the information compiled for each thematic class being reserved for supervised classification and the remaining 1/3 being reserved for classification accuracy assessment.

2.3 Image compilation and pre-processing

Pre-processing of the Landsat images in our database was performed in ENVI 5.4. The images were first clipped to provide footprint coverage of the study area. This was followed by using the layer-stack tool to select bands 1, 2, 3, 4, 5 and 6 from the TM and ETM images and bands 2, 3, 4, 5, 6 and 7 from the Landsat OLI image. Because the Landsat scenes were obtained in digital number (DN) format, they had to be converted to top-of-atmosphere (TOA) spectral radiances, which was accomplished using FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes), which is provided as a plug-in to ENVI 5.4. Thereafter, the same software's projection and transformation toolset was used to re-project all images to Universal Transverse Mercator zone 36 S. Since the Landsat scenes acquired after May 2003 have scan-line errors (stripes), the 2004 and 2008 images were corrected using the Landsat Two band gap-fill method provided in ENVI. Specific details on how the method works are provided elsewhere (Yin *et al*., 2017).

2.4 Segmentation and image classification

We employed a multiresolution GEOBIA approach to segment images, which were then classified using a supervised SVM technique. Segmentation is the partitioning of an image into discrete non-overlapping units based on specific criteria (Hay *et al*., 2005). It is a bottom-up technique in which individual pixels are iteratively merged into larger objects (Baatz and Schape, 2000). This grouping increases the discrimination of spectrally similar land-cover types by using texture, shape and context features to determine the creation of objects from individual pixels (Burnett and Blaschke, 2003). There is no single perfect algorithm that is appropriate for all images (Muñoz *et al*., 2003). In this study, multi-resolution segmentation (MRS) in eCognition was preferred following recommendations provided by Marpu *et al*. (2010). The MRS is a widely recommended technique for image segmentation, in which the size of segmented objects is controlled by user-defined scale parameters (Anders *et al*., 2011) whose selection is based on iterative screening and thresholding (Belgiu and Draˇgut¸, 2014). This segmentation was performed by weighting all bands 1 except the red and near-infrared, which were weighted 2 in order to discriminate vegetated surfaces. The scale parameter was kept at 50. The shape and compactness parameters were both set at 0.5 (G. Chen e*t al*., 2012) because the relationships of the spectrum versus the shape and compactness versus smoothness were unknown. The images that were produced from these segmentation procedures were then subjected to supervised classification by using the 60% of ground truth that was reserved for this purpose during field investigation.

In performing the classifications, the number of training pixels was determined by reference to guidelines provided in the literature. Some authors suggest a minimum of 50 training pixels/class if the area covered is <500 km^2 and the number of classes is ≤12, or 75–100 training pixels/class if the area covered is >500 km^2 and the number of classes is >12 (Bharatkar and Patel, 2013), while others suggest 30 pixels/class without providing limits on the number of classes or the size of the area covered (Mui *et al*., 2015).

Sample selection: Because the total number of classes in our study was eight and the area covered was <500 km^2 (19 000 hectares = 190 km^2), we decided to use the intermediate 30 pixels/class suggested by Mui *et al*. (2015). This translates into a recommended window of 6 × 5 pixels at Landsat's 30-m resolution (Lu and Weng, 2007; Mather and Koch, 2011; Myburgh and Van Niekerk, 2013). However, there were exceptions with classes that covered small proportions of the scenes (i.e. wetlands and grassland) because of MRS's ability to sample classes with spatial coverages below the specified window of 6 × 5 pixels.

Sample objects were trained by supplementing field-compiled information with collateral ground truth from Google Earth images and contextual information that was obtained from (1) prior knowledge of the tone, shape and texture appearance of features like water and cultivated land-holdings; and (2) habitat preferences of individual vegetation species. From these examples, water is known to be irregularly shaped while cultivated plots usually have rectangular uniform appearances, and herbaceous species like *Cyperus papyrus*, *Phragmites mauritianus* and *Phragmites australis* were expected in the permanently flooded wetland areas. This additional information boosted the reliability of signature extraction because of the established usefulness of contextual information in aiding the minimisation of classification errors (Kalra *et al*., 2013). Table 2 summarises the training pixel statistics for each of the eight LULC types that were mapped from Landsat images.

Table 2. Overall accuracy for each satellite image.

Image	Overall accuracy (%)	Kappa coefficient
1997	82	0.80
2001	81	0.79
2004	79	0.76
2008	84	0.82
2012	83	0.80
2017	88	0.86
Average	83	**0.81**

To enhance the accuracy of our classifications, SVM was selected to classify the images because of its superiority over conventional classification approaches (Oommen *et al*., 2008). SVM is a non-parametric algorithmic machine learning classification technique that is trained to find the optimal classification hyperplane by minimising the upper bounds of classification errors (Cortes and Vapnik, 1995; Mashao, 2003). In this study, SVM implementation was performed using the radial basis function (RBF) kernel as recommended by Hsu *et al*. (2003), without altering its default parameters on kernel function (0.143), penalty (100), pyramid levels (0) or classification probability threshold (0).

2.5 Classification accuracy assessment of the LULC classes

Classification accuracy assessment (CLACASS) is a common quantitative method that applies an error matrix derived from independent reference data sets (Stehman, 2000; Foody, 2002) to assess the quality of classified map outputs (Congalton and Green, 2008; Mui *et al*., 2015). In this study, CLACASS was accomplished by calculating overall accuracies and kappa coefficients (K) following procedures suggested by Campbell (2002) and by Congalton and Green (2008). Hamandawana (2012) provides an illustrated explanation of how these statistics can be calculated. Table 3 shows the overall percentage of accuracies and K coefficients that were obtained for each of the six map outputs.
In Table 3, kappa values are interpreted as follows: (1) values ≥0.75 indicate excellent agreement beyond chance, (2) values ranging from ≥0.4 to <0.75 indicate fair to good agreement beyond chance, and (3) values <0.4 indicate poor agreement beyond chance (Tana *et al*., 2013).

Table 3. Percentage compositions and percentage changes in land use land cover change (LULC) cover types that were mapped from Landsat images in the uMfolozi floodplain: 1997–2017.

	Percentage composition						Percentage change					
Cover type	1997	2001	2004	2008	2012	2017	1997–2001	2001–2004	2004–2008	2008–2012	2012–2017	1997–2017
BHF	23.01	20.49	24.67	32.80	38.65	25.56	−2.52	4.18	8.14	5.85	−13.09	2.55
FO	8.09	7.85	8.89	3.86	6.93	4.28	−0.24	1.04	−5.03	3.07	−2.65	−3.81
GR	4.45	5.90	6.47	2.45	6.45	6.60	1.45	0.57	−4.02	4.00	0.15	2.15
PL	12.67	16.87	16.63	9.61	14.46	7.25	4.21	−0.24	−7.02	4.85	−7.21	−5.42
SGF	27.52	28.95	25.03	30.36	22.22	45.63	1.43	−3.92	5.33	−8.13	23.41	18.11
WA	9.09	10.47	9.85	6.73	7.89	9.20	1.38	−0.61	−3.12	1.15	1.32	0.11
WE	15.17	9.47	8.46	14.20	3.41	1.49	−5.71	−1.00	5.73	−10.79	−1.92	−13.68
SBF	0.00	0.00	0.00	0.00	4.96	11.80	0.00	0.00	0.00	0.00	6.85	11.8

2.6 Object-based change detection analysis

After determining the accuracies of our map outputs, object-based change detection (OBCD) (Blaschke, 2005) was performed to quantify the changes in LULC in order to investigate observed patterns in spatial distributions of wetlands for the five time slices (1997–2001, 2001–2004, 2004–2008, 2008–2012 and 2012–2017) between 1997 and 2017. The change detection analysis revealed and quantified expansion, contraction or no change in specific land cover classes relative to each other. This characterisation was preferred because apart from being one of the most commonly used, it allows the detection of transitional "from–to" changes in individual cover types (Yang and LO, 2002; Yuan *et al*., 2005). We used this procedure to produce the initial map for 1997 and five change-detection maps for the above-listed time slices by performing post-classification comparisons in ArcGIS 10.6. Thereafter, these maps were overlain to produce a matrix table that summarised all time-series in the 20 years between 1997 to 2017. Paired t-tests were then performed to determine whether there were significant differences in changes among agriculture, bare land and harvested fields, plantations, forest, sugarcane farms, wetlands, and subsistence farms.

3. Results

Results of this investigation are presented in the form of (1) a table that summarises percentage compositions and percentage changes in the LULC types that were mapped from Landsat images (Table 3); (2) maps that show spatial distributions of these cover types (Figure 2); and (3) a graph that shows their percentage compositions from 1997 to 2017 (Figure 3).

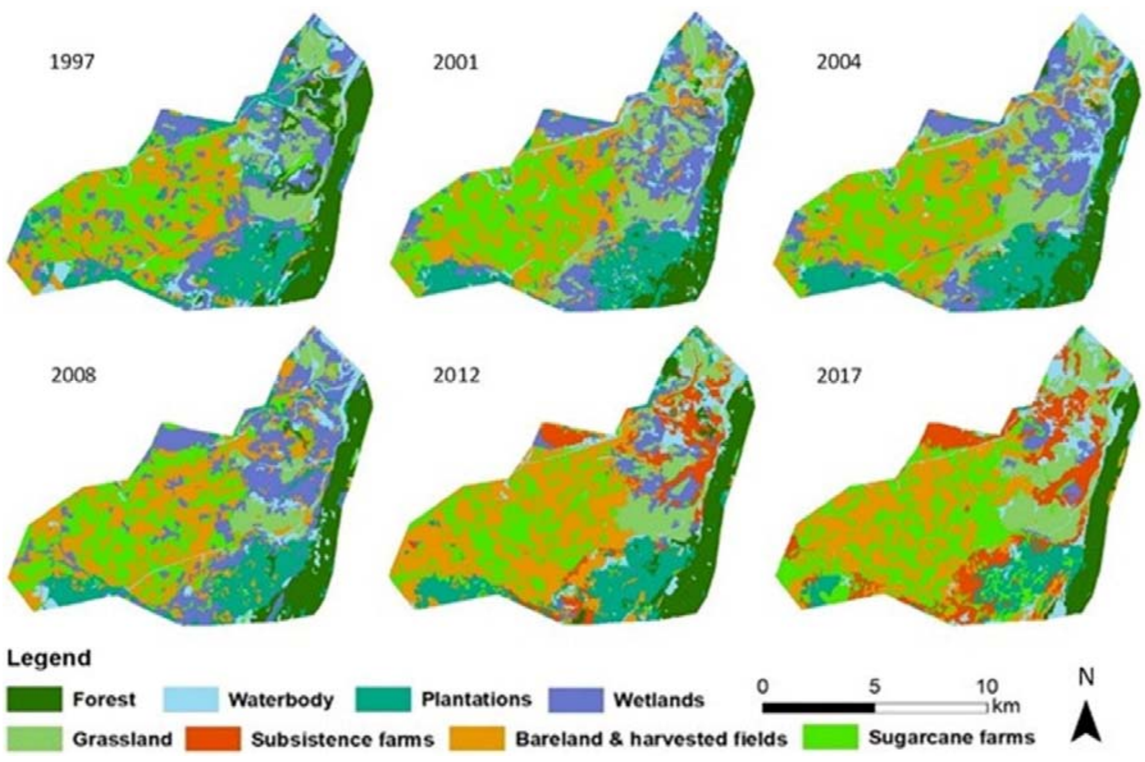

Figure 2. Spatial distribution of land cover types from Landsat images (1997–2017).

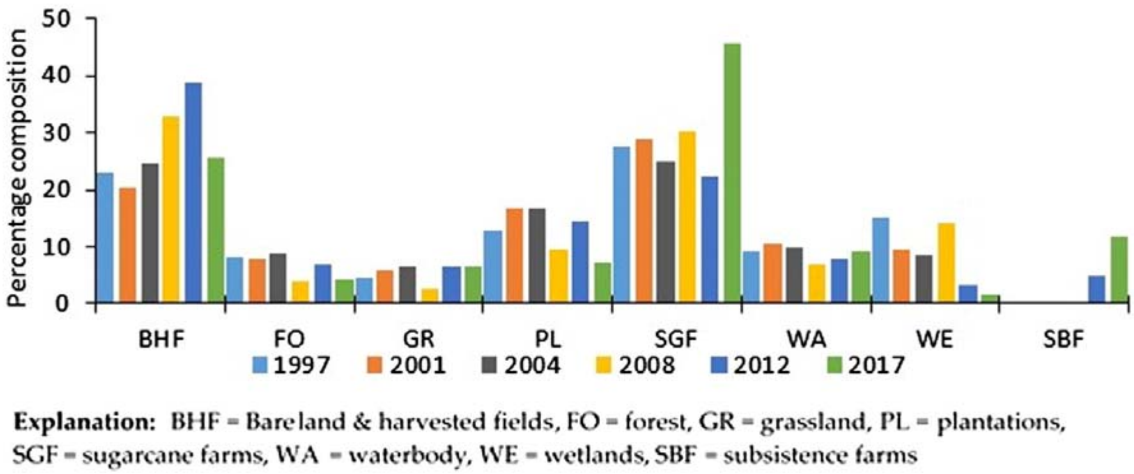

Figure 3. Percentage compositions of land cover types that were mapped from Landsat images (1997–2017).

The major long term changes that were observed include (1) a substantial decrease in wetland, by 13.68% (*p*-value, < 0.01), and a marginal decrease in plantations and forest, by 5.42% and 3.81%, respectively; (2) a substantial increase in subsistence farms and sugar cane farms, by 11.8% (p-value < 0.0001) and 18.11% (*p*-value, <0.01), respectively, and a near-equal marginal increase in bare-land and harvested fields and grassland, by 2.55% and 2.15%, respectively; and (3) a negligible increase in water, by 0.11%. The most striking observations include an abrupt emergence of subsistence farms in 2012 and a corresponding decrease in wetland areas. All cover types except subsistence farms exhibited periodic variations. The greatest long-term decrease (1997–2017) was in wetland aerial extent (Figure 3), which persistently decreased after 2008 as subsistence farms emerged and expanded rapidly (Figure 2).

4. Discussion

The main goals of this study were to (1) provide a remote sensing-based approach to quantify long-term changes in LULC in the lower uMfolozi floodplain over a period of 20 years between 1997 and 2017, (2) ascertain the major drivers of these changes, and (3) provide suggestions on what needs to be done to enhance the sustainability of this ecosystem. Eight LULC types were investigated, mapped and assessed, with subsistence farming only emerging after 2012 (Figure 2). Sugarcane farms, bare land and harvested fields, plantations and wetlands were distributed evenly over the whole study area. The observed contraction of wetland between 1997 and 2017 was investigated based on the "from–to" map-output that was obtained from the SVM classification (Figure 2). The post-classification comparison revealed an expansion of subsistence farms in the final period between 2012 and 2017 and a corresponding decrease in the wetland, with wetland areas that were present in the uMfolozi floodplain system between 1997 and 2008 gradually disappearing after 2012 as subsistence farmland increased. This observation suggests that the long-term contraction of wetland was largely the result of an inversely related expansion of subsistence farms.

The major insight from this finding is that GEOBIA is capable of teasing out time-series variations in different LULC types at high levels of detail that surpass what is commonly achievable using traditional supervised classification algorithms. This is because of the technique's ability to use spatial information on shape and texture to improve classification accuracy (Lu and Weng, 2007) in complex and heterogeneous landscapes. An additional strength of this algorithm arises from its inherent capability to reduce errors caused by spatial misregistration, which pixel-based methods are incapable of handling (McDermid *et al*., 2008). This assertion is supported by findings in which GEOBIA was successfully used to classify Landsat images in several studies that investigated long-term changes in different wetland ecosystems (Ramsey III and Laine, 1997; Munyati, 2000; Baker *et al*., 2007; Kiage *et al*., 2007; Tağil, 2007; Carreño *et al*., 2008; Frohn *et al*., 2011; Kassawmar *et al*., 2011; Thomas *et al*., 2011; Jia *et al*., 2014a). In our investigation, the high average overall accuracy of 82.83%, K = 0.81 achieved by SVM (Table 3) demonstrates the ability of our methodology to accurately quantify long-term time-series LULC changes in heterogeneous floodplain ecosystems. This information is crucial for sensitive wetland ecosystems, where accurate maps are required for national biodiversity assessments (NBA), the more so because of their widely reported deteriorating ecological conditions (Driver *et al*., 2012; Skowno *et al*., 2018). In South Africa, accurate characterisation of wetlands is more important than ever because they are ecologically vulnerable to climate change (Driver *et al*., 2012). Apart from providing ecosystem goods and services especially for rural livelihoods (Baker *et al*., 2006; Adekola and Mitchell, 2011; McCartney *et al*., 2011), wetlands also play an important role in moderating local weather conditions.

Although the average overall accuracy was 82.83%, an overall accuracy of 88%, K = 0.86 was observed for 2017, further demonstrating the ability of our proposed methodology to produce higher levels of accuracy than the standard 85% recommended by other researchers for Landsat-based classifications (Anderson, 1976). Comparative studies have also demonstrated that SVM produces superior, or at least comparable, results for multispectral and hyperspectral image classifications relative to more commonly used maximum and minimum likelihood classification techniques (Pal and Mather, 2003; Foody and Mathur, 2004; Oommen *et al*., 2008; Szuster *et al*., 2011). Uncertainties and errors in change detection results are always present and often attributed to spectral characteristics and artefacts that affect classification overall accuracies. In this study, for example, forests, sugarcane farms and plantations are often easily confused due to similarities in their spectral characteristics. This limitation was adequately addressed by the object-oriented approach, which has demonstrated the ability to reduce most misclassification errors (Immitzer *et al*., 2012). However, our CRes Landsat data sets failed to detect subsistence farms in the period 1997 and 2008. This was not unexpected because similar findings were obtained elsewhere by A.J. Rebelo e*t al*. (2017), exhibiting difficulties using historical Landsat images to produce accurate classifications of heterogeneous wetland cover types.

Although these limitations have far-reaching implications, our goal was to quantify LULC and changes thereof to ascertain the major drivers of temporal variations in these cover types. The findings of our investigation point to a substantial 17% expansion of subsistence farms in the 5years between the 2012 and 2017 periods and an inversely related long-term (1997-2017) decrease in the wetland area by 14% (Table 3); thus, it is not unreasonable to conclude that human agency has been one the major drivers of long-term LULC changes in this environment.

These observations are in agreement with Nustad (2015) who reported that smallholder farmers are destroying unique biodiversity in this area, and other studies elsewhere that report wetlands are decreasing because of encroachment by various human resource-use practices, especially crop farming (Davidson, 2014; Gardner *et al*., 2015; L. Li e*t al*., 2015). Wetlands in the study area are regarded as the main-stay of local people's livelihoods, with cultivable land being one of the most important resources (L.-M. Rebelo e*t al*., 2010). Their importance is not only confined to South Africa. They are widely acknowledged for their life-supporting services in Kenya, where their sustainability is being threatened by inappropriate human practices of resource use (Ajwang'Ondiek *et al*. 2020). This is a major cause of concern; approximately 62% of all wetland vegetation was lost in Uganda between 2002 and 2014 through the conversion of wetlands to farmland (Isunju, 2016), and as much as 52% of South Africa's Ga-Mampa wetland was lost to farmland between 1996 and 2004 (Troy *et al*., 2007).

Significant differences (p-value < 0.01) were observed between wetland and non-natural human-introduced cover types including harvested fields, plantations and sugarcane. This suggests that sizeable proportions of wetland in the uMfolozi floodplain system are being converted extensively for agricultural activities. As mentioned, the area's population has increased over the past century, with this increase being accompanying by a high unemployment rate (39%). By implication, the wetland aerial extent in the lower uMfolozi floodplain system is expected to decrease as more land is converted to agriculture in order to increase food production (Wood *et al*., 2013; Feyissa *et al*., 2019). The conversion of wetlands to cultivated land can destroy their ecological integrity by disrupting the hydrological cycle and other functional processes (Galbraith *et al*., 2005).

Preservation of wetland ecosystems is vital for the continued provision of ecosystem services, including habitat for aquatic life, mitigation of floods, providing freshwater during prolonged droughts, supporting groundwater recharge, purifying water from different terrestrial sources, and supporting agriculture by providing fertile soils. However, wetlands continue to be threatened by wide-ranging anthropogenic activities and the adverse effects of climate change. Conserving floodplain wetlands in South Africa and in other areas worldwide is a formidable challenge that requires collective efforts. The challenges confronting their sustainability include resource over-extraction by unemployed populations and the negative attitude of farmers towards wetland conservation (Keys and McConnell, 2005, Millennium Ecosystem Assessment, 2005).

Despite these problems, the sustainability of wetlands should be safeguarded by embracing sound resource-use practices. However, it is not easy to strike a balance between the conservation of biodiversity and the pressing needs of socio-economic development. Policies, too, aggravate this situation by prescribing regulation without involving local communities. This explains why in this wetland, there is a conflict between state-led conservation agencies and local communities, with the former tending to perpetuate historical tenure insecurities that deprived local communities of access to cultivable land. This has compelled local communities to rely on over-exploitation of the limited resources at their disposal. Similarly, Pimbert and Pretty (1997) and Timmer (2004) reported that the degradation of wetlands tends to be pronounced when the local communities have not been granted secure usufruct rights over the natural resources. Moreover, when few local community members hold legal titles to land, they show little inclination to participate in natural resource conservation initiatives (Pagdee *et al*., 2006; Rudel, 2006; Le Bel e*t al*., 2011). Community-based wetland management is therefore recommended. Community involvement in such matters confers a sense of ownership and accountability. This is because local communities develop responsible stewardship if they are included in making decisions that affect their daily operations (Springer and Almeida, 2015).

5. Conclusion and recommendations

From the overall research findings, the following conclusions can be drawn. Land-use information for the lower uMfolozi from 1997 to 2017 using Landsat data could be extracted with high accuracy by combining the GEOBIA method and SVM. GEOBIA demonstrated its ability to yield reliable estimates by providing outputs with overall accuracy levels approximating 83%. The dominant change that took place in the study area involved the conversion of wetlands to small-scale farms. In view of this observation, it recommended that community-based natural resource management (CBNRM) needs to be carefully reconsidered and prioritised as one of the potentially viable sustainable management strategies. This approach would (1) give the local communities opportunities to acquire rights to natural resources within their environment, (2) empower them to willingly embrace sustainable resource practices and (3) create viable income-generating opportunities that would go a long way to enhance sustainability by creating employment. Overall, CBNRM would promote wetland conservation by involving local communities in managing their own resources. We conclude by inviting those interested in the sustainability of these ecosystems to build on our initiative by making concerted efforts to fine-tune methodologies that can be used to cost-effectively provide reliable information on the nature, causes and extent of long-term changes in LULC affecting these ecosystems.

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No potential conflict of interest was reported by the author(s).

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