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Use of multispectral satellite data to assess impacts of land management practices on wetlands in the Limpopo Transfrontier River Basin, South Africa

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ABSTRACT

The study sought to assess the impacts of land use and land cover (LULC) changes on two wetland systems (Makuleke and Nylsvley Nature Reserve) in the Limpopo Transfrontier River Basin (LTRB) in South Africa between 2014 and 2018. To fulfil this objective, multi-date Landsat images were used. Furthermore, the maximum likelihood classification algorithm was used to identify various LULC classes within delineated wetlands. The LULC changes were mapped from the two wetlands, with high overall accuracies, ranging from 80% to 89% for both study areas. The spatial extent of the Makuleke wetland declined by 2% between 2014 and 2018, whereas the Nylsvley wetland decreased by 3%. Built-up areas have increased slightly over the 2014 and 2018 period because of population growth and infrastructure development, which occupy a portion of the wetland. In Nylsvley wetland, it was evident that during the 5-year monitoring period, croplands increased steadily in the Nylsvley catchment. Overall, the results demonstrated a steady decline in natural vegetation cover in both wetlands. This information can aid in enforcing wetland legislations and LULC management practices that can help protect them from further encroachment and degradation.

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Change detection; ecological status; multi-date assessment; protected wetlands; remote sensing; spatial characterization; wetland integrity

1. Introduction

Wetlands are unique ecosystems that are considered among the world's most productive and valuable ecosystems (Ollis et al., 2013), providing several environmental and socio-economic values (Al-Obaid et al., 2017). As delicate as they are, wetlands have historically been the basis for human survival due to the availability of water, biodiversity and sometimes-fertile soils (Marambanyika & Beckedahl, 2016a). Also, these highly productive ecosystems provide functions such as water security, hydrological regulation, erosion retention and other services (Jogo & Hassan, 2010; Adekola et al., 2012; Dixon et al., 2016; Gxokwe et al., 2020; Orimoloye et al., 2020; Thamaga et al., 2021). Wetlands

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provide the basis of human livelihoods in Africa through ecosystem services, for instance, the study done by Adekola et al. (2012) described some of the provisioning services provided by wetlands to the livelihoods of local stakeholders, including monetary values for some services in rural areas of South Africa. Mwita (2013) highlighted that rural communities in Western Kenya depend on water from the Yala swamp for drinking, cooking, and washing purposes. Work by Marambanyika et al. (2017) demonstrated the relevance of wetlands to rural livelihoods in rural Zimbabwe. It is, therefore, imperative to routinely assess and monitor the impacts of human development or land management practices on wetland resources.

So far, numerous legislations and treaties have been introduced to conserve and protect wetlands from degradation and even extinction. These include the 1975 Ramsar Convention, the South African National Environmental Management Act 107 of 1998 (NEMA), the National Water Act 36 of 1998 (NWA) and the environmental provisions of the Mineral and Petroleum Resources Development Act 28 of 2002 (MPRDA), and the 2006 Environmental Management Act of Zimbabwe that provides for the protection of wetlands. Despite these initiatives, wetland degradation continues at unprecedented rates due to the lack of awareness, poor policy implementation and ineffective government policies (Al-Obaid et al., 2017; Marambanyika & Beckedahl, 2016b; Omolo et al., 2018). Wetlands in semi-arid regions particularly in developing countries are at high risk of degradation due to anthropogenic activities caused by the surrounding communities within their catchments. Furthermore, Land Use and Land Cover (LULC) changes and overexploitation of unsustainable resources' harvesting, urban development, industrial expansion and agricultural intensification in these wetlands contribute to the degradation of wetlands (Mwita, 2013). Lack of information about benefits derived from wetlands results in some wetlands being considered as wastelands. Both the natural and anthropogenic forces are responsible for these changes in LULC. These changes not only fragment the landscape but alter biogeochemical cycles, climate, ecosystem processes and resilience, thereby changing the nature of ecosystem services (Namugize et al., 2018). Also, wetlands are highly vulnerable to global environmental changes through alterations of hydrological regimes which threaten wetland habitats and their-dependent species (Al-Obaid et al., 2017; Bhanga et al., 2020).

Several methods have been adopted to monitor wetland conditions. These include traditional and spatially explicit remote sensing techniques (Gxokwe et al., 2020; Thamaga et al., 2021). Although they have received much attention, traditional methods such as field surveys, map interpretation, collations of ancillary and data analysis are reported to be ineffective for routine and spatially explicit monitoring of wetlands (Ma et al., 2018). Besides, they are regarded as time-consuming, expensive, and frequently provide incompatible and inconsistent results. They remain viable in developed and easily accessible areas and this creates spatial irregularities (Masocha et al., 2018). The use of remote sensing is much more effective, cost-effective, and time-effective compared to other traditional methods (Al-doski et al., 2013). The use of satellite data provides useful tools for monitoring and managing wetland conditions even in remote areas (Mwita, 2013). Some satellites such as Landsat have been providing spatial data for the past 48 years (since 1972) and this makes it advantageous to monitor LULC changes as a proxy for understanding wetland conditions. The Landsat data series provide moderate-resolution at 30 m with a 15-day revisit time and of late Sentinel 2 MSI was introduced, with a temporal resolution of 5-days and moderate resolution of 10–20 m. The two satellite datasets provide a complementary advantage that can aid in monitoring and understanding wetland conditions especially for remote and undocumented wetland areas.

This study, therefore, sought to assess the impacts of LULC change on protected wetlands in the Limpopo Transfrontier River Basin (LTRB) in South Africa (2014–2018), using long-term Landsat datasets. To achieve the objective, two wetlands, namely, Makuleke and Nylsvley Nature Reserve were selected. These wetlands are protected by law as nature reserves. However, there is a potential that they are being affected by certain factors within and outside the protected boundaries, therefore the study will highlight those factors in these catchments, respectively.

2. Material and methods

2.1. Description of the study area

The Limpopo Transboundary River Basin (LTRB) is one of the largest catchment areas in Southern Africa and the basin has a mean altitude of 840 m, covering approximately 412,000 km^2 (Mosase et al., 2019). LTRB is located in the eastern part of Southern Africa approximately between 20°S 26°S and 25°E 35°E. The LTRB falls within a semi-arid climate region (Mosase & Ahiablame, 2018). The basin is shared among four countries, namely: Zimbabwe, South Africa, Mozambique and Botswana (See Figure 1) (Gebre and Getahun, 2016). The Limpopo Province (South Africa) has experienced a growth in its population from 5 million in 2002 to 5.8 million in 2016 (StatsSA, 2018). The southern and western parts of the catchment area are mostly underlined by sedimentary rocks such as sandstone conglomerate, whereas the metamorphic and igneous rocks such as basalt are found in the northern and eastern parts of the LTRB. The two wetlands under study, Makuleke and Nylsvley Nature Reserve wetlands are both listed under the Ramsar Convention. Makuleke wetland is located in the northern part of LTRB (22°23'S 031° 11′E), within the Kruger National Park on the floodplains of Limpopo and Luvuvhu rivers and bordered by Zimbabwe and Mozambique to the north and east, respectively (Malherbe, 2018). The Makuleke wetland covers approximately 240 km^2 and the important landscapes of the nature reserves are riparian forests, grasslands, and pans on floodplains. Floodplains are of great importance in this ecosystem as they have water even during the dry season, and therefore act as a refuge point for wildlife and waterbirds during both winter and summer months. Nylsvley wetland is in the southern part of the LTRB (24°39'S 028°42′E). The Nylsvley wetland covers approximately 40 km^2 and the main features of the Nylsvley nature reserve includes riverine floodplains, flooded river basins, and seasonally flooded grassland, with the dominant wetland type being a seasonal river associated with a grassland floodplain (Havenga et al., 2007). The wetland has the endangered roan antelope *Hippotragus equinus*, and the area serves as a breeding ground for eight South African red-listed waterbirds (African and Conservation, 1998; McCarthy et al., 2011).

Figure 1. Locations of the Makuleke and Nylsvley wetlands within the Limpopo Transboundary River Basin (Chapman & Parker, 2014).

2.2. Remote sensing data acquisition

The data used in this research included satellite data and auxiliary data. In total, 12 scenes (See Table 1) of Landsat Images were freely downloaded from the United States Geological Earth Explorer (USGS) online portal (https://earthexplorer.usgs.gov/) with less than 10% cloud coverage. These images were acquired over two seasons (wet and dry) to assess the impacts of LULC changes on wetland ecosystems from 2014 to 2018 (see Table 1). Satellite image pre-processing before any detection of change is greatly needed and has a primary unique objective of establishing a more direct relationship between the acquired data and biophysical phenomena (Butt et al., 2015). The data were pre-processed using ArcGIS 10.8 and QGIS software. All 12 images were pre-processed by performing standard pre-processing steps (geo-referencing and atmospheric corrections). The images were geometrically

Table 1. Landsat's data images used to map the inherent LULC changes.

Catchment	Sensor ID	Path/row	Date
Makuleke	LC08_LITP_169076	169_063	08–10-14
	LC08_LITP_169076	169_063	18–06-14
	LC08_LITP_169076	169_063	29–10-16
	LC08_LITP_169076	169_063	20–04-16
	LC08_LITP_169076	169_063	16–08-18
	LC08_LITP_169076	169_063	26–04-18
Nylsvlei	LC08_LITP_170077	170_077	11–07-14
	LC08_LITP_170077	170_077	16–01-14
	LC08_LITP_170077	170_077	16–07-16
	LC08_LITP_170077	170_077	05–11-16
	LC08_LITP_170077	170_077	22–07-18
	LC08_LITP_170077	170_077	11–11-18

Table 2. Landsat 8 OLI bands.

Band	Band Number	µm	Resolution (m)
Coastal	**1**	**0.433–0.453**	**30**
Blue	**2**	**0.450–0.515**	**30**
Green	**3**	**0.525–0.600**	**30**
Red	**4**	**0.630–0.680**	**30**
NIR	**5**	**0.845–0.885**	**30**
SWIR-1	**6**	**1.560–1.660**	**30**
SWIR-2	**7**	**2.100–2.300**	**30**
Panchromatic	8	0.500–0.680	15
Cirrus	9	1.360–1.390	30
TIRS-1	10	10.6–11.2	100
TIRS-1	11	11.5–12.5	100

corrected based on the World Geodetic System (WGS) 84 spheroids and atmospherically corrected using a semi-automatic classification tool which implements the Dark Object Subtraction (DOS1) (the DOS1 atmospheric correction box was checked before the atmospheric correction was run) in the GIS software. In this study, seven bands (See Table 2) namely: band 1 (Coastal), band 2 (Blue), band 3 (Green), band 4 (Red), band 5 (NIR), band 6 (SWIR-1) and band 7 (SWIR-2) were stacked and used for further processes seasonally. Band 8 (Panchromatic), band 9 (Cirrus), band 10 (TIRS 1) and band 11 (TIRS 2) were not used in the present study because band 8 combines visible light instead of separating it, band 9 collects least earth features and band 10 and 11 measure heat (temperature). Also, due to their resolutions, these bands are not useful in mapping vegetation, hence they were considered as not ideal for mapping LULC changes. Seasonal satellite images of the study area image were extracted by clipping the study area using common GIS tools. Auxiliary data include ground truth data for the LULC classes that were delineated for image classification. The ground truth data were in the form of reference data that were randomly created using GIS tools and exported to Google Earth. These points were then used for assessing the accuracy of the classified images against the satellite images. These randomly created points are important for linking image data to real features and the material on the ground and for accuracy assessment purposes.

2.3. Image classification

To determine the main LULC for change detection, a classification scheme was prepared. According to Mwita (2013) preparation of a scheme is a prerequisite in the classification process. The scheme of the study was prepared based on the Google Earth and field observations of the LULC in the Makuleke and Nylsvley Nature Reserve catchments. Google Earth was used because, as stated by Bey et al. (2016) offers free access to satellite imagery on current and past land dynamics. These classes were identified and delineated from the satellite images and further validated in the field. Field validation was only done for 2018 images. The 2014 and 2016 images were validated using 240 random points that were projected onto Google Earth against the corresponding satellite images for the respective years

Table 3. Data are used for validation.

Field Validation	Satellite Imagery Validation
Ground truthing points (40 per class)	Google Earth Engine
GPS coordinates	Random points
Field pictures	Visual inspection of the images
	Accuracy assessment

(see Table 3). These include, namely, vegetation, built-up areas, forests, grasslands, bare land, shrubs, agricultural areas (farmlands) and waterbodies (wetlands). Landsat 8 band combinations from (https://landsat.gsfc.nasa.gov/landsat-8/landsat-8-bands/) can be used to identify land features. Band combinations are very useful in visualizing features of the earth and they were of great help in identifying LULC classes in the study areas through the images. For each of the classes, training samples were selected by delimiting polygons around the representative sites of the LULC classes. The training data which consisted of areas of the known classifications were done using the digitizing feature in ArcGIS for 12 images to create Area of Interest (AOI). The AOIs ranged between different pixel sizes. Polygons were digitized and created for each of the AOI shapefiles so that each AOI contains all pixels, not partial pixels. The selection of these features was based on areas that are visible on Google Earth in all images that will be classified. After the training samples were digitized, the next step was to create Signature files for every informational class. Spectral signatures for all LULCs derived from satellite imagery were recorded using pixels enclosed by these polygons. A satisfactory spectral signature is the one ensuring that there is 'minimal confusion' among the LULCs to be mapped (Gao & Liu, 2010). Therefore, signature files (SIG) were created, these files contain information about the LULC described by the training samples. In classifying the images, Maximum likelihood algorithm (MLC) was used. The MLC is based on the probability that a pixel belongs to a particular class (Rawat & Kumar, 2015). MLC was used because supervised classification depends on the background knowledge of the area under study. The images were classified according to the classes that were selected before the classification of the images. The classes were digitized based on the selected pixels. The use of MLC in this study was to estimate the extent to which MLC can accurately classify LULC classes in semi-arid environments such as Limpopo River Basin.

2.4. Accuracy assessment

Assessment of classification accuracy between 2014 and 2018 was carried out to determine the quality of information derived from the classified images. The accuracy analysis of the results was determined by overlaying 240 unbiased randomly created points (40 per class). The accuracies for the classification results were assessed using confusion matrices, which are user's accuracy, producer's accuracy, overall accuracy, omission accuracy and commission accuracy (Olofsson et al., 2013). Figure 2 shows a flow diagram presenting a summary of the major steps that were taken.

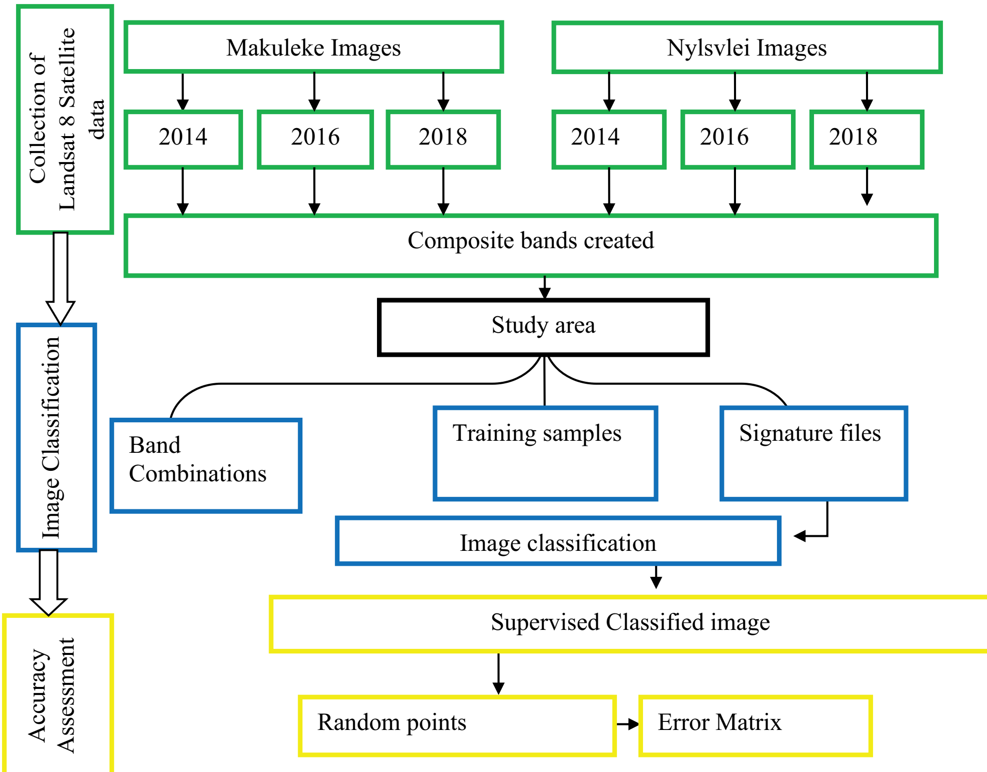


Figure 2. LULC changes and accuracy assessment workflow summary.

3. Results

3.1. Climate data

Figure 3 illustrates the climate variation in the basin during the period of understudy. The climate data was received from South African Weather Services (SAWS). The catchment is characterized by sharp peaks (the highest rainfall average in 2016 of 42.6 mm) and low rainfall amounts (the lowest of 25.79 mm in 2015). The highest temperature experienced in the basin was 26.31 Celsius in 2015 and lowest in 2014 at 11.25 Celsius.

3.2. Derived classification accuracies

The overall accuracy obtained during classification process is in conformance with the minimum threshold of 65% to 85% suggested by Anderson et al. (1976) and Sibanda et al. (2016) for LULC classification. Therefore, the maps produced had an acceptable overall accuracy, with the producer and user accuracies above 70% for most of the classes. Producer's accuracy is a measure of how well the real-world land use and land cover classes are classified and the user's accuracy represents the probability of a classified pixel matching the LULC class of its corresponding real-world location (Rwanga, 2017). Table 4 (a & b) shows satisfactory LULC classification accuracies achieved for Makuleke with

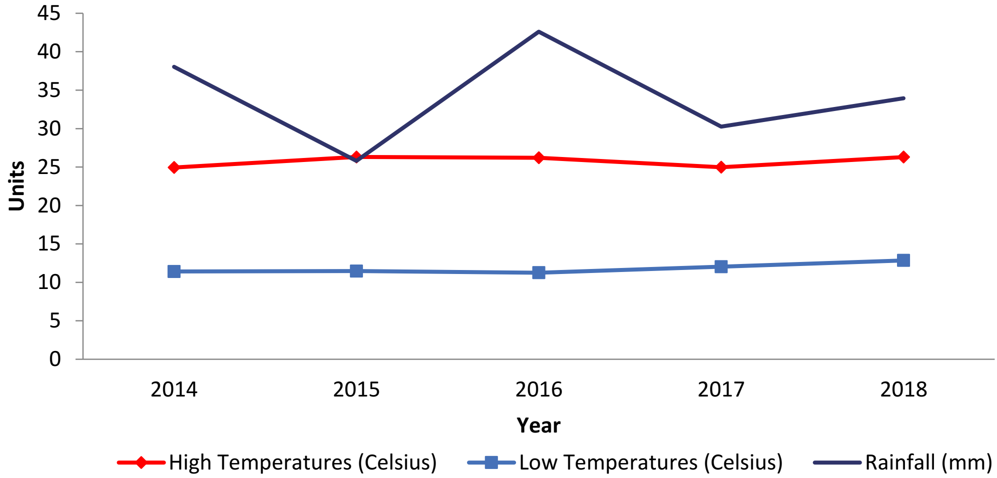


Figure 3. Climate data variation in the Limpopo River Basin between 2014–2018.

overall accuracy classification ranges between 85% and 89%, with user's and producer's accuracy between 31% and 97% for all six classes during the wet season. During the dry season the overall accuracy was between 80% and 86% with user's and producer's accuracy between 68% and 100%. In Nylsvley (See Table 4(c & d)) the overall accuracy was between 81% and 86% with all class accuracies above 70% during the wet season and had an overall accuracy between 80% and 83% during the dry season, with user's and producer's accuracy between 65% and 98% threshold during the period of study.

The omission and commissioning errors of the LULC classes are given in Figure 4 (a-f) and Figure 5 (a-f) for Makuleke and Nylsvley, respectively. The error of omission refers to reference sites that are left out (omitted) from the correct class in the classified map. The error of the Commission refers to sites that are classified as to reference sites that were left out of the correct class in the classified map. For instance, the omission error of bare land is high which means that pixels that belong to this category were not considered in this class in the case of Makuleke. The commissioning error was high in the case of built-up areas which meant that a greater number of pixels which do not fall under this category were classified as built-up areas in the case of Nylsvley.

3.3 Spatiotemporal mapping of LULC changes on protected wetlands

Figure 6a illustrates LULC changes that occurred around the Makuleke Nature Reserve over the 5 years. The classified images showed that most of the Makuleke Nature Reserve catchment was characterized mostly by grasslands, especially between 2016 and 2018 in both seasons. During 2014 both in the wet and dry season, the catchment was mostly characterized by bare land (see Figure 6a). Most of the built-up areas are located to the western part away from the wetland and natural vegetation is mostly located in the northern and eastern parts of the catchment. Change is evident in most of the LULC classes. The area occupied mainly by built-up increased from 13%, 17% and 20% of the total area in 2014, 2016 and 2018, respectively, for the catchment of Makuleke wetland. The area that is occupied by the forest has remained fairly constant from 2016 to 2018, seasonally.

Table 4. Image classification accuracies were derived from Landsat data for the Makuleke Nature Reserve wetland (a) wet season, (b) dry season and Nylsvley Nature Reserve wetland (c) wet season and (d) dry season for the period of the study.

	Wet Season – Makuleke					
[A]	**2014**		**2016**		**2018**	
Class	Producer	User	Producer	User	Producer	User
Built-up areas	61	78	81	92	82	80
Vegetation	86	80	91	80	70	76
Water bodies	95	88	90	85	97	80
Forest	70	88	67	80	81	73
Grasslands	65	90	41	88	31	70
Bare land	34	44	44	48	32	42
OA	**88%**		**89%**		**85%**	
[B]			**Dry Season**			
Class	**2014**		**2016**		**2018**	
	Producer	User	Producer	User	Producer	User
Water bodies	71	90	79	85	100	82
Vegetation	86	80	71	85	80	75
Built-up areas	80	70	78	70	96	95
Forest	78	73	68	70	75	80
Grasslands	79	85	76	73	87	75
Bare land	86	80	88	75	86	85
OA	**80%**		**81%**		**86%**	
[C]			**Wet Season- Nylsvley**			
Class	**2014**		**2016**		**2018**	
	Producer	User	Producer	User	Producer	User
Water bodies	75	92	82	79	85	78
Vegetation	82	82	88	86	82	85
Built-up areas	90	91	92	88	91	95
Agriculture	70	78	76	74	78	74
Shrubs	79	77	70	73	79	72
Bare land	85	82	81	84	79	82
OA	**81%**		**83%**		**86%**	
[D]			**Dry Season**			
Class	2014		2016		2018	
	Producer	User	Producer	User	Producer	User
Water bodies	92	88	79	89	87	98
Vegetation	85	79	85	78	73	69
Built-up areas	81	84	79	76	76	72
Agriculture	79	75	65	72	98	95
Shrubs	82	79	71	82	81	75
Bare land	76	82	80	79	75	70
OA	**80%**		**81%**		**83%**	

On the other hand, Figure 6b shows how Nylsvley wetland has been changed during the period of study. The area occupied by bare land tends to decrease in the wet season and increase in the dry season from 11% in the wet season to 17% in the dry season. It can be observed from both seasons since 2014 that the percentage of farmlands increased from 18%, 24%, and 28% of the total area in 2014, 2016 and 2018, respectively, when compared to other classes such as vegetation. The area covered by built-up area has increased over the years, the area occupied by built-up infrastructure has increased from 5%, 7% and 9% of the total area in 2014, 2016 and 2018, respectively, in the catchment of Nylsvley.

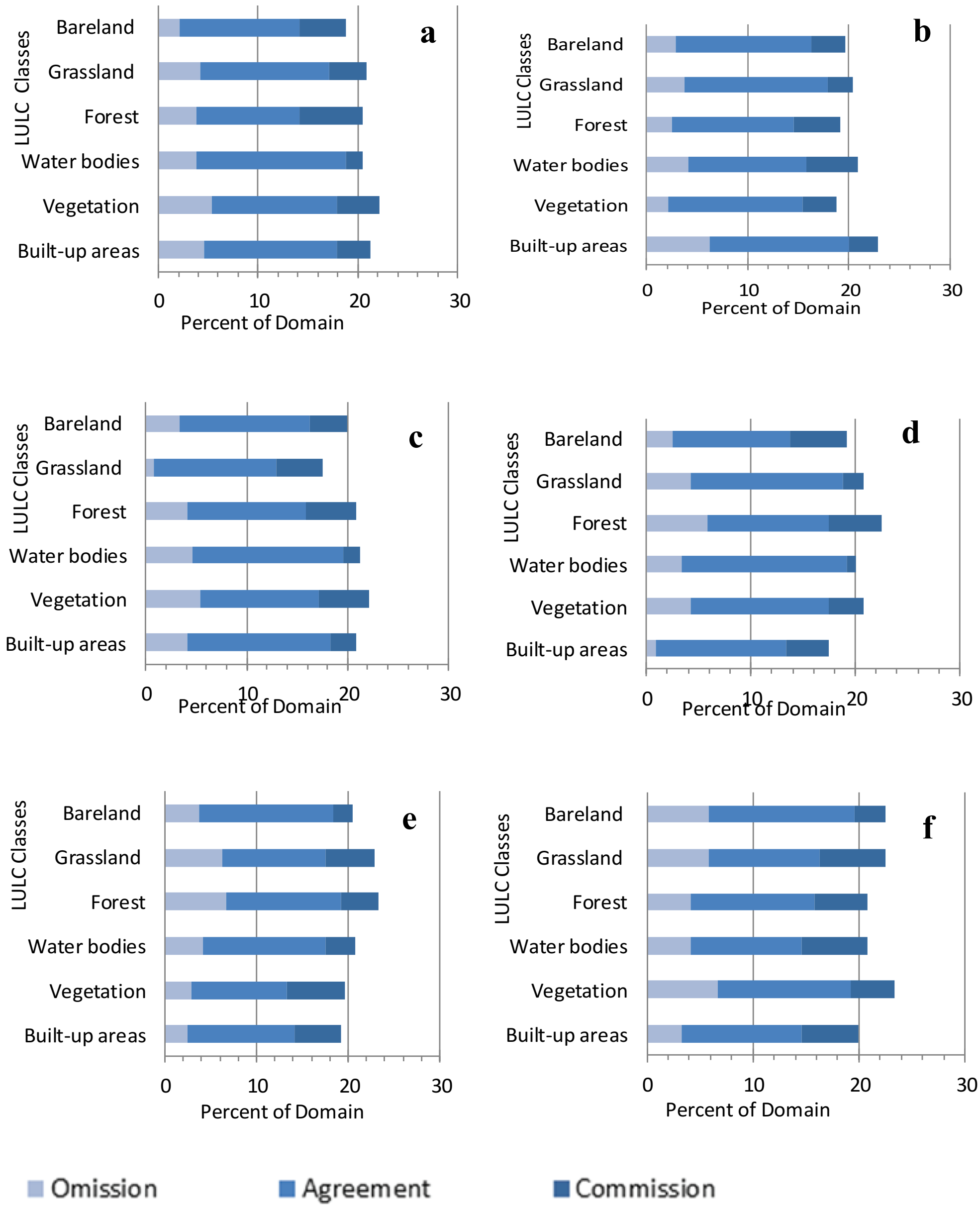


Figure 4. Commission and Omission Error graphs (a–c) 2014, 2016 and 2018 depicting wet season respectively and (d–f) 2014, 2016 and 2018 depicting dry season respectively for Makuleke.

3.4 Change detection during the period of study

Change detection is important in understanding how the land features have changed during the period of study and a summary of changes that occurred during the study period. From Figure 7a it can be observed that 10% to 18% of the total area of vegetation during wet seasons has changed. On the other hand, built-up areas slightly increased from 13% to 20% between 2014 and 2018 due to increased population growth and

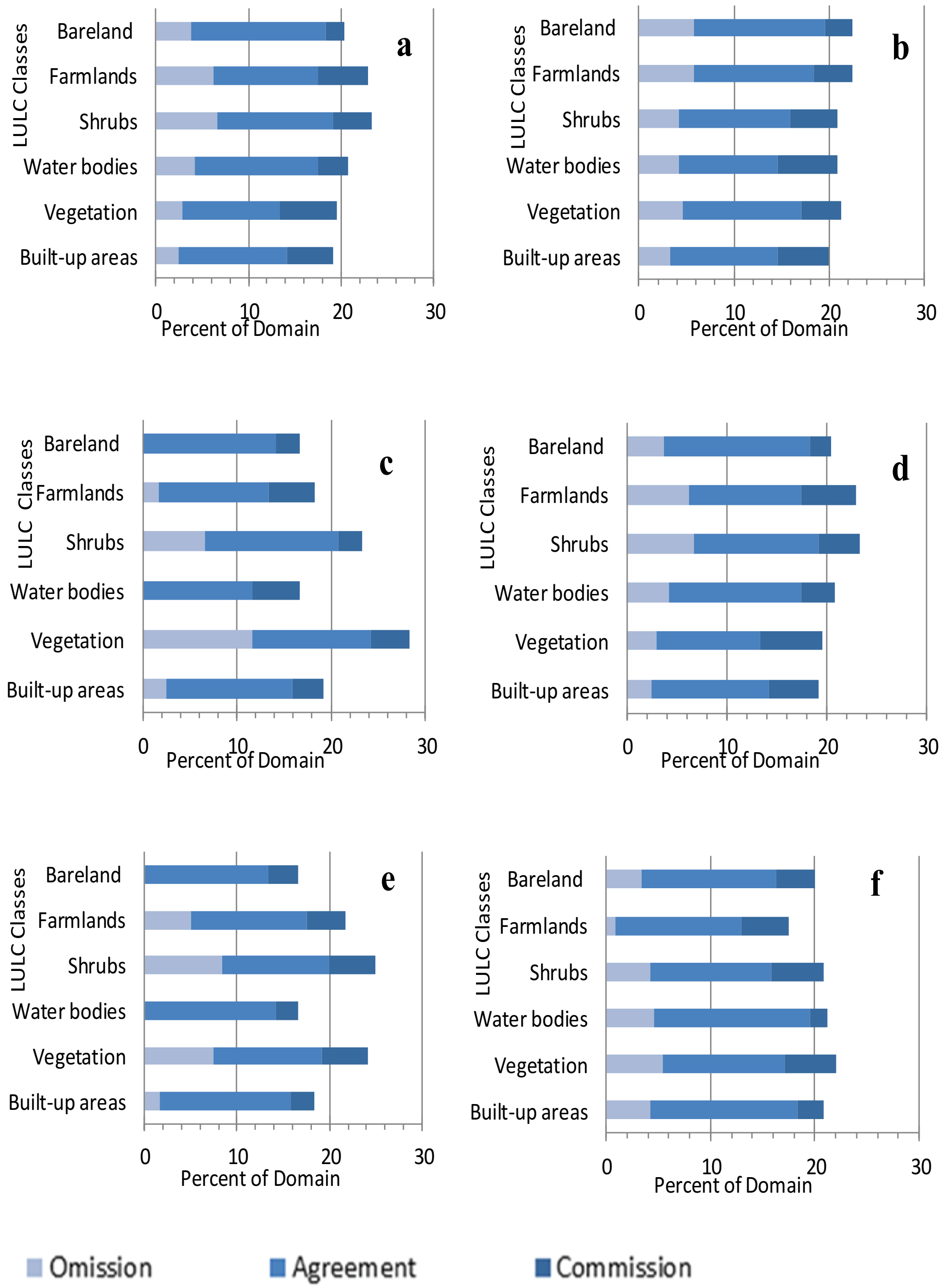
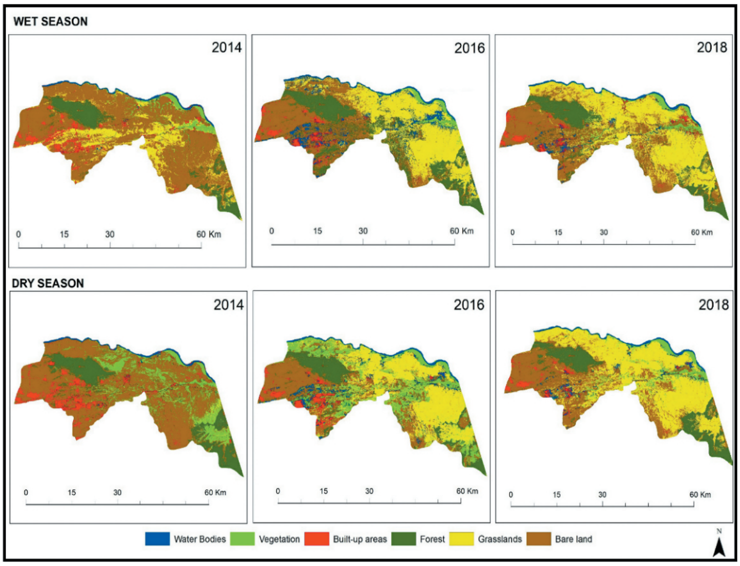
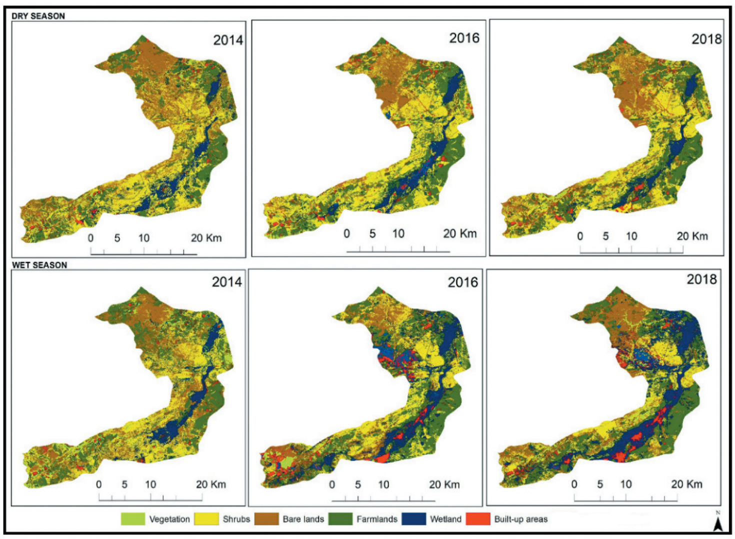


Figure 5. Nylsvley Commission and Omission Error (a–c) 2014, 2016 and 2018 depicting wet season respectively and (d–f) 2014, 2016 and 2018 depicting dry season respectively.

infrastructure development. Figure 6b displays the rate of agricultural areas (farmlands) has increased around the wetlands especially during the 2018 wet season compared to the other years. The increase in wetland farming around the Nylsvley wetland could be due to



a



b

Figure 6. (a) LULC changes of the Makuleke Basin over the period of 5 year. (b) Land use and cover changes in Nylsvley Basin from 2014–2018.

the availability of moisture in the soil. Figure 7a&b shows that some of the LULC classes can be seen increasing, some declining or remaining stable. In most cases, this is seasonal dependent, for instance, vegetation cover tends to increase during wet seasons and bare lands have remained fairly constant throughout the period under study both in wet and dry seasons.

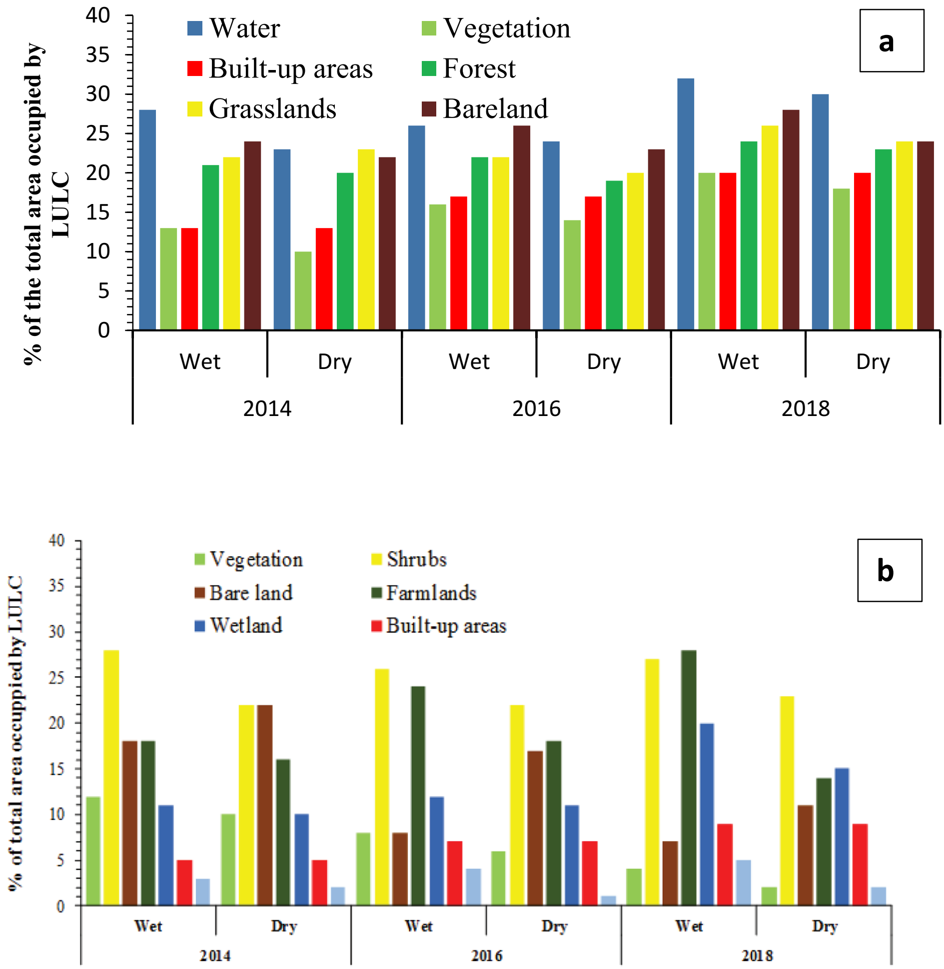


Figure 7. Satellite estimated land cover changes for the (a) Makuleke and (b) Nylsvley Nature Reserve wetland.

3.5 Comparison between Makuleke and Nylsvley

Understanding wetland loss is critical for proper wetland management and decision-making. Wetland loss is mainly caused by human activities within their catchments (Hu et al., 2017) and this is also evident in the areas under study. Between the years 2014 and 2018, the Makuleke wetland lost its spatial extent by 2% and 3% by Nylsvley, respectively. Grasslands have occupied some of the wetland areas in Makuleke Nature Reserve with a 4.38% increase from 2014 to 2018, followed by built-up areas with 6.59% change rate percentage between 2014 and 2018. Wetland areas showed a noticeable change during wet and dry seasons. In Nylsvley, the major LULC classes occupying the wetland area are shrubs (3.8%) and farmlands (7.52%) between the years' understudy (see Table 5). The results produced showed that

Table 5. Change matrix of Makuleke and Nylsvley between 2014 and 2018.

LULC	Wetland	Vegetation	Built-up	Bare land	Forest	Grassland	Farmland	Shrub	
Change rate (%)	−1.83	2.35	6.59	2	0.8	4.38	*	*	**Makuleke**
	−2.76	1.82	2.53	1.05	*	*	7.52	3.8	**Nylsvleiy**

*not applicable

farmlands are the dominant feature in the Nylsvley catchment basin and some of the areas that appear to be built-up areas in the dry years are parts of the wetlands. Farmlands and built-up areas are two main human activities that directly cause wetland loss and these activities have a direct impact also on water quality (Rashid & Romshoo, 2013).

4. Discussion

The study sought to assess LULC change impacts on the protected wetlands (Makuleke and Nylsvley Nature Reserve) located with the LRTB from 2014 to 2018 for two seasons (dry and wet) using Landsat data. The study showed that wetlands spatial extents shrank at a faster rate in LRTB mainly due to anthropogenic activities such as farming activities, infrastructure development and land conversion affecting wetland ecosystems. In recent years, similar studies have been conducted to monitor changes in wetland and their associated LULC changes. For example, the study that was done by Ghobadi et al. (2012) assessed the wetland change and degradation using multi-temporal satellite data, GIS and ancillary data. They concluded that there is a spatial reduction in the wetland with approximately 72% due to an increase in the agricultural land, increases in water demands and anthropogenic activities in the upstream areas of wetlands. Other studies that have used remote sensing in monitoring wetlands, for instance, the study done by (White et al., 2015) used Synthetic Aperture Radar (SAR) technology for monitoring changes in wetlands. They were able to map various components of wetlands and suggested that mean SAR should be considered as an important component of a wetland monitoring.

Accuracy assessment is an important step in image classification and the quality of the classified maps from satellite images is determined by its accuracy. The results from the accuracy assessment of the LULC maps varied among the LULC classes. Anderson et al. (1976) and Sibanda et al. (2016) suggested that the overall accuracy statistics for classification should be a minimum threshold of 65% to 85%. For LULC land use and cover classification of both study sites the accuracy statistics for the classified images were in accordance with the minimum threshold as suggested by regardless of some errors which could be attributed to spectral confusion between built-up areas, barren land, and farmlands (agriculture land).

There were significant changes among LULCs during the 2016–2018 period when compared to 2014 based on the classified images. The LULC classified images of Nylsvley Nature Reserve suggested that the main threat facing wetlands is agriculture around wetlands. The work done by Mwita (2013) suggested that one of the major factors that have resulted in the intensified wetland use is climate change. Over the past three decades, seasons have drastically changed and farmers and livestock have taken advantage of some fertile soil and the availability of water and pasture in wetlands (Greenfield et al., 2007). This study showed a decrease in the size of the wetlands due to parts of the wetland being converted to farmlands and this is in agreement with what was found by Ondiek et al. (2020) who concluded that agricultural expansion through drainage of wetlands has led to loss or reduction of wetlands. Agricultural expansion is the main economic activity taking place in wetlands especially in developing countries. Van Asselen et al. (2013) showed that wetlands have decreased in the past years globally due to land clearance and drainage due to urban, agricultural and industrial development activity. With the increasing population and need for food security, pressure on land will force farmers to cultivate more areas of natural ecosystems like forests and wetlands, further degrading water systems (water quantity and quality), livelihoods and economies (Uwimana et al., 2017). The decline in the wetlands and waterbodies identified in the study is also seen as a sign that the availability of agricultural land is becoming a challenging issue in the district, especially for Nylsvley wetland. The analysis revealed that the wetland is being converted into agricultural land, but this trend is happening at a slower rate than other land-use change trends identified in this study.

On the other hand, in Makuleke, the increase in bare land during 2014 could be caused by overgrazing done by livestock such as cattle mainly in rural areas around or close to the wetland. This is similar to the findings that of Dahwa et al. (2013) and Morris and Reich (2013) who also indicated that an increase in livestock grazing leads to treading, soil compaction, a decline in plant species and an increase in bare land. The study done by Butt et al. (2015) concluded that this increase in bare land could be due to rapid deforestation in the area which removes vegetation cover from the land and rendered it barren and exposed. There are a lot of open spaces categorized as bare land within the Makuleke. Due to the fact that a significantly large area of the Makuleke wetland catchment falls under barren landscapes, it becomes vital for wetland managers to increase the green cover in the form of the plantation to reduce the influx of sediment that might flow into the wetland, which might result in several ecosystem benefits for the affected wetland.

There is an increase in built-up areas in the Makuleke Nature Reserve basin when compared to Nylsvley Nature Reserve. This could have been caused by population increases in recent years. The basin has experienced a growth in its population from 5 million in 2002 to 5.8 million in 2016 (StatsSA, 2018). Cristea (2016) concluded that population growth and associated anthropogenic interferences have the tendency to deplete resources and reduced the rates of flow of ecosystem services. This is also in agreement with what was stated by Mwita (2013) as the second factor affecting wetlands - rural impoverishment and population growth. These changes have been growing at a faster rate and as a result, this will cause a change in land use and cover in most cases affecting wetlands. The increase in built-up areas during the 5 years used for the study could be attributed to increasing demand for land from the growing population as well as the infrastructure developments that are taking place. In other words, the increase in population implies the conversion of other LULC classes into built-up and this could be a reason for the general increase in the built-up area across the basin. In Makuleke Nature Reserve basin there were no settlements within or close to the wetland, people have settled far away from the wetland, and the wetland is located in a remote area that is far from most social services, whereas, in the Nylsvley, most built-up areas are located close to the wetland. A slight increase in built-up areas was expected because both wetlands (Makuleke and Nylsvley) are found in nature reserves, therefore it is expected that there will be an increase in tourism and entrepreneurial activities that surround these wetlands will most likely result in slight changes in the spatial distribution of built-up areas.

In both study areas (Makuleke and Nylsvley) there was a decrease in areas covered by vegetation. The decrease in vegetation is related to areas that were converted from either natural vegetation to farmlands. The change was attributed to increased human activities in the wetlands, agriculture during the dry season that requires vegetation clearance. The results clearly showed that there was less percentage of land occupied by vegetation in the dry season when compared to wet season in both basins. In Nylsvley basin most of the vegetation is located closer to the built-up areas (western part of the catchment) and in Makuleke mostly in the northern and eastern parts of the basin.

The major causes of land use and land cover changes in these catchments can be grouped into natural changes such as climate change and anthropogenic changes such as agricultural activities. The LULC changes in these catchments may be influenced by rainfall trends, due to high rainfall bare lands tend to decrease and grasslands tend to increase. The decrease in rainfall influenced agricultural activities but an increase in bare land. High temperatures affected vegetation cover in both study areas, vegetation cover was not constant during the period under study. Anthropogenic activities taking place caused a major change in land use and land cover especially during wet seasons when most of the catchment is covered with crops due to high fertile soil, and this was most evident in Nylsvley compared to Makuleke. Another anthropogenic activity that may have affected land use and land cover in the catchment is infrastructure areas (built-up). All these factors have a huge impact on the wetlands, for example, land area impact, environmental impact and biodiversity impact.

As the study has shown so far, it is of critical importance to monitor wetlands and their associated LULC changes. The use of remote sensed data is important and by means of it, different researchers showed different accuracies of different study areas. The types of data used include historical photography data, medium-resolution images, high-resolution images, and hyperspectral images. Much research used remote sensing data combined with field survey data to carry out many wetland studies. Therefore, the combination of in situ data (ground truth) and Landsat would be beneficial in understanding land processes and in making management decisions about wetland management. The advantages of using remotely sensed data such as Landsat data in monitoring wetlands dynamics are the images can be downloaded free of charge, records of the historic data are available on a global scale, Landsat TM and Landsat ETM have multispectral bands, with good spatial and temporal resolution and less image processing time is needed (Dube & Mutanga, 2015; Dube et al., 2015; Grundling et al., 2013). These are some of the studies that were done by Ghobadi et al. (2012), Nhamo et al. (2017), and Ma et al. (2018) that used remote sensed data to provide useful information on monitoring wetlands and LULC changes. However, there are several limitations such as cloud cover that usually limit the usability of the imagery and that usually affect the reliability of monitoring LULC and wetland.

5. Conclusion

This study focused on assessing the impacts of LULC change dynamics on the protected wetland systems (Makuleke and Nylsvley) in the LTRB in South Africa from 2014 to

2018. Landsat images with their improved capabilities were used to map the spatiotemporal pattern of wetland changes of two study sites. From the derived results, the following conclusions were drawn.

- Landsat data managed to map the wetland ecosystems of Makuleke and Nylsvley with high classification accuracy ranging from 80% to 89% seasonally throughout 5-years.
- It was observed that major changes in wetland extent decrease in natural vegetation and portion of the area are converted to farmlands.
- Even though these wetlands are protected (Makuleke and Nylsvley) they are not free from threats which are intensified by the expansion of LULC changes within and around the catchments.

Conflicting interests in the use and management of wetlands has resulted in the degradation of wetlands during the past decades, therefore it is of important to monitor wetlands to further prevent further degradation, and conserve existing wetland ecosystems. We therefore conclude and recommend that regular monitoring of LULC and wetland changes is important for proper management of the wetlands so there is a need to monitor activities that are taking place within fringes of these wetlands in order to safeguard these resources. In summary, this work demonstrates that spatially explicit catchments wetland monitoring frameworks are crucial in determining wetland conditions, particularly in data-limited environments.

Data availability Statement

Data are available upon request to the corresponding author

Disclosure of potential conflicts of interest

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

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