Received: 19 April 2024 | Revised: 8 June 2024 | Accepted: 10 June 2024

DOI: 10.1111/aje.13300

RESEARCH ARTICLE

African Journal of Ecology WILEY

Assessing the dynamics of land use and land cover change in semi-arid savannah: A focus on woody plant encroachment utilising historical satellite data

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Funding information
National Research Foundation, Grant/Award Number: 138206

Abstract

The encroachment of woody plants into grassland and the conversion of grasslands to woodlands is a worldwide phenomenon and has been regarded as a major global problem for decades. The rate of woody plant encroachment (WPE) varies across biomes and can be influenced by land use activities and climate conditions. As a result, the current study assessed the spatial distribution of woody plants and land use and land cover (LULC) change within the Letaba River catchment in the Limpopo province of South Africa's subtropical region. Landsat Thematic Mapper (TM) and Operational Land Imager (OLI) satellite data sets were used to map and quantify WPE and other LULC changes in the Letaba River catchment over a 30-year period (1989–2019). Random forest classifier was used to determine of the rate of change of WPE and LULC within the study area. The results indicated that the Letaba River catchment has undergone a significant change with an increase in woody plant species. The woody plant cover had increased from 36,014 ha in the year 1989 to approximately 561,493 ha by 2019. Meanwhile, grassland has declined by 486,322 ha (33.7%) from 1989 to 2019. The overall classification accuracy (OA) ranged between 91.7% and 95.5%. The study findings will provide critical insights and baseline information about the state of WPE in semi-arid environments, as well as provide catchment managers with the information they need to take the necessary actions to manage the rapid increase in woody plants. However, fire and herbivory are important factors that influences the WPE, and this might have also played an important role in the findings. The study suggests that WPE is an ongoing process and management strategies are required to mitigate and maintain the intensity of woody plants.

KEYWORDS
land use and land cover change, Letaba catchment, random forest classifier, semi-arid environments, woody plants encroachment

Résumé

L'envahissement des prairies par les plantes ligneuses et la conversion des prairies en forêts constituent un phénomène mondial et est considéré comme un problème mondial majeur depuis des décennies. Le taux d'empiètement des plantes ligneuses (WPE) varie selon les biomes et peut être influencé par les activités d'utilisation des terres et les conditions climatiques. Par conséquent, la présente étude a évalué la distribution spatiale des plantes ligneuses et les changements dans l'utilisation et l'occupation des sols (LULC) dans le bassin versant de la rivière Letaba, dans la province de Limpopo, qui se situe dans la région subtropicale de l'Afrique du Sud. Les données des satellites Landsat Thematic Mapper (TM) et Operational Land Imager (OLI) ont été utilisées pour représenter et quantifier les changements du WPE et d'autres LULC dans le bassin versant de la rivière Letaba sur une période de 30 ans (1989-2019). Un classificateur de forêts d'arbres décisionnels a été utilisé pour déterminer le taux de changement du WPE et de la LULC dans la zone d'étude. Les résultats indiquent que le bassin versant de la rivière Letaba a subi un changement considérable avec une augmentation des espèces de plantes ligneuses. La couverture des plantes ligneuses est passée de 36 014 ha en 1989 à environ 561 493 ha en 2019. Quant aux prairies, elles ont diminué de 486 322 ha (33,7 %) entre 1989 et 2019. La précision globale de la classification (OA) était comprise entre 91,7 % et 95,5 %. Les résultats de l'étude fourniront des informations cruciales et des données de base sur l'état du WPE dans les environnements semi-arides, ainsi que les informations dont les responsables des bassins versants ont besoin pour prendre les mesures nécessaires à la gestion de la croissance rapide des plantes ligneuses. Cependant, les incendies et les herbivores sont des facteurs importants qui influencent le WPE, ce qui pourrait également avoir joué un rôle important dans les résultats. L'étude suppose que le WPE est un processus continu et que des stratégies de gestion sont nécessaires pour atténuer et maintenir l'intensité des plantes ligneuses.

1 | INTRODUCTION

Several studies (e.g. Acharya et al., 2018; Caterina, 2012; De Klerk, 2004; Moleele et al., 2002; Ward, 2005) have suggested that the world's savannah and grasslands are being altered by a process known as woody plant encroachment (WPE). The WPE is a type of ecological succession in which woody plants replace herbaceous vegetation like grasses and forbs (Ding et al., 2020; Mokgotsi, 2018; Mokoka, 2016; Mpati, 2015). Bush thickening, woody plants invasion and plant regrowth are all synonyms for WPE (Acharya et al., 2018; Kiswaga et al., 2020; Malapane et al., 2024). It includes a wide range of woody plant species, from shrubs to trees, evergreen to deciduous, deciduous and broad-leaved to needle-leaved (Liu et al., 2013; Stahl, Hérault, et al., 2013; Stahl, Kattge, et al., 2013).

The WPE has been classified as another type of land degradation and is regarded as one of the most significant ecological changes (Oldeland et al., 2010). For more than a century, it has been recognised as a global rangeland problem (Eldridge et al., 2011; Grellier et al., 2013; Liao et al., 2020; O'Connor et al., 2014; Russell & Ward, 2014; Wilcox et al., 2022). However, not all forms of encroachment are harmful to the ecosystem, some are natural vegetation succession, that play an important role in improving the infiltrability of soil and percolation in semi-arid regions (Leite et al., 2020). The WPE can be due to overgrazing, increased atmospheric carbon dioxide, fire suppression, loss of browser herbivores, warmer temperatures and altered rainfall patterns (Belayneh & Tessema, 2017; Brunelle et al., 2014; Daskin et al., 2016; Kraham, 2017). Grazing can reduce fuel loads, resulting in the reduction fire frequency and intensity that historically kept woody plants suppressed (Venter et al., 2018). Increase in carbon dioxide concentration favours woody plants that have the C3 photosynthetic pathway over grasses that have the C4 photosynthetic pathway (Quirk et al., 2019). Venter et al. (2018) reported that rainfall is identified as one of the main causes of WPE. Nevertheless, on local scale, increase in temperatures have shown to be the main cause of WPE through declines in frost-induced tree mortality. Nonetheless, WPE is mostly associated with overgrazing and has been particularly widespread in arid and semi-arid savannahs, with approximately 20 million hectares (ha) affected in South Africa alone (Belayneh & Tessema, 2017; Case & Staver, 2017; Moleele et al., 2002; Sankaran & Anderson, 2009).

Herbivory grazing reduces biomass, therefore reducing the chances of fire, which have kept WPE in check (Pierce et al., 2019). Moreover, heavy livestock grazing has caused the replacement of palatable grass species by less palatable bushes and shrubs (Symeonakis & Higginbottom, 2014). South Africa has lost about 50% of grazing capacity in rangelands due to the replacement of palatable grass by less palatable bushes and shrubs (Gigliotti et al., 2020; Grossman & Gandar, 1989). Savannahs have also lost their mammalian fauna; therefore, this has further affected the maintenance of savannahs as they also dependant on mammals for maintenance. Fire is now the main factor left to maintain savannahs (Murphy et al., 2015). According to Kavwele et al. (2017), WPE in isolated ecosystems can lead to reduction or extinction of indigenous species and can potentially affect the diversity of species, distribution and abundance. The WPE can also change the biogeochemical, energy, processes, grassland microclimate, decrease the diversity of herbaceous species, alters the nutrient cycle, soil hydrological properties and ecosystem water budget (Petersen & Stringham, 2008).

It has also been demonstrated that an increase in woody plants has a significant impact on rangeland-based agriculture and biodiversity (Ayalew & Mulualem, 2018). About 10–20 million ha of South Africa's agricultural land has declined, and this has affected agricultural production and biodiversity due to WPE (Stafford et al., 2017). Furthermore, WPE alters species composition, ecosystem processes, carbon and nutrient cycles, groundwater recharge and increases carbon and nitrogen pools in plants and soils (Caterina et al., 2014; McKinley & Blair, 2008; Zou et al., 2016).

The WPE is most severe in arid to semi-arid environments, which cover nearly 40% of the world's land and are used for rangeland activities on about 50% of it (Huang et al., 2018; Malapane et al., 2024; Shikangalah & Mapani, 2020). According to Belayneh and Tessema (2017), semi-arid rangelands around the world have gone from grasslands to woodlands in the last 50 years. Woody plants now dominate approximately 45 million ha of savannah ecosystems worldwide (Uchezuba et al., 2019). South Africa alone has lost 8 million ha of grazing or cultivation land because of WPE, resulting in decreased food security (Stafford et al., 2017). However, there are still grasslands with less trees and savannahs with high woody cover savannahs that are healthy systems and there are savannahs that are transitioning to woodlands. The transition of vegetation in arid savannahs differs among regions, with Africa and India transitioning to closed dry thicket, South America to hummock grassland and Australia transition to shrub-like *Triodia* vegetation type. There are areas which are dry to support grass growth and areas that can support grass growth; however, other vegetation outcompetes the grass and hinders their growth.

For several decades, researchers have used remote sensing techniques to map and monitor vegetation change (Feng et al., 2015; Rawat & Kumar, 2015; Zhang et al., 2020), with WPE being one of the most performed assessments (Graw et al., 2016; Liao et al., 2018; Oldeland et al., 2010; Symeonakis & Higginbottom, 2014). Remote sensing is currently widely used as an effective tool for providing spatial and temporal information about tree cover change in savannah and grassland environments (Pérez-Cabello et al., 2021), as remote sensing techniques provide relatively accurate and up-to-date information (Adam et al., 2010; Çömert et al., 2019; Khalid et al., 2018; Wachowiak et al., 2017). Although it is less expensive and takes less time than actual field surveys, a combination of field surveys and remote sensing techniques produce the best results (Weiss et al., 2020).

Since the year 1984, Landsat data have been used to record continuous LULC changes at spatial and temporal resolutions (Wulder et al., 2012, 2016). Landsat is the longest operating earth observation satellite; therefore, it is ideal for studying long-term environmental changes (Song et al., 2021). Landsat data have also been used to assess long-term changes in forests, croplands and prairies at the local, regional and national levels (Dong et al., 2015; Helber et al., 2019; Müller et al., 2015; Zhang et al., 2014). There are various classification techniques, ranging from pixel-based to object classification (Qu et al., 2021; Sibaruddin et al., 2018; Vogel & Strohbach, 2009; Zhang et al., 2019). Deep learning classifiers have recently evolved and can achieve high accuracy in land cover classification (Abdi, 2020; Helber et al., 2019; Pan et al., 2022; Rumora et al., 2020). Because WPE is a continuous process, assessment techniques that can quickly identify and monitor these changes are required. Studies have focused on mapping woody plants in areas dominated by shrubs and grasses (e.g. Brandt et al., 2016; Higginbottom et al., 2018; Ludwig et al., 2016). As a result, the rate of change in woody plants is expected to vary across regions in relation to LULC types/changes (Archer et al., 2017). Therefore, it is critical to map and monitor the WPE in areas as well as changes in other LULC. The Letaba River catchment contains a variety of LULC types, including agriculture and urbanisation. Thus, using Landsat 5 TM and 8 OLI, this study assessed the extent of WPE over a 30-year period. Landsat data were used because it contains historical information that can be utilised to map the long-term spatial distribution of WPE (Tokar et al., 2018). The study further evaluated the changes that occurred over the 30-year period to determine the changes in LULC. While WPE is another form of land degradation not all form of WPE have negative impact to the environment. There are areas that are experiencing WPE but are healthy regardless of the transition. Moreover, WPE has been previously reported to have effect on grass species than on other LULC. However, in this study, reduction of areas covered by other LULC due to WPE is observed such as the reduction of agricultural land and grassland. Nonetheless, the study hypothesised that WPE increased with time at an expense of other LULC particularly grassland.

2 | MATERIALS AND METHODS

2.1 | Study area

The Letaba River catchment is part of the Limpopo River basin and spans 14,086 km^2. The Letaba River has three main tributaries: the Klein Letaba River in the northwest, the Middle Letaba and Groot Letaba rivers in the southwest, and other major tributaries including the Nsama, Letsitele and Molototsi rivers (Querner et al., 2016). The river together with the tributaries flow from the mountain area in the western part of the catchment to the east, where it meets the Kruger National Park's western boundary. The Letaba River flows into the Olifants River near the Mozambican border, then into the Limpopo River before emptying into the Indian Ocean (Ndara, 2017). The mountainous topography at the western headwaters of the Letaba Catchment results in a higher rainfall with the mean annual rainfall ranging between 700 and 1500 mm, while the mean annual rainfall for the remainder of the catchment varies from 450 to 800 mm (Mkwalo, 2011; Raubenheimer, 2018). The catchment has a diverse geology composed primarily of sedimentary rocks in the north and rocks in the south (Holland, 2011). The northern part of the Kruger National Park consists of high-quality coal deposits, while the mineral rich Bushveld igneous complex is found on the southern parts of the water management area (DWAF, 2004). Moreover, the western part of the Letaba Catchment is comprised of granite and gneiss with dolerite intrusions, quartzite, shale and sandstone. Furthermore, the eastern part consists of basalt, rhyolite and granophyre, and granite and gneiss with dolerite intrusions (Ndara, 2017). The Letaba River basin has a diverse range of soils, with sandy soils being the most common. In mountainous areas, composite and deep fractured aquifers predominate in relatively impermeable bedrock. The average annual precipitation in the Letaba catchment region is 612 mm, with more than 60% captured in only 6% of the total area, which is the mountainous region in the west (Olivier & Jonker, 2013). The precipitation in the western mountainous areas ranges from 500 to 1800 mm, while the east receives 450–700 mm (Heritage et al., 2001). The annual evaporation average is estimated to be 1669 mm (Olivier & Jonker, 2013). At lower elevation (<650 m NN), the area is dominated by savannah vegetation (grass and shrubs) which are interspersed by agricultural activities particularly along the river. However, the high elevation is comprised of forests, especially monoculture of eucalyptus, pine and acacia (Krause et al., 2014; Figure 1).

2.2 | Field surveys

2.2.1 | Reconnaissance survey

Before analysing the satellite images, an overview field survey of the study area was conducted. Visual observations were made to learn about the topography, vegetation, soil and general characteristics of the Letaba River catchment. Table 1 describes in detail the observed LULC classes within the study area. The classes were used to assess the accuracy of classified maps. This stage aided in the preparation of satellite images for classification as well as the collection of data on LULC types in the study area.

2.3 | Image selection

Landsat 5 TM and 8 OLI with high spatial resolution were used. The years 1989, 1998, 2004 and 2019 were chosen to evaluate the extent of WPE and other LULC changes in the Letaba River catchment (Table 2). The selection of these specific years of satellite images was

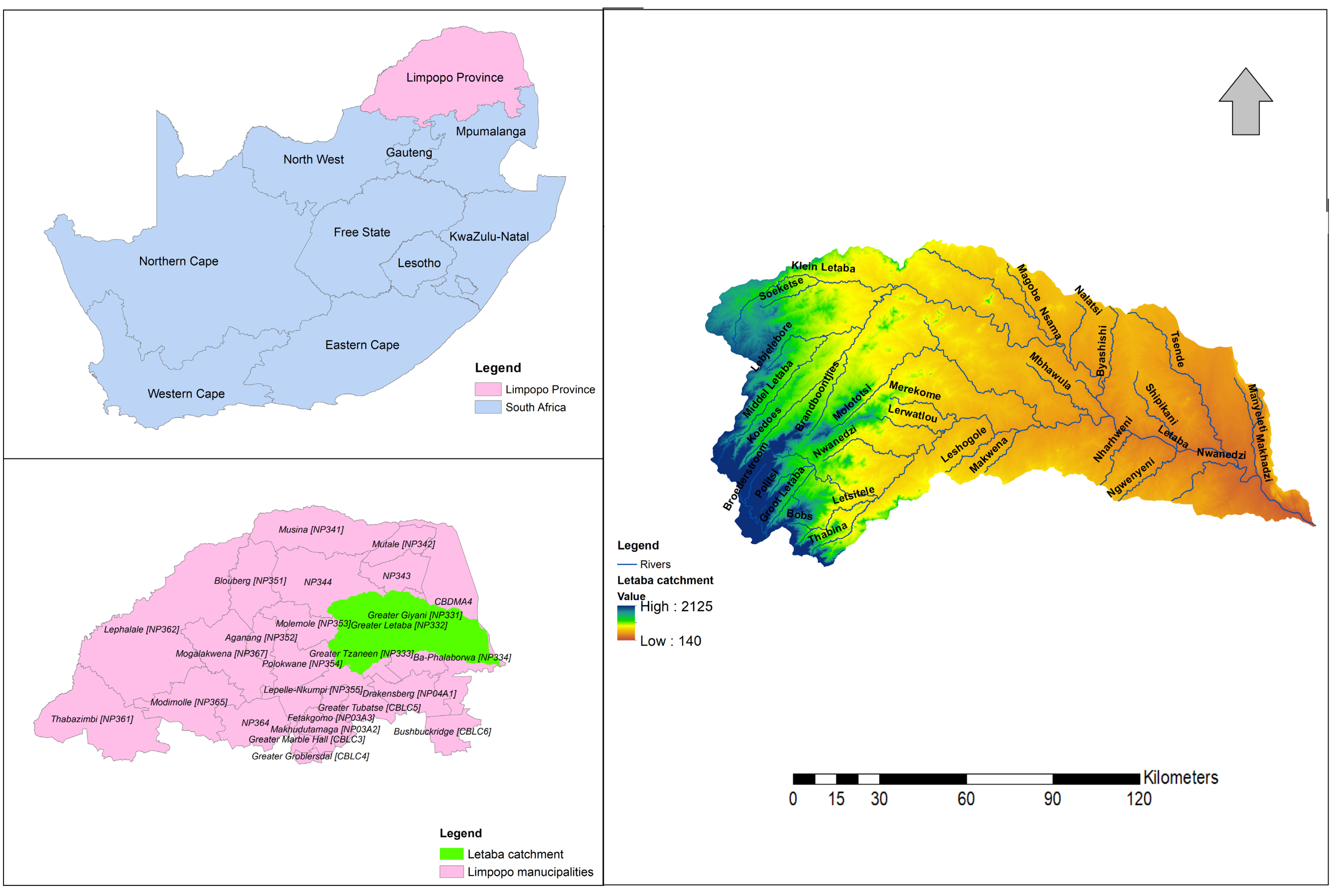

FIGURE 1 Letaba River catchment in the Limpopo Province, South Africa.

TABLE 1 Description of LULC classes within the Letaba River catchment.

Classes	Description
Forest	Natural forest
Plantation	Agricultural activities, farmlands and cultivated lands
Non-vegetated	Developed lands (urbanisation), including residential, commercial and socio-economic infrastructure and bare land (area without or with little vegetation cover)
Waterbodies	Rivers, dams, streams and lakes
Shrubland	Shrubs and bushes
Grassland	Herbaceous layers such as grass and forbs

TABLE 2 Landsat data images used in this study.

Sensor	Date of acquisition	Source
Landsat 5 TM (Thematic Mapper)	12 September 1989	USGS (United States of Geological Survey)
	20 August 1998	
	25 August 2004	
Landsat8 OLI (Operational Land Imager)	25 May 2019	

entirely based on the quality (e.g. radiometric and geometric errors) and long-time series availability. It must also be noted that four images of the same month was mosaicked into one image. During the mosaicking process it was noted that, most of the images between 2004 and 2019 had a misfit, resulting in a large gap when compared to space between other years chosen. Misfit in this case mean other images were flipped or rotated such that features do not appear to be where there are supposed to be. For examples rivers connection were not clearly or well represented on the satellite images. This would have affected the general findings of the study because LULC types would have appeared where they are not supposed to appear, for example, riparian vegetation would have appeared to be at the edge of the study area instead of where there is rivers connection are. Therefore, land cover such as riparian vegetation would have appeared where there are no river connections. The Landsat satellite imagery was chosen because it has enough historical data, it is freely available, and it has been shown to perform well in other land cover classification and woody plant analysis studies (e.g. Fashae et al., 2020; Ghaderpour & Vujadinovic, 2020; Symeonakis et al., 2016; Wang et al., 2017; Yang & Crews, 2019). The Landsat images were obtained from the Earth Explorer program of the United States Geological Survey (USGS) (usgs.gov). Landsat imagery is suitable for mapping woody plant encroachment due to its wide swath width and moderately high spatial resolution (30 m).

2.4 | Image pre–processing

The satellite imagery was pre-processed with the goal of correcting defects inherent in remotely sensed data (i.e. radiometric and geometric distortions) and improving the raw data quality to facilitate data interpretation. The images were enhanced further to improve visual interpretation and the appearance of land features. Image enhancement techniques such as linear contrast stretching, and edge enhancement filters were used to improve the image visual interpretation. Image restoration was also used to compensate for image errors, noise and geometric distortions caused by scanning, recording and playback operations. This was accomplished using ERDAS imagine 2014's geometric correction, radiometric correction (haze compensation) and noise reduction filters. The goal was to make the restored image easier to read the type of LULC for better classification maps.

2.5 | Image processing

The layer stacking tool in ArcMap 10.8 software was used to combine the individual monochromatic bands. This was accomplished by importing Landsat 5 TM bands 1–7 and Landsat 8 OLI bands 1–11 into the software and combining them with the layer stacking tool to create the necessary data set (i.e. a true colour composite map). It should be noted that the acquired remotely sensed data were in the form of individual monochromatic bands (i.e. visible bands, VNIR bands and SWIR bands) (Table 3). Because the individual bands were ineffective at identifying different LULC types, they were combined to form a single data set that could then be used to identify different LULC types. During layer stacking, the nearest neighbour resampling method was used to ensure that all pixels in the bands were reordered appropriately, and that the radiometric integrity of the data was preserved. The composited images were then overlaid with the Letaba River catchment shapefile to ensure that only the study region was extracted. Random forest classifier (RF) was used to generate classified LULC maps, because RF has a non-parametric nature, high classification accuracy and the ability to determine change or variability within the catchment (Desai & Ouarda, 2021; Janitza et al., 2018; Rodriguez-Galiano et al., 2012; Soleimannejad et al., 2019; Zhao et al., 2022).

Landsat 8 sensor	Band name	Wavelength (mm)	Spatial resolution (m)
Landsat 8 OLI			
1	Coastal/ aerosol	0.43–0.45	30
2	Blue	0.45–0.52	
4	Green	0.53–0.60	30
5	Red	0.63–0.68	30
4	Near infrared (NIR)	0.85–0.89	30
5			
6	Short-wave infrared (SWIR)1	1.56–1.66	30
7	Short-wave infrared (SWIR)2	2.10–2.30	30
8	Panchromatic	0.500–0.68	15
9	Cirrus	1.360–1.39	30
10	Long-wave infrared (LWIR) 1	10.60–11.20	30
11	Long-wave infrared (LWIR) 2	11.50–12.50	30
Landsat 5 TM			
1	Visible blue	0.45–0.52	
2	Visible green	0.52–0.60	30
3	Visible red	0.63–0.69	30
4	Near infrared (NIR)	0.76–0.90	30
5	Short-wave infrared (SWIR)1	1.55–1.75	30
6	Thermal	10.40–12.50	120
7	Short-wave infrared (SWIR) 2	2.08–2.35	30

TABLE 3 Bands description for Landsat 8 OLI and Landsat 5 TM band specifications used for 1989–2019.

2.6 | Accuracy assessment

Accuracy assessment is a critical final step in the classification process. The accuracy assessment goal was to quantify how well the pixels were classified into the correct land cover classes. RF focus for accuracy assessment pixel selection was on every part of the area to avoid biasness. It was done to compare the performance of RF classifiers for classified images. Using classified images, accuracy assessment points were created in ArcGIS 10.8. The points were then converted to KML files and imported into Google Earth. The goal of using Google Earth in this case was to determine which pixels of each land cover were correctly classified and which were incorrectly classified. A total of 400 points were chosen at random. According to Parece and Campbell (2013), selecting many points yields a more reliable set of results. The points were then represented on an attribute table to validate the classified land classes.

3 | RESULTS

3.1 | Spatial distribution of WPE and other land use and land cover types

According to the classified maps, shrubland has increased from 1989 to 2019. The area covered by shrubs has increased significantly from 36,014 ha (2.6%) in 1989–561,493 ha (46.9%) in 2019; however, the area covered by grasses has decreased from 507,454 ha (37.1%) to 21,132 ha (1.7%) (Figure 2; Table 4). Overall, shrubland increased by 525,479 ha (44.3%), while grassland decreased by 486,322 ha (35.4%) (Figures 4 and 6). In 1989, grasslands predominated over shrubland and other land use activities in the catchment area, covering approximately 507,454 ha (37.1%) of the total area, while non-vegetated areas covered approximately 653,460 ha (47.8%). In 1998, shrubland increased by 36,014 ha–146,053 ha (8%). The results also show increase in area of plantation from 1989 to 2004 of approximately 10.3% (Figures 5 and 6). Increase in area of plantation has negative environmental impacts (Spawn et al., 2020). Reduced grassland cover leaves soils less protected from soil erosion leading to reduced soil organic matter. In addition, application of commercial fertiliser can lead to high amounts of nutrient inputs into soils and eutrophication of waterways through runoff or leaching (Zhang et al., 2021).

Water bodies, forests, and non-vegetated land have all fluctuated over the last 30 years (Table 4). Waterbodies, forest, plantation and non-vegetated areas covered approximately 13,747 ha, 81,919 ha, 74,236 ha and 653,460 ha, respectively, in 1989. Waterbodies, forest, and non-vegetated area cover 21,444 ha, 54,157 ha, 109,402 ha and 427,128 ha, respectively, in 2019. Figure 2 depicts the changes in shrubland and other LULC types that occurred within the Letaba River catchment. The resulting RF classifier for the LULC classifications for the four chosen years shows a significant increase in woody plants, particularly in the western part of the region (Figures 2 and 3).

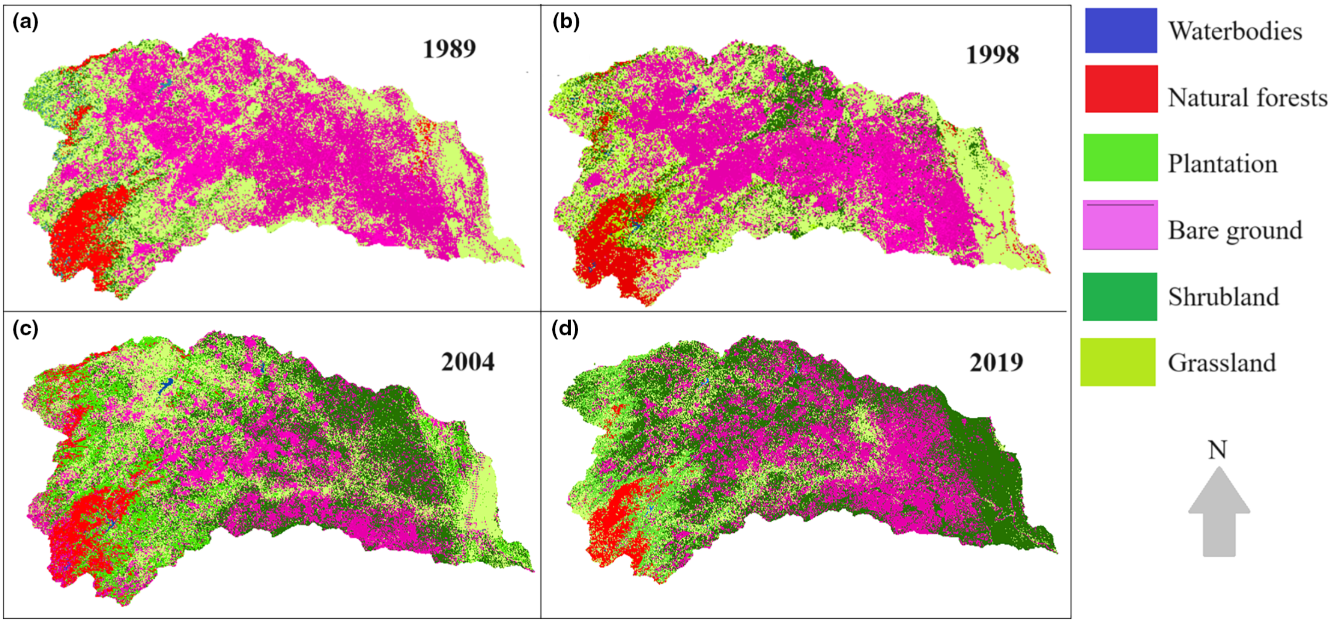

FIGURE 2 The spatial distribution of WPE and other identified LULC types within the Letaba River catchment.

TABLE 4 Area (ha) coverage in the Letaba River system catchment region between 1989 and 2019.

LULC	1989	Cover (%)	1998	Cover (%)	2004	Cover (%)	2019	Cover (%)
Shrubland	36,014	2.6	146,053	10.6	366,841	28.7	561,493	46.9
Grassland	507,454	37.1	457,555	33.4	358,669	28	21,132	1.7
Plantation	74,236	5.4	67,874	4.9	201,517	15.7	109,402	9.1
Forest	81,919	5.6	88,823	6.4	82,583	6.4	54,157	4.5
Non-vegetated	653,460	47.8	601,651	44.01	263,708	20.64	427,128	35.75
Waterbodies	13,747	1	4873	0.3	4157	0.3	21,444	1.7

Abbreviation: LULC, land use and land cover.

3.2 | Accuracy assessment derived classified maps

Validation was carried out using the four classified maps. A total number of 400 random points was distributed across the scene with a minimum number of 38 points and maximum number of 111 points allocated to the smallest class and highest class (i.e. waterbodies and nonvegetated area), respectively to ensure that an adequate number of samples was used for the assessment of every class. The RF classifier achieved high overall classification accuracies ranging from 91.7% to 95.5% between 1989 and 2019 (Tables 5–8). Overall classification accuracies achieved in 1989, 1998, 2004 and 2019 were 91.7%, 93.2%, 95.2% and 95.5%, indicating that there was agreement between reality on the ground and satellite-derived images. Furthermore, the accuracies of the producer and user ranged from 82% to 100%, respectively. Furthermore, the results revealed low error of omission and commission rates ranging from 0% to 18%, respectively (Figure 4).

4 | DISCUSSION

Over a 30-year period, the researchers examined the spatial distribution of woody plants (years 1989–2019). According to the findings, the catchment region has undergone significant changes due to an increase in woody plants. From 1989 to 2019, the area covered by woody plants increased by 44.3%, while grassland decreased by 35.4%. Similarly, other studies (e.g. Symeonakis & Higginbottom, 2014; Mpati, 2015; Browning et al., 2014) have linked an increase in woody plants to a decrease in grasslands. Over 20 years, Symeonakis and Higginbottom (2014) observed a significant aerial increase in woody plants from 58% to 67% and a significant decrease in grasslands from 41% to 33% in South Africa's North-West Province. Doyo et al. (2019) study in Ethiopia found a 70% increase in woody plants in the Borana Rangelands region, which supports the current study findings. González-Roglich et al. (2015) discovered a 27% increase in woody plant density in the Caldenal savannahs of

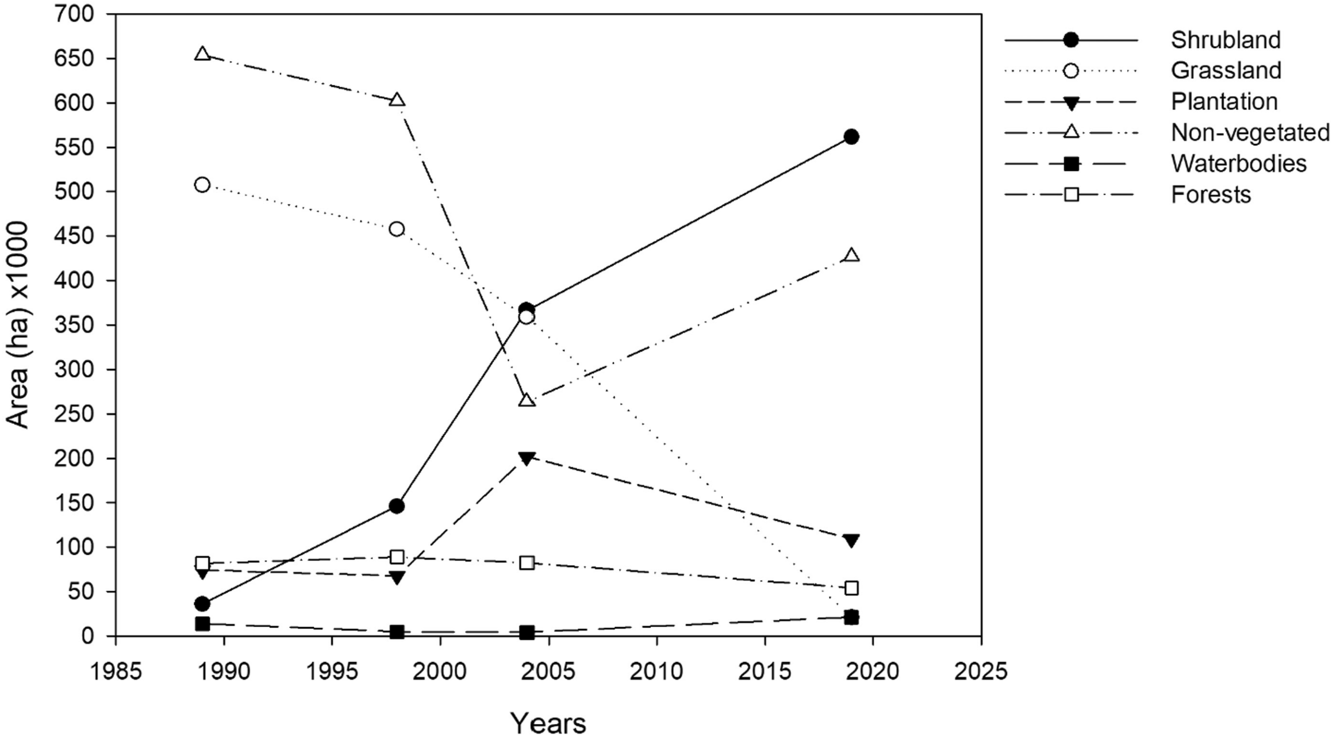

FIGURE 3 Change in the area (ha) covered by shrubland and other LULC types in the Letaba River catchment area from 1989 to 2019.

TABLE 5 Derived land use and land cover classification accuracies for 1989 in the Letaba River catchment, South Africa.

	Forest	Waterbodies	Plantation	Non-veg (bare land)	Non-veg (settlement)	Shrubland	Grassland	Total	Commission error (%)	User's accuracy (%)
Forest	52	0	0	0	0	0	0	52	0.00	100.00
Waterbodies	0	33	1	1	0	0	0	35	5.70	94.30
Plantation	9	0	55	0	0	0	1	65	15.30	84.60
Non-vegetated (bare land)	0	0	2	63	2	1	0	68	7.30	92.60
Non-vegetated (settlement)	0	2	1	0	44	0	0	47	6.30	93.60
Shrubland	0	1	2	1	0	66	1	71	7.00	93.00
Grassland	0	2	6	0	0	0	54	62	12.90	87.10
Total	61	38	67	65	46	67	56	400		
Omission error (%)	14.70	13.10	17.90	14.00	4.30	1.40	3.70			
Producer's accuracy (%)	85.20	86.80	82.00	98.60	95.60	98.60	96.40			
Overall accuracy (%)	91.70									
Kappa coefficient	0.8									

Abbreviations: non-veg, non-vegetated; OA, overall accuracy; PA, producer accuracy; UA, user accuracy.

central Argentina in the 1960s, transitioning from open savannahs to a mosaic of dense woodlands with additional agricultural clearings. Similarly, Nill et al. (2022) reported similar findings in the Western Canadian Arctic. Stevens et al. (2016) discovered an 8% increase in woody plant cover across sub-Saharan Africa over a 30-year period. Skowno et al. (2017) measured the extent to which woodlands replaced grasslands in South Africa's grassland over a 23-year period and discovered that woodlands replaced grasslands by more than 57,000 km^2.

Woody plant cover is increasing most rapidly in savannahs, according to Stafford et al. (2017), most likely due to fire suppression and land fragmentation. However, changes in grassland and savannah ecosystems to woodlands vary across different areas (Skowno et al., 2017). Areas with more than 500 mm of mean annual

TABLE 6 Derived land use and land cover classification accuracies for 1998 in the Letaba River catchment, South Africa.

	Forest	Waterbodies	Plantation	Non-veg (bare land)	Non-veg (settlements)	Shrubland	Grassland	Total	Commission error (%)	User's accuracy (%)
Forest	50	0	0	0	0	0	0	50	0.00	100.00
Waterbodies	0	34	1	1	0	0	0	36	5.50	94.40
Plantation	9	0	58	0	0	0	0	67	13.40	86.50
Non-vegetated (bare land)	1	1	0	64	0	1	1	68	5.80	94.10
Non-vegetated (settlement)	0	0	0	0	46	0	0	46	0.00	100.00
Shrubland	1	1	2	0	0	66	0	70	5.70	94.30
Grassland	0	2	6	0	0	0	55	63	12.70	87.30
Total	61	38	67	65	46	67	56	400		
Omission error (%)	18.00	10.50	13.40	1.40	0.00	1.40	1.40			
Producer's accuracy (%)	82.00	89.40	86.50	98.60	100.00	98.60	98.60			
Overall accuracy (%)	93.20									
Kappa coefficient	0.80									

Abbreviations: non-veg, non-vegetated; OA, overall accuracy; PA, producer accuracy; UA, user accuracy.

TABLE 7 Derived land use and land cover classification accuracies for 2004 in the Letaba River catchment, South Africa.

	Forest	Waterbodies	Plantation	Non-veg (bare land)	Non-veg (settlements)	Shrubland	Grassland	Total	Commission error (%)	User's accuracy (%)
Forest	58	0	0	0	0	0	0	58	0.00	100.00
Waterbodies	0	36	1	0	1	1	0	39	7.60	92.40
Plantation	0	0	59	0	1	2	0	62	4.80	95.10
Non-vegetated (bare land)	0	1	2	64	0	0	1	68	5.80	94.20
Non-vegetated (settlement)	2	1	0	1	44	0	1	49	10.20	89.80
Shrubland	1	0	1	0	0	64	0	66	3.30	96.70
Grassland	0	0	4	0	0	0	54	58	6.90	93.10
Total	61	38	67	65	46	67	56	400		
Omission error (%)	4.90	5.20	11.90	1.50	4.30	4.40	3.50			
Producer's accuracy (%)	95.20	94.70	88.10	98.50	95.70	95.60	96.50			
Overall accuracy (%)	94.70									
Kappa coefficient	0.80									

Abbreviations: non-veg, non-vegetated; OA, overall accuracy; PA, producer accuracy; UA, user accuracy.

precipitation have higher woodland rate expansions than areas with less than 500 mm. Furthermore, elephant–protected areas show a clear loss of woodlands, whereas commercial and traditional rangelands show an increase in woodland extent. Huang et al. (2018) found no increase or decrease in woody cover over a 28-year period in southern Arizona. As a result, changes in woody plants can be affected by factors such as precipitation and other climatic conditions.

The Letaba catchment is dominated by rural areas and most of these rural communities practice livestock production. Livestock grazing is the main use of grasslands globally (Asner et al., 2004) and is often associated with WPE. Livestock grazing removes fuel loads, which reduces the frequency and intensity of fire leading to WPE (Madany & West, 1983). Moreover, the introduction of livestock can be linked with displacement of indigenous browsers and seed predators, releasing woody plants from top-down controls. Furthermore, land abandoned can also influence WPE such as transition of forest to agricultural land and later abandon it. As observed from the results plantation decrease with increase in woody plats cover. While land management practices are seen as the main contributor of WPE (Wigley et al., 2009), increase in atmospheric

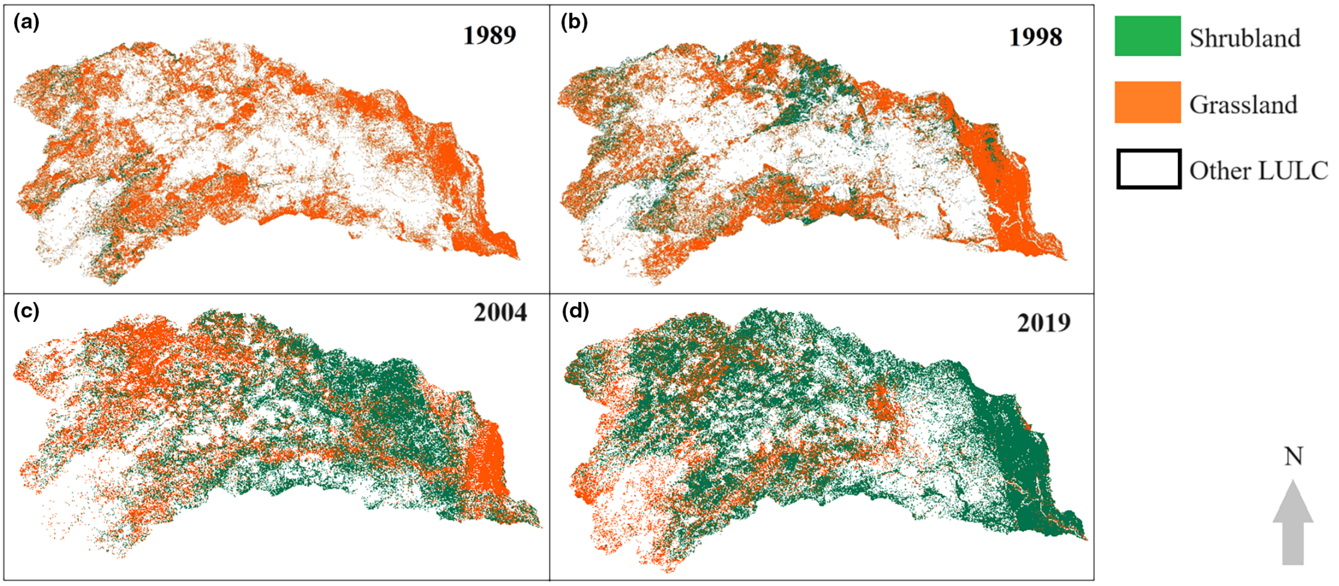

FIGURE 4 The spatial distribution of woody plants and grassland within the Letaba River catchment.

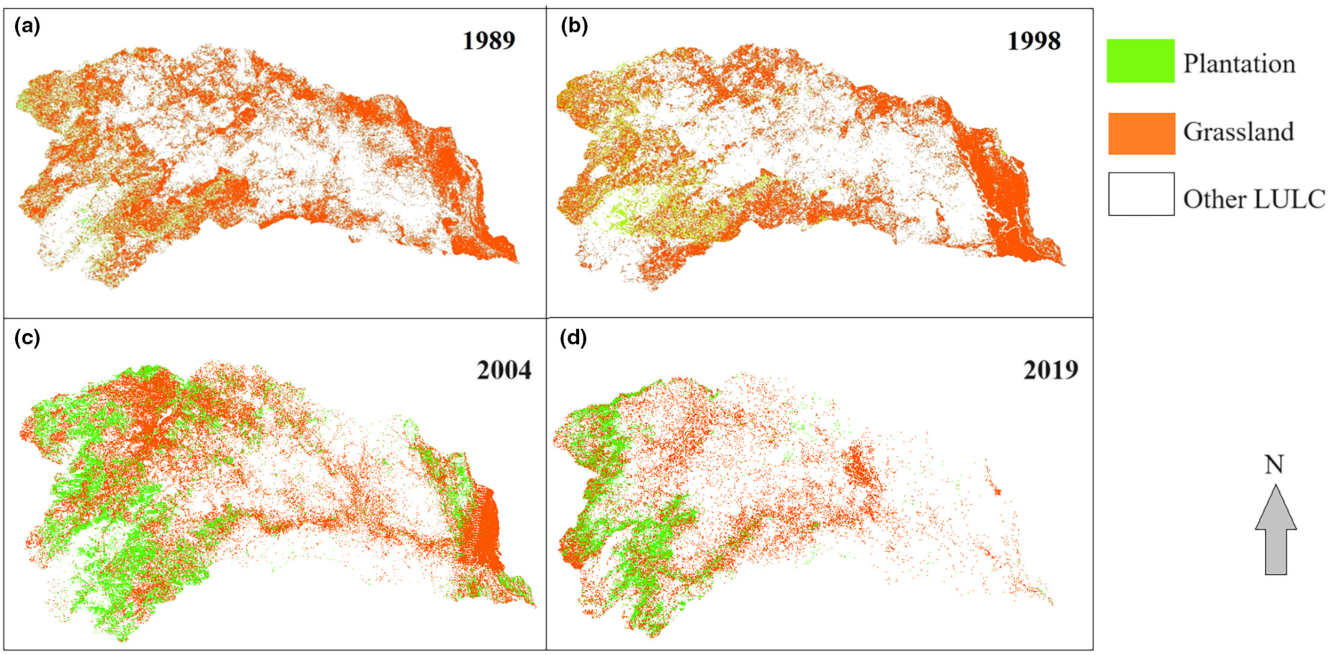

FIGURE 5 The spatial distribution of grassland and plantation within the Letaba River catchment.

concentration of greenhouse gases such as carbon dioxide has also been documented to be one of the primary factors that influence WPE (Stevens et al., 2016). Archer et al. (2017) reported that precipitation can accelerate the growth and density of woody plants further explains that precipitation can also be the cause of WPE as mesophytic grasses transition to xerophytic bushes. With regards to the Letaba catchment the pattern and trends of WPE might have also been influenced by minimal precipitation.

Mapping the spatial distribution of woody plants over time is critical for detecting and monitoring changes as well as understanding trends. Remote sensing data have been shown to be accurate in mapping environmental changes, and it is also freely available (Bechtel et al., 2015; Dong et al., 2016; Gómez et al., 2016; Tulbure et al., 2022). As a result, Landsat data with a spatial resolution of 30 m were used, and the spatial distribution of WPE has been successfully mapped for over 30 years. Hostert et al. (2003) mapped vegetation change in central Crete, Greece, between 1977 and 1996 using Landsat TM and the multispectral Scanner System (MSS). Röder et al. (2008) assessed the spatio-temporal patterns of vegetation cover development in a rangeland system in northern Greece from 1984 to 2000 using Landsat TM and Enhanced Thermatic Mapper Plus (ETM+). Sonnenschein et al. (2011) used Landsat TM and ETM+ in vegetation dynamics in a Mediterranean environment based on different vegetation indices, and all these studies demonstrated success in mapping vegetation change using Landsat data.

However, using Landsat data to map woody plants can be difficult because woody plants can have high spatial and temporal dynamics and can be the dominant vegetation type or a transitional vegetation formation (Petraitis, 2013). According to Leitão et al. (2015), woody plants have different developmental stages and densities, resulting in diverse landscape patterns. Landsat's spatial resolution of 30 m is likely to result in a high degree of spectral mixing within each 30 m pixel. However, using Landsat data, the current study produced reliable results.

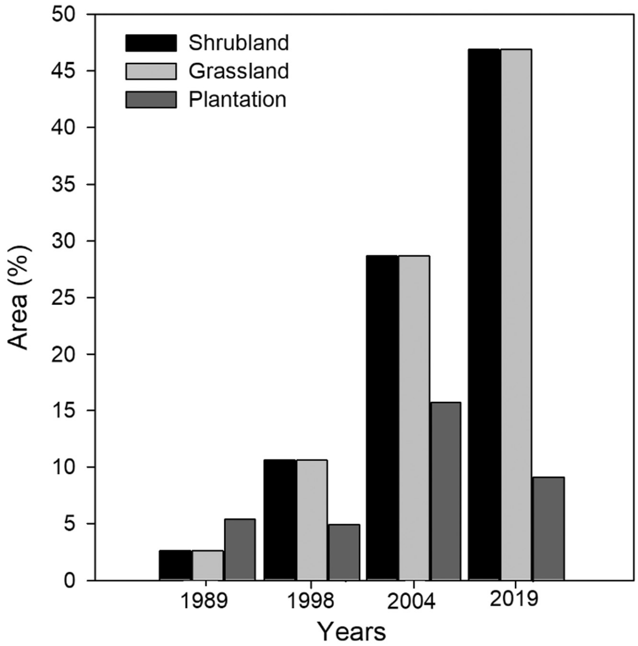

FIGURE 6 Change in the area (%) covered by shrubland, grassland and plantation in the Letaba River catchment area from 1989 to 2019.

5 | CONCLUSIONS

Woody plant encroachment has a negative impact on grasses and other species, resulting in an unbalanced ecosystem. As a result, analysing the spread and distribution of woody plants will provide insight into their nature of occurrence, structures and establishment, as well as valuable information about the relationship between woody plants and grassland and other LULC. Conservationists can also use the data to develop effective management strategies to reduce WPE. The study will also provide information on the distribution of woody plants, which is currently lacking in semi-arid areas. Through the analysis of past and current data, this will allow the prediction of future trends in the distribution and abundance of woody plants. Analysing WPE trends can help identify some of the most important implications of complex interactions between social and environmental processes. The study will also help catchment managers take the necessary steps to control the spread of woody plants. Long-term monitoring of WPE is required to improve understanding of broad-scale changes in woody vegetation and the potential link between such changes and ecosystem resilience or degradation. A retrospective analysis has yielded useful information about the rate of change in WPE as well as the nature of the occurrence. Landsat data have been used for decades and have proven to be a reliable tool in mapping WPE and other LULC change. We discovered that WPE is increasing steadily and rapidly at the expense of grassland using

TABLE 8 Derived land use and land cover classification accuracies for 2019 in the Letaba River catchment, South Africa.

	Forest	Waterbodies	Plantation	Non-veg (bare land)	Non-veg (settlements)	Shrubland	Grassland	Total	Commission error (%)	User's accuracy (%)
Forest	59	0	0	0	0	0	0	59	0.00	100.00
Waterbodies	0	36	0	0	0	0	0	36	0.00	100.00
Plantation	0	0	59	0	0	2	0	61	3.40	96.60
Non-vegetated (bare land)	0	0	0	63	0	1	1	65	3.00	97.00
Non-vegetated (settlement)	1	0	1	0	46	0	0	48	4.20	96.80
Shrubland	1	0	1	1	0	64	0	67	4.40	96.60
Grassland	0	2	6	1	0	0	55	64	14.10	85.90
Total	61	38	67	65	46	67	56	400		
Omission error (%)	330.00	5.20	11.90	3.10	0.00	4.50	1.80			
Producer's accuracy (%)	96.70	94.80	88.10	96.90	100.00	95.50	98.20			
Overall accuracy (%)	95.50									
Kappa coefficient	0.8									

Abbreviations: non-veg, non-vegetated; OA, overall accuracy; PA, producer accuracy; UA, user accuracy.

Landsat data and a random forest classifier. Overall, we conclude that the findings of this study show that remote sensing can be used to successfully map WPE. Furthermore, the study's findings show that the Random Forest classifier can produce high overall accuracies. Savannah and grasslands are undergoing rapid land cover transformation because of WPE. An increase in the density of woody plants along the Letaba Catchment decreased grass richness and agricultural land, as a result, this might have an impact on forage production for livestock, therefore, leading to food insecurity. Therefore, the study recommends that there must be policies that aim to encourage sustainable land use practices, together with the control of WPE and the restoration and rehabilitating of degraded ecosystems. Methods such as mechanical, chemical and combination treatments should be used to control and reduce the increase in densities of woody plants. Other methods such as mechanical which includes cutting, uprooting and burning of the plant is reported to be time consuming; although, it has proven to be an effective and successful method used thus far. Moreover, government-based and community-based projects aimed at controlling or mitigating the problem of WPE is required.

ACKNOWLEDGEMENTS

The authors would like to extend gratitude to the South African National Space Agency for funding this project to CM and the US Geological Survey for providing the free data (http://earthexplorer.usgs.gov). TD is supported by the National Research Foundation Thuthuka grant (#138206).

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest. The funders had no role in the design of the study, in the collection, analyses or interpretation of data, in the writing of the manuscript or in the decision to publish the results.

DATA AVAILABILITY STATEMENT

The data sets analysed during the current study are available from the authors on reasonable request.

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How to cite this article: Malapane, C., Dube, T., & Dalu, T. (2024). Assessing the dynamics of land use and land cover change in semi-arid savannah: A focus on woody plant encroachment utilising historical satellite data. *African Journal of Ecology*, *62*, e13300. https://doi.org/10.1111/aje.13300.