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ARTICLE

Land use land cover change and the comparative impact of co-management and government-management on the forest cover in Malawi (1999-2018)

Monica Fides Gondwe [a,b], Moses Azong Cho [a,b], Paxie Wanangwa Chirwa [a] and Coert Johannes Geldenhuys [a]

[a]Department of Plant and Soil Sciences, University of Pretoria, Plant Sciences Complex, Pretoria, South Africa; [b]Earth Observation group, Natural Resources, and Environment, Council for Scientific and Industrial Research (CSIR), Pretoria, South Africa

ABSTRACT

Miombo Woodland is the major Land use/land cover with important ecological functions in Africa. In Malawi, government-management was designed to manage Woodlands. However, when illegal activities continued, Participatory Forest Management (co-management) in forest reserves was institutionalised for woodland sustainability. Currently, information on co-management mitigating deforestation and degradation is scant. This study assessed woodland/forest through Land use/land cover (LULC) classification across the country (Malawi); compared forest cover within and between strategies using 11 co-management and 12 government-management forest reserves across the country between 1999 and 2018. Overall accuracies were >90%. Woodland net loses 8.4% (4.39–3.39 million ha) were to Plantation, Grassland and Agriculture transition intensities. Agriculture net gains 9.6% (1.87–3.00 million ha) were from Grassland, Settlement and Woodland transitions for the whole Malawi. Forest cover within co-management and government-management indicated loses. Sustainable management of degraded woodlands, integrated Agriculture and monitoring is encouraged. Further interpretation of transitions is recommended.

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Malawi; Land use/land cover; forest cover; co-management; government management; Miombo Woodlands

1. Introduction

Miombo woodlands in the sub-Sahara African (SSA) eco-region constitute 10% of the vegetation of Africa's continent and are highly valued because of their ecological functions (regulatory, provisioning, supporting and cultural services), and about 100 million livelihoods benefit (Angelsen et al., 2014; Chiteculo & Surovy, 2018; Dewees et al., 2010; Kalaba, Quinn, & Dougill, 2013; Mucina & Rutherford, 2006; Munishi, Temu, & Soka, 2010; Ncube, Anyanwu, & Hausken, 2014; Pullanikkatil, Mograbi, Palamuleni, Ruhiiga, & Shackleton, 2018; Syampungani et al., 2014). Even though the woodlands play a significant role in cushioning livelihoods, there have been no studies on a national scale conducted to provide information on the changes in the Miombo landscape of Malawi. Human activities play a major role in land use/cover changes (LULCC) worldwide with naturally occurring causes playing a minor role (Burka, 2008; Shah, Sen, Dar, & Kumar, 2017). The dynamics in the Miombo landscape could be better explained using Remote Sensing (RS) techniques

CONTACT Monica Fides Gondwe mfgondwe@gmail.com; malawiforestrycollege@gmail.com Department of Plant and Soil Sciences, University of Pretoria, Plant Sciences Complex, Pretoria 0002, South Africa
Supplemental data for this article can be accessed here.

including socio-economic, environmental and policy information. The high demand for land for agriculture, wood energy, and unsustainable fires lead to LULCC (Lambin & Meyfroidt, 2010; Munthali et al., 2019; Pullanikkatil et al., 2018; Zalengera et al., 2014; Zulu, 2010). LULCC has been a topical issue worldwide since the introduction of Remote Sensing (RS) (Altaweel, Alessa, Kliskey, & Bone, 2010; Kennedy et al., 2009) and are not exceptional in the Miombo eco-region (Rudel, 2013). The interest on LULCC information has been due to the implications that unsustainable changes have on the environment and socio-economic activities in the short and long term (Aldwaik & Pontius, 2012; Bi, Luo, Ding, & Liang, 2015; Pullanikkatil et al., 2018; Rudel, 2013; Song, Zhang, An, Wang, & Li, 2013; UNEP, 2015). These changes can affect the woodland ability to provide ecological functions (Obalum et al., 2012; Pullanikkatil et al., 2018; UNEP, 2015). In response to the changes, the Government of Malawi has undertaken a number of policy measures in order to mitigate forest loss and degradation. For example, Participatory Forest Management (PFM) has been institutionalised to involve communities and other stakeholders to manage forests/trees/woodlands in all land types. It is assumed that the co-management (hereafter CM) of forest reserves will improve the sustainability of Miombo woodlands in the landscape. However, the impact of CM on forest cover and whether the strategy mitigates forest loss is not known. Currently, no studies have been conducted on a national scale to provide such information. There are a few studies on LULCC in Malawi, but none covers the entire country (Munthali et al., 2019; Munthali & Murayama, 2011). Bruna and Kress (2002) and Walz (2011) have argued that information on LULCC is critical for crafting sustainable development goals and in reviewing policies for continuous improvement of forest management.

In Malawi, Agriculture is the backbone of its economy and heavily reliant on natural resources as its capital (Dewees et al., 2010; Munthali et al., 2019). Malawi's overdependency on rainfall for agro-production has consequences on environmental degradation (SADC National Vulnerability Assessment Committee, 2017). About 85% of Malawians live in remote areas and almost 80% depend on natural capital (Dewees et al., 2010; Jumbe & Angelsen, 2007; Kambewa & Utila, 2008). For instance, 97% of Malawis' rural people depend on wood energy (Bandyopadhyay, Shyamsundar, & Baccini, 2011). Wood energy demand is exacerbated as 2% out of 85% of Malawians and 6% in urban centres have rationed and expensive electricity (Kambewa & Utila, 2008; Zalengera et al., 2014; Zulu, 2010). Furthermore, the population that increased from 9.8 million (1998) to 17 million (2018) has resulted in a high demand for land resources for Agriculture and infrastructural development (Chirwa, Mahamane, & Kowero, 2017; Government of Malawi, 2018; Pullanikkatil et al., 2018). Even though natural resources are socio-economically important, the overdependency on them has an implication on LULCC especially on the loss and degradation of woodlands (Jumbe & Angelsen, 2007; Kambewa & Utila, 2008; Zalengera et al., 2014; Zulu, 2010).

Although some literature exists on LULCC in Malawi regarding the Miombo eco-region (Bone, Parks, Hudson, Tsirinzeni, & Willcock, 2016; Chavula, Brezonik, & Bauer, 2011), no such study has been conducted at a national scale. Furthermore, other studies focused on different periods that did not correspond to changes from government-management to a participatory approach, used different methods and none used the Inter-Governmental Panel on Climate Change (IPCC) LULC classes in the classification. These classes are standardised for easy comparison of the changes amongst countries and was used in this study (Penman et al., 2003). Despite LULCC reports in the Lake Malawi basin (1982–1995) (though on a small scale) which indicated 90% of the cultivated areas contributed to changes in natural vegetation, the limitation of this study was that images used were from different sensors and yielded different values for forest, cultivated areas and Woodland/Savanna/Shrub (Chavula et al., 2011). Similarly, although, Pullanikkatil et al. (2018), reported that 89% forest loss was due to an increased Agriculture area in LULCC, the study focused on the Likangala river over a period of 30 years. In addition, Kappa coefficient which was used for accuracy assessment has been proved to have errors (Jeon, Olofsson, & Woodcock, 2014; Olofsson, Foody, Stehman, & Woodcock, 2013; Pontius & Millones, 2011). Even though Bone et al. (2016) reported 12,760 km^2 (36%) forest loss from the initial time and 11,161 km^2 of newly established forest areas resulting in 5% net loss and correlated with socio-economic data after 37 years assessment of land-cover changes in Malawi, the study did not show the transitions and their intensities neither did the study indicate the magnitude of the changes from the time the management changed from government-management to participatory approach. Analysing intensities assists in understanding the classes that are dormant/active and helps to systematically identify areas with persistence, swap and net changes (Aldwaik & Pontius, 2012; Gao et al., 2016; Pontius, 2019; Quan, Pontius, & Song, 2019). Furthermore, the study of LULCC by Munthali et al. (2019) focused in one (1) out of 28 districts in Malawi and the time periods used (1991, 2001 and 2015), for the information could not be generalised for the country's developmental programmes and in managing natural resources in a Miombo landscape.

Forests/trees/woodlands in all land types were under the Forest Departments' protection (Mauambeta, Chitedze, Mumba, & Gama, 2010). Prior to PFM (CM), illegal activities continued and exacerbated forest loss and degradation due to limited financial and human resources in relation to Structural Adjustment Program (SAP) (Government of Malawi, 2018; Ofori, 2009). Furthermore, illegal harvesting of woody products escalated due to limited understanding of democratic principles instituted in 1994 (Pullanikkatil et al., 2018). Therefore, to facilitate the sustainability of the woodlands, PFM CM was adopted in 1999 to halt and curb deforestation and forest degradation (Government of Malawi, 2005, 2010; Lambin & Meyfroidt, 2010). Forest co-management involves a mutually binding agreement between the communities and the Forest Department (FD) in managing the designated FRs and Government remains accountable (Ballet, Koffi, & Komena, 2009; Phiri, Chirwa, Watts, & Syampungani, 2012; Senganimalunje, Chirwa, Babalola, & Graham, 2016). The co-managed forest reserves are divided into blocks that are shared among communities living in a 5-km buffer from the reserve boundary under a Block Management Committee supervised by a Local Forest Management Board (LFMB) (Government of Malawi, 2005; Senganimalunje et al., 2016). A block management plan includes benefit-sharing mechanisms and is a recognised document for an agreement to be signed between the Director of Forestry and the communities' Representative. These documents legalise communities' authority to sustainably manage the resources on Forest Departments' behalf (Government of Malawi, 2005). The Board is responsible for facilitating benefit sharing, resolving conflicts within and between blocks, synthesising resource use rules which are fed into the District Forest Bylaws. The community's incentives are to collect woody and non-woody products (Government of Malawi, 1996). Communities' involvement in the implementation of the management plan is regarded as the main cost. The activities may include enrichment planting in degraded areas, protecting the regeneration from bushfires, harvesting according to the plan, patrolling, and collecting revenue from sales. However, it is not established whether such activities are implemented to maintain the forest cover since a participatory approach was adopted.

On the other hand, the Forest Department's responsibility is to provide technical advice, expertise, identify training needs and, collaborate with other partners to fill the training gaps and to fetch markets for forest-based products from communities. However, these activities are hampered by limited financial and human resources. There is limited information on whether CM is viable. Even though co-management agreements are signed, monitoring is rare, often limited and in most cases lacking (Noss, 1999). Therefore, there is fear as to whether CM could maintain the forest cover and mitigate deforestation and degradation in Malawi. Alternatively, in government-managed forest reserves (hereafter, GM) is carried out by the Forestry Department staff and the focus is on patrolling and administering policy and law and has been included in the study for comparison with CM which many studies lack.

Numerous literature worldwide has documented on the successes of CM such as on regeneration, benefit-sharing and improving livelihoods (Ball, 2011; Chinangwa, Pullin, & Hockley, 2017; Gobeze, Bekele, Lemenih, & Kassa, 2009; Kobbail, 2010; Nagendra, Karmacharya, & Karna, 2005). However, the studies did not focus on forest cover. Even though other studies have reported about CM failures such as the declining forest cover with increased bush vegetation in some sites (Islam et al., 2019), the results fall short of comparison with GM forest reserves. Similarly, despite the aforesaid successes, other studies have reported low community participation and woodland fragmentation due to limited resource use rules and conflicts amongst users (Liu, Liu, & Wang, 2017; Phiri, Morgenroth, & Xu, 2019; Senganimalunje et al., 2016; Umar & Vedeld, 2012). Proper devolution processes, participatory governing principles and policy reviews related to sustainability of woodlands/forests in CM have been limited (Liu et al., 2017; Senganimalunje et al., 2016). Munthali and Murayama (2011), showed 1.7% annual forest loss equivalent to 22,000 ha (1990 and 2010); and projected 3.1% (26,700 ha) loss (2010 and 2030) in Dzalanyama GM FR, the limitation of the study is that only one FR was involved and no CM FRs were included for comparison. Furthermore, even though, Lupala, Lusambo, Ngaga, and Makatta (2015), reported increased forest cover in CM in communal woodlands compared to GM areas, the study did not include forest cover changes in CM of GM FRs. Currently, there is a limitation to the understanding of the impact of PFM CM in comparison with GM in maintaining the woodland/forest cover since no study has been conducted at a national level after 19 years of PFM implementation to mitigate deforestation and forest degradation in Malawi.

Therefore, the aims of this study were to: (i) assess LULCC for the whole of Malawi from the time Participatory Forest Management was adopted (1999) to 2018 (period of assessment) and (ii) to assess the effectiveness of PFM CM in Malawi when compared to the government-management of forests via the establishment of protected/forest reserves using selected 11 CM and 12 GM forest reserves.

2. Materials and methods

2.1. Study sites

The first phase of the study involved determining LULCC and the transition intensities for Malawi between 1999 and 2018 (Figure 1). The second phase involved determining differences in forest cover within and between 1999 and 2018 for 11 CM and 12 GM forest reserves (Figure 1, Table 1). The forest reserves cover the northern, central, and southern regions of Malawi. The country is in south-eastern Africa located between latitudes 9° and 18°S and longitudes 32° and 36°E. Malawi occupies an area of about 11.80 million ha with an approximated population of 17.56 million (Government of Malawi, 2018). It borders Mozambique on the east, south, and west, Tanzania to the northeast, and Zambia to the northwest. It has distinct dry and wet seasons. Malawi is predominantly covered by Miombo woodland (94%) of genera *Brachystegia, Isoberlinia* and *Julbernadia* (Geldenhuys, 2014; Government of Malawi, 2012; Munishi et al., 2010). It is within SSA Zambezian Miombo eco-region belonging to the largest contiguous block of vegetation in Africa (Chirwa et al., 2017; Syampungani, Chirwa, Akinnifesi, Sileshi, & Ajayi, 2009). The specific study sites for assessing the impact of management strategies in FRs (CM and GM) are in Figure 1 and Table 1.

Agricultural products are the backbone of the country's economy and maize is the main staple food followed by rice along the lake shores and swampy areas. Malawi is among the countries in SSA with a high population density of 139 people per km^2 and has an average of 4.4 people family^{-1} (Jumbe & Angelsen, 2007; Kambewa & Utila, 2008). Malawi is divided into three regions (northern, central, and southern). Malawi has public land (government owned), communal/customary land, and Private/Leasehold land (Government of Malawi, 2010). Due to the ever-increasing population, there is high demand for land for various uses including land for agriculture (Mngube, Anyona, Abuom, Matano, & Kapiyo, 2019; Munthali et al., 2019).

The Miombo woodlands in Malawi support the biodiversity of about 6,000 species of flora with high endemism (Government of Malawi, 2010). The woodlands were gazetted to protect fragile areas, to serve as water catchment and for biodiversity conservation (Government of Malawi, 2016). Before independence in 1964, all forest reserves across the country were all covered with intact woodland, but now they are fragmented to patches of grass, crop fields, and settlements (Figure 2).

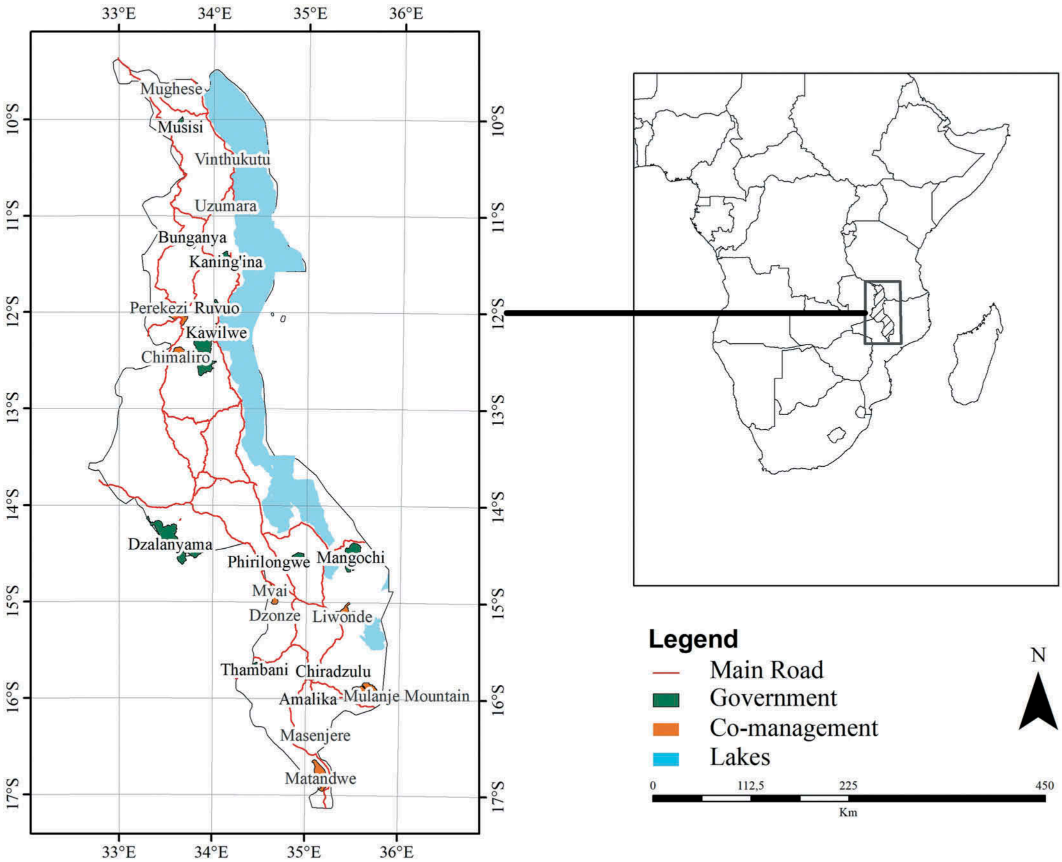

Figure 1. Map of Malawi in Southern East Africa.

Table 1. Forest reserves under co-management and government-management strategies.

Region	Co-managed forest reserves	Area (Ha)	Year gazetted	Govt-managed forest reserves	Area (Ha)	Year gazetted
Northern	Mughese	771	1948	Musisi	7,034	1948
	Uzumara	596	1948	Ruvuo	4,792.9	1935
	Vinthukutu	1,957	1948	Bunganya	3,470	1927
	Perekezi	15,370	1935	Kaning'ina	15,530	1935
	Mkuwadzi	1,608	1927	Dwambazi	788,627	–
				Kawilwe	661.5	1935
Central	Chimaliro	15,205	1926	Dzalanyama	98,827	1922
	Dzonze-Mvai	8,292	1924	–	–	–
Southern	Liwonde	27,407	1935	Mangochi	40,853	1924
	Mulanje	55,209	1913	Phililongwe	161.29	1924
	Mathandwe	26,205	1931	Amalika	370	1959
	Masenjere	276	1930	Thambani	4,680	1927
				Chiradzulu	774	1924

Source: https://www.protectedplanet.net/ and Forestry Department Headquarters management.

2.2. General methodology

The change in forest cover between 1999 (when PFM CM was introduced) and the current period (2018) was conducted. First, LULC using change detection technique from satellite imagery was performed across the country to assess change in woodland/forest cover. The change can be as a result of changes of other land uses such as abandonment of farms or reafforestation programmes,

Figure 2. Google earth pro images in Liwonde (left) (co-management) and Chiradzulu (right) (government-management) forest reserves (Miombo woodlands) in 2018.

while the decrease in forest cover commonly occurs through the conversion of woodlands to Agriculture. The methodology consists of three main parts as below.

- Classification of satellite images for 1999 and 2018 into six IPCC Land Use Land Cover. These classes are standardised for easy comparison among countries (Penman et al., 2003).
- Change detection was conducted to quantify the change in the LULC types between the two periods.
- 11 CM and 12 GM forest reserves were subset from 1999 and 2018 and analysed in R software to assess two assumptions: (i) whether PFM co-managed forest reserves have significant change in forest cover or have increased in cover from 1999 and 2018 (ii) or whether there would be no significant change in forest cover between PFM co-management and government-managed forest reserves.

2.3. Classification of land use land cover

2.3.1. Image acquisition, registration, and pre-processing

The geographical position and imagery data are authentic sources to understand the transitions and magnitudes of LULCC (Aldwaik & Pontius, 2012; Gao et al., 2016) and can be used to determine the impact of management on Woodlands (Lupala et al., 2015). Landsat images have traditionally been used for LULCC analysis (Munthali et al., 2019; Teferi, Bewket, Uhlenbrook, & Wenninger, 2013). However, when many Landsat scenes are mosaicked and used for LULCC, cross-track illumination effects often affect the classification results (Dadon, Karnieli, & Ben-Dor, 2010; San & Süzen, 2011). In this study, Google Earth images have been used because of cross-tract illumination effects which were experienced in an attempt to use Landsat mosaics of Malawi from the United States Geological Survey (USGS) downloaded images to conduct LULC classification. Therefore, Google Earth Landsat mosaics as described below were the next option and were preferred to original Landsat images from the USGS because they have been corrected from cross-track illumination effect.

In the first phase of classifying LULCC for Malawi, two images were acquired from Google Earth using the time slider function for 1999 and 2018 as also used by Tilman, Cassman, Matson, Naylor, and Polasky (2002). The Google Earth images were Landsat mosaics. The images were saved as maximum resolution (4800 x 2718). To improve the resolution, six scenes were saved for each image. Ground control points (GCPs) for each of the six scenes were saved for subsequent georeferencing, mosaicking, trimming (clipping) and producing final maps. Overlaps were allowed between scenes to allow seamless mosaicking. The GCPs are vital as they increased the accuracy of the global positioning of the image (Jensen, 2007). The mosaicking was done using the 'Map' and 'georeferenced' commands in Environment for Visualising Images (ENVI) version 4.7. A 30 m x 30 m pixel size and Universal Transverse Mercator (UTM) and World Geodetic System (WGS) 1984 datum, zone 36 south was ensured. The bands used (spectral) for 1999 (Landsat 7) and 2018 (Landsat 8) are 1, 2 & 3. The Malawi shapefile was used for clipping and enabled quick image processing (Lillesand, Kiefer, & Chipman, 2015).

2.4. Land-use land-cover (LULC) classification

The most commonly used Maximum Likelihood classifier was used to classify the images into the various IPCC land-cover land-used classes (Bauer, Yuan, & Sawaya, 2004; Kalema, Witkowski, Erasmus, & Mwavu, 2015; Munthali et al., 2019; Otukei & Blaschke, 2010; Pullanikkatil et al., 2018; Rawat, Biswas, & Kumar, 2013). The classifier uses the probability of pixels of being an endmember for each class (Bauer et al., 2004). The IPCC LULC classes (Woodland, Plantation, Agriculture, Grassland, Settlement, and Wetland) (Table 2) were used in the classification. The forest class was divided into Woodland and Plantation to purposively evaluate the change in Woodland between 1999 and 2018. The 'other land' class composed of rocks and bare areas had very few pixels and could, therefore, not be included in the classification by ENVI. The classification was conducted based on experience in interpreting images visually, knowledge of the country and use of Google Earth Pro imagery (Figure 2). Doubtful points on Google Earth were physically verified on 26–27 June and on 10 July 2017, using coordinates that were loaded in a hand-held GPSmap 62sc to reduce errors. There were high within-class variabilities in the spectral signature probability due to the mosaicking of images acquired at different times. To minimise the impact of within-class variability on the classification, each LULC was subdivided into sub-classes of similar spectral characteristics. The subclasses were later merged. The number of pixels per rectangle/polygon for training and validation varied (Table 2). A randomly stratified sample method was performed to acquire polygons for 1999 and 2018 on Google Earth Pro images, respectively for validation (Table 2).

Olofsson et al. (2013) have shown that the commonly used error or confusion matrix used in many studies to assess classification accuracies does not account for an unequal sample size of the validation dataset and often leads to misleading accuracy figures and estimation areas (extent) of LULC classes. They have recommended an error-adjusted estimator of the areas by using an error matrix of estimated area proportions for accuracy assessment and subsequent estimation of the areas of the LULC classes and their confidence intervals. Therefore, the method by Olofsson et al. (2013) was applied to conduct accuracy assessment and to estimate the areas of the land-cover classes. The method mitigates the effect of the unequal number of training and validation samples on the classification accuracy and predicted the area cover of each class with the unbiased estimation of the total area. Both 1999 and 2018 images required overall accuracies (OA) of 85% (Kamusoko & Aniya, 2007). Therefore, the AA last estimators were the user, producer, and OA. Kappa coefficient was not used as it has been regarded to have errors (Jeon et al., 2014; Olofsson et al., 2013; Pontius & Millones, 2011). Google Earth Pro and a time slider acted as baseline information to collect validation data for the 1999 Malawi Image. The imagery data for both years were collected from similar dates with the same phenotypic characteristics for easy comparison. The visual interpretation of the 1999 Malawi image was also facilitated by using the shapes, textures, tones, and the pattern of classes.

Table 2. Definitions of IPCC LULC, training, and validation data

2.5. Change detection

Change detection was conducted by comparing the 1999 and 2018 Malawi classified images in ENVI. A change detection matrix between the two time-points is generated which indicates the extent of land-cover conversion from one class to the other (Aldwaik & Pontius, 2012; Gao et al., 2016; Pontius, 2019; Pontius et al., 2013; Quan et al., 2019). Thereafter, each class was assessed on how their sizes and intensities of gross loss and gross gain vary if the distribution of changes in each interval was uniform across the years (1999 and 2018). Examining the intensities of the transitions, a single class in relation to other classes were performed to determine the class intensity of transitions in relation to

Table 2. Definitions of IPCC LULCF, training, and validation data.

		1999 training data		1999 test data		2018 training data		2018 test data	
LULCF	Definition	No. of polygons	No. of pixels	No. of polygons	No. of pixels	No. of polygons	No. of pixels	No. of polygons	No. of pixels
Grassland	Pastures, grazing both natural and recreation areas.	56	38,619	46	3742	273	12,500	41	1506
Woodland	Land > 0.5 ha with trees ≥ 5 meters and a canopy cover of ≥ 10%	816	44,856	265	10,101	1892	403,472	42	15,843
Agriculture	Cultivatable, cultivated and agroforestry areas	129	3073	52	3912	1754	260,189	41	2973
Plantation	Planted exotic tree *spp* and tea plantations	44	1051	40	1362	87	6388	50	2624
Settlements	All developed lands including transportation	50	413	54	2492	75	411	43	1913
Wetland	Areas covered by water or wet not classified as forest, crop, or grassland.	81	52,397	48	1506	231	9,272,617	28	3652

gross losses/gains using equations 1 and 2 (Aldwaik & Pontius, 2012; Gao et al., 2016; Pontius, 2019). The process helps to categorise classes that are not part of the transitions.

The three components, Quantity/Net changes, Exchange and Shift were computed using *Pontius*Matrix41 spreadsheet obtained from www.clarku.edu/~rpontius using pixels obtained from change detection. The computation helps to establish the intensities of the transitions focusing on gross gain/losses for each class and overall (Pontius, 2019; Pontius et al., 2013).

$$\text{Class Loss Intensities (CLI)} = \text{Class Loss/Class size (1999)} * 100\% \tag{1}$$

$$\text{Class Gain Intensities (CGI)} = \text{Class Gain/Class size (2018)} * 100\% \tag{2}$$

If the losses or gains of LULC classes are lower than the uniform intensity (change) then the classes are dormant and if the classes intensities have higher values than the uniform values, then, the classes are active (Gao et al., 2016).

For the analysis of transition intensities for (Woodland, Plantation, Agriculture, Settlement, Wetland, and Grassland), for instance, loss intensity of Woodland was derived by dividing area of Woodland lost to other classes by the size of that class in 2018 then multiplied by 100%. The Woodland gain intensity is derived as follows: Woodland gain to another class divided by the area of that class in 1999 multiplied by 100% as explained by Gao et al. (2016). Uniform Loss equals the total loss of a class to other classes in 2018 divided by the total area of all classes in 2018 multiplied by 100%. Uniform Gain = total gain of a class to other classes in 1999 divided by the total area of all classes in 1999 multiplied by 100% (Gao et al., 2016).

The areas derived from the adjusted error matrices were slightly varied with those from the transition matrix (Table 4). However, comparison of the results from these schemes was not the main purpose of the study.

2.6. Significance test for differences in forest cover within and between management (1999 and 2018)

To understand the comparison of woodland/forest cover in PFM (CM) and GM within and between strategies; the shapefiles for the forest reserves under CM (11) and GM (12) (Table 2) were obtained from https://www.protectedplanet.net/and Forestry Department to subset the forest reserves. Thereafter, Woodland data for 1999 and 2018 from both strategies were extracted using ENVI. The changes within CM and GM forest reserves (1999 and 2018) were further analysed in R Studio using Wilcoxon sign rank test which uses before and after scenario (R Development Core Team, 2018; Rosner, Glynn, & Lee, 2006). Again Kruskal–Wallis rank-sum test (Kruskal & Wallis, 1952) was used to test significant differences in forest cover between strategies at $p < 0.05$ between 1999 and 2018.

3. Results

3.1. Accuracies of land use land cover 1999 and 2018

The overall classification accuracies for entire Malawi images were 93.6% and 97.1% for 1999 and 2018, respectively (Table 3a & 3b). The user and producer accuracies for 1999 and 2018 were above 85% except for the Grassland user accuracy (84.1) in 1999 and for Plantation producer accuracy (77.2%) (Table 3a & 3b, Appendices A1, A2). The intensity analysis showed that Agriculture gained more from Settlement (46.2%), then from Grassland 40.9% and Woodland (16.1%).

Table 3. (a) Land use/land cover classification Malawi adjusted error matrix 1999. (b) Land use/land cover classification Malawi adjusted error matrix 2018.

		Reference pixels						
	Class	Grassland (nij)	Woodland	Agriculture	Plantation	Settlements	Wetland	User accuracy
Predicted pixels	Grassland (nij)	0.1573321	0.0236173	0.00689206	0	0	0.001097	83.3
	Woodland	0.0056019	0.3634805	0	0.0009908	0	0.001905	97.7
	Agriculture	0	0	0.15778491	0	0.000843	0	99.5
	Plantation	0	0.0002683	0	0.0143413	0	0	98.2
	Settlements	0	0	0.00020987	0.	0.043233	0	99.5
	Wetland	0.0009760	0	0.0218916	0	0	0.199534	89.7
	Column Total (P.j)	0.1639101	0.3873662	0.1867784	0.0153321	0.044076	0.222402	
	Producer accuracy	96.0	93.8	84.5	93.5	98.1	98.5	
Predicted pixels	Grassland (nij)	0.1110059	0.0123673	0	0	0.0001499	0	89.9
	Woodland	0.000458	0.2870225	0	0	0	0	99.8
	Agriculture	0	0.0019988	0.2441927	0	0.0064962	0.0016657	96.0
	Plantation	0	0	0	0.0159572	0	0	100
	Settlements	0	0.0001995	0.0010229	0	0.0457311	0	97.4
	Wetland	0	0	0	0.0047053	0	0.267025	98.3
	Column Total (P.j)	0.1114645	0.30158833	0.2452156	0.0206625	0.0523773	0.268691	
	Producer accuracy	99.6	95.2	99.6	77.2	87.3	99.4	

3.2. Land uses land-cover changes (gain, loss, persistence)

Table 4 indicates the transition matrix with area (ha), pixels, and % cross-tabulated and reconstructed from Malawi LULC classification and change detection between 1999 and 2018. The diagonally bold values show each class persistent to change. The off-diagonally, values show transitions from target class to other classes. Total values for 2018 are at the bottom of Table 4. 2018 image values are a combination of gains plus persistency. The far right column shows 1999 Malawi image total values which are a combination of losses plus persistences as in Gao et al. (2016) and Pontius (2019). The far end right bottom records the total %, area (ha) and pixels of map change for the entire country.

Tables 4 & 5 illustrate gain, loss, and persistence with a uniform change of 46.2% and persistence of 53.8% from Malawi maps (1999 and 2018). Between the period, Woodland gained 9.3% and lost 17.8% for the entire country accounting for all woodlands in all land tenurial rights. The swap change is 18.7% which is leveled off with a final net change (loss) 8.4%. Furthermore, Agriculture gained 16.6% and lost 7.1% with a net change (gain) of 9.6% while 23.7% was swapped. Grassland gain was 8.0% while the loss was 14.5% and resulted in a net change (loss) of 6.5%. Persistence, gain, and loss in each class (Tables 4, 5, Appendix B) are graphically shown in Figures 3, 4(a,b).

To further demonstrate class loss in 1999 and gain in 2018 (see Table 6).

3.3. Malawi LULC analysis of change intensities

With reference to the transition matrix (Table 4), intensities of a loss or gain have been constructed for each class (Table 6). On overall and in reference to the Malawi maps (1999 and 2018), all classes such as Woodland (47.8%), Plantation (79.5%), Agriculture (44.5%), Settlement (76.7) and Grassland (76.8%) showed high loss intensity except Wetland which showed low loss intensity (10%) in relation to uniform loss of (46.2%) (Table 6) and were active. Similarly, the classes with high gain intensities were Plantations (81.2%), Agriculture (65.4%), Settlement (78.4%), Grassland (64.5%) while Woodland (32.5%) and Wetland (26.8%) had low gain intensities compared to the uniform gain (46.2%) (Table 6).

Table 4. Malawi land-use land-cover transition matrix, 1999 in the rows to 2018 in columns with area (ha), pixels and % in Figure 3 maps.

		2018							
	Class	Woodland	Plantations	Agriculture	Settlement	Wetland	Grassland	Time 1999	Loss
1999	Woodland (Area ha)	**2,291,312.52**	128,763.18	708,138.00	80,481.51	607,401.18	573,670.71	4,389,767.10	2,098,454.58
	Pixels	**25,459,028**	1,430,702	7,868,200	894,239	6,748,902	6,374,119	48,775,190.00	23,316,162
	%	*19.42*	*1.09*	*6.00*	*0.68*	*5.15*	*4.86*	37.20	17.78
	Plantations (Area ha)	82,120.41	**35,336.16**	15,485.94	1,802.52	25,509.78	11,804.13	172,058.94	136,722.78
	Pixels	912,449	**392,624**	172,066	20,028	283,442	131,157	1,911,766.00	1,519,142
	%	*0.70*	***0.30***	*0.13*	*0.02*	*0.22*	*0.10*	1.46	1.16
	Agriculture (Area)	296,835.48	3,540.96	**1,038,545.73**	205,882.56	67,114.35	260,069.13	1,871,988.21	833,442.48
	Pixels	3,298,172	39,344	**11,539,397**	2,287,584	745,715	2,889,657	20,799,869.00	9,260,472
	%	*2.52*	*0.03*	***8.80***	*1.74*	*0.57*	*2.20*	15.86	7.06
	Settlement (Area)	62,667.81	1,531.89	236,158.11	**119,828.97**	22,355.10	70,130.61	512,672.49	392,843.52
	Pixels	696,309	17,021	2,623,979	**1,331,433**	248,390	779,229	5,696,361.00	4,364,928
	%	*0.53*	*0.01*	*2.00*	***1.02***	*0.19*	*0.59*	4.34	3.33
	Wetland (Area)	144,066.69	12,436.47	90,770.85	5,440.32	**2,347,850.70**	24,026.49	2,624,591.52	276,740.82
	Pixels	1,600,741	138,183	1,008,565	60,448	**26,087,230**	266,961	29,162,128.00	3,074,898
	%	*1.22*	*0.11*	*0.77*	*0.05*	***19.90***	*0.20*	22.24	2.35
	Grassland (Area)	515,530.71	6,702.39	912,510.18	140,660.64	136,295.01	**517,994.73**	2,229,693.66	1,711,698.93
	Pixels	5,728,119	74,471	10,139,002	1,562,896	1,514,389	**5,755,497**	24,774,374.00	19,018,877
	%	*4.37*	*0.06*	*7.73*	*1.19*	*1.15*	***4.39***	18.89	14.50
Time 2018	Area	3,392,533.62	188,311.05	3,001,608.81	554,096.52	3,206,526.12	1,457,695.80	**11,800,771.92**	5,449,903.11
	Pixels	37,694,818	2,092,345	33,351,209	6,156,628	35,628,068	16,196,620	**131,119,688.00**	60,554,479
	%	28.75	1.60	25.44	4.70	27.17	12.35	**100.00**	46.18
Total Gain	Area	1,101,221.10	152,974.89	1,963,063.08	434,267.55	858,675.42	939,701.07	5,449,903.11	
	Pixels	12,235,790.00	1,699,721.00	21,811,812.00	4,825,195.00	9,540,838.00	10,441,123.00	60,554,479.00	
	%	9.33	1.30	16.64	3.68	7.28	7.96	*46.18*	

*Bold areas represent persistence; Total area for Malawi Maps is 11.82 million hectares, % = Area of class divided by total Area of Malawi multiplied by 100%.

Table 5. Map percentages in gain, loss, persistence, swap, and net changes.

Land cover	Gain	Persistence	Loss	Class total	Swap location change	Net quantity change
Woodland	9.3	19.4	17.8	27.1	18.7	8.4 loss
Plantations	1.3	0.3	1.2	2.5	2.3	0.1 gain
Agriculture	16.6	8.8	7.1	23.7	14.1	9.6 gain
Settlement	3.7	1.0	3.3	7.0	6.7	0.3 gain
Wetland	7.3	19.9	2.4	9.6	4.7	4.9 gain
Grassland	8.0	4.4	14.5	22.5	29.0	6.5 loss
Uniform change bold	46.2	53.8	46.2	92.4		

Swap = Gain plus Loss – (Net quantity change (NQC); NQC = Gain − Loss

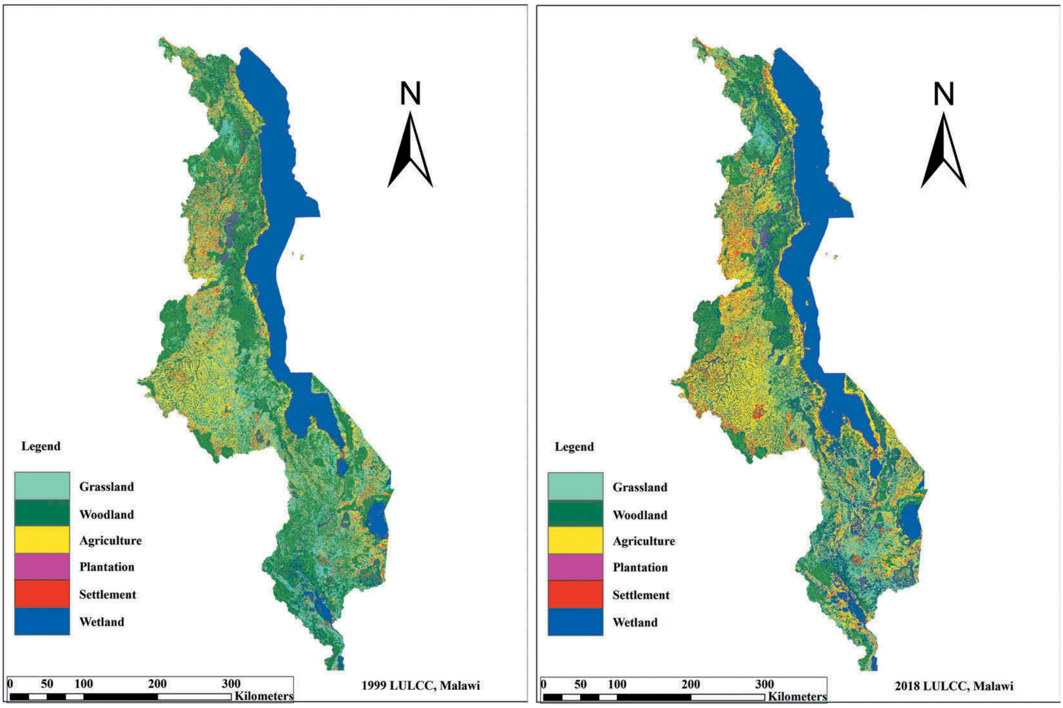

Figure 3. Classified Land use/land cover and the Forestry map of Malawi 1999 (left) and 2018 (right).

Tables 7–12 present intensity matrices for Woodland, Plantation, Agriculture, Settlement, Wetland, and Grassland, respectively. The information in the tables indicate the comparison between the observable transition intensities to the hypothetical uniformity of transition intensities.

Table 7 indicates that Woodland loss intensities were high to Plantation (68%), Grassland (39.4%), and Agriculture (23.6%) which was almost at equilibrium with the uniform loss 24.9%. Woodland gain intensities targeted Plantation (47.9%) and Grassland (23.1%) (Table 7); however, Grassland has a bigger size compared to Plantation (Table 4). Tables 8 & 10 show that Plantation and Settlement loss and gain intensities were very low and had low values in total areas (Table 4). Table 9 shows that Agriculture loss intensity was high to Settlement 37.1%, then to Grassland 17.8% and to Woodland 8.8%, and gained more from Settlement (46.1%) and from Grassland and relatively from Woodland than in any other class. Hence, Agriculture loss intensity targets Settlement and Grassland. Table 11 indicates that Wetland loss and gain intensities targeted Plantation and Woodland. Table 12 also shows that Grassland loss and gain intensities targeted Agriculture and Settlement.

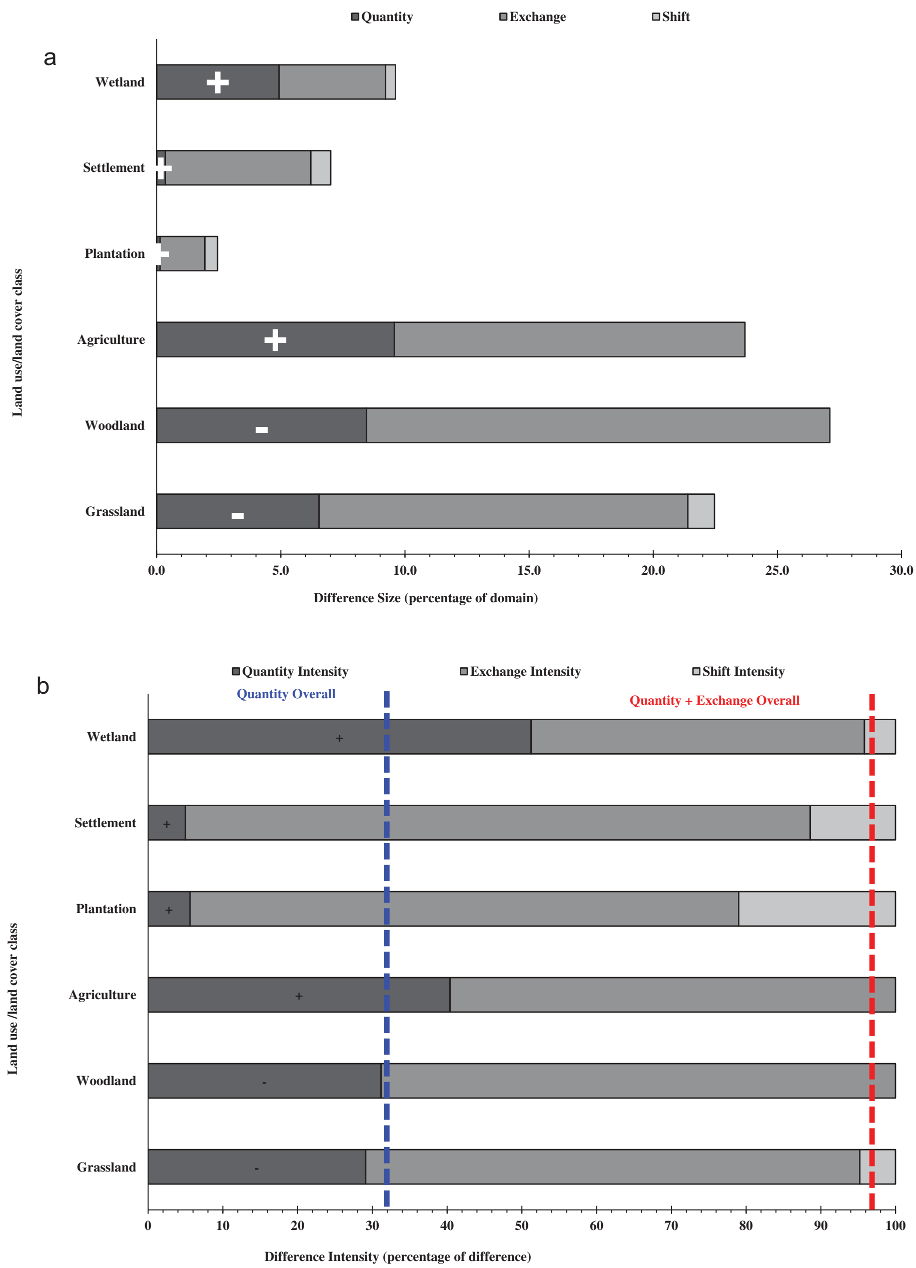

Figure 4. (a) Sizes, (b) Intensities and differences in Tables 4 & 5. + is the Quantity/Net change component indicates that the column values (2018) are compared to values in rows; – shows that column values (2018) are lower compared to the row values in 1999.

Figure 4(a) illustrates the intensity analysis showing three (3) components' sizes in Tables 4 & 5 depicting LULC classes that gained/lost. Wetland, Settlement, Plantation, and Agriculture have a positive sign in Quantity/net change component showing higher values in 2018 than in 1999 (Tables 4 & 5). Woodland and Grassland have a negative sign showing losses in 2018.

Figure 4(b) indicates the relationship of Quantity (net change), Swap separated into Exchange and Shift intensities of LULC classes and to overall components as shown in Tables 4 & 5. The

Table 6. Overall intensities of gains and losses by Land Use Land Cover classes for the whole of Malawi.

	Woodland	Plantations	Agriculture	Settlement	Wetland	Grassland
Loss	17.8	1.2	7.1	3.3	2.4	14.5
1999 total	37.2	1.5	15.9	4.3	22.2	18.9
Loss intensity	47.8	79.5	44.5	76.7	10.6	76.8
Gain	9.3	1.3	16.6	3.7	7.3	8.0
2018 total	28.7	1.6	25.4	4.7	27.2	12.4
Gain intensity	32.5	81.2	65.4	78.4	26.8	64.5
Uniform change	46.2	46.2	46.2	46.2	46.2	46.2

If gain or loss is larger than uniform the class is active. If the gain or loss is less than the uniform value then the classes are dormant

Table 7. Woodland Transition Intensity.

Woodland transition	Percent of map	Intensity (% of class)
Lost to Plantation	1.1	68.1
Plantation 2018	1.6	
Lost to Agriculture	6	23.6
Agriculture 2018	25.4	
Lost to Settlement	0.7	14.5
Settlement 2018	4.7	
Lost to Wetland	5.1	18.9
Wetland 2018	27.2	
Lost to Grassland	4.7	39.4
Grassland 2018	12.4	
Uniform loss		24.9
Gain from Plantation	0.7	47.9
Plantation 1999	1.5	
Gain from Agriculture	2.5	15.9
Agriculture 1999	15.7	
Gain from Settlement	0.5	12.2
Settlement 1999	4.3	
Gain from Wetland	1.2	5.5
Wetland 1999	22.2	
Gain from Grassland	4.4	23.1
Grassland 1999	18.9	
Uniform gain		14.9

Table 8. Plantation transition intensity.

Plantation transition	Percent of map	Intensity (% of class)
Lost to Woodland	0.7	2.4
Woodland 2018	28.7	
Lost to Agriculture	0.13	0.5
Agriculture 2018	25.4	
Lost to Settlement	0.02	0.4
Settlement 2018	4.7	
Lost to Wetland	0.2	0.8
Wetland 2018	27.2	
Lost to Grassland	0.1	0.8
Grassland 2018	12.4	
Uniform Loss		1.2
Gain from Woodland	1.1	2.9
Woodland 1999	37.2	
Gain from Agriculture	0.03	0.2
Agriculture 1999	15.7	
Gain from Settlement	0.01	0.2
Settlement 1999	4.3	
Gain from Wetland	0.1	0.5
Wetland 1999	22.2	
Gain from Grassland	0.1	0.3
Grassland 1999	18.9	
Uniform Gain		1.3

Table 9. Agriculture transition intensity.

Agriculture transitions	Percent of map	Intensity (% of class)
Lost to Woodland	2.5	8.8
Woodland 2018	28.7	
Lost to Plantation	0.03	1.9
Plantation 2018	1.6	
Lost to Settlement	1.7	37.1
Settlement 2018	4.7	
Lost to Wetland	0.6	2.1
Wetland 2018	27.2	
Lost to Grassland	2.2	17.8
Grassland 2018	12.3	
Uniform Loss		9.5
Gain from Woodland	6	16.1
Woodland 1999	37.2	
Gain from Plantation	0.1	8.9
Plantation 1999	1.5	
Gain from Settlement	2	46.1
Settlement 1999	4.3	
Gain from Wetland	0.8	3.5
Wetland 1999	22.2	
Gain from Grassland	7.7	40.9
Grassland 1999	18.9	
Uniform Gain		19.8

Table 10. Settlement transition intensity.

Settlement transition	% of map	Intensity (% of class)
Lost to Woodland	0.5	1.8
Woodland 2018	28.7	
Lost to Plantation	0.01	0.6
Plantation 2018	1.6	
Lost to Agriculture	2	7.9
Agriculture 2018	25.4	
Lost to Wetland	0.2	0.7
Wetland 2018	27.2	
Lost to Grassland	0.6	4.8
Grassland 2018	12.4	
Uniform Loss		3.5
Gain from Woodland	0.7	1.8
Woodland 1999	37.2	
Gain from Plantation	0.02	1.4
Plantation 1999	1.5	
Gain from Agriculture	1.7	11.0
Agriculture 1999	15.9	
Gain from Wetland	0.1	0.2
Wetland 1999	22.2	
Gain from Grassland	1.2	6.3
Grassland 1999	18.9	
Uniform Gain		21.6

overall Quantity/Net change component line (OQCL) is 32% of the overall differences. Agriculture land and Wetland extends its Quantity Component beyond the Quantity Component line. Woodland, Grassland, Plantation and Settlement Quantity/net change Component (QC) ends before the Quantity Component line. The Quantity and Exchange Overall line (QEOL) indicates that the summation of the Quantity/Net changes and Exchange components overall is 97% of the differences overall. The two lines difference is 65% and is equivalent to the intensity of the overall Exchange (Figure 4(b)). The intensity of Shift Overall is 3%, thus 100% minus 97%. The

Table 11. Wetland transition intensity.

Wetland transition	% of map	Intensity (% of class)
Lost to Woodland	1.2	4.2
Woodland 2018	28.7	
Lost to Plantation	0.1	6.9
Plantation 2018	1.6	
Lost to Agriculture	0.8	3.0
Agriculture 2018	25.4	
Lost to Settlement	0.1	1.1
Settlement 2018	4.7	
Lost to Grassland	0.2	1.6
Grassland 2018	12.4	
Uniform Loss		3.2
Gain from Woodland	5.2	13.8
Woodland 1999	37.2	
Gain from Plantation	0.2	15.1
Plantation 1999	1.246	
Gain from Agriculture	0.6	3.6
Agriculture 1999	15.9	
Gain from Settlement	0.2	4.4
Settlement 1999	4.3	
Gain from Grassland	1.2	6.1
Grassland 1999	18.9	
Uniform Gain		9.4

Table 12. Grassland transition intensity.

Grassland transition	% of map	Intensity (% of class)
Lost to Woodland	4.4	15.2
Woodland 2018	28.7	
Lost to Plantation	0.1	3.8
Plantation 2018	1.6	
Lost to Agriculture	7.7	30.4
Agriculture 2018	25.4	
Lost to Settlement	1.2	25.3
Settlement 2018	4.7	
Lost to Wetland	1.2	9.3
Wetland 2018	12.4	
Uniform Loss		23.5
Gain from Woodland	4.9	13.1
Woodland 1999	37.2	
Gain from Plantation	0.1	6.8
Plantation 1999	1.5	
Gain from Agriculture	2.2	13.8
Agriculture 1999	15.9	
Gain from Settlement	0.6	13.6
Settlement 1999	4.3	
Gain from Wetland	0.2	1.1
Wetland 1999	18.9	
Uniform Gain		10.2

Settlement, Plantation Wetland, and Grassland have more intensive Shift relative to Shift Overall compared to Agriculture and Woodland Shift intensity.

3.4. *Comparison of woodland cover between 1999 and 2018 in co-management and government-managed forest reserves*

The trend of decreasing Woodland/forest cover was observed in both CM and GM FRs (Table 13, Figures 2 & 3). In CM sites, 37% of forest cover was lost and the results showed significant

Table 13. Forest cover in hectares in Co-management and Government-management strategies.

Region	Co-managed forest reserves	1999 (Ha)	2018 (Ha)	Government Managed forest reserves	1999(Ha)	2018 (Ha)
Northern	Mughese	656	659	Musisi	5.194	4.031
	Uzumara	432	300	Ruvuo	3.512	2.750
	Vinthukutu	1.848	1.367	Bunganya	2.393	1.865
	Perekezi	13.228	13.600	Kaning'ina	11.897	10.872
	Mkuwadzi	968	1.326	Dwambazi	54.896	54.896
	–	–	–	Kawilwi	127	354
Central	Chimaliro	12.621	11.074	Dzalanyama	80.773	76.331
	Dzonze-Mvai	2.919	1.973	–	–	–
Southern	Liwonde	21.127	16.938	Mangochi	35.232	24.282
	Mulanje	28.647	17.221	Phililongwe	12.099	7.327
	Mathandwe	23.416	18.371	Amalika	213	32
	Masenjere	204	156	Thambani	4.473	3.694
	–		–	Chiradzulu	400	182
Total area		**105.614**	**66.0467**	**Total area**	**211.212**	**186.617**

Wilcoxon sign rank test in Co-management p = 0.04; in Government p = 0.01 in comparing woodland cover in hectares between 1999 and 2018. Kruskal–Wallis X^2 = 0.18218, df = 1, p = 0.67 between management.

differences (p 0.04) between 1999 and 2018. Of 11 FRs, one experienced an increase in the extent of forest, two showed a slight change and nine experienced a decline. Furthermore, in GM FRs, 11.6% decline of forest cover with a statistical difference (p 0.001) was revealed between the years. Out of 12 FRs, 10 experienced forest loss, one was stable, one had an increase thus >80% of GM FRs had a decline in forest cover. However, when CM and GM FRs were analysed, there were no significant differences (p 0.67) in forest cover between 1999 and 2018 between strategies (Table 13).

The Wilcoxon sign rank test in co-management p = 0.04; in government-management p = 0.01 compared woodland cover in hectares between 1999 and 2018. Kruskal–Wallis X^2 = 0.18218, df = 1, p = 0.67 between management strategies

4. Discussion

4.1. Classification accuracies

The results on IPCC LULC of 1999 and 2018 yielded high overall, user and producer accuracies in both 1999 and 2018 except in Plantation producer accuracy which yielded 77.2% (Table 3a & 3b). The low accuracy is attributed to the confusion of the signatures of Plantation with thick/closed Miombo woodland which were similar. The overall accuracies for both images were above 90%. According to Kamusoko and Aniya (2007), the recommended accuracies from the classification should be ≥85%. Initially, the accuracies were extremely low. However, the results improved by subdividing each class during the collection of training and validation data. The sub-divisions were done due to differences in signatures within a class across the country and were later combined. Furthermore, the knowledge of the area and the sub-divisions within the classes improved the results. Similarly, the results were robust because the error adjusted matrix, the area of the unbiased estimator, and confidence intervals were used in the classification (Appendices A1, A2). The method used solved the problem of unequal samples and other errors (Jeon et al., 2014; Olofsson et al., 2014, 2013). Even though the recommended classification has advantages, the method is rarely observed and has been well articulated in this study.

Alternatively, the results from the intensity analysis (IA) showed that Agriculture gained more from Settlement, than from Woodland and Grassland (Table 9). Visual interpretation of the images indicated that some Agriculture areas had a similar signature as Settlements. In addition, in Malawi small-scale farms/gardens are around Settlements. These reasons might have confused the classifier from distinguishing Agriculture from Settlement and might have introduced some errors. These results from IA (not undergone through error adjustment) of Agriculture gaining from Settlement are consistent with those reported in China by Yu, Hu, van Vliet, Verburg, and Wu (2018) and GlobeLand30 by Shafizadeh-Moghadam, Minaei, Feng, & Pontius (2019). In addition, these results confirm the argument that errors are introduced in the classification and require adjustment (Card, 1982; Jeon et al., 2014; Olofsson et al., 2014, 2013). Accuracy assessment using error adjustment (Appendices A1 & A2) and the transition intensities have been used. However, the aim of the study was not to compare the results from these methods.

4.2. Land-use land-cover change

The first objective assessed LULCC at a national scale in Malawi between 1999 and 2018. Woodland decreased with a net loss of 8.4% while Agriculture increased with 9.6% net gain (Tablea 4 & 5). The classified maps acted as baseline data to determine the impact of PFM CM in maintaining the forest cover in comparison with GM across the country. When the Woodland loses to Plantation, Agriculture, and Grassland (Tables 4 & 7), the following scenarios are expected (i) Woodland loss to Agriculture may remain permanently under cultivation, or areas that degrade in fertility may be abandoned in the search for new areas, targeting the remaining Woodlands (Figure 5). The abandoned areas may develop into grass and later into woodlands. If not managed grassy areas coupled with dry hot season fires could lead to disaster (ii) Woodland loss to Plantation suggests that when Plantations are harvested, not all are replanted and develop back to woodland. The observation could be due to limited monitoring mechanisms and plans after harvesting, however, the Plantation has low hectarage (Table 4) (iii) Woodland losing to Grassland happens when woody products are harvested and grass species emerge as the first developmental stage towards recovery and maturity and is a temporal degradation (Figure 5). If the stage is not managed, the Woodland succession may be lengthened. The loss intensity transition from Woodland to Agriculture confirm earlier reports that Agriculture is the dominant livelihood activity in SSA (Campbell, 1996; Rudel, 2013). Low Woodland gain from Agriculture (Table 9) suggests that with increasing population, Agriculture areas are rarely abandoned to regenerate towards woodlands. The LULC transition intensities at class level and on overall has also shown that Woodland and Grassland Quantity/Net change results into losses (Tables 4 & 5; Figure 4(a,b)). Large exchange intensity in Woodland with no shift intensity suggests that the Woodland gain from other classes is insignificant (Tables 4 & 5, Figure 4(a,b)). However, Agriculture gains as its Quantity/Net change extends the Quantity overall line (Figure 4(a,b)). As Woodland transitions to Agriculture and Grassland, Agriculture and Grassland transitions to Woodland in other areas with Woodland decreasing. These findings agree with earlier reports of Malawi's over-dependency on Agriculture and wood energy. Malawi's' population increased from 9.8 to 17 million (1998–2018) and contribute to high demand for land resources for Agriculture and infrastructural development (Chirwa et al., 2017; Government of Malawi, 2018; Munthali et al., 2019; Pullanikkatil et al.,

Figure 5. Dominating grass (left) and Agriculture (right) in clear-felled areas of Liwonde Co-managed forest reserve. The picture was taken during Ecological Assessments in May 2017.

2018). Jha and Bawa (2006), reported the relationship between the increased population with food production.

Similarly, Woodland transition to Grassland suggests that intensive utilisation of woody products influence the emergence of grass. These results further confirm that Woodland succession/recovery is relatively high from Grassland than from cultivated areas (Tables 4 & 7). Woodland recovery is due to its resilience to disturbance (Geldenhuys, 2010, 2014; Gonçalves et al., 2017; Syampungani, Geldenhuys, & Chirwa, 2016). Rudel (2013) reported that there is a reduced deforestation of 4.5% in SSA. It seems the trend of forest recovery from Grassland is common. Gao et al. (2016), also reported the recovery of forest from Grassland in Indonesian Peatland forest. There is more Grassland in 1999; hence, Woodland gains more from Grassland with uniform intensity gains, while avoiding all other classes (Table 7). However, the Woodland recovery from Grassland is lower than the losses to Grassland and other LULC classes. The major contributing factors to Woodland loss in Malawi are the conversion to Agriculture, high demand for woody products (firewood/charcoal and infrastructure), poverty and population increase (Munthali et al., 2019; Pullanikkatil et al., 2018; Zulu, 2010). The country's demand for wood energy and unsustainable harvesting also increases grass accumulation (Zalengera et al., 2014; Zulu, 2010). Similarly, the high area for Grassland (Table 4) agrees with reports that indicate high demand for wood energy in Africa (Campbell, 1996; Handavu, Chirwa, & Syampungani, 2019; Kalaba et al., 2013; Munthali et al., 2019; Zalengera et al., 2014; Zulu, 2010). Wood energy in Malawi accounts for more than 97% in remote areas (Bandyopadhyay et al., 2011) and is the country's' primary source of energy as hydro-electric power has challenges (Zalengera et al., 2014; Zulu, 2010). Therefore, sustainable management for Woodland quick recovery while using silvicultural practices for utilisation towards maturity is required (Geldenhuys, 2014; Lewis, Edwards, & Galbraith, 2015; Syampungani et al., 2016).

With more Woodlands being targeted for Agriculture, and wood energy, the overall ecological functions could be worsened without sustainable land management (Bi et al., 2015; Song et al., 2013). Furthermore, harmonisation of policies for combined efforts to sustainably manage Woodlands in Malawis' landscape and in the region is needed.

It is important to appropriately interpret the transition intensities to have meaningful information which could be the basis for monitoring and adaptive management including other developmental programmes, locally, nationally, regionally and globally.

4.3. Woodland/forest cover change in co-management and government-management

The second objective assessed the Woodland/forest cover within and between CM and GM between 1999 and 2018. The results showed significant changes in the forest cover within CM and GM. These results suggest that FRs in both management strategies play a significant role in peoples' livelihoods and that CM has not addressed deforestation and degradation making the challenge to remain persistent (Figures 2 & 5). In CM, the extent of forest cover declined by 37% overall. Of 11 FRs, one experienced an increase in forest cover, while two showed a slight change and nine had a decline (Table 13). These results are consistent with reports that indicate unsustainable management in forest CM (Nagendra et al., 2005; Phiri et al., 2019). Similarly, >80% of GM forest reserves experienced a decline in forest cover. Ten forest reserves among the 12, experienced forest cover loss (Table 13). Observations on Google Earth showed encroachment (Settlements, Agriculture) and intense woodland utilization with the proliferation of grass in both strategies (Figures 2 & 5). The decrease in Woodland/forest cover could be attributed to limited knowledge in implementing management plans in CM (in GM forest reserves, plans are lacking) (Tsoka and Kananji, *pers. comm*.). For instance, determining and regulating the annual allowable harvest of woody products which are viewed as a natural capital by the forest-dependent communities (Handavu et al., 2019; Kalaba et al., 2013) could be challenging. The other reason for the decrease in forest cover could be attributed to demand for land as discussed earlier. Therefore, there is a need to have viable participatory monitoring plans, diversified management in both CM and GM forest reserves.

Alternatively, when CM and GM forest reserves were compared, the findings showed no significant difference between the strategies. These results suggest that forest cover loss in both strategies has remained unabated (Table 13) and that CM has not addressed the challenge (Table 13, Figures 2 & 5). Even though the results show statistical differences within strategies with Google images indicating changes, Pontius, Shusas, and McEachern (2004) have argued that conventionally, these statistical pieces of evidence can hardly show patterns of change in the landscape. In this study, the statistical results showing Woodland/forest cover decline confirm the patterns shown in the transition intensities. The Forest Department in collaboration with the police has been slashing crops and demolishing houses in CM and GM forest reserves and have been administering court cases (*pers. observ.*).

Furthermore, other studies have shown that degraded areas could recover and mitigate forest cover loss, if the areas are not permanently changed to other land uses, and if sustainably managed due to Miombos' ecological characteristics (Geldenhuys, 2010; Gonçalves et al., 2017; Syampungani et al., 2016).

It seems monitoring and diversified management are limited and could assist in preventing further deforestation/degradation in forest reserves. Therefore, continuous decrease in Woodland/forest cover and if coupled with permanent conversion to other land uses could lead to detrimental impacts on the ecological functions if its sustainability will not be checked. Even though changes in forest cover are evident, in both strategies CM with improved institutional capacities in regulating yield could maintain the forest cover and assist in mitigating deforestation and forest degradation, locally, nationally and in the region while satisfying daily needs.

4.4. Implication

Miombo woodlands' ecological functions are vital at local and global scales and could sustain the environment, socio-economic needs; however, the Woodlands are declining in Malawi. The Woodland loss at national level from 4.39 to 3.39 million hectares and also the decline of forest cover in PFM (co-management) and government-management between 1999 and 2018 has an implication on the Miombo Woodlands ecological functions at local, national, regional and global scales. Quan et al. (2019) also reported loss of forests at three periods in China. The results are also consistent with previous studies that have indicated forest loss (Aldwaik & Pontius, 2012; Bonan, 2008; Gao et al., 2016; Lambin & Meyfroidt, 2010; Pontius & Santacruz, 2014). The ecological dominance of Miombo woodlands, its resilience and stable characteristics (Geldenhuys, 2010; Gonçalves et al., 2017; Syampungani et al., 2016), should be a motivation to practically upscale its recovery and sustainability. In addition, the inclusion of Agriculture in the Miombo landscape should enhance land management and food security. Sustainable rotational agro-production could facilitate the Woodland recovery process and could provide tangible ecological functions in the short and long term. This requires harmonisation of policies to adaptive management of LULC without jeopardising the ability of the Woodlands to provide the ecological functions in the future. Degraded areas should be considered as a temporal condition for Woodland succession. Woodland/forest cover loss in both CM and GM should be the starting point for sustainable management of degraded areas. CM is recommended because of communities' legal authority to utilise the Woodlands to cushion many livelihoods in a poverished country and in the region. However, challenges communities' encounter in the implementation need to be documented to assist in reviewing policies to re-enforce CM procedures. GM requires proper planning to minimise and to enhance sustainability and this is urgently required. The knowledge gained is a basis to evaluate future developmental programmes in both strategies. Even though the study focused in Malawi, the results have a wider conservation implication on Miombo Woodlands in SSA and in the tropics. The methods used, and the results generated should form a routine for other subsequent LULCC studies. LULC transition intensities can further be interpreted by other countries in SSA with similar conditions to assist in the sustainable management of Woodlands at local, national and regional scales.

5. Conclusions

LULCC was analysed with a focus on the Woodland and further established the impact of CM and GM on the cover in forest reserves. The error adjustment yielded substantial and robust accuracies in the classification. The transition intensities and Quantity net changes have shown decreased Woodland with a net loss of 8.4% while Agriculture had a net gain of 9.6%. The forest cover decreasing trend in both strategies showed proliferation of grass species as shown in Figure 5. The results have indicated that co-management has not maintained the forest cover. In CM forest reserves, adequate legally binding agreements, sustained annual harvests and monitoring are recommended to assist in maintaining forest cover. In GM forest reserves, access rights of woody resources should be reviewed, management plans developed, implemented and monitored to enhance biodiversity conservation and to protect fragile and water catchment areas. The findings form the foundation for reviewing policies to foster Sustainable Land Use Management (SLUM) and monitoring at local, national and in the region to mitigate detrimental changes. Future studies should investigate the challenges encountered in CM and use information to improve GM forest reserves. There is a need to harmonise policies for integrated land management. Further, interpretation of LULC transition intensities by other countries in SSA with similar conditions as Malawi is recommended. Policy reviews are required to reflect new ideas that could sustain the Woodlands in the landscape.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Geolocation information

The study was conducted in Malawi (country) in Southern East Africa in the sub-Saharan region with Miombo woodlands.

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ORCID

Monica Fides Gondwe http://orcid.org/0000-0001-8052-8777

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