An assessment of forest loss and its drivers in protected areas on the Copperbelt province of Zambia: 1972–2016

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ABSTRACT

In sub-Saharan Africa, protected areas provide a platform for conserving biodiversity. However, these areas are facing massive pressure due to deforestation, and information on forest dynamics and factors driving the changes in protected areas is generally lacking. This study has two objectives: (1) to assess forest cover changes that have occurred between 1972 and 2016 in Copperbelt Province’s protected areas, and (2) understand the drivers of forest cover changes. The study used thematic land cover maps for six selected years, which were classified using an object-based image analysis (OBIA) approach. We also applied a Classification Tree (CT) approach to assess the drivers of forest cover changes using R statistical software. The findings showed that forest cover in protected areas has been characterised by massive deforestation due to various factors. Between 1972 and 2016, primary and secondary forests showed a decrease of 2,226.43 km\textsuperscript{2} (11.06\%) and an increase of 1,082.93 km\textsuperscript{2} (4.05\%), respectively. The major factors driving forest changes include the levels of precipitation, human population density, elevation, distance from roads, towns and rivers. This study presents consistent information for long-term forest monitoring in protected areas, and informs decision-makers on the levels of deforestation and their drivers for effective forest management.

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1. Introduction

Forests are one of the most significant natural assets, especially to the rural communities of sub-Saharan Africa. These forests provide various ecosystem goods and services, which include food, fuelwood, building materials and indigenous medicines (Chidumayo 1989; Vinya 2012). This natural capital also plays an important role in mitigating the effects of climate change (e.g. carbon sequestration) and improving people’s livelihoods (Bodart et al. 2013; de Chazal and Rounsevell 2009). Over the last decades, forest resources have been exposed to different negative effects which are
driven by both natural factors (e.g. droughts, floods, forest fires) and human influences (e.g. unsustainable agricultural practices, deforestation, urbanisation). These challenges have led to the decline in the total forest area in many regions, and the tropics of sub-Saharan Africa have been characterised by this decline for a long-time (Handavu et al. 2019; Zemanova et al. 2017).

The management of forest resources differs from region to region (Bettinger et al. 2016; Chidumayo 2019). However, the most common approach to forest management has been the establishment of protected areas (Andam et al. 2008; Tranquilli et al. 2014). These protected areas are established with different objectives. For example, some protected areas have been established with the purpose of protecting and conserving wildlife resources and by so doing, forest resources are also protected. In Africa and many other countries around the world, forest areas are protected through the establishment of forest reserves (Andam et al. 2008; Jones et al. 2018). Forests in these protected areas are expected to be intact so as to provide suitable habitat for other organisms. However, these forest resources are commonly encroached, deforested, and degraded (Chidumayo 1989; Vinya 2012), and spatio-temporal information relating to forest losses in protected areas, including the driving factors, is limited in many developing countries.

Zambia, like other sub-Saharan African countries, has experienced massive deforestation (Chidumayo 2002). Most of the forest disturbances are taking place in the boundaries of these protected areas due to the edge and proximity effects (Achard et al. 2002; Chidumayo 2002). According to the Global Forest Resource Assessment (GFA) Report, Zambia losses between 250,000 and 300,000 ha per year (Phiri et al. 2019a; Vinya 2012). This trend is mainly due to the conversion of natural areas to other land uses, such as agriculture and human settlements, which are usually done through the encroachment of protected areas and existing forests (Mwamba 2015). Despite this massive pressure that the forests face, protected areas have remained the main reserves for forest resources (Morales-Hidalgo et al. 2015; Watson et al. 2014). Although studies have been conducted to assess various aspects of forest cover changes in Zambia (Lindsey et al. 2014; Phiri et al. 2019b; Vinya 2012), forest dynamics in protected areas and their drivers have not been fully explored.

Previous studies have reported different factors which drive forest cover changes (Handavu et al. 2019; Zemanova et al. 2017); these include both natural (e.g. climate, topography) and anthropogenic factors (e.g. agricultural activities). Although the impacts and types of anthropogenic factors differ from region to region, these factors have been reported as the major drivers of forest loss. These factors are broadly classified as direct (e.g. agricultural expansion, logging, and mining) and indirect factor (e.g. human population dynamics, policies, poverty), especially under the reducing emissions from deforestation and forest degradation (REDD+) program (Lindsey et al. 2014; Phiri et al. 2019b; Vinya 2012). Many studies have reported that both direct factors, such as agriculture, have a great influence on forest loss. For example, Phiri et al. (2019a,b) indicated that other factors have underlining influence on both forest losses and recoveries. Forest near urban centers and other facilities, such as roads, are at high risk of forest loss than those far from anthropogenic facilities.

Monitoring protected areas and managing the available forest resources required up-to-date information in order to inform the decision-making process by multiple
stakeholders, such as policy-makers and practitioners. Remote sensing offers a reliable approach to monitoring forest resources in protected areas, especially with the increasing and advanced technology (Phiri and Morgenroth 2017; Woodcock et al. 2008). Monitoring of forest resources on a large spatial extent is now more efficient because of the improvements in the qualities of the available remotely sensed data and the increasing computing power through Geographic Information Systems (GIS). Thus, large areas can be monitored with a historical context which is important for understanding the past and current forest status, and for future predictions. In addition, remotely sensed data which is freely available (e.g. Landsat and Sentinel data) has increasingly contributed to the effective monitoring of forest resources because financially constrained researchers and practitioners can easily access remotely sensed data (Woodcock et al. 2008). Furthermore, the combination of GIS and statistical analysis through the ever increasing computing capabilities (e.g. cloud computing, artificial intelligence and machine-learning) offers an opportunity to generate consistent and accurate information for monitoring protected areas, and natural resources in general (Phiri and Morgenroth 2017; Zhang et al. 2008).

Previous studies have been conducted in Zambia to monitor forest dynamics (Hansen et al. 2016; Lembani et al. 2019; Phiri 2019). However, few studies have focused on monitoring forest cover changes and their drivers in protected areas (Chidumayo 1989; Vinya 2012). For example, Phiri et al. (2019a) and Lembani et al. (2019) focused on monitoring forest cover changes across the entire landscape; thus, details on forest cover changes in protected areas could have not been fully captured. The novelty of this study lies in the contribution towards the assessment of forest cover losses in protected areas in developing countries. Additionally, a Classification

Figure 1. A map showing the location of the study area indicating the distribution of protected areas on the Copperbelt Province of Zambia.
Tree approach, employed in this study, has not been used to test factors of forest cover changes in protected area in developing countries. This study has two main aims: (1) to assess forest cover changes that have occurred in protected areas on the Copperbelt Province of Zambia between 1972 and 2016 using the integration of remote sensing and GIS; and (2) to determine the factors driving forest cover changes in protected areas by using a Classification Tree analysis. The information from this study will help decision-makers, especially those in wildlife and forest sectors, to make informed decision on the management of forest resources based on empirical evidence.

2. Material and methods

2.1. Study area

The study area is the Copperbelt Province of Zambia located between latitude $12^\circ\ 21'\ 07''$ and $13^\circ\ 40'\ 50''$ South, and longitude $26^\circ\ 41'\ 29''$ and $27^\circ\ 36'\ 02''$ East (Figure 1). The region has an undulating terrain ranging between 900 and 1,500 m above sea level, with the elevation occasionally broken by isolated hills (Phiri et al. 2016). The main river system is the Kafue River, which traverses the province in the southern direction, and swamps occur along the river and its numerous tributaries. This area experiences rainfall ranging from 1,000 to 1,500 mm per annum, and annual temperature range from $7^\circ\mathrm{C}$ to $35^\circ\mathrm{C}$ between the cold and the hot seasons. Broad areas of the plateau are covered with an open mixture of shrubs, trees, and tall grasses, dominated by the 'Miombo' dry tropical forest (Chidumayo 1997).

Based on the projections from the 2010 national census$^1$, the Copperbelt Province has a human population of over 2.54 million (annual growth rate of 3.5%), and the major economic activities include mining and agriculture (CSO. 2010). Copper is the primary mineral resource, and the mining activities in Zambia contribute about 35% of the total export earnings. Many people in this area practice small-scale farming, with maize as one of the major crops.

2.1.1. Protected areas based on the international union for conservation of nature (IUCN) categorisation

The protected areas on the Copperbelt Province include Game Management Areas (GMA), Forest Reserves, and a Bird Sanctuary. The Province has more than 50 forest reserves and two Game Management Areas (GMAs) (i.e. Lunga-Luswishi, Machiya-Fungulwe). The GMAs fall under Category VI of the IUCN protected area category, while the Bird Sanctuary (i.e. Chembe Bird Sanctuary) has been classified under Category II, with equivalent declaration as a national park. Forest reserves and plantations fall in IUCN protected area Category VI, which are protected areas with sustainable use of natural resources. The Copperbelt Province has over 90% of Zambia’s forest plantations ($\text{Pinus}$ and $\text{Eucalyptus}$) which are managed by a parastatal company called Zambian Forest and Forestry Company (ZAFFICO) (Ng’andwe et al. 2015; Phiri et al. 2016).
2.2. Data source

2.2.1. Land cover maps

This study used national land cover maps for Zambia, produced by Phiri et al. (2019a) which cover six-time steps: 1972, 1984, 1990, 2000, 2008 and 2016. The period for analysis was selected based on different political and economic changes that have occurred in Zambia between 1972 and 2016 (e.g. change of government in 1990, and restructuring in 1995, economic meltdown in 2008). The maps were produced using an object-based image analysis (OBIA) approach in eCognition Developer 9.3 (Trimble Navigation Ltd, Sunnyvale, California), with overall accuracies ranging from 78 to 89% (Phiri et al. 2019a). The land cover map for 1972 had the lowest accuracy, and that for 2016 had the highest accuracy. These land cover maps were prepared based on nine land cover types which included; Primary Forest, Secondary Forest, Plantation Forest, Wetland, Water body, Cropland, Irrigation,
Grassland and Settlement (Figure 2). In this study, we refer to Primary Forest as areas which are undisturbed (have intact forests), while secondary forests as those forests which are either degraded or recovering from damage. The forest which have been established through planting of exotic species are considered as plantation forests. This study focused mainly on the transition in Primary and Secondary Forests because they define the existing forest resources in the study area. In our analysis here, we did not consider plantation forests because they have a smaller spatial extent and are less affected by factors driving deforestation. Although the changes in land cover are expected to be characterised with losses of Primary Forests, few areas are expected to recover to intact forest (Primary Forest) over the 45 years study period.

2.2.2. Other datasets
Datasets such as provincial and protected area boundaries were secured from the Forest Department (FD) headquarters in Lusaka, Zambia. These were important for resizing the maps and extracting forests in protected areas. To assess the drivers of forest changes, we also used training and validation datasets for developing a Classification Tree (CT) model as explained in Section 2.4.

2.3. Forest change in protected area
Since the land cover maps were at a national scale, the Copperbelt Provincial boundary was used to resize the maps to the provincial level. The official boundaries of protected areas for Zambia were then used to extract forest areas and other land covers which are within the protected areas of the Copperbelt Province. The major statistics derived from these maps were the areas covered by each forest type in each classification year, and this information was then used to understand the forest trends between 1972 and 2016 using a transition matrix (Phiri et al. 2019a,b). The rates (%) of forest changes between the six time period were calculated using Equation (1), which uses the area at the beginning and at the end of the analysis by considering the number of years for the analysis period (Puyravaud 2003).

\[ r = \left( \frac{1}{t_2 - t_1} \right) \times \ln \left( \frac{A_1}{A_2} \right) \]

where \( r \) is the rate of forest change, \( t_2 \) is the year at the end of the analysis period, \( t_1 \) is the year at the start of the analysis period, \( \ln \) is natural log, \( A_1 \) represents the areas at the beginning of the analysis period, while \( A_2 \) denotes the area at the end of the analysis period.

2.4. Factors of forest changes in protected areas
2.4.1. Classification tree
A classification tree (CT) approach was used to understand the drivers of forest changes in protected areas. These CT models are part of the immerging machine-learning approaches used in data mining (Morgenroth et al. 2017). CTs employ the principles of decision trees during data partitioning to recursively split dataset into
mutually exclusive groups. Here, we used the CT approach to analyse the association of different factors with eight possible forest transitions (Table 1). CTs have several advantages over other approaches because they can be used to analyse non-parametric data, missing values and can be employed for both categorical and numerical values (Guo et al. 2018; Phiri et al. 2019b). Most of the CT models produce decision tree graphical diagrams, which simplifies the interpretation of results.

As a first step towards the implementation of a CT model, Pearson’s correlation analysis was used to assess the autocorrelation of the explanatory variables by removing some variables which were strongly correlated \( r = 0.6 \) (Morgenroth et al. 2017). The remaining explanatory variables were then used to model the eight forest transitions.

2.4.2. Model validation
The cross-validation approach was used to validate the CT model. The data was split into two datasets: (1) training dataset — 70% of the dataset, and (2) validation dataset — 30%. After training the model with the training dataset, we then predicted the outcome of validation dataset and compared the outcome with the actual measures (Guo et al. 2018; Phiri et al. 2019b). The output of the comparison is presented in a confusion matrix. We used measures, such as the overall, user’s and producer’s accuracy to determine the accuracy of the model. The model was pruned in order to avoid over fitting by setting the complex parameter to a minimum cross validation error of the model (Guo et al. 2018).

All the statistical analysis was conducted in R programming environment by using two packages; (1) the ‘rpart’ package for producing decision trees, and (2) the ‘rpart.plot’ for producing decision tree graphical diagrams (R Core Team 2017).

2.4.3. Response variables
We used eight forest transition scenarios (Table 1) to understand the drivers of forest changes in protected areas. Since our focus was on the changes in primary and secondary forests, the transitions considered here were associated with these two forest covers.

2.4.4. Independent variables
Different factors were used as independent (i.e. predictor) variables to analyse the forest changes in protected areas. These factors include climatic, topographic, socioeconomic and proximity factors (Table 2). Climatic factors include rainfall, temperature, and solar irradiance. Total precipitation may influence the forest cover changes because it is closely related to the growth of vegetation. The areas with high rainfall

| No. | Response variable | Description |
|-----|-------------------|-------------|
| 1   | Primary to Primary| Unchanged areas of primary forest |
| 2   | Secondary to Secondary | Unchanged areas of secondary forest |
| 3   | Primary to Secondary forest | Areas that changed from primary to secondary forests |
| 4   | Primary to Others | Change from primary forests to other land covers (e.g. grasslands) |
| 5   | Others to Primary | Change from other land covers to primary forests |
| 6   | Secondary to Primary | Change from Secondary to Primary forests |
| 7   | Other to Secondary forest | Change from other land covers to secondary forests |
| 8   | Secondary to Others | Change from Secondary forests to other covers |
activities are expected to have high vegetation growth and increasingly forest recovery potential after a disturbance. These climatic variables mainly influence the establishment of vegetation and other socioeconomic factors, such as agriculture. Thus, areas with favourable climatic conditions attract various socioeconomic activities, and hence, having an influence on forest cover changes. Topographic factors, such as elevation, slope and aspect determine the suitability of land for a particular use. Kamwi et al. (2018) reported that socioeconomic (e.g. employment, income) and proximity factors (e.g. distance to roads, towns) determine demographic and economic activities taking place in an area. Therefore, this has a major influence on forest utilisation.

### Geospatial processing

The geospatial processing was done in ArcMap 10.7.1 (Esri, Radland, California). To determine the nearest distance to sample points, we used the ‘Euclidean Distance’ tool under spatial analysis to covert features of interest such as roads, railway, towns and mines. Factors such as human population, crop yield and income were converted from shapefile to raster format. Topographic features including slope, elevation and aspects were derived from the digital elevation models (DEM) which were downloaded from the United States Geological Survey (USGS) website (https://earth-explorer.usgs.gov/). All the datasets were projected to a common projected coordinate system - the World Geodetic System 84 (WGS 84) Zone 35 South. As a final step for

### Table 2. Independent factors used to assess the drivers of forest change in protected area on the Copperbelt Province of Zambia.

| Category       | Factors and units                   | Range                | Spatial resolution | Temporal resolution | Sources                                      |
|----------------|-------------------------------------|----------------------|--------------------|---------------------|----------------------------------------------|
| Topographic    | Elevation (m)                       | 325–2296             | 30 m               | –                   | USGS                                         |
|                | Slope (°)                           | 0–57.42              | 30 m               | –                   |                                              |
|                | Aspect (°)                          | –1–359.90            | 30 m               | –                   |                                              |
| Climatic       | Total annual precipitation (mm)     | 590–1503             | 1 km               | 1970–2000           | WorldClim                                    |
|                | Solar radianse (W m⁻²)              | 15763–20511          | 1 km               | –                   |                                              |
|                | Maximum temperature (°C)            | 19.78–33.63          | 1 km               | –                   |                                              |
|                | Minimum temperature (°C)            | 8.60–21.57           | 1 km               | –                   |                                              |
|                | Mean temperature (°C)               | 14.30–26.30          | 1 km               | –                   |                                              |
| Social         | District status (urban, rural)      | –                    | District level     | Central Statistics  |                                              |
|                | Total population (count)            | 25, 294 – 1,701,640  | District level     | 1969–2010           | Office of Zambia (CSO)                       |
|                | Population density (persons km⁻²)   | 2.70–4,841.60        | District level     | 2010                |                                              |
| Proximity      | Euclidean distance to waterbody edges (km) | 0–108.62          | 30 m               | –                   | Forest Department (FD)                       |
|                | Euclidean distance to town centres (km) | 0–82.56           | 30 m               | –                   | FD                                           |
|                | Euclidean distance to road (km)     | 0–104.25             | 30 m               | –                   | Road Development Agency of Zambia           |
| Accessibility  | Euclidean distance to railway (km)  | 0–108.67             | 30 m               | –                   | FD                                           |
|                | Euclidean distance to rivers (km)   | 0–128.62             | 30 m               | –                   | FD                                           |
|                | Euclidean distance to border towns (km) | 0–355               | 30 m               | –                   | Ministry of Tourism                          |
|                | Distance to mines (km)              | 0–305                | 30 m               | –                   | Ministry of Tourism                          |
the analysis, all the datasets were resampled to a 30 m spatial resolution in order to avoid working with different spatial resolutions.

A total of 400 points were randomly generated over the study area and then used to extract values from the datasets. As explained in Section 2.4.2 the random points were separated into training (70%, 280 sample points) and validation dataset (30%, 120 sample points) as recommended by Guo et al. (2018). Figure 3 shows the major steps followed during data analysis.

3. Results

3.1. Forest cover changes in protected areas

The results show a general decline in the total forest area, which is mainly characterised by a decline in primary forests and an increase in the area covered by secondary forest between 1972 and 2016. Table 3 shows that primary forests covered 7,520.84 km² in 1972 and 5,294.41 km² in 2016, which translates into a decline of 2,226.43 km². Secondary forests occupied 1,120.87 km² in 1972 and 2,203.81 km² in 2016, indicating an increase of 1,082.93 km². Primary forests declined from 23.96% in 1972 to 16.87% in 2016, while secondary forest increased from 3.57% to 10.20% in 2000, before declining to 7.02% in 2016.

The annual rates of change show that primary forests had the highest rate of −0.04% per annum between 1990 and 2000, while secondary forests showed some increase of 0.06% during the same period (Table 4). The entire forest showed a continuous decline of −0.01% per annum between 2008 and 2016. However, a minor increase of 0.01% per annum was reported between 2008 and 2016.
3.2. Forest transition: 1972–2016

Figure 4 shows the transition of forest cover in the protected areas on the Copperbelt Province between 1972 and 2016. Generally, the pattern of forest transition was characterised by the change from primary to secondary forests. Minor changes occurred from secondary to primary forests. It was also observed that protected areas near to the urban centers changed from the two forest covers to other land covers (e.g. grassland, wetlands, cropland).

Table 5 shows a transition matrix of forest cover changes between 1972 and 2016. About 309,656.44 ha of primary forest remained unchanged, while 32,671.11 ha of secondary forest remained unchanged during the study period. A large area (228,453.98 ha) of primary forest changed to secondary forest, while 41,824.23 ha of secondary forest changed to primary forest. There was a minimal transition between land covers, such as irrigation crops and water bodies to forest covers during the study period.

3.3. Factors of forest change in protected area

Figure 5 shows the CT model for the forest transition in protected areas on the Copperbelt Province of Zambia. The CT model had an overall accuracy of 80%, with user and producer’s accuracy ranging from 63% to 80% (Table 6). The forest transition in protected area were influenced by different factors including total precipitation, human population density of a district, elevation, distance to rivers, towns and roads. The CT model showed that most of the changes that occurred were the transition from primary to secondary forest, influenced by total precipitation, human population density, elevation and distance to urban centers. Thus, areas which had a total precipitation of greater than 1200 mm per annum, population of greater than 12 people per square km, elevation of over 1229 and within a distance of 3 km from town centers were likely to change to secondary forests. On the other hand, forests which were far from the roads, towns and with low human population densities had a lower chance of changing to other land covers (e.g. cropland, grassland and wetland).

4. Discussion

Our findings clearly show changes in forest cover in the protected areas on the Copperbelt Province of Zambia between 1972 and 2016, with most of the regions...
partially or completely losing forest cover. The primary forest area decreased by 11.09% from 1972 to 2008, before increasing by 4.01% between 2008 to 2016. The highest decrease in the primary forests occurred between 1990 to 2000, at a rate of change of $-0.04\%$. Secondary forests increased by about 5% during this period (1990–2000), indicative of a slow recovery rate compared to the overall decrease in primary forests. The increase in the area covered by secondary forests occurred due to the decline of intact forests (primary forests) which was driven by agricultural activities and harvesting. The eventual decline after the year 2000 can be linked to other increasing human activities, such as establishing of settlements and farms in areas were the remnants of secondary forests existed. The decline in primary forests and the subsequent increase of secondary forests show that the changes in the forests

**Table 4.** Annual rate of change for primary, secondary, and the entire forest area in protected areas.

| Period     | Primary Forest | Secondary Forest | Entire Forest |
|------------|----------------|-----------------|--------------|
| 1972–1984  | $-0.01$        | $-0.03$         | $0.02$       |
| 1984–1990  | $-0.03$        | $0.14$          | $0.01$       |
| 1990–2000  | $-0.04$        | $0.06$          | $0.01$       |
| 2000–2008  | $0.01$         | $-0.01$         | $0.01$       |
| 2008–2016  | $0.03$         | $-0.04$         | $-0.01$      |

**Figure 4.** Maps showing forest transitions between 1972 and 2016. The forest transitions were mainly associated with primary and secondary forests.
| From 1972       | Cropland | Grassland | Irrigated crops | Plantation forest | Primary forest | Secondary forest | Settlement | Water body | Wetland | Total     |
|-----------------|----------|-----------|-----------------|-------------------|---------------|-----------------|------------|------------|---------|-----------|
| Cropland        | 1346.04  | 2913.18   |                 | 761.79            | 4058.22       | 3690.18         | 404.78     | 57.41      |         | 13894.30  |
| Grassland       | 2227.92  |           | 1010.94         | 23122.35          | 13457.09      | 488.44          | 0.32       | 40.46      | 870.62  | 13819.26  |
| Plantation Forest| 2407.73  | 2423.04   | 1831.61         | 2610.87           | 3349.51       | 285.41          | 40.46      | 870.62     |         | 13819.26  |
| Primary forest  | 39823.22 | 113158.70 | 17486.35        | 228455.98         | 14312.64      | 958.33          | 28194.69   |           |         | 752059.01 |
| Secondary Forest| 6881.53  | 20501.41  | 3688.02         | 41824.40          | 32671.11      | 2205.01         | 108.89     | 4206.79    | 112087.16|
| Settlement      | 1518.26  | 1974.86   | 1221.03         | 1439.82           | 2492.80       | 560.34          | 148.53     | 416.25     | 9771.91  |
| Water body      | 274.89   | 123.36    | 107.57          | 212.36            | 0.14          | 4.20            | 50.83      | 773.36     |         |           |
| Wetland         | 2105.57  | 8154.12   |                 | 1393.52           | 21263.75      | 12880.29        | 456.61     | 62.41      | 3041.81  | 49358.08  |
| **Total**       | **56585.17** | **162340.49** | **12.65**      | **27393.26**      | **404083.42** | **297209.32**   | **18713.38** | **1380.56** | **39689.08** | **1007407.33** |
were gradual through the process of forest degradation. These findings are in line with Mayes et al. (2015) who reported that most of the forest changes in the dry tropical areas occurred through the gradual processes of forest degradation, before being completely deforested.

The CT model indicated that forest changes were driven by different factors which included total precipitation, elevation, human population density and distance to facilities (e.g. towns and roads). It was clear from these findings that most of the forest losses occurred in areas with a high human population density, suitable rainfall activities supporting different agricultural activities and being in close proximity to town centers and main roads, because of having a high chance of changing from forest to non-forest covers, and vice-versa. These findings are in line with the Searchinger et al. (2015) who indicated that forest changes are generally influenced by socioeconomic activities, including agricultural activities. On the other hand, Phiri et al. (2019b) indicated that protected areas have the potential to recover and to maintain existing forests if proper management strategies are employed.

The changes from primary to secondary forests and the complete losses (i.e. deforestation) of forest covers were mainly due to the destruction of intact forests resulting from the ever-increasing human population, small-scale farming, and unsustainable utilisation of forest products. The finding from this study indicates that most of the forest changes in the protected areas are driven by different anthropogenic activities, and it is also possible that the rise in human population between 1972 and 2016 (Simwanda & Murayama, 2018) may have led to the conversion of forests to other forms of land cover. The human population of the study area, the Copperbelt

![Figure 5](image-url)
Table 6. A confusion matrix showing the accuracy of the transition of forest covers and other land covers. UA is user’s accuracy, PA is producer’s accuracy and OA is overall accuracy.

| Predicted | Reference | Others to secondary | Others to primary | Primary to others | Primary to primary | Primary to secondary | Secondary to others | Secondary to primary | Secondary to secondary | Total | UA (%) |
|-----------|-----------|---------------------|-------------------|------------------|-------------------|---------------------|---------------------|---------------------|-----------------------|-------|---------|
| Others to Secondary | 6 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 8 | 75 |
| Others to Primary | 0 | 5 | 0 | 1 | 1 | 0 | 0 | 0 | 7 | 71 |
| Primary to Others | 0 | 0 | 8 | 0 | 4 | 0 | 0 | 0 | 12 | 67 |
| Primary to Primary | 0 | 0 | 0 | 15 | 3 | 0 | 0 | 0 | 18 | 83 |
| Primary to Secondary | 0 | 0 | 0 | 3 | 47 | 0 | 0 | 0 | 51 | 92 |
| Secondary to Others | 0 | 0 | 0 | 2 | 0 | 4 | 0 | 0 | 6 | 67 |
| Secondary to Primary | 0 | 0 | 0 | 0 | 0 | 3 | 1 | 4 | 4 | 75 |
| Secondary to Secondary | 0 | 0 | 0 | 2 | 4 | 0 | 0 | 8 | 14 | 67 |
| **Total** | **6** | **5** | **8** | **24** | **60** | **4** | **3** | **10** | **120** | **OA = 80%** |

Table 6. A confusion matrix showing the accuracy of the transition of forest covers and other land covers. UA is user’s accuracy, PA is producer’s accuracy and OA is overall accuracy.
Province has increased from 850,000 in 1972 to over two million in 2016. In the neighbouring Congo Basin, Ernst et al. (2013) recorded similar trends in the decline of primary forest in protected areas, primarily influenced by the growing human population.

The nature of forest cover has been characterised by rising deforestation rates and low forest recovery rates. These findings are consistent with McNicol et al. (2018) who suggested that deforestation rates in sub-Saharan Africa have remained high. The proximate drivers of deforestation in Zambia are shifting agriculture, agricultural intensification, charcoal production, fuelwood collection, logging, human settlements, uncontrolled fires, industrialisation, and urban expansion (Vinya 2012), consistent with the findings of Kalaba et al. (2013) who suggested that agriculture, the growth of the highways, the excessive logging businesses and the assortment of fuelwood are the main reasons for deforestation.

An interesting finding from this study was the fact that some disturbed forest recovered during the study period. Besides forest recovery, some areas remained undisturbed during the whole study period. The main factors influencing the recovery of forest and the maintenance of some forest areas are mainly related to how accessible those areas are. Thus, forest areas which are far from settlements, roads, railway and urban centers have the potential to remain unchanged or recover after experiencing disturbance. Lindsey et al. (2014) indicated that forest encroachment was more prominent on the peripheral of National Parks, especially from communities who settle in Game Management Areas. Our findings in this study on the recovery of forest have the potential to enhance policy implementation in areas with high rates of forest losses. Thus, monitoring, awareness and provision of alternative livelihood have the potential to minimise forest losses, and hence, promoting forest recovery (Lindsey et al. 2014; Phiri et al. 2019a,b).

Protected areas in Zambia are under serious pressure from encroachment, which results in illegal human settlements. Due to increasing demand for agricultural land, both wildlife and forest protected areas have been degraded and deforested, and some of these reserves have ceased to exist as protected areas (Lindsey et al. 2014). Particularly, forest reserves which are near the mining towns have been converted into human settlements and alternative land uses. For example, Mwekera National Forest in Kitwe and Monkey Fountain Forest reserve in Ndola have been heavily degraded because of the high pressure resulting from the proximity to major towns (Chidumayo 1997).

This study provides reliable forest monitoring information on protected areas in the Copperbelt Province, beneficial to Zambia as a whole and beyond. Generally, this study makes two main contributions towards the conservation of forest resources in protected areas: (1) The information generated here has the potential to assist decision-makers to successfully implement forest management programmes, and (2) the method for exploring the drivers of forest changes can be replicated in other areas. The findings from this study could also act as a reference standard for the management of forests in protected areas of the Copperbelt Province, especially when addressing the drivers of forest changes (Leventon et al. 2014). Due to the increasing disturbances in and around the protected areas, the results from this study are
relevant for both local and regional forest resource monitoring programmes (e.g. Reducing emission from deforestation and forest degradation, REDD+) (Weatherley-Singh and Gupta 2015).

The presented findings should be viewed within the scope of the limitations of the analysis. Firstly, the generation of the results was based on Phiri et al. (2019a) adopted classified thematic land cover maps, with existing accuracy and specifications. We had no control over the accuracy of the maps. Secondly, the land cover and the recorded area values are snapshots in time, identifying the land cover of the Copperbelt Province over the past 45 years for six distinct steps in time. Consequently, an exhaustive explanation of all prevailing land cover changes within each time phase is nearly impossible. Finally, though some drivers of land cover changes were discussed above (e.g. agricultural expansion), it is acknowledged that numerous other factors contribute to forest dynamics in protected areas. Hence, future studies could focus on assessing the drivers of forest changes in protected areas by considering a broad range of factors.

5. Conclusions

The aim of this study was to assess the forest cover changes that have occurred in protected areas of the Copperbelt Province of Zambia between 1972 and 2016. In addition, we also looked at the driving factors of forest transitions using the CT approach. Overall, forest cover declined from primary to secondary forests before complete deforestation, and the rates of forest losses were high between 1990 and 2000 – a period associated with different political and socioeconomic activities. The CT model indicated that the main factors of forest changes included total precipitation, elevation, distance from town centres, main roads and rivers. In general, the forest changes in the last four decades in Zambia’s protected areas can be associated with the expansion of the agricultural sector and human population increase, especially those close to urban areas (Handavu et al. 2019; Weatherley-Singh and Gupta 2015). These drivers generally indicate that forest changes were mainly associated with anthropogenic activities as these factors determined different human activities, such as opening areas for agriculture and settlements, which drive deforestation and forest degradation. The information from this study is essential for Zambia-wide forest resource planning, monitoring, and management in protected areas, and it could also educate policy-makers on important environmental aspects, such as biodiversity conservation and climate change mitigation. Beyond the study area, this research presents a simple methodology and workflow which can be used or be replicated in other areas in order to understand forest cover dynamics and driving factors.

Disclosure statement

The authors declare no conflict of interest.

Data availability statement

The dataset generated during this study is available from the corresponding author (Darius Phiri) upon reasonable request.
Note

1. The 2010 national census remains the latest census since the census which was supposed to take place in 2020 was not completed due to the COVID-19 pandemic.

References

Achard F, Eva HD, Stibig H-J, Mayaux P, Gallego J, Richards T, Malingreau J-P. 2002. Determination of deforestation rates of the world’s humid tropical forests. Science. 297(5583):999–1002.

Andam KS, Ferraro PJ, Pfaff A, Sanchez-Azofeifa GA, Robalino JA. 2008. Measuring the effectiveness of protected area networks in reducing deforestation. Proc Natl Acad Sci USA. 105(42):16089–16094.

Bettinger P, Boston K, Siry JP, Grebner DL, 2016. Forest management and planning. 2nd ed. eBook: Academic Press.

Bodart C, Brink AB, Donnay F, Lupi A, Mayaux P, Achard FJ, 2013. Continental estimates of forest cover and forest cover changes in the dry ecosystems of Africa between 1990 and 2000. J Biogeogr. 40(6):1036–1047.

Chidumayo EN. 1997. Miombo ecology and management: an introduction. Intermediate Technology Publisher. Southampton, UK.

Chidumayo EN. 1989. Land use, deforestation and reforestation in the Zambian Copperbelt. Land Degrad Dev. 1(3), 209–216.

Chidumayo EN. 2002. Changes in Miombo woodland structure under different land tenure and use systems in central Zambia. J Biogeogr. 29(12):1619–1626.

Chidumayo EN. 2019. Management implications of tree growth patterns in Miombo woodlands of Zambia. For Ecol Manage. 456:105–116.

CSO. 2010. Zambia 2010 Census of population and housing. Lusaka, Zambia: GRZ. Retrieved from Lusaka, Zambia:

de Chazal J, Rounsevell MDA. 2009. Land-use and climate change within assessments of biodiversity change: a review. Global Environ Change. 19(2):306–315.

Ernst C, Philippe M, Astrid V, Catherine B, Musampa C, Pierre D. 2013. National forest cover change in Congo Basin: deforestation, reforestation, degradation and regeneration for the years 1990, 2000 and 2005. Glob Chang Biol. 19(4):1173–1187.

Guo T, Morgenroth J, Conway T. 2018. Redeveloping the urban forest: the effect of redevelopment and property-scale variables on tree removal and retention. Urban For Urban Green. 35:192–201.

Handavu F, Chirwa PWC, Syampungani S. 2019. Socio-economic factors influencing land-use and land-cover changes in the Miombo woodlands of the Copperbelt province in Zambia. Forest Policy and Economics. 100:75–94.

Hansen MC, Potapov PV, Goetz SJ, Turubanova S, Tyukavina A, Krylov A, Kommareddy A, Egorov A. 2016. Mapping tree height distributions in Sub-Saharan Africa using Landsat 7 and 8 data. Remote Sens Environ. 185:221–232.

Jones KR, Venter O, Fuller RA, Allan JR, Maxwell SL, Negret PJ, Watson JEM. 2018. One-third of global protected land is under intense human pressure. Science. 360(6390):788–791.

Kalaba FK, Quinn CH, Dougill AJ, Vinya R. 2013. Floristic composition, species diversity and carbon storage in charcoal and agriculture fallows and management implications in Miombo woodlands of Zambia. For Ecol Manage. 304:99–109. http://dx.doi.org/10.1016/j.foreco.2013.04.024.

Kamwi J, Cho M, Kaetsch C, Manda S, Graz F, Chirwa P, 2018. Assessing the spatial drivers of land use and land cover change in the protected and communal areas of the Zambezi region, Namibia. Land. 7(4):131–140.

Lembani RL, Knight J, & Adam E. 2019. Use of Landsat multi-temporal imagery to assess secondary growth Miombo woodlands in Luanshya, Zambia. South For: J For Sci. 18(2):129.
Leventon J, Kalaba FK, Dyer JC, Stringer LC, Dougill AJ. 2014. Delivering community benefits through REDD+: lessons from joint forest management in Zambia. For Policy Econ. 44: 10–17.

Lindsey, PA, Nyirenda VR, Barnes JJ, Becker MS, McRobb R, Tambling CJ, … ’Sas-Rolfes M, 2014. Underperformance of African protected area networks and the case for new conservation models: insights from Zambia. PLoS One. 9(5):e94109.

Mayes MT, Mustard JF, Melillo JM. 2015. Forest cover change in Miombo Woodlands: modeling land cover of African dry tropical forests with linear spectral mixture analysis. Remote Sens Environ. 165:203–215.

McNicol IM, Ryan CM, Mitchard ETA. 2018. Carbon losses from deforestation and widespread degradation offset by extensive growth in African woodlands. Nat Commun. 9(1): 3045.

Morales-Hidalgo D, Oswalt SN, Somanathan E. 2015. Status and trends in global primary forest, protected areas, and areas designated for conservation of biodiversity from the Global Forest Resources Assessment 2015. For Ecol Manage. 352:68–77.

Morgenroth J, O’Neil-Dunne J, Apiolaza LA. 2017. Redevelopment and the urban forest: a study of tree removal and retention during demolition activities. Appl Geogr. 82:1–10.

Mwamba K. 2015. Report of the auditor general sustainable forest management. Lusaka: Lusaka Provincial Adult Office.

Ng’andwe P, Mwitwa J, Muimba-Kankolongo A. 2015. Forest policy, economics, and markets in Zambia. Academic Press, London, UK.

Phiri D, Morgenroth J, Xu C. 2019a. Four decades of land cover and forest connectivity study in Zambia—an object-based image analysis approach. Int J Appl Earth Obs Geoinf. 79: 97–109.

Phiri D, Morgenroth J, Xu C. 2019b. Long-term land cover change in Zambia: an assessment of driving factors. Sci Total Environ. 697:134206.

Phiri D, Morgenroth J. 2017. Developments in Landsat land cover classification methods: a review. Remote Sens. 9(9):967.

Phiri D, Phiri E, Kasubika R, Zulu D, Lwali C. 2016. The implication of using a fixed form factor in areas under different rainfall and soil conditions for Pinus kesiya in Zambia. South For: J For Sci. 78(1):35–39.

Phiri D. 2019. Monitoring land cover dynamics for Zambia using remote sensing: 1972–2016 [PhD thesis]. University of Canterbury. http://hdl.handle.net/10092/18544.

Puyravaud J-P. 2003. Standardizing the calculation of the annual rate of deforestation. For Ecol Manage. 177(1–3):593–596.

R Core Team 2017. R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Searchinger TD, Estes L, Thornton PK, Beringer T, Notenbaert A, Rubenstein D, Heimlich R, Licker R, Herrero M. 2015. High carbon and biodiversity costs from converting Africa’s wet savannahs to cropland. Nat Clim Change. 5(5):481–486.

Simwanda M, & Murayama Y, 2018. Spatiotemporal patterns of urban land use change in the rapidly growing city of Lusaka, Zambia: implications for sustainable urban development. Sustain Cities Soc. 39(12):262–274.

Tranquilli S, Abedi-Lartey M, Abernethy K, Amsini F, Asamoah A, Balangtta C, … Brncic TM. 2014. Protected areas in tropical Africa: assessing threats and conservation activities. PLoS One. 9(12):e114154.

Vinya R. 2012. Preliminary study on the drivers of deforestation and potential for REDD + in Zambia. A consultancy report prepared for forestry department and FAO under the national UN-REDD + programme ministry of lands & natural resources. Lusaka: Zambia.

Watson JE, Dudley N, Segan DB, Hockings MJN. 2014. The performance and potential of protected areas. Nature. 515(7525):67–73.

Weatherley-Singh J, Gupta A. 2015. Drivers of deforestation and REDD + benefit-sharing: a meta-analysis of the (missing) link. Environ Sci Policy. 54:97–105.
Woodcock CE, Allen R, Anderson M, Belward A, Bindschadler R, Cohen W, Gao F, Goward SN, Helder D, Helmer E, et al. 2008. Free access to landsat imagery. Science. 320(5879):1011–1011.

Zemanova MA, Perotto-Baldivieso HL, Dickins EL, Gill AB, Leonard JP, Wester DB. 2017. Impact of deforestation on habitat connectivity thresholds for large carnivores in tropical forests. Ecol Process. 6(1):21.

Zhang H, Fritts JE, Goldman SA. 2008. Image segmentation evaluation: a survey of unsupervised methods. Comput Vis Image Underst. 110(2):260–280.