Assessment of Land Cover Changes in Litumbandyosi-Gesimasowa Game Reserve using Remote Sensing and GIS

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Abstract. As countries in Sub-Saharan Africa strive to reduce deforestation in Miombo woodlands, it is essential to use the appropriate, reliable, and cost-effective tools for assessing land cover changes. This study employed Remote Sensing and GIS techniques to assess land use and its changes in the Litumbandyosi-Gesimasowa Game Reserve between 1990 and 2020. The tools employed were GEE and Collect Earth. The study employed Sentinel-2 and Landsat-5 TM imagery and also incorporated the Atmospheric Resistant Vegetation Index (ARVI) for improving classification by overcoming the effects of Non-Photosynthetic Vegetation (NPV) and phenology. The study produced highly accurate land cover maps, with an overall accuracy of 99.53% and a kappa coefficient of 98.11% in 1990, 99.84% and a kappa coefficient of 98.69% in 2011, and 92.10% and an 89.62% kappa coefficient in 2020. The findings of the post-classification revealed an alarming change in land cover over the last 30 years, with heavy forestland decreasing by 10.77%, shrubland increasing by 12.19%, and grassland increasing by 13.35%. Furthermore, farmland expanded by 4.58%, barren land grew by 5.82%, and wetlands grew by 0.74%. Significant agents of change have been identified as forest fires, overgrazing, crop farming, and mining.

1. Introduction
Natural forests, particularly the Miombo woodlands, which make up 90% of Tanzania's forest reserves, have been severely degraded in recent decades. Anthropogenic activities (such as recurrent wildfires, overgrazing, agriculture, and mining), as well as natural events (such as climate change and wildlife pressures), have been found to have exposed Miombo woodlands and other forest types to deforestation or severe degradation. Furthermore, it directly or indirectly sustains millions of sub-Saharan local populations [1]. Nevertheless, the Miombo woodlands possess ecological potentials whereby it hosts millions of flora and fauna [2]. In addition, the Miombo trees, grasses, and shrubs form the vast global carbon sequestration region, protect watersheds, provide grazing land for domesticated livestock, and be a home of wildlife and destinations for many of the safari's tourism [3]. The Litumbandyosi-Gesimasowa Game Reserve(LGGR) in southern Tanzania is one of the Miombo woodlands forest affected by anthropogenic activities. Studies show that over 8,500 Miombo species and more than 300 tree species are endemic to Sub-Saharan Africa. However, the most widespread species are genera Brachystegia, Julbernardia, and Isoberlinia [4]. The reserve, on the other hand, has a data shortage for...
its flora and fauna status. Nevertheless, obtaining consistent and accurate land cover data over time in the Miombo woodlands' heterogeneous and complex landscape remains challenging [5].

Despite this challenge, access to correct information is crucial to understand and acquire the status quo of forest trends; thus, effective use of freely available data for assessing, monitoring, and inventorying natural resources can contain the escalation of deforestation LGGR. Many scholars have studied land cover dynamics at various geographical and temporal scales using remote sensing technology. Remote sensing technology promises the prospect of assessing widespread forests that are not easily accessible by physical patrols [6]. Previous studies indicate that Vegetation Indices (VIs), image classification, and spectral mixture analysis (SMA) are the most adopted methods by several scientists to study biomass [7]. Non-Photosynthetic Vegetation (NPV) and seasonality have been identified as a challenging issue in studying biomass in dry forests, including Miombo woodlands, however, VI’s has the ability to detect the presence of vegetation and NPV [8]. Thus, it is essential to improve the classification of land cover in Miombo woodlands when using course and moderate resolution optical images. Existing literature emphasizes the effectiveness of using VI’s to classify land use and land cover. However, it has also cautioned against using low to medium resolution products, such as MODIS (250), because they lack the detail required for resource monitoring and management [9].

The FAO recently released a guideline for monitoring land cover and deforestation using freely available resources, which uses Collet Earth in Google Earth Pro platforms for collecting training data for validation and verification data through high resolution images, as part of the Open Foris Initiative [10]. It has also been demonstrated that high-resolution images in Google Earth can facilitate in the differentiation of tropical forest, as well as soil and NPV [11]. The Google Earth Engine hosts various freely accessible data [12], including Sentinel 2 and Landsat 5 TM. It also allows computation of vegetation indices and algorithms to incorporate the vegetation indices into the original bands, which therefore helps to improve classification in Miombo woodlands. Thus, this study employed freely available remote sensing data to assess the land cover and its changes in Litumbandyosi-Gesimasowa Game Reserve between 1990, 2011, and 2020.

2. Methodology
2.1. Study location
This study was carried out in the Ruvuma region of Southern Tanzania, at the Litumbandyosi-Gesimasowa Game Reserve (LGGR). It is located at the 36S UTM zone between 35°16.803'E and 10°9.759'S which cover about 1361.26 km². Figure 1 below illustrate the study location map of the LGGR.

![Figure 1. Location map of LGGR.](image-url)
2.2. Methods
Data collection, image pre-processing, computation of ancillary data (ARVI), inserting auxiliary data into original bands of Landsat 5 and Sentinel 2 images, classification, accuracy assessment, and post-classification analysis were the processes employed in the study. The methods and procedures used to perform the analysis presented in Figure 2 below.

![Diagram of the methodological process](image)

**Figure 2.** Location map of LGGR.

2.3. Data collection
The historical land cover analysis in the study area was studied using optical imagery and ancillary data from 1990, 2011, and 2020. The WRS Path/Row 168/67 satellite scenes from the Sentinel 2 MSI and Landsat 5 TM optical sensors were collected and processed in the Google Earth Engine. The sorting by clouds, masking, and the median feature was employed in Google Earth Engine to compute and collect images pixels based on the conditioned periods. The data used for analysis in this study illustrated in Table 1 below.
Table 1. Data collected, acquisition date, resolution and sources or provider

| Satellite Image | Acquisition Date | Resolution (Meter) | Source/Provider       |
|-----------------|------------------|--------------------|-----------------------|
| Sentinel 2 MSI  | Median (April - June 2020) | 10                 | ESA/GEE               |
| Landsat 5 TM    | Median (April - June 2011)  | 30                 | USGS/GEE              |
| Landsat 5 TM    | Median (April - June 1990)  | 30                 | USGS/GEE              |
| Topo sheet of the Study boundary | April 2021 | Vector             | Ruvuma regional office |

2.4. Generation of ancillary data (ARVI) and potential for NPV detection

Previous research has suggested that Miombo woodlands are deciduous and shed their leaves during the this dry [13]. Other biophysical conditions that lead to underestimating land cover in Miombo ecoregions is plants phenology. The mechanism of plant avoid stress involve closing of stomatal pores, which regulate water loss from the leaves and limit the transpiring area through shedding leaves [14]. However, auxiliary bands in classification protocols have varying degrees of sensitivity [15]. The Atmospheric Resistance Vegetation Index (ARVI), which is resistant to atmospheric influence, excels at analysis and it has been known that the VI (through normalization) can improve satellite image quality by 10-30% [16]. The ARVI was employed in the study to prevent the impacts of Non-Photosynthetic Vegetation (NPV) in Miombo woods, which might lead the sensor to fail to identify vegetation with no green leaves during dry seasons. Equation 1 below illustrates the computation formula for the ARVI as a vegetation index applied in this study. The bands utilized in the generation of the ARVI were Band 8, Band 4, and Band 2 for Sentinel 2 images and Band 5, Band 4, and Band 2 for Landsat 5 imagery, whereby the NIR represents near-infrared band, Red represents red bands, and blur represents blue bands.

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ARVI = \frac{(NIR - (2 \times Red) + Blue)}{(NIR + (2 \times Red) + Blue)}
\]

2.5. Collect Earth and access to high-resolution data

The Collect Earth software is a free and open-source land monitoring application created by FAO with the assistance of Google Earth Outreach. It allows users to freely access high-resolution images through Google Earth Pro and Bing Map. The platforms contain various historical data from 1984 to the present, making it the platform of choice for this study as a critical source of training and validation data [13]. Data that accessed through Collector Earth includes high-resolution imagery with resolutions start from 15-meter resolution. 2.5m SPOT imagery [17]. High-resolution imagery provided by Pictometry International, CNES, Digital Global, GeoEye-1, GlobeXplorer, EarthSat, First Base Solutions, IKONOS, Spot Image, Aerometrex, and Sinclair Knight Merz is generally available free for access land cover [17]. Collect Earth allows for the quick development of surveys while adhering to FAO's guidelines 2016 and IPCC criteria by providing consistent identification of land cover types, sampling approaches, and data sharing with other platforms such as Google Earth Engine.

2.6. Collection and pre-processing of training and validation data

One of the vital components for implementing the classification process is proper training and validation data acquisition. Therefore, this study applied the Collect Earth platform in Google Earth Pro to collect ground truth data for both training and validation purposes. The six land cover type clusters were defined and created based on land cover definitions in Miombo woodlands to help with training sample collection in Collector Earth, grounded on both IPCC guidelines, cited studies in table 2 below, and the use of high-resolution imagery [18]. Stratified random sampling is a common sampling technique in remote sensing and GIS [19]. Each cluster comprised twenty points converted to stratified matric plots to yield box plots with distinct sizes. For wetlands, the size of the plots was customized to less than 4x4, while other land cover types designed to occupy 7x7 and 10x10. However, due to a lack of clear images in 1990, we followed the guideline that recommends that if the image used for evaluation is lower than
the analysed image, proper classification methods recommended. Also, the study accessed free Bird's Eyes image in Planet Scope for the year 2011.

In 1990, total training points yielded 3336, with 1498 validation points; in 2011, training points yielded 1968, with 505 validation points; and in 2020, training points yielded 868, with 384 validation points. These variations in the total training data were the result of the differences in the shape and size of polygons digitized during data collection in Collect Earth. The upload of these shapefiles to the Google Earth Engine requires the conversion from shapefiles to geometry. This conversion process produces multiple training points automatically out of these polygons. The Random Forest algorithm maintains an equal number of training data sets. It has been known that the Random Forest classifier is a bagging (Choose only part of the training data for model prediction and not all.) based algorithm [20].

Existing literature has proven that bagging performs best for algorithms that are highly sensitive to small changes in the data [21]. Therefore, to maintain the number of training data to be involved in the classification process, classifiers provide the option of using a number of trees to limit the number of training data for training classifiers (nTrees = 100). The types of data collected in Google Earth Pro and Planet Scope were points, polygons, and images; points and polygons were designed in grids forms and were exported as KML to ArcGIS software.

2.7. Data export to Google Earth Engine

The Google Earth Engine enables various geo-big data analysis and processing. The Google Earth Engine Platform offers terabytes of free data, but most of it is low to medium quality imagery, making it possible to apply directly in assessing Miombo woodlands [22]. The KML files from Google Earth were imported in ArcGIS to perform a pre-processing stage in which each land cover assigns a specific ID and class property. In addition, the Google Earth Engine allows files compatible with Google Fusion Tables or shapefiles to be imported for image classification and validation. Instead of fusion tables, this study uploaded the shapefiles, which were subsequently transformed to geometry, thus ready for training of both classifiers ready for wall-to-wall map classifications and validation operation [22].

2.8. Random forest classifier

The Random Forest classifier is considered an extensively employed algorithm from Google Earth Engine to classify land cover based on spectral signature. Furthermore, its ability to compute and overcome data disturbances and multi-dimensional datasets makes it among the excellent choice for land cover classifications [23]. Therefore, the study applied the random classifier for analysis.

2.9. Classification of land cover

Therefore, the study applied the random classifier for analysis. Image classification is a common approach for land cover analysis, with several algorithms used to identify and quantify land cover characteristics [24]. The processes' main workflow involves obtaining training data, with the recognized land covers or features possessing a property that holds the recognized class label in numeric values for predictors [25]. The training points and polygons that were re-converted to geometry using geometry scripts were applied as training and validation data. Then, the splitting algorithms introduced to divide training samples into 60% as training data and 40% as validation assessment data, which the technic adopted from previous studies, including guidelines scripts from Google Earth Engine. This study applied the Machine Learning algorithm under the supervised classification method using the Random Forest classifier, built-in algorithms in Google Earth Engine. The land cover categories were grouped as barren land, wetlands, forestland, grassland, farmland, and shrubland. Below is the summary of the land cover classification adopted from a previous study conducted in Miombo woodland regions [26].
Table 2. The land cover definitions scheme from a previous study conducted in Miombo ecoregions.

| Land cover          | Description                                                                                                                                                                                                 |
|---------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Forestland          | Forests (ecosystems that colonies around rivers and islets) are part of Riparian evergreen forests and benefit from special soil conditions in areas marked by a long dry season. The forest is characterized by dense woods (herbaceous stratum). |
| Shrubland           | Shrub plants dominate the canopy of the woody forest. It is different from trees by the low density or excess of the tree stratum and its height.                                                                   |
| Grassland           | The grassland is distinguished by the presence of an open field dominated by grasses and a lack of tree and shrub cover.                                                                                           |
| Farmland            | The agricultural land area is marked by grown or long-lasting land washed after a season or dry months in a crop rotation technique and areas for livestock grazing.                                             |
| Barrenland          | The Barrenland land distinguishes the built-up, mining, developed piece of land, rocks, soil, sandy, impervious surfaces, or occasionally paved roads.                                                          |
| Wetland             | The wetlands have been distinguished by the river channel, ponds, flooded lands, and swamps.                                                                                                                                 |

Sources [26]

2.10. Accuracy assessment and validation

It is common to use the confusion matrix for accuracy assessment in land use/land cover classification, however, according to previous research, the routine method of evaluating the accuracy of thematic maps produced by classification should not rely solely on the kappa coefficient [27]. Instead, studies have suggested using other confusion matrix outputs such as overall accuracy, user accuracy, and producer accuracy to assess the classification outputs of the thematic map [27]. Therefore, this study applied the confusion matrix algorithm in Google Earth Engine for computing classification accuracy and validating assessment using 40% of the randomly split training samples.

3. Results and Discussion

3.1. Computation and addition of ARVI

The study was effectively computed and added the ARVI data to the original bands of Landsat 5 TM and Sentinel-2 images. The ARVI data helped detect features and discriminate those features with similar characteristics based on their index values which usually range between -1 and 1. ARVIs ability to distinguish similar pixels of unique features used to identify Miombo trees with shaded leaves and those with Non-Photosynthetic Vegetation (NPV) effects, such as barren lands and grasslands, failed distinguished by human eyes. These findings are consistent with previous research, which suggested that vegetation indices can detect land covers, including vegetation and non-vegetation, because they can add sensitivity when used as additional bands [15]. It implies that by detecting Non-Photosynthetic Vegetation (NPV) and seasonality, Vegetation Indices (VIs) can aid in the classification of land cover in Miombo woodlands. The study found that it was possible to create high-resolution thematic maps that took into account seasonality between April and June while also capturing the NPV. The validation and verification results of the produced thematic maps are shown in Table 5 below.

Figure 3. (a), (b), and (c) illustrates ARVI raster and thresholds values from 1990, 2011 and 202.
The loss in forestland has also had an impact on the Litumbandyosi-Gesimasowa Game Reserve (LGGR), which the study has found a substantial reduction in forest covers in wetlands (rivers, wetlands, water sources). As a result, water sources are being exposed to direct sunlight. This suggests that the Miombo woodlands (forest and shrubs) are a potential watershed in the LGGR. Existing literature stresses that the transitions of forestland and shrub lands to other land cover types such as wetlands indicate forest degradation. These changes imply that river tributaries, large rivers (Ruhuhu, Mnywamaji, Ngaka, and Lutukila), and other water sources in the LGGR are threatened by degradation due to anthropogenic activities. Therefore, it increases the risk of drying up water resources during the dry season and may compromise social capacity and stability [30].

Previous research has shown that the Ruhuhu river provides a breeding place for Opsaridium microlepis (an indigenous fish species to Lake Nyasa), which is economically important to the population surrounding the Lake Nyasa Basin [31]. Furthermore, the study discovered that the barrenland area has increased alarmingly during the previous 30 years. Deforestation and degradation of forestland, shrub lands, abandoned farms, mined lands, burned zones, dry wetlands, and grasslands are the most prominent causes of barrenland. As a result, the LGGR ecosystem has been exposed to risks that have an impact on ecological services and, as a result, is in jeopardy. Furthermore, the study finds that the forest area (forestland, shrub land, and grassland) in the LGGR has been shrinking over the past 30 years. In comparison to the first phase of 1990, substantial changes happened between 2011 and 2020. Mining activities, mineral prospecting, and settlement development have all grown more common, causing substantial changes to forest land. Human activities such as agricultural expansion, charcoal manufacturing, illegal logging, and increasing livestock grazing have been identified to be the drivers of land cover that contribute to significant ecological risks to Miombo forests, according to current research in the Miombo woods [29].

3.2. Land cover maps in LGGR between 1990, 2011 and 2020

In the Litumbandyosi-Gesimasowa game reserve, six land cover types were identified and classified: forestland, shrubland, grassland, barren and built-up areas, farmlands, and wetlands. In the Litumbandyosi-Gesimasowa game reserve (LGGR), six land cover types were identified and classified: forestland, shrubland, grassland, barren and built-up areas, farmlands, and wetlands (Table 3). Moreover, farmland area was found to have increased continuously by 5.81 % during the study period, at the expense of decreasing forest cover (shrub land, woodland, and thick forest). It has been known from the existing literature that the activities that result in converting rangelands to agriculture may reduce ecosystem functioning by increasing soil compaction, decreasing surface cover, and reducing vegetation functional and structural diversity [28]. As a result, the LGGR ecosystem has been exposed to risks that have an impact on ecological services and, as a result, is in jeopardy. Furthermore, the study finds that the forest area (forestland, shrub land, and grassland) in the LGGR has been shrinking over the past 30 years. In comparison to the first phase of 1990, substantial changes happened between 2011 and 2020. Mining activities, mineral prospecting, and settlement development have all grown more common, causing substantial changes to forest land. Human activities such as agricultural expansion, charcoal manufacturing, illegal logging, and increasing livestock grazing have been identified to be the drivers of land cover that contribute to significant ecological risks to Miombo forests, according to current research in the Miombo woods [29].

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Figure 4. (a), (b), (c) and (d) illustrate land cover maps for 1990, 2011 and 2020, respectively, while figure 4 (d) illustrates the changing land cover between 1990 and 2020 in the Litumbandyosi-Gesimasowa Game Reserve.

Table 3. Land cover stands and land cover loss between 1990 and 2020.

| Land cover type | 1990 Area (km²) | 2011 Area (km²) | 2020 Area (km²) | 1990-2011 Area (km²) | 1990-2011 Area (km²) | 2011-2020 Area (km²) | 1990-2020 Area (km²) | Percentage (%)
|----------------|----------------|----------------|----------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Forestland     | 786.14         | 631.56         | 639.54         | -154.58              | 7.98                 | -146.60              | -10.77               |
| Shrubland      | 380.35         | 138.84         | 214.43         | -241.5               | 75.59                | -165.92              | -12.19               |
| Grassland      | 66.05          | 376.83         | 247.75         | -310.78              | -129.08              | 62.47                | 4.59                 |
| Farmlands      | 44.59          | 111.82         | 107.06         | -67.23               | -4.76                | 62.47                | 4.59                 |
| Barrenland     | 58.99          | 95.68          | 138.11         | 36.69                | 42.43                | 79.11                | 5.81                 |
| Wetlands       | 25.14          | 6.53           | 14.38          | -18.61               | 7.86                 | -10.75               | -0.79                |
| Total          | 1361.26        | 1361.26        | 1361.26        | 107                      | 125.75              | 9.13                 | 125.75              |

Table 4. Land cover matric indicating trajectories in LGGR between 1990, 2011 and 2020.

| Year - 2020 | Land cover types | Barren and built-up | Farmland | Forestland | Grassland | Shrubland | Wetland | Grand Total |
|-------------|------------------|---------------------|----------|------------|-----------|-----------|---------|-------------|
| Year - 1990 | Barren and built-up | 11.86               | 15.05    | 17.81      | 5.84      | 66.07     | 9.13    | 125.75      |
|             | Farmland          | 12.51               | 14.97    | 15.75      | 7.25      | 55.94     | 5.52    | 111.94      |
|             | Forestland        | 7.48                | 2.85     | 579.65     | 20.33     | 77.38     | 1.90    | 689.60      |
|             | Grassland         | 17.62               | 6.46     | 77.70      | 17.92     | 109.45    | 3.74    | 232.90      |
|             | Shrubland         | 8.98                | 5.04     | 89.13      | 14.35     | 68.81     | 1.95    | 188.25      |
|             | Wetland           | 0.50                | 0.19     | 6.00       | 0.35      | 2.69      | 2.89    | 12.62       |
|             | Grand Total       | 58.95               | 44.56    | 786.04     | 66.05     | 380.33    | 25.13   | 1361.07     |

Table 5. Land cover classification accuracy assessment.

| Land cover category | 1990 User Accuracy (%) | 2011 Producer Accuracy (%) | 2011 User Accuracy (%) | 2020 Producer Accuracy (%) | 1990 User Accuracy (%) | 1990 Producer Accuracy (%) |
|---------------------|------------------------|----------------------------|------------------------|----------------------------|------------------------|----------------------------|
| Forestland          | 100                    | 99.61                      | 100                    | 98.85                      | 99.09                  | 98.92                      |
| Shrubland           | 93.94                  | 98.88                      | 100                    | 98.78                      | 98.78                  | 95.29                      |
| Grassland           | 63.64                  | 100                        | 99.02                  | 100                        | 97.16                  | 98.56                      |
| Farmlands           | 100                    | 96.30                      | 98.67                  | 97.37                      | 97.73                  | 96.99                      |
| Barrenland          | 100                    | 100                        | 96.92                  | 98.44                      | 99.36                  | 99.84                      |
| Wetlands            | 97.96                  | 100                        | 100                    | 100                        | 100                    | 98.94                      |
| Overall Accuracy    | 99.53                  | 99.84                      | 99.84                  | 92.10                      | 92.10                  | 89.62                      |
4. Conclusion
According to the findings of the study, there has been an increase in human activity in the Litumbandyosi-Gesimasowa Game Reserve over the past 30 years, which has resulted in severe land cover changes. Recurrent fires, mining operations and exploration, farming and overgrazing, and legal and illegal logging are of general causes of change. The Government of United Republic of Tanzania should prioritize Miombo ecosystem restoration to avoid further ecological degradation. As a result, free remotely sensed data from tools like Collector Earth, Google Earth Engine, and Planet Scope, combined with the incorporation of vegetation index (ARVI), can help Sub-Saharan African countries monitor Miombo woodlands.

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