Three Decades of Land-Cover Change and Potential Carbon Loss in Miombo Woodlands of Hwedza District in Zimbabwe (1990-2020)

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Abstract

Land-use and land-cover change (LULC) has lately emerged as the main driver of land-use change and degradation globally, particularly in miombo landscapes. Miombo woodlands, whose extent covers most parts of southern African countries, play an important role in carbon sequestration and storage, while supporting millions of rural livelihoods. Despite uplifting and improving rural livelihoods, these woodlands are under threat from various anthropogenic activities including agricultural expansion, charcoal production and urban development. Through integration of multi-temporal remote sensing and carbon stock assessment at district level, the study provides substantial evidence on the effect of LULC on carbon stocks particularly the above-ground and below-ground carbon storage for miombo woodlands in Hwedza District, Zimbabwe. Landsat data processed in the Google Earth Engine was used to generate land-use maps for the years 1990, 2000, 2010 and 2020. Post-classification analysis produced a land-use matrix. Carbon stock changes from forest land to other land uses were estimated using

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the Tier 1 stock-difference approach. Forest cover declined from 45% in 1990 to 37.6% in 2020, coupled with an increase in cropland and grassland. About 24 949 ha of forests were converted to cropland and other land uses, resulting in estimated emissions of 3.6 million tCO_2e over 30 years. The findings demonstrate the importance of sustainable land management practices that promotes continued suppression of emissions associated with LULC, which is key to the attainment of the country's climate change commitments in various reporting obligations under the convention.

Keywords: remote sensing, carbon sequestration, greenhouse gas, geographic information systems, climate change, carbon accounting

INTRODUCTION

Land-use and land-cover change (LULC) remains one of the major drivers of environmental change globally and these changes affect ecosystem functioning, including disruption of hydrological cycles, carbon storage, soil conservation and climate regulation potential (Admasu *et al.*, 2023; Ma *et al.*, 2024). Human related activities such as agricultural expansion, urbanisation and deforestation are rapidly transforming natural rural landscapes into altered land-use systems. A growing body of research studies acknowledges that land-use change is a key driver of and a major contributor to greenhouse gas emissions globally, particularly through deforestation which has caused huge losses of carbon stocks stored as biomass and this is also the case with dryland forests (Liu *et al.*, 2023; Li *et al.*, 2024). Tropical dryland forests constitute a significant component of the global terrestrial ecosystems, occurring in various parts of the world, including Africa, Asia and Latin America, covering an estimated 0.5 to 1.1 billion hectares (; Stan and Sanchez-Azofeifa, 2019); Schröder *et al.*, 2021. Among these seasonal dryland forests are the miombo woodlands that form one of the largest continuous dry forest landscapes in southern Africa. These woodlands expand across several southern African countries, including Angola, Zambia, Zimbabwe, Malawi, Tanzania and Mozambique and covering an estimated 2.7 million square kilometres (Pienaar *et al.*, 2026). These forests are well known for the dominance of species in the genera *Brachystegia*, *Julbernardia* and *Isoberlina.* These landscapes provide a wide range of ecosystem goods and services, including provisioning, regulating and supporting functions. These services have improved and supported livelihoods of millions of households in rural and urban areas (Ryan *et al.*, 2016; Syampungani *et al.*, 2017).

Despite their ecological significance, miombo forests have experienced significant land-use changes due to deforestation and urbanisation, among other factors and this has been happening at high rates (Gao *et al.*, 2023). Expansion of agricultural land and illegal charcoal production are among key drivers of forest loss across the miombo ecoregion. Additionally, population growth and heavy reliance on fuelwood energy for tobacco curing have intensified pressure on woodland ecosystems in both urban and rural landscapes (Jew *et al.*, 2017; Nyakatonje and Jambo, 2023). Studies in miombo ecosystems have demonstrated that land-use disturbances in various forms, including agricultural expansion, illegal charcoal production and urbanisation have significantly altered species composition, diversity and carbon stocks at various scales.

Remote sensing technologies have since been used to monitor land cover dynamics and have proven to be an effective method of land-use and cover change monitoring over large spatial and temporal scales. With the coming in of high spatial and temporal resolution satellite data, LULC mapping and monitoring has improved and has been relied on widely across many applications (Mashala *et al.*, 2023). The Landsat satellite programme with over 50 years of operation, provides consistent and long-term satellite data that enables consistent and continuous land monitoring to quantify changes in vegetation and forest cover. Studies by Hansen and Loveland (2012) and Galiatsatos *et al.* (2020) have demonstrated a wide and effective applicability of Landsat data for mapping LULC and forest cover change on a global scale.

Land-cover change does not only impact landscape vegetation structure, but also impacts biodiversity and carbon storage (FAO, 2020). Conversion of forest land to agricultural landscapes is usually associated with reduction in above-ground biomass and associated carbon stocks (Legesse *et al.*, 2024). This change in forest cover and reduction of biomass stocks in the above ground results in increased carbon dioxide emissions to the atmosphere, leading to the accelerated effects of climate change (*ibid.*). Over the years, Zimbabwe has experienced overwhelming changes in land use mainly in areas nearby urban areas due to urbanisation, increased demand for fuelwood for warmth in urban areas and tobacco curing in tobacco growing areas. In Zimbabwe, agricultural expansion, tobacco curing and urban expansion, among other factors, are the key drivers of LULC change, particularly within miombo forests. Previous studies in Zimbabwe, specifically in Hwedza District, have focused more on the effect of land tenure on species composition, vegetation structure, biodiversity and above-ground biomass (Nyamugadza *et al.*, 2025; Stewart *et al.*, 2025). These studies demonstrate that biodiversity, above-ground biomass and species composition vary significantly by land tenure due to varying land-use intensity in different land tenure systems. While this study acknowledges that previous studies in Hwedza provided baseline floristics and other ecological baselines, they did not examine long-term land-use and cover dynamics on carbon loss resulting from deforestation.

Accurate estimation and quantification of LULC and its associated effects on carbon stocks are helpful in transparent reporting for the country's reporting requirements under the Enhanced Transparency Framework. For example, Zimbabwe, in its last reporting cycle to the United Nations Framework Convention on Climate Change (UNFCCC), the first Biennial Transparency Report (BTR) of Zimbabwe, indicated that the land-use and land-use change forestry (LULUCF) is the main contributor of GHG emissions in the country, accounting for about 53% of the country's GHG emissions (Zimbabwe, 2025). The aims of this study were to (i) examine the major trends in LULCs in Hwedza District over the period 1990 to 2020, (ii) assess how agricultural expansion has affected forest cover within the district and (iii) evaluate the consequences of these LULCson below and above-ground biomass stocks in the area.

Understanding emissions associated with deforestation and land cover dynamics is increasingly essential for climate change reporting in various reporting obligations, which includes the Nationally Determined Contribution, REDD+ programmes, forest reference emission levels and enhanced transparency framework under the Paris Agreement. Therefore, this contributes to aroadmap in the development of evidence-based mitigation strategies. Additionally, such information is also useful in promoting sustainable land management practices in miombo ecosystems. This study, therefore, aims to assess land-cover change and potential carbon loss in miombo woodlands of Hwedza District between 1990 and 2020.

MATERIALS AND METHODS

Hwedza District, located in the Mashonaland East Province (Figure 1), is surrounded by four other districts: Marondera, Chikomba, Makoni and Buhera. The district lies at an altitude of 1 425 m above sea level and is geographically located at centroid -18.616667 and 31.566667 latitude and longitude, respectively (Nyamugadza *et al.*, 2025). It spans three agro-ecological zones (Regions IIb, III and IV), with Region IIb being the northern part of the district, where most commercial agriculture is concentrated, while Regions III and IV are located further south of the district (Manatsa *et al.*, 2020). Like other districts in Zimbabwe, Hwedza consists of more than one land tenure system and these include communal area, old resettlement area, new resettlement area and small-scale commercial farming area (Nyamugadza *et al.*, 2025).

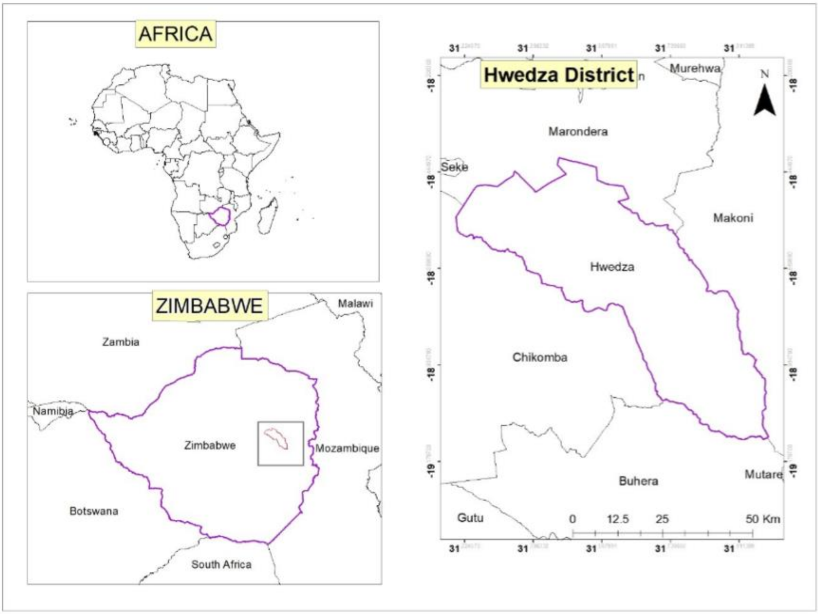

Figure 1: *The location of Hwedza District* (Authors, 2026)

The district falls within the broader miombo ecoregion (Pritchard *et al.*, 2019) with *Brachystegia spiciformis*, *Julbernadia globiflora*, *Monotis engleri* and *Burkia Africana* the dominating species. *Julbernadia globiflora* is more prevalent in the drier area of Zviyambe, whereas *Brachystegia spiciformis* more dominant in the wetter northern parts of the district (Nyamugadza *et al.*, 2025). Most of the farmers in the district are small-scale subsistence farmers who rely on rain-fed agriculture for their livelihoods (Rurinda *et al.*, 2014). The main crops grown include beans, maize, groundnuts and tobacco, with tobacco farming being a significant driver of deforestation and land degradation in the district. In addition to agriculture, some villagers in Hwedza District engage in small-scale gold mining and some alluvial mining along the Save River which forms the boundary between Hwedza and Chikomba districts (Stewart *et al.*, 2025). The co-existence of various land tenure systems in one district of Hwedza makes the district an ideal socio-ecological landscape for examining long term effects of land-use change dynamics on carbon loss due to varying degree of land-use pressure associated with each tenure type.

SATELLITE DATA ACQUISITION AND PROCESSING

Because the study aimed at analysing the long-term impact of LULC, Landsat satellite became the ideal satellite due to availability of long-term historical data with medium resolution of 30m making it suitable for long-term LULC mapping. Landsat 5 images were used for the period up to 2010 while Landsat 8 images were acquired for 2020, allowing continuous monitoring of land cover across the two time periods. Google Earth Engine (GEE) is a cloud-based geospatial tool capable of handling and processing large-scale multi-temporal remote sensing data efficiently, thereby upscaling computational efficiency necessary for land-cover change analysis (Abdelkader *et al.*, 2024) The platform enables satellite image retrieval, image manipulation and analysis of already georeferenced images through the power of high computing google servers (*ibid.*).

Dry season (May-September) images were preferred due to reduced cloud cover and seasonal vegetation variability. Despite acquiring these images, quality assessment functions in GEE were applied to remove cloud-shadow pixels as this is a common problem with Landsat surface reflectance products.

Selected images after cloud masking were used to create a composite image through a median reducer so that one representative image of that particular year could be used. The composite images were used to generate RGB combinations for both Landsat 5 and 8 with band combination B4 (red), B3 (green) and B2 (blue) used for Landsat 8 (Liu *et al.*, 2021) and B3 (red), B2 (green) and B1 (blue) applied for Landsat 5 (Dethier *et al.*, 2020).

LAND-COVER CLASSIFICATION

Land-cover classification was performed using a supervised image classification approach conducted in GEE. Reference samples were collected mainly through field observations and high-resolution image interpretation from Google Earth imagery. Secondary sources were used as supplementary data from maps developed by the Forestry Commission of Zimbabwe in their previous projects. Land-cover maps followed the IPCC land-use classification system including forest, water, grassland, cropland, settlement and other land use (Eggleston *et al.*, 2006). Training samples and reference points for each land-cover class were then merged into one large-sized feature collection database. This dataset was then randomly divided into two separate subsets that included the training and validation data, using the widely known 70/30 split (Aziz *et al.*, 2024; González-Vélez *et al.*, 2026). About 70% of the merged samples were used for training the random forest classifier, while 30% were used for validation of the random forest model. Random Forest, an ensemble and machine learning algorithm, was used for classification of the images due to its robustness against overfitting and ability to handle large datasets (Adugna *et al.*, 2022).To improve classification accuracy and reduce the noise commonly known as the “salt-and-pepper” noise, post classification filtering was applied. Post the classification process, a majority filter was applied in which a 3 x 3 kernel was used to refine and improve accuracy.

ACCURACY ASSESSMENT

Accuracy assessment was performed to evaluate the quality, consistency and reliability of classified maps across all mapping periods (Islami *et al.*, 2022). Accuracy assessment was conducted in GEE accuracy assessment metrics which include producer accuracy, user accuracy, overall accuracy and kappa statistic (Gülci *et al.*, 2025). Reference data were collected from field observations, high resolution Google Earth imagery and archived historical data. The overall accuracy, producer accuracy, user accuracy and the kappa statistics are generally used in assessing classification performance (Islami *et al.*, 2022; Nicolau *et al.*, 2024; Yi *et al.*, 2024; Gülci *et al.*, 2025). The overall accuracy measures the total number of correctly classified pixels or samples out of the total number of samples used, while producer and user accuracy assess effectively the errors of omission and commission of individual classes, respectively. Kappa statistic then assesses the agreement that exists between classified data and reference data beyond chance agreement. However, despite being a commonly used metric, Kappa statistic usually suffers from class imbalances that result from unequal land-cover class representation

The metrics were calculated as follows:

$$\boldsymbol{Overall\ accuracy} = \frac{\boldsymbol{Total\ number\ of\ correctly\ classified\ pixels}}{\boldsymbol{Total\ number\ of\ reference\ pixels}} \boldsymbol{x\ 100}$$

$$\boldsymbol{Producer\ accuracy} = \frac{\boldsymbol{Total\ number\ of\ correct\ pixel\ in\ any\ class}}{\boldsymbol{Total\ number\ of\ reference\ pixels\ of\ that\ category(row)}} \boldsymbol{x100}$$

$$\boldsymbol{User\ \ accuracy} = \frac{\boldsymbol{Total\ number\ of\ pixels\ in\ any\ class}}{\boldsymbol{Total\ number\ of\ correct\ pixels\ in\ any\ class(column)}} \boldsymbol{x\ 100}$$

$$Kappa\ statistics\ K = \frac{Po - Pc}{1 - P_c}$$

where, *Po* = proportion of units which agree, Pc is the chance agreement that is expected by chance

ESTIMATION OF POTENTIAL CARBON LOSS

Potential carbon loss from LULC were estimated using the stock-difference approach methodology widely used in the agriculture, forestry and other land use using Tier 1 approach as outlined in the 2006 Intergovernmental Panel on Climate Change (IPCC) guidelines (Eggleston *et al.*, 2006). Tier 1 was adopted due to unavailability of long-term inventory data for Hwedza and as such, this led to the adoption of country-specific emission factors derived from the Forests Reference Emission Levels (FREL for Zimbabwe (UNFCCC, 2024). The use of FREL adopted emission factors for Zimbabwe is important as it allows comparability with similar work that can be done in Zimbabwe for reporting to the UNFCCC. The analysis focused mainly on tracking GHG emissions associated with land-use change from forest to non-forest land-use classes. Forest conversion to grassland was not considered for estimation of carbon loss as this is more appropriately classified as forest degradation rather than deforestation or complete change of land use. This is consistent with the scope associated with reducing emissions from deforestation and forest degradation reporting mechanisms (Eggleston *et al.*, 2006).

A post-classification of land-use transition matrix was generated at district level to quantify conversions between land uses across the entire mapping period. The study focused mainly on land-use transition that involved forest cover to any other land uses than transition amongst other land-use categories. A forest carbon density equivalent to 146.9 tCO_2e ha^{-1}, adopted from the Zimbabwe FREL, was used (UNFCCC, 2024) and applied as an emission factor for forest conversion to other land uses. This carbon density represents the combined carbon density of both the above-ground and below-ground biomass. Accordingly, potential carbon loss in this study is defined as the loss of biomass carbon from below-ground and above-ground biomass stock only, excluding reservoirs from other carbon pools due to data limitations and constraints associated with Tier 1 methodologies. It is imperatively important to note that the analysis assumed complete oxidation of biomass carbon following forest conversion and assumed that forest carbon density is uniform across all forested areas. The stock-difference method from the IPCC guidelines on LULUCF was used. This method was employed because it works well with remote sensing data on land-use change over at least two time periods when there is no country specific data (Eggleston *et al.*, 2006; Kearney and and Smukler, 2016). GHG emissions associated with land-use change were estimated by multiplying the area of change by emission factors derived from the FREL report assuming all the biomass is converted into carbon dioxide after land-use conversion as recommended by the 2006 IPCC guidelines (Eggleston *et al.*, 2006) (Equation 5):

$$E = Area\ change \times Emission\ factor$$

where Area change is area converted derived from the land-use change matrix and the Emission factor is the numerical value that represents the amount of carbon stored per hectare of land. E is the total greenhouse gas emissions (tCO_2e).

Average GHG emissions per year were estimated by dividing the cumulative emissions over the entire period by the number of years analysed.

Land-use conversions, mainly from forest to wetland and forest to settlement, were presented in the land-use matrix change (Table 1). However, these transitions were excluded from the estimation of GHG emissions mainly because of their smaller spatial extent and high level of uncertainty associated with these classes. As such, only emissions resulting from forest conversion to cropland and forest to other land use were considered for estimation of GHG emissions estimation in this study. The broad term, other land use in this study represents area under mining and area under rock outcrop.

FINDINGS

LAND-USE AND LAND-COVER CHANGE

Critical land-use and-cover changes were observed in Hwedza for a period between 1990 and 2020 dominated mainly by decline in forest cover and expansion of cropland and grasslandrespectively. Table 1 clearly demonstrates a gradual decrease in forest cover over time, coupled with an increase in area under grassland and cropland. By 2020, area under forest had declined from 45% to about 37.6%, while grassland increased from 13.9% to 22.9% over the same period. Ecologically, continued decline in forest cover at the expense of cropland and grassland entails a continued ecosystem disturbance and decline and this could be associated with reduction of woody biomass, reduced biodiversity and habitat loss.

Table 1: Land-use and Land-cover Changes in Hwedza District from 1990 to 2020

Class	1990 Area (ha)	%	2000 Area (ha)	%	2010 Area (ha)	%	2020 Area (ha)	%
Forest	11 505.1	44.9	112738.7	44.0	90799.2	35.5	96336.6	37.6
Cropland	103 210.6	40.3	106 220	41.5	108201.1	42.3	98249.2	38.4
Wetland	203.2	0.1	560.94	0.2	593.11	0.2	333.8	0.1
Grassland	35 708.2	13.9	34 908	13.6	55074.9	21.5	58519.6	22.9
Rock-outcrop	1 854	0.7	1 506.9	0.6	1220.6	0.5	2 374	0.9
Settlement	0	0.0	46.32	0.0	92.04	0.0	167.8	0.1
Total	255 981	100	255 981	100	255 981	100.0	255 981	100

Cropland increased between 1990 and 2010 but declined by 2020 due to conversion of cropland to grassland (Figure 2).

Although cropland increased in the early years (1990-2010), its decline in 2020 brought about an increase in grassland, potentially reflecting field abandonment turning into grasslands. Expansion of grasslands on previously cropped areas suggests the dominance of intermediate plant succession following disturbance, and this promotes reduced soil erosion which decreases further degradation.

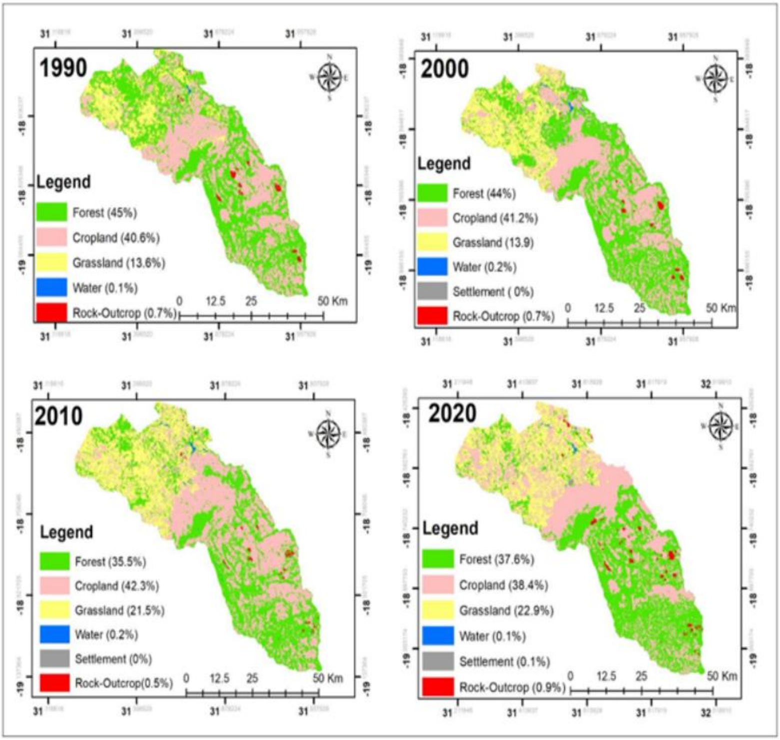

Figure 2: Land-use and-cover change from 1990 to 2020

Furthermore, a land-use transition matrix (Table 2) indicates that agricultural activity is the dominant cause of land-use conversion in Hwedza.

Table 2: Forest land to other land-use conversion matrix

Forest Conversion	Area (ha)	Deforestation (%)
Forest-Cropland	23 738	94.4
Forest-Wetland	146	0.6
Forest-Settlement	41	0.2
Forest-Other land	1 211	4.8
Total deforestation	25 136	100

Forest conversion between 1990 and 2020 resulted in huge GHG emissions from carbon loss. The estimated GHG emissions reached cumulative emissions of 3 664,008 tCO_2e, (Table 3) over 30 years.

Table 3: Land-use conversion matrix and associated emissions

Forest Conversion	Area (ha)	Emission factor (tCO_2 ha^{-1})	GHG Emissions (tCO_2e)
Forest-Cropland	23 738	146.9	3 486 122
Forest-Other land	1 211	146.9	177 886
Total	24 949		3 664 008

These emissions correspond to an average annual GHG emission of approximately 0.122 $MtCO_2$ yr^{-1}.

Classification accuracy produced acceptable results across the entire mapping period (Table 4). Overall classification accuracy ranged from 75% to 83%, while the Kappa statistic ranged from 0.62 to 0.76 across the study period (Table 5). These values indicate a reasonable agreement between classified maps and the reference data, suggesting that the results are sufficiently reliable for analysing land-use change dynamics in Hwedza.

Table 4: Accuracy assessment of LULC for Hwedza. PA indicates the producer accuracy and UA indicates the user accuracy

Year	1990		2000		2010		2020	
Class	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
Forest	72	80	90	90	90	90	50	100
Cropland	75	85	75	85	100	100	90	81
Grassland	80	80	60	60	60	60	100	100

The year 2010 produced the highest classification accuracy, with an overall accuracy of 83% and a Kappa statistic of 0.76, indicating a stronger agreement between classified maps and reference data.

Table 5: Accuracy assessment measures of overall accuracy and Kappa statistic from 1990 to 2020

	1990 (%)	2000 (%)	2010 (%)	2020 (%)
Overall accuracy	75	75	83	81
Kappa statistic	0.62	0.63	0.76	0.65

The years 1990 and 2000 produced identical overall accuracy results of 75%, with Kappa values of 0.62 and 0.63, respectively. Forest class produced higher producer accuracy, reaching 100% in 2020, suggesting that all reference forest pixels were correctly classified. Minor land-use and cover classes such as wetland and settlement were excluded from accuracy assessment due to their smaller spatial extent and that resulted in a very low sample size. The smaller sample sizes contributed to increased levels of uncertainty for these classes which may introduce validation errors. Overall, classification accuracy in this study was sufficient for further processes of land-cover change and carbon estimation analysis.

DISCUSSION

The observed LULC transitions in Hwedza District from 1990 to 2020 reflect a broader pattern of deforestation common across different parts of sub-Saharan Africa (Lisboa *et al.*, 2025; Khoji Muteya *et al.*, 2026; Mukomberanwa *et al.*, 2026)). These land-use changes and decline in forest cover are driven largely by agriculture which highlights increasing pressure on forest ecosystems from agricultural activities. The land-use matrix also highlights that agriculture is the most dominant cause of land-use change, emphasising the role of subsistence or small-holder farmers in the overal land transformation across the district. The continued expansion of agricultural land between 1990 and 2020 in Hwedza District reflects the role that land redistribution, particularly the Fast-Track Land Reform Programme, had across the district, as this brought together changes in land-use patterns as more small-holder farmers were coming in to settle in formerly large-scale commercial farms (Shonhe, 2019). Similar results of forest decline due to agricultural expansion have also been observed and reported in some parts of the country, including Shurugwi (Muringaniza *et al.*, 2025), Mt Darwin (Maruza *et al.*, 2024) and Chipinge (Jombo *et al.*, 2017).

Furthermore, decline in cropland by 2020 and subsequent expansion of grasslands may positively reflect broader environmental and ecological recovery which includes gaining of ecosystem health due to reduced soil erosion, improved accumulation of organic matter and enhanced infiltration. These positive ecological gains also highlight improved carbon sequestration, particularly soil organic carbon that comes through reduced tilling (Neuenkamp *et al.*, 2024). These dynamics point to a complex interaction between human activities and environmental constraints, where initial agricultural expansion is followed by landscape degradation and land-cover transformation. Previous ecological studies in Hwedza reported a decline in above-ground stocks, species richness and diversity among communal and resettlement areas, indicating that the effects of long-term degradation and deforestation observed at plot level reflects the effects of the broader landscape changes that have been happening (Nyamugadza *et al.*, 2025).

The relatively small changes in other land uses, such as wetlands, settlements and rock outcrops, suggest that while they are not the main drivers of change, they still contribute to the overall transformation of the landscape. The slight increase in settlement areas contributes to gradual infrastructure development, expansion and change in rural settlement patterns indicating the effects of land reform programmes. At the same time, growth in rock outcrop areas may be a sign of prolonged land degradation that comes through vegetation loss and effects of soil erosion that gradually strip away the topsoil and expose the underlying bedrock. Collectively, land transitioning in Hwedza reflects a broader aspect of land-use change that comes through a combination of factors that are beyond forest conversion but also involves other interactions between agriculture, human settlements and naturally occurring environmental degradation processes.

The accuracy assessment results indicate that the LULC classifications produced in this study are generally reliable, with overall accuracies ranging from 75% to 83% and Kappa statistics between 0.62 and 0.76. These results fall within commonly accepted thresholds for medium resolution LULC mapping (Rwanga and and Ndambuki, 2017), showing moderate to strong agreement between classified maps and reference data and providing confidence in the interpretation of observed land-use trends (*ibid.*). The notably higher classification accuracy recorded in 2010 may be attributed to factors such as better image quality, favourable seasonal conditions, or improved classifier performance for that period, a pattern also observed in other multi-temporal Landsat classification studies (Olofsson *et al.*, 2014). Although some minor land-use classes were present in classified maps, they were excluded from main accuracy assessment due to their smaller spatial extent and smaller contribution to the overall GHG emissions within the district.

IMPLICATIONS OF LAND-USE CHANGE ON CARBON EMISSIONS

The conversion of forest to cropland and grassland was the main driver of GHG emissions estimated at approximately 3.67 million tCO_2e over the study period. Most of the carbon emissions came from forests converted into cropland, highlighting the importance of forests in storing carbon and regulating the climate. The estimated average annual emissions of about 0.122 $MtCO_2$, indicates how land-use change contributes to global climate change even at local scale. The substantial GHG emissions from land-use conversion highlights the importance of miombo woodlands as carbon storage and, more importantly, as a key source of climate change mitigation. Globally, miombo woodlands are recognised as one of the largest carbon reservoirs because of their carbon sequestration and storage potential through various carbon pools (Gumbo *et al.*, 2018; Bulusu *et al.*, 2021). The estimated carbon dioxide emissions from the present study reinforce existing knowledge that land-use change has on carbon dynamics within miombo ecosystems. Various research studies on the same subject across tropical dry forests, particularly on miombo woodlands, have reported significant carbon losses associated with land-use change and forest degradation (Wilson and Scholes, 2020; Makwinja and Mkhwimba, 2025). These findings underscore the urgent need for sustainable land management practices that allow communities to maintain agricultural production, while protecting forests, helping to reduce carbon emissions and safeguarding the environment.

The results from Hwedza District have broader implications for Zimbabwe's overall GHG emissions profile and play a role in shaping the country's national GHG reporting. Zimbabwe's first Biennial Transparency Report identified the LULUCF sector as the largest contributor of national GHG emissions in Zimbabwe (Zimbabwe, 2025). In this context, land-use change analyses conducted in this study contribute to the overall strengthening of the national carbon accounting systems, thereby supporting the country's climate change reporting obligations under the Paris Agreement. Furthermore, the study highlights the importance of bringing together various processes like land-use-planning and community-based forest management into national climate change policies earmarked for reducing emissions from deforestation and degradation.

LIMITATIONS OF THE STUDY

Despite delivering important insights into land-use change and emissions associated with such land-use changes in Hwedza District, the study acknowledges several limitations. The study acknowledges that carbon loss was estimated based on biomass loss from below- and above-ground biomass pools in line with the Zimbabwe FREL report, while negating other carbon pools such as soil carbon, dead organic carbon, deadwood, litter and harvested wood products. As such, the potential carbon loss in this present study represents the loss associated with above- and below-ground biomass only, and not the overall ecosystem carbon loss. In addition, the emissions in this study assumed that after land-use changes, all the carbon is lost immediately through conversion. This assumption is usually associated with and applied in national GHG inventories under the Tier 1 approach of the IPCC. However, this is not normally the case, because after the land-use changes, some biomass will remain as part of the harvested wood products and most of the carbon is lost gradually over the years through natural processes like decomposition. As such, the results of the estimates presented by this study may not fully address changes in carbon emissions after land-use conversion.

Furthermore, this study is based on the Zimbabwe FREL based methodologies which use only emission factors from the national inventory data. The national data provides a robust basis for carbon estimation, but has challenges when cascaded down to district level. As such, the use of national estimates or emission factors at district level may introduce some degree of uncertainty which can be improved only by using data from locally intensified inventories. The use of district collected inventory data to estimate carbon stock emissions can reliably produce carbon estimates with low level uncertainty which can be usable at local scale. Finally, the land-use mapping and classification was based on interpretation of Landsat data which is a medium resolution satellite and cannot detect small-scale land-cover changes due to spatial resolution challenges. Also, the study used wall-to-wall-based methods for deriving land-use maps. These wall-to-wall-based methods are associated with statistical errors as they do not provide the degree of uncertainty associated with each map due to single-area values with no confidence intervals. The use of sample-based methods of area estimation could produce more reliable area estimates through the integration of higher resolution images and these methods could also estimate the associated degree of uncertainty of the classification process. Future studies could improve the reliability of carbon accounting procedures by using all carbon pools, use of locally derived emission factors and the use of higher resolution satellite data which would better capture land-use change and variability in the forest structure.

CONCLUSION

The study assessed LULCC and the implications on carbon loss and GHG emissions in the miombo woodlands of Hwedza District in Zimbabwe, over a period of 30 years using Google Earth Engine. The findings reveal landscape conversion and transformation marked mainly by a gradual decrease in forest cover and a corresponding increase in areas converted to agricultural activity and grassland. The land-use matrix indicates that forest conversion to cropland was the major driver of deforestation while its conversion to grassland was the major driver of forest degradation. The study further demonstrates that these land-use transitions from forest to cropland and forest to grassland had implications on forest carbon sequestration and storage capabilities and ultimately on GHG emissions. The study indicated the role that miombo woodlands play as key carbon reservoirs and ultimately as carbon sinks and the potential effect that land-use conversion has on climate change. The present study reinforces the present evidence that land-use change remains the major source of emissions within the LULUCF sector in Zimbabwe and across sub-Saharan Africa. Besides documenting landscape change in Hwedza, the study has contributed to the wider understanding of how land-use change dynamics affect carbon accounting and climate change mitigation mechanisms across miombo ecosystems. The findings underscore the urgent need for sustainable land management practices and strategies that ensure balance between agricultural development and ecosystem conservation. Several community-based interventions, such as introduction of community-based forest management practices, promotion of agroforestry-based practices and alternative methods of tobacco curing that do not depend on wood-fuel, could play an important role in reducing the degree of deforestation and degradation, thereby improving rural livelihoods. Strengthening forests monitoring systems, including the use of remote sensing technologies, is also critical as it plays an important role in monitoring near real-time land-use dynamics which is key in making informed and evidence-based climate change mitigation policies. Continued research on integrating sufficient permanent sampling plots for use in carbon estimation into higher-tier carbon accounting methodologies will further improve the accuracy and reliability of carbon stock assessments in miombo landscapes.

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