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Original Article

Recovery of Forest Land Due to Forest Landscape Restoration Following Restriction of Mining Activities in the Northern Part of Amani Nature Forest Reserve, Tanga, Tanzania

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ABSTRACT

Forest landscape restoration plays a pivotal role in preserving global biodiversity and enhancing human well-being by addressing social, economic, and ecological challenges. However, illegal mining activities pose significant threats to biodiversity hotspots, including the Amani Nature Forest Reserve (ANFR). This study evaluated forest recovery progress following the enforcement of restrictions against illegal mining in the northern part of ANFR, Tanga, Tanzania. Landsat images from 2000, 2017, and 2023 were analyzed using supervised image classification with the Random Forest algorithm on Google Earth Engine. The Results showed notable land cover transitions. In 2000, the area comprised 14.56% Closed Forest, 35.64% Open Forest, 23.91% mining, and 25.89% Cropland. By 2023, the proportion shifted to 65.77% Closed Forest, 14.37% Open Forest, 12.02% Mining, and 7.83% Cropland. Classification accuracy exceeded 80%, with Kappa coefficients above 75% for all periods, indicating substantial agreement and reliability of the classification process. Findings revealed a significant recovery of Closed Forests, replacing Open Forests, Mining, and Cropland, albeit with spatial and temporal variations. Recovery remains slow in persistent mining-affected areas. The study recommends targeted interventions such as enrichment planting and stricter law enforcement in areas with slow recovery. Further research and monitoring, including advanced technologies such as LiDAR and hyper-spectral imaging, are essential to enhance restoration efforts, sustain biodiversity, and ensure the long-term resilience of ANFR.

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INTRODUCTION

Forest Landscape restoration is a fundamental component of global environmental initiatives, addressing urgent issues such as biodiversity loss, climate change, and ecosystem degradation (Guariguata, 2021). Forests, which cover about 31% of the Earth's land area, provide habitats for over 80% of terrestrial species crucial for carbon sequestration, water regulation, and soil conservation (FAO, 2020). In the tropical regions of Africa, forests are essential for maintaining ecological balance, supporting local economies, and enhancing human livelihoods. However, these forests face severe threats from deforestation driven by agricultural expansion, logging, illegal mining, and infrastructure development. Between 2010 and 2020, the annual net loss of forests was estimated to be 3.9 million hectares, underscoring the urgent need for (FLR) to balance human needs with environmental conservation (Chazdon, 2017).

In Tanzania, the rate of deforestation is estimated at 469,420 hectares per year, with most of this loss occurring in forest reserves (MNRT, 2021; Nzunda & Midtgaard, 2019). FLR initiatives are crucial for sustainable development, conserving biodiversity, and mitigating climate change (Khalid, 2018). The Amani Nature Forest Reserve (ANFR) in Tanzania, known for its ecological significance and unique landscapes, faced severe degradation due to gold mining in its northern part (Mpanda et al., 2011). Illegal mining activities not only stripped vegetation but also disrupted soil stability and hydrological functions, leading to severe ecological consequences. The Study by Bentsi-Enchill et al. (2022) highlighted the long-lasting impacts of mining on forest structure and species composition, further emphasizing the need for targeted restoration.

In 2010 management of the reserve shifted from the Forestry and Beekeeping Division (FBD) to Tanzania Forest Services (TFS), marking a significant turning point (MRNT, 2010), leading to intensified restoration efforts including forest patrols, enrichment planting, conducting gap-filling, and deploying forest guards, which have been instrumental in mitigating degradation and promoting recovery. Despite these efforts, understanding the full extent of recovery in ANFR requires robust scientific assessments, particularly in areas affected by mining.

Advancements in remote sensing and GIS have revolutionized monitoring and managing forest ecosystems. Tools such as optical and thermal sensors are now indispensable for addressing global challenges such as climate change and pollution (Lanceman et al., 2022; Ozgeldinova et al., 2023). Remotely sensed data is vital for addressing global challenges such as climate change, water quality, pollution, and disasters. Improvements in remote sensing and GIS have made air quality measurement, mapping, and forest resources management indispensable (Maurya et al., 2021; Sówka et al., 2020). The Random Forest Classifier (RFC), a powerful machine learning algorithm, is widely used in remote sensing to handle complex datasets for applications in land cover classification, achieving high accuracy and efficiency (Koskikala et al., 2020).

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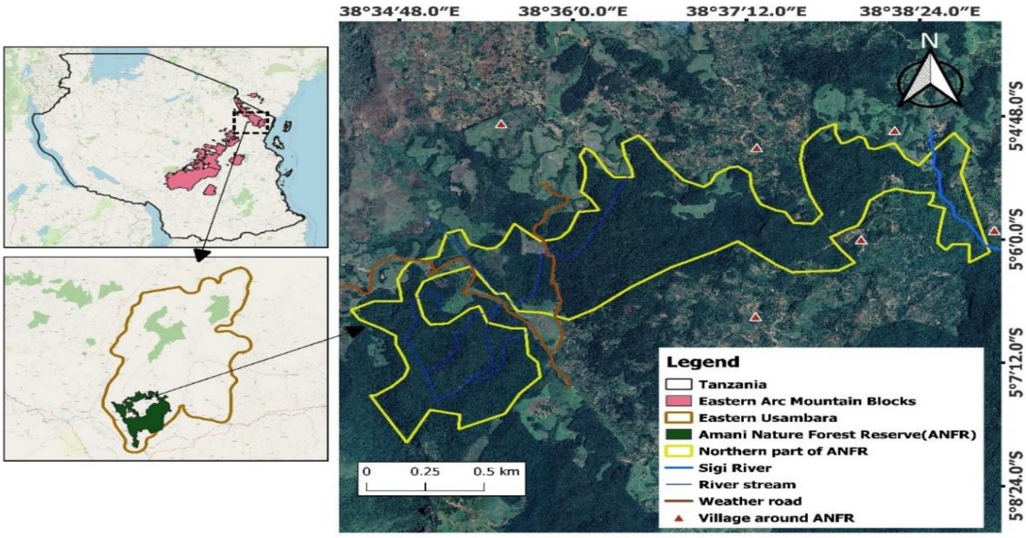
Therefore, this study employed these advanced technologies to assess forest recovery in the Northern part of the Amani Nature Forest Reserve (ANFR). While several studies have documented land cover changes at global and regional levels (Achmad, 2023; Lemma et al., 2021), few have analyzed the long-term recovery trends in biodiversity-rich areas like ANFR. Existing research in adjacent regions, such as Lolila et al., (2023) in the Eastern Usambara sub-montane forest and Tesha et al., (2023) in the West Usambara Mountains, provides valuable insights into forest composition and diversity patterns but falls short of capturing the dynamics of forest recovery after mining activities. To fill this gap this study analyzed land cover classification, classification accuracy, rate of change, persistence, trajectories, and spatial distribution of key land cover types, including closed forest, open forest, mining areas, and cropland between 2000 and 2023. By addressing these objectives, this research aims to fill critical knowledge gaps and provide actionable insights for improving forest management and restoration strategies in Tanzania.

Study area

This study was conducted in the northern part of Amani Nature Forest Reserve (ANFR), spanning the Muheza, and Korogwe Districts in the Tanga region (Figure 1). Located in the East Usambara Mountains, ANFR covers an area of 8,380 hectares (5°04'30" to 5°14'10" S and 38°30'34" to 38°40'06" E). Its elevation ranges from 190 meters to 1,130 meters above sea level (Mwendwa, 2021). ANFR is part of the Eastern Arc Mountains (EAM), a coastal mountain range extending from southern Kenya to southern Tanzania, known for its rich diversity of endemic and vulnerable species. Besides its role in preserving flora and fauna, ANFR is crucial for water catchment and carbon sequestration efforts (URT, 2019). The reserve experiences two distinct rainy seasons that start from April to May and October to December, with annual precipitation ranging from 1,200 mm in the foothills to over 2,300 mm at higher altitudes, especially in the southeast (Lolila *et al*., 2023). At approximately 900 meters altitude, the mean annual temperature is 20.6°C, with a mean daily maximum of 24.9°C and a mean daily minimum of 16.3°C (TFS, 2022) The hottest season occurs from January to February, while the coolest is in May to July.

MATERIALS AND METHODS

Figure 1. Map of the study area showing the Northern part of Amani Nature Forest Reserve.



Data Collection and Processing

Image acquisition

Multiple-temporal imagery from the Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) on Landsat 7 and 8 was collected for the years 2000, 2017, and 2023 (Table 1). These images were filtered and mosaicked to achieve a cloud cover range of 5-10% using the simple composite algorithm. The selection process was

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automated using the Google Earth Engine platform via the Google Earth library.

Table 1: Information on the collected Landsat 7 and 8 images used in this study

Satellite platform	Source	Acquisition date	Band used	Spatial resolution
Landsat 7	http://eathexplorer.usgs.gov	1 Jan 2000 - 31 Dec 2000	Near-infrared	30m
			Red	30m
			Green	30m
Landsat 7	http://eathexplorer.usgs.gov	1 Jan 2017 - 31 Dec 2017	Near-infrared	30m
			Red	30m
			Green	30m
Landsat 8	http://eathexplorer.usgs.gov	1 Jan 2023 - 31 Dec 2023	Red	30m
			Green	30m
			Blue	30m

Data analysis

Image Classification

Land cover classifications were carried out using the supervised approach with the Random Forest algorithm to categorize land cover classes, based on its capacity to handle large datasets and superior classification accuracy (Tikuye et al., 2023). To optimize model performance, key RF parameters were carefully tuned: the number of trees was set to **300**, the maximum depth of each tree was restricted to **20**, and the features considered per split were defined as "sqrt". These parameter settings balanced computational efficiency and model reliability, providing a robust framework for land cover classification (Salman et al., 2024; Xi, 2022). Ground truth data for training and verification were gathered from Google Earth Engine, Google Street View, and OpenStreetMap, selected due to their free accessibility, high-quality images, extensive coverage, and endorsement in related studies (Nguyen, 2020). Four major land cover types were identified based on local knowledge; Closed Forest, Open Forest, Mining, and Cropland. A total of 961 training sample points were collected, with 320 for the year 2000, 326 for 2017, and 315 for 2023. Of these, 80% were used to train the Random Forest model, while 20% were reserved for model validation. The validation was conducted using a confusion matrix to ensure the reliability of the classification results. The resulting land cover map and the area of each land use/cover class were exported to Google Drive for further use and analysis. A flowchart illustrating the process of classification from data collection to final map export (Figure 2).

Figure 2: Flow chart of land cover classification; Source: own elaboration.

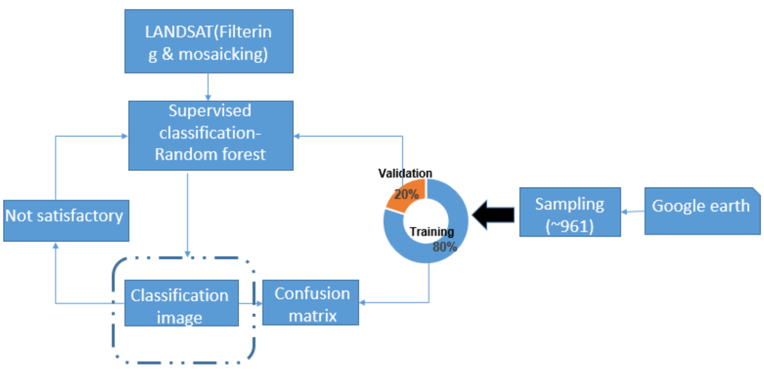

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Image analysis

The rate of change in land use/cover area was calculated using a modification of the formula used by Nzunda & Midtgaard, (2019) and You et al., (2020). Gains and losses 2000-2017 and 2017-2023 were identified using cross-tabulation matrices and plotted using Microsoft Excel. The persistence and trajectory of changes for each land cover class were analyzed spatially, and maps were created to visualize these changes using spatial overlay analysis in QGIS.

$$\boldsymbol{r} = \left(\left(\frac{\mathbf{1}}{\boldsymbol{t2}} - \boldsymbol{t1}\right)\right) \boldsymbol{x}\, \boldsymbol{ln}\left(\frac{\boldsymbol{A2}}{\boldsymbol{A1}}\right) \ldots .(\mathbf{1})$$

Equation 1 for land cover change, Where A2 and A1 are the land cover class areas at the end and the beginning, respectively, of the period being evaluated, and *t* is the number of years spanning that period (i.e. 2000–2017 = 17, 2017-2023= 6).

RESULTS

Land cover land use classification

Four land cover land use (LCLU) classes were identified; these were Closed Forest, Open Forest, Mining, and Cropland, for the years 2000, 2017, and 2023 (Figure 3). The area covered by closed forests saw a substantial increase over the years. It expanded from 19.55 ha in 2000 to 64.87 ha in 2017 and continued to grow to 88.60ha in 2023. In contrast, the area of open forest decreased from 47.87 ha in 2000 to 42.05 ha in 2017, then significantly declined to 19.36 ha by 2023 (Figure 3, Table 2). The mining area shows a fluctuating pattern, starting at 32.11 ha in 2000, sharply decreasing to 11.83 ha by 2017, and then slightly increasing to 16.20 ha in 2023 (Figure 3, Table 2). Cropland consistently decreased over the period, from 34.77 ha in 2000 to 15.95 ha in 2017, and further reduced to 10.55 ha by 2023.

Figure 3: Land cover land use classification for the Northern part of ANFR for the years 2000, 2017, and 2023

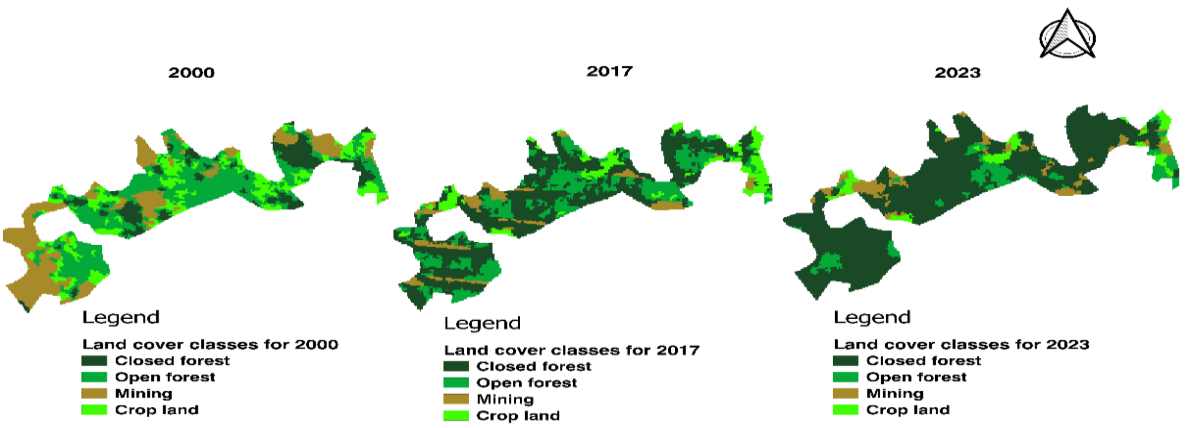

Figure 4: Percentage for land cover classes of the total study area for the Northern part of ANFR for the years 2000, 2017, and 2023

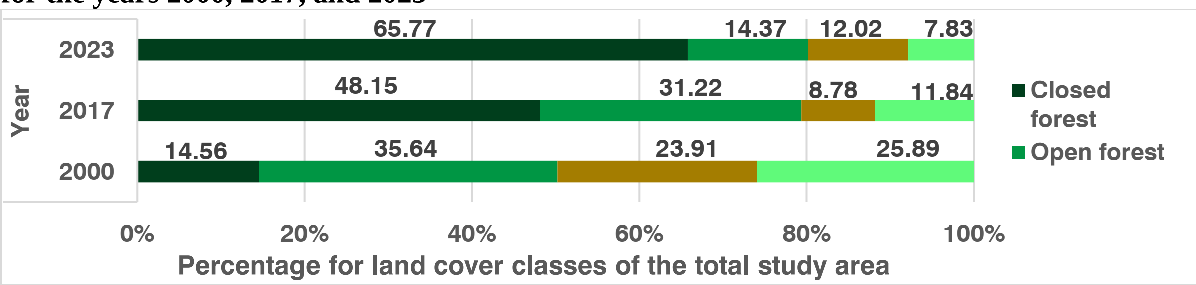

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Table 2: Area of each land cover for the Northern part of ANFR in 2000, 2017, and 2023

	Area (ha)				
Year	Closed forest	Open forest	Mining	Cropland	Total
2000	19.55	47.87	32.11	34.77	134.30
2017	64.87	42.05	11.83	15.95	134.71
2023	88.60	19.36	16.20	10.55	134.71

Accuracy of land cover land use classification for 2000, 2017, and 2023

The accuracy assessment showed that in 2000, 2017, and 2023, the random forest classifier achieved an overall accuracy of 88%, 81%, and 80% and a Kappa coefficient of 84%, 75%, and 72%, respectively (Tables 3, 4, & 5). In 2000, the classification showed high accuracy with minimal confusion. Closed forest and mining showed perfect user accuracy, indicating that all pixels classified were indeed correct. However, there was some confusion between open forest and cropland, reducing the user accuracy for open forest. In 2017, the overall accuracy decreased slightly, with noticeable confusion between open forest and cropland, as well as between closed forest and open forest. In 2023, the overall accuracy remained stable but relatively lower compared to 2000. The producer's accuracy for cropland was quite low, indicating many cropland areas were misclassified into other categories. There was also confusion between mining and cropland and between open forest and other categories. The random forest classifier showed strong performance in differentiating closed forests and mining, but less so for open forests and cropland. The decrease in overall accuracy and Kappa coefficient from 2000 to 2023 suggested that the classifier's ability to distinguish between these categories had slight limitations, possibly due to changes in land use patterns or increased complexity in the landscape. Moreover, the average user's accuracy (UA) and producer's accuracy (PA) for each class indicated that there was a higher degree of confusion between closed forest and mining than between open forest land and cropland for each respective year (Tables 3, 4, & 5).

Table 3: Confusion matrix of land cover land use classification for the year 2000 for the Northern part of ANFR

Confusion matrix 2000					
	Closed forest	Open forest	Mining	Cropland	Average UA
Closed forest	100	16.67	0	0	1.00
Open forest	0	66.67	0	11.11	0.67
Mining	0	0	100	0	1.00
Cropland	0	16.67	0	88.89	0.89
%	100	100	100	100	
Average PA	0.86	0.80	1.00	0.89	
Overall accuracy			**0.88**		
Kappa coefficient			**0.84**		

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Table 4: Confusion matrix of land cover land use classification for the year 2017 for the Northern part of ANFR

Confusion matrix 2017					
	Closed forest	Open forest	Mining	Cropland	Average UA
Closed forest	87.5	10	0	0	0.88
Open forest	12.5	60	0	12.5	0.6
Mining	0	0	100	12.5	1
Cropland	0	30	0	75	0.75
%	100	100	100	100	
Average PA	0.88	0.75	0.92	0.67	
Overall accuracy			**0.81**		
Kappa coefficient			**0.75**		

Table 5: Confusion matrix of land cover land use classification for the year 2023 for the Northern part of ANFR

Confusion matrix 2023					
	Closed forest	Open forest	Mining	Cropland	Average UA
Closed forest	94.74	5.88	0	0	0.95
Open forest	5.26	64.71	0	0	0.65
Mining	0	11.76	64.29	0	0.64
Cropland	0	17.65	35.71	100	1.00
%	100	100	100	100	
Average PA	0.95	0.92	0.82	0.47	
Overall accuracy			**0.8**		
Kappa coefficient			**0.72**		

Rate of change for each land cover land use (LCLU)

Between 2000 and 2017, closed forests experienced a higher rate of gain compared to open forests (Table 6). During this time, cropland was lost at a faster rate than mining. Closed forests showed a net gain, while open forests, mining areas, and cropland experienced net losses (Figure 4). From 2017 to 2023, closed forests continued to increase, but at a reduced rate. In contrast, both open forest and cropland decreased, reversing the trend from the previous period, and mining activities saw a slight increase. The decline in open forest and cropland from 2017 to 2023 was more pronounced than the decrease observed between 2000 and 2017.

Table 6: Rate of change for each land cover land use class for the periods 2000-2017 and 2017-2023 for the Northern part of ANFR

Land cover land use classes	**2017-2000**	**ha/year**	**2017 in 2000 in %**	**% rate of change**
Closed forest	45.32	2.67	331.8	7.06
Open forest	-5.81	-0.34	87.86	-0.76
Mining	-20.28	-1.19	36.85	-5.87
Cropland	-18.82	-1.11	45.88	-4.58
Land cover land use classes	**2023-2017**	**ha/year**	**2023 in 2017 in %**	**% rate of change**
Closed forest	23.73	3.96	136.59	5.2
Open forest	-22.69	-3.78	46.03	-12.93
Mining	4.36	0.73	136.89	5.23
Cropland	-5.4	-0.9	66.13	-6.89

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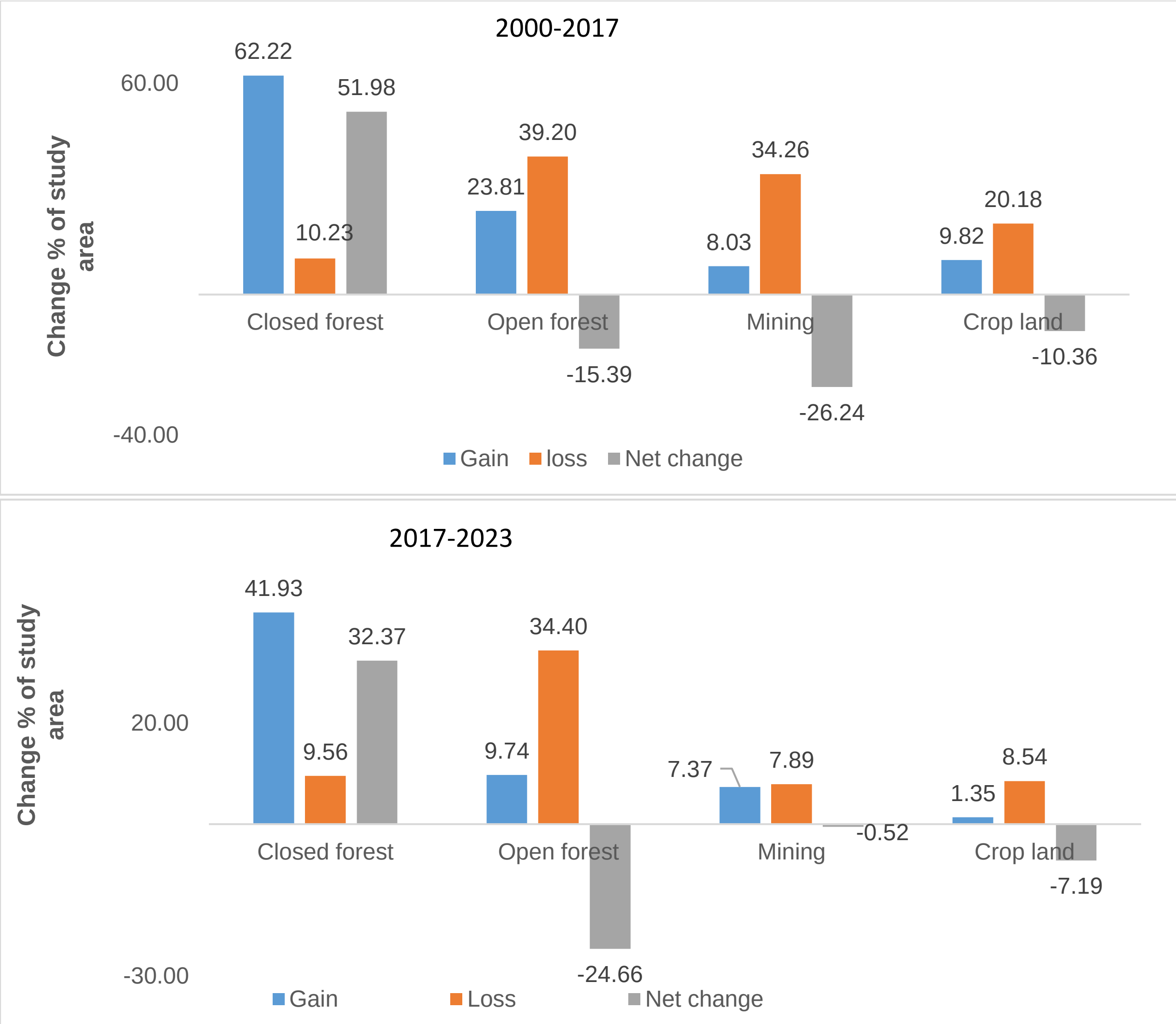
Figure 4: Showing the rate of gaining, loss, and net change for each land cover class for the years 2000-2017 to 2017-2023



Persistence and trajectories of land cover land use changes

Between 2000 and 2017, the largest part of new forest cover was derived from open forest, followed by mining and cropland (Table 7). From 2017 to 2023, the predominant forest land cover was maintained as persistent forest, with additional contributions from converting open forest, mining, and cropland to closed forest. Over the entire period from 2000 to 2023, the most significant proportion was the persistence of closed forests between 2017 and 2023 (Table 7). The main trend observed was the conversion of other land cover types to the closed forest, while the conversion of forest to other land cover types affected less than 6.2% of the study area, the largest being 45.83% of open forest, mining, and cropland transitioned to closed forest between 2017 and 2023 (Table 7). The current research revealed the change of forest to other land cover types such as mining, was probably due to classification errors since the accuracy was not 100% (Table 3, 4 & 5).

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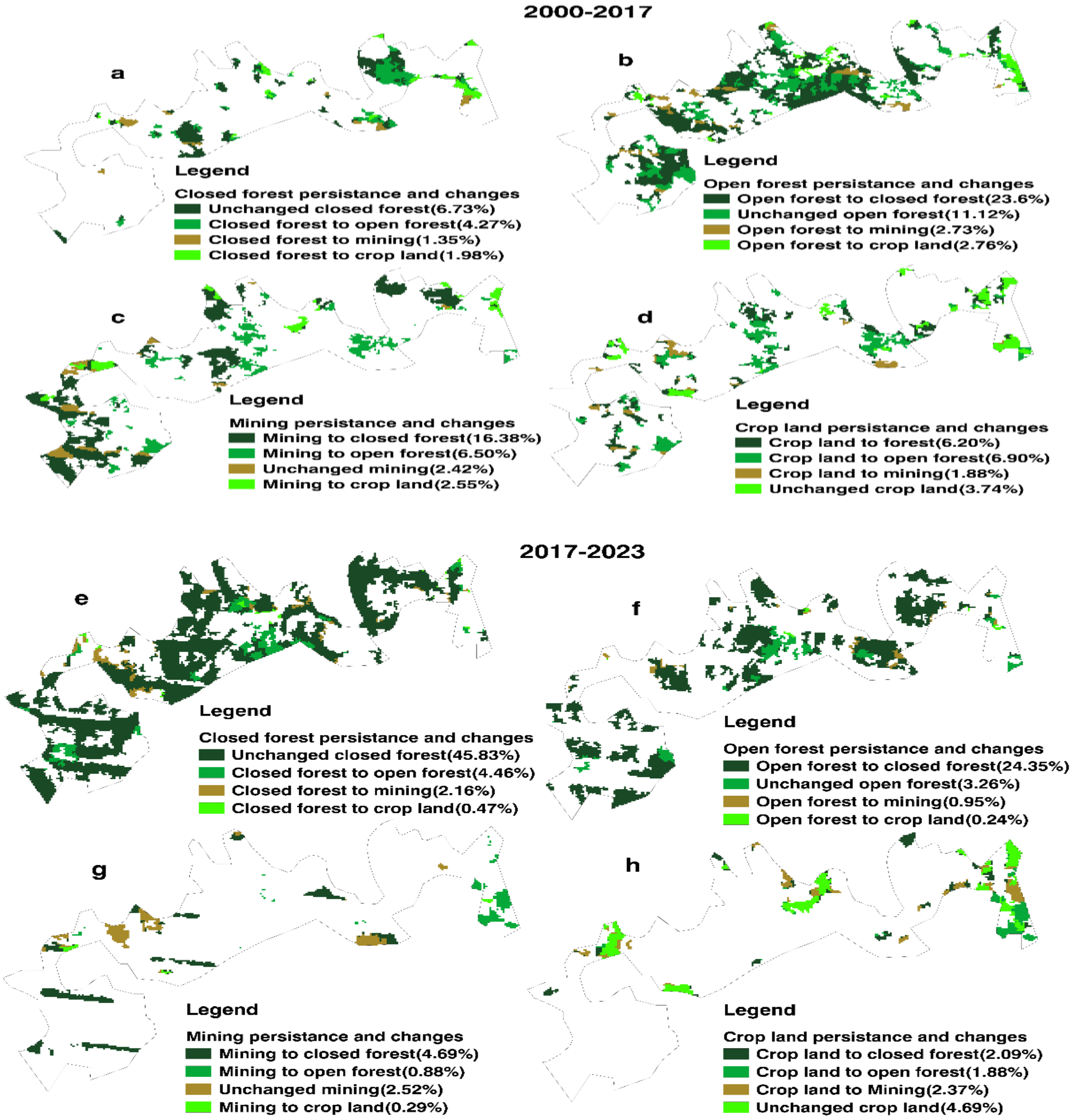
Table 7; Trajectories of changes: Land cover land use class area in 2000 that was converted to different land cover classes in periods 2000-2017 and 2017-2023 for the Northern part of ANFR

Land use land cover classes	2000-2017	Area[ha]	%Study area	2017-2023	Area [ha]	%Study area
Closed Forest	Closed Forest	9.07	6.73	Closed Forest	61.73	45.83
	Open Forest	31.8	23.6	Open Forest	32.8	24.35
	Mining	22.07	16.38	Mining	6.32	4.69
	Cropland	8.35	6.2	Cropland	2.82	2.09
	Total	**71.29**	**52.92**		**103.66**	**76.95**
Open Forest	Closed Forest	5.75	4.27	Closed Forest	6.01	4.46
	Open Forest	14.99	11.12	Open Forest	4.39	3.26
	Mining	8.76	6.5	Mining	1.19	0.88
	Cropland	9.3	6.9	Cropland	2.54	1.88
	Total	**38.79**	**28.8**		**14.13**	**10.49**
Mining	Closed Forest	1.82	1.35	Closed Forest	2.91	2.16
	Open Forest	3.68	2.73	Open Forest	1.28	0.95
	Mining	3.26	2.42	Mining	3.39	2.52
	Cropland	2.53	1.88	Cropland	3.19	2.37
	Total	**11.29**	**8.38**		**10.76**	**7.99**
Cropland	Closed Forest	2.66	1.98	Closed Forest	0.64	0.47
	Open Forest	3.72	2.76	Open Forest	0.32	0.24
	Mining	3.44	2.55	Mining	0.39	0.29
	Cropland	5.04	3.74	Cropland	6.32	4.69
	Total	**14.86**	**11.03**		**7.67**	**5.69**

Spatial distribution of land cover land use changes

The eastern and southern parts of Northern ANFR had the most of the persistence of closed forests between 2000 and 2017 (Figure 5a). This was also the area with the most change from open forest to closed forest, mining, and cropland (Figure 4b & d). The central northern-west part of the study area was also an area of change from cropland to closed forest (Figure 5d). For the same period, the change of mining to closed forest and open forest was mostly scattered throughout the area, especially along the northeastern and central part of the study area (Figure 5c). For the period 2017-2023, the southeastern part of the Northern ANFR experienced most of the persistence in forest cover (Figure 5e). The central part exhibited forest land cover persistence to some extent, but less extensive than the south-eastern part. The change from open forest to closed forest was scattered throughout the study area in a very speckled salt-and-pepper fashion, with very small patches involved (Figure 5f). The change from mining to forest was also scattered throughout but concentrated around the central and southern parts of the forest with the patches involved being bigger than those of the changes from open forest to closed forest (Figure 5g). Changes from cropland to closed forest were scattered throughout the Northern part of ANFR, in those areas that did not involve the other changes already described (Figure 5h).

Figure 5: Spatial distribution of persistence and changes for land use and cover classes studied for The Northern part of ANFR between 2000-2017 and 2017-2023. Closed Forest (a&e), Open Forest (b&f), Mining (c&g), and Cropland (d&h). Percentages are concerning the whole study area (Table 7).



DISCUSSION

The findings of this study indicate that the Northern part of Amani Nature Forest Reserve experienced a dynamic decrease and increase in closed forest from open forest, mining, and cropland during both study periods (2000 to 2017 and 2017 to 2023) following high restriction of illegal mining in 2017. The classifier utilized in the imagery classification yielded reliable results, enabling further analysis of the classified imagery. Subsequent sections of this discussion delve into the accuracy assessment of the classification, as well as aspects related to the rate of forest restoration, direct anthropogenic drivers, indirect drivers' and biophysical drivers of land cover change. These aspects of the area, rate, persistence, trajectories, and spatial distribution of land cover changes are explored.

Accuracy assessment for land use land cover change

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The accuracy assessment in this study revealed the robustness of the Random Forest classifier's performance, with overall accuracy values of 88%, 81%, and 80% and corresponding Kappa coefficients of 84%, 75%, and 72% for the years 2000, 2017, and 2023, respectively. While the high overall accuracy indicates reliable classification, the inclusion of Kappa coefficients provides a more nuanced validation by accounting for chance agreement. The higher Kappa coefficient in 2000 (84%) represents "Excellent" agreement, as defined by (Hogland et al., 2013; Rwanga & Ndambuki, 2017), while the slightly lower values in 2017 and 2023 (75% and 72%) reflect "Good" agreement and point to growing challenges in classification precision over time. The decline in Kappa coefficients highlights increasing complexity in land cover patterns and spectral confusion, particularly between categories such as Closed forest and Open forest. These commission errors, consistent with findings by Daiyoub et al., (2023) and Doggart et al., (2020), illustrate the difficulties in distinguishing classes with similar spectral signatures, especially in tropical landscapes. Rotich et al. (2022) similarly noted that spectral overlap among forest classes often complicates classification, a challenge intensified by limited ground truth data. Seasonal variations further impacted classification performance, particularly in 2023, as evidenced by the relatively lower Kappa coefficient.

Single-season imagery, as used in this study, may fail to capture the dynamic nature of vegetation phenology, leading to spectral confusion between Open Forest and Cropland. Nguyen (2020) and Pancrace et al. (2022) emphasized that seasonal rainfall and temperature fluctuations significantly alter spectral reflectance patterns, complicating differentiation between these categories. This variability can obscure the true extent of land cover transitions and exacerbate classification errors. The reliance on spectral data alone also presents limitations in distinguishing structural differences within land cover types. For instance, canopy density and vegetation height, which are critical for differentiating Closed Forests from Open forests, cannot be captured through spectral reflectance alone. Studies by Allek et al., (2023) demonstrated that incorporating structural data from LiDAR or hyperspectral imagery provides finer-scale insights, reducing classification errors associated with spectral overlap.

Rate of Forest Restoration

Over the studied period (2000 to 2017 and 2017 to 2023) the Northern part of Amani Nature Forest Reserve (ANFR) experienced a high rate of forest restoration indicated by the proportional annual rate of change ranging from 5.2% to 7.06%. These findings are consistent with other studies conducted in various parts of tropical forests with the percentage annual rate of forest cover of 7 to 32% and 19 to 56% for both active and natural restoration respectively (Camara et al., 2023; Nzyoka et al., 2021). The rate documented herein might be lower than those reported in other tropical areas due to various reasons such as location, and the extent of disturbance being discussed. Furthermore, the rate of forest restoration in the northern part of ANFR significantly exceeded the rates documented for other areas in Tanzania and elsewhere in the world including that of 4.69% for the Meatu District in Northern Tanzania (Manyanda & Kashaigili, 2022), 0.4% Masasi District southern Tanzania (Doggart et al., 2023) and 0.4% for the Brazilian Amazon (Allek et al., 2023; Balaguer et al., 2014). For instance, a study in the East Usambara landscape found that forest landscape restoration (FLR) projects initiated in 2004 by WWF and the Tanzania Forest Conservation Group (TFCG) have contributed to 88% of forest restoration (Mansourian et al., 2019; Silale & Nyambegera, 2014). This has contributed to the rapid recovery of closed forests at a high rate. The differences and similarities observed in this study are due to differences in drivers of forest landscape restoration, further discussed below.

Direct anthropogenic drivers of land cover change related to area, rate, persistence, trajectories, and spatial distribution of land cover change.

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Mining activities significantly drive land use and land cover (LULC) changes, with profound implications for the conservation of natural resources and ecosystems (Mutimba & Watanabe, 2024). The expansion of mining exploration, development, and extraction, often converts forested areas, wetlands, and other natural habitats into bare land, and agricultural land (Obodai et al., 2023). A similar pattern has been observed in the Northern part of ANFR before decommissioning and restoration strategies from deforestation and degradation of illegal mining which was prevailing. Usually, mining activities leave extensive damage to the land as a result huge efforts need to be in place to rehabilitate and restore the areas, particularly in natural forests where the rate of regeneration takes place very slowly (Bentsi-Enchill et al., 2022; Pancrace et al., 2022). Like what has been observed in this study for the spatial distribution of land cover changes another area is extensively covered by closed forest while others pick up to forest at a slow rate. Similarly, other studies that have assessed restoration in tropical landscapes have shown that forest cover can gradually recover from deforestation and degradation (Manyanda & Kashaigili, 2022; Rotich et al., 2022).

The recovery process typically progresses through stages, starting from bushland, open forest with sparse trees, and eventually to closed forest once the disturbance is eliminated (Camara et al., 2023; Timsina et al., 2022). The observed positive change in forest cover during the study period can largely be attributed to several effective initiatives, such as the deployment of SUMA JKT to conduct and protect forests. Other restoration practices, such as pit fillings and enrichment planting, played a crucial role in the observed trend of land cover change in this study.

Indirect anthropogenic drivers of land cover change related to area, rate, persistence, trajectories, and spatial distribution of land cover changes.

Indirect anthropogenic drivers, including population growth, economic factors, policy, and cultural-technological influences, significantly impact land cover changes (Esengulova et al., 2024; Melalih, 2023; Nzunda & Midtgaard, 2019). Higher population density often correlates with increased deforestation (Mohammed et al., 2021). In Muheza and Korogwe Districts, with populations of 238,260 and 272,870 respectively, Korogwe District shows a higher population, particularly in villages bordering the Northern part of the Amani Nature Forest Reserve (NBS, 2022). Compared to urban areas, the lower population density around ANFR likely reduced pressure on the northern part of ANFR, which is evident in the decline of previously mined areas. In the Northern part of ANFR, farmers use basic cultivation tools, reflecting low agricultural technology as evidenced in other studies (Kouassi et al., 2021). The method allows for the spontaneous renewal of sprouting leftovers (Nzunda, 2011), possibly contributing to the survival of forest cover between 2000 and 2017. ANFR also provides employment, opportunities, offering alternative income sources for local communities, thereby reducing deforestation pressures (Corcoran et al., 2012).

Activities such as ecotourism, non-timber forest product harvesting, and casual labour empower communities to earn income without resorting to deforestation-related activities (Vincent et al., 2021). These initiatives have shifted land cover from illegal mining to cropland, open forest, and eventually closed forest, as residents engage in conservation. Policy and institutional factors, such as participatory forest management and ecosystem service payments, are vital for forest conservation (Laudari et al., 2024). In Tanzania, the government actively promotes participatory forest management, which has been embraced by local communities as a tool. The community's dedication to forest restoration is reflected in increased forest cover following poor management that previously led to deforestation (Zahor, 2022). Research results show that there has been an increase in forest cover, affirming the community's dedication to forest restoration.

Biophysical drivers of land cover change about area, rate, persistence, trajectories, and spatial distribution of land cover change.

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Biophysical factors, including climate, natural disasters, topography, hydrology, and other aspects, are crucial in shaping landscapes (Bufebo & Elias, 2021). In the Amani Nature Forest Reserve (ANFR), precipitation ranges from 1200mm in the foothills to over 2300mm at higher altitudes (Mpanda et al., 2011), with these wet conditions suppressing fire occurrence. In contrast, drier regions experience drought, which directly hampers tree growth and indirectly leads to deforestation and slow forest recovery. Temperature and precipitation changes influence vegetation type and distribution while natural disasters like floods and wildfires cause rapid land cover changes (Sugianto et al., 2022). However, in the northern part of ANFR, floods have minimal impact due to the gentle slope, reducing flood risk and ensuring even water distribution, which facilitates rapid forest cover restoration. Although wildfires can drastically reduce forest cover and alter soil properties, this is not the case in the northern part of NFR. Elevation and slope determine vegetation types and land suitability for agriculture (Liu & Slik, 2014), with steeper slopes prone to erosion and landslides. The aspect of a slope affects sunlight exposure and microclimates, influencing vegetation and agricultural practices (Morgan et al., 2019). Water presence, including rivers like the Sigi River, significantly impacts land cover, as seen in the Northeastern part of ANFR, where higher forest cover, particularly closed forest, is observed due to the river's availability.

CONCLUSION AND RECOMMENDATION

The findings revealed a notable change in land use and land cover in the study area from 2000 to 2023. Over this period, closed forest areas increased significantly, while open forest, mining, and cropland steadily decreased. Fluctuations in illegal mining activities were observed between 2000–2017 and 2017–2023, with initial decreases followed by slight increases. Despite this, closed forests continued to expand, overtaking other land covers and indicating substantial forest land recovery and extensive prevention of illegal mining within the reserve. The spatial distribution of recovered forests varied, influenced by diverse socio-ecological factors. Therefore, this study recommends targeted intervention such as enrichment planting, and stricter law enforcement, in areas with slow recovery rates, with further monitoring and research to assess the composition of the resilient of closed forests and enhance the recovery of areas that seem to be recovering slowly and preventing further threats from illegal mining, which persists at a slow rate in some parts of the Northern ANFR. Integrating advanced technologies, such as LiDAR and hyperspectral imaging, to enhance understanding of restoration trends, ensure long-term sustainability, and preserve ANFR's critical biodiversity.

Conflict of Interest

The authors declare no conflict of interest

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Author contributions

AJAM conceptualized the study, developed the methodology, participated in the formal analysis, drafted the original manuscript and revised the manuscript. EFN and BJM contributed to the study conceptualization and methodology and reviewed the manuscript. AMR carried out the formal analysis and created the visualizations.

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