



Small-Scale Mining and Indirect Pathways of Land-Use and Land-Cover Change Beyond Mine Sites: Evidence from Msaginia Forest Reserve, Tanzania

Simon B. Yeremia*, Oswald K. Laswai, Cleophas Emmanuel, Martha Nikodemus

Institute of Resource Assessment, University of Dar es Salaam, P.O. Box 35097, Dar es Salaam

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Abstract

Objectives: Small-scale mining can influence forest landscapes beyond areas directly occupied by mine workings through interconnected demographic, livelihood, resource-use, and infrastructure pathways.

Background: This study assessed land-use and land-cover change (LULCC) and examined indirect pathways associated with small-scale mining in and around Msaginia Forest Reserve, Mpanda District, Katavi Region, Tanzania.

Methodology: A mixed-methods case-study design combined Landsat-based LULC analysis for 1990, 2007, and 2023 with a household survey of 96 respondents, 27 key-informant interviews, two focus-group discussions, and field observations.

Results: Agricultural land increased from 5,136 ha (7%) in 1990 to 23,712 ha (30%) in 2023, while woodland declined from 40,572 ha (52%) to 30,015 ha (39%) and bushland declined from 29,286 ha (38%) to 17,052 ha (22%). The mapped mining/bare-land class increased from 7 ha to 1,797 ha. In the regression analysis, agricultural activities ($B = 1.006$, $p = 0.002$), migration ($B = 4.12$, $p = 0.006$), charcoal/fuelwood collection ($B = 2.001$, $p = 0.003$), and infrastructure development ($B = 3.40$, $p = 0.001$) were positively and significantly associated with LULCC, whereas logging/timber harvesting was not statistically significant ($p = 1.000$). In addition, 70.8% of respondents reported that a migrant-miner influx exacerbated land-use change.

Conclusion: The findings indicate that the landscape influence associated with small-scale mining extends beyond mine sites through population movement, settlement and agricultural demand, forest-resource use, and infrastructure development. The study highlights the need for integrated forest monitoring that considers both direct mining disturbance and associated changes in settlement, agriculture, energy use, timber demand, and infrastructure.

Keywords: Small-Scale Mining, Land-Use/Land-Cover Change, Forest Reserve, Indirect Impacts, Tanzania

1. Introduction

Land-use and land-cover change (LULCC) is a major manifestation of human pressure on terrestrial ecosystems and an important dimension of environmental change, particularly in tropical regions [15]. LULCC occurs when natural or semi-natural land cover is transformed into agricultural land, settlements, infrastructure, mining areas, bare land, and other human-dominated land uses [14, 15]. Such transformations can alter ecosystem structure and functioning, fragment habitats, reduce biodiversity, modify hydrological processes, and affect the provision of ecosystem goods and services [15]. Importantly, LULCC rarely results from a single driver but commonly emerges from interactions among demographic change, livelihood strategies, markets, resource availability, institutions, technology, and environmental conditions [14, 15].

Consequently, understanding land-use change requires attention to both the immediate activities that transform land and the underlying socioeconomic and institutional processes that influence those activities [14].

Artisanal and small-scale mining (ASM) is an important livelihood and economic activity in many developing countries and can exert considerable pressure on terrestrial ecosystems [10]. Although mining disturbance may initially be concentrated around pits, processing areas, and associated infrastructure, its environmental footprint can extend beyond the areas directly occupied by mining operations [7]. Mining activities commonly involve vegetation clearance, excavation, soil disturbance, construction of access routes, and establishment of processing and waste-disposal areas [3, 7]. In forest environments, these activities can result in vegetation loss, habitat degradation, soil exposure, and increased pressure on forest resources [3]. In Tanzania, [3] documented substantial changes in vegetation cover

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associated with artisanal and small-scale gold mining in Bukombe-Mbogwe Forest Reserve. Their study reported a decline in dense vegetation from 46.4% to 25.62% between 1984 and 2020, accompanied by an increase in sparse vegetation and built-up land [3]. The same study reported that miners extracted logs from the forest for mine-pit construction, showing that mining-related pressure can extend beyond the immediate excavation areas [3].

The environmental footprint of ASM is therefore not necessarily restricted to direct land conversion [22]. Direct mining impacts include converting vegetation into mine pits, waste areas, processing sites, access routes, and other surfaces directly associated with mineral extraction [3, 7]. However, mining can also generate demographic and socioeconomic changes that subsequently influence other land-use activities [2, 15]. The establishment and expansion of mining areas can attract migrants seeking employment and business opportunities, leading to the development and growth of mining settlements [2]. Research in Tanzania shows that migration has strongly influenced artisanal mining settlements, with residents moving between mining sites in response to changing livelihood opportunities and economic conditions [2]. Mining settlements can also develop diversified occupational structures involving mining, trading, services, and other economic activities, extending mining's socioeconomic influence beyond mineral extraction [2].

Distinguishing direct from indirect mining-related LULCC is essential to understanding mining's full spatial effects [14, 15]. Direct pathways are immediate land-cover changes caused by mining; indirect pathways occur when mining alters demographic, economic, livelihood, or accessibility conditions, influencing other land uses [14, 15]. Population influx can drive settlement expansion by increasing demand for housing and infrastructure [2]. Greater demand for food may also expand agriculture around mining settlements, increasing pressure on land [13]. Demand for household energy and construction materials can intensify fuelwood, charcoal, and timber extraction from nearby forests [3, 13]. Mining can therefore catalyze interconnected land-use changes, not merely convert vegetation directly into mining land [13, 15]. Mining-related migration can further increase pressure on land resources [2]. In Tanzania, mining opportunities have attracted migrants and spurred the emergence and growth of mining settlements [2]. Migration may initially be temporary, but some settlements become more permanent as mining and related economic activities take hold [2]. Settlement growth raises demand for housing, food, water, energy, and other resources, potentially pressuring nearby forests when mining occurs near wooded areas [2, 3]. Thus, mining-related demographic changes can drive forest LULCC indirectly, even where land is not used for mineral extraction [14, 15].

Recent evidence from Tanzania supports this interconnected interpretation of mining-related LULCC [13]. Examining changes between 1995 and 2023 in gold-mining hotspots in Singida, [13] found substantial shifts in agricultural land, forest, shrub/grassland, bare land, and built-up areas. Agricultural land increased by 168.51 km² (587.55%), while bare land and built-up areas grew by 7.70 km² (121.45%) and 0.55 km² (134.15%), respectively. Conversely, forest and shrub/grassland declined by 97.67 km² (72.59%) and 79.09 km² (43.49%). Gold mining was identified as an important factor associated with habitat degradation, soil erosion, land displacement, livelihood losses, and resource-use conflicts [13]. These findings show that mining landscapes undergo simultaneous changes across multiple LULC categories, rather than simply converting forest to mining land. Consequently, assessments limited to mine-site footprints may underestimate mining's broader landscape impacts [22].

Despite growing evidence of mining-related vegetation loss and LULCC in Tanzania, limited research has examined the indirect pathways linking small-scale mining to broader land-use transformations within and around forest reserves [3, 13]. Studies have documented vegetation degradation in Tanzanian forest reserves, as well as mining-related migration, settlement growth, and occupational diversification [2, 3]. Recent research has also identified substantial changes in agricultural, forest, bare, shrub/grassland, and built-up areas across Tanzanian gold-mining landscapes [13]. However, less attention has been paid to how these processes generate secondary land-use changes.

This study therefore examines not only the direct spatial footprint of small-scale mining but also the broader pathways linking mining to forest LULCC in and around Msaginia Forest Reserve. The findings are expected to clarify indirect mining-related pressures relevant to forest management and land-use planning in Tanzania.

2. Materials and Methods

2.1 Study area

Msaginia Forest Reserve is located in Mpanda District, Katavi Region, western Tanzania. The reserve was declared under Government Notice No. 447 of 1954 and is managed by the Tanzania Forest Services Agency. Mlele Hills Forest Reserve borders it to the east and south, and Mpanda North East Forest Reserve borders it to the north. Mpanda District had 102,900 people in 2012 and 245,764 in 2022, illustrating substantial demographic growth during the broader period of landscape transformation.

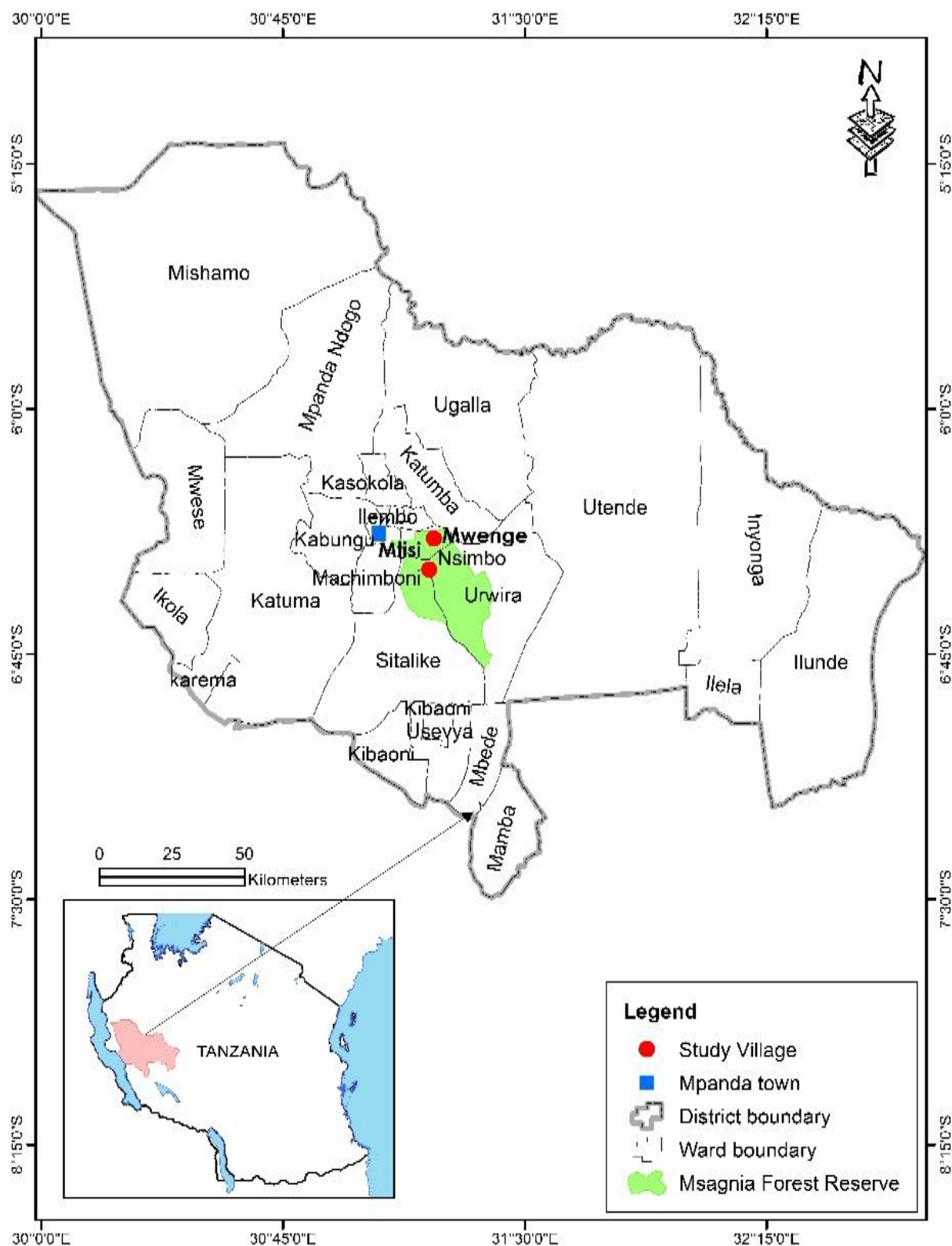


Fig. 1. Location of Msaginia Forest Reserve, Mpanda District, Katavi Region, Tanzania.

2.2 Research design and sampling

A mixed-methods case-study design was adopted to examine the indirect influence of small-scale mining on land-use/land-cover change (LULCC) in and around Msaginia Forest Reserve. The design integrated

quantitative household survey data (n=96) with qualitative evidence from key-informant interviews (n=27), focus-group discussions (FGDs), field observations, and relevant secondary information. This design was appropriate because the study required both measurement of observed LULCC and contextual

information on the social and livelihood processes associated with mining, migration, agricultural expansion, and other land-use pressures [9].

The study purposively selected two villages, Mtisi and Mwenge, from the seven villages surrounding Msaginia Forest Reserve because of their proximity to the reserve and reported links to mining and other forest-dependent activities. The selection was undertaken in consultation with the District Forest and Mining Offices. The household sampling frame comprised 2,626 households, including 1,940 in Mtisi and 686 in Mwenge.

The household sample size was determined using the Yamane formula, $n = N/[1 + N(e^2)]$, where N is the total number of households and e is the acceptable sampling error. With $N = 2,626$ and $e = 0.10$, the calculated sample was 96 households. Probability-proportional-to-size (PPS) sampling was then used to allocate the household sample between the two villages. Based on village household populations, 71 respondents were allocated to Mtisi and 25 to Mwenge, for a total of 96 respondents.

For the qualitative component, purposive sampling was used to select 27 key informants with direct knowledge of mining activities, forest management, and historical land-use change. The key informants comprised 1 mining officer, 4 elders, 2 ward executive officers, 10 small-scale mining license holders, and 10 mining operators, giving a total of 27 interviews. The study also conducted two FGDs, one in each selected village, with 10 participants per group (20 participants in total). The qualitative component complemented the household survey by providing contextual information on mining activities, migration, settlement expansion, agricultural encroachment, forest-resource use, and other processes associated with LULCC.

The household questionnaire was administered to 96 respondents and captured information on perceived small-scale mining-related factors associated with LULCC, their influences on agricultural expansion, forest fires, charcoal/fuelwood collection and timber harvesting, and migration, as well as associated environmental and livelihood effects. Qualitative interviews and FGDs were used to contextualize these responses and identify pathways linking mining to settlement expansion, agricultural encroachment, and increased pressure on forest resources.

2.3 Remote sensing and LULC analysis

Satellite data acquisition and preprocessing

Multi-temporal Landsat imagery was used to reconstruct LULC dynamics over the 33-year observation period. Landsat 5 imagery was used for 1990, Landsat 7 for 2007, and Landsat 8 for 2023. Surface Reflectance (SR) products with a spatial resolution of 30 m were accessed through the Google Earth Engine (GEE) platform. The use of GEE facilitated consistent access to the Landsat archive and preprocessing of the image collections. For each

observation year, dry-season median surface-reflectance composites were generated to reduce the influence of cloud contamination and improve temporal comparability. The use of multi-temporal Landsat data is consistent with established approaches for long-term LULC monitoring and change assessment [21].

Training and validation samples

Training and testing datasets were developed separately for the three image years. Representative samples were identified using Landsat spectral information and high-resolution Google Earth imagery, with on-screen digitization used to delineate training sites for the respective LULC classes. The researcher further checked the reference locations using knowledge of the study area and available field observations. The sampling datasets were prepared in QGIS version 3.34.3. A total of 156, 150, and 161 sample points were generated for 1990, 2007, and 2023, respectively. For each year, the available samples were randomly divided into approximately equal subsets, with 50% used to train the classifier and 50% retained for independent accuracy assessment. This separation reduced the risk of evaluating the classifier on the same observations used for model training, as established by [20].

Image classification

Supervised classification was implemented in QGIS using the DZetsaka classification plugin. The Landsat surface-reflectance bands (SR_B1–SR_B7) were used as spectral predictors. The Random Forest (RF) algorithm was selected because of its ability to handle nonlinear relationships, multiple predictor variables, and spectrally heterogeneous land-cover classes, while providing robust classification performance [8, 20]. The RF model was implemented through DZetsaka with 100 decision trees. Five LULC classes were mapped consistently across the three observation years: woodland, bushland, grassland, agricultural land, and mining/bare land. For presentation in this manuscript, the original mapped bare-soil class is termed “mining/bare land” to reflect the study focus on mining-related disturbance. However, this is a composite interpretive label rather than a spectrally isolated mining class: exposed surfaces may also represent roads, settlements, or other disturbances.

Accuracy assessment

Classification accuracy was assessed independently for each observation year using reference samples and a confusion matrix. The Semi-Automatic Classification Plugin (SCP) in QGIS supported the accuracy assessment, and stratified random sampling improved representation of the mapped classes. Overall accuracy and the Kappa coefficient were calculated from the confusion matrices. Overall accuracy represents the proportion of correctly

classified reference observations, whereas the Kappa coefficient measures agreement between the classified map and reference data while accounting for chance agreement [16]. The resulting classification accuracies were 81.92%, 89.33%, and 82.74% for 1990, 2007, and 2023, respectively, with corresponding Kappa coefficients of 0.77, 0.93, and 0.83. These results provided the basis for using the classified maps in subsequent LULC change analysis.

LULC change detection and vegetation assessment

The classified maps were compared across the 1990–2007 and 2007–2023 intervals using post-classification comparison. The area of each LULC class was calculated in hectares, and net changes were obtained by subtracting the earlier area from the later area. Annual rates of change were calculated by dividing the net area change by the number of years between the two observation dates. This approach allowed the study to identify both long-term trends and differences in the pace of landscape transformation between the two periods. Remote-sensing outputs were interpreted together with field observations and geo-tagged photographs to distinguish broader vegetation and land-surface changes from mining-related disturbance. The combination of Random Forest classification and post-classification change assessment is consistent with established LULC change methodologies applied in Tanzania [21].

Interpretation of mining-related LULC change

Because mining surfaces could not be spectrally separated reliably from other exposed surfaces, the remote-sensing analysis does not estimate the physical area of active or abandoned mining independently. The mapped mining/bare-land class represents the original bare-soil classification and is used as an indicator of exposed or disturbed land potentially associated with mining. Interpretation of mining-related LULC change therefore combines the spatial pattern of this class with field observations, Google Earth imagery and household and qualitative evidence. This distinction is important because not every mining/bare-land pixel represents a mine site. The approach consequently uses the composite class to identify disturbed-land expansion while avoiding unsupported attribution of all exposed surfaces to mining.

2.4 Household and qualitative data analysis

Quantitative household data were checked, numerically coded, and analyzed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics, including frequencies and percentages, summarized respondents' socioeconomic characteristics, livelihood activities, perceptions of land-use and land-cover change, and migration. Multiple regression assessed the statistical

association between the LULCC outcome measure and five selected variables: agricultural activities, migration, charcoal/fuelwood collection, logs and timber harvesting, and infrastructure development. The model produced $R = 0.615$, $R^2 = 0.378$, adjusted $R^2 = 0.343$, $F = 10.932$, and $p < 0.001$. Because the household study was observational and cross-sectional, regression coefficients were interpreted as statistical associations rather than causal effects. The coefficient table identifies LULCC as the dependent variable; therefore, this manuscript consistently treats LULCC as the outcome. Statistical significance was evaluated at $p < 0.05$.

Qualitative data from 27 key-informant interviews, two focus-group discussions with 10 participants each, and field observations were analysed using content analysis. Materials were organized according to the study objectives and coded into recurring categories concerning expansion, migration and settlement, agricultural expansion, and charcoal and fuelwood collection. Related responses were grouped into broader themes. Qualitative evidence contextualized patterns from the household survey and remotely sensed LULC results. This approach follows established qualitative content-analysis procedures for systematically coding and interpreting recurring meanings and patterns [11]. Triangulation compared household responses, key-informant accounts, FGD findings, field observations, and satellite-derived patterns.

2.5 Ethical considerations

The study received research clearance through the University of Dar es Salaam and relevant regional and district administrative authorities. Participants were informed about the study and participated voluntarily. Confidentiality was maintained.

3. Results and discussion

3.1 Respondent characteristics

The socio-demographic characteristics of the 96 household respondents are presented in Table 1.

Table 1. Socio-demographic characteristics of household respondents (n = 96)

Variable	Category	n	%
Gender	Male	57	59.4
	Female	39	40.6
Age (years)	18–45	20	20.8
	46–60	48	50.0
	>60	28	29.2
Education level	No formal education	9	9.4
	Primary education or lower	58	60.4
	Secondary education	19	19.8
	College/technical education	10	10.4
Household size	1–3 members	9	9.4
	4–7 members	39	40.6
	8–11 members	48	50.0

Period of residence (years)	≤20	9	8.9
	21–30	27	27.6
	31–40	23	24.4
	41–50	18	18.7
	>50	19	20.3
Main source of income	Formal employment	10	10.4
	Mining activity	29	30.2
	Agriculture	55	57.3
	Informal employment	2	2.1

Source: Field data.

Respondents were predominantly male (59.4%), while females accounted for 40.6%. Half of the respondents were aged 46–60 years (50.0%), followed by those aged above 60 years (29.2%) and those aged 18–45 years (20.8%). In terms of education, 60.4% had primary education or lower, 19.8% had secondary education, 10.4% had college or technical education, and 9.4% had no formal education. Half of the households (50.0%) had 8–11 members, while 40.6% had 4–7 members. Regarding residence duration, 20.3% had lived in the area for more than 50 years, whereas 27.6% had resided there for 21–30 years. Agriculture was the main reported source of income for 57.3% of respondents, followed by mining

(30.2%), formal employment (10.4%), and informal employment (2.1%).

3.2 Spatial and temporal LULC change

The classified Landsat images show substantial spatial and temporal transformation of the Msaginia Forest Reserve landscape between 1990 and 2023. Five LULC classes were mapped consistently across the three observation years: woodland, bushland, grassland, agricultural land, and mining/bare land. In 1990, woodland was the dominant class, covering 40,572 ha (52%), followed by bushland at 29,286 ha (38%). Agricultural land covered 5,136 ha (7%), while grassland and mining/bare land accounted for 2,899 ha (4%) and 7 ha, respectively. By 2007, agricultural land had expanded to 15,398 ha (20%), while bushland declined to 19,891 ha (26%) and woodland to 39,405 ha (51%). By 2023, agricultural land had increased further to 23,712 ha (30%), whereas woodland and bushland declined to 30,015 ha (39%) and 17,052 ha (22%), respectively. Grassland increased to 5,364 ha (7%), and mining/bare land increased to 1,797 ha (2%).

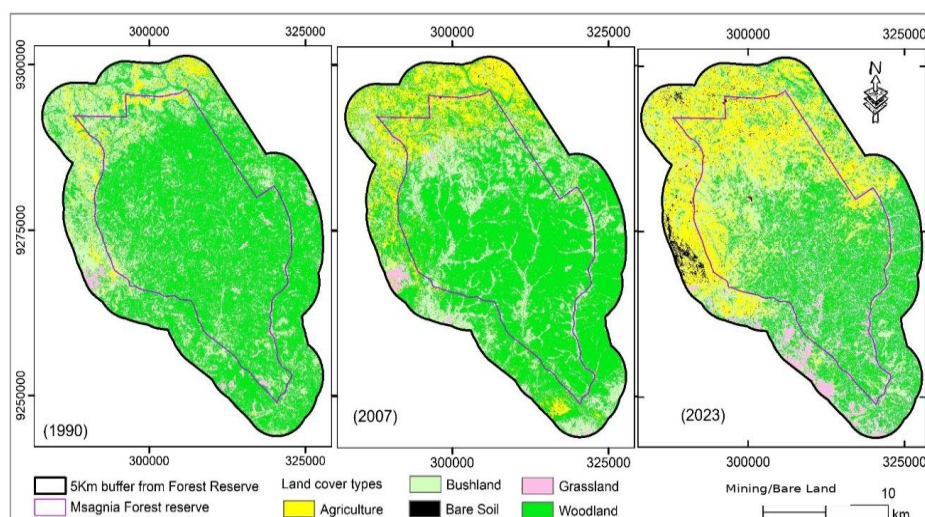


Fig. 2. Spatial distribution of LULC classes in Msaginia Forest Reserve in 1990, 2007 and 2023.

Table 2. LULC class coverage and annual area change in 1990, 2007 and 2023

LULC class	1990 (ha)	1990 (%)	2007 (ha)	2007 (%)	2023 (ha)	2023 (%)
Agricultural land	5,136	7	15,398	20	23,712	30
Mining/bare land	7	~0	147	~0	1,797	2
Bushland	29,286	38	19,891	26	17,052	22
Grassland	2,899	4	3,059	4	5,364	7
Woodland	40,572	52	39,405	51	30,015	39

The magnitude and direction of change are clearer when the three observation years are compared quantitatively (Table 2). Agricultural land recorded the largest net

increase, expanding by 18,576 ha between 1990 and 2023. The increase occurred in both intervals, rising by 10,262 ha from 1990 to 2007 and by a further 8,314 ha from 2007 to 2023, equivalent to average annual increases of approximately 604 and 520 ha year⁻¹, respectively. The mining/bare-land class increased from 7 ha in 1990 to 147 ha in 2007 and 1,797 ha in 2023, a net increase of 1,790 ha. This expansion indicates a substantial increase in exposed or disturbed surfaces, although the composite class cannot distinguish mining from other sources of bare ground.

Vegetation classes showed the opposite pattern. Bushland decreased by 9,395 ha between 1990 and 2007

and by a further 2,839 ha between 2007 and 2023, giving a net reduction of 12,234 ha. Woodland declined by 1,167 ha during 1990–2007 but by 9,390 ha during 2007–2023, resulting in a net reduction of 10,557 ha. The combined area of woodland and bushland therefore declined from 69,858 ha in 1990 to 47,067 ha in 2023, representing a 32.6% reduction in woody cover. Grassland increased by 160 ha in the first interval and by 2,305 ha in the second, giving a net increase of 2,465 ha. The substantially faster woodland decline during 2007–2023 indicates that landscape transformation intensified during the later observation period. This pattern is broadly consistent with recent evidence from Tanzania. [13], for example, reported substantial increases in agricultural, bare, and built-up land alongside marked declines in forest and shrub/grassland in gold-mining areas of Singida. Similarly, [3] documented a decline in dense vegetation and an increase in sparse vegetation and built-up land in and around Bukombe-Mbogwe Forest Reserve following the expansion of artisanal and small-scale gold mining. These studies support the interpretation that mining landscapes

may experience simultaneous expansion of several human-dominated land-cover classes rather than a simple conversion of forest directly into mine sites. The Msaginia results extend this evidence by showing that agricultural expansion and woody-cover loss were substantially larger than the mapped mining/bare-land class, highlighting the importance of assessing the wider landscape footprint of mining.

3.3 Drivers and indirect pathways associated with small-scale mining and forest land-use/land-cover change

The study identified several activities and processes associated with LULCC in the Msaginia Forest Reserve. Table 3 presents the descriptive ratings and regression coefficients in the same sequence used in the subsequent driver explanations: agriculture, migration, charcoal/fuelwood collection, logs/timber harvesting, and infrastructure development. Small-scale mining is treated as the overarching context linking these activities

Table 3. Descriptive ratings and regression associations of selected LULCC drivers/pathways

Driver/pathway	Mean	SD	B	Std. Error	Beta	t	p-value
Agriculture activities	1.78	0.602	1.006	0.507	0	4.012	0.002
Migration	3.20	0.741	4.12	1.421	0.861	2.814	0.006
Charcoal/fuelwood collection	2.41	0.658	2.001	0.663	0.967	3.018	0.003
Logs/timber harvesting	2.69	0.466	-4.79×10^{16}	0.427	0	0	1.000
Infrastructure development	3.40	0.552	3.40	0.552	0.867	2.999	0.001

Note: B = unstandardized regression coefficient; Std. Error = standard error; Beta = standardized coefficient; t = t-statistic; p-value = significance level.



Plate 1: Agricultural field in Msaginia Forest Reserve.

Source; Field Data

Agricultural Activities: According to Table 3, agriculture significantly contributes to LULCC in the Msaginia Forest Reserve. Agricultural activities had a mean score of 1.78 (SD = 0.602), and regression analysis showed a positive, statistically significant association between agricultural activities and LULCC (B = 1.006, p = .002). The positive

coefficient indicates that increases in agricultural activities were associated with corresponding increases in land-use and land-cover change.

Respondents indicated that expanding mining activities have attracted more people to mining areas, increasing demand for food, housing, and agricultural

land. Consequently, agricultural activities have expanded around areas experiencing mining-related population growth. Farmers clear forests and bushland to establish farms, while removing additional vegetation for residential development and other activities associated with growing mining settlements (Plate 1). This indicates that small-scale mining influences forest land cover indirectly, through changes in population distribution, settlement expansion, and demand for agricultural land.

This finding is consistent with evidence from other mining landscapes. Muteya et al. [24] reported substantial landscape anthropization associated with mining activities in southeastern Katanga, including a loss of more than 60% of natural vegetation cover over 41

years. Similarly, Molinario et al. [25] demonstrated that forest clearing in the Democratic Republic of Congo was strongly associated with subsistence agriculture, with population movements around mining areas contributing to agricultural expansion. These findings suggest that mining-related population dynamics can amplify agricultural pressure on forest landscapes. More broadly, [14] identify agricultural expansion and settlement growth as important interacting processes in tropical land-use change, highlighting the importance of examining indirect and direct drivers of forest-cover loss.

Charcoal/Fuel Wood Collection

Respondents rated charcoal and fuelwood collection as one of the activities associated with small-scale mining that contributes to land-use and land-cover change (LULCC) in the Msaginia Forest Reserve (Mean = 2.41, SD = 0.658). However, regression analysis showed a positive, statistically significant relationship with LULCC ($B = 2.001$, $p = 0.003$; $\beta = 0.967$), indicating that variation in this activity was significantly associated with changes in land use and land cover.

Field surveys suggest that this pressure is partly attributable to the expansion of small-scale mining. As the population of miners and other residents has grown, demand for household energy, particularly for cooking and other daily activities, has increased. Access to alternative energy sources is limited in the study area, while charcoal and fuelwood remain readily available biomass fuels, increasing the extraction of woody vegetation from surrounding forests.

Respondents also reported harvesting larger trees to produce charcoal and collecting smaller trees, branches, and shrubs for household fuelwood. Plate 2. Continued extraction can reduce woody biomass and alter vegetation structure, especially when it exceeds natural regeneration. Similar evidence from Tanzanian forest landscapes shows that woody biomass extraction contributes to forest degradation where communities rely heavily on forests for energy [26].

Repeated wood harvesting for charcoal prevents natural regeneration, leaving degraded landscapes dominated by shrubs or bare soil. These findings align

with Bailis et al. [27], who highlighted that charcoal production remains a dominant energy source in sub-Saharan Africa, contributing to forest loss and ecosystem stress. Additionally, [18] found that charcoal making is often practiced illegally, with significant ecological consequences in Tanzanian forests.



Plate 2: Illegal Charcoal production in Msaginia Forest Reserve

Source: Field Data

Logs and Timber Harvesting:

Respondents rated logs and timber harvesting as having a **low influence on LULCC** in the Msaginia Forest Reserve (Mean = 2.69, SD = 0.466). Although the regression coefficient was not statistically significant ($B = -4.79$, $p = 1.000$), field observations demonstrate that timber extraction remains an important source of localized forest disturbance. The discrepancy between the statistical result and field evidence suggests that timber harvesting may operate as a localized and cumulative pressure rather than as a dominant independent predictor of overall landscape change.

Respondents reported that the expansion of small-scale mining and associated settlements has increased demand for timber for temporary shelters, stores, residential structures, and other mining-related facilities. These activities require wooden poles, planks, and

structural supports, increasing demand for forest resources around mining areas. Consequently, mining expansion may indirectly facilitate timber extraction by increasing population concentration and construction needs.

Field observations confirmed the presence of harvested timber within the reserve, including the substantial stacks of cut timber shown in **Plate 3**. Removing mature trees for timber reduces standing biomass and can alter forest structure, particularly where harvesting is repeated or concentrated in accessible areas. Although the regression analysis did not identify timber harvesting as a statistically significant independent predictor of LULCC, its observed occurrence indicates that it contributes to cumulative forest degradation when combined with other pressures, including mining expansion, agricultural encroachment, settlement development, and charcoal production.



Plate 3: Commercial harvesting in Msaginia forest reserve
Source: Field photo

This finding is consistent with the broader human–environment perspective, which recognizes that increasing demand for forest resources can produce cumulative environmental impacts when extraction is not matched by regeneration and effective resource management [14]. Studies in Tanzania have similarly identified timber extraction, increasing market demand, livelihood dependence, and weaknesses in forest governance as factors contributing to forest degradation [28, 29]. In Msaginia, therefore, timber harvesting should be interpreted within the broader interaction of livelihood activities and mining-induced settlement expansion rather than solely through its independent statistical effect.

The large piles of cut timber suggest organized, possibly illegal logging, which contributes to forest degradation, biodiversity loss, and reduced forest cover. Similar studies in Tanzania have shown that commercial timber extraction, driven by high market demand, poverty, and weak enforcement, is a major cause of deforestation in protected areas [28, 29]. Such activities also increase soil erosion, disrupt forest structure, and undermine conservation efforts [30]. The image therefore highlights the need for stronger forest governance and sustainable management strategies to protect the reserve

Infrastructure Development: During field data collection, it was observed that infrastructure development, including road construction and electricity installation, significantly contributes to land use and land cover change in the Msaginia Forest Reserve. As a recent inventory by the Tanzania Forest Service (TFS) Office in Mpanda [23] highlights, installing an electricity line to the Katavi Mining Company will require removing 548.84 m³ of wood from various tree species. This deforestation not only affects the local ecosystem but also degrades forest resources critical for biodiversity and community livelihoods [31].

During fieldwork, the researcher observed heavy plant machinery and vehicles in the area, prompting the development of road networks that reach areas where mining or prospecting is underway (Plate 4), as well as the felling of trees for electricity line installation (Plate 5). Although Infrastructure developments are vital for economic growth and access to resources, they often lead to environmental consequences. Research has shown that road construction can facilitate further land clearing for agriculture and settlements exacerbating land use changes [17]. Therefore, it is imperative to consider sustainable development practices that minimize ecological damage while meeting infrastructural needs. The photos in plate 5 elaborate more on the development of infrastructure including road and electricity installation lines in the study area, causing destruction of vegetation.



Plate 4: Road development in Msigina Forest reserve
Source: Field photo



Plate 5: Forest clearance for electricity network

Source: Field data

Migration

The influx of people migrating from different regions into the mining areas of the study site has influenced community attitudes, behaviours, and practices related to land use and land cover. The rapid growth of mining activities has attracted many newcomers, increasing pressure on the surrounding environment. As these migrants settle in the area, they develop additional needs such as farmland for food production and space for housing. This expansion of agricultural activities and settlement areas could directly contribute to the ongoing land use and land cover changes observed in the reserve. The study also found that migration driven by mining opportunities contributed to increased land use pressure. 71% of participants reported that miners who migrated to the study area often brought their families, leading to settlement expansion and further deforestation to meet housing and agricultural needs.

The study further revealed that residents living near mining sites often receive low compensation for their land, insufficient to secure alternative farmland or sustain

their livelihoods. As a result, many displaced households are forced to clear areas within the Msaginia Forest Reserve to establish new farming plots, contributing to increased deforestation and land degradation. This process, in turn, accelerates land cover changes in the area. In line with this, one participant during an interview revealed

Land ownership in the area is informal; it's because of this people are constantly moved out of their plots by miners either by compensation or due to lack of enough information, like being told a PML claim is a land ownership document, and those who move they are only are given a total of 600,000 - 800,000/= per acre."

The finding reveals migration driven by mining, combined with weak land governance, not only intensifies competition over land but also incentivizes environmentally destructive practices such as encroachment into forest reserves. This cycle perpetuates land cover change, threatens biodiversity, and undermines the sustainability of both local livelihoods and natural ecosystems [3, 13]. Moreover, studies from Tanzania and West Africa indicate that mining-induced displacement frequently forces affected households to encroach on forest reserves and protected areas in search of alternative farmland, thereby accelerating deforestation and landscape degradation [32, 33]

6. Conclusions

The Msaginia Forest Reserve landscape underwent substantial land-use and land-cover change (LULCC) between 1990 and 2023. Agricultural land expanded from 5,136 to 23,712 ha, while the mining/bare-land class increased from 7 to 1,797 ha. Over the same period, woodland and bushland declined by 10,557 and 12,234 ha, respectively. These findings indicate that small-scale mining is associated with landscape transformation through multiple interacting pathways, including population movement, increased demand for settlements and food, and livelihood systems involving agriculture and charcoal or fuelwood collection.

The findings highlight the need to monitor mining-related forest degradation beyond the physical footprint of mine workings. Effective forest conservation in Msaginia requires integrated monitoring of mining licences, settlement expansion, agricultural conversion, and vegetation condition.

Declarations

Ethics approval and consent to participate

The study obtained research clearance through the University of Dar es Salaam and relevant regional and district administrative authorities. Participants were informed about the study and participated voluntarily.

Consent for publication

Not applicable to identifiable individual data. No identifying participant information is reported.

Availability of data and materials

The underlying household survey and qualitative data are not publicly available because they contain participant-level information. Aggregated results are presented in this article. Geospatial datasets derived from Landsat imagery can be accessed through the USGS/NASA Landsat data repositories, while site-specific field data may be made available by the author subject to ethical and institutional requirements.

Competing interests

The authors declare no competing interests.

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Author contributions

O.K.L. conceptualized the study, collected the data, conducted the analysis, interpreted the results, and prepared the manuscript. S.B.Y. contributed to the study design, interpretation of findings, and critical review and editing of the manuscript. C.E. contributed to interpreting the findings and critically reviewing and revising the manuscript. M. N. contributed to study design, data interpretation, and manuscript review. All authors read and approved the final manuscript.

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