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Mapping alluvial mine dynamics in the Atewa landscape in Ghana using Geographic Object-Based Image Analysis (GEOBIA) and GIS

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Abstract

The Atewa Range Forest Reserve (ARFR) in Ghana, a key biodiversity hotspot, is increasingly impacted by alluvial gold mining, which has been expanding in the region. However, limited research has focused on mining activities within the forest reserve or their proximity to river bodies. This study used high-resolution PlanetScope satellite imagery (2018-2023) and Geographic Object-Based Image Analysis (GEOBIA) to monitor mining activities and land use changes in the Atewa landscape. Post-classification change detection was used to determine land use land cover (LULC) classes that transitioned to alluvial mines while assessing post-mine vegetation recovery. Buffer analysis was used to examine the distance between mines and water channels. Findings revealed an annual increase in mining activities at a change rate of 12.3% between 2018 and 2023, with significant vegetation conversion in the Atewa landscape. Mining exhibited a more irregular pattern in the forest reserve, with a rate of change of -21.4%. The buffer analysis showed that a significant portion of mining occurred within 100 meters of river channels, with at least 49.7% of the mined area annually falling within this zone. The buffer analysis also indicated that at least 0.7% of mining activities in the landscape were within the 100 m buffer around the ARFR. The study highlights the increasing threat of mining to the ARFR and the importance of monitoring these impacts on the forest and surrounding ecosystems.

Keywords

Remote sensing; GIS; Geographic object-based image analysis; Mining; Forest reserve

Statements and Declarations

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Competing interests

The authors declare no competing interests

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Introduction

Mining is a significant driver of environmental degradation, particularly impacting forest ecosystems and water resources (Kahhat et al., 2019). It is an extractive activity that involves the removal of valuable minerals, metals, and other geological materials from the Earth's crust for economic purposes (Hartman, 2002). Among the various forms of mining, alluvial mining, also known as river mining, focuses on extracting precious minerals from unconsolidated sediments in riverbeds or floodplains (Hilson, 2002a; Dethier et al., 2023). Due to its reliance on simple and rudimentary tools and techniques, alluvial mining has become a viable livelihood for many small-scale artisanal miners globally (Hilson, 2002b; Schwartz et al., 2021). However, this practice has exacerbated environmental harm, particularly through the destruction of forests and the pollution of water bodies, posing significant ecological challenges (Roach et al., 2013; Asner and Tupayachi, 2017). In Ghana, mining, particularly for gold, has been a major economic driver but has also caused substantial environmental damage. The mining sector of Ghana has remained a significant contributor to exports, government revenue, and employment over the years (Okyere et al., 2021). However, despite efforts to mitigate its impact, mining has led to severe deforestation and water pollution, especially from illegal mining operations (Attigbo and Nkansah, 2017; Tenkorang, 2021). Ghana has lost about 100,000 hectares of forest mainly as a result of illegal mining activities between 2010 and 2020 (IUCN, 2024). Mining in forest reserves has been an issue of environmental concern in the country for a long time (Hilson and Nyame, 2006) as important forest reserves such as the Atewa Range Forest Reserve (ARFR), and the Offin Shelterbelt Forest Reserve have been under the threat of depletion owing to mining activities (Boadi et al., 2016). Also, some major water bodies such as the Pra, Tano, Offin, Ankobra, and Birim which serve many communities have been heavily polluted as a result of mining activities (Duncan et al., 2018). A report by the Ghana Water Resource Commission, (2021) indicated that all these major rivers had turbidity values greater than 150 Nephelometric Turbidity units (NTU), which is an indication of high values of suspended density (Azis et al., 2015) from mining activities. Thus, water resources in Ghana are in critical condition and warns of water availability threats shortly if the situation remains unchanged.

The ARFR is one of the most important forest resources in Ghana as it is the habitat for over 100 globally threatened species. Among the numerous species of wildlife in the forest, about 227 species of birds are found in the forest reserve as well. The forest serves as a source to the Birim, Densu, and Ayensu rivers which are major rivers with many tributaries, serving many communities including the capital city of Ghana, Accra (McCullough et al., 2007; Akomaning et al., 2021). The geological location of the forest reserve has led to the establishment of some registered mining companies around the forest reserve with a good number of illegal miners reported to have been operating in the reserve as well. The ARFR again bears about 960 million metric tons of bauxite deposits which in recent times has sparked the debate concerning its exploitability (Purwins, 2022). The availability of timber and minerals in this highly diversified forest reserve has attracted a lot of anthropogenic activities. Unregulated activities of miners endanger the ecosystem and hence, the biodiversity of the forest reserve. It is estimated that about 14km² of the buffer zone surrounding the forest reserve has been mined and alluvial gold recovery methods that make use of high-pressure water have increased the rate of sedimentation in rivers and have affected water quality downstream. The rate of degradation of the ARFR has remained steady in recent times with activities of miners and loggers affecting the quality of rivers that serve people in surrounding communities and over 1 million people in Accra (IUCN, 2016). However, government interventions, which have mostly been ground-based monitoring of illegal mining activities have been limited by area coverage and time factor considering the urgency of the situation.

The use of remote sensing has over the years been extremely useful in the automated mapping and monitoring of degradation caused by mining activities. Various studies have shown that remote sensing applications in the monitoring of alluvial mines are cost-effective as well as time-saving (Bruno et al., 2020; Barenblitt et al., 2021; Nyamekye et al., 2021; Moomen et al., 2022). Most studies that employ the use of remote sensing in the monitoring of mining activities do so using pixel-based methods. However, due to issues of high spectral variability, there is usually a reduction in classification accuracies where high-resolution satellite images are used (Simionato et al., 2021). The use of Geographic Object-Based Image Analysis (GEOBIA) in land use land cover (LULC) classification, especially in high-resolution satellite imagery has significantly improved classification accuracies. Segments of objects that are created by the grouping of homogenous pixels, and the subsequent classification based on object features such as shape, texture, context, and ancillary data such as Digital Elevation Model (DEM) do away with misclassification that is likely to occur in pixel-based classifications (Tonyaloglu et al., 2021; Lestari et al., 2023). The applicability of GEOBIA in LULC classification extends to terrains with varying characteristics while improving

classification accuracy. In a comparative study by Whiteside et al. (2011) in the non-mining savannas of Australia, object-based classification yielded statistically significantly higher accuracy than a pixel-based classification in an ASTER satellite image. When Grebby et al. (2016) used GEOBIA in a lithological mapping study on a 4-meter resolution Airborne Thematic Mapper (ATM) multispectral imagery, it again outperformed the pixel-based method in terms of accuracy. Simionato et al. (2021) also applied GEOBIA in identifying artisanal mining sites in the Amazon rainforest and achieved global accuracies of up to 88.18%. In a study by Nyamekye et al. (2021) in the Atewa landscape, even though the pixel-based classified images produced high accuracies, they were outperformed by the object-based classification.

While the 2017 ban on mining activities by the government of Ghana might not have been effective overall (Nyamekye et al., 2021), it succeeded in depriving many mining community members of their livelihoods which eventually led to its repeal (Kumah and Nyarko, 2018; Orleans-Boham et al., 2020). The post-ban periods, starting from 2018, have been characterized by reports of increased water turbidity and mining activities in forest reserves as miners rushed back into business (Duncan et al., 2018; Ghana Water Resource Commission, 2021). This has necessitated the need for monitoring and mapping activities of miners, especially in forest reserves and river bodies. Previous studies on mapping artisanal alluvial mines in Ghana have predominantly relied on satellite imagery with resolutions ranging from 10 to 30 meters (Kusimi, 2015; Forkuor et al., 2020; Gallwey et al., 2020; Kumi-Boateng and Stemn, 2020; Nyamekye et al., 2021) with little focus on the annual proximity patterns of mines to forests and river channels. While these studies focused on the changes in mined areas in the periods of study, they did not analyze the transition dynamics of other LULC classes to alluvial mines or provide information on post-mine vegetation recovery. This study utilizes high-resolution PlanetScope imagery at 4.77 meters, combined with GEOBIA, to accurately map alluvial mine dynamics, reducing intra-class misclassifications and enhancing overall accuracy. The study also assesses the annual proximity patterns of mines to the ARFR and water resources in the study area while providing the dynamics of class transitions to alluvial mines and post-mine vegetation recovery. While mapping changes caused by mining activities over longer time intervals with emphasis on time nodes that signify important changes is crucial, it risks missing important details on changes between such longer time intervals. An understanding of the annual dynamics of mining activities and their proximity to important resources like river bodies and the ARFR is thus necessary for understanding the possible factors that compound into substantial changes over time. The specific objectives of the study were: (1) to determine how the post-ban alluvial mining activities affect the LULC pattern of the study area annually, (2) to assess annual alluvial mine dynamics and (3) to assess the annual proximity patterns of mines to the ARFR and river channels in the study area. Results from this study will contribute to the effective management of the ARFR and provide insights into the dynamics of alluvial mines in the Atewa landscape, especially after the mandatory halt in the activity.

Materials and Methods

Study area

The study was conducted in the Atewa Range Forest Reserve (ARFR) and its surroundings referred to as the Atewa landscape in this study (Fig. 1). The study area falls between latitudes 5° 56' to 6° 23' North and longitudes 0° 24' to 0° 40' West while covering parts of eleven districts in the Eastern region of Ghana. The landscape covers three important river basins: the Birim, Densu, and Ayensu basins whose heads originate from within the ARFR. The forest reserve which lies between latitudes 5° 58' to 6° 20' North and longitudes 0°31' to 0°41' West represents the predominant highland area of the study area. It lies on the Atewa range of mountains with heights reaching 842 meters (m) above sea level (McCullough et al., 2007). It covers about 26,300 ha with a north-south orientation (Kusimi, 2015; IUCN, 2023).

The Eastern region of Ghana experiences average temperatures between 22-33° C and is characterized by semi-deciduous rainforests to the south and a transitional savanna zone to the north. The major rainy season falls between March and July while the minor is from September to November. The dry season, characterized by cold and dry weather, starts in November and ends in February (MOFA, 2024). The ARFR has an average temperature range

between 24 and 29° C with an average annual rainfall between 1200 and 1600mm. The two rainy seasons record the highest rainfall from May to July, then from September to November (McCullough et. al., 2007; Kusimi, 2015).

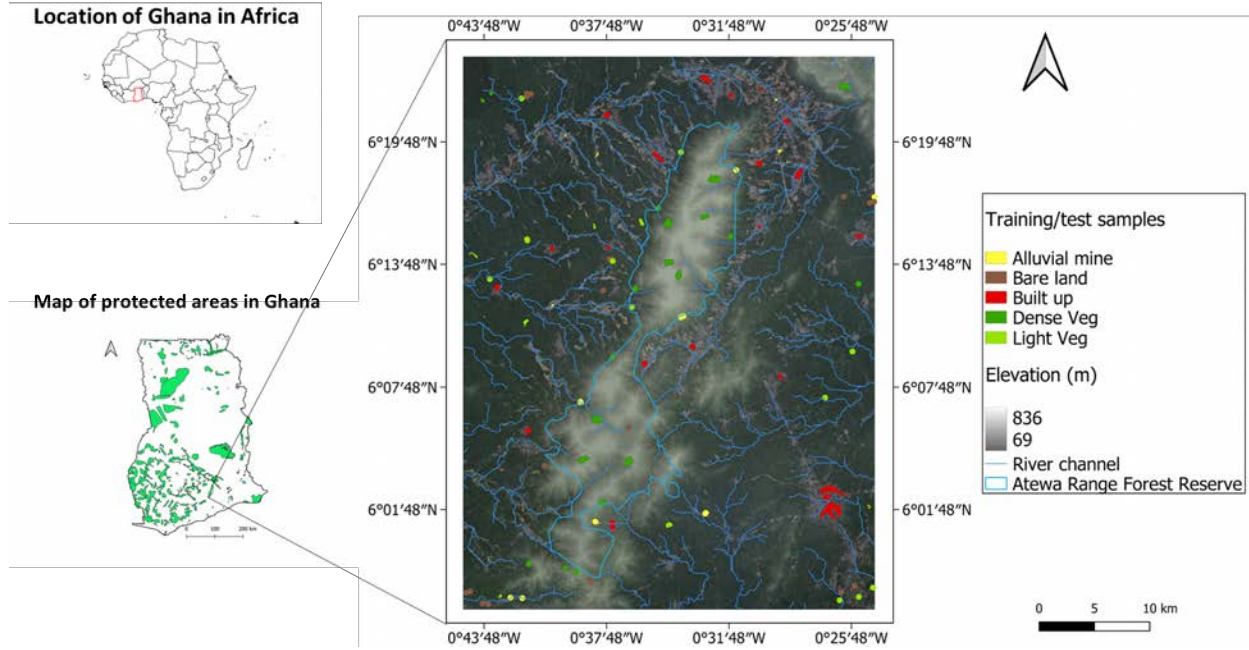


Fig. 1. Map of the study area showing the distribution of training and test samples in 2023 (Polygons represent high resolution satellite image training/test samples; corresponding points represent ground-truthed training/test points)

Satellite image and ground truthing

True color (Red, Green, and Blue - RGB) monthly mosaicked PlanetScope satellite imagery with 4.77 m resolution for the periods 2018, 2020, 2021, 2022, and 2023 were downloaded via the Planet Explorer website, <https://www.planet.com/explorer/> (Planet, 2023) for the study. To increase the chances of acquiring cloud-free data, satellite images were acquired between November and March which is mostly the dry season of the study area. The year 2019 was skipped as there was no cloud-free satellite image for the study area. Table 1 shows the dates of acquisition of the satellite images used. Despite the differences in the acquisition dates, the acquisition of all images in the dry season implies a high likelihood of exposure to similar seasonal environmental conditions to ensure consistency. A minimum of twelve (12) image tiles were downloaded for each year. The downloaded tiles were then mosaicked into a single image and clipped to the study area shape file.

Ground truthing was undertaken in 2023 for some selected safe and unrestricted parts of the study area where training and test data for the LULC types were collected using a handheld Global Navigation Satellite System receiver (Garmin GPSMAP). The training and test data were supplemented by high-resolution Google Earth Pro images, especially for inaccessible areas. In the absence of ground truth data for 2018 to 2022, training and test samples were derived from high-resolution Google Earth Pro images with guidance from existing LULC data. Each year, the data was split into 60% for training and 40% for testing. The split ratio decision was based on providing enough data to enable the classification algorithm to learn the varying characteristics of each class accurately while providing adequate data for a robust accuracy assessment. A stratified sampling technique was employed for training and testing to ensure that underrepresented classes, such as bare land and alluvial mines, were proportionally represented in the dataset. This approach helps maintain class balance and improves model performance by preventing bias toward dominant land cover types.

Data analysis

The main stages of the data analysis process of the method used in the study are displayed in Fig. 2.

Geographic Object-Based Image Analysis (GEOBIA)

Segmentation

The multiresolution segmentation algorithm in the eCognition software was used where different objects were segmented based on the parameters, scale, shape, and compactness (Baatz, 2000). These are dimensionless parameters that are used to fine-tune the segmentation process, allowing for the desired level of detail and object definition. The scale parameter, a positive integer, determines the size of objects while the shape parameter is based on pixel spectral values and shape homogeneity of segments. Compactness affects how the segmentation captures compact objects (Simionato et al., 2021). All 3 bands of each image were used for the segmentation with an assigned weight value of 1. The selection of segmentation parameter values is crucial to the subsequent classification accuracy (Kucharczyk et al., 2020). The optimal segmentation parameter values were selected based on trial and error through visual inspections where scale = 60, Shape = 0.05, and compactness = 0.8. The scale value of 60 was used because lower values led to over-segmentation which could affect the classification accuracies for built-up areas and alluvial mines due to their spectral, and textural similarities. Thus, distinguishing alluvial mine sites from other land use classes such as non-mine bare land and built-up areas was a crucial consideration in the segmentation process.

Classification

Five dominant LULC classes were identified for the study. These are Alluvial Mine, Bare Land, Built-up, Dense Vegetation, and Light Vegetation. Table 2 shows the LULC classes considered and their descriptions. The Nearest Neighbor classification algorithm in ecognition was used for the supervised classification. The Nearest Neighbor classifies objects based on their proximity to the closest training data while assigning an object the class of the majority of its neighbors (Whiteside et al., 2011).

First, object attribute features under spectral, textural, and custom features were selected. The spectral attributes comprised the mean values of all three bands while the Gray Level Co-occurrence Matrix (GLCM) contrast, entropy, and correlation were considered for the textural attributes. The GLCM contrast textural attribute consistently produced values that were significantly different for built-up areas and alluvial mine sites and was considered an important object feature in the differentiation of the two classes. On the other hand, GLCM entropy and correlation produced values that were similar for alluvial mine sites and built-up areas, and as such were discarded to save computational workload. The custom attribute used was the Green-Red Vegetation Index (GRVI) which was used to accurately detect and differentiate the different vegetation classes. In the absence of near-infrared (NIR) bands, the Normalized Difference Vegetation Index (NDVI) was not applicable, hence the application of GRVI. Equation (1) shows the formula used to compute GRVI.

$$GRVI = \frac{\rho_{green} - \rho_{red}}{\rho_{green} + \rho_{red}} \quad \text{Equation (1)}$$

Where ρ_{green} and ρ_{red} are the respective reflectance of green and red in the visible light spectrum.

Green vegetation, soil, and water may have GRVI values that are positive, negative, and near zero. At the threshold $GRVI = 0$ however, green vegetation becomes distinguishable from non-green vegetation (Motohka et al., 2010). In this study, different values for the vegetation classes were produced by the GRVI in different years. This facilitated the differentiation of vegetation from other classes. For instance, in 2023, values ranged between 0.38 and 0.44 for the Light Vegetation class while recording > 0.44 for the Dense Vegetation class. GRVI values for the other classes were < 0.38 .

The sample selection was guided by the training data through visual interpretation. This resulted in a minimum of 22 samples per class and at least 110 for all classes. The pixel count of the training and test samples are shown in Table 3. The resulting classified vector polygons were exported for further analysis. Images of a segmented satellite image and the corresponding classified vector polygons are shown in Fig. 3.

Table 1

Acquisition dates of PlanetScope monthly mosaicked images used in the study

Year	PlanetScope imagery acquisition date
2018	March 2018
2020	January 2020
2021	March 2021
2022	December 2022
2023	December 2023

Table 2

LULC classes used in the study and their descriptions

LULC Classes	Description
Alluvial Mine	Areas used for mining activities. Usually characterized by highly turbid water and dugouts of wet laterite
Bare Land	Tilled lands usually for agricultural purposes, non-vegetated surfaces of human settlements (non-mine lands)
Built-up	Human settlements in the form of buildings, villages, towns, and cities
Dense Veg	Forests, thickets, oil palm, and cocoa plantations, fully grown agric. fields (vegetation that is not easily accessible)
Light Veg	Shrub, herb, grasses, and young-stage agric. fields (vegetation that is easily accessible)

Post-classification correction

Post-classification correction is important in increasing classification accuracies by reducing misclassification resulting from similarities in spectral reflectance (Manandhar et al., 2009; Ibrahim et al., 2020). Because many alluvial mines within the study area exist close to settlements (Nyamekye et al., 2021), and because the Alluvial Mine and Built-up classes share similar spectral and textural characteristics, there was the issue of misclassification between the two classes. To minimize classification errors, OpenStreetMap data and vectorized river channels of the study area were utilized to differentiate settlements from alluvial mines. Field observations indicated that alluvial mines predominantly occur along river channels, making the presence of large settlement areas near these waterways unlikely in the classified images. Based on this knowledge, built-up areas located within a 20 m buffer of river channels were reassigned as alluvial mines, using OpenStreetMap as a reference for validation.

Accuracy assessment

Accuracy assessment is a crucial stage in the classification process as it determines the level of agreement between classified maps and reference data (Tonyaloğlu et al., 2021). A pixel-based accuracy assessment was chosen over the polygon-based approach to minimize potential bias and ensure a more objective evaluation of the classification results (Radoux and Bogaert, 2017). The confusion matrix was used in the evaluation of the accuracy of the classification. From the confusion matrix, the Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and Kappa coefficient were determined.

Post-classification change detection

Post-classification change detection was key in determining the annual changes that occurred in the study area among the LULC classes. It was employed in determining and quantifying the LULC transitions as well as their gains and losses (Radwan et al., 2021). Change detection was undertaken on an annual basis by pairing images from a particular year with that of the preceding year. For instance, using classified images from the base year (2018) and that of the preceding year (2020), and so on. To undertake change detection, the vector polygons comprising the various LULC

classes were first dissolved in ArcGIS to make the acquisition of area statistics for each class easy. The vectorized classified image was then converted into a raster file for change detection analysis. The formulas used for calculating the rate of change of the classes and the alluvial mine loss/gain percentages are presented in Equations (2) and (3) respectively.

$$\text{Rate of change} = \frac{1}{(t_2 - t_1)} \ln\left(\frac{A_2}{A_1}\right) \quad \text{Equation (2)}$$

$$\text{Loss/gain \%} = \left(\frac{\text{Change in area of final year}}{\text{Area of initial year}} \right) \times 100 \quad \text{Equation (3)}$$

where, A_1 = Area of initial year, A_2 = Area of final year, t_1 = Initial year, and t_2 = Final year.

Table 3

Pixel count of training and test samples used for classification and validation

	2018		2020		2021		2022		2023	
Class	Training sample	Test sample	Training sample	Test sample	Training sample	Test sample	Training sample	Test sample	Training sample	Test sample
Alluvial Mine	89,415	73,254	92,601	81,221	87,557	79,334	90,168	72,372	89,112	77,211
Bare Land	99,462	64,308	97,351	66,011	95,577	65,501	95,941	60,988	96,312	60,223
Built up	197,847	105,232	199,031	100,101	187,912	98,887	196,981	102,399	200,100	102,144
Dense Veg	222,740	148,493	225,665	140,236	230,010	151,278	226,110	150,477	229,458	155,364
Light Veg	268,079	175,386	283,121	235,202	281,145	269,898	275,441	241,143	277,233	198,992

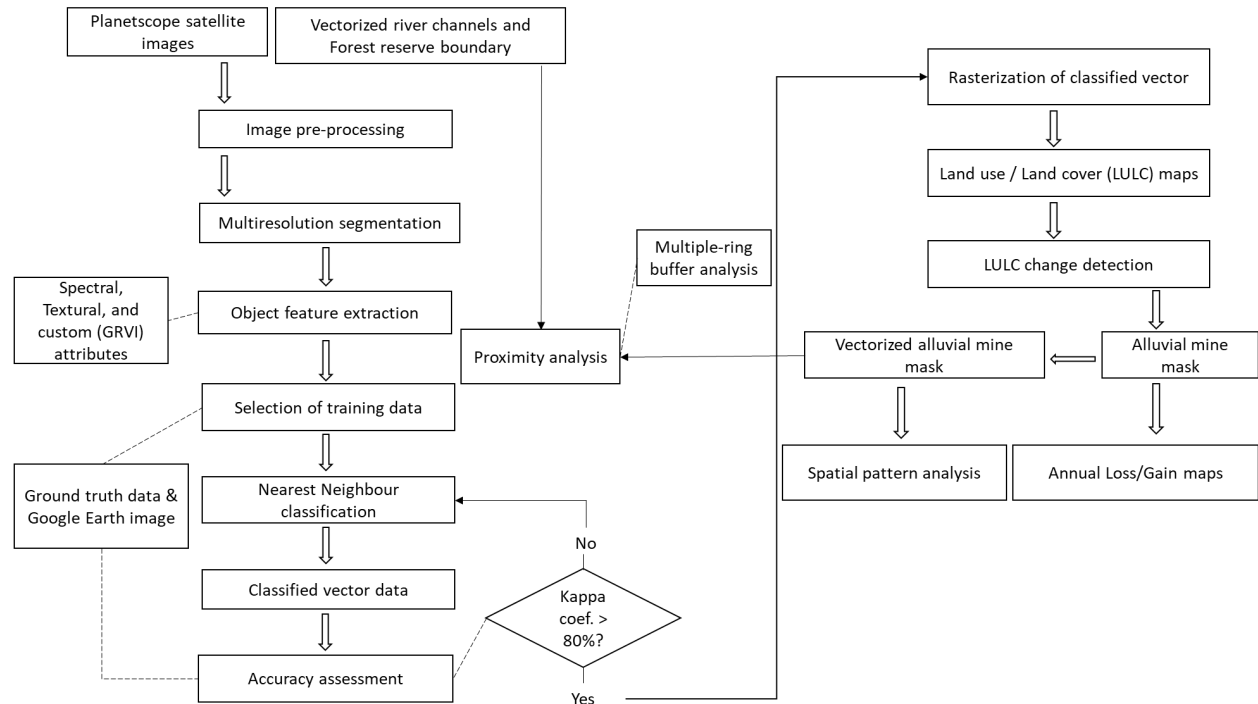


Fig. 2. Flowchart of methodology

Buffer analysis

To assess the proximity of alluvial mines to the forest reserve, experimental multiple-ring buffers of distances 100 m, 200 m, 500 m, and 1 kilometer (km) were created around the boundary of the forest reserve. The 100 m buffer was considered the most important of all the forest reserve buffers because any mining activity within the 100 m buffer is likely to have a direct or indirect effect on the forest. The rest were used to track the changes in mined areas as one moves closer to the forest edge. Multiple-ring buffer analysis was again employed to assess the proximity of alluvial mines to river channels. Buffer distances used for river channels were 100, 200, and 300 m. The base 100 m buffer was based on the Riparian Buffer Policy for Managing Freshwater Bodies in Ghana (Ministry of Water Resources, Works and Housing, 2013) which states that no human activities be undertaken within 100 m off water marks. The 200 and 300-meter buffers were used to assess the changes in mined areas as one moves closer to river channels. The area of alluvial mines within the buffers was determined and used for the proximity analysis.

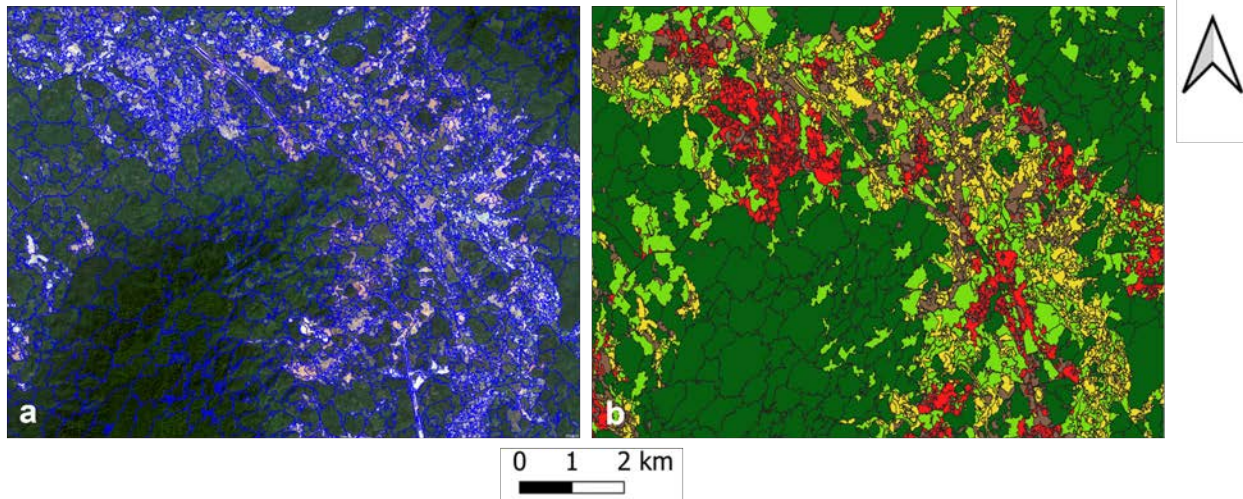


Fig. 3. (a) Multiresolution segmentation; (b) Classified vector polygons

Results

Land use land cover classification results

Accuracy assessments of the various LULC maps are displayed in Table 4. The Kappa coefficient value was used in assessing the accuracy of the classified maps. It ranges from -1 to 1 where values approaching 1 imply high accuracy and vice-versa (Pandey et al., 2023). The Kappa coefficient for the classified maps ranged from 0.82 in 2021 to 0.89 in 2018 which signifies an almost perfect agreement (Bogoliubova and Tymków, 2014).

From the annual average values in Table 5, the Alluvial Mine class remained the least dominant class in most years, except in 2022, and showed a continuous increase (Nyamekye et al., 2021), peaking at 8,005.2 ha in 2021. Between 2018 and 2023, it recorded a total change rate of 12.3%. This was followed by the Bare Land class which showed a consistent decline except in 2024. The Bare Land class changed by -21.1% between 2018 and 2023. The Built-up class followed a steady annual growth trend, with an overall change rate of 1.4%, expanding from 8,399.1 ha in 2018 to 9,011.0 ha in 2023. The Light Vegetation class exhibited a consistent decline across all years, except in 2021, with an overall change rate of -16.2%. It reached its largest extent in 2018 at 71,445.1 ha and its lowest in 2023 at 31,706.6 ha. The study area was dominated by the Dense Vegetation class, which occupied the majority of the area throughout the periods of consideration. The Dense Vegetation class recorded the highest area of 135,871.5 ha in 2023

representing 71.8% of the total landscape area while recording a low of 91,743.4 ha in 2018 making up 48.5%. Between 2018 and 2023, it exhibited a change rate of 7.9%.

In the Atewa Range Forest Reserve (ARFR), the Alluvial Mine class showed an irregular trend of increase and decrease across the periods with a high of 20.3 ha in 2018 and a low of 1.7 ha in 2020. Its recorded rate of change between 2018 and 2023 was -21.4% (Table 6). The Bare Land class recorded its highest coverage of 70.9 ha in 2021 and an annual average of 32.5 ha. It also exhibited an irregular trend of increase and decrease while changing at a rate of -54.4%. The Built-up class was the least dominant in the forest reserve. It showed a decreasing trend except in 2021 and recorded a change rate of -49.2%. The Light Vegetation showed consistency in annual decrease except in 2023 as seen from its rate of change (-4.6%) while averaging 10% of the reserve's total area annually. The Dense Vegetation class was consistently the major class with an average coverage representing 90% of the entire reserve across the five years. It recorded a positive rate of change of 0.6% even though its increase was not annually consistent. By visual inspection, Bare Land and Light Vegetation were mostly observed along the fringes of the reserve (Fig. 4).

Table 4

Summary of classification accuracies from 2018 to 2023

	2018		2020		2021		2022		2023	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Light Veg	94.21	86.33	93.66	89.45	78.91	93.11	92.15	94.44	93.84	91.5
Dense Veg	96.76	92.82	97.22	91.34	98.97	83.1	97.05	87.65	97.66	90.87
Bare Land	76.46	81.01	58.78	77.02	82.35	74.61	61.27	89.22	69.47	68.23
Alluvial Mine	80.89	93.85	85.28	94.04	77.1	77.58	65.33	90.01	63.2	95.68
Built-up	89.66	85.91	91.24	63.71	71.8	97.55	88.91	72.71	92.06	74.65
OA (%)	91.68		89.28		86.00		89.44		88.38	
Kappa	0.89		0.86		0.82		0.86		0.85	

Change detection

Post-classification change detection was useful in determining the dynamics of alluvial mining activities. The dynamics considered in this study were (i) the transition of other LULC to alluvial mines and (ii) post-mine vegetation recovery.

Light Vegetation was mostly converted into Alluvial Mine making up an annual average of 45.2% of all classes that converted to Alluvial Mine. The Dense Vegetation class followed with an annual average of 38.7% while Bare land recorded 15.4%. The Built-up class was the least converted into Alluvial Mine (Fig. 5a).

Post-mine vegetation recovery was mostly represented by a transition from Alluvial Mine to Light Vegetation and could not confirm prior mine restoration. Alluvial Mine was consistently converted into Light Vegetation in the Atewa landscape representing over 99% of the vegetation classes in the post-mine vegetation recovery (Fig. 5c). The highest post-mine vegetation recovery occurred between 2021 and 2022 representing 40% of the mined area while 2020-2021 recorded the least recovery. Between 2018 and 2023, 42.1% of the mined area had been recovered in terms of vegetation regrowth in the Atewa landscape.

In the forest reserve, the vegetation classes were mostly converted into alluvial mines with bare land being the next contributor (Fig. 5b). The highest conversion of the combined vegetation classes into Alluvial Mine occurred between 2020 and 2021 with 8.2 ha. The conversion of Bare Land into Alluvial Mine began between 2020 and 2021 with 4.2 ha while showing a decrease from 2022 - 2023 after peaking between 2021 and 2022 with 5.2 ha. Post-mine vegetation recovery in the forest reserve was dominated by the Light Vegetation class and was highest between 2021 and 2022,

representing 87.7% of the mined area. Between 2020 and 2021, there was the lowest record of post-mine vegetation recovery of 1.2%, while 46.0% of mines recovered with vegetation between 2018 and 2023. Figures 5e and 5f show the percentage of mined area that showed revegetation.

Annual loss/gain in alluvial mines

Alluvial mine loss/gain maps displayed in Fig. 6 show areas that gained, lost, or remained alluvial mines along the various river channels in the study area. In 2023, the area of alluvial mines in the landscape showed a 147% increase compared to 2018, while a 50.2% decrease was also recorded relative to the same year. This corresponded to a 48.7 and 96.9% increase and decrease respectively in the forest reserve (Table 7). The highest gain in alluvial mine activities in the landscape was recorded between 2020 and 2021 with the landscape recording a 105% increase while the ARFR recorded a 7-fold increase of over 600%. In 2022, the landscape recorded the highest loss of mines, which represented 47.5% of mines in 2021. The largest mined area lost within the forest reserve occurred between 2018 and 2020 by 98.2%. Outside the forest reserve, at least 52% of mines from the previous year remained unchanged in each new year while 49.8% of mines in 2018 remained unchanged in 2023. The area of unchanged mines within the ARFR ranged between 0 and 67.1% of the previous years' mines while 3.1% of the mines in 2018 persisted in 2023.

Forest reserve and water channel buffer analysis

To determine the proximity of mines to the forest reserve, a multiple-ring buffer of 100 m, 200 m, 500 m, and 1 km was created around the boundary of the forest reserve (Fig. 7a). The number of mines within each buffer, represented by the number of polygons and their corresponding area was calculated to determine the mines' proximity to the forest reserve. From Table 8, it is observed that at least 7.7% of the total area mined annually was within the 1 km buffer zone. The 100 m buffer zone recorded a low of 34.3 ha of mines in 2020 and a high of 119.8 ha in 2021. These represented 0.7 and 1.4% of the total mined area in 2020 and 2021 respectively.

Multiple-ring buffers of 100, 200, and 300 m were created around river channels to determine their proximity to mining activities (Fig. 7b). Most of the mining activities across the years fell within the 300 m buffer of the river channels with a high of 6,296.0 ha in 2021 and a low of 3,263.1 ha in 2018. These represented 75.9 and 78.8% of the total area mined each respective year. Within the 100 m buffer zone, 2018 recorded the lowest mining activity with 2,556.0 ha which represented 61.8% of the total mined area. The largest mined area within the 100 m buffer was recorded in 2021 with 5,010.7 ha representing 60.4% of the total mined area. At least 49.7% of the total mined area was within the 100 m buffer around the river channels.

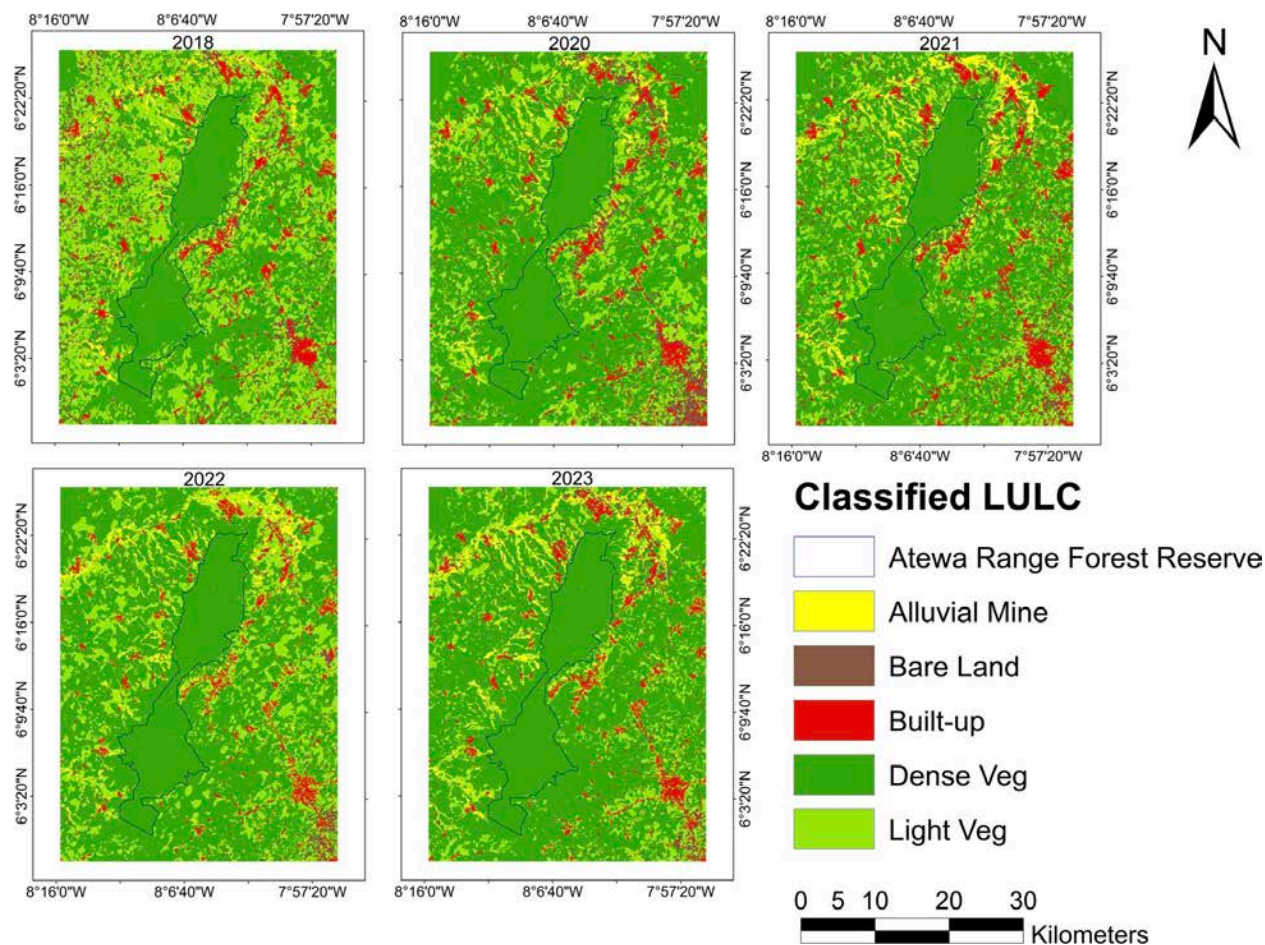


Fig. 4. LULC maps from 2018 to 2023

Table 5

LULC area (Ha) from 2018 to 2023 in the Atewa landscape

	Alluvial mine		Bare land (ha)		Built up		Dense Veg		Light Veg	
	(ha)	%		%		%		%		%
2018	4,271.7	2.3%	13,340.5	7.1%	8,399.1	4.4%	91,743.4	48.5%	71,445.1	37.8%
2020	4,563.4	2.4%	10,483.7	5.5%	8,644.1	4.6%	125,248.7	66.2%	40,259.9	21.3%
2021	8,005.2	4.2%	9,242.9	4.9%	8,698.4	4.6%	122,426.4	64.7%	40,826.9	21.6%
2022	6,424.6	3.4%	3,435.0	1.8%	9,001.5	4.8%	126,100.9	66.7%	44,237.8	23.4%
2023	7,907.1	4.2%	4,646.8	2.5%	9,011.0	4.8%	135,871.5	71.8%	31,763.4	16.78%
Ann. Av.	6,234.4	3.3%	8,229.8	4.4%	8,750.8	4.6%	120,278.2	63.6%	45,706.6	24.2%
ROC	12.3%		-21.1%		1.4%		7.9%		-16.2%	

Ann. Av. = Annual average; ROC = Rate of change (Negative values represent a decrease while positive values represent an increase)

Table 6

LULC area (Ha) from 2018 to 2023 in the Atewa Range Forest Reserve

	Alluvial mine (ha)	%	Bare land (ha)	%	Built up areas	%	Dense Veg	%	Light Veg	%
2018	20.3	0.0	54.9	0.0	0.4	0.0	21,454.8	90.0	2,608.8	10.0
2020	1.7	0.0	31.4	0.0	0.3	0.0	22,390.1	90.0	1,715.6	10.0
2021	12.7	0.0	70.9	0.0	0.4	0.0	23,090.3	100.0	964.9	0.0
2022	12.1	0.0	1.7	0.0	0.0	0.0	23,156.6	100.0	968.7	0.0
2023	7.0	0.0	3.6	0.0	0.0	0.0	22,055.6	90.0	2,073.1	10.0
Ann. Av.	10.8	0.0	32.5	0.0	0.2	0.0	22,429.5	90.0	1,666.2	10.0
ROC	-21.4%		-54.4%		-49.2%		0.6%		-4.6%	

Ann. Av. = Annual average; ROC = Rate of change (Negative values represent a decrease while positive values represent an increase)

Discussion

Land use land cover classification results

The Increasing trends in alluvial mining activities in the study area as seen from the positive rate of change (Table 5), can be attributed to the presence of the Birim and the Ayensu, rivers. Taking their sources from within the forest reserve, these rivers are known to hold economic quantities of alluvial gold deposits and have attracted large numbers of Artisanal and Small-scale miners (ASM) in the area over the years. This has led to pollution in these river bodies as sedimentation increases turbidity and heavy metal concentrations (Afum and Owusu, 2016). The Densu River, which serves over one million people in Accra, is affected by sedimentation resulting from these mining activities and has led to a constant threat to water supply (IUCN, 2016; Fianko and Boadua, 2021). The general decline in the Light Vegetation and the Bare Land classes over the years can be attributed to the steady regrowth and growth of vegetation and farmlands respectively in the study area. Except for the forest resource which sees little changes annually, the other vegetation types under the Dense Vegetation and Light Vegetation classes such as shrubs, herbs, grasses, and food crops undergo noticeable changes as they recover after removal (Fig. 4). This could explain the dynamic annual distribution of vegetation in the study area (Kusimi, 2015). The consistent but slowly increasing rate of the Built-up class implies an increasing urbanization among settlements (Li and Chen, 2023).

The irregular trend of increase and decrease of alluvial mining in the Atewa Range Forest Reserve (ARFR, Table 6) could be explained by the highly illegal nature of the mining activity within the forest which takes place as and when monitoring is relaxed. Most of the alluvial mines within the boundary of the forest reserve are extensions of mines that exist right outside the reserve's boundary. Even though mining activities show a decreasing rate of change (-21.4%), its increasing and decreasing trend is cause for concern. The ARFR is made up primarily of semi-deciduous vegetation and that explains the dominance of the Dense Vegetation class in the reserve. From the LULC analysis, it is seen that the fringes of the forest reserve continuously experience farming activities from close by communities (Kusimi, 2015). This is evident from the presence of the Light Vegetation and Bare Land classes found along the reserve's boundaries.

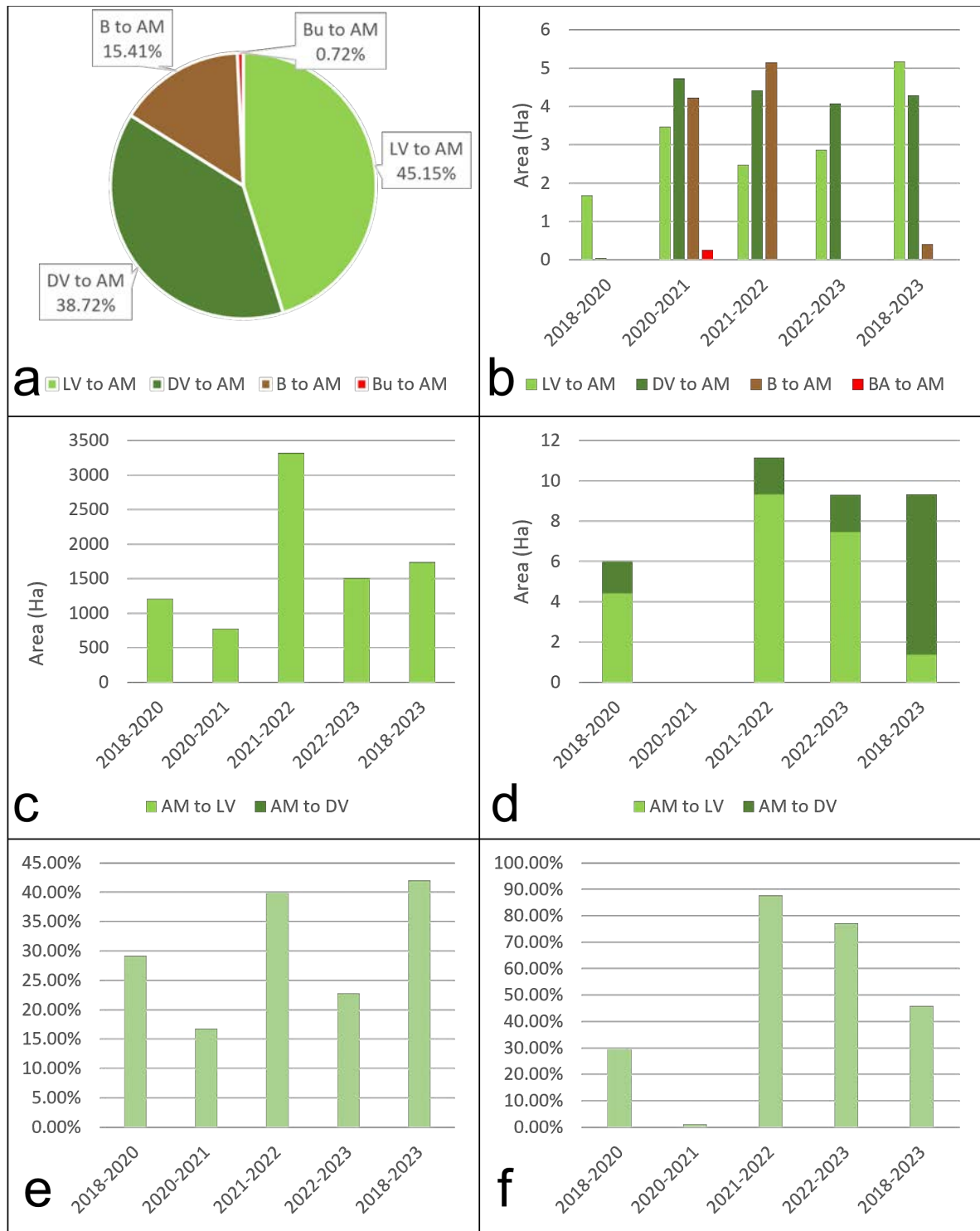


Fig. 5. (a) Four-year average of classes converted into Alluvial Mine in the Atewa landscape; **(b)** Annual conversion of other classes into Alluvial Mine in the ARFR; Area of annual post-mine vegetation recovery in **(c)** Atewa landscape, **(d)** ARFR; Percentage of mined area that has undergone revegetation in **(e)** Atewa landscape, **(f)** ARFR; AM = Alluvial Mine; B = Bare Land; Bu = Built-up; DV = Dense Veg; LV = Light Veg

Alluvial mine dynamics

The dynamics of alluvial mining in the study area were assessed on an inter-period basis. This was useful in obtaining the annual changes that occurred among the Alluvial Mine class and the other classes. In the Atewa landscape, the Light Vegetation class was mostly cleared for mining activities possibly due to the low energy requirements for heavy-duty machinery to remove such vegetation (Fig. 5a). In the forest reserve, however, the dominant semi-deciduous vegetation belonging to the Dense Vegetation class was mostly removed. Tilled farmlands, classified under Bare Land, are usually not easily leased or sold out for mining activities even though the pre-mine energy requirements would also be less. This may explain why a greater proportion of light vegetation was converted into alluvial mines than bare lands even though mining on bare lands would mean less energy required for vegetation removal.

Less than half of the mined area in the landscape showed revegetation throughout the years. This could be explained by the longer lifespan of mines outside the ARFR where only a few mined areas are decommissioned or abandoned annually. Also, post-mine revegetation is mostly effective after mining activities have halted for a long time.

Light vegetation comprising herbs, shrubs, and grasses dominated vegetation that regrew after mining activities in the study area (Peterson and Heemskerk, 2001). Even in the absence of confirmed backfilling, vegetation is known to grow on the dugout overburden. Regrowing vegetation could mitigate adverse environmental effects of mining such as increased surface run-off, thereby reducing erosion and sedimentation. It also confirms that mining activities in the study area mostly represent disturbances rather than deforestation. However, considering the cyclic nature of mining and the possible recurrence at a previous mine site (Veiga et al., 2002) there could be the possibility of deforestation in the study area where vegetation cover will be permanently transformed into other land use. The observed increased vegetation regrowth in both the Atewa landscape and the ARFR between 2018 and 2023 confirms that post-mine vegetation recovery is more effective after extended periods.

Abandoned mines are usually characterized by mine pits that collect water over time. Water collected in the abandoned mine pits becomes eutrophicated because of nutrient loading from surface runoff water (Chlot, 2011). The characteristic green color of the eutrophicated water makes it indistinguishable from the Light Vegetation class. Thus, abandoned mines could be misclassified as post-mine recovered vegetation.

From the loss/gain statistics of alluvial mines, it was observed that the study area experienced a higher annual increase in alluvial mining activities than a decrease. With at least a 39.1% gain in alluvial mines along the river channels in the landscape each year, the threat of water scarcity in communities that depend on these water sources is lurking. In the forest reserve, more alluvial mines were lost annually except between 2020 and 2021 when the peak gain was recorded for the forest reserve and the landscape (Table 7). This implies that between 2020 and 2021, post-ban mining activities were the highest in the Atewa landscape as new mines might have been well established since their resumption in 2018. The higher annual loss of mines in the forest reserve could be explained by the rushed nature of mining within the forest reserve considering its illegal nature. As such, the life span of mines in the forest reserve was shorter than those in the landscape as only 3.1% of mines within the forest reserve remained unchanged while 49.8% persisted throughout the 5 years in the landscape. The longer mine life span outside the forest reserve means that very few mines are decommissioned or abandoned annually leading to less than half of the mined area showing revegetation throughout the years. The loss/gain dynamics are useful in determining areas that are restored after degradation without confirmed backfilling.

Even though the annual increase in mining activities may signify a societal benefit of increased livelihoods, its environmental impact may transcend the local and national regimes. Results from the mine dynamics are consistent with findings by Sonter et al. (2017), Siqueira-Gay et al. (2020), Chaddad et al. (2022), and Quash et al. (2024), where mining and its associated infrastructural setup within tropical forests in the Amazon have led to the loss of forest resources. This proves that mining is indeed a crucial contributor to tropical forest loss and should be treated as an issue of global concern.

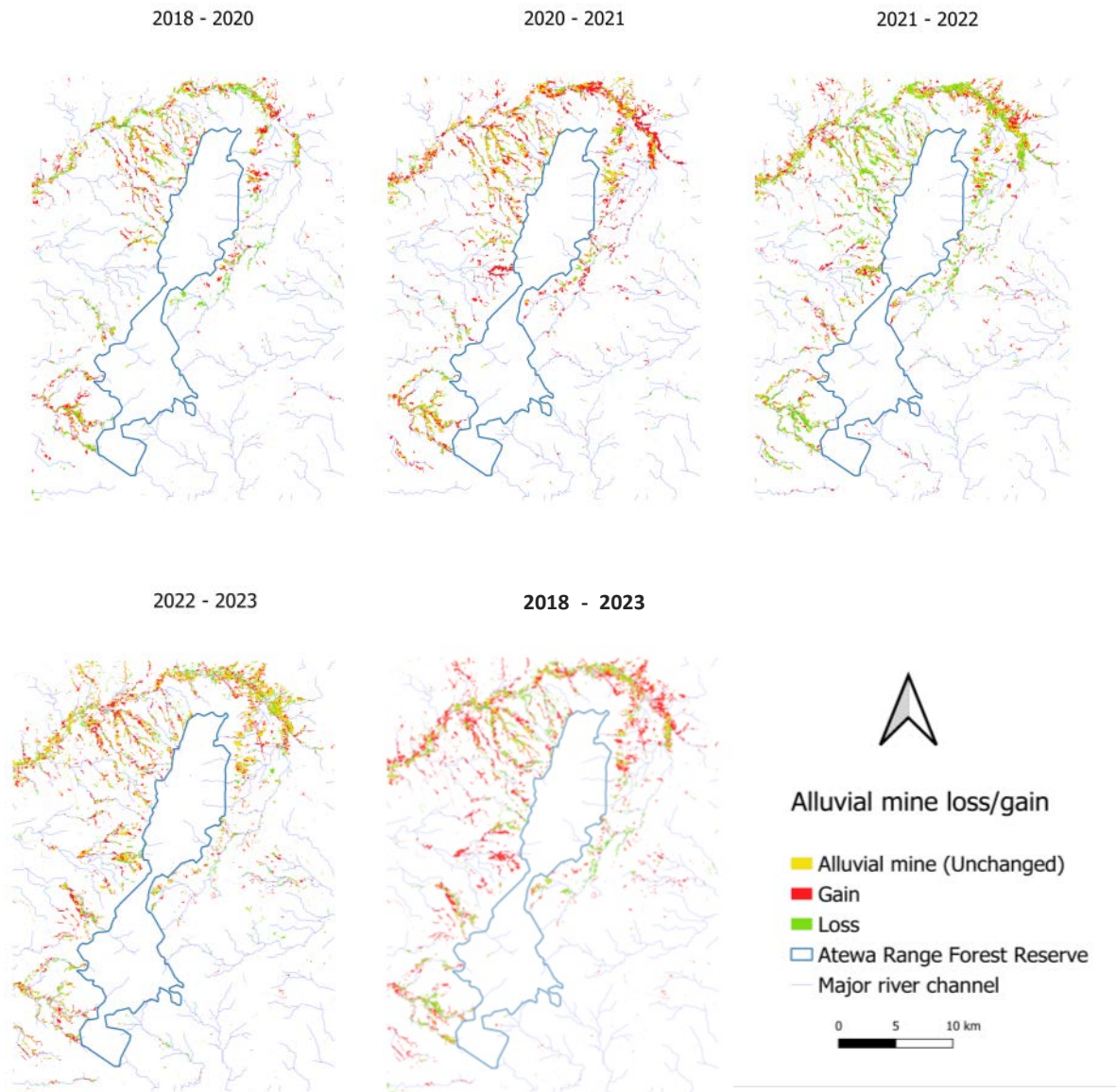


Fig. 6. Alluvial mine loss/gain maps from 2018 to 2023

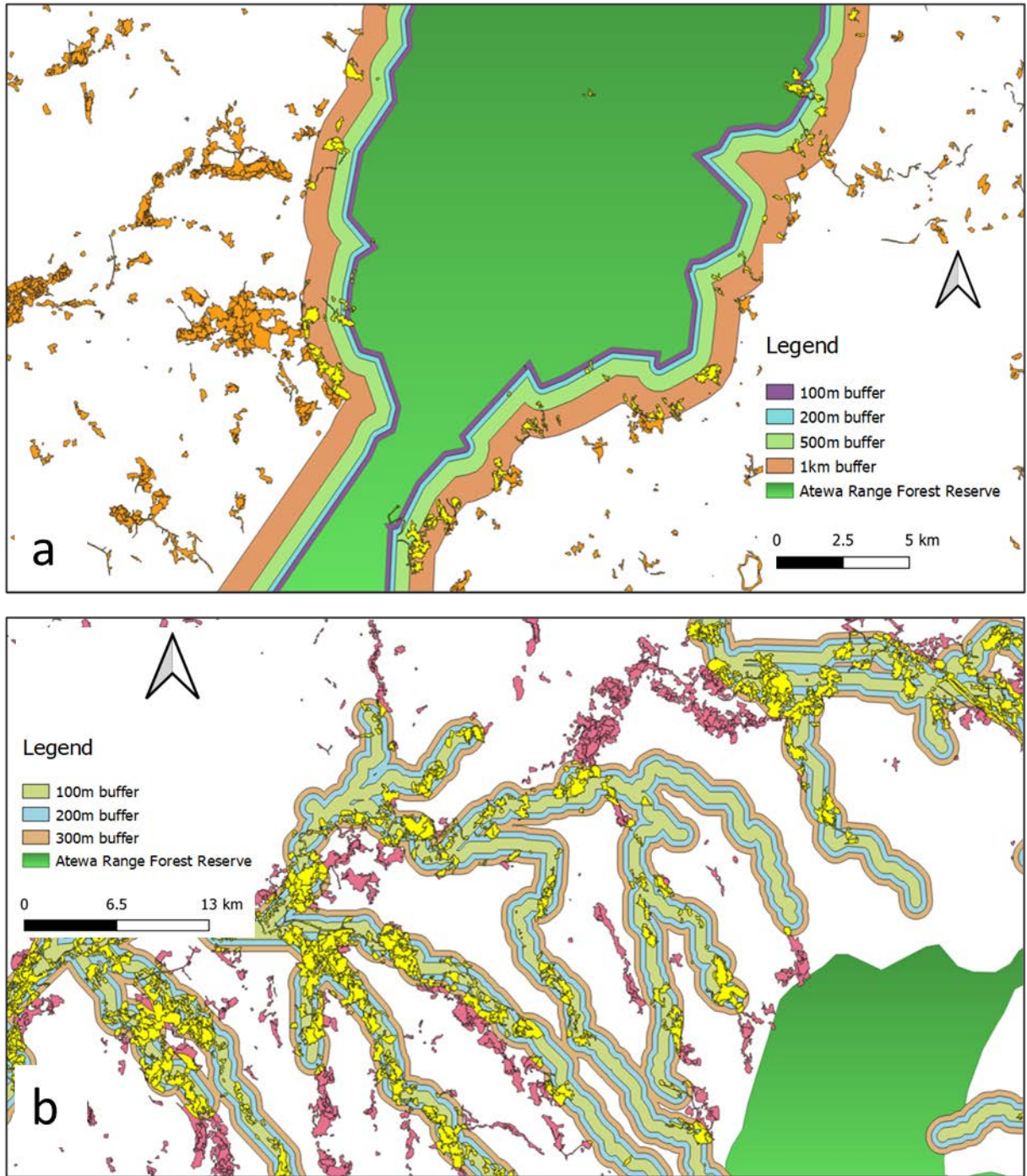


Fig. 7. Distribution of mines, where yellow polygons represent mines within a multiple-ring buffer around **(a)** a portion of the ARFR; **(b)** river channels

Mine proximity to forest reserve and river channels

From the multiple-ring buffer analysis, it is observed that the ARFR does not only co-exist with active mines but lies in close proximity to these mines. This is in agreement with findings from Kusimi (2015), Nyamekye et al. (2021), and Amponsah et al. (2022) which report increased encroachment on the forest resource as a result of human activities

on its fringes. Aside the loss of forest vegetation from mining activities, other indirect effects of habitat fragmentation, habitat destruction, and biodiversity loss could affect the general forest ecosystem functions (Alvarez-Berrios and Aide, 2015; Bradley 2020; Siqueira-Gay et al., 2020).

Major river bodies in the study area serve as the main source of water for most communities. Results from the river channel buffer analysis indicated a high concentration of mining activities within the 100 m buffer as over 49% of the total mined area was within this buffer zone annually. Thus, the Riparian Buffer Policy for Managing Freshwater Bodies in Ghana (Ministry of Water Resources, Works and Housing, 2013) was not effective throughout the years of consideration. Figure 8 shows a mining activity close to the forest reserve and a highly turbid river body resulting from mining activities. Evidence of water pollution resulting from mining activities from this study is buttressed by studies by Meißner (2021) and Ruppen et al. (2023) in which remote sensing and GIS confirmed large-scale water pollution associated with mining activities. Thus, mining poses a threat to the quality of freshwater bodies and aquatic ecosystems globally.

Table 7

Alluvial mine loss/gain statistics

	ARFR						Atewa landscape					
	Gain (ha)	%	Loss (ha)	%	Unchanged (ha)	%	Gain (ha)	%	Loss (ha)	%	Unchanged (ha)	%
2018-2020	1.7	8.6	19.9	98.2	0.0	0.0	2614.8	61.2	1887.1	44.2	2,384.6	55.8
2020-2021	10.9	627.0	0.6	34.5	1.2	67.1	4789.5	105.0	1171.2	25.7	3,392.3	74.3
2021-2022	6.6	51.5	7.1	55.8	5.5	43.4	3127.5	39.1	3804.0	47.5	4,201.1	52.5
2022-2023	7.0	57.8	8.4	69.9	3.6	29.5	4008.1	62.4	2034.6	31.7	4,390.0	68.3
2018-2023	9.9	48.7	19.7	96.9	0.6	3.1	6281.3	147.0	2144.0	50.2	2,127.7	49.8

Percentages are based on the previous year's mined area. For instance, in the Atewa landscape from 2018 to 2020, Gain % indicates that by 2020, alluvial mines increased by 61.2% of the 2018 mining area. Loss % reflects a 44.2% reduction in the 2018 mined area, while Unchanged % shows that 55.8% of 2018 mines remained intact in 2020.

Table 8

Mined area proximity to ARFR and river channels

	Atewa Forest Reserve Buffer								River channel Buffer						n
	100m (ha)	%	200m (ha)	%	500m (ha)	%	1km (ha)	%	100m (ha)	%	200m (ha)	%	300 m (ha)	%	
2018	47.1	1.1	76.5	1.9	177.3	4.3	398.2	9.6	2556.0	61.8	2915.1	70.5	3263.1	78.8	1,840
2020	34.3	0.7	62.5	1.4	197.6	4.3	401.9	8.7	2699.4	58.5	3177.8	68.8	3484.3	75.5	1,777
2021	119.8	1.4	174.1	2.1	371.4	4.5	791.6	9.5	5010.7	60.4	5723.9	69.0	6296.0	75.9	2,825
2022	93.1	1.4	129.0	2.0	288.6	4.4	536.5	8.1	3435.2	51.9	4143.9	62.7	4668.5	70.6	3,784
2023	83.0	1.1	125.7	1.6	283.5	3.6	608.9	7.7	3931.7	49.7	4733.8	59.9	5368.5	67.9	3,884

n = Number of polygons that correspond to alluvial mines



Fig. 8. (a) A mine close to the Atewa Range Forest Reserve; **(b)** Increased turbidity of a river body as a result of mining activities

Limitations of the study

This study was constrained by persistent cloud cover in the study area, limiting access to consistent cloud-free satellite imagery. To address this, we utilized PlanetScope's three-band (RGB) monthly mosaicked imagery, which was largely cloud-free but had a slightly lower spatial resolution of 4.77 m compared to the standard 3 m. However, no cloud-free image was available for 2019, impacting the consistency of the intended annual analysis. Additionally, the RGB images lacked the NIR and red-edge bands, which are essential for vegetation studies. While the GRVI was employed to classify vegetation types, indices such as NDVI and the Inverted Red-Edge Chlorophyll Index (IRECI) would have likely provided better differentiation between light and dense vegetation, and between the vegetation and non-vegetation classes. Thus, potentially reducing misclassifications and improving overall classification accuracy.

Conclusions

The conservation of the Atewa Range Forest Reserve (ARFR) has become a critical issue in Ghana due to rampant mining activities threatening its existence. The application of GEOBIA and GIS on high-resolution PlanetScope imagery proved an effective means of mapping alluvial mining activities in the Atewa landscape. Results show a continuous annual increase in alluvial mining, with most mines originating from vegetation conversion. Mining has been steadily expanding each year, with continuous activities in the sensitive 100 and 200 m buffer zones surrounding the reserve. On average, 10.8 ha of the forest reserve was found to be lost to mining annually. The results also show that at least 49.8% of mines remained active for the five years of the study in the Atewa landscape, necessitating sustainable mining methods to protect water and forest resources. The Riparian Buffer Zone Policy which prohibits human activities within a 100 m buffer of water bodies was found to be ineffective, as over 49% of mining occurred within the 100 m river channel buffer. The study suggests urgent action from the Ministry of Lands and Natural Resources and the Forestry Commission to protect the forest and water resources in the Atewa landscape.

Declarations

Funding

No funding was received for conducting this study.

Ethical approval

All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

Competing interests

The authors declare no competing interests

Contributions

Lukman B. Adams conducted the methodology, fieldwork, data analysis, and the writing of the original draft. Yuichi S. Hayakawa contributed to designing the methodology and planning the fieldwork. He also validated the results and reviewed and edited the manuscript.

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