THESIS

USING HIGH-RESOLUTION SATELLITE IMAGERY TO ASSESS LAND-USE AND LAND-COVER CHANGE ASSOCIATED WITH ARTISANAL SMALL-SCALE GOLDMINING IN GHANA

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ABSTRACT

USING HIGH-RESOLUTION SATELLITE IMAGERY TO ASSESS LAND-USE AND LAND-COVER CHANGE ASSOCIATED WITH ARTISANAL SMALL-SCALE GOLDMINING IN GHANA

As artisanal and small-scale gold mining (ASGM) expands globally in response to the growing demand for gold, there is a need to monitor and quantify the rapid land-use and land-cover changes associated with ASGM activity, particularly mining and agriculture, as they are often complementary livelihoods in communities. The use of remote sensing, with its frequent collection times and the availability of freely-accessible high-resolution imagery, is a powerful tool for analyzing land-use and land-cover change (LULCC) associated with ASGM. In this study, we utilized an interdisciplinary, mixed-methods approach, including image classification, community mapping, and interviews to determine how much land was converted to ASGM and the dominant land-use and land-cover transitions in two climatically and geologically distinct communities in Ghana between 2015/2016 and 2024. We used high-resolution (10 meter) multispectral Sentinel-2 imagery for our image classification. We also compared three different supervised classification methods, Random Forest (RF), Support Vector Machine (SVM), and Spectral Angle Mapper (SAM) to determine the best classifier for ASGM. Our results show that RF had the highest overall accuracy for almost all of the classifications, at 85% for 2015 and 87% for 2024 for the Southern site and 85% for 2016 for the Northern site. The exception was SVM outperforming RF for 2024 for the Northern site with an 86% overall accuracy. We report a 105% increase in mining for the Southern site and a 0.14% increase in mining for the Northern site. There was a surprising increase in agriculture at both sites, with a 2.4% increase in the South and a 45% increase in the North. The interdisciplinary approach used in this study provides a framework for integrating remote sensing methods and community-based social science methods to understand the complex LULCC associated with ASGM in these farming-mining communities.

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1. INTRODUCTION

Artisanal small-scale goldmining (ASGM) is an important livelihood and economic activity globally and is estimated to support approximately 20 million miners and 100 million downstream beneficiaries (UNEP, 2019). ASGM is responsible for about one fifth of all gold produced worldwide. Gold prices have risen dramatically in recent years. In early-2026, gold prices hit $5,600/ounce, quadruple the price of a decade earlier (Haddad & Ali, 2026). Due to these price spikes, ASGM has expanded rapidly (Adranyi et al., 2024; Hausermann et al. forthcoming). This trend is evident across the globe, with ASGM production in Ghana increasing from less than 20,000 ounces in 1990 to 1.6 million ounces in 2016 (Owusu et al., 2019), while the Peruvian Amazon experienced a loss of 100,000 hectares of forest between 1984 to 2017 as a result of ASGM (Caballero Espejo et al., 2018).

ASGM largely takes place in the Global South, in contexts of high unemployment and often adjacent to smallholder agriculture (Bruno et al., 2020; Adator et al., 2023; Obodai et al., 2024). ASGM has long been practiced informally using low-tech tools such as shovels, buckets, and pickaxes, which require minimal capital investment (Doumbouya et al., 2024; Ferring et al., 2016). Although these unmechanized methods are still widely practiced today, the sector has expanded to include more industrialized operations characterized by heavy machinery, large-scale extraction, and transnational investment (Doumbouya et al., 2024; Ferring et al., 2016; Kabunga & Geenen, 2022).

Increased international investment and mechanization in ASGM has led to a proliferation of mining operations and, consequently, widespread landscape and environmental changes (Ferring & Hausermann, 2019; Fonshiynwa et al., 2024; Obodai et al., 2024). Large-scale land clearing for ASGM results in biodiversity loss, land degradation, and the development of artificial lakes when mining pits are abandoned without reclamation (Gerson et al., 2020; Obodai et al., 2024; Mestanza-Ramón et al., 2022a; Adeoye, 2016). For instance, the Democratic Republic of the Congo and Niger reported ASGM presence in protected areas (Dossou Etui et al., 2024). Similarly, a study conducted in Peru reported a loss of over 500 ha of forest in the Tambopata National Reserve from 1999 to 2016 due to gold mining (Asner & Tupayachi, 2016).

Although historically ASGM co-existed with other livelihood practices, including smallholder agriculture and fishing, its recent expansion and intensification has produced several significant negative social impacts, including health issues, child labor, land-use conflicts, and food insecurity (Velez-Torrez et al., 2018; Ferring and Hausermann 2019; Hausermann et al. 2020; Baddianaah et al., 2023; Hausermann et al., 2018; Junior & Carvalho, 2023; Meutia et al., 2022). For instance, in a study conducted in Ghana, participants from a mining community described loss of farmlands, pollution to fisheries, increased food prices, and the prevalence of ultra-processed food due to ASGM expansion (Nyantakyi-Frimpong et al., 2023).

A significant focus in social science literature on ASGM highlights its frequent overlap with agricultural activities within and adjacent to local communities—mining and farming were historically framed as complexly intertwined (Hilson et al., 2013; Persaud et al., 2017; Adranyi et al., 2024). For example, mining is often practiced seasonally as a supplemental livelihood to agriculture, allowing individuals to alternate between farming and mining based on labor demands, agricultural cycles, or economic needs (Banchirigah & Hilson, 2010; Mkodzongi &

Spiegel, 2019; Bansah et al., 2023). Studies have found that farmers who participate in ASGM often use the income earned to purchase agricultural inputs, such as fertilizer and seeds, to support their farms (Hilson & Garforth 2013).

However, the rapid expansion of ASGM due to historic highs in gold prices has profoundly transformed the relationships between mining and agriculture (Doso Jnr et al., 2016; Hausermann et al., 2018; Cheng et al., 2023). ASGM can result in permanent loss of agricultural land, particularly in alluvial mining settings, where strip mining removes agricultural land-uses to access subsurface gold deposits (Hausermann et al. 2018; Awotwi et al., 2018; Amproche et al., 2020). In such cases, farmers who sell land or are dispossessed of it may be left without livelihoods to support households, leading them to mining as an alternative livelihood option (Adator et al., 2023; Ayinpoya Akafari et al., 2021). As the relationships between ASGM and farming become more complex with the increased mining activity and mechanization (Adranyi et al., 2024), there is a need for researchers to examine these relationships, including the spatial extent. Understanding the nature and scale of mining-mediated landscape change is critical to creating effective policies and regulations to support rural livelihoods.

Monitoring land-use and land-cover change (LULCC) environmental impacts of ASGM is challenging due to complex landscape dynamics in and around these mining-farming communities. Spatially, the boundaries of both ASGM and smallholder farms in the Global South can be difficult to predict. The intensive and ephemeral nature of ASGM makes monitoring difficult, as ASGM operations are often highly mobile, with mining activity typically lasting only a short period at a given site before shifting to new locations, producing rapidly evolving patterns of land-use change (Dessertine et al., 2023; Bruno et al., 2020; Adu-Baffour et al., 2021).

Smallholder agroecological systems in the Global South, like those within and adjacent to ASGM areas, are also profoundly complex and often blend polycropping, agroforestry and cash crop production (Afriyie et al., 2023; Siaw et al., 2023). In Ghana where this study takes place, smallholder farms are typically less than 2 hectares (Ministry of Food and Agriculture, 2024), which makes farms difficult to distinguish from forest and other vegetation land-cover from satellite imagery, making the classification of these land-uses challenging.

Indeed, the difficulties in characterizing LULCC associated with ASGM are reflected in remote sensing studies of landscape change mediated by other “clandestine” social processes such as drug trafficking (Tellman et al., 2012), illegal logging (Mujetahid et al., 2023), and land grabbing (Rienow et al., 2022). But the rapid spatial and temporal landscape changes wrought by ASGM, in addition to the environmental impacts, are precisely why efforts to quantify and assess these patterns are important. A solution to extensive in-field monitoring, which is not always possible in ASGM areas due to its transient and clandestine nature, is gathering data and assessing LULCC through remote sensing analysis (Ngom et al., 2023; Tetteh et al., 2026).

Remote sensing provides a powerful tool for quantifying and monitoring changes in land-use and land-cover change associated with the expansion of ASGM across diverse ecoregions by offering consistent, fine-scale, and spatially explicit data that can inform land classification models. By integrating satellite imagery and advanced classification techniques, such as machine learning and spectral angle mapper (SAM), it is possible to monitor changes in vegetation, water resources, and mining activities with high accuracy, even in areas that are otherwise difficult to access. Studies have effectively utilized remotely sensed data and classification methods to monitor ASGM in Côte d’Ivoire (Ayouba et al., 2025), Peru (Gerson et al., 2020; Caballero Espejo, 2018), Senegal (Ngom et al., 2020), and Ghana (Gallwey et al., 2020; Cudjoe et al., 2023; Hausermann et al., 2018). In those studies of complex ASGM landscapes, classification models derived from free, publicly available multispectral data such as Sentinel-2 (S2) and Landsat 7 and 8 often achieved over 80% overall accuracy. However, not many studies have done a site comparison across different ecoregions and compared how well different remote sensing techniques perform in different climatic and geological regions, particularly in these complex mining-farming landscapes, which requires further investigation.

Additionally, there is strong potential for advancing remote sensing model realism by integrating social science and remote sensing techniques, though important challenges remain (Liverman & Cuesta, 2008; Kugler et al., 2019; Devine et al., 2025). For instance, many of these pixelizing/socializing approaches can rely on *a priori* categories of land-use and land-cover. However, examples exist of remote-sensing studies which "recognize the value of local knowledge" in developing approaches to quantifying and characterizing landscape change that can both decrease classification errors and increase study efficiency (Dennis et al. 2005; Martínez-Verduzco et al. 2012, p. 5). For instance, during participatory mapping activities and focus groups, nine eco-types based on local Lozi knowledge (e.g. flooded/cultivated grasslands, ridged fields, seepage) were identified and integrated into a process of land cover classification in Zambia (Del Rio et al. 2018).

Thus, we used an interdisciplinary, mixed-methods approach that combines S2 satellite imagery, image classification methods, community mapping activities, and interviews with locals to develop a workflow for quantifying ASGM-related land use and land cover change (Figure 1). We conducted our study in two mining-farming communities in Ghana with different climatic and geologic regions. Our study aims to address the following research questions: (1) Which classification method provides the highest accuracy for detecting the presence of fine-scale ASGM activity in complex agro-ecosystems? (2) How much land was converted to ASGM between 2015/2016 and 2024 in two distinct communities in Ghana, and what are the dominant land-cover and land-use transitions associated with these changes?

Thus, our research objectives are as follows: (1) Develop a framework for monitoring and assessing LULCC associated with ASGM in complex agro-ecosystems, (2) Evaluate and compare different classification methods and determine the highest accuracy classifier for ASGM in these complex landscapes, and (3) Quantify and assess the LULCC associated with ASGM across the two sites.

2. METHODS

2.1 Study Area

ASGM in Ghana has expanded dramatically over the past 15 years, driven in part by high gold prices (Benshaul-Tolonen et al., 2019). Currently, Ghana's ASGM sector employs about 1 million people (Adranyi et al., 2024). Ghana has emerged as an ASGM hotspot – ASGM helped Ghana surpass South Africa as the continent's leading gold producer (Hausermann et al., 2018; Hilson et al., 2022; Boateng et al., 2025). In 2024, Ghana produced an estimated 140.6 tonnes of gold (World Gold Council, 2025). ASGM operates with fewer bureaucratic obstacles compared to large-scale industrial mines in the country, making it the primary contributor to the nation's gold exports, accounting for an estimated 53% (Ghana Goldbod, 2025; Robles et al., 2022).

ASGM occurs across Ghana, with marked differences in the south compared to the north as a result of sharp climatic and geological contrasts. The south is characterized by a humid, tropical climate with dense vegetation and relatively fertile soils, whereas the north experiences a much drier, semi-arid climate with limited water availability. The stark climatic regions shape the process of gold extraction and LULCC patterns across the country. In the wetter south, ASGM typically takes the form of alluvial strip mining, leading to large-scale landscape changes, deforestation, hydrological changes, and soil degradation (Caballero Espejo et al., 2018; Gilbert & Albert, 2016; Hausermann et al., 2018; Achina-Obeng & Aram, 2022; Barenblitt et al., 2021). In the drier north, where gold is often locked up in underground hard rock deposits, mining often involves underground tunneling and rock removal. Although alluvial mining can take place in northern sites as well, it does not often require large-scale removal of vegetation to access alluvial deposits. In hard rock mining contexts, e rock is crushed, milled, and processed. Although alluvial and other forms of mining can also occur in the north, the spatial footprint of ASGM is typically smaller than in the south though this study queries these differences between two climatic and geologic sites.

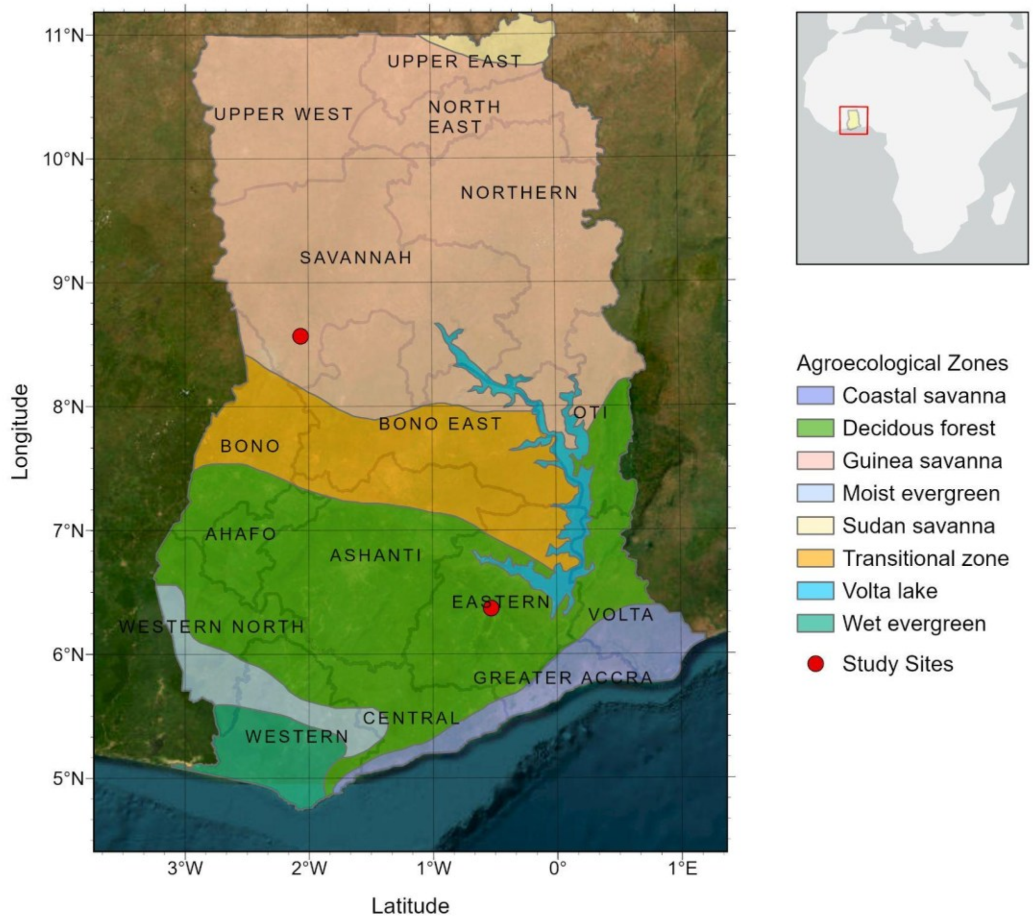

Figure 1. Study sites relative to the regions of Ghana.

The two study sites (Figure 1; Table 1) are distinctive, with the Southern site having a more humid, tropical climate with dense vegetation and the Northern site being semi-arid with less vegetation and water availability. Mining in the Southern site is alluvial, with miners employing strip-mining techniques using excavators, washing plants, and other heavy machinery. Mining at this site began to scale up in 2024 with the establishment of a new community mining site, although nearby communities with earlier mining activity were also visible in the satellite imagery used in the analysis. The area receives substantial rainfall, which often results in artificial lakes in unreclaimed ASGM areas. Indeed, alterations to hydrology and water resources, including the creation of artificial lakes, are a defining feature of ASGM (Gerson et al., 2020; Moomen et al., 2022; Espiritu et al., 2022; Mestanza-Ramón et al., 2022b).

In addition to mining, agriculture is a major source of livelihood for the Southern site community. Farming in the area is often polycropped on small farms for subsistence and regional sales, while cocoa is an important cash crop that is grown in the region. The area is also heavily forested, buffers the Atiwa Forest Reserve, and often has no clear boundaries between forest, mining, and agriculture.

In contrast, mining in the Northern site is much more diverse, with alluvial and hard-rock mining occurring simultaneously. The Northern site has a longer-established mining history than the Southern site, as mining activity has occurred in the area for the past 20-25 years (Hilson et al., 2013). Locals in the Northern site also rely on agriculture as a source of livelihood, but due to increased cattle herding in the area that damages crops, farming has declined. Farming is mostly limited to the southern part of the community, where mining and farming both occur along the river. Furthermore, farming is typically limited to the wet season to promote rainfed agriculture because of the arid climate.

The contrasts between the two study sites allowed us to evaluate the performance of the proposed classification methods across ASGM hotspots with differing mining histories, environmental settings, and land-use contexts. By comparing sites with different mining activity timelines, spatial extents of disturbance, and dominant mining types, this analysis provides insight into the robustness and transferability of the classification approach across diverse ASGM environments.

Table 1. Comparison of Study Sites

	Southern Site	Northern Site
Mining Type	Mining is primarily alluvial, with miners using heavy machinery to do strip mining	Hard rock mining in tunnels and alluvial mining in the floodplains of intermittent rivers. Changfa mining also occurs here, referring to Chinese mining equipment consisting of a hammer and a mill used to ground down ores (Ofori et al., 2025)
Climate	Tropical, wet season typically lasts from March-November	Arid, wet season occurs between April-November and Dry Season is from December-March
Land-use/cover	Polyculture farming (cocoa, plantain, maize, cocoyam, cassava), forest, mining, artificial lakes, urban	Intercropped and monoculture farming (cashews, yams, rice, maize), bush, mining, urban
Approximate year of recent mining boom	Community mining began in early 2024, but there has been active mining in the surrounding communities prior to this	~Around 2003-2013 (Hilson et al., 2013)

2.2 Overview of Classification Workflow

To address our research objectives, we utilized a mixed-methods approach, including imagery processing, community mapping, in-depth interviews, and ground-truth data collection, all of which informed the supervised classifications. Figure 2 illustrates the workflow used to train and assess the classifications and perform the post-classification change detection analysis.

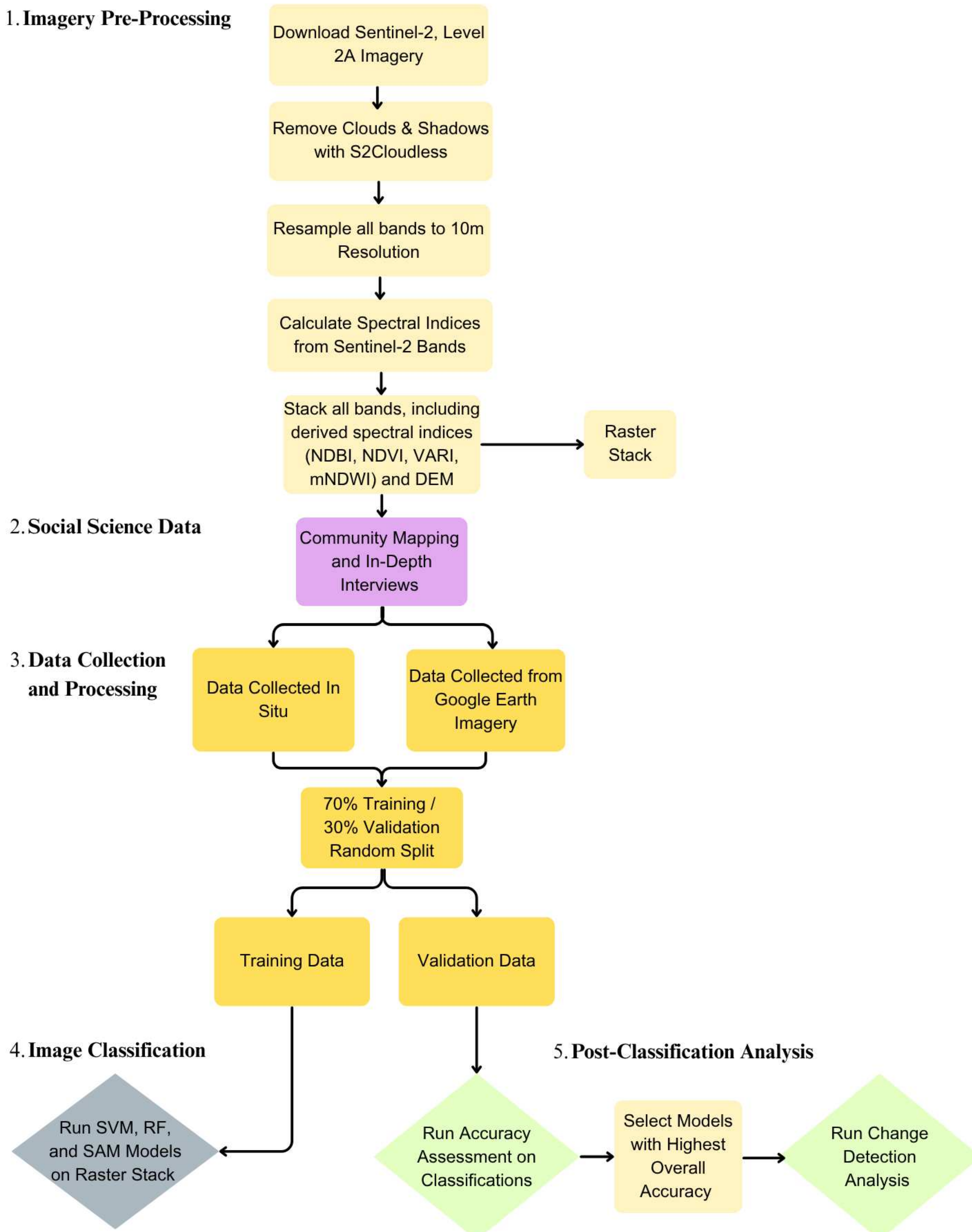

Figure 2. Image Classification and Change Detection Analysis Workflow

We used S2 imagery, with its 10-60m spatial resolution and 13 visible, near and shortwave infrared (NIR, SWIR) bands, which has sometimes provided high-accuracy (>80%) supervised land-use/land-cover classifications (Phiri et al., 2020). S2 can be effective for monitoring small-scale mining when combined with machine learning or decision tree algorithms, such as SVM or RF (Lobo et al., 2017). Based on these findings, this study utilized S2 imagery to compare SVM, RF, and SAM for land classification purposes. The spectral range of S2 data, as well as ancillary predictors such as spectral indices derived from these bands, can improve the overall accuracy of mining classifications and reduce confusion between classes with similar spectral profiles, thereby increasing the efficacy of remotely sensed data analysis (Isidro et al., 2017). This study focused on 10-20 m S2 bands (Table 2) that would best separate out the dominant land-use and land-covers, i.e. SWIR and Red Edge for water and NIR for vegetation in addition to the visible bands.

2.3 Imagery Pre-Processing

As part of our efforts to create a high-accuracy classification model, we accessed S2 Level 2A surface reflectance data from Google Earth Engine (GEE), focusing on months with low cloud coverage (i.e., less than 30%). Clouds and shadows were masked using the s2cloudless algorithm in GEE (Zupanc, 2017). The imagery pre-processing workflow included scaling, resampling, spectral index calculation, and band stacking, as detailed in Figure [1]. The imagery was scaled by 0.0001, which is the scale factor for S2 imagery. We then resampled the 20m bands to 10m through bilinear interpolation. To avoid correlated predictors, several bands were omitted from the analysis: bands 1 (aerosols), 8A (red edge 4), and 9 (water vapor) were excluded. The omission of correlated predictors reduces the risk of overfitting and ensures diversity among decision trees in the case of the random forest model (Zhou et al., 2023). The imagery was then cropped to the area of interest around each community in the study. The imagery, shown in Figure 3, covers 24 km^2 around the Southern site and 33 km^2 around the Northern site.

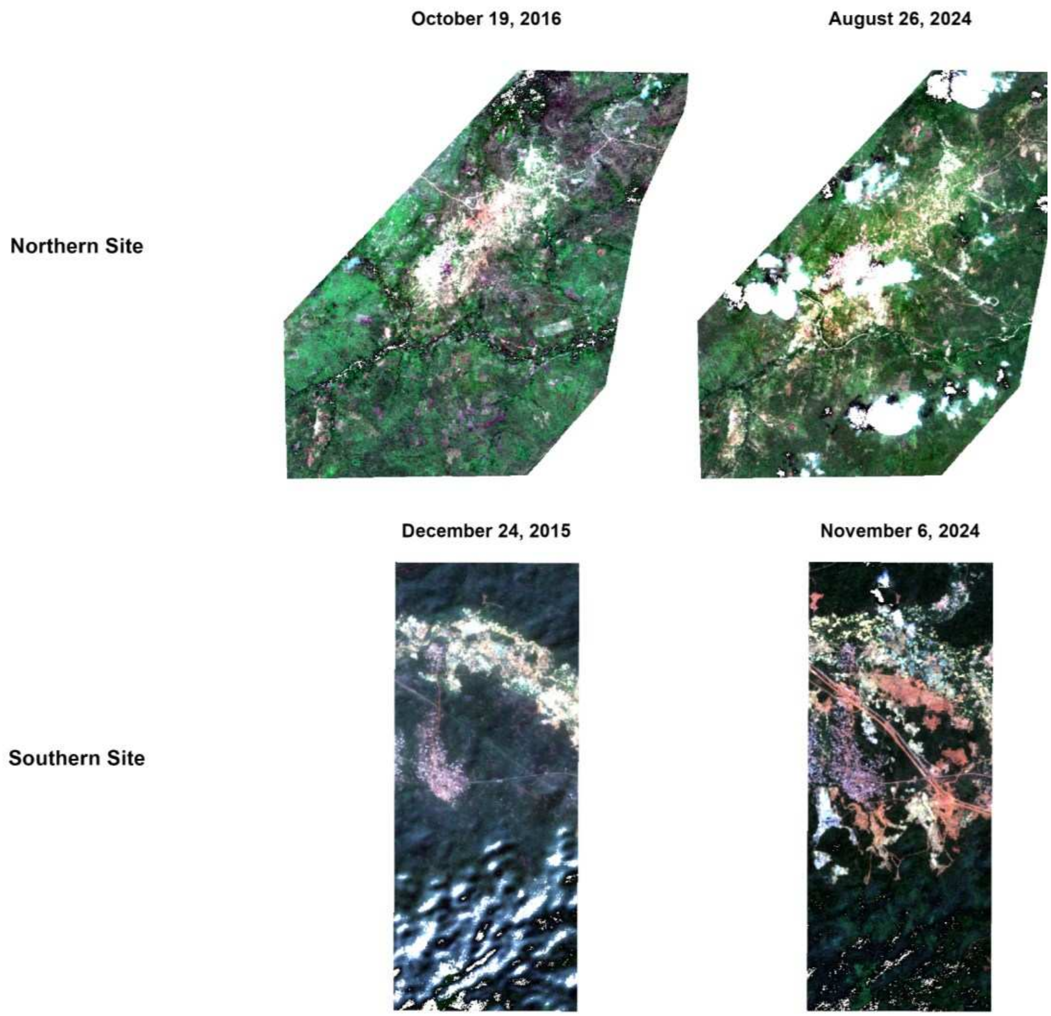

Figure 3. S2, Level 2A imagery used for each site and year.

After the bands were processed, spectral indices were calculated and included as features in the models to help distinguish between land-cover types. Because of the susceptibility of confusion between land-cover classes with similar spectral profiles (for instance, bare soil, mining, and urban areas might be easily confused by a classifier) the following indices were calculated: Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up

Index (NDBI), Visual Atmospheric Resistance Index (VARI), and Normalized Difference Moisture Index (mNDWI). In addition to the Sentinel-2 bands and spectral indices, a 30m resolution digital elevation model (DEM) from the Copernicus Global Digital Elevation Models dataset was resampled to 10m to make it compatible with the resolution of S2 for both sites. The inclusion of Digital Elevation Models (DEMs) has been found to be a key input for increasing classification accuracy (Dobrinić et al., 2021). For mining in this study region, the addition of a DEM as a predictor can also help separate classes such as mining and urban or bare areas, as these land-cover types can have similar spectral profiles but distinctive elevation differences.

Table 2. S2 bands, spectral indices and other predictors utilized for classification models

Band Order	**Original Sentinel-2 Band/Derived Spectral Index**	**Color/Spectral Indices Formula**	**Wavelength**	**Spatial Resolution**
1	2	Blue	496.6nm	10m
2	3	Green	560nm	10m
3	4	Red	664.5nm	10m
4	7	Red Edge 3	782.5nm	10m (Resampled from 20m)
5	8	NIR	835.1nm	10m
6	12	SWIR 2	2202.4nm	10m (Resampled from 20m)
7	NDBI	(SWIR - NIR) / (NIR + SWIR)		10m
8	NDVI	(NIR - Red) / (NIR + Red)		10m

9	VARI	(Green - Red) / (Green + Red – Blue)	10m
10	mNDWI	(Green - SWIR) / (Green + SWIR)	10m
11	DEM		10m (Resampled from 30m)

2.4 Social Science Data

Across the two sites, we conducted seven community mapping activities with miners and farmers. Posters containing Google Earth Imagery that captured a 5 km buffer around each community were used as part of the activity, and markers were provided for participants to indicate areas of interest (i.e. mining areas, agricultural lands, landmarks such as rivers or buildings) on the map. To gather information about landscape change in the community, we asked semi-structured interview questions that queried participants' livelihoods, the type of mining they participated in (i.e., alluvial, changfa, hard rock), where mining and farming were occurring in the community, and how mining was impacting them. The community mapping activities helped contextualize the LULCC and livelihood dynamics associated with mining and farming, as well as provided a timeline of these changes that we could compare with the remote sensing data and classification results.

2.5 Data Collection and Processing

To create our model, we collected ground-truth points from the two communities during the summer of 2024 at both sites. We also used an *in situ* dataset in the Northern site from the summer of 2015 to aid with training the classification model for the 2016 imagery. We targeted a variety of land-use and land-covers: mining, artificial lakes, forest (Southern site) or bush (Northern site), agriculture, and urban areas identified through the visual inspection of high-resolution Google Earth satellite imagery prior to fieldwork. Community mapping activities *in situ* also aided in identifying land-cover classes of interest and helped us identify additional locations to gather ground-truth data. Points were collected using a Garmin GPS unit (3.65m accuracy). Gathering *in situ* data and walking the landscapes at both sites provided valuable knowledge of land-use practices, the extent of mining that is not always visible from satellite imagery, and therefore provided a better understanding of the distinction between land-use/land-cover classes. For both sites, additional data were collected via visual interpretation of high-resolution historical Google Earth imagery, i.e. additional points that appeared to be representative of mining, agriculture, or bush/forest. Utilizing Google Earth imagery as training and validation data has been a standard practice in the literature (Phan et al., 2020; Nasiri et al., 2022; Ghorbanian et al., 2021). For the Southern site, a total of 172 points were collected for the 2015 imagery and a total of 210 points were collected for the 2024 imagery. For the Northern site, a total of 199 points were collected for the 2016 imagery, and 192 points were collected for the 2024 imagery. Table 4 summarizes the number of points collected for each class and year per site. The GPS point data and data collected from Google Earth satellite imagery were used to represent a single pixel, that is, one point was representative of one pixel. The data were then separated into 70% training and 30% validation sets using a random split in R.

Table 3. Ground-truth points collected per class and year, for use in model training and validation.

Southern Site

2015

Classes	Training	Validation	Total
Mining	29	11	40
Artificial Lake	18	12	30
Agriculture	21	8	29
Urban	29	13	42
Forest	23	8	31
Total	120	52	**172**

2024

Classes	Training	Validation	Total
Mining	33	16	49
Artificial Lake	40	17	57
Agriculture	22	12	34
Urban	33	11	44
Forest	19	7	26
Total	147	63	**210**

Northern Site

2016

Classes	Training	Validation	Total
Mining	36	16	52
Agriculture	33	16	49
Urban	34	11	45
Bush	36	17	53
Total	139	60	**199**

2024

Classes	Training	Validation	Total
Mining	42	15	57
Agriculture	34	13	47
Urban	27	15	42
Bush	31	15	46
Total	134	58	**192**

2.6 Image Classification Methods

Three classification methods were tested for each image and site of interest: SVM, RF, and SAM. The three methods were identified based on previous studies that compared different classification techniques for LULCC analysis of urban areas, bare and burnt land, and vegetation (forest and agriculture) land-uses, which establish them as high accuracy classifiers (>80% overall accuracy) (Basheer et al., 2022; Thanh Noi & Kappas, 2017, Petropoulos et al., 2010). A comparison of different classification methods is important for obtaining the best possible classification results and is standard practice in land-use classification studies (Basheer et al., 2022).

SVM is a supervised non-parametric statistical learning classifier that performs well with messy, complex datasets and, by extension, complex land-uses and land-covers. Studies have found that SVM performs well in separating complex classes (Knorn et al., 2009). SAM is a classification method that determines spectral similarity by calculating the angle between two spectra. By treating each spectrum as a vector in a multidimensional space, SAM evaluates how closely the image spectra align with the reference spectra, thereby identifying the most likely land-cover type (Kruse et al., 1993). The RF algorithm is an ensemble of decision trees that decides on a label or class (Breiman, 2001). This method is known to improve accuracy and reduce overfitting through the use of multiple decision trees. Because random forest uses multiple classifiers, it increases the efficacy of models by decreasing the variance. Furthermore, random forest assigns labels through a majority voting approach, wherein a label is assigned through the maximum number of votes from multiple classifiers, which determines the label of a sample. We utilized the random forest algorithm in the Google Earth Engine. The support vector machine and spectral angle mapper classifications were created using the supervised classification toolbox in ENVI® V.6.1. ENVI® is a registered trademark of NV5 Global, Inc.

2.7 Post-Classification Analysis

The final step of the imagery analysis workflow (as shown in Figure 2, 5. Post-Classification Analysis) was a post-classification analysis that utilized the two classified images with the highest overall accuracy. An accuracy assessment was performed based on a confusion matrix, which includes the overall accuracy, kappa coefficient, and producer's and user's accuracies, which are calculated as follows: Producer's Accuracy (PA): number of correctly classified samples for the class / total number of reference (ground truth) samples in that class; User's Accuracy (UA): number of correctly classified samples for the class / total number of samples predicted to be in that class. PA is indicative of false negatives, where a pixel has erroneously been classified as a certain class, but the reference data is a different class, while UA is indicative of false positives, where a pixel has been classified as belonging to a class it should not have been assigned to.

A post-classification method was selected because of its ease of interpretation. The change detection statistics tool in ENVI 6.1 was used on the two classification images with the highest overall accuracy among the three classification methods for each year. The change detection statistics tool reports a tabulation of changes between two classification images, including image differences within classes, as well as transitions between classes. The SAM and SVM classifications were trained and produced in ENVI 6.1, whereas the RF classification was performed in Google Earth Engine.

3. RESULTS

3.1 Classification Accuracy Assessment

For the Southern site, the classifications yielded overall accuracies of over 80% in both years. The RF classifier consistently outperformed the other approaches, producing the highest overall accuracies of 85% in 2015 and 87% in 2024 (Table 4). SVM also performed well, although with lower accuracies of 81% in 2015 and 84% in 2024. The SAM classification had the lowest accuracy of all classification methods, achieving only 73% in 2015 and 77% in 2024.

Table 4. Overall Accuracy (OA), User Accuracy (UA), and Producer Accuracy (PA) for the Southern site. The table compares the classification results of SVM, SAM, and RF. A bold font indicates the highest user and producer accuracy for each land-cover type (UR: urban; MI: mining; AL: artificial lake; AG: agriculture; FO: forest), as well as the highest overall accuracy and kappa among the models for each year. The highlighted rows indicate the model with the highest overall accuracy for that year.

			UR	MI	AL	AG	FO	OA	Kappa
2015	SAM	PA	0.77	0.73	**1.00**	**1.00**	0.00	0.73	0.66
		UA	0.77	0.80	**1.00**	0.47	0.00		
	SVM	PA	**1.00**	0.73	0.83	0.50	**0.88**	0.81	0.76
		UA	0.81	0.80	**1.00**	0.80	0.67		
	RF	PA	1.00	**0.73**	0.92	0.63	**0.88**	**0.85**	**0.81**
		UA	**0.81**	**0.89**	**1.00**	**0.83**	**0.70**		
2024	SAM	PA	0.81	0.75	0.88	0.750	0.57	0.77	0.71
		UA	0.60	0.80	**1.00**	0.692	0.80		
	SVM	PA	**1.00**	0.81	0.82	**0.833**	**0.71**	0.84	0.79
		UA	0.73	0.87	**1.00**	0.767	**0.83**		
	RF	PA	0.91	**0.88**	**0.94**	**0.92**	0.57	**0.87**	**0.84**
		UA	**0.83**	**0.93**	**1.00**	0.69	**1.00**		

For the Northern site, the classification performance (Table 5) differed between imagery years, with RF producing the highest overall accuracy in 2016 and SVM achieving higher accuracy in 2024. In 2016, RF achieved the highest accuracy at 85%, followed by SVM at 78% and SAM at 68%. However, for the 2024 image classification, SVM outperformed RF with an overall accuracy of 86%, while RF and SAM both achieved an overall accuracy of 79%

Table 5. Overall Accuracy, User accuracy, and Producer's Accuracy for the Northern site.

			UR	MI	BU	AG	OA	Kappa
2016	SAM	PA	0.55	0.44	0.88	**0.81**	0.68	0.58
		UA	0.43	0.54	0.88	0.81		
	SVM	PA	0.73	0.69	0.88	**0.81**	0.78	0.71
		UA	0.67	0.73	0.88	0.81		
	RF	PA	**1.00**	**0.75**	**0.94**	0.75	**0.85**	**0.79**
		UA	**0.77**	**0.92**	**0.84**	**0.86**		
2024	SAM	PA	0.80	0.87	0.93	0.54	0.79	0.72
		UA	0.86	0.81	0.70	**0.88**		
	SVM	PA	1.00	**1.00**	**0.73**	0.69	**0.86**	**0.82**
		UA	**1.00**	1.00	0.73	0.69		
	RF	PA	0.78	0.79	1.00	**0.71**	0.79	0.72
		UA	0.73	**1.00**	**0.73**	0.80		

3.2 Change Detection (LULCC Analysis*)*

3.2.1 Southern Site Change Detection

Since the random forest classifications performed best for the Southern site, we used this classification scheme for the change detection analysis. Mining increased by 105% from 2015 to 2024, and the mining-related class, artificial lakes (i.e., abandoned mining pits filled with rainwater), increased by 254% (Figure 4).

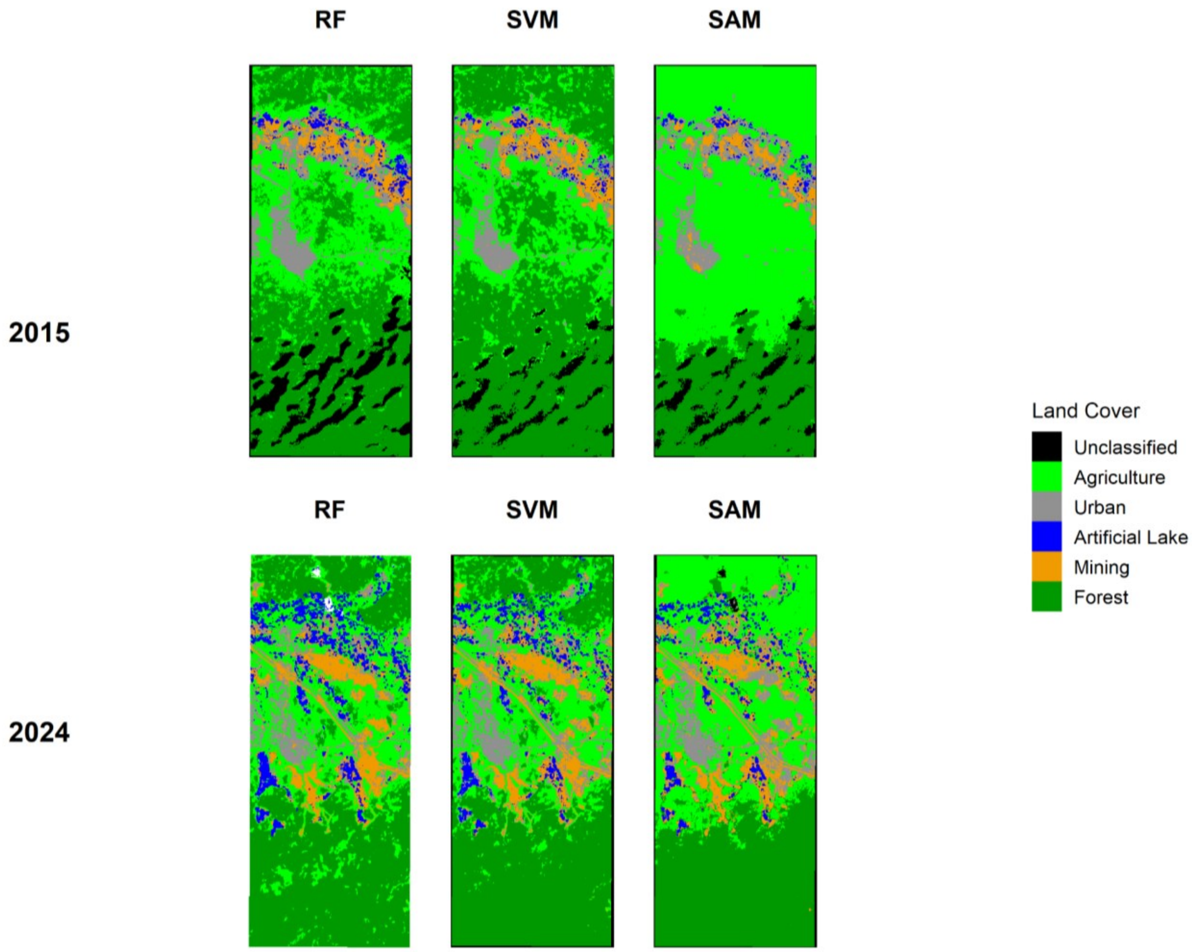

Figure 4. Land-use/land-cover classifications for each year and classification model for the Southern site.

Surprisingly, agriculture increased slightly by 2%. Decreases were observed in the urban class (11%) and forest class (4%). Approximately 28% of the land classified as mining in the 2015 imagery was converted to artificial lakes in the 2024 imagery.

Table 6. Percent change in land cover detection for the Southern site. The green numbers indicate a percent increase and the red numbers indicate a percent decrease.

Percentage		Initial State Image (2015)					
Final State Image (2024)	Classes	Unclassified	Agriculture	Artificial Lakes	Forest	Mining	Urban
	Unclassified	25.1	0.72	1.77	0.2	0.52	0.17
	Agriculture	12.95	45.47	40.95	18.62	41.01	38.39
	Artificial Lakes	0.043	8.37	42.48	3.86	28.9	13.74
	Forest	60.81	17.84	2.29	69.42	0.95	1.11
	Mining	0.433	16.74	6.97	5.61	12.62	11.14
	Urban	0.668	10.85	5.54	2.29	16	35.45
	Class Changes	74.905	54.53	57.52	30.58	87.38	64.55
	Image Difference	**-71.52**	**2.43**	**254.12**	**-4.15**	**105.59**	**-10.93**

3.2.2 Northern Site Change Detection

In contrast to the Southern site, we observed that mining essentially did not change in the Northern site from 2016 to 2024, although visually in the classification maps it appears that mining has extended further outside of the community center (see Figure 5).

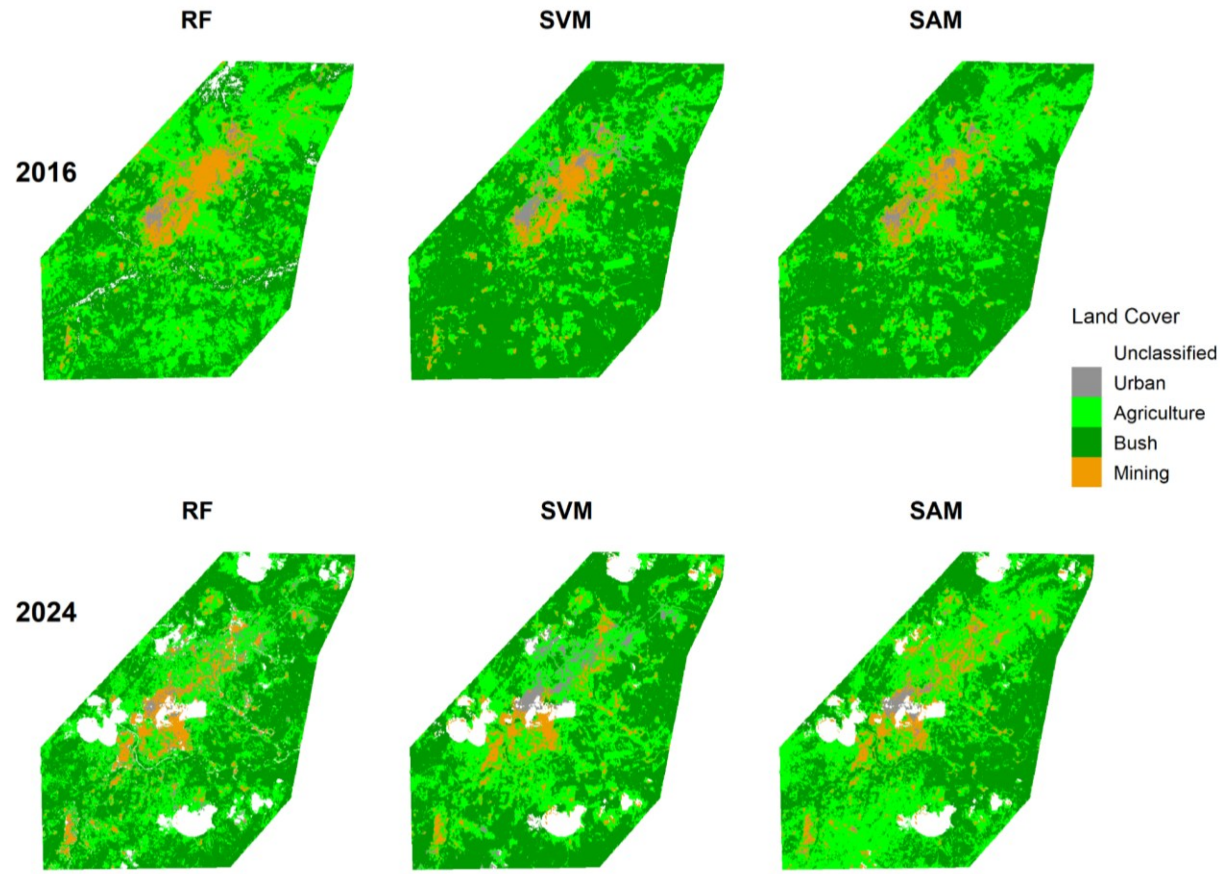

Figure 5. Land-use/land-cover classifications for each year and classification model for the Northern site.

In contrast to the near-negligible increase in mining, we saw that agriculture increased by 45% (see Table 5). The urban class increased by 91%, and the bush class decreased by 27%.

Table 5. Percent change in land cover detection for the Northern site. The green numbers indicate a percent increase and the red numbers indicate a percent decrease.

Percentage		Initial State Image (2016)				
	Classes	Unclassified	Urban	Mining	Agriculture	Bush
Final State Image (2024)	Unclassified	100	9.73	10.32	7.29	6.34
	Urban	0	41.18	14.61	3.73	0.891
	Mining	0	20.12	19.69	7.85	4.36
	Agriculture	0	26.6	42.67	43.2	28.96
	Bush	0	2.37	12.71	37.94	59.45
	Class Changes	0	58.82	80.31	56.81	40.55
	Image Difference	**13.32**	**91.26**	**0.14**	**45.51**	**-26.91**

4. DISCUSSION

4.1 Key Findings

4.1.2 Comparison of Classification Methods

RF classification achieved the highest overall accuracy in all but one of the classifications, suggesting that it is the most promising classification method for fine-scale ASGM mapping. In most cases, RF outperformed SVM, a result consistent with the findings of previous studies that compared the two models for land-use classification (Avci et al., 2023; Ouchra et al., 2023; Liu et al., 2024). However, instances in which SVM outperformed Random Forest are also supported by the literature (Nyamekye et al., 2021; Thanh Noi & Kappas, 2017). The accuracy assessment results demonstrate that RF and SVM can produce highly accurate classifications for fine-scale ASGM mapping, particularly when combined with ancillary predictors such as digital elevation models and spectral indices.

For most of the classification accuracies, including UA and PA, RF outperformed the other classifiers across the different land-use and land-cover classes. For both sites, the lowest UA and PA among the RF classifications appeared to be within the vegetation classes, i.e. bush/forest and agriculture classes. For instance, in the Southern site, the lowest PA for the RF classification was 0.63 for the agriculture class in 2015, with pixels likely being confused for the spectrally similar forest class. Similarly, in the 2016 RF classification for the Southern site, the lowest PA was 0.57 for the forest class, which likely had confusion with the agriculture class. The UA for both years was generally higher than the PA, but the lowest UA was also for the agriculture class at 0.688 in 2024. In the Northern site, for the SVM classification, PA was lower for the mining and agriculture classes in 2016 at 0.75 for both classes, while PA and UA had the lowest accuracy for the agriculture class at 0.69 in 2024. The lower PA and UA accuracies for the agriculture, mining, and forest/bush classes indicate that it's possible that these classes are not being separated correctly by the model, likely due to their similar spectral profiles.

4.1.3 Dominant LULCC transformations

While mining increased for both sites, the Southern site experienced a much more drastic 105% increase in comparison to the small 0.14% increase in the Northern site. These results are also supported by our qualitative data and community mapping activities, that demonstrated that ASGM was new in the Southern site compared to the Northern site, where ASGM had already taken place for at least 15 years. In other words, we would expect to see more dramatic expansion of mining in new ASGM areas.

Our results confirmed that the dominant land-cover transformations in the Southern site were for the artificial lakes and mining classes, with 28.9% of the pixels that were classified as mining in 2015 changing to artificial lakes in 2024. The dominant LULCC transformations for agriculture were 16.7% of agriculture class pixels in 2015 transforming to mining in 2024 and 17.8% transforming to the forest class. Conversely, 18.6% of pixels classified as forest in 2015 changed to agriculture in 2024 and 5.6% changed to mining. In contrast, the dominant land-cover transformation in the Northern site were the urban and agriculture classes. 20.1% of the pixels classified as urban in 2016 transformed to mining in 2024 and 26.6% transformed to agriculture. For the agriculture class, 37.9% of pixels classified as agriculture in 2016 transformed to bush in 2024 and 7.9% transformed to mining.

4.2 LULCC in the Southern Site

The increase in mining and artificial lakes aligns with participants' reporting in community mapping sessions, with several farmers relating experiences of mining activity destroying crops and preventing access to farmland. Yet, the slight increase in the agriculture class is inconsistent with the accounts of the participants who all described farming as decreasing due to the expansion of mining. However, the increase in agriculture may be representative of vegetation growth on unreclaimed mining land. When ground truthing, we often saw mining tailings that were covered with grasses, small shrubs, and even crops like cocoa yam that were volunteers (i.e., not intentionally planted by people). This vegetation was likely classified as agricultural by the model, since it is challenging to separate out distinct vegetation classes, which is corroborated by other studies that have classified vegetation land-uses (El Hazdour et al., 2026; Bofana et al., 2020).

Local community members overwhelmingly noted the increase in both mining and artificial lake categories and tied both landscape changes to decreases in agriculture and household food security concerns. The substantial increase in the artificial lake class was corroborated by participants who expressed concern over the dangers of the increase in stagnant water left behind in mining pits as a potential breeding ground for mosquitoes and drowning hazards. The large increase in the artificial lake class is consistent with other studies that observed LULCC in alluvial ASGM sites. For instance, a study along Ghana's Offin River found a 33,000% increase in artificial lakes from 2008 to 2013 (Ferring and Hausermann, 2019), and a similar study in ASGM-affected river basins in Peru found a 670% increase in artificial lakes between 1985 and 2018 (Gerson et al., 2020), despite remediating sites being required by law in both countries (Asiedu, 2013; Aguilar-Pesantes et al., 2021).

Furthermore, community members' concerns about the dangers and health implications of the artificial lakes are substantiated in the literature. Artificial lakes from ASGM are connected to malaria increases (Ferring and Hausermann 2019; Murta et al., 2021), drownings (Arthur-Holmes & Abrefa Busia, 2021) and significant water quality issues (Obodai et al., 2024; Dethier et al., 2023). The conversion of agricultural land into artificial lakes can also concentrate fecal contamination and mining-related pollutants (e.g. mercury), increasing risks of gastrointestinal illness and mercury exposure among surrounding communities (Gerson, 2020). Together, these findings and prior research demonstrate that the mining-driven landscape change noted in the Southern Site has consequences for agricultural production, food security, and community health.

4.3 LULCC in the Northern Site

The minor increase in mining is consistent with the history of mining in the area, wherein mining was booming circa 2015-2016, when *in situ* data was first collected, and perhaps has lessened in comparison in 2024. However, the increase in the agriculture class is surprising and inconsistent with reports from the farmers. Many farmers discussed the decline of agriculture in the community, attributing the loss of farmland largely to cattle grazing in the area. While ground-truthing in the community, we observed that many crops in the area were fenced to prevent cattle from grazing. In other cases, farms had been fenced but then abandoned due to continued damage from cattle despite the construction of fences. Similar to the Southern site, we observed many abandoned tailing piles had vegetation growth, particularly low-lying wild shrubs, which may have been incorrectly classified as agriculture instead of bush. Farmers had also reported that crops such as maize were doing well in old mining sites that had been reclaimed, which could also be a possible factor in the increased agriculture class.

Another possible factor in the increased agriculture is the difference in seasonality between the 2024 image and the 2016 image, with the 2024 image data capturing the scene during the wet season in the Northern site (August) and the 2016 image capturing the scene after the wet season (October), which could affect the amount of vegetation present in the imagery. This is reflected in Figure 7, where the NDVI value for the 2024 imagery is higher than that for the 2016 imagery. This indicates that this may not be the most accurate comparison because of the difference in seasonality, as there is inherently more vegetation in the wet season.

In general, there are challenges in accurately tracking vegetation change in Northern Ghana due to climate variability associated with this area, with the literature pointing to climate change and precipitation variability impacting farming practices (Antwi-Agyei & Nyantakyi-Frimpong, 2021; Guodaar et al., 2023). This is corroborated by several community members noting that the rainy season has become increasingly unpredictable in the Northern site. Studies have also noted that in the arid and semi-arid regions of Africa, including Ghana and Guinea, smallholder farms are likely to shift from agriculture to ASGM because of climate change impacts, such as drought conditions (Bansah et al., 2023; Shackleton et al., 2019).

4.4 Challenges and Limitations

A limitation of our classification and change detection is the temporal discrepancy between the dates when the ground-truth data were collected and when the satellite imagery was acquired. The constant cloud coverage in this region during the summer months when fieldwork was conducted limited the availability of satellite imagery. Furthermore, in the Northern site, there was the added challenge of limited vegetation and farming areas available to train the classifier, as well as some of the mining in this area occurring underground, which would not be detectable from the satellite imagery. Ancillary data such as DEM data can help with identifying underground mining and although our raster stack included a DEM, the data was collected between 2011-2015.

In observing land-use *in situ*, it became clear that these classes are complex and do not easily fit into single categories. Agriculture in Ghana is typically polyculture, and there are often no clear land divisions set aside for farming; thus, there are not always clear delineations between land-uses. It was also made more complicated by mining occurring very near urban development, with road infrastructure being built at the time of our *in situ* data collection for the Southern site. Additionally, the bush, forest, and agriculture classes have incredibly similar spectral profiles (see Figures 6 and 7). The bush class is slightly more distinct as it also includes more dry riparian regions along the riverbank in the Northern site, but overall, these are very similar spectrally.

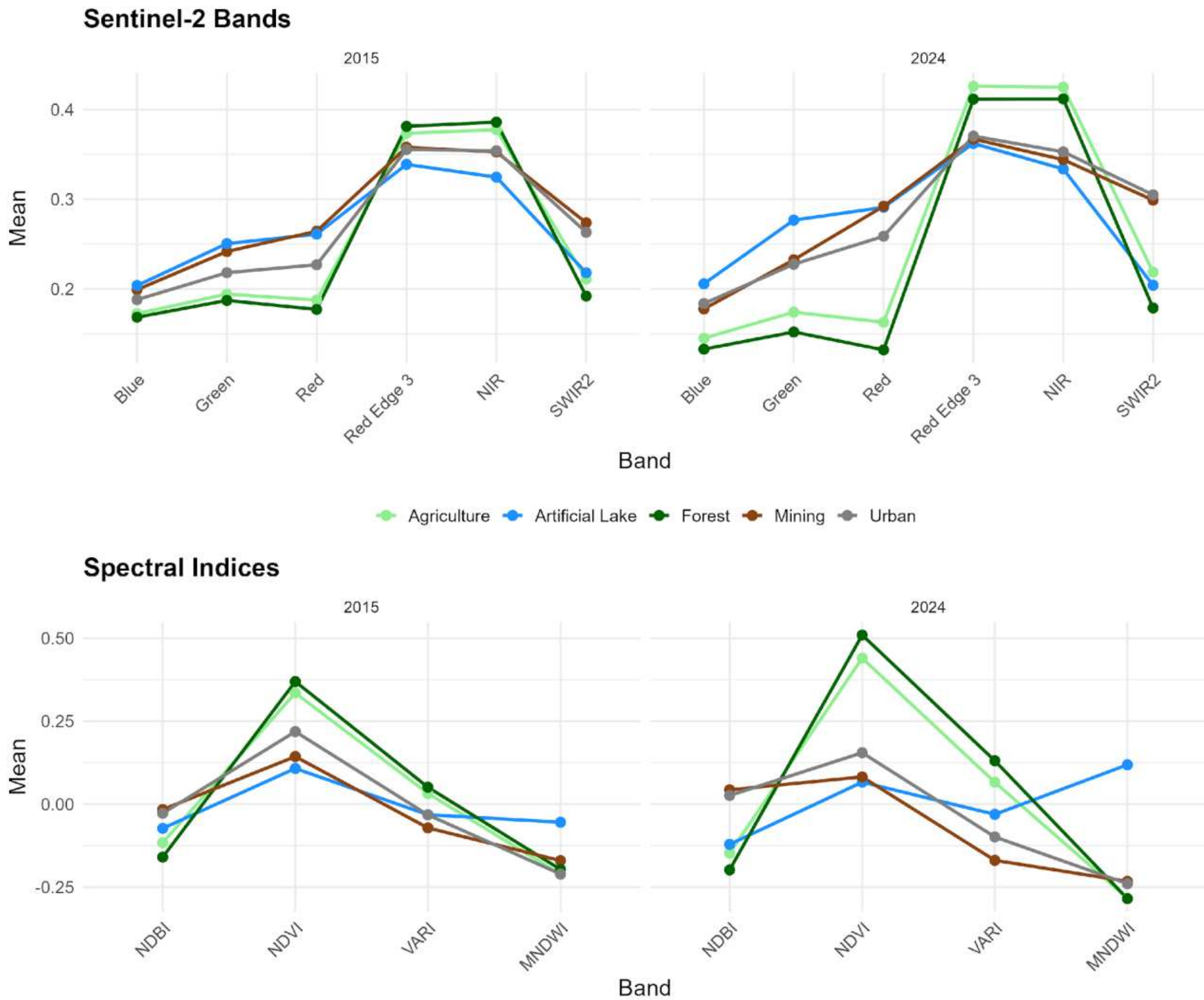

Figure 6. The mean spectral values from the highest accuracy (SVM) classifications for the Southern site. The top plots show the mean spectral values for the Sentinel-2 bands, whereas the bottom plots show the mean spectral values for the derived spectral indices.

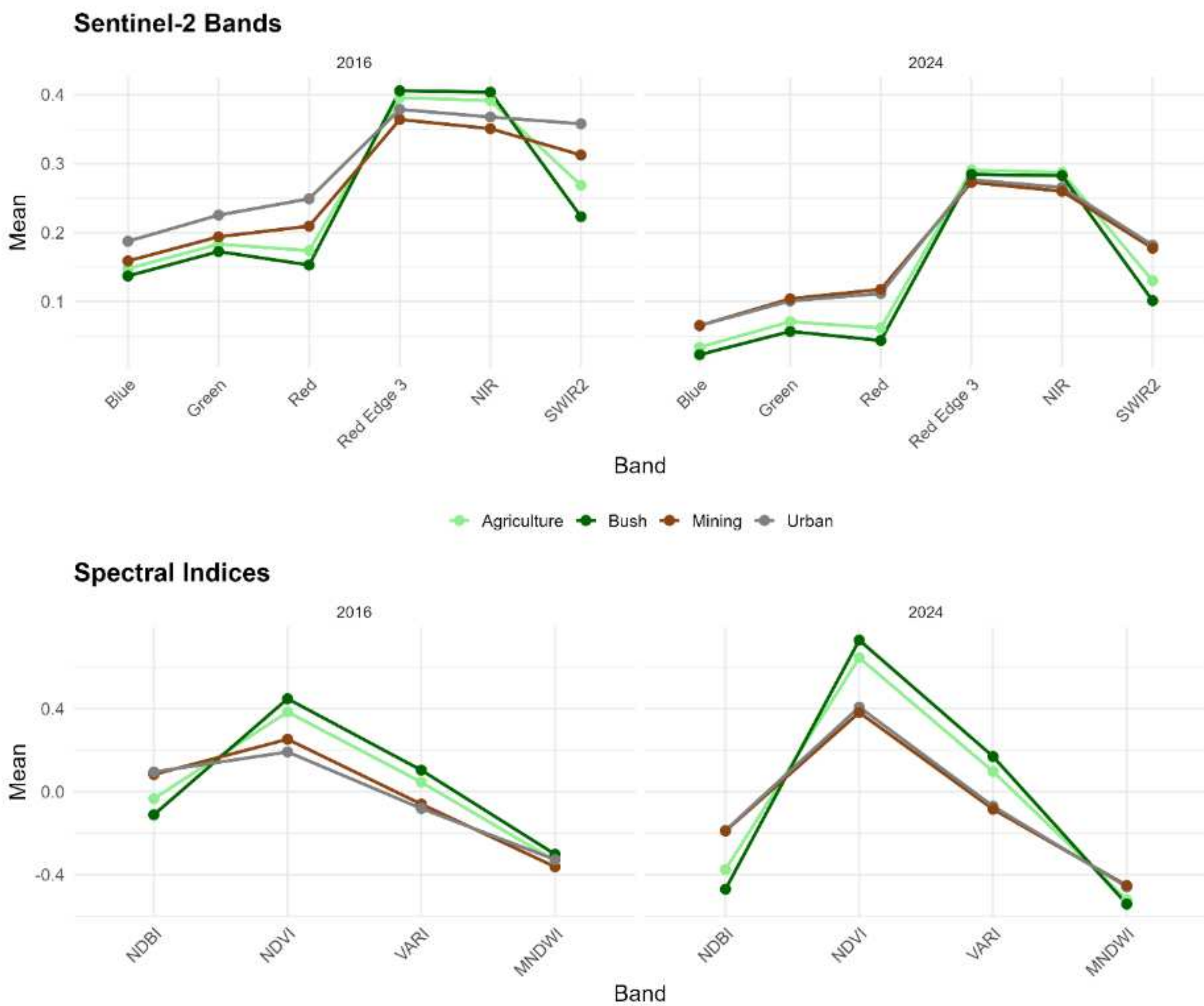

Figure 7. The mean spectral values for the bands and spectral indices were obtained from the Northern site classifications.

4.5 Importance of mixed-methods approach and suggestions for future research

While we were able to yield high-accuracy classification results, this study highlights the importance of interdisciplinary research and working directly with the community to analyze and improve the fine-scale classification of ASGM. The complex landscapes of mining communities make it challenging to categorize and classify land-use and land-cover. Input from community members helped in understanding the distinction between the different land-use and land-cover categories. The extensive ground-truthing we performed in both communities also revealed mining that would not be visible from satellite imagery, such as unreclaimed mining pits with vegetation overgrowth and underground mining. Ground-truthing also helped us make sense of the remote sensing results. For instance, increases in agriculture in both sites—produced by the remote sensing models—can be explained by in situ observations of spontaneous plant regrowth on abandoned mining sites and tailings. While boots-on-the-ground ground truthing is time consumptive and expensive, it was helpful in training and validating the classifications and interpreting results. This is perhaps most important in landscapes with complex interactions between ASGM, farming and other land-uses and polyculture agriculture that can be difficult to classify into distinct land-use categories.

The interdisciplinary framework used here could be applied to mining communities in other countries experiencing the rapid expansion of ASGM, such as the Amazon Basic, western and southern Africa, and Southeast Asia. Future research would benefit from incorporating additional years of imagery to better capture long-term land-use trajectories, reduce the influence of seasonal variability between years, and improve the understanding of mining-related LULCC in data-scarce regions. Additionally, the SWIR bands were found to be helpful in separating out the land-use and land-cover classes in this study, demonstrating the efficacy of sensors such as S2 with SWIR data in future classification efforts. Utilizing remotely sensed data can help policymakers visualize the spatial extent of ASGM and its relationship with other land-uses, which can in turn identify ASGM hotspots, overlap with agricultural lands, and unreclaimed mining sites (Nursami et al., 2024). However, as other remote sensing studies on ASGM have identified, the use of remote sensing data to monitor ASGM requires an interdisciplinary approach to address the complexity of its implications on social and environmental issues (Ngom et al., 2023). Input from community members not only enables a clearer understanding of how ASGM and other land-uses impact ecosystems differently in diverse climates but also supports the development of evidence-based strategies that can guide policymakers and empower local communities to manage their resources more sustainably.

5. CONCLUSION

This study aimed to compare different classification models across distinct ecoregions and mining-farming communities, to determine which classification method is most suitable for fine-scale ASGM classification. The results demonstrate that machine learning techniques such as RF and SVM can accurately classify ASGM across different mining types, climates, and environmental settings from freely available S2 imagery. Furthermore, the qualitative data collected through our community mapping activities aided in providing ground-truth data for interpreting the LULCC observed at both sites. The discrepancies between the change detection analysis results and the reports from community members highlights the importance of incorporating local knowledge into remote sensing results and utilizing an interdisciplinary approach. The high overall accuracies (over 80%) of the classifications we produced indicate that the analysis used here can reasonably inform ASGM policy and land-use decisions in these regions. Future studies could benefit from the inclusion of more satellite images and products, as well as broadening the spatiotemporal scale to better understand the pattern of LULCC in these complex landscapes, particularly because of the variability in climate and land-use governance in the tropics.

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