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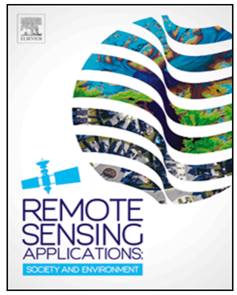

Gold mining's environmental footprints, drivers, and future predictions in Ghana

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Gold mining's environmental footprints, drivers, and future predictions in Ghana

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Abstract

The last two decades have seen a surge in gold mining operations around the world. Despite mining occupying a smaller geographical area compared to other land use/land cover (LULC) classes, it exhibits strong interconnections with various land uses and serves as a major driver for changes in mining landscapes. Understanding and evaluating historical and potential future LULC changes in these landscapes are crucial in assessing the environmental impact of mining. Traditionally, these assessments heavily rely on geospatial techniques, with limited emphasis on projecting future LULC trends. This research aims to monitor, analyse the drivers of change, and predict future changes in LULC under two scenarios: the “business as usual” scenario and the "remedial measures" scenarios. Utilising the CA-Markov model, this article predicts LULC changes and offers comprehensive insights into the environmental impacts of mining, combining geospatial and social research methodologies. The investigation spanned a 34-year period (1986–2020) and employed a blend of supervised and unsupervised image classification methods, complemented by interviews, focus groups, and field observations. The findings reveal substantial land degradation, water pollution, and a significant loss of forest cover, accounting for 27,333 hectares (36%). Continuation of current mining practices is predicted to lead to further ecological deterioration.

Keywords: land use land cover change, ecological footprint, remote sensing/GIS, CA-Markov, mining, prediction, social sciences techniques

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1. Introduction

Mining of precious minerals, particularly gold, is a vital economic activity for millions of people in Sub-Saharan Africa and a significant contributor to the gross domestic product (GDP) of numerous economies in the region. For instance, despite a notable decline in 2021, the mining sector in Ghana consistently contributed over 7% annually to the GDP of the country (The Ghana Chamber of Mines 2022). During the same year, the South African mining sector accounted for 8.7% of the country's GDP (Minerals Council South Africa, 2022), whereas in Zimbabwe, its contribution to GDP is approximately 12% (International Trade Administration, 2022). Gold mining operations in Africa can be broadly categorised into two segments: large-scale and small-scale mining. Large-scale mining involves the use of advanced, capital-intensive technology, with formal mining operations registered under existing legal frameworks, typically representing multimillion-dollar investments by multinational corporations in mineral-rich countries. In contrast, small-scale mining, legally reserved for nationals, encompasses mineral extraction and processing using rudimentary tools, relying on substantial labour (Hilson et al. 2017). Despite its labour-intensive nature, small-scale mining exhibits variability due to the involvement of foreign nationals, particularly the Chinese, using sophisticated machine(Crawford et al. 2016; Crawford and Botchwey 2017).

Over the last two decades, gold mining in Ghana, particularly in the small-scale sector, has experienced significant growth, driven in part by global market factors such as rising gold prices(Barenblitt et al. 2021). Local factors, including the 'get-rich-quick' mentality, declining agricultural fortunes, poverty, and opportunities for wealth creation, have also contributed to this growth (Banchirigah 2008; Hilson and Garforth 2012, 2013; Afriyie et al. 2016; Hilson and Hu 2022). The small-scale mining sector has emerged as a substantial source of local employment, offering opportunities to unemployed youth and women (Hilson and Maconachie 2020; Hilson and Hu 2022; Arthur-Holmes and Abrefa Busia 2022; Arthur-Holmes et al. 2022). However, despite these socioeconomic benefits, the environmental impact of small-scale mining in Ghana is well-documented, encompassing disturbances to river basins, water pollution, disruptions to agriculture, deforestation, and land degradation (Schueler et al. 2011; Awotwi et al. 2018; Hausermann et al. 2018; Obodai et al. 2019; Forkuor et al. 2020; Ofosu et al. 2020; Barenblitt et al. 2021).

The severe environmental repercussions of small-scale gold mining in riverbeds and forest reserves, which employ advanced machinery, prompted a two-year ban on small-scale activities in 2019. The government also prohibited the issuance of mining permits for gold exploration/mining in forest reserve zones and imposed a ban on excavator exports. Existing excavators at illegal small-scale mining sites were destroyed by a joint police-military task force. These actions have faced criticism for hindering efforts to formalise the small-scale mining sector (Hilson 2017; Hilson and Maconachie 2020).

Mining activities are closely intertwined with other land use and land cover (LULC) types, resulting in changes in adjoining land use/cover with multifaceted implications. Examining past and future LULC changes in mining landscapes is instrumental in understanding the environmental footprint of mining, essential for sustainable resource management and long-term planning. Therefore, this study pursues three primary objectives: (1) monitoring land use and land cover changes in a mining landscape over the past three decades; (2) analysing the drivers behind these changes; and (3) projecting potential future landscapes under two scenarios: 'business as usual' and 'remedial' measures.

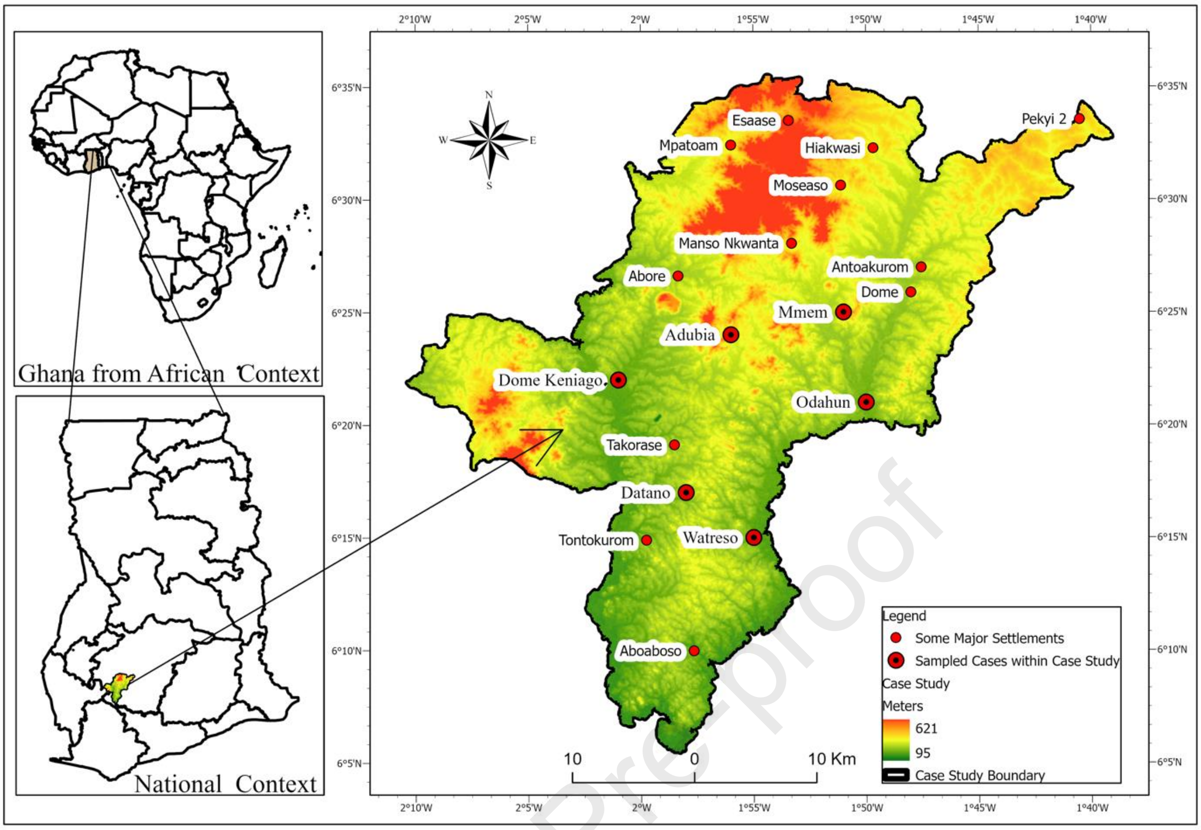
The advancement of Earth observation tools, specifically remote sensing, and geographical information systems (GIS) has significantly enhanced the ability of researchers to comprehend LULC dynamics within mining landscapes. Notable studies demonstrate the impact of these technologies. For instance, Garai and Narayana 2018) utilised Landsat satellite imagery to analyse land use and land cover changes in coal mining areas in Southern India over 24 years, revealing the direct influence of mining on forest cover. Similarly, Lobo et al. (2018) effectively mapped mining areas in the Brazilian Amazon using Sentinel-2 images, highlighting the prevalence of small-scale gold and tin mining. Another study in the Peruvian Amazon by Espejo et al. (2018) illustrated the ecological consequences of gold mining on deforestation and forest degradation, employing CLASlite and the Global Forest Change dataset. Furthermore, Barenblitt et al. (2021) employed machine learning and change detection techniques to reveal the conversion of approximately 47,000 hectares of vegetation cover to mining in southwestern Ghana. Also, Nyamekye et al. (2021), focusing on the eastern part of Ghana, used Sentinel-2 data to monitor post-ban small-scale mining activities, indicating a substantial increase in such mining. In addition to these remote sensing-based findings, several studies have established the adverse effects of small-scale mining on major natural river drainage systems in Ghana (Awotwi et al. 2018; Obodai et al. 2019; Boakye et al. 2020).

While these studies have contributed valuable insights, they primarily rely on remote sensing and GIS technologies. To achieve a more comprehensive understanding of dynamic LULC changes in mining landscapes, integrating state-of-the-art GIS technologies with social research approaches is essential. Also, few studies, apart from Awotwi et al. (2018), have attempted to predict the future LULC trends in mining areas in Ghana. This article addresses this gap by employing a combination of geospatial and social research methods to assess LULC dynamics and their driving forces in mining environment in the southwestern part of Ghana. Additionally, the study employs the CA Markov model to predict LULC changes over the next decade under both “business as usual” (BAU) and “remedial” scenarios. The subsequent section elaborates on the materials and procedures used in this study.

2. Materials and Methods

2.1 Study Area

This research was conducted in the Amansie West and South Districts (AWSD) of rural Ghana, located between Longitude 6.05º, 6.35 º West and Latitude 1.40º, 2.05 º North (Map 1). These districts account for 5% of Ghana’s Ashanti region total land area and cover a total of 1230km^2. Both the *Offin* and *Oda* rivers, as well as their tributaries, provide drainage for these areas, which are in the Wet Semi-Equatorial climate zone and see a double-maximum rainfall pattern (March to July: major season, and September to November: minor season). The rain forest type with moist semi-deciduous characteristics of the vegetation in the AWSD is responsible for the exceptionally abundant fertile grounds that sustain agriculture as a key livelihood activity across the district. The average yearly rainfall in AWSD fluctuates between 855mm and 1,500mm. From December to March, the weather is typically dry, marked by elevated temperatures and early morning fog or moisture with cold conditions. Temperatures remain consistently high year-round, averaging around 27ºC each month. Humidity levels peak during the rainy season, but from December to February, humidity drops significantly (Amansie West District Assembly, 2018). *Oda* River, *Apanprama, Jemira,* and *Gyeni* River Forest Reserves are the four most significant protected areas in the district. Anthropogenic activities such as unsustainable farming methods, illegal mining, and logging have recently posed a serious threat to these forest reserves (Ghana Statistical Service 2014).



Map 1. Study Area from continental and national contexts
Source: Obodai et. al. (2023)

2.2 Method

Fig. 1 provides a graphical flowchart of the research process that guided this investigation. The procedures and methods are then described and discussed.

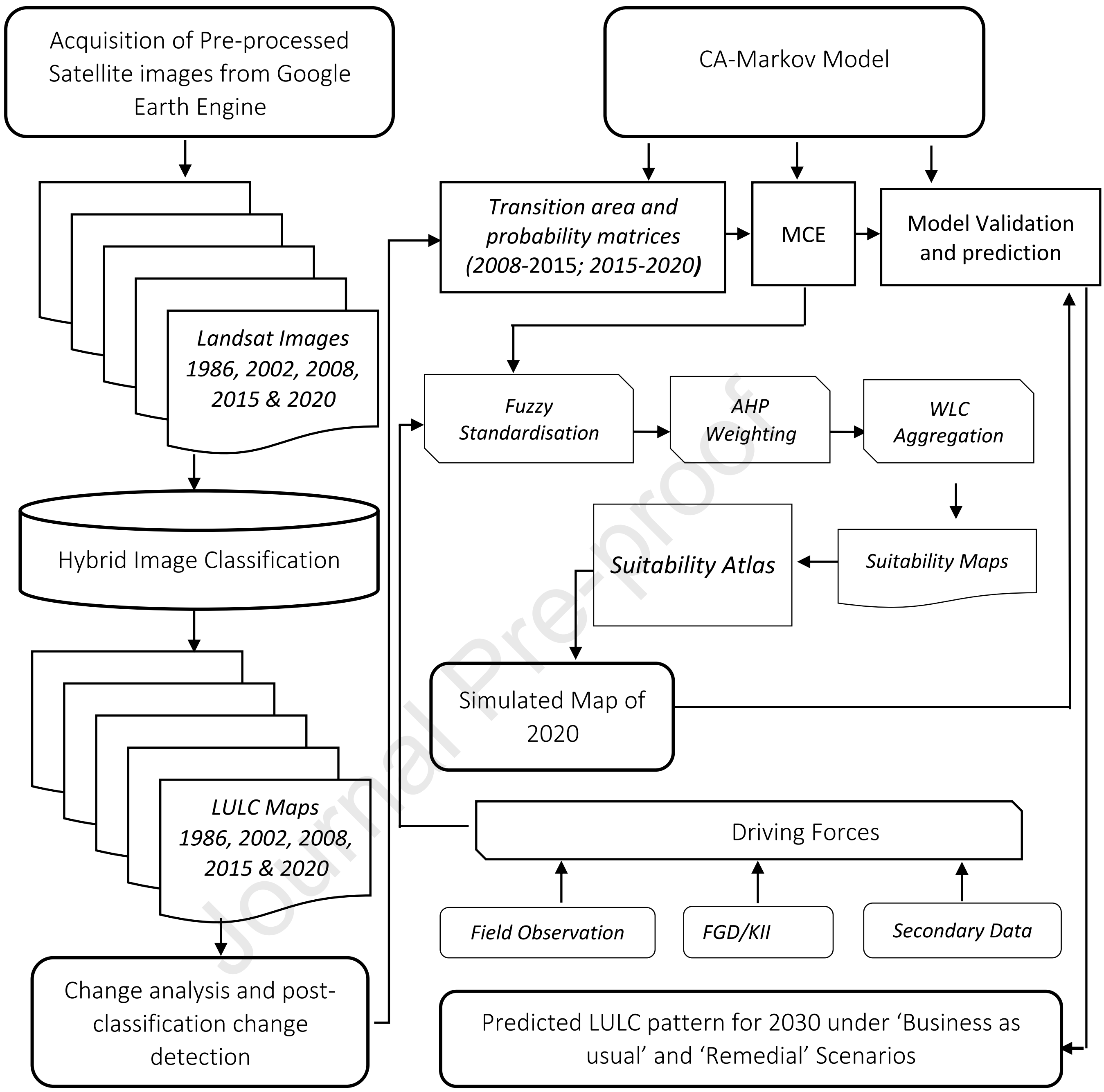


Fig. 1: Methodological Flowchart
MCE: Multi-Criteria Evaluation; AHP: Analytical Hierarchy Process; **WLC**: Weighted linear combination; **FGD**: Focus Group Discussion; **KII**: Key Informant Interview

2.2.1 Digital and qualitative data acquisition, pre-processing, and analysis
Landsat imagery from the United States Geological Survey, pertaining to our research area, was acquired via Google Earth Engine for this study. The selected images were from the pre-processed Tier 1 calibrated top-of-atmosphere (TOA) reflectance archive, based on date and time constraints. As indicated in Table 1, five cloud-free multispectral images from the years 1986, 2002, 2008, 2015, and 2020 were obtained for our analytical purposes. To address the ETM+ Scan Line Corrector off data issue, the GDAL "fill no data" tool in QGIS Desktop 3.14.16 was applied.

Table 1: The available Landsat satellite images

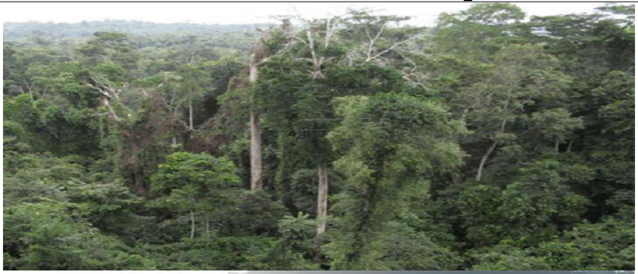
Image ID	Satellite	Sensor ID	Resolution (m)	Acquisition Date	Path/Row
LANDSAT/LC08/CO1/TI_TOA/LC08_194056_20200109	Landsat 8	OLI_TIRS	30	09-01-2020	194/056
LANDSAT/LC08/C01/T1_TOA/LC08_94056_20151229	Landsat 8	OLI_TIRS	30	29-12-2015	194/056
LANDSAT/LE07/C01/T1_TOA/LE07_194056_20080201	Landsat 7	ETM+	30	01-02-2008	194/056
LANDSAT/LE07/C01/T1_TOA/LE07_194056_20020115	Landsat 7	ETM+	30	15-01-2002	194/056
LANDSAT/LT05/C01/T1_TOA/LT05_194056_19861229	Landsat 5	TM	30	29-12-1986	194/056

In addition to utilising digital remote sensing data, the research was supplemented with qualitative data obtained through a multifaceted approach, encompassing field observations, oral histories, and interviews. Interviews were conducted with a diverse range of stakeholders, including local and national mining and farming officials, chief farmers, and small-scale miners. Furthermore, to gain a comprehensive understanding of the long-term ecological and socio-economic transformations since the base year of 1986, crucial for assessing dynamic land use and land cover changes, oral history sessions with long-term residents who had resided in the study communities since birth or for over three decades was conducted. These oral histories involved interactions with village elders, appointed and unappointed assembly members, and traditional leaders. It is noteworthy that all participants in the study volunteered their involvement, either verbally or in written form. The oral histories were meticulously recorded, transcribed, and analysed using NVivo 12 Plus. The analysis followed the thematic analysis method outlined by Braun and Clarke (2006), which consists of six distinct stages. Additionally, to enrich the primary qualitative dataset, a qualitative content analysis of pertinent literature was also conducted.

2.2.2 LULC Classification

The study employed Landsat 5 and Landsat 7 bands B1, B2, B3, B4, B5, and B7 for the years 2002, 2008, and 2015, respectively, and Landsat 8 bands B2, B3, B4, B5, B6, and B7 for the years 2015 and 2020 in the LULC classification. The classification process integrated elements of both supervised and unsupervised methods. Initially, an unsupervised classification was conducted using the ISO Cluster algorithm in ArcGIS Pro version 2.7.1 to automatically group pixels with similar spectral properties into distinct spectral clusters (classes) for preliminary interpretation (Lillesand et al. 2015). Subsequently, LULC maps were generated through a supervised image classification employing the random forest (RF) classifier, known for its higher accuracy compared to unsupervised methods (Tso and Mather 2009). Field survey data and visual interpretation from RGB compositions were utilised to establish accurate reference data for the predefined classes of interest. Six macro classes, following the USGS classification system(Anderson et al. 1976), were chosen for representation (Refer to Table 2). Misclassifications of images were anticipated in the utilisation of Landsat images from three satellites due to their medium spatial resolution, as documented in prior studies (Hassan et al. 2016; Pei et al. 2017). The predominant misclassifications were observed between open forest and croplands; mining and settlements/bare lands. To rectify the most evident misclassifications, an ArcGIS Pro post-classification algorithm (Pixel Editor tool) was utilised.

Table 2: Description of LULC types

Type	**Description**	**Pictorial view of LULC classes in practice**
Closed Forest	Densely forested areas mostly located in forest reserves	
Open Forest	Sparse forest, trees, shrubs, bushes, grasses	
Cropland	Arable land, plantation land, and heterogeneous agricultural areas	 
Water	Rivers, water in mine pits, ponds, wetlands	 
Mining	Areas where both large and small-scale surface mining has taken place	 
Settlement/Bare lands	Areas including villages, towns, cities, roads, bare areas	 

2.2.3 Accuracy Assessment

In order to enhance the utility of the maps for decision-making purposes, a quantitative accuracy assessment procedure was implemented to detect, quantify, and rectify the map errors (Congalton and Green 2009). The accuracy of the classified maps was assessed by employing both a kappa statistic and a confusion matrix, which considered both omission and commission errors. To create the error matrix required for the validation of the classified maps, data sources such as Landsat, ESRI High Definition (3m), GPS ground truth data obtained from field surveys, and Google Earth images were utilised. To ensure the reliability of the classified maps, a stratified random sampling approach was employed, involving the selection of five hundred randomly chosen points for verification. A separate set of sampling points was used to train the land use and land cover classification algorithm. As a result of these efforts, the accuracy levels of the classified maps for the years 2008, 2015, and 2020 were all greater than or equal to 90%, yielding kappa indices greater than 0.90.

2.2.4 Change detection

Quantitative analysis of LULC conversions, along with the determination of LULC change rates, was accomplished using the Post Classification Comparison (PCC) technique (Hassan et al. 2016). Notably, the PCC method offers the advantage of providing insights into the nature of changes, making it the most reliable method (Mas 1999). The assessment of LULC change was conducted using a spatial analysis model of land use dynamics, which is grounded in the dynamic degree concept proposed byShenghe and Shu-Jin (2002) and subsequently adopted by Liping et al. (2018). Given below is the formula for the spatial-based land use dynamic degree (rate of change):

ss

$$CCL = TRL_i + IRL_i \qquad \text{Equation (1)}$$

$$TRL_i = \frac{LA_{(i,t1)} - ULA_i}{LA_{(i,t1)}} \times \frac{1}{t_2 - t_1} \times 100\% \qquad \text{Equation (2)}$$

$$IRL_i = \frac{LA_{(i,t2)} - ULA_i}{LA_{(i,t1)}} \times \frac{1}{t_2 - t_1} \times 100\% \qquad \text{Equation (3)}$$

where $LA_{(i,\,t1)}$ is the area of a certain type of land use at an earlier date, while $LA_{(i,\,t2)}$ is the area of a certain type of land use at a later date. ULA_i is the part that is not changed. t_1 and t_2 represent the year before and after the change, respectively. TRL_i is the transfer-out rate, IRL_i is the transfer-in rate, and CCL_i is the sum of TRL_i and IRL_i.

2.2.5 LULC Change Scenarios

Decision-makers leverage LULC scenario modelling to gain insights into the uncertainties inherent in land processes across various potential future trajectories, their impacts, and interactions (Höjer et al. 2008; Moss et al. 2010; Armenteras et al. 2019). Two distinct LULC scenarios were developed: the “business as usual (BAU)” and the “remedial”. The BAU scenario was initially employed to predict LULC changes by modelling the rates and transition trends of change from 2008 to 2015, during which significant shifts occurred due to mining activity. Subsequently, the ‘remedial’ scenario utilised actual rates of change in LULC from 2015 to 2020, presuming the continuation and enhancement of corrective initiatives by the Ghanaian government, which began in 2016 and resulted in slight reductions in land degradation and deforestation (Forkuor et al. 2020). The modelling process involved employing the transition area matrix between 2015 and 2020, with 2020 as the base year.

2.2.6 Change Prediction

An efficient and widely employed approach, the CA-Markov model, was adopted for simulating and predicting LULC changes (Awotwi et al. 2018; Liping et al. 2018; Singh et al. 2018; Mondal et al. 2020; Tariq and Shu 2020). This model adhered to three pivotal standard procedures for LULC predictions: (a) utilising the Markov Model to establish transition matrices and probabilities, (b) employing Multi-Criteria Evaluation (MCE) for a suitability atlas, and (c) using the CA-Model for forecasting future LULC. The time periods 1986-2002, 2002-2008, 2008-2015, and 2015-2020 involved the use of Markov chain analysis to produce both the transition area matrix and the transition probability matrix. For the BAU scenario, the Markov transition area matrix data from 2008-2015 was employed to simulate the 2020 LULC map and make predictions for 2030. In contrast, for the remedial scenario, data from 2015-2020 was utilised to forecast projections for 2030.

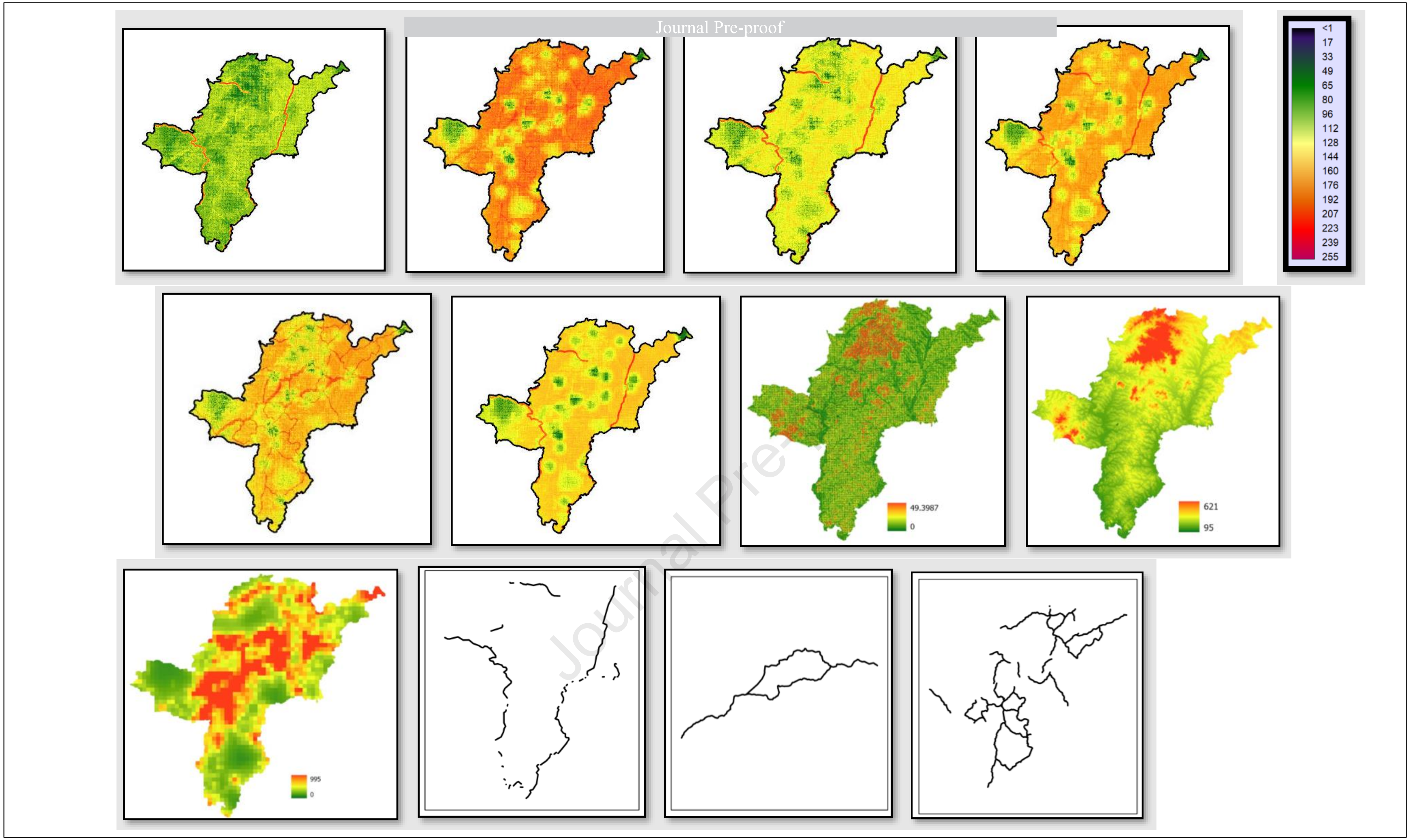
The MCE tool was utilised to create a set of suitability maps for all LULC classes, integrating various factors into a unified index for specific evaluation purposes (Liping et al. 2018; Eastman 2020)(See Map 2). Key parameters associated with LULC changes, including slope, elevation, population density, and proximity to rivers, roads, and towns, were identified through interviews with key informants and data derived from existing research(Awotwi et al. 2018; Singh et al. 2018). Low-lying areas with low elevation and gentle slopes are particularly susceptible to changes due to practices such as agriculture, mining, and settlements. Areas in proximity to river bodies are more prone to changes induced by mining activities, given the necessity of water for such operations. The population density directly correlates with changes observed in cropland, closed forest, open forest, and built-up areas. These data sets were compiled from diverse sources and processed following standard procedures before utilisation. The 30m x 30m Digital Elevation Model (DEM) of the study region was obtained from the NASA Shuttle Radar Topography Mission (SRTM) via Earth Explorer and subsequently utilised for generating the slope map. Image data from each year were compared with road and river datasets retrieved from OpenStreetMap. Settlement data, crucial for identifying major settlements in the study area, was sourced from the Land Use and Spatial Planning Authority (LUSPA) of Ghana. Population density data across different time frames was acquired from WorldPop at the University of Southampton in the UK. Following processing in ArcGIS Pro (version 2.7.1), the images were imported into TerrSet 2020 Geospatial Monitoring and Modelling Systems. Utilising the MCE in TerrSet 2020, individual LULC suitability maps were generated, combining factors through the Weighted Linear Combination (WLC) option. Standardisation of factors was achieved using the Fuzzy Module in TerrSet 2020, wherein output was normalised within a range of 0 to 255 employing various fuzzy functions and control points (refer to Appendix 1). Suitability maps for each class were subsequently created, with no predefined constraints. The Analytical Hierarchy Process (AHP), as introduced by Saaty (1977), was implemented within TerrSet 2020 to establish weights for the standardised factors, ensuring a consistency ratio of 0.03 and 0.8 for the assigned weights for each LULC class. Compilation of class-specific suitability maps into a unified set was facilitated using the Collection Editor. Employing a conventional 5x5 contiguity filter and conducting 5 iterations of cellular automata in TerrSet 2020, a simulated LULC map for the year 2020 was developed based on the collection of suitability maps, utilising the 2008–2015 Markov transition area with the 2015 categorised LULC map serving as the base map.

2.2.7 Model Validation and future LULC Change Prediction

The validation of the model involved comparing the 2020 predicted LULC classified map with the actual map, resulting in a kappa index of 82%. Consequently, the predicted LULC map was derived from the simulated LULC, serving as the basis for the 2030 model forecast under “BAU" and "remedial" scenarios.

2.2.8 Limitation of the study

The CA-Markov model used for the future prediction heavily relies on historical data and may not easily integrate real-time data or events, limiting its adaptability to rapidly changing land use patterns driven by economic, environmental, or policy factors. Notably, it struggles to capture the full complexity of emergent policy interactions and feedback loops. Despite these limitations, the CA-Markov model remains an invaluable tool for providing accurate forecasts of future land use changes.

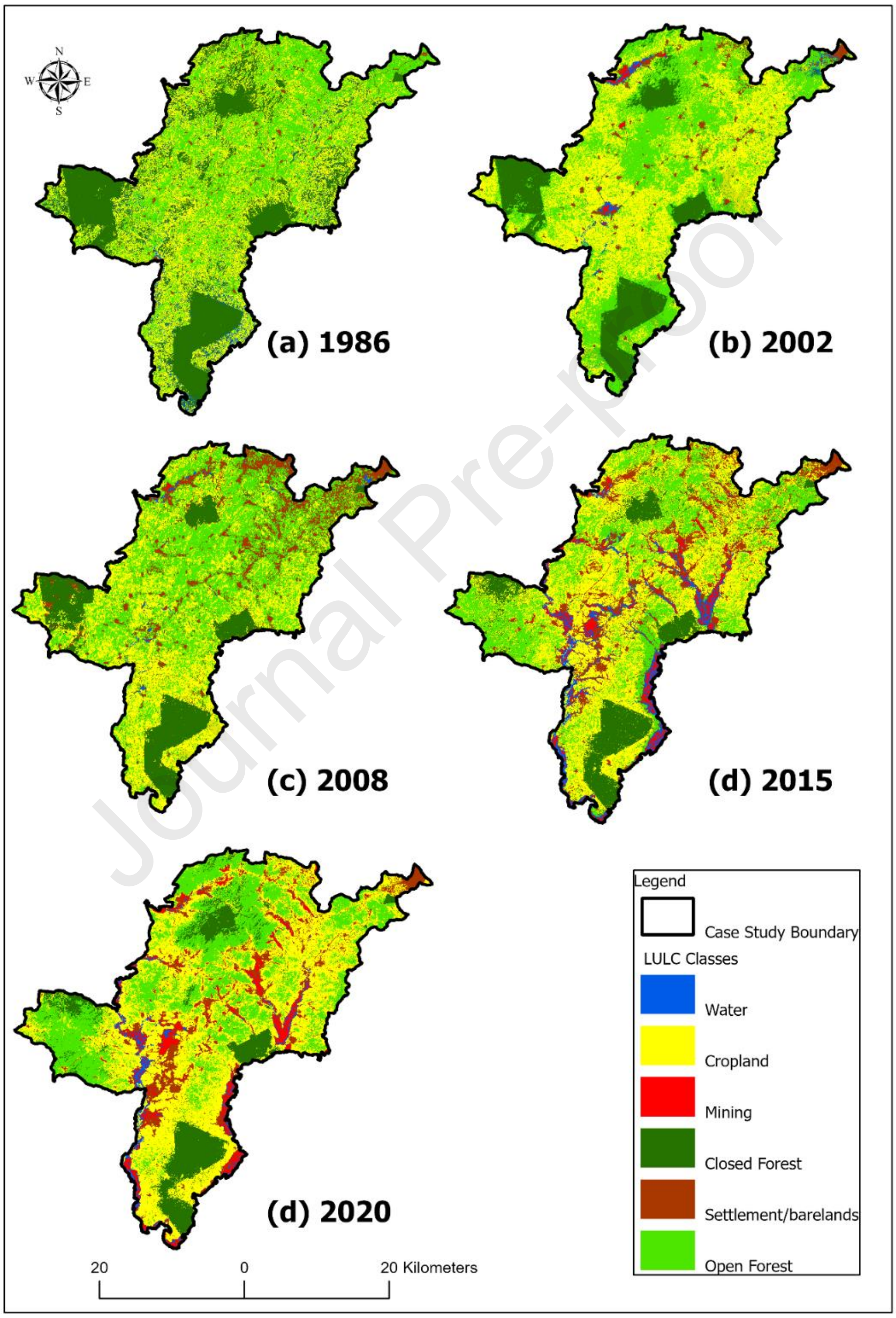


Map 2. Suitability maps for each land use and land cover class and the input datasets used in its generation. (a) Water (b) cropland (c) mining (d) Closed Forest (e) Settlements/ bare lands (f) open forest are suitability maps. (g) slope (h) DEM (i) Population Density (j)river (k) secondary roads (l) tertiary roads (m) major settlements are input map

3. Results and Discussion

3.1 Analysis of the LULC changes and their associated ecological footprints

Map 3 illustrates five LULC maps across the AWSD, encompassing six macro classifications: closed forest, open forest, farmland, water, mining, and settlement/bare lands for the years under study (1980, 2002, 2008, 2015, and 2020). Table 3 presents the percentages and corresponding statistics for these LULC categories over the specified years. The trends in LULC, evident in both Map 3 and Table 3, can be comprehended in connection with four distinct phases of LULC dynamics, which are elaborated upon below.



Map 3: LULC Classification Maps of the study area

Table 3: Area of LULC classes of the classification and the percentage area change results

LULC Classes	**1986**		**2002**		**2008**		**2015**		**2020**	
	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Water	4,798	3.90	1,800	1.46	963	0.78	6,169	5.01	3,484	2.83
Cropland	41,259	33.52	47,390	38.50	40,201	32.67	50,600	41.12	54,851	44.57
Mining	0.0000	0.00	480	0.39	98	0.08	4,276	3.47	5,589	4.54
Closed Forest	35,244	28.64	17,710	14.39	16,603	13.49	13,595	11.05	14,074	11.44
Settlement/bare lands	1,843	1.50	4,320	3.51	15,154	12.31	15,525	12.62	11,308	9.19
Open Forest	39,926	32.44	51,370	41.74	50,050	40.67	32,904	26.74	33,763	27.43
Total	123,070	100.0	123,070	100.0	123,070	100.0	123,070	100.0	123,070	100.0

3.1.1 First Phase: None to limited mining footprints

In Map 3a, no conspicuous physical evidence of mining activities is evident during the initial phase in the 1980s. However, oral histories indicate that artisanal miners utilised basic tools—such as pickaxes, shovels, and pans—on small land plots, resulting in faint traces of their work. Supporting this, an appointed assembly member and elderly resident from a study community affirmed the historically minimal ecological impact linked to mining activities as follows:

> "*Historically, this community was not well known for mining activities, though our forefathers did engage in some artisanal 'galamsey' activities. There were gold nuggets referred to as 'nkomra'. They dug deep holes on their farms to extract these golds nuggets. It was nothing like what is currently being done, where standing here [in front of a settlement shop] you can see a vast area degraded due to gold mining using mechanics" (ORH_04_AD).*

In this period, the predominant LULC comprised open forest, encompassing 32% of the total land area, and cropland, accounting for 34% of the total land extent, as indicated in Table 3. Subsequently, closed forests, predominantly situated within forest reserves, covered 29% of the total land area, amounting to 35,244 hectares. Natural water bodies, such as rivers, streams, ponds, and wetlands, occupied 4,798 hectares. Notably, the Offin and Oda rivers4,, along with their tributaries, served as the primary water sources during this period. Settlements were notably scarce in these areas.

3.1.2 Second Phase: Gradual to accelerated increase mining footprints

The classified map from 2002 (Map 3b) illustrates active mining activities and their associated social and environmental impacts during the second phase (late 1980s to early 1990s). In response to the escalating ecological effects of the mining industry and other sectors, the Ghanaian government established the Environmental Protection Agency in 1994. There was also a restructuring of the mining sector, providing substantial incentives for private entities (Akabzaa and Darimani 2001; Abdulai 2017), during this period. Consequently, licensed mining corporations primarily conducted mining activities. Specifically, in the study district, mineral licenses were granted to the Bonte Gold Mines in 1991 and to Amansie Resources Limited in 1994. Bonte Gold Mines operated for 13 years, while Amansie Resources Ltd operated for 8 years before being acquired by Resolute Amansie in 1997. The 'visible' footprint of mining activities (480 ha in 2002) was observed in the operational areas of these mining firms (Map34b). Remarkably, since 1986, there has been a notable increase in both open forest and crop land, with the former expanding from 32% to 39% and the latter from 34% to 42%. Human settlement areas also grew by 3.5%, accommodating the rising population. In contrast, closed forest areas significantly decreased from 35,244 hectares in 1986 to 17,710 hectares by 2002. By 2002, nearly half of the freshwater reserves in the district had depleted due to the disappearance of water puddles in forests. Moreover, the Offin river in the western part of the district, closer to Keniago, was concealed by trees, potentially due to illicit mining activities, such as river dredging in the upper reaches of the Offin in adjacent regions, contributing to the reduced downstream flow.

[4] *The Oda and Offin rivers are two major tributaries of the Pra River in Ghana. Together with the main Pra river, rivers Anum and Birim, and their tributaries, they form the largest river basin* of the three principal south-western basin systems of Ghana (i.e., Ankobra, Tano, and Pra). *The Pra River basin has a total basin area of approximately 23,200 km², with an area of* 1174 km^2 in the *Amansie West* and South Districts.

3.1.3 Third Phase: Sharp increases in mining footprint

From 2008 to early 2017, the third phase of gold mining in Ghana witnessed a significant upsurge in small-scale mining activities due to the escalating gold prices (Hausermann et al. 2018; Barenblitt et al. 2021). This era marked a significant ecological impact as advanced technology such as excavators and wash plants were introduced, establishing a lasting footprint on the environment of Ghana. Remarkably, it was during this period that other nationals, predominantly Chinese, and prominent political elite entered the small-scale mining industry. Research indicates a substantial level of collaboration and collusion between Chinese miners, Ghanaian miners, traditional leaders, and government officials, leveraging their positions for personal financial gain (Crawford et al. 2016, p.4). The land use and land cover dynamics in 2008 and 2015, depicted in Map 3c and 3d, illustrate fluctuations in mining activity. Map 3c showcases a decline in mining operations in the initial half of 2008, followed by a subsequent spike. The closure of significant licensed mining entities notably contributed to this initial decrease. Environmental degradation and disputes led to the revocation of licenses for Bonte Gold Mines in 2004 and the suspension of operations by Resolute Amansie in 2002, likely influenced by a downturn in gold prices during that time. Additionally, conflicts and the outbreak of Buruli ulcer in Tontokrom and adjacent communities, as reported by Freiku (2005) and Owusu-sekyere (2012) respectively, likely contributed to the decline in mining activities.

Table 3 shows the significant expansion of mining activities between 2008 (98 hectares) and 2015 (4,276 hectares), amounting to 3.5% of the total land area. Concurrently, from 2002 to 2008, the land allocated to settlements or left barren increased from 4,320 hectares (3.5%) to 15,525 hectares (12.7%). This rise in barren areas can be attributed to land clearance for agriculture and mining, accompanied by the construction of structures to accommodate the increasing number of miners in the region. The change in land use is evident in the reduction of agricultural land from 47,390 hectares (38.5%) in 2002 to 40,200 hectares (32.7%) in 2008. Similarly, the open forest area decreased from 51,370 hectares (41.7%) in 2002 to 50,050 hectares (40.7%) in 2008. Water primarily from mining pits, land surfaces, and redirected river channels increased over time, tripling from 1,800 hectares (1.5%) in 2002 to 6,170 hectares (5%) in 2015. This confirms a similar study conducted by Hausermann et al. (2018) along sections of the Offin River, highlighting a substantial 13,000% increase in mine water coverage, expanding over 200 hectares between 2008 and 2013. These findings validate the widespread increases in mine water as a land cover class in mining environments within this study. Predominantly, small-scale mining operations concentrated along the courses of major rivers—namely, the Offin and Oda Rivers. Alluvial gold dredging notably expanded the drainage basins of these rivers, consequently augmenting water accumulation. Moreover, diversion of river sources to distant locations for gold ore washing further contributed to the rise in water volume. Resultantly, effluents gather on the land and in abandoned mining pits. The substantial surge in water coverage largely stems from the development of numerous water-collecting mining pits and the accumulation of water both on land surfaces and into the primary river systems of the study districts. In 2015, the area of closed forest reduced further to 13600 hectares (11.05%), reflecting a continued long-term trend of forest area diminution.

3.1.4 Fourth Phase: Gradual decrease in mining footprint

From 2017 to 2021, a significant surge in public opposition to illegal small-scale gold mining practices occurred due to severe environmental repercussions, including deforestation, land degradation, and water contamination. The public, alongside governmental efforts, led a movement against these activities. Between March 2017 and December 2018, all forms of small-scale mining were prohibited, enforced by a combined military and police task force, resulting in the arrest of defiant miners and the confiscation of mining equipment. Ghana took further action on May 1, 2019, imposing a temporary restriction on excavator imports to tackle illegal mining. Despite prior attempts to curb unlawful mining between 2008 and 2015, the activities persisted, although at reduced rates. Research by Forkuor et al. (2020) aligned with this, showing a decline in illegal mining in southwestern Ghana from 2015/2016 to 2018/2019. Conversely, Nyamekye et al. (2021) reported an increase in scale mining activities in eastern Ghana between the period 2017 to 2018.

The data from this current study illustrated in Table 3 reveals an expansion in mining areas from 4,280 ha (3.5%) in 2015 to 5,590 ha (4.5%) in 2020. In 2015, water decreased significantly by nearly a half. However, there was an increase in the total area of croplands from 50,600 ha (41.1%) in 2015 to 54,850 ha (44.6%) in 2020, facilitated by a government initiative known as "planting for food and jobs." This program provided farmers with resources like free seedlings and nutrients, enabling increased agricultural land use. Both closed and open forest cover saw slight increases from 2015 to 2020, with closed forest expanding from 13,595 ha to 14,070 ha, and open forest growing from 32,900 ha (26.7%) to 33,760 ha (27.4%). By 2020, settlements and bare land decreased, demonstrating a change in land use patterns. The reduction primarily resulted from the decrease in bare lands, specifically those allocated for mining activities that were exhausted. Additionally, the joint military and police operations during that period likely contributed minimally to the creation of new bare land.

3.2 Analysis of the trend and patterns of the LULC changes

Fig. 2 provides visual representations while Table 4 offers numerical summaries of the LULC changes from 1986 to 2020. Four distinct phases in LULC dynamics are identified, showcasing significant changes experienced by AWSD during these periods. Notably, prominent changes in LULC occurred between 2002-2008 and 2008-2015, evident in both Fig. 2 and Table 4.

During 1986-2002, closed forest diminished by half of its original size (17,534 ha), while water bodies reduced by over 60% (Table 4). The most substantial increase, a 134% rise, was observed in settlements and bare land, expanding by 2,478 ha. Only approximately half of the original settlement/bare land shifted to other LULC categories. Open forest expanded by 11,444 ha, and cropland increased by 6,130 ha, representing 28.66% and 14.86% of the total increments, respectively. Around 50.82% and 61.78% of open forest area changed to different vegetation types. The farmland witnessed changes, with 48.22% converted from other land uses and 54.92% converted into other land uses.

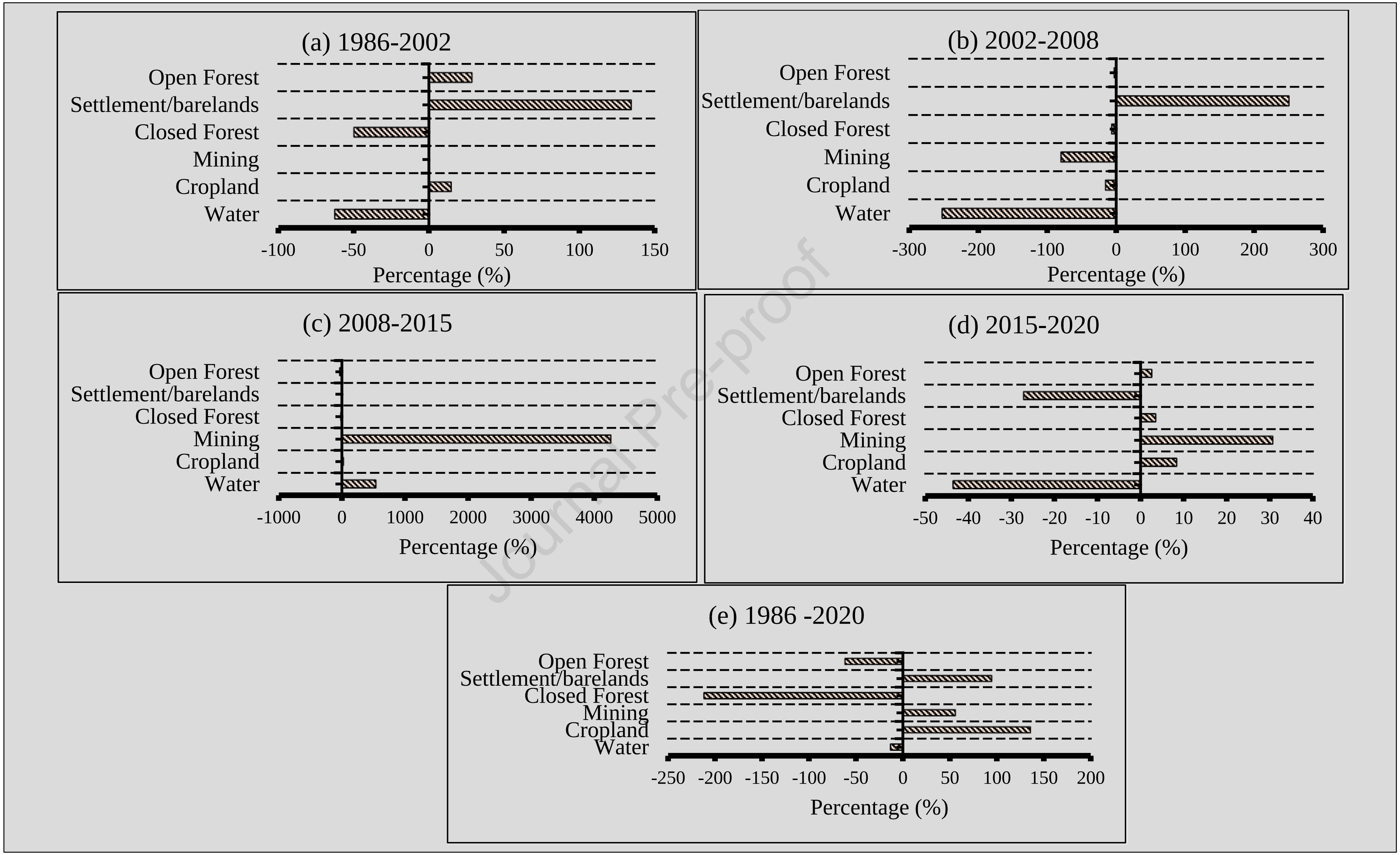


Fig. 2: Comparison of land use and land cover increases and decreases from 1986–2002, 2002–2008, 2008-2015, 2015-2020, 1986-2020

Table 4: Net Area of Change and the percentage changes in the observed LULC classes

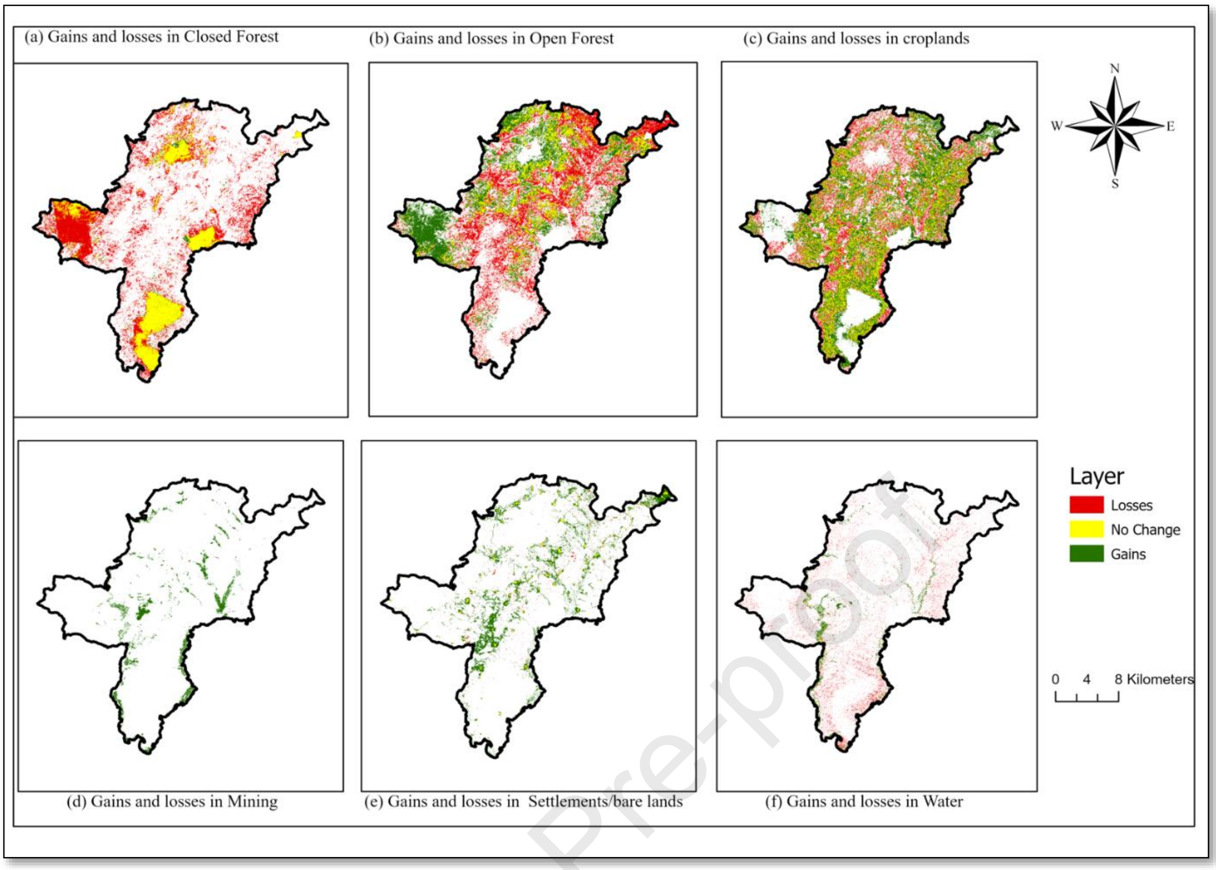
	1986-2002		**2002-2008**		**2008 - 2015**		**2015-2020**		**1986-2020**	
LULC Classes	Net area of change (Ha)	% Change	Net area of change (Ha)	% Change	Net area of change (Ha)	% Change	Net area of change (Ha)	% Change	Net area of change (Ha)	% Change
Closed Forest	-17534	-49.75	-1107	-6.25	-3008	-18.12	479	3.53	-21170	-60.06
Cropland	6130	14.86	-7188	-15.17	10399	25.87	4251	8.40	13593	32.94
Mining	483	0.00	-386	-79.75	4178	4266.73	1313	30.70	5589	100.00
Open Forest	11444	28.66	-1320	-2.57	-17146	-34.26	859	2.61	-6163	-15.43
Settlement/ bare lands	2478	134.45	10834	250.76	371	2.45	-4217	-27.16	9466	513.67
Water	-2996	-62.45	-839	-46.52	5207	540.87	-2685	-43.53	-1314	-27.38

Between 2002 and 2008, there was a decline in all LULC categories except settlement/bare lands. Remarkably, there was a substantial net increase in the settlement/bare land area by 10,834 hectares, marking a 251% rise. Only 25% of settlement/bare land transitioned to other LULC types, while 79% of all other land categories converted to these uses. Following settlement/bare lands, the most significant changes were observed in mining (80% decrease, resulting in a marginal net loss of 386 hectares) and water (-47% decrease, leading to an 839-hectare loss). Closed forest cover decreased by 1,107 hectares (6%) during this period, with the most significant net area loss occurring in cropland (7,188 hectares), while open forest experienced a smaller loss of 1,320 hectares. Approximately 58% of arable land was reassigned to other LULC classifications, and a similar amount was gained (51%).

The trends in LULC changes from 2002-2008 mirrored those observed between 2008-2015, indicating a consistent long-term pattern. The most substantial changes occurred in mining and water categories, both experiencing notable net gains in area during the preceding period. Simultaneously, all other LULC categories experienced net losses. Mining and water accounted for most recorded changes, with net gains of 4,178 hectares and 5,207 hectares, respectively. Nearly the entire extracted land came from other LULC classes. Closed forest (3,008 hectares) and open forest (17,146 hectares) saw significant net losses, representing 34% and 18% of the observable changes, respectively. However, cropland reversed its prior losses to register a net gain of 10,399 hectares, constituting 26% of the total changes. Settlement area saw a minor increase of 371 hectares, representing only 2% of the overall change during this period.

From 2015 to 2020, mining and water classes remained the most dynamic, accounting for 31% and 44% of observed changes, respectively, with a net gain of 1,313 hectares and a net loss of 2,685 hectares in area. Settlements/bare lands experienced a net loss of 4,217 hectares, marking a 27-percentage point change. Open forest area increased by 859 hectares, and closed forest increased by 479 hectares. Some net gains were recorded in cropland area (4,251 hectares), contributing to 8% of the total changes, but these gains were relatively small.

The changes in land use and land cover types between 1986 and 2020 are illustrated through change maps in Map 4 (a-f). Green and red layers represent areas gained or lost to other land uses and cover types, respectively, for each category. The yellow layer indicates areas that have remained unchanged over time. These changes highlighted in Map 4 signify significant changes over four periods, aligning with the distinct phases of LULC dynamics discussed previously. In examining the change maps from 1986 to 2020 (Map 4), notable deforestation is evident due to the conversion of open forest and closed forest land cover to other uses. Conversely, mining, croplands, and settlements/bare lands experienced substantial growth during this period. Specifically, mining activities intensified along the Oda and Offin rivers.



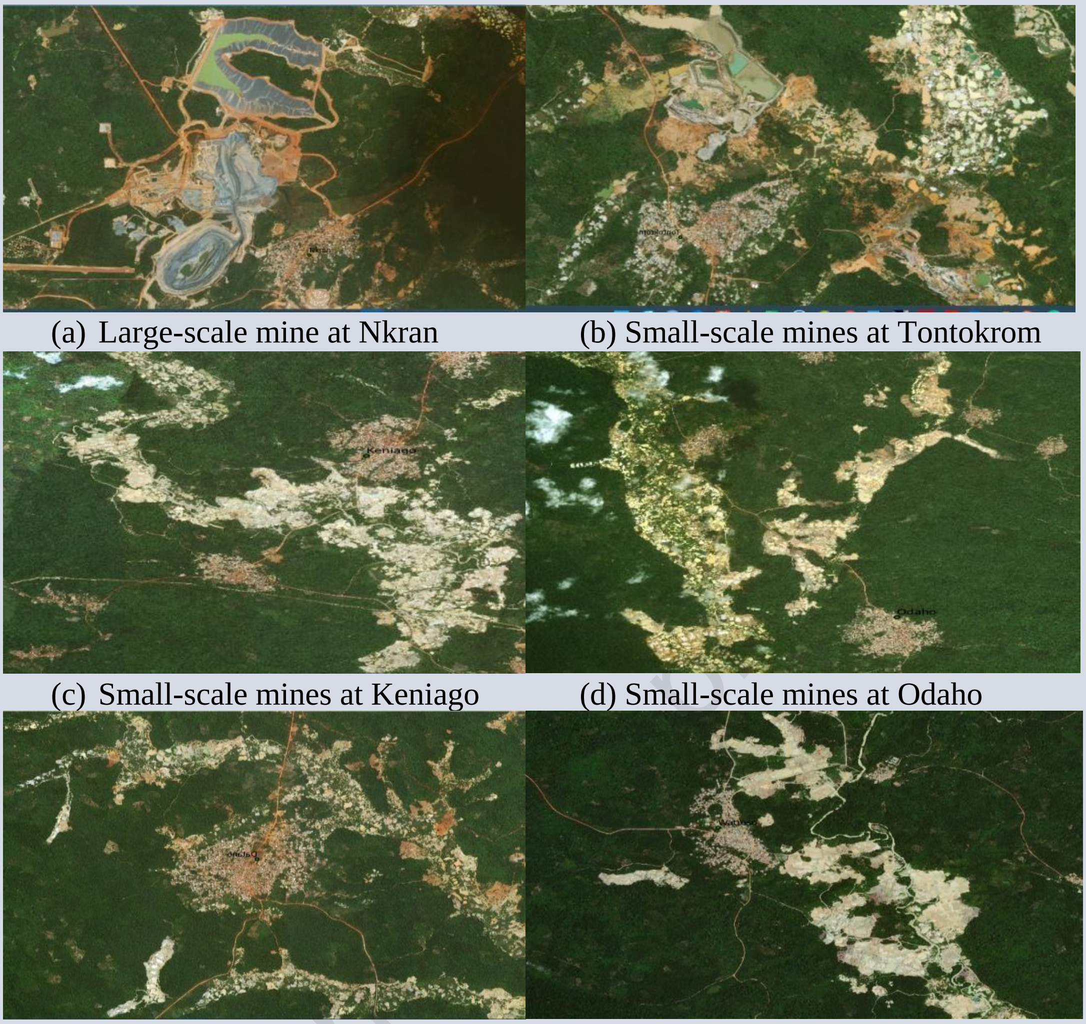
Map 4: The gains and losses in land use and land cover classes over the period 1986 to 2020.

'Gains' represent an increase in a particular land use and land cover type, 'Losses' represent a decrease in a particular land use and land cover type and 'No change' represent no change in a particular land use and land cover.

3.3 The driving forces initiating and perpetuating LULC changes and their associated footprints

The observed trends and patterns of LULC changes result from a myriad of causes and events. Simplifying these variables poses a challenge (Lambin et al. 2001). (Geist and Lambin 2002) categorised these causes into proximate and underlying factors. Proximate driving forces stem from human activities and immediate local actions that shape planned land use and impact land cover. Conversely, underlying factors are dominant social processes that directly influence national or international levels or reinforce proximate causes at the local level (Geist and Lambin, 2002).

Despite occupying a relatively small area compared to other land uses, mining significantly influences the observed patterns and trends, alongside its associated ecological footprint, according to the interviews and field observations. Small-scale gold mining activities directly cause three main ecological footprints: land degradation, water pollution and diversion, and deforestation. Significant land deterioration was observed due to the use of excavators and other sophisticated machinery for gold extraction, spanning a substantial area (refer to Map 5).



(a) Large-scale mine at Nkran (b) Small-scale mines at Tontokrom

(c) Small-scale mines at Keniago (d) Small-scale mines at Odaho

(d) Small-scale mines at Datano (e) Small-scale mines at Watreso

Map 5: A collage of satellite imagery showing the extent of land degradation from mining in 2020

Source: ESRI (2021) High Resolution 30cm Imagery

The cartographic representation in Map 5 illustrates the extent of land degradation within the primary communities of the study area. Data acquired from interviews and field observations corroborate these degradation patterns and reveal various causative factors. Notably, the adoption of advanced mining techniques by foreign nationals, particularly the Chinese, has significantly contributed to environmental ramifications. This aligns with findings of Hilson and McQuilken (2014); Crawford et al. (2016); and Owusu-Nimo et al. 2018), emphasising extensive Chinese involvement in the mining industry of Ghana and the utilisation of high-tech equipment. Addressing the profound impact of advanced Chinese technology on LULC changes, a local miner succinctly conveyed as follows:

> “Had the Chinese operations persisted, our forests would have been obliterated by now. What takes a local miner months to clear, the Chinese accomplish in days due to their superior technology” (SSI_003_M).

This perspective illuminates the substantial consequences of technological advancements as a key driver of land cover changes, echoing the shared apprehensions of a significant portion of the participants of the study.

The lax enforcement of laws exacerbates the extent of land degradation. The regulatory bodies, the Mineral Commission and the Environmental Protection Agency, mandated by law to oversee mining operations and land reclamation, have been found lacking. A report by the Ghana Audit Service (2021) revealed their failure to implement reclamation bonds, overlook submission of operating plans, neglect monitoring of reclaimed lands, and take no action to enforce pre-agreed land reclamation conditions before mining commences.

Secondly, the natural water resources, particularly the Oda and Offin rivers, suffer adverse effects from excessive water withdrawal through surface water diversions for mineral ore processing and dewatering mining zones. Illicit small-scale extraction of alluvial gold using mercury from riverbeds further impacts both the quality and quantity of these rivers. This destruction extends to smaller water bodies such as streams and ponds, crucial for household functions, significantly diminishing river water quality over time. The research participants unanimously affirmed that small-scale gold mining severely pollutes the main rivers and streams in the towns, rendering them unsuitable for human consumption or agricultural purposes. Apau and Enyemadze (2014) conducted a study involving drinking water samples collected from boreholes, hand-dug wells, and streams across 23 communities in the study area. Their findings revealed arsenic concentrations ranging between 0.24-37.22 µg/L in streams, 13.49-26.41 µg/L in boreholes, and 24.11-39.43 µg/L in hand-dug wells. On average, the study indicated that 61%, 69%, and 68% of the total arsenic constituted the more toxic arsenic (III) form in boreholes, hand-dug wells, and streams, respectively.

Fig. 3 illustrates the significant murkiness evident in parts of the Oda and Offin rivers due to this pollution. Consequently, former fishermen in these areas no longer have access to fishable waters. The pollution not only diminishes the water supply but also escalates the cost of obtaining clean, drinkable water. Interviews with vegetable farmers revealed their reliance on these water sources for year-round irrigation. Nonetheless, due to contamination from the mines, some farmers are compelled to use unsuitable mine pit water for irrigation, despite its inappropriateness for human consumption. The presence of dissolved toxins in this mining pit water raises concerns about potential contamination in the food chain over time.

Fig. 3: (a) The polluted Oda River at Watreso (b) The polluted Offin at Keniago

The examination of interviews revealed that mining significantly impacts water resources beyond its immediate vicinity, leading to direct and indirect ecological consequences. For example, despite treating the polluted River Oda, the Ghana Water Company Limited utilises it as a water reservoir to provide drinking water to communities situated far from the mining areas (see Fig. 4). This practice escalates the cost of purifying water due to increased chemical usage. Moreover, substantial amounts of purified water are wasted, resulting in inadequate and unsafe water supply to reliant communities.

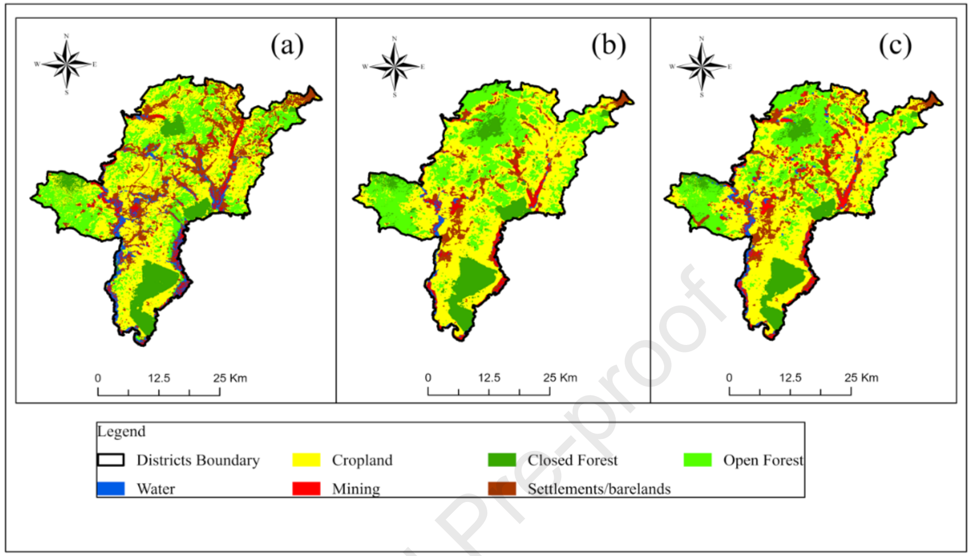
Fig. 4: Turbid water from Oda River undergoing treatment to be used as drinking water

Mining operations directly contribute to the depletion of forest cover, a correlation extensively documented in the escalating trends of mining activities. Through a comprehensive examination involving interviews, focus groups, and field observations, it was evident that extensive areas of farmland were repurposed into mining sites. This change was substantiated by our on-site investigations, revealing a consequential outcome: numerous farmers increasingly clearing forested areas to accommodate agricultural activities. The remote sensing and geospatial analysis confirmed a disconcerting reality, showcasing a loss of 36 percent of all forest cover (comprising both open and closed forests) between 1986 and 2020, amounting to 27,333 hectares. This translates to an annual deforestation rate of 1.07 percent, surpassing the 0.4% to 0.7% rates recorded by Acheampong et al. (2019) in the Ashanti Region between 1990 and 2015. This disparity underscores the higher deforestation rates within mining zones. The accelerated pace of deforestation has been associated with a reduction in ecosystem services and a decline in biodiversity, echoing established findings in various studies (Pereira et al. 2012; Costanza et al. 2014; Acheampong et al. 2019; Zabel et al. 2019; Hasan et al. 2020). Furthermore, it influences regional climate and weather patterns (Click or tap here to enter text..

While mining was highlighted as the primary immediate cause of observed changes and their ecological repercussions, participants also recognised logging, construction, and agricultural expansion as contributing factors. Inadequate law enforcement, coupled with the utilisation of advanced technologies, along with population growth (including immigration), agricultural challenges, unemployment, and poverty, were cited as additional factors. The forthcoming section of this study will forecast LULC changes and their correlated ecological impacts over the next decade to offer valuable insights for policymaking.

3.4 Prediction of future LULC changes

This section undertakes LULC predictions for the 'remedial' and 'business as usual' scenarios discussed in Section 2.2.6. The comparison in Map 6 shows the predicted LULC maps for 2030 under both scenarios against the 2020 map generated through simulations. Related statistics are detailed in Table 4. The remedial LULC modification scenario suggests a potential reduction in land degradation and deforestation, promising an enhanced local landscape and improved wellbeing for inhabitants. Projections indicate a decrease in all land uses, except for a modest 1.62% increase in cropland by 887 hectares, maintaining a positive trajectory compared to 2020 standards. Forest land cover is anticipated to show improvement in this context.



Map 6: Simulated and Predicted LULC Maps (a) Simulated LULC map of 2020 (b) Predicted LULC Map of 2030 under 'remedial' scenario (c) Predicted LULC Map of 2030 under BAU scenario.

Table 4: Area and percentage of LULC classes of 2020 classified and the predicted LULC for 2030 under remedial and business as usual scenarios

	2020 LULC		**2030 LULC 'Remedial' Scenario**		**2030 LULC 'BAU' Scenario**		**2020 to 2030 'Remedial' Scenario**		**2020 to 2030 'BAU' Scenario**	
LULC Classes	Area (Ha)	% Area	Area (Ha)	% Area	Area (Ha)	% Area	Net area of Change (Ha)	% Change	Net area of Change (Ha)	% Change
Water	3,484	2.83	2,465	2.00	4,082	3.32	-1,019	-29.25	599	3.36
Cropland	54,851	44.57	55,738	45.29	54,139	43.99	887	1.62	-712	-0.18
Mining	5,589	4.54	4,925	4.00	6,997	5.69	-663	-11.87	1,409	2.24
Closed Forest	14,074	11.44	15,236	12.38	12,525	10.18	1,162	8.25	-1,549	-0.63
Settlements/ bare land	11,308	9.19	8,951	7.27	15,772	12.82	-2,357	-20.85	4,464	1.23
Open Forest	33,763	27.43	35,752	29.05	29,552	24.01	1,990	5.89	4,210	0.26

Additionally, anticipated changes in LULC in the study area suggest a decline of 1,019 hectares (29%) in water and 663 hectares (12%) in mining activities. The interrelation between water and mining operations is evident, where reduced mining leads to less water accumulation in mine pits. Consequently, costs associated with treating drinking water, malaria prevalence, drowning risks, and other adverse effects linked to increased water-filled mine pits are expected to decrease. Furthermore, a 21% reduction in land used for settlements and bare lands is projected, primarily attributed to deforestation for mining purposes, resulting in less bare land. Forests are anticipated to experience a positive change under the remedial scenario, with an expected increase of 1,162 hectares (6%) in open forest and 1,990 hectares (8%) in closed forest. These increments stem from natural forest regeneration following reduced human intervention. However, further improvements in forest cover necessitate comprehensive initiatives focused on land reclamation and tree replacement. Simplification of regulations is imperative to ensure goal attainment, with strict criteria for land reclamation contracts to be awarded exclusively to reputable firms.

Contrarily, the 'business as usual' scenario foresees expansions in certain land uses and cover classes compared to the remedial LULC scenario. It is anticipated that water and mining land uses will expand by 599 hectares (3%) and 1,409 hectares (2%), respectively, from their 2020 projections. Predicted reductions in croplands by 712 hectares (0.18%) and closed forests by 1,549 hectares (0.63%) will notably impact smallholder farmers, who constitute the majority of the farming community in Ghana. Given that approximately 95% of farmlands in use are smaller than 10 hectares, with an average size of less than 1.6 hectares (Environmental Protection Agency 2020), these changes could displace around 445 farmers by 2030 under the 'business as usual' LULC change scenario for cropland. Moreover, the study predicts an increase of 4,464 hectares (1.23%) in settlements/bare lands and 4,210 hectares (0.26%) in open forest by 2030 under the 'business as usual' scenario. These projections underscore the potential repercussions of continuing current land use trends, especially concerning smallholder farmers and the landscape's ecological balance.

4. Conclusions and recommendation

This paper quantifies the dynamics of LULC changes, their associated footprints, and the driving forces initiating and sustaining these changes. Future projections, encompassing both "business as usual" and "remedial" outcomes, have been established. Four distinct phases of LULC dynamics for mining footprints have been identified: zero to low, slow to moderate, rapid to extreme, and steady decline. Land degradation, deforestation, and water pollution and diversions are directly and indirectly linked to these LULC dynamics, primarily stemming from mining activities. Degradation occurs across substantial regions, causing a decrease in both the quality and quantity of natural water supplies, significantly impacting individuals and communities. Over a 34-year period, forest resources diminished by 27,333 hectares, representing a 36% loss in forest cover due to an average annual deforestation rate of 1.07%. Using the CA-Markov model, the study predicts a rise in mining and water usage, adversely affecting forest ecosystems in a business-as-usual scenario. However, under a remedial scenario, the analysis foresees the preservation of forest ecosystems and livelihoods. Despite its smaller spatial coverage compared to other LULC classes, mining is intricately linked with and significantly influences observed LULC trends. The study advocates for the integration of remote sensing/geographic information systems (RS/GIS) and social sciences approaches in analysing LULC changes, asserting that their combination yields more comprehensive, robust, and nuanced insights than either approach in isolation.

Appendices

Appendix 1

Factors (s)	Membership function type	Membership function shape	Control points
Slope (^{o})	Linear	Monotonically decreasing	c = 0, d = 15
Eleven (m)	Sigmoidal	Symmetric	a = 95, b = 185 c = 190, d = 618
Proximity to rivers (m)	J Shaped	Monotonically decreasing	c = 160, d = 3000
Proximity to major settlements (m)	Sigmoidal	Symmetric	a = 225, b = 2700 c = 3000, d = 22000
Proximity to secondary roads (m)	J Shaped	Monotonically decreasing	a = 280, b = 3000
Proximity to tertiary roads (m)	J Shaped	Monotonically decreasing	a = 80, b = 1400
Population density (people per km^2)	Sigmoidal	Symmetric	a = 20, b = 60 c = 80, d = 420

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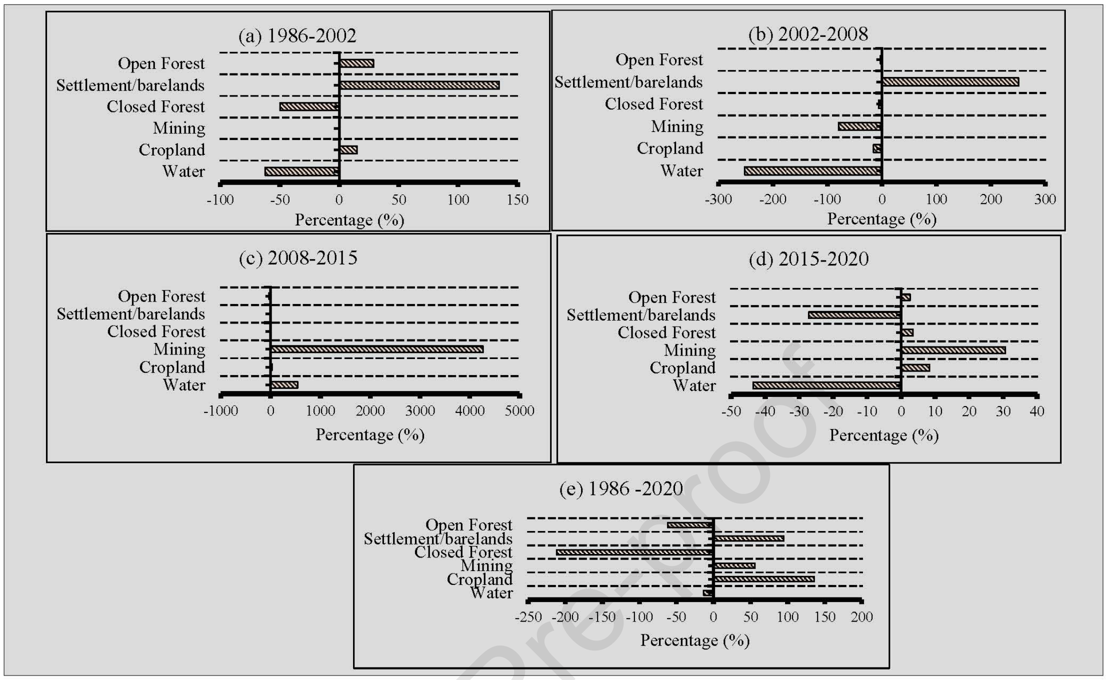
(a) 1986-2002
Open Forest
Settlement/barelands
Closed Forest
Mining
Cropland
Water
-100 -50 0 50 100 150
Percentage (%)
(b) 2002-2008
Open Forest
Settlement/barelands
Closed Forest
Mining
Cropland
Water
-300 -200 -100 0 100 200 300
Percentage (%)
(c) 2008-2015
Open Forest
Settlement/barelands
Closed Forest
Mining
Cropland
Water
-1000 0 1000 2000 3000 4000 5000
Percentage (%)
(d) 2015-2020
Open Forest
Settlement/barelands
Closed Forest
Mining
Cropland
Water
-50 -40 -30 -20 -10 0 10 20 30 40
Percentage (%)
(e) 1986 -2020
Open Forest
Settlement/barelands
Closed Forest
Mining
Cropland
Water
-250 -200 -150 -100 -50 0 50 100 150 200
Percentage (%)

Ethical considerations were taken into account throughout the data collection, analysis and writing processes, with approval received from the Human Research Ethics Committee of the Open University (Reference: HREC/3390/Jacob Obodai).

Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☒ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Jacob Obodai reports financial support was provided by The Open University Faculty of Arts and Social Sciences. Jacob Obodai reports travel was provided by The Strategic Research Areas (SRA) - The Open University. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.