

Land Use and Cover Change in Watersheds within Mining Tenements in Agusan Del Norte, Philippines

Roger Sarmiento^{1,*}, Rex Victor Cruz², Cristino Tiburan, Jr. ², Marisa Sobremisana³ and Nathaniel Bantayan²

¹Department of Forestry, College of Forestry and Environmental Sciences, Caraga State University, Ampayon, Butuan City, Philippines

²Institute of Renewable Natural Resources, College of Forestry and Natural Resources, University of the Philippines Los Baños, College, Los Baños, Laguna, Philippines

³School of Environmental Science and Management, University of the Philippines Los Baños, College, Los Baños, Laguna, Philippines

Abstract. Mining is widely regarded as a key driver of land use and land cover changes, especially in watersheds where it operates. However, when conducted responsibly, mining can also contribute to landscape conservation and protection. This study analyzed land use and cover changes within watersheds in mining tenements from 2000 to 2020 using a combination of supervised and unsupervised satellite image classification techniques. Results indicated that water bodies, croplands, and forestlands decreased by 5.87%, 84.95%, and 4.08%, respectively, while built-up areas expanded by 577.33%. Water bodies showed an increase where areas near drainage systems were opened or repurposed. Barren land surged, largely due to road construction and development activities. Binary logistic regression identified distance from roads and elevation as the most influential factors driving these changes, with coefficients of -3.729 and 2.775, respectively. Interestingly, mining activities were found to be non-significant contributors to land use and cover change during the study period.

1 Introduction

Land use and land cover change (LULCC) refers to human-induced alterations of the Earth's terrestrial surface [1-4]. This complex and dynamic process, which has been ongoing for centuries, has significant environmental implications that impact essential life-support functions and livelihoods [5-7]. Such changes are driven by both direct and indirect human activities aimed at securing critical resources [8]. Although changes to the Earth's surface can occur gradually, they often happen rapidly due to both natural and anthropogenic factors [9-10], leading to widespread and accelerating impacts on human populations and natural ecosystems [11].

* Corresponding author : rtsarmiento@carsu.edu.ph

Human-induced factors, including deforestation, wetland drainage, overgrazing, and the expansion of agriculture, industry, and urbanization, are the most immediate causes of LULCC [10, 12-14]. Natural forces, such as earthquakes, landslides, droughts, and floods, also play a role [15-16]. These changes arise from complex interactions between socioeconomic, cultural, and policy factors within the biophysical environment. As a result, they affect the availability of key resources, such as soil, vegetation, water, and animal feed, potentially reducing access to essential goods and services for human populations, livestock, and agricultural systems, while simultaneously causing environmental degradation.

Effective management of Earth's surface resources requires timely and accurate detection of land-cover changes, which helps to understand the interplay between human activities and natural processes [17]. Urbanization, driven by increased industrialization [18], has led to population growth in cities and the depopulation of rural areas, with its effects observed globally.

The Caraga Region (Region XIII) of Mindanao, Philippines, is renowned for its vast nickel reserves and is one of the country's major mineral contributors. Large-scale surface mining operations in the region have generated economic benefits, including employment and wealth, but have also resulted in severe environmental damage and the erosion of traditional societal values. Despite the evident impact of mining, there is a limited understanding of LULCC trends in watersheds where these mining operations are located. This gap in knowledge hinders effective watershed-level planning and management.

Mining is often seen as a major driver of land use and cover changes in watersheds where it operates. However, in some cases, responsible mining practices have been linked to landscape conservation efforts [19]. To better understand LULCC in these areas, it is crucial to conduct studies that clearly reveal the patterns, dynamics, and underlying drivers of change. Advanced technologies such as remote sensing, geographic information systems (GIS), and stochastic modelling can be used to investigate LULCC dynamics [20-22].

2 Materials and Methods

2.1 Study area

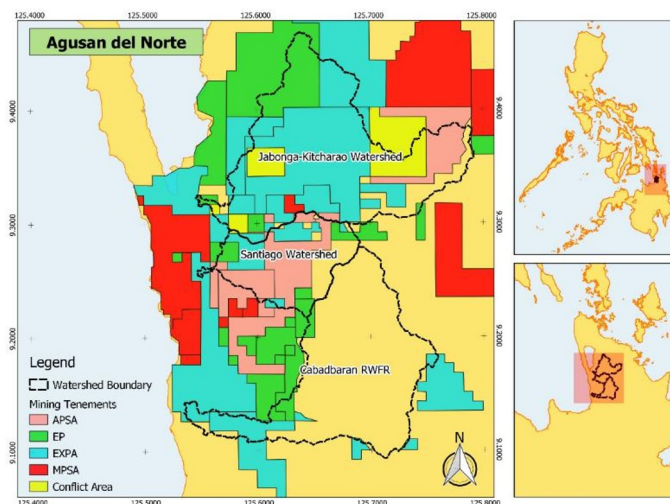


Fig. 1. Location of mining tenements and the three study watersheds.

The three watersheds are located within the geographic coordinates of 9.09° to 9.47° N latitude and 125.53° to 125.80° E longitude in Agusan del Norte, Philippines. The study area spans across five administrative regions: Cabadbaran City, Tubay, Santiago, Jabonga, and Kitcharao, encompassing a total area of roughly 53,009.37 hectares. Figure 1 illustrates the positions of the watersheds, along with the mining tenements that overlap them.

According to national census data, the population in the study area grew by 9.91% between 2015 and 2020, increasing from 164,614 to 180,929 residents [23]. This population growth is primarily due to natural increases driven by birth rates, as well as significant internal migration, particularly in regions near mining projects. Many migrants relocated to these areas in search of employment opportunities or improved access to infrastructure and services.

2.2 Data set types and sources

The datasets utilized in this study include Landsat 5 (MSS), Landsat 7 ETM+, and Landsat 8 (OLI/TIRS) satellite images, which were obtained from the United States Geological Survey (USGS) [24]. Additionally, administrative boundary shapefiles, as well as data on road and stream networks, rural communities, and existing villages within Agusan del Norte, were sourced from OpenStreetMap and Google Earth. These datasets were chosen based on their relevance as potential drivers of land use and land cover (LULC) changes, as indicated by the socio-economic survey conducted for the study. Table 1 provides a detailed list of the datasets and their respective sources.

Table 1. Dataset types and sources.

Dataset	Source	Resolution	Date
Landsat 5 MSS	U.S. Geological Survey	30 m	08/07/1997
Landsat 7 ETM+	U.S. Geological Survey	30 m	09/20/2010
Landsat 8 OLI/TIRS	U.S. Geological Survey	30 m	04/16/2020
Shapefiles	OpenStreetMap	-	05/01/2020

Due to the study area's location within a Type II Climate Zone, which experiences frequent rainfall and lacks a distinct dry season, acquiring a clear satellite image for the year 2000 was challenging. Consequently, Landsat 5 images from 1997 were used as a substitute. It is important to emphasize that significant mining operations in the region only commenced around 2006, meaning that no major land cover changes occurred between 1997 and 2000.

2.3 Driving forces of LULC change

A parallel study assessed land use and land cover change (LULCC) in the three neighboring watersheds by combining socio-economic surveys with GIS technology and remote sensing techniques. By integrating various datasets, this study identified key driving factors mentioned in previous research and employed them as independent variables for analyzing LULCC. These factors included elevation, population growth, distance from roads, rivers, and settlements, slope aspect, slope gradient, and soil classification. Table 2 presents the key driving forces of LULCC in the study area.

Table 2. Driving forces of LULC changes used in the analysis.

Driving forces	Type of force	Source of data
Population change	Socio-economic	PSA
Elevation	Physical	Digital elevation model
Distance from mining areas	Physical	Google Earth

Distance from roads	Physical	OSM
Distance from rivers	Physical	OSM
Distance from settlements	Physical	Google Earth
Slope aspect	Physical	Digital elevation model
Slope degree	Physical	Digital elevation model
Soil classification	Physical	BSWM

3 Methodology

3.1 LULCC detection

This study aimed to detect land use and land cover (LULC) changes from 2000 to 2020, serving as a basis for quantifying and mapping the shifts between different LULC categories. The Semi-Automatic Classification Plugin (SCP) in QGIS was utilized for processing and classifying satellite images to generate LULC maps. A combination of supervised and unsupervised classification techniques was employed, categorizing six LULC types: water bodies, barren land, built-up areas, agricultural land, grasslands, and forestlands. The classification process used the maximum likelihood method. To evaluate the accuracy, error classification matrices were generated for each LULC map. In total, 2013 points for the year 2000 and 4073 points for 2020 were selected for accuracy assessment. These validation points were randomly and manually chosen, utilizing both Google Maps and ground-truth data. The kappa index was used to determine classification accuracy, yielding values of 0.83 for 2000 and 0.90 for 2020. LULC changes were detected through a post-classification comparison using the MOLUSCE tool in QGIS, which helped identify spatial trends, gains, and losses in LULC over the study period.

3.2 The Logistic Regression Method (LRM) for quantifying driving forces

The Logistic Regression Model (LRM) was employed to quantify the influence of the driving forces (independent variables) identified in a parallel study. These driving factors were converted into raster format with a 30-meter resolution and analyzed using the proximity tool in QGIS. The dependent variable in this model is the occurrence of land use and land cover (LULC) changes, represented as a binary raster: a value of 1 indicates that a pixel experienced a change between 2000 and 2020, while a value of 0 indicates no change. The model assumes that the probability of LULC change (the dependent variable taking a value of 1) follows a logistic curve, which can be calculated using the formula:

$$P = (Y = 1|X) = \frac{\exp \sum_{k=0}^k b_k x_{ix}}{1 + \exp \sum_{k=0}^k b_k x_{ix}}$$

Where P is the probability of LULC change, X represents the independent variables, and b represents the estimated regression coefficients for each variable.

4 Results and Discussions

4.1 Accuracy Assessment

Table 3 displays the evaluation results for the image classifications from both time periods. The producer's and user's accuracy were derived from a confusion matrix. User's accuracy

across the different land cover categories ranged from 58.4% to 100%, while the producer's accuracy varied between 1.16% and 100%. The overall accuracy for the image classifications was 83.16% for the year 2000 and 90.43% for 2020. The kappa coefficients for the two periods were 0.492 and 0.704, respectively, indicating that the classification performance ranged from moderate to substantial, based on commonly accepted interpretations of kappa values [25-26].

Table 3. Accuracy statistics for the classification of years 2000 and 2020.

LULC Classes	2000		2020	
	PA (%)	UA (%)	PA (%)	UA (%)
Water	88.55	100.00	73.92	100.00
Barren land	93.37	98.92	95.16	77.88
Built up	01.16	100.00	40.95	100.00
Crop land	24.03	100.00	26.59	90.65
Grassland	34.19	58.04	56.12	89.92
Forestland	100.00	84.42	99.21	90.93
Water	88.55	100.00	73.92	100.00
Overall Accuracy	83.16%		90.43%	
Kappa Coefficients	0.492		0.704	

4.2 Land-use and land cover change analysis

The image classification results indicate significant land use and land cover change (LULCC) in the three watersheds from 2000 to 2020. Spatial maps illustrating these changes are presented in Figure 2. The primary driver of LULCC during this period was the expansion of open areas resulting from road construction and development activities. Most of these open areas appeared as small, scattered patches within agricultural and grassland regions. Built-up areas increased from 12.69 hectares in 2000 to 85.95 hectares by 2020. In contrast, forestland decreased by 5.08%, dropping from 46,787.13 hectares to 44,876.52 hectares. Cropland experienced a significant reduction from 1,077.30 hectares to 162.09 hectares, while water bodies saw a slight decline from 326.79 hectares to 307.62 hectares, as detailed in Table 4. Many of the transformed areas were converted into grasslands, less dense vegetation, barren lands, or croplands. Additionally, at higher elevations, some cropland areas were temporarily cleared for the cultivation of *Falcataria falcata* (Miq.) Barneby & J. W. Grimes or other tree-based forestry plantations [27-28].

Table 4. Land use and land cover change during 2000-2020.

LULC Class	Area (ha)				LULC change	
	2000	%	2020	%	Total (ha)	%
Water	326.79	0.62	307.62	0.58	- 19.17	- 5.87
Open area	929.88	1.75	1,841.67	3.47	911.79	98.05
Built up	12.69	0.02	85.95	0.16	73.26	577.30
Crop land	1,077.30	2.03	162.09	0.31	- 915.21	- 84.95
Grassland	3,875.58	7.31	5,735.52	10.82	1,859.94	47.99
Forestland	46,787.13	88.26	44,876.52	84.66	- 1,910.61	- 4.08
Totals	53,009.37	100.00	53,009.37	100.00		

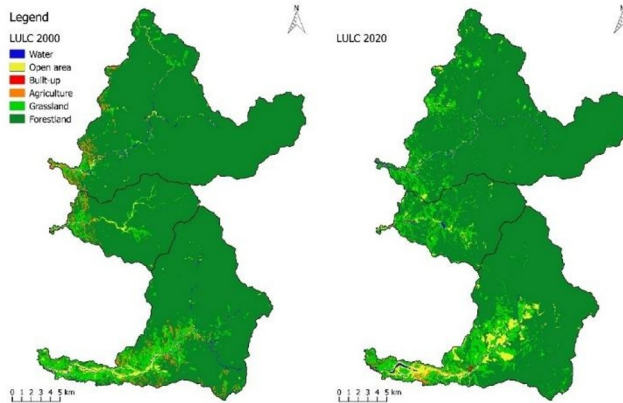


Fig. 2. Land use land cover in the study area in 2000 and 2020.

Overall, the data revealed a trend towards increased land conversion for mixed plantations and agricultural use. This shift indicates that expanded cultivation has contributed to deforestation, as certain protected forest areas were cleared and transformed into cultivated lands, including mixed plantations, tree plantations, and gradually expanding palm plantations.

The findings also highlighted a significant rise in built-up areas, which increased by approximately 577.30% between 2000 and 2020. This growth corresponded with a notable increase of 911.79 hectares in open areas, as illustrated in Figure 3. Consequently, the proportion of open areas within the total land area rose from 1.75% to 3.47%. In contrast, cropland and forestland experienced net losses of 915.21 hectares and 1,910.61 hectares, respectively, as depicted in Figure 2. Additionally, water bodies saw a minor decrease of 19.17 hectares during the same period.

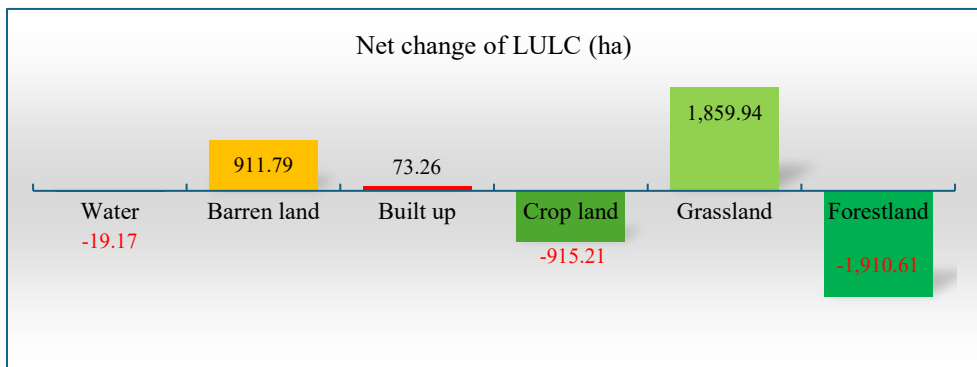


Fig. 3. Net changes in LULC in the study area from 2000 to 2020.

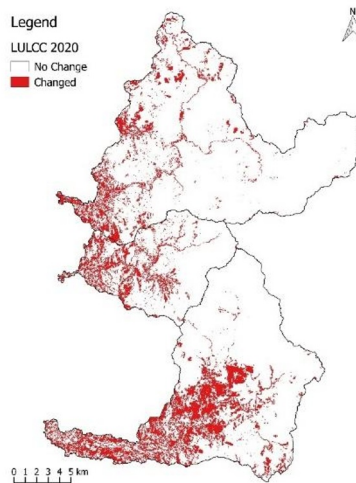
The LULCC analysis revealed that the net loss of water bodies primarily resulted from changes in barren land and forest areas (see Table 5). The expansion of barren land occurred at the expense of both grassland and forestland. Significant losses in cropland were mainly due to the conversion of grasslands and forests for other uses. Additionally, the increase in grasslands was largely linked to the loss of 3,375 hectares of forest.

Table 5. Land use and land cover change matrix from 2000 to 2020 in hectares.

LULC Classes		2020						Total
		Water	Barren	Built up	Crop	Grass	Forest	
2000	Water	102.06	73.08	0.27	1.26	37.44	112.68	326.79
	Barren	103.05	349.11	4.59	34.74	253.71	184.68	929.88
	Built up	-	0.81	9.63	-	2.16	0.09	12.69
	Crop	5.40	69.03	1.26	4.95	403.56	593.10	1,077.30
	Grass	46.71	639.45	63.36	88.56	1,662.93	1,374.57	3,875.58
	Forest	50.40	710.19	6.84	32.58	3,375.72	42,611.40	46,787.13
Total		307.62	1,841.67	85.95	162.09	5,735.52	44,876.52	53,009.37

4.3 Quantifying the influences of driving forces of LULC change

The impact of various driving forces on land use and land cover (LULC) changes in the three watersheds was analyzed using Binomial Logistic Regression. In this model, a map depicting LULC change in the study area from 2000 to 2020 served as the dependent variable for the logistic regression analysis. This map comprises two classes: LULC change (designated as changed LULC cells from 2000 to 2020), where $y=1$ indicates a change, and $y=0$ signifies no change. Figure 4 illustrates the dependent variable (Y).

**Fig. 4.** LULC changes from 2000 to 2020.

In this model, nine driving forces (variables) were utilized: distance from roads, proximity to mining areas, distance from rivers, distance from settlements, elevation, slope, aspect, population change, and soil classification (see Figure 5). The study did not incorporate other potential proximate drivers, such as enforcement of laws and regulations, government initiatives, policies, or regulations from the Department of Environment and Natural Resources (DENR), due to insufficient spatial data. The relationship between land use and land cover change (LULCC) and these driving factors was analyzed based on the number of pixels in proximity to the independent variables. Variables with higher coefficient values indicated a greater likelihood of change, while the sign of the coefficient (positive or negative) reflected the nature of the correlation with the dependent variable (LULCC).

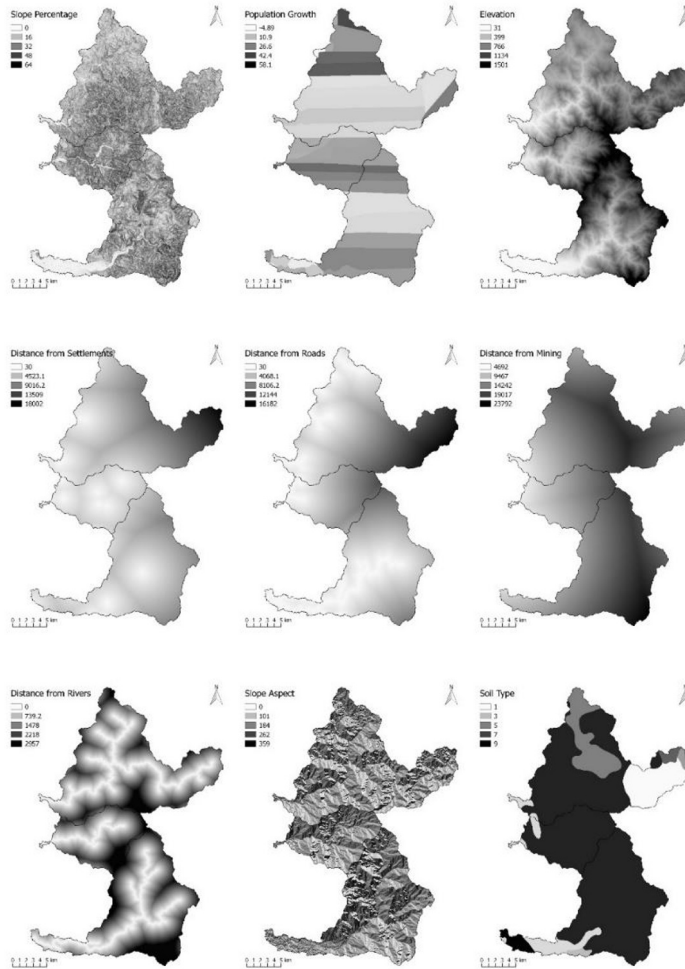


Fig. 5. Raster layers of LULCC drivers in the Binomial Logistic Regression.

The analysis revealed that distance from roads, elevation, population growth, slope percentage, and soil type exhibited negative correlations with land use and land cover (LULC) changes. Conversely, positive correlations were observed for slope aspect, distance from mining areas, distance from rivers, and distance from settlements, as illustrated in Table 6. Among these factors, distance from roads and elevation had the highest regression coefficients of -3.729 and -2.775, respectively, indicating that they were the most significant drivers of LULC change between 2000 and 2020.

Table 6. Coefficients of the nine independent variables (driving forces).

Variable	Coefficient	P-Value
Slope Aspect	0.112	0.397
Distance from Mining Projects	0.079	0.717
Distance from Rivers	1.944	0.000
Distance from Roads	-3.729	0.000
Distance from Settlements	1.930	0.000
Elevation	-2.775	0.000
Population Growth	-0.366	0.020

Slope Percent	-0.006	0.977
Soil Type	-0.349	0.008

5 Conclusion

This study examined land use and land cover change (LULCC) in the watersheds located within mining tenements in Agusan del Norte, Caraga, Philippines, over the period from 2000 to 2020. The analysis of remote sensing data revealed a significant decrease in forest cover alongside a considerable increase in open areas and grasslands across the three watersheds over the past two decades. Notably, built-up areas expanded by approximately 577.30%, equivalent to 73.26 hectares. In terms of area gained or lost, grasslands increased by a total of 1,859.94 hectares, primarily at the expense of forests, which experienced a net loss of 1,910.61 hectares. The main driving forces behind these LULC changes in the study area were identified as the distance from major roads and the elevation of the parcels during this period.

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