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Evaluation of Soil Degradation Due to Land Use Change Using Geospatial Analysis in the Ecological Zone of North Konawe Regency

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Abstract: Land use change is one of the major factors affecting environmental quality, particularly soil degradation. North Konawe Regency has experienced rapid regional development characterized by the expansion of agricultural land, oil palm plantations, settlements, and mining activities. This study aimed to evaluate soil degradation caused by land use change in the ecological zone of North Konawe Regency during 2003, 2013, and 2023. The results showed that forest area decreased from 451,821.4 ha (88.0%) in 2003 to 432,564.5 ha (84.3%) in 2013 and further declined to 421,032.7 ha (82.0%) in 2023. The reduction of 30,788.7 ha of forest area indicates an increasing extent of degraded land due to land conversion. In contrast, oil palm plantations increased from 3,413.0 ha to 24,986.4 ha, while mining areas expanded from 424.3 ha to 12,463.2 ha. Converted lands, particularly mining areas, showed higher levels of soil degradation characterized by reduced soil porosity and permeability. The findings indicate that increasing land use intensity contributes directly to soil degradation in North Konawe Regency.

Keywords: Ecological zone; Land use change; Mining land; Soil degradation

Introduction

Land use change has become one of the most significant drivers of environmental degradation worldwide, particularly in tropical regions experiencing rapid economic development (AbdelRahman, 2023; Lambin et al., 2003). The conversion of natural ecosystems into agricultural land, plantations, settlements, and mining areas has substantially altered landscape structures and ecological processes, resulting in widespread degradation of ecosystem functions and services (Lambin et al., 2003; Petrosillo et al., 2023). These changes not only reduce biodiversity but also modify hydrological processes, accelerate soil erosion, decrease soil organic matter, and ultimately contribute to soil degradation and declining land productivity (AbdelRahman, 2023; Beillouin et al., 2023; Pamba et al., 2023). As soil provides essential ecosystem services supporting agricultural productivity, water regulation, carbon storage, and biodiversity conservation, maintaining soil quality has become a global priority for achieving the Sustainable Development Goals (SDGs) and ensuring long-term environmental resilience (Olsson et al., 2023; Rodrigues et al., 2021).

Soil degradation represents the gradual decline in the physical, chemical, and biological functions of soil caused by both natural processes and anthropogenic activities, resulting in reduced soil productivity and ecosystem resilience (Lal, 2015). Among various anthropogenic drivers, land use change is widely recognized as one of the primary causes of soil degradation because land conversion commonly involves vegetation removal, intensive agricultural practices, urban expansion, and mining activities that alter soil structure and ecological functions (AbdelRahman, 2023; Borrelli et al., 2017). These disturbances frequently increase soil compaction, reduce soil porosity and permeability, disrupt water

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infiltration, accelerate surface runoff and erosion, and ultimately diminish the soil's capacity to support sustainable ecosystem services (Blanco-Canqui et al., 2010; Lal, 2020; Poesen, 2018). Consequently, understanding the relationship between land use dynamics and soil degradation has become increasingly important for developing sustainable land management strategies and supporting evidence-based environmental planning (Rodrigues et al., 2021).

Recent advances in remote sensing technology, Geographic Information Systems (GIS), and machine learning have substantially enhanced the capability to monitor land use and land cover dynamics over large spatial extents with high temporal consistency and analytical efficiency (Ma et al., 2019; Phiri et al., 2020). Medium-resolution satellite imagery, particularly the Landsat series, provides continuous historical observations spanning more than four decades, making it one of the most valuable data sources for multi-temporal land use change analysis and long-term environmental monitoring (Wulder et al., 2019; Ye et al., 2019). Furthermore, machine learning algorithms have demonstrated superior performance in land use and land cover classification compared with conventional pixel-based classification approaches because they are capable of modeling complex, nonlinear relationships among spectral features (Belgiu et al., 2016; Maxwell et al., 2018). Among these algorithms, the Support Vector Machine (SVM) has been widely recognized as one of the most accurate and robust classifiers, particularly for heterogeneous landscapes and relatively limited training datasets, owing to its strong generalization capability and effective handling of high-dimensional remote sensing data (Al-Naeem et al., 2023; Karasiak et al., 2018; Noi et al., 2017).

Numerous previous studies have successfully applied remote sensing, Geographic Information Systems (GIS), and machine learning techniques to analyze land use and land cover (LULC) dynamics with high classification accuracy. For instance, Noi et al. (2017) demonstrated that Support Vector Machine (SVM) outperformed several conventional classifiers in mapping land cover using Sentinel-2 imagery, while Phiri et al. (2020) highlighted the effectiveness of multi-temporal satellite imagery for long-term LULC monitoring. Likewise, Eshetie et al. (2023) employed machine learning techniques to evaluate the impacts of land use change on watershed hydrology, demonstrating the growing application of artificial intelligence in environmental assessment. On the other hand, soil degradation studies have primarily focused on evaluating soil physical and chemical properties through field observations and laboratory analyses, providing valuable information regarding soil quality degradation under different land management practices (Lal, 2015; Borrelli et al., 2017; AbdelRahman, 2023). Although these studies have substantially improved the understanding of environmental changes resulting from land conversion, they generally investigate land use dynamics and soil degradation independently. Remote sensing-based studies mainly emphasize the spatial distribution and temporal changes of land use without directly evaluating their impacts on soil degradation, whereas soil degradation assessments often rely on field observations with limited spatial representation and rarely integrate multi-temporal geospatial information. Consequently, the spatial relationship between land use conversion and soil degradation remains insufficiently understood, particularly in rapidly developing tropical regions where land conversion occurs intensively.

Consequently, comprehensive studies integrating multi-temporal machine learning-based land use classification with field-based soil degradation assessment remain relatively limited, particularly in tropical regions undergoing rapid land conversion (AbdelRahman, 2023; Borrelli et al., 2017). Existing studies have predominantly focused either on land use and land cover (LULC) mapping using remote sensing and machine learning techniques or on soil degradation assessment through field observations and laboratory analyses, with limited efforts to integrate both approaches within a single spatially explicit framework (Phiri et al., 2020; Eshetie et al., 2023). In addition, only a few studies have combined geospatial analysis, machine learning classification, and standardized soil degradation assessment into an analytical framework capable of quantitatively explaining how land use change influences soil degradation across different ecological zones (Lal, 2015; FAO & ITPS, 2015). This limitation restricts the development of evidence-based land management strategies that effectively balance economic development with environmental sustainability and ecosystem conservation (Borrelli et al., 2017; Rodrigues et al., 2021).

North Konawe Regency, Southeast Sulawesi Province, represents one of Indonesia's rapidly developing regions that has experienced substantial land use transformation following its administrative expansion in 2007. During the last two decades, the expansion of oil palm plantations, mining activities, agricultural land, and settlements has significantly altered the regional landscape, reflecting increasing pressure on natural ecosystems and land resources (BPS North Konawe Regency, 2024; Ministry of Environment and Forestry, 2023). Such land conversion is widely recognized as a major driver of soil degradation because it modifies soil physical properties, including bulk density, porosity, permeability, and soil structure, thereby reducing the soil's capacity to regulate water movement and sustain ecosystem functions (Lal, 2015;

AbdelRahman, 2023). Despite the rapid landscape transformation occurring in North Konawe Regency, comprehensive studies integrating multi-temporal land use dynamics with field-based soil degradation assessment remain scarce. Consequently, scientific evidence explaining the spatial relationship between land use change and soil degradation in this region is still limited, hindering the development of effective land management and environmental conservation strategies.

The novelty of this study lies in the integration of multi-temporal land use classification using the Support Vector Machine (SVM) algorithm with geospatial analysis and field-based soil degradation assessment based on the Indonesian standard criteria for soil degradation evaluation. While previous studies have primarily focused on either land use and land cover (LULC) mapping using remote sensing and machine learning techniques (Noi & Kappas, 2018; Phiri et al., 2020) or soil degradation assessment through field surveys and laboratory analyses (Lal, 2015; AbdelRahman, 2023), few have quantitatively integrated these approaches within a single spatially explicit framework. By combining multi-temporal satellite image classification, Geographic Information Systems (GIS), and standardized soil degradation evaluation, this study provides a comprehensive assessment of how land use conversion influences soil degradation across different ecological zones. The findings contribute to advancing geospatial-based environmental assessment methods while providing scientific evidence to support sustainable spatial planning, land conservation, and natural resource management in rapidly developing tropical regions.

Therefore, this study aimed to analyze land use changes in North Konawe Regency during 2003, 2013, and 2023 using multi-temporal Landsat imagery and the Support Vector Machine algorithm, and subsequently evaluate soil degradation associated with these land use changes through field observations, laboratory analyses, and geospatial assessment. The findings are expected to provide scientific information supporting sustainable land management, ecological conservation, and evidence-based regional spatial planning.

Method

Research Workflow

The overall research workflow employed in this study is presented in Figure 1. The research consisted of four main stages: (1) remote sensing and Geographic Information System (GIS)-based land use analysis, (2) field survey and soil sampling, (3) laboratory analysis of soil physical properties, and (4) soil degradation assessment and spatial analysis. The workflow integrates multi-temporal satellite image classification using the Support Vector Machine (SVM) algorithm with field observations and laboratory measurements to evaluate the impact of land use change on soil degradation in North Konawe Regency.

As illustrated in Figure 1, the study began with data collection and image pre-processing, followed by land use classification using the Support Vector Machine (SVM) algorithm and accuracy assessment. Subsequently, land use change analysis was conducted through spatial overlay techniques. In parallel, field surveys and soil sampling were carried out to obtain representative soil samples for laboratory analysis. Finally, soil degradation status was determined using the Indonesian standard criteria, and the relationship between land use change and soil degradation was evaluated.

Study Area

The study was conducted in North Konawe Regency, Southeast Sulawesi Province, Indonesia. The regency covers approximately 513,240.9 ha and has experienced rapid land use transformation following regional administrative expansion. Expansion of oil palm plantations, mining activities, agricultural land, and settlements has considerably altered the landscape during the last two decades, making the region an appropriate case study for evaluating the relationship between land use change and soil degradation.

Data and Materials

This study employed both spatial and field datasets. Spatial data consisted of Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery acquired in 2003 and 2013, Landsat 8 Operational Land Imager (OLI) imagery acquired in 2023, and the administrative boundary map of North Konawe Regency. These datasets were used for multi-temporal land use classification and spatial analysis.

Geospatial analysis was performed using QGIS version 3.22 integrated with the dzetsaka and MOLUSCE plugins. Microsoft Office 365 was used for data processing and tabulation. Field equipment included a Global Positioning System (GPS) receiver, digital camera, soil auger, ring sampler, measuring tape, and standard soil survey instruments required for field observations and soil sampling.

Research Procedure

The study began with a preparation stage through literature review and data collection. Landsat satellite imagery was collected and classified to analyze land use changes. Soil physical degradation analysis was conducted by developing land unit maps used for soil sampling, field observations, and laboratory analysis to determine soil degradation characteristics.

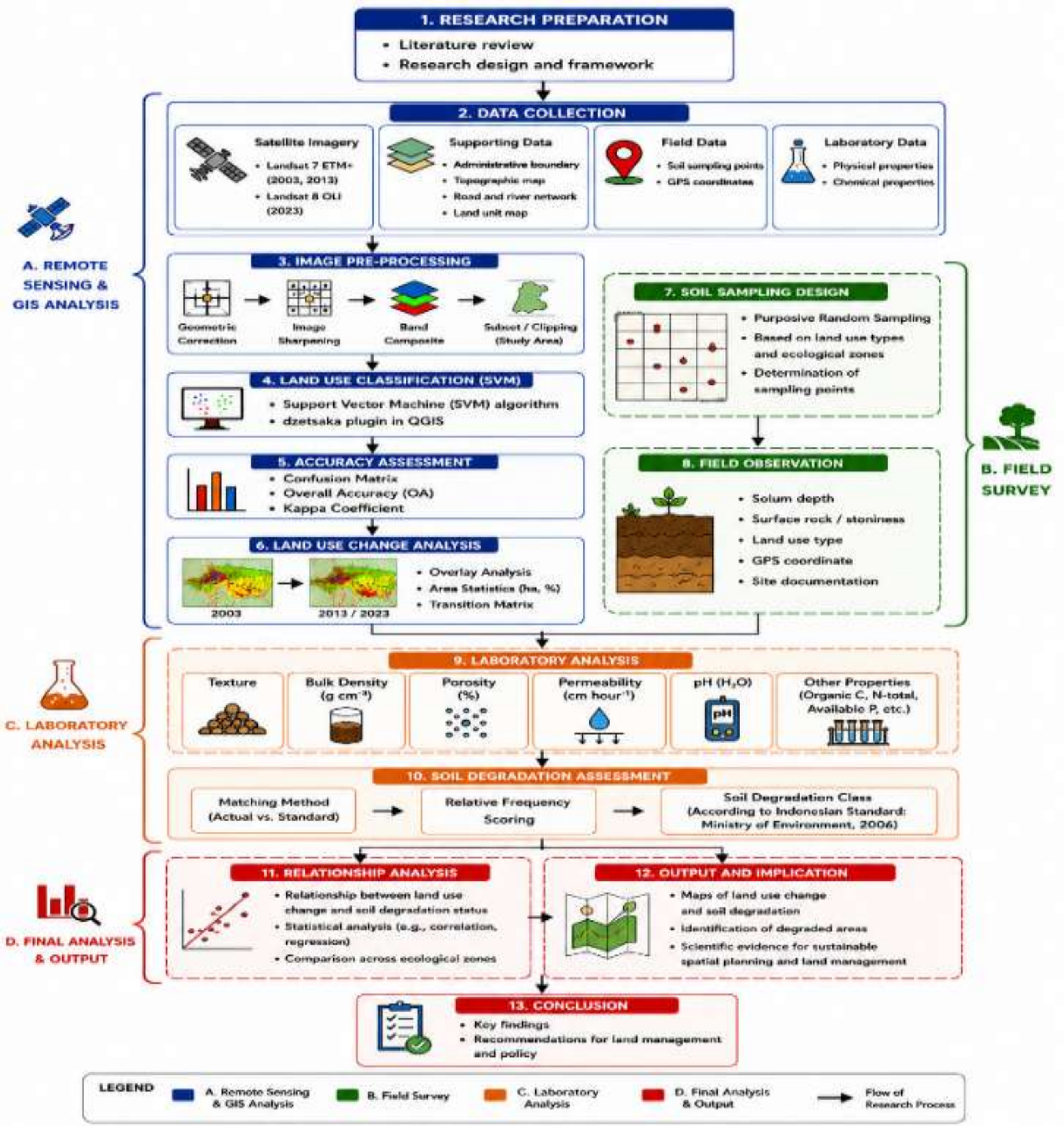

Figure 1. Research workflow for land use classification and soil degradation assessment in North Konawe Regency

Land use change analysis was initiated through land use classification using the dzetsaka plug-in available in QGIS software, which supports rapid image classification and various machine learning algorithms (Miguez et al., 2023). The data used consisted of medium-resolution Landsat 7 ETM+ imagery from 2003 and 2013 and Landsat 8 OLI imagery from 2023. The classification process included pre-processing, processing, and accuracy assessment stages.

During the pre-processing stage, geometric correction was performed to minimize geometric errors caused by satellite sensor acquisition angles and surface relief displacement (Priyanto et al., 2021). Image sharpening was applied using the panchromatic band

(Band 8) to improve image resolution. Image clipping was conducted based on the administrative boundary of North Konawe Regency to obtain imagery corresponding to the study area. Band composite processing was carried out to improve image interpretation by adjusting band combinations. Training and validation datasets were also prepared to develop the machine learning classification model.

In the processing stage, satellite image classification was conducted using the best-performing machine learning algorithm. The Support Vector Machine (SVM) algorithm was selected because it is based on a radial basis function kernel capable of producing high classification and regression accuracy (Iqbal et al. 2023).

Classification accuracy was evaluated using Overall Accuracy (OA) and Kappa Coefficient (Mudereri et al. 2019).

$$OA = \frac{\text{Number of correctly classified pixels}}{\text{Total number of pixels (N)}} \times 100 \quad (1)$$

$$Kappa = \frac{P(A) - P((E)}{1 - P((E)} \times 100 \quad (2)$$

Where (P_{ij}) represents the cell value in row (i) and column (j) of the confusion matrix, (P_{it}) is the total value of row (i), (P_{tj}) is the total value of column (j), and (c) is the number of raster categories. The interpretation of Kappa values is categorized as very low (<0.20), low (0.20–0.40), moderate (0.41–0.60), strong (0.61–0.80), and very strong (>0.80) (Landis and Koch 1977). The classification model was considered accurate when the average Kappa value exceeded 0.80, and the model meeting this criterion was used to generate land use maps for 2003, 2013, and 2023.

Land use change analysis was conducted by overlaying land use maps from 2003, 2013, and 2023. This process involved comparing the area of each land use category, which was subsequently presented in matrix form using pivot tables in Microsoft Excel.

Soil degradation analysis employed a descriptive survey method using secondary data in the form of thematic maps to determine potential soil degradation, combined with field observation data and laboratory analysis to evaluate soil degradation status. During the survey stage, land unit maps derived from thematic map overlays were used as the basis for soil sampling. Field observations included geographic coordinates, soil solum depth, slope, land use type, and vegetation cover. Geographic coordinates were recorded using a Global Positioning System (GPS). Effective soil depth was determined through field measurements using a Belgian-type soil auger at each soil sampling location.

Solum thickness observations were conducted directly on soil profiles or field exposures representing each land mapping unit using measuring tape from the soil surface to the root-restricting layer. Soil drilling was conducted to a maximum depth of 180 cm or until reaching the limiting layer. Solum thickness measurements referred to the maximum rooting depth required for optimal root development according to the Ministry of Environment Regulation No. 07 of 2006.

Surface rock measurements were conducted through the following procedures: Establishing a sampling plot measuring 2 m × 2 m, which was divided into 16 smaller plots of 0.5 m × 0.5 m to facilitate measurement; Calculating the percentage of rock distribution within the smaller plots, summing the values, and dividing them by the total number of plots (16 plots); Repeating the measurements at three different locations representing the land mapping unit and calculating the average value.

Soil sampling locations were determined using purposive random sampling. Soil samples were collected based on low to high soil degradation potential using two sampling methods: Disturbed soil samples collected using a soil auger at a depth of 0-25 cm for texture, porosity, and soil pH (H_2O) analysis; Undisturbed soil samples collected using ring samples for permeability and bulk density measurements.

Laboratory analysis was conducted based on the standard criteria for soil degradation assessment. The critical threshold values of each parameter are presented in Table 1.

Table 1. Standard Criteria for Soil Degradation

Parameter	Critical threshold
Solum thickness	< 20 cm
Surface rock	< 40 %
Soil fraction composition	< 18 % colloid; 80 % quartz sand
Bulk density	>1.4 g/cm^3
Total porosity	< 30 %; > 70 %
Water permeability	< 0.7 cm/ hour; > 8.0 cm/ hour
pH (H_2O) 1:2,5	< 4.5; > 8.5

Source: Ministry of Environment (2006)

The determination of soil degradation status was conducted through two evaluation stages, namely matching and relative frequency scoring of degraded soil based on the measurement results of each soil degradation parameter. The matching method was carried out by comparing the measured soil degradation parameters with the standard criteria for soil degradation. Matching was performed at each observation point and classified into degraded soil (R) or non-degraded soil (N).

The scoring method was conducted by considering the relative frequency of degraded soil within a land polygon based on the following formula:

$$FR = \frac{\sum \text{Degraded soil samples (measurements)}}{\sum \text{Sampling points within the polygon}} \times 100 \quad (3)$$

The soil degradation score based on relative frequency (%) is presented in Table 2.

Table 2. Soil Degradation Score Based on Relative Frequency

Relative frequency of soil degradation (%)	Score	Soil degradation status
0-10	0	Non-degraded
11-25	1	Slightly degraded
26-50	2	Moderately degraded
51-75	3	Heavily degraded
76-100	4	Very heavily degraded

Source: Ministry of Environment (2006)

Soil degradation status was determined by calculating the relative frequency (%) of each soil degradation parameter, followed by determining the relative frequency score (Table 2). The accumulated relative frequency scores were then summed and matched with the soil degradation status classification presented in Table 3.

Table 3. Soil Degradation Status Based on Accumulated Score Values

Soil degradation status	Accumulated score
Non-degraded	0
Slightly degraded	1-7
Moderately degraded	8-14
Heavily degraded	15-24
Very heavily degraded	25-28

Source: Ministry of Environment (2006)

Result and Discussion

Land Use Classification

All machine learning (ML) algorithms available in the dzetsaka plug-in were tested to determine the best algorithm for land use classification. Based on the classification results, land use in North Konawe Regency was categorized into secondary forest, shrubland, rice fields, dryland agriculture, oil palm plantations, grassland, water bodies, mining areas, mangroves, and settlements. Land use classification accuracy assessment was conducted using validation data obtained from high-resolution Google Earth imagery and field surveys.

The accuracy assessment of land use classification using Overall Accuracy (OA) and Kappa Coefficient showed varying results for each observation year. The Support Vector Machine (SVM) algorithm produced the highest classification accuracy compared with other machine learning models, with an average OA value of 93.23% and a Kappa value of 0.92, indicating excellent performance in land use classification. Similar findings were reported by Eshetie et al. (2023), who demonstrated that the SVM model provides high classification accuracy for land use mapping. Yuh et al. (2023) also reported that SVM achieved very good performance in land use classification. In addition, Wang et al. (2022) found that the SVM algorithm produced higher accuracy than Random Forest (RF) and k-Nearest Neighbor (kNN) algorithms.

The classification results showed that the OA and Kappa values in 2003 reached 93.23% and 0.92, respectively. In 2013, the OA and Kappa values were 89.27% and 0.86, while in 2023 the values slightly decreased to 88.35% and 0.84, respectively. These results indicate that the SVM algorithm consistently produced high classification accuracy across all observation years, as presented in Table 4.

Table 4. Land Use Classification Accuracy Validation

Algorithm	2003		2013		2023	
	OA	Kappa	OA	Kappa	OA	Kappa
SVM	93.23	0.92	89.27	0.86	87.54	0.84

Source: Image interpretation results using the machine learning algorithm.

The SVM algorithm was able to perform land use classification very well because it can achieve high classification accuracy even with a relatively small number of training samples (Noi et al., 2017; Santarsiero et al., 2022; Wang et al., 2022). The number of samples used in this study was still categorized as moderate according to the classification criteria proposed by Noi et al. (2017). In addition, this algorithm is effective in handling high-dimensional and non-linear data such as satellite imagery classification by utilizing kernel functions to map data into higher-dimensional feature spaces (Al-Naeem et al., 2023). The kernel implemented in the dzetsaka plug-in is the radial basis function, which provides very good classification performance (Karasiak et al., 2018). SVM is also capable of handling high heterogeneity in image data (Santarsiero et al., 2022), resulting in optimal classification outputs. Furthermore, the SVM algorithm has good capability in classifying vegetation cover such as forests and plantations, as well as water bodies such as rivers (Luzorata et al., 2023).

Land use classification in North Konawe Regency was therefore conducted using the SVM algorithm due to its highest classification accuracy. The land use maps and area distribution are presented in Figure 1 and Table 5. The dominant land use category in 2003, 2013, and 2023 was secondary forest, covering 451,821.4 ha

(88.0%), 432,564.5 ha (84.3%), and 421,032.7 ha (82.0%), respectively. Mixed agriculture was the second dominant land use, covering 24,224.6 ha (4.7%), 19,431.1 ha (3.8%), and 20,940.9 ha (4.1%), respectively. Mining and oil palm plantation areas showed significant increases during 2013 and 2023, reaching 17,997.3 ha (3.5%) and 12,463.2 ha (2.4%) for mining, and 11,835.9 ha (2.3%) and 24,986.4 ha (4.9%) for oil palm plantations, respectively.

Based on the land use analysis for 2003, 2013, and 2023, the study area experienced significant land use changes over the last two decades, although the total area remained constant at 513,240.9 ha. These changes indicate spatial dynamics driven by regional development, population growth, and the expansion of natural resource-based economic activities.

Table 5. Land Use Change Area Using the SVM Algorithm

Landuse	2003		2013		2023	
	Ha	%	Ha	%	Ha	%
Water Bodies	2,898.1	0.6	2,940.3	0.6	3,129.6	0.6
Forest	451,821.4	88.0	432,564.5	84.3	421,032.7	82.0
Mangrove	6,840.2	1.3	6,140.2	1.2	5,261.1	1.0
Savanna	9,645.3	1.9	9,645.8	1.9	9,632.3	1.9
Settlement	2,326.5	0.5	3,192.7	0.6	4,304.8	0.8
Mining	424.3	0.1	17,997.3	3.5	12,463.2	2.4
Mixed Garden	24,224.6	4.7	19,431.1	3.8	20,940.9	4.1
Rice Field	1,019.1	0.2	3,245.0	0.6	5,387.3	1.0
Oil Palm Plantation	3,413.0	0.7	11,835.9	2.3	24,986.4	4.9
Shrubland	9,861.6	1.9	4,697.7	0.9	3,692.5	0.7
Fishpond	766.9	0.1	1,550.4	0.3	2,410.1	0.5
Total	513,240.9	100	513,240.9	100	513,240.9	100

Source: Land use interpretation results using the SVM algorithm for 200-2023.

Forest cover remained the dominant land use category throughout the observation periods. In 2003, forest area covered 451,821.4 ha or 88.0% of the total area. However, it decreased to 432,564.5 ha (84.3%) in 2013 and further declined to 421,032.7 ha (82.0%) in 2023. Overall, forest area decreased by 30,788.7 ha during 2003–2023. This decline indicates ongoing deforestation, likely caused by land conversion for plantations, mining, agricultural expansion, and settlements.

Oil palm plantations showed the most significant increase among all land use categories. In 2003, oil palm plantations covered only 3,413.0 ha (0.7%), increasing sharply to 11,835.9 ha (2.3%) in 2013 and reaching 24,986.4 ha (4.9%) in 2023. The expansion of 21,573.4 ha suggests that plantation development has become one of the main drivers of land use change, likely resulting from the conversion of forest areas, shrubland, and mixed gardens.

Mining areas experienced a dramatic increase during 2003–2013, from 424.3 ha (0.1%) to 17,997.3 ha (3.5%). However, mining areas decreased to 12,463.2 ha (2.4%) in 2023. This reduction may indicate the cessation of mining activities in several locations, land reclamation processes, or post-mining land conversion into other land use classes such as shrubland or agricultural areas.

Agricultural land showed varied change patterns. Mixed garden areas decreased from 24,224.6 ha (4.7%) in 2003 to 19,431.1 ha (3.8%) in 2013 before increasing again to 20,940.9 ha (4.1%) in 2023. The initial decrease was likely related to land conversion into oil palm plantations and mining areas, whereas the later increase suggests land reutilization for agricultural activities.

In contrast, rice fields increased consistently from 1,019.1 ha (0.2%) in 2003 to 3,245.0 ha (0.6%) in 2013 and 5,387.3 ha (1.0%) in 2023. This increase reflects the strengthening of the food agriculture sector, likely influenced by food security demands and agricultural development policies.

Settlement areas gradually increased from 2,326.5 ha (0.5%) in 2003 to 4,304.8 ha (0.8%) in 2023. Although the percentage remained relatively small, this increase indicates population growth and socio-economic development that stimulated the demand for built-up areas.

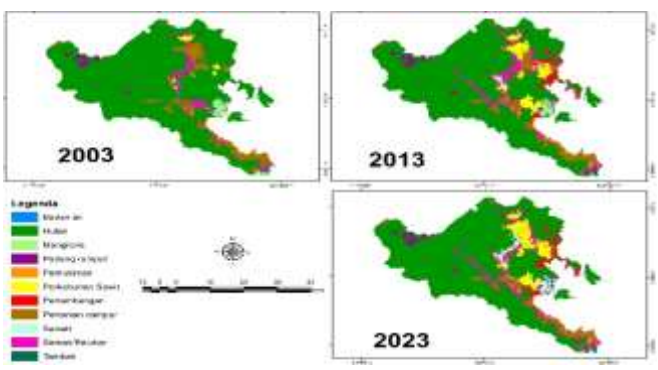

Figure 2. Land use interpretation results of north konawe regency in 2003-2023

Mangrove ecosystems declined from 6,840.2 ha (1.3%) in 2003 to 5,261.1 ha (1.0%) in 2023. In contrast, fishpond areas increased from 766.9 ha (0.1%) to 2,410.1 ha (0.5%) during the same period. This pattern indicates mangrove conversion into aquaculture ponds, which may reduce coastal ecological functions such as shoreline protection and habitat provision.

Shrubland decreased significantly from 9,861.6 ha (1.9%) in 2003 to 3,692.5 ha (0.7%) in 2023. This decline suggests that shrubland became one of the main targets of conversion into more intensive land uses such as agriculture, plantations, and built-up areas. Meanwhile, savanna areas remained relatively stable throughout the observation periods, indicating relatively low pressure for land conversion in these areas.

Land Use Change Dynamics in North Konawe Regency

The results showed that North Konawe Regency experienced highly dynamic land use changes during the periods of 2003, 2013, and 2023. The most significant increases in land use area occurred in oil palm plantations and mining/open land areas, which expanded by 21,773.39 ha and 12,038.93 ha, respectively. These significant increases were mainly associated with land conversion from forest, shrubland, and mixed garden areas. Forest areas decreased by 30,788.68 ha, shrubland by 6,169.04 ha, and mixed gardens by 2,283.68 ha during the study period.

Changes were also observed in mangrove ecosystems, where approximately 1,643.22 ha were converted into fishpond areas. Rice fields increased by 4,368.13 ha, while settlement areas expanded by 1,978.33 ha. Water bodies also showed a slight increase in area, although relatively small compared to other land use categories in North Konawe Regency.

Overall, the results indicate that land use dynamics in North Konawe Regency were strongly influenced by the expansion of plantation, mining, agricultural, and settlement activities. The land use change dynamics in North Konawe Regency during 2003-2023 are presented in Figure 2.

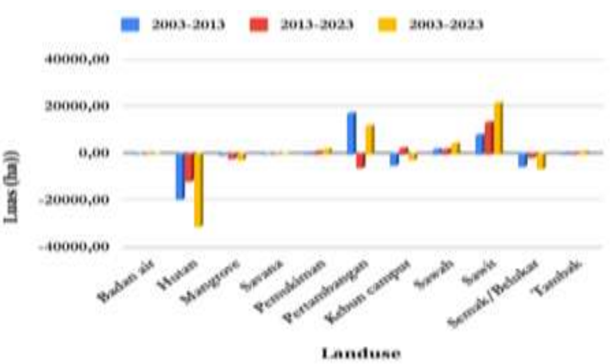

Figure 3. Land use change dynamics in north konawe regency during 2003-2023

One of the reasons for selecting multiple observation years in this study was to identify the patterns of land use change dynamics over time. Forest land showed a noticeable decline pattern, although the reduction was still relatively small compared to the total forest area in North Konawe Regency. Shrubland areas exhibited a significant decrease, particularly during the 2003–2013 period. Mangrove areas tended to decline continuously each year, while rice fields and settlement areas generally increased over time. Water bodies and savanna areas experienced relatively minor changes, although a slight increase in water bodies was observed during 2013-2023.

These findings are consistent with previous studies that identified two major patterns. First, regional administrative expansion is often associated with accelerated land use change and local infrastructure development, which subsequently promotes land conversion (Asian Development Bank, 2023). Second, the expansion of oil palm plantations and mining activities has consistently been reported as the dominant factor driving the conversion of forests and mixed land into monoculture plantations and mining areas, resulting in increased forest loss and changes in land functions (Stockholm Environment Institute, 2022). In addition, mining case studies in Indonesia have shown that mining activities leave significant land use change footprints and contribute to vegetation loss and degradation of ecological functions (Meijide et al., 2018).

After identifying the dynamics of land use change, a land use transition matrix was developed to determine whether land use categories experienced conversion or remained unchanged between the initial and final observation years. The land use transition matrix for North Konawe Regency during 2003–2023 is presented in Table 7. The matrix indicates that the conversion of forest, mixed garden, shrubland, and mangrove areas in 2003 into oil palm plantations, mining areas, settlements, and fishponds in 2023 represented the most dominant form of land use conversion in the study area

The conversion of forest and mixed garden areas into oil palm plantations was the dominant land use change in North Konawe Regency. The expansion of oil palm plantations was mainly distributed within watershed areas due to the suitability of oil palm cultivation on gently sloping land with adequate water availability, particularly in areas close to rivers where groundwater content and drainage conditions are more favorable (Aryanti et al., 2023; Utami et al., 2024). These factors explain why oil palm plantations in North Konawe Regency have rapidly developed around watershed areas that are relatively accessible and close to community activity centers.

Table 6. Land Use Change Transition Matrix in North Konawe Regency During 2003-2023

Landuse 2003	Landuse 2023										Total
	BA	HT	SV	PK	PT	PC	SW	ST	SB	TB	
Water Bodies							67.91			79.11	147.02
Forest	217.52			1,526.8	11,746.93	346.15	588.06	16,273.21	83.95	6.05	30,788.67
Mangrove					31.06					1,548.06	1,579.12
Savanna					13.56						13.56
Settlement											0
Mining	1.98	1.14	0.49	19.16					48.06		70.83
Mixed Garden		13.67		315.17	124.96		489.11	2,328.14	12.62		3,283.67
Rice Field				2.24					13.67		15.91
Oil Palm Plantation					70.99						70.99
Shrubland	7.52			114.96	51.44		3,023.05	2,972.05			6,169.02
Fishpond	4.49										4.49
Total	231.51	14.81	0.49	1,978.33	12.038,94	346.15	4,168.13	21,573.4	158.3	1,633.22	42,143.28

Source: Land use interpretation results for 2003-2023.
Notes: WB: Water Bodies; FR: Forest; SV: Savanna; ST: Settlement; MN: Mining; MG: Mixed Garden; RF: Rice Field; OP: Oil Palm Plantation; SH: Shrubland; FP: Fishpond.

In addition to oil palm plantations, forest conversion in North Konawe Regency was also significantly driven by mining activities. Mining operations, particularly nickel mining, require large-scale land clearing and result in the loss of natural forest cover. This process not only changes land functions but also contributes to vegetation loss, increased erosion, and alterations in surrounding hydrological systems. Therefore, land use change patterns in North Konawe Regency during 2013-2023 were primarily influenced by the expansion of oil palm plantations in lowland areas and mining activities within forested regions.

The conversion of these land uses requires greater attention from both central and local governments, particularly concerning food security issues. One form of government protection toward agricultural land is the enactment of Law No. 41 of 2009 concerning Sustainable Food Agricultural Land Protection (LP2B). The spatial distribution of land use changes during the observation periods indicates that the most significant changes occurred during 2003–2013 and 2013–2023, with relatively widespread distribution across most coastal areas of North Konawe Regency.

Analysis of Soil Physical Degradation

The results of soil degradation analysis in North Konawe Regency presented in Table 8 indicate that areas dominated by forest cover were generally classified as non-degraded, reflecting relatively stable soil conditions due to the protective function of natural vegetation against erosion and soil compaction. In contrast, areas utilized for oil palm plantations were predominantly categorized as slightly degraded, characterized by reduced soil porosity and permeability resulting from land clearing activities and the use of heavy machinery. Meanwhile, mining areas exhibited relatively higher levels of degradation, with several land units classified as moderately degraded, mainly influenced by changes in soil fraction composition and soil pH conditions.

Overall, increasing land use intensity from forest to plantation and mining areas was directly proportional to the increasing level of soil degradation in North Konawe Regency. The distribution of oil palm plantation concessions and mining permit areas is presented in Figure 4.

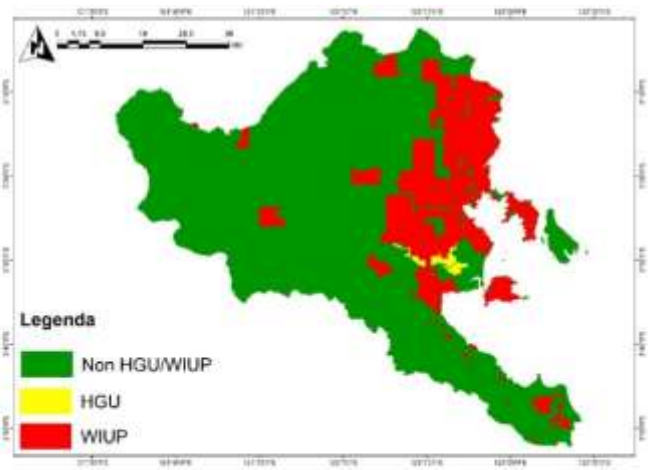

Figure 4. Map of oil palm plantation concessions (HGU) and mining permit areas (WIUP) in north konawe regency, 2022

Based on the soil degradation assessment results from various Land Mapping Units (SPL) in North Konawe Regency, the level of soil degradation showed a clear relationship with land use change. SPLs coded as H (H-DE, H-SH, H-TD, and H-TTF) all had a total score of 0 and were classified as Non-Degraded, indicating that soil physical and chemical properties remained in good condition. This condition corresponds to areas still dominated by forest cover, where natural vegetation protects the soil surface from erosion, maintains porosity, and preserves soil structure and pH stability (Arsyad, 2010; Hardjowigeno, 2015).

SPLs coded as S, St, and SB were classified as Slightly Degraded with total scores ranging from 2 to 6. The slight degradation was mainly indicated by increased soil bulk density and reduced total porosity and permeability. These conditions are generally associated with land use changes from forest to plantation areas, particularly oil palm plantations, involving land clearing and heavy machinery use that contribute to soil compaction and reduced water infiltration capacity (Hardjowigeno, 2015; Lal, 2001).

Meanwhile, SPLs coded as KC (KC-DE, KC-TD, and KC-TTF) exhibited higher degradation levels and were classified as Moderately Degraded with a total score of 8. This degradation was influenced by changes in soil fraction composition and soil pH, indicating degradation of soil physical and chemical properties. Such conditions are commonly associated with mining activities, where topsoil removal and soil layer mixing result in the loss of natural soil structure and significant declines in soil quality (Suprapto, 2019).

Table 7. Recapitulation of Soil Degradation Status Assessment

Spl code	Sd	Sr	T	Bd	Tp	P	Ph	Total score	Soil degradation status
H-DE	0	0	0	0	0	0	0	0	Non-Degraded
H-SH	0	0	0	0	0	0	0	0	Non-Degraded
H-TD	0	0	0	0	0	0	0	0	Non-Degraded
H-TTF	0	0	0	0	0	0	0	0	Non-Degraded
S-DE	0	0	0	0	1	1	0	2	Slightly Degraded
S-SH	0	0	0	0	1	1	0	2	Slightly Degraded
S-TTF	0	0	0	0	1	1	0	2	Slightly Degraded
St-DE	0	0	0	0	0	3	1	4	Slightly Degraded
St-SH	0	0	0	0	0	3	1	4	Slightly Degraded
St-TD	0	0	0	0	0	3	1	4	Slightly Degraded
St-TTF	0	0	0	0	0	3	1	4	Slightly Degraded
SB-DE	0	0	0	2	2	2	0	6	Slightly Degraded
SB-SH	0	0	0	2	2	2	0	6	Slightly Degraded
SB-TD	0	0	0	2	2	2	0	6	Slightly Degraded
SB-TTF	0	0	0	2	2	2	0	6	Slightly Degraded
KC-DE	0	0	2	0	2	2	2	8	Moderately Degraded
KC-TD	0	0	2	0	2	2	2	8	Moderately Degraded
KC-TTF	0	0	2	0	2	2	2	8	Moderately Degraded

Source: Field survey and laboratory analysis.
Notes: SD = Solum Depth; SR = Surface Rock; T = Texture; BD = Bulk Density; TP = Total Porosity; P = Permeability; H = Forest; S = Rice Field; St = Oil Palm Plantation; SB = Shrubland; KC = Mixed Garden; DE = Dystropepts; Eutropepts; SH = Sulfaquents; Hydraquents; TTF = Tropaquepts; Tropofluvents; Fluvaquents; TD = Tropudults; Dystropepts.

Based on the soil degradation assessment results from various Land Mapping Units (SPL) in North Konawe Regency, the level of soil degradation showed a clear relationship with land use change. SPLs coded as H (H-DE, H-SH, H-TD, and H-TTF) all had a total score of 0 and were classified as Non-Degraded, indicating that the physical and chemical properties of the soil remained in good condition. This condition corresponds to areas still dominated by forest cover, where natural vegetation protects the soil surface from erosion, maintains porosity, and preserves soil structure and pH stability (Arsyad, 2010; Hardjowigeno, 2015).

SPLs coded as S, St, and SB were classified as Slightly Degraded, with total scores ranging from 2 to 6. This slight degradation was mainly indicated by increased soil bulk density and reduced total porosity and permeability, as reflected in the observed soil physical parameters. These conditions are generally associated with land use changes from forest to plantation areas, particularly oil palm plantations, involving land clearing and the use of heavy machinery that contribute to soil compaction and reduce the soil's capacity to absorb and transmit water (Hardjowigeno, 2015; Lal, 2001).

Meanwhile, SPLs coded as KC (KC-DE, KC-TD, and KC-TTF) exhibited higher degradation levels and were classified as Moderately Degraded, with total scores reaching 8. This degradation was influenced by changes in soil fraction composition and soil pH, indicating degradation of both physical and chemical soil properties. Such conditions are commonly associated with mining activities, where topsoil removal and soil layer mixing result in the loss of natural soil structure and significant declines in soil quality (Wasis & Andika, 2017; Government Regulation No. 150 of 2000).

Overall, the results of this study indicate that increasing land use intensity from forest areas to plantation and mining areas is directly proportional to the increasing level of soil degradation in North Konawe Regency. These findings reinforce the concept that land use change is one of the major drivers of soil degradation, emphasizing the need for land management practices oriented toward conservation and land reclamation to maintain soil sustainability (Arsyad, 2010; Lal, 2001).

Conclusion

This study aimed to analyze land use changes in North Konawe Regency during 2003–2023 using multi-temporal Landsat imagery and the Support Vector Machine (SVM) algorithm, and to evaluate the impacts of these land use changes on soil degradation through geospatial analysis, field observations, and laboratory assessments. The results demonstrated that substantial land use transformation occurred during the study period, characterized primarily by the conversion of forest areas into oil palm plantations, mining areas, settlements, and agricultural land. These land use changes were accompanied by increasing levels of physical soil degradation, particularly in areas subjected to intensive land utilization. The findings revealed a clear spatial relationship between land use change and soil degradation across different ecological zones. Forest-dominated areas generally maintained good soil physical conditions and were classified as non-degraded, whereas land converted into plantations, shrublands, and mining areas exhibited increasing degradation levels characterized by higher bulk density, lower porosity, reduced permeability, and changes in soil physical properties. These results demonstrate that increasing land use intensity directly contributes to the deterioration of soil quality and provides scientific evidence supporting the importance of sustainable land management for maintaining ecosystem resilience. The principal scientific contribution of this study is the comprehensive evaluation of the relationship between land use dynamics and soil degradation by integrating multi-temporal geospatial analysis with field-based soil assessment. Unlike previous studies that generally focused either on land use mapping or soil degradation assessment separately, this study quantitatively linked land use conversion with variations in soil degradation status across different ecological zones. Furthermore, the application of Landsat multi-temporal image classification using the Support Vector Machine (SVM) algorithm combined with standardized soil degradation assessment based on the Indonesian Ministry of Environment criteria provides an integrated framework for evaluating environmental degradation spatially and temporally in rapidly developing tropical regions. Despite these contributions, several limitations should be acknowledged. First, the use of medium-resolution Landsat imagery may not adequately detect small-scale land use changes or fragmented landscape patterns. Second, soil degradation assessment was limited to selected physical soil properties based on the national standard criteria and therefore did not incorporate biological and more comprehensive chemical indicators of soil quality. Third, the temporal resolution of the available satellite imagery and field observations may not fully capture short-term environmental dynamics associated with seasonal land use changes. Consequently, caution should be exercised when generalizing these findings to other regions with different environmental characteristics. Future studies are recommended to integrate higher-resolution satellite imagery, such as Sentinel-2, PlanetScope, or Unmanned Aerial Vehicle (UAV) imagery, to improve land use classification accuracy and detect finer landscape changes. In addition, predictive land use change modeling using Cellular Automata–Artificial Neural Network (CA–ANN) or other machine learning approaches could be incorporated to evaluate future land degradation scenarios. Further research should also integrate socio-economic drivers of land use change, evaluate the effectiveness of soil and water conservation strategies, and develop spatial decision-support systems that can assist policymakers in implementing sustainable land management and environmental conservation programs.

Author Contributions

Conceptualization: S., W.; Methodology: S., W., D.P.T.B.; Software: S.; Validation: W., D.P.T.B.; Formal analysis: S.; Investigation: S.; Data curation: S.; Writing original draft preparation: S.; Writing review and editing: W., D.P.T.B.; Visualization: S.; Supervision: W., D.P.T.B. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest

The author declares no conflict of interest regarding the publication of this manuscript.

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