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Spatial Analysis of Land Use and Land Cover Change Using Multi-Temporal Landsat Imagery in the Biyonga Sub-Watershed, Gorontalo

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Abstract: The Biyonga Sub-Watershed in Gorontalo Regency has experienced increasing land use pressure in recent years, driven by population growth and expanding socioeconomic activities. This study analyzes land use and land cover (LULC) change dynamics in the Biyonga Sub-Watershed using multi-temporal Landsat satellite imagery for 2010, 2015, 2020, and 2025. Classification was performed using the Supervised Classification method with a Maximum Likelihood approach based on a Geographic Information System (GIS), while accuracy was evaluated through a confusion matrix, Overall Accuracy (OA), and Kappa Coefficient. Results showed that forest remained the dominant land cover class throughout the observation period, accounting for the largest proportion of the watershed area across all four scenarios. A consistent decline in paddy field area was accompanied by a rise in unused land across the four years, indicating widespread land clearing. This inverse pattern suggests that agricultural land is being progressively converted into idle land rather than sustained for cultivation. The accuracy assessment confirmed the reliability of the classification results, with Overall Accuracy ranging from 84% to 88% and Kappa Coefficient ranging from 80.79% to 85.54% across the four scenario years, corresponding to good to very good accuracy categories based on the Landis and Koch (1977) standard.

Keywords: Biyonga Sub-Watershed; Kappa coefficient; Land use; Landsat imagery; Maximum likelihood

Introduction

The Biyonga Sub-Watershed is one of the sub-watersheds of the Limboto Watershed, located in Limboto District, Gorontalo Regency, Gorontalo Province, and drains into Lake Limboto. The sub-watershed covers an area of 90.45 km² with a main river length of 27.52 km (Moningka et al., 2020). The varied topography and soil structure, influenced by the region's biophysical characteristics, render this sub-watershed vulnerable to hydrological changes when land cover is modified (Kasim et al., 2026). Several studies have reported that areas surrounding the Limboto Watershed, including the Biyonga Sub-Watershed, have experienced land degradation, sedimentation, and changes in surface runoff patterns due to increasing land use activities (L. K. O. Serang et al., 2022).

In recent years, the area has experienced increasing pressure from population growth and the expansion of socioeconomic activities. Based on hydrological studies of the Biyonga Sub-Watershed, the population growth rate is approximately 0.96% per year, accompanied by increasing demand for residential areas, agricultural land, and other land use activities (L. K. Serang, 2022). This population growth exerts greater pressure on the environmental carrying capacity, particularly with respect to land use and water resource availability. The increasing population and development activities in Gorontalo Regency over the years have further burdened the availability of water resources in the Biyonga River (Mutia et al., 2024). This pressure is

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exacerbated by the critical condition of the Limboto Watershed, which encompasses a larger area than the Biyonga Sub-Watershed, marked by land degradation resulting from land use change. These changes have reduced soil infiltration capacity and increased surface runoff, thereby weakening the function of the upstream area as a water catchment zone. Given that the Biyonga Sub-Watershed serves as one of the main sources of raw water for the surrounding region, this condition has the potential to threaten the sustainability of future water availability (Moha et al., 2020).

Land use change in the Biyonga Sub-Watershed over the past two decades has shown a significant trend. Analysis of land use for the period 2000–2020 indicates an increase in agricultural land, open land, and built-up areas, while forest cover, natural vegetation, and water bodies have declined (Cahyono et al., 2021). This land conversion process can reduce water infiltration capacity, increase surface runoff, elevate erosion risk, and diminish groundwater reserves. This is consistent with various studies affirming that the conversion of natural land cover to built-up areas or intensive agriculture disrupts watershed hydrological balance and reduces raw water availability (Ferynandari et al., 2025).

In the digital era, assessing land use change, beyond direct field observation, requires computer-based systems capable of integrating spatial and attribute data to effectively support resource management analysis, particularly in land use change studies (Saputra et al., 2024). Land change detection is an analytical technique used to identify differences in land cover and land use conditions across two or more observation periods (Lambin et al., 2003). This technique is critically important in land use dynamics research as it can reveal the location, extent, and type of changes that have occurred. Remote sensing- and GIS-based land use change analysis is widely applied to assess the impacts of urbanization, deforestation, and agricultural land use change (Roberts et al., 2021). Information derived from such analysis serves as an essential foundation for sustainable development planning and environmental management (Butt et al., 2015).

Method

Study Area

This study was conducted in the Biyonga Sub-Watershed, located in Gorontalo Regency, Gorontalo Province. The geographic reference point is the AWLR station at 0^0 37′ 38′′ N 122^0 58′ 36′′°37′38″ N, 122°58′36″ E. The sub-watershed covers an area of 90.45 km^2 ^{2} with a perimeter of 54.39 km (Ayuba, 2022). The Biyonga Sub-Watershed is part of the Limboto Watershed and serves as an important water catchment area and raw water source, draining into Lake Limboto (Karim et al., 2022).

Figure 1. Biyonga Sub-Watershed

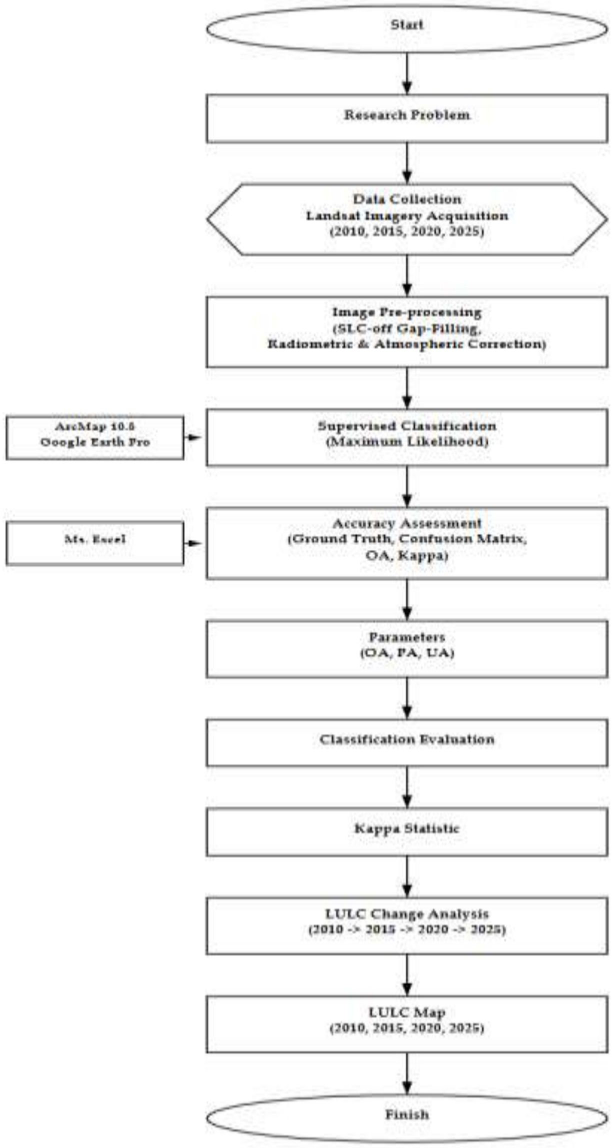

Figure 2. Flow chart

Data

This study utilized Landsat 7 and Landsat 8-9 Collection 2 Level-2 imagery acquired at five-year intervals for 2010, 2015, 2020 and 2025. Citra landsat diperoleh dari https://earthexplorer.usgs.gov/. Additionally, administrative boundary data at the city and regency levels, as well as Biyonga Sub-Watershed boundary data, were used.

Table 1. Landsat Imagery Data

Year	Satellite Data		Path/Row	Cloud Cover	Source
2010	Landsat 7	Landsat Collection 2 Level-2	114/59	0 - 25%	Earthexplorer.usgs.gov
2015	Landsat 8	Landsat Collection 2 Level-2	114/59		
2020	Landsat 8	Landsat Collection 2 Level-2	114/59		
2025	Landsat 8	Landsat Collection 2 Level-2	114/59		

Source: earthexplorer.usgs.gov

Supervised Classification

Image classification is a remote sensing analysis process aimed at identifying and grouping objects on the earth's surface based on their spectral values. In the supervised classification method, (*supervised*) method, the user defines training areas representing each land use class. This method is considered to yield higher accuracy when training data are adequately available (Reis, 2008).

Maximum Likelihood Method

Maximum Likelihood is a supervised classification method that employs a probabilistic algorithm to assign pixels to classes based on statistical likelihood. This method is available within the ArcGIS classification plugin (Stefanus et al., 2025).

Ground Truth

Independent validation sampling is an accuracy evaluation approach using samples independent of the training dataset. Independent samples are selected from points not included in the classification training data, with the objective of avoiding bias and providing a more realistic accuracy estimate (Guastaldi et al., 2013). The sample size was calculated using the following formula:

$$S = \frac{N}{1+N.e^2} \tag{1}$$

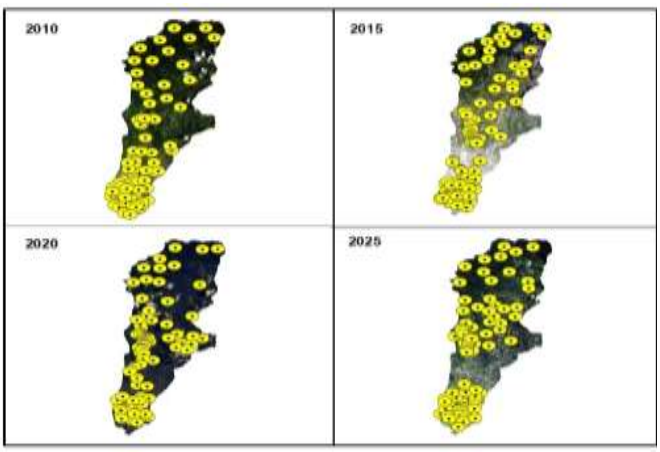

Figure 3. Sample point

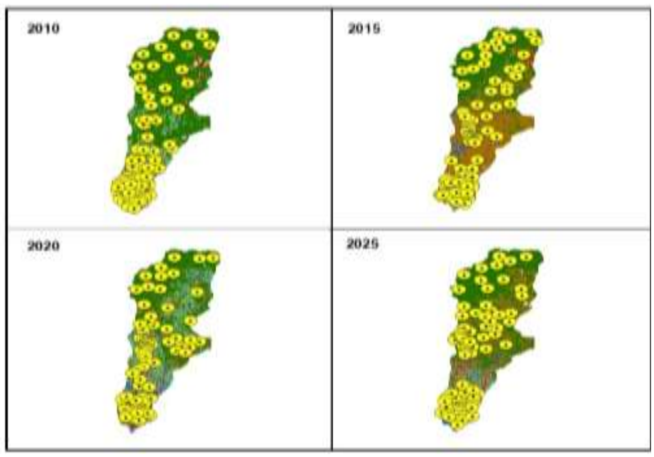

Figure 4. Land classification sample points

Table 2. Sample Point

LULC Class	$e^2 = 10\%^2$	2010 ∑Pixel = N	2010 Sample Point	2015 ∑Pixel = N	2015 Sample Point
Water Body	1%	1608	100	5095	100
Settlement		5151		3683	
Forest		68260		42424	
Paddy Field		18267		1262	
Unused Land		5161		46208	
Built-up Land		2072		1847	
∑		100519	100	100519	100
LULC Class	$e^2 = 10\%^2$				

			2020		2025
		∑Pixel = N	Sample Point	∑Pixel = N	Sample Point
Water Body		7995		4204	
Settlement		3842		5556	
Forest	1%	44062	100	52071	100
Paddy Field		28209		11063	
Unused Land		15700		26133	
Built-up Land		694		1519	
∑		100502	100	100546	100

Confusion Matrix

The accuracy evaluation method used to assess classification error in this study was the confusion matrix, incorporating the following indicators: Producer Accuracy (PA), User Accuracy (UA), Overall Accuracy (OA), and Kappa Accuracy. The matrix was computed by comparing image classification results with field-verified (ground truth) land cover conditions (Shastri et al., 2020):

$$\textit{Producer Accuracy}\ (\mathrm{PA}) = \frac{X_{ii}}{X_{i+}} \times 100\% \quad (2)$$

$$\textit{Ucer Accuracy}\ (\mathrm{UA}) = \frac{X_{ii}}{X_{+i}} \times 100\% \quad (3)$$

$$\textit{Overall Accuracy}\ (\mathrm{OA}) = \frac{\sum Xii}{N} \times 100\% \quad (4)$$

Kappa

The Kappa Coefficient is a statistical measure used to evaluate classification accuracy while accounting for chance agreement (Putri et al., 2024), calculated using the formula from (Cohen, 1960; Congalton, 1991).

$$\mathrm{K} = \frac{N \sum_i^r Xii - \sum_k^r Xi{+}X{+}i}{N^2 - \sum_i^r Xi{+}X{+}i} \quad (5)$$

The Kappa Coefficient interpretation categories (Landis et al., 1977) are as follows:

Table 3. Accuracy Classification Based on Kappa Coefficient (Cohen, 1960)

Kappa Coefficient Value	Kappa Interpretation
0 <	Poor Accuracy
0.01 – 0.20	Slight Accuracy
0.21 – 0.40	Fair Accuracy
0.41 – 0.60	Moderate Accuracy
0.61 – 0.80	Good Accuracy
0.81 – 0.99	Very Good Accuracy

Result and Discussion

Land Cover

Land cover classification of the Biyonga Sub-Watershed was performed using the Supervised Classification method with a Maximum Likelihood approach applied to Landsat imagery for 2010, 2015, 2020, and 2025. The classification results divided land cover into six classes: water bodies, settlements, forest, paddy fields, unused land, and built-up land, as illustrated in Figure 5. *Supervised Classification* method with a *Maximum Likelihood.* As shown in Table 3, forest cover dominated land cover in the Biyonga Sub-Watershed throughout the entire observation period. In 2010, the forest area was recorded at 61.66 km² (68.17%), but declined significantly in 2015 to 38.15 km² (42.18%) and in 2020 to 39.97 km² (44.19%). By 2025, the forest area recovered to 47.08 km² (52.05%). This fluctuation in forest area indicates land conversion pressure during the 2010–2020 period, followed by vegetation recovery in subsequent years, likely as a result of reforestation activities or changes in land use.

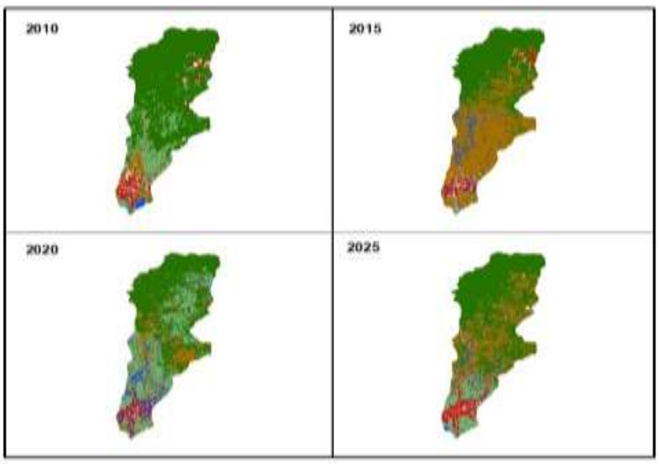

Figure 5. LULC 2010-2025

The unused land class showed a dramatic increase from 2010 to 2015, rising from 4.54 km² (5.02%) to 42.06 km² (46.50%). This surge indicates large-scale land clearing during that period, most likely driven by agricultural activities, residential expansion, or deforestation not yet followed by productive land utilization. By 2020 and 2025, unused land decreased to 13.78 km² (15.24%) and 23.48 km² (25.96%), respectively, indicating that portions of the land had begun to be utilized for productive purposes such as paddy cultivation or returning vegetation.

The paddy field class exhibited the most fluctuating dynamics throughout the study period. In 2010, the paddy field area reached 16.34 km² (18.06%), before plummeting to only 1.11 km² (1.23%) in 2015. This decline correlates with the simultaneous increase in unused land, suggesting conversion of paddy fields into open land. In 2020, the paddy field area recovered significantly to 25.69 km² (28.41%), before declining again to 9.97 km² (11.02%) in 2025. These dynamics reflect instability in agricultural land use patterns, influenced by the local socioeconomic conditions of the community. The water body class showed an increasing trend from 2010 to 2020, growing from 1.41 km² (1.56%) to 6.93 km² (7.66%), before declining in 2025 to 3.56 km² (3.94%). Changes in water body extent may be influenced by seasonal variation at the time of image acquisition, changes in inundation patterns, or the overall hydrological conditions of the watershed. The settlement class showed an increasing tendency toward the end of the observation period. The settlement area in 2010 was 4.68 km² (5.18%), temporarily declined in 2015 and 2020, then increased to 5.07 km² (5.61%) in 2025. This expansion in settlement area is consistent with the population growth rate in Limboto District of approximately 0.96% per year. Meanwhile, the built-up land class remained relatively small and stable, ranging from 0.58 to 1.82 km² throughout the study period.

Table 4. Land Cover Sub DAS Biyonga

LULC Class	2010		2015	
	Area (km²)	%	Area (km²)	%
Water Body	1.41	1.56	4.24	4.69
Settlement	4.68	5.18	3.33	3.68
Forest	61.66	68.17	38.15	42.18
Paddy Field	16.34	18.06	1.11	1.23
Unused Land	4.54	5.02	42.06	46.50
Built-up Land	1.82	2.01	1.56	1.72
	90.45	100	90.45	100
LULC Class	2020		2025	
	Area (km²)	%	Area (km²)	%
Water Body	6.93	7.66	3.56	3.94
Settlement	3.49	3.86	5.07	5.61
Forest	39.97	44.19	47.08	52.05
Paddy Field	25.69	28.41	9.97	11.02
Unused Land	13.78	15.24	23.48	25.96
Built-up Land	0.58	0.64	1.29	1.43
	90.45	100	90.45	100

Overall, the analysis results indicate that the Biyonga Sub-Watershed experienced significant land cover change dynamics during the 2010–2025 period (Figure 6). The most notable change was the decline in forest cover and the increase in unused land during the 2010–2015 period, indicating land conversion pressure that directly affects the watershed's capacity to store and sustainably supply raw water.

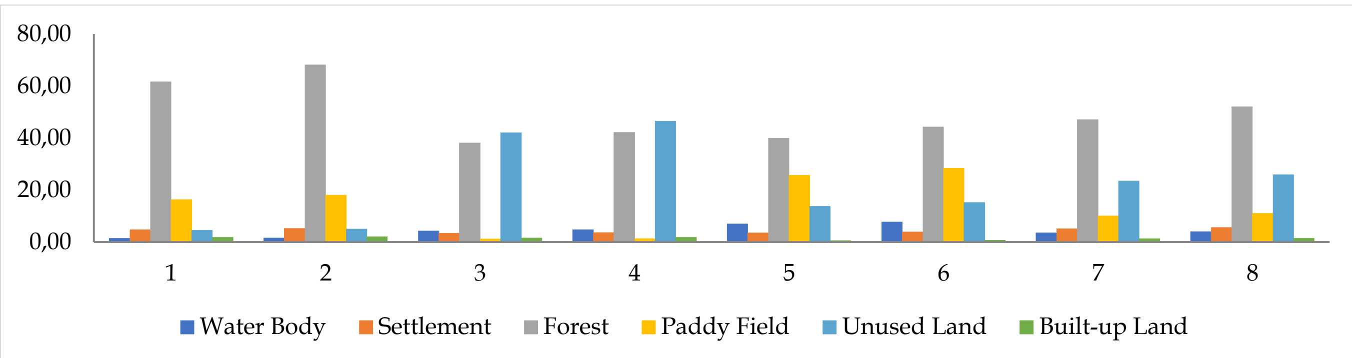

Figure 6. Area LULC 2010-2025

Accuracy Assessment

Year 2010**,** the forest class achieved the highest UA and PA values of 100% each, indicating that forest was identified with exceptional accuracy and without classification error. The built-up land class obtained a PA of 100% but a UA of 81.25%, meaning all built-up pixels were correctly identified; however, some pixels from other classes were misassigned to this class. The water body class achieved a UA of 82.35% and PA of 93.33%, while the paddy field class showed a UA of 76.47% and a PA of 56.52%, the lowest PA value for this year, indicating that a considerable number of paddy field pixels were misclassified into other classes due to spectral similarity with unused land.

Year 2015 in 2015, a general improvement in accuracy was observed. The settlement, forest, and paddy field classes achieved better UA and PA values compared to the previous year. The water body class showed an increase in UA to 94.12% and PA to 94.12%. Meanwhile, the unused land class obtained a UA of 76.47% but a PA of 86.67%, indicating that the classification system was reasonably effective in recognizing unused land, although a small proportion of pixels remained misclassified. The built-up land class again achieved a PA of 100% with a UA of 82.35%.

Year 2020 in 2020, the classification results showed the most stable accuracy across all years. The settlement class achieved a UA of 100% and PA of 80.00%, while the built-up land class obtained UA and PA values of 100%

and 94.12%, respectively. The paddy field class reached a UA of 88.24% and PA of 100%, representing the best PA value for this class throughout the study period. The water body class experienced a decline in UA to 70.59%; however, the PA remained at 100%, indicating that all water body areas were successfully identified.

Year 2025, most land cover classes demonstrated good accuracy. The paddy field and built-up land classes obtained high UA and PA values of 94.12% and 93.75% for paddy fields, and 93.75% and 100% for built-up land, respectively. However, the forest class experienced a decline in PA to 76.19% while UA remained at 94.12%, suggesting that some forest pixels were misclassified into other classes, likely due to spectral similarity with the sparsely vegetated unused land class. The water body class obtained a UA of 64.71%, the lowest value throughout the study period, despite achieving a PA of 100%.

Table 5. User Accuracy and Producer Accuracy

LULC Class	2010		2015	
	User (%)	Producer (%)	User (%)	Producer (%)
Water Body	82.35	93.33	94.12	94.12
Settlement	87.50	87.50	93.75	93.75
Forest	100.00	100.00	94.12	80.00
Paddy Field	76.47	56.52	82.35	73.68
Unused Land	76.47	81.25	76.47	86.67
Built-up Land	81.25	100.00	82.35	100.00
LULC Class	2020		2025	
	User (%)	Producer (%)	User (%)	Producer (%)
Water Body	70.59	100.00	64.71	100.00
Settlement	100.00	80.00	93.75	93.75
Forest	88.24	78.95	94.12	76.19
Paddy Field	88.24	100.00	94.12	94.12
Unused Land	76.47	76.47	76.47	65.00
Built-up Land	100.00	94.12	93.75	100.00

Based on the calculations presented in Tables 5 and 6, the Overall Accuracy and Kappa Coefficient values across all observation years indicate good to very good accuracy levels. The following provides a detailed explanation for each observation year:

Overall Accuracy

Year 2010 yielded an Overall Accuracy of *Overall Accuracy* 84.00% with a Kappa Coefficient of 80.79%, obtained from 84 correctly classified pixels out of 100 test sample points. Based on the Kappa value classification by Landis & Koch (1977), a Kappa Coefficient of 80.79% falls within the good accuracy category (range 0.61–0.80). Nevertheless, some classification errors persisted in this year, particularly for the paddy field and water body classes, which share spectral characteristics with the unused land class. The year 2010 recorded the lowest accuracy values throughout the study period, likely attributable to the Landsat 7 ETM+ imagery used, which is subject to scan line corrector *scan line corrector* (SLC-off) which can affect the quality of the resulting pixels of the classification.

Year 2015 demonstrated improved accuracy compared to the previous year, with an Overall Accuracy of*Overall Accuracy* 88.00% and a Kappa Coefficient of 85.54%, reflecting that 88 out of 100 sample points were correctly classified. Based on Landis & Koch (1977), a Kappa Coefficient of 85.54% falls within the very good accuracy category (range 0.81–0.99). The accuracy improvement in 2015 was attributed to the use of Landsat 8 OLI imagery, which offers superior radiometric quality compared to Landsat 7, as well as greater precision in training sample selection *training sample* for the forest, settlement, and paddy field classes, all of which achieved very high accuracy values in this year.

Year 2020 achieved the most balanced combination of Overall Accuracy and Kappa Coefficient,*Overall Accuracy* at 87.00% and 84.41% respectively, both classified within the very good accuracy category. In this year, 87 out of 100 sample points were correctly classified. The high accuracy values in 2020 indicate that spectral characteristics were relatively more distinct and separable across land cover classes, supported by low cloud cover in the Landsat 8 OLI imagery, which produced clean and representative spectral data.

Year 2025 yielded an Overall Accuracy of*Overall Accuracy* 86.00% and a Kappa Coefficient of 83.20%, both classified within the very good accuracy category. A total of 86 out of 100 sample points were correctly classified. Although the accuracy values in 2025 were slightly lower than those in 2020, the results still demonstrate a satisfactory level of classification reliability for further analysis. The slight decrease in accuracy is attributed to the increased complexity of land cover in 2025, particularly for the forest and unused land classes, which exhibited spectral similarity due to secondary vegetation growing in open areas.

Table 6. Assessment Kappa

Year	Kappa Coefficient	Assessment
2010	80.79	Good
2015	85.54	Very Good
2020	84.41	Very Good
2025	83.20	Very Good

Table 7. Overall Accuracy and Kappa

Year	Overall Accuracy (%	KAPPA Statisti
2010	84.0	80.7
2015	88.0	85.5
2020	87.0	84.4
2025	86.0	83.2

Conclusion

This study identified the dynamics of land use and land cover (LULC) change in the Biyonga Sub-Watershed using multi-temporal Landsat imagery for 2010, 2015, 2020, and 2025 through the Supervised Classification method with a Maximum Likelihood approach. The classification results confirm that forest remained the dominant land cover class throughout the observation period, while a consistent decline in paddy field area was accompanied by a corresponding increase in unused land, indicating widespread land clearing activities and reflecting increasing human activity pressure within the watershed. The accuracy assessment, with Overall Accuracy ranging from 84% to 88% and Kappa Coefficient ranging from 80.79% to 85.54%, confirmed that the classification results fall within the good to very good accuracy categories according to the Landis and Koch classification standard, supporting the reliability of the observed land cover change patterns. These findings indicate that ongoing land conversion in the Biyonga Sub-Watershed has the potential to affect the ecological function and hydrological balance of the catchment area if not accompanied by sustainable spatial planning and land conservation measures, particularly through stricter zoning control in the upstream forested area and the downstream zone adjacent to Lake Limboto. Future research is recommended to incorporate higher-resolution or radar-based imagery to improve classification accuracy in cloud-prone periods, apply hydrological modeling to quantify the direct impact of LULC change on streamflow and sedimentation, and extend the observation period with shorter temporal intervals to better capture the transitional dynamics of paddy field and settlement areas.

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Author Contributions
Conceptualization, E.R.H.H.; methodology, E.R.H.H.; software, E.R.H.H.; validation, E.R.H.H., M.B. and L.P.; formal analysis, E.R.H.H.; investigation, E.R.H.H.; resources, E.R.H.H.; data curation, E.R.H.H.; writing—original draft preparation, E.R.H.H.; writing—review and editing, M.B. and L.P.; visualization, E.R.H.H.; supervision, M.B. and L.P.; project administration, E.R.H.H. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest
The authors declare no conflict of interest.

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