

LAND COVER CLASSIFICATION OF KRUENG LANGSA WATERSHED USING MAXIMUM LIKELIHOOD METHOD

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ABSTRACT

Land cover classification plays an important role in supporting environmental management and spatial planning, particularly in watershed areas. However, recent studies have predominantly emphasized advanced machine learning approaches, with limited attention given to the applicability of conventional methods such as Maximum Likelihood Classification (MLC) in specific local contexts. This study aims to evaluate the performance of the MLC method in classifying land cover in the Krueng Langsa watershed using high-resolution RapidEye imagery. This research was conducted from July to October 2024 in the Krueng Langsa watershed, covering East Aceh, Aceh Tamiang, and Langsa City. Land cover classification was performed using supervised Maximum Likelihood Classification in ArcGIS 10.8.2, followed by accuracy assessment using a confusion matrix and kappa coefficient based on stratified random sampling. The results identified ten land cover classes, with dryland forest dominating the area at 38.01%, while open land had the smallest proportion at 0.80%. The classification achieved an overall accuracy of 89% and a kappa coefficient of 0.88, indicating an almost perfect level of agreement. These findings demonstrate that the MLC method remains effective and reliable for land cover classification in tropical watershed environments. This study highlights the continued relevance of conventional classification approaches and provides valuable baseline information for sustainable watershed management and regional planning in the Krueng Langsa area.

Keywords: Accuracy; Land cover; MLC; Remote sensing; Watershed.

INTRODUCTION

A river is a water drainage system starting from the source to the estuary, bounded on the right and left sides and along its course by boundary lines (Ministry of Public Works Republic of Indonesia, 1989). An area of land that is topographically bounded by mountain ridges that collect and store rainwater, which is then distributed to the sea through the main river, is called a river basin (DAS) (Sambou *et al.*, 2023; Putra *et al.*, 2024). The Krueng Langsa DAS is part of the Tamiang-Langsa watershed with an area of 49,735 hectares stretching from East Aceh Regency, Langsa City, to Aceh Tamiang Regency (BPDAS, 2024). Land classification is an important and complex process that has evolved alongside advances in remote sensing technology and Geographic Information Systems (GIS). In the context of research conducted over the past five years, land classification is defined as an effort to group types of land use based on physical and socio-economic characteristics (Digra *et al.*, 2022; Macarringue *et al.*, 2022; Marlina, 2022; Wang *et al.*, 2023; Radhinal *et al.*, 2025).

The use of remote sensing technology for land cover classification can be applied in various fields such as natural resource management, urban planning, agriculture, and environmental management (Christy, 2021). One of the land cover/land use classification systems used to classify land cover/land use using remote sensing data is the classification system, SNI 2010 Land Cover (National Standardization Agency, 2010). The land cover classification standard by the National Standardization Agency (BSN) consists of land cover classes with 3 different

scale areas and can be used with adjustments to the available images. From a remote sensing technology perspective, land cover is an image of objects in the form of biophysical appearances on the earth's surface obtained from selected sources (Miranda & Aryuni, 2021). Remote sensing technology makes it possible to obtain land cover data without direct contact with the area or phenomenon being studied. Efforts to determine the condition of land cover in an area using remote sensing can be carried out comprehensively, quickly, and with relative accuracy.

Despite the rapid development of land cover classification techniques, recent studies have predominantly focused on improving classification accuracy through advanced approaches such as machine learning and deep learning algorithms (Digra *et al.*, 2022; Marlina, 2022; Wang *et al.*, 2023; Radhinal *et al.*, 2025). These approaches are considered more adaptive in handling complex and heterogeneous landscapes. However, this trend has led to relatively limited attention being given to the applicability and performance of conventional classification methods, such as the Maximum Likelihood Classification (MLC), particularly in specific local contexts such as tropical watershed environments. Previous studies have demonstrated that MLC remains widely used and effective for land cover mapping due to its strong statistical foundation and ease of implementation (Sampurno & Thoriq, 2016; Mishra *et al.*, 2020). Nevertheless, there is still a lack of studies that specifically evaluate the reliability of MLC in localized watershed areas with diverse land cover characteristics, such as the Krueng Langsa watershed. Therefore, this study aims to fill this gap by assessing the performance of the MLC method in classifying land cover using high-resolution RapidEye imagery in a tropical watershed setting.

Therefore, it is important to evaluate whether conventional methods such as Maximum Likelihood Classification (MLC) remain effective when applied to specific environmental contexts, particularly in tropical watershed areas. In this context, remote sensing technology combined with the MLC method offers a practical approach for monitoring and analyzing land cover types. The MLC algorithm is capable of distinguishing spectral characteristics of objects in satellite imagery, thereby providing an objective representation of land cover conditions. This research is expected to contribute to sustainable watershed management in the Krueng Langsa area by providing reliable land cover information. The results of land cover classification can serve as a basis for policymakers in regional planning and environmental management. Therefore, this study aims to identify and classify land cover types in the Krueng Langsa watershed in 2024 using RapidEye satellite imagery through the Maximum Likelihood classification method.

METHOD

This research was conducted in the Krueng Langsa watershed, which administratively falls within the regions of East Aceh, Aceh Tamiang, and Langsa City. The research activities were carried out from July to October 2024. The analysis, data processing, and map creation processes were carried out at the Remote Sensing and Cartography Laboratory, Department of Soil Science, Faculty of Agriculture, Syah Kuala University. Spatially, the study area map can be seen in Figure 1.

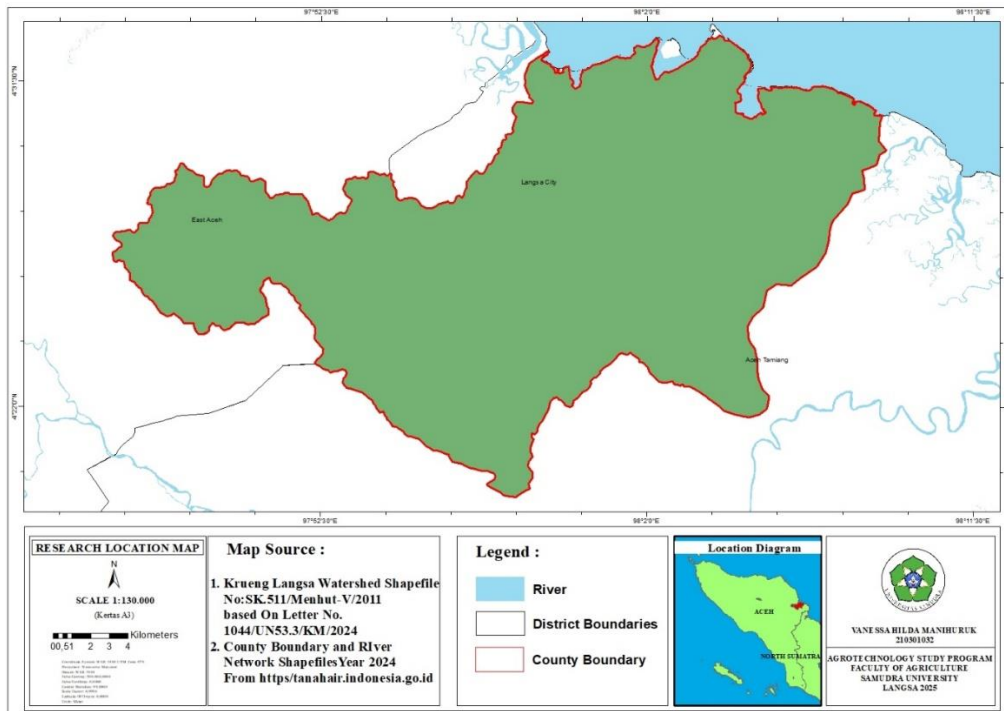


Figure 1. Administrative Map of the Krueng Langsa Watershed Research Location

The tools used in this research were laptops for processing research data and writing reports, ArcGIS 10.8.2 software to perform land classification using the Maximum Likelihood method, a camera to document each research activity, a Global Positioning System (GPS) to assist in taking ground check sample points, QGIS software to perform post-analysis or correct classifications that did not match the satellite imagery, Microsoft Excel and Microsoft Word to write and calculate the accuracy test of the ground check results. The use of GIS-based software and remote sensing tools is widely recognized as essential in land cover classification and spatial data processing (Macarrigue *et al.*, 2022; Wang *et al.*, 2023).

The materials used were RapidEye satellite images obtained from the official Planet Labs website (Planet.com), with a spatial resolution of 3–5 meters per pixel. Digital Elevation Model (DEM) data were obtained from the official Indonesian geospatial data portal (tanahair.indonesia.go.id) and used to generate topographic maps, Shapefile (SHP) administrative boundary data for the Langsa Watershed were acquired from the Watershed and Protected Forest Management Agency (BPDAS) Aceh, and non-spatial data, including journal articles, theses, and books, were utilized as supporting literature. The use of satellite imagery and DEM data is a common approach in Land Use and Land Cover (LULC) studies for spatial analysis and terrain representation (Mishra *et al.*, 2020; Tadese *et al.*, 2020).

The research stages began with radiometric and geometric image correction, image cropping, cropping of the study area, and training area. The training samples will represent variations in land cover, such as organization, forest vegetation, agricultural areas, and water bodies. The data will be processed by taking pixel samples from each type of land cover. These preprocessing steps are crucial to improve classification accuracy and ensure the quality of remote sensing data analysis (Dash *et al.*, 2023). The next stage involves classification using the supervised Maximum Likelihood method. Land cover maps will be created using ArcMap 10.8.2 software. The Maximum Likelihood classification method is one of the most commonly used supervised classification techniques due to its statistical robustness and effectiveness in distinguishing land cover classes (Sampurno & Thoriq, 2016; Macarrigue *et al.*, 2022). Data validation will be carried out using Google Earth Pro Base Map and field surveys, and accuracy testing will be conducted. Accuracy assessment is an essential step in evaluating classification performance, often using statistical measures such as confusion matrix and kappa coefficient to ensure the reliability of classification results (Cohen, 1968; Aigbokhan *et al.*, 2022;

Feizizadeh *et al.*, 2022). Accuracy assessment is performed using a contingency matrix or error matrix, which allows for a more in-depth analysis of classification performance. A confusion matrix is a matrix table that links classified pixels with data obtained from field observations or verified maps. According to (Sampurno & Thoriq, 2016), accuracy testing can be expressed mathematically using the following equation:

Table 1. Cohen's Kappa (Inter-Rater Reliability or Agreement Measurement) Suitability Category

No	Kappa's Value	Agreement Classification
1	<0	Less than change agreement
2	0.01-0.20	Slight agreement
3	0.21-0.40	Fair agreement
4	0.41-0.60	Moderate agreement
5	0.61-0.80	Substantial agreement
6	0.81-0.99	Almost perfect agreement

Source: (Cohen, 1968)

Table 2. Confussion Matrix

Classification Results	Classified Into - Class				Total Rows	Producer's
	A	B	C	D		
A	X_{ii}				X_{i+}	X_{ii}/X_{i+}
B						
...						
D				X_{ii}		
Total					N	
Kolom	X_{i+}					
User's	X_{ii}/X_{i+}					

Source: (Sampurno & Thoriq, 2016)

Mathematically, the above accuracy can be expressed as follows:

$$\text{User's accuracy} = \frac{X_{ii}}{X_{+i}} \times 100 \dots\dots\dots (1)$$

$$\text{Producer's accuracy} = \frac{X_{ii}}{X_{i+}} \times 100\% \dots\dots\dots (2)$$

$$\text{Overall accuracy} = \frac{\sum_i^r X_{ii}}{N} \times 100\% \dots\dots\dots (3)$$

$$\text{Kappa} = \frac{N \sum_i^r X_{ii} - \sum_i^r X_{i+} X_{+i}}{N^2 - \sum_i^r X_{i+} X_{+i}} \times 100\% \dots\dots\dots (4)$$

Description:

- x_{ii} = The value of the contingency matrix row - i and column - i
- x_{i+} = Number of test classes in row - i
- x_{+i} = Number of test classes in column i
- $\sum_i^r X_{ii}$ = Number of diagonal classes
- N = Total number of test classes in the matrix

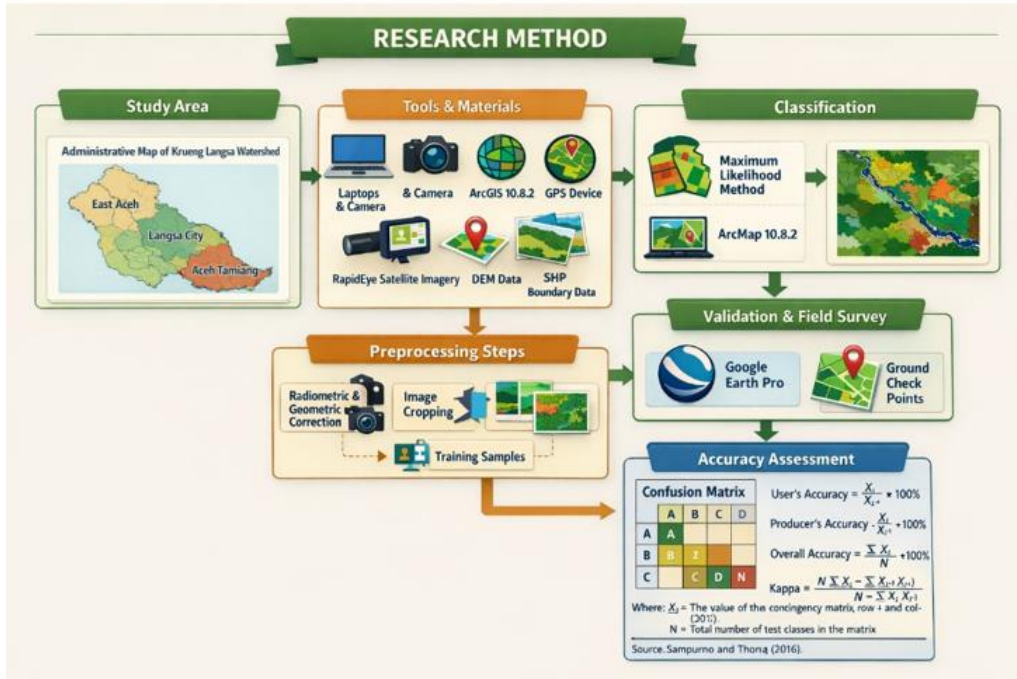


Figure 2. Research Flow

RESULTS AND DISCUSSION

The Krueng Langsa watershed is part of the Tamiang-Langsa watershed based on Indonesian Minister of Forestry Decree No. SK.511/Menhut-V/2011 on the Determination of Watersheds, which spans two districts and one city with an area of 49,735 hectares stretching from East Aceh, Langsa, to Tamiang. Geographically, the downstream section of this watershed is located at coordinates 98° 01' 58.8" E to 98° 03' 7.2" E and 4° 32' 38.4" N to 4° 31' 26.4" N. Meanwhile, the upper reaches of the watershed are located at 97° 51' 46.8" E to 97° 58' 26.4" E and 4° 25' 8.4" N to 4° 19' 30" N. The upper part of the Krueng Langsa watershed is in Birem Bayeun Village and the lower part is in Alur Sentang Manyak Payed Village, Aceh Tamiang Regency. The RapidEye image map can be seen in Figure 3.

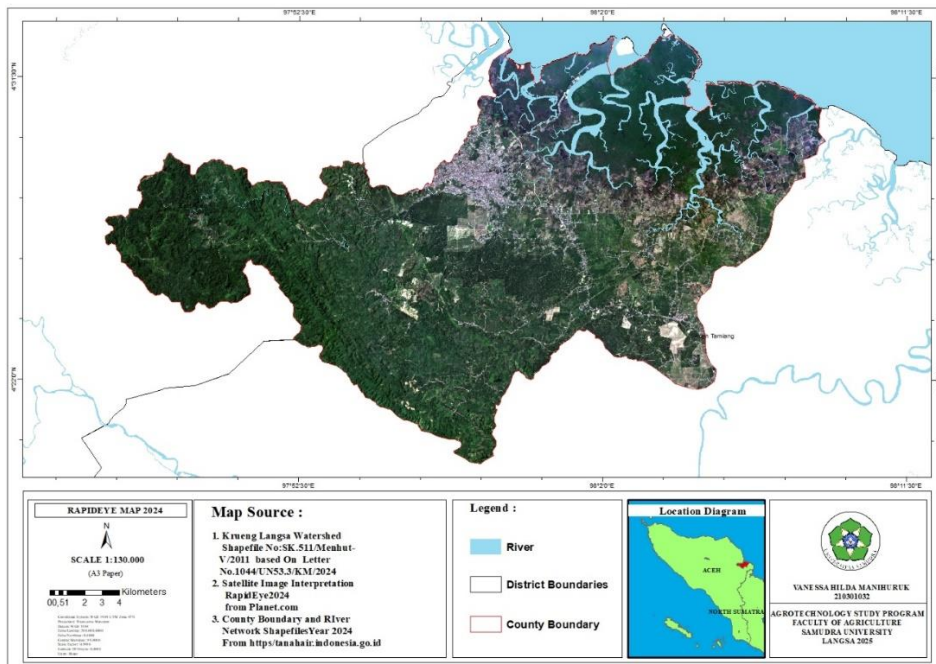


Figure 3. RapidEye Image of the Krueng Langsa Watershed

Identification of Land Use Classes

Objects on the earth's surface can be identified using satellite imagery by recognizing them visually. To distinguish each object more clearly, it is necessary to pay attention to texture, shape, and their relationship to other objects (Sampurno & Thoriq, 2016; Macarringue *et al.*, 2022). Based on the interpretation of RapidEye images in the Krueng Langsa watershed using maximum likelihood classification, 10 land cover classes were obtained, namely body of water, wet forests, dry forests, open land, mixed plantations, shrubs, road networks, ponds, rice fields, and settlements.

Wetland forests are characterized by dark shades of deep green, while dryland forests have lighter shades of green with diverse vegetation and a rough texture, as well as a layer of large tree canopies. Open land is characterized by bright reddish-purple shades with a smooth texture and low vegetation structure. Mixed plantations are characterized by a smooth green texture with neat and parallel planting patterns. Shrubs are characterized by light green with a rough texture and irregular planting patterns. Ponds are characterized by a smooth texture with a dark blue-black color and have a regular plot pattern with a dark hue. Rice fields are characterized by light to dark colors, smooth textures, homogeneous patterns, and proximity to water sources and populated areas. Settlements are characterized by a consistent pink color pattern, a slightly rough texture, and association with road networks. The results of the interpretation of RapidEye satellite images using the maximum likelihood method in ArcGIS 10.8.2 software in the form of a 2024 land cover map can be seen in Figure 4 below.

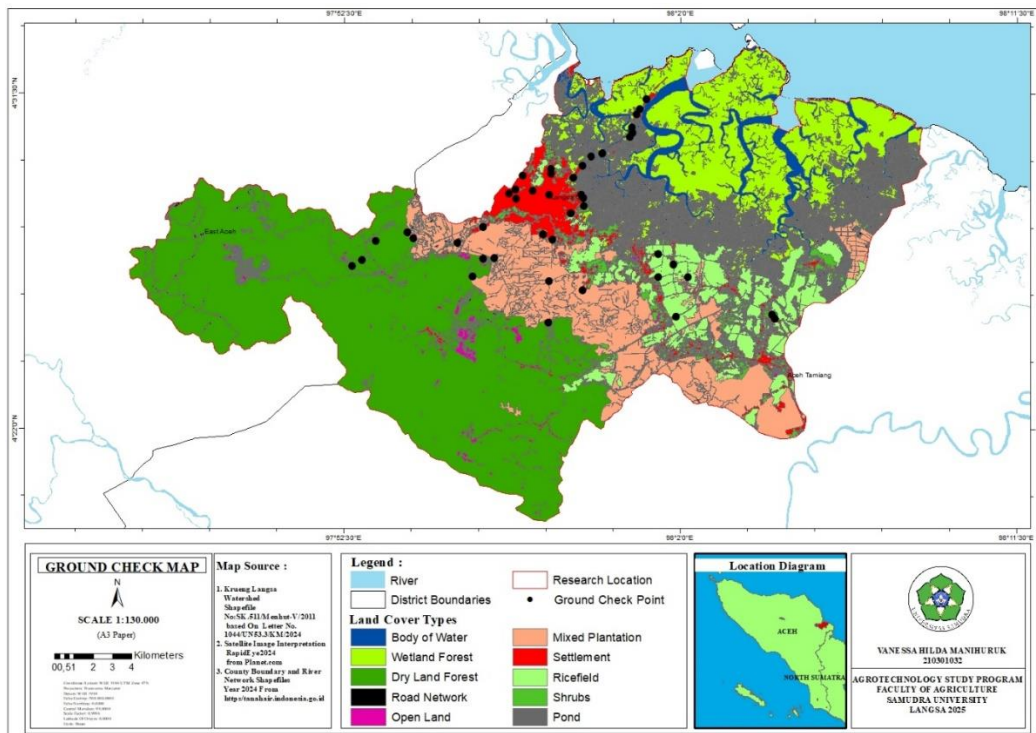


Figure 4. Land Cover Classification Map in the Krueng Langsa Watershed in 2024

The total area of the Krueng Langsa watershed is 49,735.00 ha, with the area of each land cover shown in Table 3.

Table 3. Percentage of Land Cover in the Krueng Langsa Watershed

Land Cover	Area (Ha)	% Total
Water Bodies	2275,22	4,57%
Wetland Forests	7587,49	15,26%
Dryland Forests	18903,08	38,01%
Road Networks	1565,08	3,15%
Open Land	396,17	0,80%
Mixed Plantations	6375,89	12,82%
Settlements	2682,91	5,39%
Rice Fields	3689,0	7,42%
Scrubland	1500,73	3,02%
Fish Ponds	4759,13	9,57%
Total	49.735,00	100 %

Source: Primary Data (2024)

The table above shows land cover in the Krueng Langsa watershed with a total of 49,735 hectares (Ha) having varying percentages of area. The highest percentage is in the dry forest land cover class with 38.01%, while the lowest percentage is in the open land class with 0.80%.

Accuracy Test Results (Confusion Matrix)

This accuracy test must be conducted before proceeding to a more in-depth analysis of the method. The accuracy test is carried out using a confusion matrix to calculate the accuracy rate of the classification results. Sampling for this accuracy test is conducted using the Stratified Random Sampling method, which is a random or heterogeneous sampling method. This study tests accuracy using independent data sources, where the samples for the accuracy test are different from the samples used in the classification training area.

The Stratified Random Sampling method is run on ArcGIS software using 46 samples. The results of these observations are then entered into the confusion matrix table to facilitate the accuracy test calculation process in classification. The error matrix in this study is presented in Table 4.

Table 4. Ground Check Data Confusion Matrix

Classification results	Ground Check										Total Rows	Users Accuracy
	HLK	PC	SWH	SMK	LT	PKN	HLB	JLN	BA	TBK		
HLK	5			1							6	83%
PC		5									5	100%
SWH			5								5	100%
SMK				2	1						3	67%
LT					2			1			3	67%
PKN						7		2			9	78%
HLB							5				5	100%
JLN								2			2	100%
BA									3		3	100%
TBK										5	5	100%
Total Kolom	4	7	5	3	3	7	5	5	3	5	46	
Producer	100%	100%	100%	67%	67%	100%	100%	40%	100%	100%		
Overall accuracy	89%											
Kappa accuracy	88%											

Source: Primary Data (2024)

Description:

- HLK : Dry Land Forest
- PC : Mixed Plantation
- SMK : Shrubs
- SWH : Rice Fields
- LT : Open Land
- PKN : Settlements
- HLB : Wet Land Forest
- JLN : Roads
- BA : Water Bodies
- TBK : Fish Ponds

Table 4 shows the results of Maximum Likelihood classification for ten land use classes in the Krueng Langsa watershed, with an overall accuracy of 89% and an accuracy error of 11%. This overall accuracy value is used to calculate kappa accuracy. In this study, the kappa accuracy value of land use classification using the Maximum Likelihood method reached 0.88 (88%), indicating a high level of agreement between classified results and reference data. According to (Cohen, 1968), a kappa value within the range of 0.81–0.99 is categorized as almost perfect agreement, suggesting that the classification results are highly reliable.

The accuracy level in this study has met the requirement of >81%, which is considered acceptable for satellite image use. The high accuracy obtained in this study indicates that the Maximum Likelihood Classification (MLC) method remains effective for land cover mapping, particularly when supported by appropriate preprocessing and representative training samples. Research by (Aigbokhan *et al.*, 2022) also used MLC for land cover analysis and assessed accuracy using the Principal Component Analysis approach. The researchers found that MLC showed good analytical depth for identifying land cover types from Landsat image data, demonstrating significant benefits in assessing classification accuracy for environmental monitoring purposes. In the research by (Mishra *et al.*, 2020), the Maximum Likelihood method was also used to detect changes in land use and land cover in Sikkim Himalaya, India. The data generated can ultimately be used to help identify limited resources and identify important environmental areas that can be designated as priority zones for conservation or restoration.

However, when compared with more recent approaches, several studies have highlighted the emergence of machine learning and deep learning methods, such as Random Forest and Convolutional Neural Networks (CNN), which often produce higher classification accuracy and better generalization performance, particularly in complex landscapes (Digra *et al.*, 2022; Marlina, 2022; Radhinal *et al.*, 2025). For instance, Random Forest-based classification has been shown to improve classification robustness by handling non-linear relationships and reducing classification errors in heterogeneous land cover conditions (Amini *et al.*, 2022). This indicates that although MLC is still widely used due to its simplicity and statistical foundation, it may be less adaptive compared to newer algorithms in handling highly complex spectral variations.

Despite these advancements, the results of this study demonstrate that MLC remains a relevant and practical method, especially in regions where data availability, computational resources, and methodological simplicity are important considerations. The achieved accuracy (89%) is comparable to or within the acceptable range reported in other LULC studies using conventional classification methods (Tadese *et al.*, 2020; Al-Taei *et al.*, 2023). This suggests that, when properly implemented, traditional classification approaches can still provide reliable outputs for watershed-scale analysis.

From a research gap perspective, many previous studies have focused on improving classification accuracy through advanced algorithms, particularly machine learning and deep learning approaches (Digra *et al.*, 2022; Wang *et al.*, 2023; Faradilla, 2025). However, fewer studies have emphasized the applicability of conventional methods such as Maximum Likelihood Classification (MLC) in specific local contexts, particularly in tropical watershed environments, where data characteristics and landscape heterogeneity may differ significantly (Tadese *et al.*, 2020; Macarringue *et al.*, 2022). Therefore, this study highlights the continued relevance of MLC in providing reliable classification results within such localized environmental settings.

In addition, the use of confusion matrix and kappa coefficient in this study aligns with standard practices in remote sensing accuracy assessment (Feizizadeh *et al.*, 2022; Li *et al.*, 2023), ensuring that the evaluation is not only based on overall accuracy but also considers agreement beyond chance. This strengthens the validity of the classification results and supports their use for further environmental analysis, such as land use planning and watershed management.

CONCLUSION and RECOMMENDATION

Based on the results of the research analysis and discussion, it can be concluded that the land cover classification results in the Krueng Langsa Watershed on Rapid Eye 2024 imagery using the Maximum Likelihood Classification method obtained an accuracy test value of 89% and a kappa accuracy value of 88%. Based on the classification accuracy obtained, the interpretation of Rapid Eye images using the Maximum Likelihood classification method is very good for land cover identification. It is recommended to conduct further research using higher resolution images so that class classification can be performed in greater detail. In addition, other methods need to be applied as comparators to evaluate the accuracy test results of the classification method used.

REFERENCES

- Aigbokhan, O., Essien, N., Ogoiegbone, O., Afolabi, O., & Adamu, I. (2022). Assessing Image Classification Accuracy with Principal Component Analysis Algorithm Case Study: Odeda LGA of Ogun State, Southwest Nigeria. *Journal of Applied Sciences and Environmental Management*, 26(5), 851–858.
- Al-Taei, A. I., Alesheikh, A. A., & Darvishi Bolorani, A. (2023). Land use land cover change analysis using multi-temporal remote sensing data: A case study of Tigris and Euphrates Rivers Basin. *Land*, 12(5), 1101.
- Amini, S., Saber, M., Rabiei-Dastjerdi, H., & Homayouni, S. (2022). Urban land use and land cover change analysis using random forest classification of Landsat time series. *Remote Sensing*, 14(11), 2654.
- Christy, N. T. (2021). Landsat 8 OLI Classification for Land Cover in Palembang City Using Google Earth Engine. *Jurnal Swarnabhumi*, 6(1), 75–85.
- Cohen, J. (1968). Weighted kappa: Nominal scale agreement with provision for scaled disagreement or partial credit. *Psychological Bulletin*, 70(4), 213–220.
- Dash, P., Sanders, S. L., Parajuli, P., & Ouyang, Y. (2023). Improving the accuracy of land use and land cover classification of Landsat data in an agricultural watershed. *Remote Sensing*, 15(16), 4020.
- Digra, M., Dhir, R., & Sharma, N. (2022). Land use land cover classification of remote sensing images based on deep learning approaches: A statistical analysis and review. *Arabian Journal of Geosciences*, 15(10), 1003.
- Faradilla, F. I. R. D. A. (2025). *Assessment of Watershed Quality Based on Land Cover Indicators in the Paremang Watershed*. Universitas Hasanuddin.
- Feizizadeh, B., Darabi, S., Blaschke, T., & Lakes, T. (2022). QADI as a new method and alternative to kappa for accuracy assessment of remote sensing-based image classification. *Sensors*, 22(12), 4506.
- Li, M., Gao, Q., & Yu, T. K. (2023). Kappa statistic considerations in evaluating inter-rater reliability between two raters: Which, when and context matters. *BMC Cancer*, 23, 799. <https://doi.org/10.1186/s12885-023-11325-z>
- Macarringue, L. S., Bolfe, E. L., & Pereira, P. R. M. (2022). Developments in land use and land cover classification techniques in remote sensing: A review. *Journal of Geographic Information System*, 14(1), 1–28.
- Marlina, D. (2022). Land cover classification in Sentinel-2 images of Kuningan Regency using NDVI and random forest algorithm. *STRING (Satuan Tulisan Riset Dan Inovasi Teknologi)*, 7(1), 41–49.
- Ministry of Public Works Republic of Indonesia. (1989). *Minister of Public Works Regulation No. 39/1989*.
- Miranda, E., & Aryuni, M. (2021). Land Cover Classification Using Convolutional Neural Network on Sentinel-2 Satellite Imagery. *SISTEMASI: Jurnal Sistem Informasi*, 10, 323–335.

- Mishra, P. K., Rai, A., & Rai, S. C. (2020). Land Use and Land Cover Change Detection Using Geospatial Techniques in The Sikkim Himalaya, India. *The Egyptian Journal of Remote Sensing and Space Sciences*, 23, 133–143.
- National Standardization Agency. (2010). *Specifications for presentation of topographic maps Part 3 Scale 1:50,000*. <http://www.bsn.go.id>
- Putra, E. K., Amaru, K., & Kendarto, D. R. (2024). The influence of land cover changes on hydrological responses in the Cimeta River sub-watershed using the Soil and Water Assessment Tool SWAT model. *Jurnal Triton*, 15(1), 78–92.
- Radhinal, Y., Abdi, A. P., & Ahmad, D. N. A. (2025). Urban Land Cover Classification Using Sentinel-2 Satellite Imagery and Random Forest Algorithm Machine Learning Approach. *Jurnal Kolaboratif Sains*, 8(8), 5275–5283.
- Sambou, M. H. A., Albergel, J., Vissin, E. W., Liersch, S., Koch, H., Szantoi, Z., & Toure, I. (2023). Prediction of land use and land cover change in two watersheds in the Senegal River basin West Africa using the Multilayer Perceptron and Markov chain model. *European Journal of Remote Sensing*, 56(1), 2231137.
- Sampurno, R. M., & Thoriq, A. (2016). Land Cover Classification using Landsat 8 Operational Land Imager (OLI) Data in Sumedang Regency. *Jurnal Teknotan*, 10(2), 62–71.
- Tadese, M., Kumar, L., Koech, R., & Kogo, B. K. (2020). Mapping of land-use/land-cover changes and its dynamics in Awash River Basin using remote sensing and GIS. *Remote Sensing Applications: Society and Environment*, 19, 100352.
- Wang, Y., Sun, Y., Cao, X., Wang, Y., Zhang, W., & Cheng, X. (2023). A review of regional and global scale Land Use Land Cover mapping products generated from satellite remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 206, 311–334.