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SPATIAL DYNAMICS OF FOREST LANDSCAPES AND ITS IMPACT ON CLIMATE CHANGE IN WAERUHU WATERSHED, AMBON CITY

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ABSTRACT
This study aims to analyze land cover change in Waeruhu watershed, Ambon City. This research uses a GIS approach with ArcGIS 10.8 software, Google Earth imagery recorded in 2015 and 2023. The results identified driving factors that influence land use change at the study site include forests, shrubs, open land, settlements, trade and services, and educational facilities. Land use change from 2015 to 2023, the land cover classes that experienced the largest change were forests which experienced the largest increase in area by 20.81 Ha, settlements to 14.87% and educational facilities to 6.09% and Factors affecting land cover/use changes in Das Waeruhu were settlements, roads, rivers, trade and services, and educational facilities.

Keywords: GIS, Land Change, Das Waeruhu

INTRODUCTION

Urban growth is a multidimensional social and population process where the city is perceived as the economic center and a key component in meeting human needs (Dadras, 2015). Land utilization in an urban area without careful planning can lead to disparities in urban development activities (Fuglsang, 2013). Aryany and Pradoto (2014) explain that limitations in land availability, competition for land use, and rapid population growth contribute to changes in land area and use accompanying urban development.

Changes in land cover/use are influenced by economic development, as well as environmental and social changes, such as increased industrialization, urbanization, population growth, and economic reforms (Gu, 2016). Pawitan (1999) states that changes in land use patterns impact the decrease in water availability due to increased seasonal fluctuations, leading to more extreme occurrences of floods and droughts. Global issues arising from climate change also trigger unpredictable occurrences of extreme weather events. As highlighted by Kurnia et al. (2001), changes in land use will affect land management or water use, with a shift from forests to residential areas, mining, agricultural land, or dryland farming, leading to an increased risk of floods.

The utilization of remote sensing technology and Geographic Information Systems (GIS) has proven to be a rapid assessment tool to address climate change phenomena occurring on the Earth's surface. Information on spatial and temporal variations in land use from remote sensing technology can be used to analyze trends and factors influencing land use/cover variations, as well as predict future land use variations through the development of models for anticipation and prevention efforts in vulnerable areas (Kurniawan et al., 2018).

With the dynamic development of Ambon city, it undoubtedly has a significant impact on the sustainability of the Watershed Areas in Ambon. One such area is the Waeruhu Watershed located in Galala Village, Sirimau District, Ambon city. Ronald's (2018) research indicates that the current condition of the Waeruhu Watershed is experiencing a decline in hydrological function due to inappropriate land use change patterns. This study focuses on the dynamics of land use changes in the Waeruhu Watershed through spatial analysis utilizing remote sensing data and Geographic Information Systems.

RESEARCH METHODOLOGY

Research Location and Timeframe

This research will be conducted over a period of 1 year, specifically in the year 2023, within the Waeruhu Watershed area in Ambon City.

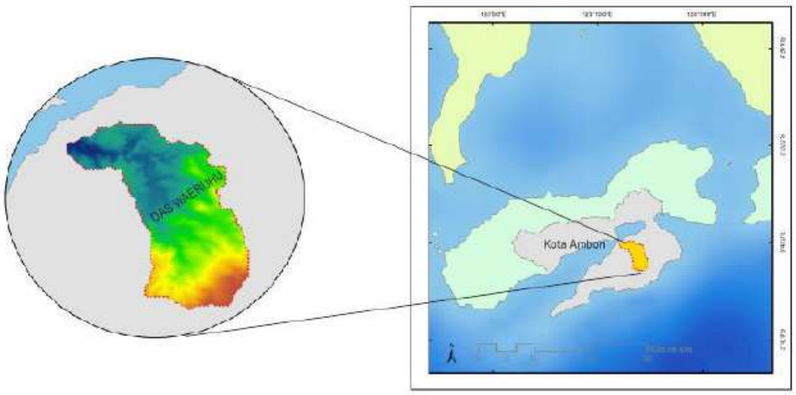


Figure 1: Research Location MapPenelitian

Data Collection Techniques

Land cover/use data for the years 2015 and 2023 were obtained from Google Earth imagery for the respective years. The land cover/use classification was carried out using a supervised classification approach with Envi 5.3 and ArcGIS ver 10.8 applications. The land cover/use classes in this study were grouped into categories such as forest, shrubland, open land, settlements, trade and services, as well as educational facilities. The accuracy of the classification results was assessed through field checks (ground truthing) at 50 points, proportionally allocated for each land cover class, with coordinates recorded using GPS.

Table 1: Approach to Land Cover/Land Use Classification Analysis Model at the Research Location

No	Data	Approach	Source
1.	*Geometrics Correction*	Placement of Ground Control Points (GCP) and Root Mean Square Error (RMSE) Values	Spatial Analysis, 2023
2.	*Cropping Image*	Cutting study area boundaries based on administrative boundaries	Spatial Analysis, 2023
3.	*Confusion Matrics*	J=kolom (referensi) / Jumlah Baris nj+ i = baris: 1, 2, K, nj+ 1: n_{11}, n_{12}, n_{1k}, n_{1+} 2: n_{21}, n_{22}, n_{2k}, n_{2+} K: n_{k1}, n_{k2}, n_{kk}, n_{k+} Jumlah kolom n+j: n_{+1}, n_{+2}, n_{+k}, N	Juniyanti dkk, 2020; Tayane, Yulien A. et al., 2021
4.	*Overall Accuracy*	$\rightarrow \text{Overall Accuracy (OA)} = \frac{\sum_{i=1}^{k} n_i}{N}$	Juniyanti dkk, 2020; Tayane, Yulien A. et al., 2021
5.	*Kappa Accuracy*	$\rightarrow \hat{k} = \frac{N\sum_{i=1}^{k} X_{ii} - \sum_{i=1}^{k} X_{i+}X_{+1}}{N^2 - \sum_{i=1}^{k} (X_{i+}X_{+1})}$	Juniyanti dkk, 2020; Tayane, Yulien A. et al., 2021
6.	Drivers of Land Change	*Logistic Regession* *Logit Y = a + b1x1 +............+bnxn*	Spatial Analysis, 2023

Table 2: Error Matrix

	j= colom (references)			Number of Rows nj+
i= baris	1	2	K	nj+
1	n_{11}	n_{12}	n_{1k}	n1+
2	n_{21}	n_{22}	n_{2k}	n2+
K	n_{k1}	n_{k2}	n_{kk}	nk+
Number of Colom n+j	n+1	n+2	n+k	N

N= Σ nij kj=1 Where N represents the total number of samples resulting from the classification of class i in remote sensing classification, n+j = Σ nij k j=1 is the total number of samples classified into class j in the reference data (Jaya, 2010).

RESULTS AND DISCUSSION

Pre-Image Processing

Geometric correction is a process aimed at adjusting the coordinates within an image to align with geographical coordinates. This correction is achieved by transforming the geometry (geo-referencing) or elements of digital images so that each pixel in the image corresponds to a position in the real-world coordinate system (Priyanto et al., 2021).

In this study, geometric correction utilized Ground Control Points (GCP) derived from RBI maps. The correction itself was implemented using ArcGIS software. The accuracy test of the geometric correction for these three images resulted in a Root Mean Square Error (RMSE) value of 0. The images used in this study were obtained from Google Earth for the years 2015 and 2023. The coordinate system applied was Datum WGS 84 with UTM Zone 52S projection.

(a)

(b)

Figure 2: Geometric Correction Results (a) 2015 and (b) 2023

Cropping Images

Cropping Images is performed with the aim of simplifying the analysis process and focusing on the specific area under investigation by eliminating unused areas in the research. In this stage, image cropping is carried out based on the research area, specifically in the watershed of the Wae Ruhu river.

Satellite Image Processing

Image Classification

The classification involves determining the number of land cover classes following the Directorate General of Forestry Planning 2015 guidelines, consisting of 6 (six) land cover classes: forest, shrubland, open land, settlements, trade and services, as well as educational facilities.

Field Verification (*Ground Truthing*)

Field verification, or ground truthing, is conducted to ensure the accuracy of the classification results by comparing them with real conditions in the field. The field verification is based on the distribution of sample points as outlined in Table 2. To facilitate the verification of point distribution in the field, Global Positioning System (GPS) technology is employed.

Table 3: Number of GCP Points

No.	Land Cover Types	Number of Sample
1	Forest	29
2	Shrubland	10
3	Open land	2
4	Settlements	6
5	Trade and Services	1
6	Educational facilities	2
Total	50	

Based on Table 3, the majority of samples are in the forest land cover class, totaling 29 samples, while the least represented class is Trade and Services, with only 1 sample. Figure 3 illustrates the distribution of sample points in the research location.

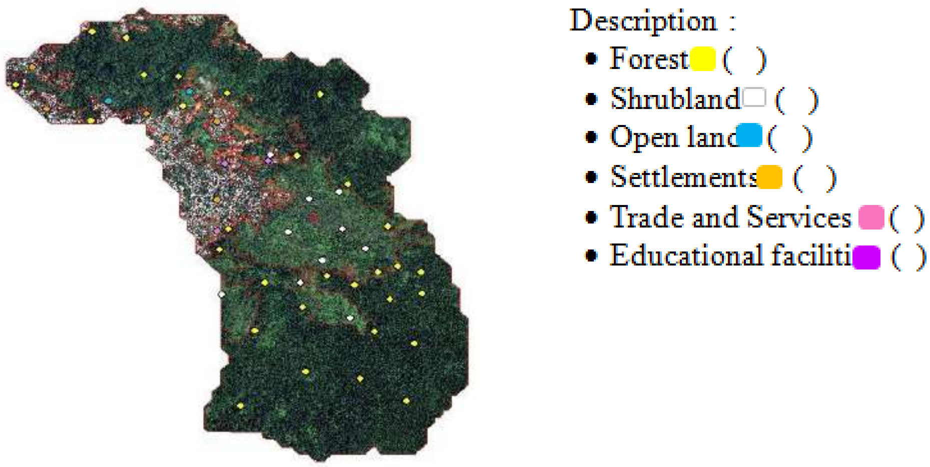


Figure 3: Distribution of Sample Points at the Research Location

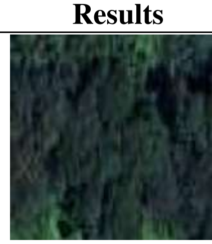
After field verification, out of the 50 sample points scattered across each land cover class, only 31 sample points were accessible for verification. The remaining 19 sample points were unreachable, and an approach was taken using maps sourced from the SAS Planet application to identify land cover from these inaccessible sample points.

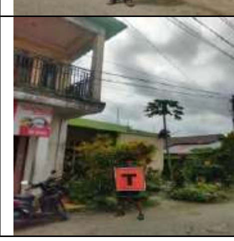
Table 4: Recapitulation of Results of Landsat 2020 Image Field Checks

No	Land Cover	Sesuai	%	Tidak Sesuai	%
1	Forest	29	100	-	-
2	Shrubland	9	90	1	10
3	Open land	2	100	-	-
4	Settlements	5	83,33	1	16,67
5	Trade and Services	1	100	-	-
6	Educational facilities	2	100	-	-

Table 4 provides insights into the field verification results, indicating that 48 sample points correspond to the specified land cover classes, while 2 sample points do not. Sample points matching the land cover classes of forest, open land, trade and services, and educational facilities exhibit a 100% correspondence. However, the other two land cover classes, shrubland, and settlements, show less than 100% correspondence, each with one mismatched point.

Table 5. Results of Satellite Image Checks in Wae Ruhu Watershed, Ambon City

Code	Land Cover	Coordinate Points		Image Interpretation Results	Field Verification Results	
		X	Y			
1.6	Forest	415481	9591647			

						
2.8	Shrubland	414477	9592131		 	 
4.2	Open land	413379	9593906		 	 
3.2	Settlements	413697	9592553		 	 

6.2	Educational facilities	413768	9593004		 	 
5.1	Trade and Services	413684	9592158		 	 

Image Reclassification

The accuracy of the classification results is assessed based on the summary provided in Table 4, utilizing a confusion matrix. The error matrix calculates measures such as producer's accuracy, user's accuracy, overall accuracy, and kappa accuracy (Panjaitan et al., 2019). The error matrix in this study is presented in Table 4.

Table 6: Confusion Matrix (Matrix of Errors)

		Estimination						
		F	SB	OL	S	TS	EF	Total
Actual Field Class	F	29	0	0	0	0	0	29
	SB	0	9	0	0	0	1	10
	OL	0	0	2	0	0	0	2
	S	0	0	0	5	1	0	6
	TS	0	0	0	0	1	0	1
	EF	0	0	0	0	0	2	2
Total		29	9	2	5	2	3	50

Description: F=Forest, SB=Shrubland, OL= Open land, S=Settlements, TS=Trade and Services, EF=Educational facilities

Actual Field Class:

$$= \frac{\text{Number of Correct Samples}}{\text{Number of Samples Taken}} \text{x}100\%$$

$$= \frac{29 + 9 + 2 + 5 + 1 + 2}{50} \text{x}100\%$$

$$= \frac{48}{50} \text{x}100\% = 96\ \%$$

Kappa :

$$\hat{k} = \frac{N \sum_{1=1}^{k} X_{ii} - \sum_{i=1}^{k} X_{i+} X_{+i}}{N^2 - \sum_{i=1}^{k} (X_{i+} X_{+i})}$$

N = 50

$$\sum_i^k = X_{ii} = 29 + 9 + 2 + 5 + 1 + 2 = 48$$

$$\sum_i^k = 1 X_{i+} X_{+i}$$

$$= (29x29) + (9x9) + (2x2) + (5x5) + (1x2) + (2x3)$$

$$= 841 + 81 + 4 + 25 + 2 + 6 = 959$$

$$\hat{k} = \frac{(50x48) - 959}{(50^2) - 959}$$

$$= \frac{2400 - 959}{2500 - 959}$$

$$= \frac{1441}{1541} = 0{,}93$$

Based on the calculations, the accuracy test conducted for overall accuracy from the matrix above is 96%, while the obtained kappa accuracy is 0.93. Both values indicate the level of accuracy in the classification results, meeting the classification accuracy requirement of >85% from USGS and a Kappa value >0.8 (Landis & Koch, 1977 as cited in Kosasih, Buce Saleh, and Budi Prasetyo, 2019). Next, to assess the contribution or contribution of each land cover class in the research location, Omission Error, Commission Error, User Accuracy, and Producer Accuracy are calculated (Tayane et al., 2021).

Table 7. Values of Omission Error, Commission Error, User Accuracy, and Producer Accuracy

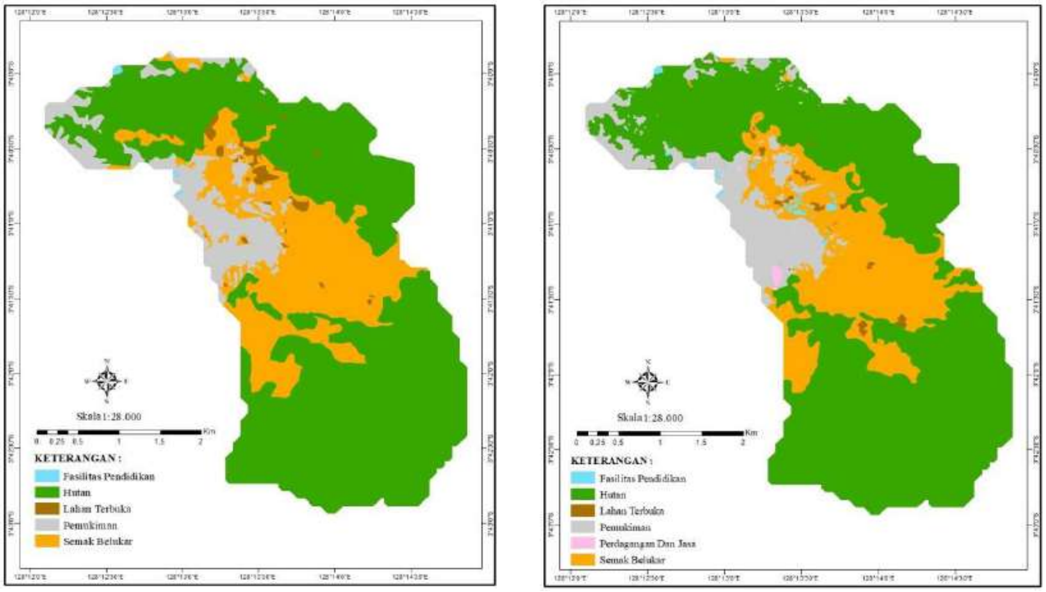
Land Cover	Ommision Error	Comission Error	User Accuracy	Procedur Accuracy
F	0	0	100 %	100 %
SB	0	0,1	100 %	90 %
OL	0	0	100 %	100 %
S	0	0,17	100 %	83%
TS	0,5	0	50 %	100 %
EF	0,33	0	67%	100 %

Description: F=Forest, SB= Shrubland, OL=Open land, S=Settlements, TS=Trade and Services, EF=Educational facilities

In the calculations above, (a) Omission Error represents errors due to sample omission, while (b) Commission Error is the error due to sample addition. On the other hand, (c) User Accuracy is the accuracy viewed from the user's perspective, and (d) Producer Accuracy is the accuracy viewed from the producer's perspective (Thernando et al., 2020).

Land Cover in the Waeruhu Watershed Area 2015-2023

Classification is a data processing stage that involves assigning classes or land cover categories to each formed segment. This process allows the identification of land cover types that have been established (Wijayanti, 2019). Based on the analysis of land cover in the image at the research location, the distribution of land cover classes can be observed in Figure 4.



(a) (b)

Figure 4: Land Cover (a) 2015 and (b) 2023

The Waeruhu Watershed covers an area of 1499.36 hectares. In 2015, the Waeruhu Watershed had only 5 land cover classes: forest, shrubland, open land, settlements, and educational facilities. By the year 2023, one additional land cover class, trade and services, has been identified in the Waeruhu Watershed.

Land Cover Change in the Waeruhu Watershed Area 2015-2023

Land cover change involves the transition of an old land cover form and location into a new one. Such changes occur when the land is utilized or repurposed. In this study, land cover changes include forest, shrubland, open land, settlements, trade and services, and educational facilities. Changes in land cover in the Waeruhu Watershed from 2015 to 2023 exhibit variations in both increased and decreased areas, as presented in Table 9 below.

Table 9. Change Matrix of Land Cover from 2015 to 2023

2023 / 2015	F	SB	OL	S	TS	EF	Total
F	915,48	45,90	1,15	8,88	0,64	0,16	**972,21**
SB	69,39	255,03	4,71	22,82	2,05	2,52	**356,52**
OL	1,97	10,49	3,38	1,44		0,11	**17,39**
S	7,32	5,71	0,09	132,91	1,65	3,67	**151,35**
TS	0,16			0,20	0,01	1,53	**1,89**
Total	**994,30**	**317,14**	**9,33**	**166,26**	**4,35**	**7,98**	**1499,36**

Description: F= Forest; SB= Shrubland; LT=Open land; P= Settlements; PJ= Trade and Services; EF= Educational facilities

= No Change

= Change Occurred

Table 9 shows changes in land cover from 2015 to 2023 for each land cover class. The area experiencing the largest change is shrubland, which decreased by 69.39 hectares and has now transformed into forest. Meanwhile, the land cover class that slightly decreased in area is settlements, reduced by 0.09 hectares, converting into open land. In 2015, there was no land cover class for trade and services, but by 2023, it covers an area of 4.35 hectares.

For changes in land cover area in the Waeruhu Watershed in 2015 and 2023, refer to Table 10.

Table 10: Changes in Land Cover Area in Waeruhu Watershed 2015 to 2023

Land Cover	Years		Change of LC 2015-2023
	2015	2023	
Forest	973,49	994,30	+ 20,81
Shrubland	356,52	317,14	- 39,38
Open land	17,39	9,33	- 8,06
Settlements	151,39	166,26	+ 14,87
Trade and Services	-	4,35	+ 4,35
Educational facilities	1,89	7,98	+ 6,09

Description: F= Forest; SB= Shrubland; OL=Open land; S= Settlements; TS= Trade and Services; EF= Educational facilities (-) decrease in area, (+) Increase in area

Table 10 illustrates that the land cover classes experiencing a decrease in area from 2015 to 2023 are shrubland and open land, with reductions of 39.38 hectares and 8.06 hectares, respectively. Meanwhile, other land cover classes have shown an increase in area. Forest experienced the largest increase, growing by 20.81 hectares, settlements increased by 14.87%, and educational facilities expanded by 6.09%. For a visual representation of land cover changes in 2015 and 2023, refer to Figure 5.

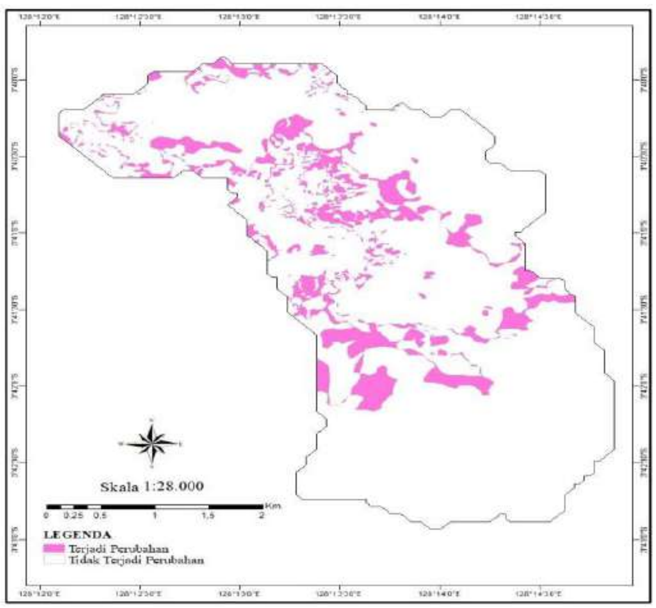


Figure 5: Land Changes 2015-2023

Factors Influencing Land Cover Changes

Based on the classification results for land cover conditions at the research site in 2015 and 2023, six land cover classes were identified: forest, shrubland, open land, settlements, trade and services, educational facilities, roads, and rivers. From these land cover classes, nine factors influencing land cover changes were identified, including settlements, trade and services, and educational facilities. The road and river networks involved in this study were sourced from OpenStreetMap data at the research location.

Putra & Rudiarto (2018) explain that land cover dynamics are influenced by settlements, roads, educational facilities, health facilities, offices, trade and services, as well as industry and warehousing. With the increasing population each year, the growing population rate necessitates additional space or land for habitation. This phenomenon makes settlements the most influential factor in driving land use changes at the research location.

CONCLUSION

1. The land cover in the research location consists of forests, shrublands, open land, settlements, trade and services, and educational facilities.
2. From 2015 to 2023, the land cover class experiencing the most significant change was the forest, with the largest increase in area by 20.81 hectares. Settlements increased by 14.87%, and educational facilities expanded by 6.09%.
3. Factors influencing land cover/use changes in the Waeruhu Watershed include settlements, roads, rivers, trade and services, and educational facilities.
4. The carbon stock in the area increased by 1.49% from 2015 to 2023.

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