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# Mapping Cacao Plantations Using Random Forest Classification and Sentinel-2A Imagery in Batulappa District, Pinrang Regency, Indonesia

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**ABSTRACT**

Remote sensing and Geographic Information System (GIS) technologies provide effective tools for mapping plantation crops and supporting sustainable land management. Cacao is an important plantation commodity in Indonesia, particularly in Pinrang Regency, South Sulawesi. This study aimed to map cacao and non-cacao land cover in Batulappa District using Sentinel-2A imagery and the Random Forest algorithm. Three input approaches were evaluated: an RGB band composite, the Normalized Difference Vegetation Index (NDVI), and Gray-Level Co-occurrence Matrix (GLCM) texture features. Ground-truth data were divided into training and validation datasets, and classification accuracy was assessed using a confusion matrix, including overall accuracy, user accuracy, and producer accuracy. The RGB band composite produced the highest overall accuracy of 85.38%, followed by GLCM with 75.47% and NDVI with 74.06%. For the cacao class, the RGB approach achieved a user accuracy of 80.00% and a producer accuracy of 86.96%, with an estimated cacao area of 4,516.80 ha, or 46.90% of the study area. These results indicate that the Sentinel-2A RGB band composite combined with Random Forest classification outperformed NDVI and GLCM for mapping cacao plantations in Batulappa District.

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## 1. INTRODUCTION

Technological advancements in the digital era provide many benefits in various aspects of life, including the management of natural resources. One of the technologies that is increasingly developing is remote sensing and Geographic Information Systems (GIS), which allow for accurate and efficient mapping of areas. This technology is very beneficial in the agricultural sector, particularly to support the management of cacao plants. By utilizing technology through GIS and remote sensing, cacao land mapping can be carried out more easily, from land mapping to monitoring plant conditions, thereby supporting sustainable management and increasing the productivity of cacao plants (Amiruddin et al., 2015).

Cacao (Theobroma cacao L.) is one of the plantation commodities that plays an important role in the global food market. This industry involves millions of farmers in various countries, helping to reduce poverty and create numerous jobs. In Indonesia's economy, cacao is one of the leading products in the plantation sector. In addition to contributing to national economic growth, cacao is also an export commodity that brings foreign exchange to the country, alongside the oil and gas sector. According to data from the International Cacao Organization for 2022/2023, Indonesia is one of the cacao-producing countries in the world with a production of 160 thousand tons of cacao. According to Indonesian cacao statistics in 2022, cacao plantations are dominated by smallholder plantations managed by small farmers, covering 1.42 million hectares or 99.63% of the total cacao plantations in Indonesia (Rohmando & Hartini, 2024).

Pinrang Regency in South Sulawesi is one of the cacao-producing areas in Indonesia, which once reached its peak during the 1990s with a land area of 18,900 hectares and production of around 9,000 tons per year. However, pest attacks, diseases, and a drop in market prices led to a decline in productivity. In an effort to restore the glory of cacao, the Pinrang Regency government has launched various initiatives, including training farmers in land management. Cacao land mapping has become an important part of this strategy, as it can assist in identifying land conditions, plant distribution, and evaluating productivity through remote sensing technology and geographic information systems. With accurate mapping, this research program will be efficient and sustainable in supporting the livelihoods of local farmers.

Cacao plant mapping is very important to help farmers manage their plantations better. One method used is through vegetation indices, such as NDVI (Normalized Difference Vegetation Index), which measures plant health based on light reflection. With this index, we can determine whether cacao plants are growing well or facing problems, such as nutrient deficiencies or pest attacks. This information helps farmers take the right actions to maintain plant quality. In addition, cacao mapping can also be done using multispectral imagery, which captures images in various colors, including light that is invisible to the human eye (Marlina, 2022). With this technique, we can distinguish cacao plants from other plants and also see the land conditions more clearly.

Random forest is defined as a machine learning method that uses a collection of decision trees to make more accurate predictions. Each tree in the random forest is trained using different subsets of data and provides its own prediction. The final result is determined based on majority voting for classification or averaging for regression, thus reducing the risk of overfitting and improving model accuracy. This algorithm is widely used in various fields such as environmental, health, and others to detect patterns and make complex predictions (Wibowo, 2020).

With the increasing development of remote sensing-based mapping technology, it is hoped that farmers and stakeholders in the cacao plantation sector can adopt this approach to improve production efficiency, reduce environmental impact, and ensure the sustainability of the cacao industry in the future. However, studies that directly compare RGB band composites, NDVI, and GLCM texture features as inputs for Random Forest-based cacao mapping in Batulappa District remain limited. Therefore, this study aims to evaluate the performance of the Sentinel-2A RGB band composite, NDVI, and GLCM texture features combined with the Random Forest algorithm for mapping cacao and non-cacao land cover in Batulappa District, Pinrang Regency. The results are expected to support more accurate plantation monitoring and provide a basis for the government and related institutions to plan and manage cacao plantations more effectively and sustainably.

## 2. MATERIALS AND METHODS

### 2.1 Study Area and Data

This research was conducted from June to August 2025 in the cacao-producing areas of Tapporang Village, Watang Kassa Village, and Kassa Village, Batulappa District, Pinrang Regency, South Sulawesi, Indonesia. Land cover classification was performed using QGIS 3.32 software. Ground-truth data were collected through field surveys using the Avenza Maps application, supported by Google Earth imagery as a visual reference. Additional data used in this study included cacao plantation location data for Batulappa District obtained from the Pinrang Regency Office of Animal Husbandry and Plantations, and the Indonesian Topographic Map of Pinrang Regency.

### *2.2 Research Procedures*

The research procedure consisted of the following stages:

#### 2.2.1 Preparation Stage

The initial stage of this research involved conducting a literature review related to Sentinel-2A imagery, random forest and land cover change analysis.

#### 2.2.2 Data Collection Stage

The field data collection stage was carried out by surveying land cover classes, taking ground truth data for each type of land cover using the Avenza Maps application, and taking documentation. In addition, Google Earth imagery was used as a visual reference in identifying land cover types and also to determine additional coordinate points to support the ground truth data. Then, this ground truth data will be divided into two, 60% for the training area and 40% for testing.

#### 2.2.3 Data Processing Stage

1. Clipping of Sentinel-2A Imagery in Batulappa District

Image clipping is done according to the boundaries of the Batulappa Subdistrict. This process can be carried out using the clip raster by mask layer tool in QGIS software. At this stage, it is important to ensure that the spatial resolution and image attribute data are maintained so that the clipping results do not lose quality.

1. NDVI Image Data Processing

The Normalized Difference Vegetation Index (NDVI) is defined as an index used to measure the greenness or photosynthetic activity of vegetation. NDVI calculations yield vegetation index values ranging from -1 to +1 (Table 1), where values of -1 to 0.2 indicate land without vegetation, while values of 0.72 to 1 indicate dense vegetation or the highest vegetation density (NASA Earth Observatory, 2000). NDVI is calculated based on a combination of red (Red) and near-infrared (NIR) band reflectance, which can be seen in equation (1) as follows (Xavier et al., 2006):

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

Table 1. Range of Vegetation Density Vulnerability

| Class | NDVI Value Range | Density Level |
|---|---|---|
| 1 | -1 – 0.12 | Land Without Vegetation |
| 2 | 0.12 – 0.22 | Very Sparse Vegetation |
| 3 | 0.22 – 0.42 | Sparse Vegetation |
| 4 | 0.42 – 0.72 | Moderate Vegetation |
| 5 | 0.72 – 1 | Dense Vegetation |

Source : NASA Earth Observatory (2000).

The reason for choosing NDVI as the stage for selecting vegetation indices is that previous studies have shown that NDVI is very effective in identifying vegetation cover, making it more accurate in distinguishing plants that have similar leaf colors (Haeruddin et al., 2023). Therefore, selecting NDVI is appropriate as a vegetation index in this study. NDVI is also one of the most popular and widely used vegetation indices in various remote sensing-based agricultural studies due to its ability to provide vegetation information in a simple yet effective manner (Haerani, 2019).

2. Sentinel-2A Image Band Composite

The band selection is adjusted to its spectral color, namely band 4 (red) for red, band 3 (green) for green, and band 2 (blue) for blue. The steps to perform band compositing are by opening the raster menu > semi-automatic classification plugin, selecting the preprocessing tab, and then adding all bands from the Sentinel-2A image. After selecting the bands, choose create RGB composite to combine the bands into a single composite image. The result of the band composite will display the original color of the objects.

3. GLCM Processing

Gray Level Co-occurrence Matrix (GLCM) is a method to measure patterns and textures in an image by examining how pixels with certain gray levels are grouped or distributed. According to Moraiti et al. (2024), GLCM works by calculating how often pairs of specific pixel values appear adjacent to each other, which allows recognition of surface patterns of objects such as rough, smooth, or patterned in an image. The steps are carried out using the Haralick texture extraction plugin > advanced texture parameters and all directions (0°, 45°, 90°, 135°).

4. Classification

At the classification stage, training data serves as a reference for the algorithm to distinguish land cover classes. Training data is a collection of pixels in satellite images whose classes are already known based on reference data, such as survey results or visual interpretation. This data is used to train the model to recognize the spectral patterns of each class in Table 2 (Mutoffar et al., 2022). As mentioned in the data collection stage, the training data will later be divided into 60% for the training area and 40% for testing. This will help ensure that the classification model not only produces data it has been trained on but is also accurate in the field.

Table 2. Land Cover Classes

| No | Land Cover Classes |
|---|---|
| 1 | Cacao Plantation |
| 2 | Rice Field |
| 3 | Fields/Rotational Crops with Secondary Crops (Corn) |
| 4 | Forest |
| 5 | Open Land |
| 6 | Built-up Land |
| 7 | Bodies of Water |

Source : Badan Standardisasi Nasional (2014).

5. Accuracy Value

The accuracy of classification results is calculated based on the overall accuracy (OA) value as a whole, while producer accuracy (PA) and user accuracy (UA) are used to assess the accuracy for each land cover class. If the PA and UA results approach 100%, the level of error in class identification can be minimized (Apriyanti et al., 2025). The accuracy level is considered acceptable if the OA is in the range of 80-89%, then the classification is rated very good if the OA reaches 90-94%, and the classification is considered highly accurate if the accuracy is above 95% (Zulfajri et al., 2021). The method applied in the confusion matrix can be seen in Table 3.

Table 3. Confusion Matrix

| | TL I | TLII | TLIII | TLIV | Total Rows |
|---|---|---|---|---|---|
| TLI | A | a | b | c | ∑ Rows 1 |
| TLII | d | B | e | f | ∑ Rows 2 |
| TLIII | g | h | C | i | ∑ Rows 3 |
| TLIV | j | k | l | D | ∑ Rows 4 |
| Total Column | ∑ Column 1 | ∑ Column 2 | ∑ Column 3 | ∑ Column 4 | ∑ Total Column and Rows |

Source : Stehman, (1997).

Description TLI,II...IV = Land cover, A,B,C,D = Number of correct pixels, a,b,c....l = Number of pixels in one class

## 3. RESULTS AND DISCUSSION

### 3.1 Sentinel-2A Image Results

Sentinel-2A imagery with an RGB band composite provides a depiction of the Earth's surface in colors that are easier to visually interpret, where each band is arranged as red (band 4), green (band 3), and blue (band 2) to show land cover conditions. As a result, vegetation areas appear clearly in green, water bodies appear white and settlements and open land can be distinguished from their surroundings. With the RGB band composite display, this map can provide information on land cover in the Batulappa area in a way that appears natural to the human eye, as shown in Figure 2.

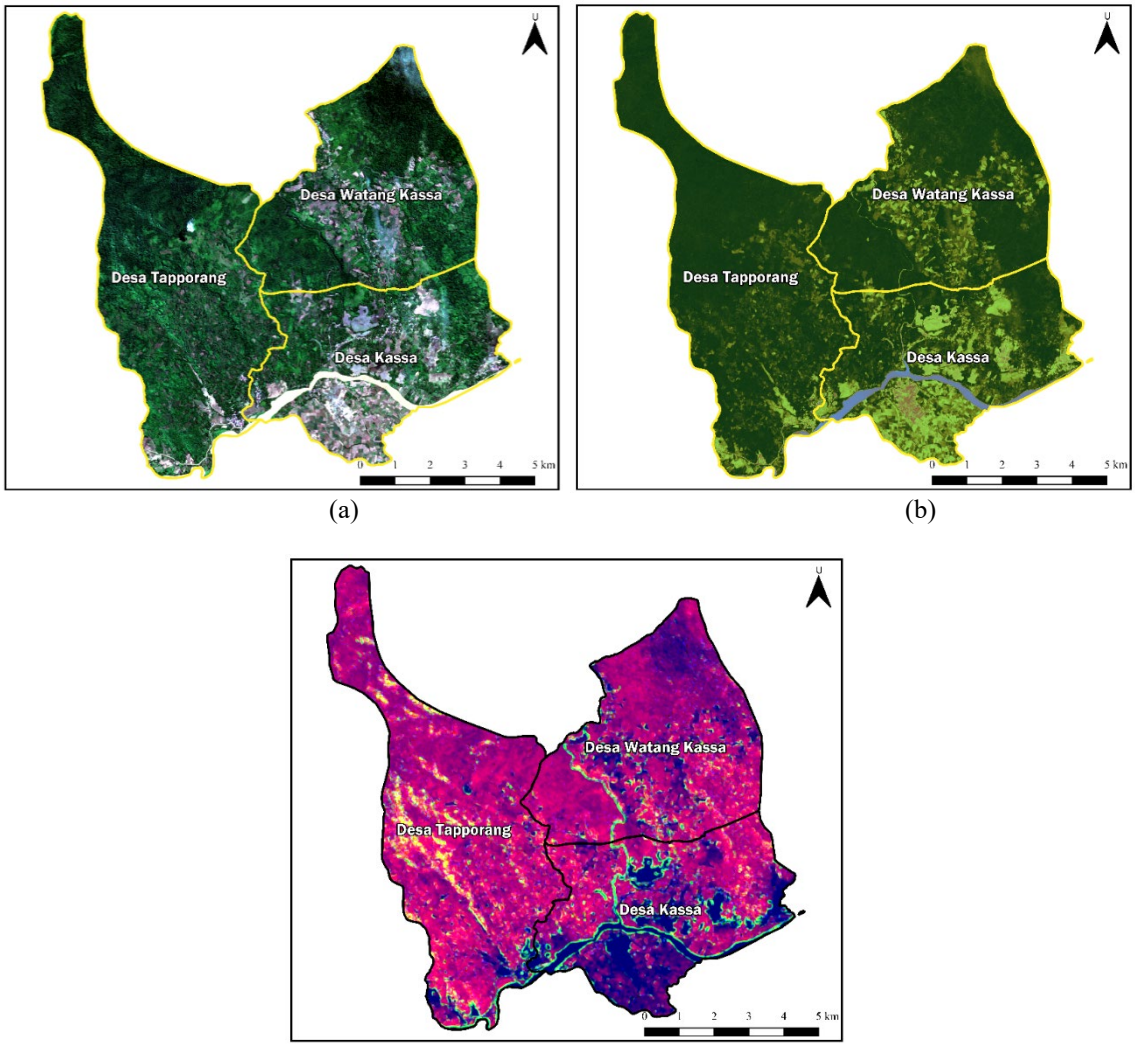



Figure 2. (a) Sentinel-2A Image RGB Band Composite, (b) Sentinel-2A Image NDVI and (c) Sentinel-2A Image GLCM

Sentinel-2A images with the NDVI Index are used to observe vegetation conditions in the study area. High index values indicate healthy vegetation with a darker green color, while low values indicate open land, dry areas, or land without vegetation or crops. Water bodies and settlements usually appear with very low values. As seen in Figure 2(b), the value of -0.472817 shown in blue indicates low values in water areas, whereas the value of 0.981408 corresponds to vegetated areas

Sentinel-2A imagery using GLCM shows the texture results on the land surface. Dense vegetation has a smoother and more uniform texture (purple color). Meanwhile, open land and settlements tend to have a rougher and irregular texture (blue color). This difference helps in distinguishing land cover types, as can be seen in Figure

**.2 Classification Results of RGB Band Composite**

The classification results of the RGB band composite show color differences that help distinguish various objects in the image. These colors appear due to the different characteristics of objects such as vegetation, water, and buildings. For example, vegetation typically appears green, while water and buildings have different colors. The results of the RGB composite classification can be seen in Figure 3 below.

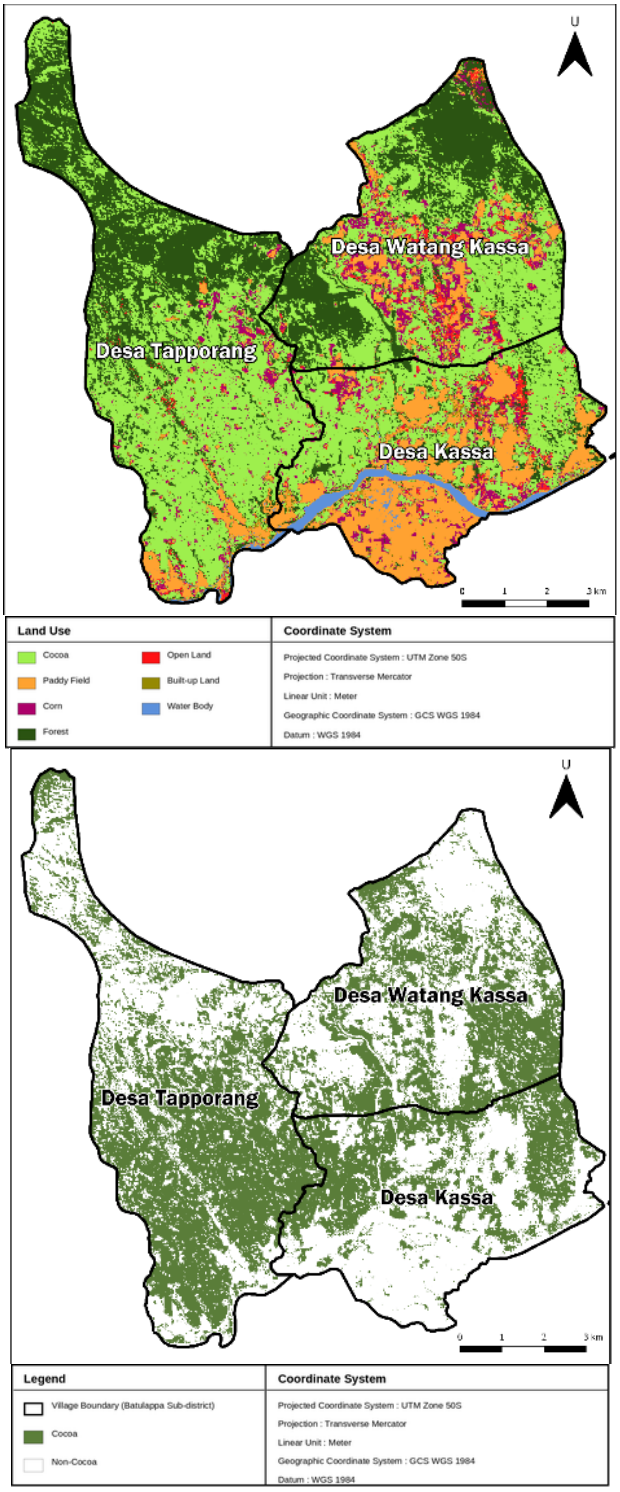



Figure 3. Map of Cacao and Non-cacao Classification Result of RGB Band Composite

The cacao classification map appears to be dominant in the research area of Tapporang Village. It was found that field conditions indeed show a dominance of cacao plants in Tapporang Village. Almost all farmers in Tapporang and Kassa plant cacao as their main commodity. Some farmers even mentioned that parts of the corn

fields have been converted into cacao, and many farmers are also expanding their cacao plantations around the protected forest areas that have started to be cultivated.

Table 4. Accuracy Results of the RGB Band Composite Confusion Matrix

| | Land Cover | Ground Check Field | | | | | | | Total | User Accuracy |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | | |
| 1 | Cacao | 40 | 0 | 5 | 4 | 1 | 0 | 0 | 50 | 80% |
| 2 | Rice Field | 0 | 76 | 0 | 0 | 1 | 6 | 4 | 87 | 87.36% |
| 3 | Corn | 3 | 0 | 10 | 1 | 1 | 1 | 0 | 16 | 62.50% |
| 4 | Forest | 3 | 0 | 0 | 35 | 0 | 0 | 0 | 38 | 92.11% |
| 5 | Open Land | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 100% |
| 6 | Built-up Land | 0 | 0 | 1 | 0 | 0 | 12 | 0 | 13 | 92.31% |
| 7 | Water Body | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 7 | 100% |
| **Total** | | 46 | 76 | 16 | 40 | 4 | 19 | 11 | 181 | **85.38%** |
| **Producer Accuracy (%)** | | 87 | 100 | 63 | 88 | 25 | 63 | 64 | 212 | |

From the accuracy result of 85.38% for the RGB band composite, it can be concluded that the classification quality falls into the good category. According to Zulfajri et al. (2021), an accuracy range of 80-89% is considered good and can be deemed acceptable, thus this result indicates that the method used already meets the expected standards. This result is in line with the research of Afininnas et al. (2024), which reported an accuracy of around 83.02% for land cover classification using the Sentinel-2A RGB band composite with a random forest algorithm that performs optimally.

The higher accuracy of the RGB band composite compared to NDVI and GLCM can be attributed to differences in the spectral and textural information each input provides. The RGB band composite retains the visible-band spectral variation of land cover objects, allowing the Random Forest algorithm to distinguish cacao from rice fields, forest, and open land based on color characteristics. NDVI, by contrast, relies on a single vegetation index derived from only two bands, so different vegetation types with similarly high greenness, such as cacao, forest, and corn, tend to overlap in their NDVI values. GLCM captures texture rather than color, which can help distinguish vegetation from non-vegetation, but at Sentinel-2A's spatial resolution, the canopy texture of cacao plantations may still resemble that of forest or other mixed vegetation, limiting its ability to separate these classes.

Table 5. Land Area Analysis Resulting from RGB Band Composite Classification

| No | Land Cover Class | Tapporang (ha) | Kassa (ha) | Watang Kassa (ha) | Total | Percent (%) |
|---|---|---|---|---|---|---|
| 1 | Cacao | 2,139.72 | 1,052.75 | 1,324.33 | 4,516.80 | 46.90 |
| 2 | Rice Field | 167.04 | 947.07 | 295.08 | 1,409.19 | 14.63 |
| 3 | Corn | 134.94 | 223.53 | 293.29 | 651.76 | 6.77 |
| 4 | Forest | 1,346.05 | 245.04 | 1,020.57 | 2,611.66 | 27.12 |
| 5 | Open Land | 26.17 | 57.63 | 46.04 | 129.84 | 1.35 |
| 6 | Built-up Land | 30.45 | 62.85 | 66.31 | 159.61 | 1.66 |
| 7 | Water Body | 27.2 | 123.71 | 0.93 | 151.84 | 1.58 |
| Total | | | | | 9,630.70 | 100 |

### *3.3 GLCM Image Classification Results*

The results of the GLCM classification in Figure 4 display land cover with different colors according to the type of land, while also showing the texture variations of the map. Unlike RGB, which only represents color according to real-world objects, GLCM is capable of revealing surface differences based on the density and arrangement of pixels (Frederick et al., 2019). Overall, land cover such as cacao plantations or vegetated areas can be more clearly distinguished from other non-vegetated classes that have different texture characteristics.

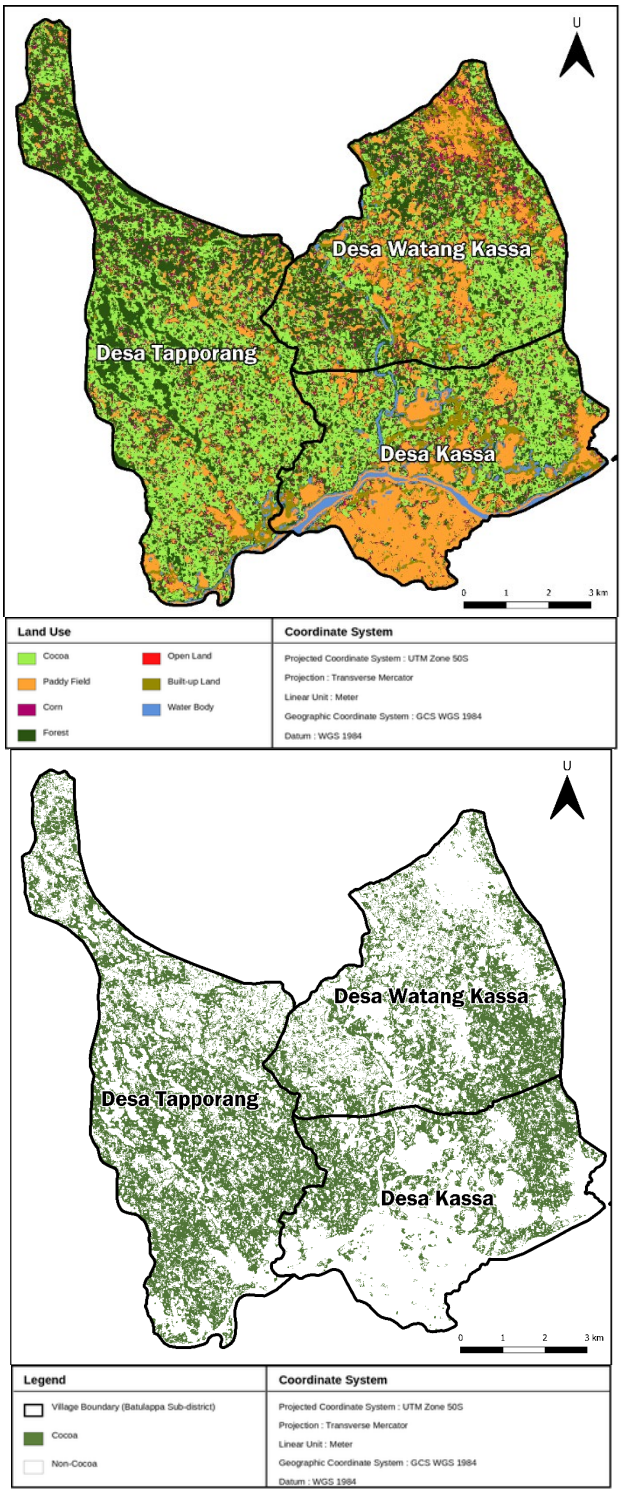



Figure 4. Map of Cacao and Non-cacao Classification Result of GLCM

Looking at Table 6, the results of the confusion matrix show an overall accuracy of 75.47%. Rice fields have the highest producer accuracy (93%), while forests (60%) and corn (38%) are the lowest. Cacao has a producer accuracy of 76% and a user accuracy of 64.81%, indicating that GLCM is able to capture the texture of cacao but is still not optimal in distinguishing uniform vegetation. The User Accuracy for the Open Land class is marked as N/A because no pixels were classified into this class using the GLCM input, making the accuracy value mathematically undefined rather than zero.

Table 6. Accuracy Results of the GLCM Confusion Matrix

| | Land Cover | Ground Check Field | | | | | | | Total | User Accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | | |
| **1** | Cacao | 35 | 1 | 4 | 12 | 1 | 1 | 0 | 54 | 64.81% |
| **2** | Rice Field | 0 | 71 | 3 | 1 | 0 | 1 | 1 | 77 | 92.21% |
| **3** | Corn | 1 | 0 | 6 | 1 | 0 | 0 | 0 | 8 | 75% |
| **4** | Forest | 10 | 0 | 2 | 24 | 1 | 0 | 0 | 37 | 64.86% |
| **5** | Open Land | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | N/A* |
| **6** | Built-up Land | 0 | 3 | 1 | 2 | 0 | 16 | 2 | 24 | 66.67% |
| **7** | Water Body | 0 | 1 | 0 | 0 | 2 | 1 | 8 | 12 | 66.67% |
| **Total** | | 46 | 76 | 16 | 40 | 4 | 19 | 11 | 160 | **75.47%** |
| **Producer Accuracy (%)** | | 76 | 93 | 38 | 60 | 0 | 84 | 73 | 212 | |

Table 7. Land Area Analysis Resulting from GLCM Classification

| No | Land Cover Class | Tapporang (ha) | Kassa (ha) | Watang Kassa (ha) | Total | Percent (%) |
|---|---|---|---|---|---|---|
| 1 | Cacao | 1,739.01 | 799.25 | 1,063.99 | 3,602.25 | 37.39 |
| 2 | Rice Field | 354.74 | 893.35 | 570.25 | 1,818.34 | 18.87 |
| 3 | Corn | 250.76 | 129.52 | 255.2 | 635.48 | 6.60 |
| 4 | Forest | 1,372.16 | 454.31 | 898.99 | 2,725.46 | 28.29 |
| 5 | Open Land | 5.73 | 11.95 | 4.53 | 22.21 | 0.23 |
| 6 | Built-up Land | 98.88 | 247.48 | 217.43 | 563.79 | 5.85 |
| 7 | Water Body | 50.83 | 178.06 | 37.58 | 266.47 | 2.77 |
| Total | | | | | 9,634.00 | 100 |

### 3.4 NDVI Classification Results

Figure 5 NDVI classification is an analysis stage that utilizes the vegetation index to differentiate areas based on the level of vegetation greenness. This approach is used to see how differences in NDVI values can help identify cacao plantations from other land covers.

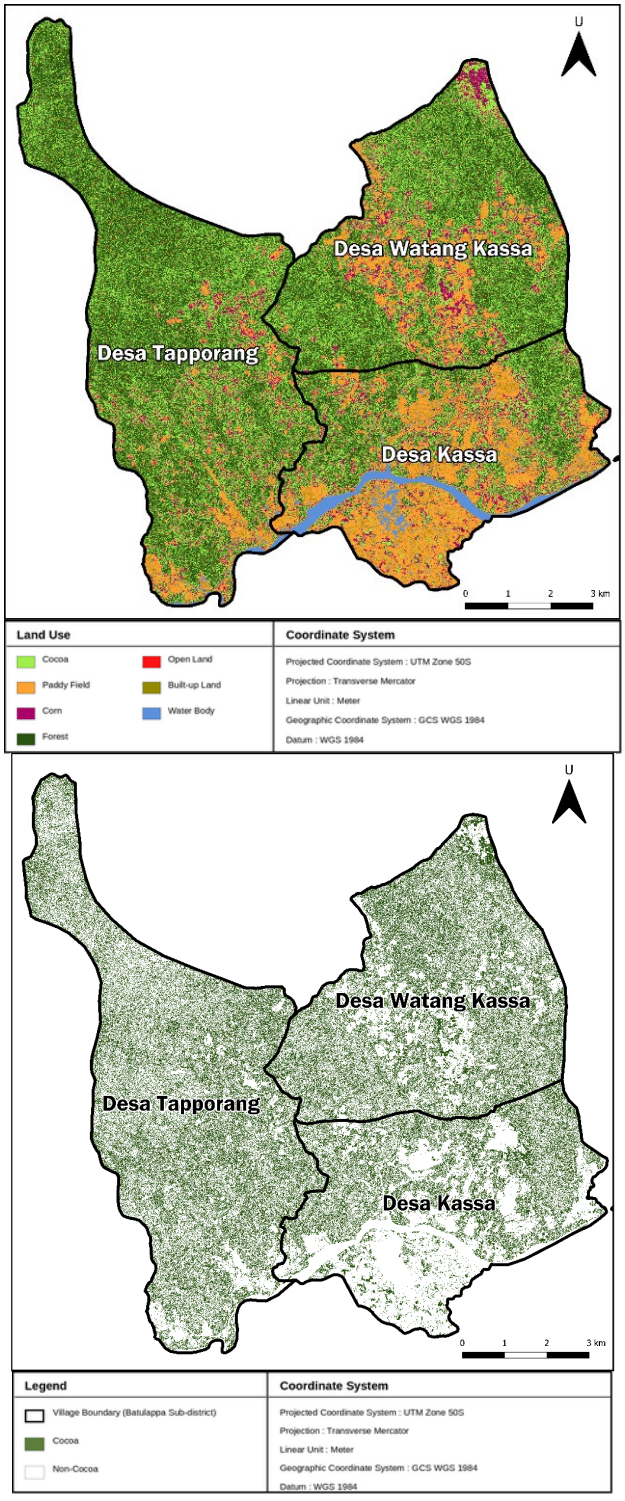



Figure 5. Map of Cacao and Non-cacao Classification Result of NDVI

It can be seen from the accuracy results that the NDVI method produces the lowest overall accuracy, which is 74.06%. In Table 8, forests have a user accuracy of 67.44% and a producer accuracy of 73%. Cacao only reaches a producer accuracy of 65% and a user accuracy of 71.43%, indicating that NDVI alone is not sufficient to

distinguish cacao from other vegetation. Many vegetation classes, such as corn, rice fields, and open land, overlap due to similar NDVI values.

Table 8a. Summary of Overall Accuracy Across the Three Classification Inputs

| Method | Correct Samples | Total Validation Samples | Overall Accuracy |
|---|---|---|---|
| RGB band composite | 181 | 212 | 85.38% |
| GLCM | 160 | 212 | 75.47% |
| NDVI | 157 | 212 | 74.06% |

Note: Correct Samples refers to the number of correctly classified validation points (the diagonal sum of each method's confusion matrix), out of 212 total validation points.

Table 8. Hasil Akurasi *Confusion Matrix* NDVI

| | Land Cover | Ground Check Field | | | | | | | Total | User Accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | | |
| **1** | Cacao | 30 | 0 | 2 | 9 | 0 | 0 | 1 | 42 | 71.43% |
| **2** | Rice Field | 0 | 65 | 4 | 0 | 0 | 5 | 2 | 76 | 85.53% |
| **3** | Corn | 1 | 3 | 9 | 0 | 1 | 0 | 0 | 14 | 64.29% |
| **4** | Forest | 13 | 0 | 0 | 29 | 1 | 0 | 0 | 43 | 67.44% |
| **5** | Open Land | 1 | 0 | 1 | 1 | 2 | 0 | 0 | 5 | 40% |
| **6** | Built-up Land | 0 | 7 | 0 | 0 | 0 | 14 | 0 | 21 | 66.67% |
| **7** | Water Body | 1 | 1 | 0 | 1 | 0 | 0 | 8 | 11 | 73% |
| **Total** | | 46 | 76 | 16 | 40 | 4 | 19 | 11 | 157 | **74.06%** |
| **Producer Accuracy (%)** | | 65 | 86 | 56 | 73 | 50 | 74 | 73 | 212 | |

Table 9. Analisis Luasan Lahan Hasil Klasifikasi NDVI

| No | Land Cover Class | Tapporang (ha) | Kassa (ha) | Watang Kassa (ha) | Total | Percent (%) |
|---|---|---|---|---|---|---|
| 1 | Cacao | 1,466.52 | 741.79 | 1,180.37 | 3,388.68 | 35.18 |
| 2 | Rice Field | 225.52 | 815.73 | 347.02 | 1,388.27 | 14.41 |
| 3 | Corn | 239.04 | 312.75 | 294.07 | 845.86 | 8.78 |
| 4 | Forest | 1,814.00 | 520 | 1,151.00 | 3,485.00 | 36.18 |
| 5 | Open Land | 71 | 27.12 | 44.67 | 142.79 | 1.48 |
| 6 | Built-up Land | 18.13 | 116.67 | 24.34 | 159.14 | 1.65 |
| 7 | Water Body | 37.64 | 178.46 | 5.29 | 221.39 | 2.30 |
| Total | | | | | 9,631.13 | 100 |

Table 10. Comparison of Cocoa Area Based on Agency Data and Classification Results

| Data Source | Tapporang (ha) | Kassa (ha) | Watang Kassa (ha) |
|---|---|---|---|
| Plantation Service FY. 2023 | 1,237.50 | 895.01 | 719.30 |
| RGB Band Composite Classification | 2,139.72 | 1,052.75 | 1,324.33 |
| GLCM Classification | 1,739.01 | 799.25 | 1,063.99 |
| NDVI Classification | 1,466.52 | 741.79 | 1,180.37 |

Table 10 shows a considerable difference between the cacao area from the 2023 Plantation Agency data and the results of image classification, especially with the RGB band composite method. The Plantation Agency recorded the cacao area in Tapporang Village as 1,237.50 ha, Kassa Village as 895.01 ha, and Watang Kassa as 719.30 ha, whereas the RGB band composite classification results show the cacao area in Tapporang Village as 2,139.72 ha and Kassa Village as 1,052.75 ha, with a difference of about 902.22 ha in Tapporang Village, 157.74 ha in Kassa Village, and 605.03 ha in Watang Kassa.

However, based on interviews with several farmers in Tapporang Village and Kassa Village, it was found that the conditions in the field indeed show a dominance of cacao plants. Almost all farmers in the three research villages grow cacao as their main commodity. Some farmers even mentioned that part of their corn fields has been converted into cacao, and many farmers have expanded their cacao gardens around the protected forest areas that are beginning to be cultivated. The development of cacao planting has been quite rapid in recent years. This field information indicates that the area of cacao gardens in these villages has likely increased after 2023, while the official data used in this study are the available data, which still reflect the conditions in 2023.

Thus, the difference between the figures from the Plantation Office and the classification results is likely influenced by several factors rather than a difference in data collection timing alone. The RGB classification results, which show higher values, are partly consistent with the cacao planting developments reported by local farmers. Meanwhile, the GLCM and NDVI methods, which produce different figures, are also a result of the characteristics of each method in recognizing cacao vegetation patterns. In addition, the difference in cacao area between the classification results and the data from the Plantation Office is suspected to be due to certain types of vegetation, such as mixed gardens, coconut, or other plants with colors similar to cacao, being classified as cacao, as well as the limited spatial resolution of Sentinel-2A imagery and the possibility that the 2023 Plantation Office data are no longer fully up to date. This condition causes the cacao area in the classification results to be larger compared to the available data from the Plantation Office.

## CONCLUSION

Based on the research "Mapping Cacao Plantations Using Random Forest Classification and Sentinel-2A Imagery in Batulappa District, Pinrang Regency, Indonesia," the following conclusions can be drawn:

1. This study shows that the RGB band composite is the most effective with the highest accuracy (85.38%), followed by GLCM (75.47%) and NDVI (74.06%). This difference indicates that using the RGB band composite is more optimal for land cover classification.
2. The results of cacao class classification show differences in accuracy for each method used. The RGB band composite shows a user accuracy of 80% and a producer accuracy of 87%, GLCM has lower accuracy with a user accuracy of 64.81% and a producer accuracy of 76%, indicating difficulties in distinguishing land textures. NDVI, with a user accuracy of 71.43% and a producer accuracy of 65%, also indicates difficulties in differentiating vegetation, making the RGB band composite more reliable for cacao mapping.

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