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Pan-Sharpening Analysis for Improved Detection Accuracy and Estimation of Coffee Plantation Land Area (Case Study: South OKU Regency, South Sumatra Province)

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ABSTRACT

The use of remote sensing technology in monitoring coffee plantations is becoming increasingly important considering the vital role of coffee in the economy as an export product that increases state revenue. However, challenges remain, especially regarding the low resolution of satellite imagery which hinders accurate and efficient monitoring of coffee fields. This study aims to improve the accuracy of coffee plantation land analysis in South OKU Regency, South Sumatra Province, by using a pan-sharpening method consisting of IHS, Brovey, and Gram-Schmidt and assisted by a composite index. Satellite image sampling data from Landsat-8 was carried out at 1800 points divided into six classes. The results of the study show that the characteristics of coffee plantation land have NDVI, EVI, and ARVI values that tend to be lower, but the NDBI and NDWI values tend to be higher than the non-coffee plantation and forest classes. This study also compares the data from the pan-sharpening method using machine learning and deep learning methods to get the best classification model. The results showed that the SVM model machine learning method on the pan-sharpening brovey data gave the best results with an ACCURACY value of 83.49 and an F1-score of 83.59 percent.

1. INTRODUCTION

Coffee is an export commodity that has a relatively high economic value in the world market. Coffee itself is one of the most traded food commodities in the world. According to the Statista Research Department, the global market for coffee shops is estimated to reach $165.7 billion in 2022 (Research and Markets, 2023). In addition, coffee is also one of the most important commodities in international trade and has a significant role in influencing the global economy. Indonesia is one of the world's main exporters of coffee commodities. In 2022, Indonesia will become the third largest coffee exporting country after Brazil and Vietnam. Indonesia produce 11.85 million bags of coffee. Meanwhile, Brazil produces 62.6 million bags of coffee. Then, Vietnam produces 29.75 million bags of coffee (USDA, 2021).

Sumatra Province is the largest contributor to coffee production in Indonesia in 2022, accounting for around 26.72 percent of total national production, with a total production of 212.4 thousand tons. Coffee production in South Sumatra increased by 0.33 percent from the previous year (Finaka *et al*., 2023). The level of coffee production is highly dependent on the area of plantation land, which can be calculated based on the area. The area of coffee plantations in South Sumatra in 2022 will reach 267,867 hectares. South OKU Regency is the largest coffee plantation area in South Sumatra Province, reaching 89,823.5 hectares or about 33.2 percent of the total coffee plantation area in the province. However, there has been a decrease in the area of coffee plantation land by 0.63 percent in South Oku Regency since 2021.

Collecting data on coffee plantation land is a crucial process to ensure the accuracy and accuracy of the information obtained. Currently, in Indonesia, a conventional approach is used to collect data on coffee plantations. The identification of coffee plantation land is carried out through the Plantation Company Survey (SKB) carried out by the Central Statistics Agency (BPS). The methods used include complete self-enumeration, as well as plantation analysis through the Accurate, Accountable, and Safe Electronic System (SEAAP) by plantation owners, as well as filling in data through the online SKB platform for those who have not done self-enumeration. In addition, data was also obtained from the Directorate General of Plantations, Ministry of Agriculture. The information collected about coffee plantation land includes land area, amount of production, productivity, plant status, and business status (BPS, 2022). In the context of the Plantation Company Survey (SKB) conducted by BPS, data was collected for plantations with the status of State Large Plantations (PBN) and Private Large Plantations (PBS). Meanwhile, the Directorate General of Plantations collects data on People Plantations (PR)

The conventional approach currently used has some significant drawbacks. One of them is the time needed to carry out surveys, which often results in delays in providing data for up to a year. In addition, this approach requires a considerable amount of labor and significant costs, especially in large or hard-to-reach plantation areas. These weaknesses encourage efforts to find more efficient alternatives in collecting data on coffee plantation land. One promising alternative is to utilize remote sensing technology. The main challenge of this technology is that the resolution of satellite images is still relatively low. Low resolution can hinder the ability to perform accurate and efficient monitoring, so pan-sharpening methods are needed to increase the resolution. This technology can provide solutions to improve the quality of data collection without sacrificing significant time and resources.

Research (Aziz & Murti, 2019) has previously discussed the use of remote sensing and satellite imagery to estimate and test the accuracy of the results of coffee crop production estimates. The study has also analyzed various vegetation indices and satellite data to identify coffee plantation land. However, this study only focused on the use of one vegetation index and there was no merger of several vegetation indices to analyze coffee fields. Meanwhile, research (Damayanti & Liyantono, 2021) has discussed the use of machine learning algorithms to identify and map coffee plantation land. This research was conducted using SVM and Random Forest technology to process Landsat-8 satellite images and identify coffee plantation land.

The development of satellite remote sensing technology today leads to an increase in spatial resolution (high resolution) and an increase in spectral channels (hyperspectral). The Landsat-8 OLI satellite has a multispectral channel and a panchromatic channel with better spatial resolution. Research (Dibs *et al.*, 2021) utilizes this development to estimate land cover (LULC). Multispectral channels provide color information, while panchromatic channels provide more prominent texture information. By combining these two information, it is expected to be able to provide more detailed and accurate information about an object.

Therefore, this research is directed at the development of remote sensing technology by providing several methods to combine images commonly called pan-sharpening and utilize vegetation indices in distinguishing coffee plantation land. These pan-sharpening methods produce images with different spectral values, according to the algorithm. In this study, we will analyze some of these pan-sharpening methods. To see which method has better accuracy, these methods will be compared with the method of conducting an accuracy test between the results of image classification against the actual data in the field. The use of Landsat-8 OLI satellite imagery needs to be reviewed. This research is directed to the study of the use of Landsat-8 OLI data on coffee fields, especially related to improving the accuracy and estimation of coffee plantation area.

2. MATERIALS AND METHODS

2.1. Study Area

South Sumatra Province is the largest coffee producing province in Indonesia. Based on BPS data, in 2022 coffee production was recorded at 201,400 tons or 26.72 percent of the total national coffee production. South OKU Regency has the largest coffee plantation area when compared to other districts and cities in South Sumatra Province, which is 89,823.5 hectares (Ha) (BPS, 2023). Therefore, South Oku district was chosen as a Region of Interest (ROI) or location study.

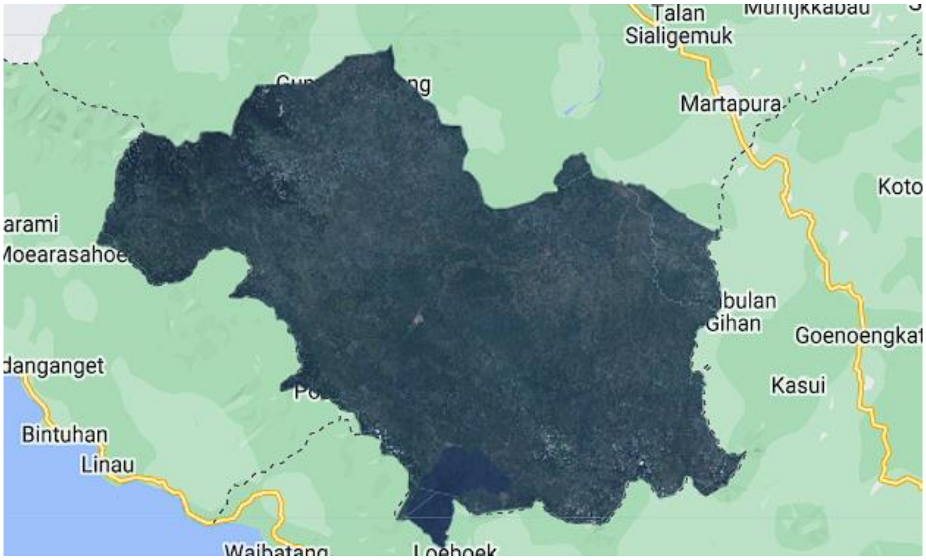

Figure 1. Image of South Oku Regency from Landsat-8

2.2. Experimental Design

2.2.1. Landsat-8 image data

The data used is Landsat 8 Collection 2 Tier 1 TOA Reflectance satellite imagery which has a spatial resolution of up to 30 meters with a temporal resolution of 16 days (Yusof *et al*., 2021). The downloaded Landsat-8 image is image data that is in the range of January 1 to December 31, 2022. Data is collected through the Google Earth Engine platform. Before being used for analysis, satellite imagery goes through a cloud masking process to remove clouds and is combined using a median reducer.

2.2.2. Sample data

The sampling points were divided into six target classes consisting of water class, coffee plantations, non-coffee plantations, forests, buildings, and land. A total of 1,800 samples were taken and each class had the same size, namely 300 samples, where each sample was in the form of a grid with a size of 1010 meters. This aims to avoid data ×imbalance, which is the condition that one or more of the existing target classes has a set that has a fairly unequal number. The first step is to geotagging the observed object. Then a geotagging pixel is obtained that represents one sample point and one target class.

In determining the minimum number of samples for each class, adhere to the rule of thumb (Haub *et al*., 2015). In this study, the number of classes used was six classes and the area of the test site was more than five hundred thousand hectares, so it required at least 75 to 100 samples in each class (Haub *et al*., 2015). Therefore, the sample points obtained have met the minimum sampling requirements for each class.

2.2.3. Labeling

Labeling is assisted by Google Earth's satellite imagery tool, sample location information from Google Earth Engine (GEE), Google Street View camera captures, plantation information registered on Google Maps and supporting data from the South OKU Regency Geoportal. This is due to the unavailability of official administrative data on coffee plantations specifically at each coordinate point in Indonesia. It should be noted that the sampling point process is the stage with the highest level of difficulty, considering that it is quite difficult to distinguish the image of the coffee plantation class from the forest class. The validation process is carried out by taking longitude and latitude coordinate information from the sample point. Then use Google Earth to go to the location and confirm again with Google Street View.

Figure 2. Image of coffee plantation (-4.78; 103.92): (a) Google Street View; (b) Google Earth

2.2.4. Pan-Sharpening Process

Pan-sharpening is performed to improve and sharpen the spatial resolution of the image in order to obtain more information than the non-diffused image. This is very necessary to increase the spatial resolution of multispectral and hyperspectral bands to spatial resolution in the panchromatic band. Image sharpening is generally only used for the purpose of improving the visual quality of images due to the limitations of the width of the panchromatic bands, which cause bands beyond the wavelength to appear to theoretically have spectral values that no longer correspond to their original values. In this study, the three pan-sharpening methods used were IHS (Intensity-Hue-Saturation), Brovey, and Gram-Schmidt, each of which was chosen for specific reasons. The IHS method was chosen because of its ability to combine color information from multispectral imagery with spatial detail from panchromatic imagery, as well as maintain good color quality, suitable for vegetation analysis and land mapping (Carper *et al*., 1990). Brovey's method was chosen because of its simplicity and ability to sharpen imagery without eliminating spectral information, often used in geological mapping and identification of urban features (Chavez *et al*., 1991). The Gram-Schmidt method was chosen because of its mathematical transformation that is effective in increasing spatial resolution without sacrificing spectral information, being very useful in the study of environmental change and monitoring of regions (Chavez *et al*., 1991). These three methods were chosen because of their superiority in maintaining spectral integrity and improving the visual quality of pan-sharpening images. The Intensity Hue Saturation (IHS) method breaks down colors into intensity (I), hue (H), and saturation (S), which is in accordance with human understanding of color (Sitanggang *et al*., 2004). The Brovey Tranformation (BT) method combines images with different resolutions, increasing the contrast and brightness of the image to provide sharper and more detailed results (Wandayani, 2007). While the Gram-Schmidt Method, or smoothing filter-based intensity modulation (SFIM), involves simulation and transformation to improve the sharpness of the image, resulting in clearer and more detailed images, in accordance with the need for more in-depth analysis (Daenodoro, 2012).

To observe the visual appearance of the results of pan-sharpening, this study took several samples for the difference in visual appearance between landsat-8 imagery, pan-sharpening method IHS, Brovey, and Gram-Schimdt. Visually, Brovey's resulting imagery has a high spatial sharpness, but the color information differs from the early multispectral imagery because Brovey's method uses only ratios of 3 spectral bands. On the other hand, Schmidt's Gram method produces clearer, sharper images, although the green color decreases slightly. In the HIS method, the resulting image almost resembles the original color, but the spatial sharpness is not as good as the Brovey method. The selection of a suitable method should be tailored to the purpose of image analysis, such as spectral observation or observation of the edges of objects.

(a) (b) (c) (d)

Figure 3. Visual appearance: (a) Original; (b) IHS; (c) Brovey; (d) Gram-Schmidt

2.2.5. Feature Collection

The feature collection consists of multiple multispectral bands and composite indices as predictor variables. A multispectral band is a spectrum or electromagnetic wave emitted from satellite images of a specific wavelength. Only three electromagnetic waves can be seen by the human eye, namely red (red), green (green), and blue (blue) or RGB. Meanwhile, other waves cannot be seen with the human eye, such as Near-Infrared (NIR) and Short Wave Infrared (SWIR). The object of observation will absorb the spectrum and the value of each wave will be processed and calculated. Table 2 shows the multispectral bands used in this study.

Table 1. Multispectral band of satellite imagery based on USGS (Sitanggang *et al*., 2004)

Landsat-8	Bands	Wavelength (micrometer)	Resolution
Blue	B2	0.45 – 0.51	30 m
Green	B3	0.53 – 0.59	30 m
Red	B4	0.64 – 0.67	30 m
NIR	B5	0.85 – 0.88	30 m
SWIR 1	B6	1.57 – 1.65	30 m
SWIR 2	B7	2.11 – 2.29	30 m

Table 2. Composite index formula

Composite Index	Similarity of bands used
NDVI	$(NIR - Red)/(NIR + Red)$
ARVI	$(NIR - \gamma * Red - Blue)/(NIR + \gamma * Red - Blue)$
EVI-2	$2.5 * (NIR - Red)/(NIR + 2.4 * Red + 1)$
NDBI	(SWIR1 − NIR) / (SWIR1 + NIR)
NDWI	(Green − NIR)/(Green + NIR)

The composite index is generated through the transformation of multiple spectral bands. Typically, composite indices are used for specific tasks (USGS, 2022). The vegetation indices used to distinguish the classes of coffee plantations, non-coffee plantations, and forests are the Normalized Difference Vegetation Index (NDVI), Atmospherically Resistant Vegetation Index (ARVI), and Enhanced Vegetation Index (EVI) (Hoeser *et al*., 2020). NDVI is a vegetation index that describes the greenness level of a plant derived from a mathematical combination between the red band and the NIR band which is used as an indicator of the presence and condition of vegetation (Bezerra *et al*., 2020). ARVI is an alternative index to reduce dependence on NDVI which utilizes atmospheric information contained in the blue band (Lillesand *et al*., 2015). EVI-2 is an alternative to EVI without blue band, which has the same consistency across different types of land cover and is independent of land cover and was developed to optimize vegetation signals through the influence of soil background and canopy signals (Rondeaux *et al*., 1996). The Normal Difference Built-up Index (NDBI) is sensitive to building land or open land (Jiang *et al*., 2008). Meanwhile, for waterlogged areas, the Normalized Difference Water Index (NDWI) is used (Hidayati *et al*., 2018). The following Table 3 is the formula of the composite indices NDVI, ARVI, EVI-2, NDBI, and NDWI.

2.3. Analysis Methods

Descriptive analysis was carried out to determine the effect of various sharpening methods to detect coffee plantation land using multispectral band data, pachromatic channels and composite indexes. Image sharpening is used automatically to combine (fusion) a color, multispectral, or hyperspectral image with a low spatial resolution grayscale image with a high spatial resolution by resampling the size of the image element (the high spatial resolution pixel). Image sharpening using panchromatic image data (Pan-sharpening) is by combining multispectral image data (color) that has low resolution with panchromatic image (black-white or grayish level) that has high resolution. The composite index used, namely NDVI, ARVI, EVI-2, NDBI, and NDWI. Array data is grouped at a specific range with natural breaks in the jenks. Jenks natural breaks is a type of optimal classification method that aims to maximize variance between classes and minimize variance within classes. Classification of data between classes based on information inherent in the data (data-driven). The level range is divided into five, namely very low, low, medium, high, and very high (Gautam *et al*., 2015). The Goodness of Variance Fit (GVF) test that produces a value close to one shows the variation between the classes that are optimally divided.

For the purpose of identifying the best classification model for coffee plantation land, a modeling process is carried out by implementing supervised classification algorithms in machine learning and deep learning. In machine learning, classification algorithms are used, namely Support Vector Machines (SVM), random forest, and Extreme Gradient Boosting (XGBoost). Meanwhile, deep learning uses Multi-Layer Perceptron (MLP) and Convolutional Neural Network (CNN-1D). In machine learning, hyperparameter tuning is carried out using grid search. Then the model evaluation was carried out using stratified 5-fold cross validation to avoid the effect of coincidence and avoid the possibility of overfitting to be more confident in the selection of the best model.

2.3.1. Machine Learning

SVM is a machine learning method used for high-dimensional data to find an optimal boundary in separating one class from another. This algorithm is not prone to overfitting and can produce high accuracy on complex nonlinear models (Verde *et al*., 2020). Random forest is an algorithm for classifying data based on decision trees. A random forest is a combination of multiple decision trees where each tree relies on a random vector value whose samples are taken independently and with the same distribution for all trees in a random forest. The random forest method is an effective classification method (Chen *et al*., 2017). The advantage of this method is that it can process large amounts of data, with many variables, and is sensitive to multicollinearity and overfitting (Breiman, 2001). XGBoost is a tree-based ensemble learning algorithm consisting of a decision tree. Decision trees are built sequentially to reduce residual errors from previous decision trees. A basic classifier is a weak classifier that matches the data. Each new classifier considers the previous classifier resulting in better performance (Triscowati *et al*., 2019). From a computational point of view, the XGBoost algorithm is faster than other gradient boosting implementations and is able to work well even with many missing values (Budholiya *et al*., 2020).

2.3.2. Deep Learning

MLP is a neural network model consisting of several hidden layers and nodes between layers are interconnected with each other. MLP architecture consists of an input layer, one or more hidden layers, and an output layer. The input layer receives a signal from the outside, then passes it to the first hidden layer to be passed so that it finally reaches the ouput layer (Putra & Azhar, 2021). CNN is a convolutional operation that combines several layers of processing and uses elements in parallel operation inspired by the biological nervous system. The CNN 1-D architecture consists of 3 layers, namely the convolutional layer, the pooling layer, and the fully connected layer (Jiang *et al*., 2018). Pooling layers along with dropouts are able to improve model performance and reduce overfitting (Hu *et al*., 2015).

2.4. Mindset

This research began with limitations in the data collection method in the Plantation Company Survey (SKB) of commodities by the Central Statistics Agency which requires a lot of energy, time, and large costs and is difficult to reach the coffee plantation area. The framework describes the course of the research starting from the problem, proposed solutions, research objectives, and evaluation indicators. The framework of thought in this study refers to (Peryanto *et al*., 2020) and is illustrated in Figure 4.

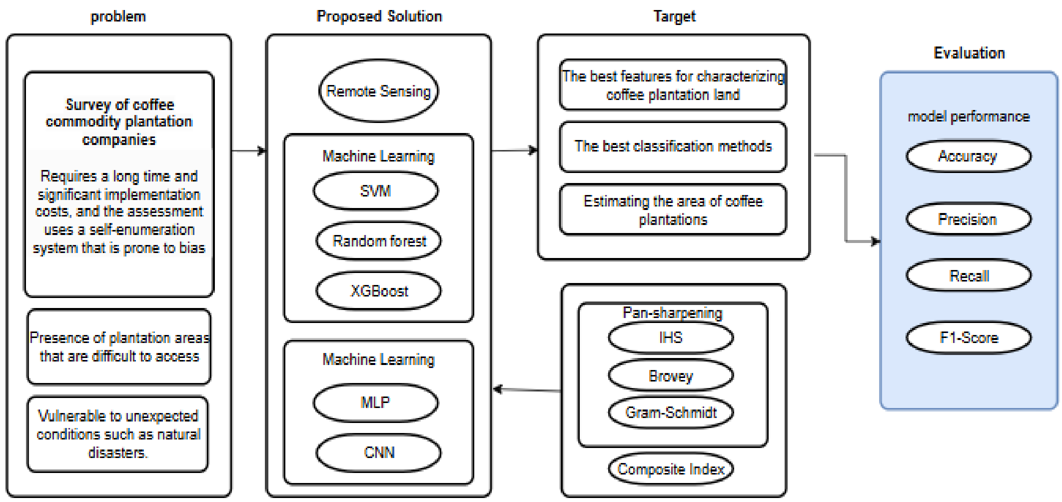

Figure 4. Mindset

3. RESULTS AND DISCUSSION

3.1. Identify the Best Features Characterizing Coffee Plantationsm

To analyze the effects of various pan-sharpening methods, descriptive analysis was used to identify features on the Landsat-8 satellite imagery. Multispectral bands are used to form composite indexes, and the entire multispectral bands and composite indices of Landsat-8 are normalized and standardized. After that, the GVF calculation is done for each feature before being divided into five levels using the natural breaks jenks method. The results show that the GVF calculation value is close to one, which indicates that the features can be grouped according to their level. The feature distribution for each class is shown by the heatmaps in Figure 5, Figure 6, Figure 7 and Figure 8. Based on those figures, information was obtained about the difference in band values in each class. The average values of the multispectral bands or built-in bands (RGB, NIR, SWIR 1, and SWIR 2) of the IHS, Brovey, or Gram-Schmidt pan-sharpening have almost no differences between classes or are similar, making it difficult to distinguish between the other classes. Therefore, a composite index which is a combination of several existing bands can be quite helpful to differentiate land

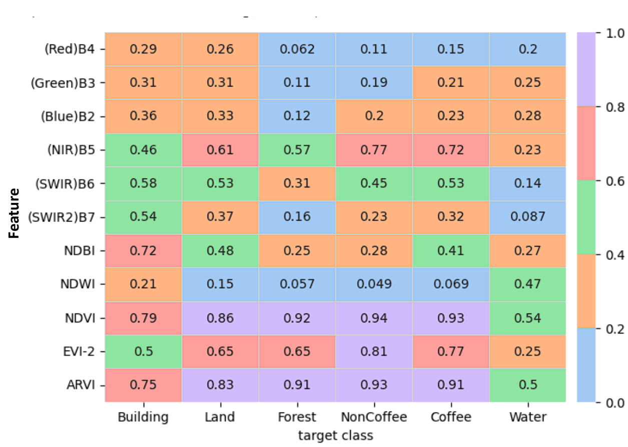

Figure 5. Features on the original image

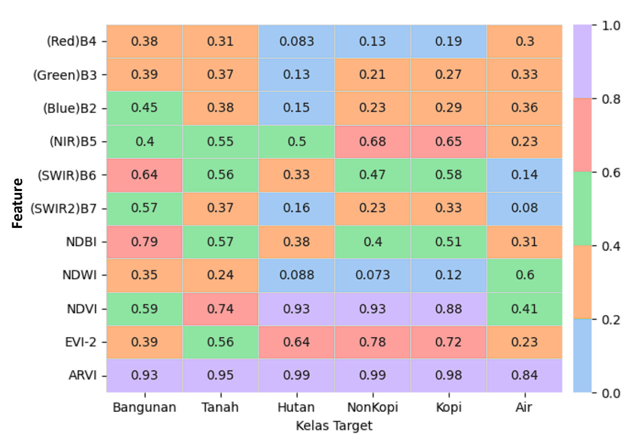

Figure 6. Feature distribution on Pan-sharpening IHS

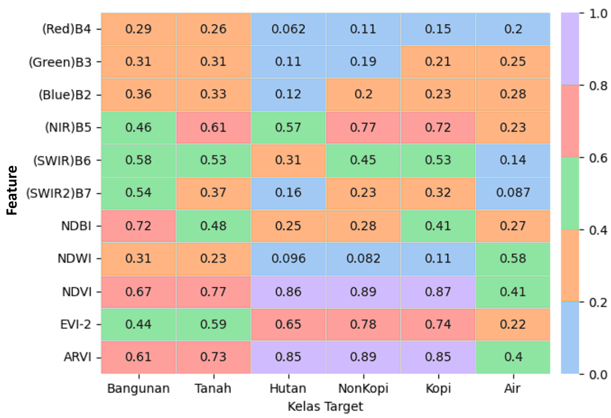

Figure 7. Feature distribution on Pan-sharpening Brovey

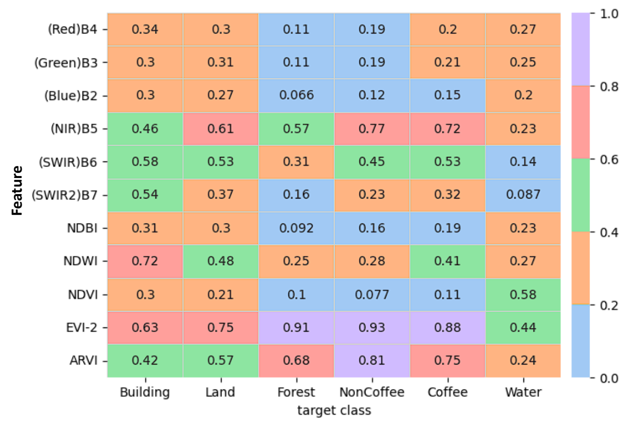

Figure 8. Feature distribution on Pan-sharpening Gram-Schmidt

cover classes. The characteristics of coffee plantation land were similar values, both IHS, Brovey, and Gram-Schmidt, namely in the NDWI feature at a very low level; the SWIR 2 feature was at a low level; SWIR2 is at a medium level; EVI-2 is at a high level and the vegetation index of NDVI, and ARVI is at a very high level, but at the RGB feature (red, green, and blue) at a level that is quite diverse for the original imagery, pan-sharpening IHS, Brovey, or Gram-Schmidt.

In more detail, NDBI is easy to distinguish building and land classes from other classes, characterized by obtaining a higher mean value than other classes and building classes have higher values than land classes. NDWI is also able to distinguish water classes from other classes. Meanwhile, in the vegetation index (NDVI, EVI-2, and ARVI) it is not possible to distinguish between coffee plantation classes, non-coffee plantations, and forests either in the original image, pan-sharpening IHS, Brovey, or Gram-Schmidt except for the forest class in pan-sharpening brovey. However, if you look further, it can be seen that the original image and the three pan-sharpening have patterns. The coffee plantation class has a lower value than the non-coffee plantation class or forest in the vegetation index and a higher value in NDBI and NDWI. By combining this information, the machine may be able to distinguish between the classes. That way, if the index value of a pixel is at the same level for the class of coffee plantations, non-coffee plantations, and forests, and the lowest value on the vegetation index, namely NDVI, EVI-2, and ARVI but higher on NDBI and NDWI, then it is likely that the pixel represents a coffee plantation.

3.2. Identification of the Best Model

The following is the performance of the machine learning model and the deep learning model used, as well as the comparison can be seen in Table 3 and Table 4. The table shows the results of stratified 5-fold cross validation on machine learning that has been carried out by hyperparameter tuning using grid search. Based on Table 3, the machine learning results on the original image show that the SVM algorithm gets the highest percentage in each aspect where it has an accuracy of 80.35 percent, a precision of 80.53 percent; recall of 80.35 percent; and F1-score of 80.38 percent. Meanwhile, the Pan-sharpening IHS shows that the SVM algorithm gets the highest percentage in all aspects of assessment, namely an accuracy value of 82.98 percent and a precision of 83.42 percent; recall of 82.98 percent; and F1-score of 83.05 percent. Meanwhile, in Pan-sharpening Brovey, the SVM algorithm with the highest percentage was also obtained, namely an accuracy value of 83.49 percent; precision of 83.98 percent; recall of 83.49 percent; and F1-score of 83.59 percent. Meanwhile, in Pan-sharpening Gram-Schmidt, the Random Forest algorithm has the highest percentage, namely an accuracy value of 80.99 percent; precision of 81.46 percent; recall of 80.99 percent; and F1-score of 81.13 percent.

The Random forest algorithm gets the lowest percentage in terms of accuracy and F1-score on both the original image and Pan-sharpening, except for Gram-Schmidt. The accuracy percentage is 80.67 percent and the F1-score is 80.79 percent in IHS, while in Brovey the accuracy percentage is 81.56 percent and the F1-score is 81.67 percent. Most algorithms show better performance results using IHS Pan-sharpening data than Brovey's Pan-sharpening data, or Gram-

Table 3. Comparison of machine learning model performance using stratified 5-fold cross validation

Data	Algorithm	Accuracy	Precision	Recall	F1-score
Original	**SVM**	**84.01%**	**84.25%**	**84.01%**	**84.05%**
	Random Forest	82.47%	82.91%	82.47%	82.56%
	XGBoost	82.44%	82.81%	82.44%	82.52%
IHS	**SVM**	**84.17%**	**84.41 %**	**84.17 %**	**84.21%**
	Random Forest	82.50%	82.96%	82.50%	82.62%
	XGBoost	82.34%	82.76%	82.34%	82.44%
Brovey	**SVM**	**84.78%**	**84.99 %**	**84.78 %**	**84.79%**
	Random Forest	84.07%	84.37%	84.07%	84.12%
	XGBoost	83.24%	83.55%	83.24%	83.29%
Gram-Schmidt	**SVM**	**84.71%**	**84.71 %**	**84.52 %**	**84.53%**
	Random Forest	82.69%	83.08%	82.69%	82.76%
	XGBoost	82.79%	83.09%	82.79%	82.88%

Table 4. Comparison of machine learning model performance using stratified 5-fold cross validation

Data	Algorithm	Accuracy	Precision	Recall	F1-score
Original	**SVM**	**84.01%**	**84.25%**	**84.01%**	**84.05%**
	MLP	82.02%	83.68%	79.52%	81.45%
	CNN	80.93%	82.24%	78.69%	80.43%
IHS	**SVM**	**84.17%**	**84.41 %**	**84.17 %**	**84.21%**
	MLP	82.12%	83.70%	79.58%	81.59%
	CNN	81.83%	83.67%	79.81%	81.69%
Brovey	**SVM**	**84.78%**	**84.99 %**	**84.78 %**	**84.79%**
	MLP	83.11%	84.39%	81.09%	82.70%
	CNN	82.24%	84.07%	80.74%	82.37%
Gram-Schmidt	**SVM**	**84.71%**	**84.71 %**	**84.52 %**	**84.53%**
	MLP	81.03%	82.54%	79.10%	80.79%
	CNN	81.03%	82.54%	79.10%	80.79%

Schmidt data. The results also showed that the performance of the Pan-sharpening Gram-Schmidt had the worst results compared to the other two pan-sharpening methods, but was still better than the original image. The thing that can cause differences in algorithm performance is the resolution that each Pan-sharpening process has, meaning that the Pan-sharpening algorithm has an influence on the performance results of the model. In addition, there is also a difference in wavelength used by each Pan-sharpening which can also be the cause of the difference in performance. Based on the results obtained, the best machine learning algorithm was selected to detect coffee plantation land, namely SVM on IHS, Brovey or Gram-Schmidt on Landsat-8 which will then be compared with the results of deep learning which is also evaluated using stratified 5-fold cross validation Table 4. Comparison of the performance of the best machine learning model with deep learning using stratified 5-fold cross validation.

The deep learning results in Table 4 show that the MLP algorithm gets a higher percentage than the CNN-1D algorithm. The percentage of accuracy value was 81.47 percent and the F1-score was 81.46 percent in IHS, and in Brovey it got a percentage of accuracy value of 81.76 percent and F1-score of 81.65 percent, while in Gram-Schmidt it got a percentage of accuracy value of 82.12 percent and F1-score of 81.84 percent. Then the CNN-1D algorithm in IHS got an accuracy score of 79.98 percent and an F1-score of 79.55 percent, and in Brovey got an accuracy score of 79.85 percent and an F1-score of 79.40 percent, while in Gram-Schmidt it got an accuracy score of 80.61 percent and an F1-score of 80.70 percent. The results show that Brovey's data gets a higher percentage value than IHS and Gram-Schmidt data or in other words, the influence of spatial resolution also applies to deep learning methods in producing model performance. Based on the descriptive analysis that has been explained, the best model results were chosen by the SVM algorithm on Brovey because it has the highest score in all aspects of the assessment.

3.3. Estimating the Area of Coffee Plantations Using the Best Model

The estimated area of coffee plantations using the SVM model on Landsat-8 satellite imagery, with pan-sharpened data using the Brovey method, resulted in an area of 1,338,907 pixels. Conversion was carried out by multiplying by 900 per pixel, considering the spatial resolution of Landsat-8 satellite imagery of 30 m, which means each pixel represents 900 m², yielding a total area of 1,205,015,600 m². The estimated rubber plantation area in South OKU Regency for the year 2022 is 120,501.56 Ha, which is 30,999.56 Ha (25.72%) higher compared to the dynamic table data from BPS of South Sumatra Province, which recorded 89,502 hectares. The comparison of the results of the estimated coffee plantation area with dynamic table data based on sub-districts in South Oku district in 2022 is shown in Table 5.

Table 5.Comparison of the estimated coffee plantation area with dynamic table based on sub-districts in South Oku district in 2022

District	Land Area (Ha)	Number of pixels	Estimate (Ha)	Difference (Ha)
Mekakau Ilir	9228	99122	8920,98	307,02
Supreme Appeal	4356	83871	7548,39	3192,4
Warkuk Ranau Selatan	5847	62555	5629,95	217,05
BPR Ranau Tengah	9264	92956	8366,04	897,96
Buay Pemaca	6640	36523	3287,07	3352,93
Simpang	101	21198	1907,82	1806,8
Buana Pemaca	1971	36160	3254,4	1283,4
Prone Buay	950	81648	7348,32	6398,3
Buay Sandang Aji	5051	68708	6183,72	1132,7
Three Pilgrims	3511	41707	3753,63	242,63
Buay Runjung	3091	59930	5393,7	2302,7
Grand Trunk	5871	91989	8279,01	2408
High Kisam	9015	220083	19807,47	10792
The Kisam	6114	53755	4837,95	1276,05
Kisam Ilir	4218	32781	2950,29	1267,71
Banyan Island	6035	129291	11636,19	5601,2
Sindang Danau	6065	60766	5468,94	596,06
Sungai Are	2174	65864	5927,76	3753,8
Total	89502	1338907	120501,56	30999,63

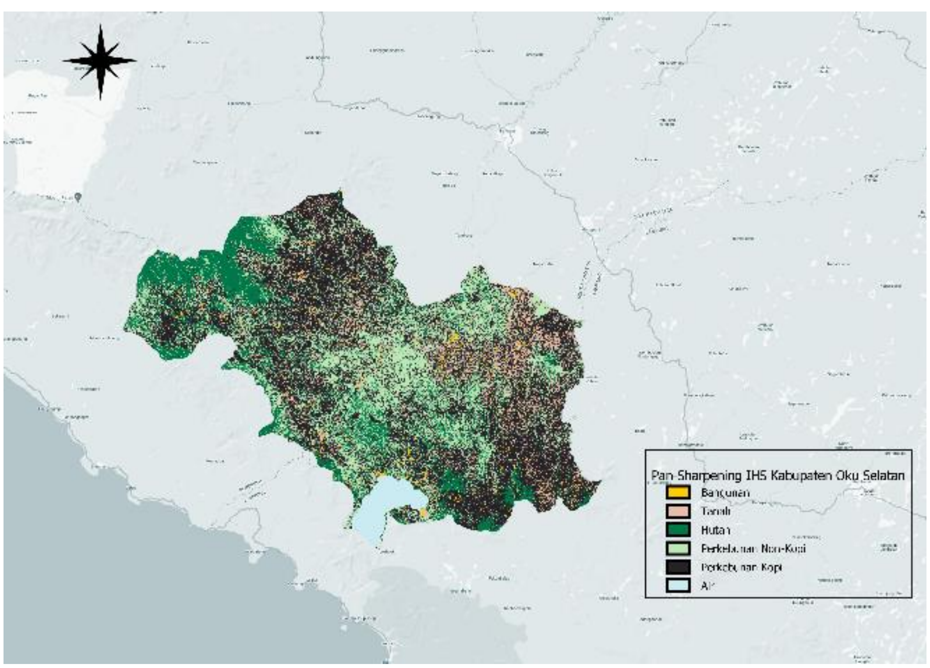

Figure 9. Results of SVM model classification on Landsat-8 satellite imagery using Brovey pan-sharpening method

Based on Table 5, there is a considerable difference in each sub-district between the area of plantation land and the estimated area of plantation land. This is because the level of precision in the administrative area that is getting smaller will cause a bigger difference. In addition, the difference in the estimated land area of coffee plantations may also be caused by the misclassification of the SVM model for the class of non-coffee plantations. Then, there are also coffee plantation class classification pixels that are not fully collected in one place, so it can be the cause of a large difference or there is a difference in the estimated results with official statistics data.

The data collection method carried out in the Plantation Company Survey (SKB) of coffee plantations is carried out by the self-enumeration method which is filled in by plantation owners based on their respective estimation results. This can also be the cause of inaccurate land area reports with the actual situation. The following is a map of land cover in South OKU Regency based on the results of random forest classification shown in Figure 9.

4. CONCLUSION

4.1. Conclusion

This study is able to detect coffee plantation land, including areas that are difficult to reach or according to the boundaries of the research area. Based on the results and discussions described earlier, several things can be concluded.

1) To determine the effect of various pan-sharpening methods in detecting coffee plantation land on Landsat-8 satellite images, this study analyzed the differences in vegetation index values (NDVI, EVI, and ARVI). The results showed that coffee plantations tended to have lower vegetation index values, but had higher values on NDBI and NDWI compared to non-coffee plantation or forest classes.
2) To get the best classification model in detecting coffee plantations, this study succeeded in producing an SVM model on Brovey data that shows superior performance. This is shown from the performance of the highest accuracy, precision, recall, and F1-score scores, namely accuracy of 83.49 percent and F1-score of 83.59 percent.
3) To estimate the area of coffee plantations using the best model of SVM, the results of the estimation of the area of coffee plantations in South Oku district in 2022 are 120,501.56 Ha on the Landsat-8 image data from Brovey's pan-sharpening.

4.2. Suggestion

Based on the results and discussions, there are several suggestions that can be submitted.

1) For the next research, post classification processing is carried out, because there are still many pixels from the land cover classification that are not in accordance with the class that should be. For example, there is a forest pixel in the middle of a non-coffee plantation or a cloud shadow that is classified as a coffee plantation pixel.
2) For further development of this study, focus research on the development or improvement of pan-sharpening methods. This is because the pan-sharpening process often sacrifices spectral information to improve spatial resolution. This can result in a decrease in the ability to distinguish between objects or features based on their spectral characteristics. These developments can include creating new algorithms or better parameter adjustments to create a more accurate and informative composite imagery.

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