Mapping built-up land & settlements: A comparison of machine learning algorithms

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ABSTRACT

Monitoring the growth of built-up land finds its challenge as a never-ending mapping process. Since the built-up maps are taken into account in development planning and measuring the achievement of SDGs objectives (Goal 11 - indicator 11.3.1), the best mapping method should be attempted. Therefore, all efforts were work on to speed up the mapping process without compromising accuracy. Various methods have been proposed, but numerous difficulties remain in accurate and efficient built-up and settlement extraction. In this study, with the combination of Sentinel and NOAA-VIIRS imageries using Google Earth Engine (GEE) platforms, we apply several machine learning methods were for mapping built-up land and settlements in Purwokerto, Central Java. More than 300 samples were collected to distinguish four classes of land covers: settlements, built-up land, waters, and others. The decision tree based supervised learning algorithms give the best performances, scilicet Random Forest (RF) and Gradient Tree Boost (GTB). Gradient boosting is a machine learning algorithm that uses an ensemble of decision trees to predict values. Gradient boosting can handle complex patterns and data when linear models cannot. RF classifier yield an overall accuracy of 99.69% (Kappa = 0.99). The Support Vector Machine (SVM) classifier produces 84.95% accuracy with Kappa = 0.79. However, The Mahalanobis classifier gives the best accuracy only of 80.56% (Kappa = 0.72). GTB classifier feature in GEE, the overall accuracy is 97.18%, and the Kappa coefficient of 0.96. On the whole, RF and GTB classifiers can distinguish between settlements and non-settlement with an accuracy of more than 95%.

Keywords: built-up land, settlement, supervised learning, random forest, ensemble classifier

1. INTRODUCTION

In the Indonesian SDGs indicator document, the economic and environmental pillars, there are several objectives whose measurement depends on the need for spatial data related to built-up land and settlements. The 9th and 11th SDGs goals are one of 2 of the 17 goals which contain indicators with national proxies that indicate the need for data on population distribution and the rate of expansion of built-up land in Indonesia. The built-up land is part of the land use/land cover type. The utilization of remote sensing data to fulfill the answer to the SDGs indicator is an unavoidable need.

Various studies related to the effort to produce land use/land cover maps with various scales have been carried out. Several land cover mapping methods implemented start from visual interpretation [1], pixel-based or object-based digital classification, and using machine learning [2]–[4] and artificial intelligence (AI) [5]. Septiani et al. [6] ompared the Supervised Classification and Unsupervised Classification Methods to Land Cover in Buleleng Regency. The object-based method has been tried to classify 9 classes of land use in the core zone of Parangtritis and overall accuracy within the range 61 – 69% over a different period [7]. Tavares [8] combined Sentinel-1 (S-1) and Sentinel-2 (S-2) to detect Land Use Land Cover (LULC) in Brazil through a Random Forest (RF) classifier. In addition, many methods of detecting built-up land have been carried out using several types of image transformation, amongst which are combining the vegetation index and the built-up land index [9]–[11].

However, the urgency of detecting built-up land, especially separating buildings with residential functions is closely related to efforts to detail spatial data on population distribution. In general, the composition of the population is displayed with a map of administrative boundaries, as if it is seen that the population inhabits the entire administrative area equally without seeing the correlation with the type of land use. In reality, the human population does not inhabit the entire LULC, but rather in the built-up area. Thus, we can understand that the distribution of humans will be closely related to the distribution of built-up land, especially settlements.

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In this initial trial, to find a method for mapping the distribution of built-up land, especially settlements, we tested a combination of input image processing with several supervised learning algorithms using cloud computing (Google Earth Engine). Over a long period, remote sensing data has become an indispensable means to observe information on land resources. So that, it would bring through the detection of settlements distribution. So that, it would bring through the detection of settlements distribution [12]. The combination of cloud computing and machine learning options is used with the hope that the mapping method can be implemented in a wider area with efficient processing time. Thus, the need for providing data on built-up land, especially settlements, to answer several SDGs indicators can be done. The Google Earth Engine (GEE) is a cloud-based platform for processing large amount of satellite imagery [3]. As computation platform, GEE also provides a set of machine learning classifiers for pixel-based classification which be very useful for land use mapping. Previous researches have felt the ease of processing with GEE [2], [13], [14] for mapping purpose. Comparing miscellaneous supervised learning algorithms in Google Earth Engine through its accuracy for land use mapping, notably for settlements and built-up land in the township area, has become our fold.

2. DATA

Study Area

The study area took place in Purwokerto, the capital of Banyumas district, Central Java province, Indonesia (**Figure 1**). The location of Purwokerto is in Banyumas Regency, with a regional structure that accommodates a mixture of typologies in urban areas yet some areas are still predominantly agrarian.

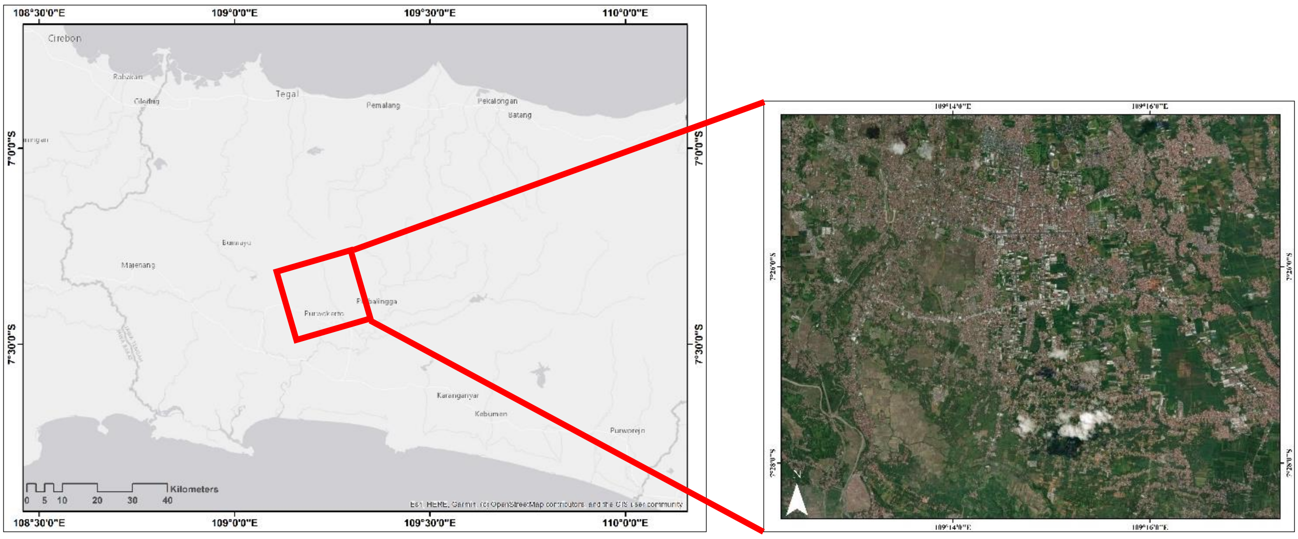

Figure 1. Study Area of Purwokerto, Banyumas District, Central Java.

Multi-source Data

Several types of data sources were carried on to carry on this research. We used Sentinel products, and others which commonly used to map impervious surface and settlements [2], [8], [12], [13], [15], [16]. Combination of Sentinel-1 Synthetic Aperture Radar (SAR), Sentinel-2 Multi Spectral Instrument (MSI), Visible Infrared Imaging Radiometer Suite supporting a Day-Night Band (VIIRS-DNB), and Shuttle Radar Topography Mission-Digital Elevation Model (SRTM-DEM) imageries were implemented to detect built-up land and settlements in study area using the GEE platform. (**Figure 1**). The image composite took time within a year 2020 (1 January 2020 - 31 December 2020).

Why Sentinel-2 MSI? The final destination of our research is to predict the population distribution based on human settlements to monitor settlement-related SDGs indicators from year to year. Before going there, of course, we must determine what parameters affect settlement sensing and what algorithm produces the best accuracy. The complex settlement system in Indonesia requires a separate approach. This time we try to modify the research method from Ji, et al [12] . The types of settlements in Indonesia are complex and are a unique type of land use. Some of the settlement types encompass not only houses but also open spaces, water bodies, and vegetation between houses. This time we try to modify the research method from Ji, et al that incorporated multi-dimensional features to improve the accuracy of 10m rural settlements mapping. Averagely, the size of a settlement (land area) is 100 m2. Though high-resolution remote sensing images can effectively be used to solve this problem, the high-cost and short-term acquisition of these images made it is not suitable for wide-area and long-term monitoring. Thus, we employed Sentinel-2 with less than 20% cloud coverage. Sentinel-2vhas regularly easy-to-access multispectral data and comprehensive bands with various resolutions (10m for RGB-NIR bands and 60 meters QA bands).

The Suomi NPP (National Polar-Orbiting Partnership) satellite equipped with the VIIRS instrument (Visible Infrared Imaging Radiometer Suite) produces night light data (VIIRS-DNB), which is generated from recordings of emitted visible and near-infrared (VNIR) radiation at night. The spatial resolution is commensurate to 0.5 km at the equator (15 arcseconds). The DN values in cities are significantly higher than in rural areas. Therefore, NTL (Night Time Light) from VIIRS-DNB is used to signify the urban areas. We used VIIRS-DNB Monthly average radiance composites version 1 data, which are the monthly average radiance composites.

For the variations of surface texture features (smoothness, smoothness, coarseness, and regularity), SAR was then utilized. Interferometric Wide swath (IW) acquisition mode from Sentinel-1 SAR and VV+VH polarization has chosen since it is the primary conflict-free mode over-land (Sentinel-1 SAR User Guide). Meanwhile, slope derived from SRTM-DEM provided by NASA Jet Propulsion Laboratory (JPL).

More than 300 samples were collected for training (reference samples) and testing purposes. The samples represent four classes of land cover: settlements, built-up land, waters, and others. Since the focus of this research is to find the best algorithm to map the human settlements, so we separated the samples of houses/settlements and other buildings. The reference samples were obtained by visual interpretation of high-resolution Google Earth imagery [12], were randomly distributed in study area. The sample contains the training and/or validation data and they are imported into Assets which can then be called up by the Google Earth Engine (GEE). This data is a Feature Collection with properties that store class labels and numeric predictor variables. This data is divided into 2, namely training data (70%) and validation data (30%) which are selected randomly.

3. METHODS

The classifier grouped the output into four classes following the reference samples: (1) others, (2) built-up land and related, (3) settlement, and (4) waterbody. 'Others' accommodate all land-use types aside from those of 3 classes (i.e., vegetation, forest, farm, or rice field). The built-up land and related class comprise all levels and built-up areas functioned as non-settlement, such as office buildings, schools, roads, bridges, and industrial and manufacture. The settlement class defines the house or multifunction building (as a residential as well as a place of trade, i.e., Ruko). The waterbody class comprises open water surfaces such as rivers and lakes.

There are several input definitions for executing feature extraction using machine learning algorithms related to our purpose[17]. First, the spectral index, in this study at least 7 indices were used to improve learning abilities in separating the features of buildings, housing, bodies of water, and vegetation. We also involve NTL data to calculate The Vegetation Adjusted NTL Urban Index [18]. The texture feature uses Haralick Texture (Gray Level Co-occurrence Matrix/GLCM) [19], [20], while slope information is obtained from SRTM data. We also add a composite image feature obtained from all selected Sentinel-2 images (RGBNIR bands) using the median reducer in GEE. Spectral indices used in this paper mentioned in **Table 1** below.

Table 1. Spectral indices selected for the land use extraction.

No	**Combination Index**	**Equation**	**References**
1	NDVI	$NDVI = \frac{B_8 - B_4}{B_8 + B_4}$	[3], [11], [16], [21], [22]
2	MNDWI	$MNDWI = \frac{B_3 - B_{11}}{B_3 + B_{11}}$	[11], [12], [16]
3	NDBI	$NDBI = \frac{B_{11} - B_8}{B_{11} + B_8}$	[9], [10], [16]
4	NBI	$NBI = {B_4 * B_{11}}/{B_8}$	[12], [16]

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5	BOBI	$RORI = \frac{B_8 - B_4}{B_8 + B_4}$	[12]
6	RRI	$RRI = {}^{B_2}/_{B_8}$	[12]
7	SI	$SI = \sqrt{B_2 * B_4}$	[12]

Notes: B1, B2, B3, B4, B8, B11, B12 refers to the nomenclature system of the Sentinel 2 Science Mission in Technical Guides document.

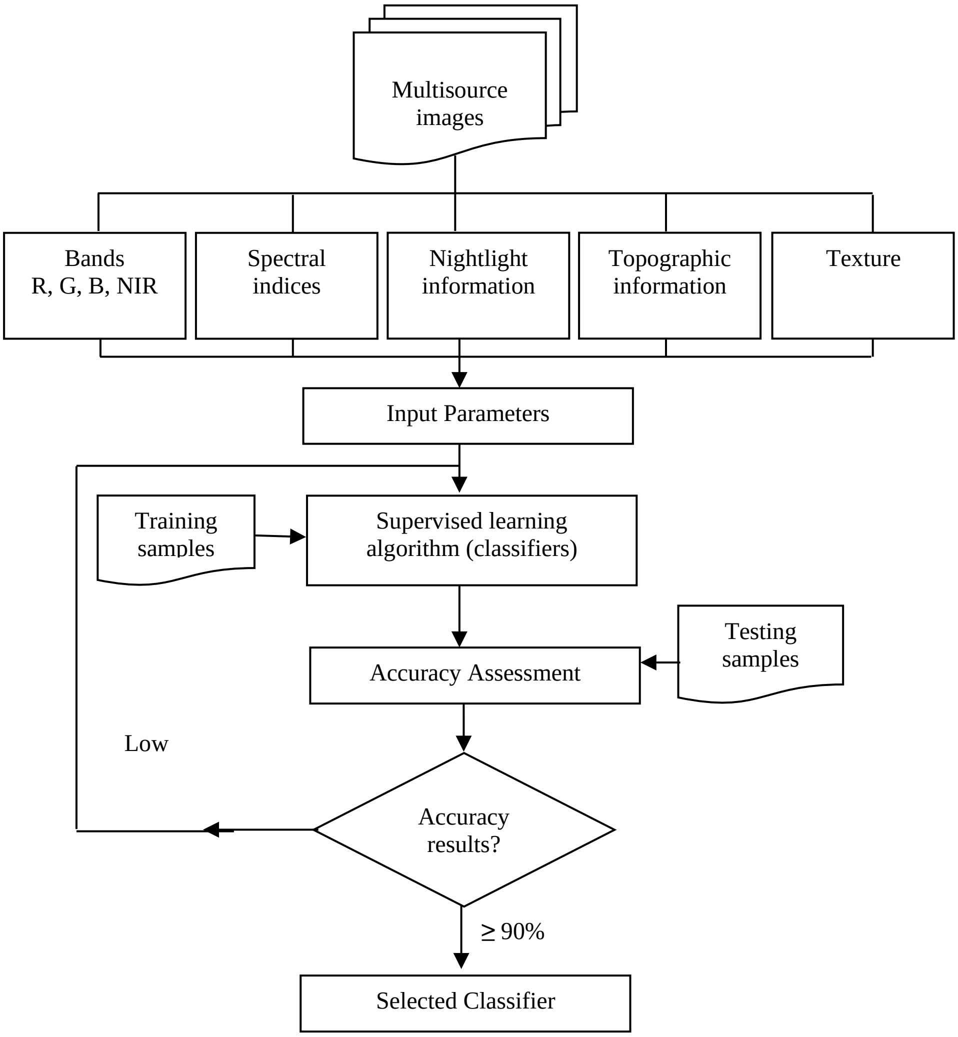

Figure 2. Workflow of research methods

The general workflow (depicted in **Figure 2**) for classification is (1) Collect training data/samples. Assemble a feature that has a property that stores a known class label and a property that stores a numeric value for the predictor; (2) Create classifier instances. Set the parameters if necessary; (3) Divide the data into training data and validation data. In this paper, the quantity ratio is 70:30 between training data and validation data; (4) Train classifiers using training data; (5) Classify images or feature collections; and (6) Estimation of misclassification with independent validation data.

We applied about 10 machine learning classifiers in GEE to yield the land-use map [3], notably built-up land and settlements. In general, we employ Random Forest (RF), Support Vector Machine (SVM), Gradient Tree Boost (GTB), and Minimum Distance classifiers. We set 100 *number Of Trees* for RF and GTB classifiers. In the SVM classifier, we try both RBF and Linear *kernel Type*, also both of 'Voting' and 'Margin' decision procedure.

Machine learning-generated map products rely heavily on samples or training data. Unfortunately, in most cases the samples contain errors, particularly when developed through image interpretation [23]. Thus, the accuracy test shall be applied and Confusion Matrix were used. In mapping, the confusion matrix is the most widely used for testing the accuracy. Using the matrix, several metrics enumerated to provide an overview of the accuracy results. The user's accuracy (Precision; the complement of commission error), producer's accuracy (Sensitivity; the complement of omission error), overall accuracy (OA), and Kappa index [10]–[13], [24], [25]. McCoy, 2005 [25] explained that an interpretation result can be used for analysis purposes if the level of accuracy reaches a minimum of 80-85%.

4. RESULTS

The dataset consists of visible channel images, image transformation results (vegetation and built-up index as listed in **Table 1**), surface albedo, elevation data, and texture features (SAR imagery mode acquisition IW, with VV+VH polarisation) are used to evaluate the performance of several machine learning algorithms in GEE. They were ten experiments carried out to select the best machine learning classifiers available in GEE. Machine Learning performance is widely determined by input data. The more recognition features, the easier for machine learning algorithms to recognize objects [3]. Table 2 show the accuracy assessment of land use classification using 10 machine learning algorithms in Google Earth Engine (GEE). **Table 2** shows the accuracy assessment of land-use classification using ten (10) machine learning algorithms in Google Earth Engine (GEE). Probability and statistical algorithms such as Fast Naive Bayes, logic-based algorithms such as Random Forests, distance-based algorithms such as Minimum Distance, support vector machine algorithms (Voting SVM and Margin SVM), as well as ensemble techniques (Gradient Boosting). The highest accuracy is obtained by Random Forests and then Gradient Tree Boost, both are decision trees based algorithms. The lowest accuracy of classification resulted from the Naïve Bayes algorithm. When using both Voting SVM and Margin SVM algorithms, the RBF kernel type provides better overall accuracy than the Linear kernel type results.

Table 2. The overall accuracy assessment of land use classification using 10 machine learning algorithms in Google Earth Engine (GEE).

No.	Classifier	Overall Accuracy (OA)	Kappa Coeff.
1	**Random Forest***	**99.69%**	**0.99**
2	NaiveBayes	34.48%	0.02
3	Minimum Distance (Mahalanobis)*	80.56%	0.72
4	Minimum Distance (Euclidean)*	43.57%	0.21
5	Minimum Distance (Cosine)	42.63%	0.22
6	**Gradient Tree Boost***	**97.18%**	**0.96**
7	Voting_L_SVM*	76.49%	0.67
8	Margin_L_SVM	71.16%	0.59
9	Voting_R_SVM*	84.95%	0.79
10	Margin_R_SVM*	84.33%	0.78

From 10 classifiers, we selected 7 classifiers from each type of classifiers to examine the classification results of each class generated. Table 3 shows a comparison of the precision and sensitivity of the Random Forest Minimum Distance (Mahalanobis) classifier, Minimum Distance (Euclidean), Gradient Tree Boost, Voting_L_SVM, Voting_R_SVM, Margin_R_SVM. The number of trees is 100 set as a parameter in the decision tree-based algorithm. The results of the spatial classification for the 4 land cover classes display in Figure 3.

By combining the information from Table 2 and Table 3, it can be seen that the Random Forest (RF) algorithm provides classification results with the best accuracy compared to other classifiers in this research. True positive rate reaches 100% for a 'Water Body', 'Settlements', and 'Others' class separation. RF classifier is a type of decision tree classification method, a set of 'shallow' trees constructed from many random samples. The method combines the results of these trees to classify or predict values rom 10 classifiers, we selected 7 classifiers from each type of classifiers to examine the classification results of each class generated. Table 3 shows a comparison of the precision and sensitivity of the Random

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Forest Minimum Distance (Mahalanobis) classifier, Minimum Distance (Euclidean), Gradient Tree Boost, Voting_L_SVM, Voting_R_SVM, Margin_R_SVM. The number of trees is 100 set as a parameter in the decision tree-based algorithm. The results of the spatial classification for the 4 land cover classes display in Figure 3.

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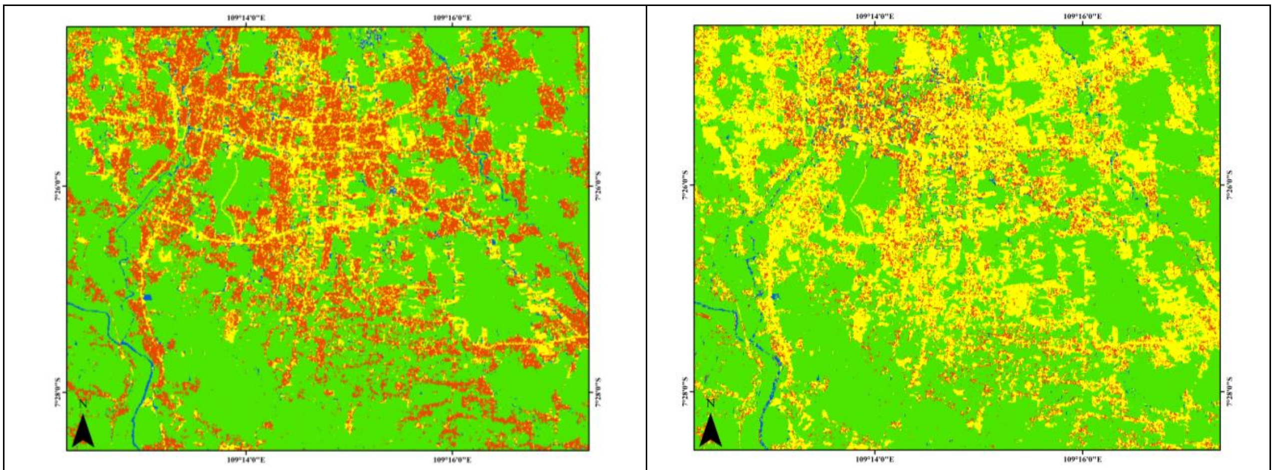
Gradient Tree Boost gives an OA result of 97.18% with a kappa coefficient of 0.96. All 311 pixels are well identified. Along with the kappa index obtained, the classification results of the 4 classes using GTB are close to the actual (identical). The sensitivity of the GTB classifier in separating 4 land cover classes is noble but still lower than RF performance. The ratio of correctly classified cases exceeds 95%. The 'built-up land' and 'settlements' classes were classified with true positive rates reaching 98% and 97.62%, respectively. All land-use classes are well classified indicated by the PA value above 95%. A commission error occurs when the classification procedure assigns a pixel to a specific class that it doesn't belong to. GTB classifier can provide a level of precision on the classification results above 90%. Among the 4 classes, respectively, “others”, “built-up areas”, and “settlements”, are more than 95% correctly classified cases relative to the total number of cases. Omission errors occur when pixels belong to a class assigned to another class (misclassified). The UA value reached 92% when separating the Waterbody feature. Based on the matrix, there were still cases classified as others and settlements. The level of sensitivity and precision is also influenced by the sample composition of the targeted classes[29]. The focus of this paper is built-up land and settlements features.

Table 3. Producer Accuracy (PrAc) and User Accuracy (UsAc) of each land use class according to 7 supervised learning algorithms in GEE.

Classifier	**Random Forest**		**Minimum Distance (Mahalanobis)**		**Minimum Distance (Euclidean)**		**Margin_R_SVM**	
Class	PrAc	UsAc	PrAc	UsAc	PrAc	UsAc	PrAc	UsAc
Others	100.00%	99.09%	93.46%	90.91%	51.83%	77.27%	89.62%	86.36%
Built Up land	100.00%	100.00%	65.52%	95.00%	47.92%	23.00%	78.45%	91.00%
Settlements	98.81%	100.00%	91.49%	51.19%	32.35%	26.19%	83.33%	83.33%
Water body	100.00%	100.00%	95.00%	76.00%	23.08%	36.00%	100.00%	52.00%
Classifier	**Gradient Tree Boost**		**Voting_L_SVM**		**Voting_R_SVM**			
Class	PrAc	UsAc	PrAc	UsAc	PrAc	UsAc		
Others	98.18%	96.43%	88.29%	89.09%	88.68%	85.45%		
Built Up land	96.00%	98.97%	72.73%	72.00%	81.25%	91.00%		
Settlements	97.62%	96.47%	65.93%	71.43%	82.56%	84.52%		
Water body	96.00%	96.00%	77.78%	56.00%	100.00%	60.00%		

Figure 3. Distribution map of built-up land and settlements from Sentinel 2 imagery using several supervised learning algorithms



(a) Random Forest (b) Mahalanobis

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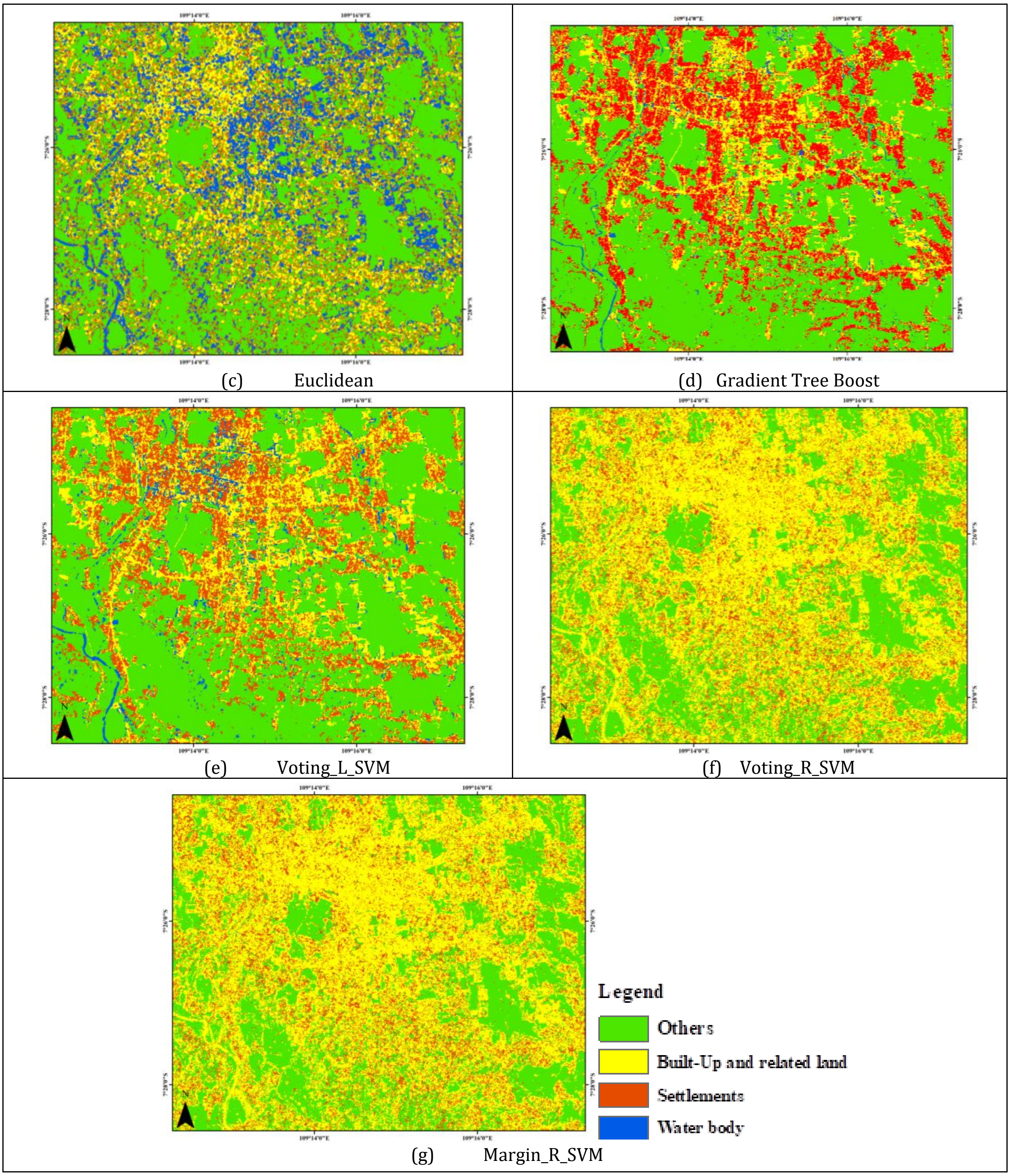

(c) Euclidean

(d) Gradient Tree Boost

(e) Voting_L_SVM

(f) Voting_R_SVM

(g) Margin_R_SVM

Minimum Distance classifier uses the average value and calculates the distance from each prominent pixel through the average value for each class. A pixel will be set onto a class based on its minimum distance, where minimum criteria can also be given, but a pixel may not be classified into any class if it does not fall within the specified minimum distance criteria. Mahalanobis Distance is a classification based on the distance of a class which is calculated statistically from the average value and variance of the covariance matrix for each class with the assumption that the covariance of all classes is the same. The distance criteria can also be an option specified as in the minimum distance. Utilizing the minimum distance classifier with various metric settings (Euclidian or cosine) and the default kNearest resulted in OA below 45% and a Kappa coefficient below 0.25. By using Minimum Distance (Cosine), the proportion of the correct number of the identified pixels of a class has a low value/contains many errors, especially built-up land and settlements (grouped into other classes). Likewise, NaiveBayes produces an OA accuracy below 45% and a Kappa coefficient below 0.25 so that these three methods will not be discussed further.

Except for the Minimum distance using Mahalanobis metric, where the overall accuracy increases to 80.56% with a Kappa coefficient of 0.72. Mahalanobis Distance is used in Digital Image Processing to identify variant values during image classification. Mahalanobis distance is a statistical method used to obtain data with a certain distance from the mean of the data so that a data distribution has a pattern concerning the mean value obtained. This method has a characteristic that is seen from the formula this method has a flexible reinforcement value so that it is easily adapted to changing conditions, this is what causes this method to be more accurate than other methods that are also used to find the value of data spread, for example, the Euclidean distance method. The amplifier of the Mahalanobis distance is in the covariance value, the value of this amplifier is what makes the Mahalanobis distance an ellipse-shaped field or area. Although the OA and kappa coefficients classified by Mahalanobis appear to be better than Euclidian or cosine, if we look further at the error commission, some pixels of 'built-up land' mistakenly assigned to 'settlements'.

The four SVM methods produce OA accuracy between 71% to 85% and produce Kappa coefficients between 0.59 to 0.79. Kappa index for SVM Voting and SVM Margin with kernel type RBF are 0.79 and 0.78, respectively. However, the accuracy of the classification results for objects that can be identified as Water body class (user accuracy) is very low as shown in Table 3, Figure 3 (f), and Figure 3 (g).

Several things affect the difficulty of distinguishing between non-residential and residential buildings. The image only sees the appearance from above, so for the class of built-up land and settlements, what is recognized is the type of tile. Based on observations in the field, it is still common to find non-residential or residential buildings using the same type of tile, namely pressed concrete, multi roof, or Soka tile. This can result in missed classification for non-residential buildings and residential buildings (houses). The same material will provide at least similar spectral values and characteristics. Settlements using multi-source and multi-combination indexes have been separated from built-up land and waterbody and others. However, there were also some false positives, such as non-residential buildings or settlements using the same type of tile, namely pressed concrete, multi roof, or Soka tile. This can result in missed classification for non-residential buildings and residential buildings (houses). The same material will provide at least similar spectral values and characteristics.

Looking back at the final goal of the research, which is to separate buildings, especially settlements, as a method in responding quickly to one of the SDGs variables, namely the existence of a population that is closely related to the distribution of built-up land, especially settlements in a large area. GEE implementation (with a supervised learning algorithm) can be a method to be reckoned with. Random Forests, Gradient Tree Boost, and Voting SVM are the top three classifiers with sequential results starting from the best in this study. From several studies, decision-based machine learning algorithms or generally referred to as logic-based algorithms in supervised machine learning also show the dominance of high-accuracy results and are quite popularly used [3]. However, the results were obtained for a simple classification with a total of 4 land use classes. It is necessary to conduct trials in other locations with variations in the distribution conditions of different built-up areas to see the performance of the three classifiers in separating classes, especially between settlements and non-settlement buildings. In addition, the red thing that needs to be understood is that when it comes to the function of the building (concerning a residence or a dual function), there will be limitations of remote sensing data because it is more determined by user preferences (humans who use it). Thus, building function data support from the results of field surveys is still needed.

5. CONCLUSIONS

The Random Forest classifier provides the best accuracy compared to all the methods used in this study. For the classification of 4 land cover classes in the study area in Purwokerto, the results obtained are overall accuracy (99.69%), Kappa Coefficient (0.99), the highest Producer's Accuracy and User Accuracy amongst all classfiers used to wit Others (100%, 99.09%), Built-up land (100.00%, 100.00%), Settlements (98.81%, 100.00%), and Waterbodies (100.00%, 100.00%).

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