Forum geografic. Studii și cercetări de geografie și protecția mediului
Volume **XX**, Issue **2** (**December** 2021), pp. **145-159**
http://dx.doi.org/**10.5775/fg.2021.034.d**

Green open space detection and mapping using planetscope-3a image with vegetation index approach and supervised classification in Banda Aceh, Indonesia

Muhammad BUDI[1], AKHYAR[2,*]

[1] School of Remote Sensing and Information Engineering, Wuhan University, Hubei Province, P.R.China
[2] Department of Mechanical Engineering, Syiah Kuala University, Darussalam, Banda Aceh 23111, Indonesia
* *Corresponding author*: akhyar@unsyiah.ac.id

Received on 19-01-2021, reviewed on 06-06-2021, accepted on 29-09-2021

Abstract

Role of Green Open Space (GOS) is essential in creating a comfortable environment in cities. It is detected using a high-resolution satellite image, Planetscope-3A. This study aimed to classify landcover in Banda Aceh using a multispectral classification of Planetscope-3A image and to assess the applicability of Planetscope-3A image to identify GOS in Banda Aceh. The multispectral classification was used with a supervised classification-maximum likelihood algorithm that refers to normalized difference vegetation index (NDVI) transformation to obtain eight landcover classes. Additionally, field observation was used to retrieve sample points determined by Stratified Random Sampling. The classification detected eight landcover classes comprising non-GOS objects (water, developed, barren) and GOS objects (trees, shrubland, herbaceous, wetland, and cultivated). The result was combined with 128 samples data of field, producing an accuracy of 76.036 % and a kappa value of 0.726. Landcover was dominated by developed class with 29.739 km2 or 53.6 % of study area total with an accuracy of 94.094 %. Furthermore, GOS in Banda Aceh included 19.589 km2 or 35.291 % of the study area, consisting of trees (6.863 km2, accuracy 79.396 %), Shrubland (8.216 km2, accuracy 59.413 %), Herbaceous (4.132 km2, accuracy 73.564 %), Cultivated (0.291 km2, accuracy 73.475 %), and Wetlands (0.088 km2, accuracy 70.185 %). This concludes that Banda Aceh has a sufficient area of GOS. The result of GOS detection using Planetscope-3A image with supervised classification-maximum likelihood algorithm could be reference data and recommendation in managing sustainable development in Banda Aceh.

Keywords: *Green Open Space, Normalized Difference Vegetation Index, Supervised Classification, Maximum-likelihood, Planetscope-3A*

Rezumat. Detectarea și cartografierea spațiului deschis verde folosind imaginea planetscope-3a cu abordarea indicelui de vegetație și clasificare supravegheată în Banda Aceh, Indonezia

Rolul Green Open Space (GOS) este esențial în crearea unui mediu confortabil în orașe. Este detectat folosind o imagine satelit de înaltă rezoluție, Planetscope-3A. Acest studiu și-a propus să clasifice acoperirea terenului în Banda Aceh folosind o clasificare multispectrală a imaginii Planetscope-3A și să evalueze aplicabilitatea imaginii Planetscope-3A pentru a identifica GOS în Banda Aceh. Clasificarea multispectrală a fost utilizată cu un algoritm de clasificare supravegheată-probabilitate maximă care se referă la transformarea indicelui normalizat de diferenţiere a vegetaţiei (NDVI) pentru a obține opt clase de acoperire a terenului. În plus, observația de teren a fost utilizată pentru a prelua punctele de eșantionare determinate prin eșantionare aleatorie stratificată. Clasificarea a detectat opt clase de acoperire a terenului cuprinzând obiecte non-GOS (apă, dezvoltare, aride) și obiecte GOS (arbori, arbuști, ierburi, zone umede și cultivate). Rezultatul a fost combinat cu 128 de probe de date de teren, producând o precizie de 76,036 % și o valoare kappa de 0,726. Acoperirea terenului a fost dominată de clasa dezvoltată cu 29,739 km^2 sau 53,6 % din totalul suprafeței de studiu, cu o precizie de 94,094 %. Mai mult, GOS din Banda Aceh a inclus 19,589 km^2 sau 35,291% din suprafața de studiu, constând în arbori (6,863 km^2, precizie 79,396 %), arbuști (8,216 km^2, precizie 59,413 %), ierburi (4,132 km^2 , cu precizie 73,564%), zone cultivate (0,291 km2, precizie 73,475 %), și zone umede (0,088 km2, precizie 70,185 %). Aceasta concluzionează că Banda Aceh are o zonă suficientă de GOS. Rezultatul detectării GOS folosind imaginea Planetscope-3A cu algoritm de clasificare supravegheată-probabilitate maximă ar putea constitui date de referință și pot fi recomandate pentru gestionarea dezvoltării durabile în Banda Aceh.

Cuvinte-cheie: *Spațiu deschis verde, indicele normalizat de diferenţiere a vegetaţiei, clasificare supravegheată, probabilitate maximă, Planetscope-3A*

Introduction

Green Open Space (GOS) is important in creating comfort for the public in a city. According to UU No. 26 2007, a city must have at least 30 % GOS of its total area. GOS comprises spaces in the city, such as an area elongated as an open path without buildings (Ministerial Regulation of PU No. 5 2008). Banda Aceh, the capital city of Aceh Province, Indonesia, has a population of 270,321, based on 2019 data by the Central Statistical Agency of Aceh Province, and it continues to grow significantly. The massive development after the great tsunami on December 26, 2004, has led to significant urbanization. This condition reduces GOS by changing landcover to non-GOS, such as built area, affecting the community's comfort. Therefore, a study should be conducted for the importance of Banda Aceh's GOS in creating a comfortable environment for the community.

Several institutions in Banda Aceh engaged in urban planning and development conducted GOS identification focusing on two main methods. These are field identification and visual interpretation using Google Earth composed of several high-resolution images with incomplete recording time. The main problems of both methods are high costs in the field operation, the long processing time, and the difficulty in obtaining the data source (high-resolution images).

An optical sensor on a remote sensing satellite transmits electromagnetic energy in penetrating city objects. It produces information such as buildings and vegetation represented by materials and leaves, respectively. A high-resolution satellite image is the right choice to identify surface distribution patterns through physical city characteristics (Xian, 2016). Therefore, Planetscope-3A is the best high-resolution remote sensing image because it is easy and free to access.

The small pixel size of Planetscope-3A image is suitable for remote sensing research that requires information on small objects, such as urban vegetation. Larger pixel sizes could result in misclassification because of mixed pixels and intra-class spectral variability of vegetation and non-vegetation, such as a building. This affects the classification process and generates the salt and pepper effect in landcover classes (Gadal et al, 2019). Furthermore, Planetscope-3A contains sufficient information, including radiometry. It is visible from a Planetscope-3A image at level 3A Ortho Tiles, and it means that the image has undergone radiometric and sensor correction. This supports that satellite images used to identify GOS should consider temporal, spatial, spectral, and radiometric characteristics (Cheng et al, 2019). Shimizu et al (2020) analyzed RMSE value distribution in the Planetscope-3A image. The study found that radiance spectral value in Planetscope-3A fulfilled the requirements for supervised classification without being radiometric corrected. This image characteristic is a suitable data source for analytical and visual applications.

GOS information of satellite images is extracted through image processing and analysis, such as multispectral classification and vegetation index transformation. The process uses the spectral value of each band, which is the characteristic of multispectral images (Pena-Salmon et al., 2014). NDVI is a simple index used globally to monitor surface objects because of its ability to adapt to variable sensor illumination, slope surface, aspect, and other factors (Lillesand et al, 2015). The method applies to an image with visible and infrared bands because the spectral characteristic of the infrared band produces a contrast appearance between building material and natural objects, such as vegetation, barren, and water. Multispectral classification on satellite images automatically categorizes all pixels into landcover classes. It recognizes similarities of spatial and spectral pattern with other classes, known as pixel-based classification (Yan et al, 2006).

The objectives were addressed to achieve the aim: (1) detecting and mapping landcover in Banda Aceh city using Planetscope-3A image through supervised classification-maximum likelihood method, (2) assessing the applicability of Planetscope-3A image for GOS detection and mapping. The results of this study are expected to be a reference and recommendation in managing GOS in Banda Aceh city.

Materials and Methods

Materials

This study uses a Planetscope-3A image with 3 meters spatial resolution with the ability to record the earth daily (revisit daily) covering 2 million km2. The scene of Planetscope-3A image is a continuous strip of four spectral bands with a separated near-infrared filter, comprising blue (455-515 nm), green (500-590 nm), red (590-670 nm), and NIR (780-860 nm) (Planet, 2020). The image was recorded on April 29, 2020, because the sky had 0 % cloud cover and is the closest study time recorded. Moreover, the Planetscope-3A data processing and classification were performed using Remote Sensing and GIS software. The image was clipped into a row of 3357 rows x 3568 columns, measuring 10.071 km x 10.704 km of Banda Aceh, which has 55.507 km2 (Fig. 1).

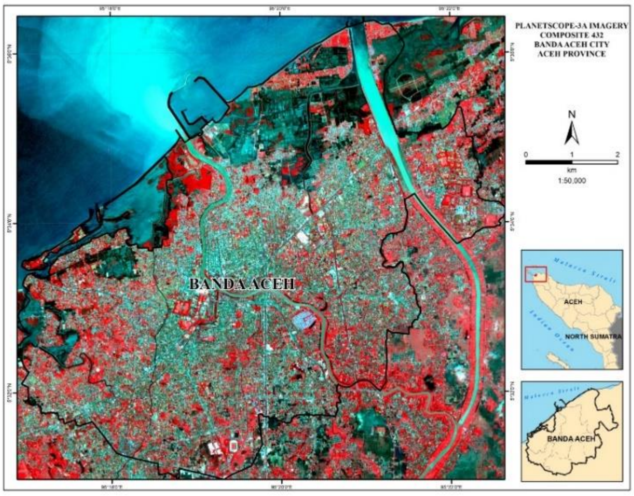


Fig. 1: Study area map

Secondary data were obtained from the RBI Topographic map on a scale of 1:50,000 used as an administrative data source and to correct the image geometry.

Research Method

This study consists of image processing (Planetscope-3A), field observation (sampling) and

Forum geografic. Studii și cercetări de geografie și protecția mediului
Volume **XX**, Issue **2** (**December 2021**), pp.**145-159**
http://dx.doi.org/**10.5775/fg.2021.034.d**

accuracy assessment. Planetscope-3A image is classified digitally using supervised classification. The satellite image used to identify GOS should consider image temporal, spatial, spectral, and radiometric characteristics (Cheng et al, 2019). This image is orthorectified and projected into UTM projection. As a result, it is a suitable data source for analytical and visual applications. Fig. 2 shows the complete flow chart of research method.

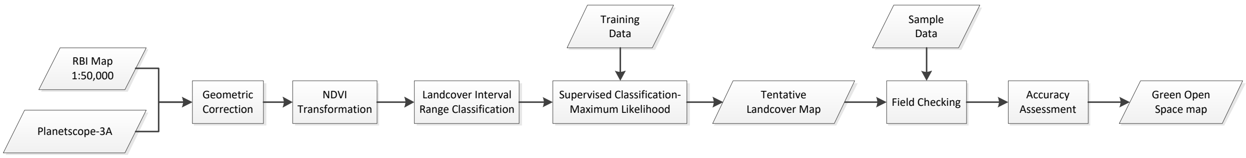


Fig. 2: Study flow chart

Geometric Correction: Image-to-Map Rectification

Image-to-Map rectification is performed using principle that the map used has more accurate coordinate and projection system so that it can be a reference by image. Applications of remote sensing that require accurate distance, direction and area measurements always require this type of geometric correction. It removes geometric distortion in the image by selecting a pair of coordinate points on the image (row-column) and on the map (x-y / latitude-longitude). The coefficients of the transformation equation used to convert the image coordinate system to the map coordinate system will be determined (Danoedoro, 2012).

Vegetation Index Transformation and Multispectral Classification

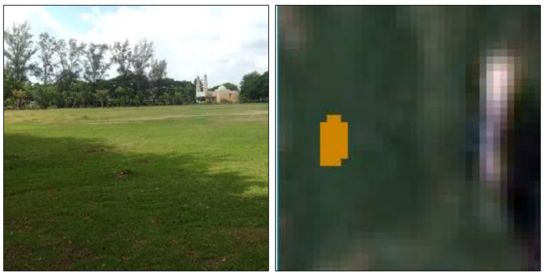
Index transformation used in this study is NDVI that is able to generate optimal thresholding value from the objects reflectance in the image through the pixel to extract vegetation information. NDVI value range was produced through density slicing, dividing the NDVI transformation result based on the Sturgess formula calculation. Furthermore, the thresholding values in the NDVI transformation are used to determine the GOS class in the classification process.

Landcover (GOS and non-GOS) classification in this study uses decision and class rule of The Multi-Resolution Land Characteristic (MRLC) Consortium known as the National Land Cover Database (NLCD) (Anderson et al, 1976). The classification applied in this study is Maximum Likelihood. It evaluates a quantitatively spectral response pattern to an unknown pixel (Lillesand et al, 2015). Similarly, Kopecka et al (2017) applied supervised classification using the Maximum Likelihood algorithm combined with vegetation index and extracted vector data to form variation values of vegetation.

GOS classification: Training Data Selection, Sampling, and Accuracy Assessment

Training data are produced in the classification process, representing each landcover object. Determining training data representing field objects in the form of pixels refers to the latest research. ESRI (2019, a) and ESRI (2019, b) recommended that each class is from 15 to 20 polygons with three main objects. These include trees in the city, herbaceous in gardens, buildings, other places, and green space at sports facilities such as golf or football. Moreover, in Jensen (2015), the total of training data is from 10n to 100n pixels, where "n" is the total of image bands used (Vigneshwaran & Kumar, 2019). Fig. 3 shows the spectral pattern recognition in the field and the image.

Shrubland class sample (95.376º BT 5.567º LU)



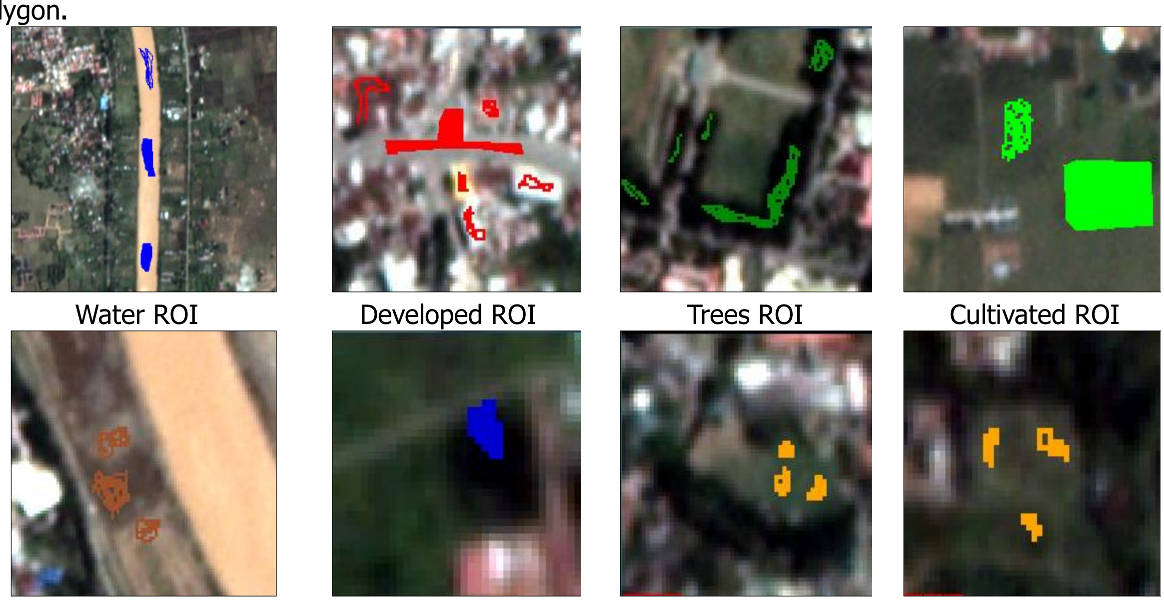
Herbaceous class sample (95.374º BT 5.566º LU)

Wetlands class sample (95.363° BT 5.583° LU) Barren class sample (95.361° BT 5.582° LU)

Fig. 3: Spectral pattern recognition in the field and the image for landcover classification

In the spectral pattern recognition, to determine the training data of landcover classification, a pixel with the same reflectance and emission value considered as same class is assumed to represent certain surface objects. Additionally, spatial pattern recognition involves the category of image pixel based on the relationship with texture, pixel proximity, size, shape, direction, and iteration pattern. The shape of training data is adjusted to the spatial pattern of objects in the image, such as point, line, and polygon.

Fig. 4 shows the results of training data selection in the selected objects of most study areas for landcover classification. Training data of point and line were used for mixed pixels with different objects that can be seen clearly by spectral properties, and training data of polygon was used for same objects with slightly different pixel color and value such as river that has different water clarity level which these are still categorized as water body class. Number of pixel included in training data is at least 100 pixels.



Water ROI, Developed ROI, Trees ROI, Cultivated ROI, Barren ROI, Wetlands ROI, Herbaceous ROI, Shrubland ROI

Fig. 4: Training data / ROI selection for landcover classification of supervised classification

Sample point distribution was determined using the Stratified Random Sampling method. This method was adopted from Danoedoro (2015), which examined the effect of the sampling method on the accuracy level of the classification result. Sample points of random sampling method were distributed randomly considering the number equality of each landcover class. The objects in the sampling process were selected based on the clarity of their spatial and spectral characteristic in the image. For instance, for 13 or fewer classes, the method uses the formula 8n, where "n" is the number of classes. Also, 8 is the minimum number of classes and could increase according to the researchers' ability and necessity.

Accuracy assessment is necessary because a map produced by image classification must be checked in the field. The checking focuses only on objects which classification could not be agreed upon and labeled correctly (Stephen in Congalton & Green, 2019). The assessment results were intersected with polygon classes from supervised classification. Every sample point represents two attributes, including classification and field reference classes. The accuracy assessment values are summarized into Overall Accuracy and Kappa coefficient. Overall

Forum geografic. Studii și cercetări de geografie și protecția mediului
Volume **XX**, Issue **2** (**December 2021**), pp.**145-159**
http://dx.doi.org/**10.5775/fg.2021.034.d**

accuracy shows the producer and user accuracy of the confusion matrix table, while the kappa coefficient method is suitable to compare differences in matrix error. The kappa coefficient method provided a statistically valid assessment of the overall class accuracy result (Abdelkareem et al, 2018). The Kappa index is calculated using the following Eq. 1.

$$K = \frac{N\sum_{1=1}^{r} Xii - \sum_{i=1}^{r} X_{i+X_{+i}})}{N^2 - \sum_{i=1}^{r} X_{i+}X_{+i})} \quad (1)$$

Where,

r = number of rows or columns in confusion matrix,

N = number of observations (pixels),

X_ii = number of observations in row i and column i,

Xi+ = total number of row i,

X+i = total number of column i

Results

NDVI Transformation

This stage produced vegetation index map of Banda Aceh (Fig. 5). Each statistic value of bands was changed to transformed image to obtain the Minimum, Maximum, Means, and Standard Deviation. Minimum values in pure image range from 1 to undefined maximum value, with a Mean of 813.444662 and a Standard Deviation of 308.458615. Moreover, the values change due to NDVI transformation, showing real reflectance ranging between -1 and 1. They represent vegetation density, which minimum and maximum values are -0.948133 and 0.999380, respectively, with a Mean of 0.253812 and a Standard Deviation of 0.248943. The statistical value of infrared and red bands is consistent with reflectance characteristics. The infrared value is highly different from the other bands, making it suitable for the NDVI index separating vegetation and non-vegetation objects. It generated five classes, representing eight objects to be classified as landcover classes. Fig. 5 shows the distribution of vegetation density.

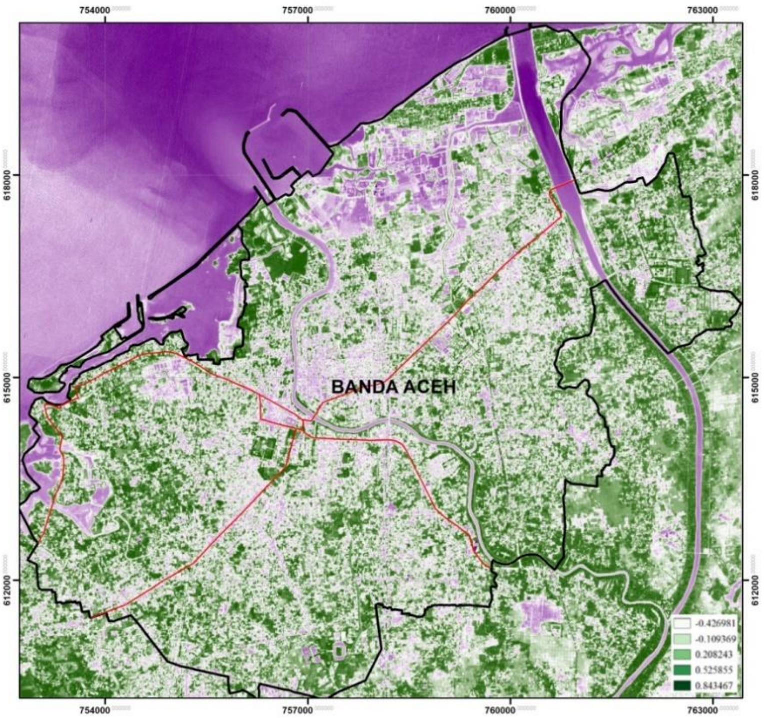


Fig. 5: Vegetation density of NDVI transformation

The green colors in Fig. 5 show high vegetation density approaching 1, while white colors show degradation of vegetation density, and the absence of vegetation is clearly seen in the water body area and around buildings. Although NDVI threshold values are a reference in classification, they are not absolute because they must be validated with field data. Determination of NDVI value range refers to some latest researches, such as Lee et al (2020). The research determined the NDVI value range at some landcovers using the Top of Canopy reflectance value of the KOMPSAT-3A image. Fig. 6 shows the NDVI threshold value of landcover classes.

Fig. 6 shows field objects following the range of vegetation index. The combination of bands helps in maximum reflectance and absorption by vegetation objects which shows the density aspect. Determination of field objects against vegetation index must be distributed in many locations of the study area. For instance, Banda Aceh has the similarity between pond, turbid and clear river water. In Figure 6, turbid water in the river has a value of -0.210652, indicating that the range value must represent all of them. Furthermore, trees, herbaceous, cultivated, and wetlands have a similar appearance in color and pattern, though they have different NDVI values. It shows that the determination of vegetation status and object in an area must use index vegetation. The result indicates that vegetation index transformation produces detailed information of vegetation objects, including density and condition. Additionally, the determination in vegetation index would be better and more valid when analyzed against many field objects.

These ranges are modified and combined referring Gandhi et al. (2015) and Weier & Herring (2000). Determination of vegetation density interval uses Sturgess formula to reduce the maximum value to a minimum and divide it by the desired number of classes. Table 1 shows the NDVI range to vegetation density level.

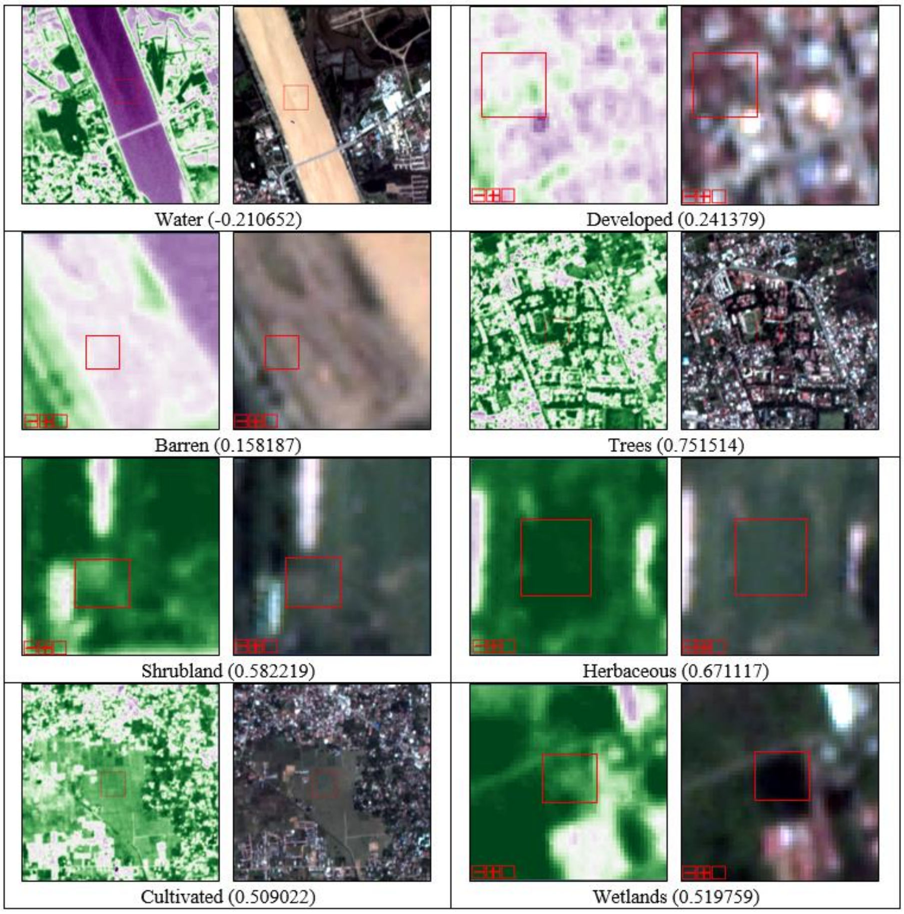


Fig. 6: NDVI threshold and objects

Table 1 NDVI threshold ranges to vegetation density and object

NDVI Range	Vegetation Status	Object
-0.426981 – 0.271762	Non vegetation	Water, Barren, Developed
0.271762 – 0.462332	Low density vegetation	Cultivated
0.462333 – 0.589377	Rather low density vegetation	Wetlands
0.589378 – 0.652898	Medium density vegetation	Shrubland, Herbaceous
0.652899 – 0.843467	High density vegetation	Trees

The NDVI values in the study area range between -0.426981 and 0.843467. Moreover, the NDVI determination shows vegetation status of GOS in Banda Aceh. All vegetation status is adjusted with the number of objects to be classified. The landcover classification was divided into eight classes, including Water, Developed, Barren, Forest or High-Density Tree, Herbaceous, Shrubland, Cultivated, and Wetlands referring to National Land Cover Database 2016.

Forum geografic. Studii și cercetări de geografie și protecția mediului
Volume **XX**, Issue **2** (**December 2021**), pp.**145-159**
http://dx.doi.org/**10.5775/fg.2021.034.d**

Range between -0.426981 and 0.271762 indicates water, barren, and developed objects. Also, four NDVI ranges show respectively vegetation status of low density ranging between 0.271762 and 0.462332 indicating cultivated. Vegetation status of rather low density ranges between 0.462333 and 0.589377, indicating wetlands. Furthermore, medium-density ranges between 0.589378 and 0.652898, indicating objects of shrubland and herbaceous, while high density ranges from 0.652899 to 0.843467, indicating trees.

GOS Classification

Fig. 7 shows the tentative landcover map resulted from supervised classification-maximum likelihood containing eight object classes. The landcover map (Fig. 7) shows the spatial distribution of the GOS classes (Trees, Cultivated, Wetlands, Herbaceous, Shrubland) and non-GOS classes (Water, Developed, Barren) within Banda Aceh. Landcover was categorized based on the similarity of objects characteristics. For instance, turbid, clear, puddle, and pond water were categorized into water classes. Moreover, parks, gardens, city forests, and buildings with dense trees were categorized into trees classes. Asphalt and cobblestone roads, road median, roadsides without trees, and buildings were categorized into developed classes. These were performed to reduce misclassification.

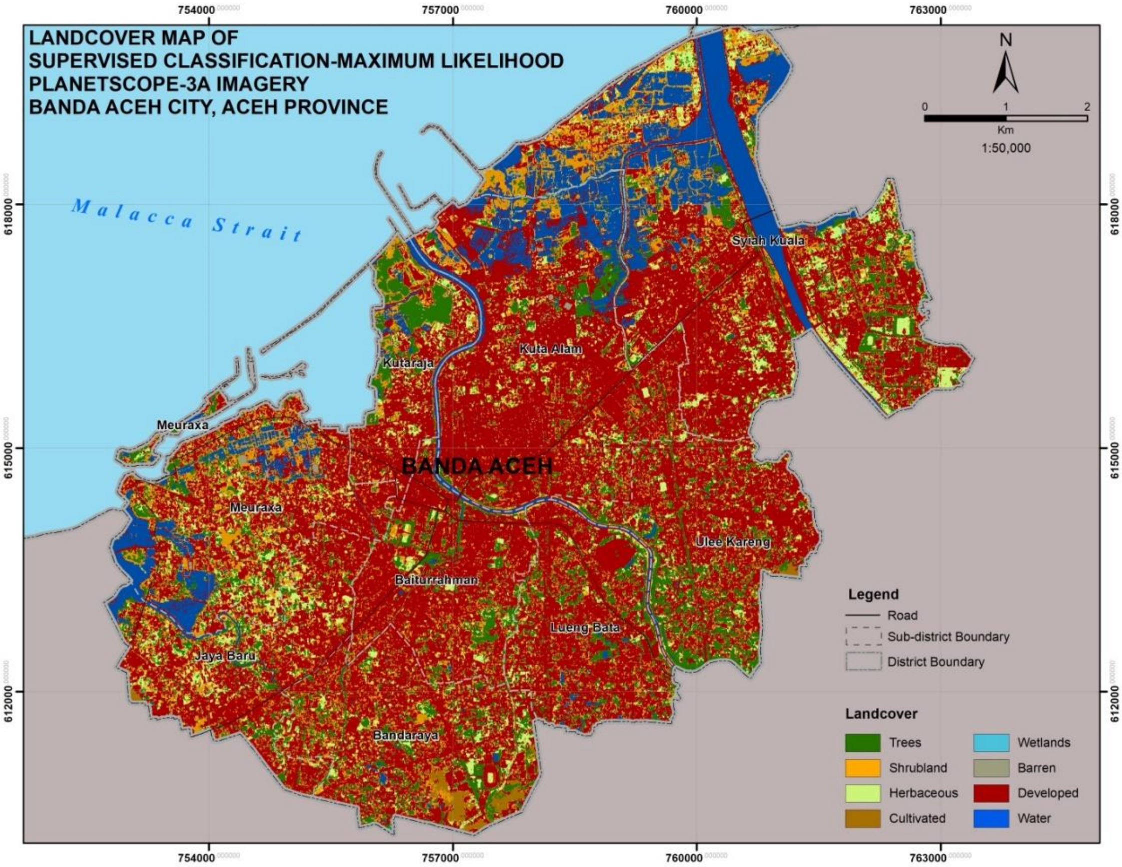


Fig. 7: Tentative landcover map of supervised classification-maximum likelihood in Banda Aceh

The landcover distribution (Fig. 7) is in line with the field conditions. Pond areas categorized into water class are on the coastal. The areas with many buildings categorized into developed classes are in the city center and densely populated areas. Furthermore, GOS of roadside and riverside follow the main road and river patterns. Table 2 shows the result of classification divided in the landcover class and area.

The preliminary landcover classification result shows that GOSs are distributed in some places in the city, such as road medians, roadsides, building yards, riversides, parks, and gardens.

The total vegetation area or GOS is 19.669 km2 or 35.435 % of the region, consisting of 6.923 km2 of trees, 8.257 km2 of shrubland, 4.182 km2 of herbaceous, 0.298 km2 of cultivated, and 0.010 km2 of wetlands.

Table 2 Tentative landcover area of supervised classification

No	Landcover Class		Area per Class (km^2)	Total (km^2)
1	Non-GOS	Water	6.044	35.838
2		Developed	29.708	
3		Barren	0.086	
4	GOS	Trees	6.923	19.669
5		Shrubland	8.257	
6		Herbaceous	4.182	
7		Cultivated	0.298	
8		Wetlands	0.010	
Total			**55.507**	**55.507**

Additionally, the total non-vegetation area or non-GOS is 35.838 km2 or 64.565 % of the region, consisting of 6.044 km2 of water, 29.708 km2 of developed, and 0.086 km2 of barren.

Sampling and Accuracy Assessment

Fig. 8 shows map of sample point distribution in the study area. Accuracy assessment of this study selects 128 samples using the 16n formula, where each class has 16 samples. Point sample (white dot) retrieval represents a polygon-shaped class in the field and requires a landcover delineation process using the high resolution as reference data. Therefore, random stratified sampling represents each landcover class. Furthermore, the selected sample locations included wide and homogeny landcover classes.

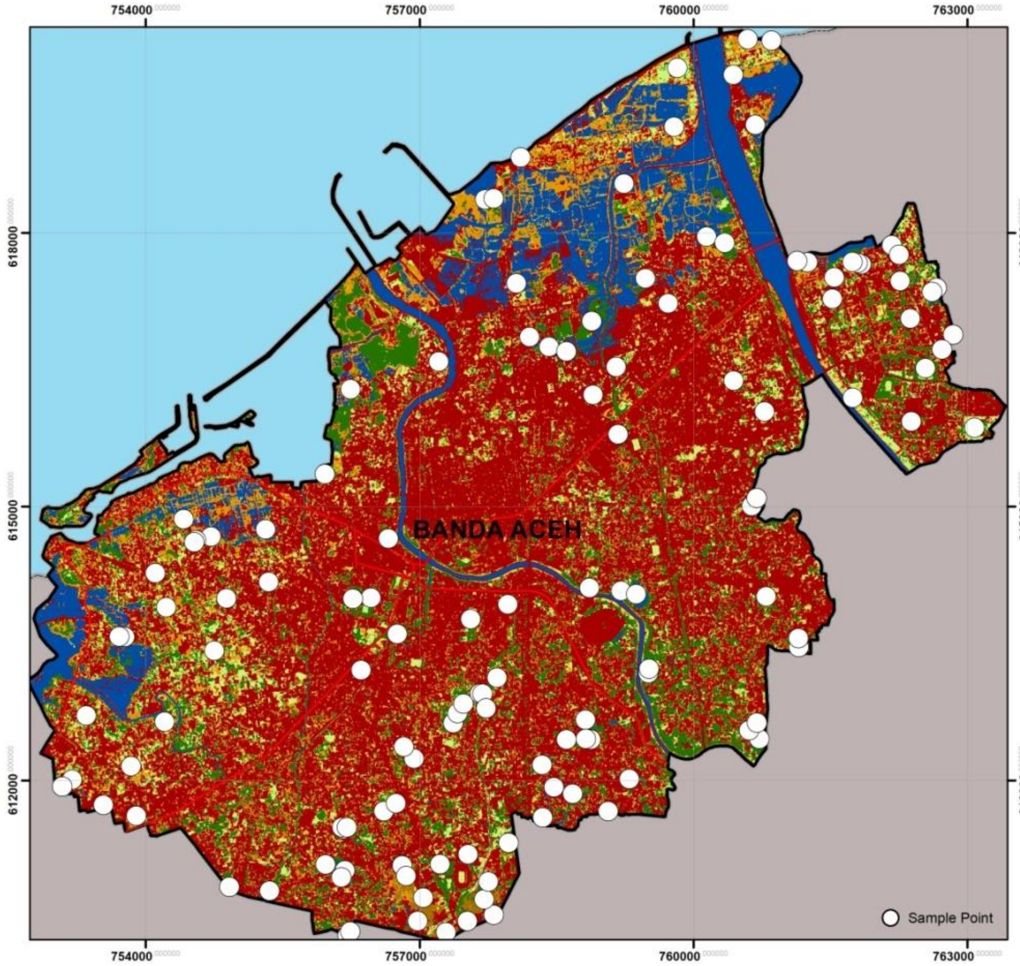


Fig. 8: Sample distribution in the study area using Stratified Random Sampling

Table 3 shows that some cells have values while others do not. The values show the classification accuracy, similarity, and difference among landcovers with reference data from field checking and visual interpretation. The highest value is 89.990% at the Barren class, and it means that field objects are detected easily by the classification process and are different from other objects in the image. The lowest value is 59.413% at the Shrubland class, which is similar to the herbaceous class. Also, it could be proven by values in the cell of herbaceous on the classification row and reference column of 14.241%. This is consistent with visual interpretation finding that herbaceous and shrubland objects are similar.

Forum geografic. Studii și cercetări de geografie și protecția mediului
Volume **XX**, Issue **2** (**December 2021**), pp.**145-159**
http://dx.doi.org/**10.5775/fg.2021.034.d**

Table 3 Confusion matrix of landcover classification data against reference data

Classification \ Reference	Water	Developed	Barren	Trees	Shrubland	Herbaceous	Cultivated	Wetlands	**Total**
Water	**68.175**	13.011	0.111	0.434	0	0	6.250	12.019	100
Developed	0	**89.990**	3.868	4.534	0.782	0.826	0	0	100
Barren	1.011	0.396	**94.094**	1.133	0	3.365	0	0	100
Trees	2.280	6.746	1.569	**79.396**	1.113	0.879	2.139	5.879	100
Shrubland	1.466	5.395	4.693	4.345	**59.413**	14.241	9.611	0.837	100
Herbaceous	0	2.316	3.234	12.428	5.482	**73.564**	0.423	2.554	100
Cultivated	0	1.675	0	5.561	0	11.848	**73.475**	7.441	100
Wetlands	8.394	2.230	0.117	7.295	1.350	1.338	9.091	**70.185**	100
Total	81.326	121.758	107.685	115.1267	68.138	106.062	100.988	98.915	**800**

This study conducted quantitative positional and thematic accuracy assessments to evaluate the validity of field objects on the map and their labels. The accuracy assessment involves overlaying reference data source of landcover classification map with field sample data. Also, it overlays the result of visual delineation using the high-resolution image including Planetscope-3A and Google Earth image. The assessment was performed on most landcovers in the study area as important pixels to assess the truth level of the classification process. The overall classification accuracy is calculated as shown in Eq. 2.

$$Overall\ accuracy = \frac{608.292}{800} \times 100 = 76.036\ \% \quad (2)$$

The overall accuracy of the supervised classification-maximum likelihood algorithm is 76.036 %. The detailed accuracy for each class is summarized in the producer and accuracy table. The producer's accuracy comprises the field objects present on the map, while the user's accuracy consists of objects on the map found in the field. Omission and commission show a mismatch between map and field (100 % – Accuracy). Table 4 shows the presence of producer's and user's accuracies in this study.

Table 4 Producer's accuracy and user's accuracy

Class	Producer accuracy		User accuracy	
	Accuracy	Omission Error	Accuracy	Comission Error
Water	83.829	16.171	68.175	31.825
Developed	73.909	26.091	89.990	10.010
Barren	**87.379**	**12.621**	**94.094**	**5.906**
Trees	**68.964**	**31.036**	79.396	20.604
Shrubland	87.194	12.806	**59.413**	**40.587**
Herbaceous	69.359	30.641	73.564	26.436
Cultivated	72.756	27.244	73.475	26.525
Wetlands	70.954	29.046	70.185	29.815

Based on Table 4, the value on Barren class shows the highest producer accuracy of 87.379 %, while Trees class shows the lowest producer accuracy of 68.964 %. This indicates that trees objects are difficult to detect in the image because of the mixed pixel with other vegetation objects. Similarly, the Barren class shows the highest user accuracy of 94.094 %, while the Shrubland class shows the lowest accuracy of 59.413 %. This means that Shrubland objects in the image are not consistent with the field.

The Kappa coefficient determines the multispectral classification accuracy to approve the strength of agreement between classification results with field objects. Table 5 shows the relationship between Statistic Kappa and the Strength of agreement. This study produces a Kappa coefficient of 0.726, shown in Table 4, it means that this classification has substantial strength of agreement. The small Kappa coefficient and overall accuracy gap mean that the classification process has fulfilled the term. Therefore, 76.036 % of landcover classification accuracy assessment is not coincidental.

Table 5 Interpretation of kappa statistic for the strength of agreement (Landis & Koch, 1977)

Kappa statistic (K)	Strength of agreement
<0.00	Poor
0.00 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost perfect

Landcover classification using Planetscope-3A image in Banda Aceh has shown good results in the overall accuracy and kappa coefficient. It detects GOS objects up to small locations, such as trees, grass near buildings, riversides, roadsides, and road medians. However, these small objects mix with developed objects in some locations, such as roads and barren. Fig. 9 shows GOS objects detected on the image. The good results of 76.036% overall accuracy and 0.726 Kappa coefficient show the suitability of Planetscope-3A image with 3 meters spatial resolution for GOS detection in Banda Aceh.

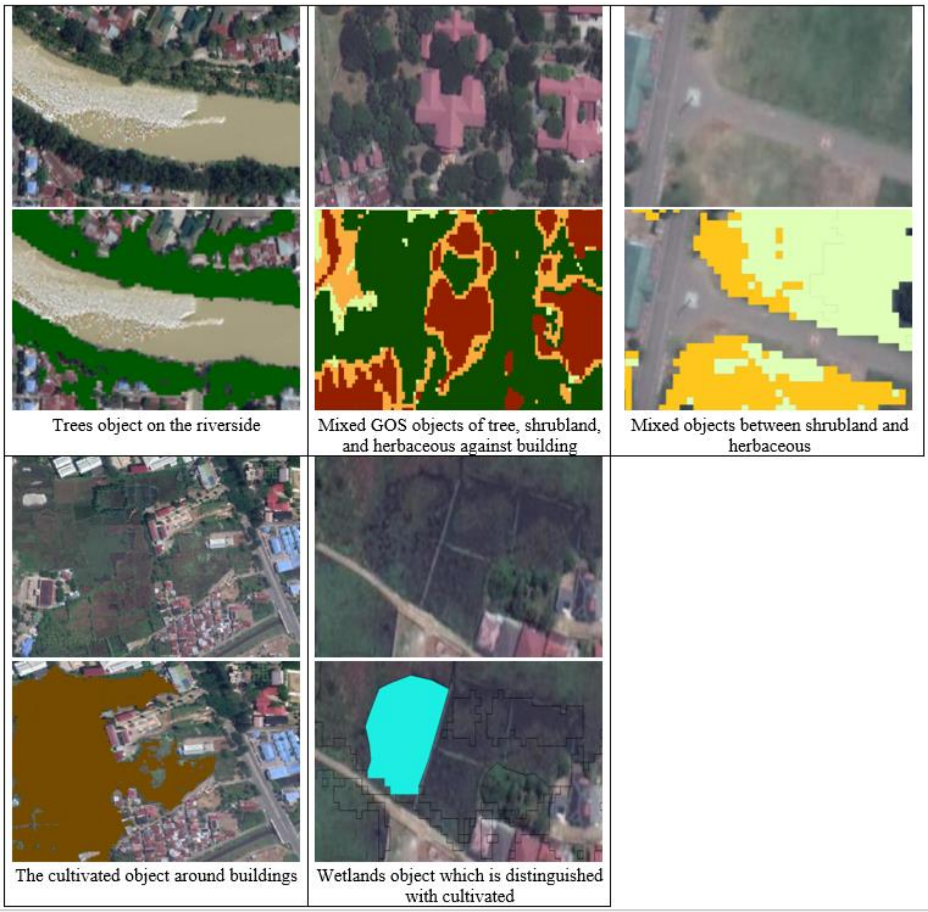


Fig. 9: GOS objects detected of supervised classification

Small and identical objects, such as wetlands, herbaceous, and shrubland, significantly influence GOS. Therefore, Planetscope-3A is a fixed reference for temporary identification in GOS.

Discussion

Reinterpretation

Reinterpretation further strengthens the classification result by using 16 sample data at each field landcover and 128 total sample data.

The area changes of each landcover class reinterpreted against the initial interpretation are very small, as shown in Table 6. The reinterpretation process changes the areas of landcover in the form of pixels.

Table 6 Landcover area based on reinterpretation process

No	Landcover Class		Area Change (km^2)	Area per Class		Total Area	
				km^2	%	km^2	%
1	Non-GOS	Water	- 0.016	6.060	10.918	35.918	64.709
2		Developed	- 0.031	29.739	53.577		
3		Barren	- 0.033	0.119	0.214		
4	GOS	Trees	+ 0.060	6.863	12.364	19.589	35.291
5		Shrubland	+ 0.041	8.216	14.802		
6		Herbaceous	+ 0.050	4.132	7.444		

Forum geografic. Studii și cercetări de geografie și protecția mediului
Volume **XX**, Issue **2** (**December 2021**), pp. **145-159**
http://dx.doi.org/**10.5775/fg.2021.034.d**

7	Cultivated	+ 0.007	0.291	0.524		
8	Wetlands	- 0.077	0.087	0.157		
Total		**0**	**55.507**	**100**	**55.507**	**100**

Reinterpretation is considered as the final GOS classification result because it combines supervised classification and field data. The reinterpretation results shows the total areas of non-GOS is larger than GOS, it is about 35.918 km2 or 64.709% and the GOS is about 19.589 km2 or 35.291% (Fig. 10).

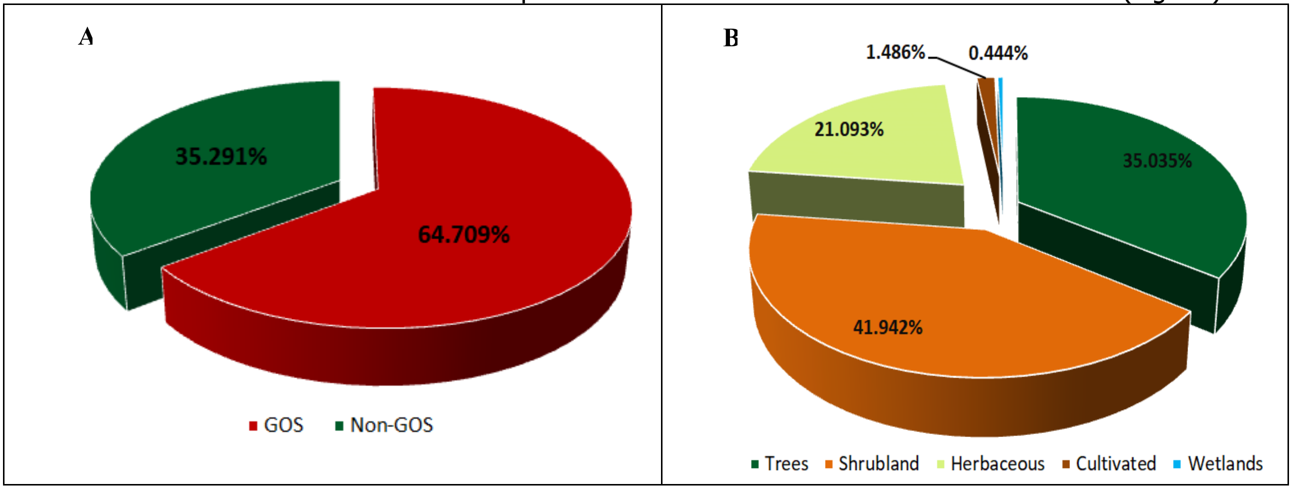


Fig. 10: Proportion between GOS and non-GOS in Banda Aceh (A) and proportion of GOS types in Banda Aceh (B) based on the supervised classification

However, according to the government rule and in scale of city, Banda Aceh has reached the standard in providing GOS to the public with more than 30% of the minimum city GOS. Table 7 shows clearly the GOS distributed in each sub-district in Banda Aceh.

Table 7 shows that each sub-district in Banda Aceh has sufficient GOS. Syiah Kuala sub-district has the most GOS with an area of 4.490 km2 which it is most strongly influenced by the existences of schools and universities, however in terms of the percentage of sub-district area, Banda Raya and Kutaraja sub-districts have the highest percentage of GOS with 44.570% and 44.564% respectively. Fig. 11 shows the GOS map and Fig. 12 shows the non-GOS map respectively.

The GOS density map of Banda Aceh obtained from supervised classification-maximum likelihood can be seen clearly in the following map (Fig. 13).

Table 7 Number of GOSs per sub-districts

No	Sub-district	GOS Class	GOS Area (ha)	Total (km^2)	Percentage (%)
1	Meuraxa	Trees	71.526	2.691	42.752
		Shrubland	141.250		
		Herbaceous	55.432		
		Cultivated	-		
		Wetlands	0.890		
2	Jaya Baru	Trees	58.896	1.937	42.623
		Shrubland	79.350		
		Herbaceous	52.219		
		Cultivated	2.082		
		Wetlands	1.152		
3	Banda Raya	Trees	92.413	2.437	44.570
		Shrubland	83.467		
		Herbaceous	44.160		
		Cultivated	22.508		
		Wetlands	1.115		
4	Baiturrahman	Trees	48.965	1.196	29.265
		Shrubland	48.170		
		Herbaceous	21.170		
		Cultivated	0.241		
		Wetlands	1.039		

5	Lueng Bata	Trees	69.753	1.428	32.862
		Shrubland	49.447		
		Herbaceous	22.568		
		Cultivated	0.193		
		Wetlands	0.863		
6	Kutaraja	Trees	58.522	1.264	44.564
		Shrubland	45.046		
		Herbaceous	21.849		
		Cultivated	-		
		Wetlands	0.948		
7	Ulee Kareng	Trees	105.157	2.034	39.851
		Shrubland	60.529		
		Herbaceous	34.197		
		Cultivated	3.499		
		Wetlands	-		
8	Kuta Alam	Trees	63.925	2.112	22.740
		Shrubland	101.421		
		Herbaceous	45.836		
		Cultivated	-		
		Wetlands	-		
9	Syiah Kuala	Trees	117.400	4.490	33.044
		Shrubland	213.209		
		Herbaceous	116.057		
		Cultivated	0.902		
		Wetlands	1.400		
	Total			19.589	36.919

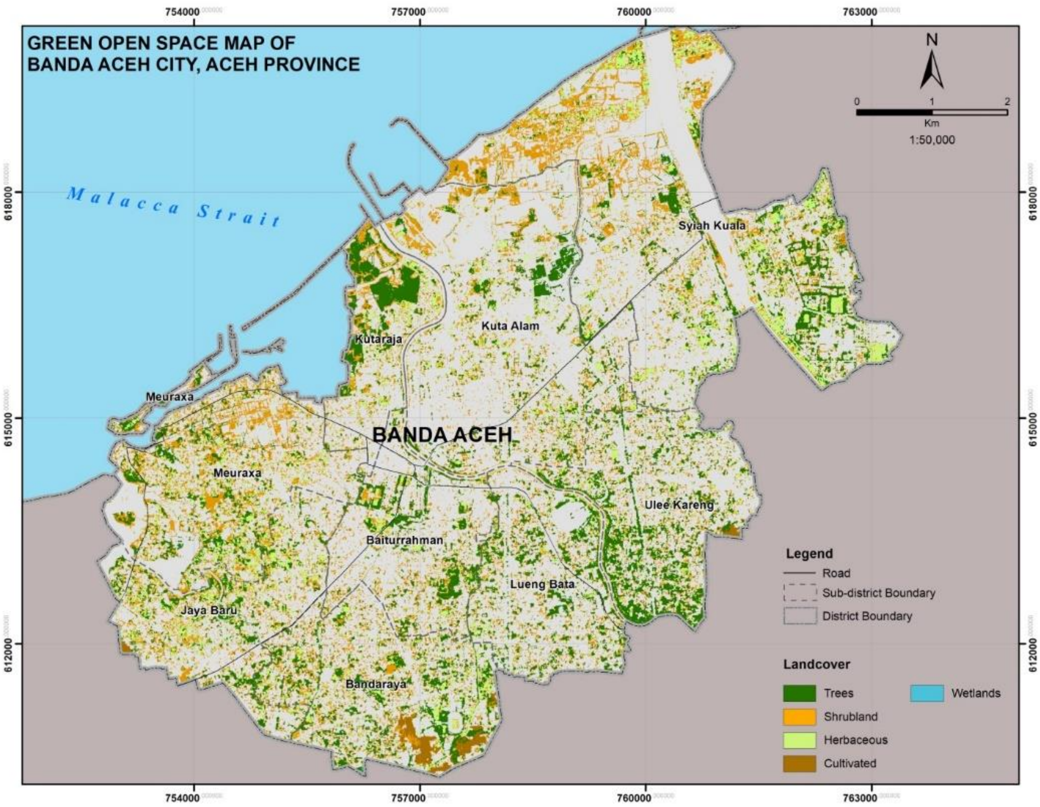


Fig. 11: GOS map of Banda Aceh based on supervised classification-maximum likelihood

Forum geografic. Studii și cercetări de geografie și protecția mediului
Volume **XX**, Issue **2** (**December 2021**), pp.**145-159**
http://dx.doi.org/**10.5775/fg.2021.034.d**

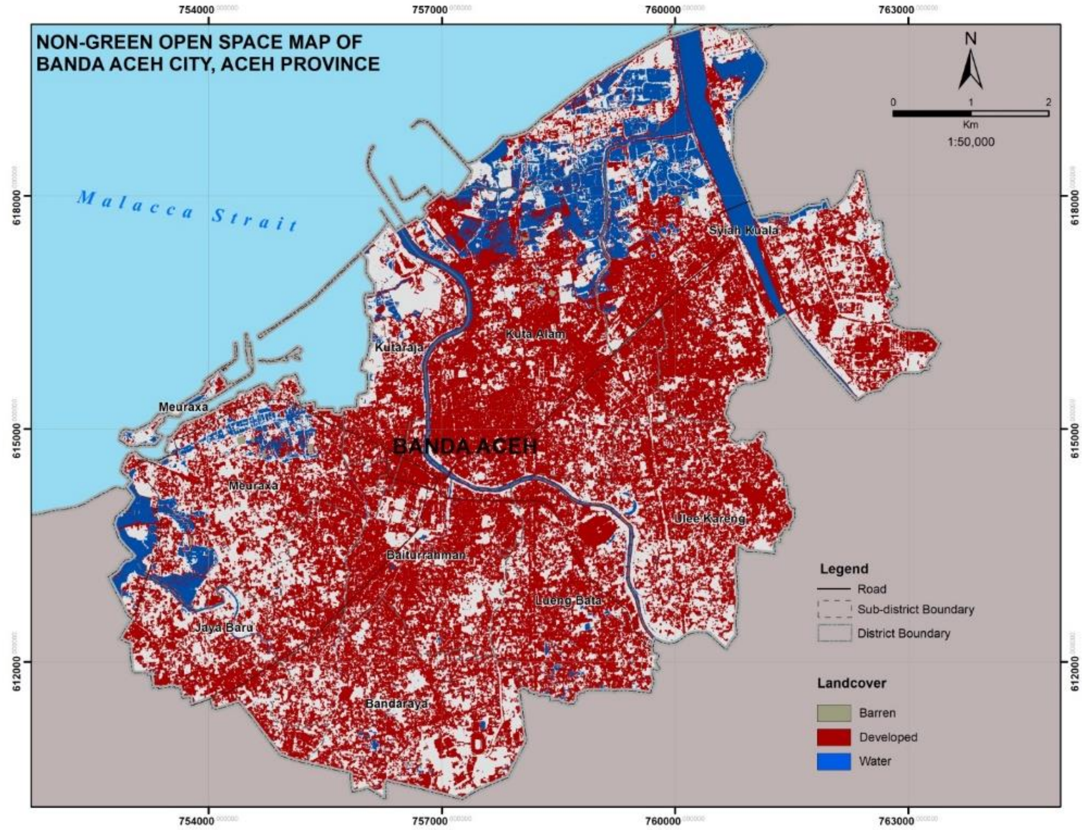


Fig. 12: Non-GOS map of Banda Aceh based on supervised classification-maximum likelihood

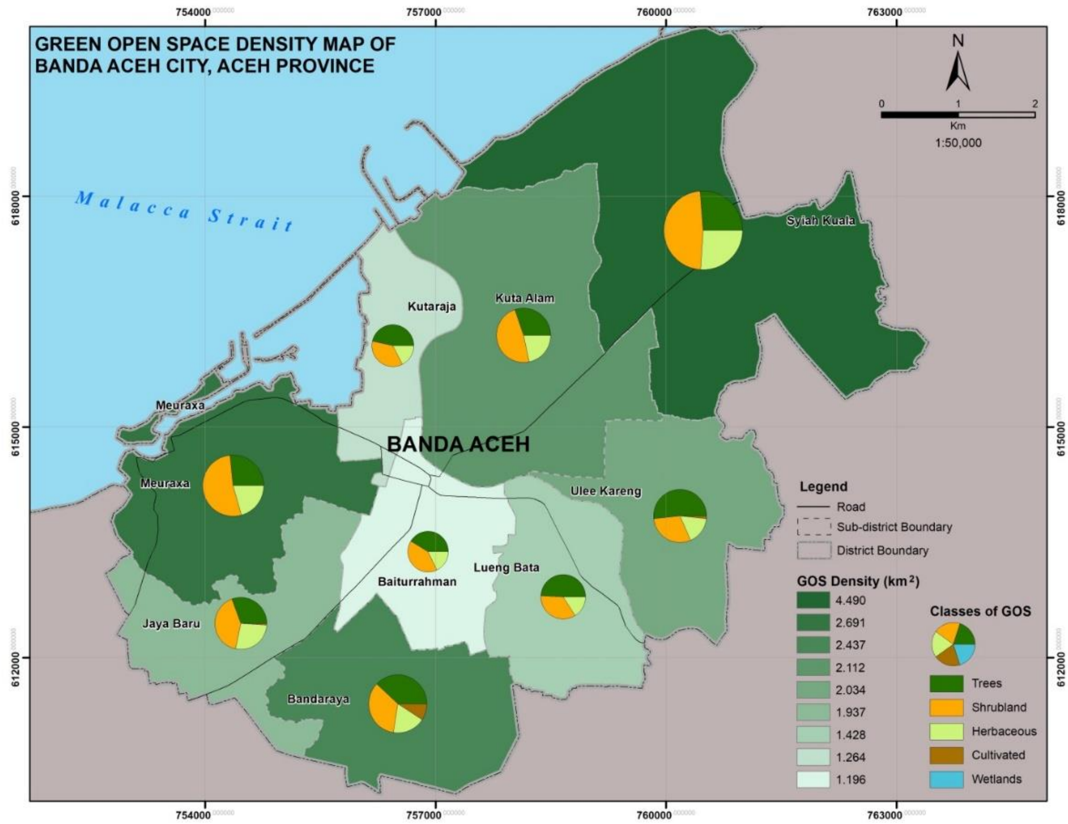


Fig. 13: GOS density map in Banda Aceh

Evaluation of Classification Result

Factors affecting the interpretation accuracy are the difference between image recording and the study time. However, small objects such as vegetation have no significant effect because the study area is not highly developed. Therefore, the highest accuracy level on the Barren class is not an absolute result because it results from the classification accuracy and landcover area. Also, few pixels are categorized as barren, reducing the possibility of misclassification. Moreover, when landcover total area is used as an assessment factor, the trees class has the highest accuracy of all the GOS objects. The number of field sample data improves classification accuracy, especially for similar objects, such as shrublands with herbaceous and wetland with water.

Conclusion

The following conclusions are made in this study:

1. Supervised classification-maximum likelihood method is suitable to detect the landcover, especially vegetation, to determine the distribution of GOS.
2. NDVI transformation contributes to supervised classification because the value ranges of vegetation and non-vegetation are useful in determining training data distribution.
3. Based on the classification result, Banda Aceh is covered mostly by non-vegetation object classes with 35.838 km2 or 64.709 % of the total area. Also, the region has GOS with 19.669 km2 or 35.291 %, with an overall accuracy of 76.036 % and a kappa coefficient of 0.726. This indicates that the area has sufficient GOS.
4. The stratified random sampling method showed consistency of sampling results and an adjusted total of class and it is useful for improving the results of image classification. Therefore, the minimum field sample data is recommended at least 16n in future research.

This study could be reference for the future research to detect landcover objects in Planetscope-3A image, especially GOS objects. The landcover classification is able to show the social condition in an area based on the availability of GOS. Therefore, future research should develop the state-of-the-art of remote sensing image processing, such as fusion technique that is able to enhance the spatial and spectral resolution. This study could be continued to more accurately identify the effect of GOS on public social conditions for a sustainable environment.

Acknowledgment

We, the author would like to thank the editor for guiding us to complete this paper and we wish to thank the anonymous reviewers for their creative comments and suggestions which significantly helped us improve this paper.

References

Abdelkareem, O.E.A., Elamin, H.M.A., Eltahir, M.E.S., Adam, H.E., Elhaja, M.E., Rahmattalla, A.M., Babatunde, O., & Elmar, C. (2018). Accuracy Assessment of Land Use Land Cover in Umabdalla Natural Reserved Forest, South Kordofan, Sudan. IJAES, Vol. 3, No. 1 (pp. 5-9)

Anderson, J.R., Hardy, E.E., Roach, J.T., & Witmer, R.E. (1976). Land use and land cover classification system for use with remote sensor data. U.S. Geological Survey Professional Paper, No. 964

Congalton, R.G., & Green, K. (2019). Assessing the Accuracy of Remotely Sensed Data: Principles and Practices, 3rd Edition (pp. 21-31). Boca Raton: CRC Press

Danoedoro, P. (2012). Pengantar Penginderaan Jauh Digital (pp. 167-180). Yogyakarta: ANDI

Danoedoro, P. (2015). Pengaruh Jumlah dan Metode Pengambilan Titik Sampel Penguji Terhadap Tingkat Akurasi Klasifikasi Citra Digital Penginderaan Jauh. Simposium Nasional Sains Geoinformasi ke-4, Universitas Gadjah Mada, Yogyakarta, Vol. 1 (pp. 161-171)

Environmental Systems Research Institute (ESRI). 2019a. Creating training samples. ArcGIS desktop help 10.6 spatial analyst extension. http://desktop.arcgis.com/en/arcmap/latest/extensions/ http://spatial-analyst/image-classification/creating-training-samples.htm

Environmental Systems Research Institute (ESRI). 2019b. NDVI function. ArcGIS desktop help 10.6 spatial analyst extension. http://desktop.arcgis.com/en/arcmap/latest/manage-data/raster-and-images/ndvi-function.htm

Gadal, S., Ouerghemmi, W., Barlatier, R., & Mozgeris, G. (2019). Critical Analysis of Urban Vegetation Mapping by Satellite Multispectral and Airborne Hyperspectral Imagery. Proceedings of the 5th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM) (pp. 97-104)

Gandhi, G.M, Parthiban, S., Thummalu, N., & Christy, A. (2015). NDVI: Vegetation Change Detection Using Remote Sensing And Gis – A Case Study of Vellore District. Procedia Computer Science. 57 (pp. 1199-1210). doi: 10.1016/j.procs.2015.07.415.

Forum geografic. Studii și cercetări de geografie și protecția mediului
Volume **XX**, Issue **2** (**December 2021**), pp.**145-159**
http://dx.doi.org/**10.5775/fg.2021.034.d**

Jensen, J.R. (2015). Introductory Digital Image Processing: A remote sensing perspective 4th edition (pp. 376-382). USA: Pearson Education

Kopecka, M., Rosina, K., & Szatmári, D. (2017). Analysis of Urban Green Spaces Based on Sentinel-2A: Case Studies from Slovakia. Land, 6. doi: 10.3390/land6020025

Landis, J.R., & Koch, G.G. (1977). The measurement of observer agreement for categorical data. Biometrics, Vol. 33, No. 1 (pp. 169-174). doi: 10.2307/2529310

Lee, K., Kim, K., Lee, S., & Kim, Y. (2020). Determination of the Normalized Difference Vegetation Index (NDVI) with Top-of-Canopy (TOC) Reflectance from a KOMPSAT-3A Image Using ORFEO ToolBox (OTB) Extension. ISPRS Int. J. Geo-Inf. Vol. 9, No. 257. doi: 10.3390/ijgi9040257

Lillesand, T.M., Kiefer, R.W., & Chipman, J.W. (2015). Remote Sensing and Image Interpretation 7th Edition (pp. 16-17, 362, 537-541, 544-546). New York: Wiley

National Land Cover Database (NLCD) 2016. https://www.mrlc.gov/data/nlcd-2019-land-cover-conus

Pena-Salmon, C., Leyva-Camacho, O., Rojas-Caldelas, R., Alonso-Navarrete, A., & Iniguez-Ayon, P. (2014). The Identification and classification of green areas for urban planning using multispectral images at Baja California, Mexico. The Sustainable City IX, Vol. 1 (pp. 611-620). doi: 10.2495/SC140511.

Peraturan Menteri Pekerjaan Umum Nomor 05/PRT/M/2008 tentang Pedoman Penyediaan dan Pemanfaatan Ruang Terbuka Hijau di Kawasan Perkotaan. Direktorat Jendral Penataan Ruang Departemen Pekerjaan Umum.

Planet. (2016). Planet Imagery Product Spesification: Planetscope & Rapideye (pp. 7-19)

Shimizu, K., Ota, T., Mizoue, N., & Saito, H. (2020). Comparison of Multi-temporal PlanetScope Data with Landsat 8 and Sentinel-2 Data for Estimating Airborne LiDAR Derived Canopy Height in Temperate Forests. Remote Sensing. doi: 12. 1876. 10.3390/rs12111876

Undang-undang (UU) RI Nomor 26 Tahun 2007 tentang Penataan Ruang. Pemerintah Pusat. LN.2007/No. 68, TLN No. 4725, LL SETNEG: 50 Hlm

Vigneshwaran, S. & Kumar, S. (2019). Comparison of classification methods for urban green space extraction using very high-resolution worldview-3 imagery. Geocarto International (pp. 1-14). doi: 10.1080/10106049.2019.1665714

Weier, J., & Herring, D. (2000). Measuring Vegetation (NDVI & EVI). The Earth Observatory NASA. https://earthobservatory.nasa.gov/features/MeasuringVegetation

Xian, G.Z. (2016). Remote Sensing Applications for the Urban Environment (pp: 7-8). Boca Raton: CRC Press

Yan, G., Mas, J.F., Maathuis, B.H.P., Zhang, X., & van Dijk, P.M. (2006). Comparison of pixel-based and object-oriented image classification approaches – a case study in a coal fire area, Wuda, Inner Mongolia, China. International Journal of Remote Sensing, Vol. 27, No. 18 (pp. 4039-4055)