DETECTION OF GREEN OPEN SPACE USING COMBINATION INDEX OF LANDSAT 8 DATA (CASE STUDY: DKI JAKARTA)

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Abstract. Spatial information about the availability and presence of green open space in urban areas to be up to date and transparent was a necessity. This study explained the technique to get the green open spaces of spatial information quickly using an index approach of Landsat 8. The purpose of this study was to evaluate the ability of the method to detect the green open spaces, especially using Landsat 8 with a combination of several indices, namely Normalized Difference Build-up Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Build-up Index (NDBI) and Normalized Difference Bareness Index (NDBaI) with a study area of Jakarta. This study found that the detection and identification of green open space classes used a combination of index and band gave good results with an accuracy of 81%.

Keywords: *green open space, NDVI, NDWI, NDBI, NDBaI, Landsat 8*

1 INTRODUCTION

Based on Ministerial Regulation of Public Works No. 05/PRT/M/ 2008, Green Open Space (GOS) was defined as lengthwise/lane and or grouping of land, which the usage had the open characteristic, a place where vegetation could grow, for both naturally and planted intentionally (Ministry of Public Works, 2008). The existence, quality and spread of green open space in urban area were necessary. Yet, pressures from some fields, such as the building of housings, industries, and offices threatened the existence of GOS. The up to date and transparence information availability of GOS by quick, easy and reliable mapping that could be understood by public to prevent or at least decrease those pressures.

The data utilization of remote sensing satellite for green open space's mapping was one of methods that had numerous advantages compared to terrestrial method. Recently, the method that was used in common for GOS mapping used satellite data was by qualitative classification (visual interpretation) or quantitative classification used vegetation index. The research of GOS mapping used *Normalize Difference Vegetation Index* (NDVI); some had done by Febrianti and Sofan (2014) from Landsat 8 data, used NDVI from SPOT 6 data by Febrianti et al (2015), used NDVI from Landsat TM by Ahmad et al (2014), used NDVI from IRS dan LIS III satellite images by Faryadi and Taheri (2009), and used NDVI from Quickbird and IRS data by Shetty and Somashekar (2016).

NDVI was basically used to measure the plantation growth and to decide the coverage area of vegetation. In NDVI calculation, it was used the wavelength of visble red and near infrared. The basic calculation was the pigment inside the leaves or chlorophyll were highly absorbing light that looked (0.4 – 0.7 um) on photosynthesis process, Meanwhile the cell structure of the leaves were highly reflective the near infrared (0.7 – 1.1 um). The moreleaves in a plant, it would more influenced reflection or absorption on the wavelength (NASA, 2015). Another well-known index was *Normalize Difference Water Index* (NDWI). It was one of the vegetation index to measure water molecules on vegetation that was interacted to incoming solar radiation. Chen et al (2006) used NDWI as one of indexes to know the characteristics of land cover in an area. Besides, Senanayake et al, (2013) also used NDWI in analyzing the vegetated land coverto separate the objects of water and cloud. Index value NDWI was big or increase on vegetation that had a lot of water content, or index increased from the dry ground object to the open water (Molidena et al, 2012). Zha *et al.*, (2003) built *Normalize Difference Built-up Index* (NDBI) to quickly identify the urban area and built-area. The making of index was based on the unique spectral response on a built-area where had higher reflectance on the short wave infrared (SWIR) compared to the wavelength of near infrared (NIR). Zhao and Chen (2005) built *Normalize Difference Baroness Index* (NDBaI) to classify the open land or bare land from Landsat image. NDBaI was sensitive enough to differentiate the bare land, semi- bare land and cultivated land. The used channel was short wave infrared (SWIR) and thermal infrared (TIR).

Each index stated above had advantages and disadvantages. That was the reason why the unification of some indexes was done to increase the accuracy of classification some land cover classes, especially GOS. On this research, GOS was defined as area, which was not only vegetated as grass, shrubs and trees, but also included bare land that still could be planted the vegetation. So in this research, it would be done classifying the GOS that included vegetated area and bare land/ ground that was potential to be planted.

Purpose of this research was to evaluate some indexes, such as NDVI, NDWI, NDBI and NDBaI in order to map the GOS. Purposes of this research were we could get information of GOS faster, practically and relatively accurateand they could be used as a basis for decision making about spatial planning of urban and as pre-information for maintenance the existence GOS. This paper was a development of an earlier paper that was published on Proceeding of National Seminar of Remote Sensing 2015.

2 MATERIALS AND METHODOLOGY

This research was done in the province of Jakarta, used satellite data of Landsat 8 sensor OLI and TIRS Level IT path/raw 122/064 the date of recording was August 25th 2013 and September 13rd 2014, and satellite data Pleiades on July 12 2013. The used data was data that had been corrected to geometric and radiometric. The corrected radiometric data has reflectance value of *Top of Atmosphere* (ToA).

To classify the land cover on data Landsat 8, it was used index NDVI, NDWI, NDBI and NDBaI. The calculation formula of NDVI mathematically was written as follow (Purevdorj *et al.*, 1998; NASA, 2015):

$$NDVI = \rho NIR\text{-}\rho RED/\rho NIR+\rho RED \quad (2\text{-}1)$$

Calculation formula for NDWI as follow (Gao, 1996; Chen *at al.*, 2006):

$$NDWI = \rho NIR\text{-}\rho SWIR/\rho NIR+\rho SWIR \quad (2\text{-}2)$$

Calculation formula for NDBI as follow (Zha *et al.*, 2003; Xu 2007):

$$NDBI = \rho SWIR\text{-}\rho NIR/\rho SWIR+\rho NIR \quad (2\text{-}3)$$

Calculation formula for NDBaI as follow (Zhao and Chen, 2005; Chen *et al.*, 2006):

$$NDBaI = dSWIR\text{-}dTIR/dSWIR+dTIR \quad (2\text{-}4)$$

Where: ρNIR, ρRED, ρSWIR were reflectance of near infrared band, the red visible and short wave infrared band, whereas dSWIR and dTIR were digital values of short wave infrared band and thermal infrared band.

Image of those indexes were used for classifying the vegetation, water body, building and bare land through threshold application. Threshold determination or rule set of every index was based on index value of land cover that was got by the making of "training area" from "ground truth" data. Because of the recording time of Landsat 8 on August 25th 2013 closed to Pleiades data which was on July 12 2013, so the ground truth data was used Pleiades image to simplify the field verification. Training area/sample on each index image had been taken on each class of land cover vegetation, water body, build area (buildings, roads) and bare land. Determining the location of training area was done by reference of Pleiades image, to get class of homogeny land cover on each pixel of index images from Landsat 8. According to training area and then counted range and average value of every index, such as NDVI, NDWI, NDBI, and NDBaI for every class.

Besides, on this research it was also done spectral analysis of every band on every object on specified training area. Afterwards, it was done the comparison between classification that had been produced by combination of spectral index and pattern on each band by classifying the one that was only produced by index image.

On this research, the classes of land cover were simplified to be class of GOS and non GOS, where GOS included vegetated area and bare land.

Phases of verification GOS classifications include:

a. Visual interpretation of class GOS and non GOS on Pleiades images,
b. Spatial operation of Union GOS and non GOS were taken by Pleiades images and Landsat 8.
c. Accuracy calculation used classification calculation of *confusion matrix* test method that tend to Short (1982) on Purwanto (2014) on formula (2-5)

Accuracy (%) =
Corrected / (Omission + Comission + Corrected) x 100% (2-5)

Where:

Corrected = the right area or overlapping,
Omission = mistakes due to those areas included to the other classes,
Commission = mistakes due to additional areas of other classes.

3 RESULTS AND DISCUSSION

On the classification of land cover and GOS, it was used combination of some indexes, such as NDVI to classify the vegetation cover, NDWI for water body, NDBI for build area and NDBaI for red land or bare land. Figure 3-1 shows the image of calculation result on each index.

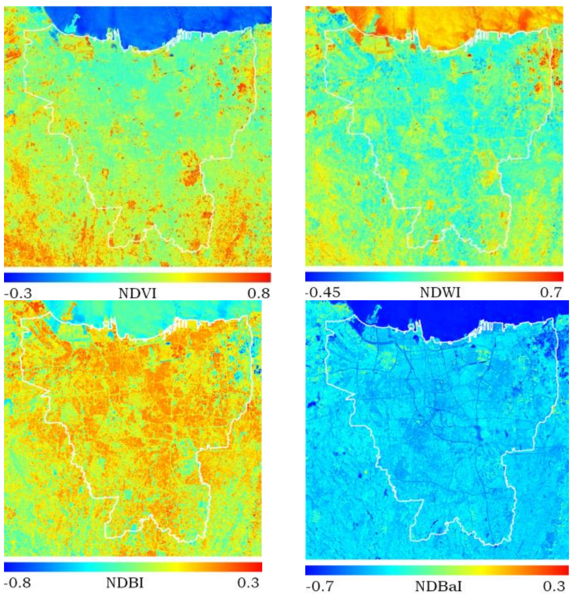

Figure 3-1: Index images of NDVI, NDWI, NDBI and NDBaI

On NDVI image, it could be seen the higher index value (red colored) shows the density and the better vegetation cover. On Molidena et al (2012) was stated the index value of NDWI was high on vegetation that had water content, or index increased from the object of dry soil to the open water. The high index value on NDBI images showed the build area. Whereas on NDBaI images it was seen the higher index value on build area and bare land. To classify GOS, it would be done the re-classification became GOS classes (vegetation and bare land) with non GOS (build area and water).

When implicating some indexes to classify the land cover, there were some problems on determine the threshold, due to there were object mixing in every index, such as in NDWI index there were little mixing between water and vegetation objects. To solve those problems, it should be done spectral analysis first to every band on every object on training area that had been decided before. On Figure 3-2, it could be seen the spectral pattern on each object (training sample) in study areas of Band 1 – Band 7 and Band 9 – Band 11 the images of Landsat 8 LDCM. Whereas Table 3-1 shows index value on every class of cover land based on training sample. On the spectral pattern, the vegetation object seem its typical patterns that differentiated them to other objects, such as on Band 4, Band 6 had reflection or small spectral whereas on Band 5 had high reflection. The water object had typical reflection on Band 4, Band 5 and Band 6 where on Band 4 there was high spectral value, and on Band 5 and Band 6 became smaller because it was absorbed by water.

After getting the spectral pattern on each object, it was used logic operation (*Boolean operator*) “and” based on spectral band that was combined with the image of the index. This method also had been applied by Chen *et al.*, (2006). As an example, appropriate to spectral pattern (Figure 3-2) and index threshold (Table 3-1) to separate the vegetation object, it was used combined operation (Band 5 – Band 4) > 0, (Band 5 – Band 6) > 0 and (0.33 > NDVI > 0.77), because there was just the vegetation that had spectral value (Band 5 – Band 4) > 0, (Band 5 – Band 6) > 0. Later, for water object it was used the combined operation (Band 4 – Band 5) > 0, (Band 5 – Band 6) > 0 and (0.08 > NDWI > 0.7). For the build areaand bare land classes, it was used combination between NDBI and NDBaI index because of while applying the spectral combination, each band was not formed different classes significantly, but when uniting between NDBI and NDBaI index especially for open land class, it was formed a more appropriate class. Class of bare land was used operation (-0.02 > NDBI > 0.04) and (-0.37 > NDBaI > -0.3), while for the build area was used threshold (-0.18 > NDBI > 0.3).

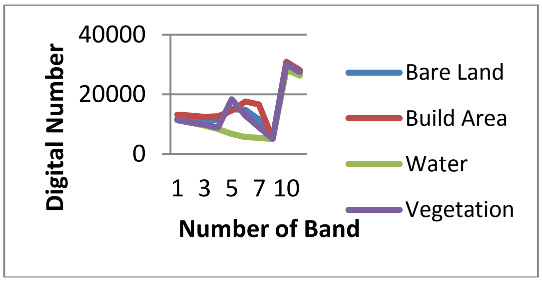

Figure 3-2: Spectral pattern of each object in study area

Table 3-1: Index value on each class of land cover based on training sample

Class	Number of Pixel Sample	NDVI			NDWI		
		Min	Max	Mean	Min	Max	Mean
Vegetation	119	**0.33**	**0.77**	0.54	-0.04	0.44	0.26
Water	151	-0.40	0.11	-0.33	**0.08**	**0.70**	0.49
Build area	107	0.05	0.29	0.11	-0.30	0.18	-0.22
Bare land	31	0.11	0.33	0.21	-0.04	0.02	0.02
Class	**Number of Pixel Sample**	**NDBI**			**NDBaI**		
		Min	**Max**	**Mean**	**Min**	**Max**	**Mean**
Vegetation	119	-0.44	0.04	-0.26	-0.49	-0.25	-0.40
Water	151	-0.7	-0.08	-0.49	-0.67	-0.60	-0.67
Build area	107	**-0.18**	**0.30**	0.22	-0.51	0.00	-0.28
Bare land	31	**-0.02**	**0.04**	-0.02	**-0.37**	**-0.30**	-0.33

Comparison of classification result just used threshold of index value, classification used combination between threshold of index value, and spectral band could be seen on Figure 3-3 and Figure 3-4. Figure 3-3b shows that if only used threshold of NDWI index, so there was still mixtures between water object and vegetation.

As shown in Figure 3-3d, if using NDBaI index, it still happened the mixture between class of bare land and build land. So, adding the combination of spectral band could produce a better classification as seen on Figure 3-4.

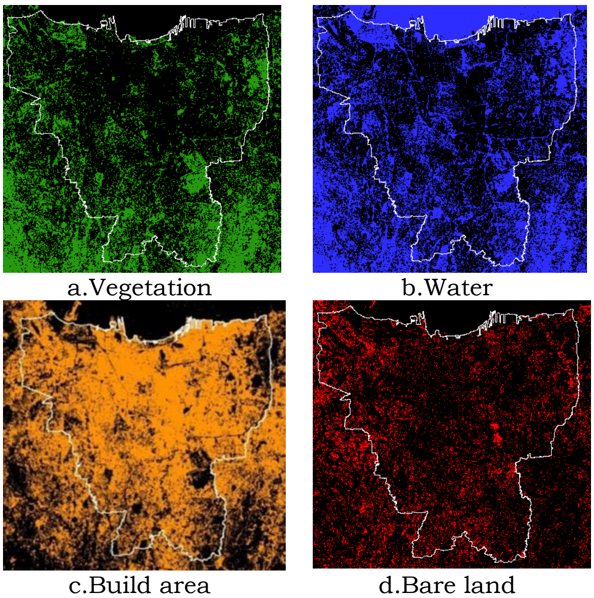

Figure 3-3: Class of landcover based on threshold of index value

The result of this land cover classification was re-classification to get class of GOS and non GOS and tested its accuracy using reference of Pleiades data. Accuracy calculation was done to GOS classification results from Landsat image on September 25 2013. As for GOS class, it was used the mixture of vegetation and bare land classes, so getting from land cover classification it was contained of 4 classes (vegetation, bare land, build land and water) were done re-classification to be 2 classes (GOS and non GOS). Accuracy calculation was done by arranging GOS classes from some indexes with GOS classification result from Pleiades data on six Areas of Interest (AoI).

Comparison accuracy between classifications just used threshold index value and classification used combination between threshold index value and spectral index shown on Table 3-2. The calculation result showed that using combination between those methods had a better accuracy, which was 81%; while using threshold index value was got the accuracy for 70.1%. On the Table 3-2a also could be seen generally in every AoI occurred higher *commission error* compared to *omission error*, which mean there were still some areas classified as GOS based on threshold index value. Meanwhile on Table 3-2b shows the higher *omission error* compared to *commission error,* which mean there is still some areas that is not classified as GOS based on index image and combined band.

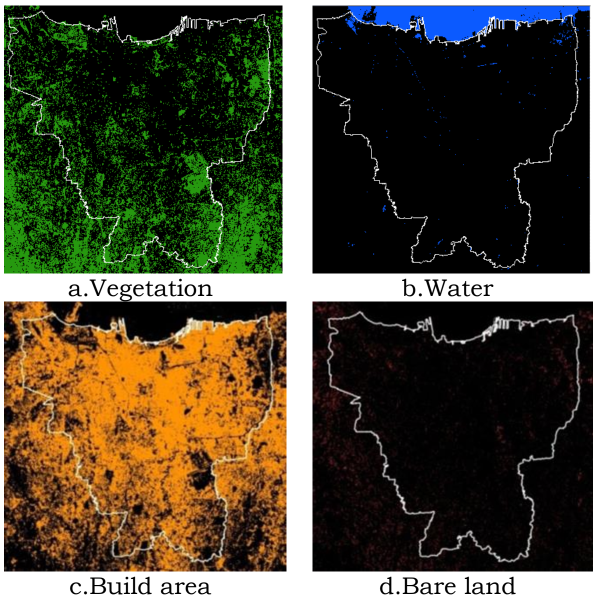

Figure 3-4: Class of land cover based on threshold of index value and band combination (source: Sulma et al, 2015)

Table 3-2: GOS classification accuracy

a. Classification based on threshold index value

No	AoI	Area (m2) Commision	Ommision	Corrected	Accuracy (%)
1	Aoi 1	62,514	114,203	823,186	82.3
2	Aoi2	599,598	431,560	2,972,306	74.2
3	Aoi3	195,031	110,144	644,977	67.9
4	Aoi4	243,983	110,968	640,860	64.4
5	Aoi5	261,671	176,777	1,114,862	71.8
6	Aoi6	288,056	77,094	552,042	60.2
		Mean of accuracy			**70.1**

b. Classification based on threshold index value and combined band

No	AoI	Area (m2) Commision	Ommision	Corrected	Accuracy (%)
1	Aoi 1	17,623	95,992	886,288	88.6
2	Aoi2	428,482	450,223	3,125,087	78.0
3	Aoi3	63,710	106,007	780,435	82.1
4	Aoi4	103,194	112,486	780,130	78.3
5	Aoi5	155,713	168,436	1,229,161	79.1
6	Aoi6	110,752	79,523	720,039	79.1
		Mean of accuracy			**81**

After doing verification of land cover images on September 13 2013 used Pleiades data on July 12 2013 and then applied the threshold or rule set on August 23rd 2014, but it was still needed further verifications to other years' data. Land cover images on 2013 and 2014 could be seen on Figure 3-5. According to calculation of the landcover area in Jakarta on 2013 and 2014, it could be seen clearly the significant changes on decreasing vegetation and increasing build land (Table 3-3). On GOS category (vegetation and bare land), there was impairments, where on 2013 the GOS percentage was about 25.5% and on 2014 it was about 23.1% of all total area of Jakarta (Table 3-4).

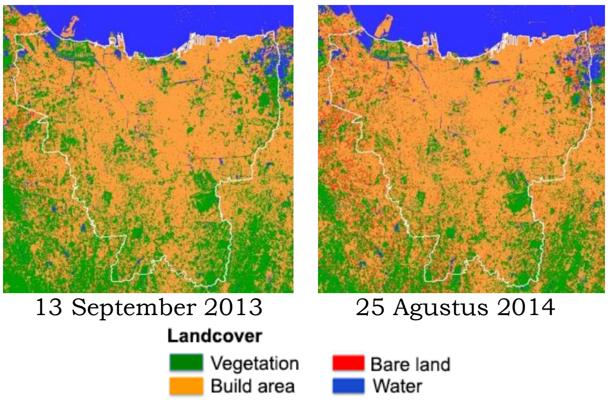

Figure 3-5: Land cover from Landsat images on year 2013 and 2014

Table 3-3: The area of landcover on 2013 and 2014

No	Landcover	Area (km2)		
		2013	2014	Change
1	Vegetation	166.24	112.82	-53.42
2	Bare land	12.25	30.95	+18.70
3	Build area	442.84	474.79	+31.95
4	Water	20.13	22.89	+2.76

Table 3-4: The area of GOS on 2013 and 2014

No	Landcover	Area (km2)		
		2013	2014	Change
1	RTH	178.49	143.77	-34.72
2	Bukan RTH	462.97	497.68	+34.71

4 CONCLUSION

This research found that detection and identification of GOS used NDVI, NDWI, NDBI and NDBaI indexes and combination of spectral band together with Landsat 8 are good enough with the accuracy degree for 81%. Further research needed to test and evaluate combination of those indexes to get the best method for detection of GOS.

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