Monitoring of Green Open Space change area from 2018 to 2022 using remote sensing approach: Study sites Palu city, Central Sulawesi

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Abstract - Population growth increase every year in the city of Palu has an impact on the increasingly massive development that occurs. While on the other hand, according to PP no 15 of 2010 green open space must be available in a city by 30%, With proportion 20% is public and 10% is private property. In 2018, liquefaction and earthquake were destroyed some part of Palu which caused changes that affected the area of green open space in the city of Palu. Knowing the condition of green open spaces in Palu City is important in order to formulate the best management actions are appropriate for existing conditions. The objective of this research is to determine green open space change from 2018 to 2022 using sentinel 2 satellite imagery. The study site of this research was located in Palu City, focused on other land use or non-forest area. Data used in this research was Sentinel 2 acquired in 2018 represented before liquefaction and 2022 represented the newest condition of the imagery. The method used in this research was post comparison classification (PCC) using the vegetation index difference by utilizing the NDVI (Normalized Difference Vegetation Index) vegetation index. NDVI is the index that sensitive to vegetation or chlorophyll. This research shown that the green open space in 2018 was 61% and decrease in 2022 (62%). In detail, 54% no change of vegetation to vegetation, 31% no change of open area to open area. Vegetation decrease from vegetation to open area were around 7% and vegetation increase 5% from open area to vegetation include liquefaction area around 180ha. The largest decrease in vegetation of 786 ha and the largest increase in vegetation of 624 ha were in Matikulore sub-district, equivalent to 0.17. Smallest change located in tawaeli than other sub-district.

Introduction

Indonesia is one of the developing countries that is experiencing growth in urban development. This growth is increased by the increase in population and the rate of urbanization which results in the need for land [1]. An adequate area or also known as an urban area is an area that has serious environmental problems. Rapid urban growth, especially due to population growth, especially urbanization, requires the development of urban facilities and infrastructure. As a logistical consequence of the rapid physical development of the city is the need for land for development. This development activity often causes impacts such as reduced green open space in urban areas. The implications of the development of green open space on environmental quality such as air and air pollution and increasing temperatures require serious attention and study [2]. It is necessary to realize the high benefits of green open space in improving and improving the quality of the urban environment. The presence of vegetated areas in urban areas brings a major influence, especially in increasing temperature quality [3].

It is undeniable that since the 1980s reliable remote sensing technology has been available for the detection of cover changes, remote sensing sensors are also capable of detecting healthy vegetation and non-vegetation objects through image processing analysis by utilizing channels that are sensitive to changes in chlorophyll content, changes in biomass, changes in the type of vegetation cover, and/or water content (validity) of open lands [4]. The channels that play a very important role in the detection are blue, green,

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near infrared, medium infrared and thermal channels [5].

Until now, conceptually and practically, the development of land cover change detection methods using remote sensing data has been widely developed, ranging from very general to specific locations and events. Conceptually, there are several techniques for detecting forest and land cover changes that are widely used, namely (1) direct multidate analysis and (2) uni-time analysis through post-classification comparison. The post classification comparison method is used because in the processing process the land cover area can be known at two different times.

Central Sulawesi is located on the plains of the Palu valley and Palu Bay. Palu City is the capital city of Central Sulawesi Province. According to the Meteorology, Climatology and Geophysics Agency on September 28, 2018, an earthquake with a magnitude of 7.7 on the Richter Scale occurred in Palu city. with a depth of 10 kilometers which caused a tsunami and liquefaction in the cities of Palu and Donggala. The earthquake, tsunami, and liquefaction that had a big impact on the city of Palu contributed to changes in the existing land cover. Monitoring of vegetation cover within the scope of green open space is needed as a basis in the preparation of rehabilitation actions after natural disasters. The purpose of this study was to determine changes in green open space from 2018 to 2022 using Sentinel 2 medium resolution images.

II. METHOD

A. Study site

Astronomically, Palu City is located between 0°36” - 0°56” South Latitude and 119°45” - 121°1” East Longitude (Figure 1). This study covers the entire Palu city area, non-forest area, which is the focus of the green open space study area. Data processing is carried out at the GIS-RS Lab, Faculty of Forestry and environment, IPB University.

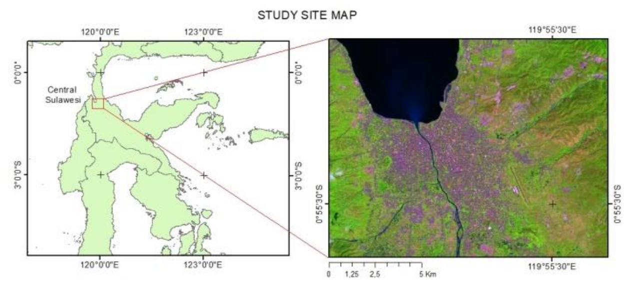


Figure 1. Study site

B. Data, Software, and Hardware

The data used in this study is medium resolution satellite imagery (Sentinel 2) recording in 2018 and 2022 which represents before and after natural disasters. The use of sentinel imagery is based on the consideration of having a complete spectral resolution making it easier to make indexes, 10m spatial resolution, complete temporal resolution. The research location is on the sentinel title T50MRE recording. Supporting data is in the form of an Earth Map (RBI), data on the function of the Indonesian region.

The hardware used in this research is a laptop, Global Positioning System (GPS), and a set of cameras. Pre-processing, and image processing were carried out using ArcGIS 10.8. Data processing was carried out using Microsoft Excel software for data analysis and making land cover change matrices. All processes are carried out on computer devices that have Intel(R) core (TM) i7-1165 processor specifications, 16 Gb RAM, and 1 Tera. This research was conducted through several stages of activities as follows: pre-image processing, making a vegetation index using image algebra.

C. Data Analysis

1. Image Pre-processing.

Geometric transformation is one of the approach that can be used for geometric corrections. This was done because the image data used has different coordinates so that the image projection becomes UTM (Universal Transverse Mercator) zone 51S and datum WGS 84 (World Geographic System 84) using ArcGIS 10.8 software. The radiometric correction made was histogram matching. Histogram matching is performed on images that have different recording times to correct for differences between two sensors with different wavelengths. This process is done in such a way that the histogram matches the reference dataset. The 2018 image is histogram matching with the 2022 image reference so that the 2018 digital number will match the 2022 image dataset. Image cropping is done to facilitate the focus of analysis activities on the area of interest (AOI) of the research location to be observed.

2. Post Comparison Classification (PCC)

PCC is one of two basic approaches for change detection analysis that already widely uses in environment sector. Basically, PCC known as a map-to-map comparison means comparative analysis of independently produced classification from different dates. This research used two set data time (2018 and 2022). In this research the PCC carried out used NDVI (Normalized differenced vegetation index), the NDVI generally can classify the variations in biomass density and surface wetness conditions of open land and water bodies because the original bands, including Red and NIR used, are susceptible to chlorophyll [6], biomass, and surface water. The general formula for NDVI is as follows:

$$\boldsymbol{NDVI = \frac{NIR - Red}{NIR + Red}}$$

3. Thresholding

The classification of vegetation and non-vegetation from NDVI developed by the data distribution of training sample for each class. The selection of training data is based on changes that occur from 2018 to 2022. The training sample created is used to determine the minimum, maximum, average, and standard deviation values as basic information to determine the upper and lower thresholds of class changes. Determination of the threshold is determined using the following formula:

$$m - (TL.SD) < m < m + (TL.SD)$$

note:

m : mean

TL : threshold level

SD : standard deviation

2.3.4 Change classification. The classes that have been created was divided into four classes to see the changes that occur in both sets of time. The four classes are classified into 2 classes that change and 2 classes do not change with the following functions:

$$\boldsymbol{C} = \begin{cases} \boldsymbol{VI : if \ \{NDVI_{2018} = 0 \ and \ NDVI_{2022} = 1\}} \\ \boldsymbol{VD : else \ if \ \{NDVI_{2018} = 1 \ and \ NDVI_{2022} = 0\}} \\ \boldsymbol{NC : else} \end{cases}$$

$$\boldsymbol{NC} = \begin{cases} \boldsymbol{NC - V : if \{NDVI_{2018} = 1 \ and \ NDVI_{2022} = 1\}} \\ \boldsymbol{NC - NV : else \ if \ \{NDVI_{2018} = 0 \ andNDVI_{2022} = 1\}} \\ \boldsymbol{C : else} \end{cases}$$

Note:

1 : Vegetation

0 : Non vegetation

C : Change

VI : Vegetation increase

VD : Vegetation decrease

NC-V : No change vegetation

NC-NV: No change non vegetation

The term of vegetation increase was the change from open area to vegetation and the term of vegetation decrease was the change from vegetation to open area. This term based on the change of chlorophyll and biomass represented on vegetation by differenced digital number value

4. Validation

The validation derived by comparing the classification result with ground truth data from higher spatial resolution satellite imagery (World View). Ground truth point made with stratified sampling that has number of samplings 40 plots (10 plots for each change classes). Jaya (2010) said that the recommended accuracy is kappa accuracy (KA), because overall accuracy (OA) generally produces an overestimated accuracy value. KA considers all elements contained in the error matrix. However, the calculation of accuracy is carried out by assessing the KA recommended by [7] which is 0-20% low, 21-40% less, 41-60% moderate, 61-80% good, and 81-100% very good. OA and KA values are calculated using the following formula. Validation calculated by the kappa value of accuracy and overall accuracy with the following formula.

TABLE 1. CONTINGENCY MATRIX FOR VALIDATION

Referenced data	Classified class					Total	PA
	K1	K2	K3	K4	K5		
K1	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{1+}	X_{11} / X_{1+}
K2	X_{21}	X_{22}	X_{23}	X_{24}	X_{25}	X_{2+}	X_{22} / X_{2+}
K3	...					...	...
K4	..					...	...
K5	X_{51}	X_{52}	X_{53}	X_{54}	X_{55}	X_{5+}	X_{55} / X_{+5}
Total	X_{+1}	X_{+2}	X_{+3}	X_{+4}	X_{+5}	X_{ii}	
UA	X_{11} / X_{+1}	X_{22} / X_{+2}	X_{33} / X_{+3}	X_{44} / X_{+4}	X_{55} / X_{+5}		

Keterangan : K (Class name); PA (*Producer's accuracy*); UA (*User's accuracy*)

$$Overall\ accuracy = \frac{\sum X_{ii}}{N}$$

$$Kappa\ Accuracy = \frac{N\sum X_{ii} - \sum X_{i+}X_{+i}}{N^2 - \sum X_{i+}X_{+i}}$$

Note:

N : Total matrix value

X_{ii} : the diagonal values of the i-th row and i-th column contingency matrices

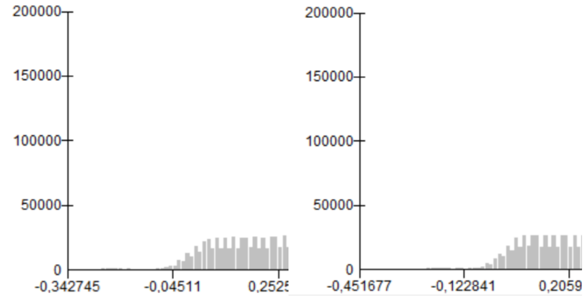
X_{i+} : the number of values in the j-th column

X_{+i} : the number of values in the i-th line

N : number of observations

III. RESULT

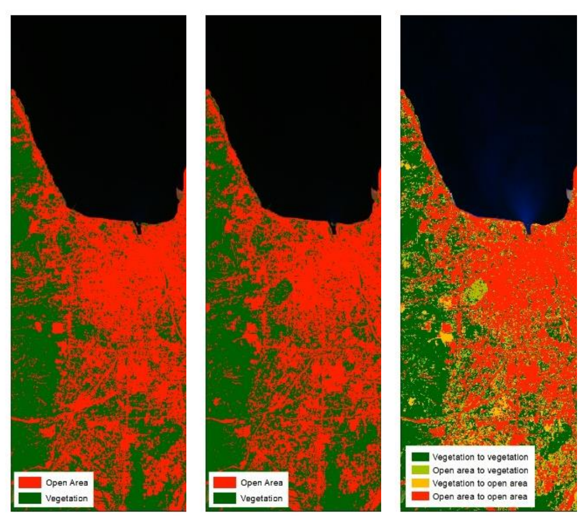
Monitoring of green open space estimation is carried out using the NDVI vegetation index which has the advantage of being sensitive to chlorophyll content, biomass and moisture in vegetation. To separate between vegetation and non-vegetation, the thresholding method is used for reclassification [8-10]. The threshold of vegetation and non-vegetation is 0.44, where the determination of the threshold will be based on the distribution of data that considers the digital number of the training area.



(a) (b)

Figure 2. (a) thresholding in imagery 2018 (b) thresholding in imagery 2022

Comparative analysis of independently produced classifications from different dates (post-classification comparison: map-to-map comparison) used in this research referred from [11]. Vegetation and non-vegetation class boundaries that have been obtained are used as the basis for seeing changes that occured in the research location. The class of change that can be described is no change which includes vegetation to vegetation and open areas to open areas. While the changing classes include vegetation classes to open areas and open areas to vegetation. The four classes are visualized as follows. This research shown that the green open space in 2018 was 61% and decrease in 2022 (62%). In detail, 54% no change of vegetation to vegetation, 31% no change of open area to open area. Vegetation decrease from vegetation to open area were around 7% and vegetation increase 5% from open area to vegetation include liquefaction area around 180ha.



(a) (b) (c)

Figure 3. (a) Classification in 2018 (b) classification in 2022 (c) change classification using PCC

Vegetation classes that do not change are represented in dark green while the open area classes that do not change are represented in red. Meanwhile, the changing vegetation increase class is represented using light green color and the vegetation decrease class is represented using orange color. Detailed information related to increasing or decreasing vegetation is carried out by overlaying it with administrative boundaries. It can be seen in Figure 4 that the biggest change is in the Mantikulore sub-district while the smallest is in the Tawaeli sub-district. The largest decrease in vegetation of 786 ha and the largest increase in vegetation of 624 ha were in Matikulore sub-district, equivalent to 0.17. When viewed in percentage terms, the largest decrease and increase in vegetation was in the southern Palu sub-district (24%) from the total area of 1883ha. Smallest change located in tawaeli than other sub-district.

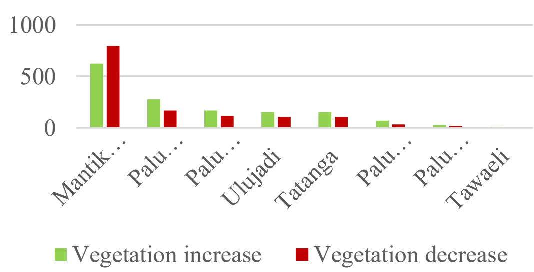
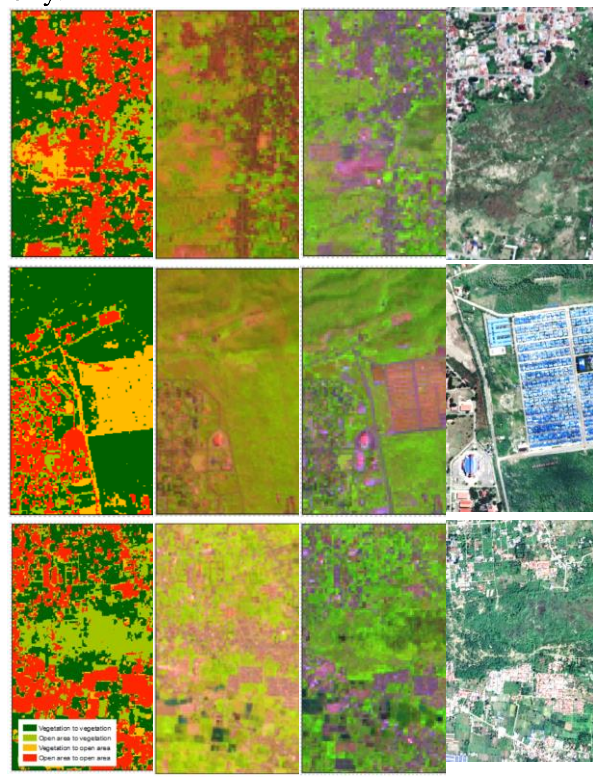


Figure 4. Change of vegetation distribution in each sub district

Validation is carried out on each class of changes by doing ground truth to see changes from T1 to T2. Some changes in land cover that occur due to natural disasters can be seen at the liquefaction location as an increase in vegetation (decreased openness of the area) from settlements to vegetated land. And for other change class was defined by the conversion of the vegetation to build-up land cover. For example one of the validation test we found that the change was the permanent resident for the sufferers of the natural disaster. It known by the blue color of the imagery and the pattern indicated of the settlement (blue is one of the roof colour in Indonesia). There were 4 settlements built after the earthquake (Duyu, Balaroa, Mandiri and Tondo) in Palu City.



Change classes | July 2018 | January 2022 | Ground truth (August 2022)

Figure 5. validation of the classification

The occurrence of natural disasters in the city of Palu caused a lot of revegetation, but on the other hand, land conversion was also carried out for the needs of community facilities and infrastructure affected by natural disasters. Changes in land cover which are very dynamic after a natural disaster must be monitored quickly, responsibly and accurately. the reliability of remote sensing technology can be used for monitoring the cover of green open spaces and urban settlements in mitigation and land use rehabilitation activities in the future.

IV. CONCLUSION

This research shown that the green open space in 2018 was 61% and decrease in 2022 (62%). In detail, 54% no change of vegetation to vegetation, 31% no change of open area to open area. Vegetation decrease from vegetation to open area were around 7% and vegetation increase 5% from open area to vegetation include liquefaction area around 180ha. The largest decrease in vegetation of 786 ha and the largest increase in vegetation of 624 ha were in Matikulore sub-district, equivalent to 0.17. Smallest change located in tawaeli than other sub-district. the reliability of remote sensing technology can be used for monitoring the cover of green open spaces and urban settlements in mitigation and land use rehabilitation activities in the future.

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