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Urban Vegetation Quality Assessment Using Vegetation Index and Leaf Area Index from Spot 7 Data with Fuzzy Logic Algorithm

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***Abstract*— Urban vegetation plays an essential role in the health and comfort of the urban environment. On the other hand, the decrease of urban vegetation is mostly due to land cover change from vegetation to build up the area. Detection of urban vegetation objects is essential for monitoring the distribution and the extent of vegetation in realizing a sustainable urban environment. SPOT 7 satellite image data with high spatial resolution can display objects in urban areas, including vegetation. With this capability, the extraction of vegetation objects can be conducted more accurately. This study aims to assess urban vegetation quality using vegetation index and Leaf Area Index (LAI) from SPOT 7 data. The method proposed in this study was the fuzzy logic on each vegetation index and LAI, which was extended by involving all indexes. The results showed that urban vegetation quality classification could be done using vegetation index NDVI, SR, RDVI, and another index LAI extracted from SPOT 7 data using a fuzzy logic algorithm. Based on these four variables' overlay, the highest quality of vegetation was shown with a fuzzy value of 0.928, and the lowest quality has a fuzzy value of 0.004. The highest quality of vegetation was in paddy fields and mixed garden, while the lowest quality of vegetation was in bare land with grass plantation. Based on the results, the appropriate treatment of urban vegetation in the study area can be determined.**

***Keywords*— urban vegetation; vegetation index; Leaf Area Index; fuzzy logic; SPOT 7 data.**

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I. INTRODUCTION

Vegetation in urban environments, both parks, and other green open spaces, has an essential function in urban areas' sustainability. Urban vegetation's role is to create physical and psychological comfort in urban residents, and a healthy urban community, especially on urban vegetation [1]. Besides, both quantity and quality degradation are threatened by urban vegetation due to the plantations' physical development that encourages changes in land cover from vegetation to built-up land [2].

The degradation trend of vegetation in the urban environment makes it essential to detect urban vegetation distribution to determine the vegetation distribution pattern and monitor the amount of vegetation cover to meet the vegetation requirements of 30% of the total urban area. The method used to detect urban vegetation is remote sensing data and vegetation index extraction from the data.

One of the vegetation indices used was NDVI in both low and high resolution, which helped differentiate vegetation land cover with different densities and vegetation types seen from the NDVI range of each vegetation object in the image [3], [4]. Multitemporal NDVI values can also be used for land cover/ land use classification for change detection purposes [5], [6]. Furthermore, NDVI can be applied to annual forest cover mapping, forest monitoring, yield modeling, hierarchical vegetation mapping, temporal plant condition, plant phenology mapping, abandoned farmland mapping, and urban forest planning [7]–[13].

The use of similar data to extract vegetation objects by calculating other vegetation indices such as EVI, NDVI, and multi-temporal WDRVI from MODIS imagery data was conducted to estimate the phenological metrics of French autumn forests [14]. Leaf phenology study seen from NDVI and EVI MODIS data had also been carried out in North and Central America [15]. Then in another study, there was an evaluation of the Plant Phenology Index (PPI), NDVI, and EVI for the northern hemisphere boreal forest zone [16].

Research related to the extraction of vegetation index from medium spatial resolution remote sensing data was carried out in India's districts to see vegetation cover changes in the region [17]. Subsequent research that uses remote sensing data with very high resolution (VHR) was the use of IKONOS data to identify different types of vegetation with the extraction of Leaf Area Index (LAI) [18]. The importance of LAI, which is used in this research, in vegetation analysis is its ability to show plant development or plant growth stage and estimate fractional vegetation cover [19]–[21].

The relationship between the vegetation index NDVI and LAI was carried out to see the relationship between these two indices in a reasonably long range of years from 1996 to 2001 for the autumn forest area [22]. For Indonesia area, the LAI or Leaf Area Index calculation had been done on forest land cover using SPOT-2 data[23]. Extraction of LAI values with Sentinel-2 and RapidEye satellite images had also been carried out [24]. However, LAI extraction showed different values due to atmospheric correction of satellite image data [25].

The fuzzy logic method was developed to determine the level of membership of a set that has a range of values of zero to one [26]. This method had been applied in research related to remote sensing technology, including the application of fuzzy logic related to wind erosion hazards in Algeria and the assessment of areas prone to land conversion in the wetlands of East Kolkata ([27]; [28]). Related to the study in this research, namely urban vegetation, the fuzzy model from remote sensing data was carried out for vegetation mapping [29]. In further research, a fuzzy model for the detection of wheat vegetation had been carried out using a vegetation index derived from remote resolution intermediate resolution data of Landsat 7 ETM + and phenological transition zone mapping ([30], [31]). The development of the use of fuzzy models using NDVI had so far been used in various applications, such as the classification of coastal zones that have been used for human activities, calculating vegetative drought, and analysis of the impact of lockdowns during the COVID-19 pandemic on environmental quality [32]–[34].

In previous studies, identification of vegetation with various vegetation indices as well as Leaf Area Index from remote sensing data of various resolutions, identification of land changes from multitemporal vegetation index, besides the application of the fuzzy logic method was carried out in the identification of vegetation from remote sensing data, but not on data high resolution such as SPOT 7. This study aims to classify vegetation quality in urban areas using vegetation index and Leaf Area Index (LAI) with the fuzzy logic algorithm.

II. MATERIALS AND METHOD

A. Material

The data in this study was multispectral pansharpened SPOT 7 imagery data acquired on May 29, 2018. The coverage area was West Java International Airport (BIJB), Kertajati, Majalengka, West Java, and the surrounding area. This area was the area of previous research study related to agricultural land conversion [35].

B. Method

This study's data processing steps began with preparing the SPOT 7 multispectral pan-sharpened area of the study area and the steps presented in Figure 1.

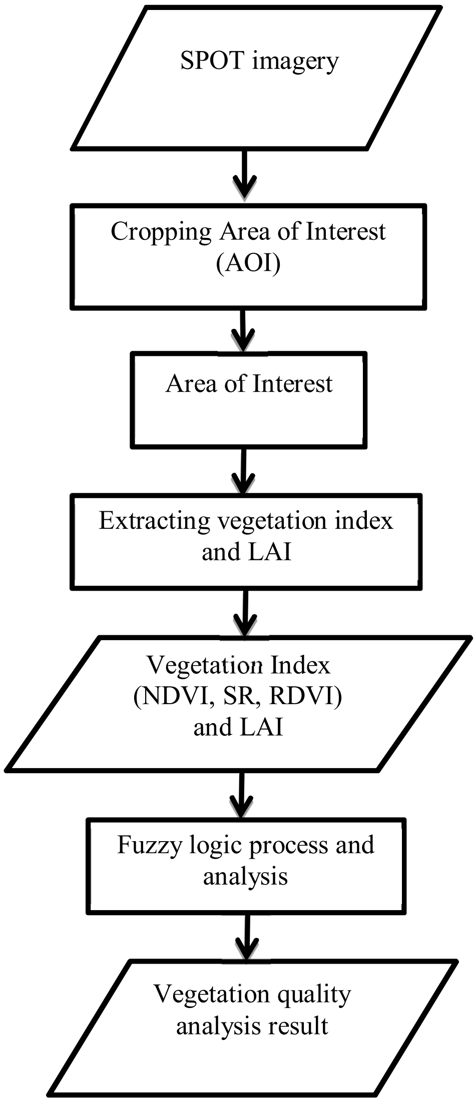

Fig. 1 Flowchart of vegetation quality analysis

The SPOT 7 imagery used in this study was selected then was cropped in the study area to become an Area of Interest (AOI), followed by calculation of the vegetation index and Leaf Area Index (LAI). After these indices were obtained, the fuzzy logic process was performed at each vegetation index and LAI. Fuzzy results on each vegetation index and LAI in raster format were then overlaid and analyzed to know how the vegetation quality classes in the study area were. Detailed stages of data processing were as follows:

1) Vegetation index extraction: Vegetation indices derived from existing bands in the SPOT 7 imagery in this study were:

- NDVI (Normalized Difference Vegetation Index) NDVI values were derived from NIR and Red bands. If formulated, NDVI values were obtained from:

$$\mathrm{NDVI} = \frac{\mathrm{NIR-Red}}{\mathrm{NIR+Red}} \tag{1}$$

- SR (Simple Ratio). SR or Simple Ratio values were simple equations that were easy to understand and effective in various types of vegetation detection conditions. This index was formulated with a ratio between NIR and Red bands [18], which has the highest reflectance for vegetation and wavelengths capable of absorption of chlorophyll. The SR formula is as follows:

$$\mathrm{SR} = \frac{\mathrm{NIR}}{\mathrm{Red}} \tag{2}$$

- RDVI (Renormalized Difference Vegetation Index). RDVI values were derived from differences in NIR and Red bands' wavelengths, which were commonly used for the detection of healthy vegetation, but were not sensitive to the effect of soil appearance [36]. The formula is:

$$\mathrm{RDVI} = \frac{\mathrm{NIR-Red}}{\sqrt{\mathrm{NIR+Red}}} \tag{3}$$

2) Leaf Area Index (LAI) extraction: LAI values extraction from remote sensing data has been carried out by [25] to calculate LAI from NIR and Red bands. As in this study the LAI values were calculated from the formula:

$$\mathrm{LAI} = \mathrm{e}^{\frac{\mathrm{NDVI}-0{,}496}{0{,}211}} \tag{4}$$

Where e = 2,71828, which was developed in research by [23] to calculate LAI in forest and has a high coefficient of determination namely $R^2 = 0{,}982$.

3) Fuzzy logic and overlay process: Fuzzy logic theory was developed to see how the membership level of a set and represented by values from 0 to 1 [26]. This happened because an object class was not clearly defined that its characteristics fit into a particular class that had been defined. The membership function was formulated as follows:

$$fA(x) = \frac{fc(x) - fb(x)}{fA(x) - B(x)} \tag{5}$$

The fuzzy process was carried out on the vegetation index and LAI to be further carried out as fuzzy overlay so that the vegetation quality in the study area was obtained.

III. Results and Discussion

The first research result was AOI (Area of Interest) obtained from selecting and cropping the SPOT 7 imagery in the study area (Figure 2). From the imagery, most of the land cover of the study area was vegetation, followed by a built-up area in the form of the infrastructure of the West Java International Airport (BIJB) Kertajati, Majalengka.

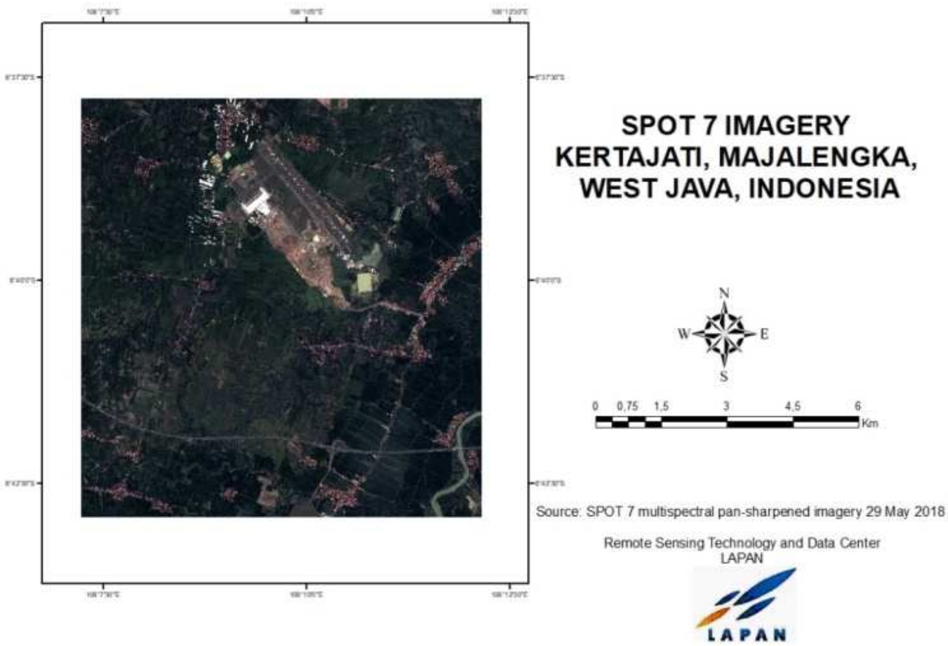

Fig. 2 Area of Interest

The next research result was the classification of the values of each extracted vegetation index and LAI. The first index whose values to be given a new weight was NDVI. Table 1 showed the initial values of NDVI extraction result and the weights given to each class. Low NDVI values were given a low weight of -0.3 to 0 given a weight of 1, 0 to 0.2 were given a weight of 2, then the higher the NDVI value means the higher level of health or quality of the vegetation, which means the higher the weight was given, in this case the highest NDVI value was 0.6 to 0.8 which was given a weight of 5.

TABLE I
NDVI WEIGHTING

Reclassification	
Old values	New values
-0,355553 - 0	1
0 – 0,2	2
0,2 – 0,4	3
0,4 – 0,6	4
0,6 – 0,8	5
No Data	No Data

Figure 3 showed how the distribution of NDVI weighting results from classes 1 to 5, where NDVI with class 1 was represented by light green color and then, the higher the

NDVI class, the older the class color. The darkest green color that indicated healthy green vegetation was seen mostly in paddy fields and mixed garden vegetation. This showed that the quality of rice field vegetation in the study area was good. Meanwhile, the lowest NDVI value was built up land, which was the BIJB infrastructure and open land with sparse grass vegetation.

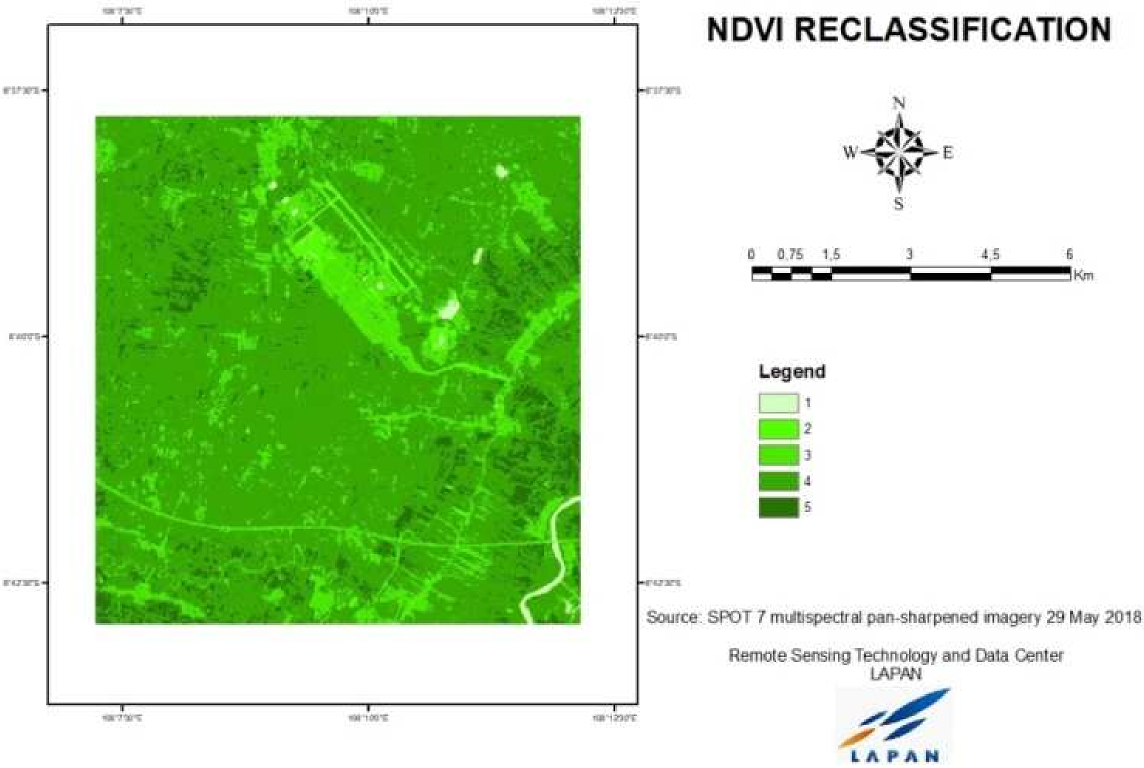

Fig. 3 NDVI Reclassification

Furthermore, the second index made to be given a new weight was SR. Table 2 showed the initial values of SR extraction result and the weight given to each class. The low SR value was given a low weight, that was 0.48 to 1.38, it was weighted 1, then the higher the SR value, which means the better the health or quality of the vegetation, the higher the weight was given as well, in this case the highest SR value is 4.08 to 4.98 were given a weight of 5. In contrast to NDVI, this SR value did not have a negative value, but its highest value was more than NDVI.

TABLE II
SR WEIGHTING

Reclassification	
Old values	New values
0,480601 – 1,381162	1
1,381162 – 2,281722	2
2,281722 – 3,182283	3
3,182283 – 4,082844	4
4,082844 – 4,983405	5
No Data	No Data

Figure 4 showed how the SR index weighting results were the same as NDVI, starting from class 1 to 5, where SR with class 1 was represented by pink color and the higher the SR class, the older the class color was NDVI. The deep red color that indicated healthy green vegetation was seen mostly in paddy field and mixed garden vegetation. This showed that the quality of rice field vegetation in the study area was good with a high vegetation index value NDVI and SR. Meanwhile, a low SR value was in the area of built-up land or non-vegetation area which was the BIJB infrastructure as well as open land with not so dense grass vegetation.

Furthermore, the third index classified for new weighting was RDVI. Table 3 showed the initial values of RDVI extraction results and the weights given to each new class based on weighting. A low RDVI value was given a low weight of -11.31 to -2 given a new weight of 1 then a higher RDVI value which meant the better the quality of vegetation was given a higher weight, in this case the highest RDVI value was 22.17 to 30 which was given a weight of 5. RDVI was the same as NDVI where this RDVI had a negative value, but because the lowest value was lower than NDVI and the highest value was more than NDVI.

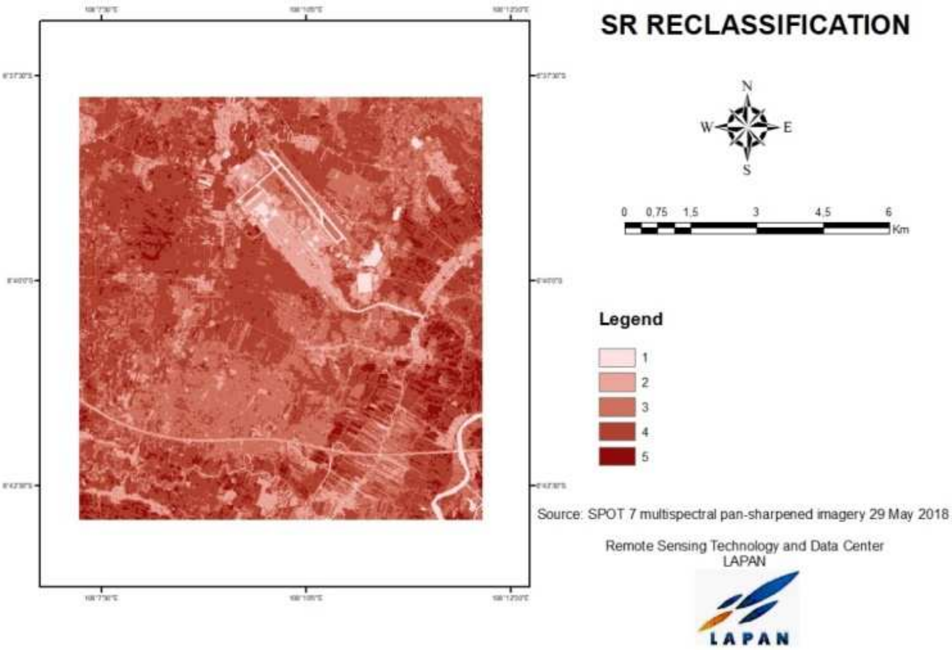

Fig. 4 SR Reclassification

TABLE III
RDVI WEIGHTING

Reclassification	
Old values	New values
-11,311189 – -2	1
-2 – 5,430537	2
5,430537 – 13,8014	3
13,8014 – 22,172263	4
22,172263 – 30	5
No Data	No Data

Figure 5 showed how the distribution of the vegetation index weighting result, namely RDVI which was the same as the other indices, from classes 1 to 5, where RDVI with class 1 was represented by a light brown color and the higher the RDVI class, the class colors got older as NDVI and SR. The dark brown color that showed healthy vegetation was seen mostly on paddy land and mixed garden vegetation, with a class 5 or healthy vegetation distribution that was wider than class 5 on the two previous vegetation indices. This showed that rice field vegetation in the study area was classified as good with a high vegetation index value, both NDVI, SR and RDVI. Meanwhile, the low RDVI value also existed in non-vegetation areas in the built-up area of BIJB infrastructure, roads were also open land with sparse grass vegetation.

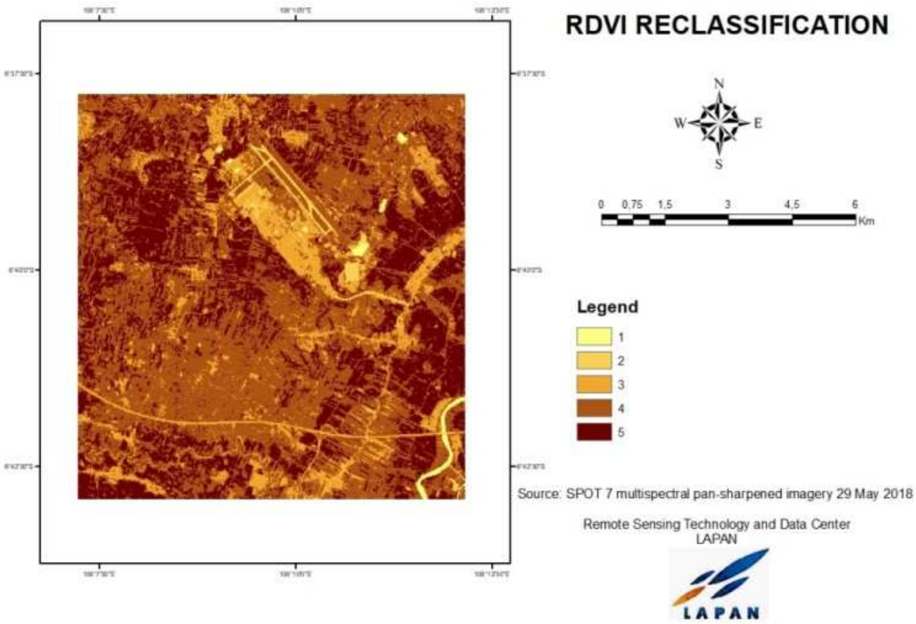

Fig. 5 RDVI Reclassification

Furthermore, the last index classified by weighting was LAI. Table 4 showed the initial values of LAI extraction results and the new values in the form of weights given to each new class. The low LAI value was given a low weight, that is 0.02 to 0.46, it was given a weight of 1, then the higher the LAI value, which meant that the vegetation canopy was denser and the quality was higher, the higher the weight was given, in this case the highest LAI value was 1.79 to 2.23 which was weighted 5. LAI had no negative value, but the lowest value was lower than NDVI and the highest value was more than NDVI.

TABLE IV
LAI WEIGHTING

Reclassification	
Old values	New values
0,025688 – 0,467945	1
0,467945 – 0,910202	2
0,910202 – 1,352459	3
1,352459 – 1,794715	4
1,794715 – 2,236972	5
No Data	No Data

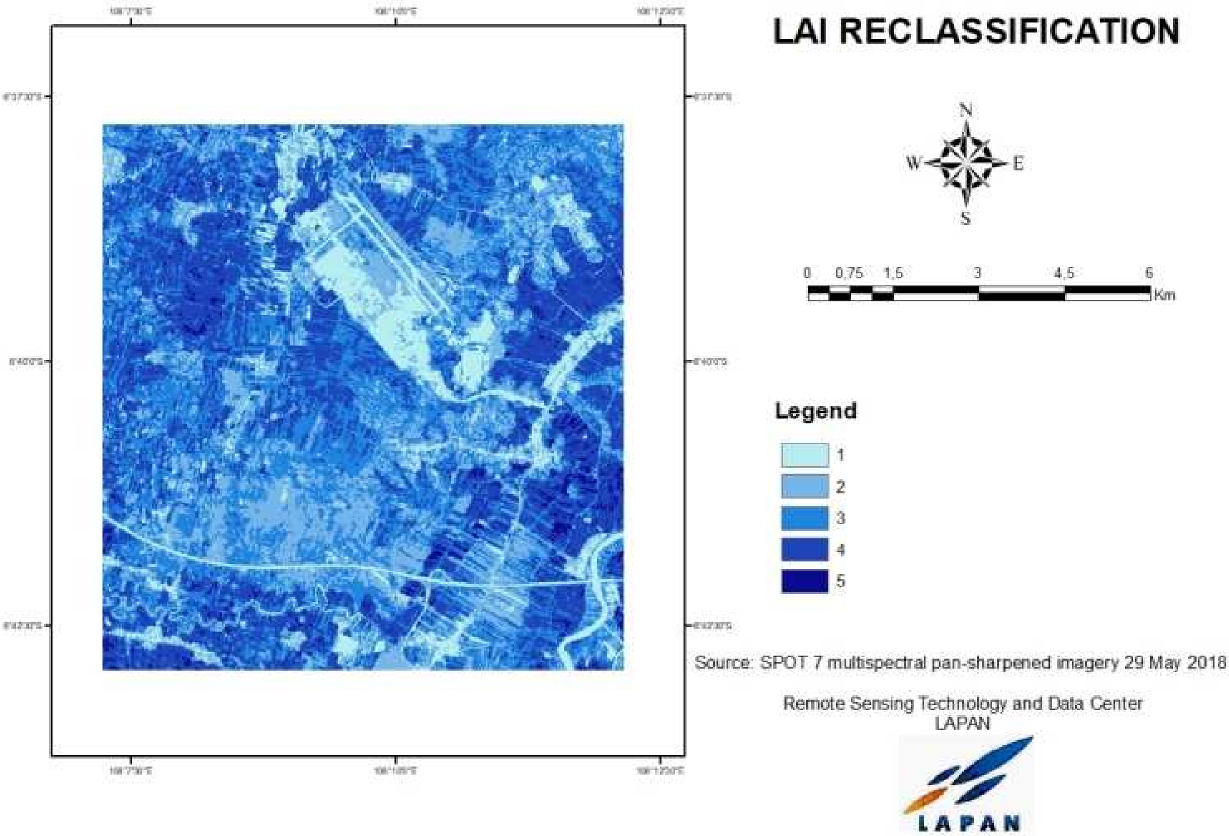

Fig. 6 LAI Reclassification

Figure 6 showed how the distribution of the weighted index results calculated subsequently was the same LAI as the other indices from class 1 to 5, where the LAI with class 1 was represented by light blue and the higher the LAI class, the older the class color, like the vegetation index. In the class distribution for LAI, the same as the vegetation index, the dark blue color indicated healthy vegetation with dense canopy seen mostly in mixed garden and rice field vegetation. However, the most distribution was for class 4. This showed that the density of healthy canopies in the paddy fields and mixed gardens of the study area was relatively high with good LAI values. Meanwhile, the low LAI value also existed in non-vegetation areas in the built-up area of BIJB infrastructure, roads, also open land with sparse grass vegetation as illustrated by the vegetation index.

The next research results were the fuzzy logic process results carried out on the four results of the index class classification, which had been given their respective weights. The fuzzy value for the lowest value was 0.004 and the highest value is 0.927. To see how the distribution of fuzzy values was used in shades of gray where light colors and low fuzzy colors represented high fuzzy values are given dark colors. From the results, it was known that the distribution of membership of NDVI and RDVI values was almost the same. Meanwhile, the distribution of SR and LAI was different where the membership which had a lower weight was wider distributed in areas especially non-vegetation such as infrastructure and open land.

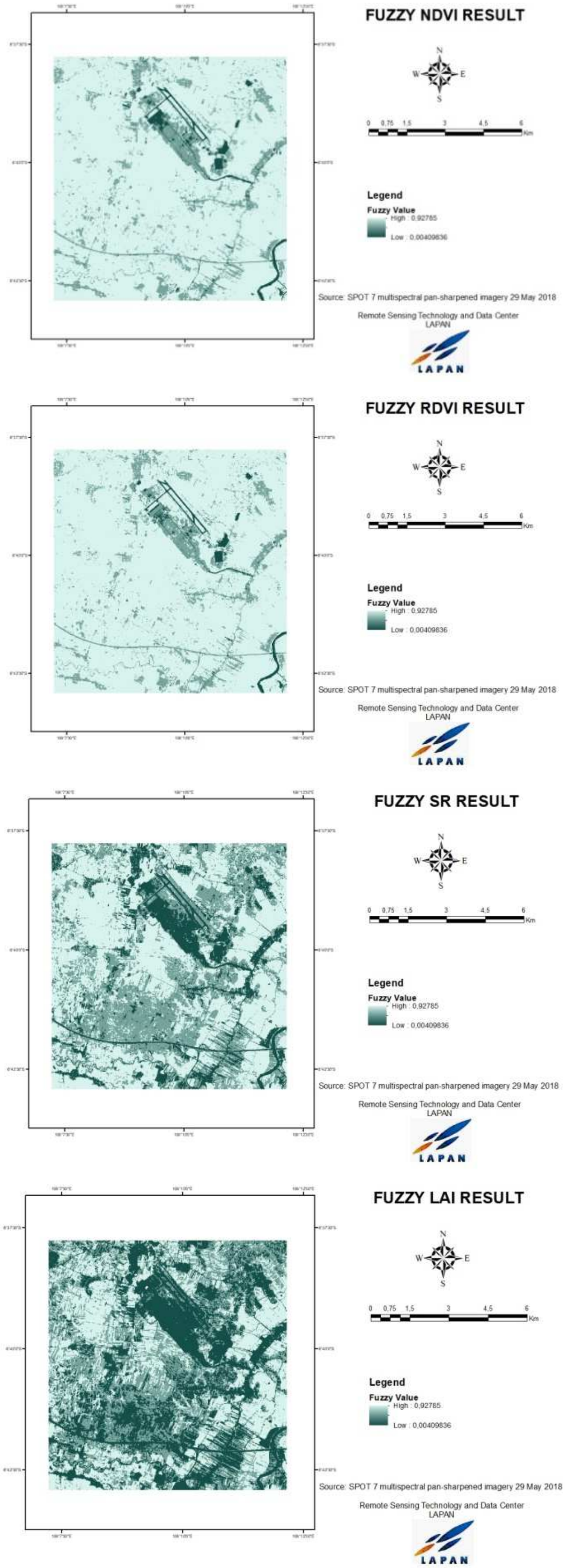

Fig. 7 Fuzzy logic result

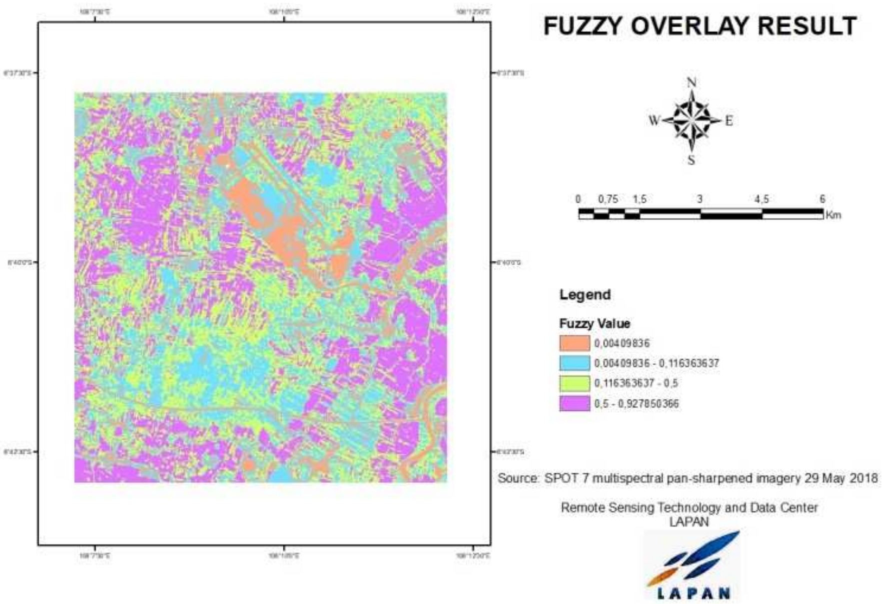

Fig. 8 Overlay result of NDVI, RDVI, SR and LAI

The last result was the result of fuzzy overlay conducted on the four NDVI, RDVI, SR and LAI indices that had been processed fuzzy before. These results showed how the study area's level of vegetation quality was seen from the four indices. The lowest vegetation quality was represented by the fuzzy value of 0.004 salmon color in the BIJB infrastructure area, then the medium quality was depicted in light blue and light green that spread on the vegetation cover that was not tight in the study area. Furthermore, the light purple color with fuzzy values of 0.5 to 0.928 indicated areas with high vegetation quality in the paddy fields and mixed gardens with high vegetation greenness and high vegetation density.

Based on the results obtained, it can be determined how the appropriate treatment of urban vegetation in the study area. This can be in the form of maintaining vegetation in green spaces, adding urban green spaces to areas where vegetation is still sparse. Thus, a sustainable urban environment can be realized.

IV. Conclusions

Based on research conducted in the study area, it was known that the classification of urban vegetation quality can be done by using vegetation index NDVI, SR and RDVI as well as LAI extracted from SPOT 7 data using fuzzy logic algorithm. Based on the four variables' overlay, the highest quality vegetation results were shown with fuzzy values of 0.5 to 0.928 and the lowest quality had a fuzzy value of 0.004. The highest quality of vegetation was in paddy fields and mixed gardens with high greenness and vegetation density, while the lowest quality of vegetation was in open land with grass plantation. Thus, it can be determined how the appropriate treatment of urban vegetation in the study area.

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