Urban tree analysis using unmanned aerial vehicle (uav) images and object-based classification (case study: university of indonesia campus)

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Abstract. This paper aims to analyze the urban trees located in University of Indonesia campus using UAV image and Object-based Image Analysis (OBIA). Herein, DJI Phantom 4 Pro was flown at 90 meter height to take image above the study area with spatial resolution of 2.4 cm/pixel. The image from UAV then processed using Agisoft Photoscan and underwent geometric correction. The image containing red, green and blue (RGB) bands then segmented with multi-resolution algorithm. Four Vegetation Indices (VIs) namely Normalized Green-red Difference Index (NGRDI), Visible Atmospherically Resistant Index (VARI), Visible-band Difference Vegetation Index (VDVI) and Red-Green Ratio Index (RGRI) were used to develop rules for land use land cover (LULC) classification. Vegetation class was separated from LULC image to be further analysed with ArcGIS using information from ground truth observation. Final product is urban tree map containing tree names and LULC classes.

1. Introduction
Object-based Image Analysis (OBIA) has been applied in many topics related to urban tree analysis, like monitoring urban tree cover for urban ecosystems [1]. With the growing use of unmanned aerial vehicle (UAV) which produce very high resolution image, OBIA can be incorporated to classify image from UAV by modifying its shape and compactness homogeneity with multi-resolution segmentation.

In addition, trees located in urban environment are important to be analyzed because each tree has its own spatial characteristics such as trees locations and grouping behaviour. This information of urban trees are very useful for landscaping manager to decide maintenance operational and schedule. Since tree images can be captured by UAV with rapidly and high resolution, therefore the use of UAV will be an advantage. Furthermore, UAV image contains red, green and blue (RGB) bands which can be computed into various vegetation indices (VIs) [2]. As a large campus, University of Indonesia Campus has many tree species which are needed to be analyzed to give information for the stakeholders. However, ordinary surveying method might not provide the information of tree canopy extent which is vital for analysis. On the other hand, UAV covers the canopy surface with high resolution. Therefore, this paper aims to analyse trees located in selected site of University of Indonesia campus using UAV image and OBIA.
1.1 The study area
Located within University of Indonesia campus, Faculty of Mathematics and Natural Science (FMIPA) building complex has an area of approximately 5.35 hectares (Figure 1). In this case, as a part of FMIPA building complex, the Department of Geography is selected as study location for this paper.

![Study area](source)

**Figure 1. Study area**

2. Methods
Overall research framework can be seen in Figure 2. Firstly, UAV was flown at 90 m height to cover the study area. Secondly, image from UAV was processed using Argisoft software to generate image containing red, green, and blue (RGB) bands. Geometric correction within ArcGIS was performed for acquired UAV image using Google Earth image served as ground truth coordinates. Geo-referenced RGB image then input into eCognition software to be classified using combined OBIA and rule sets development. Resulted classification then exported into vector layer to be further

![Research framework](source)

**Figure 2. Research framework**

Geo-referenced RGB image then input into eCognition software to be classified using combined OBIA and rule sets development. Resulted classification then exported into vector layer to be further
separated into single vegetation land cover. Trees identification resulted from ground truth observation then input into vegetation land cover spatial attribute. The final product is the urban tree map containing land use classes and trees names.

2.1. Object-based image classification
In this paper, 4 vegetation indices (VIs) were used to perform OBIA classification namely; Visible-band Difference Vegetation Index (VDVI), Visible Atmospherically Resistant Index (VARI), Normalized Green-red Difference Index (NGRDI), and Red-Green Ratio Index (RGRI). Previously, these 4 VIs gave the good results when used to classify flower coverage area of oilseed rape [3]. These 4 VIs were computed from digital number (DN) values in each of red, green and blue (RGB) bands resulted from UAV image capturing operation. The formula of each VI can be observed in Table 1.

| Vegetation Indice                  | Formula                                      |
|------------------------------------|----------------------------------------------|
| Visible-band Difference Vegetation Index (VDVI) | \(\frac{2(G-R-B)}{2(G+R+B)}\)                  |
| Visible Atmospherically Resistant Index (VARI) | \(\frac{G-R}{G+R-B}\)                        |
| Normalized Green-red Difference Index (NGRDI) | \(\frac{G-R}{G+B}\)                         |
| Red-Green Ratio Index (RGRI)       | \(\frac{R}{G}\)                              |

When input into eCognition software, values of these VIs were estimated based on its characteristics in pixel-level after multi-resolution segmentation operation. VIs were derived from arithmetic function computation in feature image display menu of eCognition software. The next process is to run assign class for each classification using input of estimated VIs and RGB bands (Table 2) [5-7]. For LULC classification, shadow was integrated with pavement to form a new pavement class.

| Classification | VIs  | RGB bands |
|----------------|------|-----------|
|                | VDVI | VARI      | NGRDI | RGRI | Red (mean) | Green (mean) |
| Trees          | ≥ 0.09 | ≤ 0       | ≤ 0.03 | ≥ 0.83 | -             | -             |
| Lawn           | ≥ 0.05 | -         | ≤ 0.012 | -    | -             | -             |
| Shadow         | -     | -         | -     | -    | ≤ 150        | ≤ 160         |
| Pavement       | -     | -         | -     | -    | ≥ 180        | ≥ 170         |
| Building       | -     | ≤ 0       | ≤ -0.089 | -    | -             | -             |

2.2. Accuracy assessment
This study used \(K\) or Kappa estimation [4] for accuracy assessment, which can be written as follows:

\[
\hat{K} = \frac{\sum_{i=1}^{r}(X_{ii} - \sum_{c} \sum_{r}C_{c}R_{r})}{N^2 - \sum_{i=1}^{r}(\sum_{c} \sum_{r}C_{c}R_{r})}
\]

where \(r = \) number of rows and columns in the error matrix, \(X_{ii} = \) number of observations in row \(i\) and column \(i\), \(\sum_{c} = \) marginal total of column \(i\), \(\sum_{r} = \) marginal total of row \(i\), \(N = \) total number of observations. Higher value of \(K\) indicates high agreement between expected and observed LULC classes. Furthermore,
minimum sample size for accuracy assessment in this study is 204 points with expected accuracy is 85% and 15% allowable errors [4].

2.3. Urban tree analysis
In order to detect species of urban tree within the study area, classified image from eCognition was convert into vector layer. This layer was separated into land use classes and vegetation land cover. The vegetation land cover then adjusted to true interpretation from ground observation by changing the class name in the spatial attribute using ArcGIS software. The final vector map displays urban tree locations altogether with other land use classes.

3. Results and Discussion
LULC classification based on combined OBIA and rule sets is shown in Figure 3. Using Equation (1), it was computed that $K = 0.87$. Higher $K$ value indicates higher agreement between classified image and reference data, in other words used algorithm of OBIA and rule sets were quite good to classify LULC from UAV image. Visually, it can be observed in Figure 3 that group of trees displayed in dark green located in the edges of parking area and along the road shown in grey color.

Urban tree map is successfully generated from UAV image containing tree names and LULC classes (Figure 4). This map is mainly resulted from developed rule sets from VIs, RGB channels and ground truth observation. It can be observed from Figure 4 that some tree canopies are not fully belong to one tree species but rather mixed.
In addition, a mixed canopy can be detected in UAV image where 2 trees with almost similar height located closely (Figure 5a). This can be the advantage of OBIA technique where multi-resolution segmentation method can detect different canopy tree based on their shape. Moreover, it can be observed from Figure 5 (b) that a small yellow palm tree is covered underneath a bigger tree. Therefore, for urban tree mapping, UAV can only detect the top tree canopy but for lower canopy tree cannot be captured by UAV. In this kind of mixed trees situation, a detail survey of tree locations is needed a part from UAV operation.

Figure 4. Urban tree map

Figure 5. (a) mixed tree canopy, (b) a smaller tree is under larger tree canopies
4. Conclusion

Urban tree map has been successfully generated from UAV image using OBIA with rule sets development of VIs, RGB channels and ground truth observation. Together with building and paving land use classification, urban tree map displays information about tree names and locations which can be useful for building or landscaping manager to maintain those trees.

It can be concluded that VIs and RGB bands from UAV image can be used for rule sets development in OBIA to generate LULC classification. Furthermore, to generate urban tree map from UAV image and OBIA, additional ground truth survey is needed. However, it is crucial to note that for smaller trees located under big tree canopy, a detail ground truth survey should be performed to add more spatial information of those trees.

References

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