Urban slum identification in Bogor Tengah Sub-District, Bogor City using Unmanned Aerial Vehicle (UAV) Images and Object-Based Image Analysis

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Abstract. Urban Slum settlements continue to occur as one of the impacts of urbanization so that it becomes one of the main problems and focuses on city planners. Planning and structuring slum settlements require an up-to-date base map as an accurate source that describes the slum's local situation of the slum. Unmanned Aerial Vehicle (UAV) can provide it. This study used UAV to extract physical characteristics of urban slum settlements located in the Cibogor area within the Bogor Tengah sub-district near Cibalok River banks Bogor-Jakarta railways. The point dense cloud process performed to extract elevation consists of Digital Terrain Model (DTM) and Digital Surface Model (DSM). Both elevations were used to generate normalized DSM (nDSM) and integrated with Multi-Resolution Segmentation (MRS) to provide the first classification stage. RGB indexes are computed to provide the second classification stage from the images. Physical characteristics were successfully identified to classify slum settlements and distinguish from formal settlements. The resulted map from OBIA has shown valuable spatial information of slum area to support Development Goals (SDGs), precisely at point 11 regarding Sustainable Cities and Communities, to improve the quality of slum settlements.

1. Introduction

The phenomenon of urbanization occurs everywhere, especially in developing countries. Urbanization is a process of changing the social order and transforming the landscape of a city. However, urbanization is always followed by the growth of slum settlements [1]. An increase follows rapid urbanization in the urban population associated with housing problems, causing urban residents to live in slum areas, which is an early stage, and a significant contributor to the slum settlements increase and spread [2]. Slum household lacking any of the following five indicators: secure tenure, access to safe water, access to sanitation, a sufficient living area, and durability of housing [3]; it refers to the building structure permanency such as walls, roof material, and floor [4].

Slum settlements are one of the main focuses for planners; this is evidenced by the stipulation of one of the 2030 Sustainable Development Goals (SDGs), precisely at point 11 regarding Sustainable Cities and Communities to improve the quality of slum settlements. Planning and structuring slum settlements require a reference in the form of an up-to-date base map as an accurate source that describes the slum's local situation of the slum [5]. To produce this base map, remote sensing data can be a valuable source, especially in representing the physical characteristics of slum areas [6]. Remote sensing is used to detect, identify, and monitor slum settlements both in space and time and enable a better understanding of the
physical manifestations of slums [7]. Unmanned Aerial Vehicle (UAV) is becoming increasingly popular in mapping. Because of their very high resolution and limited flight time, UAVs are generally most suitable for small and local areas or specific locations such as a slum improvement project [8]. Aerial photo data is included in a very high-resolution image with a spatial resolution of fewer than 0.5 meters to be applied to map areas at a scale of 1: 500 - 1: 5,000[9].

The availability of very high-resolution satellite imagery (VHR) allows a greater focus on object-based image analysis, or OBIA [10]. This object-based analysis is carried out in two stages. First, image segmentation, which segment images based on their contextual properties. Including spatial and spectral properties into homogeneous objects and classification of identified objects into many categories of land use and land cover [11]. The ability to extract objects and view their relationships can offer invaluable information to study slum settlements, with limitations mainly related to these settlements' excessive heterogeneity. The use of high-resolution imagery such as UAV and object-based or object-oriented analysis in slum settlement studies used to identify the presence of slum settlement [12], slum settlement indicators mapping [13] and identify slum settlements changes.

Slum settlement studies based on remote sensing can also identify the physical characteristics of slum settlements [7]. Physical characteristics of slum settlements can be defined through three levels of the ontology of slum settlements, namely at the level of object, settlement, and environment [14]. At the object level, the information generated through building characteristics and accessibility, at the settlement level, building density and settlement shape, and finally, the characteristics of the environment in the form of proximity to public green, proximity to blue spaces, and proximity to hazardous areas.

This study aims to identify the physical characteristics of slum settlements using UAVs and object-based analysis and see the difference with formal settlements. The research was conducted in Bogor City, precisely in Central Bogor District, one of the areas included in the KOTAKU program and the National Slum Upgrading Program (NSUP). The research results are expected to provide information on slum settlements on a local scale and produce a basic map that can help plan and fix slum settlement problems to create sustainable cities and communities.

2. **Method**

2.1. **Study Area**

Central Bogor Sub-district is the center of Bogor City, the center of office/government activities supported by trade and service activities, settlements, and tourism. Central Bogor District is a sub-district with the smallest area: 8.13 km2 or about 7% of the Bogor City area but has the highest population density level [15]. Central Bogor District is flowed by two large rivers, Ciwung in the middle of the city and Cisadane as the boundary with the West Bogor sub-district.

2.2. **Data collection**

The research data analyzed in this study was taken from 165 m x 164 m, located in Cibogor, Bogor Tengah Sub-district. The test area's location is adjacent to Ciwaringin, Bogor Tengah subdistrict, and is traversed by rivers and railroads. Data was taken on September 19, 2020, using DJI Phantom 4 Pro with Overlap (Sidelap-front lap) 40-80%, at an altitude of up to 90m, and a flight speed 9m / s – 10 m / s. The UAV data was processed using Agisoft software to generate an image containing red, green, blue (RGB), mosaic processing, and elevation extraction. Object-based image analysis was performed using eCognition 9.1 software, while the final stage of map-making and refinement was carried out using ArcGIS 10.1.
2.3. Elevation extraction
Extraction of elevation done by carrying out the Dense Point Clouds build process to build a collection of high points in the number of thousands to millions resulting from photogrammetric processing of aerial photographs. DEM build process with dense cloud data source parameters is carried out to extract the Digital Surface Model (DSM). Meanwhile, in the Digital Terrain Model (DTM) extraction, point classify is necessary to determine the object's point to be processed in the height extraction. In DTM extraction, the extracted high point is the high ground point as the terrain height. The DSM and DTM in the raster form will be used as additional layers when performing object-based analysis.

2.4. Object-based Image Analysis

2.4.1. Image Segmentation. Many methods can be used in the segmentation process, such as multi-resolution, chessboard, contrast split, quadtree, multi-threshold, spectral difference, and contrast filter [16]. In this study, multi-resolution segmentation (MRS) was used. MRS is one of the most frequently used segmentations. In urban research, MRS has been shown to provide excellent accuracy. As in the research of Kavzoglu and Tonbul [17], MRS, compared to other methods, has an accuracy of up to 90.1%. Similar research has conducted by Shukla and Jain, who tried to extract buildings and other land uses and produced a correctness value of 96% [18]. The segmentation process's main purpose is to delineate similar objects in an analyzed image to minimize the image's heterogeneity. Segmentation uses parameters like scale, shape, size, texture, etc. In the eCognition software, the segmentation process is obtained using additional parameters such as scale, shape, compactness, and weight of layers. In this study the parameters used are SP = 50 shape = 0.7 compactness = 0.5. With this parameter, objects are segmented properly according to their object class.
2.4.2. Object classification. After the segmentation process is completed, the second step is classification. In this step, objects were classified into specific classes. Classifying, the subjects in this study were carried out using the rule-based classification using the eCognition software. This study's ruleset is divided into two stages; the first is to create an elevation class, namely objects with elevation and no elevation using the Normalized Digital Surface Model. The second stage is to classify objects in a specific class using several indexes Table 1.

Table 1. The index used in the study.

| Indice                               | Formula                                      | References |
|--------------------------------------|----------------------------------------------|------------|
| Normalized Digital Surface Model (nDSM) | DSM - DTM                                    | [18]       |
| Brightness Index (BI)                | $\frac{1}{n} \sum_{i=1}^{n} c_i$            | [19]       |
| Average Band Ratio (ABR)             | $\frac{Red + Blue + Green}{3}$               | [20]       |
| Excess Vegetation Index (EVI)        | $(2 \times Green) - Blue - Red$              | [21]       |
| Green Leaf Index (GLI)               | $\frac{(2 \times Green) - Blue - Red}{(2 \times Green) + Blue + Red}$ | [22] |
| Green Band Ratio (GBR)               | $\frac{Green}{Blue + Green + Red}$           | [20]       |

Normalized Digital Surface Model (nDSM) is used to separate ground objects and estimate an object's height. [18] The brightness Index is used to define the shadow. Besides, the shadow can also be defined using the Average Band Ratio (ABR) [20]. The Excess Vegetation Index (EVI) serves to outline objects in the form of vegetation, such as trees and grass. In this research, EVI is also used to define other objects using the object's color representation. EVI is used to distinguish the color of the roof of a building, which can indicate the difference between the roofing material. Usually, slums have a
composition of houses dominated by zinc roofing materials. Green Leaf Index (GLI) can define a brown roof, which indicates a roof made from clay. In object classification, it is necessary to add a threshold to define the range of values for every index for each object. In Table 2, the parameters and threshold values used in this study are presented. In the classification stage, ground objects are classified first, then buildings with different roof colors are classified. The classification results are then exported and refined using ArcGIS software so that all objects are formed.

Table 2. The parameter used in rule-set developed.

| Class                  | Parameter  | Class          | Parameter |
|------------------------|------------|----------------|-----------|
| Ground Object/         | nDSM < 1   | Big Trees      | nDSM > 2 m|
| Road/ Railway (Not     | EVI ≥ 25   |                |           |
| Elevated Object)      |            |                |           |
| Brown Roof            | -30 < EVI ≤ -10 | Small Trees | 1 ≤ nDSM < 2|
|                        | -0.08 < GLI ≤ -0.06 |            | EVI ≥ 25  |
| Purple Roof           | EVI ≤ -30  | Lawn / Grass   | nDSM < 1  |
| Grey Roof             | 0.31 ≤ GBR ≤ 0.36 | Shadow      | EVI ≥ 25  |
| White Roof            | 0.31 ≤ GBR ≤ 0.36 |            | ABR < 43  |
|                        | BI ≥ 235   |                | BI < 60   |

3. Results and discussion

3.1. Classification Result
The classification uses two stages: the elevation and RGB Index, which can extract objects into different classes. The initial classification using elevation can distinguish ground objects, buildings, and trees, making classification at the next stage using the RGB Index easier. The RGB index can extract differences in the appearance of the roof’s color, which, when examined further, can reveal the material from the roofs of the buildings. However, there is a weakness in the classification because it cannot extract the water body's color in the form of a stream that crosses the study area. So there is a need for manual adjustments to classify objects in the form of streams. The existence of the shadow classification provides information on the height difference to the object. In this study, OBIA produced several object classifications. Buildings with four different roof colors, including brown, purple, gray, and white roofs, with trees, small trees, lawn/grass, roads, and shadows Figure 3.

3.2. Physical Characteristics
From the classification results, the physical characteristics of slum settlements and their differences from formal settlements are visualized. In terms of building size, buildings in slum settlements have a smaller size than those informal settlements. The slum settlement is dominated by gray and purple roofs representing roofing materials (zinc and asbestos Figure 4). Meanwhile, formal settlements have a larger building size and have a compact and precise shape—formal Settlement dominated by brown roofs representing clay roofing materials. In the slum area, the access road is very narrow, almost invisible. This is because a road segment crosses a slum covered by the roof of a very dense house. Meanwhile, informal settlements, roads are visible, although the roads are not too broad in terms of size. The building patterns in slum settlements are also irregular and unorganized. While informal settlements, the house buildings are well-segmented following the road that crosses the settlement.
Figure 3. Classification results use nDSM and RGB Index.
Figure 4. The roof of the slum settlement of the OBIA and field observations. The Brown roof represents clay roof; the Purple roof represents a zinc roof, Gray Roof represents asbestos and the zinc roof.

| No. | Class                     | Range  |
|-----|---------------------------|--------|
| 1   | Not Elevated / Ground Object | <1 m   |
| 2   | Floor 1                   | 1 – 3.5 m |
| 3   | Floor 2                   | 3.5 – 7 m  |
| 4   | Floor 3                   | >7 m    |

The building height classification is obtained from the extraction of nDSM. Height is made into several classes [17] in Table 3. Based on this high-value range, it can be seen that slum settlements and formal settlements have houses with the same building height. Both have buildings with all three Building Height classes but have a different composition. Informal settlements more buildings are ranging in height from 3.5 - 7 m and > 7 m Fig 5. Meanwhile, the slum areas are dominated by buildings with a height of 1 - 3.5 m and 3.5 - 7 m Fig 5. Based on the results of field observations, building differences also lie in the building material structure. In slum settlements, there are tall houses, but the building materials are made of non-permanent materials Fig 5.
The slum sites in the study area are close to the river. The distance of the slum to the river is less than 15 meters. The slum settlements are in an area with the potential for flooding; despite their proximity to formal settlements, there is a clear difference between slum settlements and formal settlements in the study area.

4. Conclusion
A combination of UAV images and OBIA was a success in providing information on the physical characteristics of slum settlements and visualizing the differences between slum settlements and formal settlements. The resulted maps can represent the spatial conditions of the slum settlements in the study area. Indicators of physical characteristics that can differentiate well between slum settlements and formal settlements are road networks and house buildings' size. In addition to describing the conditions of accessibility in the two types of settlement, the road network can also describe the pattern and regularity of house buildings so that there are differences in regularity patterns between slums and formal settlements. The association of roof color showing the dominance of building roofs in settlements can also distinguish between slums and formal settlements. Several additional indicators are needed to obtain variations in the characterization of slum settlements and distinguish them from formal settlements so that the discussion of slum settlements' characteristics becomes more comprehensive and holistic.

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