

SEMI-AUTOMATED DELINEATION OF INFORMAL SETTLEMENT STRUCTURES FROM DRONE RGB IMAGERY USING OBJECT-BASED IMAGE ANALYSIS

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ABSTRACT:

With the problem of informal settlements in the Philippines, mapping such areas is the first step towards improvement. Object-based image analysis (OBIA) has been a powerful tool for mapping and feature extraction, especially for high-resolution datasets. In this study, an informal settlement area in UP Diliman, Quezon City was chosen to be the subject site, where individual informal settlement structures (ISS) were delineated and estimated using OBIA. With the help of photogrammetry and image enhancement techniques, derivatives such as elevation model and orthophotos were produced for easier interpretation. An initial rule-set was developed to remove all non-ISS features from the base image—utilizing spectral values and thematic layers as main classifiers. This classification technique yielded a 94% accuracy for non-ISS class, and 92% for the possible ISS class. Another rule-set was then developed to delineate individual ISS based on the texture and elevation model of the area, which paved the way for the estimation of ISS count. To test the robustness of the methodology developed, the estimation results were compared to the manual count obtained through an online survey form, and the classification and delineation results were assessed through overall and individual quality checks. The estimation yielded a relative accuracy of 60%, which came from the delineation rate of 63%. On the other hand, delineation accuracy was calculated through area-based and number-based measures, yielding 58% and 95%, respectively. Issues such as noisy elevation models and physical limitations of the area and survey done affected the accuracy of the results.

1. INTRODUCTION

Over the past few years, the increase and spread of informal settlements have been a problem in different countries, especially those developing ones that are engaging towards industrialization. Problems such as sub-standard sanitary situations and high crime rates are often related and can be seen around informal settlement communities (Hofmann, et al., 2008). In the Philippines, informal settlements in Metro Manila house approximately 2.7 million Filipinos (PSA, 2017) and approximately 15% of the total urban population in the Philippines (HUDCC, 2014); these are commonly located in areas where housing is not suitable. Because of these, loss of life due to disasters is common in areas where informal settlements are present. In these kinds of situations, modern technology proves to be helpful - as photogrammetry and remote sensing can aid in mapping and monitoring of these areas.

Informal settlements, as defined by the Glossary of Environment Statistics, are lands where structures exist despite lacking legal occupation rights. Areas where existing structures that do not follow planning and building regulations or standards are also considered to be informal settlements (GES, 1997). In the local setting, informal dwellers or “squatters” are people who live in informal settlements and were described by the Philippine Statistics Authority as those who occupy lands without any right, title, or permission of the owner (PSA, 2017).

Aerial surveys, on the other hand, is a rising methodology in the field of Geomatics due to its economic and technical advantages. Unmanned Aerial Vehicles (UAVs) are now taking the spotlight of aerial surveying. The use of GPS technology and high-resolution sensors attached in these UAVs makes it suitable for high accuracy surveying while limiting human intervention. UAV surveys are advantageous as they pose less risks, and give access to dangerous and restricted areas while providing

satisfactory accuracy at lower costs (T&A Surveys, 2019). Multiple outputs can be derived from the data acquired from above, such as orthomosaics, 3D-reconstructed models, and digital surface models in the form of point clouds and geo-tagged images. These data files contain useful information to differentiate individual informal settlement structures from each other through image analysis.

For a long period of time, pixel-based image analysis was the trend due to its wide array of applications. However, just recently, the concept of object-based image analysis (OBIA) - a great alternative to the traditional approach, was introduced. OBIA, as defined by Hay (2014), is a “sub-discipline of GIScience that is devoted to partitioning remote sensing imagery into meaningful objects”. In contrast to the old pixel-based approach which only looks into the spectral characteristics of every cell, OBIA also takes into consideration the other ‘neglected’ spatial information of a certain group of pixels, called objects, to identify and determine their respective classifications. These objects are grouped depending on a wide variety of external variables, such as time, shape and neighbourhood (Addink, 2010). In general, OBIA has two major parts; segmentation and classification. The former groups the pixels into homogenous objects while the latter uses the available information to classify the objects.

1.1 Scope and Limitation

This study is limited only to RGB aerial images, gathered using an unmanned aerial vehicle and derivatives as the inputs for classification.

For the sake of this research, informal settlement structures (ISS) will be the main focus of analysis. ISS can be defined as any distinguishable structure either from a formal or informal settlement area and those with slum-like characteristics such as

small size in terms of area, irregular in shape and orientation, and varying roof materials. In this research, it is also assumed that a single roof corresponds only to a single informal settlement structure.

All the developed parameters, methodology, and definition are only applicable to the Philippine context of informal settlements. Moreover, these parameters, especially the threshold values, are adaptive and flexible depending on the area on which the methodology will be applied.

2. RELATED LITERATURE

2.1 Applications of OBIA in Delineation and Extraction

Object-based image analysis can be used in the field of Geomatics, especially in aerial photogrammetry and remote sensing. The use of Unmanned Aerial Vehicles (UAV) images has been one of the reasons why there is an increase in the spatial resolution of images, aside from the ever improving camera development. Based on the study by Mason and Baltsavias, the quality of the image is a big factor affecting the accuracy of the analysis. Mason, et al. (1997) noted that the detection of informal settlements, shacks, and slums are included in the applications of imagery and image analysis. Images with finer resolutions can easily detect facilities while colored images and shadows are needed for a more accurate interpretation. These characteristics of aerial imagery will be taken into consideration in this research for optimal results. Two-dimensional and three-dimensional outputs can be obtained from surveys done using UAVs, which include DSM, orthomosaics, 3D features, and many more. In a study done by Gevaert et al. in 2016, where their subject area is an unplanned settlement in Kigali, Rwanda, they created an algorithm that will classify the image of the subject area, then extracted structure models from it. These features were grouped into two and then were classified again, where a higher overall accuracy of classification was obtained for the unplanned settlements. Their research showed that integrating these multi-dimensional factors are very important in feature isolation and can definitely help in solving the challenging scenes where fundamental building algorithms do not hold.

2.2 Informal Settlement Delineation using OBIA

For the delineation of urban spaces, there is a greater degree of complexity since the features present have different shapes, sizes, materials, and characteristics depending on what type of structure it is. In object-based analysis, parameters, which include these spectral signatures, must be set depending on the feature or land use being classified. In this case, slums and informal settlements need to be delineated individually so their defining characteristics and variables must be known first, and it is location dependent. (Asmat et al., 2011)

In the research done by Kohli et al. (2012) where they proposed the concept of slum ontology, they divided it into three levels; environs, settlement, and object. These ontologies can be the basis of parameters to be used in this study, as it can be adapted locally with minimal modification. In the study conducted by Fallatah et al. in 2018, they used the following parameters for classifying informal settlements; dwelling size, vegetation, lacunarity of housing structures, road segment type and materials, text measures, road accessibility, consistency of housing orientation, dwelling shape, building density, proximity to hazards, geomorphology of terrain, and proximity to the city center and social services. To classify informal settlements individually, they used the following parameters; Multi-spectral

bands (RGB and Infrared), border index, standard deviation, brightness, relative border, asymmetry, roundness, and compactness. These parameters can be used or followed in this research and can be combined with other variables for optimal results. Also, to help in the delineation of the slums in an area, we can combine texture to further improve the classification accuracy and further differentiate slums to other similar objects (Rhinane, et al., 2011).

2.3 Optimum Parameters for Informal Settlement Delineation

There are multiple ways to identify individual structures from informal settlements such as through DSM models - which are digital orthoimages and digital elevation models both with different resolutions (Ioannidis et al., 2009). The use of RGB-based images from UAVs can also be used to produce orthoimages, elevation models, and point clouds, which are useful in extracting features' heights using top-hat filter algorithms (Gevaert et al., 2017). To further classify the individual structures Ribeiro et al. (2019) used Airborne Laser Scanning (ALS) to obtain point data of the area, due to the fact that the ground is almost invisible from above's perspective. Using 2.5D, the reconstruction of buildings using a minimal number of Z (elevation) values can be used to know the properties of the buildings such as vertices, breaklines, and segments to know the connection of the buildings. (Ribeiro et al., 2019).

The usage of objects in OBIA instead of pixel values reduces the salt and pepper effect of the images on classification. More information after segmentation can be formed such as texture, shape, and context that can help in the classification. Multi-resolution segmentation in eCognition is one of the successful segmentation algorithms used for object-based image analysis. Parameters are needed to be set for segmentation and multi-resolution segmentation uses three main parameters which are scale, shape, and compactness that affect the performance of the algorithm (Aguilar et al., 2016).

In identifying the informal structures on an image, other features seen on the map must also be classified. Vegetation is a common feature that can be found along with residential structures. A study conducted by Woebbecke et al. (1995) the excess green produced a near-binary intensity image in which these identified the boundaries of the vegetation in interest. The use of NDVI (Normalized Difference Vegetation Index), Excess Green, which the formula is located below, and a modified hue image was used to identify the soil and vegetation in an image using only R, G, and B bands. (Woebbecke et al., 1995)

$$2 \left(\frac{Green}{Red + Green + Blue} \right) - \left(\frac{Green}{Red + Green + Blue} \right) - \left(\frac{Green}{Red + Green + Blue} \right)$$

2.4 Image Enhancement Techniques for Informal Settlement Delineation

Texture is one of the properties that can be extracted using the different bands available in an image. Gray Level Co-occurrence matrix is one of the texture extraction algorithms that uses co-occurrence matrices in which the gray level spatial dependency in a two-dimensional image is described (Lam and Stephen, 1996). Gray Level Co-occurrence matrix uses the spatial relationship of pixels to create texture and it is computed by how frequently a gray-level intensity value appears in an area where there is a spatial relationship based on the pixels near it.

Statistical properties can be derived using the produced GLCM such as contrast, correlation, and homogeneity. Contrast which focuses on the local variations, correlation in which the specified pixel pairs' joint probability occurrence can be measured, and homogeneity in which the closeness of the GLCM elements' distribution to the GLCM diagonal are measured (Lursinap et al., 2013).

There are other color features that can be extracted from R,G,B components of an image. Hue, saturation, and intensity are one examples that can be used for segmentation of colored images. Intensity shows the average gray level while hue shows the color feature which is relatively less affected by the shadows made by the light source and lastly, saturation displays the degree of purity of the hue (Carron et al, 1994).

Other factors such as height which can be created using the nDSM can be created using the difference of the DSM and the DTM. Vegetation must be classified to remove non-building structures in the image. The Normalized Difference Vegetation Index and the Near Infra-Red Ratio can be used to classify the vegetation features on the map. Multi resolution segmentation was used in the segmentation process with parameters 0.1, 0.5 and 20 for the shape, compactness and scale parameters, respectively. Overall, the IHS color system was used to define the edges or boundaries of the building while the nDSM was used to further enhance the classification of only using spectral images. This methodology was successful in building detection (Jabari et al, 2014).

In a study conducted by Chamundeeswari et al. (2009), unsupervised classification of SAR images were done with the help of PCA (Principal Component Analysis) of texture measures. According to the study presented by Chamundeeswari et al. (2009), variance is the best textural measure to be used in extracting the edges and boundaries of buildings as well as identifying heterogeneous areas.

Another way for building extraction is by using region properties which was shown in the study conducted by Aburaed et al.(2018). The first step in their study is image enhancement and edge detection to identify the edge and boundaries of the buildings in an area. According to the study, buildings cover a large area therefore you can use this as a basis to identify the buildings in the image. Setting a threshold value was used to identify other buildings since they may vary in shape and sizes. (Aburaed et al., 2012)

3. METHODOLOGY

3.1 Study Site

The chosen site for this study is the residential area of Villages A and B in UP Diliman, Quezon City. The area is a combination of formal and informal settlements, with self-built houses and structures popping out after the original formal settlement area. Despite the subject area being not officially declared as an informal settlement area, most structures existing display slum-like characteristics that can be seen in a typical Filipino informal settlement area.

3.2 Methodology

Figure 2 shows the step-by-step procedures in delineating informal settlement structures (ISS) from the UAV-based RGB images. Input layers were created through GIS and photogrammetric software, as well as the derivative layers. The

semi-automated delineation and classification were all done in eCognition, a software for object-based image analysis, using its process tree to set threshold and parameter values and perform iterative processes.

General Methodology of the Research

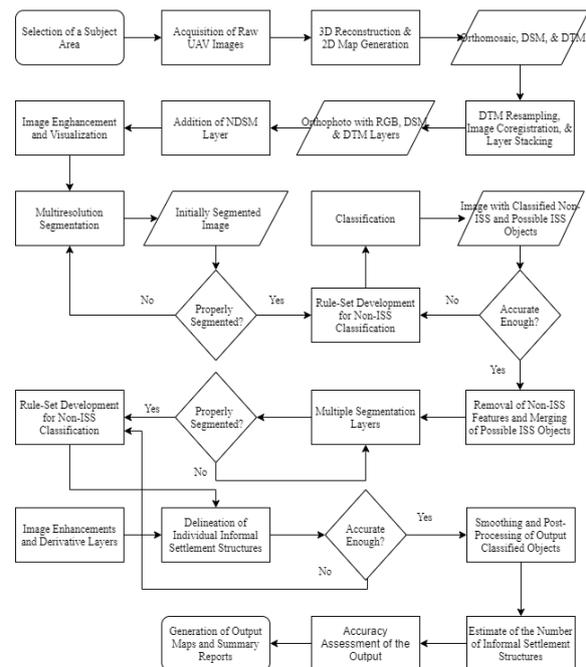


Figure 1. Flowchart of the methodology.

The aerial survey of the area was done on April 30, 2016 using a Sensefly eBee equipped with a Sony DSC-WX220 camera with RGB sensors. A total of 205 geo-tagged aerial images were taken, with each image having a size of 4896 x 3672 pixels.

3.3 Layer Generation from Drone RGB Images

The aerial images of the site were processed in Agisoft Metashape, where the orthophoto, DSM, and DTM of the site were exported. Two normalized DSM (nDSM) of the site were generated; one using basic raster calculation in eCognition similar to the methodology used by Sefercik, et al. in 2014, and the other using WhiteBoxTool's RemoveObjectsOffTerrain tool. A layer that highlights the edges shown in the orthomosaic was also created using the Canny Edge Extraction tool.

Image enhancement techniques like Gray-Level Co-Occurrence Matrix (GLCM), Canny-Edge Extraction, and Principal Component Analysis (PCA) were used to further extract information from the RGB and elevation-based layers. ENVI's GLCM tool was used to generate different texture layers of the images using different variables of the GLCM tool. Covariance, dissimilarity, homogeneity, contrast, and entropy GLCMs were applied on Red, Green, Blue, and DSM layers. The principal components of all layers were computed using the covariance matrix, and the normalization of the same layers were performed using the correlation matrix. The layers that showed useful results are the following: red (R), green (G), blue (B), DSM, variance GLCM's RGB bands, contrast GLCM's RGB bands, and homogeneity GLCM's RGB bands. The principal components of red (R), green (G), blue (B), and DSM layers were also computed separately using the same tool in ENVI.



Figure 2. Orthophoto (left) and nDSM (right) of the site.

The following are all of the image layers used in the process:

1. RGB image layer (3)
2. DSM (1)
3. PCA Correlation (5)
4. PCA Covariance (5)
5. Canny Edge Extraction (1)
6. nDSM (1)
7. HSV (3)

3.4 Removal of Non-ISS Features

The first developed rule-set, as seen in the figure above, removed all non-informal settlement structure (non-ISS) features from the base image; utilizing spectral values and thematic layers as main classifiers.

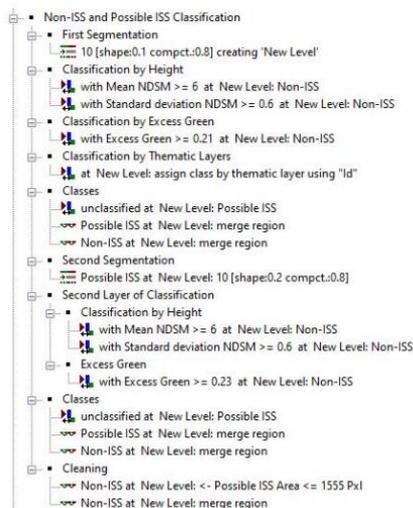


Figure 3. Detailed non-ISS removal rule-set.

The default input layers are the red (R), green (G), blue (B), and DSM bands of the image, while all the texture layers created in ENVI were also included. A thematic layer was also included in the form of a vector file, which is the feature delineation of all roads that can be seen in the image. Using the multiresolution segmentation algorithm, image objects were created. The image layers used in this segmentation were NDSM, R, G, and B bands with all the weight set to 1. Parameter values were set to 0.1, 0.8 and 10 for the shape, compactness, and scale parameter, respectively. A second set of segmentation and classification was done to further improve the accuracy of the resulting classes.

The next step after segmentation was the classification which was divided into three parts; the first one is the classification of height which uses the NDSM layers, the second is the usage of the Excess Green parameter, and last is the thematic layer overlay to take account of the roads. To further classify the Non-ISS objects, a second layer of classification was used but it just followed the procedures in the first classification, with minimal threshold and parameter values adjustments.

The final parameters considered for the individual delineation were the following:

1. nDSM mean greater than or equal to 6
2. Excess Green greater than or equal to 0.21 and 0.23
3. Standard deviation of nDSM greater than or equal to 0.6

3.5 Delineation of Individual ISS Features

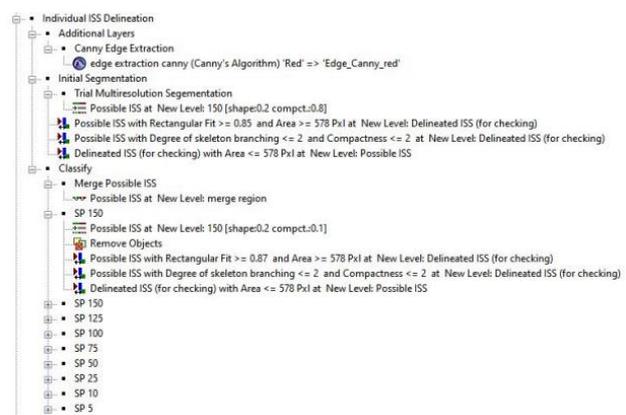


Figure 4. Detailed ISS delineation rule-set.

After segregating the site to Non-ISS and Possible ISS zones, the latter underwent multiresolution segmentation first on an image object level, using all the texture layers and enhanced images created in the previous processes. The initial scale parameter was set to 150 to produce larger objects, and the resulting objects were classified under modified parameters which include rectangular fit, compactness, area, and degree of skeleton branching. The rectangular fit threshold was set to 0.8, the area threshold was set to 578 pixels or 5 sqm., while both the compactness and degree of skeleton branching threshold were set to 2. All segmented objects that satisfied all the said parameters were assigned to the ISS class. The segmentation and delineation process were done iteratively, until satisfactory results were obtained. The scale parameter was changed every iteration, starting from the value of 150 which produced larger objects, down to the value of 5 that provided more coarse objects. After every iteration, the possible ISS class was reduced as the objects that were already correctly delineated were assigned to a different class in the project. The layers used for the segmentation are the Canny Edge Extraction layer, PCA layers, Saturation layer and GLCM texture layers. The repetition of the process was stopped when the most satisfactory results from the present dataset were obtained. The detailed rule-set and iteration of the delineation can be seen in the figure below.

The final parameters considered for the individual delineation were the following:

1. Area greater than or equal to 578 pxl
2. Rectangular Fit greater than or equal to 0.85
3. Compactness less than or equal to 2

4. Degree of Skeleton Branching less than or equal to 2

Before extraction of the delineated ISS features, the classified objects were subjected to checking first. A combination of manual checking and automated checking via a rule-set was done, which removed erroneously classified objects from the ISS class. The remaining objects then were modified using several vector layer operations in eCognition such as vector smoothing, vector simplification, and vector orthogonalization. The parameters for each operation were adjusted to avoid oversimplification of the feature delineation.

3.6 Accuracy Assessment

Since ground truth data is not available because of the COVID-19 pandemic, the researchers opted to go with results validation through relative accuracy and statistical analyses. Accuracy assessment of the delineation was done on two levels - individual level and general level.

For the general level accuracy assessment, the total area of classified ISS features is computed and compared to the manually digitized classification for validation. This validation is verified and approved by people who are living or familiar with the study area. This kind of validation was also used for the accuracy assessment of non-ISS and possible ISS classification in the methodology.

Accuracy Measure		Adapted Formula	where:
Number-based	Accuracy	$\frac{\# \text{ of } TP_{\text{Sample}}}{\# \text{ of } Total_{\text{Sample}}}$	TP - True Positive
Feature Similarity-based	Similarity	$\frac{\min(X_{SA}, X_M)}{\max(X_{SA}, X_M)}$	X - Selected Feature (ic. Area, Radius)
	Improved Similarity	$1 - \frac{ X_{SA} - X_M }{\min(X_{SA}, X_M)}$	
	Comprehensive Similarity	$\frac{X(SA \cap M)}{X(SA \cap M) + X(SA - M) + X(M - SA)}$	M - Manual
Area-based	Completeness	$\frac{Area_{\text{correctly delineated}}}{Area_{\text{possible ISS}}}$	-
	Correctness	$\frac{Area_{\text{correctly delineated}}}{Area_{\text{delineated ISS}}}$	
	Quality	$\frac{Area_{\text{correctly delineated}}}{Area_{\text{correctly delineated}} + Area_{\text{possible ISS}} + Area_{\text{delineated ISS}}}$	

Table 1. Summary of accuracy measures adapted for the study.

For the individual level of accuracy assessment, 10% of the total delineated objects was used as the sample set. The relative accuracy was obtained through comparing randomly selected output objects with its manually delineated counterparts. A total of 10% of the automatically delineated ISS objects were taken as samples and became the basis for the entire population. The same set was used in checking the completeness and correctness of each delineated feature. This same sample set was used in counting false positives (FP) and true positives (TP) from the delineated features, to somehow generalize the overall accuracy of the delineation process. Three accuracy measures from the study of Cai et al. in 2018 were also used in the samples and overall accuracy, namely: number-based, feature similarity-based and area-based accuracy. The number-based accuracy measure is good for checking the estimation of ISS count obtained from the methodology. The feature similarity-based is for assessing the delineation of each ISS feature with regards to a reference delineated feature. Lastly, the area-based accuracy check for measuring the reliability of the methodology developed for delineating and estimating informal settlement structures.

Listed in Table 1 is the summary of the formula used, which was adapted from the study of Cai in 2018 about accuracy measures for objects extracted for remote sensing.

4. RESULTS & DISCUSSION

The first output of the entire process tree reveals two classifications; where in Figure X (left), the non-ISS class is in color red, and the possible ISS class is in color yellow. The subject area has a total land cover of 82,252.69 square meters, and more than half of it is covered with non-ISS features. As can be seen in the table above, 47.18% only of the total area are classified as possible ISS features. The remaining 52.82% of the study area was classified as non-ISS features.

Even though the subject area should represent mostly informal settlement structures, the area of non-ISS is still larger than the ISS. The road is one of the major contributors of the high area coverage of the non-ISS class. Since the area is residential in the middle of the roads is normal. The trees also occupy a large area of the image even though the trees do not exactly cover the same land area; its canopy covers a large area based on the aerial image acquired. Other areas covered as Non-ISS are the narrow alleys and spaces in between the houses. The remaining area, which is 47.18% of the study area, is the possible ISS class, which is the main focus of this study.

Class	Area in m ² (eCognition)	Area in m ² (Validation)	Area Difference in m ²	Relative Accuracy (%)
Non-ISS	43,448.741	46,426.998	2,978.257	93.59
Possible ISS	38,803.952	35,825.691	2,978.257	92.12

Table 2. Relative accuracy of the Non-ISS removal.

The result of the classification was validated by comparing it to a manually digitized classification of the area. The validation data was verified by locals and individuals who are either living or familiar with the subject area. Due to the limitation of actual ground data of classification, verification was only done through online interviews.

A relative accuracy of 93.99% was calculated for the non-ISS classification, while it is 92.12% for the possible ISS classification, when compared to the validation data as seen on the table above. Out of the roughly 8.2 hectares of study area, only 0.298 hectare was classified wrongly, which is high considering the limitations of the input images.

However, the false positives and false negatives of non-ISS removal through classification of this step was not considered due to the limitations of the researchers. The relative accuracy obtained is based only on the area of the classification and not the truthfulness and correctness of the classification of each pixel.

From the possible ISS class, two sub-classes were obtained: delineated ISS and undelineated ISS classes. The delineated ISS class consists of the objects that are classified and delineated as individual informal settlement structures, while the undelineated ISS class contains the objects and features that are not delineated due to the limitations of the research.

The delineated ISS class, colored in green in the image below (right), has 1,482 objects which are all considered as individual ISS features. This covers a land area of roughly 2.4 hectares and accounts for 63.31% of the entire possible ISS class. The remaining area of 36.69% of the possible ISS class is placed under the undelineated ISS class. These are objects that are ISS

but were not delineated properly using the developed methodology.

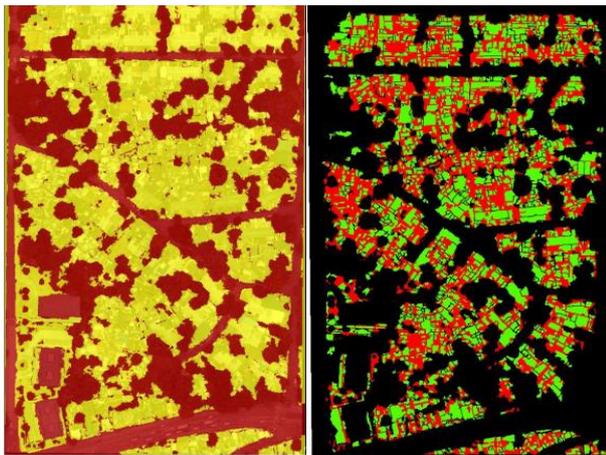


Figure 5. Non-ISS Removal output (left) and delineated ISS features (right) of the site.

Class	Area (m ²)	Percentage (%)	Object Count
Delineated ISS	24,566.467	63.31	1,482
Undelineated ISS	14,237.485	36.69	-

Table 3. Summary of ISS delineation done in eCognition.

There are several reasons for the low delineation rate in the possible ISS class. First is the limitation of the information that was used as input in the methodology. Ideally, the main bases for the delineation are the heights and slope values that can be derived from the generated surface models. Spectral values and topology should only be supporting information for the delineation and detection of individual informal settlement structures. However, since the basis of elevation values is the DSM, which is derived only from RGB images, it is not as accurate as directly-measured elevation values. This resulted in the poor performance of elevation-based delineation.

Random Sampling	
Total Population	1,500
Total Sample	150
True Positive	142
False Positive	8
Summary	
Accuracy (%)	94.67

Table 4. Assessment by random sampling.

To test the accuracy of the individually delineated ISS, a set manually delineated ISS features was used as a basis for checking the correctness, completeness, and accuracy of the delineation. 150 samples were chosen through random sampling to represent the entire population of delineated objects. This accounts for roughly 10% of the entire population. The corresponding ISS features of each sample delineated feature were manually digitized for comparison in terms of area and shape.

The correctness percentage is the ratio of the true positive (TP) objects and the total objects used as samples. Based on the chosen samples, 142 objects out of 150 are true positives, meaning this percentage of objects are correctly identified as informal settlement structures. If allowed to generalize, 94.67% of the population, or roughly 9 for every 10 delineated objects, are true

positives. True positives are correctly delineated objects in terms that it has a corresponding ISS in actuality.

Another basis for assessment is the 3-parameter area-based accuracy measures by Cai et al. in 2018; namely completeness, correctness, and quality. Completeness is the ratio of the total delineated area and the total ISS area. Correctness, on the other hand, is the ratio of correctly delineated area and the total delineated area. Lastly, quality, designed to balance the first two measures, is the ratio of the correctly delineated area over the sum of the delineated area and total ISS area minus the correctly delineated area. This shows the accuracy of the results and a good measure for the estimation and delineation capability of the methodology. The table below shows the summary of these three measures and their corresponding values in this delineation result.

	Completeness (%)	Correctness (%)	Quality (%)
Delineated ISS	59.93	94.67	57.98

Table 5. Area-based assessment.

Another 3-parameter accuracy measure was adapted from the study of Cai et al. in 2018, however, it was for the check of delineation reliability this time. Similarity, which takes into account the ratio of the reference and extracted object was used. Improved similarity, on the other hand, takes into account the difference of the reference and extracted object. To combine these two, the comprehensive similarity variable was developed which takes into account both the similarity in intersection and symmetric difference of the reference and extracted object. The table below shows the summary of the calculated accuracy measures of the samples, both for the area and perimeter feature.

	Similarity (%)	Improved Similarity (%)	Comprehensive Similarity (%)
Delineated ISS	76.04	84.54	69.13

Table 6. Feature (area) similarity-based assessment.

	Similarity (%)	Improved Similarity (%)	Comprehensive Similarity (%)
Delineated ISS	66.85	45.74	34.53

Table 7. Feature (perimeter) similarity-based assessment.

The relatively low values of comprehensive similarity and quality measures could be caused by the limitations of the available data, such as inappropriate flying height, noisy and inaccurate elevation models, and varying morphology of the area. This can also be caused by the fact that classification and delineation is highly dependent on image quality in the developed methodology. The input images were not specifically gathered for the purpose of individual ISS mapping.

From the mean ISS count of 1,061 obtained from a survey form published online to crowdsource the number of ISS they can see from the aerial image of the site, a relative accuracy of the delineation count can be obtained. However, this is based solely on the crowd-based ISS count and does not reflect the absolute accuracy of the ISS detection and delineation. An error of 421 ISS can be computed when the two counts are compared, and it yielded a 60.32 % accuracy. These can be seen in the table below.

Total ISS Count	
eCognition	1,482
Survey Form	1,061
Summary	
Relative Error	421
Percent Error (%)	39.68
Relative Accuracy (%)	60.32

Table 8. Summary of the ISS count through eCognition and through crowdsourcing.

In Figure 7, a portion of the output with simplified vectors of delineated ISS can be seen. However, since the algorithm of smoothing vector functions in eCognition does not consider the topology or the neighborhood of individual informal settlement objects, overlaps can be observed in the output. From the total area of 24,566.47 square meters of the originally delineated ISS features, the new total area of the smoothed features is 29,468.54 square meters. The huge difference in area can be attributed to the overlaps between polygons and the generalization effects brought by the applied smoothing algorithms.



Figure 6. Smoothed delineated objects of the informal settlement structures.

5. CONCLUSIONS

The use of RGB images taken using an Unmanned Aerial Vehicle was able to produce 2.5D maps that can be used as primary dataset for the delineation and estimation of informal settlement structures. Object-based image analysis was used to classify, delineate, and estimate informal settlement structures; which satisfies the specific objectives of this study. With the limited time frame, the researchers were able to develop a methodology that:

- Can create different image layers from raw aerial imagery. 3D maps and models were produced and from it, an orthophoto and a DSM were created. Using DSM with the help of various softwares, the DTM of the subject area was also produced, which was necessary for the nDSM generation
- Uses RGB images and elevation models to create derivative texture layers and use it in the image analysis of the subject area. Different image enhancement methods were used to create more derivative and texture layers that were beneficial to the cause of segmentation and classification of image objects in eCognition.

- Can classify non-ISS features from the map, using object-based image analysis fed with parameters and thresholds based on elevation and spectral values.
- Can delineate and estimate informal settlement structures using a set of parameters and thresholds based on spectral, derivative, and texture layer values.

The researchers were also able to develop a rule-set that is adaptive depending on the subject area. The backbone of this study is the process tree in eCognition that holds all of the processes and outputs of object-based image analysis. The process tree serves as the general flow from the non-ISS removal up to the delineation and smoothing of individual informal settlement structures.

The researchers have developed a ruleset that can be used to delineate individual informal settlement structures by using the process tree of the eCognition program. Multiple image layers and object features were used in the ruleset. The delineation was made possible using the developed ruleset and have shown relatively accurate results in areas where there is a low standard deviation in color since the visual capacity of the respondents was used in counting the houses therefore low color variation visually relates to the low variation on the values on the image.

Tabulated below are the strengths, weaknesses, and potential that was observed from the use of OBIA on UAV-based RGB images for ISS classification, delineation and estimation. These inputs are good for non-ISS classification and ISS count estimation, however delineated ISS features are of low quality, since the process is highly dependent on image equality. For better results, better quality images that are obtained specifically for this purpose should be used. Elevation parameters can also improve the delineation process, since the ruleset developed is heavily reliant on geometric and RGB-based parameters.

STRENGTHS	WEAKNESSES	POTENTIAL
<ul style="list-style-type: none"> • Accurate non-ISS classification • Good for ISS estimation • Fit for RGB-based parameters 	<ul style="list-style-type: none"> • Image-quality dependent • Low-quality delineation for individual ISS 	<ul style="list-style-type: none"> • Better quality images can result to better delineation • Elevation-based parameters can improve delineation

Table 9. Summary of the strengths, weaknesses, and potential of the methodology.

Semi-automation was done for the classification, delineation, and estimation of individual informal settlement structures, with the help of a developed rule-set in eCognition. Human interventions present in the methodology include the expert interpretation of the sufficient classification and delineation accuracy, and the manual selection of threshold values for the chosen parameters. Automation, on the other hand, was done in the actual classification, delineation, and estimation of ISS features in eCognition and in GIS.

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