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Assessment of Spatial Patterns of Backyard Shacks Using Landscape Metrics

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Abstract: Urban informality in developing economies like South Africa takes two forms: freestanding shacks are built in informal settlements, and backyard shacks are built in the yard of a formal house. The latter is evident in established townships around South African cities. In contrast to freestanding shacks, the number of backyard shacks has increased significantly in recent years. The study assessed the spatial patterns of backyard shacks in a formal settlement containing low-cost government houses (LCHs) using Unmanned Aerial Vehicle (UAV) products and landscape metrics. The backyard shacks were mapped using Object-Based Image Analysis (OBIA), which uses height information, vegetation index, and radiometric values. We assessed the effectiveness of rule-based and Random Forest (RF) OBIA techniques in detecting formal and informal structures. Informal structures were further classified as backyard shacks using spatial analysis. The spatial patterns of backyard shacks were assessed using eight shapes, aggregation, and landscape metrics. The analysis of the shape metrics shows that the backyard shacks are primarily square, as confirmed by a higher shape index value and a lower fractional dimension index value. The contiguity index of backyard shack patches is 0.6. The values of the shape metrics of backyard shacks were almost the same as those of formal and informal dwelling structures. The values of the assessed aggregation metrics of backyard shacks were more distinct from formal and informal structures compared with the shape metrics. The aggregation metrics show that the backyard shacks are less connected, less dense, and more isolated from each other compared with formal and freestanding shacks. The Shannon's Diversity Index and Simpson's Evenness Index values of informal settlements and formal areas with backyard shacks are almost the same. The results achieved in this study can be used to understand and manage informality in formal settlements.

Keywords: backyard shacks; informal settlements; unmanned aerial vehicles; object-based image analysis

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1. Introduction

The proportion of people living in urban areas is expected to increase to 70% in 2030 [1]. Most of this growth is expected to occur in developing countries already struggling with the increased expansion of informal settlements or slums and overburdened infrastructure [1]. There is an increasing demand for accurate and timely information regarding the extent, environmental, and socioeconomic characteristics of urban areas and settlements to support the planning and development of evidence-based policies [2].

Countries like South Africa, which struggle with rapid informal settlement developments, also battle with the development of shacks in the backyard of formal dwelling structures known as backyard shacks [3]. Backyard shacks are primarily found in townships around cities, home to medium-to-low-income populations [4], and have become the most prevalent and fast-growing form of informal rental housing [3]. The growth of backyard shacks can be attributed to urban-rural migration, the lack of affordable rental opportunities in the cities, and the slower rate of house provisions for people experiencing poverty. Backyard shacks do not have direct access to essential services but generally have access to services from the existing formal property [5].

Most occupants have more formal jobs than those living in informal settlements [6]. Accessing services from a formal property attracts more people to move or rent backyard shacks than to stay in informal settlements [7]. The development of backyard shacks is also observed in newly developed government-subsidized low-cost houses, as many beneficiaries of the houses are unemployed and end up renting out their backyards to generate income, creating informality in formal areas [8]. Information on backyard shacks is usually captured during censuses [9], resulting in temporal gaps.

Unmanned Aerial Vehicles (UAV) or drone technology provide more evidence-based decision-making and accurate spatial information than conventional remote sensing techniques [10–12]. The UAV mapping technology provides products such as 2D orthophotos, digital surface terrain models (DTM), digital surface models (DSM), and 3D point cloud data. The use of these products in geospatial applications has been on the rise in recent years. This may be attributed to reduced costs relating to drone operations compared with ground surveys [13]. Drone technology provides imagery with very high spatial resolution at sub-decimeters compared with satellite and aerial observations [10,14]. In addition, drone technology can provide high-temporal-resolution imagery required for accurate and on-demand spatial data to support urban planning and infrastructure monitoring [15]. Another advantage of drones is their flexibility to define spatial and temporal resolutions of images depending on the applications [4].

Integrating 3D information in urban land use mapping increases classification accuracy by reducing some of the challenges posed by 2D images, such as spectral signature confusion [16,17]. Several studies have investigated building morphology using 3D information from LiDAR or orthophotos [18–20]. Other studies have extracted or assessed topographic information using UAV products [21,22]. The high spatial resolution data and height information provided by drone images provide detailed information to classify and assess land-use changes in informal settlements compared with aerial photography or satellite imagery [23,24]. Methodologies for the classification of urban land use features using very high spatial resolution images and 3D information include spatial pattern analysis [20], Object-Based Image Analysis (OBIA) [20,22,25], and machine learning techniques [26–28].

Spatial information on housing informality, i.e., free-standing informal structures and backyard shacks, is crucial for effective planning, decision-making, and interventions toward improving the lives of people living in informal settlements [29]. Even though several studies have focused on developing tools to map and monitor informal settlements [30–35], limited studies have focused on mapping backyard shacks [4]. Understanding the spatial patterns of informal settlement structures can help develop the required emergency responses during health, natural, and man-made disasters [36].

The objectives of this paper are threefold: firstly, to investigate a methodology to map land-use features in an area that has both informal settlement and formal settlement with backyard shacks using 2D and 3D information acquired by UAV, and secondly, to assess the spatial pattern of backyard shacks using landscape metrics. Lastly, the study assesses the degree of association between selected shape and aggregation metrics.

2. Study Area

The study area is in Mamelodi Township, in the City of Tshwane Metropolitan Municipality. The rapid growth of informal settlements and backyard shacks is a problem in South Africa's big cities, including the City of Tshwane [37]. In 2013, about 83,378 households in the City of Tshwane lived in backyard shacks [38]. The number of backyard shacks in the City of Tshwane increased by almost 400% between 2001 and 2011 [39]. The backyard shacks contain similar physical characteristics to informal settlement dwelling structures [9]. The study area contains single-story government-subsidized houses, low-cost houses, backyard shacks, and freestanding shacks. The formal area also contains "backrooms" houses. These are houses that are built using suitable-quality building materials.

3. Material and Methods

3.1. Materials

Drone Solutions International flew the drone images on 11 December 2020. Table 1 contains information about the drone used and the parameters of the flight plan.

Table 1. The drone specifications and the flight plan parameters.

Characteristic	Specification
Camera	Sony A6000, 20 mm lens
Altitude	120 m
Side lap	80%
Forward lap	80%
Spatial resolution	3 cm
Ground control points	29
Imagery bands	Red (R), Green (G), Blue (B)

The images were received as orthophotos. The images, DSM, and DTM were processed and projected to the Transverse Mercator, Lo 29°, and Hartebeeshoek Datum. Figures 1–3 show the orthophoto, DSM, and DTM used in this study.

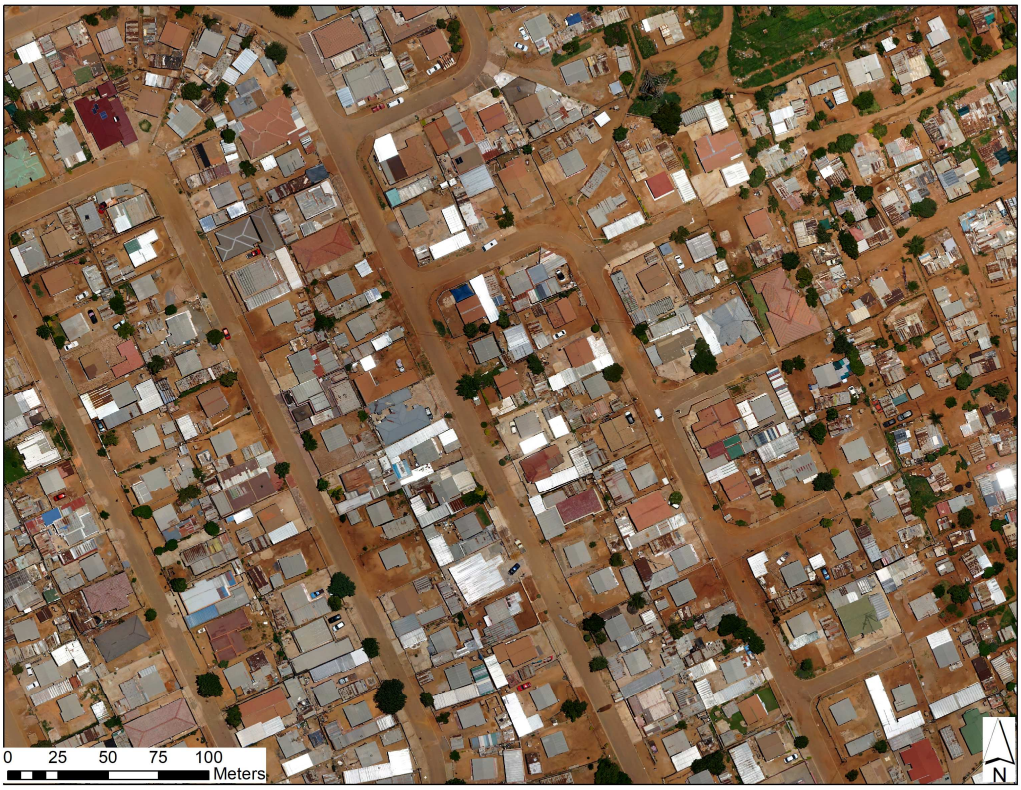

Figure 1. An RGB orthophoto of the study area, showing formal settlement with backyard shacks and informal settlements.

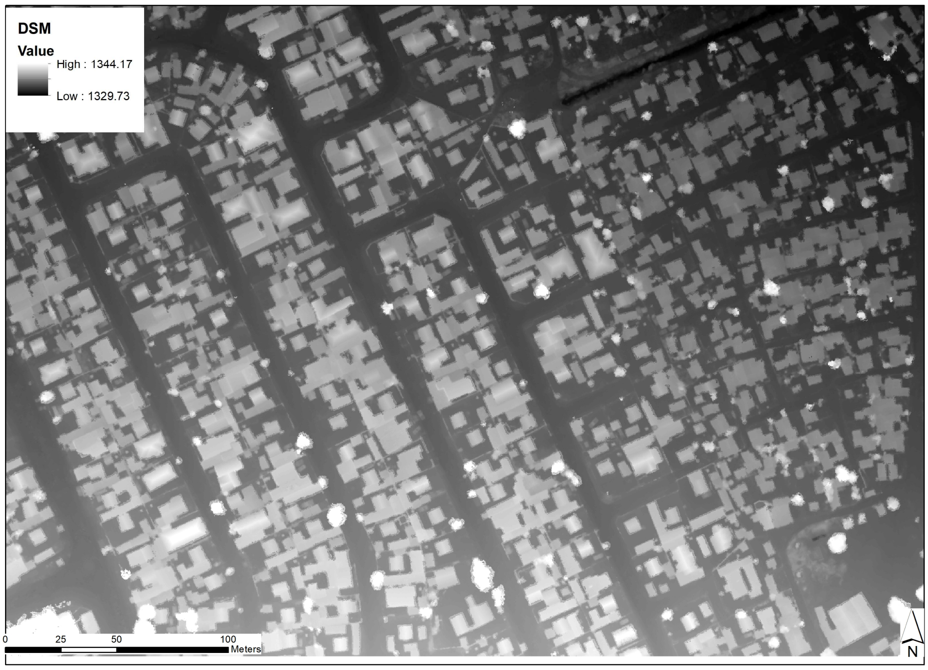

Figure 2. A DSM of the study area, generated using data collected the flyover.

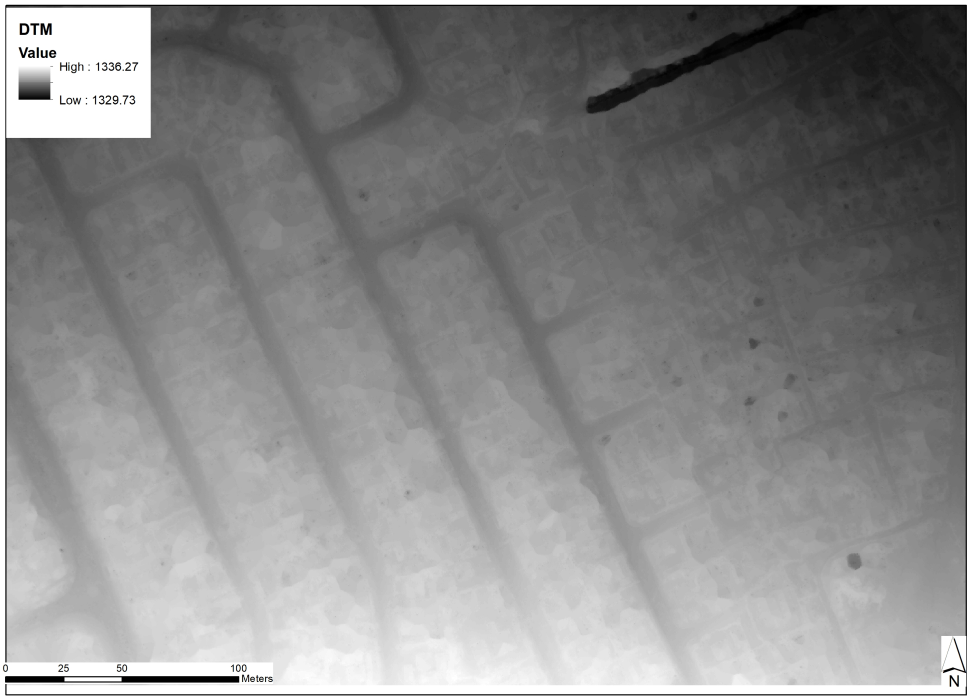

Figure 3. DTM of the study area, generated using data collected the flyover.

3.2. Methods

The methodology followed in this study is shown in Figure 4. The workflow contains four main steps: estimation of height values, classification of informal and formal structures, classification of backyard shacks, and assessment of spatial patterns of informal, backyard shacks, and formal settlements.

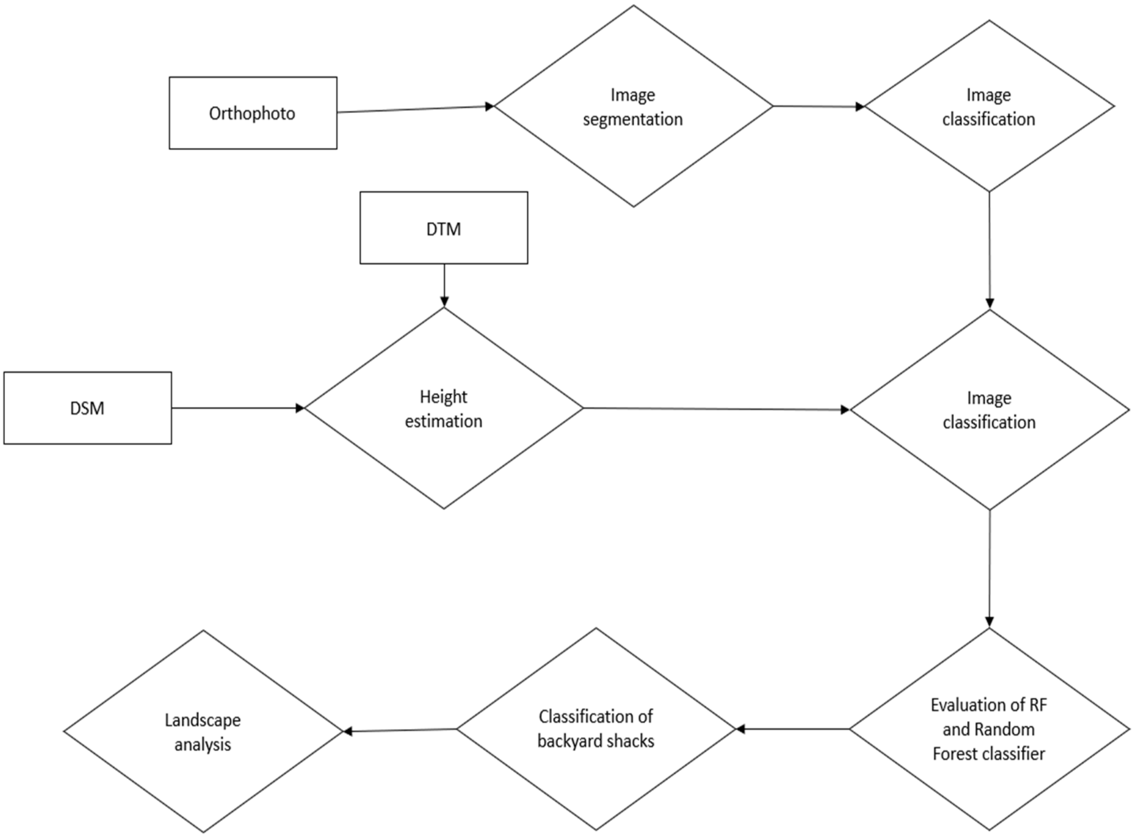

Figure 4. Flowchart illustrating the methodology followed to extract backyard shacks and assess the spatial patterns of backyard shacks and informal settlement dwelling structures.

3.2.1. Classification of Formal and Informal Building Structures

Image classification was completed using Trimble eCognition Software 10.2. We used the OBIA technique to classify land use features in the study area. Unlike pixel-based classification, OBIA techniques use spectral, spatial, topographical, and contextual information to classify land cover and land use objects. These techniques have been used in urban land use mapping and provide better results than pixel-based classification methods.

The first step in OBIA classification is the segmentation of an image into image objects that represent the objects of interest. The multiresolution segmentation algorithm created image objects representing land use features in the study area. Multiresolution segmentation is a bottom-up, region-merging technique that segments an image into image objects of homogeneous regions at any given resolution [40]. In the eCognition environment, the size of image objects resulting from the multiresolution segmentation algorithm is determined by scale parameters, shape, and compactness values. The ortho photo's spectral bands, i.e., R, G, and B, were used with equal weight during segmentation. We used a supervised segmentation process to determine the parameters that best separate informal and formal dwelling structures. A supervised segmentation approach is a trial-and-error approach that allows the user to test the segmentation parameters and compare the results with expected objects via visual image recognition [16]. Scale parameter, shape, and compactness values of 60, 0.3, and 0.5, respectively, were used during segmentation. To improve the quality of the image objects, the spectral difference segmentation technique was applied to multiresolution segmentation results to allow for the merging of spectrally similar image objects, resulting in larger image objects representing the objects of interest. The spectral difference threshold of 4 was selected using the supervised segmentation method used during the multiresolution segmentation. We tested and evaluated the effectiveness of the Random Forest (RF) Classifier and rule-based classification technique that uses height information and OBIA to detect formal and informal building structures.

Random Forest Classifier

Object-based machine learning algorithms are becoming an area of interest in feature extraction [41–43]. The RF classification algorithm is an ensemble of decision trees trained using a combination of learning models [44]. An RF classifier is defined as a classifier made up of several tree-structured classifiers $\{h(x, \Theta_k); k = 1, \ldots\}$ where x is the input vector and $\{\Theta_k\}$ are the independent and identically distributed random vectors [44].

The classification was completed using the eCognition built-in RF classifier. We used radiometric values, excess green vegetation (ExG) [45], and estimated height information during classification. We used 16 maximum categories, 50 maximum trees, and 0.01 forest accuracy during the training of the RF classifier. The height information was estimated by subtracting the DTM from the DSM. The ExG index was suitable for the classification since the UAV imagery lacked the Near Infrared (NIR) band. ExG is calculated as follows:

$$ExG = 2G - R - B \tag{1}$$

Training samples representing informal, formal, tree, and grass classes were created using visual image interpretation. 25 formal and 46 informal structures, 10 grass, and 19 tree samples were created and used as samples. The classification used the RGB layers, height information, and ExG index. Maximum categories, maximum trees, and forest accuracy of 16, 50, and 0.01 were used during the classification.

Rule-Based Classifier

A rule-based classifier makes a class decision based on "if-else" rules and is one of the most commonly used object-based classification techniques. The rule-based classification relies on expert knowledge of the classes under investigation. The rules and facts about the objects under investigation are converted into a sequence of logical statements [46]. We developed a rule set that uses ExG and height information to classify formal, informal, grass, and tree classes through visual assessment. The classification was completed using a thresholding technique. The first step performed was to classify vegetated and non-vegetated areas using ExG. Vegetated areas have higher ExG values of 20 or higher than non-vegetated areas. The vegetated areas were further classified into grass and trees using the estimated height values. Vegetated areas with less than 1 m of height were classified as grass, while those taller than 1 m were classified as trees. Building structures were separated from non-vegetated areas by thresholding the height values. Non-vegetated areas with less than 1 m height values were classified as open. Building structures taller than 2.3 m were classified as formal dwelling structures, whereas those shorter than 2.3 m were classified as informal dwelling structures. Formal and informal dwelling structures were classified using estimated height information. Formal structures are expected to be taller than informal settlement dwelling structures.

3.3. Classification of Backyard Shacks

Backyard shacks are informal dwelling structures in the yards of formal properties and have the same properties as informal settlement dwelling structures. The classification of backyard shacks was done using the classification results achieved from a methodology that achieved higher accuracy. We developed a rule set that uses contextual information to classify backyard shacks as informal settlement dwelling structures. We used proximity to formal structures to classify backyard shacks as freestanding, informal structures. The distance between formal structures and backyard shacks was assessed visually and used to classify backyard shacks as freestanding informal settlement structures. Backyard shacks are situated within 5 m of the formal dwelling structures.

3.4. Accuracy Assessment

The accuracy assessment of the classification results was done using the similarity metrics of STEP (Shape, Theme, Edge and Position) [47]. The STEP measures the accuracy of the boundaries of the classified objects compared with reference shapes. The overall accuracy assessment was done by evaluating the weighted theme error matrices. Reference objects were digitized using visual image interpretation of the images due to a lack of ancillary data mapped at similar spatial resolution and during the date of acquisition. A quality assessment was done in an area that covers about 10% of the study area.

3.5. Spatial Pattern Analysis

We used landscape metrics to assess the characteristics and spatial patterns of backyard shacks and formal and informal dwelling structures in the study area. Landscape metrics have been widely used in landscape ecology to understand the relationship between landscape patterns and ecological processes [48,49]. Understanding the spatial patterns of land use activities in a settlement or city can help manage a city or settlement and develop policies to manage development in a city or settlement [50,51]. In addition, understanding the spatial pattern of dwelling structures in informal settlements can help improve decision-making when planning informal settlement upgrade projects. Understanding the spatial patterns of land use can also help manage biodiversity in cities or settlements, which is crucial for achieving sustainable development goals [52].

In this study, we assessed eight shape, aggregation, and landscape metrics to analyze the shape and spatial patterns of the backyard shacks and informal and formal structures. The metrics assessed are listed in Table 2.

Table 2. List of landscape metrics assessed.

Landscape Metric Type	Landscape Metrics Assessed *
Shape	Shape index (SHAPE) Fractal Dimension Index (FRAC) Continuity Index (CONTIG)
Landscape	Simpson's diversity index (SIDI) Shannon's Evenness Index (SEI)
Aggregation	Euclidean Nearest-Neighbour Distance Aggregation Index (AI) Cohesion Index

* developed by [53].

We used Fragstats software [53] to derive and assess the spatial metrics of backyard shacks. The shape and aggregation metrics were assessed at the patch and class levels. The diversity analysis was done at the settlement level, i.e., informal settlement and formal settlement with backyard shacks. In addition, we used the Pearson correlation coefficient to assess the degree of association between the shape and aggregation metrics of backyard shacks and formal and informal dwelling structures. The Pearson correlation coefficient is a statistical method that assesses the strength of a linear association between two quantitative variables. The results of this analysis vary from +1 to −1, where +1 represents a strong positive association, whereas −1 represents a strong negative association.

4. Results and Discussions

4.1. Segmentation Results

The multiresolution segmentation with scale, shape, and compactness values of 60, 0.3, and 0.5, respectively, created images representing formal and informal building structures and other land use features. Most of the building structures in informal were over-segmented. The formal building structures were also over-segmented but with bigger segments than the informal settlement structures. Some of the backrooms were also over-segmented. The spectral difference segmentation technique reduced the over-segmentation of some of the building structures (Figure 5). Most informal settlement building structures continued to experience over-segmentation even after applying the spectral difference segmentation algorithm. This may be attributed to the heterogeneity of the roofing material of informal building structures. Some of the roofs in informal settlements contained old, corrugated iron sheets, resulting in different grayscale levels on one roof (Figure 5). The same results were observed in some parts of the backrooms in the formal area. After applying spectral difference segmentation, most formal structures were covered by one or two image objects.

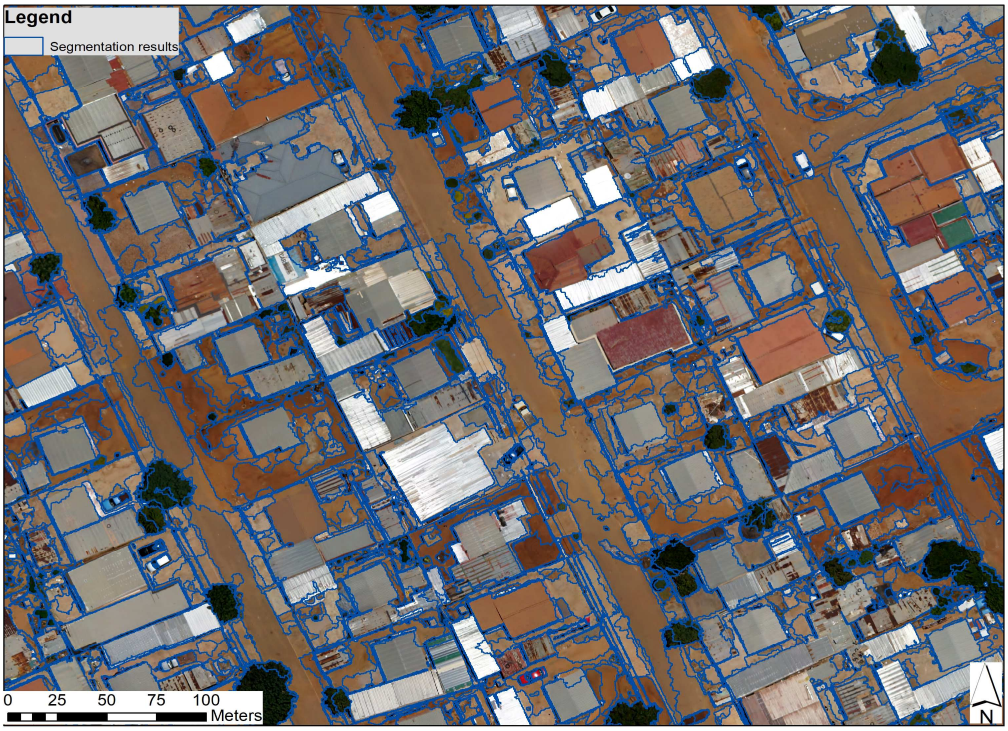

Figure 5. Zoom-in image of the spectral different segmentation results, threshold scale: 4.

4.2. Classification Results

In this section, we compare the results achieved using RF and rule-based classification techniques. The classification results of the RF classifier are shown in Figure 6. The results show that the study area is mostly covered by building structures compared with trees and grass classes. The backyard shacks are located closer to the formal structures. The informal structures are located at the top right corner of the study area. The assessment of the results shows that some of the formal building structures were classified as informal dwelling structures or backyard shacks. This is attributed to the misclassification of the backrooms as backyard shacks, as some of the roofs of the backrooms contain old corrugated iron sheets similar to those of informal building structures. Some of the pixels on the edges of the formal building structures were misclassified as backyard shacks or trees. Some fences around the formal areas, edges of trees, and shorter trees were misclassified as grass. There were also a few cases where the edges of the trees were misclassified as grass. In addition, some of the formal busing structures were classified as informal settlement dwelling structures. This may be influenced by using proximity measures to classify backyard shacks as informal settlement structures.

The rule-based classification technique was able to separate backyard shacks, formal and informal dwelling structures, grass, and tree classes with high accuracy compared with the RF classifier (Figure 7). Most of the edges of the formal structures were misclassified as backyard shacks compared with results achieved using the RF classifier. There were a few cases where building structures were misclassified as trees. Most informal settlement dwelling structures were correctly classified. Some of the backyard shacks were misclassified as free-standing informal settlement dwelling structures. This may be attributed to the use of proximity analysis to classify backyard shacks as free-standing informal dwelling structures, as some of the building structures in informal settlements are almost the same height as formal structures.

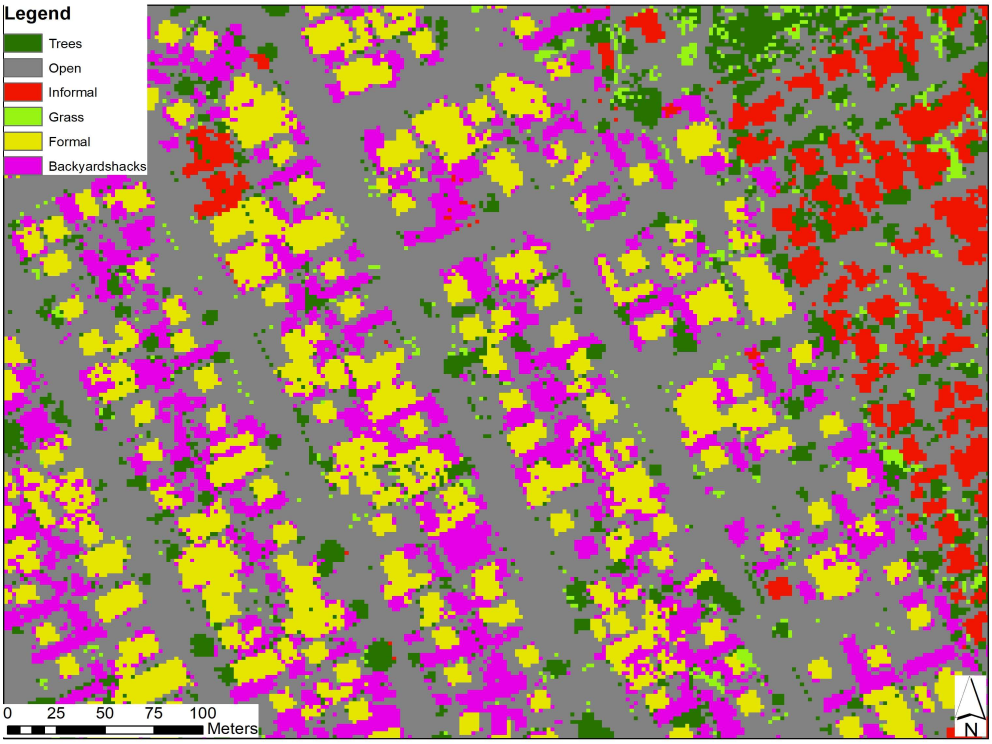

Figure 6. Classification results achieved using RF classifier, after applying proximity analysis to classify backyard shacks.

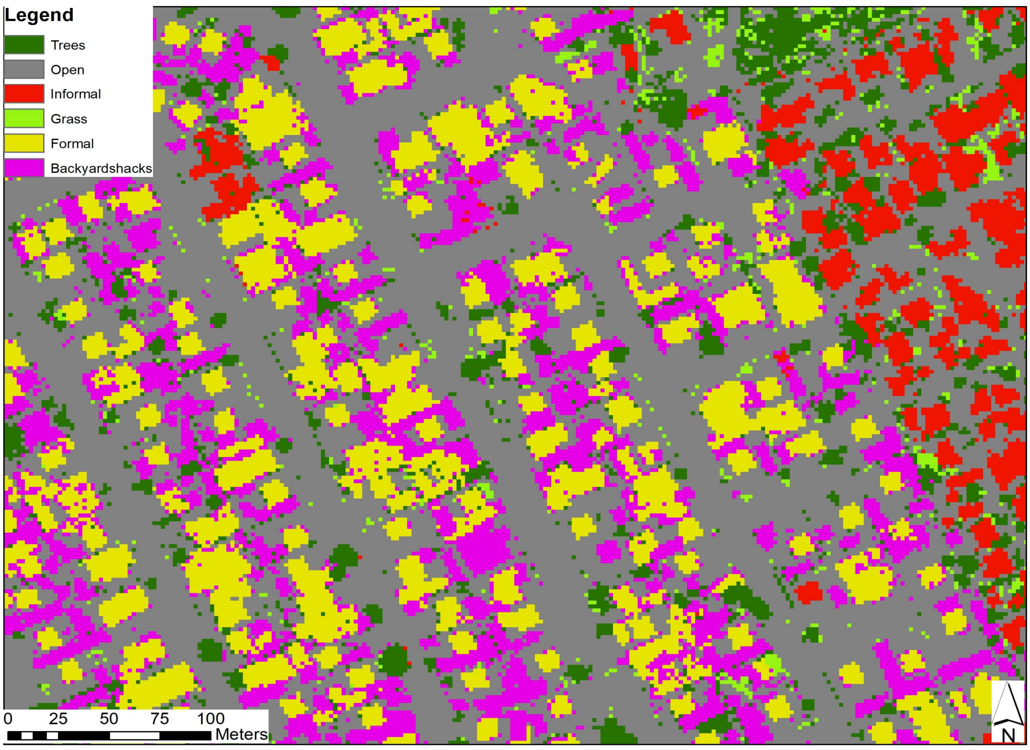

Figure 7. OBIA classification results achieved using rule-based classification techniques, after applying proximity analysis to classify backyard shacks.

The tree class is scattered around both formal and informal settlements. The big patches of trees and grasses are found on the top left, closer to informal settlement structures. The separation of the green spaces from other classes is attributed to using the ExG index used during the classification. The use of the ExG and height information was able to separate the tree class from the grass class. There were, however, areas where the shadows of the trees and fences were misclassified as grass. The number of grass patches is limited in the study area. However, more grass patches can be observed around the informal settlement. The tree class in formal areas is located mainly in the streets, while the trees in informal settlements seem more organic.

The RF classifier could not separate some informal settlement dwelling structures from backroom structures, even though the two structures have different heights (Figure 4). Spectral values might influence this during the RF learning process, as the two dwelling types have similar spectral values. Therefore, using spatial analysis to classify backyard shacks resulted in some backroom structures being classified as backyard shacks due to their proximity to formal dwelling structures. The rule-based classification method, however, distinguished backroom structures from informal settlement dwelling structures. The rule-based classification method also reduced the confusion between formal and informal structures, thereby reducing the confusion between backyard shacks and formal classes (Figure 5). There were, however, a few cases where parts of informal settlement dwelling structures were classified as formal during rule-based classification. This resulted in some informal settlement dwelling structures being classified as backyard shacks.

Some of the edges of formal structures and trees were misclassified as informal settlement structures or backyard shacks during the RF classification. This can be attributed to creating image objects that combine the edges of the structures and shadows, resulting in the average height of the structures being like that of informal structures. Some man-made structures, such as cars, were also misclassified as backyard shacks or informal settlement structures, as some of the cars have height and spectral properties like those of informal dwelling structures.

4.3. Accuracy Assessment

The STEP metrics assessment results for the RF classifier are shown in Table 3. The STEP accuracy measurements range from 0 to 1, with 0 representing poor and 1 representing excellent. The similarity assessment results show that none of the assessed metrics achieved excellent accuracy, i.e., a value of 1. The theme similarity metric achieved higher accuracy than position, edges, and shape metrics, with the backyard shacks class achieving the highest accuracy of 0.86 compared with other classes. The results show that the shape similarity was poor for all the classes produced during the RF classification method compared with edges and position metrics.

Table 3. STEP accuracy assessment results of land use classes derived using RF classifier.

Category	Shape	Theme	Edge	Position
Backyard shacks	0.28	0.86	0.59	0.29
Formal	0.27	0.49	0.33	0.34
Grass	0.07	0.10	0.07	0.08
Informal	0.35	0.67	0.41	0.46
Trees	0.44	0.84	0.49	0.73

The similarity assessment of classification results achieved using rule-based classification techniques is shown in Table 4. The theme similarity assessment results range from 0.61 to 0.85, presenting the most accurate metrics compared with shape, edge, and position metrics. The shape, edges, and position similarity assessment results achieved using the rule-based classification method were slightly higher than the results achieved using the RF classifier.

Table 4. The STEP metrics assessment results of land use classes derived using rule-based classification method.

Category	Shape	Theme	Edge	Position
Backyard shacks	0.22	0.74	0.50	0.34
Formal	0.42	0.83	0.57	0.43
Grass	0.44	0.61	0.43	0.46
Informal	0.33	0.71	0.42	0.49
Trees	0.48	0.85	0.49	0.75

The overall accuracy assessment of RF and rule-based classification results is shown in Table 5. The overall quality assessment of the RF classifier was 60%, with informal settlement dwelling structures achieving the highest producer and user accuracy compared with formal and informal dwelling structures. The formal building structure and grass classes achieved the lowest user accuracy of 12% and 11%, respectively.

Table 5. The overall producer and user accuracy assessment results are based on the theme similarity metric of the land use classes.

	Random Forest Classifier		Rule-Based Classification	
	Producer Accuracy %	User Accuracy %	Producer Accuracy %	User Accuracy %
Backyard shacks	69	96	89	93
Formal	92	11	88	57
Grass	91	12	99	77
Informal	97	72	90	93
Trees	73	99	72	99
Overall accuracy %	60		82	

The overall accuracy theme similarity of the rule-based classifier was 82% (Table 5). These results are aligned with studies that assessed the use of UAV 2D and 3D products and rule-based classification techniques to map urban land use features [54,55]. Overall, the rule-based classification produced higher producer and user accuracies of over 70%, except for the formal class, which achieved a user accuracy of 57% compared with the RF classifier. The informal settlement class achieved the highest overall accuracy of the building structure classes.

4.4. Spatial Pattern Analysis

The spatial pattern analysis was done using the rule-based classification results. The Sections 4.4.1–4.4.3 describe the results obtained in assessing the shape, aggregation, and landscape metrics.

4.4.1. Shape Metrics

The patches of formal structures had an average shape index of 1.6, whereas the backyard shack and informal classes had an average shape index of 1.4. The slightly lower shape index value of backyard shacks and informal dwelling structures can be attributed to the heterogeneous roof material, which resulted in multiple irregular image object segments. A shape index of more than one means that the dwelling building structure classes are mostly square. The visual interpretation of the results shows that most of the backyard shacks are rectangular, especially those located on the sides of the formal structures. Formal structures are mostly square. The backrooms seemed rectangular. The shapes of informal settlement dwelling structures are mostly rectangular. The results achieved in this study show the dependency of this metric on the accuracy of the shapes of the image objects created during segmentation or used for analysis.

The average contiguity index of formal and informal class patches was 0.7, whereas the contiguity index of backyard shacks was 0.6. The slightly lower contiguity index implies that backyard shacks in the study areas share fewer edges than formal and informal structures. The visual interpretation of the results shows that the study area contained more formal structures than backyard shacks. The slightly higher value of the contiguity index of formal structures in this study may be attributed to the availability of backrooms that are classified as formal.

The average FRAC value of formal structures and backyard shacks was 1.2, whereas the average FRAC value of informal structures was 1.1. These values show that the dwelling structures in the study area have regular square shapes. Since the FRAC index is based on patch area and perimeter and the shape accuracy of the informal and backyard shacks was poor, the values of this index may change with improved shape accuracy.

The evaluation of the degree of association of the shape metrics shows that the CONTIG and Shape indices have an insignificant positive correlation with a Pearson coefficient correlation, r, of 0.16. The CONTIG and FRAC indices have an insignificant negative correlation coefficient of −0.27. The shape and FRAC indices have a lower correlation coefficient of 0.45. Overall, the assessed shape metrics are not strongly correlated.

4.4.2. Aggregation Metrics

The results show that formal, informal, and backyard shack classes are connected, as indicated by high cohesion index values (Table 6). The backyard shack class seems less connected than the formal and informal classes. This can be attributed to the lower density of shacks in the formal stand and the availability of backrooms, which increase the average distance between backyard shacks. The availability of regular roads may also increase the space between backyard shacks. The results show that informal dwelling structures are more connected than formal structures and backyard shacks. The results imply that informal settlements have smaller yards or stands than formal settlements. The narrow paths in informal settlements may also contribute to a higher cohesion index in informal settlements.

Table 6. Class aggregation metrics assessment results of building structure classes.

Class	Euclidean Nearest-Neighbour Distance	Cohesion Index	Aggregation Index
Formal	142.023	83.39	80.75
Backyard shacks	147.610	73.71	57.7
Informal	116.553	89.54	80.74

The analysis of the ED shows that the backyard shacks have the highest mean ED, followed by formal class and then informal class (Table 6). This shows that the study area's backyard shack class is less dense than other dwelling types. This could be attributed to the fact that this class is in the yard of formal structures separated by a formal road network. The lower mean ED of the informal class means dwelling structures in informal settlement structures are closer to each other compared with the formal and backyard shack classes. This shows that the informal structure class is dense compared with the study area's formal and backyard shack classes.

The average AI value of the backyard shacks class is significantly lower than those of formal and informal structures (Table 6). This shows that backyard shack structures are more isolated than formal and informal structures. The higher AI values of formal and informal dwelling structures may be influenced by the availability of backrooms, which increases the adjacency of formal structures and smaller yards in informal settlements.

The analysis of the degree of association shows the cohesion index and ED of formal and informal settlement dwelling structures have a strong negative correlation coefficient r of −0.88. In contrast, the cohesion index and AI have a strong positive correlation coefficient of 0.92.

4.4.3. Landscape Metrics

The SIDI values of the formal and informal settlements are 1.24 and 1.18. The lower value of SIDI in the informal settlement may be attributed to the limited patches of backyard shack class in informal settlements. The SIEI values of formal and informal settlements are 0.79 and 0.87, respectively. The slightly higher value of SIEI in informal settlements is likely attributed to the limited patches of backyard shacks, which increased the chance of equally spreading the classes in informal settlements.

5. Conclusions

The study demonstrated that 2D and 3D datasets acquired by UAV were successful in capturing land use features in an area containing formal properties with backyard shacks and informal settlements. The study shows that the rule-based classification was more effective in classifying formal and informal settlement dwelling structures than the RF classifier. The results show that both methodologies failed to extract boundaries similar to reference data, as shown by poor edge, shape, and position accuracy. The proximity analysis was successful in classifying backyard shacks as free-standing informal dwelling structures. The assessment of the landscape metrics showed that there is no significant difference in shape characteristics of backyard shacks or formal and informal dwelling structures extracted. Since the shape index metrics strongly depend on the shape of the objects assessed, there is a need to investigate the methods that can improve the accuracy of the shapes produced during segmentation and the impact of accurate shapes on shape metrics analysis. The study revealed that the cohesion index, AI, and ED characteristics of backyard shacks are more district compared with the shape metrics of formal and informal structures. The results show backyard shacks are less connected than formal and informal dwelling structures. AI showed an excellent split of the aggregation of backyard shacks from other dwelling structures in the study. The degree of association between aggregation metrics was significantly high. This means that the aggregation metric may be used to classify backyard shacks as formal and informal structures in a settlement with similar characteristics as the study area.

The results achieved in this study demonstrate that drone images and landscape metrics can be used to map and derive new information on the spatial distribution of backyard shacks and other building structures. The spatial patterns of backyard shacks may vary from one settlement to the next due to several factors, including the age of the township. The information derived from this study can be used to understand the degree of informality in formal areas. This information can be used to develop plans to formalize or manage backyard rentals in low-income formal areas. The information can also be used during the management of health pandemics such as COVID-19, where spatial information, including the density of dwelling structures and access to services, is required to support the management of the pandemic. Spatial distribution of informal settlement dwelling structures is also required during decision-making relating to fire disaster management, planning of services, and upgrading or formalizing informal settlements and backyard shacks.

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