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COMPARATIVE ASSESSMENT OF PIXEL-BASED AND OBJECT-ORIENTED CLASSIFICATION TECHNIQUES USING SENTINEL-2 IMAGERY OF THE FEDERAL UNIVERSITY OF TECHNOLOGY, AKURE (FUTA) CAMPUS

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Abstract

Precise classification of land cover is essential for effective environmental and urban planning, particularly in diverse landscapes with intricate spatial patterns. This study offers a comparative evaluation of pixel-based and object-oriented image classification techniques using Sentinel-2 satellite imagery of the Federal University of Technology, Akure (FUTA), Nigeria. The pixel-based classification applied the Maximum Likelihood Classification (MLC) method, which depended exclusively on spectral data, while the object-oriented approach integrated multi-resolution segmentation and contextual features such as shape and texture. Ground truth data were gathered from thirty (30) georeferenced locations using a mobile GPS for validation. Results show that while using the pixel-based method, the vegetation covers 2.515 km² (37%), compared to 2.266 km² (33%) from object-oriented classification; Farmland accounts for 1.917 km² (28%) versus 1.803 km² (27%); Bare Ground is recorded at 1.206 km² (18%) as opposed to 1.232 km² (18%); and Built-up is measured at 1.161 km² (17%) compared to 1.496 km² (22%) from the pixel-based classification. Accuracy assessments using confusion matrices revealed that the object-oriented method outperformed the pixel-based method, achieving an overall accuracy of 90% with a Kappa coefficient of 0.8663, compared to 80% accuracy for the pixel-based method. The object-oriented classification proved more effective in distinguishing built-up and bare ground areas, while both methods performed similarly in classifying vegetation. This study concludes that object-oriented classification is preferable for complex and urban environments where accuracy is critical. Expanding ground-truth data beyond thirty points and employing higher-resolution imagery would further enhance classification reliability and precision.

Keywords: Land Cover Classification, Pixel-Based Classification, Object-Oriented Classification, Sentinel-2 Imagery, Accuracy Assessment

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1.0 INTRODUCTION

Satellite imagery, an essential element of remote sensing, delivers a comprehensive perspective of the Earth's surface by capturing information across different spectral bands. These images are produced by satellites circling the Earth, which are fitted with sensors that detect reflected or emitted electromagnetic radiation. The data obtained provides crucial insights into land use, environmental status, and human activities [12]

Image classification is the process of categorizing all pixels in a satellite image into land images to extract meaningful information about the Earth's surface. According to [12], image classification is a fundamental technique in remote sensing that enables the conversion of complex image data into more understandable maps and datasets.

Image classification methods can be broadly divided into two categories. The Supervised Classification requires that the analyst provide training data samples of known land cover types to guide the classification process. The algorithm uses these samples to classify the entire image. Supervised classification is advantageous when the analyst has detailed knowledge of the area being studied, allowing for more accurate results [12]. However, the Unsupervised Classification does not require training data. Instead, the algorithm automatically groups pixels into clusters based on their spectral properties. The analyst then assigns these clusters to land cover classes. Unsupervised classification is useful when prior knowledge of the area is limited, but it may be less accurate than supervised methods [10].

These classification methods can be categorized into two main approaches: pixel-based classification and object-oriented classification. The Pixel-based classification is a traditional approach that classifies each pixel individually based on its spectral properties. While this method is straightforward and widely used, it often struggles with mixed pixels and noise, leading to less accurate results in heterogeneous areas [10]. [12] Noted that the current pixel-based classification method has limitations, particularly with high-resolution data such as Quickbird images, leading to poor outcomes when identifying objects of interest. To address this issue, an object-oriented classification technique that employs image segmentation along with fuzzy classification of the segmented results is recommended. The Object-oriented classification segments the image into meaningful objects or regions before classification. This method considers spatial, spectral, and textural information, providing a more comprehensive analysis, especially for high-resolution images [1].

Numerous ongoing projects and initiatives focus on developing different classification methods to enhance data extraction from satellite information. [12] Proposed the hierarchical object-based classification which combined the object-based and pixel-based classification techniques. [10] Explained that the detailed accuracy results were found as error matrices and they showed that the overall accuracy of object based classification is better than pixel based techniques like parallelepiped classification, minimum distance classification and maximum likelihood classification.

Despite the widespread use and prominence of the image classification are pixel-based and object-oriented method of image classification, there is an ongoing debate about their respective efficacies, particularly in different environmental contexts and application domains, especially in environments with diverse land cover types and complex spatial patterns [11]. Therefore, there is a need for a comparative evaluation of the performance of these methods in accurately classifying land cover.

[2] compared supervised and unsupervised Multi-Resolution Segmentation (MRS) approaches using QuickBird and WorldView-2 imagery for building classification. Their results showed that supervised and one of the unsupervised methods produced almost identical segmentation geometries and classification accuracies (82–86%), while another unsupervised method generated different geometries but still achieved comparable classification performance.

Similarly, [8] demonstrated that the object-oriented approach consistently outperformed pixel-based classification, yielding higher producers' and users' accuracy for most land cover classes. This aligns with the broader trends in literatures, where comparative studies repeatedly show that object-based classification tends to deliver higher overall and class-specific accuracy than traditional pixel-based methods, particularly when working with high-resolution imagery such as QuickBird or WorldView [4]. The advantage of object-based classification is especially evident in environments where land-cover classes are heterogeneous or shaped by contextual features, such as urban structures, tree patches, or other built-up areas.

At the same time, object based classification is not without challenges, it requires careful tuning of segmentation parameters and a more nuanced accuracy assessment. Pixel-based methods, on the other hand, remain useful for coarser imagery, spectrally distinct classes, or when a rapid and reproducible workflow is needed [1].

For a case study like FUTA, a pragmatic strategy is to adopt both methods side by side. This not only allows for harmonized accuracy assessment but also enables the development of a hybrid workflow. Such an approach validates insights from literatures while ensuring that the most suitable method for the campus' unique data and mapping objectives is identified.

By applying both techniques to satellite images of FUTA, this study seeks to identify the strengths and weaknesses of each approach in a real-world context. The findings will contribute to improving classification accuracy and efficacy in geospatial studies, supporting better decision-making processes in environmental and urban management. This study aims to carry out a comparative assessment of pixel-based and object-oriented classification of a satellite image of the Federal University of Technology, Akure (FUTA), with a view to identifying the most suitable method for producing reliable and detailed land cover classification. Ojectives of this study includes to independently conduct pixel-based classification of the satellite imagery using traditional techniques and also perform object-oriented classification of the same satellite imagery, validate the classification results through ground truth and accuracy assessment using field observations and reference data, compare the accuracy and efficiency of pixel-based and object-oriented classification methods in accurately delineating different land cover types within the FUTA campus; and analyze the strengths and limitations of each classification approach in handling spectral variability, spatial heterogeneity, and complex land cover patterns.

2.0 MATERIALS AND METHODS

2.1 Study Area

The study area is the Federal University of Technology Akure (FUTA) campus, situated in south-western Nigeria. FUTA's campus serves as the focal point for this project because it encompasses an array of land cover types and features. The study area is within latitude 7º 17' 30" N and 7º 19' 00"N, longitude 5º 07' 00" E and 5º 09' 00" E. Figure 1 shows the map of Nigeria, Ondo state, Akure South local government and FUTA. Spanning a significant area, FUTA's campus incorporates diverse elements such as academic buildings, residential areas, recreational spaces, vegetation patches, water bodies, and other infrastructure. This diversity offers a rich landscape for examining land cover dynamics and classification techniques.

The campus environment reflects a blend of urban development and natural ecosystems, providing a compelling setting for studying the interactions between human activities and the environment.

By focusing on FUTA as the study area, this project aims to gain insights into land cover classification methodologies' efficacy within a university campus context, contributing valuable knowledge to environmental management and spatial planning endeavours.

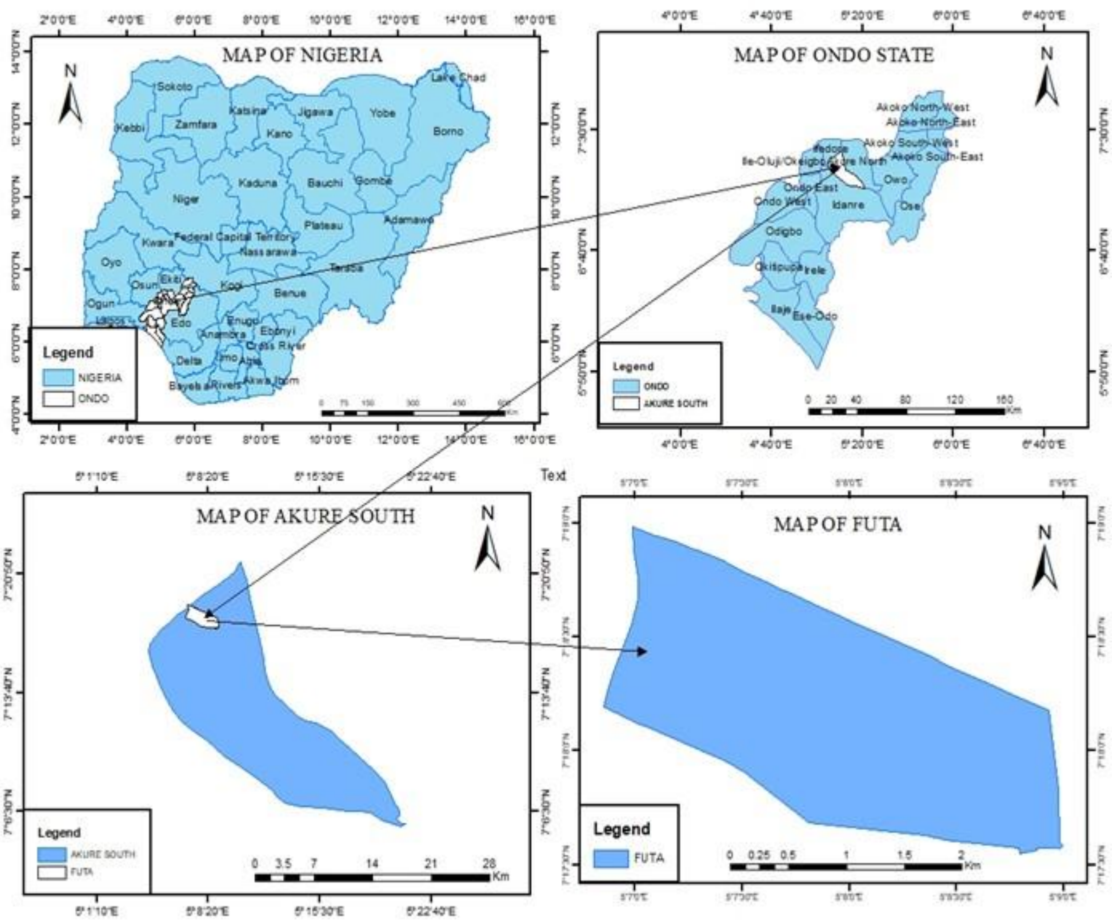

Figure 1. Study Area Map.

2.2 Methodology

This study employs a structured methodology to classify and analyze land cover within the FUTA campus using high-resolution Sentinel-2 satellite imagery. Data acquisition, quality assessment, and processing stages were meticulously followed to ensure reliable results. The Sentinel-2 satellite imagery was chosen as the main data source for this study due to its multispectral

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capabilities and high spatial resolution. Sentinel-2 provides imagery in 13 spectral bands, covering the visible, near-infrared (NIR), and shortwave infrared (SWIR) parts of the spectrum. The imagery used in this study has a spatial resolution ranging from 10 meters for the visible and NIR bands to 20 meters for the SWIR bands, which is sufficient to capture detailed land cover features across the study area. Sentinel-2 image of FUTA is presented in Figure 2

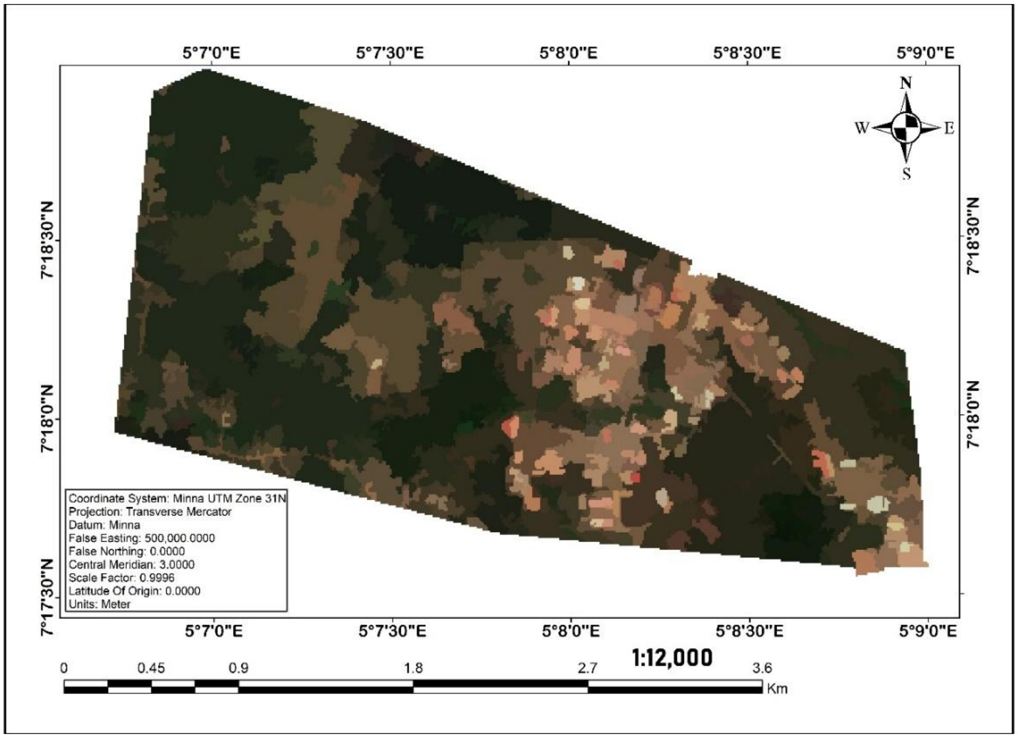

Figure 2. Sentinel-2 Satellite Image of FUTA

Field surveys were conducted using mobile Topographer to capture the precise coordinates of various land cover types within the study area, including vegetation, water bodies, built-up areas, and bare land for ground truthing. The field data collection was carried out across multiple locations in the study area, ensuring adequate spatial distribution to represent the diversity of land cover present in the region. The ground truth data serves as a reference for training the classification algorithms and validating the final classified maps, enhancing the reliability and accuracy of the study's results.

The field data collected during ground truthing consists of precise GPS coordinates corresponding to different land cover types within the study area. 30 points distributed across the study area were selected. These points were strategically selected across the FUTA to capture the diversity of land cover types present in the study area. The coordinates of these points were used as training samples in the classification process and served as validation points to assess the accuracy of the resulting land cover maps. The variety of land cover types represented in the ground truthing data ensures a comprehensive evaluation of the classification results.

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Data Quality

The quality of data plays a crucial role in ensuring the accuracy and reliability of classification results. For this study, Sentinel-2 imagery was utilized due to its high spatial, spectral, and temporal resolution, making it suitable for detailed land cover classification of the Federal University of Technology, Akure (FUTA) campus. After data acquisition using Mobile Topographer, several steps were taken to assess and validate the data through control checks and instrument tests to guarantee accuracy, consistency, and reliability in the final analysis.

Data Processing

Data processing is the key phase where the raw Sentinel-2 data is transformed into valuable information through image classification techniques. In the pixel-based classification, the Maximum Likelihood Classification (MLC) algorithm was employed. Training samples representing the major land cover classes were selected based on ground truth data. Each pixel in the image was classified individually based on its spectral properties, with the algorithm assigning class labels based on the highest probability of class membership. Post-classification processing involved filtering and smoothing techniques to reduce noise and eliminate misclassified pixels, thereby enhancing the overall map quality. For the object-oriented approach, the image was first segmented into meaningful objects using a multi-resolution segmentation algorithm. This process grouped pixels into objects based on spectral similarity, shape, and texture, providing a more contextual representation of the land cover features. The classification of these objects was performed using the Maximum Likelihood Classification, which utilized the spectral, spatial, and textural attributes of the segments. This method allowed for the integration of additional information, such as shape and context, improving classification accuracy in complex areas.

3.0 PRESENTATION OF RESULTS

This section presents the results of the project which include the findings and analyses. The results presented are in accordance with the objectives

Object-Based Classification

Before the classification, the classes were assigned and the classification rules to describe each class were selected. According to the ground truth, four classes were distinguished in this test: vegetation, farmland, bareground, and built-up. The maximum likelihood classifier was used to assign each segmented object or group of pixels to a specific class. The object based classification of the image of the study area is as shown in Figure 3

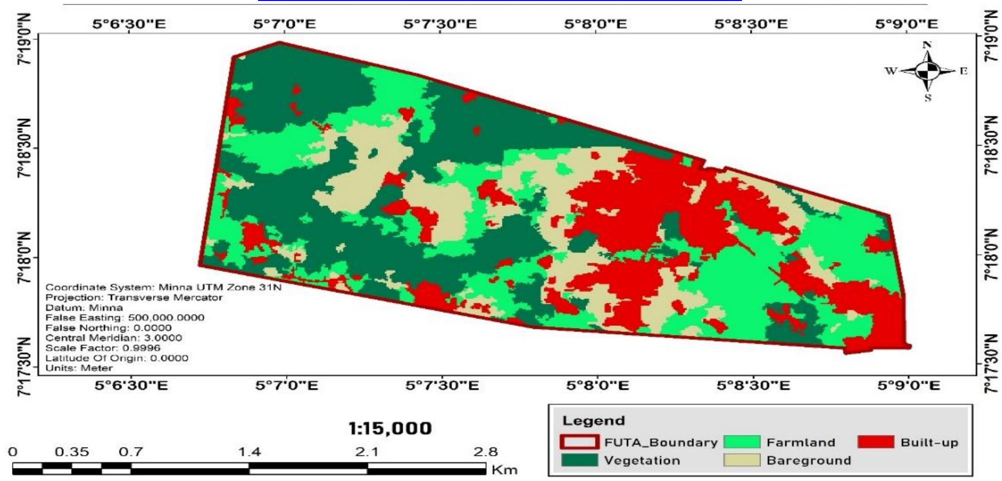

Figure 3. The Object-Based Land Cover Classification.

Pixel-Based Classification

The pixel-based classification was undertaken using ArcMap 10.8 image processing software. It was a standard supervised classification using the maximum likelihood algorithm. This involved the selection of training areas representative of the four land cover classes. A number of training areas were selected to represent each class. The signature (or spectral mean) of the training area was then used to determine to which class the pixels were assigned. Supervised classification algorithms are applied in pixel-based classification. In this study, maximum likelihood classifier is implemented. For comparison with object-oriented techniques, the same classes with the same color information are designed in both classification approaches. The outcome of the pixel-based classification is as presented in Figure 4

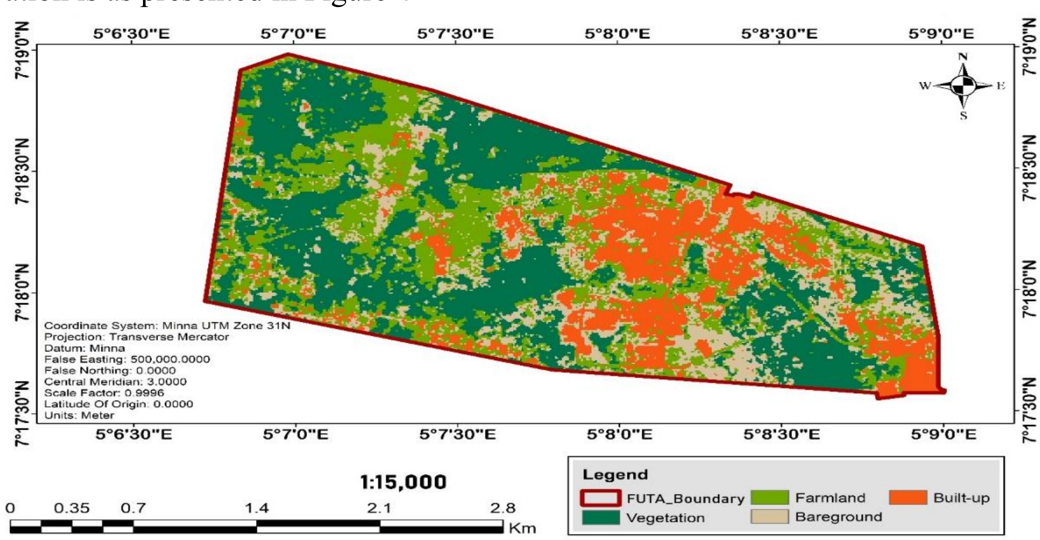

Figure 4. Pixel-Based Land Cover Classification.

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Comparison of Object-Based and Pixel-Based Classification

A visual comparison of the resultant land cover images shows the differences between the classifications (Figure 5). While both methods produce aggregations of pixels based on land cover classes, the object-oriented classification yields multi-pixel features, whereas the pixel-based classification contains many small groups of pixels or individual pixels. This produces classes with mixed clusters of pixels as displayed by the heterogeneous nature of the image.

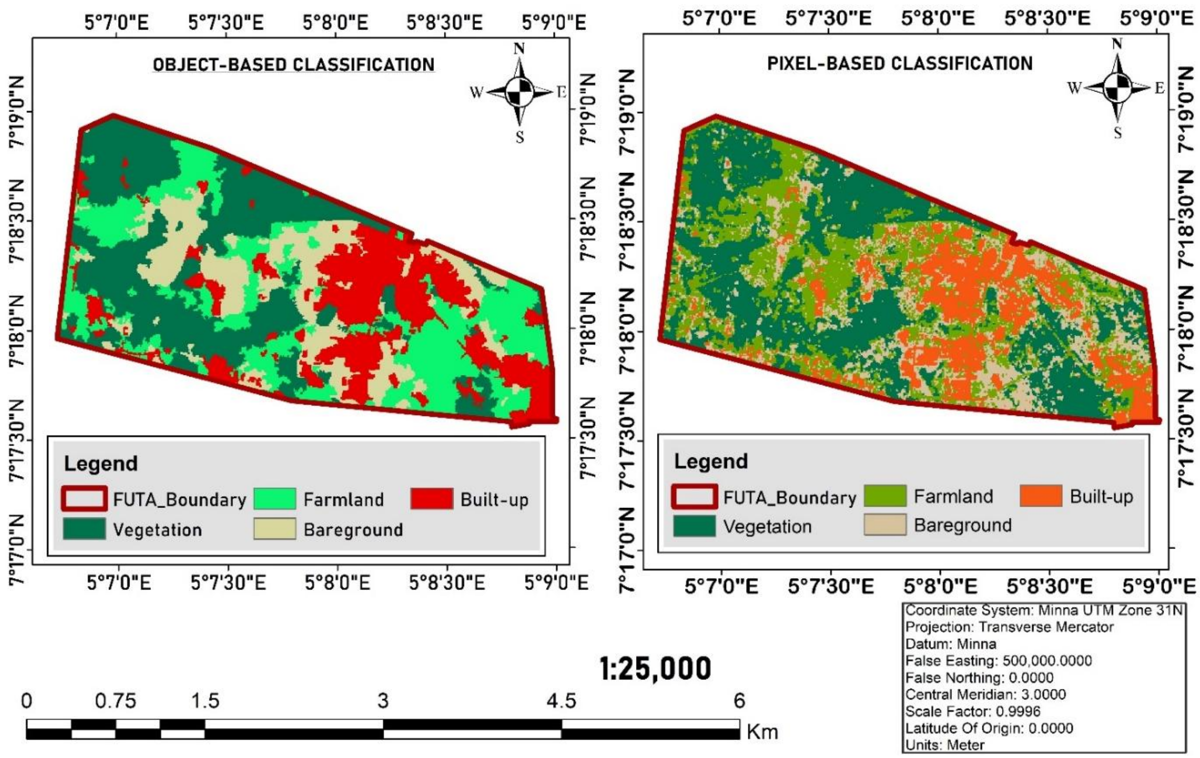

Figure 5. Comparison of Object-Oriented and Pixel-Based classification

Accuracy Assessment Points

To assess the accuracy of the classified image in both pixel-based and object-oriented method, 30 purposively and evenly distributed random points were selected for ground-truthing across the entire study area as presented in Table 1.

This accuracy analysis was done in ArcMap 10.8. Before the accuracy assessment was done, the classified images were re-projected in ArcCatalogue to re-assign the projection system which had been lost during export from Spring to Tiff (.tif). The result of the accuracy assessment showed that the Pixel-based classification had up to 80% accuracy.

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Table 1. Selected Accuracy Assessment points

FID	Object_User	Pixel_User	Producer	X	Y
1	1	1	1	734961.4508	808427.3797
2	1	1	1	733582.3074	808539.8278
3	1	1	1	733714.5993	807990.8163
4	1	1	1	735114.4685	807489.9811
5	1	1	1	736722.08	806774.5464
6	4	4	4	735699.4634	807888.9736
7	4	4	4	735749.0729	807710.3795
8	4	4	4	735646.6789	807219.0472
9	4	4	4	735437.1285	807168.2471
10	4	4	4	737240.5321	806717.3962
11	3	3	3	734133.2592	808463.6497
12	4	3	3	734416.8931	808618.1667
13	3	3	3	735991.1671	807048.6552
14	4	3	3	736672.4705	807266.9369
15	4	3	3	736216.0634	806823.759
16	3	2	2	734689.194	807995.4245
17	2	2	2	735660.8782	807371.668
18	2	2	2	734207.7837	808943.2962
19	2	2	2	733852.183	808320.9949
20	2	2	2	734421.1441	807577.6201
21	2	3	2	734520.363	807421.251
22	1	1	1	734818.0199	807337.9071
23	1	1	1	733861.5492	807568.0951
24	1	1	3	733288.8905	807452.2074
25	3	3	3	733247.6154	807501.42
26	2	4	2	733287.303	807655.4078
27	3	4	4	733569.8786	807282.3445
28	3	3	3	734024.7203	807150.7912
29	4	4	4	734015.1953	807215.3497
30	4	4	4	737097.6079	806966.4556

Confusion Matrix

Confusion matrix for both the pixel-based and Object-oriented classification shows the users' arrangement in the column and the producer's arrangement in rows (Table 2).

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The essence of the confusion matrix lies in its ability to evaluate the accuracy and performance of a classification model, particularly in remote sensing, image analysis, and machine learning. It provides a detailed breakdown of how well the classifier performed by comparing the predicted (classified) labels against the actual (reference or ground truth) labels.

Table 2. Confusion Matrix

	PIXEL-BASED USER					OBJECT-BASED USER				
	V	F	BG	BU	**TOTAL**	V	F	BG	BU	**TOTAL**
V	7				**7**	7				**7**
F		6	1		**7**		5	1	1	**7**
BG	1		4	3	**8**	1		7		**8**
BU			1	7	**8**				8	**8**
	8	**6**	**6**	**10**	**30**	**8**	**5**	**8**	**9**	**30**

V= VEGETATION, F= FARMLAND, BG= BAREGROUND, BU= BUILT-UP

Accuracy Assessment

The accuracy assessment compares the results of pixel-based classification and object-oriented classification of Sentinel-2 imagery. A total of 30 samples (pixels) were randomly selected (as shown in Table 2) using ground truth data as reference samples. Subsequently, error matrices were created, and the assessment metrics, including producer's accuracy, user's accuracy, and kappa statistics, are presented in Table 3. Overall and per-class accuracy indicate that Object-Based Classification surpasses Pixel-Based Classification, particularly for Bareground and Built-up categories. Both methods demonstrate consistent and highly accurate vegetation classification. By taking into account shape, texture, and neighborhood, object-based classification enhances contextual interpretation, which may account for the higher accuracy observed, especially in urban (Built-up) and mixed-surface (Bare ground) regions. Table 3 presents the error matrices that summarize classification accuracy statistics derived from confusion matrices for both Pixel-Based and Object-Oriented classification methods.

Table 3. Error matrices for both Pixel-Based and Object-Oriented classification methods.

CLASS NAME	PIXEL-BASED CLASSIFICATION		OBJECT-ORIENTED CLASSIFICATION	
	PRODUCER'S ACCURACY %	USER'S ACCURACY %	PRODUCER'S ACCURACY %	USER'S ACCURACY %
V	87.50	100.00	87.50	100.00
F	100.00	85.71	100.00	71.43
BG	50.00	50.00	87.50	87.50
BU	70.00	87.50	88.89	100.00
	Overall Accuracy: 80%		**Overall Accuracy: 90%**	
	Overall Kappa: 0.7329		**Overall Kappa: 0.8663**	

From Table 3, we can see that Object-Oriented Classification performs better overall, both in terms of accuracy (90%) and agreement (Kappa = 0.8663). Moreover, because pixel-based classification relies solely on the spectral information of individual pixels, the results often appear fragmented, resembling a pepper-and-salt pattern. Vegetation class is well-classified in both methods (100% user accuracy). Bareground saw major improvement in object-oriented classification (from 50% to 87.5%), while Farmland classification was more accurate in pixel-based (producer's = 100%, user's = 85.71%) than in object-oriented. The Kappa values confirm that object-oriented classification is more reliable overall.

Comparison of Land Use Themes

Table 4 compares the total area and the relative proportions (in percentages) of different land use themes as determined by the Pixel-Based and Object-Oriented classification.

Table 4. *Comparison of Land use themes*

	Pixel-Based (Km²)	%	Object-Oriented (Km²)	%
Vegetation	2.515	37%	2.266	33%
Forest	1.917	28%	1.803	27%
Bareground	1.206	18%	1.232	18%
Built-Up	1.161	17%	1.496	22%
TOTAL	**6.799**	**100%**	**6.798**	**100%**

Source: Authors Work (2025)

Analyzing the land use area presented in Table 4, the object-based classification technique proved effective in identifying and leaving unclassified regions that did not correspond with any of the training data. On the other hand, the pixel-based classification approach, which relies exclusively on the values of pixels, mistakenly categorized these regions into one of the four land use types. This misclassification resulted in differences in the estimated area for each land use theme. The area calculated using object-based image classification is more precise since it aligns more closely with the area depicted in the vector map than that obtained from the pixel-based method. The vector map indicates that the area is primarily dominated by Vegetation, followed by Farmland, and then Bare Ground and Built-up, which represent the smallest areas among the categories. According to the pixel-based method, the vegetation covers 2.515 km² (37%), compared to 2.266 km² (33%) from object-oriented classification; Farmland accounts for 1.917 km² (28%) versus 1.803 km² (27%); Bare Ground is recorded at 1.206 km² (18%) as opposed to 1.232 km² (18%); and Built-up is measured at 1.161 km² (17%) compared to 1.496 km² (22%) from the pixel-based classification. The total area calculated is almost the same, with the pixel-based method estimating 6.799 km² and the object-oriented method estimating 6.798 km², suggesting that, while the distribution of areas across various themes slightly differs between the methods, the overall extent of the study area is reliably estimated.

Discussion of Result

The findings indicate that object-based classification typically outperforms pixel-based classification regarding overall accuracy and reliability, especially in diverse landscapes like urban and mixed land cover settings. With an overall classification accuracy of 90% and a kappa coefficient of 0.8663, the object-based method provided a more coherent and less fragmented representation of land use types. This is especially evident in the classification of bareground and built-up areas, where spatial context, texture, and shape were critical for accurate identification.

The significance of these results is considerable for uses in urban development, ecological monitoring, and agricultural resource management. By integrating spatial and contextual aspects beyond mere pixel spectral values, object-based classification yields a more detailed and interpretable output, especially in intricate urban landscapes. This supports findings from previous research, including those by [12] and [12] which highlight the benefits of Object-Based Image Analysis (OBIA) compared to traditional pixel-based techniques in high-resolution remote sensing.

4.0 CONCLUSION AND RECOMMENDATIONS

This study has demonstrated the effectiveness of object-oriented and pixel-based classification techniques in land cover analysis using Sentinel-2 imagery. The comparison revealed that object-oriented classification consistently outperformed the pixel-based method in both accuracy and reliability. By incorporating spatial context and relationships between pixels, the object-oriented approach produced a more cohesive and realistic representation of land cover classes, reducing the fragmentation often observed in pixel-based outputs. Accuracy assessment showed that the object-oriented method achieved an overall accuracy of 90%, compared to 80% for the pixel-based method, with a higher Kappa coefficient further confirming its superior performance.

These findings highlight the value of object-oriented classification for both scientific research and practical applications. For land managers and urban planners, its improved precision in mapping built-up areas offers a stronger foundation for planning and infrastructure development. For environmental assessments, its better differentiation of vegetation and bare land provides a more reliable guide for conservation and resource allocation. While both methods successfully identified the major land cover types: vegetation, farmland, bare ground, and built-up areas, the object-oriented approach proved particularly effective in reducing misclassification between vegetation and urban areas. Overall, this study underscores the suitability of object-oriented methods for complex land cover studies and emphasizes their potential to support informed decision-making in environmental and urban planning.

In light of these results, it is recommended that object-oriented classification be prioritized in future land cover studies, particularly in heterogeneous and urban landscapes where accuracy is critical. Expanding the number of ground-truthing points beyond the thirty (30) used in this study would strengthen the validation process and enhance reliability. Future research should also explore the use of higher-resolution imagery, such as WorldView, QuickBird, or UAV data, to further refine classification outputs in diverse landscapes.

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