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Analysis and Validation of Image Classification Techniques in Mapping Urban Areas Using High Resolution Satellite Imagery

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Abstract

This study aimed at an analysis and validation of image classification techniques in mapping urban areas using high resolution satellite imagery. It's objectives were to identify and extract regions of interest (ROI) from the study area subset of the high-resolution imagery, to perform image classification using Maximum Likelihood Classifier, Support Vector Machine, rule-based, example-based and index-based classifiers and to evaluate the performances of Maximum Likelihood Classifier, Support Vector Machine, rule-based, example-based and index-based classifiers using error matrix, kappa, correlation coefficient, standard deviation, standard error, mean square error and root mean square error. The methodology covered data acquisition of high-resolution satellite image data, data preprocessing for the acquired image data, image classification and image classification assessment with error matrix, kappa, correlation coefficient, standard deviation, standard error, mean square error and root mean square error. The classification results obtained from maximum likelihood, support vector machine, rule-based, example-based and index-based classification indicated that maximum likelihood and support vector machine classifiers achieved higher classification values for agricultural area and commercial area, while achieving lower values for the classification of open space and residential areas. Rule-based, example-based and index-based classifies, all had the values for agricultural, commercial areas, open space, industrial and residential areas in similar range. In the classification of waterbody, all classifiers had all their values in the same range. Using the final ranking of the results from error matrix, kappa, correlation coefficient, standard deviation, standard error, mean square error and root mean square error, example-based classification ranked as the best in the group, rule-based classification ranked second best, support vector machine classification and index-based classification ranked third best, while maximum likelihood classification ranked fourth. The study recommends the example based object-oriented classification approach as it is a robust and efficient tool for mapping different features within the settings of an urban landscape.

Keywords: Accuracy Assessment, LULC, Support Vector Machine, Object-based Classification

1. Introduction

Urban dynamics provide a foundational framework for interpreting historical and contemporary development patterns, including the interactions between human activities and environmental resources. Such understanding is indispensable for achieving informed and sustainable land allocation for future development. Within the Nigerian context, numerous urban development initiatives have historically proceeded with limited integration of land use and land cover information, thereby constraining effective planning and management (Adamatzky, 1994) [1].

Rapid economic growth and population expansion have significantly altered global land cover over the past two centuries, with projections suggesting further intensification of these transformations. Urban change exerts influence on the capacity of land systems to sustain human activities by modifying ecosystem services, while associated economic processes contribute to climate variability and broader environmental change (Ayodeji, 2006) [2]. Continuous and systematic monitoring of land cover is therefore required to capture both long-term trends and inter-annual variability, while maintaining sufficient spatial resolution to detect anthropogenic influences (Hathout, 2002) [6].

Efficient land utilization depends not only on knowledge of existing urban conditions but also on the ability to accurately monitor and represent spatial and temporal patterns of urban expansion. These dynamics are driven by population pressures and natural processes that continuously reshape the landscape. A comprehensive understanding of urban spatial patterns facilitates the evaluation of complex interactions and supports projections of future land use trajectories (Lambin *et al*., 2003) [7]. Consequently, the analysis of urban dynamics has become integral to strategies aimed at environmental monitoring and sustainable resource management.

Accurate mapping of urban dynamics requires the application of appropriate analytical techniques. Remote sensing and Geographic Information Systems have emerged as effective tools due to their capacity to generate rapid, reliable, and cost-efficient spatial data, particularly in rapidly developing regions. Remote sensing provides essential information on land cover and land use metrics, which can be integrated with demographic and ancillary datasets within a GIS environment for comprehensive spatial analysis (Yagoub, 2006) [11]. The integration of these technologies enhances analytical capability and supports informed decision-making processes. As emphasized by Igbokwe (2012) [5], the combination of GIS and remote sensing represents a powerful approach for solving complex spatial problems.

The accuracy of urban mapping is not solely dependent on the availability of remotely sensed data. The selection and implementation of classification algorithms significantly influence the quality of extracted information. Consequently, comparative evaluation of classification techniques is necessary to determine the most suitable approaches for producing reliable urban maps (Blaschke, 2010) [3]. Such evaluations provide a quantitative basis for selecting appropriate methodologies in urban studies.

The city of Owerri has experienced substantial physical expansion, driven by the proliferation of socio-economic infrastructure and institutional development facilitated by both public and private sector investments. These developments have contributed to significant transformation of the urban landscape, reflecting broader patterns of modernization and growth.

Remote sensing-based mapping of land use and land cover has been extensively applied across multiple disciplines, including geography, wetland ecology, forestry, natural resource management, geology, agriculture, and urban planning (Lillesand & Kiefer, 2003) [8]. Over the past three decades, satellite remote sensing has become instrumental in advancing understanding of land cover processes at both regional and global scales (Schowengerdt, 1997) [13].

Land use change in Owerri represents a continuous and inevitable phenomenon, influenced by both temporary and permanent human activities. These transformations occur across varying spatial scales and temporal dimensions, reflecting broader global patterns of land use dynamics. The increasing complexity of urban environments necessitates precise classification and characterization of land use patterns to support sustainable development. Population growth remains a dominant driver of urban change, although multiple interacting factors contribute to observed spatial transformations (Ramankutty *et al*., 2002) [12]. Accurate modelling and representation of urban systems are highly dependent on the availability and quality of spatial data (Tayyebi *et al*., 2010) [14].

Previous studies within Imo State have applied remote sensing techniques for urban mapping (Njoku *et al*., 2010; Okeke, 2015) [9, 10]. These studies predominantly employed maximum likelihood supervised classification without conducting comprehensive evaluations of alternative classification methods. Recent advancements have introduced algorithms such as support vector machines, artificial neural networks, random forest classifiers, principal component analysis, and object-based image analysis, which offer potential improvements in classification accuracy. Despite these developments, limited research has systematically assessed the performance of these techniques within the Owerri context.

The absence of comparative analysis among contemporary classification approaches highlights a significant research gap. Addressing this gap is necessary to identify the most effective technique for urban mapping within the study area. Such evaluation will enhance the accuracy of spatial outputs and provide reliable datasets to support urban planning, policy formulation, and sustainable environmental management in Owerri.

2. Material and Methods

2.1. Study Area

Owerri serves as the administrative capital and largest urban center of Imo State, Nigeria. The metropolitan area comprises three Local Government Areas, namely Owerri Municipal, Owerri North, and Owerri West. The city occupies an approximate land area of 100 square kilometers and had an estimated population exceeding 1.4 million as of 2016. Geographically, it is bounded by the Otamiri River to the east and the Nworie River to the south, and is located between latitudes 5°20′N and 5°30′N and longitudes 6°55′E and 7°05′E.

2.2. Materials and Methods

The methodological framework adopted for this study comprised the acquisition of high-resolution satellite imagery, followed by a sequence of preprocessing, classification, and accuracy evaluation procedures. Each stage was systematically implemented to ensure reliable extraction and validation of land use and land cover information within the study area.

2.2.1. Image Processing

Preprocessing operations were conducted to enhance the quality and reliability of the satellite imagery. Atmospheric correction was applied to minimize distortions caused by atmospheric conditions, sensor geometry, and illumination variability. The autonomous atmospheric correction module in ERDAS Imagine was employed to convert recorded radiance values into surface reflectance. This procedure mitigated the effects of atmospheric scattering, sensor viewing angles, and instrumental noise, thereby improving spectral consistency and enhancing the performance of subsequent classification algorithms.

2.2.2. Image Subsetting

Spatial extraction of the study area was undertaken to isolate the region of interest from the full satellite scene. This process involved the use of a predefined boundary shapefile corresponding to the study area. The operation was executed within the ArcGIS 10.7 environment, ensuring that subsequent analyses were restricted to the relevant geographic extent.

2.2.3. Delineation of Regions of Interest

Representative training samples were identified and delineated to support supervised classification. These samples, referred to as Regions of Interest, were selected based on prior knowledge of the study area obtained through reconnaissance surveys. Each region corresponded to a distinct land use or land cover category, enabling the extraction of spectral statistics required for classification. A Level III classification scheme was adopted to achieve adequate feature discrimination, consistent with the spatial resolution of the imagery. The identified classes included agricultural land, commercial areas, industrial zones, open spaces, recreational areas, residential zones, and water bodies.

2.2.4. Ground Truth Data Collection

Field verification was conducted to provide reference data for classification validation. A total of 600 sample points representing various land cover types were collected across the study area. The sampling locations were determined using a random sampling approach to ensure spatial representativeness. Geographic coordinates of these points were acquired using a Garmin 76 handheld Global Positioning System receiver. The collected field data served as an independent dataset for evaluating classification accuracy.

2.2.5. Image Classification and Accuracy Assessment

Classification procedures were implemented to derive land use and land cover categories from the processed imagery. Multiple classification techniques were applied, including maximum likelihood, support vector machine, rule-based, example-based, and index-based approaches. Comparative analysis indicated that the maximum likelihood and support vector machine algorithms produced superior classification outcomes.

Evaluation of classification performance was carried out using standard statistical measures. These included the error matrix, Kappa coefficient, correlation coefficient, standard deviation, standard error, mean square error, and root mean square error. These metrics provided quantitative insight into the reliability and precision of the classification results, thereby ensuring the robustness of the derived spatial information.

3. Results

3.1. Pixel-Based Urban mapping

3.1.1. Maximum Likelihood Classifier

The classification output derived from the maximum likelihood algorithm, as illustrated in Figure 3.1, reveals a clear dominance of agricultural land within the study area. This category occupies approximately 45.83% of the total area, corresponding to about 224.92 km². Residential land use represents the second most extensive class, covering 28.10% or roughly 150.15 km².

Other land use categories exhibit comparatively smaller spatial extents. Recreational areas account for 7.63% of the landscape, covering approximately 40.78 km², while commercial land use constitutes 6.44%, equivalent to about 34.44 km². Industrial zones occupy 5.97% of the area, translating to approximately 31.89 km². Open spaces represent 4.06%, with an estimated coverage of 21.68 km². Water bodies form the least represented class, accounting for 1.97% of the total area, which corresponds to approximately 10.53 km².

These results demonstrate a landscape largely characterized by agricultural and residential land uses, with other categories distributed in relatively smaller proportions across the study area.

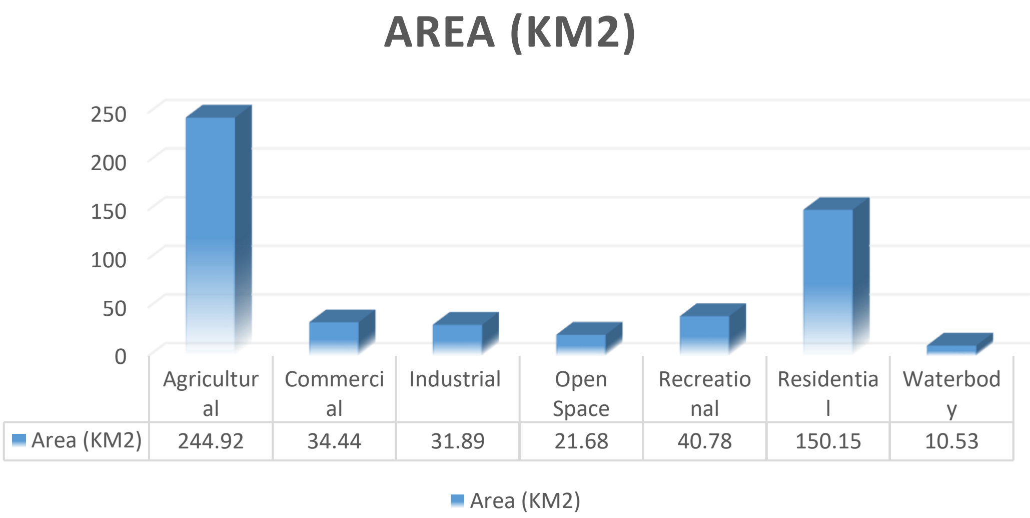


Fig 1: Landcover/landuse distribution from MLC classifier

3.1.2. Support Vector Machine Classifier

The classification results generated using the support vector machine algorithm, as presented in Figure 3.2, indicate that agricultural land constitutes the most extensive land use category within the study area. This class covers approximately 46.02% of the total area, corresponding to about 245.92 km². Residential land use follows, occupying 28.47% with an estimated spatial extent of 152.15 km².

Commercial areas account for 6.44% of the landscape, covering approximately 34.44 km², while industrial land use represents 5.97%, equivalent to about 31.89 km². Recreational areas occupy 7.26% of the total area, translating to approximately 38.78 km². Open spaces cover 3.87%, corresponding to an area of about 20.68 km². Water bodies remain the least dominant class, accounting for 1.97% with a spatial extent of approximately 10.53 km².

These findings reflect a land use structure in which agricultural and residential classes dominate, while other categories are more sparsely distributed across the study area.

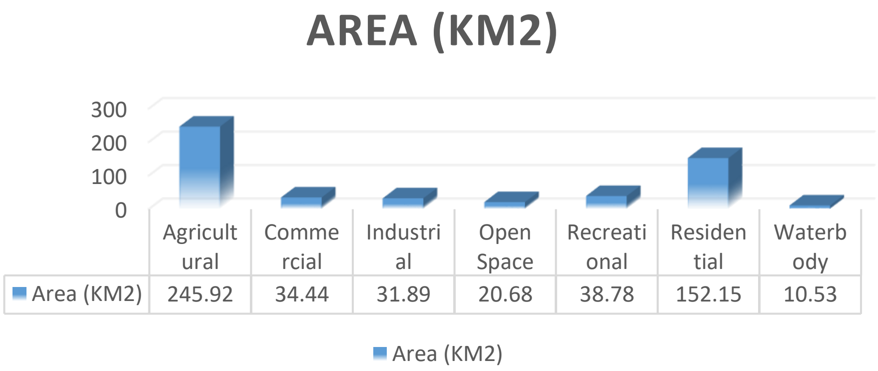


Fig 2: Landcover/landuse distribution from SVM classifier

3.2. Object-Based Urban Mapping

3.2.1. Rule-based object classifier

The output derived from the rule-based classification approach, as illustrated in Figure 3.3, shows that agricultural land remains the predominant land use category within the study area. This class occupies approximately 42.59% of the total land area, equivalent to about 227.57 km². Residential areas constitute the second largest category, accounting for 29.26% with an estimated coverage of 156.38 km².

Commercial land use represents 7.02% of the study area, corresponding to approximately 37.49 km², while industrial zones cover 6.48%, translating to about 34.63 km². Recreational areas account for 7.53%, with a spatial extent of approximately 40.24 km². Open spaces occupy 5.37% of the area, equivalent to about 28.69 km². Water bodies represent the smallest class, covering 1.76% of the total area, which corresponds to approximately 9.38 km².

Overall, the results highlight a landscape largely dominated by agricultural and residential land uses, with other categories distributed in smaller proportions across the study area.

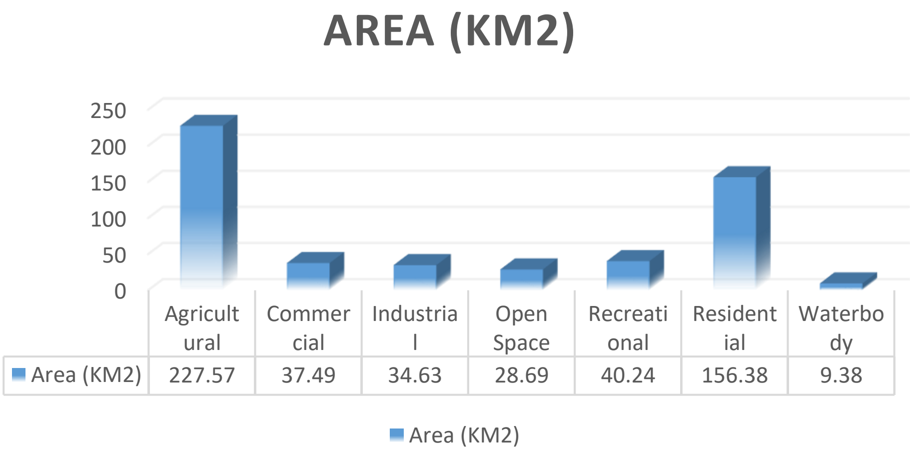


Fig 3: Landcover/landuse distribution from rule-based object classifier

3.2.2. Example-based object classifier

The results produced from the example-based classification method, as presented in Table 3.4, indicate that agricultural land constitutes the largest proportion of land use within the study area. This category covers approximately 42.34% of the total area, corresponding to about 226.27 km². Residential land use follows, occupying 29.43% with an estimated spatial extent of 157.27 km².

Commercial areas account for 7.23% of the landscape, covering approximately 38.62 km², while industrial land use represents a similar proportion of 7.23%, with an area of about 32.99 km². Recreational areas occupy 7.25% of the total area, translating to approximately 38.72 km². Open spaces cover 5.58%, equivalent to about 29.82 km². Water

bodies represent the least extensive class, accounting for 2.00% with a spatial coverage of approximately 10.69 km².
These findings indicate a land use pattern dominated by agricultural and residential activities, with other categories occupying relatively smaller portions of the study area.

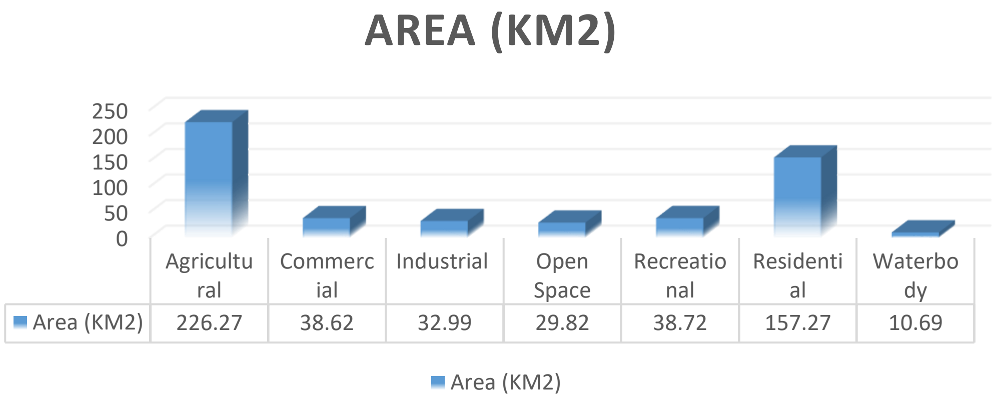


Fig 4: Landcover/landuse distribution from example-based object classifier

3.3. Index-based Urban Mapping

The classification output derived from the index-based approach, as presented in Table 3.5, indicates that agricultural land remains the most extensive land use category within the study area. This class covers approximately 42.92% of the total area, corresponding to about 219.33 km². Residential areas constitute the next largest category, accounting for 29.45% with an estimated spatial extent of 157.37 km².
Commercial land use represents 6.93% of the landscape, equivalent to approximately 37.02 km², while industrial areas occupy 6.29%, corresponding to about 33.59 km². Recreational areas cover 7.38% of the study area, translating to approximately 39.44 km². Open spaces account for 5.17%, with an area of about 27.64 km². Water bodies remain the least represented class, covering 1.87% of the total area, which corresponds to approximately 9.99 km².
Overall, the results reflect a spatial distribution dominated by agricultural and residential land uses, with other categories occupying comparatively smaller proportions across the study area.

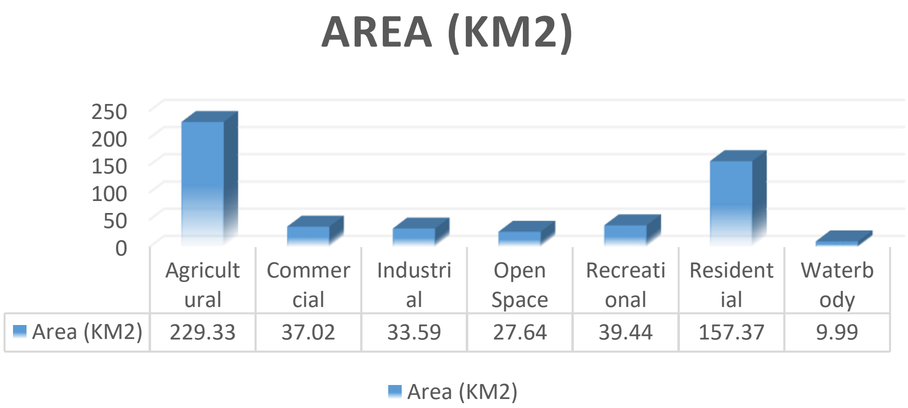


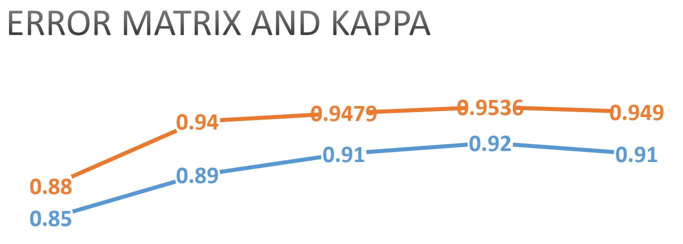
Fig 5: Landcover/landuse distribution from index-based classifier

3.4. Assessment of Classification Accuracy

The assessment of classification performance in this study was conducted using a range of statistical indicators, including the error matrix, Kappa coefficient, correlation coefficient, standard deviation, standard error, mean square error, root mean square error, and an overall ranking of classifier performance.

3.4.1. Error Matrix and Kappa Statistics

Classification accuracy was evaluated through the construction of a confusion matrix, which facilitated the comparison between classified outputs and reference data. This matrix provides insight into classification performance by identifying instances of agreement and misclassification across different land use and land cover categories. It is particularly useful in detecting inaccuracies arising from overlapping spectral characteristics, where distinct features exhibit similar reflectance properties, thereby complicating their discrimination (Ndukwe, 1997).
The reliability of the classified imagery was further examined by comparing classification results with ground truth data collected from the field. This validation process enabled the quantification of classification accuracy and ensured that the derived land cover information adequately represents real-world conditions, as illustrated in Figure 3.6.



	MLC	SVM	Rule-Based	Example-Based	Index-Based
Overall Accuracy	0.85	0.89	0.91	0.92	0.91
Kappa	0.88	0.94	0.9479	0.9536	0.949

Fig 6: Overall Accuracy and Kappa

3.4.2. Pearson's Correlation Coefficient

Pearson's correlation coefficient is employed to quantify the degree of linear association between two continuous variables. This statistical measure, derived from covariance, is widely regarded as a reliable approach for evaluating relationships between variables of interest. It provides insight into both the strength and direction of the association. A coefficient value of +1 signifies a perfect positive relationship, whereas a value of −1 represents a perfect negative relationship. The scatter plots illustrating these relationships are presented in Figures 3.7 to 3.11, followed by detailed interpretation.

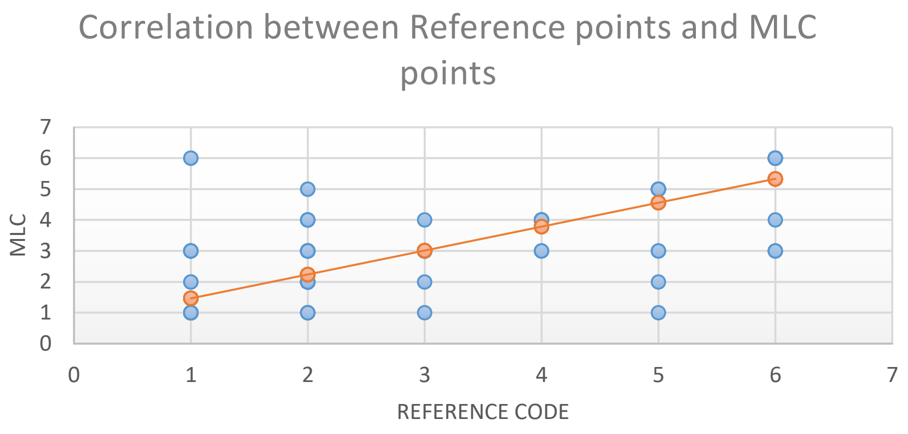


Fig 7: Reference against MLC fit graph

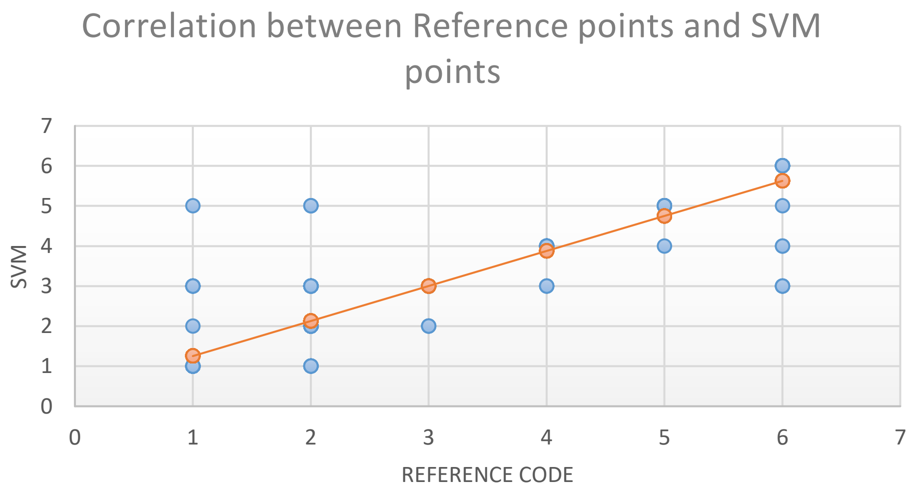


Fig 8: Reference against SVM fit graph

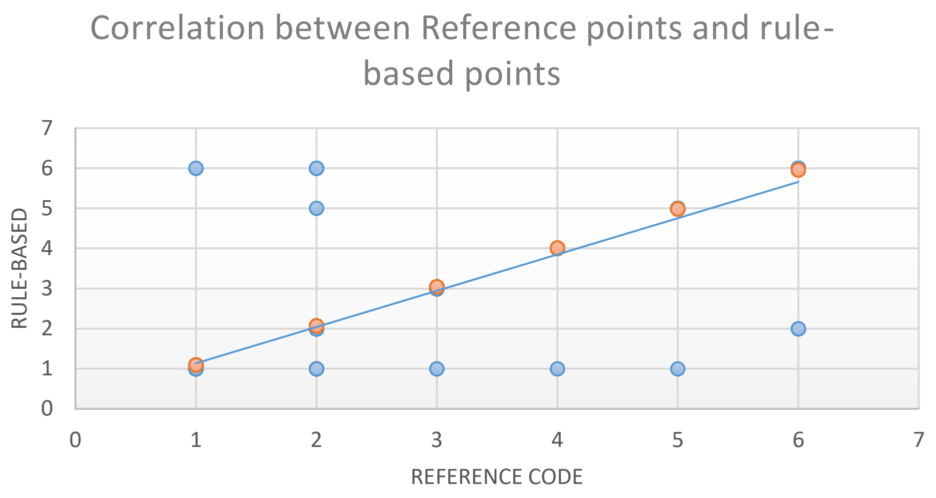


Fig 9: Reference against Rule-based fit graph

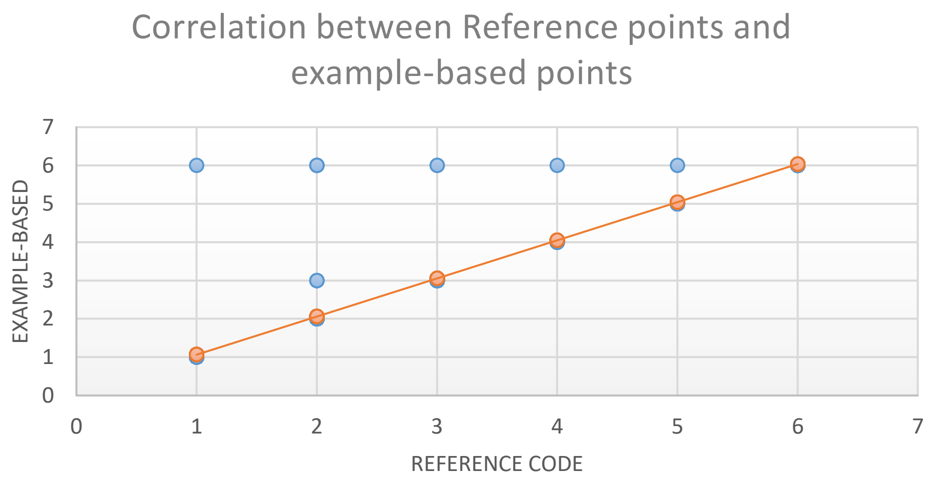


Fig 10: Reference against example-based fit graph

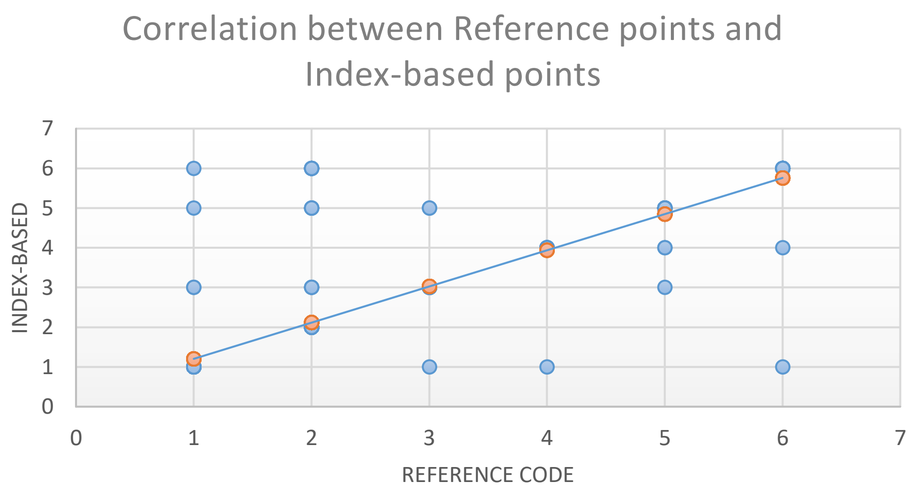


Fig 11: Reference against index-based-based fit graph

The results presented in Figures 3.7 to 3.11 indicate varying degrees of agreement between the classified outputs and the ground reference data. The maximum likelihood classifier produced a correlation coefficient of 0.8059, while the support vector machine yielded a value of 0.8832. The rule-based approach recorded a coefficient of 0.9231, and the example-based method achieved the highest value at 0.9381. The index-based classifier produced a coefficient of 0.8534.

These values demonstrate that all classification techniques exhibit a strong positive relationship with the reference data, with the example-based method showing the highest level of agreement, followed by the rule-based approach, support vector machine, index-based method, and finally the maximum likelihood classifier.

3.4.3. Standard Deviation

Standard deviation was employed to quantify the extent of variability between the classification outputs and the corresponding ground reference data. This statistical measure indicates how closely the observed values cluster around the mean. Lower standard deviation values suggest that the data points are closely grouped around the mean, reflecting greater consistency, whereas higher values indicate a wider dispersion of observations. The computed results are illustrated in Figure 3.12.

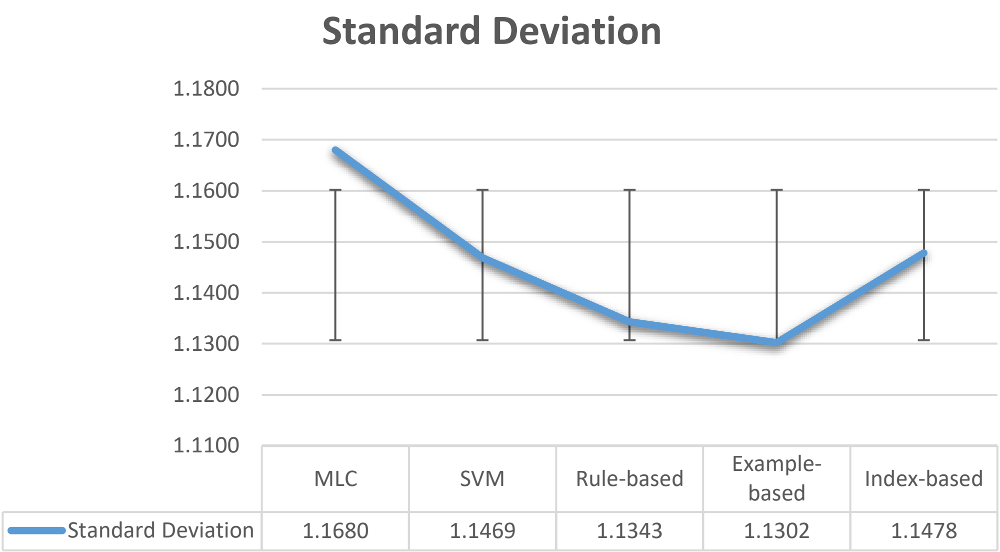


Fig 12: Standard deviation for the different classifiers

The values presented in Figure 3.12 reveal differences in the level of dispersion between the classification outputs and the corresponding ground reference data. The maximum likelihood classifier produced a standard deviation of 1.167, while the support vector machine yielded a value of 1.146. The rule-based approach recorded a standard deviation of 1.134, and the example-based method showed the lowest value at 1.130. The index-based classifier produced a value of 1.147. These results indicate that the example-based method exhibits the least variability relative to the reference data, followed in ascending order by the rule-based approach, support vector machine, index-based method, and finally the maximum likelihood classifier, which shows the greatest dispersion.

3.4.4. Standard Error

Standard error was applied as a statistical indicator to evaluate the precision of the sample mean in representing the true population mean. This measure reflects the extent to which sample means are expected to vary from the actual population mean. Lower standard error values suggest a higher level of accuracy and consistency, whereas higher values indicate greater uncertainty and reduced representativeness. In this study, standard error was utilized to assess the degree of agreement between the classification outputs and the reference data. The results are presented in Figure 3.13.

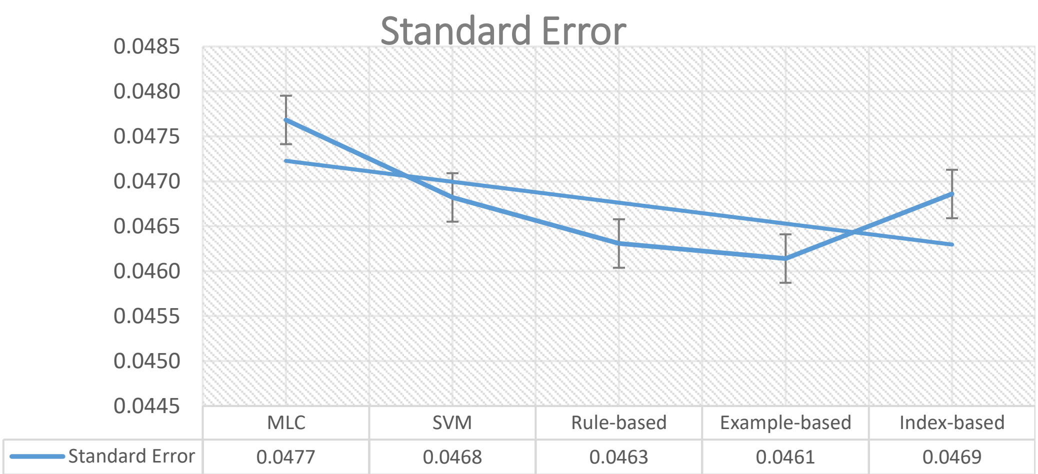


Fig 13: Standard Error for the classifiers

The results indicate that the maximum likelihood classifier produced a standard error value of 0.0477, while the support vector machine yielded 0.0468. The rule-based method recorded a value of 0.0463, and the example-based approach produced the lowest standard error at 0.0461. The index-based classifier returned a value of 0.0469. These outcomes demonstrate that the example-based method exhibits the highest level of precision relative to the reference data, followed by the rule-based approach, support vector machine, and index-based method, whereas the maximum likelihood classifier shows the greatest deviation.

3.4.5. Mean Square Error

Mean square error (MSE) represents the average of the squared differences between predicted values and observed values, thereby providing a quantitative measure of estimation accuracy (Lehmann & George, 1998). This metric serves as an indicator of the performance of an estimator, with values approaching zero reflecting improved accuracy. Within this study, MSE was applied to evaluate the performance of the classification techniques by comparing their outputs with the reference data. The corresponding results are illustrated in Figure 3.15.

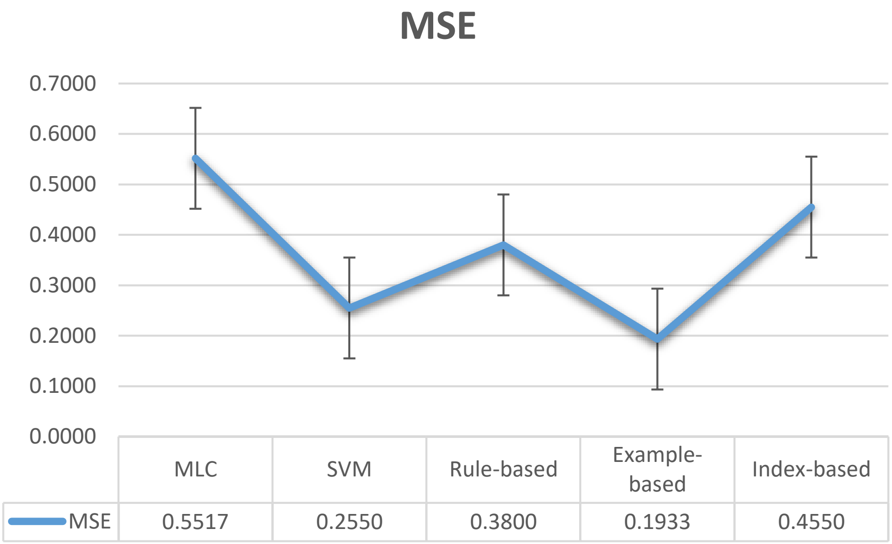


Fig 15: Mean square error of the classifiers

The values presented in Figure 3.15 indicate variations in the performance of the classification methods based on mean square error. The maximum likelihood classifier produced an MSE of 0.5515, while the support vector machine yielded a value of 0.2550. The rule-based approach recorded 0.3800, and the example-based method achieved the lowest value at 0.1933. The index-based classifier produced an MSE of 0.4550. These results demonstrate that the example-based method exhibits the highest level of accuracy relative to the reference data, followed by the support vector machine, rule-based approach, and index-based method, whereas the maximum likelihood classifier shows the largest deviation.

3.4.6. Root Mean Square Error

Root mean square error (RMSE) represents the square root of the variance of the residuals and provides a measure of how closely predicted values correspond to observed data. It reflects the overall fit of the model, with lower values indicating better agreement between predicted and actual values. In this study, RMSE was applied to evaluate the performance of the classification techniques by comparing their outputs with the reference data. The results are presented in Figure 3.16.

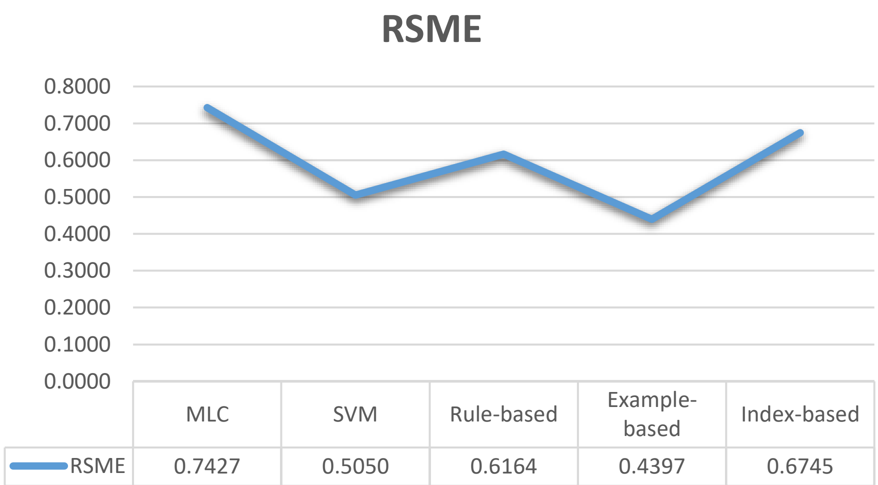


Fig 16: Mean square error of the classifiers

The results presented in Figure 3.16 demonstrate variations in classifier performance based on root mean square error. The maximum likelihood classifier recorded an RMSE value of 0.7427, while the support vector machine produced a value of 0.5050. The rule-based method yielded 0.6164, and the example-based approach achieved the lowest value at 0.4397. The index-based classifier returned an RMSE of 0.6745. Similar to the pattern observed with mean square error, these values indicate that the example-based method exhibits the highest level of agreement with the reference data, followed by the support vector machine, rule-based method, and index-based approach, whereas the maximum likelihood classifier shows the greatest deviation.

4.6.8. Summary of Accuracy Assessment and Ranking

The comparative evaluation of classification techniques across multiple accuracy metrics reveals consistent variations in performance. Based on the Kappa statistic, the example-based, rule-based, and index-based classifiers attained the highest ranking, while the support vector machine occupied the second position and the maximum likelihood classifier ranked lowest.

Analysis using the correlation coefficient indicates that the example-based method achieved the highest ranking, followed by the rule-based approach, support vector machine, index-based method, and maximum likelihood classifier in descending order.

Assessment using standard deviation shows that the example-based and rule-based methods performed best, with support vector machine and index-based classifiers occupying the next position, while the maximum likelihood method ranked lowest.

Evaluation based on standard error reveals that the example-based classifier maintained the highest accuracy, followed by the rule-based method, support vector machine, index-based classifier, and finally the maximum likelihood approach.

Using mean square error as a criterion, the example-based method again ranked highest, followed by the rule-based classifier, support vector machine, index-based approach, and maximum likelihood classifier. A similar pattern is observed with root mean square error, where the example-based method ranked first, followed by the rule-based classifier, while support vector machine and index-based methods shared the next position, and the maximum likelihood classifier ranked lowest.

A synthesis of all evaluation metrics indicates that the example-based classification approach consistently outperformed the other methods. The rule-based classifier ranked second overall, while the support vector machine and index-based approaches demonstrated comparable performance in the third position. The maximum likelihood classifier recorded the lowest overall performance among the evaluated methods. The comprehensive ranking summary is presented in Table 3.1.

Table 1: Summary of Accuracy Assessment Metrics

	Metric													
Class	**EM**	**RK**	**K^**	**RK**	**CoR**	**RK**	**SD**	**RK**	**SE**	**RK**	**MSE**	**RK**	**RSME**	**RK**	**Final Rank**
MLC	0.85	4	0.88	3	0.80	5	1.16	3	0.0477	5	0.55	5	0.74	5	4
SVM	0.89	3	0.94	2	0.88	3	1.14	2	0.0468	3	0.25	2	0.50	2	3
Rule-Based	0.91	2	0.95	1	0.92	2	1.13	1	0.0463	2	0.38	3	0.61	3	2
Example-Based	0.92	1	0.95	1	0.94	1	1.13	1	0.0461	1	0.19	1	0.44	1	1
Index-Based	0.91	2	0.95	1	0.85	4	1.14	2	0.0469	4	0.45	4	0.67	4	3

Where 1 = Best in the group
2 = Better than average
3 = Average
4 = Below Average

5. Summary and Conclusion

Image classification techniques have long been established within remote sensing practice and remain widely utilized in contemporary spatial analysis. Current research efforts are increasingly directed toward identifying the most appropriate classification approach for urban applications, particularly those capable of producing results that closely correspond to observed ground conditions. In this context, many existing studies rely primarily on the error matrix and Kappa coefficient as standard measures of classification accuracy. The present study extends beyond these conventional metrics by incorporating additional statistical indicators, including correlation coefficient, standard deviation, standard error, mean square error, and root mean square error. These measures provide a more comprehensive evaluation framework, as they facilitate detailed comparison between predicted classification outputs and observed reference data, thereby enhancing the assessment of model performance.

Findings from the analysis demonstrate that the example-based classification approach exhibits superior performance in urban mapping applications. Its effectiveness is reflected in its consistent ability to produce results that closely align with ground reference data, indicating a high level of classification reliability and efficiency in complex urban environments.

The results also indicate that alternative classification approaches, including pixel-based, rule-based, and index-based methods, should not be regarded as ineffective. Each method possesses inherent strengths and operational requirements that must be carefully considered. Pixel-based classification performs optimally in situations where land cover classes exhibit clear spectral separability, although post-classification filtering techniques may be required to address issues such as pixel fragmentation. Rule-based and index-based approaches, on the other hand, depend heavily on the availability and quality of ancillary data, as well as the appropriate definition of classification rules and thresholds that accurately represent the characteristics of target features.

The study provides a comprehensive comparative evaluation of multiple urban mapping techniques using high-resolution satellite imagery. Based on the analytical outcomes and practical observations, several recommendations are proposed. The example-based object-oriented classification method is strongly advised for urban mapping due to its demonstrated efficiency and reliability in delineating complex land use patterns. Careful consideration is required when applying pixel-based classification to high-resolution imagery, as spectral similarities among different classes may result in increased misclassification. The rule-based object-oriented approach also presents a viable alternative for urban feature extraction; however, its performance is highly dependent on the effectiveness of segmentation parameters and the accuracy of the rule sets applied.

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