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Optimizing Land Use Classification Using Google Earth Engine: A Comparative Analysis of Machine Learning Algorithms

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Abstract

Land use and land cover (LULC) mapping provides crucial information for sustainable development, urban planning, disaster risk assessment, and mitigation. Various approaches are used for LULC classification in remote sensing, but machine learning has recently gained significant popularity. This paper investigates the application of machine learning algorithms for LULC mapping in Al Ain city, UAE. The study utilizes the Gradient Tree Boosting (GTB), Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART) classifiers within the Google Earth Engine (GEE) platform. The objective is to evaluate and compare the performance of these algorithms using Sentinel-2 imagery from 2024 while also assessing GEE's suitability for handling both the dataset and algorithms. Various parameters influence algorithm performance. Algorithm performance is evaluated based on overall accuracy and kappa coefficient metrics along with user and producer accuracy. The results indicate that RF and GTB achieved the highest overall accuracy, with GTB's Kappa coefficient slightly lower than RF's, followed by SVM. CART demonstrated a comparatively lower overall accuracy and Kappa coefficient than the other classifiers. These findings provide insights into the suitability of these algorithms and highlight GEE's limitations -particularly its memory constraints- for LULC mapping in arid environments like Al Ain. This research contributes to the development of LULC mapping methodologies and their applicability in a sustainable development context.

1. Introduction

Land use and land cover (LULC) maps are designed and produced to display the features on the surface of the earth and provide information about visible features such as water bodies, vegetation cover, and built-up areas. This information is vital for urban planning and sustainable development management (Aryal et al., 2023). LULC classification is a crucial process that assigns specific land cover categories to every pixel in an image (Hsiao & Cheng, 2016). This fundamental information supports geospatial analysis and environmental management, enabling a comprehensive understanding of the composition and distribution of land cover types within a given area. By tracking land cover changes and assessing their environmental and socio-economic impacts, LULC maps empower researchers and decision-makers to make informed choices for sustainable land management and resource allocation. Leveraging this knowledge, stakeholders can effectively analyze and manage land resources, ensuring sustainable development and optimizing land use practices.

Remote sensing is an effective approach in LULC mapping, assessing their patterns and trends. Various classification techniques are available, including pixel-based (Enderle & Weih, 2005), object-based (Qinghua et al., 2007), and machine learning methods (Liao et al., 2019). However, classifying complex urban landscapes can be a challenge due to the diversity and heterogeneity of land surface features. In such cases, machine learning algorithms can provide valuable solutions (Dahy et al., 2022).

In the current era of big datasets, continued development, and environmental change, an effective approach to enhance and automate the process of LULC classification is needed, and it could be achieved through a specialized toolset based on robust geospatial cyberinfrastructure. Such an infrastructure offers access to powerful computational resources (Feizizadeh et al., 2023). Integrating these resources with geospatial cyberinfrastructure can significantly enhance geospatial analysis, such as LULC mapping and accuracy assessment. It enables the use of more sophisticated machine learning techniques, allowing for better discrimination and interpretation of different LULC categories. Additionally, the availability of substantial computational resources helps process vast geospatial datasets efficiently, making it a valuable tool for researchers and practitioners in the field of environmental science and geospatial analysis.

Google Earth Engine (GEE) is a cloud-based platform known for granting users access to an extensive repository of geospatial data and an array of powerful tools, which makes it particularly well-suited for large-scale monitoring and modelling of the Earth's features (Yang et al., 2022). GEE offers a free, open-source environment and access to an extensive library of reusable code, making it a robust platform for remote sensing applications that rely on satellite imagery (Yu, 2022). These capabilities of GEE lead to a wide array of applications, including crop mapping, forest mapping, monitoring urban heat islands, and detection, LULC changes, among others.

The United Arab Emirates (UAE) is one of the fastest-developing countries, where the economy primarily depends on oil reserves. However, the country's development is not limited to the oil industry alone. Cities such as Al Ain, which was selected for this study, demonstrate planned and comprehensive development efforts (Hamouche, 1999). Al Ain is the second largest city in the Emirate of Abu Dhabi and has been experiencing rapid growth and development. Given the ongoing changes, it is crucial to map the distribution of LULC classes. While previous studies have examined land cover and its transformations in Al Ain, this research aims to identify the most suitable machine learning algorithm that delivers the highest performance using Sentinel-2 imagery in the study area. Additionally, it will assess the suitability of the GEE platform for LULC mapping with the selected algorithms, considering factors such as computational efficiency, memory limitations, and overall performance.

2. Materials and Methods

2.1 Study Area

The study focuses on Al Ain (Fig. 1), which is located in the Emirate of Abu Dhabi, UAE. Al Ain's diverse landscape, characterized by urban, agricultural, and natural land cover (Sharaf, 2019), provides an ideal setting for evaluating machine learning algorithms for LULC mapping.

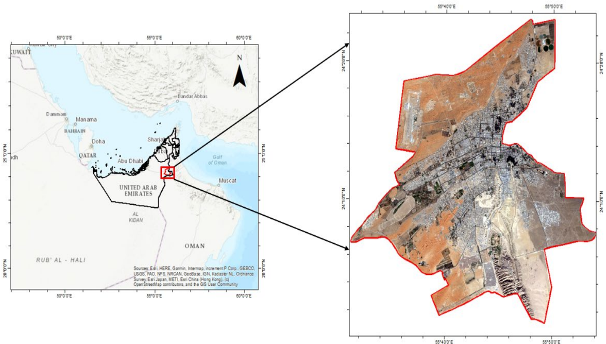

Figure 1. Study Area Map

2.2 Methodology

The Sentinel-2 satellite imagery from the year 2024 (with less than 1% cloud cover) is utilized as the primary data source for LULC classification. This multispectral data, with its relatively moderate spatial resolution and spectral bands, enables detailed analysis of the study area (Table.1).

Table 1: Date of acquisition and specifications of Sentinel-2 imagery used in this Study.

Date	Spectral Bands
25August 2024	Band 2: Blue (458-523 nm) Band 3: Green (543-578 nm) Band 4: Red (650-680 nm) Band 5: Red-Edge 1 (698-713 nm) Band 6: Red-Edge 2 (733-748 nm) Band 7: Red-Edge 3 (773-793 nm) Band 8: Near-Infra-Red (785-899 nm) Band 11: Short-Wave Infra-Red 1 (1565-1655 nm) Band 12: Short-Wave Infra-Red (2100-2280 nm)

A shapefile of Al Ain city is used to clip the study area from the acquired satellite image. Following this, a literature review and careful visual interpretation of the study area found that the surface features can be grouped into four main LULC classes, i.e. desert, built areas, vegetation, and water. Hence, for the classification process, the sample data was acquired through GEE by creating representative polygons from each class (Table 2). This data contributed to training the classifiers and to the accuracy assessment of the classification results.

Table 2: Distribution of polygons and pixels across different land cover classes in training and validation data.

Training Data		
Class	Number of Polygons	Number of Pixels
Water	21	2,092
Vegetation	37	24,825
Built Areas	28	27,171
Desert	32	24,242
Validation Data		
Class	Number of Polygons	Number of Pixels
Water	7	200
Vegetation	18	5,011
Built Areas	10	6,681
Desert	7	8,928

2.3 Machine Learning Classifiers

GEE provides built-in classifiers for LULC mapping. From this inventory, four supervised classifiers have been selected: Random Forest (RF), Classification and Regression Tree (CART), Support Vector Machine (SVM), and Gradient Tree Boosting (GTB). These classifiers have been recognized in the literature for their reliability and efficiency in handling the complexities associated with remote sensing data and LULC tasks (Ouma et al., 2022).

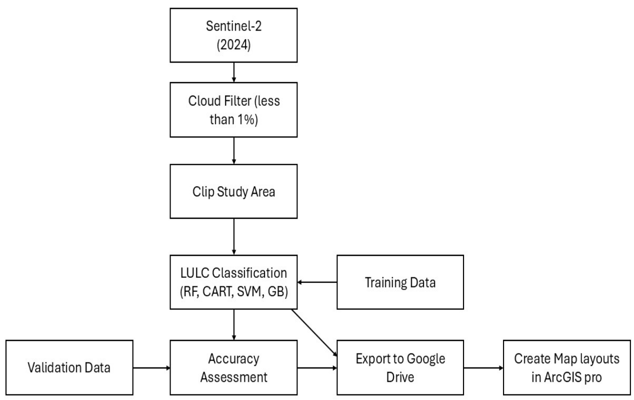

Figure 2. Flow chart of the methodology for LULC mapping of Al Ain city in the GEE platform.

RF and GTB are ensemble methods that have demonstrated high accuracy and robustness in managing complex data distributions, making them particularly suitable for heterogeneous landscapes (Orieschnig et al., 2021). CART offers simplicity and interpretability, which facilitates understanding the classification decision process. SVM is effective in high-dimensional data scenarios and with small sample sizes, which is advantageous for accurately capturing detailed class boundaries (Shetty, 2019). The parameters of each classifier were customized to align with the specific

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characteristics of the study area, further improving classification accuracy. Fig. 2 illustrates the flow of the adopted study methodology.

2.3.1 Random Forest (RF): A non-parametric ensemble machine-learning algorithm based on decision trees (Breiman, 2001). It is a modified version of CART and intends to resolve the overfitting issue observed with CART (Belgiu & Drăguţ, 2016). The number of trees (n-tree) and the number of variables used in each split (m-try) are essential parameters (Breiman, 2001). The study explored the impact of the number of trees and variables on the accuracy of the RF algorithm. It was found that using approximately 150 trees provided the most reliable results, with a slight improvement in accuracy using 500 trees but at a significantly higher processing time. The final parameters used in the study were 150 trees and 3 variables.

2.3.2 Support Vector Machine (SVM): SVM is designed for classification and regression tasks (Gunn, 1997), and works by finding an optimal hyperplane that separates the decision boundary between different classes. The parameters used in this study are as follows: an Radial Basis Function (RBF) kernel type to capture non-linear relationships in the data; a cost parameter (C) set to 1.0, achieving a balanced trade-off between a smooth decision boundary and accurate classification of training points; and a gamma parameter of 0.1 specified for the RBF kernel, influencing the width of the kernel and balancing between capturing fine details and avoiding overfitting.

2.3.3 Classification and Regression Tree: A decision tree-based algorithm that splits data based on the most significant attribute was used. CART is comparatively a simple model hence computationally efficient. However, it can sometimes lead to overfitting. While in some cases CART can lead to complex trees. To overcome these issues following parameters were used in this study, each tree had a maximum of 36 leaf nodes and a minimum leaf population of 16 data points prevent excessive complexity and ensuring that the tree model remains more generalizable.

2.3.4 Gradient Tree Boosting (GTB): GTB is an ensemble algorithm combining multiple weak decision tree based classifiers to create the model(Ouma et al., 2022). GTB iteratively adds new trees to correct the errors made by previous trees, resulting in improved predictive accuracy. For this study number of trees were kept 100 and learning rate of 0.005.

2.3.5 Performance Evaluation: The accuracy and efficiency of the machine learning algorithms are evaluated based on measures of overall accuracy, kappa coefficient, and confusion matrices. The impact of Sentinel-2 imagery from 2024 on classification results is analyzed. Performance parameters, such as the number of trees in RF, kernel type, and cost parameter in SVM, and maximum leaf nodes and minimum leaf population in CART, are systematically varied to understand their influence on classification accuracy and processing time.

2.4 Google Earth Engine Implementation

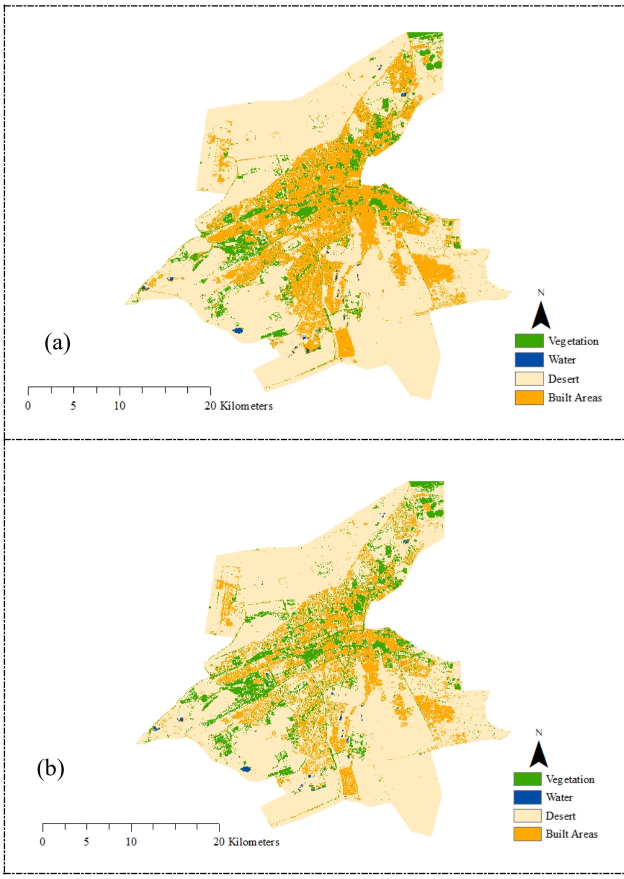
GEE was chosen due to its ability to handle extensive datasets and provide powerful processing tools without requiring significant local computational resources. The study uses the GEE platform for the efficient processing of satellite imagery and the implementation of machine learning algorithms. The JavaScript client libraries were utilized to access and implement the classifiers within the GEE code editor. GEE allows users to import their own datasets too, in this study, the Al Ain city Shapefile was imported to define the Area of Interest (AOI), thus avoiding the processing of entire tiles, which would demand more computational power and time. The classifiers were applied to Sentinel-2 imagery, and results were validated accuracy assessment using validation data.

3. Results and Discussion

The LULC mapping of an urban area in the mainly arid and desert country of the UAE highlights how the accuracy of different land cover classes varies with various machine learning algorithms. It also demonstrates the responsiveness of GEE to these classifiers and the impact of parameter adjustments on classification performance.

3.1 LULC Classification Maps

The study's primary outcome is the generation of LULC classification maps for Al Ain using the GEE platform.



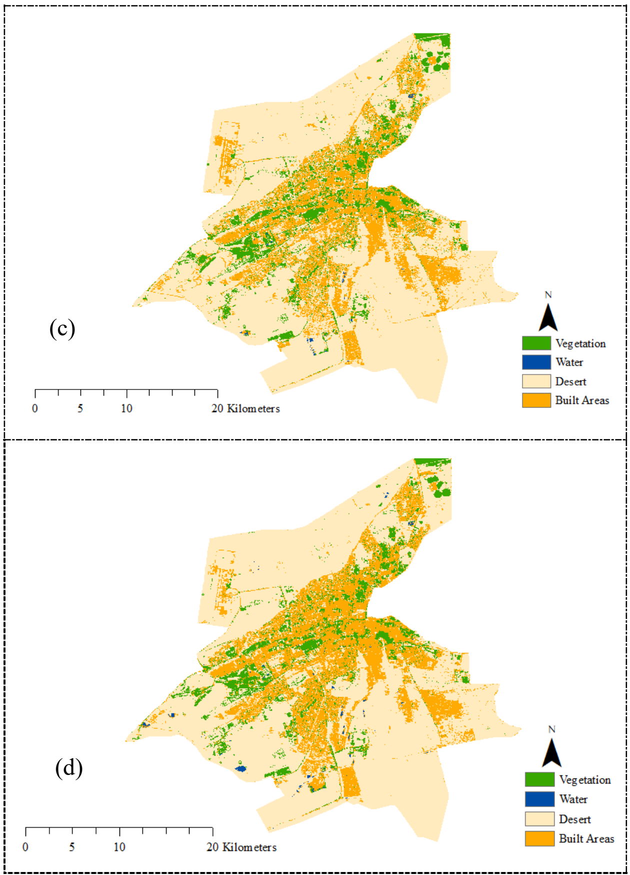


Figure 3: Sentinel 2 classified images of year 2024, (a): RF, (b): CART, (c): SVM and (d): GTB.

These maps, derived from Sentinel-2 imagery, offer a visual representation of the spatial distribution of various land use categories, such as built areas, vegetation, water, and desert. Fig. 3 gives the visual representation of classified maps with all four tested algorithms.

The RF classifier estimates vegetation covers 82 km², water covers 2 km², the desert spans 548 km², and built areas cover 138 km². The CART classifier estimates vegetation covers 75 km², water covers 2 km², the desert spans 527 km², and built areas cover 161 km². The SVM classifier estimates vegetation covers 73 km², water covers 3 km², the desert spans 516 km², and built areas cover 179 km². The GTB classifier estimates vegetation covers 80 km², water covers 2 km², the desert spans 520 km², and built areas cover 168 km².

The analysis indicates that the desert is the dominant land cover class in the study area, followed by built areas, vegetation, and water. The RF and GTB classifiers exhibit the most consistent results, particularly in estimating vegetation and water cover. In contrast, the SVM classifier presents a slightly different picture, with higher estimates for built areas and lower estimates for vegetation cover. The CART classifier shows the highest variability in its estimates.

3.2 Accuracy Assessment

This section compares the performances of the four machine learning algorithms used in the study over Sentinel-2 imagery in UAE’s arid environment. The performance metrics, including user's accuracy, Producer's accuracy, kappa accuracy, and overall accuracy, all derived from the confusion matrices of the classification results (Table 3).

Table 3: Performance metrics of machine learning classifiers.

Random Forest		
Class	User's Accuracy (%)	Producer's Accuracy (%)
Vegetation	98.45	99.61
Water	61.54	72.73
Desert	99.45	97.43
Built Area	91.44	91.33
Overall accuracy	0.97	
Kappa accuracy	0.94	
Classification and Regression Tree		
Vegetation	96.5	95.2
Water	62.5	19.2
Desert	96.8	94.7
Built Area	78.8	85.6
Overall accuracy	0.93	
Kappa accuracy	0.89	
Support Vector Machine		
Vegetation	98.06	98.05
Water	66.67	44.83
Desert	96.14	99.12
Built Area	98.93	85.51
Overall accuracy	0.96	
Kappa accuracy	0.91	
Gradient Tree Boosting		
Vegetation	98.73	98.97
Water	62.79	54.83
Desert	97.01	99.14
Built Area	98.99	87.51
Overall accuracy	0.97	
Kappa accuracy	0.93	

Studies have explored the potential of machine learning classifiers for accurate LULC classification in arid and semi-arid regions (Bouaziz et al., 2017; Kuemmerle et al., 2013; Sultan et al., 2024). While machine learning classifiers generally perform well in these regions, their actual effectiveness depends heavily on the quality and characteristics of the training data (Abida et al., 2022). To perform a fair comparison, we used the same training and validation data along with consistent satellite imagery to across all classifiers. Fig. 4 shows the charts showing producer and user accuracy for LULC classes across all classifiers.

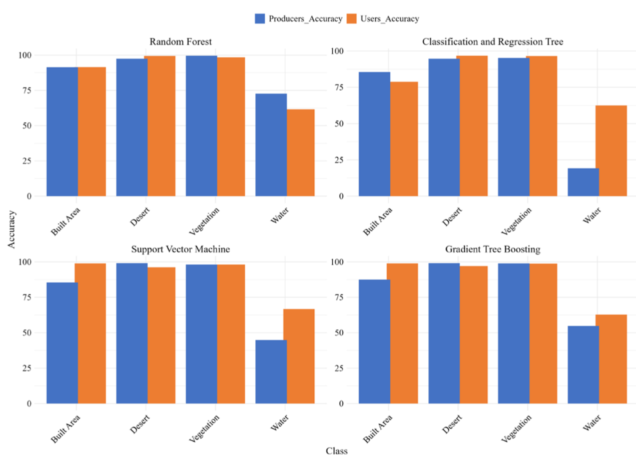


Figure 4. User and producer accuracy charts for all classifiers.

One of the key challenges in the arid environments is the spectral similarity between desert surfaces and built-up areas, which often leads to classification errors (Dahy et al., 2021; Sultan et al., 2024). High reflectance of desert surfaces and low soil moisture creates a complex spectral landscape that can lead to misclassification in arid environments(Weng et al., 2020). RF and GTB emerged as top performers achieving overall accuracy of 0.97 and Kappa coefficients of 0.94 and 0.93, respectively. GTB combines multiple weak decision trees, iteratively improving classification accuracy,(Patil & Panhalkar, 2023) making it particularly effective for challenging classes like built-up and desert surfaces. RF, which aggregates the output of multiple decision trees through majority voting, demonstrated stable and consistent performance across various land cover types due to its robust generalization capability and tolerance for spectral variability.

SVM achieved competitive results but showed some inconsistencies in distinguishing complex class boundaries. This can be attributed to its reliance on a hyperplane to separate classes, which may struggle when class distinctions are subtle or non-linear in arid regions(Awad & Khanna, 2015). For example, the spectral overlap between desert and built-up areas poses a significant challenge for SVM, as the algorithm may fail to capture the differences in reflectance patterns. The kernel function adjustments or inclusion of additional spectral bands could improve its performance in such environments.

CART classifier resulted in lowest performance, with overall accuracy of 0.93 and kappa coefficient of 0.90. It exhibited higher misclassification rates, particularly in vegetation and water. This suggests it may not generalize well in complex classes due to its tendency to overfit the training data, and the inherent complexity of these classes(Kulithalai Shiyam Sundar & Deka, 2022).

When using fewer spectral bands (B2, B3, B4, B5, B6, B7, and B8A), the classifiers showed lower accuracy due to the limited ability of these bands to distinguish between built-up areas and deserts. The inclusion of B11 and B12, which represent shortwave infrared bands, significantly improved the overall accuracy by enhancing the differentiation between these classes. This suggests that instead of relying on multiple bands from the red-edge portion of the electromagnetic spectrum, which may provide redundant information, it may be more effective to reduce their number and incorporate bands from the shortwave infrared region for better classification results.

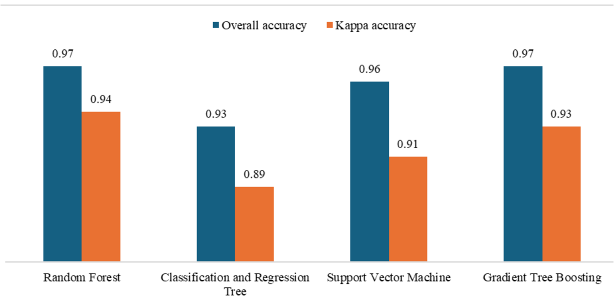


Figure 5: Illustrating the overall accuracy and kappa coefficient accuracy amongst classifiers.

GTB and RF emerged as the most reliable classifiers for LULC mapping in arid environments. GTB's strength lies in its ability to better distinguish built-up areas and desert surfaces, while RF demonstrated stable performance across different land cover types. SVM offered competitive results but showed some inconsistencies in complex class boundaries. Meanwhile, the CART was less effective due to higher errors. While this study focused on Sentinel-2 imagery, previous studies on different remote sensing data sets tested classifiers and found that RF and GTB classifier performed highest across all tested sensors i.e., Landsat 7, Landsat 8 and Sentinel-2 (Gupta et al., 2024; Issa & Sultan, 2024). These findings suggest that RF and GTB are robust and reliable choices for LULC classification in arid and semi-arid regions, regardless of the specific remote sensing data used.

3.3 Google Earth Engine Performance

The use of advanced machine learning algorithms has prevailed and proven effective compared to traditional classification algorithms (Dahy et al., 2022; Issa et al., 2021). However, these algorithms often require proficiency in programming languages and GEE's Application Programming Interfaces (APIs), which may pose challenges for users with limited technical expertise (Elmahal & Ganwa, 2024). To address this, GEE provides language programming libraries, such as JavaScript and Python client libraries, to simplify the platform's use and enable the implementation of complex machine learning techniques (Tamiminia et al., 2020).

In the current study, we used GEE's JavaScript library, employing several classifiers: RF (ee.Classifier.smileRandomForest), CART (ee.Classifier.smileCart), SVM (ee.Classifier.libsvm), and GTB (ee.Classifier.smileGradientTreeBoost). For a comparatively smaller study area like Al Ain city covering an area of 770 $km^{2,}$ GEE provided an efficient platform to acquire sentinel-2 images of the study area and to perform LULC classification using various classifiers. Overall, GEE performed well for all classifiers. However, with the change in classification parameters, such as adding more spectral bands for LULC classification, other classifiers performed better. While SVM also showed an increase in accuracy, its processing time was excessively long. The GEE platform failed to print the accuracy assessment results and the classified image. Additionally, exporting to Google Drive took more time than other classifiers' images, taking up to 10 hours for one classified image with SVM classifier.

Similarly, with an increase in the number of trees in RF and GTB with an increase in the number of trees, the processing time increased. GTB had higher computational demands, so the number of trees was kept 100. For RF, although the GEE platform efficiently handled up to 300 trees, accuracy improvements beyond 150 trees were negligible, leading to the selection of 150 for this study. This highlights the importance of selecting an optimal number of trees since beyond a certain point, processing time increases significantly with little to no accuracy improvement. Memory constraints and time-outs in GEE further hindered complex analyses and handling high-dimensional datasets. Therefore, careful parameter selection is essential for efficient and effective LULC classification using GEE.

Although GEE provides limited memory, careful consideration of parameters such as the bands to be considered is necessary. It is important not to lose bands that carry vital information for capturing spectral variabilities, such as bands 5 to 8A, which all cover near-infrared (Phiri et al., 2020). Therefore, band reduction should be done in these areas rather than compromising bands 11 and 12, which assist in separability in urban and built areas. GEE provides data visualization capabilities, but our study encountered limitations. The visualization failed due to computational limitations when using a larger number of bands for classification with the SVM classifier, while other classifiers gave smooth visualization. To address this issue, external tools could be added, or images could be exported to Google Drive and visualized using desktop-based software like ArcGIS Pro, as in our case.

The spectral heterogeneity in complex environments like arid regions presents challenges that lead to confusion between LULC classes, particularly between built areas and desert regions. Addressing this issue requires the inclusion of additional spectral bands, indices, and topographic information to enhance classification accuracy (Adepoju & Adelabu, 2020). However, due to GEE’s computational limitations, incorporating more classification variables may result in excessively long processing times or computational time-outs, leading to execution failure. For example, in our study, increasing spectral inputs significantly impacted processing time while using the SVM classifier, which failed to generate results and was impacted by computational time out. This issue can be addressed by dividing the area into smaller tiles or by reducing the complexity of commands and breaking them into smaller parallel tasks (Shafizadeh-Moghadam et al., 2021). Simplifying commands or structuring workflows into smaller steps can further alleviate computational and memory constraints. Alternatively, preprocessing some analyses outside the GEE platform before importing data for further processing can help optimize performance.

4. Conclusion

This study evaluated the performance of different machine learning algorithms for LULC classification in Al Ain, UAE, using Sentinel-2 imagery and the GEE platform. The findings indicate that RF and GTB classifiers achieved the highest accuracies, with CART demonstrating the lowest accuracy. GTB performed marginally better in vegetation classification, while SVM showed slightly higher misclassification rates, particularly in-built Areas and desert classes, which present known challenges in arid environments. The lower accuracy of the CART classifier suggests its limited generalizability in complex urban and natural landscapes, making CART and SVM the least suitable for LULC mapping in arid regions like Al Ain city.

The GEE platform proved to be an effective tool for acquiring and processing rapid data from satellite imagery. It enabled the use of classification algorithms from GEE’s JavaScript library, allowing for parameter adjustments to optimize accuracy. While processing was generally smooth, the study faced computational limitations, including prolonged processing times, memory constraints, and time-outs when dealing with high-dimensional datasets and complex analyses. However, these challenges can be sorted either by reducing data dimensionality or simplifying operations.

These findings suggest that high-accuracy classifiers like RF and GTB can be implemented in other parts of the country and for longer-term studies. Insights from these LULC studies can support planned development in growing urban areas like Al Ain city. Future research should address GEE's limitations by integrating alternative computational frameworks or developing custom algorithm implementations to enhance scalability and processing efficiency.

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