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Machine Learning-Driven Land Use Land Cover Classification using Different Algorithms on Sentinel-1 and Sentinel-2 Imagery

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***Abstract*:** Land Use Land Cover (LULC) classification is crucial for understanding and managing the planet's resources. The present study examines LULC classification using machine learning (ML) algorithms and geospatial data in the Karulai region of Kerala. Sentinel-1 and Sentinel-2A satellites provided Multispectral and radar imagery, offering high-resolution (10 m), frequent data. Three ML models Random Forest (RF), Classification and Regression Trees (CART), and K-Nearest Neighbors (KNN) were evaluated for classification accuracy. RF achieved the highest accuracy (93.87%) and Kappa coefficient (0.916), outperforming CART and KNN in complex land cover types, particularly forest and built-up areas. RF accurately detected 101.7 ha of water and 19,692.67 ha of forest, while CART and KNN showed variability in urban and plantation areas. Producer and user accuracy metrics further validated RF's reliability, with 98% producer accuracy for teak plantations. Challenges emerged in classifying rubber plantations and built-up areas, but RF remained the most robust model. These findings highlight the importance of ML in LULC mapping, with applications in urban planning, forest monitoring, and agricultural management. This study improves LULC classification accuracy, aiding sustainable land management and planning.

***Keywords*:** Land use land cover, Machine learning, Random forest, Classification, Regression trees, K-nearest neighbors

Land, as a fundamental resource, undergoes significant changes due to human activities, shaping landscapes and impacting natural systems (Geri et al., 2010, Plieninger et al., 2015 and Wassie 2020). Land use land cover (LULC) classification has emerged as a critical aspect of environmental management (Wang et al., 2022) and urban planning (Gaur and Singh 2023), owing to its significance in understanding and managing natural resources (Olorunfemi et al., 2020). Land use involves managing and transforming natural environments into urban areas, agricultural lands, and infrastructure (Mitchell, 2023). Land cover is the observed physical and biological cover on the Earth's surface, including vegetation types, built environments, and water bodies (Wang et al., 2023, Mosca et al., 2024). These categories help in assessing the ecological balance, monitoring environmental changes, and planning sustainable development. Earlier LULC classification was primarily conducted using ground surveys and aerial photography, which were labour-intensive and time-consuming (Santosh et al., 2019). Over the past decades, the concept and methodology of LULC have evolved significantly, driven by advancements in remote sensing technologies and computational techniques. With the advent of satellite imagery, particularly with the launch of the Landsat program in the 1970s, the field experienced a paradigm shift (Khan et al., 2018). Satellite images provide a broader and more frequent view of the Earth's surface, enabling more efficient and comprehensive LULC analysis (Li and Stein 2020). The launch of Sentinel-1 and Sentinel-2 satellites by the European Space Agency (ESA) has further revolutionized the field by providing high-resolution radar imagery and multispectral imagery with a revisit time of six days (Languille et al., 2017, Phiri et al., 2020, Upadhyay et al., 2022). This advancement has opened new avenues for precise and timely LULC classification. Accurate Land Use Land Cover (LULC) data is vital for various applications, including urban planning, agriculture management, forest monitoring, and disaster management (Moayedi et al., 2020, Vandansambuu et al., 2020). Understanding urban expansion patterns aids in infrastructure development. Monitoring deforestation is essential for biodiversity conservation and climate change mitigation. In agriculture, LULC data assists in crop monitoring and yield prediction, enhancing food security. In the context of climate change, LULC studies help understand carbon sequestration patterns and formulate mitigation strategies (Sohl et al., 2012, Rajbanshi and Das 2021). In forestry LULC classification is essential for forest management, conservation, and policy-making, offering vital data on ecological dynamics and environmental changes (Junaid et al., 2023).

Machine learning (ML), a key area of artificial intelligence, develops algorithms that allow computers to learn from data without explicit programming, with broad applications across many fields (Munde 2024). Recently, the combination of machine learning (ML) techniques with satellite data for ecosystem monitoring has gathered considerable attention (Sharma and Chishty 2019,Masolele et al., 2021, Morais et al., 2021, Veeramani et al., 2024, Markuna and Dumka 2024). Machine Learning (ML) has emerged as a powerful tool in the realm of LULC classification (Rawat et al., 2024) and outperform traditional statistical methods by assessing complex non-linear relationships (Garg and Tai 2013) between reflectance and ecosystem structure, without requiring prior assumptions about the underlying processes or data distribution (Ghosh and Behera 2018). ML algorithms can automatically detect patterns and relationships in large datasets (Oprea and Bâra 2021). This capability makes ML particularly suited for handling the complex and high-dimensional data obtained from satellite imagery. The role of ML in LULC classification is multifaceted (Tassi and Vizzari 2020). ML algorithms can handle the vast amounts of data generated by modern satellites (Bhattacharyya et al., 2023), processing them efficiently to produce accurate classifications. ML can also integrate various types of data, such as spectral, spatial, and temporal information, to improve classification accuracy (Du et al., 2020). These algorithms can adapt to changes in data patterns (Naqa and Murphy 2015), making them robust against varying environmental conditions and seasonal changes (Huntingford et al., 2019, Balogun et al., 2021).

The importance of this study lies in its potential to enhance understanding and management of land resources through advanced LULC classification techniques. By leveraging ML algorithms on Sentinel-1 and Sentinel-2 imagery this study aims to improve LULC classification accuracy and emphasizes the broader implications for sustainable development and environmental management, by systematically exploring the intersection of ML and LULC classification.

MATERIAL AND METHODS

Study area: The study was conducted in the Karulai forest of Nilambur South division in Malappuram district, Kerala, located between 76°18'19.65"- 76°32'51.88"E longitude and 11°23'14.05"- 11°13'42.70"N latitude (Fig. 2). This area spans altitudes from 50 to 2600 meters MSL covers a total area of 26,285 ha and includes tropical evergreen, semi-evergreen, moist deciduous forests, and teak plantations. The climate is hot and humid, with temperatures ranging from 20 to 30°C and an average annual rainfall of 2900 mm. Malappuram consist of 3 natural divisions, lowland, midland and highland. The district has dry season from December to February, hot season from March to May, the south west monsoon from October to November and usually very heavy and nearly 75 percent of the annual rains are received during this season. The climate is generally hot and humid (Haani and Murari 2022).

Satellite data: This study used open-source European Space Agency (ESA's) Sentinel-1 (S1) and Sentinel-2 (S2) satellite data. S1 satellites operate at 693 km (431 mi) altitude, with 3-axis altitude stabilization. provides dual-polarized (VV and VH) C-band which provides a collection of data in all-weather conditions at a spatial resolution of 10 m, and the sensor operates at a central frequency of 5.405 GHz. Over the land S1 acquires images with interferometric wide (IW, 250 km) swath mode. S2 provides multispectral optical data with 13 bands ranging from 443 to 2190 nm wavelength and a spatial resolution of 10–60 m and 290 km field of view. Both S1 and S2 data were regularly available over the test site with an average temporal resolution of six days. Sentinel-1A (S1A) ground resolution detected (GRD) level-1 product consists of multi-view (10 m × 10 m) and ground range projected images using ellipsoid model WGS84. Sentinel- 2A (S2A) Level-2A orthorectified atmospherically corrected surface reflectance data were used.

Modelling and calibration: The study was conducted using the Google Earth Engine. Filed visits are conducted for sample point data collection. To enhance the dataset, three indices were calculated and added as bands: the normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and enhanced vegetation index (EVI). This data was median-composited and merged with the Sentinel data image stack. A total of 3886 sample points representing water, built-up, bare land, rubber plantation, teak plantation, grassland, and forest classes were merged, forming a labelled dataset for supervised classification. LULC class water body include river and pond in the study area. Using the collected bands, samples were generated from the study region and split into training (70%) and testing (30%) subsets. A CART, RF, and KNN classifier were trained and applied to the image stack, producing a land use land cover (LULC) classification. Model performance evaluated using producer's accuracy user's accuracy, kappa coefficient and overall accuracy and its formulas are:

$$Producer's\ Accuracy == \frac{True\ Positives\ (for\ a\ class) \times 100}{Total\ Actual\ Pixels\ (for\ that\ class)}$$

$$User's\ Accuracy = \frac{True\ Positives\ (for\ a\ class)}{Total\ Predicted\ Pixels\ (for\ that\ class)} \times 100$$

$$Overall\ Accuracy = \frac{\sum True\ Positives}{Total\ Pixels} \times 100$$

$$Kappa\ Coefficient = \frac{po - pe}{1 - pe}$$

po = observed accuracy (Overall Accuracy),
pe = expected accuracy (probability of random agreement).

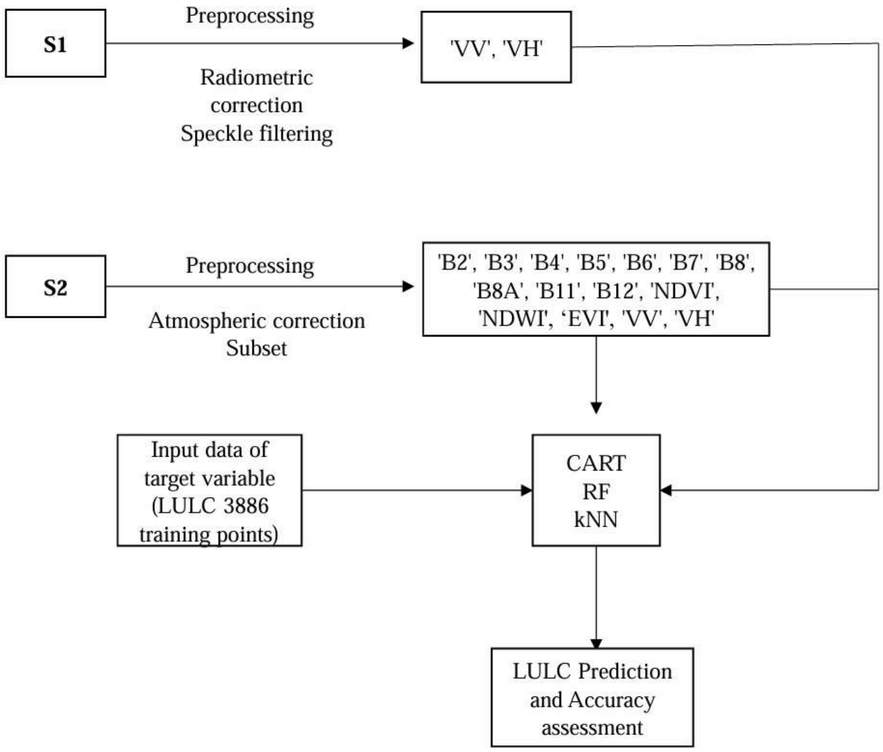

Fig. 1. Flow chart of the methodology for LULC

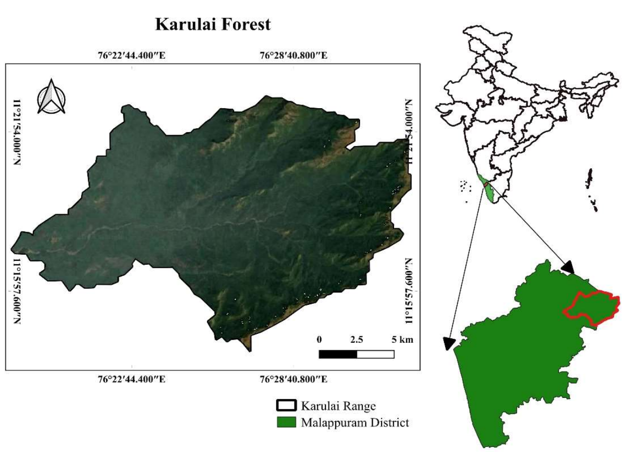

Fig. 2. Map of the study area

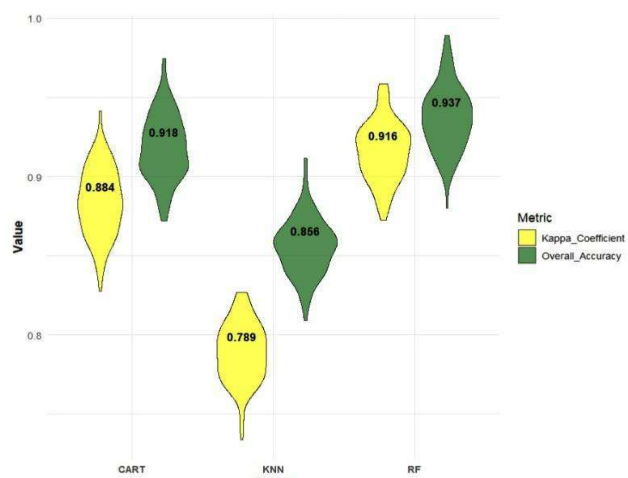

Fig. 3. Overall accuracy and Kappa Coefficient of CART, RF and KNN model

RESULTS AND DISCUSSION

Model performance and LULC mapping: The Land use land cover (LULC) models were predicted using three machine learning algorithms: classification and regression trees (CART), random forest (RF) and k-nearest neighbors (KNN) (Fig. 4). All models achieved an overall accuracy exceeding 85% and a Kappa coefficient of 78% (Fig.3), indicating strong agreement between predicted and actual classifications. The model accuracies were further evaluated using the producer's accuracy, user's accuracy, and Kappa values (Fig. 3, Fig. 6). Among the models, the random forest algorithm exhibited the highest overall performance, with an accuracy of 0.937, outperforming both CART and KNN. The Kappa coefficient was utilized as a robust metric to assess the classification accuracy of various machine learning models. It indicates the model's agreement with actual classifications, adjusted for the possibility of random chance. RF model exhibited the highest Kappa value of 0.916, indicating substantial agreement beyond random chance, followed by CART with a Kappa value of 0.884, KNN model exhibited the lowest Kappa score at 0.789 (Fig. 3), suggesting relatively lower classification reliability in comparison to the other models. The findings confirm Kappa as a valuable complement to overall accuracy in evaluating model performance.

Quantification of LULC classification: The results of the area under different land use land cover classifications using different machine learning algorithms exhibited significant differences between the algorithms (*i.e.,* RF, CART, and KNN) in their performance. RF demonstrated the most consistent and accurate results across various land cover types. RF identified 101.7 ha for the water area, while CART and KNN detected significantly different values of 116.2 ha and 162.3 ha, respectively. In built-up areas, RF's classification of 4.03 ha starkly contrasted with CART's 100.9 ha and KNN's 28.51 ha, showing major discrepancies in urban area detection. RF also displayed superior accuracy in forest area classification, capturing 19,692.67 ha, compared to CART's 19,090.68 ha and KNN's 15,950.64 ha.

Minor deviations were observed in bare land detection, with RF, CART, and KNN identifying 1358.9, 1308.5 and 1387.9 ha, respectively. However, significant variations arose in rubber and teak plantation classifications. For rubber plantations, RF classified 176.8 ha, while CART and KNN overestimated the area at 383.9 ha and 368.3 ha. Similarly, teak plantations showed stark contrasts, with RF identifying 4286.6 ha, CART 4318.1 ha, and KNN an inflated 7375.4 ha.

Grassland classification also reflected algorithmic variability, with RF detecting 664.2 ha, compared to CART's 966.6 ha and KNN's 1011.8 ha. These results underscore RF's superior performance in land cover classification, particularly in forest and built-up areas, where the other algorithms showed significant limitations. RF provided the most consistent and accurate results, making it a robust tool for capturing the complex landscape of Karulai. These findings suggest RF's reliability in handling diverse land cover types, outperforming CART and KNN.

RF model showed the highest producer accuracy (PA) for teak plantation (0.98) indicating that out of 10000 pixels of teak plantation in the ground, 9803 pixels are correctly labelled as Teak plantation in the RF model. KNN model showed the lowest (0.4355) representing that if the 10000 pixels are built up areas in the ground only 4355 pixels are labelled as Builtup area in the model. RF model built up area showed highest users' accuracy (1) indicating that all the pixels are labelled as built up area by the model belongs to Builtup area in ground truth data. lowest UA (0.6136) in built up area class of KNN model indicating that when classifier model labelled 10000 pixels as built up area but only 6136 pixels are built up area in ground truth data.

The random forest (RF) model demonstrated superior performance in LULC classification compared to CART and KNN. RF achieved the highest overall accuracy and Kappa coefficient, indicating strong agreement with reference data and minimal random chance. This superior performance of RF is attributed to ensemble learning nature (Mienye and

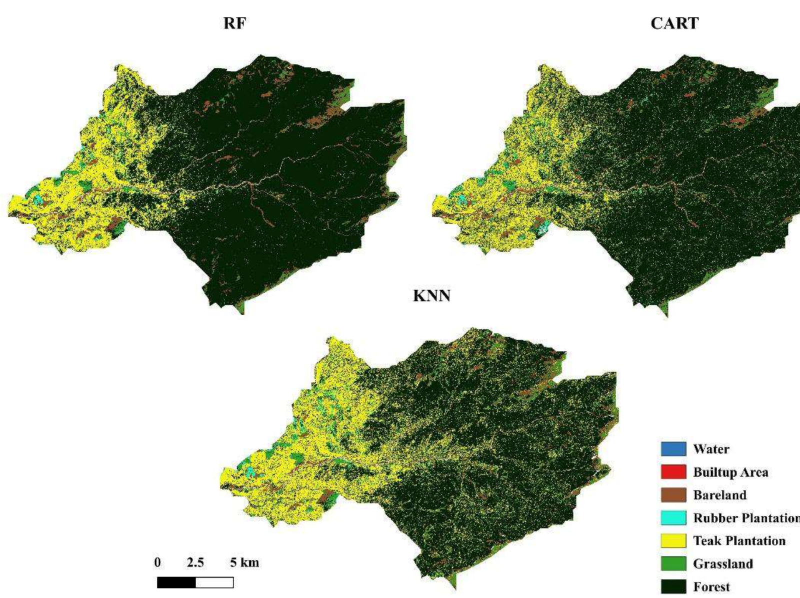

Fig. 4. LULC maps of the study area using RF, CART and KNN machine learning algorithm

Sun 2022) i.e., combining multiple decision trees, handle complex spatial patterns (Mariano and Monica 2021), reduce overfitting (Ali et al., 2012 and Belgiu and Drăguţ 2016), and improve generalization (Fawagreh et al., 2014). RF's ability to assess feature importance enables it to focus on the most relevant information (Hapfelmeier et al., 2014 and Gregorutti et al., 2017), leading to more accurate classifications. CART, a single decision tree algorithm, is susceptible to overfitting (Zhao et al., 2021), especially when the tree depth is too large . KNN, which relies on distance-based similarity measures, can struggle with high-dimensional data and noisy samples (Halder et al., 2024). Since our model is trained with 15-

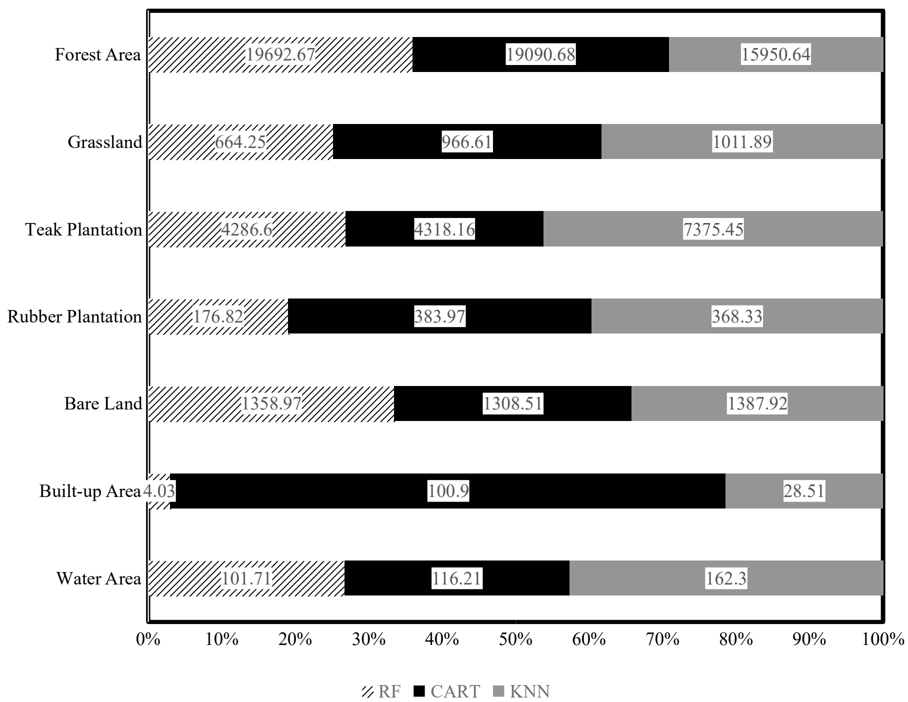

Fig. 5. Area under different LULC class as predicted by RF, CART and KNN model

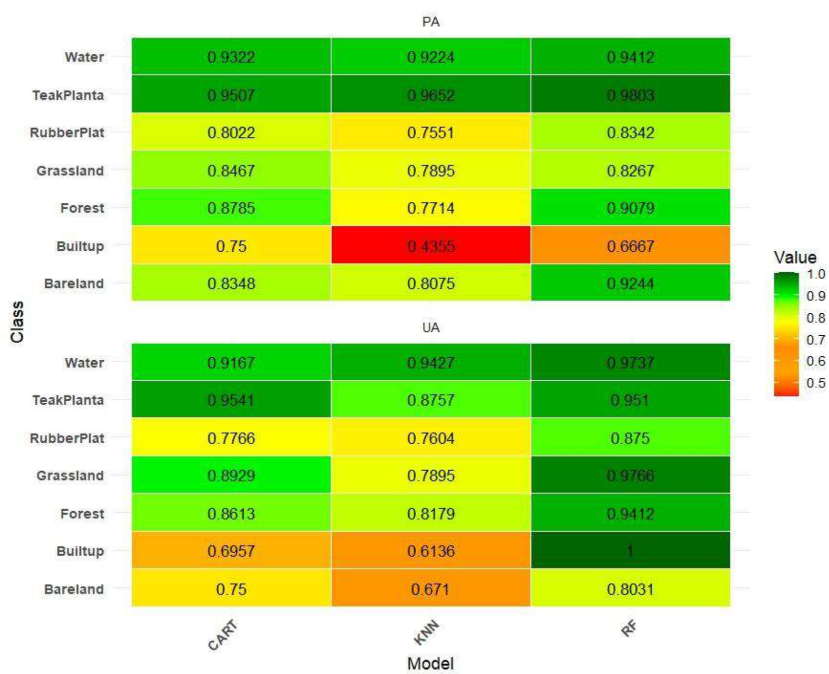

Fig. 6. Producers and users' accuracy heatmap of CART, RF and KNN model

dimensional data, it may become a hurdle to handle by the KNN algorithm. Hence the performance of CART and KNN algorithms was not as high as RF. The results highlight the importance of model selection in LULC mapping. RF's robustness and versatility make it a valuable tool for accurate and reliable land cover assessments, particularly in diverse landscapes like Karulai.

CONCLUSION

The study reveals significant insights into environmental modeling through a combination of ground truth, geospatial data, and machine learning. Machine learning algorithms enhance the accuracy of LULC classification significantly compared to traditional methods. Among the evaluated models, random forest achieved the highest overall accuracy of 93.87% and a Kappa coefficient of 0.916. RF demonstrated superior performance in identifying complex land cover types. Producer accuracy for teak plantations reached 98%, indicating RF's reliability in classifying specific vegetation types. Challenges persisted in classifying rubber plantations and built-up areas. Integrating multiple data types, including spectral and temporal information, improved classification outcomes. The study emphasizes the transformative role of advanced technologies in understanding and managing earth's resources effectively.

AUTHOR'S CONTRIBUTION

This study was conducted as part of the Master's research project under Kerala Agricultural University. Co-author K.S. Aneesh contributed to the conceptualization of the study and provided theoretical and academic inputs. K.T. Shanid assisted with field visits and communication in the local language. K.V. Murali contributed to the development of JavaScript and R scripts. K. Mahathwa, C. Gayathri, and N.J. Meenakshi supported the interpretation of the results.

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