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Research Article

Enhanced Land Cover Classification by Integrating Multispectral Satellite Imagery and Machine Learning Techniques

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ABSTRACT

For resource management, urban planning, and environmental monitoring, accurate land use and land cover (LULC) categorization is essential. Nevertheless, spectral similarity across land cover categories, feature redundancy, and the shortcomings of conventional classification methods make it difficult to achieve high classification accuracy. The majority of research uses either object-based (OB) or pixel-based (PB) classification, not making use of their complementing advantages. Furthermore, feature selection is frequently done by manual analysis which does not necessarily provide accurate classification results. This paper suggests a hybrid OB-PB classification strategy in which OB classification is used for fine-tuning mapping after PB classification is used for initial segmentation. Recursive feature elimination (RFE) is an automated feature selection method that replaces traditional manual selection of textural (GLCM) and statistical (PCA) features in order to further improve classification accuracy. The study's emphasis is Rajasthan, India, which spans 219,676.75 km² and is divided into five LULC types: desert, agricultural, water, forest, and urban. Four machine learning classifiers Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Trees (CART), and Gradient Tree Boosting (GTB) were used with 249 training examples. The kappa coefficient and the confusion matrix were used to evaluate accuracy. The results show that the hybrid OB-PB technique performs better in terms of segmentation and classification precision than the independent OB and PB approaches. The classifier's eligibility for LULC mapping was confirmed by GTB's greatest accuracy among the others. For LULC classification, this paper offers a unique framework that combines automated feature selection with hybrid classification, providing a more precise, effective, and scalable method. Improved classification techniques and better decision-making for ecological surveillance and management of land are two benefits of the research.

Keywords: Land cover classification; remote sensing; object-based image classification; pixel-based image classification; LULC, machine learning classifiers.

INTRODUCTION

The effective management of land resources is pivotal for environmental sustainability, urban development, and agriculture, underlining the importance of accurate land use and land cover (LULC) classification. Within remote sensing, LULC classification serves as a fundamental process to convert raw satellite imagery into meaningful thematic maps that can inform policy and decision-making. Rapid advancements in Machine Learning (ML) algorithms and prepared ease of use of big datasets put geographies on the threshold of impressive growth. To manage natural resources, it is necessary to classify remote sensing images to derive usable information from their land cover type spectral signatures [1]. To classify land cover types for a particular area, it uses remotely sensed multispectral satellite images. Remote sensing techniques are a reliable way to define land cover classes because these techniques provide easily accessible large-scale data. Artificial Intelligence (AI), ML and deep learning (DL) are innovative systems with remote sensing (RS) images for image processing. Land cover classification is the most fundamental source of information when managing environmental and agricultural monitoring tasks [2]. GEE gives users the option to define various ways for combining the input data, making it possible to efficiently create a light, cloud-free, multi-temporal composite dataset without running into problems because of a lack of adequate local processing resources [3, 4].

With the advent of advanced satellite sensors and enhanced computational capabilities, there has been a significant shift in classification approaches, notably from traditional pixel-based (PB) methods to more sophisticated object-based (OB) methods. In PB, Spectral features are extracted from each pixel, typically the reflectance values from each band in the multispectral image. PB classification has been the backbone of remote sensing LULC studies for decades. This method relies on the spectral information of individual pixels without considering their spatial context, which can lead to significant misclassification in heterogeneous landscapes [5]. The classification accuracy of PB methods is often hampered by the ‘salt and pepper’ effect, where isolated pixels are incorrectly classified due to spectral variability within land cover types [6, 7]. With PB methods, additional features like texture or vegetation indices can be evaluated.

In contrast, object-based image analysis (OBIA) presents a paradigm shift by considering the spatial arrangement and relationship between pixels. By grouping pixels into meaningful objects based on spectral, spatial, and textural homogeneity, OBIA aims to mirror human visual interpretation more closely [8, 9]. This method is particularly effective with high-resolution images where the increased detail can be leveraged to distinguish between different land cover types more accurately. With OB, the image is divided into meaningful segments based on spectral and spatial properties. Each segment becomes an object with its characteristics. Although PB approaches are normally suggested for lower resolutions, despite the higher computing costs of segmentation and the use of several features for the classification, OB approaches usually produce superior results on higher-resolution data.

Despite these advancements, there is still a considerable research gap in directly comparing the performance of OB and PB methods, especially when applied to diverse and complex environments. The desert state of Rajasthan, India, with its rich tapestry of land cover ranging from the arid Thar Desert to the lush Aravalli Range, and bustling urban centers to sparse rural settlements, presents an ideal study area for such comparative analysis. The selection of Rajasthan as the study area was deliberate due to its ecological and geographical diversity. This region’s coordinates, spanning a vast area, encompass a variety of ecosystems that challenge the capabilities of LULC classification methods. The choice of this locale offers a comprehensive understanding of the algorithm's performance in discriminating between contrasting land cover types within a single geographic domain.

The three primary steps of the overall procedure are the composite initial dataset, the LULC classification, and the accuracy evaluation. Every LULC classification has an important stage in the development of the base dataset. This application, assembled the dataset for the L8 and S2 data in GEE, starting from a filtered and cloud-masked image collection. The Simple Non-Iterative Clustering algorithm, which is provided in GEE, was effective at recognizing probable distinct objects and grouping comparable pixels [10]. Following segmentation, GEOBIA typically performs the final object classification by combining spectral, spatial, texture, and context data from the image [11]. Using the very efficient Gray-Level Co-occurrence Matrix (GLCM) method, 18 textural indices may be extracted from 8-bit greyscale images, which are included in the GEE. Given that it allows the GEOBIA application to operate even on greyscale photos, this functionality seems to be quite helpful. Principal Component Analysis (PCA) can then effectively reduce the large dimensionality of GLCM outputs into some representative bands [12].

The introduction of sophisticated textural and statistical techniques such as GLCM and PCA adds a cutting-edge dimension to the novelty of this work. GLCM allows for a nuanced analysis of texture in object-based classification, providing a means to quantify and classify the variability in pixel intensities, which can be critical in distinguishing between similar land cover types [13]. By integrating GLCM, this research enhances the textural assessment within high-resolution imagery, facilitating a more accurate interpretation of complex land patterns, which is a significant departure from conventional classification methods that rely heavily on spectral data alone.

Meanwhile, PCA contributes to the novelty of the study by reducing the dimensionality of the dataset without losing the variability of the data, thereby improving processing times and computational efficiency while retaining essential information for classification. The employment of PCA is particularly innovative in the way it's combined with object-based methods, as it allows the study to overcome the common challenge of high dimensionality in multispectral datasets. It helps in identifying the most informative features, which can be especially advantageous when dealing with the large datasets typical of satellite imagery.

Together, the incorporation of GLCM and PCA represents a novel approach to remote sensing classification tasks, providing a richer, more detailed analysis and leveraging both textural and structural information. This multi-faceted approach not only underscores the study's innovation but also its potential to set a new standard in LULC classification, significantly contributing to the precision and reliability of environmental monitoring practices.

The primary objective of this work is to implement PB and OB classification techniques suitable for heterogeneous landscapes and complex object shapes, combining the GLCM for computing cluster textural indices, the SNIC algorithm for identifying spatial clusters, and four well-liked ML techniques (RF, CART, SVM, and Gradient Tree Boost) for classification. RF is known for its high efficiency and accuracy, making it a preferred classifier in the context of LULC classification [14, 15]. CART operates as a simple binary decision tree classifier that functions by applying a set predetermined threshold [16]. SVM is recognized for its effective classification capabilities, though it presents a degree of complexity due to the necessity for selecting and fine-tuning kernels and additional input parameters [17, 18]. GTB is a robust machine learning technique that enhances predictive accuracy through the sequential combination of weak decision tree models. It involves iteratively refining predictions by addressing errors from previous models, which can require careful adjustment of parameters to optimize performance [19]. The efficacy of OB and PB methods in classifying and interpreting the complex landscape of Rajasthan using LULC data from Landsat 8 and Sentinel-2 satellites from multispectral satellite imagery are compared and analyzed.

The proposed method is implemented in an open-source, user-friendly GEE script that can perform OB classification tuning various parameters (such as selecting the input bands, selecting the classification technique, and evaluating various segmentation scales), and contrast it with a PB method suitable for fine-grained analysis and homogeneous landscapes. Two confusion matrices and their associated statistics (Kappa co-efficient) are used to compare the two approaches' accuracy quantitatively.

Therefore, this research is poised to make significant contributions to the field of remote sensing by providing a detailed comparative analysis of LULC classification methodologies. Through this study, we aim to enhance the understanding of these methods in the context of Rajasthan's diverse landscape, which holds implications for similar environments globally. By addressing the outlined research objectives, this study paves the way for more accurate and reliable LULC classification, supporting sustainable land management practices.

STUDY AREA

With GPS coordinates of 27° 23' 28.5972" N and 73° 25' 57.4212" E, Rajasthan is in India and is one of the States that was chosen as the research study area for developing and evaluating the suggested technique. In Figure 1., we can see the study region area covered 219676.75 km2 of Rajasthan. The largest province of India, Rajasthan, is situated on the border with Pakistan in the country's northwest. It covers over 132000 square miles in total and accounts for 10% of the land [20]

Rajasthan is a unique State that exhibits significant regional variance. The Thar Desert in the west, the Aravalli Hills in the east, and the plateau in the southeast make up Rajasthan's three main geographic zones. 16,036 km2 of the State is covered by forests or 4.69 % of the overall land area [20]. Rajasthan, which is in India's dry and semi-arid regions, has a low area (4768.84 km2) covered by water bodies (including wetlands) and makes up 1.39% of the country's overall land area. Rajasthan is primarily used for agriculture, covering about 250123.15 km2 (73.08%) [21]

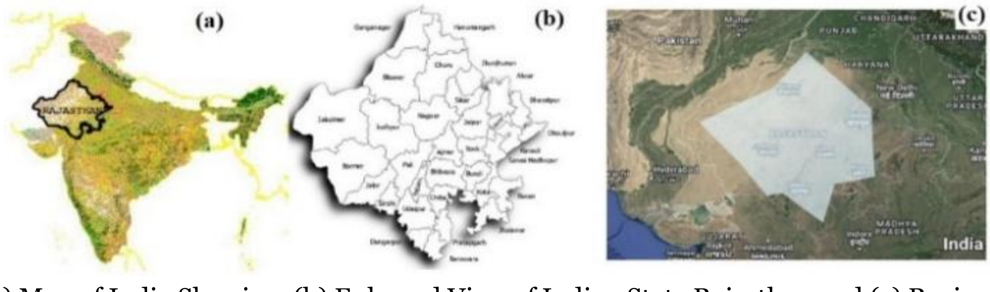

Figure 1. (a) Map of India Showing, (b) Enlarged View of Indian State Rajasthan and (c) Region Area Covered 219676.75 Km2 Methods.

DATA COMPOSITION

The initial stage of the LULC classification is data composition. In this approach, Landsat8, and Sentinel 2 are both datasets firstly filtered by area and time duration; to remove cloud contamination, cloud-masking functions are used for image collection. After that, each image's bare soil index (BSI) and normalized difference vegetation index (NDVI) are computed. It is usual practice to employ these extra indices to enhance LULC classification. The export of the dataset's desired bands is the last step in data composition.

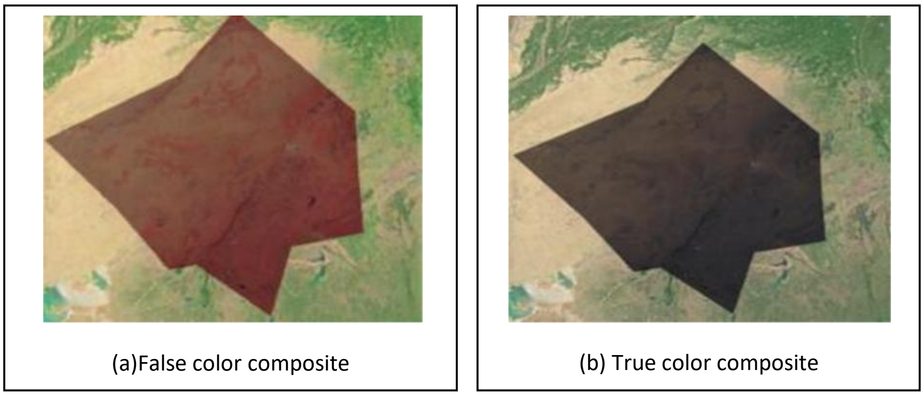

Figure 2. (a) False and (b) True color composite of the data

First, the collection of raw satellite images by study area of the region of interest (Rajasthan), then filtered by the specific time duration (from 1 Jan 2020 to 02 July 2022) an initial image collection was filtered by the desired time then filtered metadata for avoiding cloud shadow. It provided a QA60 band in GEE for cloud cover masking for the Sentinel 2 dataset and to perform cloud cover masking for the Landsat 8 dataset GEE provides a 'pixel_qa' band [3]. In the research region, this selection method generated two imagery data collections, comprising 119 photos intended for the S2 and 43 images used for the L8. The "inBands" were chosen from S2 10 m spatial resolution bands B2 (490 nm), B3 (560 nm), B4 (665 nm), and S2 20 m spatial resolution bands: B6 (740 nm), B8 (865 nm), B11 (1610 nm) and median bands were calculated. Figure 2 shows a false and true color composite of the data composition. Each image's NDVI and BSI are calculated, and the reduction functions are used to produce the relative spectral index statistics. Only the intended bands ("outBands") that were previously defined are considered in the final exporting process. NDVI mean, NDVI Std. Dev. (Standard Deviation), Bands 2, 3, 4, 6, 8, and BSI mean were chosen in this approach to construct the first S2 dataset. NDVI mean, Dev. (Standard Deviation), Bands 2, 3, 4, 5, 6, 7, and BSI means were chosen to make up the initial L8 dataset.

METHODOLOGY OF LULC CLASSIFICATION

Image classification is a process of assigning a pixel of raster data to a specified class. Typically, land cover classification utilizing remote sensing images involves classifying the pixels into different types of land cover based on specific criteria. In this work, landcover identification was done using remote sensing data from satellites with a resolution of 30 meters, such as Landsat 8 and Sentinel 2 with a resolution of 10 meters, which were both studied from 1 Jan 2020 to 02 July 2022. There are two kinds of image classification methods Pixel-based image classification and Object-based image classification. In this research, both classification methods are utilized to perform land use land cover classification of the Rajasthan area. In the pixel-based classification method, each pixel is classified into land cover types according to the spectral value of each pixel. On the other hand, the object-based image classification method consists of two steps first a spatial clustering phase that groups related and adjacent pixels together called segmentation, a subsequent calculation of textural indices based on the clusters, and a classification step at the end. Figure 3 shows the step-by-step process of the object-based Image analysis methodology.

For the segmentation, Simple Non-Iterative Clustering (SNIC) is used to generate the clusters called image objects. The function "Image. Segmentation.seedGrid" which needs a superpixel seed location spacing, delivers a regular grid of seeds on the same bands as the PB categorization that are used as SNIC input (in pixels). It impacts cluster size and can be adjusted to achieve the best result. Some parameters were adjusted as follows in our approach, always considering the features of the study area: compactness = 0, connectedness = 8, and neighborhoodsize = 256. These parameters need to be set for SINC. A smaller value of the “compactness” parameter provides the less compact clusters. The “connectivity” parameter takes the value 4 or 8, used when merging the adjacent clusters determined by Rook's or Queen's contiguity. This avoids the next parameter "neighborhoodsize", tile border artifacts. Algorithm 1 shows the SNIC algorithm's pseudo-code which is used to generate the data segments.

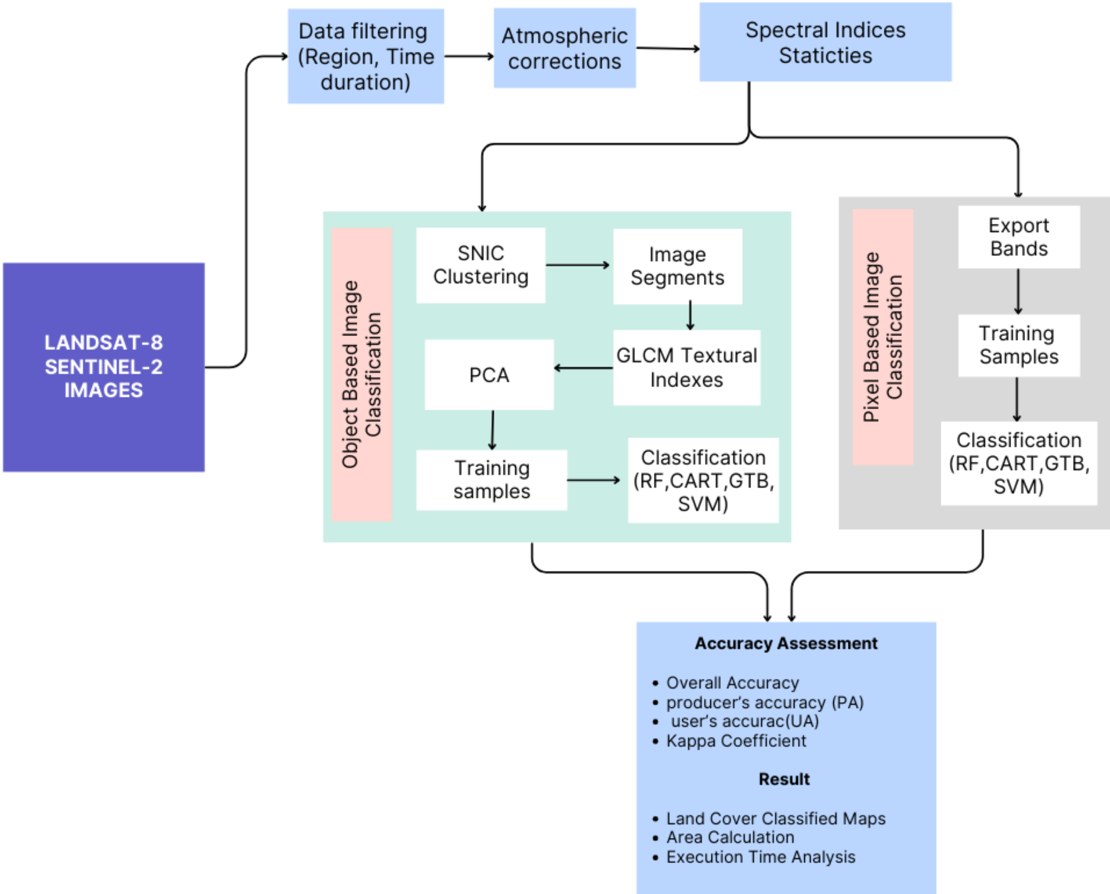

Figure 3. Flow chart of the object-based Image analysis methodology

The second phase is feature extraction, which involves calculating the textural features based on each segment to create a feature vector. This GLCM algorithm requires an input image for an 8-bit gray level, this 8-bit gray level is generated by following the formula;

For each pixel (x, y):

$$\mathrm{Gray}_{\mathrm{Level}} = (0.3 * \mathrm{NIR}_{\mathrm{BAND}}) + (0.59 * \mathrm{RED}_{\mathrm{BAND}}) + (0.11 * \mathrm{GREEN}_{\mathrm{BAND}}) \qquad (1)$$

The GLCM algorithm is effective in analyzing texture features such as roughness, smoothness, and directionality in an image. It is relatively easy to compute from an image. It involves counting the occurrences of pairs of pixel values at specified offsets within the image. It provides quantitative measures of texture such as contrast, correlation, energy, and homogeneity. GLCM can be used in conjunction with other image-processing techniques to enhance the overall analysis of images. Consequently, it can be combined with feature extraction methods or machine learning algorithms for improved performance in tasks like object recognition. The texture features extracted using GLCM are often interpretable thereby providing insights into the underlying properties of the image texture.

For a picture in grayscale, G

$$GLCM(d,\theta)x,y = count\ of\ instances\ in\ which\ a\ pixel\ pair(p,q)contains\ values\ x\ and\ y$$

Extract GLCM features

$$Contrast = \sum_{x,y} (x-y)2 \cdot GLCM(x,y) \qquad (2)$$

$$Correlation = \frac{\sum_{x,y}(x-\mu x)(y-\mu y)\cdot GLCM(x,y)}{\sigma x \cdot \sigma y} \quad (3)$$

where:

σx and σy are the $standered$ $devitaion$ of x and y

$$\mu x = \sum_x x \cdot GLCM(x,y) \quad (4)$$

$$\mu y = \sum_y y \cdot GLCM(x,y) \quad (5)$$

In this study, we have demonstrated how to improve segmentation accuracy by combining texture GLCM features with PCA fusion. To apply PCA, we must first integrate the data from the GLCM to get the segmentation for texture results. Then, texture feature fusion is accomplished using a

PCA fusion technique. The average of the first PC for each object that belongs to the SNIC "clusters" band is then calculated in a distinct band. The bands produced by the SNIC segmentation method are finally combined with the first PC object averaged band.

The third stage involves classifying each item (segment) according to one or more pixel-level textural attributes. For classification popular machine learning classification algorithms, the RF, CART, SVM, or GTB are used. PB and OB both approaches used the same training dataset. Then at last accuracy assessment was carried out for individual approaches applying a confusion matrix and the identity validation data as before.

Algorithm 1: SNIC Algorithm for segmentation

Input: Input satellite image SI, n initial centroids C[n] = {xn, cn} Consistent grid sampled data, Color normalization digit

Output: La label assigned

Initialization:

Set La[:] <- 0

Loop Process

for n = 1 to N do
    Element E {xn, cn, n, 0}
    Insert E in priority queue Pq
end for
while Pq is not empty do
    Remove from Pq to get Ei
    if La[xi] is 0 then
        La[xi] = ni
        Update centroid C[ni] online with xi and ci
        for every connected neighbour xj of xi do
            Generate element Ej = {xj, cj, ki, dj, ki}
            if La[xj] is 0 then
            Insert Ej on Pq
            end if
        end for
    end if
end while

19: return La

TRAINING SAMPLE SELELCTION

For this study, six major classes are selected for land cover classification in Rajasthan, India. Water: includes ponds, valleys, rivers and dams, and other land water resources. Forest: the area that is covered by natural or planted tree stands but is not used for trade, Crop: land used for framing and growing crops, built up: land includes buildings, roads, mines, and any other structures that were consciously built to support human activity, Desert: dry area with often little vegetation. It manually labels 249 validation points at the Google Map Foundation layer. Table 1 has details of the training points with a class label.

Table 1. The total sum of LULC (land use-land cover) validation points for every class.

Class name	No. of Validation-Points
Water	52
Forest	50
Crop Land	53
Urban	50
Desert	44
Total	**249**

CLASSIFICATION

Supervised classification methodology must gather the data from the training points to train the classifiers for the LULC classification. This study performed Pixel-based and object-based classifications using the same dataset, same region, and same training data collection. The image is quickly classified in the PB classification process as it is a traditional ML technique. The OO classification stage consists of a spatial clustering phase that groups related and adjacent pixels together. This is called segmentation, a subsequent calculation of textural indices based on the clusters, and a classification step at the end. So, the object-based method required more time for execution than the pixel-based classification method. The pixel-based and the object-based approaches were applied to classify Rajasthan's land cover map using RF, SVM, CART, and Gradient Tree Boost machine learning classification methods. Here RF and SVM CRAT classifiers are commonly used classifiers, but the GTB classifier is not used by others to perform land use land cover classification using multispectral satellite images.

SVMs are effective with minimal-sized training data but capable of handling high-dimensional data. The feature extraction technique such as Kernel Principal Component Analysis where RFs can handle diverse feature types and non-linear relationships. Decision Trees (DTs) are considered decipherable models for understanding feature importance. DT belongs to Ensemble method Boosting which designates multiple models for improved accuracy.

Figure 4 shows the different classified maps of the study region of the selected classification methods. To get the overall area (in km2 and percentage) for each LULC class, a final calculation is performed by counting the number of pixels that belong to each class. In the end execution, the time of both approaches is also calculated and compared with different datasets.

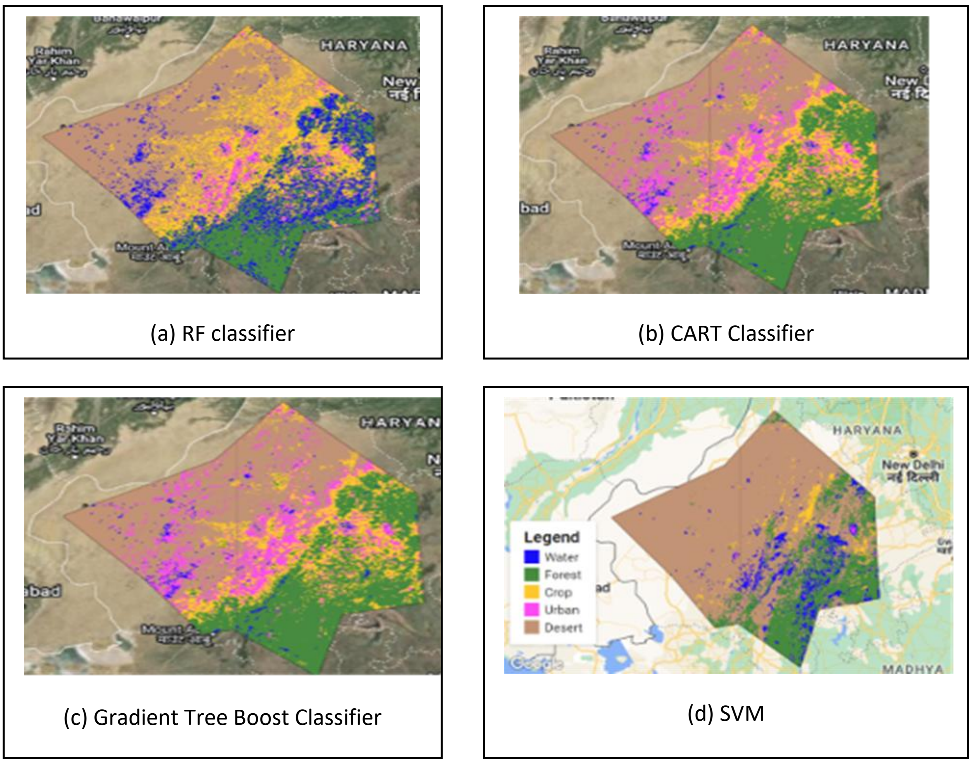

Figure 4. Classified map of study region using (a) Random Forest, (b) CART, (c) Gradient tree boost, and (d) SVM

RESULTS AND ACCURACY ASSESSMENT

GEE framework uses a confusion matrix for accuracy assessment. The accuracy assessment determines how confident the classified maps are. The calculation of overall accuracy is the basic need, according to various studies, and the kappa coefficient is used to measure the correctness of the classification process. The preliminary comparison of the results by overall accuracy and kappa coefficient.

The most OO and PB methodologies combinations were chosen for each dataset (L8 and S2) using four different classifiers, and they were compared visually and in terms of the percentage of the total area and overall accuracy. The execution time of the chosen classification was also assessed and compared. Finally, classified maps of the ultimate land cover are provided. The total area occupied by each type of land cover was extracted and included. So, the results are divided into two parts one is the overall accuracy of RF, SVM, CART, and GTB classifiers using the object-based image classification method using the Sentinel 2 dataset. The second part is the overall accuracy of RF, SVM, CART, and GTB classifiers using the Pixel-based image classification method using Landsat 8 and Sentinel 2 datasets. Image pre-processing and feature engineering can significantly impact classification accuracy.

PERFORMANCE OF OBJECT- BASED METHODOLOGY

The overall accuracy of the object-based classification methodology applied for different classifiers is successfully evaluated with the outcomes shown in Table 2 OB GTB, OB RF, OB CART, and OB SVM algorithms respectively (91%,86%,90%, and 47%). These values suggest that CART is quite effective at handling the object-based classification tasks with the given dataset. The standout result comes from the GTB classifier along with GLCM, which outperforms the other classifiers with the highest OA of 91% and a Kappa Coefficient of 0.88. This reflects a very high level of agreement between the classified output and the reference data, indicating that GTB is highly effective for object-based classification using Sentinel 2 data in this study. The comparative graph (shown in Figure 5) presents the Producer's Accuracy (PA) and User's Accuracy (UA) for different LULC classes using object-based image classifications with GTB, RF, and CART. GTB shows a balanced performance with both PA and UA consistently high across most classes, indicating reliable classification and user trust in the results. RF exhibits strong PA but slightly varied UA, suggesting good class representation but potential user misinterpretation or sampling errors. CART displays the most fluctuation in both PA and UA, implying variability in both classification consistency and user expectation. The PA is generally higher than UA across all classifiers, which could indicate that while classes are wellrepresented, users might be experiencing difficulties in correctly identifying certain classes, possibly due to class similarities. The OB method performs better using the Sentinel 2 dataset because of its higher spatial resolution. Textural features improve the OA of OBIC.

Table 2. The overall accuracy of OB approach classification using the Sentinel 2 dataset.

Classifier	Overall Accuracy (OA)	Kappa Coefficient
SVM	47%	0.34
RF	86%	0.82
CART	90%	0.86
Gradient Tree Boost	91%	0.88

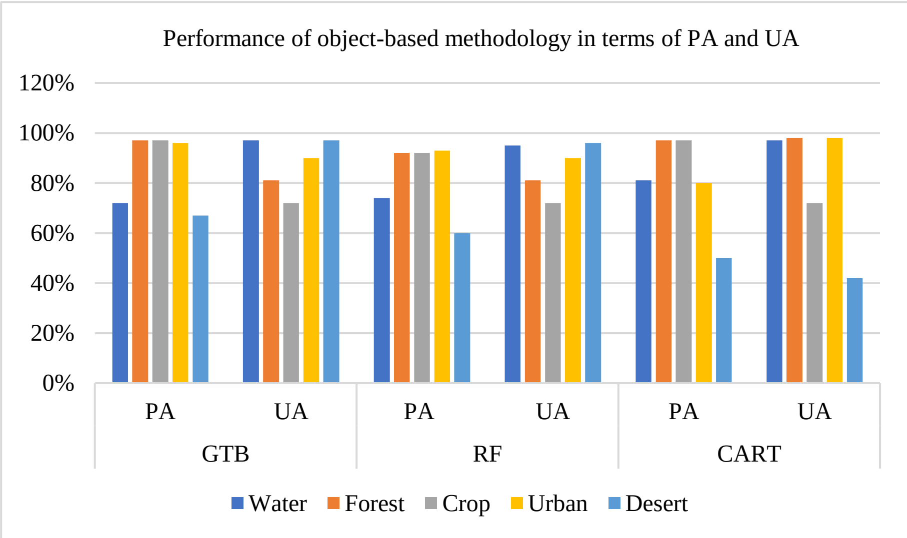

Figure 5. Comparison of producer's accuracy (PA) and user's accuracy (UA) of the LULC classes predicted by OBIC.

PERFORMANCE OF PIXEL-BASED METHODOLOGY

The PB method was applied to two data sets Landsat8 and Sentinel 2 and the results are shown in Table 3. The outcome shows this method provides better Overall accuracy while using the Landsat 8 dataset. Our results of OA for four classifiers while using the Landsat 8 dataset are respectively PB GTB, PB RF, PB CART, and PB SVM (92%,87%,89%, and 63%). From Table 3, we can see the best outcomes delivered by Pixel-based techniques were accomplished with GTB, which had a kappa of 0.89 and an OA of 92%. Similarly, we evaluated OA for a PB method using the Sentinel 2 dataset and did a comparative analysis of OB and PB methods. The outcomes of the PB method using the Sentinel 2 dataset exhibit respectively PB GTB, PB RF, PB CART, and PB SVM algorithms (76%,75%,62%, and 74%). The PB method provides better accuracy while using the Landsat 8 dataset. Thus, the GTB classifier demonstrates the highest overall accuracy in pixel-based classification for both Landsat 8 and Sentinel 2 datasets, while the CART classifier shows varied results, performing better with Landsat 8 than with Sentinel 2.

Table 3. The overall accuracy of Pixel-based approach classification using Landsat8 and S2 dataset.

Classifier	OA (L8)	Kappa Coefficient (L8)	OA (S2)	Kappa Coefficient (S2)
SVM	63%	0.59	74%	0.68
RF	87%	0.83	75%	0.70
CART	89%	0.85	62%	0.53
Gradient Tree Boost	92%	0.89	76%	0.70

The choice of classification approach depends on the study area and its land cover complexity. OB methods generally outperformed PB methods in terms of overall accuracy and kappa coefficient for the above-mentioned land cover classes methods were particularly effective for complex landscapes with heterogeneous land cover types. However, PB methods could be more efficient for simpler landscapes with large, homogenous land cover classes.

COMPARATIVE ANALYSIS

In this section, a comparative analysis of the proposed work and existing work has been done. According to several studies [27, 28], the accuracy of the classification depends on the methods, datasets, time, space, and techniques. The accuracy evaluation in this study reveals a difference between the outputs of the classifiers applied in this instance. A LULC classification's accuracy varies not only with the classifier but also with datasets (L8 and S2) and Technique (PB and OB). This may be a result of fluctuations in the atmosphere, surface, time, and, space [22]. The most widely used method for evaluating accuracy is the Kappa coefficient. kappa index (K), which is obtained from a confusion matrix, is the most popular statistic for measuring the accuracy of LULC classification [23]. The result demonstrates in our case the maximum accuracy has been noted (0.89) of the GTB classifier. According to the existing studies [24, 25], the Gradient tree boost classifier outperforms the other approaches used for comparison and the overall accuracy for GTB was 0.8905. Another Study [26] contrasted extreme gradient boosting with benchmark classifiers like SVM and RF. The LULC change analysis has an overall classification accuracy of 83.17 % and the kappa coefficient value (k) was found 0.80.[30]. One study [29] carried out the comparative analysis of machine learning algorithms for land use land cover classification that shows Random forest classfier performs better. This study did not explore the GTB classifier. The findings show that, especially for larger sample sizes, extreme gradient boosting, parameterized with a Bayesian approach, consistently outperformed RF and SVM.

In our work, the outcomes demonstrate that performance is contingent upon the choice of dataset and classification techniques. Employing the Sentinel 2 dataset, the OB approach with the GTB classifier surpassed the PB method with the GTB classifier, showing a discernible difference in OA. Specifically, the OB method utilizing the GTB classifier achieved an OA of 91% with a Kappa Coefficient of 0.88. In contrast, the PB method with GTB yielded an OA of 76% when applied to the Sentinel 2 dataset, indicating a 15% increase in accuracy when using the OB method over the PB method with the same classifier.

Further analysis revealed that the RF classifier under OB achieved an OA of 86%, whereas PB with RF on the Sentinel 2 dataset had a slightly lower OA of 75%. The CART classifier demonstrated variable results, with an OA of 90% for OB and 62% for PB using Sentinel 2 data. The SVM classifier showed a reversal in the expected pattern; OB with SVM had a lower OA of 47%, while PB with SVM reached an OA of 74% on the Sentinel 2 dataset.

Our comparative analysis of both OB and PB approaches using the Sentinel 2 dataset underscores the superiority of the OB method, particularly when coupled with the GTB classifier, which achieved a Kappa Coefficient of 0.88 and an OA of 91%. Landsat 2 data performed 16% better than Sentinel-2 for the PB method, and Sentinel 2 data performed 12% better for the OB method, according to the GTB classifier.

AREA CALCULATION

Figure 6 shows the part (in %) of the entire area occupied by individual classes using the selected classification methods and Table 4 shows the detailed area in km occupied by each class, which is calculated by counting the number of pixels for each class type.

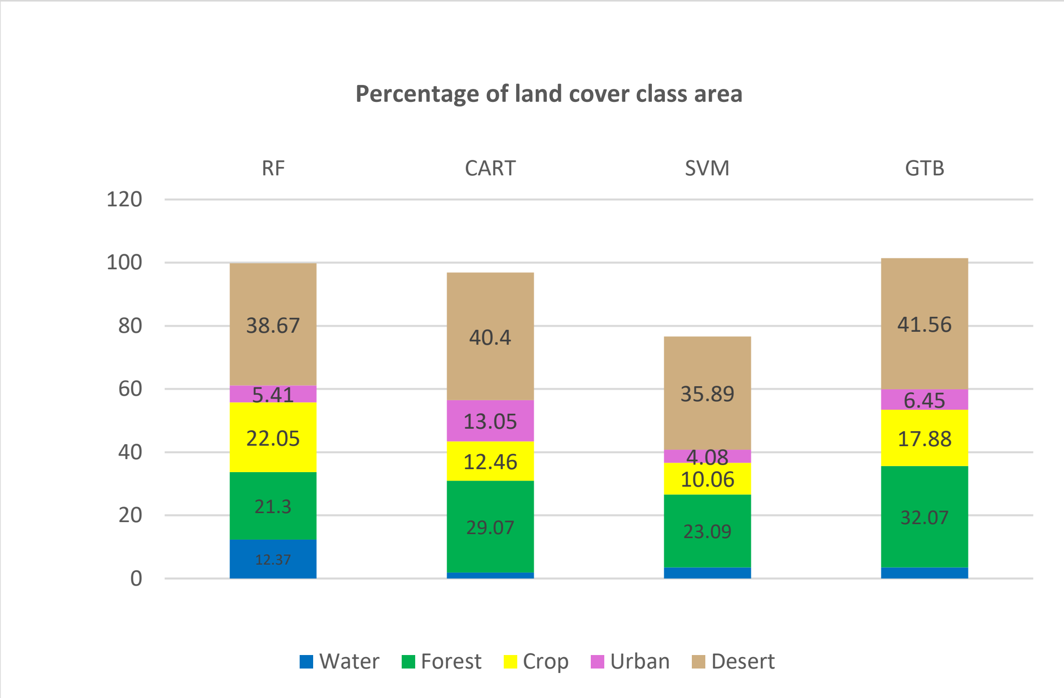

Figure 6. Total area (in percentage) enclosed by every LULC class for selected classifications algorithm.

Table 4. Total area (in km2) enclosed by every LULC class for selected classifications algorithm.

Class Name	RF	CART	GTB
Water	27185.17	4171.62	4058.76
Forest	46796.35	63860.3	70470.30
Crop	48445.32	35106.77	39281.48
Urban	11900.86	27378.37	14172.14
Desert	91301.67	88767.25	91301.67

EXECUTION TIME ANALYSIS

The execution times of both approaches are inversely correlated with the processing complexity and image resolution. As a result, shown in Table 5 the OB approach typically takes longer than the PB technique (Landsat 8: 18.76 s vs. 8.35 s; Sentinel 2: 33.74 s vs. 5.12 s). This time includes total execution time and exporting the final LULC classified map.

Table 5. Execution time of both techniques using two different datasets (in sec.)

Classification Technique	Landsat 8	Sentinel 2
Pixel-based	8.35	5.12
Object-based	18.76	33.74

DISCUSSIONS

This research is carried out to Performance Evaluation of Object-Based and Pixel-Based Land Use and Land Cover Classification Using Multispectral Satellite Images and Machine Learning Algorithms. In this work, we have analyzed that the overall accuracy of the LULC classification depends on the dataset, classification techniques, and different classifiers.

We have evaluated the performance of the object-based classification technique and pixel-based classification technique using two different datasets Landsat 8 and Sentinel 2 with four types of machine learning classifiers named Random Forest, CART, SVM, and Gradient tree boost classifier using the tool Google Earth Engine. A study [23] revealed that with machine learning methods applied to data with varying spatial resolutions, LULC in coastal areas may be mapped. As a result, the final LULC maps differ, and the number of LULC classes found was determined by the resolution picked. Sentinel-2 data had a reduced resolution but produced useful maps. The quality and quantity of training data are pivotal for any machine learning algorithm.

The study findings, based on Tables 2 and 3, indicate that the Sentinel 2 data, when processed using the OB approach with the inclusion of GLCM textural information, yields the highest Overall Accuracy (OA) of 91%. Furthermore, the GTB classifier out-performs other classifiers in both OB and PB methods, with the OB method achieving a Kappa coefficient of 0.88 and an OA of 91%, compared to the PB method's 0.89 Kappa and 92% OA with the GTB classifier.

The research also highlights that the Sentinel 2 dataset is better suited to the OB method due to its higher spatial resolution, which enhances classification accuracy when textural features are taken into account. Moreover, the study provides new insights into the effectiveness of the GTB classifier, which has not been as extensively researched as the RF and CART classifiers. It underscores the GTB classifier's superior performance over the commonly used RF classifier in the realm of LULC classification.

When comparing the two approaches with different datasets, it is observed that the PB method yields better accuracy with the Landsat 8 dataset. Specifically, the OA re-sults for the Landsat 8 dataset are 92% for GTB, 87% for RF, 89% for CART, and 63% for SVM. For the Sentinel 2 dataset, the corresponding accuracies are 76% for GTB, 75% for RF, 62% for CART, and 74% for SVM. These results suggest that while the GTB classifier leads to the highest accuracy across both datasets, the choice of dataset plays a crucial role in determining the effectiveness of the classification method. The study concludes that the OB approach when paired with the Sentinel 2 dataset and GTB classifier, provides the most accurate LULC classification results, showcasing the importance of matching the classification approach to the specific attributes of the dataset used.

CONCLUSIONS

The objective of this study is to carry out a performance Evaluation of Object-Based and Pixel-Based Land Use and Land Cover Classification Using Multispectral Satellite Images and Machine Learning Algorithms. This evaluation helped to find out the best approach for land use and land cover classification.

This work evaluated an OB classification technique using the SNIC algorithm to locate spatial clusters, GLCM to compute object textural features, and four popular machine-learning algorithms RF, CART SVM, and Gradient tree Boost ML algorithm to carry out the final classification within the GEE environment. The method was put into effect in an approachable code that can contrast the OB and PB classification approaches while using two different datasets Landsat 8 and Sentinel 2. We found that the Gradient Tree Boost Classifier produces the best accuracy in both approaches. It performed better than RF, CART, and SVM.

According to this our experimental results Landsat 8 dataset provides better results with pixel-based methodology and sentinel 2 performed better with Object-based classification methodology. According to the comparative analysis of both approaches Object based method outperforms over pixel-based approach. Because the best outcomes delivered by OB techniques were accomplished with the Sentinel 2 dataset using the GTB classifier.

These datasets and methods are used to track upcoming changes, the LULC planning procedure, and other related studies. Future research will incorporate an optimization-based feature selection methodology into the suggestion to determine whether the LULC classification accuracy can be further enhanced.

The outcome of the comparative evaluation of object-based and pixel-based classification methods using machine learning algorithms for multispectral satellite imagery is a significant step forward in the field of remote sensing, particularly for complex and diverse landscapes like that of Rajasthan, India. This research offers a comprehensive analysis that meticulously delineates the strengths and weaknesses of each classification approach across varied land cover types. The findings reveal that object-based methods when paired with advanced machine learning algorithms such as GTB, provide superior accuracy in classifying high-resolution satellite images. This is a pivotal discovery, as it underscores the potential of object-based approaches to better interpret and classify the intricate patterns and textures of the earth's surface, which are especially prevalent in heterogeneous regions. Additionally, the study highlights the considerable improvement in classification results when employing machine learning over traditional statistical methods, paving the way for enhanced LULC mapping.

The contributions of this study to the research community are manifold. Firstly, it presents a novel, rigorous comparison of classification methods within a real-world setting, providing empirical evidence to guide future remote sensing projects. This study not only fills a crucial gap in comparative LULC analysis but also sets a benchmark for the evaluation of classification methods in similar geographic settings. Secondly, the research introduces the use of GTB in LULC classification, a method not commonly applied in this context. The promising results obtained with GTB offer a new tool for researchers and practitioners, potentially leading to more accurate and efficient land cover mapping. Collectively, the outcomes of this study enhance our methodological toolkit and provide a reference point for future investigations into the optimization of LULC classification techniques, thereby supporting the sustainable management of land resources through improved environmental monitoring and planning.

To summarize, the present study highlights the significance of the determined selection of both the classification approach and machine learning algorithm for accurate land use and land cover classification utilizing multispectral satellite images. It also draws attention to the need for further research to explore the prospects of advanced techniques like deep learning in this field. Deep learning algorithms like CNNs were not precisely tested in this study, but they are being claimed as the evolving popular technique for satellite image classification furthermore could potentially provide extremely higher accuracy.

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