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Accuracy Assessment of different classifiers for Sustainable Development in Landuse and Landcover mapping using Sentinel SAR and Landsat-8 data

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Abstract

Sentinel satellites make use of Synthetic Aperture Radar (SAR) which produces images with backscattered signals at fine spatial resolution from 10 m to 50 m. This study is mainly focused on evaluating and assessing the accuracy of various supervised classifiers like Random Forest classifier, Minimum Distance to mean classifier, KDTree KNN classifier, and Maximum Likelihood classifier for landuse / landcover mapping in Maduranthakam Taluk, Kancheepuram district, Tamilnadu, India. These classifiers are widely used for classifying the Sentinel SAR images. The SAR images were processed using speckle and terrain correction and converted to backscattered energy. The training datasets for the landcover classes, such as vegetation, waterbodies, settlement, and barren land, were collected from Google Earth images in high-resolution mode. These collected training datasets were given as input for the various classifiers during the classification. The obtained classified output results of various classifiers were analyzed and compared using the overall classification accuracy. The overall accuracy achieved by the Random Forest classifier for the polarization VV and VH was 92.86%, whereas the classified accuracy of various classifiers such as KDTree KNN, Minimum distance to mean, and Maximum Likelihood are found to be 81.68%, 83.17%, and 85.64% respectively. The random forest classifier yields a higher classification accuracy value due to its greater stability in allocating the pixels to the right landuse class. In order to compare and validate the results with sentinel data, the random classifier is applied with optical Landsat-8 satellite data. The classification accuracy obtained for Landsat-8 data is 84.61%. It is clearly proved that the random forest classifier with sentinel data gives the best classification accuracy results due to its high spatial resolution and spectral sensitivity. Thus accurate landuse and landcover mapping promote sustainable development by supporting decision-making at local, regional, and national levels.

Keywords: Synthetic Aperture Radar (SAR), Random Forest Classifier, Maximum Likelihood Classifier, Minimum Distance to Mean Classifier and KDTree KNN Classifier..

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1. Introduction

Landcover refers to the features on the earth's surface, such as water bodies, snow, forests, etc. Landuse refers to how the land is put to use by humans, including activities like cultivation, habitation, highways, etc. Growth in society solely depends on social, ecological, and economic development. It is important to consider how social and economic growth affects regional ecological patterns[1]. Therefore, landuse and landcover mapping are essential to study how changes in landuse and landcover mapping affect the ecosystem and environmental improvement [2]. The results of the landuse and landcover mapping and detection analysis would be utilized to make decisions on sustainable development [3]. The different landuse / landcover (LULC) classes in an area give a challenging task to identify the different types of classes. Also, it results in identifying the different types of crops in agricultural areas[4]. In conventional optical remote sensing, LULC mapping is difficult due to the textural features of optical images and also more mixed pixels[5]. The land features on the earth purely depend on their tonal properties. It always affects the accuracy of LULC classification.

However, in microwave remote sensing, it depends on surface roughness and dielectric properties. Microwave remote sensors can penetrate through clouds, haze, and moderate rain[6]. It has certain advantages that make imaging possible in all weather and also makes day/night operations possible. The Sentinel-1 satellite was launched by the European Space Agency in April 2014 and operated in the C band [7]. It has a high spatial resolution that ranges from 10 m to 60 m over land and coastal regions.

In this study, Sentinel 1A SAR image is used to process and classify the image. Sentinel has multi-modal acquisition similar to RISAT with SM (Strip Map mode, 5m resolution, quad pole capability), IW (Interferometric wide swath mode, 5 x 20m resolution, quad pole capability), EW (Extra wide swath mode, 20 x 40m resolution, quad pole capability) and WM (Wave mode, 5 x 5m resolution, single pole)[8]. The advantage of using this data in the study is having high spatial resolution over land areas and high penetration capability.

There are many classifiers available in supervised classification. They are Random Forest[9], k-nearest neighbour (KNN), kDTree KNN, Maximum Likelihood, Minimum distance to mean, Support Vector Machine (SVM), etc. Random Forest classifier, kDTree KNN classifier[10], Maximum Likelihood Classifier, and Minimum Distance Classifier are used in this study to perform the classification with the help of input training pixels. The output of the classified images was analyzed and compared with the ground truth data and assessed using the overall classification accuracy[11].

2. Literature Review

Sara Dahhan et al. (2022)[12] evaluated the overall performance of various classifiers such as random forest (RF), KD tree KNN, and maximum likelihood. They have performed the LULC mapping for agricultural areas using Sentinel data in the Kaffrine region of Senegal. From their results, the RF classification gave the best performance in terms of accuracy of 84%.

S. Abdikan et al. (2016)[13] have implemented SVM to classify the landcover classes in urban areas in Turkey. Different polarization combinations of VV and VH of Sentinel data have been compared, and the classified output images have been evaluated. It is clearly shown that the overall classification accuracy of the combination of VV and VH is 93.28%, whereas the individual polarization of VV and VH are found to be 73.85% and 70.74%, respectively.

Mishra et al. (2014)[14] used ALOS PALSAR satellite data to perform landcover classification using a supervised classification based on Pauli decomposition and Wishart classification. The decision tree classifier discriminated all landcover classes with a higher accuracy level from the training pixels than the traditional methods.

From the literature review, many researchers have reported that the texture of the image reduces the improved classification accuracy in optical satellite data. Some researchers have analyzed both the optical and Sentinel SAR satellite images[15], [16]. Also, they have reported that the small spectral differences between these two satellite images affect the classification accuracy, but the sentinel landuse classification has high classification accuracy for most of the landuse classes[17]. Based on the literature review findings, this study explores the capabilities of Sentinel SAR data for mapping landuse and landcover types in the mixed heterogonous landuse types using various classifiers and the comparison of different classified images using Random Forest, Minimum distance to mean, Maximum Likelihood and KDTree KNN Classifiers for mixed crops. It is also studied to determine the most effective classifier for mixed crops.

3. Study Area

The study area is chosen as a part of Maduranthakam Taluk, Kancheepuram district, Tamilnadu, India, covering an area of about 3175 sq. km. The study area geographically extends from 13°05'49''N, 79°04'34''E to 12°20'14''N, 79°47'23''E. This study area has many different varieties of agricultural crop types. Figure 1 depicts the study area.

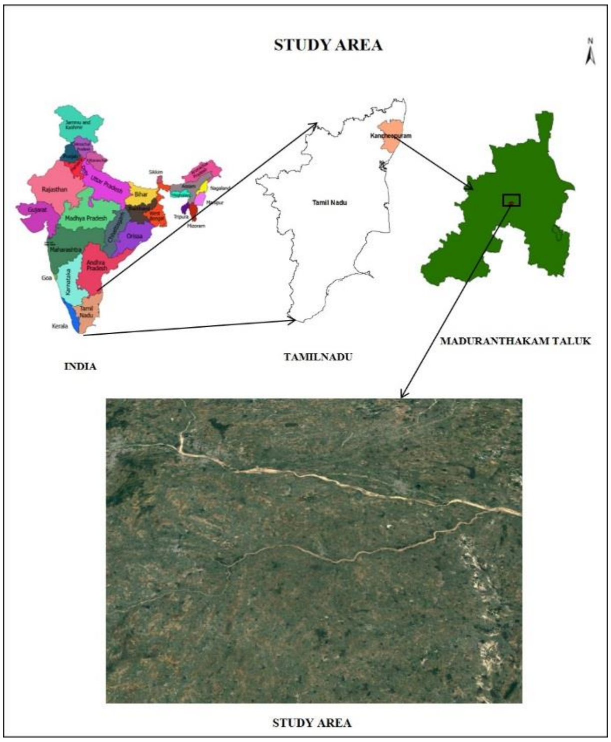

Figure 1. Study Area

4. Methodology

4.1. Data Products

In this study, a Level-1 Sentinel data product - Ground Range Detected (GRD) and Landsat-8 satellite image were used. The Sentinel image was acquired on February 8th, 2022, in Maduranthakam Taluk, Kancheepuram district, Tamilnadu, India. The details of Sentinel data and Landsat-8 data[18] are given below in Tables 1 & 2, respectively.

Table 1:Details of Sentinel and Landsat Data

Specifications	Sentinel-1 data	Landsat-8 data
Acquisition time	February 8th, 2022	February 10th, 2022
Data product used	GRD Level-1	Landsat Level-1
Band Information	C-band	11 spectral bands
Resolution	20 m	15 m at pan and 30 m at multi-spectral

4.2. Software Used

The Sentinel-1 data was processed with the help of SNAP (Sentinel Application Platform) software which is provided by ESA. SNAP is an open-source software for exploring the earth observation satellite data. It comprises many tools such as calibration, co-registration, speckle filtering, orthorectification, etc. It can analyze large archives of satellite data by automated image processing techniques using Python scripts.

In the Sentinel Application Platform (SNAP), the Sentinel data is opened and viewed in the display. The subset function will perform both spatial and spectral resampling because the bands in Sentinel data were all various sizes and resolutions[19]. As a result, the resampling approach was used to create all bands with the same size and resolution. The methodology is depicted in Figure 2.

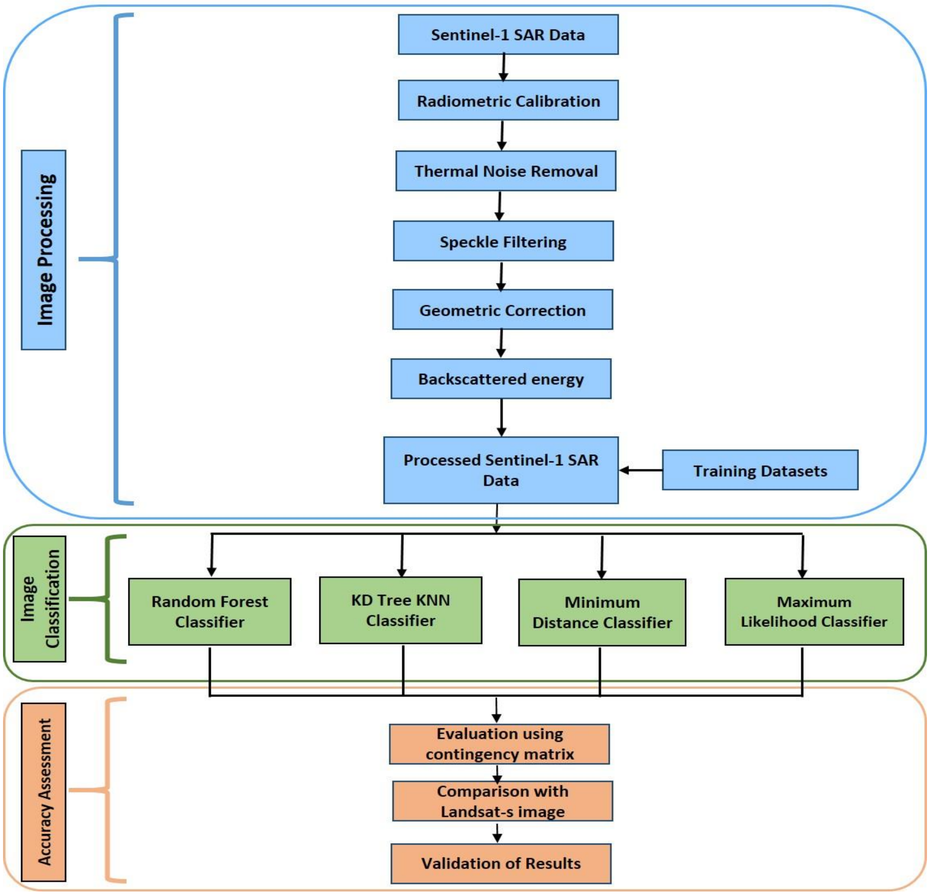

Figure 2: Methodology to Process and Classify SAR Data

4.3. Image Pre-processing

The pre-processing of the image consists of both radiometric calibration and geometric or terrain correction. The radiometric calibration was done in SNAP to remove or reduce the variations in the image that occurred during the data acquisition[20]. In radar images, a speckle refers to the random noise in an image. Thus the speckle filter was performed in SNAP to remove the random noise in the image. Now, the image was perfectly filtered by Lee adaptive filter with kernel size 5x5 to remove the speckle noise. This is an important step to be carried out before performing landuse / landcover classification, as speckle introduces unwanted effects in the classified image results. The geometric correction was carried out to remove the impacts of the side-looking geometry of Sentinel images with the help of range-doppler terrain correction. The SRTM DEM, along with the bilinear interpolation resampling technique, was employed for geometric correction[11]. Thus the pre-processing of the Sentinel data was done by correcting the radiometric calibration and geometric correction.

In SNAP, the brightness values or DN values of SAR data were converted into radar-backscattered numbers in decibel format[21]. Figure 3 depicts the processed Sentinel SAR image of the study area.

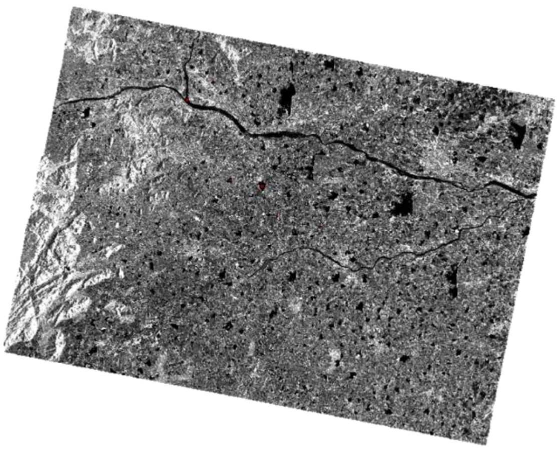

Figure 3: Processed Sentinel SAR image

Similarly, the Landsat-8 satellite image was processed for image classification[16]. The resampling technique and the geometric correction were carried out in SNAP. The Landsat-8 satellite image was shown as a false color composite (FCC) with different band combinations in Figure 4.

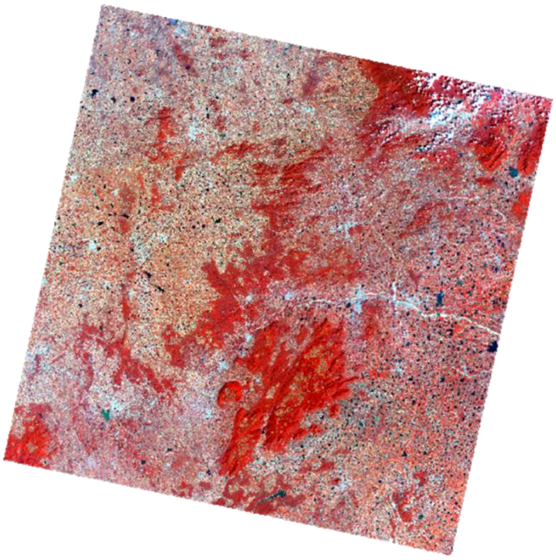

Figure 4: Landsat-8 Satellite Image

4.3. Image Classification

There are different classifiers in supervised classification like Random Forest, Artificial Neural Network (ANN), KDTree KNN Classifier, Minimum distance to mean, Maximum Likelihood Classifier, KNN Classifier, Support Vector Machine (SVM), etc. These classifiers are widely used in remote sensing to classify Sentinel SAR images. In this study, classifiers like Random Forest, KDTree KNN, Minimum distance to mean, and Maximum likelihood Classifiers are used to classify an image.

Random Forest classifier is a technique for supervised classification and regression trees. This classifier creates classification trees by randomly selecting input data samples. In comparison to a single classification tree, the classification output from this classifier indicates the statistical mode of several decision trees. The average of the parallel, unpruned regression trees is represented in this classifier output for regression. The iterative nature of this classifier gives a clear picture over the other conventional methods since it effectively improves the data for more reliable predictions by feeding random portions of training data. This lessens the connectivity between the trees.

Although the KDtree KNN classifier should perform better than the slow KNN classifier, it should still produce the same results. This classifier classifies the features based on the nearby training samples. It is a non-parametric classification technique. It is also known as the instance-based learning method, and it is one of the simplest machine learning algorithms that classify an object by a majority vote of its neighboring pixels.

Minimum distance to mean classifier is a technique for categorizing feature vectors that involves choosing the input vector's shortest distance from each class center and allocating the vector to the center with the shortest distance. The distance between a pixel's image data and the means of the classes deriving from the training sets is used by the minimal distance classifier to categorize every pixel in the image. The class with the shortest distance is given the pixel.

The maximum likelihood classifier, which assigns the class to the pixel with the highest likelihood, is the most commonly used classification technique. The likelihood is defined by the posterior probability of a pixel belonging to a given class. If the highest chance is less than a certain threshold, the pixel is classified under the unclassified class. A consistent approach to parameter estimate issues is offered by this method.

The input training datasets for the landcover classes, such as vegetation, waterbodies, settlement, and barren land, were created as vector data in SNAP. These training sets were created as a vector geometry for each landuse and landcover class. These training pixels were collected from Google Earth images in high-resolution mode. Table 2 shows the input training data statistics for each landuse and landcover class. In SNAP, the same input training datasets were given for the various classifiers like Random Forest, Minimum distance to mean, KDTree KNN, and Maximum Likelihood classifier during the classification. The classified output images of various classifiers were obtained with the help of the given input training pixels[22].

Table 2: Input Training Dataset Statistics

Sl. No.	Landuse / Landcover Class	Number of pixels for training
1.	Vegetation	1024
2.	Waterbodies	858
3.	Settlement	521
4.	Barren land	687

Figure 5 illustrates the classified output images from various classifiers.

The same input training pixels were given for the Landsat-8 satellite image to perform supervised classification with the help of a random forest classifier. Since the random forest classifier gives a good overall classification accuracy and all the pixels were classified more appropriately to a particular class. Figure 6 shows the classified image of Landsat-8 from a random forest classifier.

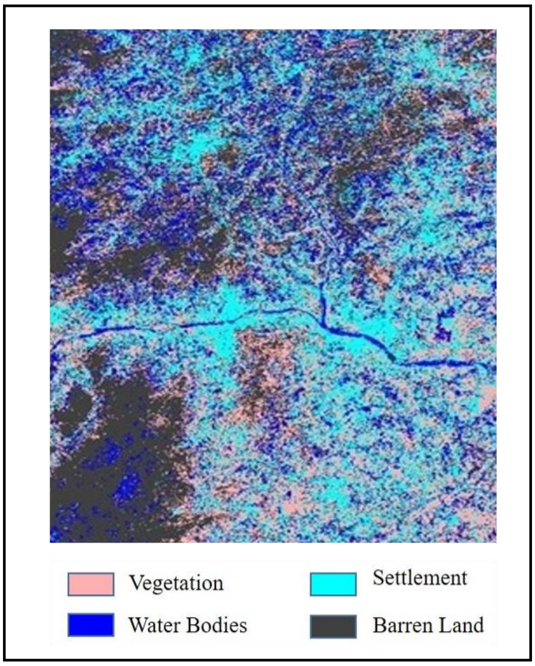

Figure 5: Classified Image of Landsat-8 Data from Random Forest Classifier

5. Results and Discussion

In this study, Sentinel 1 SAR data has been used to interpret and map the various landuse / landcover classes with the help of using supervised classification techniques. Supervised classification techniques like Random Forest, kDTree KNN classifier, Minimum Distance to mean, and Maximum likelihood classifier are used in this study to classify the pixels in the image based on the input training dataset statistics. The input training pixels were created for the classes like vegetation, waterbodies, settlement, and barren land. Generally, the water pixels have lower backscattering values[23], and the vegetation pixels have higher backscattering values in the processed SAR image[24]. The classified images were obtained from the various classifiers. The results were validated with ground-truthing samples. The overall classification accuracy of the landuse and landcover classes for each classifier was evaluated and assessed through the contingency matrix[25]. The accuracy of the classified image of the Random Forest Classifier through the contingency matrix[26] is depicted below in Table 3.

Table 3: Contingency Matrix from Random Forest Classifier

Landuse / Landcover Classes	**Number of Pixels**					**User's Accuracy (%)**
	Vegetation	**Water Bodies**	**Settlement**	**Barren Land**	**Row Total**	
Vegetation	4991	106	56	30	5183	96.30
Water Bodies	124	3343	51	10	3528	94.76
Settlement	118	53	1824	40	2035	89.63
Barren land	120	102	48	994	1264	78.64
Column Total	5353	3604	1979	1074	12010	
Producer's Accuracy (%)	93.24	92.76	92.17	92.55		**Overall Accuracy = 92.86%**

The overall accuracy of the SAR Sentinel image through the random Forest classifier is 92.86%, whereas the classified accuracy of the kDTree KNN classifier is found to be 81.68%, the classified accuracy of the Maximum Likelihood Classifier is found to be 85.64%, and the classified accuracy of Minimum Distance to mean classifier is found to be 83.17%.

While the maximum likelihood classifier does not yield as good of results as the random forest classifier, it may be more suitable for optical remote sensing data and more specific homogenous regions[25]. The neighboring range of pixels is also classified as landcover classes in minimum distance to the mean classifier. Although the input training data provided in this study may not be sufficient for some classifiers, KD tree KNN and Minimum distance to mean classifiers require more training datasets to acquire results efficiently[33]. In a random forest classifier, the number of classes that were specified for the given input training data has improved the efficiency and correlation of the classifier, producing good results[27]. When compared to other classifiers, the random forest classifier produces accurate results[28].

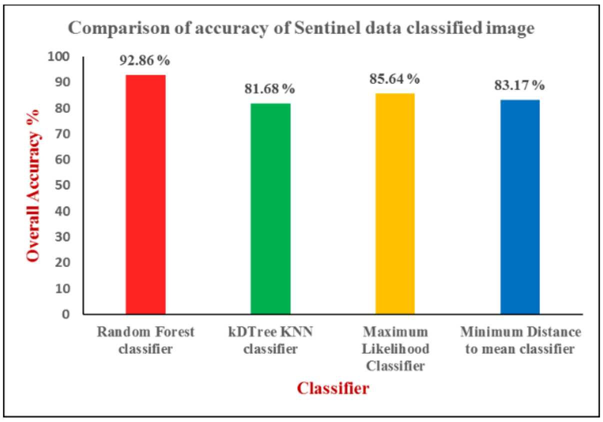

Figure 7: Comparison of Overall Classification Accuracy among Classifiers

Figure 7 shows the comparison of the overall classification accuracy of the sentinel data among classifiers.

The random forest classifier is applied with Landsat-8 data to classify the image because this classifier has such a high accuracy value with sentinel data. The same training datasets provided earlier were used for this satellite image also. The accuracy of the classified image of Landsat-8 data was evaluated and assessed. The overall classification accuracy obtained for Landsat-8 data is 84.61%. Table 4 shows the comparison between the classified accuracy of Sentinel SAR data and Landsat-8 data, and it is illustrated in Figure 8.

Table 4. Comparison between the classified accuracy of Sentinel SAR data andLandsat-8 data

Landuse / Landcover Class	Producers's Accuracy %	
	Sentinel SAR data	Landsat-8 data
Vegetation	93.24	83.65
Water Bodies	92.76	84.61
Settlement	92.17	85.06
Barren land	92.55	85.11

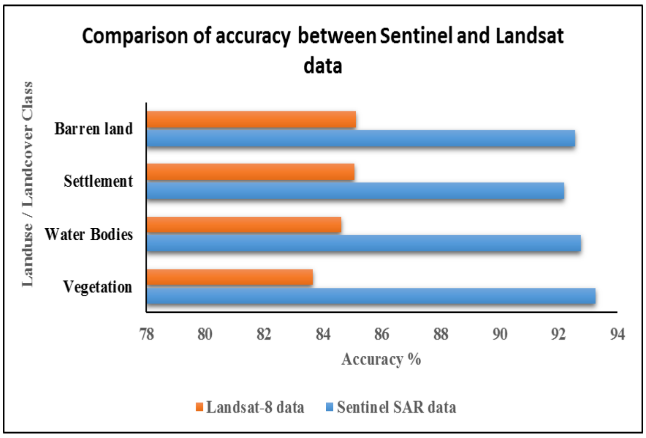

Figure 8: Comparison between the Classified Accuracy of Sentinel SAR Data and Landsat-8 Data

From the results of the overall classification accuracy from the random forest classifier for Sentinel and Landsat-8 data, it is found that the vegetation landuse class has the highest accuracy in Sentinel data among the other classes[29]. But in Landsat-8 data, the vegetation landuse class has the lowest accuracy among the other classes. Therefore, it is evident that the Sentinel data classification from the random forest classifier helps to identify the different types of mixed heterogeneous crops because the vegetation pixels have high backscattered values[30].

6. Summary and Conclusion

In this study, the different classifiers were applied to Sentinel-1 satellite data in Maduranthakam Taluk, Kancheepuram district, Tamilnadu, India, to classify the landuse and landcover classes. In mapping the landcover classes using the given dataset and a nominal training set, it has been found that the random forest classifier gives good results followed by maximum likelihood, minimal distance to mean, and kDTree KNN classifier. The random forest classifier accurately classifies the set of pixels into classes based on their similar characteristics. The random forest classifier was again applied to optical Landsat-8 data to compare and evaluate the classification accuracy results. From the output of the results, it is clearly stated that the combination of sentinel data and the random forest classifier yields better accuracy values than the other classifiers due to the high spatial resolution and spectral sensitivity of Sentinel data[31]. In general, misclassification of pixels with respect to other classes of pixels might occasionally cause the projected accuracy level to be over or understated[32]. However, the random forest classifier is crucial in avoiding the misclassification of pixels. Therefore, it is easy to apply in different mixed-crop regions.

The Sentinel landuse and landcover classification can be applied in many applications, such as land cover change, crop monitoring, and management, and forest parameter estimation, such as leaf area index, chlorophyll content, etc. From this study, it is clearly proved that the sentinel SAR classification using a random forest classifier can be applied for environmental and ecological applications such as ecosystem biodiversity changes, ecological imbalance, etc. This study can be extended for the above applications.

Declarations

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Conflicts of Interest

The authors declare no conflict of interest.

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