__Original Research Article__

COMPARING THE EFFECTIVENESS OF DIFFERENT MACHINE LEARNING ALGORITHMS FOR CROP COVER CLASSIFICATION USING SENTINEL 2

Abstract

Crop cover mapping is an essential tool for controlling and enhancing agricultural productivity. By determining the spatial distribution of different crop types, solidified judgements regarding crop planning, crop management, and risk management can be made. Crop cover classification using optical data pose constraints in terms of spatial and spectral resolution. With Sentinel – 2 data providing the ground information at 10m resolution, users may choose the best spectral band combinations and temporal frame by analysing the spectral-temporal information of different crops. The crop categorization map for the Kallakurichi and Villupuram districts were created in this study using the Random Forest (RF) and Decision tree (C5.0) classifiers. The study mainly focuses on comparing the classification accuracy of two classifiers and figuring out the best classifiers for crop cover mapping with respect to the study area. The ground truth information collected, were partitioned into calibration and validation datasets and the validation resulted with the Overall Accuracy (OA) and kappa coefficient of 66% ; 0.63 and 60%; 0.67 for RF and C5.0 algorithms, respectively. From the results, it could be concluded that the RF classifier performed comparatively better than C5.0, thus making it suitable for crop cover classification.

Keywords: Sentinel 2, Machine learning, Random Forest, C5 decision tree, Crop cover classification

Introduction

Agriculture is a way of life for millions of people around the world. Agriculture plays vital in food security, environmental sustainability and economic development. To ensure abundant and secure food supply, managing agricultural lands is vital. The spatial distribution of the different land use and land cover classes varies across a given landscapes and it is the function of respective topography and other ecological, anthropogenic and climatic characteristics. Land use land cover (LULC) classification helps to address how land is used, changed, and maintained in the physical and functional aspects. (Orynbaikyzy *et al.*, 2019 and Twisa and Buchroithner, 2019). Categorizing and mapping different land cover types, such as agriculture, forest, water bodies, range land, settlements, waterlogged areas, and other categories, fall under the shade of LULC concept (Parsa and Salehi 2016). In the 328.7 M hectares geographical area of India, Tamil Nadu covers 13.0 M hectares and out of which, 2.15 M hectares is forest and 4.83 M hectares is agricultural areas (Indiastat, 2020-21). Developing nation encounters continuous growth in population, and thus demand for food also increases. Thus spatial distribution and condition of food and other crops at global, national and even regional levels are quite necessary (Orynbaikyzy *et al.,* 2019). Though several methodologies can be utilized for the land use and land cover classification, performing the LULC classification at crop level can pose constraints with respect to the spatial, spectral and temporal information, as abundant information is required to be parameterized for the effective classification of the crop cover especially of date of sowing, vegetative stages, flowering stages, and maturity stage. To incorporate such information, several of the studies included the multi temporal information from high resolution satellites as composite, besides the required spectral information. To incorporate such information, this study extends Land cover classification to a crop-specific level over an area includes Kallakurichi and Villupuram districts.

There is a significant need for up-to-date, precise information on the various kinds of crops to facilitate the required policy decisions. Regional agricultural boards, insurance companies, and national and international agricultural organisations all produce crop cover maps to compile an inventory of the crops that were cultivated in the given agricultural year season -wise. The free access data policy advantage made Sentinel 2 widely used for various purposes. Sentinel 2 was found to have great potential in crop mapping, land surface monitoring and mapping since it has a wide swath and high temporal resolution (Campos-Taberner *et al.,* 2019; Phiri *et al.,* 2020). Although precise, the identification of vegetation canopies using conventional methods, like as survey missions has significant drawbacks. A single crop parcel might need a lot of time to map. Cropland can be difficult to access, and the number of parcels that can be accessible is constrained by unwilling farmers and landowners. Crop mapping still relies on inefficient and expensive field work (Elmansouri 2017).

The identification of plant canopies using remote sensing data has begun to be utilised as an alternative to conventional field survey from the early 1970s (Suits 1971). Remote sensing-based crop mapping research has been more important over the past few decades (Weiss *et al.,* 2020) On the basis of mid- to high-resolution satellite data, supervised Machine Learning (ML) models have demonstrated their ability to detect crops with high accuracy. In this study, The two most used classification algorithms for land cover classification, Random forest classifier and Decision tree classifier (Maxwell *et al.,* 2019; Millard and Richardson 2015; Cavur et al., 2019; Phan *et al.,* 2020; Colditz, 2015) that works on pixel-based classification method that considers brightness levels and neighbourhoods of each individual pixel to classify the satellite images were considered.

Review of literature

Need for LULC classification at crop level:

According to Adrian *et al.* (2021), Crop type mapping is necessary in order to forecast yield, create statistics from agricultural data, track crop rotation, map soil productivity, identify crop stress, assess crop damage, and keep tracks on farming activity. However, in situ crop type mapping is frequently costly, time-consuming, and damaging. Remote sensing-derived crop type maps can produce a quick, precise, and non-destructive crop inventory.

Sentinel 2 for LULC classification:

In order to classify land cover and usage, (Delfan *et al.,* 2022) compared the applications of Landsat and Sentinel 2. As per Delfan et al. (2022), Sentinel-2 and Landsat-8 have Kappa statistics of 0.83 and 0.81, respectively. He came upon the conclusion that Sentinel 2 satellite images perform better than Landsat 8 satellite images in terms of preparing maps of land use and land cover. This appears to be because Sentinel 2 has a higher spatial resolution (10-meter pixels in the near infrared and visible bands) than Landsat 8 (30-meter pixels in the near infrared and visible bands). When comparing Landsat-8 with Sentinel-2, Sentinel-2 provides marginally superior results for estimating the tree canopy coverage and leaf area index (LAI) of boreal forests. (Korhonen *et al.,* 2017)

Machine learning algorithm for crop classification:

Neetu and Ray, (2019), investigated the capacity of several machine learning classification algorithms, such as Random Forest (RF), Classification and Regression Trees (CART) and Support Vector Machine (SVM) for crop categorization. Random Forest (93.3%, 0.9178) and CART (73.4%, 0.6755) fared better than SVM (74.3%, 0.6867) classifier in terms of total classification accuracy and kappa coefficient. Using Landsat-5 data for complicated land cover and land use categories, Rodriguez-Galiano *et al.* (2012) investigated the performance of RF classifiers. The findings revealed that RF generated outstanding accuracy in classification and that it worked well for limited training data as well as being resilient to noise.

Study area

The study area of this research comprises two districts, Kallakurichi and Villupuram that spreads between 78˚36 ’ to 80˚00 ’ East longitudes and 11˚30 ’ to 12˚27 ’ North latitudes covering a geographical area of 7256.12 sq. km or 725612 hectares. It is surrounded by Kalvarayan hills on the west, Tiruvannamalai and Kancheepuram districts on the north, Pondicherry and Bay of Bengal on the east and Cuddalore district on the south. Since the study area exhibits a diverse land cover/land use pattern, an attempt has been made to identify its spatial distribution using various classification algorithms. Food crops including rice, maize, cassava, coconut, sugarcane, cashew, mango, and wood crops like casuarina and eucalyptus are common in this region.

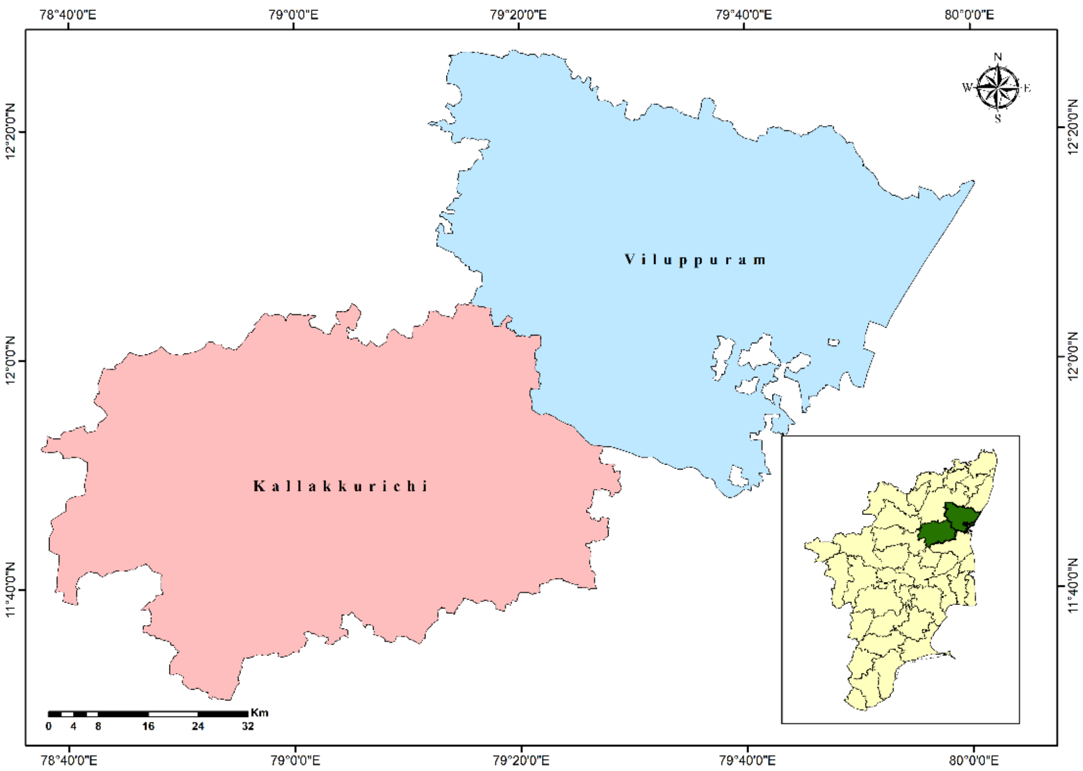

Figure 1. STUDY AREA MAP

Materials and Methods

Data used

Sentinel 2, was made up of two identical satellites, Sentinel 2A and 2B. Sentinel 2A's multi-spectral data was launched on June 23rd, 2015, and consists of a total of 13 bands. Sentinel 2A's spatial resolution varies by band and is 10m, 20m, and 60m. The band parameters for Sentinel 2's single Multi-Spectral Instrument, which has 13 spectral channels, are listed in Table1. Satellite image resulting from a combination of bands 2, 3, 4, 5, 6, 7, 8, 8A, 11 and 12 Sentinel-2 were used for this research (Miranda *et al.*, 2018). The bands were then resampled to 10 m resolution from 20 m resolution to facilitate the stacking of the bands for classification.

Table 1: The wavelength and resolution of the bands on Sentinel 2A

Sentinel 2 bands	Wavelength (μm)	Resolution (m)
1 - Coastal aerosol	0.443	60
2 - Blue	0.490	10
3 - Green	0.560	10
4 - Red	0.665	10
5 - Vegetation Red Edge (VRE)	0.705	20
6 - VRE	0.740	20
7 - VRE	0.783	20
8 - NIR	0.842	10

8A - VRE	0.865	20
9 - Water vapour	0.945	60
10 - SWIR – Cirrus	1.375	60
11 - SWIR	1.610	20
12 - SWIR	2.190	20

The ground truth information is collected in the month of May since it covers most crops' peak vegetative stage. The representative sample approach was used to gather field data for the classification of the image, with points collected according to the categories of land use/land cover that predominated. Using a handheld GPS, coordinates were selected at each place, and the field sheet was used to record both the land use at that location and the adjacent land use.

Besides the initial ground truth information, and the visual interpretation (Phan *et al.*, 2020), a total of 1241 ground truth points was collected on various crops of which 60 per cent (747) is for training and 40 per cent (496) is for testing the algorithm. The software packages like ArcGIS 10.8, R studio and Google Earth Engine, a cloud-based geospatial analysis platform were employed at various stages of analysis.

Methodology

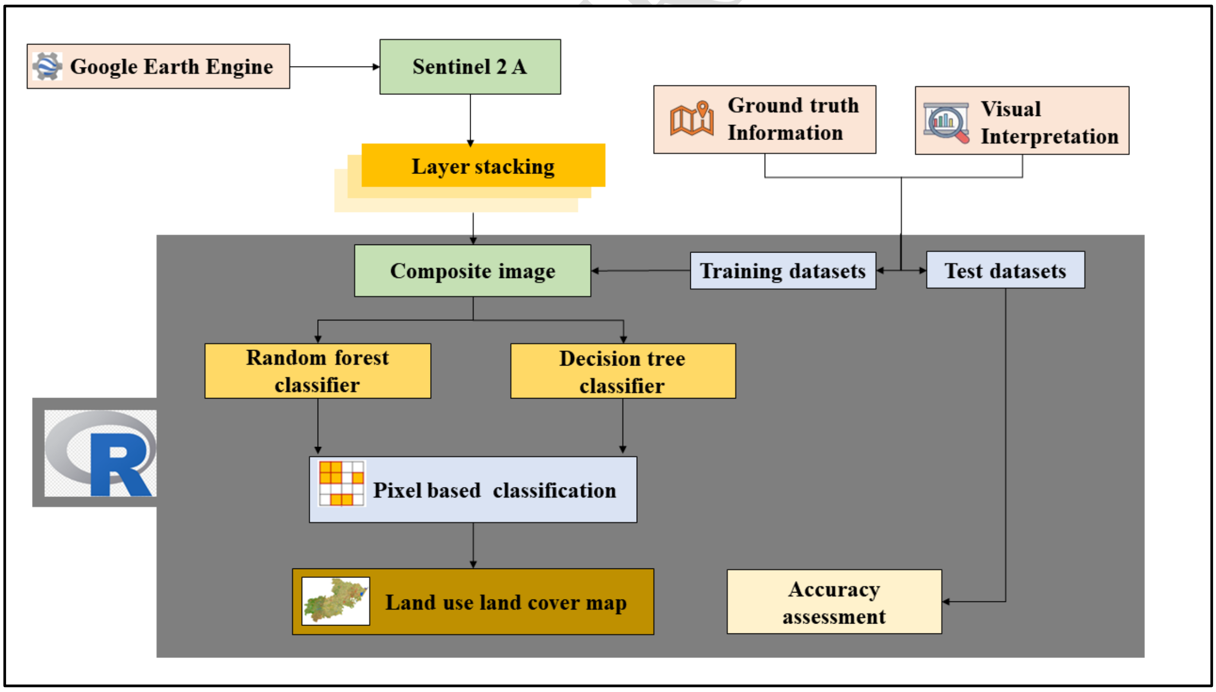

Figure 2: Methodology for land use land cover mapping

LULC Classes

The main aim of this study is to classify land cover of the study area specific to crop-wise, and the major crops that were predominantly found in the study area were taken into consideration for classification (Table 2).

Table 2: Classes considered for crop classification

S.No.	Classes	S.No.	Classes	S.No.	Classes
1	Cashew	6	Fallow land	11	Rice
2	Cassava	7	Forest	12	Settlement
3	Casuarina	8	Maize	13	Sugarcane
4	Coconut	9	Mango	14	Wasteland
5	Eucalyptus	10	Prosopis	15	Water body

Satellite data download

The land cover of the Kallakurchi and Villupuram region is the one researched in this study. The Cloud free-satellite image is downloaded from the Google earth engine platform for the month of March, April, May, June and a single temporal image composites comprising of four months were made. Figure 3 shows a false colour composite image of the study area.

Figure 3: False colour composite image of the study area

Classification algorithm

The overall methodology of the crop cover classification have been depicted in the Figure 2.The classification was carried out with two classifiers Random forest classifier and C50 Decision tree classifier, using R packages randomForest and C50 respectively.

Random Forest (RF) created by Breiman, (2001) is an ensemble learning algorithm that constructs a group of decision trees to make predictions. Each tree in the group votes for the most likely class for a new data point, and the class with the most votes is the final prediction. RF uses a random subset of input features to split each node in the decision tree, which helps to reduce overfitting and improve the generalization performance of the model. In addition, RF uses bagging, which means that each tree is trained on a different bootstrap sample of the training data, to further reduce overfitting. Random forest has been shown to be very effective for land use landcover classification. In a study by Kulkarni and Lowe, (2016) RF was found to outperform other machine learning algorithms, such as maximum likelihood, minimum distance, decision tree, neural network, and support vector machine, in terms of classification accuracy.

Decision trees are a type of supervised machine learning algorithm that can also be used for classification tasks. According to Pandya and Pandya, (2015) The C5.0 algorithm decision trees perform almost as well but are far simpler to comprehend and apply when compared to more sophisticated and complex machine learning models (such as neural networks and support vector machines) They work by recursively partitioning the feature space into smaller and smaller regions, until each region is assigned to a single class. The decision tree is built by starting at the root node and asking a question about the feature space. The answer to this question determines which child node the data point will be passed to. This process is repeated until the data point reaches a leaf node, which represents a class label. (Yang *et al.,* 2017) Decision trees have been shown to be effective for land use land cover classification. (Pacheco *et al.,* 2021; Kulkarni and Lowe, 2016)

Result and Discussion

The present study was undertaken to classify major growing crops in Kallakurchi and Villupuram districts. The classification was carried out to separate the major classes such as Cashew, Cassava, Casuarina, Coconut, Eucalyptus, Fallow land, Forest, Maize, Mango, Prosopis, Rice, Settlement, Sugarcane, Wasteland and Waterbody. Utilising the RF and C5 algorithms in R Studio, various crops may be distinguished from one another. Crop categorization is accomplished in two steps: First, 60% of the datasets are used to train the algorithms, and predictions are based on the training datasets. Second, the algorithm's performance accuracy is computed using the remaining 40% of the datasets.

One of the most important metrics in remote sensing to assess the quality of the created map, suitability for a given application, and comprehension of inaccuracy and implications is the accuracy of LULC maps (Foody 2002). The RF classifier has a kappa coefficient of 0.63 and a highest accuracy of 66%. Figure 4 displays the categorization of crops using the RF classification technique. The C5 classifier on the other hand, has the lowest accuracy, at 60%, and a kappa coefficient of 0.60. Figure 5 displays the categorization of crops using the C5 classification method. Crop type classification accuracy of RF and C5 were listed on table 5. On tables 3 and 4, the confusion matrices for the two approaches are displayed.

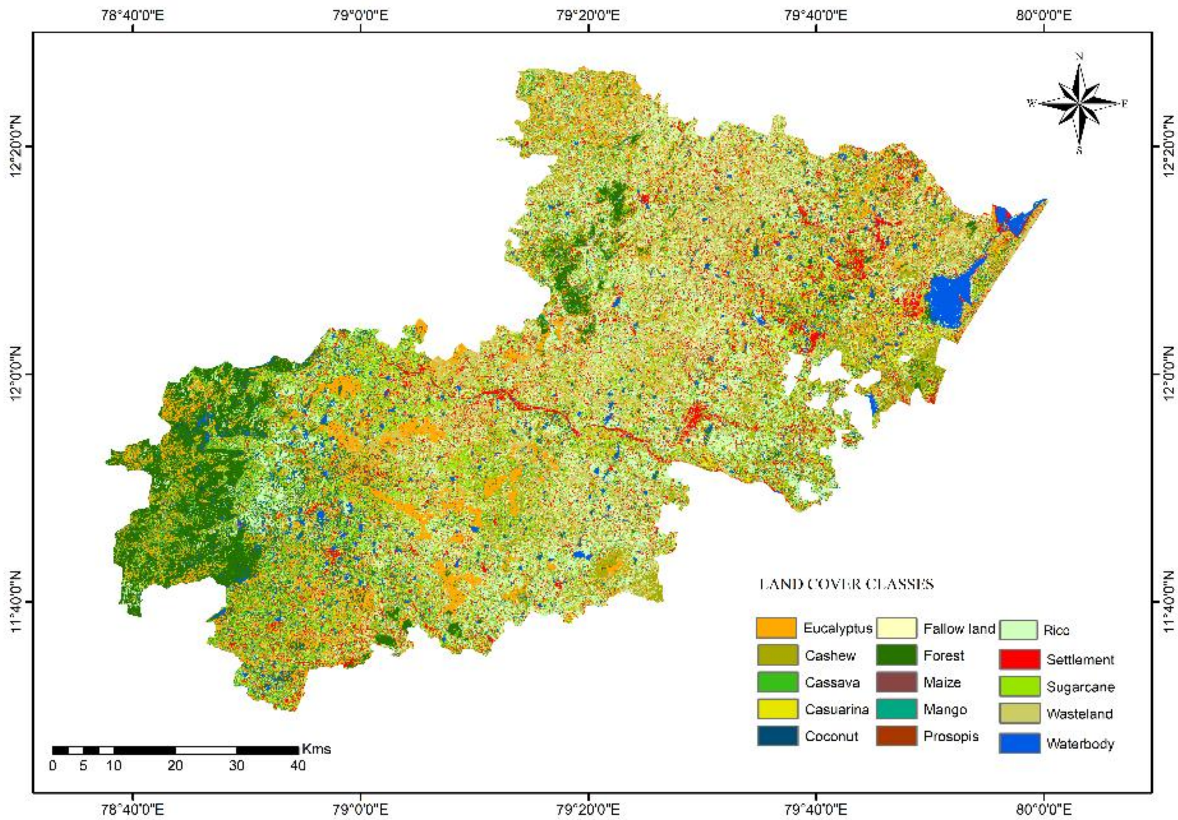

Figure 4: Crop classification using RF classifier

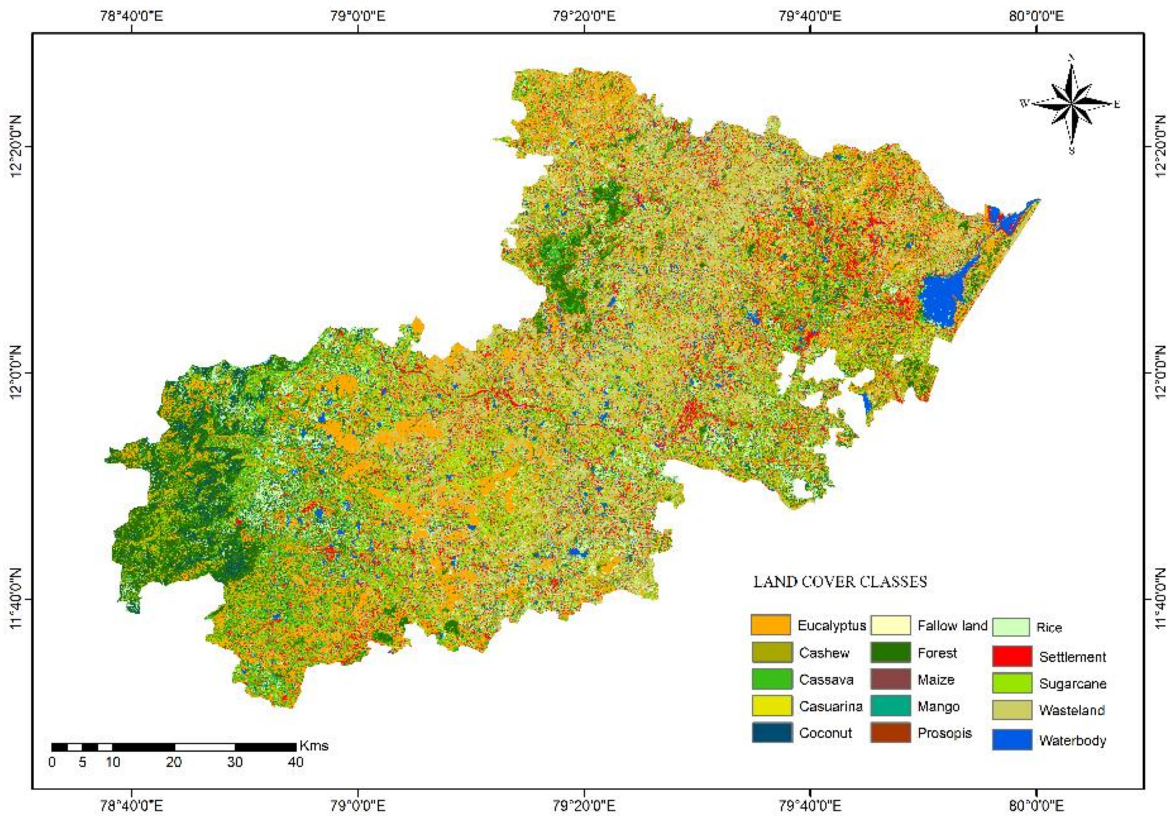

Figure 5: Crop classification using C5 classifier

Table 3: Confusion matrix for RF classifier

Class	Cashew	Cassava	Casuarina	Coconut	Eucalyptus	Fallow land	Forest	Maize	Mango	Prosopis	Rice	Settlement	Sugarcane	Waste land	Water body	Total	UA
Cashew	29	4	0	0	0	0	0	0	2	3	0	0	0	0	0	38	76
Cassava	5	6	0	0	0	0	1	1	0	1	0	0	0	0	0	14	43
Casuarina	2	2	22	0	0	0	6	0	3	2	0	0	2	0	0	39	56
Coconut	1	0	0	15	0	1	0	1	0	0	1	0	0	1	0	20	75
Eucalyptus	0	0	0	6	21	5	0	0	0	0	2	2	0	3	0	39	54
Fallow land	0	0	0	0	2	13	0	0	0	0	0	3	0	3	1	22	59
Forest	1	0	8	0	1	0	42	0	2	3	0	0	1	0	0	58	72
Maize	0	0	0	2	0	0	0	10	0	0	3	0	0	0	0	15	67
Mango	3	1	0	0	0	0	0	0	9	3	0	0	1	0	0	17	53
Prosopis	2	0	0	0	0	0	0	0	3	8	0	0	0	2	0	15	53
Rice	2	2	0	0	0	4	0	1	1	0	45	1	4	0	6	66	68
Settlement	0	0	0	1	1	6	0	0	0	0	2	36	1	4	2	53	68
Sugarcane	0	0	0	2	0	0	0	6	0	0	4	0	19	0	0	31	61
Wasteland	0	0	0	0	2	2	0	0	0	0	0	2	0	14	2	22	64
Waterbody	0	0	0	0	0	0	0	0	0	0	6	1	0	1	40	48	83
Total	45	15	30	26	27	31	49	19	20	20	63	45	28	28	51	329	
PA	64	40	73	58	78	42	86	53	45	40	71	80	68	50	78		66.3

Table 4: Confusion matrix for Decision tree C5 classifier

Class	Cashew	Cassava	Casuarina	Coconut	Eucalyptus	Fallow land	Forest	Maize	Mango	Prosopis	Rice	Settlement	Sugarcane	Waste land	Water body	Total	UA
Cashew	26	4	0	0	0	0	2	0	5	1	0	0	0	0	0	38	68
Cassava	4	6	0	0	0	0	2	2	0	0	0	0	0	0	0	14	43
Casuarina	2	1	27	0	0	0	5	0	2	1	0	0	2	0	0	40	68
Coconut	2	0	0	14	1	0	0	2	0	0	0	0	0	1	0	20	70
Eucalyptus	0	0	0	0	18	6	0	3	0	5	4	3	0	0	0	39	46
Fallow land	0	0	0	1	0	0	0	0	0	0	0	5	0	15	1	22	0
Forest	1	0	8	0	0	0	45	0	2	2	0	0	0	0	0	58	78
Maize	1	6	2	0	0	0	0	0	2	2	1	0	1	0	0	15	0
Mango	3	5	0	0	7	0	0	2	0	0	0	0	0	0	0	17	0
Prosopis	5	0	0	0	5	0	1	0	2	0	0	0	0	0	0	13	0
Rice	0	0	0	0	0	4	0	3	0	0	49	0	4	0	6	66	74
Settlement	0	0	0	1	0	6	0	0	0	0	2	38	0	4	2	53	72
Sugarcane	0	1	0	2	0	0	0	5	0	0	3	0	20	0	0	31	65
Wasteland	0	0	0	0	2	2	0	0	0	0	0	3	0	15	0	22	68
Waterbody	0	0	0	0	0	0	0	0	0	0	6	1	0	1	40	48	83
Total	44	23	37	18	33	18	55	17	13	11	65	50	27	36	49	298	
PA	59	26	73	78	55	0	82	0	0	0	75	76	74	42	82		60.0

Table 5: Comparision of classification accuracy of RF and C5 algorithm in crop type classification

Classifiers	Overall accuracy (%)	Kappa coefficient
RF	66	0.63
C5	60	0.57

The research's conclusions supported those of Hudait and Patel, (2022); Panjala *et al.*, (2022) who came to the conclusion that the RF classifier would be the most effective for classifying crop types. The C5 algorithm failed to classify maize, mango, prosopis and fallow land. The C5 categorization approach has limitations since crops like maize, mango, and prosopis have similar spectral features. Additionally, wasteland and fallow land are frequently misclassified. These are a few causes of poor categorization accuracy. An essential tool for monitoring and mapping agricultural land, crop phenology, and crop growth is the NDVI. The NDVI, a potent indicator of crop development, is made up of the red wavelength energy absorbed by plant chlorophyll and the infrared (IR) energy reflected by the structure of plant cells (Boori *et al.*, 2019). The source of misclassification was investigated using the NDVI values of typical pixels for each class. The interaction of NDVI values between classes in figure 6 demonstrates that the majority of crops have identical NDVI during the month of May, i.e., peak vegetative, which is the cause of the misperception.

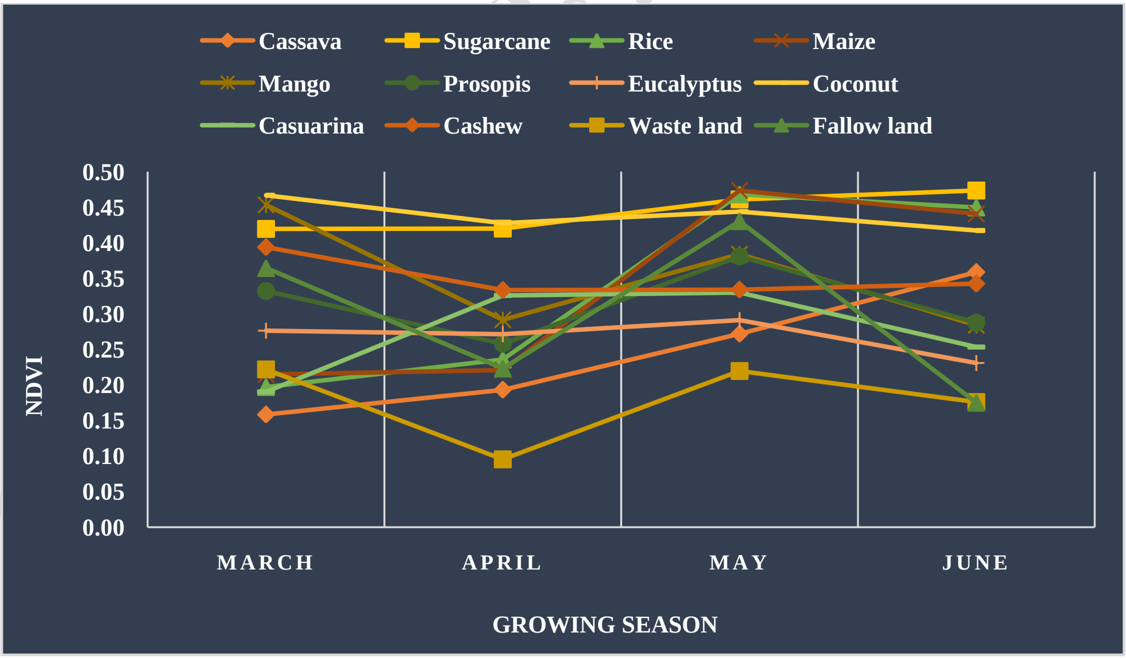

Figure 6: NDVI trends of different crops from March - June

Furthermore, RF performs better at classifying data than C5 does because a multi-tree ensemble technique is more resilient than a single decision tree. However, RF is less susceptible to changes in parameter. When tree and split are acting together to regulate RF, split values have a bigger impact than tree values. This is because RF's ultimate classification effect depends on each tree, whereas split values have an impact only on a single tree's growth.

Conclusion

Crop mapping is essential for managing agricultural productivity and ensuring food security, and machine-learning algorithms like RF and C5 offer significant assistance in this regard. For the purpose of identifying and mapping various crops in the Kallakurchi and Villupuram region, we coupled Sentinel-2 multispectral pictures with the RF and C5 algorithms using the R platform. By comparing the two machine-learning algorithms' classification outcomes, it can be shown that RF has the relatively best classification performance with an OA of 66% and kappa coefficient of 0.63.

References

Adrian, Jarrett, Vasit Sagan, and Maitiniyazi Maimaitijiang. 2021. "Sentinel SAR-Optical Fusion for Crop Type Mapping Using Deep Learning and Google Earth Engine." *ISPRS Journal of Photogrammetry and Remote Sensing* 175: 215–35. https://doi.org/https://doi.org/10.1016/j.isprsjprs.2021.02.018.

Boori, Mukesh Singh, Komal Choudhary, Rustam Paringer, Amit Kumar Sharma, Alexander Kupriyanov, and Samuel Corgne. 2019. "Monitoring Crop Phenology Using NDVI Time Series from Sentinel 2 Satellite Data." In *2019 5th International Conference on Frontiers of Signal Processing (ICFSP),* 62–66. https://doi.org/10.1109/ICFSP48124.2019.8938078.

Breiman, Leo. 2001. "Random Forests." *Machine Learning* 45: 5–32.

Campos-Taberner, Manuel, Francisco Javier Garc\'\ia-Haro, Beatriz Mart\'\inez, Sergio Sánchez-Ru\'\iz, and Mar\'\ia Amparo Gilabert. 2019. "A Copernicus Sentinel-1 and Sentinel-2 Classification Framework for the 2020+ European Common Agricultural Policy: A Case Study in València (Spain)." *Agronomy* 9 (9): 556.

Cavur, M, H S Duzgun, S Kemec, and D C Demirkan. 2019. "Land Use and Land Cover Classification of Sentinel 2-A: St Petersburg Case Study." *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 42: 13–16.

Colditz, René Roland. 2015. "An Evaluation of Different Training Sample Allocation Schemes for Discrete and Continuous Land Cover Classification Using Decision Tree-Based Algorithms." *Remote Sensing* 7 (8): 9655–81. https://doi.org/10.3390/rs70809655.

Delfan, Elham, Hamed Naghavi, Rahim Maleknia, and Ahmadreza Nouredini. 2022. "Comparing the Capability of Sentinel 2 and Landsat 8 Satellite Imagery in Land Use and Land Cover Mapping Using Pixel-Based and Object-Based Classification Methods." *Desert Ecosystem Engineering* 8 (25): 1–12.

Elmansouri, Loubna. 2017. "Multiple Classifier Combination for Crop Types Phenology Based Mapping." In *2017 International Conference on Advanced Technologies for*

Signal and Image Processing (ATSIP), 1–6.

Foody, Giles M. 2002. "Status of Land Cover Classification Accuracy Assessment." *Remote Sensing of Environment* 80 (1): 185–201.

Hudait, Manas, and Priyank Pravin Patel. 2022. "Crop-Type Mapping and Acreage Estimation in Smallholding Plots Using Sentinel-2 Images and Machine Learning Algorithms: Some Comparisons." *The Egyptian Journal of Remote Sensing and Space Science* 25 (1): 147–56.

Korhonen, Lauri, Hadi, Petteri Packalen, and Miina Rautiainen. 2017. "Comparison of Sentinel-2 and Landsat 8 in the Estimation of Boreal Forest Canopy Cover and Leaf Area Index." *Remote Sensing of Environment* 195: 259–74. https://doi.org/https://doi.org/10.1016/j.rse.2017.03.021.

Kulkarni, Arun D, and Barrett Lowe. 2016. "Random Forest Algorithm for Land Cover Classification."

Maxwell, Aaron E, Michael P Strager, Timothy A Warner, Christopher A Ramezan, Alice N Morgan, and Cameron E Pauley. 2019. "Large-Area, High Spatial Resolution Land Cover Mapping Using Random Forests, GEOBIA, and NAIP Orthophotography: Findings and Recommendations." *Remote Sensing* 11 (12). https://doi.org/10.3390/rs11121409.

Millard, Koreen, and Murray Richardson. 2015. "On the Importance of Training Data Sample Selection in Random Forest Image Classification: A Case Study in Peatland Ecosystem Mapping." *Remote Sensing* 7 (7): 8489–8515. https://doi.org/10.3390/rs70708489.

Miranda, Eka, Achmad Benny Mutiara, Wahvu Catur Wibowo, and others. 2018. "Classification of Land Cover from Sentinel-2 Imagery Using Supervised Classification Technique (Preliminary Study)." In *2018 International Conference on Information Management and Technology (ICIMTech)*, 69–74.

Neetu, and S S Ray. 2019. "EXPLORING MACHINE LEARNING CLASSIFICATION ALGORITHMS FOR CROP CLASSIFICATION USING SENTINEL 2 DATA." *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XLII-3/W6: 573–78. https://doi.org/10.5194/isprs-archives-XLII-3-W6-573-2019.

Orynbaikyzy, Aiym, Ursula Gessner, and Christopher Conrad. 2019. "Crop Type Classification Using a Combination of Optical and Radar Remote Sensing Data: A Review." *International Journal of Remote Sensing* 40 (17): 6553–95. https://doi.org/10.1080/01431161.2019.1569791.

Pacheco, Flávia Domingos, Ma\'\ira Ramalho Matias, G MÁXIMO, ARDE SOUZA, Yosio Edemir Shimabukuro, M ISABEL, and S ESCADA. 2021. "Image Classification Methods Assessment for Identification of Small-Scale Agriculture in Brazilian Amazon." In *The Thirteenth International Conference on Advanced Geographic Information Systems, Applications, and Services, n. C*, 12–19.

Pandya, Rutvija, and Jayati Pandya. 2015. "C5. 0 Algorithm to Improved Decision Tree with

Feature Selection and Reduced Error Pruning." *International Journal of Computer Applications* 117 (16): 18–21. https://doi.org/10.5120/20639-3318.

Panjala, Pranay, Murali Krishna Gumma, and Pardhasaradhi Teluguntla. 2022. "Machine Learning Approaches and Sentinel-2 Data in Crop Type Mapping." *Data Science in Agriculture and Natural Resource Management*, 161–80.

Parsa, Vahid Amini, and Esmail Salehi. 2016. "Spatio-Temporal Analysis and Simulation Pattern of Land Use/Cover Changes, Case Study: Naghadeh, Iran." *Journal of Urban Management* 5 (2): 43–51.

Phan, Thanh Noi, Verena Kuch, and Lukas W Lehnert. 2020. "Land Cover Classification Using Google Earth Engine and Random Forest Classifier—The Role of Image Composition." *Remote Sensing* 12 (15). https://doi.org/10.3390/rs12152411.

Phiri, Darius, Matamyo Simwanda, Serajis Salekin, Vincent R Nyirenda, Yuji Murayama, and Manjula Ranagalage. 2020. "Sentinel-2 Data for Land Cover/Use Mapping: A Review." *Remote Sensing* 12 (14). https://doi.org/10.3390/rs12142291.

Rodriguez-Galiano, Victor Francisco, Bardan Ghimire, John Rogan, Mario Chica-Olmo, and Juan Pedro Rigol-Sanchez. 2012. "An Assessment of the Effectiveness of a Random Forest Classifier for Land-Cover Classification." *ISPRS Journal of Photogrammetry and Remote Sensing* 67: 93–104.

Suits, Gwynn H. 1971. "The Calculation of the Directional Reflectance of a Vegetative Canopy." *Remote Sensing of Environment* 2: 117–25.

Twisa, Sekela, and Manfred F Buchroithner. 2019. "Land-Use and Land-Cover (LULC) Change Detection in Wami River Basin, Tanzania." *Land* 8 (9): 136.

Weiss, Marie, Frédéric Jacob, and Grgory Duveiller. 2020. "Remote Sensing for Agricultural Applications: A Meta-Review." *Remote Sensing of Environment* 236: 111402.

Yang, Chao, Guofeng Wu, Kai Ding, Tiezhu Shi, Qingquan Li, and Jinliang Wang. 2017. "Improving Land Use/Land Cover Classification by Integrating Pixel Unmixing and Decision Tree Methods." *Remote Sensing* 9 (12): 1222.