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Machine learning classifiers on sentinel-2 satellite image for the classification of banana (*Musa* Sp.) plantations of Theni district, Tamil Nadu, India

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Abstract
Remote sensing offers to visualize, map and monitor the agricultural systems at varied resolution. Classification methods have been established to identify crop, patterns and intensity. This paper analyses the potentials of machine learning classification techniques namely RF (Object-based), RF, CART and SVM technique in identification of Banana crop of Theni District, Tamil Nadu through Sentinel 2 satellite image. Initial Principal Component Analysis of data depicted that majority of the information could be derived from Near Infrared (NIR) and Short wave Infra-red (SWIR). This information in original bands is maximized to the lowest number of primary bands. The overall classification accuracy using algorithms was 91.1%, 92.1%, 89.6% & 87.6% with the Kappa co-efficient of 0.89, 0.90, 0.88 and 0.85 for RF (OB), RF, CART and SVM respectively. However, RF was found to be robust against RF (OB), CART and SVM in classification of banana plantations while visually inspecting the outputs. The outputs illustrate that machine learning algorithms on Sentinel2 image are suitable for classifying banana plantations from other agricultural crops.

Keywords: Banana, principal component analysis, classification, machine learning, support vector machine (SVM), classification & regression tree (CART), random forest (RF), object-based (OB)

1. Introduction

India exhibits multiple agro-climatic conditions viz., tropical, subtropical and temperate. It is second largest producer of agricultural crops like wheat, rice and pulses and horticultural crops comprising fresh fruits like banana, mango, guava, papaya and lemon which are either seasonal or perennial. Accurate estimation of the extent of the cultivated crop is essential information for management of cultivation and also for production estimation from micro scale i.e., at farm level to macro scale at national level. Banana is second largest tropical fruits in area and production in India (Agriculture Annual Report, 2018) [1]. A temperature range 25-30 °C is congenial, deep rich sandy loamy soil of uplands with pH range 5.5-7.5 are most preferred for banana cultivation (POP, 2019) [18]. Being an important commercial fruit of tropical areas of the world, time critical information on extent of cropped area is essential for farmers, policy-makers and traders.

Agricultural crop area data is extrapolated regionally through crop surveys, crop cutting experiments and other ancillary sources by statistical and extension personnel. However, this methodology produces inconsistencies in statistical data besides being laborious and costly exercise. (Atzberger, 2015) [2].

Remote sensing is being explored intensively for various applications in horticulture mapping to precision orchard management. Orchard crops like mango, coconut, oranges, and banana have been mapped using data sets from Indian Remote Sensing (IRS) Linear Imaging Self Scanner (LISS III) satellites (Hebbar & Rao, 2002; Yadav *et al.* 2002 ; Savita *et al.*2015) [13, 22, 21]. The resolution and accessibility of spatial information has improved, as provided by freely available Sentinel-2 series offers immense opportunities to derive information and time-based distinction in agricultural production systems which facilitates quantitative/accurate management. Studies on advantages of Sentinel2 data for classifying agricultural crops (Novelli *et al.* 2016) [17] have been reported with positive results.

As far as image processing techniques applied on remote sensing data are concerned pixel-based classifiers such as Maximum Likelihood (MXL), Spectral Distance method (SD), Support Vector Machine (SVM) and Neural Network (NN) are popular along with many pre-processing algorithms viz., data dimensionality reduction methods like Principal Component Analysis (PCA), Minimum Noise Fraction (MNF) etc. (Gupta *et al.* 2013; Estornell *et al.* 2013; Yankovich *et al*. 2019) [12, 10, 23]. Object-oriented classification using high resolution imagery for mapping has resulted in dependable method for banana and other perennial crops (Johansen *et al.* 2009) [15]. Delineation of orchard plantations through a partial-automated classification methodology using higher resolution IRS images has been explored (Gamanya *et al*. 2007) [10]. The traditional pixel-based classifiers have been inefficient in classifying horticultural crops and proven to achieve limited accuracies as they exhibit differences spatially. These techniques have limitations in terms of longer processing time, information depends profoundly on data distributed normally in every input band which leads to over-classify spectral information with fairly bulky values in the covariance matrix.

Recent times Machine Learning techniques viz., Neural Networks, Fuzzy Systems, Heritable Algorithms, Intellectual Agents and Support Vector Machines aiming to improve the accuracy levels have been developed (Yang, 2011; Kulkarni & Lowe 2016) [24, 16]. Classification of multi-source multi-sensor data is being enabled by Random forests classifier, a concerted algorithm that shapes numerous decision trees randomly (Breiman, 2001) [4]. Boosting and bagging are well-known and extensively used ensemble methods used for image-data analysis (Pal, 2005) [19]. RF has attained effectual outputs in classification of satellite data, consumes less memory space coupled with efficiency in processing time and generates exceptional results (Csillik & Belgiu, 2017) [7].

Aligning with recent trends in improving the classification accuracy using machine learning algorithms, the objective of this research was set to evaluate the best classification technique and achieve mapping horticultural crops with higher accuracy. We used Machine learning classification methods namely viz., RF, RF (OB), CART and SVM to classify banana plantations in multi cropped area of Theni District, Tamil Nadu, India.

2. Study area and Data

2.1. Study area

Theni district lies between north latitudes of 9° 53’ 0” to 10° 22’ 0” and east longitudes of 77° 17’ 0” to 77° 67’ 0”, and geographically spread over an area of 2,889 Sq. Km. (Fig. 1). Agriculture is predominant with intensive agriculture and irrigated by Vagai/Manjalar Dam. Theni District is gifted with moderate climate suitable for cultivation of major tropical and sub-tropical horticulture crops. The important fruit crops grown are Banana, Mango, Guava and Grapes. The temperature ranges between 20° and 40 °C with an annual average rainfall of about 951 mm.

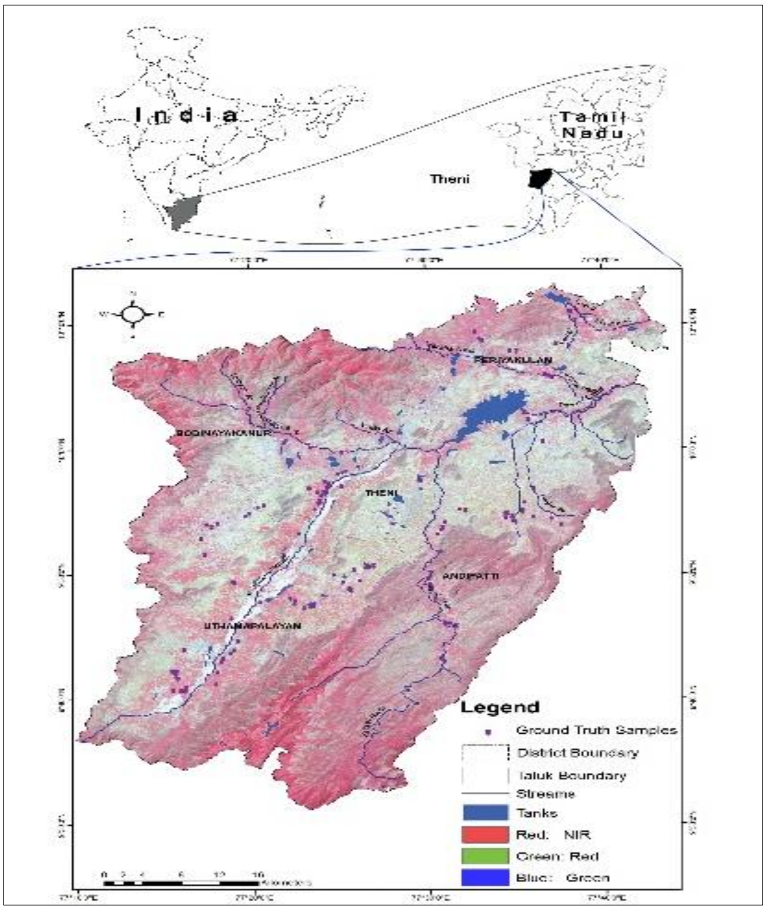

Fig 1: False Color Composite of Study area Theni District, Tamil Nadu, India. Sentinel 2 February 2018

2.2 Data

2.2.1 Satellite data

Sentinel-2 (Level 1C) has data in 13 bands in the visible, near infrared, and short-wave infrared (ESA, 2016) [9]. The multi-spectral Sentinel-2, close to zero (< 1%) cloud free data of February 2018 was accessed through www. glovis. usgs. gov platform and used in current study.

2.2.2 Ground Truth data
Extensive crop exploration was carried out during January 2017 and June 2018 to understand the cropping systems and major crops of Theni district. Fifteen sample points for each horticultural crop cultivated in the area namely banana, coconut, mango and other agricultural crops namely paddy, ragi, sugarcane were collected which are distributed throughout the study area.

3. Methodology
The process flow for analysis of satellite data (Fig. 2) consists of (1) pre-processing of data in ERDAS 2011 (2) Processing of data, training site selection and sampling (3) Classification of imagery — optimizing data, fitting of model in script for analysis (for RF(OB), RF, CART in Python), SVM (Envi 5.3) (4) Validation of result and accuracy assessment.

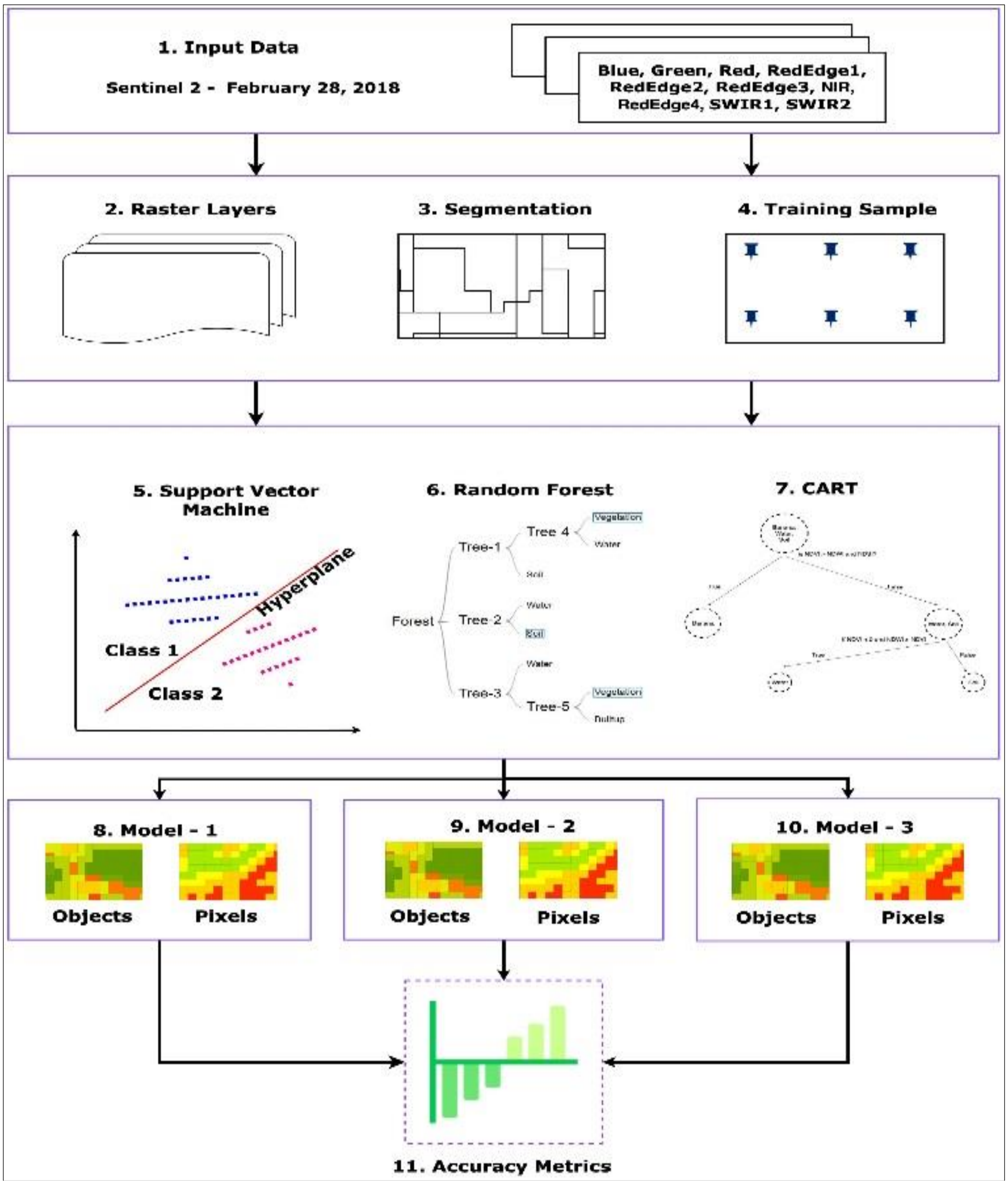

Fig 2: Flow chart explaining the algorithms of (a) SVM (b) CART (c) RF (Pixels based) (b) RF (Object based) with sample classes and decision rules

3.1 Data Preparation
The accessed Sentinel-2 data (Level-1C S2) for Theni area were stacked with bands B2, B3, B4, B5, B6, B7 and near-infrared band (B8 and B8a) and mosaicked as the study area spreads in 2 scenes. Level-1C data is pre-processed for radiometric correction and orthorectified to Universal Transverse Mercator (UTM) with sub-pixel level accuracy. Data contained within Theni district boundary is extracted from mosaicked image for further analysis.

3.2 Sampling using Principal component analysis (PCA)
The objective of PCA transformation was to identify the number of possible classes for classification. We performed PCA transformation on Sentinel 2 (1C) and the resultant image was able differentiate the varied vegetation types in the study area. Within cultivated region we could identify Banana, Coconut, Mango distinctly from other agricultural crops. As PCA was able to distinguish banana from other major agricultural crops, we grouped all other agricultural crops in to one class, 'other crops'. When the color composite of first three PCA components was interpreted, banana crop was identified in purple color and other crops were in varying shades of pink and green (Fig.3). PCA information was correlated with ground truth data for identifying the samples for training sites.

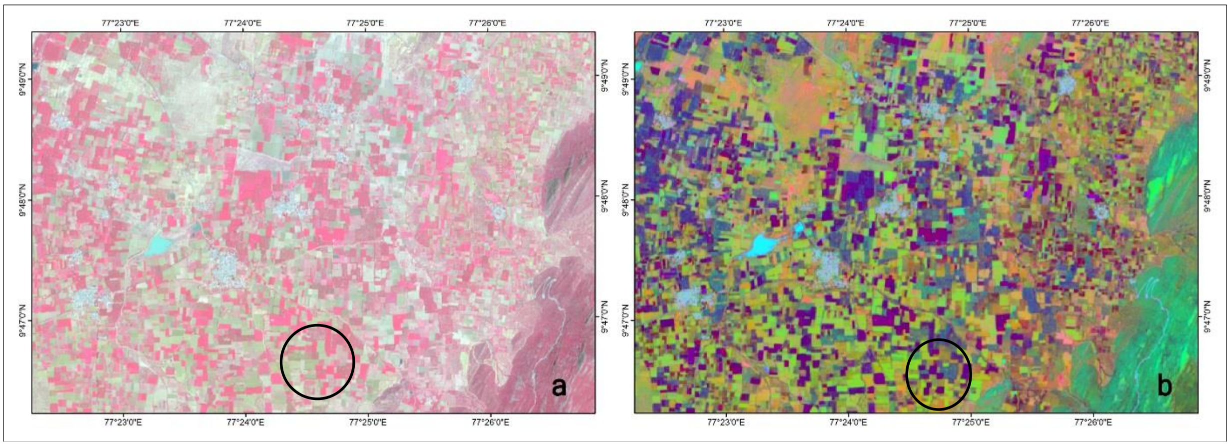

Fig 3: (a) False Color composite (b) PCA output. Purple color (encircled) in PCA shows the presence of banana which is not distinguishable from FCC

3.3. Classification

3.3.1 Training Samples

Training samples were created co-relating information from PCA image with ground truth points. Samples of major perennial crops of the study area namely banana, coconut, mango and other crops and land cover features comprising of forest, fallow, built-up, wasteland, water body and aquatic vegetation with total ten classes were selected for classification. Training samples were converted to ASCII format for classification process in Python platform.

We used PCA composite for selecting the training samples only but used all bands for classification process. Spectral signatures of the samples indicate clear separability between the crop classes in Red Edge (1- 4) and SWIR spectrum (Fig. 4).

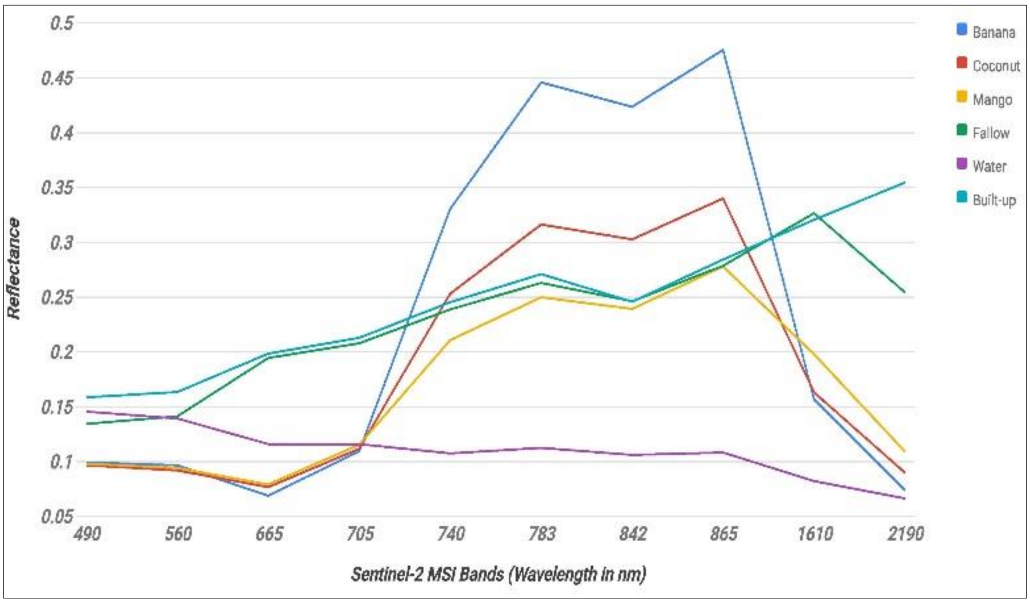

Fig 4: Spectral values of classes based on ground truth samples depicting separability in the data

3.3.3 Support Vector Machine

Machine learning algorithm SVM is a kernel-based technique that separates the classes with a decision surface that maximizes the spectral margin between the classes (Huang *et al.* 2002) [14]. In this study Radial Basis Function kernel was chosen at 0.33 (gamma), 100 (penalty parameter) and pyramid parameter at 0 for classification which was carried out in ENVI 5.3 Image processing software.

3.3.4 Classification and Regression Trees (CART)

CART classifier uses top down approach to decompose the tree and determines the partition of classes (Breiman, 2001) [4]. Algorithm proceeds from root node and split for decreasing its entropy measure and improving information gain. In learning process of CART algorithm samples are taken from main training sets for selecting the variables or number of features at a split resulting in higher number of leaves.

During the study CART classifier was implemented in Python. The data was transformed for scaler for optimization of the algorithm, training samples were split as training: testing samples using built-in modules. CART algorithm was tuned based on ‘n’ number of trees, created from entire training data set and number of variables for splitting nodes. Model was executed over 1000 estimators and square root of features was selected from available variables.

3.3.5 Random Forest — Pixel based and Object based Classification

Random forest algorithm is a supervised classification technique and generates several small decision trees from arbitrary subsets of data (Breiman, 2001) [4]. Each of decision trees gives a biased classifier and each tree captures diverse trends in the data. The collective trees are similar to a crew of specialists, each with minimal knowledge over the complete theme but in-depth respective area of proficiency. During process of classification the popular choice is segregated to classify a class.

In this study RF was implemented in Python based script for pixel and object based (OB) classification process. Multi-resolution Segmentation (MRS) is one of intensive segmentation method under OBIA (Object-based Image Analysis). MRS method was implemented in eCognition Developer (v9.2.1, Trimble Geospatial) to segment Sentinel2 imagery for generating homogenous objects from pixels. MRS operates based on region growing algorithm that begins at pixel level and grouping into objects up to maximum threshold (Baatz *et al*. 2004) [3].

MRS is optimized by defining parameters for tuning the algorithm to achieve efficient segmentation results. Three levels of scale 100, 50, 20 was combined with shape factor of 0.25 and compactness of 0.10 was tested and one optimum set of scale parameter was selected. The third level of scale parameter 20 selected with the given shape factor and compactness for analysis that resulted in best visualization of land cover categories to form homogeneity.

Tuning/optimization of algorithm were performed and data was transformed into standard scalar values. Samples were split as training and testing data frames based on random sampling at 70:30 ratio with train: test split of samples. For our study we optimized the algorithm at 1000 trees, as there is no error recorded beyond this level and the number of features selected at auto mode is square root of available variables which is best suited for Out of bag error report throughout the process.

3.3.6 Accuracy assessment and validation

The classification accuracies of OB (RF), SVM, CART and RF algorithms for the study area were assessed through confusion matrix (Congalton, 1991) [6]. Related parameters like Kappa coefficient, overall accuracy, Producer's accuracy, User's accuracy and conditional kappa were also assessed (Cohen, 1960) [5].

4. Results and Discussion

The multi-spectral images of February 2018 were processed with 4 cores out of 4 cores with a system configuration 3.2 GHz processor and 16 GB RAM space. The script execution time varied from 2 - 2.5 hours for RF, CART & Object-oriented (RF) and 30 – 36 hrs for SVM algorithm as the data was large.

The PCA transformed data assisted to deduce the number of classes for classification of February 2018 image. Horticulture plantations like Banana, Coconut, Mango and Others (Seasonal crops, Grapes, Guava & Agro-forestry etc.) are main crop classes. The classified outputs with 10 classes generated from 10 m Sentinel 2 (Level 1C) February 2018 deploying RF (Object based), RF (Pixel based), CART and SVM classifiers. The estimated average area of banana in classified output using machine learning algorithms was 5132 hectares.

Accuracy matrices for classification techniques depicting the producer, user, overall accuracies kappa coefficient and conditional kappa are tabulated in Table 1. The overall classification accuracy using algorithms was 91.1%, 92.1%, 89.6% & 87.6% with the Kappa co-efficient of 0.89, 0.90, 0.88 and 0.85 for RF (OB), RF, CART and SVM respectively. The co-efficient demonstrate the classified results are in agreement with sampled data. Random forest classifier achieved the highest overall accuracy (OA) of 92.1% with kappa co-efficient of 0.90 and lowest OA of 87.6% was in SVM classifier. In crop identification studies individual class accuracies are important for better understanding of performance of algorithms. The machine learning algorithms exhibit better performance in terms of overall accuracy in land use classification (Table 1). In crop classes classification RF classifier achieved highest producer's accuracy (PA) for Banana (91.9%) against lowest PA for Mango (90.8%). Highest user's accuracy (UA) for crop classes was obtained by RF classifier for Banana (94.3%). The producer's accuracy for non-crop classes was highest for water body (93.2%) RF classifier whereas lowest was in aquatic vegetation (83.3%) in SVM classifier. Highest user's accuracy for non-crop classes was obtained in SVM for water body (98.7%) and lowest for aquatic vegetation (81.4%) in CART classifier.

Table 1: Accuracy matrices – Over accuracy (OA), Kappa co-efficient Producer's accuracy (PA), User's accuracy (UA)

			Producer's and User's Accuracy											
Classification Techniques	**Overall Accuracy %**	**Kappa Co-efficient**	**Banana**				**Coconut**				**Mango**			
			PA	**CKC**	**UA**	**CKC**	**PA**	**CKC**	**UA**	**CKC**	**PA**	**CKC**	**UA**	**CKC**
RF (OB)	91.1	0.89	91.0	0.91	93.1	0.88	91.8	0.88	91.2	0.90	89.5	0.90	90.3	0.89
RF	92.1	0.90	91.9	0.92	94.3	0.90	92.7	0.90	92.1	0.91	90.8	0.90	90.6	0.91
CART	89.6	0.88	89.7	0.89	91.3	0.87	90.9	0.85	88.2	0.88	87.8	0.88	88.8	0.87
SVM	87.6	0.85	88.0	0.85	88.6	0.85	88.3	0.86	89.1	0.85	85.7	0.82	81.9	0.86

	Producer's and User's Accuracy															
	Other crops				**Fallow**				**Forest**				**Water body**			
	PA	**CKC**	**UA**	**CKC**	**PA**	**CKC**	**UA**	**CKC**	**PA**	**CKC**	**UA**	**CKC**	**PA**	**CKC**	**UA**	**CKC**
RF (OB)	90.1	0.88	88.7	0.90	92.3	0.88	89.8	0.90	90.3	0.97	90.3	0.88	89.5	0.89	97.3	0.89
RF	91.2	0.89	89.6	0.90	93.2	0.89	90.8	0.91	91.4	0.98	91.6	0.90	93.2	0.90	90.8	0.90
CART	88.6	0.84	85.4	0.88	90.0	0.82	91.2	0.87	88.9	0.94	87.0	0.87	87.9	0.85	95.1	0.88
SVM	86.0	0.87	88.5	0.85	88.6	0.83	88.2	0.85	87.1	0.98	82.2	0.84	85.3	0.81	98.7	0.86

	Producer's and User's Accuracy											
	Wasteland				**Aquatic vegetation**				**Built-up**			
	PA	**CKC**	**UA**	**CKC**	**PA**	**CKC**	**UA**	**CKC**	**PA**	**CKC**	**UA**	**CKC**
RF (OB)	90.3	0.87	88.8	0.90	89.4	0.88	88.0	0.90	89.7	0.97	89.1	0.89
RF	91.5	0.88	89.8	0.91	90.3	0.89	89.2	0.90	90.8	0.90	90.7	0.91
CART	88.4	0.88	90.4	0.87	87.5	0.88	81.4	0.88	88.0	0.83	83.3	0.88
SVM	86.9	0.84	81.6	0.85	85.3	0.81	82.7	0.86	85.8	0.85	83.3	0.85

OB (RF): Object based method, RF: Random Forest, CART: Classification and Regression Technique SVM: Support Vector Machine.
PA: Producer's accuracy, UA: User's accuracy, CKC: Conditional Kappa co-efficient

RF classifier achieved highest producer's accuracy for banana crop (94.3%) and lowest (88.0%) in SVM classifier. User's accuracy for banana was lowest (88.6%) SVM classifier and RF resulted in highest UA (94.3%). Object-based classification, with RF algorithm performed in coherence with RF algorithm for almost all classes. SVM algorithm achieved lowest overall accuracy and Kappa co-efficient as compared to RF (OB), RF and CART. Conditional Kappa calculates the per category agreement while adjusting for the expected proportion correct due to chance (Rosenfield and Fitzpatrick-Lins 1986) [20]. Conditional kappa for banana is close in agreement in RF (OB), RF and CART as compared to SVM.

Mixing of pixels with adjacent crop is observed in multiple cropping systems due to spectral similarities from different stages of growth and development of crops prevailing on the date satellite data acquisition (Fig. 5) similar to the ones reported (Duro *et al.* 2012) [8]. Lowest user's accuracy (85.4%) was observed in other crops as misclassification with forest, mango and coconut plantations adjoining forest areas. Consequently, forest areas were also misclassified as other crops due to spectral similarities of exposed/deciduous forest areas. Misclassification was also observed amongst mango & coconut, forest & wasteland, forest & water, built-up & wasteland as depicted results. The similar trend was observed in SVM, CART.

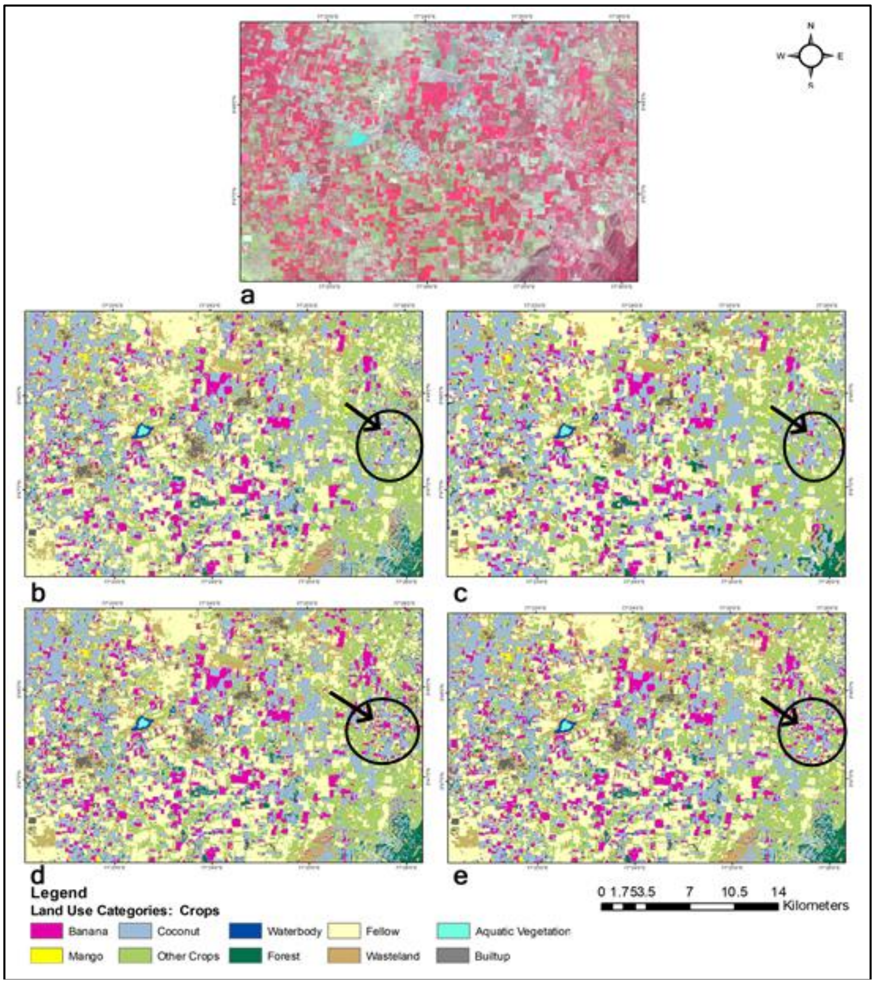

Fig 5: Classification results: (a) False Colour Composite (b) RF (Pixel based) (c) RF (Object based) (d) CART (e) SVM. Arrow depicts misclassified areas of banana in CART and SVM

Individual class accuracies indicate that RF was effective in enhancing the classification accuracy for Banana plantations. The classified outputs and corresponding accuracies indicate that there was no significant difference between Random Forest (Pixel based) classifier versus RF (Object based) in classifying banana plantations in study area Theni.

Our study has explored the potentials of high resolution Sentinel2 data for crop identification using machine learning algorithms namely RF (Pixel based), RF (Object based), CART & SVM. Though the land holdings are small and fragmented individual fields of cropped areas could be identified from outputs generated especially in Banana dominant areas. The outputs from our methods of analysis show banana plantations clearly with individual field boundaries and very much distinguishable from neighbouring crops like coconut.

5. Conclusion

Machine learning algorithms are found efficient in processing large data sets. Considering the intensive agriculture and diversity of crops prevailing in tropical countries like India crop identification is complex and time consuming. The attempt was one of the firsts in analysis of remote sensing satellite data using advanced machine learning algorithms for mapping banana crop of a district which is cultivated in a heterogeneous cropping environment.

In this study, multispectral Sentinel 2 data was used for banana crop identification using supervised machine learning methods like Random Forest (Object & Pixel based) (RF), Classification and Regression Technique (CART) and Support Vector Machine (SVM) in Theni district, Tamil Nadu, India for February 2018 aiming to evaluate the best classifier. RF has gained better overall accuracy compared to

RF (OB), SVM, CART classifiers for the study area. Sentinel2 data is suitable for crop identification and discrimination among the agricultural and horticultural crops in a given region.

The process and techniques can be deployed for crop mapping at regional scales with the availability of continuous open source high resolution data like Sentinel constellation. Further work may be directed to develop spectral indices using time series data sets like Sentinel2 for mapping and estimating the extent of horticultural crops and sufficing crop management practices.

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