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Digital Image Classification of Mango and Coconut for Natham Taluk, Dindigul District Using Sentinel-2A Optical Data

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ABSTRACT
Remote sensing and GIS have been widely applied in agriculture. Several methods exist for mango classification of satellite data which can be utilized by the agricultural sector. This study focuses on using supervised classification approaches to classify mango and coconut plantations Natham Taluk, Dindigul district Tamil Nadu. Sentinel 2A acquired on 3rd February 2018 was used for image classification. Ground truth data collection was performed through the Taluk. The land use and land cover of the study area were distinguished into five classes viz., coconut, mango, cropland, settlements and water body.

Supervised image classification technique such as Mahalanobis Distance, Maximum likelihood Classifier, Spectral angle mapper and Spectral correlation mapper methods were applied over the image. The accuracy measures, such as producer's accuracy, user's accuracy, overall accuracy and kappa coefficient were estimated.

The results showed that maximum likelihood supervised classifier had the highest overall accuracy of 51.4% while other supervised classifier such as Mahalanobis Distance (32.4%), Minimum Distance classifier (42.86%), Spectral Angle Mapper (42.85%), Spectral Angle Mapper (42.85%) and Spectral Correlation Mapper (34.53%) had lower accuracy. It is suggested to utilize multi-date data for classification for crop discrimination utilizing the unique phenology of various crops for better accuracy.

Keywords **-** Mahalanobis distance, Minimum distance classifier, SAM, SCM.

I. INTRODUCTION

The intent of the image classification process is to categorize all pixels in a digital image into one of several land cover classes, or "themes". This categorized data may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization (Lillesand and Kiefer, 1994). The objective of image classification is to identify and portray, as a unique gray level (or colour), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground. Image classification is perhaps the most important part of digital image analysis. It is very nice to have a "pretty picture" or an image, showing a magnitude of colours illustrating various features of the underlying terrain, but it is quite useless unless to know what the colors mean. (PCI, 1997).

II. OBJECTIVE

Based on the above mentioned facts and details the objectives taken up for this study are.

- Crop discrimination using Sentinel-2A optical data.
- Find the most suitable classification technique for classification of plantation crop

III. MATERIALS AND METHODS

3.1 STUDY AREA

The study is carried out in Natham Taluk of Dindigul district in Tamil Nadu. Natham is located at 14.13°N 78.13°E. It has an average altitude of 252 meters.

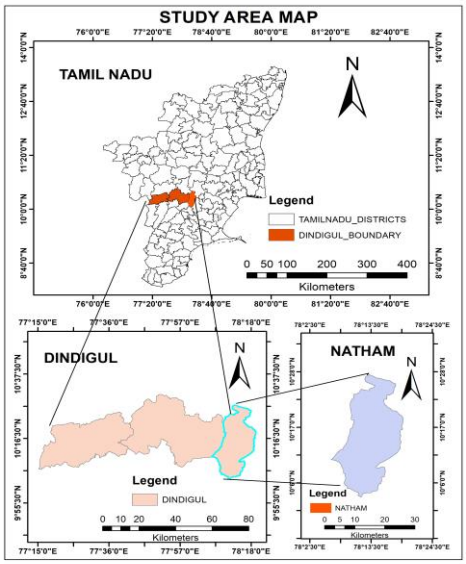

Fig.1. Location Map of the Study Area

3.2 DATA USED

Sentinel-2A optical data was used for classification of plantation crops is the study area. The data sets were acquired for 3rd February 2018.

IV. METHODOLOGY

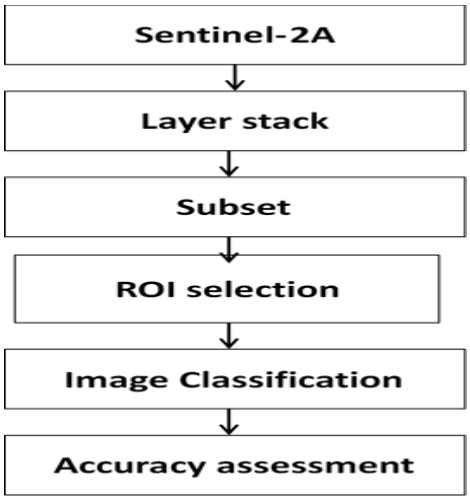

Fig.2.Methodological flow of the process involved in Digital image classification.

Sentine-2A data consisted of 13 bands. All the bands were layer stacked. After layer stacking, Region of Interests (ROI) were selected that represent various classes referring to high resolution satellite data and GPS points of that region to accurately identify spectral characteristics of individual plantation crops in the region. Finally, multi temporal speckle filtering was performed. After speckle filtering sentinel, 1A SAR images values are converted into decibels using the linear to dB conversion tool and exported as geo-tiff for further processing.

- Supervised image classification was carried out on the image using the above collected training samples. Classification methods like, Mahalanobis distance, Maximum likelihood classification, Minimum Distance, Spectral Angle Mapper and Spectral Correlation Mapper was evaluated.

- After the classification process, Accuracy assessment was done to calculate the overall accuracy and Kappa coefficient value for each supervised classification methods respectively with the help of independent ground truth coordinates.

V. RESULTS AND DISCUSSIONS

5.1 MAHALANOBIS DISTANCE CLASSIFICATION

Accuracy Assessment of Mahalanobis Distance classified image is carried out using confusion matrix algorithm taking ground truth points. Producer's accuracy & User's accuracy of all classes, overall accuracy and Kappa coefficient is calculated and tabulated in the above table The Mahalanobis distance classified images shows an overall accuracy of 32.14% and its Kappa coefficient is 0.17.

5.2 MAXIMUM LIKELIHOOD CLASSIFICATION

Accuracy Assessment of Maximum Likelihood classified image is carried out using confusion matrix algorithm taking ground truth points. Producer's accuracy & User's accuracy of all classes, overall accuracy and Kappa coefficient is calculated and tabulated in the above table The Mahalanobis distance classified images shows an

overall accuracy of 51.43% and its Kappa coefficient is 0.35.

5.3 MINIMUM DISTANCE CLASSIFICATION

Accuracy Assessment of Minimum Distance classified image is carried out using confusion matrix algorithm taking ground truth points. Producer's accuracy & User's accuracy of all classes, overall accuracy and Kappa coefficient is calculated and tabulated in the above table The Minimum distance classified images shows an overall accuracy of 42.85% and its Kappa coefficient is 0.24.

5.4 SPECTRAL ANGLE MAPPER CLASSIFICATION

Accuracy Assessment of Spectral Angle Mapper classified image is carried out using confusion matrix algorithm taking ground truth points. Producer's accuracy & User's accuracy of all classes, overall accuracy and Kappa coefficient is calculated and tabulated in the above table The Mahalanobis distance classified images shows an overall accuracy of 42.86% and its Kappa coefficient is 0.24.

5.5 SPECTRAL CORRELATION MAPPER CLASSIFICATION

Accuracy Assessment of Spectral Correlation Mapper classified image is carried out using confusion matrix algorithm taking ground truth points. Producer's accuracy & User's accuracy of all classes, overall accuracy and Kappa coefficient is calculated and tabulated in the above table 5. The Mahalanobis distance classified images shows an overall accuracy of 34.53% and its Kappa coefficient is 0.16.

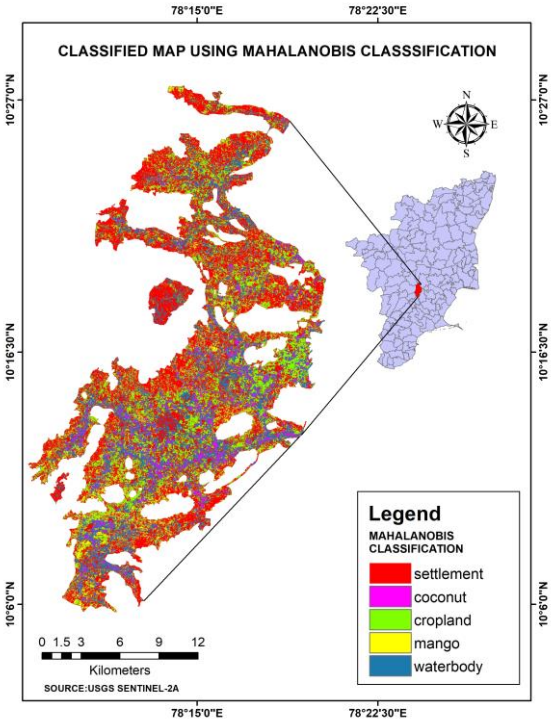

Fig.3. Mahalanobis Distance Classification

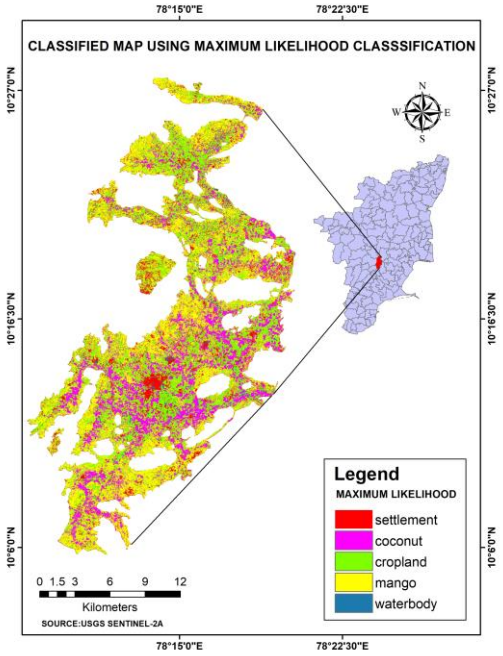

Fig.4. Maximum Likelihood Classification

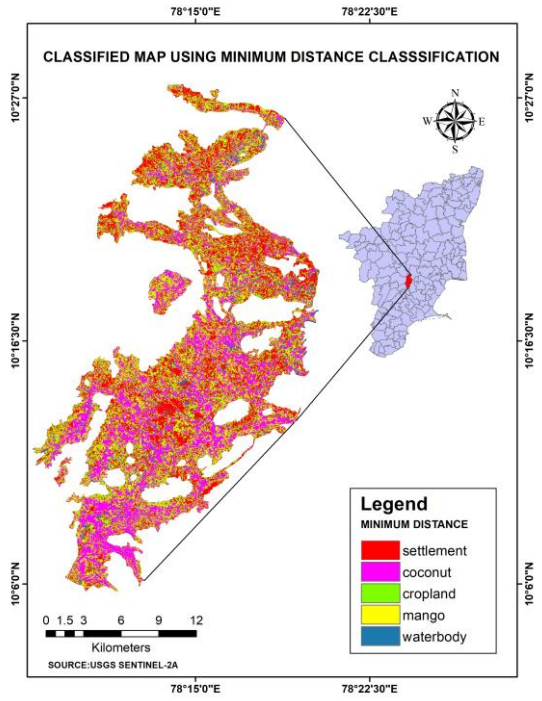

Fig.5. Minimum Distance Classification

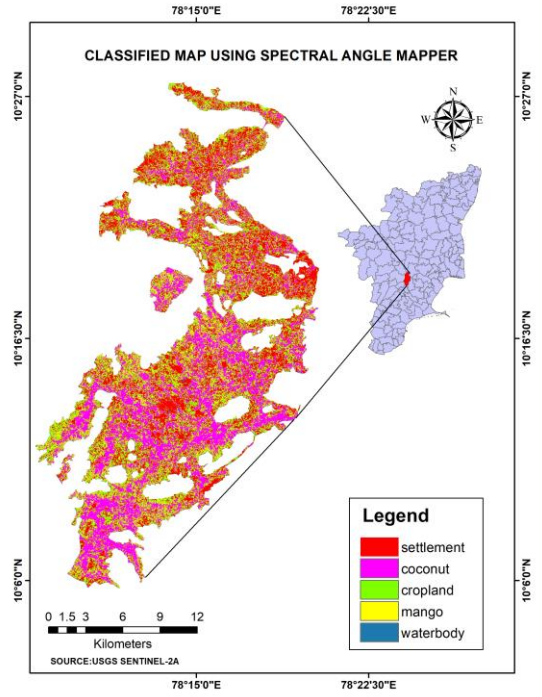

Fig.6. Spectral Angle Mapper Classification

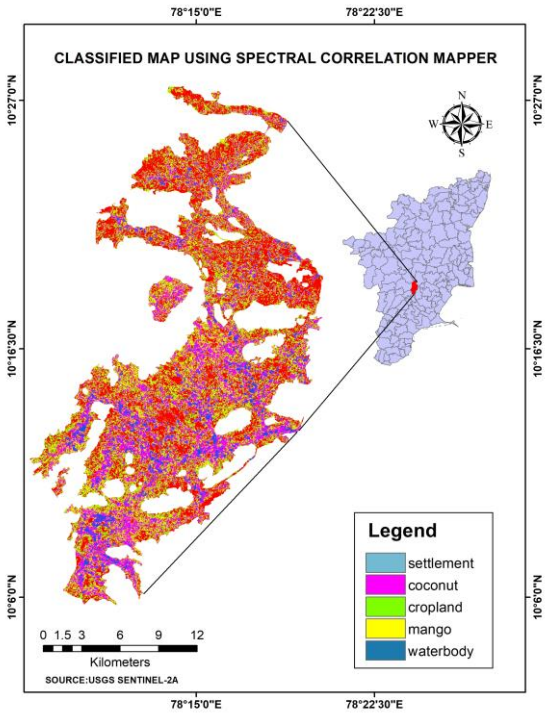

Fig.7. Spectral Correlation Mapper Classification

1. From this study, experimental results indicate that among all the supervised image classification method Maximum Likelihood (51.4%) showed highest accuracy results for the classification. This is because Maximum Likelihood classifier takes advantage of the information of multivariate spreads of each class. The accuracy can be further improved by using temporal satellite data product and by improving the producer's accuracy and improving image processing skills of the user. The other classifiers showed lower accuracy (less than fifty).

2. It can also be noted that the mango plantations were misclassified and had low accuracies. This is because the area has both high density and low density planting of mango orchards.

Classes	Settlement	Coconut	Cropland	Mango	Water body	Total	Users Accuracy
Settlement	22	11	12	22	2	69	31.88
Coconut	1	10	1	3	0	15	66.67
Cropland	1	4	9	7	1	22	40.91
Mango	1	1	1	2	0	5	40.00
Water body	5	14	2	6	2	29	6.90
Total	30	40	25	40	5	45	
Producers Accuracy	73.33	25	36	5	40		
Overall Accuracy = 32.14%							
Kappa coefficient = 0.17							

Table- I. Accuracy Assessment table for Mahalanobis distance classification

Classes	Settlement	Coconut	Cropland	Mango	Water body	Total	Users Accuracy
Settlement	18	1	4	3	0	26	69.23
Coconut	5	23	2	7	1	38	60.53
Cropland	3	8	13	12	2	38	34.21
Mango	4	7	6	18	2	37	48.65
Water body	0	1	0	0	0	1	0
Total	30	40	25	40	5	72	
Producers Accuracy	60	57.50	52	45	0		
Overall Accuracy = 51.43%							
Kappa coefficient = 0.35							

Table- II. Accuracy Assessment table for Maximum Likelihood classification

Classes	Settlement	Coconut	Cropland	Mango	Water body	Total	Users Accuracy
Settlement	20	3	10	14	0	47	42.55
Coconut	4	27	2	13	1	47	57.45
Cropland	2	3	4	4	1	14	28.57
Mango	2	7	8	9	3	29	31.03
Water body	2	0	1	0	0	3	0
Total	30	40	25	40	5	60	
Producers Accuracy	66.67	67.5	16	22.50	0		
Overall Accuracy = 42.85%							
Kappa coefficient = 0.24							

Table- III. Accuracy Assessment table for Minimum distance classification

Classes	Settlement	Coconut	Cropland	Mango	Water body	Total	Users Accuracy
Settlement	22	1	11	13	0	47	46.81
Coconut	4	29	5	14	1	53	54.72
Cropland	3	5	4	8	1	21	19.05
Mango	1	4	5	5	3	18	27.78
Water body	0	1	0	0	0	1	0
Total	30	40	25	40	5	60	
Producers Accuracy	73.33	72.50	16	12.50	0		
Overall Accuracy = 42.86%							
Kappa coefficient = 0.24							

Table- IV. Accuracy Assessment table for Spectral Angle Mapper classification

Classes	Settlement	Coconut	Cropland	Mango	Water body	Total	Users Accuracy
Settlement	22	3	14	15	0	54	40.74
Coconut	3	19	2	8	0	32	59.38
Cropland	3	3	1	7	0	14	7.14
Mango	1	5	7	5	4	22	22.73
Water body	1	9	1	5	1	17	5.88
Total	30	39	25	40	5	48	
Producers Accuracy	73.33	48.72	4	12.5	20		
Overall Accuracy = 34.53%							
Kappa coefficient = 0.16							

Table- V. Accuracy Assessment table for Spectral Correlation Mapper classification

3. The reflectance from soil contributes to the error percentage. The coconut plantations on the other hand were spread uniformly and hence have a better percentage of accuracy.

4. The classification can be accuracy can be further increased by Using temporal data for crop classification rather than single day data. This helps in understanding the crop stages and its reflectance that change accordingly.

5. By improving the producer's accuracy and improving image processing skills of the user for better classification results.

6. Use of different classes for mango crop that varies in age and fractional vegetation cover would also improve classification accuracy.

7. Based on the results, it could be concluded that use of multi-temporal data can further improve discrimination of crops as it can capture the complete phenology of the crops during the cropping period. Accuracy can be improved if more classes are incorporated like, other crops grown in the region, fallow lands, wastelands etc.

VI. CONCLUSION

In the present study, the potential of Sentinel-2A data for classifying mango and coconut plantations were examined. Image classification for the area was performed by five supervised image classification techniques such as Mahalanobis Distance, Maximum Likelihood classifier, Minimum Distance classifier, Spectral Angle Mapper and Spectral Correlation Mapper.

- The study was carried out in Natham taluk of Dindigul district of Tamil Nadu which has large extent of mango and coconut. Ground truth observations were carried out for mango and coconut. The ground truth data were used for training the classifiers and for validating the classified images.

- The training was done for five classes namely mango, coconut, settlement, cropland and water bodies. The Sentinel-2A satellite image taken on 3rd February 2018 was used for classification. The classified images were then checked for their accuary.

Algorithm	***Overall Accuracy %***
Maximum Likelihood	51.43
Spectral Angle Mapper	42.86
Minimum Distance	42.85
Spectral Correlation Mapper	34.53
Mahalanobis Distance	32.14

Table- VI: Classification Accuracy Table

- The results showed that maximum likelihood supervised classification had an overall accuracy of 51.4% which turned out to be the highest. It is followed by Spectral Angle Mapper, Minimum Distance, Spectral Correlation Mapper and Mahalanobis Distance.

- It can be concluded that use of multi-temporal data can further improve discrimination of crops as it can capture the complete phenology of the crops during the cropping period. Accuracy can be improved if more classes are incorporated like, other crops grown in the region, fallow lands, wastelands etc.

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