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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 methodsexist 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 February2018wasusedforimageclassification.Groundtruthdatacollectionwasperformed through the taluk. The land use and land cover of the study area were distinguished into five classes viz., coconut, mango, cropland, settlements and waterbody.Supervised image classification technique such as Mahalanobis Distance, Maximum likelihood Classifier, Spectral angle mapper and Spectral correlation mapper methods were appliedovertheimage.Theaccuracymeasures,suchasproducer'saccuracy,user'saccuracy, overall accuracy and kappa coefficient wereestimated.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 utilising the unique phenology of various crops for betteraccuracy.***

## 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, showingamagnitudeofcoloursillustratingvariousfeaturesoftheunderlyingterrain,butitis quite useless unless to know what the colors mean. (PCI,1997).

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## II.OBJECTIVE

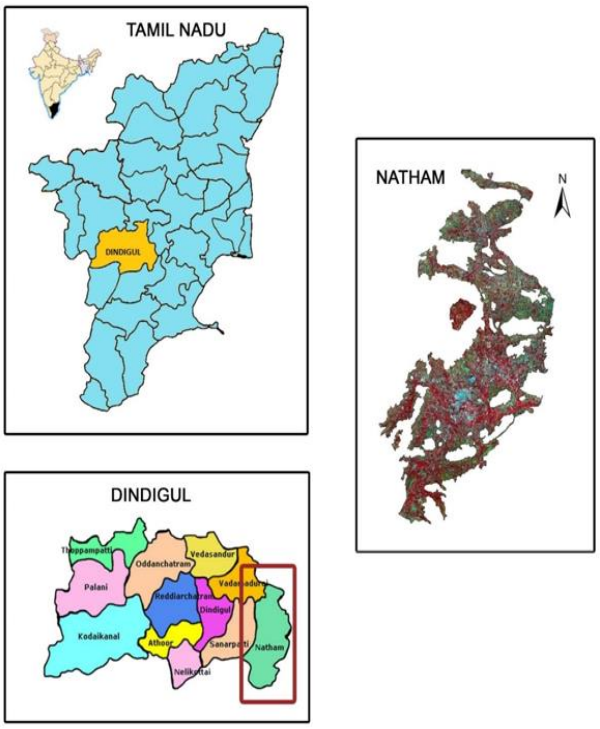
Based on the above mentioned facts and details the objectives taken up for this study are

- Crop discrimination using Sentinel-2A opticaldata.
- Find the most suitable classification technique for classification of plantationcrops.

**Materials and Methods:**

**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 (827 feet).




**Data used**

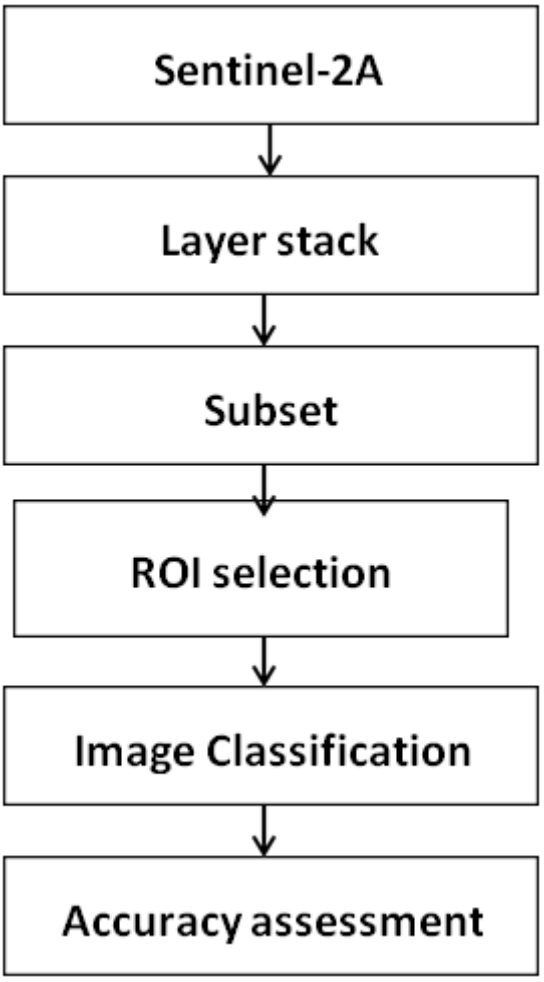
Sentinel-2A optical data was used for classification of plantation crops is the study area. The sourceoftheseopticaldatasetsisEarthExplorerwebsite.Thedatasetswereacquiredfor3rd February2018.

**Software used**

- ERDAS IMAGINE
- ArcMap
- ENVI

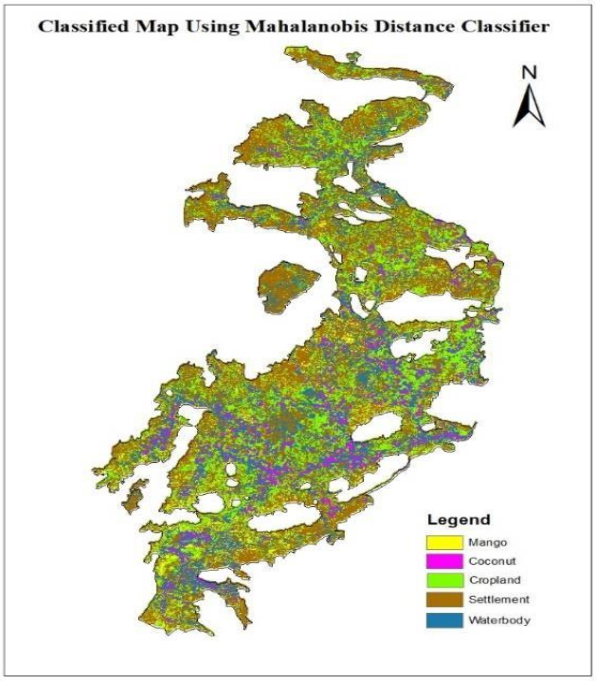
## III.METHODOLOGY

The following flow chart shows the steps followed in the study.S




Sentine-2Adataconsistedof13bands.Allthebandswerelayerstackedusi ngErdasIMAGINE software. 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 theregion.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.

## IV.RESULTS AND DISCUSSION MAHALANOBIS CLASSIFICATION PROCESS




**Classified Map Using Mahalanobis Distance for Natham Taluk**

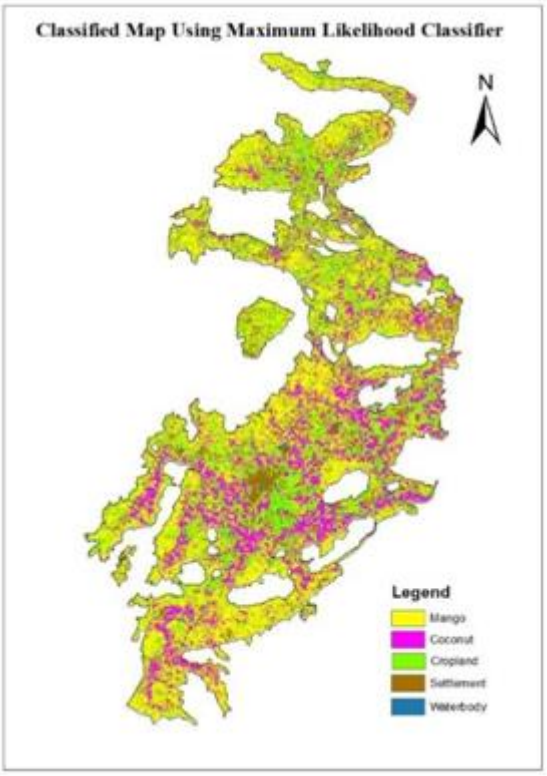
**Table: Accuracy Assessment table for Mahalanobis Distance classification**

| Classes | Settlement | Coconut | Cropland | Mango | Waterbody | 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 |
| Waterbody | 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 | | | | | | | |

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 TheMahalanobisdistanceclassifiedimagesshowsanoverallaccuracyof32.14%anditsKappa coefficient is0.17.

## V.MAXIMUM LIKELIHOOD CLASSIFICATION PROCESS



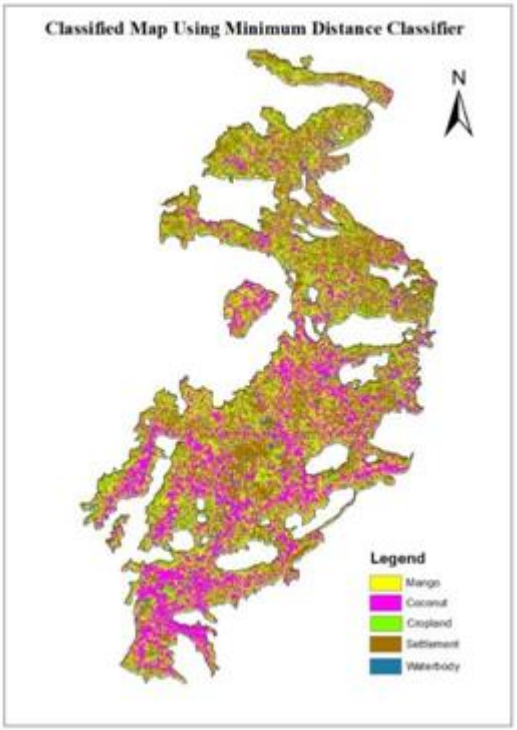

**Classified Map Using Maximum Likelihood Distance for Natham Taluk**

**Table: Accuracy Assessment table for Maximum Likelihood classification**

| Classes | Settlement | Coconut | Cropland | Mango | Waterbody | 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 |
| Waterbody | 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 | | | | | | | |

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 TheMahalanobisdistanceclassifiedimagesshowsanoverallaccuracyof51.43%anditsKappa coefficient is0.35.

## VI.MINIMUM DISTANCE CLASSIFICATION PROCESS



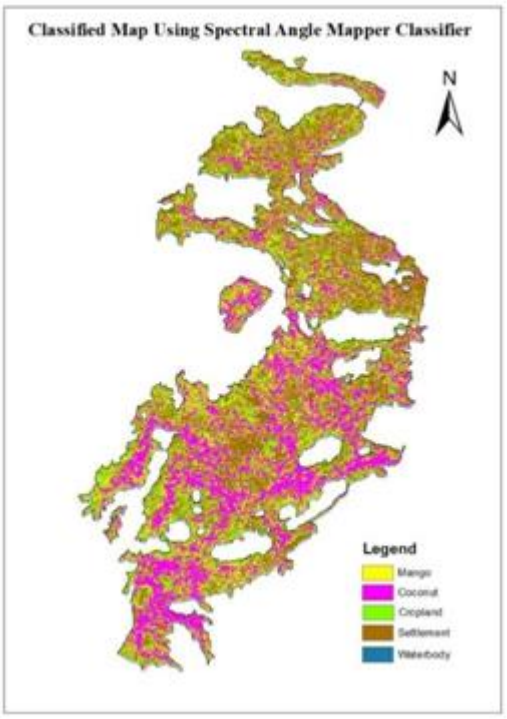

**Classified Map Using Minimum Distance for Natham Taluk**

**Table: Accuracy Assessment table for Minimum Distance classification**

| Classes | Settlement | Coconut | Cropland | Mango | Waterbody | 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 |
| Waterbody | 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 | | | | | | | |

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 tableTheMahalanobisdistanceclassifiedimagesshowsanoverallaccuracyof42.85%anditsKappa coefficient is0.24.

## VII.SPECTRAL ANGLE MAPPER CLASSIFICATION PROCESS



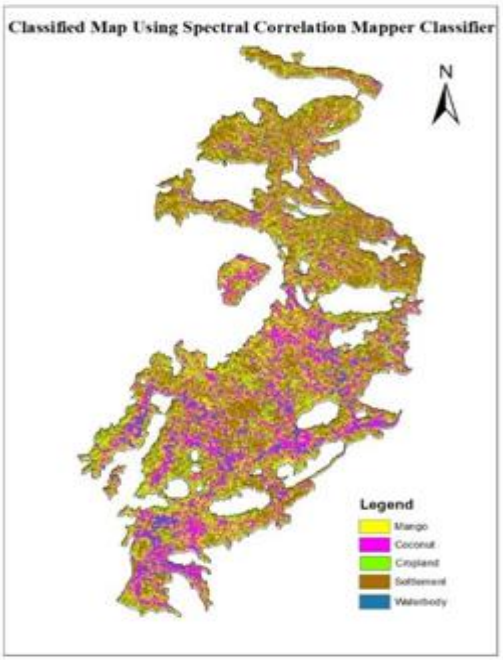

**Classified Map Using Spectral Angle Mapper for Natham Taluk**

**Table: Accuracy Assessment table for SAM classification**

| Classes | Settlement | Coconut | Cropland | Mango | Waterbody | 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 |
| Waterbody | 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 | | | | | | | |

AccuracyAssessmentofSpectralAngleMapperclassifiedimageiscarriedoutusingconfusion 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 abovetableTheMahalanobisdistanceclassifiedimagesshowsanoverallaccuracyof42.86%anditsKappa coefficient is0.24.

## VIII.SPECTRAL CORRELATION MAPPER CLASSIFICATION PROCESS




**Classified Map Using Spectral Correlation Mapper for Natham Taluk**

**Table: Accuracy Assessment table for SCM classification**

| Classes | Settlement | Coconut | Cropland | Mango | Waterbody | 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 |
| Waterbody | 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 | | | | | | | |

Accuracy Assessment of Spectral Correlation Mapper classified image is carried out using confusionmatrixalgorithmtakinggroundtruthpoints.Produce r'saccuracy&User'saccuracy of all classes, overall accuracy and Kappa coefficient is calculated and tabulated in theabove Table 5. The Mahalanobis distance classified images shows an overall accuracy of 34.53% and its Kappa coefficient is 0.16.

## IX.DISSCUSSION

Five different classifiers were used for classifying the image namely, Mahalanobis Distance, Minimum Distance, SAM, Maximum Likelihood, SCM and accuracy assessment was carried out for the classified images .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 usingtemporalsatellitedataproductandbyimprovingtheprodu cer'saccuracyandimproving image processing skills of the user. The other classifiers showed lower accuracy (less than fifty).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.Alsotheageofthemangotreesvariesalot.Astheyoun gertreeshadsmallercanopy cover. In both cases of small canopies and low density planting, the reflectance from soil contributes to the errorpercentage.The coconut plantations on the other hand were spread uniformly and hence have a better percentage of accuracy.

***The classification can be improved 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 . This can help differentiate crops from other classes and amongthemselves.
- By improving the producer's accuracy and improving image processing skills of the user for better classificationresults.
- Use of different classes for mango crop that varies in age and fractional vegetation cover would also improve classification accuracy.

Based on the results, it could be concluded that use of multi-temporal data can furtherimprove 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.*

## X.SUMMARY

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

| 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 |

Theresultsshowedthatmaximumlikelihoodsupervisedclassification hadanoverallaccuracy of 51.4% which turned out to be the highest. It is followed by Spectral Angle Mapper, Minimum Distance , Spectral Correlation Mapper and MahalanobisDistance.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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