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Mapping and Area Estimation of Mango Orchards of Lucknow Region by Applying Knowledge Based Decision Tree to Landsat 8 OLI Satellite Images

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Abstract: ***Mango is a very important fruit which is liked by majority of the population due to its nutritional value and excellent taste. India is the largest producer of mango in the world. Accurate information is required for policy decision making in terms of providing subsidy, area expansion, and crop insurance planning. Hence, this type of information may be retrieve through satellite images by using the image classification techniques, which are playing a crucial role in crop cover classification, yield prediction and crop monitoring etc. Classification of optical satellite images is still a challenging task due to effect of changing atmospheric conditions such as cloud, snow, haze, dust, fog, and rain etc. In this paper, knowledge based decision tree classification (DTC) has been proposed to classify the mango orchards of Lucknow district using multi-temporal Landsat 8 operational land imager (OLI) images from year 2015 to 2017 and further mango orchard area were also estimated. In order to develop the DTC, separability analysis for various land cover classes was carried out on different vegetation indices namely, normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI), and soil adjusted vegetation index (SAVI). In order to analyze the performance of DTC, most commonly used satellite image classifiers such as unsupervised classifier (i.e. ISODATA) and supervised classifier (i.e. Maximum Likelihood) have been used and it is observed that the proposed DTC outperformed these traditional classifiers. Also, accuracy assessment has been carried out to measure the performance of proposed DTC and it is observed that all of the three images from 2015 to 2017 are classified with high overall accuracy, which is ranging from 70.66% to 86.69%. Kappa Coefficient (KC) for all the three images ranged from 0.65 to 0.83, which indicates that classified images are highly acceptable for area estimation.***

Keywords: ***Classification, Area Estimation, Decision Tree Classification.***

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I. INTRODUCTION

India has its own importance in mango (*Mangifera Indica* L.) production and it is the leading country whereas the contribution of orchards from the Uttar Pradesh is also remarkable.

In Uttar Pradesh, there are several mango growing areas like: Lucknow, Saharanpur, Moradabad, Sitapur, Barabanki, Faizabad, and Varanasi, etc. Accurate classification and area estimation of mango orchard is an important task for policy decision by the government for its area expansion and monitoring, providing subsidy to the farmers, crop insurance and yield estimation. Satellite images play crucial role in accurate classification and area estimation of fruit crops. In literature it is found that satellite images are also playing an important role in orchard monitoring.

The resolution of satellite image is an important factor affecting the crop classification. Both types of resolutions namely, spatial and temporal plays crucial role in orchard monitoring or area estimation. A high spatial resolution image acquires maximum information of the terrain surface. Using a high resolution image, orchard can be mapped accurately but a satellite image with coarse spatial resolution is unable to acquire and provide detailed information of the targeted area. So using coarse resolution images, it is very difficult to map the orchard accurately. Similarly, high temporal resolution images provides more fine spatial information in given time period and acquires phenophase of crop in better way, however with images of coarse resolution it is not possible. Cost of the satellite image is other factor that affects its uses. Some Satellite images are freely available such as Landsat and Sentinel series images. However some others are priced and costly such as WorldView series, QuickBird (60cm), GeoEye-1, IKONOS, RapidEye, etc. [1].

Satellite images have various applications for mango crop such as crop classification and monitoring, change detection, crop acreage estimation, identification of crop stress, and yield prediction, etc. In brief literature review, it has been observed that high resolution IRS LISS series of images have been mostly used for mango orchard mapping [2-4]. Reference [3] used IRS 1C LISS-II data for estimation of mango orchard acreage and production in Krishna district of Andhra Pradesh.

Authors concluded that satellite image of summer season provides information on acreage of mango orchard. In another study, a model for delineation of plantation crops was developed [3]. They used LISS-IV satellite images of Malihabad and it is observed that for discrimination of mango plantations, February month data was more suitable mainly due to harvesting of competing agricultural crops.

In another study relate to land suitability analysis of integrated use of GIS, AHP and SPOT-6 satellite data [4]. In which it was observed that multi criteria analysis can be used to prioritize the development of tropical high altitude vegetable crops.

In order to classify mango and citrus, *p*ixel based hybrid classification i.e. unsupervised ISODATA clustering plus supervised Maximum Likelihood (ML) classification as well as Object Based Classification (OBC) of high resolution data (Resourcesat LISS III and/or LISS-IV, Cartosat – 1 PAN) was performed [5]. In this study, mango orchard area was estimated and it was compared with the statistical area of the region or district reported earlier from available sources. Post classification, overall accuracy was estimated as 80 to 90% and it is observed that relative deviation of the RS estimated mango area compared the area reported by the state Department of Horticulture were upto 37%. The authors concluded that this higher deviations in area suggest the over or under reported area by the Department.

Satellite images provide rapid and cost effective method for mapping orchard from other land uses (LU) for taking decision and precision farming [6-9]. Since satellite images are collected digitally, hence, there is no loss of data in satellite images, since they are collected in digital form. These images contain lot of information, cover a larger ground area than aerial photos, and provide updates of the target area every few days. At present, Landsat data are considered to be the very good, free of cost source, for land cover classification over large areas. This is due to its comparatively high temporal resolution, fine spatial resolution and large swath [10].

Image classification of the satellite images is the most common way to analyse and to obtain the useful information of the Earth. The image classification methods can be grouped as parametric and non-parametric, or supervised and unsupervised classification [11]. There are two most common unsupervised classification methods *viz.,* ISODATA (Iterative Self Organizing Data Analysis) and K-Means. Supervised classification technique includes Parallelepiped, Minimum Distance, Mahalanobis Distance, Maximum Likelihood (ML), Artificial Neural Networks (ANN) and Support Vector Machines (SVM) Classifiers. Among these techniques, Maximum likelihood is one of the most popular supervised classification method used for satellite image classification [12].

In recent years, the use of decision tree classifier for land cover classification of satellite data has been increased considerably, because decision tree classification is computationally efficient algorithm [13]. Some of the other advantages provided by decision tree classifier are- its flexibility, simplicity, and ability to handle noisy and missing data [14-15]. The classification of orchard using satellite data processing can provide supplementary facts for management decision making, such as the assessment of fruit yield, the quantification of proper fertilizer application, irrigation needs, and the application of pesticides for pest and disease management [16-17]. The traditional approaches of crop area assessment involved field surveys based reckoning, which are time consuming and costly [18-19]. However, satellite image based crop area estimation is cost effective, takes less time and effort.

In this paper, a knowledge based decision tree classifier (DTC) has been developed with the help of separability index by calculating the decision boundaries for seven classes (i.e. water body, urban area, bare soil, sparse vegetation, medium vegetation, mango orchard, and dense vegetation) by obtaining the minimum and maximum spectral values of different indices for all seven land cover classes.

II. STUDY AREA AND DATA USED

A. Study Area

This study was conducted on Lucknow district, the capital of Uttar Pradesh State of India, which is almost centrally located in the State, on the Gomti River. Lucknow district lies between 26^0 30’ and 27^o 10’ N latitude and 80^o 34’ and 81^o 12’ E longitude. The city stands at ground elevation of approximately 123m above Mean Sea Level. Total geographical area of Lucknow district is 2,528 square kilometres [20]. It is surrounded by the districts Sitapur in the north, Barabanki in the east, Rae Bareli in the south, Hardoi in the north-west and Unnao in the south-west. It is famous for mango cv. Dashehari. The study area (i.e. Lucknow District) on India map is shown in Fig. 1 and false colour composite (FCC) images is shown in Fig. 2.

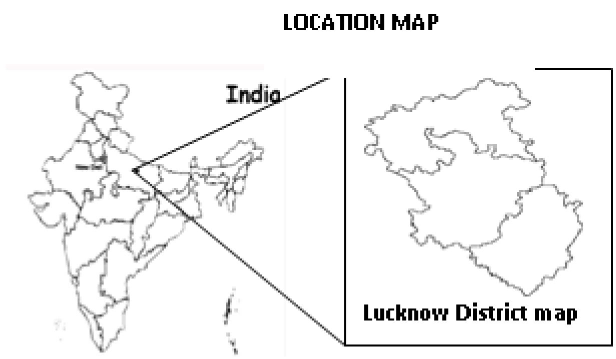


Fig. 1. Location of study area on India map.

B. Satellite Images Used

For this study, Landsat 8 OLI images were used due to its good spatial resolution and availability of long time series images. Three numbers of Landsat 8 images of Lucknow with path and row of 144 and 41, respectively were downloaded from USGS Earthexplorer as shown in Table 1. In this study, satellite images for the months of February and first fortnight of March for the years 2015, 2016, and 2017 were taken because during these months, the standing vegetative cover other than permanent vegetation in area is minimal.

Wheat and Sugarcane are two major competing crops, out of these sugarcane get harvested and wheat crop becomes mature by month of February in Lucknow region. So it will make sure that there will be either no or minimal overlapping of spectral signature of mango orchard with sugarcane and wheat crops.

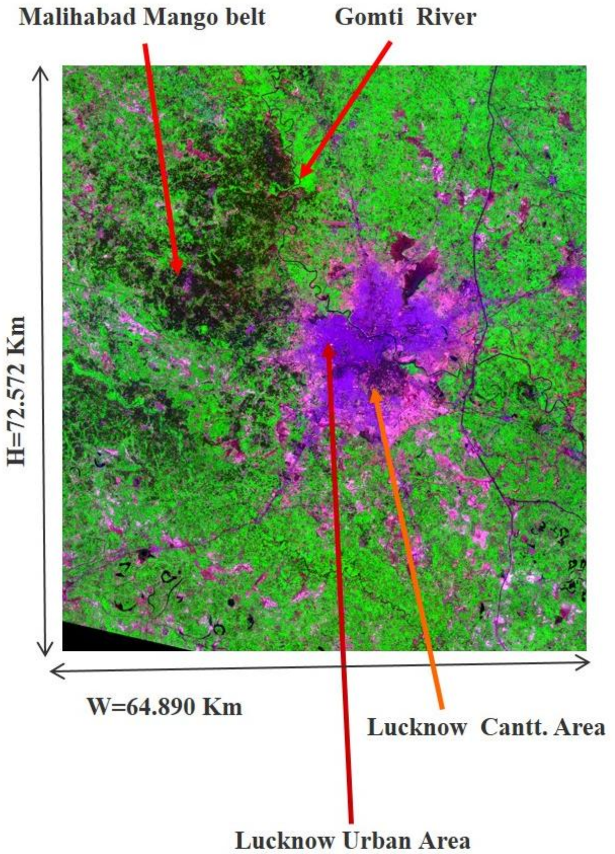


Fig. 2. FCC image of Lucknow district.

Each image has eleven spectral bands, out of it Visible, NIR, SWIR 1, SWIR 2 and cirrus bands have 30-m spatial resolution, panchromatic band has 15 m spatial resolution, and both Thermal bands have 100 m.

Table- I: Details of LS 8 OLI images used for study.

Acquisition Date	Acquisition ID	Resolution (m)
14-02-2015	LC08_L1TP_144041_20150214_20170413_01_T1	30
17-02-2016	LC08_L1TP_144041_20160217_20170329_01_T1	30
03-02-2017	LC08_L1TP_144041_20170203_20170215_01_T1	30

III. THE ORETICAL BACKGROUND

A. Pre-processing of Images

Landsat images were already geo-referenced at the Universal Transverse Mercator projection system (zone: 44° N, datum: WGS–84). These images covering Lucknow district were pre-processed by performing the Radiometric Calibration (Conversion of Digital Number into Reflectance). These images were also atmospherically corrected to remove atmospheric effect from it.

B. Various Indices used

Landsat-8 OLI image was pre-processed and then using the variation in reflectance properties, various indices such as NDVI, MNDWI and SAVI are considered, which represent a measure of presence of particular feature of undertaken study region. Details and mathematical formulation of vegetation indices are given below:

(I) **Normalized Difference Vegetation Index (NDVI)**:

NDVI quantify the vegetation, which indicates the greenness or crop canopy density [21]. The mathematical formulation for calculation of NDVI is given below:

$$NDVI = \frac{(\rho_{NIR} - \rho_R)}{(\rho_{NIR} + \rho_R)} \qquad (1)$$

Where, ρ_R, ρ_{NIR} are values of spectral bands Red (R), and Near Infra-red (NIR), respectively.

(II) Modified Normalized Difference Water Index (MNDWI):

It is used to detect and quantify the presence of water on earth surface [22]. It can be derive using following equation:

$$MNDWI = \frac{(\rho_G - \rho_{SWIR1})}{(\rho_G + \rho_{SWIR1})} \qquad (2)$$

Where ρ_G and ρ_{SWIR1} are values of spectral bands Green (G), and Short Wave Infrared 1(SWIR1), respectively. MNDWI represents the presence of water.

(III) **Soil Adjusted Vegetation Index (SAVI)**:

SAVI minimizes soil brightness influences using soil-brightness correction factor L. The value of L is adjusted based on the amount of vegetation. L=0.5 is the default value and works well in most situations [23]. It can be calculated as follows:

$$SAVI = \frac{(\rho_{NIR} - \rho_R)*(1+L)}{(\rho_{NIR} + \rho_R + L)} \qquad (3)$$

Where, ρ_R, ρ_{NIR} are values of spectral bands Red (R), and Near Infra-red (NIR), respectively.

For classifying the land cover in seven classes namely, water body, urban area, bare soil, sparse vegetation, medium vegetation, mango orchard and dense vegetation various indices *viz*., normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI) and soil adjusted vegetation index (SAVI), are used.

C. Separability Index

Separability index (SI) is used for estimating separability features of two classes. It is also used to make decision boundary for separation of various classes. For computation of separability index, initially four classes viz. water body, urban area, bare soil and vegetation were considered.

The vegetation class is further decomposed as sparse vegetation, medium vegetation, mango orchard, and dense vegetation. Separability Indices were computed as follows:

$$SI = \frac{|\mu_1 - \mu_2|}{\sigma_1 - \sigma_2} \qquad (4)$$

Where, μ_1 and μ_2 are means of class 1 and class 2, and σ_1 and σ_2 are standard deviation of class 1 and class 2.

A Higher value of separability index is desirable for efficiently separating the two classes for a given index. If the value of separability index lies between 0.8 and 1.5 then the particular index can represent a valid land cover class separation. Separability index of value above 1.5 defines as a good parameter boundary [24].

D. Image Classification

Image classification is an important task for satellite image analysis and is a process in which labels (class identifiers) are attached to individual pixels on the ground of their spectral characteristics in given bands. Supervised and unsupervised classification techniques are traditional classification techniques, where unsupervised classification technique is non-parametric in nature. In this technique no *a priori* information is needed to classify the images. It groups the pixels in different classes based on similarity. Unsupervised learning examines the underlying structure of the data and automatically groups them based on it, without any training data [13]. Supervised classification method is a parametric classification technique, which requires input training data. In this method training data is the key factor in image classification. Accuracy of the classification methods highly depends on the correctness of training/ ground truth data collected and used [25].

There are mainly four supervised classifications techniques such as Parallelepiped, Minimum Distance, Mahalanobis Distance, and Maximum Likelihood (ML). The supervised classification technique is gaining popularity for land cover classification of large area [9], and it is currently most commonly used for land cover classification [18-19]. Furthermore, the use of parametric supervised classifiers namely, maximum likelihood and minimum distance, are not suitable assuming that data follows a known distribution [16]. But, in real situation, generally satellites images do not follow a normal distribution, especially in complex landscapes [17]. The main advantages of supervised classifiers are: (1) The classifier can be trained in a way which has a perfect decision boundary to distinguish different classes accurately, and (2) It can specifically determine how many classes you want to have. The disadvantages are: (1) Decision boundary may be over fitted; (2) Accurate *a priori* information is required, otherwise in case of inaccurate may produce erroneous classified image. Therefore, to obtain an accurate classified image a knowledge based decision tree may require, which be able to produce the accurate classified image.

E. Knowledge Based Decision Tree

Decision Tree is binary tree that have a hierarchical structure of nodes, branches and leaves. Each node has decision expression, the outcome of which is either true or false. Leaf node represents a class. Decision tree is a kind of machine learning tool, which is a non-parametric in nature [27]. In a decision tree approach, features of data (i.e., Spectral Bands) are predictor variables whereas the class to be mapped is referred to as the target variable [27]. Training a decision tree classifier is much faster [28-29].

F. Area Estimation

Number of pixels covering each class can easily be obtained from classified image. Area of particular class can be calculated as follows:

$$A_c = P_c * r * r / 100000 \qquad (5)$$

Where, A_c is the area of class c in ha;
P_c is the total number of pixels in class c;
and r is the resolution of image e.g. in case of Landsat 8 OLI, r=30 m.

IV. MODEL DEVELOPMENT

To identify the mango orchard of Lucknow, Landsat 8 OLI images were undertaken and pre-processed. Several vegetation indices such as NDVI, MNDWI, SAVI, MSAVI and BSI were calculated and separabilty index was critically analysed and after thorough critical analysis, it is observed that NDVI, MNDWI and SAVI are segregating the taken seven land cover classes, namely, water body, urban area, bare coil, sparse vegetation, medium vegetation, mango orchard and dense vegetation, and ground truth data for these classes were also collected. After it, by using the observed decision boundaries knowledge based decision tree classification (DTC) was applied and classified image was retrieved. Accuracy assessment has been carried out to measure the performance of DTC and to compare the performance of DTC, ISODATA and ML were used.

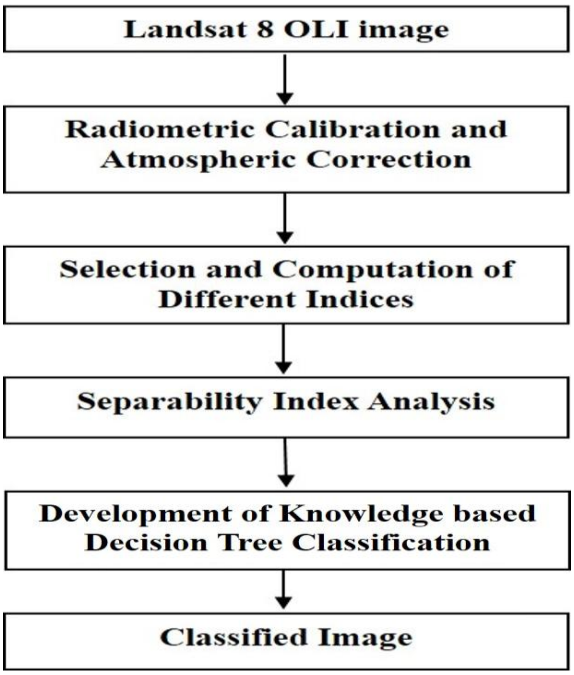
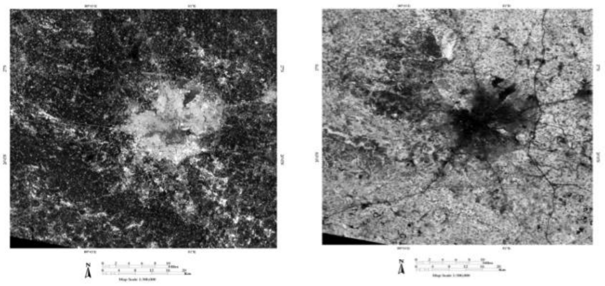


Fig. 3. Flow chart showing the steps performed for the image classification.

To develop the decision tree, three different years from 2015 to 2017 images has been considered, where 2015 image is used to develop the DTC, 2016 is used to test the and 2017 image is considered to validate the performance of proposed DTC. After retrieving the classified mango regions, area estimation has been performed on all three years images to compute the actual mango area presented there. The estimated mango areas are also verified with the information reported by Department of Agriculture, Cooperation and Farmers welfare, Govt. of India and it is observed that estimated area is very much near to the received ground truth data.

A. Pre-processed images

The image pre-processing involves radiometric calibration and atmospheric correction. Radiometric calibrations convert DN values to reflectance values and also correct the pixel value errors. It improves the quality of satellite image by reducing the noise. Images were also atmospherically corrected by removing atmospheric effects to determine the true surface reflectance values. Radiometrically calibrated Red and NIR bands images are shown in Fig 4 (a) and 4 (b).

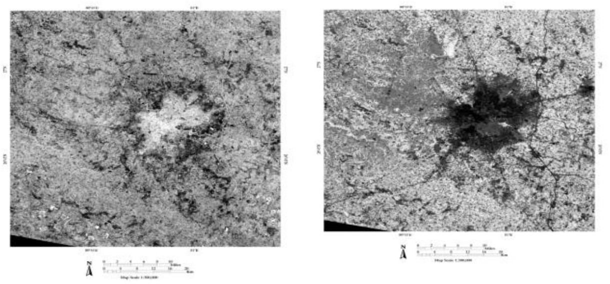


(a) **(b)**

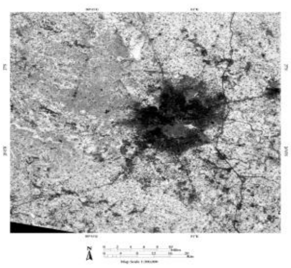
Fig. 4. Pre-processed images, (a) Red, and (b) NIR band

B. Calculation of NDVI, MNDWI and SAVI

The NDVI, MNDWI and SAVI images were derived using "(1)", "(2)" and "(3)", respectively and these images are shown in Fig. 5 (a), 5 (b) and 5 (c).



(a) **(b)**



(c)

Fig. 5. Vegetation indices, (a) MNDWI, (b) NDVI and (c) SAVI

NDVI image provide information of vegetation and non-vegetation presence, MNDWI image provide information of water presence such as seasonal Rivers, ponds, lakes, etc., and SAVI image provide presence of vegetation by removing background soil effect.

C. Separability Analysis

For the classification of multi-temporal satellite images, the undertaken images were atmospherically corrected to nullify the effect of year to year and seasonal variations in weather condition on the images. MNDWI, NDVI, SAVI, MSAVI and BSI were computed using atmospherically corrected images. These Indices were used to classify the water bodies, vegetations, built-up areas and bare soil. But, it was found that MNDWI was failed to classify the water bodies correctly. Similarly, in case of NDVI, MSAVI the spectral values of these indices increased significantly and classification accuracies were low. However, MNDWI and NDVI performed well when computed directly from satellite images without atmospherically correcting these images. But different vegetation classes viz. sparse vegetation, medium vegetation, mango orchard and dense vegetation, were successfully classified using SAVI image. Keeping these facts in view, the separability index for MNDWI, NDVI, MSAVI and BSI were derived using "(4)".

Table- II: Separability index value for different land covers classes under different indices

CLASS 1	CLASS 2	SEPARABILITY INDEX
	NDVI	
water body	bare soil, urban, vegetation	1.12
vegetation	bare soil, urban	**1.67**
urban	bare soil	**2.11**
	MNDWI	
water body	bare soil, urban, vegetation	**3.07**
vegetation	bare soil, urban	0.6
urban	bare soil	1.5
	SAVI	
water body	bare soil, urban, vegetation	1.02
vegetation	bare soil, urban	1.11
urban	bare soil	2.08

The separability index from Table-II, clearly indicated that separability of water body from other classes is very good and highest as well, using MNDWI, hence water body was segregated first from all other classes. Separability between bare soil and urban area is better using NDVI than other indices. Similarly, separability between vegetation and bare soil including urban land derived by NDVI is better among other four indices.

In case of MSAVI and BSI, either the separability indices between different class's combinations are too low to accept or other indices like: MNDWI, NDVI, and SAVI provide better separability index values. Hence, MSAVI and BSI were dropped and only MNDWI and NDVI, and SAVI images were considered for development of DTC.

D. Development of Knowledge based Decision Tree Classification

In order to develop the DTC, Landsat 8 OLI images of 14-Feb-2015 were undertaken. Thereafter, Vegetation Indices MNDWI, NDVI, and SAVI were computed and separability analysis thoroughly performed. The schematic diagram of Knowledge based Decision Tree classification is shown in Fig. 6. In this DTC, classes are at leaves and each node contains decision expression. Decision boundaries were obtained by using the minimum and maximum index values of each class in corresponding indices.

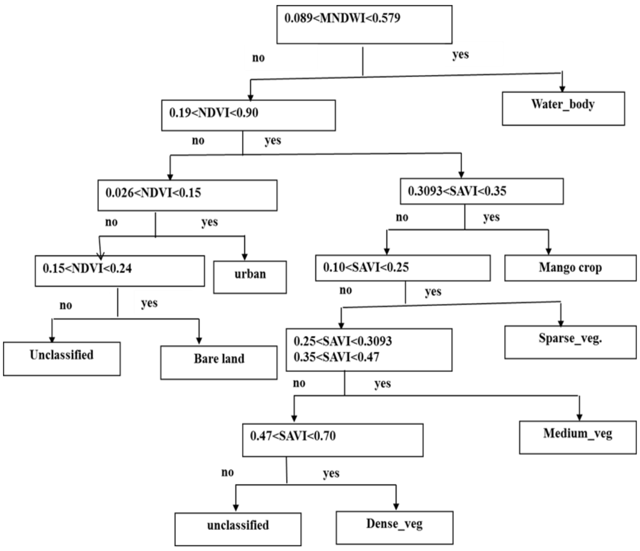


Fig. 6. Proposed Decision Tree Classifier

From Fig. 6, it is observed that initially water class is separated by using MNDWI index and after that urban and bare soil classes are segregated through NDVI index. Vegetation class is classified using SAVI index, which is later decomposed into Mango, sparse vegetation, medium vegetation and dense vegetation.

V. RESULT AND DISCUSSIONS

A. Knowledge based Decision Tree Classification (DTC)

The proposed DTC is applied to classify the NDVI, MNDWI and SAVI images of the year 2015 and it is observed that proposed DTC has classified the Lucknow region image effectively and efficiently. To assess the performance of the classified image, classification accuracy has been retrieved. The classified image is shown in Fig. 7, where red, yellow, blue, cyan, light green, deep green and medium green colors represent the urban areas, bare soil, water bodies, sparse vegetation, medium vegetation, mango orchard and dense vegetation, respectively.

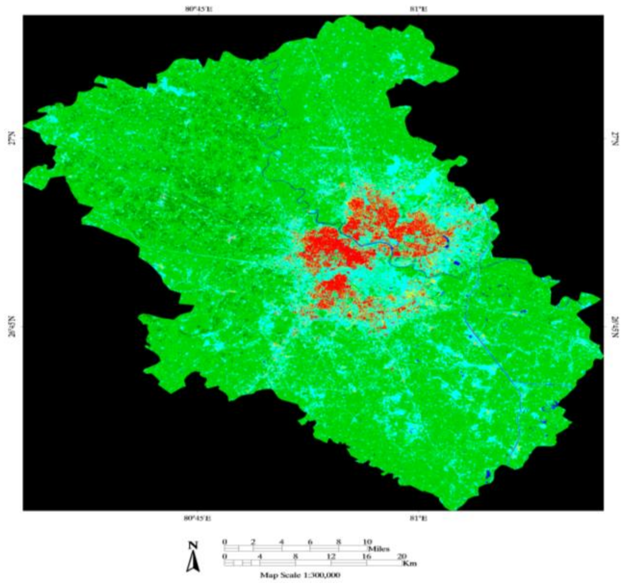


Fig.7. Classified Landsat 8 OLI image of 14-Feb-2015.

In next step, performance of DTC was assessed by utilizing the classified image of 14-Feb-2015 image as the reference image and by computing the Overall Accuracy (OA) and Kappa Coefficient (KC). The performance of proposed DTC was compared with ISODATA and ML classifiers. Various accuracy parameters of ISODATA, ML and DTC were computed from confusion matrix and is shown in Table III.

Table- III: Producer accuracy, user accuracy, overall accuracy and Kappa coefficient of image of 14-Feb-2015 classified by using proposed Decision Tree, ISODATA and Maximum Likelihood (ML) classifiers.

Class	Producer's/ User's Accuracy					
	DTC		*ISODATA*		*ML*	
	Prod. Acc. (%)	User's Acc. (%)	Prod. Acc. (%)	User's Acc. (%)	Prod. Acc. (%)	User's Acc. (%)
Water body	97.13	100	76.98	23.62	97.84	93.97
Urban area	98.25	99.41	82.4	26.50	97.56	99.38
Bare Soil	45.33	91.89	00	00	76.74	96.35
Mango orchard	73.44	79.66	59.65	75.56	39.47	100
Sparse Vegetation	99.57	64.62	00	00	99.30	71.00
Medium Vegetation	67.56	91.40	50.51	73.53	71.00	49.62
Dense Vegetation	100	99.09	00	100	100	99.62
	OA=86.69, KC=0.83		OA=51.79, KC=0.41		OA=84.61, KC=0.81	

The result of proposed DTC produces very good Overall Accuracy and Kappa Coefficient values as 86.69% and 0.83, respectively which is highest among ISODATA, ML and DTC. Furthermore, producer and user accuracies of DTC are very good for all classes. It proves that DTC is the best classifier among these classifiers. DTC is further tested and validated using images of 2016 and 2017, respectively.

B. Testing of proposed Decision Tree Classifier

As testing phase the developed DTC has been used to classify the 2016 year image to test the performance of it. The classified image is shown in Fig. 8, where red, yellow, blue, cyan, light green, deep green and medium green colors represent the urban areas, bare soil, water bodies, sparse vegetation, medium vegetation, Mango Orchard and dense vegetation respectively. Also, the performance of DTC was compared with ISODATA and ML and obtained accuracies are given in Table IV.

The result from Table IV revealed that Overall Accuracy is 70.66% and Kappa Coefficient is 0.65. Producer and user accuracies are also very good for all classes. This testing result showed that proposed DTC has classified the 2016 year image quite efficiently.

C. Validation of proposed Decision Tree Classifier

With the aim to validate the performance of Decision Tree Classifier, Landsat 8 OLI image of year 2017 was classified. The classified image is shown in Fig. 9, where red, yellow, blue, cyan, light green, deep green and medium green colors represent the urban areas, bare soil, water bodies, sparse vegetation, medium vegetation, mango orchard and dense vegetation respectively. Thereafter, the performance of decision tree was accessed in terms of overall accuracy and Kappa coefficient. User and producer accuracies were also computed and compared with ISODATA and ML and obtained accuracies are given in Table IV.

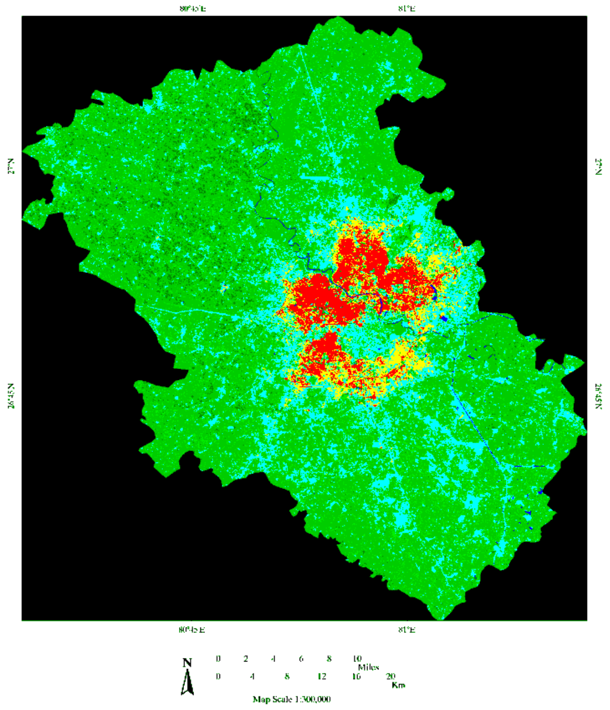


Fig. 8. Classified Landsat 8 OLI image of 17-Feb-2016.

Table- IV: Producer, user and overall accuracies and Kappa coefficient of image of 17-Feb-2016 classified by using proposed Decision Tree.

Class	Producer's/ User's Accuracy	
	Prod. Acc. (%)	*User's Acc. (%)*
Water body	93.14	100.00
Urban area	99.42	91.89
Bare Soil	50.67	56.72
Mango Orchard	68.75	34.58
Sparse Vegetation	68.67	64.52
Medium vegetation	42.81	58.45
Dense vegetation	77.88	97.69
	OA= 70.66 KC=0.65	

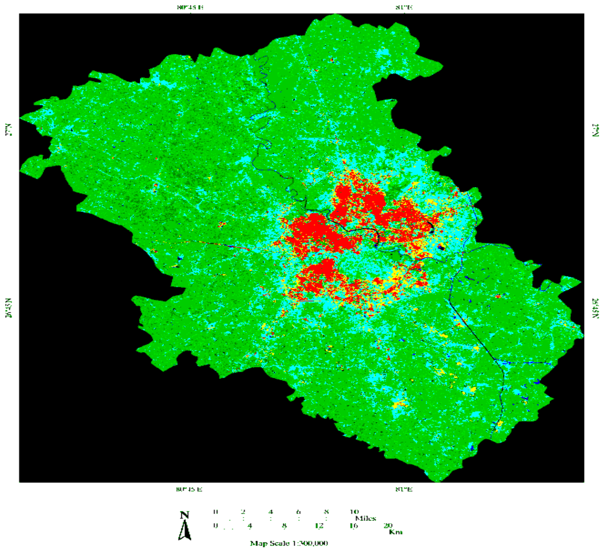


Fig. 9. Classified Landsat 8 OLI image of 3-Feb-2017.

From Table V, it is found that producer and user accuracies are also obtained very well for all the classes. The result also revealed that the OA is 75.51% and, KC is 0.70 for the image of year 2017, which indicates that proposed DTC is also effectively validated on 2017 year image.

Table-V: Producer, user and overall accuracies and Kappa coefficient of image of 3-Feb-2017 classified by using Decision Tree.

Class	Producer's/ User's accuracy	
	Prod. Acc. (%)	*User's Acc. (%)*
Water body	70.59	100.00
Urban area	100.00	86.80
Bare Soil	66.67	84.75
Mango Orchard	60.94	33.33
Sparse vegetation	69.96	69.36
Medium vegetation	57.53	67.72
Dense vegetation	95.85	95.85
	OA=75.51, KC=0.70	

For all three years images from 2015 to 2017, it is observed that overall accuracies varied 70.66% for the image of year 2016 to 86.69% for the image of year 2015. Similarly, KC varied from 0.65 for the image of the year 2016 to 0.83 for the image of year 2015, which suggest that the proposed DTC is quite acceptable to classify the Landsat 8 OLI images to monitor the Mango Orchards.

From the results of Tables III, IV and V, it can be seen that values of overall accuracy and Kappa coefficient of DTC are 86.69 and 0.83, respectively which are highest among all classifiers. Furthermore, the mango orchard area estimated by the image classified by Decision tree is 28,225.71 ha, which is in very good agreement with the area reported by Department of Agriculture, Cooperation and Farmers welfare, Govt. of India as given in Table VI. Even though, overall accuracy and Kappa coefficient values of ML classifier are also satisfactory but in this case mango orchard area is underestimated. Hence, this classifier was rejected. For the rest of classifiers except DTC, either OA or KC is too low or mango orchard area is under/over estimated. Hence, these classifiers are rejected. Therefore, it can be concluded that knowledge based Decision Tree is the best classifier among five classifiers (one unsupervised and four supervised) to monitor the mango orchard.

D. Area estimation of mango orchard for years 2015-17

Mango Orchard areas identified in Lucknow region is estimated by using the "(2)" all three years (2015-2017) images. The estimated areas are given in Table VI.

Table-VI: Estimated area ('000 ha) of mango orchard by using image classified by DTC vs. mango area reported by concerned Govt. Department.

Year	2015	2016	2017
Estimated Area ('000 ha) by DTC	28.22	29.41	28.00
Reported Area (´000 ha)	28.07	29.47	29.66

Mango Area as reported by 'Horticultural statistics at a glance of corresponding years(2015-17)', Department of Agriculture, Cooperation and Farmers welfare, Min. of Agriculture and Farmers welfare, Govt. of India. This study revealed that the mango orchard area estimated by proposed Decision Tree Classifier has good agreement with the area reported by concerned Govt. Department. In future, this type of information may be utilized for better understanding of Mango Orchard and their monitoring.

VI. CONCLUSION

The study shown that mango orchard can be classified with high accuracy using Landsat 8 OLI images. It also showed that with the multi-temporal image classification can be performed for perennial fruit crops like mango, with high degree of accuracy. It can also be concluded that Decision tree classifier outperformed ISODATA and ML classifiers. It is concluded that cloud free satellite images of the month of February is most suitable for mango orchard classification. This type of study is useful for crop planning, making decision on development of infrastructure and crop area expansion. For mango orchard, the use of satellite data for assessment of area is feasible due to medium to big orchard that is perennial in nature. In the future, DTC based approach would be used to develop the Fruit Crop Monitoring System to monitor the growth of Mango fruit trees at regular interval.

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REFERENCES

1. S. Kumaravel, T. Ramkumar, B. Gurunanam, M. Suresh and K. Dharanirajan, "An Application of Remote Sensing and GIS Based Shoreline Change Studies – A Case Study in the Cuddalore District, East Coast of Tamilnadu, South India," *International Journal of Innovative Technology and Exploring Engineering (IJITEE),* 2013, Vol. 2, No. 4, pp.211-215.
2. I.S. Yadav, N.K. Srinivasa Rao, B.M.C. Reddy ., R.D. Rawal, V.R. Srinivasan, N.T. Sujatha, C. Bhattacharya, P.P. Nageswara Rao, K.S.Ramesh and S. Elango " Acreage and production estimation of mango orchard using Indian Remote Sensing (IRS) satellite data," *Scientia Horticulturea*, 2002, Vol. 93, pp. 105-123.
3. R. Hebbara, H. M. Ravishankara, Shivam Trivedia, S.R. Subramoniama, Uday Raja and V.K. Dadhwal. "Object oriented classification of high resolution data for inventory of horticultural crops," The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2014, Vol. XL-8, Doi: 10.5194/ isprsarchives-XL-8-745-2014.
4. Widiatmaka. "Integrated use of GIS, AHP and remote sensing in land use planning for tropical high altitude vegetable crops," *Journal of Applied Horticulture* , 2016, Vol. 18, No. 2, pp. 87-99.
5. K. Chaudhari, N. Nishant, G. Upadhyay, R. More1, N. Singh, S. P. Vyas and B. K. Bhattacharya," Crop inventory of orchard crops in India using remotely sensed data," The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2019, Vol. XLII-3/W6, ISPRS-GEOGLAM-ISRS Joint Int. Workshop on "*Earth Observations for Agricultural Monitoring*", 18–20 February 2019, New Delhi, India).
6. S.S. Panda, and G.J.P. Hoogenboom, "Distinguishing blueberry bushes from mixed vegetation land-use using high resolution satellite imagery and geospatial techniques," *Computers and Electronics in Agriculture*, 2009, Nol. 67, No. 1–2, pp.51–59.
7. K. Usha,and S. Bhupinder, "Potential applications of remote sensing in horticulture—A review," *Scientia Horticulturae*, 2013, Vol. *153*, pp. 71–83.
8. Van Aardt, J.A.N., H.W. Randolph, and J.A. Scrivani, "Lidar-based mapping of forest volume and biomass by taxonomic group using structurally homogenous segments," *Photogramm. Eng. Remote Sensing*, 2008, Vol. 74, 1033–1044.
9. Q.U. Zaman, A.W. Schumann, D.C. Percival, , S. Read, and T. J. Esau, "Performance evaluation of a prototype variable rate sprayer for spot-application of agrochemicals in wild blueberry fields," *In*: 10th International Precision Agriculture Conference ASA., 2010, Colorado State University/International Plant Nutrition Institute/Foundation for Agronomic Research, Denver, CO.
10. C. Gómez, J.C. White, and M.A. Wulder, "Optical remotely sensed time series data for land cover classification: A review," *ISPRS Journal of Photogrammetry and Remote Sensing*, 2016, Vol.116, pp. 55-72.
11. N. Thakur and D. Maheshwari, "A review of image classification techniques," *International Research Journal of Engineering and Technology (IRJET)*, 2017, Vol.4, No. 11, pp. 1588-1591.
12. Y. Hu, K. Ashenayi, R. Veltri, G. O'Dowd, G. Miller, R. Hurst, R. Bonner," A comparison of neural network and fuzzy c-means methods in bladder cancer cell classification," IEEE International Conference on Neural Networks, IEEE *World Congress on Computational Intelligence*, 1994, Vol. 6, pp. 3461 – 3466.

13. F. S., Al-Ahmadi, & A. S. Hames,. "Comparison of Four Classification Methods to Extract Land Use and Land Cover from Raw Satellite Images for Some Remote Arid Areas, Kingdom of Saudi Arabia," *JKAU Earth Sci*., 2009, Vol. 20, No.1, pp. 167-191.
14. Lu, & Q. Weng, "A survey of image classification methods and techniques for improving classification performance", *International Journal of Remote Sensing*, 2007, Vol. 28, pp. 823-870.
15. Mishra, P and Singh, D.," Land cover classification of PALSAR images by knowledge based decision tree classifier and supervised classifiers based on SAR observables," *Progress In Electromagnetics Research B*, 2011, Vol. 30, pp. 47–70.
16. M.A., Friedl and C. E. Brodley, "Decision tree classification of land cover from remotely sensed data," *Remote Sensing of Environment*, 1997, Vol. 61, pp.399–409.
17. G. De'ath,, and K.E. Fabricius, "Classification and regression trees: A powerful yet simple technique for ecological data analysis," *Ecology*, 2000, Vol. 81, No.11, pp.3178–3192.
18. S.S. Panda, G.J.P. Hoogenboom and O.P. Joel, "Remote sensing and geospatial technological applications for site-specific management of fruit and nut crops: A review," *Remote Sensing*, 2010, Vol. 2, pp. 1973-1997.
19. S. Roy, R. More, M.M. Kimothi, S. Mamatha, S.P Vyas and S.S. Ray, "Comparative analysis of object based and pixel based classification for mapping of mango orchard in Sitapur district of Uttar Pradesh", *Journal of Geomatics*, 2018, Vol. 12, pp. 69-76.
20. A. Kumar, "*Ground Water Brochure of Lucknow District, Uttar Pradesh*", 2009, (A.A.P.: 2008-09).
21. J.W. Rouse,"Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation," Final rep. NASA/GSFC, Greenbelt, MD**,** 1974.
22. H.Q Xu,. "Modification of normalised difference water index (MNDWI) to enhance open water features in remotely sensed imagery," *Int. J. Remote Sens.* 2006, Vol. 27, 3025–3033.
23. A. R. Huete, "A soil-adjusted vegetation index (SAVI'", *Remote Sensing of Environment*, 1988, Vol. 25, 53-70.
24. L. Meghwal, T. Ahmed, D. Singh, and B. Raman, "Classification of Land Cover Using Different Indices on MODIS Imagery," National Conference Recent Trends on Microwave Techniques and applications, 2012, Jaipur, India.
25. A. E. Maxwell, A. Timothy. Warner and Fang Fang, "Implementation of machine-learning classification in remote sensing: an applied review," *International Journal of Remote Sensing*, 2018, Vol. 39, No. 9, pp. 2784-2817.
26. B.Dixon and V. Uddameri, "Image classification methods," In: *GIS and Geocomputation for water resource science and engineering*, 2015, 545P.
27. W.M. Shen, W.J. Wang and H.J. Luo, "Classification Methods of Remote Sensing Image Based on Decision Tree Technologies," *Remote Sensing Technology and Application*, 2007, Vol. 2, No. 3, pp. 333-338.
28. L., Breiman, J.H., Friedman, R.A, Olshen and C.J. Stone, "Classification and Regression Trees," Wadsworth, Belmont, 1984.
29. M. Pal, and P.M. Mather, "A comparison of decision tree and backpropagation neural network classifiers for land use classification," IEEE International Geoscience and Remote Sensing Symposium, 2002, IGRASS 02, Vol. 6, pp.503-505.

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