Rule base Knowledge and Fuzzy Approach for Classification of Specific Crop and Acreage Estimation

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ABSTRACT
Estimation of specific crop and acreage plays a vital role in the field of crop planning, monitoring, crop condition, yield forecasting and acreage estimation. There have been several studies conducted to classify the crops at continental to the regional level, but still, work is needed to map small area covered by different crops using Remote Sensing technology.
The main objective of the present study is to explore whether the Fuzzy classifier can improve the accuracy of crop classification as compared to other traditional Classifiers, such as Maximum likelihood, Mahalanobis etc. The attempt has been done to classify different crops at a smaller scale. The Landsat time series 8 band OLI data was used to investigate multiple crop phenomena. Two scenes were acquired in Kharif seasons (September 28 and October 30, 2014). Three indices such as NDVI, SAVI, and RVI, were used to know vegetation condition. The Spectral signatures generated from data for the residues of Sugarcane and Maize based on prior knowledge of the field work. Four techniques based on Maximum Likelihood, Mahalanobis Classifier, Knowledge classifier and fuzzy classification techniques were used to extract the crops information based on the signatures. The resulting overall classification accuracy was calculated using stratified random sampling method. The corresponding performance efficiency of these four methods was found to be 84%, 85%, 87% and 90.67%, respectively, indicating the fuzzy method to be the most efficient as compared with other classification techniques.

Keywords
Crop Classification, Fuzzy Classifier, Knowledge Classifier, Landsat Data, NDVI.

1. INTRODUCTION
The field of remote sensing plays a very important role in the process of decision making. It depends on the classification techniques for better estimation. Several classification techniques for remote sensing have been used to identify and classify the feature for the different purpose [1], [2], [3]. The crop identification and acreage estimation are very important for countries with the agricultural based economy [4]. Maximum Likelihood Classifier is the method used for classification purpose but the misclassification error is unavoidable [5]. To overcome the mixed pixel classification problem, Zadeh proposed a theory called "Fuzzy Sets" in 1965. The theory works on the principle that a single pixel is composed of more than one feature, so each feature must be classified differently. Fuzzy logic is a relatively better theory that can be used to solve the mixed pixel problems [6], [7]. The application area of fuzzy logic has a wide range such as process control, management and decision making, operations research, economics, pattern recognition and classification [8], [9].The knowledge-based classification system is used to gain better classification accuracy over traditional classifiers. This system helps to reduce the dimensionality of features and decreases the misclassification errors. Due to this ability, an expert system of classification is used for many real-time applications [10], [11].

Landsat is widely used for monitoring earth from space. The First Satellite was launched in 1972. Landsat provides global coverage; it covers the global area with wall to wall scanning. Landsat carries Multi Spectral Scanner (MSS), whereas Landsat 7 carries Enhanced Thematic Mapper (ETM+) sensor. In 2011 USGS Launched 8 band satellite i.e. Landsat 8 OLI (Operational Land imager). Landsat data were coupled with ground knowledge and cropping pattern during September and October 2014. Table 1 shows the details about satellite data for two different days of the year with their acquisition time [12].

The literature study investigates the various approaches proposed on the fuzzy classifier in Fuzzy C-Means (FCM), Possibilistic C-Means (PCM) and Soft Classification [12]. During the past decade, many scientists have used fuzzy classification techniques for land cover mapping, crop classification and discrimination of specific crops [13], [14]. Fuzzy c-means (FCM) algorithms are mostly used for discrimination of specific crops. It is unsupervised classification technique based on clustering algorithm that determines the membership value. It does not require any prior knowledge about study area [14], [15]. [16] used fuzzy classification for enhancing complexity and heterogeneity of vegetation [17]. The Bayu Andrianto Wirawan used Fuzzy c-means (FCM), fuzzy shape and fuzzy adjusted for complex land cover mapping from central Java, Indonesia on Landsat ETM + data [18]. [17] have done studies on fuzzy classifier for mapping forestry, urban planning and savanna woodlands using supervised fuzzy convolution filter to reduce the ambiguity of natural land covers where they disappear and dominated by medium to tall grasslands [19]. Three cities in the state of Sao Paulo, Brazil used 12 images of Landsat satellite from 2002 to 2004 for classification of the agricultural crop (Sugarcane, Soybeans, and Corn) based on Hidden Markov Model (HMM) and achieved 93% accuracy on the identification of correct crops [20]. Mapping of sugarcane planted area using artificial intelligence; object-based image analysis and Data mining were used in a study area located in Sao Paulo state, which is well representative of the agriculture of large regions of Brazil and other countries [21]. Unsupervised classification techniques, ISODATA clustering algorithm was used for analysis of Kharif crop and cropping pattern in Utter Pradesh an indo-genetic plain, India. The crops that were discriminated were paddy, maize, and sugarcane [17]. Since 2000 to 2005 Southwestern Brazilian Amazon used MODIS time series data and applied wavelet transformation to determine the growth of row crops and raising the number of crops grown in the area, they got an overall accuracy of 94% [22].

To study cropping phenology several studies conducted at local to regional level using fine resolution multispectral data. The data of Landsat 8 band OLI can also be used for this purpose [23], [24], [25], [26], [27]. The selection of appropriate sensors which are best suitable for the studies depends on the study area, global or regional use, user's need with respect to their spatial, spectral and temporal resolution, availability of data and their cost. The main objective of this study is to find out the crop identification and acreage which will be helpful for the Crop Acerage and Production Estimation (CAPE) and Forecasting Agricultural output using Space, Agrometeorology and Land based observations (FASAL) program of the government of India [28].

2. STUDY AREA

Vaijapur is headquarter of Vaijapur Tehsil of Aurangabad district (Maharashtra) (19° 55' 12" N 74° 43' 48" E) located on the bank of Narangi River. It is also known as the Gateway of Marathwada. Agriculture is the main economic activity in the region. Local people depend on the water availability of Narangi River and Nandur- Madhmeshwar Canal. The study area has good diversity due to occurrence of urban built-up that comprises of different types of built up areas such as densely populated area, moderate populated area and less populated area with more vegetation and open area. There are two main cropping seasons: KHARIF (June to October) and Rabbi (November to April). Principle crops in Vaijapur region are Cotton, Jowar, Wheat, Pulses, Groundnut, Maize, and Sugarcane. The present study focuses on distinguishing individual agricultural crops of Vaijapur Tehsil.

3. DATA USED

The two temporal images have been acquired in kharif seasons for the months of September and October 2014, respectively. The reason behind the selection of these temporal images is that Maize gets harvested in the month of October. The two Landsat 8 Band OLI cloud free data (path/row: 147/46 and 147/46, 45) were procured during the period from September 28, 2014 and October-30, 2014. It was mandatory to acquire the Landsat 8 band satellite datasets of the same dates. The medium resolution of Landsat 8 OLI sensor is 30m, having the repeativity of 16 days. Data were projected in WGS 84 Datum.

4. METHODOLOGY

We have defined some variables which are suitable to extract relevant information about small area. As per the Fig. 1, Temporal data sets Landsat 8 Band OLI were acquired from NASA and the United States Geological Survey (USGS). The quality of OLI data was slightly better than the ETM+ data in the visible bands, especially near-infrared band of OLI. The OLI data is reliable source for monitoring land cover changes and earth Observation (earthexplorer.usgs.gov).

The topographical maps (1:250 000) scale obtained from Survey of India (SOI) were used for selection of ground control points (GCPs) for georeferencing purpose and also for verification of data acquired at the field [29], [30]. The satellite images were downloaded and imported in ERDAS for further analysis such as Layer Stacking, Resampling etc. The Contrast enhancement technique was applied to improve image quality using linear stretching and histogram equalization algorithms. The tehsil boundary was demarcated from SOI toposheet. We have generated standard spectral signature from training sets of AOI with collected ground control points (GCP), field survey of study area was very helpful to vary a doubtful land cover classes [31]. The scheme adopted for this work is shown in figure 1.

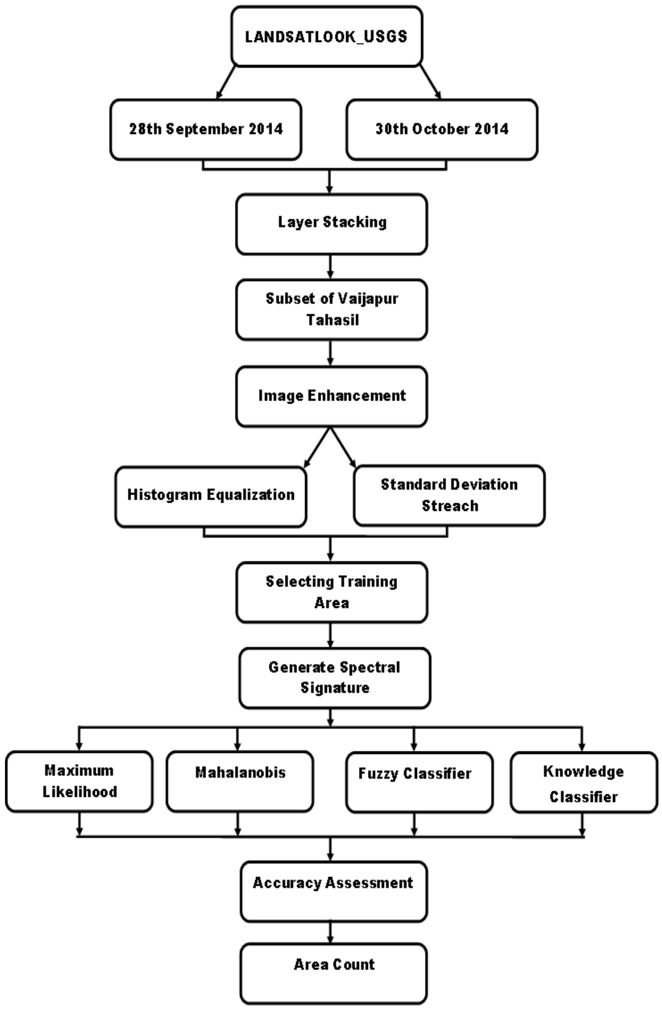


Fig 1 Flow Chart of Classification Scheme

5. FUZZY CLASSIFICATION

Fuzzy classification approach have been successfully applied in remote sensing domain for Land use Land cover, Change Detection and Classification of Remotely sensed data [32]. The limitation between different occurrences and heterogeneity within a class means fuzzy .There are many uncertainty in mixed pixel, Each pixel has a membership values for m classes (from 0 to 1) [33]. The fuzzy classification was treated coupled with Mahalanobis distance and maximum likelihood algorithm to determine the superior results and to [34], [35], [36], [37] resolve the issues regarding to imprecise pixel Berchtold, Martin, et al. 2008). It is not a remedy but it offers significant potential for extracting spatio-contextual information from imprecise pixel. [38].

We have used fuzzy rule based algorithm to classify fields as per crops i.e. Sugarcane and Maize. An important part of the study is that fuzzy convolution filter was applied to the final result. The Fuzzy Convolution operation creates a single classification layer by calculating the total weighted inverse distance of all the classes in a given window of pixels. The formula used for supervised fuzzy classifier is as follows,

$$T[k] = \sum_{i=0}^{s} \quad \sum_{j=0}^{s} \quad \sum_{l=0}^{n} \quad \frac{w_{ij}}{D_{ijl}[k]} \qquad \ldots 1)$$

Where,

i = Row Index of Window,
j = Column Index of Window,
s = Size of Window (3, 5, Or 7),
L = Layer Index of Fuzzy Set,
n = Number of Fuzzy Bands Used,
w = Weight Table for Window,
K = Class Value,
Dk = Distance File Value for Class K,
Tk = Total Weighted Distance of Window for Class K,

The center pixel is assigned the class with the maximum T(k).

This technique smoothens the image and also reduces the mixed pixel problems into classified image. Convolve image applies a user-specified convolution to the image [39], [40], It assigns the center pixel in the class with the largest total [41]. The order parameter represents the number of columns and rows in the filter kernel, and kernel is a two-dimensional array representing the convolution kernel. A 3 x 3 window size was used in the convolution process and distance used as a neighborhood weighting factor inverse distance summed over the entire set of fuzzy classification layers [41], [42].

5. KNOWLEDGE CLASSIFIER

The expert system based knowledge classifier provides a rule based approach for multispectral images. The classification techniques based on Decision Tree approach. Knowledge classifier are divided in two category knowledge engineer and knowledge classifier, Knowledge engineer provides an interface to build up decision tree define the hypothesis , rules and variables based on computed Indices value [43]. For example typical rule used by the expert system in remote sensing is

IF blue reflectance is (Condition) <15%
AND green reflectance is (Condition)<25%
AND red reflectance is (Condition)<15%
AND near-infrared reflectance is (Condition)>45%

THEN there is strong suggestive evidence that the pixel is vegetated [38].

The expert system uses the decision tree structure where the rules and condition are evaluated in order to test hypothesis. The trees are made with the hypothesis, rules and condition. The hypothesis considers root as node of the tree, each rule is the branch of the tree, and condition is the leaf [38]. The figure below represents a single branch of a decision tree depicting a hypothesis, its rule, and conditions.

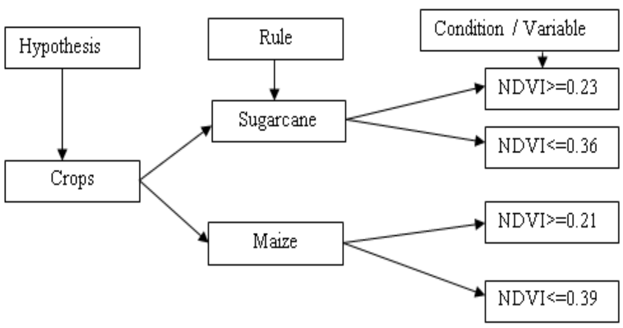


Fig 2 Variable used for Decision tree in Knowledge Classifier

Following are knowledge IF-THEN rules are derived from the decision tree

IF Class is >0.23 AND <0.36
Class type= maize
Then YES
IF class is >0.23 AND <0.36
Class type= Water OR Settlement
Then NO
IF Class is >0.21 and <0.39
Class type =Sugarcane
Then YES.

Three vegetation indices were generated.

The Normalized Difference Vegetation Index (NDVI) is calculated from this equation

NDVI = (NIR-RED) / (NIR+RED)

Where, NIR and RED represent as vegetation reflectance for IR and Red radiations, respectively. The NDVI value varies from -1 to +1.

The Soil Adjust vegetation Index (SAVI) is expressed

SAVI = (((NIR- RED)/ (NIR+RED+L)) *(1+L))

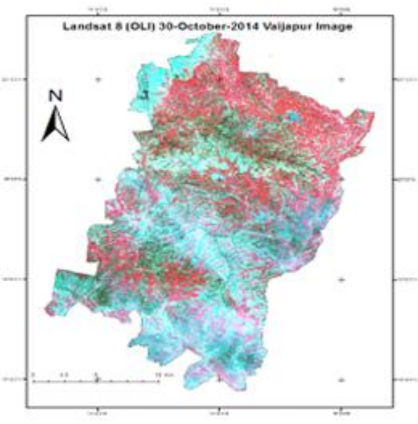
The Ratio vegetation Index (RVI) is computed from (IR/R) these two bands.

These parameters indicate the chlorophyll activity and density of vegetation cover to depict phenological changes [44]. We extracted the threshold values of evaluated indices for Sugarcane, Maize, Mixed crop, Barren Land, Fallow Land, Settlement and Water body. These threshold values are useful for Construction of decision tree in Knowledge Engineer console [45]. The standard procedure was used for classification techniques parallelepiped as non-parametric rule and parametric rule as Maximum likelihood Classifier and Mahalanobis Distance. It also generates knowledge classifier for identification of crops based on decision tree that uses time series of three vegetation indices, NDVI, SAVI, and RVI derived from Landsat OLI data corresponding to selected training sample [25], [31], [45]. Finally, we performed the accuracy assessment on the basis of stratified random sampling method and area count in hectare.

6. RESULT AND DISCUSSION

The temporal images of the study area are shown in Fig. 3(a) and 3(b). The images contain details regarding vegetation, Urban and other Land cover classes in the study area. The images are classified in seven different classes according to their land use and land cover type with the help of four classification techniques as shown in fig.1. The classified images show the significant discrimination of Sugarcane, Maize and other land cover classes in Vaijapur region.

The output of classified images using four classification techniques for the two periods are shown in figure 4 and 5, respectively .The sugarcane area appears in dark green color while maize field is shown in Lime color. It was difficult to classify the specific crop like sugarcane and Maize due to the similarity of their reflectance property. Because in the month of September health of Maize crop was better, its height and canopy structures were quite similar to sugarcane.



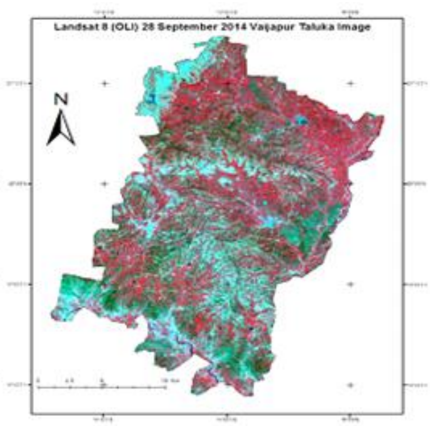


Fig 3 (a) **Fig 3 (b)**

Fig 3 Landsat 8 band OLI FCC images of study Area

So the similarity makes classification confusing resulting increased sugarcane area in month of October [46], [47]. Very few maize fields exited, as Maize would be harvested from September onwards. Harvested area gets converted into the fallow land. Therefore, the area for maize crop gets converted into fallow land. So, fallow land increased [43], [48].

Fig. 4(a-d) shows the results obtained from the four classification techniques for the period of 28 September, 2014. The Table 1 gives the results of classifications for different crops as classifications for different crops obtained from the methods. From the Table 1, mixed crop is found to be very large in the central and northern part of the study area. It may because the area is non-irrigated type. The MLC method allows a single feature per pixel which is major drawback of this classification technique. The areas of Sugarcane and Maize obtained from the MLC are 9283.41 ha and 21140.3 ha respectively. The field of Maize and sugarcane are mostly cultivated in south and north area because of water availability from Dam, Canal and River. Fig. 4 (b) shows the results obtained by Mahalanobis classifier that has almost the same results. Fig. 4 (c) shows the results obtained by Knowledge classifier. Here the barren land and fallow land is increased to 43220.0 ha and 35522.0 ha, respectively, as compared with other classifiers. The area of Sugarcane and Maize shows significant changes i. e. 7237.35 and 39342.1 ha respectively, (see Table 1) as compared with other classifiers.

The area of other crops has been increased to 67512.7 ha in the central part of the study area as shown in Fig4 (d).

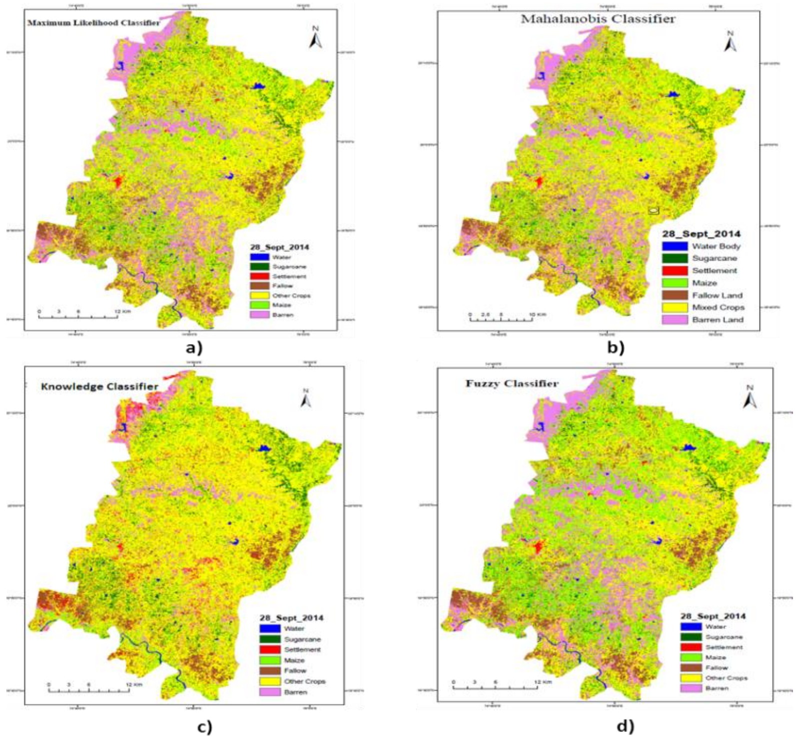


Fig 4 Classified Images for 28-Sept-2014

a) Maximum Likelihood Classifier (b) Mahalanobis Classifier (c) Knowledge Classifier (d) Fuzzy Classifier

Fig. 5(a-d) shows similar results for the period of 30 October, 2014. Fig. 5 (a) shows the results of Maximum likelihood classifier method which shows the fallow land is covering the maximum area that is 55338.5 ha. It may be due to the harvesting of Maize during the month of October so the crop land is converted into the Fallow land. The Fig. 5 (b) shows the results as obtained by Mahalanobis classifier. It shows increased area of other crops to 49761.5 ha and barren land is about 40118.7 ha. The Fig. 5(c) shows the results obtained by Knowledge classifier. Here the area of other crops is increased to 49761.5 ha. The total settlement area has been reduced to 977.06 ha which is very less as compared to value obtained by other classifiers. Fallow land has been increased to 55671.5 ha. The fig. 5 (d) shows that the result obtained by Fuzzy classifier. As per the method, the area for the Maize crop is reduced to 3187.53 ha. The area for mixed crop is also reduced to 40322.5 ha due to the harvesting of other crops. The rainfall also reduced so, change in water bodies can be seen in the form of change in its area to 320.33 ha where as in the month of Sept. it was 1338.91ha as shown in table 1.

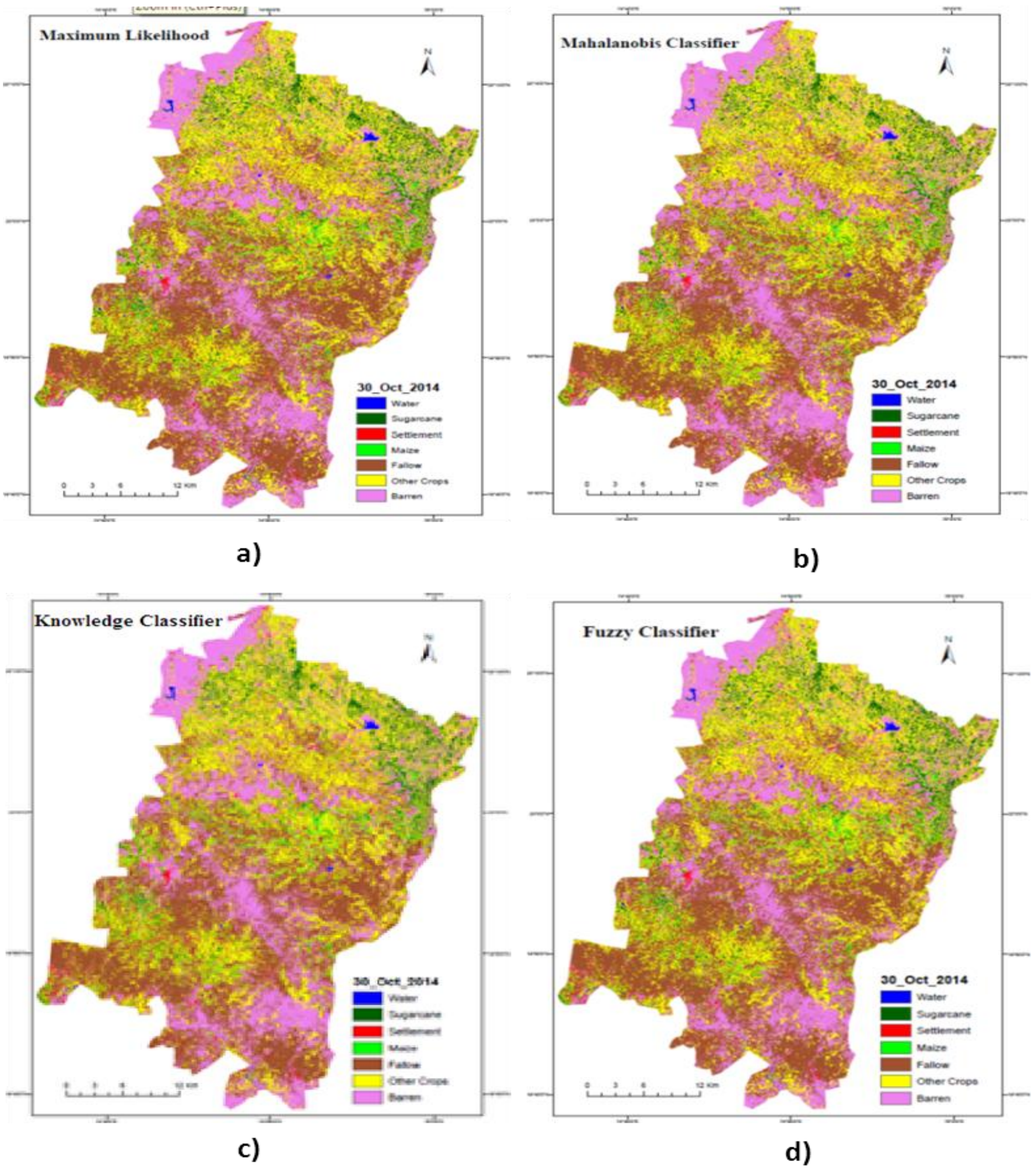


Fig 5 classified Images of 30-October-2014

a) Maximum Likelihood Classifier b) Mahalanobis Classifier c) Knowledge Classifier d) Fuzzy Classifier

Table 1 shows the results, about crop cover area in hector using Fuzzy techniques. 7237.35ha Sugarcane and 39342.1ha Maize in the month of September was determined. The area about 9479.79 ha for Sugarcane and 3187.53 ha for Maize have been occupied for the month of October from overall 159473.4 ha of Vaijapur geographical area. During the last week of October sugarcane can be easily identified as compare to other crops because maize fields are probably harvested while Rabbi Crops are in the initial stage of growth like Jowar, wheat, onion in the October month end.

Table 1. Comparison of different classification techniques for different Land use classes of September 28, 2014

Method	Fuzzy Classifier	Knowledge Classifier	Mahalanobis classifier	Maximum Likelihood
Class Name	**Area in Hector**			
Water	1338.91	1580.13	1344.6	1152.38
Sugarcane	7237.35	16282.0	8673.37	9291.41
Maize	39342.1	17254.0	21441.3	21165.4
Fellow Land	15827.5	35522.0	15436.3	16037.3
Barren Land	26608.1	43220.0	28329.1	27199.8
Settlement	1606.79	1587.22	1589.78	1587.7
Other Crops	67512.7	44028.1	82659.0	82939.0
Total	159473.5	159473.5	159473.5	159473.5

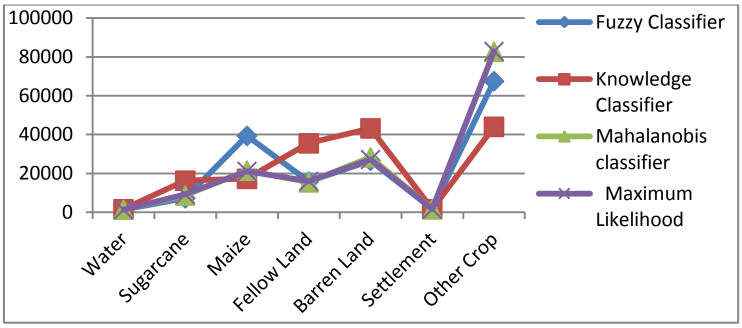


Fig 6. Distribution of land covers area in different classification methods for September 28, 2014

The spectral growth curve obtained from four classification techniques, MLC classifier, Mahalanobis, Knowledge Classifier and Fuzzy Classifier, are shown in Fig. 6. The graph for growth profile of MLC and Mahalanobis is higher as compared to knowledge and fuzzy classifier. In particular the MXL classifier cannot be used effectively for Discrimination of vegetation types, while fuzzy had relatively better performance for identification of sugarcane and Maize crop.

Table 2. Comparison of different classification techniques for different Land use classes of October 30, 2014

Methods	Fuzzy Classifier	Knowledge Classifier	Mahalanobis classifier	Maximum Likelihood
Class Names	**Area in Hector**			
Water	320.332	355.2	351.697	355.186
Sugarcane	9479.77	10989.79	10529.1	10989.8
Maize	3187.53	3687.28	3332.32	3687.2
Fellow Land	79473.2	55671.5	53510.1	55338.5
Barren Land	25062.5	38031.2	40118.7	37332.4
Settlement	1627.57	977.06	2026.13	2018.9
Other Crops	40322.5	49761.47	49605.5	49751.4
Total	159473.5	159473.5	159473.5	159473.5

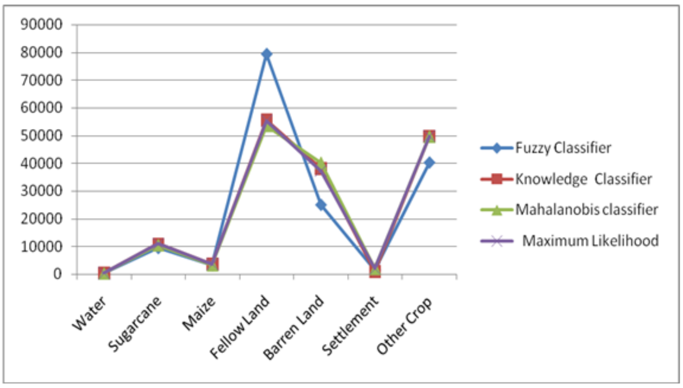


Fig 7 Distribution of land covers area in different classification methods for October 30, 2014

The table 2 shows results corresponding to different classifiers. The fuzzy classifier shows the different values as compared with the other classifiers. As our main focus is on crop discrimination, Sugarcane and Maize area is varying considerably in Fuzzy classifier as compared with other classifiers. The Mahalanobis and Maximum likelihood classifier show the area about 3687 ha whereas the Fuzzy classifier shows 3187 ha for Maize crop. This difference may be due to the increase of fallow land at the same time. The same principle is applicable for the sugarcane also.

Crop Spectral Growth Profile

NDVI images were generated from a finer Resolution (15 m) of Landsat OLI sensor data. These were generated for temporal spectral crop growth profile. The temporal NDVI training data set values for all seven classes are shown in Figs.8 and 9. It may be observed that values of NDVI for sugarcane and maize after the month of October always remain less as compared to corresponding values for the month of September. During the two temporal sets, it shows the difference between the growth pattern of sugarcane and maize crop [41], [20]. Computed values of NDVI images from Landsat 8 Band OLI for the study area were used for creating the crop growth profile. The NDVI values for two datasets are also given in their spectral growth profile.

7. ACCURACY ASSESMENT

To validate the multiple crop estimation, accuracy assessment is carried out using stratified random sampling method. The equal numbers of sample points, 150, were allocated for each stratum. Also it estimates through confusion matrix or error matrix in terms of Producer's accuracy, User's accuracy and overall accuracy with Kappa coefficient are generated. Overall classification accuracy results and kappa coefficient for different techniques are summarized in tables 3 to 6, respectively. The Mahalanobis method gives poor classification performance for the classification types as compared to other Techniques. The MLC also shows almost same result.

Table3. Classification Accuracy Assessment of Knowledge Classifier for 28 Sept- 2014

Class Name	Reference Total	Classified Total	Number Correct	Producers Accuracy	User Accuracy
Maize	10	14	10	100.00%	71.43%
Settlement	9	10	9	100.00%	90.00%
Water	8	10	8	100.00%	80.00%
Fellow Land	19	13	13	68.42%	100.00%
Barren Land	15	15	13	86.67%	86.67%
Sugarcane	13	12	12	92.31%	100.00%`
Other Crops	26	26	22	84.62%	84.62%
Total	100	100	87	87%	

Overall Classification Accuracy = 87.00%
KAPPA (K^) STATISTICS = 0.84

Table4 .Classification Accuracy Assessment of Fuzzy Classifier for 28 Sept- 2014

Class Name	Reference Total	Classified Total	Number Correct	Producers Accuracy	User Accuracy
Maize	26	30	25	96.15%	83.33%
Settlement	11	10	10	90.91%	100.00%
Water	9	10	9	100.00%	90.00%
Fellow Land	24	18	18	75.00%	100.00%
Barren Land	25	24	23	92.00%	95.83%
Sugarcane	14	13	12	85.71%	92.31%
Other Crops	41	45	39	95.12%	86.67%
Total	150	150	136	90.66%	

Overall Classification Accuracy = 90.67%
KAPPA (K^) STATISTICS = 0.86

Table5. Classification Accuracy Assessment of Knowledge Classifier for 30 October 2014

Class Name	Reference Total	Classified Total	Number Correct	Producers Accuracy	User Accuracy
Maize	7	8	7	100.00%	87.50%
Settlement	2	2	2	100.00%	100.00%
Water	4	3	3	75.00%	90.00%
Fellow Land	29	29	25	86.21%	84.62%
Barren Land	18	21	17	94.44%	80.95%
Sugarcane	13	11	11	84.62%	100.00%
Other Crops	27	26	22	81.48%	84.62%
Total	100	100	87	87%	

Overall Classification Accuracy = 87.00%
KAPPA (K^) STATISTICS = 0.83

Table 6. Classification Accuracy Assessment Report for Fuzzy Classifier30 October 2014

Class Name	Reference Total	Classified Total	Number Correct	Producers Accuracy	User Accuracy
Maize	3	3	3	100.00%	100.00%
Settlement	5	6	5	100.00%	83.33%
Water	3	3	3	100.00%	100.00%
Fellow Land	47	44	42	89.36%	95.45%
Barren Land	31	35	29	93.55%	82.86%
Sugarcane	19	21	18	94.74%	85.71%
Other Crops	45	41	37	82.22%	90.24%
Total	150	150	137	91.33%	

Overall Classification Accuracy = 91.33%
KAPPA (K^) STATISTICS = 0.88

The above table shows that Fuzzy Classification method gives better results as compared three methods. The accuracies for the two periods were 90.67% and 91.33% with kappa coefficient ranging from 0.86 to 0.88 respectively. It was concluded that the fuzzy classification technique is more appropriate for the classification of crops in the present study.

8. DISCUSSION

The study was time specific and of a shorter duration, only few areas in the temporal discrimination of crops could be actively explored. The remote sensing data used in this study was of the period 28-September and 30-October, 2014. The field work was also conducted during the same time. The study was based on four classification techniques and information about crop growth and its pattern were determined.

From the present visual interpretation and quantitative analysis, the satisfactory result of specific crop type mapping from Landsat OLI data using different techniques was found. The fuzzy classifier is efficient to classify the sugarcane and maize fields. In the month of October, maize field might have similar spectral property with mixed crop (mainly cotton fields and shrubs). In the month of October, the results show the large unclassified area which includes basically the barren land and fellow land nearby. The maize field was larger than sugarcane in month of September, typically in October sugarcane gets increased. Fuzzy classification method appears to differentiate crops more accurately. To assess the data performance, Landsat 8 OLI was also used for land cover classification (identification of specific crop) in Vaijapur Tehsil, Aurangabad Maharashtra. The performance of Landsat OLI data was good especially in the NIR band of the OLI data, where an improvement was achieved.

9. CONCLUSION

The present study shows the potential use of remote sensing in the field of agriculture for crop classification; we have used time series Landsat multispectral satellite images at tehsil level. It is useful to study the multicrop seperability at small scale for predictable yield to have better agricultural productivity. The different supervised classification techniques show their usefulness in the field of agriculture for crop classification but the fuzzy classification technique based on convolution filter is found to be more efficient to extract a multiple crop such as Sugarcane and Maize. This Study demonstrated that the actual area covered by the crops Sugarcane and Maize from Landsat 8 (OLI data) can be estimated with satisfactory results. Therefore OLI data indicates satisfactory performance in classification of land cover. The observed overall accuracy using supervised fuzzy convolution filter is 90.67% in the month of September and in the month of October is 91.33%. It is found that Fuzzy classifier is more appropriate for classification of temporal images to get crop information.

10. ACKNOWLEDGEMENT

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