# THRESHOLDING IN TEMPORAL DATA

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## ABSTRACT

The objective of this research work was to discriminate specific crops that are of interest to specific industries or the government agencies for better decision making process.. Any shortage in the any crop would have large effects on the country in the end. Hence there is a need to prepare specific crop maps in order to be well equipped for any shortage in agricultural produce. The need of temporal data for continuous monitoring of crops and the unavailability of continuous temporal data is a well-known problem. So this problem was tried to be solved by using data from different optical sensors LISS-III (from IRS-P6) . For an accurate estimation of area, PCM (Possiblistic c Means), a possibilistic fuzzy based classifier capable of extracting single class in an image was used. A spectral separability analysis (using single sensor data from LISS-III and AWiFS separately) was conducted between the class of interest and the non-interest classes to select the best 2, 3, 4 ... dates combination to discriminate the class of interest. Combinations of these best dates were then classified using PCM classifier to extract specific class to find the best overall dates combination to discriminate the same class.

# ACKNOWLEDGEMENTS

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# 1.INTRODUCTION

## 1.1.BACKGROUND

India is an agrarian economy and about two-thirds of its population are directly or indirectly involved in agriculture (National Portal Content Management Team, 2011). The agricultural sector contributes to the GDP by about 7% since 2001 (FAO, 2011). The last half a century has witnessed several revolutionary programmes like the white revolution (in the dairy sector) and the green revolution (in production of food grains). This has made India not only self-sufficient to meet the domestic food needs but also has helped it in becoming a key exporter of agricultural commodities in the world. India has come a long way from being an agro-economically weak nation to a rising economic power in the world with a sizeable share in the world export market. But a buoyant economy and a rising population rate has its own share of problems. An increasing population with 1.21 billion people as per census 2011 (National Portal Content Management Team, 2011), to feed and with the total cultivable land area decreasing with time, there is an urgent need to usher in a second phase of revolution to meet the growing domestic as well as international needs. There is also a need to manage the volatile production pattern of agriculture when there is a surplus or deficit produce. In the year 2002 the rice and wheat stocks reached a peak of 63 million tonnes incurring huge losses due to decrease in food grain prices whereas, in 2007 it plummeted to 16 million tonnes raising concerns about food deficit (Nandakumar et al., 2010). Such situations in the future could be handled well if there is availability of up-to-date information about crop status in the fields. This calls for a need of time and cost efficient ways to monitor, manage and estimate agricultural production to address the national food security concern. For an efficient agricultural resource management up-to-date information about the location of crops and their acreage is needed. The use of remote sensing images for identifying and mapping specific crops in the last few decades has increased rapidly. Remote sensing techniques allow mapping large areas in a faster and economical way. And mapping specific crop can be helpful in estimating the acreage, yield and cropping pattern present in an area (Kumar and Roy, 2011; Panigrahy et al., 2009). The results from remotely sensed data providing acreage and spatial distribution of individual crop can be of immense help to certain people like policy makers, scientists, businessmen, etc who are more concerned about individual crops than mapping all the crops in an area.

## 1.2.PROBLEM STATEMENT

The areas that need to be addressed in this study is to consider the mixed pixel problem and increase the temporal data sampling using the multi sensor approach to accurately discriminate specific crops. So it is necessary for the mills to account and plan for the actual amount of crop harvested in the fields and the amount received in the mills. Traditionally the information about the volume of crop present in the fields has been collected through manual field surveys which are an expensive and time consuming process. The use of remote sensing techniques in retrieving information about the status of the staggered harvest of crop can provide a cheap and faster alternative to conventional data collection methods. Such specific crop maps can prove to be an immense help in planning and decision making when expecting deficit or surplus production of any crop and take decisions accordingly. While mapping specific crops the knowledge of other crops present in the area is also important. And the fact that the spectral response of different crops might overlap with each other on any given date makes the process of mapping specific crops using single date imagery is a real challenge. Temporal analysis of crop can however provide a good solution for discriminating among various crops and vegetation classes using the differences in their growth patterns as a discriminating factor. The need of temporal data for continuous monitoring of crops and the unavailability of continuous temporal data is also a well-known problem. Hence a multi sensor approach for increasing the temporal data sampling for monitoring crops has to be evaluated for its effectiveness. Another important consideration while generating accurate crop maps is the occurrence of mixed pixels. In order to make accurate class cover estimation, the sub-pixel fractions of the class along with the homogenous pixels need to be accounted for. This problem of un-mixing classes present in a pixel can be handled through various available techniques like Linear Mixture Models, Fuzzy classification, Neural Networks, etc. The use of such techniques that can estimate the proportion of classes within a pixel can help in precise area estimation of land cover classes in both high and coarse resolution remote sensing images (Dadhwal et al., 2002).

## 1.3.PROJECT OBJECTIVES

The main objective of this study is to discriminate a specific crop using a temporal single and multi-sensor data approach. This objective can be further divided into the following sub-objectives:

a) To identify crop spectral growth profile using a temporal and multi sensor approach.
b) To study the separability between the target crop and other crops or vegetation based on their spectral growth profile.
c) To classify mixed pixels using fuzzy technique.
d) Thresholding of pixels obtained from PCM fuzzy classification.

## 1.4.PROJECCT APPROACH

Temporal data from the sensorLISS-III from IRS P-6 (Resourcesat 1) was used for discriminating crop. The temporal data sets were first pre-processed with respect to atmospheric correction and image to image registration. Vegetation index images (NDVI) were generated for reducing the dimensionality of data and enhancing the class of interest in temporal analysis. A Single sensor temporal analysis using AWiFS and LISS III images separately was conducted for specific crop discrimination and then a fuzzy based classification (Possibilistic c-Means) technique was use for extracting the single class of interest (sugarcane-plant and ratoon). Then in the second case Landsat-5 TM image was used with best temporal LISS III images (dates) to study the effects of a multi sensor approach. The results of the classified outputs of the coarser resolution AWiFS temporal images were assessed against the classified output of the finer resolution LISS III best temporal dates classified images. Then these classified outputs of tempoal images were used for thresholding of classess.

## 2.INDICES AND CLASSIFICATION APPROACH

This chapter describes the classification approach used and the reason for choosing the vegetation index, NDVI (Normalised Difference Vegetation Index) for the crop discrimination study. The various accuracy assessment techniques such as FERM (Fuzzy Error Matrix) and entropy measure are also explained in the following sections.

### 2.1. VEGETATION INDICES (NDVI)

Remote sensing images have been used since a long time for characterizing and detecting the land cover- land use classes present in an area. Each class based on its surface properties and composition reflects a specific amount of light incident on it, this unique spectral property can be used to detect the same class present in the remote sensing image. This is done by categorizing the reflectance properties of different classes present on the land surface and then conducting analyses to find similarities between known properties and unknown classes. Thus unknown classes can be assigned to class categories to generate class-cover maps of an area. But since the amount of solar radiance and the atmospheric conditions varies with time, such a simple method of characterization of classes using reflectance properties alone is not possible in a repeated manner. For conducting temporal studies such as vegetation mapping, change detection, etc. the effects due to atmosphere and time of image acquisition need to be reduced. This problem can be solved to some degree by combining data from two or more spectral bands to form the extensively used vegetation index (VI) (Jackson and Huete, 1991). Vegetation indices are generally calculated by ratioing, differencing, summing, linearly combining, etc. data from two or more spectral bands. They are dimensionless and radiometric measures that are intended to minimize the solar irradiance and soil background while enhancing the signal from vegetation. The use of vegetation index can normalise the effects of differential illumination of features in an area and can also help in extracting specific vegetation classes in an area. Jensen, 2009 lists the advantages of using vegetation indices as follows;

a) It maximises the sensitivity to plant biophysical parameters,

b) Consistent spatial and temporal comparisons can be made due to normalising or modelling of sun angle, viewing angle effects and atmosphere,

c) Canopy background, topography and soil variations, etc. can be normalised

d) It reduces the dimension of the multispectral data for temporal analysis studies.

Many studies in the past involving use of NDVI (Normalised Difference Vegetation Index) for time series vegetation and crop discrimination studies have been found to provide encouraging results (Chen et al., 2004; Doriaswamy et al., 2006; Vincent and Pierre, 2003; Wardlow et al., 2007; Ying et al., 2010). Xie et al., 2008 reviewed various literatures dealing with the use of remote sensing data in vegetation mapping and also found the use of NDVI to be advantageous. They noted that in addition to providing an indication greeness of the vegetation, the discrimination of particular groups of vegetation was possible using the dynamic NDVI signals in multi temporal images. The main principle of detecting vegetation using NDVI is the high absorptivity of vegetation pigments (chlorophyll) in the red spectral region and high reflectance in the near infrared spectral region. NDVI is highly correlated to the photosynthetic activity and indicates the greenness of the vegetation. Hence NDVI has been used for this temporal and multispectral data set for enhancement of the vegetation class and discriminating specific crops

The NDVI is calculated as given in Eq. (1):

$$\text{NDVI} = \frac{\sigma nir - \sigma r}{\sigma nir + \sigma r} \, .$$

where,

$\sigma nir$ = near infra-red band of sensor, and

$\sigma r$ = red band of sensor.

## 2.2.CLASSIFICATION APPROACH

Geographical information captured through remote sensing is generally represented by assigning a single class to a pixel. But complex conditions such as class mixtures, etc. that occur in remotely sensed images cannot be represented by such methods (Wang, 1990). Most often when the size of a pixel is larger than the class size on the ground or at inter-class boundaries spectral mixing takes place. Labelling of such mixed pixels with only one class cover will lead to overestimation of one class and underestimation of other classes. This causes generation of inaccurate results in classification of pixels when conventional methods of assigning single class per pixel are followed. This problem of un-mixing classes present in a pixel can be handled through various available techniques like Linear Mixture Models, Fuzzy classification, Neural Networks, etc. (Chen et al., 2004; Dave, 1991; Kumar et al., 2010; Winkantika et al., 2002; Zadeh, 1965). The use of such techniques that can estimate the proportion of classes within a pixel can help in precise area estimation of land cover classes in both high and coarse resolution remote sensing images (Dadhwal et al., 2002). But some of these techniques have been found to have several limitations. While the neural networks take a long time in the learning phase of classification which is a serious drawback when dealing with large datasets (Kumar and Saggar, 2008), the Linear Mixture Model needs the sum of all the class memberships in a pixel to be unity (Chen et al., 2004). In order to overcome all these problems and to achieve the objective of specific crop discrimination fuzzy classification techniques can be used. The fuzzy classification technique solves the problem of un-mixing mixed pixels by assigning class membership grades to pixels to describe class cover mixtures. In this technique each pixel is assigned a degree of belongingness or membership grade to all classes based on its nearness to the classes' mean. The membership assigned to a class in a pixel is proportional to the percentage cover of the class in the pixel (Wang, 1990). This fuzzy technique can be useful in estimating accurate class area and fulfil the objective of generating single class-specific crop maps. It has been found from past research works that using the already established PCM (Possibilistic c-Means) classifier (Kumar et al., 2010) for this purpose of specific crop mapping and handling mixed pixels can help in achieving the objectives of this study.

2.2.1.

Fuzzy c-Means (FCM)

* Fuzzy c-Means (FCM) clustering technique assigns some degree of belongingness to each data point in a cluster according a membership grade (Bezdek, 1981). It is an iterative clustering method. The sum of these memberships in a pixel must be unity. This is achieved by minimising the following objective function in Eq. (2):

$$J_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{c}(\mu_{ij})^m \parallel X_i - V_j \parallel_A^2 \qquad (2)$$

with constraints,

For all i $\quad \sum_{j=1}^{C} \mu_{ij} = 1$

For all j $\quad \sum_{i=1}^{N} \mu_{ij} > 0$

For all i, j $\quad 0 \leq \mu_{ij} \leq 1$

---

where, $d_{ij}^2 = \parallel X_i - V_j \parallel_A^2$ and the distance in feature space between $X_i$ and $V_j$ ,

$$d_{ij}^2 = \parallel X_i - V_j \parallel_A^2 = (X_i - V_j)^T A \left(X_i - V_j\right) \qquad (3)$$

And $\mu_{ij}$ is the membership of pixel i in class j, N is the total number of pixels, $V_j$ is the cluster center for class j, $X_i$ is the feature vector for pixel i, A is the weight matrix and the Euclidean norm used here. m is the weighted constant ($1< m < \infty$) that controls the degree of fuzziness (at m=1 the partitions that minimise the $J_m$ function become hard and as m tends to $\infty$ the partitions becomes increasingly fuzzy or soft).

The FCM method is essentially an iterative method of partitioning pixels by assigning them different class membership values. The Fuzzy c partition is obtained by optimising the following equations (4) and (5). The cluster centre is updated by using Eq. (4),

$$V_j = \sum_{i=1}^{N}(\mu_{ij})^m * X_i / \sum_{i=1}^{N}(\mu_{ij})^m \qquad (4)$$

And the class membership $\mu_{ij}$ is then calculated as given in Eq. (5):

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(d_{ij}^2/d_{ik}^2\right)^{1/(m-1)}} \qquad (5)$$

Where $d_{ik}^2 = \sum_{j=1}^{C} d_{ij}^2$

The FCM algorithm (El-Aziz, 2004) is as follows:

1) Fixing values for m, c (number of classes to be extracted), A and maximum number of iterations.

2) An initial membership matrix, , is selected and its elements are assigned membership values ranging from 0 to 1 to for fuzzy classification.

3) Cluster centre is calculated as given in equation (4).

4) The distance is computed based on the selected A norm using equation (3).

5) The U matrix is updated for the next iteration until the user defined error limit is reached.
6) The final U matrix will represent the class proportions.

Possibilistic c-Means (PCM)
* PCM (Possibilistic c-Means) is a modified form of FCM clustering technique that assigns representative feature points the highest possible membership, while unrepresentative points get low memberships (Krishnapuram and Keller, 1993). Thus to satisfy this requirement the objective function of FCM (Eq. (2))
has been modified to as given in Eq. (6):

$$J_m(U,V)=\sum_{i=1}^{N}\sum_{j=1}^{c}(\mu_{ij})^m \parallel X_i - V_j \parallel_A^2 + \sum_{j=1}^{c}\eta_j\sum_{i=1}^{N}\left(1-\mu_{ij}\right)^m \qquad (6)$$

The equation (6) is subject to constraints,
For all i $\ {}^{max}{}_{j}\mu_{ij} > 0$
For all j $\ \sum_{i=1}^{N}\mu_{ij} > 0$
For all i, j $\ 0 \le \mu_{ij} \le 1$
$d_{ij}^2 = \parallel X_i - V_j \parallel_A^2$ and the distance in feature space, $\mu_{ij}$ is the membership of pixel i in class j, N is the total number of pixels, m is the weighted constant (1< m < ∞), $V_j$ is the cluster center for class j, $X_i$ is the feature vector for pixel i, A is the weight matrix and the Euclidean norm used here.

$\eta_j$ is dependent on the shape and average size of cluster j and is computed as in Eq. (7):

$$\eta_j = K\,\frac{\sum_{i=1}^{N}\mu_{ij}^m d_{ij}^2}{\sum_{i=1}^{N}\mu_{ij}^m} \qquad (7)$$

K is a constant generally kept as unity.
There after class memberships ($\mu_{ij}$) are calculated as in Eq. (8):

$$\mu_{ij} = \frac{1}{1+\left(d_{ij}^2/\eta_j\right)^{1/(m-1)}} \qquad (8)$$

From equation (5) it can be seen that the membership values generated for pixels are dependent on the number of classes to be extracted, where $d_{ik}^2 = \sum_{j=1}^{C} d_{ij}^2$. While extracting a single class from a remote sensing image the following case of $d_{ik}^2 = d_{ij}^2$ is encountered and the memberships ($\mu_{ij}$) of all pixels in class j become unity. This means that all the pixels in the image belong to the same class j which is not the case. In such a case while using PCM, from Eq. (7) $\eta_j = K\,\frac{\sum_{i=1}^{N}\mu_{ij}^m}{N}$ and the class memberships are calculated as given in Eq. (8).

The PCM algorithm (El-Aziz, 2004) is also the same as that of the FCM algorithm but with some
significant changes.
1) Fixing values for m, c (number of classes to be extracted), A and maximum number of iterations.

2) An initial membership matrix, , is selected and its elements are assigned membership values ranging
from 0 to 1 to for fuzzy classification.
3) Then is estimated from equation (7).
4) The cluster centre is calculated as in equation (4).
5) The distance is computed based on the selected A norm using equation (3).
6) The U matrix is updated for the next iteration until the user defined error limit is reached.
7) The final value of is estimated from equation (7) using the updated U matrix.
8) the elements of U matrix is then again computed from the final value.
9) The final U matrix will represent the class proportions.

FCM and PCM are essentially unsupervised classifiers, but they can be applied in the supervised mode by assigning the class means from training data sets instead of cluster centre As in this study supervised PCM method is used, only one iteration provides the solution. The unique feature of PCM classifier is its non-conformation to the rule of summation of all meu should be unity that requires the sum of all class memberships in a pixel to be unity. This means that the memberships assigned to a class in a pixel is independent of the memberships assigned to other classes in the pixel. The PCM classifier is thus capable of extracting a single class of interest and is appropriate for the objective of specific crop discrimination in this project work.
*the above explanations for fuzzy classifiers and equations have been adapted from Kumar et al., 2010.

## 3.THRESHOLDING METHODS

Hard and soft classification techniques are the conventional methods of image classification for satellite data, but they have their own advantages and drawbacks. In order to obtain accurate classification results, we took advantages of both traditional hard classification methods (HCM) and soft classification models (SCM), and developed a new method called the hard and soft classification model (HSCM) based on adaptive threshold calculation. The authors tested the new method in land cover mapping applications. According to the results of confusion matrix, the overall accuracy of HCM, SCM, and HSCM is 71.06%, 67.86%, and 71.10%, respectively. And the kappa coefficient is 60.03%, 56.12%, and 60.07%, respectively. Therefore, the HSCM is better than HCM and SCM. Experimental results proved that the new method can obviously improve the land cover and land use classification accuracy.

### 3.1 SOFT CLASSIFICATION

A pixel does not belong fully to one class but it has different degrees of membership in several classes. The mixed pixel problem is more pronounced in lower resolution data. In fuzzy classification, or pixel unmixing, the proportion of the land cover classes from a mixed pixel is calculated.

While thresholding the soft classification is as follows:

a) If $\mu >= \mu_{th}$ then value of $\mu$ is kept same as it was.

b) If $\mu < \mu_{th}$ then value of $\mu$ becomes zero.

Java Code for thresholding using soft Classification:-

```
if(b>=bth){                                   //byte is taken unsigned
                fout.write(b);                // fout is output file to be written
                }
                else{
                b=0;
               fout.write(b);
                }
```

### 3.2 HARD CLASSIFICATION

A pixel can only have one and only one category. In urban regions, a pixel in reality may have more than one category because of the heterogeneity of the land cover composing that pixel. We call this a mixed pixel.

While thresholding the soft classification is as follows:

a) If $\mu >= \mu_{th}$ then value of $\mu$ is kept same as it was.

b) If $\mu < \mu_{th}$ then value of $\mu$ becomes zero.

Java Code for thresholding using soft Classification:-

```
if(b>=bth){                                   //byte is taken unsigned
              b=255;
              fout.write(b);                  // fout is output file to be written
              }
              else{
              b=0;
             fout.write(b);
              }
```

4.RESULTS AND DISCUSSIONS

4.1. PCM CLASSIFICATION RESULTS

This section deals with the presentation of PCM classification results for specific crop, mapping using temporal date combinations from sensors like LISS-III and AWiFS. The selection of best dates for classification of specific crop was done and then the analysis of a multi sensor approach using Landsat-5 TM data with LISS III temporal dates was also carried out.

The Pcm classification results are shown using screenshot:-

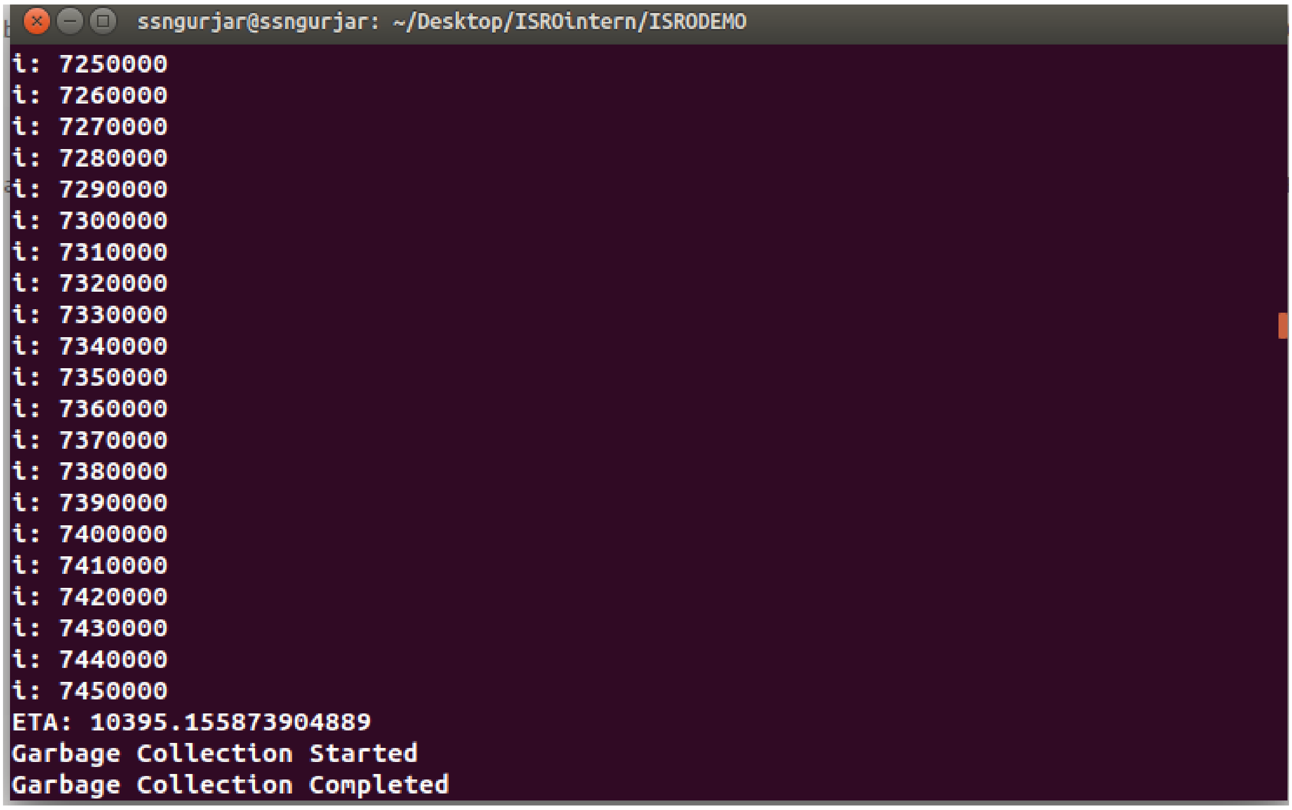
Temporal Image:-

Band Ratio Calculation:-

```
ssngurjar@ssngurjar: ~/Desktop/ISROintern/ISRODEMO
Band Ratio for other files:

1): /home/ssngurjar/Desktop/ISROintern/ISRODEMO/LISS III Pantnagar/08jan2009
Value stored at Band No. 0, 73
Value stored at Band No. 1, 38
Value stored at Band No. 2, 61
Value stored at Band No. 3, 49
Minimum : 38, Maximum : 73
Band Ratio for first file : 0.5205479452054794

2): /home/ssngurjar/Desktop/ISROintern/ISRODEMO/LISS III Pantnagar/14april2009
Value stored at Band No. 0, 74
Value stored at Band No. 1, 70
Value stored at Band No. 2, 77
Value stored at Band No. 3, 68
Minimum : 68, Maximum : 77
Band Ratio for first file : 0.8831168831168831

3): /home/ssngurjar/Desktop/ISROintern/ISRODEMO/LISS III Pantnagar/21nov2008
Value stored at Band No. 0, 71
Value stored at Band No. 1, 42
Value stored at Band No. 2, 51
Value stored at Band No. 3, 52
Minimum : 42, Maximum : 71
```

Eta value calculation:-

```
ssngurjar@ssngurjar: ~/Desktop/ISROintern/ISRODEMO
Band Ratio for first file : 0.5915492957746479
Saving Output File : 0
Completed : 0
Saving Output File : 1
Completed : 1
Saving Output File : 2
Completed : 2
Saving Output File : 3
Completed : 3
ReadImage Band : 4
ReadImage Row : 2798
This is col1: 002663
Rows : 2798
Cols : 2663
Vector V:83     132     225     150

Calculating ETA From i=0 to 7451074...
i: 0
i: 10000
i: 20000
i: 30000
i: 40000
i: 50000
i: 60000
```

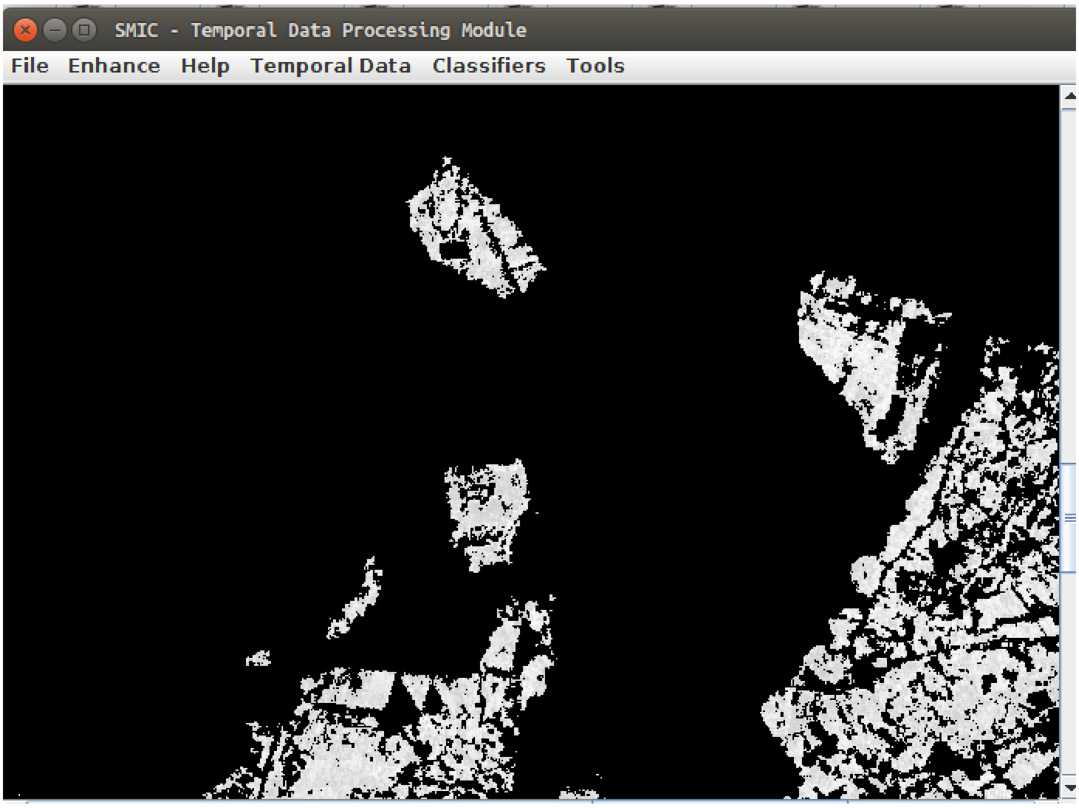

ssngurjar@ssngurjar: ~/Desktop/ISROintern/ISRODEMO
i: 7250000
i: 7260000
i: 7270000
i: 7280000
i: 7290000
i: 7300000
i: 7310000
i: 7320000
i: 7330000
i: 7340000
i: 7350000
i: 7360000
i: 7370000
i: 7380000
i: 7390000
i: 7400000
i: 7410000
i: 7420000
i: 7430000
i: 7440000
i: 7450000
ETA: 10395.155873904889
Garbage Collection Started
Garbage Collection Completed

## 4.2 SOFT CLASSIFICATION RESULTS

Calculation of thresholding values:-

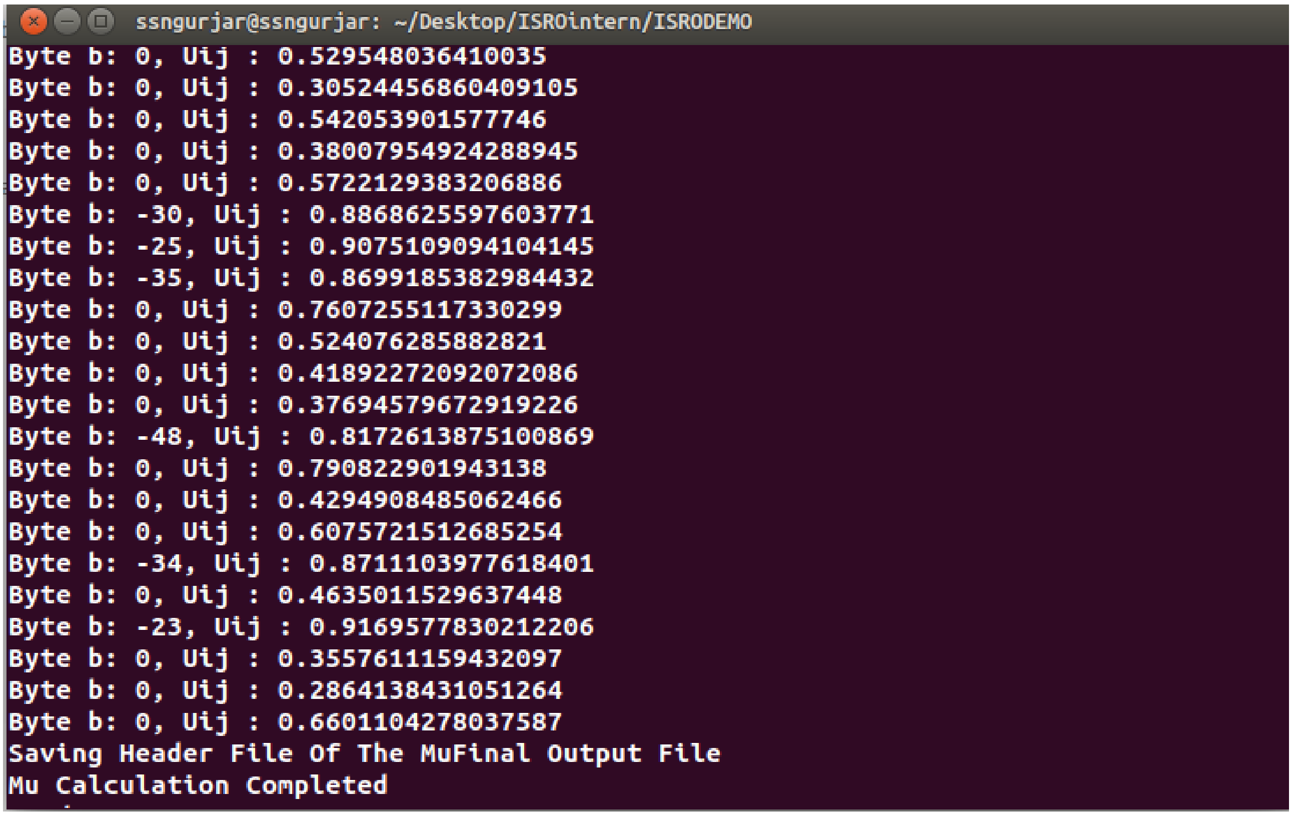
```
ssngurjar@ssngurjar: ~/Desktop/ISROintern/ISRODEMO
Byte b: 0, Uij : 0.529548036410035
Byte b: 0, Uij : 0.30524456860409105
Byte b: 0, Uij : 0.542053901577746
Byte b: 0, Uij : 0.38007954924288945
Byte b: 0, Uij : 0.5722129383206886
Byte b: -30, Uij : 0.8868625597603771
Byte b: -25, Uij : 0.9075109094104145
Byte b: -35, Uij : 0.8699185382984432
Byte b: 0, Uij : 0.7607255117330299
Byte b: 0, Uij : 0.524076285882821
Byte b: 0, Uij : 0.41892272092072086
Byte b: 0, Uij : 0.37694579672919226
Byte b: -48, Uij : 0.8172613875100869
Byte b: 0, Uij : 0.790822901943138
Byte b: 0, Uij : 0.4294908485062466
Byte b: 0, Uij : 0.6075721512685254
Byte b: -34, Uij : 0.8711103977618401
Byte b: 0, Uij : 0.4635011529637448
Byte b: -23, Uij : 0.9169577830212206
Byte b: 0, Uij : 0.3557611159432097
Byte b: 0, Uij : 0.2864138431051264
Byte b: 0, Uij : 0.6601104278037587
Saving Header File Of The MuFinal Output File
Mu Calculation Completed
```

Image after Soft Classification:-



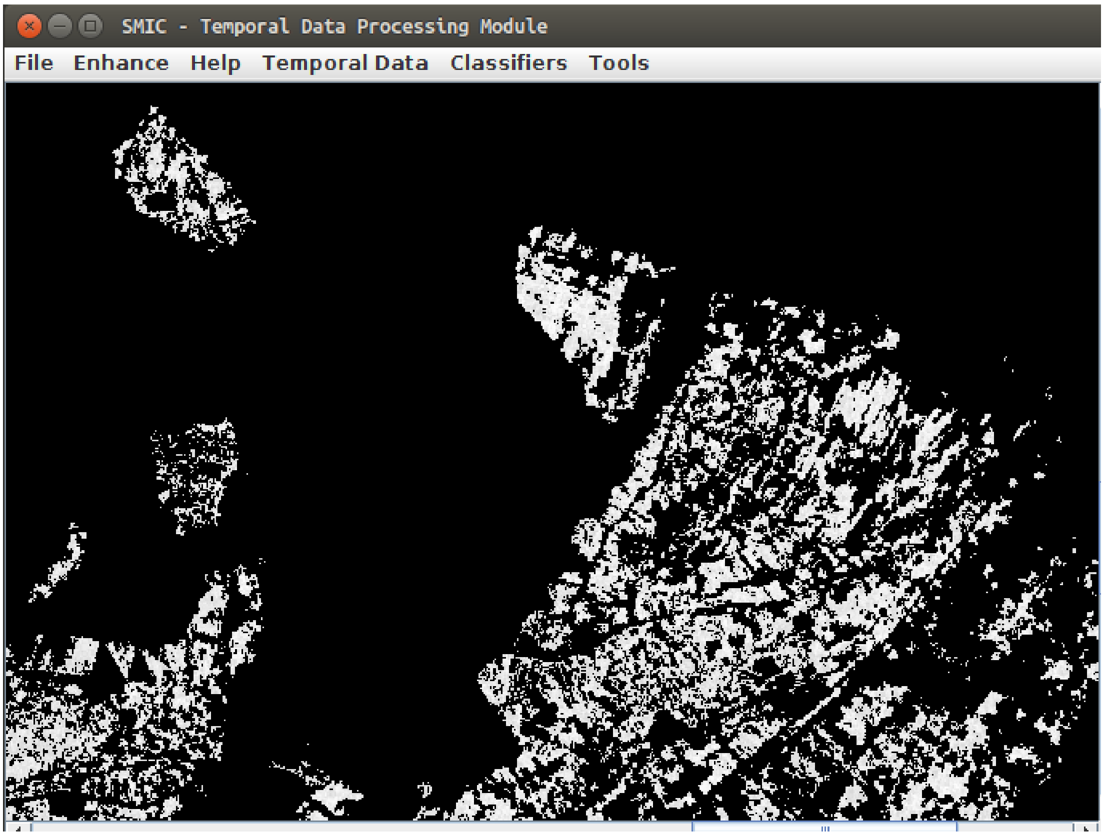
## 4.3 HARD CLASSIFICATION RESULTS

Threshold value calculation :-



```
ssngurjar@ssngurjar: ~/Desktop/ISROintern/ISRODEMO
Byte b: 0, Uij : 0.529548036410035
Byte b: 0, Uij : 0.30524456860409105
Byte b: 0, Uij : 0.542053901577746
Byte b: 0, Uij : 0.38007954924288945
Byte b: 0, Uij : 0.5722129383206886
Byte b: -30, Uij : 0.8868625597603771
Byte b: -25, Uij : 0.9075109094104145
Byte b: -35, Uij : 0.8699185382984432
Byte b: 0, Uij : 0.7607255117330299
Byte b: 0, Uij : 0.524076285882821
Byte b: 0, Uij : 0.41892272092072086
Byte b: 0, Uij : 0.37694579672919226
Byte b: -48, Uij : 0.8172613875100869
Byte b: 0, Uij : 0.790822901943138
Byte b: 0, Uij : 0.4294908485062466
Byte b: 0, Uij : 0.6075721512685254
Byte b: -34, Uij : 0.8711103977618401
Byte b: 0, Uij : 0.4635011529637448
Byte b: -23, Uij : 0.9169577830212206
Byte b: 0, Uij : 0.3557611159432097
Byte b: 0, Uij : 0.2864138431051264
Byte b: 0, Uij : 0.6601104278037587
Saving Header File Of The MuFinal Output File
Mu Calculation Completed
```

Image after hard classification:-



## 5.CONCLUSIONS AND RECOMMENDATIONS

The study carried out in this thesis indicates the potential of multi sensor approach in the temporal analysis studies.

a) The temporal specific crop growth profiles were generated successfully using data from LISS-III and AWiFS. The sugarcane crop growth profiles generated for plant and ratoon using AwiFS temporal data showed mixing of signatures because of the coarser resolution of the sensor. The overall sugarcane crop could however be satisfactorily discriminated from other classes present in the study area. While, the sugarcane crop growth profiles for plant and ratoon both could be satisfactorily generated using LISS temporal data showing distinct patterns indicating the differences in their growing seasons.

b) The use of Euclidean distance measure for conducting the separability analysis between the specific crop and the other non-interest classes worked well. As the dates combinations increased from initial 2 to the maximum dates possible the unbiased sugarcane sites were assigned higher memberships. The need for classifying numerous images for selection of the best 2, 3, 4... dates combination for discrimination of crop was reduced by the use of this technique. The selection of the best 2, 3, 4.... dates from spectral separability analysis gradually reduced the confusion between the class of interest and the non-interest class by maximising the best minimum distance. As the best minimum distance started to saturate in the higher dates combinations (i.e. beyond 5- 6 date combinations) the best overall (optimum) temporal date combination for discriminating the specific crop was found by evaluating the results from actual fuzzy classification techniques.

c) The study also proves the need of optimising the dates combination selection while conducting temporal studies as using all the available temporal dates data proved to be counterproductive. For selecting the best dates for sugarcane crop discrimination using AWiFS an image to image accuracy assessment using various operators was conducted. To optimize the temporal dates combination the results of MIN and the PROD operator were maximised and the LEAST operator results were minimised. The results of MIN and the LEAST operators were optimized on the same dates combination which indicate that any of these two operators could have been used interchangeably for accuracy assessment. The PROD operator however didn't show any clear results when analysed solely.

d) From the results of the study, an increase in the classification accuracy was observed as a result of the addition of Landsat- 5 TM image to the best dates combination for LISS-III. This proves the effectiveness of the use of a multi sensor approach for discrimination of sugarcane crop when temporal data from LISS-III sensor was having long periods of unusable data. A multi sensor approach could however not be evaluated for AWiFS because of the absence of any other sensor with similar spatial resolution as that of AWiFS.

e) The selected PCM classifier worked well for extracting sugarcane crop (single class extraction) by providing high accuracies in the range of 91-94% for temporal AWiFS data and with lower entropies for temporal LISS-III temporal data.

f) The selected best dates for discrimination of crops can help in providing a temporal window for monitoring of crops. This approach would help in generating accurate crop maps with the help of an optimum number of strategically selected temporal remote sensing images covering the growing season of the crop, thus helping save resources spent in mapping too. Even though all the proposed research objectives for this study were achieved, a few areas could still be explored even more.

g) The thresholding of temporal data help us to clearly indicate the proportion of specific class present in that area over $\mu_{th}$.

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