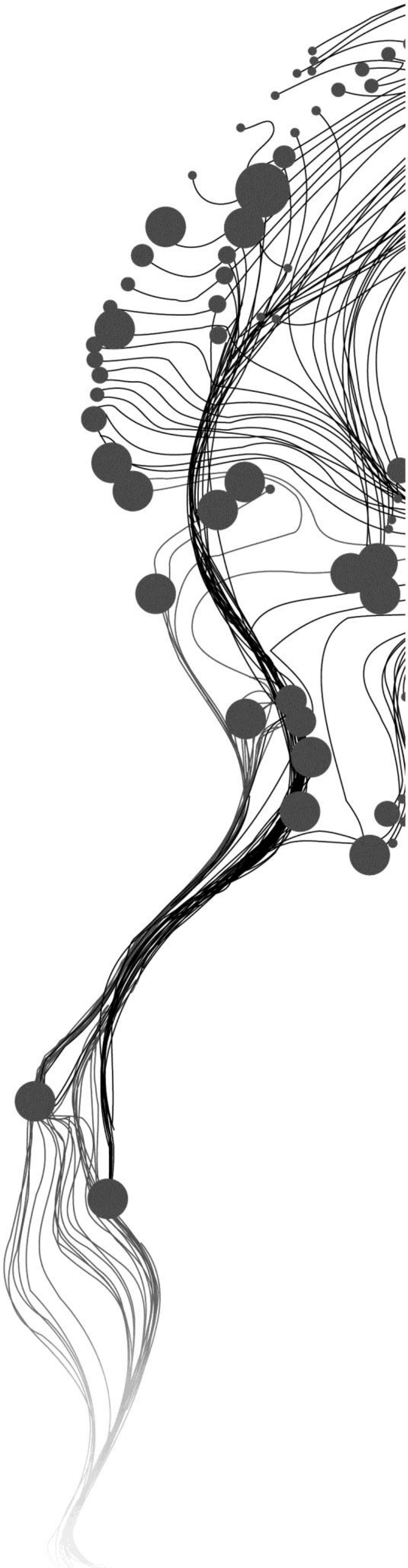
MAPPING SPECIFIC CROPS AND THEIR PEHNOLOGY – MULTI SENSOR AND TEMPORAL APPROACH

GOURAV MISRA
March, 2012

SUPERVISORS:
Dr. Anil Kumar, IIRS
Dr. Raul Zurita-Milla, ITC
Dr. N. R. Patel, IIRS



MAPPING SPECIFIC CROPS AND THEIR PHENOLOGY – MULTI SENSOR AND TEMPORAL APPROACH

GOUROV MISRA

Enschede, The Netherlands, March, 2012

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Geoinformatics

SUPERVISORS:
Dr. Anil Kumar, IIRS
Dr. Raul Zurita-Milla, ITC
Dr. N. R. Patel, IIRS

THESIS ASSESSMENT BOARD:
Dr. Alfred Stein, ITC (Chair)
Dr. R. D. Garg (External Examiner, IIT, Roorkee)

ABSTRACT

The objective of this research work was to discriminate specific crops (here sugarcane) that are of interest to specific industries or the government agencies for better decision making process. Sugarcane in India is a high priority crop for the government given the fact that India is the second largest producer of sugar in the world and the largest consumer of the sugar produced in the world. Any shortage in the sugar produce would have large effects on the sugarcane and its by-product industry and also 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 like LISS-III and AWiFS (from IRS-P6) and TM from Landsat-5. 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 (sugarcane plant and ratoon) 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. In the absence of any reference data the soft classified outputs from LISS-III sensor were assessed using an entropy measure criterion. The date combinations providing the least entropy was selected as the optimum date combination for discriminating the specific class. This date combination from LISS-III was used as a reference for assessing the soft classified outputs from AWiFS sensor using an image to image accuracy assessment technique. Various operators like MIN, LEAST and PROD were also evaluated for their assessing their behaviour and effectiveness in image to image accuracy assessment.

In the second case the effect of data from another sensor i.e. Landsat-5 TM when added to the optimum date combination from LISS-III was also evaluated. It was found that the entropy of the classified outputs from the selected best dates combination and multi sensor approach was lower than the entropy measured from the single sensor (LISS-III) approach. Lower entropy meant the uncertainty associated with classification was lower and accuracy was higher, and vice-versa.

This study explored the applicability of temporal single and multi-sensor data for discrimination of specific crop, sugarcane plant and ratoon. A multi sensor approach helped in increasing the temporal data sampling for the continuous monitoring of crops when data available from any single sensor approach was insufficient. The end result of this study was the detection of best temporal dates for discriminating a specific crop, sugarcane-plant and ratoon. Such information can be used by agricultural scientists in selecting an optimum number of strategically placed temporal images in the crop growing season for discriminating the specific crop accurately.

Index Terms- *Temporal, Multi sensor, PCM, FERM, Image to image based accuracy assessment, Entropy.*

ACKNOWLEDGEMENTS

A research of this kind requires ample resources, support and motivation. I therefore take this opportunity to thank the people who have encouraged and supported me during the course of this M.Sc. programme.

My deepest sense of gratitude is expressed to my ITC Supervisor, Dr. Raul Zurita-Milla, for helping me during the advanced modules at ITC. Your concern, suggestions, comments and constructive criticisms for my work starting from the initial research proposal writing phase till the evaluation of final results kept me motivated and has helped in bringing this thesis to its final form.

My sincerest thanks to my IIRS Supervisor, Dr. Anil Kumar for his constant support, guidance and encouragement. I highly appreciate the patience you showed during the numerous discussions that we had during the progress of this research work. You really have been a source of great motivation for me.

Thanks to my other IIRS Supervisor, Dr. N. R. Patel for helping me with the concepts relating to crop monitoring and agriculture. Your suggestions and comments have helped me to carry out my work properly.

I would also like to thank Dr. P. S. Roy, Director-IIRS for taking active interest in the research activities of the students. Special thanks are also reserved for the faculty of IIRS, Geoinformatics division, Mr. P. L. N. Raju and Dr. S. K. Srivastav, and Mr. Shashi Kumar for their help and guidance during the M.Sc. programme.

Thanks to my friends at IIRS and ITC for making this study experience truly a memorable and pleasant one.

No amount of gratitude would suffice for the unconditional support and unfailing faith that my family has showed in me. I would be forever indebted for their love.

Gourav Misra

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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.

This study deals with specific crop mapping of sugarcane crop. India is the second largest sugarcane producer in the world and its largest sugar consumer. The sugarcane industry generates a good amount of revenue for the government in duties and taxes. It also helps in creating employment opportunities and mobilising resources in the rural areas of the country. About 45 million sugarcane farmers and other agricultural workers depend on the sugar industry for their livelihoods (Murthy, 2010). Though the sugarcane crop is mainly used for production of sugar, it is also used for making jaggery (an unrefined form of lumpy brown sugar). Sugarcane molasses are used in alcohol production, the fibrous refuse called bagasse is used as fuel and in paper industry, the green tops are used as cattle feed and its by-product called pressmud is used as a source of plant micro-nutrients. Almost all the sugarcane produced in India is consumed domestically. In recent years the sugarcane production in the country has been erratic and has led to serious situations. In 2006, the government banned exports of sugarcane to prevent rising sugar prices and to prevent a re-occurrence of the 2004 fiasco when there was a severe shortage in the domestic sugarcane production (Murthy, 2010). The sugarcane industry undoubtedly holds a very important position in the policies of the government and the lives of the people, and the importance of monitoring and mapping the sugarcane crop cannot be overlooked.

1.2. PROBLEM STATEMENT

The sugarcane crop consists of two growth stages namely sugarcane-plant and sugarcane-ratoon. The sugarcane-plant is the fresh seed that is sown in the field and has a 12 month growing season in India from April-May of 1st year to February-March of 2nd year. The sugarcane-ratoon is the crop that regrows from the harvested of sugarcane-plant and has a 9 month growing season in India i.e. February-March to November of the same year. The sugarcane-ratoon having a shorter growing season reaches the sugarcane mill earlier than the sugarcane-plant for processing as it is harvested earlier. The farmers sell most of their production to the local sugarcane mills for further processing and a small amount of the harvested crop is also sold to the local Kolhus (local jaggery making units). 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 sugarcane mills after losing a share to the local Kolhus. 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 sugarcane crop can provide a cheap and faster alternative to conventional data collection methods.

A specific crop map of sugarcane can help the sugarcane-mill owners, the government agencies, etc. to plan or prepare themselves for the expected volume of harvest of ratoon or plant of sugarcane at any particular time. 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).

Hence 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 namely sugarcane plant and ratoon.

1.3. RESEARCH 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) To investigate the accuracy of the fuzzy classification method adopted with few operators like MIN, LEAST and PROD.

1.4. RESEACH QUESTIONS

In order to achieve the above listed objectives the following questions need to be answered.

a) How to combine temporal single and multi-sensor data in order to build a crop spectral growth profile?

b) How measures of separability can help discriminate the specific crop from other crops or vegetation and which dates are most appropriate to discriminate crops?

c) How effective is fuzzy classification technique for estimating classes in mixed pixel?

d) How to evaluate the effectiveness of image to image based accuracy assessment method used?

1.5. INNOVATIONS AIMED AT

Based on the research objectives and research questions the innovations that are aimed to be introduced in this study are as listed below.

a) The use of multi sensors to build a spectral crop growth profile and the determination of best dates to discriminate a specific crop.

b) Importance of entropy measures criterion in accuracy assessment.

c) Efficiency of image to image based accuracy assessment is to be tested with a number of operators like MIN, LEAST and PROD.

1.6. RESEARCH APPROACH

Temporal data from the sensors AWiFS and LISS-III from IRS P-6 (Resourcesat 1) and from Landsat-5 TM was used for discriminating sugarcane. 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. In the absence of a finer resolution data for LISS III and the multi sensor LISS III-Landsat 5 TM classified outputs, the accuracy assessment for these data sets were done as an entropy measurement. It was aimed to prepare a specific crop map of sugarcane using temporal-multi sensor data.

1.7. STRUCTURE OF THE THESIS

This thesis contains seven chapters. The first chapter with the title introduction deals with the defining the problem statement and the motivation for the study, the research objectives and questions that are needed to be answered, etc. The previous works or study carried out by various scientists has been reviewed in the second chapter titled literature review. The third chapter is on the discussion of the classification approach and the vegetation index used for the analysis of the temporal data. It also deals with the aspect of the accuracy assessment of classified outputs. The fourth chapter describes the study area, field work conducted and the data used from the various sensors for the multi sensor and temporal study of the specific crop. The methodology adopted in the study carried for this thesis is outlined in the fifth chapter titled methodology. It describes the various pre-processing steps of the data, spectral separability analysis, the classifier used and the techniques used in the accuracy assessment of the classified outputs. The sixth chapter presents the results and discussions of the study. The last and the seventh chapter provides the conclusions of the temporal- multi sensor study and also presents some recommendations for future studies.

2. LITERATURE REVIEW

In India like in many other parts of the world, crop monocultures are uncommon. This means that in most of the cases different crops are grown in the vicinity of each other. Given this and that the spectral response of a crop may overlap with that of another class on any single date, one can safely say that crop mapping using single date imagery is a real challenge (Masialeti *et al.*, 2010; Wardlow *et al.*, 2007).
This spectral overlap among crop classes and different vegetation types may be due to the cultural practices followed by the farmer, the planting date, the physiological status of the crop, etc. Temporal analysis of a crop can however provide a good solution for discriminating among various crops and vegetation classes. Several studies have been carried out in the past using time series data for discriminating vegetation classes. Vincent and Pierre, 2003 used time-series high resolution SPOT images to create a NDVI profile of each pixel and classified them into 4 land class viz. bare soil, herbaceous crops, trees on bare soil and trees along with herbaceous crops. The classification accuracy was found to be 83% when 3 images (one each at beginning, maximum and end of season) were used whereas, 5 images well distributed over the time season provided an accuracy of 85%. Doraiswamy *et al.*, 2006 studied the 8 date composite data from MODIS in a three year time series. Long duration vegetation like trees, shrubs and grasses were eliminated using the yearlong data. The crop of interest, soybean could be extracted using the short crop growth season and its unique NDVI pattern. Similarly Wardlow *et al.,* 2007 used a 12 month time series of MODIS EVI and NDVI from agricultural fields. They found that most crops were separable at some point of their growing season and spectral separability was influenced by intra class variability and because of planting dates and climate. It was found that even though EVI and NDVI had a strong correlation during the growing season, their differences were highly pronounced during the senescence phase of the crops. Panigrahy *et al.*, 2009 used multi-date data AWiFS data for classifying crops based on their growing season and their difference in crop calendar. The bands providing the highest minimum Transformed Divergence (TD) were considered as the best bands for discriminating the crop classes. Based on this criterion it was found that incorporating Red, Near Infra Red (NIR) and Short Wave Infra Red (SWIR) bands in maximum likelihood classification increased the overall accuracy in discrimination of winter crops like winter rice, groundnut, vegetables and other vegetation. This proved the need of selection of proper bands when discriminating crops or classes. Ying *et al.*, 2010 used 4 temporal MODIS NDVI product images to create a winter wheat mask on TM image to distinguish wheat from other crops. Also using the class separability criteria, a set of selected 5 band TM image was used for winter wheat classification using MLC (Maximum Likelihood Classification) supervised classification technique. The study concluded that the selection of proper band and the application of a wheat mask increased the accuracy for winter wheat classification to 94%.

The most important requirement for temporal analysis studies is the availability of atmospheric conditions free of rain, haze and clouds so that sufficient data can be acquired for the entire crop growth season. This continuous monitoring of the crop provides data about the important crop growth stages that can act as a discriminating factor in the temporal spectral separability analysis among different crop or vegetation classes. This knowledge of the important crop growth stages in the time domain otherwise known as crop phenology can help in discriminating various crops or vegetation (El Hajj *et al.*, 2007). But this requirement of continuous data availability for regular crop growth monitoring is rarely met partly because of the occurrence of atmospheric disturbances that results in periods of non-usable data and also the repeat cycle of the satellite sensor that causes periods of unavailable data. This provides gaps in temporal data sampling and hampers the temporal analysis study results (Steven *et al.*, 2003). The use of multiple sensors for filling up these periods of long absence in temporal data available from any single sensor may provide a solution to this problem. McNairn *et al.*, 2005 used temporal optical data (Landsat and SPOT) and microwave data (RADARSAT-1 and Envisat - ASAR) to map annual crop inventories. They used decision tree and maximum likelihood classification to reach accuracies up to 80%. Similarly Shang et al., 2008 carried out a decision tree classification using multi temporal and multi sensor data to study their effect on the accuracy of crop mapping. It was found that a multi sensor and multi temporal approach in the form of a combination optical and microwave data provided accuracies of more than 87%.

The literatures reviewed till now proves the importance of conducting multi sensor time series analysis while discriminating vegetation classes. A unique multi sensor approach without fusing of images but rather calibrating the vegetation indices responses from different sensors was conducted by Steven et al., 2003. The authors compared the NDVI and SAVI from a range of satellite sensors and found them to be in strong linear relation. They also found that the vegetation indices from different sensors could be interconverted with an error of about 1-2%. Thus, allowing inter-calibration of vegetation indices from different sensors for better and continuous monitoring of crops. This study was carried out by getting spectral responses from field sites for maize and sugar beet using a spectroradiometer in 945 channels in the range 350-2500 nm. NDVI values were then simulated for various satellite sensors by using the reference spectra for NIR and Red bands responses from the respective satellite data providers. The main disadvantage of this study was the use of simulated NDVI values for various sensors and completely ignoring factors like atmospheric effects, sensor characteristics and radiometry, etc. that may affect response from sensors in the real scenario.

Studies involving classification beyond 3rd level of classification (i.e. discriminating between various agricultural crops and their varieties) can make use of the growth patterns of the different classes of vegetation. The information about the varying crop growth pattern or length of crop growth season, and the occurrence of various crop growth stages in time can help in discriminating or identifying crops using remote sensing techniques. And a multi sensor approach can help in increasing the temporal sampling of data in order to continuously monitor the different crop growth patterns that would be useful in discriminating various crops.

The use of indices from multiple sensors for crop mapping using time series data is however an area not studied extensively so far. This is the one of the main innovations that is aimed to be introduced in this research study.

An important requirement while conducting time series studies is the selection of the optimum number of temporal date combination for class discrimination. The classification exercise is to be conducted only on the best temporal date combination (combination of temporal date providing the best minimum separability between the class of interest and other classes of non-interest). This selection of best temporal date combination is necessary as using all the available temporal data sets may be counterproductive. The reason for this lies in the basics of classification process. The unknown pixels in an image are assigned class labels based on their similarity to the training class statistics. A pixel that might belong to a specific class, say sugarcane ratoon while using an N number of temporal images might start becoming dissimilar from the ratoon class on the addition of more images. This happens because the training pixels statistics start become more specific to the training pixels itself and start differing from the other unknown pixels where the temporal activity might slightly differ. For example, say the ratoon can be discriminated accurately using N dates combination but when more dates are added, the classification accuracy decreases. At N dates combination the temporal training class signature is more general in nature and can account for pixels that belongs to the same ratoon class but have slight different temporal activity. But on addition of more dates the temporal signature becomes more rigid and specific to the pixels used for training and starts becoming different from the unknown pixels having slightly different temporal activity but belonging to the same ratoon class.

Several techniques have been found in literature that deals with the selection of best temporal dates combination. Murthy *et al.*, 2003 studied the temporal spectral overlap between various wheat and various other crops, and demonstrated the need of multi date data for classification. He calculated the Bhattacharya Distance (BD) for various combination of dates (one-date, two-date and three-dates) and found that the highest separability in the three date combination. A similar study on optimisation of number of temporal data sets was conducted by Van Niel and Mc Vicar, 2004. They performed various multi-date classifications for determining the best temporal window for both overall and single class classification using a per-pixel maximum likelihood classifier. The best temporal windows for optimum overall accuracy and single class accuracy were also found to be different. The use of the best temporal window for crop discrimination improved the overall classification accuracy. Zurita-Milla *et al.*, 2011 used fully constrained linear spectral un-mixing method for land cover mapping from temporal MERIS images. They found similar classification results in both the best mono-temporal image and multi-temporal approach. Another important finding was the occurrence of spectral confusion between classes while un mixing and so the authors stress on the importance of considering the spectral separability among classes. This proved the importance of selection of dates for un-mixing.

The earlier studies on time series data indicate the importance of selection of dates from a set of available data for achieving better classification results. This will help not only save time required for data-preparation, processing and analysis time but also improve the classification accuracy. The review of various literature also indicate that the selection of best temporal dates for crop discrimination could be done using a spectral separability analysis study. Some of the prominent distance measures that have been previously used for class separability analysis for discriminating various crops are Jeffries-Matusita (JM) distance (Masialeti *et al.*, 2010; Wardlow *et al.*, 2007) and the Bhattacharya distance (Murthy *et al.*, 2003). These class separability or distance measures can help in measuring the amount of spectral separability present between different classes in the feature space. The spectral separability among the classes when studied for different temporal dates combination can help in selecting the optimum dates for discrimination of classes. So higher the spectral separability among the classes, the lesser is the confusion and better is the results of classification.

Another important consideration while dealing with land cover classification using remote sensing data is the occurrence of mixed pixels. 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. In order to accurately assign the class cover in a pixel the phenomenon of mixed pixel has to be considered. 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. Zadeh, 1965 and Wang,1990 described a fuzzy supervised classification technique that allows a pixel to have multiple class memberships and in turn help in achieving a higher accuracy of classification. Dave, 1991 developed a fuzzy k-means algorithm to detect good clusters amongst noisy data points. It proceeds by defining a noise prototype where all the noisy data points are dumped before the classification is applied on the good clusters. It created an excellent partition of data providing good clusters for improving the classification accuracy. The classification results showed a considerable improvement when Wikantika *et al.*, 2002 and Chen et al., 2004 applied the spectral linear un-mixing model to classify the agricultural fields. Luo *et al.*, 2011 used linear spectral un-mixing to create crop maps. It was found that the un mixing of the pixels to predict the crop classes improved the prediction of crop production considerably. Liang and Chunyu, 2009 used Landsat-TM image and applied fuzzy method for classification of surface features. They found a definite improvement of 5-10% in the accuracy for the classes in the fuzzy classified outputs when compared to the hard classification technique of MLC (Maximum Likelihood Classifier). This proved the efficiency of using the fuzzy classifier to handle mixed pixels in comparison to using traditional hard classifiers. Kumar *et al.*, 2010 extracted single class i.e. water from mixed pixels in AWiFS sensor of Resourcesat-1 satellite. They used PCM (Possibilistic C Means) algorithm where the membership of a class in a pixel is independent of the memberships of other classes in the pixel i.e. the sum of the memberships of the classes in a pixel may not be equal to one. The accuracy of the classified output was found to be in the range of 84-99%. The unique approach of this study is the extraction of a single class independent of the presence of other classes in the image. Such an approach can help in extracting specific class in an image. The above studies prove that the use of un mixing techniques for mixed pixels improved the classification results. The inclusion of such techniques can help in accurate class cover estimation in a mixed pixel. But some of these techniques have been found to have several limitations. 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). And the Linear Mixture Model needs the sum of all the class memberships in a pixel to be unity and requires the number of classes that are to be unmixed to be less or equal to the number of bands present in the data (Chen et al., 2004). In order to overcome all these problems and to achieve the objective of specific crop discrimination fuzzy classification techniques especially PCM can be used. The detail of the PCM classification method has been described in chapter 3. Use of such un-mixing techniques can help in fulfilling the objective of accurate specific crop area discrimination for this M.Sc. research work.

A study is never complete without assessing the accuracy of the results obtained. Accuracy of a classified output is generally assessed by comparing the class assignments as generated by the classifier against the actual classes assigned according to a reference data. The results of the classified output classes are compared against the reference data classes and are arranged in a matrix called error matrix, whose diagonal elements correspond to the number of pixels correctly classified and the off diagonal elements are the overestimation and underestimation class errors. But such an error matrix can only be used for hard classified outputs and hardened reference data. In case of reference and outputs data being soft output measures or membership grades, the data have to be hardened in order to use the conventional error matrix for accuracy assessment. This hardening of soft classified data leads to loss of information (Binaghi *et al.*, 1999).

In order to carry out accuracy assessment while preserving the soft classified data, a modified error matrix for fuzzy outputs i.e. FERM (Fuzzy Error Matrix) has been proposed by researchers (Binaghi *et al.*, 1999; Silvan-Cardenas and Wang, 2008). The FERM is used the same way as the conventional error matrix but the only difference is that the elements of the matrix are calculated based on the fuzzy set theory (Zadeh, 1965). The overlap between classes of the fuzzy/ soft reference and classified data is calculated based on operators like MIN, LEAST, PROD, etc. (Silvan-Cardenas and Wang, 2008). Since the behaviour of these operators in the image to image accuracy assessment method has not been evaluated, so the testing of these operators is also an objective of this study.

The accuracy of classified outputs can also be assessed by measuring the uncertainty in the results. Uncertainty in the data is introduced from the initial step of data acquisition and propagates with each step of processing, transmission and classification. The knowledge of the uncertainty in the results can help in judging its accuracy and the reliability. Deghan and Ghassemian, 2006 evaluated several uncertainty measures like MRE (Mean Root Error), RMSE (Root Mean Square Error), LCC (Linear Correlation Coefficient) and entropy. They found MRE, RMSE and LCC to be dependent on the error of the results and sensitive to error variations. However the entropy being dependent on the actual outputs of the classifier was found to be sensitive to uncertain variations. The entropy measured the pure uncertainty in the classification results. The advantages of using an entropy based accuracy assessment technique were also proven by Kumar and Dadhwal, 2010. They used fuzzy overall accuracy and fuzzy kappa coefficient for relative measures of accuracy assessment. The use of entropy based accuracy assessment however provided an absolute uncertainty indication in the classified results. The use of entropy measure along with the conventional overall accuracy and kappa coefficient results improved the information retrieved from the accuracy assessment study.

Various gaps were noticed while reviewing the past works relating to discrimination of crops using temporal data like;

a) Integration of data from multi sensors for crop monitoring/ discrimination studies is not studied enough.
b) Accuracy assessment of soft classified outputs using various operators MIN, LEAST and PROD in image to image accuracy assessment method has to be tested.

These gaps were addressed in this M.Sc. research study.
The temporal single and multi-sensor data used, the classification methods, methodology adopted, and the results and discussions for this study are explained in detail in the following chapters of this thesis.

3. 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.

3.1. 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, sugarcane-plant and ratoon.

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

$$\mathrm{NDVI} = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \qquad (1)$$

where, ρ_{nir}= near infra-red band of sensor, and ρ_{red}= red band of sensor.

3.2. 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.

3.2.1. 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, $d_{ij}^2 = \| X_i - V_j \|_A^2$ and the distance in feature space between X_i and V_j ,

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

And μ_{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 < ∞) that controls the degree of fuzziness (at m=1 the partitions that minimise the J_m function become hard and as m tends to ∞ 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 μ_{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, U^i, 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.

3.2.2. 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):

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

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 $0 \le \mu_{ij} \le 1$

$d_{ij}^2 = \| X_i - V_j \|_A^2$ and the distance in feature space, μ_{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.

η_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 (μ_{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 (μ_{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, U^i, is selected and its elements are assigned membership values ranging from 0 to 1 to for fuzzy classification.
3) Then η_j 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 η_j is estimated from equation (7) using the updated U matrix.
8) the elements of U matrix is then again computed from the final η_j 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 (X_j) from training data sets instead of cluster centre(V_j). 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 ($\sum_{j=1}^{C} \mu_{ij} = 1$), 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 M.Sc. research work.
* the above explanations for fuzzy classifiers and equations have been adapted from Kumar et al., 2010.

3.3. ACCURACY ASSESSMENT

Accuracy assessment of classified outputs from a coarse resolution image can be evaluated with the classified output of a finer resolution image as an image to image based accuracy assessment technique. This technique of image to image based accuracy assessment is followed as generating a reference dataset for the area is not possible as the sugarcane fields are changing every year. In such a situation higher spatial resolution imagery can be used for assessing the classified outputs of coarse resolution imagery.

This sub-section describes the various accuracy assessments techniques namely FERM (Fuzzy Error Matrix) and entropy based accuracy assessment.

3.3.1. Fuzzy Error Matrix (FERM) AND DIFFERENT OPERATORS

Accuracy of a classified output is generally assessed by comparing the class assignments as generated by the classifier against the actual classes assigned according to a reference data. The comparison results of the classified output classes against the reference data classes are arranged in a matrix called error matrix, whose diagonal elements correspond to the number of pixels correctly classified and the off diagonal elements are the overestimation and underestimation class errors. But such an error matrix can only be used for hard classified outputs and hardened reference data. In case of reference and outputs data being in soft output measures or membership grades, the data have to be hardened in order to use the conventional error matrix for accuracy assessment. This hardening of soft classified data leads to loss of information (Binaghi et al., 1999).

Therefore in order to carry out accuracy assessment while preserving the soft classified data, a modified error matrix for fuzzy outputs i.e. FERM (Fuzzy Error Matrix) has been proposed by scientists (Binaghi et al., 1999; Silvan-Cardenas and Wang, 2008). The layout of FERM is the same as the conventional error matrix but the only difference is that the elements of the matrix are calculated based on the fuzzy set theory (Zadeh, 1965). The overlap between classes of the fuzzy/ soft reference and classified data is calculated based on operators like MIN, LEAST, PROD, etc. The MIN (minimum operator) is a fuzzy set intersection operator that measures the maximum possible sub-pixel overlap that can occur between the reference and classified classes. This operator has been the natural choice for accuracy assessment using FERM. The LEAST operator measures the minimum possible sub-pixel overlap between classes. The PROD operator measures the expected class overlap between the classified and reference sub-pixel partitions (Silvan-Cardenas and Wang, 2008). The mathematical expressions of the operators are as follows;

1) The MIN operator calculates the maximum overlap as min $(\mathrm{R}_{nk}, \mathrm{S}_{nl})$.

2) The LEAST operator calculates the minimum overlap as max $(\mathrm{R}_{nk} + \mathrm{S}_{nl} - 100{,}0)$.

3) The PROD operator calculates the expected overlap by chance as $(\mathrm{R}_{nk} * \mathrm{S}_{nl})$.

where, R_{nk}= is the grade membership of pixel n assigned to class k by the classified dataset.

and S_{nk}= is the grade membership of pixel n assigned to class l by the reference dataset.

The elements of the FERM are calculated by the using specific operators for measuring the overlap between the classified and the reference datasets. Then the overall accuracy of the classified outputs is then calculated as done in the usual error matrix case.

The FERM can be used to derive several accuracy measures similar to that of the normal error matrix used for the conventional hard classification outputs. One of the objectives of this study is also to test MIN, LEAST and PROD operators for image to image based accuracy assessment of fuzzy outputs.

3.3.2. ENTROPY FOR ACCURACY ASSESSMENT

Classification accuracy is usually evaluated by the use of an error matrix but for this study generating reference data for LISS III images was not possible because of the unavailability of any higher resolution image for the study area. The sugarcane fields are also changing every year and the crops grown in the fields being a one-time event makes it impossible to generate reference data for it. But for this study test sugarcane-plant and ratoon fields were identified, and these sites were used to measure the uncertainty in classification of these unbiased belonging sites (sugarcane sites that were not used in training of the classifier). In such a case accuracy assessment was conducted using entropy as an indirect absolute classification accuracy indicator. The unbiased belonging sites in the classified outputs are expected to have lower entropy than non-belonging sites (i.e. sites of the non-interest classes).

Uncertainty in remote sensing data is introduced along with image acquisition and it propagates with every step of processing, transmitting and classification. This uncertainty eventually affects the information quality and therefore has to be quantified for evaluation the correctness of data or information. The various the sources of uncertainty in classification process are the uncertainty in determination of number of land cover classes, existence of mixed pixels, limitation in number of training samples and the use of an improper classifier. Several measures like MRE (Mean Root Error), RMSE (Root Mean Square Error), LCC (Linear Correlation Coefficient), membership vectors and entropy can be used for measuring the uncertainty in a dataset. The benefits of using entropy for uncertainty measurement are explained in chapter 2 Literature review.

The uncertainty associated with any soft classification process can be derived from the class memberships assigned to the pixel. The elements of the pixel correspond to the membership values assigned to different classes in a pixel.
For pixel x, the membership vector can be defined as given in Eq. (9):

$$\mu\,(W/x) \;=\; \begin{bmatrix} \mu\,(W_1/x) \\ \vdots \\ \mu\,(W_M/x) \end{bmatrix} \qquad (9)$$

where, $\mu\,(W_M/x)$ is the membership of class "M" in pixel "x". The uncertainty associated with the classification results is high when all the class memberships for a pixel are the same.

In order to assess the uncertainty in the process of data analysis, Deghan and Ghassemian, (2006) improved on the results of membership vector. They proposed an entropy measurement technique for expressing the extent of uncertainty in classification results. Unlike the membership vector this entropy criterion can summarize the uncertainty as a single number per pixel per class in an image.
The entropy of the classified outputs is calculated as given in Eq. (10):

$$\text{Entropy (x)} = \sum_{i=1}^{M} -\mu\left({}^{w_i}/_{x}\right) \log_2 \left(\mu\left({}^{w_i}/_{x}\right)\right) \qquad (10)$$

where, M= the total number of classes i.e. 1 for this study and $\mu\left({}^{w_i}/_{x}\right)$= the membership of pixel x in class w.
The entropy measure used here provides a measure of uncertainty in the classified outputs at unbiased belonging (sugarcane sites of interest class not used in training of classifier) and non-belonging sites (non-interest classes). It can range from 0.0 (low uncertainty) to 1.0 (high uncertainty). A classified output with lower entropy measure at unbiased belonging sites will have higher classification accuracy with lower uncertainty. This estimation of uncertainty is essential to evaluate the classification results.

In this chapter an overview of the vegetation index and the classification approach used is presented. The utility of the FERM in assessing soft classified outputs with soft reference data has also been highlighted. The next chapter explains about the study area, the data used and field visit conducted for this study.

4. STUDY AREA AND DATA USED

This chapter deals with the descriptions of the study area, the data sets and the field visit of the area conducted for the purpose of specific crop mapping.

4.1. STUDY AREA

The study area selected for this research work was Deoband city in Saharanpur district of the state of Uttar Pradesh, India. It is located in the upper doab region of Uttar Pradesh. This city lies to the northern part of India with a centre latitude and longitude of 29.62^0 N and 77.67^0 E respectively with an average elevation of 250 metres. Figures 4-1 and 4-2 show the location of the study area in the Indian landmass.

The study area spans about 15 kms in the East-West direction and about 6 kms in the North-South direction. The main crops grown in this area is sugarcane along with wheat and plantation crops like mango, poplar, etc. The many sugarcane processing mills present in this area procure the bulk of the sugarcane produce providing a steady source of income for the farmers and also help in generating employment for the many seasonal agricultural labourers. The abundance of sugarcane farming and ready availability of data were the main reasons for the selection of the area for this study.

Figure 4-1: Political map of India
(Source: www.surveyofindia.gov.in/soi_geo.html)

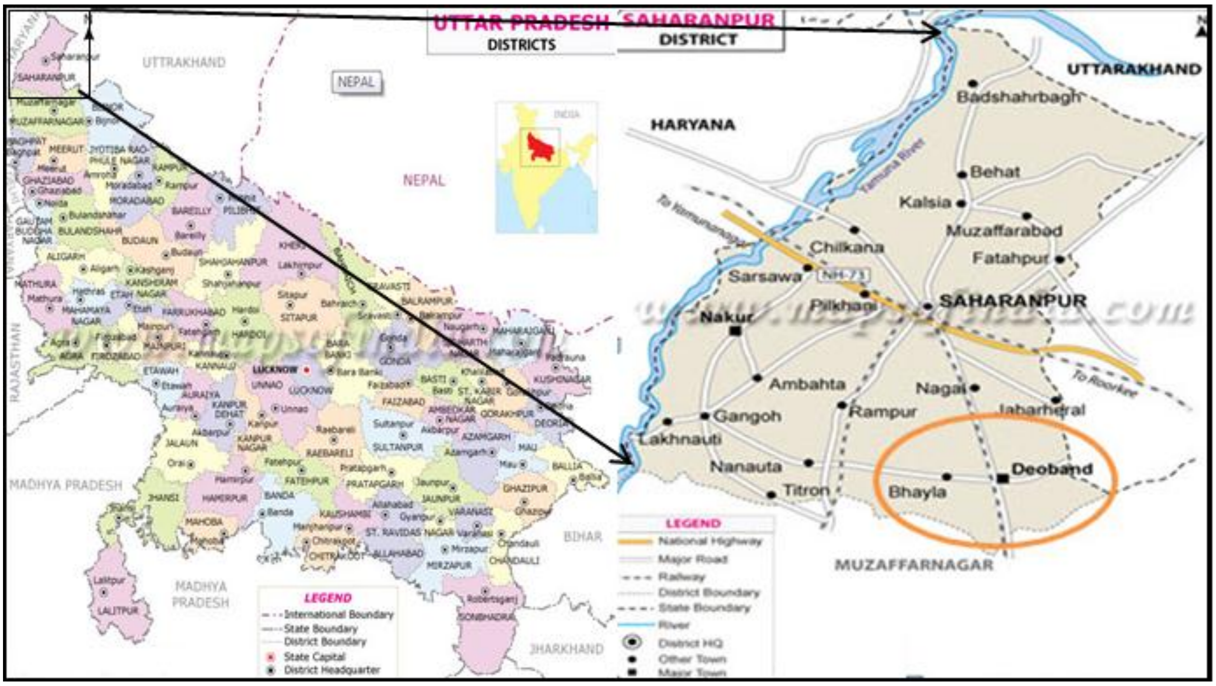


Figure 4-2: Study area (Deoband, Saharanpur district, Uttar Pradesh), (source: www.mapsof india.com).

4.2. DATA USED

This study deals with the multi sensor data various sensors like LISS III (Linear Imaging Self Scanner) and AWiFS (Advanced Wide Field Sensor) from IRS-P6 (RESORECSAT-1) satellite and TM sensor aboard Landsat-5 satellite. The sensor details are listed in the following sections.

4.2.1. IRS-P6 (RESOURCESAT-1)

The IRS-P6 (RESOURCESAT-1) satellite was launched by India in October 2003. The sensors on-board it are LISS IV, LISS III and AWiFS (Advanced Wide Field Scanner).
The LISS III sensor is multispectral and is operational in the visible to mid infra-red region with a spatial resolution of 23.5m, and swath width of 140 Km. The spatial resolution of LISS IV is 5.8m. The multi-spectral (visible to near infra-red) swath width is 24 Km and for the panchromatic mode the swath width is 70 Km. The spatial resolution of AWiFS is 60m and swath width is 740 km. Radiometric resolution of AWiFS is 10 bits and it has a 5 day revisit time. Radiometric resolution of LISS III and LISS IV is 7 bits, while the AWiFS has 10-bit.This orbit of the satellite is polar, circular and sun-synchronous with an apogee of 800-km, and has a 24-day repeat cycle for the LISS III sensor and the repeat cycle for LISS IV is 5 days (Oza et al., 2008). The sensor characteristics of the IRS-P6 satellite are listed in the tables 4-1, 4-2 and 4-3.

BAND	WAVELENGTH (µm)	RESOLUTION(m)
2	0.52-0.59 (green)	23.5
3	0.62-0.68(red)	23.5
4	0.77-0.86(near-IR)	23.5
5	1.55-1.70(SWIR)	23.5

Table 4-1: LISS III Specifications

BAND	WAVELENGTH (μm)	RESOLUTION(m)
2	0.52-0.59(green)	5.8
3	0.62-0.68(red)	5.8
4	0.77-0.86(near-IR)	5.8

Table 4-2: LISS IV Specifications

BAND	WAVELENGTH(μm)	RESOLUTION(m)
2	0.52-0.59(green)	60
3	0.62-0.68(red)	60
4	0.77-0.86(near-IR)	60
5	1.55-1.70(SWIR)	60

Table 4-3: AWiFS Specifications

4.2.2. LANDSAT- 5 TM

The Landsat-5 satellite was launched by the National Aeronautics and Space Administration (NASA) in the year 1984 with two sensors TM and MSS (NASA, 2011). The MSS sensor is no more functional. The TM (Thematic Mapper) is an advanced multispectral scanning, earth resources sensor with a temporal resolution of 16 days. It has a swath width of 185 kms. Its spatial resolution of 30 metres is similar to that of the LISS III (23.5 metres) sensor of IRS-P6. The Landsat-5 TM has a higher temporal resolution of 16 days in comparison to LISS III (24 days revisit) and may help in acquiring images in the periods of unavailability of data from LISS III. The Landsat-5 TM sensor details (NASA, 2011) are as listed in table 4-4.

BAND	WAVELENGTH(μm)	RESOLUTION(m)
1	0.45-0.52	30
2	0.52-0.60 (green)	30
3	0.63-0.69 (red)	30
4	0.76-0.90 (near-IR)	30
5	1.55-1.75	30
6 (Thermal Band)	10.4-12.5	120
7	2.08-2.35	30

Table 4-4: Landsat-5 TM Specifications

4.2.3. TEMPORAL DATA AVAILABILITY

The data used in this study was temporal in nature and acquired from different sensors i.e. LISS III, AWiFS and Landsat-5 TM. The data from LISS IV sensor was not included, since enough temporal data covering the study area was not available. There were 9 LISS III, 11 AWiFS and 1 Landsat-5 TM imageries available for conducting the study. The available multi sensor data are as listed in table 4-5.

LISS III (23.5 m)	Landsat-5 TM	AWiFS (56 m)
		20 February 2010
11 March 2010		06 March 2010
04 April 2010		
28 April 2010		28 April 2010
22 May 2010		22 May 2010
15 June 2010		15 June 2010
		14 July 2010
	12 October 2010	28 September 2010
30 November 2010		05 December 2010
24 December 2010		
		05 February 2011
06 March 2011		06 March 2011
30 March 2011		30 March 2011

Table 4-5: Available temporal dates from multi sensors

4.2.4. FIELD VISIT

A field visit of the study area (Deoband, Uttar Pradesh) was also conducted for collecting information about the location of the various land use and land cover classes present in the area. The main classes present in the study area were urban area, sugarcane crop (plant and ratoon), wheat crop and mango orchards. Information about the location of sugarcane plant and ratoon was collected by visiting the field sites and also from the help of agricultural land survey records of the area maintained by a sugarcane-mill operating in the area. Since most of the farmers of the study area belonged to the small and marginal category with fragmented land holdings, only the sugarcane fields that were big enough to be identifiable on AWiFS image were selected. The average size of the selected sugarcane field site was about 100 * 100 square metres.

Sugarcane farming villages around the city of Deoband like Hashimpur, Bhaila and Makbara were visited in the last week of October, 2011 for collection of field data. Locations of 4 sites each for sugarcane-plant and ratoon were collected from each of these three locations i.e. 12 fields for plant and 12 for ratoon in total. The temporal images that were used in the study belong to the period February, 2010- March, 2011 and the field data was collected in October, 2011. So the fields that had sugarcane-ratoon crop during field visit in October, 2011 were actually sugarcane-plant during the period February, 2010- March, 2011. Similarly the fields having sugarcane-plant during field visit were having sugarcane-ratoon crop in the previous year (i.e. the period of study). This fact was kept in mind while collecting the field data. Images of some of the sugarcane sites visited during the field visit are shown in figures 4-3 to 4-6.

Figure 4-3. Sugarcane-plant site in Oct.2011 (ratoon in 2010)_ Location: Village Makbara

Figure 4-4. Sugarcane-ratoon site in Oct.2011 (plant in 2010)_Location: Village Makbara

Figure 4-5. Sugarcane-ratoon site in Oct.2011 (plant in 2010)_Location: Village Bhaila

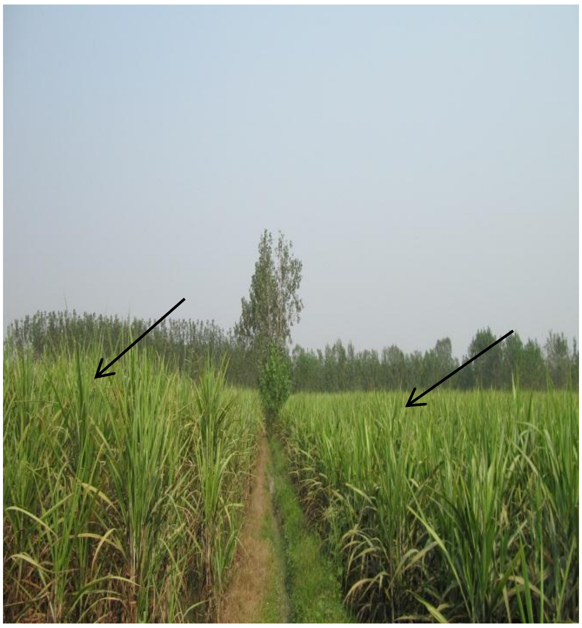


Figure 4-6. Sugarcane-plant site in Oct.2011 (ratoon in 2010)_Location: Village Hashimpur

Figures 4-3 to 4-6: Location of some of the Sugarcane sites collected during field visit of the study area, Deoband.

The sugarcane sites were collected around the farming villages of Makbara, Hashimpur and Bhaila of Deoband city. The lat./ long. of the farming areas are listed below:

Makbara: 29.72^0 /77.69^0 (lat/ lon)
Hashimpur: 29.70^0/77.70^0 (lat/ lon)
Bhaila: 29.70^0 /77.61^0 (lat/ lon)

The location of the perennial mango orchards and the urban areas were also noted with the help of Google Earth and field visit both. Since there was no wheat crop present in the fields at the time of field visit, its location had to be ascertained by interviewing the farmers and by analysing the temporal remote sensing images of the sites. These sites were used in the spectral separability analysis between specific class of interest and other non-interest classes and for accuracy assessment of LISS-III outputs using entropy measurement method. However for classification of specific crop, only the sugarcane-plant and ratoon sites were used for training the PCM classifier.

The chapters till now have presented the problem statement, literature review, data used, fuzzy classification and soft outputs accuracy assessment methods. Finally building on the concepts of the spectral separability analysis, soft classification methods and accuracy assessment; the methodology adopted, the results, discussions and conclusions are presented in the concluding chapters.

5. METHODOLOGY

This chapter describes the research methodology followed for executing this study of crop discrimination using temporal single and multi-sensor data. The pre-processing steps, those including image to image registration and atmospheric correction are first explained in this chapter. After that the generation of NDVI images and temporal crop profiles, class- separability analysis, classification of temporal dates using fuzzy classifier (PCM) and selection of best dates are also explained.

5.1. METHODOLOGY ADOPTED

This section provides an overview of the methodology adopted for the study. The flowchart of the methodology followed for this study is shown in figure 5-1. The detailed explanation of the methodology followed for discrimination of specific crop using the temporal single and multi-sensor approach is explained in the following sections of this chapter.

One of the objectives of this study was to select the best temporal dates combination from a single optical sensor for the discrimination of a specific crop i.e. sugarcane plant and ratoon. First of all the available temporal images for both LISS-III and AWiFS were pre-processed using image to image registration and atmospheric corrections. NDVI images for the available temporal dates of LISS-III and AWiFS were generated and a class separability analysis was conducted to select the best 2, 3, 4 …. dates combinations for both the sensors. This saved the work of classifying all the possible dates (n_{C_r}) combinations (where, n = the available temporal dates of a sensor, and r = the number of best temporal dates to be selected). These best dates were then used for discrimination of the specific crop using training sites for sugarcane-plant and ratoon separately in the PCM supervised Classifier. Six sugarcane sites (each for plant and ratoon) collected during field work were used in the training of the classifier to generate specific crop maps for sugarcane-plant and ratoon separately. The rest of the unbiased sites not used in training the classifier (six sites each for plant and ratoon) were used in accuracy assessment of the classified output images for LISS-III. The accuracy assessment of PCM classification outputs was conducted as an entropy measurement for LISS-III temporal combination outputs. The accuracy measurement of the AWiFS temporal combination outputs was conducted against the best accuracy LISS-III temporal output as an image to image based accuracy assessment technique using a sample of 500 randomly drawn pixels. Then an available image (12 October 2010) from Landsat-5 TM was used for filling up the gap period in the best temporal dates combination from LISS-III sensor. This was done in order to assess the effects of a temporal and multi-sensor approach in the discrimination of the specific crop.

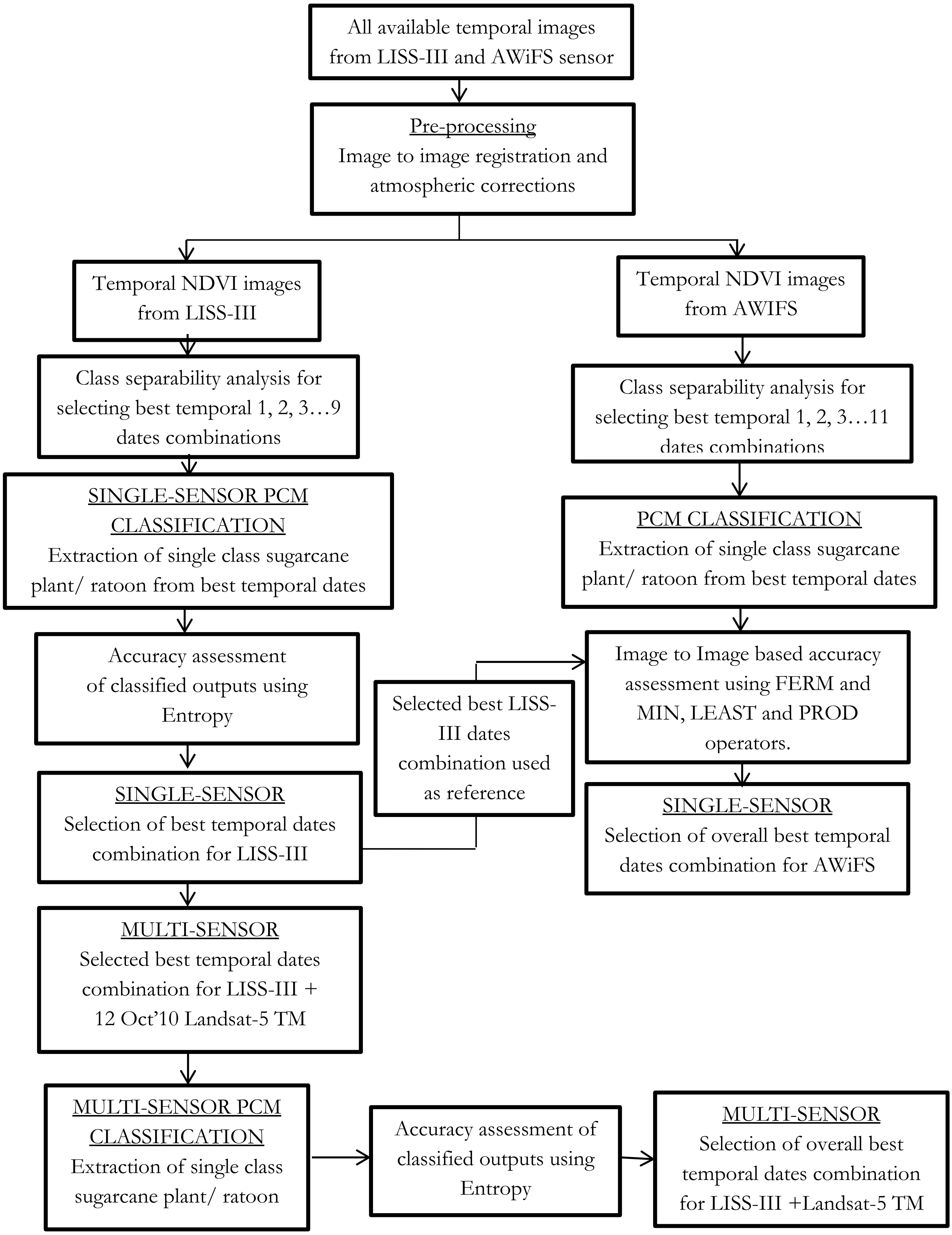


Figure 5-1: Flowchart showing methodology for the temporal and multi sensor specific crop discrimination study

5.2. PRE-PROCESSING

Pre-processing of remote sensing images is necessary for reducing the noise due to atmospheric conditions and to increase the interpretability of information from the data. Especially when conducting vegetation studies using temporal images, the images need to be spatially and spectrally compatible. The idea behind pre-processing the temporal images was to reduce the noise introduced into the data because of atmosphere and to make the images spatially compatible to each other. Thus the available temporal images of LISS-III and AWiFS were pre-processed with respect to image registration and atmospheric corrections for their use in the temporal study.

Image to image registration technique was carried out for registering the temporal images with each other. A clear image (28 April 2010) with no haze and cloud cover from the higher resolution LISS-III sensor was selected as reference and all other temporal images of LISS-III and AWiFS sensor were registered with it. The Erdas Auto Sync module was used for this purpose and the R.M.S.E (Root mean Square Error) was kept under 0.5. This was done so that when the temporal images were stacked over each other the corresponding class on the temporal images lie over each and there was near perfect correspondence of the pixels. (Note: this is a pixel based supervised classification where the changes in a pixel are tracked over the time and hence perfect correspondence of the pixels in the temporally stacked images is of great importance). A nearest neighbour resampling technique was used during the image registration exercise as it retains the original DN values and doesn't average them as done by other resampling techniques (Erdas Inc., 2010). The LISS-III and AWiFS images were resampled to 20 metres and 60 metres respectively. This was conducted in order to have a near perfect match and a 1:9 correspondence between the respective AWiFS and LISS-III pixels. Such a correspondence between the pixels of both the LISS-III and AWiFS was helpful in the accuracy assessment of the classified AWiFS against the classified LISS-III reference.

Since this crop discrimination study was carried out over a period of a year, there was a need to normalise the effects of the changes in the atmospheric conditions on the temporal images. In order to account for these temporal atmospheric conditions and the atmospheric disturbances like haze, aerosol, etc. atmospheric corrections were applied on all the images of LISS-III and AWiFS. For this purpose of atmospheric corrections, the ATCOR module of Erdas Imagine software was used. This atmospheric correction module (ATCOR) used calibrated files for specific sensor (here IRS-P6's LISS-III and AWiFS) for correcting the effects of the atmospheric disturbances. The aerosol effect was also removed using the atmospheric model for temperate-rural conditions.

5.3. NDVI AND TEMPORAL CROP GROWTH PROFILE

After carrying out the initial pre-processing steps, the next step was to generate NDVI outputs for the temporal AWiFS and LISS-III images. The NDVI images from the temporal LISS-III and AWiFS images were generated using the Spatial Modeller option of Erdas Imagine software. The NDVI images enhanced the vegetation class in the images and helped in distinguishing it from other non-vegetation classes.

The NDVI outputs of the temporal dates for each sensor (LISS-III and AWiFS) were stacked separately in a chronological order of their dates. Temporal Crop growth profiles were generated for sugarcane-plant and ratoon for use in training of the PCM Classifier and also to get a visual representation of the differences in the growth profiles of sugarcane plant and ratoon. The NDVI values within a field were averaged in a 3*3 pixel window, and then these averaged NDVI values from six sugarcane training sites were again averaged for generating sugarcane crop growth profiles (plant and ratoon) for both LISS-III and AWiFS sensors separately. A 3*3 pixel window was selected as an optimum size for averaging of the spectral responses with in a field from LISS-III and AWiFS so that the window area does not exceed training sites area. Only the sugarcane fields with dimensions comparable to 3*3 pixels were selected for creating temporal crop growth profiles. This averaging of the spectral responses in a 9 pixel (3*3) window was done to capture the differences in the crop growth present with in a field. The errors that might have crept into the data and eventually the temporal crop spectral signatures because of mis-registration were reduced due to this averaging technique. The crop growth profiles are illustrated in chapter 6 Results and Discussions. These temporal signatures of sugarcane-plant and ratoon (separately) were also used in the classifier to generate specific crop classified outputs for sugarcane-plant and ratoon separately.

5.4. SPECTRAL SEPARABILITY ANALYSIS

In this study a Euclidean distance measure that uses mean of the training class has been used for the spectral separability analysis. This was done in order to minimise the effect of noise that could have been introduced as a result of spectral mixing of different crop responses in training data. Literatures (Tso and Mather, 2009) indicate the advantage of using a distance measure based on class mean while expecting noise in data. In such a case Euclidean distance that uses that uses mean of a class is least affected, while other distance measures like JM (Jeffries-Matusita) and Mahalanobis distance,etc. that use variance-covariance statistics for the class are the most affected and provide poor results. Hence the use of Euclidean distance measure in this study was done. The Euclidean distance measure (Erdas Inc., 2010) is the distance between the unknown pixel and the training class mean. It is calculated as given in Eq. (1):

$$D = \sqrt[2]{\sum_{i=1}^{n}(d_i - e_i)^2} \qquad (1)$$

where, D = Spectral distance,

n = number of bands,

d_i = DN value of pixel d in band i,

e_i = DN value of pixel e in band i.

When there are only two bands i.e. i and j, the Eq. (1) reduces to;

$$D = \sqrt[2]{(d_i - e_i)^2 + (d_j - e_j)^2}$$

The same averaged NDVI values used earlier for the generation of crop growth profiles were used in the spectral separability analysis. The NDVI values for the non-interest classes like urban area, orchard and wheat were also averaged the same way as done for the class of interest i.e. sugarcane plant and ratoon. A spectral separability analysis to select the best temporal 1, 2, 3…. dates combination for LISS-III and AWIFS sensors was then conducted. This was done to save the work of classifying all the possible dates (n_{C_r}) combinations (where, n = the available temporal dates of a sensor, and r = the number of best temporal dates to be selected) and to select the best temporal dates combinations. For example, in AWiFS there were 10 available temporal images and in order to select the best 5 date combination for discriminating specific crop (say sugarcane-ratoon) 10_{C_5} or 252 images had to be classified. But a spectral separability analysis between the sugarcane-ratoon and other non-interest classes (sugarcane-plant, urban area, wheat crop and orchard) reduced the need of classifying all the possible 252 AWiFS dates combination images. The best 5 AWiFS dates combination for discriminating sugarcane-ratoon was thus found by maximising the minimum Euclidean distance between sugarcane-ratoon and the nearest non-interest class. The non-interest class (say sugarcane-plant) that has the minimum distance Euclidean distance separability from sugarcane-ratoon (class of interest) on any particular dates combination is expected to be more confused as ratoon than other non-interest classes (urban area, wheat and orchard). So by maximising this minimum Euclidean distance the confusion between the class of interest and the non-interest class was expected to be minimised leading to higher classification accuracy. Similarly in an analysis of temporal combination of 10 dates there would be 10_{C_1} + 10_{C_2} + ….. + $10_{C_{10}}$ = hundreds of images would need to be classified. Therefore a spectral analysis helped in reducing the effort in classifying hundreds of possible temporal image combinations for selecting the best 1, 2, 3…. dates combinations for a sensor while discriminating a specific crop. As the best minimum distance between the class of interest and non-interest class increases in the feature space, the confusion between them decreases and thus the classification accuracy increases. Thus the best 1, 2, 3,…11 dates combination for AWiFS sugarcane-plant and ratoon was found separately. Similarly the best 1, 2, 3,…9 dates combination for LISS- III sugarcane-plant and ratoon were also found separately.

5.5. CLASSIFICATION

Since the best 1, 2, 3,….. dates for specific crop discrimination have been selected from the previously conducted spectral separability analysis, the next step was to select an overall best dates combination. The best 1, 2, 3,… dates had been selected previously and it was observed that the minimum spectral separability of those dates combinations kept increasing on addition of extra dates from the initial 2 dates combination. However this increasing minimum separability measure did not provide any information about the dates combination with the maximum classification accuracy. This overall best dates combination would give an indication of the dates around which the specific crop discrimination to be done for achieving maximum classification accuracy. A fuzzy based PCM supervised classification was thus carried on the selected dates combinations to select the overall best dates combination from the available best 2, 3, 4…… dates combination. The same averaged NDVI values used earlier for the generation of crop growth profiles and spectral separability analysis were used in the training of the PCM classifier. Based on these mean NDVI training values, all other other unknown pixels are assigned memberships for their degree of belongingness to the specific class in a PCM classified output. The equations describing the working of the PCM classifier has already been discussed in chapter 3 (Indices and Classification Approach). The main consideration while selecting the best dates was that the memberships assigned to the crop of interest should be maximum and the non-interest class should be minimum. This PCM classification technique was carried out using SMIC (Sub-Pixel Mapping Image Classifier), a JAVA based image processing package (Kumar et al., 2006). A screenshot of the SMIC classifier is given in the figure.5-2.

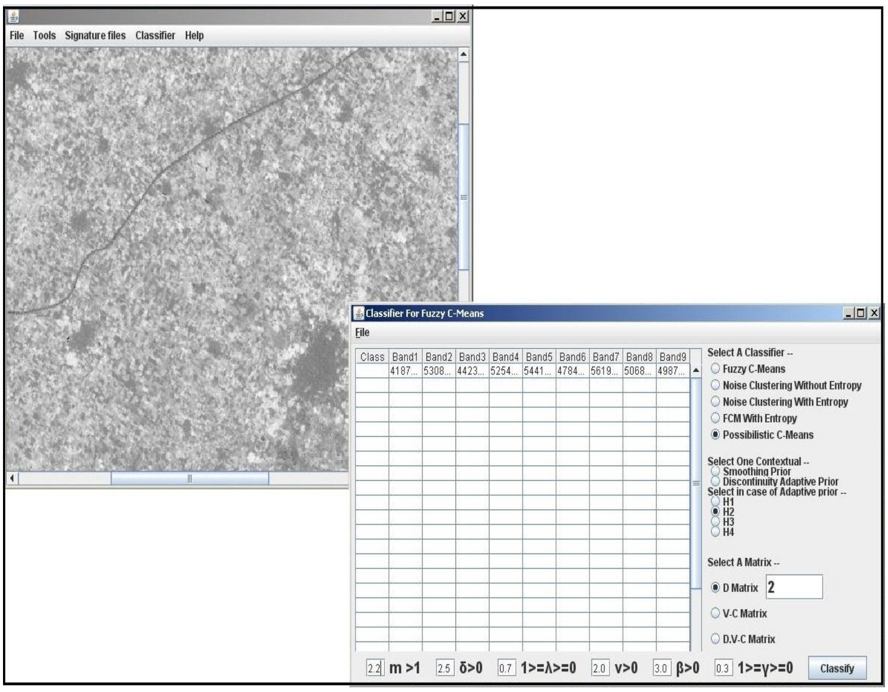


Figure 5-2: Screenshot of SMIC image processing package used for PCM Classification

5.6. ACCURACY ASSESSMENT

There was no high resolution imagery against which the accuracy assessment of specific crop classified outputs of the LISS-III could be the done. Therefore the accuracy of the LISS-III specific crop classified outputs was done as an entropy measure. The entropy of the classified unbiased ratoon sites in a classified image specific to ratoon class (image classified using temporal ratoon signature) was measured using the mean of the memberships of the unbiased sites. This entropy measured at the unbiased belonging sites (ratoon sites not used in training) should have low entropy. Low entropy indicates higher classification accuracy with lower uncertainty. The dates combination having the least entropy for the belonging ratoon sites (unbiased ratoon sites not used in training of classifier) was selected as the LISS-III overall best dates combination for discriminating ratoon crop. Similarly the overall best dates combination for discriminating sugarcane-plant was also selected. So different best overall LISS-III dates combination were obtained for both sugarcane-plant and ratoon using this procedure. These overall best dates combination then served as reference for assessing the accuracy of AWiFS specific crop classified outputs. The best overall LISS-III dates combination was then used with a pre-processed Landsat-5 TM NDVI image and classified for extracting specific crop as explained earlier. The outputs of the classified temporal LISS-III and Landsat-5 TM dates combination was then assessed using entropy measurement technique to analyse the effects of a multi-sensor approach on specific crop discrimination.

The accuracy of classified AWiFS outputs was assessed against the selected best dates combination for LISS-III using an image to image based accuracy assessment technique. The overlap between the class memberships (represented by fuzzy sets) in LISS-III reference image and the AWiFS classified outputs was measured by the use of operators like MIN, LEAST and PROD. The image to image based accuracy assessment of the soft classified outputs and soft reference was done using the SMIC software. A screen shot of the soft accuracy assessment module of the SMIC software is shown in figure. 5-3.

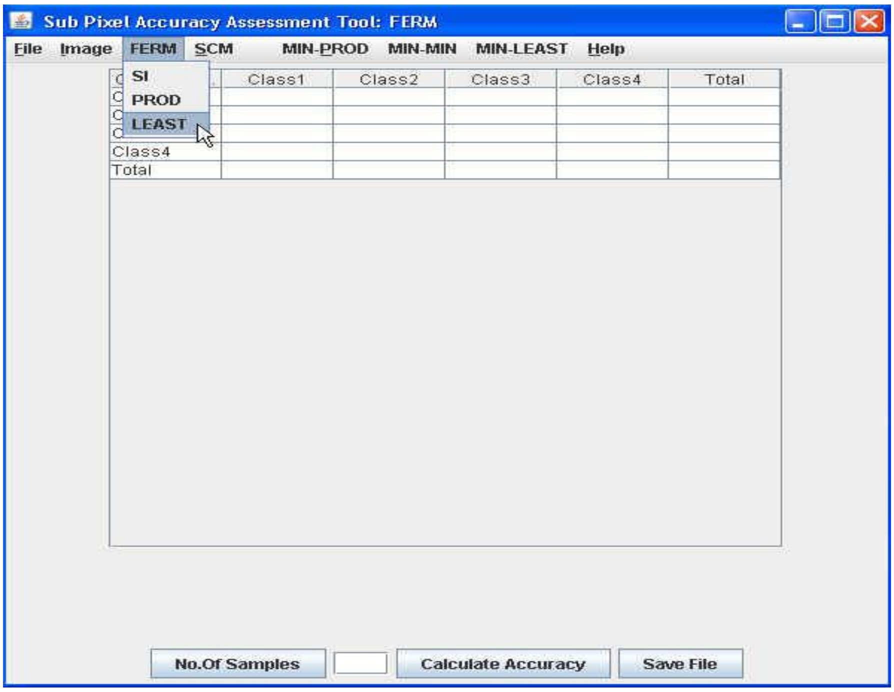


Figure 5-3: Screenshot of SMIC image processing package used for image to image based accuracy assessment

The basic explanation of the operators is as given in chapter.3, section. 3.3.1. The behaviour of these operators in the case of image to image accuracy assessment have not been analysed before and hence they were used in this study. Each of these three operators give different information about the class overlap and hence all of them were studied for their effect on assessing classification accuracy. These operators follow the basic fuzzy set theory (Zadeh, 1965), where the MIN operator measures the maximum possible overlap between two classes. And hence the overlap calculated from MIN operator should be maximum for the best overall dates combination. Similarly the LEAST operator that gives the minimum possible overlap between two clases should be minimum, and the PROD operator that gives the chance overlap between the classes should be the maximum for the best overall dates combination. The dates combinations providing the highest classification accuracy was then selected as the best overall dates combination for discriminating specific crop sugarcane-plant and ratoon. Further explanations about the selection of the highest accuracy dates combination using FERM and different operators is given in chapter 6.

6. RESULTS AND DISCUSSION

This chapter presents the results and discussions obtained as a result of the specific crop mapping using temporal single and multi-sensor approach. This chapter presents the results in three sections dealing with construction of crop spectral growth profile, spectral separability analysis results, PCM classification results and accuracy assessment of soft classified outputs. NDVI values were used for temporal growth analysis and spectral separability analysis of sugarcane plant and ratoon as it enhances the vegetation class in the remotely sensed images.

6.1. CROP SPECTRAL GROWTH PROFILES

NDVI images were generated from a finer resolution (23.5 metres) LISS-III sensor data. These were used to generate temporal spectral sugarcane crop growth profiles. The temporal NDVI training data for the sugarcane-plant and ratoon are listed in table 6-1 and a visual representation of the sugarcane crop spectral growth curves is given in the figure 6-1.

Temporal LISS-III Dates	Plant site NDVI	Ratoon site NDVI
1 (11 March 2010)	0.135	0.445
2 (4 April 2010)	0.261	0.588
3 (28 April 2010)	0.443	0.417
4 (22 May 2010)	0.782	0.668
5 (15 June 2010)	0.907	0.802
6 (30 November 2010)	0.944	0.669
7 (24 December 2010)	0.695	0.514
8 (6 March 2011)	0.656	0.346
9 (30 March 2011)	0.643	0.296

Table 6-1: LISS III available temporal dates and NDVI of Sugarcane ratoon and plant sites.

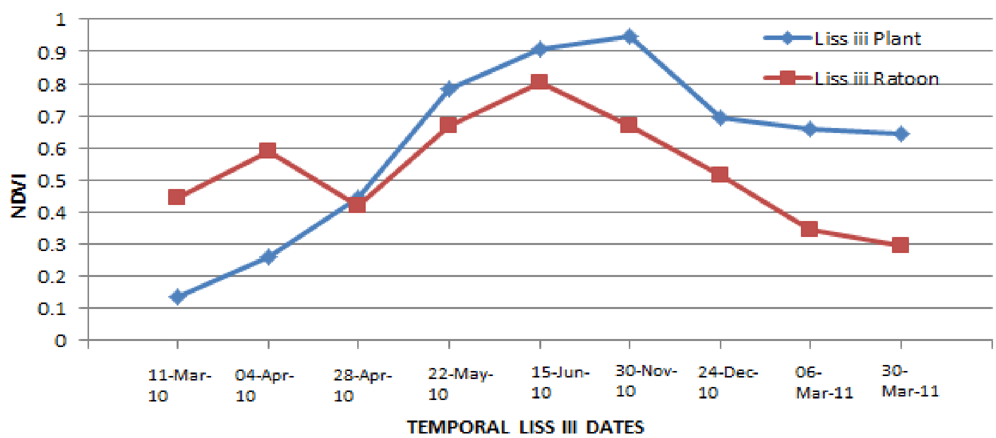


Figure 6-1: Temporal LISS III Sugarcane crop (Plant and Ratoon) spectral growth profile.

It can be observed from table 6-1 and figure 6-1 that ratoon crop NDVI values after the month of April always remained below the NDVI values of sugarcane plant. During the first two temporal dates a clear difference between the growth patterns of both crops can be seen. The ratoon crop as it regrows from the harvested sugarcane plant had a higher initial NDVI on the 2nd temporal date i.e. 4 April 2010. The NDVI value for the ratoon crop peaked on 5th date i.e. 15 June 2010 and then dropped on 6th date i.e. 30 Nov. 2010. Similarly NDVI values for sugarcane plant peaked on 30 Nov. 2010 and then dropped on 24 Dec. 2010. There was a long gap period between the 5th date-15 June 2010 and 6th date-30 Nov. 2010. The gap period corresponds to the Indian monsoon season that causes atmospheric disturbances like clouds, rain, etc. and results in unusable optical sensor data. This caused interruption in continuous crop growth monitoring and eventually there was an absence of NDVI values during this period. As there was no information during this gap period, it can be safely assumed that NDVI for ratoon and sugarcane plant both peaked during this gap period between June and November. However the use of a multi sensor approach for addition of information about crop growth during this gap (no information) period would be of immense help in specific crop discrimination studies. Apart from this period of lack of information, LISS-III sugarcane crop growth profiles for sugarcane plant and ratoon were clearly distinct from each other. This was better than that of AWiFS sugarcane crop growth profiles shown in figure 6-2 and in accordance to the knowledge of sugarcane crop phenology.

The temporal NDVI images generated from AWiFS for the study area was used for creating sugarcane crop temporal spectral growth profiles. The NDVI values for training sugarcane plant and ratoon site are given in table 6-2 and their spectral crop growth profile is as shown in figure 6-2.

Temporal AWiFS Dates	Plant site NDVI	Ratoon site NDVI
1 (20 February 2010)	0.495	0.673
2 (6 March 2010)	0.501	0.544
3 (28 April 2010)	0.300	0.264
4 (22 May 2010)	0.614	0.445
5 (15 June 2010)	0.582	0.444
6 (14 July 2010)	0.780	0.736
7 (28 September 2010)	0.868	0.913
8 (5 December 2010)	0.836	0.760
9 (5 February 2011)	0.545	0.638
10 (6 March 2011)	0.594	0.714
11 (30 March 2011)	0.631	0.550

Table 6-2: AWiFS available temporal dates and NDVI of Sugarcane ratoon and plant sites

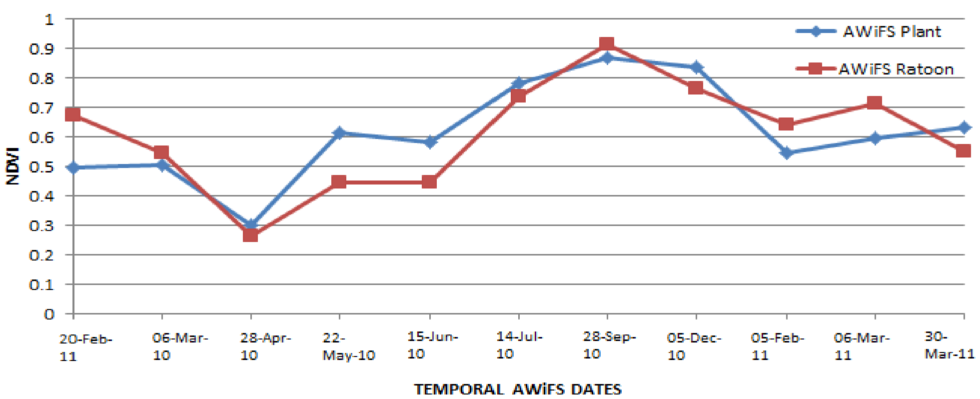


Figure 6-2: Temporal AWiFS Sugarcane crop (Plant and Ratoon) spectral growth profile.

It can be observed from figure 6-2 that ratoon crop NDVI values always remained below the NDVI values of sugarcane plant and reached the maximum value at 7th date i.e. 28 September 2010 and went above the NDVI value for plant. This period around the 7th date corresponds to the maximum vegetative growth stage of the Sugarcane crop and hence explains the increase in NDVI value to the maximum. After this period of saturated values, the NDVI again started decreasing as it entered the stage of maturity or senescence. Around the 7th date the ratoon crop was just 2 months short of the harvesting season and in the yellowing stage where as during this time the sugarcane plant was in its highest vegetative stage and still 5 months away from its harvest season. This can be observed from the crop spectral growth profiles for ratoon which peaked at 7th date and then dropped sharply at 8th date i.e. 5 Dec. 2010 which was the ratoon harvest season that generally starts in November every year. The spectral crop growth profile for sugarcane plant also peaked at 7th date but remained saturated for some months showing a longer vegetative phase than ratoon and then the curve starts declining after 8th date i.e. 5 Dec. 2010 that marked the senescence of sugarcane plant. The sugarcane crop is then ready for harvest after February which continues till March-April in a staggered manner every year. The spectral growth curves generated using AWiFS for both sugarcane plant and ratoon were almost identical except some small differences during the initial period of starting of crop and the end of season. This difference in the crop growth pattern for both sugarcane plant and ratoon was however not as pronounced as expected. This observation indicates the limitations in use of a coarser resolution sensor like AWiFS (56 metres) when generating spectral growth profiles for crops involving classifications beyond 4th level where sugarcane plant and ratoon are expected to be discriminated. One of the main reasons for this was also the high concentration of low and marginal farmers in the study area whose land holdings were very small (smaller than 100*100 sq. metres). Thus there are high chances of spectral mixing of crop signatures when using a coarse resolution sensor like AWiFS.

Studying the spectral growth profiles for both the sugarcane crops and using phenological knowledge of the sugarcane crop it can be assumed that the ratoon crop was sown around late March to early April and the crop was harvested during the month of December of the same year. The Sugarcane plant on the other hand was sown in the month of April and harvested around the month of February-March.

6.2. SPECTRAL SEPARABILITY ANALYSIS

The need for optimization of temporal date combinations has already been discussed in chapter 2 and chapter 5.

The spectral separability analysis using best minimum distance is based on the objective of correctly classifying the class of interest, here say sugarcane plant without bothering about the classification accuracy of other non-interest classes like ratoon, urban area, orchard and wheat crop. The expected result is to have an accurate sugarcane plant classified output without any error of commission or omission for the same class. For this purpose the non-interest class that is spectrally nearest to the sugarcane plant has to be found out as this class has the maximum probability of being confused with the class of interest. To reduce this problem of misclassification the date combinations have to be optimised by maximising the best minimum distance between the class of interest and the non-interest class.

The results obtained from the spectral separability analysis between the various class signatures from coarse resolution AWiFS data are shown in table 6-3. The table lists the Euclidean distance measure between class of interest sugarcane plant and other non-interest classes when finding the best 1 date for specific crop, sugarcane-plant discrimination. The best minimum distance between the class of interest sugarcane plant and other non-interest classes was maximised to find the best 1 date combination for discriminating the specific sugarcane plant crop. The table 6-3 results show that in the first row or the first date (20 feb. 2010) the minimum Euclidean distance between sugarcane plant and other non-interest crop was 1791. And the crop with minimum distance between sugarcane plant was orchard. Similarly on the second date (6 mar 2010) the minimum Euclidean distance was between sugarcane plant and wheat crop i.e. 1607. Hence the best minimum Euclidean distance between the class of interest and other non-interest class was 1791 from these first two dates. The overall best minimum Euclidean distance from all the available single dates AWiFS combinations was found by maximising this minimum distance between sugarcane plant and other non-interest class for all 11 dates. So the best 1 date where the minimum distance between the specific class of interest sugarcane-plant and other non-interest class maximised was the 11th date (i.e. 30 March 2011) i.e. 11226. The class that had the best minimum distance with the sugarcane-plant was sugarcane-ratoon. The results obtained for the class separability between all possible class pairs are shown in appendix table A-1.

Dates	Euclidean distance between sugarcane plant (1) and other non-interest classes (2, 3, 4 and 5).				Minimum Euclidean distance between class pairs per date combination
	1:2	1:3	1:4	1:5	
1(20feb2010)	25972	4063	1791	3557	1791
2(6mar2010)	28753	12559	9772	1607	1607
3(28apr2010)	7241	2317	9218	680	680
4(22may2010)	9249	6255	24144	1724	1724
5(15jun2010)	21587	5558	6009	17075	5558
6(14july2010)	24568	292	1720	4522	292
7(28sept2010)	28271	548	760	26027	548
8(5dec2010)	27055	2395	5105	15177	2395
9(5feb2011)	16958	1492	2115	8819	1492
10(6mar2011)	26474	241	8830	5410	241
11(30mar2011)	13244	11226	25028	13314	**11226 (best min separability)**

Table 6-3: Spectral separability analysis between sugarcane plant and other non-interest classes using temporal AWiFS data; Where class 1= sugarcane plant; class 2=urban area; class 3= sugarcane ratoon; class 4=orchard and class 5=wheat crop

Similar spectral separability analysis to find the best 2, 3, 4… dates combination to discriminate specific crop of interest i.e. sugarcane-plant and ratoon was done separately for both AWiFS and LISS-III sensors. The results of the best temporal 1, 2, 3,… dates combination for discriminating the specific crop of interest using both AWiFS and LISS-III sensor has been listed in tables 6-4, 6-5, 6-6 and 6-7.

The results of the spectral separability analysis for different date combinations for classifying sugarcane plant using temporal AWiFS sensor temporal NDVI data are shown in table 6-4. The results of table 6-4 demonstrate the advantage of temporal spectral separability analysis for crop classification studies. It can been seen from the results that as more dates were added to the initial best 1 date obtained from spectral separability analysis, the best minimum Euclidean distance measure between class of interest (sugarcane-plant) and other non-interest class increased. The best minimum distance increased as the date combination increased from 1 date to 6 dates but then started saturating from 7 date combination onwards. The inclusion of more dates after the 6 dates or 7 dates combination might not provide satisfactory results or may be counterproductive. This proves the need for optimising the dates for temporal studies to have a clear understanding of the best date combinations and the accuracy of classified specific class outputs.

No. of dates per combination (AWiFS)	Dates with best min separability between Sugarcane plant and other class	Other classes with best minimum separability with Sugarcane- plant	Best minimum Euclidean distance measure
1 date	11	Plant: Ratoon	11226
2 dates	2:11	Plant: Wheat	13411
3 dates	2:5:11	Plant: Ratoon	17738
4 dates	2:4:5:11	Plant: Ratoon	18809
5 dates	1:2:4:5:11	Plant: Ratoon	19243
6 dates	1:2:4:5:8:11	Plant: Ratoon	19391
7 dates	1:2:3:4:5:8:11	Plant: Ratoon	19529
8 dates	1:2:3:4:5:8:9:11	Plant: Ratoon	19586
9 dates	1:2:3:4:5:7:8:9:11	Plant: Ratoon	19594
10 dates	1:2:3:4:5:6:7:8:9:11	Plant: Ratoon	19596
11 dates	1:2:3:4:5:6:7:8:9:10:11	Plant: Ratoon	19597

Table 6-4: AWiFS Temporal Spectral separability analysis between class of interest (Sugarcane-plant) and other classes of non-interest.

For AWiFS sensor, Date-1=20-Feb-10;Date-2=06-Mar-10;Date-3=28-Apr-10;Date-4=22-May-10; Date-5=15-Jun-10;Date-6=14-Jul-10;Date-7=28-Sep-10;Date-8=05-Dec-10;Date-9=05-Feb-11;Date-10=06-Mar-11 and Date-11=30-Mar-11.

The results of the spectral separability analysis using different temporal date combinations for classifying sugarcane ratoon with AWiFS sensor temporal NDVI data are shown in table 6-5.

No. of dates per combination (AWiFS)	Dates with best min separability between Sugarcane ratoon and other class	Other classes with best minimum separability with Sugarcane- ratoon	Best minimum Euclidean distance measure
1 date	4	Ratoon: Plant	06255
2 dates	2:11	Ratoon: Orchard	14081
3 dates	2:5:11	Ratoon: Plant	17738
4 dates	2:4:5:11	Ratoon: Plant	18809
5 dates	1:2:4:5:11	Ratoon: Plant	19243
6 dates	1:2:4:5:8:11	Ratoon: Plant	19391
7 dates	1:2:3:4:5:8:11	Ratoon: Plant	19529
8 dates	1:2:3:4:5:8:9:11	Ratoon: Plant	19586
9 dates	1:2:3:4:5:7:8:9:11	Ratoon: Plant	19594
10 dates	1:2:3:4:5:6:7:8:9:11	Ratoon: Plant	19596
11 dates	1:2:3:4:5:6:7:8:9:10:11	Ratoon: Plant	19597

Table 6-5: AWiFS Temporal Spectral separability analysis between class of interest (Sugarcane-ratoon) and other classes of non-interest.

For AWiFS sensor, Date-1=20-Feb-10;Date-2=06-Mar-10;Date-3=28-Apr-10;Date-4=22-May-10; Date-5=15-Jun-10;Date-6=14-Jul-10;Date-7=28-Sep-10;Date-8=05-Dec-10;Date-9=05-Feb-11;Date-10=06-Mar-11 & Date-11=30-Mar-11.

The analysis of spectral separability between ratoon crop and other non-interest crops (in this case sugarcane plant, urban area, orchard and wheat crop) for optimization of temporal dates for classification showed an increase in the best minimum spectral separability. The best minimum Euclidean distance measure between class of interest ratoon and the closest non-interest class increased from the 1 date to 6 dates combination and then started saturating from the 7 dates combination onwards. This increasing trend of the best minimum spectral separability proved that the addition of dates to the initial single date classification reduced the confusion between the class of interest ratoon and the nearest non-interest class. However the best minimum separability from 7 dates onwards did not show much improvement numerically. Therefore there was a need for optimization of date combinations for temporal specific crop discrimination in order to select a best overall dates combination that would provide the highest accuracy in specific crop classification. This selection of the best overall (optimum) dates for discrimination of specific crop sugarcane-plant and ratoon was done after conducting actual classification of the best temporal dates results available from spectral separability analysis.

The next task was to conduct the same separability analyses using the medium resolution LISS-III temporal NDVI data. The results and the discussions for this analysis are explained in detail in the upcoming pages. Spectral separability analysis was also done between for sugarcane plant with non-interest crops using LISS-III temporal NDVI data. The results of the temporal spectral separability analysis between class of interest sugarcane plant and other non-interest crops (ratoon, urban area, orchard and wheat crop) are shown in table 6-6.

No. of dates per combination (LISS-III)	Dates with best min separability between Sugarcane plant and other class	Other classes with best minimum separability with Sugarcane- plant	Best minimum Euclidean distance measure
1 date	5	Plant: Orchard	03781
2 dates	6:9	Plant: Wheat	17115
3 dates	5:6:9	Plant: Ratoon	18189
4 dates	4:5:6:9	Plant: Ratoon	21181
5 dates	4:5:6:7:9	Plant: Ratoon	21484
6 dates	3:4:5:6:7:9	Plant: Ratoon	21748
7 dates	2:3:4:5:6:7:9	Plant: Ratoon	21969
8 dates	1:2:3:4:5:6:7:9	Plant: Ratoon	22158
9 dates	1:2:3:4:5:6:7:8:9	Plant: Ratoon	22158

Table 6-6: LISS-III Temporal Spectral separability analysis between class of interest (Sugarcane-plant) and other classes of non-interest

For LISS-III, Date-1=11-Mar-10; Date-2=04-Apr-10; Date-3=28-Apr-10; Date-4=22-May-10; Date-5= 15- Jun-10; Date-6=30-Nov 10; Date-7=24-Dec-10; Date-8=06-Mar-11 and Date-9=30-Mar-11.

The results of the temporal spectral separability analysis between class of interest sugarcane ratoon and other non-interest crops (ratoon, urban area, orchard and wheat crop) are shown in table 6-7.

No. of dates per combination (LISS-III)	Dates with best min separability between Sugarcane ratoon and other class	Other classes with best minimum separability with Sugarcane- ratoon	Best minimum Euclidean distance measure
1 date	6	Ratoon: Urban	05158
2 dates	5:6	Ratoon: Wheat	16355
3 dates	4:5:6	Ratoon: Orchard	18231
4 dates	4:5:6:9	Ratoon: Plant	21181
5 dates	4:5:6:7:9	Ratoon: Plant	21484
6 dates	3:4:5:6:7:9	Ratoon: Plant	21748
7 dates	2:3:4:5:6:7:9	Ratoon: Plant	21969
8 dates	1:2:3:4:5:6:7:9	Ratoon: Plant	22158
9 dates	1:2:3:4:5:6:7:8:9	Ratoon: Plant	22158

Table 6-7: LISS-III Temporal Spectral separability analysis between class of interest (Sugarcane-ratoon) and other classes of non-interest

For LISS-III, Date-1=11-Mar-10; Date-2=04-Apr-10; Date-3=28-Apr-10; Date-4=22-May-10; Date-5= 15- Jun-10; Date-6=30-Nov 10; Date-7=24-Dec-10; Date-8=06-Mar-11 and Date-9=30-Mar-11.

Similar to the results obtained in the spectral separability analysis of temporal AWiFS data, the results from temporal LISS-III data were also obtained. It can be observed from table 6-6 and table 6-7 that the best minimum distance between the class of interest and other closest non-interest increased from 1 date to 6 dates combinations and then started saturating from 7 dates combination onwards. As already observed from the separability analysis of AWiFS data, the results from tables 6-6 and 6-7 also show an increase in the best minimum spectral separability as the number of temporal dates combinations were increased form the initial single date data. This means that as the best minimum separability between the class of interest and the other non-interest class increased, the confusion between them also decreased. This eventually will have positive effects on the specific crop classification results. Observations made from the separability analysis of temporal LISS-III data show that from 7 dates onwards the best minimum separability did not show much improvement numerically. Similar results were also obtained from the separability analysis of temporal AWiFS data where this saturation of best minimum separability took place. Therefore classification of all the selected best temporal combinations was done to analyse where the best minimum separability gives the highest accuracy for specific crop discrimination.

Therefore there was a need to optimise the temporal date combinations for LISS III and AWiFS images for temporal discrimination of specific crop sugarcane. The results of the PCM classification for extracting the single class of interest have been described in detail in next section 6.3. The selection of a best overall dates combination for discrimination of specific crop has also been described.

6.3. PCM CLASSIFICATION RESULTS AND ACCURACY ASSESSMENT:

This section deals with the presentation of PCM classification results for specific crop, sugarcane-plant and ratoon 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.

6.3.1. LISS III Classification results:

The results of PCM classification on the best temporal date combinations for sugarcane plant using LISS-III data is presented in table 6-8(a).

The results from table 6-8(a) show that as the temporal dates combination were increased, the unbiased sugarcane plant sites (UP- these sugarcane plant sites were not used in training the classifier) were assigned higher memberships. The memberships for sugarcane plant increased from 139 for 2 dates combination to 180 for 9 dates combination. The memberships for the other non-interest classes (orchard, urban area and wheat crop) also decreased as the temporal date combinations increased. The difference between the memberships of class of interest i.e. sugarcane plant and spectrally closest ratoon class also increased with addition of dates from the initial 21 at 2 date combination to the maximum 36 at 9 dates combination. The entropy measure that was used as an indirect measure of the accuracy also decreased as the dates combinations were increased. A decrease in entropy leads to a decrease in the uncertainty in the classified outputs. Hence a 9 date combination with a high membership of 180 to sugarcane plant and a least entropy of 0.353 provided the best dates combination for classification of the class of interest. Figures 6-3 to 6-10 show the sugarcane-plant membership result images obtained for the temporal LISS-III best dates combinations.

No. of dates combination	Biased plant site (μ)	(UP) Unbiased plant (μ), entropy in brackets	Other known sites (μ) (other non-interest classes)	Best minimum difference between UP and other classes
2	250	139 (0.475)	O: 98; U:77; R:118; W: 110	UP: R = 21
3	251	148 (0.452)	O: 115; U:66; R: 128; W: 86	UP: R = 20
4	252	159 (0.424)	O: 104; U:73; R: 131; W: 93	UP: R = 28
5	252	166 (0.403)	O: 112; U:70; R:139; W: 103	UP: R = 27
6	254	172 (0.382)	O: 102; U:76; R:142; W: 107	UP: R = 30
7	254	172 (0.382)	O: 90; U:81; R:140; W: 114	UP: R = 32
8	254	177 (0.363)	O: 80; U:83; R:148; W: 117	UP: R = 29
9	**254**	**180 (0.353)**	**O: 81; U:80; R:144; W: 115**	**UP: R = 36**

Table 6-8(a): PCM Classification results for LISS-III using training for Sugarcane plant
Where O- Orchard; U-Urban; R: Sugarcane Ratoon; W: Wheat; UP: Unbiased plant
and μ = Class membership values in 8 bits.
(Note: Date combinations corresponding to numbers in table 6-8(a) are listed in table 6-6)

(Note: Biased plant sites were the sugarcane plant sites used in training the PCM classifier and unbiased plant sites were the sugarcane plant sites not used in training but kept aside for testing of the classified outputs of the classifier. The membership values of the various classes in the tables in this chapter have been shown in the 8 bit range i.e. 0 to 255 which corresponds to the generally used membership value range 0 to 1. Similar logic was applied when evaluating the results from other tables in this chapter.)

The 9 dates combination selected as the best dates for sugarcane plant discrimination using LISS-III temporal data corresponds to fallow period (11 Mar.10), initial crop growth phase (4 Apr.10 and 28 Apr.10), maximum growth period (22 May 10, 15 June 10 and 30 Nov.10), late senescence phase and harvest period (24 Dec.10, 6 Mar.11 and 30 Mar.11). Around 30 March every year, the harvesting of sugarcane-plant in most of the fields in Deoband is finished and the fields are readied for the succeeding ratoon crop season.

This 9 date combination of LISS-III along with a Landsat-5 TM data was then analysed for its effect on classification results as a multi sensor approach. The results of this multi sensor data classification are presented in table 6-8 (b).

There was a decrease in the membership values assigned to the sugarcane plant on addition of 12 Oct. 2010 Landsat-5 TM data to the LISS-III 9 temporal date combination. This can be observed from the results in table 6-8(b). The difference between the sugarcane plant and ratoon also decreased from the earlier 34 for AWiFS9 dates combination to 29. This multi sensor approach when tried with other dates combinations like LISS-III 4, 5, 6, 7 and 8 dates combination also provided identical results. But there was a definite increase in the memberships values assigned to sugarcane ratoon for the 4 and 5 dates combination when a multi sensor approach was used. The multi sensor approach when used with LISS-III 4 dates combination provided a membership of 172 to sugarcane plant and entropy of 0.382. The entropy (0.353) for the selected best overall classified LISS-III dates (9 dates) for sugarcane-plant reached entropy of 0.378 on addition of Landsat-5 TM data. However the entropy (0.424) for LISS-III 4 dates combination decreased to 0.382 on addition of Landsat-5 TM data which was similar to the results from the single sensor LISS-III, 7 dates combination. The results from the single sensor LISS-III, 7 dates combination was replicated using the multi sensor approach of adding Landsat-5 TM data to the single sensor LISS-III, 4 dates combination. These results of accuracy obtained from a large number of images from single sensor could be achieved by using lower number of images from a multi sensor approach. This proves the positive effect of a multi sensor approach on classification accuracy results.

No. of dates combination	Biased plant site (μ)	(UP) Unbiased plant (μ), entropy in brackets	Other known sites (μ) (other non-interest classes)	Best minimum difference between UP and other classes
4 dates LISS-III + Landsat-5 TM	254	172 (0.382)	O: 104; U:71; R:144; W: 101	UP: R = 28
5 dates LISS-III + Landsat-5 TM	254	173 (0.378)	O: 104; U:71; R:144; W: 101	UP: R = 29
6 dates LISS-III + Landsat-5 TM	254	173 (0.378)	O: 104; U:71; R:144; W: 101	UP: R = 29
7 dates LISS-III + Landsat-5 TM	254	173 (0.378)	O: 104; U:71; R:144; W: 101	UP: R = 29
8 dates LISS-III + Landsat-5 TM	254	173 (0.378)	O: 104; U:71; R:144; W: 101	UP: R = 29
9 dates LISS-III + Landsat-5 TM	254	173 (0.378)	O: 104; U:71; R:144; W: 101	UP: R = 29

Table 6-8(b): PCM Classification results for LISS-III temporal dates combination + 12 Oct. 2010 Landsat-5 TM (multi sensor approach) using training for Sugarcane plant

(Note: Date combinations corresponding to numbers in table 6-8(b) are listed in table 6-6)

The results from both table 6-8 (a) and table 6-8 (b) show highest classification accuracy with least uncertainty at single sensor LISS-III 9 temporal date combination. The sugarcane plant however showed a decrease in the membership when an additional Landsat-5 TM image was added to the selected best LISS-III 9 dates combination. The membership assigned to unbiased sugarcane plant decreased from the initial 180 for the LISS-III 9 dates combination to 173 on addition of the Landsat-5 TM data to the 9 dates combination. But a clear increase in the memberships assigned (159) with an entropy of 0.424 for LISS-III 4 dates combination can be seen, as the membership increases to 172 with a decrease in entropy to 0.382 on addition of the Landsat data. Similar increase in the memberships for unbiased plant sites with a decrease in entropy was observed for the LISS-III 5, 6 and 7 dates combination on addition of Landsat-5 TM data. Hence it can be concluded that the results of high accuracy obtained from a large number of images from single sensor LISS-III could be achieved by using lower number of images from a multi sensor approach. This proves the positive effect of a multi sensor approach on classification accuracy results.

The PCM classification technique classification technique was applied to the best 2, 3, 4…. dates combinations for LISS-III sensor for extracting sugarcane plant. Figures 6-3 to 6-10 show the classified sugarcane-plant membership resultant images obtained for the LISS-III best temporal date combinations. The resultant sugarcane crop outputs obtained on using a multi sensor approach of using LISS-III and Landsat-5 TM data are also shown. Figures 6-11 to 6-16 show the sugarcane-plant membership result images obtained on the addition of Landsat-5 TM image to the best LISS-III temporal date combinations from best 4 dates onwards.

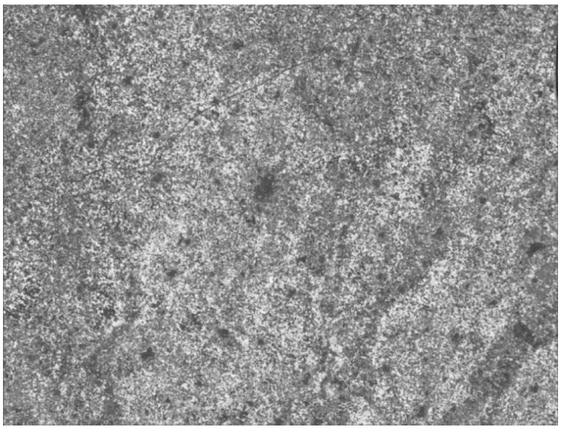


Figure 6-3 LISS-III_plant 2 dates combination PCM results

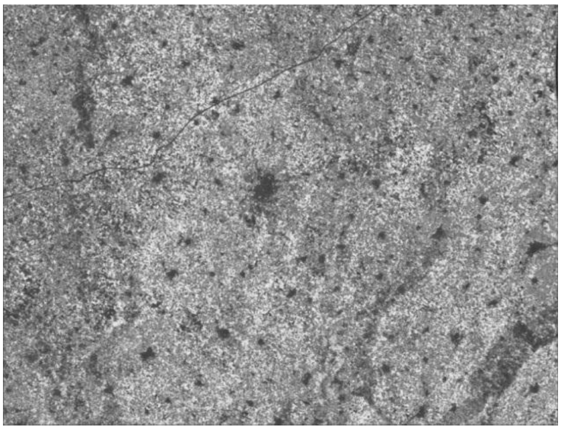


Figure 6-4 LISS-III_plant 3 dates combination PCM results

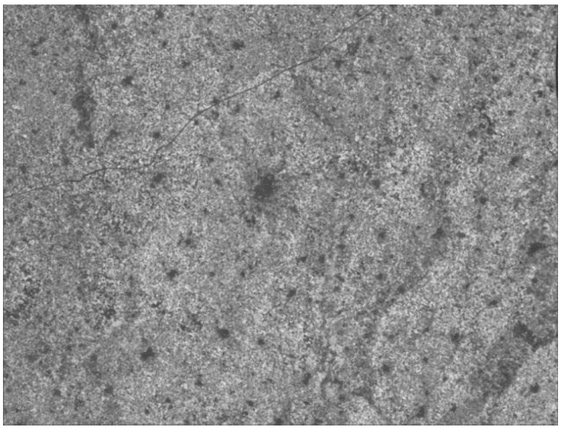


Figure 6-5 LISS-III_plant 4 dates combination PCM results

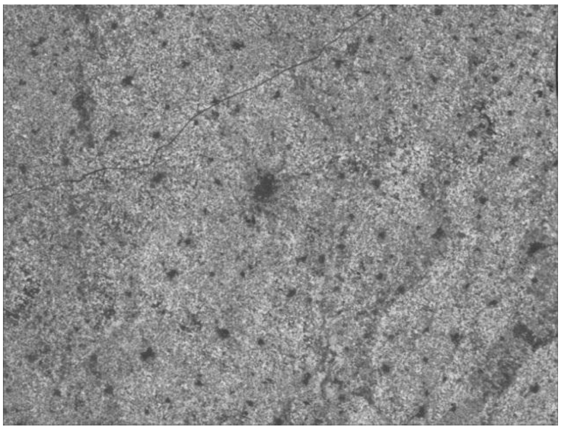


Figure 6-6 LISS-III_plant 5 dates combination PCM results

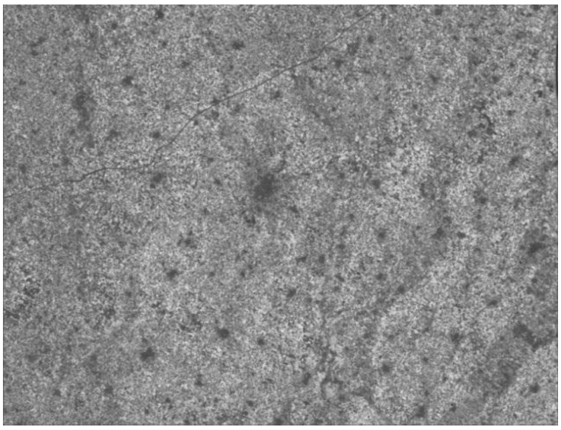


Figure 6-7 LISS-III_plant 6 dates combination PCM results

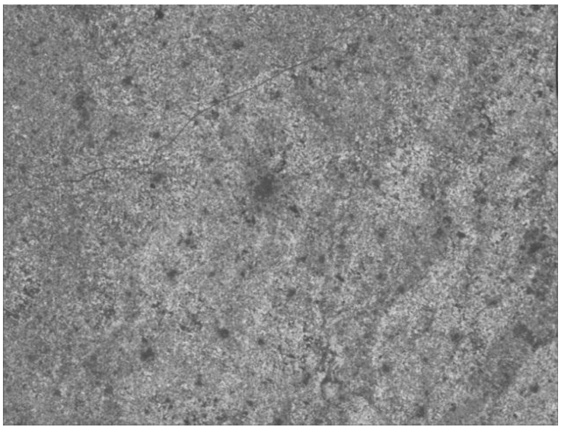


Figure 6-8 LISS-III_plant 7 dates combination PCM results

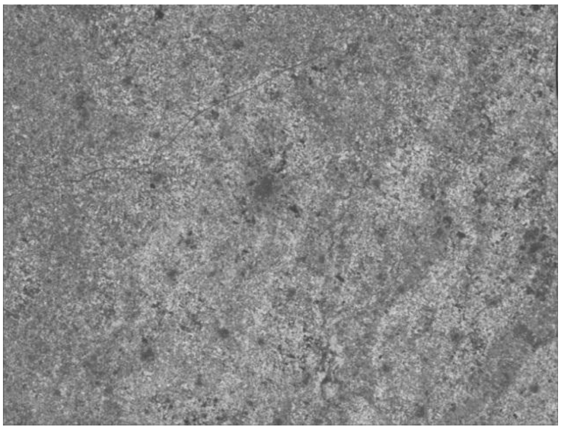


Figure 6-9 LISS-III_plant 8 dates combination PCM results

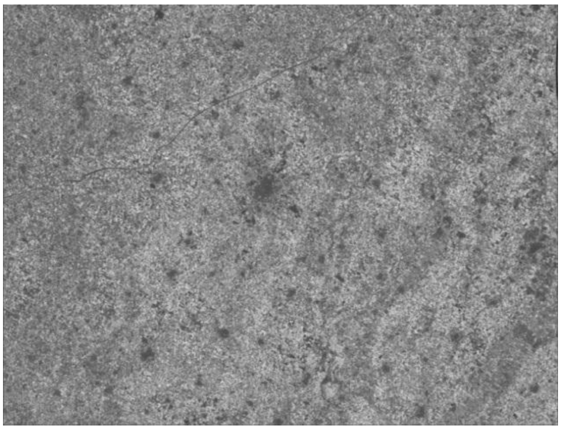


Figure 6-10 LISS-III_plant 9 dates combination PCM results

Figures 6-3 to 6-10: Sugarcane-Plant temporal membership images from single sensor LISS-III dates combination classified results

Note: The PCM method for extracting single class assigns memberships to the pixels in the images by minimising the fuzzy objective function as already explained in chapter 3. Hence these classified images generated shows the membership values assigned to the various pixels according to their distance from the mean of class of interest (training values) in the feature space. The whole image is thus assigned membership grades in this manner. So, higher the membership value of a pixel, lower is the uncertainty and higher is the certainty of the specific class to be present in the pixel. This rule is applicable to all the results (images) generated as a result of extracting single class using PCM classification method.

Figures 6-11 to 6-16 show the sugarcane-plant membership result images obtained on the addition of Landsat-5 TM image to the best LISS-III temporal dates combination from best 4 dates onwards.

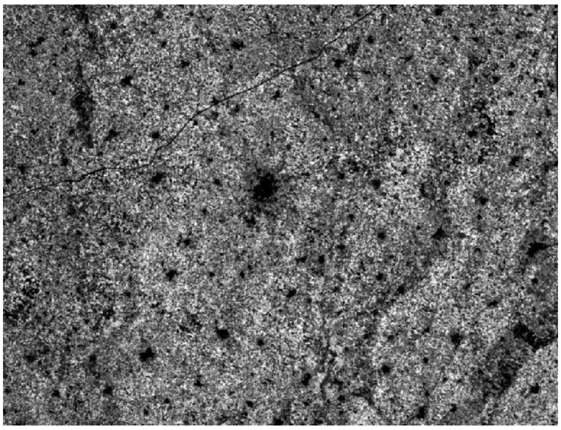


Figure 6-11 LISS-III 4 dates + Landsat-5 TM_plant combination PCM results

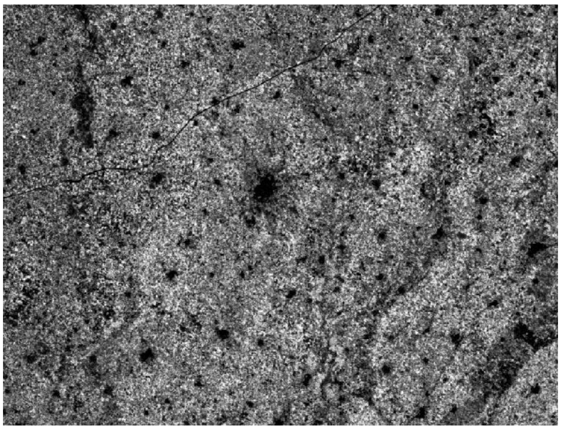


Figure 6-12 LISS-III 5 dates + Landsat-5 TM_plant combination PCM results

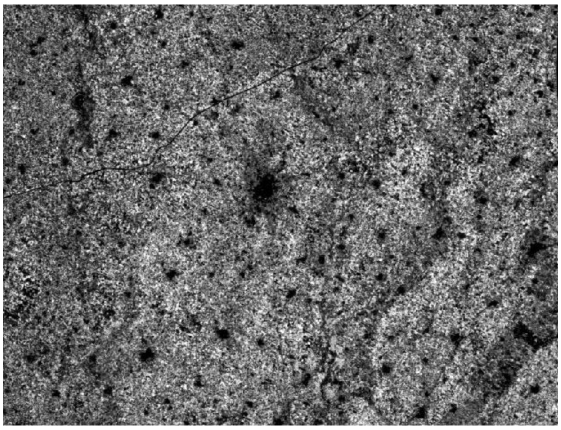


Figure 6-13 LISS-III 6 dates + Landsat-5 TM_plant combination PCM results

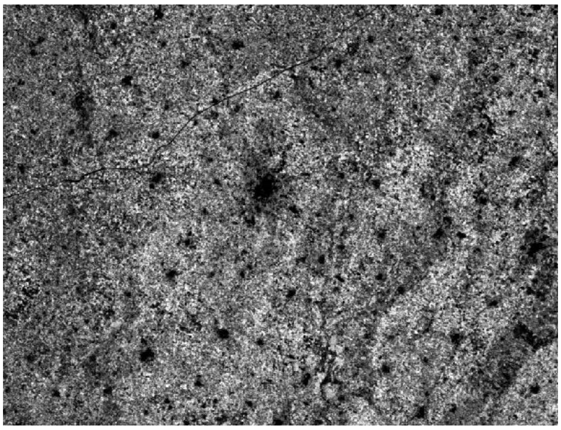


Figure 6-14 LISS-III 7 dates + Landsat-5 TM_plant combination PCM results

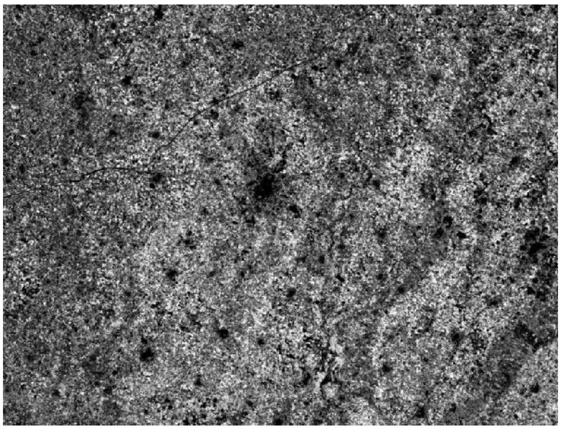


Figure 6-15 LISS-III 8 dates + Landsat-5 TM_plant combination PCM results

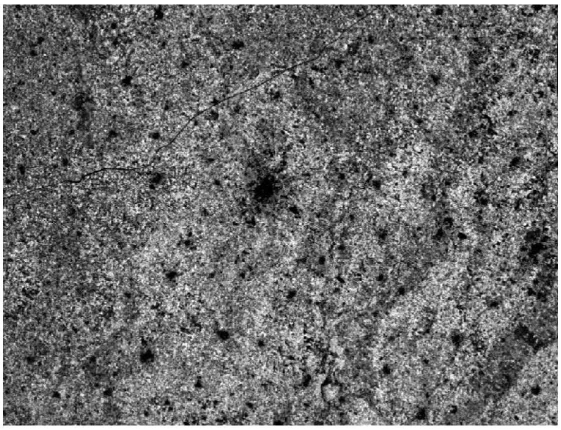


Figure 6-16 LISS-III 9 dates + Landsat-5 TM_plant combination for PCM results

Figures 6-11 to 6-16: Sugarcane-Plant temporal membership images from multi-sensor LISS-III dates+Landsat-5 TM combination classified results.

The results of PCM classification on the best date combinations for sugarcane ratoon using LISS-III data is presented in table 6-9(a).

It can be observed from table 6-9(a) that as more dates were added to the initial best two date combination for LISS-III, the memberships for unbiased sugarcane-ratoon increased. But this increasing trend for membership to ratoon stops at 6 dates combination (i.e. 155) and then decreased with further addition of dates. The difference of the memberships allotted to sugarcane-ratoon and the closest non-interest class when evaluated also aids in selecting the overall best dates combinations. For example in best 2 dates combination unbiased ratoon got a membership of 129 whereas the closest non-interest class (wheat) got a membership of 106, with a difference of 23. This difference along with the memberships assigned to sugarcane-ratoon had to be maximized through the dates for selecting the best (optimum) dates combination for maximum mapped crop accuracy. The entropy measure gave an idea about the uncertainty present in the classification results. So, higher the entropy higher would be the uncertainty in classification and vice-versa. The best 6 dates combination with a membership of 155 to ratoon and entropy of 0.437 satisfied the above criteria and were selected as the best (optimum) temporal date combination for LISS-III for extracting ratoon. Figures 6-17 to 6-24 show the sugarcane-ratoon membership result images obtained for the temporal LISS-III best dates combinations.

No. of dates combination	Biased ratoon site (μ)	(UR) Unbiased ratoon (μ), entropy in brackets	Other known sites (μ) (other non-interest classes)	Best minimum difference between UR and other classes
2	239	129 (0.497)	O: 100; U:83; P:105; W: 106	UR: W = 23
3	246	134 (0.488)	O: 104; U:85; P:103; W: 118	UR: W = 16
4	248	146 (0.460)	O: 91; U:96; P:116; W: 118	UR: W = 28
5	248	153 (0.442)	O: 97; U:86; P:122; W: 122	UR: P & W = 31
6	**248**	**155 (0.437)**	**O: 92; U:87; P:123; W: 123**	**UR: P & W = 32**
7	246	128 (0.499)	O: 87; U:82; P:123; W: 119	UR: P = 5
8	245	130 (0.495)	O: 75; U:85; P:131; W: 122	UR: P = -1
9	243	133 (0.490)	O: 77; U:86; P:136; W: 114	UR: P = -3

Table 6-9(a). PCM Classification results for LISS III using training for Sugarcane ratoon.
Where O- Orchard; U-Urban; P: Sugarcane Plant; W: Wheat; UR: Unbiased ratoon
and μ = Class membership values in 8 bits
(Note: Date combinations corresponding to numbers in table 6-9(a) are listed in table 6-7)

The 6 dates combination selected as the best dates for sugarcane ratoon discrimination using LISS-III temporal data corresponds to initial growth period (28 Apr.10 and 22 May 10), maximum growth period (15 June 10), senescence period (30 Nov.10), harvest period (24 Dec.10) and fallow condition (30 Mar. 11).

On addition of a Landsat-5 TM NDVI image (12 October 2010) to this best dates combination of LISS-III, the following results as in table 6-9(b) were achieved.

It can be observed from table 6-9(b) that while adopting a multisensory strategy the uncertainty in the classified output decreased, the ratoon sites got higher memberships, and the difference between the ratoon and closest non-interest class also increased. This as a result improved the classification accuracy.

No. of dates combination	Biased ratoon site (μ)	(UR) Unbiased ratoon (μ), entropy in brackets	Other known sites (μ) (other non-interest classes)	Best minimum difference between UR and other classes
5 dates LISS-III + 12 Oct. 2010 Landsat-5 TM	245	165 (0.405)	O: 102; U:69; P:131; W: 100	UR: P = 34
6 dates LISS-III + 12 Oct. 2010 Landsat-5 TM	**245**	**166 (0.403)**	**O: 96; U:70; P:132; W: 100**	**UR: P = 34**

Table 6-9(b): PCM Classification results for LISS-III temporal dates combination + Landsat-5 TM (multi sensor approach) using training for Sugarcane ratoon

(Note: Date combinations corresponding to numbers in table 6-9(a) are listed in table 6-7)

Therefore on using a multi sensor the earlier best dates combinations from LISS-III for discriminating sugarcane-ratoon was updated from best 6 dates combination to a best 7 dates combination that corresponds to initial growth period (28 Apr.10 and 22 May 10), maximum growth period (15 June 10), senescence period (12 Oct.10 and 30 Nov.10), harvest period (24 Dec.10) and fallow condition (30 Mar. 11).

Figures 6-17 to 6-24 shows the sugarcane-ratoon membership result images obtained on the addition of Landsat-5 TM image to the best LISS-III temporal dates combination (6 dates combination) and the second best dates combination (5 dates combination).

The analysis of results obtained from tables 6-8(a), 6-8 (b), 6-9 (a) and 6-9 (b) reveals that the memberships assigned to the non-interest classes (urban, orchard and wheat) were very low when compared to sugarcane plant and ratoon crop. This shows that the specific crop of sugarcane as a whole has been successfully extracted in the image but some degree of confusion exists between sugarcane-plant and ratoon. This confusion could be minimised by applying a threshold to the soft classified outputs but this would need specific knowledge for partitioning sugarcane crop into sugarcane-plant and ratoon. However the sites with the high memberships for sugarcane-plant or ratoon are more certain to belong to plant and ratoon respectively. The resultant specific crop (sugarcane-plant and ratoon) maps (membership images) are hence shown as soft outputs, since hardening of soft classified results which would then lead to loss of information.

The PCM classification technique classification technique was applied to the best 2, 3, 4…. dates combinations for LISS-III sensor for extracting sugarcane ratoon and Figures 6-17 to 6-24 show the sugarcane-ratoon membership result images obtained for the temporal LISS-III best dates combinations. The resultant sugarcane crop outputs obtained on using a multi sensor approach of using LISS-III and Landsat-5 TM data are also shown. Figures 6-25 to 6-26 show the sugarcane-ratoon membership result images obtained on the addition of Landsat-5 TM image to the best LISS-III temporal dates combination from best 4 dates onwards.

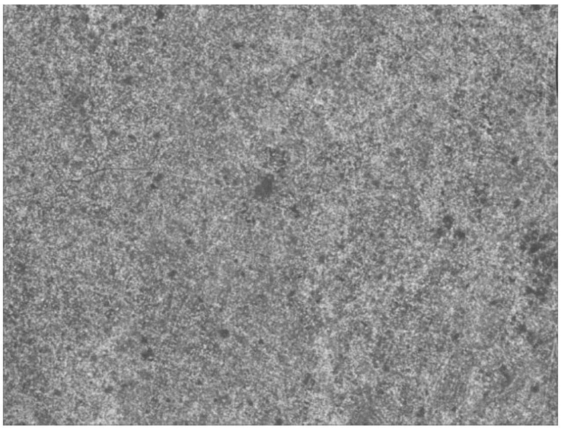


Figure 6-17 LISS-III_ratoon 2 dates combination PCM results

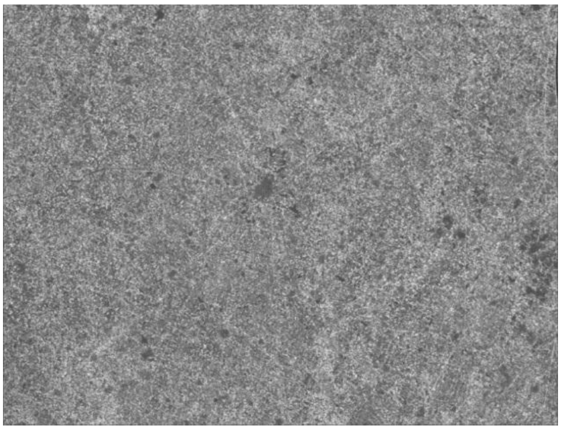


Figure 6-18 LISS-III_ratoon 3 dates combination PCM results

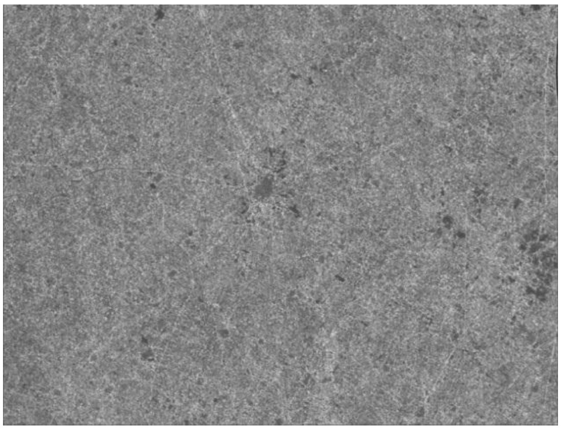


Figure 6-19 LISS-III_ratoon 4 dates combination PCM results

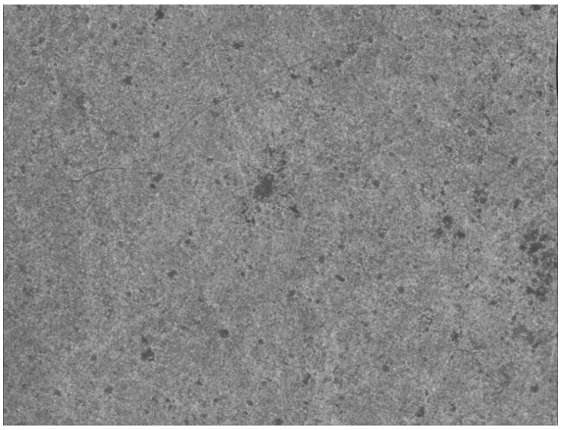


Figure 6-20 LISS-III_ratoon 5 dates combination PCM results

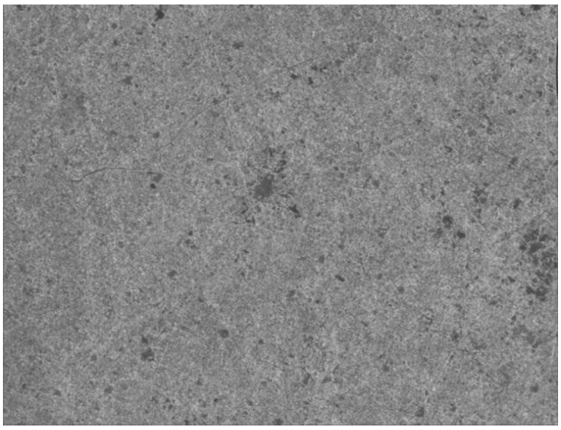


Figure 6-21 LISS-III_ratoon 6 dates combination PCM results

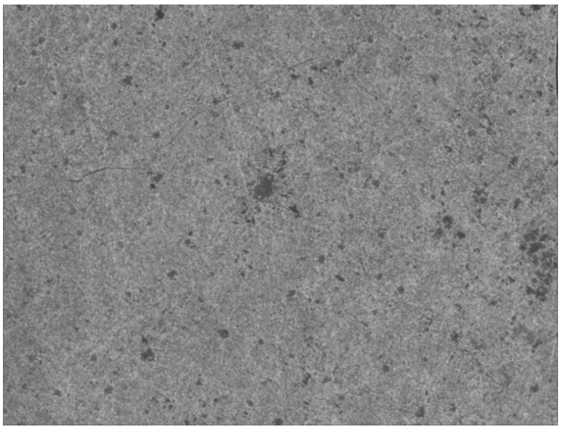


Figure 6-22 LISS-III_ratoon 7 dates combination PCM results

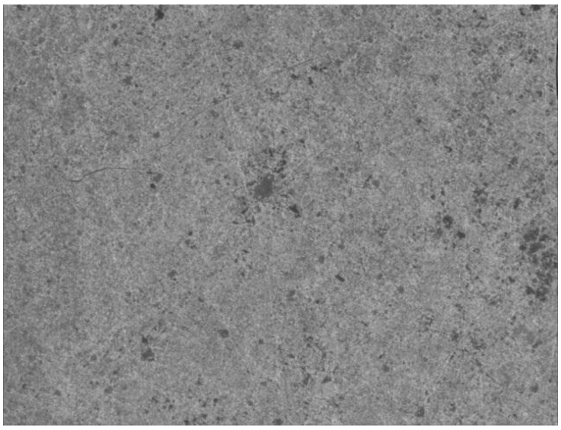


Figure 6-23 LISS-III_ratoon 8 dates combination PCM results

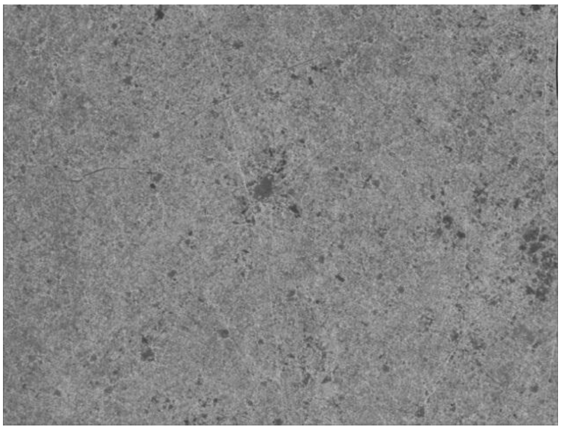


Figure 6-24 LISS-III_ratoon 9 dates combination PCM results

Figures 6-17 to 6-24: Sugarcane-Ratoon temporal membership images from single sensor LISS-III dates combination classified results.

Figures 6-25 to 6-26 show the sugarcane-ratoon membership result images obtained on the addition of Landsat-5 TM image to the best and the second best LISS-III temporal dates combination.

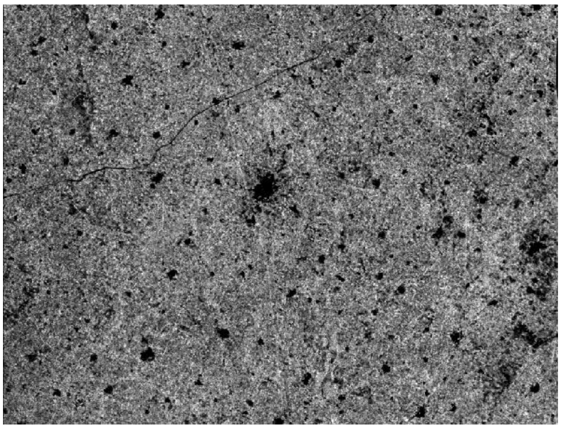


Figure 6-25 LISS-III 5 dates + Landsat-5 TM_ratoon combination PCM results.

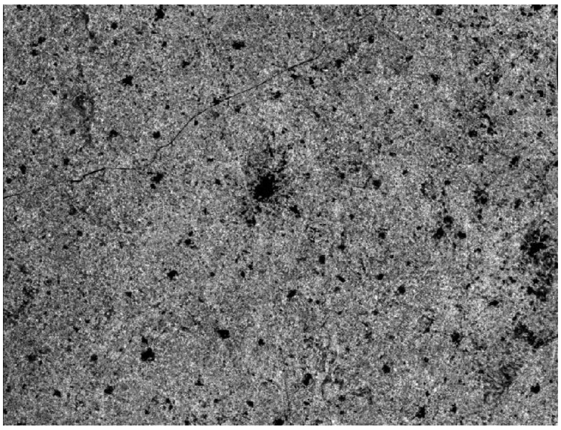


Figure 6-26 LISS-III 6 dates + Landsat-5 TM_ratoon combination PCM results.

Figures 6-25 and 6-26: Sugarcane-Ratoon temporal membership images from multi-sensor LISS-III dates+Landsat-5 TM combination classified results

6.3.2. AWiFS Classification results:

The results of the Possibilistic c-Means (PCM) classification of specific crop i.e. sugarcane plant using temporal AWiFS data are shown in table 6-10.

No. of dates combination	Biased plant site (μ)	Unbiased plant (μ) (UP)	Other known sites (μ) (other non-interest classes)	Best minimum difference between UP and other classes	Accuracy Assessment (FERM)		
					MIN (%)	LEAST (%)	PROD (%)
2	250	169	O: 76; U:63; R:142;W: 124	UP: R = 27	91.415	22.492	54.854
3	250	172	O: 86; U:55; R: 153;W:101	UP: R = 19	92.356	20.321	53.800
4	250	179	O: 68; U:60; R: 161;W: 10	UP:R = 18	92.223	20.158	54.587
5	251	180	O: 75; U:50; R:164;W: 117	UP: R = 16	92.927	20.583	54.327
6	251	175	O: 81; U:46; R:171; W:118	UP: R = 4	91.939	21.222	53.682
7	246	**179**	O: 75; U:47; R:170; W:126	UP: R = 9	**93.650**	**18.239**	54.439
8	245	180	O: 78; U:45; R:167; W:119	UP: R = 13	93.224	19.506	53.995
9	251	178	O: 83; U:40; R:172;W:94	UP: R = 6	93.512	20.777	54.731
10	246	180	O: 82; U:39; R:173; W:95	UP: R = 7	93.237	23.146	**55.780**
11	245	182	O: 83; U:38; R:175; W:96	UP: R = 7	92.707	22.382	55.264

Table 6-10: PCM Classification and Accuracy Assessment results
for AWiFS using training for Sugarcane plant
Where O- Orchard; U-Urban; R: Sugarcane Ratoon; W: Wheat; UP: Unbiased plant
and μ = Class membership values in 8 bits
(Note: Date combinations corresponding to numbers in table 6-10 are listed in table 6-4)

The results of the image to image based classification accuracy assessment are also listed alongside the classification results in the table 6-10. Figures 6-27 to 6-36 show the sugarcane-plant membership classification result images obtained for the temporal AWiFS best dates combinations. The accuracy assessment of the classified outputs of temporal AWiFS images was done against the LISS-III best date image combination (9 dates combination) classified outputs for discrimination of sugarcane plant. The various operators like MIN, LEAST and PROD were used for accuracy assessment (FERM- Fuzzy Error Matrix) of classified AWiFS output. The finer resolution LISS-III 9 dates combination classified output served as a reference for AWiFS classified outputs where the operators like MIN, LEAST and PROD helped in populating the fuzzy error matrix. The elements of the fuzzy error matrix were calculated from the maximum possible overlap (MIN) between reference class and classified class in a pixel, minimum possible overlap (LEAST) and the expected or chance overlap given by PROD operator (Sivan-Cardenas

and Wang, 2008). In order to optimize the temporal date combinations the results of MIN operator had to be maximised, the LEAST operator results had to be minimised and the PROD operator results that provides the expected overlap had to be maximised.
It can be observed from table 6-10 that as the AWiFS temporal date combinations increased from the initial 1 date, higher memberships were assigned to the class of interest sugarcane plant and lower memberships were assigned to other non-interest classes like orchard, urban area and wheat crop. With the use of temporal AWiFS data the non-interest classes could be discriminated properly from the class sugarcane plant but it gave unsatisfactory results for ratoon class by assigning it higher memberships. The best minimum difference between sugarcane plant and ratoon crop decreased as the number of temporal dates combinations were increased. This shows the poor performance of AWiFS sensor data in discriminating classes beyond 4th level of classification i.e. discriminating sugarcane crop into plant and ratoon. The results of the accuracy assessment of classified AWiFS output for sugarcane plant were analysed using MIN, LEAST and PROD operator. The MIN operator results showed an increase in the maximum overlap between the reference and classified class memberships. The maximum possible overlap (MIN) increased from the initial 91.425 % for 2 dates combination to 93.650 % for 7 dates combination after which it started declining. The minimum possible overlap (LEAST) results among different temporal dates combination decreases from the initial 22.492 % for 2 dates combination to 18.239 % for 7 dates combination and then continued increasing. The PROD operator results however was maximum at 10 dates combination with a value of 55.780 % and with 54.439 % expected overlap for 7 dates combination which was fairly high than other dates combinations. Therefore a 7 dates combination was selected as the optimized temporal dates combination for classifying specific crop sugarcane plant using temporal AWiFS data. The sugarcane plant however was not properly discriminated from ratoon but overall the sugarcane crop memberships were higher in the classified output as compared to other classes like orchard, urban area and wheat crop.

The 7 dates combination selected as the best dates for sugarcane plant discrimination using AWiFS temporal data corresponds to fallow period (20 Feb.10 and 6 Mar.10), initial crop growth phase (28 Apr. 10), maximum growth phase (22 May10 and 15 June 10), harvest period (5 Dec.10 and 30 Mar.11). Around 30 March every year, the sugarcane plant in most of the fields in Deoband is already harvested and the field is readied for the beginning of ratoon crop season.

The PCM classification technique classification technique was applied to the best 2, 3, 4…. dates combinations for AWiFS sensor for extracting sugarcane plant. Figures 6-27 to 6-36 show the sugarcane-plant membership result images obtained for the temporal AWiFS best dates combinations.

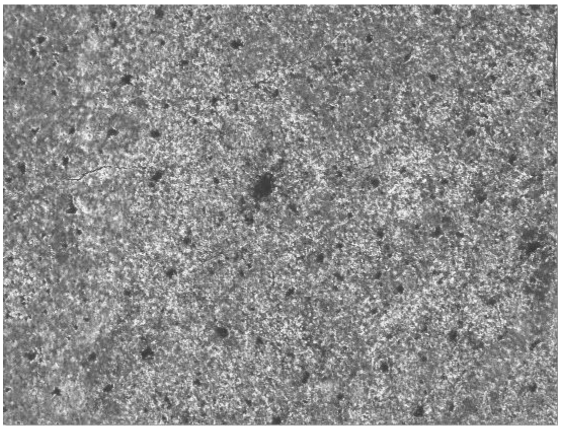


Figure 6-27 AWiFS_plant 2 dates combination PCM results

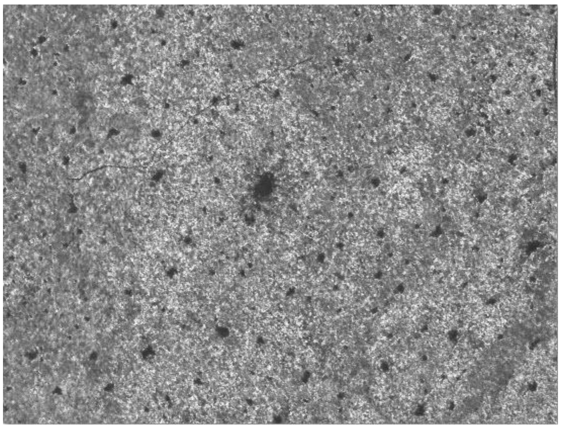


Figure 6-28 AWiFS_plant 3 dates combination PCM results

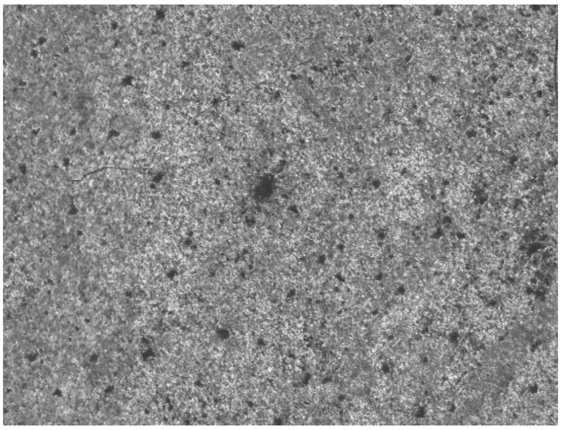


Figure 6-29 AWiFS_plant 4 dates combination PCM results

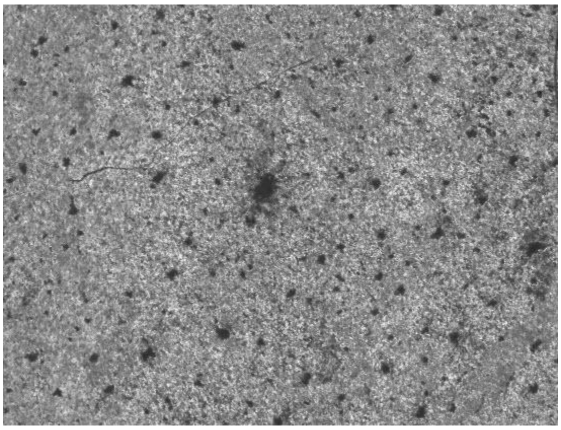


Figure 6-30 AWiFS_plant 5 dates combination PCM results

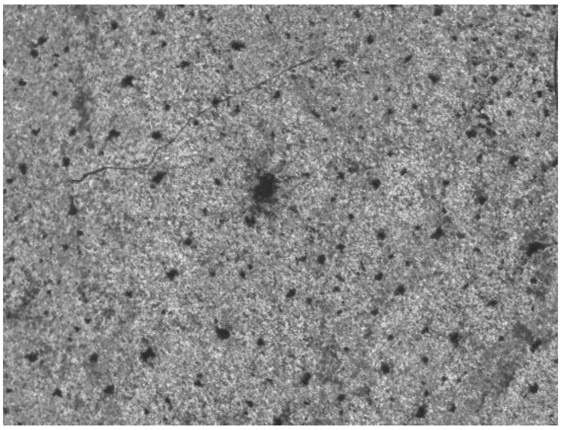


Figure 6-31 AWiFS_plant 6 dates combination PCM results

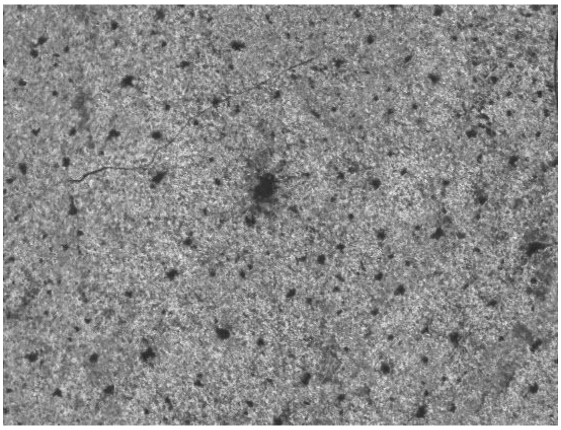


Figure 6-32 AWiFS_plant 7 dates combination PCM results

0 1

μ = Membership Value

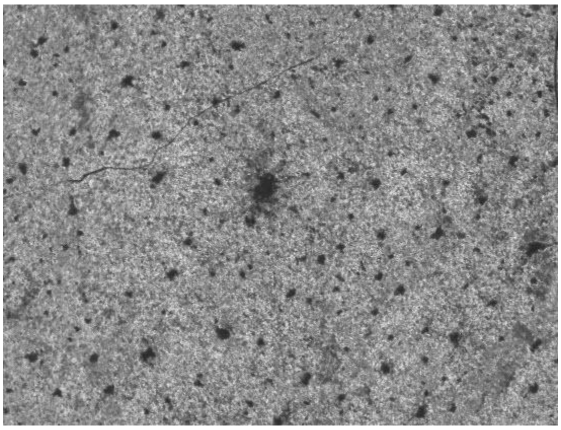


Figure 6-33 AWiFS_plant 8 dates combination PCM results

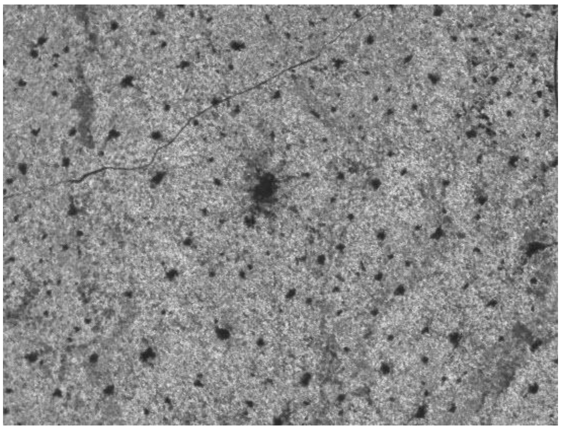


Figure 6-34 AWiFS_plant 9 dates combination PCM results

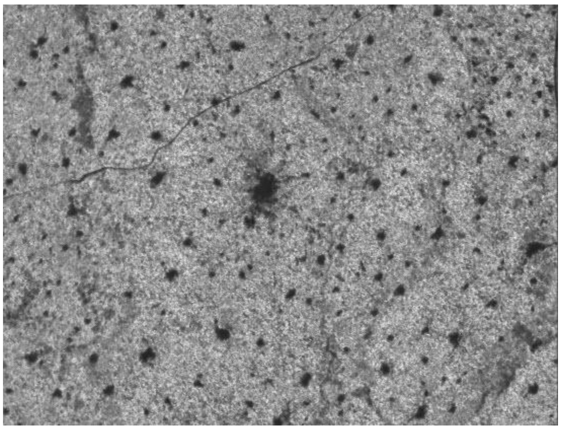


Figure 6-35 AWiFS_plant 10 dates combination PCM results

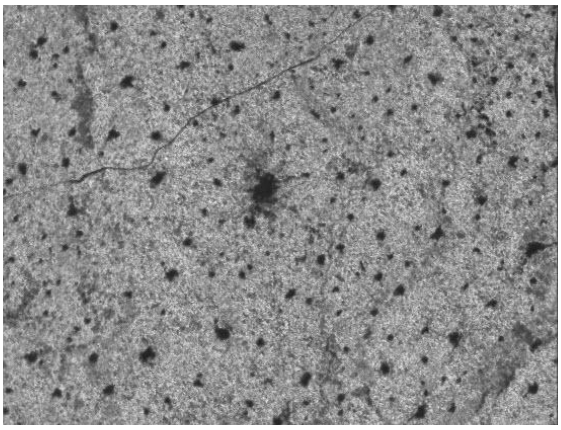


Figure 6-36 AWiFS_plant 11 dates combination PCM results

Figures 6-27 to 6-36: Sugarcane-Plant temporal membership images from single sensor AWiFS dates combination classified results

Similar analysis as table 6-10 was also done for discriminating sugarcane ratoon using temporal AWiFS data. The results of this analysis are listed in table 6-11.

No. of dates combination	Biased ratoon site (μ)	Unbiased ratoon (μ) (UR)	Other known sites (μ) (other non-interest classes)	Best minimum difference between UR and other classes	Accuracy Assessment (FERM)		
					MIN (%)	LEAST (%)	PROD (%)
2	230	176	O: 83; U:27; P:123; W: 145	UR: W = 21	91.953	36.702	**62.349**
3	245	167	O: 127; U:28; P:117; W: 107	UR: O = 40	92.140	31.098	60.770
4	225	173	O: 86; U:30; P:121; W: 105	UR: P = 52	91.291	27.800	58.358
5	229	171	O: 76; U:30; P:149; W: 112	UR: P = 22	92.645	26.539	59.195
6	232	184	O: 104; U:30; P:139; W: 109	UR:P = 45	92.604	26.816	58.531
7	234	182	O: 77; U:31; P:164; W: 119	UR: P = 18	92.724	25.313	58.539
8	233	179	O: 102; U:30; P:148; W: 117	UR: P = 31	91.748	25.709	58.288
9	231	**185**	O: 87; U:29; P:175; W: 90	UR: P = 10	**92.822**	**25.317**	58.858
10	236	181	O: 105; U:28; P:153; W: 94	UR: P = 28	92.648	26.597	58.150
11	229	184	O: 89; U:28; P:181; W: 93	UR: P = 3	92.659	26.574	57.425

Table 6-11: PCM Classification and Accuracy Assessment results
for AWiFS using training for Sugarcane ratoon
Where O- Orchard; U-Urban; P: Sugarcane Plant; W: Wheat; UR: Unbiased ratoon
and μ = Class membership values in 8 bits
(Note: Date combinations corresponding to numbers in table 6-11 are listed in table 6-5)

The results of the FERM accuracy assessment using MIN, LEAST and PROD operators can be seen in table 6-11. Figures 6-37 to 6-46 show the sugarcane-ratoon membership result images obtained for the temporal AWiFS best dates combinations. The accuracy assessment of the classified outputs of temporal AWiFS images was done against the LISS- III best (optimum) date image combination (6 dates combination) classified outputs for discrimination of sugarcane ratoon. The selection of the optimized temporal dates combination for classification of crop of interest sugarcane ratoon was done by maximising MIN and PROD operator results and by minimising the LEAST operator results.

It can be observed from table 6-11 that as the temporal AWiFS dates were increased from the initial 2 dates combination the crop of interest i.e. sugarcane-ratoon was assigned higher values which however saturated after 6 dates combination. The maximum possible overlap (MIN) also increased from the initial 91.953 % for 2 dates combination to 92.822 % for 9 dates combination after which it started declining. The minimum possible overlap (LEAST) results from different temporal dates combination decreased from the initial 36.702 % for 2 dates combination to 25.317 % for 9 dates combination and then continued increasing. The PROD operator results however were maximum at 2 dates combination with a value of 62.340 % and with 58.858 % expected overlap for 9 dates combination which was fairly higher than other dates combinations. Therefore the 9 dates combination was selected the optimized temporal dates combination for classifying specific crop sugarcane ratoon using temporal AWiFS data.

The 9 dates combination selected as the best dates for sugarcane ratoon discrimination using AWiFS temporal data corresponds to fallow period (20 Feb.10 and 6 Mar.10), initial crop growth phase (28 Apr.10 and 22 May 10), maximum growth phase (15 June 10), senescence phase (28 Sept.10), harvest period (5 Dec.10 and 5 Feb.11) and fallow condition (30 Mar.11). A multi sensor approach using AWiFS and some other sensor's data could not be tried for this study due to the unavailability of a sensor that had similar spatial resolution like that of AWiFS.

The analysis of results obtained from tables 6-10 and 6-11 show that the memberships assigned to the non-interest classes (urban, orchard and wheat) were very low when compared to sugarcane plant and ratoon crop. This shows that the specific crop of sugarcane as a whole has been successfully extracted in the image but some degree of confusion exists between sugarcane-plant and ratoon. This confusion could be minimised by applying a threshold to the soft classified outputs but this would need specific knowledge for partitioning sugarcane crop into sugarcane-plant and ratoon. However the sites with the high memberships for sugarcane-plant or ratoon are more certain to belong to plant and ratoon respectively. The resultant specific crop (sugarcane-plant and ratoon) maps (membership images) are hence shown as soft outputs, since hardening of soft classified results which would then lead to loss of information.

The PCM classification technique classification technique was applied to the best 2, 3, 4…. dates combinations for AWiFS sensor for extracting sugarcane ratoon. Figures 6-37 to 6-46 show the sugarcane-ratoon membership result images obtained for the temporal AWiFS best dates combinations.

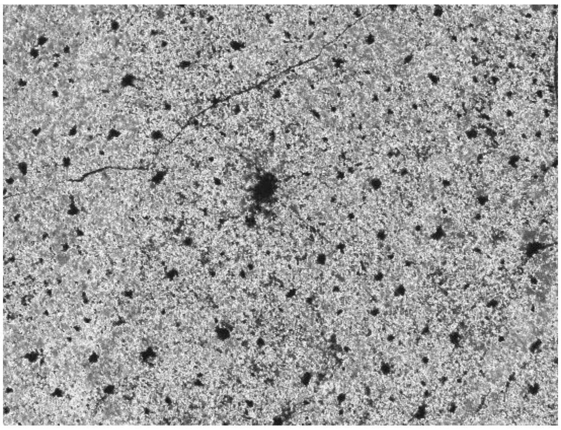


Figure 6-37 AWiFS_ratoon 2 dates combination PCM results

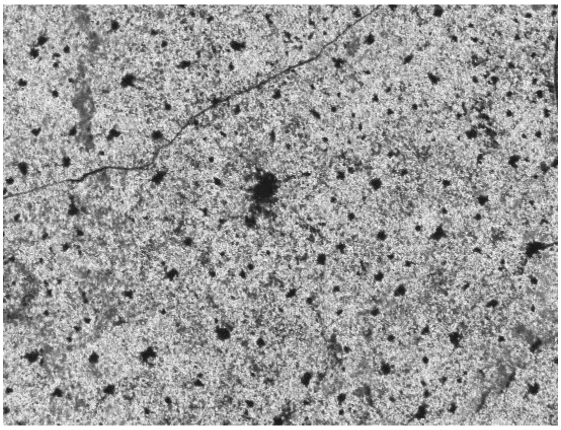


Figure 6-38 AWiFS_ratoon 3 dates combination PCM results

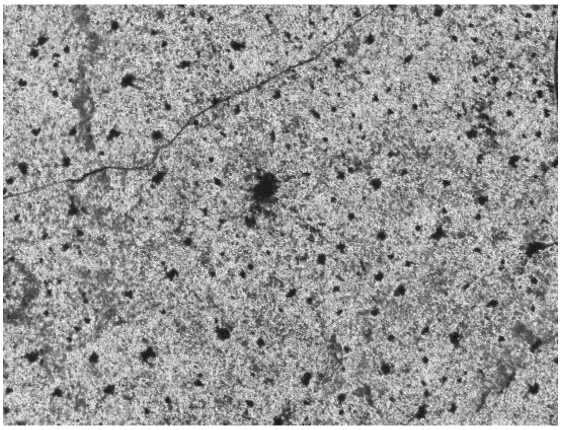


Figure 6-39 AWiFS_ratoon 4 dates combination PCM results

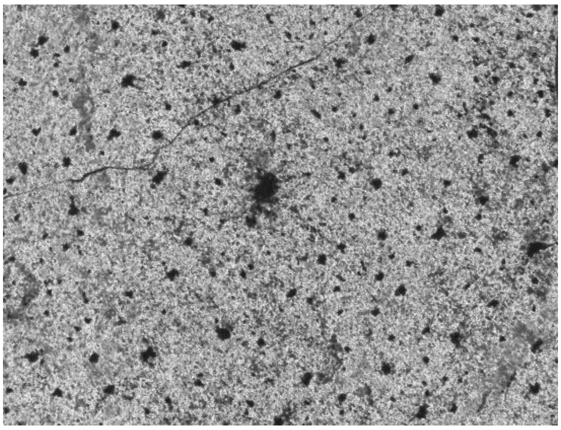


Figure 6-40 AWiFS_ratoon 5 dates combination PCM results

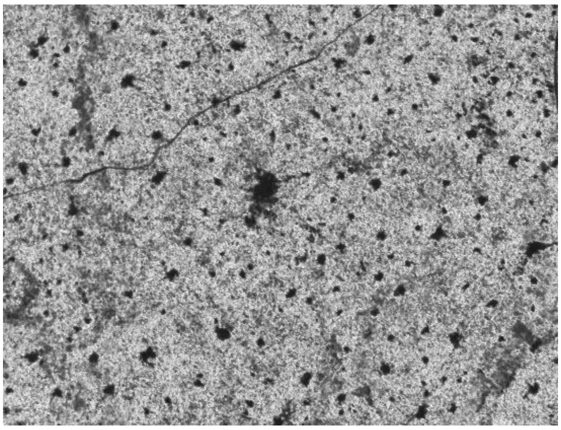


Figure 6-41 AWiFS_ratoon 6 dates combination PCM results

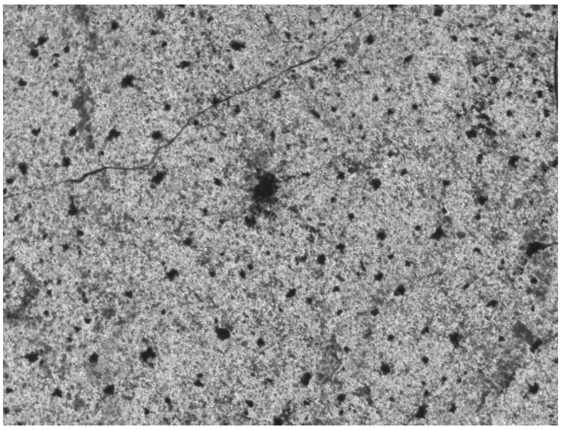


Figure 6-42 AWiFS_ratoon 7 dates combination PCM results

μ = Membership Value

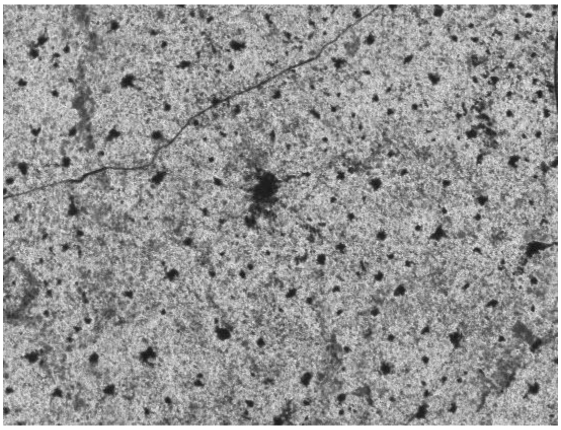


Figure 6-43 AWiFS_ratoon 8 dates combination PCM results

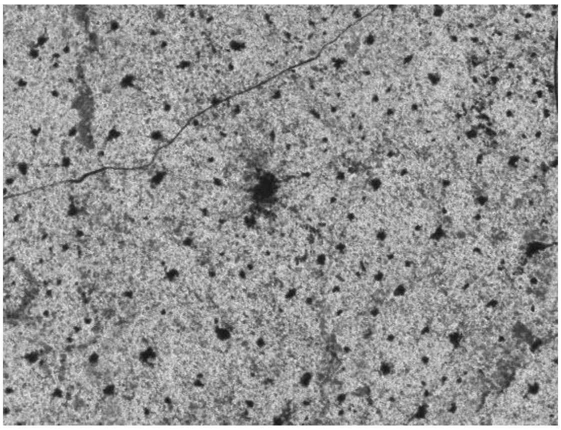


Figure 6-44 AWiFS_ratoon 9 dates combination PCM results

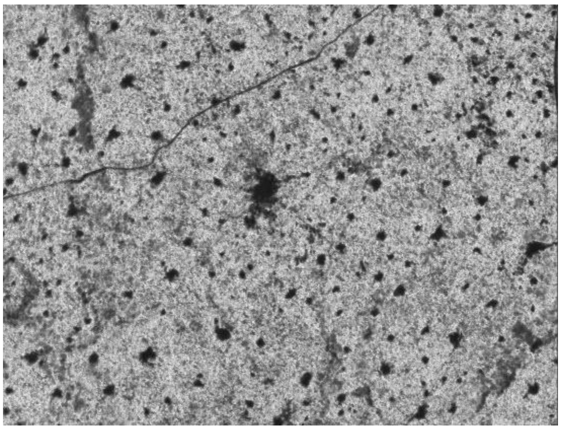


Figure 6-45 AWiFS_ratoon 10 dates combination PCM results

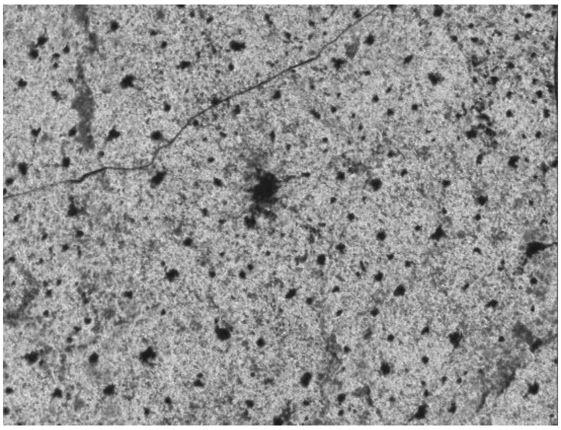


Figure 6-46 AWiFS_ratoon 11 dates combination PCM results

Figures 6-37 to 6-46: Sugarcane-Ratoon temporal membership images from single sensor AWiFS dates combination classified results

7. 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.

a) As this study was time bound and of a shorter duration, only a few areas in the temporal discrimination of crops could be actively explored. Since the remote sensing data used in this study was of the period Feb.10-Mar.11, field work in Oct.12 was mainly done based on expert knowledge available about the crop growth pattern and the agricultural land survey records of the area. This study could be further extended to include real time data, when latest remote sensing data is procured and the field work is conducted at the same time.

b) More optical sensors with similar spatial resolutions could be tried to be included in order to increase the temporal data sampling and then the discrimination of the specific class should be conducted.

LIST OF REFERENCES

1. Bezdek, J. C. (1981). Pattern Recognition with Fuzzy Objective Function Algorithms. Plenum. New York. USA.
2. Binaghi, E., Brivio, P. A., Ghezzi, P. and Rampini, A. (1999). A Fuzzy Set based accuracy assessment of soft classification. Pattern Recognition of Letters (20). pp: 935-948.
3. Chen, Z., Uchida, S., Tang, H. and Xu, B. (2004). NDVI-Based Winter Wheat Un Mixing for Accurate Area Estimation. IEEE International Geoscience and Remote Sensing Symposium. Vol-6. pp: 3977-3980.
4. Dadhwal, V. K., Singh, R. P. and Parihar, J. S. (2002). Remote sensing based crop inventory: A Review of Indian experience. Tropical Ecology 43(1): 107-122.
5. Dave, R., N. (1991). Characterization of Noise in Clustering. Pattern Recognition of Letters (12), pp: 657-664.
6. Deghan, H. and Ghassemian, H. (2006). Measurement of uncertainty by the entropy: application to the classification of MSS data. International Journal of Remote Sensing. Vol.27. No.18. pp. 4005-4014.
7. Doriaswamy, P. C., Akhmedov, B., and Stern, A. J. (2006). Improved techniques for crop classification using MODIS imagery. IEEE International Conference on Geoscience and Remote Sensing Symposium (IGARSS'06), pp: 2084-2087.
8. El Hajj, M., Begue, A. and Guillaume, S.(2007). Multi source information fusion: Monitoring sugar cane harvest using multi temporal images, Crop growth modeling and Expert knowledge. Paper presented at the International workshop on Analysis of Multi temporal Remote Sensing Images.
9. El-Aziz, M. A. E. I. A. (2004). Evaluation of Soft Classifiers for Remote Sensing Data. PhD. Thesis. IIT Roorkee. India. pp: 39-95.
10. Erdas Inc. (2010). Erdas Field Guide.
11. FAO, (2011), Country briefs, retrieved on 5 Feb. 2012 from www.fao.org/countries/55528/en/ind/
12. Jackson, R. D. and Huete, A. R. (1991). Interpreting vegetation indices. Preventory Veterinary Medicine 11: 185-200.
13. Jensen., J. R. (2009). Remote Sensing of the Environment. 2nd Edition. Pearson Education. pp: 382-399.
14. Krishnapuram R. and Keller J. M. (1993). A possiblistic approach to clustering. IEEE Transactions on Fuzzy Systems. Vol. 1. pp. 98 – 108.
15. Kumar, A. and Roy, P. S. (2011). Effect on Specific Crop Mapping using Worldview-2 multispectral add-on bands- A Soft Classification Approach. Special Sessions on Digital Globe. pp. 1-10.
16. Kumar, A. and Saggar, S. (2008). Class based ratioing effect on sub-pixel land cover automatic mapping.The International Archives of the Photogrammetry. Remote Sensing and Spatial Information Sciences. Vol. 37. Part B7. Beijing.
17. Kumar, A., Ghosh, S. K. and Dadhwal, V. K. (2006). Sub-Pixel Land Cover Mapping: SMIC System. ISPRS International Symposium on Geospatial Databases for Sustainable Development. Goa. India.
18. Kumar, A., Ghosh, S., K. and Dadhwal, V.K. (2010). ALCM: Automatic Land Cover Mapping. Journal Indian Society of Remote Sensing. Vol-38. pp: 239-245.

19. Liang, P. and Chunyu, Y. (2009). Study on mixed pixel classification method of remote sensing image based on fuzzy theory. 2009 Urban Remote Sensing Joint Event. in IEEE conference. pp. 1-7.
20. Luo, B., Yang, C. and Chanussot, J. (2011). Linear Un Mixing of Multi Date Hyper spectral Imagery for crop yield estimation. IEEE International Geoscience and Remote Sensing Symposium. pp: 1573-1576.
21. Masialeti, I., Egbert, S. and Wardlow, B.D. (2010). A comparative analysis of phonological curves for major crops in Kansas. GIScience and Remote Sensing. 47(2). pp: 241-259.
22. McNairn, H., Champagne, C., Huffman, E., Smith, A., Fisette, T.(2005). A multi-sensor Approach to inventorying Agricultural land use. Proceedings of 31st International Symposium on Remote Sensing of Environment. Petersburg. Russia .
23. Murthy, C.S., Raju, P.V. and Badrinath, K.V.S. (2003). Classification of wheat crop with multi temporal images: Performance of Maximum Likelihood Classifier and Artificial Neural Networks. International Journal of Remote Sensing. 24(23). pp: 4871-4890.
24. Murthy, S. R. S. (2010). Economics of Sugarcane Production and Processing. Department of Economic Analysis and Research, National Bank for Agriculture and Rural Development. Mumbai. Occasional Paper- 54: 1-200.
25. Nandakumar, T., Ganguly, K., Sharma, P. and Gulati, A. (2010). Food and Nutrition Security Status in India. Asian Development Bank Sustainable Development Working Paper Series No. 16: 1-48.
26. NASA, (2011), Landsat Science Technical Details, retrieved on 25 July 2011 from http://landsat.gsfc.nasa.gov/about/tm.html.
27. National Portal Content Management Team, (2011), Agriculture: National Portal of India, retrieved on 25 July 2011 from www.india.gov.in/citizen/agriculture/index.php.
28. Oza, M. P., Pandya, M. R. and Rajak, D. R. (2008). Evaluation and use of Resourcesat-1 data for agricultural applications. International Journal of Applied Earth Observation and Geoinformation 10: 194-205.
29. Panigrahy, R .K., Ray, S. S. and Panigrahy, S. (2009). Study on utility of IRS-P6 SWIR band for crop discrimination and classification. Journal of Indian Society of Remote Sensing. 37(2): 325-333.
30. Shang, J., Mc Nairn, H., Champagne, C. and Jiao, X. (2008). Contribution of multi frequency, multi sensor and multi temporal radar data to operational annual crop mapping. IEEE International Geoscience and Remote Sensing Symposium (IGARSS'08). Vol-3. pp: 378-381.
31. Silvan-Cardenas, J. L. and Wang, L. (2008). Sub-Pixel Confusion Uncertainty Matrix for Assessing Soft Classifications. Remote Sensing of Environment (112). pp: 1081-1095.
32. Steven, M. D., Malthus, T. J., Baret, F., Xu, H. and Chopping, M. J. (2003). Intercalibration of vegetation indices from different sensor systems. Remote Sensing of Environment. pp: 412-422.
33. Tso, B. and Mather, P. M. (2009). Classification Methods for Remotely Sensed Data. CRC Press. 2nd Edition. pp. 69
34. Van Niel, T. G. and T. R. Mc Vicar. (2004). Determining temporal windows for crop discrimination with remote sensing: A case study in South-Eastern Australia. Computers and Electronics in Agriculture (45). pp: 91-108
35. Vincent, S. and Pierre, F. (2003). Identifying main crop classes in an irrigated area using high resolution image time series. IEEE International Conference on Geoscience and Remote Sensing Symposium (IGARSS'03). pp: 252-254.
36. Wang, F. (1990). Fuzzy Supervised Classification of Remote Sensing Images. IEEE Transactions on Geoscience and Remote Sensing Symposium. Vol-28. pp: 194-201.

37. Wardlow, B. D., Egbert, S. L. and Kastens, J. H. (2007). Analysis of time series MODIS 250m vegetation index data for crop classification in the U.S. Central Great Plains. Remote Sensing of Environment (108), pp: 290-310.
38. Winkantika, K., Uchida, S. and Yamamoto, Y. (2002). Mapping Vegetable Area with Spectral Mixture Analysis of the Landsat-ETM. IEEE International Geoscience and Remote Sensing Symposium. Vol-4. pp: 1965-1967.
39. Xie, Y., Sha, Z. and Yu, M. (2008). Remote sensing imagery in vegetation mapping: a review. Journal of Plant Ecology. Vol-1. No-1 . pp: 9-23.
40. Ying, L., Xiuwan, C., Hongwei, D. and Lingkui, M. (2010). An improved multi temporal masking classification method for winter wheat identification. International Conference on Audio Language and Image Processing (ICALIP'10). pp: 1648-1651, 2010.
41. Zadeh, L. A. (1965). Fuzzy Sets. Information and Control. Vol:8. pp: 338-353.
42. Zurita-Milla, R., Gomez-Chova, L., Guanter, L., Clevers, J., G., P., W., and Camps-Valls, G. (2011). Multi temporal Un-mixing of Medium Spatial Resolution Satellite Images: A case study using MERIS Images for land cover mapping. IEEE Transactions on Geoscience and Remote Sensing Symposium. pp. 1-10.

APPENDIX A

1) **Signature Separability Listing**

```
File: g:/spectral separability/awifs_single sensor/spectralsep_awifs.sig
Distance measure: Euclidean Distance
Using bands: 1 2 3 4 5 6 7 8 9 10 11
Taken 1 at a time
       Class
   1   sugarcane plant
   2   urban
   3   sugarcane ratoon
   4   orchard
   5   wheat
                         Separability Listing

  Bands          AVE    MIN    Class Pairs:
                                1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                                3: 4   3: 5   4: 5
  1            12624   1791   25972   4063   1791   3557  21909  24181  29529
                                2272   7620   5348

  Bands          AVE    MIN    Class Pairs:
                                1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                                3: 4   3: 5   4: 5
  2            14656   1607   28753  12559   9772   1607  16194  18981  30360
                                2787  14166  11379

  Bands          AVE    MIN    Class Pairs:
                                1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                                3: 4   3: 5   4: 5
  3             7047    680    7241   2317   9218    680   9558  16459   7921
                                6901   1637   8538

  Bands          AVE    MIN    Class Pairs:
                                1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                                3: 4   3: 5   4: 5
  4            14953   1724    9249   6255  24144   1724  15504  33393   7525
                               17889   7979  25868

  Bands          AVE    MIN    Class Pairs:
                                1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                                3: 4   3: 5   4: 5
  5            14453   4512   21587   5558   6009  17075  16029  27596   4512
                               11567  11517  23084

  Bands          AVE    MIN    Class Pairs:
                                1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                                3: 4   3: 5   4: 5
  6            11478    292   24568    292   1720   4522  24860  26288  20046
                                1428   4814   6242

  Bands          AVE    MIN    Class Pairs:
                                1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                                3: 4   3: 5   4: 5
  7            16927    212   28271    548    760  26027  28819  29031   2244
                                 212  26575  26787
```

```
  Bands         AVE    MIN    Class Pairs:
                              1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                              3: 4   3: 5   4: 5
 8            15899   2395   27055   2395   5105  15177  24660  32160  11878
                              7500  12782  20282

Bands         AVE    MIN    Class Pairs:
                              1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                              3: 4   3: 5   4: 5
 9            10734    623   16958   1492   2115   8819  18450  19073  25777
                               623   7327   6704

  Bands         AVE    MIN    Class Pairs:
                              1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                              3: 4   3: 5   4: 5
10            15252    241   26474    241   8830   5410  26233  35304  31884
                              9071   5651   3420

  Bands         AVE    MIN    Class Pairs:
                              1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                              3: 4   3: 5   4: 5
11            17972   2088   13244  11226  25028  13314  24470  38272  26558
                             13802   2088  11714
```

Table A-1: Signature Separability Listing between different class pairs for AWiFS sensor

2) Publications related to this research study:

a) Misra, G., Kumar, A., Patel, N. R. and Zurita-Milla, R. (2012). Mapping Specific Crop - A Temporal and Multi Sensor Approach. IEEE International Geoscience and Remote Sensing Symposium (IGARSS' 2012). Munich. (Paper Submitted).

b) Misra, G., Kumar, A., Patel, N. R. and Zurita-Milla, R. (2012). Mapping Specific Crop Sugarcane Ratoon - A Temporal Approach. Journal of the Indian Society of Remote Sensing. (Paper Submitted).

c) Misra, G., Kumar, A., Patel, N. R. and Zurita-Milla, R. (2012). Mapping Specific Crop Sugarcane - A Temporal Approach. Journal of Applied Remote Sensing. (Paper Submitted).

d) Misra, G., Kumar, A., Patel, N. R. and Zurita-Milla, R. (2012). Mapping Specific Crop - Temporal Multi sensor Approach. International Journal of Applied Earth Observation and Geoinformation. (Paper under progress).