SPECIFIC CROP IDENTITIFCATION USING KERNEL BASED FUZZY APPROACH FROM TEMPORAL DATA

Thesis submitted to the Andhra University, Visakhapatnam in partial fulfillment of the requirement for the award of *Master of Technology in Remote Sensing and GIS*

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DECLARATION

I, Ridhika Aggarwal, hereby declare that this dissertation entitled "Specific Crop Identification using Kernel based Fuzzy Approach from Temporal Data" submitted to Andhra University, Visakhapatnam in partial fulfillment of the requirements for the award of M.Tech in Remote Sensing and GIS, is my own work and that to the best of my knowledge and belief. It is a record of original research carried out be me under the guidance and supervision of

Dr. Anil Kumar, Scientist/Engineer-SF, Photogrammetry and Remote Sensing Department, Indian Institute of Remote Sensing, ISRO, Dehradun and Dr. G. Byju, Prinicpal Scientist (Soil Science), ICAR- CTCRI, Thiruvananthapuram, Kerala. It contains no material previously published or written by another person nor material which to a substantial extent nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgement has been made in the text.

Place: Dehradun Ms. Ridhika Aggarwal

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CERTIFICATE

This is to certify that this thesis work entitled "Specific Crop Identification Using Kernel Based Fuzzy Approach from Temporal Data" is submitted by Ms. Ridhika Aggarwal in partial fulfillment of the requirement for the award of Master of Technology in Remote Sensing and GIS by the Andhra University. The research work presented here in this thesis is an original work of the candidate and has been carried out in Photogrammetry and Remote Sensing Department under the guidance of Dr. Anil Kumar, Scientist/Engineer-SF and Dr. G. Byju, Principal Scientist (SoilScience), ICAR- CTCRI, Thiruvananthapuram at Indian Institute of Remote Sensing, ISRO, Dehradun, India.

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Dedicated to Mommy and Dad

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ABSTRACT

Agriculture holds a pivotal role in context to India, which is basically agrarian economy. Accurate and periodic information regarding the spatial distribution of crop is indispensable for crop yield and area estimation. However, it is very challenging to identify a specific crop using single date imagery. Hence, it is highly important to go for multi-temporal analysis approach for specific crop identification. The novelty in the proposed methodology is consideration of problem of non- linear separation between the classes that can be resolved by incorporation of kernels in the algorithm. The objective of the current study was implementation of fuzzy classifier; Kernel based Possibilistic*c*- Means (KPCM) and Contextual Information based Kernel Possibilistic*c*-Means (C-KPCM), using temporal data of Landsat 8- OLI (Operational Land Imager) and FORMOSAT-2 for identification of specific crops viz.; identification of timing of flooding or transplanting of rice fields and discriminate the fields from water body, rice fields and varieties of cassava in Radaur City, Haryana, Haridwar, Uttarakhand and Salem, India.

The temporal window during the growing phase of the specific crop was optimized using spectral separability analysis, which was noticed to have a significant impact on the accuracy of the classified outputs. Although the four local kernels (Gaussian, KMOD, Inverse Multiqadratic, Radial Kernel) incorporated in the PCM could well identify the specific classes at the optimized weighted constant value but, the linear, polynomial and sigmoid kernel based PCM failed to identify the water bodies and cassvain the study area. While, the incorporation of contextual information using Markov Random Field (MRF) removed the isolated pixels of the class of interest in the output imagery. The accuracy of the fractional images was measured by calculating average entropy at 75 testing sites for each target class. Entropy is as uncertainity indicator, where a low value represents higher certainty of existence of the class at the pixel. The entropy at testing sites using Inverse Multiquadratic PCM was found to be minimum. The transplantation time could be discriminated in 95% cases with an accuracy of ±5 days.

The study signifies that Landsat 8 and FORMOSAT along with Inverse Multiquadratice kernel based Possibilistic c- Means classifier is an effective technique to identify specific crops.

Keywords: PCM, Kernel, Contextual Information, Temporal Image, Vegetation Index, Rice, Cassava and Entropy.

Table of Contents

List of Figures

List of Tables

1. INTRODUCTION

1.1 Background

Reliable information from local to global land cover has always been an essential element for providing assistantship in finding the solution to wide range of environmental problems (Townshend et al., 1991). Satellite imageries whichare acquired by exploiting the information stored in the various regions of electromagnetic spectrum have been utilized in various domains. The unique spectral signature of every target aids into identification of the various land cover classes present on the ground. For instance, IRS- 1C LISS-III was used to assess plant richness in Barsey Rhododendron Sanctuary, Sikkim (Kushwaha, et al., 2005).While, AWiFS on-board IRS-P6 was used to estimate wheat yield in Haryana, India (Patel et al., 2006).

India is an agrirain economy, where it is hihgly important to monitor the crops and timely give accurate estimation about crop yeild and acreage. The continuous synoptic and repetitve coverage by satellite remote sensing, makes it an effective option for crop monitoring. But, reliable land use mapping of agriculture areas requires high resolution remote sensing data and/ or robust classification techniques. Traditional techniques, like maximum likelihood classifier have widely been used for crop mapping. But, the results obtained by the traditional technqiues are either over or under estimated (Dadhwal et al., 2002) . These hard classification techniques overlook the possibility of existance of mixed pixels and non- linear separation between the classes. The reason of occurrence of mixed pixles is either due to mismatch between the class size on the ground with the spatial resolution of the sensor and occurrence of different classes at the boundaries of two adjacent scenes. In such a case, it is necessary to assign multiple classes to a pixel. This can be achieved by using soft classification approach based on fuzzy set theory proposed by Zadeh (1965). One of the soft classication algorithims is Possibilistic *c*- Means (PCM), which was introduced by Krishnapuram and Keller (1993). PCM is basically a modification of Fuzzy *c*-Means algorithm proposed by Bezdek (1981). The algorithm has an ability to extract single class of interest owing to the constraints put on the objective function. In recent time, few researches have carried out studies to extract single class using PCM (Misra, 2012).

The problems of non- linear separation between the classes can be resolved by incorporation of kernels in the algorithm. Kernels are mathematical tools that map the data from input spectral feature space to a higher dimension data in feature space, such that the classes are well separable via a hyper plane. Kernels have been integrated in SVM for multispectral and hyperspectral image classification (Kumar et al., 2006, Camps and Bruzzone, 2005).

Unlike PCM which exploits information in spectral domain, contextual exploits information in spatial domain also. The technique has the capability to preserve the edges and reduce noisy data, thereby increase the overall accuracy of the results by 2-4%. (Chawala, 2010)

The proposed kernel based fuzzy approach would be tested onto the two imperative crops with respect to India and world too. The first crop is rice (*Oryza sativa)*, a major food crop for the people of the world in general and Asians in particular; nearly 90% of the world's rice is produced and consumed in this region. Furthermore, rice is a staple food for nearly 2.4 billion people in Asia, and except for Pakistan and some parts of India and China, rice provides two thirds of the calories for most Asians with rice-based diets. Rice is the major staple food of the people of India especially in eastern and southern states and is grown in an area of 43.5 million ha with a total production of 159.2 million kg, thus having an average productivity of 3.66 t ha^{-1}(www. faostat.fao.org). Paddy rice fields are known to be amongst the major source of anthropogenic methane in the atmosphere, contributing to over 10% of the total methane flux into the atmosphere. (Prather and Ehhalt, 2001, Manjunath and Panigrahy, 2009)

Although, many studies using optical data (Xiao, 2005, KurniaJayanti, 2012, Fang, 1998).and/ or microwave data (Panigrahy et al., 1997, Chakraborty et al., 2002, Manjunath and Panigrahy, 2009)at local to global level have been carried out in past to estimate rice growing areas, only a few studies could estimate the timing of flooding and transplanting of rice fields, due to the limitation of temporal resolution of the satellite and cloud covered data.

The other crop is a tropical tuber crop called cassava (Manihot esculenta Crantz). The crop is a rich source of energy and yeilds 250,000 cal $ha^{-1}day^{-1}$ of energy compared to maize(200,000), rice (176,000), and wheat (110,000). It is the most important root crop and fourth most important source of food calories in the tropics after wheat, rice and maize and is a staple food for more than 800 million people. In India, cassava is grown in an area of 0.21 million ha with a total production of 7.2 million tonnes having an average productivity of 35.00 t ha. The crop is mostly grown in the southern states of Tamil Nadu, Kerala and Andhra Pradesh and is consumed as a secondary staple along with rice and in many other forms such as sago (sabudana), wafers, papad, chips, flour etc. Cassava starch from the roots is also used for the production of a number of industrial products. It is used in textile industry as sizing agent, in pharmaceutical industries, making adhesives, dextrin manufacturing, paper industry, laundry and in many fast food preparations. Approximately 300,000 tons of sago and starch are manufactured from cassava roots by nearly 1200 starch and sago factories in Tamil Nadu, India. Here, cassava is found grown intercropped with cowpea, groundnut and turmeric or these crops are cultivated in adjacent fields (Byju et al., 2012, 2013). Accurate and periodic information regarding the spatial distribution of crop is indispensable for precise crop and nutrient management, yield and acreage estimation, crop condition assessment, yield losses due to pest and diseases and to study the impact of climate change crop suitability.

Accuracy assessment of the classified outputs is necessary to validate the results. The crop fields are dynamic in nature, hence previous year temporal images cannot be used as reference to carry out image to image accuracy assessment using Fuzzy Error matrix (FERM) (Binaghi,1999). Thus an indirect approach; Entropy, given by DehghanandGhassemia (2006), has been used to indicate the uncertainty in the classified results.

1.2 Research Rationale and Problem Statement

Accurate and timely information about location and area of different crop types has got greater significance for precision crop and nutrition management, crop condition assessment, yield forecasting, pest and disease surveillance and climate change studies. Such near-real time crop area estimation has got high significance in assessing the food security of a country. It has been proved that soft classification approach provides more realistic results for acreage estimation as compared to hard classification. Adding Kernels and contextual information would lead to greater accuracy of the classified results.

Hence, the research work proposes a robust classification approach for paddy rice fields mapping at the transplanting stage and identification of rice and cassava by supervised soft classification from temporal medium spatial resolution optical database.

1.3 Research Objectives

The study aims at implementation of kernel based fuzzy classification approach for specific crop identification using temporal Landsat- 8 OLI data. The following sub- objectives need to be achieved for successful accomplishment of the objective.

- To implement the stated fuzzy classifiers:
    - Fuzzy based classifier without kernel approach.
    - Fuzzy based classifier with various kernels.
    - Kernel based Fuzzy based classifier with contextual information.

For mapping of paddy rice fields and cassava using satellite imagery. The following objectives have to be achieved:

- To identify paddy rice fields depending upon the transplanting information and discriminate rice from water bodies.
- To identify the specific crop cassava (*Manihotesculenta*Crantz) and estimate its area.
- To evaluate number of temporal images, best suitable for specific crop identification.

1.4 Research Questions

Successful accomplishment of the research objectives will answer the following research questions:

- How to distinguish paddy rice fields from water body, using early rice growing phase information?
- Would kernel based classifier help in better discrimination of target crop?
- To what degree does the classification accuracy improve upon incorporating the MRF classifier with KPCM compared to KPCM?
- How well can cassava be discriminated from other crops present in the cropping pattern of a particular area?
- Which are the best dates suitable for identification of the specific crop- cassava?
- Does selection of kernel depend upon the study area and various crops?

1.5 Innovations Aimed at

The innovations involved in the work are mentioned below:

- Applicability of kernel based classifier to process temporal data for specific class identification.
- Fuzzy based approach to distinguish paddy rice fields from water body, using early rice growing phase information.
- Identification and area estimation of cassava using fuzzy classification technique.

1.6 Outline of the Thesis

The thesis is basically divided into seven chapters such that;

Chapter 1: *Introduction:* The chapter gives background of fuzzy classifiers and motivation behind carrying the work. While, in the subsequent sub- sections the research objectives and corresponding research questions have been enlsited.

Chapter 2: Literature Review: The chapter reviews the work done on vegetation indices, fuzzy based classification, kernels, contextual information and validation technique.

Chapter 3: Theoretical Framework*:* The section explains in detail the theorectical and mathermatical concepts of vegetation indices, fuzzy classifiers highlighting PCM, Kernels, KPCM, Contextual Information and technique for validation of results.

Chapter 4: Study Area and Materials Used: Highlights the study area and the dataset used for this research.

Chapter 5: Methodology: The section deals with giving details about the methodology adopted to achieve the objectives.

Chapter 6: Results and Discussion: In this chapter, optimization of the weighted constant and discrimination of the paddy rice fields from water body has been discussed. Following it are the results regarding the discrimination of cassava and area estimation using temporal data.

Chapter 7: Conclusion and Future Recommendations: Conclusions drawn from the carried out research has been discussed and also, recommendations for the future work have been put forward.

2. LITERATURE REVIEW

The following chapter deals with the literature and related work done to this research.

2.1 Temporal Vegetation Index

The temporal data acquired over a period provides information regarding the changes for a land cover, thus, it is an efficient method for mapping a specific land cover class. For example, if the specific class is under vegetation category, then its unique phenological changes over a period can be utilized to extract vegetation from the other classes. Recently, time series remote sensing data have been used for many applications, such as, forest fire (Goetz et al., 2006, Morton et al., 2011), estimation of forest biomass (Powell et al., 2010), flood study (Sakamoto et al., 2007), forest mapping (Hilker et al., 2009) and land scape changes (Millward et al., 2006). The multi- temporal MODIS data have been used for identification of crop in many studies (Xiao et al., 2006; Wardlow et al., 2007; Wardlow and Egbert, 2008; Pan et al., 2012). Due to the moderate spatial resolution, MODIS dataset is suitable for the crop mapping at local and regional scale. MODIS time series data at 250 m spatial resolution has been used for different application such as tropical forest phenology (Pennec et al., 2011), forest area estimation (Maselli, 2011), identifications of cropping activity (Pringle et al., 2012) and gross primary production (Schubert et al., 2012). Limited studies have been carried out for single land cover identification. Some of the studies are discussed in the following sections.

In India, different crop are gown in proximity of each other, and thus it is commonly observed that spectra; response of a crop overlaps with another crop or is not a true representation of that particular crop/ class. Crop mapping using single date imagery still remains a challenge and cannot accurately map the crop. (Masialetietal., 2010;Wardlowetal.,2007).

It is observed that cultural practices by farmer vary, that is, they plant and harvest the same crop at different times. Also the physiology of crops and their varieties are different. Both the reasons are the reasons of spectral overlap between the vegetation classes. Discrimination of these classes is possible by carrying a research using temporal dataset. Many studies have been carried out since long, to discriminate vegetation classes.

The importance of proper selection of bands in multispectral images was clearly highlighted by the research carried out by Ying et al., 2010. The research utilized four temporal MODIS generated NDVI images to discriminate wheat from other crops. Mask of winter wheat was created so that it could be distinguished from other crops. Proper selection of bands and application of wheat mast increased the accuracy for winter wheat classification to 94%. Similar study was carried out by Panigrahyetal, 2009 where, multi- date AWiFsdata was used for discriminating winter crops. The bases of classification were differences between their growing season and crop calendar. Transformed Divergence between the bands were calculated, and the ones giving highest minimum TD were used to discriminate the crops. It was found that, red, NIR and SWIR bands met the criterion and maximum likelihood classification was used to carry out the classification.

Wardlow et al., 2007 used a yearlong MODIS generated NDVI and EVI dataset to distinguish agricultural fields. It was observed that intra class variability due to difference in planting date and climate influences the spectral separability of the crops but the use of vegetation indices helped to segregate the classes at some point in their growing season. Another conclusion drawn from the research carried out was that correlation between the two indices varied during the growing and senescence phase of the crops. While, the correlation was high during growing phase but decreased in the latter phase. Similarly, Doraiswamy et al., 2006 used three year MODIS 8 day composite data to extract the class of interest that was soyabean. The basis of identification of crop of interest was its differences in the length of greenness with the other vegetation classes; trees and shrubs present in the study area.

Vincent and Pierre, 2003 carried out classification of temporal SPOT images using NDVI as the vegetation index. The four classes were; bare soil, herbaceous crops. Trees on bare soil and trees along with herbaceous crops. It was found that the number of temporal images used for classification has a slight impact on the accuracy of the classified results. While, using three images, the accuracy obtained was 83% it increased by 2% when 5 images were used covering the complete phenological cycle.

One of the prime necessities for carrying out temporal studies is the availability of cloud free dataset covering the complete growth stages of crop phenology. The continuous monitoring of the crop over its various growth stages aids into discrimination of different crop or vegetation type. The characteristic spectral signature at the important crop growth stages in the time domain otherwise known as crop phenology can help in discriminating various crops or vegetation (ElHajjetal.,2007). But, the atmospheric conditions are not always favorable, and thus there exists data gaps. The occurrence of atmospheric disturbance gives clouded optical data, which can’t be used for the research. The clouded data creates gap in the temporal data and decreased the accuracy of results obtained by temporal analysis study. (Stevenetal.,2003). In such a case, data from multiple sensors are used to reduce the gaps in temporal data. A research by Mc Nairn et al., 2005 was carried out in the same direction. The research was carried out with an aim to generate annual crop inventories. It used temporal Landsat and SPOT as optical dataset along with microwave data acquired by RADARSAT-1 and Envisat- ASAR and employed maximum likelihood classification to generate the desired results with accuracy upto 80%. Another research by Shang et al., 2008 was carried out on the similar lines. The research utilized multi temporal and multi sensor data for crop mapping. Decision tree classification was used to obtain the results. The results obtained clearly indicated that the accuracy increased with incorporation of microwave data into temporal optical data. The accuracy obtained was approximately 87%.

It is highly important to select the best combination of date to achieve higher accuracy. Murthy et al., 2003 concluded the best date combination that came out to be three date out of the other date combination, that were, one and two date combination. Bhattacharya Distance (BD) was calculated to separate wheat from other crops in the study area using temporal dataset. Similarly, Van Niel and Mc Vicar (2004) carried out a study to optimize the number of temporal date. The study used per- pixel maximum likelihood classification algorithm to determine the best temporal window for overall and single class identification. It was found that the temporal window for overall accuracy and single class accuracy varied. The use of the best temporal window for crop discrimination improved the overall classification accuracy.

Zurita-Milla et al., 2011 carried out a research using temporal MERIS data for land cover mapping. The study explored the effect of fully constrained spectral un-mixing method onto the results single and multi- temporal approach. The study observed mixing between the classes and thus, it was concluded that it is highly important to consider the spectral separability among the classes.

The prior studies on time series data show the significance of determination of dates from an arrangement of accessible information for accomplishing better classification results. This will help not just spare time needed for data preparation, processing and investigation time additionally enhance the classification accuracy. The audit of different literature likewise show that the choice of best temporal dates for crop discrimination should be possible utilizing spectral separability analysis study. A percentage of the conspicuous distance measures that have been already utilized for class distinctness examination for segregating different 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 measure of spectral separability present between diverse classes in the feature space. The spectral separability among the classes when mulled over for diverse temporal dates combination can help in selecting the ideal dates for separation of classes. So higher the spectral separability among the classes, the lesser is the perplexity and better is the consequences of classification.

2.2 Fuzzy Classifier

Another vital thought while managing land cover classification utilizing remote sensing information is the event of mixed pixels. Regularly when the size of a pixel is bigger than the class size on the ground or at between class limits, spectral mixing happens. Marking of such mixed pixels with one and only class cover will prompt overestimation of one class and underestimation of different classes. So as to precisely assign the class cover in a pixel the phenomenon of mixed pixel must be considered. This issue of un-mixing classes introduced in a pixel can be taken care of through different available procedures like Linear Mixture Models, Fuzzy classification, Neural Networks, and so on. Zadeh, 1965 and Wang,1990 depicted a fuzzy supervised classification strategy that permits a pixel to have different class memberships and thus help in accomplishing a higher accuracy of classification. Dave, 1991 added to a fuzzy k-means algorithm to distinguish good clusters amongst boisterous data points. It continues by characterizing a noise prototype where all the noisy data points are dumped before the grouping is connected on the good clusters. It made a great part of information giving good clusters for enhancing the classification accuracy. The classification results demonstrated an impressive change when Wikantika et al., 2002 and Chen et al., 2004 implemented the spectral linear un-mixing model to classify the agricultural fields. Luo et al., 2011 utilized linear spectral un-mixing to make crop maps. It was found that the un-mixing of the pixels to anticipate the crop classes enhanced the forecast of crop production significantly. Liang and Chunyu, 2009 utilized Landsat- TM picture and applied fuzzy strategy for classification of surface elements. They discovered definite improvement of 5-10% in the accuracy for the classes in the fuzzy classified outputs when contrasted with the hard classification system of MLC (Maximum Likelihood Classifier). This demonstrated the productivity of utilizing the fuzzy classifier to handle mixed pixels in correlation to utilizing conventional hard classifiers. Kumar *et al*., 2010 extracted single class i.e. water from mixed pixels in AWiFS sensor of Resourcesat-1 satellite. They utilized PCM (Possibilistic C Means) algorithm where the membership of a class in a pixel is autonomous of the membership of different classes in the pixel i.e. the total of the memberships of the classes in a pixel may not be equivalent to one. The accuracy of the classified outcome was discovered to be in the scope of 84-99%. The special methodology of this study is the extraction of a solitary class autonomous of the presence of different classes in the image. Such a methodology can help in separating particular class in an image. The above studies demonstrate that the utilization of un mixing techniques for mixed pixels enhanced the classification results. The incorporation of such methods can help in exact class cover estimation in a mixed pixel. However, some of these methods have been found to have a few limits. The neural systems take quite a while in the learning period of classification which is a genuine downside when managing vast datasets (Kumar and Saggar, 2008). Furthermore, the Linear Mixture Model needs the total of all the class memberships in a pixel to be solidarity and obliges the quantity of classes that are to be unmixed to be less or equivalent to the number of bands present in the data (Chen et al., 2004). So as to beat every one of these issues and to accomplish the target of particular crop discrimination fuzzy classification methods particularly PCM can be utilized. 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.Tech. research work.

Ling et al., 2010 stated that the soft classification only provides the area proportion of each class, actual spatial distribution of each class in these mixed pixels are not distinguishable. In this study, a super resolution land cover mapping technique which uses multiple sub pixel shifted remote sensing images was proposed to predict the spatial land cover distribution within the mixed pixel. The super resolution mapping is also known as sub pixel sharpening at sub pixel mapping and can be considered as the post processing of the soft classification output. The Hopfield Neural Network (HNN) method was used for the mapping the multiple soft classified images. It was observed that, more information can be extracted for the super resolution land cover mapping by using multiple sub pixel shifted images.

Ghosh et al., 2011 used a fuzzy clustering algorithm and image difference technique to detect change between remote sensed images of different dates. Pixels in the difference image which belong to two clusters were found to be not separable by sharp boundaries and fuzzy clustering technqiues appear to be more appropriate because they provided a realistic choice to separate these clusters, they used FCM and GKC soft classification technique for this task. Various image feautres were extracted using neighborhood information of pixels for clustering pursposed, separate experiments were conducted on multi- temporal Landsat 7 ETM+ for a small part in Mexico country and on multi- temporal Landsat 5 TM of Sardinia Island, Italy. The results were compared with MRF and NN based algorithms and were found to be superior.

Geman and Geman (1984) did maximum a priroi (MAP) estimation as statistical criterion using simulated annealing and Gibbs Sampler for MRF model based image restoration. It was found improved restorations at low signal- to- noise ratio. It explains the equivalence between Gibbs distribution and Markov Random Field (MRF). The restoration was performed using the simulated annealing theorem which converges to the global maxima of the posterior energy without sticking in a local minimum.

Solberg et al.,1996, used MRF model to include contact for multisource satellite images. It was found tht MRF model can model spatial class dependencies as well as temporal class dependencies. MRF model achieved 2% higher classification accuracy when same set of images used for two different models. Finally it was concluded that MRF model provide better results for classification of multisource satellite images.

Pham, 2002, included spatial constraints using MRF model on the membership function of FCM for image segmentation and it was names as Robust Fuzzy c- Means (RFCM) algorithm. The value of smoothness controller ß was obtained by penalty function or objective function. In this work the new formulation of FCM was applied on Magnetic Resonance Images (MRI) of brain and it was found that RFCM to be more robust to noise than FCM classification. The comparative results calculated by misclassified rate (MCR) was 14.14% for FCM and for RFCM it was 0.52%.

Melgani and Serpico, 2003, used MRF model to integrate contextual and spatio- temporal information for the classification of Landsat TM and ERS-1 SAR images. In this work it was proposed a mutual approach for image classification. In this study, it was found that proposed mutual method shows improvement of 1%- 3% in classification accuracy as compared to reference MRF model based classifier.

Tso and Olsen (2005), used contextual and multiscale fuzzy line process for classification of IKONOS image. MRF model was used for contextual information, wavelet and fuzzy fusion process to extract line features. The accuracy was improved to 13% while using MRF model based contextual and edge information image classification.

Kaserkasem et al. (2005), used MRF model for super- resolution land cover mapping. In this work, the proposed MRF model based approach was applied on IKONOS MSS and Landsat ETM+ images. The results showed a significant improvement in accuracy of land cover maps over that obtained from Land cover mapping at sub pixel scales using Linear Optimization approach given by Verhoeye and Wulf, 2002.

Moser and Serpico (2010), proposed contextual support vector machines classifier based of MRF model. To minimize the execution time and to automatically rune its input parameters hierarchical clustering and parameter optimization algorithm was also integrated with SVM. The developed method was applied on SAR and multispectral high resolution images. The overall accuracy was 0.93292 and 0.9898 for traditional SVM and proposed MRF model based SVM respectively.

In 1995 to avoid over smoothing, Li introduced the concept of discontinuity adaptive (DA) MRF models. The basic principle behind the DA model is, at the point of discontinuity it minimizes the smoothing strength accordingly. The innovation in different discontinuity adaptive MRF model was the way neighboring points would interact and taking into control the smoothing strength.

Discontinuity adaptive MRF model has been used in remote sensing domain since long. Smits and Dellepiane (1997) used the model in conjunction with gamma distribution for segmentation of SAR images. The results showed that the methodology was successful to preserve the fine structure and borders of the features in images.

Homen et al. (1994), employed the use of MRF model to reconstruct images using Iterated conditional modes (ICM) algorithm to find MAP solution. Discontinuity adaptive framework was used to avoid over smoothness of MAP- MRF formulations for sixteen low-resolution images. While, Kand and Roh (2001) presented a new method to increase the performance of edge- preserving image smoothing of MRF function by the parameter tuning. The method was based on an automatic control of smoothing strength in discontinuity adaptive MRF function from discontinuities of image intensity. An algorithm as proposed which used parameter modification to increase the piecewise smoothness of images in a DA- MRF modelling. The proposed method was well preserved the object boundaries in comparison to conventional DA smoothing.

Singha, (2013) explored the applicability of DA- MRF models for incorporation of spatial contextual information. While observing the fuzzy accuracy measure it was found that FCM DA- MRF (H3) performs better than the other FCM DA-MRF models. It was observed that the discontinuity adaptive MRF models improve the overall classification accuracy as well as preserves the edges at boundaries and generates the spectrally and spatially consistent classified output.

2.3 Kernels

Earth Observation is allowed by remotely sensed images with unprecedented accuracy. New satellite sensors acquire images with high spectral and spatial resolution, and the revisiting time is constantly reduced. Processing data is becoming more complex in such situations and many problems can be tackled with recent machine learning tools.

Kernel methods allow us to transform almost any linear method into a nonlinear one, while still operating with linear algebra. The methods essentially rely on embedding the examples into a high dimensional space where a linear method is designed and applied. Access to the mapped samples is done implicitly through kernel functions. The impact and development of kernel methods in the remote sensing area during the last decade has been large and fruitful, overcoming some of the problems posed both by the recent satellite sensors acquired data, and the limitations of other machine learning methods. Kernel methods have proven effective in the analysis of images of the Earth acquired by airborne and satellite sensors. Kernel methods provide a consistent and well-founded theoretical framework for developing nonlinear techniques and have useful properties when dealing with low number of (potentially high dimensional) training samples, the presence of heterogeneous multimodalities, and different noise sources in the data. These properties are particularly appropriate for remote sensing data analysis. In fact, kernel methods have improved results of parametric linear methods and neural networks in applications such as natural resource control, detection and monitoring of anthropic infrastructures, agriculture inventorying, disaster prevention and damage assessment, anomaly and target detection, biophysical parameter estimation, band selection, and feature extraction.

It is well known, that complete and representative training set is essential for a successful classification. In particular, it is noteworthy that little attention has been paid to the case of having an incomplete knowledge of the classes present in the investigated scene. This may be critical since, in many applications, acquiring ground truth information for all classes is very difficult, especially when complex and heterogeneous geographical areas are analyzed. A kernel based method for one- class SVM was originally introduced for anomaly detection (Mercier and Girard-Ardhuin, 2006), then analyzed for dealing with incomplete and unreliable training data (Mu˜nozMar´I et al., 2007), and later on reformulated for change detection (Camps-Valls, 2008).

Composite kernels have been specifically designed and applied for the efficient combination of multitemporal, multisensor and multisource information (Camps-Valls, 2008, Tuia et al., 2009). The previous approaches exploited some properties of kernel methods (such as the direct sum of Hilbert spaces, see Section 1.2.3) to combine kernels dedicated to process different signal sources, e.g. the sum of a kernel on spectral feature vectors can be summed up to a kernel defined over spatially-extracted feature vectors. This approach yielded very good results but it was limited to the combination of few kernels (Camps-Valls, 2006), as the optimization of kernel parameters was an issue.

Another algorithm in which kernel has been included is PCA. The main limitation of PCA is that it does not consider class separability since it does not take into account the target variables y of the input vectors. PCA simply performs a coordinate rotation that aligns the transformed axes with the directions of maximum variance of the original data distribution. Thus, there is no guarantee that the directions of maximum variance will contain good features for discrimination or regression. The inclusion of kernels in PCA overcomes all the loopholes.

Roman Rosipal et al., (2003) proposed a new kernel PLS-SVC classification technique. The results achieved on 13 benchmark data sets demonstrate usefulness of the proposed method and its competitiveness with other state-of-the-art classification methods. On six benchmark data sets a statistically significant superiority of kernel PLS-SVC over C-SVC was observed. In contrast, this tendency was observed only in one case for C-SVC. In terms of averaged classification error the superiority of kernel PLS- SVC over kernel Fisher DA was observed in 10 out of 13 benchmark data sets. In seven cases this was achieved using more than one score vector, which suggests, that a single direction extracted by kernel Fisher DA on these data sets is not adequate to discriminate two different classes.

Zhang and Chen, (2004) presented a novel algorithm for fuzzy segmentation of magnetic resonance imaging (MRI) data. The algorithm is realized by modifying the objective function in the conventional fuzzy C-means (FCM) algorithm using a kernel-induced distance metric and a spatial penalty on the membership functions. Firstly, the original Euclidean distance in the FCM is replaced by a kernel-induced distance, and thus the corresponding algorithm is derived and called as the kernelized fuzzy C-means (KFCM) algorithm, which is shown to be more robust than FCM. Then a spatial penalty is added to the objective function in KFCM to compensate for the intensity inhomogeneities of MR image and to allow the labeling of a pixel to be influenced by its neighbors in the image. The penalty term acts as a regularizer and has a coefficient ranging from zero to one. Experimental results on both synthetic and real MR images show that the proposed algorithms have better performance when noise and other artifacts are present than the standard algorithms.

Kumar et al., (2006) support Vector Machines (SVMs) are a statistical learning theory based techniques and have been applied to different fields. For the pattern recognition case, SVMs have been used for isolated handwritten digit recognition, object recognition, charmed quark detection, face detection in images and text categorization. SVM have been shown to perform well for density estimation also where the probability distribution function of the feature vector can be inferred from a random sample. In this work SVM has been used for density estimation, and it uses Mean Field (MF) theory for developing an easy and efficient learning procedure for the SVM. In SVM a kernel function determines the characteristic of an SVM. The kernel functions used in SVM are defined as local kernels, global kernels and spectral kernels. In the case of local kernel only the data that are close or in the proximity of each others have an influence on the kernel values. In global kernel samples that are far away from each other still have an influence on the kernel value. A spectral kernel uses the spectral knowledge into SVM classification, which reduces false alarms for thematic classification. In this paper the effect of different mixed kernels generated while taking spectral kernel with local or global kernels have been studied on overall sub-pixel classification accuracy of remote sensing data using Fuzzy Error Matrix (FERM).

2.4 Accuracy Assessment

A study is never finished without evaluating the accuracy of the outcomes generated. Accuracy of a classified output is by and large surveyed by looking at the class assignments as produced by the classifier against the actual classes relegated by reference information.. The after effects of the classified output classes are thought about against the reference data classes and are arranged in a matrix called error matrix, whose diagonal components compare to the quantity of pixels effectively classified and the off diagonal components are the overestimation and underestimation class errors. Be that as it may, such an error matrix must be utilized for hard classified outputs and hardened reference information. If there should be an occurrence of reference and outputs information being soft output measures or membership grades, the data must be hardened with a specific end goal to utilize the conventional error matrix for accuracy assessment. This hardening of soft classified data leads to loss of information (Binaghi *et al*., 1999).

Pontius and Millones (2011) raised some serious comments on the use of Kappa as an accuracy assessment index. It was found that Kappa and its variants have computational complexities and at times difficult to understand. As a result, remote sensing community was urged to utilize two less difficult summary parameters that are, quantity disagreement and allocation disagreement for abridging the cross tabulation matrix. Further, it was suggested that the utilization of Kappa coefficient be abandoned in view of three reasons. In the first place, Kappa list is a ratio and can present issues in calculation and interpretation. If the denominator is 0, then the ratio is undetermined, while for any defined ratio, it is not clear whether the ratio size is inferable from extensive numerator and little denominator, and the other way around. Second, it is more essential to comprehend the two components of contradiction than to have a single summary statistic of conformity when translating results and formulating the following steps. Third and most essential reason is that Kappa index endeavor to compute the observed accuracy with respect to a gauge of exactness anticipated that due would randomness, which itself is discovered to be uninteresting, immaterial and misdirecting standard.

With a specific end goal to do accuracy assessment while safeguarding the soft classified data, a changed error matrix for fuzzy outputs i.e. FERM (Fuzzy Error Matrix) has been proposed via scientists (Binaghi *et al*., 1999; Silvan-Cardenas and Wang, 2008). The FERM is utilized the same route as the conventional error matrix however the main contrast is that the components of the matrix are ascertained taking into account the fuzzy set theory (Zadeh, 1965). The overlap between classes of the fuzzy / soft reference and classified data is figured out based on operators like MIN, LEAST, PROD, etc. (Silvan-Cardenas and Wang, 2008). The conduct of these operators in image to image accuracy assessment method was assessed by G. Misra, 2012.

The correctness of classified outputs can likewise be assessed by measuring the vulnerability in the outcomes. Uncertainty in the information is presented from the starting stride of data acquisition and engenders with every progression of preparing, transmission and classification. The information of the classification in the outcomes can help in passing judgment on its accuracy and the reliability. Entropy which is based on the information theory (Foddy, 1996; Shannon 1948) can be used to estimate the uncertainty in the classification. It communicates the circulation and degree of uncertainty in a solitary number in information theory. Entropy of an irregular variable is identified with the minimum attainable error probability (Feder et al., 1994). Dissimilar to the membership vector, this measure has the capacity to summarize the classification in a solitary number for every pixel, per class or per image (Goodchild, 1995). It demonstrates the quality of class membership relegated to specific class in the classification output. A low level of entropy means membership related totally with one class and the other way around. The entropy is computed by formula proposed by Dehghan and Ghassemian, 2006. 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 utilization of entropy based accuracy assessment however gave an outright uncertainty indication in the classified outcomes. The utilization of entropy measure alongside the customary general accuracy and kappa coefficient results enhanced the information retrieved from the accuracy assessment study.

Goncalves, 2012 connected both the uncertainty measure and the conventional accuracy lists acquired from the error matrix to assess the performance of supervised Bayes classifier and supervised fuzzy classifier. It was watched that in the event of both the uncertainty measure and accuracy indices, the characterization exactness was almost the same. Further, keeping in mind the end goal to enhance the characterization accuracy, they have reclassified the training sample of non-vegetated class for fuzzy based classifier. It was seen from the study, that redefinition of training specimen has enhanced the general exactness by 8% for fuzzy based classifier.

3. THEORETICAL FRAMEWORK

The chapter describes phenology of rice and cassava, followed by description of the vegetation indices used. In the subsequent section mathematical description of various classification approaches adoptedviz; Possibilistic *C*- Means (PCM), Possibilistic *C*- Means-Spatial Contextual Information (PCM- MRF), Kernel base Possibilistic *C*- Means (KPCM), and Possibilistic *C*- Means- Spatial Contextual Information (KPCM- MRF) have been described. In the last section of the chapter, explanation of the accuracy assessment technique using entropy has been provided.

3.1 Phenology of the Crops

Remote sensing data plays a key role in monitoring the dynamics of vegetation at local to global scales. The continuous synoptic and repetitive coverage allows studying the phenology of a particular vegetation type. Leith, 1974, defined phenology as a study of the timing of recurring biological events, the causes of their timing with regard to biotic and abiotic forces, and interrelation between phases of the same or different species

Phenological information of every vegetation type is its characteristic signature which helps to discriminate it from other vegetation present on the ground, in the area. It is a daunting task to differentiate a target crop from other crops using single date imagery. To comprehend the temporal satellite imagery for specific crop identification, it is very important to understand the phenological stages of a crop. The subsequent sub- sections explains the phenology of Rice and Cassava.

3.1.1 Growth stages of Rice

Rice is a kharif crop in India, which is primarily grown in rain fed or highly irrigated areas. Information on rice phenology is essential for many applications, such as evaluating crop productivity, deciding time boundary conditions for yield modelling, supporting decisions about water supply, crop classification from flooded rice fields and methane estimation.

The figure 3.1 depicts the growth stages of rice. Basically, a 120- day variety, when planted in tropical environment, spends about 60 days in vegetative phase, 30 days in the reproductive phase and 30 days in the ripening phase. A brief about the three phases has been discussed.

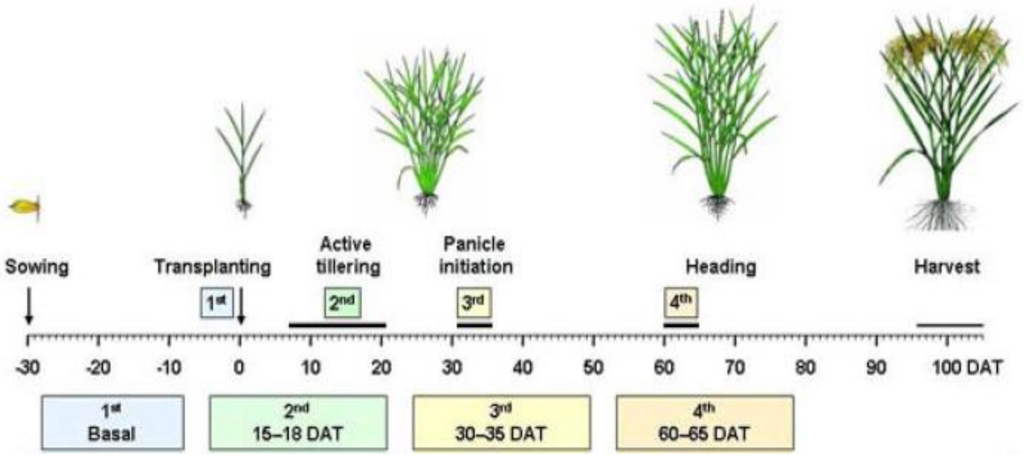


Figure 3-1Growth Stages of Rice
(Source: http://www.fao.org/docrep/t7202e/t7202e07.htm)

**DAT stands for Days After Transplanting*

I. A 120- day variety spends about 60 days in the **vegetative stage.** The early vegetation phase begins as soon as the seed germinates indo a seedling and ends at the tillering. Germination, early seed growth and tillering happen. Rice is sown in nursery and after certain days it is transplanted into paddy fields. The seedling starts just after the first root and shoot emerge, and lasts until just before the first tiller appears. During this stage, seminal roots and upto five leaves appear. The vegetative phase is marked by pause in height growth which occurs roughly after 52 days after sowing..Figure 3.2 depicts the growth of rice in vegetative stage.

Figure 3-2 Growth of rice in Vegetative Stage

II. It is followed by **reproductive stage**. The stage is marked by emergence of last leaf and culm elongation. Also, panicle initiation happens 25 days pre heading and anthesis begins on the same day as heading.

III. Finally, the crop is in final phenological stage called **ripening**. After fertilization the rice appear milky, yellow- ripe and are mature. Length of ripening is dependent upon the variety and varies from 15 to 40 days.

3.1.2 Growth stages of Cassava

Cassava is a perennial shrub of the family Euphorbiaceae, cultivated mainly for its starchy roots. It is the fourth most important source of energy. On a world wise basis it is ranked as the sixth most important source of calories in the human diet. In India, cassava is consumed as a secondary staple along with the main staple, rice, and many rural poor consume it as the staple in different forms of preparations. Although cassava is a perennial crop, the storage roots can be harvested from 6 to 24 months after planting (MAP). There are total five phenological stages of the crop which have been depicted in figure 3.3 and explained subsequently.

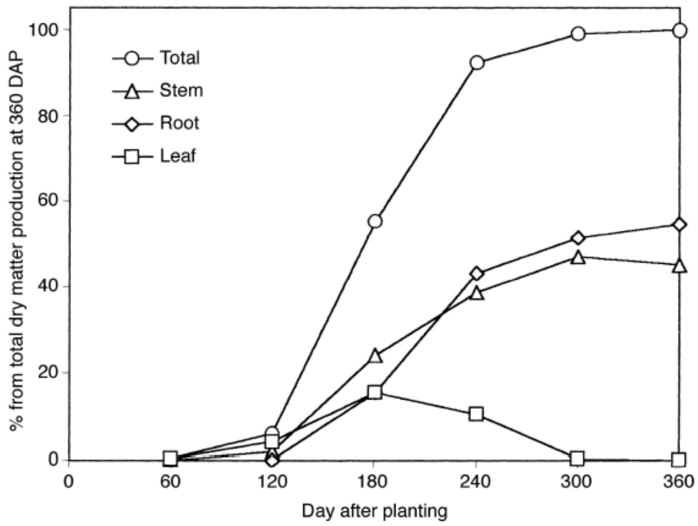


Figure 3-3 Growth of Cassava plant during the first cycle (12 months). Average of two varieties, DAP, Days After Planting.
(Source:Alves, A. A. C. "Cassava botany and physiology." Cassava: biology, production and utilization (2002): 67-89.)

I. Emergence of Sprouting (5-15 DAP): In this stage, first adventitious roots arise from the stake, followed by first sprouting and emergence of small leaves.

II. Beginning of leaf development and formation of root system (15-90 DAP): Till around 30 DAP, the true leaves start to expand and fibrous roots replace first adventitious roots and start to grow and penetrate 40-50 cm deep in soil.

III. Development of stems and leaves (90-180 DAP): The stage marks the maximum growth rate of leaves and stems. The storage root continues to bulk. The most active vegetative growth for cassava occurs in this period.

IV. High carbohydrate translocation to roots (180-300 DAP): Photoassimilate partition from leaves to roots is accelerated, making the bulking of storage roots faster. During this phase stem becomes lignified and leaf senescence increases.

V. Dormancy (300-360 DAP): The plant completes its 12- month cycle, in which rate of leaf production decreases. The growth of shoot vegetative finishes and almost all leaves fall. Only translocation of starch to root is kept and maximum DM partition to the roots is attained.

3.2 Temporal Vegetation Indices

We know that, the classification approach takes only one dimension of data. But, therawtemporal data has two dimensions; spectral and temporal. The solution to the problem is generation of temporal vegetation indiceswhichreducesthe spectral dimensionality of the data. Vegetation indices are dimensionless quantities which are calculated using operations on two (or more) spectral bands. Other advantages of using vegetation indices are, it enhances vegetation signal, while normalizing the sun angle, minimizing solar irradiance, shadow and soil background effect. The temporal vegetation indices help to identify and discriminate target crop from rest of the crops/ vegetation type present on ground.

Modified Normalized Difference Water Index (MNDWI), was proposed by Han-qiu, in 2005 and has been used for paddy rice field identification.The index is capable of highlighting the water information in the study area while suppressing the build- up land information. Unlike, NDWI the index is successful in removing shadow from water information and detect subtle water bodies. The index has a range from -1 to +1. The MNDWI algorithm subtracts Green reflectance values from Short Wave Infra-red and divided by sum of Green reflectance values from Short Wave Infra-Red. The mathematical formula of MNDVI is given by equation 1:

$$MNDWI = \frac{\rho_{Green} - \rho_{SWIR}}{\rho_{Green} + \rho_{SWIR}} \qquad (1)$$

Simple ratio has been used to identify the variety of cassava. Two bands have been ratioed to maximize the difference between the target class from other non- interest classes.

Another vegetation index called Normalized Difference Vegetation Index (NDVI) has been used in the research to identify rice fields in Haridwar. NDVI is a greenness indicator, describing the condition of plants and estimate quantity of biomass. It iscalculated by rationing the difference between near infrared band and red band to the sum of the two bands. Mathematically, it is given as equation 2:

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \qquad (2)$$

The principle behind detection of target crop using NDVI is high absorption of electro-magnetic radiation in red region by chlorophyll pigments and high reflectance in the near infrared region. NDVI ranges from -1 to +1, where higher the value indicates the greenness of vegetation.

The Figure 3.4 shows the nature of healthy, unhealthy vegetation. Healthy vegetation absorbs large portion of the visible light falling on it while reflecting most of the near-infrared light. Whereas, unhealthy or sparse vegetation reflects more visible light and less near- infrared light.

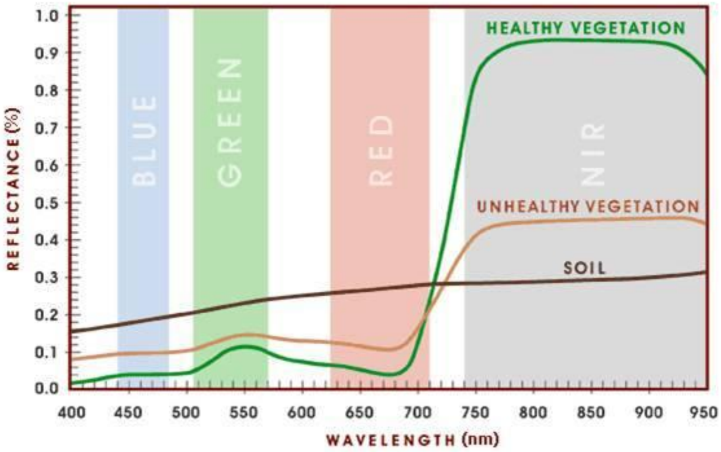


Figure 3-4 Spectral response of Vegetation types and Soil
(Source:http://www.coe.montana.edu/ee/seniordesign/archive/FL10/tethered_balloon/index.html)

Practically, it has been found that extreme negative values and zero represent water and bare soil respectivey. While, typical values for vegetation are from 0.2 to 1, for plants in good condition are above 0.6 (Wang et al., 2004).

3.3 Classification Approach

The traditional hard classification technique of assigning single class per pixel is unrealistic. As they overlook the condition of occurrence of mixed pixels in a remotely sensed image. Spectral mixing takes place either when the size of pixel is larger than the spatial resolution of the sensor or at inter- class boundaries. Assignment of single class to a mixed pixel yields over or underestimated results.

Many classification techniques have been proposed to handle the problem of spectral mixing in satellite imagery. For example; Linear Mixture Models, Fuzzy Classification, Neural Networks and Support vector Machine etc. These techniques are capable enough to estimate precise area estimation of land use land cover classes in from high to coarse resolution remote sensing images (Dadhwal et al., 2002). But there are few limitations with many of these techniques. For instance 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 Possibilistic based 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). Thus, the technique is useful in estimating accurate class area and fulfill 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.

3.3.1 Why PCM over FCM?

The membership value in FCM gives the degree of sharing of pixel in the various clusters in the feature space. While, in PCM membership value can be interpreted as the degree to which a pixel belongs to a class or compatibility. In other words, it means the degree by which pixel is compatible to other pixels in cluster or typicality that helps to differentiate in between highly atypical member of cluster versus moderately atypical member of the cluster. PCM out performs FCM in many conditions. The algorithm is capable enough to accurately classify rare pixels which belong to a class but are at larger distance from the cluster in the feature space as compared to other pixels of the same class; Outliers. Also, estimation of cluster center is not affected by noise present in the data. Another most important feature of PCM is, it out performs FCM in case of untrained classes during supervised classification.

The uniqueness 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 same pixel. The PCM classifier is thus capable of extracting a single class of interest and is appropriate for specific crop identification

3.3.2 Possibilistic c- Means (PCM)

In PCM, the memberships for representative feature points to be as high as possible, while unrepresentative points to have low membership in all clusters. The objective function for PCM was modified by Krishnapuram and Keller (1993), which is as equation 3,

$$J_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{c}(\mu_{ij})^m \| X_i - v_j \|_A^2 + \sum_{j=1}^{c}\eta_j \sum_{i=1}^{N}(1-\mu_{ij})^m \tag{3}$$

Subjected to constraints;

$$\max_j \mu_{ij} > 0 \text{ for all i}$$

$$\sum_{i=1}^{N}\mu_{ij} > 0 \text{ for all j} \tag{4}$$

$$0 \le \mu_{ij} \le 1 \text{ for all i, j}$$

Where, η_j is the suitable positive number, called as bandwidth or scale or resolution parameter and is estimated from the data. It is dependent on the shape and average size of cluster j. The first term demands that the distances from the feature vectors to the prototypes be as low as possible, whereas the second term forces the μ_{ij}tobe as large as possible, thus avoiding the trivial solution. Generally, η_j depends on the shape and average size of the cluster *j* and its value may be computed as given by equation (5);

$$\eta_j = K\frac{\sum_{i=1}^{N}\mu_{ij}^m d_{ij}^2}{\sum_{i=1}^{N}\mu_{ij}^m} \tag{5}$$

where K is a constant and is generally kept as 1. The class memberships, $\mu_{ij}$are obtained from equation (6) as;

$$\mu_{ij} = \frac{1}{1+\left(\frac{d_{ij}^2}{\eta_j}\right)^{1/(m-1)}} \tag{6}$$

3.3.3 PCM- MRF

An important and overlooked aspect in digital image interpretation is contextual information. Contextual information can be retrieved from spectral, temporal or spatial domain. It has been observed that incorporation of context substantially improves the accuracy by recovering missing information and correction of errors. While, considering contextual for digital image interpretation; unlike standard PCM, the pixels are considered to have statistical dependence with its neighbouring pixels.

The two prior energy priors are; Smoothness and Discontinuity Adaptive prior. The smoothness prior over smoothens at discontinuities where the derivative is finite. However Discontinuity Adaptive prior manages and accordingly diminishes the interaction at discontinuity. Chawla, 2010 concluded that the third DA outperforms amongst the four available DA models. On that basis, present research work uses the third DA model the model represented by equation (7) has been used in the thesis.

$$g_{4\Upsilon}(\eta) = \Upsilon|\eta| - \Upsilon^2 ln\left(1 + \frac{|\eta|}{\Upsilon}\right) \quad (7)$$

Thus the modified objective function of PCM with Discontinuity Adaptive Priors is given in the equation (8)

$$U(u_{ij}|d) = \sum_{i=1}^{N}\sum_{j=1}^{c}(\mu_{ij})^m D(X_i, v_j) + \sum_{j=1}^{c}\eta_j \sum_{i=1}^{N}(1-\mu_{ij})^m (1-\lambda) + \lambda\left(\sum_{i=1}^{N}\sum_{j=1}^{c}\sum_{j' \in N_j}\left(\Upsilon|\eta| - \Upsilon 2ln1+|\eta|/\Upsilon \right.\right. \quad (8)$$

3.3.4 Kernel Approach

The information contained in multispectral data allows the characterization, identification, and classification of land covers with improved accuracy and robustness. In the remote sensing literature, many supervised and unsupervised methods have been developed for multispectral image.

There might be condition of nonlinear classification where classes may not be separable by a linear boundary. Kernels can turn a non-linear model into a linear one. By following ways:

- Mapping data to higher dimension where it exhibits linear patterns
- Apply linear model in input space
- Mapping ≡ changing the feature space.

For example: Consider a binary classification problem as shown in the figure 3.5, where no linear separator exists for this data.

Figure 3-5 Binary Classification Problem

Now let each example be mapped as x → {x, x^2}.and thus, each example now has two features. As it can be seen clearly from the figure 3.6. Data now becomes linearly separable in the new representation. Another figure 3.7, gives diagrammatic explanation of impact of kernels.

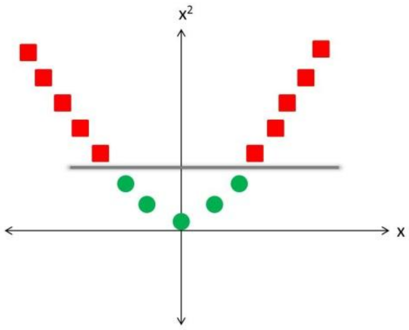


Figure 3-6 Linearly Separable Classes

Chang and Lin, 2001 used kernel methods such as support vector machines (SVMs) or kernel Fisher discriminate analysis and demonstrated excellent performance in multispectral data classification in terms of accuracy and robustness. The properties of kernel methods make them well-suited to tackle the problem of multispectral image classification since they can handle large input spaces efficiently, work with a relatively low number of labeled training samples, and deal with noisy samples in a robust way.

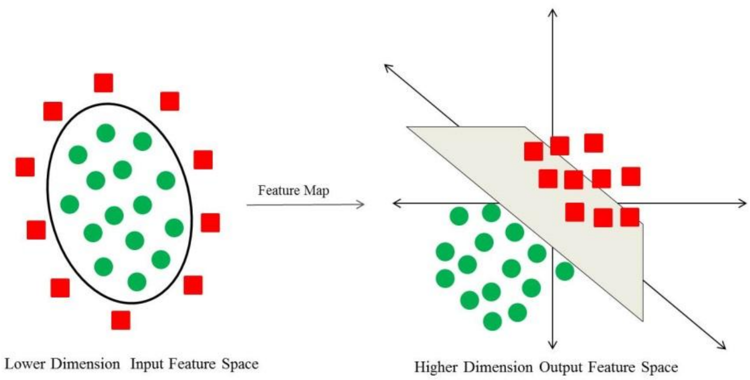


Figure 3-7 Class separation in Higher Dimension using Kernel Approach

For nonlinear decision surfaces, a feature vector is mapped into a higher dimensional Euclidean Space, via a nonlinear vector function, but it is quite expensive, to cope with this problem, the concept of kernel function is being introduced.

Every function $K(x_i, v_j)$ which satisfies Mercer's condition that is, $K(x_i, v_j) \geq 0$ is called an eligible kernel (Kumar, 2007). The research work explores the effect of local and global kernels on the specific crop identification. A brief about the two general categories of kernel is as follows:

I. **Local Kernels:** Only the data that are close in the proximity of each others have an influence on the kernel values (Kumar, 2007). All local kernels are based on a distance function. The different local kernels that have been considered in the research work are listed from equation 9 to 12

- **Gaussian Kernel:**
  $K(x_i, v_j) = exp(-0.5(x_i - V_j)A^{-1}(x_i - V_j)^T$(Mohamed & Farag, 2004) (9)

  Where, A is a weight matrix known as norm. It can take three different norms

Euclidean Norm,	A=I
Diagonal Norm ,	$A=D^{-1}{}_j$
Mahalonobis Norm,	$A= C^{-1}$

- **KMOD Kernel:** $K(x_i, v_j) = exp\left(\frac{1}{1+\|x_i-v_j\|^2}\right) - 1$ (10)
- **Inverse Multiquadratic Kernel:** $K(x_i, v_j) = exp\left(\frac{1}{\|x_i-v_j\|^2+1}\right)$ (11)
- **Radial Bases Kernel:** $K(x_i, v_j) = exp(-\| x_i - v_j \|^2)$ (12)

II. **Global Kernels:** When sample are far away from each other, yet have an influence on the kernel value then all the kernels based on the dot product are known as global kernels (Kumar, 2007). The various Global kernels used in the present study are given from equation 13 to 15:

- **Linear Kernel:** $K(x_i, v_j) = x_i . v_j$ (13)
- **Polynomial Kernel:** $K(x_i, v_j) = x_i . v_j + 1$ (14)
- **Sigmoid Kernel:** $K(x_i, v_j) = tanh(x_i . v_j + 1)$ (15)

3.3.5 Kernel Based Fuzzy Classifier

Consider a nonlinear feature space as $\Phi: x \to \phi(x) \in F, where x \in X$. X denotes the data space and F the transformed feature space with higher dimension. KPCM minimizes the following objective function given in equation (16);

$$J_{mKPCM}(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{c} \mu_{ij}^m \| \phi(x_i) - \Phi(V_j) \|^2 + \sum_{i=1}^{N} \eta_i \sum_{j=1}^{n} (1 - \mu_{ij})^m \quad (16)$$

The membership value from KPCM objective function can be computed as given by equation (17);

$$\mu_{ij} = \frac{1}{(1+(2(1-K(x_i,V_j)))/\eta_i)^{1/(m-1)}} \quad (17)$$

While, the modified objective function of KPCM- MRF is given by equation (18) as:

$$U(u_{ij}|d) = \sum_{i=1}^{N}\sum_{j=1}^{c}\left(\mu_{ij}\right)^{m} \parallel \phi(x_i) - \Phi(V_j) \parallel^2 + \sum_{j=1}^{c}\eta_j \sum_{i=1}^{N}\left(1-\mu_{ij}\right)^{m}(1-\lambda) +$$
$$\lambda i{=}1Nj{=}1cj'{\in}Nj\Upsilon\eta{-}\Upsilon 2ln1{+}|\eta|\Upsilon \quad (18)$$

3.4 Accuracy Assessment

The unavailability of higher resolution temporal data constrained to evaluate accuracy using error matrix; which is a general method for assessment. Also, the agricultural fields are dynamic in nature; hence the previous year satellite imagery cannot be used as reference data. Thus, it is not possible to generate reference data, which is essential for error matrix evaluation.

In such a case, entropy is used to conduct accuracy assessment. Entropy is an indirect absolute classification accuracy indicator based on information theory (Foody 1996; Shannon 1948). The unbiased belonging sites in the classified outputs are expected to have lower entropy than non- belonging sites.

In order to assess the uncertainty in the process of data analysis, Deghan and Ghassemian (2006), proposed an entropy measurement technique. The criterion can summarize the uncertainty as a single number per pixel of all the classes from output fraction images. The entropy of the classified outputs is calculated as given in equation (19)

$$\text{Entropy}\ (x) = \sum_{j=1}^{c} -\mu\left({}^{w_j}/_{x}\right)\log_2\left(\mu\left({}^{w_j}/_{x}\right)\right) \quad (19)$$

Where,

c= the total number of classes i.e. 1 for this study

$\mu\left({}^{w_j}/_{x}\right)$= the membership of pixel x in class w.

The lowest entropy value is 0.0, which represents to low uncertainty. A classified output with lower entropy measure at unbiased belonging sites will have higher classification accuracy with lower uncertainty.

4. STUDY AREA AND MATERIALS USED

The chapter gives a detailed description of the and materials which have been chosen to achieve the research objectives.

4.1 Study Area

4.1.1 Study Area I- Radaur City (mapping paddy rice fields)

The study area selected for paddy rice identification is Raduar city, a part of Haryana state.Radaur is a tehsil which lies in Yamunanagar district. The city is located on the Yamuna Nagar to Karnal road, and is also close to the towns of kurukshetra, Shahbad and Ladwa. The central latitude and longitude of the study are 30.03˚ N and 77.15˚ E respectively, and average elevation of 260 m above sea level. Western Yamuna canal of the river Yamuna flows on one side of the city. The canal servers the irrigation needs of the farmers. Due to the presence of plenty of water and good fertile soil, main crops grown in the area are sugarcane, rice, wheat and garlic, etc. One of the main sources of the income of farmers of Yamuna Nagar is agri-forestry, in which farmers grow poplar and eucalyptus besides conventional farming. The figure 4.1 depicts one of the study area.

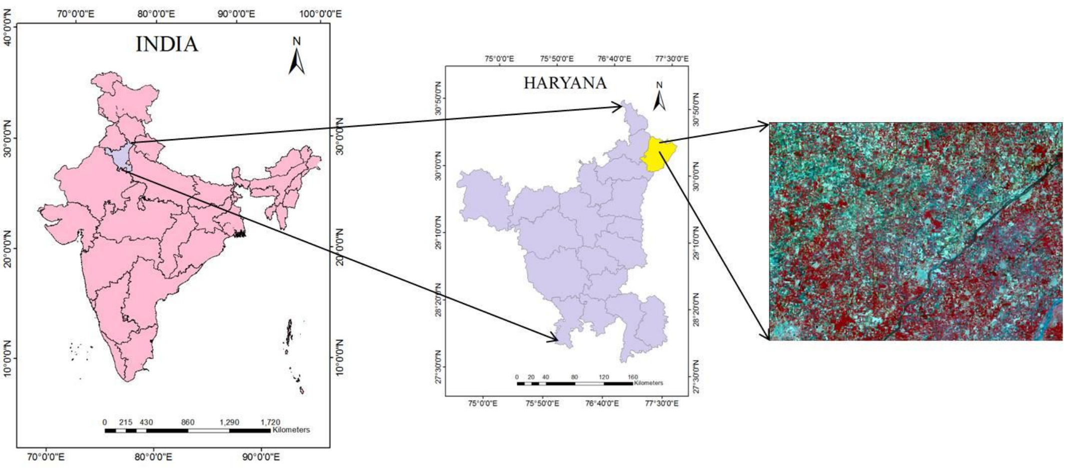


Figure 4-1 Study Area I- Radaur City, Haryana

4.1.2 Study Area II- Salem District

The area chosen for identification of Cassava is Salem district, Tamil Nadu. Salem District is a district of Tamil Nadu state in southern India. It extends from latitude 11°14' to 2°53' North and longitudes 77°44' to 78°50' East. It covers the geographical area of 5205 Sq. km and has 12 talukas. Salem district is ringed by district Dharmapuriin North, Erode District in the east, Viluppuram District in the west and on the south by Namakkalditrict and Tiruchirappalli District, Tamil Nadu.

The district forms part of the upland plateau region of Tamil Nadu with many hill ranges, hillocks and undulating terrain with a gentle slope towards east. The prominent geomorphic units identified in the district are plateau, structural hills, bazada zone, valley fill, pediments, shallow pediments and buried pediments. The district receives the rain under the influence of both southwest and northeast monsoons. The northeast monsoon chiefly contributes to the rainfall in the district. The average rainfall received by the district is 842.34 mm. The district enjoys a tropical climate.

Agriculture is the main stay of Salem district as about 70 % of the population is engaged in Agriculture. The district is well known for cassava and mango cultivation, sago industries and steel production. The other crops grown in the region are banana, okra, coconut and many more. The figure 4.2 depicts one of the study area**.**

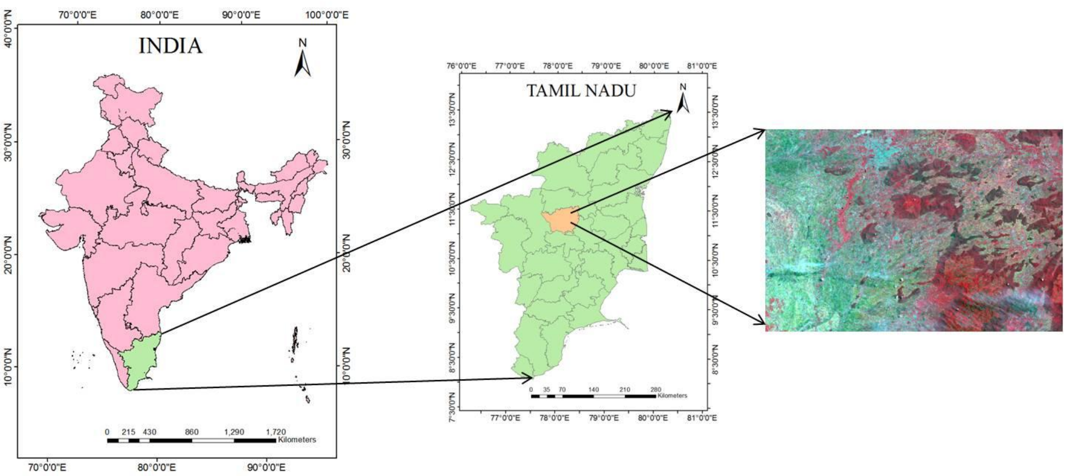


Figure 4-2 Study Area II- Salem District, Tamil Nadu

4.1.3 Study Area III- Haridwar

The study area selected for rice field identification using FORMOSAT-2 data is Haridwar, Uttarakhand and is shown in Figure 4-3. The district shares its boundaries by Dehradun in the north, PauriGarhwal in the east while, west and south are bounded by districts of Uttar Pradesh. The central latitude and longitude of the district are 29.956˚ N and 78.170˚ E respectively. The land is fertile with river Ganga flowing through the district, Agriculture remains the mainstay of the district. River Ganga flows in the district and the agriculture is the mainstay of this well irrigated district.

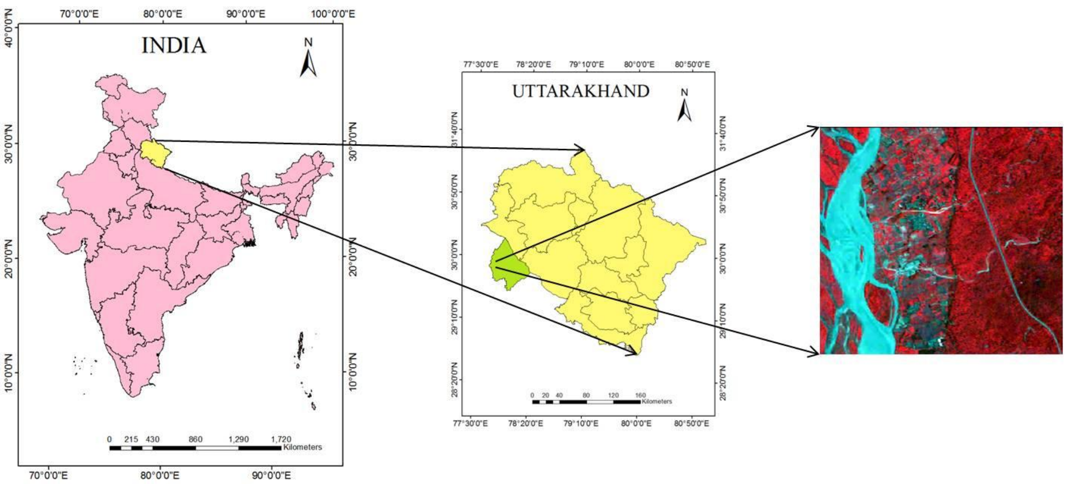


Figure 4-3 Study Area III- Haridwar, Uttarakhand

4.2 Materials Used

4.2.1 Salient Features of the Satellite Image Used

Satellite imagery acquired by Landsat- 8 and FORMOST- 2 have been used to test the kernel based fuzzy classification approach. The salient features of these satellite images have been given in the following sections

4.2.1.1 Specifications of Landsat- 8 (OLI)

Optical imagery acquired by Operational Land Imager (OLI) on- board Landsat 8 was used for the research. Landsat 8 was launched on February 11, 2013, developed as collaboration between NASA and the U.S. Geological Survey (USGS). The Landsat 8 satellite payload consists of two science instruments—the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). These two sensors provide seasonal coverage of the global landmass at a spatial resolution of 30 meters (Visible, NIR, SWIR); 100 meters (thermal);

and 15 meters (panchromatic). The OLI is a push-broom sensor with 12-bit quantization. Size of a scene is 185-km-cross-track-by-180-km-along-track. It collects data for visible, near infrared, and short wave infrared spectral bands as well as a panchromatic band. The sensor details are mentioned in Table 4.1, highlighting the wavelength and spatial resolution of various bands.

Table 4-1 Landsat- 8 OLI Specifications
(Source: http://landsat.usgs.gov/band_designations_landsat_satellites.php)

Band	**Wavelength (micrometers)**	**Spatial Resolution (meters)**
Band 1 - Coastal aerosol	0.43 - 0.45	30
Band 2 – Blue	0.45 - 0.51	30
Band 3 – Green	0.53 - 0.59	30
Band 4 – Red	0.64 - 0.67	30
Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
Band 6 - SWIR 1	1.57 - 1.65	30
Band 7 - SWIR 2	2.11 - 2.29	30
Band 8 – Panchromatic	0.50 - 0.68	15
Band 9 – Cirrus	1.36 - 1.38	30

4.2.1.2 Specifications of FORMOSAT-2

FORMOSAT – 2 is the first remote sensing satellite developed by National Space Organization (NSPO), which was successfully launched on May 21, 2004 onto the Sun-synchronous orbit located at 891 kilometers above ground. The satellite has been designed to carry out “remote sensing” and “scientific observation” over terrestrial and oceanic regions of the entire Earth.

The satellite captures panchromatic and multispectral data simultaneously with 2m and 8m spatial resolution respectively.The sensor footprint is 24*24 km and is designed in such a way to **re**visit the same point on the globe every day in the same viewing conditions.

The sensor spectral bands specifications have been enlisted in Table 4.2.

Table 4-2 FORMOSAT- 2 Sensor Specifications
(Source :http://www.satimagingcorp.com/satellite-sensors/other-satellite-sensors/formosat-2/)

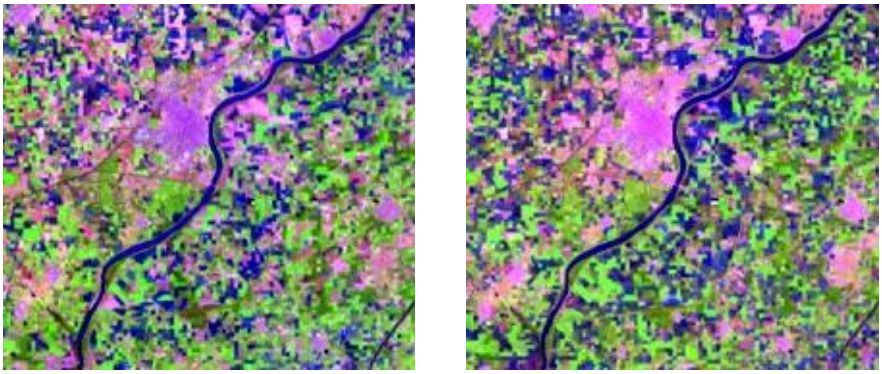
Band	**Wavelength (micrometers)**	**Spatial Resolution (meters)**
Band 1 –Blue	0.43 - 0.52	8
Band 2 –Green	0.52 - 0.60	8
Band 3 –Red	0.63 - 0.69	8
Band 4 - Near Infrared (NIR)	0.76 - 0.90	8
P - Panchromatic	0.45 – 0.90	2

4.2.2 Data for Study Area I (Radaur City)

The subsequent section describes the satellite images and field data used to distinguishpaddy rice fields based on the date of transplantation and from water body present in the study area; Raduar City, Haryana.

4.2.2.1 Temporal Data Availability

Temporal data (path:147, row 39) of June 8, June 24 and July 10, 2014 acquired by Landsat 8 were used for Figure 4.4a and 4.4b represents the multi- temporal dataset in False Color Composition (FCC), generated from Landsat 8 spectral bands B6 (R), B4 (G) and B3 (B).



June 24, 2014 **(a)** **July 10, 2014** **(b)**

Figure 4-4 FCC of Temporal L8- OLI Data for Radaur City, Haryana

4.2.2.2 Field Data

The supervised classification approach was adopted for this research. The essential requirement for implementation of the technique is availability of training and testing sites (Congalton, 1991; Foddy, 2002; Congalton and Green, 2009). Thus, for both the study area field work was conducted in the growing season of the crop. Field visit was carried on June 16, 2014 and August 28, 2014 to identify sites of homogenous paddy rice fields. In all 75 rice sites, such that the size is greater than 100m × 100m were identified using hand held GPS; Timber Juno.Locations of eight sites were noted, out of which four have been used for training the data and the rest were used for testing the classified results. Photographs of some of the visited wheat fields during the field visit are shown in figure 4.5

Field Photographs – June 16, 2014

Field Photographs – August 28, 2014

Figure 4-5 Field Photographs of Raduar City, Haryana

4.2.3 Data for Study Area II (Salem, Tamil Nadu)

The subsequent section describes the satellite images and field data used to identify varieties of cassava and optimize the temporal images required for its identification in Salem district, Tamil Nadu.

4.2.3.1 Temporal Data Availability

Cloud free temporal data of path 143 and row 52 from December, 2013 to January 2015, acquired by Landsat- 8 were used to discriminate the varieties of cassava with other crops of in the Salem District, part of Tamil Nadu state of India. The temporal data used has been enlisted in the table 4.3

Table 4-3 Temporal L-8 OLI Data for Salem, Tamil Nadu

February 4, 2014	August 15, 2014
March 8, 2014	December 5, 2014
March 24, 2014	January 22. 2015
May 27, 2014	

4.2.3.2 Field Data

A field visit to Salem District, Tamil Nadu was conducted by Dr. G. Byju and his team from CTCRI on August 14, 2014 to collect the information regarding the major crops existing in the area. The major crop grown in the study area is Cassava. In Salem district majorly five varieties of cassava are harvested viz.; Variety M833, Kumkum Rose, Rasi Seeds, Mulluvadi and Thailand variety. While, the other crops grown in the area are fodder, sorghum, turmeric, okra, onion, banana, sugarcane, cotton, soybean and maize. Snapshots of some of the visited fields during the field visit are shown in figure 4.6.

Cassava Variety M833

Fodder Sorghum

Turmeric

Okra (Lady Finger)

Cassava

Cassava, Variety Mulluvadi

Field Photographs – August 14, 2014

Figure 4-6 Field Photographs of SalemeDistrci, Tamil Nadu

4.2.4 Data for Study Area III (Haridwar, Uttarakhand)

The subsequent section describes the satellite images and field data used to identify rice fields in Haridwar, Uttarakhand using FORMOSAT- 2 temporal data.

4.2.4.1 Temporal Data Availability

Temporal data acquired by FORMOSAT-2 during the growing season of rice was obtained for its identification using kernel based fuzzy approach. Three temporal dates viz.; 10 August, 25 September and 13 October 2014 have been used in the research.

4.2.4.2 Field Visit

A field visit to Haridwar, Uttarakhand was conducted on October 21, 2014 to collect the GPS location of the rice fields and other important major crops and land use land cover present in the study area. It was observed that many of the rice fields were harvested by then. The other classes observed were sugarcane, mango orchard, popolar, eucalyptus, forest, scrub and shrub land, settlements. Some of the photographs taken during the field have been shown in figure 4-7.

Figure 4-7 Field Photographs of Haridwar, Uttarakhnad

5. Methodology Adopted

The chapter describes the materials and methodology adopted to achieve the objectives of the research. Since the research has three study regions and slightly different approach has been adopted for the two regions, the materials and methodology for a particular study area has been explained in parts.

5.1 Study of Fuzzy Based Classifier for mapping paddy rice fields and rice fields

The section gives a detail explanation of the methodology adopted for implementation of kernel based soft classification approach for identification of paddy rice fields depending upon the transplanting stage and discriminate rice from water bodies using temporal Landsat- 8 OLI data in the study area is shown in Figure 5.1.

The study deals with usage of cloud free temporal dataset of Landsat 8 from June to July 2014. Therefore, to normalize the atmospheric conditions and enhance the class of interest, MNDVI images from the raw temporal Landsat 8 images were generated using the Spatial Modeller option in ERDAS Imagine software. The generated MNDVI outputs of the temporal dates were stacked in chronological order of their dates. Training data for three classes viz.; paddy rice fields prepared for transplanting/ transplanted on June 24, 2014 and July 10, 2014 and water bodies were created from the field data carried on June 16, 2014 and August 28, 2014 and Google Earth. Temporal crop growth profile of the three classes were generated for by averaging the MNDWI values from the training sites.

Various supervised fuzzy classification were carried out on the stacked temporal indices database. The different classification approaches used were Possibilistic *c*- Means (PCM), Kernel based PCM (KPCM), Contextual information with PCM and KPCM. Classification of the data was carried out using SMIC (Sub- Pixel Mapping Image Classifier), a JAVA based image processing package. The averaged MNDVI values at the training sites were used to train the classifer. All the pixels in the MNDWI image were assigned membership value for all the specified classes in the output fractional image. The membership value was calculated using equation (19), explained in the chapter 3. The basis of assignment was the difference in averaged MNDWI value from value at a pixel. In order to match the fuzziness on the ground with that on the satellite imagery, the weighted component 'm' was constantly varied to optimise the parameter.

Remaining unbiased sites were used for accuracy assessment of the classified output images. The accuracy assessment of the fractional classified outputs was carried out using entropy criterion. The mean of the membership values at the unbiased testing sites were calculated using the equation (19), given in chapter 3. Higher classification accuracy is represented by lower entropy value.

The same methodology has been adopted for Haridwar study area, with the only difference in vegetation index used. For the temporal FORMOSAT-2 data Normalized Difference Vegetation Index was used, and there after various kernel based fuzzy classification approaches were tested

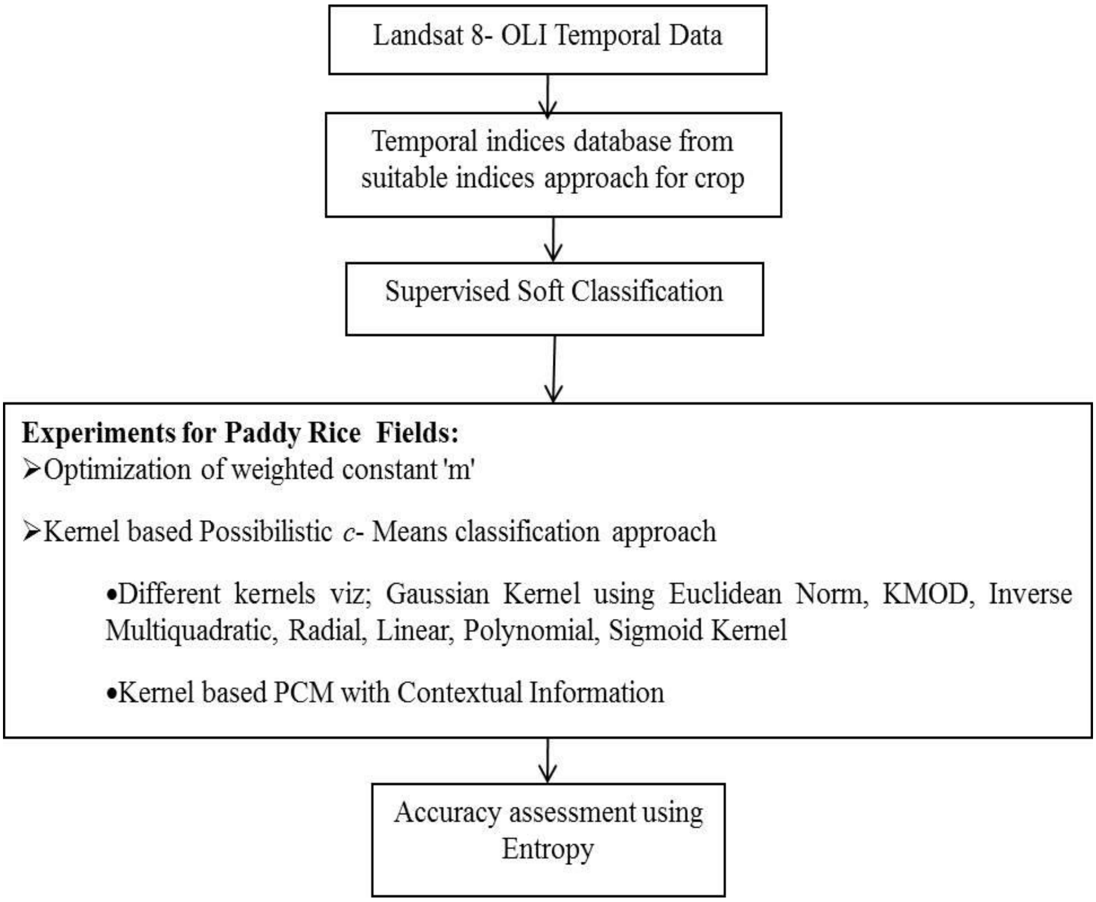


Figure 5-1 Methodology Adopted for rice identification

5.2 Study of Fuzzy Based Classifier for identification of cassava

A detailed explanation of the methodology adopted for implementation of kernel based fuzzy classification approach for identification of cassava (*Manihotesculenta*Crantz) in Salem District, Tamil using temporal Landsat- 8 OLI data has been shown in Figure 5.2.

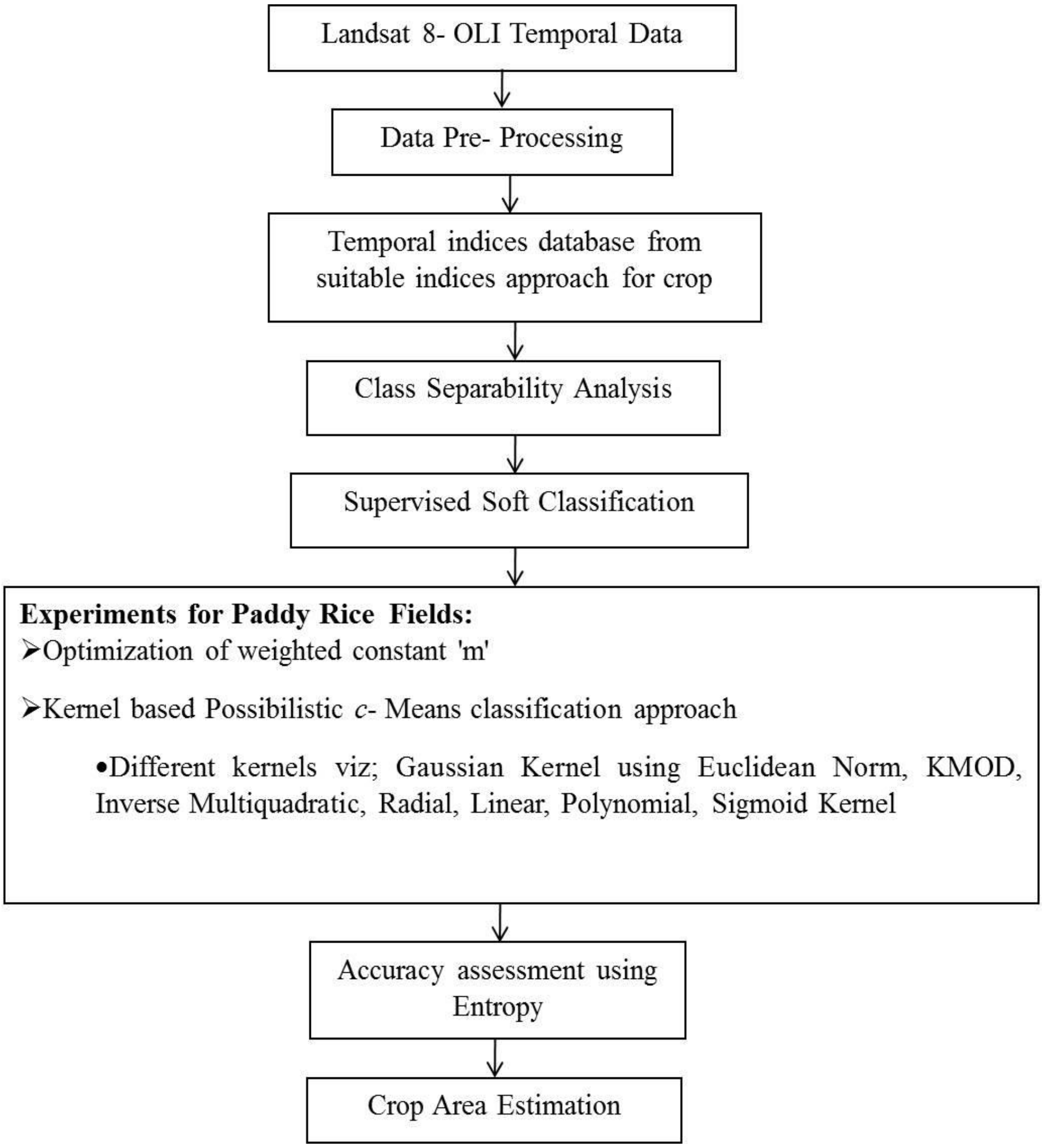


Figure 5-2 Methodology Adopted for cassava identification

5.2.1 Pre- Processing Approach

Since temporal data covering the complete phenological cycle of the crop has been used to identify the target crop, it was essential to normalize the effects of the changes in the atmospheric conditions in the temporal images. The atmospheric conditionseg. Haze, aerosol etc. changes over the time. Hence, the temporal dataset from January 2014 to January 2015 was atmospherically corrected using ATCOR- 2 module of Erdas Imagine.

5.2.1.1 NDVI and Temporal Crop Growth Profile

The data has temporal and spectral dimensions. Thus to carry out classification on the data, it was necessary to reduce it's dimensionality. It was accomplished byratioing two spectral bands to generate image highlighting the class of interest while supressing the other classes. The images generated were subsequently stacked in chronological order of their acquisition dates.

Temporal changes in the average ratioing values at training sites was graphically visualized at training sites to understand and depict the phenological cycle of the crops . These unbiased sited were chosen from the field data and were used to train the classifier and generate fractional output images.

5.2.1.2 Separability Analysis

In this study Euclidean distance measure was used for spectral separability analysis. It uses the mean of the SR values at the training sites and helps to selectthe best temporal 1, 2, 3… dates combination. The best date combination for discriminating cassava was found by maximising the minimum Euclidean distance between target crop and other crops. The non-Interest class that had minimum Euclidean distance separation from cassava on any particular dates combination is expected to be more confused with cassava.

5.2.1.3 Classification

The step mentioned in section 5.2.1.2 could succesfuly select the best date's combination. But as observed, that the minimum spectral seprability kept on increasing from 2 date combination. The spectral separability analysis could not give qualitative or quantitve result for classification accuracy. Thus, fuzzy based supervised classification was carried out on the selected date combinations to find the overall best dates combination.

The unbiased sites used for generating crop growth profile of different crops were taken to train the classifier. Three classification algorithms viz., Possibilistic *c*- Means (PCM), Kernel based PCM (KPCM), Contextual information with PCM and KPCM were implemented on the temporal SR stack. In KPCM, seven different kernels were tested. In order to optimize the weighted constant ‘m’, its value was varied from 1.1 to 2.4. The classification was carried out using using a JAVA based image processing package; SMIC (Sub- Pixel Mapping Image Classifier). Classification of the temporal data generates fractional images, in which each pixel has a memebership value assigned with it. The membership value is a function of difference in the mean cluster value from the pixel value. It represents the degree of belongingness. The mathematics of the classifier has been discussed in chapter 3 (Indices and Classification Approach)

5.2.1.4 Accuracy Assessment

Absence of high resolution temporal images lead to usage of Entropy measurement for accuracy assessment of the classified outputs. Entropy at other unbiased sites (testing sites) was calculated using the equation (19), given in chapter 3. Entropy at unibiased site should have low value. Lower entropy value indicates higher certainity of presence of that particular class at the unbiased site. The dates combination corresponding to lowest entropy was considered to be the best for crop identifation.

6. RESULTS & DISCUSSIONS

This chapter discusses the results obtained upon adopting the methodology for specific crop identification. The chapter begins with section 6.1 which deals with implementation of kernel based fuzzy approach for identification of paddy rice fields which are flooded or transplanted at different time and discriminating them from water bodies. The next segment 6.2 outlines the results obtained upon classifying the Landsat 8 data for identification of varieties of cassava. Finally, section 6.3 describes the results retrieved from processing the temporal FORMOSAT-2data to answer the sixth research question.

6.1 Robust Kernel Based Fuzzy Classification Approach for Rice Field Mapping

The subsequent sections in detail explain the output of every step carried out with reference to the proposed methodology.

6.1.1 Spectral Profile

Phenology of every crop is nearly distinct and the temporal remote sensing data is an effective tool to discriminate the specific crop/ vegetation type. MNDWI was calculated from the three temporal L8- OLI data, and subsequently mean MNDWI values from the 5 training sites have been plotted against the temporal date, which has been shown in figure 6.1.

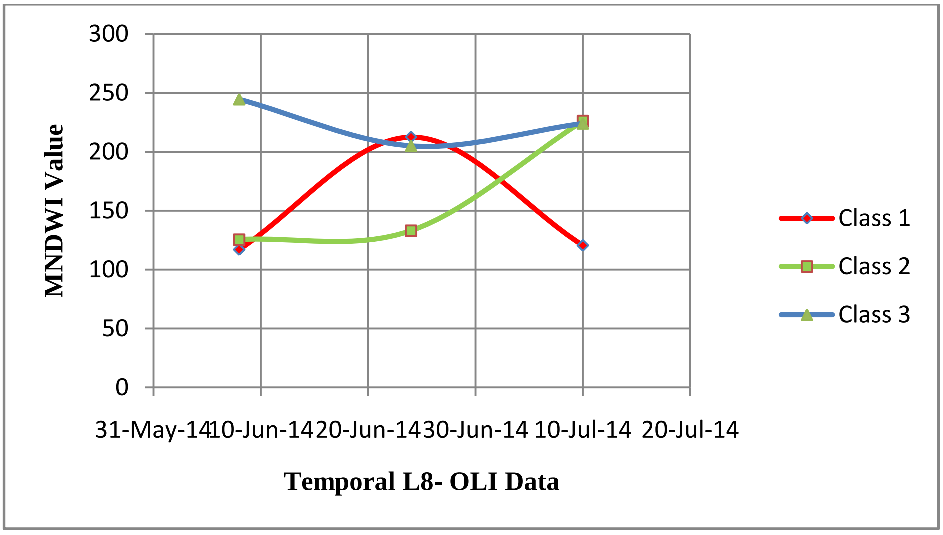


Figure 6-1 Spectral Growth Profile of the target classes

(Class 1: Rice Plant transplanted on and around 24 June 2014, Rice plant transplanted on and around 10 July, Water body)

6.1.2 Classification Results

Various soft classification algorithms were tested to understand the behavior of the kernels of the identification of the classes of interest. The three classes of interest were rice plant transplanted on and around 24 June 2014, rice plant transplanted on and around 10 July 2014 and water body.

The proposed algorithm has been tested for seven kernels in all, out of which four falls under local kernel while the three under global kernel category. The algorithm has a varying factor called the weighted constant ‘m’, which has to be optimized in order to assure the finest of classification results. The factor was varied from 2.0 to minimum of 1.001; in case of inverse- multiquadratic kernel. Following to it, at the best kernel for the optimized weighted constant contextual information was also added he optimized value of m for each kernel has been summarized in the table 6-1.

Table 6-1Membership value at unbiased sites in respective fractional images at optimized ‘m’ values

Kernel		**Optimized ‘m’**	**Membership Value (at unbiased sites) on 8 bit scale**		
			Class 1	Class 2	Class 3
Local Kernel	Gaussian	1.300	249	254	254
	Radial	1.350	245	253	254
	KMOD	1.350	245	253	254
	IM	1.002	254	254	255
Global Kernel	Linear	1.005	254	255	254
	Polynomial	1.01	254	254	254
	Sigmoid	1.01	254	254	255

Class 1 corresponds to paddy rice fields transplanted in and around June 24, 2014, while class 2 represents the paddy rice plant transplanted in and around July 10, 2014 and class 3 refers to the water bodies. The membership value at unbiased sites for three classes were observed. While, a higher value; 245 and above were observed at the test site in the respective fractional images, while they were as close as to zero when the membership values were checked at the other class location in the target class fractional image.

The fractional images at optimized m value for each of the seven kernels has been shown below in figurefrom 6-2 to figure 6.8. While, figure 6.9 corresponds to MRF based IM - PCM.Pixels in white correspond represents the class of interest, while the darker pixels represent other classes. A visual interpretation of the outputs using local kernels suggests that all the three target classes could be well identified, while there is prominent misclassification of class 3; water bodies in the results obtained upon implementation of global kernel based PCM.

Paddy rice plant transplanted on and around June 24, 2014 | **Paddy rice plant transplanted on and around July 10, 2014** | **Water**

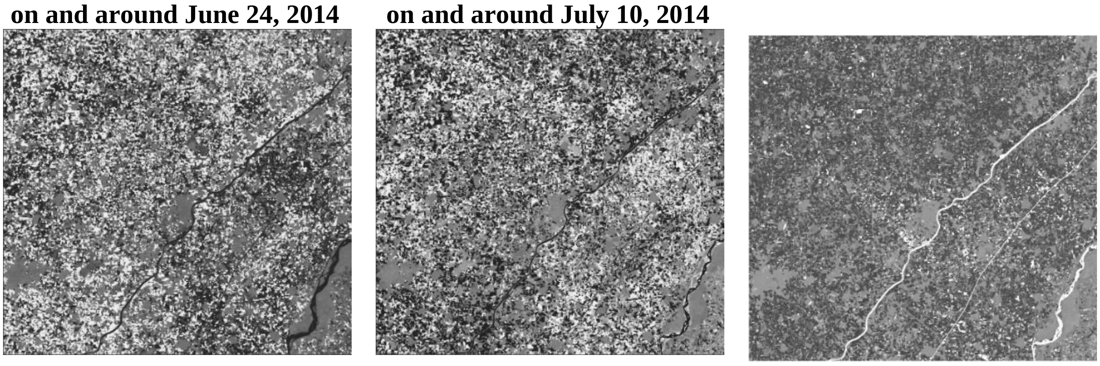


Figure 6-2 Fractional images generated for optimized m values for KPCM classifier for Gaussian Kernel with ED norm

Paddy rice plant transplanted on and around June 24, 2014 | **Paddy rice plant transplanted on and around July 10, 2014** | **Water**

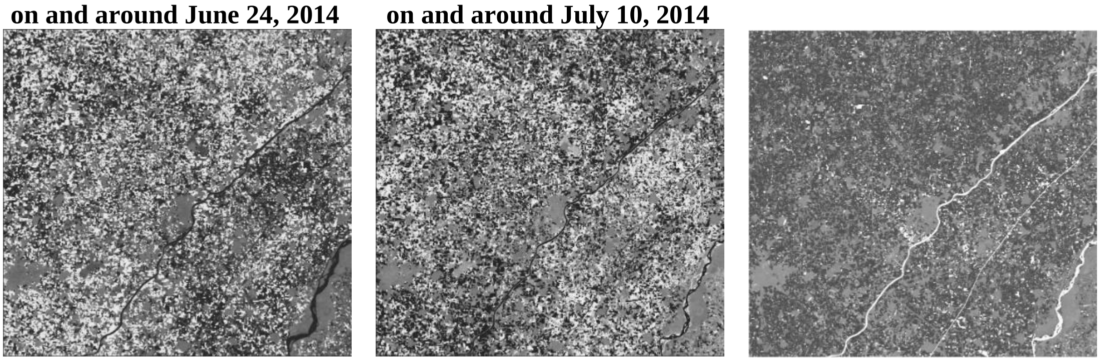


Figure 6-3 Fractional images generated for optimized m for KPCM classifier for Radial Kernel

Paddy rice plant transplanted on and around June 24, 2014 | **Paddy rice plant transplanted on and around July 10, 2014** | **Water**

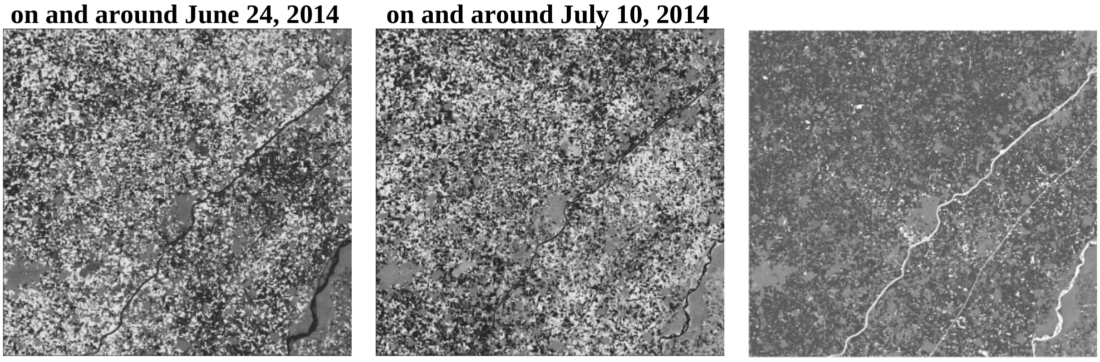


Figure 6-4 Fractional images generated for optimized m for KPCM classifier for KMOD Kernel

Paddy rice plant transplanted on and around June 24, 2014 | **Paddy rice plant transplanted on and around July 10, 2014** | **Water**

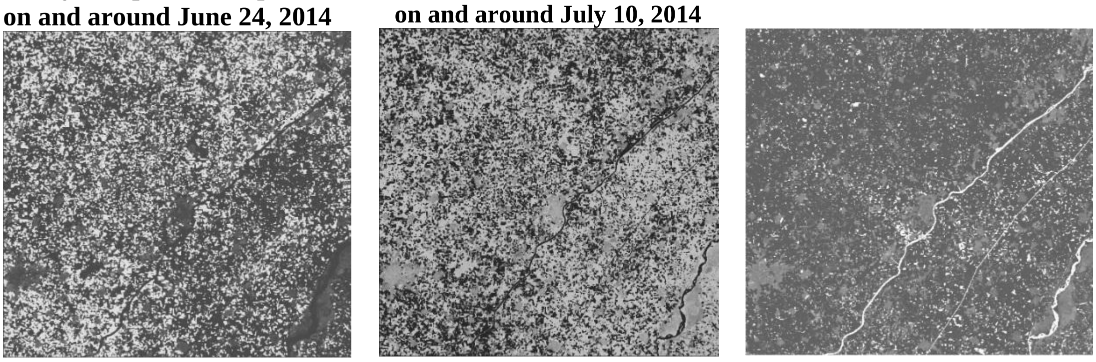


Figure 6-5 Fractional images generated for optimized m values for KPCM classifier for Inverse-Multiquadratic Kernel

Paddy rice plant transplanted on and around June 24, 2014 | **Paddy rice plant transplanted on and around July 10, 2014** | **Water**

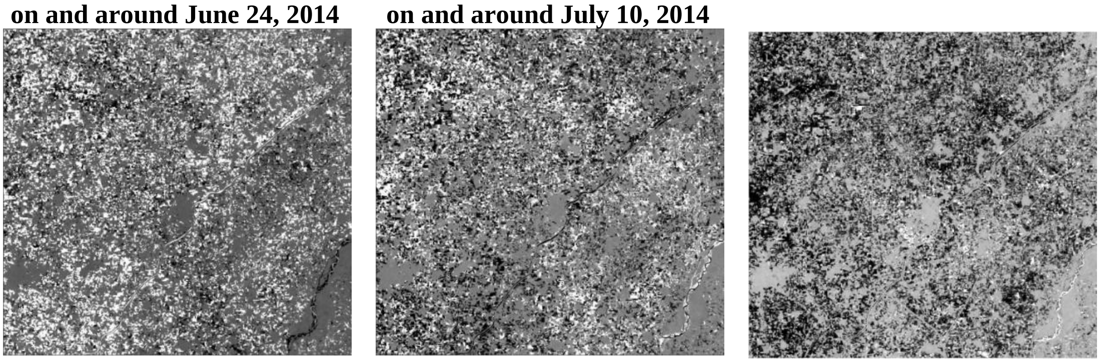


Figure 6-6 Fractional images generated for optimized m values for KPCM classifier for Linear Kernel

Paddy rice plant transplanted on and around June 24, 2014 | **Paddy rice plant transplanted on and around July 10, 2014** | **Water**

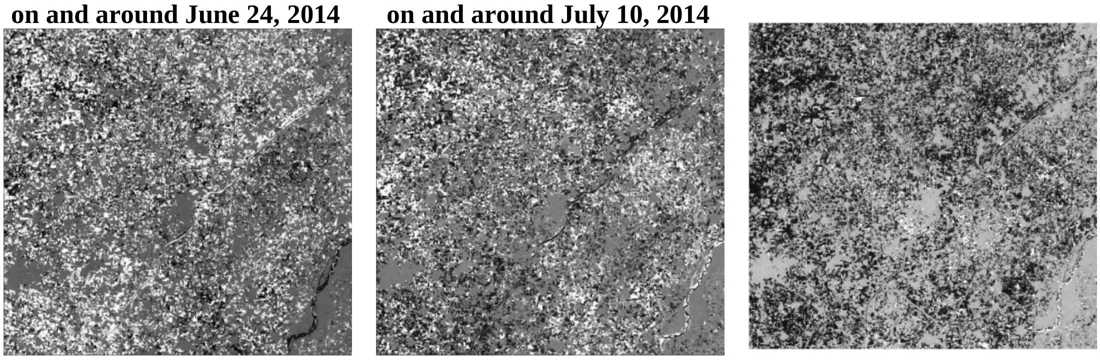


Figure 6-7 Fractional images generated for optimized m values for KPCM classifier for Polynomial Kernel

Paddy rice plant transplanted on and around June 24, 2014 | **Paddy rice plant transplanted on and around July 10, 2014** | **Water**

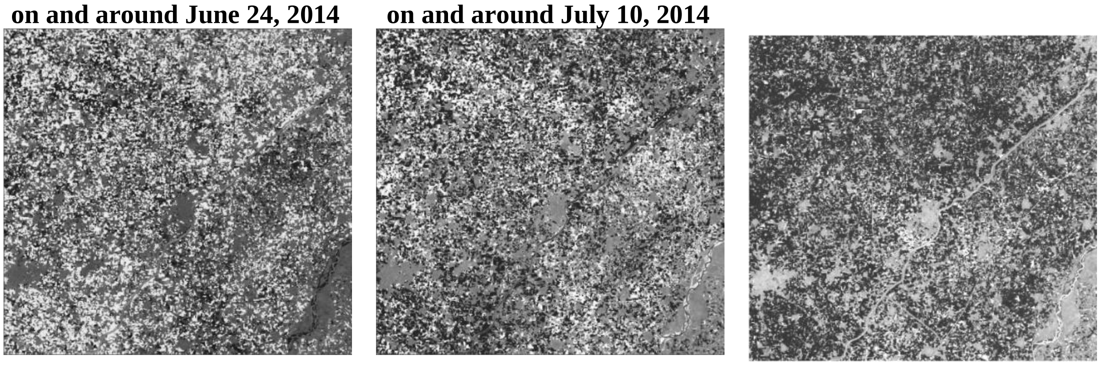


Figure 6-8Fractional images generated for optimized m for KPCM classifier for Sigmoid Kernel

Paddy rice plant transplanted on and around June 24, 2014 | **Paddy rice plant transplanted on and around July 10, 2014** | **Water**

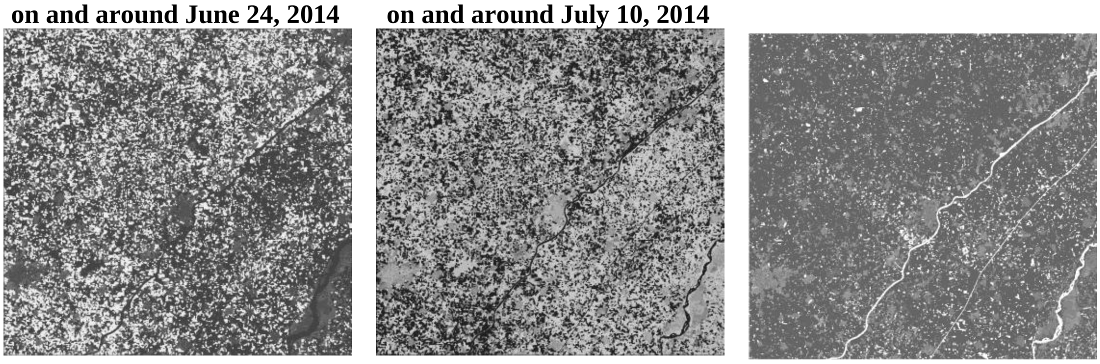
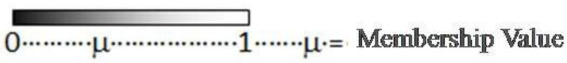


Figure 6-9 Fractional images generated for optimized m for MRF- KPCM for IM kernel



Temporal FORMOSAT- 2 data after atmospheric correction in ATCOR-2, followed by NDVI generation was classified using the same approach.

Rice fields harvested after13th October 2014 **Rice fields harvested before 13th October 2014**

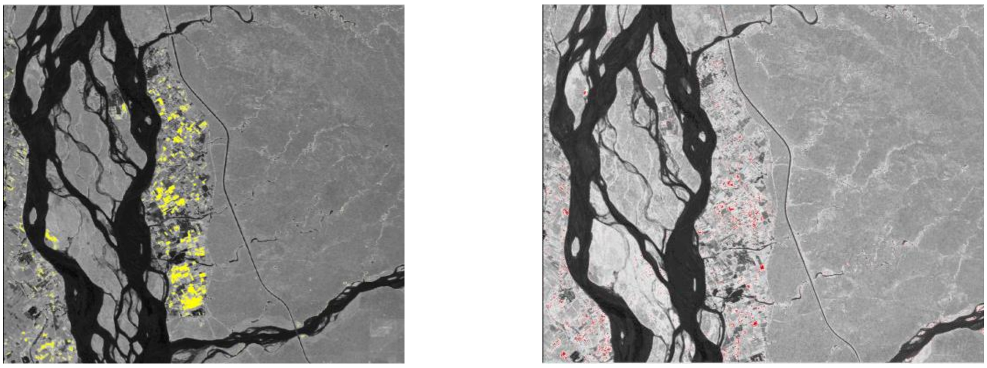


Figure 6-10 Fractional images generated for optimized m for KPCM classifier for IM Kernel

The figure 6-11 depicts the overall adopted scheme. The results have been hardened to give a complete glimpse of the locations of the three target classes identified after implementation of kernel based fuzzy classifier.

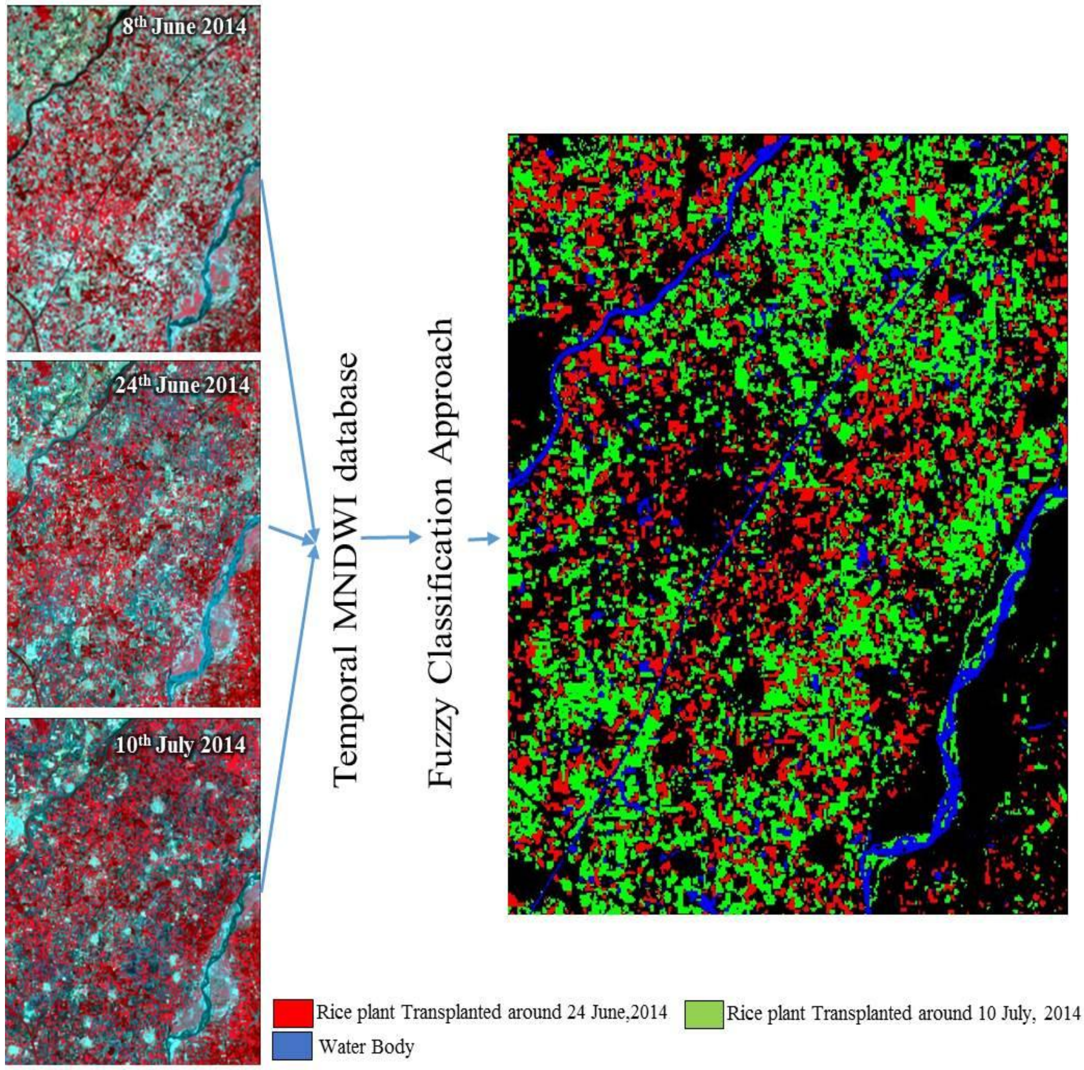
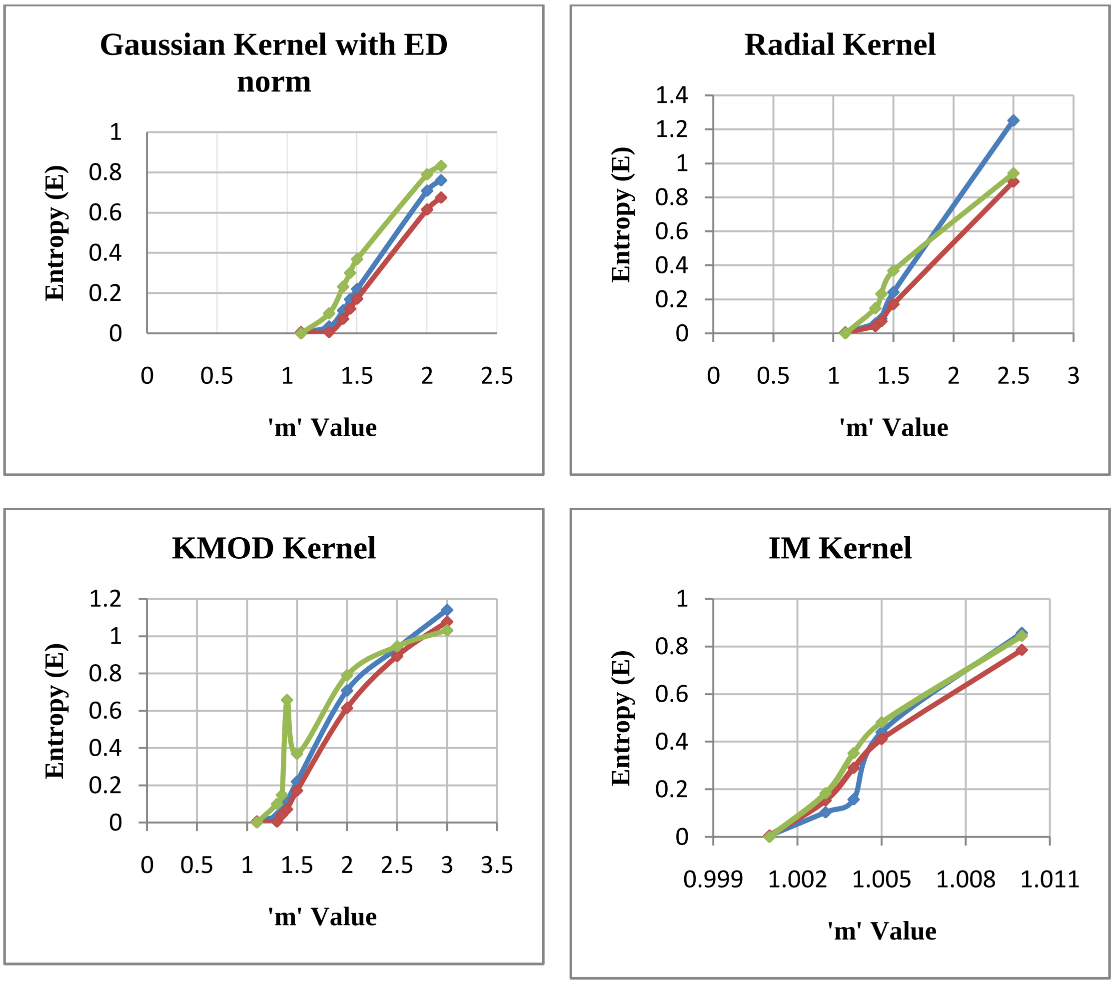


Figure 6-11 Classified output from the temporal L8- OLI

6.1.3 Accuracy Assessment

Entropy was used as an indicator for the accuracy assessment of the classified outputs. Lower entropy value indicates higher certainty of existence of the class of interest at the particular pixel. The graphs in figure 6-12 show the variation of entropy upon varied weighted constant values. It was observed that at the optimized m values, the entropy was as very low. For instance, the entropy value for Gaussian kernel based PCM algorithm varied from 0.7 to 0.005 as the weighted constant was varied from 2.1 to 1.1 for the class 1. Similar behavior was observed in all the kernels and the entropy values.



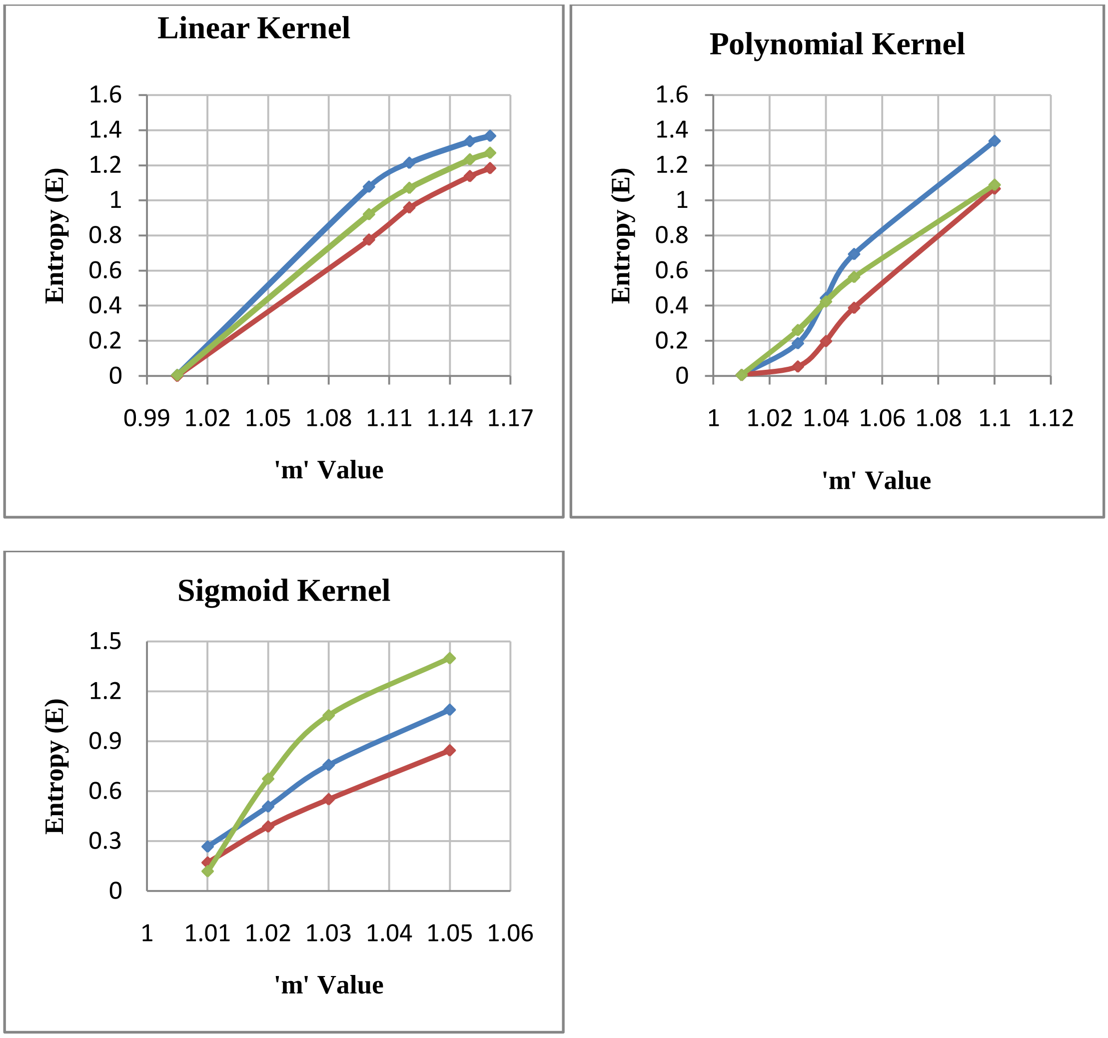


Figure 6-12 Variation in Entropy with changes in m for the seven kernels

6.2 Novel Kernel Based Classification Technique for Cassava Identification

IN the following section output obtained with reference to sub- objective two and three have been discussed in subsequent sections..

6.2.1 Atmospheric Correction using ATCOR

The pre- requisite to work with temporal data is non-dependency on the atmospheric conditions prevailing at the time of data acquisition. In order to remove the atmospheric effects, ATCOR- 2 has been used. The parameters in the module were fed using the metadata file, which comes along with the satellite imagery. Tropical rural was selected as the model for solar region. Following to it, the scene visibility was calculated by the software. Figure 6-13 highlights the spectral profile of class Water and Vegetation in the January 2015 Landsat 8- OLI dataset, after carrying out atmospheric correction.

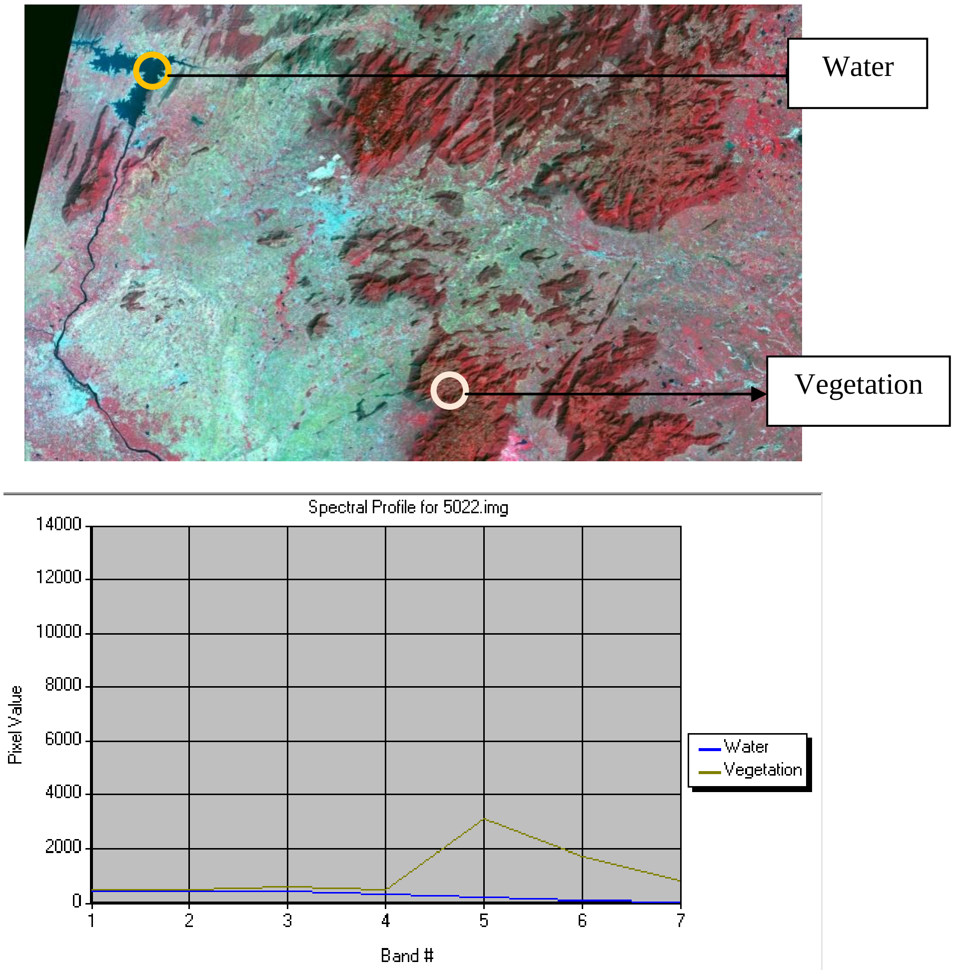


Figure 6-13 Spectral Profile of Water and Vegetation after Atmospheric Crooection

6.2.2 Spectral Profile

SR was calculated from the atmospherically corrected dataset. The images thus obtained were stacked and the spectral profile at the training sites has been shown in the figure 6-14.The graph depicts the subtle changes in the pixel values over the time of the six different classes viz.; Cassava, Sree Athulaya, Mulluvadi, Thailand, Banana and Turmeric which have been considered in the research.

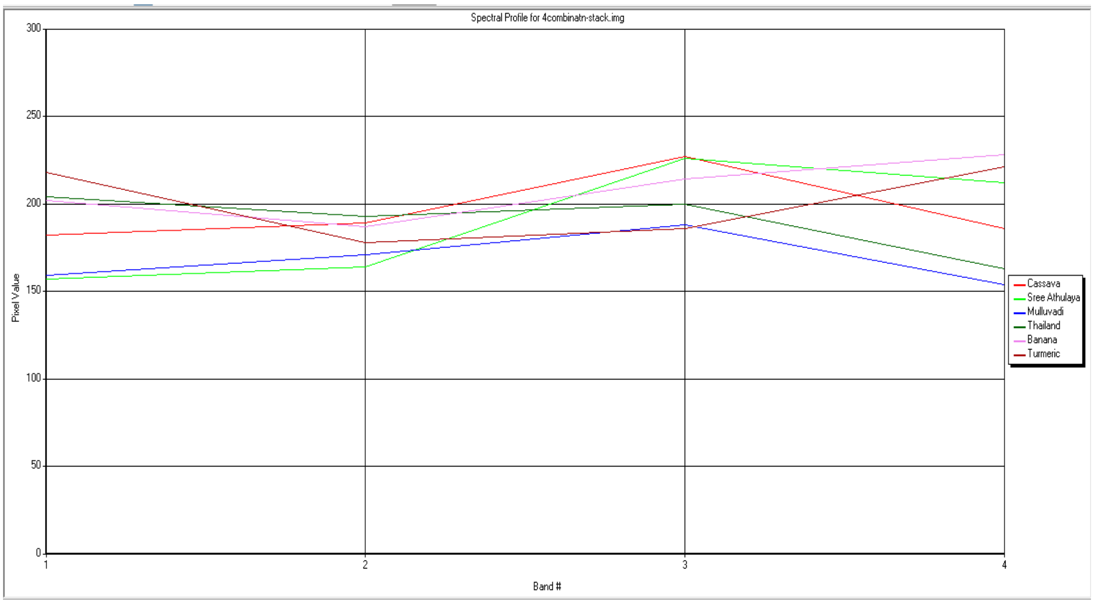


Figure 6-14 Spectral Profile of the classes for best 4- date combination

6.2.3 Spectral Separability Analysis

Spectral separability analysis using best minimum distance was carried out to have an accurate cassava classified output without any misclassification of the other classes. The best date combination corresponds to the fact that the minimum distance between the spectrally similar classes was maximum. The table 6-2 shows that out of the possible many date combination, the best combination and corresponding minimum Euclidean distance measure. So the best 4 date combination where the minimum distance was found to be 32, could successfully separate class cassava with class mulluvadi.

Table 6-2 Temporal spectral separability analysis between cassava and other classes

No. of dates per combination	Dates with best min seprability between target and other non- target classes	Best minimum Euclidean Distance measure
2 date	1,7	22
3 date	1, 5, 7	25
4 date	1, 2, 5, 7	32 (Best Minimum Seperability)
5 date	1, 2, 4, 5, 7	34
6 date	1, 2, 3, 4, 7	35
7 date	1, 2, 3, 4, 5, 6, 7	35

Date 1: 4 February '14, Date 2: 8 March '14, Date 3: 24 March '14, Date 4: 27 May '14, Date 5: 15 August '14, Date 6: 5 December '14 and Date 7: 22 January '15

6.2.4 Classification Results

The proposed algorithms were tested for best 3-, 4- and 5- date combination. The table 6-3, table 6-4 and table 6-5 show the mean membership value of the classes; cassava and mulluvadi at the testing site at the optimized weighted constant value for the best 3-, 4- and 5- date combination respectively.

It is important to notice the differences in the membership value between the two classes with the three different date combination. Although, the classes are separable in all the local kernels, but the difference in the best 4- date combination using Inverse Multiquadratic kernel at optimized weighted constant was found to be maximum.

Table 6-3 Mean membership value of Cassava and Mulluvadi at optimized m for best 3- Date Combination

Kernel	Optimized m	Mean membership of Cassava (at unbiased site) on 8 bit scale	Mean membership of Mulluvadi (at unbiased site) on 8 bit scale
Gaussian	1.400	254.0	191.0
Radial	1.300	253.5	248.5
KMOD	1.400	254.0	201.5
IM	1.005	254.5	111.5
Linear	1.100	196.5	164.5
Polynomial	1.010	254.0	251.5
Sigmoid	1.010	254.0	245.5

Table 6-4 clearly shows the mean membership of the classes of interest. The mena membership of cassava at optimized m for all the kernels is always observed to have high values, except in the case of linear kernel. The difference in mean membership value was observed to be 67.5 in the three local kernels, while it was maximum as 254 in the case of IM kernel.

Table 6-4 Mean membership value of Cassava and Mulluvadi at optimized m for best 4- Date Combination

Kernel	Optimized m	Mean membership of Cassava (at unbiased site) on 8 bit scale	Mean membership of Mulluvadi (at unbiased site) on 8 bit scale
Gaussian	1.300	253.5	186.0
Radial	1.300	253.5	186.0
KMOD	1.300	253.5	186.0
IM	1.002	254.0	0.0
Linear	1.100	149.5	149.5
Polynomial	1.010	248.5	55.5
Sigmoid	1.010	237.0	85.0

While, from table 6-5 it is evident that there is not prominent difference in the mean membership of the two classes in the case of local kernels. Although, the global kernels have better difference in membership values, but misclassification was observed in the outputs.

Table 6-5 Mean membership value of Cassava and Mulluvadi at optimized m for best 5- Date Combination

Kernel	Optimized m	Mean membership of Cassava (at unbiased site) on 8 bit scale	Mean membership of Mulluvadi (at unbiased site) on 8 bit scale
Gaussian	1.200	252.0	205.0
Radial	1.100	254.0	227.5
KMOD	1.200	252.0	205.0
IM	1.100	142.5	129.0
Linear	1.100	204.5	115.0
Polynomial	1.010	254.0	66.0
Sigmoid	1.010	254.0	138.5

Figure 6-15 and 6-16 show the fractional images of class cassava obtained from local and global kernel based PCM respectively at optimized weighted constant using best 3-, 4- and 5- date combination. It can be observed that the classification results of the local kernels are correct, but the results obtained by global kernels are misclassified. As the forest area, lower right of the images has been assigned with highest values.

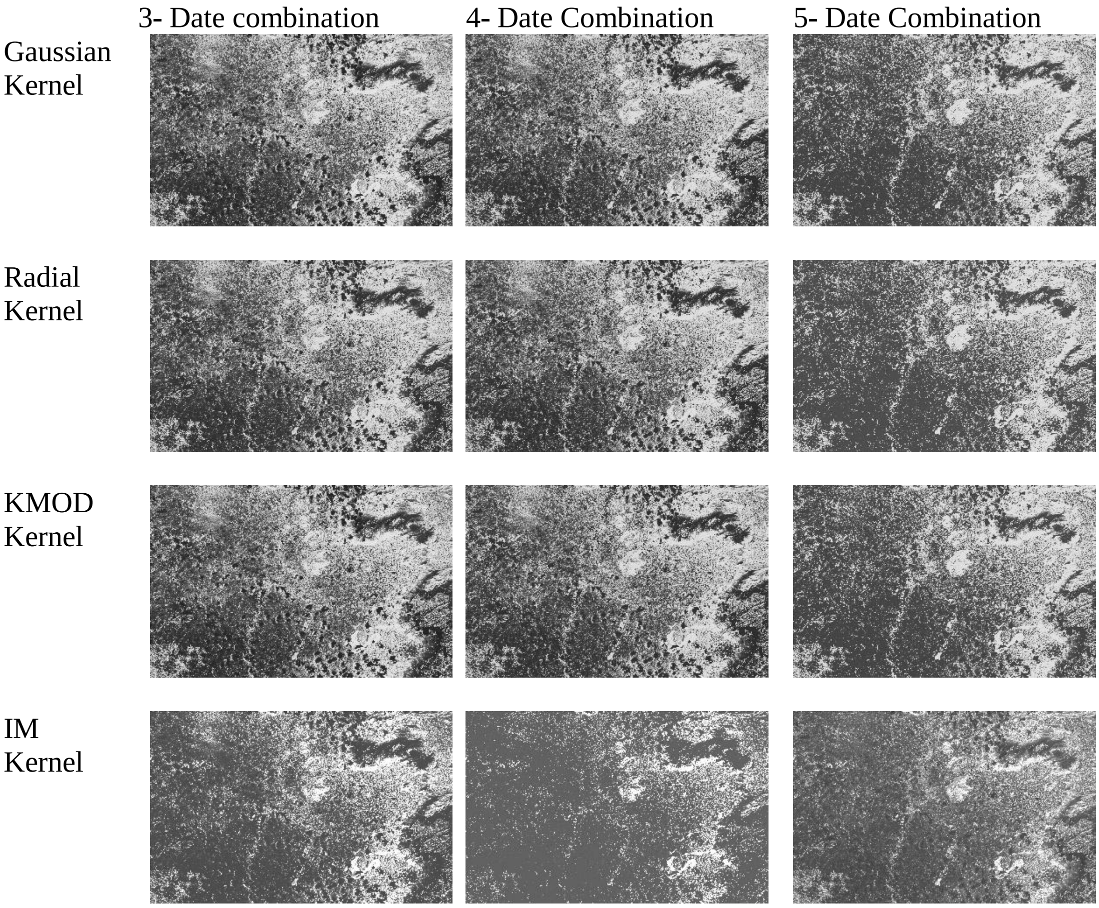
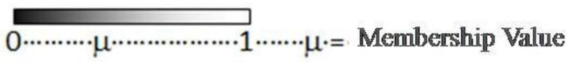


Figure 6-15 Local kernel based PCM generated fractional images for cassava using best 3, 4 and 5 date combination



Linear Kernel

Polynomial Kernel

Sigmoid Kernel

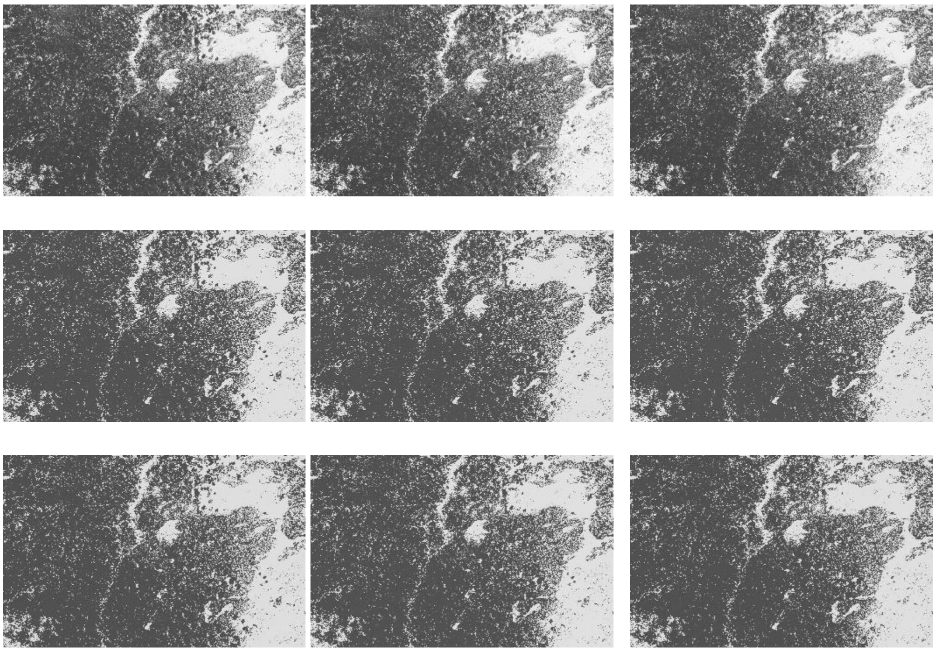


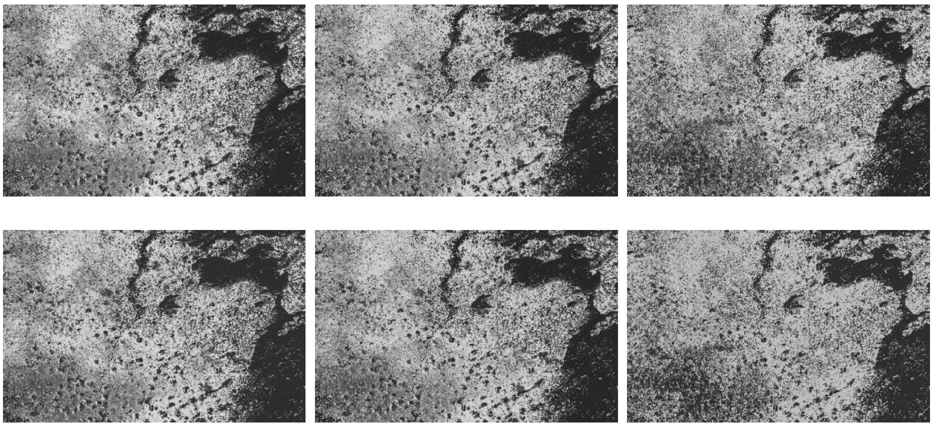
Figure 6-16 Global kernel based PCM generated fractional images for cassava using best 3, 4 and 5 date combination

Figure 6-17 and 6-18 show the fractional images of class mulluvadi obtained from local and global kernel based PCM respectively at optimized weighted constant using best 3-, 4- and 5- date combination. Similar observation, as in the case of class cassava can be made here for mulluvadi.

3- Date combination 4- Date Combination 5- Date Combination

Gaussian Kernel

Radial Kernel



KMOD Kernel

IM Kernel

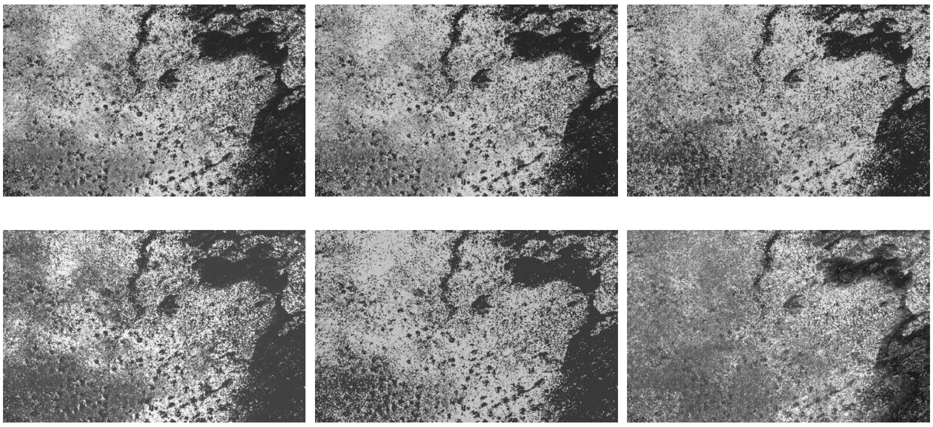


Figure 6-17 Local kernel based PCM generated fractional images for mulluvadi using best 3, 4 and 5 date combination

Linear Kernel

Polynomial Kernel

Sigmoid Kernel

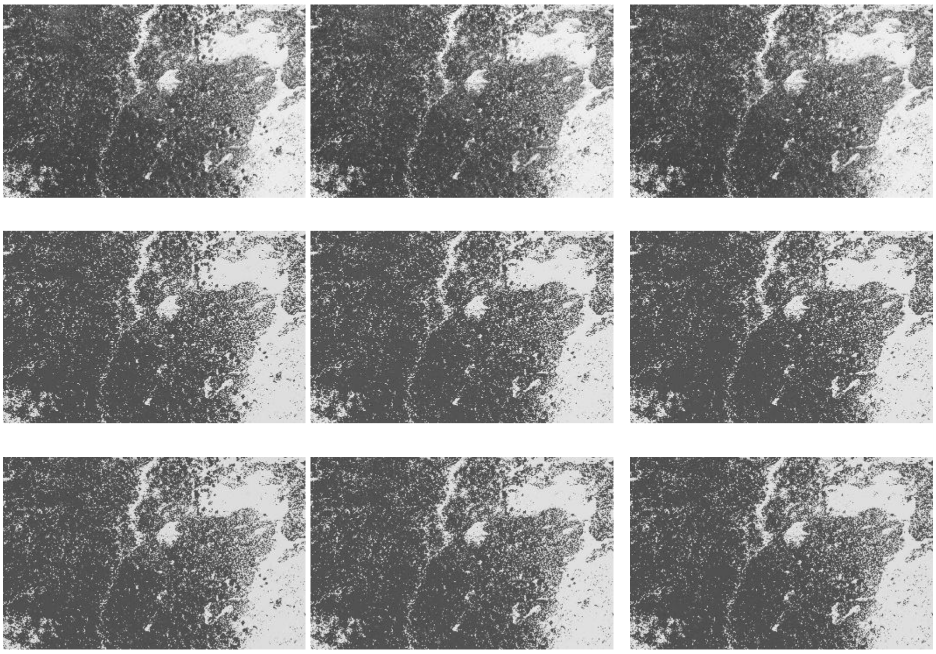
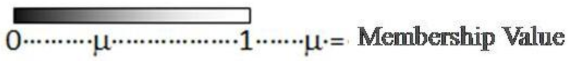
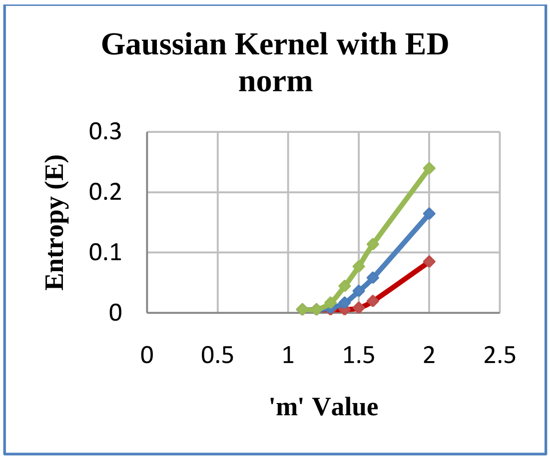


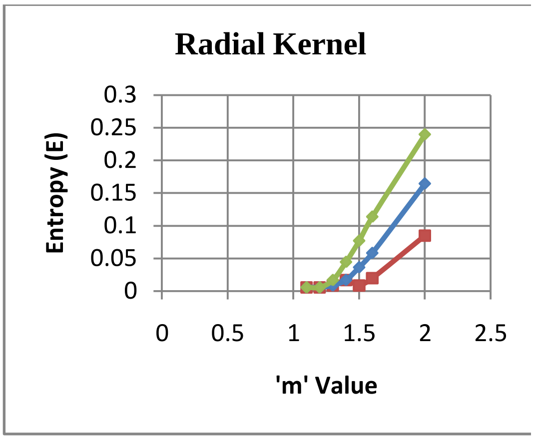
Figure 6-18 Globall kernel based PCM generated fractional images for mulluvadi using best 3, 4 and 5 date combination

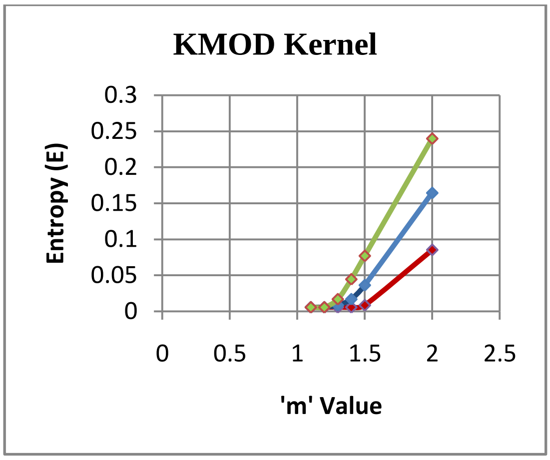


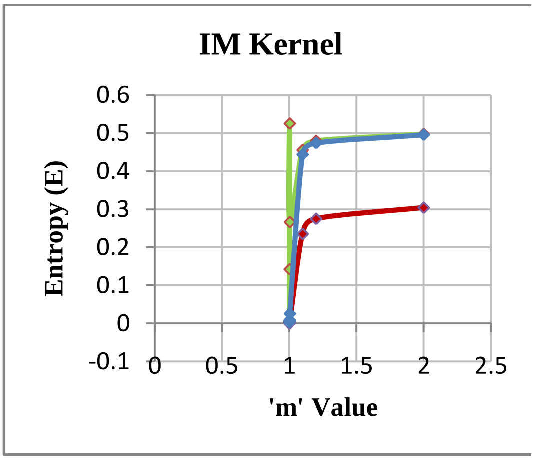
6.2.5 Accuracy Assessment

The accuracy of the classified output was carried out using entropy. Entropy assessment of class cassava has been computed and shown via graphs between the entropy and ‘m’ value in fugure 6-19. As the weighted constant value is lowered down, the entropy decreases and thus at the optimized weighted constant value, the entropy is near to minimum.









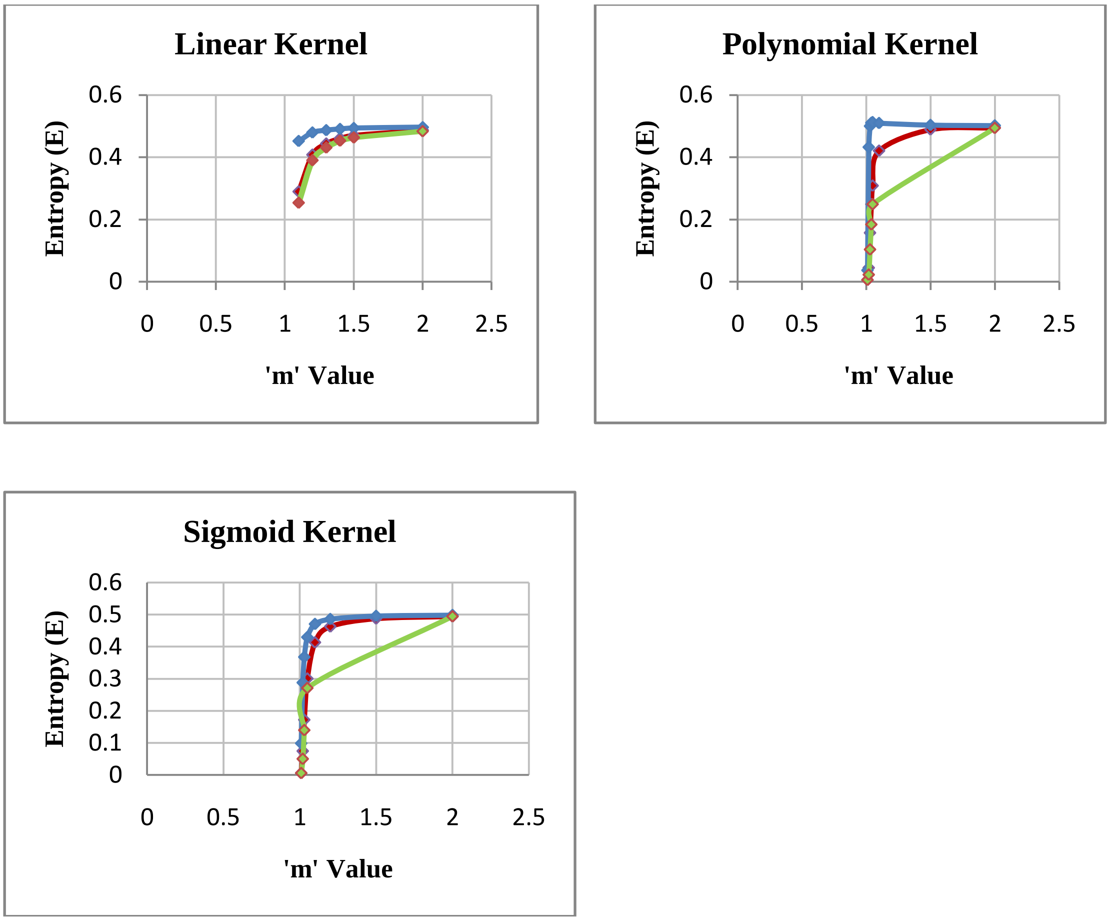
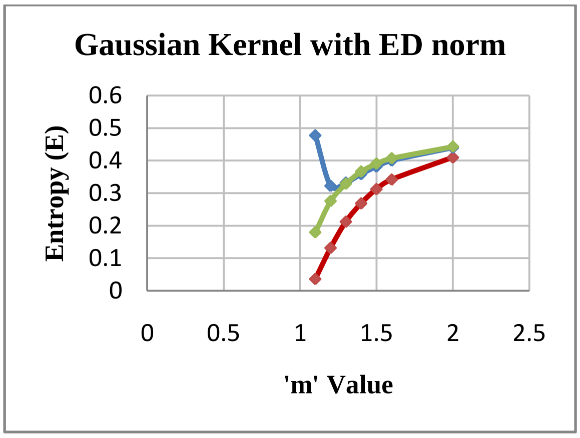
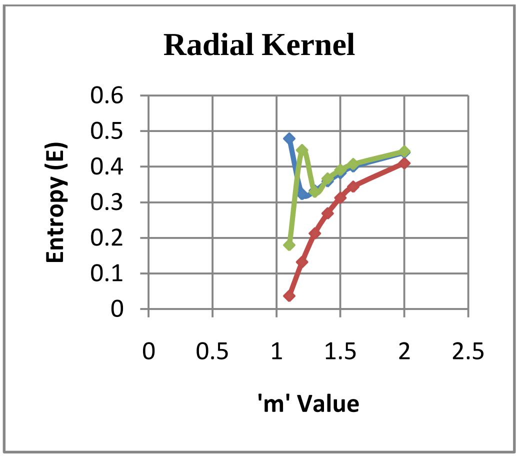


Figure 6-19Variation of Entropy with ‘m’ for Cassava with best 3, 4 and 5 date combination

The accuracy of the classified output was carried out using entropy. Entropy assessment of class cassava has been computed and shown via graphs between the entropy and ‘m’ value in fugure 6-19. As the weighted constant value is lowered down, the entropy decreases and thus at the optimized weighted constant value, the entropy is near to minimum.





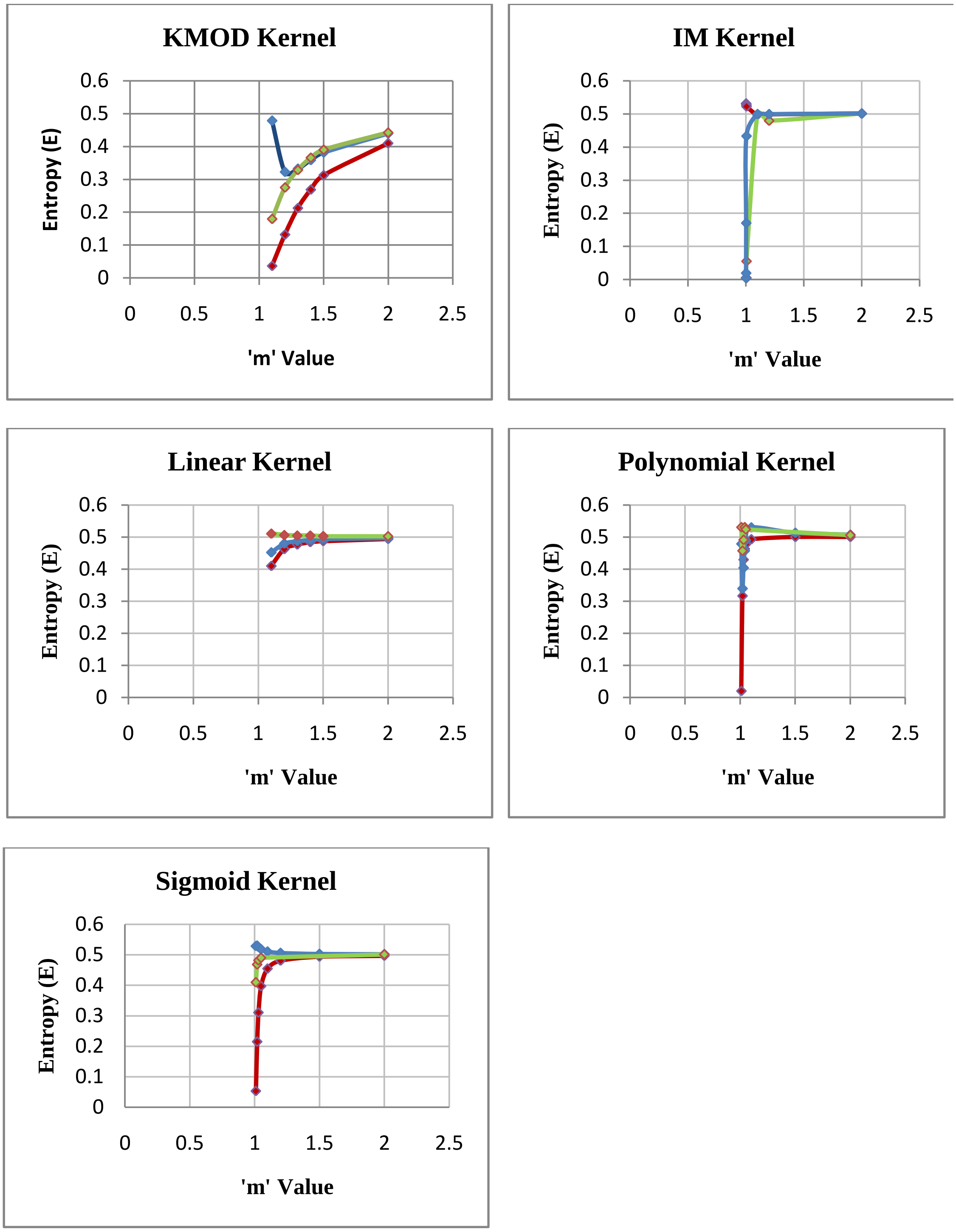


Figure 6-20 Variation of Entropy with ‘m’ for Mulluvadi with best 3, 4 and 5 date combination

Although the entropy is low at lower values of weighted constant ‘m’ and at optimized m, but the visual interpretation clearly points out to the misclassification in the results by global kernel, which does not come up in the graph.

6.2.6 Area Estimation

The soft classified outputs were used to calculate the total area covered by the two varieties of the target crop viz; cassava and mulluvadi.

At optimized weighted constant for Inverse multiquadratic based Possibilistic c- Means for best 4- date combination, the total estimated area was found to be 4234.101529 Ha and 2175.633176 Ha for Cassava and mulluvadi respectively.

7. CONCLUSION & RECOMMENDATIONS

7.1 CONCLUSIONS

Existence of mixed pixels in the satellite images has always been an area of concern. Adding to the difficulty is occurrence of non- linearity between the classes, which is generally overlooked. Sub- pixel classification approach is an effective way to handle the mixed pixel problem. While, kernels can be used to reduce the misclassification between the classes due to non- linear separation. Thus, the study makes an attempt to solve the two frequently occurring problems by kernel based fuzzy approach

The main objective of the research work was to identify specific crops using KPCM approach. In all, four local kernels and three global kernels were tested for three different study sites and two different crops. From the complete analysis of the results obtained, it is concluded that optimization of weighted constant ‘m’ plays a significant role in the accuracy of the classified results. The constant ‘m’ is optimized at a certain specific value for every kernel despite the differences in data set used, crop considered and study area location.

It was observed that inverse multiquadratic kernel based Possibilistic *C*- Means at optimized weighted constant has the best overall performance among the seven tested kernels in all the three test sites. The entropy values at the unbiased sites were very low; in the order of 0.001. Also, the distance between the classes was well appreciable, for instance, it was as high as 254 (on the 8 bit scale) for class paddy rice field transplanted on and around 24 June, 2014 from other classes. This ensured that there is no overlapping between the classes, and minimum human intervention to carry out density slicing. Similar observations were made for other test sites and crops. The incorporation of contextual information in IM based fuzzy classifier helped to make the boundary of the fields more prominent.

Also, none of the global kernels performed upto the mark. A lot of misclassification was observed in the outputs generated, even after optimizing the weighted constant. Although, the entropy was not too high, for instance 0.036 for class cassava using best 4- date combination still that could not give the exact idea of the misclassification.

Also it was observed that it is highly essential to optimize the temporal date combination for crop identification. As indicated upon class separability analysis, the best 4- date combination should have had given the best result. So was observed after carrying classification on best 3-, 4- and 5- date combination. The class separation was minimum for 4- date combination with higher entropy values at testing sites while, classes were maximum separated out using 4- date combination. The entropy obtained from 4- date combination at optimized ‘m’ was observed to be minimum.

Accuracy of the fractional images thus obtained was calculated using entropy. It is highly important to match the fuzziness on the ground to the fuzziness in the imagery. Therefore, upon varying the weighted constant it was observed that as the ‘m’ was lowered, the entropy decreased and after a certain point the slope decreased and finally the reaches 0 when ‘m’ is a little higher than 0. A lower entropy value indicates that the certainty in the existence of the class at the particular is high.

Thus, the research concludes that kernel based fuzzy approach is a robust algorithm to handle the challenges in the classification of satellite imagery. The optimized weighted constant values for the kernels and especially IM based PCM and incorporation of MRF in IM based PCM are effective to identify specific crops.

7.2 ANSWER TO RESEARCH QUESTIONS

Q1. How to distinguish paddy rice fields from water body, using early rice growing phase information?

A1. Paddy rice fields based upon the different transplantation date could be well discriminated from the water body using Kernel based Possibilistic c- Means fuzzy algorithm. The early rice growing phase information was used to generate MNDVI images and following it, different Kernels were tested upon optimizing the weighted component ‘m’. Local kernels outperformed the global kernels.

Q2. Would kernel based classifier help in better discrimination of target crop?

A2. There is non- linear separation or overlap between the classes in the dataset. Kernels map the lower dimension input feature space to higher dimension feature space where the classes exhibit linear separation. The input data has non linearity in the classes which can be visualized through figure 7-1, where, a scatterplot taking two bands at a time that is; band 2-3, band 3- 4 and band 4-5 has been generated.

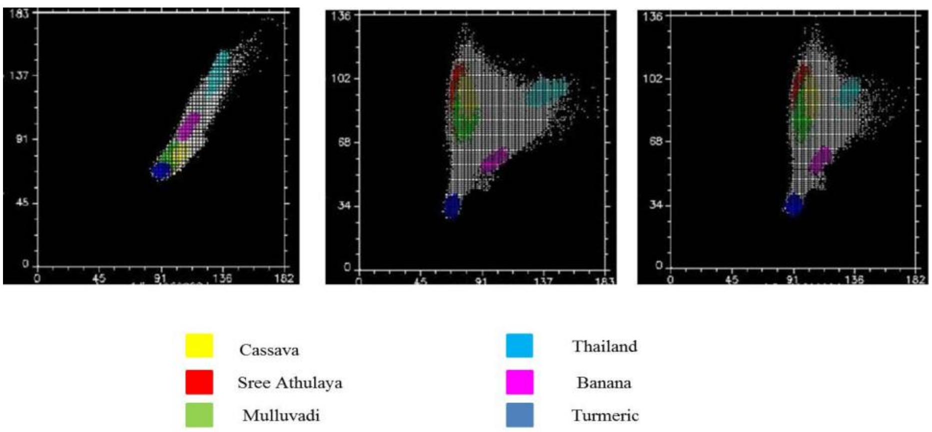


Figure 7-12D scatterplot highlighting the non-Linearity in different classes

Although, visualization of the linear separation between the classes after the application of kernel based fuzzy approach was not possible, but the impact of it could be seen in the fractional outputs. More number of fields could be rightly classified henceforth.

Q3. To what degree does the classification accuracy improve upon incorporating the MRF classifier with KPCM compared to KPCM?

A3. Incorporation of contextual information marginally improved the classified results. The classification results had more prominent field boundaries visible and the isolated pixels were removed.

Q4. How well can cassava be discriminated from other crops present in the cropping pattern of a particular area?

A4. Cassava can be well discriminated from other crops in the study area. Also, a successful attempt was made to discriminate between the different varities of the cassava that were, cassava and mulluvadi.

Q5. Which are the best dates suitable for identification of the specific crop- cassava?

A5. The best suitable date combination for identification of cassava was found to be of four date that are, 4 February, 8 April, 15 August 2014 and 22 January 2015.

Q6. Does selection of kernel depend upon the study area and various crops?

A6. The algorithm was successfully tested on two crops and three test sites. Kernel based fuzzy classification was implemented to identify rice at two locations; Radaur city, Haryana and Haridwar, Uttarakhand The other crop considered was cassava in Salem district, Tamil Nadu. After a thorough study of the results it can be concluded that the selection of kernel is independent of the study area and crop.

The results obtained through the carried out research work clearly indicates that for any crop and any area, inverse multiquadratic kernel at optimized m value of 1.001 outperformed the rest of the six kernels.

7.3 RECOMMENDATIONS

Based on the results and thorough analysis of the work carried out, the future scope of the work has been suggested as below:

1) Fuzzy Error Matrix (FERM) could be explored to carry out the accuracy assessment of the results. This would require higher spatial resolution reference soft classification outputs.
2) Microwave dataset should be incorporated in the temporal optical database to reduce the temporal data gaps, due to cloud cover. And, over the stacked imagery Kernel based Possibilistic*c*- Means could be implemented.
3) Composite kernels using weighted summation, stacked approach or direct summation kernel method can be implemented in the fuzzy classifier to study the effect of it in the identification of specific crops
4) Thoughkernel based Possibilistic *c*- means could identify the class of interest with higher accuracy, still spatial distributions of the specific class within the mixed pixel could not be mapped. For the same, theory of spatial dependence could be explored.

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APPENDIX

List of Publications

I. Aggarwal R., Kumar A., Raju P. L. N. and Krishna Murthy Y. V. N., (2014), Gaussian Kernel Based Classification Approach for Wheat Identification, ISPRS TC VIII Mid- Term Symposium December 9- 12, 2014 in Hyderabad, India. (Case Study)

II. Aggarwal R., Kumar A., Byju G., Manjunath K. R., Raju P. L. N. and Krishna Murthy Y. V. N., Robust Kernel Based Fuzzy Classification Approach for Paddy Rice Field Mapping using Temporal Landsat 8 Data ready for communication to a journal.

III. Aggarwal R., Kumar A., Byju G., A Novel Kernel based Fuzzy Classification Technique for Cassava Idetification; A Case study of Salem District, Tamil Nadu ready for communication to a journal.

IV. Kumar R., Kumar A. and Aggarwal R., Specific Crop Identification using Kernel based Fuzzy Approach from Temporal FORMOSAT-2 Data ready for communication to a journal.