Temporal Dual Polarization SAR Data for Multi Crop Classification Using Different Classifiers

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Abstract: ***The curiosity in crop inventory since beginning was the use of multitemporal microwave data so as to achieve a near perfect crop discrimination. Till recently, the multi - temporal amplitude data has been used for crop discrimination as well as biomass estimation. With the availability of dual - polarized data, the disparity response of crop geometry at different crop growth stages to different polarizations is being exploited for discrimination and classification of crops. The crop signature analysis has been made for Synthetic Aperture Radar (SAR) backscatter coefficient (σ0) of paddy crop shows significant sequential behaviour and a large range during its growth period, which is due to the interaction of microwave energy with the crop canopy, increasing from the transplantion stage to the reproductive stage. This temporal variation of SAR backscatter clearly differentiates paddy fields from other land cover classes and also various crop signature shows unique pattern. The different classifiers were performed in this study site and comparison study was also carried out. The decision tree classifier based on the temporal assessment of SAR backscatter was attempted to classify crops and land use features, showed more than 84% accuracy. An attempt has been made in the current study using RISAT1 C - band dual, polarized data for crop inventory. The three date dual polarized data gave comparable results for crops like Green gram, Cluster beans, Ladies Finger, Paddy, Cotton, Fallow, water body and settlement.***

Keywords: Remote Sensing, Synthetic Aperture Radar (SAR), Crop Discrimination

1. Introduction

In vision of the advancements in the microwave remote sensing technology it is necessary to evaluate and demonstrate the application potentials of microwave data for various crop signature retrieval [18]. The key benefit of Space - borne SAR imaging is the independence from cloud cover and as it is an active sensing system, also from sun - induced reflection. Consequently, SAR imagery has become an important tool to distinguish agricultural crops [9]. SAR polarimetry, techniques are among the advanced method that can provide very valuable information about the land resources. Synthetic aperture radar (SAR) has tremendous potential to characterize crops due to its higher sensitivity to crop cover [3]. Several studies have demonstrated the capability of multi - temporal SAR data in retrieving crop parameters [5]. In this present study C band (RISAT - 1) multi - temporal SAR data have been used to evaluate the crop signatures. Based on the studies on response of SAR backscatter to various crop parameters in different polarizations, regression models based on frequency (C band) SAR data was developed to improve the evaluation of crop signatures [25].

2. Materials and Methods

2.1 Study Area

The study has been carried out in Hisar, district, Haryana, India. The test site lies between 29° 11′ - 29° 20′ N latitudes and 75° 36′ - 75° 45′ E longitudes. This is a farmland of considerable size where large experimental crop fields are maintained for seed generation and distribution to the state farmers. The major agricultural crops grown in this area include Green gram, Cluster beans, Ladies Finger, Paddy, Cotton and pulses during kharif (summer) and wheat, sugarcane, mustard, gram, peas during rabi (winter) seasons. This site was selected for developing methodology for crop discrimination and classification using data of various polarimetric modes synthesized from RISAT - 1 SAR polarimetric data [12]. The paddy and cotton were the predominant crops grown in irrigated and rain fed regions, respectively in the Hisar test site. The paddy crop is transplanted in the month of June and extends up to early September at Hisar test site, while the cotton crop sowings commence from the month of July onwards [23].

2.2 Satellite Data

Three sets of SAR data at different crop growth stages have been planned based on the crop calendar. The first date coincided with the initial crop stage (25 - 30 day crop corresponding to June end), the second date coincided with the peak vegetative stage (August Mid) and the third date was acquired before the harvest of the crop (Sep beginning). RISAT - 1 MRS (Medium Resolution) multi - date dataset [C - band, HH and HV polarization, incidence angle 36.8º and 2 - looks have been used as data source for the major crops in Hisar district. The MRS data has been selected for its large area coverage (115 - km swath) and acceptable pixel spacing (18m) [www.isro. gov. in]. The data acquisitions were made from June 26, August 15 and September 04, 2013.

2.3 Ground Truth Data

The crop is sown during last week of mid June. The data acquisition was considered coinciding with the crop season. The Ground truth data were collected synchronous with all the passes of the satellite. The coordinates of Ground Truth points were gathered by using Global Positioning System (GPS) receivers. During the GT campaign, crop parameters like type, age, vigor, extent, height and density were measured and biomass parameters like canopy and Leaf area index were noted qualitatively. The training sites samples collected during ground truth were transferred to the image. Care was taken to choose sites, which have at least 3 hectares in contiguity. Also the information on other land cover was also collected.

2.4 Pre - Processing

The methodology involved preprocessing of SAR data, image geo - referencing, Co - registration, transfer of ground truth data and classification of images. Processing of the RISAT - 1 data was carried out using PCI Geomatica (ver.9.0) software. L2 product is available in. tiff format. HH and HV images are imported to native raster format of PCI Geomatica (. pix) and transferred to a single file as two separate channels. Re - projection (if needed) is done and then the image is filtered by enhanced Lee adaptive filter with kernel size 5 × 5, as established by standard procedures. Most of the scenes had abrupt brightness variations in the near and far range side and banding at equal interval along the track due to mosaicing of data of beams used to form the MRS data. These unwanted patterns were removed by marking a transect across the image and adjusting the brightness by plotting the variations in brightness across the pixels. The coefficient and central pixel values are used to correct this pattern. Calibration for HH and HV polarization amplitude image were carried out using the calibration constant in product. xml as: Value in dB (in 32 - bit real channel)

$$= 20 \times \log10 (DN) – \text{calibration constant.}$$

The three - date images were co - registered by fitting manual GCPs with about 25 well - distributed points throughout the image scene. A second - order polynomial model was fitted to register the second and third date image with respect to the first date image [5].

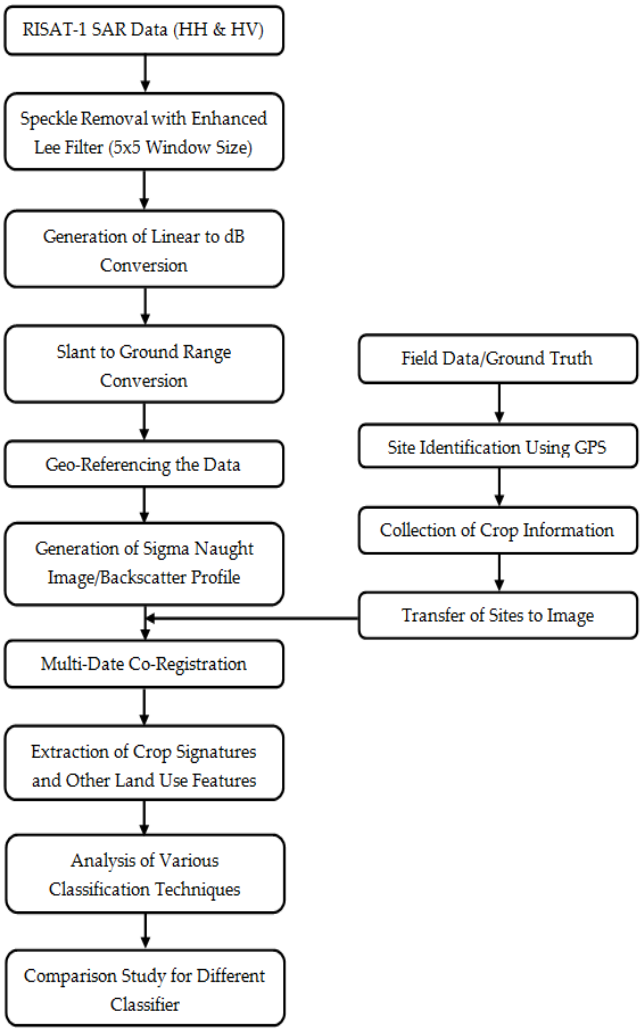

Figure 1: Flow Chart for Amplitude SAR Data Analysis

2.4 Image Classification

Supervised classifications usually performed better than unsupervised strategies. Consequently, this study followed a supervised classification strategy. Several supervised classification algorithms exist and each of them has certain advantages and disadvantages [16]. The Gaussian maximum - likelihood classifier (MLC) is perhaps the most frequently used algorithm, and thus it is widely available in commercial software packages. The MLC decision rule is based on the probability that a pixel belongs to a particular crop (or land use) class. The basic equation can incorporate a priori probabilities assigned to each class, and the input bands are assumed to follow normal distribution functions. When the a - priori probabilities are known, the MLC rule is known as the Bayesian decision [16]. An ANN is a mathematical algorithm which is inspired by a human brain. It is capable to simulate non - linear and complex patterns with appropriate topological structures. The structure of the ANN used in the image classification consists of an input layer, one hidden layer and an output layer [2]. A neuron in the input layer represents one of the input features such as one satellite image band. In the present study, the input layer contains 3 bands as a number of neurons. A single hidden layer contains 8 neurons. The output layer contains 6 neurons as crop classes used for the classification. The used ANN algorithm is a layered feed forward model in ENVI version 5.1. It uses standard back propagation for supervised learning and minimizes the root mean square error (RMSE) between the actual output of a multilayer feed forward ANN and the desired output [20]. Total, 1000 number of training iterations with RMSE 0.01 was taken. The three - layer structure of the ANN is shown in the Fig.2

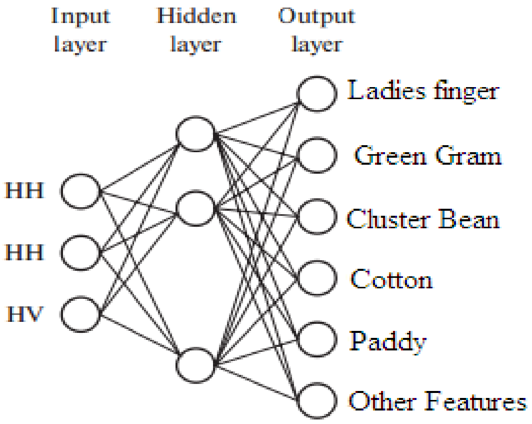

Figure 2: Three Layer Structure of the ANN

Support Vector Machines, a popular and powerful kernel - based classification algorithm, has been extensively and successfully implemented in remote sensing for classification and regression problems. This method aims to define the optimal hyper plane separating two classes with maximum margin width [19]. The underlying reason of SVM's popularity for classification is achieving the high classification accuracy with a small number of training data and able to outperform than other conventional methods such as ANN and ML classification [19]. If it was not possible to separate two classes by linearly, SVM utilizes kernel functions to separate classes in higher dimensional space. Kernel functions need user - defined parameters and choice of suitable kernel type and corresponding parameters have a great impact of the performance of SVM [19]. In this study, Radial Basis Function (RBF) as a kernel type was implemented and optimum parameters for RBF kernel have been determined by using grid search method as 0.2 and 300 for kernel width and penalty parameter, respectively [17]. The Decision Tree is a simple and effective hierarchical classifier. The Decision Tree classifier performs multistage classifications by using a series of binary decisions to place pixels into classes. Each decision divides the pixels in a set of images into two classes based on an expression. Each new class can be divided into two more classes based on another expression. There is no limitation on number of decision nodes. The results of the decisions are classes. The potential of knowledge rules in inferring information classes of crops on historical imagery using decision tree classifier [13]. Here, the knowledge can be heuristic, i. e. based on experience and reasoning. It uses a logical and mathematical approach. This approach is applied pixel by pixel to produce a label for each pixel solely dependent on the class signatures and characteristics of the data. Some expert knowledge is applied to the process by the user as per the requirement of the analyst [13].

3. Results

The results are increasing in the order of three levels of complexity while using the RISAT - 1 amplitude alone.

3.1 Crop Signature Analysis

SAR signatures were collected from all the land - cover classes (paddy, water body, Green gram, Ladies Finger, fallow, cotton, Cluster bean and Settlements) [24]. Multitemporal RISAT - 1 SAR data for individual dates of detailed crop signature was investigated and found the upper and lower limits of the backscattering values of a given pixel n the particular class [24].

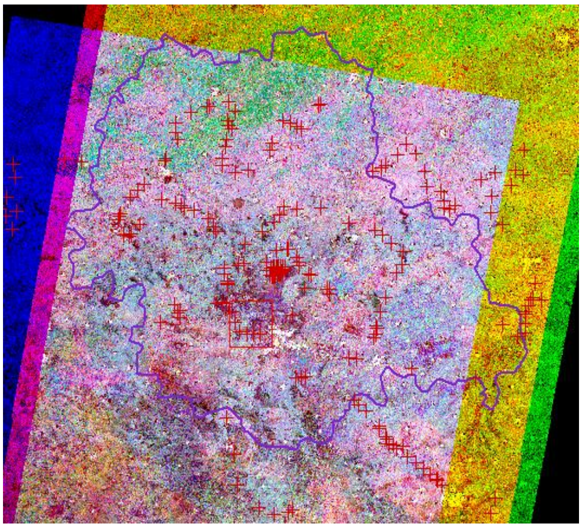

Figure 3: Muli – Temporal HH data - Three date Composite (June.26, Aug.15, and Sep.09 – 2013)

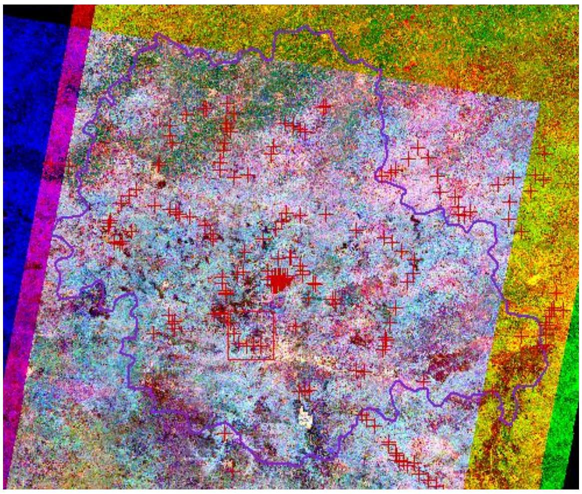

Figure 4: Muli – Temporal HV data - Three date Composite (June.26, Aug.15, and Sep.09 – 2013)

The backscatter values were extracted for the just transplanted paddy crop (lowest) for the paddy class as well as for each other crop (highest) class. Similarly, the lower and upper limits of backscatter values were recorded for other land covers, in order to generate the threshold level. The range of threshold values was expanded up to the 3 - sigma boundary for an individual class in order to include all the possible number of pixels for that particular class [8].

The RISAT - 1 amplitude data was used in Hisar test site for discrimination of crops and classification of cotton crop and paddy crop in growing areas. The SAR backscatter values of - 18 to - 15.0 dB in HH polarization found in the time of puddling stage and transplantation stage [23].

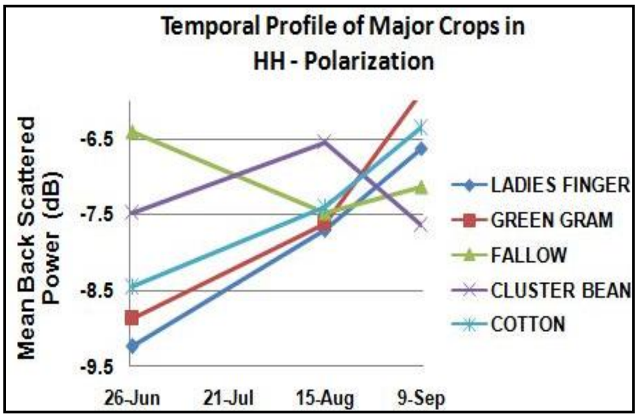

Figure 5: Temporal Back Scatter Response of Kharif Crops in HH

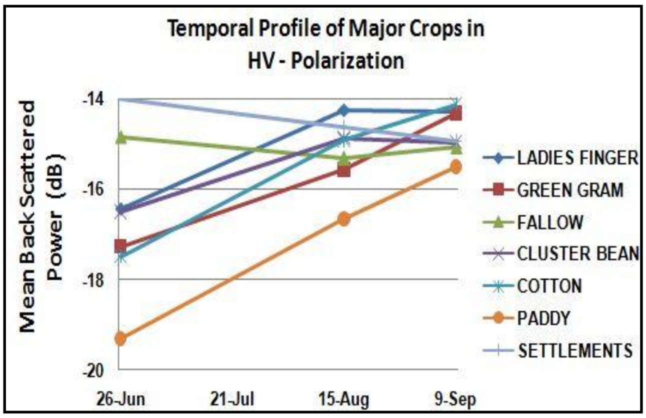

Figure 6: Temporal Back Scatter Response of Kharif Crops in HV

With the increase in leaf area and canopy volume, the backscatter from paddy canopy increased for initial transplantation stage to final maximum vegetative and reproductive stage and decreased thereafter which can be shown in figure 6 [23]. Same as cotton crop, the SAR backscatter values of ranges from - 8 to - 6 dB during the crop growth. when compared to HH polarization, the HV polarization response of the paddy and cotton crop is less. The maximum backscatter values of - 14.0 dB were observed in HV polarization [23].

Table 1: The Pixel Based Classification Results Expressed in Percentage.

S. No	Classification Method	Overall Accuracy (%)	Kappa Coefficient
1	Unsupervised Classification (K - Mean & Isodata)	30.19	0.183
2	Maximum Likelihood Classification	78.77	0.754
3	Artificial Neural Net Classification	63.23	0.561
4	Support Vector Machine Classification	70.67	0.643
5	Decision Tree Classification	84.34	0.734

In principle, the classification accuracy of crop types by SAR data mainly depends on the sensitivity of the radar backscattering coefficient to the difference in the biophysical characteristics of the plant structure, i. e., the different interaction behavior between radar backscatter and the structure of the canopy [11]. In addition, the backscattering characteristics of the SAR signal is influenced by soil conditions for plants in the early crop growth stages. As plants grow, their radar backscattering characteristics vary with the variety of canopy structure and weaken the influence of soil conditions. Thus, multi - temporal data adds useful information for improving crop classification accuracy [7]. Similarly, the radar backscattering characteristics of crops change with the different frequency and polarization based on different scattering mechanisms. Thus, multi - frequency and multi - polarized SAR data can increase the classification accuracy [11]. These phenomena were also observed in this study. The different classification methods were adopted in the test site and the accuracy of each classification are analyzed. The unsupervised K - mean and isodata algorithm, maximum likelihood algorithm, artificial neural net algorithm, support vector machine algorithm and decision tree algorithm provided the overall accuracy for 30.19%, 78.77%, 63.23%, 70.67% and 84.34% respectively.

3.2 Unsupervised Classification

Unsupervised classification involves the calculation of initial class means evenly distributed in the data space then iteratively clusters the pixels into the nearest class using a minimum distance technique. Each iteration recalculates the mean of class and reclassifies pixels with respect to the new mean. Unless a standard deviation or distance threshold is specified, all pixels are classified to the nearest class in which case some pixels may be unclassified if they do not meet the selected criteria. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached [1].

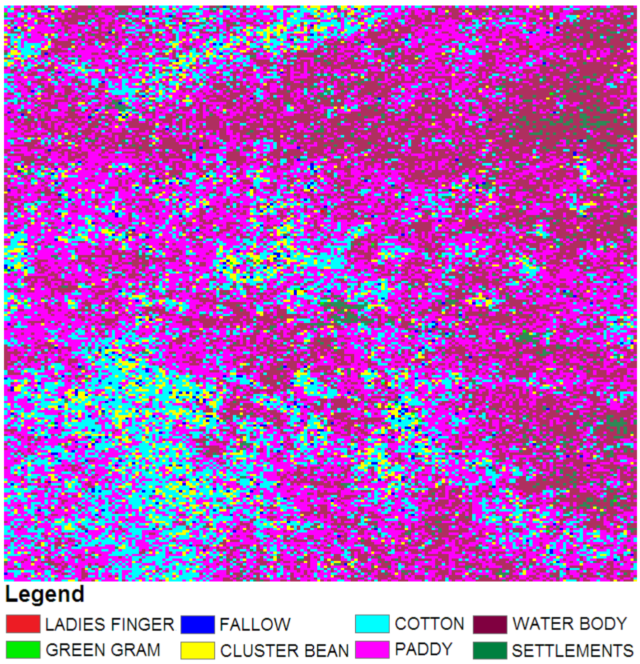

Figure 7: Classified Image using K - Means & Isodata method

The results are found that some classes like Green gram, Ladies Finger and Cluster beans are classified as a misclassified single class and some places the land class is misclassified as Paddy. It was observed that K - means and iso data method of classifier gives poor classification accuracy (around 30%) [1].

3.3 Supervised Classification

The Maximum Likelihood classifier was applied on the two band combination C - HH, C - HV after applying Lee speckle filter. The training sites were chosen in order to train the classifier (finding mean and standard deviation of the different classes region of interest and then the corresponding posterior). The region of interest or training sites that were given included Ladies Finger, paddy, Cluster beans, cotton, Green gram, fallow, water body and settlement class [15].

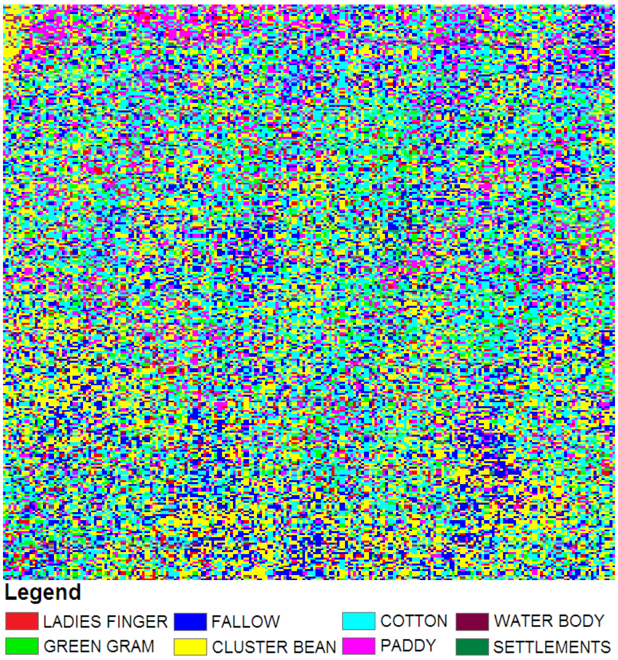

Figure 8: Classified Image using MLC method

In order to discriminate between those crops with similar responses, the priori probabilities plays a major role, as probability distributions are adapted according to the given a priori probability value. In order to refine all classifications that were performed, the typical value of each plot in its assignment to a particular class was used. This value indicates the reliability of belonging to that class. The overall classification accuracy was attained 78.77% and kappa coefficient 0.754 [15].

3.4 Artificial Neural Net Classification

Per - field classification with an Artificial Neural Network proved to be effective. The crop classification accuracies improved by using the combination of June, August and September SAR data. Although these overall classification accuracies (63%) are not sufficiently high for operational crop inventory and analysis, the abilities to discriminate certain crops in the early - and mid - season have been demonstrated by the Multi temporal SAR data. For instance, paddy, cotton, Green gram and Ladies Finger could be differentiated perfectly from others using the combination of the three - date SAR [21]. The results are found that some classes like Green gram, Ladies Finger and Cluster beans were classified as a misclassified single class and some places the land class is misclassified as Cotton [21].

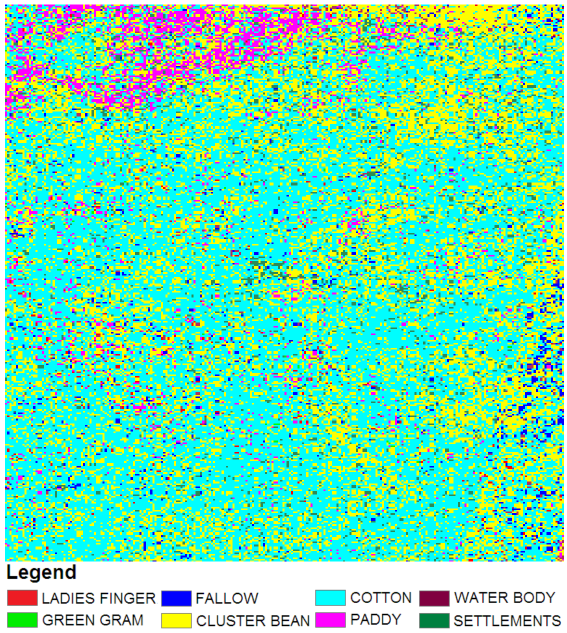

Figure 9: Classified Image using ANN method

3.5 Support Vector Machine Classification

The potential of SVM to classify different crop types was examined. The Different classes of the data are separated optimally by SVM using a hyper plane. A training dataset is used to determine an optimum hyper plane, and its generalization ability is verified using a validation dataset. Training vectors are projected into a higher dimensional space by the function. In this higher dimensional space, SVM finds a linear separating hyper plane with the maximal margin. This study used a polynomial kernel and employed 'one - against - one' technique to allow multi - class classification [22]. Major crop types identified were Paddy and cotton. Kharif crops classification accuracy was found to be slightly higher (71%, k = 0.64) than ANN.

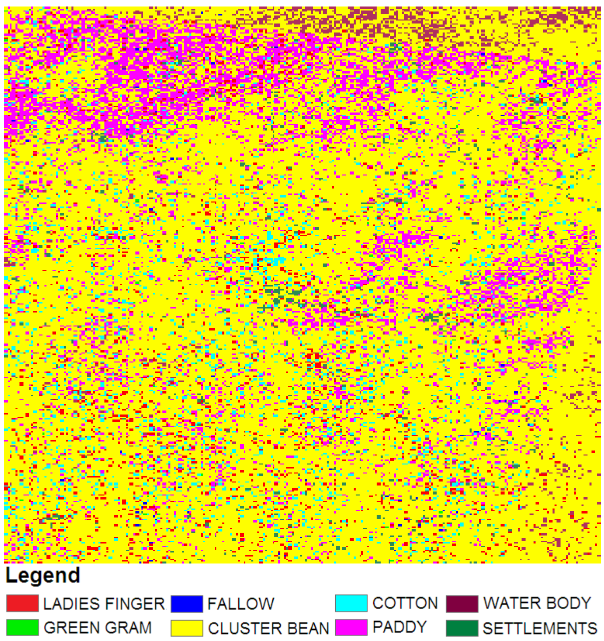

Figure 10: Classified Image using SVM method

3.6 Decision Tree Classification

In order to classify the paddy and other crops, Hierarchical knowledge - based decision rule classifier was attempted. Hierarchical decision trees are an efficient form for representing the decision processes for classifying patterns in the data where a tree functions in a hierarchical structure based on a knowledge - based approach. At each step, there is a decision regarding classification output [5]. In order to handle the large variability observed in the multi - date SAR data, the knowledge - based classifier was found to be well suited. The study area was classified as paddy and other crop areas as shown in Figure.10. The other crops were cotton, cluster bean and land use features such as settlements, and water body. In order to classify only the paddy class, two date's data are sufficient. But to classify both paddy and other crop classes, it is essential to include data from the third date for separation of water and other land - cover classes from each other. It was observed that by using the knowledge - based classifier, only 2.5% of the whole study area remained unclassified. Thus by using this approach, it is feasible to separate various crop classes based on the growth stages and other classes (Settlements, and water body) [5].

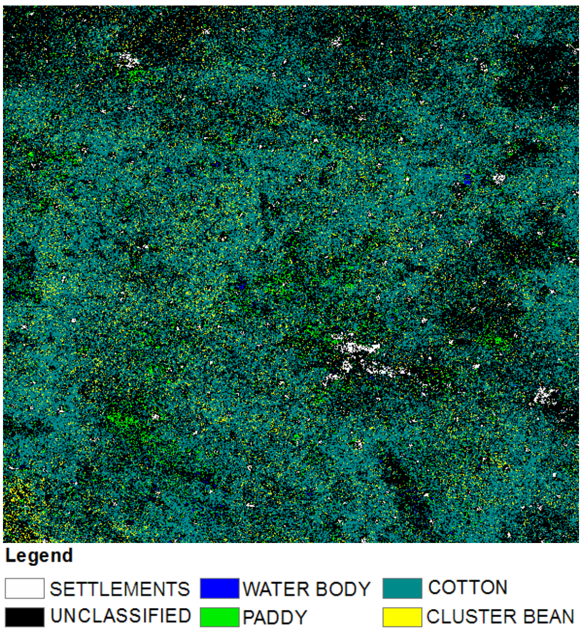

Figure 11: Classified Image using DTC method

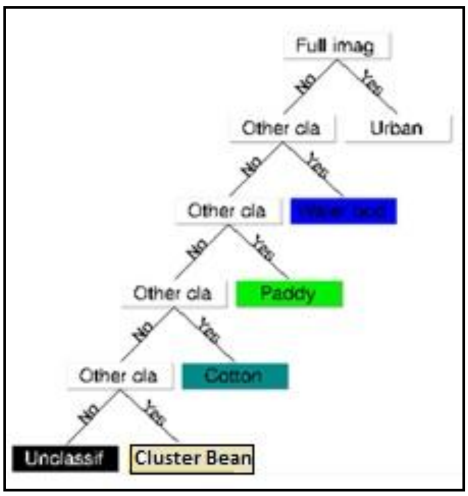

Figure 12: Decision Tree Expressions

The decision rule based classification approach was performed on temporal Medium resolution amplitude data with HH and HV polarization. The overall accuracy was found to be more than (84%, k=0.73) in the study site.

3.7 Accuracy Assessment

Multi date dual polarization data of C - band is used for achieving classification accuracies of agricultural crops in Central State Farm, Hisar, Haryana. Accuracy validation of the classified crops and other features was based on the independent validation samples. The validation samples were easily identified and located within the study area from SAR images and ground survey for each class. In order to evaluate the classification results derived from different combinations of the SAR data, the overall classification accuracy and kappa statistics estimated from the confusion matrix using the validation samples [10] were selected. For further validation, these validation samples were visited during another period of field data collection. The performance of the Unsupervised classification was very poor because of this algorithm does not consists of training samples. The ANN consistently produced the lowest overall accuracies across the test sites. Given this constraint and the accuracies reported, an ANN approach would not be optimal for delivering operational inventories [6]. As the samples collected for this particular class are known to be mostly mixed pixels that encompass a substantial region in the feature space compared to the other features, many pixels were identified as fallow by the ML classification. The decision rule classifier scheme has been used to pick up the kharif crops area. The three date dual polarimetric data gave high accuracy for crops in Decision tree classification compared to the other classification methods. The main advantage of the DT classifier in this study is that it is simpler to formulate and one can compute it very efficiently. The overall accuracy for decision tree classification was achieved as 84% and kappa co efficient as 0.734 [14].

4. Conclusions

The multi - temporal SAR signature investigations of kharif crops using RISAT - 1 SAR (MRS) data gave a promising result for monitoring the Kharif crops, in addition to its conditions and growth. The method includes investigation of multi - temporal SAR signatures of crops and other land - cover classes for the Hissar district, Haryana, where a variety of crops growth conditions have been observed. During its growth period, the paddy crop has shown characteristic temporal performance and a large vibrant range of backscatter and it is useful for assessing temporal behavior of crop growth during its growth cycle. On the other hand, for this type of data, it is assessed that the unsupervised classification technique didn't perform well when compared to other classification techniques. The Decision tree algorithm is efficient tool for the multi temporal dual polarimetric SAR data classification due to its separation of classes by using expressions. Various classification algorithms were carried out to classify crops and other land cover features but particularly knowledge - based decision tree classifier was found to be optimum classifier for the SAR data, which has huge signature variability. When compared to other classification techniques, the overall accuracy was found to be more than 84% in the case of decision tree classification. The results indicate that RISAT - 1 SAR data can play a vital role in the crops areas assessment and monitoring where the accessibility of optical remote sensing data is very scarce due to continual cloud cover problems. The methodology developed in this current study can be used for other crops - growing areas. With the suitable acquired ground data, this will facilitate in better understanding the temporal backscatter performance of crop fields.

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