CHAPTER 4

ARTIFICIAL NEURAL NETWORK WITH DIFFERENT LEARNING PARAMETERS FOR CROP CLASSIFICATION USING MULTI-SENSOR SATELLITE DATA

4.1 INTRODUCTION

The present study offers significant information about the different crop existing in the area. Such information is vital for successful management and monitoring of diversity, crop productivity, disaster compensation and environmental monitoring. Despite of so many research articles published in the remote sensing, limited research has been conducted to examine LISS-IV and RISAT-1 imagery or to compare it with Landsat 8-OLI for the crop classification and mapping in Varanasi (Mishra et al., 2014; 2015). Several algorithms have been developed for the crop classification; however the higher classification accuracy algorithms need to be developed.

The popular ANN algorithm has been used for the crop classification because it has no prior assumptions about the statistics of data (Foody, 2004). The ANN algorithm has been used broadly for different applications such as crop classification and estimation of crop parameters (Kavzoglu and Mather, 2003; Prasad et al., 2012; Gupta et al., 2015). However, numerous studies have reported some problems during use of back propagation ANN for the classification of land use/cover features. The dimensionality variation of remotely sensed data as well as training and testing data-set may affect significantly the classification accuracy (Foody and Arora, 1997). The utility of temporal microwave data has been shown for crop classification and monitoring (Hoogeboom, 1983).

The objectives of this research work are (i) to classify various crops by changing learning parameters of ANN using LISS-IV and Landsat 8-OLI satellite data-sets and comparison of accuracy results and (ii) evaluation of dual polarimetric RISAT-1 data-set for the classification of crops and non-crop classes.

PART A

4.2 DESCRIPTION OF THE STUDY AREA

A part of Varanasi district of Uttar Pradesh, India was selected as the study area for the comparative study of different learning parameters based discrimination of different crop. The main crops were grown as wheat in Rabi and paddy in the Kharif seasons in Varanasi. The study area covers a total area of 260 km^2. The location maps of the study area are shown in Figure 4.1 (a) LISS-IV and (b) Landsat 8-OLI data-sets.

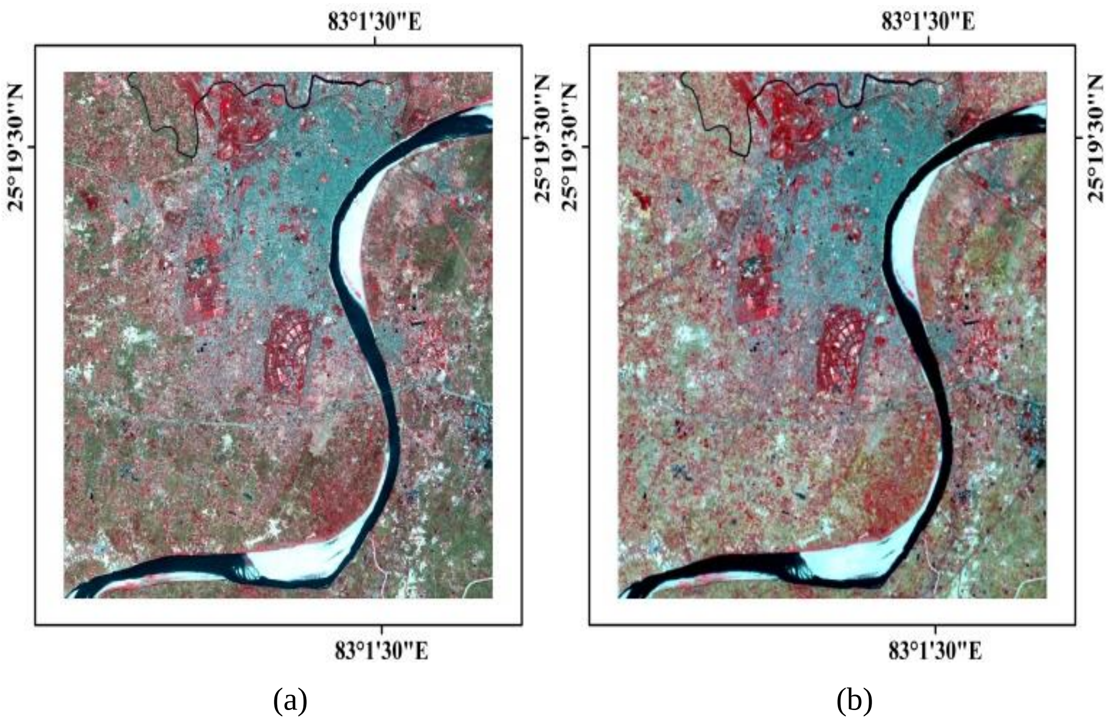

Figure 4.1 (a) Study area using LISS-IV data and (b) using Landsat 8-OLI data

4.3 MATERIALS AND METHODOLOGY

4.3.1 Ground reference data collection

The area which is to classify and asses the accuracy should be well known. The field wise ground reference information was collected in the BHU agriculture farm house as well as at few other well distributed sites within the study area with the help of

GPS. This ground truth data used as a reference data for the LISS-IV satellite image was taken on 6 April 2013 whereas Landsat 8-OLI data was acquired on 15 April 2013.

4.3.2 Remotely sensed data collection

The multispectral satellite data of LISS-IV with 5.8-m spatial resolution contain bands B2 (green, 0.52-0.59 µm), B3 (red, 0.62-0.68 µm) and B4 (NIR, 0.77-0.86 µm) acquired on 6 April 2013 and Landsat 8-OLI data of 15 April 2013 with spatial resolution of 30-m contains bands B1 (coastal aerosol, 0.43-0.45 µm), B2 (blue, 0.45-0.51 µm), B3(green, 0.53-0.59 µm), B4 (red, 0.64-0.67 µm), B5 (NIR, 0.85-0.88 µm), B6 (SWIR1, 1.57-1.65 µm), B7 (SWIR2, 2.11-2.29 µm), B8 (PAN, 0.50-0.68 µm), and B9 (cirrus, 1.36-1.38 µm) were evaluated for the classification of various crop and accuracy assessment using different learning parameters.

4.3.3 Image processing of remotely sensed data

Image pre-processing is very essential including geometric correction or image registration, atmospheric correction and radiometric correction. An accurate image registration or geometric correction of remotely sensed data is the prerequisite for different data source in a classification process. The RMSE values less than 1.0 pixel in the geometric correction indicates that the images are located with an accuracy of less than a pixel. Multi-sensor and multi-temporal data-sets require atmospheric and radiometric calibration. The image registration and layer stacking were performed using image processing software ENVI version 5.1. After layer stacking of bands, sub-setting was performed in order to get a portion of a large image file in to one smaller file as study area.

4.3.4 Creation of region of interest files

Two ROI files were generated one for the training of algorithm and other as testing data-set. Training and testing data-sets taken for the comparative study using LISS-IV and Landsat 8-OLI data-sets are given in Table 4.1.

Table 4.1 Training and testing data-sets used for the classification study by different satellite imagery

Class name	Training data	Testing data	Class name	Training data	Testing data
Barley	127	46	Sugarcane	91	31
Wheat	181	73	Other crops	142	54
Lentil	138	50	Water	132	45
Mustard	109	38	Sand	172	61
Pigeon pea	136	44	Built up	149	53
Linseed	146	53	Fallow land	139	44
Corn	93	32	Sparse vegetation	168	58
Pea	115	39	Dense vegetation	144	52

4.3.5 Image classification

The supervised algorithm is the most famous algorithm which needs prior knowledge of the study area. The process of prior knowledge is known as ground truthing (Lillesand and Kiefer, 1999). An ANN classification algorithm was used in this investigation.

4.3.5.1 Artificial neural network based classification

An ANN algorithm has a non-parametric nature. It is capable to simulate non-linear and complex patterns with an appropriate topological structure. The back propagation ANN usually comprises one input layer, one or two hidden layers and one output layer. The layers used in the ANN consisting of processing nodes which are fully interconnected to each other, except that there are no interconnections between nodes within the same layer (Kavzoglu and Mather, 2003 Atkinson and Tatnall, 1997). Neurons in the input layer representing one of the input features such as one satellite image band, whereas each neuron in the output layer corresponds to one of the classes (Srivastava et al., 2012). Hidden layers in the back propagation ANN are used for the computations, and the values associated with each node are estimated from the sum of the multiplications between input node values and weights of the links connected to that node (Kavzoglu and Mather, 2003).

In ANN, parameter such as learning rate decides the size of the steps taken in the search for the global minimum of the error function in the training process. The learning rate may be the key factor for ANN algorithm because it controls the speed and effectiveness of the learning process. One of the disadvantages of the backpropagation ANN learning algorithm is its slow convergence. If the value of learning rate is fixed too high then large steps will be taken, and the system will be unstable, oscillating, and failing to converge. If the learning rate is set too low, small steps will be taken, resulting in longer training times and a greater likelihood of the search becoming trapped in a local minimum or on a plateau area in the error surface. The momentum term applicable in the ANN uses the previous weight configuration to determine the direction of search for the global minimum of the error. So, it is necessary to choose appropriate values of learning rate and momentum for the smooth convergence to a global minimum (Kavzoglu and Mather, 2003).

4.4 RESULTS AND DISCUSSION

The images were classified into ten classes of various crop such as corn, linseed, lentil, mustard, barley, wheat, pigeon pea, pea, sugarcane and other crops and six non-crop such as fallow land, sparse vegetation, dense vegetation, sand, built up and water classes. To assess the classification accuracy, actual land cover types for all the fields were checked on the ground and compared with the pixels or polygons from classified maps developed from remotely sensed data (Congalton, 1991; Jensen, 2005). The *OA* was computed by dividing the total number of correctly classified pixels to the total number of reference pixels (Lillesand and Kiefer, 1999).

The variability in the growth of crop was clearly seen in the different fields under the study area. All the crops were in the growing condition during the filed data collection. In the crop classes, wheat crop was found to be dominant crop and corn was the minor crop cover type. The corn crop has been found to be minor crop because it was not the seasonal crop. This crop was grown at BHU agriculture farm house for research purpose and few other places in Varanasi. The most common means of expressing classification accuracy is the preparation of a classification error matrix at different learning parameters such as learning rate, momentum value, RMSE and different iterations.

The highest overall classification accuracy 88.09% was achieved using LISS-IV data which indicates that the probability of image pixel being correctly identified was approximately 88% in the map. The second highest overall accuracy was found 87.96% using configuration 0.01-0.99-0.01 at 8000 number of iterations. Changes in *OA* were noted for LISS-IV data, ranging from 73% to 89%. The results were found to be same for the configuration 0.003-0.99-0.003 using iterations 6000 and 11000. Same accuracy result was found for the configuration 0.01-0.99-0.01 and iteration value 6000 using LISS-IV data. A large accuracy difference was found in the configuration 0.003-0.99-0.003 using iterations 1000 and 11000. The overall good classification accuracies were found for the combination 0.01-0.99-0.01 except at iterations 2000. The overall similar classification results were found for all combinations using LISS-IV data except the combination 0.003-0.99-0.003 and 0.01-0.99-0.01. The overall classification accuracies produced by different learning parameters using LISS-IV data are presented in Figure 4.2.

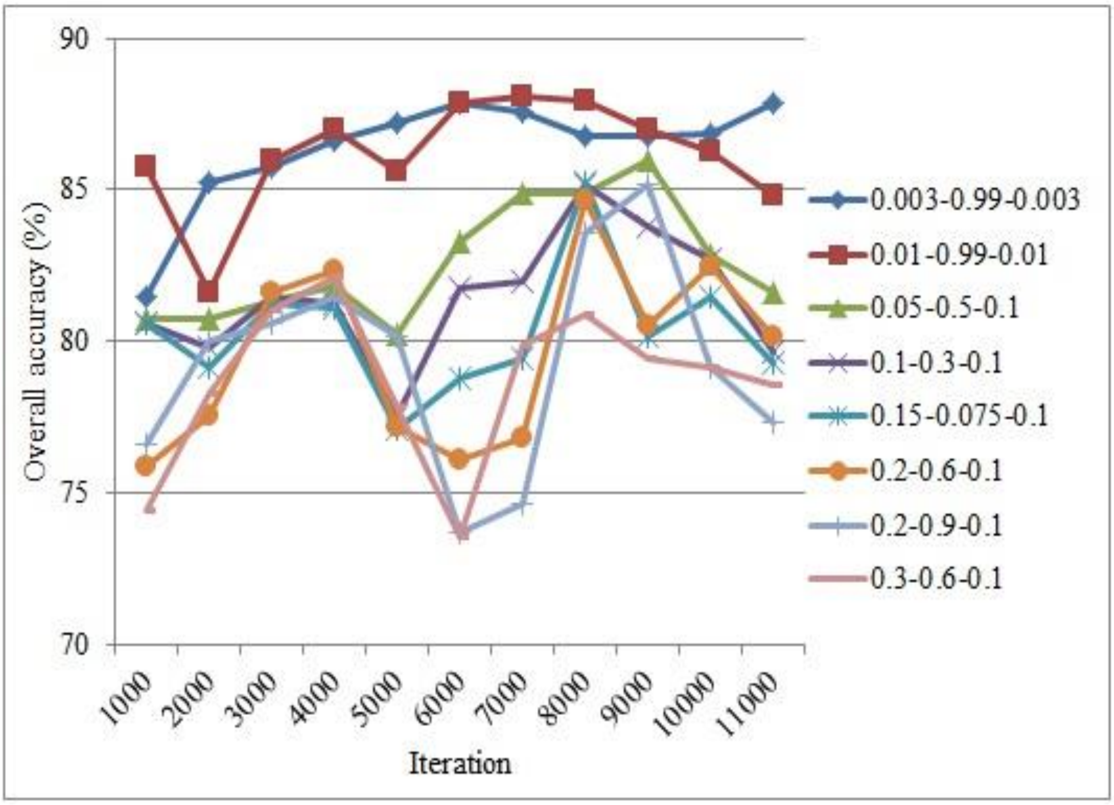

Figure 4.2 Overall classification accuracies produced for different configurations of the learning rate (first value), momentum term (second value) and RMSE (last value) using LISS-IV data

For the Landsat 8-OLI data, the highest classification accuracy of 87.49% was achieved for the iterations 10000 using combination 0.01-0.99-0.01. The second highest overall accuracy 87.08% was achieved with the 7000 iterations. The accuracy results 86.94% were found comparable for the iterations 8000 and 9000. Changes in *OA* were estimated for Landsat 8-OLI data, ranging from 71% to 88%. On increasing the number of input neurons in the input layer, the ANN network did not resulted an increase in accuracy; on the contrary, nearly similar or moreover less accuracy results were obtained using Landsat 8-OLI data. The overall classification accuracies produced for different learning parameters using Landsat 8-OLI data are presented in Figure 4.3.

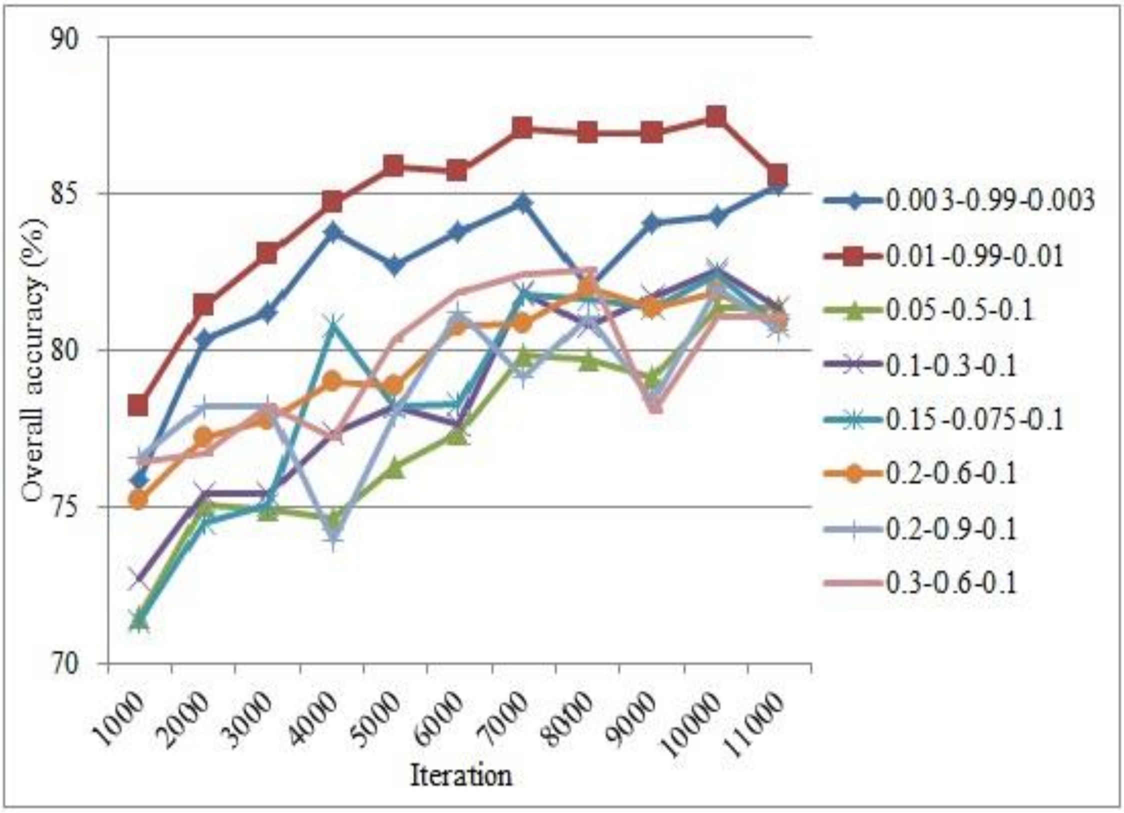

Figure 4.3 Overall classification accuracies produced for different configurations of the learning rate (first value), momentum term (second value) and RMSE (last value) using Landsat 8-OLI data.

From the work reported here, it was observed that a combination of 0.01-0.99-0.01 and 0.003-0.99-0.003 can lead to higher values of classification accuracies. Results in both the data-sets showed large fluctuations in classification accuracy using combination 0.15-0.075-0.1. The selection of low value of the momentum term may be the reason of low and fluctuations in the classification accuracy. Figure 4.2 showed highest classification accuracy of the network using leaning rate 0.01. However, high values of classification accuracy were also achieved using learning rate 0.003. The opposite behaviour was found using the learning rates of 0.2 and 0.3. Unlike the state shown in Figure 4.2, the overall accuracies were found more consistent produced for the Landsat 8-OLI data as shown in Figure 4.3. There was some constancy found in the performance using learning rates 0.003 and 0.01. Although, a combination of 0.05-0.5 and 0.1-0.3 initially performed well for LISS-IV data but it did not maintain this performance during the whole training process. These combinations didn't perform well using Landsat 8-OLI data for classification.

The heuristics proposed by Partridge and Yates (1996) and Ardo et al. (1997) using these combinations achieved good results seemed to fail here using these data-sets. Large values of the learning rate such as 0.2 and 0.3 resulted oscillations, producing large deviations in overall accuracy for a small increase in the number of iterations. Sometimes, these oscillations led the network to work well at certain stages. This showed that the high learning rate is problem dependent. However, generally positive effect of employing small learning rates should not be disregarded using ANN algorithm. The highest classification accuracies were achieved by the combinations having small learning rates of 0.003 and 0.01. Consistently good results were produced for both the data-sets by the combinations of 0.003-0.99-0.003 and 0.01-0.99-0.01. The performances were not found good for high learning rates. This outcome may be due to oscillations produced by using large values of learning rate. Further, the high values of the momentum term also increase the effect of oscillations by extending steps taken in the wrong direction. The addition of a momentum term considerably slows down the learning process. It is apparent from the Figures that low values of the learning rate produced consistent and accurate results, whereas high learning rates appeared to cause oscillations and inconsistent results in the classification.

4.5 CONCLUSION

The multispectral sensors were found very much useful for the classification of crop and its comparative study using cloud free images. The high spatial resolution of LISS-IV sensor made it easier to delineate boundaries among various crop fields. It also enabled improvement for crop discrimination by avoiding overlapping of land covers. Some difficulties were found in the delineation of crop boundaries using Landsat 8-OLI data due to medium resolution. However, Landsat 8-OLI data also showed good classification results. The overall high classification accuracy was achieved using LISS-IV data but this data didn't show the consistency in the classification accuracies except using learning rates 0.003 and 0.01. However, good overall consistency was shown in the classification accuracies using Landsat 8-OLI data excluding some results. The present study showed that the ANN classification algorithm had a significant potential for the classification and comparative studies using LISS-IV and Landsat 8-OLI data-sets at different learning parameters.

PART B

4.6 STUDY AREA AND DATA-SETS

The location map of the study area is shown in the Figure 4.4.

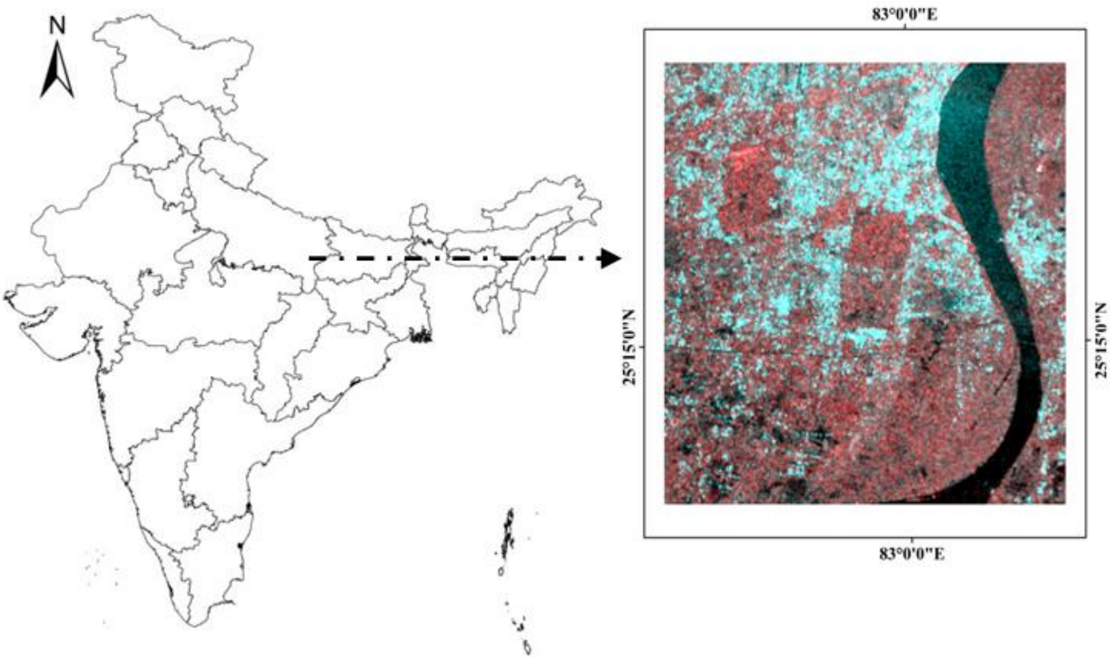

Figure 4.4 Location map of the study area using RISAT-1 data (Red-HV, Green-HH, Blue-HH)

The C-band dual polarimetric (HH, HV), temporal data of RISAT-1 satellite with medium resolution (MRS) mode were used for the classification. The level 1 (L1) products with spatial resolution of 25 m and incidence angle of 36.66° were acquired on 9 August and 28 September 2013.

4.7 METHODOLOGY

4.7.1 Image processing

HH and HV polarization data were imported and multilooking was done 2 times in azimuth and 2 times in range direction. Images were filtered with 5×5 window size using frost filter to remove the speckle noise. Sigma naught images were generated using calibration constant given in the metadata. The amount of information was increased by introducing HH polarization band with the original two polarizations (HH and HV) and layer stacking was done to get FCC images. After the generation of FCC, the ROI file was generated to train the ANN algorithm with 478 pixels. Before the classification of images, the separability was analysed. Another ROI file with the 159 pixels was generated for the ground validation.

4.7.2 Separability analysis

The separability analysis was performed using *TD* and *J-M* method to analyse the class separability between the classes before classification. It was calculated from means and covariance matrices of each class and its ranged from 0.0 to 2.0. A *TD* and *J-M* value greater than 1.9 indicates better separability between the classes. The values ranging from 1.0 to 1.9 and 0.0 to 1.0 indicate moderate and poor separability, respectively (Swain and Davis, 1978).

4.7.3 Artificial neural network based Classification

In the present study, the input layer contained 3 bands as a number of neurons. A single hidden layer contained 8 neurons. The output layer contained 6 neurons as crop classes used for the classification. The used ANN algorithm was a layered feed forward model in ENVI version 5.1 with SARscape module. It uses standard back propagation for supervised learning and minimizes RMSE between the actual output of a multilayer feed forward ANN and the desired output (Paola and Schowengerdt, 1995). Total, 1000 number of training iterations with RMSE 0.01 was taken.

4.8 RESULTS AND DISCUSSION

The crops such as rice, corn, pigeon pea, green gram, and some other crop grown in Kharif season in Varanasi district were classified. Rice crop was found to be the dominant crop in comparison to other crop grown in the study area. Water, built up, fallow land, sparse vegetation and dense vegetation classes were classified and merged in to non-crop class. The separability analysis done by *TD* method was found better in comparison to *J-M* method. The data acquired on 28 September 2013 showed better separability in comparison to the data acquired on 9 August 2013 by both the methods. The separability was found significant because the crops were in the growing stages. The *OA*, *PA* and *UA* were calculated using error matrix analysis (Congalton and Green 1999; Jensen, 2005).

The *OA* achieved by ANN were 74.21% and 77.36% using data of 9 August and 28 September 2013, respectively. The highest *PA* and *UA* were found for non-crop class due to less mixing of pigeon pea, corn, green gram and other crop classes and unique backscattering of water, fallow land and built up. In the crop classes, same *PA* and *UA* for rice crop indicate that the areas that were identified on the ground are found actually in the classification. The high accuracy of rice crop indicates that there was less mixing of pigeon pea, green gram and other crop classes. The detailed information about the classification accuracy is given in Table 4.2.

Table 4.2 Error matrix produced by ANN using RISAT-1 data-sets

	9 August 2013		28 September 2013	
Crop type	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)
Pigeon pea	71.43	75.00	76.19	76.19
Green gram	73.33	68.75	76.67	71.88
Rice	76.00	76.00	80.00	80.00
Corn	70.00	73.68	75.00	78.95
Other crop	67.67	69.70	70.59	72.73
Non-crop	86.21	83.33	86.21	86.21
OA	118/159 = 74.21%		123/159 = 77.36%	

In case of green gram and non-crop classes, less *UA* was found in comparison to *PA*. The overall less accuracy was found for the other crop class. The reason may be due to high mixing between green gram, rice and corn classes due to similar backscattering values. The mixing between the classes may be due to some intrafield variability and similar backscattering values between the classes.

4.9 CONCLUSION

The *OA*, *PA* and *UA* were increased for the data acquired on 28 September 2013 in comparison to the data acquired on 9 August 2013. This was due to the fact that crops were in the highly growing stage on 28 September 2013 which may cause to increase the better separation between the classes with the crop growth stages.