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IRS P6 LISS-IV Image Classification using Simple, Fuzzy Logic and Artificial Neural Network Techniques: A Comparison Study

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Abstract - Numerous efforts `have been made over the past years to develop automated procedures for preparation of land use maps from remotely sensed multispectral data. Despite best efforts, the situation is still one where there is a considerable gap between the needs and availability due to newer data with higher spectral and spatial resolution. In this study, we used both supervised and unsupervised technique to classify Indian Remote sensing (IRS P6) LISS IV satellite imagery of Jaipur city (13 October 2008) by multi model criteria to achieve comparative analysis of Simple, Fuzzy logic and ANN type of classification to identifying, their efficacy with regard to differences in spectral and spatial resolutions. The performance of different classification method was evaluated in terms of accuracy. It was found that LISS IV datasets can be classified up to level 3 of land use/land cover classes of NRSC. The results obtained by comparative analysis are in terms of accuracy and simple classification technique achieves 88 per cent accuracy, Fuzzy classification technique achieves 89.26 per cent accuracy, and Adaptive Neuro-Fuzzy Inference System technique achieves 95.04 per cent accuracy. It can be concluded that objects based approach of classification is better than pixel based classification to classify surface water bodies and Built Up and Roads. In Fuzzy Classification, beside accuracy is lower than ANN classification but separability of each class is better than other classification method. Further improvements need to be done to use a combination of classification techniques to develop automated procedures for preparation of land use maps from remotely sensed multispectral data.

Keywords - Artificial Neural Network, Classification, Fuzzy Logic, GIS, RS

1. INTRODUCTION

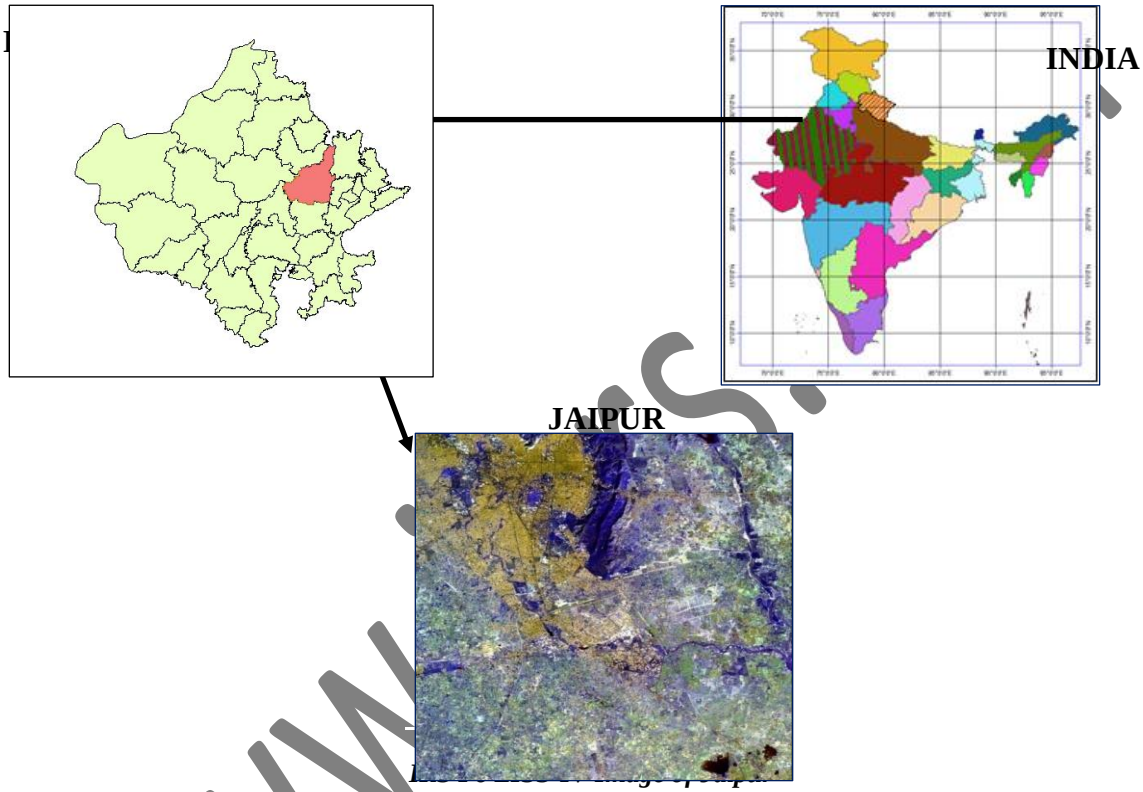
Several researches have been made over the past decades to develop automated procedures for preparation of land use maps from remotely sensed multispectral data. Despite best efforts, the situation is still one where there is a considerable gap between the needs and availability due to newer data with higher spectral and spatial resolution. Contemporary image analysis routines have had severe limitations when dealing with the information content of high resolution imagery. In order to effectively highlight the rich information present in image data, researchers are drifting from the usual pixel-based classification algorithms to object-oriented analysis systems. Remote-sensing research focusing on image classification is important because classification results are the basis for many environmental and socioeconomic applications. Classifying remotely sensed data into a thematic map is very challenging because of many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, and image processing and classification approaches, may affect the success of a classification. Many advanced classification approaches, such as artificial neural networks, fuzzy sets, and expert systems have been widely applied for image classification. Combination of different classification approaches is more helpful in the enhancement of classification accuracy.

Multispectral image classification is the process of sorting pixels into a finite number of individual classes or categories of data, based on their data file values. If a pixel satisfies a certain set of criteria, the pixel is assigned to the class that corresponds to those criteria. This process is also referred to as image segmentation. The major steps of image classification may include determination of a suitable classification system, selection of training samples, image preprocessing, and feature extraction, selection of suitable classification approaches, post-classification processing, and accuracy assessment. The two main techniques for image classification are supervised and unsupervised classification techniques. Unsupervised classification technique, classifies the image automatically by finding the clusters based on certain criterion. On the other hand in supervised classification technique the location and the identity of some cover type, for example urban, forest, and water are known before. The data is collected by a field work, maps, and personal experience. The analyst tries to locate these areas on the remotely sensed data.

These areas are known as “training sites”. An analyst can guide a classifier with the help of these training sites to learn the relationship between the data and the classes. This manual technique of selecting training sets could be difficult when ground truth is not available.

2. STUDY AREA

The Jaipur district of Rajasthan state in India is chosen as the study area in this work as shown in Fig.1. The study area is situated in the eastern part of Rajsthan and lies between 26°42'N to 26°55'5"N latitude, 72°43' E to 75°56'4" E longitude and at 432 meters above the sea level. The total area covered 528 square kilometers. Jaipur city also popularly known as the 'Pink City’ and is the capital city of the Indian state Rajasthan.



City, Rajasthan (*13 October 2008*)

Fig. 2.1 Location of Study Area

3. LITERATURE REVIEW

Many studies have been done on the satellite image classification. Ashwini T. Sapkal et al. 2006 [16] have implemented two different algorithms namely K-means algorithm and back propagation algorithm of ANN for segmentation and classification of satellite images. They have used wide database of images to test both the algorithms. Madhubala, M. et al., 2010 [9] have done pixel based classification of LISS-III satellite image into different classes. They classify each pixel of the satellite image into three belonging classes, using a neural network back propagation technique. In this study the error between desired output and actual output is also calculated by obtaining error matrix.

Soo Beom Park, Jae Won Lee, Sang Kyoon Kim [4] used neural network for content-based image classification. In this study, they propose a method of content-based image classification using a neural network. The images for classification are object images into foreground and background. To deal with the object images efficiently, in the preprocessing step they extract the object region using a region segmentation technique. Features for the classification are shape-based texture features extracted from wavelet-transformed images. The neural network classifier is constructed for the features using the back-propagation learning algorithm. Among the various texture

features, the diagonal moment was the most effective. A test with 300 training data and 300 test data composed of 10 images from each of 30 classes show classification rates of 81.7 per cent and 76.7 per cent correct, respectively.

Alexsandro Machado Jacob at el. [3] has done the SAR Image Classification using Supervised Neural Classifiers. In this study he investigate about four supervised neural classifiers based on the Minkovski-r error and the modified Fisher criterion is evaluated to classify a double textured SAR amplitude image. Regions around pre-classified pixels are presented to train the neural network that learns a sub-optimal set of masks via back propagation algorithm. Classification performance is evaluated using kappa statistics. The neural classifiers showed almost the same performance for different window mask sizes and training samples. However, the Minkovski-r=1. 1 error showed a slightly better performance than the others, and best results are obtained when the neural classified image is followed by an erosion process via Median filter. The results outperformed the classification performance of two statistical classifiers: the Minimum Bayes error and the Kullback-Liebler distance.

There is another study of Samy Sadek, Ayoub Al-Hamadi, Bernd Michaelis, Usama Sayed, [5]. They proposed a new supervised method for color image classification based on multi-level sigmoidal neural networks (MSNN) model. In this method, images are classified into five categories, i.e., “Car”, “Building”, “Mountain”, “Farm” and “Coast”. This classification is performed without any segmentation processes. To verify the learning capabilities of the proposed method, they compare the MSNN model with the traditional Sigmoidal Neural Network (SNN) model. Results of comparison have shown that the MSNN model performs better than the traditional SNN model in the context of training run time and classification rate. Both color moments and multi-level wavelets decomposition technique are used to extract features from images. They also tested the proposed method on a variety of real and synthetic images.

Many advanced image classification approaches, such as artificial neural networks, fuzzy sets, and expert systems have been widely applied for image classification. Combination of different classification approaches is more helpful in the enhancement of classification accuracy. In this study we have used four techniques for the IRS P6 LISS-IV Image classification of Jaipur City, Rajasthan state of India and also evaluate the comparative performance of all the techniques in terms of accuracy.

4. METHODOLOGY

The complete method of classification using all the techniques is shown in the form of flow chart and also in detailed heads.

4.1 FLOW CHART

The basic theme of this study is analyzing Comparative analysis of Unsupervised, Supervised, Fuzzy logic and Artificial neural network Classification. The overall process of this study can be summarized as flow diagrams which are depicted below in Fig. 4.1

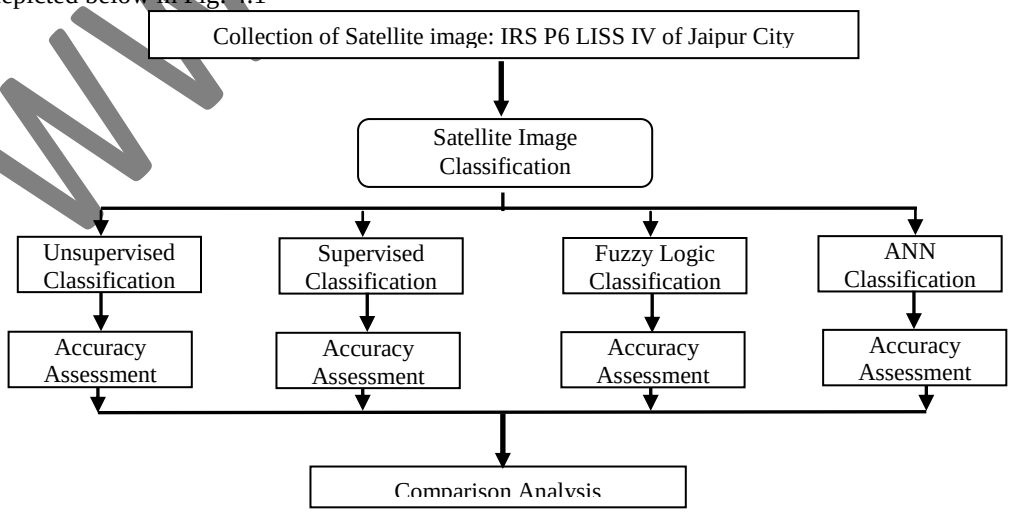


Fig. 4.1 Flow Chart of overall Process

4.2 IMAGE CLASSIFICATION

Image classification refers to the extraction of different classes or themes, usually land cover and land-use categories, from raw remotely sensed digital satellite data. The information contained in a remotely sensed image which can be used to conduct image classification includes spectral pattern, spatial pattern and temporal pattern. For this study four standard methods of image classification were used:

- Unsupervised Classification
- Supervised Classification
- Fuzzy Logic Based Classification
- Neural Network Classification

Land cover classes of the study area were mainly defined in accordance with the Manual of National Land Use Land Cover Mapping Using Multi-Temporal Satellite Data (NRSA 2006). The land use/land cover classification has been proposed with multi-level hierarchic configuration, with each higher level containing information of increasing specificity. In the first level, general land cover types are built up land, agriculture land, forest, natural/semi natural grassland, grazing land, waste land, wetland, water bodies, snow cover/glacial area. In the second level each class is divided into subclasses, for instance water bodies are subdivided into rivers, canals, lakes, reservoirs, streams, etc. In the third level the land covers are further divided into more detailed classes, e.g. streams are divided into perennial, dry, etc. Table 1 depicts the level of classes used for land cover classification of the study area. Classes of land use/land cover sought in this study were mainly those of the First level, but in some cases the third level was also mapped.

Table 4.1 Levels of land cover classes used for classification of the study area

No.	First Level	Second Level	Third Level
1.	Built up land	Residential	
		Industrial	
2.	Agriculture land	Cropland	
		Fallow land	
3.	Forest	Evergreen	Dense
			Open
4.	Forest	River	Dry/Perennial
			Water

4.2.1 UNSUPERVISED CLASSIFICATION

Unsupervised Classification does not utilize training data as the basis for classification. Rather, this family of classifiers involves algorithms that examine the unknown pixel in an image and aggregate them into a number of classes based on the natural groupings or cluster present in the image value. It perform very well in case where the values within a given cover type are close together in the measurement space, data in different classes are comparatively well separated. This classification technique we have performed in ERDAS Imagine software.

Unsupervised classifiers do not consider training data as the basis for classification. These classifiers examine the unknown pixels in an image and aggregate them into a number of classes based on the natural groupings or clusters present in the image values. The “K-means” approach accepts the number of clusters to be located in the data, from the analyst. The algorithm then arbitrarily locates number of cluster centers in the multidimensional measurement space. Each pixel in the image is next assigned to the cluster whose arbitrary mean vector is closest. After all pixels have been classified in this manner, revised mean vectors for each of the clusters are computed. The revised means are used as the basis to reclassify the image data. The procedure continues until there is no significant change in the location of class mean vectors between successive iterations of the algorithm. When this point is reached, the analyst determines spectral signatures identity of each spectral class. The results of separability analysis for LISS IV data are shown in Table 2.

Table 4.2 Separability analysis of LISS IV image of the study area

Distance measure: Transformed Divergence Using layers: 1 2 3 Taken 3 at a time Best Average Separability: 1911 Combination: 1 2 3								
Signature Name	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Open Land	0	1272	1879	2000	1808	2000	1996	2000
Sandy Area	1272	0	2000	1997	2000	2000	2000	1999
Shadow	1879	2000	0	2000	2000	1857	2000	1994
Crop Land	2000	1997	2000	0	1732	2000	1958	2000
Road	1808	2000	2000	1732	0	2000	1660	2000
Water Bodies	2000	2000	1857	2000	2000	0	2000	2000
Built Up	1996	2000	2000	1999	1958	2000	0	2000
Open Forest	2000	1999	1994	2000	2000	1665	2000	0

Maximum Likelihood Classifier: For classifying a pixel, the MLC classifier quantitatively evaluates the variance and covariance of the spectral response of an identified class. A Gaussian distribution is assumed for the cloud of points constituting the data representing a particular training set (Lillesand and Kiefer 1999). A suitable classification system and sufficient number of training samples are prerequisites for a meaningful classification (Hubert-Moy *et al*. 2001, Chen and Stow 2002, Landgrebe 2003, Mather 2004). Most image processing applications provide the per-pixel based classification option. All pixel-based classification methods assign a pixel to a class according to the spectral similarities across the set of bands indicated by the user. Class separability using transformed divergence and feature space analysis was performed on the LISS IV datasets (Tables 4). In transformed divergence a value of 2000 indicates 100% separability. Decreasing values indicate correspondingly lesser separability. The results of separability analysis for LISS IV data are shown in Table 3.

Table 4.3 Separability analysis of LISS IV image of the study area

Distance measure: Transformed Divergence Using layers: 1 2 3 Taken 3 at a time Best Average Separability: 1983 Combination: 1 2 3								
Signature Name	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Open Land	0	2000	2000	2000	2000	2000	2000	2000
Sandy Area	2000	0	2000	1932	2000	2000	2000	1997
Shadow	2000	2000	0	2000	2000	1958	2000	1994
Crop Land	2000	2000	2000	0	1993	2000	1999	2000
Road	2000	2000	2000	1993	0	2000	1660	2000
Water Bodies	2000	2000	1958	2000	2000	0	2000	2000
Built Up	2000	2000	2000	1999	1660	2000	0	2000
Open Forest	2000	1997	1994	2000	2000	2000	2000	0

4.2.2 SUPERVISED CLASSIFICATION

Supervised classification refers to a class of methods used in the quantitative analysis of remote sensing image data. These methods require that the user provide the set of cover types in the image e.g., water, Built Up, deciduous forest, etc. as well as a training field for each cover type. The training field typically corresponds to an area in the image that contains the cover type, and the collection of all training fields is known as the training set or ground-truth data. The ground-truth data is then used to assign each pixel to its most probable cover type. The quality of a supervised classification depends on the quality of the training sites. All the supervised classifications usually have a sequence of operations that must be followed. 1. Defining of the Training Sites. 2. Extraction of Signatures. 3. Classification of the Image. The training sites are done with digitized features. Usually two or three training sites are selected. The more training site is selected; the better results can be gained. This procedure assures both the accuracy of classification and the true interpretation of the results. After the training site areas are digitized then the statistical characterizations of the information are created. These are called signatures. Finally the classification methods are applied. In this study this classification techniques we have performed in ERDAS Imagine software.

4.2.3 FUZZY LOGIC CLASSIFICATION

Over the past few decades, *fuzzy logic* has been used in a wide range of problem domains. Although the fuzzy logic is relatively young theory, the areas of applications are very wide: process control, management and decision making, operations research, economies and most important, pattern recognition and classification. Dealing with simple' black' and 'white' answers is no longer satisfactory enough; a *degree of membership* (suggested by Prof. Zadeh in 1965) became a new way of solving the problems. A *fuzzy set* is a set whose elements have degrees of membership. An element of a fuzzy set can be full member (100% membership) or a partial member (between 0% and 100% membership). That is, the membership value assigned to an element is no longer restricted to just two values, but can be 0, 1 or any value in-between. Mathematical function which defines the degree of an element's membership in a fuzzy set is called *membership function*. The natural description of problems, in *linguistic* terms, rather than in terms of relationships between precise numerical values is the major advantage of this theory. In this study we have used Sugeno model and trained by Adaptive Neuro Fuzzy Inference System (ANFIS) technique based fuzzy logic and done in MATLAB software.

ANFIS Model: Adaptive Neuro-Fuzzy Inference Sys-tem (ANFIS) is one of the most successful hybrid modeling technique which combines the adaptive learning capability of Artificial Neural Network (ANN) along with the intuitive Fuzzy logic (FL) into a single capsule. For a given input/output dataset, the ANFIS generates the fuzzy inference system (FIS) using grid partition technique and membership functions parameters are adjusted (tuned) automatically until reach the optimal solution using either a back propagation algorithm or in combination with least squares type method (hybrid learning method). We use the adaptive Neuro-fuzzy inference system (ANFIS) which use the back propagation algorithm to create rules and adjust membership function parameters to fit the training data. The membership functions used in ANFIS are Gaussian functions for inputs and constant functions for output. We train our ANFIS under 100 epochs.

Fuzzy logic Toolbox is a compilation of functions built on the MATLAB® numeric computing environment and provides tools for creating and editing *fuzzy inference systems* within the framework of MATLAB. Depending on the types of fuzzy reasoning and "if- then" rules, Sugeno's fuzzy model, the output of each rule is a linear combination of input variables plus a constant term or purely constant, because membership function of output variable are only linear or constant type and the final output is the weighted average of each rule's output. In our case we chose the Gaussian membership function for the output variable. The ANFIS is like a fuzzy inference systems, except that here by using a learning algorithm (either a back propagation alone or in combination with a least squares estimation) the parameters of input and output membership function of a fuzzy inference system constructed by ANFIS, have been tuned (adjusted) automatically based on the training data until reach the optimal solution.

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The process of fuzzy inference involves: *membership functions*, *fuzzy logic operators* and *if-then rules.* Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant. This fuzzy inference system was introduced in 1985 and also is called Takagi-Sugeno-Kang. Sugeno

output membership functions (z, in the following equation) are either linear or constant. A typical rule in a Sugeno fuzzy model has the following form:

IF Input 1 = x AND Input 2 = y, THEN Output is z = ax + by + c

For a zero-order Sugeno model, the output level *z* is a constant *(a=b =0).In this project we use Sugeno-type Fuzzy inference system.*

4.2.4 ARTIFICIAL NEURAL NETWORK (ANN) CLASSIFICATION

Artificial Neural Network is a parallel distributed processor that has a tendency for storing experimental knowledge. Satellite image classification using neural networks is done by texture feature extraction and then applying the back propagation algorithm. These networks usually organize their units into several layers. The first layer is called the input layer, the last one is the output layer. The intermediate layers are called the hidden layers. The information to be analyzed is fed to the neurons of the first layer and then propagated to the next layer and so on until the last layer. Each unit receives some information from other units and processes this information, which will be converted into the output of the unit. The goal of the network is to learn or to discover some association between input and output patterns, or to analyze, or to find the structure of the input patterns. The learning process is achieved through the modification of the connection weights between units.

4.3 SOFTWARE USED

In this whole study we used four softwares for the classification of different features of satellite data

- ERDAS Imagine 10
- MATLAB
- ENVI 4.7
- ArcGIS 10

4.4 DATA PREPARATION

IRS-P6 LISS-IV (RESOURCESAT) is a high resolution optical sensor which covers comparatively narrow region of Electromagnetic radiation which starts from the visible and ends up-to near infrared by 3 spectral bands. All three bands of the IRS – P6 LISS-IV image in the Visible Infrared region have a spatial resolution of 5.8 m (~6 m). In this project, we have made use of land cover images obtained from remote sensing for experimentation. The IRS-P6 LISS-IV (Indian Remote Sensing – Linear Imaging Self-Scanning Sensor IV) multispectral sensor operating in bands Visible and NIR with a swath of 23.9 km (multispectral mode). The dataset consists of 4993 x 5290 pixels and covers Jaipur, Rajasthan. The advantage of using this dataset is the availability of the referenced image produced from field survey, which is used for the accuracy purpose in this research.

Selection of training dataset: Training data extraction is a critical step in a supervised image classification process. As the success of a classification highly depends on the quality of the training data, these must be selected from the regions representative of the land cover classes under investigation. Data should thus be collected from relatively homogeneous areas consisting of those classes. The collection of training data is generally a time consuming and tedious process, as it involves strenuous field surveys and accumulation of reference data from various sources. Therefore, the size of the training data set is kept small. Nevertheless, the number of pixels constituting the training data set must be large enough to accurately characterize the land cover classes. As a rule of thumb, the number of training pixels for each class may be kept as 30 times the number of bands under consideration (Mather, 1999).

The number of training samples for each class was chosen in proportion to the area covered by the respective classes on the ground. First, the image was visually interpreted on screen based on the characteristics and the previous knowledge of the study area to delineate eight land cover classes. Wherever there appeared to be confusion in identifying the classes, these were verified in the field. The image derived land cover information was used to demarcate training areas on LISS IV image. The quality of training areas, thus identified, was evaluated through histogram plots. Majority of training areas were normally distributed having single peak.

4.5 ACCURACY ASSESSMENT

Once a satellite image has been classified, the accuracy is computed by comparing it with desired output, which is produced manually. To determine the accuracy of classification, a sample of testing pixels is selected on the classified image and their class identity is compared with the reference data (ground truth). The choice of a suitable sampling scheme and the determination of an appropriate sample size for testing data play a key role in the assessment of classification accuracy (Arora and Agarwal, 2002).The pixels of agreement and disagreement are generally compiled in the form of an error matrix. It is a *c* x *c* matrix (*c* is the number of classes), the elements of which indicate the number of pixels in the testing data. The columns of the matrix depict the number of pixels per class for the reference data, and the rows show the number of pixels per class for the classified image. From this error matrix, a number of accuracy measures such as *overall accuracy, user's* and *producer's accuracy*, may be determined (Congalton, 1991).

Overall accuracy is computed by dividing the total number of correctly classified pixels (the sum of the elements along the main diagonal) by the total number of reference pixels. The overall accuracy is calculated from the correct number of agriculture, urban and water body pixels present in the actual output. The output class of the pixel (i, j) in the actual output is compared with its class in the desired output. If both match, then that pixel (i, j) is correctly classified. This is used to obtain the correct number of agriculture, urban and water body pixels. Once they are known, their sum is divided by the total number of pixels, to obtain the accuracy.

5. RESULTS AND DISCUSSION

5.1 UNSUPERVISED CLASSIFICATION

IRS-P6 LISS IV dataset are classified using K-Means algorithms of Unsupervised Classification in ERDAS imagine. The "K-means" approach accepts the number of clusters to be located in the data, from the analyst. The algorithm then arbitrarily locates number of cluster centers in the multidimensional measurement space. Each pixel in the image is next assigned to the cluster whose arbitrary mean vector is closest. After all pixels have been classified in this manner, revised mean vectors for each of the clusters are computed. Fig. 3 shows classified image of LISS-IV (13 October 2008) of Jaipur district by K-Means algorithm.

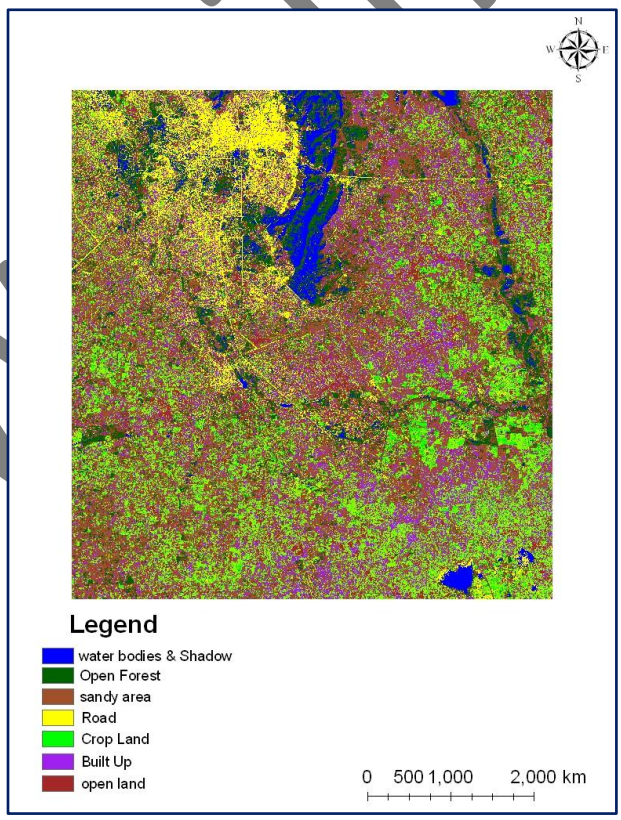


Fig. 5.1 Classified images of LISS IV by Unsupervised Classification

Accuracy assessment: For IRS-P6 LISS IV dataset stratified random sampling methods were used for assessment of the accuracy. This result indicates that built up and roads shows very less separability. In this dataset Shadow and Water Bodies also show less separability. Other Classes are fully distinguishable in this dataset. The overall classification accuracy was 88.00 per cent and kappa coefficient is 0.83.

5.2 SUPERVISED CLASSIFICATION

For Supervised Classification of IRS-P6 LISS IV dataset Maximum Likelihood Classifier are used. For classifying a pixel, the MLC classifier quantitatively evaluates the variance and covariance of the spectral response of an identified class. A Gaussian distribution is assumed for the cloud of points constituting the data representing a particular training set (Lillesand and Kiefer 1999).This classifier is based on the decision rule that the pixels of unknown class membership are allocated to those classes with which they have the highest likelihood of membership (Foody*et al*., 1992).

Classified image of LISS-IV (13 October 2008) of Jaipur district by MLC algorithm and corresponding area covered by a particular class are shown in Fig. 4.

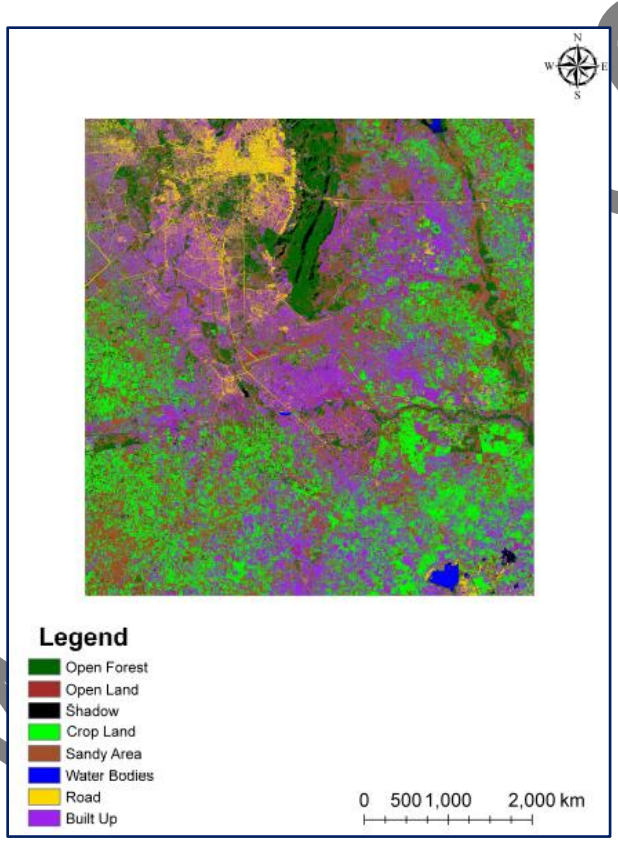


Fig. 5.2 Classified images of LISS IV by Supervised Classification

Accuracy assessment of ML: For LISS IV dataset stratified random sampling methods also were used for assessment of the accuracy. This result indicates that built up and roads shows very less separability. In this dataset Shadow and Water Bodies show more separability then unsupervised Classification. Other Classes are fully distinguishable in this dataset. The overall classification accuracy was 88.00 per cent and kappa coefficient is 0.83.

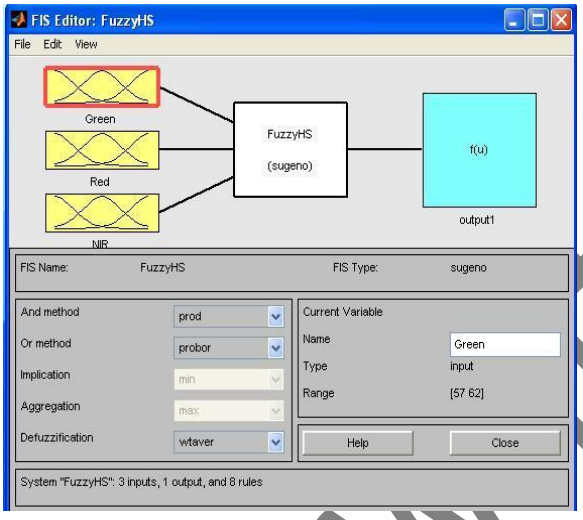
5.3 FUZZY LOGIC CLASSIFICATION

Creation of the membership functions for the output variables is done in the similar manner. Since this is Sugeno-type inference (precisely, zero-order Sugeno), *constant* type of output variable fits the best to the given set of outputs (land classes). When the variables have been named and the membership functions have appropriate shapes and names, everything is ready for writing down the rules. Based on the descriptions of the input (green, red and

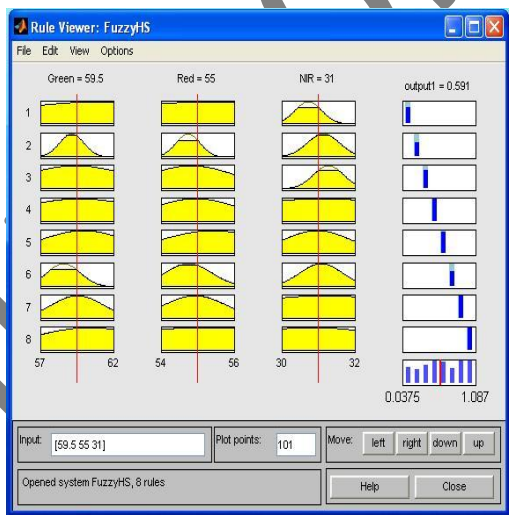
NIR channels) and output variables (water, Open Land, Open Forest, Built Up, Roads, Sandy Area, Shadow, crop Land), the rule statements can be constructed in the *Rule Editor*. Fuzzy Rules for image classification procedure in verbose format are as follows:

IF (**GREEN** is *mf1*) AND (**RED** is *mf1*) AND (**NIR** is *mf1*) THEN (Class is **Open Forest**)
IF (**GREEN** is *mf2*) AND (**RED** is *mf2*) AND (**NIR** is *mf2*) THEN (Class is **Open Land**)
IF (**GREEN** is *mf3*) AND (**RED** is *mf3*) AND (**NIR** is *mf3*) THEN (Class is **Shadow**)
IF (**GREEN** is *mf4*) AND (**RED** is *mf4*) AND (**NIR** is *mf4*) THEN (Class is **Crop Land**)
IF (**GREEN** is *mf5*) AND (**RED** is *mf5*) AND (**NIR** is *mf5*) THEN (Class is **Sandy Area**)
IF (**GREEN** is *mf6*) AND (**RED** is *mf6*) AND (**NIR** is *mf6*) THEN (Class is **Water Bodies**)
IF (**GREEN** is *mf7*) AND (**RED** is *mf7*) AND (**NIR** is *mf7*) THEN (Class is **Road**)
IF (**GREEN** is *mf8*) AND (**RED** is *mf8*) AND (**NIR** is *mf8*) THEN (Class is **Built Up**)

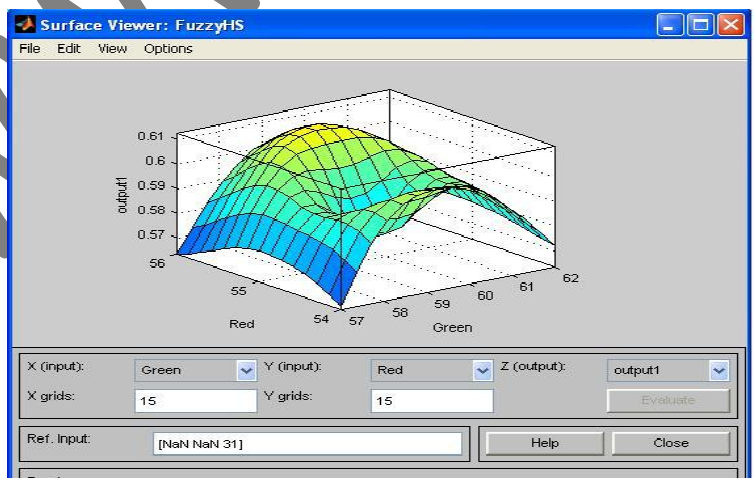
A simple diagram with the names of each input variable (green, red and NIR channel) and those of each output variable (water Bodies, Open Land, Open Forest, Built Up, Roads, Sandy Area, Shadow, Crop Land) as shown in Fig. 5. The *Membership Function Editor* is used to display the model and edit all membership functions associated with all of the input and output variables for the entire fuzzy inference system Fig. 5(a), the fuzzy rule viewer is shown in Fig. 5(b) and surface viewer in Fig. 5(c) .



(a)



(b)



(c)

Fig. 5.3 (a) Adjustment of MF in FIS editor (b) FIS Rule Viewer (c) 3D surface of Output

The fuzzy logic based classified image with different classes is shown in the Fig. 5.4

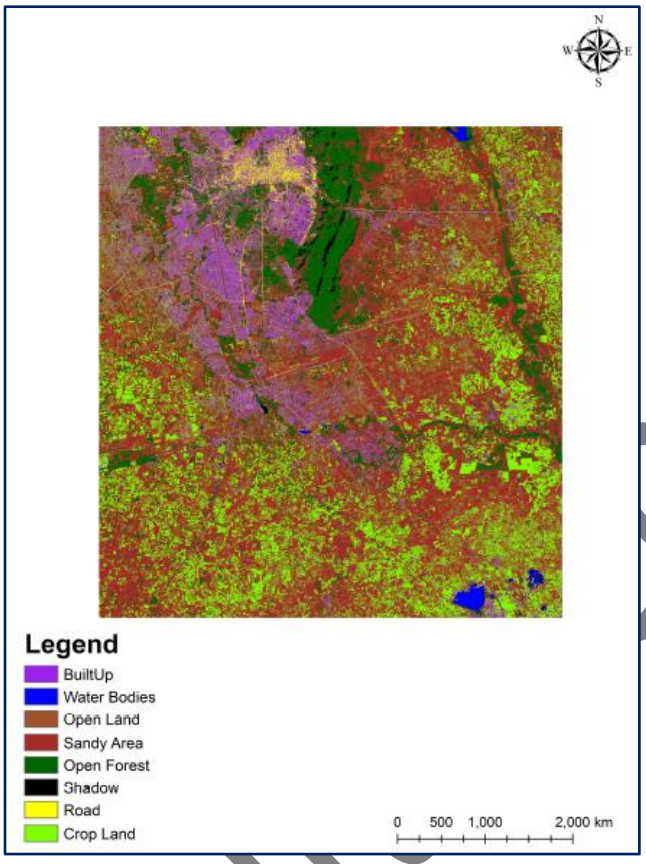


Fig. 5.4 Classified images of LISS IV by Fuzzy Classification

The statistical parameters (mean and standard deviation) of training dataset are shown in the Table 4.

Table 5.1 Mean and standard deviation values of training areas

Channel	Mean	St. Deviation
Open Forest		
Green*(mf1)*	41.80	1.91
Red*(mf1)*	37.65	2.76
NIR*(mf1)*	48.22	3.09
Open Land		
Green*(mf2)*	94.17	5.36
Red*(mf2)*	120.06	5.79
NIR*(mf2)*	59.70	2.20
Shadow		
Green*(mf3)*	36.83	1.19
Red*(mf3)*	31.97	1.42
NIR*(mf3)*	26.77	1.86
Crop Land		
Green*(mf4)*	53.90	2.41
Red*(mf4)*	68.70	4.25
NIR*(mf4)*	39.12	2.67
Sandy Area		
Green*(mf5)*	48.41	1.41

Red*(mf5)*	53.36	2.35
NIR*(mf5)*	41.45	1.39
Water Bodies		
Green*(mf6)*	42.50	1.27
Red*(mf6)*	33.92	1.36
NIR*(mf6)*	21.71	1.44
Road		
Green*(mf7)*	56.78	2.50
Red*(mf7)*	63.57	3.13
NIR*(mf7)*	34.18	2.53
Built Up		
Green*(mf8)*	55.37	3.53
Red*(mf8)*	60.39	3.91
NIR*(mf8)*	30.83	2.34

Accuracy assessment: Accuracy assessment of object-oriented classification For IRS-P6 LISS IV dataset stratified random sampling methods were used for assessment of the accuracy by the arbitrary Random Point Generation in ERDAS. In LISS IV error matrix; classes have a good separability without any overlap. Roads and built up are well separated. The overall accuracy achieved by object-oriented classification is 89.26 per cent and kappa is 0.86.

5.4 ANN CLASSIFICATION

The Neural Net technique for image classification in ENVI software uses standard back propagation for supervised learning as shown in Fig.7. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back propagated through the network and weight adjustment is made using a recursive method.

A multi-layered feed-forward ANN is used to perform a non-linear classification. This model consists of one input layer, at least one hidden layer and one output layer and uses standard back propagation for supervised learning. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back propagated through the network and weight adjustment is made using a recursive method.

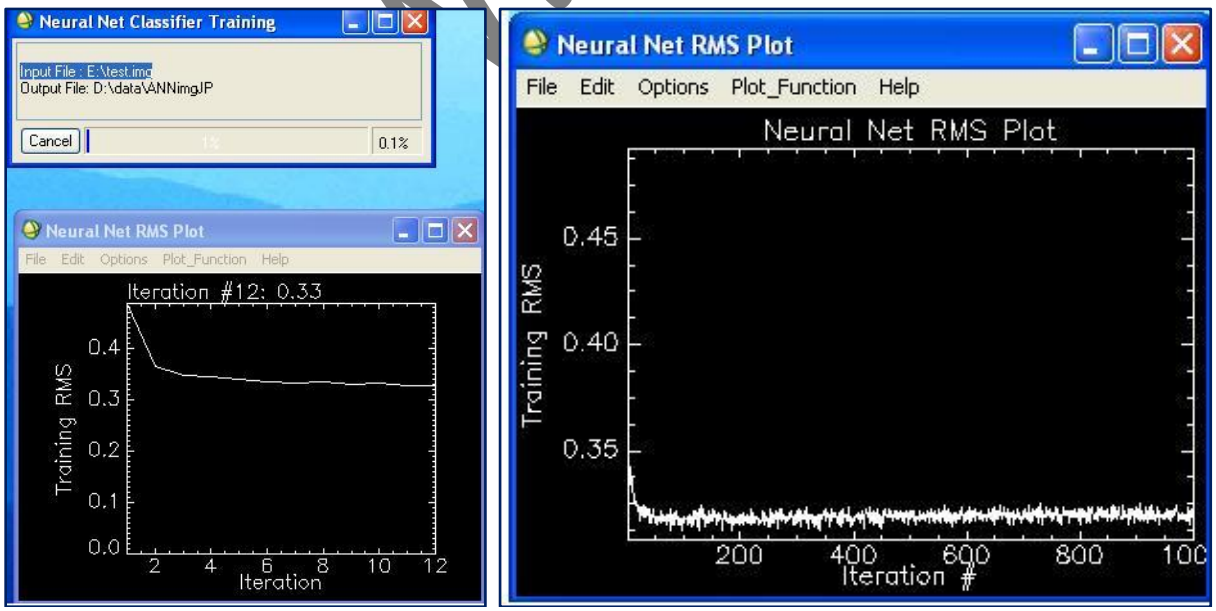


Fig. 5.5 Neural Network Classifier in ENVI software

The supervised classification of LISS-IV dataset is carried out after creating training sites, and the task was performed and the classification was carried out using neural network classification method. The classified image of respective classifier and as well as area covered by individual class are shown as in Fig. 8.

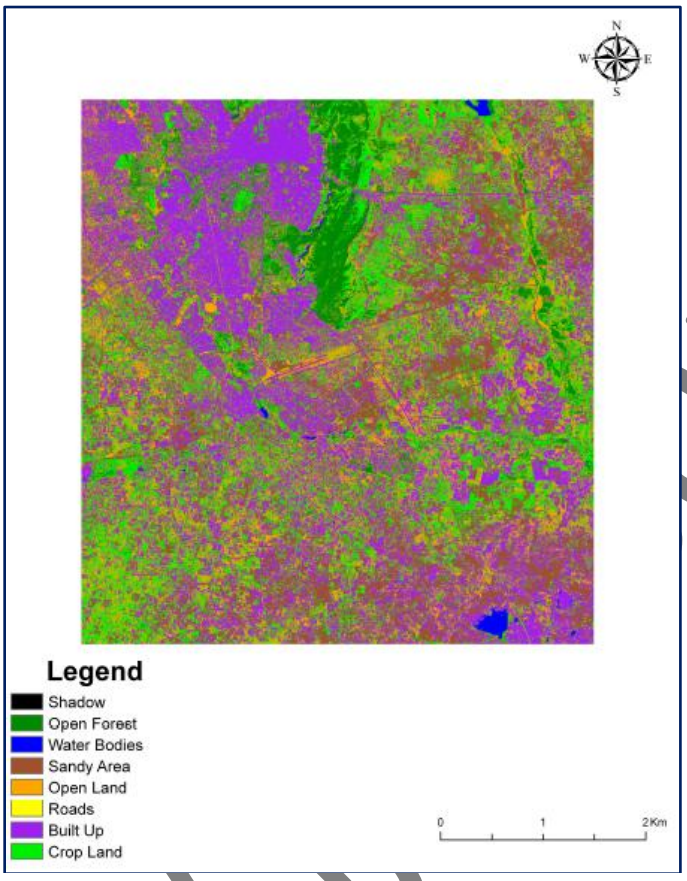


Fig. 5.6 Classified images of LISS IV by ANN Classification

Accuracy assessment: Accuracy assessment of Neural Network Classification assessed using confusion matrix which are calculated by generate random sample using Ground Truth ROI in Post Classification of ENVI. In LISS IV confusion matrix; classes have a good separability without any overlap. The overall accuracy achieved by Neural Network Classification is 95.04 per cent and kappa is 0.93.

5.5. COMPARISON OF ACCURACIES

The overall accuracy and kappa coefficient obtained by various methods are given in Table 5. The comparison of accuracy achieved with different approaches reveals that object-oriented and Neural Network classification methods provide better results as compared to Unsupervised Classification and MLC.

Table 5.2 Overall accuracies (OA) & Kappa (K) achieved through various classification methods.

Dataset	Unsupervised Classification	MLC Approach	Fuzzy Logic Classification	Neural Network Classification
LISS IV (OA)	66.00%	88.00%	89.26%	95.046%
LISS IV (K)	0.62	0.83	0.86	0.93

6. CONCLUSIONS

Image classification methods and their efficacy with regard to differences in spectral and spatial resolutions have been analyzed through the present study. The datasets comprised LISS IV data of IRS satellites pertaining to the Jaipur area of Rajasthan. Identification of land use/land cover classes up to second and third levels has been attempted by different classification approaches – pixel based(Unsupervised and ML Classification), object based(Fuzzy Logic Classification) and Artificial Neural Network Classification. The performance of different classification method was evaluated in terms of accuracy. It was found that LISS IV datasets can be classified up to level 3 of land use/land cover classes of NRSC. Increasing the level of classification degrades the accuracy of classification. Accuracy assessment of each method showed that objects based approach of classification is better than pixel based classification. ANN confusion matrix shown the maximum accuracy in above four method and Fuzzy classification error matrix shown more accuracy than Unsupervised Classification and MLC but less then ANN Classification. Beside Accuracy assessment each classified image showed the separability of classes in each method. In unsupervised classified image its show mixed pixels of the Road, Built Up and Water Bodies but other classes are well separated. In MLC, its accuracy almost 20 percent greater than unsupervised classification but it also does not separate Road and Built Up area pixels other are well separated but Shadow and Water Bodies classes not well separated. In Fuzzy Classification, beside accuracy is lower than ANN classification but separability of each class is better than other classification method. In Fuzzy, Roads, Built Up and Shadow, Water Bodies are well separated (figure). ANN Classification gets maximum accuracy then all method but it unable to separate Roads and Built Up area pixels properly.

It can be concluded that Surface water bodies and Built Up and Roads are better classified by the Fuzzy Logic classifier as compared to the MLC and Unsupervised Classification. That's why Fuzzy Logic Classification is the better Method to classify LISS-IV dataset. Further improvements need to be done to use a combination of classification techniques to develop automated procedures for preparation of land use maps from remotely sensed multispectral data.

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