A Novel Classification Technique for Accuracy Assessment Applied to Digital Imagery

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ABSTRACT
This study is to classify satellite data based on supervised fuzzy classification technique. Attempts to classify remote sensed data with traditional statistical classification technique faced number of challenges as the traditional per-pixel classifier examine only the spectral variance ignoring the spatial distribution of the pixels, corresponding to the land cover classes and correlation between bands causes problems in classifying the data and its result. Hence in this work, we use fuzzy classification.this makes no assumption about stastical distribution of the data & it provides more complete information for a thorough image analysis.The results show that fuzzy supervised technique algorithm showed an improvement of more than 5% of accuracy at 12 classes on comparison with MLC.

Keywords
Fuzzy Supervised Classification, MLC, Remote Sensing

1. INTRODUCTION
Remote Sensed imagery classification involves the grouping of image data into a finite number of discrete classes.Extraction of land cover map information from remote sensed images is a very important task of RS technology. Hence, in the above context, accurate image classification results are a prerequisite. Remote sensing imagery with high resolution data (spatial, spectral, radiometric and temporal) have made analysts to constantly explore the image processing and data mining techniques to exploit their potential in extracting the desired information efficiently from the RS data to improve classification accuracy [3]. Geographical information obtained from remotely sensed imagery is imprecise in nature.Consider a classification accuracy over urban/ semi urban land use/ land cover (LU/ LC) classes, a piece of land with sparse grass can be classified as grassland or soil and other example is that urban/ semi urban areas comprise of roof tops made of reinforced concrete slabs, concrete roads can be misclassified. Apart from the above, tall trees and buildings casting shadows on the adjacent classes, the orientation and geometry of the roof tops, and various man-made structures that are constructed with same material in different colors stand spectrally distinct though they belong to the same class. In addition to that, the urban landscapes composed of features that are smaller than the spatial resolution of the sensors lead to mixed pixel problem.

In general, a classification of a remotely sensed image consists of i) Training, ii) Class Allocation, iii) Validation. Conventionally the classification is based on unique relationship between a given materials or land cover class & its reflected radiation at certain wavelength (reflectance) contained in spectral band of an image, a one-pixel-one class relationship.Numerous methods for remote-sensing classification are grouped as supervised and unsupervised classifiers based on the training process. Unsupervised classification is used when there is little or no external information about the distribution of land cover types. In supervised classification, the analyst supervises the pixel categorisation process by specifying to the computer algorithm, numerical descriptors of various land cover types present in an image. Parametric (statistical) and non-parametric (non-statistical) classifiers based on their theoretical modelling considering the type of distribution of data [1]; soft and hard classifiers examine only the spectral variance ignoring the spatial distribution of the pixels belonging to the classes. Some of the hard classifiers are parallelepiped, minimum distance-to-means, maximum likelihood classifier, Bayesian classifier but they show limited success on spectrally overlapping features [2, 3]. Soft classifiers include fuzzy classification.

The most commonly used classification algorithm for remotely sensed imagery is Maximum Likelihood Classification. MLC assumes that the training data statistics are Gaussian distributed , which for many data sources is a valid assumption. The distribution of pattern can be described by the mean vector and covariance. MLC is based on Bayes Decision Theory, and makes full use of the both mean and covariance statistics from the training data. The Bayes classification rule is to classify sample x as the class that has the maximum a posteriori probability given the sample,

P (ω_k/x). So, x is classified as ω_c if and only

$$P(\omega_c/x) > P(\omega_k/x) \ \forall\ k \neq c$$

Whereas a fuzzy classification is used to find out uncertainty in the boundary between classes and to extract the mixed pixel information. This is achieved by applying a function called "membership function" on remotely sensed images. This approach allows for different groups of classes to be classified using the features best suited for discrimination between those classes. This alleviates the problem of features simultaneously decreasing the confusion between one set of classes and increasing it for another set.

2. DATA PRODUCT
2.1 Data Product
Table 1 gives the specification of the image data products being used in this study. The data are of LISS-IV (Linear Imaging and Self Scanning) sensor of IRS P-6 (Indian Remote Sensing

Satellite). The satellite data were obtained from the Master Control Facility, Hassan, India.

Table 1. Details of the data products used in our research work

	Satellite and Data type	Date of Acquisition	Spectral Resolution	Spatial Resolution
1.	IRS P-6 (Resourcesat1) Multi-spectral	July 2002	Green (0.52-0.59µm); Red (0.62-0.68µm); Infrared (0.77-0.86µm)	5.8m

2.2 Study Area

The study area considered for our work is semi urban area of Arsikere. It is situated in Hassan, Karnataka, India, its geographical coordinates are 13° 18' 50" North, 76° 15' 22" East and its original name (with diacritics) is Arsikere. It has an average elevation of 807 meters (2647 feet).The image dimension of the study area is 607×645 pixels in MS data.

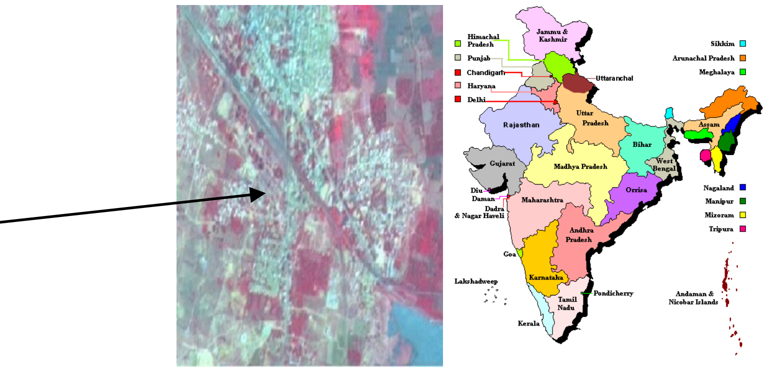


Fig. 1 Study area: Arsikere, Hassan, Karnataka, India.

2.3 Supervised Fuzzy Classification

Due to the large numbers of spectrally similar land cover types present in the urban environment, traditional classification approaches such as maximum likelihood often result in significant numbers of misclassifications, especially between the Road and Building classes, and the Grass and Tree classes. By utilizing spatial features in addition to the spectral information, the fuzzy pixel-based classifier is able to more accurately classify high-resolution imagery of urban areas. This classifier uses the results of an initial maximum likelihood classification of the imagery to group the classes where significant misclassifications occur together into sets. Subsequent processing using spatial features are then performed to differentiate between the spectrally similar classes.

This approach allows for different groups of classes to be classified using the features best suited for discrimination between those classes. This alleviates the problem of features simultaneously decreasing the confusion between one set of classes and increasing it for another set [15].

The fuzzy pixel-based classification technique is significantly more accurate than maximum likelihood classification. However, more detail is needed to accurately represent the land cover types present in dense urban areas. A non-road, nonbuilding Impervious Surface class is also needed to represent features such as parking lots, concrete plazas, etc. To distinguish between these urban land cover classes, an object based classification approach is used to examine features such as object shape and context (neighborhood) and then classify the image objects using a fuzzy logic rule base. To facilitate object classification, the imagery is first segmented with a region merging segmentation technique. Several features are extracted from the image objects and used by the object-based classifier along with the fuzzy pixel-based classificationas.

3. ACCURACY ASSESSMENT

A No classification is complete until its accuracy has been assessed Lillesand,2001).In this context, the "accuracy" means the level of agreement between labels assigned by the classifier and the class allocations on the ground collected by the user.

Accuracy assessment of a classified image is a complex subject and fairly a immature one. The purpose of the accuracy assessment is to allow the user to determine the map's "fitness for use" for their application. Map accuracy assessment is not a standardize procedure. There are many kinds of accuracy assessment techniques like spatial accuracy, thematic accuracy, temporal accuracy and topological accuracy.

Spatial accuracy assessment is the determination of positional accuracy of objects (points, lines, polygons, or pixels) relative to known locations. Thematic accuracy concerns the measure of errors in the attributes associated with the objects. Thematic accuracy is assessed by comparing the reported values with that of the standard values. Topological accuracy also called the logical consistency is measuring the errors associated more with the processed data than interpretation. Temporal accuracy assessment has not much importance as in large scale map preparation; very negligible change may occur in between the field observation and map preparation [17].

When performing accuracy assessment for the whole classified image, the known reference data should be another set of data, different from the set used for training the classifier. If training samples are used as reference data then the result of the accuracy assessment only indicates how the training sample are classified, but does not indicate how the classifier performs elsewhere in a scene [43]. The following are the most commonly used methods to do the accuracy assessment.

1. The Error Matrix

Error matrix (Table 2) is a square, with the same number of information classes that will be assessed as the row and column. Numbers in rows are the classification result and numbers in columns are reference data (ground truth). In this square, elements along the main diagonal are pixels that are correctly classified. Overall accuracy, user's accuracy, and producer's accuracy is calculated using error matrix.

2. Overall Accuracy

Overall accuracy is the proportion of all reference pixels, which are classified correctly. It is computed by dividing the total number of correctly classified pixels (the sum of elements along the main diagonal) by the total number of reference pixels.

Table 2 Error Matrix

	Reference Data			
	Class1	Class2	….. ClassN	Row Total
Class1	a_{11}	a_{12}	a_{1n}	$\sum_{K=1}^{N} a_{1k}$
Class2	a_{21}	a_{22}	a_{2n}	$\sum_{K=1}^{N} a_{2K}$
…….				………
ClassN	a_{n1}	a_{n2}	a_{nn}	$\sum_{K=1}^{N} a_{NK}$
Column Total	$\sum_{K=1}^{N} a_{K1}$	$\sum_{K=1}^{N} a_{K2}$	$\sum_{K=1}^{N-} a_{KN}$	N= $\sum_{1,K=1}^{N} a_{iK}$

According to the error matrix above, the overall accuracy can be calculated as:

$$OA= \frac{\sum_{K=1}^{N} a_{kk}}{\sum_{i,k=1}^{N} a_{ik}} = \frac{1}{n}\sum_{K=1}^{N} a_{kk}$$

3. Producer's Accuracy

Producer's accuracy estimates the probability that a pixel, which is of class I in the reference classification, is correctly classified. It is estimated with the reference pixels of class I divided by the pixels where classification and reference classification agree in class I. Given the error matrix above, the producer's accuracy can be calculated as:

$$PA\ (class\ I) = \frac{a_{ii}}{\sum_{i=1}^{N} a_{ki}}$$

Producer's accuracy tells how well the classification agrees with reference classification.

4. User's Accuracy

User's accuracy is estimated by dividing the number of pixels of the classification result for class I with the number of pixels that agree with the reference data in class I. It can be calculated as:

$$UA\ (class\ I) = \frac{a_{ii}}{\sum_{i=1}^{N} a_{ik}}$$

User's accuracy predicts the probability that a pixel classified as class I is actually belonging to class I.

5. Kappa Statistics

The Kappa analysis is a discrete multivariate technique used in accuracy assessment for statistically determining if one error matrix is significantly different than another. Kappa Statistic is based on the difference between the actual agreement in the error matrix (i.e., the agreement between the remotely sensed classification and the reference data is indicated by the major diagonal) and the chance agreement, which is indicated by the row and column totals (i.e., marginals).

4. IMPLEMENTATION AND RESULT

The image classification and evaluation was performed using ERDAS IMAGINE V8.5 software .Combining the fieldwork survey of the study area and also the image classification objective, there are 12 classes: RCC, Tiled Roof, Tar Road, Mud Road, Water, Barren ground, Play Ground, Trees, Shrubs, Grassland, Ploughed Land, and Dry Grass as shown in Figure 2. Training samples are selected according to the ground truth from the field work. The proposed task was carried on MS data. The polygonal regions of interest were drawn on various features in ERDAS IMAGINE and training samples were collected as shown in Figure 3. We have considered two sets of training samples. One set consists of 395 training samples and the other consists of 205 training samples. Once the training samples have been systematically collected for each class, we have to determine the bands that are most effective. This process is commonly called as feature selection. It involves statistical and graphical analysis to determine the degree of between-class separability in the training data.

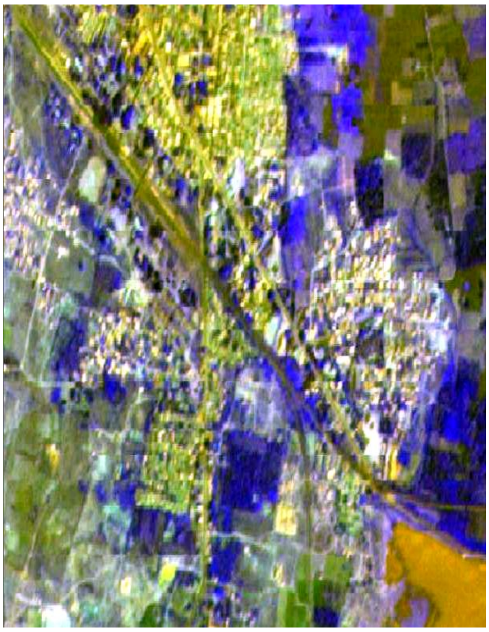


Figure 2 Snapshot of Input image (5.8m MS data)

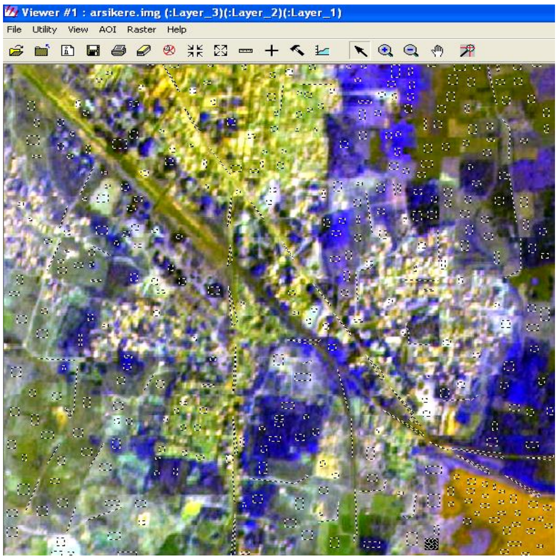


Figure 3. Training samples for classification

When the classifier was trained with 395 training samples the classified image after applying MLC is as shown in Figure 10(a). As it can be seen from Figure 4(a) that tar road is classified as RCC, and the regions around water is also classified as tar road. Few areas of grassland are classified as ploughed land. This is mainly because classes have similar spectral reflectance value.

Whereas when the classifier was trained with less number of training samples i.e., 205 samples the classified image is as shown in Figure 4(b). From the figure we can note that there are large numbers of misclassifications. There is no significance of ploughed land which is classified as grassland. Tiled Roof is classified as tar road. This indicates the importance of the training samples required to train the classifier.

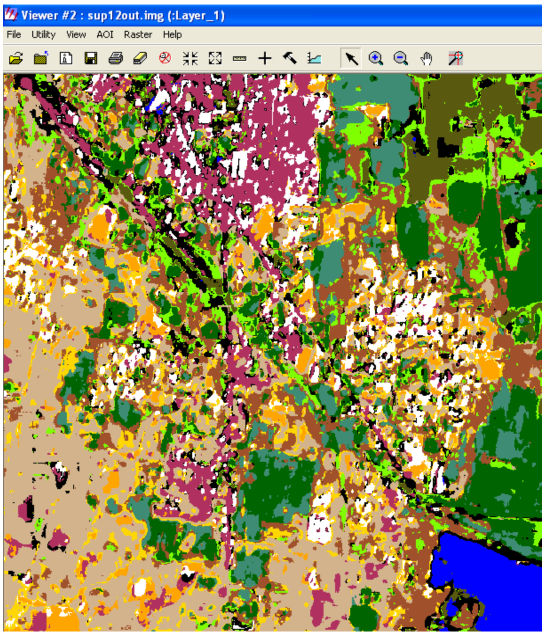


Figure 10(a) Image obtained using 395 training samples

b) Image obtained using 205 training samples

RCC Mud Road Water

Grassland Dry Grass

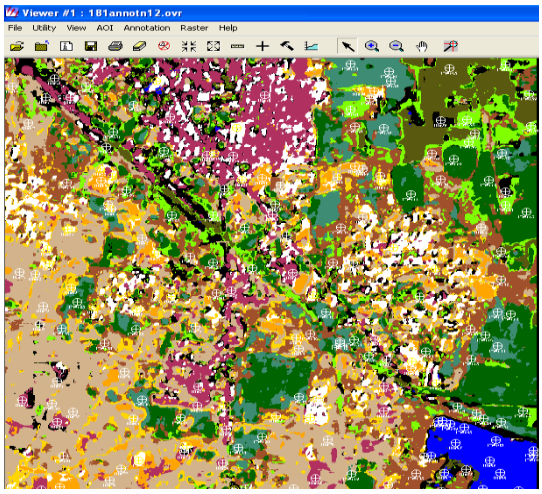
Tiled Roof Barren Land Trees

Ploughed Land Tar Road

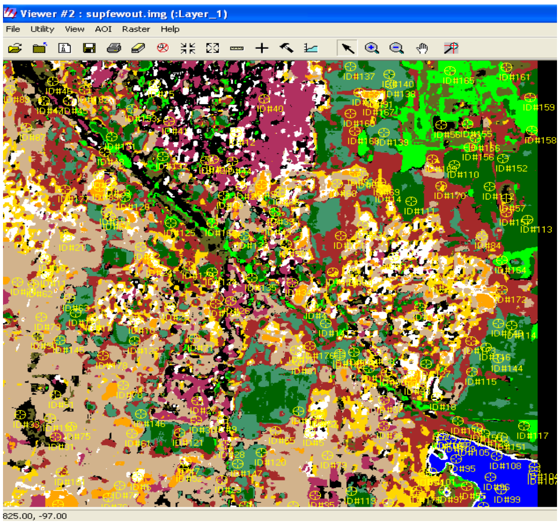
Play Ground

Shrubs

The distributions of the test areas (ground truth or reference data) used for accuracy assessment of the classification quality are as shown in Figure 5. Test areas are collected from the field survey by recording the coordinates of homogeneous land cover areas. Test areas used as reference data to form the error matrix are different data from the data used to train the classifier to ensure the independent validity of the accuracy assessment.



(a) Classified image of 395 training samples

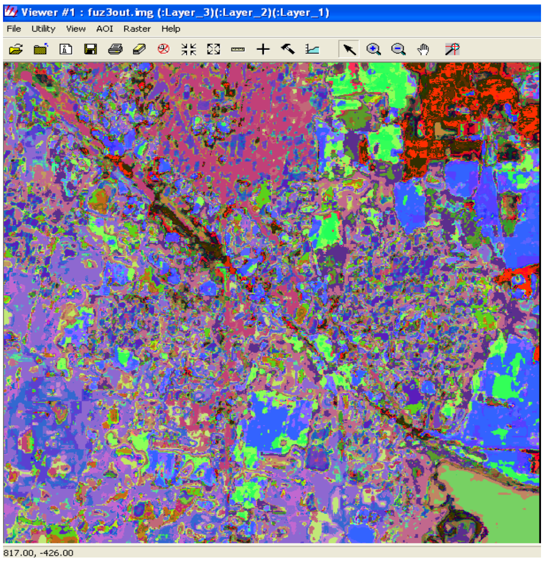


(b) Classified image of 205 training samples

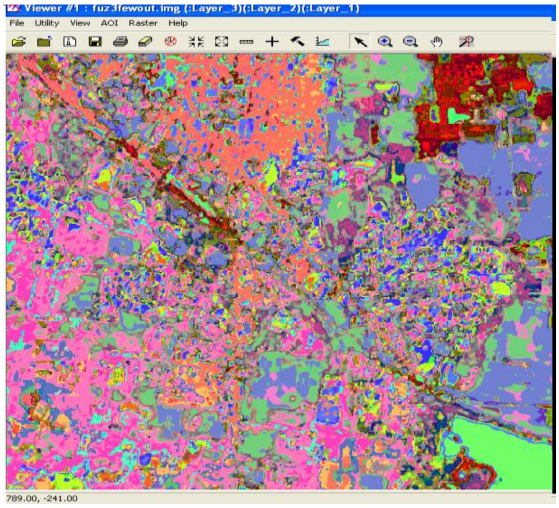
Figure 5 Reference points chosen on the classified images

As we can see the accuracy is less when the classifier is trained with less number of samples. When the training samples were 205 then the accuracy obtained is 62.98%.The plough land is not classified at all. As the training samples were increased to 395, then the accuracy increased to 72.93%. The third set of data consisted of 395 samples and 310 validation points, which led to further increase in accuracy. The accuracy increased to 74.19%.

Using the same training samples we performed a fuzzy supervised classification. We considered 3 classes per pixel. The first classification layer indicates the most probable classification for each pixel. The second layer indicates the second most probable classification for each pixel. The third layer indicates the third most probable classification for each pixel. Comparing these layers can provide good insights into which classes are being confused by the algorithm, but also may be a real indicator of mixed pixels, where a given pixel may contain trees and shrubs. Figure 6 (a) and (b) shows the fuzzy classified image using 395 and 205 training samples.



(a) Image obtained using 395 training samples



(b) Image obtained using 205 training samples

Figure 6 Fuzzy Supervised Classified Images

When the training samples were 205 then the accuracy obtained is 70.17%.As the training samples were increased to 395, then the accuracy increased to 78.45%. The third set of data consisted of 395 samples and 310 validation points, which led to further increase in accuracy. The accuracy increased to 80.65%.

Table 3
Performance Of Fuzzy Supervised And Mlc For 12 Classes (Training Dataset Size: 395 Samples And 310 Validation Points)

	Producer's Accuracy (%)		**User's accuracy (%)**		**Kappa Statistics**	
Classes	MLC	Fuzzy	MLC	Fuzzy	MLC	Fuzzy
RCC	88.00	81.48	100.00	100	1.0000	1.0000
Tiled Roof	100.00	100	93.55	86.864.524	0.9288	0.6207
Tar Road	100.00	93.02	54.10	70.265.571	0.4863	0.6003
Mud Road	70.97	88.89	75.86	79.482.769	0.7318	0.8111
Barren Land	52.78	57.14	79.17	58.083.330	0.7643	0.8121
Play Ground	100.00	100	53.33	78.286.673	0.5240	0.8608
Water	52.00	52.00	100.00	100.00	1.0000	1.0000
Trees	68.42	85.29	81.25	90.63	0.7863	0.8947
Shrubs	66.67	85.19	78.26	100.00	0.7619	1.0000
Grassland	72.23	85.00	76.19	80.95	0.7437	0.7964
Ploughed Land	80.00	90.00	50.00	56.25	0.4833	0.5479
Dry grass	66.67	68.97	69.57	86.96	0.6701	0.8561
OCA	**74.19**	**80.65**				
Kappa	**0.7163**	**0.7866**				

Table 4. Comparison Of Accuracy Between Mlc And Fuzzy Supervised Classification

No. of Training Sites	No. of Validation Sites	MLC	Fuzzy Supervised Classification
295	181	62.98%	70.17%
395	181	72.93%	78.45%
395	310	74.19%	80.65%

5. CONCLUSION

In our study area considered is Arsikere taluk in Hassan district. It is a semiconductor area with moderate rainfall. This place is connected to various important cities in the state via bus and rail transport. The township is undergoing lot of changes. Our objective was to study this area for classification purpose using fuzzy logic. The accuracy obtained for 205 and 395 samples with 181 test points 62.98%, 72.93% respectively and the accuracy obtained for 395 samples with 310 test points is 74.19%in MLC. The accuracy obtained for 205 and 395 samples with 181 test points 70.17%, 78.45% respectively and the accuracy obtained for 395 samples with 310 test points is 80.65% using fuzzy logic. Using supervised classification the results can be further classified for its authenticity. As training samples were increased accuracy also increased by 2 %. It is found that higher the training samples higher the OCA in both the classifiers.

6. REFERENCES

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