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Maximum Likelihood Classification of High-Resolution Multispectral Data OverArasikere Semi-urban Area

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ABSTRACT

Remote sensing refers to the science of identification of earth surface features and estimation of their geophysical properties using electromagnetic radiation as a medium of interaction. Spectral, Spatial, Temporal and Polarization signatures are major characteristics of the sensor or target, which facilitates target discrimination. Earth surface data are seen by the sensors in different wavelengths (Reflected, Scattered and/or Emitted) is radiometrically and geometrically corrected before extraction of spectral information. Image classification is the process of categorizing all the pixels automatically in an image into a finite number of land use/land cover classes. The major operational application themes, in which India has extensively used remote sensing data are agriculture, forestry, water resources, LU/LC, urban sprawl, geology environment, coastal zone, marine resources, snow and glacier, disaster and mitigation, infrastructure development etc. In Remote Sensing, image classification approaches can be grouped as supervised and unsupervised, or parametric and non-parametric, or hard and soft (fuzzy) classification, or per pixel, sub pixel and per field. Based on whether training is used or not the classifiers are classified into supervised and unsupervised classifiers. In this paper maximum likelihood supervised classification technique is employed on remotely sensed satellite image data for classification of urban features. The accuracy assessment was conducted based on Overall Classification Accuracy (OCA) and Kappa Statistics. This experiment was conducted using Erdas Imagine V9.2 RS software. Finally, the suitability of MLC is verified on Arasikere Semi-urban area and Overall Classification Accuracy 83.33% and 90.15% was obtained for 180 training sites with 132 validation sites and 562 training sites with 132 training sites respectively.

Keywords: Remote Sensing, Semi-urban Area, Maximum Likelihood Classification, Erdas Imagine

I. INTRODUCTION

Remote Sensing (RS) science has always been a fascinating topic over the years. With the advent of the earth observation satellite and a host of advanced instruments with the capability to monitor closely the land, air, ocean interactions. The field has expanded dramatically covering almost all the areas, say from cartography to climate. The advances in the imaging optics, devices, signal processing and materials, not to speak of the developments in modeling and algorithms, remote sensing as a science has seen a quantum jump in the recent times [1, 2, 3, 4, 5, 6].

Improving classification accuracy of digital data has always been an important concern to extract the real world situation in the form of thematic maps. One of the main problems when generating land cover maps from digital images is the confusion of spectral responses. The possibility, that two or more different features having the same spectral behavior is eventually classified as the same class, not only creates the difficulties in extracting the valid information but also introduces errors in the classification. Therefore, the type of image and consequently the spatial and spectral resolutions influences the classification accuracy. Finally any image classification result is influenced by the data itself, data preprocessing, enhancement techniques and classification schemes being used.

Robert. A. Schowengerdt [7] provided an overview of remote sensing science and technology in his book Remote Sensing Models and Methods for Image Processing. He describes the basic parameters for optical remote sensing, Information extraction from Remote Sensing images, spectral factor in remote sensing. Thomas. N. Lillesand [8] has explained basic concepts and elements necessary to conceptulize an ideal remote sensing and applications in the book Remote Sensing and Image Interpretation. D. LU and Q. WENG [9] explain Image classification process and different techniques of image classification. Giles M. Foody [10] has explained the background and methods of classification accuracy assessment that are commonly used and recommended. He has also explained different types of errors encountered in an image classification. He has concluded that the value of thematic map is a function of accuracy of the classification and the assessment of classification accuracy is not a simple task.

As supervised classification classifies pixels based on known properties of each cover type, it requires representative land cover information, in the form of training pixels. Signatures generated from the training data will be in a different form, depending on the classifier type used. For ML classification the class signature will be in the form of class mean vectors and the covariance matrices. However, the disadvantage is that the derived classes may not be statistically separable. The parallelepiped classifier, known as the 'box decision rule', is often considered to be the simplest supervised algorithm [11]. This algorithm makes use of the ranges of values within the training data to define regions within a multidimensional data space. The Mahalanobis distance uses statistics for each class but assumes that all class covariances are equal. All pixels are classified to the closest region of interest (ROI) class, depending on the distance threshold specified by users; some pixels may be unclassified if they do not meet the threshold [12]. The minimum distance classifier employs the central values of the spectral data that forms the training data set to classify pixels. The neural network classification is a self adaptive method that is able to estimate the posterior probabilities, which provide a basis for establishing the classification rule [13]. The support vector machine method involves a learning process based on structural risk minimization, which can minimize classification error without the need to assume data distribution [14]. It is capable of handling data with a limited training sample. However, it often linked to high computational requirements and processing times. An ML classifier is a powerful classification technique based on the maximum likelihood decision rule and depends on the quality of training samples, which are usually determined based on ground-verified land cover maps and knowledge of the area. Due to its practicality, objectivity and ability to discriminate between land covers effectively, Maximum Likelihood Classification is often preferred by many remote sensing data users to classify land covers worldwide [15].

Al-Ahmadi and Hames [16] performed three methods, i.e. ML, Mahalanobis Distance and Minimum Distance, to classify four land covers of Saudi Arabia (rock outcrop, alluvial, agriculture and urban) recorded from Landsat 5 TM satellite. The outcomes of their study showed that ML (80%) has the best overall classification accuracy, followed by Mahalanobis distance (74%) and minimum distance (67%). Baban and Yusof [17] used ML classification to map land covers on a mountainous tropical island, Langkawi recorded from Landsat satellite.

ML classification was carried out on eight classes, namely, inland forest, mangrove forest, rubber, paddy fields, mixed horticulture, grassland, urban and water. The overall classification accuracy was 90% with individual class accuracy ranging from 74% for rubber to 100% for paddy. Another study was conducted by Ismail and Jusoff [18], where ML classification was used to classify five forms of land use and land covers in Pahang, Malaysia observed from Landsat satellite, viz. primary forest, logged over forest, agriculture crops, water and cleared lands. The overall accuracy of the classification was 89% with a kappa coefficient of 0.8. Besides these, there are many other successful stories of ML reported elsewhere; nevertheless, there is almost no attempt to investigate the ML in-depth.

In this work, an attempt is made to analyze the suitability of MLC on Arasikere Semi-urban area is OCA and Kappa Statistics. The MLC was carries out on six classes Built-up, Agriculture, Forest, wasteland, waterbodies, wetland and the OCA was 83.33% and 90.15% for 180 and 562 training sites with 132 validation sites.

II. REMOTE SENSING IMAGE CLASSIFICATION

Remote Sensing Image Classification is a process of automatically categorizing all pixels in an image into finite number of classes or themes. A pixel is characterized by its spectral signature, which is determined by the relative reflectance in different wavelength bands. Multi-spectral classification is an information extraction process that analyses these spectral signatures and assigns the pixels to classes based on similar signatures. Image classification has formed as an important part in the field of Remote Sensing and Pattern Recognition. The classification process is based on the assumptions: Patterns of their DN usually in multichannel data (Spectral Classification), Spatial Relationship with neighbouring pixels and Relationships between the data acquired on different dates. The Pattern Recognition, Spectral Classification, Textural Analysis and Change Detection are different forms of classification that are focused on three major objectives: 1) Detection of different kinds of features in an image; 2) Discrimination of distinctive shapes and spatial patterns and 3) Identification of temporal changes in image [19, 20].

The major steps of image classification may include determination of a suitable classification system, selection of training samples, image pre-processing, and feature extraction, selection of suitable classification approaches, post-classification processing and accuracy assessment.

1) Feature Determination: Initially, we do not know what set of features is best for the given classification problem. Thus, first we determine some appropriate set of features. Since it is relatively easy to delete redundant features but difficult to add necessary features, as we set a sufficient number of features.

2) Data Gathering:We gather samples of the features for each class and normalize the samples so that the range of the samples for each feature is [0, 1]. This is to make each feature that has different physical meaning have an equal weight. Normalization is a necessary step for neural networks since they do not have scale invariance.

3) Feature Optimization:Features can be optimized either by the feature selection or feature extraction. In feature selection, we analyze the gathered samples or extracted features whether they can be classifiedcorrectly. The overlaps of the class regions are analyzed and delete the redundant features. If the input features are not sufficient to separate classes, some more features are added to guarantee class separability. In feature extraction, original features are reduced into a smaller number of features by linear or non-linear transformation.

4) Division of Data:The samples of the data are divided into training data set and the test data set. Since the training data set needs to be representation of the events that will occur, the training data set should not be biased. Thus, the data set is divided into the training data set and test data set so that their characteristics become similar.

5) Classifier Evaluation: Classifier is trained using training data set and evaluate classifier using test data set. If the performance is not sufficient, parameters of the classifier are changed, or more samples for training & test are added, or classifiers are changed.

6) Field Test:The classifier is implemented into the field and its performance is evaluated. If the performance is not satisfactory, the classifier is tuned using the field data.

Image classification approaches can be grouped as supervised and unsupervised, or parametric and non-parametric, or hard and soft classification, or per-pixel, sub-pixel, and per-field. Based on whether training samples are used or not the classifiers are of two types: supervised classifiers and unsupervised classifiers.

A. Supervised Image Classification

In supervised image classification, the image analyst "supervises" pixel categorization process by specifying the computer algorithm to numerical descriptors of the various land cover types present in a scene. To do this representative sample sites of known cover type, called training areas, are used to compile a numerical "interpretation key" that describes the spectral attributes for feature type of interest. Each pixel in the data set is then compared numerically to each category in the interpretation key and labelled. There are a number of numerical strategies that can be employed to make this comparison between unknown pixels and training set pixels. Examples of supervised classification are Maximum likelihood, Minimum Distance, Mahalonobis distance, etc., [21, 22].

1) Maximum Likelihood Classifier:The maximum likelihood classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. An assumption that the distribution of the cloud of points forming the category training data is Gaussian is

made. With this assumption the distribution of a category response pattern can be completely described by the mean vector and the covariance matrix. Given these parameters statistical probability of a given pixel value being a member of a particular land cover class can be computed. In essence, the maximum likelihood classifier delineates ellipsoidal "equi-probability contours" in the scatter diagram and these decision regions are shown in Figure 1. The shape of the equi-probability contours expresses the sensitivity of the likelihood classifier to covariance. For example because of the sensitivity it can be seen that pixel 1 would be appropriately assigned to the "corn" category [23, 24, 25, 26].

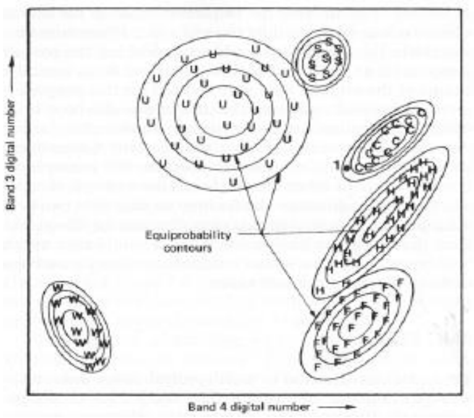


Figure 1: Equi-probability contours defined by MLC

B. Unsupervised Image Classification

Unsupervised image classification (commonly referred to as clustering) is an effective method of partitioning remote sensor image data in multispectral feature space and extracting land-cover information. Compared to supervised classification, unsupervised classification normally requires only a minimal amount of initial input from the analyst. This is because clustering does not normally require training data. The unsupervised procedures are applied in two separate steps. In the unsupervised approach the image data are first classified by aggregating them into the natural spectral groupings or clusters. Then the image analyst determines the land cover identity of these spectral groups by comparing the classified image data to ground reference data.

C. Accuracy Assessment

No classification is complete until its accuracy has been assessed. 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 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. The following are the most commonly used methods to do the accuracy assessment [27, 28, 29, 30, 31].

1) The Error Matrix:The Error matrix (Table I) 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.

TABLE I
THE ERROR MATRIX

Reference Data	
Class1 Class2 ….. Class N	Row Total
Class 1 a_{11} a_{12} ….. a_{1n}	$\sum_{K=1}^{N} a_{1k}$
Class 2 a_{21} a_{22} ….. a_{2n}	$\sum_{K=1}^{N} a_{2K}$
…….	………
Class N 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= $\sum_{1,K=1}^{N} a_{iK}$

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

$$OA= \frac{\sum_{K=1}^{N} a_{kk}}{\sum_{i,k=1}^{N} a_{ik}} = \frac{1}{n}\sum_{K=1}^{N} a_{kk} \quad \text{.......... (1)}$$

b)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. Producer's accuracy tells how well the classification agrees with reference classification. Given the error matrix above, the producer's accuracy can be calculated as:

$$\text{PA (class I)} = \frac{a_{ii}}{\sum_{i=1}^{N} a_{ki}} \qquad \text{.........(2)}$$

c) 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. User's accuracy predicts the probability that a pixel classified as class I is actually belonging to class I. It can be calculated as:

$$\text{UA (class I)} = \frac{a_{ii}}{\sum_{i=1}^{N} a_{ik}} \qquad \textbf{.......... (3)}$$

2) 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) [30, 31].

In summary, uncertainty & confidence analysis of classification results has gained some attention recently & spatially explicit data on mapping confidence are regarded as an important aspect in effectively employing classification results for decision making.

III. STUDY AREA & METHODOLOGY

A. **Study Area**

The study area considered for the experimentation is a Semi-urban area of Arsikere situated in Hassan District, Karnataka State, India and 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). Arasikere is the talukcenterin Hassan district and is known for its coconut production and Malekallu Tirupathi hill. There is also an old temple built by Hoysala rulers by name "Shivalaya", built by Jakanachari. The town is set at the foot of Tirupathi hills and surrounded by many other smaller hills with unique temples. Arsikere is also a major railway junction of Karnataka. It has a population of about 50,000. The Malekallu Tirupathi hill has 1300 steps and it's believed that lord Rama had visited this place. It's the only place you can see a standing Venkateshwara idol other than famous Tirupati of Andhra Pradesh.

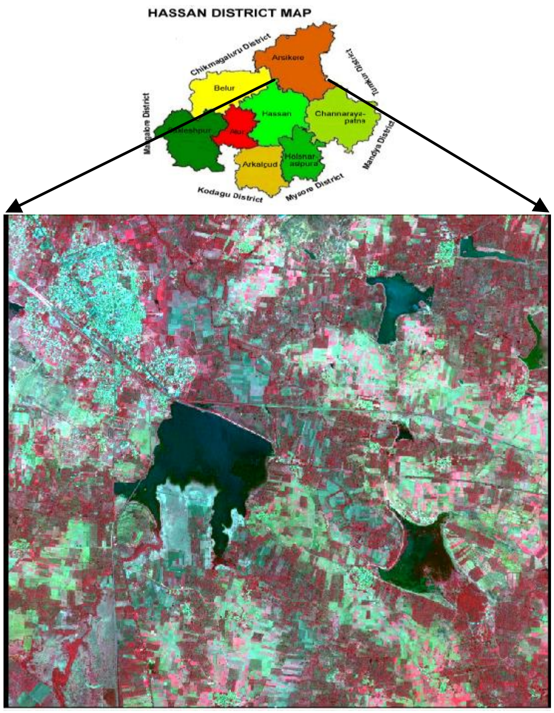


Figure 2: Arsikere Semi-urban Study Area of Karnataka, INDIA

The Arasikere town place has its importance not only as a main railway junction but also as a financial center and central place to visit some of the world famous places like Belur [40kms], Halebedu [25kms] and Sravanabelagola [80kms]. Arsikere was one of the important towns along with neighboring Banavara during Hoysala tenure. The name "Arsikere" comes from one of the Princess ["Arasi" in kannada] of the Hoysala dynasty who built the big Pond ["kere" in kannada]. So its "Arasiya+Kere" [in Kannada] which means "Princess's Pond". Also, there is a history from the times of the Chalukyas. This was built during the regime of the Hoysala King Narasimha the second. In the commercial street of the town, there lays a Basadi known as SahasraKootaJinalaya, only the navaranga and Garbagruha remain here today.

B. **Satellite Data Product**

The Table II gives the specifications of image data products used in this work. The data is of LISS-IV (Linear Imaging andSelf Scanning) sensor of IRS-P6 satellite (Indian Remote Sensing Satellite).The multispectral image dimension of the study area considered is 2926×2615 pixels.

TABLE III

DETAILS OF THESATELLITE DATA PRODUCT USED

Satellite and Data type	Spectral Resolution	Spatial Resolution
IRS-P6 (Resourcesat1) Multi-spectral	Green (0.52-0.59µm); Red (0.62-0.68 µm); Infrared (0.77-0.86 µm);	5 m

C. **Methodology**

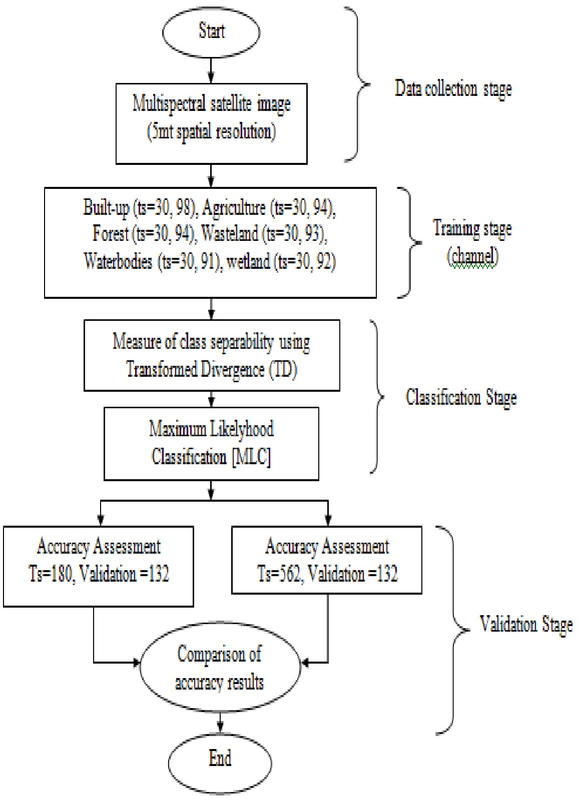


Figure 3: Flow chat of methodology used in supervised classification

The Figure 3 shows, Flow chart of the methodology used to evaluate the suitability of MLC on Semi-urban area.

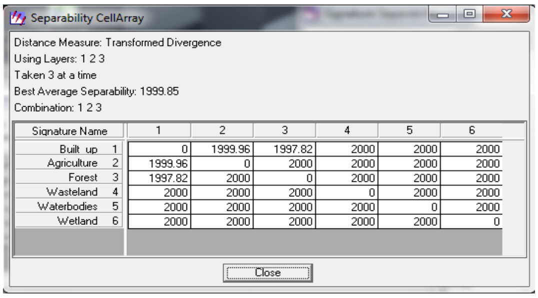
IV. RESULTS & DISCUSSIONS

The classification of multispectral 5m spatial resolution data has been made using maximum likelihood classification technique. Accuracy assessment was carried out in ERDAS IMAGINE V 9.2 remote sensing image processing software. The classifier was trained with two sets of data viz. 180 and 562 instances and with 132 validation points and error matrices were computed for performance analysis.Maximum Likelihood Supervised classification is performed using 5m LISS-IV data. In supervised classification, the basic steps followed are: (1) select training samples which are representative and typical for that information class; (2) perform classification after specifying the training samples set and classification algorithms; (3) assess the accuracy of the classified image though analysis of a confusion matrix which is generated either through random sampling or using test areas as reference data. From the field survey of the study area and the visual interpretation of data, the following 6 classes were identified, which included major classes and sub-classes for the present study. The 6 classes are: Built-up, Agriculture, Forest, Wasteland, Waterbodies, Wetlandsas shown in Figure 4. The screen shot of training samples considered is shown in Figure 5.

Figure 4: Snapshot of Input image (5m MS data)

Figure 5: Training samples for classification

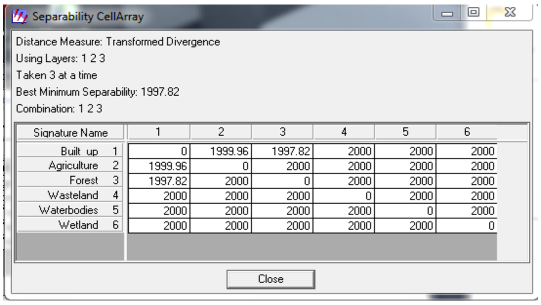
The screenshots of transformed divergence for 180 training samples are as shown in Figure 6 and 7 and that for 562 samples is as shown in Figures 8 and 9. The classified image for MLC after having trained with 180 training samples is as shown in Figure 10. This is mainly attributed to the fact that the classes exhibit similar spectral reflectance value and poor TD between them (Figure 6). The built-up and forest show a TD of 1997.82 and, built-up and agriculture exhibit a TD of 1999.96 – both are considered to be low.


Separability CellArray
Distance Measure: Transformed Divergence
Using Layers: 1 2 3
Taken 3 at a time
Best Average Separability: 1999.85
Combination: 1 2 3

Signature Name	1	2	3	4	5	6
Built up 1	0	1999.96	1997.82	2000	2000	2000
Agriculture 2	1999.96	0	2000	2000	2000	2000
Forest 3	1997.82	2000	0	2000	2000	2000
Wasteland 4	2000	2000	2000	0	2000	2000
Waterbodies 5	2000	2000	2000	2000	0	2000
Wetland 6	2000	2000	2000	2000	2000	0

Close

Figure 6: TD for Best Average Separability: 1999.85

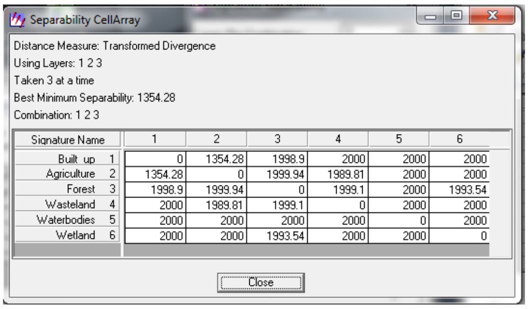

Separability CellArray
Distance Measure: Transformed Divergence
Using Layers: 1 2 3
Taken 3 at a time
Best Minimum Separability: 1997.82
Combination: 1 2 3

Signature Name	1	2	3	4	5	6
Built up 1	0	1999.96	1997.82	2000	2000	2000
Agriculture 2	1999.96	0	2000	2000	2000	2000
Forest 3	1997.82	2000	0	2000	2000	2000
Wasteland 4	2000	2000	2000	0	2000	2000
Waterbodies 5	2000	2000	2000	2000	0	2000
Wetland 6	2000	2000	2000	2000	2000	0

Close

Figure 7: TD for Best Minimum Separability: 1997.82

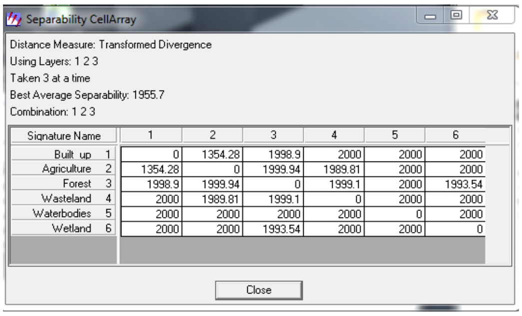
The Figure 8 is the transformed divergence obtained for 562 training samples. Built-up and agriculture shows an average separability of 1354.28, which is very low. Figure 11 shows agriculture pixels are misclassified in large amount. Water exhibits the maximum TD of 2000 as it is distinct from other classes.


Separability CellArray
Distance Measure: Transformed Divergence
Using Layers: 1 2 3
Taken 3 at a time
Best Minimum Separability: 1354.28
Combination: 1 2 3

Signature Name	1	2	3	4	5	6
Built up 1	0	1354.28	1998.9	2000	2000	2000
Agriculture 2	1354.28	0	1999.94	1989.81	2000	2000
Forest 3	1998.9	1999.94	0	1999.1	2000	1993.54
Wasteland 4	2000	1989.81	1999.1	0	2000	2000
Waterbodies 5	2000	2000	2000	2000	0	2000
Wetland 6	2000	2000	1993.54	2000	2000	0

Close

Figure 8: TD for Best Minimum Separability: 1354.28


Separability CellArray
Distance Measure: Transformed Divergence
Using Layers: 1 2 3
Taken 3 at a time
Best Average Separability: 1955.7
Combination: 1 2 3

Signature Name	1	2	3	4	5	6
Built up 1	0	1354.28	1998.9	2000	2000	2000
Agriculture 2	1354.28	0	1999.94	1989.81	2000	2000
Forest 3	1998.9	1999.94	0	1999.1	2000	1993.54
Wasteland 4	2000	1989.81	1999.1	0	2000	2000
Waterbodies 5	2000	2000	2000	2000	0	2000
Wetland 6	2000	2000	1993.54	2000	2000	0

Close

Figure 9: TD for Best Average Separability: 1955.7

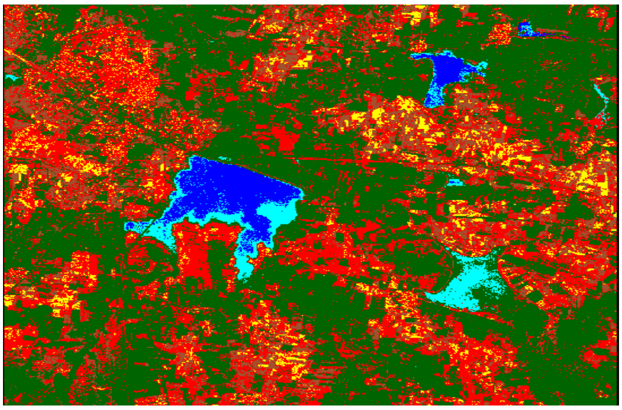


Figure 10: Classified images using Maximum Likelihood Classification with 180 training sets & 132 validation sites

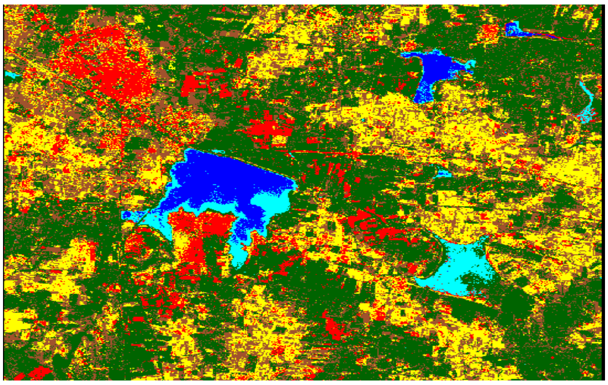


Figure 11: Classified images using Maximum Likelihood Classification with 562 training sets & 132 validation sites

Legends:

Built-up Agriculture

Forest Wasteland

Waterbodies Wetland

Further, the classifier was also trained with less number of training samples i.e., 562 training sampals, and thus obtained classified image is shown in Figure 11. From thisfigure it can be noted that there are large numbers of misclassifications. There is no significant area of built-up since it has been classified as agriculture. This indicates the importance of the training samples required to train the classifier.

TABLE IIIII
ERROR MATRIX FOR 180 TRAINING SAMPLES AND 132 TEST POINTS

CLASSES	1	2	3	4	5	6	ROW TOTAL
1	23	0	2	1	0	0	26
2	0	17	0	7	0	0	24
3	0	0	18	0	0	0	18
4	0	5	0	11	0	0	16
5	0	0	1	5	20	0	26
6	0	0	1	0	0	21	22
COLUMN TOTAL	23	22	22	24	20	21	132

Reference Data

Legend:1= Forest, 2= Built-up, 3= Waterbodies,
4= Agriculture, 5= Wasteland, 6= Wetland,
RT= Row Total, CT= Column Total**.**

TABLE IVV
ACCURACY AND KAPPA TABLE FOR DATA GIVEN IN TABLE III

Class Name	PA (%)	UA (%)	Kappa
1	100.00	88.46	0.8603
2	77.27	70.83	0.6500
3	81.82	100.00	1.0000
4	45.83	68.75	0.6181
5	100.00	76.92	0.7280
6	100.00	95.45	0.9459

Overall Classification Accuracy = 83.33%
Overall Kappa Statistics = 0.8002

TABLE V
ERROR MATRIX FOR 562 TRAINING SAMPLES AND 132 TEST POINTS
REFERENCE DATA

CLASSES	1	2	3	4	5	6	ROW TOTAL
1	**21**	0	0	0	0	1	22
2	0	**21**	0	1	0	0	22
3	0	0	**17**	0	1	0	18
4	0	0	0	**18**	0	0	18
5	0	0	2	4	**21**	0	27
6	0	0	3	1	0	**21**	25
COLUMN TOTAL	21	21	22	24	22	22	**132**

Legend:1= Forest, 2= Wetland, 3= Agriculture,
4= Waterbodies, 5= Built-up, 6= Wasteland,
RT= Row Total, CT= Column Total

TABLE VI
ACCURACY AND KAPPA TABLE FOR DATA GIVEN IN TABLE V

Class Name	PA (%)	UA (%)	Kappa
1	100.00	95.45	0.9459
2	100.00	95.45	0.9459
3	77.27	94.44	0.9333
4	75.00	100.00	1.0000
5	95.45	77.78	0.7333
6	95.45	84.00	0.8080

Overall Classification Accuracy = 90.15%Overall Kappa Statistics = 0.8819

From the above results, we can observe that the accuracy has increased with the increase in number of training samples. This has been tabulated and shown in Table VII. We can still improve the accuracy by applying MLC to fused images. Also, using GIS manipulations classification results of pixel based image analysis can be further improved to obtain higher accuracy.

TABLE VII
ACCURACY ASSESSMENT OF MAXIMUM LIKELIHOOD SUPERVISED CLASSIFICATION

No. of Training Sites	No. of Validation Sites	Maximum Likelihood Classification
180	132	83.33%
562	132	90.15%

V. CONCLUSION

In this work, the study area considered is Arsikeretaluk in Hassan district of Karnataka state, India. 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. The objective was to study this area for classification purpose using Maximum Likelihood Classifier.

The accuracy obtained for 180 and 562 samples with 132 test points are 83.33% and 90.15% respectively. Using Maximum Likelihood Supervised Classification the results can be further classified for its authenticity and as training samples were increased accuracy also increased approximately by 7 %. Also, it is found that higher the training samples higher the OCA of classifier.Also, it is to be noted that the number of training samples depends upon the complexity of the study area considered. If the study area is simple then it consists of well-defined crisp classes then less number of pixels can also give better accuracy. This study does not include knowledge base. If knowledge base is incorporated into the system, the accuracy of classification would improve certainly.

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