A Review of different Approaches of Land Cover Mapping

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Abstract: In this study, a survey of land cover mapping and their classification techniques is done. Land cover mapping plays a very important role in making land policy, land management and land analysis. In this survey different approaches are studied that were applied for land cover mapping such as an Artificial Neural Network (ANNs), Fuzzy Logic, Supervised, Unsupervised and Maximum Likelihood. The objective of this research is to analyze, evaluate and compare different algorithms for the classification of land cover and also evaluate and compare the methods to overcome the problems which are faced during classifications

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1. Introduction

The land cover mapping is very valuable for planning, resources management, identification of environmental changes, identifying deforestation and forecasting. Many organizations require accurate land cover and land use information for a variety of applications. Several researchers point out the importance of land cover information such as [3] presents that the land cover information is required for different purposes e.g. Scientific research (e.g. Climate change modeling, flood prediction) and management (e.g. City planning, disaster mitigation). The approach of remote sensing is the biggest source of acquiring information on land cover and land use [15]. It is too hard to classify the remote sensing data manually [14]. Therefore computer aided techniques are used to extract information from remotely sensed data by means of classification. The land cover and land use classification of satellite images are vital activities for extracting geospatial data for military and civil purposes like crop disease monitoring, flood disaster analysis and unreachable areas etc. Therefore [14] proposed the soft computing techniques used for image classification because these techniques are based on uncertainty e.g. ANN, fuzzy set theory and rough set theory. Classification of land cover and land use are important to the modeling of global changes and management of ecosystem [13]. According to the importance of classify land cover and land use which is related to modeling of global change and the management of other natural resources for this purpose there are some local and international organizations which are working for the monitoring and prediction of land cover and land use changes and promoting awareness among the people about the management of land resources, one of these is ICIMOD (International Centre for Integrated Mountain Development) ICIMOD is working for development of HKH (Hindu Kush-Himalayas) and monitoring the changes in mountain regions. The objective of this research is to analyze and evaluate and compare different algorithms for the classification of land cover and also evaluate and compare methods to overcome the problems which are faced during classifications. Constructing a mathematical modeling approach in which spatial operations of multi-dimensional spaces are integrated through incorporation of formal methods in [26]. The formal methods are the languages based on predicate logic, set theory and functions use for specification and verification of software and hardware systems [25-32].

The organization of the paper is as follows. We first discuss the background of the paper in section 2, examine the different approaches for the land cover and land use classification. Section 3, Discus the problems with remote sensing image classification and the approaches which are used to solve mix pixel problems and summarize our findings in Section 4.

2 Background

This research survey is about the land cover map classification. The different algorithms of land cover classification such as artificial neural network, fuzzy logic, maximum likelihood and linear mixing have been proposed. Land cover map can be generated by different ways but remote sensing has the strong ability to generate the land cover map. There are many classification techniques exist such as the statistical algorithms and soft computing techniques. In statistical algorithm included discriminate analysis and the maximum likelihood classification techniques. The maximum likelihood, which assign each image pixel to the land cover class based on highest probability of membership [21]. The soft classification techniques such as an Artificial Neural Network (ANNs) and Fuzzy Logic are used for classification. ANN may be more robust when distribution is powerfully non-Gaussian because Neural-network classifiers are nonparametric. The ANNs forming arbitrary decision boundaries in the feature space during training. The authors proposed ANNs and GIS for predicting the changes of Land use [1]. GIS can be defined as a powerful set of tools used to capture, store, and process, analyze and interpret Spatial data. GIS used in paper [1] to create a GIS layer which includes Digital Elevation Model (DEM) and resampling resolution to 90 m. The DEM is a digital representation of land surface geography. The land images acquired by different satellite in [11] authors used MODIS-MYD3Q1 satellite images for classification. The Moderate Resolution Imaging Spectrora diameter (MODIS) launched in December 1999. MODIS provides continuous global coverage every one to two days. ANN based five models was presented to classify the MODIS image. The models used NDVI (Normalized Difference Vegetation index), EVI (Enhanced Vegetation Index), red (RED) and NIR reflectance as input. The NDVI is a simple graphical sign that used to analyze remote sensing measurements. The EVI was developed to improve the sensitivity of vegetation signal in high biomass areas and enhanced vegetation monitoring. New Supervised learning of ANNs [12] is proposed: the data were acquired by two different ways one was used optical detector and a second was used microwave radar. The optical detector is a device that measures a physical quantity of the light and the becomes a signal which can be read by an observer or by an instrument using the radar to microwave high frequency radiation. Its accuracy and ability to penetrate the clouds give it great navigation and to the achievement of images used. ANNs approach to classify land use land cover using ancillary data [10]. The ancillary data is the data from other sources than remote sensing that can be used to aid in the classification. Three approaches were presented [21] which used the data of IKNOS multispectral Satellite. The IKONOS satellite is publicly available with high resolution imagery up to 1 to 4 meter resolution.

The common problem with remote sensing is the mixed pixel. The mixed pixel represents the area which occupies more than one feature of land cover. To solve the problems of mixed pixels in paper [18] authors proposed two methods maximum likelihood and Fuzzy Classifier the data were acquired from global land cover network. The classifications were performing in forestry, urban planning and Swana woodland (grassland). Similarly in [19] [18] the authors present the methods to estimate the components of land cover features to solve the mix pixels problems. In [23] the authors present Maximum a Posteriori (MAP) model to provide the solutions to the mix pixel problem.

3 Approaches for land cover classification

Several ways [12] in which classifies the image of land cover and land use such as statistical techniques and soft computing. The statistical technique such as the maximum likelihood method was used for the classification of land cover and land use based on multi-band data which acquired by the satellite. These techniques need distribution assumption of observed data, but generally the observed data do not satisfy the assumption so the using of statistical techniques failed in classification. However, the ANN BP recently has been applied for image classification, BP method as learning technique which does not need the distribution assumptions.

In paper [14] presents the importance and advantages of ANNs for image classification, ANN is tool for pattern classification. ANN are may be more robust when distribution is powerfully non-Gaussian because ANN classifiers are nonparametric. ANNs is able of drawing arbitrary decision boundaries in the feature space, during training. The advantages of ANNs can thus be summarized as:

- Ability of noise resistance
- Tolerance to distorted patterns/image
- Greater ability to recognize overlapping pattern classes with high nonlinear boundaries or Partially or Degraded Image
- Potential for parallel processing
- Non parametric

In consequence of above advantages the ANNs method generally can acquire more high precision of the output and this approach widely used in land cover and land use classification.

a. ANNs and GIS applied to forecast land use changes [1].

In this paper author applied a spatial model for prediction of land cover changes. Combining ANNs and GIS, the model applied on the Lesvos NE Greece Island for the time period between 1975 and 1999 for predicting the pattern of growth of the island's urban areas and olive grove.

The Feed Forward ANNs has been developed with one hidden layer. In the first step the data that were collected imported into GIS and make different GIS layers, referencing to cartographic projection. The data included the transportation network, coastline vector, geological and soil data and DEM, classification information on land cover and population data for the years 1975, 1990 and 1999. The Hellenic Geodetic Reference system used and resample resolution of 90 m. In the second step, the ANNs trained using an independent data and applied for the years 1975 to 1990. The model used the year 1975 data as input and the year 1990 data as output. The model is applied to forecast the changes in urban growth and pattern of olive cultivation in for the year 1999.

The accuracies of classification of urban and olive grove classes were 96% and 94% respectively for year 1975 and 96% and 93% for the year 1990. The back propagation algorithm used for training process the network trained after 500 iterations. The model was then applied to predict changes in urban land cover. The model produces two numbers within the range 0 and 1 the predicting urban growth class cells for the year 1999 as shown in Figure. 1. The cell's value greater than 0.5 is representing the likelihood greater than 50% which shows belonging to the urban class. Similarly the model applied for the year 1999 to predict the olive grave patterns as a result the value generates a very low (between 0 and 0.17).

Figure 1. Result of the model [1]

Thus the result shows that the model performs well in forecasting urban growth as compared to predict the changes in the pattern of olive cultivation.

b. ANNs models for land use classification from satellite images [11].

In this paper author proposed ANNs Models to classify land cover images. The satellite image of MODIS-MYD13Q1 and data of 85 plots in Cordoba, Argentina were using the data that comprised 13% of the plots covered bare soil, 63.5 % were grown with soybean and corn with 23.5%. Five different ANN model of multi-layer feed-forward perceptron were developed shown in Figure.2. The input used by the four models were NDVI (Normalized Difference Vegetation index), EVI (Enhanced Vegetation Index), red (RED) and near infrared (NIR), the numbers of input neurons used by the fifth model were RED and NIR reflectance. The model one to four built with 3 neurons in the input layer and 6 numbers of input neurons in the hidden layer. For all models the numbers of neurons in hidden layer were same. The results of all models were good for land use estimation; all models correctly classify the Soil, Corn and Bare Soil. The performance was quantified. All models evaluated the accuracy and Kappa statistic as shown in Table 1.

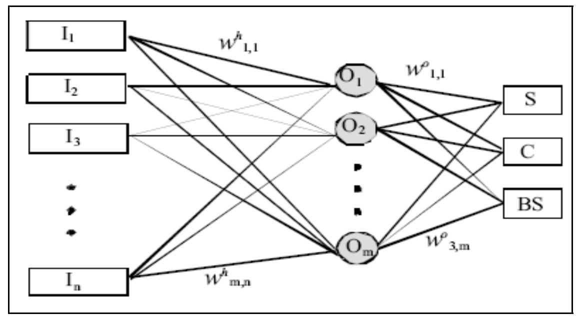

Figure 2. Scheme of an ANN of the multilayer perceptron type [11].

Ii. Input neurons,
Oj Hidden neurons wh
i, j Connection weight between Ii and Oj, wo
k, j weight between Oj and the output layer
Soybean(S), Corn(C) and Bare Soil(BS)
(For 1 ≤ i≤n, 1≤j≤m).

c. New supervised learning of ANNs for satellite image classification [12].

A new technique proposed consists of three layered ANNs using the concept of domain of recognition in the input space. The multi band data were acquired by two different ways, one is by an optical sensor and second used microwave radar. The model has been used to classify the multiband data and assigned some categories. Recently the author proposed the same technique for the 7 band observation data which obtained by an optical sensor. In proposed work to improve the classification accuracy by using not only multiband data of an optical sensor but also used to process the data which obtained by microwave radar. For leaning designed two ANNs models, one model was learnt using seven bands TM data, and the other was learnt using eight band data by adding an Active microwave instrument (AMI) data to the 7 bands. However the result shows the classification of 8 band data was good and decrease unclassified pixel in the map as compared to those which construct using 7 bands data thus shows that the classification ability of ANN depends on the choice of training data.

Table 1. The Accuracy and kappa statistic of all models with different combinations of input data [11].

Models	Overall Accuracy%	Accuracy Procedure/user (%)			Kappa statistics(%)
Model1	85.70	89.30/89.30	80.00/80.00	75.00/75.0	70.80
Model2	83.30	89.30/86.20	60.00/66.70	100/100	65.30
Model3	76.20	85.70/80.00	70.00/70.00	25.00/50.00	48.50
Model4	81.00	92..90/81.30	40.00/80.00	00/80.00	7.90
Model5	92.90	92.90/96.30	90.00/81.80	00/100	85.70

d. An ANNs approach to map land use/cover using Land sat imagery and ancillary data [10].

In this paper author discussed the errors with remote sensing image classification. The accuracy of land cover feature classification depends on the spectral signature and on the methodology of classification procedure. Different land cover class has a many similar spectral features and unique signature. This confusion of interclass introduced spectral classification errors. In [8] [9] Applied ancillary data to improve the spectral classification accuracy. The ancillary data cannot use directly because statistical assumption of the statistical algorithm e.g. maximum likelihood. Therefore in [2] proposed a model to provide a new approach to classify spectral and ancillary information using ANNs.

In the paper [10] the multilayer perceptron (MLP) applied for land cover mapping. In this research, the multilayer perceptron (MLP) was trained by back propagation (BP) algorithm. In the proposed work the data were acquired from the National Institute of Geography the data include a Landsat ETM+ image dated April 3, 2000, a digital model of elevation along with soil, land cover and land use, and digital maps of road network with a scale of 1:250,000. There are two classification models were designed. The first model trained the division of land cover and land use class for making spatial relationships between the land use, land cover map and the ancillary information. The first model creates a digital fuzzy map which shows the likelihood of the presence of each land cover and land use type through by each pixel. Similarly the second classifier used remotely sensed images and produced a fuzzy map using a spectral classification. Thus there were two fuzzy maps for each pixel which indicated a membership value. These maps were describing the likelihood of the occurrence of a land cover class from its spectral features, respectively. In [6] presents a model used AND operator to combine the two fuzzy map, the model calculates the minimum of two values of belonging. A final no fuzzy map has been generated and marks each pixel with the greater value of belonging. The MLP training process used the BP training algorithm. The data including the training set, the verification set, and the test set. The verification set shall apply to determine the best network and to stop the process of training in the case of over learning occurred. The test set was given the independent judgment of network performance when the network design process was completed.

In the proposed work the image was divided into 6 land cover and land use classes: 1) tropical forest, 2) mangroves, 3) wetlands, 4) agriculture (grasslands, pasturelands and croplands), 5) water and, 6) urban areas. There were nine inputs: six soils type, elevation distance to the road and distance to the coast to MLP for classification and 6 hidden nodes. The result of classification of the test set is 73% correctly classified. The spectral classification the MLP with 5 inputs bands 2, 3, 4, 5 and 7 and two hidden layers with 3 and 4 nodes respectively. The classification results show good performance 82% accurate classification of the test set. The first classification result obtained using spectral information, classifying each pixel into the class which have the higher membership value. Table 2 shows the errors for the classification of crop, water, Mangrove, Forest, Wetland and Urban areas

As a summarize step, the ancillary maps combined with spectral fuzzy maps. The accuracy of the resulting map was verified with same verification data. Overall accuracy improved to 79%. The accuracy of different land cover classes' improves significantly by using the ancillary. Both commission and omission errors reduce 25% but for the error of commission of the crop/pasture land and both commission and omission errors of urban area which remained the same as shown in Table 2.

e. Land Cover Classification of IKONOS Multispectral Satellite Data [21].

The paper presents the maximum likelihood classifier. In the maximum likelihood classification each image pixel is assigned to land cover class based on highest probability of membership. The IKNOS satellite data were used. It is imaged over the part of Daejeon city, Korea. The image consisted of 399 lines, with 550 cells per line, a cell's size of about 4x4m and one near-infrared and three visible bands. In this research channel 1, 2, 3 and 4 of the images were used. Nine classes of the land cover features were acquired in the training sites for getting training datasets.

Table 2. Omission and Commission Errors of Land Class Classifications [10]

Land use class	Spectral	Spectral	Spectral + Ancillary	Spectral + Ancillary
Map	Error of omission	Err of commission	Error of omission	Err of commission
Crop/pasture	0.53	0.29	0.20	0.31
Water	0.02	0.02	0.06	0.00
Mangrove	0.30	0.14	0.22	0.11
Tropical forest	0.31	0.24	0.22	0.22
Wetlands	0.23	0.52	0.23	0.23
Urban AREAS	0.43	0.50	0.43	0.43

The topographic map was used for calculation of classification accuracy.

The steps for land cover classification are as follows.

Step1. Identify the land cover classes within an image which is to be classified, for example water, grass, building, etc.

Step2. Select pixel which is the representation of the desired set of classes.

Step3. Estimate the parameters of the algorithm by using training data. These parameters will be used as properties of the probability model.

Step4. Label every pixel in the image into their corresponding land cover type.

Step5. Generate thematic maps.

The maximum likelihood classification was applied to the IKNOS image. The overall accuracy of maximum likelihood classifier is 76.20% and kappa coefficient is 0.73 as shows in Figure 8. The same data is classified by using neural network and the overall accuracy is 79.00% and the kappa coefficient is 0.76.

The same data are also classified by neuro fuzzy model. The overall accuracy of the model is 85.6 and the kappa coefficient is 0.83. The results of the three model shows that the performance of the neuro fuzzy model is better than neural network and maximum likelihood as shown in Table 3.

Table 3. Performance of Maximum Likelihood, Neural Network AND NEURO-fuzzy methods [22].

	Classification Performance	
Method	Overall Accuracy	Kappa Coefficient
Maximum Likelihood	76.2	0.73
Neural Network	79.0	0.76
Neuro-Fuzzy	85.6	0.83

f. Comparison of maximum likelihood, Neural Network and Neur-fuzzy classifier.

The approaches which are used for classification of land cover and land use are summarized in (Table 4). The comparison shows that the performance of all models of ANNs is good as compared to the statistical technique such as Maximum likelihood. There are some problems with statistical technique such as the integration of ancillary data and assumed normal distribution.

g. Fuzzy logic applied in the remote sensing image classification [16]

Fuzzy logic can be applied in remote sensing for the classification of images. The benefits of this method are that it does not need assumption about the statistical distribution of the data and provide more accurate results for image classification. This paper contains a hierarchical expert system for the classification of remote sensing. The model was tested for land cover classification. The data were obtained by Lansat 7 ETM+ over the Rio Rancho area. 8 spectral bands, DEM and NDVI used as input. If the normal type rules are used then the number of rules would be very large for classification, so requires a long time for classification. To overcome this problem the Hierarchical structure is presented. All the classes were grouped together and each group would be further divided into subgroups. It was important to generate appropriate fuzzy rules by using the fuzzy expert knowledge The main problem of using the fuzzy expert system is the chance to lose some information.

In the proposed work authors used an Adaptive-Neural-Network Based fuzzy Inference to generate fuzzy rules. The system is tested on the images which are taken by Land sat 7 ETM+. There are 9 different land cover classes: water, vegetation, urban irrigated vegetation, barren, calichebarren, Basque, shrub land, natural grassland and juniper. The urban area is blocked by street and mixed with vegetation which creates a problem in classification, similarly natural grassland; shrub land and juniper are highly mixed so its classification is difficult, the result of the proposed model compared with that of maximum likelihood classifier and ANN algorithm

The comparison shows that the result of the proposed work betters than the results of Maximum likelihood classifier and back propagation. The overall accuracy fuzzy system is 91.55% which is higher than maximum likelihood and back propagation algorithms.

Table 4. Comparison of different classification approaches.

Technique	ANN Supervised	ANNs Multilayer Perceptron	Maximum Likelihood	ANNs Back propagation	Nuero-Fuzzy
Approach	ANNs	ANNs	Probabilistic	ANNs	ANNs
Classification	Satellite Image	Satellite Image	Satellite Image	Satellite Image	Satellite Image
Data Source	Optical Sensor and microwave radar	Landsat ETM	IKNOS Satellite	IKNOS Satellite	IKNOS Satellite
Model	7 band and 8 band	M1=Ancillary Data, M2=Spectral Data, M3= Combination of M1 and M2	MLC	BP	Multi-layer Neuro-fuzzy
Accuracy	accuracy of 8 band data better than 7 band data	M1=73%, M2=82% M3=79%	MLC=76.2 Kappa=0.73	BP=79.2 Kappa =0.76	The overall accuracy is 85.2 the Kappa is 0.83

Table 5. Classification matrix for the study area by using MLC [16]

Actual class	Predicted classes									Accuracy
	wt	ui	ziv	br	cb	bq	sb	ng	jp	
WT	0	225	1	0	0	0	0	0	0	0
UI	0	863	0	22	16	0	50	0	8	89.99
IV	0	20	506	0	0	0	0	0	0	96.20
BR	0	53	0	786	384	0	10	31	85	58.27
CB	0	0	0	18	74	0	0	0	0	80.43
BQ	0	81	0	0	0	0	0	0	0	0
SB	0	17	0	0	0	0	296	36	29	78.31
NG	0	4	0	0	0	0	145	44	6	21.89
JP	0	12	0	0	0	0	64	2	89	50.86
	Average accuracy (%)=52.88 overall accuracy (%)=66.67									

Table 6. Classification matrix for the study area by using BP [16]

Actual class	Predicted classes									Accuracy
	wt	ui	iv	br	cb	bq	sb	ng	jp	
WT	223	0	1	0	0	2	0	0	0	98.67
UI	0	852	1	55	0	0	43	5	5	88.84
IV	0	1	522	2	0	1	0	0	0	99.24
BR	0	12	0	1310	0	0	3	3	21	97.11
CB	0	0	0	92	0	0	0	0	0	0
BQ	0	0	0	0	0	81	0	0	0	100
SB	0	19	0	2	0	0	327	25	5	86.51
NG	0	4	0	36	0	0	99	57	5	28.36
JP	0	8	0	45	0	0	47	12	63	36.00
	Average accuracy (%)=70.53 overall accuracy (%)=86.53									

Table 7. Classification matrix for the study area by using Fuzzy System [16]

Actual class	Predicted classes									Accuracy
	wt	ui	iv	br	cb	bq	sb	ng	jp	
WT	215	0	1	0	0	10	0	0	0	95.13
UI	3	933	0	17	0	0	23	1	3	97.29
IV	1	4	510	0	0	11	0	0	0	96.96
BR	4	20	0	1271	35	0	5	6	8	94.22
CB	0	0	0	10	82	0	0	0	0	89.13
BQ	0	0	0	0	0	81	0	0	0	100
SB	0	0	0	1	0	0	356	18	3	94.18
NG	0	0	0	27	0	0	92	68	14	33.83
JP	0	2	0	29	4	0	6	0	134	76.57
	Average accuracy (%)=86.37 overall accuracy (%)=91.55									

4. Methods to solve the mix pixel problems.

The mix pixel is the common problem of remote sensed images [12]. A mixed pixel represents the areas which occupy more than one variable. There are two situations in which the mixed pixel problem occurs. The first case is when the pixel attached with large area objects such as agriculture field. The second case is that when the object is relatively small compared to the spatial resolution of the scanner. Therefore, to accurately estimate the land cover sub pixel analysis is important there are different techniques are used to solve the mixed pixel problem supervised fuzzy c means classification, the spectral mixture model, the nearest neighbor classifier and multilayer perceptron. In different papers presented different techniques to solve the mix pixels problem.

a. Maximum Likelihood and Fuzzy Classifier [18].

The spatial pattern of ground cover features information can obtained by Remote Sensing, but the imagery which is obtained by Remote Sensing have problems of class mixing within pixels. This paper presents the maximum likelihood and fuzzy classifier, which are used in urban planning, forestry, urban and savanna woodlands. The data for features extraction got from global land cover network. Eight detail land cover classes were mapped for the shire River catchment. First used maximum likelihood classifier this method involves the selection of training area which represent the eight land cover classes, Then signature of training area used to determine to which class were assigned to image pixels. Second use Fuzzy Convolution filter Classification. This method process completes in two steps the first step involves filtering in which create a single classification layer into a window of pixel and total weighted inverse distance of all the classes calculated then assigning the center pixel to the class which have largest total inverse distance. The pixel based classification approach maximum likelihood used in this paper provides results with 87% accuracy while fuzzy convolution provides 77% accurate results. This shows that the maximum likelihood classification performance is good when extracting land covers information from satellite imagery. The comparison of both classification methods is shown in Table 5.

The comparisons of maximum likelihood and fuzzy classifier are summarized in (Table 8). The pixel based classification method maximum likelihood was used in this paper for the classification of forestry, urban planning and savanna woodlands. The maximum likelihood provides results with 87% accuracy while fuzzy convolution provides 77%. This shows that the maximum likelihood analysis has the great ability of classification in the land cover with heterogeneous and higher resolution imagery.

The accuracy of maximum likelihood is better than fuzzy convolution filter. The maximum likelihood classifier is useful in discriminating environments, which is well suited for application such as hydrological modeling.

b. Sub pixel Estimation of land cover in remotely sensed image [19].

There were different approaches proposed to correctly estimate the components of land cover such as Spectral un-mixing, Unsupervised and Supervised Methods [18]. Spectral un-mixing technique was used to estimate the fraction of each component in a pixel using multispectral data. The linear mixing models were used to estimate the proportion of component spectra from training data. However, when the spectral characteristic of the categories within objective areas does not satisfy by the training data, large errors may be occurred with the result. The unsupervised estimation was used to overcome the problems of linear mixing model [20].

This method is good to solve the problem when the variation of pure pixel is small otherwise large error may be appeared in the results.

In a paper [19] authors proposed Semi-supervised estimation this method overcomes the problems of unsupervised estimation in which the variation of pure pixels is large, Semi-supervised estimate the component spectra depends on the surrounding information of pixels, it used the small size of initial training data and first step identifies pure pixel in the image as shown in Figure 3.

Pure pixels which consist of a single class of features exist around a certain point in a feature space. If two classes are mixed within a pixel, It will show that the observed data will exist between the two classes and represent the intermediate characteristic of spectra. The pixel can consider is pure if it exists within a small distance from each features class center. The mean vector and covariance matrix are used to calculate the distance between pixel and category. Next use the pure pixels to predict adaptively the feature spectra in the surrounding areas of each mix pixels. When pure pixels exist in the surrounding area of only one class as shown in Figure 4, and then classify the cells into the same class with neighbors. When there are more than two categories of pure cells in the surrounding areas, then component spectra for each class and use for sub cells estimation.

The result shows that the proposed method works well when the variations of pure pixels are large. The comparison of Supervised, Unsupervised and Semi Supervised methods based on sub pixel mapping as summarized in Table. 9.

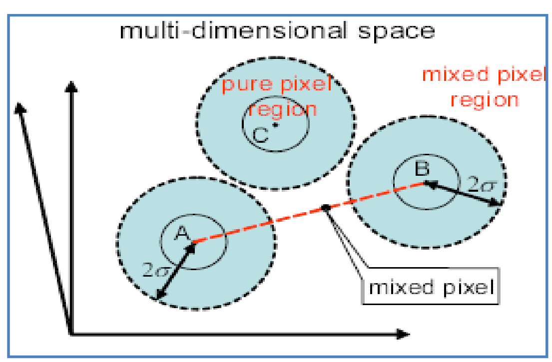

Figure 3. Determination of pure pixels [19].

Table 8. Comparison of maximum likelihood and fuzzy classifier.

Technique	Maximum Likelihood	Fuzzy Classifier
Approach	Statistical	Fuzzy Logic
Classification	Satellite images with mix pixels.	Satellite images with mix pixels.
Data	Forestry, Urban, Swana Woodland	Forestry, Urban, Swana Woodland
Model	Maximum Likelihood classifier	Fuzzy Convolution Filter
Accuracy	1. Overall accuracy 87% 2. Accurately mapped individual classes in more details. 3. Successful in heterogeneous environment.	1. Overall accuracy 77% 2. Not good to map individual classes in more detail. 3. Misclassify pixels
Advantages	High Potential to classify higher resolution imagery.	Good in homogeneous environment.

c. Sub-pixel Mapping of Remote Sensing Image Based on MAP model [23]

In this paper author proposed a new sub pixel mapping approach Maximum a Posteriori (MAP). The MAP model can be used to predict the location of class proportion within each pixel. The locations of the sub pixel in the central pixel identified by using the spatial arrangement of the different class fraction in surrounding pixels. The sub-pixel mapping algorithm is to be applied to high spatial resolution fraction images. The experiment is performed on artificial imagery and real imagery. The result shows that the model performs well against artificial imagery (Table.10)

Similarly the performance of the model is good for real imagery and the result is compared with other classification method which shown in (Table.11).

The confusion matrix (Table.12) shows that the MAP model produces good result as compared to the maximum likelihood classifier.

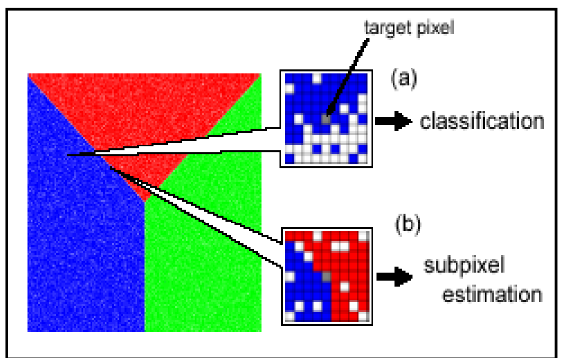

Figure 4. Sub pixel estimation for mixed pixel [19]

Table 9. Comparison of Supervised, Unsupervised and Semi Supervised

Technique	Linear Mixing Model	Unsupervised Analysis	Semi Supervised Analysis
Approach	Supervised	Unsupervised	Semi-Supervised
Performance	Depends on the training data	The result is good when the variation of pure pixels is small	Depends on the initial training data and the pure determination
Limitation	When the training does not represent the spectral characteristic of the categories within objective area	When the variation of pure pixel is large	When the class composition of every pixel is estimated , the spatial distribution of these class components within each pixel remains unknown

Table 10. The accuracy static of the classification result of two methods [23]

Method	PCC	Kappa coefficient
Hard Classification	0.906	0.752
MAP	0.987	0.861

Table 11. The accuracy static of the classification result with MLC and MAP [23]

Method	PCC	Kappa coefficient
Hard Classification	0.813	0.832
MAP	0.907	0.961

Table.12 The classification result by Confusion Matrix (R, L, V, U: River, Lake, Vegetation, Urban) [23]

Method		r	l	v	u
MLC	R	89	89	7	2
	L	8	8	8	6
	V	3	3	66	21
	U	0	0	19	71
MAP	R	95	95	0	2
	L	2	2	6	8
	V	2	2	82	10
	U	1	1	12	79

Conclusion and Recommendations

The increasing demand of land cover and land use information has raised the importance of classification and forecasting of land cover and land use. In this study a survey of current approaches of land cover mapping such as ANN, Fuzzy logic and Statistical techniques is done. The multilayer Feed Forward ANN used for the classification the overall results of this approach is good as compared to the statistical approach. ANN has the very strong ability to recognize mix classes. The performance of statistical approach is good as compared to the fuzzy classifier although Maximum Likelihood classification assumes a normal distribution. This approach can be used to produce a land cover map. Moreover, the survey included the study of different approaches such as ANNs, Maximum Likelihood, Supervised, Unsupervised and Semi Supervised to solve the mix pixel problems. The semi-supervised has the ability to solve the problems of mix pixels. The semi-supervised technique adaptively estimates the proportion of components where the object characteristics changes with the location of the mixed pixels. The majority of approaches discussed in this study are based on ANNs, Fuzzy logic, and probabilistic techniques. The ANNs and fuzzy set theory has the potential to overcome the limitation of probabilistic techniques such as maximum likelihood classifier and parallelepiped etc. In some cases e.g. when the spectral signature of the area is same the Maximum Likelihood produce good result as compared to ANNs and Fuzzy logic, however when the spectral signatures of the area are not same than ANNs and Fuzzy logic are better than Maximum Likelihood.

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