Investigation on Land Cover Mapping of Large RS Imagery Using Fuzzy Based Maximum Likelihood Classifier

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Abstract The success of a large number of real-world applications such as mapping, forestry, and change detection depends on the effectiveness with which land cover classes are extracted from Remotely Sensed (RS) imagery. Application of Fuzzy theory in remote sensing has been of great interest in the remote sensing fraternity particularly when the data are inherently Fuzzy. In this paper, a Fuzzy theory based Maximum Likelihood Classifier (MLC) is discussed. The study aims at amplifying the classification accuracy of large heterogeneous multispectral remote sensor data characterized by the overlapping of spectral classes and mixed pixels. Landsat 8 multispectral data of North Canara District was collected from USGS website and is considered for the research. Seven land use land cover classes were identified over the study area. The study also aims at achieving classification results with a confidence level of 95% with $\pm 4\%$ error margin. The conducted research attains the predicted classification accuracy and proves to be a valuable technique for classification of large heterogeneous RS multispectral imagery.

1 Introduction

Classification of multispectral imagery has formed itself as one of the most sought-after technique for information extraction. The process of image classification, in the context or remote sensing, has been broadly classified into hard and soft classification techniques. In hard classification, a pixel is assumed to be an indecomposable part of the image and belongs to just one of the defined land cover class. However, in the real world due to the presence of mixed pixels (mixels), which form the salient feature of heterogeneous study areas, hard classifiers are shown to produce poor

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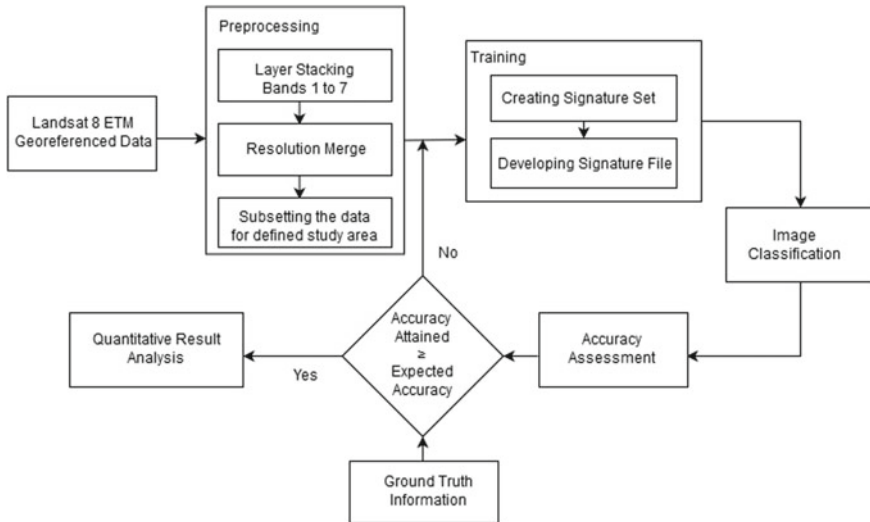
Fig. 1 General flow of the methodology

results as the ground data is imprecise [1–3]. Soft or Fuzzy classification comes in handy under these eventualities and has been known for its capability to extract a lot of helpful data from heterogeneous RS data [2, 4]. A large number of studies have been conducted for classifying RS data using Fuzzy logic [2, 5–8]. Though a large number of researchers have conferred their study towards remotely sensed image classification using different classifiers, it has still remained a challenging task within the remote sensing fraternity [1, 9–12]. Hence, it has become necessary to research and produce new classification techniques for obtaining better classification results.

Zadeh's concept of Fuzzy set theory has provided some very useful options for operating with heterogeneous datasets [13]. Using Fuzzy set concepts a pixel in an image is described with a membership function that links the pixel a real number from 0 to 1. This membership function is treated as the probability of the pixel belonging to each class [1, 13]. This principle is shown to provide an efficient solution for mixed pixel issue [3, 8].

The objective of this study is to perform LULC mapping of the considered study area using Fuzzy theory based MLC. The goal of classification is to obtain results with a confidence level of 95% with ±4% error margin. The methodology followed is illustrated in Fig. 1.

The rest of the paper is organized as follows. Section 2 discusses the data and study area used. Section 3 discusses the classification method employed. Section 4 presents the results obtained during the study. Section 5 presents the conclusions drawn from the results.

2 Materials and Methodology

Land Satellite (Landsat) 8 data was accessed by U.S. Geological Survey (USGS) website. Figure 2 indicates the study area considered and it envelops the North Canara District in Karnataka, India. The Western Ghats form the main geographic feature of the region and runs from North to South. The average rainfall on the coastal part is 3000 mm (120 in) and is as high as 5000 mm (200 in) in the west-facing slopes of Western Ghats. East facing ridge of the Western Ghats is the rain shadow region and receives, on an average, only 1000 mm (39 in) rainfall annually [14]. High rainfall in the region supports lavish forests that coat over 70% of the coverage area. The north part of the Western Ghats forms Moist Deciduous Forests ranging from 250 to 1000 m in elevation. Above 1000 m elevation are the Evergreen rain forests [15]. The study area also has chunks of degraded scrub jungles and savanna. The beach region is characterized by coconut plantations and screw pine. The study area is recognized as a coastal agro-climatic zone by the government of India. The overall spatial resolution of the image is 15 m. This data was acquired on May 18 2016, which is the mid-summer season and is free from clouds. Layer stacking of first seven bands produces a low-resolution multispectral (MS) imagery of 30 m. Resolution merge technique is used to merge the 30 m MS image with higher spatial resolution band 8 to obtain high resolution 15 m multispectral image. This image is then used for further processing.

2.1 Feature Extraction/Signature Collection

There are several methods of collecting the training data, including; in situ data collection, on-screen selection of polygonal data, and/or on-screen seeding of training data [1]. By employing an on-screen selection of polygonal data technique, seven land use land cover classes were identified over the study area; (i) Water Body, (ii) Kharif, (iii) Built Up, (iv) Scrub Land, (v) Double Crop/Horticultural Plantations, (vi) Moist Deciduous Forest, and (vii) Evergreen Forest. Spectral signatures were collected for each class with at least 300 sample pixels per class. The study considered both pure and mixed pixels for training the algorithm.

The considered study area exhibits the characteristics of a heterogeneous dataset with more than two classes severely overlapping one another. Class separability was measured in terms of Euclidean distance considering two classes at a time. The Euclidean distance was redefined to measure the severity of land cover overlapping and is used as the spectral similarity index (SSI). Highest class separability was measured between Water Body and Kharif classes and was considered as the reference for other classes. Classes with a SSI value of less than 0.4 were determined to be severely overlapping one another at certain locations. SSI measurements for all possible class pairs are shown in Table 1.
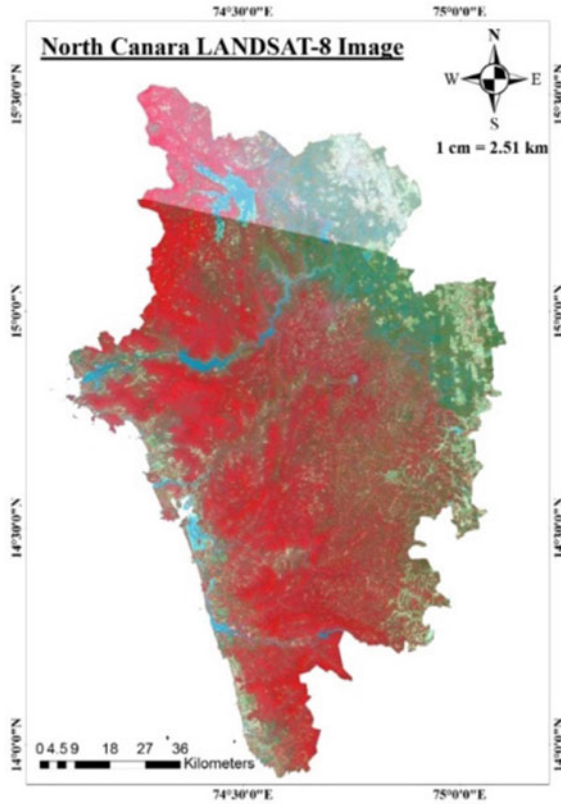
Fig. 2 15 m spatial resolution map of the study area [16]

3   Fuzzy Theory Based Maximum Likelihood Classifier

The Fuzzy theory based ML classifier discussed in this paper works in three stages; (i) Fuzzification of the data, (ii) Classification using Fuzzy theory based MLC, and (iii) Defuzzification.

3.1   Fuzzification

In the Fuzzification step, each pixel on the input image is converted into a pixel measurement vector, x, of membership grades. The Fuzzy membership function for any x must lie in the range 0–1, they should all add up to unity, and should be positive values. These characteristics are listed in (1), (2), and (3) [1].

Table 1 Class separability in terms of spectral similarity index

Class Pair	SSI	Class pair	SSI	Class pair	SSI
1:2	1	2:4	0.441	3:7	0.963
1:3	0.879	2:5	0.796	4:5	0.544
1:4	0.628	2:6	0.486	4:6	**0.061**
1:5	0.666	2:7	0.968	4:7	0.649
1:6	0.598	3:4	0.528	5:6	0.518
1:7	0.668	3:5	0.774	5:7	**0.210**
2:3	**0.338**	3:6	0.562	6:7	0.612

1: Water Body, 2: Kharif, 3: Built Up, 4: Scrub Land, 5: Double Crop/Horticultural Plantations, 6: Moist Deciduous Forest, 7: Evergreen Forest
Bold characters represent the spectral similarity index for the most severely overlapping class pairs. The class pairs having spectral similarity index (SSI) value of 0.3 and lesser are the most severely overlapping class pairs. It is highlighted to make it easy for the reader to identify the severely overlapping class pairs easily

$$0 \leq f_{F_i}(x) \leq 1 \qquad (1)$$

$$\sum_{x \in X} f_{F_i}(x) > 0 \qquad (2)$$

$$\sum_{i=1}^{m} f_{F_i}(x) = 1, \qquad (3)$$

where, F_i is one of the spectral classes, X represents all pixels in the dataset, x is a pixel measurement vector, m is the number of classes, and f_{F_i} is the membership function of the Fuzzy set $F_i (1 \leq i \leq m)$. All the membership function values are recorded as a Fuzzy partition matrix

$$\begin{bmatrix} f_{F_1}(x_1) & f_{F_1}(x_2) & \dots & f_{F_1}(x_n) \\ f_2(x_1) & f_{F_2}(x_2) & \dots & f_{F_2}(x_n) \\ \vdots & \vdots & \dots & \vdots \\ f_{F_m}(x_1) & f_{F_m}(x_2) & \dots & f_{F_m}(x_n) \end{bmatrix}, \qquad (4)$$

where, n represents the total number of pixels, and x_i is the ith pixel's measurement vector [1].

3.2 Classification

Fuzzy based classification involves the use of Fuzzy mean and covariance matrices. For class c, Fuzzy mean is computed as

$$\mu_c^* = \frac{\sum_{i=1}^{n} f_c(x_i) x_i}{\sum_{i=1}^{n} f_c(x_i)}, \tag{5}$$

where, x_i is a sample pixel measurement vector ($1 \leq i \leq n$), f_c is the membership function of class c, and n is the total number of sample pixel measurement vectors [1].

The Fuzzy covariance matrix V_c^* is computed as;

$$V_c^* = \frac{\sum_{i=1}^{n} f_c(x_i)(x_i - \mu_c^*)(x_i - \mu_c^*)^T}{\sum_{i=1}^{n} f_c(x_i)} \tag{6}$$

These mean and covariance values replace the conventional mean and covariance matrix in the classical MLC algorithm. This will convert a classical MLC algorithm into a Fuzzy based soft classification algorithm [1].

Fuzzy set theory solely provides membership functions for every pixel over the defined number of classes and requires a parametric rule for assigning those pixels to relevant classes. Parametric rules such as Maximum Likelihood, Mahalanobis Distance et al. may be used in the process. This study involves the utilization of Maximum Likelihood classifier as the parametric rule.

Fuzzy based Maximum Likelihood classifier uses Fuzzy mean and Covariance matrices replacing the conventional mean and covariance matrices. For an n-band multispectral image the likelihood function for a pixel belonging to class k is given by [1],

$$p^*(x|w_i) = \frac{1}{(2\pi)^{n/2}|V_k^*|^{1/2}} \exp\left[-\frac{1}{2}(x - \mu_k^*)V_k^{*-1}(x - \mu_k^*)^T\right], \tag{7}$$

where, x is one of the brightness values on the x-axis, μ_k^* is the Fuzzy mean as in (5), V_k^* is the Fuzzy covariance matrix as in (6), and $(x - \mu_k^*)^T$ is the transpose of vector $(x - \mu_k^*)$. Similarly, $p^*(x|w_i)$ is calculated for each pixel for all classes. A membership function then enables the algorithm to decide to which class the corresponding pixel is to be assigned. For Maximum Likelihood classifier, the membership function can be defined as [1];

$$f_c(x) = \frac{p^*(x|w_k)}{\sum_{i=1}^{m} p^*(x|w_k)} \tag{8}$$

The membership grades of a pixel vector depend on x's position in the vector space. $f_c(x)$ increases exponentially with the decrease of $(x - \mu_k^*)V_k^{*-1}(x - \mu_k^*)^T$, i.e., the Mahalanobis distance between x and class k. The factor $\sum_{i=1}^{m} p^*(x|w_k)$ is a normalization factor [1]. Applying this type of Fuzzy logic creates a membership grade matrix for each pixel.

3.3 Defuzzification Using Fuzzy Convolution

Fuzzy convolution technique is used to convert the n-layer output of classification into a map like structure. It creates the map by computing the total weighted inverse distance of all the classes in a window of pixels. The process first computes the total inverse distance summed over the entire set of Fuzzy classification layers for each class. It then assigns the center pixel to the class for which the value $T[k]$ is largest. The total inverse distance, $T[k]$, can be computed using [17]:

$$T[k] = \sum_{i=0}^{s} \sum_{j=0}^{s} \sum_{l=0}^{n} \frac{w_{ij}}{D_{ijl}[k]} \tag{9}$$

where, i is the row index of window, j is the column index of window, s is the size of window, l is the layer index of fuzzy layers used, n is the number of fuzzy layers used, W is the weight table for window, k is the class value, $D[k]$ is the distance file value for class k, and $T[k]$ is the total weighted distance of window for class k [17]. This study considers a 5×5 size window given by

$$\begin{bmatrix} 0.500 & 0.605 & 0.646 & 0.605 & 0.500 \\ 0.605 & 0.750 & 0.823 & 0.750 & 0.605 \\ 0.646 & 0.823 & 1.000 & 0.823 & 0.646 \\ 0.605 & 0.750 & 0.823 & 0.750 & 0.605 \\ 0.500 & 0.605 & 0.646 & 0.605 & 0.500 \end{bmatrix} \tag{10}$$

4 Results and Discussion

Figure 3 illustrates the Fuzzy topology based maximum likelihood classification map of the study area. Table 2 shows the results obtained after accuracy assessment. User's Accuracy and Kappa value are considered as the pivotal parameters in judging the classification process [18]. The classifier extracted dominant classes (Evergreen Forest and Deciduous Forest) very efficiently. Less dominant classes (Double Crop and Built Up) are extracted very poorly by the classifier. Fuzzy topology based maximum likelihood classifier has shown significant improvement in classification performance [12]. An overall Kappa value of 0.7870 indicates an excellent performance from the classifier [18].

To illustrate the usefulness of using the inverse weighted distance of all classes from the weight windows for pixels for assigning pixels to class values, Table 3 indicates the inverse weighted distance, $T[k]$, for 10 pixels randomly selected from the study area. A hard classified map is created by assigning a pixel to the class for which the distance measure, $T[k]$, is maximum.

Table 2 Results of Fuzzy topology based maximum likelihood classification

Class name	Reference totals	Classified totals	Number correct	Producer's accuracy (%)	User's accuracy (%)	Kappa value (k_{hat})
Evergreen Forest	534	538	502	94.01	93.31	0.8564
Scrub Land	59	70	40	67.80	57.14	0.5446
Moist Deciduous Forest	235	214	205	87.23	95.79	0.9450
Built Up	5	14	3	60.00	21.43	0.2103
Double Crop/Horticultural Plantations	57	80	37	64.91	46.25	0.4300
Water Body	31	16	16	51.61	100.00	1.0000
Kharif	79	68	59	74.68	86.76	0.8563
Total	1000	1000	862			
Overall classification accuracy = 86.2%						
Overall Kappa Statistic = 0.7870						

Table 3 Total inverse weighted distance of all classes for selected pixels

Pixel no.	Weighted inverse distance ($T[k]$) from							Class assigned
	EGF[a]	SL[b]	MDF[c]	BU[d]	DC/HP[e]	WB[f]	KH[g]	
1	**0.1988**	0.1199	0.1159	0.0654	0.1664	0.0026	0.0463	**EGF[a]**
2	0.1243	**0.1714**	0.1593	0.0821	0.1359	0.0011	0.1041	**SL[b]**
3	0.1426	0.1592	**0.1701**	0.0949	0.1348	0.0012	0.0815	**MDF[c]**
4	0.0639	0.1140	0.0576	**0.1655**	0.1443	0.0022	0.1345	**BU[d]**
5	0.0635	0.1561	0.0989	0.1361	**0.1709**	0.0019	0.1431	**DC/HP[e]**
6	0.0468	0.0587	0.0432	0.0951	0.0768	**0.1552**	0.0701	**WB[f]**
7	0.0148	0.1188	0.1634	0.1366	0.0540	0.0011	**0.1748**	**KH[g]**
8	0.0295	0.1161	0.0541	0.1059	0.0920	0.0007	**0.1939**	**KH[g]**
9	0.0215	0.0761	0.0314	**0.1742**	0.0582	0.0025	0.1235	**BU[d]**
10	0.1791	0.0758	0.0568	0.0326	**0.2013**	0.0018	0.0229	**DC/HP[e]**

EGF[a]: Evergreen Forest, SL[b]: Scrub Land, MDF[c]: Moist Deciduous Forest, BU[d]: Built Up, DC/HP[e]: Double Crop/Horticultural Plantations, WB[f]: Water Body, KH[g]: Kharif

Bold characters represent the spectral similarity index for the most severely overlapping class pairs. The class pairs having spectral similarity index (SSI) value of 0.3 and lesser are the most severely overlapping class pairs. It is highlighted to make it easy for the reader to identify the severely overlapping class pairs easily

Fig. 3 Fuzzy topology based maximum likelihood classified map of the study area
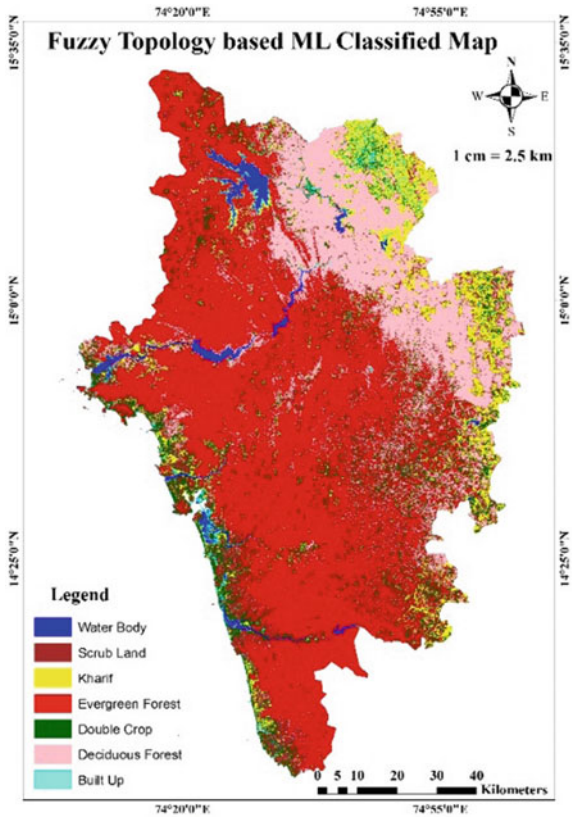
4.1 Placing Confidence Limits on Assessed Accuracy

A straightforward statistical approach may be used to express the interval within which the true map accuracy lies, say, with 95% certainty. It is possible to use the normal distribution to obtain this interval by the expression [2];

$$-Z_{\alpha/2} < \frac{x - nP}{\sqrt{nP(1 - P)}} < Z_{\alpha/2}, \tag{11}$$

where, n is the number of testing pixels, $x(=np)$ is the number of correctly labelled pixels, P is the thematic map accuracy in percentage, $p(=x/n)$ is the proportion of pixels correctly classified, $Z_{\alpha/2}$ is the value of the normal distribution beyond which on both tails α of the population is excluded [2].

From Eq. (11), the estimate of the thematic map accuracy, P, estimated by the proportion of pixels that are correctly classified in the testing set, at the 95% confidence level, for large values of n and x, and for reasonable accuracies are [2],

$$\frac{x \pm 1.960\sqrt{\frac{x(n-x)}{n}} + 0.960}{n} = p \pm \frac{1.960}{n}\sqrt{\frac{x(n-x)}{n}} + 0.960 \qquad (12)$$

For 1000 testing pixels and a minimum of 80% of expected accuracy, it is expected to have, at least, 800 pixels to be correctly classified. From (12), the bounds on the estimated map accuracy are $P = p \pm 0.039$ or, in percentage terms, the map accuracy is approximated to be between 82.1 and 89.9%.

5 Conclusion

In this paper, a novel method for classification of large RS imagery through embedding Fuzzy theory into classical Maximum Likelihood Classifier (MLC) is discussed. A pixel is the basic building block of an image and is indecomposable in hard classification applications. The study proves that a pixel can be used as a decomposable unit in image classification. The results obtained indicate that Fuzzy theory based MLC permits obtaining accurate results for large heterogeneous study areas in the presence of mixed pixels and spectrally overlapping classes. The study conjointly confirms that one can use mixed pixels as training data and yet achieve good results. The objective of obtaining classification results with confidence level of 95% with ±4% error margin is achieved. Hence, it can be concluded that the discussed Fuzzy topology based MLC handles mixed pixel issue more successfully. However, more investigation is needed on the classification performance of some classes, such as Built Up and Double Crop/Horticultural Plantations. Future scope of the work involves exploring the information richness provided by embedding Fuzzy theory into MLC for other sensor data.

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