IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG)
e-ISSN: 2321–0990, p-ISSN: 2321–0982.Volume 5, Issue 4 Ver. III (Jul. – Aug. 2017), PP 33-40
www.iosrjournals.org

Fuzzy Methodology for Enhancing the Classification Accuracy ofSpectral Correlation Mapper Classifier:A Case Study over North Canara District, India

Shivakumar.B.R[1*], S.V.Rajashekararadhya[2]
[1](*Department of E & C Engineering, NMAM Institute of Technology, Nitte, India)*
[2](*Department of E & C Engineering, Kalpataru Institute of Technology, Tiptur, India)*
**Corresponding author: Shivakumar.B.R*

Abstract: *Remotely sensed (RS) image classification has come to be the most generally used technique for categorizing land use land cover (LULC) units on Earth surface. Precise categorization of LULC information has been an arena of research over the past few decades in the remote sensing community. Efficient classification of heterogeneous RS data has been a challenge for researchers over the last two decades. In this paper, embedding the Fuzzy methodology into Spectral Correlation Mapper (SCM) to enhance the classification accuracy of heterogeneous RS data is presented. Accuracy assessment is carried out to quantify the results. Heterogeneous Landsat 8 multispectral data of North Canara district, India was used as study area. A considerable increase in the classification accuracy was noticed with the use of Fuzzy methodology.*

Keywords: *Accuracy Assessment, Classification, Fuzzy theory, Remote Sensing, Spectral Correlation Mapper*

Date of Submission: 08-08-2017 Date of acceptance: 25-08-2017

I. Introduction

Remote sensing has formed itself as a central source for real world applications such as urban planning, natural resource management, climate prediction and many others. Most of these applications require spatially distributed information such as multispectral or hyperspectral imagery for their success [1]. Since it is highly difficult to obtain such information by merely depending upon in situ data measurements, great importance is set to obtain spatial information using remote sensing science [2][3]. Scientists have accepted on a formal plan to address real world problems such as urban planning, climate prediction etc., with at least five elements: i. Stating the problem, ii. Forming the research hypothesis, iii. Observing and experimenting, iv. Interpreting data, and v. Drawing conclusions [4].

Image classification in the remote sensing viewpoint can be defined as the process of effectively recognizing different land use land cover (LULC) units on the earth surface by using a suitable classification algorithm. Research over multispectral data classification has been in progress since the early 1970s when ERTS (Earth Resources Technology Satellite) (later LANDSAT-1) multispectral scanner (MSS) data became available [5]. In the next few years, classification techniques such as maximum likelihood, parallelepiped, and minimum distance methods were developed [4]. As remote sensing technology saw improvements, higher spatial resolution data and additional bands near the mid-infrared wavebands became available. With the availability of additional information, it was anticipated to perceive growth in the classification accuracy. Surprisingly, as revealed by Cushnie [6], no improvement in classification accuracy was observed, and in some cases was reduced. Woodcock and Strahler suggested this to be the consequence of an increase in within class spectral variability as spatial resolution increased [5][7]. Hughes reported that with the addition of new features, classification accuracy decreased [8]. This effect was termed as the curse of dimensionality.

Heterogeneous remotely sensed data does not have ideal boundaries between its land cover units. Such data are said to be imprecise at their boundaries. These boundaries are said to be constituted of mixed pixels and it is these mixed pixels that pose a challenge in effectively classifying the RS data. Further, heterogeneity may exist within a class due to variation in health, age, species, and so on, adding to the complexity.

Classification algorithms are broadly classified into hard and soft classifiers based on whether the output is an absolute judgment about the LULC class or not. Hard classifiers make an explicit decision about the LULC class such that a pixel is assigned to a single class. As our study shows, in the presence of mixed pixels and spectral overlapping classes, hard classifiers produce misclassifications and fail to impress. Soft classifiers were initially introduced for the purpose of addressing mixed pixel issues in data sets. These classifiers calculate the percentage of similarity of a pixel for every class and assign that pixel to the class with the highest proportion of similarity [9].

Spectral overlapping between LULC classes was measured in terms of Euclidean distance and was normalized to the range 0 to 1. This normalized Euclidean distance was considered as the primary spectral similarity index (SSI) for analyzing the classification algorithm's performance. Class pairs with a spectral similarity of 1 were considered to be spectrally non-overlapping. As the spectral similarity index decreases, classes overlap each other and the overlap region is constituted of mixed pixels. Class pairs with SSI of 0.4 and lesser were observed to be severely overlapping each other. Classes that are spectrally independent of other classes were observed to have SSI greater than 0.7.

The objective of this study is to show that Fuzzy methodology can be used to enhance the performance of Spectral Correlation Mapper classifier in mapping different LULC classes over the study area. The methodology involves classifying the study area using conventional SCM and then classifying the study area using Fuzzy methodology based SCM. The results are compared and analyzed to draw useful conclusions.

The rest of the paper is organized as follows. Section 2 provides information about the heterogeneous study areas used. In section 3, a brief introduction to data products and preprocessing steps is presented. Section 4 provides an insight to the conventional SCM classification. Section 5 illustrates how Fuzzy methodology can be embedded into conventional SCM classifier. Section 6 presents metrics used for analyzing the results. Section 7 presents the results and their analysis. In section 7 conclusions drawn by analyzing the results are presented.

II. Study Area

Coastal zone study area as in Fig. 1 is a Landsat-8 multispectral data covering North Canara District of Karnataka, India. The study area primarily features the Western Ghats and Deciduous Forest which structure the major land cover types of the south-western part of Indian subcontinent. Seven land use land cover (LULC) classes were identified over the study area: i. Scrub Land, ii. Built-up, iii. Double Crop, iv. Water Body, v. Kharif, vi. Evergreen Forest, and vii. Deciduous Forest. The primary cause for selecting this study area was because of its heterogeneous nature. The study area demonstrated liberal overlapping between its LULC classes. This data was acquired on 18th of March, 2016, which is the pre-summer season and it is free from clouds.

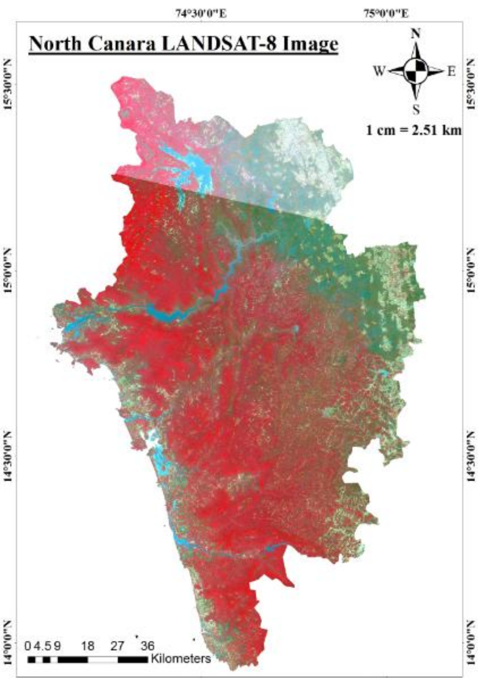

Fig:1 Coastal zone Landsat-8 study area (Data courtesy USGS[10]).

III. Data and Preprocessing

This section provides a brief overview of the data products considered for the study and preprocessing methods employed.

3.1 Landsat-8 Data

Landsat 8 is an American Earth observation satellite launched on February 11, 2013, in joint collaboration between North Atlantic Space Association (NASA) and United States Geological Survey (USGS) [11]. Landsat 8 satellite images the entire Earth surface every 16 days. It carries two push-broom instruments:

Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) [12]. Landsat 8 data originally consists of 11 spectral bands. For this study, the first 8 bands are made use of. The first eight bands are: Coastal Aerosol (0.430.45 µm), Blue (0.45-0.51 µm), Green (0.53-0.59 µm), Red (0.64-0.67 µm), Near Infrared (NIR) (0.85-0.88 µm), Short-Wave Infrared-1 (SWIR 1) (1.57-1.65 µm), Short-Wave Infrared-2 (SWIR 2) (2.11-2.29 µm) and Panchromatic (0.50-0.68 µm). The remaining bands are Cirrus (1.36-1.38 µm), Thermal Infrared 1 (TIRS 1) (10.60-11.19 µm), and Thermal Infrared 2 (TIRS 2) (11.50-12.51 µm) [12]. The Spatial resolution of initial seven bands is 30 m, Panchromatic is 15 m, Cirrus is 30 m, and TIRS 1 and TIRS 2 are 100 m respectively.

3.2 Preprocessing

Landsat-8 data was obtained in the form of individual bands and preprocessed to form a 15meter spatial resolution multispectral image that can be utilized for further processing. This is done by performing layer stacking and resolution merge. The first seven bands are layer stacked to produce a 30 meter multispectral image. Resolution merge technique is used for increasing the spatial resolution of layer stacked image. Resolution merge technique resamples the 30meter layer stacked image and combines it with the panchromatic band (Band 8) to produce a 15m multispectral image with a spatial resolution of 15meter[13]. Training samples were collected for classification. For conventional SCM, spectral signatures were collected by selecting only pure pixels from the study area. For Fuzzy based SCM, spectral signatures were collected by selecting both pure and border pixels.

TABLE 1 indicates the spectral similarityindex in terms of normalized Euclidean distance between class pairs in signature collected for conventional SCM. From the data provided in TABLE 1, major spectral overlapping were observed between the following class pairs: Scrub Land and Kharif, Scrub Land and Deciduous Forest, Built Up and Kharif, Double Crop and Evergreen Forest, and Kharif and Deciduous Forest.

Table 1: Class separability in normalized euclidean distance for conventional SCM.

Class Pair	Normalized Euclidean Distance	Class Pair	Normalized Euclidean Distance	Class Pair	Normalized Euclidean Distance
1:2	0.442	2:4	0.797	3:7	0.729
1:3	0.76	2:5	0.363	4:5	0.876
1:4	0.719	2:6	1	4:6	0.859
1:5	0.216	2:7	0.537	4:7	0.73
1:6	0.856	3:4	0.856	5:6	0.916
1:7	0.151	3:5	0.798	5:7	0.275
2:3	0.886	3:6	0.143	6:7	0.816

1: Scrub Land, 2: Built Up, 3: Double Crop, 4: Water Body, 5: Kharif, 6: Evergreen Forest, 7: Deciduous Forest

For Fuzzy based SCM, new signature were collected which form a combination of pure pixels and mixed pixels. As Fuzzy based classification uses membership functions to assign a pixel to a LULC class, mixed pixels were anticipated to be correctly classified. TABLE 2 indicates the class separability in normalized Euclidean distance for signature collected for Fuzzy classification. The class order for Fuzzy signature are as follows; i. Evergreen Forest, ii. Deciduous Forest, iii. Built Up, iv. Scrub Land, v. Kharif, vi. Double Crop, and vii. Water Body. Considering the spectral similarity with classes that overlap each other (SSI<0.4), major class overlapping were noticed between Evergreen Forest and Double Crop, Deciduous Forest and Built Up, Deciduous Forest and Scrub Land, Built Up and Scrub Land, Built Up and Kharif, and Scrub Land and Kharif. Since mixed pixels were considered for this signature, SSI value has further reduced for similar looking classes.

Table 2: Class separability in normalized euclidean distance for Fuzzy based SCM.

Class Pair	Normalized Euclidean Distance	Class Pair	Normalized Euclidean Distance	Class Pair	Normalized Euclidean Distance
1:2	0.7347	2:4	0.1746	3:7	0.6929
1:3	0.8992	2:5	0.4190	4:5	0.2663
1:4	0.8053	2:6	0.7208	4:6	0.7771
1:5	1	2:7	0.6331	4:7	0.7711
1:6	0.0873	3:4	0.3133	5:6	0.9559
1:7	0.7302	3:5	0.3564	5:7	0.9876
2:3	0.3377	3:6	0.8617	6:7	0.7506

1: Evergreen Forest, 2: Deciduous Forest, 3: Built UP, 4: Scrub Land, 5: Kharif, 6: Double Crop, 7: Water Body

IV. Spectral Correlation Mapper (SCM) Classifier

Spectral Correlation Mapper (SCM) algorithm works on the principle of assigning pixels to the classes to which the pixel shows highest correlation. It was presented as a modification to Spectral Angle Mapper (SAM) classifier which uses spectral angle for assigning pixels to classes.Initially, SAMalgorithm was assumed to produce shading effectsas it quantifies only vector direction, not magnitude[14].SCM overcomes the drawbacks of SAM by normalizing the data and centering on the average of the two spectra [14]. This normalization is proven to produce several advantages [14][15]. Carvalho et. al., were the first to propose that the function cos(SAM) is similar to the Pearsonian Correlation Coefficient [14]. Given two n-dimensional spectral signatures$S_i = (s_{i1}, s_{i2}, .. s_{in})^T$and $S_j = (s_{j1}, s_{j2}, .. s_{jn})^T$, the Pearsonian correlation coefficient is defined as [14]:

$$r_{S_i,S_j} = \frac{\sum_i (S_i - S_i') \sum_j (S_j - S_j')}{\sqrt{\sum_i (S_i - S_i')^2 \sum_j (S_j - S_j')^2}} \tag{1}$$

where, r_{S_i,S_j} is a dimensionless quantity that takes values anywhere between -1 to 1 and describes the level of linear relationship between any two spectra, n is the number of spectral bands, and S_i' and S_j' represent the sample means of S_i and S_j, respectively. Bajwa et. al., presented a method to convert $r_{S_i,S_j}$to angle (in radians) [16]:

$$SCA(S_i, S_j) = cos^{-1}\left(\frac{r_{S_i,S_j}+1}{2}\right) \text{in radians} \tag{2}$$

where, $SCA(S_i, S_j)$ is the spectral correlation angle between S_i and S_j, and it can take values from 0 to 1.570796 [17].

V. Fuzzy based Spectral Correlation Mapper (SCM) Classifier

Zadeh's concept of Fuzzy set theory has provided some very useful options for working with heterogeneous data sets. Fuzzy theory uses membership functions for assigning pixels to classes. If *n*is the number of LULC classes, each test pixel will be assigned a membership value corresponding to each of the LULC classes. Hence, each test pixel can be treated as an n-dimensional vector of membership values.

The Fuzzy membership function for any x must lie in the range 0 to 1, they should all add up to unity, and should be positive values. These characteristics are listed in equations (3), (4), and (5), respectively [18].

$$0 \leq f_{F_i}(x) \leq 1 \tag{3}$$

$$\sum_{x \in X} f_{F_i}(x) > 0 \tag{4}$$

$$\sum_{i=1}^{m} f_{F_i}(x) = 1 \tag{5}$$

where, F_i is one of the spectral classes, X represents all pixels in the dataset, m is the number of classes, x is a pixel measurement vector, and f_{F_i} is the membership function of the Fuzzy set F_i $(1 \leq i \leq m)$ [4][18].

Fuzzy logic may be used to compute Fuzzy mean and covariance matrices. Fuzzy mean can be expressed as [19]:

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

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

The Fuzzy covariance matrix Vc* is computed as:

$$V_c^* = \frac{\sum_{i=1}^{n} f_c(x_i)(x_i - \mu_c^*)(x_i - \mu_c^*)^T}{\sum_{i=1}^{n} f_c(x_i)} \tag{7}$$

Conventional SCM can be converted into Fuzzy based SCM by replacing conventional mean and covariance matrices by Fuzzy mean and covariance Matrices [19]. Fuzzy set theory only provides membership functions to each 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, Minimum Distance to Mean and others can be used in the process. In this study, Spectral Correlation Mapper classifier is used as parametric rules for assigning pixels to classes.

A membership function is to be defined for each class to perform Fuzzy feature space partitioning. For spectral correlation mapper classifier, membership function can be defined for class c as:

$$f_c(x) = \frac{SCA(S_i, S_j)^*}{\sum_{i=1}^{m} SCA(S_i, S_j)^*} \tag{8}$$

where, $SCA(S_i, S_j) = cos^{-1}\left(\frac{r_{S_i,S_j}+1}{2}\right)$, and $\sum_{i=1}^{m} SCA(S_i, S_j)^*$ is the normalization factor. SCM then assigns a pixel to class c for which the membership function $f_c(x)$ in (8) is minimum.

VI. Accuracy Assessment

Accuracy assessment begins by selecting a certain number of ground reference points or pixels on the classified map that have been assigned to a class by the classifier algorithm, and verify their correctness. The analyst needs to identify the accuracy confidence he/she expects from the classification process with an error margin. This study aims at obtaining 85% classification accuracy, with an error margin of ±4% with 95%

confidence. To satisfy this constraint, the minimum number of pixels required for accuracy assessment can be given by [20];

$$N = \frac{4P(1-P)}{e^2} \tag{9}$$

where, N is the minimum number of pixels required for accuracy assessment, P is the map accuracy expected (in %), and e is the error margin acceptable. For 85% of expected classification accuracy, N =319.

The outcome of accuracy assessment is tabulated through an error matrix (also referred to as contingency matrix or confusion matrix) that needs to be analyzed to quantify the classification accuracy correctness. This study considers the following metrics in (10), (11), (12), (13), (14), (16), (17), and (18) for validating the results.

$$Producer's\ Accuracy\ (PA) = \frac{n_{ii}}{\sum_{i=1}^{M} n_{ik}} \times 100 \tag{10}$$

$$User's\ Accuracy\ (UA) = \frac{n_{ii}}{\sum_{i=1}^{M} n_{ki}} \times 100 \tag{11}$$

$$Omission\ Error\ (OE) = \left(1 - \frac{n_{ii}}{\sum_{i=1}^{M} n_{ik}}\right) \times 100 \tag{12}$$

$$Commission\ Error\ (CE) = \left(1 - \frac{n_{ii}}{\sum_{i=1}^{M} n_{ki}}\right) \times 100 \tag{13}$$

$$Overall\ Classification\ Accuracy\ (OCA) = \frac{\sum_{i=1}^{M} n_{ii}}{N} \tag{14}$$

where, n_{ii} is the diagonal element of class i, $\sum_{i=1}^{M} n_{ik}$ is the column total of class i and $\sum_{i=1}^{M} n_{ki}$ is the row total of class i, and M is the number of classes[20].

By representing the sum over the rows and columns of the error matrix respectively, as:

$$n_{+i} = \sum_{i=1}^{M} n_{ki}\ ;\ n_{i+} = \sum_{i=1}^{M} n_{ik} \tag{15}$$

Kappa coefficient is given by [20]:

$$Kappa\ Statistic\ (k_{\text{hat}}) = \frac{N\sum_{i=1}^{M} n_{ii} - \sum_{i=1}^{M} n_{+i}n_{i+}}{N^2 - \sum_{i=1}^{M} n_{+i}n_{i+}} \tag{16}$$

$$Quantity\ Disagreement = Q = \frac{1}{2}\sum_{i=1}^{M} |p_{+i} - p_{i+}| \tag{17}$$

where, p_{+i} is the proportion of row total for class i and p_{i+} is the proportion of the column total for class i.

$$\text{Allocation Disagreement} = A = \sum_{i=1}^{M} min\{(p_{+i} - p_{ii}), (p_{i+} - p_{ii})\} \tag{18}$$

where, $(p_{+i} - p_{ii})$ represents the Commission error and $(p_{i+} - p_{ii})$ represents the Omission error. This metric also states that for a specific value of Commission error there is a corresponding value of Omission error.

Lastly, the total error which is the disagreement between the reference data and the classified map can be viewed as the sum of Quantity disagreement and Allocation disagreement, given by [20];

$$1 - P = A + Q \tag{19}$$

VII. Results and Discussions

In this section, results obtained by classifying the selected study areas using the considered algorithms are presented and analyzed.

7.1 Conventional Spectral Correlation Mapper Results for Coastal data

Fig. 2 shows the SCM classified map of the coastal study area and TABLE 3 shows the error matrix produced by SCM classifier for the same. Water Body class was excellently extracted by the SCM classifier as it did not show significant spectral overlap with any other class. This can beobserved from TABLE I. During accuracy assessment, 19 ground truth points were identified as reference points of Water Body class and all 19were correctly assigned to the same class by SCMproducing User's accuracy (UA) of 100.00% andKappa statistic (k_{hat}) of 1.0000. Evergreen Forestclass is a dominant land cover in this study area and is also well extracted (UA = 99.34 % and k_{hat}= 0.9849). Deciduous Forest class is also extractedwith good accuracy values (UA = 72.41 % and k_{hat}= 0.6729). As per TABLE 1, Kharif class overlaps withDeciduous Forest, Scrub Land, and Built Up classesseverely with spectral similarity index (SSI) measured in normalized Euclidean distances of 0.275,0.216 and 0.363 respectively. This has led to pooridentification of Kharif class by SCM classifier.During accuracy assessment it is observed that outof 68 reference points identified as belonging toKharif, only 30 points were correctly belonging to itwhile 22 ground truth points belonged to DeciduousForest and 14 points belonged to Scrub Land (UA= 44.13 % and k_{hat}=0.3745). Kharif and Built Upclasses were very well separated by the classifiera midst having spectral similarity index (SSI) of0.363. Scrub Land class was seen to spectrallyoverlap with Kharif and Deciduous Forest classeswith SSI of 0.216 and 0.151 respectively. Again,during accuracy assessment, out of 8 ground truthpoints identified as belonging to Scrub Land, 5points were seen to belong to Deciduous Forest (UA= 37.50 % and k_{hat} =0.3242).

Double Crop and Evergreen Forest classes haveshown significant amount of spectral overlapping(SSI=0.143). This has led to a major proportionof Double crop class pixels misclassified to Evergreen Forest class. Out of 37 pixels identified asbelonging to Double crop by the classifier, only8 truly belonged to it declining its class accuracy(UA = 21.62 % and k_{hat} =0.1961). Lastly, out of6 pixels identified as belonging to Built Up classby the classifier, only 3 pixels correctly belongedto it causing the rest of the pixels to misclassify.Surprisingly, Built Up pixels were not misclassifiedto Kharif, although they showed significant spectraloverlap. The overall classification accuracy andKappa statistic of the classified map after accuracyassessment was calculated to be 73.67 % and 0.6158respectively. Also, 66 pixels out of 319 pixelsconsidered for the accuracy assessment were calculated as Quantity Disagreement (20.69%) and 18pixels were calculated as Allocation Disagreement(5.64%). The total error of the classification processis 26.33 %, which equals the sum of QuantityDisagreement and Allocation Disagreement. Theresults of accuracy assessment are summarized in TABLE4.

Table 3: Error matrix of SCM classification for coastal study area.

Class Name	Kharif	Deciduous Forest	Scrub Land	Built Up	Evergreen Forest	Double Crop	Water Body	Row Total
Kharif	30	22	14	0	2	0	0	68
Deciduous Forest	4	21	4	0	0	0	0	29
Scrub Land	0	5	3	0	0	0	0	8
Built Up	0	1	1	3	0	0	1	6
Evergreen Forest	0	0	1	0	151	0	0	152
Double Crop	0	1	1	0	27	8	0	37
Water Body	0	0	0	0	0	0	19	19
Column Total	34	50	24	3	180	8	20	319

Table 4: Results of SCM classification for coastal study area.

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy (%)	Omission Error (%)	User's Accuracy (%)	Commission Error (%)	Kappa Value (k_{hat})
Kharif	34	68	30	88.24 %	11.76 %	44.12 %	55.88 %	0.3745
Deciduous Forest	50	29	21	42.00 %	58.00 %	72.41 %	27.59 %	0.6729
Scrub Land	24	8	3	12.50 %	87.50 %	37.50 %	62.50 %	0.3242
Built Up	3	6	3	100.00 %	0.00 %	50.00 %	50.00 %	0.4953
Evergreen Forest	180	152	151	83.89 %	16.11 %	99.34 %	00.66 %	0.9849
Double Crop	8	37	8	100.00 %	0.00 %	21.62 %	78.38 %	0.1961
Water Body	20	19	19	95.00 %	05.00 %	100.00 %	00.00 %	1.0000
Total	319	319	235					
Overall Classification Accuracy				(235/319)*100 = 73.67 %				
Overall Kappa Statistic				0.6158				
Quantity Disagreement (Q)				(66/319)*100 = 20.69 %				
Allocation Disagreement (A)				(18/319)*100 = 5.64 %				
Total Error $\rightarrow (1 - p_0)$ **= A + Q**				(100 – 73.67) % = ((66+18)/319)*100 26.33 % = = 26.33 %				

7.2 Fuzzy based Spectral Correlation Mapper Results for Coastal Data

Fig. 3 shows the Fuzzy based SCM classifiedmap of Coastal study area, TABLE 5 shows the errormatrix produced and TABLE 6 indicates the accuracy results for this technique, respectively. Fuzzy-based SCM extracted spectrally overlapping classeswith higher precision as compared to regular SCM.As seen from TABLE 6, Kharif class has seen anincrease in User's accuracy by 26.33%, DeciduousForest by 22.03%, Scrub Land by 17.05%, BuiltUp by 16.67%, and Double Crop by 7.55%. Thishas led to improvements in overall classificationaccuracy and Kappa statistics to 82.76% and 0.7225respectively. Improvement in overall classificationaccuracy has reduced Quantity Disagreement to 35pixels (10.97%). It is observed that Fuzzy-basedtechnique has failed to extract Evergreen Forestclass with the same precision as regular SCM.This has changed Allocation Disagreement to 20pixels. However, the total error of classification hasreduced to 17.24% which is again verified to bethe sum of Quantity Disagreement and AllocationDisagreement proportion.

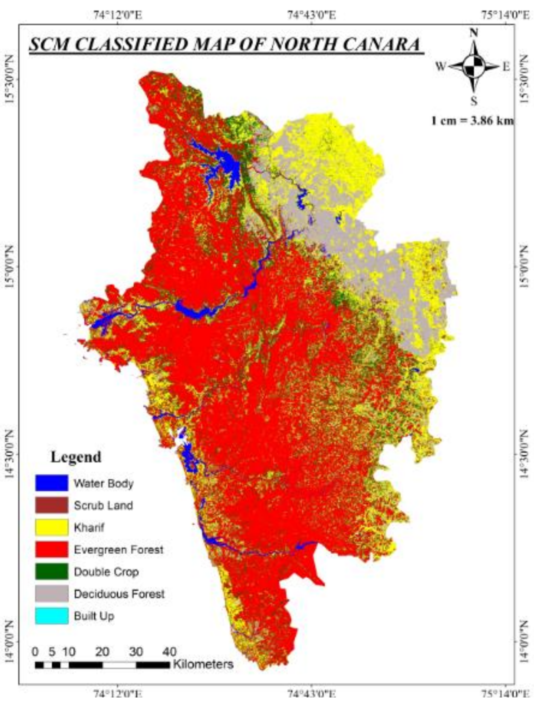

Fig 2: SCM classified map of coastal study area. by conventional SCM

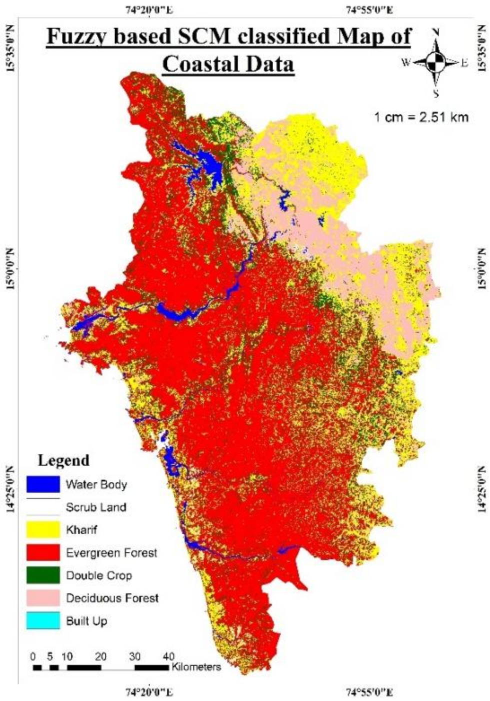

Fig 3: Fuzzy based SCM classified map of coastal study area.

Table 5: Error matrix of Fuzzy based SCM classification for coastal study area.

Class Name	Built Up	Water Body	EGF	Deciduous	Kharif	Double Crop	Scrub Land	Row Total
Built Up	2	0	0	0	1	0	0	3
Water Body	0	7	0	0	0	0	0	7
EGF	1	0	176	0	1	0	1	179
Deciduous	0	0	0	17	0	0	1	18
Kharif	1	0	0	1	31	0	11	44
Double Crop	0	0	17	0	0	7	0	24
Scrub Land	0	0	0	20	0	0	24	44
Column Total	4	7	193	38	33	7	37	319

Table 6: Results of Fuzzy based SCM classification for coastal study area.

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	Omission Error (%)	User's Accuracy	Commission Error (%)	Kappa Value (k_{hat})
Built Up	4	3	2	50.00	50.00	66.67	33.33	0.6624
Water Body	7	7	7	100.00	00.00	100.00	00.00	1.0000
EGF	193	179	176	91.19	08.81	98.32	01.68	0.9576
Deciduous	38	18	17	44.74	55.26	94.44	05.56	0.9369
Kharif	33	44	31	93.94	06.06	70.45	29.55	0.6705
Double Crop	7	24	7	100.00	00.00	29.17	70.83	0.2758
Scrub Land	37	44	24	64.86	35.14	54.55	45.45	0.4858
Total	319	319	264					
Overall Classification Accuracy				(216/319) x 100 = 82.76 %				
Overall Kappa Statistic				0.7225				
Quantity Disagreement (Q)				(35/319) x 100 = 10.97 %				
Allocation Disagreement (A)				(20/319) x 100 = 6.27%				
Total Error → $(1 - p_0)$ = A + Q				100% - 82.76% = 10.97% + 6.269% 17.24 = 17.24 %				

VIII. Conclusion

Remote sensed data classification finds enormous applications in the real world, making it very essential to produce highly reliable classified maps. Hence, it is very essential to attenuate thenumber of misclassifications. In this paper, an attempt has been made to reduce misclassificationsover a heterogeneous study area by embeddingFuzzy methodology into conventional SCM classifier. Classes with spectral similarity index (SSI)of 0.4 and/or less were the main focus in thestudy, since these classes are the originators ofmixed pixels and Fuzzy boundaries. As seen fromresults, conventional SCM algorithm has producedpoor class accuracy values for these classes (SSI≤0.4). Upon embedding Fuzzy methodology intoconventional SCM, results obtained have shownsignificant improvements in class accuracy valuesfor the classes of interest (i.e., SSI ≤ 0.4). Also,the overall classification accuracy values have seena considerable improvement. The results are accounted to be true for 95% of confidence level with an error margin of ±4%. Comparing the resultsof traditional SCM and Fuzzy based SCM, it canbe concluded that Fuzzy methodology brings newconception in remote sensing for the successfulidentification of spectrally overlapping classes.

Acknowledgements
We would like to thank U.S. Geological Survey for availing the remotely sensed data for the study.

References

[1]. C. J. Johannsen, G. W. Petersen, P. G. Carter, and M. T. Morgan, “Remote sensing changing natural resource management,” J. Soil Water Conserv., vol. 58, no. 2, p. 42A–45A, 2003.
[2]. S. J. Goetz, “Recent advances in remote sensing of biophysical variables: An overview of the special issue,” Remote Sens. Environ., vol. 79, no. 2–3, pp. 145–146, 2002.
[3]. R. R. Nemani et al., “Climate-Driven Increases in Global Terrestrial Net Primary Production from 1982 to 1999,” Science (80-.)., vol. 300, no. 5625, pp. 1560–1563, 2003.
[4]. J. R. Jensen, Introductory digital image processing: a remote sensing perspective, 3rd ed. New Jersey: Prentice-Hall Inc., 2000.
[5]. M. Pal and P. M. Mather, “Some issues in the classification of DAIS hyperspectral data,” Int. J. Remote Sens., vol. 27, no. 14, pp. 2895–2916, 2006.
[6]. J. L. Cushnie, “The interactive effect of spatial resolution and degree of internal variability within land-cover types on classification accuracies,” Int. J. Remote Sens., vol. 8, no. 1, pp. 15–29, 1987.
[7]. C. E. Woodcock and A. H. Strahler, “The factor of scale in remote sensing,” Remote Sens. Environ., vol. 21, no. 3, pp. 311–332, 1987.
[8]. G. F. Hughes, “On the Mean Accuracy of Statistical Pattern Recognizers,” IEEE Trans. Inf. Theory, vol. 14, no. 1, pp. 55–63, 1968.
[9]. G. Palubinskas, R. M. Lucas, G. M. Foody, and P. J. Curran, “An Evaluation of Fuzzy and Texture-Based Classification Approaches for Mapping Regenerating Tropical Forest Classes from Landsat-Tm Data,” Int. J. Remote Sens., vol. 16, no. 4, pp. 747–759, 1995.
[10]. USGS, “Earthexplorer.” [Online]. Available: https://earthexplorer.usgs.gov/. [Accessed: 01-Jan-2017].
[11]. J. Lim and M. Choi, “Assessment of water quality based on Landsat 8 operational land imager associated with human activities in Korea,” Environ. Monit. Assess., vol. 187, no. 6, pp. 1–17, 2015.
[12]. K. Zanter, “Landsat 8 (L8) Data Users Handbook,” LSDS-1574 Version, vol. 2.0, no. 1993, 2016.
[13]. M. Erdogan, H. Maras, and a Yilmaz, “Resolution Merge of 1: 35.000 Scale Aerial Photographs With Landsat 7 Etm Imagery,” Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci., pp. 1281–1286, 2008.
[14]. O. A. de Carvalho Jr and P. R. Meneses, “Spectral Correlation Mapper (SCM): An Improvement on the Spectral Angle Mapper (SAM),” Summ. 9th JPL Airborne Earth Sci. Work. JPL Publ. 00-18, vol. 9, 2000.
[15]. K. C. Tiwari, M. K. Arora, D. Singh, and D. Yadav, “Military target detection using spectrally modeled algorithms and independent component analysis,” Opt. Eng., vol. 52, no. 2, p. 26402, 2013.
[16]. S. Bajwa and P. Bajcsy, “Hyperspectral Image Data Mining for Band Selection in Agricultural Applications,” Am. Soc. Agric. Eng., vol. 47, no. 3, pp. 895–908, 2004.
[17]. M. Kumar et al., “A new hybrid spectral similarity measure for discrimination among Vigna species,” Int. J. Remote Sens., vol. 32, no. 14, pp. 4041–4053, 2011.
[18]. F. Wang, “Fuzzy Supervised Classification of Remote Sensing Images,” IEEE Trans. Geosci. Remote Sens., vol. 28, no. 2, pp. 194–201, 1990.
[19]. F. Wang, “Improving Remote-Sensing Image-Analysis through Fuzzy Information Representation,” Photogramm. Eng. Remote Sensing, vol. 56, no. 8, pp. 1163–1169, 1990.
[20]. J. A. Richards, Remote Sensing Digital Image Analysis- An Introduction, 5th ed. Springer, 2006.

IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG) is UGC approved Journal with Sl. No. 5021, Journal no. 49115.

Shivakumar.B.R. “Fuzzy Methodology for Enhancing the Classification Accuracy ofSpectral Correlation Mapper Classifier:A Case Study over North Canara District, India.” IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG) , vol. 5, no. 4, 2017, pp. 33-40.