International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307, Volume-2, Issue-3, July 2012

Study of Fuzzy Based Classifier Parameter using Fuzzy Matrix

Rakesh Dwivedi, Anil Kumar, S. K. Ghosh

Abstract: In the area of remote sensing, the decision making are not generally deterministic due to the involvement of fuzziness in the classification of remotely sensed imagery. A considerable number of identification errors are due to pixels that show an affinity with several information classes. The fuzzy concept is a valuable tool for dealing with classification problems. In remote sensing classification, fuzzy based classifiers are becoming increasingly popular. Due to the wide acceptance of fuzzy c-mean (FCM) and possibilistic c-means (PCM) classifiers, this has been used as a benchmark to evaluate the performance of other classifiers with optimized value of weighting exponent 'm' in this research. Evaluation of soft classification through FERM, SCM and Fuzzy kappa coefficient, using Euclidean norm based measures led to an improvement wherein FCM-Overall accuracy (MIN-LEAST) operator reflects higher classification accuracy, i.e., 97% and the value of Fuzzy Kappa coefficient is 0.97 with minimum uncertainty in it, for the optimized value of weighting exponent 'm' i.e. 4.0. In this experimentation two supervised classifiers namely FCM and PCM have been selected to demonstrate the improvement in the classification accuracy by FERM, SCM, MIN-MIN, MIN-LEAST, Fuzzy Kappa coefficient and uncertainty in SCM and Fuzzy Kappa coefficients.

Index Terms: Fuzzy c-Mean (FCM), Fuzzy Error Matrix (FERM), Possiblistic c-Mean (PCM), Sub-pixel confusion-uncertainty matrix(SCM),

I. INTRODUCTION

Remote sensing images contain a mixture of pure and mixed pixels. While digital image classification, however, a pixel is frequently considered as a unit belonging to a single land cover class. However, due to limited image resolution, pixels often represent ground areas, which comprise by two or more discrete land cover classes. For this reason, it has been proposed that fuzziness should be accommodated in the classification procedure so that pixels may have multiple or partial class membership [1]. In this case, a measure of the strength of membership for each class is output by the classifier, resulting in a soft classification technique [2]. Also recent advances in supervised image classification have shown that conventional 'hard' classification techniques, which allocate each pixel to a specific class, are often inappropriate for applications where mixed pixels are abundant in the image [3].

[4] – [6] used nonlinearity to fuzzify the crisp c-means. The method of [4] – [5] and [7] has another feature: it smoothes the crisp solution into a differentiable one. Moreover this fuzzy solution approximates the crisp one in the sense that the fuzzy solution converges to the crisp solution as; $m \longrightarrow 1$.

Mixed pixels are assigned to the class with the highest proportion of coverage to yield a hard classification. Due to which a considerable amount of information is lost. To overcome this loss, soft classification was introduced. A soft classification assigns a pixel to different classes according to the area it represents inside the pixel. This soft classification yields a number of fraction images equal to the number of land cover classes. Several researchers have addressed this soft mixture problem. Among the most popular techniques for soft classification are artificial neural networks [8], mixture modeling [9] and supervised fuzzy c-means classification [10].

The use of fuzzy set based classification methods in remote sensing has received growing interests for their particular value in situations where the geographical phenomena are inherently fuzzy [11]. The role of 'm' weighting exponent, controls the degree of fuzziness in FCM and PCM classifier. However, in FCM, as 'm' increases, it represents increase in sharing of pixel in all clusters, whereas in PCM, increased value of 'm' represents increased possibility of all pixels in the dataset completely belonging to a given cluster. The output generated by soft classification amounts some degree of uncertainty in the class allocation of each pixel [12]. Further, soft reference data may also indicate the uncertainty in class allocation on reference data. For the evaluation of uncertainty in classification results, the SCM uncertainty, and uncertainty analysis in Fuzzy Kappa coefficient, criterion is proposed. This paper follows the parameter optimization of weighting exponent 'm' across all spatial resolution in the classification process. As commercially available image processing software's were not having soft classification algorithms used in this work. So in-house developed SMIC (Sub-pixel Multi-Spectral Image Classifier) System [13] having fuzzy and entropy based fuzzy classifier with accuracy assessment module for fraction images used in this research work.

II. CLASSIFIERS AND ACCURACY APPROACHES

Fuzzy c-Means (FCM) was originally introduced by [5]. In this supervised classification technique each data point belongs to a cluster to some degree that is specified by a membership grade, and the sum of the memberships for each pixel must be unity. This can be achieved by minimizing the generalized least - square error objective function given in Eq. (1), and subject to Eq. (2),

$$J_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{c}\left(\mu_{ij}\right)^m \left\|X_i - x_j\right\|_A^2 \quad (1)$$

Manuscript received on July, 2012.

Rakesh Dwivedi, Deptt. Of Civil Engineering, Indian Institute of Technology Roorkee, Roorkee, India,

Anil Kumar, Deptt. Of Photogramatry and Remote Sensing, Indian Institute of Remote Sensing Dehradun, Dehradun, India,

S. K. Ghosh, Deptt. Of Civil Engineering, Indian Institute of Technology Roorkee, Roorkee, India,

Subject to constraints,

$$\sum_{j=1}^{c}\mu_{ij}=1 \; for\ all\ i$$
$$\sum_{i=1}^{N}\mu_{ij}>0 \qquad for\ all\ j \qquad (2)$$
$$0\le\mu_{ij}\le 1 \qquad for\ all\ i,j$$

where X_i is the vector denoting spectral response of a pixel i, x is the collection of vector of cluster centers x_j, μ_{ij} is class membership values of a pixel, c and N are number of clusters and pixels respectively, m is a weighting exponent ($1<m<\infty$), which controls the degree of fuzziness, $\|X_i-x_j\|_A^2$ is the squared distance (d_{ij}) between X_i and x_j, and is given in Eq. (3),

$$d_{ij}^2=\|X_i-x_j\|_A^2=(X_i-X_j)^T A(X_i-X_j) \qquad (3)$$

Where A is the weight matrix. Amongst a number of A-norms, three namely Euclidean, Diagonal and Mahalonobis norm, each induced by specific weight matrix, are widely used. The formulations of each norm are given in Eq. (4), [5],

$$\begin{aligned} &A=I && Euclidean\ Norm\\ &A=D_j^{-1} && Diagonal\ Norm\\ &A=C_j^{-1} && Mahalonbis\ Norm \end{aligned} \qquad (4)$$

Where I is the identity matrix, D_j is the diagonal matrix having diagonal elements as the eigen values of the variance covariance matrix, C_j given in Eq.(5),

$$C_j=\sum_{i=1}^{N}(X_i-x_j)(X_i-x_j)^T \qquad (5)$$

The class membership matrix μ_{ij} is obtained using Eq. (6) wherein d_{ik}^2 is computed using Eq. (7),

$$\mu_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}^2}{d_{ik}^2}\right)^{1/(m-1)}} \qquad (6)$$

$$where \quad d_{ik}^2=\sum_{j=1}^{c}d_{ij}^2 \qquad (7)$$

In PCM, for a good classification is it expected that actual feature classes will have high membership value, while unrepresentative features will have low membership values [14]. The objective function, which satisfies this requirement, may be formulated as given in Eq. (8) and constraint criterion is mentioned in Eq. (9);

$$J_m(U,V)=\sum_{i=1}^{N}\sum_{j=1}^{c}(\mu_{ij})^m\|X_i-v_j\|_A^2+\sum_{j=1}^{c}\eta_j\sum_{i=1}^{N}(1-\mu_{ij})^m \qquad (8)$$

Subject to constraints;

$$\max_j u_{ij}>0 \qquad for\ all\ i$$
$$\sum_{i=1}^{N}\mu_{ij}>0 \qquad for\ all\ j \qquad (9)$$
$$0\le\mu_{ij}\le 1 \qquad for\ all\ i,j$$

μ_{ij} is calculated from Eq. (6).

In Eq. (8) where η_j is the suitable positive number, first term demands that the distances from the feature vectors to the prototypes be as low as possible, whereas the second term forces the μ_{ij} to be as large as possible, thus avoiding the trivial solution. Generally, η_j depends on the shape and average size of the cluster j and its value may be computed as given in Eq. (10);

$$\eta_j=K\frac{\sum_{i=1}^{N}\mu_{ij}^m d_{ij}^2}{\sum_{i=1}^{N}\mu_{ij}^m} \qquad (10)$$

Where K is a constant and is generally kept as one. After this, class memberships, μ_{ij} are obtained as mentioned in Eq. (11);

$$\mu_{ij}=\frac{1}{1+\left(\frac{d_{ij}^2}{\eta_j}\right)^{1/(m-1)}} \qquad (11)$$

SOFT ACCURACY ASSESSMENT APPROACH

While allocating the class as soft, i.e. pixels with varying class membership values both in the classified image and reference data, Euclidean and the L_1 distance [15], cross-entropy [16] and correlation coefficients measures were sought for accuracy assessment. All these measures may be treated as indirect methods of assessing the accuracy of soft classification because the accuracy evaluation is interpretative than a representation of actual value as denoted by the traditional error matrix measures. [6] Put forth the concept of fuzzy error matrix (FERM) to assess the accuracy of soft classification. This is a new concept that has been developed to assess the accuracy of soft classifiers [6]. The layout of a fuzzy error matrix is similar to the traditional error matrix that is used for assessing the accuracy of hard classifiers. The exception is that elements of a fuzzy error matrix can be any non-negative real number as opposable to non-negative integer numbers used for hard classifiers. The elements of the fuzzy error matrix represent class proportions, corresponding to soft reference data (R_n) and soft classified data (C_m), to class n and m, respectively. The procedure used to construct the fuzzy error matrix employs a fuzzy minimum operator to determine the matrix elements M (m, n), in which the degree of membership in the fuzzy intersection ($C_m \cap R_n$) is computed from Eq. (12),

$$M(m,n)=\left|C_m\cap R_n\right|=\sum_{x\in X}\min(\mu_{C_m},\mu_{R_n}) \qquad (12)$$

Where X is testing sample data set and x denotes a testing sample in X.

Here, $\mu_{R_n}(x)$ and $\mu_{C_n}(x)$ is the class membership (or class proportion) of the testing sample x in Rn and Cm respectively.

From FERM, overall accuracy (OA) may be calculated from Eq. (13),

$$OA=\frac{\sum_{j=1}^{c}M_{(i,j)}}{\sum_{j=1}^{c}R_j} \qquad (13)$$

Where c is number of classes.

Similarly, User's (UAj) and Producer's accuracy (PAj) of class j may be computed from Eq. (14),

$$UA_j = \frac{M_{(i,j)}}{C_j} \quad \text{and} \quad PA_j = \frac{M_{(i,j)}}{R_j} \qquad (14)$$

The applicability of generating accuracy indices such as the overall accuracy, the user and producer accuracy, the kappa and the conditional kappa coefficients (e.g., [6] – [7], [17] gives types of accuracy indication. Indeed, derived indices do not account for the off-diagonal cells of the matrix; rather, they are based only on the diagonal cells and the total grades from the reference and assessed datasets [6]. Recently, a composite operator was proposed for computing a cross comparison matrix that exhibits some of the aforementioned desirable characteristics [18]. [18] Showed how the composite operator can be used for a multi-resolution assessment of raster maps and compared it with other alternatives, including the traditional hardening pixels, the minimum operator [6], and the product operator [19]. This composite operator was also suggested as a viable tool for the soft comparison of maps [20]. Although several desirable properties are found in the composite operator, its utility has been only demonstrated on the use of traditional accuracy indices [18], [20] – [21] reviewed existing accuracy assessment methods for soft accuracy assessment, while identifying major drawbacks and desirable properties based on cross-comparison matrices. [22] Developed theoretical grounds, for a more general accuracy assessment of soft classifications, which account for the soft class distribution uncertainty.

In formal grounds, one requires the agreement - disagreement measure to conform Eq. (15), where A and D denote agreement and disagreement operators respectively, where s'_{nk} and r'_{nl} denote the over and underestimation errors at pixel n.

$$C(s_{nk}, r_{nl}) = \begin{cases} A(s_{nk}, r_{nl}) & if \quad k = 1 \\ D(s'_{nk}, r'_{nl}) & if \quad k \neq 1 \end{cases} \qquad (15)$$

$$s'_{nk} = s_{nk} - \min(s_{nk}, r_{nk})$$

$$r'_{nl} = r_{nl} - \min(s_{nl}, r_{nl})$$

Different operators have been developed under distinct pixel otologies, listed in Table I.

The minimum operator (MIN) is the classic fuzzy set intersection operator. This operator has been suggested as the natural choice for producing cross-comparison matrices for fuzzy classifications [6]. The MIN matrix can overestimate the actual soft agreement-disagreement and, consequently, the marginal sums can be greater than the sup-pixel fractions. Also even in case of a perfect match, non-null degrees of mismatch are obtained for the off-diagonal cells. These characteristics generally limit the matrix's utility for drawing a conclusion about the confusion among the classes.

Table I: Four basic operators

Operator ID	Operator of the form[a] C (s_{nk}, r_{nl})	Traditional interpretation	Soft interpretation
MIN	$\min(s_{nk}, r_{nl})$	Fuzzy set intersection	Maximum overlap
SI	$1 - \frac{\lvert s_{nk} - r_{nl} \rvert}{s_{nk} + r_{nl}}$	Similarity index	Normalized maximum
PROD	$s_{nk} \times r_{nl}$	Joint probability	Expected overlap
LEAST	$\max(s_{nk} + r_{nl} - 1, 0)$	Minimum overlap	Minimum overlap

[a] s_{nk} and r_{nk} denote assessed and reference grades of class K at pixel n.

A variant of the MIN operator is sometimes used as a similarity index (SI) for comparing soft classifications. This variant results after normalizing the MIN operator by the sum of the grade values, and can be expressed as shown in Table I. The SI operator is also meaning for soft comparison, as it corresponds to a normalized maximum soft; overlap. Nevertheless, it does not satisfy the homogeneity property, as it is invariant under scaling of grade values. A cross-comparison matrix based on the SI operator does not satisfy the diagonalization and marginal sums characterstics.

The product operator (PROD) arises from a pure probabilistic view of the pixel-class relationship. In the traditional probabilistic ontology, the pixel-class relationship represents the probability that pixel belongs to a class, and the PROD operator gives the joint probability that the reference and assessed pixels belong to two given classes, provided that the pixels have been independently classified. A cross-comparison matrix based on the PROD operator has marginal sums that agree with the per-class areas. However, non-null disagreement values can result from the perfect matching case. In fact, it does not satisfy the upper-bound and homogeneity properties.

LEAST operator was recently incorporated in the soft comparison of maps [20]. LEAST operator measures the minimum possible soft overlap between two classes. Even though this operator is meaningful for soft accuracy assessment, it may be of little use for other contexts, as it has even more counter institutive characteristics than the PROD operator. Specifically, this operator fails to fulfill all but the commutativity and nullity properties.

The single operator does not satisfy diagonalization characteristic; indeed, composite operator can exhibit the diagonalization characteristic.

The MIN-PROD composite operator was recently proposed by [18]. It uses the minimum operator for the diagonal cells and a normalized product operator for the off-diagonal cells, thus combining the fuzzy set view with the probabilities view.

The MIN-MIN composite operator uses the minimum operator for both agreement and disagreement. However, it differs from the MIN operator in that it assigns agreement in a first step and then, in a second step, it computes the disagreement based on the over and under estimation errors.

Table II: List of Composite operators

Operator ID	Agreement[a]	Disagreement[b] (k≠l)	Soft confusion
MIN-PROD	$\min(s_{nk}, r_{nl})$	$s'_{nk} \times r'_{nl} / \sum_i r'_{ni}$	Constrained expected
MIN-MIN	$\min(s_{nk}, r_{nl})$	$\min(s'_{nk}, r'_{nl})$	Constrained maximum
MIN- LEAST	$\min(s_{nk}, r_{nl})$	$\min(s'_{nk} + r'_{nl} - \sum_i r'_{ni}, 0)$	Constrained minimum

[a] s_{nk} and r_{nk} denote the assessed and reference grades for class K at pixel n.

[b] s'_{nk} and r'_{nk} denote the over and under estimation errors of class i at pixel n.

The MIN-LEAST composite operator uses the MIN operator for the diagonal cells and a re-normalized LEAST operator for the off-diagonal cells (Table II).

A composite operator is necessary to warrant the diagonalization characteristic and the MIN operator is the most appropriate candidate for agreement measure. Nevertheless, there is no unique way to exactly allocate the remaining soft proportion into the off-diagonal cells. However, the confusion interval $[P_{kl}^{MIN-LEAST}, P_{KL}^{MIN-MIN}]$, formed by the MIN-LEAST and MIN-MIN operator accounts soft distribution uncertainty. Practically, it is convenient to express each confusion interval in the form $P_{kl} \pm U_{kl}$, where P_{kl} and U_{kl} are the interval center and the interval half-width, respectively. These are computed as indicated by Eq. (16) and (17), respectively.

$$P_{kl} = \frac{P_{kl}^{MIN-MIN} + P_{KL}^{MIN-LEAST}}{2} \qquad (16)$$

$$U_{kl} = \frac{P_{kl}^{MIN-MIN} - P_{kl}^{MIN-LEAST}}{2} \qquad (17)$$

The accuracy indices so-derived can not reflect the uncertainty of confusion as they do not depend on the off-diagonal cells. Another possibility, which is pursued here, is to consider column and rows totals as intervals. These intervals can be used to derive intervals of accuracy indices that reflect the uncertain nature of class soft distribution [22]. Table III shows the general structure of the sub-pixel confusion-uncertainty matrix (SCM) with derive intervals of accuracy indices that reflect the uncertain nature of class soft distribution.

Table III: General structure of the SCM (a) and derived sub-pixel accuracy-uncertainty indices (b)

Class	Reference				Row total
	Class1	**Class2**	**…**	**Class K**	
Class 1	P_{11}	$P_{12} \pm U_{12}$	…	$P_{1K} \pm U_{1K}$	$P_{1+} \pm U_{1+}$
Class 2	$P_{21} \pm U_{21}$	P_{22}	…	$P_{2K} \pm U_{2K}$	$P_{2+} \pm U_{2+}$
. . .	. . .	. . .	…	…	
Class K	P_{K1}	$P_{K2} \pm U_{K2}$	…	P_{KK}	$P_{K+} \pm U_{K+}$
Column total	$P_{+1} \pm U_{+1}$	$P_{+2} \pm U_{+2}$	…	$P_{+K} \pm U_{+K}$	$P_{++} \pm U_{++}$

Sub-pixel Accuracy Index	**Center**	**Uncertainty**
Overall accuracy, AO_s	$\frac{P_{++} \sum_k P_{kk}}{P_{++}^2 - U_{++}^2}$	$\frac{U_{++} \sum_k P_{kk}}{P_{++}^2 - U_{++}^2}$
k-th User Accuracy, UA_s (k)	$\frac{P_{kk} P_{k+}}{P_{++}^2 - U_{++}^2}$	$\frac{P_{kk} U_{k+}}{P_{++}^2 - U_{++}^2}$
k-th Producer Accuracy, UA_s (k)	$\frac{P_{kk} P_{+k}}{P_{+k}^2 - U_{+k}^2}$	$\frac{P_{kk} U_{+k}}{P_{+k}^2 - U_{+k}^2}$
Kappa Coefficient, K_s	$\frac{(P_0 - P_e)(1 - P_e) - (*U_0 + U_e)U_e}{(1 - P_e)^2 - U_e^2}$	$\frac{*(1 - P_e)U_e + (1 - P_e)U_0}{(1 - P_e)^2 - U_e^2}$

*=sign of $(1 - P_0 - U_0)(1 - P_e - U_e)$

With the availability of IRS-P6 satellite data it is possible to acquire spectrally same and spatial different data sets of same area with same acquition time. Due to the uniqueness of availability of these data sets, soft fraction images generated from coarser resolution data set (e.g. AWIFS, IRS-P6) can be evaluated from fraction images generated from finer resolution data sets (e.g. LISS-III/LISS-IV, IRS-P6) as reference data set acquired at same time.

III. STUDY AREA AND DATA USED

The study area is located near Pantnagar town between 28° 53' 57.12" N - 28° 56' 31.22" N latitudes and 79° 34' 22.92" E - 79° 36' 35.27" E longitudes (Fig. 1). Pantnagar town is a mix of university town and industrial area, hosting the first agricultural university of India as well as the first Integrated Industrial Estate in the Kumaon region. Pantnagar is famous for having the first agricultural university of India since 1960 and to have, breed amongst the best agriculturists and horticulturists globally. Previously it was called Uttar Pradesh Agricultural University, or Pantnagar University, it is now known as Govind Ballabh Pant University of Agriculture and Technology. SIDCUL has established the first Integrated Industrial Estate (IIE) in Kumaon region at Pantnagar. IIE Pantnagar is located at National Highway No. NH-87, 235 KM (Rudrapur-Haldwani road) from National Capital Delhi and 300 KM from state capital Dehradun. Industries like Dabur, Nestle, Tata Motors, Britannia Industries Ltd. and Havell's India Ltd. have already set up their units at IIE Pantnagar. Pantnagar also have the only airport in the Kumaon region capable for landing commercial flights.

ResourceSat-1 (IRS-P6), satellite is unique in providing multi-spectral data at different spatial resolution, while preserving the spectral information. In this research work, AWIFS, LISS-III and LISS-IV data sets from ResourceSat-1 (IRS-P6) satellite have been used as shown in Fig.(1). The fraction images and entropy would be used for the purpose of accuracy assessment.

(a).LISS-IV (b). LISS-III (c). AWIFS

Fig. 1. Location of study area

IV. METHODOLOGY

All the three datasets (AWiFS, LISS-III and LISS-IV) were geometrically corrected with RMSE less than 1/3 of a pixel and resampled using nearest neighbor resample method at 60m, 20m and 5m spatial resolution respectively to maintain the correspondence of a AWiFS pixel with specific number of LISS-III pixels (here 9, corresponding to AWIFS) as well as with LISS-IV pixels (here 144 pixels, corresponding to AWIFS) with respect to sampling during accuracy assessment.

Training data set was collected from AWiFS, LISS-III and LISS-IV imageries with reference to toposheet of the same area. There are six information classes i ,e. Sal forest, and Eucalyptus plantations are treated as a heterogeneous classes and agriculture land with crop, agriculture moist land without crop, agriculture dry land without crop, and water body classes are considered as an homogenous classes. For the purpose of experimentation, 40 pixels were selected as sample according to 10*n* rule (Jensen, 1996) to train the classifiers. For accuracy assessment 100 pixels per class were randomly selected from corresponding images. The flow chart of the methodology adopted is shown in Fig. 2.

After pre-processing and training dataset collection the AWiFS image was separately classified by FCM and PCM algorithm using Euclidean norm. In this study a Euclidean distance measure that uses mean of the training class has been used for the spectral separability analysis.

Euclidean Norm of weight matrix 'A' in Eq. (4) has been taken, as it gives maximum classification accuracy compared to other weighted norms and less effected with noise outlier present in training data. As Euclidean Norm uses only mean value but other norms uses mean as well as variance-covariance. Mean is less affected than variance-covariance due to the presence of noise in training data [23] – [24]. The accuracy of classified imagery is validated using, FERM, SCM and Fuzzy Kappa Coefficients. The uncertainty in SCM and Fuzzy Kappa Coefficient determines the classification appropriateness in the classified results.

After preprocessing and training dataset collection the AWiFS image was separately classified by traditional FCM and PCM algorithm. Later output fraction images by both algorithms were validated with respect to the soft reference dataset generated from finer resolution dataset. For accuracy assessment different operators has been used [22].

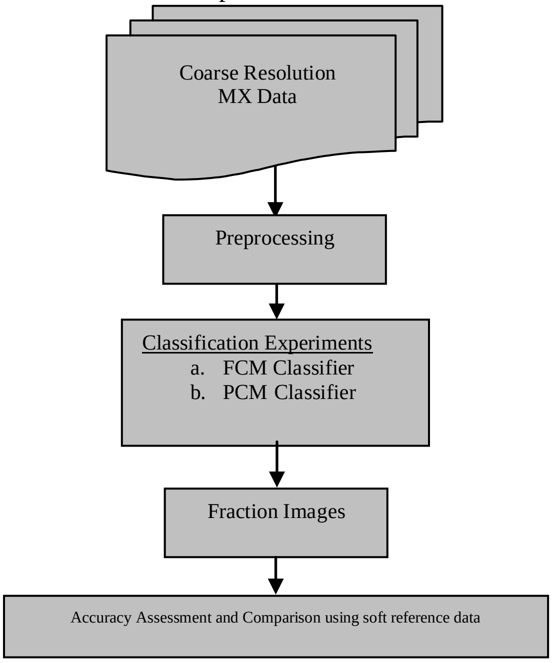

Fig. 2: Methodology adopted

V. RESULTS AND DISCUSSIONS

Determining land cover information accurately from remote sensing imagery is crucial to understand ecological and climatic processes occurring at a range of scales. Soft classification offers a flexible way to infer sub-pixel land cover information. In this paper, we have shown that the fuzzy confusion thicket can be unraveled when membership values correspond to land cover fractions, and the amount of sub-pixel match among the referenced and assessed pixels are shown in Fig. 3, 4, and 5 using FERM, SCM, MIN-MIN, and MIN-LEAST operator for FCM and PCM classifiers with respect to AWIFS and LISS-III comparison, AWIFS and LISS-IV comparison and LISS-III with LISS-IV comparison. Using this cross comparison analysis we have identified that Overall accuracy using MIN-LEAST operator for FCM classifier found a perfect match between the reference and assessed data at the pixel level, wherein the value of weighting exponent was set to 4.0. The observation of fuzzy kappa coefficient of MIN-LEAST operator can also be seen from Fig. 6, 7 and 8 , for FCM classifier found 0.97, 0.95 and 0.96 for AWIFS with LISS-III comparison, AWIFS with LISS-IV comparison and LISS-III with LISS-IV comparison respectively. This also states the match agreement of classification has achieved the 90% accuracy. Apart from this the other measures like uncertainty in SCM and Fuzzy kappa coefficients shown in Fig. 9, 10, 11, 12, 13 and 14 can provide better classification accuracy for FCM and PCM classifiers can be achieved, using the optimized value of ‘m’ i.e. 4.0. For setting the value of ‘m’, a number of experiments have been performed for both classifiers by varying ‘m’ from 1.1 to 4.0. The accuracy of FCM and PCM clustering increases by increasing the value of ‘m’ until ‘m’=4.0, after which the accuracy become stable. Thus, the optimum value of ‘m’ for FCM and PCM classifier has been fixed as 4.0 for classification.

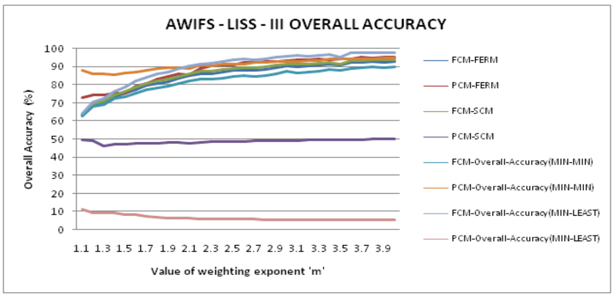

Fig. 3: Overall Accuracy for FCM and PCM classifiers of AWIFS with LISS-III

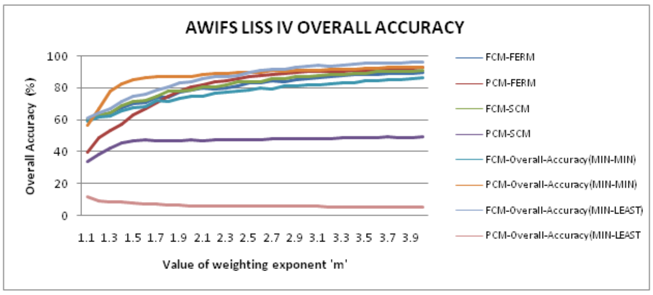

Fig. 4: Overall Accuracy for FCM and PCM classifiers of AWIFS with LISS-IV

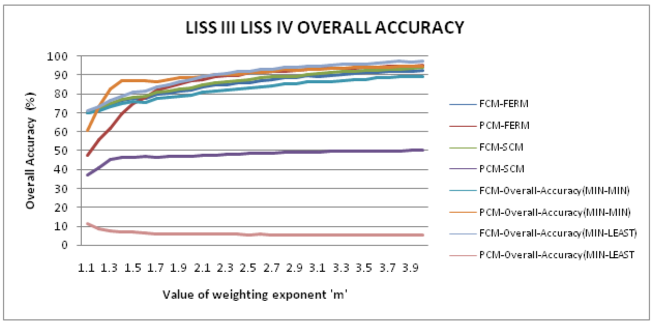

Fig. 5: Overall Accuracy for FCM and PCM classifiers of LISS-III with LISS-IV

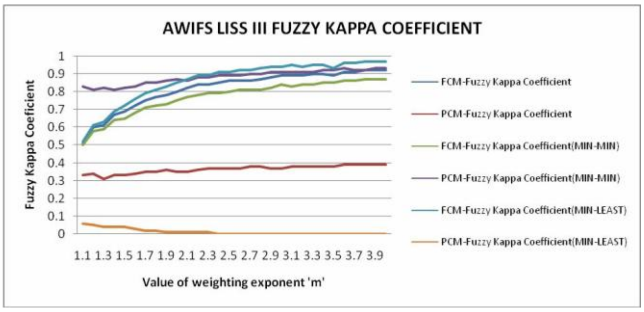

Fig. 6: Fuzzy Kappa Coefficient for FCM and PCM classifiers of AWIFS with LISS-III

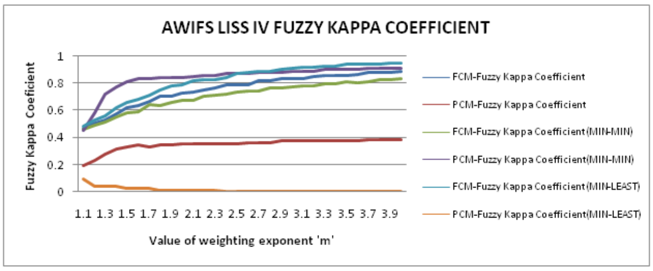

Fig. 7: Fuzzy Kappa Coefficient for FCM and PCM classifiers of AWIFS with LISS-IV

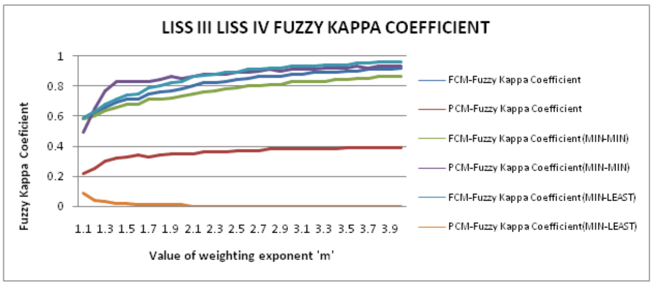

Fig. 8: Fuzzy Kappa Coefficient for FCM and PCM classifiers of LISS-III with LISS-IV

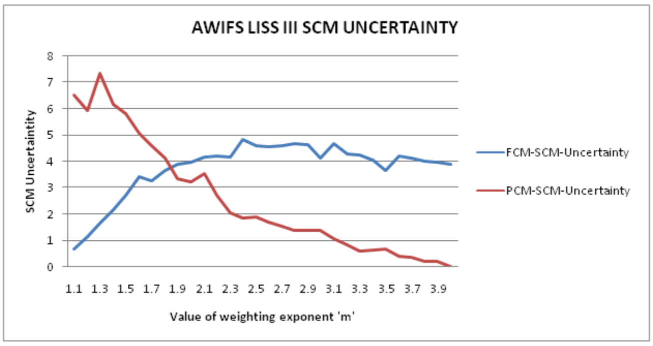

Fig. 9: SCM Uncertainty for PCM and FCM classifiers of AWIFS with LISS-III

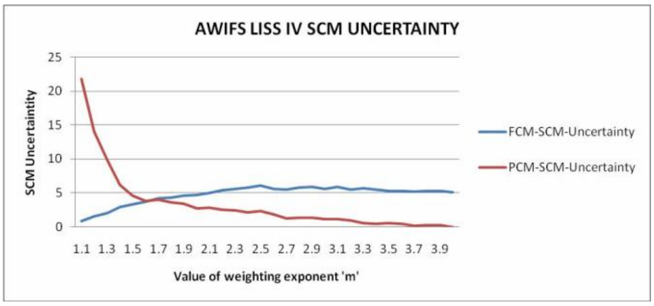

Fig. 10: SCM Uncertainty for PCM and FCM classifiers of AWIFS with LISS-IV

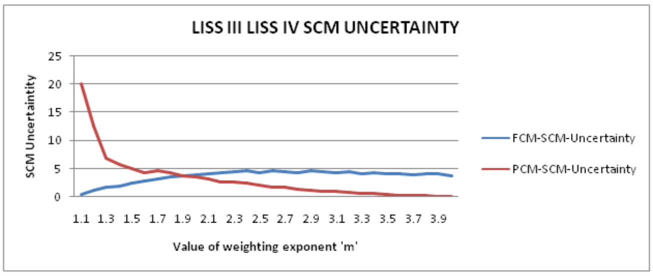

Fig. 11: SCM Uncertainty for PCM and FCM classifiers of LISS-III with LISS-IV

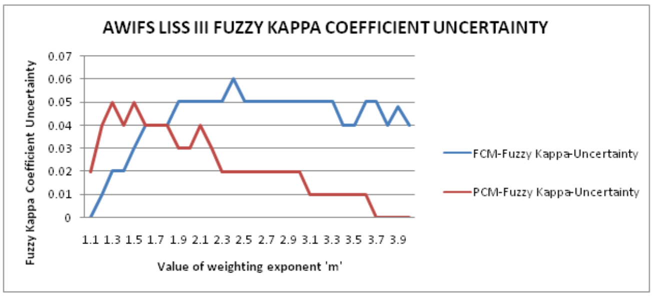

Fig. 12: Fuzzy Kappa Coefficient uncertainty for FCM and PCM classifiers of AWIFS with LISS-III

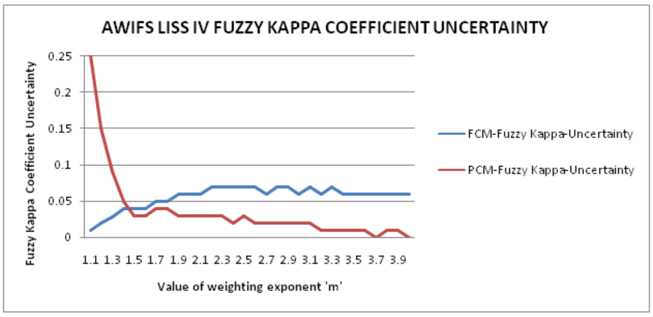

Fig. 13: Fuzzy Kappa Coefficient uncertainty for FCM and PCM classifiers of AWIFS with LISS-IV

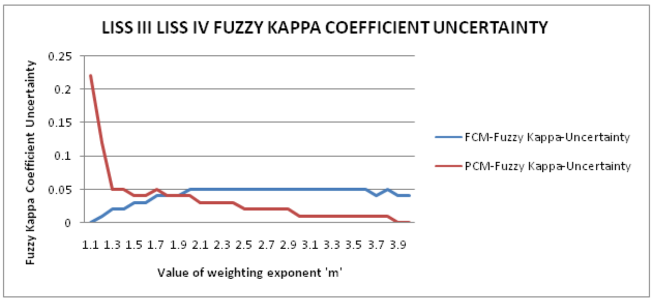

Fig. 14: Fuzzy Kappa Coefficient uncertainty for FCM and PCM classifiers of AWIFS with LISS-IV

VI. CONCLUSION

In this research work it has been tried to generate fraction outputs from FCM and PCM classifiers using Euclidean norms. These outputs have been generated from AWIFS, LISS-III and LISS-IV images of IRS-P6 data. FERM and overall accuracy with various accuracy assessment operators like MIN-MIN MIN-LEAST and Fuzzy kappa coefficients and their respective uncertainties are being used as assessment parameters of accuracy, for various land cover classes i.e. water bodies, Sal forest, Eucalyptus plantation, agriculture land with crop, agriculture moist land without crop, agriculture dry land without crop. Uncertainty is intrinsic in spatial data and this generally refers to error, inexactness, fuzziness and ambiguity. The objective of this research on spatial data to is to investigate, how uncertainties arise, or are created and propagated in the spatial data. Based on information theory, considering the characteristics of randomness of positional data and fuzziness of attribute data and taking FERM, SCM and Fuzzy Kappa coefficient as a measure, this paper proposes the significant advances on the use of remote sensing data for the estimation of land cover information with optimized value of weighting exponent 'm' for FCM and PCM classifiers. In the area of remote sensing, the decision making are not generally deterministic due to the involvement of fuzziness in the classification of remotely sensed imagery. A considerable number of identification errors are due to pixels that show an affinity with several information classes. The fuzzy concept is a valuable tool for dealing with classification problems. In remote sensing classification, fuzzy based classifiers are becoming increasingly popular. Due to the wide acceptance of FCM and PCM classifiers, this has been used as a benchmark to evaluate the performance of other classifiers with optimized value of weighting exponent 'm' in this research. Evaluation of soft classification through FERM, SCM and Fuzzy kappa coefficient, using Euclidean norm based measures led to an improvement wherein FCM-Overall accuracy (MIN-LEAST) operator reflects higher classification accuracy, i.e., 97% and the value of Fuzzy Kappa coefficient is 0.97 with minimum uncertainty in it, for the optimized value of weighting exponent 'm' i.e. 4.0. It is shown in Fig. 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13 and 14. In this experimentation two supervised classifiers namely FCM and PCM have been selected to demonstrate the improvement in the classification accuracy by FERM, SCM, MIN-MIN, MIN-LEAST, Fuzzy Kappa coefficient and uncertainty in SCM and Fuzzy Kappa coefficients. In this experiment the value of weighting exponent 'm' is varying from 1.1 to 4.0 for both the classifiers. It may be mentioned that the value of m and its interpretation is different in the PCM than in FCM. The weighting exponent m in PCM determines the rate of decay of the membership values, however in FCM this reflects the degree of sharing. In FCM, as 'm' increases, it represents the increase in sharing of pixels in all clusters, whereas in PCM, it represents increased possibility of all pixels in the data set completely belonging to a given cluster.

REFERENCES

1. Foody, G. M., Lucas, R. M., Curran, P. J. and Honzak, M., "Non-linear mixture modelling without end-members using an artificial neural network," International Journal of Remote Sensing, vol. 18, no. 4, 1997. pp. 937 – 953.
2. Yannis, S. A., and Stefanos, D. K., Fuzzy Image Classification Using Multi-resolution Neural with Applications to Remote Sensing. Electrical Engineering Department, National Technical University of Athens, Zographou 15773, Greece, 1999.
3. Foody, G. M., "Approaches for the production and evaluation of fuzzy land cover classifications from remotely sensed data," International Journal of Remote Sensing, vol. 17, no. 7, 1996, pp. 1317 – 1340.
4. Dunn J. C., "A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters," Journal of Cybernetics, 1973, pp. 3: 32 – 57.
5. Bezdek, J. C., Pattern Recognition with Fuzzy Objective Function Algorithms, Plenum, New York, USA, 1981.
6. Binaghi, E., Brivio, P. A., Chessi, P. and Rampini, A. A fuzzy Set based Accuracy Assessment of Soft Classification, Pattern Recognition letters, 20, 1999, pp. 935 – 948.
7. Okeke, F. and Karnieli, A., "Methods for fuzzy classification and accuracy assessment of historical aerial photographs for vegetation change analysis. Part I: Algorithm development," International Journal of Remote Sensing, 27 (1 – 2), 2006, pp. 153 – 176.
8. Kanellopoulos, I., Varfis, A., Wilkinson, G. G. and Megier, J., "Land cover discrimination in SPOT HRV imagery using an artificial neural network: a 20-class experiment," International Journal of Remote Sensing, vol. 13, no.5, 1992, pp. 917 – 924.
9. Kerdiles, H. and Grondona, M. O., "NOAA-AVHRR NDVI decomposition and subpixel classification using linear mixing in the Argentinean Pampa," International Journal of Remote Sensing, vol. 16, no. 7, 1996, pp. 1303 – 1325.
10. Verhoeye J., and Robert D. W., Sub-pixel Mapping of Sahelian Wetlands using Multi-temporal SPOT Vegetation Images. Laboratory of Forest Management and Spatial Information Techniques, Faculty of Agricultural and

Applied Biological Sciences, University of Gent, 2000.
11. Zhang, J., Foody, G. M., "Fully-fuzzy supervised classification of sub-urban land cover from remotely sensed imagery: statistical and artificial neural network Approaches," International Journal of Remote Sensing, vol. 22, No. 4, 1998, pp. 615–628,
12. Shi, W., Z., Ehlrs, M., and Temphli, K., "Analysis modeling of positional and thematic uncertainty in integration of remote sensing and GIS," Transaction in GIS, vol. 3, 1999, pp. 119 – 136.
13. Kumar, A., Ghosh, S. K. and Dadhwal, V. K. "Advanced Supervised Soft Multi-Spectral Image Classifier", Map Asia 2005 conference, Jakarta. Indonesia, 2005.
14. Krishnapuram ,R., and Keller J., M., "A possibilistic approach to clustering," IEEE Transactions on Fuzzy Systems, vol. 1, 1993, pp. 98 – 108.
15. Foody, G.M. and Arora, M. K., Incorporating mixed pixels in the training, allocation and testing stages of supervised classification, Pattern Recognition Letters, 17, 1996, pp. 1389 – 1398.
16. Foody G. M., "Cross-entropy for the evaluation of the accuracy of a fuzzy land cover classification with fuzzy ground data," ISPRS Journal of Photogrammetry and remote sensing, vol. 50, 1995, pp. 2 – 12.
17. Shabanov, N. V., Lo, K., Gopal, S., and Myneni, R. B., "Subpixel burn detection inModerate Resolution Imaging Spectroradiometer 500-m data with ARTMAP neural networks," Journal of Geophysical Research, vol. 110, 2005, pp. 1 – 17.
18. Pontius, R. G., Jr., and Cheuk, M. L., "A generalized cross-tabulation matrix to compare soft-classified maps at multiple resolutions," International Journal of Geographical Information Science, vol. 20(1), 2006, pp. 1 – 30.
19. Lewis, H. G., and Brown, M., "A generalized confusion matrix for assessing area estimates from remotely sensed data," International Journal of Remote Sensing, vol. 22, 2001, pp. 3223 – 3235.
20. Pontius, R. G., Jr., and Connors, J., (2006). Expanding the conceptual, mathematical and practical methods for map comparison. Proc. of the Spatial Accuracy Meeting 2006. Lisbon, Portugal 16 pp., (available from www.clarku.edu/~rpontius).
21. Kuzera, K., and Pontius, R. G., Jr., (2004) Categorical coefficients for assessing soft-classified maps at multiple resolutions. Proc. of the joint meeting of The 15th Annual Conference of the International Environmental Society and the 6th Annual Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences. Portland ME, 28 June–1 July 2004, Portland Maine (St. Paul, Minnesota: Spatial Accuracy Symposium).
22. Silván-Cárdenas, J. L., and Wang L., (2007) Sub-pixel confusion–uncertainty matrix for assessing soft classifications, Remote Sensing of Environment (2007), doi: 10.1016/j.rse.2007.07.017.
23. Aziz,M. A. Evaluation of soft classifiers for remote sensing data, unpublished Ph.D thesis, IIT Roorkee, Roorkee, India, 2004.
24. Kumar, A., Ghosh, S. K., and Dadhwal V. K. (2006). A comparison of the performance of fuzzy algorithm versus statistical algorithm based sub-pixel classifier for remote sensing data. Proceedings of mid-term symposium ISPRS, 8–11th May 2006, ITC-The Netherlands.

AUTHORS PROFILE

Rakesh Dwivedi is a PhD research scholar at Indian Institute of Technology Roorkee, Roorkee, India. He received his M.Techc degree in Computer Science and Engineering from H.B.T.I. Kanpur, Uttar Pradesh , India in 2010 and M.C.A. degree, from Mahatma Gandhi Chitrakoot Gramodaya, University Chitrakoot, Satna (M.P.), India in 1997. He is working as an Associate Professor with Teerthanker Mahaveer University, Moradabad (U.P.), India from 2002 to till date. His research interest includes the soft computing, Fuzzy based Hybrid Soft Classification, Parameter Optimization and Algorithm design.

Anil Kumar has been a scientist/engineer 'SF' at Indian Institute of Remote Sensing, Indian Space Research Organization, Dehradun, Indiasince 1998. He received his BTech degree in civil engineering from University of Lucknow, India, and MEng degree in photogrammetry and remote sensing and PhD in soft computing from Indian Institute of Technology, Roorkee, India. His research interests include soft computing, digital photogrammetry, GPS and LiDAR.

Sanjay Kumar Ghosh is professor at Department of Civil Engineering, Indian Institute of Technology, Roorkee, Uttarakhand, India. He received his BE Civil and ME Civil, both from University of Roorkee (now IIT Roorkee) in 1980 and 1982, respectively. He was awarded his PhD degree from University of Strathclyde, Glasgow in 1991, under the Commonwealth. Fellowship program of the British Council U.K. He has published more than 80 papers in various journals and conferences and guided 11 PhD thesis, and 6 are in progress under his guidance. Further he has also guided 61 MTech thesis and 3 are under progress. His current interests are in the area of remote sensing, image processing, and GIS applications.