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"A NOVEL SOFT CLASSIFICATION APPROACH TO DETECT OBJECT FOR MULTI SPECTRAL SATELLITE IMAGERY"

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ABSTRACT

Nowadays, modern earth observation programs produce massive volumes of satellite data time series (SITS) that can be beneficial to display geographical regions thru time. A way to effectively examine such kind of facts continues to be an open query with in the far flung sensing subject. To differing size, direction and background of target object, object detection very challenging in research area. Due Some of the leading GIS software which have well defined image processing module are ERDAS Imagine, IDRISI, ENVI, and ER Mapper but the assessment of accuracy is not support by these software for the evaluation of soft classified output. So, in this research article I am proposing two new algorithms which capable detection of area with high accuracy in comparison of two built algorithm.

Our contributions are 1) the assessment of accuracy percentage is equal to referential value be 2.385 mean less than 3 which indicate maximum accuracy.

2) The classification value is less than 1 in soft classifiers like FCM nd PCM and other hybridize classifiers (PCME and FCME).

3) I have trained model by different algorithm and testing of model using independent indicator "Entropy"

Abbreviation used in paper

1	FCM	Fuzzy c-mean
2.	PCM	Possibilistic c-Means
3.	FCME	Fuzzy c-mean Entropy
4.	PCME	Possibilistic c-Means Entropy

Keywords: Pure pixel, Mixed pixel, Assessment of Accuracy, Entropy, Fuzzy c-mean Entropy, Possibilistic c-Means Entropy.

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INTRODUCTION

Modern earth observation packages produce massive volumes of remotely sensed data every day. Such statistics may be organized in time series of satellite data and images that can be beneficial to display geographical zones thru time. effectively control and examine remote sensing time series continues to be an open venture inside the far off sensing discipline, Geographic Information Systems (GIS) are a novel and growing thought and helpfulness in great feature to the proceeding and frequent growth the processing of remote sensing. The process of remote sensing plays a great job in the progress of any GIS, and in most cases, it allows data to be used for multiple applications[1][2][3].
Hard classifiers are commonly used in image classification, where a pixel has a membership value of either 0 or 1, thus it is considered as a pure pixel. The nature of pixel in soft classifier is mixed[4]. The pixel of soft classifiers belongs to multiple classes. By theory of fuzzy set we can resolve the problem of multiple belongingness pixel of image. The ranges of membership value in fuzzy set are 0 and 1 where the value between 0 and 1 defines the proportion of occurrence of information within a pixel. This concept has been used in many applications, such as sensor signal analysis, uncertainty minimization.
In general, multispectral classifiers provide a complete suite of options for image classification [5][6] using supervised, unsupervised or fuzzy based approaches. The image processing falls into 10 categories: restoration of image, image enhancement, image transformation, signature development of image, hard classifiers and soft classifiers for image, hardeners and hyper spectral analysis of image and accuracy assessment of result. The performance of image processing software has improved tremendously with the advancement of computer hardware technologies.
Moreover, removing them from the classification may also result into loss of information contained within those mixed pixels. Therefore, these need to be incorporated in the training stage itself while doing supervised classification[7][8] .

LITERATURE REVIEW OF RESEARCH

The remote sensing image includes a combination of varied and pure pixels. In digital image taxonomy, image or a pixel is habitually measured like a unit belongs to only land cover category. However, due to constricted image resolution, pixel often represents ground area, which consists of more than single isolated land cover classes. For this cause, it has been considered that fuzziness should be accommodated in the categorization technique so that pixels may have multiple or partial class membership . In this case, a determine of the strong point of membership or relationship for every class is output by the classifier, resultant in a soft classification. A unsurprising ‘hard’ classification technique, which allocates each pixel to a explicit class, is often unsuitable for application where miscellaneous pixels are profuse in the image.
Some of the commercially available digital image processing software, such as, Environment for Visualizing Images (ENVI), Earth Resource Data Analysis System (ERDAS), Earth Resource Mapping software (ER Mapper) and IDRISI do not provide any corresponding

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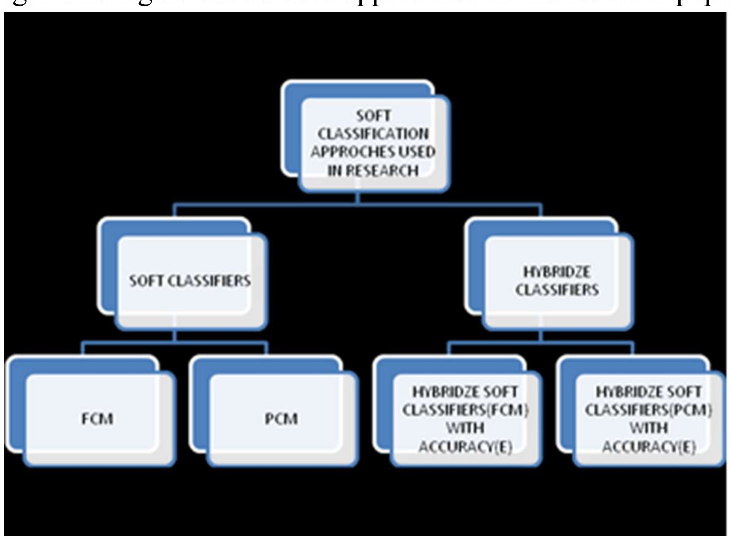
accuracy measures for soft classified output of their evaluation. So, in this study, a designed two hybrid algorithm which overcome such problems, In general, none of the commercially available software has incorporated entropy and contextual based hybridization and SCM based approach to assess the accuracy of a classified image. Further, such software packages provide an option for entropy for multi-spectral remote sensing data at sub-pixel classification. Thus, in this study, it was necessary to develop a package having the sub-pixel classification algorithms used for different experiments. but in this research proposal I have designed two hybrid algorithm PCME and FEME : where PCME is stand Possibilistic c-Means integrated Entropy and FCME is stand for Fuzzy c-mean integrated entropy which are hybrid soft classifiers with entropy.

OBJECTIVE OF RESEARCH

In this study, fuzzy soft classifiers and hybrid fuzzy based classifier with entropy, entropy based noise clustering have been used to learn the result of accuracy method(entropy) on classifiers output for multi-spectral data sets at pixel level. But any classification is considered to be incomplete without assessment of its accuracy. Previous study can work either classification or accuracy only this research has deail in both manner.

Fig:1 This figure shows used approaches in this research paper



I have used total four classifiers. Among four two classifiers are soft classifiers named as FCM and PCM and remaining two classifiers has proposed in hybridize model with accuracy, Various commercial companies have introduced variety of image processing tool which offer a related module to data input, visualization, enhancements, transformations, classification, accuracy assessment and output coupled with other GIS based modules. Some of the leading GIS software which have well defined image processing module are ERDAS Imagine, IDRISI, ENVI, and ER Mapper but the assessment of accuracy is not support by theses software but

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assessment of result of classifiers our research study is not completed. Accuracy is very important key for assessment of output of classifiers.

Features of research proposal

This research has broadly divided into two modules first one is soft classification and another one is soft classifiers with entropy. Classifiers their accuracy with absolute indicator by Entropy. The working of classifiers support 2 studies: which named as

Fuzzy set theory based soft classifier
a) Fuzzy c-Means (FCM) classifier.
b) Possibilistic c-Means (PCM) classifier.

Hybridization Fuzzy set theory based soft classifier with accuracy assessment (entropy)
a) Fuzzy c-Means (FCM) classifier integrated with absolute indicator (Entropy)
b) Possibilistic c-Means (PCM) integrated with absolute indicator (Entropy)

METHODOLOGY OF RESEARCH PAPER

Both supervised [9] and unsupervised categorization may be useful to execute pure and mixed classification[10]. In hard categorization, pixel is billed to one and only one class, which may create wrong outcome, mainly in classifying coarse spatial resolution imagery. It is thus vital that soft classification (fig 1) is use to create division magnitude within a element of picture will arrange to raise the classification accuracy and to produce significant and suitable ground cover work.

Fuzzy c-Means (FCM) Clustering FCM

One of the most admired fuzzy clustering method is the fuzzy c-means (FCM) which is an unconfirmed classifier that in an repetitious technique assign class membership values to pixels of an image by reduce an intention role. The major limitations of FCM in comparison PCM soft classifier. The probabilistic sum of soft classifier FCM is one constraint.FCM, is and iterative technique. The key is to symbolize the similarly that a pixel share with each cluster with a function (membership function) whose value lie down among 0 and 1. Memberships secure to unity signify a high scale of resemblance between the pixel and that cluster. The remaining result of such a role for clustering is to produce fuzzy c-partitions (U) of a given data. A fuzzy c-partition of the data is the one which characterize the association of each pixel in all the clusters by a link function which ranges from zero to one. in addition, for each pixel's sum of membership value must be unity. This is a obtain by minimize the general least-square function

$$j_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{C}(\mu_{ij})^m \, ||x_i - v_j||_A^2 \quad \ldots$$

From eq1 :Where xi is the vector representing spectral response and the group of cluster's vector centers is V, class membership values of a pixel is represented by vj µij and,c and n are the number of cluster is represented by c and respectively, m is a weighting exponent the value

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of m lies between 1 to ∞ , which represented control the scale of uncertainty in soft classifier FCM.

Possibilistic c-Means (PCM)

The working method are same for soft classifiers PCM and FCM .But the PCM also included an added term is called regularizing term. The least- square error objective function, the minimize the generalized least- square error objective function are given by in Eq(2),

$$j_m(U,V)=\sum_{i=1}^{N}\sum_{j=1}^{C}\left(\mu_{ij}\right)^m \|\mathrm{x}_i-v_j\|_A^2+\sum_{i=1}^{c}\left(1-\mu_{ij}\right)^m \quad (2)$$

Hybridize Algorithm (Fuzzy c-Mean plus Entropy:FCMPE)

The betterment of output of classifiers I have purposed a hybridize algorithm with accuracy FCM with Entropy.

The objective function of an algorithm is given in eq(3):

$$J_{FCMWE}(U,V)=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ki}D(x_k,v_i)+v\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ki}\log u_{ki},(v>0) \quad (3)$$

HYBRIDIZE ALGORITHM (FUZZY C-MEAN PLUS ENTROPY) (PCMPE)

Hybridize Algorithm (Possibilistic c-Means plu Entropy: FCMPE)

This is another soft hybrid algorithm is PCM with entropy. The objective function of an algorithm is shown in eq (4)

$$J_{FCMWE}(U,V)=\sum_{i=1}^{c}\sum_{k=1}^{n}\left(\mu_{ij}\right)^m \|\mathrm{x}_i-v_j\|_A^2+v\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ki}\log u_{ki},(v>0) \quad (4)$$

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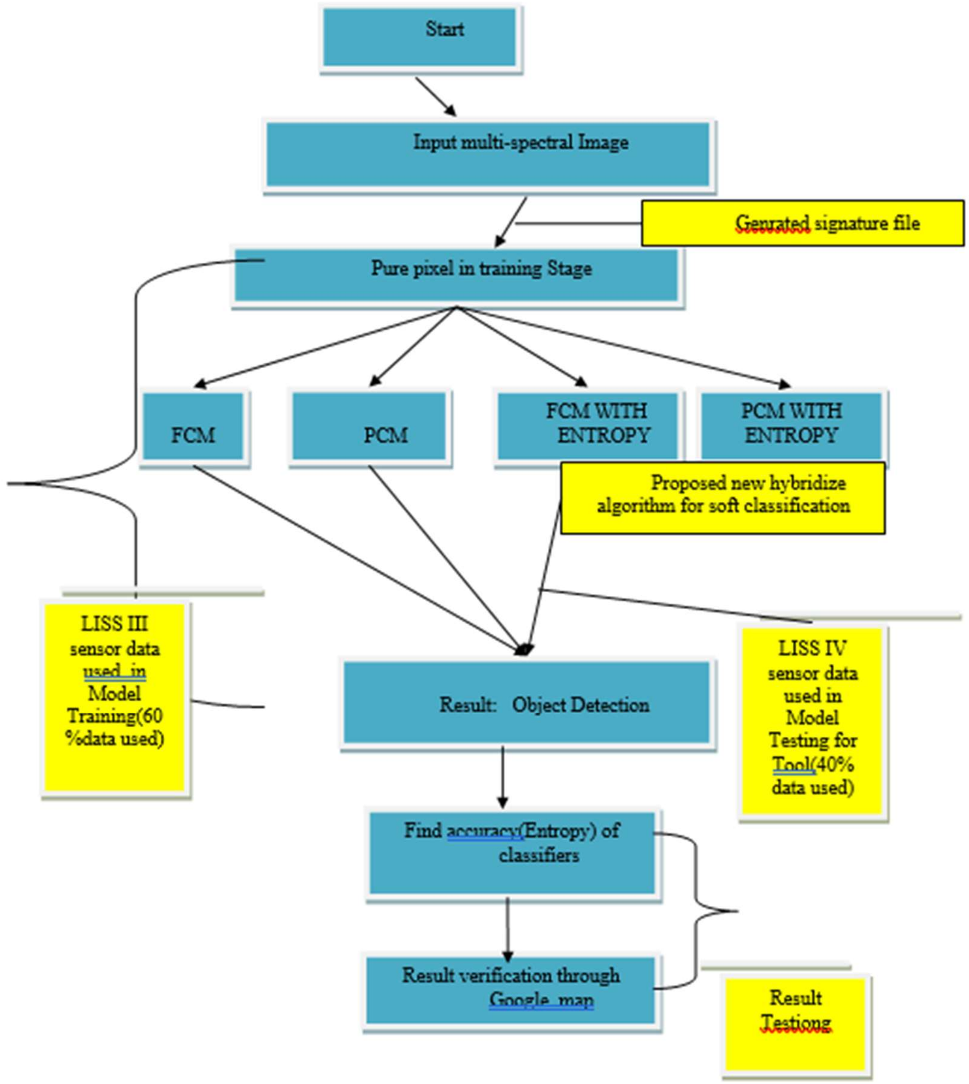

Fig 2: This is block diagram of methodology of research

THE STUDY AREA AND DATA SET INFORMATION

As a way to prove the generality of our notion, it has been tested over two unique far off-sensing primarily based datasets. The first is a collection of spatial gadgets described by way of a set nearby data extracted from very excessive spatial resolution LISS III ,LISS IV(characteristics explain in figure 4) however with a constrained temporal depth. the second one is a pixel-based dataset, extra noisy but richer in both spectral and temporal decision. certain descriptions are furnished within the following subsections.

The area located at Sitarganj Tehsil near Pant Naga, Uttarakhand state, Bharat. This research area holds dissimilar

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area detection[11] classes[16][17] like infertile land, natural forest, farming, water body and wet land as shown in.Table 1 represent the characteristic of sensor like band color, resolution of pixel and etc.
I have choosen three sensors named LISSIII, LISS IV satellite dataset for this study in fig 3. Theses sensors work on hyper spectral.

Fig 3: This figure shows study area of research proposal

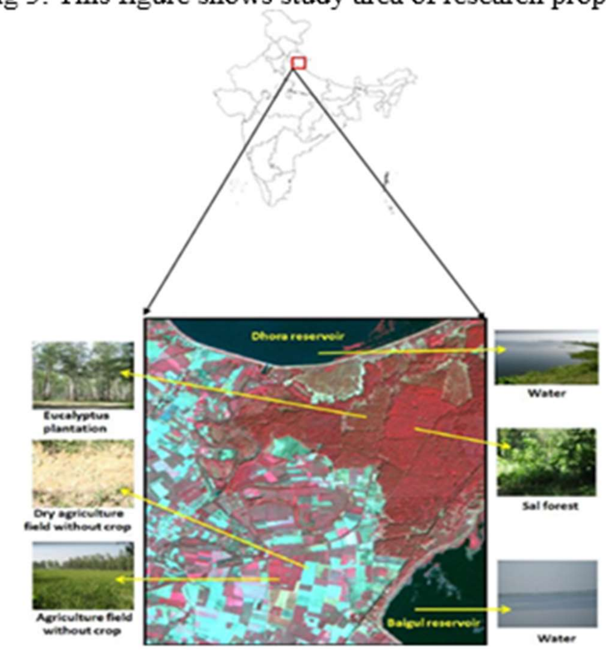

Table 1: This is Table shown information of sensors

Sensor's Name	Band-color	Resolution of pixel [m]	Swath [km]	Quantization [bits]
Mono mode(LISS-IV Sensor)	Band color is Red color	5.801	70.3	7.01
MX mode (LISS – IV)	LISS IV band color R is green red NIR	5.801	70.3	7 .01
Sensor(LISS-III)	LISS III band coloris green red NIR SWIR	23	141.01	10

Classification[12][13][14] correctness is in the main calculated by an inaccuracy matrix. However, in this study, it is not possible generation of reference data for LISS-IV image due to additional advanced resolution image for the study area. as fine as it is not achievable to generate fraction reference result from earth with large number of samples. In such case, entropy is used as complete quantify of uncertainty. Entropy is complete process of assessment there is no required for comparison other assessment Eqn (3). Uncertainty estimation [17][18]

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by entropy works without reference data. we can calculated the entropy for classified fraction output by Eq (3)

$$H = -\sum_{i=1}^{C} \mu_{ij}(\frac{w_i}{x}) \log_2 \left(\mu_{ij}(\frac{w_i}{x}) \right) \quad ....(5)$$

EXPERIMENTAL RESULT AND VERIFICATION RESULT

According to methodology my research article. I have divided result assessment into two group first group embedded algorithm and second part has to support for proposed algorithms. I have used 80% data in tranning and testing of model by using type approaches multispectral soft classifiers[23][24] and hybrid approaches using sensor LISSIII and LISSIV. And 20% percentage data used in vaildation for and I have chosen entropy for assessing the generated result. After testing result I have verify assurance or verifying result by goggle map. There are numerous graph which shows classifications result of classifiers with minimum entropy[19][20][21].

Graphical respresentaion of accuracy of different land groups from soft classifiers “FCM”and “PCM” for LISS-III,LISSIV

Fig:4 This figures shows membership value and weighted exponent LISSII of FCM

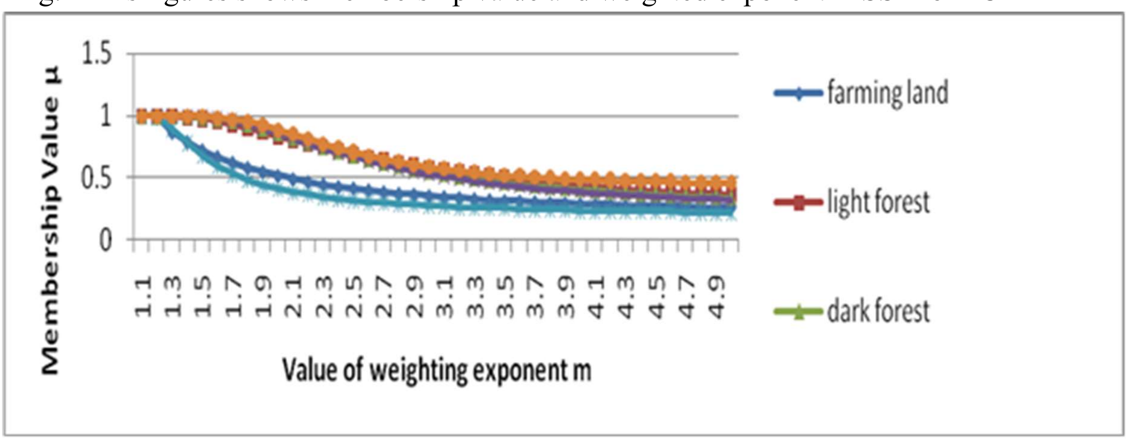

Fig: 5 This graph plotted between accuract(Entropy) and weghted exponent LISSII of FCM

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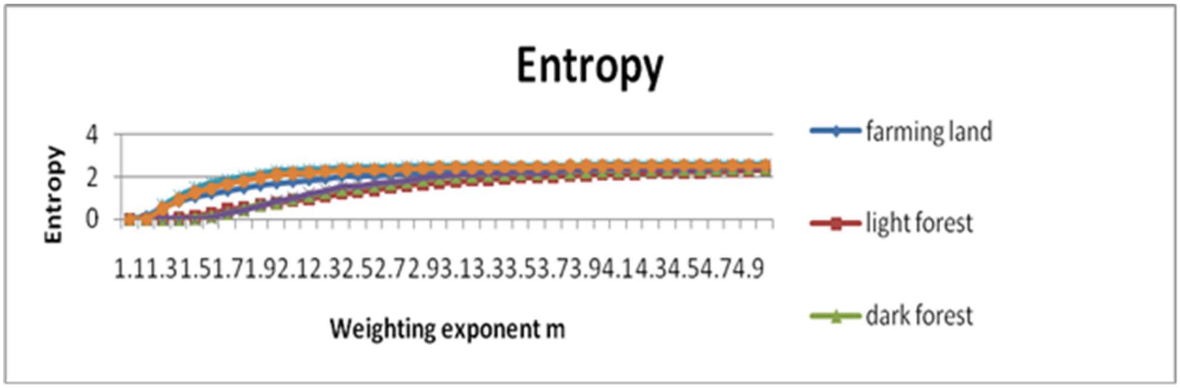

Fig: 6 This figures shows membership value and weighted exponent LISSIV of FCM

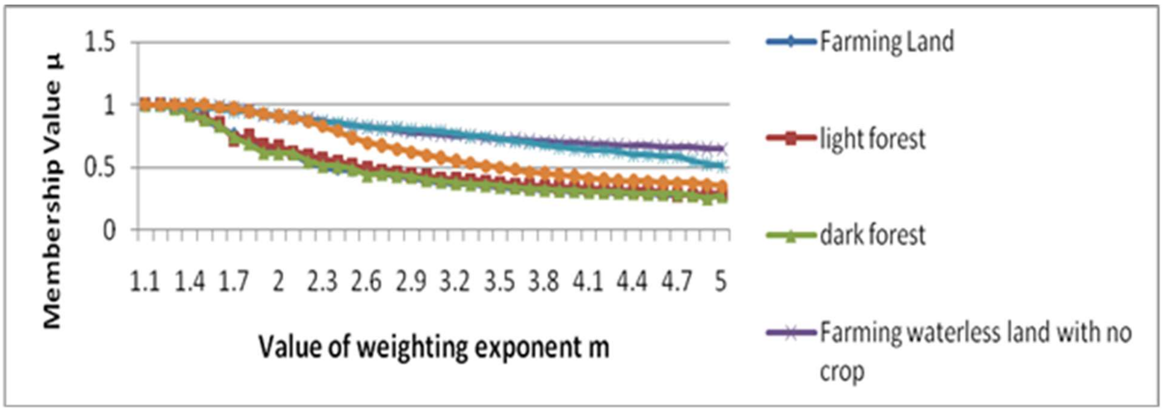

Fig: 7 This graph plotted between accuract(Entropy) and weghted exponent LISSIV of FCM

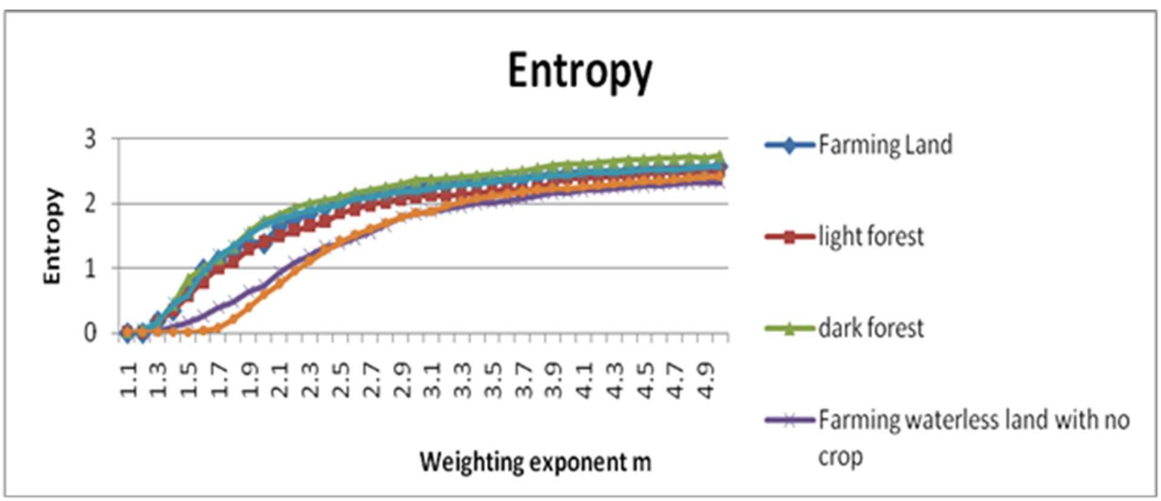

Table 2: This is Table shown result of FCM for sensor LISS III and LISSSIV

	FCM Classifier

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The result of FCM classifiers for different land groups	Entropy estimation for sensor LISS-III Entropy		Entropy estimation for sensor LISS-IV	
	lowest value	highest value	lowest value	highest value
Farming ground	.005 on m=1.10	2.19 on m=4.7	.005 on m=1.10	1.41 on m=4.8
light forest	.005 on m=1.10	2.00 on m=4.7	.005 on m=1.10	1.61 on m=4.8
dark forest	0 on m=1.10	1.88 on m=4.7	0.0 on m=1.10	1.32 on m=4.8
Farming waterless ground with no crop	.005 on m=1.10	2.05 on m=4.7	.005 on m=1.10	1.3 on m=4.8
Farming wet ground with no crop	.005 on m=1.10	1.91 on m=4.7	0.0 on m=1.10	1.43 on m=4.8
Water Area	0 on m=1.10	2.40 on m=4.7	.005 on m=1.10	1.46 on m=4.8

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Fig:8 FCM classification output of LISSIV image where μ lies between 0 to 1

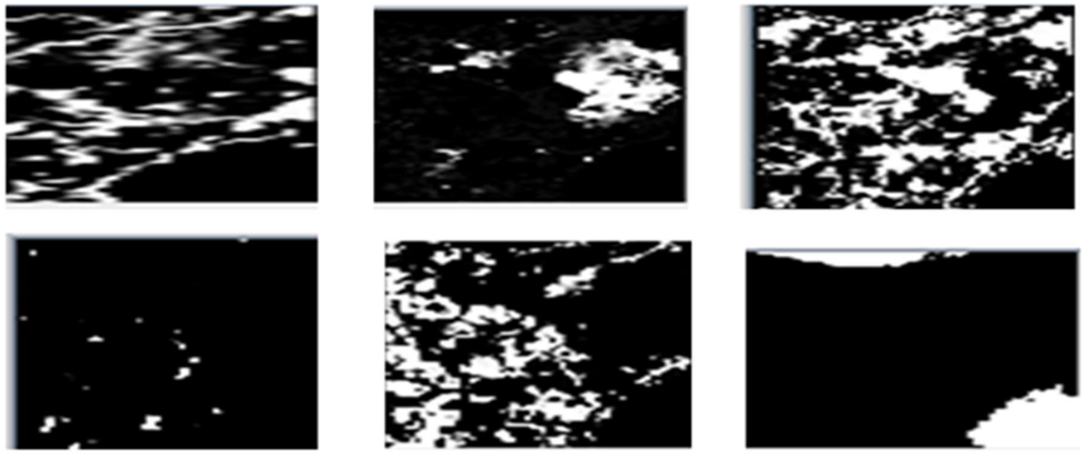

Fig:9 This figures shows membership value and weighted exponent LISSII of PCM

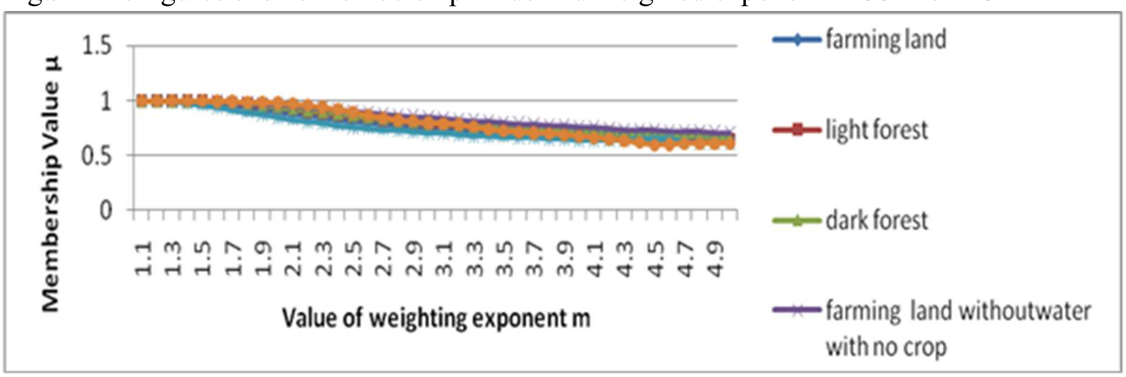

Fig:10 This graph plotted between accuract(Entropy) and weghted exponent LISSII of PCM

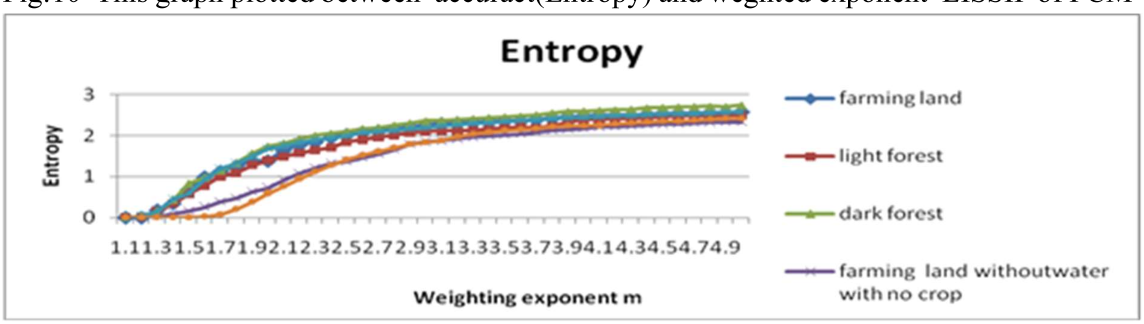

Fig:11 This figures shows membership value and weighted exponent LISS IV of PCM

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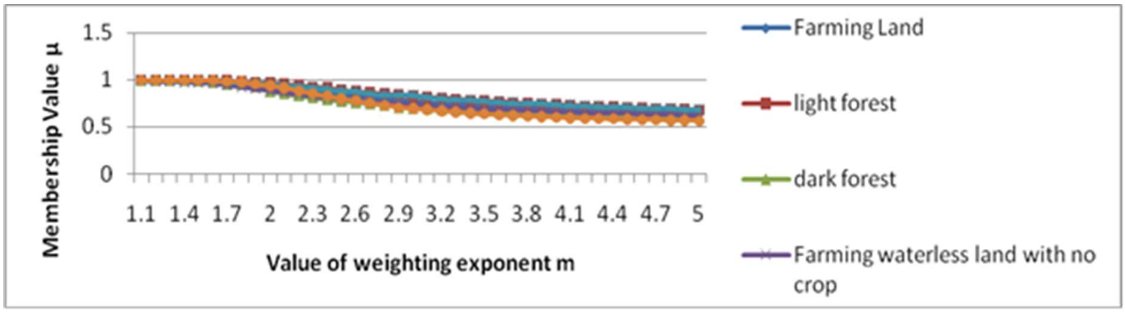
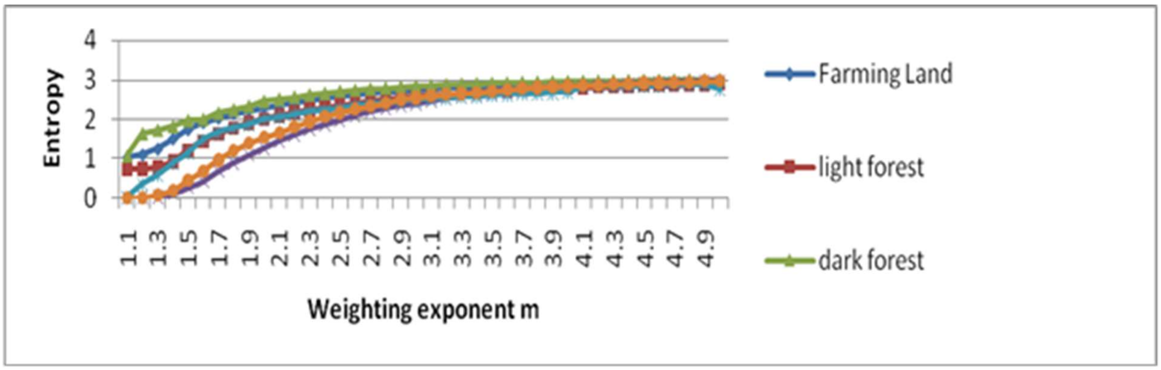


Fig:12 This graph plotted between accuract(Entropy) and weghted exponent LISSIV of PCM



PCM Classifier

Table 3: This is Table shown result of PCM for sensor LISS III and LISSSIV

The result of PCM classifiers for different land groups	**PCM Classifier**			
	Entropy estimation for sensor LISS-III		**Entropy estimation for sensor LISS-IV**	
	lowest value	**highest value**	**lowest value**	**highest value**
Farming ground	.082 on m=1.10	.76 on m=4.7	0.84 on m=1.10	1.84 on m=4.8
light forest	.031 on m=1.10	.56 on m=4.7	.73 on m=1.10	1.89 on m=4.8
dark forest	.145 on m=1.10	.52 on m=4.7	.87 on m=1.10	1.71 on m=4.8

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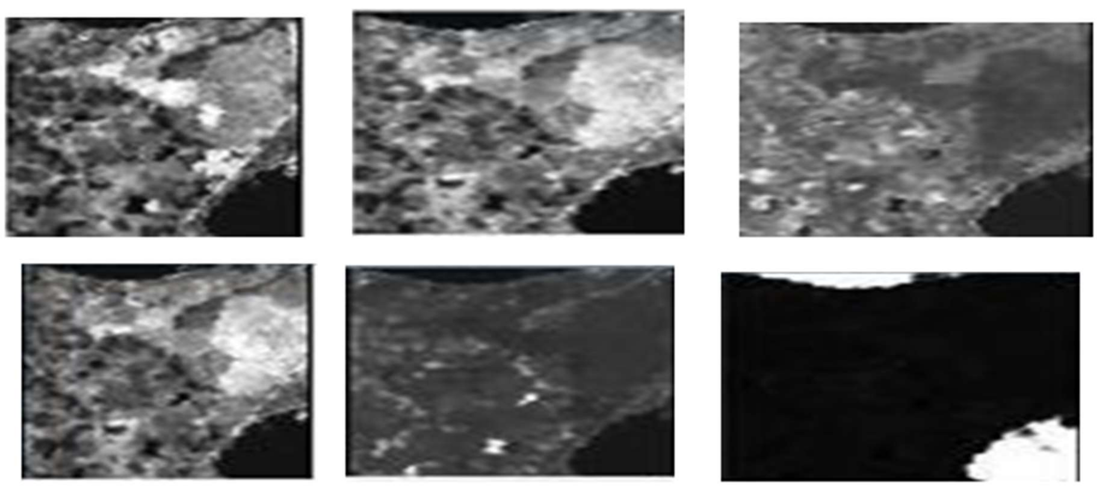
Farming waterless ground with no crop	.261 on m=1.10	.51 on m=4.7	.25 on m=1.10	2.48 on m=4.8
Farming wet ground with no crop	.005 on m=1.10	.33 on m=4.7	1.04 on m=1.10	1.43 on m=4.8
Water Area	.060 on m=1.10	.43 on m=4.7	0.0 on m=1.10	1.79 on m=4.8

Fig:13 PCM classification output of LISSIII image where μ lies between 0 to 1



Graphical respresentaion of accuracy of different land groups from soft classifiers “FCMPE and PCMPE” for LISS- III,LISSIV

Fig:14 This figures shows membership value and weighted exponent LISSII of FCMPE

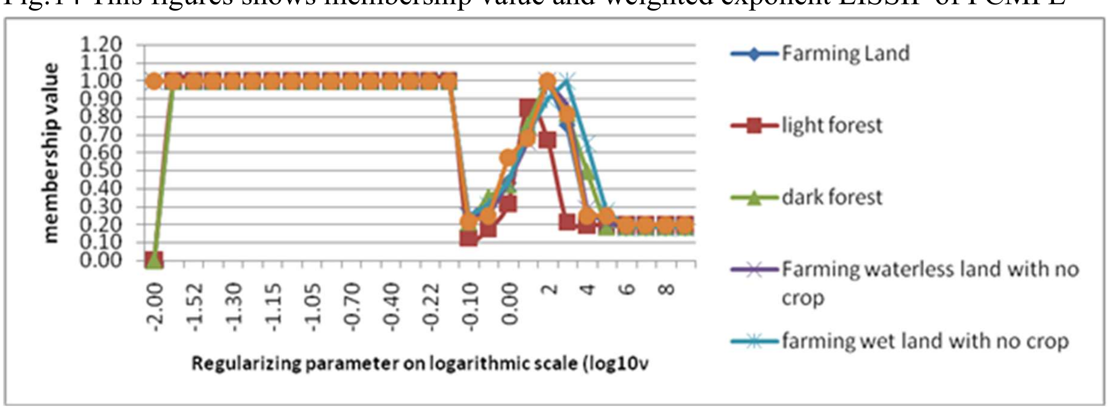


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Fig:15 This graph plotted between accuract(Entropy) and weghted exponent LISSII of FCMPE

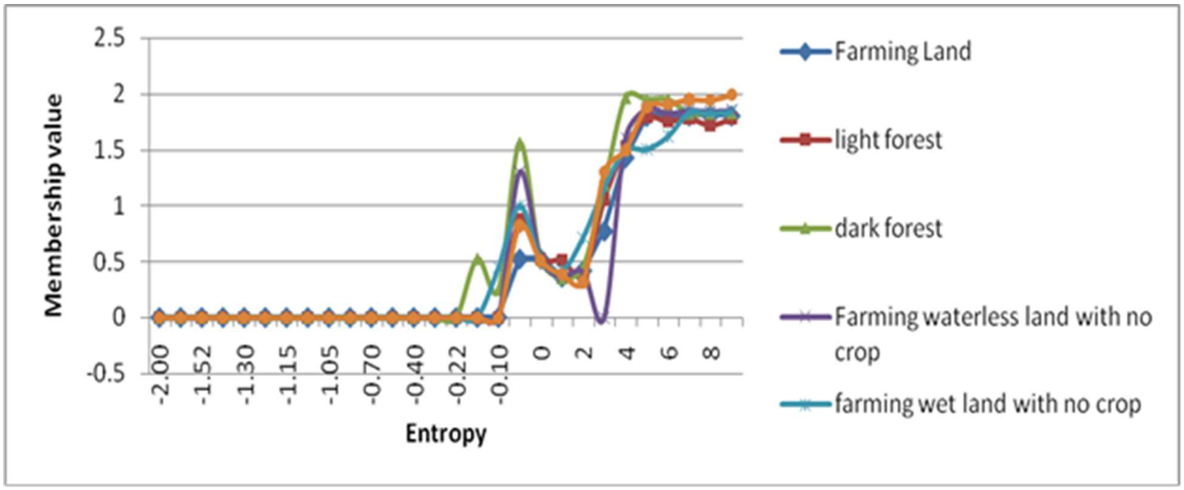

Fig 16 This figures shows membership value and weighted exponent LISSIV of FCMPE

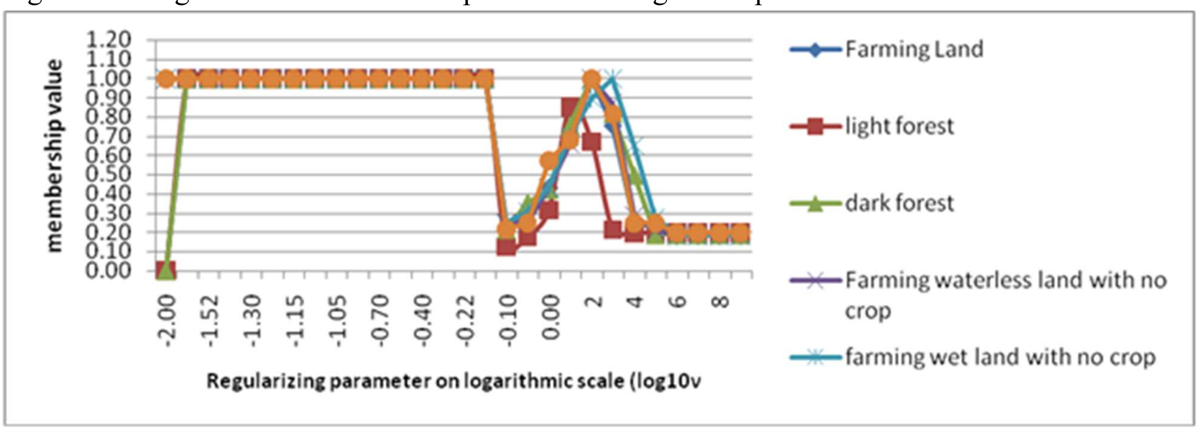

Fig:17 This graph plotted between accuract(Entropy) and weghted exponent LISSIV of FCME

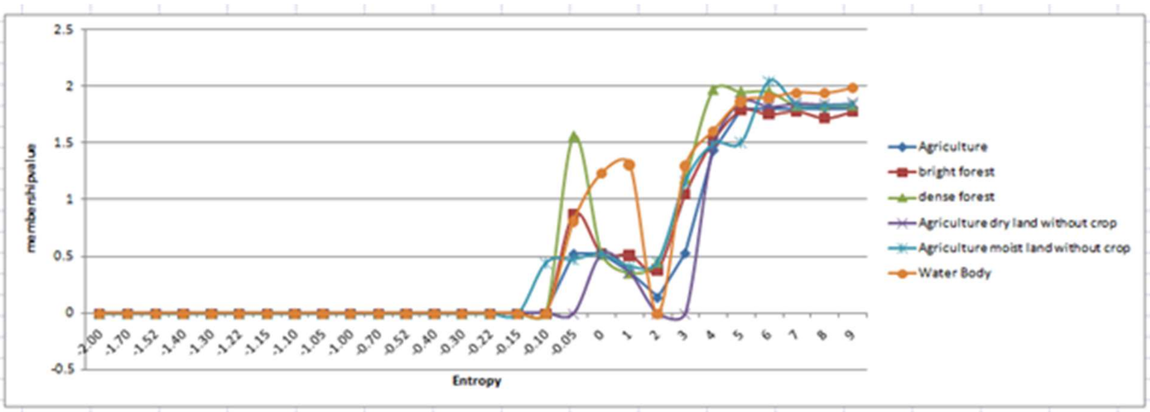

Table 4: This is Table shown result of FCME for sensor LISS III and LISSSIV

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Class	Class membership		Entropy		
	LISS-III	LISS-IV	LISS-III	LISS-IV	Optimized Mean value
Farming ground	10^3	10^3	10^2	10^3	$7.7x10^2$
light forest	10^2	10^3	10^3	10^3	$7.7x10^2$
dark forest	10^3	10^3	10^2	10^2	$5.5x10^2$
Farming waterless ground with no crop	10^3	10^3	10^2	10^2	5.510^2
Farming wet ground with no crop	10^3	10^2	10^2	10^2	$3.25x10^2$
Water Area	10^2	10^2	10^2	10^2	10^2

Fig:18 FCME classification output of LISSIII image where μ lies between 0 to 1

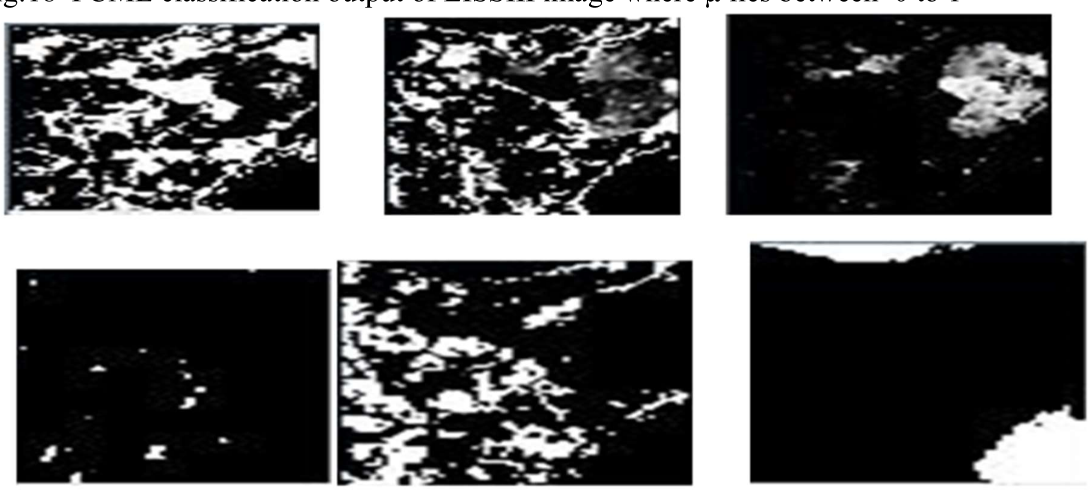

Fig:19 This figures shows membership value and weighted exponent LISSII of PCME

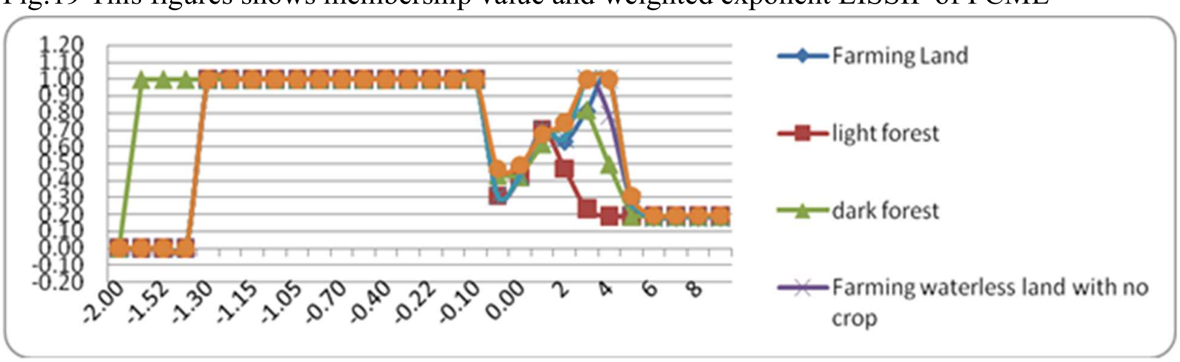

Fig:20 This graph plotted between accuract(Entropy) and weghted exponent LISSII of PCME

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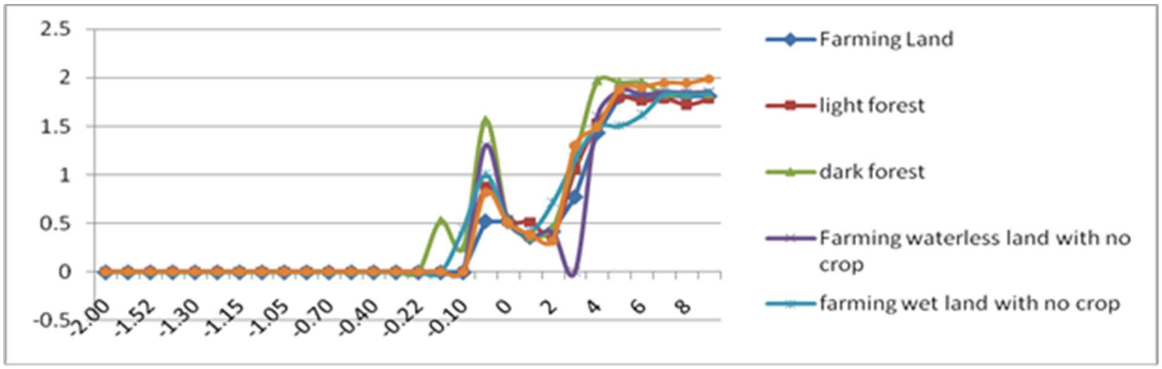

Fig:21 This figures shows membership value and weighted exponent LISSIV of PCME

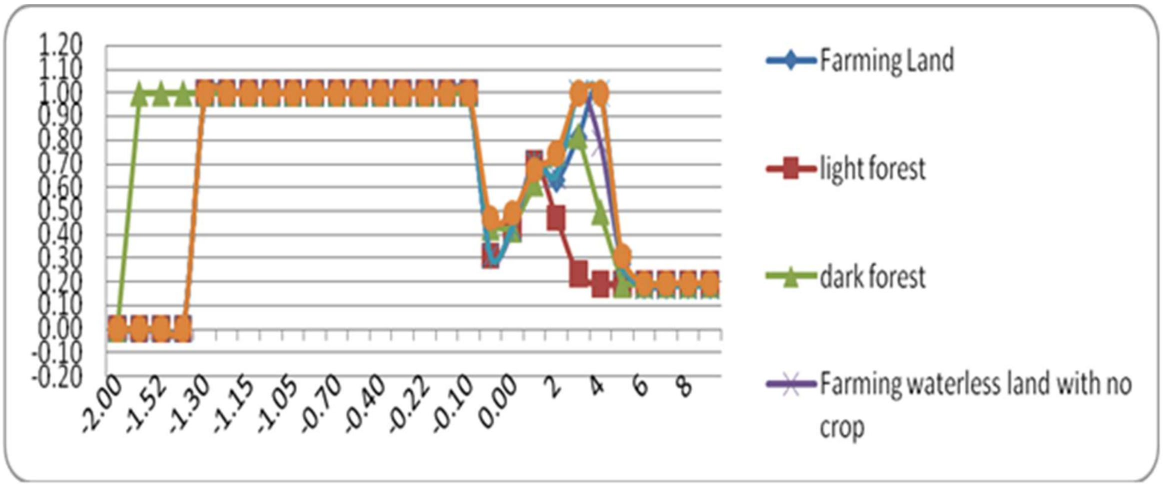

Fig:22 This graph plotted between accuract(Entropy) and weghted exponent LISSIV of PCME

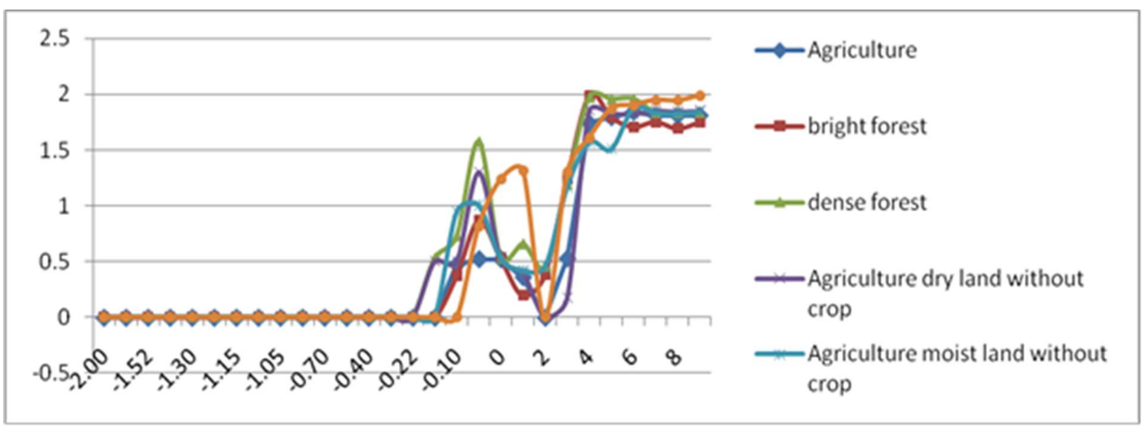

Table 5: This is Table shown result of PCMPE for sensor LISS III and LISSSIV

Class	Class membership		Entropy		Optimized Mean value
	LISS-III	LISS-IV	LISS-III	LISS-IV	
Agriculture	10^3	10^2	10^2	10^2	$3.25x10^2$

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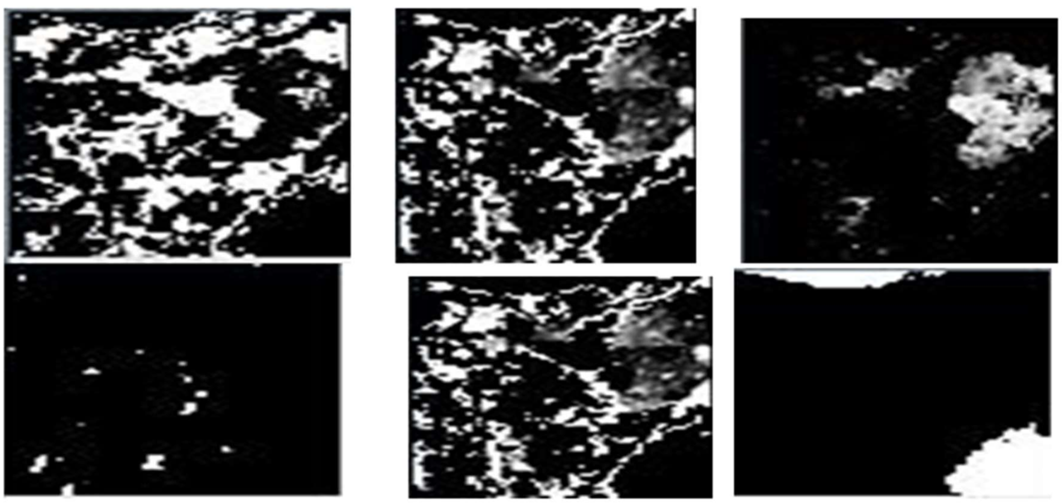
Bright Forest	10^3	10^3	10^2	10^2	$5.5x10^2$
Dense Forest	10^3	10^3	10^2	10^2	$5.5x10^2$
Agriculture Dry land	10^2	10^2	10^2	10^2	10^2
Agriculture Moist land	10^3	10^3	10^3	10^2	$7.7x10^2$
Water Body	10^2	10^2	10^2	10^2	10^2

Fig: 23 PCMPE classification output of LISSIII image where μ lies between 0 to 1



The assessment of entropy(accuracy of result) is a important subject in the categorization of satellite data. The entropy assessment of the categorization outcome is essential and required to estimate the classifier presentation. This study focus the area detection and assessment of uncertainty of detected area[25][26],

All the classification algorithms of this study have been tested in supervised mode using Euclidian weighted norm to classify the remote sensing imagery and entropy is used to measure the accuracy in terms of uncertainty without using any kind of ground reference data.

In FCM classifier, it's been observed that irrespective of location , of weighting exponent((m) (finest assesment) for 2.19 has been observed to farming land, 2.0 for light light forest, 1.88 for dense light forest, 2.05 for farming waterless ground with no crop, 1.9 for farming waterless ground with no crop,, 2 for water area. For PCM classifier, it has been observed that regardless of vicinity, of weighting exponent((m) (surest value) for 1.84 r has been determined to farming land, 1.89 for light forest, 1.71 for dense forest area, 2.48 for farming waterless ground with no crop, 1.45 for farming waterless ground and no crop, 2.40 for water category area .

To perform the FCME type, a set fixed value of m=1 has been used for exclusive values of ν. it has been located that regardless of datasets used, m =7.7×102is discovered to be most appropriate in classifying farming land and light forest, m= 7.2 ×102 . but, for dense forest is

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5.5x102 farming waterless ground with no crop, ν =3.25×102 and farming moist ground without a crop m=3.25×102and water, m=102 is observed to be suitable for category the use of FCME class technique.

To carry out the PCME type, a set fee of m=1 has been used for special values of ν. it's been observed that no matter datasets used, m =3.2×102 is located to be maximum appropriate in classifying farming land and

light forest, m= m= 5.5 ×102. However, for dense forest area is 5.5x102 farming waterless ground with no crop, m=102 and farming wet ground with no crop m=7.7×102and water, m=102is observed to be appropriate for category the usage of PCME class method.

CONCLUSION

It is observed from the outcome of table 3 to 4 , that assessment of accuracy percentage is approximately equal to referential value 2.685. To producing higher accuracy with lowest amount level of uncertainty by soft classifiers FCM and PCM. The computation of entropy is total reflector of an improbability. For locate the optimized measurement of m, a number of research have been carry out autonomously for commonly classifiers by not fixed m from graph 1.10 to 4.90.

The calculate entropy vary between the range of [0, 2.385] as shown in graphs fig 5, fig 7 fig 10,fig 12for embedded soft classifiers(FCM,PCM) [29][30]and hybrid soft classifiers in fig 15,fig 17,fig 20,fig 22. The uncertainty is not more than 3 percentage. This research automate the accuracy assessment of finding area also. From these results it may be concluded that coarse resolution like LISS III has higher effect of sampling rather. So I have chosen LISSIII sensor soft classifiers FCM and PCM and two hybridize classifiers FCME, PCME for training data .For testing purpose I have taken LISS IV sensor . for all classifiers like(FCM,PCM,FCME,PCME).

The results show that the proposed algorithm reaches the maximum accuracy in comparison of previous classifiers like FCM and PCM. The proposed method performs much better than other comparative methods The result show[25][26][27 that the proposed system research the high accuracy][28].

This model is perfect to find different area like farming,, dense area, water area. if we will find proper land for specific requirement so our rate of growth will increase right manner.

It has been investigational from the resulting graph 1to 6 that for homogenous module.

VERIFICATION OF DATA AREA AND RESULT

Automatic target detection in satellite imagery has great significance in area. In our work, we propose the use of FCM and PCM algorithms and two hybridize algorithm PCME and FCME for object for classification and assessment of accuracy by absolute indicator by entropy in satellite images. The hybride algorithm effectively learn optimum features directly from huge amount of data automatically .The Soft classification technique to capable to detect objects or classification. FCM and PCM effectively learn optimum features directly from huge mixed nature of data automatically. In our future work, we will try to improve the performance of our

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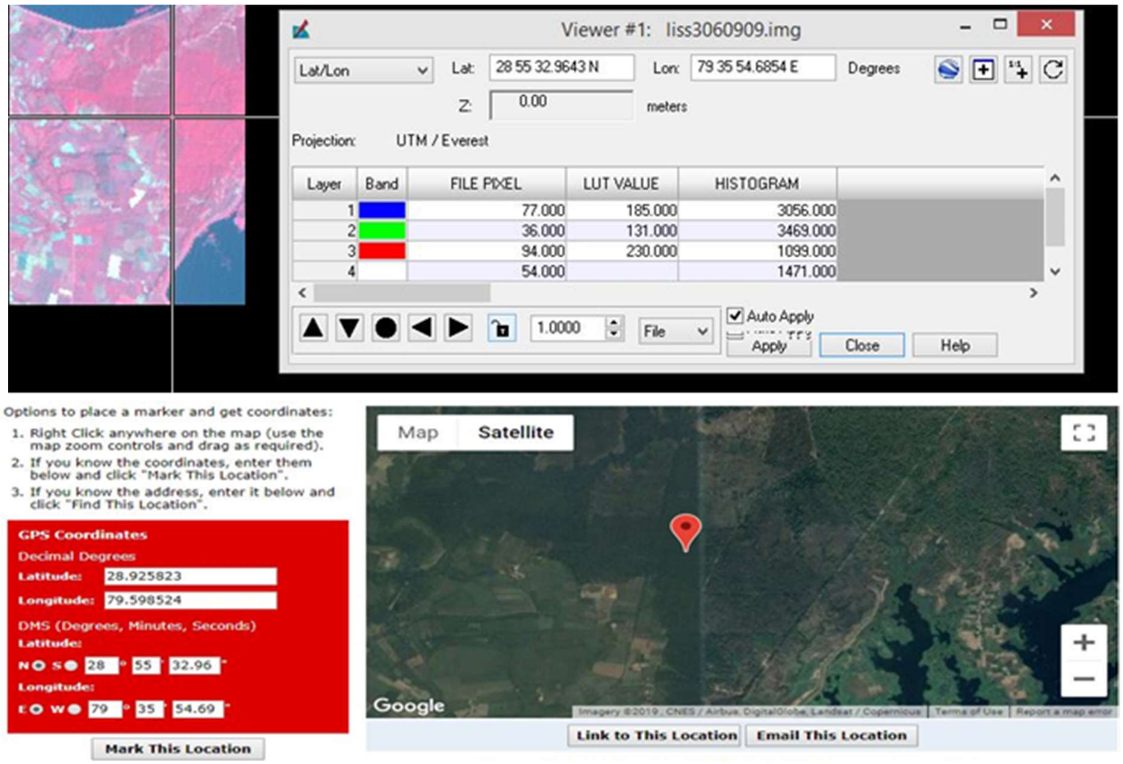
system and lower the computational cost with deep learning. We will also apply it in other areas where target detection is used.

I have cross check object detection with goggle map. and result of classifiers shows low entropy result[30][31] and low entropy shows the method of object detection is right manner.

Fig:24 This figure shows resul vaildation through google map



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