OPEN ACCESS Freely available online

Journal of Remote Sensing & GIS

ISSN: 2469-4134

Research Article

Data Identification of a Temporal Data for Soft classifiers FCM & PCM

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ABSTRACT

In general, multispectral classifiers provide a complete suite of options for image classification 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. 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. 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 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. 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 these software for the evaluation of soft classified output. So, a tool has been developed to handle such problems in this study. This tool mainly focuses soft classification algorithm. It has been named as Fuzzy Based Image classifier Tool (FBICET) which incorporates Entropy. The satellite image has been successfully classified with good accuracy using the FBICET.

Keywords: Pure pixel, Mixed pixel, Assessment of Accuracy, Entropy, Fuzzy Based Tool (FBICET).

INTRODUCTION

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 (Alqurashi, 2013; Chandra,2006; Harris, 1983,2005, Stein,2005,2006) plays a great job in the progress of any GIS, and in most cases, it allows data to be used for multiple applications.

The heart of a digital image processing is a dedicated computer with the necessary hardware peripherals and well developed image processing software capable of performing the necessary analysis. The performance of image processing software has

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Received Date: June 29,2020, **Accepted date:** August 31,2021, **Published Date:** September 11,2021

Citation: Sharma R(2020). Data Identification of a Temporal Data for Soft classifiers FCM & PCM.J Remote Sens 10p:305

improved tremendously with the advancement of computer hardware technologies. (Fig 1) shows a general flow chart of the basic image processing utilities available in any image processing software. Classification of images having mixed pixels (Aziz, 2004) is a difficult task; the simplest way could be to ignore these pixels in the training stage itself. This may be achieved by studying the histograms of the training data of each class present. These histograms may be used for identifying the pixels whose spectral response is far away from the mean, and hence are likely to be the outliers.

An alternative way to separate mixed pixels is by measuring the spectral distance from the class mean (Arora, 2002; Chen, 2004). The pixels which have large spectral distances from class mean are unlikely to belong to that class, and thus these pixels may be treated as mixed. These mixed pixels are then removed from the training data and a new set of training pixels may be generated. Although, the classification (Zhao et al,2016) accuracy may be increased by using this approach, it may not be useful when the image is particularly subject by mixed pixels. For example, ignoring or removing mixed pixels may result in an unrepresentative training sample size, which may adversely affect the classification (Ghamisi.,2016), particularly the statistical classifiers. 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 (Zang, 2001). The image processing function fall into categories

Reqiurement of Tool

This tool is beneficial for classification for satellite data. This tool is able to store membership value. This tool generates Fraction image.

The Feaurtes of The Tool

- This tool has an option for store the membership values generate through sub-pixel classifier option using any ten grouping of taxonomy algorithms integrated in this tool.
- This tool provides to generate fractions image. This feature provides only this tool.
- The developed software is broadly divided into two modules first one is FCM classification and another one is PCM Classifiers.

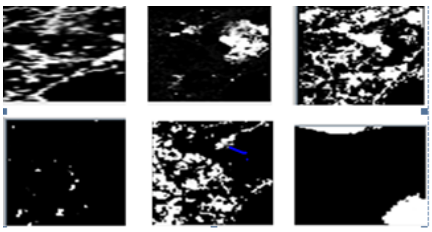


Fig. 1: FCM classification output of AWiFS image Where μ lies between 0 to 1.

In this tool is able to find classification and I have also find their accuracy with absolute indicator by Entropy. The working of classifiers support 2 studies: which named as

- This classifier is also iterative in nature (Ferna´ Ndez-Prieto, D., 2002)so a number of iterations and fixed optimized value of weighting exponents, limiting error parameters are provided along with the value of spatial resolution parameter (δ) and regularizing parameter ν are specified in the input text box .

The Types of Soft Classification Technique

Both supervised and unsupervised categorization may be useful to execute pure and mixed classification. 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 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) (Bezdek et. al., 1981, 1984) 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 (Bezdek, et. al., 1981;1984; Upadhyay et al.,2013,2014,2016). 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.

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 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 (Dadhwal,2006; Foody,1995: Krishnapuram and Keller, 1993), the minimize the generalized least- square error objective function are given by,

Assessment of Accuarcy Using Entropy

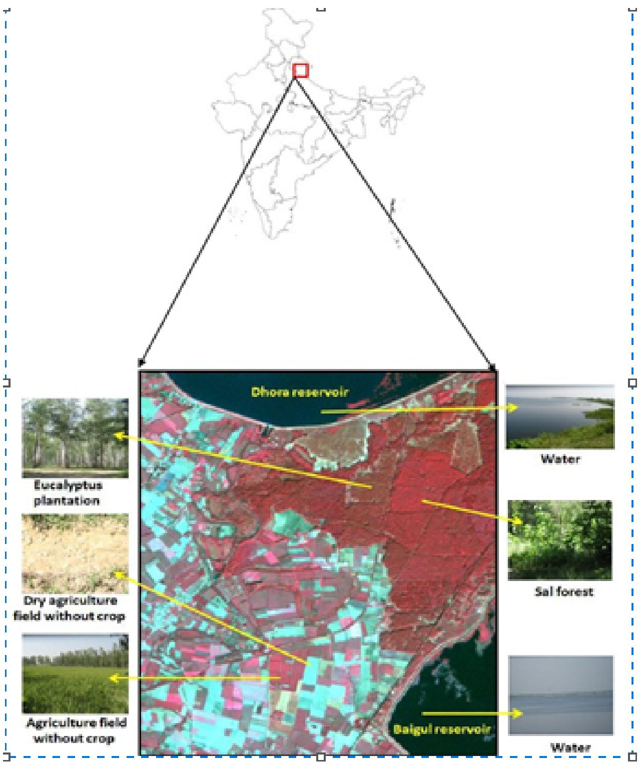
The accuracy assessment is based on the comparison of two maps. one based on the analysis of remote sensing data(Alqurashi;2018) and second based on information derived from the actual ground also known as reference map. The accuracy assessment is presented as an overall classification of map. Classification 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 (Dehghan and Ghassemian, 2006). Entropy is complete process of assessment there is no required for comparison other assessment Eqn (3). Uncertainty estimation (Jeyakanthan et al.,2006) by entropy works without reference data. we can calculated the entropy for classified fraction output by Eq (3)

$$Entropy\ (x) = \sum_{i=1}^{c} -\mu(w_i/x)\ log_2(\mu(w_i/x))$$

The Study Area and Data Set Information

The area located at Sitarganj Tehsil near Pant Naga, Uttarakhand state, Bharat. This research area holds dissimilar land cover classes like infertile land, natural forest, farming, water body and wet land as shown in Fig 2

Figure 2: study Area



We are using LISS-III and AWIFS sensor images have been used for categorization, whereas the superior resolution of LISS-IV sensor image has been used in support of the generation of reference data. In this research I have taken three sensors AWifs, LISSIII, LISS IV satellite dataset (Piyoosh et al.,2017)Theses sensors works on hyper spectral.

Sensor's NAme	Band-color	Resolution of pixel [m]	Swath [km]	Quantization [bits]
LISS-IV Mono mode	Red color	5.801	70.3	7.01
LISS-IV MX mode	green red NIR	5.801	70.3	7 .01
LISS-III	green red NIR SWIR	23	141.01	10
AWiFS	green red NIR SWIR	56 (nadir) ... 70.00 (edge)	74	10 .00

RESULT

Table 1: AWIFS assessment entropy of different land groups from soft classifiers "FCM"

Membership value of pixel	farming land	light forest	dark forest	farming waterless land with no crop	farming wet land with no crop	water land
1.1	0	0	0	0	0	0
1.3	0	0	0.495736	0	0	0
1.5	0.005467	0.720845	0.534943	0.849842	0.005367	0
1.7	0.005467	0.940597	0.515882	0.917776	0.005467	0
1.9	0.005467	0.946656	0.595713	0.935023	0.005467	0
2.1	0.005467	0.964544	0.602792	0.935123	0.005467	0.005467
2.3	1.384303	1.019733	0.702464	0.965318	0.577753	0.005467
2.5	1.387307	1.023422	0.900355	0.968763	0.972232	0.005467
2.7	1.422581	1.024074	0.995432	0.989227	0.974703	0.005467
2.9	1.465228	1.164332	0.996447	0.995615	0.995284	0.005467
3.1	1.493104	1.184121	1.066262	0.998253	1.053199	0.005467
3.3	1.493358	1.205586	1.095641	1.008426	1.073952	0.569343

3.5	1.512936	1.367753	1.103133	1.058917	1.111597	0.766624
3.7	1.519854	1.376267	1.119413	1.071182	1.114941	0.892742
3.9	1.612968	1.438993	1.130292	1.13371	1.117274	1.013136
4.1	1.663884	1.445044	1.130667	1.171032	1.150236	1.273812
4.3	1.691301	1.462738	1.133811	1.129528	1.151883	1.348145
4.5	1.746609	1.536414	1.143972	1.232213	1.204916	1.395559
4.7	1.874828	1.652529	1.199741	1.317273	1.246343	1.404511

Table 2: AWIFS assessment entropy of different land groups from soft classifiers "PCM"

The weighting Exponent 'm' Value	Farming Land	light forest	dark forest	Farming waterless land with no crop	farming wet land with no crop
1.3	0.005467	0.736859	0.512141	1.767632	0.148713
1.5	1.008899	1.367812	1.447692	1.889344	0.351794
1.7	1.332123	1.913273	1.612612	1.897803	1.045161
1.9	1.793764	2.129042	2.208573	1.920894	1.703991
2.1	1.807692	2.195612	2.221902	1.949303	2.128513
2.3	2.039422	2.237213	2.305632	2.158725	2.161042
2.5	2.154332	2.282121	2.311101	2.175263	2.175322
2.7	2.318821	2.364093	2.390272	2.232621	2.292072
2.9	2.374502	2.464812	2.526811	2.246323	2.332822
3.1	2.468742	2.527434	2.623163	2.261632	2.335781
3.3	2.529201	2.562382	2.641666	2.301333	2.361682
3.5	2.568622	2.570971	2.674092	2.303366	2.374181
3.7	2.590672	2.652583	2.676683	2.363675	2.386284
3.9	2.711462	2.662441	2.701551	2.375423	2.410972
4.1	2.745752	2.709623	2.722823	2.399412	2.421413
4.3	2.770013	2.722491	2.724243	2.402553	2.461273
4.5	2.808861	2.742042	2.735312	2.535892	2.467631
4.7	2.820822	2.763934	2.769083	2.5375	2.504702

Table 3: LISS-III assessment entropy of different land groups from soft classifiers "FCM"

The weighting Exponent 'm' value	Farming Land	light forest	dark forest	Farming waterless land with no crop	farming wet land with no crop	Water Area
1.1	0.005467	0.005467	0	0.005467	0.005467	0
1.3	0.005467	0.005467	0.005467	0.005467	0.005467	0
1.5	0.779405	0.005467	0.005467	0.005467	0.438642	0.005467
1.7	0.931645	0.005467	0.005467	0.005467	0.763175	0.005467
1.9	1.127571	0.39192	0.005467	0.005467	0.763175	0.013378
2.1	1.232044	0.511242	0.563636	0.438642	0.809914	0.024543
2.3	1.326871	0.542583	0.563636	0.791327	0.941826	0.034452
2.5	1.652153	0.569752	0.727911	0.807417	0.941826	0.062745
2.7	1.688436	0.655323	0.969694	0.873741	1.221659	0.241127
2.9	1.754211	0.676722	1.039694	0.937979	1.301497	0.328685
3.1	1.757712	0.847891	1.279952	0.937978	1.377741	0.648482
3.3	1.778682	1.200501	1.282442	1.178672	1.475438	0.735558
3.5	1.819442	1.270168	1.313101	1.390444	1.605331	0.763175

3.7	1.922052	1.447131	1.038836	2.262667	1.721542	0.842908
3.9	1.929977	1.921121	1.46009	2.416888	1.728663	0.996008
4.1	2.037131	1.922161	1.579462	2.431601	1.759872	1.221666
4.3	2.105483	2.009722	1.873003	2.462511	1.852662	1.721545
4.5	2.171182	2.010009	1.878811	2.514282	1.936013	1.852669
4.7	2.195477	2.001995	1.889438	2.555633	1.978663	2.431606

Table 4: LISS-III assessment entropy of different land groups from soft classifiers "PCM".

The weighting	Farming Land	light forest	dark forest	Farming waterless land with no crop	farming wet land with no crop	Water Area
1.1	0.082296	0.312813	0.145561	0.261922	0.005467	0.060873
1.3	0.082296	0.318418	0.191692	0.261922	0.005467	0.060873
1.5	0.129172	0.318418	0.347173	0.261922	0.005467	0.060873
1.7	0.164498	0.318418	0.347173	0.261922	0.005467	0.060873
1.9	0.280155	0.318418	0.347173	0.261922	0.005467	0.060873
2.1	0.291677	0.318418	0.347173	0.261922	0.005467	0.060873
2.3	0.291677	0.318418	0.347173	0.261922	0.005467	0.066262
2.5	0.291677	0.318418	0.347173	0.261922	0.001127	0.082311
2.7	0.291677	0.318418	0.347173	0.458111	0.001127	0.144362
2.9	0.291677	0.411201	0.347173	0.458111	0.001127	0.169172
3.1	0.291677	0.411201	0.347173	0.458111	0.001127	0.183752
3.3	0.291677	0.411201	0.476851	0.458111	0.001127	0.198121
3.5	0.653329	0.411201	0.476851	0.458111	0.001127	0.221502
3.7	0.768237	0.411201	0.476851	0.511747	0.001127	0.266272
3.9	0.768237	0.422413	0.529402	0.511747	0.001127	0.266272
4.1	0.768237	0.422413	0.529402	0.511747	0.001127	0.362012
4.3	0.768237	0.568105	0.529402	0.511747	0.033354	0.369202
4.5	0.768237	0.568105	0.529402	0.511747	0.033354	0.383181
4.7	0.768237	0.568105	0.529402	0.511747	0.033354	0.43371

Table 5: LISS-IV assessment entropy of different land groups from soft classifiers "FCM"

The weighting	**Farming Land**	**light forest**	**dark forest**	**Farming waterless land with no crop**	**farming wet land with no crop**	**Water Area**
1.1	0.005467	0.0054671	0	0.005467	0	0.005467
1.3	0.005467	0.0054671	0	0.005467	0	0.005467
1.5	0.833044	0.881731	0.0054671	0.005467	0.334012	1.040795
1.7	0.937921	0.935478	0.9061821	0.906182	0.455002	1.090845
1.9	0.996273	0.987775	1.0389402	1.038942	0.493181	1.162071
2.1	1.023482	1.020236	1.0944618	1.094468	0.532189	1.171888
2.3	1.060396	1.082032	1.1713399	1.171339	0.534927	1.185138
2.5	1.072108	1.142591	1.1793185	1.179382	0.568119	1.202941
2.7	1.160526	1.150218	1.1816308	1.181601	0.578823	1.234021
2.9	1.165481	1.150845	1.1911233	1.191133	0.779312	1.240433
3.1	1.178855	1.185337	1.2121169	1.212162	0.883869	1.250456

3.3	1.192471	1.196408	1.2265277	1.226573	0.947832	1.361682
3.5	1.215419	1.207132	1.2445197	1.244592	0.968205	1.362612
3.7	1.244101	1.216975	1.2554464	1.255466	1.166506	1.387322
3.9	1.322856	1.307276	1.2656272	1.265671	1.195226	1.400068
4.1	1.341925	1.405056	1.2697196	1.269792	1.271948	1.413906
4.3	1.352694	1.444529	1.3138847	1.313843	1.271948	1.429775
4.5	1.380341	1.476361	1.3386163	1.338663	1.351788	1.437714
4.7	1.417581	1.670912	1.3715191	1.371592	1.432229	1.465357

Table 6: LISS-IV assessment entropy of different land groups from soft classifiers "PCM".

The weighting exponent 'm' value	Farming Land	light forest	dark forest	Farming waterless land with no crop	Farming wet land with no crop	Water Area
1.1	0.843221	0.730502	0.878227	0.250139	1.047766	0
1.3	1.323761	0.883423	0.938221	0.421331	1.06537	0
1.5	1.333845	0.897781	0.94131	0.425241	1.074268	0.941433
1.7	1.421572	0.921513	0.967715	0.46913	1.079826	0.964241
1.9	1.436191	0.983432	0.969112	0.505533	1.136713	1.073135
2.1	1.457712	1.016672	0.990947	0.532261	1.251724	1.11544
2.3	1.470833	1.027514	1.025024	0.538119	1.263022	1.245533
2.5	1.483332	1.033032	1.025851	0.543651	1.347817	1.343561
2.7	1.598703	1.044511	1.111458	0.587138	1.356648	1.370213
2.9	1.607403	1.060001	1.200118	0.65457	1.362123	1.370721
3.1	1.610912	1.070652	1.204233	0.675279	1.371718	1.382166
3.3	1.612711	1.121911	1.250021	0.719115	1.377222	1.413067
3.5	1.634203	1.292062	1.256728	0.863328	1.380816	1.413122
3.7	1.673342	1.324343	1.323257	0.903348	1.394415	1.491635
3.9	1.713572	1.338264	1.323965	1.349627	1.397559	1.593333
4.1	1.767143	1.488574	1.515628	1.477202	1.397737	1.599142
4.3	1.830622	1.614534	1.589812	1.57015	1.405513	1.688356
4.5	1.839582	1.668213	1.684349	2.452375	1.436315	1.719092
4.7	1.845372	1.893283	1.71781	2.487123	1.438329	1.798187

Table 7: Entropy variation for FCM Classifier

	Entropy estimation for sensor AWiFS		Entropy estimation for sensor LISS-III Entropy		Entropy estimation for sensor LISS-IV	
	Min value	Max value	Min value	Max value	Min value	Max value
Farming Land	0.0 on m=1.1	1.87 on m=4.7	.005 on m=1.1	2.19 on m=4.7	.005 on m=1.1	1.41 on m=4.7
light forest	0.0 on m=1.1	1.65 on m=4.7	.005 on m=1.1	2.00 on m=4.7	.005 on m=1.1	1.61 on m=4.7
dark forest	0.0 om m=1.1	1.19 on m=4.7	0 on m=1.1	1.88 on m=4.7	0.0 on m=1.1	1.32 on m=4.7
Farming waterless land with no crop	0.0 on m=1.1	1.31 on m=4.7	.005 on m=1.1	2.05 on m=4.7	.005 on m=1.1	1.3 on m=4.7
Farming wet land with no crop	0.0 on m=1.1	1.24 on m=4.7	.005 on m=1.1	1.91 on m=4.7	0.0 on m=1.1	1.43 on m=4.7
Water Area	0.0 om m=1.1	1.41 on m=4.7	0 on m=1.1	2.40 on m=4.7	.005 on m=1.1	1.46 on m=4.7

Table 8: Entropy variation for PCM Classifier

The result of PCM classifiers for different land groups	Entropy estimation for sensor AWiFS		Entropy estimation for sensor LISS-III	Entropy estimation for sensor LISS-IV		
	Min value	Max value	Min value	Max value	Min value	Max value
Farming Land	.005 on m=1.1	2.82 on m=4.7	.082 on m=1.1	.76 on m=4.7	0.84 on m=1.1	1.84 on m=4.7
light forest	.361 on m=1.1	2.76 on m=4.7	.031 on m=1.1	.56 on m=4.7	.73 on m=1.1	1.89 on m=4.7
dark forest	.016 on m=1.1	2.76 on m=4.7	.145 on m=1.1	.52 on m=4.7	.87 on m=1.1	1.71 on m=4.9
Farming waterless land with no crop	.279 on m=1.1	2.53 on m=4.7	.261 on m=1.1	.51 on m=4.7	.25 on m=1.1	2.48 on m=4.7
Farming wet land with no crop	.108 on m=1.1	2.50 on m=4.7	.005 on m=1.1	.33 on m=4.7	1.04 on m=1.1	1.43 on m=4.7
Water Area	0.0 on m=1.1	2.83 on m=4.7	.060 on m=1.1	.43 on m=4.7	0.0 on m=1.1	1.79 on m=4.7

The assessment of entropy 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 assessment of uncertainty, depended upon soft classifiers FCM and PCM.

To examine the produce of unsure pixels in soft classifiers like FCM (fuzzy c-mean) and PCM (possibilstic- mean), Euclidean norm has been selected for mutually the classifiers where the values of weighting exponent m fluctuate from unlike values.

CONCLUSION

It is observed from the outcome graph 1to 6, 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.

It has been investigational from the resulting graph 1to 6 that for homogenous module . The optimized values of m in soft classifiers PCM and FCM are 2.89 and 2.82. in the same way for optimized values of m in soft classifiers PCM and FCM are2.90 and 2.70 mixed classes. the calculate entropy vary between the range of [0, 2.9] as shown in graphs1 to 6. So uncertainty is not more than 3 percentage . The tool automate the accuracy assessment process therefore it was possible to perform two set of experiments with varying sampling size and different number of strata for assessment of accuracy. From these results it may be concluded that coarse resolution like AWiFS has higher effect of sampling rather than comparative high resolution data like LISS-III.

RESULT

I have checked my result. I have cross checked generated fraction image form tool with goggle map. This is also same.

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