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Comparative evaluation of fuzzy based object-oriented image classification method with parametric and non-parametric classifiers

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Abstract

The aim of this study is to demonstrate the efficacy of different classification methods to improve accuracy in an area dominated by different landuse types. The main issue addressed through this study is the poor separability of common land cover classes. This study focuses on feature space analysis of different classifiers to evaluate the overlapping of classes. The study also includes comparison of the influence of spatial and spectral resolution on the results of classification using different methods in the area around Dehradun (India). The comparison is based upon the assessment of different classification approaches, which include parametric maximum likelihood, fuzzy-based object-oriented method, and non parametric expert classifier. Different levels of landuse/landcover classes as proposed by National Remote Sensing Agency (NRSA, Department of Space, Government of India) identifiable in different image datasets have also been attempted. The resulting land cover maps obtained by different methods of classification were visually compared. The accuracies of these maps were assessed with the conventional methods such as overall accuracy and kappa coefficient. The classification results of object-oriented classification were 6.33% more accurate than maximum likelihood (per-pixel) approach for LISS-III and 23.47% for LISS-IV. The same data were classified using the expert classifier and the results were found to be only 12.31% more accurate than per-pixel method in case of LISS-IV, and no significant improvement was observed for the LISS-III data. The object-oriented and expert classification approaches thus provide more accurate land cover discrimination.

KEY WORDS: Fuzzy based Object-Oriented classification, Maximum Likelihood Classification, Classification, Expert Classifier, Feature space

1. Introduction

Numerous efforts have been made over the past years to develop automated procedures for preparation of landuse maps from remotely sensed multispectral data. Despite best efforts, the situation is still one where there is a considerable gap between the needs and availability due to newer data with higher spectral and spatial resolution. Contemporary image analysis routines have had severe limitations when dealing with the information content of high resolution imagery. In order to effectively highlight the rich information present in

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image data, researchers are drifting from the usual pixel-based classification algorithms to object-oriented analysis systems.

Conventional image classification approaches can generally be classed as parametric and non-parametric. The parametric approach uses such statistical methods as minimum distance to mean, maximum likelihood, Euclidian distance, etc., but have their limitations, particularly in relation to distributional assumptions and to the restrictions on data input. The classifications have a minimum overall probability of error assuming a Gaussian distribution for each class training set. Nonparametric approach includes expert classifiers, decision tree and artificial neural networks, etc. The assumption of a normal distribution of dataset is not required for non-parametric classifiers, and no statistical parameters are needed to separate image classes. This allows for non-parametric classifiers to be used for classification of non-spectral data as well.

There has been a realization in recent years that probabilistic and evidential methods should be used in remote sensing studies for handling multi-source data in order to produce reliable landuse maps (Kontoes and Rokos 1996). Thus many advanced classification approaches, such as artificial neural networks, fuzzy-sets, and expert systems have been widely applied for image classification. Combinations of different classification approaches has proved to be helpful in the enhancement of classification accuracy (Benediktsson and Kanellopoulos 1999, Steele 2000, Lunetta *et al*. 2003)

Object-oriented approach classifies objects instead of single pixels. The idea of classifying objects instead of pixels accrues from the fact that most image data exhibit a characteristic texture that is disregarded by conventional classification approaches (Blaschke and Strobl 2001). The initial application of object-oriented classification was limited by hardware, software and poor resolution of images, but since the mid-1990s, with better tools and data, the demand for object-oriented analysis has also increased. The preliminary step in object-oriented image classification is image segmentation, which is a process of partitioning the image into homogeneous, non-intersecting regions, such that no two regions adjacent to each other have homogeneity (Pal and Pal 1993). The object-oriented image analysis approach thus uses textural and contextual information as well as the spectral information, which enables it to produce land cover maps with a higher accuracy.

The purpose of this study is to compare fuzzy based object-oriented classification algorithm with the traditional parametric maximum likelihood classification, and non parametric knowledge base method. This study also evaluates the feature space of different classification algorithms and classification accuracies for different image data sets viz., LISS III and LISS IV.

2. Study area and Data

The study area is located in Dehradun district of Uttarakhand state, between latitudes 30^{o} 19’N and 30^{o} 26’ N and longitudes 77^{o} 49’E and 77^{o} 57’ E, and covers an area of approximately 157 km^2. The difference between highest and lowest altitude in the study area is about 160 m. For this study, ERDAS Imagine^{TM} was used for maximum likelihood and expert classifications, and eCognition^{TM} was used for object-oriented classification. Figure 1 shows the study area.

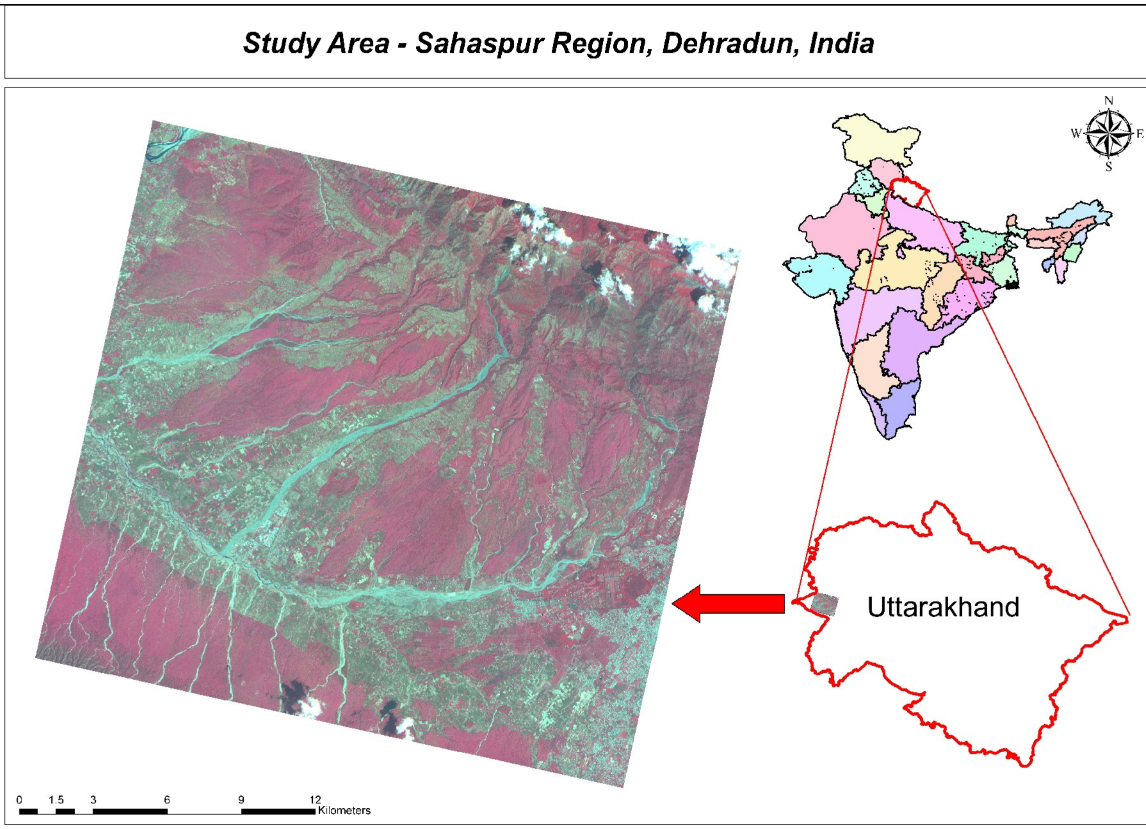


Fig 1: Study area Sahaspur Region, Dehradun, India

LISS III and LISS IV data of IRS P6 have been used to identify the landuse and land cover types in the study area. The reason for selecting IRS-P6 data was that it provides 23.5 m spatial resolution for all four bands of LISS III, as against the LISS III data of other platforms like IRS 1C and IRS 1D, which have a spatial resolution of 23.5 m for bands 1–3 and 72.5 m for band 4. It was considered essential to have the same spatial resolution of all bands in order to get a better class separability. The relevant details of LISS III and LISS IV data used in the present study are given in Table 1.

Table - 1: The details of LISS III and LISS IV satellite data used in the present study

PARAMETER	LISS-IV	LISS-III
Spatial resolution (m)	5.8	23.5
Spectral Bands (micron)	0.52-0.59 0.62-0.68 0.77-0.86	0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70
Quantization (bits)	7	7

It is well known that the error in the results of classification increase with the degree of heterogeneity of terrain, since the differences in spectral signatures narrow down as the number of discreet classes in a dataset increases. It was premised that heterogeneity of terrain and diversity of landuse/land cover classes would be a more rigorous test for various methods of classification, and thus lead to identification of the most appropriate method that could be used with the greatest efficiency in mountainous terrains. The reason for selecting this particular area was the moderately undulating terrain and a mixed landuse/land cover pattern, with a dominant agricultural use and forest cover, so that a proper comparison of different classification approaches could be made. The data sets selected for this study contain most of the landuse classes which can show mixed spectral reflectance viz., industrial, built up, dry river beds, fallow land, agricultural land, open and dense forest, etc.

3. Methodology

Both images were classified using three different approaches viz., maximum likelihood, object-oriented and expert classifier. The training sets used for the maximum likelihood classification were carefully selected on the basis of field observations in areas where the image data showed a mixing of different classes on visual examination. For the object-oriented classification, fuzzy rules were formulated on the basis of different measures. Layer values, shape features and texture parameters were tested in different combinations to explore the features that would classify the segments into the most appropriate class. A normalised difference vegetation index (NDVI) image and the classified image obtained by the maximum likelihood classification were used to train the expert classifier. Feature space analysis of different classes for all classifiers was performed in order to assess the separability of classes.

Accuracy of classification results was checked by querying the coordinates of randomly selected pixels classified by various methods and making field visits to verify the results of classification. Errors in classification were used to generate the error matrix for each of the classifiers. The results of accuracy analysis were used to compare the efficiency of different methods.

4. Image Classification

Image classification refers to the extraction of different classes or themes, usually land cover and land-use categories, from raw remotely sensed digital satellite data. The information contained in a remotely sensed image which can be used to conduct image classification includes spectral pattern, spatial pattern and temporal pattern. For this study three standard methods of image classification were used:

i. Maximum Likelihood Classification (Per Pixel Approach)
ii. Object-oriented Classification (Fuzzy Based Approach)
iii. Expert Classification (Knowledge Based Approach)

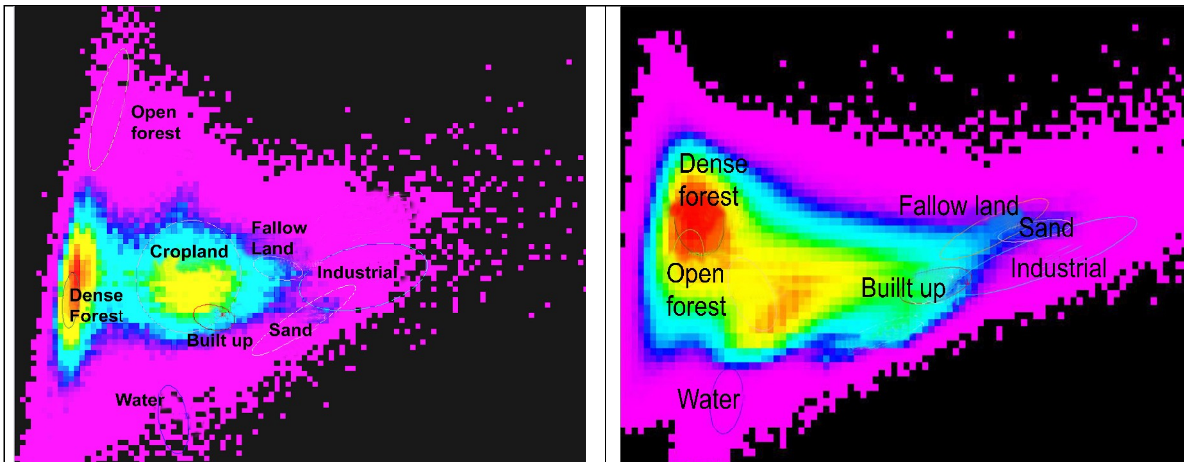
Land cover classes of the study area were mainly defined in accordance with the Manual of National Land Use Land Cover Mapping Using Multi-Temporal Satellite Data (NRSA 2006). The landuse/land cover classification has been proposed with multi-level hierarchic configuration, with each higher level containing information of increasing specificity. In the first level, general land cover types are built up land, agriculture land, forest, natural/semi natural grassland, grazing land, waste land, wetland, water bodies, snow cover/glacial area. In the second level each class is divided into subclasses, for instance water bodies are subdivided into rivers, canals, lakes, reservoirs, streams, etc. In the third level the land covers are further divided into more detailed classes, e.g. streams are divided into perennial, dry, etc. Table -2 depicts the level of classes used for land cover classification of the study area. Classes of landuse/land cover sought in this study were mainly those of the second level, but in some cases the third level was also mapped.

Table 2: Levels of land cover classes used for classification of the study area

No.	First Level	Second Level	Third Level
1.	Built up land	Residential	
		Industrial	
2.	Agriculture land	Cropland	
		Fallow land	
3.	Forest	Evergreen	Dense
			Open
4.	Water bodies	River	Dry/Perennial
			Water

4.1. Maximum Likelihood Classification (Per Pixel Approach)

For classifying a pixel, the MLC classifier quantitatively evaluates the variance and covariance of the spectral response of an identified class. A Gaussian distribution is assumed for the cloud of points constituting the data representing a particular training set (Lillesand and Kiefer 1999). A suitable classification system and sufficient number of training samples are prerequisites for a meaningful classification (Hubert-Moy *et al.* 2001, Chen and Stow 2002, Landgrebe 2003, Mather 2004). Most image processing applications provide the per-pixel based classification option. All pixel-based classification methods assign a pixel to a class according to the spectral similarities across the set of bands indicated by the user. The first classification used in this study is the maximum likelihood method which is the most prevalent method of image classification. Class separability using transformed divergence and feature space analysis was performed on the LISS III and LISS IV datasets (Tables 3 and 4). In transformed divergence a value of 2000 indicates 100% separability. Decreasing values indicate correspondingly lesser separabilities. It was found that the spectral signature of dry river and built up areas was more or less the same for the LISS IV data, whereas these classes were more separable in the LISS III data. The same situation was found with the open and dense forests, which were more separable in LISS III than in LISS IV data. The results of feature space and separability analysis for LISS III and LISS IV data are shown in figure 2.



(a) *(b)*

Figure - 2: Feature space of LISS III using bands 1& 4 (a) and LISS IV using bands 1& 3 (b) (per-pixel approach)

Table 3: Separability analysis of LISS III of the study area

Distance Measure: Transformed Divergence
Using layers: 1 2 3 4
Taken 4 at a time
Best Average Separability: 1960.34
Combination: 1 2 3 4

Signature Name	1	2	3	4	5	6	7	8
Industrial - 1	0	1998.09	1914.14	2000	2000	2000	1957.1	1316.6
Built up - 2	1998.09	0	1983.59	2000	2000	2000	1911.82	1971.3
Fallow land - 3	1914.14	1983.59	0	2000	2000	2000	1993.72	1854.63
Dense Forest- 4	2000	2000	2000	0	1994.58	2000	2000	2000
Open forest - 5	2000	2000	2000	1994.58	0	2000	2000	2000
Water - 6	2000	2000	2000	2000	2000	0	2000	2000
Cropland - 7	1957.1	1911.82	1993.72	2000	2000	2000	0	1993.89

Dry channel - 8	1316.6	1971.3	1854.63	2000	2000	2000	1993.89	0

Table 4: Separability analysis of LISS IV of the study area

Distance Measure: Transformed Divergence
Using layers: 1 2 3
Taken 3 at a time
Best Average Separability: 1780.63
Combination: 1 2 3

Signature Name	1	2	3	4	5	6	7	8
Industrial - 1	0	1340.11	1893.76	2000	2000	2000	2000	1289.82
Built up - 2	1340.11	0	1612.09	2000	2000	2000	1999.96	708.003
Fallow land - 3	1893.76	1612.09	0	2000	2000	2000	2000	1429.24
Dense Forest- 4	2000	2000	2000	0	619.885	1999.26	1302.55	2000
Open forest - 5	2000	2000	2000	619.885	0	1984.59	1696.56	2000
Water - 6	2000	2000	2000	1999.26	1984.59	0	1981.92	2000
Cropland - 7	2000	1999.96	2000	1302.55	1696.56	1981.92	0	2000
Dry channel - 8	1289.82	708.003	1429.24	2000	2000	2000	2000	0

4.2 Object-Oriented Classification (Fuzzy Based Approach)

The second approach used in this study is object-oriented classification – an outcome of recent researches in image processing. The concept behind object-oriented classification is that important semantic information necessary to interpret an image is not represented in individual pixels, but in meaningful image objects and their mutual relationships. The basic difference, especially when compared to pixel-based procedures, is that object based classification does not classify single pixels but rather image objects which are extracted through a segmentation procedure (Baatz, *et al*. 2004).

Object-oriented classification is mainly based upon fuzzy logic – a mathematical technique of quantifying uncertainty of statements. Fuzzy logic seeks to replace the two strictly logical statements "yes" and "no" by the continuous range of values from 0 to 1, where 0 means "absolutely no" and 1 means "absolutely yes." Values between 0 and 1 represent various states of certainty between "no" and "yes." This approach emulates human thinking and takes into account even linguistic rules. Fuzzy rules are "if – then" rules. If a condition is fulfilled, an action takes place.

Fuzzy classification systems are considered well suited for handling vagueness in remote sensing data. In fuzzy classification, the membership degree of each land cover or land use class is defined. This allows detailed performance analysis and gives insight into the class mixture for each image object. The maximum membership degree determines the final classification of the object.

Object-based classification is composed of three basic procedures: image segmentation, object metric extraction, and classification (Yinghai Ke. et. al 2010). Segmentation of an image divides it into a network of homogeneous regions at any chosen resolution. These image object primitives represent image information in an abstracted form, serving as building blocks and information carriers for subsequent classification.

Image segmentation methods fall into two main domains: knowledge driven methods (top-down) and data driven methods (bottom-up). In the top-down approach the user already knows what he wants to extract from the image, but he does not know how to perform the extraction. The system tries to find the best processing method to extract the objects by formulating a model of the desired objects. The formulated object models give the object an implicit meaning. In the bottom-up approach the segments are generated on the basis of a set of parameters and statistical methods for processing the whole image (Baatz *et al*. 2004).

In this study a region growing segmentation method based on the similarity of adjacent pixels was used. This was restricted by shape parameters to form homogeneous, compact segments as proposed by Lucier (2008).

4.2.1 Segmentation Parameters:

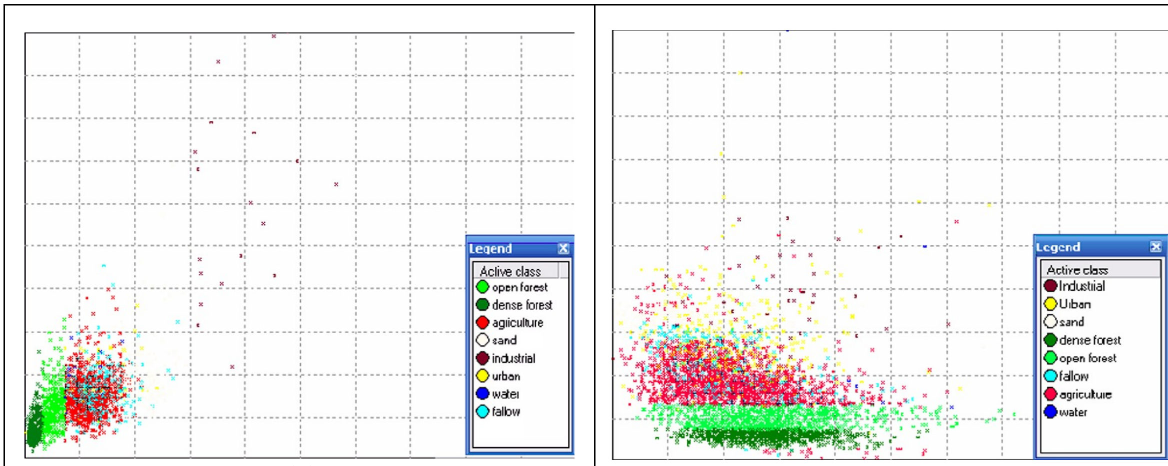
Scale and heterogeneity are the two main parameters which were used for image segmentation. Scale affects the object size – higher the scale, bigger is the object and vice versa. This is one of the drawbacks of the method because there is no explicit relationship between the scale and measures related to image objects. Thus, finding the most suitable segmentation level requires repeated trials and visual examination of results (Hay *et al.* 2005). eCognition^{TM} considers four heterogeneity criteria: colour, shape, smoothness and compactness. These are applied together in various combinations. For most cases colour is the most important criterion for creating meaningful objects and is mainly based upon the spectral characteristics. However a certain degree of shape homogeneity often improves the quality of object extraction (Baatz *et al.* 2004)

Different scale parameters were applied to decipher the optimum segmentation. To extract objects from LISS III data (spatial resolution 23.5 m), smaller segments were required (scale 10) as compared to LISS IV (spatial resolution 5.8 m) for which bigger segments were required (scale 25). The criteria given in Table 5 were used for image segmentation:

Table 5: Segmentation parameters for object-oriented classification of LISS III & LISS IV data.

Sensor	Scale	Colour	Shape	Compactness	Smoothness
LISS III	10	0.8	0.2	0.6	0.4
LISS IV	25	0.8	0.2	0.6	0.4

Fuzzy rules are required prior to object-oriented classification. This consists of one or more conditions which are combined by operators. To include features into a fuzzy rule base membership, functions for the considered features have to be defined. Layer values are the features concerning the pixel channel values of an image object. Shape value of an image object can be described using the object itself or its sub objects (Baatz *et al*. 2004). Texture features evaluate the texture of an image object based on its sub-objects or on the grey-level co-occurrence matrix (GLCM) (Haralick *et al*. 1973). In this study thresholding of different object features, coupled with the combination of conditions connected by operators like “and”, “or” and “not” were used to classify the classes. Various combinations of object features viz. layer values, shape features and texture parameters were tested in different combinations to explore the features that would classify the segments into the most appropriate class. These parameters were used in the subsequent classification stage to differentiate objects and assign them to different landcover classes. The two dimensional feature space optimization tool was used for class separability analysis. Uncorrelated bands of both datasets were used to identify the class separability. The results of separability analysis of LISS III and LISS IV are given in figure 3.



(a) *(b)*

Figure - 3: Feature space of LISS III(a) using bands 1& 4 and LISS IV (b) using bands 1& 3 (per-object approach)

4.3 Expert Classification (Knowledge Based Approach)

Expert knowledge has been widely used to improve the accuracy of the classification of remotely sensed data. An expert system separates the knowledge required to solve the pixel classification problem from the problem-solving mechanism. (Kontoes and Rokos, 1996). The system uses human geographical knowledge to improve the classification results, providing a significant improvement compared to conventional statistical methods. Expert classification systems describe, through a hierarchy of rules, the conditions under which a set of low level constituent information gets abstracted into a set of high level informational classes. Rules used for classification with expert systems are conditional statements, or list of conditional statements, about the data values and/or attributes of a variable that determine an informational component or hypothesis. Linking together multiple rules and hypotheses into a hierarchy ultimately describes target informational classes or ultimate hypotheses.

The Expert Classifier therefore captures the process that an expert in a particular field of expertise would use to sift through, process and analyze geographic data, then compare and combine results, to infer information about a geographic location. The captured process can then be repeated by someone who may not be an expert in either the application field or in the use of software tools. But by recording the expert's inference process, expert classifier can repeat it with new data, consistently producing reliable and repeatable results.

The expert classifier is represented by a tree diagram consisting of final and intermediate class definitions (hypotheses), rules (conditional statements concerning variables), and variables (raster, vector, or scalar). Hypothesis mainly represents the output. Rules are the conditional statements, or a list of conditional statements about the variable data values and/or attributes that determine an informational component or hypothesis. Multiple rules and hypotheses can be linked together into a hierarchy that ultimately describes a final set of target informational classes or terminal classes.

Confidence value associated with each condition is also combined to provide a confidence image corresponding to the final classified image. The disadvantage of using expert systems is that they need a large amount of knowledge to classify the data correctly (Murai and Omatu, 1997).

In this study expert classification was applied to the LISS IV data because there was a need to distinguish between open and dense forest, which was indistinguishable by classification using the per-pixel approach. To train the expert classifier for distinguishing dense forest from open forest an NDVI image was used as an input along with the classified image of the MLC. Visual inspection of NDVI image was used to discriminate dense and open forest and the histogram values were calculated for these classes. Different ranges of thresholding were used to distinguish dense and open forest using NDVI image. The threshold that best discriminated dense from open forest, along with classified image was used for making rules as input. For rest of the classes, the rules were provided using the classified data of LISS IV of maximum likelihood classification. Once the classification rules were generated they served as a knowledge base, and were used directly to classify the image.

5. Accuracy Assessment

Image processing entails many steps during which data is manipulated in different ways. Accuracy assessment of the classified multispectral data is therefore an absolutely necessary step in any image processing exercise for extraction of meaningful information. The process of classification needs to be evaluated for accuracy since errors from many different sources may affect the efficacy of the classification process. These involve geometric and radiometric corrections, image enhancement and rectification, etc. The classification process itself, whatever it may be, has some inherent limitations – non-representative training areas, high variability in the spectral signature of a particular land cover class, mixed land cover within a pixel area, providing imprecise and ambiguous rules, use of inappropriate algorithms or weightage to various attributes. All these factors affect classification accuracy (Lu and Weng 2007). Accuracy assessment is also necessary in order to perform self-evaluation and take corrective measures to improve results and be able to compare different methods/algorithms/analyses.

In the process of accuracy assessment, it is commonly assumed that the difference between an image classification result and the reference data is due to errors in the classification process. There are a number of ways to investigate the accuracy/error in classified data including, but not limited to, visual inspection. Some of the methods are site-specific analysis, generating difference images, error budget analysis, and quantitative accuracy assessment (Luneeta and Lyon 2000).

Classes extracted from different datasets by various methods have different accuracies primarily because of different spatial and spectral resolutions. In the present study, maps generated by different classification methods were assessed qualitatively and quantitatively. The classification results were visually examined and standard methods of classification accuracy assessment such as error matrix, overall accuracy and kappa index were derived for each classified image. Accuracy of classification was assessed by ground verification of system generated random points.

Some researches suggest that the conventional methods of assessing accuracies based on per-pixel measures are inadequate for assessing the quality of per-object classification because the spatial unit is no longer a pixel but an object (Zhan *et al*. 2005). In this study the accuracy of object based classification was assessed by the error matrix based on training and test areas (TTA) mask.

5.1. Accuracy assessment of MLC

For LISS III dataset stratified random sampling methods were used for accuracy assesment. It is apparent from the tabulated results that some classes like industrial and built up areas or sandy patches show less separability. Fallow and crop land show good separability along with the dense and open forest. Water is fully distinguishable. The overall classification accuracy is 84% and kappa coefficient is 0.8.

For LISS IV dataset stratified random sampling methods were also used for assessment of the accuracy. This result indicates that industrial, built up and sand shows very less separability. In this dataset dense and open forest also show less separability as compared to the LISS III dataset. Fallow land also shows less accuracy as compared to the LISS III datasets. Water is fully distinguishable in this dataset also. The overall classification accuracy was 71.59% and kappa coefficient is 0.62.

The comparison of overall accuracy achieved by the maximum likelihood classifier shows that LISS III data classifies with greater accuracy as compared to LISS IV.

5.2. Accuracy assessment of Object-oriented Classification

Accuracy assessment of object-oriented classification is based upon the TTA mask. In LISS III error matrix some pixels representing classes like dry river, dense and open forest have been classed as fallow, open forest and agricultural land respectively. The overall accuracy achieved by object-oriented classification is 89.15% and kappa is 0.86.

In LISS IV error matrix, classes have a good separability without any overlap. Dry river, industrial, built up and fallow land are well separated. The overall accuracy achieved by object-oriented classification is 89.26% and kappa is 0.86.

As can be seen, the overall accuracy of object-oriented classification of both datasets is nearly the same, which is contrary to the general assumption that high resolution datasets classify more accurately as compared to low resolution data. In LISS III datasets, small objects were carefully selected for classification. Another advantage of the LISS III data is the higher spectral resolution which was an advantage in segmentation.

5.3. Accuracy Assessment of Expert Classification

The maximum likelihood classification of LISS III data provides acceptable results as is evident from the excellent separability of the dense and open forest classes. However, in the case of LISS IV, the maximum likelihood classifier yielded poor results since the two forest classes were merged to a considerable extent. For this reason the expert classifier was applied on LISS IV data. An NDVI image along with the LISS IV maximum likelihood classified image was used for making rules. The accuracy improvement obtained through this approach was mainly in the forest classes. The expert classifier gives very good results for dense and open forest. The overall classification accuracy is 80.94% and Kappa statistic is 74.88%.

5.4. Comparison of Overall Accuracy and Kappa for different Classification Methods

The overall accuracy and kappa coefficient obtained by various methods are given in Table 6. The comparison of accuracy achieved with different approaches reveals that object-oriented and knowledge base classification methods provide better results as compared to MLC. The kappa coefficient of LISS III obtained for object-oriented classification is 6.33% more than that of the per-pixel approach. But in LISS IV kappa coefficient of object-oriented classification shows more accuracy as compared to MLC of LISS III. The Kappa coefficient of object-oriented classification of LISS IV is 23.47% higher as compared to maximum likelihood classification results. In case of expert classifier, an enhancement of only 12.31% in the Kappa coefficient is achieved as compared to MLC.

Table 6: Overall accuracies (OA) & Kappa (K) achieved through various classification methods.

Dataset	Pixel based Classification approach(MLC)	Object based	Expert classifier	Increase in accuracy from MLC to Object Based	Increase in accuracy from MLC to Expert classifier
LISS IV (OA)	71.59	89.26	80.94	17.67	9.35
LISS III (OA)	84.00	89.15	-	5.15	-
LISS IV (K)	62.57	86.04	74.88	23.47	12.31
LISS III (K)	80.33	86.66	-	6.33	

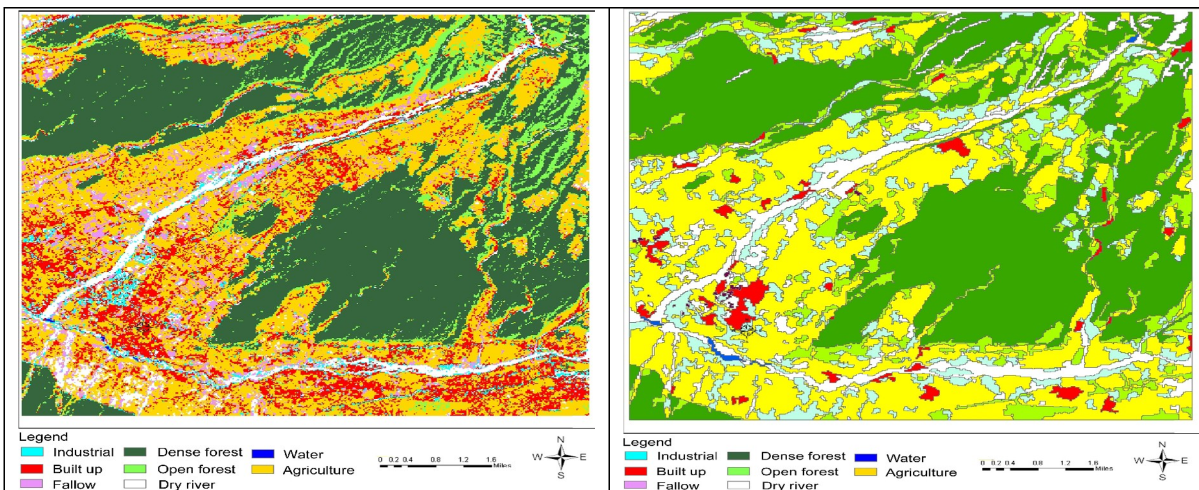
6. Results and Discussion

Image classification methods and their efficacy with regard to differences in spectral and spatial resolutions have been analyzed through the present study. The datasets comprised LISS III and LISS IV data of IRS satellites pertaining to the Sahaspur and Rampur area of Dehradun. Identification of landuse/land cover classes up to second and third levels has been attempted by different classification approaches – pixel based, object based and knowledge based. The performance of different classification method was evaluated in terms of accuracy. It was found that both LISS III and LISS IV datasets can be classified up to level 3 of landuse/land cover classes of NRSC. Increasing the level of classification degrades the accuracy of classification.

Object-oriented classification can yield appreciably better results when applied on low and medium resolution satellite data with second and third level of classification, contrary to the view that it is mainly applicable for high resolution satellite data. To take full advantage of low spatial resolution of satellite data it is essential to take smaller objects into consideration very carefully for classification. Higher spectral resolution of low spatial resolution satellite data could however, compensate the segmentation process. During this study it was also found that defining multiple attributes of objects with Boolean operators like AND, OR or NOT improved the classification results significantly.

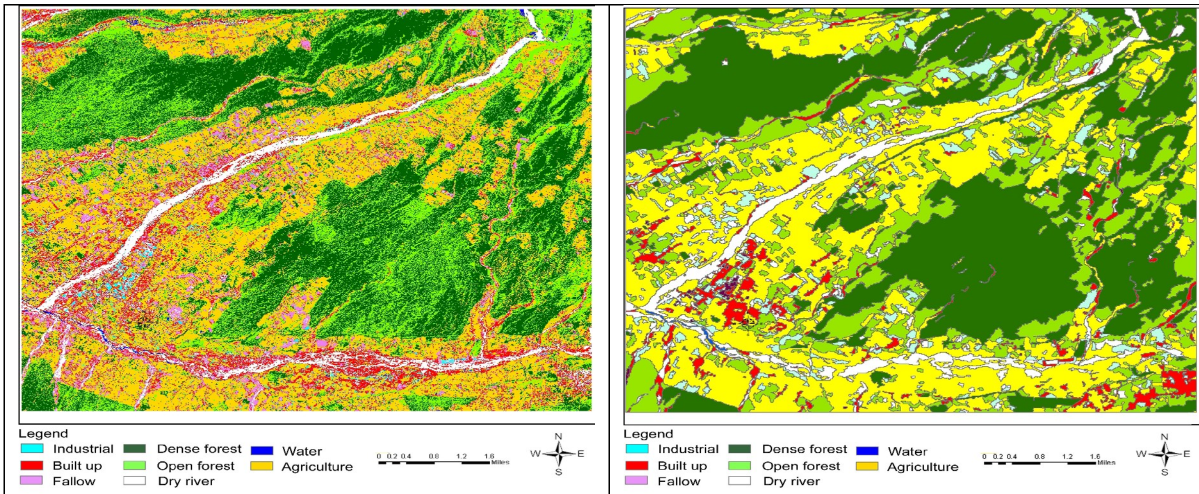
The classification of LISS III and LISS IV data in terms of eight most common land cover classes were attempted through various methods. This was necessitated because of poor separability of built up areas from fallow land, dense from open forest and river channels from industrial areas. To analyze the results visually a series of maps – two using maximum likelihood, two using object-oriented and one using expert classifier, were prepared.

Figure 4 shows the results of classifications of LISS III by MLC and object-oriented classification methods. As can be seen from an examination of figure 4 *(a)*, the problem of mixed pixels exists in the MLC, for instance some pixels of industrial and built up areas are seen in the dry river channel and some pixels of open forest are seen in the dense forest. This is the cause of the lowering of accuracy. The problem of mixed pixels has improved in the object-oriented classification. As can be seen from figure 4 *(b)*, the river channel, industrial areas, dense and open forests are more separated as compared to MLC. Surface water bodies are also better demarcated through object-oriented classification as compared to MLC.



(a) *(b)*

Figure - 4: Classified images of LISS III by MLC(a) & object based(b)classifier



(a) *(b)*

Figure - 5: Classified images of LISS IV by MLC(a) & object based(b)classifier

The results of MLC and object-oriented classification of LISS IV are shown in figure 5. As can be appreciated, the results of both classifications are similar to those of LISS III. The problem of mixed pixels still exists, but in object-oriented classification it is much less. Analysis of open and dense forest areas suggests that:

1. Mixing of pixels is more pronounced in LISS IV as compared to LISS III data when classified with the maximum likelihood classifier.
2. Using the maximum likelihood classifier, most land cover classes are more separable in LISS III as compared to LISS IV data. This is due to a higher spectral resolution of LISS III data as compared to LISS IV (Table 1).
3. LISS IV gives better results in terms of clean separability of open and dense forests using the object oriented classification, as compared to what the LISS IV data provides using the MLC or expert systems approach (Figure 6), or the LISS III data using either MLC or object oriented classification.
4. Surface water bodies are better classified by the object based classifier as compared to the MLC.
5. The separability of open and dense forest areas using LISS IV data with MLC is not as good as the LISS III data.

It can be concluded that LISS IV is the better of the two datasets for delineating surface water bodies with the object based classifier, while LISS III is better for delineating open and dense forests with MLC.

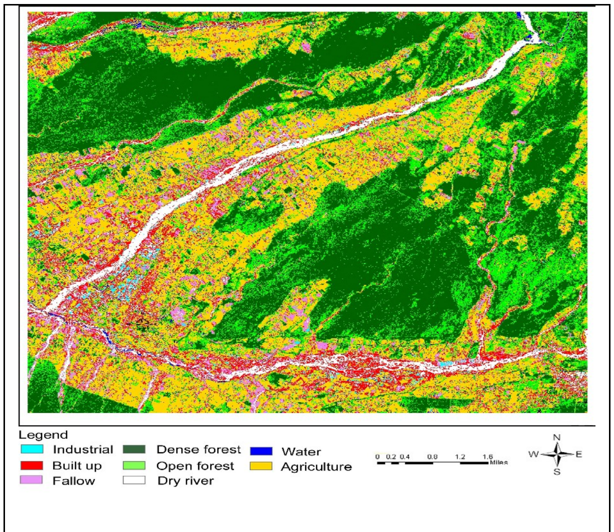


Figure 6: Classified image of LISS IV by Expert classifier

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