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RESEARCH ARTICLE

Multi-resolution Segmentation for Object-based Classification and Accuracy Assessment of Land Use/Land Cover Classification using Remotely Sensed Data

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Introduction

In recent years, the significance of spatial data technologies, especially the application of remotely sensed data and geographic information systems (GIS) has greatly increased. In the classic image classification approach the unit is a single pixel. This approach utilizes spectral information of the pixels to classify the image, and the ability of this method to classify images is limited when objects have similar spectral information. In most cases, information needed for image analysis and understanding is not represented in pixels, but in meaningful image objects and their mutual relations. Therefore, to partition images to sets of useful objects is a fundamental procedure for successful image analysis as part of image interpretation (Gorte, 1998; Baatz and Schape, 2000; Blaschke *et al*., 2000). The two most evident differences between pixel-based image analysis and object-oriented image analysis are: (i) in object-oriented image analysis, the basic processing units are image objects (segments), not single pixels; (ii) object-oriented image analysis uses soft classifiers that are based on fuzzy logic, not hard classifiers. In these respects, image segmentation is critical for subsequent image analysis, and even for further image understanding.

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Object-oriented approach and multi-resolution segmentation

Object-oriented approach takes the form, texture and spectral information into account. Its classification phase starts with the crucial initial step of grouping neighboring pixels into meaningful areas, which can be handled in the later step of classification. Such segmentation and topology generation must be set according to the resolution and the scale of the expected objects. By this method, single pixels are not classified but homogenous image objects are extracted during a previous segmentation step. This segmentation can be done in multiple resolutions, thus allowing differentiation several levels of object categories. In remote sensing, the process of image segmentation is defined as: "....the search for homogenous regions in an image and later the classification of these regions" (Mather, 1999). The *eCognition* software offers a segmentation technique called *Multiresolution* S*egmentation*. This is a bottom-up region merging technique and is regarded as a region-based algorithm. It starts by considering each pixel as a separate object and subsequently, pairs of image objects are merged to form bigger segments.

The merging decision is based on a local homogeneity criterion, describing the similarity between adjacent image objects. The pair of image objects with the smallest increase in the defined criterion is merged. The process terminates when the smallest increase of homogeneity exceeds a user-defined threshold (the so-called *Scale Parameter*). Scale parameter is an important parameter in multiresolution segmentation and is used to determine the upper limit for a permitted change of heterogeneity throughout the segmentation process. The scale parameter determines the average image object size. Therefore a higher scale parameter will allow more merging and consequently bigger objects, and vice versa. The segmentation algorithm does not only rely on the single pixel value, but also on pixel spatial continuity (texture, topology). The organized image objects carry not only the value and statistical information of the pixels of which they consist, but also information on texture and shape as well as their position within the hierarchical network (Ambiente, 2000). The homogeneity criterion is a combination of *colour* (spectral value) and *shape* properties (*shape* splits up into *smoothness* and *compactness*). With colour and shape parameters the influence of color vs. shape homogeneity on the object's generation can be adjusted. The higher the shape criterion the lesser the spectral homogeneity influences the object generation. On the other hand with smoothness/compactness, when the shape criterion is larger than 0 the user can determine whether the objects should become more compact (fringed) or more smooth. By applying different *scale parameter* and *colour/shape* of combinations, the user is able to create a hierarchical network of image objects (Definiens Imagine, 2003).

After segmentation, all image objects were automatically linked to a network in which each image object knows its neighbours, thus affording important context information for the classification step. In the second step the image segments are classified by generating class hierarchy, which is based on fuzzy logic. Each class of a classification scheme contains a class description and each class description consists of a set of fuzzy expressions allowing the evaluation of specific features and their logical operation. A fuzzy rule can have one single condition or can consist of a combination of several conditions that have to be fulfilled for an object to be assigned to a class. The fuzzy sets are defined by membership functions that identify those values of a feature that are regarded as typical, less typical, or not typical of a class, i.e., they have a high, low or zero membership respectively, of the fuzzy set. Soft classifiers (mainly fuzzy systems), use a degree of membership/a probability to express an object's assignment to a class. The membership value usually lies between 1.0 and 0.0; where 1.0 expresses full membership/probability (a complete assignment) to a class and 0.0 expresses absolutely nonmembership/improbability. Thereby the degree of membership/probability depends on the degree to which the objects fulfill the class-describing properties/conditions. The main advantage of these soft methods lies in their possibility to express uncertainties about the classes' descriptions. It makes it also possible to express each object's membership in more than just one class or the probability of belonging to other classes, but with different degrees of membership or probabilities.

Objectives of the study

The study was initiated with the following objectives:

- to classify land use/land cover, based on object-oriented image analysis.
- to classify land use/land cover according to pixel-based image analysis.
- to compare object-based classification with pixel-based classification and accuracy assessment of the classifications.

Study area

The spatial extent of the study area is between $24^0 32'30''$ to $25^0 06'34''$ N latitude and $88^0 57'50''$ to $89^0 44'00''$ E longitude. This area is within the Bogra district of Rajshshi division in Bangladesh. Bogra district, with an area of 2911.90 km^2, is bounded by the Gaibandha and Joypurhat districts in the north, Nator and Sirajganj districts in the south, Tangail in the east and Naogaon district in the west. It consists of 11 *upazila*/*thanas* (third order administrative unit from the lower level) namely Shibganj, Sonatola, Sariakandi, Gabtali, Bogra Sadar, Dhupchanchia, Kahaloo, Adamdighi, Dhunat, Nandigram and Sherpur (Fig. 1). The main crops of the study area are paddy, wheat, potato, onion, garlic, mulberry plant etc.

Data used and methodology

In this study, IRS P6 LISS III data acquired on 6 February 2005 with a spatial resolution of 23.5m

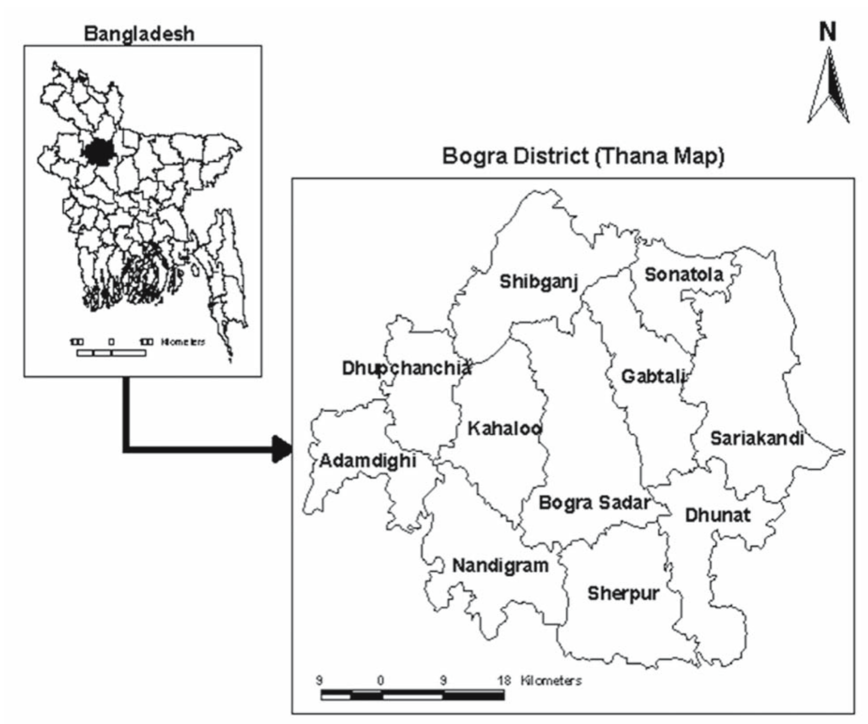


Fig. 1 Map showing study area.

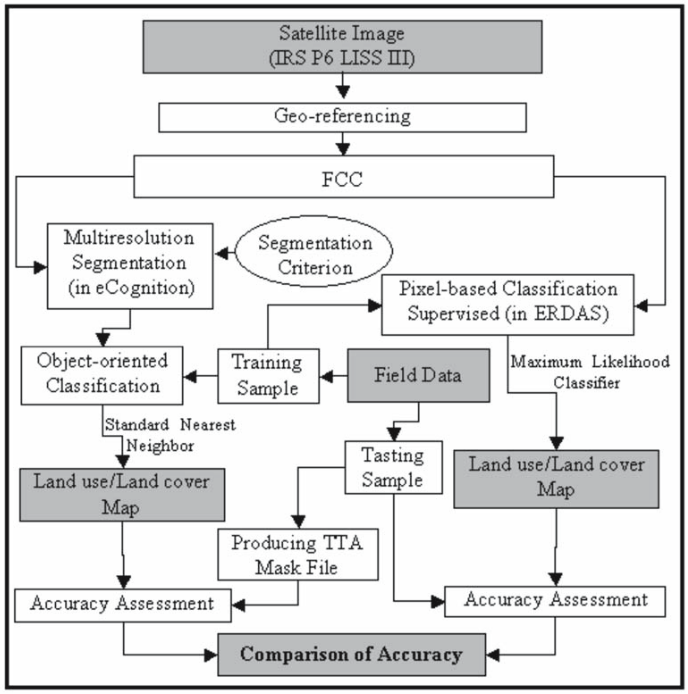


Fig. 2 Flowchart showing image processing and analysis methodology of the study.

and three spectral bands (green, red, NIR) were used. Two vector layers; District boundary and *Thana* boundary, which were extracted from the District boundary, and *Thana* boundary digital polygon map of Bangladesh (prepared by the Bangladesh Agricultural Research Council, Dhaka) were used. Data obtained by GPS (Global Positioning System) were used as ground truth information for the classification of the image. *eCognition* 4.0 and *Erdas Imagine* 8.6 were used for object-oriented and pixel-based image classifications respectively. ILWIS (Integrated Land and Water Information System) image processing and GIS software were also used to compare the classification and accuracy assessment and for visualization of the data. The overall methodology for this study is shown in Figure 2, and the method is discussed in the following sections.

Geo-Referencing

The main purpose of this study is to compare the accuracy of the classification of land use/land cover from the satellite image based on object-oriented and pixel-based classification approaches. To fulfill the objective of the study, satellite data were first spatially geo-referenced to a Universal Transverse Marcator (UTM) projection using 30 ground control points (GCPs). The GCPs were selected on the basis of being defined in the image. The image was then resampled using a nearest neighbour algorithm with first order affine transformation and 23.5m pixel size. The root mean square error for resampling was accepted less quarter pixel. Following resampling the geometrically corrected near-infra red, red and green bands of the IRS P6 LISS III data were used to generate a false color composite (FCC) of the study

Table 1 Segmentation criterion used for IRS P6 LISS III.

Level	Scale parameter	Colour	Shape	Smoothness	Compactness
1	20	0.75	0.25	0.1	0.9
2	20	0.9	0.1	0.1	0.9
3	25	0.9	0.1	0.1	0.9
4	30	0.9	0.1	.01	0.9

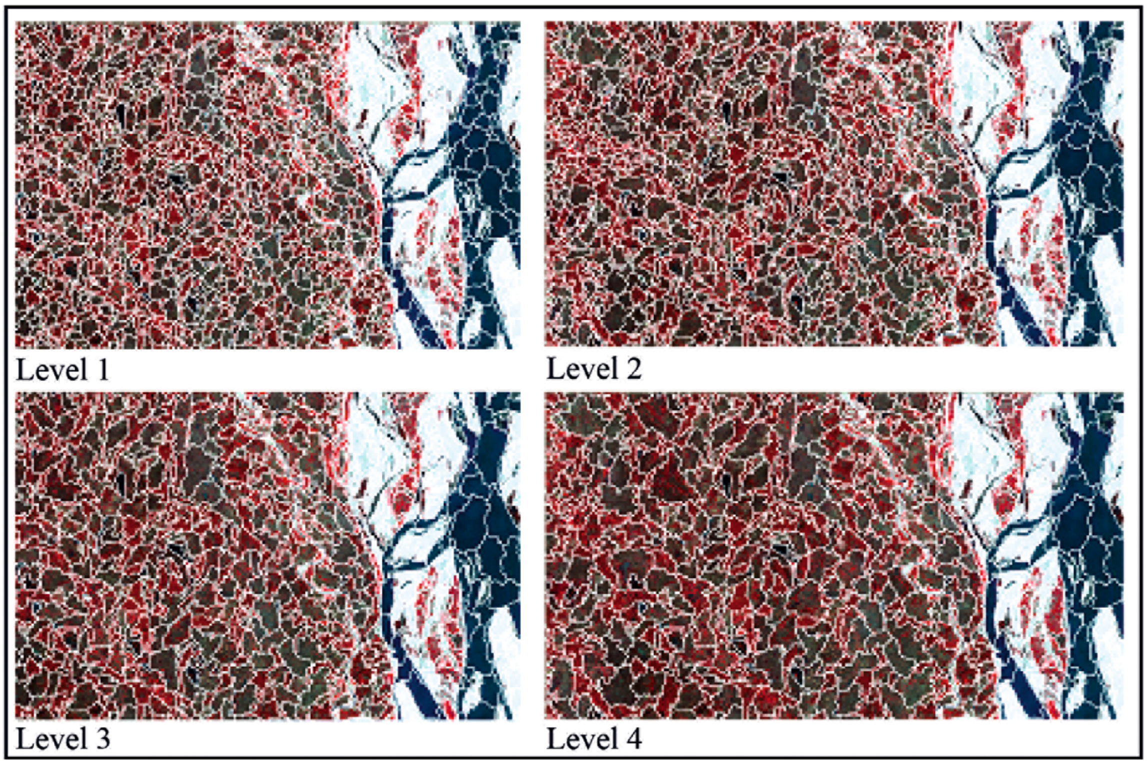


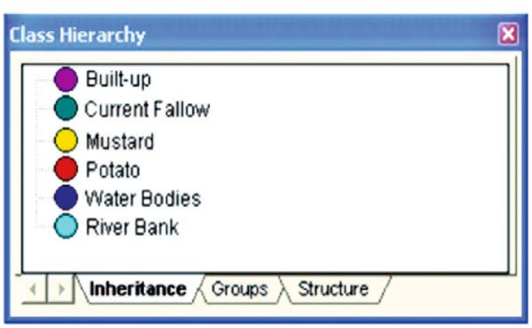
Fig. 3 Image segmentation using four different segmentation criterions (details in Table 1).

area. From the FCC, object-oriented and pixel-based classifications of the land use/land cover map were generated.

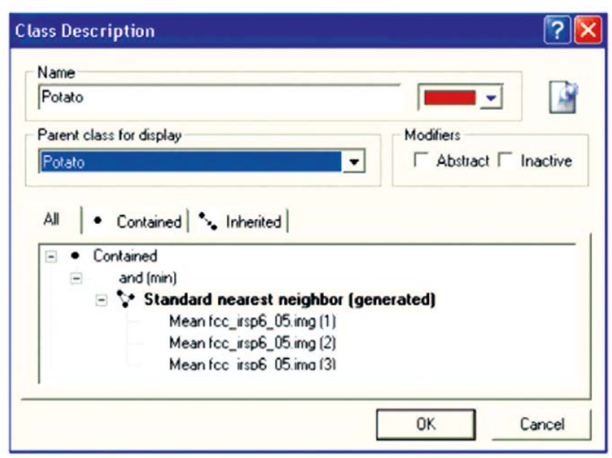
Object-oriented classification

Object-oriented approach for image classification has been discussed elaborately in the introductory section. In this approach the first step of the classification is to identify the image objects. This is achieved by using a multi-resolution segmentation approach as implemented in the software package eCognition (Baatz and Schape, 2000). For this study, the image was segmented separately into four layers. The specific segmentation criteria of these four layers are listed in Table 1. In the level 1, for segmentation criterion *scale parameter* was set to 20, with 75% of the criterion dependent on *colour* and 25% on *shape*. The later factor was divided between *smoothness* and *compactness,* with the criterion dependent 10% and 90%, respectively. In level 2, more emphasis was given to *colour* (increased from 75% to 90%) and consequently the *shape* factor was decreased from 25% to 10%. The relative emphasis on *smoothness* and *compactness* were the same in level 2 as level 1. It may be mentioned here that more emphasis was given to *colour* because feature identification in medium spatial resolution images like IRS P6 LISS III data (23.5m), *shape* is not as dominant as *colour*. In the other two levels (level 3 and 4), the *scale parameter* was increased to 25 and 30, respectively. The *shape, smoothness* and *compactness* factors remained the same as level 2. The results of segmentation at different settings of scale parameters are shown in figure 3. The figure highlights that if the scale parameter is increased in the segmentation procedure (level 1 to level 4 of figure 3), the segmented object size in the image is also increased and vice versa. In the segmentation of image, which scale parameter is suitable, cannot be identified prior to the segmentation. It is necessary to segment image with some set of scale parameter and according to the objective of the study and prior knowledge of the study area (ground truth), suitable scale parameter has to be selected for final classification. On the basis of visual inspection of the number of segmented images using the different parameters (Fig. 3) and prior knowledge of the study area, level 2 parameters were selected for the final classification procedure of land use/land cover.

It was mentioned that throughout the segmentation procedure, the whole image is segmented and image objects are generated based upon several adjustable criteria of homogeneity or heterogeneity in colour and shape. Adjusting the scale parameter indirectly influences the average object size: a large value leads to bigger objects and vice versa. During the segmentation processes all generated image objects are linked to each other automatically. Therefore, the next step is to classify the segmented image (level 2) into six land use/land cover classes (potato, mustard, water bodies, current fallow, river bank and built-up area) by a generating class hierarchy [Fig. 4(a)]. The class hierarchy contains all classes of a classification scheme in a hierarchically structured form. Inheritance class descriptions defined in parent classes are passed down to their child class. A class can inherit descriptions from more than one parent class. Based on the same inherited feature descriptions, the inheritance hierarchy is



(a)



(b)

Fig. 4 **(a)** Class hierarchy and **(b)** Class description for object-based classification.

a hierarchy of similarities. The inheritance hierarchy and the groups hierarchy essentially complement each other while the inheritance hierarchy is used to subsequently separate and differentiate classes in the feature space, the groups hierarchy permits the meaningful grouping of the resulting classes. Inheritance hierarchy is used for reduction of redundancy and complexity in the class description. After generating a class hierarchy with inheritance hierarchy, sample sites or training sites were selected for each class on the basis of ground information. Then for each class of the classification scheme, a class description i.e., standard nearest neighbour (generated) was selected which consists of a fuzzy expression allowing the evaluation of a specific feature and its logical operation and to classify the image.

An example for the potato class is provided in Fig. 4(b). This simple hierarchical grouping offers an astonishing range for the formulation of image semantics and for different analysis strategies. The user interacts with the procedure and based on statistics, texture, form and mutual relations among objects defines training areas. The segmentation algorithm does not only rely on the single pixel value, but also on pixel spatial continuity (texture, topology). The formatted objects have now not only the value and statistic information of the pixels that they consist of they also carry texture, form (spatial features) and topology information in a common attribute table. (Ioannis, 2001).

Pixel-based classification

There are two primary types of pixel-based classification algorithms applied to remotely sensed data: unsupervised and supervised. In supervised classification, the image analyst supervises the pixel categorization process. In this study the supervised classification method was applied for pixel-based land use/land cover classification. In the process of supervised classification, first training sites were selected for each of the land use classes in the sample sets. For selection of the training samples for each land use type, ground information was incorporated and finally maximum likelihood classifier was used for classification of the image. Classification based on pixel-based approaches to image analysis is limited nowadays. Typically, they have considerable difficulties dealing with the rich information content of Very High Resolution (VHR) or moderate resolution such as Landsat TM data. It produces a characteristic, inconsistent salt-and-pepper classification, and they are far from being capable of extracting objects of interest (Tso and Mather, 2001). The ability of this approach is limited when objects have similar spectral information. In this circumstance, with this approach the image cannot be classified correctly. The classic pixel-based approach is based on "binary theory". In the case of the pixels in the over- lapping areas of the feature space, by binary theory, those pixels will be labeled into only one class but they shows affinity with more than one class. With binary theory the classification result will not be accurate.

Accuracy assessment

Evaluating the quality of a classification result is of high importance in remote sensing since it gives evidence of how well the classifier is capable of extracting the desired objects from the image. Therefore, a thorough classification accuracy assessment is critical as part of this assessment process. In order to conduct a classification accuracy assessment, validation data are required to compare with the classification predictions. Such validation data are often called "ground truth" or referenced data (Verbyla, 2002).

In this study two statistical accuracy assessment techniques were used. The first is the Error Matrix (EM) which reports three accuracy measures: *Producer's*, *User's* and *Overall Accuracy* (Jensen, 1996). An error matrix is a square array that expresses the number of sample units (i.e., pixels, clusters of pixels or polygons) assigned to a particular category relative to the actual category as verified in the field. An error matrix is a very effective way to represent accuracy because the accuracy of each category is clearly described, along with both the errors of inclusion (commission error) and errors of exclusion (omission error) (Jensen, 1996). The second technique is the KAPPA analysis (K_{hat}). KAPPA analysis is a discrete multivariate technique of use in accuracy assessment (Congalton and Mead, 1983). KAPPA analysis yields a K_{hat} statistic (an estimation of KAPPA) that is a measure of agreement or accuracy (Rosenfield and Fitz-patrick-Lins, 1986; Congalton, 1991). The accuracy assessment of the object-oriented and pixel-based classifications was carried out in eCognition and ERDAS imagine, using the available accuracy assessment tools in the respective software packages. These assessment tools provide the error matrix and calculate the producer's, user's, overall accuracy, as well as the Kappa accuracy level. Producer's accuracy indicates how well training set pixels of the given cover type are classified. User's accuracy indicates the probability that a pixel classified into a given category actually represents that category on the ground. On the other hand, Kappa statistics indicate how much better the classification is compared to one where randomly assigned class value to each pixel. The principal advantage of computing *KHAT* is the ability to use their value as a basis for determining the statistical significance of any given matrix. In the object-based and pixel-based classification accuracy assessment, test sample points were identified for each land use/land cover from the ground truth data (GPS data). The error matrices were then used to perform a comparison of the accuracy of two classifications.

Results and discussion

Based on the results of the object-oriented and pixel-based classification techniques, the classified images are shown in Figs. 5 and 6, and classification statistics are presented in Table 2; the tables

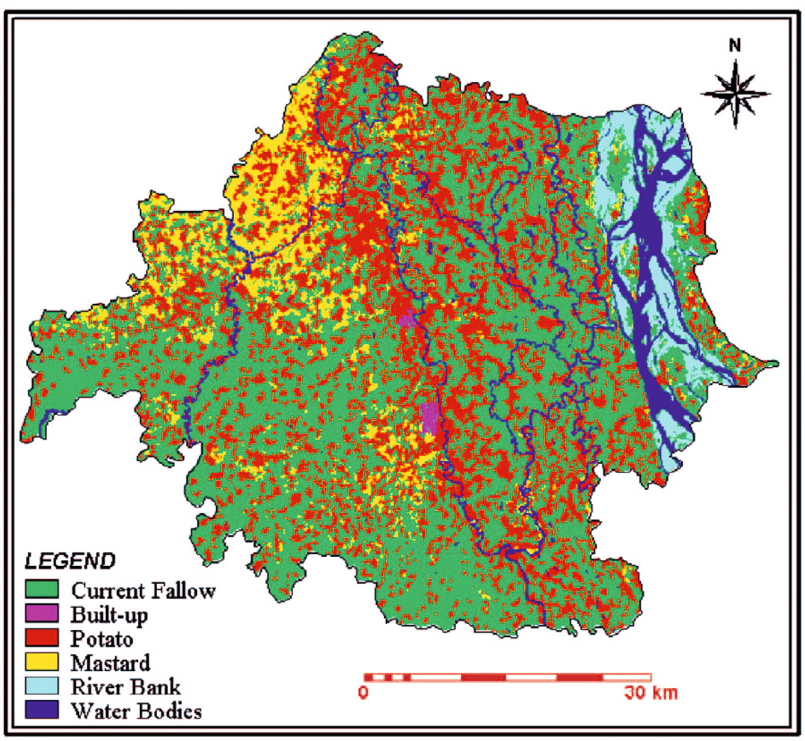


Fig. 5 Land use/land cover (object-based classification).

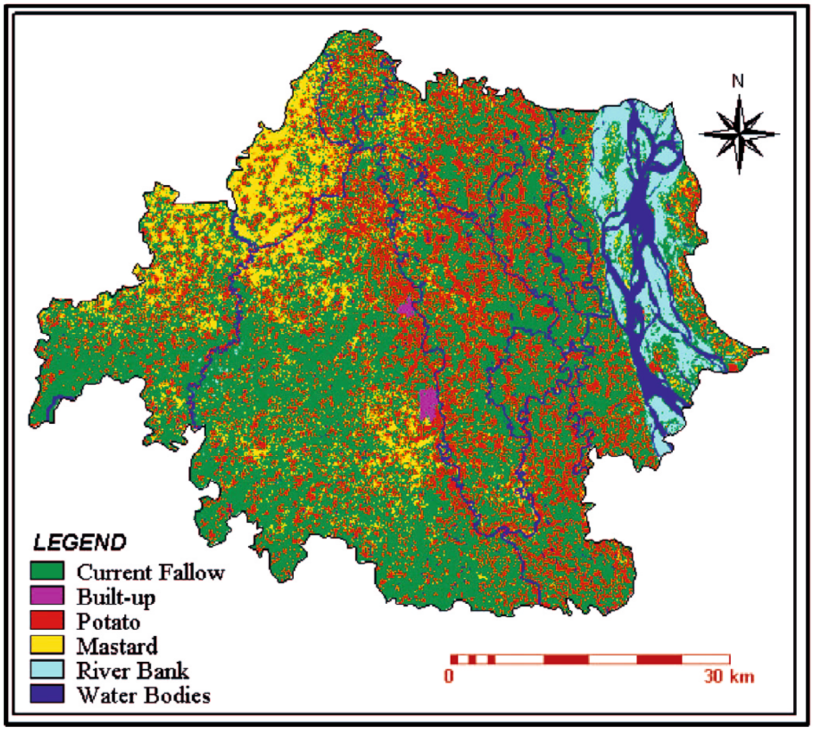


Fig. 6 Land use/land cover (pixel-based classification).

Table 2 Spatial extent of land use/land cover classification

Land use/land cover	Object-based classification		Pixel-based classification		Deviation from the object-based classification (%)
	Area in km^2	% of the total area	Area in km^2	% of the total area	
Current Fallow	1532.61	52.63	1685.31	57.88	+5.25
Built-up	7.80	0.27	7.80	0.27	0
Potato	911.08	31.29	722.07	24.80	–6.49
Mustard	219.10	7.52	249.87	8.58	+1.06
River Bank	106.36	3.65	117.17	4.02	+0.61
Water Bodies	134.95	4.63	129.68	4.45	–0.18
Total	2911.90	100.00	2911.90	100.00	

depict some differences in the classification results of the two methods. In the object-based classification, the area under potato was 31.29% of the total area whereas the pixel-based classifier identified 24.80% of total area under potato. The table also depicted that the area under mustard was 8.58% in the pixel-based classification and 7.52% of the total area in the object-based classification. For this reason it may be said that pixel-based classification implies the spectral values only in the clas-

Table 3 Error matrix: accuracy assessment for object-based land use/land cover classification.

Classified data	Reference data						
	Potato	Current fallow	Mustard	River bank	Water bodies	Built-up	Row total
Potato	9000	0	1124	0	0	0	10124
Current Fallow	408	20000	0	500	0	100	21008
Mustard	299	0	7427	0	0	0	7726
River Bank	0	2040	0	4626	0	0	6666
Water bodies	0	0	0	0	20633	0	20633
Built-up	0	701	0	0	0	2823	3524
Column total	9707	22741	8551	5126	20633	2923	69681
Accuracy							
Producer's accuracy (%)	92.72	87.95	86.86	90.25	100	96.58	
User's accuracy (%)	88.90	95.20	96.13	79.40	100	80.11	
Overall accuracy (%)				**92**			
Overall Kappa accuracy (%)				**90**			

Table 4 Error matrix: accuracy assessment for pixel-based land use/land cover classification.

Classified data	Reference data						
	Potato	Current fallow	Mustard	River bank	Water bodies	Built-up	Row total
Potato	1026	0	20	0	0	0	1046
Current fallow	105	989	142	142	22	0	1400
Mustard	155	42	1011	0	0	0	1208
River bank	0	38	0	850	0	90	978
Water bodies	0	0	0	0	600	0	600
Built-up	0	112	0	0	0	918	1030
Column total	1286	1181	1173	992	622	1008	6262
Producer's accuracy (%)	79.78	83.74	86.19	85.69	96.46	91.07	
User's accuracy (%)	98.09	70.64	83.69	86.91	100	89.13	
Overall accuracy (%)				**86.00**			
Overall Kappa accuracy (%)				**83.00**			

sification rules whereas object-based classification consider the spectral values, shape and texture information along with fuzzy logic for the classification. The formation of the objects is carried out in a way that an overall homogeneous resolution is kept.

On the other hand, if we compare Fig. 5 and 6, it is clear that the pixel-based classified image produced an image substantial classification noise (salt and pepper). Conversely, the classified image derived from object-based classification produce a

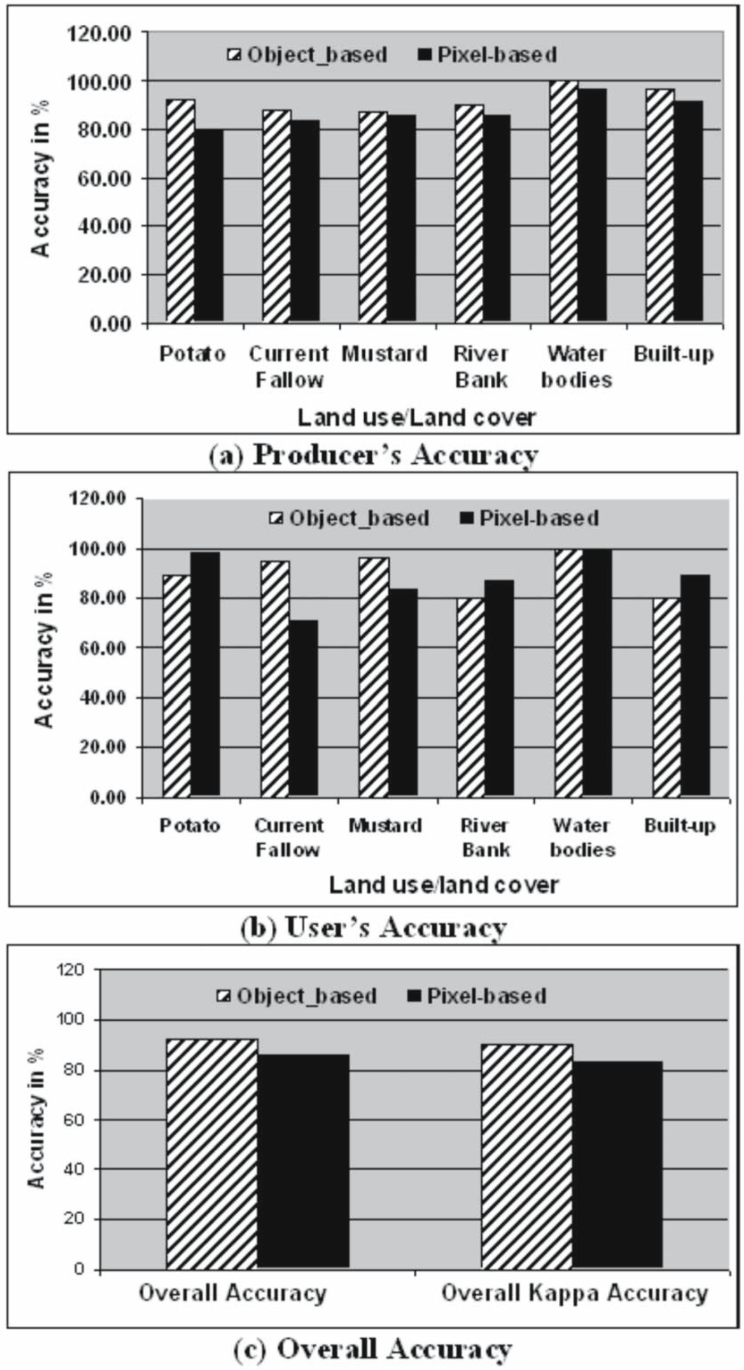


Fig. 7 Comparison of accuracy assessment.

much more uniform classification which is close to that achieved through human visual interpretation. According to the comparison of the results of the two classification procedures it may be said that object-based classification gives better results than pixel-based classification. However, to compare further between these two techniques, accuracy assessment was performed using error matrix and Kappa statistics (Tables 3 and 4).

In accuracy assessment, Tables 3 and 4 depicted that the training set pixels that were correctly classified into their land use/land cover categories are located along the major diagonal of the error matrix. All the non-diagonal elements of the matrix represented errors of omission or commission. Omission errors correspond to non-diagonal column elements (e.g., in Table 3, 408 and 299 pixels that should have been classified as potato, were omitted from that category). On the other hand, commission errors correspond to non-diagonal row elements (e.g. in Table 3, 299 potato pixels were improperly included in the mustard category). The data in Tables 3 and 4 are used to compute the *Producer's* (Error of omission*)* and *User's* (Error of commission) accuracy of individual land use/land cover category and also showed the overall accuracy of the classification.

The *Producer's* accuracy for the object-based classification was more than the pixel-based classification in all the land use/land cover classes [Fig. 7(a)]. Whereas the *User's* accuracy was more in the pixel-based classification in potato, river bank and built-up area, in the mustard and current fallow category, the accuracy was greater in the object-based classification [Fig. 7(b)]. The *User's* accuracy was 100 per cent for water bodies in both the object-base and pixel-based classifications. However, overall classification, accuracy indicated that in the object-based classification accuracy was 92 per cent whereas it was 86 per cent in the pixel-based classification [Fig. 7(c)]. Moreover, KAPPA statistics depicted that the overall Kappa accuracy was higher in the object-oriented classification than the pixel-based classification technique (Tables 3 and 4) and it was found to be 90 per cent in the object-based classification and 83 per cent in the pixel-based classification [Fig. 7(c)].

From the characteristics of the two classification methods, it is observed that in object-oriented image analysis, objects, not single pixels take part in the classification. Properly performed segmentation creates good image objects that facilitate the extraction of land cover information from the image. From the classifiers that are used in the two approaches, in object-oriented approach, the classifier is Nearest Neighbour. The Nearest Neighbour (NN) classifier evaluates the correlation between object features favourably; overlaps in the feature space increase with its dimension and can be handled much easier with NN, and NN allows very fast and easy handling of the class hierarchy for the classification (without class-related features). In pixel-based approach, the classifier is the Maximum likelihood classifier, it has the assumption that the selected training samples have to be normally distributed, but in the real world, this is not easy to realize and not normally distributed training samples influence the classification quality. So it may be said that using object-oriented image analysis, better classification results can be obtained than by a pixel-based image analysis approach for a medium resolution image like IRS P6 LISS III.

Conclusions

In this study, two-classification procedure i.e., object-oriented and pixel-based classifications were applied for land use/land cover classification. In order to compare the accuracy of these two techniques, accuracy assessments were completed for each classification approach using the same images over the same target area. In this study, overall classification accuracy indicated that in the object-based classification accuracy was 92% whereas it was 86% in the pixel-based classification. Moreover, overall Kappa accuracy was also higher in the object-based classification (90%) than in the pixel-based classification (83%). So, the results concerning their accuracy showed that an object-oriented classification approach allows a superior differentiation of basic land use/land cover types and the multi-resolution segmentation method applied appears to be very effective in extracting the segments required for the classification of land features. Object-based classification is especially good for high resolution image analysis; in this study it is also found that using object-oriented image analysis, better classification results for land use/land cover can be obtained than by a pixel-based image analysis approach for a medium resolution image like IRS P6 LISS III. Therefore, object-based image analysis, which is implemented in this study, can be the suitable image processing method for information extraction to support land use/land cover classification. Concluding remarks of this study is that the object-oriented approach produced a better classification result than the pixel-based classification and this study suggests that the land use/land cover classification can be done using object-based rules rather than pixel-based rules, as they simplify the complexity of the information and produce a better classification with better accuracy.

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