



A Comparative Assessment between Visual Interpretation and Pixel based Approach for Land Use/Cover Mapping using IRS LISS-III Imagery

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ABSTRACT

The information about land use /cover information is required for urban planning, eco-systems research and developing short and long term plans for the sustainable use, conservation and development of natural resources. A number of techniques have been used for extracting land use/cover information from satellite imagery. The most commonly used techniques are visual interpretation and pixel based classification (unsupervised and supervised classification). In this study, we compared visual interpretation, unsupervised and supervised classification techniques to extract the land use/cover information from Resorcesat-2 Linear Imaging Self Scanning Sensor-III (LISS-III) satellite imagery (Indian Remote Sensing (IRS) Satellite with spatial resolution of 23.5 m) on 1:50,000 scale in the Barnala district of Punjab (India). Ground data was collected from field and accuracy assessments of the three classifications were undertaken. Five land use/cover classes (built-up, agriculture land, forest, wastelands and water bodies) were extracted and the results were compared among these. The overall accuracies showed that visual interpretation (83.6%) performed better results than unsupervised and supervised classification techniques. Between both the pixel based classification techniques, supervised classification (75.5%) was better than unsupervised classification (64.3%). The major variations in accuracy assessment were due to agriculture land and forest extracted using all of the three techniques. These results suggest that visual interpretation technique is better for extracting land use/cover but it takes more time than supervised classification which may be used for getting quick information about land use/cover of an area.

Keywords

Digital classification, Land use/Land Cover, LISS-III, Visual interpretation

1. INTRODUCTION

Land use and land cover classes represent analytical units, which allow establishing a first quantitative link among human activities, environmental impacts and its geographical (spatial) dimension [1]. The information on land cover is of special value integrating the temporal dimension. Land cover/ land use maps play an important role for making the development plan both in rural and urban sectors, infrastructure planning, impact assessment and environmental hazard zonation etc [2]. As a result of technological advancements, changes of the earth's surface have become visible by satellite imagery and remote sensing has become the most effective tool for assessing and

monitoring all these transitions [3]. Satellite remote sensing has become a major data source for mapping applications, because of the repetitive data acquisition capabilities, digital format suitability for computer processing and lower cost than those associated with traditional methods [4].

The information about land cover is extracted from satellite image using visual interpretation and computer aided analysis. In visual interpretation, various interpretation elements like tone, texture, shape, size, association and pattern are used to produce the land cover map. The most commonly used computer aided analysis for land cover mapping is pixel based approach using unsupervised and supervised classification. The unsupervised classification seeks to group together cases by their relative spectral similarity, whereas supervised classification allocate cases on the basis of their similarity to a set of predefined classes that have been characterized spectrally [5]. Visual image interpretation is flexible and efficient for extracting spatial information from heterogeneous landscape with considerable degree of accuracy, but it requires more time for image interpretation with different interpreters producing different results. Both the methods of digital classification can simultaneously analyse many spectral bands at a time and process larger data sets much faster than visual interpretation. Moreover, the results of digital classification are objective with more consistent results than visual interpretation which is a subjective technique [6]. Previous studies have shown the contrasting results about the choice of method for classifying the satellite imagery for extracting land use/land cover in different parts of the world [7, 8, 9 and 10]. Puig et al. [7] compared digital classification and visual interpretation for extracting different land cover classes in humid tropical forests of Peruvian Amazon using Landsat TM satellite imagery and found that both the methodologies gave a similar precision. Wang et al. [11] used the high resolution aerial image (20 cm) to compare the visual interpretation and pixel based classification techniques (supervised classification). They found that supervised classification provided very high automaticity for extracting feature but it is not suitable for accurately classifying all the classes of interest. Bahadur et al. [12] classified the Landsat and IRS image for extracting land use/land cover information of Galaudu watershed of Nepal and found the higher accuracy with supervised classification technique than unsupervised classification. While there have been some studies comparing visual interpretation and pixel-based classification techniques but little has been conducted in Punjab (India). We compared visual interpretation, unsupervised and supervised classification techniques for

mapping land use/land cover on 1:50,000 scale in the Barnala district of Punjab (India).

2. STUDY AREA

The study area is a part of South Punjab (Barnala district) and covers an area of 1423 sq km which is 2.83 per cent of total geographical area of the state. It lies between 75° 15' 13" and 75° 43' 56" E longitudes, and 30° 08' 17" and 30° 36' 28" N latitudes, (Figure 1). The climate is sub-tropical and the mean winter temperature is 15.7°C and the mean summer temperature is 33.8°C.

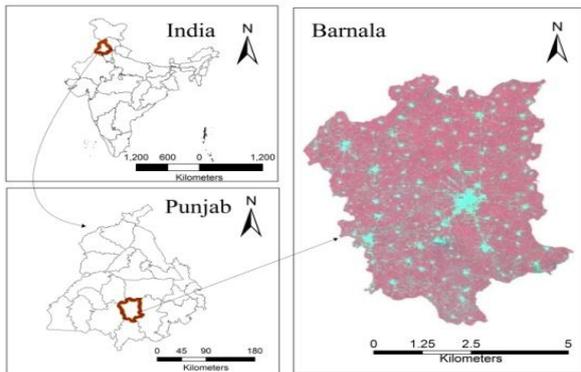


Figure 1: Location of the study area

3. DATA AND METHODS

Terrain corrected multispectral Resourcesat-2 satellite imagery of winter (Rabi Season) 2012 was used for extracting land cover features in the study area. The imagery was provided as four spectral bands [band-2 (VIS), band-3 (VIS), band-4 (NIR) & band-5 (SWIR) with wavelength ranges from 0.52-0.59, 0.62-0.68, 0.77-0.86 and 1.55-1.7 μm respectively. The imagery was provided as 10 bit integer data georeferenced to UTM projection. The geolocation accuracy of standard ortho-rectified imagery was 23.5 m and swath of 141 km. All the four bands were mosaicked using ERDAS Imagine 2010. The satellite imagery was classified using visual interpretation and pixel based classification (unsupervised and supervised). Visual interpretation was performed by onscreen digitization using ArcGIS 10.1. It was based on variation in color, tone, texture, shape, size, location and association of false color composite which was infrared, red and green bands of the satellite image. For unsupervised classification techniques, Iterative Self-Organizing Data analysis technique (ISODATA) was used. This technique repeatedly performs an entire classification and recalculates statistics with minimum user inputs for locating clusters. For supervised classification, maximum likelihood algorithm was used. This involved the selection of training areas representative of the different land cover classes. A number of training areas were selected to represent each class. The signature (or spectral mean) of the training area was then used to determine to which class the pixels were assigned. The detailed methodology is given in Figure 2.

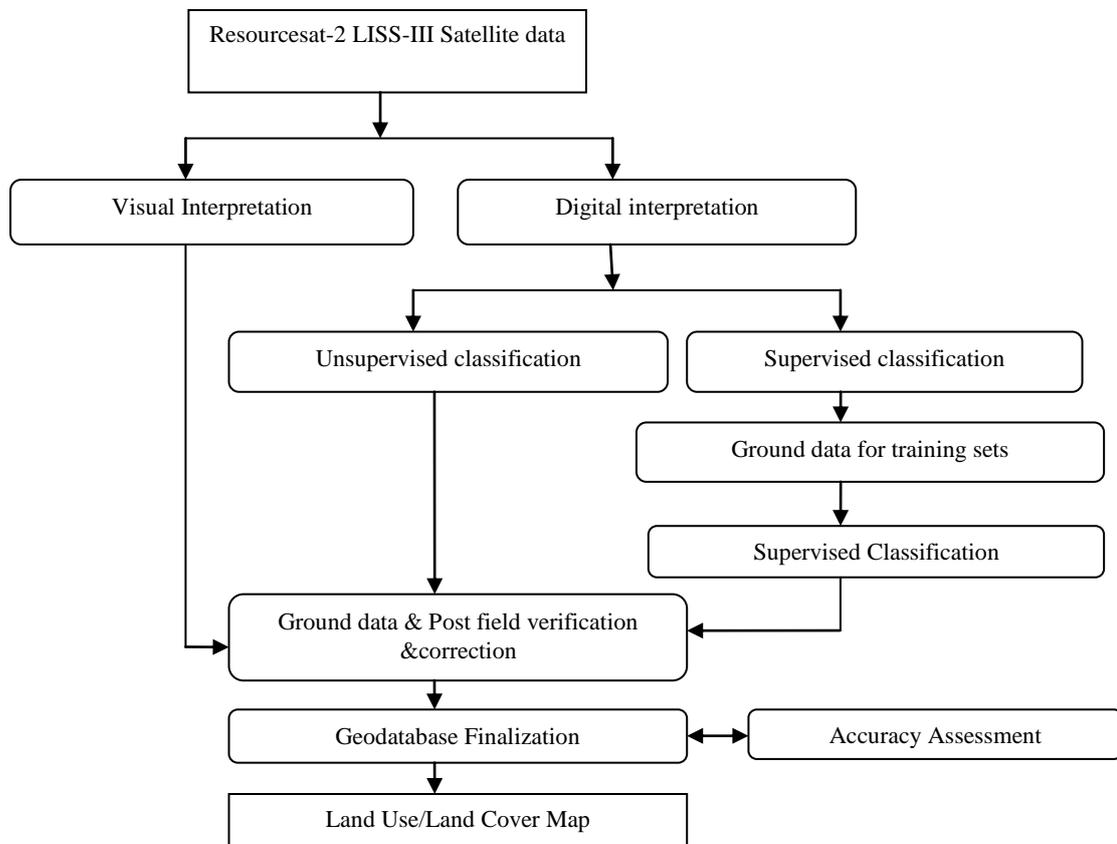


Figure2. Methodology for classifying the satellite imagery (Resourcesat-2) for Landuse /Land cover mapping

4. ACCURACY ASSESSMENT

Field survey was carried out to evaluate the classification accuracy. For each land cover class, total 55 sample points were collected using Garmin GPS. Accuracy assessments of the three classifications were undertaken using confusion matrices and Kappa statistics.

5. RESULTS AND DISCUSSION:

The satellite image was classified into five land use/cover classes: agriculture, built up, forest, water bodies and wastelands. Among all these classes, major part of the study area is under agriculture (Table 1). The area under agriculture classified using visual, unsupervised and supervised classification techniques was approximately similar in the three techniques (Table 1).

Table 1: Area (percent) under different classes using the three classification techniques

Landuse Class	Visual Interpretation	Unsupervised Classification	Supervised Classification
Built up	6.65	5.29	6.23
Agriculture Land	92.3	92.2	92.7
Forest	0.27	1.41	0.60
Wastelands	0.12	0.11	0.15
Water Bodies	0.70	1.00	0.29

The main confusions were among built up, forest, water bodies and wastelands. These errors affect the spatial representation and also the statistics of area of land use/cover types derived from the classified image. The area under built up classified using visual interpretation (6.65% of total area) and supervised classification (6.23% of total area) was almost similar, but it was significantly lower when extracted using unsupervised classification (5.26% of total area). This was mainly due to outer boundary of built up with vegetation cover (Figure 3) which couldn't be delineated on 1:50 000 scale in visual interpretation technique, but it was separated in both pixel based digital classification techniques.

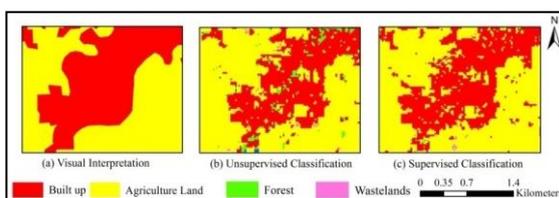


Figure 3: A subset of the classified image with built up extracted using (a) visual interpretation, (b) unsupervised classification technique, and (c) supervised classification technique

The area classified under forest using three techniques was in the order: unsupervised classification (1.41% of total area) > supervised classification (0.60% of total area) > visual interpretation (0.27% of total area). It was observed

that tree clad area (tree cover lying outside the forest but the tree cover along the canals and roads) was discriminated by unsupervised and supervised classification techniques, but not with visual interpretation on 1:50,000 scale (Figure 4).

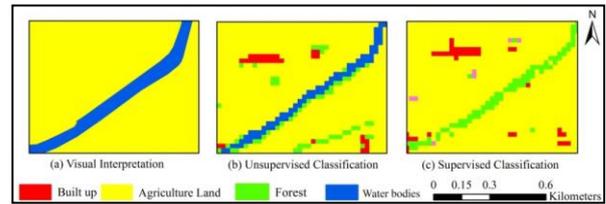


Figure 4: A subset of the classified image with tree clad area (along with water bodies and canal) extracted using (a) visual interpretation, (b) unsupervised classification technique, and (c) supervised classification technique

The higher forest area with unsupervised classification than supervised classification was due to mixing of scrub land and forest area in the former technique (Figure 5). The spectral signatures of tree clad area were not uniform in the satellite image of the study area which caused dissimilarity in the forest area extracted using supervised and unsupervised techniques.

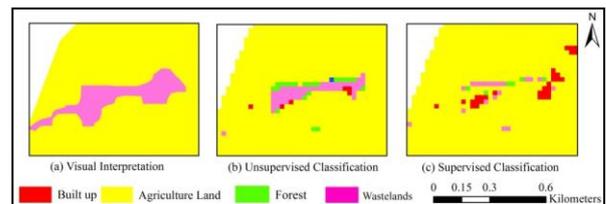


Figure 5: A subset of the classified image with scrub land extracted using (a) visual interpretation, (b) unsupervised classification technique, and (c) supervised classification technique

Water bodies represented 0.70% of total area for visual interpretation, 1.00% for unsupervised classification and 0.29% for supervised classification. The difference among different classification techniques is obvious because small water patches like minor distributaries couldn't be extracted using visual interpretation on 1: 50000 scale (Figures 6 and 7).

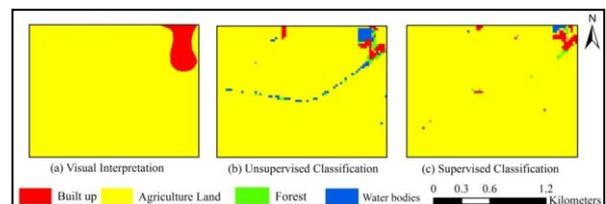


Figure 6: A subset of the classified image with water bodies extracted using (a) visual interpretation, (b) unsupervised classification technique, and (c) supervised classification technique

Table 2: Error matrix and the accuracy of visual interpretation, unsupervised and supervised classification techniques of different landuse/land cover classes

Land use Class	Number of ground control points	Visual Interpretation		Unsupervised Classification		Supervised Classification	
		Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (%)	User Accuracy (%)
Built up	17	72.7	88.9	47.1	66.7	93.8	68.8
Agriculture Land	19	85.0	89.5	84.2	59.3	84.2	69.6
Forest	2	100	100	100	28.6	100	50.0
Wastelands	6	100	83.3	---	---	---	---
Water Bodies	11	100	60.0	81.8	100	70.0	100
Overall Accuracy		83.6		64.3		75.5	
Kappa Statistics		0.78		0.51		0.65	

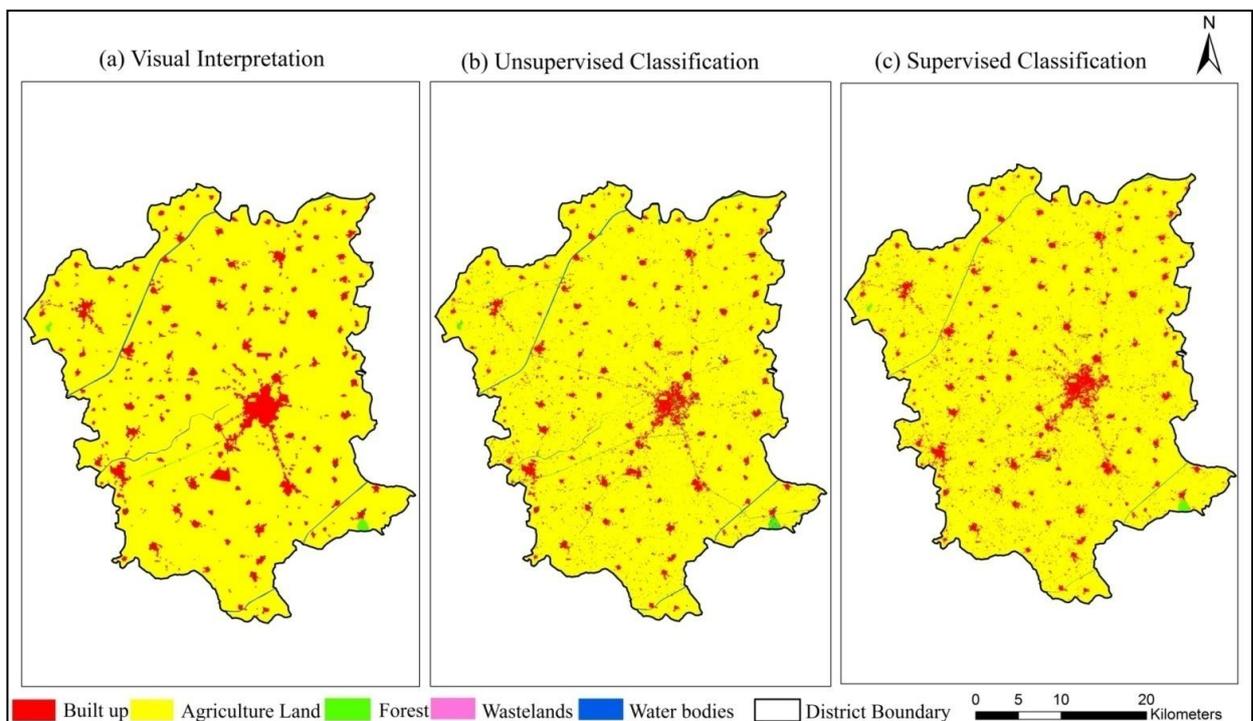


Figure 7 Landuse/Land cover map of the study area classified using (a) visual Interpretation (b) unsupervised classification technique, and (c) supervised classification technique

However, this problem may be overcome using pixel based classification technique but the training sets for minor tributaries taken in supervised classification had spectral mixing with other land cover features. These training sets were not homogenous throughout the image which resulted a significant difference in water bodies area extracted using both the digital classification techniques.

Although there is no confirmed standard for accuracy assessment, a common accuracy which is acceptable is more than 80%. Based on this statement, only visual interpretation met the acceptable value, but the other two methods did not. From the results of the confusion matrices (Table 2), the overall accuracy of visual interpretation (83.6%) was better than unsupervised (64.3%) and supervised classification (75.5%). This was also the case for the overall Kappa

statistic. The Kappa value was 0.78 ($p < 0.05$) for visual interpretation, 0.51 ($p < 0.05$) for unsupervised classification and 0.65 ($p < 0.05$) for supervised classification. The producer and user accuracies were greater for the majority of visual interpretation. However, built up was more accurately classified using supervised classification (Figure 7). The class that had poor accuracy in unsupervised and supervised classifications was forest. This is possibly due to small number of reference data points for this class.

6. CONCLUSIONS

The results of this study showed that land use/cover classes extracted from Resourcesat-2 satellite image using visual interpretation techniques had higher accuracy than unsupervised and supervised classification techniques. These



results are useful for making the developmental plans both in rural and urban sectors of the study area, infrastructure planning, impact assessment and environmental hazard zonation. The variation in accuracy assessment of visual and supervised classification was due to agriculture and forest. Though visual interpretation is better than supervised but it is difficult to extract the features with areas lesser than minimum mapping units in visual interpretation but a single pixel is, classified in supervised classification. The lesser number of reference points were one of the major causes of variation in accuracy assessment but further research is required using selection of training area, interpretation approaches and number of reference data for accurately extracting the information about land use/cover of an area.

7. REFERENCES

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