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RESEARCH ARTICLE

Effect of Canal on Land Use/Land Cover using Remote Sensing and GIS

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Abstract The monitoring of land use/land covers (LULCs) is an indispensable exercise for all those involved in executing policies to optimize the use of natural resources and minimize the ill impacts on the environment. The study here aims at analyzing the changes that occurred in LULC over a time span from 1990 to 2005 using multi date data of a part of Punjab. The digital data consisted of two sets of Landsat Thematic Mapper (TM) data and one set of IRS-1C data. Utilizing hybrid classification technique for interpretation and on field validation, it has been found that canal irrigation leads to changes in LULC as there is a change in cropping pattern as well as increase in water logged area.

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Introduction

Land use is the manner in which human beings employ the land and its resources; it includes agriculture, urban development, grazing, logging, and mining. In contrast, land cover describes the physical state of the land surface, which includes cropland, forests, wetlands, pasture, roads, and urban areas (Jaisawal *et al*., 1999). The term land cover originally referred to the kind and state of vegetation, such as forest or grass cover, but it has broadened in subsequent usage to include human structures such as buildings, pavements and other aspect of the natural environment, including soil type, biodiversity, surface water and groundwater (Chen *et al.*, 2008 and Meyer, 1995). LULC changes are important elements of the global environmental change processes (Jaisawal *et al.*, 2001). The detection and monitoring of change using multi-spectral satellite image has been a topic of interest in remote sensing. Change detection generally employs one of two basic methods: pixel-to-pixel comparison and post-classification comparison (Jaisawal *et al.*, 1999). The post classification method compares two or more separately classified images of different dates (Pilon *et al.,* 1988; Fung and Zhang, 1989). It is considered to be one of the most appropriate and commonly used methods for change detection (Jensen, 1996). The aim of this study was to analyze LULC changes between 1990–2000 and 2002–2005 for the Batala region of Punjab, using Landsat Thematic Mapper (TM) and IRS-1C data that has occurred due to development of canal irrigation, and increased crop production.

Study area

The coordinates of the study area are Longitude 75°00’00" E to 75°30’00" E and Latitude 32°00’00" N to 31°30’00" N (Fig. 1). The climate of the plains of Punjab is excessively hot and dry between April and August, with temperatures as high as 49°C. The monsoon season begins at the end of June and winters are cold with some frosts. Annual rainfall varies from about 915 mm in the North to 102 mm in the South. More than 70 per cent of the annual rainfall occurs during the monsoon season from July to September. The average temperature in January is 13°C, although at night the temperature sometimes lowers to freezing point. In June the average temperature is 34°C, occasionally climbing as high as 45°C. Most of Punjab is a fertile plain; towards the south-east one finds semi-arid and desert landscape; a belt of undulating hills extends along the north-east at the foot of the Himalayas. The Beas river flows across the study area in south-westerly

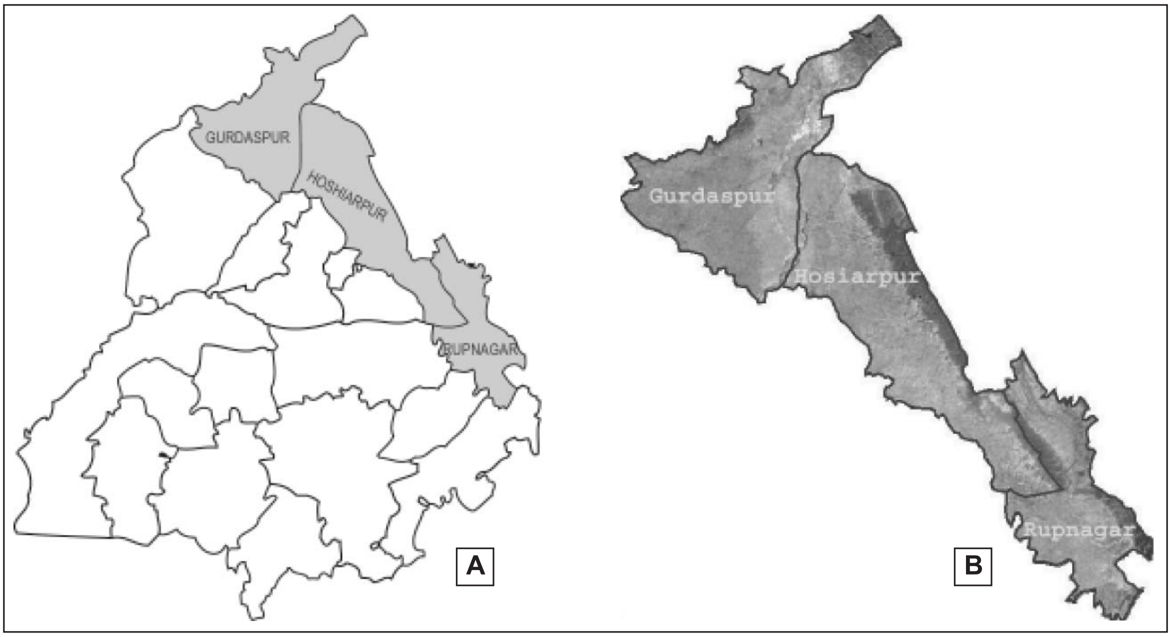

Fig. 1 **A)** District maps of Punjab highlighting the study area; **B)** False Colour Composite (FCC) changed to grey scale of IRS-1D LISS III Satellite Image.

direction, with numerous small and seasonal tributaries. In addition, Batala is watered by an extensive canal system; most important is Upper Doab Canal.

Methodology

Image registration

SOI toposheets (45M/1, 45M/2, 45M/5, 45M/6) at the scale of 1:50,000 were geometrically corrected and were mosaicked. Since the study involved detecting changes in the LULC, Multi date satellite data that is two sets of Landsat-7 TM images dated 16 October 1990 and 22 October 2000 for Path 148 Row 38 and one set of IRS1C dated 17 November 2005, were used for analyses of change detection of LULC. The toposheets were geometrically transformed utilizing the Geographic projection system, where well-distributed geographic control points were obtained, which was used as reference for projecting the image datasets. A root mean square error (RMSE) evaluation was then performed to assess image to map rectification accuracy. The RMSE for the rectified images was less than 0.4 pixel. All the images were then reprojected in polyconic projection system with Everest as spheroid. Subsequently, datasets were resampled to 24 pixel dimensions using nearest neighborhood algorithm.

Supervised classification requires training sets as the reference signature, on the basis of these training sets, the whole population of pixels are classified (Fig. 2). A detailed process for generation

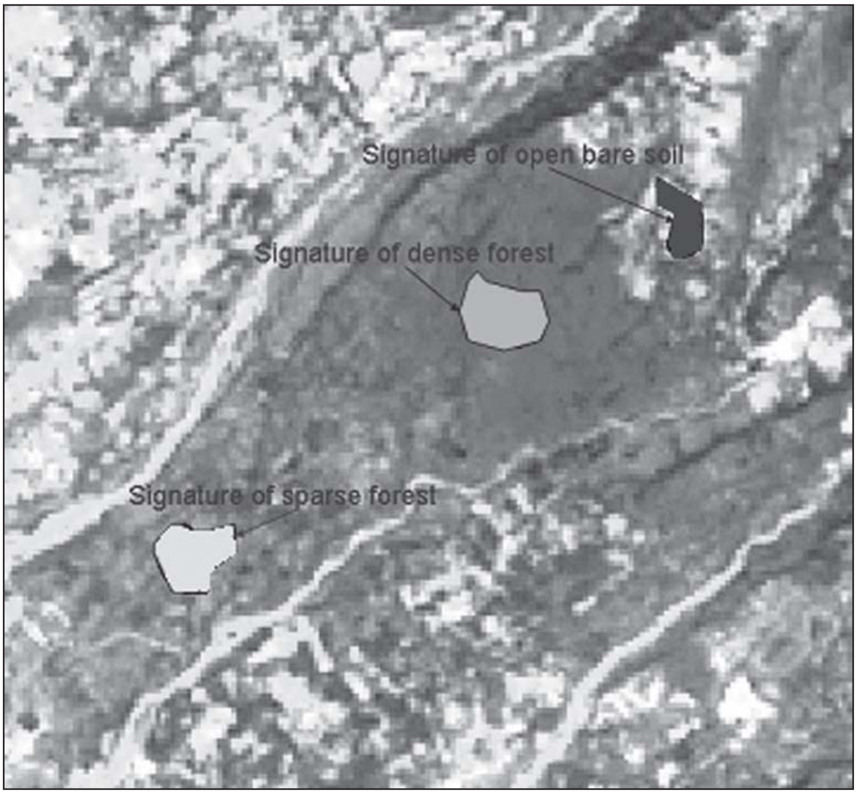

Fig. 2 Sample training areas for supervised classification of the study area.

of LULC is shown in (Fig. 3). A sub-area of 2315 by 1986 pixels covering the study area was extracted from the images and it was geometrically corrected with toposheet and re-sampled to same pixel dimension. The radiometric correction was performed on Landsat images of 1990 and 2000 using de-striping, high-pass filtering and reverse principal component transformations. Spectral bands display a range of correlation from one band to another which can be observed by scatter plot of digital data between various bands for instance between band 1 and band 2 (Fig. 4). Bands which are spectrally close to one another contain nearly same element of information and such bands (that are highly correlated) can predict same brightness results as of other band. Therefore, bands that are well correlated and nearly spectrally similar may not be of use when attempting to isolate spectrally similar objects. In this study, we observe that there is (initially) a strong correlation when DN values are low, but as these increase for both bands, the plot widens and again at the end in small range they show good correlation. This means, for much of the DN value range, the two bands are less correlated and should serve increasingly well as discriminators in any classification, therefore they can be used for identifying contribution of varied spectral types (soil, water, vegetation).

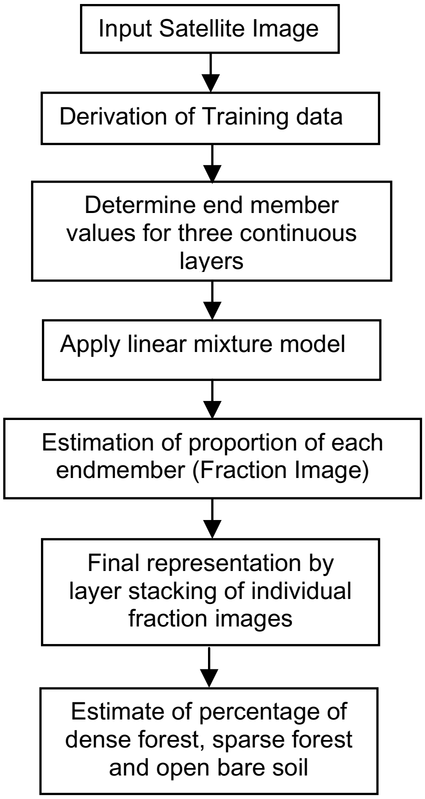

Fig. 3 Normalized difference vegetation index (NDVI) map of the study area.

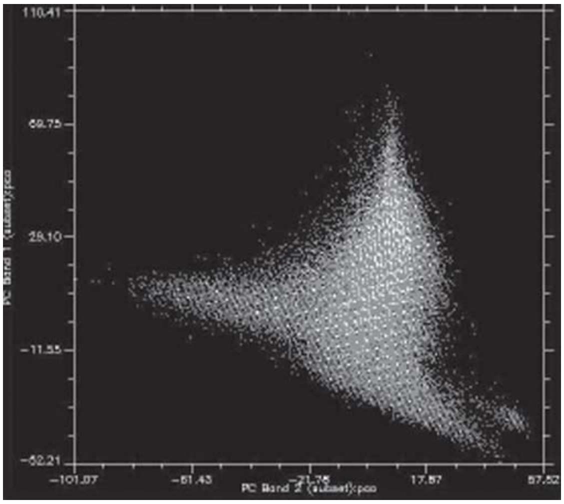

Fig. 4 Flow diagram of the SMA process.

Image enhancement and satellite image interpretation

Four different types of approaches, using data training sets, were adopted for identification of dense forest, sparse forest and open bare soil such as unsupervised, supervised, NDVI based (Fig. 5) and spectral mixture analysis method. PCA (principal component analysis) (Fung and LeDrew, 1987; Eastman and Fulk, 1993) that has been widely used in pattern recognition and remote sensing applications, mathematically establishes a new set of variables, which describe the variance in the original data set. Therefore, principal components analysis can be used in image classification to improve the accuracy. PCA is a multivariate statistical transformation technique, which is based on statistical properties of vector representations. PCA provides a systematic means of reducing the dimensionality of multispectral data. To perform the PCA, the axes of the spectral space are rotated, which changes the coordinates of each pixel in spectral space as well as data values. Principal components are independent of one another; a color combination of the first three components can be useful in providing maximum visual separation of image features. Mathematically for PCA, if' $\mathbf{X}^{\mathbf{T}} = [x^1, x^2, \ldots, x^n]$ is an N dimensional random variable with mean vector $\mathbf{X}^{\sim}$ and covariance matrix **C** and let A be a matrix whose rows are formed from, the eigenvectors of **C,** ordered so that the first row of **B** is the eigenvector corresponding to the largest eigenvalue, and the last row is the eigenvector

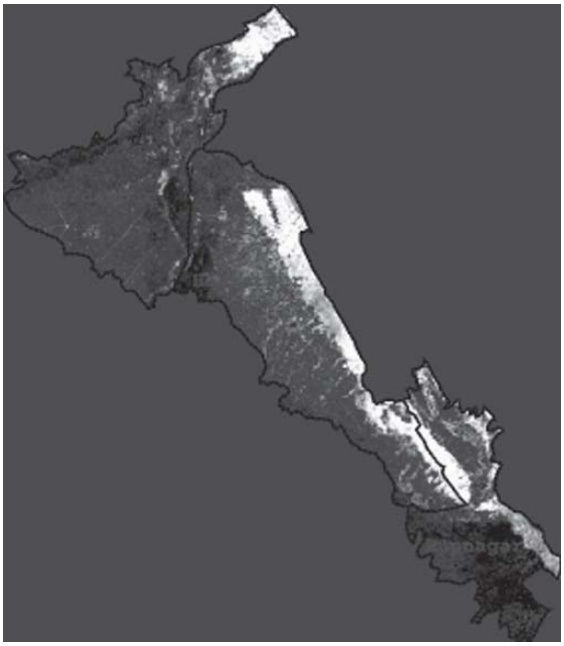

Fig. 5 Scatter plots of PC Band 1 and PC Band 2.

corresponding to the smallest eigenvalue, then the PCA transformation is

$$\mathbf{Y} = \mathbf{B}\,(\mathbf{X} - \mathbf{X}^{\sim})$$

where, $\mathbf{Y} = [y^1, y^2, \ldots\ldots y^n]^T$ is the transpose and each vector y, is the $\mathbf{i^{th}}$ principal component.

The end member spectra for the three land cover that are dense forest, sparse forest and open bare soil that were extracted separately (Fig. 6) shows the fraction of contribution of three end members within a pixel in different bands (Fig. 7).

Satellite image classification is a statistical technique to group population of pixels in broad classes as per their inherent DN values which are of two types–supervised and unsupervised. A combination of supervised and unsupervised classification techniques is the hybrid classification technique, which was used to derive the LULC of the study area. Unsupervised classification was carried out on the three datasets of the images separately, using a histogram peak cluster technique to identify dense areas or frequently occurring pixels (Lillesand and Kiefer, 1979). Thus, using the spectral signature and colour the classes initially identified were vegetation layer and non-vegetation layer that included urban and water body. The vegetation layer and non-vegetation layers were extracted and treated separately for further classification. The vegetation and non-vegetation classes were handled separately so that there is no mix-up, at least in the two broad pixel classes, at the same time maintaining good quality and accurate data in other classes as well. The processed vegetation and non-vegetation layers were finally mosaicked to generate one single land use/land cover layer. Once the vegetation and non-vegetation classes were separated, training site-based classification technology was used, which is nothing but the supervised classification technique to further categorize the images into classes. More than 50 GPS locations were used as reference signatures for training the system. In this crop and plantation layers were separated from vegetation layer, built-up layers were refined. Waterlogged area

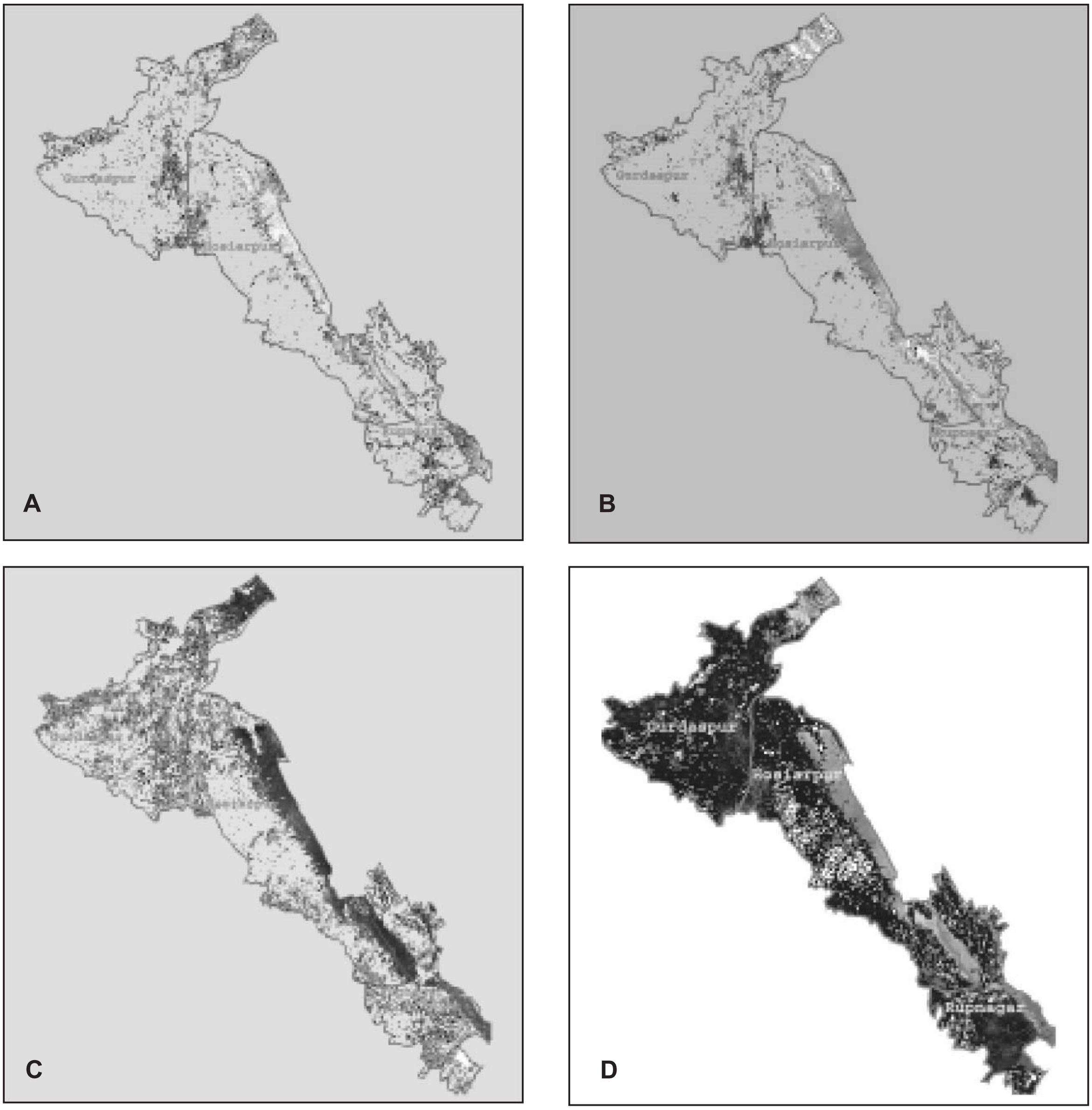

Fig. 6 Fraction images of **A)** dense forest, **B)** sparse forest, **C)** open bare soil, **D)** Color composite changed to grey scale of the fraction images for the three endmembers. Open bare soil as very dark tone, sparse forest as less dark tone and dense forest as very light tone.

was delineated from the area initially considered under water body. Fallow land was derived from the remaining areas. Thus, a total of six LULC classes were obtained from the study areas that are cropland, plantation, fallow land, urban, water body and water logged area.

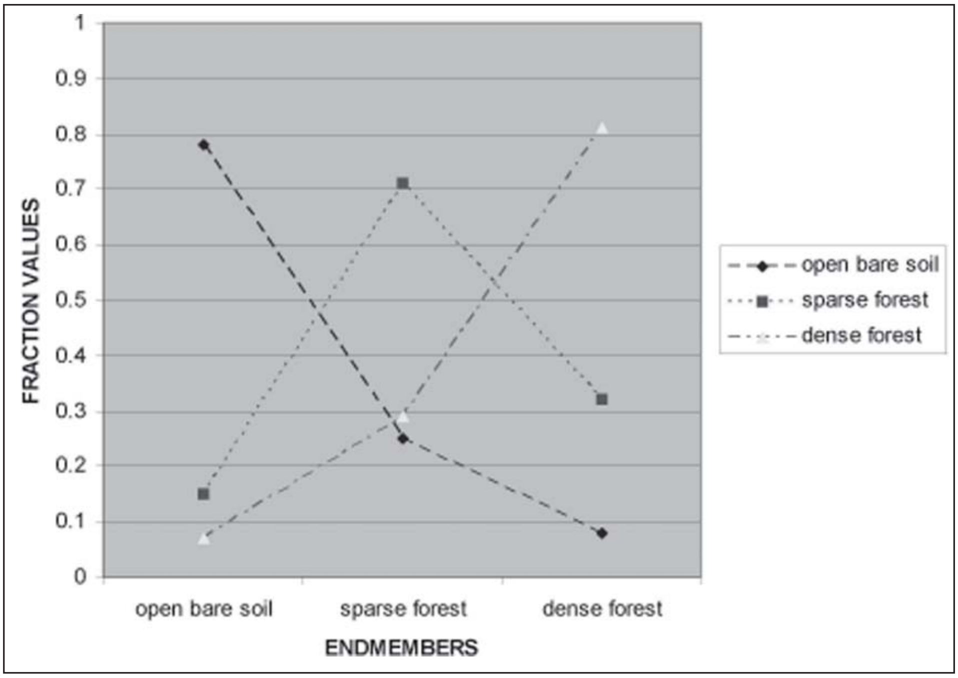

Fig. 7 Comparative study of fraction features among three end member (open bare soil, sparse forest and dense forest) within a pixel.

Accuracy assessment and change detection

In order to evaluate the performance, the accuracy assessment was carried out using the randomly stratified sampling method. The sampling method assured that sampling effort was distributed in a rational pattern so that a specific number of observations were assigned to each category on the classified image to be evaluated. A total of 50 reference points were selected to calculate the detection accuracy. Subsequently, the Kappa accuracy was computed as (Bishop *et al*., 1975):

$$\kappa = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(x_{i+})(x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+})(x_{+i})}$$

where, r is the number of rows in the matrix, Xii is the number of observations in row i and column i (the diagonal elements), $x{+}i$ and $xi{+}$ are the marginal totals of row r and column i, respectively, and N is the number of observations.

Change detection is important to discriminate areas of land cover change between dates of imaging. Post classification comparison method was used for change detection, which involved independent registration and classification of multidate images and further calculating the statistics. The calculation gives the change that occurs in region. The accuracy of this depends upon the accuracy of each independent classification used in the analysis. On comparison of the outputs obtained using the above mentioned four approaches: unsupervised, supervised, NDVI based and spectral mixture analysis method (Figs. 8 and 9) it gives a very clear picture that SMA based approach is most accurate as it is almost similar to state forest report of Punjab both in the case of dense forest and sparse forest.

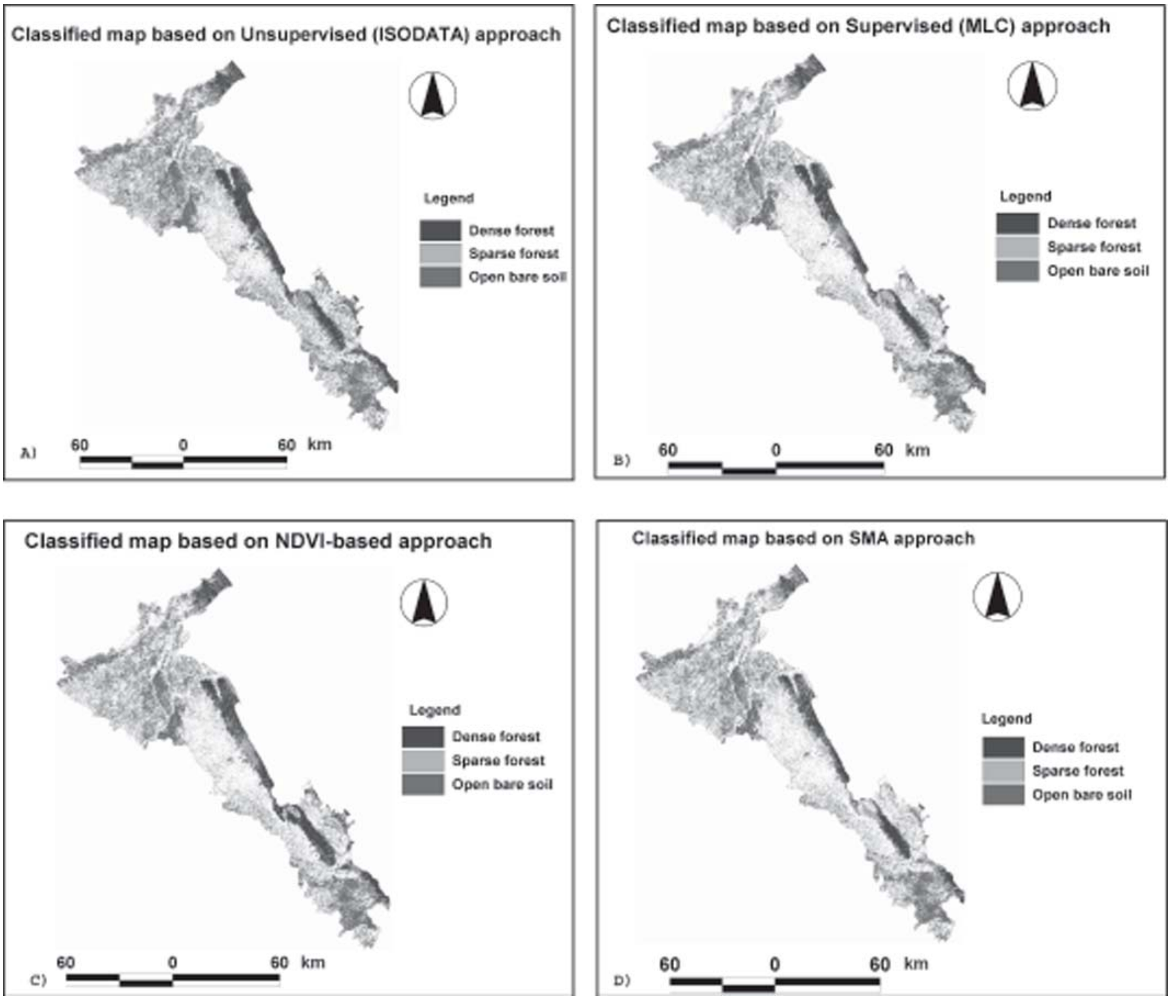

Fig. 8 Classified output of four approaches **A)** Unsupervised approach, **B)** Supervised approach, **C)** NDVI approach, **D)** SMA approach.

Results

LULC classification of the study area has been made for understanding the present utilization pattern and status assessment (Jaiswal *et al.*, 2001). The Kappa accuracy obtained is about 85% for 2005 image about 80% and 88% for 1990 and 2000 image respectively. Overall accuracy for PCA is about 81% for 1990 and for 2000 and 2005 it is 82% and 78% respectively. The introduction of canal irrigation has brought a change in LULC within the time period of 25 year from 1990 to 2005. On the basis of post classification (Fig. 10 and Table 1) it was observed that there was a drastic and rapid increase in two of the identified classes: urban and water logged area, Increase in waterlogged area has caused the cropping pattern of region to change, which is visible in the area between the Beas and Doab canal (diverges from the Beas river). There is also a reduction of cropping in this area from 1990–2005. So there has been a shifting of cropland from canal and nearby river area to the southwestern part of the studied area. The reason may be a significant cause for increase in fallow land. Plantation decreased from 1990 to 2000, but increased in 2005 and this increase area along the side of canal from the area in between and around the canal. The waterlogged area has increased at an alarming rate, specifically in canal area and if this continues, in future, it may result in consequences like change in ground water (Chen *et al.*, 2008) soil quality and cropping pattern of the region (Table 1).

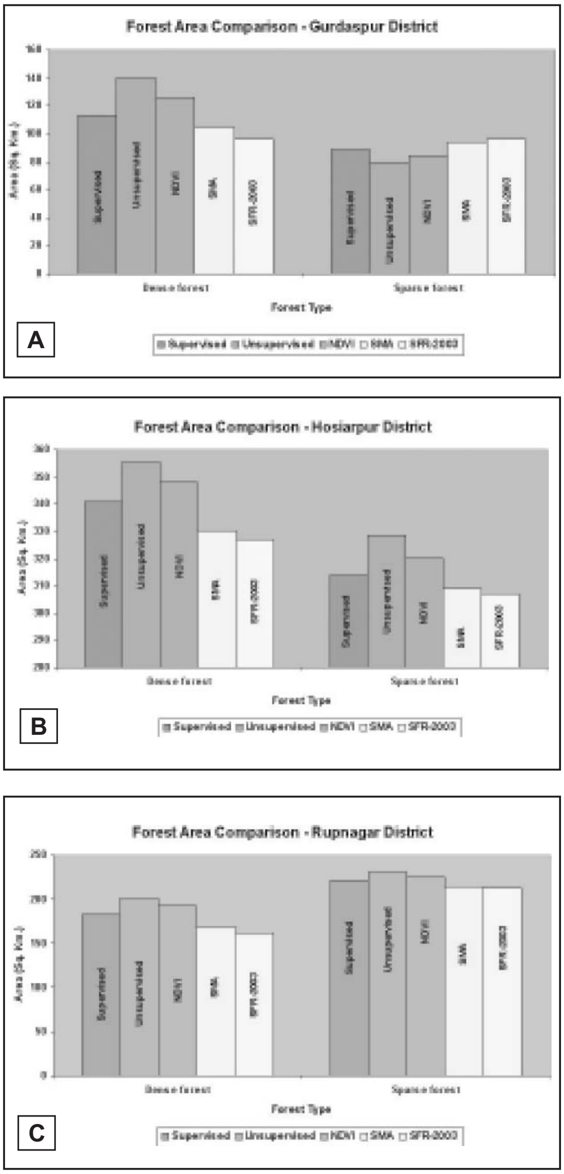

Fig. 9 Graphical representation of outputs obtained through different models for three districts of Punjab (**A:** Gurdaspur District, **B:** Hosiarpur District, **C:** Rupnagar District).

Conclusions

Satellite remote sensing can be used as an effective tool for generating the necessary dynamic information for surveying and monitoring LULC in a region. The canal irrigation plays an important role in development of agriculture however, without proper management it has led to increase in water logged areas. This increase has caused a change in land use behavior because the areas where cropping was started have turned into fallow lands and new areas have to be utilized for agriculture. There is a fast increase in area of fallow land. Thus, study of hydrological conditions of area along with irrigation requirement according to cropping pattern forms a crucial element for the development. The monitoring of LULC change using remote sensing data in Punjab region forms an essential element for implementing policies and for judicious use of natural resources.

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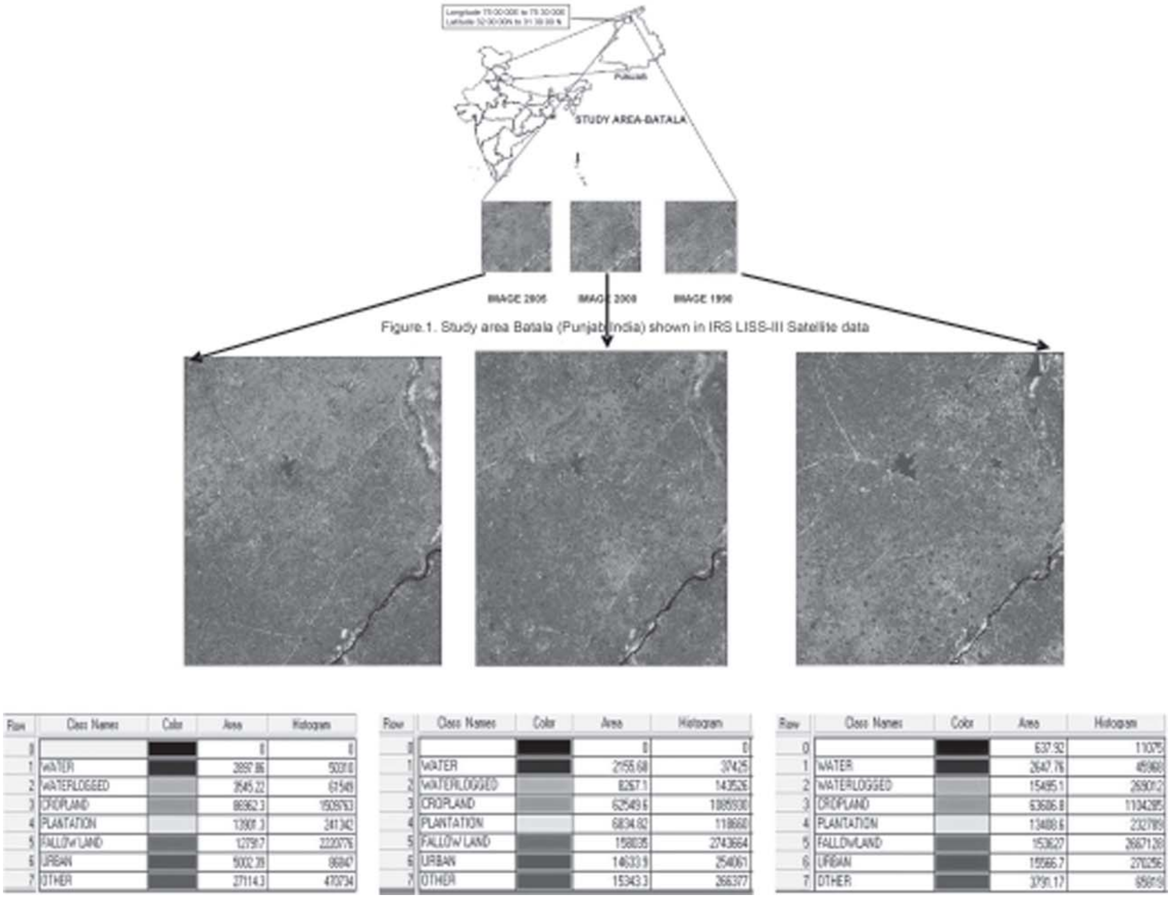

Fig. 10 Grey scale LULC of images of year 1999, 2000 and 2005 together with there attributes.

Table 1 Area Statistics of the region interpreted from satellite data

S.No.	Class	Area (1990) in Hec	Area (2000) in Hec	Area (2005) in Hec	Increase/ Decrease 1990-2000	Increase/ Decrease 2000-2005	Increase/ Decrease 1990-2005	Overall % change
1	Water	2897.86	2155.68	2647.76	-742.18	492.08	-250.1	9.45
2	Waterlogged	3545.22	8267.1	15495.1	4721.88	7228	11949.88	77.12
3	Cropland	86962.3	62549.6	63606.8	-24412.7	1057.2	-23355.5	36.72
4	Plantation	13901.3	6834.82	13408.6	-7066.48	6573.78	-492.7	3.67
5	Fallowland	127917	158035	153627	30118	-4408	25710	16.74
6	Urban	5002.39	14633.9	15566.7	9631.51	932.8	10564.31	67.86

the author's and are not attributable to the University or funding sources.

References

Bishop Y, Fienberg S and Holland P (1975) Discrete Multivariate Analysis—Theory and Practices Cambridge, Massachusetts: MITR Press

Chen X, Yan JF, Chen Z, Luo GP and Xu WQ (2008) A geospatial analysis approach for assessing the impact of landuse on groundwater resources in the SanGong Oasis region. *Journ. Agri. Food Env. Sc.* 2(1): 1–10

Don J, Mcfarlane D and Williamson R (2002) An overview of water logging and salinity in southwestern Australia as related to the 'Ucarro' experimental catchment, *Agricultural Water Management* 53: 5–29

Eastman J R and Fulk M (1993) Long sequence time series evaluation using standardized principle components. *Photogrammetric Engineering and Remote Sensing* 59: 991–996

Fung T and Ledrew E (1987) Application of principal components analysis change detection. *Photogrammetric Engineering and Remote Sensing* 53: 1649–1658

Fung T and Zhang Q (1989) Land use change detection and identification with Landsat digital data in the Kitchener–Waterloo area, *In Remote Sensing and Methodologies of Land Use Change Analysis*, eds CR Bryant, EF LeDrew, C

Green K, Kempka D and Lackey L (1994) Using remote sensing to detect and monitoring land-cover and land-use change. *Photogram. Eng. Rem. Sens*. 60: 331–337

Jaisawal RK, Saxena R and Mukherjee S (1999) Applications of Remote sensing technology for Landuse/Landcover change analysis. *J. Indian Soc. Remote Sens.* 27(2): 123–128

Jaisawal RK, Saxena R and Mukherjee S (2001) Land use/ Land cover mapping using IRS 1C LISS III false colour composite (a case study of a part of Shahdol district, Madhya Pradesh. *Journ. Tropical Forestry* 17(1): 33–40

Jensen J R (1996) *Digital Image Processing*: *a Remote Sensing Perspective* Englewood Cliffs, New Jersey: Prentice Hall

Lillesand TM and Kiefer RW (1979) *Remote Sensing and Image Interpretation,* New York: Wiley

Meyer WB (1995) Past and Present Land-use and Land-cover in the U.S.A. *Consequences*

Pilon PG, Howarth PJ and Bullock RAQ (1988) An enhanced classification approach to change detection in semi-arid environments. *Photogram. Eng. Rem. Sens.* 54: 1709–1716