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Spatio-Temporal Change Detection Analysis of Land Use Land Cover of Bathinda District, Punjab, India

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Due to rapid industrialization and urban sprawl in the last few decades, the land use pattern and its consumption takes place at a large scale that could lead to problems such as over-exploitation of land resources, food insecurity and pollution. It becomes imperative to carry out monitoring and subsequent modelling of land use land cover (LULC) changes. An attempt was made to study the changes in the LULC pattern of district of Bathinda, Punjab, India. Remote sensing (RS) and geographical information system (GIS) were used to perform the analysis of satellite data using image processing and classification procedures. For preparing LULC maps, supervised classification was carried out using maximum likelihood classification (MLC) algorithm, aided with Earth Resources Data Analysis System (ERDAS) Imagine 2014 and ArcGIS 10.3 software. Further, change detection study was done using multi-temporal Linear Imaging Self Scanning Sensor-III (LISS-III) data sets of the year 2006 and 2018 to analyze the temporal changes. It was observed that the region is occupied by various ground features such as water, built-up area, agricultural land, vegetation/trees and fallow land. The results revealed that the area under water bodies have increased by 0.413km2 in 2018. The built-up areas including human settlements, commercial infrastructures, roads and other pavements, have increased from 584.448km2 to 852.140km2 between 2006 and 2018, whereas the agricultural land has reduced from 2686.121km2 to 2398.384km2 during the period. The area under vegetation (trees) indicated that there was an increasing trend from 28.490km2 to 54.678km2 during 12years of time span whereas, the fallow land/barren land showed a decreasing trend from 26.361km2 to 18.367km2. It is suggested that the LULC change detection studies are very significant to conserve the land resources and to avoid further degradation.

Keywords: Built-up area; Classification; Climate; Monitoring; Management; Temporal; Urban; Vegetation.

Land is considered as a limited natural resource[1,2] that provides habitat and sustenance for living organisms, and a major source of economic activities[3]. *Land cover* includes physical and biological properties of the earth's system such as rocks, soil, vegetation, snow and settlements whereas, the purpose for which land is being used by humans is referred to as *land use*[4] or human activities that take place on the land surface, for example, agricultural, residential or industrial area[5]. Land cover is an essential factor of ecosystem, biological and geo-chemical processes,

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for example carbon sequestration in vegetation[6], geo-chemical nutrient cycling such as nitrogen (N_2) fixation[7] and evapotranspiration[8]. The changes in land cover takes place not only as a result of human activities, but naturally as well[9] such as succession and other natural disturbances. The growing human requirements and activities determine fate of land use[10, 11]. The inadequate supply of land resource is a key factor of production for economic activities, human settlements and other built-up infrastructure[12]. The anthropogenic practices that affect freshwater resources, ecosystems, quality of air, climate change[13] and other services comprise agricultural activities, mining, settlements and other built up areas[14-17]. *'Land conversion'* or *'land use change'* is a continuous process or phenomenon that is almost unavoidable during economic development and population growth[18]. However, uncontrolled conversion has serious consequences that occur at the cost of natural environment[19]. The information on the rate and kind of such changes is essential for proper planning, management and their regularization[20].

Amid rapid industrialization, urbanization and other anthropogenic activities, the consumption of natural resources exceeds the capacity of nature to replenish. For such anthropogenic activities, land is a prime target that poses a serious threat to plants and animal species, food resources and forest resources. Therefore, it becomes very important to monitor the changes in land use land cover in the region to conserve the land resources for both present and future generation.

For the impact assessment of anthropogenic activities on the ecosystems, the data and related information on land use land cover (LULC) changes is very significant[21-23] besides future research projects on climate change[24] & better management of land resource. To understand the mechanism in land dynamics, monitoring and subsequent modelling is very important[25] that differ in space and time[26-30]. Such information based monitoring offers significant input to decision-makers at all levels (national and international) for the proper understanding, utilization and management of natural resources, human-environment relationship and future planning framework[31-36]. The pervasive LULC changes occur as a result of human interactions and the natural processes, climate change and socio-economic factors[37-41]. Thus, the factors like population explosion[19, 42] urbanization, rapid industrial revolution, increasing anthropogenic activities[43] has led to continuous, uncontrolled and unplanned LULC changes[44-49]. The impact of population growth on limited resources; lead to the change in land cover[50]. The process of urbanization or urban sprawl includes modernization, socio-economic aspects and population growth[51] and is continuous trend globally influenced by various biological factors and anthropogenic practices[52]. The LULC changes are very significant worldwide as they adversely affect ecosystems and their services, social development and environment[53-55] besides landscape modification, loss of biodiversity, deforestation, atmospheric processes, floods and global warming[49, 56-58]. The changes in LULC can be monitored in terms of loss of agricultural land and urbanization[59, 60], loss of vegetation and forests; to design a better sustainable land policy[61, 62].

The term *change detection* is recognized as the process of identifying variations in ground features at different time intervals by comparing two or more images of the same area[63]. The change detection can be very useful for efficient conservation and management of resources[64] that has a wide range of applications- urbanization[65], monitoring of changes in forest and vegetation[66], wetland[67], LULC change[68] and landscape monitoring[69]. Such change detection techniques rely on multi-temporal satellite images provided by remote sensing (RS) and are categorized into two main approaches: object-based and pixel-based[70].

In India, a number of studies have reported about LULC change detection analysis. In Saharanpur city, with the help of satellite images, change detection study was reported related to urban sprawl, population growth and loss of agricultural land[71]. The results revealed that non-agricultural lands were the prime targets of landscape change. For assessment of densely populated Allahabad city[72] using remote sensing (RS) and geographical information system (GIS) in Tirupati[73], the results revealed that loss of agricultural land to human settlements and other purposes, took place as a result of urban sprawl in the region. In Sahibganj- Jharkhand, to monitor the LULC change in crop system in between 2005-2011[74] the geospatial technology was used. It was reported that land use change took place in different categories such as agricultural land, fallow land, forest land was changed to quarry class while as, wasteland-dense scrub changed to industrial area. Khanday and Javed reported about spatio-temporal land cover changes in a semi-arid watershed in central India[75]. The study was carried out using IRS 1A Linear Imaging Self Scanning Sensor II (LISS-II) and IRS 1D LISS-III satellite data for the year 1989 and 2011, respectively. A change detection map was prepared for the watershed that reveal changes in different land use categories in almost 26% of the region and rest 74% of the total area extent remain unchanged. Leelambar and Katpatal revealed the time series analysis of LULC and vegetation index change using LISS-III data with the help of remote sensing (RS) and geographical information system (GIS) in Nagpur, Maharashtra[76]. The analysis provided information essential to preserve natural resources and their judicious utilization. The geospatial technology helped in monitoring the changes in LULC due to climate change. Basha *et al.* carried out the LULC study in Somavathi River Anantapur, Andhra Pradesh, India using geospatial technology[77]. The LULC map was prepared by using IRS P-6 LISS-III multi-temporal data sets of 2005-06 and 2010-11 through ArcGIS and ERDAS Imagine 9.3 software. The results revealed that ground features like built-up area and fallow land have changed a little percentage whereas; the agricultural fields have decreased during this period of time.

The two methods mainly used for obtaining information regarding land cover are *field survey* and analysis by remote sensing satellite images[78]. The remote sensing (RS) and geographical information system (GIS) technology has gained a considerable support world-wide[33, 79-81] and is very significant for studying and monitoring the changes in ground elements, and management of environmental resources[82, 83]. The technology plays a vital role by offering a platform effective for quantifying the changes in land features[84, 85] based on series of satellite data images[86] and the resultant information in less time with better accuracy[42] at different levels with positive outcomes[87]. Some of the important applications of RS technology are detection, monitoring and mapping of LULC changes[88, 89].

Multivariate Analysis of LISS-III Satellite images

Principal Component Analysis (PCA) is a statistical tool used for signal analysis in multivariate methods, including data compression, optimal representation and visualizing the multispectral satellite images[90]. PCA is one of the common methods used in most of the remote sensing (RS) applications such as estimation of the spectral differences[91] between two images for effective extraction of features. Change detection using PCA is one of the simple techniques that have potential to augment the information on change[92, 93]. On the basis of Eigen vector analysis, PCA captures maximum variances in limited orthogonal components. The change detection techniques such as image differencing, image ratioing, vegetation index differencing, change vector analysis (CVA) and PCA are very significant in determining the spectral information of satellite images[94]. Based on PCA results, information can be extracted using processes like image classification or image segmentation. The efficiency of classification is increased through high-speed processing time and classification of data for better accuracy[90]. Image classification is based on the fact where spectral response patterns of land cover classes are detected[95] which helps in the identifying, demarcating and mapping of the LULC changes.

There are various approaches available for classification of remote sensing satellite images such as *Supervised and Unsupervised classification*. Supervised classification is done to classify image pixels into different features in order to identify the changes in LULC. The analysis of temporal satellite images and subsequently the extraction of different features are done through classification method where images are clustered into several predefined classes[96].

Maximum likelihood classification (MLC)

The MLC is considered as one of the most accurate classifier algorithm[97] which is based on highest likelihood membership of pixels of unknown class allocated to a special land use class. As a parametric classifier, the MLC is based on Baye's theorem which takes into consideration the variance-covariance in the class distribution data and shows significantly better efficiency than other parametric classifiers. MLC method actually measures the probability for a pixel[98] to be categorized in a most possibly related class assigned for a feature. The classification algorithm for MLC is described in Eq. (1) as:

$$P\left(\frac{v}{C_i}\right) = (2\pi)^{-N/2}|Yi| - \frac{1}{2}\, exp\{-\frac{1}{2}\,(v - Z_i)^T\} Yi^{-T}\,(v - Z_i) \quad ...(1)$$

Where, $P(v/C_i)$ is a multi-variate normal distribution (Gaussian distribution), N- the number of classes for determining the class with vector v measurement, the conditional probabilities, C_1 as classes can be characterized in Baye's classification, Z_i and Y_i represents mean vector and covariance matrix of the data in class C_i and T is the transpose of a matrix is an operator which flips a matrix over its diagonal.

In this paper, change detection comparison (pixel by pixel) technique was applied to the land use\land cover maps derived from satellite images which were classified into different classes based on maximum likelihood (MLC) algorithm.

MATERIALS AND METHODS

Study area

Bathinda is one of the districts of the Punjab state, located in southern part in Malwa region, Punjab, India. The study area lies between 29Ú-33ìì and 30Ú-36ì North latitude and between 74Ú-38ì and 75Ú-46ì East longitude. The total geographical extent of the district is 3327.523km². The study area map was composed in ArcGIS 10.3 software as shown in Figure 1.

Methodology

A geographic information system (GIS) is used to collect, store, manipulate, analyze, manage, and finally display all types of data related to geography of earth's system[99]. For the purpose of LULC dynamics, different data sets are first collected and generated from the sources like topographical maps, satellite images (LISS-III, Landsat, CARTOSAT-I). This is followed by georeferencing of satellite images or topographical maps in image processing software such as ERDAS Imagine 2014 and ArcGIS 10.3 software. The georeferenced images were then allowed to for land use land cover maps using image processing, false color composite (FCC) generation, visual interpretation of ground features and image classification procedures. Finally, the output data/ land use land cover map presents the overall information related to the total area extent of the region, area under different features and subsequent changes over a period of time.

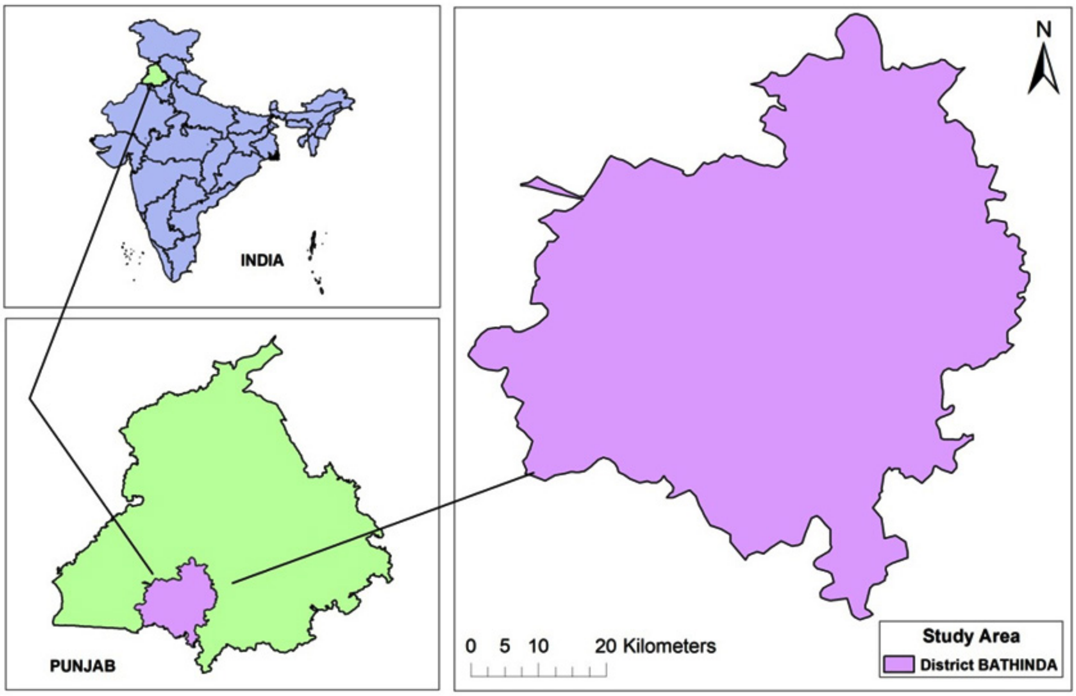

Fig. 1. Study area map (Bathinda district)

Before supervised classification of FCC images for different ground features such as water bodies, agricultural land, vegetation/trees, fallow/ barren land and forests, it becomes essential to have validated classification algorithms (Maximum Likelihood Classifier - MLC) algorithm, in order to determine changes in land cover features. The overview of the methodology is given in Figure 2.

For change detection studies, Linear Imaging Self Scanning Sensor-III (LISS-III) data of the year 2006 and 2018 was procured from National Remote Sensing Centre (NRSC), Hyderabad. This was followed by preparation of interpretation keys (Table 3) based on FCC image of different ground features in the study area. The classification method was based on maximum likelihood classification

Table 1. Characteristics of LISS-III sensor

Sensor	Spectral resolution (µm)	Radiometric resolution	Temporal resolution	Spatial resolution
LISS-III	Band-2 [0.52-0.59 (green)] Band-3 [0.62-0.68 (red)] Band-4 [0.77-0.86 (near IR)] Band-5 [1.55-1.70 (mid-IR)]	7 bits	24 days	23.5m

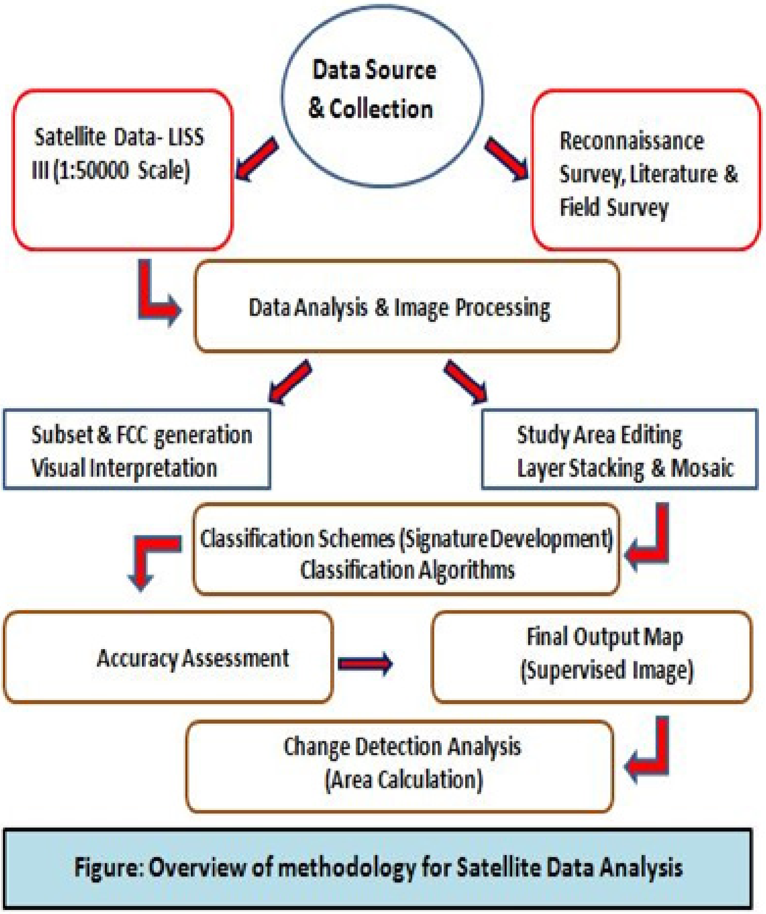

Fig. 2. Overview of methodology for satellite data analysis

(MLC) algorithm for classifying the region in different classes based on different ground features such as water bodies, built-up area/human settlements, agricultural land, vegetation, forest cover, fallow land. The supervised classification of the satellite images and was done with the help of ERDAS Imagine 2014 and ArcGIS 10.3 software.

RESULTS AND DISCUSSION

Satellite Data Used

Linear Imaging Self Scanning Sensor-III (LISS-III), a multi-spectral and multi-temporal satellite data was procured from National Remote Sensing Centre (NRSC)[100] Hyderabad of the year 2006 and 2018 which covers a span of 12years. The LISS-III data consists of 4 bands with 23.5m spatial resolution. The details of digital satellite data used in the study are given in Table 1 and 2.

Satellite Data Analysis
Software

For the purpose of change detection studies, ERDAS Imagine 2014 and ArcGIS 10.3 software were used for false color composite (FCC) generation, image classification and composition of final output map of classified images.

False Color Composite (FCC) image generation

Using 'Layer stacking' and 'Mosaic' processes, the FCC images of the satellite data (Figure 3) were generated on 1:50000 scale for the year 2006 and 2018. For the purpose of 'layer stacking', '**432**' band combination was used for each LISS-III satellite data of the year 2006 and 2018. The images of each data for Bathinda district consist of two scenes (Path/Row93/49 and 93/50) that were merged together through 'mosaic process'. Thereafter, subsets were created for each satellite data using *shape file* of Bathinda district.

Table 2. Details of LISS-III satellite data

Path/Row	Acquiring date	Satellite ID	Agency	Type	Product ID
93/49	17-03-2006	IRS-P6	NRSC, Hyderabad	GEO_ RPC	1.9E+08
93/50					1.9E+08
93/49	26-03-2018	IRS-R2A	NRSC, Hyderabad	GEO_ RPC	1.8E+08
93/50					1.8E+08

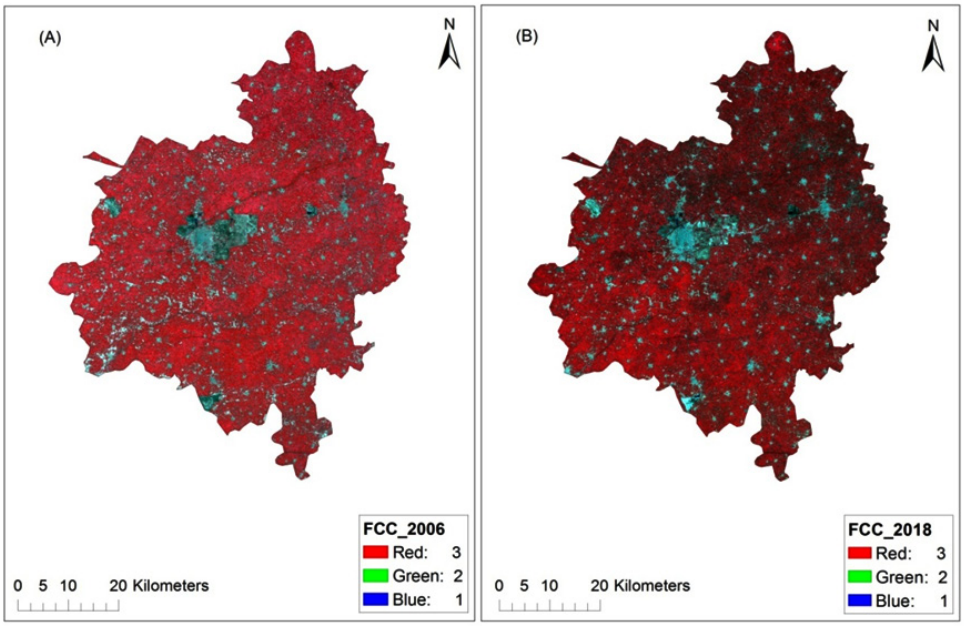

Fig. 3. FCC images of the Bathinda district: (A) 2006; (B) 2018

Visual Interpretation

With the help of visual interpretation elements like tone, texture, and pattern and shape/size, the FCC subset images (Figure 3) of each satellite data were used for visual interpretation and identification of different ground features like water body, agricultural land, forest cover/vegetation, built-up area/human settlements, present in the study area as shown in Table 3.

Multivariate Analysis of LISS-III Satellite images

Multivariate analysis was carried out by using principal component analysis (PCA) for the three raster bands of the LISS-III multi-temporal data sets of the year 2006 and 2018. Principal component data usually captures all the spectral information from the bands, and then compresses the data into principal components. In PCA results, PC1 has the most spectral information which is followed by PC2 that stores rest of the spectral information and so on. The three input layers-Red, Green and Blue were marked as 1, 2 and 3 respectively.

Three principal components PC1, PC2 and PC3 having Eigen value greater than 1 and total percent of Eigen values 71.070%, 28.406% and 0.525% were selected. From the results (Table 4), high loading for the layer 2 in PC1, layer 3 in

Table 3. Visual Interpretation keys of LISS-III satellite data

S. No.	Ground feature	Interpretation keys			
		Tone	Texture	Shape/size	Pattern
1	Water	Light to dark blue	Smooth	Regular	Dispersed
2	Agricultural land	Light to dark pink; Light brown	Smooth	Fixed	Regular
3	Built-up area	Cyan; Grey	Mottled	Irregular	Clustered
4	Vegetation/Tree/ Forest cover	Dark pink; Light red	Rough	Irregular	Dispersed
5	Fallow land/ Barren land	Bright white; Grey mixed	Medium to Coarse	Irregular	Dispersed

Table 4. Weight of three principal components of input layers of LISS-III raster bands (2006)

Input Layer	PC1	PC2	PC3
1	0.491	0.349	0.798
2	0.708	0.372	-0.56
3	-0.506	0.859	-0.064
Eigen values	168.334	67.281	1.243
Eigen values (%)	71.07	28.406	0.525
Cumulative Eigen values (%)	71.07	99.475	100

Table 5. Weight of three principal components of input layers of LISS-III raster bands (2018)

Input Layer	PC1	PC2	PC3
1	-0.236	0.566	0.79
2	-0.357	0.705	-0.612
3	0.904	0.427	-0.036
Eigen values	590.516	316.491	2.536
Eigen values (%)	64.925	34.797	0.279
Cumulative Eigen values (%)	64.925	99.721	100

PC2 and layer 1 in PC3 were observed for the year 2006.

Three principal components PC1, PC2 and PC3 having Eigen value greater than 1 and total percent of Eigen values 64.925%, 34.797% and 0.279% were selected. From the results (Table 5), high loading for the layer 3 in PC1, layer 2 in PC2 and layer 1 in PC3 were observed for the year 2018.

From the PCA results for the two images of satellite data for the year 2006 and 2018, it was revealed that the maximum spectral information

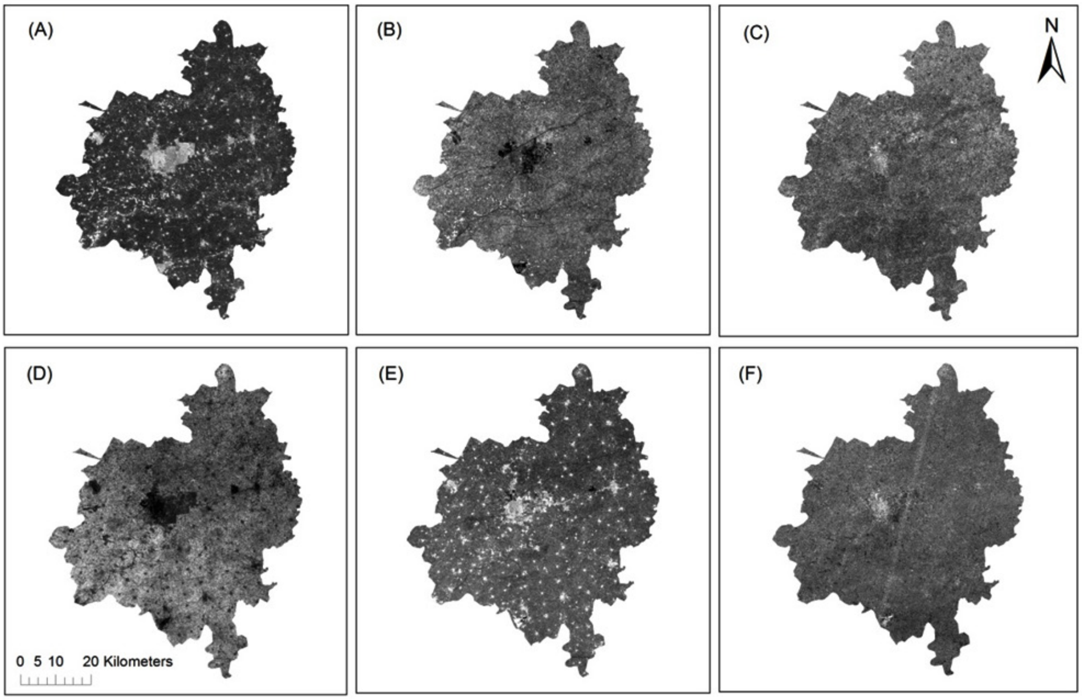

Fig. 4. First three principal components of the year 2006 (A-C) and 2018 (D-F)

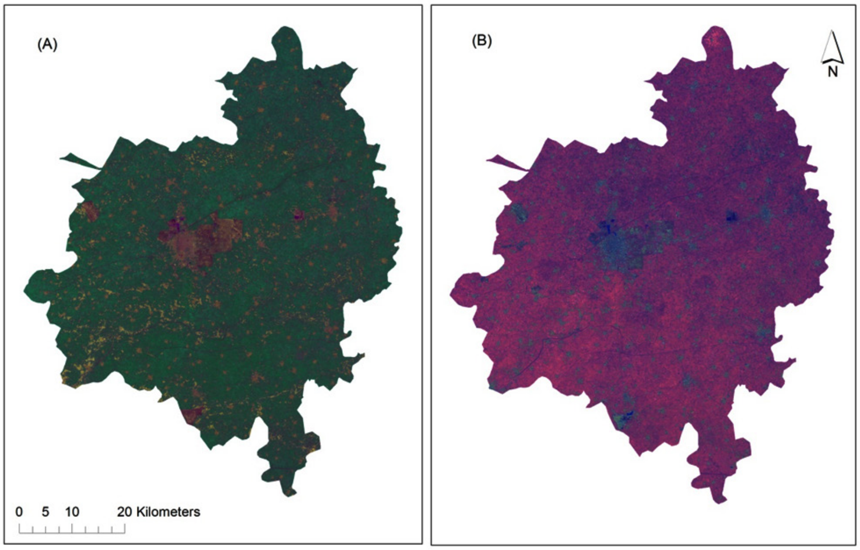

Fig. 5. RGB composition images of the year 2006 (A) and 2018 (B)

between two images was obtained for the input layer 2 and 3, respectively and hence showing high correlation for unchanged areas. The three principal components and RGB obtained through PCA-multivariate analysis are given in Figure 4 and 5.

Image Classification

For classification of satellite data using supervised classification, maximum likelihood

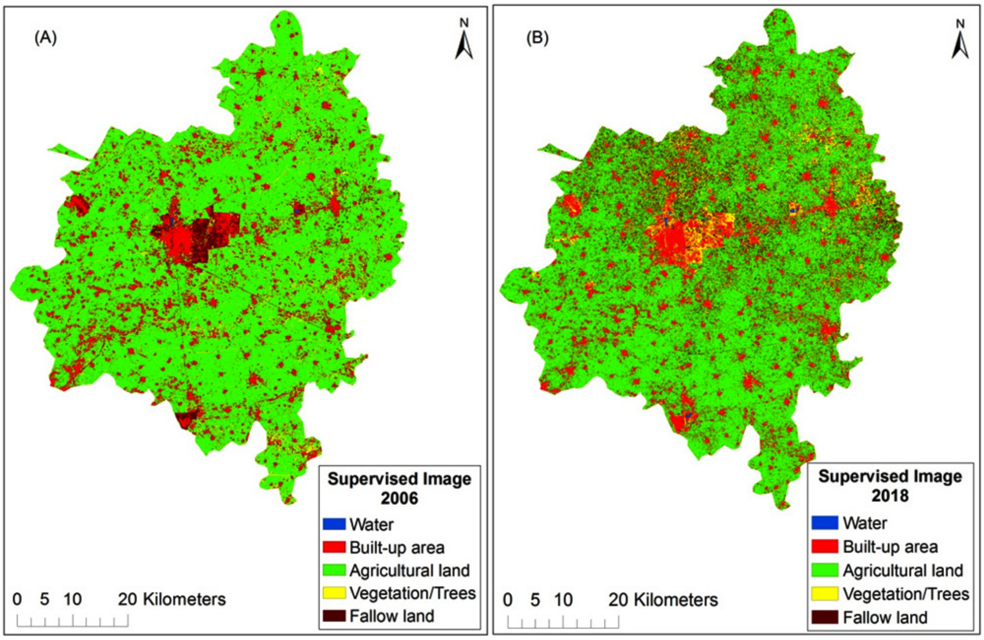

Fig. 6. Supervised images of the Bathinda district: (A) year 2006; (B) year 2018

Table 6. Accuracy Assessment Report (2006)

(a) Accuracy Report
Accuracy Totals

S. No.	Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
1	Water	0	0	0	——-	——-
2	Built-up area	35	34	29	82.85%	85.29%
3	Agricultural land	64	66	63	98.44%	95.45%
4	Vegetation/Trees	1	0	0	——-	——-
5	Fallow land	1	1	1	100%	100%
6	TOTAL	248	248	245		

(b) Kappa (K^) Statistics
Conditional Kappa Statistics

S. No.	Class Name	Kappa (K^)
1	Water	0.0000
2	Built-up area	0.8234
3	Agricultural land	0.9314
4	Vegetation/Trees	0.0000
5	Fallow land	1.0000

classification (MLC) method was used which performs much better than other methods of classification such as hybrid and parallelepiped classification[101]. Unsupervised classification gives an idea about the spectral variability which provided a basis for carrying out supervised classification. In supervised classification, training samples were prepared of five different ground features which include water, built-up area, agricultural land, vegetation/trees and fallow land as shown in Figure 6, the spectral *signature file* was created based on *training samples* using 'Areas of Interest (AOI) tool'. This was followed by the determination of the classes of interest for all features. The spectral signatures (input to MLC) and training data were used for the satellite images to categorize the pixel values to similar/corresponding classes based on the classifier used.

Accuracy Assessment

The overall classification accuracy of LISS-III data for the year 2006 was found to be 96.58% and the overall Kappa statistics equaled to 0.9483 as shown in Table 6. Similarly, the overall classification accuracy of LISS-III data for the year 2018 was found to be 91.43% and the overall Kappa statistics equaled to 0.8804 as shown in Table 7.

The accuracy assessment report along with Kappa statistics (K^) (Table 6 and 7) were generated by comparing the products of classification with reference data. The reports determines the quality of images classified (supervised) whereas, the Kappa statistics reveals about the measurement of agreement between the classified images and the reference data or statistical value reflected which is significantly better than random values included in an error matrix[102].

Change Detection Analysis

From the results (Table 8a), it was revealed that the land area occupied under different LULC classes water bodies, built-up areas, agricultural land, vegetation/trees and barren/ fallow land found to be 2.103km^2, 584.448km^2, 2686.121km^2, 28.490km^2 and 26.361km^2 in 2006 while as in 2018, it was found to be 2.516km^2, 852.140km^2, 2398.384km^2, 54.678km^2 and 18.367km^2, respectively. The total area extent of the study area was found to be 3327.523km^2. Since the state of Punjab is an agrarian state; where most of the land is being occupied by agricultural

Table 7. Accuracy Assessment Report (2018)

(a) Accuracy Report
Accuracy Totals

S. No.	Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
1	Water	0	0	0	-----	-----
2	Built-up area	24	29	23	95.83%	79.31%
3	Agricultural land	65	59	58	89.23%	89.23%
4	Vegetation/Trees	32	31	30	93.75%	93.75%
5	Fallow land	0	0	0	-----	-----
6	TOTAL	248	248	244		

(b) Kappa (K^) Statistics
Conditional Kappa Statistics

S. No.	Class Name	Kappa (K^)
1	Water	0.0000
2	Built-up area	0.7727
3	Agricultural land	0.8659
4	Vegetation/Trees	0.9125
5	Fallow land	0.0000

fields with more than 4.2 million hectares (83%) under cultivation[103] followed by settlements and other infrastructures. Therefore, the major changes would have taken place in these two features as a result of population explosion, urban sprawl and industrialization. The area under water bodies showed a slight increase of 0.413km^2 in 2018. The built-up areas include human settlements, commercial structures, malls, roads and other pavements, have increased from 584.448km^2 to 852.140km^2 in the 12years span of time. The area under agricultural land has decreased from 2686.121km^2 to 2398.384km^2 between 2006 and 2018. The vegetation (trees) showed an increasing trend between 2006 and 2018 from 28.490km^2 to 54.678km^2, respectively. Finally, the area under fallow land/barren land showed a decrease of 7.994km^2 from 26.361km^2 to 18.367km^{2}during 12years of time.

Table 8(a) and 8(b) shows area covered by different land use land cover classes and subsequent change detection between 2006 and 2018. The increasing trend 267.692km^2 (8.024%) found in built-up area may be due to the increase in human settlements and their activities as a result of increasing population, urbanization, or other commercial activities[43]. The decrease in the area extent of agricultural land may be attributed to the increase in built-up areas[48] or vegetation/forest cover as revealed from the study. The agricultural land has decreased by 287.737km^2 (8.744%) which is a cause of concern so far as the food security is concerned. The agricultural land conversion reduces production of grains which ultimately causes threat to food security[104]. The appreciable amount of increase in built-up areas and other commercial infrastructure (roads, railway tracks and buildings) could be a result of urbanization

Table 8(a). Area covered by different land use land cover classes between 2006 and 2018

Table I: Total area (km^2) covered by different land use land cover classes (2006-2018)

S. No.	LULC Class	Area (km^2) in 2006	Area (km^2) in 2018
1	Water	2.103	2.516
2	Built-up area	584.448	852.140
3	Agricultural land	2686.121	2398.384
4	Vegetation/Trees	28.490	54.678
5	Fallow land	26.361	18.367

Table II: Total area (%) covered by different land use land cover classes (2006-2018)

S. No.	LULC Class	Area (%) in 2006	Area (%) in 2018
1	Water	0.063	0.076
2	Built-up area	17.585	25.609
3	Agricultural land	80.821	72.077
4	Vegetation/Trees	0.857	1.643
5	Fallow land	0.793	0.552

Table 8(b). Change detection in different land use land cover classes between 2006 and 2018

S. No.	LULC Class	Change detection (km^2)	Change detection (%)
1	Water	(+) 0.413	(+) 0.013
2	Built-up area	(+) 267.692	(+) 8.024
3	Agricultural land	(-) 287.737	(-) 8.744
4	Vegetation/Trees	(+) 26.188	(+) 0.786
5	Fallow land	(-) 7.994	(-) 0.241

and expansion of commercial activities in the past 10-20years. For settlements and commercial infrastructure, the agricultural land has been a prime target to be converted for non-agricultural purposes[105] which could be a major threat to the croplands[106]. It was reported that a number of households, especially in developing countries; depend on land and other natural resources for fulfilling their immediate needs and achieving their long-term ambitions[107]. The land under vegetation/forest cover showed an increasing trend from 0.857km^2 to 1.643km^2 (0.786%) which could be due to increase in plantation programmes, social forestry, agro-forestry, urban

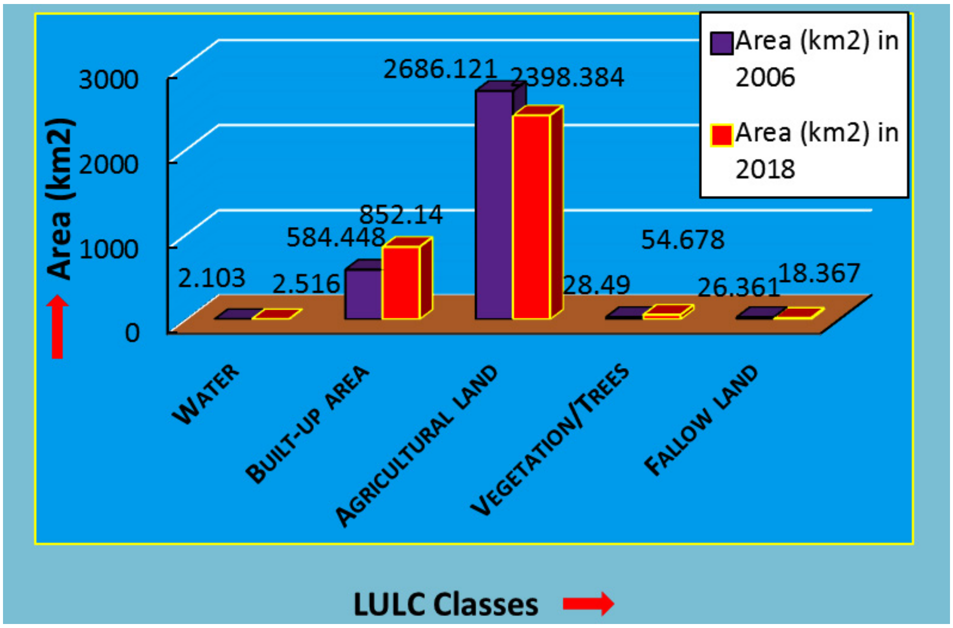

Fig. 7. Area-wise (km^2) change detection in different LULC classes

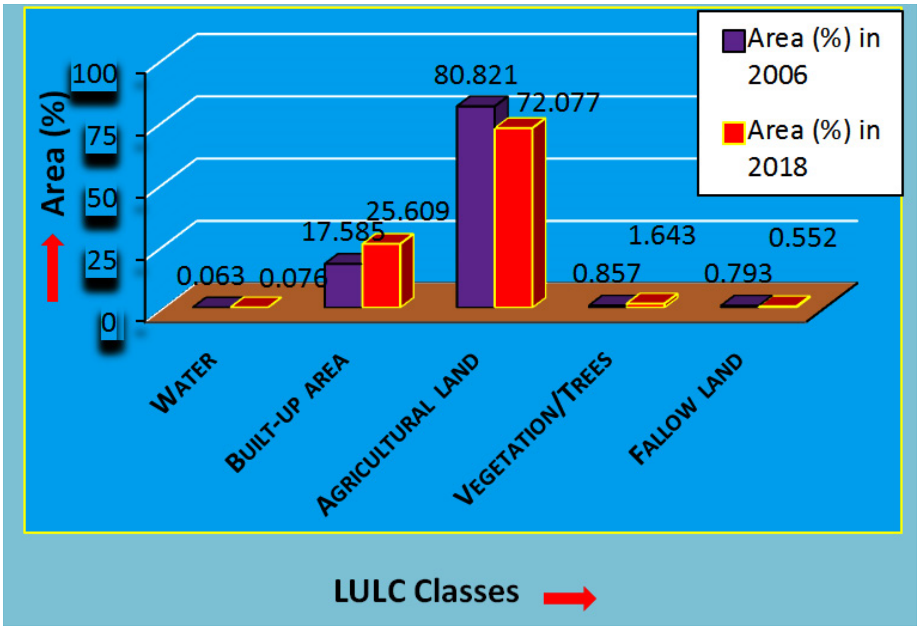

Fig. 8. Percent-wise (%) change detection in different LULC classes

forestry initiatives and other land use and forest policy programmes launched by government of India (GOI) under National Action Plan on Climate Change (NAPCC), State Action Plan on Climate Change (SAPCC) and Atal Mission for Rejuvenation and Urban Transformation (AMRUT). The main goal of 2015 AMRUT policy is to increase green cover to 15% in various cities[108]. Green India Mission (GIM) under 2014 NAPCC aimed at protection, restoration and increasing the forest and tree cover in urban, sub-urban areas with the main target to increase the tree and forest cover by 5 million hectares (Mha), and to enhance the quality of the current trees and forest cover in another 5 Mha of degraded forest lands in forest areas in next 10years[109]. Green Punjab Mission (GPM) under SAPCC includes primary target of covering 15% of total geographical extent of the state under trees and forest cover[110]. The successful execution of such policies can be clearly seen in the supervised image of the year 2018 (Figure 6) with increasing vegetation and decreasing fallow lands; and is considered as a good sign for management and restoration of diminishing forest resources, degraded lands (barren lands/fallow lands); and other natural landscapes and biodiversity. The decrease in the barren/fallow land from 0.793km^2 to 0.552km^2 (0.241%) may be attributed to the increase in vegetation/trees as a result of different plantation programs as mentioned earlier at various levels offered by government or to some extent engulfed by built-up and commercial settlements.

Figure 7 and 8 reveal the column chart representation of changes in different LULC classes from the year 2006 to 2018. It was clear that the land area under the human settlements (built-up area) and other commercial infrastructures has increased by 8.024% while the area under agricultural activities has decreased by 8.744% within a span of 12years. Generally, the expansion of built-up areas takes place either on urban extremes or alongside transportation pathways[111] which resulted in increased land uses in urban sectors. The urban sprawl that leads to growth of infrastructure; buildings, road and communication facilities, promotes land to be different from its original use[112]. The other LULC classes have also shown some considerable amount of changes in the respective area extent as shown in the Figure 7 and 8. The decrease of 0.241% in the area under fallow land could be due to the urban sprawl (settlements and other man-made infrastructures) and other anthropogenic activities[110] or to some extent attributed to increase in the vegetation cover.

The increase in area extent under vegetation/trees LULC class by 0.78% in the region may be attributed to greenery and maintenance of open spaces (parks) and other plantation programs like AMRUT, GIM and GPM organized at different levels in the recent past[85]. The increasing temperature in urban cities i.e., UHI, at global level and at micro-climate level due to sprawl of built-up structures and other pavement surfaces[113, 114] can be countered by increasing the green cover through urban forestry schemes like AMRUT and other social forestry programs in suburban and urban areas. When a huge amount of natural land is replaced by artificial built surface (as evident from the Figure 4 and Table 6b) that absorbs incoming solar radiation or heat and re-radiates it at night, the UHI develops[115, 116]. The fact is that the UHI phenomenon exists in almost every big city[117] around the world. The district of Bathinda is very hot in summer season with daily temperature reaching up to 49ÚC; the forestry schemes (AMRUT) especially in urban areas plays an important role in minimizing the heat generated during hot days, thereby reducing the impact of UHI, a local climate change phenomenon. Therefore, the promotion and execution of urban forestry (such as AMRUT scheme) and social forestry initiatives will reduce the costs of maintaining the rising temperature and related impacts to a low level as compared to the regions where green cover is inadequate especially in arid and semi-arid regions.

RS and GIS plays a crucial role in this case to estimate the changes in land use land cover such as, loss of agricultural land[118], industrial and human settlement expansion[119], forest encroachment[120, 121] and road network expansion[122]. The change detection studies in the Bathinda district proved to be very significant in monitoring the changes in ground features such as settlement and agricultural land and it would serve as a baseline for future monitoring and assessment of LULC changes in the region. On the basis of change detection studies, it will be very easy to focus on the area which are under serious threat such as decrease in agricultural land due to rapid expansion of human settlements and decrease in forest cover.

Remote sensing (RS) can monitor UHI on regional or continental scales which could be very useful in understanding urban/suburban environment and its relationship with urban sprawl[123]. It also provides an opportunity to investigate the temperature differences between urban and rural areas, estimate land surface temperatures (LST) and urban heat islands[124]. A number of studies are evident that suggested the applicability of RS satellite images in measuring LST and UHI on spectral, spatial and temporal scales[125-130] besides the use of satellite sensors for detection and assessment of UHI[131]. Various other studies revealed the significance of satellite images in detecting the relationship between LST and the changes in LULC[132-135] due to urbanization and other anthropogenic activities.

CONCLUSIONS

From the results, it was revealed that the changes in different ground features such as agricultural land or built-up areas have taken place because of different human activities. During the study, the major changes were observed in built-up areas and agricultural sector where the land area under built-up area increased and the area under agricultural land showed a decreasing trend in the last 12years of time span. The classes such as water bodies, vegetation/trees and fallow land have also experienced some changes. The increase in vegetation cover and decrease in fallow land is attributed to various land use and forest policy programmes launched under NAPCC, SAPCC and AMRUT. The increase in areas especially vegetation/trees cover would help in combating the global warming, UHI and to some extent; and restoration of degraded forest areas. Thus, it was proved that monitoring of LULC changes and subsequent management of the resources is possible by using satellite data information aided with geospatial technology supported by different land use policies and plantation programmes recently launched by the central and state governments of India.

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