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ORIGINAL PAPER

Change Detection and Feature Extraction Using High-Resolution Remote Sensing Images

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Abstract

Change detection using high temporal resolution remote sensing satellite data for identifying changes on the Earth's surface is critical in urban applications, including vacant land site monitoring. Physical ground surveys, for monitoring the vacant site, are a time-consuming process. Results of analysis of satellite data for identifying changes vary, based on the image interpretation skills and satellite data resolution. The application of computer vision tools and libraries for change detection using image interpretation has shown some excellent results. It can be further enhanced by adding machine learning techniques. This study focuses on integration of binary change detection with machine learning techniques for identifying the change detection and for monitoring the vacant sites in an urban area. Edge detection technique coupled with principal component analysis and k-means clustering for generating change map successfully depicts the changes. Change detection results are further enhanced by adding feature type information derived using machine learning–based classifiers. Random forest classifiers are used to classify and identify different land use classes within the urban area: water bodies, cropland, built-up, roads, and bare land. The approach is evaluated on different areas, giving an overall accuracy of 88.2%, precision of 84.8%, and an F1 score of 81.6% for classification. The classification results are integrated with change detection results to identify changes where the bare land is transformed into built-up by identifying buildings/houses. The work will be helpful in urban planning bodies having multiple vacant land sites for monitoring.

Keywords Remote sensing satellite data · Canny edge detection · Principal component analysis · K-Means clustering · Random forest classifier

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1 Introduction

Constellations of Earth observation satellites are being used in applications of land, water, cartography, ocean, weather, and climate studies. Analysis of remote sensing satellite data enables change monitoring at regional or global levels for land, water, and environmental problems. It plays an important role in solving one of the important questions of Earth system science, namely, Earth surface change. Study of Earth surface change is extremely important in assessing and responding to extreme events and natural disasters. It involves identifying changes in satellite images over the same study area at different time intervals. Researchers have successfully utilized remote sensing satellite images to identify changes in land use, land cover, urban growth, and deforestation [1],De Bem et al. 2021). It minimizes the need of field surveys, previously organized to identify and map the changes. However, field surveys can be used to improve the accuracy of identified changes by verifying the results obtained using satellite data analysis. The changes identified may be natural or man-made. Differentiation in changes depends on satellite data usage for the targeted application. High-resolution satellite data is needed for flood monitoring and damage assessment in urban areas. Change detection based on a series of temporal satellite images needs a different algorithm from change detection for real-time applications. Algebra-based [2], transform-based [3], classification-based [4], and customized models [5] are the primary change detection methods capable of detecting changes using remote sensing satellite images. Obtaining different images by applying mathematical operation on each image pixel, using image differencing, rationing, and change vector analysis (CVA), is the basic principle of the algebra-based change detection approach [6]. The algebra-based approach is easier to implement for identifying the changes,however, it lacks complete information of changes identified. Instead, change detection using transforms by applying Gramm-Schmidt transformation, principal component analysis (PCA, and Tasseled Cap transformation minimizes the duplicate information between bands and provides good results compared to algebra-based methods for identifying changes. It can be further improved by utilizing discrete wavelet transform (DWT on fused satellite images [7].

It is very difficult and needs a lot of expertise to label change area information obtained using transformation methods. Change detection using classification can be attempted using AI techniques like artificial neural network supervised and unsupervised classification methods. Change detection using classification methods minimizes external factors' effect. However, the results completely depend on training datasets. Classification methods with inadequate training datasets can result in inaccuracy and unsatisfactory results. The availability of rich training datasets for implementing change detection using classification is also a challenge [8]. Analysis of multispectral images using object-based analysis, gray-level co-occurrence matrix, and fuzzy logic membership functionality has successfully been implemented for landslide delineation and landslide-related change detection for smaller study areas [9]. For attempting change detection studies in larger areas using heterogeneous multi-source information and temporal coverage, Geographical Information System (GIS) has shown promising results [10]. This type of study includes calculating the Normalized Difference Vegetation Index (NDVI) using temporal satellite images over the same area. Comparison of NDVI obtained from a pair of images can be used for identifying the changes. Detailed information of methods and techniques used by researchers for remote sensing-based applications is given in Table 1.

The change detection methods discussed are used for identifying the changes over a large area with a theme that can be identified using image analysis techniques like image differencing (ID), modified ID, principal component differencing, and change vector analysis, and combinations of them. The binary change detection technique has shown promising results in identifying the changes using calibration approach from QuickBird satellite data and hyperspectral imagery [11, 12], as it involves detecting change or no change, i.e., binary change information. Usage of a single variable and threshold may not be suitable for identifying changes over large areas. For multi-band images, identifying the optimum threshold value is a challenge. This study aims to improve the efficiency of the binary change detection method by applying masks, removing noise, and assessing the accuracy by automated scripts. Also, the improved technique is to be tested and used for identifying the changes over a smaller area like asset/property monitoring for identifying encroachment/changes over a period in an urban area. Implementation of change detection in an urban area needs very high-resolution satellite data over the study area. Merely identifying change only is not sufficient. Once the changes are identified, another important objective is to identify the feature type in the identified change [13]. Identification of relevant information from satellite images using computer vision or image processing libraries is attempted based on color, shape, or texture information. Different techniques for extracting features can be applied based on image features and their properties including pixel level, local level, and global level. General features from satellite images can be extracted based on color by applying color histogram, color coherence vector, color moments, and color correlogram techniques. In contrast, spatial and spectral properties are used for texture information extraction. Region and contour properties are used to extract features based on shape [14].

Table 1 Change detection methods techniques for remote sensing-based application

Application	Method used for change detection	Model/author
Wetland change detection	Spectral mixture analysis and change vector analysis	[28]
Land use land cover change detection	Binary change detection (CD) task and a multiclass CD	[29]
Forest change detection	Visual saliency and random forest	[30]
Urban change detection	Object-based change detection	Zang et al. 2017
Urban change detection	Convolution neural networks	[31]

Feature properties, including mean, median, standard variance, intensity, and skewness, are used by various models like the Gaussian mixture model, stochastic model, and probabilistic model, where the intensity of features can be used for its extraction (Li and Ai 2018). Machine learning and deep learning models have shown promising results in feature extraction and image classification using remote sensing satellite images [15, 16]. However, it demands high-performance processors, skill sets, and rich training datasets. Edges in remote sensing satellite data play a vital role in representing the local intensity change. Intensity difference in an image can be helpful in region separation within an object and identifying illumination change [17]. Canny edge detector algorithm used for detecting the edges can be modified to demarcate the feature edges in a satellite image [18–20]. Feature extraction using Canny algorithm involves a sequence of steps namely, image filtering, image gradient calculation, non-maximum suppression, and checking connecting edges. The results may contain noise, which can be minimized by updating the Canny algorithm with scale multiplication and increasing the image gradient area [19]. The algorithm has the potential to be integrated with the latest supervised machine learning algorithm [21]. This study proposes integrating the binary change detection method with a Canny edge detection algorithm and supervised machine learning algorithms for developing an automated framework capable of identifying the changes and extracting the features using heterogeneous high-resolution satellite data. Machine learning algorithm is used to identify different land use classes within the urban area for increasing the accuracy of feature detection. It is to automate the time-consuming manual analysis of temporal satellite datasets for identifying the changes. Performance of binary change detection approaches like edge detection technique has been increased by integrating it with supervised machine learning algorithms for detecting changes. Information of features going under change with respect to time is of much importance. It is very important in detecting, characterizing, and monitoring urban land change. Furthermore, it can be used to analyze urban water demand and impact on water resources, by assessing the changes in land use. However, the approach is new and lots of improvement can be done in the future. The present work opens another approach to solve the problem of change detection using high-resolution multi-temporal satellite images.

2 Material and Methods

2.1 Study Area

The study area, Delhi National Capital Territory (NCT), is geographically located at 28.7041°N, 77.1025°E, and lies in northern India (Figure 1). It covers a geographical area of 1490km^2, divided into two parts, East Delhi and West Delhi, by Yamuna River. Yamuna River dominates Delhi's physiography. The Delhi Ridge and its four sections, the northern, the central, the south central, and the southern, constitute the farthest extension of the Aravalli Range, its spurs meeting the Yamuna at two points, in the north and the east. The area under plain are New Delhi and Delhi cantonment along with a vast stretch of numerous villages observing significant changes in settlement areas, as a lot of new construction activities have taken place in the past few years, making it suitable for carrying out this study.

2.2 Data Used

This study used temporal high-resolution satellite data of QUICK BIRD and Cartosat 2S for two time periods, viz., 2006 (T0) and 2019 (T1) for the change detection. QUICK BIRD (Digital Globe) high-resolution satellite provides panchromatic imagery at 61-cm resolution and multispectral imagery at 2.44- to 1.63-m resolution, making it suitable for studying changes in the urban area, including infrastructure-like buildings. Cartosat 2S high-resolution satellite data providing panchromatic imagery at 65-cm resolution and multispectral imagery at 2-m resolution are used as T1 data. Multiple scenes (10 scenes of QuickBird and 70 scenes of C2S) covering the study area were processed for generating a high-resolution satellite database. Ancillary data in terms of administrative boundaries obtained from the SIS-DP (Space-Based Information Support for Decentralized Planning) project has also been used to meet the objectives of the study.

2.3 Methodology

The detailed methodology adopted in this study is shown in Fig. 2. Temporal high-resolution satellite data covering the study area was acquired from satellite data providers. At first, the satellite data was pre-processed by performing radiometric and geometric corrections using standard GIS software. It is very much needed as the data used for change detection analysis is obtained from different sensors at different periods with slightly varying spatial resolution. Furthermore, the input satellite data is processed by applying convolutional filtering to remove the noise. It has been fine-tuned by applying gridding and threshold techniques. Gridding helped in comparison of the pixel values in T0 and T1 satellite images to identify changes. In contrast, the threshold approach is useful for segregating the features from satellite imagery that has not been used to identify

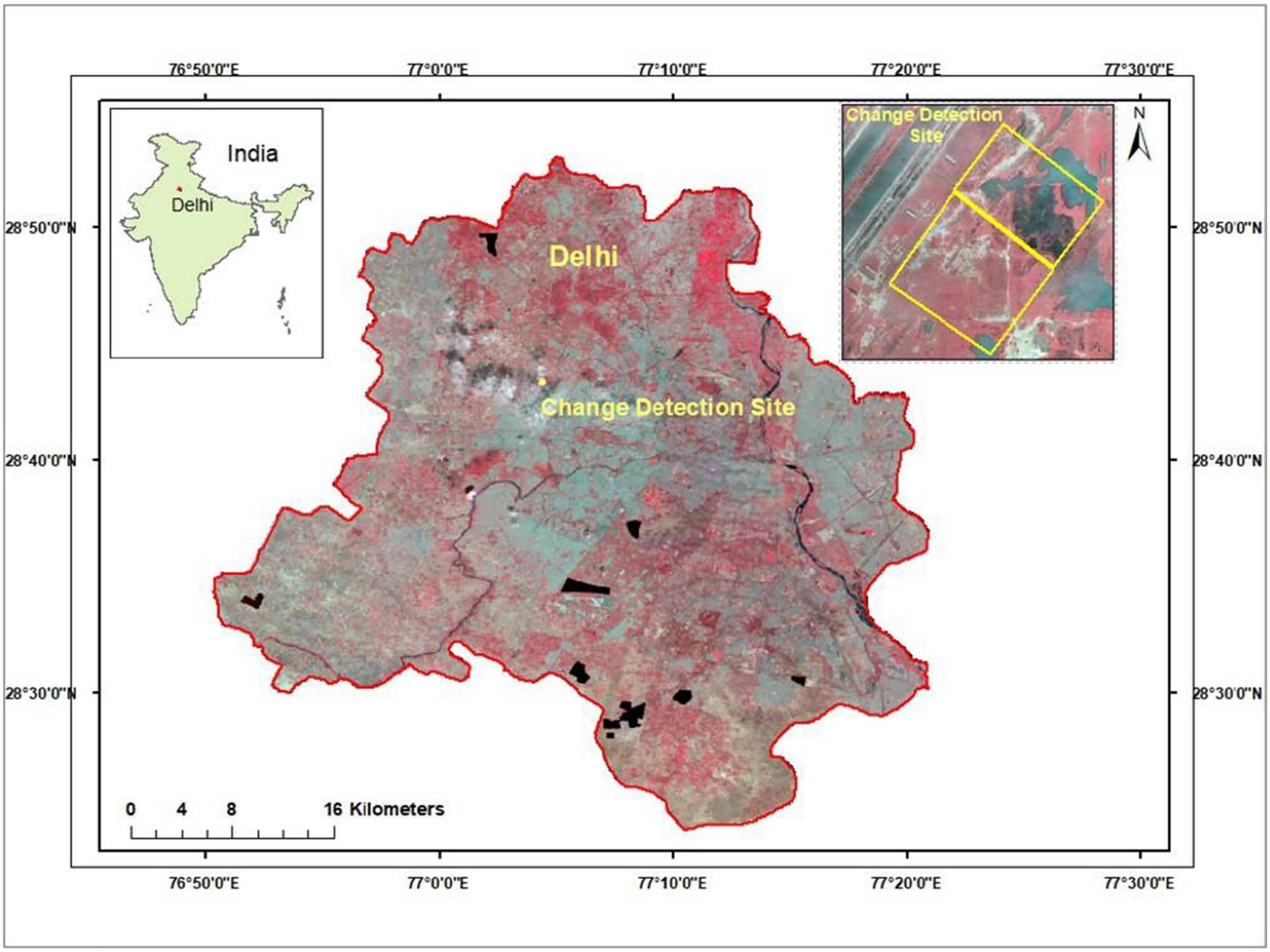

Fig. 1 Location map of the study area

the changes. Change identification for regular monitoring of the assets/boundaries is of much importance to various development authorities. For user-defined change detection approach, a provision to supply the area of interest (AOI) in the form of a.shp file (ESRI shape file) is provided. For identifying the decadal changes, multi-temporal satellite data is needed. Obtaining the temporal cloud-free satellite data over the entire city is a challenge. For proof of concept, temporal cloud-free satellite data over a few pockets has been used for this study. For detecting changes, a minimum of 2 sets of input satellite images, acquired at times T0 and T1, are needed. Once the 2 images are selected, satellite data pre-processing techniques were applied on it for performing radiometric and geometric corrections. Essential steps including atmospheric correction, Earth-Sun distance correction, sun elevation corrections, and radiometric normalization (using linear radiometric normalization methods and histogram matching) are performed in pre-processing of satellite data. These are very essential pre-processing steps, needed for analyzing multisensory satellite datasets. The radiometric and geometric–corrected images were further processed by applying convolutional filtering. Different matrix combinations, including 3×3 and 5×5, were applied. With a larger matrix, the local information needed for identifying changes gets reduced, whereas the processing time increases with a smaller matrix. Furthermore, a grid vector is prepared, covering the study area and integrated with corrected and filtered input satellite images. The range of threshold values was tested over a wide range of satellite images acquired using different sensors. The input images are now pre-processed and ready for further processing.

Software module using Python programming language and OpenCV (Open Computer Vision Library) is developed for change detection and feature extraction. The temporal input images are supplied to the module; it reads and resizes the satellite images. Once its resized clipping operation is executed, clipping the input image to the AOI, supplied as a vector file, over which the change analysis is performed. The input image further gets differenced. The geo-processing operations in python are executed using the open-source

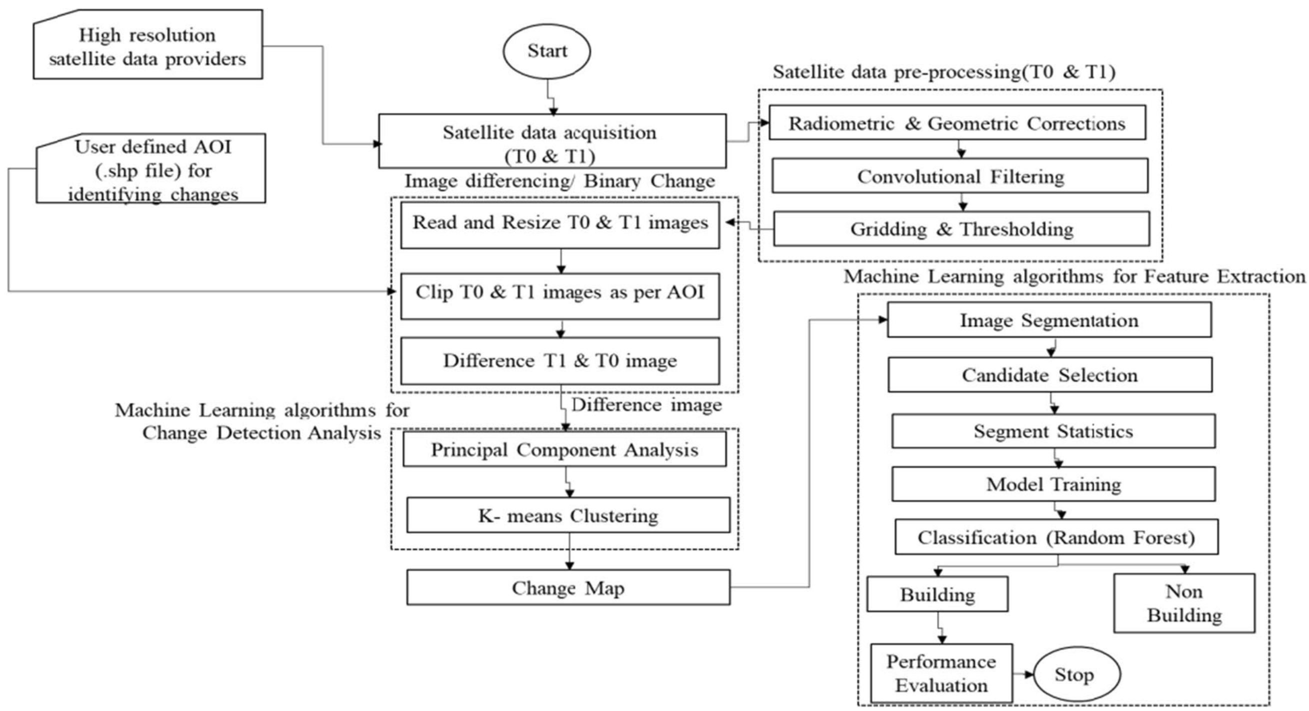

Fig. 2 Methodology flowchart for change detection and feature extraction using temporal satellite data

Geopanda library. The machine learning algorithm is applied to identify the correlations using the covariance matrix. Principal component analysis unsupervised machine learning algorithm is applied to identify the principal components. It does so by computing eigenvalues and eigenvectors of the covariance matrix. The clustering algorithm is applied to the PCA output for generating feature vector space. K-Means clustering algorithm is applied to the feature vector space of T0 and T1 images to generate a change map. The change map depicts and highlights the changes in AOI by analyzing the T0 and T1 images. The changes observed over the study area can be further classified to know the type of change. Feature extraction can help in identifying the change type, i.e., a new development, encroachment, or vegetation change. In the urban monitoring system, development of built-up (planned or encroached) is of much importance. Random forest, a machine learning classification algorithm, is applied to the satellite image (change map) to classify the image into a building or non-building class. For this, the satellite image are segmented using Quickshift segmentation algorithm [22]. Candidate selection is implemented onto the segmented image to exclude the natural changes like vegetation, water, etc. Removal of shadows from input images is attempted [23]. In segment statistics, for each segment of the image, minimum, maximum, mean, variance, skewness, and kurtosis for each band are calculated and saved for further processing. Furthermore, the training datasets were generated, and a suitable ratio of training and validation dataset ratio (80:20) is maintained for model training. To increase the number and diversity of training samples, data were augmented by scaling, rotation, and rescaling. Each image with 446 × 446 pixels generated 3 additional images by applying 90° rotation. Similarly, slicing and rescaling enriched training datasets for effective implementation of the algorithm. Furthermore, the RF classification is applied to classify the input feature into building and non-building classes. The results obtained are evaluated using various performance parameters. Further identification of different land use classes within the urban area is attempted.

3 Results and Discussion

This study takes the temporal high-resolution satellite data of QuickBird and Cartosat 2S data of 2006 (T0) and 2019 (T1). The subset of the satellite data is taken as AOI for executing the procedure (Figure 3).

The input images are pre-processed and binary change detection is attempted on satellite images using edge detection techniques. Edge detected over the AOI is shown in Figure 4.

Various grid sizes are checked to get the best result. Grid size of 25×25 shows the good results over the AOI. Vector grids of 25 × 25 integrated with input satellite image are shown in Figure 5.

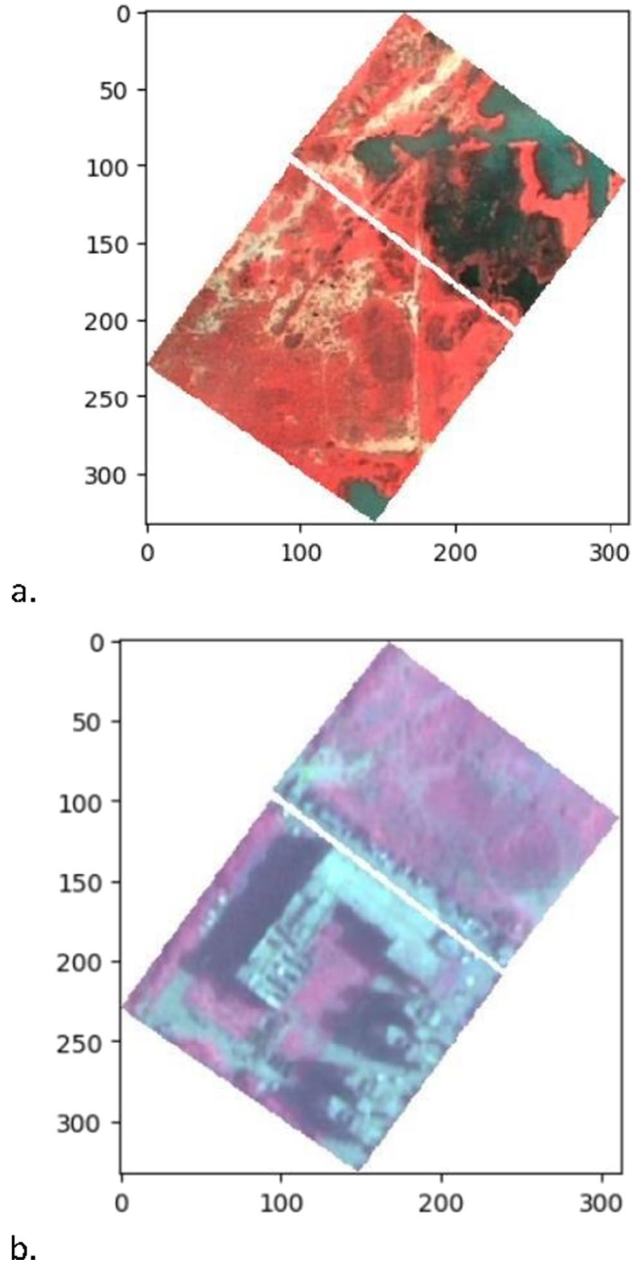

Fig. 3 **a** Temporal satellite image (T0, QuickBird-2006). **b** Temporal satellite image (T1, Cartosat 2S-2019)

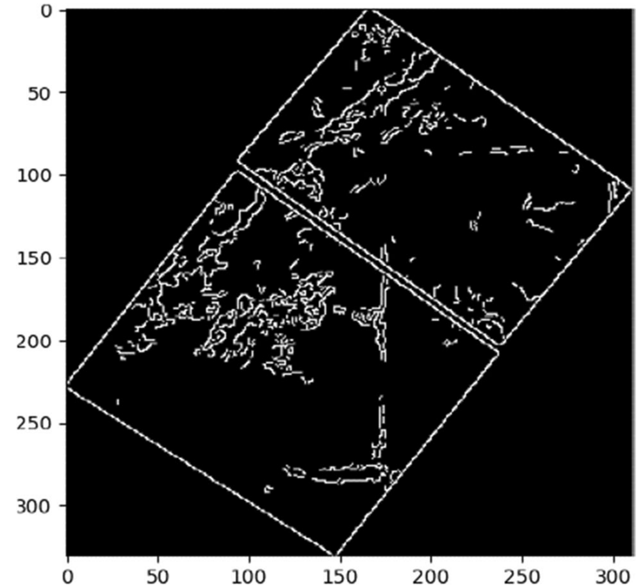

Fig. 4 Edge detected over AOI

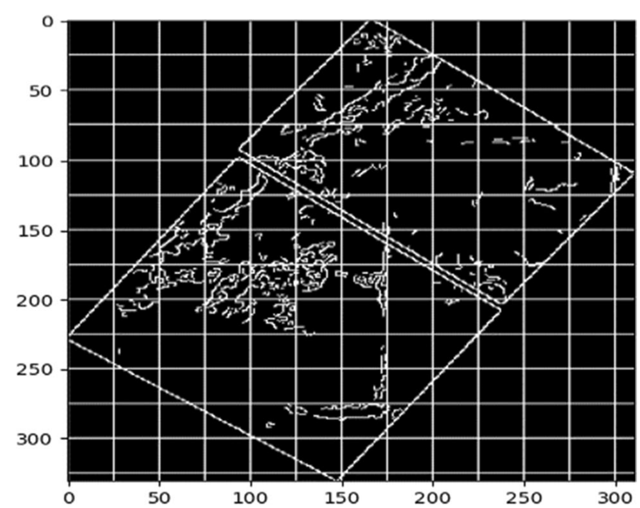

Fig. 5 Input satellite image integrated with vector grids of size 25 × 25

Principal component analysis (PCA) and K-means machine learning algorithms are applied to difference images obtained earlier for change identification. Changed location can be identified, as a result of ML algorithm as shown in Figure 6 where Figure 6a shows the results of change in area and Fig. 6b shows clustering of the changed pixels.

An attempt to improve results is attempted by using single- and multi-band images. In the case of applying the algorithm to each band and then combining the results, it was observed that few of the false polygons can be identified and removed, increasing the accuracy, as shown in Figure 6c and d. Finally, the filter was applied (3 × 3) to remove the noise.

The final change detection map was generated using the binary edge detection approach. Figure 7 shows the change map (white pixel, change; black pixel, no change) generated using binary edge detection technique and ML algorithm.

The tool developed is tested over different locations and different sensors; Figure 8 shows the change map generated to identify changes using multi-temporal Triplesat data.

Information of features in the change detection process is very important, like for identifying encroachment and land use change (water body to built-up area), built-up

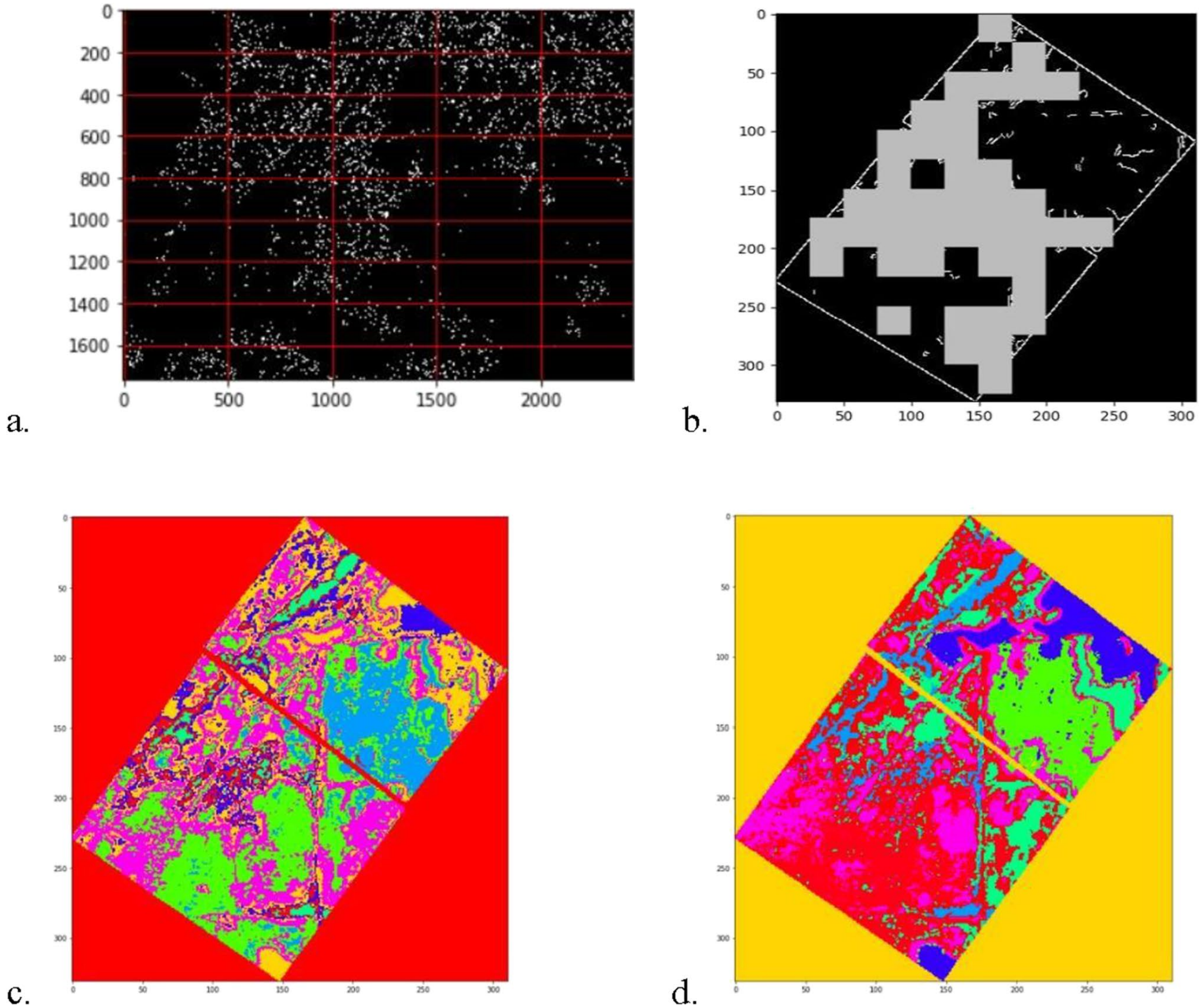

Fig. 6 Change detection using a machine learning algorithm. **a** Changed area pixels. **b** Clustering in changed area. **c** Change detection using a single-band image. **d** Improved change detection result using a multi-band image

identification in the changed map is of interest. It is very essential in estimating the urban water demand and impact of urbanization on water resources. Manual verification of built-up in change map is a time-consuming process and needs visual interpretation expertise. Automatic identification of features can avoid the manual verification process, and a larger area can be analyzed in less time, frequently. To achieve this, a software module for extracting features using machine learning–based segmentation and classification algorithms is developed. The satellite dataset used is not labelled initially. A vector file is created, where different feature classes, namely cropland, house/building/built-up, roads, bare land, and water bodies, are labelled using 125 data points for each class. Figure 9a shows the same. A standard ratio of 70:30 is followed for training and testing. Once the training and testing data are ready, the image segmentation process is implemented. Quickshift segmentation methodology [24] with a threshold value 5 is used for image segmentation. Oversegmentation problem is observed with increase in the threshold value, and the approach is compared with Felzenswalb's efficient graph-based image segmentation [25], Simple Linear Iterative Clustering (SLIC) [26], and compact watershed segmentation [27]. Quickshift segmentation (yields 4591 segments) and SLIC segmentation (yields 1652 segments) show promising results in demarcating the house/building boundaries. Among two, Quickshift segmentation performance is found to be good for the study area (Figure 9b. Classes other than buildings/houses like water can be removed with the candidate selection process. For each segment of the image, the pixel-based

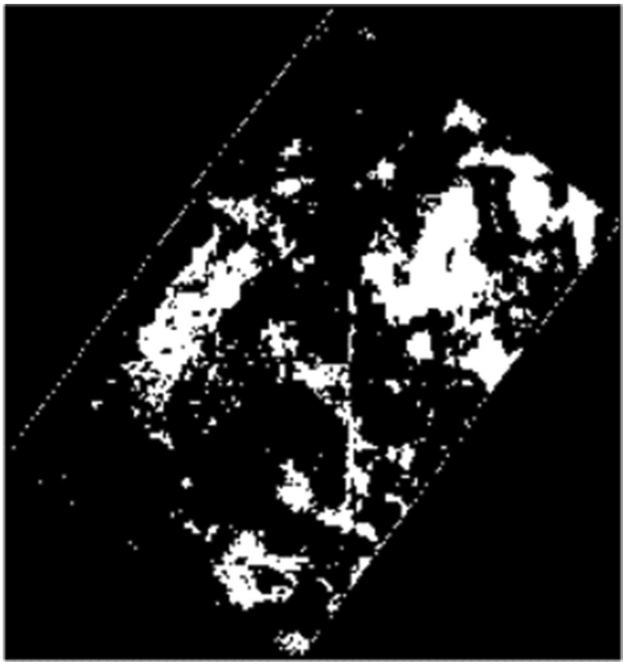

Fig. 7 Change map (white pixel, change; black pixel, no change) generated using binary edge detection technique and ML algorithm

information is collected by calculating the minimum, maximum, mean, variance, skewness, and kurtosis for each band and saved in feature variables. The program assigned each segment a unique segment ID; pixels of the segment are also assigned with the same segment ID. The point object array from the truth vector file is extracted and assigned to the segment. The process is repeated for test and training datasets for classification. A supervised learning approach of random forest classifier is used to classify all the segments (Figure 9c), with the parameters shown in Table 2. Results of random forest machine learning classification are shown in Figure 9c. The approach is able to classify different classes with reasonable accuracy, i.e., water bodies (91%), cropland (90%), house/building/built-up (88%), roads (87%), and bare land (86%), where building class is further classified into industrial and residential. Identification of water bodies with an accuracy of 91% is useful in monitoring urban water bodies. Temporal high-resolution satellite images can be used to monitor the changes in urban water bodies using this approach, solving an important question of Earth system science. Furthermore, the built-up class can be further classified into industrial built-up and other built-up (house/building) as industries are having a specific building structure and mainly constructed in specific areas (industrial area). A mask is generated having the location information (polygon) of approved industrial areas. Built-up falling into the mask is categorized as industrial built-up. It is observed that the program was able to identify big houses and buildings with good accuracy; however, small houses get missed sometimes.

The approach is evaluated on different image input sets (Table 3), giving an overall accuracy of 88.2% and precision of 84.8% with an F1 score of 81.6%.

The output of change detection and classification are integrated to identify the feature class going through change detection using high-resolution satellite images. It has potential to draw a relationship between local change detection with an important question of use of Earth system science research to provide benefits to society. It will be useful in identifying the encroachments on urban water bodies, land use changes, and urban sprawl, and its impact on urban water demand. High-resolution satellite datasets are very useful in identifying changes on small water bodies in urban areas. Hence, the potential of high-resolution satellite data and machine learning techniques is used in identifying and managing the local changes in urban areas using automated procedures. Upscaling of this procedure over a bigger area

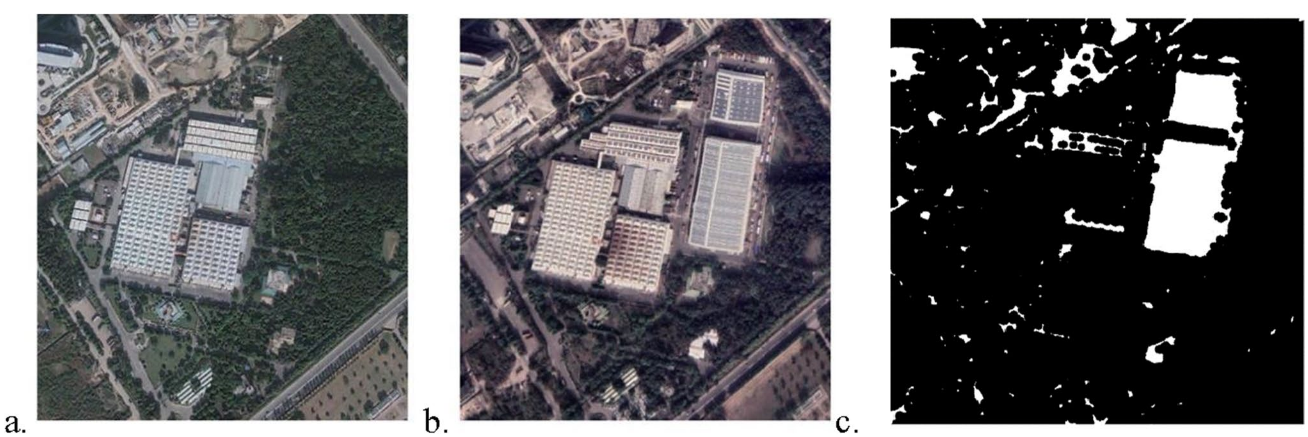

Fig. 8 Change map generated using binary edge detection techniques and ML algo on temporal Triplesat data 2015 and 2018. **a** T0, pre-image; **b** post-image; **c** change map (white pixel, change; black pixel, no change)

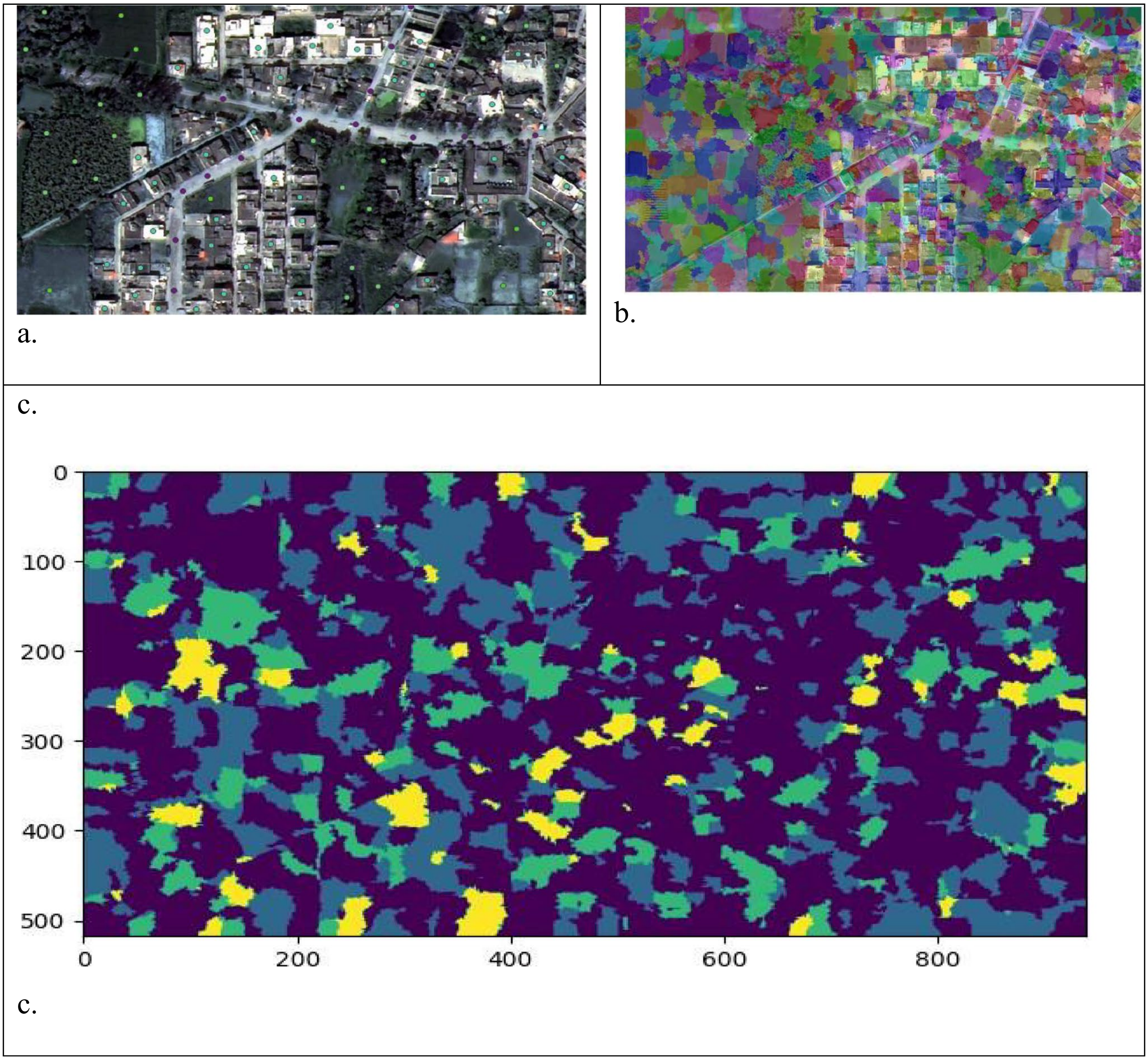

Fig. 9 Feature extraction using machine learning algorithm. **a** Feature classes identified and labelled using satellite data. **b** Image segmentation using Quickshift segmentation methodology. **c** Random forest classification for feature identification

Table 2 Random forest parameters for image classification

Classifier	Parameters	Description
Random forest	No. of trees = 45	Total number of trees in random forest
	Split attribute = 26	Number of tried attributes when splitting nodes

Table 3 Random forest evaluation for classification of classes in the study area

Classifier	Test set	Accuracy	Precision	F1 score
Random forest	Set 1	0.926	0.879	0.892
	Set 2	0.898	0.825	0.825
	Set 3	0.905	0.855	0.828
	Set 4	0.840	0.830	0.749
	Overall	0.882	0.848	0.816

can be useful in protecting the water bodies in urban areas and helpful in optimization of available water, contributing at the regional level in solving water and land problems.

4 Conclusions

Temporal high-resolution satellite images are useful for carrying out change detection studies. Manual analysis of temporal satellite datasets for identifying the changes is a time-consuming process and needs visual image interpretation skills. Performance of binary change detection approaches like edge detection techniques can be increased by integrating it with supervised machine learning algorithms for detecting changes. Information of features going under change with respect to time is of much importance. Planning institutes holding vacant lands spend huge amounts of money to deploy a ground force to monitor their properties. Change detection approach with feature information in new change using temporal satellite data can alert the authorities about the encroachments/construction activities going on in their properties without physical visits. It will reduce time and a large number of sites can be monitored in shorter time duration. The machine learning–based classification approach random forest classifier is successfully integrated with binary change detection for completing the cycle of change detection and feature extraction. An accuracy up to 88.2% is used to identify the houses/building using the combined approach. Open-source technologies including GDAL and Python libraries (Geopanda, skimage, sklearn, and numpy) are used to develop the framework. The software tool is successfully tested to identify urban changes over Delhi NCR region.

Data Availability The data that support the findings of this study are available from NRSC but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the NRSC.

Declarations

Conflict of Interest The authors declare no competing interests.

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