Spectral Indices Based Change Detection in an Urban Area Using Landsat Data

Abhishek Bhatt, S.K. Ghosh and Anil Kumar

Abstract This paper proposes a technique to detect the change in some dominantly available classes in an urban area such as vegetation, built-up, and water bodies. Landsat Thematic Mapper (TM) and Landsat 8 imageries have been selected for a particular area of NCR (National Capital Region), New Delhi, India. In this study, three spectral indices have been used to characterize three foremost urban land-use classes, i.e., normalized difference built-up index (NDBI) to characterize built-up area, modified normalized difference water index (MNDWI) to signify open water and modified soil-adjusted vegetation index ($MSAVI_2$) to symbolize green vegetation. Subsequently, for reducing the dimensionality of Landsat data, a new FCC has been generated using above mentioned indices, which consist of three thematic-oriented bands in place of the seven Landsat bands. Hence, a substantial reduction is accomplished in correlation and redundancy among raw satellite data, and consequently reduces the spectral misperception of the three land-use classes. Thus, uniqueness has been gained in the spectral signature values of the three dominant land-use classes existing in an urban area. Further, the benefits of using $MSAVI_2$ as compared with NDVI and MNDWI as compared to NDWI for the highly urbanized area have been emphasized in this research work. Through a supervised classification, the three classes have been identified on the imageries and the change between the image pairs has been found. The overall accuracy (OA) of change detection is 92.6 %. Therefore, the study shows that this technique is effective and reliable for detection of change.

Keywords Urban land use · MNDWI · $MSAVI_2$ · NDBI · Change detection

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1 Introduction

Urbanization for human society, is a gift, if it is well-ordered, harmonized, and planned. However, unplanned urbanization is a profanity. In 2008, it was found that more than 50 % of the total world's population were urban inhabitants and that this figure is likely to reach 81 % by 2030 [1]. In developing countries, like India, where urbanization rates are high because of mass relocation of individuals from rural places to urban fringes and from smaller to larger urban agglomerations as well. When we go to way back 1970s, the Industrial Revolution seemed as the factor which give thrust to the urbanization process in India. However, during 1990s urbanization further gained momentum due to the globalization. Many mega cities such as Delhi are facing various problems due to rapid urbanization and one of them is extremely high levels of pollution due to a speedy infrastructure development a speedy infrastructure development [2]. Due to global urbanization, there has been an increasing interest in understanding its consequences with respect to ecological factors that includes harm of agricultural land, habitat devastation, and decline in traditional vegetation.

Satellite data provides both spectral and temporal information to such dynamic phenomenon. Using temporal data, change detection at the same geographical location between two images may be carried. If the deviation in spectral response is more than the statistically determined threshold value, then one thematic class is assumed to have been converted into another thematic class [3]. In the context of urban change detection, it is found that dry soil tends to create misidentification of urban areas due to confusing spectral signature of urban feature when using raw data. To resolve such issues with raw data, certain mathematical transformation is available commonly known as spectral indices [4]. These indices tend to normalize and highlight a specific information such as, normalized difference vegetation index (NDVI), which highlights vegetation areas or normalized difference water index (NDWI), which highlights water or normalized difference built-up index (NDBI), which highlights urban areas, etc.

The objective of this research work is to cultivate and investigate the suitability of a new change detection technique using spectral indices based thematic bands for an unevenly urbanized area like New Delhi, India using the spectral indices such as modified normalized difference water index (MNDWI), modified soil-adjusted vegetation index ($MSAVI_2$), and NDBI. This method would appreciate in such a sense that it allows urban planning authorities and policy makers to appropriately update as well as review urban growth pattern with associated land-use changes along with cognizant in terms of justifiable treatment of the precious nature land. The transformed indices havd been proven a powerful tool for analyzing and detection of spatial-frequency characteristics of non-stationary images in a more comprehensive manner [5].

Thus, in this work, some spectral indices for urban change detection have been examined using Landsat 5 TM and Landsat 8 OLI_TIRS dataset have been developed. Further, the comparison of performance of the proposed change detection technique using indiced image and the change detection using raw data have been compared and urban change over a span of 14 years from 2000 to 2014 has been computed.

2 Literature Review

Many studies significantly use satellite imagery to differentiate the built-up class from non-built-up [6]. Ever since multispectral satellite-based land-use and land cover classification had been carried out, it was observed that specifically urban area as a land-use class had been identified. However, due to the non-homogeneity of urban area, since it many include many land cover classes such as vegetation, built-up, and water bodies, it was found that the accuracy of identification of urban area is normally less than 80 %. Results of various research show that there has not been a single technique to classify the built-up area but one can combine the qualities of two techniques in order to create a hybrid approach to enhance the extraction accuracy of urban land use.

Masek et al. [7] applied the NDVI-differencing approach with the support of an unsupervised classification to identify built-up areas of the metropolitan area in Washington D.C., using time series Landsat imagery while achieving an overall accuracy (OA) of 85 % [7]. Xu [8] utilizes a hybrid approach of combining supervised classification. The concept used has been centered around investigation of spectral variation between built-up and non-built land for the Fuqing City in southeastern China [8]. Built-up information was extracted, and finally, incorporated with a land cover classification output to create a final output with a great improvement in results.

Zhang et al. [9] uses spectral data further combined with road density layer and detect the change in Beijing, China using post-classification approach. Hence, it significantly reduced spectral misperception as well as improved the accuracy [9]. Zha et al. [10] proposed NDBI using TM4 and TM5 for extracting urban areas of Nanjing City, China from a Landsat TM image [10]. The thematic map derived through indices contains the vegetation noise and further filtered with the help of NDVI to eliminate the vegetation noise.

Xian and Crane [11] utilizes the regression tree algorithm and unsupervised classification to measure urban land-use development in Florida, Tampa Bay Watershed by mapping urban impervious surfaces and to divulge associated urban land use. The accuracy achieved with such an approach has been greater than 85 % [11].

Li and Liu [12] compared the associations of land surface temperature (LST) with NDBI and NDVI images using moderate resolution imaging spectroradiometer (MODIS) data acquired from four different periods of Changsha–Zhuzhou–Xiangtan metropolitan area, China [13]. However, the binary NDBI and NDVI images are created under the assumption that all positive values of continuous NDBI and NDVI images belong to built-up regions and vegetation regions, respectively. This assumption, however, makes that this approach is unable to accurately identify the built-up regions as well as built-up change regions.

El Gammal et al. [14] have used several Landsat images of different time periods (1972, 1982, 1987, 2000, 2003, and 2008) and processed these images to analyze the changes in the shores of the lake and in its water volume [14].

El-Asmar et al. [15] have applied remote sensing indices, in the Burullus Lagoon, North of the Nile Delta, Egypt for quantifying the change in the water body area of the lagoon during 1973–2011. NDWI and the MNDWI have been used for the study [15].

Bouhennache and Bouden [5] extracted the expansion in urban areas using various indices, i.e., difference soil-adjusted vegetation index (DSAVI), difference normalized difference built-up index (DNDBI). Further post-classification of multispectral and multi-temporal L5 and L7 Landsat satellite using a MLC has been carried out [5].

3 Spectral Indices Used in Study

3.1 $MSAVI_2$-Derived Image for Extraction of Vegetation

NDVI is a widely used index for getting information about the vegetation cover, but it is influenced by the soil background, so SAVI has been suggested by Huete [16]. This index include a constant L, in the denominator of the NDVI calculation and called it factor, in order to minimalize the effects of soil background on the vegetation. Normally SAVI can be represented by the following equation [16]:

$$\mathrm{SAVI} = \frac{(\mathrm{NIR} - \mathrm{RED})(1 + l)}{\mathrm{NIR} + \mathrm{RED} + 1}\ldots \tag{1}$$

where *l,* signify a soil correction factor, whose value ranges from 0 to 1, where 0 stands for maximum densities to 1 for lowest densities.

Subsequently, Baret et al. [17] suggested TSAVI, which was further amended by Qi et al. [18], and based on the optimal value of the soil adjustment factor of the SAVI. It has been envisioned to provide better correction to the brightness of soil background under diverse vegetation cover situation. This study employed $MSAVI_2$ to represent vegetation due to its benefit over NDVI when applied specially for urban areas where plant cover has been less. $MSAVI_2$ can perform well in the urban area even with a minimum plant cover of 15 %, whereas for NDVI the minimum plant cover required should be above 30 % [18]. The $MSAVI_2$ can be computed using the following equation:

$$\mathrm{MSAVI_2} = \frac{2 * \mathrm{NIR} + 1 - \sqrt{(2 * \mathrm{NIR} + 1)^2 - 8(\mathrm{NIR} - \mathrm{RED})}}{2} \tag{2}$$

SAVI needs an earlier knowledge about vegetation densities in order to find an optimal value of *L*, while $MSAVI_2$ automatically adjusts the value of *L* to optimal one iteratively. It is the quality of $MSAVI_2$ that it raised the vegetation feature impressively and simultaneously reduces the soil-induced variation. Hence, $MSAVI_2$ can be said a more thoughtful indicator for finding degree of vegetation over SAVI as well as other indices.

3.2 MNDWI-Derived Image for Extraction of Open Water Bodies

NDWI as proposed by Gao [19] is a measure of liquid water molecules in vegetation canopies that interacts with the incoming solar radiation using two near IR channels.

$$\mathrm{NDWI_{GAO}} = \frac{\mathrm{NIR} - \mathrm{MIR}}{\mathrm{NIR} + \mathrm{MIR}} \tag{3}$$

Subsequently, Mc Feeters, [20] used NDWI to delineate open water features, by replacing IR band with Green band and MIR band with NIR expressed as follows [20]:

$$\mathrm{NDWI} = \frac{\mathrm{GREEN} - \mathrm{MIR}}{\mathrm{GREEN} + \mathrm{MIR}} \tag{4}$$

where GREEN band like TM2, and NIR band like TM4, for Landsat 5 dataset. As a result, positive values have been recoded for water class and zeroed or negative values have been recorded owing to vegetation. Hence, vegetation and soli have suppressed and water class has enhanced in NDWI images.

The applications of the NDWI in highly urbanized areas like New Delhi city, were not as successful as expected because here the open water body exists with built-up land as dominated background. When water bodies are extracted they often gets mixed up with built-up land due to the reason that many built-up areas also contains positive values in the NDWI-derived indiced image. To provide a suitable remedy to this problem, modified NDWI as proposed by Xu [21] has been used. MIR band, such as, TM5 of Landsat 5 has been used in place of the NIR band during calculation. The MNDWI can be articulated as follows [21]:

$$\mathrm{MNDWI} = \frac{\mathrm{GREEN} - \mathrm{MIR}}{\mathrm{GREEN} + \mathrm{MIR}} \tag{5}$$

3.3 NDBI-Derived Image for Extraction of Built-up Land

The NDBI has been used to highlight information related to built-up. The evolution of this index based on the exclusive spectral values of built-up lands, which have lower value of reflectance in NIR wavelength range as compared to reflectance in MIR wavelength range. So, NDBI can be represented by the following equation [10]:

$$\mathrm{NDBI} = \frac{\mathrm{MIR} - \mathrm{NIR}}{\mathrm{MIR} + \mathrm{NIR}} \quad (6)$$

It has been observed at some places that, built-up may have lower reflectance in MIR wavelength range, resulting in negative values in NDBI imagery. Whereas, in some conditions, water may reflect MIR waves stronger as compared to NIR spectra, if it contains high suspended matter concentration (SMC). Hence, there is a shift in the peak reflectance near the higher wavelength spectrum and this phenomenon becomes more dominant with intensification in suspended matter [22].

Moreover, the contrast of the NDBI image has not been good when compared to MSAVI_2 and MNDWI images, thus many studies have suggested to make use of combination of indices rather than extraction of the built-up land merely based on an NDBI image independently. Hence, this study proposes to use a combination of NDBI, MSAVI_2 and MNDWI to extract built-up and other dominant classes in an urban fringe. This may also lead to the improvement in the accuracy of classification.

4 Study Area and Dataset Used

The study area selected is located between Latitude 28°15′38″N to 28°54′39″N and longitude 77°26′54″E to 76°57′12″E (Fig. 1) and belongs to New Delhi and its surrounding region commonly known as the National Capital Region (NCR). The altitude of the study area lies between approximately 213–305 m above the *sea level* with 293 m (961 ft) an average altitude.

New Delhi during the past six decades or so has witnessed a phenomenal growth in population. It has increased from 1.74 million in 1951 to 16.7 million in 2011

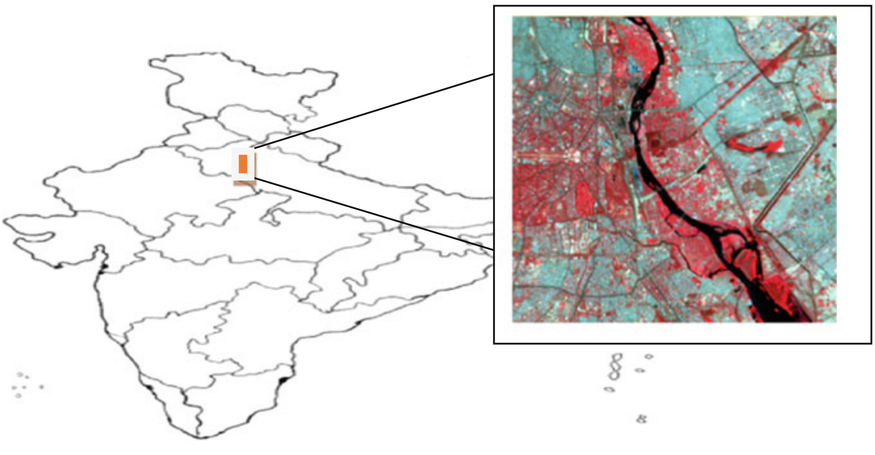

Fig. 1 Study area, i.e., New Delhi and its nearby area, India

Table 1 Summary of dataset used

Satellite	Sensor	Date of image acquisition	Path/row	Datum
Landsat 5	TM	9 May 2000	146/40	WGS 84
Landsat 8	OLI_TIRS	9May 2014	146/40	WGS 84

[Census report 2011]. To detect and analyze the change in urban built-up areas, Landsat data have been used. Satellite data selected for this purpose belong to May 2000 and May 2014 [23]. One of the main reasons for selecting this time of the year is that this is summer time and the foliage of green vegetation is nominal and the water bodies also have the smallest spread. Thus, built-up area is greatly highlighted in comparison to other urban land-use classes. Details of temporal dataset used in this study are summarized in Table 1.

5 Methodology Adopted for Proposed Change Detection

A new method has been proposed in this research work for the detection of change in urban agglomeration (Fig. 2). The change detected has been largely focused on a new FCC image generated using three thematic indices, $MSAVI_2$, MNDWI, and NDBI. The proposed approach has been validated through the detection of change in Delhi city, India using Landsat time series data of past 14 years period (i.e., from 2000 to 2014).

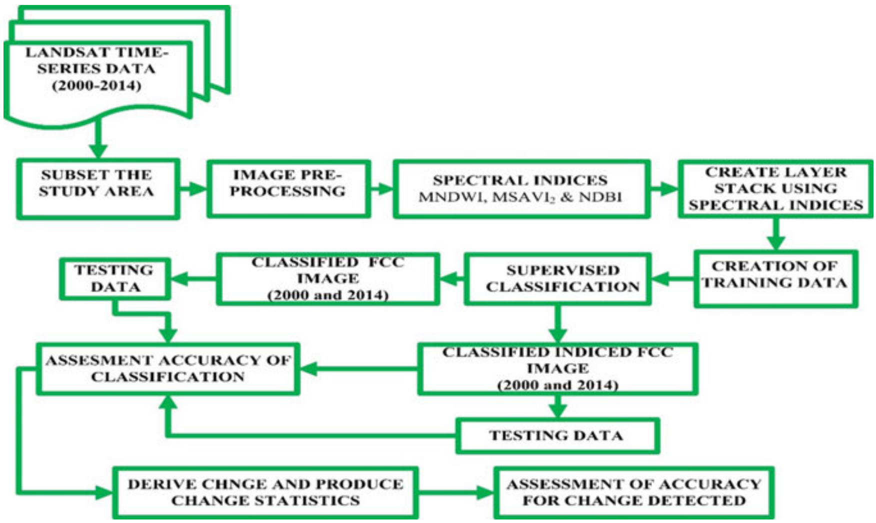

Fig. 2 Flow chart for methodology of change detection

5.1 Preprocessing of Landsat Imagery

Landsat images of have been used in this study being cloud free and of good quality, then radiometric correction was performed [24, 25]. After applying preprocessing, study area has been subset from the whole image.

5.2 Generation of Index-Derived Images

A highly urbanized area can be represented as a complex environment composed of heterogeneous ingredients. However, there have been still some generalizing constituents among these ingredients. Ridd [26] uses three components to describe an urban environment, i.e., vegetation, impervious surface, and bare earth while ignoring open water class [26]. Nevertheless, the open water also has been taken into concern in this research work as it characterizes an important element of the urban surface.

Consequently, the urban area has been categorized into the three generalized classes, i.e., built-up land, green vegetation, and open water body. Three spectral indices have used to represent each of the three dominant class, i.e., NDBI used to signify built-up, $MSAVI_2$ to represent vegetation, and MNDWI is used to characterize open water. Further FCC is generated using the above said three spectral indices.

5.3 Classification Using MLC Classifier

MLC classifier has been used for classification. The maximum likelihood (ML) classifier has turned out to be very popular and widespread in remote sensing society due to its robustness [27, 28]. ML classifier assumes the normal distribution, i.e., each class in each band can be assumed to be normally distributed. Each pixel of image has been allocated to the class with the highest probability among all classes available. For each land-use class training samples have been collected and from these known pixel labels, i.e., training data remaining pixels of images have been assigned labels.

5.4 Assessment of Accuracy for Classification

Assessment of accuracy has been an important part. Land-use map obtained after classification has been compared with the reference information collected in order to evaluate the accuracy of classified image. A total of 256 sample points have been used as the reference data by considering stratified random sampling. Handheld GPS has been used for field verification during the visits. The reference points so obtained were used to authenticate the accuracy of classification.

The three main parameters utilized for assessments of accuracy include OA, user's and producer's accuracy (UA and PA), and kappa coefficient (KC) [29–31].

5.5 Change Detection

5.5.1 Theory of Change Detection

A variety of change detection techniques are available for monitoring land-use/land cover change [32]. These techniques can be grouped into two main categories: post-classification comparison techniques and enhancement change detection techniques [33]. The post-classification technique involves the independent production and subsequent comparison of spectral classifications for the same area at two different time periods [34].

The proposed method using spectral indices for change detection used in this study utilize classified indiced image obtained for different years and then compares and analyzes these classified images using a change-detecting matrix and analyzed for 2000–2014 duration.

5.5.2 Assessment of Accuracy for Change Detection

The simplest method to estimate the expected accuracy of change maps is to multiply the distinct classification map accuracies. A more rigorous approach has been used here that consists of selecting the randomly sample areas divided into two categories, i.e., change and no-change and further determine the accuracy of change detected [35].

An error matrix (Table 2) has been built to compute several accuracy indicators based on Eqs. (7) to (10) for identifying change detection [29, 31].

OA is computed for whole of the image dataset and calculated using error matrix. It is the ratio of samples which are detected correctly to the total number of samples taken for assessment of accuracy, given as:

$$\mathrm{OA} = \frac{C_\mathrm{C} + U_\mathrm{U}}{T} \times 100\,\% \tag{7}$$

When described as a percentage it is nothing but the percentage of correctly changed and unchanged identified pixels to the quantity of total test samples used as reference points.

Kappa coefficient $(\hat{K})$ The kappa indicator integrates the off diagonal components of the error matrices and represents agreement gained after eliminating the amount of agreement that could be estimated to occur by chance. Kappa reveals the

Table 2 Error matrix for change detection accuracy assesment

Detection results	Changed (C)	Unchanged (U)	Total (T)
Detected changed (C)	C_c	C_u	T_c
Detected unchanged (U)	U_c	U_u	T_u
Total (T)	T_c	T_u	T

internal consistency of change detection results. It describes detection accuracy more objectively than OA.

$$\hat{K} = \frac{T(C_c + U_u) - (T_c \times T_c + T_u \times T_u)}{T^2 - (T_c \times T_c + T_u \times T_u)} \times 100\,\% \tag{8}$$

False elarm rate (*commission error*): False alarm rate can be defined as the ratio of false detected changes to total detected changes. It is the percentage of false change so called commission error. It means that the number of pixels that are not actually gone under change but have been detected as changed pixel in the final output.

$$P_F = \frac{C_u}{T_c} \times 100\,\% \tag{9}$$

Miss detection rate (*omission error*): Miss detection rate can be defined as the ratio of undetected changes to total true changes. It means that the number of pixels that are actually gone under change but have been detected as unchanged pixel in the final output. It is also called omission error.

$$P_O = \frac{U_c}{T_c} \times 100\,\% \tag{10}$$

6 Results and Discussion

6.1 Creation of Indiced Image and Classification

Landsat images acquired on two different time period over New Delhi city and its nearby area, India were selected to evaluate the proposed change detection scheme. The size of the image is 417 × 386 pixels. The images were registered using quadratic polynomial with the error less than 0.4 pixels. For each dataset corresponding spectral indices ($MSAVI_2$, MNDWI, and NDBI) are created and using these thematic information an indiced image is generated (Fig. 3).

To create the thematic map for the dominant land cover classes available the MLC classification is carried out for FCC images of years, i.e., 2000 and 2014 (Fig. 4a, b). The same classification is carried out for indiced images created using spectral indices (Fig. 4c, d). Three major classes were identified, i.e., vegetation,

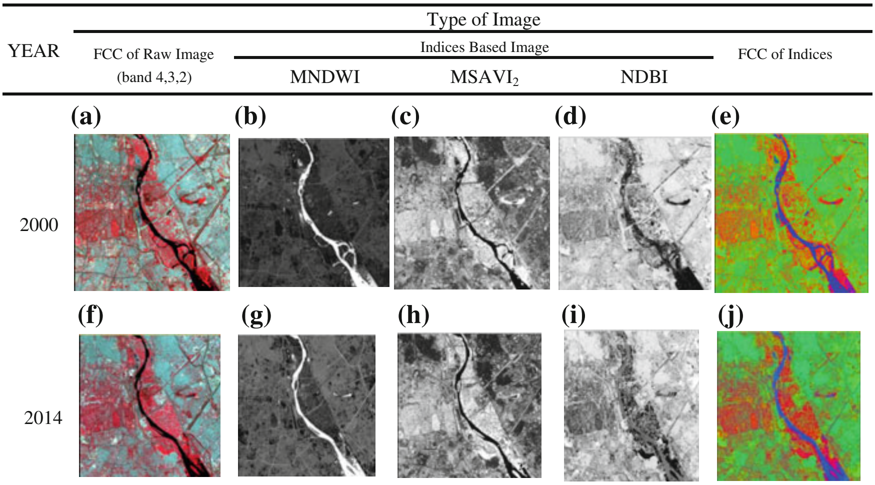

Fig. 3 Landsat FCC image of Delhi area created using band numbers 4, 3, and 2 for different years, i.e., 2000 and 2014 (**a**, **f**), respectively, with their derived MNDWI (**b**, **g**); MSAVI$_2$ (**c**, **h**); and NDBI (**d**, **i**); and the indiced FCC created using all three derived images for each year (**e**, **j**)

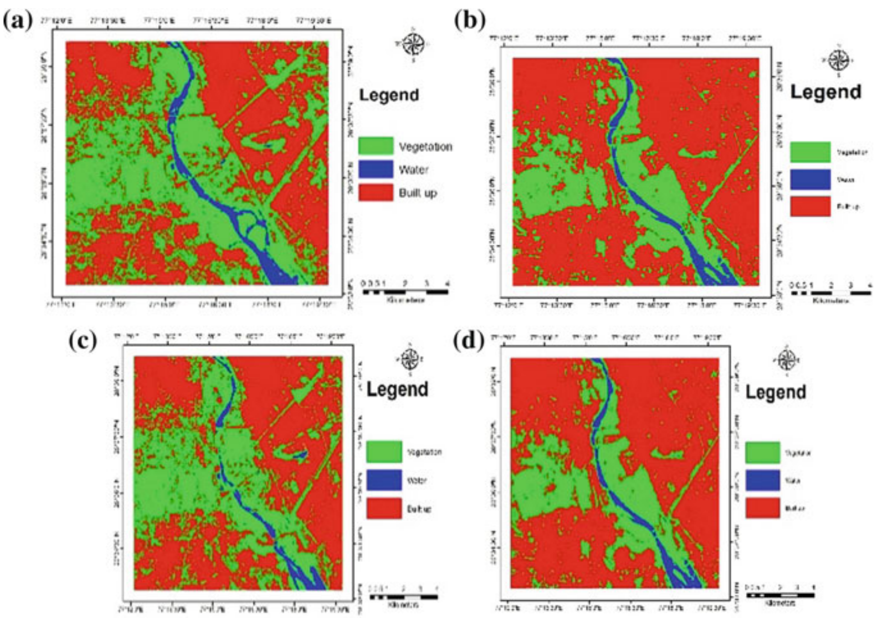

Fig. 4 LULC classified image for different years 2000 (**a**, **c**) and for 2014 (**b**, **d**)

Table 3 Assessment of accuracy for classification

Land cover	Year wise classification accuracy							
	FCC image of RAW data				Indices FCC image			
	2000		2014		2000		2014	
	PA	UA	PA	UA	PA	UA	PA	UA
Vegetation	63	95	52	80	100	83	100	83
Water	100	75	100	100	89	92	100	100
built-up	94	62	91	75	100	88	94	79
OA	76		77		86		89	
KC	0.564		0.507		0.712		0.816	

UA User accuracy (%); *PA* producer accuracy (%); *OA* overall accuracy (%); *KC* kappa coefficient

water, and built-up. The LULC classified images provide the information about the land-use pattern of the study area. The green colour represents the vegetation area; blue colour represents the water bodies whereas built-up area has been represented by red colour.

6.2 Accuracy of Classification

Accuracy is judged in terms of error matrix. A total of 256 sample pixels are chosen as testing data for assessment of accuracy of classification and their summary is given in Table 3.

The OA for the study area has been calculated using FCC image is 76 % for year 2000 and 77 % for year 2014 datasets, whereas for the same study area, OA is 86 % for the year 2000 and 89 % for year 2014 when the indiced dataset is used. This clearly shows that there is a significant rise in the accuracy of classification. Even the kappa coefficient shows a significant rise, thereby indicating that the error due to chance has also decreased. Further, as per USGS classification scheme, the OA exceeds the threshold accuracy of 85 %. Naturally, the base maps with respect to which change is to be detected will be better, leading better change detection.

7 Assessment of Accuracy for Change Detected

7.1 Change Analysis

The analysis for change enumerated in this research work has been centred around the statistics pulled out from the land-use and land cover maps of the given study area for different time period, i.e., 2000–2014. The change map derived from

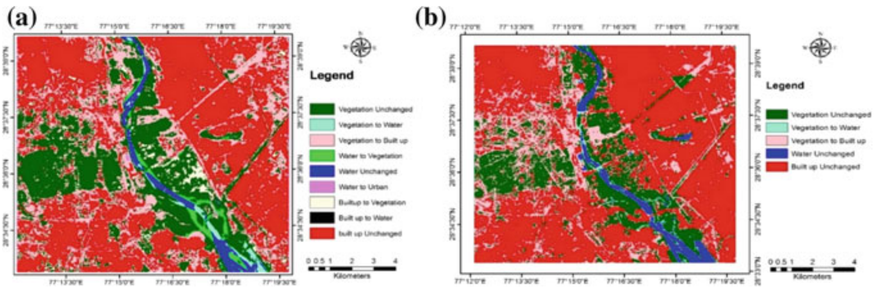

Fig. 5 Change map for the duration 2000–2014. **a** Using FCC. **b** Using indiced image

post-classification change detection are shown in Fig. 5. The change map produced for both the methods, i.e., the normal MLC classification and as well as for the proposed approach.

Using the change map of Fig. 5, the following post-classification change statistics have been created and summarized in the table for study area in the time duration 2000–2014 (Tables 4 and 5).

Table 4 represents the change obtained using the FCC image (Band 4, 3, 2), however, Table 5 represents the change that was obtained by converting the bands of Landsat data into spectral indices and execute the classification process on the indiced image generated using the spectral indices ($MSAVI_2$, MNDWI, and NDBI). Table 4 shows that that water has also been converted to vegetation and some part of the water bodies are also changed to urban whereas in case of using indiced image none of the water pixel has been changed to vegetation the same case has occurred with urban area also. The change results obtained and summarized in Table 5 are more justifiable theoretically as none of the pixel of urban change to vegetation or water as well as there is no change from water to vegetation as well as to urban. However, in both the cases (Tables 4 and 5) the urban class is increasing by compromising in vegetation and water land cover.

Table 4 Post-classification change matrix (using FCC image)

2000	2014			
	Vegetation	Water	built-up	Total
Vegetation	38,220	1555	33,934	74,309
Water	2252	3361	927	6540
Built-up	6119	3	73,991	80,113
Total	47,191	4919	108,852	160,962

Table 5 Post-classification change matrix (using indiced image)

2000	2014			
	Vegetation	Water	built-up	Total
Vegetation	32,099	2615	32,400	67,114
Water	0	4274	0	4274
built-up	0	0	89,574	89,574
Total	32,099	6889	121,974	160,962

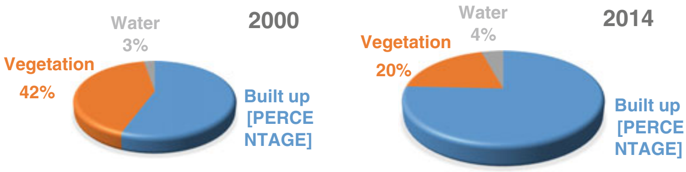

Fig. 6 Land cover for New Delhi and its nearby area (using proposed approach)

7.2 *Change Statistics*

The figure below shows (Fig. 6) percentage of change that has been occurred in individual land cover class. The built-up area has been changed drastically from 2000 to 2014. Built-up area has been increased by 21 %, vegetation area has also been decreased by 22 %, whereas there is a small change in the area of water bodies and it increases by merely 1 %. The increase in built-up area has many reasons. New Delhi, the capital of India is famous for industrial, educational institutions, IT sector and corresponding infrastructure developments lead to the increase of urban/built-up area.

7.3 *Evaluation of the Proposed Change Detection Method*

In order to evaluate the accuracy of change detected, a conventional pixel-based method was experimented. The confusion matrix (Table 6) has been assembled with the help of the existing ground truth data, i.e., a group of changed reference data (105 pixels), and a group of unchanged reference data (45 pixels) being used as test samples to evaluate accuracies of change detection methods.

After computation of *OA, kappa coefficient, false alarm rate,* and *miss detection rate* all have been calculated from the values obtained from Table 6. Using the proposed approach of change detection, i.e., FCC of spectral indices the accuracy that obtained has been 92.60 %, whereas for the same duration the accuracy achieved with raw FCC image has been 80.6 %. Table 7 summarizes the various

Table 6 Error matrix for accuracy for change detected

Class	Using FCC of raw image			Using proposed approach		
	Ground truth		Total	Ground truth		Total
	Change	Unchanged		Change	Unchanged	
Change	84	8	92	98	4	102
Unchanged	21	37	68	7	41	48
Total	105	45	150	105	45	150

Table 7 Assessment of accuracy for change detected

Change detection approach	OA	Kappa	Omission rate (%)	Commission rate (%)
Using FCC of raw image	80.6	0.57	22.8	8.7
Proposed approach	92.6	0.82	7.3	4.2

accuracy measures of change detected for the duration 2000–2014 calculated using the Eqs. (7–10) for the study area as shown in Fig. 1.

Table 7 shows the estimation of the various change accuracy measures as previously discussed in Eqs. (7–10). It may be noted that the value of OA has increased from 80.6 to 92.6 % along with there is an improvement in kappa values together with lower commission and omission rates.

It is found that the proposed approach using spectral indices to detect the change yields the best results in terms of OA, kappa, rate of omission and rate of commission in comparison to traditional approaches. Thus, it can be inferred that the proposed approach tends to preserve the change information compared with previously available techniques.

By visual analysis to the change method used, it is observed that for a highly urbanized area like New Delhi the changed pixels are fairly consistent throughout the physical urban expansion tendency. Primarily, the main changes occurred in the peri urban areas, as a result of urban planning and prompt construction

8 Conclusion

Change detection using remote sensing data proved to be a powerful approach for enumerating and investigating the amount and magnitude of landscape changes as a result of urbanization process. Subsequently, it becomes easier to present the outcomes of such evaluation to urban planners and policy-makers as well as the general public in a visually compelling and effective manner. The results of this proposed spectral indices based change detection approach for the given study area reveals that by using the given indices, i.e., MNDWI, NDBI, and $MSAVI_2$, they not only give dimensionality reduction of the data as well as more accurately changed result.

The method proposed has been beneficial and can be used in variable spectral phenomenon as this approach mostly relies on the fact that it takes the advantage of indices that differentiate the classes based on the variation in band reflectance values for each class that can be understood by examining the spectral profile of the classes.

The given approach is a more generalized approach in terms of OA calculation. The OA obtained for the land cover classification has been very much reflected in the accuracy of change detection in turn this proposed approach demonstrates its capabilities to be used for change detection.

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