CHANGE DETECTION OF MULTI TEMPORAL REMOTE SENSING DATA USING PRINCIPAL COMPONENTS, CASE STUDY: PIMPRI CHINCHWAD MUNICIPAL CORPORATION (PCMC) INDIA

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ABSTRACT

Most of the research in Remote Sensing is focused on developing well-defined and reliable automated processes for the extraction of information about material, objects or an area from different types of images. Change detection of man made objects using satellite images being one of the important applications. One of the major advantages of remote sensing technique is timeliness in the availability of information over larger areas, cost effectiveness and simultaneous observation making it possible for multi-temporal change detection. In this study a time series change detection using multi-temporal and multi-sensor Landsat ETM+ and ALOS AVNIR-2 images for the period between 1999, 2003 and 2007 using the Principal Components (PC) will be attempted. Since the first PC contains maximum variance, higher order PCs which contain the change information will be analyzed. The study area is the Pimpri Chinchwad Municipal Corporation (PCMC) India, the township has grown at a disquieting rate due to rapid growth of industrialization and urbanization since the 1970's resulting in reduction of vegetated landcover and pressure on the already limited natural resources. Therefore detecting change is necessary to highlight the introduction of new urban features and changes to vegetation that can be approximately dated.

1. INTRODUCTION

Multi-temporal remote sensing data provides us the most reliable, up-to-date and consistent means of monitoring landuse/cover changes associated with urbanization. Rapid urbanization and industrialization have known to cause degradation in quality of water, air and land. History of land-cover changes due to urban expansion is one of the essential data to assess and predict for better management and planning of urban areas in the future. A lot of important information for urban area monitoring can be derived such as the detection of new buildings or the discovery of modifications in the existing case by using multi-temporal satellite imageries.

The primary objective of this study was to detect the changes in the study area using the datasets obtained at different periods of time. For this purpose the Principal component analysis (PCA) which is a vector space transform often used to reduce multidimensional data sets to lower dimensions for analysis was used. An attempt to understand what information each principal component contains and how it can be used to detect change has been made. It was found that the resulting change vector polygons obtained captured significant landuse changes, especially conversion from vegetated areas to developed areas.

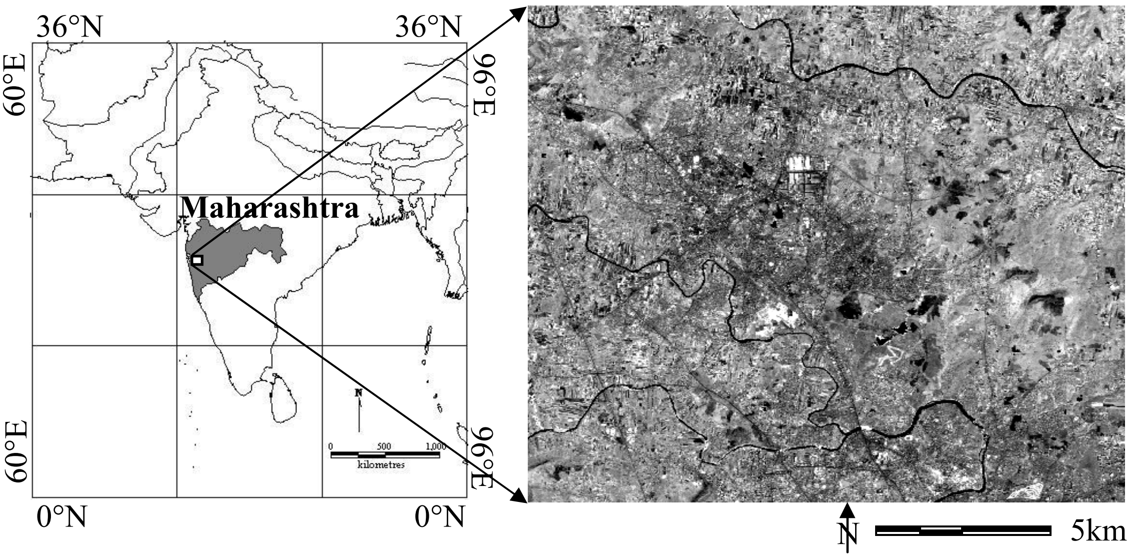


Figure 1. ALOS - AVNIR 2, band 4 showing location map of the study area.

2. MATERIAL AND METHOD

2.1 Study Area

The study area is the Pimpri Chinchwad Municipal Corporation (PCMC) located in Western India in the state of Maharashtra (Figure 1). It is a major industrial centre and also the eight largest urban agglomerations in India with an area of about 206 km^2. The centre is located at 18°22'12'' North and 73°28'48'' East. The urbanization in the area has been accelerated after the government established an industrial development corporation in 1962 to achieve balanced industrial and infrastructural development for developing as well as underdeveloped parts of the district. This has resulted in tremendous change in landuse/cover pattern which needs to be monitored for better urban planning.

2.2 Data Acquisition and Processing

In this study Landsat ETM+ images of 14 November 1999 and 30 March 2003 along with an ALOS AVNIR-2 image acquired on 6 February 2007 has been used. To analyze the changes the multi-temporal datasets need to be co-registered. All the images were rectified to a common reference using the high resolution ALOS PRISM 2.5m image and resampling was done using the nearest neighbor algorithm with a pixel size of 10m by 10m for all images. The RMSE of rectification was less then 0.08 pixel.

2.3 Principal Component Analysis

The Principal Component Analysis (PCA) is an orthogonal linear transformation performed to reduce the dimensionality of the dataset. The transformation is computed from the original spectral statistics by using the covariance matrix. Using this matrix eigenvalues and eigenvectors can be calculated. It results in uncorrelated multispectral data that has certain ordered variance properties. The first new component will account for maximum variance. Subsequent components will account for smaller portions of the remaining variance (Aldakheel and Abdulrahman, 2005). The steps for PC generation are shown in Figure 2.

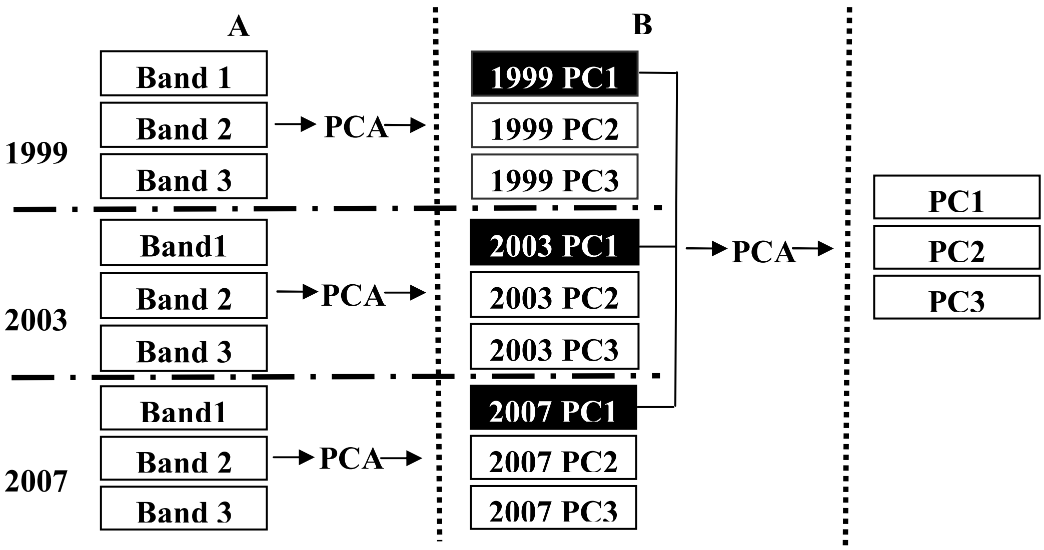
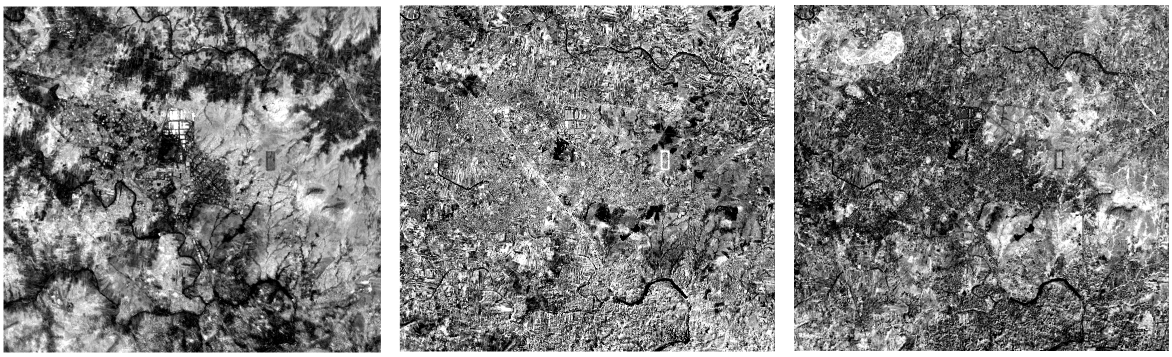


Figure 2. Steps for PC generation.



a. PC1 **b. PC2** **c. PC3**

Figure 3. PC's containing information for the three years.

To generate the first set of PC's, the bands covering the blue, green and red wavelength of each year (designated as Band1, Band2 and Band3) as shown in step A was used. These three bands were used as they have higher reflectance for urban areas, roads and barren land compared to other features and hence can be useful for identifying urban landscape. This step was done to compress the useful information of all the bands into a single band. In step B the first PC of each year (1999 PC1, 2003 PC1, and 2007 PC1) was picked up as the representative input, since we know the first component has maximum variance indicating that all the unchanged pixels lie along the first PC. On the other hand, pixels which have experienced change in their spectral appearance are expected to lie far away from this axis (Phalke and Couloigner, 2005). This can also be shown by equation (1), (Jensen, 1986). The results of the calculation are shown in Table 1.Finally three new images namely PC1, PC2 and PC3 with different variances were obtained.

$$\mathrm{p}(\%) = \frac{\lambda_p}{\sum_{p=1}^{n} \lambda_p} \times 100 \qquad (1)$$

where n is the number of input bands and λ_p is p^{th} eigenvalue of the possible n eigenvalues.

Table 1. Table showing variance percentage for PC generated for each year.

Bands	Variance Percentage		
	PC1 (%)	PC2 (%)	PC3 (%)
1999	40.9	31.9	27.1
2003	41.1	29.9	28.8
2007	49.8	33.3	16.7

3. INTERPRETATION OF PC IMAGES

Each PC contains different information, so we need to understand what each of the new components represent and how each is contributing to get the change information. Much important information can be obtained using the covariance values, eigenvalues and eigenvectors. For example from the eigenvector and covariance value, the percent of variance contributed by each band to each PC can be calculated as shown in equation (2). Using equation (3) the Load factor (factor loadings) which gives the degree of correlation between each component and each input band year can also be calculated (Jensen, 1986). Table 2 and 3 show the result for each of the calculation.

$$S_{kp}(\%) = \frac{\left(a_{kp}\right)^2}{\sum_{i=1}^{n}\left(a_{(i)p}\right)^2} \times 100 \tag{2}$$

where a_{kp} is eigenvector for band k.

$$R_{kp}(\%) = \frac{a_{kp} \times \sqrt{\lambda_p}}{\sqrt{\mathrm{Var}_k}} \tag{3}$$

where Var_k is the input band variance for band k.

Table 2. Percent Variance contributed by bands.

Band	PC1 (%)	PC2 (%)	PC3 (%)
1999 PC1	31.3	3.1	65.5
2003 PC1	37.7	32.1	30.1
2007 PC1	30.8	64.8	4.3

Table 3. Variance contributed by each band to each PC.

Band	PC1	PC2	PC3
1999PC1	0.8	-0.2	-1.0
2003PC1	0.4	-0.3	0.3
2007PC1	0.3	0.5	0.1

Table 2 explains the percent variance contributed by each band to each PC and it was found that all the three bands contribute equally to PC1 whereas 2003 PC1 and 2007 PC1 contributes more to PC2 indicating that more information in PC2 has been contributed by this two bands, likewise 1999 PC1 and 2003 contributes more to PC3. This gives us an idea of which PC would reveal more information for the different years, to confirm this Load factor value calculated by using equation 3 was plotted (Figure 4). After plotting the values it was

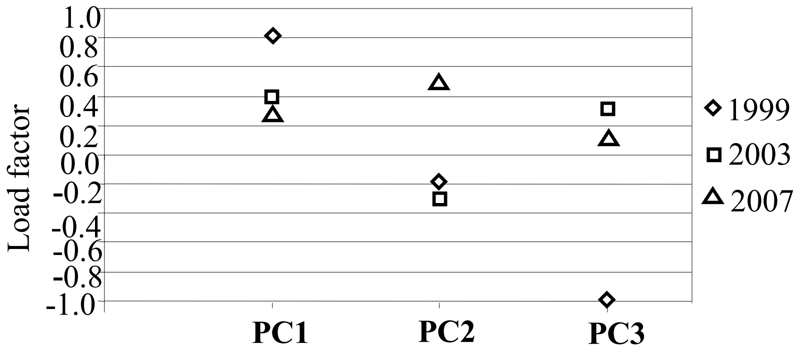


Figure 4. Graph showing Load factor value.

found that the changes between the years 1999-2003 can be explained by PC3 and the changes between 2003-2007 can be explained by PC2 based on the results.

4. EXTRACTING CHANGE VECTORS

After knowing which PC contains the change information for each year, we can extract the change vectors from them. The flowchart for extracting the change vectors is shown in Figure 5. By statistical calculations, the 3rd quartile value can be obtained. The 3rd quartile cuts off the highest 25% of the data, this value is used as the delineating value, as the high PCA values in the PC is considered as change (Neteler and Mitasova, 2008). A raster map depicting change is obtained after making the values less then the 3rd quartile as null. After converting the raster into a vector map, the small areas can be cleaned by defining the threshold depending on the number of pixels needed to be removed. In this study vectors less then 9 pixels were removed, by defining the threshold value as 8100 m^2.

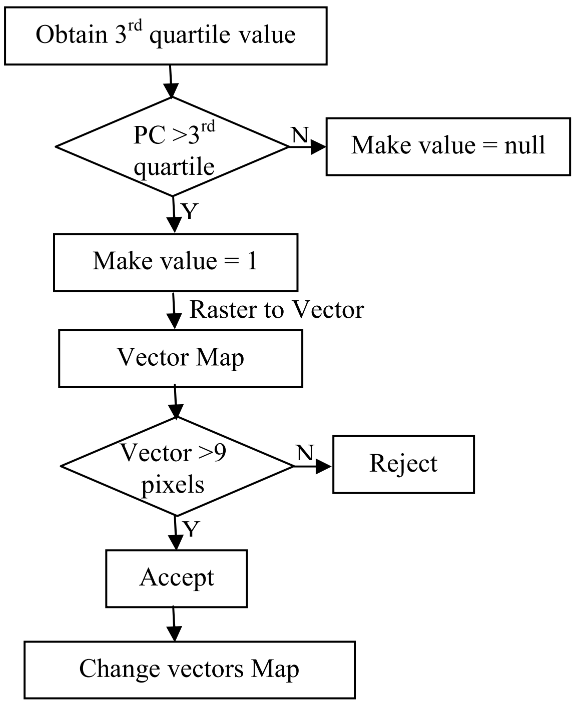


Figure 5. Flowchart showing steps for change vector extraction.

5. RESULTS AND CONCLUSION

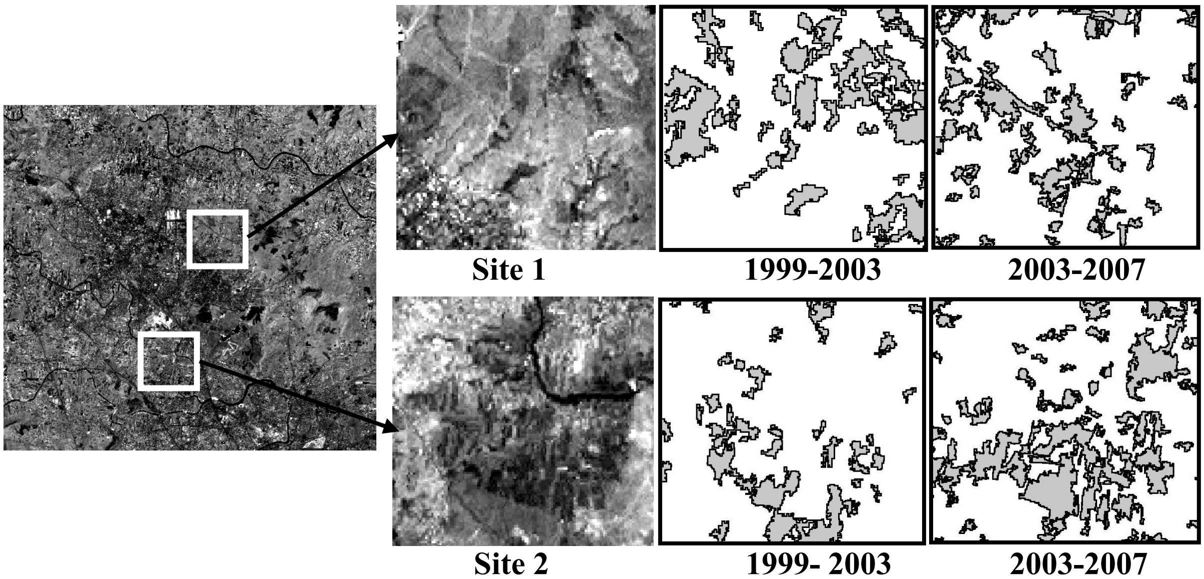


Figure 6. Vectors showing change in two sites.

It was found that by performing necessary calculations relationship between the bands and the principal components derived from them can be understood. This information helps in revealing what each PC contains for extracting the change vectors. Figure 6 shows the change vectors for 2003 and 2007 that were extracted. Two sites representing urban areas and agricultural areas as well as barren areas were chosen to overlay the vectors and verify the result. Significant encroachments in the agricultural and barren area by urban built-up were observed. Conversion from vegetated or green areas to barren land due to seasonal change could also be identified.

It was found that PCA method can be applied in multi-temporal change detection and is capable of highlighting the introduction of new urban features and changes to vegetation that can be approximately dated, but it could not provide quantitative information as to how much change has occurred as the vectors cannot explain the changes separately for each landuse. So in future other change detection method to extract each landuse/cover will be investigated to obtain quantitative results. But it is useful as it highlights areas for further investigation.

6. REFERENCES

Aldakheel, Y and Abdulrahman, A.H., 2005. The use of multi-temporal Landsat TM imagery to detect land cover/use changes in Al-Hassa, Saudi Arabia. *Scientific Journal of King Faisal University (Basic and Applied Sciences)*, Vol 6, 111-126.

Jensen, J. R., 1986. *Introductory Digital Image Processing*: *A Remote Sensing Perspective,* New Jersey: Prentice-Hall, 379p.

Neteler, M. and Mitasova, H., 2008. *Open source GIS: A GRASS GIS Approach*, New York: Springer, 406p.

Phalke, S. and Couloigner, I., 2005. Change Detection of Linear Man-Made Objects Using Feature Extraction Technique. *International Archives of Photogrammetry and Remote Sensing*, Vol 36.