Monitoring land use changes associated with urbanization: An object based image analysis approach

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Abstract
Land use/land cover (LULC) change occurs due to natural and anthropogenic causes. In developing countries, rapid industrialization and urbanization imposes a major threat to natural environment. Present study was carried out to monitor the LULC changes due to urbanization in a rapidly changing river basin, India. The purpose of choosing the river basin was to analyze past changes and predict possible consequences within a defined natural boundary. Multi-temporal images acquired from Landsat and Indian Remote Sensing (IRS) satellites between 1992-2009 as well as a digital elevation model was used to generate historical and current LULC pattern in the basin. An object based image analysis technique was employed for precise classification of multi-temporal images followed by GIS-based change detection studies. The study reveals that the built up area has increased significantly and added 288 km² between 1992 - 2009. Increase in built up area is attributed to decrease in wastelands and agricultural land. The expansion of built up area along major transportation networks, specifically after the year 2000 shows the rapid rate of urbanization in the basin.

Keywords: GIS, Upper Bhima basin, urbanization, object based image analysis, change matrix.

Introduction
Land use/land cover (LULC) is most important component of the earth surface, which interacts with the atmosphere and lithosphere simultaneously. LULC information is crucial in areas such as natural resource management, environmental impact assessment and risk management [Aydinoglu and Gungor, 2010]. Over a period of time, LULC has been changing, which is more rapid nowadays due to anthropogenic activities, such as industrialization and urbanization. By 2100, LULC change is predicted to have the greatest effect on global ecological systems, including a more significant effect than climate change and invasive species threats [Chapin et al., 2000]. The urbanization process is associated with increase in built up areas and population growth, which subsequently influences surrounding natural resources. Rapid urbanization, especially in the developing world, will
continue to be one of the crucial issues of global change in the 21st century affecting the human dimensions [Sui and Zeng, 2001]. Land use has generally been considered a local environmental issue, but it is becoming a force of global importance. Worldwide changes to forests, farmlands, waterways and air are being driven by the need to provide food, fibre, water, and shelter to more than six billion people [Foley et al., 2005]. Given the pace and scale of urban expansion in many parts of the globe, urban environments are playing an increasingly important role in daily quality of life issues, ecological processes, climate, material flows, and land transformations [Schneider, 2012]. Understanding the urban growth and change brought on by urbanization is critical to study urban dynamics, manage land resources and provide services in these rapidly changing environments [Yang and Lo, 2002]. Analyzing spatio-temporal characteristics of land use change is essential for understanding and assessing ecological consequence of urbanization. More importantly, such analysis can provide basic information for appropriate decision-making [Deng et al., 2009]. Developing nation like India, where rapid economic development and uncontrolled expansion of urbanization due to inefficient policy and planning have affected its natural resources significantly. These effects need to be assessed and changes should be quantified through proper monitoring approaches. However, the methods to detect urban development are diverse, often location-dependent, and there is a significant lack of consensus on the best practices for monitoring urban expansion [Schneider, 2012]. Remote sensing images have been used as one of the most important dataset for studying spatial and temporal LULC changes [Fichera et al., 2012; Ceccarelli et al., 2013]. In this context, remote sensing represents a major, though still under-used, source of urban information by providing spatially consistent coverage of large areas with both high spatial detail and temporal frequency, including historical time series [Jensen and Cowen 2003; Donnay et al., 2001]. During the last two decades, we have made important strides toward developing remote sensing methods that allow for the accurate characterization of LULC change [Rogan and Chen, 2004], including urban expansion [Chan et al., 2001]. With increased availability and improved resolutions of remote sensing images, it is now possible to monitor and analyze urban expansion and land use change in a timely and cost-effective ways [Yang et al., 2003]. Moreover, the opening of the 2.6 million image USGS Landsat archive for no cost access to Landsat data [Woodcock et al., 2008] in late 2008 gives a new dimension for LULC monitoring. Successful implementation of remote sensing requires adequate consideration and understanding of these specific urban landscape characteristics in order to fully explore the capabilities and limitation of remote sensing data and to evaluate appropriate image analysis techniques [Herold et al., 2005]. Delineation of urban/built up areas requires finer image resolution where single building boundaries can be extracted. There are also many challenges of extracting urban features, which are heterogeneous in nature at the scale of Landsat resolution (30 m spatial resolution). In the present study, our main focus is on identifying changes in urban agglomerations, which do not need detailed differentiation within the city. The urban expansion and associated LULC changes within a river basin can be depicted from multi-temporal Earth Observation (EO) satellite images. An object based image classification approach, which has advantages over pixel based classification, was implemented for LULC classification from time series of satellite images. Object-based approach, which operate at the scale of real-world objects rather than pixels, offer a means of analyzing EO data in a realistic context by integrating associated ancillary
information to support real-world applications [Aplin and Smith, 2011]. Sometimes our focus remains on the spatial extent of LULC classes like forests or water bodies, where an object based approach gives better solution. In time series image analysis, deriving consistent LULC maps is a major challenge due to difference in spectral and spatial characteristics of remote sensing images. For example, in multi-temporal image analysis, the extent of built up class needs to be classified consistently. This is because built up areas are highly irreversible in nature. However, in reality maintaining such consistency in time series classification is a challenging task. This is where pixel based classification causes inconsistency due to the problems of salt and pepper effects; thereby accuracy reduces due to noise. In the present study, an effort has been made to monitor LULC changes due to urbanization using an object based image analysis approach which may have fewer significant errors in large entities like forest land, water bodies, and urban areas. The outcome of the study might be helpful towards better land use planning and natural resources management in the region.

Study area
The Upper Bhima river basin is originated from the Western Ghats region and extended over an area of 6736 km² (Fig. 1). The geographical extension is between 73° 20’11” - 73° 20’11” E longitude to 18°17’38” - 19°05’26” N latitude. The elevation ranges from 499 to 1298 m above mean sea level. The western margin the basin is highly rugged due to presence of Western Ghats which gradually merges towards basin outlet. Due to natural barrier, the western part of the basin receives more than 3000 mm of rainfall and decreases towards east [Samal and Gedam, 2015]. Heavy rainfall in Ghats region leads to construction of several reservoirs for storing water and use it during non-monsoon months. The city of Pune, one of the fastest growing cities in India, is located near the confluence of the Mula and Mutha river. The landscape of study basin has undergone various changes due to city expansion and other anthropogenic activities, which is more rapid in recent years. There are number of tributaries of the Bhima rivers that are originated and flow through the basin. These rives are fed through monsoon period and attains immediate base flow during non-monsoon periods.

Data sources
Landsat and IRS images acquired between 1992 and 2009 were used to monitor LULC changes associated with urbanization. Three of these images are Landsat TM acquired in 1992, 2009, and 2010; two ETM+ images in the year 2000 and one IRS image in 2009 were used in the study. The characteristics of the satellite images were given in Table 1. All the Landsat scenes were obtained from the USGS Landsat archive as L1 data products. Similarly, the IRS data was obtained from the National Remote Sensing Center (NRSC). The digital elevation model (30 m spatial resolution) was obtained from ASTER GDEM. All the datasets used in the study are available with no cost. The main aim behind integrating the DEM with satellite imagery was to exploit topographic attributes attached to various LULC classes in the study area. Additionally, the NDVI (Normalized Difference Vegetation Index) was used as additional layer for better separability among agricultural land and forest cover. Reference data such as Survey of India (SoI) topographical map (1:50,000 scale), Wastelands Atlas of India (NRSC, 2005; NRSC, 2011) and District socio economic review (DES, 2010) were included for overall improvement of classification results.
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Figure 1 - Location map of the Upper Bhima river basin.

Table 1 - Characteristics of the satellite images used for LULC mapping in the Upper Bhima basin.

| Date         | Type of imagery | Landsat No. | Spatial Resolution | Path/Row |
|--------------|-----------------|-------------|--------------------|----------|
| 04 Dec 1992  | TM              | Landsat-5   | 30                 | 147/47   |
| 02 Feb 2000  | ETM+            | Landsat-7   | 30                 | 147/47   |
| 02 Dec 2000  | ETM+            | Landsat-7   | 30                 | 147/47   |
| 01 Nov 2009  | TM              | Landsat-5   | 30                 | 147/47   |
| 20 Nov 2009  | LISS-III        | Resourcesat-1| 24                  | 95/59, 96/59 |

Pre-processing
In order to perform time series analysis of LULC change, a consistent geometric and radiometric image set are required [Hansen and Loveland, 2012]. A relative geometric correction method was employed to maintain geometric consistency of all images. The recent image of Landsat TM was used as reference for image co-registration. The RMSE
value less than 0.5 was set as criteria for geometrically rectified images. After geometric rectification all the images were brought to common spatial reference system (UTM/WGS-84) for better alignment of geographical features.

Radiometric consistency among different remotely sensed datasets are difficult to attain because of difference in sensor characteristics, atmospheric condition, solar angle, sensor observation angle, and pheonological characteristics [Song et al., 2001; Du et al., 2002; Chel et al., 2005; Teillet et al., 2007]. Studies also have demonstrated that after radiometric corrections (absolute and relative correction method) multi-sensor images were not necessarily comparable because of variation in spectral and spatial resolution [Teillet et al., 1997; Schroeder et al., 2006; Teillet et al., 2007]. In the present study, images were obtained from different sensors (TM, ETM, ETM+, and LISS-III), as a result the spectral characteristics of a particular land use feature and their representation in the data may vary over time. Therefore, we have used simpler approach by visually evaluating the spectral response of LULC features (appears to be same tonal variation) for the same sensor group before classification. The preferred images were acquired in the post-monsoon season which are associated with cloud free, vigorous vegetation growth, filled water bodies, and fully sown agricultural land.

**Methodology**

Methodology includes object based image classification of EO satellite images, accuracy assessment followed by GIS based change detection study (Fig. 2). The object based classification starts with image segmentation, sample selection of target LULC classes, fuzzy based sample evaluation, standard nearest neighbour (NN) classification, field verification, and LULC map preparation. Object based image classification was carried out in eCognition developer (ver. 8.4). It has the flexibility to incorporate several ancillary information and gives GIS ready output. The first and foremost process is image segmentation which divides large heterogeneous image into a finite number of homogenous groups of pixels called image objects. The image objects carry several properties about a particular object, which were classified based on their different spectral and textural characteristics. The traditional pixel-based nearest-neighbour classifier computes the Euclidean distance from the pixel to be classified to the nearest training data pixel in n-dimensional feature space and assigns it to that class [Jensen, 2005]. An object-based nearest-neighbour classifier works in a similar way, except it classifies image objects instead of individual pixels. The standard nearest neighbour classification was employed using various object features, namely the mean red, NIR, green, NDVI values of the object and the corresponding standard deviation of red, NIR, green and NDVI values and DEM. The first four features were related to spectral measures and last four features related to textural measures for classification. The number of object features used in the classification varies from image to image.

Agricultural land, built up area, forest cover, wastelands and water bodies were selected for image classification. The study was carried out at river basin so these broad LULC classes would give any signature of change occurred due to urbanization during last two decades. Training samples for each class were selected from similar regions in all images to maintain consistency during classification. The quality of training samples were evaluated through fuzzy based membership functions. The higher the membership value the more reliable is the sample class. The membership value more than or equal to 0.5 is considered as ideal samples for that selected class.
Finally, the feature space distance was evaluated for better separability among LULC classes. Among various combinations of object features used in the classification, the optimum combination of object features associated with higher euclidean distances were chosen for classification. However, it has also been observed that object features with highest Euclidean distance do not always produce good classification results. Therefore, visual estimation of the of classified image objects are further analyzed before giving it final shape. These steps were performed in an iterative manner to get a visually satisfying classification output. DEM and NDVI layers were added to refine the classification process. Image objects classified under different LULC classes were brought to the GIS environment for map preparation and change detection studies. The eCognition developer has the flexibility to export classified image objects into GIS compatible data format (*.shp). Several thousands of image objects of a particular class were merged under the same class. The remaining unclassified image objects (<1% of total geographical area) were assigned to their respective classes based on visual image interpretation. Three LULC layers for 1992, 2000, and 2009 were integrated in GIS for change detection. False change areas due to misclassification or spectral confusion were rectified in change matrix. Similarly irreversible classes such as built up area taken due consideration in change detection studies. The GIS overlay function was used to represent the dynamics of major LULC classes in the basin.
Accuracy assessment
In thematic mapping from remotely sensed data, the term accuracy is used typically to express the degree of correctness of a classified map [Foody, 2002]. The confusion matrix based accuracy assessment is a widely used approach that includes a simple cross-tabulation of the mapped class label against that observed on the ground (or reference data) for a sample of cases at specified locations. It is difficult to carry out accuracy assessment for all of the LULC maps due to a lack of ground truth data. Therefore, any recent TM based accuracy assessment would represent the overall accuracy of other classified maps. A large number of ground truth samples were available for the year 2009 and a confusion matrix was prepared using corresponding LULC map. A simple random sampling of 498 pixels belonging to corresponding image objects were selected and verified against reference data. The results showed an overall accuracy of 92.7% and kappa index of agreement of 0.91 (Tab. 2). In terms of producer’s accuracy, all classes were over 90%, except forest class, while in terms of user’s accuracy, all the classes were very close to or more than 90%. Both producer’s and user’s accuracy are found to be consistent for all LULC classes. A similar kind of accuracy level can be expected from past LULC maps with a very little deviation. From the accuracy assessment, it is evident that the present classification approach has been effective in producing consistent results irrespective of differences in spatial, spectral, and radiometric resolution of satellite images.

Change detection analysis
Considerable progress has been made in the development of monitoring and change detection methods using remote sensing data [Singh, 1989; Kam, 1995; Ridd and Liu, 1998; Sohl, 1999; Seto and Liu, 2003]. The most commonly used methods are spectrally-based (image to image) and classification-based (map-to-map) change detection [Green et al., 1994; Loveland et al., 2002; Yang and Lo, 2002], which includes bi or multi temporal change analysis [Coppin et al., 2004].

Table 2 - Accuracy assessment of the 2009 LULC map produced from Landsat TM data representing both the confusion matrix and the Kappa statistics.

| Classified Data | Reference data | Row Total | User’s Accuracy (%) | Kappa |
|-----------------|----------------|-----------|---------------------|-------|
| AG              | AG: Agricultural land, BU: Built up, F: Forest, WL: Waste land, WB: Water body, Overall accuracy=0.92 | 116 3 7 2 0 | 129 | 89.92 |
| BU              | 116 70 0 2 0 | 75 | 93.33 |
| F               | 7 0 92 0 0 | 99 | 92.93 |
| WL              | 2 1 5 121 1 | 130 | 93.08 |
| WB              | 0 0 1 1 63 65 | 65 | 96.92 |
| Column total    | 128 71 105 129 65 | 498 |       |
| Producer’s Accuracy (%) | 90.63 98.59 87.62 93.80 96.92 |       | 0.91 |
Change is quantified via spectral or thematic contrast. Such techniques can often employ a thematic base map to better isolate or target the change of interest. In the present study, post-classification comparison change detection approach was employed through a change matrix. It involves comparing two independently produced classified LULC maps from images of two different dates. It was found to be an accurate procedure for LULC change detection, provided that the LULC maps had been accurately produced [Singh, 1989]. GIS minimum and maximum dominant overlay functions [Yang and Lo, 2002] were used to show the dynamics of major LULC classes in spatio-temporal scale. In the GIS minimum dominant overlay function, any LULC class of the earlier period will show up fully while only the net addition in the following years in the time sequence will be shown. Similarly, in the GIS maximum dominant overlay method, only the net loss of the target LULC classes will be shown in the time sequence.

Figure 3, Figure 4, and Figure 5 illustrates the classified LULC maps and its corresponding satellite images for the year 1992, 2000, and 2009, respectively. Similarly, Table 3 represents both areal and percentage of change with respect to 1992 LULC as baseline scenario. Built up area and wastelands were highly dynamic during the study period followed by water bodies, agricultural land, and forest. The spatial extent of built up and water bodies have increased, while wasteland, agricultural land, and forest cover decreased (Fig. 6). The change in built up area was shown through GIS minimum dominant overlay function, where the addition of built up areas after 1992 is represented graphically (Fig. 7). Major parts of the built up area are confined to the Pune urban agglomeration/metropolitan region, which constitutes Pune city and Pimpri-Chinchwad town. The Pimpri-Chinchwad region is located north-west of Pune city. In total, the built up area has expanded massively and added 288 km² since 1992, which constitutes 6.6% of the total basin area (Fig. 7). The Pune city, one of the fastest growing cities in India is the epicentre of urbanization in the basin (Fig. 1). It is not different from any other cities in India, where rapid economic development, uncontrolled expansion of urbanization, and population growth mainly due to migration are most common phenomena. Its spatial expansion was clearly visible in subsequent years (Fig. 7). Significant growth of built up areas had taken place over the 2000-2009 period and a linear pattern of growth along major transportation networks such as national highways was noticed in the basin. In terms of population growth, from 1.69 million (1981) to 3.11 million (2011) people. In between 1991 and 2001, the growth was nearly 50%, which was highest among all previous decades. It clearly indicates close association between population growth and urbanization.

Although the areal extent of the built up area is much less compared to other major classes, it has the potential to influence the existing LULC pattern for demand of goods and services to sustain the increasing population. Most of the water requirement for the domestic, agriculture and industrial sectors was fulfilled by surface water supplied from dams/reservoirs constructed in the upper reaches of the basin (Fig. 1). The numbers of reservoirs have increased during the study period, which can be identified from multi-temporal satellite imagery and indicates increasing water demand in the region. As a result, water bodies have increased from 3.3% (1992) to 4.3% (2009) of the basin area (Tab. 3), which represents an increase of 28.9%. Agricultural land has marginally reduced from 36.1% (1992) to 35.2% (2009) of total basin area. In terms of change, it has decreased by 2.3% since 1992. However agricultural activities have grown up due to availability of water from the reservoirs. Therefore, overall yield of the catchment in terms of stream flow has been reduced in the region [Samal and Gedam, 2012]. Another significant change was the continuing decline in wasteland in the basin. In 1992, 2698
km² of basin area was under wasteland (or 40.1 %), which declined to 2414 km² (or 35.8 %). It represents a decrease of 10.6% (Tab. 3). A major proportion of wasteland is converted to built up area and marginal change in forest area has been detected. The forest cover is mainly confined to hilly terrain with poor road networks, which hinders its decline process, however visible changes in forest canopy in the region were observed due to the gradual penetration of human settlements into the hilly region.

Figure 3 - Standard FCC of Landsat TM image (left) and corresponding LULC map (right) for the year 1992.

Figure 4 - Standard FCC of Landsat ETM+ image (left) and corresponding LULC map (right) for the year 2000.
The LULC maps for the year 1992, 2000, and 2009 showed only spatial extent of individual class. However, the nature of change is unknown unless we had a change matrix showing “from to” change class. The change matrix was prepared in GIS environment by integrating three LULC maps for the year 1992, 2000, and 2009. The change areas were identified and attributed carefully. The change matrix (Tab. 4) shows the conversion of a particular LULC class to other classes between 1992 to 2009. In change matrix, each row represents how a particular LULC class has been converted to different classes. In contrast, each column represents the conversion of various LULC classes to a particular class during two time periods. For example, wasteland followed by agricultural land has contributed significantly to increase in built up area. In terms of areal extent, 3% of basin area under wasteland and 0.5% under agricultural land converted to built up land. The change in built up area is confined to the city periphery and along the major transportation networks. Similarly, 0.6% and 0.2% of basin area under wasteland and agricultural land respectively have been converted to water bodies. The change in water bodies is attributed to water spreading area in the basin due to construction of new reservoirs during study period. In total, nearly 6% of basin area has changed due to increase in built up area and water bodies. Conversion of wastelands and agricultural lands to large impervious built up are might have influenced the local environment and hydrological cycle. Choosing an appropriate model and simulating various hydrological components with respect to LULC change might provide some understanding about the impacts of land use change on hydrology in the Upper Bhima basin.

**Summary and conclusions**
The study has demonstrated the applicability of object based image analysis approach for multi-temporal LULC monitoring. Various earth observation satellite images were incorporated to study the influence of urbanization on existing LULC patterns at a river basin scale.
Table 3 - Land use change in the Upper Bhima basin between 1992 - 2009.

| LULC Class | 1992 (km²) | %  | 2000 (km²) | %  | 2009 (km²) | %  | Change (2009-1992) (km²) | Change (%) |
|------------|------------|----|------------|----|------------|----|-------------------------|------------|
| AG         | 2429       | 36.1| 2428       | 36.0| 2372       | 35.2| -57                     | -2.3       |
| BU         | 159        | 2.4 | 227        | 3.4 | 447        | 6.6 | +288                    | +181.1     |
| F          | 1225       | 18.2| 1225       | 18.2| 1214       | 18.0| -11                     | -0.9       |
| WB         | 225        | 3.3 | 249        | 3.7 | 289        | 4.3 | +65                     | +28.9      |
| WL         | 2698       | 40.1| 2607       | 38.7| 2414       | 35.8| -285                    | -10.6      |
| Total      | 6736       | 100 | 6736       | 100 | 6736       | 100 |                         |            |

*+ (-) indicates area increase(decrease) of LULC classes

Table 4 - Change matrix showing LULC conversion between the year 1992 and 2009.

| LULC Class | AG   | BU   | F    | WB   | WL   | LULC1992 |
|------------|------|------|------|------|------|----------|
| AG         | 34.6 | 1.2  | -    | 0.2  | -    | 36.1     |
| BU         | -    | 2.4  | -    | -    | -    | 2.4      |
| F          | 0.1  | -    | 17.9 | 0.1  | -    | 18.2     |
| WB         | -    | -    | -    | 3.3  | -    | 3.3      |
| WL         | 0.5  | 3.0  | 0.1  | 0.6  | 35.8 | 40.1     |
| LULC2009   | 35.2 | 6.6  | 18.0 | 4.3  | 35.8 | 100      |

*Figures indicate the percentage of basin area

Figure 6 - Bar plot showing LULC changing pattern for the year 1992, 2000, and 2009.
Object based image analysis combined with change matrix not only shows the magnitude of change but also identifies the nature of LULC conversion. The methodology implemented in the study partially overcomes the classification inconsistency in multi-temporal image analysis. The study also demonstrated that the object based image analysis approach, which was specifically devised for higher resolution images, can be implemented with medium resolution images. The impact of urbanization is being felt throughout the basin. Built up areas are not only confined to the city area, but are expanding along the major transport networks. The expansion of built up area, decline in wasteland, and increase in water bodies are clearly evident from satellite images. However, the major challenges were to extract this information through proper techniques. Object based image analysis approach along with GIS based change detection method made it possible to classify and quantify various aspects of LULC change with reasonable accuracy. The built up area has expanded massively, which is highly irreversible in nature. The extent of the built up area is very less in comparison to other major LULC classes, however it has a great potential to influence the entire basin. LULC change at this magnitude must have impacted the micro climatic condition in the region. Increase in water use at source has reduced the stream flow to down-stream areas. Specifically, agricultural intensification, inter-basin water transfer, and increase in water demand for domestic and industrial sector leads to significant decrease in stream flow discharge from the basin. Water sharing conflicts among various stake holders have showed the need for better management of water resources in the region. In this scenario, an alternate source of water as well as the judicious use of existing water resources can only make the basin sustainable in future.
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