Remote sensing based time-series analysis for monitoring urban sprawl: A case study of Chandigarh capital region

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Abstract: Urban growth is a global phenomenon, which is happening at unprecedented rates. According to the United Nations, the current world population of 7.6 billion is expected to reach 8.6 billion in 2030 out of which 5 billion will be urban population. Much of this urbanization will unfold in Africa and Asia, bringing huge social, economic and environmental transformations. The main reasons for urban growth are an unorganized expansion, increased immigration, and population explosion. In this context, changes in land cover are considered one of the central components for managing natural resources and monitoring environmental impacts. In the present study, a supervised classification applied to a time-series data of Landsat collected over time (1990, 2001, and 2015) gave an insight into the urban sprawl patterns in the Chandigarh capital region. The results show an increasing trend of urban sprawl in the outskirts of the city, especially in the northwestern and southern directions as a result of the development of an international airport, new sectors, and approach roads. Post-classification change detection points to the fact that maximum changes were seen in the class vegetation as it has rapidly changed to built-up/urban areas. Based on the results of such studies, the city and town planners may be able to take timely and appropriate steps to minimize the environmental implications associated with such urbanization.

Keywords: Urban sprawl, land cover classification, environmental impact, Chandigarh capital region.

1. Introduction

Urbanization is a global phenomenon, which is happening at unprecedented rates. According to the United Nations, the current world population of 7.6 billion is expected to reach 8.6 billion in 2030 out of which 5 billion will be urban population (UNDESA 2017). Urban sprawl, also called sprawl or suburban sprawl, is the rapid expansion of urban areas outside the geographic extent of existing cities and towns. It is a natural process of urbanization but is haphazard and unplanned expansion and therefore, its boundary cannot be determined. Sprawl is characterized by low-density, mono-functional or single-use communities where use of private automobile is the main source of transportation. The process of sprawl begin with initiation of migration of people from other areas to the urban areas. With time, migration leads to increase in population and in the long run the sprawl will occur due to natural growth. The rates of urban sprawl are not accelerating in industrialized nations as 75% of their population has already been urbanized (UNDESA, 2004). However, by 2050, 2.5 billion people will be added to world's urban population, with almost 90% of this growth unfolding in Africa and Asia, bringing huge social, economic and environmental transformations (UNDESA, 2018).

One very glaring consequence of sprawl in developing countries is the change of agricultural land to urban built-up areas. Infact, many cities are growing at their fringes transforming the villages and agricultural lands to industrial, commercial or low density residential clusters (Huang et al., 2009). A number of Indian cities have been studied in the context of urban sprawl (Bhat et al., 2017; Jain and Sharma, 2018; Anees et al., 2018). Thus, urban sprawl has become a major issue facing many cities and it is critical to study and monitor it in a spatial context. In the case study described here, urban sprawl is seen as an increase in built-up area transformed from rural and agricultural lands. One of the methods to detect changes in an area is by comparing multi-temporal classification derived from satellite images. Remote sensing technology coupled with geographic information system (GIS) tools by virtue of its several advantages has cemented its place in many applications and thus may also prove useful in characterize the dynamics of land cover change in the present study as well. In the present paper, firstly we instigate the context of the study, then we describe the study area and the methodology adopted, and later discuss the results of our study.

2. Materials and Methods

2.1 Description of study area

Chandigarh, also called the City Beautiful, is the first planned city of India which is located in North India at 76° 47' 14" E and 30° 44' 14" N with an average elevation of 335 m above mean sea level. It was inaugurated in 1952 by the first Prime minister of independent India Jawaharlal Nehru and was designed by French architect- Le Corbusier. Chandigarh was declared a union territory on 01 November 1966 and serves as the administrative capital of the states of Punjab and Haryana and lies 160 miles north of the national capital New Delhi. The total area of the city is 114 m^2. It is bordered on three sides by Punjab (north, west, and south) and on the eastern side by Haryana. It is a part of the Chandigarh capital region (CCR) which includes Chandigarh and the neighbouring cities of Panchkula (in Haryana), Sahibzada Ajit Singh (SAS) Nagar, Zirakpur, Kharar, and Mullanpur (all in Punjab). For the present study, this region (total area approx. 675 sq km) has been taken into consideration (Figure 1).

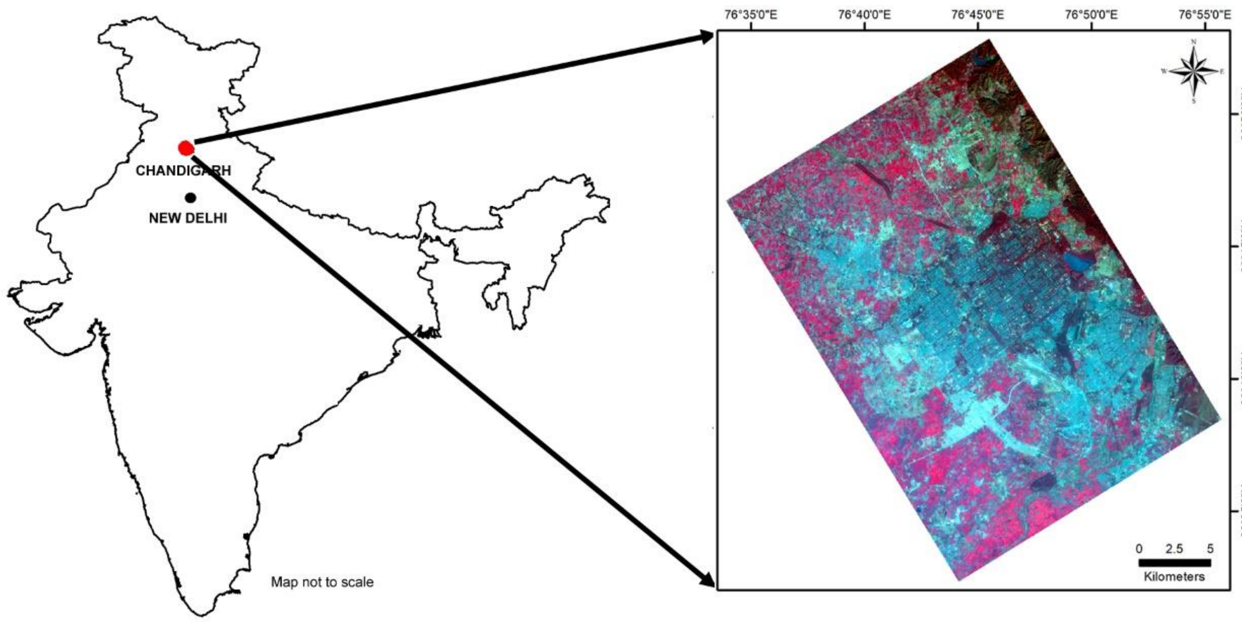

Figure 1: Geographic location and Landsat OLI image (FCC: R = NIR, G = Red, B = Green, Dec. 2015) of the study area

2.2 Data used

Cloud-free multi-temporal datasets of the study area, acquired from TM, ETM+ and OLI sensors on-board Landsat satellites, and covering a span of 25 years from 1990 to 2015, were acquired from the USGS Landsat archives as L1 data products. The optical data is available at 30 m spatial resolution and is available free of cost for anybody to use. Ancillary data such as Survey of India topographical maps (Nos. H43K9, H43K10, H43K13, H43K14); at a scale of 1:50000 were used to georeference the satellite data.

2.3 Land cover classification

In order to obtain information about land cover and urban sprawl areas, a time-series data of Landsat pertaining to three years - 1990 (TM), 2001 (ETM+) and 2015 (OLI) have been processed and classified. The data belonged to same season so as to avoid any uncertainness due to inter-annual variability. Although several image classification techniques have been proposed in literature (Mountrakis et al., 2011; Ranga et al., 2011; Wenzhi et al., 2012) but the most prominent classification techniques is pixel based image classification which is largely based on the spectral information of the pixels.

Digital image processing software ERDAS Imagine (v. 2016) has been used to process, analyse, and integrate the spatial data. Firstly, the multi-temporal data was geometrically registered and later atmospheric correction was carried out using the ATCOR module of ERDAS Imagine. The corrected images were then classified into five classes namely Built-up, Sparse to Moderate vegetation, Dense vegetation, Barren Land and Water. A congruous number of training pixels were selected to train the classifier. Then, Maximum Likelihood Classifier algorithm was applied to each image and three different land cover maps were produced. Post-classification comparison was carried out by following the procedures defined in literature (Jensen et al., 1987; Dimyati et al., 1996; Ward et al., 2000). This method offers the advantage to allow the creation and the update of GIS databases, as class/categories are given, and quantitative values of each class can be determined (Fischera et al., 2012). Since our main focus is on the extent of Built-up/Urban area

2.4 Accuracy assessment

The accuracy of the classified objects was estimated using the error matrix approach (Congalton, 1991). For an unbiased assessment, the equalized random sampling method (Jensen et al., 1987) was used to select samples for each class. Three types of accuracies were calculated for each image namely- user's (UA), producer's (PA) and overall accuracy (OA) along with Kappa index of Agreement (KIA).

3. Results and discussion

In order to understand, characterize, and monitor the urban expansion process, the availability of time-series data is essential. The results of this study are shown in figure 2, which indicate that the built-up/Urban area has considerably modified the land cover of the study area, with significant land conversions. Table 1 shows the area of different land cover classes. The urbanization happened in all directions but maximum urbanization took place in the south (Zirakpur) and north-west (Kharar) directions outside the city, as a result of the development of an international airport, new sectors and approach roads on the vegetated areas. This exponential growth of built-up or urban areas has probably happened because of the increased educational and employment opportunities and better living standards in the CCR. Table 2 provides the results of the accuracies attained by means of a confusion matrix. The accuracies of all the three years is above the minimum accuracy threshold of 85% (Anderson et al., 1976). Out of the three years, the highest overall accuracy of 92.7% with a KIA of 0.912 was for the year 2015 A number of classes were more accurately identified than others such as class 'Sparse to Moderate Vegetation' (UA 93.7% and PA 95.8%) and 'Water' (UA 93.7% and PA 97.8%). The high accuracy of 2015 OLI data could be attributed to its high radiometric resolution. Also, it is because of the fact of availability of more detailed and higher resolution reference maps (such as Google Earth imagery) in recent times for carrying out accuracy assessment.

Over the entire study period, agriculture land was the predominant land cover type, although it declined over time by being changed to built-up/urban or barren land. Since we were mainly concerned with the extent of urban sprawl, therefore, for post-classification change detection, we compared the increase in built-up area versus Non built-up area for the three years (Figure 3). It could be observed that the built-up/urban area showed significant increase (~79%) over the 25-year period.

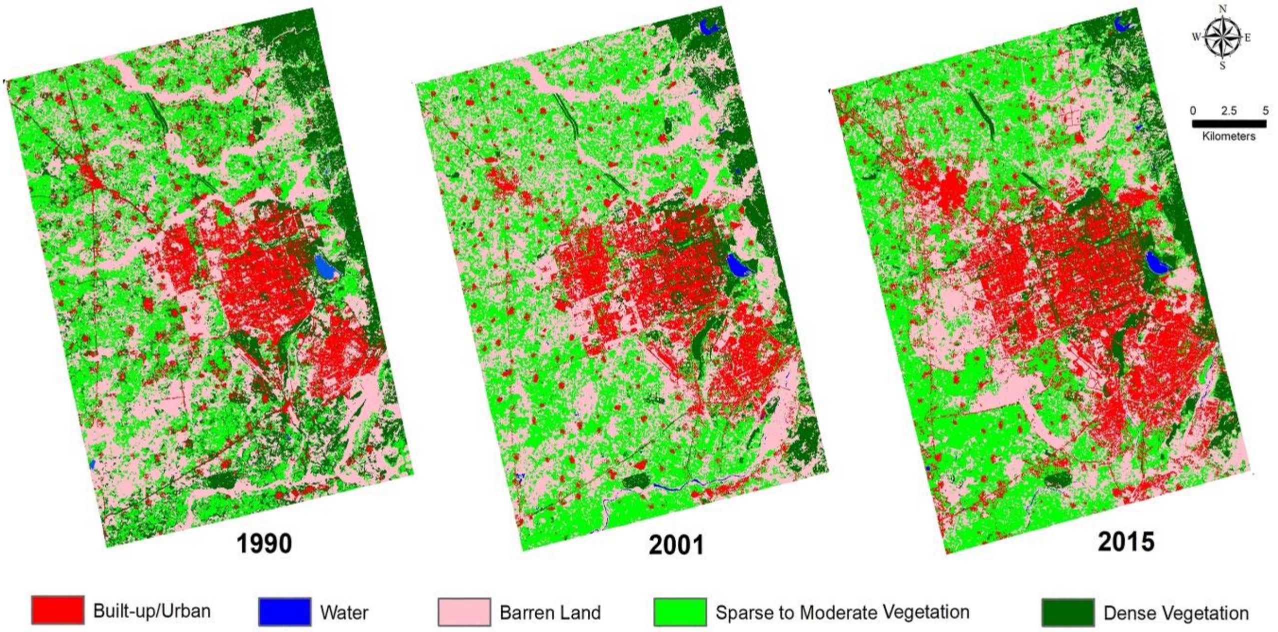

Figure 2: Land cover maps for the three years. Note the expansion in Built-up area (red) over the 25 year period

Table 1: Area of different land-cover classes

Land Cover Class	1990	2001	2015
Barren Land	85.7	94.9	153.3
Built-up	129.2	66.5	67.5
Sparse to Moderate Vegetation	192.1	233.2	227.7
Dense vegetation	266.9	277.5	224.4
Water	1.9	3.5	2.7

Table 2: Summary of the classification accuracies

Land cover class	**1990 (TM)**		**2001 (ETM+)**		**2015 (OLI)**	
	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
Built-up/Urban	87.5	100	87.5	82.3	87.5	93.3
Water	93.7	100	87.5	100	93.7	97.8
Barren Land	93.8	87.5	93.8	78.9	92.4	84.3
Sparse to Moderate Veg.	91.5	78.9	85.7	93.3	94.6	88.2
Dense Vegetation	88.3	87.5	92.4	98.7	93.7	95.8
Overall Accuracy (%)	91.2		90.0		92.7	
Kappa Statistic	0.891		0.875		0.912	

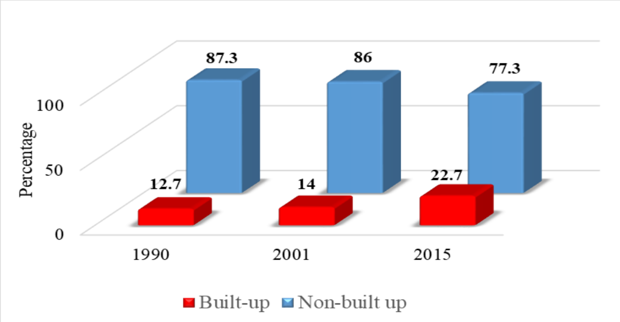

Figure 3: Percent cover of study area under built-up and non built-up

Urban sprawl is a complex diffusion process that is spreading dramatically and affecting rural landscape differently in space and at different scales. The continuing land cover changes in the CCR have different implications. Such kind of drastic change in land cover can negatively alter the potential use of an area and may ultimately lead to loss of productivity. This could, in turn, affect the local people by reducing the means of livelihood of those who depend on agriculture. Other implication associated with the increasing urbanization is increasing pressure on the available environmental resources and infrastructure of the city. Furthermore, such studies can provide information as indicators of the direction of change in the study area over the given period. The city and town planners may thus be able to take timely and appropriate steps to minimize the environmental implications associated with such urbanization.

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