Mapping Environmental Impacts of Rapid Urbanisation and Deriving Relationship between NDVI, NDBI and Surface Temperature: A Case Study

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Abstract. Urbanisation is a complex global phenomenon driven by unorganised expansion, increased immigration, and population explosion. Changes in land cover are one of the most critical components for managing natural resources and monitoring environmental impacts in this context. In the present study, a hybrid classification approach was applied to Landsat data to get insight into the urbanisation of the Chandigarh capital region from 2000 to 2020. The results demonstrate an increasing urbanisation tendency on the city's outskirts, particularly in the north-western and southern directions. The most considerable alterations were seen in the class vegetation as it swiftly transformed to built-up regions. Two indices, namely NDVI and NDBI and surface temperature images, were also derived from studying their inter-relationships. The paper suggests a positive linear relationship between surface temperature and NDBI while a negative correlation between NDVI and NDBI. Such studies may help city planners to take timely and appropriate efforts to reduce the environmental consequences of urbanisation.

1. Introduction

Urbanisation is popularly defined as the increase in the population of urban areas. [1] defined urbanisation as follows, “Urbanisation is not a product. It is a process by which people, instead of living in predominantly dispersed agricultural villages, start living in towns and cities dominated by industrial and service functionaries. It involves multiplication of urban places and/or an increase in size of cities.”

The phenomenon of urbanisation is global. The current population of the world is 7.9 bn, and it has been predicted to increase to 8.5 billion by 2030 [2], out of which 5 bn people will be living in cities. India is not far behind in this global phenomenon. It has been projected that India will add 416 million urban dwellers by 2050 – the highest amongst all the countries [3]. An increase in urban areas leads to the development of built infrastructure, which traps the incoming solar radiation, the heat released from vehicular exhausts and other such sources, leading to the urban heat island effect. With its inherent ability of synoptic, periodic and cost-effective coverage, remote sensing is gaining popularity to study such an increase in urbanisation. Several authors [4–11] have reported the suitability of remote sensing data to map, monitor and detect changes associated with rapid urbanisation [12]. In the case of Chandigarh, the study area of this research, it is projected that by the year 2021, its population would be around 1.95 mn (at the current growth rate), almost four times for which it was initially built. Thus, the present study aims to map the environmental impacts of increasing urban areas in Chandigarh and its neighbouring cities over the past two decades using satellite data. A comparison between the surface...
temperature and built-up area has also been carried out to assess their inter-relationship. Until recently, no such research has been reported from the study area.

2. Materials and methods

2.1. Study area
The city of Chandigarh lies 250 km north of New Delhi, the national capital of India. It lies between longitudes 76°43'17" E - 76°50'19" and latitudes 30°39'57" N - 30°47'05" N. It was designed by a French architect and has the distinction of being the first planned city of India. The study area of Chandigarh capital region (CCR) includes Chandigarh and the neighbouring cities of Zirakpur, Kharar, Mullanpur, Sahibzada Ajit Singh (SAS) Nagar and Panchkula (Figure 1).

![Figure 1. Location map of the study area.](image)

2.2. Data set
Multi-temporal Landsat datasets covering a time frame of two decades from 2000 (ETM+) to 2020 (OLI) were acquired from the USGS Earthexplorer website. The data were obtained from nearly the same day (15 Oct. 2000 and 14 Oct. 2020) each year to eliminate seasonal variance. Georeferencing of the satellite data was done using the 1:50000 scale topographical maps obtained from the Survey of India department. The municipal boundaries of individual cities were digitised using the maps obtained from the respective urban planning departments. Fieldwork is essential for any type of remote sensing analysis. In the present study, land use/land cover (LULC) information and ground control points (GCPs) were collected during the fieldwork.

2.3. Methodology

2.3.1. Deriving radiance images. For ETM+, the digital number (DN) values have been converted to top-of-atmosphere (TOA) spectral radiance using equation (1) [13] and for OLI data using equation (2) [14]

\[
L^* = \frac{(L_{\text{max}} - L_{\text{min}})DN + L_{\text{min}}}{DN_{\text{max}}}
\]  

(1)

\[
L^* = M_L * DN + A_L
\]  

(2)

where \(L^*\) is the TOA radiance received at the sensor; \(L_{\text{min}}\) and \(L_{\text{max}}\) are the minimum and maximum spectral radiance for the sensor, respectively; \(DN\) is the quantised and calibrated standard product pixel values; \(DN_{\text{max}}\) is the maximum grey level; \(M_L\) is band-specific multiplicative rescaling factor; \(A_L\) is band-specific additive rescaling factor. Atmospheric correction of the radiance images was done using the FLAASH function of ENVI software.
2.3.2. Deriving surface temperature images. The radiance images derived from thermal bands were used to calculate brightness temperature using the formula given by [13]

\[ T_r = \frac{K_2}{\ln \left( \frac{K_1 L^* + 1}{T_r} \right)} \] (3)

where \( T_r \) = TOA brightness temperature (°K); \( K_1 \) and \( K_2 \) = band-specific thermal conversion constant from the metadata, respectively.

2.3.3. Calculation of indices. Normalised Difference Vegetation Index (NDVI), given by [15], was calculated to assess the vegetation cover, and Normalized Difference Built-up Index (NDBI) [16] was calculated to delineate the built-up area. Later, relationships between NDVI, NDBI and temperature images were assessed.

2.3.4. Image classification. The objective of the present research is to map the urban areas and vegetation; therefore, the images were divided into only three level-1 classes [17] - Built-up, Vegetation and Others. A hybrid approach of utilising both unsupervised and supervised classification was used. Firstly, unsupervised ISODATA clustering was used to classify the images yielding 20 spectral clusters. The truly homogeneous clusters corresponding to a particular LULC were merged and labelled based on the field data. Accuracy assessment was carried out using the well-known error or confusion matrix approach [18]. Equalised random sampling method was used to select 30 samples from each class. Google Earth imagery was used as a reference for the classified images.

3. Results and Discussion

3.1. Image classification and accuracy assessment

Figure 2 depicts the resulting land cover maps. The maps show that the land use pattern is changing rapidly, with the Built-up area significantly modifying the LULC of the study area. The city of Chandigarh has urbanised in all directions, but maximum urbanisation (increase in class Built-up) occurred outside the city in Zirakpur (south) and Kharar (north-west). One of the major causes of this increase is the expansion of the existing domestic airport to an international airport. An airport road (black arrow in figure 2) was built to cater to the increasing traffic. This caused the development of urban areas on both sides and the subsequent population of nearby towns. Table 1 shows the classification accuracies derived from error matrices. The overall accuracy of 2000 and 2020 maps was 94.4 per cent and 95.5 per cent, respectively, above the standard threshold of 85 per cent. The high accuracy could be attributed to classification comprising of only three level-1 classes.

| LULC Class   | 2000 UA(%) | 2000 PA(%) | 2020 UA(%) | 2020 PA(%) |
|--------------|------------|------------|------------|------------|
| Built-up     | 90.3       | 100        | 93.7       | 100        |
| Vegetation   | 96.4       | 93.1       | 96.5       | 96.6       |
| Others       | 96.7       | 90.6       | 96.6       | 90.3       |
| Overall Accuracy (%) | 94.4 | 95.5 |
| Kappa statistic | 0.91 | 0.93 |
3.2. Spatiotemporal patterns of temperature images

The surface temperature derived from satellite images gives an overview of global, regional and local variations over time. It is critical to obtain surface temperatures and use them in various analyses to evaluate the problem linked with the environment [19]. The temperature images for 2000 and 2020 are given in figure 3. Vegetated areas tend to lower the temperature due to evapotranspiration that maintains the heat flux [20]. However, as this cover is lost and changed into impervious surfaces, the solar radiation is reflected, leading to higher temperatures captured by the thermal satellite sensors. In the present study, vegetation loss over the two decades leads to an increase in thermal signature, especially in the western parts of the 2020 image (figure 3b). Note that the black arrow in figure 3b shows the newly constructed airport road and a corresponding higher temperature than vegetated areas. The red arrow marks the location of the international airport, which has grown in size over the two decades. In October (the month of satellite images), the average temperature remains around 24°C in the study area. Because of increasing urbanisation, this temperature could be seen to have risen above 40°C in 2020, pointing to the urban heat island effect.

![Figure 2. Classified maps of (a) 2000 and (b) 2020.](image)

![Figure 3. Spatio-temporal variation of temperature from (a) 2000 to (b) 2020 in the study area.](image)

3.3. Relationship between NDVI, NDBI and temperature images

Figure 4(a-b) shows the relationships between NDVI and NDBI, while figure 4(c-d) shows between NDVI and NDBI. It could be observed that the relationship of NDBI and temperature for the year 2020
(figure 4b) shows a moderate positive correlation indicating that as built-up areas increase, they trap heat and thus, the surface temperature increases. The results are in line with published literature [21–25]. Since the newly developed built-up areas have expanded at the expense of vegetated areas, thus the NDVI and NDBI show a negative correlation for both years (figures 4c-d). This complements the results of land use changes in figure 2. The negative correlation between NDVI and NDBI corroborates the fact that vegetation lowers the temperature. [22] reported that the expansion of built-up areas could be characterised utilising NDVI. Thus, either of the indices–NDVI indirectly or NDBI directly- could be used to assist surface temperature measurements.

![Figure 4. Relationship between temperature (x-axis) and NDBI (y-axis) for (a) 2000, (b) 2020 and NDBI (x-axis) and NDVI (y-axis) for (c) 2000 (d) 2020.](image)

4. Conclusion
Urbanisation is a complex diffusion process and a critical driver of land use change. The burden on already scant environmental resources and infrastructure increases as the urban population grows. It is evident from the land use maps of the present research that built-up areas are increasing at the expanse of surrounding agricultural/vegetated lands. This study also implies that remote sensing data helps indicate the direction of change of land use over a period of time. The expansion of urban areas will inevitably continue in the future, but careful review and modification of land use regulations and decisions are required to limit this development. Such studies should indeed be conducted regularly to assist city planners in focusing on the specific locations and prioritising their strategies to combat the environmental consequences of urbanisation.

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References
[1] Misra R P 1997 Urbanisation in India: challenges and opportunities (New Delhi: Regency Publication)
[2] United Nations World population prospects Highlights, 2019 revision Available online: https://www.un.org/development/desa/publications/world-population-prospects-2019-highlights.html Accessed: 2/9/2021
[3] World Urbanization Prospects - Population Division - United Nations 2018 Available online: https://population.un.org/wup/ Accessed: 2/9/2021
[4] Mahmoud S H and Gan T Y 2018 Long-term impact of rapid urbanisation on urban climate and human thermal comfort in hot-arid environment Build. Environ. 142 83–100
[5] Zhu Y-G 2012 Environmental impacts of rapid urbanisation in China: a showcase of recent research developments Environ. Sci. Pollut. Res. 19 1351–1351
[6] Sharma R and Joshi P K 2016 Mapping environmental impacts of rapid urbanisation in the National Capital Region of India using remote sensing inputs Urban Clim. 15 70–82
[7] Meng L, Sun Y and Zhao S 2020 Comparing the spatial and temporal dynamics of urban expansion in Guangzhou and Shenzhen from 1975 to 2015: A case study of pioneer cities in China's rapid urbanisation Land Use Policy 97 104753
[8] Li D, Wu S, Liang Z and Li S 2020 The impacts of urbanisation and climate change on urban vegetation dynamics in China Urban For. Urban Green. 54 126764
[9] Civco D L, Hurd J D, Wilson E H, Arnold C L and Prisloe Jr M P 2002 Quantifying and describing urbanising landscapes in the northeast United States Photogram. Engng. Remote Sens. 68 1083–90
[10] Yang X 2002 Satellite Monitoring of Urban Spatial Growth in the Atlanta Metropolitan Area Photogram. Engng. Remote Sens. 68 725–34
[11] Saini V and Tiwari R K 2019 Remote sensing based time-series analysis for monitoring urban sprawl: A case study of Chandigarh capital region. J. Geom. 13 94–7
[12] Saini V and Tiwari R K 2018 Proc. of SPIE Remote Sens. Remote Sensing Technologies and Applications in Urban Environments ed N Chrysoulakis, T Erbertseder and Y Zhang (Berlin, Germany: SPIE) p 1-8
[13] Chander G, Markham B L and Helder D L 2009 Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors Remote Sens. Environ. 113 893–903
[14] Using the USGS Landsat Level-1 Data Product Available online: https://www.usgs.gov/core-science-systems/nli/landsat/using-usgs-landsat-level-1-data-product Accessed 2/9/2021
[15] Rouse J, Haas R H, Schell J A and Deering D 1973 Proc. 3d ERTS-I Symp. vol 1, Section A (NASA. Goddard Space Flight Center) pp 309–17
[16] Zha Y, Gao J and Ni S 2003 Use of normalised difference built-up index in automatically mapping urban areas from TM imagery Int. J. Remote Sens. 24 583–94
[17] Anderson J R, Hardy E E, Roach J T and Witmer R E 1976 A land use and land cover classification system for use with remote sensor data paper 964 p 28
[18] Congalton R G 1991 A review of assessing the accuracy of classifications of remotely sensed data Remote Sens. Environ. 37 35–46
[19] Orhan O, Ekercin S and Dadaser-Celik F 2014 Use of Landsat Land Surface Temperature and Vegetation Indices for Monitoring Drought in the Salt Lake Basin Area, Turkey The Sci. World J. 2014 142939
[20] Joshi J P and Bhatt B 2012 Estimating temporal land surface temperature using remote sensing: a study of Vadodara urban area, Gujarat Int. J. Geol. Earth Environ. Sci. 2 123–30
[21] Malik M S, Shukla J P and Mishra S 2019 Relationship of LST, NDBI and NDVI using Landsat-8 data in Kandaihimmat Watershed, Hoshangabad, India Indian J. Geo Marine Sci. 48 25–31
[22] Chen L, Li M, Huang F and Xu S 2013 Proc. Int. Congr. Image Signal Process. vol 2 (Hangzhou, China) pp 840–5
[23] Guha S, Govil H, Dey A and Gill N 2018 Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI and TIRS data in Florence and Naples city, Italy *Eur. J. Remote Sens.* **51** 667–78.

[24] Zhang Y, Odeh I O A and Han C 2009 Bi-temporal characterisation of land surface temperature in relation to impervious surface area, NDVI and NDBI, using a sub-pixel image analysis *Int. J. Appl. Earth Obs. Geoinf.* **11** 256–64.

[25] Saini V and Tiwari R K 2017 *Proc. 38th Asian Conf. Remote Sens.* (New Delhi, India: ASRS) p 10