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Random forest classification of urban landscape using Landsat archive and ancillary data: Combining seasonal maps with decision level fusion

Aniruddha Ghosh, Richa Sharma, P.K. Joshi

Department of Natural Resources, TERI University, New Delhi, India

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- Decision level fusion
- DEM
- Landsat
- Multi-season
- Random forest
- Urban

Abstract

Mapping urban landscapes in a rapidly urbanizing region can contribute significantly to quantifying, monitoring and understanding the complex process of urbanization. However, mapping such urban areas is a challenging task due to issues of spatial heterogeneity and dynamic land use practices. In this study we propose an operational mapping algorithm using multi-season Landsat and ancillary data with minimum image pre-processing and limited training samples. The methodology was applied to produce a detailed land use land cover (LULC) map of National Capital Region of India. Seasonal maps (with nine LULC classes) were produced by using Random Forest (RF). A second classification involving seasonal maps with decision level fusion based on expert knowledge resulted in annual composite map with increased number (eleven) of LULC classes. These detailed maps have moderately high (>60%) overall accuracies. The maps generated over different seasons are especially significant in identifying areas with mixed land use practices (like agriculture) occurring over an annual cycle. The annual map as the end product of the decision fusion summarizes the LULC dynamics of the study area with the help of eleven LULC classes. The significance of this work lies not only in generating accurately classified LULC maps, but also in detecting the seasonal dynamics of land use practices in a complex urbanizing landscape. Furthermore, reproducibility of the developed methodology will aid the extension of research for different time periods and with newer sensors in investigating the patterns and dynamics of land use and urban planning activities.

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Introduction

Urbanization is a major form of anthropogenic land-use activity influencing the climate (Kalnay & Cai, 2003). In the last hundred years the urban population as per cent to total global population has increased from 10% to more than 50% (Grimm et al., 2008). The current rate of spatial expansion of urban areas is twice as fast as their population (Angel, Parent, Civco, Blei, & Potere, 2011). Urban expansion whether planned or unplanned—threatens biodiversity (McKinney, 2002), affects quality of life, causes habitat loss (McDonald, Kareiva, & Forman, 2008) and results in loss of above-ground carbon storage (Imhoff et al., 2004). In addition, many of the urban agglomerations are exposed to natural hazards such as flood, drought or earthquake (Cutter, 1996; Sherbinin, Schiller, & Pulsipher, 2007). Existence of these phenomena strongly validates the argument for sustainable cities. One of the foremost requirements for planning, design, management and development activities leading to sustainability are accurate and reliable information of the current spatial distribution of urban components. In addition, this information is also essential for estimating greenhouse emission and predicting the likely growth of urban areas.

Remotely sensed data from various earth observation satellites can provide accurate and timely geospatial information of urban and peri-urban areas at diverse spectral, spatial and temporal scales (Taubenböck et al., 2012). These dataset are increasingly becoming an attractive alternative to ground based survey and mapping methods due to the advantages of cost and time saving for larger areas. However, use of remote sensing data to map an urban area is often challenging given the spatial complexity and dynamics of the area under study (Schneider, 2012). Often the characteristic scale of occurrence and shape of many urban features lead to the problem...
of ‘mixed pixel’ (Small, 2003) which can be addressed by the use of very high resolution (VHR) dataset with spatial resolution less than 5 m from sensors such as IKONOS, QuickBird or World View 2 (Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011; Small, 2003; Welch, 1982). But, along with low swath, the VHR dataset also suffers from the constraint of limited scene availability (spatially and temporally) which restricts its wide use. Medium-resolution Landsat has a regularly sampled historical archive of 40 years and provides an optimum solution to minimize the trade-off between coverage, temporal and spatial resolution thereby satisfying the requirement for local to global scale studies (Goward, Masek, Williams, Irons, & Thompson, 2001).

Various agencies concerned with the issues of urbanization require accurate and timely geospatial information about the patterns and dynamics of urban components. Given the rapid growth of urban areas in developing countries like China and India, annual monitoring is more essential than decadal monitoring. In areas with high inter- and intra-annual variability of land use practices, it is nearly impossible to use medium-resolution data sources to separate LULC classes at a single point in time (Heller et al., 2012). Thus generating a single annual map is difficult owing to the fact that many of the LULC features are under the process of rapid change such as transitional urban (exposed land which has been cleared for construction purposes) or exhibit different phenological behavior in forms of different stages of crop (seedling, bloom, and harvesting stage), forest types, and leaf-on and leaf-off conditions (O’Hara, King, Cartwright, & King, 2003).

In this context, few studies have attempted to use multi-seasonal remote sensing data for monitoring LULC classes in urban areas (Schneider, 2012). Multi-seasonal information has proven beneficial for reducing class confusion for vegetation by exploiting the phenological behavior of different vegetation types in complex landscapes (Joshi, Roy, Singh, Agrawal, & Yadav, 2006; Rodriguez-Galiano, Chica-Olmo, Abarca-Hernandez, Atkinson, & Jeganathan, 2012). Yuen, Sawaya, Loeffelholz, and Bauer (2005) used spring–summer Landsat imagery to map Twin Cities Metropolitan Area of Minnesota, Punjab, and Porwal (2011) explored the potential of seasonal (Monsoon–Winter–Summer) IRS-P6 AWIFS data for mapping LULC of Delhi. These studies reported significant increase in overall accuracy regardless of the difference in the study areas.

Majority of previous studies stacked the seasonal data to create a single raster following a radiometric normalization and classified this raster using exhaustive training sets involving all the seasonally/temporally varying class information (for example cropping patterns, transitional lands) (Punia et al., 2011; Schneider, 2012). The difficulty with such mapping process is that it is largely dependent on the classifiers’ ability to handle the vast and diverse dataset. At the same time, generation of training database consisting of all LULC classes present in study area throughout the year is a challenging task and requires multiple rigorous field visits and special emphasis on seasonally/temporally varying classes. In the light of these considerations, this study proposes a simple operational methodology to produce annual LULC map based on decision level fusion of the classified multi-seasonal data, which requires relatively lower a priori spatial information of the temporally varying classes. We tested this methodology for three different seasons corresponding to the crop cultivation calendar, i.e., kharif or monsoon (June–November), rabi or winter (October–March) and zaid or summer (March–July) for three different annual crop cultivation cycles (1998–99, 2002–03, 2010–11). DEM derived three ancillary input features were also used to improve the classification accuracy. Furthermore we assessed the importance of the input variables and analyzed their seasonal variability across three different years.

Methodology

Study area and class description

Delhi, the capital of India, is the second most populated megacity in the world with nearly 17 million people with an area of 1483 km². Population in Delhi has risen from 1.7 million in 1951 to 13 million in 2001, finally crossing the mark of 16.7 million in 2011 (Census of India, 2011), as one of the fastest growing urban areas in history (United Nations, 2012). This unprecedented escalation has attracted a wide community of researchers to map the complex LULC of Delhi (Cole, Wentz, & Christensen, 2005; Mookherjee & Hoerauf, 2004; Punia et al., 2011; Rahman, Kumar, Fazal, & Bhaskaran, 2011; Sokhi, Sharma, & Uttawar, 1989; Wentz, Nelson, Rahman, Stefanow, & Roy, 2008). In 1991, the urban core of Delhi was expanded to nearby interstate city areas such as Ghaziabad and Noida of Uttar Pradesh and Faridabad and Gurgaon of Haryana forming the National Capital Region (NCR). Following this elevated status, this region has experienced rapid spatial changes in its LULC patterns. These changes — whether conversion of agricultural land to industry and civic facilities, or sparse built-up areas to dense built-up areas — have impacted the residential patterns, agricultural practices and urban forest distribution in the city. Delhi is characterized by highly heterogeneous land use practices with impervious surfaces dominating the commercial, industrial as well as residential areas; and patches of forests at the heart of the city, in the north and the south. Peri-urban areas and banks of river Yamuna are predominantly covered with agricultural lands. Such high heterogeneity of land use provides high dynamism to land transformations along both long-term as well as short-term scales. Over short-term, seasonal changes in crop and plant phenology play an important role to discriminate between the vegetation classes. The city experiences five major seasons; Winter (Nov–Feb), Spring (late Feb–Mar), Summer (Apr–Jun), Monsoon (Jul–Sep), and Post-monsoon (Oct–early Nov). Based on these seasons, four cropping practices are followed; kharif (Monsoon crop), rabi (Winter crop), zaid (Summer crop) and double crop (two or more than two cropping is done) (Punia et al., 2011) (Fig. 1).

For selecting the representative LULC of the study area, we did not follow any particular classification scheme. We conducted four extensive field visits to identify the dominant LULC classes during 2010–11. Based on the field visits and expert knowledge, we identified 9 major LULC classes for each season (Table 1). For the other two years (1998–99 and 2002–03), we followed this designed classification schemes. The annual LULC map for each time period has with eleven classes (Table 1). The details of generation of annual map are presented in Knowledge based classification of seasonal maps to generate the annual map section.

Collection of training samples

For each season in each period, an inventory of unique training sites was generated. For 2010–11, training sites were collected through field visits using handheld GPS unit. For 2002–03, training sites were selected following on screen digitization through visual interpretation of seasonal Landsat data and Google Earth imagery. For 1998–99, due to the unavailability of Google Earth imagery, only seasonal Landsat imagery and expert knowledge derived from other periods were used to select training sites. During the collection of training samples of agriculture land use, only cropped or non-cropped lands were identified for seasonal data classification, which mean no a priori knowledge for, kharif (monsoon), rabi (winter), zaid (summer) and double crop practices were present for classifying the seasonal data. To minimize any kind of errors related to mixed pixels, homogenous polygons were selected as training...
sites. Finally from the training polygons, 200 sample points for each class were generated following a stratified random sampling to remove any kind of bias arising from under/over-representation of a particular class. Additionally, independent samples (~25 sample points for each LULC class) were collected for accuracy assessment including information on cropping practices along with other LULC classes.

Data description

To accomplish the research goals, we used satellite dataset from three different seasons for multiple years. After analyzing the characteristics of the study area, we decided to use the data corresponding to the three prevailing crop cultivation seasons: kharif (monsoon), rabi (winter) and zaid (summer). The details of the Landsat TM/ETM data used for the study are given as Supplementary material. Cloud-free terrain-corrected (LIT) Landsat data was downloaded from the USGS archive. Each dataset (corresponding to a particular season) was analyzed separately. Spectral information and training samples derived from one dataset were not transferred to the other cases. This discounted the need to perform any radiometric normalization or atmospheric correction (Song, Woodcock, Seto, Lenney, & Macomber, 2001). None of the thermal band was used for the analysis. While most of the study area is a flat terrain, some specific areas under the extended part of ridge show undulations. Therefore to increase the separability between LULC classes, along with spectral bands, we decided to use digital elevation model (DEM). The DEM used for this study was extracted from the Global DEM (GDEM) product generated from ASTER data version 2 with 30 m spatial resolution (METI & NASA, 2011). From DEM, the following features were used as ancillary information for classification: i) Elevation ii) Slope (0°–90°) and iii) Aspect (0°–360°). Finally, a single raster with 9 layers was generated using 6 spectral bands and 3 ancillary layers for each of the seasons.

Classification

For classifying multi-source or large number of input data, Random forest (RF), an ensemble based classification algorithm, have been reported to outperform parametric approaches like maximum likelihood (Gislason, Benediktsson, & Sveinsson, 2006) or non-parametric approaches like decision trees (DT) and neural networks (Chan & Paelinckx, 2008; Dietterich, 2000; Pal, 2005; Rodriguez-Galiano, Ghimire, Rogan, Chica-Olmo, & Rigol-Sanchez, 2012). Among the ensemble based classifiers, RF classifier was selected because: a) it is efficient for input predictors with different nature, b) it is possible to get variable importance measure which can be further used for feature extraction from multi-source data classification c) it is insensitive to noise, outliers and overtraining, d) it is computationally much faster than boosting based ensemble methods and somewhat faster than simple bagging (Breiman, 2001; Cutler, Edwards, Beard, Cutler, & Hess, 2007; Hastie, Tibshirani, & Friedman, 2009). Details of the RF algorithm used for remote sensing data classification can be found in works by Chan and Paelinckx (2008), Rodriguez-Galiano, Ghimire, et al. (2012) and Ghosh and Joshi (2014).

Table 1

<table>
<thead>
<tr>
<th>LULC</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>Agricultural areas cropped in corresponding seasons</td>
</tr>
<tr>
<td>Double crop</td>
<td>Agricultural areas cropped for twice or more seasons in a year; often irrigated</td>
</tr>
<tr>
<td>Rabi (winter) crop</td>
<td>Agricultural areas cropped between November/December to February/March (winter season); associated with areas under assured irrigation irrespective of source</td>
</tr>
<tr>
<td>Kharif (monsoon) crop</td>
<td>Agricultural areas cropped between June/July and September/October (southwest monsoon season); associated with rain-fed crops under dry land farming, limited or no irrigation and areas of rain-fed rice and other dry crops</td>
</tr>
<tr>
<td>Zaid (summer) crop</td>
<td>Agricultural areas cropped during the third season (summer) which are mostly associate with irrigated areas with fertile soils</td>
</tr>
<tr>
<td>Dense built-up</td>
<td>Areas that have higher density of built-up and are characterized by lesser proportion of vegetations or open lands</td>
</tr>
<tr>
<td>Exposed area</td>
<td>Land covered with sand (e.g., river beds), barren rocky area, negligible current fallow lands; appear bright due to higher reflectance</td>
</tr>
<tr>
<td>Fallow</td>
<td>Mainly agricultural fallow or current fallow</td>
</tr>
<tr>
<td>Forest</td>
<td>Tree (naturally growing) canopy cover of more than 10% and occupying more than 0.5 ha area primarily not under agriculture, plantation or other non-forest land use; mostly distributed in parts of central and northern ridge</td>
</tr>
<tr>
<td>Plantation</td>
<td>Tree crops of agricultural or non-agricultural significance (part of policy and management processes, afforestation attempts) and trees along the roads as well</td>
</tr>
<tr>
<td>Scrub</td>
<td>Mainly dominated by scrub vegetation (invasive species such as Prosopis juliflora, Lantana Camara), highly erosion prone areas often mixed with cropped lands</td>
</tr>
<tr>
<td>Sparse built-up</td>
<td>Area that is mainly covered with human settlements and built-ups but has some proportion of vegetations and open lands in between</td>
</tr>
<tr>
<td>Water</td>
<td>Surface water bodies such as reservoirs, rivers, canals, ponds, lakes etc</td>
</tr>
</tbody>
</table>

Classes present only in annual maps.
Classes present only in seasonal maps.
Algorithm implementation

Two parameters are required to construct an RF framework: the number of DT (k) in the ensemble and the number of input predictors (m) randomly selected at each node. For a classification process, generally the m value is set to one-third of the total input variables. However, optimization of m with fixed large k can minimize the generalization error to construct a robust RF classifier (Breiman & Cutler, 2004).

The RF classifier as described in the above section was implemented using the “caret” (Kuhn, 2008) and “raster” (Hijmans & Etten, 2012) package within R (version 2.15, 64 bit) open-source statistical software (R Development Core Team, 2012). The RF algorithm in the “caret” uses “randomForest” package (Liaw & Wiener, 2002). Since classification accuracy is more sensitive to m, k was fixed at a default value of 500 and m was tested for 9 values. This parameter tuning process was performed following a 3 time repeated 10-fold cross-validation process.

Variable importance

It is possible to measure the importance of input variables in RF framework. This measure is useful to gain an insight into the classification problems involving multi-source data. To measure the importance of an input variable, that particular variable is excluded from the RF framework while keeping the rest of the variables unchanged. For each DT in RF framework, there is a misclassification rate for the OOB samples. The difference between the misclassification rate for the modified and original RF, divided by the standard error gives the importance of the excluded variable.

Knowledge based classification of seasonal maps to generate the annual map

Combining the seasonal LULC maps to produce the annual map is a challenging task due to the unavailability of adequate and quality ground truth information. To resolve this issue, we developed an expert (interpreter/analyst) knowledge base analysis method. The knowledge was gained through repeated field visits and long working experience on the study area. A second classification method was performed using the seasonal LULC maps as input layers and expert knowledge from the field. We used the simplest production rule of the form “if condition then inference” linked through logical form “or”, “and” and “not” operations to capture the expert knowledge (Richards & Jia, 1999). The input of the rules (logical expressions) can be any input class from the seasonal maps and the output is a class in the annual map.

All the seasonal maps are classified into nine LULC classes each. We assume that a single pixel can remain unchanged in the same class throughout the year or may represent different LULC owing to seasonality. As a result, a sample may be classified as agriculture in one or two season(s). If it is classified as agriculture in winter and remains fallow in other seasons, it certainly falls under rabi (winter) crop. Similarly, a pixel classified as agriculture only in summer or monsoon season will belong to zaid (summer) or kharif (monsoon) respectively. At the same time, a pixel classified as agriculture for exactly two seasons should come under double crop. To combine the seasonal information on agriculture to form the annual composite map, the following set of rule can be used for the possibilities mentioned above:

if agriculture in winter and fallow (other class) in other seasons  
then rabi (winter) crop

if agriculture in summer and fallow (other class) in other seasons  
then zaid (summer) crop

if agriculture in monsoon and fallow (other class) in other seasons  
then kharif (monsoon) crop

if agriculture in season 1 and 2 and open/agriculture in season 3  
then double crop

Using these set of rule sets, four new agricultural classes in the annual map can be generated from a single agriculture class in seasonal maps. In another example, a sample pixel may be classified as built-up (dense or sparse) in all three seasons.

if dense built-up in season 1, season 2 and season 3 then dense built-up

Theoretically any single pixel can have any class label among the nine LULC classes in any season, which will give rise to a large number of possibilities for rule generation. However in practice such dynamicity is not observed. We further assume some restrictions and sometimes introduced majority voting to assign the annual class. For example, if any pixel falls under agriculture in all three seasons, most likely it is confusion between agriculture and young plantations, because no agricultural land is cultivated throughout the year in the study area. Therefore that particular pixel should be labeled as plantations. On the other hand, pixels having high reflectance such as bare soil in exposed area can belong to agricultural fallow (in the drought/harvested season) or under-construction areas in a particular season (say summer). Now if that pixel is classified as agriculture in winter it should come under rabi (winter) crop. For all the three years tested, we found that there are around 600 possibilities to capture the seasonal variability and maximum of these center around the vegetation classes. These 600 possibilities are structured according to the corresponding production rules for merging the seasonal maps and are combined to form the entire knowledge base using interpreters’ understanding of the study area and analysis of seasonal satellite imagery. The knowledge base developed for 2010–11 is extended to the other years with slight yet similar modifications.

Accuracy assessment

The accuracy of the annual LULC maps produced was evaluated using overall (OA), producer’s (PA), user’s (UA) and Kappa (k) accuracy. PA quantifies the error of omission, while UA quantifies error of commission. Kappa is the measure of chance agreement and has been found to be more robust than OA, as it takes into account the agreement occurring by chance.

We assessed the classification accuracy at two levels of complexity. At level I, the classes are aggregated into four categories: agriculture, canopy, impervious and water. At level II, all eleven classes are considered. Since the performance the proposed methodology is not directly compared with other methods (Punia et al., 2011; Schneider, 2012), the classification accuracy is compared with previous studies on the LULC classification of Delhi. The detailed methodological flowchart is shown in Fig. 2.

Results

Seasonal variation of LULC

Merging of seasonal maps with nine LULC classes over three years produced a composite annual map with eleven LULC classes of varying accuracy. Fig. 3 depicts the seasonal variation owing to shifts in cropping practices for 2010–11. In October 2010, northern part of the study area was under agriculture for kharif (monsoon) crop cultivation. The planted trees were in full vigor during monsoon, and were thus classified as forest. In March, extensive cultivation was carried out with irrigation. During May 2011, cultivation was carried out in negligible areas. Therefore areas that

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were cultivated during rabi (winter) seasons were classified as fallow in May, while rain-fed areas (long fallow, cultivated in May) were misclassified as dense built-up due to very high reflectance and low moisture content.

**Variable importance**

The primary objective behind the variable importance analysis was to identify the most important features for classification and how these vary with seasons over the years. Since the number of input features was relatively low, we did not perform any feature selection to reduce the feature subset before classification. The result of variable importance is presented in Fig. 4. The general trend observed was that the five most important features are composed of one DEM feature and four spectral bands. We found that elevation was the most important input feature (except for the month of March of year 1998–99 and 2002–03). Certain Landsat spectral bands such as NIR, Blue and MIR 1 were consistently among the five most important features for all the cases. However for May 1998–99, the trend is significantly different and three DEM derived features (Elevation, Slope and Aspect) appeared among the five most important features.

**Classified maps and accuracy of classification**

Classification accuracy for classified maps was analyzed at two levels: level I and level II as explained previously to assess the impacts of changing class complexities on classification accuracy. The overall accuracies (OA), producer’s accuracy (PA), user’s accuracy (UA) at level I and III for all the three years are summarized in Tables 2 and 3. Related error matrices are presented as Supplementary material. The OA for 1998–99, 2002–03 and 2010–11 were 83%, 79% and 82%, with k of 74%, 69% and 73% respectively. UA and PA of individual classes were consistently higher than 74%, except for the PA (69%) of water in 2002–03 and PA (66%) of impervious area in 2010–11. Scrub in the leaf-off condition is dominated by soil reflectance and thus has spectral signature similar to impervious areas. The confusion between agriculture and impervious arises from the long fallow or transitional fallow. The low PA of water in 2002–03 can be explained by waterlogged areas during monsoon which usually belong to some other classes in other seasons.

At level II, OA for 1998–99, 2002–03 and 2010–11 were 64%, 65% and 69%, with k of 61%, 60% and 65% respectively (Table 3). Thus, it is evident that as the scale of classification complexity increases the overall accuracy falls down. For instance, canopy classes (forest, scrub and plantation) at level II had PA varying from 66% to 75% and UA ranging between 83% and 91%. At level II, for individual classes PA varied between 58% and 73% for forest, 29%–33% for plantation, and 51%–58% for scrub. Poor accuracy for plantation was reported due to spectral and phonological similarity of plantations with both forest and scrub. Below we describe and analyze the level II classification accuracies for all the classes. The classified maps for these three years are shown in Fig. 5.

1998–99: UA of dense built and water were more than 95%. Among the crop classes, UA of rabi (winter) crop was higher than 73%. Many forest pixels were classified as double crop which reduced the UA of double crop to 62%. Pixels of exposed area, plantation, forest and scrub were classified as kharif (monsoon) crop (UA = 45%). There was confusion between plantation, scrub and forest as all three are vegetation classes and follow similar phenological patterns. On the other hand, PA of double crop, rabi (winter) crop and water were more than 90%. But very low PA was observed in case of zaid (summer) crop (PA = 0.35) and plantation (PA = 0.29). Many plantation pixels were misclassified with scrub and forest due to their spectral similarity. Zaid (summer) crop was mostly misclassified as sparse built because of the land being fallow for a long period in the other seasons. Kharif (monsoon) crop was misclassified as rabi (winter) and double crop in some occasions.

2002–03: High UA was observed for kharif (monsoon) and zaid (summer) crop, dense built, plantation and water (UA > 85%). The increase in UA for two crops and plantation classes from the previous year can be validated by more areas under vegetation which is visible from the FCC image. This can be linked to the higher
rainfall in 2002–03 due to which the vegetation during the nonwinter seasons was in full vigor. PA of zaid (summer) was particularly low (0.32), as majority of the zaid (summer) pixels were classified as sparse built owing to its long fallow period interspersed with cropped season bearing similarity to sparse built-up that exhibited plantation bloom with availability of abundant water through rainfall precipitation and laying fallow otherwise. This also brings down the UA for sparse built-up to the minimum UA of 41%. Sparse built-up on the other hand had maximum PA of 84%. 100% fallow land in monsoon season can be covered with vegetation that exhibited plantation bloom with availability of abundant water, with scrub, which can be attributed to the encroachment of scrub in vegetation dominated sparsely built areas where most of the trees shed their leaves during winter.

2010–11: Rabi (winter) crop, forest, dense built and water were classified with high UA (>85%). UA of double cropped was significantly lower than other years (UA = 43%). Forest and plantations were classified as double crop due to the confusion arising from their similar spectral signatures and phenology. This intermixing depreciated the PA of plantation and forest as well. PA of plantation was 33% and for forest was 60%. Plantation also exhibited mixing with scrub, which can be attributed to the encroachment of scrub in plantation areas and vice versa situation where plantation attempts were carried out in scrub. Some plantations were present around the river Yamuna at close vicinity to agricultural lands, which might cause a spatial mixing with the double cropped lands. PA for agricultural classes was pretty high with highest PA of 100% for double crop and lowest of 67% for zaid (summer) crop.

Annual variation of LULC statistics

Annual statistics of agriculture for the three years display a trend that first increases and then decreases (Table 4). The agriculture in 1998–99 covered an area of 1056 km² that reduced to 872 km² in 2002–03 but then increased subsequently, finally reaching 942 km² in 2010–11. Dense built-up exhibited a continually increasing trend. The dense built-up land increased from 78 km² in 1998–99 to 160 km² in 2002–03 and 317 km² in 2010–11. Similar variations in statistics were illustrated by exposed area (288 km² in 1998–99, 292 km² in 2002–03 and 410 km² in 2010–11) and plantation (72 km² in 1998–99, 99 km² in 2002–03 and 167 km² in 2010–11). Contrary to this, the class that continually decreased in its land cover was water which fell from 15 km² to 12 km² and finally 11 km² in 1998–99, 2002–03 and 2010–11 respectively. Forest and sparse built-up demonstrated peculiar trend in their land cover statics. These classes increased their cover from 1998–99 to 2002–03 and then declined during 2002–03 to

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During 2002–03, heavy monsoonal rains were recorded which improved the vigor of vegetation (both plantation and scrub) resulting in over estimation of forest cover. Thus, an increase in forest cover was observed for 2002–03. Sparse built-up increase was due to conversion of more land into built-up areas, but with the transformation of this land into dense built-up, a decrease in sparse built-up category was observed.

Discussion

The outcome of this study indicates that moderate resolution multi-seasonal multi-spectral data combined with DEM derived features are useful for mapping complex heterogeneous urbanized landscape experiencing rapid changes. The knowledge based

Table 2

Accuracy statistics using independent validation points for the annual map at level 1.

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>0.79</td>
<td>0.88</td>
<td>0.77</td>
</tr>
<tr>
<td>Canopy</td>
<td>0.84</td>
<td>0.83</td>
<td>0.75</td>
</tr>
<tr>
<td>Impervious</td>
<td>0.83</td>
<td>0.74</td>
<td>0.86</td>
</tr>
<tr>
<td>Water</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>OA</td>
<td>0.83</td>
<td>0.79</td>
<td>0.82</td>
</tr>
<tr>
<td>Kappa</td>
<td>0.74</td>
<td>0.69</td>
<td>0.73</td>
</tr>
</tbody>
</table>

Fig. 4. Variable importance of different input layers in terms of OOB mean decrease in accuracy.
classification of seasonal maps to produce annual maps overcomes the difficulty of discriminating between classes having close spectral characteristics (plantation and forest; exposed area and dense built) or exhibiting similar phenology (different crops with other vegetation). The robustness of the methodology is tested for three time periods. Delhi has been experiencing unprecedented footprints of urbanization over the past few decades through various processes of leapfrog, in

The requirement for multi-temporal data

Merging of seasonal LULC information improves mapping accuracy of sparse and dense built-up classes despite the scale of occurrence of these land uses and complex spatial heterogeneity of Delhi. It is not possible to map the crop practices such as double crop using data from only one season (Heller et al., 2012). Often a single time image is insufficient to discriminate between crops and other vegetation such as plantation. In some occasions it is discriminating between classes such as of bare ground, fallow or post-harvest agriculture, and new construction. On the other hand, few classes over the study area are under rapid transition: these could be seasonal as well as permanent conversion of agricultural land to other form, including efforts at deforestation and afforestation. The major drivers behind the land use change of Delhi are expansion of road and metro network and construction of new industrial as well as residential complexes (Mohan, Pathan, Narendrareddy, Kandya, & Pandey, 2011). These results in sequential conversion of agriculture land to fallow (or exposed area) to built-up (in the form of new construction) or conversion of plantation and scrub to built-up areas. Many of the pixels under such transitional zone change their spectral characteristics owing to these dynamic shifts that can occur over a year. Therefore it is very difficult to generate exhaustive production rules for these classes.

The requirement for multi-source data

The selection of the important bands can be explained by the heterogeneous land use land cover of the region. The results suggest

Table 3

<table>
<thead>
<tr>
<th>Year</th>
<th>OA</th>
<th>PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998–99</td>
<td>0.64</td>
<td>0.65</td>
</tr>
<tr>
<td>2002–03</td>
<td>0.61</td>
<td>0.65</td>
</tr>
<tr>
<td>2010–11</td>
<td>0.61</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Table 4

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>1055.6</td>
<td>871.5</td>
<td>942.4</td>
</tr>
<tr>
<td>Dense built-up</td>
<td>78.1</td>
<td>160.3</td>
<td>316.9</td>
</tr>
<tr>
<td>Exposed area</td>
<td>287.9</td>
<td>292.1</td>
<td>408.9</td>
</tr>
<tr>
<td>Forest</td>
<td>150.6</td>
<td>216.5</td>
<td>85.9</td>
</tr>
<tr>
<td>Plantation</td>
<td>73.2</td>
<td>98.5</td>
<td>167.2</td>
</tr>
<tr>
<td>Scrub</td>
<td>206.8</td>
<td>168.0</td>
<td>166.9</td>
</tr>
<tr>
<td>Sparse built-up</td>
<td>565.2</td>
<td>661.0</td>
<td>379.6</td>
</tr>
<tr>
<td>Water</td>
<td>15.1</td>
<td>11.7</td>
<td>16.9</td>
</tr>
</tbody>
</table>

Fig. 5. Composite annual maps for three time periods.
that elevation can play a crucial role even for classifying some area which has lower topographical variation. In this study elevation was important for discriminating between different types of vegetation as most of the agricultural lands are located at a relatively lower elevation than other vegetation like scrub and forest (mostly situated in the ridge areas). Running, Loveland, and Pierce (1994) also reported that ancillary elevation information is useful for discriminating between crops and green areas. This is also important to discriminate scrub from the exposed area and fallow land, as during winter most of the scrub is in leaf-off condition and the rocky exposure under their canopies can easily be confused with exposed area or fallow land. The importance of NIR can be explained by the presence agricultural land, forest and plantation. NIR is less important for the month of May 1998–99 as in that particular season, due to some anomaly in the rainfall pattern vegetation was mostly mapped as scrub, whereas non-vegetated areas were dominated by fallow land. This reduced the variation between different kinds of vegetation. NIR I is sensitive to moisture or water content and appears to be important for discriminating between various vegetation types or built-up with fallow and exposed areas (Panigrahy & Parihar, 1992). Additionally, Blue bands are useful for identifying water bodies and sometimes for discriminating between vegetation types.

Comparison with previous studies

In this section we compare the result of our study with earlier attempts to classify LULC cover of Delhi, Punia et al. (2011) used 6 multi-temporal AWIFS data from a crop calendar with eleven LULC classes and put more emphasis on crop classes. Higher accuracy of kharif (monsoon) and zaid (summer) crops were reported compared to the present study. Accuracy of rabi (winter) crop mapping was higher using the present method. The mapping of rabi (winter) crop is generally much easier as the other vegetation classes in winter exhibit different phenology. The consistent higher accuracy achieved by Punia et al. (2011) can also be attributed to the lower number of independent validation points (~ 10), Wentz et al. (2008) used single ASTER data at 15 m resolution for the classification. Due the availability of higher spatial resolution they emphasized more on the impervious LULC classes and hence the results are not directly comparable for all the classes. But the accuracy of dense and sparse built classes (Urban high density and low density) is similar in some of the cases. Further Wentz et al. (2008) discussed geographic (spatial) transferability of the expert system developed. On the contrary, we established the temporal transferability of the methodology followed in this research. There is a definite need to test the reproducibility of the methodology across different spatial and temporal scales.

Generalization of the methodology

The methodology developed in this study relies on the availability of seasonal remote sensing data. Different types of remote sensing data (for example optical, SAR, thermal) can be used to produce the seasonal maps. If specific optical data is not available for any season, another optical or SAR data can be used as substitute (Esch et al., 2013; Taubenböck et al., 2012). For a long-term monitoring project, the production rule generated in one year can be used for other years as demonstrated in this research. However if the LULC classes between different years vary with each other, then transferring the knowledge created from one year to another will not be possible or would require more effort. The knowledge base can produce erroneous results when some unexpected variation in LULC takes place; for example, if an agricultural area is permanently converted to urban or industrial area. Moreover no accuracy assessment is carried out in the seasonal maps. The error in seasonal maps is accumulated in the annual map and modeling the propagation of this error is required for improving the accuracy of the composite annual map. The proposed methodology has potential i) to differentiate between rain-fed and irrigated agriculture practices; ii) to identify forest cover disturbance due to natural disasters or anthropogenic activities using multi-source/seasonal data.

Since the seasonal images are classified independently with unique training sets, there is no need to perform radiometric normalization of the seasonal images before classification (Song et al., 2001), which proves to be one of the strongest advantages of the proposed methodology. However applicability of the methodology presented in this study across different study areas over different time frames can be limited by the following factors: 1) lack of availability of historical remote sensing data during the period of 1980 to late 1990 for specific regions around the Globe (Goward et al., 2006); 2) atmospheric effects such as cloud contamination and haze in the desired/requird scene (Ju & Roy, 2008; Kowalsky & Roy, 2013); 3) interpreter's experience and processing time of the seasonal/temporal database. While the problem of lack of historical data cannot always be addressed with remote sensing resources, images from other sensors such as SPOT, ASTER, LISS can be used as an alternative in case of unavailability of Landsat data or of presence of atmospheric effects (Schneider, 2012).

Additionally, successful application requires a wise choice of classifiers to classify spectral and other derived features using small number of training samples (Foody & Mathur, 2004) and careful generation of the production rule to merge the seasonal LULC. Use of machine learning based classifier will be critical to find out patterns in the complex feature space while minimizing the issue of data dimensionality (Richards & Jia, 1999). Future research in this context can explore the potential of other machine learning based classifiers such as support vector machine for classifying the seasonal data. With increasing availability of multi-source data, issues related to data volume and computation costs need to be addressed. Classification of larger geographical areas using similar methodology can be a serious challenge. However parallel processing of classification tasks (Plaza & Chang, 2007), use of services similar to Google cloud (Hansen et al., 2013) or Web-Enabled Landsat Data (WELD) project (Hansen et al., 2011).

Conclusion

Remote sensing of urban and peri-urban areas is a challenging and complex task owing to spatial heterogeneity of the component LULC. In summary, we arrive at several important conclusions from this study. This research illustrates that, when LULC exhibits temporal variability, multi-temporal imagery are of enormous importance to identify and map the particular land use land cover types with unique temporal profiles. This study evaluates the utility of multi-seasonal imagery to characterize and classify the rapidly changing urban landscape of Delhi-NCR. The methodology developed for combining the seasonal information can easily be transferred to other years for another specific study area given the LULC classes remain the same. The methodology proved to be efficient in mapping the overall agricultural land, in contrast to conventional single season data mapping where agricultural land for only one season could be mapped. With the increasing availability of data products from operating sensors (Landsat 8, LISS 3 and 4, AWIFS, SPOT) and in view of the soon-to-be-available sensors (Sentinel-2), the proposed methodology can be extended to data from any of these sensors and aid in extensive mapping and monitoring of urban footprints. The study also highlighted the patterns and
dynamics of changes in land use land cover of a rapidly urbanizing
city and its environs. The impact of urbanization on agriculture,
water and green cover is implicitly visible with continuously
increasing built-up and rapidly dwindling forest and agricultural
lands from 1998 to 2011.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://
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Rapidly Urbanizing Indian Cities: The Problem of Local Heat but a Global Challenge

Richa Sharma and P. K. Joshi

Urbanisation is increasingly modifying the micro-climate of cities across the globe. The most illustrious manifestation of such an altered urban climate is the Urban Heat Island (UHI) effect, which is currently experienced in almost all global megacities. However, in a developing nation like India, which falls second to China in terms of pace and scale of urbanisation, this phenomenon and its associated socio-environmental impacts are in need of further study (e.g., impacts on human health and liveability, biodiversity and the water cycle) (Pauchard et al., 2006). UHI monitoring thus becomes imperative, if not only from a human health perspective, since typical Indian cities are often very dense with large concentrations of the population inhabiting relatively small areas of land. In fact, India currently holds three of the world’s megacities (Delhi, Mumbai and Kolkata), and Chennai, Hyderabad and Bangalore are expected to become megacities by year 2021 (UN, 2012) (See Figure 1). Given current pace and trends of urbanisation, India is often referred to as a pseudo urbanised nation, wherein the number of urban centres are increasing and expanding, but the basic infrastructure to support such vast systems is insufficient.

This work investigates the decadal changes in land use/land cover patterns in the four cities of Delhi, Mumbai, Kolkata and Chennai (see Figure 2), which are the loci of economic and political activities attracting in-migration in vast numbers. The research also focuses on the simultaneously implicated alterations in land surface temperature (LST) distribution across these cities and the concurrent shift in patterns of UHI and its intensities (Voogt & Oke, 2003). In urban areas, the conversion of vegetated land to non-vegetated built-up area results in a ‘heating-up’ of the land, which can be attributed to a number of factors. For example, the loss of vegetation cover results in decreased cooling due to the lack of evapo-transpiration and loss of moisture content (Grimmond, 2007). Moreover, the thermal properties of concrete structures are such that they absorb more heat and tend to remain hotter for
longer time periods, and given their impervious nature, the lack of moisture inhibits their capability to cool down easily. Increasing urbanisation thus heats up cities, creating UHIs at local scales.

The capital city — Delhi

Delhi is the capital city of India and has an ever-expanding history from ancient Mauryan times to the present era. The city has undergone phases of severe sprawl, particularly during medieval times and as such, is considered the ‘Seven Cities’. Nowadays, urban sprawl is still occurring, but at a much faster pace.

Landsat TM satellite data was used to study the land use changes in the city from 1998 to 2011. In Delhi, the area of urban land use more than doubled from year 1998 (67.71 km$^2$) to 2011 (181.97 km$^2$). The urban land transformations in Delhi indicate a complex chain rather than simple from-to conversions. Overall statistics might indicate a slight increase in agriculture, but a more detailed analysis reveals environmentally degrading trends with infringement on neighbouring forest and riverbeds. Analysis reveals that agricultural land has been lost to built-up area, but in turn, there have been encroachments onto the Asola Bhati Sanctuary and Yamuna riverbeds for agricultural purposes. Sparse built-up area was also found to have decreased over the time period, which could be attributed to the transformation of sparse to dense built-up area. Another disturbing trend is the increase in open area, as open areas in the city are mostly lands that have been cleared for construction activities.

Simultaneously, Land Surface Temperature (LST) trends were analysed for the city with respect to land use patterns. The city experienced new hotter patches of LST in the north, which correspond to development of the Narela and Bawana industrial
Cities like these can serve as role models for other urban agglomerations that are quickly evolving into megacities. Better planning, such as prudent green cover, creation of green roofs and walls, use of more appropriate materials and colors in urban constructions may aid in mitigating such impacts.

of Navi Mumbai and Thane. The city is often considered to be the financial capital of the country, as it is the wealthiest city with highest GDP, and has experienced soaring rates of in-migration especially during the 1990s. 1992 and 2009 Landsat images of Mumbai were produced and studied to analyse the urbanisation pattern and its impact on surface temperatures. Mumbai is shown to have expanded its built-up area from 183.15 km$^2$ in 1992 to 218.35 km$^2$ in 2009. Built-up area increased mainly at the expense of vegetation and inland water bodies such as lakes or ponds. Since the city is bound by ocean in the south and by Sanjay Gandhi National Park in the north, the city does not have much space for expansion. Consequently, intense pressure from competing land uses has caused a decline in the city’s vegetation, water bodies and mangroves - 30% (52 km$^2$), 25% (10 km$^2$) and 26% (21 km$^2$) respectively. The only positive trend observed for Mumbai is the gain in forest cover by 15%. A more detailed analysis highlights that this gain has come from mangrove area in south-eastern parts of the city.

The LST distribution of the city for 1998 and 2009 illustrates elevated temperatures mainly in the city centre and in parts of the south. Areas of non-urban land that were converted to built-up area during this period got warmer by an average increase of 4.45°C. The area in central Mumbai has shown a tremendous increase in temperature (15-20°C), which corresponds with the construction of the new airport. The construction activities along the eastern coastal areas did not increase much beyond 4-5°C, which could be attributed to their ocean proximity. Shivaji Nagar, Nirankar Nagar, New Gautam Nagar, Vaibhav Nagar and Ramabai Ambedkar Nagar in the south-east; Jogeshwari East near Sanjay Gandhi National Park; and Asalfa, Mairwadi, Mohili, Lokmanya Tilak Nagar and Dharavi in the central parts of the city have all advanced towards becoming potential locations for UHIs.

City of joy — Kolkata
Kolkata has been a city of importance ever since the colonial period when it served as the capital of the British Indian Empire and has been for many years the major port supporting the economy of the eastern states. Kolkata is now the capital of the state of West Bengal and is considered the financial and cultural centre of East India. The city is densely populated with a population of 14.1 million living within an area of 1886 km$^2$. 

sites. The mean LST for land parcels that experienced urban transformation increased from 31.2°C in 1998 to 32.5°C in 2011. Analysis of UHI intensity for the years 1998 and 2011 reveals that parts of central Delhi (Old Delhi), including the industrial areas of Mayapuri, Azadpur and Narayana exhibit high UHI intensities across this time period. The Indira Gandhi Airport and Narela-Bawana industrial areas have emerged as new UHI peak zones in 2011 corresponding to drastic changes in land use in these areas. The LST of agriculturally dominated areas in the northern parts of the city was in range of 20-30°C for year 1998, but has increased dramatically to 30-35°C in 2011 after conversion to built-up land.

The entertainment capital — Mumbai
Mumbai is the capital city of the state of Maharashtra. The city is one of the most populous cities of the world, around 21 million, with the metropolitan area including neighbouring urban areas
Kolkata has witnessed an increase in urban built-up land (76.81 km²) between 1989 and 2010; and it has expanded in all directions, but more so on the eastern side of the river. Major contributors to the built-up category are plantations, agriculture (the largest contributor at 37.3 km²) and agricultural fallow. Moreover, wetland vegetation, commercial plantation and open area also lost 8.2 km², 21.2 km² and 10.7 km² to built-up area, respectively. Land use dynamics show that plantation, agriculture and commercial plantation first became converted to sparse built-up land, which has subsequently transformed into dense built-up area.

The increase has been simultaneously marked by an elevation of 6.14°C in mean LST of the land that has undergone non-urban (1989) to urban (2010) transformation. In the north, areas that have emerged as heat island locations are located near the areas of Chitpur, Ghosh Bagan, Kadapara, Kashipur, Sawadagarh Pally and Ultadanga. On the western banks of the river, Hughly, Liluah, and North-east Ghusuri exhibited very high temperatures (> 35°C). On the eastern side of the river in the south, mainly the industrial regions of Taratala, Garden and other industrial sites along the riverbanks appear to be hotspots for heat island formation.

Most liveable city in India — Chennai
Chennai or Madras became a major industrial hub in the post-independence era and has been developing further as such. The city is rapidly progressing on the path of becoming a megacity following the footsteps of Delhi, Mumbai and Kolkata. Urban cover for Chennai has increased from 44 km² in 1991 to 70 km² in 2006. Lands for agriculture have experienced the largest major urban land transformation (22 km²) and sparse built-up lands have been gradually converted to dense built-up area over this time. The city is majorly expanding in the southern parts including a mushrooming of industries.

The LST analysis for the city indicates that mean LST for non-urban to urban land cover increased by 8.3°C from 32.28°C in 1991 to 40.59°C in 2006. The areas of southern Chennai, including CIT Nagar, Moovender, Appavu Nagar, and industrial sites of Sarathi Nagar, Suriyammapet exhibited elevated temperatures in 2006 making these the potential sites for UHI development. In northern parts of Chennai, specifically near the main city area, Kasimedu, Grace Garden, Bhogipalayam, Wadia Nagar, Chintadripet and Seethakadi Nagar experienced an increase in LST from 1991 to 2006. This increase is evident in minimum, maximum and mean LST for urban areas from 1998 to 2009. The increase has been in the range of 6-7°C.
Cities across the globe are experiencing altered micro-climatic conditions with green (agriculture, plantation, etc.) to grey (built-up) land conversions resulting in the elevation of land surface temperatures. In response, a number of researchers are specifically focussing on UHI impacts on human health and heat waves (Tan et al., 2010), results of which are important for urban planners and policymakers. The present research highlights urban land transformations in India and their impact on urban surface temperatures which is imperative for managing and mitigating the phenomenon of UHI in cities. Such an assessment accentuates the need and scope for policy interventions to curb the rising temperatures in urban areas. Though rapidly urbanising, the nation is still largely rural and is undergoing what is known as pseudo-urbanisation. The work emphasises the plight of the four metro cities of India, and how these swiftly urbanising landscapes are consequently experiencing elevated temperatures. These results can serve as a learning source for other Indian cities such as Ahmedabad, Jaipur, Kanpur, Surat, Poona and Lucknow, all of which are following the development footprints of the four metropolitan cities (Joshi et al., 2011). Currently, these cities are urbanising rampantly without consideration of the potential indirect impacts associated with such drastic land use/cover changes.

The good news is that the national government of India is taking steps towards better planning and coordination of urban development and renewal. One such urban renaissance project in India is the Jawaharlal Nehru National Urban Renewal Mission (JNNURM). The UHI effect is treated as a major environmental issue under the project’s module, Environmental and Social Safeguards. Policy related to land acquisition (Land Acquisition Act, 1984) and provisions of the Environmental Impact Assessment (EIA) or Environment Protection Act (1986) function as umbrella legislation and tend to address this issue, but in a very diluted and indirect manner. Other commendable initiatives by government include programmes such as the Green Rating for Integrated Habitat Assessment (GRIHA) and Association for Development and Research of Sustainable Habitats (ADaRSH) for promoting green buildings and help to find solutions for a number of environmental issues.

However, no policy framework has been dedicated solely towards combating this issue. One city showing progress in this regard is Surat in Gujarat. The city has often been lauded as exemplifying smart urbanisation in the overburdened country of India. It has made improvements in existing infrastructure, health and waste disposal sectors while developing on economic fronts. Another good example is the city of Ahmedabad, which for instance has launched the ‘Heat Action Plan’ to combat the ill effects of UHI. Cities like these can serve as role models for other urban agglomerations that are quickly evolving into megacities. Better planning, such as prudent green cover, creation of green roofs and walls, use of more appropriate materials and colors in urban constructions may aid in mitigating such impacts. Governments across the globe, specifically in developing countries, must focus on efficient urban planning strategies that should be modified and adapted examples of best practices for sustainable development in the true sense. Our research is a first step towards assisting in this endeavour.

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References
Identifying seasonal heat islands in urban settings of Delhi (India) using remotely sensed data - An anomaly based approach

Abstract
This paper analyses seasonal variation in spatial patterns of urban heat island (UHI) in semi-arid environment of Delhi. Temporal variation in UHI intensity was also studied and analyzed with respect to land use land cover practices. Landsat TM data for each of the five seasons (winter, spring, summer, monsoon and post-monsoon) for year 2010-11 was used to map Land Surface Temperature (LST) for the city. An anomaly based approach was used to quantify seasonal and annual UHI. Maximum and minimum seasonal UHIs were observed in summer (intensity = 16.7ºC) and winter (intensity = 7.4ºC) respectively. Mean annual LST anomaly map helped in identification of UHI vulnerable locations in the city. Major commercial and industrial sites across the city and airport area in south have higher UHI effect. Thus a, b, c, and d are the most vulnerable locations.

Keywords: Landsat TM, LST, UHI intensity, Anomaly, Seasonal Variation

Introduction
In recent years Urban Heat Island (UHI) has become a topic of high interest among academicians and governing bodies both. Researchers are interested in this phenomenon to understand its causes (Huang et al., 2011), impacts (Imhoff et al., 2010) and its complexity (Mirzaei and Haghighat, 2010); the information which can then fed into policy-making processes. UHI is increasingly gaining interest as it directly affects both environmental (Ferguson and Woodbury, 2007) and human health (Lo and Quattrochi, 2003; Tomilson et al., 2011). It has dual relationship with environmental variables, on one hand impacts environmental well-being and on the contrary governed by these (Sharma et al., 2012). UHI affects the region through heat pollution (Papanastasiou and Kittas, 2012) and such areas are more likely to witness an increased number of smog events (Sham et al., 2012), larger number of heat-related health problems (Harlan and Ruddel, 2011), higher energy consumptions (Kolokotroni, 2012), and impacts on human comfort (Steeneveld et al., 2011). UHIs also have the tendency to elevate heat wave intensities as observed in case of Chicago in 1995 and Russia in 2003 (Sailor and Lu, 2004) and recently in Shanghai, China (Tan et al., 2010).
UHI manifests itself in two basic forms (i) Surface UHI (SUHI) and (ii) Atmospheric UHI (AUHI). Table 1 briefly summarizes distinction between forms of UHIs. SUHI is the phenomenon of temperature difference between surfaces of urban and surrounding rural areas. The phenomenon exhibits high spatial and temporal variability (Stathopoulou and Cartalis, 2009). SUHI is studied using Land Surface Temperature (LST) retrieved from thermal satellite sensors (Shwarz et al., 2011). AUHI encompasses difference in pattern of air temperature between urban and rural settings. AUHI further falls in one of the two categories viz., Canopy layer or Boundary layer. Canopy layer UHI influence the atmosphere extending from surface to mean building height or tree canopy, while the Boundary layer UHI accounts for air beyond canopy layer (Weng, 2003).

Table 1 Summary of forms of UHIs

AUHI is studied using meteorological data (Saaroni et al., 2000). Such data have often been delved in for studying monthly or seasonal variations. Gallo and Owen (1999) for instance, analyzed urban-rural temperature (using observation stations) and Normalized Difference Vegetation Index (NDVI) (using NOAA-AVHRR, National Oceanic and Atmospheric Administration–Advanced Very High Resolution Radiometer) of 28 cities on monthly and seasonal basis to study UHI. UHI intensity in Bangkok, Chiang Mai and Songkhla cities were investigated using urban and rural meteorological station data (Jongtanom et al., 2011). Cayan and Douglas (1984), Fujibe (2009), Jauregui (1997), Liu et al. (2007), Gaffin et al. (2008), and Hua et al. (2008) have also conducted similar researches. Thus it is evident that elaborate work is available on seasonal studies of atmospheric UHI, but such detailed literature for surface urban heat islands (SUHI) is lacking. This needs study of temporal land surface temperature (LST) to analyze seasonal patterns of SUHI. Some recent publications demonstrated potential of remotely sensed LST in analyzing inter-annual variability of SUHI (Hu and Brunsell, 2013; Buyantuyev and Wu, 2010). But similar attempts are missing over Indian cities and are pre-requisites for urban planning and development.
This paper fills the research gaps in seasonal studies on SUHI, while focusing on a tropical city. Apart from studying seasonal patterns of SUHI, this work also aims at identifying causal factors for UHI formation. For in depth understanding of the phenomenon studies are required at both qualitative and quantitative scales. Spatial distribution of UHI in different seasons was studied for qualitative analysis of the phenomenon. For quantification of UHI, intensity of the phenomenon was measured. UHI Intensity (UHII) thus gives a quantitative measure of UHI. Thus, this is a comprehensive study of seasonal patterns of UHI in a tropical semi-arid metropolitan city. It explains the influence of heterogeneous land use land cover (LULC) on distribution of heat and cool islands over the space (within city at a time) and time (through various seasons).

**Study Area – Delhi**

Delhi, the capital city of India, covering an area of approximately 1483 sqkm is between the geographic coordinates 28°40’ N to 28°67’ N and 77°14’ E to 77°22’ E. Location of the study area is given in figure 1. City represents a flat terrain with an average elevation of 216 meters above sea level. River Yamuna passes through the city dividing it in two parts with the eastern part often referred as ‘Yamuna paar’ (which means across Yamuna). City is characterized by highly heterogeneous land use ranging from highly urban centers of commercial activity and residential areas to rural agricultural lands. A LULC map of Delhi prepared using Landsat TM data is shown in Figure 2. Table 1 describes the distribution of LULC.

Figure 1: Location of study area

Figure 2: Land use land cover map of Delhi

Built-up characterize most of the central and eastern parts of Delhi. Scattered patches of newly formed settlements (built-up) are in the northern and south-western parts of the city. All together the built-up accounts for 569 sqkm. City has one domestic and one international airport that forms part of open land category which comprise of exposed land, sandy areas and open lands without vegetation. This category covers 11% of total land use. A patch of forest is at the heart of
the city (referred as ‘Lungs of the city’) and other scattered forest patches are distributed in the southern part. The latter is notified as Asola Bhati Wildlife Sanctuary. The forest patches (including Kamla Nehru Ridge in the north) together constitute a total of 101 sqkm area. 102 sqkm area is covered by other vegetation characterized by city parks like Lodhi Garden, Japanese Park and others, and is inclusive of roadside tree plantations. Rural area is broadly exemplified by agriculture (including horticulture, floriculture, dairy and poultry farming land) (297 sqkm) and agricultural fallow land (225 sqkm) traversed nearly 35.4% of total area. Rest 1.4% is covered by water bodies including river, lakes (e.g. Badhkal lake) and wetlands (e.g. Yamuna Biodiversity Park).

Table 2: Land use land cover category and details for year 2011

Like any other city in the developing nations, urban population and area in Delhi is also rapidly increasing. Population in Delhi has increased from 9.42 M (million) in 1991 to 13.85 M in 2001 reaching 16.75 M in 2011. Of which 8.47 M, 12.91 M and 16.33 M was urban in years 1991, 2001 and 2011 respectively. The expansion of urban area is gradually encroaching non-urban and agricultural land. Rapidly growing population and fast expanding urban built-up areas have made the city an ideal target for SUHI development. Understanding and analyzing the nature and behavior of UHI development thus becomes imperative to the city planning processes and also to take appropriate mitigation measures.

**Satellite data used**

According to Voogt and Oke (2003), thermal remote sensors are used to study SUHI. These sensors observe the surface emitted upwelling thermal radiance. SUHI in contrast to atmospheric UHIs can be best studied at daytime when SUHI intensity is supposedly highest (Roth et al., 1989). Satellite data is being increasingly used for observing SUHIs, because such data have potential to capture thermal responses of various land surfaces. Additionally their coverage is synoptic and periodical. Thus satellite sensor data is used for spatial and temporal continuity for urban studies at much lesser cost. Many authors have utilized the potential of satellite thermal infrared (TIR) information to study SUHI employing medium resolution sensors such as Landsat and ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) (Li et al.,
Landsat TM (Thematic Mapper) a medium resolution (30m and 120 m) sensor is one of the most commonly used satellite data for environmental studies. The data comprises of seven bands, six of which are located in visible and near infrared regions (0.45-1.75 μm) and one band (Band 6) is in thermal wavelength range (10.4-12.5 μm). This band is widely used to measure surface temperatures for a range of studies including forest fires, climate change indicators, heat budget, soil moisture, thermal inertia, insect-vector disease proliferation and others (Anderson et al., 2012). Five Landsat TM5 satellite images for year 2010 were downloaded from USGS website (www.earthexplorer.usgs.gov). The data was selected carefully to cover all the seasons and preferably cloud-free. The details of the satellite data used and other meteorological data on data acquisition date are given in table 2.

Table 3: Description of data used and climatic variables

LST retrieval from Landsat TM
LST was retrieved from thermal band using a mono-window algorithm (Qin et al., 2001; Sobrino et al., 2004; Sun et al., 2010). It has the advantage of independence from radiosounding data. The retrieval process was performed in five steps namely radiometric calibration, calculation of reflectance, calculation of brightness temperature, emissivity correction and final LST calculation.

Radiometric calibration was carried out using calibration constant values from Landsat handbook. DN values were converted to at-sensor radiance using the following equation (Chander and Markham, 2003);

\[
\text{Radiance} = \frac{L_{\text{Max}} - L_{\text{Min}}}{(QCal_{\text{Max}} - QCal_{\text{Min}})} \times (QCal - QCal_{\text{Min}}) + L_{\text{Min}}
\]

(1)

Where, \(L_{\text{Max}}\) and \(L_{\text{Min}}\) were spectral radiances for thermal band (Band 6) at digital numbers 1 and 255 respectively i.e. \(QCal_{\text{Min}}\) and \(QCal_{\text{Max}}\) values, and \(QCal\) represents the DN value.
Calculation of reflectance values was performed for all the radiance bands except the thermal.

\[ \text{Reflectance} = \frac{\pi \times d^2 \times \text{Radiance}}{\text{ESUN} \times \cos \theta} \]  

(2)

Where, \( d \) is Earth-sun distance in astronomical units, \( \text{ESUN} \) is mean solar exoatmospheric irradiance and \( \theta \) is solar zenith angle.

All the six reflectance bands were used in LULC mapping and band 3 and 4 reflectance were used for computing NDVI. NDVI was used to determine emissivity image (Valor and Caselles, 1996). The emissivity thus obtained was employed to correct at-sensor brightness temperature retrieved from thermal band radiance. This was done because at-sensor brightness temperature assumes unit emissivity and thus the temperature estimated is for blackbody. The thermal band radiance was converted to \textit{At-sensor brightness temperature} using modified Planck’s equation;

\[ T_B = \frac{K_2}{\ln\left(\frac{K_1}{L} + 1\right)} \]  

(3)

Where \( T_B \) is at-sensor brightness temperature (in Kelvin), \( L \) is spectral radiance (in \( \text{W/(m2/sr-mm)} \)), \( K_1 \) (607.76 \( \text{W/(m2/sr-mm)} \)) and \( K_2 \) (1260.56 \( \text{K} \)) are pre-launch satellite calibration constants.

NDVI was employed for \textit{emissivity correction}. Emissivity for NDVI range of 0.157 to 0.727 could be expressed as:

\[ \varepsilon_6 = 1.0094 + 0.047 \times \ln(\text{NDVI}) \]  

(4)

For NDVI values out of this range, different emissivity values are assigned to three different ranges (Zhang \textit{et al.}, 2006). These values are summarized in table 4.

Table 4: NDVI values for emissivity calculation

Mono-window algorithm (Equation 7) was then used for computing \textit{final LST}, wherein \( C \) and \( D \) parameters were derived from emissivity and transmittance (Equations 5 and 6). Figure 3 provides broad paradigm of the study.

\[ C_6 = \varepsilon_6 \times \tau_6 \]  

(5)
\( D_6 = (1 - \tau_6) \left[ 1 + (1 - \varepsilon_6) \right] \times \tau_6 \)  

(6)

\[
LST = \frac{\left[ a(1 - C - D) + b(1 - C - D) + C + D \right] \times T_B - D \times T_a}{C}
\]

(7)

Where \( \tau_6 \) is the transmittance estimated from Qin et al. (2001) and \( T_a \) is the mean atmospheric temperature calculated using near surface air temperature while, \( a \) and \( b \) are two constants of value 67.355351 and 0.458606, respectively and \( LST \) is the final land surface temperature retrieved.

**Anomaly assessment**

Spatial seasonal \((A_{ST})\) and annual \((A_{AT})\) thermal anomalies were computed. Seasonal anomalies helped in quantifying UHI on monthly basis to study its seasonal variation.

\[
A_{ST_i} = LST_i - \left( \frac{\sum_{i=1}^{n} LST_i}{n} \right)
\]

(8)

Where \( A_{ST} \) is the seasonal temperature anomaly, \( A_{ST_i} \) is seasonal temperature anomaly for any pixel \( i \), \( LST_i \) is the land surface temperature for any pixel \( i \), \( n \) is the total number of pixels in the image.

Annual UHII was estimated based on annual thermal anomaly computed using equation 9. This further helped in identification of locations that are UHI vulnerable as these tend to remain hotter throughout the year.

\[
A_{AT_i} = MLST_i - \left( \frac{\sum_{i=1}^{n} MLST_i}{n} \right)
\]

(9)

Where \( A_{AT} \) is the annual temperature anomaly, \( A_{AT_i} \) is annual temperature anomaly for any pixel \( i \), \( MLST_i \) is the annual mean land surface temperature for any pixel \( i \), \( n \) is the total number of pixels in the image. \( MLST_i \) is computed as given below:

\[
MLST_i = \frac{\sum_{k=1}^{5} LST_{ik}}{5}
\]

(10)

Where \( MLST_i \) is the annual mean land surface temperature for any pixel \( i \), \( k \) is any given season from the total of five seasons under study.

**UHI Intensity**
For quantitative analysis of UHI, measuring UHI intensity becomes imperative. Authors have used various methods for UHI quantification. Keramitsoglou et al., (2011) have used difference between LST and reference LST (RLST) to assess UHI intensity. Zhang et al., (2009) calculated LST differences between different impervious surface area categories and water as an estimate for UHI intensity. Zhang and Wang (2008) proposed hot island area (HIA) as UHI intensity estimate that is based on standard deviation segmentation of LST image. In present research, anomaly in LST was used to determine UHI intensity. Anomaly images computed above were categorized into three classes; (i) UCI (\(A_{ST} \text{ or } A_{AT} < 0\)), (ii) UHI (\(A_{ST} \text{ or } A_{AT} > 0\)) and (ii) heat neutral (\(A_{ST} \text{ or } A_{AT} = 0\)) categories.

Figure 3: Paradigm of the study

Results and discussion

Anomaly analysis for UHI and UCI intensities

LST image were studied to analyze spatial patterns of UHI through five seasons; winter (January), spring (March), summer (April), monsoon (September) and post-monsoon (October). The table 4 summarizes the minimum, maximum and mean LST values for each season. Winter season shows lowest values for all minimum, maximum and mean LST. This season receives lowest solar radiation which explains the minimum observations for LST statistics. Maximum values are observed in monsoon and summer seasons, when incoming solar radiation is very high. The highest LST values are observed during monsoon season. Similar results have also been reported by Cui and Foy (2012) for Mexico city, where MODIS was used data to study seasonal UHI and found that UHI for wet season is higher than dry seasons. A detailed analysis of monsoon image reveals that very few pixels have very high LST and these too are clustered in airport exposed area. During spring and post-monsoon, LST statistics were intermediary as these are also the transition seasons.

For each image thermal mean anomaly was computed, which was used as an indicator of UHI Intensity (UHII). The higher the anomaly value, higher is the intensity of UHI. More negative anomalies indicated higher intensity of cool islands. Spatial shifts in UHI were observed over the seasons which are attributed to seasonal cycles of vegetation, changes in solar angle, synoptic
weather types, moisture availability, crop cycles and differential response of various land use parcels to the seasonal stimuli of temperature variation and precipitation.

Table 5: Summary of LST for different seasons

**Seasonal UHI and UCI intensities and distribution**

Largest UHII (16.2°C) was recorded for summer season when solar radiation is very high and most of the agricultural fields are fallow. Fallow land tends to heat up easily due to its low thermal capacity. The winter season experienced lowest UHII (7.4°C) as this is the season when incoming solar radiation is low as well the agricultural land is covered with crops and is rich in moisture. This results in increased thermal capacity of the surface and thus heating gets slowed down. Figure 4 shows the UHI and UCI intensities during different seasons.

Cool island intensity was found to be strongest for post-monsoon (-12.4°C). This is attributed to harvested agricultural lands when the fallow results in higher mean LST, but the overall incoming solar radiation is not high and thus the heating up of other land surface is less. The results difference between mean and minimum LST higher for post-monsoon period which shoots up the UCII for this season. UCII was weakest for winter season (-6.4°C) due to less heating up of the surface in this season does not receive much of the solar radiation. There is not much variation in overall distribution of LST during winters, which minimizes both UHI and UCI intensities for this season.

Winter season data comprised of January month. Maximum UHII observed for this season was around 7°C and maximum UCII was found to be around 6°C. The patches of urban heat island are randomly distributed in the entire area (Figure 5). However, a set of islands are linearly distributed along the north-south axis of the city, starting from Bawana-Narela in north to Airport area in south. The north-west parts of Delhi (encompassing Rohini, Nangloi, Mundka, Badli, and Jehangirpuri), Dwarka in south-west, and Okhla in south-east were found to be prime regions under influence of UHI during winter month. Winter UCI was observed in agricultural areas of Bhaktawarpur, Auchandi, and Jaffarpur Kalan located towards the city peripheries that were under Rabi crop.
March month image represented the spring season. UHII for spring season increased to 12°C from 7°C in winters. The areas that experienced maximum UHI during winter continued to experience maximum UHI during spring season as well. The heat island appeared to be spread out to other parts of the city as well. Notably in eastern Delhi a 2°C (approx.) winter UCI was replaced with 2-4°C UHI during spring season (Figure 5). In contrast to winter UHI pattern, when scattered random patches of UHI were seen across the city, spring exhibited more smooth and continuous UHI surface covering built-up areas of the city.

Figure 4: Distribution of Urban heat and cool islands through different seasons (Winter, Spring, Summer, Monsoon and Post-monsoon); y-axis represents area in sqkm from 0 to 700, x-axis represents LST anomaly in degrees Celsius from -10 to 16 (at an interval of 1°C).

UHI intensity reached its maximum (16°C) during summers. Summer UHI appears in extreme south-west Delhi, the area that is majorly agricultural land and is left fallow during summers (Figure 5). The exposed fallow land with low heat capacity gets heated up easily. This heating up of agricultural fallsows is further supported by the high amount of incoming solar radiation during this season. Summer UHI-UCI maps present a distinct pattern, where urban areas appeared to be cool islands while agricultural (or rural) areas emerge as heat island sites. This is attributed to open fallow land which exhibit lower thermal capability. Such results have also been reported by Buyantuyev and Wu (2010) for October daytime data for Phoenix, Arizona where city behaved as a cool island against the hot surrounding desert area.

Monsoon exhibited the second highest UHI intensity (13.8°C). This is despite the fact that monsoon season receives maximum rains. But spatially, high UHII values are restricted to industrial and commercial regions across the city (Bawan-Narela in extreme north, Mundka in west, Azadpur and Wazirpur industrial sites extending from north-west to Old Delhi in centre, Narayana-Mayapuri from centre to Najafgarh in south-west, Okhla-Badarpur in south) and airport area (Figure 5). The city otherwise remains cool or neutral in other parts. This is because industrial areas are concrete and asbestos dominated surfaces, which do not retain moisture for long. During monsoons when most of city land has abundant moisture the industrial and airport
impervious areas are still largely devoid of moisture and thus such surfaces emerge as UHI areas with high intensities.

Post-monsoon season UHI pattern is similar to that of summer season as UHI dominance is observed in periphery of the city (Figure 5). But post-monsoonal UHII is relatively smaller than that of summer. The city displays low UHI but highest UCI intensities. Cool Island of 6°C intensity is observed around the central ridge and along the river. Due to prevalence of fallow lands, UHII is high but when compared with summer season incoming radiation is comparatively less. This brings UHII values down to 10.5°C. Fallow lands drag the mean LST to higher side, but due to less heating of other land surfaces, UCI tends to be high during post-monsoons.

Thus as city progresses from winters to summers both heat and cool island intensities keep on increasing. Shift in season from summers to winters via. Post-monsoon, causes heat island intensity to fall down with an exception of monsoon season. Simultaneously, the cool island also becomes milder with change in season from winter to summer.

**Annual mean UHI and UCI analysis**

An annual mean LST image (Figure 6 (a)) was generated using seasonal LST layers. An anomaly computation was performed for the mean LST layer to study the intensity and pattern of annual UHI over Delhi (Figure 6(b)). Based on spatial distribution of anomaly values, ten locations with very high anomalies were identified as UHI vulnerable areas. Six of these are industrial areas, viz., Narela-Bawana, Samaipur-Badli, Wazirpur, Zakhira-Anand Parbat, Mayapuri and Okhla. The reason for these areas behaving as UHI will be explained in later section. The vast expanse of airport is another area that exhibits higher UHII values. Relatively huge stretch of land, largely open or concrete and lack of vegetation canopy make airport highly prone to UHI. The airport thus as vast surface exposed to radiation and being concrete in nature, it gets heated up easily and contributes towards development of UHI. Rest three locations were residential areas of Rohini, Najafgarh-Dwarka area and Mangolpuri and Nangloi colonies. Rohini and Najafgarh are areas where urban sprawl is still in action with many new and rapid constructions coming up in the area. Vast stretches of land are in under-construction stage that is exposed lands, which are result in excessive heating. Nangloi colony is a slum dominated area, most houses have asbestos
roofs. The colony is densely packed with almost nil vegetation cover. Due to these two factors this area develops a tendency for UHI phenomenon.

Very high annual UHI intensities were observed over Samaipur-Badli industrial area (anomaly ≈ 7°C), Nangloi (anomaly ≈ 7°C), Kondli and Kondli-extension (anomaly ≈ 6.7°C) and Airport (anomaly ≈ 6.5°C). Relatively lower intensities were recorded for Dwarka (anomaly ≈ 5.6°C), Wazirpur (anomaly ≈ 5°C), Jehangirpuri-Azadpur (anomaly ≈ 5°C), Sadar Bazar and Chandni Chowkn (anomaly ≈ 5°C), Mayapuri (anomaly ≈ 4.5°C) and Rohini (anomaly ≈ 4.5°C). Areas such as Narela-Bawana (anomaly ≈ 4°C), Zakhira (anomaly ≈ 4°C), Ghazipur (anomaly ≈ 3.8°C), Najafgarh road industrial area (anomaly ≈ 3.5°C) and Paharganj (anomaly ≈ 3°C) display lowest intensity of UHI.

Most of the sites identified were found to be in industrial zones which mainly comprise of high density built-up and are mostly devoid of green cover. Concrete structures are abundant in the industrial environment where they perform a variety of functions. Due to their thermal properties and low emissivity these structures absorb more radiations and emit less. In addition to this, the exposed vegetation-devoid lands of industrial set-up lack moisture and thus contribute to the warming effect. Dominance of asbestos roofs in such areas further increases susceptibility towards UHI. As a cumulative effect of all these factors, heat gets accumulated in the area gradually converting them into heat islands.

Figure 5: (a) Annual Mean LST and (b) Annual Mean Anomaly Map

Other locations are either areas with high commercial activities such as Paharganj and Chandni Chowk or are residential lands with dense built-up that exhibit poor thermal insolations. The cool islands were seen over the agricultural lands of Jharoda Kalan, Jaffarpur Kalan, Auchandi, and Jhangola villages and forests of central ridge, Cantonment area and Asola Bhati Wildlife
Sanctuary areas demonstrating the fact that vegetated areas tend to be cooler than surrounding built-up lands. As these have more shade and moisture such land surfaces absorb lesser heat and also emit more due to evaporation.

**Conclusion**

LST analysis for the city of Delhi established the existence of UHI influence. Areas that are primarily urban exhibit higher temperature as compared to agricultural rural lands. With establishment of the fact that Delhi is under influence of UHI and considering the prevalence of heterogeneous and highly dynamic land use, seasonal patterns of UHI are analyzed. With changing seasons, changes in land use specifically in agricultural areas and vegetation phenology are observed. These changes further trigger the alterations in distribution of UHI intensity as well as its spatial distribution.

Anomaly based approach to quantify UHI is proposed in this paper. This is applied to study the seasonal variation in spatial distribution and magnitude of UHI in Delhi. Maximum UHI intensity is found to vary in order of summer > monsoon > spring > post-monsoon > winter. Apart from variation in intensity, UHI also varied with respect to distribution in space throughout the city. UHI is dominant in the city centre during spring and monsoon, while it shifts to south-west part in summers and post-monsoon harvesting seasons.

Such seasonal distribution needs through study so that appropriate mitigation measures could be suggested. One of the ways to mitigate such seasonal peripheral pseudo-UHI could be adoption of better cropping practices so that fallow period could be minimized. In winters, it was predominant in the major industrial and commercial and dense residential regions. The winter UHI, promoting concept of green roofing or usage of porous concrete for construction could help mitigate the impacts. The paper thus demonstrated UHI seasonal patterns with respect to space and magnitude in semi-arid conditions of a tropical developing country. Detailed study of seasonal variation in UHI is important from mitigation viewpoints, as these variations indicate that a measure based on single season will not provide us an appropriate solution as UHI manifestation gets altered with changing seasons.
To identify the areas that remain under UHI stress throughout the year, annual UHI map is generated for annual mean anomaly values. Annual anomalies illustrate that most of industrial areas, some of the residential areas and airport, are under the influence of UHI throughout the year. These areas thus call for special attention from urban planners with respect to UHI mitigation. The study has been conducted at city level using medium resolution data, but UHI is a phenomenon that is localized in nature and thus requires detailed study at different levels such as based on various administrative boundaries, planning units, or beyond physical boundaries to different land use levels. Scale dependence of the phenomenon makes it imperative to study it at different scales and using different resolutions to visualize it at broadest and finest levels. Not only spatial scales need scrutiny but temporal variations also need to be focused on for better understanding of the phenomenon.

Acknowledgement

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Table 1 Summary of forms of UHIs

<table>
<thead>
<tr>
<th>Atmospheric UHI</th>
<th>Surface UHI</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prominent during night</td>
<td>Prominent both during day and night</td>
<td>Yuan and Bauer, 2007</td>
</tr>
<tr>
<td>More intense during winters</td>
<td>More intense during summers</td>
<td>Imhoff et al., 2010; Papanastasiou and Kittas, 2012</td>
</tr>
<tr>
<td>UHI intensity is low</td>
<td>UHI intensity is very high</td>
<td>Grimmond, 2007</td>
</tr>
<tr>
<td>Studied using ground-based air temperature measurements taken from standard meteorological stations.</td>
<td>Observed using airborne or satellite thermal remote sensors.</td>
<td>Hung et al., 2006; Voogt and Oke, 2003</td>
</tr>
<tr>
<td>Best to study under calm and clear conditions at night.</td>
<td>Satellite or aircraft thermal data of acquired at daytime when heat island intensities are greatest</td>
<td>Roth et al., 1989</td>
</tr>
</tbody>
</table>

**Boundary Layer**

<table>
<thead>
<tr>
<th>Canopy Layer</th>
<th>Prominent at mesoscale</th>
<th>Prominent at local and microscale</th>
<th>Schwarz et al., 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed using tower sodar (fixed) and aircraft, tetroon (mobile)</td>
<td>Observed using screen (fixed) and automobiles (mobile)</td>
<td>Cermak et al., 1994</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Land use land cover category and details for year 2011

<table>
<thead>
<tr>
<th>Category</th>
<th>Area (sqkm)</th>
<th>Area (%)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-up</td>
<td>569.18</td>
<td>38.2</td>
<td>An area of human habitation developed due to non-agricultural use and that has a cover of buildings, transport and communication utilities in association with water, vegetation and vacant lands</td>
</tr>
<tr>
<td>Agriculture</td>
<td>296.93</td>
<td>20.0</td>
<td>Land primarily used for farming and for production of food, fiber and other commercial and horticultural crops. It includes land under crops (irrigated and un-irrigated, plantations etc.)</td>
</tr>
<tr>
<td>Fallow land</td>
<td>225.36</td>
<td>15.4</td>
<td>It includes agricultural lands that are currently laid fallow</td>
</tr>
<tr>
<td>Forest</td>
<td>100.98</td>
<td>6.8</td>
<td>Forests are areas bearing an association predominantly of dense tree covers and other vegetation types (notified forest boundaries)</td>
</tr>
<tr>
<td>Vegetation</td>
<td>101.85</td>
<td>6.9</td>
<td>This class includes vegetation other than agriculture and forest. It mainly comprises of roadside plantations, residential/public parks or</td>
</tr>
<tr>
<td>Vegetation Type</td>
<td>Area (m²)</td>
<td>Emissivity</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------</td>
<td>-----------</td>
<td>------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Open area</td>
<td>166.85</td>
<td>11.3</td>
<td>This encompasses land that is left exposed or open without any vegetation or scrub cover (e.g. land left vacant pre-construction stage, or vast exposed stretches of airport etc.)</td>
</tr>
<tr>
<td>Water</td>
<td>21.41</td>
<td>1.4</td>
<td>Land covered with water and water bodies such as lakes, rivers or ponds.</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>1482.57</strong></td>
<td><strong>100</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Description of data used and climatic variables

<table>
<thead>
<tr>
<th>Months</th>
<th>Seasons</th>
<th>Acquisition Date</th>
<th>Air Temperature (°C)</th>
<th>Relative Humidity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>Winter</td>
<td>29/1/2010</td>
<td>Minimum 14, Maximum 26, Mean 20</td>
<td>44</td>
</tr>
<tr>
<td>March</td>
<td>Spring</td>
<td>4/3/2011</td>
<td>Minimum 14, Maximum 22, Mean 18</td>
<td>64</td>
</tr>
<tr>
<td>April</td>
<td>Summer</td>
<td>3/4/2010</td>
<td>Minimum 25, Maximum 37, Mean 31</td>
<td>18</td>
</tr>
<tr>
<td>September</td>
<td>Monsoon</td>
<td>26/9/2010</td>
<td>Minimum 23, Maximum 32, Mean 28</td>
<td>66</td>
</tr>
<tr>
<td>October</td>
<td>Post-monsoon</td>
<td>28/10/2010</td>
<td>Minimum 15, Maximum 29, Mean 22</td>
<td>42</td>
</tr>
</tbody>
</table>

Table 4: NDVI values for emissivity calculation

<table>
<thead>
<tr>
<th>NDVI</th>
<th>Emissivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than -0.18</td>
<td>0.985</td>
</tr>
<tr>
<td>-0.18 to 0.157</td>
<td>0.955</td>
</tr>
<tr>
<td>Greater than 0.727</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Table 5: Summary of LST for different seasons

<table>
<thead>
<tr>
<th>Season</th>
<th>Month</th>
<th>LST(°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>Winter</td>
<td>January</td>
<td>24.51± 1.97</td>
</tr>
<tr>
<td>Spring</td>
<td>March</td>
<td>28.03± 2.54</td>
</tr>
<tr>
<td>Summer</td>
<td>April</td>
<td>43.10± 3.17</td>
</tr>
<tr>
<td>Monsoon</td>
<td>September</td>
<td>46.28± 2.80</td>
</tr>
<tr>
<td>Post-monsoon</td>
<td>October</td>
<td>35.56± 2.58</td>
</tr>
</tbody>
</table>

Richa Sharma · P. K. Joshi

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Abstract Urbanization is increasingly becoming a widespread phenomenon at all scales of development around the globe. Be it developing or developed nations, all are witnessing urbanization at very high pace. In order to study its impacts, various methodologies and techniques are being implemented to measure growth of urban extents over spatial and temporal domains. But urbanization being a very dynamic phenomenon has been facing ambiguities regarding methods to study its dynamism. This paper aims at quantifying urban expansion in Delhi, the capital city of India. The process has been studied using urban land cover pattern derived from Landsat TM/ETM satellite data for two decades (1998–2011). These maps show that built-up increased by 417 ha in first time period (1998–2003) and 6,633 ha during next period (2003–2011) of study. For quantification of metrics for urban expansion, the Urban Landscape Analysis Tool (ULAT) was employed. Land cover mapping was done with accuracy of 92.67 %, 93.3 % and 96 % respectively for years 1998, 2003 and 2011. Three major land covers classes mapped are; (i) built-up, (ii) water and (iii) other or non-built-up. The maps were then utilized to extract degree of urbanization based on spatial density of built-up area consisting of seven classes, (i) Urban built-up, (ii) Sub-urban built-up,(iii) Rural built-up, (iv) Urbanized open land, (v) Captured open land, (vi) Rural open land and (vii) Water. These classes were demarcated based on the urbanness of cells. Similarly urban footprint maps were generated. The two time maps were compared to qualitatively and quantitatively capture the dynamics of urban expansion in the city. Along with urbanized area and urban footprint maps, the new development areas during the study time periods were also identified. The new development areas consisted of three major categories of developments, (i) infill, (ii) extension and (iii) leapfrog.

Keywords Delhi · Satellite data · Urban footprint · Urbanized area · New development

Introduction

Urbanization has often been described in terms of its patterns (land use patterns (Thapa and Murayama 2009; Tian et al. 2011)), process (extension of urbanized areas (Xiao et al. 2006)), causes (changing land use practices Li and Yeh (2004) and their consequences (Galster et al. 2001). Since urbanization is a name for many conditions, thus defining it becomes very difficult (Bhatta et al. 2010). Monitoring of urban growth is highly imperative to ensure a more sustainable existence of human society. Urban expansion impacts environment in more than one ways. For example,
creating social segregation (Azocar et al. 2007), fragmentation of natural landscapes (Su et al. 2010), changing ecology (Nilsson et al. 2003) and biodiversity of the region (Savard et al. 2000; Hasse and Lathrop 2003; Blair 2004), depleting natural resources (Ghosh 2007) and altering hydrology (Nilsson et al. 2003, Carlson 2004) and air quality in the area (Zhang et al. 2004). Urbanization is considered to be one of the most dynamic and irreversible land use changes (Owen et al. 1998) that are massively occurring across the globe (Brockerhoff 2000). This is truer in developing countries (Cohen 2006).

India has been undergoing rapid urbanization with tremendous growth rates in urban areas (Taubenbock et al. 2009; Joshi et al. 2011). The urban population of India is expected to increase by 167 M from year 2009 to 2025 (Fig. 1). From 2025 to 2050, the country is expected to contribute maximum to urban population which will be about 352 M and will be the country with second highest urban populace with 0.9 billion urban population (UN 2010). Delhi, the capital city of India, has been the capital seat for 100 years (since 1911). The city has evolved through seven phases of growth and development finally forming the present day metropolitan Delhi. The urban expansion of city over the years is firmly established by gradual engulfment of several villages by the city. The number of villages has decreased from 231 in 1981 to 165 in 2001 to 112 in 2011 (Mishra 2011). The city has shown vast expansion of built-up space within as well as beyond its boundaries (Mallick et al. 2009). The expansion within Delhi has been well represented by development of million plus sub-cities like Rohini and Dwarka (Delhi Master Plan 2021). Other million plus cities in adjoining states such as Faridabad, Gurgaon, Ghaziabad and Noida symbolize the latter category (Dutta and Bandopadhyay 2011)

In order to make this urbanization a boon and not a burden for the country, urban planners need to work towards more effective policies for the large-scale urbanization process that is taking place in developing nations like India. Among other tools and techniques being used by urban planners worldwide, remote sensing is one that is highly efficient and is frequently used (Cralson 2003). Geospatial technology is being increasingly used to monitor urban landscapes in numerous ways such as studying land use changes (Mas 1999, Fan et al. 2008), monitoring (Taubenbock et al. 2012), and modelling urban expansion (Pijanowski et al. 2006). This paper uses remote sensing inputs and urban landscape analysis tools (ULATin GIS domain) to measure and monitor ULD over spatial and temporal domains since 1998 through 2011 with an objective to map and monitor ULD over Delhi for past decade.

Study Area

Geographically the city is located between 28°23′17″ N to 28°53′00″ N and 76°50′24″ E to 77°20′37″ E, covering an area of 1483 sqkm. The elevation ranges from

Fig. 1 Growth of urban population from 1901 to 2011 (Census of India 2011)
213 to 305 m. The city is located on banks of river Yamuna and is neighbored by two states, Haryana and Uttar Pradesh. Rapidly expanding fringes of the city indicate high rates of breakneck metro-politanisation that is a characteristic for urbanization in India. The main driver for this phenomenon is rural to urban migration (Diwakar and Qureshi 1992). The city population has increased from 1.7 million in 1951 to 13 million in 2001, to 16.7 million in 2011 and is expected to be 28.6 million by 2025 (UN 2010). Apart from increasing size of urban area, the city is also witnessing the problem of haphazard and unplanned growth (Jain et al. 2011) resulting in problems of basic amenities like water supply, sanitation, transport, housing etc.

**Material and Methods**

**Data**

Landsat TM/ETM satellite data for three times over the two decades (1998–2011) were procured from USGS website (www.usgs.gov) in GeoTIFF file format projected in UTM projection and WGS 84 datum. Landsat TM5 data has seven bands; three visible (blue, green, red) and four infrared bands (near IR, two mid IR, thermal IR). All bands except thermal IR have 30 m of spatial resolution, while thermal band (Band 6) has 120 m resolution.

**Urban Landscape Analysis Tool (ULAT)**

ULAT was used for quantification of dynamics of urban expansion (Parent 2011). The tool has been developed by Centre for Land use Education and Research (CLEAR), University of Connecticut. It identifies and classifies developed lands of different built-up density levels, non-developed areas, and developed lands that are prone to degradation. Based on urbanness and edge disturbance zone, we mapped Urban Footprint (UF), Urbanized Area (UA) and New Development (ND) lands. Thus, ULAT determines areas where, developed areas entrench on open lands and thus have discrepant impacts on open land.

**Methodology**

**LULC Characterization**

LULC is one of the fundamental information required for studies involving environmental monitoring, natural resource management, or even science based-policy making. Thus, the prime step of this methodology was mapping of LULC using knowledge based-classification techniques (Fig. 2). Since the objective of this study was to study the impact of built-up areas on other land use and land cover categories; thus only three broad classes were mapped. Three major land covers mapped are; built-up, water and others. Two indices were used to map built-up and water. The rest area was categorized as ‘Other’ class.

Built-up Index was computed to map out built-up areas from the imageries. This index (Zha et al. 2003) could differentiate built-up from non-built-up areas. Band 5 and band 4 were employed to compute this:

\[
\text{Built-up Index} = \frac{\text{Band}5 - \text{Band}4}{\text{Band}5 + \text{Band}4}
\]

Another index used was Water Index (WI) that efficiently maps out water covered areas (Parent et al. 2008);

\[
\text{Water Index} = \frac{\text{Band}1 + \text{Band}2 + \text{Band}3}{\text{Band}4 + \text{Band}5 + \text{Band}6 + \text{Band}7}
\]

Following this classification scheme, temporal land cover maps were prepared for years 1998, 2003 and 2011. For accuracy assessment of the classification, 150 stratified random points were generated and used. Thus 50 random locations for each class helped assess the accuracy against reference data. Producer’s and User’s accuracies were computed and compared against different years.

**Urban Footprint Mapping**

Urban Footprint maps consisted of seven categories based on urbanness values and their land cover attributes (Table 1). Urban footprint categorizes spatial density of urbanization. This is crucial from the perspective that low spatial density built-up areas have greater impact with respect to open land degradation. Another important category identified by footprint mapping is fringe open land, which behaves as edge-disturbance zone. These are the regions at edge that are prone to degradation by adjacent environments. Captured open land is yet another important category of open land as this is susceptible to degradation due to its existence in isolation from other open lands.
**Delineating Urbanized Area**

Urbanized area maps constituted of six classes similar to urban footprint maps, except fringe open land. Instead of fringe open land, urbanized area portrayed urbanized open land. This class consisted of undeveloped land with urbanness of more than 50% (Table 1). Thus, such areas are undeveloped and due to their location in high density built-up areas, they have high tendency to be impacted by surrounding developments. Thus, both urban footprint and urbanized area maps are highly crucial in identifying lands which are urbanized to various levels and the lands which have higher inclinations to degradation due to built-up areas.

**Identifying New Development Areas**

New development depicts the area that has developed between the two time periods under analysis. It illustrates the results in three categories, infill, extension and leapfrog. Infill developments are urban areas that have developed in urbanized open lands. Developments that occurred in fringe open lands are extensions. Leapfrog developments surface at places outside of rural open lands.

**Results & Discussion**

**Land Cover Characterization**

Land cover mapping of Delhi for three times indicates a continuously increasing trend of built-up areas that comprises of urban, suburban and rural built-ups (Fig. 3,
Built-up increased by 416.9 ha from 1998 to 2003 and 6632.8 ha during 2003 to 2011 phase. Water composition in land cover was more or less same, with initial decrease in amount of water covered area which again increased in 2011. Other class also followed an opposite trend witnessing an initial increase of 317 ha and a later fall of 6989 ha.

**Accuracy Assessment**

Producer’s and User’s accuracies were computed (Table 3) and compared against different years. User’s accuracy was highest for water (100 %) in all the years. Producer’s accuracy varied from 85.45 % (built-up class) in year 1998 to 98.41 % (other class) in 2011. Classified data of year 2011 had maximum overall accuracy of 96 % (kappa=0.94) and minimum accuracy of 92.67 % (kappa=0.89) was observed for year 1998. Accuracy for 2003 was 93.3 % (kappa=0.9). During all the years water consistently had higher accuracy with kappa values of 1 (Table 3).

**Assessing Urban Footprint on Open Lands**

Urban and suburban built-up land increased by 285 and 6,889 ha during 1998–2003 and 2003–2011 time periods with simultaneous fall of 9,786 and 3,135 ha in rural open land. Urbanization of villages has initially resulted in increase of rural built-up from 957 ha to 1,088 ha but has later decreased by 3,062 ha. The decrease could be due to conversion of rural built-up to suburban and urban built-ups. Due to greater role of leapfrog development in first time period of study an increase of 9,492 and 611 ha was noticed for fringe and captured open lands. But the pre-eminence of extension during the second time period, these two classes decreased by 3,061 and 792 ha respectively (Fig. 4).

**Urbanized Area Analysis**

Apart from urban footprints, urbanized area classes were also analyzed to see impacts of different levels of urbanization. Seven classes were mapped for urbanized area; urban built-up, suburban built-up, rural built-up, water, captured open land, rural open land and urbanized open land (Fig. 5). Basis for designating land to these classes has been explained in Table 4. Urbanized open land is a class that is important from viewpoint of high degradation vulnerability of undeveloped land patches, present in between developed lands. New developments, converted large chunks of other classes such as rural open land to urbanized open lands. This resulted in increase of urbanized open lands from 1998 to 2003 by 1,717 ha. During 2003–2011, urbanized open land decreased by 2829.69 ha. This was due to limited availability of undeveloped lands for creating urbanized open land patches as most of undeveloped lands had got degraded during 1998–2003.

Regression analysis was performed for the urbanized area (UA) and urban footprint (UF) statistics

<table>
<thead>
<tr>
<th>Classes</th>
<th>Area (hectares)</th>
<th>1998</th>
<th>2003</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other</td>
<td>87784.9</td>
<td>88101.9</td>
<td>81113.1</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>2818.26</td>
<td>2084.4</td>
<td>2440.35</td>
<td></td>
</tr>
<tr>
<td>Built-up</td>
<td>57654.6</td>
<td>58071.5</td>
<td>64704.3</td>
<td></td>
</tr>
</tbody>
</table>
Table 3  Accuracy assessment of LULC maps

<table>
<thead>
<tr>
<th>Years</th>
<th>Statistic Computed</th>
<th>Classes</th>
<th>Overall Accuracy</th>
<th>Overall Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Other</td>
<td>Water</td>
<td>Built-up</td>
</tr>
<tr>
<td>1998</td>
<td>Reference</td>
<td>44</td>
<td>51</td>
<td>55</td>
</tr>
<tr>
<td></td>
<td>Classified</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>Correct</td>
<td>42</td>
<td>50</td>
<td>47</td>
</tr>
<tr>
<td></td>
<td>Producer’s Accuracy</td>
<td>95.45</td>
<td>98.04</td>
<td>85.45</td>
</tr>
<tr>
<td></td>
<td>User’s Accuracy (%)</td>
<td>84</td>
<td>100</td>
<td>94</td>
</tr>
<tr>
<td></td>
<td>Kappa</td>
<td>0.77</td>
<td>1</td>
<td>0.91</td>
</tr>
<tr>
<td>2003</td>
<td>Reference</td>
<td>63</td>
<td>37</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>Classified</td>
<td>65</td>
<td>35</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>Correct</td>
<td>59</td>
<td>35</td>
<td>46</td>
</tr>
<tr>
<td></td>
<td>Producer’s Accuracy</td>
<td>93.65</td>
<td>94.59</td>
<td>92</td>
</tr>
<tr>
<td></td>
<td>User’s Accuracy (%)</td>
<td>90.77</td>
<td>100</td>
<td>92</td>
</tr>
<tr>
<td></td>
<td>Kappa</td>
<td>0.84</td>
<td>1</td>
<td>0.88</td>
</tr>
<tr>
<td>2011</td>
<td>Reference</td>
<td>63</td>
<td>30</td>
<td>57</td>
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<td></td>
<td>Classified</td>
<td>67</td>
<td>29</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>Correct</td>
<td>62</td>
<td>29</td>
<td>53</td>
</tr>
<tr>
<td></td>
<td>Producer’s Accuracy</td>
<td>98.41</td>
<td>96.67</td>
<td>92.98</td>
</tr>
<tr>
<td></td>
<td>User’s Accuracy (%)</td>
<td>92.54</td>
<td>100</td>
<td>98.15</td>
</tr>
<tr>
<td></td>
<td>Kappa</td>
<td>0.87</td>
<td>1</td>
<td>0.97</td>
</tr>
</tbody>
</table>

(Right 3). Rural open land has been found to follow a decreasing trend with 0.946 and 0.832 $R^2$ values for both UA and UF. Contrary to this has been the increasing trend of Urban built-up and Suburban built-up with 0.811 and 0.981 regression values. Urbanized open land exhibits strongly positive trend with
0.999 $R^2$. The results thus reinforce the notion of expanding dimensions of built-up area in Delhi. Weak and non-consistent trends were observed for Captured open land. Rural built-up also exhibited a weak decreasing trend with a $R^2$ of 0.357.

**New Developments**

New Development statistics helped in analyzing the pattern and type of urban growth that is taking place in city. From 1998 to 2003, greater part of new development could be attributed to extension that accounts for more than 50% of new developments. Leapfrog contributed 12% to new development area and the rest 32% developed through infill. For 2003 to 2011, the contribution from leapfrog development decreased to 3%, extension constituted 60% of new development and rest 37% was infill. Initially, vast tracts of land were available at peripheries which eventually got developed by leapfrog process. This constrained the availability of new lands for further leapfrog developments. Thus additional developments could only occur through extension and infill processes, which is clearly evident from Table 4.

Qualitative analysis of new development maps (Fig. 6) indicates that, from 1998 to 2003 development in western and south western parts of the city has been dominated by Leapfrog process which could be attributed to coming up of new establishment of sub-city of Dwarka. The same process is more scattered over north and north western parts from 2003 to 2011. Infill governed the development mainly in the central and eastern parts of Delhi during both the time periods. Extension prevailed in other developed areas that include the suburbs of the city and areas along the Yamuna banks and the parts of New Delhi and central ridge area. Extension patches of Bawana and Narela sub-city areas could more dominantly be observed during later study period in north and north western parts. Urban expansions in Dwarka sub-city resulted in extensions in south and south western Delhi.

**Ribbon Development Across the City Suburbs**

The detailed visual analysis of the maps suggested that most of the developments occurred along the road and highway networks, in typical ribbon fashion. To further analyze this, a 500 m buffer along the major road network was used (Fig. 7). This showed four major sites of development over the two decade study period. A large stretch of newly urbanized area is observed along the NH-1(area marked by ellipse in northern part). This could be attributed to establishment of Narela subcity that is a major newly allocated industrial centre to relocate industries from inside of the city to peripherals. Establishment of second industrial area called Bawana (top left circle in Fig. 7) has resulted in urbanization along the road, MD 138. Huge expansion of urban built-up is observed in Najafgarh area (bottom left circle). The urban expansion is tremendous in the area owing to development of Dwarka subcity.

![Image](Author's personal copy)

**Table 4** New development area statistics for Delhi

<table>
<thead>
<tr>
<th>Classes</th>
<th>Area (hectares)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infill</td>
<td>4504.14</td>
</tr>
<tr>
<td>Extension</td>
<td>7757.73</td>
</tr>
<tr>
<td>Leapfrog</td>
<td>1613.16</td>
</tr>
</tbody>
</table>

![Image](Urbanized area map)
under Urban Expansion Plan of DDA in its vicinity. Development has thus taken place along the roads; Kanjhawala Road, Nangloi-Najafgarh Road and Shivi Road, almost in all directions from Najafgarh. Another location of major urban development is near Bahadurgarh (circle in western part of the city) which contributes to development along the Rohtak Road as well.

Conclusion

The work analyzed the process and pattern of urbanization in Delhi from 1998 to 2011 in both quantitative and qualitative domains. Three land cover maps were prepared for each year and used as an input to ULAT tool. The study demonstrated that built-up has increased by 417 ha in from 1998–2003 and by 6,633 ha during 2003–2011. The expansion of built-up in the city has been majorly due to extension development accounting for 56 % and 60 % of total development in the two phases of study. The urbanized area and urban footprint map statistics show that urban-suburban built-up increased by 285 and 6,889 ha during the two time periods complemented with a decrease of 9,786 and 3,135 ha in rural open lands. Trend analysis for various urbanized area and urban footprint, was carried out. This showed strong positive trends for urban built-up, suburban built-up, urbanized open land and strong negative one for rural open land.

The western and south western parts of the city mainly developed due to leapfrog process. Infill and extension processes of development dominate the central to eastern parts; and suburbs, region along Yamuna and parts of New Delhi and central ridge area respectively. Development of sub-cities of Bwana and Narela in northern part and Dwarka in south-western Delhi under Urban Expansion plans of DDA account for extension-associated development in second time period. The study clearly illustrated how urbanization is taking over the rural lands of Delhi. It demonstrates the importance of monitoring the processes and patterns of urbanization in the city, which can be then put to use by the urban planners for more efficient planning.
Acknowledgments Authors are thankful to anonymous reviewers for suggestions. Authors also thank the Department of Science and Technology (DST), Ministry of Science and Technology (Government of India) for the funding and support.

References


Spatio-temporal footprints of urbanisation in Surat, the Diamond City of India (1990–2009)

Richa Sharma · Aniruddha Ghosh · Pawan Kumar Joshi

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Abstract Urbanisation is a ubiquitous phenomenon with greater prominence in developing nations. Urban expansion involves land conversions from vegetated moisture-rich to impervious moisture-deficient land surfaces. The urban land transformations alter biophysical parameters in a mode that promotes development of heat islands and degrades environmental health. This study elaborates relationships among various environmental variables using remote sensing dataset to study spatio-temporal footprint of urbanisation in Surat city. Landsat Thematic Mapper satellite data were used in conjugation with geo-spatial techniques to study urbanisation and correlation among various satellite-derived biophysical parameters, [Normalised Difference Vegetation Index, Normalised Difference Built-up Index, Normalised Difference Water Index, Normalised Difference Bareness Index, Modified NDWI and land surface temperature (LST)]. Land use land cover was prepared using hierarchical decision tree classification with an accuracy of 90.4% (kappa=0.88) for 1990 and 85% (kappa=0.81) for 2009. It was found that the city has expanded over 42.75 km² within a decade, and these changes resulted in elevated surface temperatures. For example, transformation from vegetation to built-up has resulted in $5.5 \pm 2.6 \degree{C}$ increase in land surface temperature, vegetation to fallow $6.7 \pm 3 \degree{C}$, fallow to built-up is $3.5 \pm 2.9 \degree{C}$ and built-up to dense built-up is $5.3 \pm 2.8 \degree{C}$. Directional profiling for LST was done to study spatial patterns of LST in and around Surat city. Emergence of two new LST peaks for 2009 was observed in N–S and NE–SW profiles.

Keywords Biophysical parameters · Expert classification · LST · LULC changes · Urbanisation

Introduction

Urbanisation is the most important anthropogenic activity after greenhouse gas emissions that impact climate (Kalnay and Cai 2003). Urbanisation on one hand benefits economic welfare of society; on the contrary, it threatens the biophysical health of the city itself. It causes detriment to environmental quality, including biodiversity (McKinney 2006; Delgado-V and French 2012; Threlfall et al. 2012), soil fertility (Chen 2007), water quality (Kaushal et al. 2008; Paul and Meyer 2001), and impacts other natural resources (Huang et al. 2010) along with ecosystem services (Alberti 2005; Bolund and Hunhammar 1999). Urban land transformations are most complex and dramatically irreversible land use changes and are thus one of the most studied phenomena (Wenhu 2012; Jiang and Tian 2010; Taubenböck et al. 2009; Souch and Grimmond 2006). Urban land use changes such as loss of vegetation (Scolozzi and Geneletti 2012), increased built-up and open areas (Ng et al. 2011) along
with increased expanse of urban fabrics such as concrete and asphalt altogether alter the local climate of a city by modifying various biological and physical characteristics of the environment. These include vegetation cover, impervious built-up covers, presence of moisture, surface and air temperatures, soil properties and others, which in turn are governed by land use characteristics (Voogt and Oke 2003).

With urbanisation taking over the world at an unprecedented pace, Indian cities are no exception. By 2050, India is expected to inhabit 0.9 billion urban population with a projection from 29.7 % in 2009 to about 54.2 % by 2050 (UN 2010). Delhi, Mumbai and Kolkata already fall in the category of the mega-cities, and Chennai is soon going to join these along with Hyderabad and Bangalore (Joshi et al. 2011). Apart from megacities, a number of smaller urban agglomerations are showing tremendous growth since the past decade (Taubenböck et al. 2009). Surat, for instance, has great potential of transforming into a megacity. Surprisingly, not enough work has been done to study its urban sprawl and related impacts. The city has been expanding ever since 1951 when it had a population of 0.24 million that gradually increased to 0.49 in 1971, to 1.52 in 1991 and finally crossing 2.8 in 2001 and reaching 4.46 million in 2011 (Census of India 2011). It is expected to inhabit 5.57 million people by 2025 (UN 2010).

Land surface temperature (LST) is the most studied biophysical parameter related to urban health. It has a two-way relationship with environmental parameters as it influences some of them and in turn gets influenced by others. Some literature is available on former part of this interaction. Baur and Baur (1993) found that urbanisation-related changes in LST resulted in local extinction of land snails in Basel. Whitford et al. (2001) stated LST as one of the four ecological performance indicators. LST also directly impacts surface energy budget (Bastiaanssen et al. 1998) and thus influences air temperature of the area. This results in emergence of two types of urban heat Islands (UHI) in same area, viz., surface UHI and atmospheric UHI. This paper examines formal half of LST and environment interaction using satellite-derived equivalents of various parameters. This study thus employs remote sensing to demonstrate how different environmental parameters like vegetation cover and health, moisture intensity and bareness influence LST.

With the advent of geospatial technology, it has become possible to remotely monitor the biophysical variables and changing land use patterns and to analyse their interactions (Buyantuyev and Wu 2012). Though a number of studies have been carried out to examine the variability among greenness, surface temperature (Son et al. 2012; Julien and Sobrino 2009; Raynolds et al. 2008; Julien et al. 2006; Weng et al. 2004; Sandholt et al. 2002; Owen et al. 1998; Gillies et al. 1997; Goetz 1997) and land use associations (Amiri et al. 2009; Zhou et al. 2011; Jiang and Tian 2010; Xiao et al. 2008; Xiao and Weng 2007), little work has been done in assessing the variability of other biophysical factors in context to LST (Uddin et al. 2010; Chen et al. 2006). Limited research material could be found on the relationship of these parameters with respect to each other and how this relationship differs for different land uses. Uddin et al. (2010) and Chen et al. (2006) have attempted classification using four main indices, viz., Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Normalised Difference Built-up Index (NDBI) and Normalised Difference Bareness Index (NDBaI). In the present study, an additional modified water index was developed, Modified Normalised Water Index (MNDWI), for extracting water. All these factors were considered as these could account to assess spatio-temporal footprints of urbanisation.

**Surat—the Diamond City**

Surat city is the commercial capital city of Gujarat (India) and also serves as administrative capital of Surat district. It is situated on the banks of Tapi river which perennially flows northeast to southwest finally joining the Arabian Sea, situated 22 km west to the city. The city is situated at 21.25° N and 72.87° E (Fig. 1). The region experiences hot summers with temperature ranging from 38 to 45 °C. Winters are mild, but the months of December and January are coldest with temperatures varying between 10 and 15.5 °C. The average annual rainfall is 1,143 mm (Surat Municipal Corporation 2011).

Being a commercial hub, the region has witnessed tremendous urbanisation over the past few decades. It ranks 36th in the list of the world’s largest cities with a population of over 2.5 million
in 2001 (population density of 1,376 persons/km$^2$) and the third cleanest metropolitan region in India. The city has total population of more than 6 million of which 80 % is urban population and the remaining 1.24 million is rural (Census of India 2011). Surat has immense business and job opportunities that trigger high immigration rates to the city resulting in increased population. The two major economic activities are agriculture and diamond cutting. A large number of small-scale diamond cutting industries have given the name ‘Diamond City’ to this place.

The study area extends spatially from 21.29° N and 21.12° N to 72.74° E and 72.94° E, spanning across 386.28 km$^2$ covering the city (city limits of 326 km$^2$) and peripheral urban–rural fringe. The study area mainly falls in the Chorasi taluk of Surat district but also covers parts of adjoining taluks of OLPad in the north, Kamrej in the east and Palsana in the south-east. It is bound by Navsari on the south.

Materials and methods

Satellite data

Landsat 5/4 Thematic Mapper (TM) satellite images (Path/Row, 148/45) dated October 19, 1990 and October 23, 2009 were used. Landsat is a medium-resolution (30 and 120 m) data with seven bands that are most commonly used for environmental studies. Landsat TM data consist of seven bands of which the first three are visible bands, the fourth is near-infrared, bands five and seven fall in shortwave infrared regions and sixth is the thermal band. The geometrically and radiometrically corrected images rectified to a common Universal Transverse Mercator were procured from the USGS Earth Resource Observation Systems Data Center. The details and characteristics of the satellite data used are given in Table 1.

Spectral enhancement was done using band ratioing to compute various indices. This performed a twofold
Table 1 Landsat 5 TM sensor system characteristics

<table>
<thead>
<tr>
<th>Band</th>
<th>Spectral details; wavelength (μm)</th>
<th>Spatial resolution (m)</th>
<th>Applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM1</td>
<td>Blue (0.45–0.52)</td>
<td>30</td>
<td>Can penetrate water bodies, thus help in coastal water studies, identifying cultural features</td>
</tr>
<tr>
<td>TM2</td>
<td>Green (0.52–0.6)</td>
<td>30</td>
<td>Studying water turbidity, vegetation studies</td>
</tr>
<tr>
<td>TM3</td>
<td>Red (0.63–0.69)</td>
<td>30</td>
<td>Monitoring vegetation health</td>
</tr>
<tr>
<td>TM4</td>
<td>Near-infrared (0.76–0.9)</td>
<td>30</td>
<td>Studying land–water and cropped–non-cropped lands, identifying crops</td>
</tr>
<tr>
<td>TM5</td>
<td>Shortwave infrared (1.55–175)</td>
<td>30</td>
<td>Cloud and snow studies, studying geological features, monitoring vegetation moisture</td>
</tr>
<tr>
<td>TM6</td>
<td>Thermal infrared (10.40–12.5)</td>
<td>120</td>
<td>Surface temperature studies, LST estimation, vegetation stress studies</td>
</tr>
<tr>
<td>TM7</td>
<td>Shortwave infrared (2.08–2.35)</td>
<td>30</td>
<td>Studying vegetation moisture content, studying rocks and minerals</td>
</tr>
</tbody>
</table>

function: firstly, these served as variables in classification, and secondly, these were used to study dynamics of different biophysical parameters (viz., greenness, wetness, bareness and built-up intensity) with respect to each other and that to thermal response of environment. Red (TM 3) and infrared (TM4) bands helped to enhance greenness (Maxwell and Sylvester 2012; Purevdorj et al. 1998), infrared (TM4) and shortwave...
infrared (TM5) were used to enhance built-up areas (Bridhikitti and Overcamp 2012; Ma et al. 2010; Zhang et al. 2009) and enhance canopy vegetation water content (Jackson et al. 2004; Serrano et al. 2000; Gao 1996). Shortwave infrared (TM5) and thermal infrared (TM6) were employed for enhancing bare lands (Nasipuri and Chatterjee 2009). LST retrieval was performed using thermal information of TM6 band. For more accurate mapping and extraction of water bodies from image, MNDWI was computed by transforming blue (TM1) and shortwave infrared (TM5) bands. Figure 2 briefly describes the methodology followed.

Data processing

*Estimating biophysical parameters*

NDVI, NDBI and MNDWI were used to map land use and land cover (LULC) classes. These metrics along with NDBaI and NDWI were used to investigate correlation of various biophysical parameters (intensity of moisture, greenness, build-up density and extent of bareness) with that of thermal response of urbanised areas in contrast to vegetated areas. Table 2 presents a brief review of various indices used, their computation and uses along with references.

**Table 2** Description of various image transformation used with references

<table>
<thead>
<tr>
<th>Transformation</th>
<th>Algorithm</th>
<th>Application</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>$\frac{\rho_4 - \rho_3}{\rho_4 + \rho_3}$</td>
<td>Vegetation studies (fractional vegetation cover, leaf area index, plant phenology, productivity, and chlorophyll density), forest cover estimation, canopy studies, studying rainfall patterns, drought monitoring, estimating biomass, studying urbanisation, as surface urban heat islands (SUHI) indicator</td>
<td>Anyamba and Tucker (2005); Weiss et al. (2004); Zhou et al. (2004); Gallo et al. (1995); Carlson and Ripley (1997); Jong et al. (2011); Yuan and Bauer (2007); Li and Fox (2012).</td>
</tr>
<tr>
<td>NDBI</td>
<td>$\frac{\rho_5 - \rho_4}{\rho_4 + \rho_4}$</td>
<td>Extraction of built-up areas and to study SUHI</td>
<td>Zha et al. (2003); Zhang et al. (2009).</td>
</tr>
<tr>
<td>NDWI</td>
<td>$\frac{\rho_5 - \rho_4}{\rho_4 + \rho_5}$</td>
<td>Used in vegetation studies as it gives an indication of vegetation liquid</td>
<td>Gao (1996); Gabor and Jombach (2009); Maki et al. 2004</td>
</tr>
<tr>
<td>NDBaI</td>
<td>$\frac{\rho_5 - \rho_6}{\rho_4 + \rho_6}$</td>
<td>Extraction of bare areas that are moisture deficient</td>
<td>Chen et al. (2006)</td>
</tr>
<tr>
<td>MNDWI</td>
<td>$\frac{\rho_1 - \rho_5}{\rho_1 + \rho_5}$</td>
<td>Mapping areas covered by water</td>
<td>Introduced$^a$</td>
</tr>
</tbody>
</table>

$^a$This index is introduced in this paper

Land surface temperature retrieval

Landsat TM band 6 has been extensively exploited to study thermal dynamics of various earth surface features (Qin et al. 2001; Schott et al. 2001). LST was derived using thermal infrared (TM6) band (10.40–12.50 μm), with effective wavelength of 11.457 μm, has relatively lower radiometric sensitivity and coarser spatial resolution of 120×120 m. Qin et al. (2001) mono-window algorithm (Sun et al. 2010) was used to retrieve LST from thermal DN values, and NDVI was used here for emissivity correction to obtain final LST images.

**Table 3** Hypothesis, rules and variables for 1990 and 2009 satellite images

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Rules</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-up</td>
<td>Built-up areas and rooftops</td>
<td>NDVI &lt;0.02 and NDWI &lt;0.2 AND NDBI ≥0.15 AND NDBaI &lt;−0.25</td>
</tr>
<tr>
<td>Sediment</td>
<td>Riverbed, silt and sandy</td>
<td>−0.75 ≤NDBaI ≤−0.6</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Agriculture and urban green</td>
<td>NDVI &gt;0.3 and 0 &lt;NDWI &lt;0.3 AND −0.6 &lt;NDBaI &lt;0.3 and −0.2 &lt;NDBI &lt;−0.02</td>
</tr>
<tr>
<td>Water body</td>
<td>Rivers and water bodies</td>
<td>MNDWI ≥0.3</td>
</tr>
<tr>
<td>Fallow land</td>
<td>Agricultural fallow</td>
<td>NDVI &lt;0.2 and −0.25 ≤NDWI ≤−0.1 and NDBaI ≤−0.3 and 0.1 &lt;NDBI &lt;−0.3</td>
</tr>
</tbody>
</table>
Characterising land use patterns

Five broad categories of LULC were identified based on visual image interpretation keys; (1) Built-up comprised of urban features and impervious structures like asphalt and concrete roads; (2) River bed included sediments along river and other sandy and silt deposition structures; (3) A broad class named ‘Vegetation’ included land under agriculture as well as urban vegetation and other canopy; (4) Agricultural land without any vegetation cover including agricultural fallow was classified as Fallow land; and (5) Water body covered Tapi river and other small water storage tanks.

Knowledge-based classification technique was employed to categorise satellite images into LULC classes. It is a type of hierarchical decision tree algorithm based on hypothesis testing that evaluates various rules and conditions defined by the user. Rules are condition (IF) and action (THEN) statements. Hypothesis, rules and condition represented in linear dendritic decision tree are inferred and processed to generate outputs (Table 3). Indices computed earlier were fed into knowledge engineer as variables for different LULC classes (the hypothesis), and their threshold values defined the rules for each hypothesis. Due to high efficiency of MNDWI in identifying water pixels, it was used alone for water extraction. The decision tree thus generated was executed to map LULC. To assess the classification accuracy, 150 randomly

Table 4  Accuracy assessment for 1990 and 2009 classification

<table>
<thead>
<tr>
<th>Class name</th>
<th>1990</th>
<th>2009</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PA (%)</td>
<td>UA (%)</td>
</tr>
<tr>
<td>Built-up</td>
<td>90.2</td>
<td>92</td>
</tr>
<tr>
<td>Sediment</td>
<td>86.27</td>
<td>88</td>
</tr>
<tr>
<td>Vegetation</td>
<td>90.2</td>
<td>92</td>
</tr>
<tr>
<td>Water</td>
<td>93.88</td>
<td>92</td>
</tr>
<tr>
<td>Fallow</td>
<td>91.67</td>
<td>88</td>
</tr>
<tr>
<td>Overall</td>
<td>90.4</td>
<td>88</td>
</tr>
</tbody>
</table>

Fig. 3  Expansion in built-up from 1990 to 2009
generated points were overlaid on the satellite image. Statistically valid sampling strategy was adopted to assess commission, omission and overall accuracy (Stehman 1996).

Statistical analysis

**Biophysical parameters**

Urban land transformations have great impacts on the biophysical health of the environment. To examine the complexity and dynamics of this relationship, 150 experimental and 150 control points were randomly generated. All the points were well distributed among the LULC classes and the entire study area. At least 30 points per LULC were generated to extract values of each of the parameters under study. These were then used to mine out the values of biophysical parameters two times for analyzing the influence of LULC change on the biophysical environment. Correlation and regression techniques were employed to exemplify how the environment responds to stimulus of urbanisation.

**Directional profiles of LST**

Based on the spatial patterns of urban expansion in the area, four directional profiles for LST were selected: north–south (N–S), east–west (E–W), northeast–southwest (NE–SW) and northwest–southeast (NW–SE) profiles. LST values for these spatial profiles were analysed across the background of expansion in the built-up area over the study period.

**Results and discussion**

**LULCC analysis**

1990 and 2009 LULC maps were analysed to study expansion of urban area. The classes mapped were built-up, vegetation, fallow, river bed and water. Area statistics for LULC ascertained massive expansion (nearly three times) in urban expanse at the cost of vegetation and fallow lands. The urban extent increase has been equal to 42.74 km$^2$ from 1990 to 2009. With improved connectivity through roads, highways and bridges, the city has expanded in almost all directions (Fig. 3) resulting in newer settlements in Amroli, Nana Varachha, Choriyasi, Athwa, Vishal Nagar, Sima Nagar and Jain Wadi. Udhana has been the centre for highly denser sprawls that could be attributed to its high economic importance for diamond cutting and polishing works. Overall classification accuracy of LULC map for 1990 was 90.4 % and for 2009 was 84.4 % (Table 4). The expert classification accuracy is remarkably good as compared to hard classification methods (Punia et al. 2011; Wentz et al. 2008). Due to
similar spectral responses of long fallow and less dense built-up areas, 2009 image has poorer accuracy for fallow and built-up classes.

Analysis of biophysical parameters

For quantification of relationship between biophysical parameters under study (Fig. 4), correlation analysis was carried out using 300 point values. The analysis demonstrated that LST shoots up with a fall in NDVI or greenness. A similar relationship was observed for NDWI also. Lesser will be the water content, lesser will be evaporation and hence reduced cooling will result in higher temperature. This explanation also supports a positive correlation between NDVI and NDWI (Fig. 5). NDBI represents built-up intensity of land. The higher the built-up intensity, the more impervious and the lower the moisture content. Thus, LST–NDBI behaves asynchronously. NDBI and NDWI exhibited a perfectly negative relationship as the two indices have exactly the same numerical values but antonymous signs.

Fig. 5 Scatter plots and coefficient of determination for different parameters in 1990 and 2009
Bareness index did not exhibit a strong correlation with any of the parameters. Similar results have been observed by Essa et al. (2012). NDBaI exemplified a negative correlation with NDVI and NDWI and a positive one with LST and NDBI for both years. But this relationship shows inconsistency when analysed separately for control and experimental points showing positive values for year 1990 (0.032 for control and 0.183 for experimental) and negative for year 2009 (−0.09 for control and −0.20671 for experimental). Uddin et al. (2010) also state that in some isolated cases, NDBaI and LST have a positive variability with respect to each other (Fig. 5).

LST characterisation

Experimental and control point values of LST were analysed to assess thermal response of different LULC classes. The average temperature of experimental built-up points is relatively higher than that for vegetation areas. LST for vegetation to built-up change areas increased by 8.8±2.6 °C, and fallow land to built-up increased by 6.6 ±2.8 °C, while 8.6±2.8 °C change was observed for increase in built-up density.

Increase in average temperature for unchanged vegetated areas was assessed using control points and was found to be 3.3±3.4 °C. Hence, the net increase in the temperature for changes from vegetation to built-up is around 5.5±2.6 °C, vegetation to fallow is 6.7±3 °C, fallow land to built-up is 3.5±2.9 °C and built-up to dense built-up is 5.3±2.8 °C. Temperature change for vegetation to fallow is higher than vegetation to built-up which could be due to land being fallow for long and thus being deficient in moisture. Also, as compared to fallow land, which is completely bare, built-up areas are characterised by shadow effects from building structures.

Temporal analysis of LST demonstrated that built-up areas have a higher temperature as compared to vegetation thus forming the foundation for phenomenon of urban heat island in the area (Schwarz et al. 2012; Liu and Zhang 2011) (Fig. 6). Built-up areas that have come up by replacing vegetation show elevated temperatures as compared to other areas. Urban areas contain impervious surfaces that decrease local...
infiltration, percolation and soil moisture (Brun and Band 2000). Due to their thermal properties, heat island phenomenon is triggered. LST is one of the key factors that control physical, chemical and biological processes in the environment and in turn is governed by them. Urbanisation in particular changes the thermal environment due to physical properties of its urban fabric (Pu et al. 2006) and encourages the development of urban heat island.

Spatial profile analysis

For a detailed analysis of spatial distribution of LST in the study area, four directional profiles were studied (Fig. 7). The profiles were constructed based on directions in which built-up area has expanded. N–S profile ran from Kosam and Sherdi villages in north of the river to Udhana industrial centre, in south of Surat city. Spatial N–S profile of LST for 1990 and 2009 improved our understanding that industrialised area increased thermal environment. The curve became flatter for Surat city in 2009, and new peaks were observed in Udhana centre which were not there in 1990. This could be explained based on the expansion of built-up in Udhana area. E–W profile starts with agricultural lands of Bhesan and Melgama villages, passing built-up area of Jain Wadi crossing the river to industrial areas of Bharat Nagar, through the city of Surat, and finally ending in the agricultural lands of Kosmada and Ladvi villages. E–W profile exhibited results similar to N–S profile with low thermal response of agriculture. In 1990, only one major peak was observed in built-up area in and around Surat, while in 2009, profile flattened with higher temperature values illustrating impacts of increased built-up on LST.

The NW–SE profile sets out from agricultural areas of Talad and Sarol Gam villages; crossing across the river, it passes through Katargam, Surat and Shakti Nagar areas finally terminating through agricultural

![Fig. 7 Directional profiling of LST distribution in 1990 and 2009](#)
areas of Bonand and Kharsava villages. Temperature values (Fig. 7) for agricultural areas, in the beginning and end of the profile, were generally lower with sporadic peaks due to fallow land. Built-up areas of Katargam, Surat and Shakti Nagar gave high temperature responses. Profile corresponding to river showed a steep depression in temperature. Such an observation was recorded for all four profiles regarding encountering river in between. NE–SW profile begins at fields of Abrama crossing the river passing through Kodiyar Nagar and Surat city through Krishnanaganj and Athwa to Vesu village. A peak was observed for the new built-up in 2009, towards the northern bank of the river. In 1990, fewer peaks were observed for Surat, Kishanganj and Athwa areas, but more and higher peaks were observed in 2009.

Conclusion

The study was taken up to assess spatio-temporal footprints of urbanisation in Surat city. Over a span of two decades, the city has spread over an area of 42.75 km², with multi-directional expansion of its built-up. The city has densely spread to the south in Udhana industrial hub and comparatively less dense northward spreads in Amroli and Kosad Navi Vasahat. Choriyasi, a small satellite town, manifests the eastward spread of the city, while Athawa manifested the same for the southwestern spreads. Older parts of Sima Nagar and Jain Wadi served as centres of urban growth for the west.

The urban expansion has altered the state of various biophysical parameters (including surface temperatures, moisture contents and vegetation cover) which govern the health of the environment. In this study, we qualitatively studied the multifaceted interactions of biophysical parameters and quantified relationships among them. The selected parameters retrieved from satellite data are LST (thermal behaviour of surface), NDVI (intensity of greenness), NDBI (intensity of built-up), NDWI (moisture status of surface) and NDBaI (bareness). Of these, LST–NDVI and LST–NDWI were found to vary inversely, while LST–NDBI and NDVI–NDWI had a strong positive correlation. Of these, NDBaI was one parameter that could not give consistent results and was characterised by very weak correlations with the other parameters. Although NDBaI has been successfully employed by Chen et al. (2006), in this work, some inconsistent results were obtained for this index. Thus, we found that this index gave site-specific results, and there is further scope of developing a more robust index to measure the bareness intensity of the earth surface.

In face of urban heat island (UHI), LST parameter was more intensely analysed with respect to its changing spatial distribution against the background of changing LULC patterns. LST through UHI can have severe impacts on human and environmental health by increasing the frequency and intensity of heat waves (Tan et al. 2010). It was observed that with southward expansion of Udhana industrial area, new peaks for LST came up in 2009. Similar results were found for Athwa, Jain Wadi and Surat city areas. Apart from urban areas, some peaks came up for agricultural fallow lands.

Global urbanisation needs accurate information on the expansion of impervious surfaces and associated parameters. The parameters discussed in this study are of prime importance to assess the impact of urbanisation-linked development. Eco-planning in urban sector could use such information to achieve the goals of sustainable practices and planning. The information generated can also aid in understanding the contribution of local effects on the global phenomena of climate change and associated changes. These should be explored to understand the health of urban ecosystem and linkages with human well-being.

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References


India: Patterns of an Urbanizing Nation  
*P K Joshi, Richa Sharma, Brij Mohan Bairwa and Vinay Sinha*

The first urbanized empire, the Harappan civilization, existed during the Bronze Age (3500 to 1200 B.C.E) and was marked by an astonishing level of complex development, while the second urbanization phase occurred during the Iron Age (1200-550 B.C.E.) in the Gangetic plains (Gangal et al., 2010). Due to the pace and scale of urbanization, it would be appropriate to term this era as the “Urban Age”, for today more than half of human civilization resides in urban areas and the United Nations (UN) has projected that by 2030, 60% of the world’s population will be urban. Although most developed nations have stabilized over time, developing nations are still urbanizing. By 2030, Asia and Africa will have the highest number of urban dwellers, accounting for seven out of every ten urban residents worldwide. India, in particular, has witnessed tremendously high rates of urbanization over the past forty years. By 2021, India is expected to house six mega cities (Bangalore, Chennai and Hyderabad) including the present three (Delhi, Mumbai and Kolkatta).

Cities serve as powerful engines of growth and although urbanization can be a good indicator of progress, particularly of developing nations, it has important social, cultural, and environmental implications at both regional and global scales. Some of the associated negative consequences include the development of urban heat islands, altered regional hydrology patterns with changes in peak flows and rainfall run-off values, adverse impacts on ecosystem services, scarcity of urban services and housing facilities, poor infrastructure, etc.

Furthermore, as 87% of Earth’s land cover has been altered because of anthropogenic activities like urbanization, investigation and analysis of land use land cover (LULC) patterns and their change thus becomes an important tool for gathering information about the urban growth process, its drivers and outcomes. The monitoring, measurement and assessment of urban growth along temporal and spatial domains is an essential prerequisite for city planners, economists, environmentalists, ecologists, resource managers and policymakers in defining a more viable path of development. In this regard, multi-temporal satellite data serves as a significant data-gathering tool for such LULC change information.

In our study, we used multi-temporal DMSP-OLS cloud-free data (1999-2009) to study the urban footprints of twelve large Indian cities (Taubenböck et al., 2009). These images were
used to generate one stable light image per year and were used to systematically study the patterns and process of urbanization in India (Batty and Howes, 2001; Chand et al., 2009). We believe that the knowledge generated from this study, described here, will aid in the development of a well-managed path of growth for Indian cities, which is imperative for building a sustainable urban society.

Patterns of urbanization

In 1995, abrupt changes took place in the North-Western Plains and down south around Mumbai and Bangalore. During 1996–97 remarkable urban expansion occurred around Delhi, Surat, Hyderabad, Bangalore, Kolkatta and Mumbai, with even more extensive expansion occurring in 2007. The three mega cities have shown unique patterns of urbanization; Delhi is characterized by radial growth and Kolkatta and Mumbai exemplify elongated and disaggregated growth. The incipient cities (Hyderabad, Chennai, Ahmedabad and Bangalore) demonstrate complex and unstructured sprawls. Three of the urban agglomerations (Jaipur, Kanpur and Lucknow) experienced a tremendous change in 2007 while the other two (Pune and Surat) sprawled out in 1996 and 2000 respectively. Recently, these have shifted from mono to polycentric cities exhibiting complex, unstructured growth patterns, while giving rise to satellite cities. These medium sized cities were found to be the fastest growing urban areas.

Urban morphology of Delhi

This study has illustrated not only the multi-level hierarchical succession of India’s giant urban centers from urban agglomerations to incipient cities and mega cities, but has also described the urban morphology in India, accounting for these area’s urban footprints. For example, India’s capital of Delhi has been urbanizing at an inconceivable pace and has witnessed tremendous changes in the LULC practices over the past four decades. This demonstrates the evolution of the regional urban pattern; for instance, large tracts of agricultural land in northern Delhi have been taken over by small and large concrete structures accounting for low and high density construction over the course of the 1970s to 1990s. Similar changes have been recorded in the southwestern parts of the city, including a very large patch of sparse vegetation and scrubland which was gradually converted to built-up area. Within a decade from 1999, large parts of Delhi that were less dense became denser. Additionally, vast tracts of agricultural land were taken over by scrubland. A broad overview (1977–2009) of the directional analysis of the changes in land use and land cover practices in the city suggests that the conversion of scrub and bare soil to low density construction has taken place in the south and south-eastern parts of the city. North and northwestern Delhi exhibit a changing trend from agricultural to built-up lands of

Figure 1  | DMSP OLS data for India, showing the variation in human dimensions over space and time
lower density. Extreme southeastern parts of the city have been dominated by the transformation of land from sparse vegetation to built-up area of lower density. High density construction has occurred replacing the scrub and bare soil in the extreme eastern and south eastern parts, while in central to eastern Delhi the same change has occurred with low density built-up area.

The study reveals that there has been tremendous loss of agricultural areas, bare soil and scrubland at the hands of built-up areas (high and low density). An attempt to relate the density of the built-up area with population density and land surface temperature with population densities in Delhi for the year 2001 indicates that population growth has contributed to the elevated land surface temperatures and thus, has affected the micro-climate of Delhi. It was also found that the tremendous and complex urbanization patterns of Delhi have contributed to a 1-2°C rise in mean surface temperature over the span of just four years (2001-2005); these population and urbanization trends are contributing to the development of the Urban Heat Island phenomenon within the city (Mallick et al., 2009).

**Final thoughts**

Urban areas and the environment interact bi-directionally with global environmental change serving both as a driver and outcome of complex political, social, economical, cultural and physical interactions within urban areas. As illustrated in the above findings, urbanization in India has been increasing, creating the need for more efficient and sustainable plans in order to manage the urban growth with regard to social, political, economic and environmental contexts. Unfortunately, India is overburdened and under-planned despite the pace of its urbanization. In order to overcome these challenges, better integrated sustainable plans and policies must be developed. Instead of converting metropolises into mega cities, a greater focus should be put on developing smaller towns as magnets for rural populations. This will ultimately help in curbing the source of increased pressure on urban centers; in India, urbanization occurs not because of urban pull but is due to the rural push.

Some headway is, however, being made through various initiatives to curb the patterns of unsustainable growth that continues in India. One example is Providing Urban Amenities in Rural Areas (PUR), one of the sustainable strategies initiated by former President of India, Dr. A. P. J. Abdul Kalam. This strategy aims at bringing urban amenities to rural communities so as to prevent rural to urban migration. Apart from such preventive measures to reduce the burden on cities, living conditions in the existing urban areas must be improved. This includes working towards improved transportation facilities, better water and sanitation facilities, improved sewage and solid disposal services and well-managed infrastructure as proposed under the Jawaharlal Nehru National Urban Renewal Mission (JNNURM). While planning for an urban area, the focus should lie not only on the planning for a well-managed city but on a sustainable city (Monto and Malhotra, 2011). This includes consideration of the relationship between the state and dynamics of environmental resources and services (ecological environment); the livability of urban infrastructures for all citizens without causing any harm to the urban environment (built-up environment); promoting public participation (political environment); promoting equal rights to support livelihoods of local communities with special emphasis on the marginalized sector of society (social environment); and long-term development of communities without increasing the ecological footprint of the city (economic environment). Thus, urban planning needs to become an integrated process as cities cannot serve as islands of reform in isolation, due to their complex interaction with global political and economic domains and periurban, sub-urban and rural areas.

**References Cited**


Assessing urbanization patterns over India using temporal DMSP–OLS night-time satellite data

Many of the important and most significant changes around the world are associated with urbanization. Incidentally, more than half of the population (3.3 billion people) resides in the urban areas and by 2030 more than 70% of the population will be concentrated in the urban areas\(^1\)-\(^3\). As of now, 19 mega cities and 22 cities exist, holding more than 10 million and 5–10 million population respectively. Apart from this, 370 cities with 1–5 million people, and 433 cities with 0.5–1 million people are growing at a high rate\(^1\),\(^4\),\(^5\). The current rate of urbanization (0.8%) will grow in a rapid and unbalanced pace (1.6%), most dominantly in the developing countries\(^6\). Asia being one of the most populous realms is expected to have more than 54% of the world’s urban population by 2050. This will result in political and economic transformations, including migration of communities and urbanization.

In India, urbanization has witnessed an unprecedented rate of growth over the last four decades. During the last 50 years, the population of India (today 1.2 billion) has grown more than double and the urban population nearly five times. Around 400 million people (~28%) live in the cities, in sharp contrast to 60 million people (~15%) in 1947. It is estimated that 140 million people will move to the cities by 2020, and another 700 million by 2050. The number of Indian mega cities will increase from the current three (Mumbai, Delhi and Kolkata) to six (including Bangalore, Chennai and Hyderabad) by 2021, when India will have the largest concentration of mega cities in the world\(^7\),\(^8\). The number of cities is expected to be 68 by 2021, which will result in urban housing shortage of about 30 million units. Such interactions will create a coupling impact between the global environmental changes and the local environment of urban areas.

Monitoring, measurement and assessment of this urban growth is essential for city-planners, economists, environmentalists, ecologists, resource managers and the government at large. Such information will enhance the ongoing initiatives to use spatial data for local planning and better governance. Multi-temporal remote sensing is one of the important data-gathering tools for analysing land-use and land-cover changes\(^9\). The potential use of Defense Meteorological Satellite Program–Operational Linescan System (DMSP–OLS) night-time satellite data in population studies, inventories of human settlements and energy consumption patterns has been noted since the early 1980s (refs 10 and 11). The potential use of this in mapping the population and urban areas\(^12\), socio-economic parameters and greenhouse gas emissions\(^13\), urban heat island\(^14\) and energy consumption\(^15\) has also been documented.

In this study we used temporal night-time DMSP–OLS satellite data over the Indian region, to detect urban footprints and their changes, with a special emphasis on 12 large Indian cities (currently ranging from 2.5 to 20 million inhabitants). Development of a country is best represented in the spatial increase in towns and cities (urban sprawl or agglomeration), as they provide living for people of all groups and are the centres of attraction. Spatial analysis on enhancement in the night-time lights is a potential indicator of urban sprawl. The study attempts to characterize the spatial pattern of the cities to detect similarities and differences in spatial growth in the large Indian urban agglomerations.

Figure 1 shows a map of India with state boundaries and location of important cities. It also shows the population growth between 1991 and 2001. The mega cities in India are Mumbai, Delhi and Kolkata\(^2\), of which Delhi (4.1%) and Mumbai (3.1%) have the highest population growth rate of all mega cities in the world. The other important cities are Chennai, Hyderabad and Bangalore. Besides these, other urban agglomerations (Ahmedabad, Jaipur, Poona, Kanpur, Lucknow and Surat) currently have more than 2.5 million inhabitants\(^7\). These cities...
along with other developing cities are flooded with immigrant populations from different parts of the country every year, resulting in rapid urban agglomeration.

DMSP operates in sun-synchronous orbits with night-time overpasses covering the Indian region from 7 to 10 pm local time. The Indian region is observed in two or three OLS orbital passes on a swath width of 3000 km. The OLS is an oscillating scan radiometer with two spectral bands, visible (0.5–0.9 μm) and thermal (10.5–12.5 μm), and has a unique capability of picking up faint sources of visible–near infrared emissions (lights) at night on the Earth’s surface, including cities, towns and villages, with a DN value ranging from 1 to 63. DMSP–OLS is basically designed for global observation of cloud cover. At night, the visible band is intensified with a photo-multiplier tube to permit detection of clouds illuminated by moonlight. The light intensification enables observation of faint sources of visible–near infrared emissions present at night on the Earth’s surface, including cities, towns, villages, gas flares, heavily lit fishing boats and fires. It provides a contrasting image of urbanization through the detection of city lights as they are seen from space. The stark contrast between lighted and unlighted lands and the large area covered per scene makes it an obvious choice for classifying and mapping land transformation to urban and suburban uses over large areas.

Methodologies for deriving stable light images from DMSP–OLS along with the sensor characteristics are explained in detail elsewhere. ‘Stable light image’ refers to temporal composite build-up of cloud-free images of the Earth at night over a six-month (October–March) period. Night-time light images for cloud-free dates given by the DMSP–OLS from 1992 to 2009 were segregated into the respective years and were integrated to generate one ‘stable light image’ per year. In this, city lights were identified because they are temporally stable, represented as small areas of saturated DN values decreasing towards the periphery. So for mapping the large city footprints, its spatial dimension and developments over the years, the data provided enough information for assessing changes. Comparative analysis on the increase in the number of DMSP–OLS light pixels and the number of saturated light pixels with respect to the previous one was carried out. DN values along linear transects passing from the periphery through the centre of major Indian cities were plotted in order to study the periphery development (extension and spread of the city). In India, the urban population apart from industrial, agricultural and domestic sectors, consumes most of the commercial energy. The rest of the population in rural areas still depends on non-commercial sources of energy such as wood, cow dung and agriculture by-products to meet major energy needs.

Datasets of 1992–94 did not show many changes in the urbanization pattern (Figure 2). However, the dataset of 1995 indicated a rapid change in the northwestern plains of India with acute increase in light intensity. Variations were also observed in southern India, indicating changes around Mumbai and Bangalore. The light intensity increased in 1996 and the rate of expansion accelerated in 1997, with incremental variation in northwestern India. The expansion around Delhi was also remarkable, with indication of increase in Surat, Hyderabad, Bangalore, Kolkata and Mumbai. Year 2007 and onwards such expansions have been relatively fast; showing increase in energy usage pattern and urbanized work represented by the bright pixels of night-time data.

The mega cities, like Delhi, Kolkata and Mumbai clearly stand out from the other urban agglomerations in India. With 15.1, 14.3 and 18.2 million inhabitants respectively, in 2005 and high average annual population growth rates of 3.1%, 4.1% and 2.0% respectively, between 1975 and 2000 (ref. 2), the mega cities represent a unique cluster of urban agglomeration. Mumbai is expected to have population of more than 25 million, whereas Kolkata and Delhi will have more than 16 million by 2015 (ref. 2). These cities show a unique pattern of high built-up density at the core with decrease towards the buffer. Kolkata and Mumbai showed an elongated and disaggregated growth unlike Delhi, which had grown radially over the periods (Figure 3 (i–iii)). In the recent past, Kolkata and Mumbai have also shown radial growth as a result of amalgamation of developed urban centres in the peripheries. The degree and extent of brightness indicated that energy consumption in Delhi has
The urban agglomeration with 2.5–5 million inhabitants, such as Jaipur, Kanpur, Lucknow, Poona and Surat are the third set of cities having extensive urban sprawl. Poona shows a distinct characteristic in terms of increase in population, which may go beyond 5 million by 2015. Lucknow, Surat and Jaimpur have also shown steep growth in urban population, unlike Kanpur. The urban sprawl timeline is distinct for these cities, as Jaipur, Kanpur and Lucknow showed a steep change in 2007, whereas Poona emerged in 1996 and Surat in 2000 (Figure 3 (viii)–(xii)). These cities have monocentric and dense settlements with complex expansion over time and at the periphery. But in recent periods, these have shifted from mono-centric to poly-centric, with complex spatial growth pattern, low density spatial urbanization and satellite cities.

The study has demonstrated urbanization patterns over India, with a comparison across 12 mega cities. The chosen DMSP–OLS night-time satellite data are not exhaustive, but provide a specific feature of the urban system for all mega cities, incipient mega cities and urban agglomerations. The temporal dataset adequately provides the details and pattern of urbanization over the period. It is also suitable to differentiate between the urbanized and non-urbanized areas. Such measurement of both areal coverage and spatial distribution is necessary to describe the urban morphology adequately.
The fastest growing urban areas in India are medium-sized cities\(^5\). These face similar problems as those of mega cities; they have significantly fewer resources to devote to the complex infrastructural, social and environmental issues associated with rapid urbanization. Urban growth is characterized as complex and diversified at various spatial scales\(^6\). It is linked to topography, land use, lifestyle, social structure and economic type, but is closely related to demography and economic changes in any city\(^7\). Temporal monitoring of the urban areas of India indicates stark changes in time. The incipient mega cities show similar trend of expansion and increase in the population growth pattern and eco-


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P. K. JOSHI\(^{1,*}\)  
BRIJ MOHAN BAIRWA\(^{2}\)  
RICHA SHARMA\(^{3}\)  
VINAY S. P. SINHA\(^{1,2}\)

\(^{1}\)TERI University, New Delhi 110 070, India  
\(^{2}\)The Energy and Resources Institute, New Delhi 110 003, India  
\(^{*}\)For correspondence.  
e-mail: pkjoshi27@hotmail.com
Analyzing monthly dynamics of SUHI in Delhi using satellite information

R. Sharma and P.K. Joshi
Department of Natural resources
TERI University
New Delhi, India
pkjoshi27@hotmail.com

Abstract—This work attempts to study the behavior of UHI with respect to spatial pattern and its strength through a temporal domain. The study revealed that UHI exhibits variation in spatial distribution patterns during different months of a year. The intensity also varies over different months due to altered climatological condition and seasonal changes in land use patterns especially agricultural lands.

I. INTRODUCTION
Unprecedented pace and scale of urbanization makes its essential to understand and regularly monitor these spatio-temporal landscape transformations and their implied repercussions for environment. Urban Heat Island (UHI) is one of such consequences that are having severe impacts on urban environment across the globe. The cities all over the world are experiencing warmth as compared to their sub-urban, per-urban or rural environs. Such modification in thermal environment of urban areas is referred to as UHI. UHI has several ill effects on environment, such as altered plant phenology, impact on rainfall pattern, bearing upon the local climatic conditions of the city and most importantly it adversely impacts the human health, and comfort.

Geospatial data and techniques have been widely employed to study this phenomenon as they possess the advantage of synoptic viewing and repeated coverage [1]. Remotely sensed data convey information about surface or skin temperature of the land mass under study. Thus, UHI studied using satellite data is termed as Surface UHI or SUHI. Numerous authors have utilized various satellite data to derive information of thermal status of cities, but the field still holds a lot of scope for research.

II. STUDY AREA
The study area comprises of the national capital city of India, Delhi. It covers nearly 1483 sq km and ranges from 28 40°N to 28 67°N and from 77 14°E to 77 22°E. City is majorly characterized by flat plains with an average elevation of 216 meters above sea level except in southern Aravalli extensions. Temperature varies from 40.3°C (mean maximum) in summers to 6 °C (mean minimum) in winters. May and June are hottest months, with August receiving maximum precipitation (251.1 mm). Average annual rainfall for the region is 845mm, and July-September, are monsoonal months that receive maximum rainfall during a year.

City exhibits diverse range of land uses and land covers. Delhi being the national capital has been growing and expanding enormously with rapid tremendous increase in its population. The population of the city was 9.42 million in 1991 that increased to 13.85 million in 2001. As per statistics Delhi’s population reached 16.75 million in year 2011. The constantly rising population levels are exerting tremendous pressure on environment and natural resources, most importantly land. Land transformation is one the most direct effect of urbanization. Altered land use patterns in turn give rise to other related consequences, such as changes in greenness, moisture status, bareness intensity and surface temperatures. Changing surface temperatures are gradually converting the cities into islands of heat with Delhi too following this trend.

III. DATA AND METHODOLOGY
For current study thermal bands of Landsat TM (Thematic Mapper) images of year 2010 were employed to estimate land surface temperature throughout the year. The idea was to procure satellite data for consecutive 12 months throughout the year, but due to various constraints such as cloud covers or data availability only nine images could be procured; January, February, March, April, May, June, September, October and November. For month of March, 2010 cloud free image was not available, so instead same image for 2011 was employed. Cloud-free images for other three months were not available even for previous (2009) or next (2011) years. The procured dataset were in UTM projection and has seven bands, of which sixth band is the only thermal band with 120m spatial resolution and other bands are either visible or middle and short wave infrared of 30m pixel size. The data used were for following dates; 29 Jan’10, 14 Feb’10, 4 Mar’11, 3 Apr’10, 5 May’10, 22 Jun’10, 26 Sep’10, 28 Oct’10 and 29 Nov’10.

A. Derivation of UHI patterns
UHI was quantified to get UHI Intensity (UHII) for each month, as the atmospheric conditions vary across the multiple dates. Thus it is not appropriate to directly compare the LST through multiple time
periods. Hence monthly UHII were estimated and compared. This was done using standard deviation method, where the UHI image statistics were the mean and first, second and third standard deviations of LST were used. Using these statistics UHII was measured, under five categories, first two being cool island intensities, third represents thermally neutral category and last two measures the intensity for heat island.

**LST retrieval using Qin et al.’s Mono-window algorithm**

The brightness temperature could be retrieved from thermal band of Landsat TM data using calibration equations provided by NASA in Landsat Handbook. But there are many atmospheric correction barriers in retrieving LST from the one thermal band available in TM. Qin et al. [2] proposed mono-window algorithm to solve this problem. The algorithm is based on thermal radiance transfer equation. To account for atmospheric correction three parameters are required; emissivity, transmittance and effective mean atmospheric temperature.

Thus LST retrieval was a multi-step process; (i) DN to at-sensor brightness temperature, (ii) Estimating emissivity, (iii) Emissivity correction to convert at-sensor brightness temperature into LST.

**DN to at-sensor brightness temperature**

Calibration equations provided by NASA were used to radiometrically correct the data and convert DN values into radiance.

\[
\text{Radiance} = \frac{L_{\text{Max}} - L_{\text{Min}}}{(Q\text{Cal}_{\text{Max}} - Q\text{Cal}_{\text{Min}})} \times (Q\text{Cal} - Q\text{Cal}_{\text{Min}}) + L_{\text{Min}}
\]

Where, \(L_{\text{Max}}\) and \(L_{\text{Min}}\) were spectral radiances for thermal band (Band 6) at digital numbers 1 and 255 respectively i.e. \(Q\text{Cal}_{\text{Min}}\) and \(Q\text{Cal}_{\text{Max}}\) values, and \(Q\text{Cal}\) represents the DN value.

TM 6 radiance was then used to compute at-sensor brightness temperature using modified Planck’s equation;

\[
T_B = \frac{K_2}{\ln\left(\frac{K_1}{T} + 1\right)}
\]

Where \(T_B\) is at-sensor brightness temperature (in Kelvin), \(L\) is spectral radiance (in W/(m2/sr-mm)), \(K_1\) (607.76 W/(m2/sr-mm)) and \(K_2\) (1260.56 K) are pre-launch satellite calibration constants.

**Estimation of emissivity**

The at-sensor brightness temperature assumes all the objects to be black bodies. Since black body is only theoretical concept, thus emissivity needs to be constructed and considered to obtain actual land surface temperatures.

Emissivity was estimated using Normalised Difference Vegetation Index

\[
\text{Reflectance} = \frac{\pi * d^2 * \text{Radiance}}{\text{ESUN} * \cos \theta}
\]

Where, \(d\) is Earth-sun distance in astronomical units, ESUN is mean solar exoatmospheric irradiance and \(\theta\) is solar zenith angle. All the six reflectance bands were used in LULC mapping and band 3 and 4 reflectance were additionally used for computing NDVI. NDVI was then used to determine emissivity image [3]. The emissivity thus obtained was employed to correct at-sensor brightness temperature retrieved from thermal band radiance. This was done because; at-sensor brightness temperature assumes unit emissivity and thus the temperature estimated is for blackbody. NDVI based method was employed for emissivity correction. Emissivity for NDVI range of 0.157 to 0.727 could be expressed as;

\[
e = 1.0094 + 0.047 \times \ln(\text{NDVI})
\]

For NDVI values out of this range, different emissivity values are assigned to three different ranges [4]. These values have been summarized in table.

<table>
<thead>
<tr>
<th>NDVI</th>
<th>Emissivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than -0.18</td>
<td>0.985</td>
</tr>
<tr>
<td>-0.18 to 0.157</td>
<td>0.955</td>
</tr>
<tr>
<td>Greater than 0.727</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Mono-window algorithm was then used for computing final LST, wherein \(C\) and \(D\) parameters were derived from emissivity and transmittance.

**B. UHI Intensity estimation using standard deviations**

For estimating and analyzing UHI intensity variation through different months, each image was segmented into 5 categories; Very Cold Island (less than mean minus second S.D.), Cold Island (greater than very cold island category upto mean minus first S.D.), Neutral (from mean minus first S.D. to mean plus first S.D.), Hot Island (greater than neutral upto mean plus second S.D.) and Very Hot Island (greater than mean plus second S.D.).

IV. RESULTS AND DISCUSSIONS

**A. UHI patterns**

LST mapping for the nine months is done to study thermal variations across the city for different times of the year (Figure 1). Of all the months, the winter
months of January, February and November displayed least variation in LST viz., 14º, 17º and 13º C respectively. Highest maximum temperature was observed for September and lowest for January. Highest and lowest minimum temperature was again exhibited by September and January respectively.

Spatial patterns of UHI were studied using LST maps of the city. Figure 1, shows that high temperature area (UHI influenced) during winter months were located in and around built-up areas of the city which are mainly located towards interior parts. But during summer months of April to June, UHI pattern was skewed towards south-western parts of the city. This is because, peripheral northern, western and south-western parts of the city are agricultural lands and during summer months these tend to lay fallow. Such fallow lands have an inclination to exhibit high surface temperatures.

**B. UHI intensity estimation and analysis**

The nine UHI intensity maps were prepared to complement UHI pattern study and to quantify UHI (Figure 2). Very Cold Island class is least visible except in the area under water body (i.e. along the Yamuna river). Hot Island area is more or less scattered through the built-up areas. Very Hot Island pixels show maximum variation in space through different months. These tend to be concentrated towards interior regions of the city during January, February, March and September months. But for May, June and October, these are dominant in the agricultural areas due to abundance of harvested fallow lands. April and November are two months when the Very Hot Island class is well scattered in built-up as well as agricultural areas.

Area for each of UHII class was quantified to study variation in different UHII categories at different times of the year (Figure 3). The figure shows that Very Cold Island category is least dominant with considerable area coverage during April, May and June months. February and March are two months when Cold Island showed its highest coverage percentage (~5% of total area). Neutral UHII category ranges from 86% in October to 80% in April and September. Overall this class remained most dominant UHII classes. Hot Island dominated the months of September and April the most, the two months when Neutral UHII reached its lowest. Very Hot Island category was highest in coverage during harvesting months of May, June and October and lowest during February, March and September.
For each month, range for each category was; Very Cold Island- 0 to 0.5%, Cold Island- 0.8 to 4.6%, Neutral- 80-85%, Hot Island- 8 to 16% and Very Hot Island- 0.5 to 6%.

V. CONCLUSION
Quantitative and qualitative analysis of this work present the temporal changes in pattern and intensity of UHI over Delhi.

The study portrays the role of seasonal changes in land use and cropping cycles in monitoring of UHI. The selection of appropriate month and date of satellite data for UHI analysis is highly crucial as slight seasonal land cover greatly influence the thermal distribution over an area.

This also highlights the sensitivity of thermal environment to land use and its related changes. Land use has been found to be fundamental factor that significantly contributes to UHI formation.

The work also suggests the advantages that remote sensing as an effective technique to understand and monitor the spatial and temporal dynamics of urban thermal environments.

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Background

DEFINITIONS

Urbanization: Increase in the proportion of a population living in urban areas; Process by which a large number of people becomes permanently concentrated in relatively small areas, forming cities. (Source: OECD Glossary of Statistical Terms)

Urban Greens: Land within an urban area that consists predominantly of unsealed, permeable, ‘soft’ surfaces such as soil, grass, shrubs and trees

Ecosystem Services: Ecosystem services are the transformation of a set of natural assets (soil, plants and animals, air and water) into things that we value.

Sustainable Development: Development that meets present needs without compromising the ability of future generations to meet their needs

ISSUES

Global urbanization presents major socio-economic and environmental challenges

– Impacts surface and atmospheric properties of the region giving rise to new and modified ‘urban climate’
– Quality of life in some urban areas in the developing world is even worse than in rural areas due to high rates of poverty among pockets of the urban populations
– Influences the functioning of local and global earth ecosystems and their services
– Fragments, isolates, and degrades natural habitats; simplifies and homogenizes species composition; disrupts hydrological systems; and modifies energy flow and nutrient cycling

SCOPE

Urbanization is truth of present and a reality for future global scenarios. Thus, it should not be considered as an obstacle but an opportunity for attaining sustainability. Urban trees contribute to urban diversity, reduce atmospheric carbon emissions, help mitigate the urban heat island effects

Methodology

• Satellite Data Analysis
  • Data Procurement
  • Data Processing
• Field Work
  • Inventorization
  • Stakeholder

Objectives

• Characterizing and conducting a district-wise economic evaluation of urban trees in Delhi
• Performance index of sustainability for each district

Study Area

Geographically the city is located between 28°23′17″ N to 28°53′00″ N and 76°50′24″ E to 77°20′37″ E, covering an area of 1483 sq.km.


Expected Outcomes

Urban tree mapping using satellite data
  - Landsat TM data (low resolution)
  - WorldView-2 (high resolution)

Evaluate carbon potential and listing ecosystem services

Performance index of different districts with context to ecosystem service availability
Inputs for policy framework and implementation

Challenges

• Listing all the ecosystem services
• Accounting these services
• Procuring and processing high resolution images
• Bringing together all the stakeholders

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Submitted by

Richa Sharma

Under the supervision of

Dr P K Joshi

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TERI University
Department of Natural Resources Management
10, Institutional Area, Vasant Kunj,
New Delhi -110070, India

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