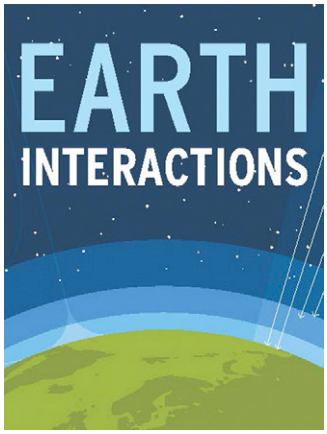


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Urban Sprawl Patterns and Processes in Delhi from 1977 to 2014 Based on Remote Sensing and Spatial Metrics Approaches

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Received 24 June 2015; in final form 5 January 2016

ABSTRACT: Recent decades have witnessed rapid urbanization and urban population growth resulting in urban sprawl of cities. This paper analyzes the spatiotemporal dynamics of the urbanization process (using remote sensing and spatial metrics) that has occurred in Delhi, the capital city of India, which is divided into nine districts. The urban patterns and processes within the nine administrative districts of the city based on raw satellite data have been taken

Supplemental information related to this paper is available at the Journals Online website: http://dx.doi.org/10.1175/EI-D-15-0040.s1.

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DOI: 10.1175/EI-D-15-0040.1

into consideration. Area, population, patch, edge, and shape metrics along with Pearson's chi statistics and Shannon's entropy have been calculated. Three types of urban patterns exist in the city: 1) highly sprawled districts, namely, West, North, North East, and East; 2) medium sprawled districts, namely, North West, South, and South West; and 3) least sprawled districts—Central and New Delhi. Relative entropy, which scales Shannon's entropy values from 0 to 1, is calculated for the districts and time spans. Its values are 0.80, 0.92, and 0.50 from 1977 to 1993, 1993 to 2006, and 2006 to 2014, respectively, indicating a high degree of urban sprawl. Parametric and nonparametric correlation tests suggest the existence of associations between built-up density and population density, area-weighted mean patch fractal dimension (AWMPFD) and area-weighted mean shape index (AWMSI), compactness index and edge density, normalized compactness index and number of patches, and AWMPFD and built-up density.

KEYWORDS: Observational techniques and algorithms; Data processing; Geographic information systems (GIS); Remote sensing; Satellite observations

1. Introduction

In India there were 53 urban agglomerations with over 1 million people in 2011 as compared to 35 in 2001 (Census of India 2011). Out of these urban agglomerations, three megacities, namely, Delhi, Mumbai, and Kolkata, can be identified as having population greater than 10 million. Chennai, Bangalore, Hyderabad, Ahmedabad, and Pune are the current incipient megacities (population between 5 and 10 million), which are likely to transition to being megacities because of the extremely high growth rates. It is important to study the urban dynamics of the megacities, as the effects of rapid urbanization are likely to be faced by incipient megacities in the future (Taubenböck et al. 2009).

A spatial metrics approach has been used in this paper. Previous studies on urban spatial metrics focused either on a single city (Palmer 2004; Thapa and Murayama 2009) or a comparison between different cities (Galster et al. 2001; Schneider and Woodcock 2008; Pham et al. 2011). In this study, urban patterns and processes for Delhi were examined at the city and district level. In addition to urban indices obtained from spatial metrics, entropy considerations have also been taken into account to provide a holistic approach on urban growth. The study is based on 38 years of times series data collected in the form of raw satellite images. The study objective is to investigate different urban dynamics delineated within the city. Examining these surface processes is the first step of a broader ongoing study that seeks to understand possible urbanization-driven micro and macro environmental changes.

2. Background

Genesis of the earliest cities and urban societies is widely accepted to have been dated as far back as in 4000 BC in Mesopotamia (Oates et al. 2007), and since then numerous urban settlements have evolved. The start of the twentieth century accounted for only 16 cities worldwide constituting a million plus population and these were mostly concentrated in the advanced industrial countries. The number

grew to around 400 cities (population greater than 1 million) by the beginning of the twenty-first century and about 70% of them were found in developing countries (Cohen 2006). This whirlwind speed of global urban growth in the past decades is altogether alarming, more so in the developing countries.

Global demographics suggest that population concentration in any place is usually the driver of accelerated urban growth. As per the United Nations (UN) Population Division (United Nations 2013), the world population of 7.2 billion is expected to increase by almost 1 billion people in 2025, and the majority of this growth will be concentrated in the countries of the developing world, including India. The world's urban population surpassed its rural population in 2007 for the first time in history and has been predominantly urban thereafter (United Nations 2013). Another 2.5 billion people are projected to increase the global urban population by 2050 through the process of continued urbanization and natural increases in population in urban areas (United Nations 2014). Of this, nearly a 90% increase is expected to be concentrated in Asian and African countries. The UN report also states that the global urban population is expected to rise to about 66% by 2050. This figure is roughly the inverse of the global rural–urban population distribution of the midtwentieth century, which was almost 70% rural at that time.

Montgomery (2008) explains that the urban demographic transformation influences and is in turn swayed by four trends in worldwide economic development: first is the phenomenon of globalization, second is the process of decentralization of governments in poor countries, third is the evolution of international development strategies with the aim to fulfill Millennium Development Goals, and fourth are the urban implications due to global climate change. The progressive change in the economic and social structure of a community that led to or was accompanied by a sudden population rise explains the overall process of city evolution in a nutshell (Childe 1950).

Conversely, urbanization can be attributed as the driver of detrimental environmental change at the local (White and Greer 2006; Huong and Pathirana 2013), regional (Karl and Trenberth 2003; Trusilova and Churkina 2008), and global scale (Grimm et al. 2008). There are several well-documented impacts on the environment such as land transformations (Vitousek et al. 1997), altered biogeochemical cycles (Kaye et al. 2006; Guan et al. 2009), modification of climate (Oke 1982; Karl et al. 1988; Grimmond 2007; Kishtawal et al. 2010; Mitra et al. 2012), changed hydrological patterns (Vörösmarty et al. 2010), as well as human-dictated urban species composition (Grimm et al. 2008). As urbanization continues, challenges pertaining to the idea of sustainable development are more likely to be faced by cities in lower–middle income nations where rapid urbanization rates have been recorded (United Nations 2014).

The urban city form can be of two types—compact and sprawled. Several important characteristics of a compact city include mixed land-use patterns with high residential and employment densities, contiguous development, multimodal transportation, low open space ratios, and possibly more energy efficient in comparison to a sprawled city due to the close connectivity in the urban center (Neuman 2005). A sprawled city exhibits a segregated pattern of land use, low residential density, unlimited scope for outward expansion of growth, and a far greater reliance on private transportation. Which of the two urban forms is sustainable in nature is a matter of debate (Gordon and Richardson 1997; Burgess

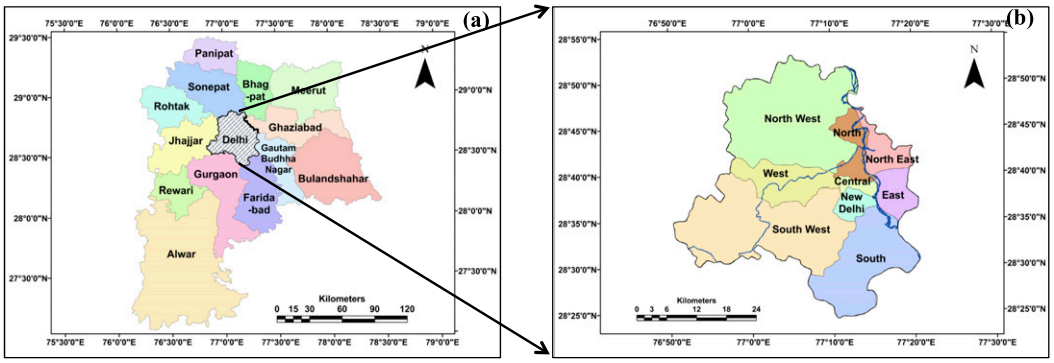


Figure 1. Maps showing (a) the study area within the National Capital Region and (b) the nine administrative districts of Delhi as per census 2011.

2000; Catalán et al. 2008; Echenique et al. 2012). Urban growth along with its patterns and processes need to be studied so that the ever-rising impacts on the environment can be tackled. The pattern explains the configuration of the urban area or city in its spatial dimension at any given time, while the process takes into consideration time series data and explains how time has brought changes in the urban spatial structure (Bhatta et al. 2010).

3. Study area

The National Capital Territory (NCT) of Delhi covers an area of 1483 km^2 and lies between the coordinates of 28.41°N, 76.84°E by 28.88°N, 77.35°E. It is situated in the core of the National Capital Region (NCR) flanked by the Ghaziabad, Gautam Budhha Nagar, Bhagpat, Sonepat, Jhajjar, Faridabad, and Gurgaon districts at its administrative boundary (Figure 1a). The NCR region also includes the Panipat, Rohtak, Rewari, Alwar, Bulandshahar, and Meerut districts. In the larger domain, the city lies between the Himalayas in the north and the Aravalis in the south, with the Yamuna River cutting through the city on the eastern side. Delhi is located in the plains with its elevation ranging from 213 to 290 m. Hot and dry summers and fairly cold winters characterize the climate in this area. Maximum temperatures cross 45°C in summer and minimum temperatures drop below 5°C in winter. Indian summer monsoons dominate the precipitation pattern, and maximum rainfall is recorded during the months of July to September. At the time of the 1961 census, Delhi was composed of one district and one tehsil. A tehsil forms a part of the Indian administrative hierarchy system and is roughly similar to a county. The Delhi revenue district was then further divided into two tehsils: Delhi and Mehrauli. This administrative setup existed from the 1971 to 1991 census. In 1996, however, the national capital was bifurcated into nine revenue districts, and this setup continued until the 2011 census. These districts are Central, East, New Delhi, North, North East, North West, South, South West, and West (Figure 1b). Presently, Delhi has 11 districts instead of 9. Since the available official census data from 1961 to 2011 has only been projected for the earlier 9 districts, this study follows the administrative setup of 2011.

Table 1. Data source and details of satellite onboard sensors with the location of scene and data bands. Landsat and IRS satellite scenes for four distinct years have been considered. Note that OLI refers to the Operational Land Imager, LISS refers to the Linear Imaging Self Scanning Sensor, and MSS refers to the Multispectral Scanner.

Satellite	Sensor	Path/row	Date of acquisition	Data type and bands
Landsat	OLI	146/40	9 Feb 2014	Digital (1, 2, 3, 4, 5, 6, 7)
IRS-P6	LISS III	096/051	2 Jan 2006	Digital (2, 3, 4, 5)
IRS-P3	LISS III	029/047	5 Nov 1993	Digital (2, 3, 4, 5)
Landsat	MSS	157/040	8 Mar 1977	Digital (4, 5, 6, 7)

Over the past four decades, Delhi has shown notable land-use land-cover (LULC) changes, and urbanization can be attributed as the primary driver of such change (Jain et al. 2016). Several factors, such as independence of the country, being the capital of the nation, an influx of immigrants, and a shift in the economy from a primary (agriculture) to tertiary (service) sector over the years, have led to rapid infrastructure development. In turn, job creation in the service sector attracts more immigrants to the city. Thus, a pattern is formed where job creation leads to population increases, which, in turn, lead to infrastructure development (housing, offices, road connectivity, etc.) The urban morphology of Delhi has also changed with time, rulers, and administrative policies. At a district level, a varying pattern in urban growth dynamics can be witnessed in Delhi. Historically speaking, the earliest urban centers in Delhi, namely, Old Delhi (in the Central District), Shahdara (in the East District), and Mehrauli (in the South District), were built in a highly compact manner because of fortification and protective functions rather than insufficient building space. As the urban community tended to reside in close quarters, high population density was recorded. The highly compact urban structure and extreme densification still persists in these centers. On the other hand, the British constructed the Lutyen zone in the New Delhi District in a planned manner, and the current government policies have been effective in containing any major sprawl in that area. The rest of the urban pockets developed with time (some planned while some unplanned), catering to the demands of infrastructure development as well as population pressures. The present study aims to see if the effects of different planning mindsets at a district level can also be seen in the urban growth indicators. If so, then it can most likely form an important dimension in tackling detrimental environmental effects of urbanization.

4. Data and methodology

Cloud-free imageries of the study area were acquired from Landsat and Indian Remote Sensing (IRS) satellites for the years 1977, 1993, 2006, and 2014 (Table 1). Ancillary data from the Survey of India (SOI) toposheet at 1:50 000 scale, Census of India decadal demographic database, and the Master Plan of Delhi were gathered. Software ERDAS Imagine 9.1 and ArcGIS 9.3 were used for digital image processing and creation of the GIS database. State and district boundaries were prepared. Imageries were brought to the World Geodetic System (WGS84) reference datum and zone 43 north projection of Universal Transverse Mercator system (UTM), that is, UTM WGS84 43N projection. Satellite image

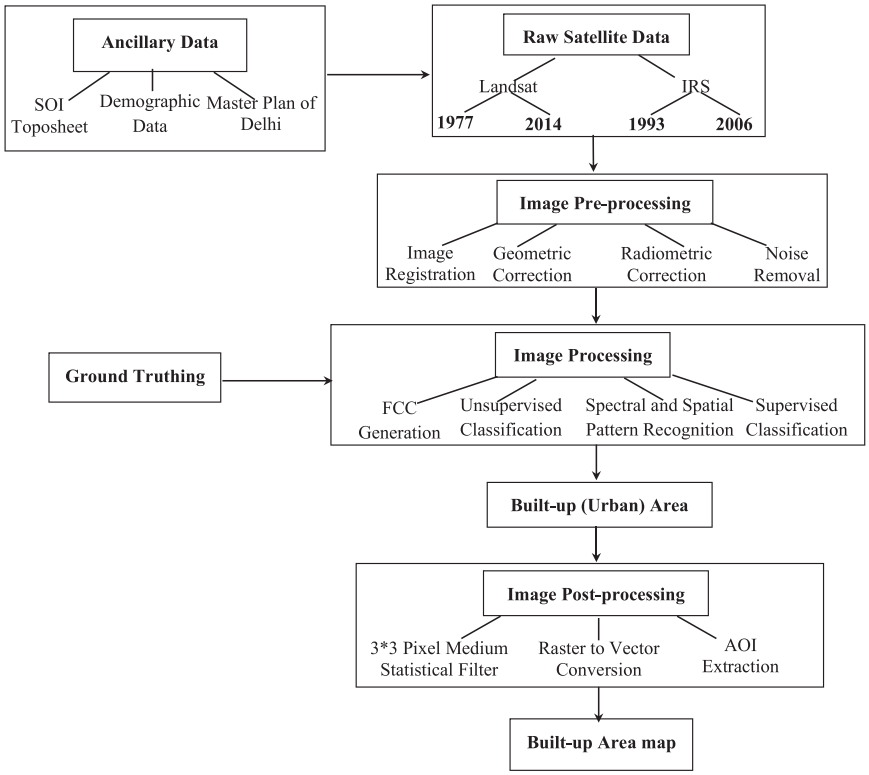


Figure 2. Flowchart of methodology adopted for generation of built-up area maps using satellite data.

interpretation involved the use of image preprocessing, processing, and post-processing techniques. Figure 2 shows the flowchart of the methodology followed in the generation of built-up area maps for the study years.

Image preprocessing methods included initial processing of raw image data for geometric corrections of any inherent distortions, radiometric calibration of the data, and elimination of the noise present in the data. Bands near-infrared (NIR), red, and green were channeled through the red, green, and blue guns, respectively, to create the false color composite (FCC) images as a part of image processing. These FCC's are shown in Figure 3. Red areas in the FCC's should be interpreted as vegetation and white as waste/barren land, while deep waters appear black and urban areas appear as cyan. Color tones of the urban area vary with material use and density. All images were brought to the same platform, that is, the UTM WGS84 43N projection. Resampling of 60-m spatial resolution imagery to 30 m was performed using the cubic convolution method (Homer et al. 2004). This downscale resampling produces a smaller pixel size but does not have the accuracy of the nonresampled 30-m image (Dixon and Earls 2009). Upscaling to a common coarser resolution of 60 m was not performed as it would have lowered the classification accuracy of the rest of the imageries. A supervised classification scheme was applied after doing a primary unsupervised classification of 10 subsequent iterations on the imageries. A USGS level I classification was used to differentiate

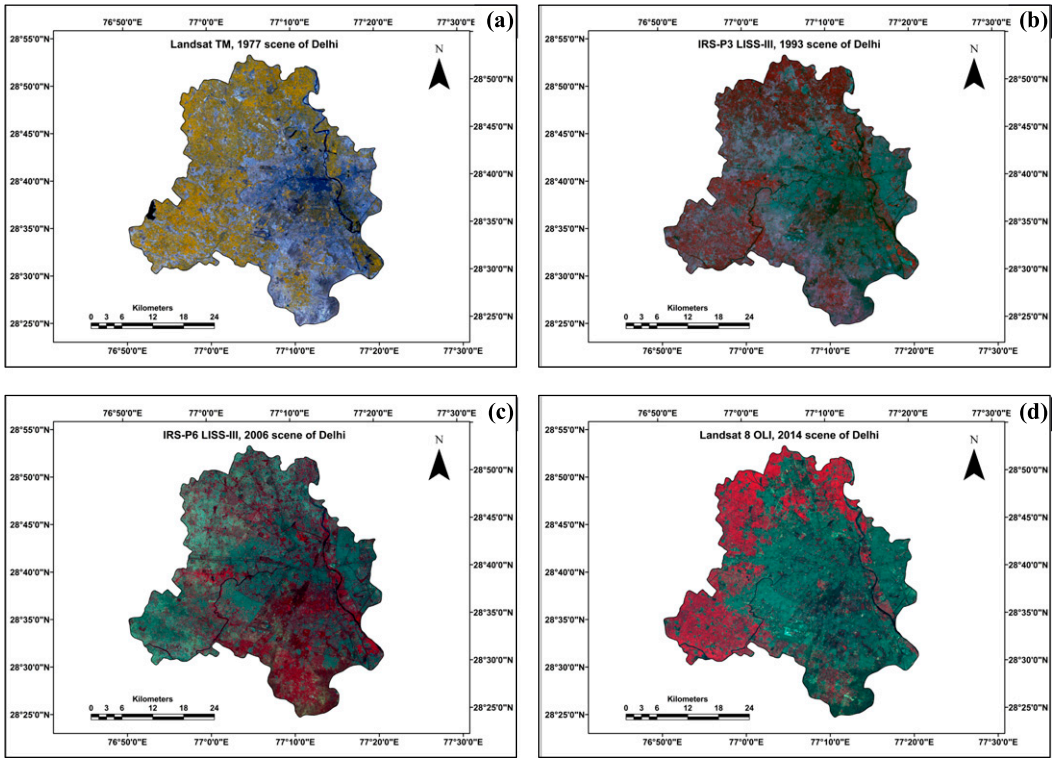


Figure 3. FCCs of Delhi for the years (a) 1977, (b) 1993, (c) 2006, and (d) 2014. Layer stack of bands NIR, red, and green have been used for creation of all the FCCs.

urban or built-up land from nonurban (non-built-up) land. The USGS level I classification provided by Anderson et al. (1976) differentiates urban or built-up land from other land-use classes such as agricultural land, forest land, water, etc., while level II classification gives a detailed inventory of level I classes. For the urban (built-up) area class, the level II classification separates the residential, commercial, industrial areas, etc., in the imagery. Since the satellite imageries acquired from Landsat and IRS had moderate spatial resolution, and specific use of urban (built-up) areas was not necessitated, the classification was limited to the level I scheme (Anderson et al. 1976). Spatial and spectral pattern recognition, including the use of elements like tone, texture, shape, and location of pixel groups in the image were adopted for identification of urban areas. The above hybrid classification scheme was used to extract the class of built-up area, and the classification output was checked by ground-surveying methods. This kind of hybrid classification scheme, though time consuming, produces highly refined and accurate class outputs as compared to either the unsupervised or supervised classification alone.

Once classified, image postprocessing was carried out and a 3×3 medium statistical filter was applied to the data. Vector polygons of the urban (built-up) area were made. Clipping of the map with the area of interest (AOI), that is, state or district boundary was done to extract the final built-up area maps for the 4 years. A

subsequent accuracy assessment following Currit (2005) was done to check the overall classification accuracy rate. There were 50 reference test pixels corresponding to the class of built-up area that were chosen using stratified random sampling method for the FCC of each year. It was ensured that the test pixels were distributed evenly across the imageries. These pixels were matched to the classified output pixels to compute the accuracy rate of the classification. Producer's accuracy of 83.4%, 92.0%, 88.2%, and 98.0% was achieved for the year 1977, 1993, 2006, and 2014, respectively, for the above class. This level of accuracy is deemed satisfactory for a USGS level 1 classification (Anderson et al. 1976). Overall, the kappa index of agreement (Currit 2005) for the classified images ranged from 90.0% to 90.5%. In addition, as the demographic data for the districts of Delhi provided in the India census records were decadal in nature, they were consequently interpolated for each study year.

Use of spatial metrics is critical in urban sprawl studies, and they prove to be a handy tool in description, analysis, and modeling of urban form and its changes (Taubenböck et al. 2009). Indices so developed can be used to objectively quantify the pattern and process of the urban area. Area, population, patch, edge, and shape metrics were computed from the generated built-up area database. Some spatial metrics such as the number of patches, total edge, area-weighted mean shape index (AWMSI), and area-weighted mean patch fractal dimension (AWMPFD) were calculated through Patch Analyst, a freely available landscape analysis tool (Rempel et al. 2012). Pearson's chi-square statistics was applied to test the discrepancies in observed and expected growth, and Shannon's entropy was estimated for sprawl estimations. Further discussion on these urban growth indicators is provided in the next section.

5. Results

5.1. Urban growth indicators

Area, population, patch, edge, and shape metrics are discussed in the following sections. Variation of urban growth indicators over four decades is presented as a part of the supplementary figures (Figures A1a–j). Districtwise spatial metrics for the year 1977, 1993, 2006, and 2014 are tabulated in Tables 2, 3, 4, and 5, respectively.

5.1.1. Area metrics

Area metrics quantify the landscape composition. Here the landscape area refers to the administrative area of the state and each district obtained through the census data. Anderson et al. (1976, p. 10) define urban or built-up land as "areas of intensive use with much of the land covered by structures." It includes towns, villages, strip development along highways, and complexes and institutions that may be isolated from the core urban area. The impervious (concretized) area in a FCC has a unique spectral reflectance pattern than other materials such as mud, grass, water, etc., and along with the color, tone, and texture of the image, pixels are used to differentiate built-up areas from non-built-up areas. Urban area over a landscape is generally synonymous with the built-up area extracted from the

Table 2. Districtwise spatial metrics for urban (built-up) areas in 1977. Note that the district area is measured in km^2, population as persons, class area in km^2, population density as persons per square kilometer, number of patches in count, patch density in patches per square kilometer, total edge in km, and edge density in $m\,ha^{-1}$. Built-up density, AWMSI, AWMPFD, CI, and NCI are unitless quantities.

District	District area	Population	Class area	Built-up density	Population density	No. of patches	Patch density	Total edge	Edge density	AWMSI	AWMPFD	CI	Normalized CI
Central	25	691 429	8.82	0.35	27 657	83	3.32	95.32	108.07	2.52	1.31	0.75	9.04×10^{-3}
East	64	496 803	16.60	0.26	7763	124	1.94	185.51	111.75	2.92	1.32	0.75	6.04×10^{-3}
New Delhi	35	152 350	1.92	0.05	4353	86	2.46	55.89	291.09	1.77	1.33	0.77	8.93×10^{-3}
North	60	655 855	16.51	0.28	10 931	111	1.85	183.35	111.05	2.84	1.32	0.73	6.57×10^{-3}
North East	60	355 384	7.05	0.12	5923	33	0.55	84.87	120.38	2.68	1.33	0.66	2.01×10^{-2}
North West	440	774 879	11.52	0.03	1761	157	0.36	190.85	165.67	2.16	1.33	0.74	4.72×10^{-3}
South	250	828 096	17.89	0.07	3312	228	0.91	278.26	155.54	2.19	1.32	0.74	3.23×10^{-3}
South West	420	599 178	17.91	0.04	1427	264	0.63	328.20	183.25	2.63	1.34	0.74	2.80×10^{-3}
West	129	804 549	15.55	0.12	6237	131	1.02	210.29	135.23	2.53	1.32	0.72	5.48×10^{-3}
Delhi (State)	1483	5 358 523	113.77	0.08	3613	1137	0.77	1566.90	137.73	2.70	1.33	0.75	6.56×10^{-4}

Table 3. Districtwise spatial metrics for urban (built-up) areas in 1993. Note that the district area is measured in km^2, population as persons, class area in km^2, population density as persons per square kilometer, number of patches in count, patch density in patches per square kilometer, total edge in km, and edge density in $m\,ha^{-1}$. Built-up density, AWMSI, AWMPFD, CI, and NCI are unitless quantities.

District	District area	Population	Class area	Built-up density	Population density	No. of patches	Patch density	Total edge	Edge density	AWMSI	AWM–PFD	CI	Normalized CI
Central	25	654 503	9.53	0.38	26 180	230	9.20	218.04	228.79	3.08	1.37	0.68	2.95×10^{-3}
East	64	1 111 179	31.26	0.49	17 362	1365	21.33	948.76	303.51	3.17	1.38	0.70	5.16×10^{-4}
New Delhi	35	170 758	6.23	0.18	4879	419	11.97	236.98	380.39	2.92	1.39	0.71	1.70×10^{-3}
North	60	705 628	15.73	0.26	11 760	924	15.40	536.78	341.25	2.70	1.38	0.71	7.64×10^{-4}
North East	60	1 221 812	23.91	0.40	20 364	1109	18.48	729.64	305.16	2.97	1.38	0.70	6.35×10^{-4}
North West	440	1 994 548	95.05	0.22	4533	6987	15.88	3937.83	414.29	2.31	1.38	0.70	1.01×10^{-4}
South	250	1 654 909	59.00	0.24	6620	3240	12.96	2004.37	339.72	3.63	1.39	0.70	2.17×10^{-4}
South West	420	1 221 067	56.94	0.14	2907	4945	11.77	2465.60	433.02	2.52	1.38	0.71	1.44×10^{-4}
West	129	1 572 212	47.34	0.37	12 188	2597	20.13	1629.78	344.27	2.58	1.37	0.70	2.70×10^{-4}
Delhi (State)	1483	10 306 617	344.99	0.23	6950	21 444	14.46	12 684.93	367.69	2.87	1.38	0.71	3.29×10^{-5}

Table 4. Districtwise spatial metrics for urban (built-up) areas in 2006. Note that the district area is measured in km^2, population as persons, class area in km^2, population density as persons per square kilometer, number of patches in count, patch density in patches per square kilometer, total edge in km, and edge density in $m\,ha^{-1}$. Built-up density, AWMSI, AWMPFD, CI, and NCI are unitless quantities.

District	District area	Population	Class area	Built-up density	Population density	No. of patches	Patch density	Total edge	Edge density	AWMSI	AWM–PFD	CI	Normalized CI
Central	25	612 528	9.75	0.39	24 501	1929	77.16	558.80	573.13	4.16	1.44	0.78	4.02×10^{-4}
East	64	1 585 654	39.94	0.62	24 776	8844	138.19	2557.74	640.40	3.89	1.44	0.78	8.77×10^{-5}
New Delhi	35	156 413	8.51	0.24	4469	2289	65.40	592.62	696.38	2.69	1.43	0.78	3.42×10^{-4}
North	60	832 472	25.32	0.42	13 875	7554	125.90	1809.02	714.46	3.10	1.43	0.79	1.04×10^{-4}
North East	60	2 004 405	37.00	0.62	33 407	7527	125.45	2254.57	609.34	4.31	1.44	0.78	1.03×10^{-4}
North West	440	3 256 065	149.64	0.34	7400	60 772	138.12	12 292.02	821.44	2.47	1.43	0.80	1.31×10^{-5}
South	250	2 500 388	80.42	0.32	10 002	20 279	81.12	5536.62	688.46	3.11	1.43	0.78	3.82×10^{-5}
South West	420	2 023 702	115.63	0.28	4818	39 518	94.09	8556.24	739.97	3.07	1.43	0.79	2.00×10^{-5}
West	129	2 330 246	74.28	0.58	18 064	22 288	172.78	5393.17	726.06	2.66	1.43	0.78	3.51×10^{-5}
Delhi (State)	1483	15 301 871	540.49	0.36	10 318	170 458	114.94	39 589.13	732.47	3.10	1.43	0.79	4.63×10^{-6}

Table 5. Districtwise spatial metrics for urban (built-up) areas in 2014. Note that the district area is measured in km^2, population as persons, class area in km^2, population density as persons per square kilometer, number of patches in count, patch density in patches per square kilometer, total edge in km, and edge density in $m\,ha^{-1}$. Built-up density, AWMSI, AWMPFD, CI, and NCI are unitless quantities.

District	District area	Population	Class area	Built-up density	Population density	No. of patches	Patch density	Total edge	Edge density	AWMSI	AWM–PFD	CI	Normalized CI
Central	25	560 485	9.69	0.39	22 419	2342	93.68	623.52	643.47	3.05	1.42	0.81	3.46×10^{-4}
East	64	1 793 185	38.67	0.60	28 019	8854	138.34	2519.40	651.51	1.43	1.43	0.81	9.15×10^{-5}
New Delhi	35	123 545	8.66	0.25	3530	4361	124.60	801.07	925.02	1.47	1.40	0.83	1.91×10^{-4}
North	60	917 971	25.87	0.43	15 300	7179	119.65	1845.09	713.22	2.46	1.42	0.81	1.13×10^{-4}
North East	60	2 420 467	37.25	0.62	40 341	7154	119.23	2235.06	600.02	4.41	1.44	0.81	1.13×10^{-4}
North West	440	3 953 889	149.58	0.34	8986	39 981	90.87	10 328.98	690.53	2.49	1.41	0.81	2.03×10^{-5}
South	250	2 902 597	87.90	0.35	11 610	23 876	95.50	6270.62	713.38	2.84	1.42	0.81	3.40×10^{-5}
South West	420	2 502 911	132.83	0.32	5959	36 688	87.35	9283.23	698.88	2.90	1.41	0.81	2.22×10^{-5}
West	129	2 675 235	77.19	0.60	20 738	16 077	124.63	4868.09	630.66	3.77	1.43	0.80	5.0×10^{-5}
Delhi (State)	1483	17 850 286	567.64	0.38	12 037	145 830	98.33	38 793.86	683.42	3.08	1.42	0.81	5.58×10^{-6}

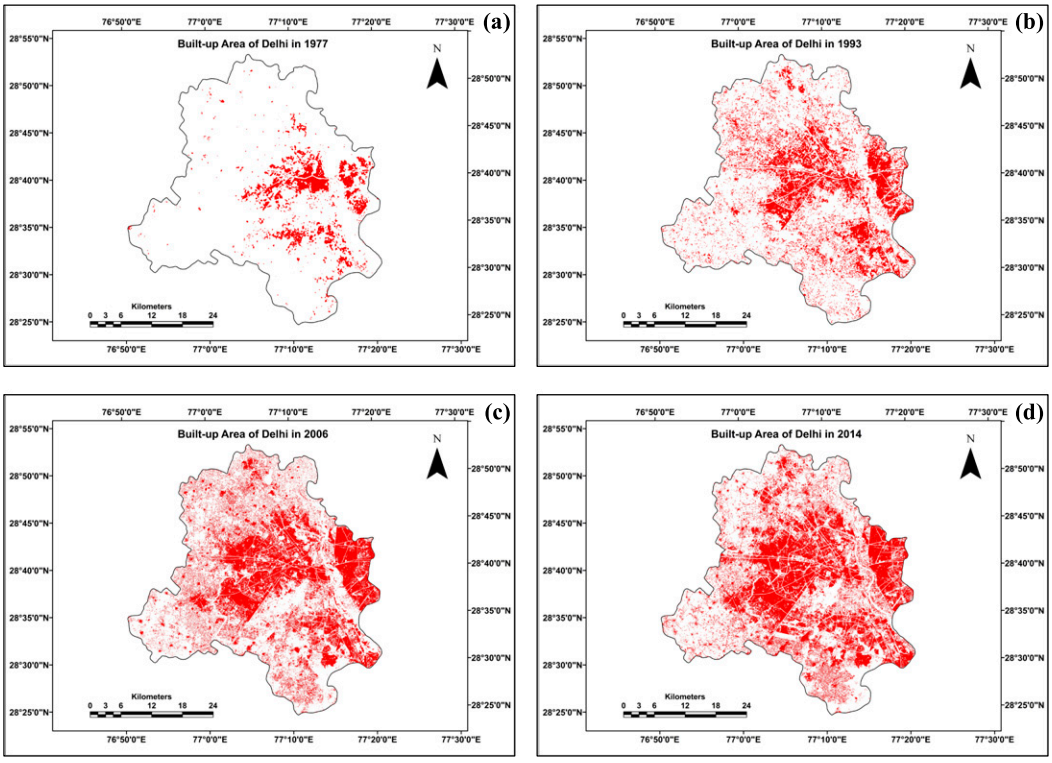


Figure 4. Built-up (urban) area maps for the years (a) 1977, (b) 1993, (c) 2006, and (d) 2014. Red color denotes the built-up area for individual years.

satellite imagery (Zha et al. 2003). The built-up area in the study refers to residential, commercial, institutional, and industrial areas but excludes the paved road/rail network. The sum of all urban area patches in the defined boundary of the landscape quantifies the built-up area in absolute terms and can be considered as a straightforward measure of urban growth (Torrens and Alberti 2000; Barnes et al. 2001). It is expressed as

$$\sum_{i=1}^{i=N} s_i,$$

where s_i is the area of ith patch, and N is the total number of patches.

The built-up areas for 1977, 1993, 2006, and 2014 are mapped in Figure 4. The spatial location of these urban patches in any given time frame depends totally on anthropogenic factors. Over time, existing patches expand with further construction, and new patches may sprout up in different locations. It explains one dimension of compactness and sprawl in cities. Unevenness in the distribution of urban areas between the districts of Delhi is visible from the data obtained through supervised and unsupervised classification of raw satellite imageries. The North West, South West, and South district record the highest absolute built-up (urban) area. Since the sizes of all districts are not uniform, built-up density is a better-suited measure of

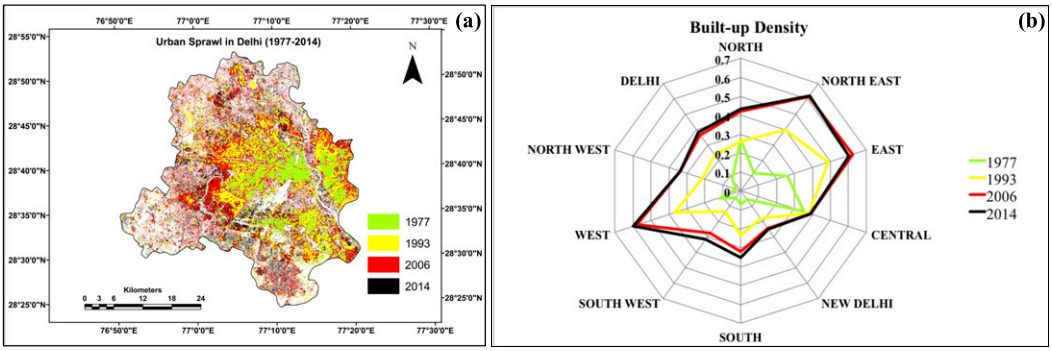


Figure 5. Urban sprawl in Delhi over 38 years shown using (a) an overlay map of built-up areas and (b) a spider chart of built-up density.

urban expanse. Urban growth can be calculated based on the rate of increase of built-up area with time. Built-up density is the ratio of the urbanized (built-up) area to the total landscape area at any point in time. It simply indicates quantitatively how dense the urban area is, irrespective of the location of urban patches within the administrative boundary. An overlay map of the built-up area over the years (Figure 5a) shows the sprawl of urban areas in Delhi pictorially. Information about the districts with the most urban growth can be estimated from the spider chart of built-up density (Figure 5b). All districts except the North district show a rise in the built-up density from 1977 to 1993. This can be attributed to the repeated flooding (Delhi Disaster Management Authority 2015), eviction, and demolition drives of unauthorized dwellings as well as stable population (Census of India 2011) in the district for this time frame. Major flooding due to increased discharge from the Tajewala barrage took place in 1977, 1978, and 1988, inundating most of the low-lying areas in this district. Substandard houses along North Delhi and Trans Yamuna were washed away. Some colonies constructed were at 3–4 m below 1978 flood level, which were again affected in 1988 (Delhi Disaster Management Authority 2015). In addition, many unauthorized dwellings, Jhuggi–Jhopri (JJ) clusters, godowns, dairies, and other establishments, were demolished and relocated to the outskirts of Delhi. From 1993 to 2006, North Delhi showed a fairly high increase in built-up area. Construction of the Right Marginal Embankment and its extension along the Wazirabad–Palla stretch reduced the flood problem (Jain 2009), and afterward the town of Burari was developed. After 1993, the Central district shows a fairly constant urban density with the New Delhi district also following a similar pattern. A marked increase in the built-up density was noted from the period 1993–2006 for the rest of the districts as well as Delhi as a city. From 2006 to 2014, the urban density has not changed much except for a considerable increase in the South West district, which can be attributed to the construction of subcity Dwarka and various other smaller settlements. In 2014, as much as 60% of the administrative land in the East, North East, and West districts is under the built-up area class. It is a testament to the gross urban saturation faced by certain districts within the city. On the other hand, only about 25% of the administrative area is built-up in New Delhi making it the least dense district in terms of built-up density.

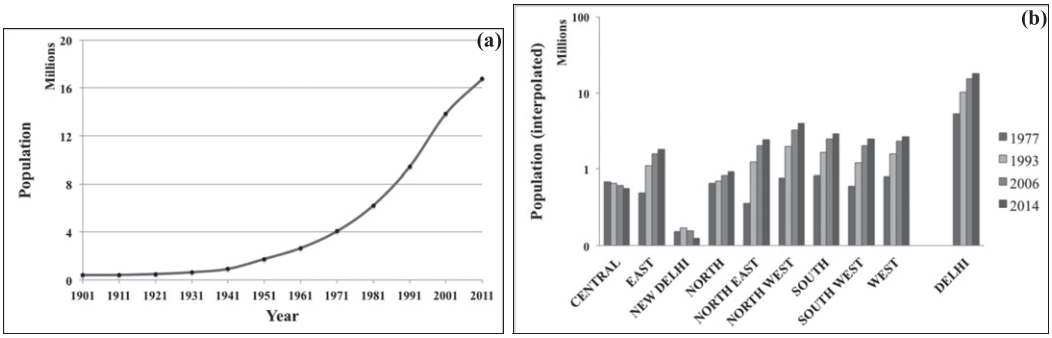


Figure 6. (a) Population growth in Delhi from 1901 to 2011 (source: Census of India 2011) and (b) districtwise interpolated population for years 1977, 1993, 2006, and 2014.

5.1.2. Population metrics

In the past hundred years, Delhi has witnessed an exponential increase in its resident population, as shown in Figure 6a (Census of India 2011). Districtwise population for the years 1977, 1993, 2006, and 2014 was calculated from interpolation techniques based on decadal population variation rates and can be seen in Figure 6b. Population for the year 2014 was calculated by assuming a constant growth rate as recorded in the 2001–11 census. As per calculations, the overall population of Delhi in 2014 has exceeded 17 million. Except for the Central, New Delhi, and North districts, the remaining six districts have crossed the 1 million mark. Population density is calculated by comparing the number of individuals residing in the area to the landscape area. In principle, urban population density should only consider the ratio of urban population and urban area (as demarcated by the administrative agencies). However, in the case of Delhi, the rural–urban population census data for the nine districts are not available prior to 2001, and the total rural population of the state has remained fairly constant over the years, whereas a significant rise in urban population is noted (Census of India 2011). In a way, the pattern of urban population density mirrors that of total population density. Therefore, in the present paper, urban population density has been determined by dividing the total population by the built-up areas extracted from the satellite imagery. In terms of urban population density, it can be noted that the North East (40 341 persons per square kilometer), East (28 019 persons per square kilometer), and Central (22 419 persons per square kilometer) districts are most dense. Extremely rapid increase in the density can be seen in the North East, East, and West districts from the first time span (1977–93) to the last (2006–14). It is interesting to note that the urban population density has been continuously decreasing in the Central district from 1977 onward. In the last decade, removal of the slum cluster Yamuna Pushta has displaced people, and large-scale commercialization (i.e., altered land-use planning) has forced them to shift to other parts of Delhi (Government of National Capital Territory of Delhi 2013). The New Delhi district also follows the same trend; although it did show a rise in density in 1993, the population density declined in the following decades.

5.1.3. Patch and edge metrics

A patch is a dynamic pocket occurring at various scales. Kotliar and Wiens (1990) define a patch at an arbitrary scale as one having its structure that mirrors the patchiness at finer resolutions while also determining the patchiness of the whole mosaic at larger scales. Thus, patches depend on the resolution taken into consideration. In landscapes of equal class areas, the one having a higher patch number has a finer grain, implying occurrence of spatial heterogeneity (McGarigal and Marks 1995). Since equal class areas are not present, patch density (number of patches per unit area) has been calculated to get a better comparison and interpretation of the index. Patch density accounts for less than 25 patches per square kilometer for all nine districts individually as well as for Delhi on the whole until 1993. A sudden rise after that, as much as 4 to 9 times, in the patch density can be observed in most districts. The city recorded an eightfold increase in the patch density. Compared to other districts, the increase is less in the Central and New Delhi districts from 1993 to 2006. The majority of the districts in 2014 show a decline in patch density as compared to 2006.

At patch level, the edge defines the perimeter of the individual urban pocket. At landscape level, the total edge gives the absolute value of the edge length across all urban patches. The total edge is given by

$$\sum_{i=1}^{i=N} p_i,$$

where p_i is the perimeter of ith patch, and N is the total number of patches.

Edge density quantifies the total edge relative to the class area allowing comparisons to be made over time. The metric is an expression of spatial heterogeneity in the landscape. Patches with higher perimeter-to-area ratio, that is, greater edge density, will have complex urban block shapes. A twofold rise in edge density can be noted for all districts in general except for Central and New Delhi from 1977 to 1993. A similar marked three to fourfold rise can be observed in the next time frame in all regions. It means that new urban patches were added along the existing patch perimeter in a manner that gave it a fragmented look, increasing the landscape heterogeneity. In 2014, some districts (New Delhi, Central, and East) show an increase, while the rest show a decrease in the edge density. If new urban patches infill the open spaces of existing patches thereby reducing the patch perimeter, then it would amount to a decreasing edge density. Edge density metrics show that the city's built-up area is consolidating and moving toward spatial homogeneity.

5.1.4. Shape metrics

Shape metrics quantify the irregularity in shape present in the landscape patches (Huang et al. 2007). Patch shape can be simple or complex. In the first case, urban blocks of simple shape boundaries are present, while in the second, ragged patch boundaries are present making the patch shape highly complex. Computation of AWMSI and AWMPFD has been utilized in this study. AWMSI is a weight normalized index describing the average shape of urban patches, making larger urban patches weigh more than their smaller counterparts (McGarigal and Marks 1995). It is calculated by

$$\frac{\sum_{i=1}^{i=N} \frac{p_i}{4\sqrt{s_i}}}{N} \times \frac{s_i}{\sum_{i=1}^{i=N} s_i},$$

where s_i and p_i are the area and perimeter of the ith patch, and N is the total number of patches.

AWMSI expresses the irregularity in shape of the landscape patches with a greater value indicating greater irregularity. When all patches correspond to the simplest shape (i.e., that of a circle), then the index value equals 1 and increases without limit as the patch shapes become more irregular. Results show that all values across space and time are greater than 1, implying the presence of irregular shapes. A general trend on increasing AWMSI for the city can be observed from 1977 to 2006 with a slight decrease in the value in 2014. Only the North East, North West, and West districts show a continuously increasing AWMSI over the whole time span of 38 years.

Patch shapes can be expressed in fractal dimensions. A fractal is an entity that exhibits structure in its geometric form at all spatial scales (Mandelbrot 1983). Essentially, AWMPFD describes the raggedness of the patch boundary and is calculated using the formula

$$\frac{\sum_{i=1}^{i=N} \frac{2\ln 0.25 p_i}{\ln s_i}}{N} \times \frac{s_i}{\sum_{i-1}^{i=N} s_i},$$

where s_i and p_i are area and perimeter of the ith patch, and N is the total number of patches.

A fractal dimension of more than 1 indicates a departure from Euclidean geometry, implying an increase in patch shape complexity (McGarigal and Marks 1995; Herold et al. 2003). The AWMPFD index value tends to be 1 for patches having simple perimeters, such as those of circles or squares, but approaches 2 in the case of patches departing from Euclidean geometry and showing highly complex perimeters (Huang et al. 2007). In the present analysis, all nine districts as well as the city as a whole reflect a departure from simple geometry. AWMPFD increases from 1977 to 1993 to 2006 and shows a slight decline in 2014, almost matching the AWMSI trend. Newer urban blocks may be added along the existing fractal in such a way that a more complex shape is formed. New patches might also be added in the interstitial spaces of the existing fractal, thereby decreasing its perimeter and simplifying the shape. In another scenario, new urban patches may sprout up at a location near the main fractal and ultimately be joined over time with subsequent construction. In such densification situations after a primary urban sprawl, AWMSI and AWMPFD will decrease.

Compactness of a patch is defined by the amount of the shape area fitted in the shape perimeter. It is expressed as

$$\frac{\sum_{i=1}^{i=N} 2\pi \frac{\sqrt{\frac{s_i}{\pi}}}{p_i}}{N^2},$$

where s_i and p_i are the area and perimeter of ith patch, and N is the total number of patches.

Compactness reaches its maximum value as the shape tends to a circle. The compactness index (CI) compares the perimeter of the urban patch to that of a circle having the same area. When the value of CI increases, the development becomes more compact. CI is normalized in order to minimize the bias toward a large number of small patches (Li and Yeh 2004). The normalized compactness index (NCI) is achieved by dividing CI by the total number of urban patches. In general, the CI of urban areas in Delhi decreased from 74.56% in 1977 to 70.59% in 1993. In 2006, it rose to 79.00%, and it rose to 81.33% in 2014. In a districtwise scenario, a similar trend of decreasing CI in 1993 and then a continuous increase can be observed. On the other hand, NCI continued to decrease in all districts until 2006. In 2014, an uneven pattern is observed with some of the districts recording an increase in NCI, while others showed a decrease. This suggests there was increasing urban sprawl until 2006, which now may be moving toward compactness in 2014.

Spider charts showing the calculated area, population, patch, edge, and shape metrics for the nine districts and Delhi state are plotted in Figure 7. Three kinds of urban patterns can be observed in the districts of the city from these charts: first, where high sprawl conditions are present in the West, North, North East, and East districts (Figures 7a–d); second, having medium sprawl in the North West, South, and South West districts (Figures 7e–g); and third are the least sprawl observed in the Central and New Delhi districts (Figures 7h,i). The Delhi state shows sprawl similar to that of medium sprawl districts (Figure 7j).

5.1.5. Pearson's chi-square statistics

Table 6 gives an account of the observed growth in the built-up area in the districts of Delhi. Discrepancies in built-up area growth in each district and time span were calculated by computing expected growth (Table 7) compared with observed growth. Expected growth is calculated by using the formula

$$M_{ij}^{E} = \frac{M_i^S \times M_j^S}{M_g},$$

where M_i^S is the row total, M_j^S is the column total, and M_g is the grand total.

This generated an observed minus expected growth table (Table 8). The expected built-up area growth has been statistically quantified by following the method provided by Bhatta et al. (2010). Negative values of discrepancy reflect less urban growth, and positive values reflect higher urban expansion than what was expected. The magnitude tells about the degree of deviation from the expected urban growth value. In general, the time span 1977–93 records higher growth than the remaining

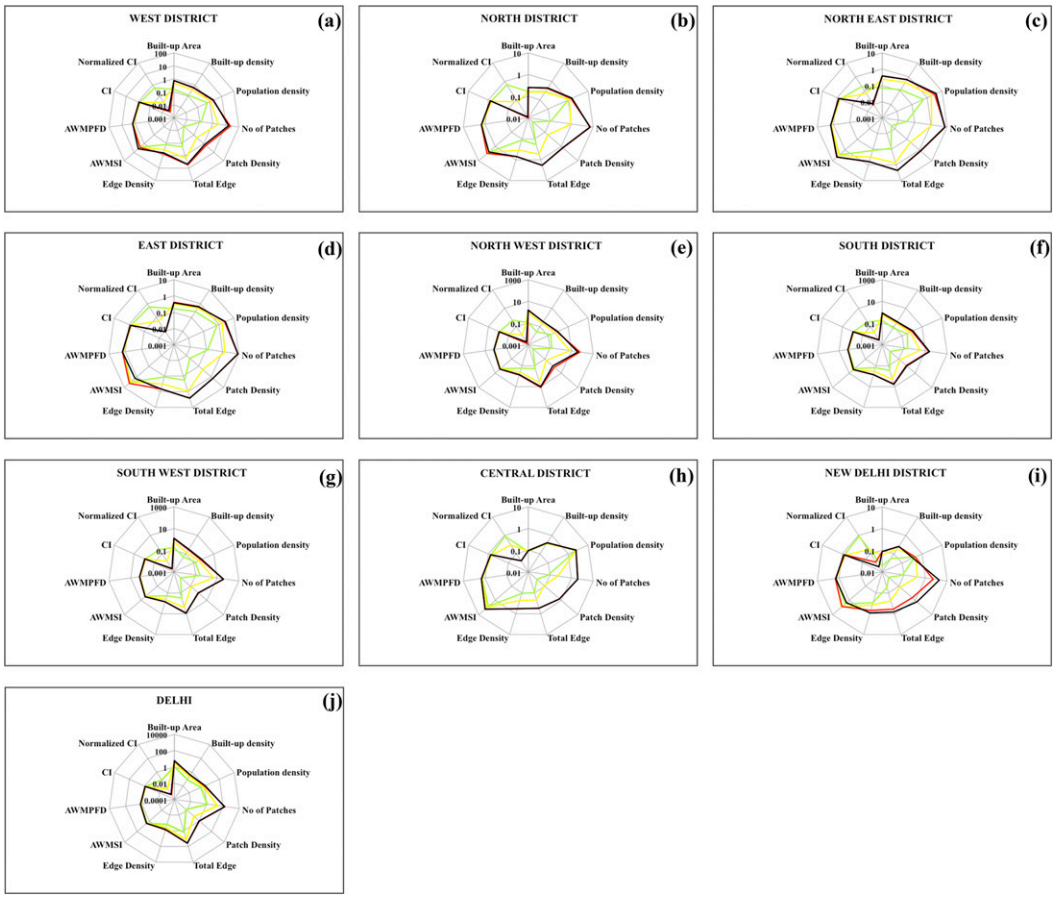


Figure 7. Spider charts showing spatiotemporal urban patterns with (a),(b),(c),(d) as high sprawl districts; (e),(f),(g) as medium sprawl districts; and (h),(i) as least sprawled districts. (j) The Delhi state is shown for reference. Year 1977 is shown in green, 1993 in yellow, 2006 in red, and 2014 in black. Built-up area is measured in km^2, population density as persons per square kilometer, number of patches in count, patch density in patches per square kilometer, total edge in km, and edge density in $m\,ha^{-1}$. Built-up density, AWMSI, AWMPFD, CI, and NCI are unitless quantities.

two spans. In districtwise analysis, Central, New Delhi, and West show the least disparity of urban growth in terms of deviation from the expected values, while the South, North West, and South West show the most.

Pearson's chi-square statistics were used to calculate the degrees of freedom (DOF) for urban growth in each district as well as time span. It is calculated by

$$\chi_i^2 = \sum_{j=1}^{j=m} \frac{(M_j - M_j^E)^2}{M_j^E},$$

where ${\chi_i}^2$ is the degree of freedom for ith temporal span, M_j is the observed built-up area in jth column, and M_j^E is the expected built-up area in jth column.

Table 6. Observed growth in built-up areas (km^2) in various districts of Delhi for three time spans.

	Central	East	New Delhi	North	North East	North West	South	South West	West	Row total
1977–93	0.71	14.66	4.31	−0.78	16.86	83.53	41.11	39.03	31.79	231.22
1993–2006	0.22	8.68	2.28	9.59	13.09	54.59	21.42	58.69	26.94	195.5
2006–14	−0.06	−1.27	0.15	0.55	0.25	−0.06	7.48	17.2	2.91	27.15
Column total	0.87	22.07	6.74	9.36	30.2	138.06	70.01	114.92	61.64	453.87

When the expected urban growth matches the observed growth, then the chi-square value equals 0. Table 9 shows that the chi-square value for each time span in the Central, New Delhi, and West districts approaches 0 and accounts for the least DOF. It represents very controlled urban growth in these three districts. The North, North West, and South West districts show a very high overall degree of freedom, indicating lack of consistency in planning and unstable development. Also high variation among time span chi-square values for these districts can be noted, indicating unequal weightage of DOF. Higher DOF in any time span should be viewed as the presence of greater interdistrict unevenness in the growth of built-up areas and were found to be highest between the years 2006 and 2014. Higher DOF are indicative of an imbalance in the urban growth process rather than being a representation of sprawl.

5.1.6. Shannon entropy and relative entropy

Shannon's entropy has been used to determine the urban sprawl in the nine districts of Delhi. Entropy is the degree of disorder in any system. The following formula defines Shannon's entropy for temporal span i:

$$H_i = -\sum_{j=1}^{j=m} p_j \log_2(p_j),$$

where p_j is the proportion of built-up growth rate in the jth district, and m is the total number of districts.

In case of Shannon's entropy calculation for district j, the above equation can be rewritten as

$$H_j = -\sum_{i=1}^{i=n} p_i \log_2(p_i),$$

where p_i is the proportion of built-up growth rate in the ith temporal span and n is the total time spans.

Table 7. Expected growth in built-up areas (km^2) in various districts of Delhi for three time spans.

	Central	East	New Delhi	North	North East	North West	South	South West	West
1977–93	0.44	11.24	3.43	4.77	15.39	70.33	35.67	58.54	31.40
1993–2006	0.37	9.51	2.90	4.03	13.01	59.47	30.16	49.50	26.55
2006–14	0.05	1.32	0.40	0.56	1.81	8.26	4.19	6.87	3.69

Table 8. Observed minus expected growth in built-up areas (km^2) in various districts of Delhi for three time spans.

	Central	East	New Delhi	North	North East	North West	South	South West	West
1977–93	0.27	3.42	0.88	−5.55	1.47	13.20	5.44	−19.51	0.39
1993–2006	−0.15	−0.83	−0.62	5.56	0.08	−4.88	−8.74	9.19	0.39
2006–14	−0.11	−2.59	−0.25	−0.01	−1.56	−8.32	3.29	10.33	−0.78

The value of Shannon's entropy for any temporal span ranges from 0 to $\log_2(m)$. Sprawl is a manifestation of disorder in the urban landscape, and higher values of entropy [$>\log_2(m/2)$] indicate urban sprawl in that district for a particular time frame. The city can be sprawled, but the sprawled pattern might be decreasing with time. Decreasing sprawl does not mean not sprawling. Entropy values below $\log_2(m/2)$ indicates nonsprawl. The percent of urban growth for three time spans, 1977–93, 1993–2006, and 2006–14, for the nine districts of Delhi was calculated using

$$\frac{(\text{Present urban area} - \text{Past urban area}) \times 100}{\text{Past urban area}}.$$

When reviewing these growth values (Table 10), note that in the time span 2006–14, the Central, East, and North West districts show a slight negative growth rate. This decline in growth could possibly be ascribed to the large-scale sealing and demolition drives carried out by the Municipal Corporation of Delhi (MCD) from 2006 to 2007. Since then, with the implementation of the latest master plan of Delhi 2021 (Delhi Development Authority 2007), a higher floor-to-area ratio (FAR) is permitted, thereby clearing the way for taller buildings and redensification of existing colonies instead of a sprawl. As the log for negative values is undefined, an imaginary log has been used and its real part has been taken wherever such instances occurred. Relative entropy is used to scale the calculated Shannon's entropy to a value that ranges from 0 to 1 (Yeh and Li 2001). For any district relative entropy is computed as $H_j/\log_2(n)$, while for a temporal span it is $H_i/\log_2(m)$. Table 11 details Shannon's entropy and relative entropy values calculated for each district. The South West district shows the highest entropy districtwise at 1.13. The maximum value of entropy for any district can be $\log_2(n)$, that is,1.58. The West, South, and North East follow the South West district in decreasing order of entropy value. Similar interpretation can be achieved by using relative entropy where the values range until a maximum of one (i.e., the highest degree of sprawl). The rest of the districts show relative entropy values of less than 0.40, indicating nonsprawl. In terms of time span, the relative entropy values are 0.80, 0.92, and

Table 9. Pearson's chi-square statistics showing degrees of freedom for each district as well as each time span.

	Central	East	New Delhi	North	North East	North West	South	South West	West	DOF (time span)
1977–93	0.17	1.04	0.23	6.46	0.14	2.48	0.83	6.50	4.8×10^{-3}	17.84
1993–2006	0.06	0.07	0.13	7.67	4.9×10^{-4}	0.40	2.53	1.71	0.01	12.58
2006–14	0.24	5.08	0.16	1.8×10^{-4}	1.34	8.38	2.58	15.53	0.16	33.49
DOF (district)	0.47	6.19	0.51	14.13	1.49	11.26	5.95	23.74	0.18	63.91

Table 10. Percent growth rate of built-up areas.

	Central	East	New Delhi	North	North East	North West	South	South West	West	Row sum
1977–93	8.05	88.31	224.48	−4.72	239.15	725.09	229.79	217.92	204.44	1932.51
1993–2006	2.31	27.77	36.60	60.97	54.75	57.43	36.31	103.07	56.91	436.10
2006–14	−0.62	−3.18	1.76	2.17	0.68	−0.04	9.30	14.88	3.92	28.87
Column sum	9.74	112.90	262.84	58.41	294.57	782.48	275.40	335.87	265.26	2397.48

0.50 from 1977 to 1993, 1993 to 2006, and 2006 to 2014, respectively (Table 12). As clearly seen overall, Delhi has experienced a very high degree of sprawl. It is interesting to note that the period 1993–2006 coincides with the period of economic reforms implemented in the state that boosted real estate and infrastructure development and accounts for the increased degree of sprawl in that time span. From 2006 to 2014, stringent actions were taken on illegal construction, and higher vertical development of buildings was also allowed. Since the focus has shifted to the emergence of taller urban landscapes rather than horizontal expansion, sprawl has considerably reduced. It is important to note that it does not imply that urban construction has slowed down, rather a redensification pattern can be seen.

5.1.7. Degree of goodness

Bhatta et al. (2010) define the degree of goodness as "the extent to which the observed growth relates the expected growth and the magnitude of compactness." It is expressed as

$$G_i = \log_2\left\{\frac{1}{\chi_i^2\left[\dfrac{H_i}{\log_2(m)}\right]}\right\},$$

where G_i is the degree of goodness for ith temporal span, ${\chi_i}^2$ is the degree of freedom for ith temporal span, H_i is Shannon's entropy for ith temporal span, and m is the total number of districts.

Goodness in urban growth is reflected by positive outcomes and badness is reflected by negative outcomes. It can act as one of the indicators for sustainable development. If districtwise analysis is done, then nearly half the districts show goodness in growth, while the other half shows badness. This was calculated in both the spatial and temporal sense (Tables 11 and 12). The Central, New Delhi, and West districts show a high degree of goodness, while the North and North East districts show a lower degree of goodness. The East, North West, and South districts have a low degree of badness with the South West district showing a high

Table 11. Shannon entropy, relative entropy, and degree of goodness for nine districts of Delhi.

	Central	East	New Delhi	North	North East	North West	South	South West	West
Shannon entropy	0.47	0.63	0.64	−0.18	0.72	0.38	0.77	1.13	0.86
Relative entropy	0.30	0.40	0.40	−0.11	0.45	0.24	0.48	0.71	0.54
Degree of goodness	3.85	−0.30	3.27	0.31	1.58	−0.42	−0.53	−3.08	4.40

Table 12. Shannon entropy, relative entropy, and degree of goodness for time spans 1977–93, 1993–2006, and 2006–14.

	Shannon entropy	Relative entropy	Degree of goodness
1977–93	2.54	0.80	−4.84
1993–2006	2.92	0.92	−4.54
2006–14	1.58	0.50	−5.06

degree of badness. In terms of time, all three time spans show a very high degree of badness, suggesting that the observed urban growth matches dismally to the expected built-up area growth and compactness.

5.2. Urban metrics interdependencies

Associations between various spatial metrics have been tested to see if any interdependencies exist between the variables. In most cases, redundant metrics (e.g., landscape level patch density and mean patch size) will be very highly or even perfectly correlated and therefore are just another way of expressing the same information. Despite that, empirical redundancy in any specific application may be present because various landscape structure aspects are correlated statistically. The dissimilarity between both forms of redundancy is that little can be learned from inherently redundant metrics, but critical information about the landscape can be gathered by interpreting empirically redundant ones (McGarigal and Marks 1995). Parametric (coefficient of determination R^2 and Pearson's r) and nonparametric (Spearman's ρ and Kendall's τ) correlation tests have been applied to the datasets. Pearson's correlation quantifies the linear relationship between the considered variables in terms of its magnitude and direction, while Spearman's correlation measures how well an arbitrary monotonic function describes the dependence of one variable on the other. Neither Spearman's nor Kendall's correlation assumes any inherent linearity in the data and can be used to explain certain associations between the variables considered. Spatiotemporal plots of each of the following sets of variables were prepared along with a tabulation of correlation coefficients between them. Variation of correlation coefficients of these variables over distinct years (1977, 1993, 2006, and 2014) has been added as a part of the supplementary tables.

5.2.1. Built-up density vs. population density

A causal relationship exists between urbanized built-up areas extracted from remotely sensed images and settlement population size (Jensen and Cowen 1999). The same can be seen from the current dataset (Table 13). A strong positive correlation (>0.85) with a two-tailed p value being 0 can be established from Pearson as well as Spearman coefficients. It is indicative of a linear relationship between the variables; that is, as population density increases with time so does built-up density (Figure 8a). If the association is seen separately for each year, then a very strong positive relationship between the variables can be established. See Table A1 in the supplemental material.

Table 13. Urban metrics interdependencies calculated using parametric and nonparametric correlation coefficients.

	Coefficient of determination (R^2)	Pearson's correlation coefficient (r)	Spearman rank correlation (ρ)	Kendall rank correlation (τ)
Built-up density vs population density	0.73	0.86	0.91	0.74
AWMPFD vs AWMSI	0.19	0.44	0.54	0.39
Compactness index vs edge density	0.62	0.79	0.73	0.50
Normalized compactness index vs number of patches	0.06	−0.23	−1.00	−0.97
AWMPFD vs built-up density	0.51	0.72	0.68	0.51

5.2.2. AWMPFD vs. AWMSI

Since AWMSI and AWMPFD are nonredundant metrics, there should not be any statistical association between the two. An overall weak positive correlation (Spearman correlation = 0.54) was established from the data (Table 13). The two-tailed p value of Spearman rho was 0.0003. It is interesting to note that if graphs are plotted for 1977, 1993, 2006, and 2014 (Figure 8b; supplemental material: Table A2) then there is a shift in all the correlation coefficients from a weak negative to moderate positive to a strong positive correlation from 1977 to 2006. The value of R^2 is always positive, as it is a squared term. Essentially as the mean shape of urban patches becomes higher, its fractal shape departs from simple geometry. In 2014, the association is weaker than the study year prior to it. It might be because newer urban patches that have been constructed simplified the overall geometry without much impact on the mean shape of the urban patch. Since it is a complex phenomenon, additional assessment is recommended in future studies.

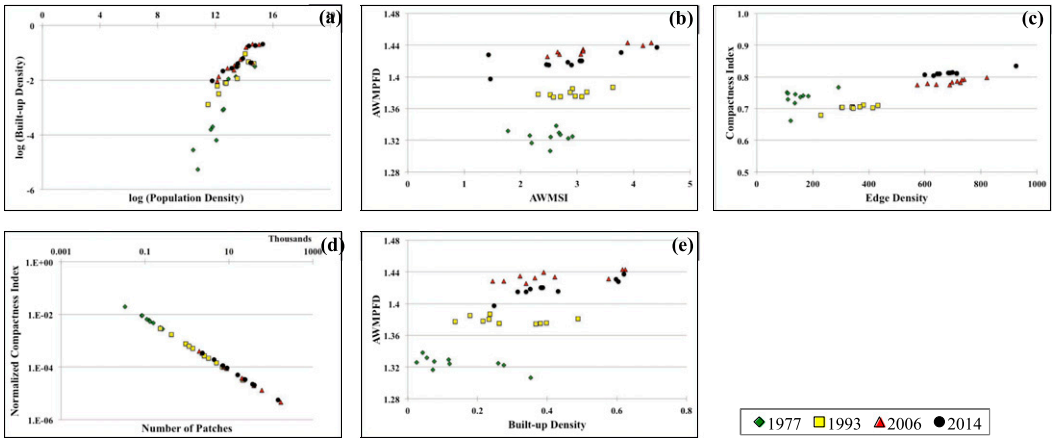


Figure 8. Spatiotemporal plots depicting relationships between (a) built-up density and population density, (b) AWMFPD and AWMSI, (c) compactness index and edge density, (d) normalized compactness index and number of patches, and (e) AWMFPD and built-up density. Year 1977 is shown in green, 1993 in yellow, 2006 in red, and 2014 in black.

5.2.3. CI vs. edge density

As the edge density of the districts of Delhi increases, the compactness index of the urban patches also increases in that district. Table 13 indicates strong positive correlation coefficients (Pearson = 0.79, Spearman = 0.73, and Kendall = 0.50). A two-tailed p value equal to 0 indicates correlation to be statistically significant. Over time, the association between the variables has grown stronger (Figure 8c; supplemental material: Table A3).

5.2.4. NCI vs. number of patches

A weak negative correlation is seen for the parametric tests, while a very strong negative relationship (Spearman = −1.00, Kendall = −0.97, and two-tailed p value = 0) can be established for the nonparametric tests (Table 13). There is no linear relation between the number of patches and NCI; instead, it decreases as a function of power series when the number of patches is increased. A perfect negative Spearman rho and Kendall tau are obtained for the years 1977 and 1993 (Figure 8d; supplemental material: Table A4). Meanwhile the values of nonparametric correlation coefficients are greater than 0.95 for the remaining 2 years.

5.2.5. AWMPFD vs. built-up density

The spatiotemporal plot between AWMPFD and built-up density indicates a statistically significant moderate positive correlation (Table 13). In 1977, the association was moderately negative as the built-up density increased and a departure from Euclidian geometry decreased (Figure 8e; supplemental material: Table A5). It means that high-density areas existed as huge simple shape blocks. Over time it has shifted from weakly negative to moderately positive to a strongly positive correlation. Presently, as the built-up density is increasing, so is the AWMPFD (i.e., high-density areas are most likely to have much more complex fractal geometries than their low-density counterparts). The parametric as well as nonparametric tests are able to capture the dynamic urban changes happening in Delhi and its districts over time.

6. Conclusions

Spatial dynamics of urban sprawl from 1975 to 2010 (Taubenböck et al. 2012) indicate that the fastest growth occurs in cities of developing countries (Kinshasa–Brazzaville, Manila, Cairo, Mumbai, etc.), but only a marginal spread occurs in cities of developed countries (e.g., London and New York). In India, megacities, including Delhi, show high urban area, built-up density, and landscape shape index values (Taubenböck et al. 2009). City level results in the present study are consistent with previous findings. Large urban clusters away from the urban core are agglomerating with time similar to that seen in the city of Kathmandu (Thapa and Murayama 2009). On a district level analysis, three kinds of urban patterns exist inside Delhi: highly sprawled districts, medium sprawled districts, and least sprawled districts. High sprawl can be noted in the West, North, North East, and East districts; medium sprawl is found in the North West, South, and South West districts; and the least sprawl is observed in the Central and New Delhi districts.

Delhi state on the whole shows a pattern similar to that of medium sprawled districts.

People are moving outward from the city core where there is hardly any scope for urban expansion. This can be corroborated from decadal population growth rates. Clark (1951) generalized that barring the central business area, in all big cities there are densely populated districts in its interior with a progressive reduction in population density as one proceeds to the outer suburbs. In conjunction, as time goes on, population density has a tendency to decline from the innermost highly populous districts, migrate, and rise in the outer districts. The city on the whole tends to spread itself out in terms of population this way. Both of the above-mentioned generalizations are true for the ground reality situation in Delhi.

The South West district shows the highest Shannon's entropy value, implying maximum sprawl out of all the districts. In terms of time span, the relative entropy values are 0.80, 0.92, and 0.50 from 1977 to 1993, 1993 to 2006, and 2006 to 2014, respectively. A very high degree of sprawl exists in 1993–2006; a period coinciding with economic reform boosted infrastructure development. A decreased degree of sprawl in 2006–14 is noted where the focus has shifted to the emergence of vertical densification instead of horizontal owing to compliance to the master plan of Delhi 2021. An already established relationship between built-up density and population density in previous studies has been found to exist in the current dataset and also suggests the presence of associations between AWMPFD and AWMSI, compactness index and edge density, NCI and the number of patches, and AWMPFD and built-up density.

Acknowledgments. The authors acknowledge the provision of raw satellite data scenes for the years 1993 and 2006 that were made available by the Centre for Inter-Disciplinary Studies of Mountain and Hill Environment (CISMHE), University of Delhi, New Delhi. Madhavi Jain acknowledges the junior research fellowship granted by the Council of Scientific and Industrial Research (CSIR). Dev Niyogi acknowledges support through NSF CAREER (AGS 0847872).

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