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CHANGES IN VEGETATION VIGOR AND URBAN GREENNESS IN SIX DIFFERENT CITIES OF INDIA—ANALYSIS FROM COARSE RESOLUTION REMOTE SENSING DATASETS

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ABSTRACT

Urban sprawl is gaining increasing attention in developing countries of the world. With a population of some 1,027 million people, India has more than 10 cities that have one million population. This population is bound to grow and is a major concern of urban sprawl in most of the cities. In this study, we analyze the trends in vegetation greenness patterns in six different cities of India. An attempt has also been made to relate these vegetation changes to population densities. Temporal changes in vegetation vigor from 1984 till 2000 have been analyzed using vegetation greenness index and change detection methodology using NOAA AVHRR remote sensing data. Results from this analysis suggested different patterns of vegetation changes over a period of time. Of the six cities, Hyderabad and Mumbai had similar patterns of vegetation change, where the "vegetation loss" has considerably decreased from 1984 till 2000. Calcutta showed increasing vegetation loss from 1996 to 2000. To infer the patterns of vegetation dispersion resulting from urban sprawl and land development, entropy index has been used. Results from this index suggested that the city of Bangalore had much less dispersion in vegetation compared to Hyderabad and New Delhi. Further, results for Calcutta and Hyderabad suggested that the vegetation has been changing toward concentrated pattern. Results from correlation analysis suggested that as population density increased, the entropy of vegetation greenness decreased in the cities of Calcutta, Bangalore, and Mumbai and Hyderabad

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compared to Chennai and Delhi. These results suggest that as the density of population increased, the vegetation greenness became more concentrated in these cities. These results on vegetation changes will be useful for urban planners and researchers in addressing some urban climate issues in the rapidly growing cities of India.

INTRODUCTION

Urban ecosystems represent the most complex mosaic of vegetative land cover and multiple land uses. The ever-growing size and density of cities, especially in developing countries, has major repercussions not only on the quality of the human life but also on the environment and atmosphere [1-3]. Rapid exploitation of natural resources in and around the urban areas raise concerns such as air pollution, deforestation, habitat destruction, and climatic imbalances [4]. Further, urbanization tends to accentuate a number of problems such as inadequate housing and urban services (water, sanitation, transport, and so on), spiraling land prices and construction costs, proliferation of slums, etc. [5]. Thus, monitoring such events and consequences is critical for measuring sustainable levels of urban expansion [6]. For the same, knowledge on the physical structure, biophysical characteristics, and form of cities is important [3, 7]. Most importantly, urban centers/cities contain the majority of the world's people. This is particularly true for Indian scenario. With a population of some 1,027 million people, India is now the second country in the world after China, to cross the one billion mark [8]. As per the Census 2001 figures, the population density in India is 324 persons per sq km against 267 in 1991. It implies that 57 more persons live in a sq km area than a decade ago. The 10 heavily populated districts of the country are Calcutta, Chennai, Greater Mumbai, Hyderabad, Delhi, Chandigarh, Mahe, Howrah, Kanpur City, and Bangalore (Table 1). Contrary to popular concepts of a predominantly rural India, an increasingly larger percentage of Indian population lives in the urban areas. Today, India's urban population is second largest in the world after China, and is higher than the total urban population of all countries put together barring China, United States, and Russia. Over the last 50 years, while the country's population has grown by 2.5 times (Table 2), in the urban areas it has grown by five times. All of them have density of above 2,000 persons per square kilometer and 5.01% of the country's population lives in these urban centers and districts. In 2001, India had 35 cities/urban agglomerations with a population of more than one million people [8]. In total, some 108 million Indians, or 10.5% of the national population, live in the country's 35 largest cities. This population is bound to grow and is a major concern of urban sprawl in most of the cities.

Several researchers used different indicators of urban growth and sprawl. Urban sprawl has been traditionally studied and assessed using the demographic information. Measurement of population traits and additional attributes are used

Table 1. India's Ten Largest Cities/
Urban Areas with Population

Rank	City/urban area	Population
1	Mumbai (Bombay)	16,368,000
2	Kolkata (Calcutta)	13,217,000
3	Delhi	12,791,000
4	Chennai (Madras)	6,425,000
5	Bangalore	5,687,000
6	Hyderabad	5,534,000
7	Ahmadabad	4,519,000
8	Pune	3,756,000
9	Surat	2,811,000
10	Kanpur	2,690,000

Source: India's National Census of 2001.

Table 2. Trends in Indian Population Growth

		Population growth (1951-2001)		
Years	(in million)	Growth (%)	Annual growth (%)	(Per.Sq.km)
1951	361.09	13.31	1.25	117
1961	439.23	21.64	1.96	142
1971	548.16	24.8	2.2	177
1981	683.33	24.66	2.22	216
1991	846.39	23.86	2.14	267
2001	1027.02	21.34	1.93	324

to develop standardized indices of sprawl development and their impacts [9]. For example, Nelson [10] employed an array of indicators, including land-use conversion, population change, traffic and vehicle miles traveled, energy consumption, and fiscal measures. Hasse and Lathrop [11] used land resource impact indicators such as density of new urbanization, loss of prime farmland, loss of natural wetlands, loss of core forest habitat, and increase in impervious surface, to study the urban sprawl and growth. Earlier reviews on the use of such indices can be found in Lo [3, 12]. Other researchers focused on measuring sprawl through the use of population and detailed land-use data [1, 3, 13]. While these studies mostly included socioeconomic data, several recent studies have examined post-detection of urban growth patterns affecting the urban climate [4, 14]. For example, Jendritzky and Nubler [15] investigated the thermal environment in Freiburg, Germany by determining the spatial distribution of physiologically equivalent temperature (PET) values by day and night. For urban planners, PET has been considered as one of the useful measure for assessing the bioclimate. Unger [16] used the thermo hygrometric index (THI), defined by air temperature and relative humidity on the bioclimatological conditions of human beings. With the help of suitable indices, differences in the annual and diurnal variation of human bioclimatic characteristics between an urban and rural environment are evaluated. In addition to these studies, application of remote sensing for sustainable management of natural resources including urban studies and cities has been widely attempted by several researchers [3, 17-19]. Remote sensing technology with its multitemporal, multispectral, synoptic and repetitive coverage provides valuable information on mapping of natural resources in a cost effective manner.

Of the several applications of remote sensing, monitoring changes in vegetation and land cover by periodic mapping of the resource in question is an important application. Further, of the several parameters relating to the urban climate, "heat island effect" has become very important from the human environmental point of view, because of the increasing trend toward people living in urban areas [3]. The urban heat island refers to warmer nighttime temperatures occurring in the core of the built environment when compared to the surrounding rural environment. lt is a complex phenomenon, which results from various interactions between human and environmental factors and has numerous other social and economic consequences [20]. Thus, urban climate affects depend not only on the land cover changes within the city over time, but also on the land cover specifics of rural environs with which urban sites interact. In particular, changes in vegetation cover have implications for urban heat island effect. Vegetation influences urban environmental conditions and energy fluxes by selective reflection and absorption of solar radiation and by modulation of evapotranspiration [21]. Vegetation absorbs the carbon dioxide that is produced in the city. Urban vegetation also plays an important role in the purification of the air and acts as a filter for noise from road traffic [22]. Thus, the presence and abundance of vegetation in urban areas has long been recognized as a strong influence on energy demand and development of urban heat island [6, 9, 12]. Urban vegetation abundance may also influence air quality and human health [23] because trees provide surface area for sequestration of particulate matter and ozone. Considering these effects, Brezina and Schmidt [24] referred green-spaces/parks as to "the lungs of the metropolis" in one of their famous papers.

In India, few studies have attempted to link the spatial patterns of changes of vegetation to urban sprawl, particularly in the cities. The purpose of this article is to examine the vegetation greenness variability in and around six major cities of India, i.e., Delhi, Mumbai (formerly Bombay) Chennai (formerly Madras), Bangalore, Hyderabad, and Calcutta. In this study, we analyze the temporal changes in vegetation along the "rural-urban gradient" in these six major cities. We view this "rural-urban gradient" zone as the gradient ranging spatially from the central city to the farms and forests. From the ecological perspective, this zone represents functional differences in transitional patches between city and countryside [18]. Understanding the historic trends in vegetation changes along this urban-rural gradient is useful in evaluating various impacts resulting from past land transformations and land use changes [14, 16]. In addition, an attempt has been made to link the overall changes of vegetation greenness to population density changes.

Materials and Methods

In this study, we used Normalized difference vegetation index (NDVI) as an indicator for vegetation greenness. NDVI values have been calculated from the Advanced Very High Resolution Radiometer (AVHRR) on board the USA's NOAA polar orbiting meteorological satellites. The reflectance measured from Channel 1 (visible: 0.58-0.68 microns) and Channel 2 (near infrared: 0.725-1.0 microns) are used to calculate the NDVI as:

$$\text{NDVI} = (\text{Ch2}-\text{Ch1})/(\text{Ch2}+\text{Ch1})$$

The differential reflectance in these bands provides a means of monitoring density and vigor of green vegetation growth using the spectral reflectivity of solar radiation [25]. Green leaves commonly have larger reflectance in the near infrared than in the visible range. As the leaves come under water stress, become diseased or die back, they become more yellow and reflect significantly less in the near infrared range. Clouds, water, and snow have larger reflectance in the visible than in the near infrared while the difference is almost zero for rock and bare soil. Vegetation NDVI typically ranges from 0.1 up to 0.6, with higher values associated with greater density and greenness of the plant canopy. Surrounding soil and rock values are close to zero while the water bodies such as rivers, dams have the opposite trend to vegetation, and the index is negative.

AVHRR-NDVI time series data from 1980 till 2000 were derived from NOAA NASA Land (PAL) datasets, which are 10-day composites and have a resolution of 8 km. These datasets were further processed by the center from Environmental Remote Sensing (CEReS), Chiba University, Japan and Park and Tateishi [26]. Specifically, CEReS applied two types of processing to the source data. One is the transformation of the map projection from Interrupted Goode Homolosine projection to Plate Carree projection for easier usage and other relating to reducing the cloud effects, and to account for the changes in NDVI variations due to atmospheric attenuation, solar zenith angle (SZA) and cloud. Park and Tateishi (1999) employed Temporal Window Operation (TWO) on the PAL NDVI datasets to remove these affects. TWO algorithm starts at the beginning of the NDVI (start point) curve and checks whether the NDVI for the current period is equal to or greater than the previous NDVI value within the window. If it is higher, current value is assigned as the start point of next window (window 1,s1-> s2). If there is no higher value within the window, select the biggest value as a next start point and replacing these by linearly interpolated value from current start point to next start point (window 6,s6->s7). Using these datasets, we selected NDVI values corresponding to different cities (Figure 1), from 1984 till 2000, with a four-year interval.

We calculated the relative greenness (RG) index as [27]:

$$(NDmin) / (NDmx-NDmn) * 100$$

Where, for every pixel, NDmax = Maximum of NDVI daily values over the time period of the study. NDmin = Minimum of NDVI daily values over the time period

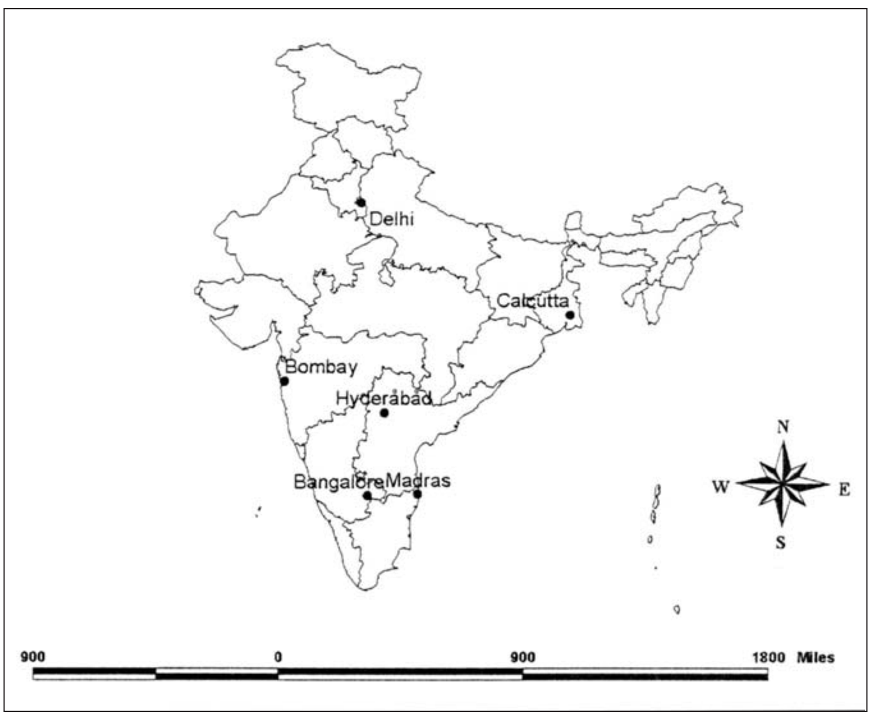


Figure 1. Location map of six largest cities in India.

of the study. Relative greenness is a percentage value expressing how green each pixel is compared to the maximum values obtained in the previous year.

In addition to relative greenness index, we employed change detection technique to assess the vegetation changes over different years. Change detection in remote sensing is defined as the process of identifying differences in the state of an object or phenomenon by observing it at different times [28]. Of the several methods of change detection, i.e., univariate image differencing [29], image ratioing [30], post classification comparison [29], direct multidate classification, vegetation index differencing [25], principal component analysis [31], background subtraction [32], image regression [28], fuzzy set operation [33], curve-theorem based approach [34], etc., we used the NDVI image differencing technique. Image differencing is the simplest technique of change detection. The unitless NDVI (ranging from –1 to 1) was derived from the NOAA AVHRR PAL data. The difference images for subsequent years (1984, 1988, 1992, 1996, and 2000) have been calculated. In the process, the annual average years of 1984 and 1985 were added together and divided by two, creating a 1984/85 average composite. Similarly, 88/89, 92/93, 96/97, and 2000/2001 average composites were created, to further reduce any climatic extremes or other potential abnormalities in the data. This was done mainly to reduce seasonal or short-term inter annual variation. The average image composite of 84/85 was then subtracted from the 88/89 image composite creating a difference image where positive values indicate increases in NDVI (vegetation vigor) during the time period and negative values indicate decreases. The above process has been repeated for other years. Finally we analyzed the NDVI changes in a buffer region covering 256 sq.km around each city.

Further, we also used the concept of entropy, to measure the distribution of vegetation change in six different cities. Shannon's entropy (E) has been used to measure the degree of spatial concentration and dispersion exhibited by NDVI and has been calculated as [35]:

$$E = \Sigma\, p_i \log (1/p_i) / \log (n)$$

Where $p_i = X_i / \Sigma X_i$ and x_i is the observed NDVI value from the center of buffer radius covering the full zone (256 sq.kms) and "n" is the number of NDVI values. The value ranges from 0 to 1. If the distribution is maximally concentrated, the lowest value, zero, will be obtained. Conversely, an evenly disperse distribution across space will give a maximum value of 1.

RESULTS AND DISCUSSION

Long-term time series remote sensing data from 1988 till 2000 provided an opportunity to assess quantitatively and qualitatively the vegetation cover status in different cities of India. Results obtained from relative greenness calculation for different cites is shown in Figure 2. Except for the Hyderabad, all other cities

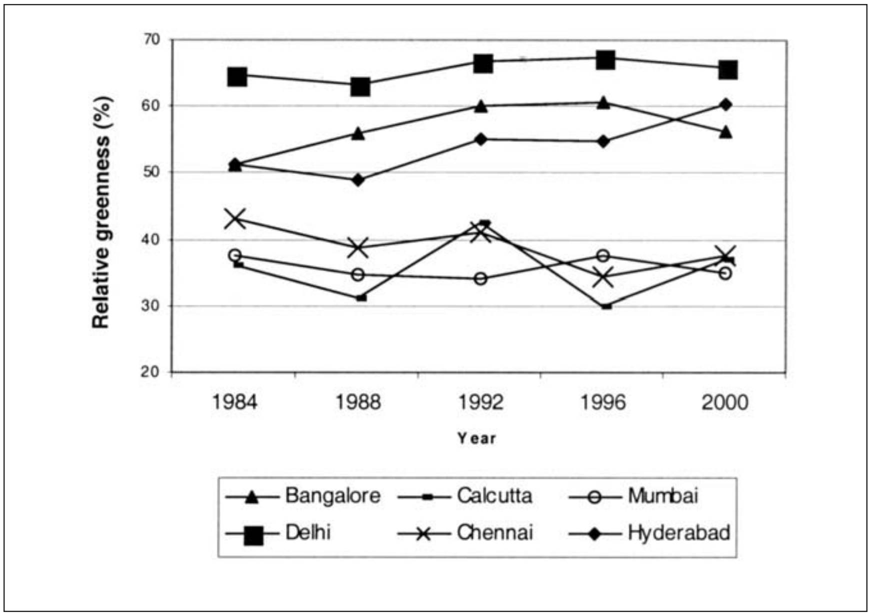
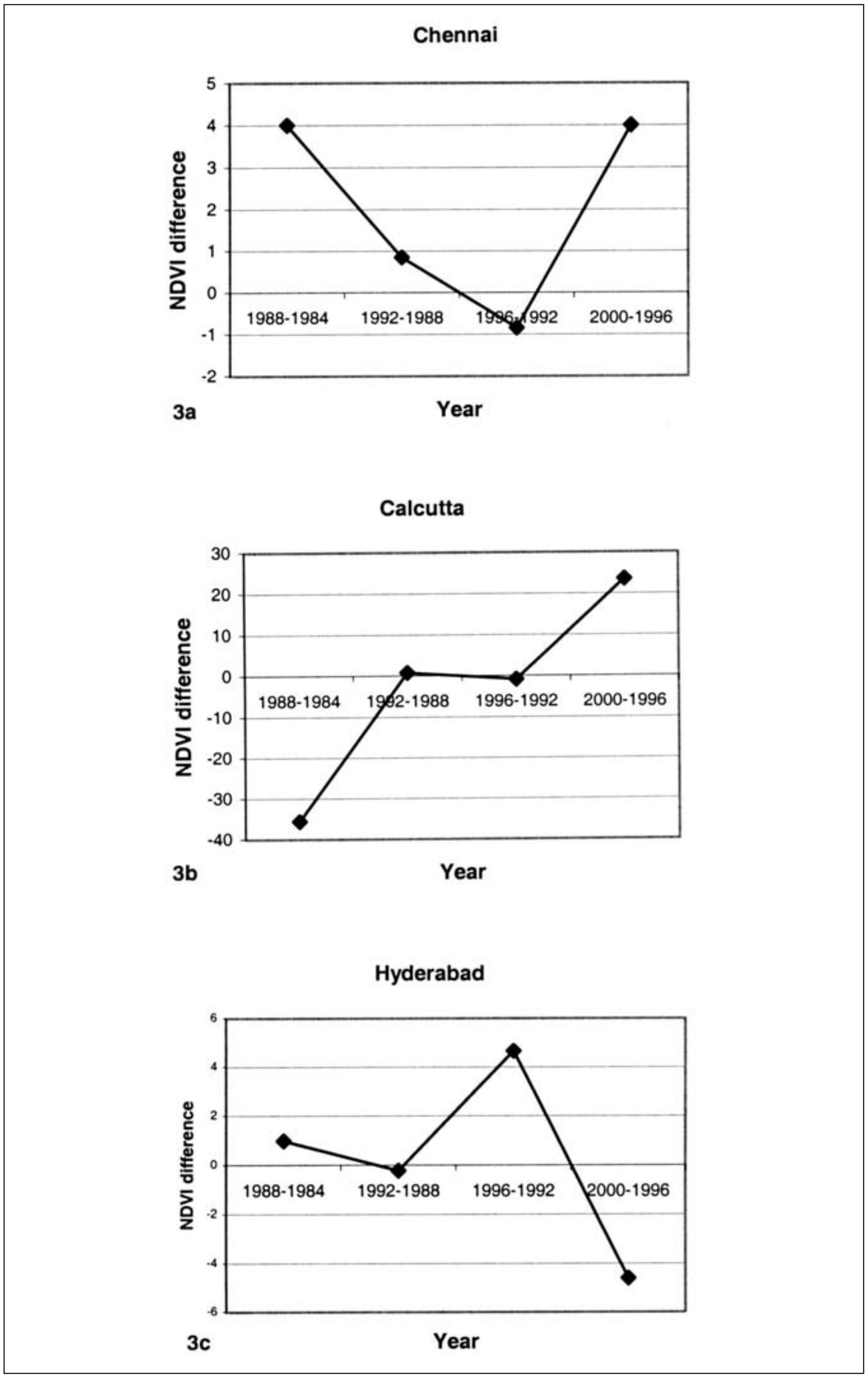


Figure 2. Relative greenness (%) for different cities (1984-2000).

showed much lesser greenness compared to the base year of 1984. Further, Chennai showed a continuous decline in vegetation greenness unlike cities of Bangalore and Delhi which had an increase in vegetation from 1984 till 1996, and then decrease till 2000. Vegetation greenness in Calcutta was much more variable compared to other cities (Figure 2). Results obtained from change detection in vegetation greenness for different cities are shown in Figure 3a-f. Different cities had different patterns of vegetation changes. For example, Hyderabad and Mumbai had similar patterns of vegetation change, wherein the vegetation loss has considerably decreased over a period of time. However, Mumbai had the highest magnitude of change compared to other cities. Chennai showed a continuous decrease in vegetation loss till 1992, however, vegetation loss again increased thereafter. In the case of Calcutta, vegetation loss has been increasing from 1996 to 2000. New Delhi showed a considerable decrease in vegetation loss compared to 1992 and 1996. Finally, Bangalore showed an increase in vegetation loss during 2000 compared to 1988-1992, although the loss was relatively smaller compared to 1988-1984. Thus, of all the cities, Hyderabad and New Delhi had comparatively less vegetation loss compared to other cities (Figure 3c and 3d).

To infer the patterns of vegetation dispersion resulting due to urban sprawl and land development, entropy index has been used. This measure is based on the notion that landscape entropy, or disorganization, increases with sprawl. Thus, the larger the entropy index, the larger the dispersion [4]. Relative comparison of the entropy index for the year 2000 (alone) suggests that vegetation is highly dispersed in the cities of Hyderabad and Delhi compared to other cities (as reflected in higher entropy value) (Figure 4c and 4d). It is interesting to note that the famous "green city" Bangalore had comparatively much less dispersion (lower entropy) in vegetation compared to Hyderabad and New Delhi, suggesting the concentrated nature of vegetation (e.g., parks). Further, results from the temporal changes for entropy suggested significant differences of the entropy index (Figure 4a-d). Thus, in the case of Calcutta and Hyderabad, the vegetation that was highly dispersed has been changing toward concentrated pattern. In contrast, for Chennai, the entropy in vegetation greenness has been increasing suggesting highly dispersed pattern. Overall, these changes in the entropy values suggest changes in land development toward a more dispersed (sprawl) or compact pattern that is also reflected in the vegetation greenness index.

In recent years, the relationship between population characteristics and environmental variables in urban areas has been increasingly explored, for a variety of purposes and applications [36, 37]. Several researchers used remote sensing and GIS for studying the physical expressions and patterns of urban sprawl on landscapes. For example, Weber and Hirsch [38] used high-resolution SPOT-XS image data in combination with cartographic and population census data to measure the urban life quality of Strasbourg, France. Lo [12] used the LANDSAT TM data for quality of life assessment in an urban environment. Langford and Dobson [39] employed dasymetric mapping, an area based cartographic method, for generating urban population density models by both eliminating non-urban land cover (through image classification) and establishing a density relationship between census counts and built land cover. Harvey [40] explored the possibility of estimating populations at the individual pixel level using the expectation maximization technique to fit linear models between zonal population counts and untransformed LANDSAT TM bands, iteratively. Several other details on the use of Remote sensing data relating population counts/densities with urban environmental quality can be found in Mesev [3 and references therein]. In contrast to the above studies, use of vegetation greenness index from NDVI for analyzing vegetation changes and the changing population trends in the Indian cities, has not been attempted so far. According to World development report, the average density of population in the world is 46 persons per sq km in 1999. The high-income countries have an average density of 29, middle-income countries have a density of 40, and low-income countries have an average density of 73. In contrast to these figures, Indian population density (per sq.km) has gone up from 117 in 1951 to 324 persons in 2001 (Table 2). Further, between 1951 and 1981, the growth rate was very high, rising from 1.96% per annum during 1961 to 2.22% in 1981. Thereafter, the rate of growth though still high has shown signs of decline. During, 1981-94, the annual average rate of growth came


Chennai
NDVI difference
5
4
3
2
1
0
-1
-2
1988-1984
1992-1988
1996-1992
2000-1996
3a
Year
Calcutta
NDVI difference
30
20
10
0
-10
-20
-30
-40
1988-1984
1992-1988
1996-1992
2000-1996
3b
Year
Hyderabad
NDVI difference
6
4
2
0
-2
-4
-6
1988-1984
1992-1988
1996-1992
2000-1996
3c
Year

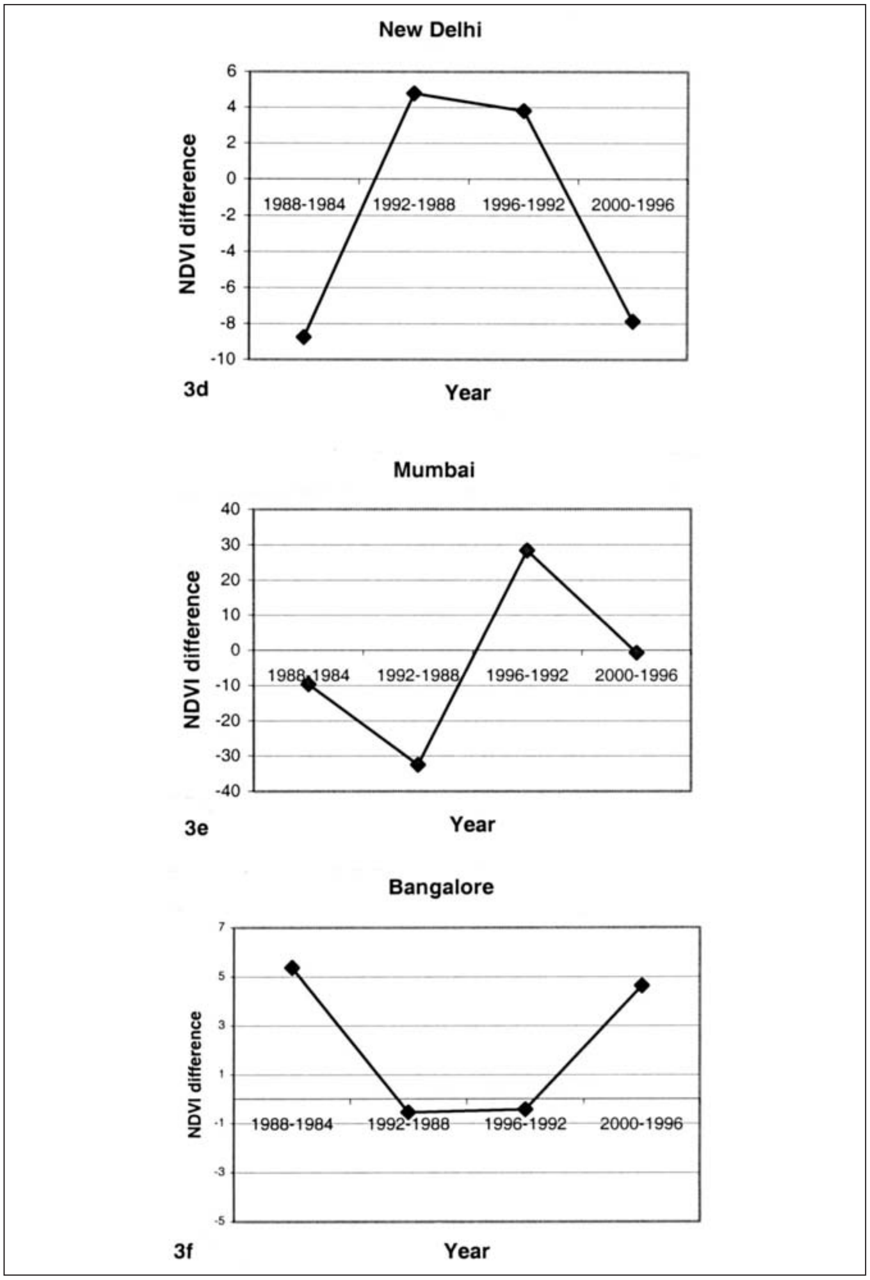
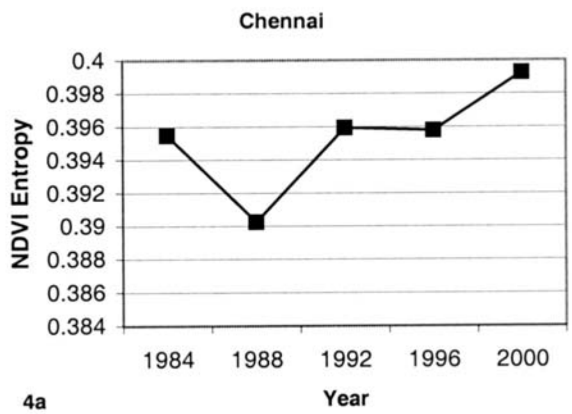
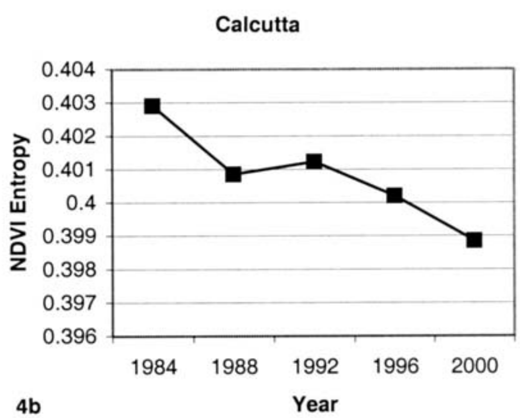


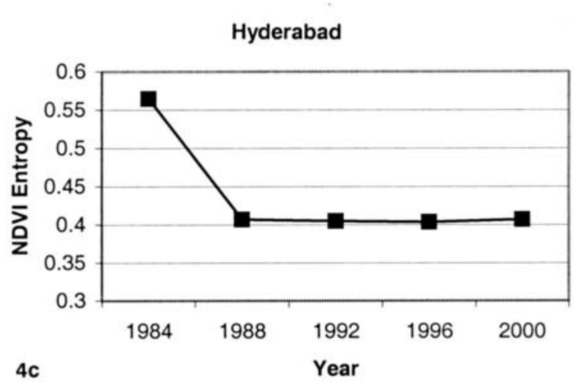
Figure 3. Changes in vegetation greenness derived from NDVI differencing (1984-2000). Raw NDVI values were used in calculation.


Chennai
NDVI Entropy
0.4
0.398
0.396
0.394
0.392
0.39
0.388
0.386
0.384
1984
1988
1992
1996
2000
Year

4a


Calcutta
NDVI Entropy
0.404
0.403
0.402
0.401
0.4
0.399
0.398
0.397
0.396
1984
1988
1992
1996
2000
Year

4b


Hyderabad
NDVI Entropy
0.6
0.55
0.5
0.45
0.4
0.35
0.3
1984
1988
1992
1996
2000
Year

4c

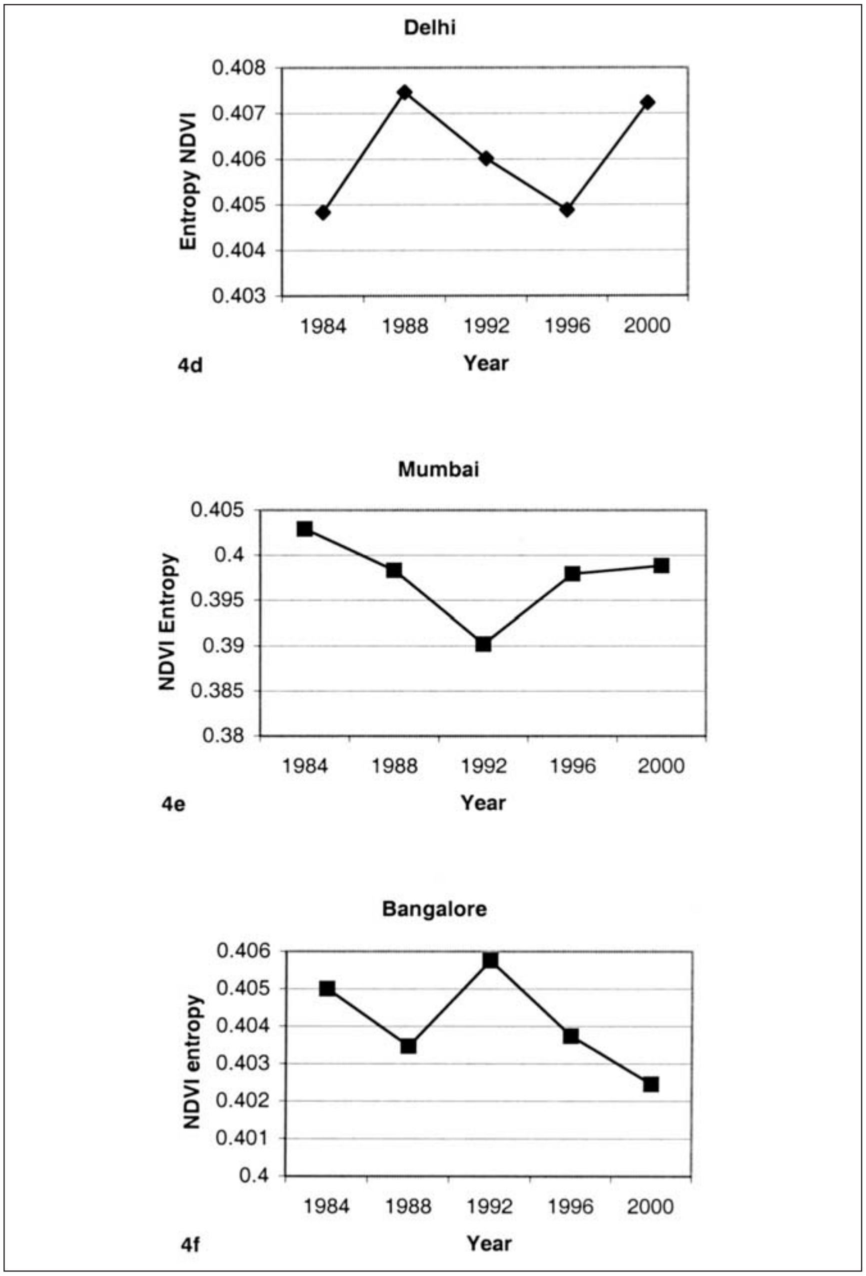


Figure 4. Changes in vegetation sprawl patterns derived from entropy index (1988-2000).

down to 2.14% and during 1991-2001, it fell further to 1.93%. Thus, by world standards, India can be classified as one of the most high-population density countries of the world. Further, Mumbai (Bombay) with a population of more than 16 million is now the world's fourth-largest urban area followed by Kolkata (Calcutta) in fifth place. The urban population density (sq.km) and temporal change in densities for different cities has been obtained from Census of India (2001) and are given in Figure 1. The population figures for intermediate years of census years (from decadal census data, i.e., 1981, 1991, and 2001) has been obtained through interpolation and fitting the data for consecutive years. Of all the cities, Mumbai, Chennai, and Calcutta had highly dense population per square kilometer compared to Hyderabad, Delhi, and Bangalore (Figure 5). To infer and relate the urban population density changes with the vegetation change patterns in urban areas (NDVI entropy), correlation analysis has been undertaken. Results from this correlation analysis revealed quite different patterns of changes in six different cities. For example, as population density increased, the NDVI entropy decreased in the cities of Calcutta ($R^2 = -0.93$), Bangalore ($R^2 = -0.5730$), Mumbai ($R^2 = 0.377$), and Hyderabad ($R^2 = -0.04$). These results suggest that as the density

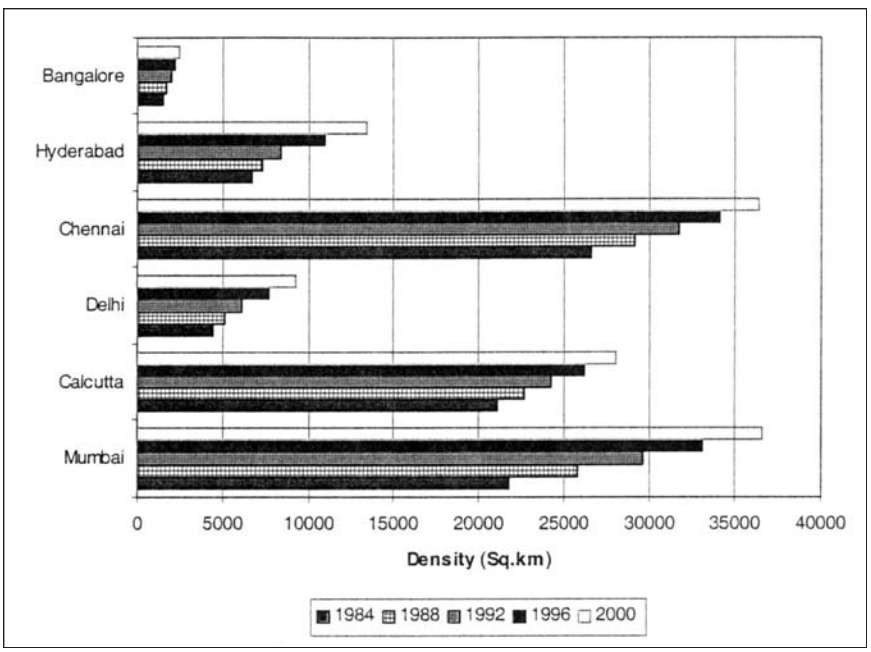


Figure 5. Population density (sq.km) changes in different cities.

of population increased, the vegetation greenness became more concentrated in these cities. In contrast, for Chennai (0.6024) and Delhi (R^2 = 0.249) increase in urban population density resulted in more dispersed nature of vegetation. Thus, the relationship between population densities and vegetation greenness appears to be quite different for Indian cities, unlike the "S" shaped relationship between population increase and vehicles [2]. Overall, in addition to the changing urban population, the differences in the vegetation characteristics observed for different cities reflect to a large extent, the difference in the history of urban development and the government policies that were implemented to preserve the urban parks/green spaces over different years. Thus, the results depict the overall physical structure in the form of "green space," in different cities. Although population density changes in these cities were quite useful to discern some trends, the approach followed in this study can be further modified by using information on residential patterns and other variables on city morphology and infrastructure, such as roads and land use/land cover. The present study is limited as such data is not readily available over different time periods. In particular, use of high resolution satellite imagery from IKONOS may provide robust information with the approach followed in this study. Further, the results from this study can be linked with several other variables such as pollution intensities (especially Sulphur dioxide and Ozone) to further study the variation in bioclimatological characteristics in urban areas. Furthermore, these results on vegetation greenness can also be integrated with several other socioeconomic variables to relate the spatial process of urban expansion. Finally, policy makers and researchers may use these results on vegetation changes to address the questions relating to bioclimatology in urban areas.

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