Understanding the dynamics of urban form:

A comparison of Chinese and Indian cases

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Abstract

One of the major social scientific challenges of the twenty-first century lies in understanding and managing the rapid urbanization that is now under way in the developing world. More of this urbanization is taking place in China and India than anywhere else. This analysis presents the first multi-city, multi-temporal, cross-national overview of the transformation of urban form in these two countries. Based on 24 spatial metrics compiled from four decades of remote sensing data in twenty cities, the analysis combines principal components analysis with a canonical correlation analysis to compare changes in urban form in both countries. Despite numerous cross-national parallels in trajectories of urbanization, the results show dramatic variations between Chinese and Indian patterns of peri-urban development. Some of the contrasts are common to all cities in both countries. Others appear primarily in urban centers of foreign investment and accompanying economic growth. The analysis underscores the importance of national settings for the course and consequences of urbanization.

Keywords: China, India, remote sensing, spatial metrics, urban form, urban sprawl

In the next half century, ninety percent or more of global population growth will take place in the rapidly urbanizing areas of the developing world (United Nations Dept. of International Economic and Social Affairs., 2005). The dramatic urbanization now under way there constitutes one of the epochal transformations in human history. The environmental, social and economic implications of this “urban revolution” (Lefebvre, 2003) are only beginning to be grasped by contemporary social science. There is an urgent need for tools to describe and analyze these ongoing processes, and to provide useable knowledge for those seeking to better manage the process and its consequences. A growing body of research has harnessed new technologies of remote sensing and GIS to describe pathways of urban and peri-urban development. To date, this research has been slow to exploit the potential of these new technologies to facilitate systematic comparative analysis of urban developmental trajectories. To realize this potential requires research designs that incorporate urban trajectories in diverse national settings, that encompass long term processes of change, and that capture multiple dimensions of urban spatial transformation.

This study applies such a design to analyze three decades of urban transformation in the two largest developing countries. The study employs a total of 24 landscape metrics to measure development at the urban fringe in a stratified, matched sample of ten Chinese and ten Indian urban regions. The analysis points to major divergences between countries as well as among cities in the dynamics and consequences of this revolution.

1. **Background and Theory**

As the two urbanizing giants of Asia, China and India stand at the revolution’s epicenter. Between 1970 and 2010 these two countries alone added one billion new urban residents, or nearly half of global urban population growth. Over 2010-2030, as cities in both countries continue to expand, the United Nations projects a further increase of 500 million people—a figure equivalent to the current population of the European Union (United Nations, 2009). From 20 percent in 1970, India's urban population has grown to 30 percent in 2010 and is projected to reach 50 percent by 2045. China's has grown even faster, from only 17 percent in 1970 to 40 percent in 2010, and is expected to top 70 percent by mid-century.

A burgeoning literature points to similar drivers of urban expansion throughout the developing countries of the Global South (Angel et al., 2005; Seto et al., 2011). In both India and China, shifts over the last three decades toward economic liberalization, government decentralization, and local planning have fostered aggressive pursuit of urban development among local and intermediate level officials and firms (Kennedy, 2007; Laurence J. C. Ma & Wu, 2005). In both, poor rural residents have flocked in growing numbers to urbanizing regions (Haan, 1997; Wang, 2004). New factories, offices and housing developments have expanded into the peri-urban regions of both Chinese and Indian cities (E.g., Deng et al., 2009; Sudhira et al., 2004).

Despite these parallels, stark contrasts mark the economic and political systems of the two countries. A sizeable and growing literature now contrasts the state-dominated national model of economic development of the party regime in China with the more liberal model of democratic India (Bardhan, 2010; Eichengreen et al., 2010). At the urban level, the infrastructure of institutions and the associated social, political and market dynamics impose different conditions for peri-urban expansion. Chinese local governments possess institutional instruments to initiate, finance and drive new peripheral settlement that Indian local governments usually lack (Dobbs & Sankhe, 2010; L. J. C. Ma, 2002; Sankhe, 2011). Legal property rights, planning practices, and rights of democratic participation often provide protections for landowners and peri-urban citizens in India in ways that have remained limited in China (Han & Wang, 2003; Zhang, 2006-2007). Chinese residency restrictions, although recently partly relaxed, still impose constraints on movement of rural residents to the cities that are not present in India (Chan & Zhang, 1999).

To date, the growing communities of researchers who have examined urban development and its consequences within India and within China have rarely considered the implications of these differences. Increasingly, researchers have found remote sensing and GIS useful to describe changes in urban form in both China (Gaubatz, 1999; Seto & Fragkias, 2005; Yeh & Wu, 1996) and India (Sudhira, et al., 2004; Taubenböck et al., 2009). Remote sensing data offers more precisely identical yardsticks for comparative analysis than most types of census or economic data in developing country settings can provide. To date, however, even remote sensing studies of urbanization in the two countries have proceeded in mutual isolation. This reflects a more general deficiency in the application of these techniques. Alongside multiple local case studies that focus on a single country (Gaubatz, 1999; Seto & Fragkias, ibid.), it is now possible to find global studies that encompass remote sensing from a wide variety of world regions (Angel, et al., 2005; Huang et al., 2007; Schneider & Woodcock, 2008). Mid-level comparative designs built around testing country-level and subnational variations simultaneously remain almost entirely missing from this spectrum of approaches. This study seeks to demonstrate how this mid-level approach to comparative urban analysis can deliver new insights beyond the reach of either global or local analyses.

The next section of this article explains the methodological choices that framed the study. Next, we outline the metrics generated from the remote sensing data, and employ principal components analysis to summarize the main patterns in the metrics. A final section utilizes a canonical correlation analysis of the metrics along with main drivers of urban expansion to compare the transformations in urban form.

2. Methodology

With the rapid development of remote sensing technology, metrics derived from satellite images have become imperative tools for understanding the structure, function and dynamics of landscapes. Spatial metrics first developed to quantify patterns of vegetation in natural landscapes (Batty, 1987; O'Neill et al., 1988), and quickly proliferated (H. Li & Reynolds, 1993; McGarigal & Marks, 1994). Landscape metrics also provided precise tools to measure temporal change (Dunn et al., 1991; Frohn, 1998). The same metrics have been adapted to quantify the dynamics of landscape change associated with urban growth (Alberti & Waddell, 2000; Mesev et al., 1995).

A growing number of studies have employed metrics of this kind to measure aspects of urbanization in both China (E.g.,Seto & Fragkias, 2005; Xiao et al., 2006) and India (E.g., Sudhira, et al., 2004; Taubenböck, et al., 2009). For developing countries like China and India, where much of urban growth has taken place since the introduction of moderate resolution remote sensing technology in the 1970s, it is now possible to employ these metrics to describe and compare long-term national patterns of change in urban form. To arrive at such an analysis in this study required close attention to several methodological imperatives: 1) a comparative case design that enabled inferences about effects at the national as well as the urban level; 2) a series of remote sensing images, processed and classified according to a uniform protocol, at intervals that encompassed the main temporal transformations; and 3) a set of metrics sufficient to capture the main dimensions of variation in urban form.

2.1 Case selection

To analyze the consequences of the national differences fully, the study employed a design that focused comparison on diverse types of cities in both China and India. Following a quasi-experimental logic of matching similar observations in different countries (Rubin, 1973), the design produced a parallel series of nested comparisons between comparable sets of cities. The twenty urban regions selected for the analysis provided a parallel comparative overview of similar variations among urban trajectories within each country. The samples in each country were stratified by metropolitan size (Figure 3), foreign investment and regional settings.

[insert Figure 3 bout here]

First, the samples included both national capitals (Delhi and Beijing), and the other megacities (i.e., urban regions with populations of 10 million or more) of Shanghai in China, and Kolkata and Mumbai in India.

Regional urban centers with populations of 3.5 to 8 million comprised a second group. These included six of the ten next largest cities in China (Guangdong, Wuhan, Chengdu, Xi'an, Nanjing and Haerbin in China, and all five of the next largest cities in India (Chennai, Bangalore, Hyderabad, Ahmadabad and Pune).

A final group of cities ranging between one and three million in population (Hangzhou and Zhengzhou in China, and Bhopal and Coimbatore in India) extended the comparative sample to the smaller and mid-sized urban regions that contain a large proportion of the urban population in both countries.

Additional criteria enabled controls for a variety of economic and social variables. The selection also encompassed the urban regions with the most intensive foreign direct investment (Beijing, Guangdong, Nanjing and Shanghai in China, and Mumbai, Delhi, Bangalore, Pune, Hyderabad and Chennai in India) as well as ones with low levels (Chengdu, Xi'an and Haerbin in China and Ahmedabad, Bhopal, and Coimbatore in India). In each country, both the regional centers and smaller cities included some with population growth rates above the national average for cities over 1980-2005, and others with rates below average (Table 1). The urban regions in each country also spanned a variety of regional cultures, mixes of policy and planning strategies and topographies (Figure 1 and Figure 2).

[Insert Figure 1 about here]

[Insert Figure 2 about here]

2.2 Remote sensing images.

Images in four periods from the 1970s to 2010 were downloaded from the GLCF (Global Land Cover Facility) or the USGS (U.S. Geological Survey) (Table 1). Those missing from these two sources were collected from the China Remote Sensing Satellite Ground Station (CRSSGS) and the Indian Remote Sensing agency (IRS).

[insert Table 1 about here]

To enable a consistent basis for comparison, spatial consistency among various types of images had to be assured. Images from GLCF and USGS apply the UTM/WGS84 coordinate reference system (CRS), while those from CRSSGS use the Gauss-Kruger/Beijing 1954 system. To standardize the CRS, all images were re-projected into UTM/WGS84. Consistent resolution was critical for the computation of some spatial metrics, especially those measuring characteristics of the urban edge or boundary. To assure this consistency, MSS, TM, ETM images with divergent spatial resolutions were resampled into the same pixel size of 30 meters.

The urban regions were clipped according to the latest developed area, as indicated by the final images. To capture the peri-urban geography, the clipped images included a buffer of 10 kilometers beyond the latest line of development.[1] Four land use types were classified, including vegetation (e.g. forest, shrubbery, grassland and growing agricultural plants), urban area, water bodies, and others. For this purpose, bands 3,2, and 1 for MSS, and bands 4, 3, and 2 bands for TM and ETM in RGB were combined. The combination facilitated the differentiation of urban area, which appeared bluish-grey to steel-grey, from the non-urban

[1] For Guangzhou, continuity in the built-up fabric made it difficult to delineate an unambiguous border from other urban areas. This analysis therefore employs the administrative boundary for that city. Alternative tests with a border based on continuous settlement generated a much larger urban region than for any other city, but otherwise similar results.

area. Supervised classification of Maximum Likelihood was carried out with the same probability of 0.99 (i.e. value lower than this threshold was assigned into "other" type).

Image processing was implemented in ENVI 3.5, GRASS GIS and IDRISI. Afterwards, classified images were transformed into "shape" files, and introduced into ArcGIS or MapInfo Professional 10.0 for further analysis. Accuracy of the classifications was checked by means of a "confusion matrix" based on the interpretation of selected points in images from Google Earth for the latest image, then for each image from the subsequent image of the same area (Foody, 2002). Overall accuracy of the classifications for the 79 images was 83.6 percent, with a standard deviation of 10.3 percent.

2.3 Spatial metrics

Using the remotely sensed land cover data, spatial metrics were calculated to quantify patterns of spatio-temporal urban growth dynamics over the past four decades. As is well-recognized, a diverse assortment of metrics is necessary in order to describe urban form and its dynamics fully (Galster et al., 2001; Torrens & Alberti, 2000). The twenty-three metrics selected for this analysis captured the principal spatial property of urban form: area, shape, centralization, border definition and compactness or dispersion. Alternative metrics for each property enabled the analysis to capture a variety of distinct dimensions as well as to confirm overall patterns.

Area metrics measure the overall extent of the built-up areas, but also features of the built-up patches. The mean size of built-up patches, the size of the largest patch, and the density of patches in relation to the built-up area each indicate different dimensions of urban spatial consolidation or fragmentation (McGarigal & Marks).

Shape metrics describe variations in the shape of built-up patches. Based on the ratio of the patch perimeter to its area, the mean shape index and the normalized landscape shape index measure the regularity of patch shape (ibid). The coefficient of variation measures the how much the landscape shape varies among patches (ibid). Within this dimension we also include a metric for open space within the patches (Huang, et al., 2007).

Centrality metrics quantify the distance of the centroid of each patch from the center of the urbanized area (ibid), or the distance from the largest built-up patches (McGarigal & Marks).

Metrics for *edge complexity* describe the border between built-up areas and the other classifications. In various ways, these metrics quantify the length and distribution of these edges. Edge density provides a standardized measure of the length of urban patch edges throughout the landscape (ibid). The mean patch fractal dimension provides a fractal measure that ranges higher the more complex the edge (ibid). We include an area-weighted version of this measure, along with a measure of the variance in it.

A final set of metrics measure *compactness and dispersion*. These metrics assess the overall configuration of urban patches. Compactness, applied to the largest patch as well as to patches in general, measures the how far patches converge toward a circular shape that makes any point within a patch closer to others within the patch (X. Li & Yeh)**.** A revised Compactness Index designed by Li and Yeh (ibid) controls for bias due to large numbers of small patches an opposite cross national contrast. The Euclidean Nearest Neighbor index measures the dispersion between each patch and others(McGarigal & Marks). Clumpiness describes how far patches tend to be grouped together in the landscape.(ibid)

3. Results & Discussion

Analysis of the patterns began with comparative examination of individual metrics. A principal components analysis examined relations among similar metrics, and summarized the tendencies in each distinct dimension of urban form. In the final stage, a canonical correlation analysis explored the relationship between the consolidated metrics for each dimension and major sources of variations in urban form. At each stage, the analysis confirmed major divergences between Chinese and Indian trajectories of urban spatial expansion.

3.1 Visual inspection

Image processing produced clear pictures of the overall progression of built-up areas in all ten cities. Visual inspection of these images suggests a number of consistent patterns in trajectories of urbanization, both within and between the two countries.

The contrasts between Chinese and Indian urban form were striking even in the 1970s, when peri-urban patterns in both countries reflected the dominance of rural settlement. In China since 1948, collectivization of landed property, the institution of work units as the basis of social and economic organization, restrictions on migration, the consolidation of traditional villages and the institution of legal divides between rural and urban territories had produced a centralized, clearly demarcated urban form (Knapp & Shen, 1992). With the partial exception of Beijing, urban areas clustered tightly around a few densely built-up nodes. Agricultural lands and occasional clusters of village settlements dominated the periphery beyond the urban border.

[insert Figure 4 about here]

Indian cities of the 1970s reflected the traditional and postcolonial patterns of development there (Figure 5). The urban cores of the cities typically remained quite small. Around them, settlement appeared comparatively fragmented and interspersed with undeveloped spaces. In outlying areas that would become dominated by peri-urban dynamics, small landholders and laborers populated a dense network of small villages (E.g., Qadeer, 2000; Singh, 1968). Especially in smaller urban regions like Bhopal and Coimbatore, no clear line of demarcation separated rural from urban settlement.

[insert Figure 5 about here]

The rapid spatial expansion of the larger Chinese cities began in the 1980s following the initial economic reforms. The superimposed multi-temporal images of urban settlement show a steady, remarkably symmetrical progression outwards over each decade. The distinctive pattern of urban spatial expansion appears closely related to the domination of local land markets by local governments, and the emergence of land rents as a primary means of local public finance (Zhu, 1999). Up to the 2000s, development proceeded in large, continuous blocks in nearly every direction out from the central core. In the regions surrounding coastal cities of Beijing, Shanghai, Guangzhou, where national and local governments had mobilized to bring in foreign investment, the expansion of developed land was especially spectacular. By the late 2000s the built up areas in these regions extended throughout most of the landscape area (Figure 5). Over this decade, following partial liberalization of property and migration restrictions, new development followed more fragmented and dispersed patterns than before.

In the Indian cities, the most rapid peri-urban expansion followed the economic liberalization and decentralization of the early 1990s (Shaw & Satish, 2007). Over the 1980s, a tight band of new development had already appeared around several larger Indian cities (Delhi, Bangalore, and Ahmedabad) (Figure 5). In the 1990s new construction advanced out narrow transportation corridors, and small settlement clusters proliferated throughout the peri-urban regions of most cities. Over the final decade, infill development in some regions accompanied a general process of growing dispersion. Throughout the study period, the largest cities (Delhi, Mumbai and Kolkata) clearly experienced less extensive expansion than their Chinese counterparts.

3.2 Patterns in the metrics

Comparison of spatial metrics confirms markedly different trajectories of urbanization in China and India, as well as between different cities in each country. The different institutional and policy conditions of property markets, combined with contrasts in the preexisting structures of settlement, have brought about major cross-national contrasts in the shape of urban built up areas. Application of principal components analysis to the multiple metrics designed to capture each dimensions of urban form generated more precise comparative metrics for understanding how each dimension has varied. This analysis in turn produced a set of indicators for an assessment of the drivers of peri-urban change.

3.2.1 Urban extent

Simple figures on the urbanized area point to a major difference between the expansion of the largest Chinese urban regions with the strongest outside investment, and similar processes in both other Chinese cities and in their Indian counterparts (Figure 6). In Shanghai, Guangzhou, and Beijing, and to a lesser extent in the smaller coastal city of Hangzhou, the expansion of the built up area has proceeded at a pace that outstripped those elsewhere. In India, expansion of the urban area remained more limited in the bigger as well as the smaller cities. Only Delhi as the national capital, and in the last decade Bangalore, expanded at rates that stood out. Principal components analysis of the urbanized area in hectares and the urbanized proportion of the landscape produced a single component that loaded at .95 for both, and explained 90 percent of the variation (Table 2).

[insert Figure 6 about here]

[insert Table 2 about here]

3.2.2 Other area metrics

Other metrics of area for the built-up zones revealed more consistent contrasts between Chinese and Indian urban form, and helped to capture the sources of the more dramatic land expansion in the Chinese urban areas.

As the built up areas of most Chinese cities expanded over the study period, the model of state-led development concentrated development even more in large blocks of land. From the state socialist period, urban development produced much larger average built-up patches in most cities than in even the biggest Indian urban regions (Figure 7). Except in Chengdu and Wuhan, the built-up area in this era also concentrated more in the largest urban patch, which included the urban center, than in nearly every Indian city (Figure 8). Mean patch size grew in most Chinese cities, even as the largest patch generally occupied less and less of built-up land. In Beijing and Guangzhou, some consolidation into the largest patch marked the period after 2000.

[insert Figure 7 about here]

[insert Figure 8 about here]

In India, the small village centers of the surrounding rural region dominated the regional landscapes of the 1970s. Despite limited growth in mean patch size in the largest two urban regions (Delhi and Mumbai), the contrast with the large average patches of the Chinese urban regions persisted into the 2000s. In contrast with the expansion by large blocks in China, much of peri-urban growth in India took the form of proliferating small patches. Especially outside the largest Indian urban regions, small outlying settlements like these increased dramatically up to 2000 (Figure 9). An overall measure of patch density, or the concentration of patches in relation to the landscape remained consistently lower in the Indian settings.

[insert Figure 9 about here]

At the same time, especially following liberalization in the 1990s, the growth of the largest built up patches in most Indian urban regions reveals a process of consolidation and infill development that was also at odds with the trends in China (Figure 7). As the largest patches in the Chinese cities made up a shrinking portion of the expanding built-up land, the largest patches of most Indian cities grew to encompass more and more of it. By 2010 the proportion of built-up pixels in the central patch had converged between the two countries, and the proportion in Bangalore exceeded the levels in most Chinese cities.

State-dominated development in China had clearly enabled peri-urban land to be developed in larger blocks than in India, and had pushed development more consistently beyond the largest patch. The single component generated through principal components analysis, designated "Patch Concentration," captured 51 percent of the variance, and loaded at .5 or more in the expected direction on each metric (Table 3).

[insert Table 3 about here]

3.2.3 Shape

Systematic contrasts between Chinese and Indian patterns also marked the shape of urban patches. The larger patches of the Chinese built-up areas consistently assumed a more irregular shape.

The Mean Shape Index (MSI), a measure of complexity in relation to a perfectly round shape, showed an increase in Chinese cities as the complexity in Indian cities remained much lower (Figure 10). An area-weighted version of this index revealed this to be largely a consequence of the more rounded smaller urban patches that predominated in India. Area-weighted patch shape complexity remained generally higher among the Chinese cities in each size class than in the Indian cities. With the size of patches controlled, however, the largest, most rapidly growing cities of both countries registered greater shape complexity than others

(Figure 11). The Normalized Landscape Shape Index (NLSI) further highlighted the disaggregation of built-up areas in the Indian urban regions, especially the smaller and midsized ones (see Appendix).

[insert Figure 10 about here]

[insert Figure 11 about here]

Principal components analysis of all five area metrics (Table 4) yielded two components. The first, designated "Shape Irregularity," accounted for 63 percent of the variance. This component loaded positively at .68 or more on both the mean and the area-weighted mean versions of the shape index, and on the ratio of open space. Since it also loaded negatively on the NLSI (-.69), and positively on variation in patch shapes (.93), the component captured both more aggregated shapes and more systematic variation in patch shapes. A second component, accounting for an additional 22 percent of the variance, corresponded to shapes that were more regular (-.63 loading for the MSI) and more aggregated (.49 for the NLSI), but that still contained more open space within patches (.58 for the Ratio of Open Space (ROS)). We will refer to this component as "Shape Consolidation".

[insert Table 4 about here]

3.2.4 Centrality

A further set of metrics measured the centralization of urban patches and the distances from the largest (usually the central) urban patch. Area-weighted and unweighted versions of these metrics generated very similar results. In this set of metrics as well, trajectories of Chinese urban land expansion contrasted with Indian patterns.

As measured by both versions of the centrality index, Chinese cities remained highly centralized throughout the study period (Figure 12). Instead, the networks of village settlement surrounding the smaller Indian cities in the 1970s registered the greatest decentralization. By this measure, urban form in the Indian cities had converged toward the values in the Chinese and the larger Indian urban regions.

The measures of distance from the largest patch, however, reflected the growing spread of most Chinese cities (Figure 13). Especially in Guangzhou and Shanghai, but also in several other smaller and mid-sized cities, the distance to the largest patch grew steadily after 1990. These trajectories contrasted starkly with the relative consolidation in most Indian cities. In Mumbai, Chennai, and Pune as well as in the smallest cities, infill development and growth closer to the urban center had brought about more consolidated settlement.

[insert Figure 12 about here]

[insert Figure 13 about here]

Principal components analysis generated two distinct components that accounted for 90 percent of the variance in these metrics (Table 5). One, the most consistent measure of Centrality, loaded significantly (.59 or better) on all of the metrics, but especially heavily on the two centrality metrics (.84 or higher). This component comprised 54 percent of the variance. The second corresponded to greater average distance from the largest patch (with loadings of at least .68), but to lower centrality (loadings of -.48 or lower). This component encompassed 37 percent of the variance.

[insert Table 5 about here]

3.2.5 Edge complexity

Differences in the border between urban and nonurban land types accompanied these cross national contrasts in the shape of urban settlement. In Chinese cities, the fractal measure of the complexity in the border between urban and nonurban land uses showed highly consistent levels that rose over time (Figure 14). These values appear related to national rules for peri-urban development, such as requirements to reserve a portion of land for agriculture in newly developed peripheral areas (Bertaud, 2007).

[insert Figure 14 about here]

In the Indian urban regions, by contrast, the complexity of the urban boundary was both lower and differed more widely. It remained lowest in the smaller urban regions of Bhopal and Coimbatore, where small village patches continued to dominate the landscape. In the more economically dynamic urban regions of Delhi, Mumbai and Bangalore, the complexity of the boundary rose to levels approaching the uniform values in the Chinese urban regions. Boundaries in most Indian cities began the 1970s with much less complex urban boundaries than in Chinese cities, but grew more rapidly in complexity over this time.

Metrics for the complexity of the border between urban and nonurban uses also included a measure of the variation in this index between patches in a landscape, and a measure of edge density in relation to the built-up area (Table 6) (see Appendix). A single component that loaded at .6 or more on all three of the metrics demonstrated the correspondence between them. This component, labeled "Edge complexity," accounted for nearly 57 percent of all the variance in the metrics (Table 6).

[insert Table 6 about here]

3.2.6 Compactness and dispersion

The simple compactness index that measured the dispersion of the landscape as well as individual patches produced consistently higher values for all the Indian cities than in any of the Chinese cities (Figure 15). The revised Compactness Index designed by Li and Yeh (2004) to control for bias due to large numbers of small patches produced an opposite cross national contrast (Figure 16). With the control for small exurban patches, somewhat higher compactness marked most Chinese urban regions. Clumpiness, another measure of relative dispersion across the landscapes, also showed consistently high values in all the Chinese regions (Figure 17). Only in the largest and fastest growing Indian urban regions did the values for this index approach the uniform levels in China.

[insert Figure 15 about here]

[insert Figure 16 about here]

[insert Figure 17 about here]

Along with these three metrics, the principal components analysis of dispersion included a measure of compactness for the largest patch, average and area-weighted indicators for Euclidean Nearest Neighbor Distance, and the coefficient of variation for the latter (Table 7).

Two subtly distinct components accounted for 76 percent of the variance in these metrics. A component labeled "Clumpiness", encompassing 43 percent of the variance, corresponded most positively to the Clumpiness index and to variation in the Euclidean Nearest Neighbor Distance, but also loaded negatively on the first compactness index. The second component, designated "Compactness," corresponded to high levels of compactness according to the revised index, along with compactness of the largest patch. Compactness as measured by this component also went along with greater dispersion among the patches as measured by Euclidean distance. The component accounted for a further 33 percent of the variance.

[insert Table 7 about here]

3.3 Overall patterns and drivers of urban developmental trajectories

As measures of the diverse dimensions of the built up areas over time, the metrics provide the first fully systematic overview of the contrasts and similarities in Chinese and Indian urban development trajectories. Canonical correlation analysis (CCA) offers a method to summarize the relationships among the dimensions of urban form, and explore their relation to national and other sources of urban dynamics. The analysis underscores the important national contrasts in these trajectories, and simultaneously reveals variations common to the dynamics of urban expansion in both countries.

CCA is particularly suited to examination of relationships between a set of intercorrelated dependent variables and another set of intercorrelated independent variables. Although CCA is generally considered unreliable when the number of variables is large in relation to the number of observations, the principal components analysis reduced the ratio (5.6) to a level within the range of existing published studies (Weinberg & Darlington, 1976). Cross-validation also employed partitioned training and test samples from the same dataset to confirm the results of the full sample (see Appendix 2).

Alongside a dichotomous variable to test for overall differences between Chinese and Indian patterns, the analysis focused on two well-established drivers of peri-urban expansion. Population growth is intrinsic to urbanization, although urban land expansion has frequently outstripped increases in urban population (Seto, et al., 2011). The measure of population here employed United Nations estimates of growth in each urban agglomeration (United Nations, 2009).[2] Foreign direct investment (FDI) in a region indicates the mobilization of domestic governments and firms as well as foreign business enterprises around peri-urban expansion (E.g., Gaubatz, 1999; Kennedy, 2007). Measures of FDI came from official city-level figures in the Chinese *City Yearbooks*, and annual figures on new projects by region in the CapEx Database (Center for Monitoring the Indian Economy, 2011).[3]

The canonical correlation analysis included these three indicators as explanatory variables, and the summary metrics from the principal components analysis as the dependent variables. Analysis of the full and the two partitioned datasets yielded very similar results. Each of the three canonical correlations produced registered as significant in f-tests (Table 8). Redundancy tests showed the three variates in the analysis to account for 53 percent of the

[2] Although based on official national statistics, the U.N estimates reflect an attempt to assess population growth in the contiguous urban area rather than within central urban jurisdictions only.

[3] The analysis utilized cumulative totals for FDI over all available years. Within each country, FDI figures were standardized to reflect a similar scale of variation.

overall variance in the metrics. The first and second correlated variates explained 97 percent of this variance.

[insert Table 8 about here]

The first, unmistakably a measure of national differences, accounted for the largest proportion of variance in the metrics (35 percent). Correlations of the consolidated metrics with these canonical variates confirmed systematic differences in urban form between the Chinese and Indian cities (Table 9).

Measures for Patch concentration (.88) and Clumpiness (.84) correlated most strongly. Shape Consolidation correlated at .65, and Shape Irregularity at -.64. Edge Complexity was also higher (.53). Chinese cities were also more extensive than the comparable Indian ones (.56).

[insert Table 9 about here]

These effects from cross-national differences amounted to more than a legacy of pre-existing settlement patterns. Comparison of the city scores over time showed that the differences generally grew over 1980-2000, as Chinese cities mobilized around urban land expansion (Figure 18). After 2000, the trends suggest a degree of convergence. In six of ten Chinese cities, falling scores along this dimension indicate shifts toward less clumpy, more small-scale, less extensive development. In Indian cities like Delhi, Bangalore, Pune, Chennai, and Ahmedabad, development shifted over the same period toward more concentrated, more extensive, clumpier, and more spatially irregular forms.

[insert Figure 19 about here]

Although the national differences in urban form persisted even into this last period, the second set of canonical variates affirms significant commonalities in the evolving urban form of the two countries. Numerous differences in the consolidated metrics correspond to larger or expanding population (.77) and higher levels of foreign direct investment (.59).

Bigger cities with more foreign investment extend further (.47); display more complex (.52) and irregular (.49) urban shapes; exhibit greater edge complexity (.49) and less compactness (-.53); and extend further from the largest patch (.55). Although these relationships generally proved less consistent than those corresponding to national differences, cross-validation confirmed most of them. Comparison over time confirms that these relationships were largely the result of trends common to most urbanizing regions (Figure 19). Although the relationship remained constant over time among Indian cities, it grew stronger after 1990 in China.

[insert Figure 19 about here]

This analysis confirmed numerous broad dimensions of contrast between the patterns in India and China. For the three decades after the 1970s, despite equivalent population growth, urban land in the Chinese cities expanded more. Even more systematic cross-national contrasts in other dimensions of urban form confirmed that this difference was linked to the way peri-urban expansion took place. Patch Concentration, Clumpiness, Shape Irregularity, and Edge Complexity also ranged systematically higher in Chinese cities. In both countries, foreign direct investment and population growth also correlated with several components of urban form. Development patterns linked to both corresponded to greater expansion out from the urban center, greater distance of patches from the largest patch, greater edge complexity, and greater shape irregularity.

4. Conclusions

The ongoing urban revolution in China and Indian stems from parallel trajectories of land market liberalization, industrialization, population migration and peri-urban expansion. Despite the many similar circumstances surround this process, urbanization has proceeded in highly distinctive ways in each country, and continues to produce and reproduce divergent urban forms. Each society entered the era of rapid urban expansion with different legacies from previous political regimes, policies and practices. In the first decades after 1970, different social, institutional and policy conditions brought about growing divergences in the process of urban spatial transformation. Only in the most recent period is it possible to observe a limited convergence between the national patterns of peri-urban growth.

In China, a variety of institutional, social and economic conditions that have set distinctive terms of peri-urban development from those in India. The macro-level comparative perspective of this study for the first time makes it possible to assess the wider consequences of these differences for peri-urban development. The results demonstrate how the state-dominated development process has in certain circumstances created powerful growth machines that have driven peri-urban expansion far beyond the extent evident in India. Urban land expansion in China has perpetuated concentrated but sprawling, systematically complex and irregularly shaped urban forms. These consequences have proven especially dramatic in the larger and coastal cities, where economic growth has been most dramatic, but have increasingly characterized inland cities as well. These patterns reflect widespread inefficiencies in land use that have been the object of numerous critiques (E.g., Bertaud, 2007) and recent attempts at reform (Ho, 2005).

In India, many of the same influences have driven peri-urban expansion. But the different conditions of urban development there have left peri-urban development a more fragmented, piecemeal, and privatized process. Despite equally dramatic growth in urban populations, the built up areas of Indian cities have expanded significantly more slowly than Chinese counterparts. Greater compactness, less irregularity in shape along the urban border, and retention of small rural village centers in the exurban periphery mark the overall Indian patterns of peri-urban development. In urban regions of greater sprawl, such as Bangalore and Delhi, intensification and infill development have matched and even counterbalanced ongoing expansion.

Further analysis at the micro-level remains necessary to explore the mechanisms that have produced these divergent trajectories. The present analysis provides an empirical and analytical bridge between this ongoing work and more global conclusions. These findings underscore the major differences that national institutions, economies and cultures make for the global dynamics of urbanization.

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Figures

Figure 1. Selected Chinese cities

Figure 2. Selected Indian Cities

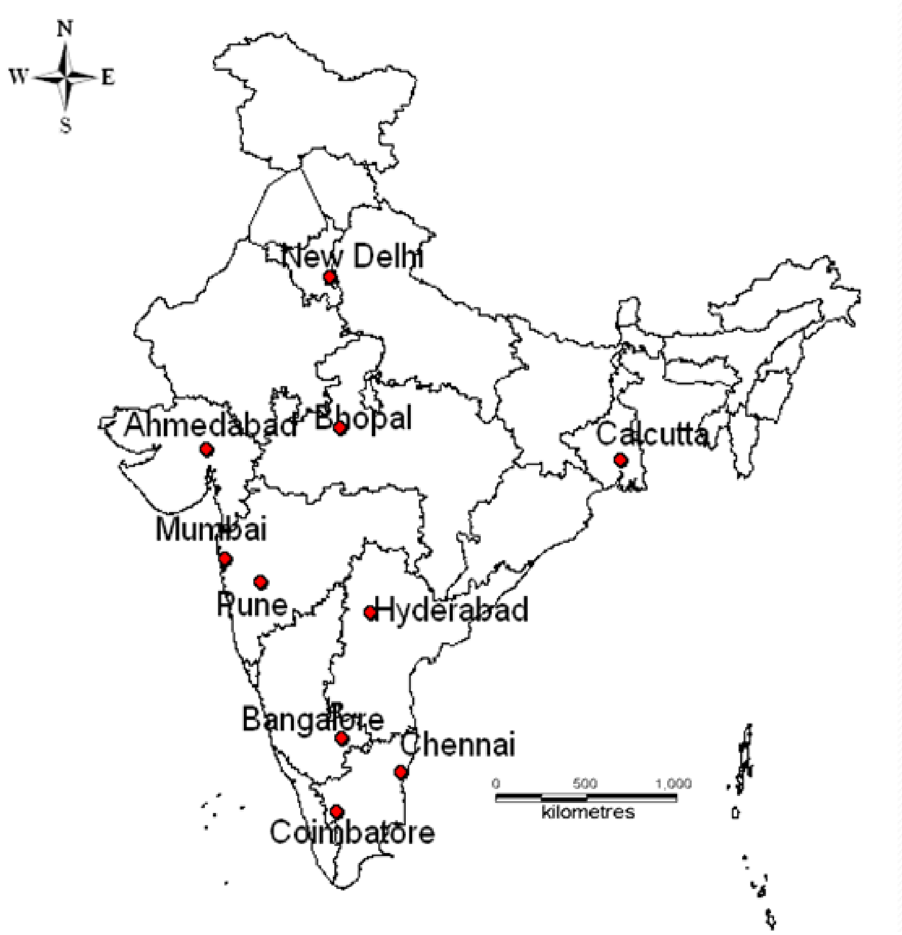
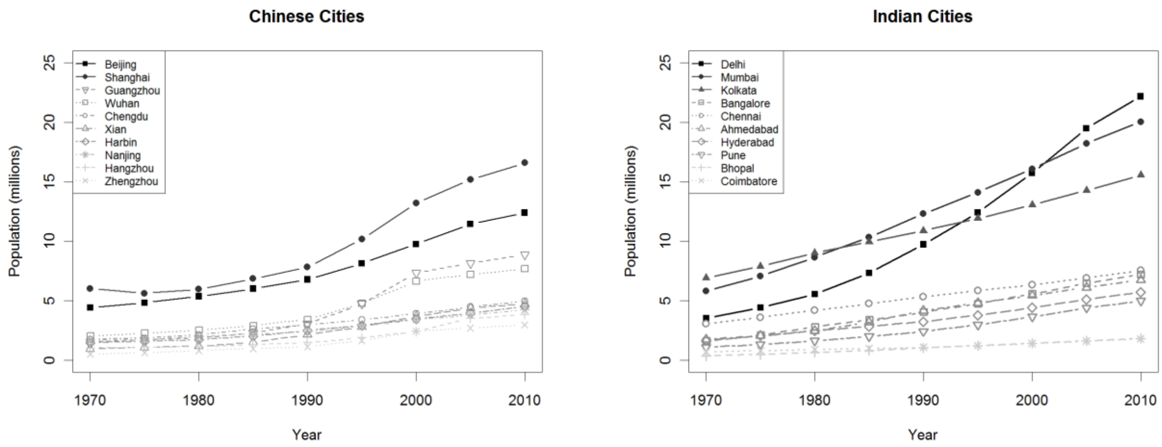


Figure 3. Population growth in selected urban agglomerations, 1970-2010



SOURCE: (United Nations, 2009)

Figure 4. Progression of urbanization in Chinese cities, 1970s-2000s

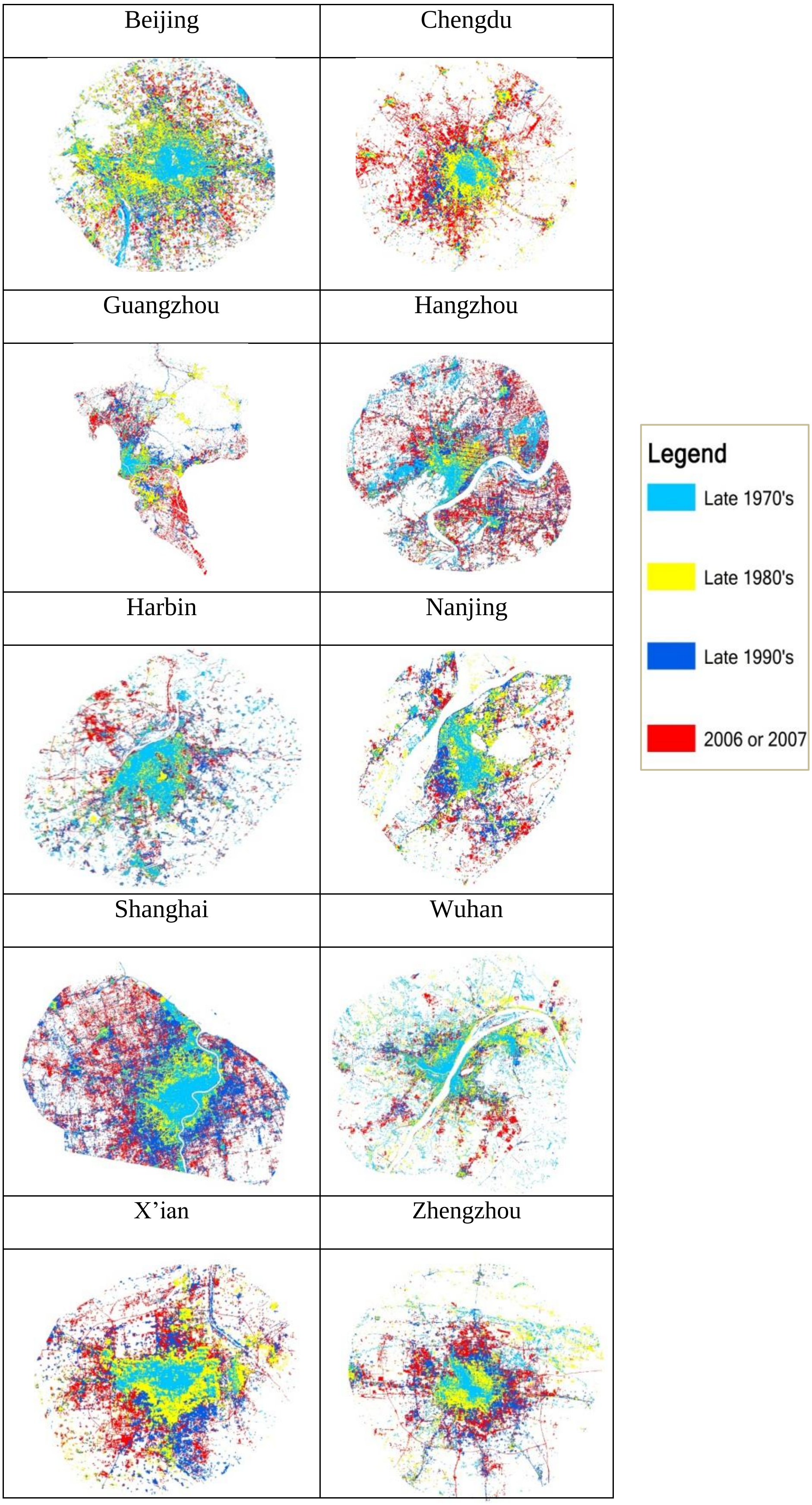


Figure 5. Progression of urbanization in Indian cities, 1970s-2000s

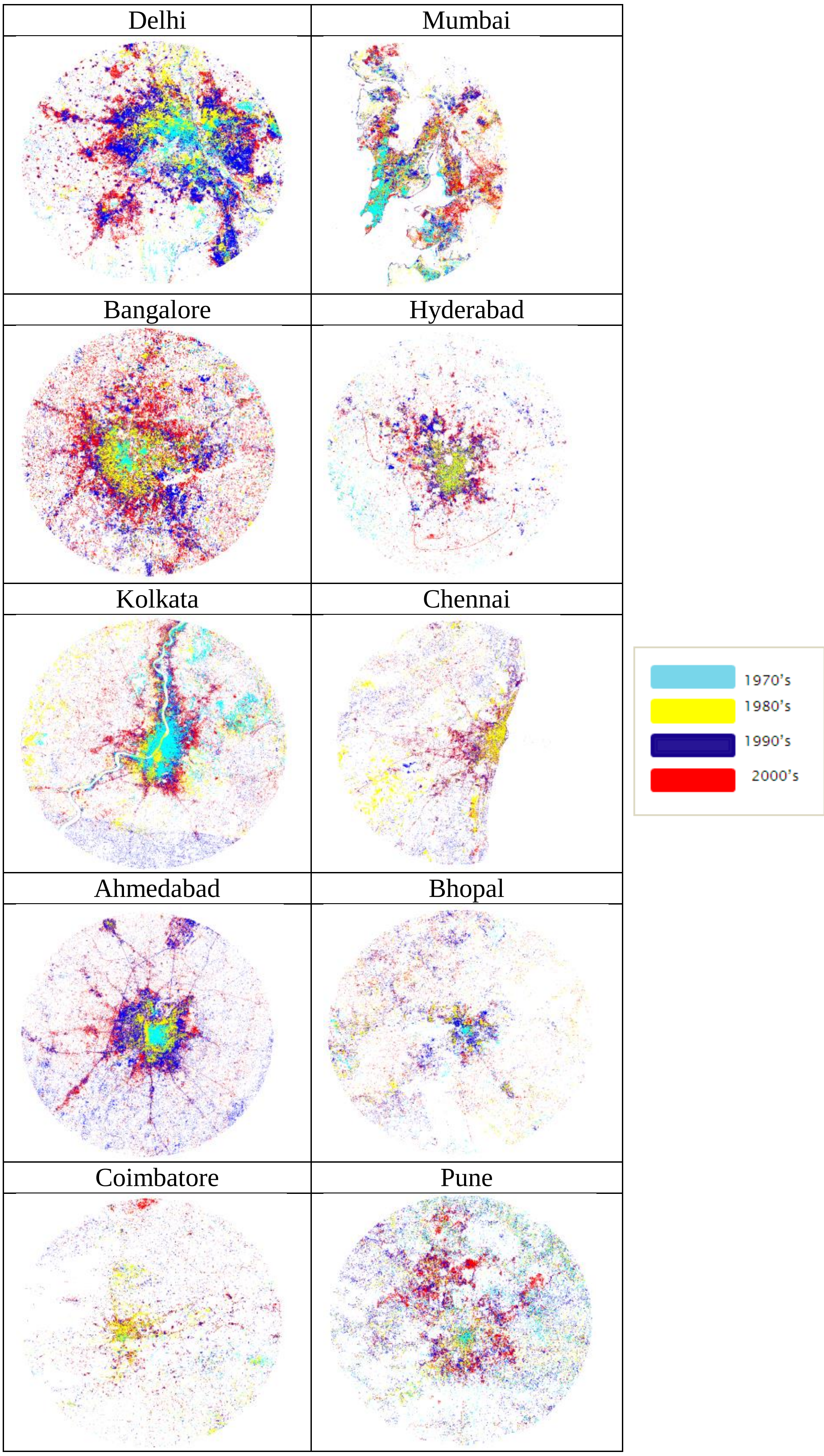
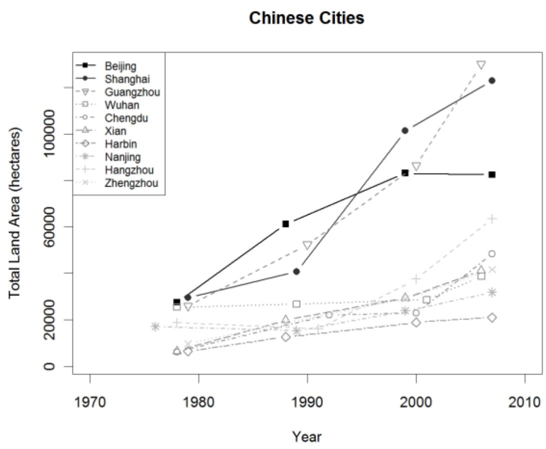


Figure 6. Urbanized area (hectares)



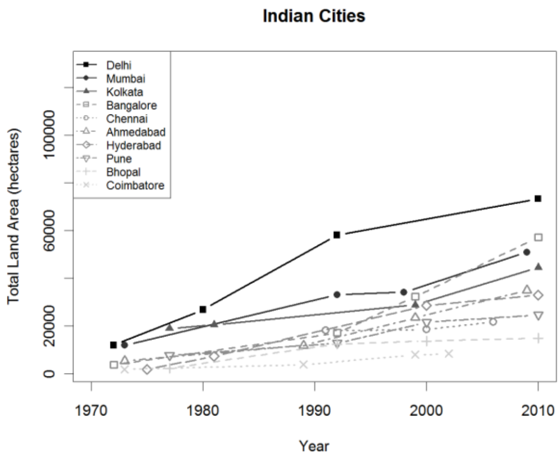
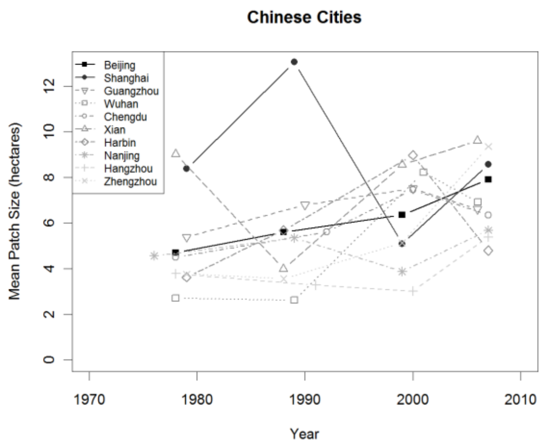


Figure 7. Mean patch size (hectares)



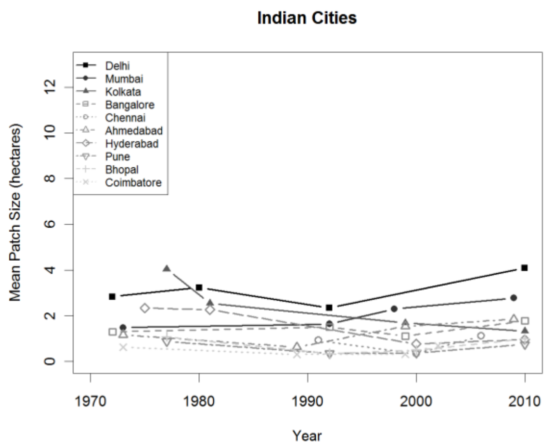


Figure 8. Largest patch index (percent of built up area)

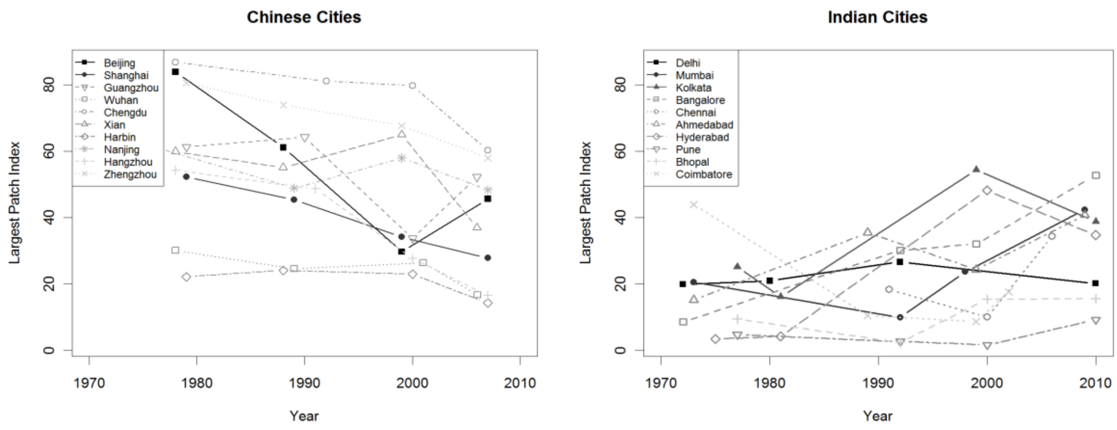


Figure 9. Number of Patches

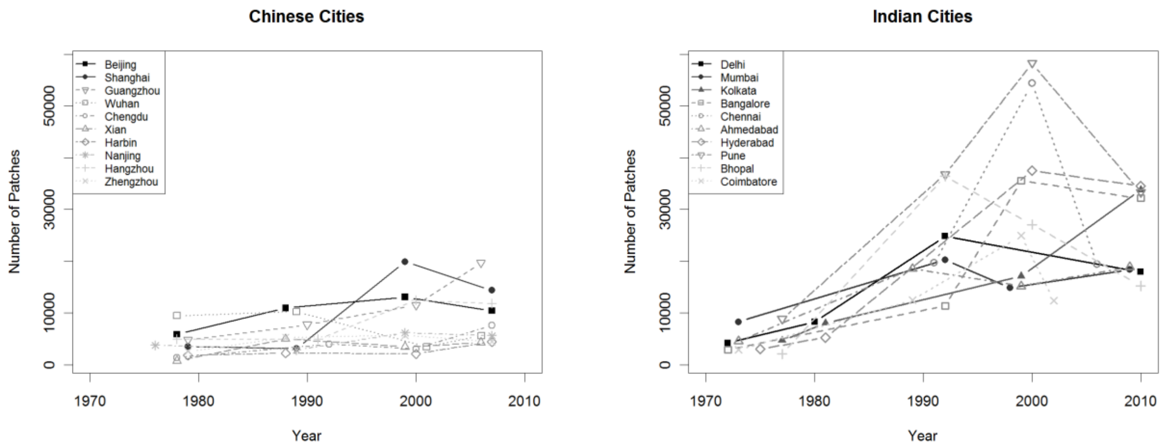


Figure 10. Shape of Patches (Mean Shape Index)

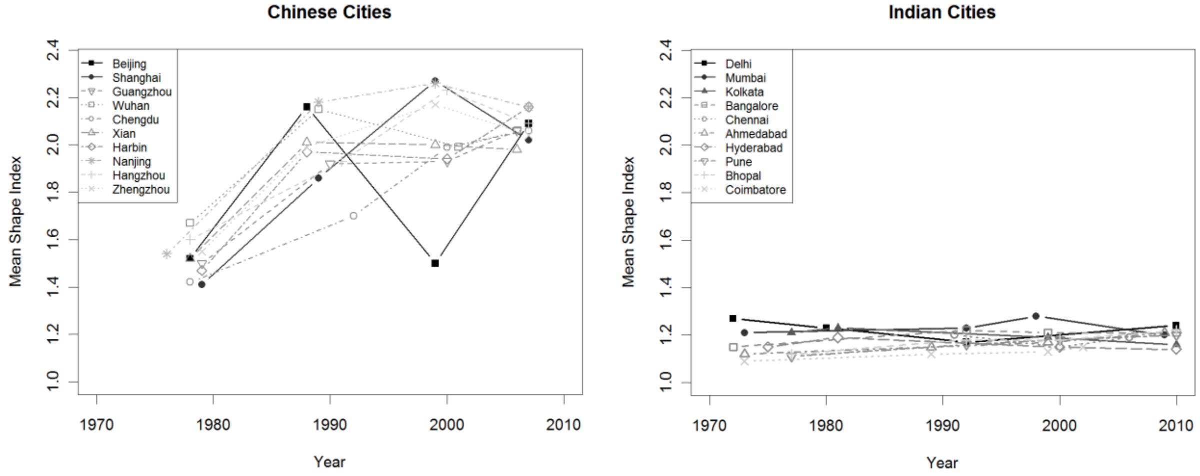


Figure 11. Shape of Patches (Area weighted mean shape index)

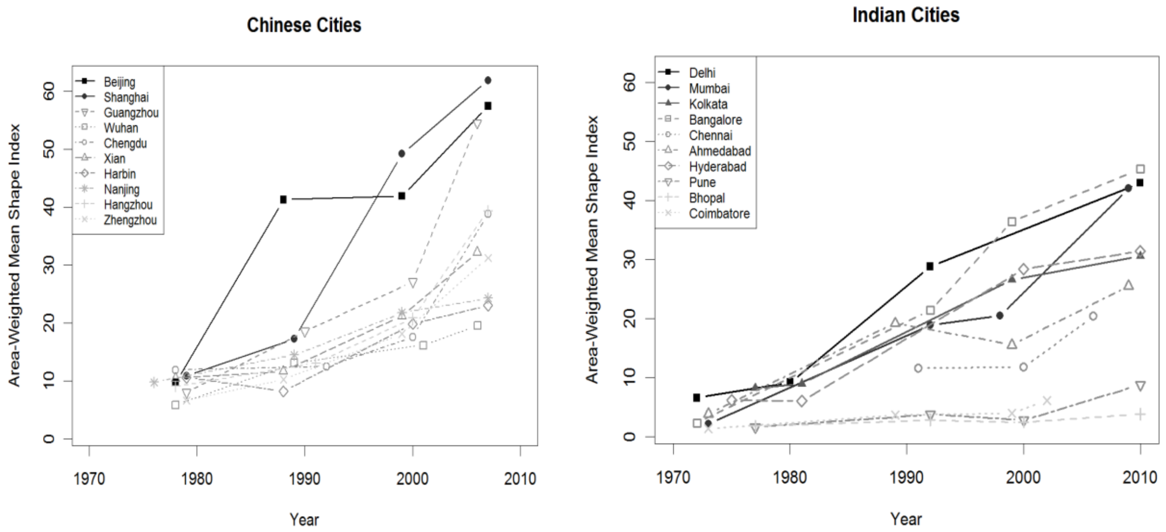


Figure 12. Centralization index (Area weighted)

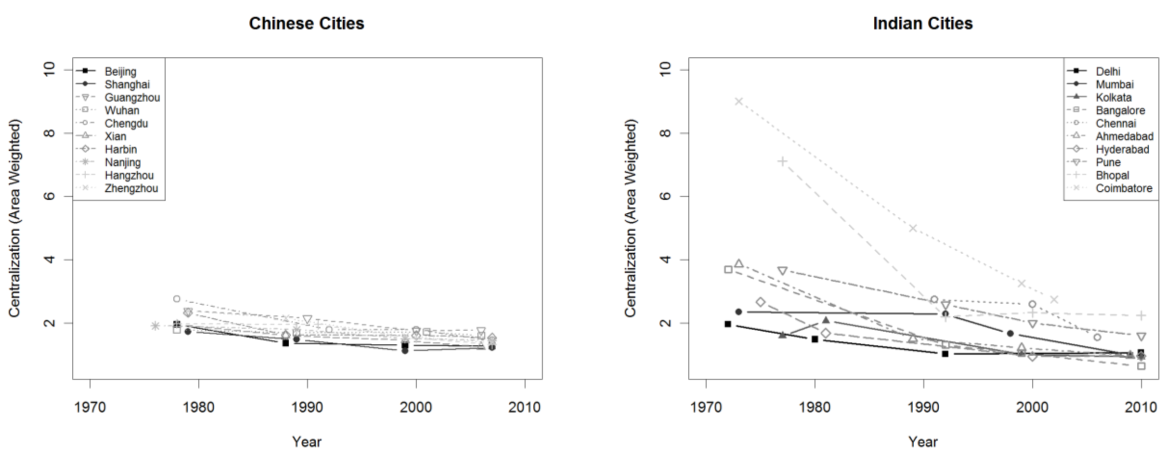


Figure 13. Average distance from largest patch (Area weighted)

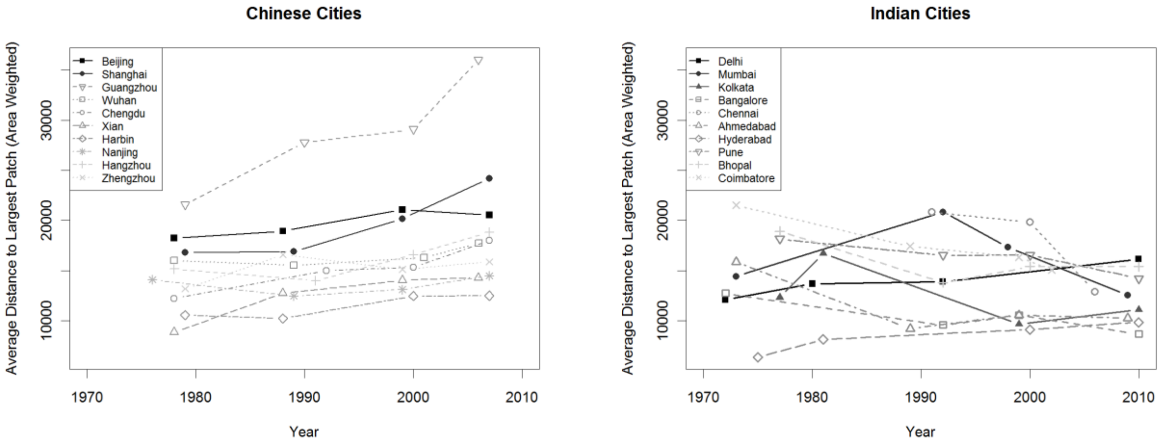


Figure 14. Complexity of urban/nonurban border (Area weighted mean patch fractal index)

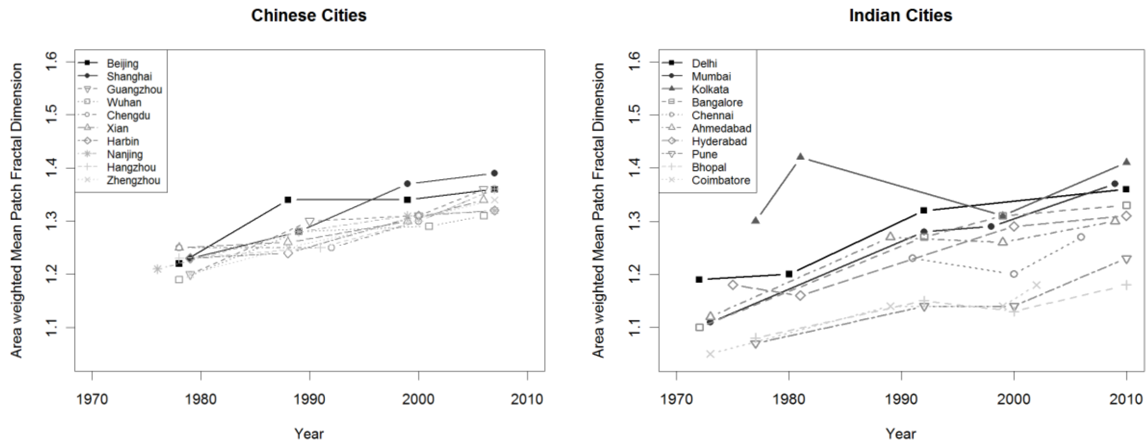


Figure 15. Compactness Index

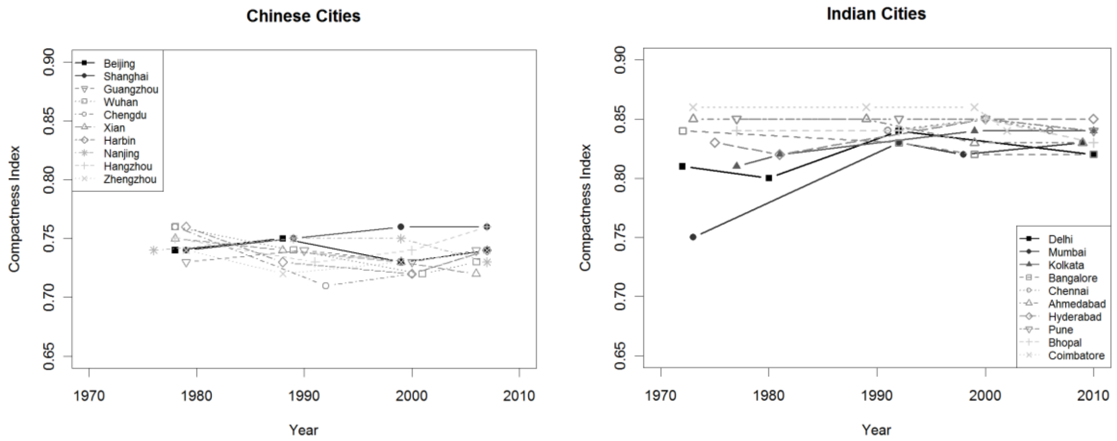


Figure 16. Revised Compactness Index

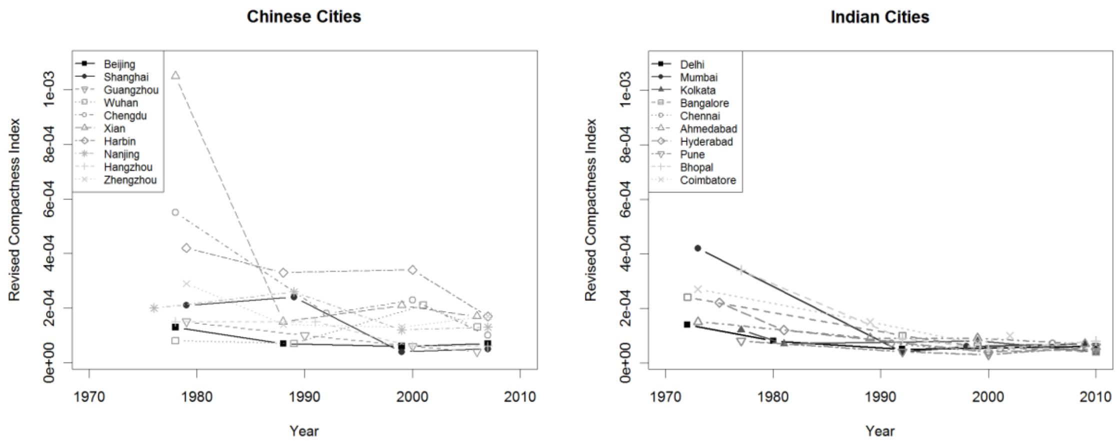


Figure 17. Clumpiness Index

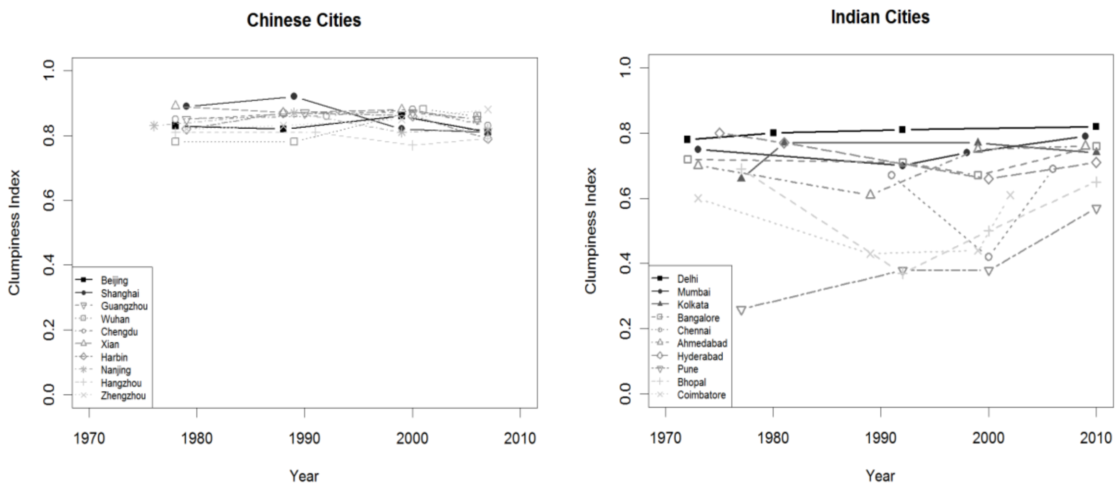


Figure 18. Weights for correlate one (national differences), by year of observation

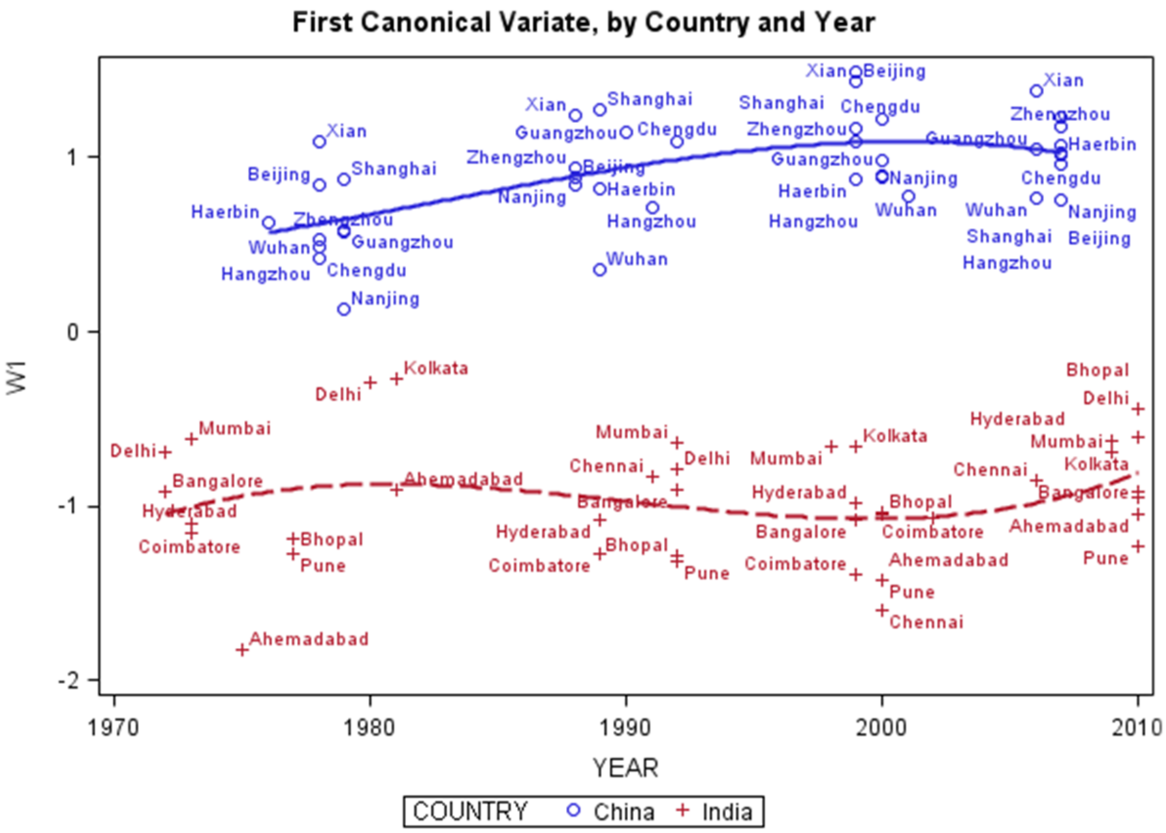
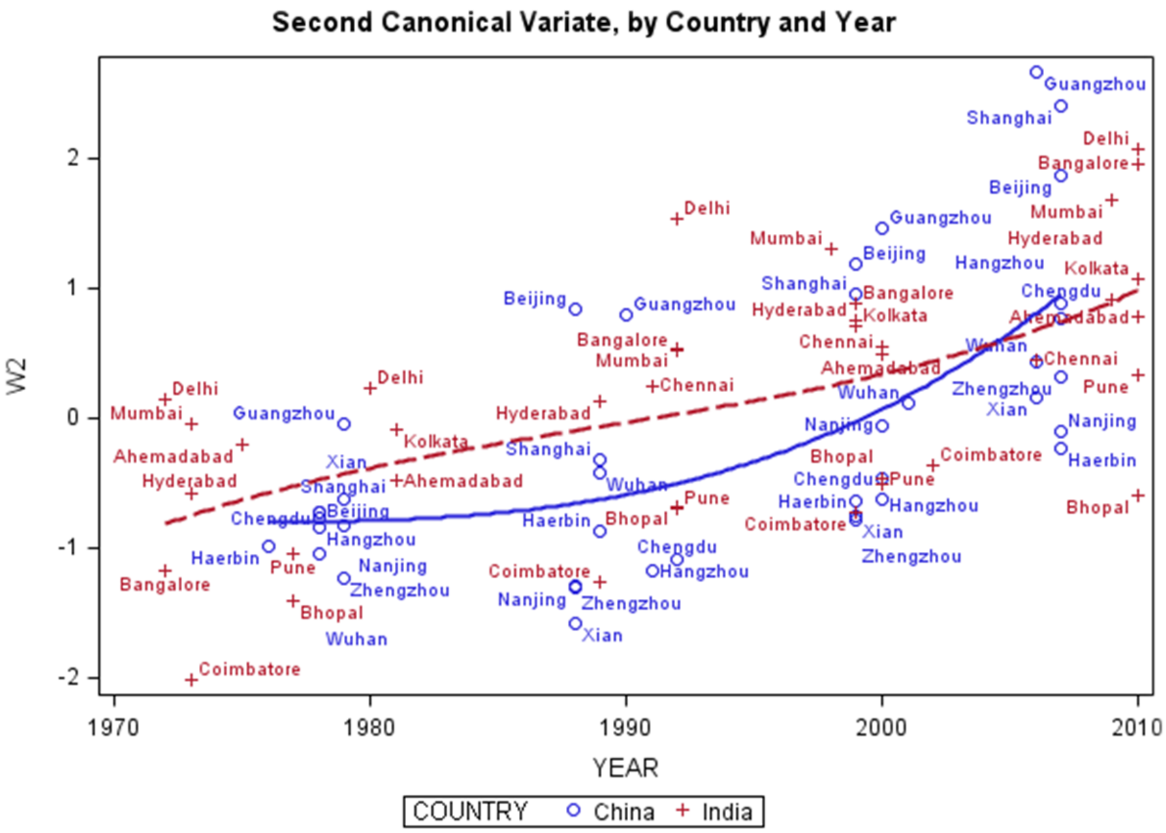


Figure 19. Weight for canonical w2, by year and observation



Tables

Table 1. Downloaded images

	1970s	Late 1980s - early 1990s	Late 1990s - early 2000s	2000s
Chinese cities				
Beijing	9/20/1978	12/15/1988	8/2/1999	5/28/2007
Chengdu	8/21/1978	8/16/1992	11/2/2000	5/6/2007
Guangzhou	10/19/1979	10/13/1990	9/14/2000	11/10/2006
Hangzhou	7/5/1978	7/23/1991	10/11/2000	3/29/2007
Harbin	8/28/1976	9/12/1989	10/18/1999	8/29/2007
Nanjing	8/6/1979	7/5/1988	9/16/2000	7/26/2007
Shanghai	8/4/1979	8/11/1989	11/3/1999	7/28/2007
Wuhan	10/16/1978	2/11/1989	7/22/2001	8/29/2006
Xi'an	8/19/1978	8/23/1988	8/14/1999	8/9/2006
Zhengzhou	5/21/1979	5/14/1988	11/29/1999	5/19/2007
Indian cities				
Ahmedabad	2/14/1975	10/19/1990	4/12/2000	2/3/2010
Bangalore	2/27/1973	1/14/1992	2/2/1999	2/8/2010
Bhopal	1/30/1977	10/3/1992	19/2/2000 16/4/2000	4/12/2010
Chennai	NA	8/25/1991	2/7/2000	1/30/2006
Coimbatore	9/2/1973 10/2/1973 7/2/1973	11/21/1989	11/9/1999	12/3/2002
Delhi	3/8/1977	1/7/1980	9/24/1992	2/14/2010
Hyderabad	2/27/1973	11/21/1989	4/7/1999	9/9/2009
Kolkata	1/17/1980	11/14/1990	11/15/1999	2/22/2010
Mumbai	1/9/1973	11/9/1992	4/15/1998	12/10/2009
Pune	9/25/1977	12/4/1992	3/29/2000	3/25/2010

Table 2. Principal components analysis, urban extent

Total Variance Explained			
Component	Initial Eigenvalues		
	Total	Percent variance	Cumulative percent
1 (Extent)	**1.8**	**90.3**	**90.3**
2	.2	9.7	100.0

Component Matrix	
	Component
	1
Built-up land (percent)	.950
Total built up land area (hectares)	.950

Table 3. Principal components analysis, other area metrics

Total Variance Explained			
Component	Initial Eigenvalues		
	Total	Percent variance	Cumulative percent
1 (Patch Concentration)	**2.06**	**51.4**	**51.4**
2	.95	23.8	75.3
3	.64	16.1	91.4
4	.35	8.6	100.0

Component Matrix	
	Component
	1
Mean patch size	.880
Number of patches	-.729
Largest Patch Index	.703
Patch Density	.507

Table 4. Principal components analysis, shape metrics

Total Variance Explained			
Component	Initial Eigenvalues		
	Total	Percent variance	Cumulative percent
1 (Shape Irregularity)	**3.2**	**63.5**	**63.5**
2 (Shape Consolidation)	**1.1**	**22.1**	**85.6**
3	.4	8.9	94.5
4	.2	3.0	97.5
5	.1	2.5	100.0

Component Matrix		
	Component	
	1	2
Mean Shape index	.676	-.634
Mean Shape Index (area-weighted)	.884	.349
Mean Shape index coefficient of variation	.933	.020
Ratio of open space	.766	.580
Normalized landscape shape index	-.693	.495

Table 5. Principal components analysis, centrality metrics

Total Variance Explained			
Component	Initial Eigenvalues		
	Total	Percent variance	Cumulative percent
1 (Centrality)	**2.2**	**54.4**	**54.4**
2 (Largest Patch centrality)	**1.5**	**36.5**	**90.9**
3	.4	8.8	99.7
4	.0	.3	100.0

Component Matrix		
	Component	
	1	2
Centrality	.845	-.507
Centrality (area-weighted)	.857	-.481
Average distance from the largest patch	.615	.685
Average distance from the largest patch (area-weighted)	.591	.710

Table 6. Principal components analysis, complexity of the urban border

Total Variance Explained			
Component	Initial Eigenvalues		
	Total	Percent variance	Cumulative percent
1 (Edge complexity)	**1.7**	**56.9**	**56.9**
2	.9	30.7	87.6
3	.4	12.4	100.0

Component Matrix	
	Component
	1
Mean Patch Fractal Dimension (area-weighted)	.896
Mean Patch Fractal Dimension (coefficient of variation)	.603
Edge density	.736

Table 7. Principal components analysis, metrics for compactness or dispersion

Total Variance Explained

Component	Initial Eigenvalues		
	Total	Percent variance	Cumulative percent
1 (Clumpiness)	**2.6**	**43.3**	**43.3**
2 (Compactness)	**2.0**	**32.7**	**76.0**
3	.5	8.7	84.8
4	.5	7.9	92.6
5	.3	4.6	97.2
6	.2	2.8	100.0

Component Matrix

	Component	
	1	2
Clumpiness	.904	-.013
Compactness Index	-.886	-.025
Compactness Index of the Largest Patch	-.586	.723
Revised Compactness Index	.403	.722
Euclidean Nearest Neighbor Distance (area-weighted)	.669	.448
Euclidean Nearest Neighbor Distance (Coefficient of variation)	-.211	.847

Table 8. Canonical correlation analysis

Variates	Canonical Correlation	Squared Canonical Correlation	Eigenvalues			F test			Explained variance in metrics	
			Eigenvalue	Prop.	Cum.	F	d.f.	Pr > F	Prop.	Cum.
1	0.96	0.92	11.87	85%	85%	19.9	27	<.0001	35%	35%
2	0.78	0.61	1.56	11%	97%	7.85	16	<.0001	17%	52%
3	0.56	0.32	0.47	3%	100%	4.53	7	0.0003	1%	53%

Table 9. Canonical structure

Correlations between the contextual factors and canonical variates						
	V1	W1	V2	W2	V3	W3
Foreign Direct Investment	-0.24	-0.24	**0.75****	*0.59***	-0.61*	-0.35
Population (agglomeration)	-0.01	-0.01	**0.99****	**0.77****	0.15	0.09
China (0) /India (1)	**-0.99****	**-0.95****	0.16	0.13	0.02	0.01
Correlations between the land use metrics and canonical variates						
	V1	W1	V2	W2	V3	W3
Extent	0.56**	0.59**	0.47*	0.60**	0.07	0.13
Patch concentration	**0.88****	**0.92****	-0.04	-0.05	-0.02	-0.03
Shape irregularity	*0.65***	*0.67***	0.52**	0.67**	0.12	0.22
Shape consolidation	-0.64**	-0.66**	0.49*	0.63*	0.08	0.15
Centrality	-0.31	-0.33	-0.14	-0.18	-0.08	-0.13
Largest patch centrality	0.34	0.35	0.55**	*0.70***	-0.12	-0.22
Edge complexity	0.53**	0.55**	0.49	0.63	0.23	0.41
Clumpiness	**0.84****	**0.87****	0.08	0.11	-0.02	-0.03
Compactness	-0.02	-0.02	-0.53**	-0.67**	-0.04	-0.07

**Cross-validated in both samples at .45 or higher

*Validated in one sample at .45 or higher

Boldface: cross-validated at .7 or higher

Italics: Validated in one sample at .7 or higher

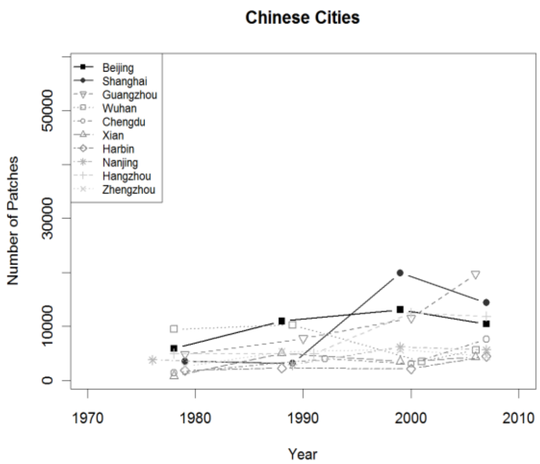
Appendix 1

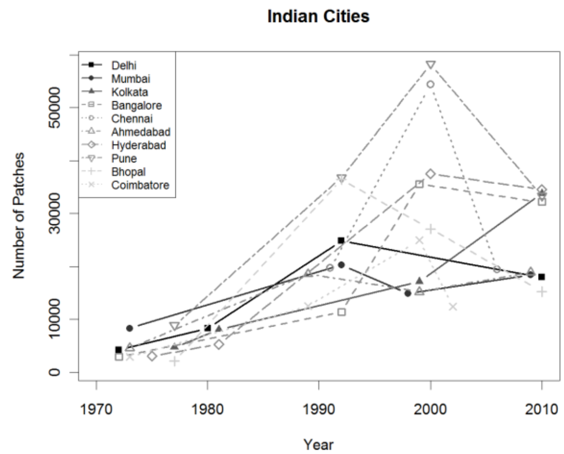
Overall accuracy of classifications

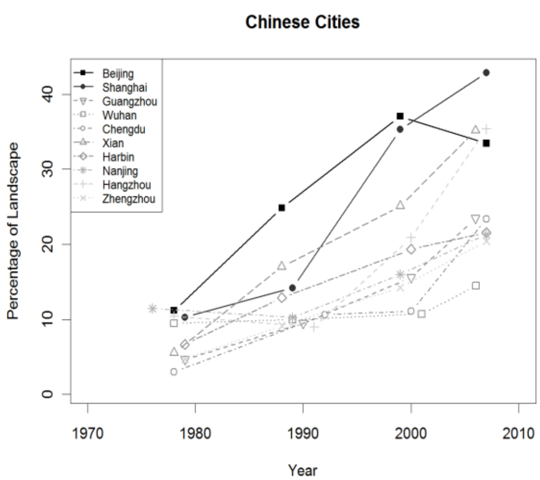
Cities	Overall accuracy (percent)			
	1970s	1980s	1990s	2000s
India				
Delhi	89.0	99.0	97.0	88.0
Mumbai	73.0	98.0	99.0	99.0
Bangalore	93.0	79.0	88.0	99.0
Hyderabad	81.0	84.0	99.0	76.0
Kolkata	99.0	88.0	93.0	93.0
Chennai	-	96.0	89.0	99.0
Ahmedabad	77.0	74.0	70.0	68.0
Coimbatore	97.0	95.0	96.0	92.0
Bhopal	98.0	98.0	96.0	99.0
Pune	91.0	91.0	91.0	98.0
Mean	88.7	90.2	91.8	91.1
s.d.	9.0	8.3	8.2	10.4
China				
Beijing	70.0	75.0	81.0	73.0
Chengdu	73.0	72.0	77.0	77.0
Guangzhou	69.0	75.0	82.0	79.0
Harbin	71.0	74.0	84.0	78.0
Hangzhou	67.0	75.0	86.0	84.0
Nanjing	63.0	80.0	86.0	78.0
Shanghai	70.0	78.0	85.0	79.0
Wuhan	74.0	77.0	86.0	82.0
Xi'an	69.0	73.0	87.0	83.0
Zhengzhou	69.0	76.0	84.0	78.0
Mean	69.5	75.5	83.8	79.1
s.d.	2.9	2.2	2.9	3.0
Pooled				
Decadal Mean	78.6	82.9	87.8	85.1
s.d.	11.9	9.5	7.3	9.7
Overall mean	83.6			
s.d.	10.3			

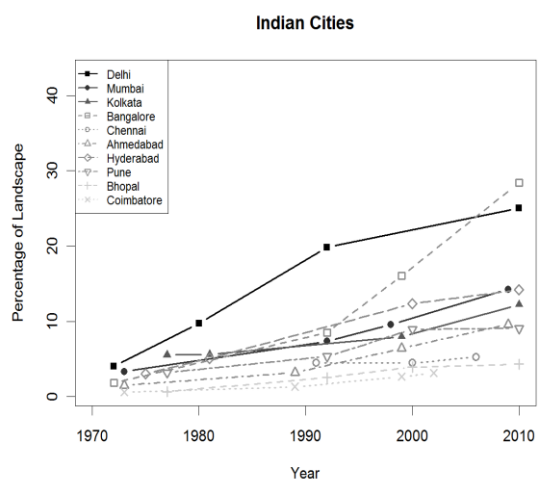
Appendix 2: Additional metrics used in analysis

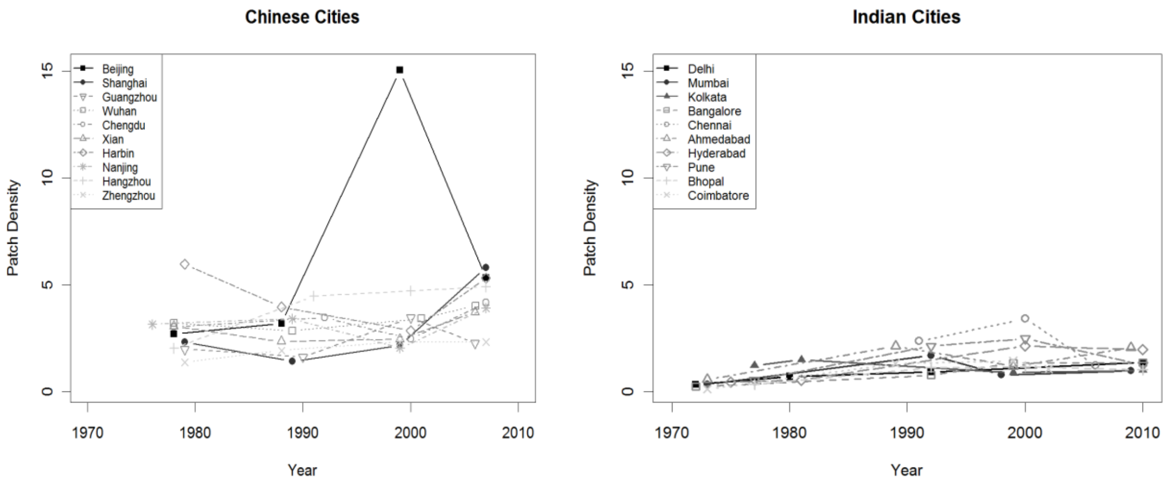
a) Additional Area metrics



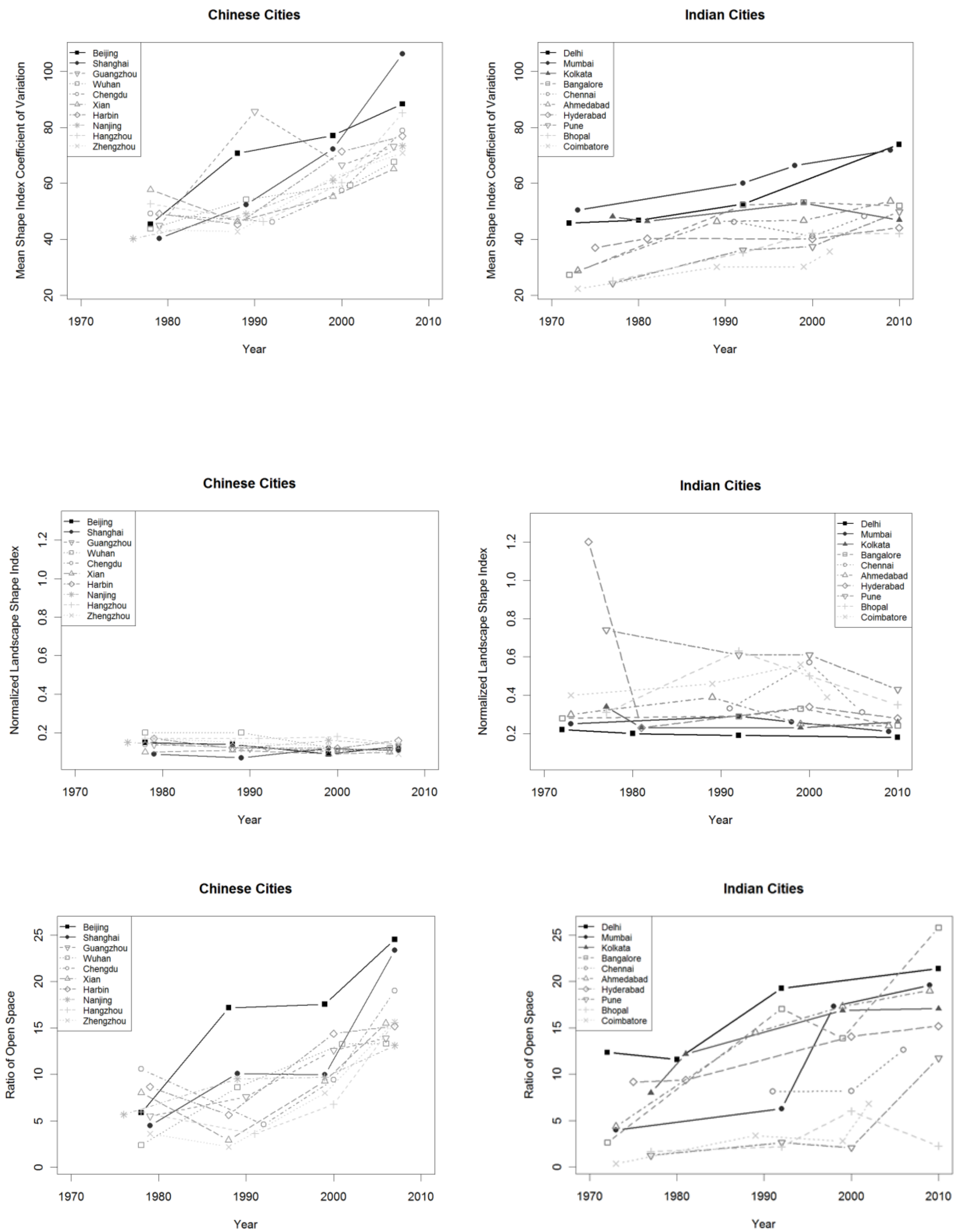




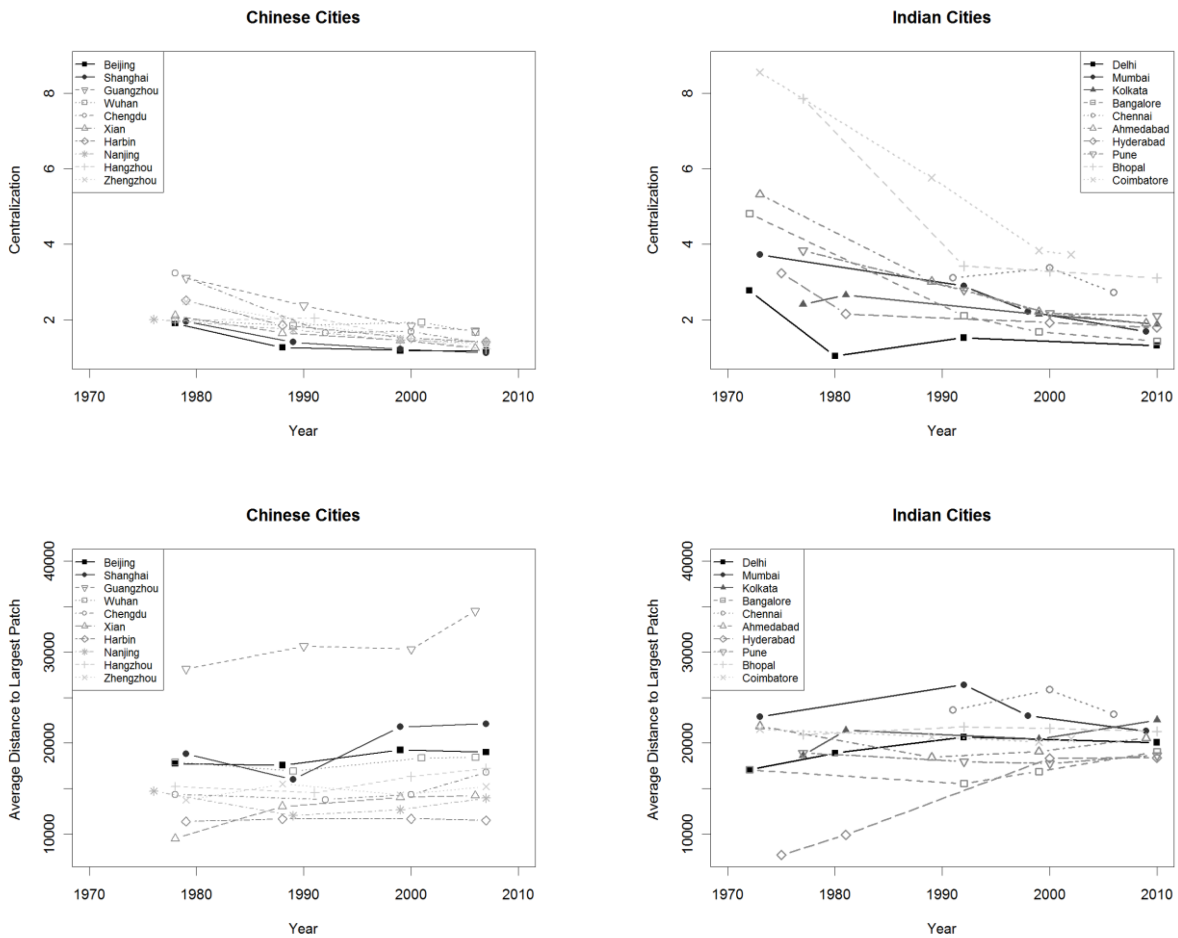



Chinese Cities
Patch Density
Year
Beijing
Shanghai
Guangzhou
Wuhan
Chengdu
Xian
Harbin
Nanjing
Hangzhou
Zhengzhou
Indian Cities
Patch Density
Year
Delhi
Mumbai
Kolkata
Bangalore
Chennai
Ahmedabad
Hyderabad
Pune
Bhopal
Coimbatore

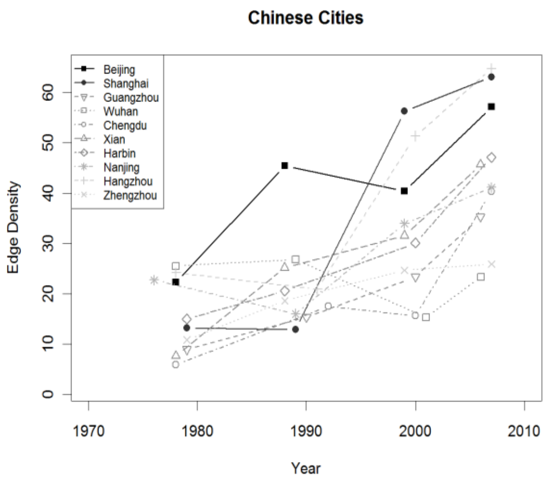
b) Additional metrics for shape complexity of patches

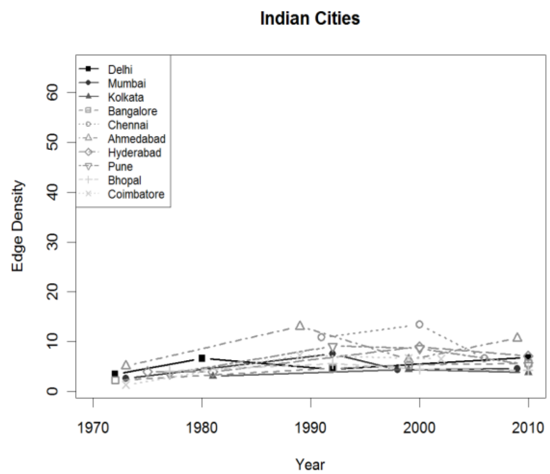


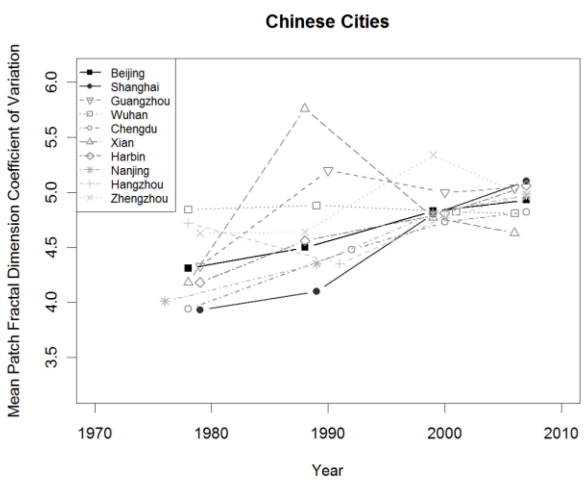
c) Additional metrics for centralization

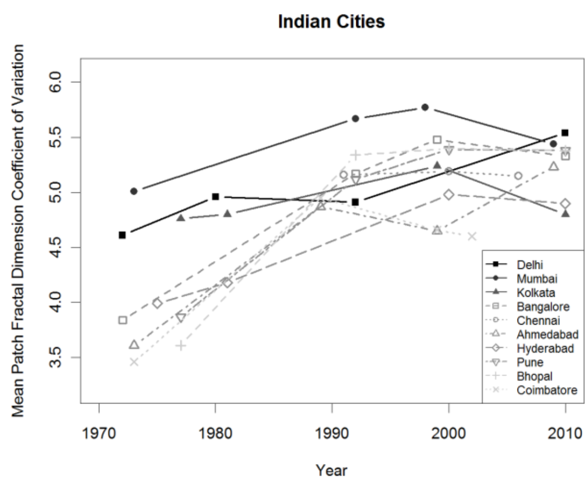


d) Additional Edge/ Border Metrics

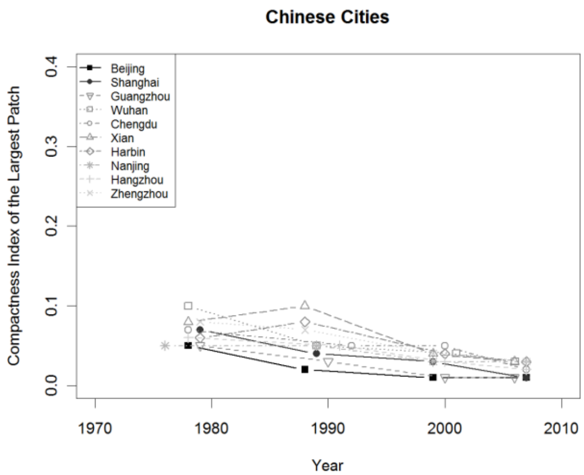


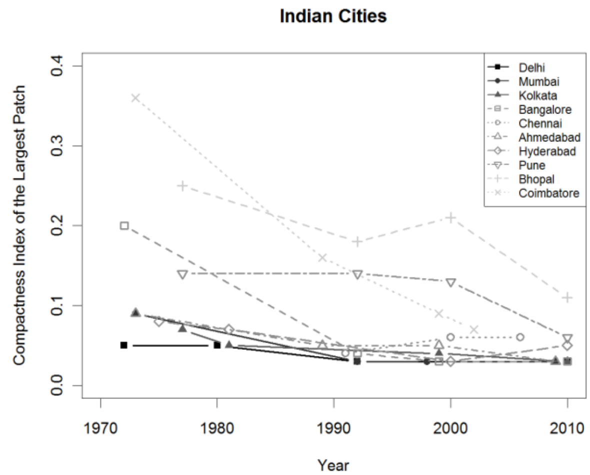


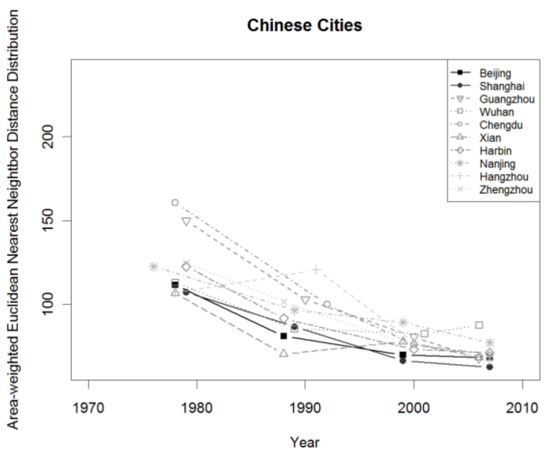


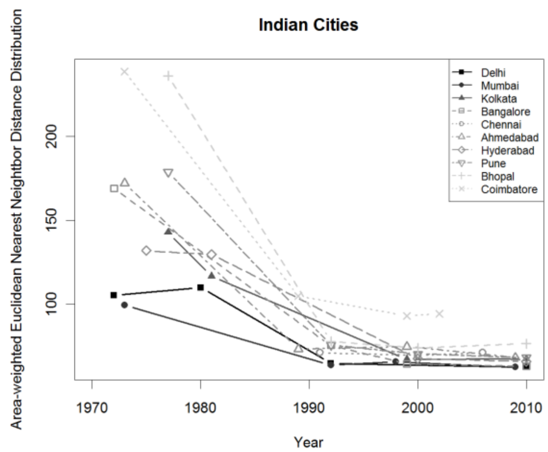


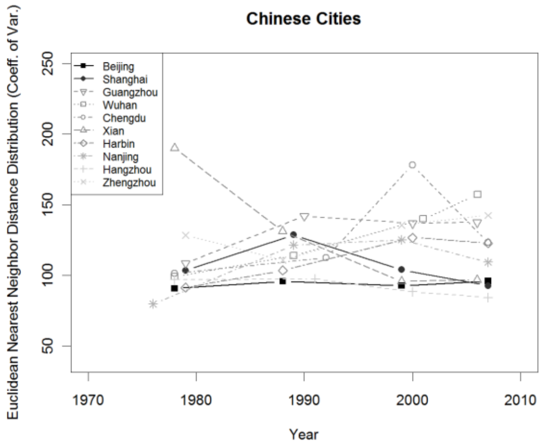
e) Additional Compactness metrics

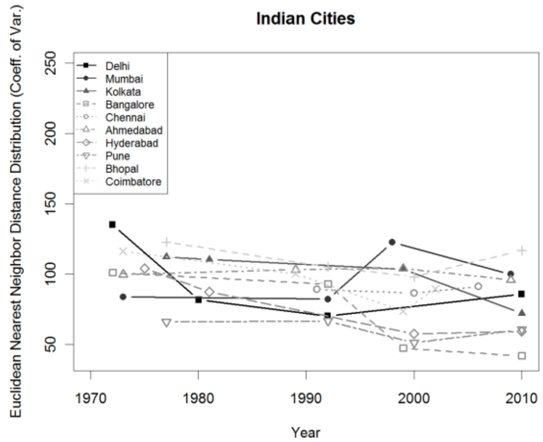









Chinese Cities
Euclidean Nearest Neighbor Distance Distribution (Coeff. of Var.)
Year
Beijing
Shanghai
Guangzhou
Wuhan
Chengdu
Xian
Harbin
Nanjing
Hangzhou
Zhengzhou
1970
1980
1990
2000
2010
50
100
150
200
250


Indian Cities
Euclidean Nearest Neighbor Distance Distribution (Coeff. of Var.)
Year
Delhi
Mumbai
Kolkata
Bangalore
Chennai
Ahmedabad
Hyderabad
Pune
Bhopal
Coimbatore
1970
1980
1990
2000
2010
50
100
150
200
250

Appendix 3: Cross-validation of canonical correlation analysis

a) Partition of sample: Sample was partitioned equally based on two sets of covariates: 1) the three size classes (megacities, regional centers and smaller cities), 2) foreign direct investment. Selection was otherwise random.

b) Training sample (n=39)

Variates	Canonical Correlation	Squared Canonical Correlation	Eigenvalues			F test			Explained variance in metrics	
			Eigenvalue	Prop.	Cum.	F	d.f.	Pr > F	Prop.	Cum.
1	0.97	0.93	14.31	81%	81%	11.1	27	<.0001	33%	33%
2	0.85	0.72	2.57	15%	96%	5.26	16	<.0001	20%	53%
3	0.66	0.43	0.76	4%	100%	3.13	7	0.0137	4%	57%

Correlations between the contextual factors and canonical variates

	V1	W1	V2	W2	V3	W3
Foreign Direct Investment	0.26	0.26	0.83	0.71	-0.48	-0.32
Population (agglomeration)	0.15	0.14	0.86	0.73	0.48	0.32
China (0) /India (1)	0.99	0.96	0.12	0.10	0.00	0.00

Correlations between the land use metrics and canonical variates

	V1	W1	V2	W2	V3	W3
Extent	-0.50	-0.51	0.53	0.62	0.22	0.34
Patch concentration	-0.92	-0.95	-0.04	-0.05	0.03	0.04
Shape regularity	-0.56	-0.58	0.58	0.69	0.21	0.32
Shape consolidation	0.64	0.66	0.54	0.63	0.17	0.27
Centrality	0.21	0.22	-0.23	-0.27	-0.12	-0.19
Largest patch centrality	-0.37	-0.39	0.58	0.68	0.01	0.01
Edge complexity	-0.48	-0.50	0.47	0.55	0.38	0.57
Clumpiness	-0.86	-0.89	0.09	0.11	0.02	0.03
Compactness	-0.02	-0.02	-0.55	-0.65	-0.18	-0.28

c) Test sample (n=39)

Variates	Canonical Correlation	Squared Canonical Correlation	Eigenvalues			F test			Explained variance in metrics	
			Eigenvalue	Prop.	Cum.	F	d.f.	Pr > F	Prop.	Cum.
1	0.97	0.94	17.04	78%	78%	14.51	27	<.0001	37%	37%
2	0.88	0.78	3.60	16%	95%	7.58	16	<.0001	16%	53%
3	0.74	0.54	1.18	5%	100%	4.89	7	0.001	1%	55%

Correlations between the contextual factors and canonical variates						
	V1	W1	V2	W2	V3	W3
Foreign Direct Investment	-0.28	-0.27	0.82	0.73	-0.50	-0.37
Population (agglomeration)	0.06	0.06	1.00	0.88	0.08	0.06
China (0) /India (1)	-0.99	-0.96	0.14	0.12	0.09	0.06

Correlations between the land use metrics and canonical variates						
	V1	W1	V2	W2	V3	W3
Extent	0.60	0.62	0.41	0.46	0.05	0.06
Patch concentration	0.87	0.90	0.00	-0.01	-0.10	-0.13
Shape regularity	0.72	0.74	0.49	0.55	0.18	0.25
Shape consolidation	-0.67	-0.69	0.39	0.44	0.13	0.17
Centrality	-0.45	-0.46	0.00	0.00	-0.02	-0.03
Largest patch centrality	0.27	0.28	0.64	0.72	-0.04	-0.06
Edge complexity	0.55	0.57	0.47	0.53	0.24	0.33
Clumpiness	0.83	0.86	0.13	0.15	-0.03	-0.04
Compactness	-0.03	-0.03	-0.48	-0.54	-0.03	-0.04