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Fifteen Years of Fragmentation and Land Cover Change in India's Ten Largest Cities – A Google Earth Engine Analysis

Urbanization is one of the most transformative drivers of global environmental change today, with India representing one of the fastest urbanizing countries. We map the urban expansion of India's ten largest cities from 2001 to 2016, through a regression tree classification of Landsat data in Google Earth Engine. Indian cities are growing through sprawl, and simultaneously densifying through in-filling. In Delhi, Mumbai and Pune, urban growth is multinucleated, aggregating to form a larger urban region. However, the dominant pattern in most cities is mono-nucleated growth via edge-expansion. The colonial signature is visible in many cities such as Bangalore, where due to the British colonial practice of planting trees in the cantonment, the city interior has lower urban density at the core as compared to the periphery. Much of the urban growth between 2001-2016 is at the expense of agriculture and fallow areas. Across all cities, urban patches have expanded and coalesced into larger units. At the same time, there is an overall loss of surface water cover within cities. Urban growth has led to fragmentation of tree cover, agriculture/fallow and water bodies. This paper demonstrates that India's urbanization is leading to severe impacts on water security (because of the loss of surface water), biodiversity (because of the fragmentation of tree cover and the conversion of agriculture and fallow lands to built up urban cover), factors which if left unaddressed will severely impact the sustainability of Indian urbanization.

Keywords
Google Earth Engine, urbanization, fragmentation, land cover change, mapping, cities and spatial analysis

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INTRODUCTION

Urbanization is one of the most transformative drivers of global environmental change today. By 2050, the global urban population is expected to double, exceeding 6 billion. By 2050, two out of every three people will live in cities (United Nations, 2014). Consequently, over the past decade there has been increasing interest in studying changes in urban land cover growth. Much of this research has focused on examining changes in a single city over time. The increasing availability of large-scale remote sensing datasets has opened the door for semi-automated approaches that can help in mapping the growth of multiple cities. This is especially feasible with the advent of Google Earth Engine and its ability to consolidate large datasets, capitalizing on the power of cloud computing for swift analysis (Agarwal and Nagendra, 2020; Sidhu et al., 2018).

Research at the regional or multi-city scale has largely been conducted at relatively broad spatial scales (Li et al., 2018). Yet, to understand patterns of urban growth, which are typically quite fragmented and fine scale, imagery at a correspondingly detailed spatial scale (i.e. sub-100 m scale) is needed. Second, research on urban land cover change tends to focus primarily on the dynamics of the urban land cover class itself (e.g. Fu et al., 2019; Li et al., 2018; Song et al., 2016; Xu et al., 2019). In doing so, the changes wrought by urban expansion on vegetation, water and other types of land cover, though equally important, are less studied. This is in part due to the complexity of the urban landscape, where frequent and fine-scale inter-class transformations between different types of land cover are often observed (Song et al., 2016).

The fastest rates of urban growth will take place in Asia (India and China) and Africa (United Nations, 2014). Understanding the patterns of urbanization and their impact on ecosystems is especially critical in cities of the global South, which constitute some of the fastest urbanizing regions of the world today. Yet, despite the need, much less is known about patterns of urban growth in the global South as compared to cities of the global North (Nagendra et al., 2018). Indian cities are anticipated to contain many as 400 million urban residents by 2050 (United Nations, 2014). Such rapid growth will lead to major changes in ecology and land cover.

Developing a country-level understanding of the complex dynamics of urbanization in India, and its impact on ecological and environmental sustainability, will be essential to balance imperatives of growth with ecological sustainability. Urbanization constitutes an often irreversible transformation on land cover, with severe impacts on ecological cover such as vegetation, water agricultural land and fallow areas, leading to landscape fragmentation and impacting local biodiversity (Seto et al., 2011). The conversion of water bodies – lakes, rivers and wetlands – within cities further impacts water scarcity and leads to an increased risk of droughts as well as flooding (Faridatul et al., 2019; Srinivasan et al., 2013). Research suggests that some of the highest rates of growth in urban and cover have occurred in regions such as India (X. Liu et al., 2020; Seto et al., 2011). Yet, given the lack of availability of reliable, fine spatial-scale data on land cover change in India at the country level (Moulds et al., 2018; Tian et al., 2014), an analysis of fine-scale changes across multiple cities remains challenging.

A number of global datasets of land cover and analyses of urbanization have been recently developed and analysed. Güneralp et al. (2020) conducted a global synthesis of urbanization, focusing on land expansion, changes in population densities, and land conversion.

Their results emphasize the need for proactive management of small and medium-sized cities. Similarly, Pandey and Seto (2015) investigated the impacts of urbanization on agricultural land loss in India and predicted future urbanization trends, using MODIS imagery with a resolution of 250 meters. Pandey et al. (2018) implemented a time series approach to detect the timing of urban conversion of agricultural land in India. However, these study focus was limited to a focus on specific land cover types and did not encompass the comprehensive analysis of multiple land cover types that we aimed to achieve in our study. Furthermore, existing global datasets such as the forest analysis by Hansen and Loveland (2012), classification of land use and land cover (H. Liu et al., 2020) and the mapping of water bodies using high-resolution images (Pekel et al., 2016) did not provide accurate information for urban tree cover and water bodies specific to each city in India. These studies focused on broader-scale monitoring and did not account for the unique characteristics of individual Indian cities.

We focus on generating land cover change data specifically for Indian cities, due to their complexity. Indian cities exhibit unique characteristics, including the presence of urban trees, parks, agricultural areas in the periphery, and water bodies with eutrophication issues. These specific features are often mistakenly classified in the existing global datasets. Global datasets are based on a broad-scale analysis and do not provide the necessary level of accuracy and individual attention required for each city in India. For instance, the deforestation data from Hansen and Loveland (2012) does not focus on mapping urban trees. Furthermore, existing urban maps do not provide comprehensive details on other land cover types such as trees, agriculture, and water bodies. By developing a classification method specific to our purpose, we can ensure high level accuracy and providing a more detailed understanding of patterns of land cover change in Indian cities.

In this paper, we capitalize on the capacity of Google Earth Engine to process large volumes of high spatial resolution Landsat satellite imagery for large-scale analyses of urbanization across multiple cities. Accordingly, we use a classification tree algorithm to classify land cover change in the ten largest cities in India over a time period of 15 years, from 2001-2016. We further assess the growth of urban cover and its impact on natural land cover – vegetation, water bodies and agricultural and fallow areas, as well as the fragmentation of land cover change following urbanization.

METHODS

We use Google Earth Engine on Landsat satellite imagery for a 2-date classification, using Random Forest Classifier and a global classification model that pools training site data across all cities, as further described below. We developed a classification script in Google Earth Engine to classify the ten most populated cities in India, which can be accessed at the following link: https://code.earthengine.google.com/2a4351e000571b94096bcdb3a560d82b.

Land Cover Classification

We selected India's ten largest (most populated) cities: Mumbai, Delhi, Bangalore, Hyderabad, Ahmedabad, Chennai, Kolkata, Surat, Pune and Jaipur, based on 2011 Census records. Our interest was in understanding land cover change during a 15 year period when Indian cities have grown rapidly – 2001 to 2016. For each city, we selected cloud-free images from Landsat 7 and 8 sensors that covered the city between January 2016 and December 2016, and from Landsat 5 and 7 sensors that were available for the time period between January 2001 and December 2001. Four indices – the Enhanced Vegetation Index (EVI), Normalized Difference Built Index (NDBI), Normalized Difference Moisture Index (NDMI) and Normalized Difference Vegetation Index (NDVI) - were computed for all selected images, as these are known to be useful in classification of vegetation, urban cover, and water. These indices were combined with the Blue, Green, Near Infra-Red (NIR), Short Wave Infra-Red 1 (SWIR1), and Short Wave Infra-Red 2 (SWIR2) bands of Landsat images to create a layer stack.

Finally, the minimum and maximum values for each pixel representing a single band or index value, across all image dates, were computed for each of the specified bands and indices. The composites for each city finally comprised 18 bands, i.e. with minimum and maximum values of EVI, NDBI, NDMI, NDVI, Blue, Green, SWIR1, SWIR2, and NIR. This enabled us to capture the seasonal variation in agriculture, deciduous tree cover, and urban water bodies with seasonal eutrophication. This approach builds on methods used in Deines et al. (2019), and Agarwal and Nagendra (2020).

For ground training, we manually selected the areas of interest (AOIs) in 2001 and 2016 based on Google Earth images of the corresponding years. The classes selected were dense trees, grassland, water, water hyacinth, fallow land, agriculture land, sparse trees and urban cover. We utilized Google Earth images to manually generate 3682 AOIs for conducting supervised classification of ten Indian cities. The count of AOIs allocated for urban, agriculture/fallow, tree, and water categories varies among the cities due to differences in pixel heterogeneity and area, as illustrated below: Urban AOIs range from 50-112, agriculture/fallow AOIs range from 85-156, tree AOIs range from 80-157, and water AOIs range from 37-87. For further information on AOIs, please refer to Agarwal and Nagendra (2020). Next, a random forest classifier was used to classify images of 2001 and 2016, using a global model that pooled training site information from all cities. In Random Forest, ten decision tree is trained independently on a randomly sampled subset of the training data. Using this approach, we classified Landsat images from 2001 and 2016 to analyse land cover change as a consequence of urban growth between 2001 and 2016.

After classification, agriculture, fallow land, and grassland were grouped to a single class - 'agriculture/fallow land'. Many Indian cities have water bodies which have undergone eutrophication due to sewage inflow, and there is substantial growth of water weeds like water hyacinth on the surface of the water, whose coverage varies considerably from month to month depending on sewage inflow and rainfall. Although these classes are spectrally different, in terms of land cover they can be treated as a single class. Accordingly, open water and water hyacinth categories were merged after classification into a single class called 'water body'. Dense and sparse tree cover categories, classified separately, were merged post-classification into a 'tree' class. At the end, we had four land cover classes for each time period – urban, tree, water and agriculture/fallow land. In order to address the heterogeneity among cities, we merged the classes after the classification process. We had previously tried to develop training samples with consolidated classes, but the accuracy was lower, due to the heterogeneity between cities – starting with more detail and then consolidating, was a better approach. Since we employed a global model, merging the classes after classification is a valid approach – this draws on a methodology previously demonstrated and utilized in Agarwal and Nagendra (2020), as cited in the Methods section.

Accuracy Assessment

Accuracy assessment was performed using the Erdas Imagine satellite image processing software. 30 independent randomly generated points were identified for each land cover class in each city, adopting a stratified random sampling approach, resulting in a total of 120 points from four land cover classes used for accuracy assessment in each city, i.e. 1200 points across 10 cities were used for accuracy assessment in total. We selected points that were at a distance from each other, and used an independent set of points for accuracy assessment that were not used in training the classifier, to minimize errors of autocorrelation. The same ground truth points were selected for both dates. Classification accuracy was assessed using Google Earth images on dates corresponding to the Landsat imagery, i.e. of 2001 and 2016.

Delineating Urban Boundaries

Urban boundaries of the selected 10 cities were delineated using the Global Human Settlement Built-up layer (GHS-BU), provided globally by https://ghsl.jrc.ec.europa.eu/datasets.php. The GHS-BU layer, generated in 2015 using the Global Human Settlement Layer methodology (as defined further on the GHS-BU website), provides values ranging from 0 to 1 for each 250 m pixel, based on a combination of urban built cover and population density. We reclassified the layer into a binary image, achieving a maximum classification of urban cover by classifying areas with values ranging from 0.01 to 1 to urban and from 0 to 0.01 to non-urban. The reclassified binary image was converted into a vector file and used to delineate the urban boundary of each city in 2016 (hereafter called ‘city core’). A 10 km GIS buffer around each city was also created (hereafter referred to as ‘city periphery’). For coastal cities, all boundaries were clipped using an India shape file, to exclude coastal areas as we were interested only in the land surface area.

Land Cover Change and Fragmentation Analysis

The four-class classified images of 2001 and 2016 were used for analysis of land cover change and fragmentation within the city core and periphery. Following Jiao (2015) and Xu et al. (2019), we graphed the change in urban land densities using 1 km concentric rings spreading from the centre of the city into the periphery. In addition, we modified this approach to also study changes in density of land cover of the other three classes - tree, agriculture/fallow and water bodies.

Using the open source software Fragstats (v4.2.1) we assessed the fragmentation of land cover within the city core and periphery (as defined above). Following Taubenböck et al. (2009), we used spider charts to characterize the spatial landscape pattern of urban growth in the city core and periphery, and to understand changes in landscape pattern between 2001 and 2016. Spider graphs were separately generated for each of the four land cover categories – urban, tree, agriculture/fallow and water. We used six different quantitative parameters of landscape pattern computed using Fragstats as different axes on the spider graph. Each of these parameters defined a different aspect of landscape pattern: percentage of area (area), mean shape index (shape); mean euclidean nearest neighbour distance between patches (ENN); patch density (patch density), clumpiness (clumpy) and interspersion-juxtaposition index (IJI).

Although in practice there are dozens of different landscape metrics that can be used, we used metrics that are known to represent different aspects of landscape pattern. Percentage area tells us how dominant the land cover category is, while the shape index gives us a sense of the compactness of patches of that land cover category. The more compact a patch, the lower its shape index. ENN is the average of the distance of each patch to the nearest neighbouring patch of the same land cover class, based on the shortest edge-to-edge distance, and tells us how close patches of the same type tend to be to each other, while the clumpiness index informs us about the overall tendency of a land cover category to form aggregations, and IJI describes the tendency of a land cover to be mixed or interspersed with other categories of cover. Taken together, these can help us to compare landscape pattern within the city core and periphery, and to understand the changes in landscape spatial pattern as a consequence of urbanization over time.

RESULTS AND DISCUSSION

The overall classification accuracy ranged from 82.5-91.7% for the 2001 classification, and from 81.7-90.1% for the 2016 classification. Kappa values ranged from 75.0 to 89.5 (Appendix 1). Within the city core, land cover was dominated by urban and agricultural/fallow land categories in 2001. There was a significant increase in urban cover within the city core in 2016, largely at the expense of a decline in agricultural/fallow land (Table 1). In contrast, land cover in the periphery, i.e. the 10 km GIS buffer surrounding the city core, is almost overwhelmingly dominated by agriculture and fallow areas. The land cover in the periphery also seems to be much more variable, with agricultural areas giving way to trees, and tree cover seen over built areas – (Table 1) presumably a result of tree plantation in and around many peri-urban residential and commercial spaces, as seen in cities like Bengaluru and Delhi (Nagendra, 2016; Paul et al., 2021). Contrary to the impression that urban land cover change is irreversible, we find that transformations between agriculture/fallow areas, tree cover and urban cover is actually quite dynamic, even in the city core but especially in the city periphery, with agricultural/fallow areas experiencing the greatest amount of transformation.

From looking at the patterns of land cover change, urban expansion seems to largely take place around the nucleus of existing urban areas (Figure 1). Urban growth in coastal cities like Chennai and Mumbai seems to be additionally shaped by their proximity to the coast, with the urban cover following the shape of the coastline. The exception is Kolkata. Though a coastal city, growth along the coastline is buffered by the East Kolkata Wetlands, which lie between the city and the sea to the south-east. In addition to the coast, urban growth is also spatially delimited by large protected areas that exist around many cities like Bengaluru, Delhi and Jaipur, clearly visible in the images as large patches of tree cover located at the city periphery (Figure 1).

Table 1.
Percentage of area occupied by different land cover change categories, between 2011-2016, for India's ten largest cities.

	Area percentage of change classes						
City names	Stable urban	Increase in urban	Stable agriculture/ fallow	Increase in agriculture/f allow	Stable tree	Increase in tree	Water
Ahmedabad	8.66	5.77	53.50	20.24	2.65	7.75	1.42
Bangalore	4.88	9.07	58.69	4.35	9.83	11.34	1.84
Chennai	6.17	9.36	28.64	23.64	8.23	13.42	10.53
Delhi	10.84	10.12	46.95	13.75	6.81	10.39	1.15
Hyderabad	7.00	7.42	43.00	19.12	7.97	12.24	3.26
Jaipur	5.80	5.91	59.75	18.34	3.41	6.26	0.52
Kolkata	3.60	4.61	17.49	15.32	20.34	26.51	12.13
Mumbai	5.74	8.04	15.92	19.74	25.89	18.63	6.03
Pune	5.80	11.06	26.95	20.70	13.72	19.89	1.89
Surat	7.47	9.49	31.33	20.53	7.30	18.51	5.37

Corroborating the findings of Jiao (2015) in 28 Chinese cities, and Xu et al. (2019) in 25 African cities, we find that urban land cover density decreases with every 1 km increase from the city centre (Figure 2). However, contrary to these studies, we find that this pattern is not consistent across all cities. In India's capital city Delhi, which is actually an agglomeration of multiple urban neighbourhoods distributed across different states (Paul et al., 2021), urban cover density decreases, and then increases again, as new urban neighbourhoods develop at the fringe of older areas. Mumbai and Pune, which are also constituted as urban agglomerates rather than defined as single nucleated cities (Figure 2), also demonstrate anomalous patterns of dips and rises in urban density with distance from the urban centre. In contrast, smaller cities like Surat and Jaipur show a fairly steady inverse S-shaped decline in urban cover with distance from the city centre, mirroring the patterns observed in China and Africa. All cities demonstrated a clear increase in urban cover near the city centre between 2001 and 2016 (Figure 2). Proportion of tree cover was much more variable, however. Of the ten cities studied here, most are colonial cities, with a clear colonial footprint in terms of having formerly colonial government-protected areas of high tree cover in the heart of the city. Thus, we observe that tree cover shows an increase with distance from the city centre for some time, before declining. This is perhaps especially apparent in Chennai, Delhi and Kolkata, which are known to have large expanses of tree cover in the heart of the city in former colonially controlled administrative areas, within administrative and military compounds and parks – as also seen for instance, in a previous study in another former colonial city of Bengaluru (Nagendra et al., 2012).

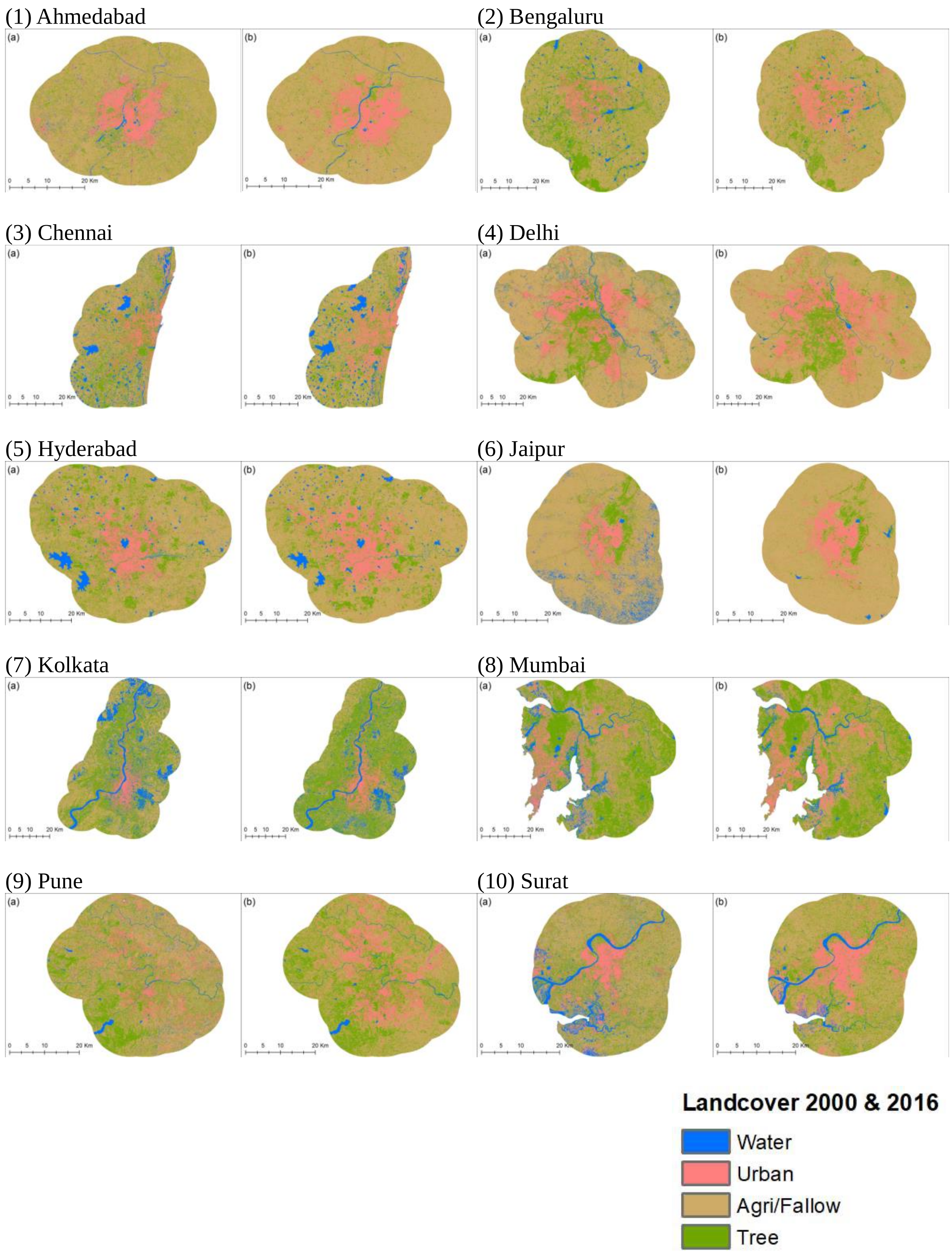
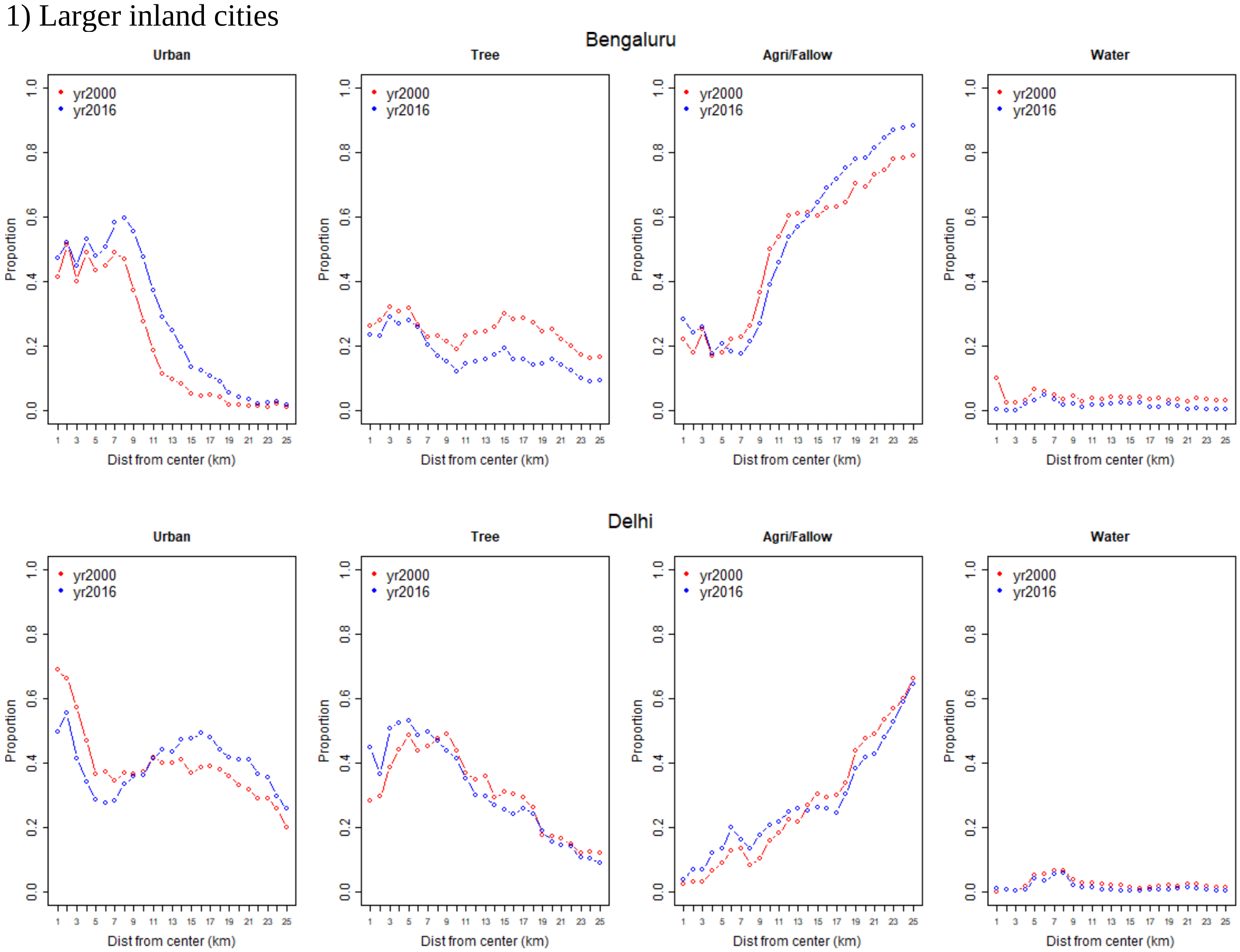


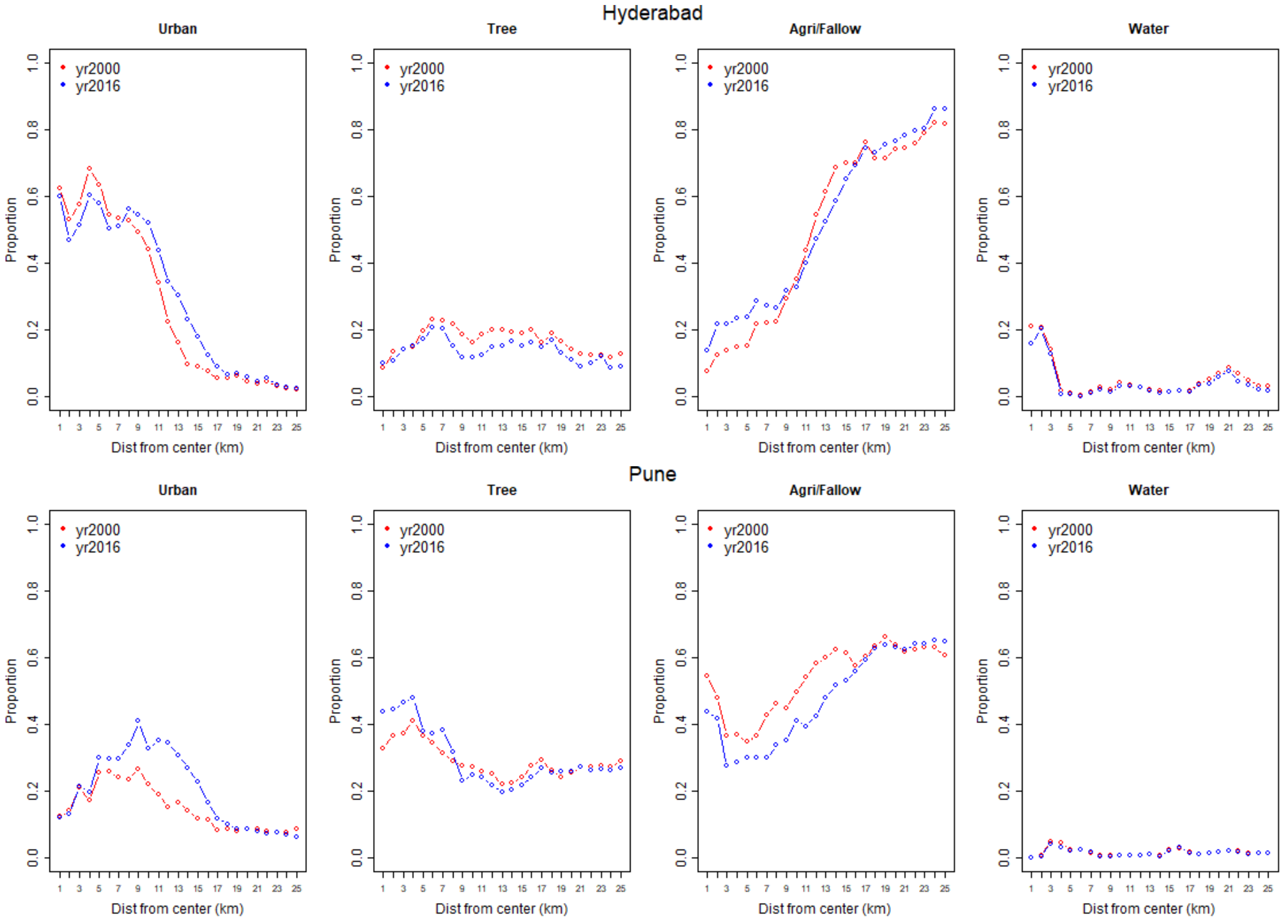
Figure 1. Land cover in 2001 and 2016 for India's ten largest cities.

The smaller cities - Jaipur, Ahmedabad and Surat – are especially densified at the centre, with urban cover comprising close to 80% in the innermost circle of 1 km around the city centre. Delhi, Hyderabad and Bangalore – larger inland cities - demonstrate intermediate levels of urban density at the core, but show clear traces of increasing densification between 2001 and 2016, with urban cover increasing as a proportion of the landscape over this fifteen year period. In coastal cities - Kolkata, Mumbai, and Chennai - urban growth is not concentric, constrained as it is by water. In Kolkata, urban growth appears to be linear, concentrated along the Hooghly River at the centre of the city, while in Mumbai and Chennai the contours of urban settlements largely follow the complex contours of the coastline. The approach of using concentric rings around the city centre to assess urban growth breaks down in situations like these, where growth is not concentric.

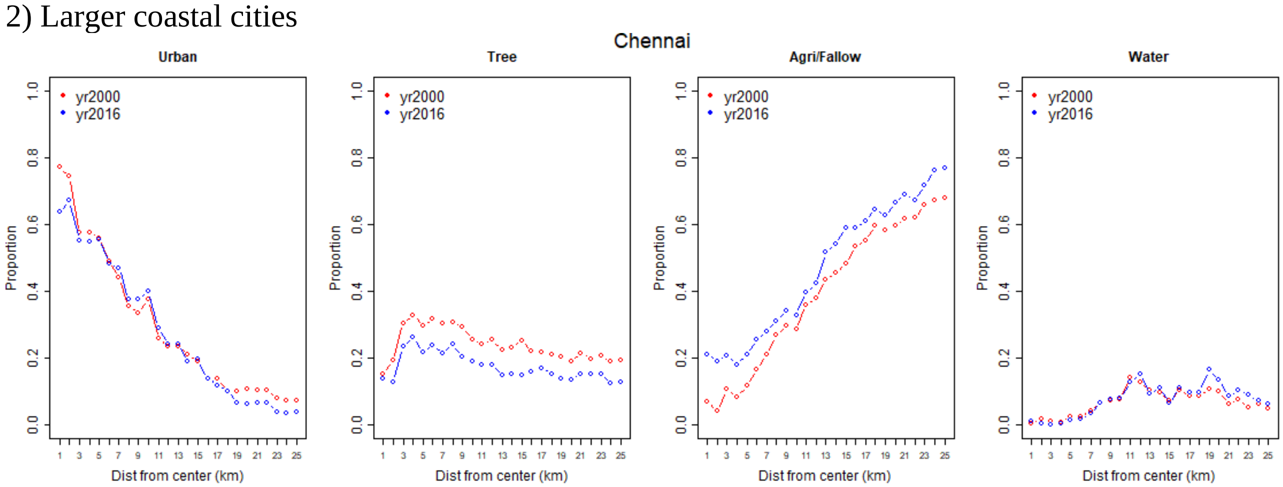
1) Larger inland cities



(Figure 2, continued)



2) Larger coastal cities



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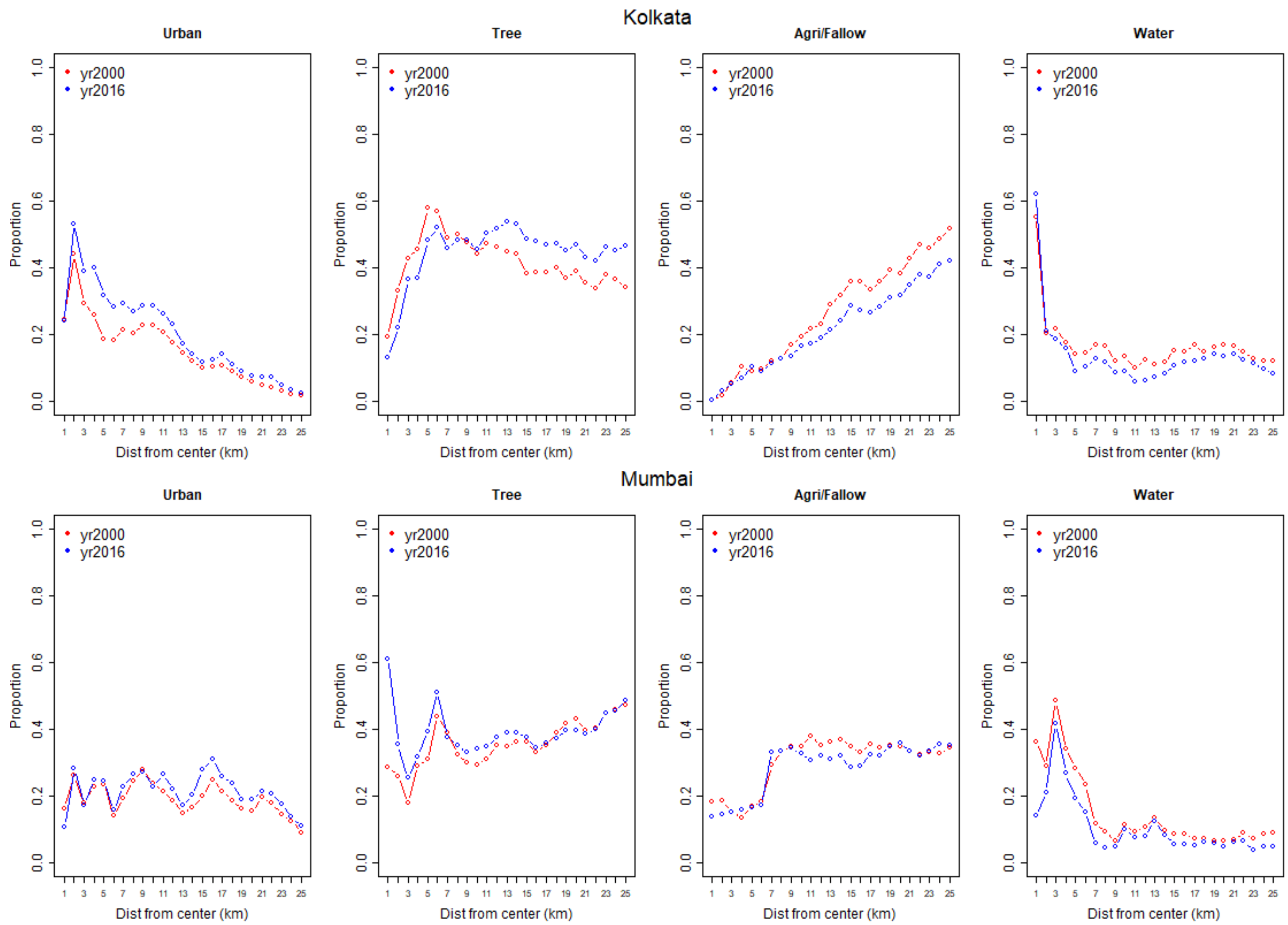
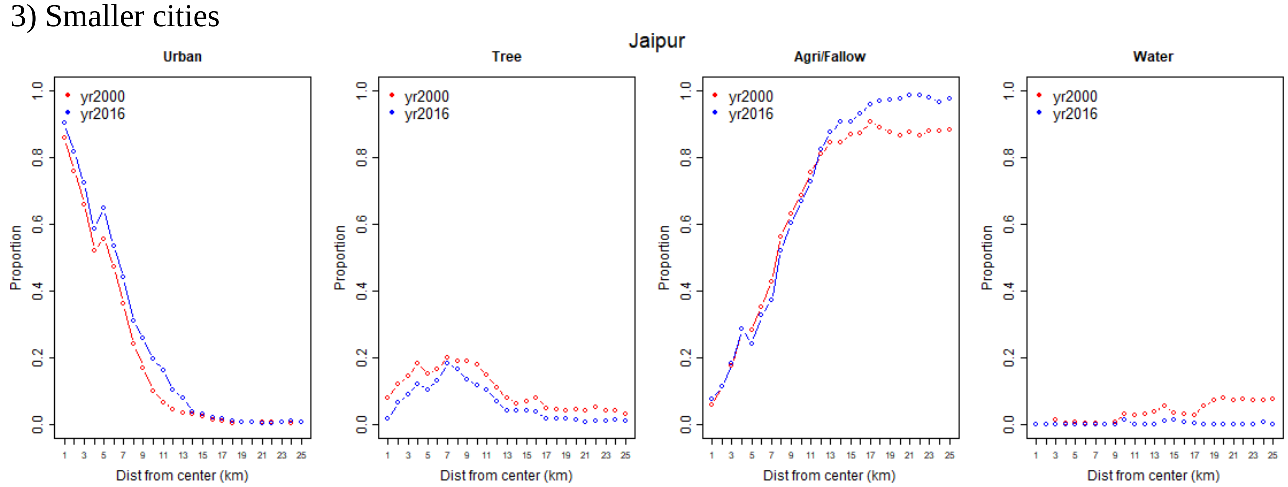


3) Smaller cities



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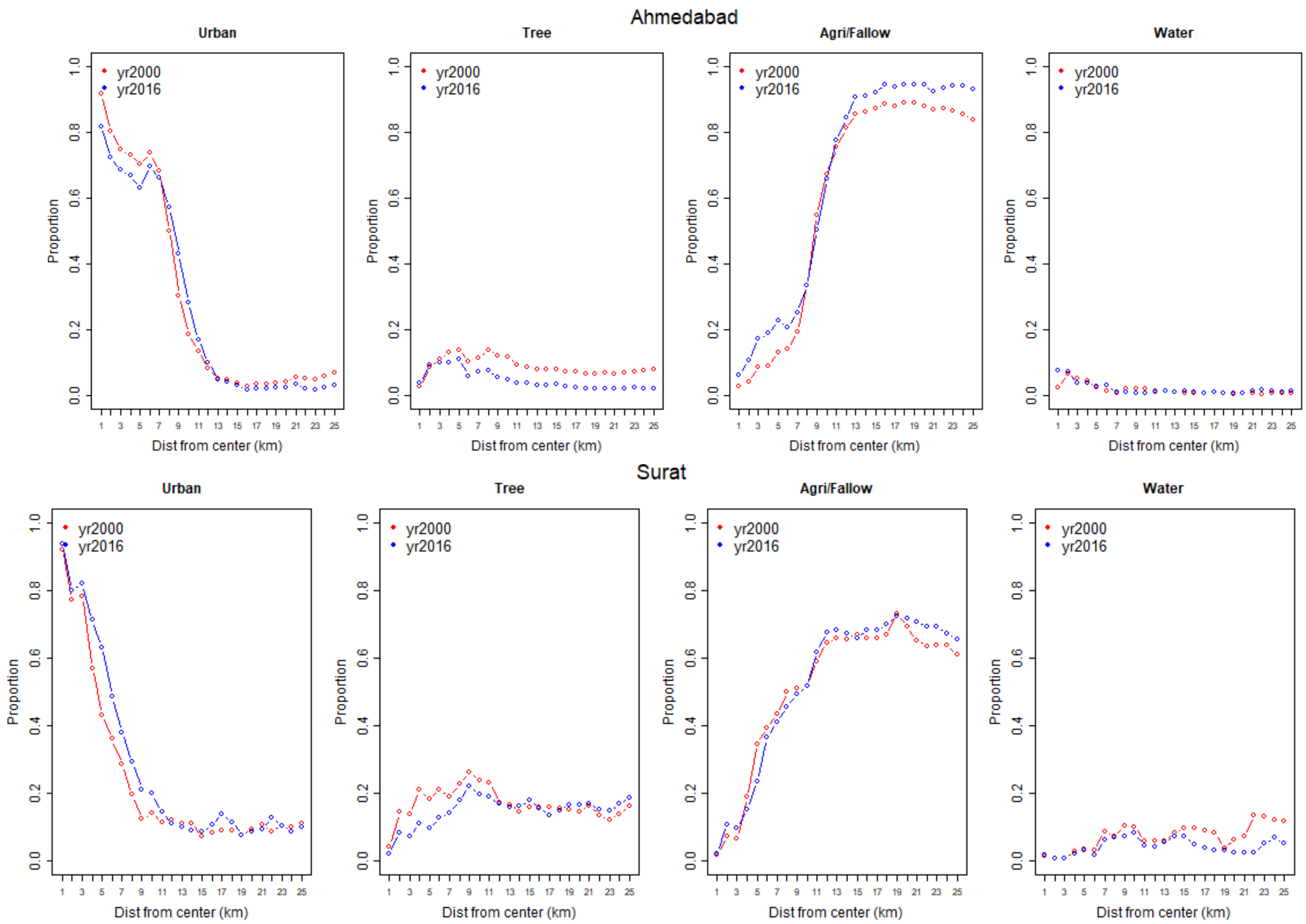


Figure 2. Distance decay in land cover for four types of land cover, calculated at 1 km intervals from the city centre for India's ten largest cities: 1) larger inland cities, 2) larger coastal cities, and 3) smaller cities.

Across all cities (Appendix 2), the spider charts demonstrate that urban patches in the core increase in area and shape complexity, also becoming less interspersed with other cover types (greater interspersion-juxtaposition index (IJI)) indicating that there is both urban expansion and densification, with urban patches agglomerating into larger and more cohesive units over the 15 year period of study. A largely similar trend is observed over time in the city periphery, although not to the same extent, and with some variations, demonstrating that urbanization is less pronounced in the periphery. Tree cover, agriculture/fallow and water bodies largely display an opposite trend, decreasing in area over time, and displaying visible fragmentation in the city core, with smaller and therefore more compact patches that are also clustered together in specific areas, as indicated by the decreased mean euclidean nearest neighbour distance between patches (ENN) or distance between patches, the increased clumpiness, and decreased interspersion with other patches.

We further tested the significance of these landscape changes using a landscape metric that measures landscape fragmentation – interspersion-juxtaposition index (IJI), which assesses whether patches of a given land cover type tend to be interspersed or well mixed with other land cover patches in the vicinity (Figure 3). Statistical significance was assessed using a Wilcox test (Appendix 3). Over time, in both core and periphery, the urban, tree and agriculture/fallow land cover categories had become significantly less interspersed with other categories (Appendix 3). This corroborates the results of the spider diagram indicating that urbanization patterns in Indian cities are becoming larger and more cohesive (less interspersed over time), both in the city centre and in the peripheral areas.

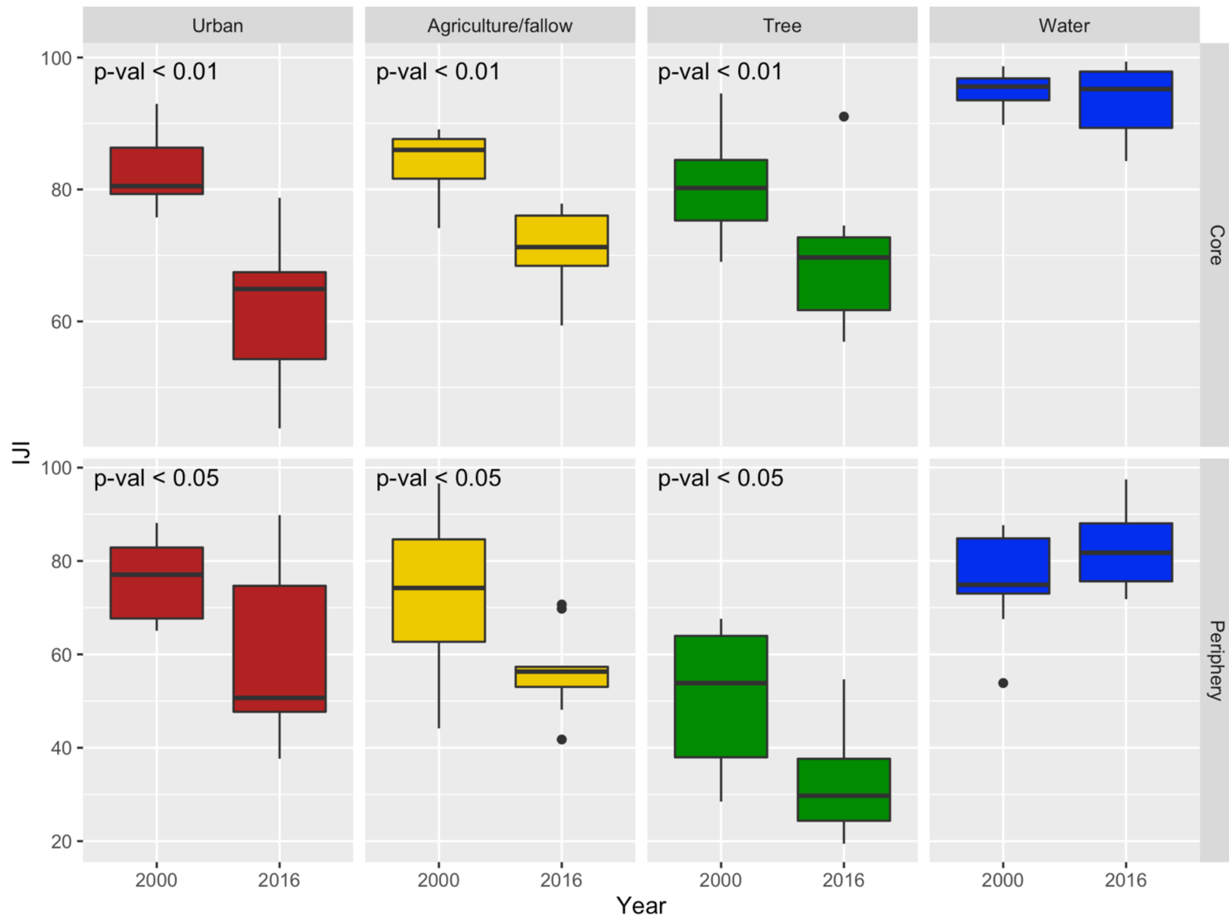


Figure 3. Box and whisker plots demonstrating differences in a metric of landscape fragmentation –interspersion-juxtaposition index or IJI – between 2001 and 2016 for city core and periphery, across four types of land cover.

CONCLUSIONS

Rapid and accelerating urbanization, especially in the global South, has led to large-scale reshaping of the overall landscape, with severe implications for biodiversity and overall ecosystem sustainability. India, which is expected to shortly overtake China to become the most populous country in the world, is anticipated to go through perhaps the world's biggest urban transition, moving from a country that is around 33% urban today, to one that is more than 50% urban by the mid-century (UN Habitat, 2014). This unprecedented urban transition will place severe stresses on urban planning, requiring urban services such as electricity, transport, water supply and sewerage systems as well as economic development, and appropriate urban governance (Sahasranaman and Bettencourt, 2019).

Yet all Indian cities are not the same and cannot be planned for in the same way. Urban growth in India encompasses coastal cities and inland cities, and small towns that are just growing into cities and massive urban agglomerations that are centuries old. In order to better plan for and guide India's massive urban transformation in the next few decades, it is first essential to understand how these cities have grown in the past – and to assess their impact on other types of vulnerable land cover including agriculture vegetation, and water bodies which are essential for urban resilience. However, despite a plethora of single-city studies, such kinds of multi-city data are largely missing in India – as indeed they are for much of the global south as well (Nagendra et al., 2018).

Urban growth can be of different morphologies. Broadly, cities can grow through densification or through sprawl. Using the approach, we have developed in this paper, via analysis of two-date Landsat satellite images, it is clear that India's ten largest cities are growing through sprawl, though they may of course also simultaneously be densifying through in-filling. In addition, urban growth can be mono-centric or multi-nucleated in type, growing out from a single focal area. We observe mono-nucleated growth in the majority of the cities studied, including Surat, Jaipur, Ahmedabad, Bangalore and Hyderabad. Research by He et al. (2017) on 363 cities in China found that urban expansion in the majority of Chinese cities took place through such growth, which they term "edge-expansion". Urban growth can also be coalescent, via multinucleated locations which later aggregate to form a larger urban region (He et al., 2017; Taubenböck et al., 2009). In Delhi, Mumbai and Pune, we observe this form of growth.

Overall, as Lemoine-Rodríguez et al. (2020) find in a global study of 194 cities, we find that most cities exhibit a transitional pattern of growth, with some densification and a tendency towards urban compactness, but also overall sprawl – with coastal cities of Kolkata, Mumbai, and Chennai acting as exceptions to this trend. Mid-sized cities like Jaipur, Ahmedabad and Surat are very dynamic, undergoing especially rapid changes in land cover composition as well as landscape pattern. Spider graphs help us additionally assess patterns of landscape change over time, within the core and periphery. Urban patches have expanded in total area coverage and coalesced into larger units, at the expense of fragmentation of tree cover, agriculture/fallow and water bodies. Thus as urbanization expands, trees, agriculture/fallow areas and water bodies seem to be increasingly confined to specific parts of the city, perhaps in areas where they are protected due to a former colonial history of establishment, or because of their location in areas with a protected status such as the Delhi Ridge, or the Guindy National Park in Chennai. The lack of interspersion of tree and agriculture/fallow patches has significant implications for the biodiversity of many native animal, bird and insect species which are dependent on movement between patches of natural habitat for their survival and long term persistence.

The substantial loss of water cover within the city core, as also demonstrated by the spider graphs, is especially disconcerting and has especial implications for the long term water security of these ten largest Indian cities, many of which are already facing repeated problems of water scarcity as well as flooding. Urban water bodies play a critical role in cities, acting as sponges to buffer and control the city's hydrological cycle (Ma et al., 2020). This evidence of urban water body loss in this study should serve as an important danger signal for urban planners (X. Liu et al., 2020).

The mapping approach is repeatable across urban landscapes in India – we plan to extend it across other cities of India in a subsequent analysis. This approach can be deployed with finer scale data, especially Sentinel data which is available with a resolution of 10 m since 2015. Such data could be used to track changes in land cover at shorter temporal intervals as well, every 2-3 years. However, this data is only available since 2015. Our future research plans include ongoing work to build on the approach used here to classify and examine patterns of urban expansion and associated landscape fragmentation in the top 100 Indian cities, and to explore the use of artificial intelligence approaches to map urban landscape change in greater detail using a larger number of land cover change categories. We hope the approach developed here can be useful for mapping urban change in other data-poor global south cities as well.

APPENDICES:

Appendix 1: Land cover accuracy Assessment of 2001 and 2016 images.

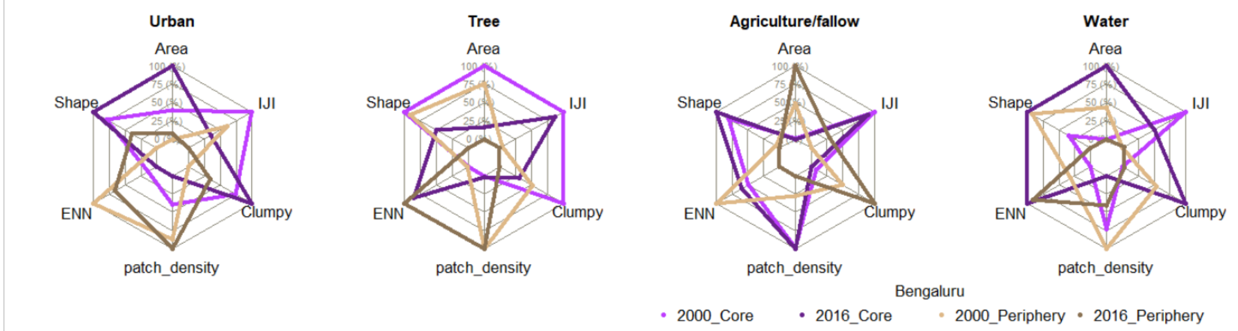
City	Land cover class	Producers Accuracy	Overall accuracy	Kappa estimate	Producers Accuracy	Overall accuracy	Kappa estimate
		2001			2016		
Bangalore	Urban	95	87.5	82.9	82.1	84.2	78.5
	Agri/fallow	77.5			92.3		
	Tree	87.5			75.9		
	Water	100			83.3		
Delhi	Urban	100	91.7	87.3	84.8	81.7	75
	Agri/fallow	90.4			76.9		
	Tree	82.6			90		
	Water	100			72.2		
Hyderabad	Urban	100	92.5	89.5	72.7	90.8	87.4
	Agri/fallow	95.6			97.6		
	Tree	92			93.3		
	Water	100			92.3		
Pune	Urban	92.3	85.8	78.6	87.3	85.8	80.7
	Agri/fallow	79.1			76.6		
	Tree	94.1			95.7		
	Water	95.6			90.9		

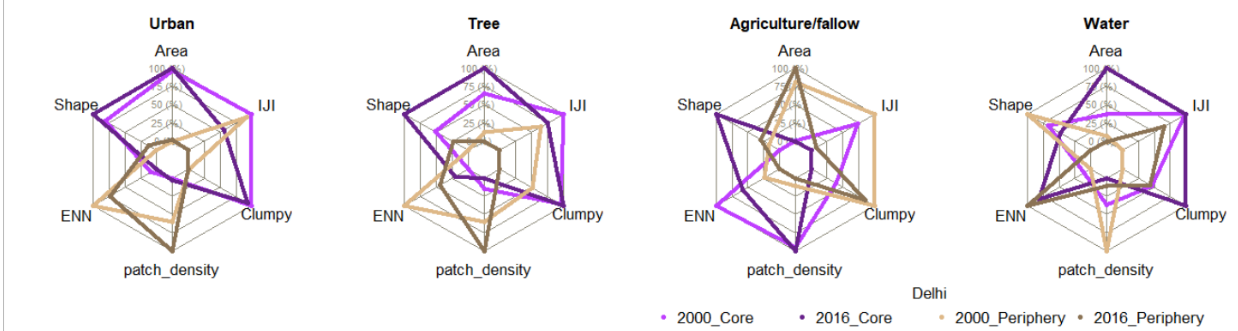
Appendix 1, continued

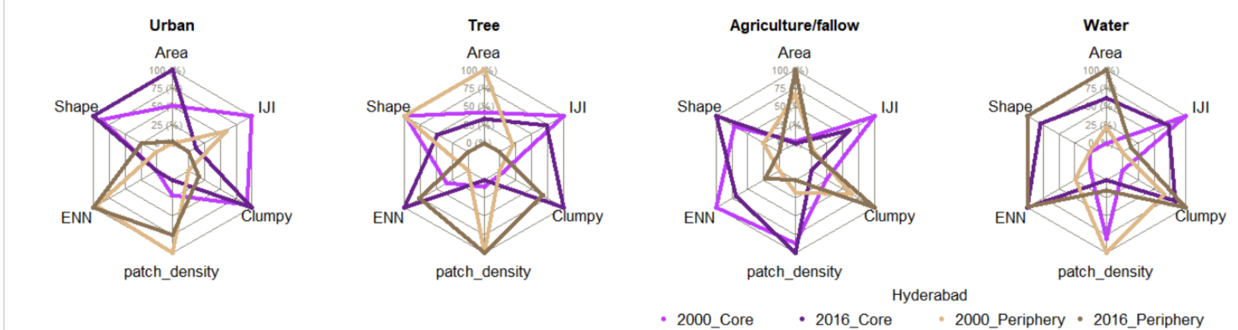
City	Land cover class	Producers Accuracy	Overall accuracy	Kappa estimate	Producers Accuracy	Overall accuracy	Kappa estimate
			2001			2016	
Chennai	Urban	100	85	78.1	76.5	85.8	80.7
	Agri/fallow	83.6			87.8		
	Tree	86.9			94.7		
	Water	70.6			88.5		
Kolkata	Urban	78.6	87.5	82.7	76.2	82.5	76.2
	Agri/fallow	83.8			75		
	Tree	97.2			100		
	Water	84.8			80.8		
Mumbai	Urban	85	85	79.6	87.5	84.9	79.6
	Agri/fallow	75			75		
	Tree	93.7			88.6		
	Water	91.7			91.7		
Ahmedabad	Urban	96.4	91.7	87.8	88	84.2	77.3
	Agri/fallow	98.1			92.2		
	Tree	72.7			70		
	Water	87.5			75		
Jaipur	Urban	78.6	87.5	82.7	75.9	87.5	82.9
	Agri/fallow	83.8			90.2		
	Tree	97.2			88.9		
	Water	84.8			95.7		
Surat	Urban	100	82.5	75	87.5	83.3	77
	Agri/fallow	75.4			73.1		
	Tree	80.7			90		
	Water	92			95.8		

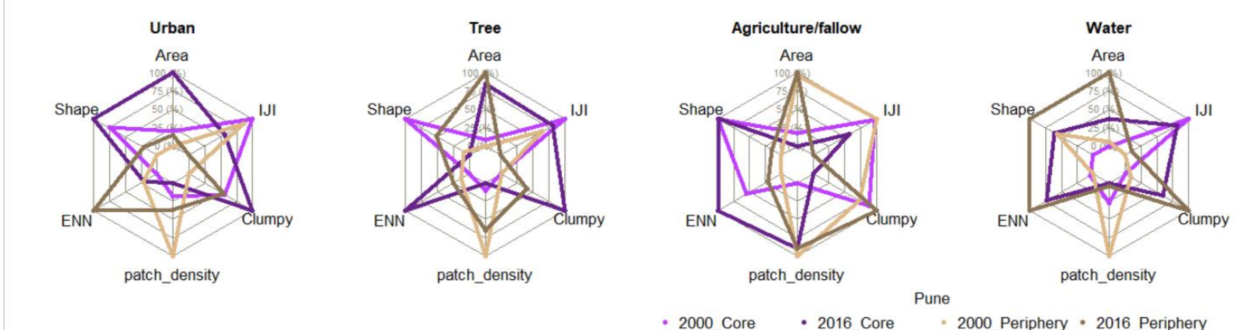
Appendix 2 (description below).

1) Larger inland cities









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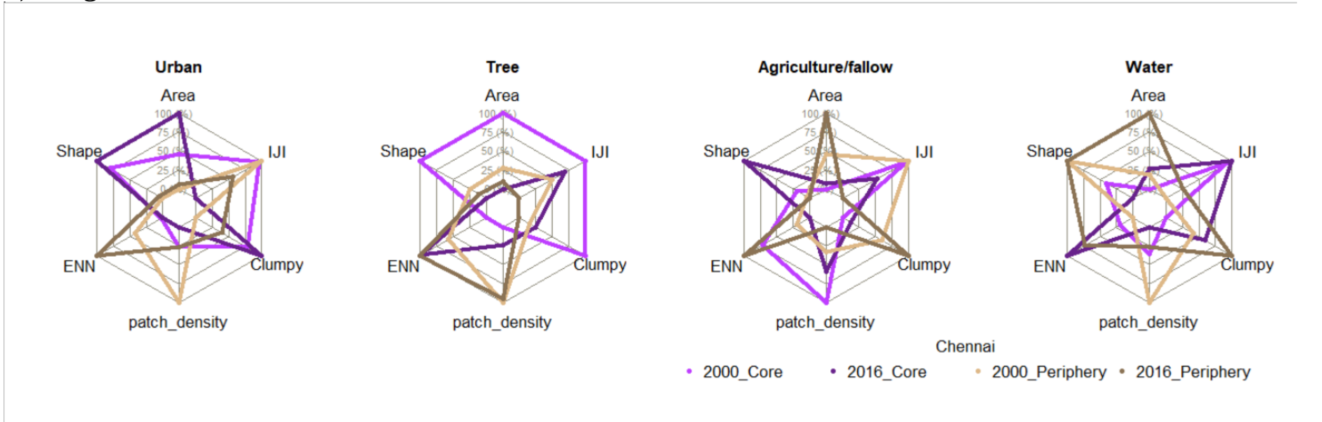
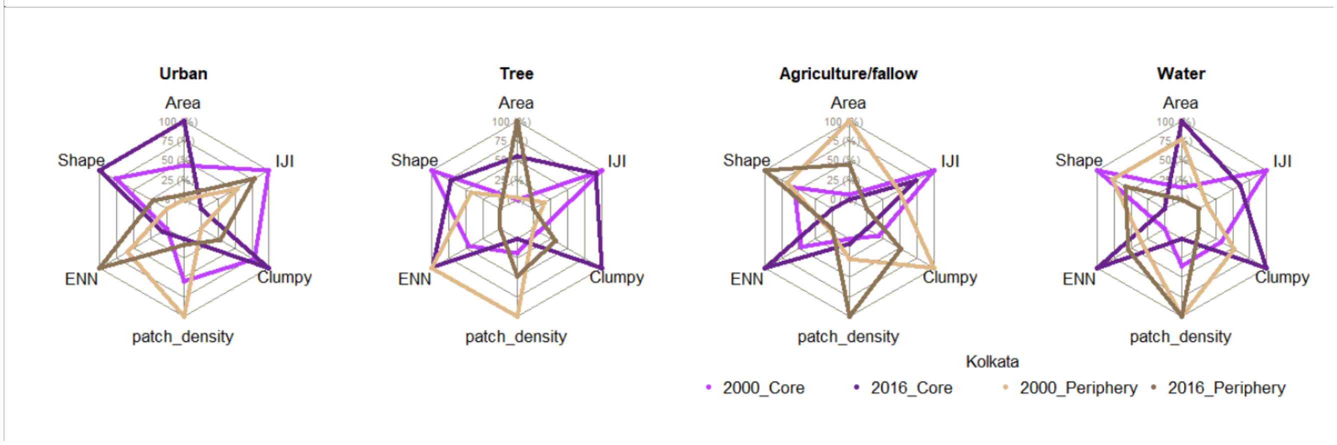
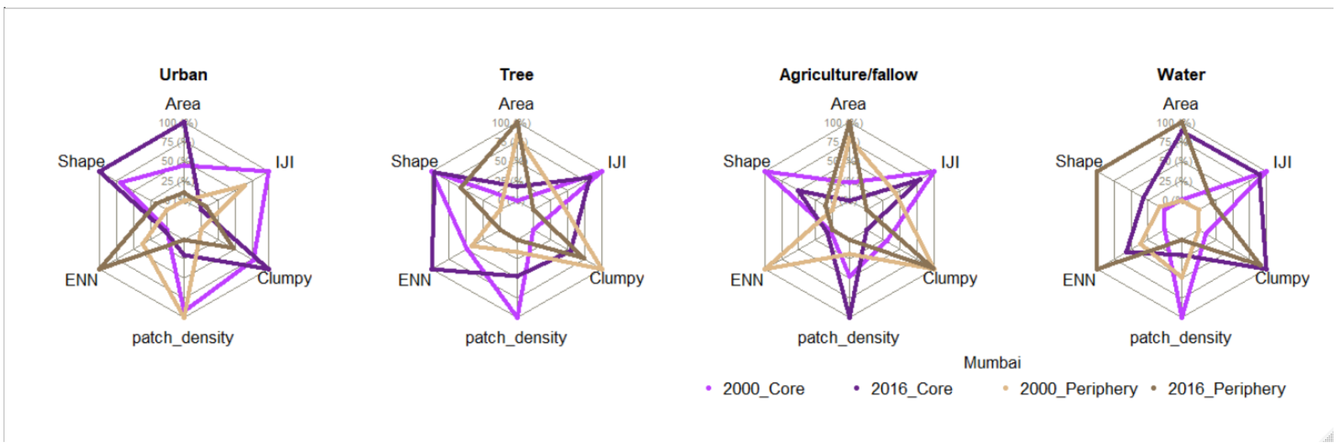
Appendix 2, continued

2) Larger coastal cities

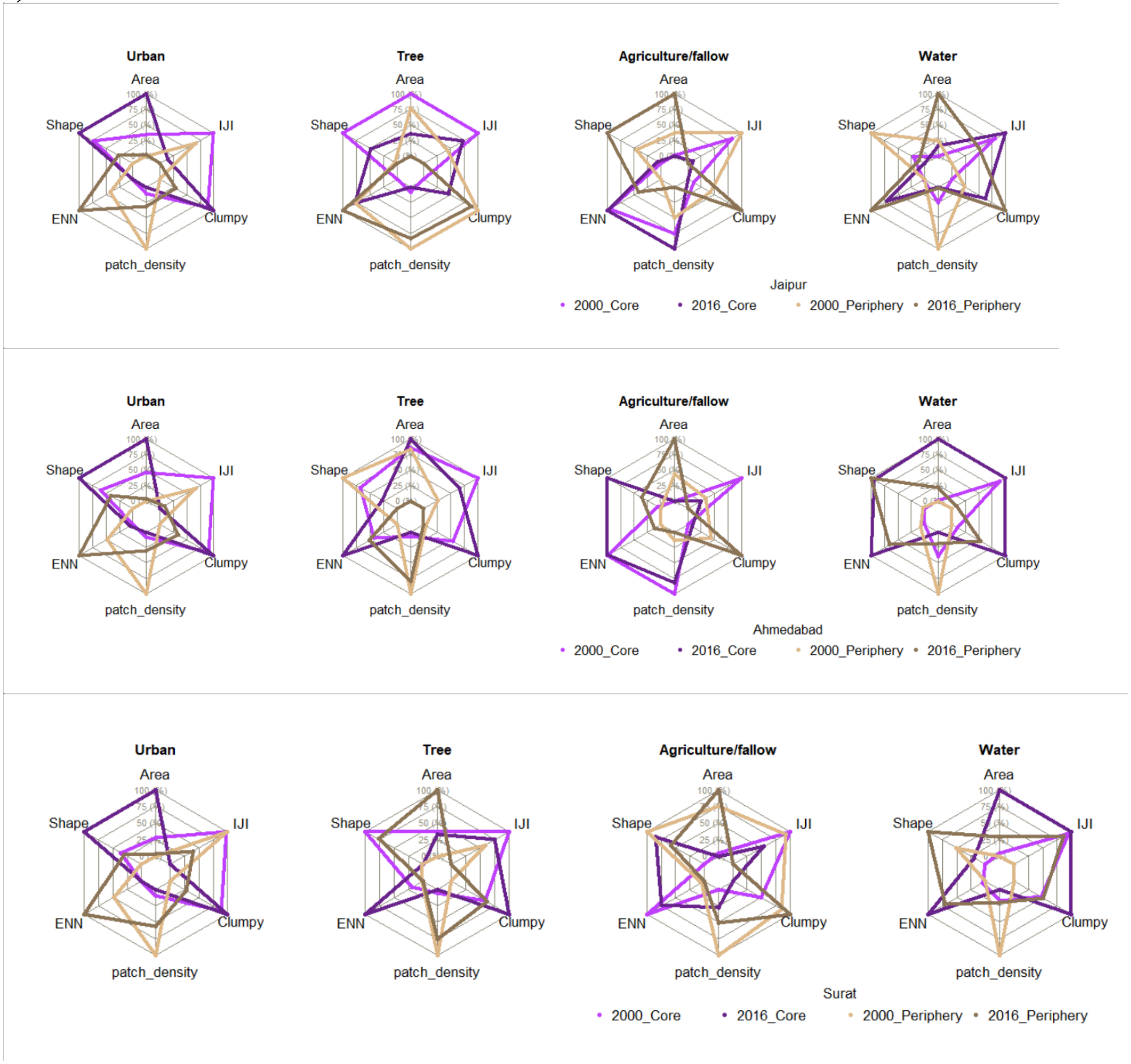






Appendix 2, continued

3) Smaller cities



Appendix 2. Spider charts that characterize the spatial landscape pattern in the city core and periphery across four types of land cover, for India's ten largest cities in 2001 and 2016 for larger inland, larger coastal, and smaller cities. Six parameters of landscape pattern are depicted: percentage of area (area), mean shape index (shape); mean euclidean nearest neighbour distance between patches (ENN); patch density (patch_density), clumpiness (clumpy) and interspersion-juxtaposition index (IJI).

Appendix 3: Wilcox test results

City	Region	Class	Wilcox	p value
Bengaluru	Periphery	Periphery_AREA	3876371971	8.35E-13
Bengaluru	Periphery	Periphery_SHAPE	3.94E+09	0.6653
Bengaluru	Periphery	Periphery_ENN	3747524618	< 2.2e-16
Delhi	Periphery	Periphery_AREA	1.12E+10	3.66E-16
Delhi	Periphery	Periphery_SHAPE	1.12E+10	4.94E-14
Delhi	Periphery	Periphery_ENN	1.17E+10	< 2.2e-16
Hyderabad	Periphery	Periphery_AREA	4202088077	1.11E-04
Hyderabad	Periphery	Periphery_SHAPE	4.24E+09	8.31E-01
Hyderabad	Periphery	Periphery_ENN	4.18E+09	1.26E-09
Pune	Periphery	Periphery_AREA	3677331703	< 2.2e-16
Pune	Periphery	Periphery_SHAPE	3766459612	< 2.2e-16
Pune	Periphery	Periphery_ENN	4116860500	< 2.2e-16
Chennai	Periphery	Periphery_AREA	2673927461	< 2.2e-16
Chennai	Periphery	Periphery_SHAPE	2707660170	1.48E-09
Chennai	Periphery	Periphery_ENN	2.67E+09	< 2.2e-16
Kolkata	Periphery	Periphery_AREA	9.40E+09	7.18E-06
Kolkata	Periphery	Periphery_SHAPE	9.39E+09	4.44E-09
Kolkata	Periphery	Periphery_ENN	9.89E+09	< 2.2e-16
Mumbai	Periphery	Periphery_AREA	3299507175	< 2.2e-16
Mumbai	Periphery	Periphery_SHAPE	3.37E+09	< 2.2e-16
Mumbai	Periphery	Periphery_ENN	3647660676	< 2.2e-16
Jaipur	Periphery	Periphery_AREA	1.76E+09	0.03386
Jaipur	Periphery	Periphery_SHAPE	1765069736	2.89E-05
Jaipur	Periphery	Periphery_ENN	1656105356	< 2.2e-16
Ahmedabad	Periphery	Periphery_AREA	2701700950	5.53E-13
Ahmedabad	Periphery	Periphery_SHAPE	2715096850	< 2.2e-16
Ahmedabad	Periphery	Periphery_ENN	2446510844	< 2.2e-16
Surat	Periphery	Periphery_AREA	2533222073	< 2.2e-16
Surat	Periphe0ry	Periphery_SHAPE	2595717518	< 2.2e-16
Surat	Periphery	Periphery_ENN	2836320790	< 2.2e-16

Appendix 3, continued

City	Region	Class	Wilcox	p value
Bengaluru	Core	Core_AREA	1507670412	< 2.2e-16
Bengaluru	Core	Core_SHAPE	1547930492	< 2.2e-16
Bengaluru	Core	Core_ENN	1.67E+09	< 2.2e-16
Delhi	Core	Core_AREA	5408851863	< 2.2e-16
Delhi	Core	Core_SHAPE	5548450526	< 2.2e-16
Delhi	Core	Core_ENN	6131608128	< 2.2e-16
Hyderabad	Core	Core_AREA	1382858874	< 2.2e-16
Hyderabad	Core	Core_SHAPE	1412185156	< 2.2e-16
Hyderabad	Core	Core_ENN	1514359167	< 2.2e-16
Pune	Core	Core_AREA	573396514	< 2.2e-16
Pune	Core	Core_SHAPE	589725294	< 2.2e-16
Pune	Core	Core_ENN	620548810	1.87E-05
Chennai	Core	Core_AREA	1332455356	< 2.2e-16
Chennai	Core	Core_SHAPE	1354331104	< 2.2e-16
Chennai	Core	Core_ENN	1413138063	1.99E-07
Kolkata	Core	Core_AREA	2681682685	0.2096
Kolkata	Core	Core_SHAPE	2.72E+09	0.0004062
Kolkata	Core	Core_ENN	2525093850	< 2.2e-16
Mumbai	Core	Core_AREA	5497243498	< 2.2e-16
Mumbai	Core	Core_SHAPE	5620657758	< 2.2e-16
Mumbai	Core	Core_ENN	5846375330	1.88E-10
Ahmedabad	Core	Core_AREA	239517832	5.03E-15
Ahmedabad	Core	Core_SHAPE	242601352	2.20E-10
Ahmedabad	Core	Core_ENN	253444272	0.002666
Jaipur	Core	Core_AREA	180913650	9.83E-08
Jaipur	Core	Core_SHAPE	184992748	0.09339
Jaipur	Core	Core_ENN	188702287	0.03198
Surat	Core	Core_AREA	132752968	< 2.2e-16
Surat	Core	Core_SHAPE	135900604	< 2.2e-16
Surat	Core	Core_ENN	145079378	0.01876

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