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INSIGHTS TO 11 SMART CITIES OF UTTAR PRADESH, INDIA THROUGH SPATIAL PATTERN ANALYSIS OF LAND USE/ LAND COVER

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ABSTRACT:

Urban planning of a smart city needs to be done in conjunction to Urban Green Spaces (UGS). Landscape Metrics are one of the efficient ways to analyze the patterns of Land use/Land cover (LU/LC) in a study area. Spatio-temporal change in the urban dynamics of the 11 smart cities of Uttar Pradesh state of India namely "Agra", "Aligarh", "Bareilly", "Jhansi", "Kanpur", "Lucknow", "Moradabad", "Prayagraj", "Rampur", "Saharanpur" and "Varanasi" are studied using Landscape Metrics with the help of publically available classified data such as, for years 1985, 1995 and 2005, Decadal Land use data of India and for year 2015, Copernicus Global Land service Dynamic Land Cover layers (CGLS-LC100 products). Landscape Shape Index (LSI), Largest Patch Index (LPI), Mean Euclidean Nearest Neighbor Distance (ENN_MN) and Aggregation Index (AI) are 4 general metrics used to map LU/LC patterns. Results indicate high positive relationship between LSI and AI values but negligible relationship between LPI and ENN_MN values of built-up and vegetation patches in study area. LPI and LSI show increase in values over the years with LSI showing more steep change in duration, but values of ENN_MN and AI show gradual decreasing trend over the years. Among 11 smart cities, only “Kanpur”, “Agra” and “Moradabad” are most similar in values at higher, average and lower side of metrics with “Lucknow” showing highest complexity for both classes. In general, a heterogenous growth of patches appear in the study area with “Rampur” being the most consistent in metrics while “Jhansi” and “Saharanpur” being most inconsistent.

1. INTRODUCTION

Analysing characteristics of ever changing urbanisation pattern of long duration and its impact on environment can help us achieve sustainable urban planning of the city (Li & Gong, 2016). Land use within a city can be used for ecological and economical benefits for short duration but in the long term, this land use is directly correlated to sustainable inclusive growth of city (Luo et al., 2019). Landscape metrics introduced by McGarigal and Marks, 1995 (McGarigal & Marks, 1995) can describe the form of urbanisation taking place in a city which can be explained by its irregularity, centrality, compactness and complexity (Ji et al. 2006, Sun et al. 2013). Landscape Pattern analysis brings a useful and effective angle to urban planning in terms of sustainability by affecting energy and material flow in inner urban ecosystem (Yang et al. 2019).

Analysis of spatial metrics, qualitative in nature is the first aspect for any city to understand it’s urban sprawl and expansion factors being quantitative in nature is the second one (Huang et al. 2007 and Maimaiti et al. 2017). Intrinsic urban sprawl characteristics of any individual city may be best shown by geo-spatial index, which is a combination of 13 factors in 3 main category of spatial configuration, growth efficiency and external impacts (Jiang et al. 2007). However, in deciding sprawl characteristics of a city, at the level of temporal resolution and neighbourhood level finer scale, spatial metrics prove to be much better options (Ramachandra et al. 2019b). Spatial metrics may bring out an impartial investigation into sprawl characteristics of any urban area and help boosting its settlement policies for future (Berling-Wolff and Wu, 2004).

In making a city more sustainable, more intuitive factors may be used to access a tricky matter like urban planning (Abastante et al. 2020). In recent years, Indian cities have become more complex and dispersed in urbanisation due to rigid state policies and lack of infrastructure at basic level (Ramachandra et al. 2019a). Unplanned urban areas may cause severe environmental impacts on biodiversity, ecosystem and local climate of city resulting in change in land use /land cover (LULC) and Urban Heat Island (UHI) in city (Celik et al. 2019). Diversification of Land Use is bound to happen when event of urbanisation takes place in the city (Liu et al. 2016). The spatio-temporal change in LULC is directly related to UHI and UHI depends on type of LULC classes present in the city (Nega et al. 2022). Analysis of neighbouring land cover patterns give an important insight in UHI management to city planners (Feng & Myint, 2016). It is widely accepted that loss in vegetation can cause UHI in any city (Taha, 1997). Analysing patterns of green spaces can help inform a cooling factor in urban centres of city (Shih, 2017).

Easily available datasets such as Google earth engine (GEE) or Earth observation (EO) data cubes can be very useful in big data analysis (Mugiraneza et al. 2020). Publicly available datasets are best tools to analyse factors affecting local environment (Acosta et al. 2021). Resolution of classified images is a factor with no sounding effect on understanding of a spatio-temporal urbanisation by spatial metrics (Wu et al. 2011). Study of urbanisation done with considering green spaces can have different results based on resolution of images (Qian et al. 2019). This study is determining spatio-temporal change in spatial patterns of two main land use classes Built-up and Vegetation of 11 urban centres of Uttar Pradesh state of

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India for understanding characteristics they represent in urbanisation of study area by using publically available data at resolution of 100m.

2. STUDY AREA

“SMART city Mission” was inaugurated by Government of India in year 2014 for implicating a better standard of living for its citizens in 100 smart cities. The largest states of India, Uttar Pradesh got its 11 cities nominated in different phases of mission, to be developed as smart cities. Cities of "Agra", "Aligarh", "Bareilly", "Jhansi", "Kanpur", "Lucknow", "Moradabad", "Prayagraj", "Rampur", "Saharanpur" and "Varanasi" are shown in Figure 1 and are part of study.

The study comprising these 11 smart cities, is a part of fertile Ganga-Yamuna Plane (Doab region). Capital of Uttar Pradesh state, Lucknow is the largest smart city by area (1232.45 km^2) and Rampur being the smallest with area of 77.44 km^2. A total of 5074.27 km^2 area has been acquired by the study area. These Cities comprise of rivers, canals passing through center of it as well as forest reserves. These 11 cities are some of the largest urban agglomerations in Uttar Pradesh and have seen most of the urbanization in last 3 decades.

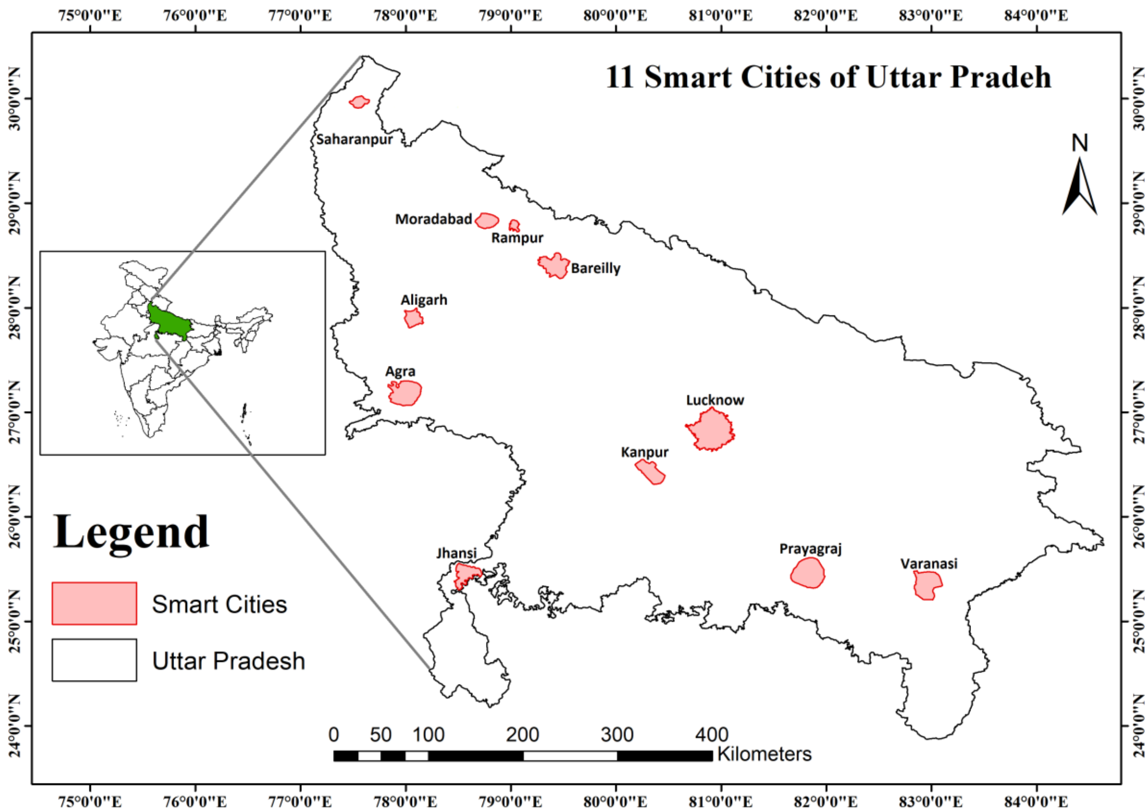


Figure 1. Study area of 11smart cities in Uttar Pradesh, India.

3. METHODOLOGY

The study has been undertaken to study the impact of urbanisation on vegetation present in these 11 smart cities of Uttar Pradesh. 11 Smart cities of Uttar Pradesh state of India are studied for Spatio-temporal change analysis in their LULC spatial pattern especially for the Built-up and Vegetation classes.

3.1 Data used

For years 1985, 1995 and 2005, Decadal Land use data of India at 100m resolution assessed by The Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) website (Roy et al. 2016) has been used.

Copernicus Global Land Service Dynamic Land Cover classified map at 100m resolution with assessed accuracy of 80.6+/-0.4% at discrete map Level 1, otherwise known as CGLS-LC100 product, (Buchhorn et al. 2020) has been used for year 2015.

Most of the LULC classes in Decadal Land use data of India for year 1985, 1995 and 2005, show accuracies of more than 90% except for plantation, wasteland, and barren land. However, the accuracies of these three latter classes are also within the acceptable limits. An overall mapping accuracy of 94.46% and the Kappa accuracy of 0.9445 were achieved for classified map of year 2005 (Roy et al., 2015) and similar results can be assumed for years 1995 and 1985 also (Roy et al., 2015).

ESPG 4326/WGS84 geographic coordinate reference system (CRS) of latitude and longitude was used for reprojection of Copernicus Global Land Service Dynamic Land Cover layer obtained from GEE.

Master plans provided by authorities were used to digitize boundaries of all smart cities were through geo-referencing of maps.

3.2 Workflow of study

All the classified images of smart cities were clipped directly from Decadal ORNL DAAC LULC classified images and CGLS-LC100 product for further analysis. Both of data thus obtained as classified images for year 1985, 1995, 2005 and 2015, are of same 100m resolution.

Decadal ORNL DAAC LULC classified images comprise of 17 land use classes in boundary of India and 9 land use classes in Uttar Pradesh's study area of smart cities, respectively. These 9 classes were reclassified into 5 analysis-ready classes as shown in Table 1.

Land use class used in study	**Land Use classes merged in Decadal ORNL DAAC data**	**Land Use classes merged in CGLS-LC100 product**
Built-up	Built-up Land	Built-up
Vegetation	Deciduous Broadleaf Forest, Shrub land and Plantations	Shrubs, Herbaceous vegetation, Closed Forest, deciduous broad leaf/ not matching any of the other definitions and Open forest, deciduous broad leaf/ not matching any of the other definitions
Water	Water Bodies	Permanent water bodies
Agricultural	Cropland	Cultivated and managed vegetation / agriculture
Other	Fallow Land, Wasteland and Permanent Wetlands	Bare / sparse vegetation and Herbaceous wetland

Table 1. Land use classes reclassified in the study.

Similar to Decadal ORNL DAAC LULC classified images, CGLS-LC100 product for year also contained 11 land use classes, which were reclassified into 5 land use classes, similar to reclassified ORNL DAAC reclassified images shown in Table 1 for analysis in the study.

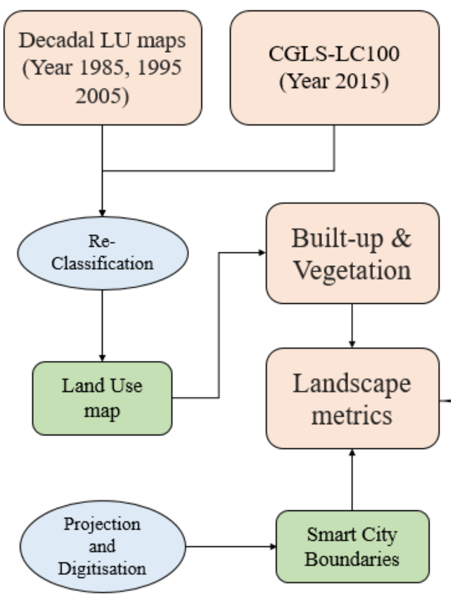
Landscape, its patches and classes can be studied quantitatively by Landscape metrics, Properties such as compactness, complexity, continuity and centrality. In this particular study, metrics were calculated for 2 land use classes (built-up and vegetation) in each of the 11 smart cities to find their spatio-temporal pattern as depicted below (Figure 2).

Continuity is the property which can be represented by LPI (Largest patch index), as it assesses continuing size of the landscape pattern over the study area. Complexity is the property denoting the irregularity in patch size of land use class and it is measured by Landscape shape Index (LSI) as it denotes complexity of patches.

The Mean Euclidean Nearest-Neighbor distance (ENN_MN) measures the shortest edge to edge distance (Euclidean distance) between a patch from nearest patch of concerned class in its neighborhood and it helps determining centrality of landscape by evaluating dispersion of land use patches in a landscape.

Aggregation Index (AI) computes the compactness of land use patches in landscape. Compactness defines the spatial organisation of patches of similar properties, and it mainly depends upon shape of patches and distance between them. These landscape metrics can be calculated using FRAGSTATS (McGarigal & Marks, 1995) as depicted below (Figure 2).

Reclassified images of study area obtained using Decadal ORNL DAAC LULC classified images and CGLS-LC100 product from year 1985 to 2015, saved in GeoTIFF file format were imported in batch in FRAGSTATS and processed for computation of various Landscape Metrics and values of metrics thus obtained were analysed for urban sprawl pattern in study area over change duration of 30 years in 11 smart cities.



LANDSCAPE METRIC	**FORMULA**
Landscape shape Index (LSI) (LSI is one if patch is square but it increase without limit s edges increase in patches)	$LSI = \frac{0.25\,E}{\sqrt{A}}$; Range ≥ 1 without limit where, E is sum of edge of patch (true edge or segment of edges doesn't matter) and A is total area of landscape.
Largest Patch Index (LPI) (It increases with increase in area of largest patch in landscape)	$LPI = (100)\frac{Max\_a_{ij}}{A}$; 0 ≤ LPI ≤ 100 where a_i is area of patch and A is total landscape area.
Mean Euclidean Nearest-Neighbor distance (ENN_MN) (It increases when distance between respective patches keep increasing)	$ENN_{MN} = \frac{\sum_{j=1}^{n} h_{ij}}{n_i}$; Range ≥ 1 without limit where, h_{ij} is Euclidean distance between patches i and j and n_i is total no. of patches present in landscape.
Aggregation Index (AI) (It is 0 when patch have no like adjacency and reaches to 100 when landscape consists of single patch)	$AI = \frac{a_{ij}}{a\_max_{ij}}$; Range from 0 to 100 where, a_{ij} is number of like adjacencies existing between pixels of patch j to that of I and a_max_{ij} is maximum no. of like adjacency existing in landscape

Figure 2. Flow chart showing methodology used in study.

4. ANALYSIS OF RESULTS & DISCUSSION

4.1 Land Use Change

The process of urbanisation caused imprinting effects on agricultural land and Vegetation class in study area of 11 smart cities in Uttar Pradesh, the latter being more affected in this spatio-temporal dynamics. 2/3rd of original amount of "Vegetation" LU class of year 1985 got converted to "Agricultural" LU class and 16.5% to "Built-up" LU class up to year 2015. Due to new urbanization policies taking place in the concerned part of country after year 2005, Vegetation suffered massive loss in year 2015 (10% of total study area in year 1985 to 3% in year 2015) mainly because of a dispersed form of urbanisation happening in the latter years of the study.

Another LU class which saw massive change in area was "Other" LU class present in the study area. It reduced by an amount of more than 90% of its original area of year 1985. This reduction in "Other" LU class caused increase in "Agricultural" LU class and this increase was in turn also contributed from "Vegetation" LU class (Figure 3).

The study area being in middle of Ganga-Yamuna Doab plain, which is home of perennial rivers like Ganga, Yamuna and its tributaries flowing in this vast plane supported negligible change in "Water" LU class over the years (Table 2).

Smart cities of Uttar Pradesh underwent significantly with extensive urbanisation over the period of 30 years. A significantly notifiable increase of 50% in urbanisation is visible during early change duration of 1985 to 1995. It was due to massive contribution of "Other" LU class in the process through conversion of "Other" LU class to "Built-up" LU class mainly. Later years of study also witnessed urbanisation but in a much more dispersed and more centralised growth (Verma & Garg, 2021). In year 1985, in context of Built-up area, Agra was a massive contributor with 24% of whole urban area alone whereas, after 1995 and so on Lucknow and Kanpur have been the first and second most urbanised cities. Bareilly, Prayagraj and Varanasi increased their part in urbanisation but in very little amount of 3% of total urbanisation in year 2015 whereas, Aligarh, Jhansi and Saharanpur had their part reduced by almost the same percentage.

LU Classes	**Built-up**	**Vegetation**	**Agricultural**	**Other**	**Water**	**1985**	***Decreased***
Built-up	*422.32*	6.54	68.92	0.68	7.59	506.04	*83.72*
Vegetation	80.00	*64.69*	326.23	6.38	14.10	491.40	*426.72*
Agricultural	379.35	84.83	*2895.74*	10.02	35.64	3405.58	*509.84*
Other	189.21	12.16	290.14	*5.91*	22.09	519.51	*513.60*
Water	8.23	3.43	67.73	21.71	*37.45*	138.54	*101.09*
2015	1079.10	171.65	3648.76	44.69	116.87		
Increased	*656.79*	*106.96*	*753.02*	*38.78*	*79.42*	***Area (km²)***	

Table 2. Change Matrix for Land use classes in 11 smart cities of Uttar Pradesh for 1985 to 2015.

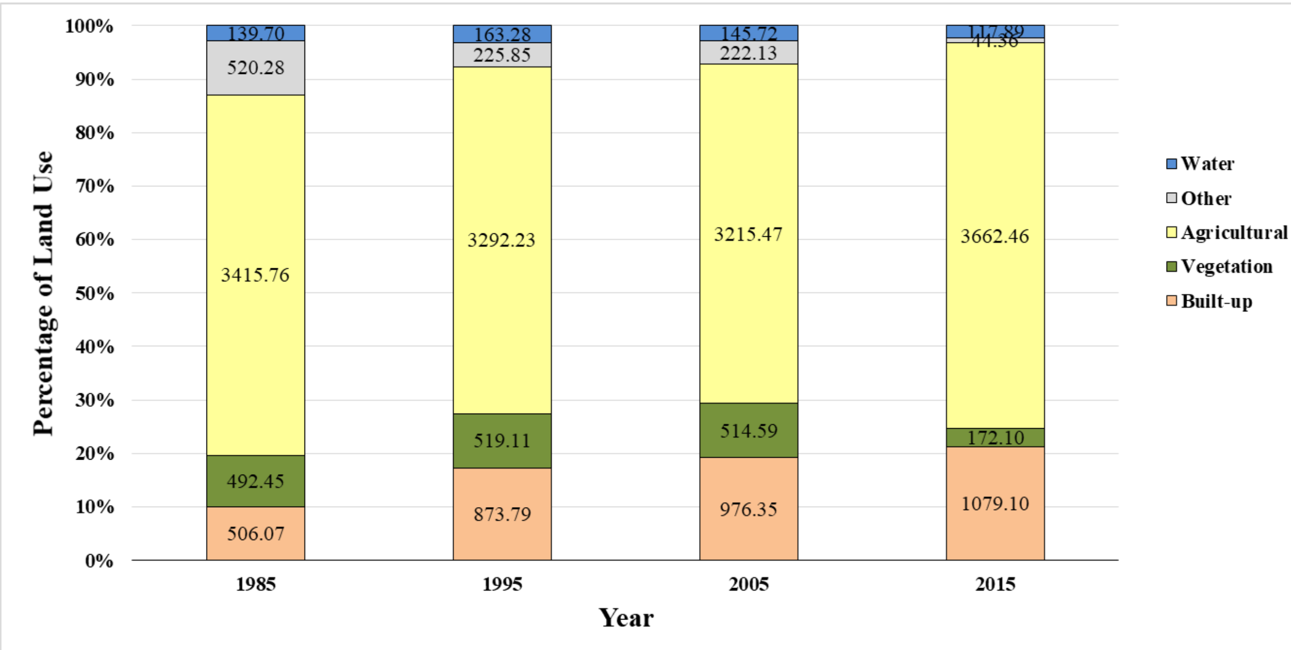


Figure 3. Cumulative land use change in study area of 11 smart cities of Uttar Pradesh (Numbers within bars depict the area in km²)

4.2 Landscape Metrics

All the detailed Landscape metrics, LPI, LSI, ENN_MN and AI were calculated using equations shown in Figure 2 from FRAGSTATS, for understanding a clear spatio-temporal pattern of Land use class patches and characteristics they represent in urbanisation of study area. Figure 4 depicts the trend of the metrics LPI, LSI, ENN_MN and AI over the years of 1985 to 2015 for LU/LC patches of urban and vegetation in study area of 11 smart cities of Uttar Pradesh state of India. All 11 smart

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cities exhibited the highest values of LSI in year 2015, indicating the higher complexity in shapes of urban and vegetation patches in study area (Figure 4).

Higher values of LSI may be indicating formation of more irregular built-up patches in year 2015 in almost all the 11 smart cities of study area. Higher values of LSI suggest that patches are having more and more unpredictability in their shape, which may be due to the generation of new built-up patches more in number but smaller in size.

The urbanisation of area with formation of new patches is the cause of this pattern. Prayagraj had the lowest LPI over the years, indicating insignificant urbanisation over the change duration which also matches with findings in Figure 4. LPI saw a gradual increase over the years 1985 to 2015, indicating an increase in size of largest patch of built-up and vegetation land use class. LPI was highest for built-up class in year 2005 and then decreasing in year 2015 indicating more formation of new large patches of built-up class but smaller in size hence resulting in more edge type growth than newly formed patches of outlying type.

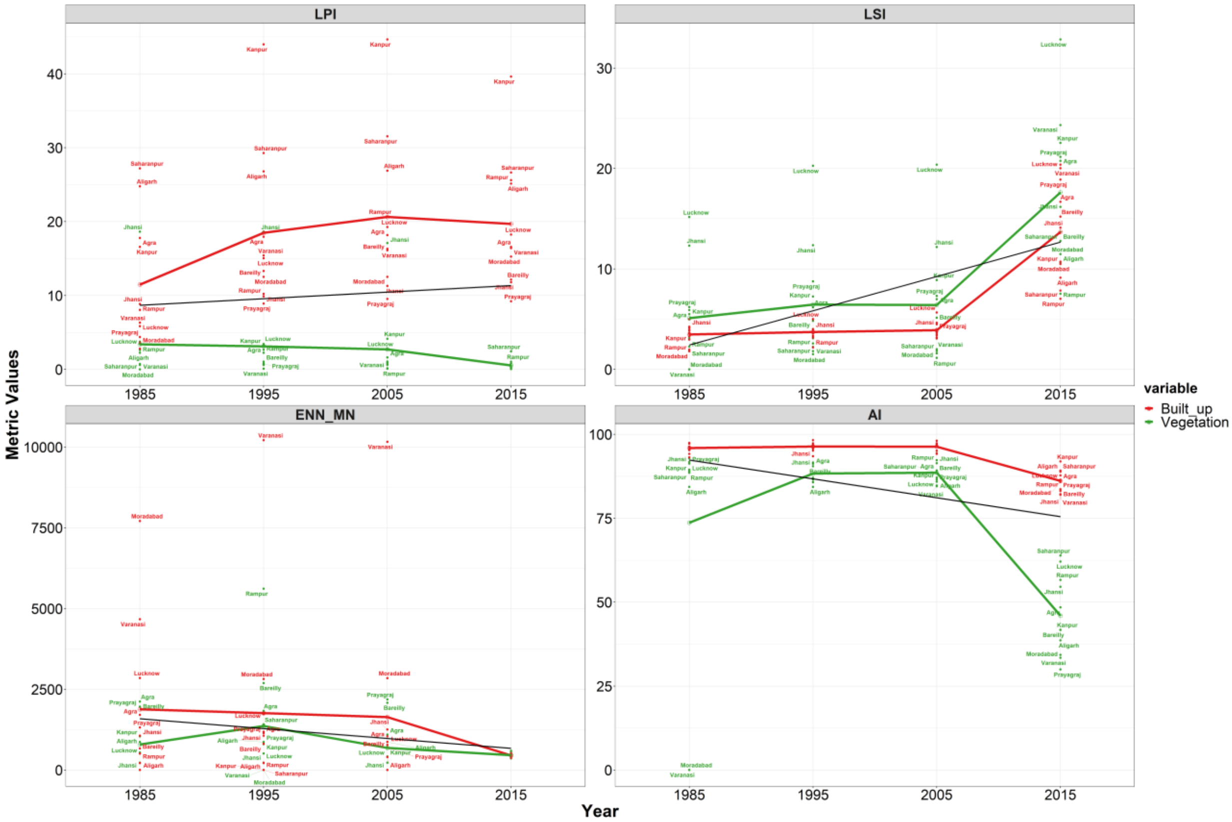

Figure 4. Trend of landscape metrics for Built-up and Vegetation patches across 11smart cities of Uttar Pradesh over years.

ENN_MN in Figure 4 shows that centrality is maximum for Built-up patches in year 1985 and then decreases to minimum in year 2015, whereas for vegetation class patches, ENN_MN shows no particular trend over the years. In total, ENN_MN has a very steady gradual decreasing trend towards the study period form year 1985 to 2015 indicating less centralised patches at centre of urban areas or smart cities. In year 2015, ENN_MN values for built-up and vegetation land use class was almost similar but smaller in comparison from previous year of 2005 in case of Built-up and more in case of Vegetation, indicating a slight increase in dispersion of Built-up patches away from city centre but concentration of Vegetation land use class at urban centre. The reason behind the vegetation class showing no specific trend or increasing-decreasing trend over the previous-next years is the simple counter approach by authorities to mitigate urbanisation in any way possible, hence more vegetation at centre of smart cities.

Compactness of urban area is depicted by the AI value shown by built-up and vegetation patches in the study area, i.e., bordering of one land use class by any other land use classes present in study area. Each of the 11 smart cities show higher values of AI for built-up patches in each year except for year 2015, which indicates that all the built-up patches are being surrounded by one or many other land use classes classified in area which in final result indicates less compactness in year 2015. Vegetation land use class is also showing lowest value of AI for all 11 smart cities indicating surrounding of vegetation land use class patches by fewer other classes hence by itself only. AI in general shows a decreasing trend in years 1985 to 2015 for these 11 smart cities, indicating less formation of outlying patches of built-up land use class and intensifying of more edge type growth in study area.

Figure 5 shows the relationship through calculation of the coefficient of determination (R^2) between metrics of Built-up land use class to the metrics of Vegetation land use class over the change duration. LPI and ENN_MN show a negligible negative relationship of less than 0.1 between metric values of patches of both classes. LPI and ENN_MN values of Built-up and Vegetation land use classes were changing irrespective of each other, but LSI and AI of both classes were very much susceptible to changes in each other. The same can be inferred from Figure 4 also. On the other hand, LSI and AI show a

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significant positive relationship between land use classes of built-up and vegetation in 11 smart cities of Uttar Pradesh. Increase in irregularity in patches of Built-up land use class strongly suggests increase in complexity of shape of vegetation land use class patches as depicted by strong positive relationship value of 0.66 for LSI in Figure 5.

If built-up patches are surrounded more by other classes, same will be the case for patches of vegetation land use class in study area of 11 smart cities, as suggested by a positive relationship value of 0.36 for AI in Figure 5. Slightly separate values of LSI and AI in year 2015 may be because of the fact that LSI and AI are shape oriented metrics rather than size oriented and that's why LPI and ENN_MN values for year 2015 are in same range of other previous years values. Since the data used for year 2015 are different than for years 1985, 1995 and 2005, hence it could be the reason of slight deflect in values of metrics LSI and AI in year 2015.

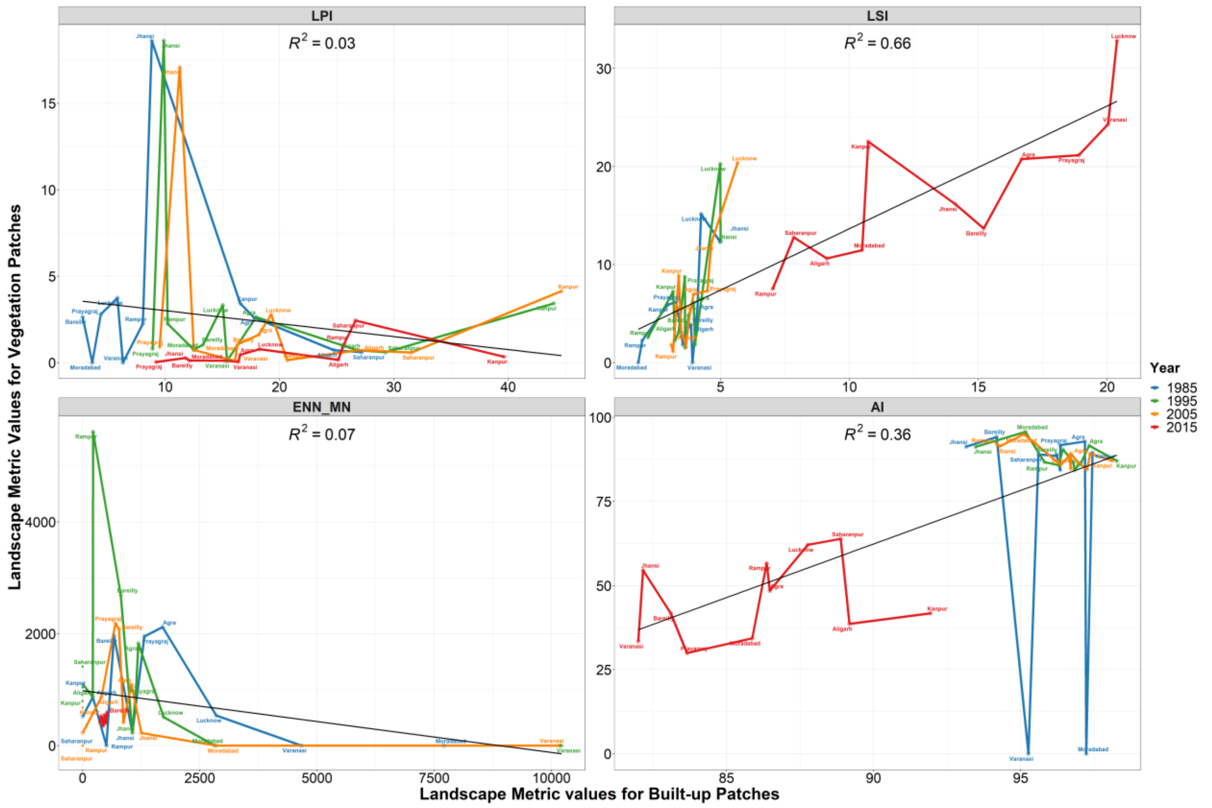
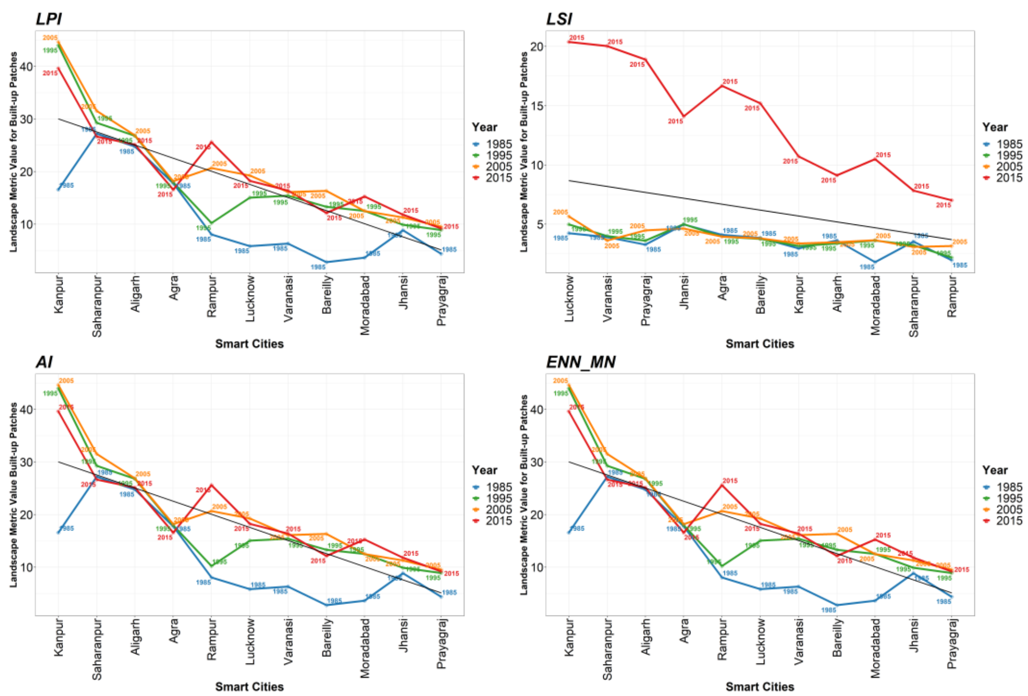
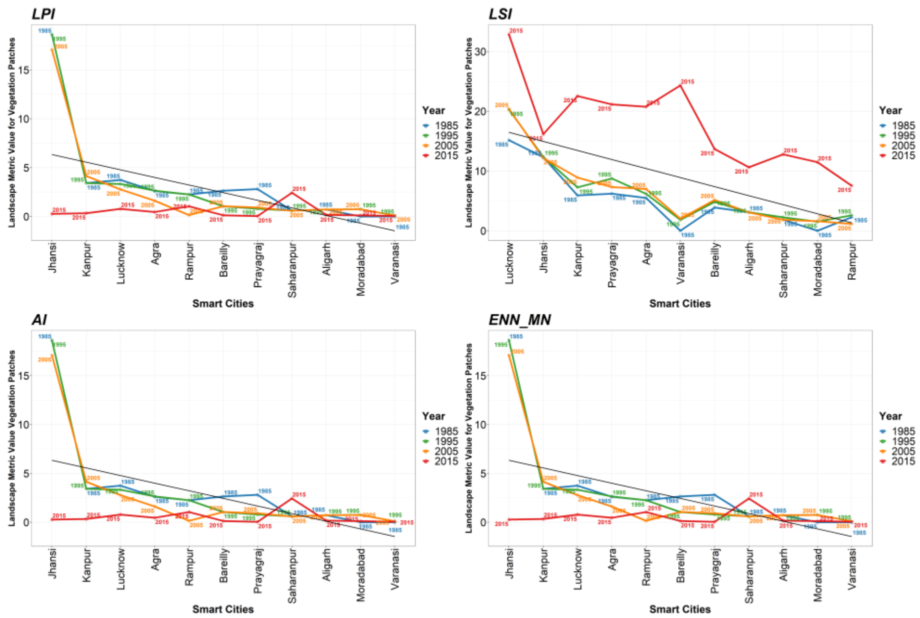


Figure 5. Relationship between landscape metrics for Built-up and Vegetation patches across 11smart cities of Uttar Pradesh.



(a)



(b)

Figure 6. Landscape metric values of (a) built-up and (b) vegetation LU class across 11smart cities of Uttar Pradesh.

Figure 6 best explains metrics values of each smart cities in both land use classes at individual level. Kanpur is the highest at all values except LSI for built-up patches, in which Lucknow the capital city of Uttar Pradesh is with the highest mean value for all years. Same is the case for lowest values of all metrics for built-up land use class except for LSI in which Rampur replaces Prayagraj having lowest in terms of LPI, AI and ENN_MN. The same trend follows in metric value plot for vegetation patches. Here, Lucknow again is the highest for LSI and Jhansi showing exceptionally larger values for LPI, AI and ENN_MN. Rampur is lowest in LSI and Varanasi for all other metrics for Vegetation patches. Kanpur, Agra and Moradabad seem to be standing their position as higher, average and lower values level respectively in each metrics for both land use classes.

Agra being on no. 4 in LPI, ENN_MN and AI and no. 5 in LSI from higher range seems to be most consistent smart city in terms of metric value for built-up and vegetation classes. The capital city of Uttar Pradesh state of India, Lucknow is channelling a very complex or irregular shape of patches in its boundary of smart city by being in higher range of metric values for vegetation patches, in middle or average range of metric values for built-up patches and being the highest in LSI for both land use classes. The reason behind this phenomenon can be explained as this city being in constant focus of authorities, as it is capital city and immigrants from nearby districts or towns come to work and tend to settle in its periphery. Jhansi and Saharanpur are most inconsistent cities in terms of metric values for both classes. It could be because of geographical location of these 2 cities, as Jhansi being most southern and Saharanpur being most northern city in Uttar Pradesh state that their position at the border caused lack of facilities to implement development plans at its best.

5. CONCLUSIONS

Spatio-temporal analysis for any city provides a clear perspective of its environment changes and the long-term effect they bring upon. Urban growth pattern analysis by the help of Landscape metrics certainly brings a clear thinking for planners to develop city in much more sustainable way fulfilling all the development goals. These types of studies done over a large area such as in this study over 11 smart cities covering a total area of almost 5000 km^2 can prove to be tricky and challenging in nature. Use of publically available data certainly helps in cost perspective of analysis and as they are already detailed with better accuracy of classification of land use, city planners can definitely rely upon these data for analysis of urban dynamics at a certain level. Planners can be greatly benefitted from using this way of study of urbanisation for a large study area and long change duration. In the study are of 11 smart cities of Uttar Pradesh, Built-up and Vegetation LU/LC LSI and AI landscape metrics are showing a very distinctive positive relationship spatially but temporally, LSI being only metrics with the very distinct trend which can be attributed to formation of new patches with higher irregularity in study area.

Lucknow, Kanpur and Jhansi are the most affected cities by urbanisation, but Lucknow, Kanpur and Agra seem to be more consistent in metrics than Jhansi. Rampur, Moradabad and Varanasi are the least affected by urbanisation, which indicates heterogenous growth of urban area in these 11 smart cities of Uttar Pradesh. Landscape metrics are such effective indices to showcase parameters of urban growth that, Compactness and centrality can be used to define the allocation of Urban Green Space (UGS) in form of urban parks in city areas. Similarly, from point of city planners, major part of aesthetics of any city can be detailed by continuity and complexity of built-up patches present in its boundary which if taken into account by planners, can benefit hugely in resource allocations of communication networks in city.

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REFERENCES

Abastante, F., Lami, I. M., La Riccia, L., Gaballo, M. (2020). Supporting Resilient Urban Planning through Walkability Assessment. *Sustainability*, 12(19), 8131.

Acosta, M. P., Vahdatikhaki, F., Santos, J., Hammad, A., Dorée, A. G. (2021). How to bring UHI to the urban planning table? A data-driven modeling approach. *Sustainable Cities and Society*, 71, 102948.

Berling-Wolff, S., Wu, J., 2004a. Modeling urban landscape dynamics: A case study in Phoenix, USA. *Urban ecosystems*, *7*(3), 215-240.

Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.E., Linlin, L., Tarko, A., 2020. *Copernicus Global Land Service: Land Cover 100m: Version 3 Globe 2015-2019*, Product User Manual; Zenodo, Geneve, Switzerland, September 2020.

Celik, B., Kaya, S., Alganci, U., Seker, D. Z. (2019). Assessment of the relationship between land use/cover changes and land surface temperatures: a case study of thermal remote sensing. FEB Fresenius Environ. Bull, 3, 541.

Feng, X., Myint, S. W. (2016). Exploring the effect of neighboring land cover pattern on land surface temperature of central building objects. Building and Environment, 95, 346-354.

Huang, J., Lu, X. X., Sellers, J. M. 2007. A global comparative analysis of urban form: Applying spatial metrics and remote sensing. *Landscape and urban planning*, *82*(4), 184-197.

Ji, W., Ma, J., Twibell, R. W., Underhill, K., 2006. Characterizing urban sprawl using multi-stage remote sensing images and landscape metrics. Computers, *Environment and Urban Systems*, 30(6), 861-879.

Jiang, F., Liu, S., Yuan, H., Zhang, Q. 2007. Measuring urban sprawl in Beijing with geo-spatial indices. *Journal of Geographical Sciences*, *17*(4), 469-478.
.

Li, X., Gong, P. (2016). An “exclusion-inclusion” framework for extracting human settlements in rapidly developing regions of China from Landsat images. *Remote Sensing of Environment*, 186, 286-296.

Liu, Z., C. He, Wu, J., 2016. General spatiotemporal patterns of urbanization: An examination of 16 world cities. *Sustainability*, *8*(1), p.41.

McGarigal, K., Marks, B. J., 1995 *FRAGSTATS: spatial pattern analysis program for quantifying landscape structure* (Gen. Tech. Rep. PNW-GTR-351. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, 122 p.)

Maimaiti, B., Ding, J., Simayi, Z., Kasimu, A., 2017. Characterizing urban expansion of Korla City and its spatial-temporal patterns using remote sensing and GIS methods. *Journal of Arid Land*, *9*(3), 458-470.

Mugiraneza, T., Nascetti, A., Ban, Y. (2020). Continuous monitoring of urban land cover change trajectories with landsat time series and landtrendr-google earth engine cloud computing. *Remote Sensing*, 12(18), 2883.

Nega, W., Balew, A. (2022). The relationship between land use land cover and land surface temperature using remote sensing: systematic reviews of studies globally over the past 5 years. Environmental Science and Pollution Research, 1-16.

Qian, Y., Chen, Y., Lin, C., Wang, W., Zhou, W. (2019). Revealing patterns of greenspace in urban areas resulting from three urban growth types. Physics and Chemistry of the Earth, Parts A/B/C, 110, 14-20.

Ramachandra, T. V., Sellers, J., Bharath, H. A., Setturu, B. (2019a). Micro level analyses of environmentally disastrous urbanization in Bangalore. *Environmental monitoring and assessmen*t, 191(3), 1-13.

Ramachandra, T. V., Sellers, J., Bharath, H. A., Vinay, S. (2019b). Geo-visualization of landscape dynamics in the proposed mega industrial corridor. *Environmental monitoring and assessment*, *191*(3), 1-18.

Roy, P.S., Meiyappan, P., Joshi, P.K., Kale, M.P., Srivastav, V.K., Srivasatava, S.K., Behera, M.D., Roy, A., Sharma, Y., Ramachandran, R.M. and Bhavani, P., Decadal Land Use and Land Cover Classifications across India, 1985, 1995, 2005, 2016. ORNL DAAC, Oak Ridge, Tennessee, USA. doi:10.3390/rs70302401.

Shih, W. (2017). Greenspace patterns and the mitigation of land surface temperature in Taipei metropolis. Habitat International, 60, 69-80.

Sun, C., Wu, Z. F., Lv, Z. Q., Yao, N., Wei, J. B., 2013. Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *21*, 409-417.

Taha, H. (1997). Urban climates and heat islands: albedo, evapotranspiration, and anthropogenic heat. Energy and buildings, 25(2), 99-103.

Verma, R. Garg, P. K. (2021). Analysis of spatio-temporal urban dynamics in 11 smart cities of Uttar Pradesh, India, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLVI-4/W5-2021, 557–564.

Wu, J., Jenerette, G. D., Buyantuyev, A., Redman, C. L., 2011. Quantifying spatiotemporal patterns of urbanization: The case of the two fastest growing metropolitan regions in the United States. *Ecological Complexity*, *8*(1), 1-8.

Yang, J., Li, S., Lu, H., 2019. Quantitative influence of land-use changes and urban expansion intensity on landscape pattern in Qingdao, China: Implications for urban sustainability. *Sustainability*, *11*(21), 6174.