MULTI-TEMPORAL LAND USE PATTERNS IN LUCKNOW, INDIA

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ABSTRACT: These Several studies conducted in past have revealed the nature of urban expansion in various cities all over the world based on 4 basic properties of urban expansion: Complexity, Centrality, Compactness and Porosity. However very few have studied the relation of these properties for vegetation in respect to urban expansion. In this paper, Decadal Land use data for India for years 1985, 1995 and 2005 has been used and Landsat- 8 OLI data for year 2017 has been used to prepare Land Use maps by Hybrid approach of Maximum Likelihood Classification for multi-temporal analysis of urban expansion and vegetation change for 5 Assembly constituencies (AC) of Lucknow city named as Cantonment (Cantt.), Lucknow East (LE), Lucknow North (LN) and Lucknow West (LW). Land Use map for year 2017 was resampled for 100m resolution to match the Decadal Land use data for year 1985, 1995 and 2005. The matrices used to find relation between Built-up and Vegetation class are Number of Patches (NP), Landscape Shape Index (LSI), Largest Patch Index (LPI), Mean Euclidean Nearest neighbor Distance (ENN_MN), Proportion of Like Adjacencies (PLADJ) and Aggregation Index (AI) calculated from FRAGSTAS. Results of study showed that LSI for Built-up and Vegetation is correlated highly ($R^2 = 0.65$) that too positively, which shows that increase in complexity of shapes of Built-up patches is also causing increase in complexity of shapes of Vegetation patches. LPI is least correlated for both LU classes. Decrease in LPI and NP over the years is observed for Vegetation class which is causing increase in NP but decrease in LPI for Built-up class explaining the increase of Built-up class over the years but also the more dispersion of urban area in the study area. North (LN) and West (LW) AC of Lucknow city area being poor in Vegetation are having highest ENN_MN which is decreasing over the years causing less dispersion but still less dispersion of vegetation than other ACs causing more centrality. PLADJ is continuously decreasing for vegetation over the years which explains the establishment of new Built-up patches around Vegetation. AI and PLADJ is same for Built-up patches over the years from 1985 to 2017 which is due to either edge-filling or outlying urban expansion in study area. All 3 change duration 1985-1995, 1995-2005 and 2005-2017 area showing edge expansion type urban increase in Lucknow city which stands out as the reason for no change in PLADJ and AI for built-up patches in all ACs for all years. Among all 5 ACs Cantonment is having best performance in all landscape matrices due to less decrease in vegetation and hence less built-up patches over the years.

1. INTRODUCTION

More than 4 billion people of world population live in urban centres which are in way of becoming highly dense cities (Ritchie and Roser, 2019). Urbanisation being a unique phenomenon to each city, brings changes to its environment and socioeconomic conditional in a unique manner (Liu et al., 2016). Analysis of general trends of urbanisation and its two staged spatio-temporal pattern is an hour of need for planners of cities to understand the urbanisation process taking place in the particular city (Zhao et al., 2015). In short term, due to economic constraints, ecological and economic benefits of urban land use can be shortened but in long term, these effects are more correlated in terms of sustainable and inclusive growth of city (Luo et al., 2019).

Urban sprawl having no specific universally accepted definition, has been best explained by its qualitative, quantitative, and attitudinal landscape patterns. Such an attempt to best describe these characteristics was successfully made by characterising urban growth in 5 different types as in infilling, extension, linear development, sprawl and large-scale projects (Camagni et al., 2002). Urban growth type was classified into basically 3 types Edge-expansion, Infilling and Outlying using equation involving common perimeter of new and old urban patch (Xu et al., 2007) and using Landscape Expansion Index (LEI), calculated by common area lying in buffer around new and old urban patches (Liu et al., 2010).

Studying urbanisation through Landscape metrics in Indian cities of unplanned concentrated growth is an effective way (Ramachandra et al., 2012). Landscape Metrics are quantitative indices representing physical characteristics of landscape of area (Huang et al., 2007; Ramachandra et al., 2019). These landscape metrics best explain centrality, complexity, compactness, density and porosity of urban patches in area (Dutta and Das, 2019; Huang et al., 2007). Landscape metrics provide better understanding of temporal changes in landscape than traditional approaches for analysis of pattern and process of urbanisation in an area (Crews-Meyer, 2002). Landscape metrics area the products of FRAGSTATS analysis (McGarigal and Marks, 1995).

In this paper, analysis of urbanisation with loss of vegetation has been attempted through landscape metrics and urban growth types for 5 assembly constituencies of Lucknow city from year 1985 to 2017. Decadal land use land cover for year 1985, 1995, 2005 and Landsat- 8 data for year 2017 has been used in achieving so.

2. STUDY AREA

Lucknow, a metropolitan city in Uttar Pradesh state of India is chosen as study area (Fig. 1). It is one of the 100 cities ordained by Indian central government for projects under Smart City Mission. It is administrative headquarter of Lucknow District, which has 2 parliamentary constituencies in it named Mohanlalganj and Lucknow. Study area falls in Lucknow Parliamentary constituency which is comprised of 5 Assembly constituencies (ACs) named Cantonment (Cantt.), Lucknow Central (LC), Lucknow East (LE), Lucknow North (LN) and Lucknow West (LW). River Gomti passes through almost all of 5 ACs in between of study area.

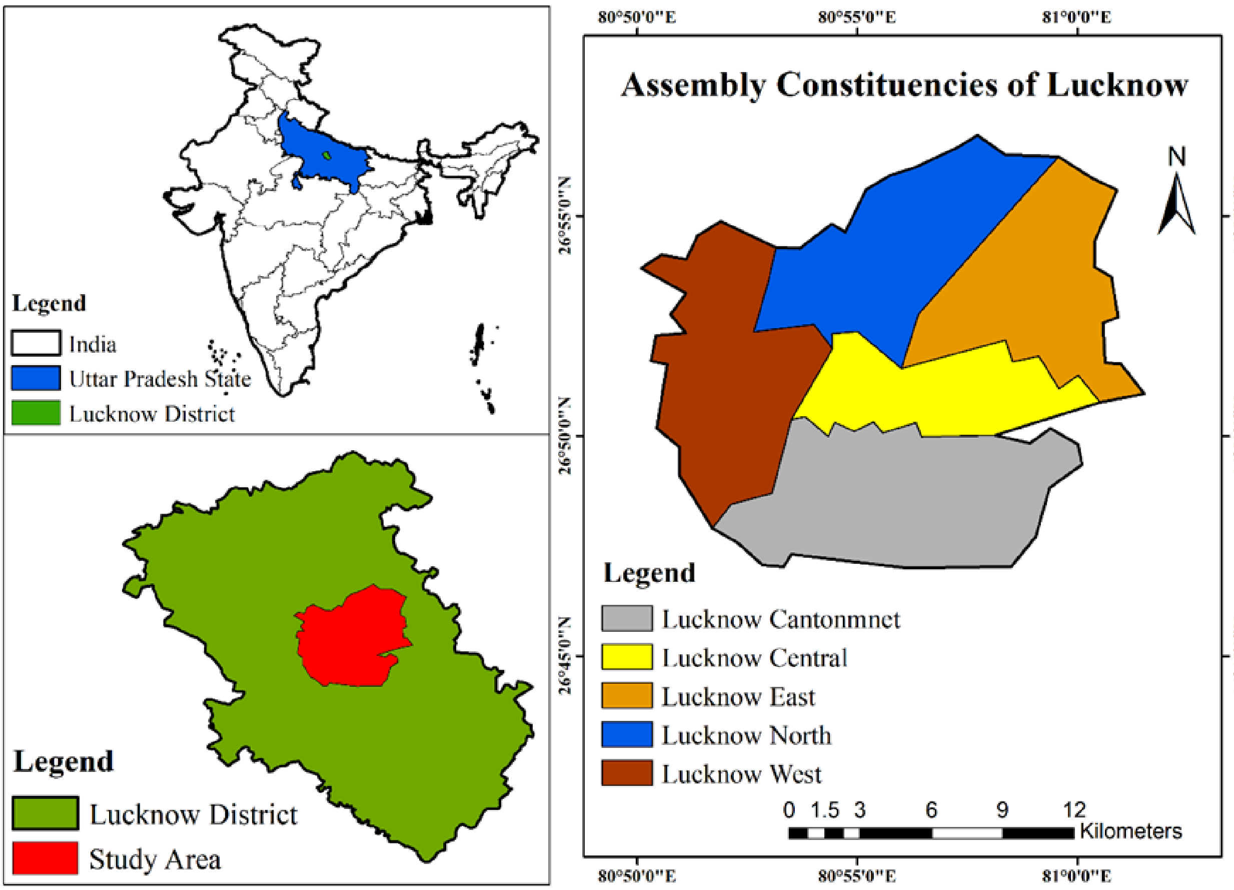


Figure 1. Location of study area in Lucknow City.

3. MATERIAL AND METHODS

3.1 Data collection and processing

The title Collection of data for spatiotemporal changes in Lucknow from 1985 to 2017 has been a difficult process, since Landsat series data at this particular location was not available for particular time. For classification purpose Decadal Land use/Land cover data available at ORNL DAAC has been used for year 1985, 1995 and 2005 (Roy et al., 2016) whereas for 2017 Landsat- 8 OLI data has been used. Data used in this study has been listed in table 1.

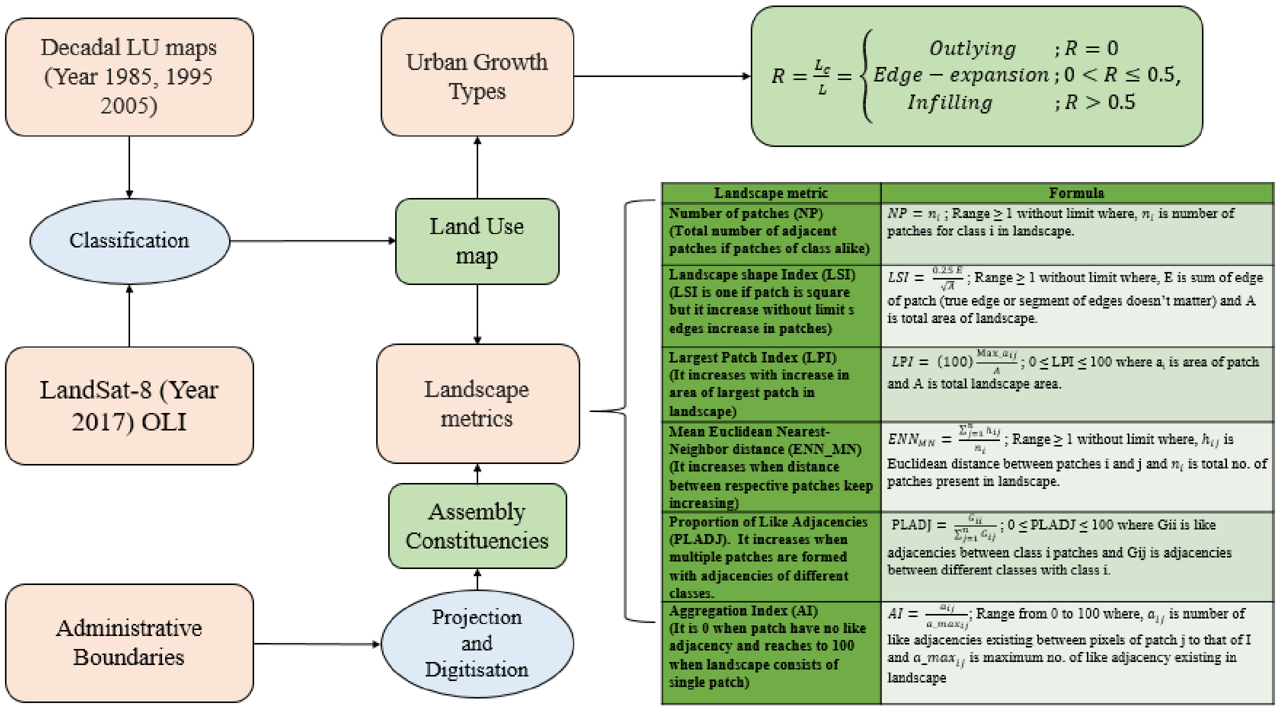
Table 1. Materials used in study.

Name	Date	Data providing Agency
Landsat 5 MSS and TM images	19/01/1988, 05/03/1993 & 02/02/2005 (100 m resolution)	USGS Earth Explorer
Landsat 8 OLI and TIRS images (Level 2- On demand Processed data)	26/05/2017 (30 m resolution)	
Assembly Constituency Boundaries	June, 2017	Maps master

Landsat images used in this study are of different resolution. In order to remove this problem, downscaling of resolution is applied over Landsat- 8 image to change the resolution from 30 to 100 m, matching to that of Landsat- 5 classified and downloaded images. Downscaling is done by resampling tool available in ArcGIS® using Nearest Neighbourhood method.

3.2 Urban Growth Analysis

With the use of spatio-temporal analysis of urban change, three types of urban growth can be identified which are edge- expansion, infilling and Outlying (Li et al., 2013). A field "*R*", was defined in attribute table of polygon containing new built-up patches which will classify them accordingly into 3 categories. Landscape metrics are calculated using FRAGSTATS (McGarigal & Marks, 1995) as listed in below figure (Figure2). Urban growth analysis through all its agents has been studied for all 5 zones for different periods (Dutta and Das, 2019; Zhao et al., 2015).



Landscape metric	Formula
Number of patches (NP) (Total number of adjacent patches if patches of class alike)	$NP = n_i$; Range ≥ 1 without limit where, n_i is number of patches for class i in landscape.
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.
Proportion of Like Adjacencies (PLADJ). It increases when multiple patches are formed with adjacencies of different classes.	$PLADJ = \frac{G_{ii}}{\sum_{j=1}^{n} G_{ij}}$; 0 ≤ PLADJ ≤ 100 where Gii is like adjacencies between class i patches and Gij is adjacencies between different classes with class i.
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 analysis of urban dynamics in study area.

4. RESULTS

4.1 Land Use Change

Decadal land use land cover images for India for year 1985, 1995 and 1995 were used as classified land use images for analysis. Classified images of 1985, 1995 and 2005 having total of 19 LU classes in Pan India classified image shows only 7 LU classes for Lucknow city. These 7 classes, which are merged and shown in 5 classes namely "Built-up", "Vegetation", "Water", "Agricultural" and "Other" for this particular study (Table 2). For year 2017, Landsat- 8 OLI images were used for FCC mosaic and this FCC is used for maximum likelihood classification with hybrid approach for Land use classification in 5 land use classes of "Built-up", "Vegetation", "Water", "Agricultural" and "Other" (Figure 2).

Table 2. Land use classes defined in study.

Land use class used in study	Land Use classes merged in from Decadal LULC data
Built-up	Built-up Land
Vegetation	Deciduous Broadleaf Forest, Shrub land and Plantations
Water	Water Bodies
Agricultural	Cropland
Other	Fallow Land, Wasteland and Permanent Wetlands

For year 2017, classified image is obtained using classifying FCC image prepared using band 5, 4 and 3 of Landsat-8 data downloaded from USGS earth explorer. With the help of google earth signatures are obtained for 5 LU classes for study area namely Built-up, Vegetation, Water, Agricultural and Other land (Figure 3). Hybrid approach of Maximum likelihood supervised classification algorithm is used to obtain classified image of Lucknow city area after training FCC.

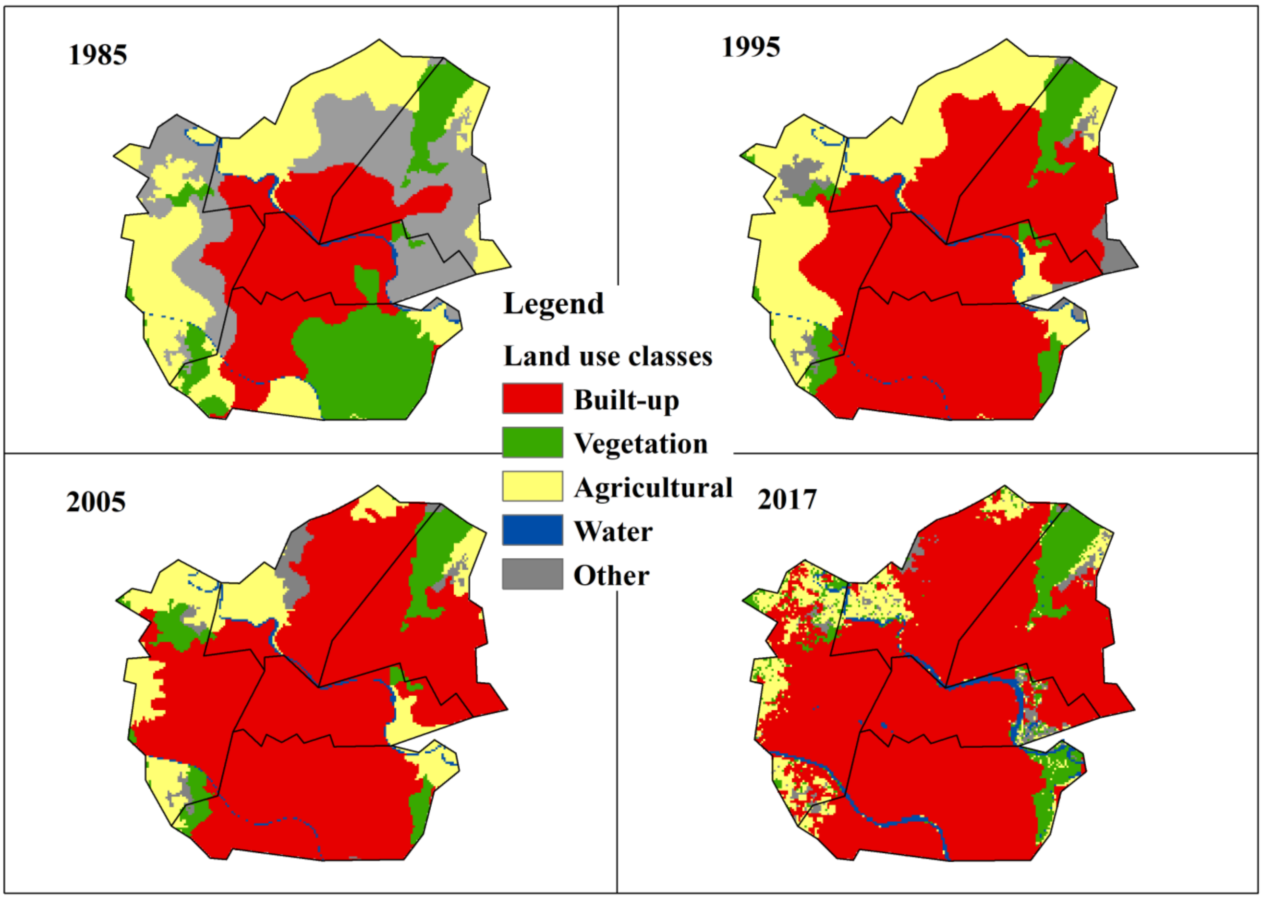
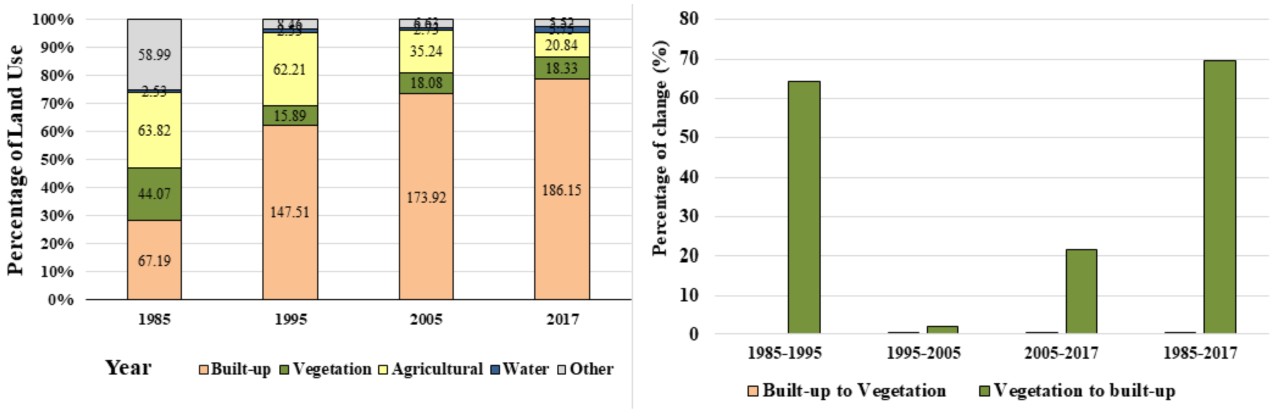


Figure 3. Land use map of study area from year 1985 to 2017.

An overall accuracy of classified image for year 2005 was found to be 94.46% and the kappa accuracy of 0.9445. For year 1985 and 1995, accuracy of classified image was assumed to be same of year 2005 (Roy et al., 2016). For accuracy assessment of classified map of city for year 2017, field data has been collected using Trimble GPS (5m accuracy) and used for Accuracy Assessment in ERDAS Imagine® which show accuracy of classification as 84.85% and overall kappa accuracy of 0.8138.

Land use in study area has gone some vast changes over years from 1985 to 2017. Built-up has increased from acquiring 28.4% of study area in year 1985 to 78.7% in year 2017. This increase in built-up is mainly from change of “Other” land use class, which contains classes like fallow land or barren land suitable for conversion to built-up by construction. Decrease in “Other” LU class from 24.9% of study area in 1985 to 2.3% in year 2017 shows same. Vegetation and agricultural LU class has also gone under deterrent over the years but agricultural land has taken more decrease i.e, 26.9% in 1985 to 8.8% in 2017 in comparison to vegetation which is 18.6% in 1985 to 7.7% in year 2017 (Figure 4a). Loss of vegetation towards gain of Built-up has been a prominent factor in change duration of year 1985-1995 but for 1995-2005 and 2005-2017, it remained second at top in loss among 5 LU classes of study area. In change towards built-up, vegetation LU class remained at third from top among 5 classes in study area form year 1985 to 2017 (Figure 4b). In the change duration 1985-1995 vegetation LU class was converted to Built-up at most culminating a total area of 28.38 km^2 as loss towards built-up up, which increased to a total of 30.76 km^2 up to year 2017.



(a) (b)

Figure 4. (a) Land use change in study area from year 1985 to 2017 (b) Gain and loss in Built-up and Vegetation land use of study area in different durations.

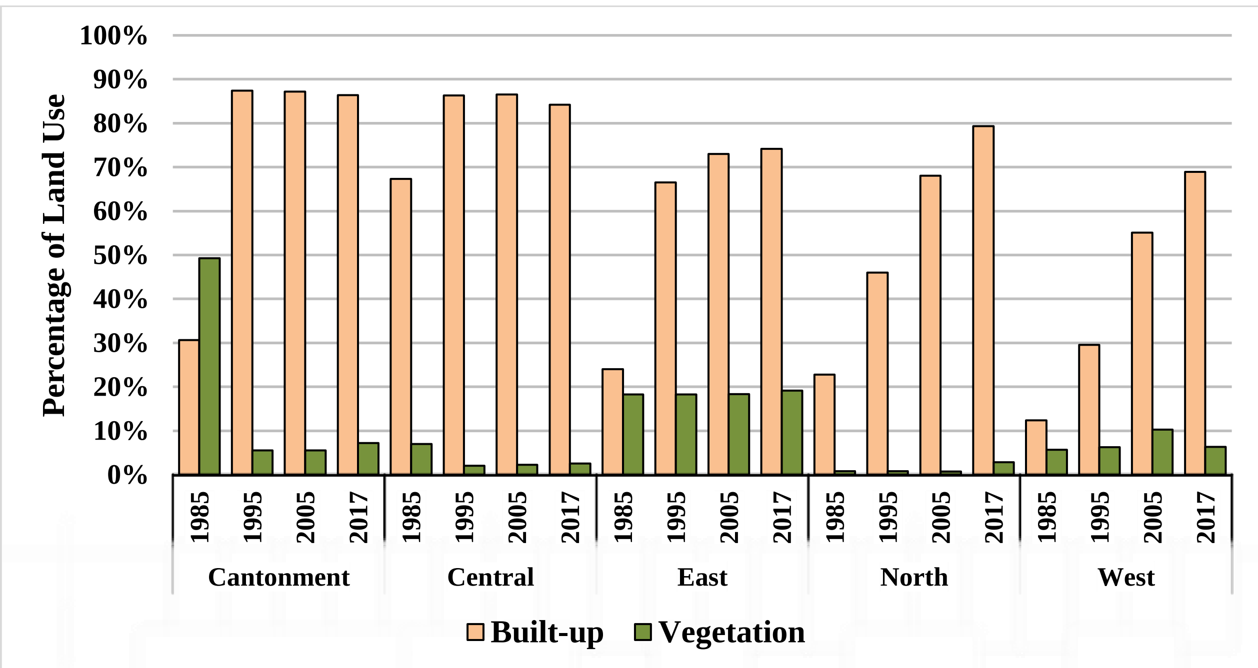


Figure 5. Built-up and Vegetation Land Use (%) in different assembly constituencies

Cantonment (Cantt.) AC is having largest Built-up gain in from 1985-1995 and after that it remains almost similar up to 2017. Same pattern is seen in Lucknow East (LE) AC. Lucknow North (LN) and Lucknow West (LW) assembly constituencies of Lucknow are having risen in built-up area in all durations continuously.

Lucknow Central AC is having a little increase in its Built-up percentage only once that too in 1985-1995 after that, it is almost same. LE and LW both constituencies are having largest percentage of their area as "Other" LU class which in turn gets converted to Built-up over the years from 1985 to 2017. Cantonment AC lost largest percentage of vegetation among its area but Central and West AC retained its vegetation percentage almost exact as in year 1985 to year 2017. North AC is one among all ACs having lowest percentage of its area as vegetation which remains same throughout the study period from 1985-2017 (Figure 5).

4.2 Urban Growth

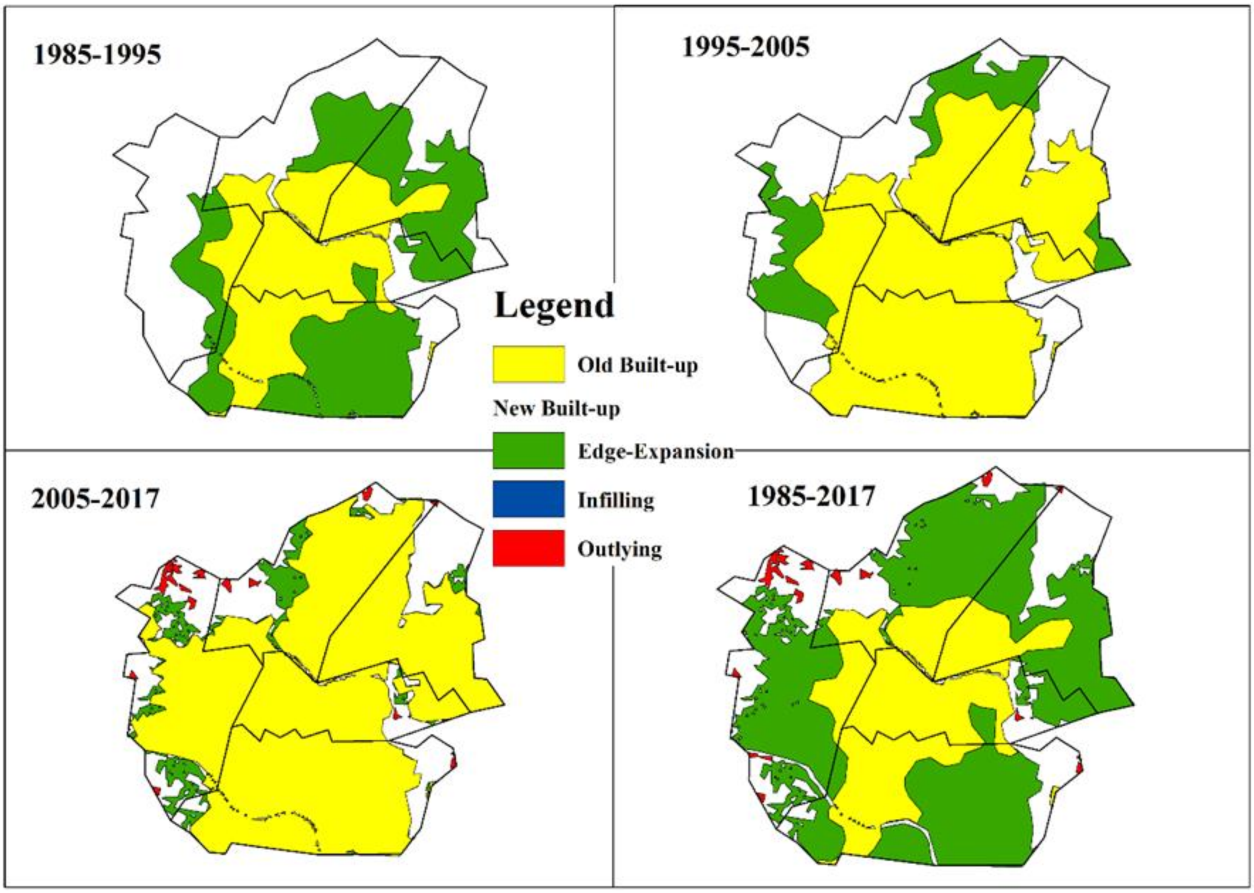


Figure 6. Different Urban growth types in study area from 1985 to 2017.

In period 1985-1995, edge-expansion occurred in all 5 assembly constituencies. In period 1995-2005, edge-expansion occurred but less in amount from previous change period and in less constituencies also. Same pattern is seen in period 2005-2017. Amount of urban growth is lesser in 2005-2017 from previous one and also in lesser number of constituencies. In fact, only Lucknow North and Lucknow West are 2 constituencies, which see outlying patches of urban growth for study area (Figure 6).

4.3 Landscape Metric

Number of Patches (NP) is showing negative trends for built-up and vegetation simultaneously from year 1985 to 2017 and in all 5 ACs. As the number of patches increase in any constituency number of vegetation patches decrease and vice-versa, which also coincides with the results shown in figures 4 and 5. Among ACs Lucknow central is having most no. of built-up patches and likewise least number of patches of vegetation (Figure 7).

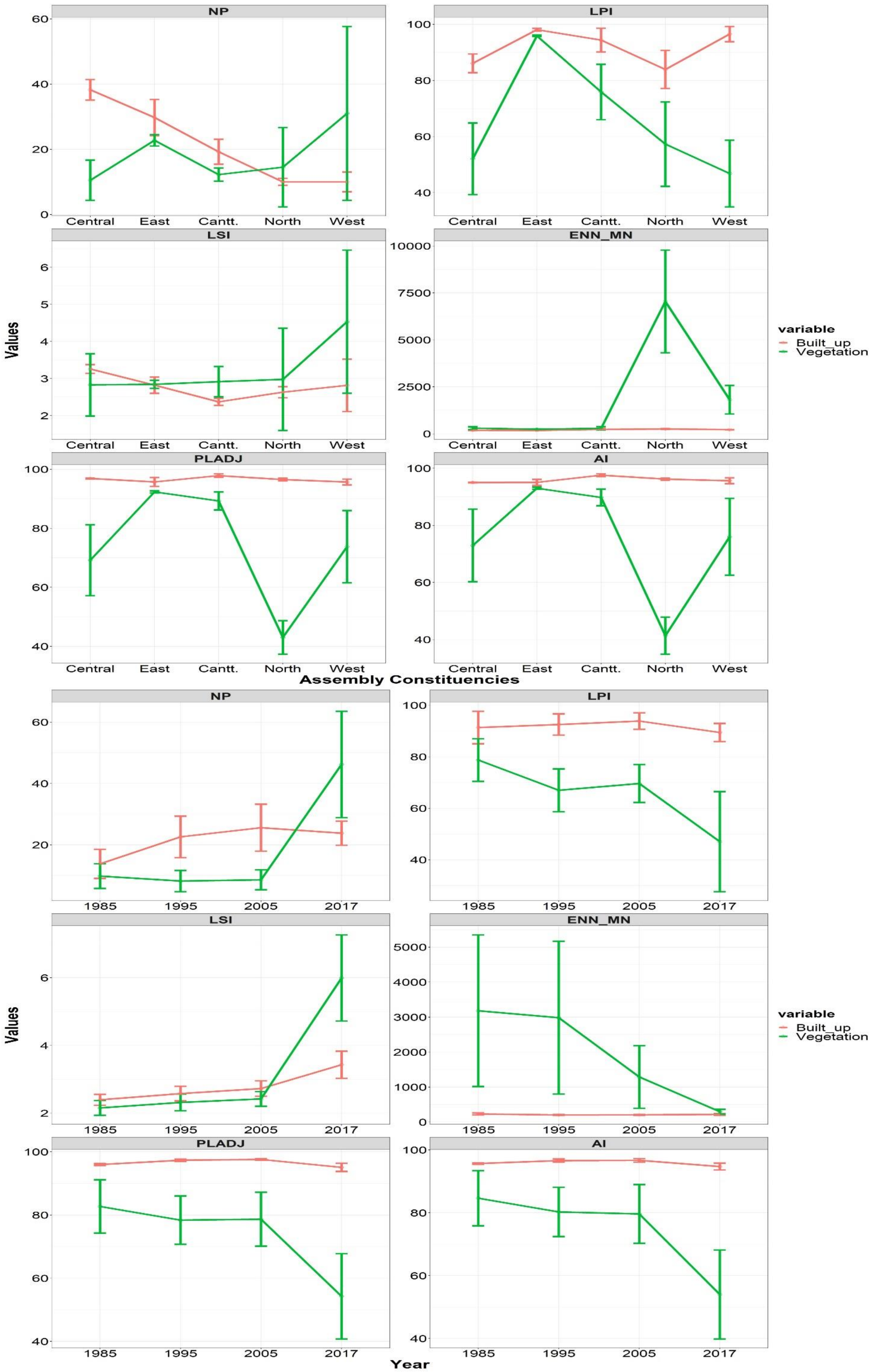


Figure 7. Trend of Landscape metrics for built-up and vegetation over years and zones

NP and LPI show density of patches. Lucknow North and Lucknow West are having least NP, indicating less no. of Built-up patches hence, less urbanisation in these ACs. Largest Patch Index (LPI) trend is same for both LU classes in all years and all 5 ACs. LPI for vegetation is always more than those of built-up patches indicating vegetation is always present in bulk amount in compacted not dispersed form, whereas, except for year 1985 and Lucknow East (LE) AC, LPI for built-up patch is never more than 70-80%, indicating less dense built-up in rest 4 ACs and 3 years from 1995 to 2017. LSI shows complexity of patches. All ACs area having almost same LSI but in increasing pattern from year 1985 to 2017. Lucknow West is having very large LSI value in year 2017, which is due to generation of new built-up patches in this AC as outlying patches in year 2017. ENN_MN showing centrality of patches is following exact opposite pattern across years in all 5 ACs. As no. of patches increase or decrease in ACs over year from 1985 to 2017, new patches are lying at more or less distance from each other respectively. ENN_MN is largest for Cantonment AC in year 1985, which is because of more area of Cantonment AC being filled with vegetation, hence whatever little amount of built-up patches were present, it was with much more distance than in coming years. PLADJ and AI are almost same in number for all ACs but over years it kept decreasing for built-up patches being very low for year 2017, which shows generation of more new patches of built-up surrounded by vegetation or other LU class patches. It is close to 100 (92-98) for all patches existing in study. AI depicting compactness of patches, is indicating that almost every AC in each year is comprising of 1 large built-up patch in it (Figure 7).

LSI is showing highest positive correlation of R^2 = 0.65, for built-up and vegetation patches indicating increase in complexity of vegetation patches with increase in complexity of built-up patches. ENN_MN is having negative correlation of R^2 = 0.36. With increase in distance of built-up patches from centre of study area, distance of vegetation patches form study area centre decreases. As more and more urbanisation takes place, built-up patches have increasing distance form centre and vegetation patches will have less change in distance from previous year to new one. NP is also showing negative trend with a low correlation coefficient. Urbanisation is causing decrease in vegetation in form of less patches of vegetation with more no. of built-up patches. LPI and AI are only two metrics not having any correlation for vegetation and built-up patches. PLADJ is having more value of correlation than AI despite showing almost similar trends (Figure 8).

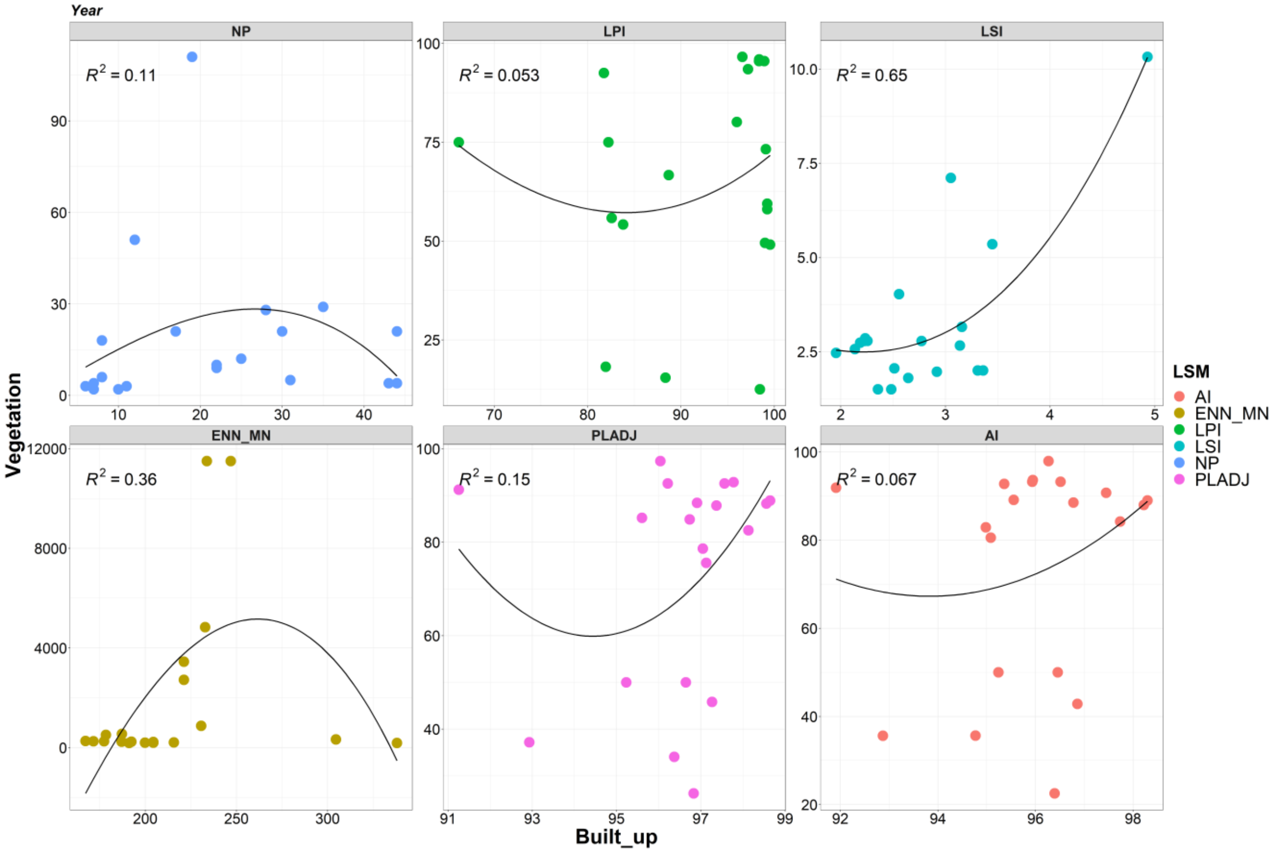


Figure 8. Correlation in Landscape metrics for built-up and vegetation

5. DISCUSSIONS

Results of study shows a direct connection between effects of change in built-up class upon change in vegetation class. Relation of built-up to vegetation change is shown over landscape metrics (Qian et al., 2019). Edge- expansion is most prevalent type of urban growth type in change durations from year 1985 to 2017 in study area. Outlying type of urban growth is showing best relations in landscape metrics for both LU classes. Among landscape metrics Landscape Shape Index (LSI) shows best correlation coefficient for change in vegetation patches to change in built-up patches. Urbanisation is causing drastic change in landscape of all 5 ACs. Landscape metrics are following a regular trend from year 1985 to 2005, but due to drastic urbanisation in year 2017 metrics are either of the trend i.e., either sudden increase or sudden decrease in value for both vegetation and built-up LU classes. Vegetation class is one of the biggest contributor towards urbanisation causing 70% of its change into built-up from 1985 to 2017.

Present scenario of urbanisation in year 2017 is indicating more formation of new built-up patches in Lucknow North (LN) and Lucknow West (LW) ACs. Area beyond these combined ACs in Lucknow city be formulated and planned accordingly keeping in mind the new upcoming outlying patches of built-up in these 2 ACs.

6. CONCLUSIONS

Vegetation loss has always been a major contribution towards urbanisation in study areas but relation between shape and sizes of vegetation and built-up patches for urbanisation has been studied in very less studies. Arrangement of Urban Green Spaces (UGS) and mitigation of Urban Heat Island (UHI) effect can be efficiently integrated in analysis of urbanisation. Results of this study are falling in line to the study previously done. Contribution, change in shape and size of both LU class patches have prolific relation. Urbanisation planning can be done keeping in arrangement of the patches in future. Future predictions for 5 assembly constituencies should be done keeping in mind the vast effect of unavailability of vegetation in study area for residents of built-up patches.

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