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Micro level analyses of environmentally disastrous urbanization in Bangalore

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Abstract Indian metropolitan (tier I) cities have been undergoing rapid urbanization during the post-globalization era with the unprecedented market interventions, which have led to the rapid land cover changes affecting the ecology, climate, hydrology, and local environment. The unplanned urbanization has given way to the dispersed, haphazard growth at the city outskirts with the lack of basic amenities and infrastructure as the planners lack advance information of sprawl regions. This has necessitated understanding and visualization of urbanization patterns for planning towards sustainable cities. The analyses of urban dynamics during 1973–2017 using temporal remote sensing data reveal 1028% increase in urban area with the decline of 88% vegetation and 79% of water bodies. Consequences of the unplanned urbanization are the increase in greenhouse gas emissions, decline in vegetation cover, loss of groundwater table (from 28 to 300 m), contamination of water sources, increase in land surface temperature, increase in disease vectors, etc. An attempt is made to understand the implications of unplanned growth at the micro level by considering the prime growth poles such as Peenya Industrial Estate (PIE), Whitefield (WF), Bangalore South Region (BSR). The spatial analyses reveal the decline of vegetation and open spaces with intense urbanization of 86.35% (in BSR), 87.39% (PIE) and 81.61% (WF) in 2017. WF witnessed the drastic transformation from agrarian ecosystem to a concrete jungle during the past four decades. Spatial patterns of urbanization were assessed through the landscape metrics and rule-based modeling which confirms intense urbanization with single class dominance. Specifically, NP metrics depicts PIE region had sprawl growth till 2003 with numerous patches and is transformed by 2017 it has become to a single dense urban patch. This necessitates appropriate planning strategies to mitigate further erosion of environmental resources and ensure clean air, water, and environment to all residents.

Keywords Urbanization · Landscape metrics · Rule-based modeling · Bangalore · Micro level analysis · Sustainability

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Introduction

Urbanization refers to the population transition from rural to urban pockets for better employment opportunities. This process gained momentum leading to the rapid transformation of landscape with globalization and subsequent opening up of Indian markets. Globally, the population has grown rapidly, of which 54% residing in urban areas. Projections show that 66% of the world's population to be urban by 2050 with close to 90% of the increase concentrated in Asia (India, China) and Africa (Nigeria) (UN 2016). India is projected to add 404 million urban dwellers highest among all other countries in Asia. Economic reforms and growing employment opportunities in cities are accelerating the pace of urbanization, resulting in peri-urban growth such as sprawl. Urbanization and urban sprawl is a demographic and social process whereby people move from urban areas to rural areas involving key land use land cover (LULC) changes which impact the functional capability impairing the provision of ecosystem services with impacts on the local ecology, biodiversity, hydrologic regime, etc. (Jaeger and Schwick 2014; Ramachandra and Bharath 2016; Gollin et al. 2016). The current trend of urbanization due to rapid economic social development is exerting sustained pressure on the natural resources (Zhou et al. 2017) across the world threatening the sustainability and people's livelihood (Zhang 2016). Unplanned urbanization does not integrate LU planning with the crucial factors such as mobility, infrastructure, and basic amenities. Rapid urbanization with globalization is alienating people and their vital association with ecosystems (Folke et al. 2002), access to resources in addition to impacting ecosystem functions outside the boundaries and also within the jurisdiction. The unplanned urbanization with the disruption of biogeochemical and hydrological processes is posing serious environmental challenges at the local, regional, and global scales (Fletcher et al. 2013). The rapid urban growth has resulted in serious environmental problems such as water scarcity, contamination, high emission, insufficient sanitation, land shortage, loss of pervious surfaces, and microclimate alterations. (Ramachandra and Kumar 2010; Bharath et al. 2013a; Ramachandra and Bharath 2016; Ramachandra et al. 2017; Miller and Hutchins 2017; Guan et al. 2018).

Urban growth is being influenced by multi agents at interweaving levels such as policy, behavior, process, and pattern. Among all, the policy decision-making process at micro scale has proven to be the most influential driving force of urbanization (Cheng et al. 2003). The urban decisions of forming new towns, satellite townships, and larger urban agglomerations (industries) are often bureaucratic approach devoid of either stakeholders' participation or ecosystem conservation process. These ad hoc approaches are resulting in imbalances in the existing ecosystem with precedence for sprawl, affecting the livelihood of local inhabitants, especially the vulnerable. The unprecedented population increase, and the demand for land by urban inhabitants, industrial establishments, and ad hoc policy interventions with the fragmented un-coordinated governance have been threatening the supply of food, energy, and other materials, apart from land use conversions beyond urban agglomeration (Ramachandra et al. 2012a). A robust understanding of urbanization process and factors influencing the urban system is essential for regulating urban development, addressing the issues and evaluating designated policies (Engelen et al. 2007; Parnell 2016). Consequently, quantitative analysis of the impact of urbanization on vegetation, agricultural land is critical for the management and preservation of green spaces, agricultural land, and other natural resources. Landscape metrics or spatial pattern indices have been helpful to interpret, quantify landscape characteristics at a temporal scale (McGarigal and Marks 1995; Herold et al. 2003; Ramachandra et al. 2012a, b). Multi-resolution remote sensing data with spatial pattern indices would provide consistent and detailed information that helps in framing the strategies for effective planning.

The modeling of urban systems and visualization of likely urban growth aids in evolving prudent urban planning towards the design of sustainable regions. Modeling LULC changes help to derive temporal changes and factors responsible for probabilistic prediction based on historical transitions (Behera et al. 2012; Hua 2017). Markov chain analysis works on the probability using spatial dependent land use data of different time periods (Arsanjani et al. 2013). The CA model has an effective open structure, flexibility, intuitiveness, and the ability to integrate the spatial and temporal dimensions of the processes, which can be integrated with other models to simulate and predict landscape patterns (Clark 2001; Kamusoko et al. 2009; Bharath et al. 2014). The Markov chain integrated with the cellular automata model (CA-Markov) is simple and provides advantages of the stochastic spatial CA two-way transitions and predictions, helps in the linking macro to micro approaches as compared with other techniques (Halmy et al. 2015; Aburas et al. 2016). Bangalore has been witnessing rapid urbanization since 1990s, which has brought large-scale land use changes. The conversions between urban land, vegetation, and water were the major change types in the region. The urbanization has marched towards city suburbs and adversely affecting local ecology (Ramachandra et al. 2012a). The analyses of urban dynamics during 1973–2017 using temporal remote sensing data reveal of 1028% increase in urban area (concrete area, paved surfaces) with the decline of 88% vegetation and water bodies by 79% (Ramachandra and Bharath 2016). The consequences of the unplanned urbanization are evident from the increase in greenhouse gas emissions, loss of groundwater table (from 28 to 300 m), contamination of water sources, escalation in land surface temperatures, increase in disease vectors, etc. (Ramachandra and Kumar 2010; Ramachandra and Shwetmala 2012; Ramachandra et al. 2015, 2017, 2018b; Ramachandra and Bharath 2016). The main objective of the current research is to investigate the impact of urbanization at microscale and its response in landscape transition. The specifical attempt has been made to (1) characterize the urbanization and change in land uses across three diverse landscape gradients during 1973 and 2017; (2) quantify spatiotemporal patterns using landscape metrics to understand relationships between landscape pattern changes and urbanization; and (3) modeling urban growth and visualizing likely changes of these regions in 2022.

Materials and method

Study area

Bengaluru (commonly referred as Bangalore), the capital of Karnataka State, India, is the cosmopolitan city located at 949 m asl with the spatial extent of 741 sq. km. Bangalore has grown spatially more than ten times (741 sq. km) since 1949 (69 sq. km.). Due to rapid urban growth, Bangalore has been experiencing changes in the temperature and is becoming an urban heat island (Ramachandra and Kumar 2010). The unrealistic unplanned growth has been posing a plethora of serious challenges such as climate change, enhanced greenhouse gases (GHG) emissions, lack of appropriate infrastructure, traffic congestion, and lack of basic amenities (electricity, water, and sanitation) in many localities (Ramachandra and Bharath 2016). Peenya Industrial Estate (PIE), Bangalore South Region (BSR), and Whitefield area (WF) are considered (Fig. 1) to understand the driving forces of urban growth at micro levels. PIE is one of the oldest and largest industrial areas in south-east Asia with the spatial extent of 922 ha, established in 1977 by the Karnataka State Small Industries Development Corporation (KSSIDC) in two stages with an annual turnover of around Rs. 110,000 million. The industrial estate houses small-, medium-, and large-scale industries and it lies between Bangalore-Mangalore Highway (NH-48) and Bangalore- Mumbai (NH-4), convenient for transportation. BSR with the spatial expanse of 3422 ha is primarily dominated by residential, commercial complexes and IT companies, located on Bannerghatta road connecting outer ring road. Whitefield region has developed with an intention to attract major global technology players, a number of multinational information technology (IT) companies. Until the late 1980s, WF was a small village with a retirement colony of Anglo-Indians covering an area of 2205 ha. The Export Promotion Industrial Park (EPIP) is one of the country's first information technology parks—(ITPB), which houses offices of many IT and ITES companies. The residential constructions were started later 1990s and especially during 2002 onwards leading to mushrooming of apartment complexes. The field investigations were carried out to understand the growth, type of growth, and consequences on the local environment at these locations.

Method

Figure 2 outlines the method adopted for understanding land use dynamics, which involved (i) data collection and image pre-processing, (ii) land use analysis and quantification of spatial metrics, and (iii) modeling and visualization.

Data collection and image pre-processing: The primary data (Remote Sensing) includes multi temporal Landsat 1-MSS (1973), Landsat 5-TM (1992, 2003, 2008), Landsat 7-ETM+ (2012), Landsat 8-OLI (2017) and Google Earth (http://earth.google.com). Landsat data is cost-effective and available free for downloading from public domains such as USGS (http://glovis.usgs.gov, http://earthexplorer.usgs.gov). Survey of India (SOI) topo-sheets of 1:50000 and 1:250000 scales (http://www.thesurveyofindia.gov.in) were used to generate base layers of the boundary. Ground control points collected from the field using pre-calibrated handheld GPS (Global Positioning System), online

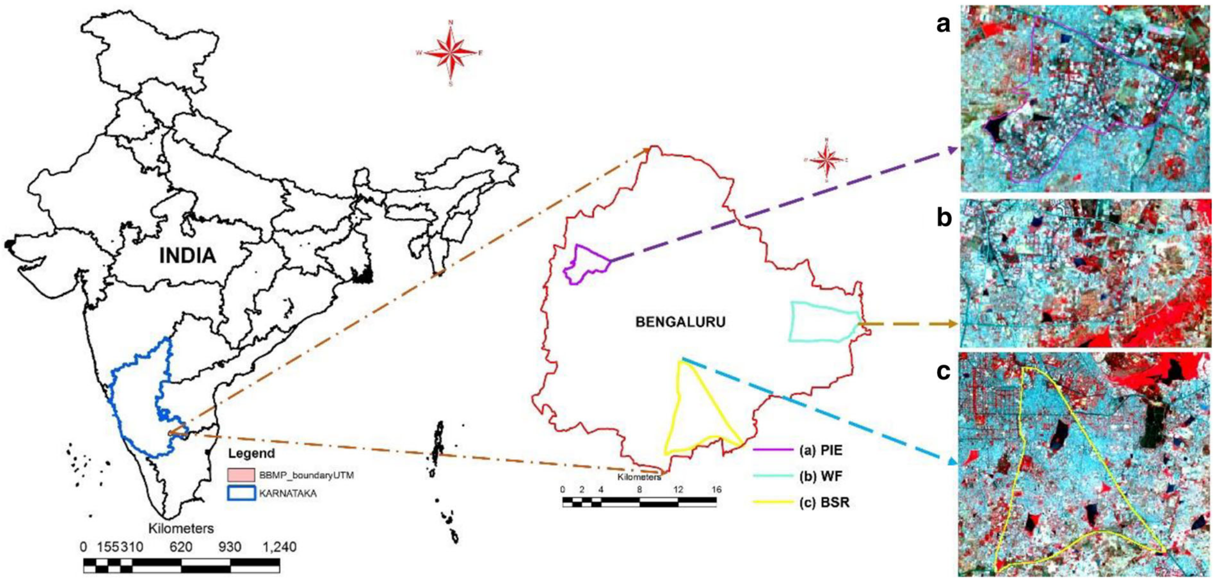

Fig. 1 Bangalore and the major growth centers. (a) Peenya Industrial Estate (PIE). (b) Whitefield area (WF). (c) Bangalore South Region (BSR)

spatial data portals Bhuvan (http://bhuvan.nrsc.gov.in), and Google Earth (http://earth.google.com) are used for geometric correction of remote sensing data. Then geo-corrected data was resampled to 30 m to maintain uniform resolutions across multiple datasets.

Land use analysis and quantification of spatial metrics: Land use analysis involved (i) creation of FCC (false color composite) by using multispectral bands and (ii) training polygons were selected by locating heterogeneous patches on the FCC. These training polygons are distributed uniformly across the region (iii) 60% of polygons converted into signatures and land use classification has been carried out by using supervised Gaussian maximum likelihood classification algorithm using GRASS GIS. This classifier has been considered one of the most superior methods which perform classification on the basis of probability density function (Bharath et al. 2013b; Ramachandra et al. 2018a). (iv) 40% of polygons are used for accessing accuracy through Kappa statistics. Spatial metrics are a series of quantitative indices analyzed using FRAGSTAT 3.3 (https://www.umass.edu/landeco/research/fragstats/fragstats.html). Table 1 lists the prioritized spatial metrics and their significance chosen for assessing spatiotemporal patterns of urbanization (Herold et al. 2005; Uuemaa et al. 2009; Aguilera et al. 2011; Bharath et al. 2012, 2017; Ramachandra et al. 2012b) at these locations.

Modeling and visualization: Markov approach has provided information about transition probability between two LU classes with respect to time (t to time $t+1$) and transitional area matrix with respect to likely land use changes (extent) of each class. Transitional probability matrix and area matrix are obtained by Eqs. 1 and 2.

$$P = \begin{bmatrix} P_{11} & P_{12} & \ldots P_{1n} \\ \vdots & \vdots & \vdots \\ P_{n1} & P_{n2} & \ldots P_{nn} \end{bmatrix} \tag{1}$$

where P is the transitional probability matrix; P_{ij} is the probability of i^{th} land use to convert into j^{th} class during the transition period; n is the number of land use classes.

Transition area matrix is obtained by

$$A = \begin{bmatrix} A_{11} & A_{12} & \ldots A_{1n} \\ \vdots & \vdots & \vdots \\ A_{n1} & A_{n2} & \ldots A_{nn} \end{bmatrix} \tag{2}$$

where A is the transitional area matrix; P_{ij} is the sum of the area of i^{th} land use to convert into j^{th} class during the transition period.

Cellular automata (CA) was used to obtain a spatial context and distribution map. A's transition rules use its current neighborhood of pixels to judge land use type in the future. CA aided in simulating and predicting land use changes based on the transitional rules depending on

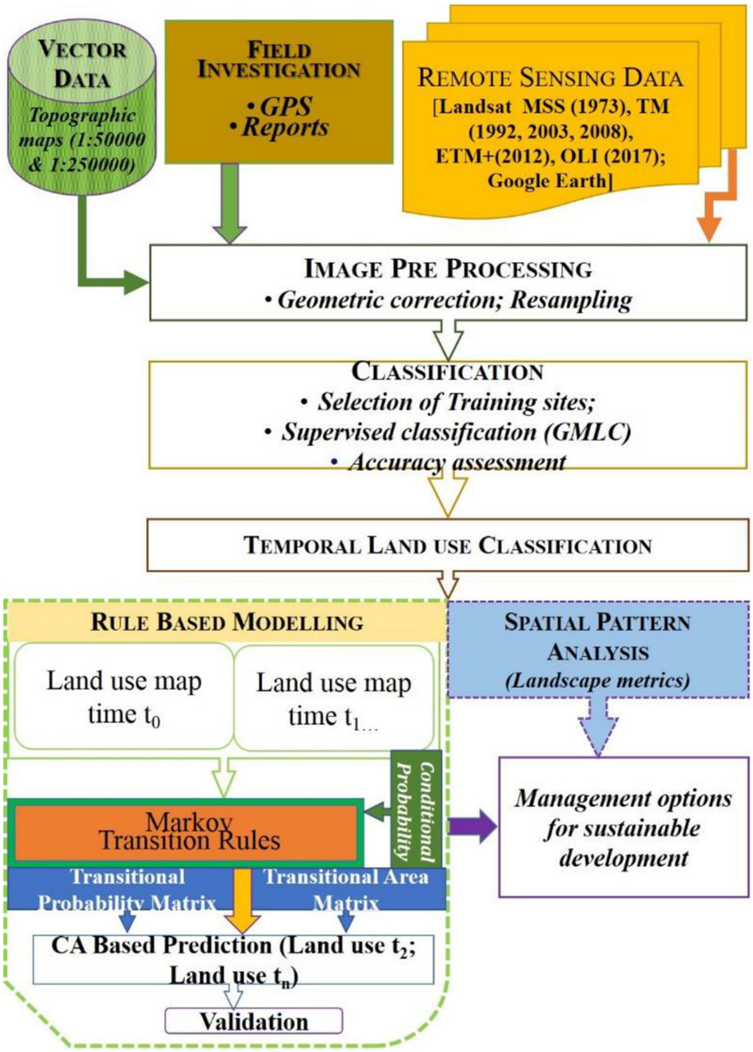

Fig. 2 Method adopted for urbanization analysis

the state of cell changes according to the neighborhood cells and the previous state of the current cell with the local and regional interactions. CA transition rule based on land use transition is governed by maximum probability transition and will follow the constraint of cell transition that happens only once to a particular land use, which will never be changed further during simulation.

The land use change patterns follow the Markovain random process properties with various constrains that include average transfer state of land use structure stable and different land use classes may transform to other land use class given certain condition (such as non-transition of urban class to water or vice versa). Thus, Markov was used for deriving the land use change probability map for the study region. CA coupled with Markov chain was then used to predict urban land uses using Eq. 3. CA-Markov incorporates the transitional rules and probabilities collectively and provides better results.

$$L_{(t+1)} = P^{*}L_{(t)} \tag{3}$$

where $L_{(t+1)}$ is the land use status at time $t+1$; $L_{(t)}$ is the land use status at time t.

A contiguity filter of kernel size 5×5 was used to account the behavior of neighborhood pixels. State of each cell is affected by the states of its neighboring cells in the filter. Past land use data (of 2003, 2008, and 2012) were used for estimating transition probability and area matrices through Markov model. The transition probability matrices of three gradients depict transition of vegetation and other class to built-up (Table 2). The diagonal values represent the persistence of the class

Table 1 Landscape metrics analyzed and their description

S no	Indicators	Formula	Range	Significance
1	Class area (CA)	$CA = \frac{A_{LU}}{A}$ A_{LU} = Area of land use A = Total landscape area	> 0	It represents the area covered by each land use feature to the total landscape area.
2	Number of patches (built-up)	$NP = n$ NP equals the number of built-up patches in the landscape.	NP > 0, without limit	It is a fragmentation Index. Higher the value more the fragmentation
3	Largest patch index (percentage of built-up)	$\mathrm{LPI} = \frac{_{(i=1\ldots n)}\max(a_i)}{A}(100)$ a_i = area (m^2) of patch i A = total landscape area	$0 \leq \mathrm{LPI} \leq 100$	LPI = 0 when largest patch of the patch type becomes increasingly smaller. LPI = 100 when the entire landscape consists of a single patch comprise 100% of the landscape.
4	Area weighted mean patch fractal dimension (AWMPFD)	$AWMPFD = \frac{\sum_{i=1}^{i=N} 2\ln 0.25 p_i / \ln S_i}{N} \times \frac{s_i}{\sum_{i=1}^{i=N} s_i}$ where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches	$1 \leq \mathrm{AWMPFD} \leq 2$	AWMPFD approaches 1 for shapes with very simple perimeters, such as circles or squares, and approaches 2 for shapes with highly convoluted perimeter.
5	Ratio of open space (ROS)	$\mathrm{ROS} = \frac{s'}{s} \times 100\%$ where s' is the summarization area of all "holes" inside the extracted urban area, s is summarization area of all patches	Represented as percentage	The ratio, in a development of open space to developed land.

from 2012 to 2017. Then, Markov-CA model was used to simulate land uses of 2012 and 2017, which was compared with the actual land uses, and the accuracy of the simulation is assessed through Kappa statistics. The traditional Kappa statistics lacks in assessing prediction error with respect to pixel location (Pontius and Millones 2011). The revised kappa statistics were used to understand the accuracies of the prediction as compared with traditional kappa (Kstandard), a revised general kappa defined as kappa for no ability (Kno), Kquantity and Klocation. The Kquantity and Klocation are able to distinguish clearly between quantification error and location error, respectively (Pontius 2000; Ahmed et al. 2013). After successful validation, land use for the year 2022 is predicted with the aid of actual land uses of 2012–2017.

Results and discussion

Land use dynamics: The temporal land use analyses using multi-resolution spatial data reveal of the decline in vegetation cover during 1973 to 2017 with an unprecedented increase in built-up area (Table 3) in all these three regions (Figs. 3 and 4). PIE shows the decline of vegetation from 70.22 to 2.11% (1973–2017), with an increase in built-up area from 0.33 to 87.39% (Fig. 3(a)). Now, PIE has more than 7500 registered industries and 75% of these industries are mainly engineering and garments sectors, which comes under the Peenya Industrial Association. The land use change with an increase in urban area is due to the expansion of major and small-scale industries during 1992 to 2003 under second phase (Fig. 4(a), Table 3). The major drivers of urban growth are major roads, small-scale industries, bus stops, bus depots, communication industries, banking, finance centers, and residential areas. Similarly, WF region reflects the major changes in its vegetation cover from 2003 to 2008 (Fig. 3(b)). The vegetation cover has declined from 61.54 to 15.01% with an increase in built-up area from 1.6 to 81.61% by 2017 (Fig. 4(b), Table 3). The IT companies such as TCS, IBM, Dell, Accenture, and Oracle are located in this region. The large-scale residential apartments, biotechnology research centers, and commercial

Table 2 Transition probability matrices of three gradients from 2012 to 2017

Gradient➔	PIE				WF				BSR			
2012➔ 2017	BU	V	W	O	BU	V	W	O	BU	V	W	O
Built-up (BU)	0.89	0.111	0.000	0.000	0.85	0.05	0.05	0.05	0.85	0.050	0.05	0.05
Vegetation (V)	0.9	0.103	0.00	0.00	0.861	0.139	0.00	0.00	0.948	0.052	0.00	0.00
Water (W)	0.12	0.00	0.88	0.000	0.173	0.014	0.813	0.00	0.184	0.00	0.816	0.00
Others (O)	0.62	0.004	0.00	0.382	0.461	0.016	0.00	0.523	0.272	0.009	0.00	0.718

complexes are also located in this region as part of the industrial expansion. The region has 85% IT companies (4000 small to large-scale industries), largest biotechnology companies (265). All these interventions have transformed the rural landscape into highly dense urban region covering 81.61% with higher amounts of pollutants in the air and water environment (Ramachandra and Shwetmala 2009, 2012; Ramachandra et al. 2015, 2017, 2018b; Ramachandra and Bharath 2016).

BSR has 86.35% of the built-up area (Fig. 3(c)) at the cost of open spaces and vegetation cover from 55.17 to 2.66% from 1973 to 2017 (Fig. 4(c), Table 3). The open spaces, parks cover, etc. (categorized under "others," Table 3) was 37.67% earlier is now reduced to 7.23% (2017). Mushrooming of multinational IT industries with large-scale residential apartments has resulted in the loss of vegetation cover. High-rise apartments, low-rise apartments, and luxury apartments are blooming after 2003. The infrastructure developments with the

Table 3 Land use analysis of three micro gradients

Year/land use type (Ha)	Built-up (paved surfaces; roads; buildings)	Vegetation (tree cover; parks; scrub	Water (lakes; river; streams)	Others (open spaces; barren; fallow; agriculture land)	Overall accuracy; kappa
PIE					
1973	3.06	647.37	2.79	268.65	88.76; 0.81
1992	301.32	508.05	5.31	107.19	84.08; 0.82
2003	645.57	191.79	10	74.51	88.91; 0.85
2008	686.79	147.96	8.1	79.02	85.53; 0.79
2012	777.42	31.43	9.07	103.95	90.16; 0.83
2017	805.59	19.42	9.02	87.84	91.33; 0.9
WF					
1973	35.46	1357.11	25.65	787.05	88.56; 0.82
1992	217.98	1232.73	8.64	745.92	88.01; 0.86
2003	712.17	658.62	0.99	833.49	83.37; 0.79
2008	825.93	580.41	12.42	786.51	90.29; 0.88
2012	1512.27	172.35	36.09	484.56	91.02; 0.86
2017	1799.64	39.42	35.28	330.93	88.91;0.87
BSR					
1973	72.18	1880.11	171.98	1298.25	81.31; 0.78
1992	563.76	1588.86	159.03	1110.87	86.66; 0.84
2003	1299.87	583.92	64.98	1473.75	89.07; 0.86
2008	2026.08	558.9	81.09	756.45	85.6; 0.81
2012	2702.34	129.96	134.55	455.67	84.36; 0.85
2017	2955.42	91.08	128.7	247.32	90.41; 0.89

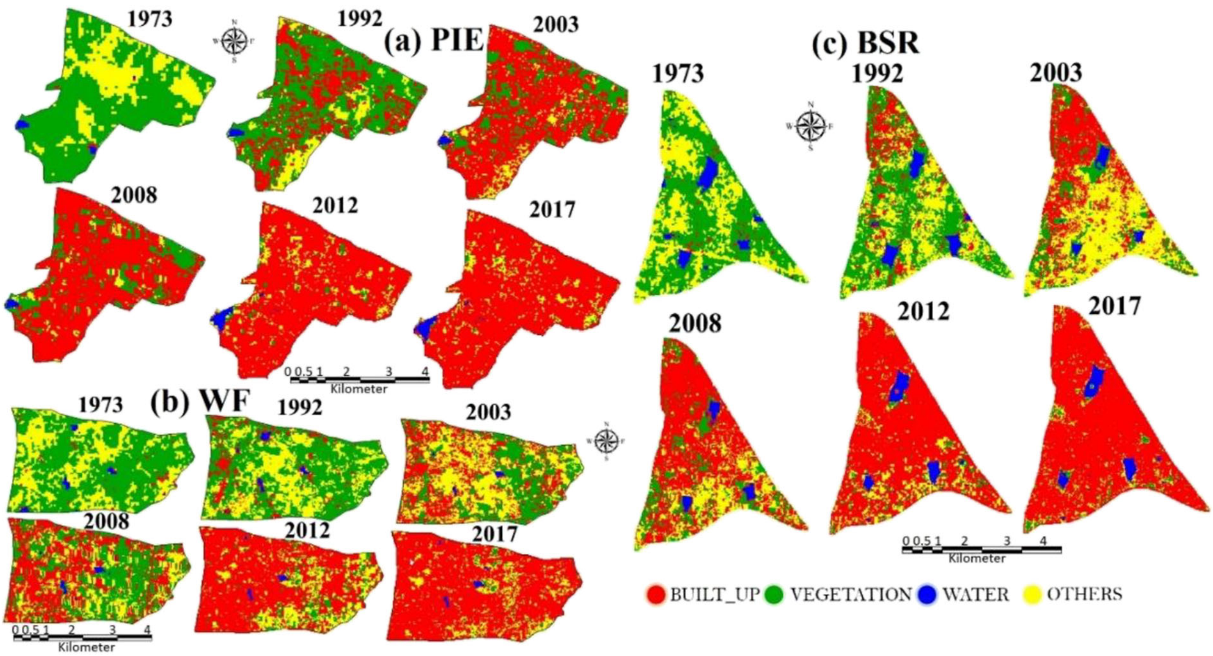

Fig. 3 Temporal land use analysis across three micro gradients (PIE: Peenya Industrial Estate; WF: White Field, BSR: Bangalore South Region) from 1973 to 2017

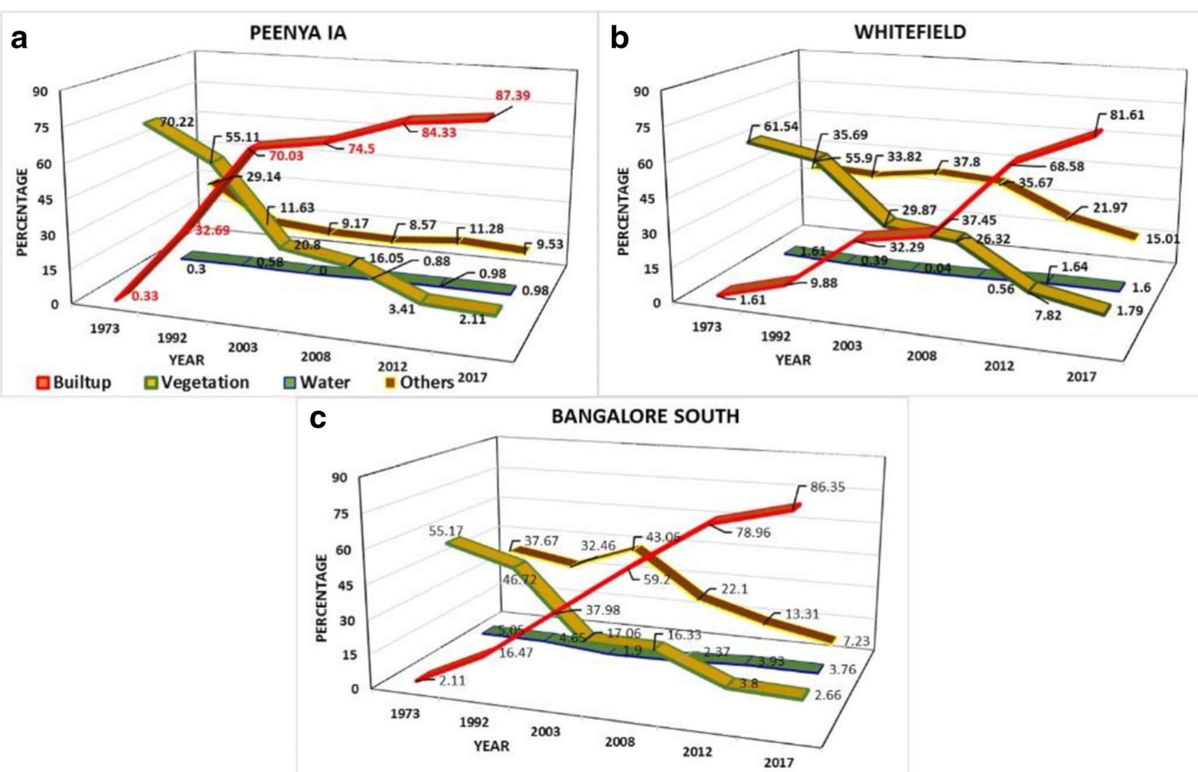

Fig. 4 Temporal land use analysis across three micro gradients (a. PIE: Peenya Industrial Estate; b. WF: White Field, BSR: c. Bangalore South Region) from 1973 to 2017

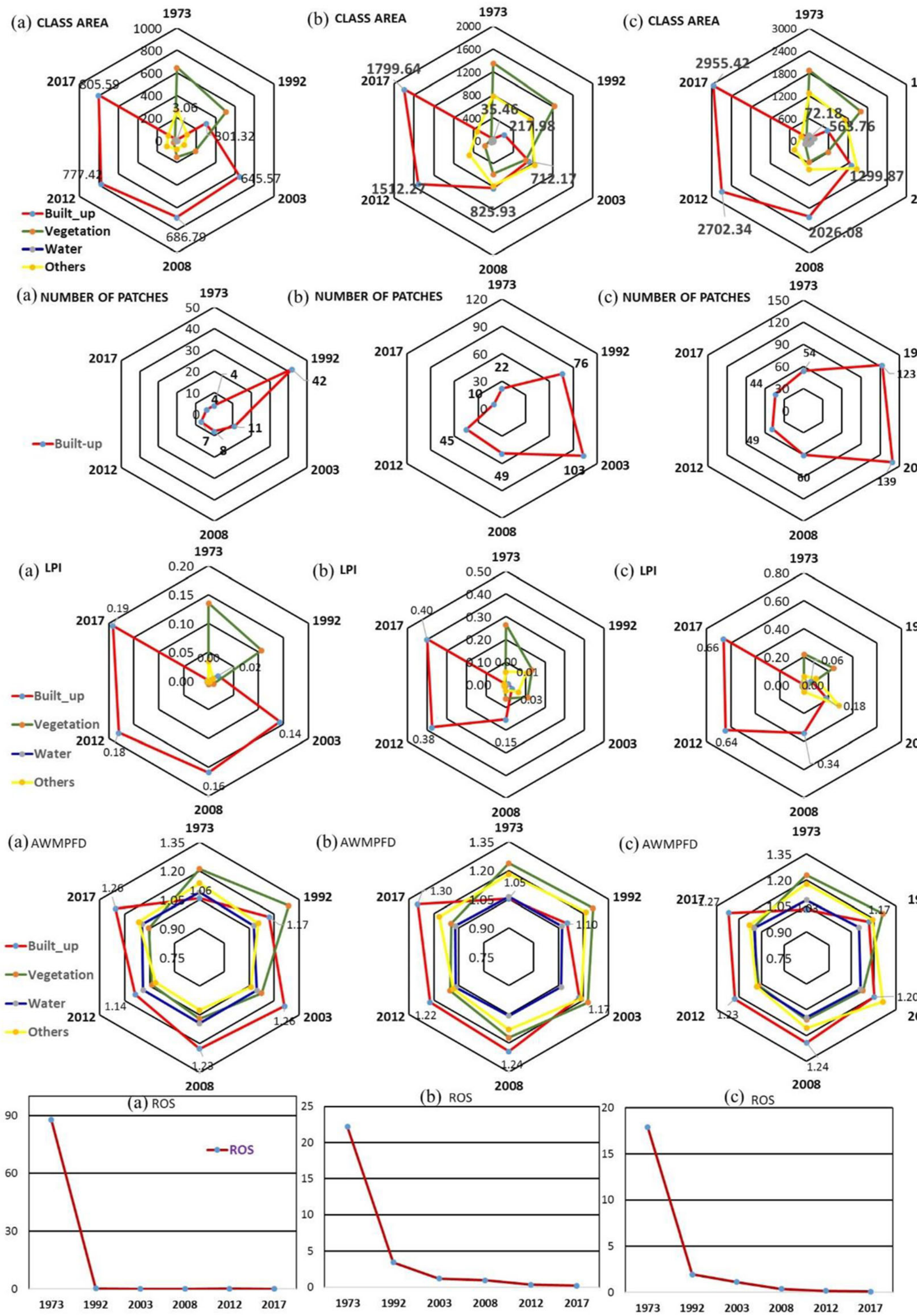

Fig. 5 Spatial pattern analysis across (a) PIE, (b) WF, and (c) BSR regions

widening of Hosur road, the elevated expressways, etc. have led to the spread of commercial complexes towards east, southeast, and south of Bangalore. The current urban growth across the regions are posing pressures on the biophysical environment while triggering water bodies pollution, biodiversity loss, and drastic changes in the local climate. With an increase of impervious surfaces, replacing soil and vegetation has altered albedo and surface runoff water characteristics that significantly influence the processes of the surface atmospheric energy exchange at the local and regional scales (Madanian et al. 2018). These ecological and environmental changes have affected ecosystem services, ultimately influencing their ability to sustain the urban population and its infrastructure (Keshtkar and Voigt 2016).

Spatial pattern of LU dynamics: The spatial pattern of LU changes during 1973 to 2017 is assessed through chosen landscape metrics (Fig. 5). CA shows PIE region has the least cover of built-up in 1973 and reached 805.59 ha by 2017 and depicts the larger land use category. CA of WF shows vegetation cover dominated until 2003 and by 2012, built-up has become a most dominating feature, the same trend can be seen in BSR. NP metrics depicts PIE has a larger number of patches until 2003 indicating fragmentation. NP value has come down by 2017, with the formation of intermediate patches, and resulting in a single dense urban patch. The same trend can be observed in the other two regions with the decline of vital land uses due to the expansion of built-up area. LPI index shows that vegetation was a dominant class with the largest patch across all regions during 1973. But by 2003, the built-up region is the largest patch, due to an increase in built-up cover, PIE, WF region. LPI depicts dominance of built-up with an uneven distribution of other land use classes. AWMPFD shows built-up class values approach 2 (shapes with highly convoluted perimeter) due to intense urbanization at the expense of open spaces. ROS depicts open space cover in the region, and least open space ratio exists across three regions. BSR shows ratio as 0.08 depicts dominance of a single class such as built-up cover from 1973 to 2017.

Modeling and visualization of LU changes: The visualization and future land use transitions for three urban gradients are calculated using CA-Markov chain process considering land uses of 2003, 2008, and 2012. The transition probability matrices for three regions were estimated, which aided in the simulation and prediction of likely changes. The prediction has been done considering water bodies as a constraint with an assumption that water bodies would remain constant overall time period due to the stringent norms with awakened citizens. The model was validated by comparing the predicted versus the actual for the years 2012 and 2017 land uses with an allowable error of 0.15. Analysis and comparison of the simulated and actual land uses of 2012 and 2017 reveal that the CA-Markov model is a reliable estimator in terms of change quantification and for continuous space change modeling (Table 4 and Fig. 6). The PIE region shows a noticeable change in its land use due to existing facilities and the requirement of expansion of amenities to cater the demand of burgeoning population. Built-up is likely to cover 92.12% of PIE region at the cost of open areas and vegetation. Eighty-nine percent of the WF landscape will be urbanized by 2022 from 1.6% (1973) at the cost of vegetation cover. This rural landscape has earlier catered the vegetable and milk demand of Bangalore. The urbanization has replaced the regions under

Table 4 Land use details of simulated (2017), projected (2022) and their accuracy

Region	PIE				WF				BSR			
Year	Simulated 2017		Projected 2022		Simulated 2017		Projected 2022		Simulated 2017		Projected 2022	
Category	Ha	%	Ha	%	Ha	%	Ha	%	Ha	%	Ha	%
Built-up	809.75	87.84	849.24	92.12	1815.63	82.33	1983.06	89.92	2999.34	87.64	3088.53	90.24
Vegetation	9.18	1.00	2.43	0.26	39.6	1.80	29.07	1.32	50.67	1.48	31.5	0.92
Water	14.9	1.62	18.27	1.98	22.5	1.02	24.3	1.1	136.35	3.98	128.7	3.76
Others	88	9.55	51.93	5.63	327.54	14.9	168.84	7.66	236.16	6.9	173.79	5.08
Total area	921.87				2205.27				3422.52			
Kno	0.89				0.86				0.88			
Klocation	0.84				0.87				0.86			
Kstandard	0.82				0.83				0.83			

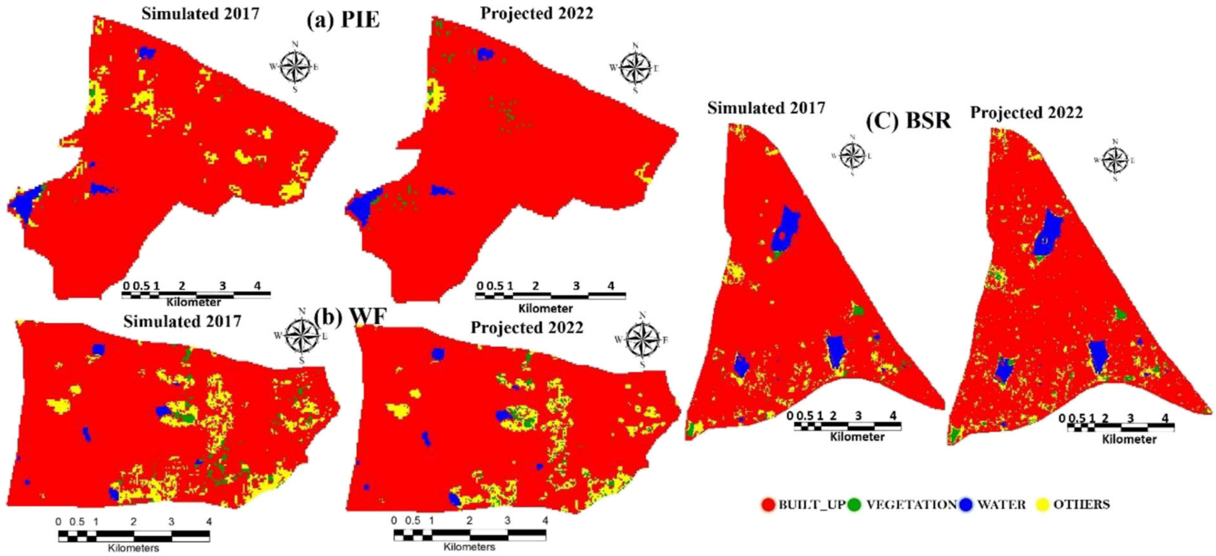

Fig. 6 Simulated and projected land use of micro gradients. (a) Peenya. (b) Whitefield. (c) Bangalore South

agriculture and horticulture crops with paved surfaces, posing serious challenges to the local ecology. BSR region is likely to be occupied up to 90% under built-up. The region has a good number of water bodies, but with the sustained inflow of untreated sewage and industrial effluents has adversely affected water quality (surface as well as ground water) and ecology. The irrational increase in built-up has impacted vegetation and open spaces in all these three micro gradients. The analysis of temporal changes in these growth centers highlights the need for policy interventions to regulate unrealistic urban expansions in the region.

Conclusion

Planned urbanization through policy interventions is quintessential for the sustenance of natural resources and also people's livelihood. This entails holistic approaches in urban development while preserving the areas of ecological and environmental significance to ensure the inter-generational equity. Land use changes due to unplanned urbanization have led to a severe decline in open spaces leading to imbalances with the scarcity of natural resources (water, etc.). Urban analyses at microscales highlight the role of agents such as IT revolution, industrialization, commercial activities in urbanization, and the loss of vegetation cover. BSR has lost major vegetation and open spaces and resulted in 86.35% of the built-up area by 2017. PIE has 87.39% region covered with the built-up area and only 2.11% under vegetation. WF has transformed from village-based ecosystem to highly polluted urban pocket within four decades covering 81.61% built-up area. These regions highlight the extent of mismanagement of open spaces (vegetation cover, water bodies, etc.) in the city, though the unplanned developmental activities in these regions have provided direct-indirect employment and business opportunities, but resulted in degradation of the biophysical environment, affecting the health of citizen and also a scarcity of natural resources. Spatial patterns of urbanization in three regions through landscape metrics show least NP values representing single class dominance. ROS depicts least ratios of open space with the more convoluted shape as compared with 1973 due to progression in built-up cover. The results highlight the necessity of effective planning and restriction on further exploitation of other land use features for human well-being. There is an urgent need to mitigate the impacts through integrated planning strategies and policies. Modeling and visualization reveal built-up area likely to cover 92.12% of PIE region at the cost of open areas and vegetation as compared with others. The rampant urbanization due to accelerated economic performance in three micro gradients is signified vast LU transition through stressing the environment, degrading vital natural resources. Mapping and modeling LULC changes using multi-resolution remote sensing data have provided an accurate, spatially detailed and consistent urban mapping capabilities over a temporal scale, which enables decision-makers to evolve appropriate land use strategies with conservation measures to protect the vital ecosystems from further degradations.

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