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Characterization and Visualization of Spatial Patterns of Urbanisation and Sprawl through Metrics and Modeling

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Characterisation of spatial patterns of urban dynamics of Coimbatore, India is done using temporal remote sensing data of 1989 to 2013 with spatial metrics. Urban morphology at local levels is assessed through density gradients and zonal approach show of higher spatial heterogeneity during late1980's and early 90's. Urban expansion picked up at city outskirts and buffer region dominated with large number of urban fragments indicating the sprawl. Urban space has increased from 1.87% (1989) to 21.26 % (2013) with the decline of other land uses particularly vegetation. Higher heterogeneous land use classes during 90's, give way for a homogeneous landscape (with simple shapes and less edges) indicating the domination of urban category in 2013. Complex landscape with high number of patches and edges in the buffer region indicate of fragmentation due to urban sprawl in the region. Visualisation of urban growth through Fuzzy-AHP-CA model shows that built up area would increase to 32.64% by 2025. The trend points to lack of appropriate regional planning leading to intensification of spatial discontinuity with the unsustainable urban growth.

Keywords
Spatial patterns, Urbanisation, Urban Sprawl, metrics, modeling, geo-visualisation

Acknowledgements
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INTRODUCTION

Urbanization is a dynamic process involving the expansion of urban pockets in response to the population growth, industrialization, political, cultural and other socio-economic factors. Insights to the spatial patterns of urbanization are essential for an effective and better planning (Ramachandra et al. 2012). Unplanned urbanization often leads to the large scale land use changes altering the landscape structure affecting the ecological integrity with degradation of the environment, enormous consumption of resources, creation of urban heat islands, changes in local climate, soil erosion, changes in hydrological cycle impairing surface water and ground water regime (Sudhira et al. 2004; Bharath H.A. 2012).

Human migration from the rural to the urban areas leads to the increase in urban pockets (United Nations 2011). The process of urbanization gained impetus with the industrial revolution 200 years ago and accelerated in many parts of India due to globalization and opening up of markets in 1990's. Unplanned urbanization affected the quality and sustenance of natural resources creating a major problem in most parts of the world (Martinuzzi et al. 2007; Verzosa et al. 2010). Current global population is approximately 7.06 billion and urban populations constitute more than 50% (United Nations 2007; Population Reference Bureau 2012). Urban population has been increasing three times faster than the rural population, mainly due to migration to cities and towns (Girardet 1996; Massay et al. 1999; Griffiths et al. 2010). Urbanization could be planned (in the form of townships) or unplanned (organic). Unplanned urbanization leads to urban sprawl or haphazard, uncontrolled growth of urban pockets with the reduction of natural spaces such as vegetation, water bodies and isolated or vacant tracts (Yeh and Li 1999; Verzosa et al. 2010; Ramachandra et al. 2012a, b; Bharath H.A. et al. 2012; Bharath S. et al. 2012). The phenomena of urban sprawl are widespread in India (Sudhira et al. 2004; Nath et al. 2007; Bhatta 2009; Bhatta 2010; Taurbocock 2009; Ramachandra et al. 2012a) and this uncontrolled expansion occurs at periphery in a non-contiguous way (Martinuzzi et al. 2007). Sprawl is often accompanied with drastic land use and land cover (LULC) changes leading to improper allocation of basic amenities and infrastructure, increased energy consumption, depletion of natural resources (Peiser 2001; Ji et al. 2006; Verzosa et al. 2010), deteriorating water quality, loss of open and green space, increased water and air pollution (Ramachandra and Kumar 2009). Alterations in the ecosystem structure, impacts its functional abilities threatening the sustainable development (Yeh and Li, 1999; Ji et al. 2001; Weng 2001; Li and Yeh 2004; Chen et al. 2005; Xiao et al. 2006; Liu et al. 2007; Vinay et al. 2013).

Urban expansion is one of the most direct forms of land use change, involving changes in land use pattern and urban space distributions due to the social and economic pressures (Pathan et al. 1989, 1991; Gillies et al. 2003; Alphan et al. 2009; Bhatta 2009; Ramachandra et al. 2012b). Urbanization processes are evolving and emerging in unforeseen ways (example sprawl), these kinds of developments are also referred to as "geography of nowhere" (Paul 2006, Kunstler 1993). Sprawl is considered to be serious issue since it involves direct costs for providing infrastructure and services, lack of air quality, water availability, increased travel cost and time (Paul 2006). Sprawl occurs with space, geography and time, due to which understanding sprawl over time becomes necessary to plan and set the policies. Urban sprawl is characterized through three key parameters i.e., (i) disperse population in low-density developments, (ii) disconnected, widely separated constructions and buildings, and (iii) Fresh

developments beyond the urban core within the city outskirts (Ewing et al. 2002; Moghadam and Helbich 2012). These can be analyzed in two ways namely land cover and land use analyses. Land Cover (LC) refers to the observed (bio) physical cover on the Earth's surface (Di Gregorio and Jansen 1997; Jansen and Di Gregorio 1998; Codjoe 2004) that currently covers the ground, particularly vegetation, permanent snow and ice fields, water bodies or structures (USDA Forest Service 1989) and the ecological state and physical appearance of the land surface, (Turner and Meyer 1994; Clapham 2003; Codjoe 2004). Thus, land cover analysis helps in distinguishing the regions under vegetation and non-vegetation. Land Use (LU) refers to the socio-economic use of land (for example, agriculture, forestry, recreation or residential use) or deploying the area for predominant purposes (USDA Forest Service 1989; Ramachandra et al. 2012a, c), activities and inputs humans undertake in a certain land cover type to produce changes or maintain it (Di Gregorio and Jansen 1997; Jansen and Di Gregorio 1998). Understanding LULC dynamics provides a detailed explanation to the changes that the region has experienced.

Implementation of appropriate management strategies require the cost effective spatial monitoring of urbanization process (Bhatta et al. 2010; Kong et al. 2012). Data acquired remotely at regular intervals through space borne sensors provides a birds-eye view of the region that helps in the inventory of spatial and temporal urban land-uses and mapping of urban expansions. Integration of the analysis of temporal remote sensing (RS) data with geographic information system (GIS), aids in the monitoring of earth resources (Batty 1992; Barnes et al. 2001; Longley 2002; Ramachandra et al. 2012a; Helmer and Ruefenacht 2005; Seto and Liu 2003; Lopez et al. 2001; Martinuzzi et al. 2007), urban sprawl (Clapman 2003; Sutton 2003; Gillies et al. 2003; Milesi et al. 2003) and other environmental implications (Ramachandra et al. 2012a). Analysis of spatial patterns of urbanization through landscape ecology techniques help in quantifying and monitoring the urbanization process (Sudhira et al. 2004), including issues such as energy, land use land cover (LULC) dynamics and climate (Roth et al. 1989; Jothimani 1997; Grimm et. al 2000; Lata et al. 2001; Grimmond and Oke 2002; Voogt and Oke 2003; Sudhira et al. 2003, 2004; Griffiths et al. 2010; Ramachandra et al. 2012a) across various parts of the world.

Temporal LULC analyses with spatial metrics are useful to quantify spatial patterns of landscape dynamics (Cheng and Masser 2003; Herold et al. 2003; Jat et al. 2008; Ramachandra et al. 2012c; Bharath S. et al. 2012) to understand the urban phenomena through attributes such as patch, shape, contagion, epoch, edge, etc. (McGarigal and Marks 1995), which provides valuable insights to the inherent spatial structures over time (Wu et al. 2011) with growth patterns.

Further, simulation and modeling of urban growth, helps in understanding the future impacts of land use policies, developments (Jose and Luca 2003). The model outputs can be used in the decision support system which helps in understanding various aspects of "what if situations, evaluation of likely scenarios, evaluation of alternatives, etc.". Over the last few decades, various agent based (actor based) and non-agent based (pattern) models (Perez et al 2012; Castella and Verburg 2007; Verburg 2006; Bharath H.A. et al. 2013a) have been used in order to simulate the LULC. Some of the models commonly used are Cellular Automata, Land Change Modeler, DINAMICA, GEOMOD (Geo-Modeler), CLUES, SLUETH which are/can be integrated with various aspects of assessment namely Artificial Neural Networks, Multi Criteria Evaluation, Markov Chains, Fuzzy Logic, Analytical Hierarchical Process, Boolean algebra, Ant Colony Optimisation (Zhou et al. 2012; Ramachandra et al. 2016). This paper integrates aspects

of fuzzy logic, analytical hierarchical process, multi criteria evaluation, Boolean algebra, Markov chains and cellular automata to simulate future land use considering various aspects of change (growth factors and constraints).

Fuzzy Logic (Zadeh 1965) is used to standardize criteria for agents of growth (Gorsevski et al. 2012) due to its good capability to mimic human control logic (Kaehler 2015). Standardization process transforms and rescales (considering variable values, while allowing intermediate values) criteria into comparable units (Gorsevski et al. 2012; Sui 1992). Process of standardization (Fuzzy) is based on simple rules, which takes into account the rate of change along with significant values in a membership function (Dernoncourt 2013). The membership functions can be monotonically increasing or decreasing; sigmoidal, *etc*. these membership functions represent the magnitude of participation of each criterion (Hellmann 2001; Eastman 2001).

Similar to Fuzzy, Boolean algebra is used to standardize the constraints of growth. Boolean, unlike Fuzzy doesn't consider variable values, it considers either 0(false) or 1(true), true for all the possible pixels of change and false where there is no change. In modeling "*continuous factors of multi-criteria decision making are fuzzy membership functions, whereas Boolean constraints are crisp set membership functions*" (Eastmann 2001).

Analytical Hierarchical Process is a multi-criteria decision making approach which uses a pairwise comparison approach for decision making (Satty 1990), where in the factors are organized in hierarchical structure (Triantaphyllou and Mann 1995). Decision making involves various criteria's, which are used to rank the agents of change (Satty 2008). Weightages of criteria's in AHP depend on the expert's opinion in order to derive the priorities/ranks i.e., normalized principal vectors (Tecknomo 2005) are the factors compared by scaling one's importance over the other. The weights once assigned are subjected to validation by calculating the consistency ratio.

Site Suitability / site selection (Dapueto et al. 2015) is one of the major aspects that need to be understood for identifying potential locations for development and a complicated spatial decision process since it has large number of alternatives and involves decision making (Kamruzzaman and Baker 2013; Krois and Schulte 2014). Integrating GIS with MCE allows solving spatially complex issues (Li 2013). Weights along with appropriate factors from the AHP and constrain maps from the Boolean are used to derive site suitability maps using Multi Criteria Evaluation (MCE) which depicts pixels indicating locations and levels (high to low) of change for various land use types. These site suitability maps are used in the current study along with the CA Markov to derive future landscapes.

CA-Markov process is one of the widely used models for understanding landscape dynamics across time and space (Zhou et al. 2012, Ramachandra et al. 2015a, Ramachandra et al. 2015b). In Cellular Automata (CA), each cell represents a land use class, and the state of cells represents the different land uses across time. Current state of pixel undergoes change based on the previous state, and state of neighboring pixels, constraints and set of transition rules (White and Engelen 1993; White et al. 1997; Lagarias 2012). Markov chains gives the change probabilities of a pixel converting from class 'a' to class 'b' (Bharath H.A. et al. 2014a; Bharath H.A. et al. 2014b; Bharath H.A. 2013b; Samrat et al. 2011) and change in areas between land uses based on two time frames (t and t-1) to predict at the third time step t+1. In order to

eliminate differences of time steps for simulation, standard time intervals are applied (Pastor et al. 1993).

The current study investigates land use patterns and quantifies the changes using various metrics through gradient and zonal approaches, and predicts future land use considering various agents of change and constraints of growth for Coimbatore an industrial capital of India.

Study Area

Coimbatore city lies between 10° 11' 27" N to 10° 11' 40" N and 76° 37' 24" N to 77° 31' 55" E on the banks of the river Noyyal in the rain shadow region of the Western Ghats. It is the second largest city in the state of Tamil Nadu, India, encompassing a total area of 246 sq. km and enjoys a pleasant climate throughout the year. The study has been carried out in the administrative region of Coimbatore city with a 10 km buffer accounting to 1078.56 sq. km (Figure 1). The rich black soil of the region has also contributed greatly to the agricultural industry especially in the successful growth of cotton that has served as a foundation for the establishment of textile industries in this region and is popularly known as the Manchester of Southern India due to the presence of numerous textile mills and engineering industries built over the last 100 years. The industrial sector with the automobile and trade business has been playing a vital role in sustaining Coimbatore's economy. The population of Coimbatore is about 2.1 million in 2011, which was 1.4 million in 2001 (Figure 2). Coimbatore city is governed by Coimbatore City Municipal Corporation (CCMC).

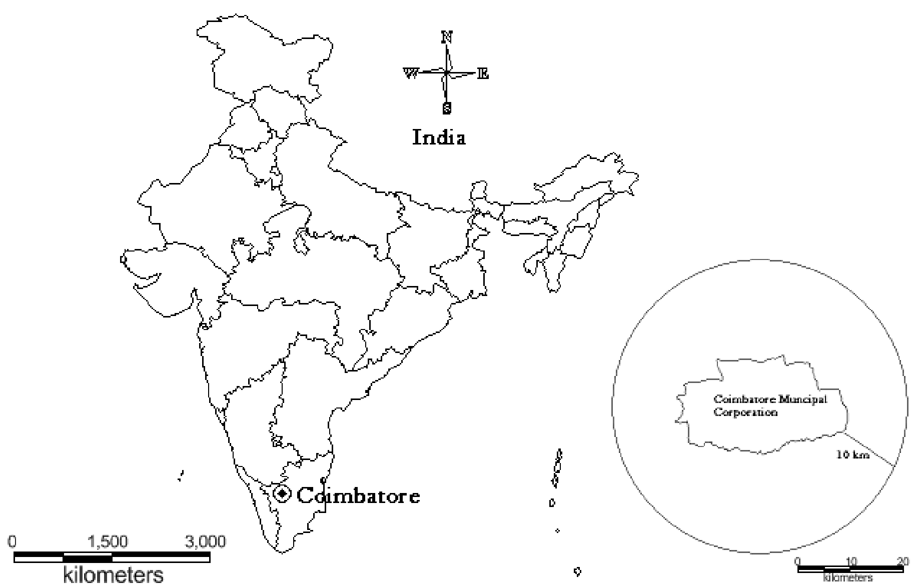


Figure 1. Study area and its environs.

METHODS

The spatial patterns of urban dynamics of Coimbatore have been assessed using temporal remote sensing data (of 1989 to 2013) through open source geospatial tools and spatial metrics. Figure 3 outlines the analysis, which includes pre-processing, analysis of land cover and land use, and finally, computation of gradient and zone wise metrics to assess the urbanization patterns at local levels.

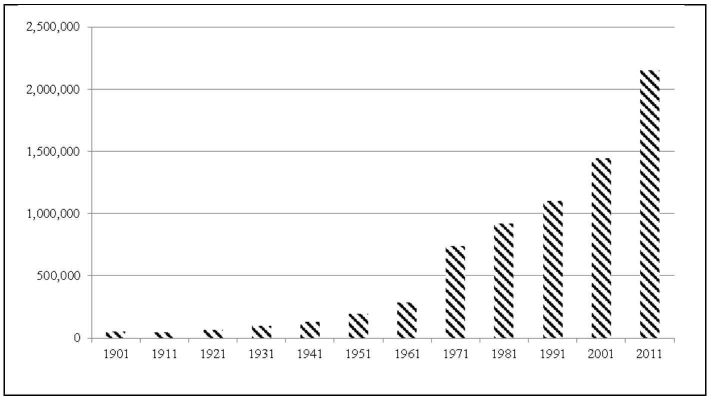


Figure 2. Population of Coimbatore from 1901-2011.

Preprocessing

Temporal remote sensing data (Landsat series) for Coimbatore, acquired for different time periods, were geo-referenced, geo-corrected, rectified and cropped pertaining to the study area. Geo-registration of remote sensing data (Landsat data) has been done using ground control points collected from the field using pre calibrated GPS (Global Positioning System) and also from known points (such as road intersections, etc.) collected from geo-referenced topographic maps published by the Survey of India. The Landsat satellite data of 1989, 1999, 2003 (30 m x 30 m nominal resolution) were downloaded from the public domain http://glovis.org) and IRS LISS III data of spatial resolution 23.5 m x 23.5 m for the year 2013was procured from National Remote Sensing centre, Hyderabad (http://nrsc.gov.in). Further these were resampled to 30 m in order to maintain uniformity in spatial resolution across different time periods. The study has been carried out for the Coimbatore administrative area with 10 km buffer, which helps in evaluating the regions experiencing sprawl.

Land Cover Analysis

Land cover analysis was performed to understand the changes in the vegetation cover through the computation of Normalised Difference Vegetation Index (NDVI). NDVI values range from -1 to +1 and typically very low values of NDVI (-0.1 and below) correspond to soil or barren areas of rock, sand, or urban built up. Zero indicates water cover. Moderate values represent low density vegetation (0.1 to 0.3), while high values indicate thick canopied vegetation (0.6 to 0.8).

Land Use Analysis

The method involves i) generation of False Colour Composite (FCC) of remote sensing data (bands – green, red and NIR). This helped in locating heterogeneous patches in the landscape ii) selection of training polygons (these correspond to heterogeneous patches in FCC) covering 15% of the study area and uniformly distributed over the entire study area, iii) loading these training polygons co-ordinates into pre-calibrated GPS, iv) collection of the corresponding attribute data (land use types) for these polygons from the field. GPS helped in locating respective training polygons in the field, v) supplementing this information with Google Earth (http://googleearth.com) and Bhuvan (http://bhuvan.nrsc.gov.in), vi) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment.

Land use analysis was carried out using supervised pattern classifier - Gaussian Maximum Likelihood Classifier (GMLC) algorithm through GRASS (open source GIS, http://ces.iisc.ernet.in/grass). Remote sensing data was classified using signatures from training sites that include all the land use types detailed in Table 1. Mean and covariance matrix are computed using estimate of maximum likelihood estimator. This technique has proven to be a superior classifier as it (Duda et al. 2000; Ramachandra et al. 2012a).

Table 1. Land use classification categories used to understand temporal land use change.

Land Use Class	Land Uses Included in the Class
Urban	This category includes residential area, industrial area, and all paved surfaces and mixed pixels having built up area.
Water bodies	Tanks, Lakes, Reservoirs
Vegetation	Forest, Cropland, Nurseries
Others	Rocks, Quarry Pits, Open Ground (at building sites), Kaccha Roads

Gaussian Maximum likelihood classifier (GMLC) is then used to classify the data using these signatures generated. Mean and covariance matrix were computed using estimate of maximum likelihood estimator. Land use was computed using the temporal data through the open source program GRASS - Geographic Resource Analysis Support System (http://ces.iisc.ernet.in/foss). Signatures were collected from field visits and with the help of Google Earth (http://earth.google.com). Classes of the resulting image were re-classed and recoded to form four land-use classes

Statistical assessment of classifier performance is done based on the performance of spectral classification considering reference pixels (Mitrakis et al. 2008), through computation of Kappa coefficients (Congalton et al. 1983; Congalton and Green 2009) and overall (producer's and user's) accuracy with confusion matrix. Accuracy assessment and Kappa coefficient are common measurements used to demonstrate the effectiveness of the classifications (Congalton 1991; Lillesand et al. 2003). Recent remote sensing data (2013) was classified using the training data collected from field. Classification of earlier time remote sensing data is done through the training polygons (with attribute details) compiled from the previously published topographic maps, vegetation maps, revenue maps, etc.

Zonal Analysis

City boundary along with the buffer region was divided into 4 zones: Northeast (NE), Southwest (SW), Northwest (NW), Southeast (SE) to account spatial patterns of urbanization in all directions. As most of the definitions of a city or its growth are defined in terms of directions, it was considered more appropriate to divide the region in four zones based on direction. The growth of the urban areas along with the agents of changes is understood in each zone separately through the computation of urban density for different periods.

Division of these zones to concentric circles (Gradient Analysis): All of the zones were divided into concentric circles with a consecutive circle of 1 km incremental radius from the central pixel (Central Business District). This analysis helps in visualising the urbanization process at local levels and understanding the role of agents responsible for changes. This helps in identifying the causal factors and locations experiencing various levels (sprawl, compact growth, etc.) of urbanization in response to the economic, social and political forces. This approach (zones, concentric circles) also helps in visualizing the forms of urban sprawl (low density, ribbon, leaf-frog development). The built up density in each circle is monitored overtime using time series analysis. This helps the city administration in understanding the urbanization dynamics to provide appropriate infrastructure and basic amenities.

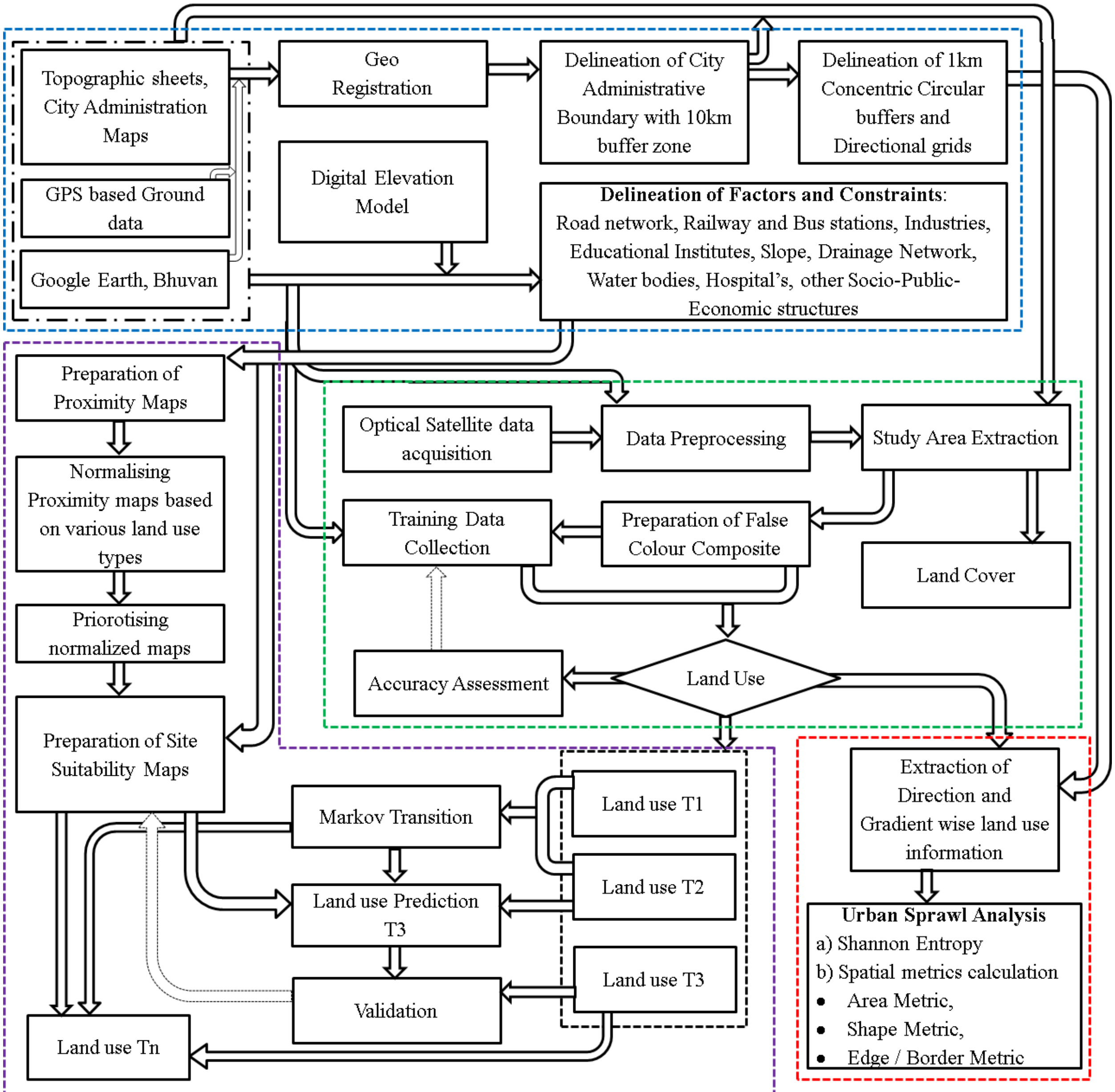


Figure 3. Procedure followed to analyze urban sprawl.

Shannon's Entropy

Urbanization process in each zone is assessed as compact or divergent through Shannon's entropy (Lata et al. 2001; Ramachandra et al. 2012a) calculated as given in equation 1.

$$Hn = -\sum_{i=1}^{n} Pi \log(Pi) \qquad \text{….. (1)}$$

Where, Pi is the proportion of the built-up in the ith concentric circle. Shannon's Entropy (Hn) explains the urbanization and its characteristics. H_n will be zero, if the distribution is maximally concentrated and will have maximum of log n, if evenly distributed across the concentric circles.

Computation of Spatial Metrics

Spatial metrics are helpful in quantifying spatial characteristics of the landscape. Select spatial metrics given in Table 2 (with characteristics of each metrics) were used to analyse and understand the urban dynamics. This is computed zone wise for each gradient through FRAGSTATS (McGarigal and Marks 1995) at three levels: patch, class and landscape

Table 2. Landscape Metrics calculated to understand the landscape configuration.

Indicator	Formula
Number of Patches (Built-up) (NP)	$N = n_i$; Range: NP$\geq$ 1
Patch Density (PD)	$PD = \frac{n_i}{A}(10{,}000)(100)$; Range: PD> 0
Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{e_i - \min e_i}{\max e_i - \min e_i}$; Range: 0 to 1
Total edge	TE=E, E=no of edges, TE $\geq$ 0, without limit.
Clumpiness Index (Clumpy)	$G_i = \left[\frac{g_{ii}}{(\sum_{k=1}^{m} g_{ik}) - \min e_i}\right]$ $CLUMPY = \left(\begin{matrix}\left[\frac{G_i - P_i}{P_i}\right] \text{ for } G_i < P_i \; P_i < 5; else \\ \frac{G_i - P_i}{1 - P_i}\end{matrix}\right)$ Range: Clumpiness ranges from -1 to 1
Percentage of Land Adjacencies (Pladj)	$PLADJ = \left(g_{ii} / \sum_{k=1}^{m} g_{ik}\right)(100)$ g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) i based on the *double-count* method. g_{ik} = number of adjacencies (joins) between pixels of patch types (classes) i and k based on the *double-count* method. 0<=PLADJ<=100
Cohesion Index	$Cohesion = \left[1 - \left(\sum_{j=1}^{n} P_{ij} \Big/ \sum_{j=1}^{n} P_{ij}\sqrt{a_{\square j}}\right)\right]\left[1 - \frac{1}{\sqrt{A}}\right]^{-1} * 100$ Range:0$\leq$cohesion<100

Agent-Based Modeling and Simulation of Land Use

Agents contributing to urban dynamics namely road network, bus and railway stations, industrial areas, educational institutes, hospitals and other socio economic features were delineated from the virtual earth databases such as Google Earth (http://earth.google.com), Bhuvan (http://bhuvan.nrsc.gov.in), open street maps and the Survey of India topographic maps. Influence of these features were determined using the fuzzy approach considering the sigmoidal increase or decrease with respect to the land use category, for example if roads are considered as factor for influencing the dynamics, farer the distance from the roads, vegetation and agriculture have higher tendency to prevail, whereas near to the roads, built-up area have higher tendency to prevail, thus urban landscape is considered to decrease as we move away from the road where as vegetation shall tend to increase away from the road. Analytical Hierarchical Process (AHP) was used in order to determine the weightage of each of the factors on the dynamics. Factors with higher weightages had higher influence on the landscape dynamics. Multi criteria evaluation was further used to derive the site suitability maps considering various factors and their weightages, and constraints of development for each land use category. The derived site suitability maps were further used for simulating known land use using Markov Chain and Cellular Automata.

Markov chain considers the transition between two time periods i.e., 1999 and 2003, to determine transition probabilities for the year 2003 to 2013. The transition probabilities along with the site suitability maps and a kernel (filter) are used as input to Cellular automata to simulate land use of 2013. Comparison of the simulated and the actual landscape for the year 2013 were made. The model was subjected to calibration by altering the weightage of each factor; recreating site suitability maps and simulating the land use for the year 2013 until the model simulated land use were near accurate. Overall accuracy of the model was obtained to be 89.03% with Kappa coefficient of 0.863 showing good agreement between the simulated and actual land use. The calibrated model, using the transition between 2003 and 2013 was used to predict the landscape for the years 2025.

RESULTS AND DISCUSSION

Land Cover Analysis

Spatial extent of vegetation analyzed through NDVI are listed in Table 3, which indicates the decline of vegetative cover from 29.63 (1989) to 18.61% (2013). NDVI based on the reflectivity of vegetation in red and near infrared, enables classifying the region under vegetation and non-vegetation. Figure 4 depicts the temporal changes of vegetation in the study area.

Land Use Analysis

Land use analysis based on Gaussian Maximum likelihood algorithm was done considering the training data collected from the field, Google earth and SOI topo maps. Results of the classification are given in Figure 5 and statistics are tabulated in table 4. Results indicate that urban paved surface increased by 650 times from 2 (1989) to 13% (2013) with the decline of vegetation cover from 25.2 to 18.6%. Water bodies remained fairly constant and other class (which included open area, agricultural plots without crop) decreased overtime from 73% to 67%. Overall accuracy and kappa was calculated for all classified data and are listed in Table 5. Urbanization is evident during the past 4 decades from figure 6.

Table 3. Land covers statistics computed for the study region.

Year	Vegetation (%)	Non-Vegetation (%)
1989	29.63	70.37
1999	26.47	73.53
2003	18.82	81.18
2013	18.31	81.69

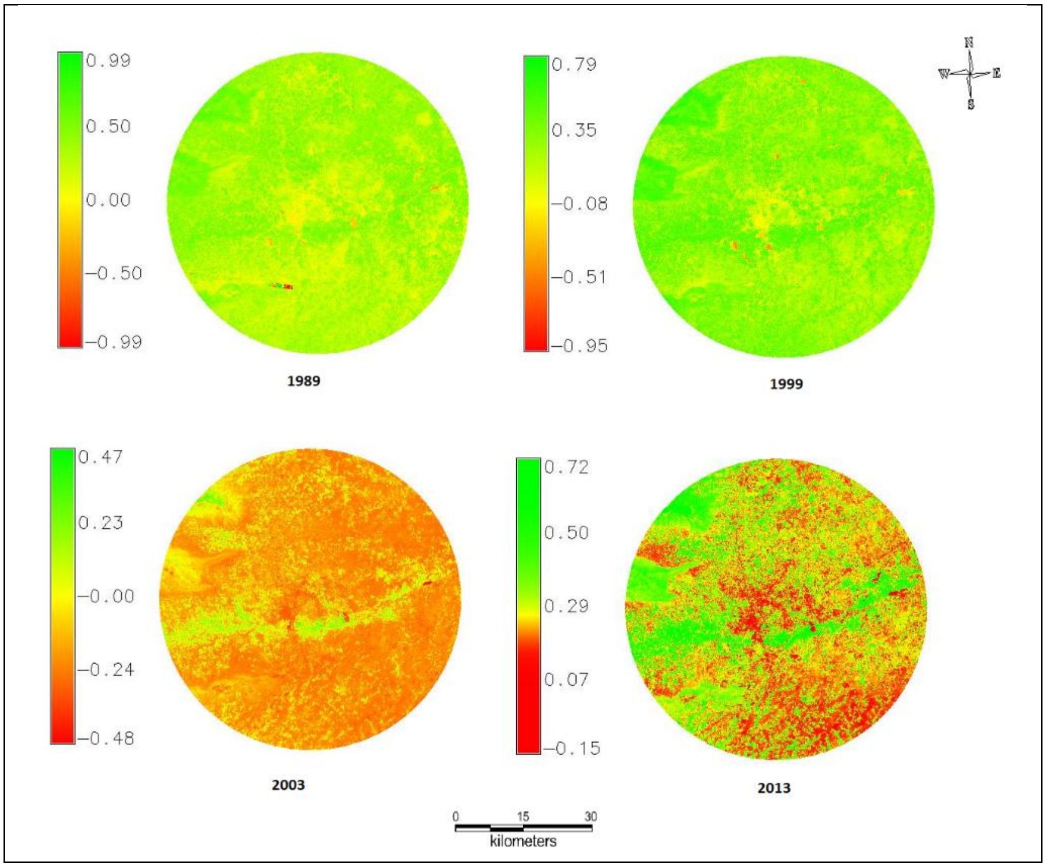


Figure 4. Results of the analysis of land cover analysis of Coimbatore and buffer.

Table 4. Land use statistics computed for study region.

Year ↓	Urban in %	Water in %	Vegetation in %	Others in %
1989	1.87	0.32	25.21	72.61
1999	6.81	0.45	24.87	67.87
2003	11.12	0.17	18.55	70.15
2013	21.26	0.29	17.79	60.66

Table 5. Overall Accuracy (OA) and kappa statistics of classified images.

1989		1999		2003		2013	
OA	kappa	OA	kappa	OA	kappa	OA	kappa
88.27	0.74	97.2	0.932	95.20	0.95	96.32	0.931

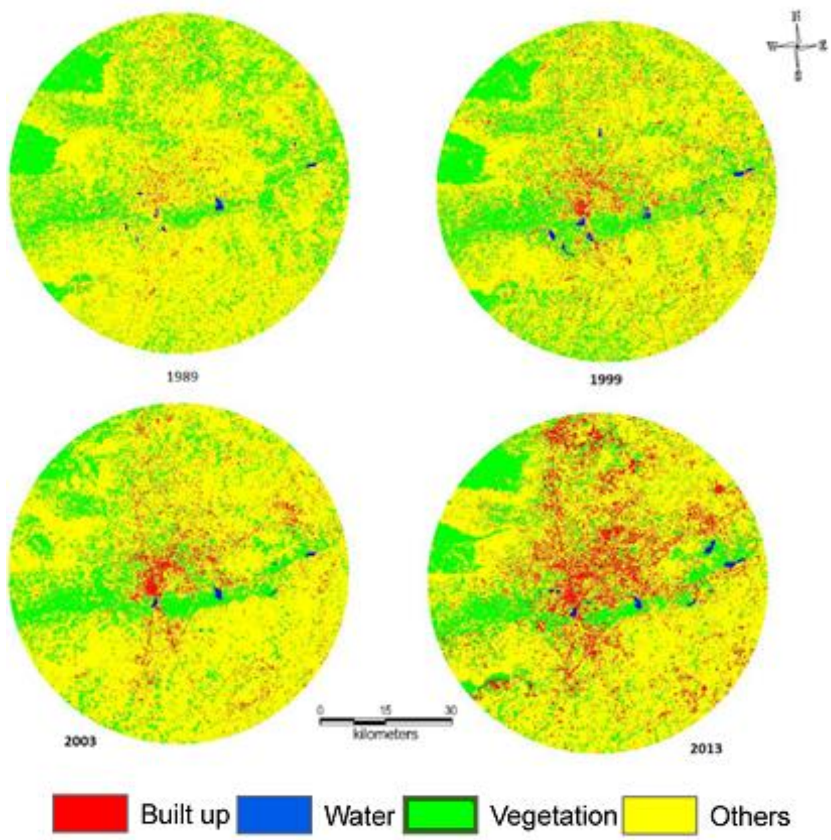


Figure 5. Results of the analysis of land use of Coimbatore and buffer.

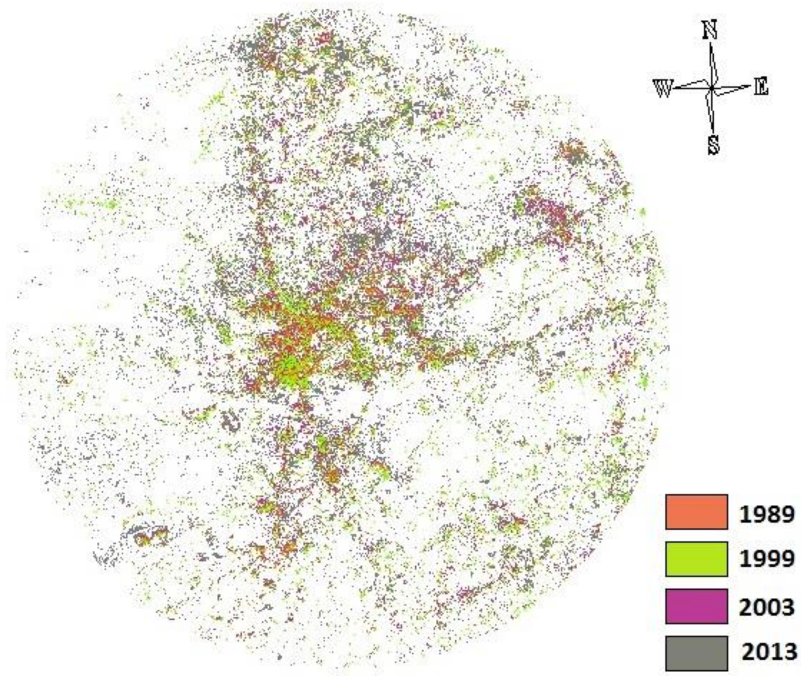


Figure 6. Temporal urban growth pattern for the study region.

Shannon Entropy Analysis

Shannon entropy analysis was performed zone wise based on cardinal directions with one km radius gradients. Computed value closer to log of the gradients indicates that the region is fragmented and value close to zero indicates of clumped growth. Figure 7 highlights the tendency of sprawl in SW and NE directions.

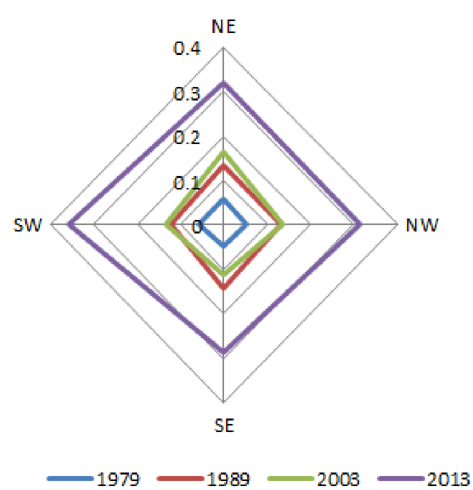
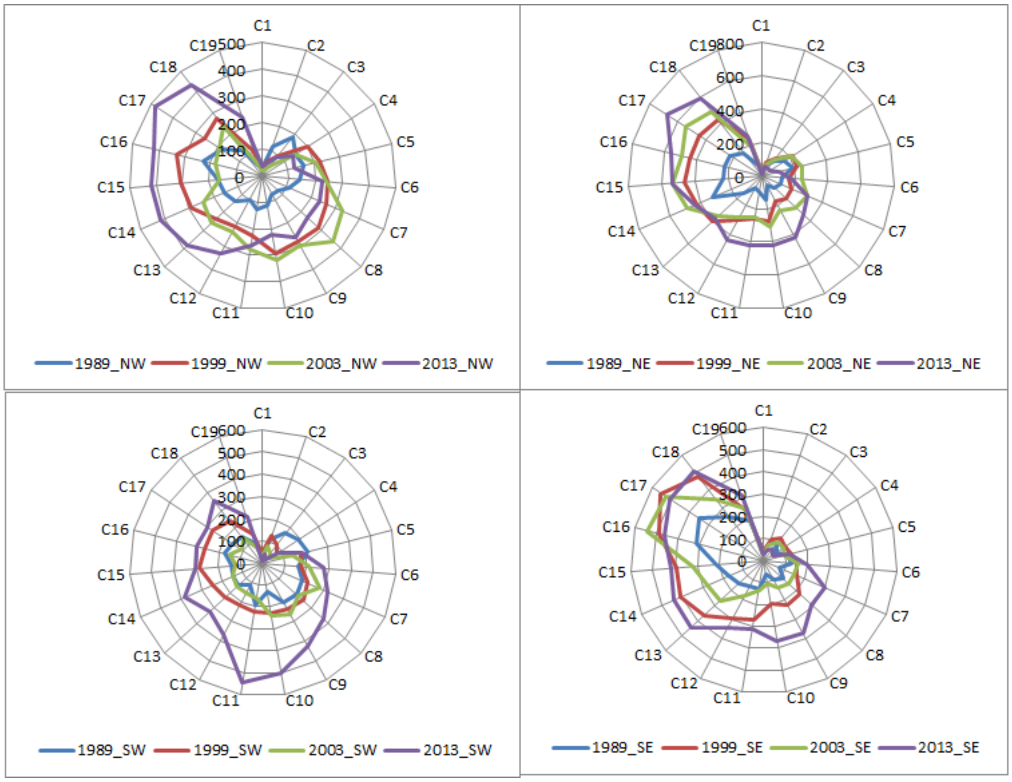


Figure 7. Shannon entropy index calculated for study region from 1979-2013.

Spatial Metrics

Spatial metrics were computed zone-wise for each gradient for all years. Each metric is explained below.

a) Number of urban patches (NP) and patch density (PD): This metric explains the order of fragmentation or clumped growth in terms of urban area calculated as a patch. Patch density provides the number of urban patch units per unit area. NP calculated zone wise for each gradient shows that zones NE and SE are highly fragmented. Figure 8a indicates that buffer region with large number of patches distributed haphazardly and the core area having a clumped growth. Core area started to clump during 2003 and higher growth of patches to an order of 500 – 600 is noticed in buffer region post 2003. Growth of patches in these regions highlights of spurt in urban growth and consequent sprawl. This phenomena of increasing number of patches (400-600 in circles 16-18) in SE, NE and NW directions in 2013 indicates that the buffer zones are experiencing severe outgrowth in terms of sprawl.

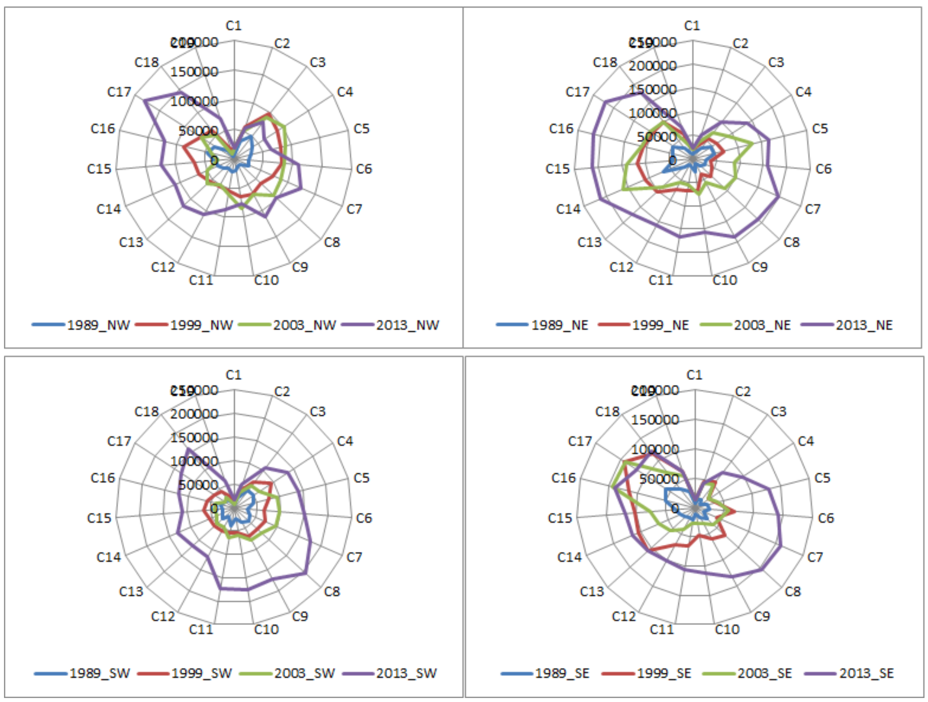


NE – Northeast; NW – Northwest; SE -Southeast; SW- Southwest

Figure 8a. Number of urban patches calculated for study region from 1979-2013.

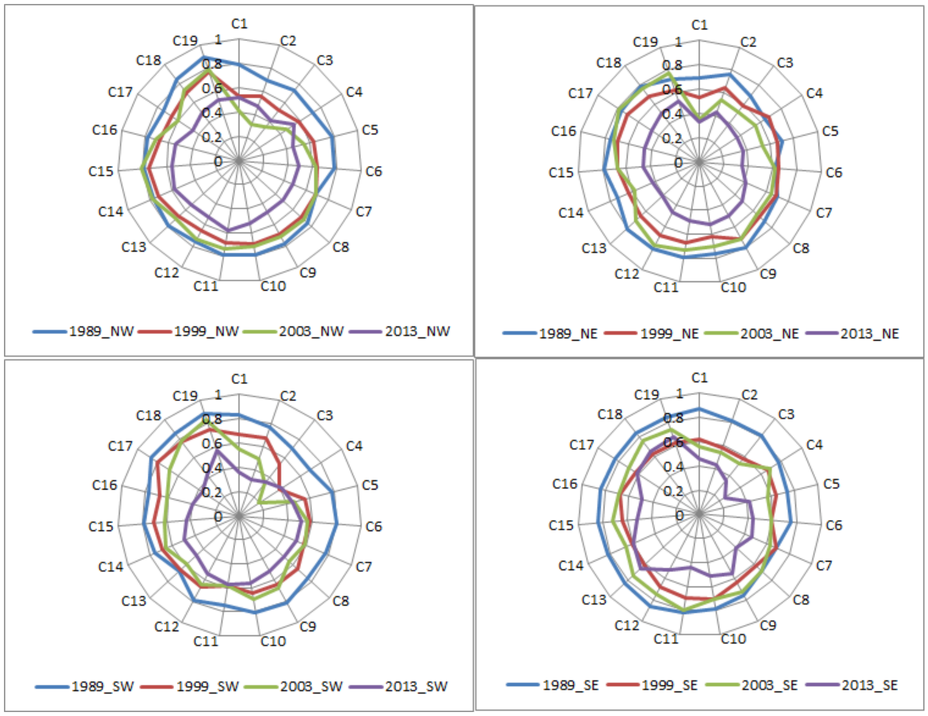
b) Total edge and edge density: Total edge counts number of edges in the landscape, which in turn is also the indicator of fragmented or dispersed growth (Figure 8b). Higher number of edges show that the regions have a mix of land uses and while lower number indicates only a particular land use in the region. In 1989 edges counted are as less as 50000 both in core and outskirts indicating that the regions are dominated by urban patches and edges are less indicative of homogenous transformation in each land use with less urban domination. During 1999 - 2003, edges in the landscape have increased at outskirts. in northeast and northwest directions (~150000 edges) indicating that land is fragmented and is under the influence of sprawl at outskirts, while the core regions are experiencing concentrated growth. This has further aggravated in 2013 with the gradients near the periphery (7-10) experiencing the effects of sprawl.

c) Normalized shape index (NLSI): NLSI is concerned with the shape and the value ranges from 0 (maximally compact patch) to 1 (disaggregated landscape). Figure 8c highlights NLSI values closer to 1 in all gradients of all zones during 1989. However, NLSI of 1999 and 2003 shows a decreasing value for circles 1-5 confirming that these regions are transforming in to a compact patch of simple shape. Outskirts of the regions have a relatively high value of 0.6-0.8. NLSI values for 2013 in core gradients have values closer to 0 (0.3-0.4) indicating a complete clumped uniform shaped growth. Outskirts (Gradients 6-8) and buffer zones have higher values closer to 1 indicating that these regions have irregular shape and sprawl in the region. Most of the zones have the same patterns of growth in all years.



NE – Northeast; NW – Northwest; SE -Southeast; SW- Southwest

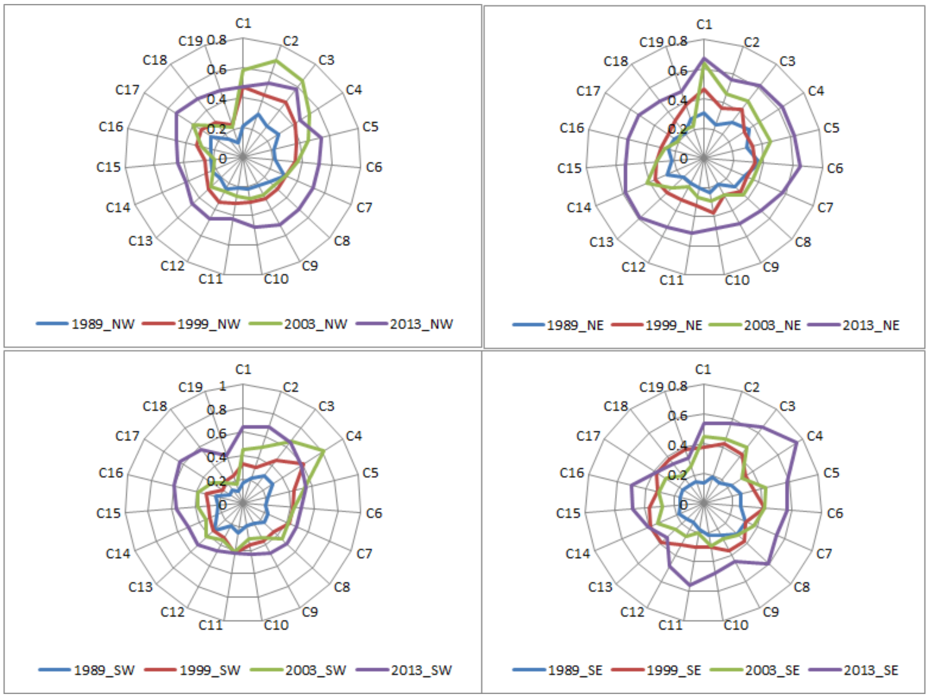
Figure 8b. Total edge calculated for study region from 1979-2013.



NE – Northaast; NW – Northwest; SE -Southeast; SW- Southwest

Figure 8c. Normalized landscape shape index calculated for study region from 1979-2013.

d) Clumpiness index (Clumpy): CLUMPY indicates of aggregation (when clumpy = 1) or disaggregation (clumpy = 0) of the class in the landscape. Figure 8f shows that gradients reaching aggregation or single patch class in the landscape in core areas and sprawl in the buffer regions. Values closer to zero in 1989, indicates that growth is disaggregated. During 1999, NW and SW shows a huge aggregation in gradients close to the center (3-6) and core region shows aggregation, while buffer maintains the same disaggregation as in previous years. But in 2013, gradients (2-7) shows a value close to 1 indicating aggregation in NW, NE and SE.



NE – Northeast; NW – Northwest; SE -Southeast; SW- Southwest

Figure 8d. Clumpiness index calculated for study region from 1979-2013.

All metrics highlight of sprawl, especially the periphery of the city and the buffer zones. This requires immediate attention by the city administrators and decision makers in providing basic amenities.

Modeling and Simulation

Model was built to simulate land use of 2013 based on consecutive datasets (1999 and 2003). Various criterion i.e., factors of development as shown in Figure 9 and constraints of development are as shown in Figure 10. In addition, water bodies in 2013 were considered under protected zone for prediction of 2025 land use.

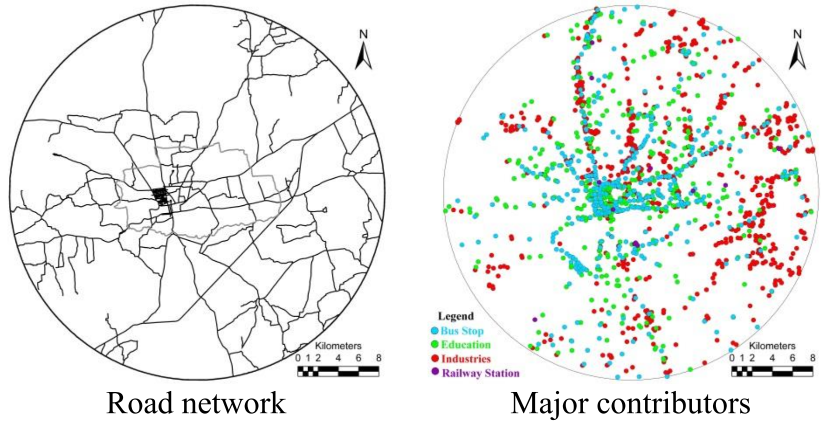


Figure 9. Factors of Growth considered for study region.

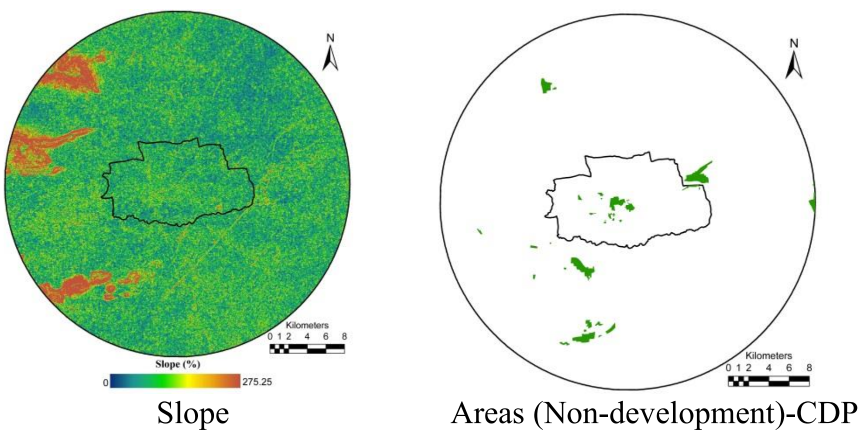


Figure 10. Examples of constraints of growth for study region.

Factors were normalized using fuzzy logic (0 to 255, 255 representing higher influence and 0 representing lower influence) and constraints using Boolean logic (0 and 1, 0 representing areas which shall not alter, 1 representing areas can alter). Slopes higher than 15% were considered as constraint for urban development. AHP based weightages for the factors are as depicted in Table 6. Of all the factors of growth considered, road networks showed higher influence i.e., about 44.96% for the landscape dynamics followed by industries, bus stations.

Table 6. Weights generated under each factor was considered.

Factor	Weightage
Road Network	0.4496
Industries	0.2149
Bus Station	0.1592
Educational Institutes	0.0924
Socio Economic Places	0.0531
Hospital	0.0307

Figure 11 presents site suitability maps developed for various landscapes using both criterion i.e., factors and constraints. Site suitability essentially involves creating agent based interactive land maps to access most suitable and least suitable regions for further simulations. Agents are necessarily ranked based on its characteristics and influences and this would provide a weighted score to calculate the most suitable and least suitable areas for a class. Urban suitability map given in Figure 11 shows a high value where changes are prominent and most suited based on its neighborhood that is contributed by the agent's behavior. Similarly, vegetation suitability map, with higher values indicate the most suitable regions to retain as vegetation, while low indicates the most impacted regions in this category of land use.

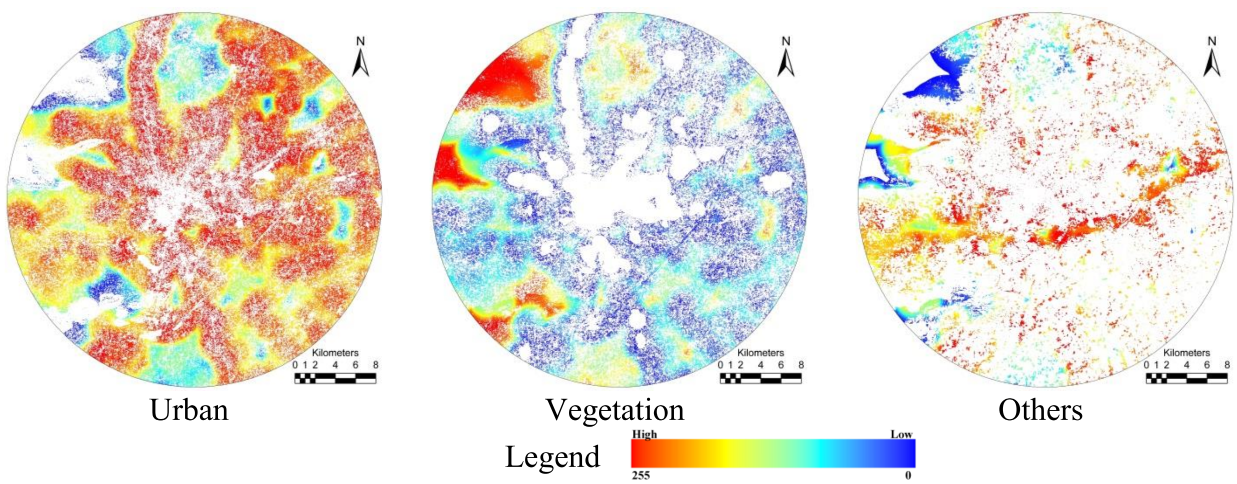


Figure 11. Site Suitability Maps.

Markov chain was used to understand the landscape dynamics between 1999 and 2003, to simulate for the year 2013. Transition probability with an allowable error of 15% for the year 2013 is tabulated in Table 8. The transition indicates that 46% of the vegetation area shall remain as vegetation and 46% converts to other land use category, whereas 19 % of the other land use category change to built up area (and 16% can change back to vegetation), 19% of water bodies can change to vegetation category and 10% of water can change to built up area.

Table 7. Markov transition probability 1999 - 2003 to 2013.

	Year 2013				
	Land use	Urban	Water	Vegetation	Others
Year 2003	Urban	0.85	0.05	0.05	0.05
	Water	0.10	0.64	0.19	0.07
	Vegetation	0.08	0.003	0.46	0.46
	Others	0.19	0.002	0.16	0.65

Simulated landscape for the year 2013 is depicted in Figure 12, and the land use statistics are listed in Table 8. Simulated output for the year 2013 was compared with 2013 land use (actual) to understand the efficiency of the model, the accuracy of the model is 89.03%, with Kappa (standard) of 0.83 and Kappa (location) of 0.84 respectively. Based on the outcome of higher agreement (simulated with actual land uses), the model was further used to predict the land use pattern in 2025.

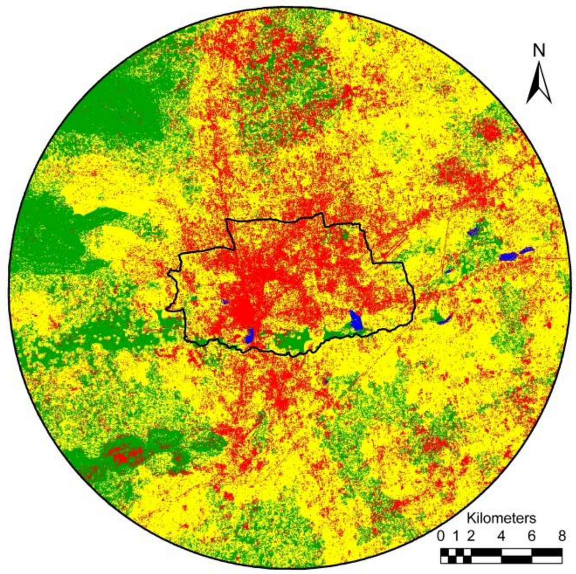


Figure 12. Simulated land use for the year 2013.

Table 8. Simulated land use for the year 2013.

	Built up in %	Water in %	Vegetation in %	Others in %
Simulated image of 2013 for validation	24.15	0.24	18.73	56.89

Prediction

The calibrated model along with Markov transition between 2003 and 2013 was used to predict land use for the year 2025. Figure 13 depict the predicted land use for the year 2025 and statistics of land use is as shown in Table 9.

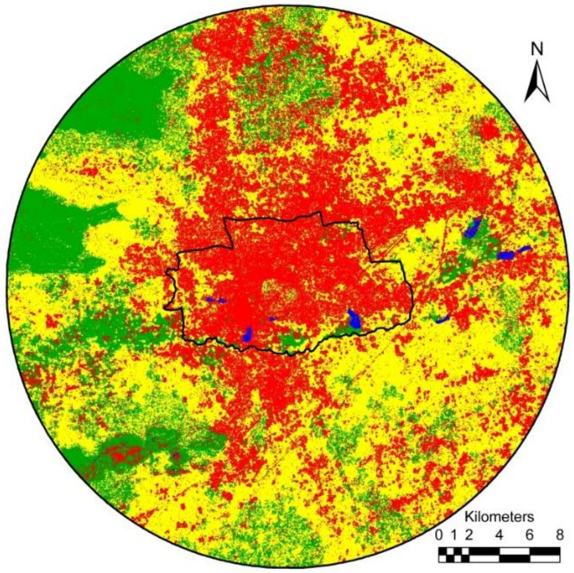


Figure 13. Predicted land use 2025.

Table 9. Land use 2025.

	Built up (%)	Water (%)	Vegetation (%)	Others (%)
Predicted land use for 2025	32.64	0.29	17.14	49.94

In the next twelve years, urban area tends to increase at a rate of 53.5% i.e., 32.64% of the total area in 2025 (from 21.26% in 2013). The outskirts of the city show an increase in vegetation, whereas region towards the CBD vegetation area tends to decline due to the urban growth. The increase in vegetation in the outskirts in the northwest and southwest zones can be attributed to increase in horticulture activities such as coconut plantation that can be observed in regions of Nanjandapuram, Periyanaickenpalyam, along Palkad main road, Ettimada, Thekkupalyam, Muthukallur, etc. and also some of these regions have rich forest cover necessitating appropriate policy interventions to mitigate the impact. On prediction, urban concentration was observed to be prominent along the north, northeast and partially in the southern directions. Industrialization along Gundlupet highway in the northern direction of Coimbatore has led to current urbanization scenario, same trend would further lead intense developments by 2025. Airport associated real estate developments, followed by setting up of large scale industries were observed along Salem Highway and Trichy road which has led to intense urbanization in the northeastern and east directions, due to these developments, educational institutions and other socio economic structures have come up in the vicinity of the newly set up layouts and along the highways, hence boosting urban development. Presence of Industrial estates has led to new housing colonies in the southern direction along madukkarai road, NH 207. Based on the study, places namely Gadalur (N), Kovipalyam (N), Ondipudhar (E), Vallalore (E), Sulur (E), Marappalam (S), Echanari (S), KG Chavdi (SW), and Maruthimalai (W) in around their vicinity have higher potential for urban growth.

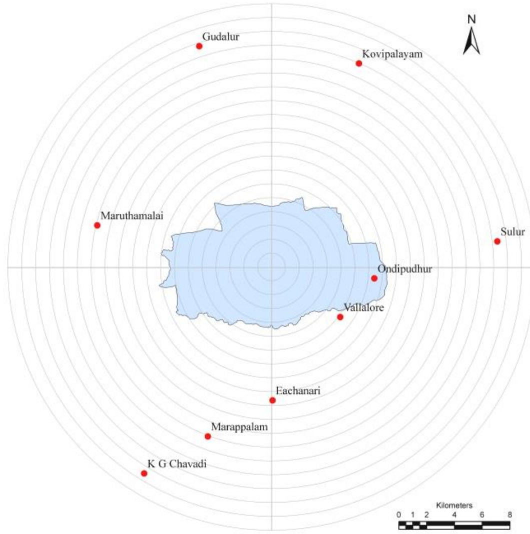


Figure 14. Possible locations of future growth.

CONCLUSION

Tier I cities (such as Coimbatore) in India are in the process of rapid urban transition. Spatial characterization and quantification highlight the urban expansion due to the enhanced economic activities. This necessitates prudent land use planning to ensure sustainable development with better policy alternatives. Land use analysis in Coimbatore city with 10 km buffer highlights an increase in urban area from 1.87 (1989) to 13.58 % (2013). Post 1990's the city has experienced infilling/concentrated growth at the Centre, while peri-urban pockets and buffer region experiencing dispersed growth. Spatial metrics further confirm this phenomena of dispersed growth at city outskirts. Visualization of growth based on modeling, shows that core urban area densifies, whereas the fringes and along the arteries, urbanization is lateral. Main factors that contribute to the growth were due to Road network followed by Industrial areas and other amenities. Simulated results indicate urban areas grow to 32.6% of the total area by 2025. The outcome of the metrics aids in advance visualization of the patterns of urbanization, which help in planning sustainable cities in India.

The study has attempted to understand LULC changes, the extent of urban expansion and urban sprawl in Coimbatore city, quantified by defining important metrics (Complexity, Patchiness, Density and contagion/dispersion) using gradients, zonal approach and modelling the land use for future prediction. Urban growth trends reveal of likely degradation of environmental conditions. Results of modelling demonstrate that the urban extent primarily consists of residential and commercial use. Different location conditions, such as road networks, business center, urban center, etc., were considered with various weights (transition probability) based on their relative significance. Agent Based Model (ABM) could also bring out the major regions of growth such as and that are in the influence of urbanization recently. These results will aid planners with prior visualization of growth for effective policy intervention. ABM approach is capable of estimating probable sites for urban planning which synchronize with real scenario. Thus agent based modelling approach is appropriate for developing future scenarios and would help in understanding the dynamics to plan towards providing basic amenities, infrastructure, etc.

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