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Prediction of Land use Dynamics in the Rapidly Urbanising Landscape using Land Change Modeller

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***Abstract*—Landscape transformations in the rapidly urbanizing landscape are the most dynamic process altering the local ecology, hydrology and environment. This necessitates understanding of spatial patterns of the growth for an effective urban planning. Remote sensing data acquired at regular intervals through satellite borne sensors enables the synoptic monitoring and visualization of urban growth patterns and dynamics. Focus of this communication is to model the land use dynamics in a rapidly urbanizing landscape with 10 km buffer considering all agents. Due to the unplanned urbanization, Bangalore a Silicon Valley of India has been facing numerous challenges of loss of green space, mobility constraints, higher pollution levels, flooding, indiscriminate disposal of solid and liquid waste, etc. Land Change Modeller (LCM) with Markov Cellular Automata was used to predict likely land use in 2020 with the knowledge of land use changes during 2006-2012 with the constraint of no-change in land use of water category. The results suggest an urban expansion of 108% (from 59103.9 in 2012 to 123061.6 hectares in 2020), with the decline of green space to 7% from 33.68% (2012). The visualised urban growth provide vital insights for better planning of urban space to ensure Bangalore regain the status of liveable and sustainable city.**

***Index Terms*— Urban growth, Modelling, Land change modeller, Cellular automata, Bangalore.**

I. Introduction

Large scale land-use land-cover (LULC) dynamics leading to the decline of vegetation cover is one of the drivers of global climate changes and alteration of biogeochemical cycles. Global warming and consequent changes in the climate has given momentum to investigate the causes of LULC by mapping and modelling landscape patterns and dynamics and evaluate these in the context of human-environment interactions in the rapidly urbanizing landscapes. Human induced environmental changes and consequences are not uniformly distributed over the earth. However their impacts threaten the sustenance of human-environmental relationships. Post-independence period in India, particularly during the globalization era in 1990's, the government facilitated the interactions of global industries with in-house industries. Large scale industrialization paved way for major LULC changes, caused by migration of people from different parts of the country, also from other parts of the globe and country for the employment opportunities. These led to intense urbanisation of major metropolitan cities with spurt in human population due to migration and also sprawl in peri-urban pockets. Unplanned urbanisation are characterized by the loss of diversity, with changes in the coherence and identity of the existing landscapes. The drastic landscape changes are a threat or a negative evolution, as it affects the sustenance of natural resources. Urbanisation process leads to conversion of ecological land use (such as vegetation. Open area, cultivable lands, water) into impervious layers on the earth surface. Increasing unplanned urbanisation is an important cause for depletion of resources species extension, hydro-geological alterations, loss of crop lands [1, 2]. Unplanned urbanisation has various underlying effects such as dispersed growth or sprawl.

Urban Sprawl refers to an uncontrolled, unplanned, scattered urban growth as a consequence of socio economic infrastructural development leading to increase in traffic, deficit of resources by depletion of the locally available resources while creating demand for more resources [3], often exceeding the carrying capacity of the land. Sprawl causes a major imbalance between urban spatial expansion and the underlying population growth [4].The dispersed growth or sprawl occurs basically in the periphery and the outskirts and these regions are devoid of any basic amenities or infrastructure. Sprawl can be in the radial direction encircling the city center or in linear direction along the highways, ring roads, etc. This necessitates visualization of urban trajectory for an effective urban planning.

Urban area currently with about 4 billion population, is projected to reach 8 billion by 2050 [4], which would be about 72% of the global population. Megacities, large agglomerations, are main consumers of natural resources (energy, food, etc.) with the generation of waste [5] beyond assimilative capacity of the region, continue to evolve and grow [6] with further loss of biodiversity, environmental degradation, affecting human health [1]. This phenomenon is most prevalent in developing countries [1, 6] especially the rapidly developing regions in India and other Asian countries [3]. This development may be due to various factors such as political, geographical, shortage of viable land for development etc., based on region and national scale [1, 2]. Urban sprawl with lack of appropriate infrastructure and basic amenities, affects urban space with due to the loss of agricultural and rural land, degradation of natural ecosystems, etc. The major causes of sprawl are attributed to huge growth of population, migration from rural to urban areas and unplanned developments. The urbanisation of core region also fuels the growth at outskirts as the population tends to move outskirts due to their lack of affordability. Demographic change not only imply the shift from high to low rates of fertility and mortality and is also associated with the development of households and features of their life cycle. The family or life-cycle features relate mainly to labour availability at the level of households, which is linked to migration, urbanization, and the breakdown of extended families into several nuclear families. At longer timescales, the increase of population also has a large impact on land use in a region. Hence there is a need for better planning and administration. For better land use planning changes in current land use patterns temporally is essential. This necessitates the analysis of land use changes and the prediction of likely changes in the future.

Availability of spatio-temporal data with the advancement of remote sensing technologies [7] has enabled unbiased land use analysis. Analysis of land use dynamics has attained research attention both at global and Indian contexts focusing on dynamically evolving cities [8]. Temporal land use changes at regional levels have s been attempted by various researchers [9, 10]. Several studies have assessed urban growth in various megacities around the world [1, 11, 12]. These studies though mapped and focused on temporally evolved current land use across various cities, have not addressed the likely growth required for the regional planning. Prediction of future growth are essential to control the uncontrolled development and plan for sustainable cities. Predictive models become very significant as they foresee spatial changes based on the historical land uses, which helps the decision makers in planning the growth including sprawl across the city periphery.

Urban growth models can be broadly grouped as (a) statistical models, based on regression and Markov chain [13] (b) dynamic evolving models, such as Cellular Automata (CA) [14]. Dynamic models are better suited to predict land use changes. Dynamical models coupled with agents of changes based on elements of different modelling techniques will help in better understanding of past land use changes for modelling land use dynamics.

A Multi-layer perceptron (MLP) based CA-Markov model with a capability to incorporate the agents of spatial changes is a powerful tool [15] to predict the growth. MLP helps in calibrating the agents and its relationship with land use changes. Markov chain helps in generating transition probability matrices based on the understanding of land use changes [16]. CA with markov considering spatial context based on neighbourhood configuration generates transition potential maps [17]. CA-Markov model is effective to model urbanisation [15]. However, for models to be effective there is a need for incorporating the agents such as social factors, economic factors, geography of an area which have decisive role in the urban process of a region. This has been demonstrated through incorporation of socioeconomic data into CA-Markov to predict land use changes [15]. this highlights the need for considering agents of changes, which still remains a research challenge.

The objective of this study is to simulate future land use changes in Bangalore, India based on the MLP-CA-Markov model considering the agents of current changes. MLP was used to calibrate the agents considering the transition of land use changes. Transition matrix is computed using the transition potential sub models based on the land use maps (2008, 2010, 2012) using the Markov chain module in Land use change modeller. Finally, spatial distribution of land uses from 2012 to 2020 are simulated through CA model with transition matrix and transition potential map.

II. Study Area And Data

Greater Bangalore capital of Karnataka, India with a spatial extent of 741 km^2 is geographically located at $12^o49'5''$N to $13^o8'32''$N and $77^o27'29''$ E to $77^o47'2''$E in the south eastern part of Karnataka state (Fig. 1). Bangalore urban area has spatially increased from 69 sq.km (1901) to 741 sq.km (2006) [1]. The study has been carried out for Bangalore with ten km buffer (with a gross area of 2290 sq.km) to account for likely sprawl in peri-urban regions.

The undulating terrain with elevation ranging from 700 m to about 962m AMSL of the region has aided in the formation of cascaded lakes with interconnecting drains. Large number of water bodies with green cover has aided in moderating the city climate and maintaining salubrious climate. Temperature varies from 22°C to 38 ˚C during summer and 14 ˚C to 27 ˚C in winter. Bangalore receives an annual average rainfall of 824 mm. geologically the area consists of Granitic and Gneisses rocks in large scale [16].

The population [1] of Bangalore (BBMP) has increased to a large extent in a decade at a rate 44% i.e., from 5,840,165 (2001) to 8,395,947 (2011) at a rate of 4.4% annually, higher than the national average of 2.5%. The population density in the region has increased from 8179 (2001) to 11756 persons/km^2 (2011). Bangalore has a decadal increase of 44%, which is very high compared to that of Karnataka state (31.5%) and India (31.8%).

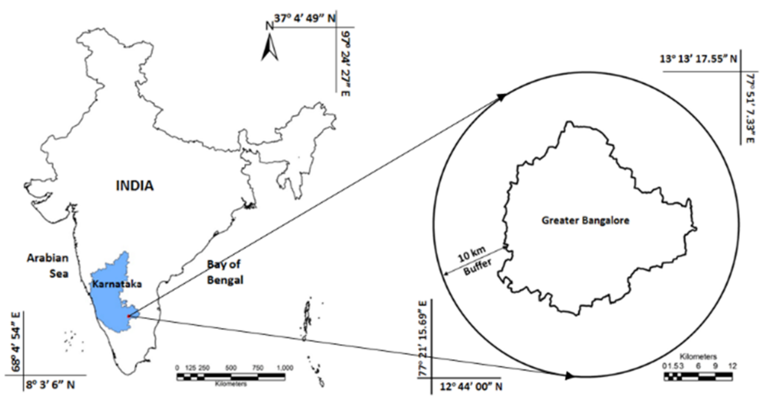

Fig.1. Study Area

Table 1 lists the data used for land use analysis. Temporal remote sensing data of Landsat TM and ETM+ were used to analyse and model LULC changes. Remote sensing data were supplemented with the Survey of India toposheets of 1:50000 and 1:250000 scale, and Bhuvan data, which were used to generate base layers of the administrative boundary, drainage network, Road network etc. Ground control points (GCPs) and training data were collected using pre calibrated Global Positioning System (GPS) and virtual online spatial maps such as Google Earth and Bhuvan GCPs were useful in geometric correction of remote sensing data.

Training data were used for classification, verification and validation of the classified results. Google earth data was also used to extract the point data such as location of industries, bus stops, railway stations, metro stations, social, religious structure's, cemeteries, educational and others (police stations, hospitals, theatres) and line features such as road network. These features were verified in the field using handheld calibrated GPS.

TABLE1: MATERIALS USED IN ANALYSIS

Data	Year	Description
Landsat TM (28.5m)	2008, 2010, 2012	Land Use Land Cover Analysis
ASTER DEM (30 m)	2012	Generation of Slope map
SOI toposheets		1:250000 and 1: 50000 toposheets for delineating administrative boundaries, and geometric correction, Delineation of road network
Bhuvan		Support data for Site data, Delineation of road network, Delineation of village and city boundaries
GPS		classification and data validation
Google Earth		Support data for site data, Delineation of road network, preparation of point database files as input for modelling
Census	1991, 2001, Provisional 2011	Population census for growth monitoring

III. METHOD

Modelling of urbanization and sprawl as outlined in Fig. 2, involved

i) Remote Sensing data acquisition, geometric correction, field data collection,
ii) Classification of remote sensing data and accuracy assessment using GRASS,
iii) Identification of agents and development of attribute information using MapInfo,
iv) Designing three scenarios of urban growth and calibrating the model to find out the best weights based on the influence on the neighborhood pixels,
v) accuracy assessment and validation of the model,
vi) Prediction of future growth based on validated data
vii) Computation of spatial metrics and analysis.

Image pre-processing: The remote sensing data of Landsat TM with spatial resolution of 30 m were acquired from USGS. These data were geometrical corrected using polynomial transformations and pre-processed for noise removal.

Land use analysis: Analysis was carried out using supervised pattern classifier - Gaussian maximum likelihood algorithm. This method has already been proved as a superior method as it uses various classification decisions using probability and cost functions [17]. Mean and covariance matrix are computed using estimate of maximum likelihood estimator. Four major types of land use classes were considered: built-up area, vegetation, open area, and water body as described in table 2. The method involves a) generation of false colour composite (FCC) of remote sensing data (bands – green, red and NIR). This helped in locating heterogeneous patches in the landscape b) 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, c) loading these training polygons co-ordinates into pre-calibrated GPS, d) 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, e) supplementing this information with Google Earth f) 60% of the training data has been used for classification of the data, while the balance is used for validation or accuracy assessment.

Training data was collected in order to classify and also to validate the results of the classification. Land use analysis was carried out with supervised classification scheme using training data. The supervised classification approach is adopted as it preserves the basic land cover characteristics through statistical classification techniques using a number of well-distributed training pixels. Maximum likelihood algorithm is a common, appropriate and efficient method in supervised classification techniques by using availability of multi-temporal “ground truth” information to obtain a suitable training set for classifier learning. Supervised training areas are located in regions of homogeneous cover type. All spectral classes in the scene are represented in the various subareas and then clustered independently to determine their identity. ***GRASS GIS (Geographical Analysis Support System)*** an open source software has been used for the analysis, which has the robust support for processing both vector and raster files accessible at [18]

Accuracy assessment: Accuracy assessments decide the quality of the information derived from remotely sensed data. The accuracy assessment is the process of measuring the spectral classification inaccuracies by a set of reference pixels. These test samples are then used to create error matrix (also referred as confusion matrix), kappa (κ) statistics and producer's and user's accuracies to assess the classification accuracies. Kappa is an accuracy statistic that permits us to compare two or more matrices and weighs cells in error matrix according to the magnitude of misclassification [1, 2].

TABLE II: LAND USE CATEGORIES

Land use Class	Land use included in class
Urban	Residential Area, Industrial Area, Paved surfaces, mixed pixels with built-up area
Water	Tanks, Lakes, Reservoirs, Drainages
Vegetation	Forest, Plantations
Others	Rocks, quarry pits, open ground at building sites, unpaved roads, Croplands, Nurseries, bare land

Modelling Land use scenario: Land use Change Modeller (LCM), an ecological modeller was used for modelling the land use scenario based on the data of 2008, 2010 and 2012. LCM module provides quantitative assessment of category-wise land use changes in terms of gains and losses with respect to each land use class. This can also be observed and analysed by net change module in LCM. The Change analysis was performed between the images of 2008 and 2010, 2010 and 2012, to understand the transitions of land use classes during the years. Threshold of greater than 0.1 ha were considered for transitions. CROSSTAB was used between two images to generate a cross tabulation table in order to see the consistency of images and distribution of image cells between the land use categories. Multi-Layer perceptron neural network was used to calibrate the module and relate the effects of agents considered and obtain transition potential sub models. Further markov module was used to generate transition probabilities, which were used as input in cellular automata for prediction of future transitions. This has been analysed LCM or using the CA_Markov.

Validation: Land use of 2012 was predicted using land use transition during 2008 to 2010 considering 2008 as base year. The predicted 2012 land use was compared with classified land use of 2012 (based on remote sensing data of 2012). This was repeated with 2010 data as base year considering the transition during 2010 to 2012. Validation was performed using validate, calculating Kappa, K_{loc}, $K_{no,}$ $K_{standard}$ for simulated images and classified image of 2012. Similarly, prediction for 2020 was done considering 2010 and 2012 as base images.

Spatial pattern analysis: Spatial metrics provide quantitative description of the composition and configuration of urban landscape. These metrics were computed for classified land use data at the landscape level using FRAGSTATS. Urban dynamics is characterized by select spatial metrics [1, 3, 11, 13] listed in Table 3, chosen based on shape, edge, complexity, and density criteria. The metrics include the patch area, shape, epoch/contagion/ dispersion.

IV. RESULTS AND DISCUSSION

Land use analysis: Land use analysis was done using Maximum Likelihood classifier (MLC) considering training data collected from field. Land use analysis show an increase in urban area from 49915.42 (2008) to 59103 hectares (2012) which constitute about 30%. Fig. 3 illustrates the increase in urban area and the same is listed in table 4. Land use changes are due to various agents that have played role in urban growth. These agents include large IT sectors (in south east), Bangalore international airport (north east), several industrial areas (west and south west), etc. Gradual increase urban aggregations at periphery is noticed due to large availability of land at affordable price.

Accuracy assessment: Accuracy assessment of land use analysis was performed by generating the reference image through the 30% of training data. Overall accuracy and Kappa was calculated using the module r.kappa in *GRASS*. The results of accuracy assessment are as shown in table 5.

Visualising the urban growth by 2020: Urban data (2008, 2010) were used as input to the land change modeller. MLP, was used to obtain transition considering various agents. The markov module provided the

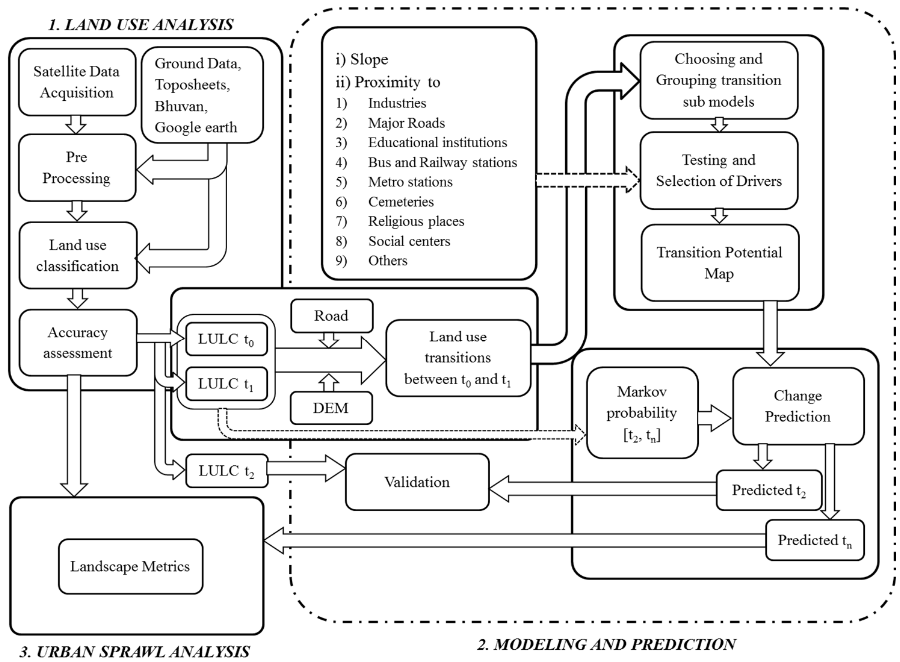

Fig. 2. Spatio-temporal analysis procedure

TABLE III: LANDSCAPE METRICS ANALYSED

	Indicators	Formula
1	Number of Urban Patches (NPU)	$NPU = n$ NP equals the number of patches in the landscape.
2	Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.
3	Total Edge (TE)	$TE = \sum_{k=1}^{m} e_{ik}$ where, e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i.
4	Clumpiness index(Clumpy)	$G_i = \left[\frac{g_{ii}}{(\sum_{k=1}^{m} g_{ik}) - \min e_i}\right]$ $CLUMPY = \left(\begin{matrix} \left[\frac{G_i - P_i}{P_i}\right] \text{ for } G_i < P_i \; and \; P_i < 5; else \\ \frac{G_i - P_i}{1 - P_i} \end{matrix} \right)$ Range: Clumpiness ranges from -1 to 1
5	Percentage of Land adjacency (Pladj)	$PLADJ = 100 * \left(g_{ij} / \sum_{k=1}^{m} g_{ik} \right)$ g_{ii} = number of like adjacencies (joins) between pixels of patch type g_{ik} = number of adjacencies between pixels of patch types i and k Range: 0<=PLADJ<=100

transition probability matric and finally growth for 2012 is predicted through CA_Markov (Fig. 4). The module was trained until the optimum accuracy was reached with good kappa value (Table 6). This module was optimized and calibrated to the evolving agents with urban change patterns. Considering the agents and the training data, prediction for the year 2020 was performed and given in Fig. 5 and table 7.

The predicted land use reveals of similar patterns of urbanisation of last decade. The main concentration will be mainly in the vicinity of arterial roads and proposed outer ring roads. Predicted land use also indicate of densification of urban utilities near the Bangalore international airport limited (BIAL) and surroundings. Further an exuberant increase in the urban paved surface growth due to IT Hubs in south east and north east. The results also indicated the growth of suburban towns such as Yelahanka, Hesaragatta, Hoskote and Attibele with urban intensification at the core area. The predicted urban area is about 123,061.59 hectares (62%), a considerable increase of 208 times by 2020 (compared to 2012). This highlights the need for appropriate infrastructure to cope up with the visualized growth to minimize drudgery to the common public.

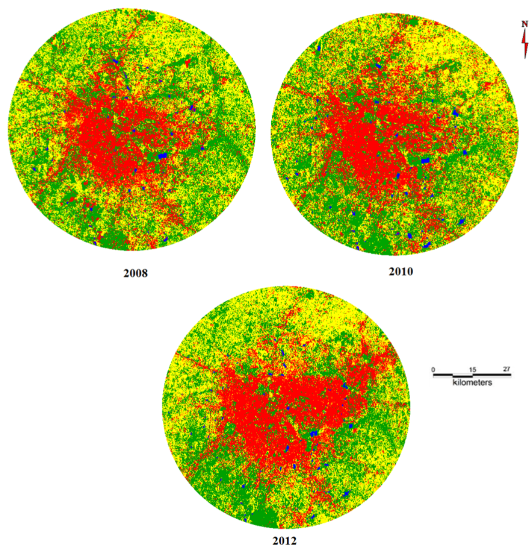

Fig. 3. Land use transitions during 2008 to 2012

TABLE IV: LAND USE DURING 2008, 2010 AND 2012

Class Year	Built-up Area		Water	
	Ha	%	Ha	%
2008	49915.42	24.85	1068.94	0.53
2010	57208.40	28.48	1571.41	0.78
2012	59103.90	29.33	1169.82	0.58

Class Year	Vegetation		Others	
	Ha	%	Ha	%
2008	77036.96	38.35	72851.95	36.27
2010	73460.57	36.57	68,656.40	34.17
2012	67883.85	33.68	73385.73	36.41

TABLE V: ACCURACY ASSESSMENT

Year	Overall accuracy %	Kappa
2008	86.35	0.78
2010	91.62	0.86
2012	90.43	0.85

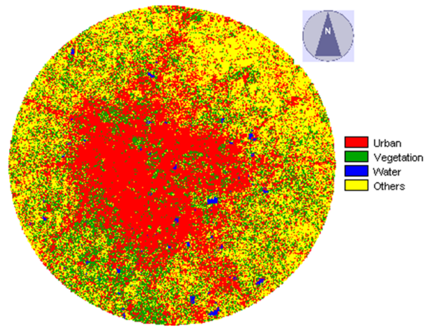

Fig. 4. Growth in 2012 (predicted) Bangalore

TABLE VI: COMPARISON OF PREDICTED LAND USE WITH ACTUAL LAND USE OF 2012 -ACCURACY AND KAPPA STATISTICS

Class Year	Built-up Area	Water	Vegetation	Others
	%	%	%	%
2012 classified	29.33	0.58	33.68	36.41
2012 predicted	31.13	0.6	29.42	38.85
Overall accuracy:93.64, Kappa:0.91, K_{loc}: 0.9265, K_{no}: 0.8938, $K_{standard}$: 0.8874				

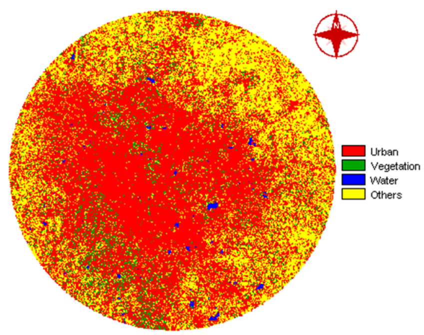

Fig. 5: Predicted growth of Bangalore by 2020 using LCM

TABLE VII: LAND USE STATISTICS OF BANGALORE FOR 2020

Class Year	Built-up Area	Water	Vegetation	Others
	%	%	%	%
2020 Predicted	61.27	0.55	7.00	31.18

Landscape metrics and urban analysis: Landscape metrics were calculated using Fragstat software to understand the extent of urban growth, its characteristics such as shape and contagion, etc.

Number of urban patches (NP): NP signifies the urban class growth in the landscape. It explains the kind of growth (patched/fragmented or unpatched/clumped) in the considered region. The results of this metric explains that there was increase in number of patches from 2008 to 2012, this signifies that there was a patched/fragmented growth. Post 2012 (Fig. 6) the NP decreases which indicates that there will be coalescence of grown urban patches to a single patch. Thus by 2020 urban densification is evident with the loss of other land uses.

Normalized landscape shape index (NLSI): This measures the shape of the class in the landscape and NLSI = 0 when the landscape consists of a single square or maximally compact and reaches 1 if the class becomes increasingly disaggregated or fragmented or shows convoluted shapes. This highlights of clumped growth by 2020 in conformity to the reduction of NP. Fig. 7 highlights the consolidation of urban patched to a clump.

Clumpiness index: Clumpiness index is a measure of adjacency indicating the extent of clumped or fragmentations in the urban growth. This values ranges from -1 (complete disaggregation) to 1 (maximal aggregation) and values near to 0 indicates of random distribution of patches. This index also indicates of highly concentrated aggregated clumped growth by 2020(Fig. 7).

Edge density: Edge density is also a fragmentation index, which counts the edges formed by forming new classes in the landscape, the edge density increases between 2008 to 2010 indicative of fragmented growth and during 2010 to 2020 declines, indicative of clumped growth (Fig. 8).

Percentage of land adjacencies (PLADJ): This index shows how adjacent are the same features, based on neighborhood adjacencies. Values close to 100 shows the adjacent growth (with disappearance of other land uses), values close to 0 indicates of the presence of heterogeneous landscape with all land use categories. Values close to 100 in 2020 is indicative of adjacent clumped growth in the region (Fig. 8).

These spatial metrics highlight of aggregated growth by 2020 and the formation of concrete jungle with the disappearance of all other land uses. This haphazard growth would fuel unsustainability with the decline of vegetation, etc.

V. Conclusion

The prediction of urban growth considering various agents of development with the knowledge of historical land uses through Land use change modeller with the help of Markov- CA. Integration of temporal remote sensing data with Geoinformatics are helpful to visualise the urban growth. Incorporation of agents in the modelling exercise provided a realistic picture of the growth. LCM model output validated with the actual data (2012) showed reliability and good accuracy.

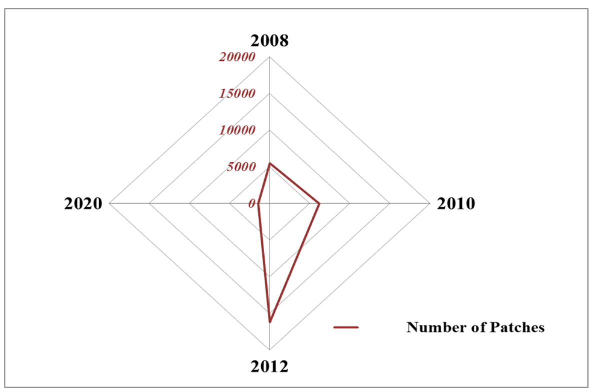

Fig. 6. Number of urban patches

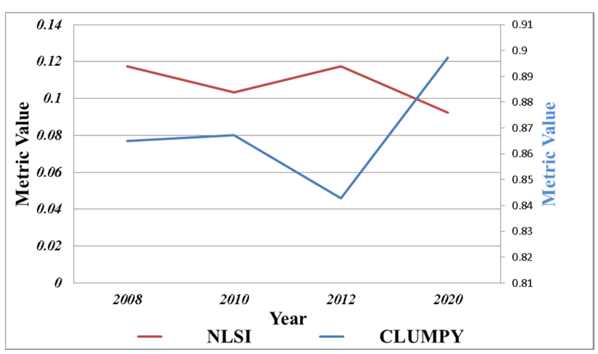

Fig. 7. Normalized landscape shape index and Clumpiness index

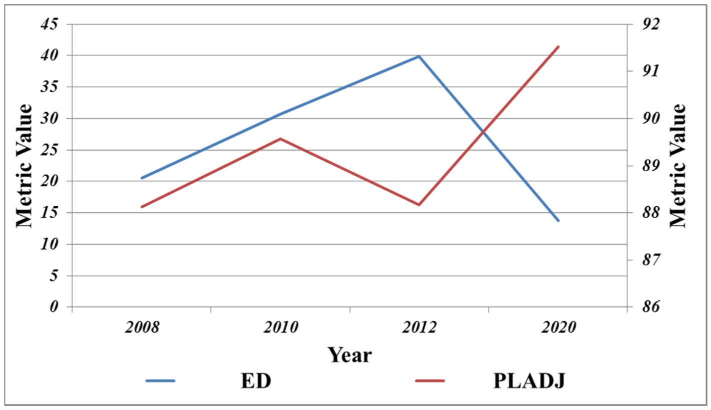

Fig. 8. Edge density and Percentage of land adjacencies

Validation of LCM with agents is further used to simulate the land uses by 2020. The land use scenario show a drastic increase from 24.85 % (2008) to 61.27% (by 2020) with the decline of vegetation and other category. Due to imposing constraint of no-change ion water category, remained constant. The spatial pattern analysis reveal of concentrated intensified growth at city centre with the increase in urban pockets at suburban, peripheral towns around Bangalore. The city would reach a threshold of urban development by 2020, with the continuation of current approach of urbanisation. This growth would ultimately threaten sustainability of natural resources affecting the livelihood of residents. The trajectory growth is a pointer to the city planners to provision basic amenities apart from conservation of vital natural resources. Land use modelling with the integration of agents (of changes) into Markov–CA and with GIS technology has aided in successful simulation of spatial changes and with the reliable forecast. This helps the decision makers in planning sustainable city with the provision of basic infrastructure and amenities. This exercise helps the local land use planners and city administrators with insights to the dynamically evolving complex land use system for conserving the ecological entities and other forms of land uses.

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