Modeling and Simulation of Urbanisation in Greater Bangalore, India

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***Abstract*—the potential of Markov chain and cellular automata model for predicting the spatial and temporal urban growth dynamics has been evaluated for rapidly urbanizing Bangalore, India. The growth of Bangalore is visualized for the year 2020 using business as usual scenario. Multi temporal land use information, derived from remote sensing data of 2008, 2010 and 2012 have been used for simulation and validation. Urban growth patterns and processes were quantitatively assessed with the use of landscape metrics. The results indicate that the future expansion of greater Bangalore will be in the peri- urban landscapes, due to the current clumped urbanisation at the city core with little scope for further urban densification. Urban simulation modeling in conjunction with spatial metrics is effective in capturing and visualizing the spatio–temporal patterns of urbanisation with insights to the trajectory of urban growth for effective planning of the city.**

Keywords: Urban sprawl, Remote Sensing, Cellular Automata, Markov Chain, Modeling

I. INTRODUCTION

Urbanisation is a dynamic process involving the horizontal and vertical expansion of urban pockets in response to the population growth, industrialization, political, cultural and other socio-economic factors[1][2][3]. Unplanned urbanisation leads to the large scale land cover changes [4] affecting the ecological diversity with degradation of the environment, enormous consumption of resources, creation of urban heat islands, changes in local climate [5][6], soil erosion, changes in hydrological cycle impairing surface water and ground water regime [7]. This process often leads to unstable development with increasing economic, social and environmental problems [8] such as radical changes of vegetation, water bodies, etc., with the irretrievable loss of ground prospects due to drastic change in the landscape [9]. These are often driven by the uncontrolled and dispersed growth along the periphery, which is referred as urban sprawl. The process of urban sprawl is common in rapidly urbanizing metropolitan cities. Rapid rise in urban population has caused serious environmental damages with problems such as increasing slums, decrease in standard of living, etc. [10]. The urban sprawl process has been studied in many developing regions [11][12][13][14][15][16] as it leads to drastic change in the landscape. Therefore spatio-temporal changes in urbanisation pattern would help in assessing land use changes, which would provide insights to the extent and rate of urban sprawl. Land use refers to use of the land surface through modifications due to anthropogenic activities or natural phenomena [1][12][17]. Quantification of impervious manmade surfaces in and around the city through mapping would help in estimating the dispersed growth of urban pockets. . The traditional surveying and mapping techniques to monitor landscape changes over different time frames entails high expenses due to time as well as requirement of resources for mapping and inventorying exercises. Recent advancements in mapping and modeling [18] through spatial data acquired remotely through space-borne sensors (remote sensing data) and the analysis of spatial data through Geographic Information System [GIS] have enhanced the abilities of spatial data analysis. Remote sensing technique [1][12][15][16][17][18] has advantages such as wider synoptic coverage of the earth surface with varied temporal, spatial and spectral resolutions. Classifications of these data through already proven classification algorithms [1][17][18] provide land use information. These temporal information helps to measure, monitor and visualise changes, which are necessary to model and simulate the likely changes in spatial patterns. Modelling enables the prediction of likely future land cover changes, required for evolving strategies for appropriate decisions and policies, interventions [19] to mitigate the drastic land cover changes. Prediction of changes based on the current trend will help in understanding the role of influencing factors and constraints. Research in this direction have focused on modelling and predicting changes in forest and hydrology, effect of urbanisation on runoff, soil erosion, urban sprawl, etc. [19][20][21][22][23][24]. Models such as Cellular Automata (CA), CA-Markov, Geomod, Land Change Modeler

(LCM), Sleuth, Agent Based Modeling (ABM), Multi Criteria Evaluation (MCE), Regression, Neural Networks, etc., have been used for simulating urban sprawl [20][25][26][27][28][29] [30]. Studies have demonstrated the use of Markov chains combined with cellular automata as one of the effective technique in modeling urban sprawl pattern [20][26][28][29].
Markov chain and cellular automata:Cellular Automata (CA) are algorithms which define the state of the cell based on the previous state of the cells within a neighborhood, using a set of transition rules. CA have a potential for modelling complex spatio-temporal processes such as urban process. CA is made up of elements represented by an array of cells, each residing in a state at any one time, discrete number of class (states), the neighborhood effect and the transition functions, which define what the state of any given cell is going to be in the future time period. The cell space digitally in the CA consists of a rectangular grid of square cells each representing an area 30mx30m and matches the size as the minimum area mapped in urban areas in the land use datasets. Basic assumption that was used is cells are not homogeneous and are characterized by a vector of suitabilities, deciding the future land use. The suitabilities are defined as a weighted linear sum of a series various affecting factors characterizing each cell. They are normalized to values in the range of 0–1, and represent the inherent capacity of a cell to support a particular activity or land use which can be generated by Markovian random process, which is a stochastic process. In this urban cellular automaton, the neighborhood space is defined as a square region around the central cell with a radius of five cells. The neighborhood thus contains 24. The neighborhood influence area and the interactive area for urban land uses and its neighbors. The model uses 4 cell states. The active functions is urban land uses which are forced by demands for land generated exogenously to the cellular automaton in response to the growth of the urban area. Passive is represented by other land use classes. The effect on the neighborhood is thus calculated as summed effect of each transitional potential and its interaction with its neighbors and the transition rules: were determined by various demands of the land use classes, population growth etc.

Finally, spatial metrics have been useful to quantify the land use based on patch, shape, edge etc. This quantification provide insights to the historical and current spatial patterns, which is useful in evaluating the landscape heterogeneity in relation with urban growth [30][31][32]. The objective of the current research is to simulate urbanisation process of Bangalore city for 2020 through CA and CA-Markov model considering transition probabilities (based on Markov chain analysis). Spatial patterns of urbanisation is quantified using landscape metrics.

II. Study area

Bangalore the IT hub of India is located in the southern part of the country of Karnataka state. The region was known as "Bendakaaluru" (land of boiled beans), "land of lakes" where a large number of lakes were constructed to store water, during the regime of erstwhile princely state. Numerous parks, gardens such as Lalbhag, Cubbon Park etc. exist in the region, which aptly gave the name "Garden City". However, during the post-independence due to industrialization, unplanned urbanisation the city has witnessed the decline in parks as well as water bodies / lakes. With the spurt in IT industries in the region during late 1990's, the city was termed "Silicon Valley". This policy interventions created job opportunities to different category of people. The city has grown spatially during the last year by 10 times and the current spatial extent is about 741 km^2.

Geographically Bangalore is located in the Deccan plateau, toward the south east of Karnataka state extending from 12^{o}49'5"N to 13^{o}8'32" N and 77^{o}27'29" E to 77^{o}47'2"E. To account for developments in the peri urban regions, the study area includes ten km buffer (from the administrative boundary) with a gross area of over 2250 km^2 as shown in Fig. 1. Bangalore has spatially increased from 69 sq.km (1901) to 741 sq.km (2006) [1].The decadal (2001 to 2011) increase in population for urban areas of India is 31.8% and in Karnataka is 31.5%, but Bangalore has a decadal increase of 44% very large compared to that of the state and country. The population has increased from 5.8 Million in 2001 (BMP – Bangalore Mahanagara Palike limits) to 8.4 Million in 2011 (current spatial extent of 741 sq.km, under jurisdiction of BBMP-Bruhat Bangalore Mahanagara Palike) [34][35]. The population density has increased from 7880 persons per square kilometer to over 11330 persons per square kilometer during the last ten years [34][36]. Bangalore receives an annual average rainfall of 896 mm [35][37]. The undulating terrain varying from about 700 m to about 962m AMSL in the region has resulted in the formation of large number of drainage network with inter connected lakes. Vegetation and water bodies are responsible for moderating the local climate and cooler days during summer.

Geologically [38][39], the prevailing rocks are light to dark grey Biotitic Granitic Gneiss and varies from place to place in texture, structure and appearance based on the fineness or coarseness of the grains, mode of disposition of dark minerals.

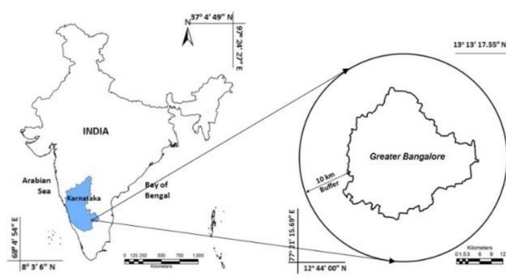

Fig.1. Study Area- greater Bangalore with 10 km buffer

The drainage network in Bangalore flows to Cauvery through its tributaries Arkavathi (East flowing), Pinakini/Pennar (East Flowing) and Shimsha (West Flowing). The central, northern and eastern portion is undulating with the upland tracts occupied by scrubs, while the low lands occupied by series of tanks formed by embanking the streams along the valley for irrigation purposes. These valleys vary in size with small ponds to large lakes. The southern portion of the land consists of hills that are close together and are surrounded by thick jungles.

III. DATA USED

Temporal remote sensing data of *Landsat 7 ETM+* sensors for the year 2008, 2010 and 2012 with resolution of 30 m were were downloaded from public domain (http://glcf.umiacs.umd.edu/data). Ground control points to register and geo-correct remote sensing data were collected using hand held pre-calibrated GPS (Global Positioning System), Survey of India topo-sheet (1:50000 and 1:250000), Google earth (http://earth.google.com) and Bhuvan (http://bhuvan.nrsc.gov.in).

IV. METHOD

The process of urbanisation and sprawl in Bangalore (study area) have been assessed as outlined in Fig. 2, which includes (i) Land use analysis, (ii) Modeling and prediction, (iii) Urban Sprawl Analysis

A. Land use analysis:

The land use analysis was carried out for the 3 temporal data using the Gaussian maximum likelihood classifier. The data were classified under 4 different classes as shown in Table I. Satellite data classification involved (i) Preprocessing (ii) Classification (iii) Accuracy assessment.
Preprocessing: The raw satellite images geo-corrected, followed by radiometric correction and resampled to 30 m resolution to maintain uniformity for multi temporal data comparisons and for modeling.

Table I. 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

Land use classification and accuracy assessment: The method involves i) generation of False Color 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 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, vi) collection of the corresponding attribute data (land use types) for these polygons from the field, iv) Supplementing this information with Google Earth/Bhuvan. Land use classification was done using supervised pattern classifier - Gaussian maximum likelihood algorithm based on various classification decisions using probability and cost functions [40].

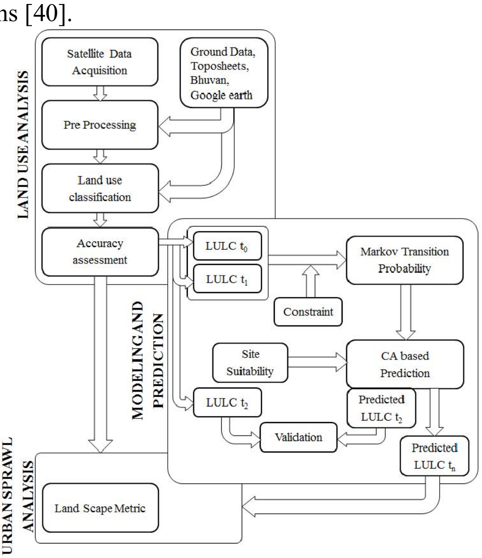

Fig .2. Procedure followed to model, understand the landscape changes

Land uses during the different period were computed using the temporal remote sensing data through open source GIS: GRASS- Geographic Resource Analysis Support System (http://ces.iisc.ernet.in/grass). Four major types of land use classes considered were built-up, vegetation, cultivation area (since major portion is under cultivation), and water body. 60% of the derived signatures (training polygons) were used for classification and the rest for validation. Statistical assessment of classifier performance based on the performance of spectral classification considering reference pixels is done which include computation of kappa (κ) statistics.

Modeling and Prediction: The land use pattern is evolving dynamically and follows 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 and was applied using Markov module. The probability distribution map was developed through Markov process. A first-order Markov model based on probability distribution over next state of the current cell that is assumed to only depend on current state [41]. CA was used to obtain a spatial context and distribution map. CA's transition rules use its current neighborhood of pixels to judge land use type in the future. State of each cell is affected by the states of its neighboring cells in the filter considered. Besides using CA transition rule and 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. CA coupled with Markov chain was then used to predict urban land use state in 2020

Urban sprawl analysis: Post prediction and valdation with spatial metrics were employed to quantify the urban growth pattern. Spatial metrics aid in quantifying the land use pattern at a particular time [1][42]. Spatial metrics such as Number of urban patches (NP), Normalised landscape shape index (NLSI), edge density (ED), Clumpy, Pladj were used in the analysis.These selected metrics signify patch, contagion, edge, shape and adjacency.

V. Results and Discussions

A. Land use: Land use analysis was carried out for the year 2008, 2010, and 2012 using the Gaussian maximum likelihood classifier . Fig. 3 depicts land use and categorywise changes are listed in Table II. This illustrate an increase in urban area by about 2 folds i.e., from 24.86 % (in 2008) to 48.39% (2012) with the decline of vegetation from 38.34% to 26.40% and other category from 36.26% to 26.85% respectively, indicating a rapid urbanisation process.

B. Accuracy Assessment: Accuracy assessment of the classified information of land use was performed by generating the reference image through the traing data (30% of the ground truth data). Overall accuracy and Kappa was calculated using the module r.kappa in GRASS. The results of accuracy assessment are as shown in Table III.

C. Modeling and Prediction

Land use [LU] transitions were calculated to predict land use for the year 2012, using markov chain based on 2008 and 2010 LU and CA loop time of 2 years. With the knowledge of 2008 and 2012, LU for 2020 is predicted. CA filter (Fig.4) was used to generate spatially explicit contiguity weightage factor to change the state of the cell based on neighborhoods. This prediction has been done considering water bodies as constraint and assumed to remain constant over all time frames.

The Multi criterion analysis was used to generate transition probability areas based on transition rules and constraints for 2010 and 2012 LU data. The transition probabilities from Markov and the transition areas from CA were used to predict land use for the year 2012 (Fig. 3). The model was scrutinized for allowable error by validating the predicted versus the actual 2012 land use (Fig. 3). The validation results (Table V) showed a very good agreement between the actual and predicted 2012 LU with kappa of 0.73. On similar lines, LU is simulated for 2020 (Fig.5). The simulated land use (Table V, Fig.5) shows an increase in built up from 48.66 % (2012) to 70.64% (2020). The process of urbanization is observed to be high in the North East direction, near arterial roads and the national/state highways.

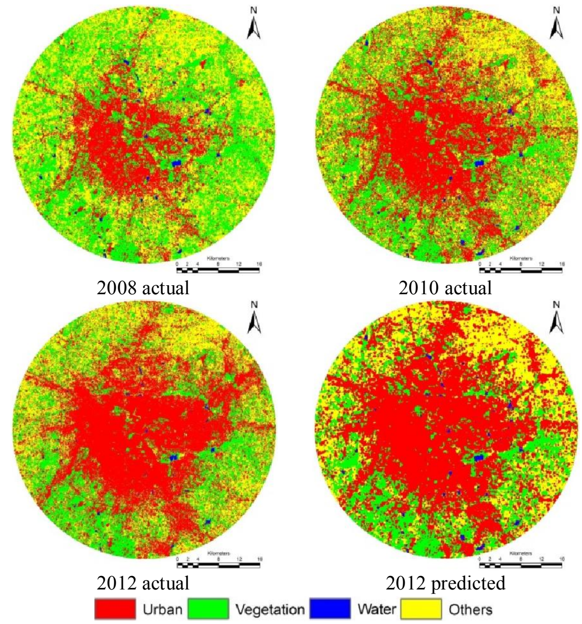

Fig.3. Time series land use maps between 2008 and 2012

TABLE I. Land use statistics

Year	2008	
Land use	Area in hectares	Percent
Urban	49,958.91	24.86
Vegetation	77,042.07	38.34
Water	1069.20	0.53
Others	72,852.48	36.26
Year	**2010**	
Land use	Area in hectares	Percent
Urban	85,012.20	42.30
Vegetation	57,148.47	28.44
Water	1271.43	0.63
Others	57,524.58	28.63
Year	**2012**	
Land use	Area in hectares	Percent
Urban	97,531.11	48.66
Vegetation	49,175.64	24.40
Water	723.60	0.63
Others	54,115.02	26.85
Year	**2012 - Predicted**	
Land use	Area in hectares	Percent
Urban	107,754.48	51.62
Vegetation	44,287.92	23.04
Water	1491.21	0.74
Others	47,423.07	21.60

TABLE II. Accuracy Assessment

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

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Fig.4. Filter designed for analysis

TABLE III. MARKOV TRANSITION PROBABILITIES

	Urban	Vegetation	Water	Other
Urban	0.8	0.0667	0.0667	0.0667
Vegetation	0.2443	0.4697	0.0047	0.2813
Water	0.3372	0	0.6628	0
Other	0.3476	0.2046	0.0018	0.446

TABLE IV. VALIDATION BETWEEN PREDICTED AND ACTUAL 2012

Kno	0.8443
Klocation	0.8678
Kstandard	0.8557

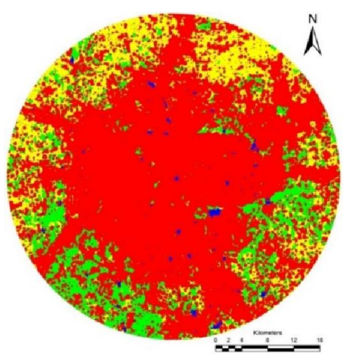

Fig.5. Predicted land use map for 2020

TABLE V. LAND USE 2020

Year	2020 - Predicted	
Land use	Area in hectares	Percent
Urban	142,381.08	70.64
Vegetation	27,316.44	13.55
Water	1491.21	0.74
Others	30,356.64	15.07

D. Urbanisation pattern analysis through spatial metrics:

Number of urban patches that gives us degree of fragmentation was calculated for the urban class. The results of the analysis showed the landscape was highly fragmented with 16000 patches in 2012 and by 2020 gets clumped to form an aggregated core connected (along highways) and some clumped developments at outskirts. This signifies the formation of an urban core (Fig. 6) with loss of all other land use (except water) and fragmented urban patches.

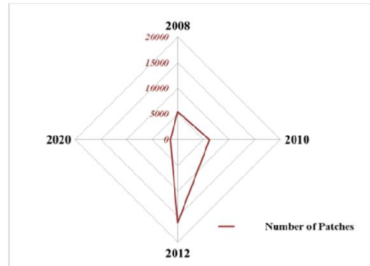

Fig. 6. Number of urban patches

Edge density and Percentage land adjacencies (Pladj) (Fig. 7) were also calculated. Edge is formed when the urban landscape in covered by other land uses. Edge density are significantly higher in 2012 due to fragmented urban landscape and in 2020, the edge density declines to 15 signifying the formation of homogenous urban landscape. Pladj metric accounts to percentage of adjacent landforms of same land use. This also implies that in 2020 the urban class becomes most adjacent dominating class with the loss of other classes.

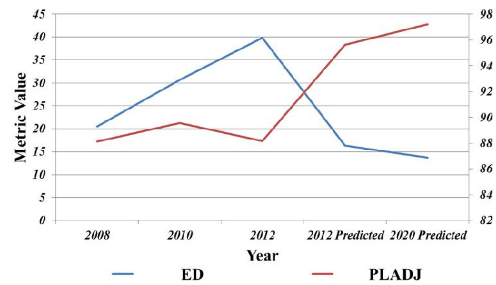

Fig. 7. Edge density and percentage of land adjacencies

Finally NLSI (Normalised landscape shape index) and clumpiness indices were calculated to understand the shape of the landscape and its form. NLSI shows increased value indicating a simple shape or clumped growth. While, in 2008 the lower value indicating convoluted shape, indicating heterogeneous or fragmented landscape with the presence of all land uses next to urban.

Clumpiness index show of clumped growth with the domination of urban land use in 2020, whereas in 2012 the region is with significantly higher proportion of other contributing land uses. Spatial metrics conform of clumped urban growth in Bangalore by 2020 with the loss of all other LU's indicating an urban paved jungle. This necessitates integrated approaches in land use planning to minimize the damage on local ecology and hydrology due to decline of LU other than urban category. The visualized outcome for 2020 indicates the certain doomsday for the Bangalore city with the current lopsided approaches in urban planning. This will lead to further changes in the regional climate; enhance pollutants in air and water, increase of temperature, consequent thriving of disease vectors and loss of vital natural resources.

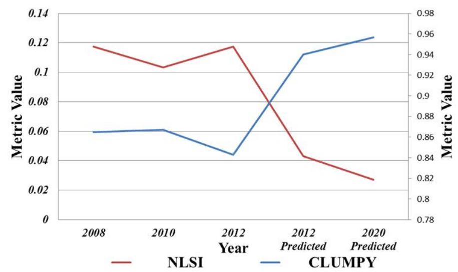

Fig. 8. Normalised Landscape Shape index and Clumpiness index

VI. Conclusion

Bangalore is in the forefront among rapidly urbanizing cities in India. The uncontrolled growth has led to the decline of landscape heterogeneity affecting the natural resources as well as local ecology. Visualization of the patterns of urbanisation provides insights required for an effective regional planning to ensure sustainability. The current work in this regard, through Markov based CA modeling predicts the urbanisation patterns in 2012 and compares with the actual growth. As there was a good agreement between the actual and predicted 2012, exercise was extended to predict LU in 2020.

This research demonstrate the applicability of urban growth modeling using Markov chain and CA. Visualization of likely changes (based on the current pattern of urbanisation) will provide crucial insights necessary to develop and plan for sustainable Bangalore. In this context, the prediction of homogenous landscape with clumped urban growth by 2020, and the disappearance of ecologically important landscape elements – vegetation, open spaces and water bodies. This necessitates integrated approaches in land use planning to minimize the damage on local ecology and hydrology due to decline of LU other than urban category. The visualized outcome for 2020 highlights the implications of the current lopsided approaches in urban planning. This will lead to further changes in the regional climate; enhance pollutants in air and water, increase of temperature, consequent thriving of disease vectors and loss of vital natural resources. However, the city development plans and policy documents still emphasize the continuation of the current approaches of urban expansion during the next decade. This would only lead to the concrete jungle with polluted environment and scarcity of lifeline (water and clean air) of the city.

Predicted scenario of 2020 reveals that apart from distinct developments driving urbanization in main urban road corridors, there will be spurt in the built-up area in northeast and northwest of Bangalore. This can be attributed to small towns gaining importance industrially and residentially due to Kempegowda international airport in the region. This research shows that new urban nuclei will emerge in the next two decades and will be significantly clustered in space, while the outer buffer region will be more fragmented. This endeavor provide invaluable inputs for sustainable city planning. Nevertheless the exercise is fruitful only when bureaucracy - policy makers, urban planners and city managers take note of the implications of poor planning. Further research in progress in this domain focusses on integration of various agents and evaluation of proposed development plans and likely scenario of integrating land use with mobility.

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References

[1] T.V. Ramachandra, Bharath H. Aithal and D.S. Durgappa, "Insights to urban dynamics through landscape spatial pattern analysis", International Journal of Applied Earth Observation and Geoinformation, vol.18, p. 329-343, 2012.

[2] H. Wang, S. He, X. Liu, L. Dai, P. Pan, S. Hong, W. Zhang, "Simulating urban expansion using a cloud-basied cellular model: A case study of Jiangxia, China", Landscape and Urban Planning, vol.110, p. 99-112, 2013.

[3] H. Wang, S. He, X. Liu, L. Dai, P. Pan, and W. Zhang, "Simulating urban expansion using a cloud-based cellular automoat model: A case study of Juangxia,Wuhu,China", Landscape and Urban Planning , vol.110, p. 99 – 112, 2013

[4] J. Mahesh Kumar , P.K. Garg, and K. Deepak, "Monitoring and modelling of urban sprawl using remote sensing and GIS techniques" International Journal of Applied Earth Observation and Geoinformation, vol.10, p. 26-43, 2008

[5] J.A. Foley, R. DeFries, G.P. Asner, C. Barford, G. Bonan, S.R. Carpenter, F.S. Chapin III, M.T. Coe, G.C. Daily, H.K. Gibbs, J.H. Helkowski, T. Holloway, E.A. Howard, C.J. Kucharik, C. Monfreda, J.A. Patz, C. PrenticenI, N. Ramankutty and P.K. Snyder, "Global consequences of land use", Science, vol.309, p. 570–574, 2005.

[6] N.B. Grimm, S.H. Faeth, N.E.Golubiewski, C.L.Redman, J.G. Wu, X.M. Bai and J.M. Briggs, "Global change and the ecology of cities", Science, vol.319, pp 756–760, 2008.

[7] Qihao Weng., 2001. “Modeling urban growth effects on surface runoff with the integration of remote sensing and GIS”. Environment. Management, vol.28 (6), p. 737–748

[8] P.A. Jean, “Urban sprawl modeling: A methodological approach”, 12th European Colloquium on Quantitative and Theoretical Geography. St-Valery-en-Caux, France, September 7-11, 2001.

[9] S.K. Pathan, J.G. Patel, R.J. Bhanderi Ajai, Kulshrestha, V.P. Goyal, D.L. Banarjee, S. Marthe, V.K. Nagar, and V. Katare, “Urban planning with specific reference to master plan of lndore city using RS and GIS techniques”. Proc. of GSDI-7 International Conference on Spatial Data Infrastructure for Sustainable Development, held at Bangalore from Feb, 2-6, 2004.

[10] V. Nath; and S.K. Aggarwa, “Urbanisation, Urban Development, and Metropolitan Cities in India”. Concept Publishing Company. pp. 3, 2007

[11] K.M. Lata, C.H.S. Rao, V.K. Prasad, K.V.S. Badarianth, and V. Raghavasamy, “Measuring Urban sprawl: A case study of Hyderabad”. gis@development, vol. 5(12), p. 26-29, 2001

[12] H.S. Sudhira, T.V. Ramachandra and K.S Jagadish, 2004, “Urban sprawl: metrics, dynamics and modelling using GIS”. International Journal of Applied Earth Observation and Geoinformation, vol. 5, p. 29-30.

[13] A. Yeh, X. Li, “Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. Photogrammetric engineering & remote sensing”, vol. 67 (1), p. 83-87, 2001

[14] F. Fan, Y. Wang and Z. Wang, “Temporal and spatial change detecting (1998–2003) and predicting of land use and land cover in Core corridor of Pearl River Delta (China) by using TM and ETM+ images”, Environ Monit Assess, vol. 137, p.127–147, 2008.

[15] T.V. Ramachandra, and H.A. Bharath, “Spatio-Temporal Pattern of Landscape Dynamics in Shimoga, Tier II City, Karnataka State, India” International Journal of Emerging Technology and Advanced Engineering, vol.2(9) ,p. 563-576, 2012.

[16] T.V. Ramachandra, H.A. Bharath and S. Sreekantha, “Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis”, International Journal of Advanced Research in Artificial Intelligence,vol.1(1), p. 48 – 57, 2012

[17] M.T. Lillesand, W.R. Kiefer, and W.J. Chipman, “Remote Sensing and Image Interpretation”, 5th ed. John Wiley and Sons. 2004

[18] E. Jeanne, P. Karen, and K. Elizabeth, “Techniques for mapping suburban sprawl”. Photogrammetric engineering & remote sensing, vol. 63 (9), p.913–918, 2002

[19] M. Pinki Mondal and S. Jane, “Evaluation of conservation interventions using a cellular automata-Markov model” Forest Ecology and Management, vol.260, p. 1716–1725, 2010

[20] C. Xu, Y.S. Xiao and Z.A. Ping, “Evaluation of Spatiotemporal Dynamics of Simulated Land Use/Cover in China Using a Probabilistic Cellular Automata-Markov Model”, Pedosphere, vol.23(2), p. 243–255, 2013.

[21] P. Sushant, Y. Fei , “ Assessing landscape changes and dynamics using patch analysis and GIS Modelling” ,International Journal of Applied Earth Observation and Geoinformation, vol.16, p. 66-76, 2012.

[22] R.G. Pontius Jr., D.C. Joseph, A.S. Charles Hall, “Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica” Agriculture, Ecosystems and Environment, vol. 85, p. 191–203, 2001.

[23] F. Oñate-Valdivieso, Joaquín Bosque Sendra, “Application of GIS and remote sensing techniques in generation of land use scenarios for hydrological modeling”, Journal of Hydrology, vol.395, p. 256–263, 2010

[24] D. Stevens, S. Dragicevic, and K. Rothley, 2007, “iCity: A GIS-CA modelling tool for urban planning and decision making”, Environmental Modeling and Software, vol.22, p. 761-773, 2007

[25] C.King, N.Baghdadi, and V. Lecomte, O. Cerdan, 2005, “The application of Remote Sensing data to monitoring and modelling soil erosion”, CATENA, vol.62, p. 79-93, 2005.

[26] H. Wang, S. He, X. Liu, L. Dai, P. Pan, S. Hong, W. Zhang, “Simulating urban expansion using a cloud-basied cellular model: A case study of Jiangxia, China”, Landscape and Urban Planning, vol.110, p. 99-112, 2013.

[27] L. Apostolos, “Urban sprawl simulation linking macro-scale process to micro-dynamics through cellular automata, an application in Thessaloniki, Greece”, Applied Geography, vol.34, p. 146-160, 2012

[28] D. Guan, H. Li, T.Inohae, W. Su, T. Nagaie, and Kazunori, “Modeling urban land use change by the integration of cellular automaton and Markov chain”, ecological Modelling, vol.222, p. 3761 – 3722, 2011.

[29] J.A. Jokar, M. Helbich, W. Kainz, and B.A. Darvishi, “ Integration of Logistic Regression and Markov Chain Models to Simulate Urban Expansion”, International Journal of Applied Earth Observation and Geoinformation, vol.21, p. 265-275,2013

[30] M. Herold, H. Couclelis, K.C. Clarke, “The role of spatial metrics in the analysis and modeling of urban land use change,” Computers, Environment and Urban Systems, Vol. 29, pp.369–399, 2005.

[31] JI. Wei, Jia Mia, R. W. Twibell, K. Underhill, “Characterizing Urban Sprawl using Multi Stage Remote Sensing Images and Landscape Metrics,” Computers, Environment and Urban Systems, Vol.30, pp 861 – 879, 2004.

[32] McGarigal K, Marks BJ (1995) “FRAGSTATS: spatial pattern analysis program for quantifying landscape structure”. USDA Forest Service General Technical Report PNW-351 http://www.fs.fed.us/pnw/pubs/gtr_351.pdf

[33] Ye.B and Bai.Z, “Simulating Land Use/Cover Changes of Nenjiang County Based on CA-Markov Model”, Computer and Computing Technologies In Agriculture, vol. 1, p. 321 – 329, 2008

[34] Census India, http://censusindia.gov.in/, accessed on 1 August 2013

[35] Bangalore urban district at a glance, Jilla Statistics Department Bangalore Urban, 2011-2012

[36] http://www.bbmp.gov.in/.

[37] http://www.imd.gov.in

[38] Bangalore District Gazetteer, 2012