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Modelling and geo-visulaisation of urban growth

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ABSTRACT
Understanding urban growth pattern and modelling plays an important role in the planning process scenario evaluation and providing better provisions of basic amenities. As a result, many simulation applications and planning tools have been developed and successfully been implemented to simulate the urban developments and patterns in future decades. This paper used CA based models to generate realistic simulation and prediction of informal settlements in the context of unplanned areas such as in city outskirts and buffer zones of Bangalore. Models presented allow for a detailed urban growth simulation and are flexible enough to incorporate changes in development control regulations and settings for spatial interaction. Therefore, it shows that these models can help in visualizing growth for other cities and could help urban planners and decision makers to understand the consequences of their decisions on urban growth and development.

Keywords: *Bangalore, India, Land change modeller, AHP-CA*

INTODUCTION
Rapid urbanization is one of most important factors of loss of biodiversity and most recognized facts in India post 1990 (Shivaramakrishnan et al., 2005; MOUD., India, 2011; Ramachandra et al., 2012; Bharath H. A., 2012; Ramachandra et al., 2014a). The process of preparing visionary documents such as developmental plans are being ineffective considering the fact that spatial patterns and dynamic behaviour of growth is not considered and lack of skills and tools to help in informed decision making (Geertman & Stillwell, 2004;Adhvaryu, 2011; Bharath H.A., et al., 2014; Ramachandra et al., 2014b; Ramachandra et al., 2014d). The dynamically increasing urban growth is driven by the fact of availability of land resources and ageing pattern (Batty et al., 1999). Nivola (1999) clearly mentions that urban growth is possible in all directions so as to say “in, up, down and out” which suggests that the main objective of urban growth model is to make absolute decision and informed decisions and should be flexible to identify the specific pockets of development (Ramachandra et al., 2014c).

Many studies suggested that traditional large-scale urban simulation approaches existing in early 90’s were based on theories, and suffered from significant weaknesses such as poor handling of space-time dynamics and too much generalisation of data. This was further significantly reduced with introduction of spatial models as they consider a space and its attributes within a discrete time frame. The integration of space, time, and attributes in modeling was further enhanced with introduction Cellular automata (CA) models (Allen 1997; Batty 1998; EPA 2000; Alberti and Waddell 2000).

CA modeling is capable of addressing the spatial complexity with discrete time change. A number of CA-based models of urban growth have produced satisfactory simulations of spatial urban expansion over time (Clarke et al., 1997; Leao et al. 2004; Bharath and Ramachandra, 2013; Ramachandra et al., 2013; Arsanjani et al., 2013)

The main advantages of CA are in their simplicity, easy integration with raster GIS, and adaptability to various urban growth situations. CA models can realistically generate and represent complex patterns through the use of simple rules and considering its neighbouring properties since these models operate on basis of cell states, size, neighbourhood and transition rules (White and Engelen 2000).

Models such as Land use change modeller (Bharath H.A. et al., 2013) and Fuzzy AHP based CA (Bharath H.A et al., 2014) models were developed in this context. This paper documents the process of applying the both of these models to the local characteristics of the greater Bangalore and its buffer region of 10km.

STUDY AREA

Greater Bangalore located at 12°49'N to 13°8'N and 77°27'E to 77°47'E, is the commercial and industrial nucleus and now is undergoing rapid urbanization due to industrialization and infrastructural activities, was considered for Modelling (Fig. 1), Bangalore has grown spatially from 69 sq.km (in early 1950's) to 741sq.km (2006) (Fig. 2) with decadal increase of population by 43.76% during 2001 and 2011 *Figure 3) and currently in the verge of becoming one of the megacity of India. The study region includes ten km buffer from the administrative boundary was considered with a gross area of over 2250 km^2 to account for developments in the peri-urban regions.

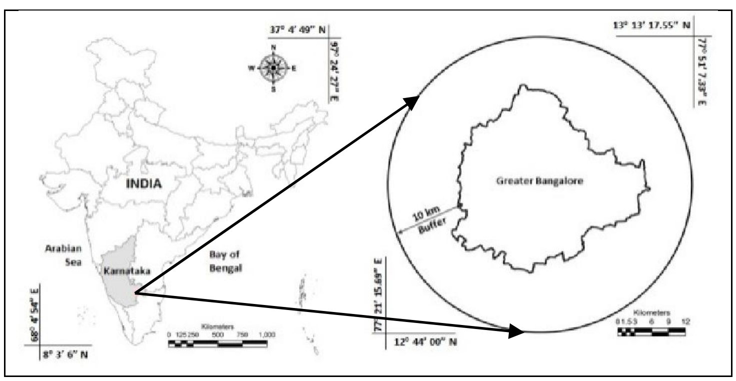
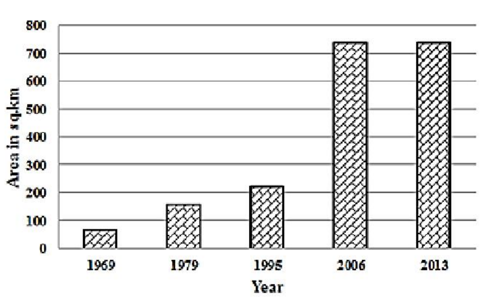
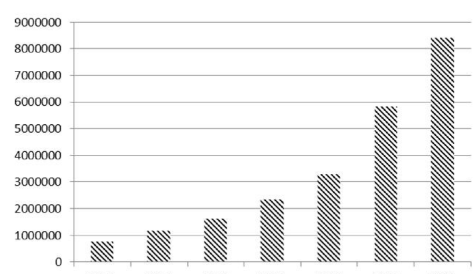


Figure 1: Study area: Bangalore



Source: Vagale and Uday 2004, Gazetteer

Figure 2: Spatial Growth of Bangalore City



Source: Census India, District at a Glance

Figure 3: Population growth in Bangalore city

DATA AND METHOD

Temporal remote sensing data (2008, 2010, 2012) of Landsat TM and ETM+ downloaded from GLCF were used to analyse and model LULC changes. Slope map is generated using ASTER DEM (30 m). Remote sensing data were supplemented with the Survey of India toposheets of 1:50000 and 1:250000 scale, 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. GCPs were useful in geometric correction of remote sensing data. Census data (1991, 2001 and 2011) was used to capture population dynamics.

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

Land use analysis was carried out using supervised pattern classifier - Gaussian maximum likelihood algorithm based on probability and cost functions (Duda et al., 2000). The method involves a) generation of false color 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 covering major part of the study area and uniformly distributed over the entire study area, c) loading these training polygons coordinates into pre-calibrated GPS, d) collection of the corresponding attribute data (land use types) for these polygons from the field using GPS. e) Supplementing this information with Google Earth f) 60% of the well-distributed training data has been used for classification of the data, while the balance is used for validation or accuracy assessment. Supervised classification is performed into four classes as in (Ramachandra et al., 2012). Post classification the accuracy assessment is done through error matrix, kappa (κ) statistics, to assess the classification accuracies.

MODELLING LAND USE SCENARIO USING LCM: 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. 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.

MODELLING USING FUZZY AHP-CA

Using the combination of Fuzzy Logic, Analytical Hierarchical Process (AHP), Multi Criteria Evaluation (MCE), Markov chains and Cellular Automata (CA). Agents of urbanisation such as roads, industries, educational institutions, bus stands, railway stations, metro, population, etc. were normalized. Conservation regions as per city development plan (CDP) water bodies were considered as constraints. The fuzzy based analysis is used to normalize the contributing factors between 0 and 255, where 255 showing the maximum probability of change and 0 indicating no change, for different land uses. The normalized agents were taken as input to AHP to determine the weights of driving factors using pair wise comparisons i^{th} weights as Eigen vectors. The weights analysed and calibrated through AHP is verified using measured consistency ratio (CR). CR below 0.1, the model is consistent and used for subsequent processes.

These weights along with the factors of growth are combined along with the constraints to obtain site suitability maps for different land uses using equation 1

$$LC = \frac{1}{n} * \sum_{i=1}^{n} D_i * W_i \qquad \ldots\ldots 1$$

Where LC is the linear combination of weights, n is the number of factors, D decision factor, W is the weight of the factor.

The Markov chains are used to determine the change probability between two historical datasets to derive the growth in the future scenarios based on different criteria's. The Markovian transition matrix indicates the probability of the particular land use being converted to other land uses on single time step. The cellular automata 1 process based on the site suitability and the transition matrix is used to spatially predict the changes in land use based on current land use at every single time step, based on the neighbouring pixels. Two scenarios were designed to predict the land use changes as shown in table 1.

Validation of the simulated datasets of 2012 with classified data of 2012 through kappa indices, as a measure of agreement. The available classified data were used to model and simulate for the year 2012, based on the accuracy and agreement, the combination 2008 and 2012 data with time step of 4 years were found to provide higher accuracy spatially and were further used to predict for the year 2016 and 2020 respectively.

Criteria	Factors and Constraints
Without CDP as a constraint	Slope, Distance from roads, Distance to industries, Distance to Bus stops and Railway stations, Distance from metro, Distance from educational institutions, **Population Density**
With CDP	Slope, Distance from roads, Distance to industries, Distance to Bus stops and Railway stations, Distance from metro, Distance from educational institutions, **City Development Plan, Population Density**

Table 1: Criteria's for simulating and predicting urban sprawl

RESULTS

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. 4 illustrates the increase in urban area and the same is listed in table 2. Overall accuracy and Kappa was calculated using the module r.kappa in GRASS and results shows an accuracy of 85% and 0.9 kappa was obtained on average.

Validation: Predicted land uses of 2010 and 2012 were compared with actual land uses of 2010 and 2012 classified based on remote sensing data with field data. The weights for each scenario was then obtained based on validation per pixel basis so that the developed semantics match the original land use. Validation of predicated land use was done using the actual land uses as reference and accuracy assessment was done with Kappa values which are given in table 5. Results reveal that predicted and actual land uses are in conformity to an extent of 87 to 91%. The prediction exercise is repeated for 2020 keeping 2012 as base year.

MODELLING: USING AHP CA

Influencing agents were prioritized and considered which include slope, proximity to roads, industries, educational institutions, bus, railway and metro stations. Factors such as hospitals, socio-cultural buildings etc. have minimal role in urbanization. All these factors were generalized using Fuzzy analytical process and prioritized using AHP in order to weight the factors based on land use type. The weightages from the AHP and the constraints as Boolean were used to generate transition suitability maps for different land use using MCE.

The transition suitability (of MCE) along with transition probabilities (from Markov) were used to calibrate the parameters and simulate the sprawl for the year 2012 based in Cellular Automata using CA-Markov transitions. Validation of the simulated output was carried out with respect to the classified data for the year 2012. The simulated model for the year 2012 closely agrees with that of the classified land use with kappa of 0.8. The calibrated parameters were further used to derive the land use for the year 2016 and 2020, based on two criteria's i.e., effect of presence or absence of CDP (City Development Plan) policies and also effect of population.

Markov chain based Land Use (LU) transitions probabilities (table 3) were computed to predict land use for the year 2012, based on 2008 and 2010 LU and CA loop time of 2 years. Validation of predicated land use for 2012 with the actual growth showed good agreement (Fig. 6). Then, LU for 2016 and 2020 were predicted, with the knowledge of 2008, 2010 and 2012. This prediction has been done assuming water bodies to remain constant over all time frames, due to recent stringent norms.

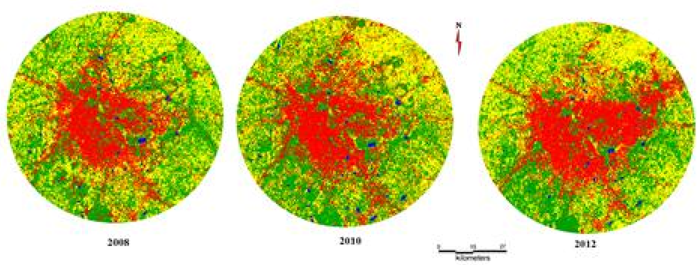


Figure 4: Land use transitions during 2008 to 2012

Class	Built-up Area		Water		Vegetation		Others	
Year	Ha	%	Ha	%	Ha	%	Ha	%
2008	49915.42	24.85	1068.94	0.53	77036.96	38.35	72851.95	36.27
2010	57208.4	28.48	1571.41	0.78	73460.57	36.57	68,656.40	34.17
2012	59103.9	29.33	1169.82	0.58	67883.85	33.68	73385.73	36.41

Table 2: Land use during 2008, 2010 and 2012

MODELLING FOR THE YEAR 2020 USING AHP CA

The simulated results for 2016 and 2020 are given in table 4 and fig. 7 respectively, indicating different scenarios of prediction. The simulation shows a predominant growth along the east and south directions showing the effect of upcoming industrial hubs in these directions. The effect of CDP can be envisioned near Bellandur lake, where in the valley region, land use remains the same as that of 2012, and the process of urbanization intensifies along outskirts and main roads. The process of urbanization in the simulated results is evident along the arterial roads, at the core of the city, the built up density increases in lateral directions to a very large extent almost to the verge of being saturated followed by gradual sprawl along the boundary of the city.

Visualising the urban growth by 2020 using LCM: 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 transition probability matrix and finally growth for 2012 is predicted through CA_Markov. The module was trained until the optimum accuracy was reached with good kappa value. 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. 8 and table 5.

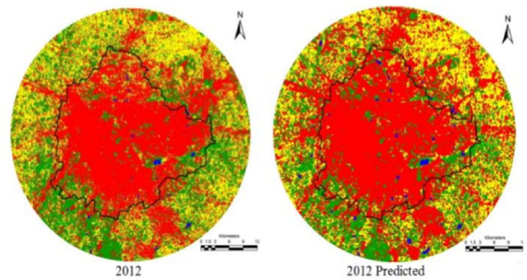


Figure 6: Actual and Predicted Land use 2012

Land use	Urban	Vegetation	Water	Other
Urban	0.88	0.01	0.01	0.08
Vegetation	0.23	0.49	0.00	0.26
Water	0.05	0.00	0.94	0.00
Other	0.38	0.18	0.00	0.58

Table 3: Example of Markov transition probability for 2012 using base layers of 2008 and 2010

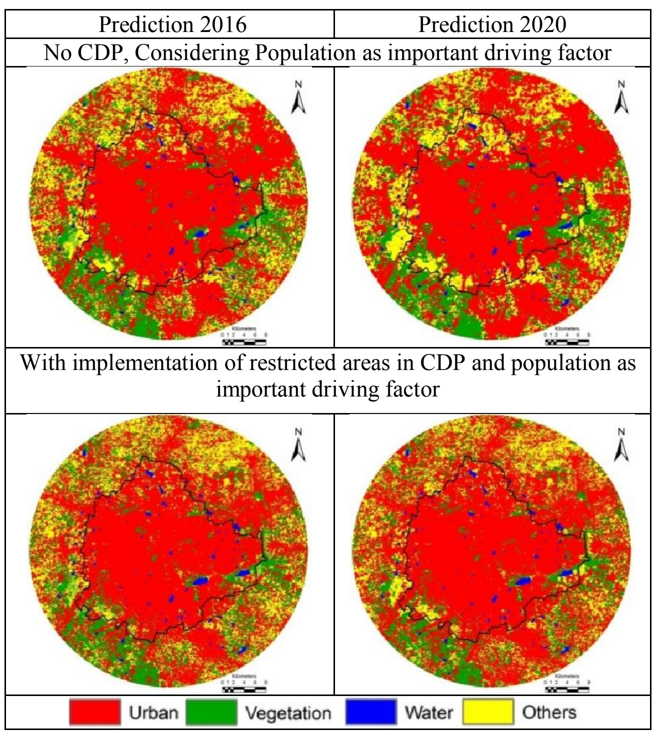


Figure 7: Predicted Land use using AHP

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 indicates 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).

Criteria	Without CDP				With CDP			
Year	2016		2020		2016		2020	
Land use	Area in ha	%	Area ha	Area %	Area ha	Area %	Area ha	Area %
Urban	125599.3	62.15%	129946.8	64.30%	125557.7	62.13%	134044.5	66.24%
Veg	35163.9	17.40%	32109.75	15.89%	35103.42	17.37%	30283.38	14.96%
Water	2453.04	1.21%	2767.41	1.37%	2579.22	1.28%	3188.43	1.58%
Others	38881.26	19.24%	37273.59	18.44%	38857.23	19.23%	34849.35	17.22%

Table 4: LU for the year 2016 and 2020 using fuzzy-AHP CA

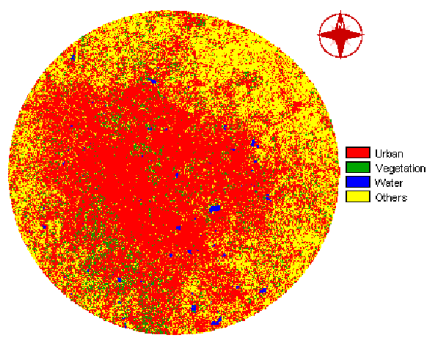


Figure 8: Predicted growth of Bangalore by 2020 using LCM

Year	2020 - Predicted
Land use	%
Urban	61.27
Vegetation	7.00
Water	0.55
Others	31.18

Table 5: Land use statistics of Bangalore for 2020 using LCM.

DISCUSSION

Modelling techniques considered show relatively good accuracy with validation dataset. Comparatively using 4 land use classes Fuzzy AHP CA provides better visual interpretation since it uses agents to derive the growth. 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 indicates 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 in almost all modelling techniques used. The results indicate that the urban area would cover close to 50 to 60 % of the total land use in and surrounding Bangalore. Thus providing insights to relevant information. Further modelling can be improved using nature and bio inspired techniques.

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