Urban Sprawl Modeling using RS and GIS Technique in Kirtipur Municipality

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Keywords

Urban Sprawl; Urban dynamics; Multi-criteria Evaluation; CA-Markov

Abstract

Urban sprawl refers to the urbanization extent, which is mainly caused by population growth and large scale migration and it is a global phenomenon. In developing countries like Nepal, where the population growth and internal migration rate in urban area is high, it has posed serious implication on the resources of the region. Effective and efficient infrastructure planning of an urban environment require information related to the rate of urban growth along with its trend, pattern and extent of urban sprawl. The pattern and extent of urban sprawl is identified and modeled using remotely sensed data along with collateral data. RS and GIS are used to analyze and interpret the urban land use changes. Cellular Automate Markov (CA-Markov) process is used to urban sprawl modeling to identify possible pattern of sprawl and subsequently predict the nature of future sprawl.

1. Introduction

Urbanization refers to process whereby an increasing proportion of country's population comes to live in cities by growth and migration of population transformed from predominantly rural to urban area and closely associated with the level of economic activities, land-use, population distribution and urban facilities (Johnston et al., 2003). The process of urbanization is an universal phenomenon taking place all over the world. In Nepal, unprecedented population growth and internal migration coupled with unplanned developmental activities has resulted in urbanization, which lack infrastructure facilities. This has also posed serious implications on the resources base of the region. The urbanization takes place either in radial direction around a well established city or linearly along the highways. This dispersed development along highways, or surrounding the city and in rural countryside is often referred as sprawl. All developing countries are facing with such phenomenon; due to the increase in population growth, economy, proximity to resources and basic amenities of infrastructure initiatives. The urban sprawl refers to the extent of urbanization and expansion of urban concentrations, it refers more to the pace and magnitude of land conversion to urban use and areal expansion of the city. The extent of urbanization or the sprawl is one such phenomenon that drives the change in land use patterns (Sudhira et al., 2003). Patterns and trends of urban sprawl are identified and modeled using remote sensed data (aerial photographs/ satellite images) along with collateral data. Identification and analyses of the patterns of urban sprawl in advance would help in effective infrastructure planning in urban area. In order to estimate and understand the behavior of such urban sprawls, which is crucial for sound environmental planning and resource management. The study on urban sprawl is attempted in the developed countries (Hurd et al., 2001; Epstein et al., 2002) and recently in developing countries such as China (Yeh and Li, 2001; Masser, 2001); India (Jothimani, 1997; Lata et al., 2001; Sudhira et al., 2003) and Nepal (Thapa & Murayama, 2009;Bhandari, 2010; Rimal, 2011). GIS and RS along with land related technologies are therefore very useful in the formulation and implementation of the land related component of the sustainable regional development strategy, which can be generalized as determination of objectives, resource inventory, analyses of the existing situation, modeling and projection, development of planning options, selection of planning options, plan implementation, and plan evaluation, monitoring and feedback (Yeh and Li, 2001).

The built-up is generally considered as the key feature or parameter for quantifying urban sprawl (Torrens and Alberti, 2000; Barnes et al., 2001; Epstein et al., 2002: Sudhira et al., 2003). The built-up area is determined in the topographical maps/ aerial photographs /satellite images. The integration of GIS, RS and database management systems (DBMS) with geospatial tool are used to analyze and interpret urban sprawl, urban land use land cover (LULC) change and its quantification. The concentration and dispersion of sprawl measurement is computed in GIS environment with consideration of fragmentation, patchiness, porosity, patch density, interspersion and juxtaposition, relative richness, diversity, and dominance of landscape properties. The urban sprawl and its dynamics is the quantification of the change in built-up area by Shannon's entropy index which define the sprawl phenomenon with respect to mathematical relationship. With the development and infrastructure initiatives mostly around the urban centers, the impacts of urban sprawl would be on the resources and ecology. The planning should also focus on a dispersed economic structure for generating balanced ecological, social, and economic system without hampering the resources and disturbing the rural setup. Modeling of the spatial urban dynamics rests mostly with LULC change studies (Lo and Yang, 2002) or urban growth studies. In order to predict the scenarios of land use change, Cellular Automata Markov (CA-Markov) process is used. These processes identify the possible pattern of sprawl and subsequently predict the nature of future sprawl with the availability of historic spatio-temporal data, which is cost effectively and efficiently.

CA-Markov process is a combined cellular automata and Markov Chain prediction procedure that adds element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to Markov change analysis. These two are termed as the geo-simulation techniques used to produce land use predictions (Sun et al. 2007). However, a CA procedure very specify to the context of predictive land cover change modeling. CA-Markov takes land cover map from which changes should be projected as input; the transition area file produced by Markov from analysis of that image and an earlier one and a collection of suitability images which is produced from multi-criteria evaluation (MCE) in GIS that express the suitability of a pixel for each class of the land cover type under consideration. Then, it begins an iterative process of reallocating land cover until it meets the area total predicted by the Markov process (Eastman, 2009).The logic of CA-Markov is that; the total number of iterations is based on the number of time steps set by the user. Within each iteration process, every land cover class will typically lose some of its land to one or more of the other classes. CA component arises from the iterative process of land allocation that filtering stage with each iteration process in part from a stage reduces the suitability of land away from the existing area of that type. By filtering, a Boolean mask of the class being considered the mean contiguity filter yields a value of 1 when it is entirely within the existing class and 0 when it is entirely outside of it. However, when it crosses the boundary, it will yield values that quickly transition from 1 to 0. This result is multiplied by the images for that class, thereby progressively down weighting the suitability maps of different land use classes as one move away from exiting instances of that class. CA-Markov can simulate land use land cover change among several categories (Li & Reynolds, 1997; Wu & Webster, 1998; Pontius & Malanson, 2005).

2. Study Area & Data used

Study Area

Kirtipur municipality was chosen for the study where urban growth has high rate and urban sprawl has prevalent. There is need of a comprehensive city plan for the establishment systematic dreamland town planning policy. The location of study area is shown in Figure1.

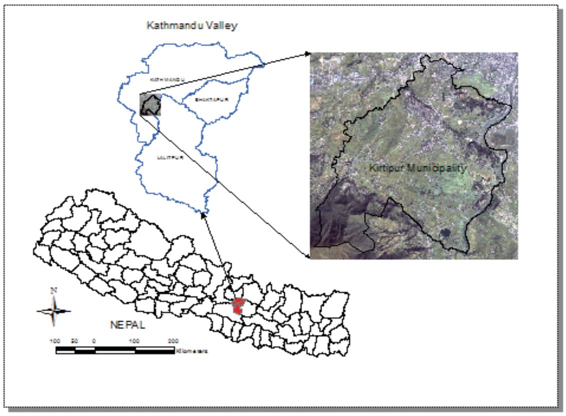


Figure1: Study Area

Its loction is 27º 38’ 37" to 27º41’ 36" N and 85º 14’ 64" to 85º 18’ 00" E with it extent and at present has 19 wards and covers 17.87 sq. km. It is bordered by the Bagmati river with Lalitpur Submetropolitian City to the east, Machhengaun Village Development Committee (VDC) to the west, Kathmandu metropolitan city (KMC) to the north, and Chalnakhel VDC to the south. The town was built initially within a wall surrounded strategically by dense vegetation and then open ground as outer rings.

Data used

The following datasets were used in the study; these are listed below in Table 1.

Table1: Description of Data used

Data Type	Year	Scale / Resolution	Source
Remotely Sensed Data:			
Aerial Photographs	1998	1:5000	DOS
IKONOS	2006	4m	NLUP
GeoEye -1	2012	2m	UBMP
Base Map:			
Topo map	1996	1:25000	DOS
Urban map	1998	1:2000	DOHUD
Ancillary Vector Layers/Data:			
Geology	2007	1:30000	NLUP
Hazard	2007	1:30000	NLUP
Geomorphology	2007	1:10000	NLUP
Land Capability	2007	1:10000	NLUP
Population Data	2011		CBS
Field Data:			
Ground Control Point (GCP)	2012		Field Works
Ground Truth	2012		Field Works

3 Methodology

The availability of high resolution aerial/satellite data made it feasible to monitor and evaluate urban environment consistently at desirable spatial and temporal scales. In this study, digital elevation model (DEM) was generated with contours having 2m contour interval of urban base map. The orthophoto for year 1998 was generated with stereo aerial photographs of scale 1:15000 and DEM along with 36 GCPs collected with DGPS technique. The orthoimages for year 2006 and 2012 were generately satellite images IKONOS and Geoeye1 respectively with RCP file provided by vendors, GCPs and DEM. The land use maps for year 1998 was prepared from orthophoto and for years 2006 and 2012 were prepared from MSS IKONOS and Geoeye1 satellite images respectively with Artificial Neural Network (ANN) supervised classification technique. The road network layers of year 2006 and 2012 were extracted by manual digitization process from orthoimages.

Geospatial tools in GIS were used to quantify LULC changes from classified remote sensing data in space and time to show the spatial pattern and composition of LULC representation as a dynamic phenomenon. The transition matrix and transition maps were generated. Urban sprawl was measured with Shanon entropy index which is computed by (Wilson et al., 2003):

$$E_n = \frac{\sum_i^n p_i \log\left(\frac{1}{p_i}\right)}{\log(n)}$$

Where, pi is the density of land development, which equals the amount of built-up land divided by the total amount of land in the ith of n total zones. The difference in entropy between two different periods of time can also be used to indicate the change in the degree of dispersal of land development or urban sprawl which is computed by (Yeh and Li 2001):

$$\Delta E_n = E_n(t+1) - E_n(t)$$

Where, ΔEn is the difference of the relative entropy values between two time periods, En(t+1) is the relative entropy value at time period t+1, En(t) is the relative entropy value at time period t.

The suitability maps of each land use class were generated using MCE along with analytical hierarchy process (AHP), these suitability maps were standardized with fuzzy set to membership functions type (sigmoid, J-shape and Linear) and membership function shape (monotonically increase, decrease or symmetric).Spatial modeling of sprawl for year 2012 was predicted with LULC maps of 1998 and 2006 using CA-Markov process and validate with reference LULC map 2012. As the validation results has sufficient reliable limit of kappa index of agreement (KIA), LULC maps for year 2020 and 2030 were predicted.

4 Results and Analysis

The land use map for year 1998 was prepared from orthophoto by manual digitization based on photo interpretation elements such as tone, shape, size, texture, pattern, shadow, association, site etc. The land use maps for year 2006 and 2012 were prepared from MSS IKONOS and Geoeye1 respectively by artificial neural network (ANN) supervised classification technique with additional information such as PCAs, NDVI, and NDWI. The overall accuracies for 2006 and 2012 are found 88.67% and 87.67% respectively and KIA (kappa statistics) for 2006 and 2012 are found 0.8449 and 0.8337 respectively. . The land use maps of year 1998, 2006 and 2012 are shown in Figure 2.

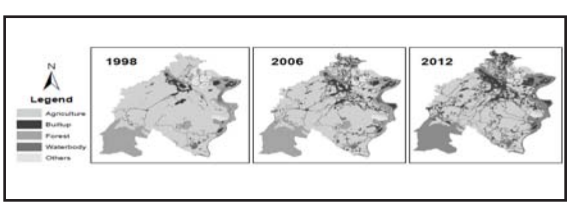
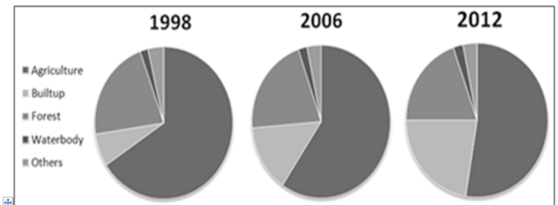


Figure2: Land Use Maps

The post-classification change detection was done and quantified in hectares by individual class, visualized with pie charts with classified images for the three study periods 1998, 2006 and 2012. The quantification of land use maps of year 1998, 2006 and 2012 were represented in pie chart which is shown in Figure 3.



Land use Category	Area in Hectares		
	1998	2006	2012
Agriculture	995.5027	911.7876	806.4543
Built-up	119.0138	218.5567	344.476
Forest	334.4377	321.7198	300.1835
Waterbody	28.4547	31.0728	33.9782
Others	56.7107	50.9824	49.0273

Figure3: Quantification of Land use Maps

The comparison of land use/cover change (LUCC) was also done with statistically with the computation of LUCC in hectares and in percentage of individual class area between two LULC maps of year 1998 versus year 2006, year 2006 versus year 2012 and year 1998 versus year 2012. The change in LULC between 1998-2006, 2006-2012 and 1998-2012 is presented in Table 2.

Table 2: Comparison of LULC change

	Area Change in Hectares			Area Change in Percentage		
Land use Category	1998-2006	2006-2012	1998-2012	1998-2006	2006-2012	1998-2012
Agriculture	-83.7	-105.3	-189.0	-8.41	-11.55	-18.99
Built-up	99.5	125.9	225.5	83.64	57.61	189.44
Forest	-12.7	-21.5	-34.3	-3.8	-6.69	-10.24
Waterbody	2.6	2.9	5.5	9.2	9.35	19.41
Others	-5.7	-1.9	-7.6	-10.1	-3.83	-13.55

Change detection was also analyzed with the map transition option in the LCM of Idrisi Tiaga. The transition map of LULC from 1998 to 2006 and from 2006 to 2012 into all classes to built-up class was prepared and presented in Figure 4.

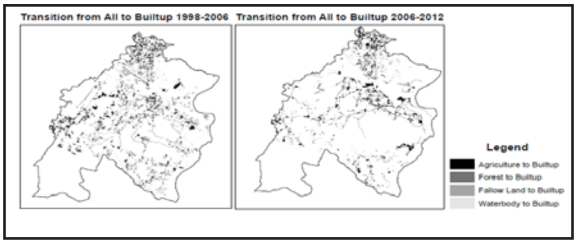


Figure 4: Transition Map

A temporal database can be visualized as a sequence of maps with each time period and changes in LULC shows in dynamic pattern. The temporal dynamics revealing patterns and trends were not possible to distinguish in tabular data. So, spatial expansion (growth) of the built-up areas was represented in maps during the study periods which are shown in Figure 5.

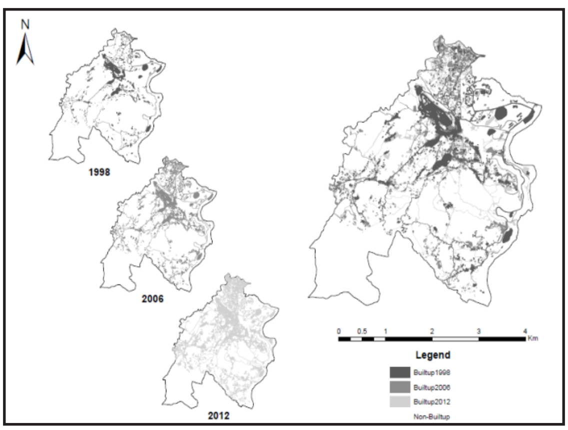


Figure 5: Growth in Built-up Areas

In this study, concentration and dispersion of sprawl computation, circular ring were generated around the city centre with 500 m interval. The number of zones refers the number of buffers around the city centre. Since entropy can be used to measure the distribution of a geographical phenomenon where as the difference in entropy has indicated the temporal change in the degree of dispersal of land development or urban sprawl. The Shannon entropy of urban sprawl in 1998, 2006 and 2012 was computed; similarly difference in entropy between 1998- 2006, 2006- 2012 and 1998-2012 was also computed for determining the trend of sprawl growth. The Shannon entropy and difference in entropy are presented in Table 3.

Table 3: Shannon's entropy and its difference

E_n(Entropy during the 3 Study Period)			ΔEn (Difference in Entropy)		
1998	2006	2012	1998-2006	2006-2012	1998-2012
0.14	0.22	0.31	0.08	0.09	0.17

Urban Sprawl Modeling with Markov Chain was produced the transition probability matrix from the two period images and on the basic of this transition matrix a set of condition probability images for each LULC classes has generated by analyzing with two qualitative LULC maps The Markov transition probability matrix of changing among LULC from 1998 to 2006 with conditional probability error 10 %; is presented in Table 4.

Table 4: Transitional Probability Matrix

	Forest	Water body	Agriculture	Built-up	Others
Forest	0.8568	0.0125	0.0498	0.0769	0.0041
Water body	0.0000	0.8969	0.0662	0.0370	0.0000
Agriculture	0.0118	0.0005	0.8365	0.1511	0.0001
Built-up	0.0129	0.0095	0.0862	0.8901	0.0013
Others	0.0000	0.0000	0.0120	0.1648	0.8231

The suitability map of LULC classes built-up, agriculture and forest for transition rule selection were prepared from MCE-AHP process and for water body and others were generated with distance function considering so that near the existing LULC classes, there are more chance of changing into this class. The weight used in the MCE was computed from the pair wise comparison in the AHP process. In AHP process, each criterion of factor or constraint maps was evaluated with pair wise comparison in decision support system tool in Idrisi Tiaga software. The suitability maps determine that pixels will change as per the highest suitability of each LULC type. The higher the suitability of a pixel, the possibility of the neighboring pixels to change into that particular class is higher. The suitability maps of each LULC were standardized with the fuzzy factor standardization. Therefore a simple linear distance decay function is appropriate for this basic assumption. It serves the basic idea of contiguity. The LULC maps have been standardized to the same continuous suitability scale (0–255) using fuzzy set membership analysis process. The basic assumption for preparing suitability images is the pixel closer to an existing LULC type has the higher suitability. It means a pixel that is completely within vegetation has the highest suitability value

(255) and pixels far from existing vegetation pixels will have less suitability values. The farthest pixels from vegetation will show the lowest suitability values. The standardized suitability LULC images of agriculture, built-up and forest classes with fuzzy function are presented in the Figure 6.

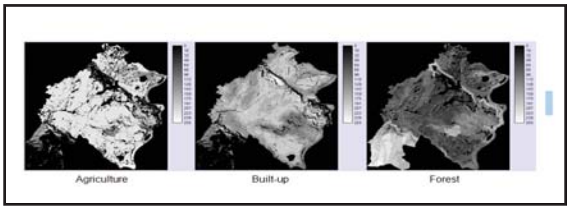


Figure 6: Standardized Suitability Map

The prediction of LULC in 2012 was done using CA-Markov with reference to LULC map of year 2006, Markov transition probability area matrix, standardized group suitability maps and 5x5 contiguity filters. The projected LULC map for year 2012 is shown in Figure 7.

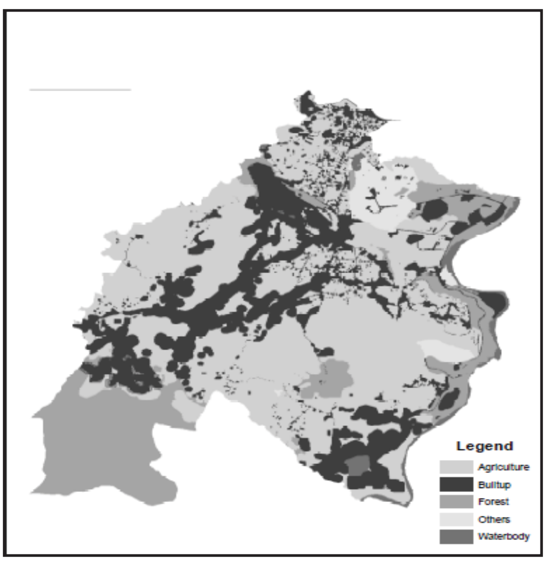


Figure 7: Projected LULC Map 2012

The validation process has been done by comparing simulation of predicted LULC map 2012 with reference to actual LULC map of 2012 based on KIA. Kappa Index gives: Kno, Klocation and Kquantity in order to compare the predicted with the actual land use map. The result of validation shows that Kno, *Klocation and Kquantity* are 0.8815, 0.8673 and 0.8582 respectively.

The future urban sprawl for short period of 2020 is shown in Figure 8.

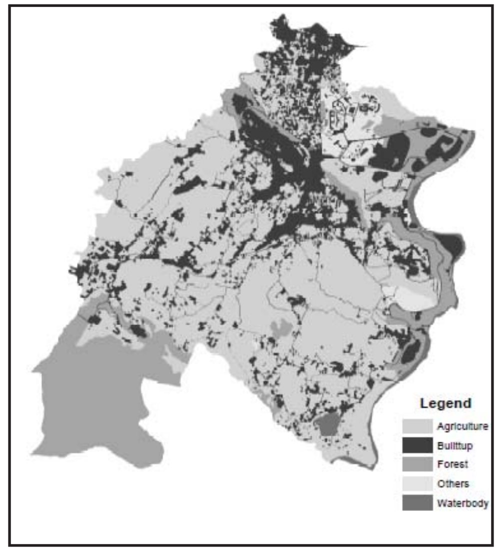


Figure 8: Projected LULC Map 2020

The future urban sprawl for long period of 2030 is shown in Figure 9.

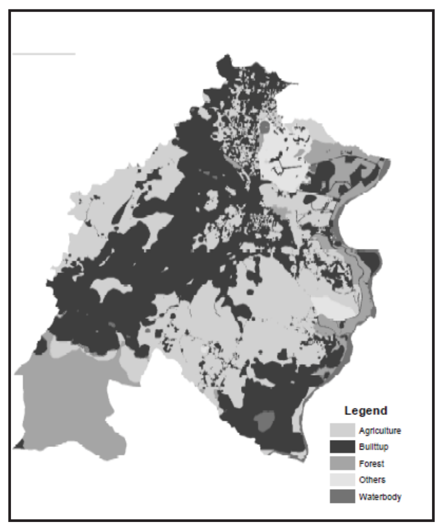


Figure 9: Projected LULC Map 2030

5) Conclusion

The urban sprawl trend shows that urban growth has rapidly increased in North West direction which is mainly influenced from Kathmandu metropolitan city. The entropy value indicates that the degree of spatial concentration and dispersion has high rate and continuously increasing in the study area. Landscape predictions for year 2020 and 2030 are predicted for future developable urban area based on land use policies and environmental factors. The situation assessment of urban growth analysis and simulation of urban sprawl modeling are important information for land managers, urban planners, policy makers, conservation agencies and other stakeholders to play a part in policy formulation for the betterment and conservation consent of sustainable urban development.

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