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Research Article

Geospatial Analysis of Land use Land Cover Change Predictive Modeling at Phewa Lake Watershed of Nepal

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Abstract

Improper practices of land use/ land cover (LULC) are deteriorating watershed conditions. Remote sensing and GIS tools were used to study LULC dynamics using Cellular Automata (CA)–Markov and GEOMOD model and predict the future LULC scenario for years 2015 and 2020, in terms of magnitude and direction, based on past trend in Phewa Lake watershed, Kaski district, Nepal. The analysis of LULC pattern during 1995, 2000, 2005 and 2010 using satellite-derived maps has shown that the infrastructure and socio-economic drivers (road network & human settlement) and terrain physical drivers (DEM derived slope) have influenced the spatial pattern of the watershed LULC. These lead to an accretive linear growth of Medium to Fairly Dense Forest, Open Forest, Waste Land and Built-up Land but decrease in other LULC classes. Annual rates of increase from 1995 to 2010 in Medium to Fairly Dense Forest, Open Forest, Bush/Scrub, Waste Land and Built-up land were 9.16, 8.14, 20.66,15.27 and 27.77 ha/year respectively, while the rates decrease in Dense Forest, Terrace Agriculture, Valley Agriculture and Grass land were 39.17, 10.30, 23.32 and 3.78 ha/year respectively. The result of CA Markov showed that Dense Forest, Terrace Agriculture, Valley Agriculture, Wetland and Grass Land are predicted to decrease by 174.60 ha, 39.24 ha, 59.76 ha, 8.91 ha and 2.07 ha, while Medium to Fairly Dense Forest, Open Forest, Bush/Scrub, Waste Land and Built-up- Land are projected to increase by 50.85 ha, 28.80 ha, 45.45 ha, 50.85 ha and 115.65 ha; and GEOMOD prediction for major LULC showed that Dense Forest, Terrace Agriculture, Valley Agriculture, decreased by 175.19 ha, 39.78 ha and 60.56 ha, respectively, whereas, Medium to Fairly Dense Forest, Open Forest, Waste Land and Built-up Land increased by 52.08 ha, 29.53 ha, 50.04 ha and 116.43 ha, respectively between the years 2010 to 2015. . Similar patterns of changes of these LULC classes are predicted by both models between the years of 2010 to 2020. The predicted LULC scenario for 2015 and 2020, with reasonably good accuracy would provide useful inputs to the LULC planners for effective management of the watershed.

Keywords: *GIS, sub-watershed, biophysical drivers, socio-economic drivers, Open Forest, Built-up land, GEOMOD*

Introduction

The land use/land cover pattern of a region is an outcome of natural and socioeconomic factors and their utilization by man in time and space. Knowledge of land cover and land use change is important for many planning and management activities (Lillesand and Kirfer 1999). Land use is the human use of land and land cover refers to physical and biological cover on the surface of land (Rimal 2011). In the mountain geography, micro level accurate mapping on the surface of parameters, such as surface morphometry, land use, land cover resources and population parameters is often a big problem, but mandatory for watershed management (Poudel 2010). In Nepal, forestry and land use change alone contribute about 85% of national account of green house gases emission. These complexities necessitate a systematic approach to find out the proper utilization techniques and sustainable management plans (Gautam*et al*. 2003). The capability of GIS to analyze temporal and spatial data helps in quantifying the land use changes (Awasthi, 2002).

Land-Use and Cover Change modeling is growing rapidly in scientific field. There are many modeling tools in use but the performance of different modeling tools is difficult to compare because LULC change models can be fundamentally different in a variety of ways (Pontius and Chen 2006). Among many land use land cover modeling tools and techniques, the commonly used models are the Cellular Automata (CA) Markov, Markov chain, GEOMOD, etc. In this study the CA Markov and GEOMOD available in Idrisi were implemented to predict and compare the land uses for some further period. This may require more advanced spatial techniques supported by the policy makers involving shifting of emphasis from basic geographic data handling into manipulation, analysis and modeling in order to solve the real problem (Ramachandran 2010). This paper focuses on analysis of LULC change modelling by using remote sensing and GIS techniques with CA–Markov and GEOMOD model in Phewa Lake watershed of Nepal.

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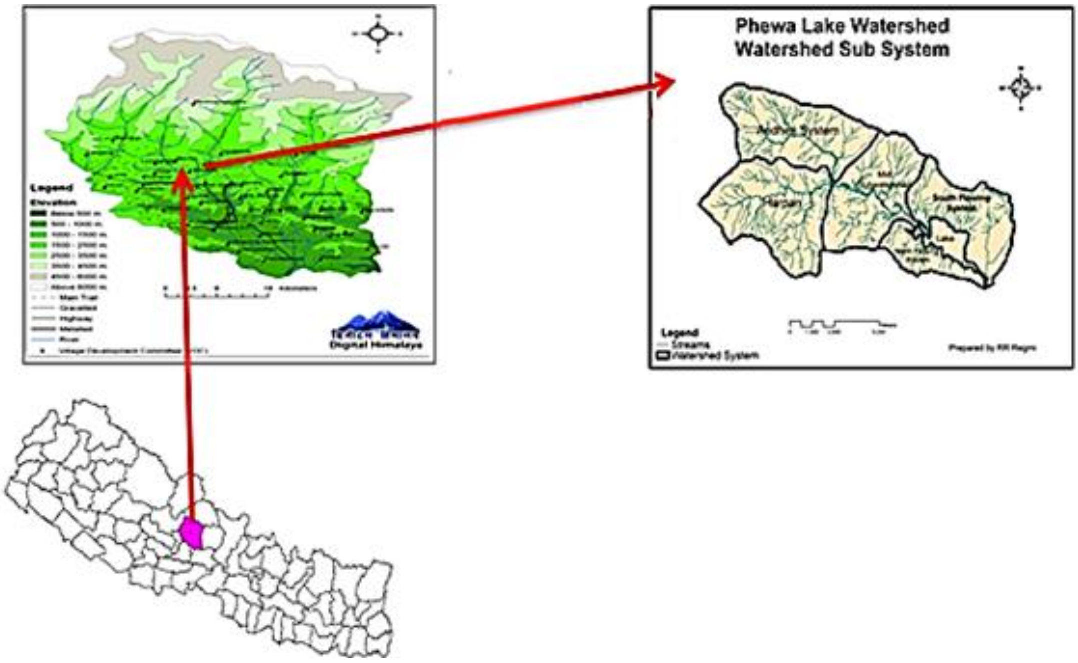

Figure 1 Location Map of the Study Area

Table 1 Satellite data specifications

Year	Satellite	Resolution (m)	Path /row	Band combination	Date ofProcurement
1995	Landsat, TM	30	142/040	1.2.3.4.5.6.7	20-Nov-95
2000	Landsat, TM	30	142/040	1.2.3.4.5.6.7	13-Nov-00
2005	Landsat, TM	30	142/040	1.2.3.4.5.6.7	8-Nov-05
2010	Landsat, TM	30	142/040	1.2.3.4.5.6.7	7-Nov-10

Materials and methods

Study area

Phewa Lake watershed is located between 28˚9’N and 28˚19’N latitude and 83˚45’ and 84˚00’E longitudes covering 120 km^2 area of Pokhara Valley in western Nepal (Figure 1). Its east-west length is 17 km and width 7 km on an average. Phewa Lake area covers 4.55 km^2. The watershed belongs to a semi- agricultural watershed in mid-hill belt (800-2500 above msl) of mountain ecosystem. Phewa Lake is silted up by 180,000 cu m annually due to rapid change of anthropogenic factors (SILT Consultants (P) Ltd., 2002).

Satellite data

The main data used in the research included temporal satellite data of Landsat TM of the years 1995, 2000, 2005 and 2010 for the past 15 years with 5 years interval for LULC mapping (Table 1). All the images were of the month of November. Sufficient GPS points are taken in the entire study area for LULC mapping, which are also used for accuracy assessment. Topographic maps of 1:25,000 scales and digital topographic data with contour interval of 20 m published by the Survey Department, Government of Nepal were used as ancillary data. The Landsat satellite data provided by Global Land Cover Network (GLCN) was radiometrically and geometrically (orthorectification with UTM/WGS 84 projection) corrected.

LULC Mapping

In the present study datasets were geo-referenced in UTM/WGS 84 projection. The study area was extracted from the acquired satellite images using digital topographical maps of 1:25000 scale and field data from subset tools in Erdas Imagine. A classification scheme was developed to obtain a broad level of classification to derive various LULC classes, such as Dense Forest, Medium to Fairly Dense Forest, Open Forest, Terrace Agriculture, Valley Agriculture, Bush/Scrub, Grass Land, Waste Land, Water Body, Wetland and Built-up Land (Figure 2). The fields were visited to complete reconnaissance survey, ancillary data collection, LULC classification, validation and % LULC change. LULC classification was performed using supervised classification technique for years 1995, 2000, 2005 and 2010 (Figure 2). In the study accuracy for all four classified maps were assessed with the test samples generated from ground truth data against high resolution references. The overall test samples generated were 114 for each of the 1995, 2000, 2005 and 2010 classified maps. Eye bird satellite of high resolution 2010, Google Earth, ESRI online, digital topographic map and other layers were used as reference due to lack of high resolution satellite data. The LULC Maps of all periods were

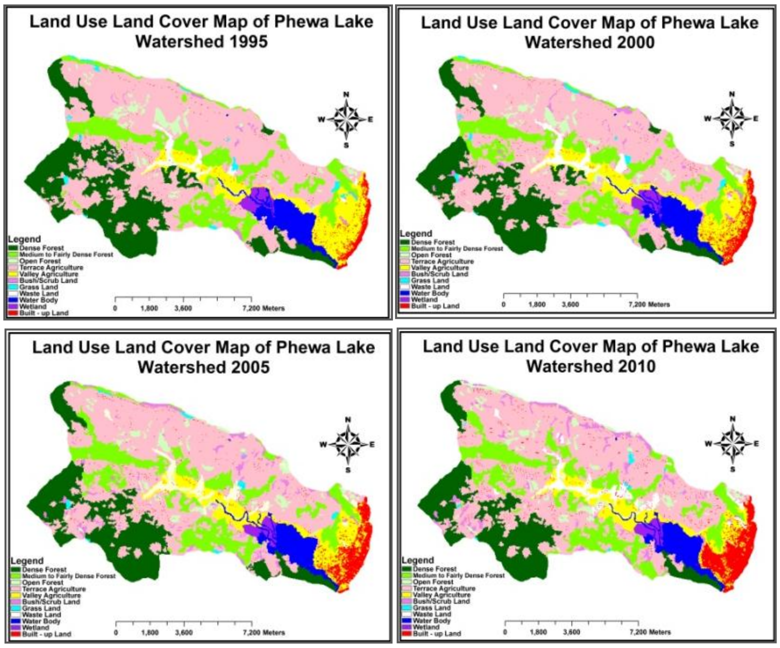

Figure 2 LULC classifications for years 1995, 2000, 2005 and 2010

imported in ARCGIS 9.3 whose area statistics is presented in Table 4. The LULC change modeling for 2015 and 2020 period was carried out using Idrisi Taiga. Preparation of LULC map for four periods using temporal satellite data, identification and quantification of LULC changes and prediction of LULC for 2015 and 2020 for both real and projected periods have been studied over the entire study area. The spatial layers of ancillary database including different socioeconomic and biophysical drivers of LULC change were prepared using data from topographic map and relevant information (CBS 2004). CA–Markov model was employed to predict future LULC dynamics in the watershed using a multicriteria decision-making approach. However, GEOMOD uses suitability maps along with beginning land use map, ending time as well as ending time land classes pixel quantities. Therefore in this study GEOMOD modeling was employed for comparing dominant LULC classes for the predicted LULC 2010, 2015 and 2020. This task was accomplished by using IDRISI software package developed by Clark Lab.

Multi-criteria evaluation (MCE) technique

It is impossible to find a single solution to multiple problems of watershed simultaneously. The decisions that were needed generally include site selection or land allocation decisions that satisfy multiple objectives, each relating to its own suitability level of land conversion (Soe and Le 2006). To achieve the said objective, multi-criteria evaluation approach was adopted, which deals with situations in which a single decision-maker is faced with a multiplicity of usually incompatible criteria or in which a number of decision-makers must consider criteria, each of which depends upon the decisions of all the decision-makers (Ademiluyi and Otun 2009). Here socioeconomic data (road network and settlements) was integrated with biophysical data (DEM and SLOPE) of the watershed through MCE technique for both CA–Markov and GEOMOD. To use MCE technique, it is necessary need to develop criteria for making decision about various land uses.

Criterion development: Constraints / factors

Different criteria were considered to determine, which LULC classes of watershed are suitable for changing from one class to another with time including proximity from road and settlement, socio-economic drivers, and biophysical drivers (slope). In this study these criteria were divided into different types: factors /constraints can pertain either to attributes of the individual or to an entire decision set.These principles generally should be based on the government policy formulated according to environmental and socio-economic consideration. The development of Built-up areas should mostly be preferable to underutilized places but, these kinds of areas are rarely available in the cities. So, agricultural areas having relatively flat slopes are being extensively utilized nowadays for urban development. It is also supposed that the urban development takes place closest to existing road networks and developed unoccupied areas. However, as the distances of such areas increase, they are less preferred due to cost effectiveness. Nearness to Dense Forest and Water Body should also be avoided for urban development. Considering these general principles the factors with Non Boolean condition of WLH approach were standardized into fuzzy rule, i.e. suitability of contiguous range of 0 = least suitable to 255 = most suitable using MCE in Idrisi.

The fuzzy module available in Idrisi is characterized to standardization of Boolean factors into entire range of criteria of none to full possibilities to transform into either a binary (0 and 1) or a byte (0 to 255) output data

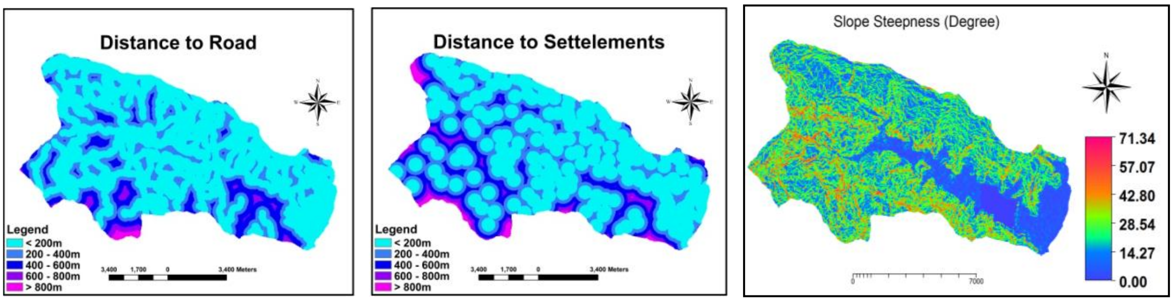

Figure 3 Watershed LULC change driver distance from road and settlements and slope

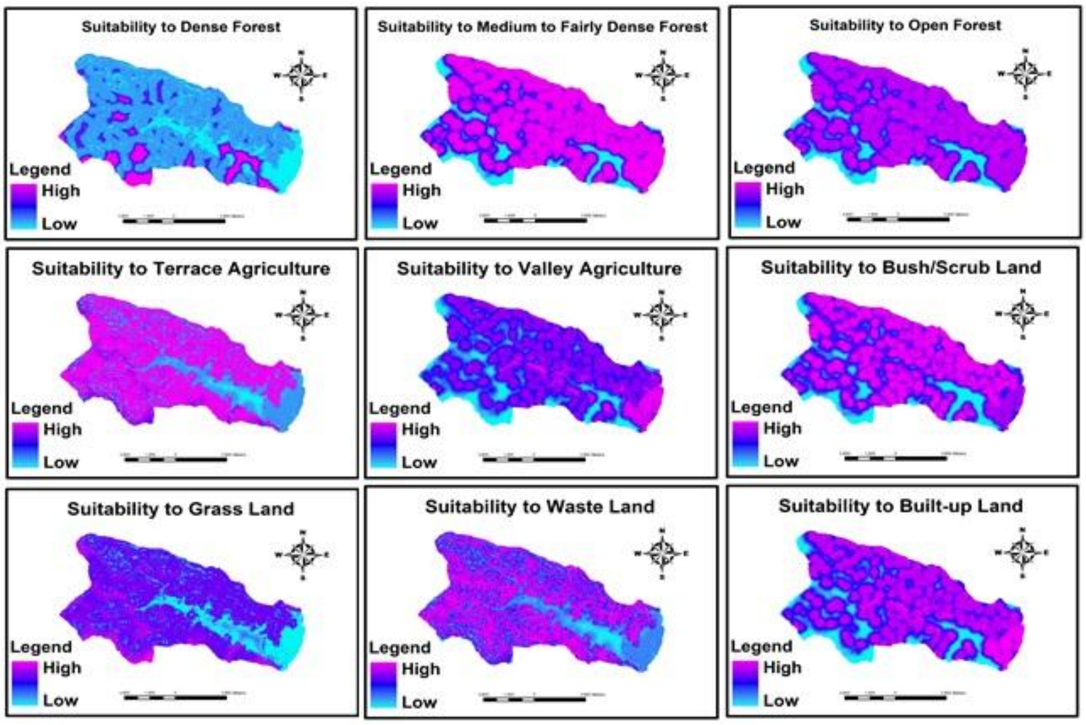

Figure 4 Suitability Maps for LULC Classes

format without sharp boundaries as 0 = lowest to 255 = highest suitability for growth where the latter output data format option is recommended because the MCE module has been optimized for using a 0-255 level of standardization (Eastman 2006). The Idrisi supported monotonically increasing, monotonically decreasing, symmetric and asymmetric variants and the fuzzy set membership functions: sigmoid, j-shaped and linear (Eastman 2006), are available to be utilized as control points for the set membership function. The selection of these variants and range of control points fully depends on the analyst's familiarity to the study area. The perfectness of selection can be measured in the model validation stage. The following factor images were derived from the processes as described above in a continuous scale (Figure 3).

MCE process was used by involving criteria of varying importance according to decision makers and information about the relative importance of the criteria. This is usually obtained by assigning a weight to each factor. Different factors have different importance affecting LULC change while creating overall suitability. Therefore, the weight to each of the factor image was assigned according to its importance for each land use class. The Analytic Hierarchy Process (AHP) is a theory of measurement through pair wise comparisons and relies on the judgments' of experts to derive priority scales. This process requires weighting factors rate from extremely less important (1) to more important (9). Consistency ratio (CR) is calculated as the AHP ratings are filled out to identify the inconsistencies in the pair-wise comparison ratings. Eastman (2006) and Satty and Vargas (2001) indicate that CR greater than 0.1 should be re-evaluated. The assignment of rating needs analyst's intuition and repetition unless the consistency is acceptable. As an example, Dense Forest suitability map was prepared by assigning weights to factors like slope, road and settlement distance as 0.0778, 0.4353 and 0.4869 respectively. The larger the weight, the more important the criterion is in the overall utility (Malczewski 1999).

The weights assigned to different factors were obtained by AHP. To provide a systematic procedure for developing factor weights, AHP was used in which a pair-wise comparison matrix was created by setting out one row and one column for each factor (Satty and Vargas 2001). In developing the weights, an individual factor compared with every other possible pairing, entered the ratings into a pair-wise comparison matrix. To illustrate this process, first few ratings were considered. It was observed that settlement distance was more important than slope, and thus, received a rating of 7. Importance of settlement distance relative to other factors, such as road distance was rated more. This procedure then continued until all of the cells in the lower triangular half of the matrix were filled. In this study, Weighted Linear Combination (WLC) method was used for aggregation of parameters. This process carries the lowest possible risk as the areas considered suitable are those considered suitable with all criteria fulfilled. The effect of 'order of weights' is most easily understood in terms of levels of risk and trade off. It was neither extremely risk-averse nor extremely risk-taking (Soe and Le 2006). Here, the suitability of areas was determined with consideration of drivers or factors, i.e., slope and distance from road and settlements. The standardized suitability land use land cover images of Dense Forest, Medium to Fairly Dense Forest, Open Forest, Terrace Agriculture, Valley Agriculture, Bush/ Scrub Land, Grass Land, Waste Land, and Built-up Land classes with fuzzy function are presented in Figure 4.

Markov chain and Cellular Automata

A Markovian process is one in which the state of a system at time (*t*2) can be predicted by the state of the system at time (*t*1) (Thomas and Laurence 2006). In this study, Markovian process was used to obtain a transition area matrix from transition probability matrix. In a transition probability matrix, the transition probabilities express the likelihood that a pixel of a given class will change to any other class (or stay the same) in the next time period. It is a text file that records the probability that each LULC category will change to every other category. A transition area matrix expresses the total area (in cells) expected to change in the next time period. It is also a text file that records the number of pixels that are expected to change from one LULC type to other over the specified number of time units. It is produced by multiplication of each column in transition probability matrix by number of pixels of corresponding class in the later image. Transition probability matrix is represented in a text file that records the probability that each LULC category would change to any other category; while the transition area matrix, also represented in a text file records the number of pixels that are expected to change from one LULC type to the other over specified number of time units. The transition area matrix obtained from two time periods was used as the basis for predicting the future LULC scenario.

The 2000 LULC image of Phewa Lake watershed was used as the base (*t*1) image while 2005 LULC map as the later (*t*2) image in Markov model to obtain the transition area matrix between 2000 and 2005 years for prediction of LULC in 2010. The same image of 2005 was used as base image to obtain the transition area matrix between the years 2005 and 2010 for prediction of LULC of 2015 and the image of 2000 as base image to obtain the transition area matrix between 2000 and 2010 for prediction of 2020. The Markov's module in IDRISI created conditional probability images that report the probability of any LULC class to be found at a location. Even though, the transition probabilities were accurate on a per category basis, there was a *salt and pepper* effect in the output image, since this model did not consider the spatial distribution of the occurrences within each category (Soe and Le 2006). The real 2010 LULC map was used as the base map for estimating future LULC scenario for 2015 and 2020.

GEOMOD Model

GEOMOD is the model that has been used frequently to analyze baseline scenarios of deforestation for carbon offset projects, as called for by the international agreements on climate change, such as the Kyoto Protocol (Pontius and Chen, 2006). It is a grid-based land-use and land-cover change model, which simulates the spatial pattern of land change forwards or backwards in time. It simulates the change between exactly two land categories denoted as 1 and 2 for non-developed and developed respectively, but 1 and 2 could represent any two categories for any particular application (Eastman, 2009). It requires only one beginning land-use map for calibration, while some algorithms for other popular models require maps from four times for calibration (Silva and Clarke, 2002).

GEOMOD has their ability to model land use change spatially but it require exogenously define the deforested area. Brown *et al.,* (2007) compared the Forest Area Change (FAC) model, the Land Use and Carbon Sequestration (LUCS) model and GEOMOD for simulating deforestation trends at the regional scale. Only GEOMOD provided results that could be used for dynamic deforestation determination under different driving factors, but GEOMOD only predicts the location of land-use change and not the quantity. Additionally, the model has been applied to more than 50 countries in Europe, Asia, and Latin America.

The GEOMOD (Pontius and Chen, 2006) however is a grid-based LULC change Model and simulates the change between two LULC categories only. Therefore, in this study, GEOMOD Model was implemented to predict and compare changes in the major land uses for 2010, 2015 and 2020 periods. For projecting LULC maps of 2015 and 2020 using GEOMOD modelling, LULC maps of 2005 and 2010, and LULC maps of 2000 and 2010, respectively were provided as basic inputs. Modelling for the future LULC the previously re-classified LULC maps were used along with the suitability map of each LULC class. Both the models used suitability maps derived from MCE-AHP process. Before projecting future LULC, the projected maps of 2010 derived by CA-MARKOV and GEOMOD were compared with actual LULC map of 2010 prepared by digital analysis of satellite data for assessment of accuracies of LULC prediction by the both LULC change predictive models.

Model validation

After any model generates a simulated map, it is desirable to validate the accuracy of the prediction. Therefore,

Table 2 Kappa Parameters of Projected LULC of 2010 by CA Markov Against actual LULC of 2010

Kappa	Value
Kno	0.8895
Klocation	0.8749
KlocationStrata	0.8749
KStandard	0.8625

Table 3 Kappa Parameters of LULC class wise Projected LULC of 2010 by GEOMOD model against actual LULC of 2010

LULC	Validation Result of Projected 2010 (GEOMOD)			
	Kno	Klocation	Klocation strata	Kstandard
Dense Forest	0.964	0.921	0.921	0.921
Medium to Fairly Dense Forest	0.912	0.903	0.903	0.903
Open Forest	0.941	0.933	0.933	0.925
Terrace Agriculture	0.884	0.883	0.883	0.889
Valley Agriculture	0.976	0.970	0.970	0.969
Waste Land	0.990	0.986	0.986	0.986
Built up land	0.997	0.996	0.996	0.996

Table 4 Area statistics of LULC classes for the study periods

	1995		2000		2005		2010	
LULC Class	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Dense Forest	2460.24	20.52	2231.01	18.61	2082.24	17.37	1872.72	15.62
Medium to Fairly Dense Forest	1622.43	13.53	1663.74	13.88	1713.96	14.30	1759.86	14.68
Open Forest	275.85	2.30	303.75	2.53	350.01	2.92	397.98	3.32
Terrace Agriculture	5337.27	44.52	5290.65	44.13	5234.49	43.66	5182.74	43.23
Valley Agriculture	1073.43	8.95	983.79	8.21	853.83	7.12	723.60	6.04
Bush/Scrub Land	85.59	0.71	205.20	1.71	308.16	2.57	395.55	3.30
Grass Land	90.00	0.75	80.37	0.67	60.12	0.50	33.30	0.28
Waste Land	185.76	1.55	281.97	2.35	338.49	2.82	414.81	3.46
Water Body	529.29	4.41	512.10	4.27	496.08	4.14	485.19	4.05
Wetland	129.87	1.08	120.51	1.01	111.33	0.93	107.37	0.90
Built up Land	199.80	1.67	316.44	2.64	440.82	3.68	616.41	5.14
Total	**11989.53**	**100.00**	**11989.53**	**100.00**	**11989.53**	**100.00**	**11989.53**	**100.00**

Table 5 Accuracy assessments of classified LULC maps in 1995, 2000, 2005 and 2010

	1995		2000		2005		2010	
LULC classes	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**
Dense Forest	90.91	90.91	90.91	90.91	90.91	90.91	90.91	90.91
Medium to Fairly Dense Forest	93.75	93.75	93.75	93.75	93.75	93.75	93.75	93.75
Open Forest	85.71	85.71	85.71	85.71	85.71	85.71	85.71	85.71
Terrace Agriculture	86.67	81.25	90.00	84.38	87.10	84.38	87.50	87.50
Valley Agriculture	80.00	92.31	84.62	84.62	91.67	84.62	91.67	84.62
Bush/Scrub	66.67	80.00	66.67	80.00	66.67	66.67	66.67	66.67
Grass -Land	75.00	60.00	60.00	60.00	75.00	75.00	75.00	75.00
Waste- Land	71.43	71.43	75.00	75.00	75.00	85.71	75.00	85.71
Water Body	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Wetland	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Built up- land	83.33	83.33	83.33	83.33	83.33	83.33	83.33	83.33
Year	**1995**		**2000**		**2005**		**2010**	
Overall Classification Accuracy	86.09		86.96		86.96		87.83	
Overall Kappa Statistics	0.85		0.85		0.85		0.86	

(Note: UA=User Accuracy, PA=Producer Accuracy)

model validation is one of the important stages in the prediction regime of land uses. The VALIDATE module involves a comparative analysis of the simulated and real maps based on the Kappa Index. However, it is different from traditional Kappa statistics in that it breaks the validation into several components, each with special form of Kappa such as Kno, Klocation, Kstandard, etc. and the associated statistics (Pontius and Chen 2006 and Eastman

Table 6 Area statistics of LULC change in the watershed (% area)

LULC Class	Change area in (ha) %				
	1995-2000	**2000-2005**	**2005-2010**	**1995-2010**	**Annual rate of change (ha/year)**
DF	-229.23(-1.91)	-148.77(-1.24)	-209.52(-1.75)	-587.52(-4.90)	-39.17
MF	41.31(0.34)	50.22(0.42)	45.9(0.38)	137.43(1.15)	9.16
OF	27.90(0.23)	46.26(0.39)	47.97(0.40)	122.13(1.02)	8.14
TA	-46.62(-0.39)	-56.16(-0.47)	-51.75(-0.43)	-154.53(-1.29)	-10.30
VA	-89.64(-0.75)	-129.96(-1.08)	-130.23(-1.09)	-349.83(-2.92)	-23.32
BA	119.61(1.00)	102.96(0.86)	87.39(0.73)	309.96(2.59)	20.66
GS	-9.63(-0.08)	-20.25(-0.17)	-26.82(-0.22)	-56.7(-0.47)	-3.78
WS	96.21(0.80)	56.52(0.47)	76.32(0.64)	229.05(1.91)	15.27
WB	-17.19(-0.14)	-16.02(-0.13)	-10.89(-0.09)	-44.1(-0.37)	-2.94
WE	-9.36(-0.08)	-9.18(-0.08)	-3.96(-0.03)	-22.5(-0.19)	-1.50
BU	116.64(0.97)	124.38(1.04)	175.59(1.46)	416.61(3.47)	27.77

(Note: DF=Dense Forest, MF = Medium to Fairly Dense Forest, OF=Open Forest, TA=terrace Agriculture, VA= valley Agriculture BA=Bush/Scrub land, GS =Grass Land, WS=Waste Land, WB=Water Body, WE=wetland, BU=Built-up Land.)

2006). Validation results of comparison of projected LULC of 2010 by CA Markov and GEOMOD model with actual LULC of 2010 are presented in Table – 2 and 3 respectively. The overall Kappa parameters values were 85% or more indicating good agreement of CA-MAKOV model predicted LULC output vs. actual LULC map.

The data presented in Table 3 indicated that the overall Kappa parameters values were more than 90% each LULC classes showing very good agreement of GEOMOD model predicted LULC outputs (each LULC class wise) vs. actual LULC map. The overall accuracy of prediction results from GEOMOD model has high value of Kappa Index (0.997). Therefore, accuracy results of this study indicated that GEOMOD model was more accurate in predicting LULC compared to CA- Markov model.

Results and Discussions

LULC dynamics

The LULC change dynamics of Phewa Lake watershed was studied over more than a decade from 1995 to 2010.The results of LULC distribution in 1995, 2000, 2005 and 2010 showed that Terrace Agriculture, Dense Forest and Medium to Fairly Dense Forest were the dominant LULC category (Table 4). Overall, Medium to Fairly Dense Forest, Open Forest, Bush/Scrub, Waste Land and Built-up Land increased, whereas other land uses decreased significantly during all periods (Table 4). Overall classification accuracy and Kappa values for all the four time period LULC maps was greater than 85% and 0.85 or more, respectively (table 5).

In assessing LULC classification accuracy (Table 5) it was observed that only Water Body and Wetland provided the highest producer's accuracy and user's accuracy of 100%. The forests, agriculture categories and Built – up Land reached above 80% producer's accuracy and user's accuracy. The lower producer's accuracy and user's accuracy below 75% were produced by Waste Land, Bush / Scrub Land and Grass Land. The spectral mixing of these LULC classes attributed lower PA and UA accuracies.

Temporal LULC analysis was carried out for 15 years (1995 – 2010) and this period was divided into four study periods of five years such as 1995-2000, 2000-2005 and 2005-2010 LULC change statistics of the study periods are tabulated in Table 6. Medium to Fairly Dense Forest, Open Forest, Bush/Scrub, Waste Land and Built-up land increased by 9.16, 8.14, 20.66,15.27 and 27.77 ha/year respectively, while Dense Forest, Terrace Agriculture, Valley Agriculture and Grass land decreased by 39.17, 10.30, 23.32 and 3.78 ha/year respectively, from 1995 to 2010.

The data in Table 6 indicated that Medium to Fairly Dense Forest, Open Forest, Waste Land, Bush/Scrub and Built-up Land have exhibited a positive rate of change for all the change study periods (1995 to 2000, 2000 to 2005, 2005 to 2010 and 1995 to 2010). On the contrary, while Dense Forest, Terrace Agriculture, Valley Agriculture; Grass Land, Water Body and Wetland experienced a negative change in all change study periods. The percentage rate changes of area statistics in Dense Forest, Waste Land and Bush/Scrub Land classes during 1995 to 2000 were very high when compared with change between 2000 and 2005 and 2005 and 2010; while Open Forest, Valley Agriculture, Grass Land and Wetland was higher in 2005 and 2010. Also the change of Medium to Fairly Dense Forest and Terrace Agriculture were observed high in 2000 to 2005. However the rate of change of area statistics was observed highest in 1995 to 2010 for all LULC categories

LULC change detection analysis revealed that Waste Land, Built-up Land and Bushy areas were increased at the expense of Terrace, Valley Agriculture; Open Forest & Grass Lands. Whereas, Medium to Fairly Dense Forest and Open Forest areas, were increased at the expense of Dense Forest for the change study periods.

LULC prediction

The area statistics of CA-MARKOV model projected LULC classes for the year 2015 and 2020 as well as actual for the year 2010 are presented in Table 7. The data presented in the Table 7 showed that the major changes were found in Dense Forest, Medium to Fairly Dense Forest, Open Forest, Terrace Agriculture, Valley Agriculture, Bush/Scrub and Waste Land. Minor changes were observed in other LULC classes. Dense Forest, Terrace Agriculture, Valley Agriculture, Wetland and Grass Land are predicted to decrease by 174.60 ha, 39.24

Table 7 Area Statistics of Actual for the year 2010 and CA-MARKOV Model Predicted LULC classes for the year 2015 and 2020

LULC Class	Area in (ha)		
	2010	**2015**	**2020**
Dense Forest	1872.72	1698.12	1530.13
Medium to Fairly Dense Forest	1759.86	1810.71	1860.39
Open Forest	397.98	426.78	454.41
Terrace Agriculture Land	5182.74	5143.50	5103.18
Valley Agriculture Land	723.60	663.84	603.45
Bush/Scrub Land	395.55	441.00	485.31
Grass Land	33.30	31.23	28.98
Waste Land	414.81	465.66	515.34
Water Body	485.19	478.17	472.05
Wetland	107.37	98.46	91.35
Built- up Land	616.41	732.06	844.94
Total	**11989.53**	**11989.53**	**11989.53**

Table 8: Area Statistics of Actual for the year 2010 and GEOMOD Model Predicted LULC classes for the year 2015 and 2020

LULC Class	Area in (ha)		
	2010	**2015**	**2020**
Dense Forest	1872.72	1697.53	1529.51
Medium to Fairly Dense Forest	1759.86	1811.94	1863.55
Open Forest	397.98	427.51	455.21
Terrace Agriculture Land	5182.74	5142.96	5104.01
Valley Agriculture Land	723.60	663.04	603.15
Waste Land	414.81	464.85	515.12
Built- up Land	616.41	732.84	841.29
Total LULC	**11989.53**	**11989.53**	**11989.53**

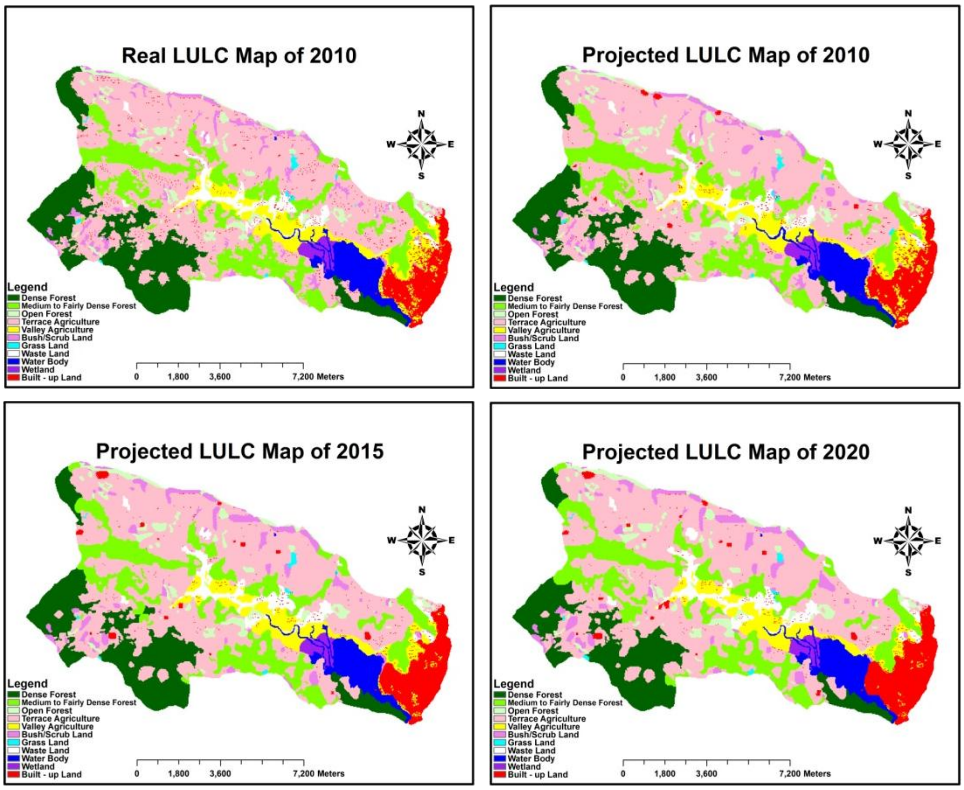

Figure 5 Predicted LULC maps for 2010, 2015 and 2020

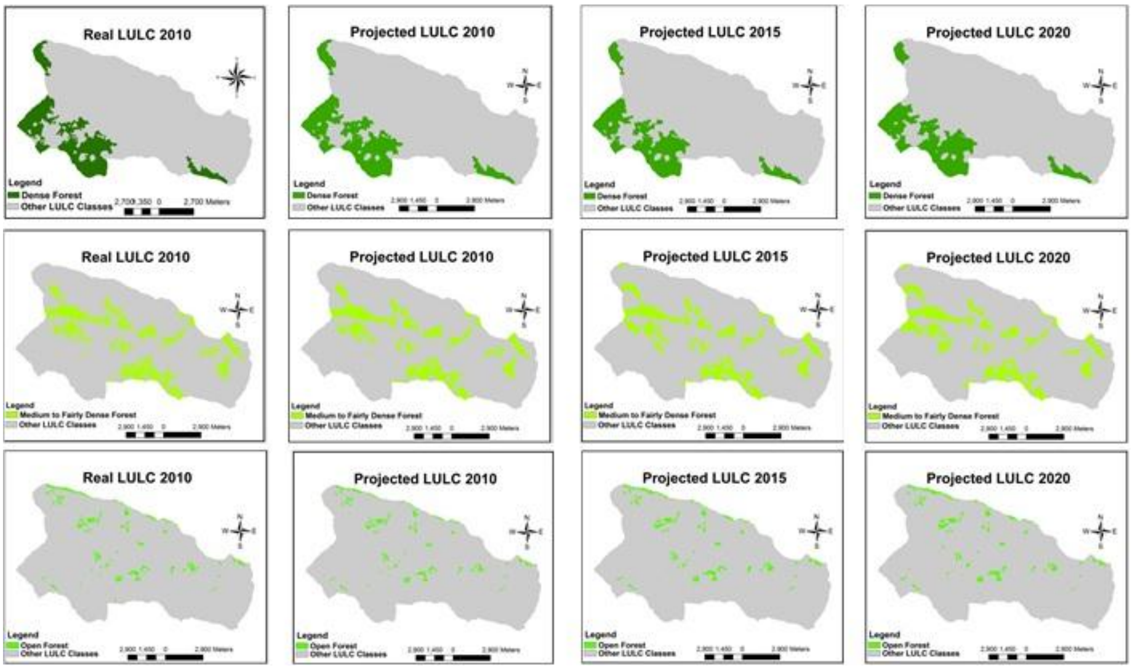

Figure 6 GEOMOD Predicted Forest LULC Classes

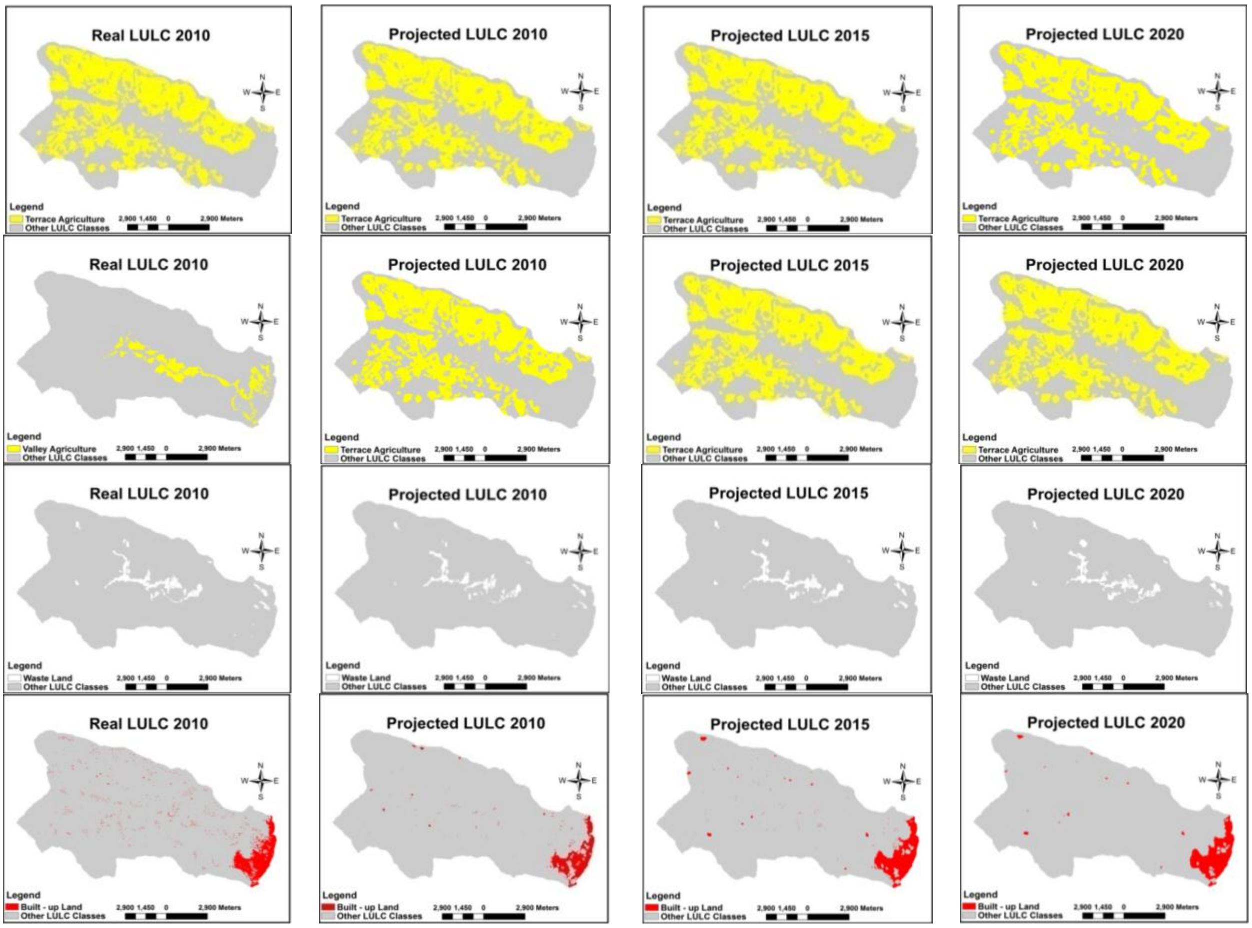

Figure 7 GEOMOD Predicted Non Forest LULC Classes

ha, 59.76 ha, 8.91 ha and 2.07 ha, respectively, while Medium to Fairly Dense Forest, Open Forest, Bush/Scrub, Waste Land and Built-up- Land are projected to increase by 50.85 ha, 28.80 ha, 45.45 ha, 50.85 ha and 115.65 ha, respectively between the years of 2010 to 2015. Similar patterns of changes of these LULC classes are predicted by CA-MARKOV model between the years of 2010 to 2020.

The results of areal distributions of GEOMOD model predicted major LULC classes for the year 2015 and 2020 and actual for the year 2010 are presented in Table 8. The results of this analysis indicated that the major changes were found in the LULC classes of Dense Forest, Medium to Fairly Dense Forest, Open Forest, Terrace Agriculture, Valley Agriculture, Waste Land and Built-up Land. Dense Forest, Terrace Agriculture, Valley Agriculture, decreased by 175.19 ha, 39.78 ha and 60.56 ha, respectively, whereas, Medium to Fairly Dense Forest, Open Forest, Waste Land and Built-up Land increased by 52.08 ha, 29.53 ha, 50.04 ha and 116.43 ha, respectively between the years 2010 to 2015. Similar patterns of changes were also predicted between the years of 2010 to 2020**.**

The Real 2010 LULC map was used as the base map for estimating future LULC scenario for 2015 and 2020 in both model. Both the models used suitability maps derived from MCE-AHP process. Before projecting future LULC, the projected maps of 2010 derived by CA-MARKOV and GEOMOD were compared with actual LULC map of 2010 prepared by digital analysis of satellite data for assessment of accuracies of LULC prediction by the both LULC change models. The projected LULC maps of 2010, 2015 and 2020 generated by CA-MARKOV and GEOMOD are presented below in Figures - 5, 6 and 7, respectively.

The LULC projection / prediction results of both the change prediction models revealed the similar trends of changes in LULC classes in all projection periods. The rates of changes of LULC are approximately same in both the models because GEOMOD used the same number of grid cells as real LULC during the simulation process and CA Markov employed inputs of LULC changes develop as a growth process in areas of higher suitability adjacent to existing areas.

In the prediction of future LULC scenarios, the expected area to change in transition area matrix was observed to be Dense Forest, Medium to Fairly Dense Forest, Open Forest, Terrace Agriculture and Built-up Land. It could be due to settlements expansion, construction of road trials, unscientific agriculture practices and involvement of both socio-economic and biophysical drivers. In multi-criteria decision-making process, different biophysical and socio-economic drivers, and their relative importance for change in watershed dynamics were considered. The present study investigated the human induced LULC patterns, land cover change and hydrologic change in LULC of watershed.

The prediction of LULC in watershed in 2015 and 2020 was based on change in driver's impact with time and trend of LULC change from 2000 to 2010 and the weight applied for different factors in LULC prediction for years between 2005- 2010 and 2000-2010. It was found that the integration of Markov model and Cellular Automata were effective in projecting future LULC scenario. It produced Kappa value of above 85% when compared to predict LULC map with the real LULC 2010.This is well above the acceptable limit of accuracy (Anderson *et al*.1976). Hence, the projected LULC change based on the four time period 1995, 2000, 2005 and 2010 LULC changes (more than five years) and considering the impact of biophysical and socio-economic drivers in watershed showed the potential of modeling exercise for LULC change in the watershed.

Conclusion

This study demonstrated utilization of remote sensing and GIS tools to analyze and model the LULC dynamics in Phewa Lake watershed using CA–Markov, GEOMOD and predicted the future LULC scenario in 2015 and 2020 with reasonably good accuracy. Future LULC change scenarios were addressed based on the past LULC change trends considering infrastructure and socio-economic drivers (road network & human settlement) and terrain physical drivers (DEM derived slope). The accuracy of both CA - Markov and GEOMOD predictive models when compared to predicted LULC map of 2010 with the real LULC map of 2010 were good as the Kappa values for both the models were above 85%. CA-Markov method is best for predicting LULC including all classes, whereas GEOMOD is good for prediction for LULC class wise only. Long term LULC change analysis from 1995 to 2010 of each five years interval and predicted LULC scenario for 2015 and 2020 showed that major LULC such as Medium to Fairly Dense Forest, Open Forest, Bush/Scrub, Waste Land and Built-up area were in increasing order while other LULC were in decreasing order for all periods. Similar trends will be predicted in future years. The integration of the topographic and remotely sensed data within a GIS environment provided an effective means of assessing LULC change modeling within the watershed. This study has demonstrated some guidelines to foresee and examine possible future LULC growth in the watershed with different suitability rankings in multi-criteria decision-making in relation to different environmental, economic, planning and land development settings with proper use of the CA–Markov and GEOMOD modeling. It would be helpful for planning and management of watershed resources also for restoring water availability, and improving ecological condition of watershed by the identification of areas suitable for water and soil conservation structures to restore the watershed dynamics. The LULC management prescriptions for the Phewa Lake watershed can include construction of small water and soil conservation structures, such as check dams, percolation ponds, etc.; participation of rural people and stakeholders to prevent further land degradation, and to reduce soil erosion; and improvement in agriculture production following better agricultural practices.

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