Proceedings of 10th IOE Graduate Conference
Peer Reviewed
ISSN: 2350-8914 (Online), 2350-8906 (Print)
Year: 2021 Month: October Volume: 10

Assessment of Future Land Use/Cover Change of Kathmandu Valley Using Two Models of Land Change

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Abstract

Land use/cover (LULC) play an important role in ecological and hydrological processes. Hydrological processes such as groundwater recharge, overland flow, and eco-biodiversity are associated with LULC. Kathmandu valley (KV) and its surrounding areas have been experiencing rapid LULC change because of rapid urbanization. A large swath of agricultural land in KV has been converted into build-up areas.Further studies of LULC change adopting different models give a comprehensive understanding of LULC change and implement area-specific actions to mitigate adverse effects. For LULC, this study extracted historic LULC of 2005 and 2015 from Landsat imagery. The classified maps were validated by comparing with ground truths taken from historic Google earth imageries. The confusion matrix showed a higher resemblance between Classified LULC and ground truths. It gave a Kappa coefficient of over 88% in each classified LULC. These two maps along with driving forces of LULC including road networks, slope, and elevations were used to simulate future LULC. DINAMICA EGO model is based on cellular automata, and the Land change modeler operates on the philosophy of multilayer perception Markov chain Neural Network method. We evaluated the simulated LULC of both maps using the error matrix module in IDRISI Selva. The Kappa coefficient of the simulated map of 2020 and produced LULC of 2020 are 70% and 78% for DINAMICA EGO and LCM. Both models predict that agricultural land in the valley is transforming into urban areas. Both models predicted that around 80% of the flat area in the valley will be of urban form in 2050.

Keywords

Land use/cover (LULC) change, Landsat, Dinamica EGO, Land Change Modeler(LCM), Urbanization

1. Introduction

Nepal is one of the least urbanized countries in the world. However, the urban population of Nepal has been increasing at a steady rate of 3.43%. Kathmandu Valley (KV), the capital city of Nepal, contributes 22.4% of the total urban population [1] . It is also one of the fastest-growing cities in the world [2]. In consequence, the urban expansion in KV is increasing rapidly. The Mountainous terrine and the scarce land resources of KV are challenges for further expansion results in haphazard urbanization [3]. The notion of land use policy in Nepal was developed only with the Eighth Five-Year Plan (1992-1996) which, established land use plan as a long-term fundamental agenda to address the problems in land management [4]. But consequent civil war, political upheavals, increase in household income due to remittance of migrant workers accelerated urbanization while decreasing government actions to properly manage urbanization and enforce regulations worsen the situation. This human intervention results in significant changes in land use land cover (LULC) patterns in KV and its surrounding area over the years. It has unintended impacts on ecology, environment, streamflow, groundwater recharge, ground water etc. [5, 6].Future LULC simulation are necessary for future planning and policymaking to mitigate future water scarcity, ecological conservation, maintain biodiversity, reduction of groundwater depletion by adopting new groundwater recharge strategies and maintain stream water flow throughout the year for sustainability of the area. Many LULC change modeling studies have used either of CLUE[7], SLEUTH[8], DINAMICA EGO[9], Land Change Modeler[10], etc. for their purpose. These models adopt different techniques such as linear interpolation, statistical interpolation, cellular automation, Markov chain to simulate the change of land categories. [11]

LULC changes in different locations are affected by various factors natural or anthropogenic. The complex interaction between factors and government policy could affect future LULC.[11, 12, 13] Further studies using different models give a comprehensive understanding of LULC change over the years, and implement area specific actions to mitigate adverse effects resulting from this change. In the project work, simulation of future LULC change of Kathmandu, Bhaktapur and Lalitpur districts using DINAMICA EGO, and Land change Modeler(LCM) is carried out. These models are related to different modeling styles. DINAMICA EGO is a cellular automata model highly used to model projection of future physical and biological processes due to present and past human actions that directly or indirectly affect natural phenomenon.[9] Similarly, the Land change modeler operates on the philosophy of multilayer perception Markov chain Neural Network method(MLP-MC) [10].

The comparative study of different land use models gives a tool to better understand the LULC change of any area. As change model performance is based on the underlying governing mathematical relationship between existing LULC, driving variables, and transition potential, some models might perform better on a specific region with datasets, thus helping to choose an effective method.[14, 12] In this study, we choose two dominantly used land cover change models to explore the LULC change of KV.

The rapid growth of the population in Kathmandu valley results in the transition of the rural and semi-rural areas to urban forms. This transformation results in the transition of a vast swath of agricultural land to settlements and sped up deforestation in surrounding forests. The conversion of agricultural land to build up area results in an expansion in impervious surface affecting hydrological processes, as these processes are a function of land cover. An increase in the impervious area increases the runoff during rainfall and reduces the amount of infiltration, therefore increasing the vulnerability of floods during rainfall and depleting must necessary groundwater resources during the dry season. If this trend continues, the severity of the problem caused by land-use transform will worsen. Knowing future LULC could help to cope with future conditions and adopt additional measures to mitigate further damages caused by human interventions. Future simulated LULC not only helps to identify future dire conditions but still expect future changes, to identify potential zones of rapid change or zones that demand further attention for policy intervention promptly to mitigate effects The Main objective of the study is Projection of Land-use/ Land-cover of Kathmandu using Land change modeler and Dinamica Ego and compare their result.

2. Materials and Methods

2.1 Study Area

The study area encompasses Kathmandu, Bhaktapur, and Lalitpur districts situated in the lesser Himalayan region in the central part of Nepal. The geographic area lies between 27^o25’ to 25^o50’ latitude and 85^o10’ to 85^o50’ longitude. The region represents wide ranges of topographic features of a bowl-shaped valley (named Kathmandu Valley) surrounded by four mountain ranges Shivapuri, Phulchoki, Nagarjuna, and Chandragiri. It has an average elevation of 1350m. Temperate climate having dry winter and hot summer with a mean annual temperature of 16^oC to 20^oC and mean annual precipitation of 1200 to 1400 mm dominated by Four months of monsoon.[15].The entire area is drained by Bagmati river.

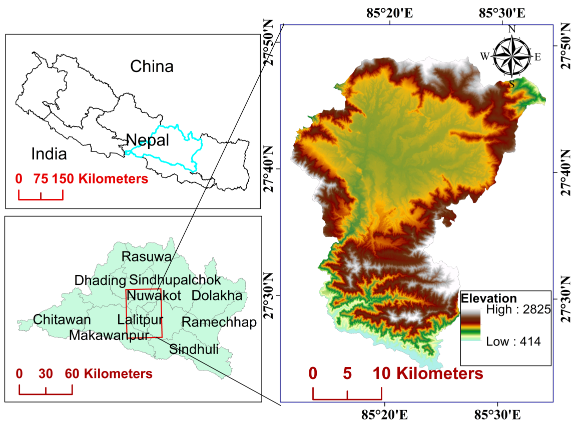

Figure 1: Study Area

Plain topography and fertile soil of KV (lake deposition) have been an attraction for the settler throughout history. However, since 1980 urbanization in Nepal has paced rapidly in addition civil war started in 1996 pushed it into new level as a result the population of KV is booming, Kathmandu metropolitan in KV is growing at a rate of 4 percent per year. The lack of sound government’s land use policies to restricts haphazard urban sprawl puts tremendous pressure on natural resources endangering its fragile ecosystem [16]. The urban and peri-urban area of the region is divided into two metropolitan and surrounding 16 municipalities. Most of the urban sprawl is limited in the valley area, whereas the southern portion and surrounding mountains are composed of steep high hills unsuitable for settlements and agricultural production. A section of the northern part lies in Shivapuri national park.

2.2 Data Acquisition and Processing

Remote sensing data for LULC classification were acquired from Landsat 7 and Landsat 8 data based on their availability(Figure 2). Monsoon season is best season for collecting remote sensing images as it is the flourishing time for vegetation but during this time of the year most of the area were covered with the clouds preventing acquiring cloud free data. The data were acquired in the month of September to December. Landsat 7 imagery used for the classification of LULC of 2005. the data had with data gap caused by scan line corrector failure therefore these gaps were filled using Landsat gapfill tool for ENVI software. The spatial resolution of Landsat images were 30m.The characteristics of Landsat images are included in Table 1

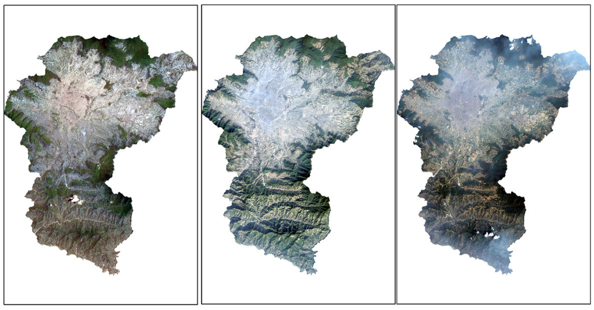

Figure 2: Natural band combination of Landsat TM and OLI sensors of study area of year 2005, 2015 and 2020

The various parameters govern the LULC change,including government policies, socioeconomic factors, land change patterns, road networks, rivers, soil type, slope, elevation, etc.[17]. Due to the limited data availability, the drivers of LULC changes in the study area included are distance from the road networks, slope of the area, elevation, soil type, and reserved land. The driving variables for the LULC change analysis were gathered from various sources. Digital Elevation Model (DEM) of resolution 30m of the area was downloaded from SRTM. DEM was further processed to fill up sinks using ArcMap. A slope map of the region was prepared using the slope tool in ArcMap.

Road network and National park boundary were obtained from ICIMOD data repository. The road networks were classified into highway, metalled, and main trailed. Using road networks, road to distance variable was prepared using Euclidian distance algorithm in ArcMap. The soil data used in the study were acquired from FAO's world soil data portal. According to FAO's soil data study area includes only two types of soil. All of the data were converted into raster of resolution 30m and clipped by study area boundary.Drivers of LULC are shown in Figure 3

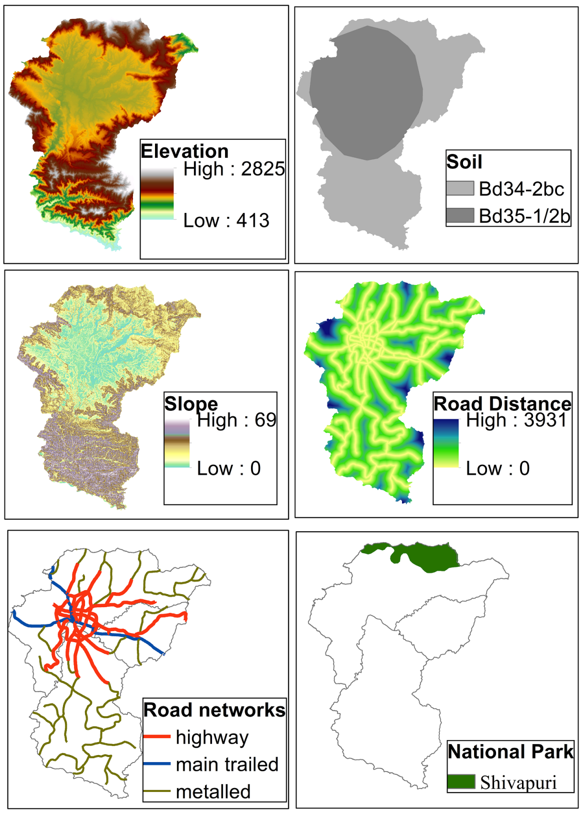

Figure 3: Additional data sets for LULC change simulation

2.3 Land use/cover classification

2.3.1 Collection of Satellite Imagery

USGS is the free, open sourced, and extensively used primary source of remote sensed earth's surface data. Landsat 7 and Landsat 8 are the most widely used satellite imagery from USGS for LULC classification. Landsat 7 data were selected for the year 2005, and Landsat 8 data were used for the year of 2015 and

Table 1: Characteristics of the Landsat images

SN	Date	Satellite	Sensor	Path	Row	Resolution
1	9/9/2005	LANDSAT 7	Enhanced Thematic Mapper(ETM)	141	41	30
2	12/26/2015	LANDSAT 8	Operational Land Imager (OLI)	141	41	30
3	11/5/2020	LANDSAT 8	Operational Land Imager (OLI)	141	41	30

2020. All of the data gathered had either no or less than 5% cloud cover and taken at the relatively same period of the year to avoid cloud masking and seasonal variation.

2.3.2 Landsat Image Processing

Landsat 7 imagery used for the classification of LULC of 2005 had with data gap caused by scan line corrector failure so, these gaps were filled using Landsat gap-fill tool for ENVI software. Landsat image processing involves preprocessing and post-processing. Two software packages widely applied for image processing are ArcGIS and ENVI. ArcGIS is generally adopted for different geoprocessing activities where as ENVI is utilized for the classification of LULC from remote sensed imagery.

This study makes use of ENVI software for radiometric correction of each band in the preprocessing process. The unnecessary data were removed by clipping corrected imagery using a boundary shapefile. The rectified bands were combined to form composite bands to identify land-use types in the area. Different band combinations are useful to recognize various categories of land use. For example, 5,6,4 band combination of Landsat 8 is helpful to separate water bodies and land.[18]

The band combinations were employed to create training sample polygons that are regions of interest for classification purposes. Based on the training samples, LULC was categorized into four dominant categories: urban, agriculture, forest, and water bodies using a maximum likelihood classification classifier. The process was repeated numerous times till desired LULC Map was obtained.[19]

2.3.3 Accuracy assessment of the LULC classification

Classified LULCs were compared with ground truth prepared from the historical google earth map. One hundred and eighties random sample points were selected such that each Category has at least minimum numbers of ground truth points. The accuracy of the land use map was Carried out using the Kappa coefficient determined from the confusion matrix.

$$Kappa = \frac{TotalAccuracy - RandomAccuracy}{1 - RandomAccuracy} \quad (1)$$

If the accuracy of the classified LULC was below the acceptable value, the process of land use classification was repeated until required accuracy criteria would meet, which involves creation of additional regions of interests for each Category.[20]

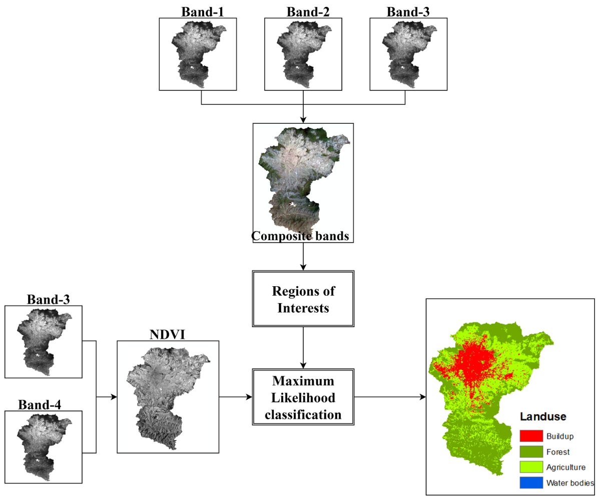

Figure 4: Flow chart of LULC classification

2.4 LULC simulation using DINAMICA EGO

The DINAMICA EGO models are based on cellular automata. It has a user-friendly environment showing diagrams of a sequence of tasks represented by each functor (collection of algorithms that perform a specific task) and connected by a connector. By connecting several functors, we can create an advanced model, such as land change modeling.The methodological flowchart of DINAMICA EGO is shwon in Figure 4 [9]

2.4.1 Calculation of the Transition Rates

From the available historical LULC map, a historical transition matrix is calculated. The transition matrix represents the transition rate of one class to another over discrete time increments. The cells of a class that transformed to another class in terms of numbers of cells is obtained by multiplying the transition rate by the total numbers of cells. The sum of transitional rate of a category is always equal to one. The transition rate defines the simulation of future LULC, i.e. the percentage of land that will change to another state in the future.[9]

2.4.2 The Weights of evidence and calculation of the probability map

Depending on unique elements of evidence, the weights of evidence statistical method calculates the likelihood of an event happening. The probabilities in the model give the possibility of a cell transforming from one category to another. Our study considered various static variables such as distance from the road, slope, soil types, distance from existing LULC as evidence for the most suitable area to transform to another category. The model applies the Bayesian method of weights of evidence is integrated for the process. The weight of the evidence method considers that the predictor's patterns are provisionally independent. DINAMICA EGO provides assessing the independence hypotheses, a functor that defines the weights of probabilities correlation.[21]

2.4.3 Transition functions (expander and patcher)

The transition functions tool determines the suitable plots in the LULC that transform based on changes figure out by the model. The expander can only expand in a previous class of land cover. The patcher uses a sowing method to manage the first fresh patches. Patcher chooses the central patch of a separate patch, and then specified cells are worked out for the transition surrounding this nucleus patch. To switch between the two transition functions, the model splits cells. The patcher function creates most patches; the program typically inserts these patches near previously transitioned areas and road networks.[21]

2.4.4 Calibration and Validation of the Model Fitting

The model determined parameters of coefficient of the weights of evidence, and transition rates using LULC of year 2005 and 2015. The rate in the simulation depends on a reasonable match between simulated and reference maps. The model validates the process after calibration of the model. validation ensures performance of the model to meet desired purpose.

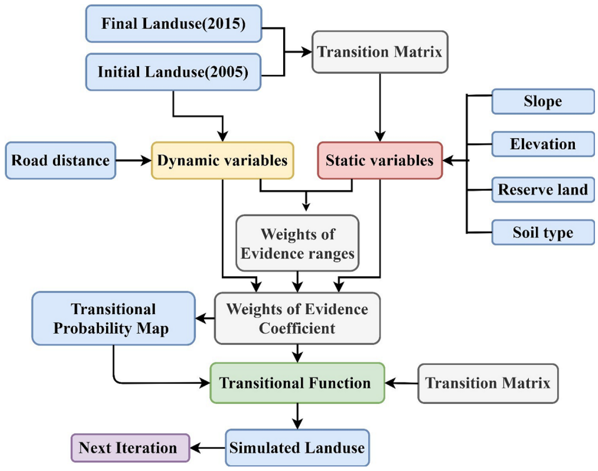

Figure 5: Flow chart of LULC classification procedure of LULC modeling using DINAMICA EGO

2.5 LULC Simulation using Land Change Modeler

Multi-layer Perceptron- Markov Chain (MLP-MC) neural network technique available in LCM tool in IDRISI Selva was implemented for projection of future LULC. The LCM tool has functions to determine LULC changes, net gain, net loss, and net transformation from one category to another LULC category. The system has a simple interface and is extensively used for LULC change analysis around the world. The model utilized both dynamic and static variables to determine the likely LULC of the future.[22]

Independent and dependent variables such as elevation, slope, distance from a road, distance from existing land, distance from rivers, the port play a vital role in LULC change prediction.[17] Even though these parameters will change in the future, the model treats them as the dependent variable. We used the LULC of the previous time step as an independent variable. Transition potentials for the change were modeled using MLP neural network method using LULC of 2005 and 2015. The algorithm used for the model was backpropagation (BP) with one input layer, one or more hidden layers, and one output layer, its model transition rate using non-linear function. The model takes a sample of pixels that transition from one category to another for the training of the transitional potential model. The model was trained using 50At the beginning of the process, the default hidden nodes were implemented. After further tests were carried out, and value was updated until the process improve the overall accuracy and skill score of the model. The outcomes of the MPL performance are total accuracy and skill test score to the result. We tested model skills by equation 2.

$$S = \frac{(A - E(A))}{1 - E(A)} \quad (2)$$

where: $E(A)$=The excepted accuracy, and A=The measured accuracy.

$$S = \frac{1}{T + P} \quad (3)$$

where T is the number of transitions in the sub-model, and P is the number of persistence classes in the sub-model. Using backward stepwise analysis, it is needed to remove the parameters with no power in order to improve simulation accuracy and skill score. When performing a sub-model with all the parameters, each variable was maintained constant one by one until the one of the least effect on modeling was identified.

2.5.1 Markov Chain (MC) Modeling

The Markov Chain (MC) modeling was used to conduct LULC change prediction, with the projection date in 5-year periods beginning from 2020 and using all transition potential sub-models. Current LULC to the LULC of a future date, the MC determines the probability of LULC change. It calculated the amount of land that could change from the subsequent time to the simulation date. We used classifications as states of a chain in the Markov Chain procedure. The state at the preceding time t+1, (X_{t+1}) only depends on the time t (X_t) and is independent of the process passing through X_t.[17]

$$X_{(t+1)} = f(X_t) \quad (4)$$

If P represents the transition probabilities matrix, X_{t+1} is given by:

$$X_{t+1} = X_t.P \quad (5)$$

The Markov Chain analysis can create a transitional probabilities file, which analyzes the likelihood of LULC change in different periods. After that, we analyze the loss and gain of land of each category using a multi-objective land allocation method. We assigned and superimposed all the class changed land to produce the output while this assignment operation was operating.

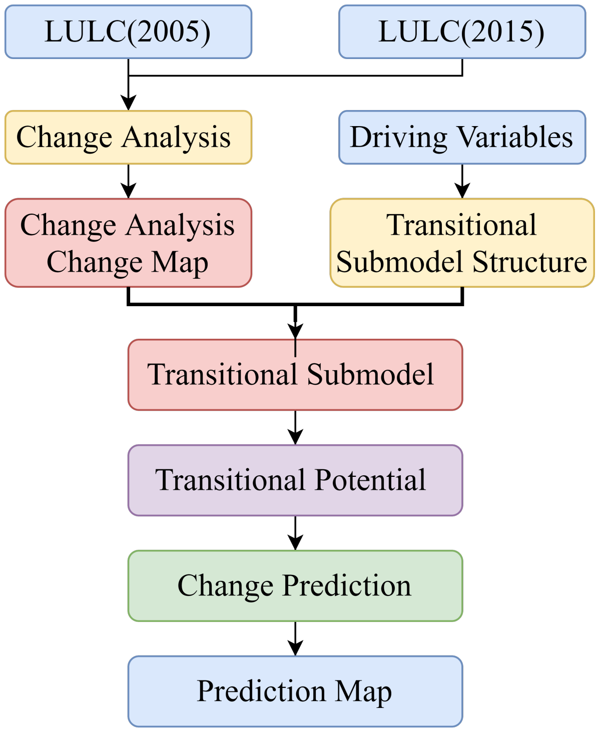

Figure 6: LULC Simulation using Land Change Modeler

3. RESULT

3.1 LULC Classification

Figure 7 shows the Land use and land cover classification of study area extracted from LANDSAT imagery. The accuracy of LULCs were determined by 180 samples points taken from historical Google Earth map. These sample ground truths represents ground cover of that time period. These points are compared with classified LULC to preapare transition matrix. Table 2 shows the overall accuracy and total accuracy of prepared LULC. It shows that all of the maps were classified with reasonable degree of accuracy. Overall accuracy of all of the maps are over 90% and Kappa coefficient is above 88%

Table 2: Characteristics of the Landsat images

SN	Year	Overall.Accuracy	Kappa.Coefficient
1	2005	92.78%	89.68%
2	2015	95.56%	93.68%
3	2020	92.22%	88.72%

3.2 Future LULC Simulation and Validation

This study simulated future LULC map using LULC of 2005 and 2015, by two models: DINAMICA EGO and LCM. The simulated maps are validated by LULC map of 2020. This study used ERR MATRIX module in IDRISI SELVA for this purpose. Each simulated maps are within reasonable degree of accuracy.

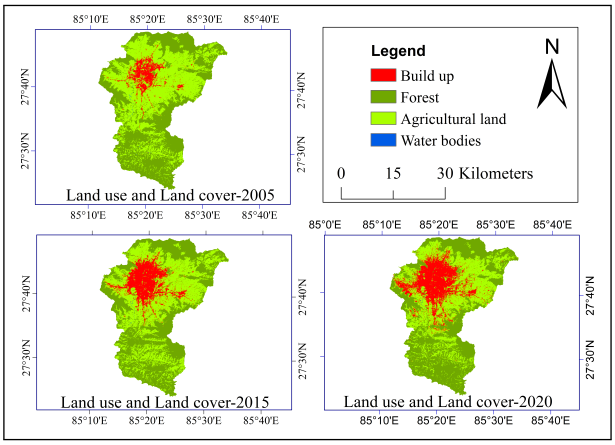

Figure 7: Simulated LULC for 2005, 2015 and 2020

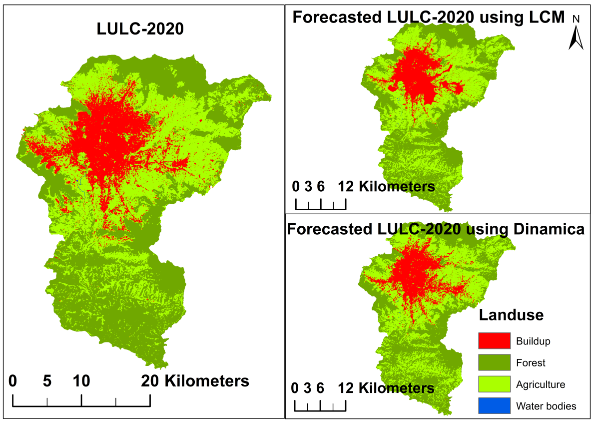

Figure 8: Validation of simulated LULC

The Error Matrix Analysis module of IDRISI Selva gave 78.6 percent accuracy of LULC simulated using Land change modeler and similarly 70.3 percent accuracy of LULC simulated using DINAMICA EGO. These two values are within acceptable limits. Among the categories, DINAMICA EGO has less accurately predicted water bodies in comparison to other categories while Land Change modeler predicted all categories with similar accuracy. The results also show that the patches formed from DINAMICA EGO looks more realistic than bulky patches of LCM.(Figure 8)

3.3 Simulated LULC of 2025, 2030 and 2030 using DINAMICA EGO and LCM

The change pattern in both model showed the plane valley areas in proximity to urban center are highly likely to convertible into buildup area where as mountainous surrounding areas are likely to remain same throughout the simulation period.

The trend shows that build up areas are increasing steadily, whereas, agricultural land and forest areas are decreasing. The result of change in water bodies are contrasting. This is because water bodies constitute only minor fraction of LULC and likelihood of misclassification of water bodies also higher due to grid size and width and area of stream. Among two methods, DINAMICA EGO gave more realistic pictures of future LULC.

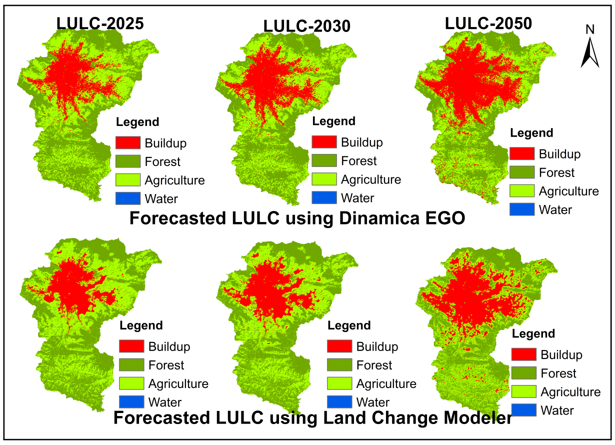

Figure 9: Simulated Future LULC of 2025, 2030 and 2050 using DINAMICA EGO and LCM

Result also shows that the surrounding mountainous regions of valley are less likely to convert other categories. The changes are only seen in the foot of the hill, where tendency of conversion of forest land to agricultural land is dominant. The majority of change of other categories of LULC to build up area can be seen in valley area. This drastic change of LULC could be result of flat land, existing road networks and nearer to existing settlements.

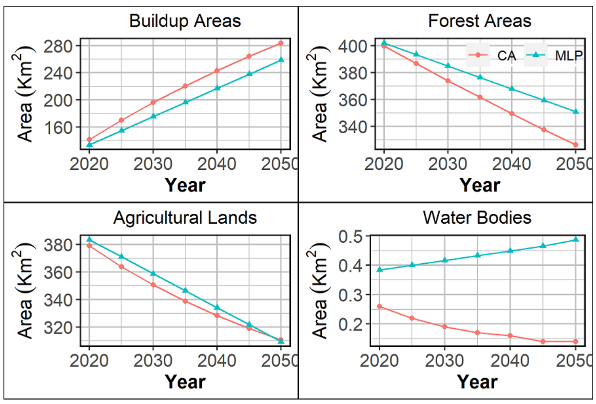

Figure 10: Trend of LULC change

4. Discussion and Conclusion

LULC map of 2005, 2015 and 2020 were prepared from remote sensed imagery and validated using Kappa statistics. Future LULC of different future period were simulated based on historical change pattern and different LULC change driving parameters. Projected LULC was evaluated using Error Matrix Module in IDRISI selva. The comparison of simulated LULC and prepared LULC of 2020 shows that Kappa coefficient for simulated map from LCM resulted in higher kappa coefficient.

The higher Kappa coefficient of LULC from LCM is due to model strictly restricts the quantity, extent, and magnitude of the appropriation of the changes in more susceptible area. Whereas Cellular Automata have the flexibility to occur a shift in moderate susceptible area. However, DINAMICA also have advantages in setting pruning factors in each transition to improve the model. It gives control of each transformation independently based on pruning factors. Different prune factors for different LULC categories allow changes to occur in some areas having medium susceptibility, and some transition occurs only in higher susceptibility. By doing so, most of the changes occur in the more likely locations other than those unexpected LULC changes that happen in the area, which is beyond the model's capability to predict. While interpreting the result of LULC modeling, it is imperative to look at the realism of forecasted LULC patterns. The model could give higher accuracy at the expense of realism. The incorporation of various factors of LULC change also plays a vital role in determining the future landscape. However, it is utterly tedious to incorporate all the variables. In this regard Cellular Automata showed more realistic projection. Projection of a realistic LULC map and spatial accuracy sometimes comes into conflict with each other. It also depends on the purpose we carry the modeling and modeling effort put forth. The unique qualities of the proposed maps can be critical. Based on the modeling requirement, the best fit between the modeled and the changes seems sensible for identifying areas that are likely to change in the future. However, the uncertainty involved with modeling a fuzzy map that shows the range of changes could express better prospects of the change.

Lamichhane & Shakya (2021)[23] studied LULC change of KV using the CLUE-S model. The study resulted in a growing buildup area by 21.3% in an expanse of reduction in forest and agricultural land by 20.4%. The outcomes of this study showed a similar trend of LULC change. However, because of consideration of the extensive area in this study (920 km^2) could have resulted different transition potential resulting in difference in rate of expansion of urban area.

LULC patterns can be essential when LULC models apply to phenomenon when the composition of a LULC involves. It influences the hydrological processes such as runoff, infiltration, evaporation, time of concentration. Hence LULC modeling for future scenarios is not always essential to spatial accuracy of LULC forecast, but forecasting accurate patch placement and appearances represent fundamental importance. However, the accuracy assessment of projected LULC for the future period depends on the model's ability to exactly replicate the spatial location of changes. It gives good information but does not capture patterns of change that could be important parameters to assess the model's performance. We could further improve the result by integrating social parameters like population growth, distance from basic infrastructures such as hospitals, schools, etc. Additional information, such as government policies and intervention, would expect to enhance results.

The simulated future LULC's can be utilized for future study of change in the stream-flow characteristics of the basin,[24] impact on microclimate and extreme precipitation because of urban heat island effect,[25] study of alteration of groundwater recharge area [26], change in water quality, [27] etc.

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