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Land use and Land Cover Change Modelling using CA-Markov Case Study: Deforestation Analysis of Doon Valley

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Abstract—*In this paper, the modelling of land use change for Doon valley was done. The modelling was begun with known land use at two different periods (2006 and 2013) and used them to project and model change into the future (2020). The two techniques used to model land use change are Markov Chain Analysis and Cellular Automata Analysis. This transition probability matrix was developed to show the land use land cover change from 2006 to 2013, which was used to predict for 2020. The transition probabilities was accurate on a per category basis, but there was lack of knowledge of the spatial distribution about the instances within each land use category, i.e., there was no spatial component in the modelling outcome. Cellular automata (CA) helped to add character which had been spatially distributed to the model. CA_Markov was used to 'grow out' land use from 2013 to 2020 along with contiguity filter. In essence, the CA filter would develop a spatially-explicit weighting factor which would be applied to each of the suitabilities, measuring more heavily areas that were close to existing land uses. This ensured that land use change occurs proximate to existing land use classes, and not wholly random. The model was validated with 1999 LULC MAP and 2006 LULC MAP, and 2013 LULC MAP was predicted. The predicted 2013 LULC MAP was compared with actual 2013 LULC MAP which gave a comparable result with an overall error of 0.019%. The final predicted 2020 LULC MAP showed an overall increase in agricultural land, fallow land and vacant land by 124.42%, 0.77% and 3.77% respectively, and an overall decrease in forest land and waterbody by 15.20% and 17.32% respectively. The analysis of the data and generation of prediction map had been accomplished through CA_Markov process.*

1. INTRODUCTION

Land use and land cover are two basic elements to comprehend the status of land globally. These elements are dynamic in nature and hence require regular monitoring for sustainable environment (Reveshty, 2011). The major cause of loss is biodiversity is the change in land use and land cover and its associated environments (Sala et al., 2000). This kind of change is usually the resultant of not only human activities (like deforestation, intensive agriculture, degradation of land, etc.) but also natural factors (Lambin, 1997). Geographic information science (GIS) along with remote sensing techniques form a powerful method to detect the change in land use and land cover (LULC). This method also provides the information on the LULC change that has occurred (Yuan et al. 2005). LULC change detection and modelling is one of the major work in the geo-spatial world. There exist many modelling tools due to the variability in the methods of LULC change models. Among all the tools available, the vastly used models are the Cellular Automata Markov (CA_Markov), GEOMOD, Markov chain, etc. (Prakasam, 2010).

According to the context, the estimation of land cover change is very much required over the period of time and also predict the future status of the Doon Valley, of the state of Uttarakh and in India, due to the faster increase in population in this region. In this study, an analysis has been performed by a Land Change Modeler (LCM) method on remotely sensed images. Supported on the previous trend (1999 – 2013) of land cover changes, the prediction map of land cover changes at 2020 has generated of the Doon Valley region. The results show that there will be significant change in some of the land use and land cover classes, which may pose threats to the environment. This procedural study can be used in development of sustainable environment.

2. STUDY AREA

The Doon Valley is a long and wide valley within the Shivalik Hills of Himalayas, in the state of Uttarakhand, India. Dehradun, the capital of Uttarakhand state, lies in the valley. The Doon valley is situated in between two ranges of the Himalayas. It has boundary of mountain ranges on all sides, with one range gives a boundary in a semi-circular arc from the west to the east; and another at the southern part of the valley covering from Poanta Sahib to Haridwar. The valley also has a watershed for the Yamuna and Ganges river systems. The rivers Yamuna and Ganges are closest to one another as they pass through the valley, with the western boundary being created by the Yamuna and the eastern by the Ganges. It comprises of varied LULC including dense forest land, open forest land agricultural land, fallow land, vacant land, and water bodies. Much of the forests and wetlands, however have been removed as a result of agricultural expansion and for the development of residential area.

3. DATA SET AND PREPARATION

In this study, we selected Landsat ETM+ images pertaining to the years 1999, 2006 and 2013 for LULC mapping. For model validation 1999 dataset was used. The study area were extracted from the acquired satellite images using LULC boundary generated with the help of ERDAS. We used UTM coordinate system with zone 43 north and datum WGS for satellite images. A broad level of classification has been obtained as a classification schemed was developed, and hence has been used to derive various LULC classes, i.e., Agriculture, Dense forest, Open Forest, Fallow Land, Vacant land and Water Bodies. An unsupervised classification method was used for LULC classification was for years 1999, 2006 and 2013 (figs. below). A high degree of objectivity has been achieved through an unsupervised classification approach allowing spectral clustering. Classification accuracy assessment was performed for each LULC maps. CA–Markov model was employed to predict future LULC dynamics using land allocation and multi-criteria decision-making approach. This task was accomplished by using IDRISI software package developed in Clark Labs, Worcester, Mass.

Fig. 1: Showing location of Doon Valley

4. METHODOLOGY

4.1 Multi–Criteria Evaluation Technique

To find a solution that can accomplish all the goals simultaneously for cumulative problems of LULC is really challenging and quite impossible. Hence, the judgement that need to be taken in general include selection of site or decisions related to allocation of land that fulfil various goals, each subject to its own favorable criteria for conversion of land (Soe and Le, 2006). The aforesaid goal can be achieved an approach of multi-criteria evaluation technique has been adopted. This technique deals with states of things in which a decision maker faces multiple criteria that are incompatible to each other or a situation that has a number of decision makers and decision to be considered is in unanimous of all decision-makers (Ademiluyi and Otun 2009). Here, all decisions considered were of biophysical data of LULC through multi-criteria evaluation (MCE) technique and CA_Markov.

4.2 Markov chain and Cellular Automata:

In this work, as we begin with known land use at two different periods and with the help of those the prediction and modelling of the change for a future is done. The techniques used for this work are Markov Chain analysis along with Cellular Automata (CA) analysis. Markov chain analysis is a suitable tool for land use change modelling where the processes and changes are inconvenient to describe. A Markovian method a process of predicting the future state from an immediate preceding state. Markov chain analysis describes LULC change from a period to another and on the basis of the change predicts a future period for LULC. This is achieved by creating a transition matrix of LULC change from one period to another, which helps to project the change of a future period. Besides, the accuracy of the transition probabilities may be high on a per class category, but there is lack of knowledge of occurrences' spatial distribution within each class of LULC, which denotes that there is lack of spatial element in the outcome of the models. So, to add the spatial element to the model Cellular Automata (CA) is used. CA_Markov process combines CA and Markov Chain LULC prediction methods. It is an extended version of MCE techniques. Here, the outputs of the Markov chain analysis, mainly the Transition Area Matrix files is used by CA_Markov along with contiguity filter to get the change from period two to a period in future. The 2006 LULC map of Doon Valley was used as the base map while 2013 LULC map as the later in Markov model. This was used to get the transition area matrix between 2006 and 2013, and hence used to predict the LULC of 2020. CA_Markov model was used, wherein the transition area files were obtained from the Markov Chain analysis of 2006 and 2013.

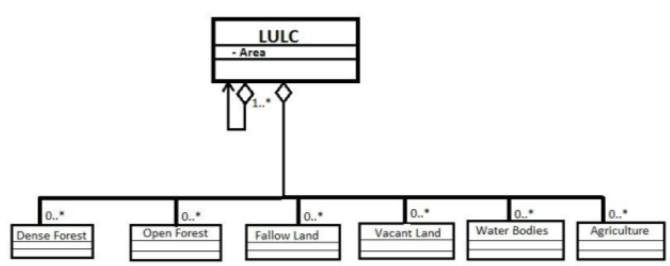

Fig. 2: UML for model building

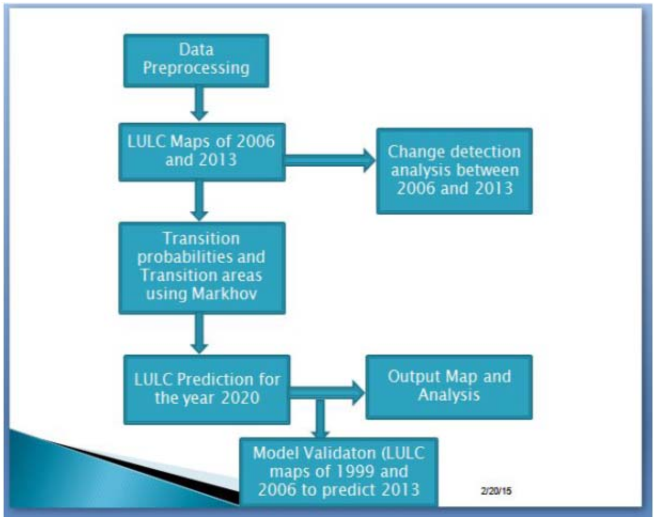

Fig. 3: Flow diagram of the methodology

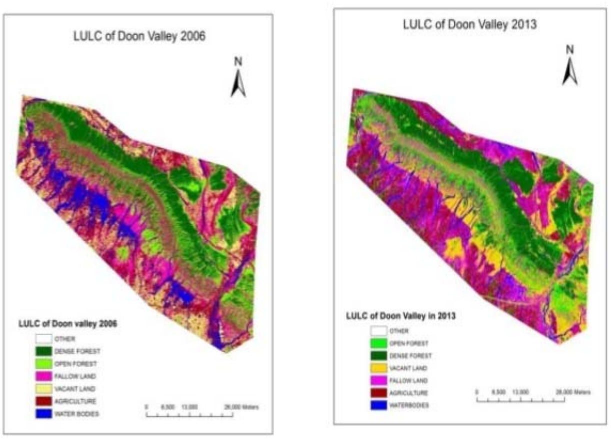

Fig. 4: Classified LULC maps for 2006 and 2013 for change detection.

The weights were assigned to different drivers in accordance of their importance, thus addressing the LULC trend of the past to predict the future. According to the weights which were allocated to the drivers, the maps of each LULC were produced while using MCE that concludes the inheritance of each pixel for a particular class in the LULC.

5. RESULTS AND DISCUSSION

Table 1: Change analysis of LULC from 2006 to 2013

LULC type	Area(sq.km) 2006	Area(sq.km) 2013	Change %
Agriculture	143.30	357.33	149.35
Open forest	818.33	498.48	-39.07
Dense forest	916.86	1033.17	12.68
Fallow land	812.86	981.96	20.80
Vacant land	445.44	960.30	115.58
Waterbody	401.78	284.16	-29.27

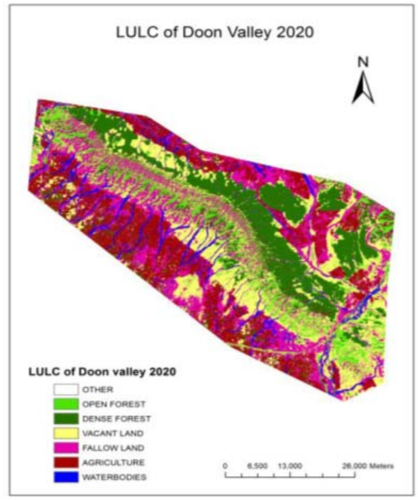

Fig. 5: Predicted LULC for the year 2020.

Above analysis clearly shows the indication of deforestation between the periods of 2006 and 2013 with the decrease in open forest and increase in fallow land and vacant land. Hence with this assumption LULC of 2020 is predicted.

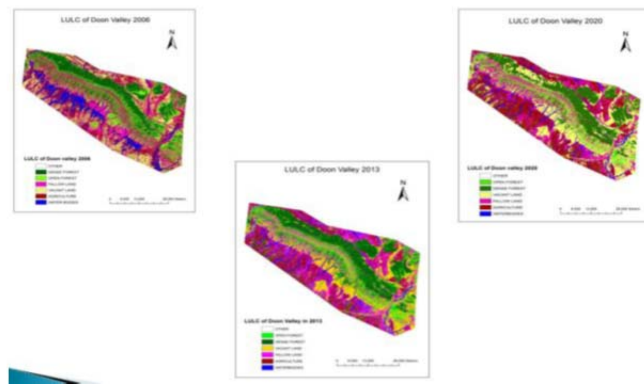

Fig. 6: LULC images obtained for different years

Table 2: LULC change analysis from 2013 to 2020

LULC type	Area(sq.km) 2013	Area(sq.km) 2020
Agriculture	357.33	801.94
Open forest	498.48	419.73
Dense forest	1033.17	879.09
Fallow land	981.96	989.52
Vacant land	960.30	996.48
Waterbody	284.16	234.93

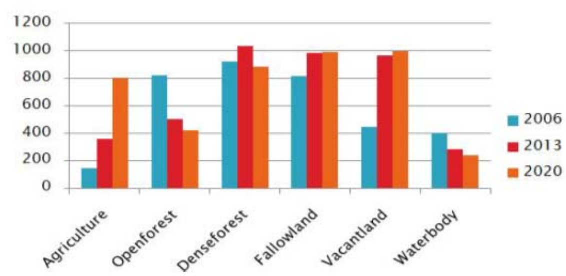

Fig. 7: LULC changes for years from 2006 to 2020

The resultant images of LULC and their analysis was shown in this section. The LULC images for the years 2006 and 2013 along with the future map of 2020 are presented in the above figs. (Fig.5 and Fig. 6). Table 1 and table 2 shows the overall LULC change analysis between the years 2006 and 2020. This study showed that agricultural field expansion (due to increase in population, development of residential areas) is the main and important driving force for loss of forest, wetland and vacant land in the total LULC and has the potential to continue in future.

Table 3: LULC change analysis from 2006 to 2020

LULC type	Area(sq.km) 2006	Area(sq.km) 2020	Change (sq. km)
Agriculture	143.30	801.94	658.64
Open forest	818.33	419.73	-398.60
Dense forest	916.86	879.09	-37.77
Fallow land	812.86	989.52	176.66
Vacant land	445.44	996.48	551.04
Waterbody	401.78	234.93	-166.85

5.1 Model Validation

The model was validated with 1999 LULC and 2006 LULC, so that we can predict 2013 which was later compared with the actual LULC of 2013. The actual and predicted areas of both LULC were compared which gave a reasonable result and gave a good confidence level that the predicted 2020 was predicted at a good level of accuracy.

Table 4: Area comparison of 2013 (actual and predicted)

LULC Types	Area(sq.km) of 2013 actual	Area(sq.km) of 2013 predicted
Agriculture	357.33	330.55
Open forest	498.48	534.87
Dense forest	1033.17	1002.27
Fallow land	981.96	959.46
Vacant land	960.30	878.74
Waterbody	284.16	410.33

The total actual area observed in 2013 is 4115.40 sq. km and the total area predicted from the model of 2013 is 4116.22 sq. km. The above result shows that the model is valid as the overall error percent is of 0.02%, which is negligible.

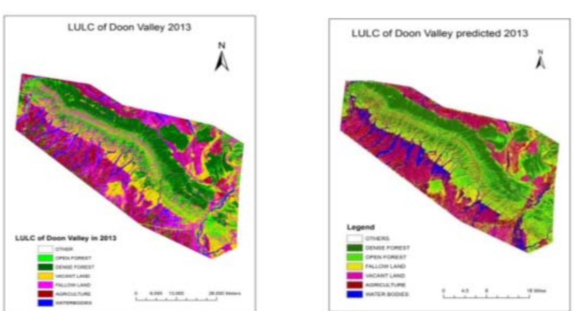

Fig. 8: Shows the overall LULC of 2013-actual (left) and the overall LULC of 2013-predicted (right).

Given : Probability of changing to :

	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6
Class 1 :	0.2726	0.6328	0.0649	0.0208	0.0064	0.0024
Class 2 :	0.1871	0.3470	0.3510	0.0759	0.0320	0.0070
Class 3 :	0.0701	0.0981	0.4732	0.2594	0.0766	0.0226
Class 4 :	0.0031	0.0841	0.0382	0.2845	0.5521	0.0380
Class 5 :	0.0250	0.0437	0.1708	0.4807	0.1806	0.0992
Class 6 :	0.0217	0.0125	0.0471	0.3565	0.1694	0.3928

Fig. 9: Shows the transition probability matrix

Class 1 → Agriculture; Class 2 → Open forest

Class 3 → Dense forest; Class 4 → Fallow land

Class 5 → Vacant land; Class 6 → Waterbody

6. CONCLUSION AND LIMITATIONS

In this work, the overall land use land cover of a growing Doon valley has been studied over a period of 14 years in the past (from 1999 to 2013) to predict the future forest cover of the region in the year 2020. Landsat satellite images of 1999, 2006 and 2013 are used to for this work. A total area of 4115.40 sq. km was taken into consideration as a study area. Land use land cover maps are developed in Q-GIS along with the database and other fractional portions for queries are done on postgresql with PostGIS. The forest cover change was visualized in Q-GIS using PostgreSQL with PostGIS by using the vector data of the cover areas. The future prediction model of land use and land cover was accomplished by using Land Change Modeller of IDRISI Selva. The results show that forest area of Doon Valley has decreased overall from 1735.19 sq. km in 2006 to 1531.65 sq. km in 2013 and finally 1298.82 sq. km in 2020. The percentage decrease in forest area in 2006 to 2020 is 11.73% and that from 2006 to 2020 is 25.14%. An accuracy of more than 90% was obtained for all the classes, except that of the class waterbody which shows an accuracy of nearly 70% in the validation model. But, there is a significant increase of dense forest area from 2006 to 2013 of 116.31 sq. km and decrease in area of dense forest in the period from 2013 to 2020 of 154.08 sq. km.

The result indicates that in 2020 there will be 55 % increase in agricultural land which will be the result of decrease in 15% of dense forest and further 3% decrease in open forest when compared with 2013 LULC data.

The accuracy of the results should be analyzed properly as Cellular Automata analysis and Markov chain analysis are stochastic techniques and are dependent on a probability function. Model validation has been performed but as unsupervised classification was performed so some pixels can be interpreted into other classes, whereas it might have been in some other class.

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