

Land use / Land Cover Change Detection and Forecasting using GEE and Hybrid Markov-CA Model in the Nainital District of Uttarakhand State, India

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Abstract

Analyzing and predicting changes in land use/ land cover (LU/LC) is a very essential study for decision makers to manage and control environmental sustainability by assessing the effects of global climate change. This study, aims to evaluate LULC changes in the last two decades from 2000 to 2020, as well as, to predict land cover changes in 2030 using Google Earth Engine and IDRISI software. Random Forest classification scheme in GEE is used for classifying land covers. Based upon 2000 and 2010 classified maps, the “transition probability” matrix is determined by using IDRISI SILVA 17.0 software. The Markov-CA integrated method in IDRISI is used to predict 2020 LULC pattern and it is validated by actual LU/LC classified map of 2020 with a kappa index of 0.93. Finally, the LU/LC map of 2030 is predicted to analyze land cover changes for controlling and monitoring environment sustainability. Based on the results of the current analysis, Nainital, a district of Uttarakhand State, India has undergone a significant increase in urban area and agricultural area particularly in west and south direction (plain region of study area), whereas there is a sharp decrease in forest and waterbody area. In

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this aspect, Remote sensing (RS) methods and geographic information systems (GIS) are crucial tools that can be utilized to identify the driving elements linked with the surrounding environment that lead to altering climate and biodiversity loss.

Keywords

Google Earth Engine, LU/LC changes, Markov-CA, Random Forest, Remote sensing.

1. Introduction

The physical land type on the earth's surface is indicated by the land cover, which includes forest, agriculture, water bodies etc. An alteration to the Earth's surface caused by human activity is called a land use /land cover (LU/LC) change. Human being shifts from rural areas to city for better education, good health facilities, employment and comfortable living. This process of shifting leads to urbanization. This urbanization has resulted negative effects on society, the economy, and the environment [1]. So it is very important for academics and policymakers worldwide to monitor and reduce the negative consequences of LU/LC changes for several management and scheduling tasks [2].

Land cover classification is essential for identifying changes, planning for urbanization, mapping and observing the distribution of land cover on the surface of the globe [3]. Machine learning classifier that gives highest accuracy is always in demand in order to get accurate land use land cover classification of hyperspectral remote sensing data. In recent time, web based powerful user friendly and open-source cloud computing tool such as Google earth engine (GEE) is widely used for reliable land cover classification of LANDSAT data. In recent times, GEE and machine learning algorithms have gained appeal in a variety of satellite data applications, including LU/LC categorization, deforestation, drought, agricultural monitoring, hydrology and land cover mapping and monitoring, and environmental protection [4]. Users of GEE can assess all publicly accessible, large volumes of LANDSAT and SENTINEL data without needing to download it to their personal computer [5].

In remote sensing land cover classification, random forest is the most popular algorithm [6]. Random Forest is a non-parametric machine learning classifier that can be used to classify heterogeneous areas. The number of trees (m-tree) and the number of split variables (n-tree) are the only two input parameters that must be chosen by the user, making RF a straightforward classifier to use [7]. Several studies have discovered that the accuracy of conventional land cover classification systems suffers from a number of limitations [8, 9]. Numerous

investigations have revealed that among the six different machine learning classifiers, RF and SVM have the highest overall accuracy [7].

Geographic information systems (GIS) and remote sensing (RS) give crucial tools in providing precise and up-to-date LU/LC data as well as analysing patterns in a study area [8]. Nainital, a district of Uttarakhand State, India has experienced considerable built-up growth during the past 20 years after forming a new state, Uttarakhand in 2000. Due to this, urban sprawl has occurred, with detrimental social, economic, and environmental effects [1]. Therefore, it is crucial for policymakers to examine LULC changes in the past and present in order to understand the factors that contribute to environmental changes and to consider potential remedial action [10].

The Cellular automata (CA)-Markov model has been used in a number of studies to anticipate past and present land cover changes, which helps land use planners and policy makers make decisions about potential land use concerns such as changes in ecosystems, urbanization, environmental and risk assessment [10,11,12,13,14,15]. Therefore, it is crucial for decision makers to examine land use land cover changes in the present past and future in order to understand the factors that contribute to environmental changes and to corrective action for [10].

A combination of the Cellular Automata and Markov models is known as CA-Markov model. Forecasting of LU/LC trends and side effect of urbanization can be studied using the CA-Markov model in TerrSet software, especially in places that are developing quickly [16]. The CA-Markov model is frequently used to produce the transition probability matrix from two different time periods derived land cover maps. In GIS investigations of changes in land-use and land-cover, transition probability matrices are frequently employed to objectively quantify the pace of change.

This research aims to detect the LU/LC change from 2000 to 2020 with its driving factors and to predict LU/LC pattern in 2030 by using powerful tools Google Earth Engine and IDRISI software in the study area. The Nainital district extends over 4250 sq. km and geographically it is divided into two regions viz. plain and hilly. The Nainital district's sustainability particularly in south and west direction (plain region of Nainital District such as Haldwani and Ramnagar etc.) may face difficulties due to the increasing small-scale industrialization and urbanization. Previous research revealed a number of issues with data quality, classifier accuracy and data validation. Additionally, it appears from the literature that no research has

been done to look into changes in LU/LC patterns and their prediction in the study area [20]. Finally, machine learning Random Forest classifier is used to get high accuracy. The results of the study are used to identify the critical elements that affect LU/LC dynamics and improve land use policy for sustainable land use planning and development.

2. Material and Method

2.1 Study area

Nainital, a district of Uttarakhand State, India (Figure 1), has been carried out due to the diversified topography. Nainital is situated in the Kumaun division of Uttarakhand, India. The Nainital district is bordered by the Almora district to the north and the Udham Singh Nagar district to the south. Its three neighbouring districts are Pauri Gahwal on the west, Udham Singh Nagar in the south, and Champawat on the east. Its latitudes are $29^{\circ} 00'$ and $29^{\circ} 05'$ north and its longitudes are $80^{\circ} 14'$ and $78^{\circ} 80'$ east. As per 2011 census it extends over 4251 sq km. On the northern side are the Himalayan Mountain ranges, and on the southern side are the plains. For the most part, forests surround the Nainital district. The largest amount of forest is found in the Nainital district in the Indian state of Uttarakhand. There are areas of very dense, moderately dense, and open forest, as well as urban areas, water bodies, agricultural areas, and arid territory. India's Uttarakhand state's Nainital district is well known for its lakes. Nainital District consists of hilly and plain region. Flapping and steep topography are included in this district. Plain region is mostly bounded by agriculture and built –up area. Hilly region is mostly bounded by Forests.

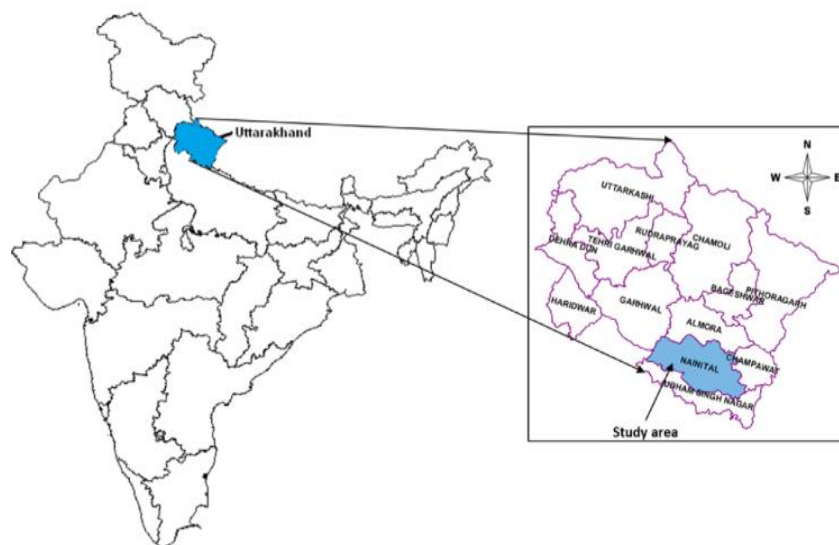


Fig.1 The study region is shown on a map as the Nainital District in Uttarakhand, India.

2.2 Data used

Two LANDSAT 5 (TM) images of the months of April in the years 2000, 2010 and one LANDSAT 8 image of the month April, 2020 with path 145 and row 40 (Datum : WGS84 and UTM zone: 44) are received from USGS (<http://earthexplorer.usgs.gov/>). Visible band combination of 3, 4 and 5 were used for LANDSAT 5 and 4, 5, 6 are used for LANDSAT 8. Using a machine learning Random Forest classifier in Google Earth Engine (GEE), these images were classified into five different LULC classes such as water bodies, urban area, barren land, agriculture and forest. For the accuracy evaluation, the kappa statistics, overall accuracy, user's accuracy and producer's accuracy were calculated.

2.3 Methodology

Workflow chart is shown as in Fig.2. LANDSAT images the years 2000, 2010 and 2020 were received from USGS (<http://earthexplorer.usgs.gov/>). India Districts Shapefile downloaded from <https://www.igismap.com> was used to create subset (study area). In Google Earth Engine by using machine learning Random Forest classifier, these images were classified into five different LU/LC classes such as water bodies, urban area, barren land, agriculture and forest. For the accuracy evaluation, the kappa statistics, overall accuracy, user's accuracy and producer's accuracy were calculated. Simulated classified LU/LC maps of 2000 and 2010 were used to predict 2020 LULC map in IDRISI SILVA 17.0 software using Markov model. Finally 2010 and 2020 classified maps were used to predict 2030 map in IDRISI SILVA 17.0 software using hybrid CA-Markov model.

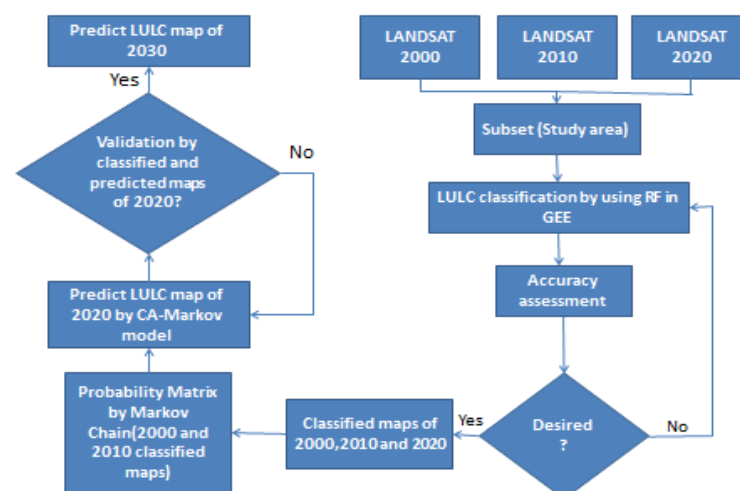


Fig. 2 Workflow chart used in this study.

2.4 Markov model for LULC changes

Past and present LU/LC changes are identified to predict future LU/LC patterns in order to manage and control environmental sustainability by measuring the consequences of global climate change. Markov chain model was utilised to accomplish this in an efficient manner. A good method for predicting future LU/LC pattern in a heterogeneous landscape is the Markov model. The transition probability matrix from the generated land cover maps of two different time periods is typically produced using the Markov model. Forecasting future state requires a system to transition from one state to another state. This change from one state to another is represented by the transition probability matrix written as follows:

$$PM = PM_{ij}$$

$$= \begin{bmatrix} PM_{11} & PM_{12} & PM_{13} & PM_{14} & \dots & PM_{1n} \\ PM_{21} & PM_{22} & PM_{23} & PM_{24} & \dots & PM_{2n} \\ PM_{31} & PM_{32} & PM_{33} & PM_{34} & \dots & PM_{3n} \\ PM_{41} & PM_{42} & PM_{43} & PM_{44} & \dots & PM_{4n} \\ PM_{51} & PM_{52} & PM_{53} & PM_{54} & \dots & PM_{5n} \end{bmatrix} \quad (1)$$

Where PM is the probability of moving from one state (i) to another (j). The features of a transition probability matrix include the following [17]:

- It is a square matrix.
- All elements of transition probability matrix are values between 0 and 1.
- The total of each element in a row must equal one.

$$S_{t+1} = PM_{ij} \times S_t \quad (2)$$

Where PM_{ij} is the transition probability matrix. S_{t+1} and S_t is land use status matrix at $t+1$ time and t time [18].

2.5 Markov-CA model

The Markov-CA model combines cellular automata with a transition probability matrix that is produced by Markov model. Cellular Automata is a dynamic process model that is used for the land use land cover changes in a heterogeneous landscape. It is frequently used model for projecting future LU/LC pattern with the help of existing past simulated past maps.

2.6 Validation of the model

In this first of all classified maps of 2000, 2010 and 2020 are obtained by using RF classifier. In order to get transition probability matrix 2000 and 2010 classified maps were used in Markov chain model. With the help of 2000 and 2010 classified map, 2020 maps was predicted using

CA-Markov chain model. Finally 2020 classified map and projected map was compared for further validation and testing of model. After successful validation of 2020 maps, 2030 map was predicted in order to understand the elements that influence environmental change to take corrective action for land cover changes.

3. Result and Discussion

3.1 LULC Classification

A tree-based classifier called RF is flexible enough to handle both random and systematic categorization. The study area was divided into five different land cover classes such as water bodies, built-up area, forest, agriculture and barren land using RF machine learning classifier in Google Earth Engine (GEE). Figure 3 displays the classified output maps for each LANDSAT image. For the classified LULC maps, an accuracy evaluation was done.

Table 1 Performance metrics for each LU/LC class in year 2000, 2010 and 2020 when RF Learning Algorithm was employed.

Year	LULC Class	UA (%)	PA (%)	OA (%)& KC
2000	Water Bodies	95.42	93.76	94.8% & .92
	Urban Area	97.35	94.91	
	Barren Land	85.12	86.58	
	Agriculture	96.44	97.34	
	Forest	98.48	96.49	
2010	Water Bodies	93.18	91.95	92.79% & .91
	Urban Area	94.96	95.76	
	Barren Land	87.84	89.24	
	Agriculture	98.82	96.35	
	Forest	96.67	95.82	
2020	Water Bodies	92.9	92.78	90.84% & .93

	Urban Area	95.10	96.72	
	Barren Land	86.38	85.79	
	Agriculture	92.48	95.25	
	Forest	97.16	97.78	

Overall classifier accuracy (OA) shows that nearly all reference sites were accurately identified. The Kappa coefficient (KC), which is a recommended method in the literature for measuring and comparing picture categorization accuracy, is used [19, 21]. Calculated producer's accuracy (PA) and user's accuracy (UA) values of each land cover class were shown in Table 1. The PA of all classified map for each class was more than 85%. Forest and agriculture had more than 95% PA for each year classified map. In 2000 classified map Forest had 98.48 % UA.

3.2 Land use Land cover change detection in the research area

The area and percentage area of each land cover class in the study area from 2000 to 2020 were shown in table 2. Analysing the data in Table 2 revealed that the Nainital district is mostly covered by forest (70%). The urban area was increased from 72.98 sq.km in 2000 to 131.08 sq. km in 2020. It indicates that after forming a new state Uttarakhand in 2000 from Uttar Pradesh, small scale industry and built-up area were devolved in Ramnagar and Haldwani in last two decade.

Compared to other land cover classes, Nainital has the highest percentage of forest cover, the most likely cause of this is flapping and steep topography are included in this district. So this type of land cannot be used for farming and built-up purpose. Nainital district consists of hill region in north direction and plain region south direction. From figure 3 it is clear that built-up (urban area) and agriculture area were found in south direction of study area. It is because of small scale industry, transportation and education are developed in south and west direction of study area. Water body's area was decreased from 193.74 sq. km in 2000 to 164.5 sq. km in 2020. Urban area were increased from 72.98 sq. km in 2000 to 131.08 sq. km in 2020. This increase in built-up area could be due to the small scale industries, education and health development in the study area particularly in the south region of the study area (plain area such as Haldwani and Ramnagar). Barren land was increased over a period of 20 years. On the other hand agriculture area was increased from 407.74 sq. km to 445 sq. km in 2020.

Table 2 Areas and percentage of LULC from 2000 to 2020 classified map in the study area.

Land Cover Classes	2000		2010		2020	
	Area in sq. km	%	Area in sq. km	%	Area in sq. km	%
Water Bodies	193.74	4.55	173	4.07	164.5	3.87
Urban Area	72.98	1.71	102.58	2.41	131.08	3.08
Barren Land	528.54	12.43	546.94	12.86	537.44	12.64
Agriculture	405.74	9.54	387.74	9.12	445	10.47
Forest	3049	71.74	3039.74	71.52	2971.98	69.92
Total	4250	100	4250		4250	100

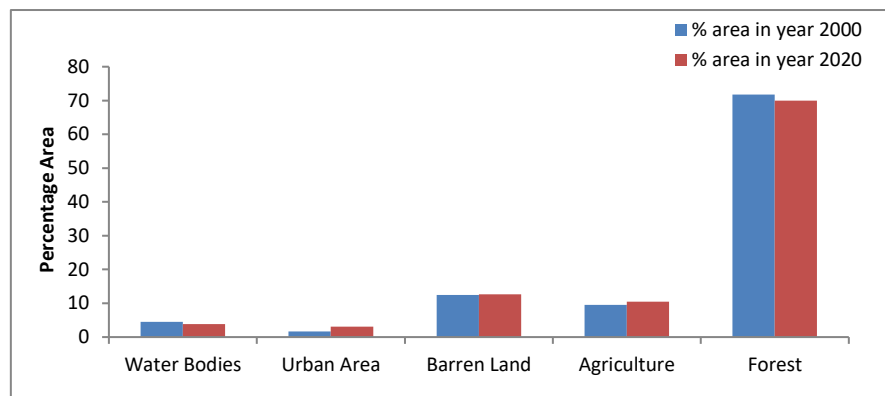
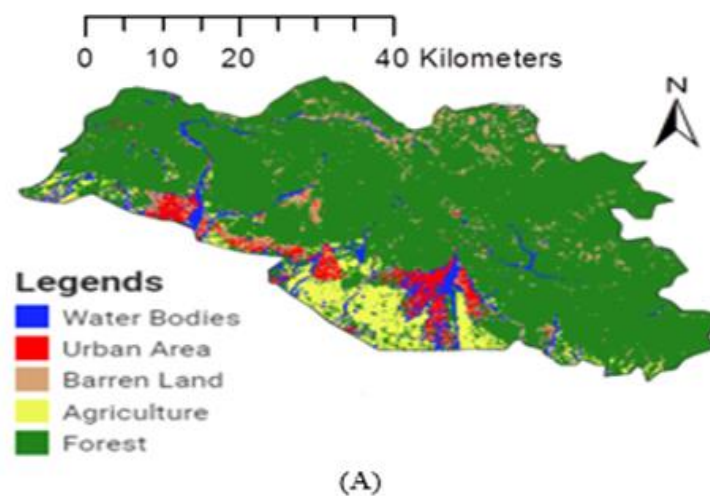


Fig.3 Areas and percentage area of LULC from 2000 to 2020 classified map in the research area.



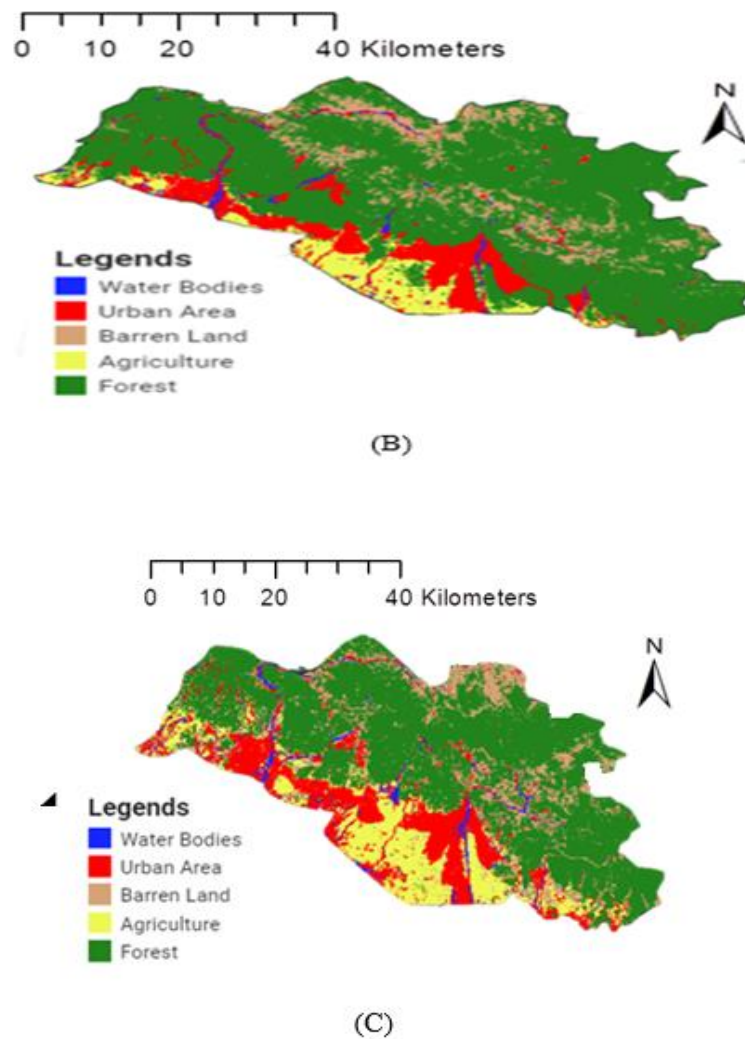


Fig.4 LU/LC classified maps (A) 2000, (B) 2010 and (C) 2020.

3.3 Markov chain Transition Probability matrix

Transition probability matrix provides the percentage likelihood that land use will change in the future for a specified duration. The transition matrix for time duration 2000 to 2010 is shown in table 3. It is anticipated that 14.6 percent of the area in 2000 covered by barren land will become urban area in 2010. From year 2000 to 2010 around 12 percent agriculture land is expected to be change into barren land. It's anticipated that urban areas will replace barren terrain in a ratio of about 14.6%. It's anticipated that water bodies will replace agriculture area in a ratio of about 6%. From 2000 to 2010, it is anticipated that 91% of the forest area would not change. The transition matrix for time duration 2010 to 2020 is shown in table 4. From year 2010 to 2020, it is anticipated that about 17 percent water bodies' area was expected to change in agriculture. At same time about 5.6 percent barren land area was expected to change in urban area.

Table 3 Transition probability matrix between several land cover types from 2000 to 2010.

Land cover class	Water Bodies	Urban Area	Barren Land	Agriculture	Forest
Water Bodies	0.808	0.101	0.023	0.068	0
Urban Area	0.006	0.836	0.091	0.008	0.059
Barren Land	0.005	0.146	0.612	0.125	0.111
Agriculture	0.016	0.054	0.120	0.806	0.004
Forest	0.001	0.024	0.005	0.058	0.912

Table 4 Transition probability matrix between several land cover types from 2010 to 2020

Land cover class	Water Bodies	Urban Area	Barren Land	Agriculture	Forest
Water Bodies	0.707	0.055	0.023	0.169	0.056
Urban Area	0.036	0.700	0.084	0.013	0.167
Barren Land	0.005	0.056	0.802	0.123	0.013
Agriculture	0.022	0.154	0.110	0.700	0.014
Forest	0.004	0.106	0.005	0.055	0.830

3.4 Predicted land use / land cover map in 2020 and 2030

Simulated classified LU/LC maps of 2000 and 2010 were used to predict the 2020 LU/LC map. In order to further anticipate maps and identify the driving forces linked with the environment, validation is a crucial element. Statistics were used to compare the quality of the predicted 2020 map (shown in figure 5) to the classified 2020 map using TerrSet's validation module. Kappa index was found more than 90 %. It indicates classified 2020 map is almost similar to predicted 2020 map therefore, future map can be projected. Finally, 2010 and 2020 classified maps were used to predict the 2030 map. 2030 predicted map was shown in figure 6. From Table 5 it is clear that, urban area has experienced a rapid change from 133 sq. km in 2020 to 209.08 sq. km in 2030. This expected change is experienced particularly in west and south direction of the study area (Haldwani and Ramnagar). Barren land and forest have minimal changes among all the five land cover classes. The significant decrease is expected in the water bodies from 2020 to 2030. Agriculture land is expected to increase from 2020 to 2030. This could be due to increasing population, food demand is increased in the study area.

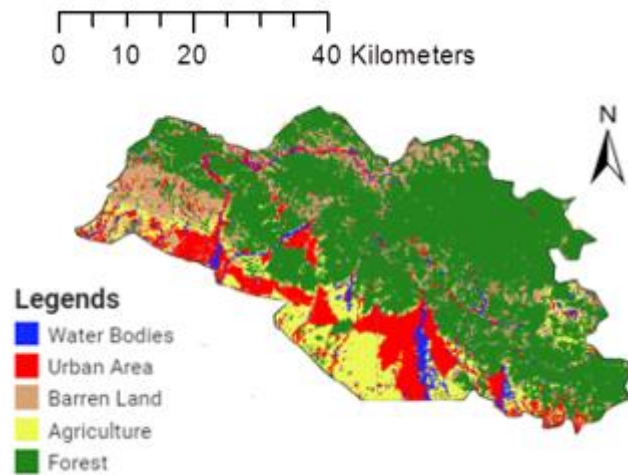


Fig. 5 LU/LC predicted of 2020.

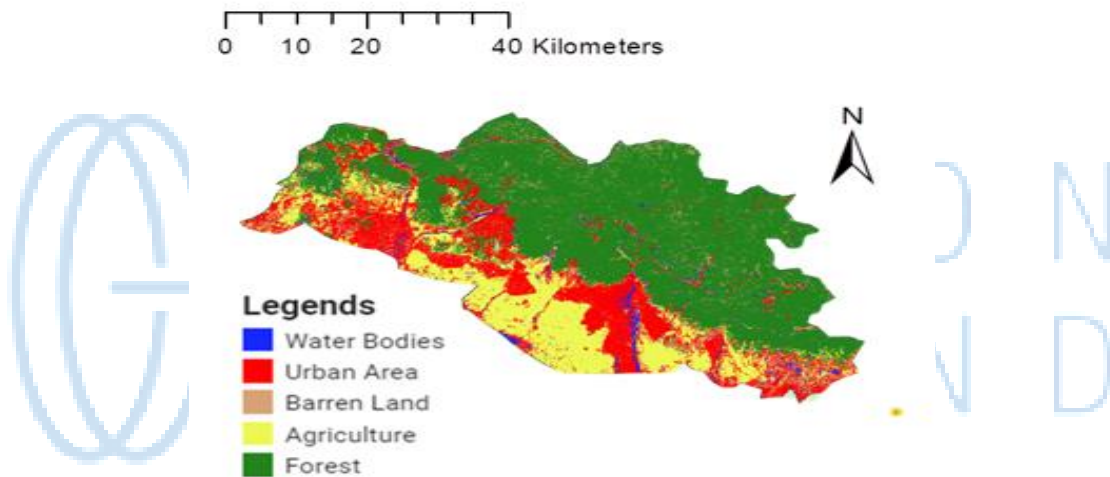


Fig.6 LU/LC predicted of 2030.

Table 5 Areas and percentage of LU/LC from 2020 and 2030 predicted maps.

Land Cove Classes	2020		2030	
	Area in sq. km	% change	Area in sq. km	% change
Water Bodies	165.98	3.9	102.5	2.41
Urban Area	133	3.12	209.08	4.91
Barren Land	544.07	12.8	537.45	12.64

Agriculture	450.45	10.59	500.32	11.77
Forest	2956.5	69.55	2900.65	68.25
Total	4250	100	4250	100

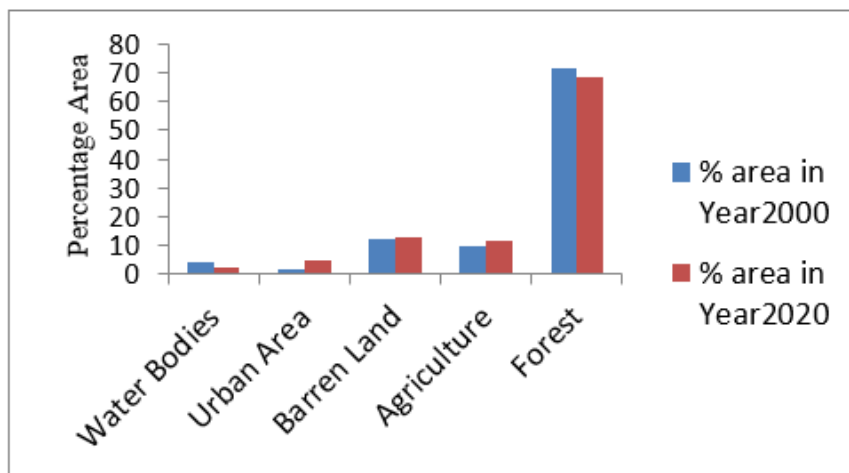


Fig.7 percentage area of LU/LC from 2000 to 2020 classified map in the study area.

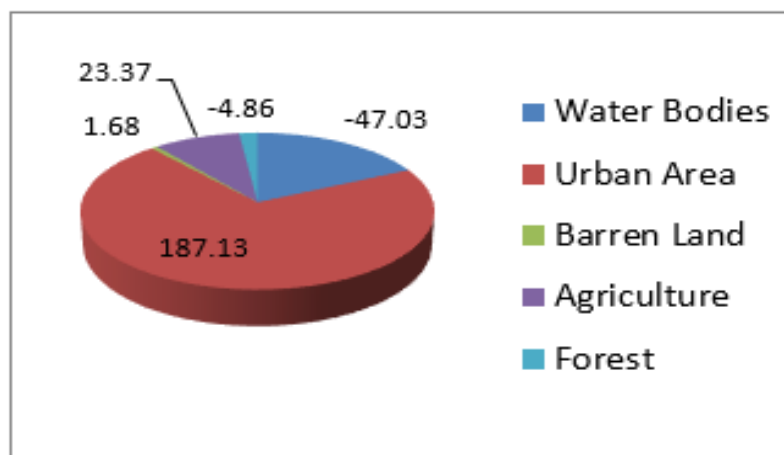


Fig.8 Percentage area change 2000 to 2030 in the study area.

Conclusions

The study determined the changes in LU/LC trends in the Nainital district from 2000 to 2020 when Uttarakhand state, India is separated from Uttar Pradesh state, India by using modern information processing tools GIS and RS. In addition to this markov-CA model could help in predicting future LU/LC changes. Based on the results of the simulated classified maps, the percentage of urban area increased quickly from 1.71% in 2000 to 3.08 % in 2020. It is because

of small scale industry, transportation and education are developed particularly in south and west direction of the study area. Forest declined by only 2 % throughout the research period, indicating, Compared to other land cover classes, Forest was not much converted into other land cover classes (particularly in north and east direction of study area). The most likely cause of this is flapping and steep topography included in north and east direction of Nainital district. So this type of land cannot be used for farming and built-up purpose. Agriculture area was increased from 9.54 % in 2000 to 10.47 % in 2020. This could be due to population pressure, food demand was increased in plain region of the study area. Water bodies were decreased from 4.55 % in 2000 to 3.87 % in 2020. On the other hand barren land was little bit increased from 12.43 % to 12.64 % from 2000 to 2020.

Based on the results of the classified map of 2000 and projected map of 2030 the percentage change of urban area was 187.13 % from 2000 to 2030. This could be as a result of increasing population, industrialisation, and settlement being made possible by clearing forest particularly in south and west direction of the study area. The land cover classes of forest and barren showed only minor changes in LU/LC.

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