

LAND USE / LAND COVER CHANGES IN SEMI-ARID MOUNTAIN LANDSCAPE IN SOUTHERN INDIA: A GEOINFORMATICS BASED MARKOV CHAIN APPROACH

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ABSTRACT:

Nowadays land use/ land cover in mountain landscape is in critical condition; it leads to high risky and uncertain environments. These areas are facing multiple stresses including degradation of land resources; vagaries of climate and depletion of water resources continuously affect land use practices and livelihoods. To understand the Land use/Land cover (Lu/Lc) changes in a semi-arid mountain landscape, Kallar watershed of Bhavani basin, in southern India has been chosen. Most of the hilly part in the study area covers with forest, plantation, orchards and vegetables and which are highly affected by severe soil erosion, landslide, frequent rainfall failures and associated drought. The foothill regions are mainly utilized for agriculture practices; due to water scarcity and meagre income, the productive agriculture lands are converted into settlement plots and wasteland. Hence, land use/land cover change deduction; a stochastic processed based method is indispensable for future prediction. For identification of land use/land cover, and vegetation changes, Landsat TM, ETM (1995, 2005) and IRS P6- LISS IV (2015) images were used. Through CA-Markov chain analysis, Lu/Lc changes in past three decades (1995, 2005, and 2015) were identified and projected for (2020 and 2025); Normalized Difference Vegetation Index (NDVI) were used to find the vegetation changes. The result shows that, maximum changes occur in the plantation and slight changes found in forest cover in the hilly terrain. In foothill areas, agriculture lands were decreased while wastelands and settlement plots were increased. The outcome of the results helps to farmer and policy makers to draw optimal lands use planning and better management strategies for sustainable development of natural resources.

1. INTRODUCTION

1.1 General Instructions

Globally, land use change impacts biodiversity, water and radiation budgets, emission of greenhouse gasses, carbon cycling, and livelihoods. The study of Land Use and Cover Change (LUCC) and its dynamics is crucial for environmental management, especially with regard to sustainable agriculture and forestry. Today, there is increased recognition that land use and land cover change (LULCC) is a major driver of global change, through its interaction with climate, ecosystem processes, biogeochemical cycles, biodiversity and even more importantly the human activities (NRC 1999). Changes in land cover (biophysical attributes of the earth's surface) and land use (human modified earth's surface) has been accelerating as a result of socio-economic and biophysical drivers (Turner et al. 1995; Lambin et al. 1999).

The analysis and modeling of LULC dynamics in a hydrological unit of a watershed provide understanding in totality. It is a two-way process when LULCC in watershed changes the performance characteristics of the watershed which includes the water infiltration rate, soil erosion rate, runoff, etc., and vice versa (Zhang et al. 2007). Improper practices of LULC including deforestation, uncontrolled and excessive grazing, expansion of agriculture, and infrastructure development are deteriorating watershed conditions (Bishaw 2001), at various temporal and spatial scales (Bisht and Tiwari 1996).

There are a lot of methods for land cover change detection such as image rationing, image difference, change vector analysis, image regression, composite analysis and post classification (Coppin et al., 2004). There are several methods for land cover and land use change modelling that includes mathematical equation based, system dynamic, statistical, expert system, evolutionary, cellular, and hybrid models. Cellular models (CM) include cellular automata (CA) and Markov models. In CA, each cell exists in one of a finite set of states, and future states depend on transition rules based on a local spatiotemporal neighbourhood (Parker, 2002).

Markov chain analysis is a convenient tool for modelling land cover and land use changes when changes and processes in the landscape are difficult to describe. Markov chains model is able to predict land use and land cover changes from one period to another and uses this as the basis to project future changes (Estmen, 1995). CA-Markov has the ability to simulate land use changes among multiple categories and combines the CA and Markov chain procedures (Estmen, 2003). Cellular Automata (CA) incorporates the spatial component (Soe and Le 2006) and thereby adds direction to modeling.

The aim of the study is to the prediction of land use and land cover map using CA-Markov model in the study area and investigation of validation maps by comparing land cover maps produced by a hybrid method of image classification and NDVI.

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2. MATERIALS AND METHODS

2.1 Study Area

The study area is located between 11°17'0" N to 11°31'0" N latitudes and 76° 39' 0" E to 77° 8' 45" E longitudes with an area of about 1,283 sq.km. Covering three districts, namely, The Nilgiris, Coimbatore, and Erode. It altogether covers 7 taluks such as Coonoor, Kothagiri, Udhamandalam, Mettupalayam, Coimbatore north, Annur, and Sathyamangalam with 79 Revenue villages, (Figure 1). The maximum and minimum elevation of the study area ranges from 177m to 2,615m above MSL, (Figure 2). About 50% of areas are mountains, covered with diverse plant communities that form various types of forest and hill farming like tea, coffee, vegetables, and orchards. The climate of this area is temperate and salubrious for more than half of the year. The average day temperature of the sub watershed fluctuates between 20°C and 30°C. The average rainfall is about more than 1,400 mm. The maximum rainfall is during the month of October and November. The winter is relatively cool. The Kallar streams flow from Southwest to Northeast and it connects the Bhavani River at Mettupalayam, which finally empties into Bhavanisagar Dam which lies in the north-eastern part of the watershed. Bhavanisagar Dam primarily serves as a source of irrigation and hydroelectric power generation. The area covered by clay soil, loamy soil and rock outcrop on steep to narrow sloping grounds. Geologically, the area is made up of granite and fissile hornblende-biotite gneiss. Geomorphologically, the watershed is characterized by structural hills, denudational hills, narrow gorges, and intermountain valleys.

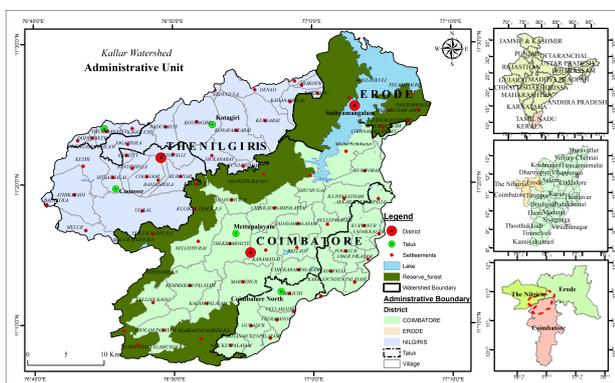


Figure 1. Study Area

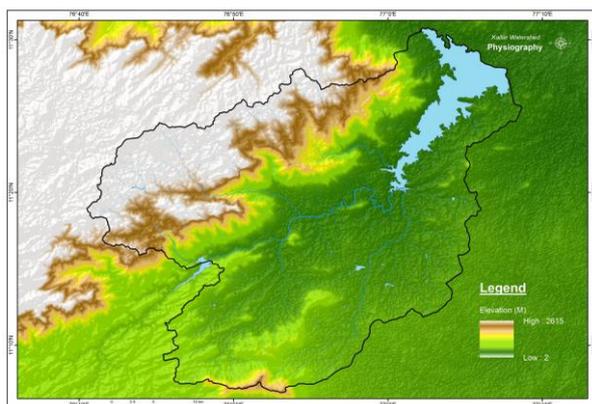


Figure 2. Physiography

2.2 Data Sets

Remote sensing data sets are playing a major role in the land use/land cover change deduction. In this study, following imageries were used to identify and predict the land use changes. Landsat TM and ETM (1995, 2005) images were collected from Global Land Cover Facility of the University of Maryland (USA). IRS P6- LISS IV (2015) image were purchased from the National Remote Sensing Centre (NRSC) under the aegis of Indian Space Research Organisation (ISRO).

Characteristics / Sensor	Date	Spatial Resolution
Landsat TM	23 Feb 1995	30m
Landsat ETM+	10 Feb 2005	30m
IRS P6 -LISS IV	16 Feb 2015	5.8m

Table 1. Satellite images used in this study

2.3 Methodology

The method involved in understanding the land use change and dynamics is as presented in Figure 3.

2.3.1 Pre-processing: The remote data obtained was geo-referenced, rectified and cropped according to the study area. The 1995 and 2005 images were previously geometrically and radiometrically corrected by USGS Earth Resource Observation Systems Data Centre (EROS) to a quality level of 1G. The 2015 IRS LISS IV image were geometrically and radiometrically corrected by NRSC to level 2 qualities.

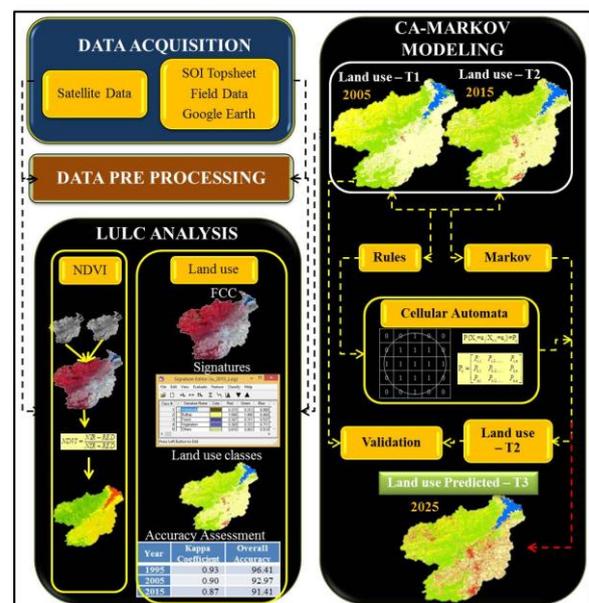


Figure 3. Land use change workflow

2.3.2 Land cover and Land use analysis: Land cover analysis was performed using Normalized Differential Vegetation Index (NDVI) to estimate the vegetation cover and to monitor the changes over time. It uses near-infrared and red region of the spectrum to calculate the vegetation cover. The value of NDVI ranges from -1 to +1. Very low values of NDVI (-0.1 and below) correspond to soil or barren areas of rock, sand, or urban built-up. Zero indicates the water bodies. Moderate values represent low-density vegetation (0.1-0.3), while high values indicate thick canopy vegetation (0.6-0.8).

Land use analysis was carried out using supervised classification method based on Gaussian maximum likelihood algorithm. This has been proved superior classifier as it uses various classification decisions using probability and cost functions (Ramachandra et al 2012). The mean and covariance matrix are computed using an estimate of maximum likelihood estimator.

3. LAND USE MODELING

3.1 Markov modeling of land use and land cover changes: Markov chains have been used to model changes in land use and land cover at a variety of spatial scales. Markov chain models have several assumptions (Parzen, 1962; Haan, 1977; Wang, 1986; Stewart, 1994). One basic assumption is to regard land use and land cover change as a stochastic process, and different categories are the states of a chain. A chain is defined as a stochastic process having the property that the value of the process at time t , X_t , depends only on its value at time $t-1$, X_{t-1} , and not on the sequence of values $X_{t-2}, X_{t-3}, \dots, X_0$ that the process passed through in arriving at X_{t-1} . It can be expressed as:

$$P\{X_t=a_j|X_0=a_0, X_1=a_1, \dots, X_{t-1}=a_i\} = P\{X_t=a_j|X_{t-1}=a_i\} \quad (1)$$

Moreover, it is convenient to regard the change process as one which is discrete in time ($t=0, 1, 2, \dots$).

The $P\{X_t=a_j|X_0=a_1, \dots, X_{t-1}=a_i\}$ known as the one-step transitional probability gives the probability that the process makes the transition from state a_i to state a_j in one time period. When ℓ steps are needed to implement this transition, the $P\{X_t=a_j|X_0=a_1, \dots, X_{t-1}=a_i\}$ is then called the ℓ step transition probability, $P_{ij}^{(\ell)}$. If the $P_{ij}^{(\ell)}$ is independent of times and dependent only upon states a_i, a_j , and ℓ , then the Markov chain is said to be homogeneous. The treatment of Markov chains in this study will be limited to first order homogeneous Markov chains. In this event:

$$P\{X_t=a_j|X_{t-1}=a_i\} = P_{ij} \quad (2)$$

where P_{ij} can be estimated from observed data by tabulating the number of times the observed data went from state i to j , n_{ij} , and by summing the number of times that state a_i occurred, n_i . Then

$$P_{ij} = n_{ij} / n_i \quad (3)$$

$$P_{ij} = \begin{bmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,n} \\ P_{2,1} & P_{2,2} & \dots & P_{2,n} \\ \dots & \dots & \dots & \dots \\ P_{n,1} & P_{n,2} & \dots & P_{n,n} \end{bmatrix} \quad (4)$$

and $(0 < P_{ij} < 1 \text{ and } \sum_{j=1}^n P_{ij} = 1, (i, j = 1, 2, \dots, n))$

P_{ij} is the matrix of transition probability in a state. The transition probability matrix can be used as an input for modelling land cover change. Markov analysis considers only the temporal changes occurred in the landscape. In order to obtain the spatial dynamics of the landscape, CA is integrated with Markov Chain.

Cellular Automata is a cell-based approach to model processes in a two-dimensional space. In CA, the state of a cell can

change only based on the transition rules and it gives the result of spatial modelling based on the transition rules. These rules control the transformation of a cell state to another cell state over the specific period of time depending on the neighborhood of the cells. A simple transition rule in a cellular automaton model is given by Li and Yeh (2000) as,

$$S^{t+1} \approx f(S^t, N) \quad (5)$$

With $s \in S$ (S set of all possible cell states like built-up or vegetation or open land, etc.). N is the neighbourhood of the cell, which acts as inputs for the transition rules. The function f defines the transition rules from time period t to $t + 1$. A cellular automaton is a cellular entity that independently varies its condition based on its previous state (according to a Markov transition rule) and adjacent neighbours (Eastman J.R, 2003). The following 5×5 contiguity filter was utilized in this work:

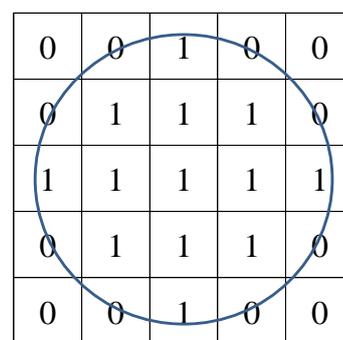


Figure 4: Circular CA Filter of 5 x 5 neighbourhoods

Thus CA-Markov model was used to visualize the land use changes for the year 2020, 2025.

4. RESULT AND DISCUSSION

CA- Markov based land use land cover change and dynamic analysis was carried out in the Kallar watershed.

4.1 Land cover analysis

In this study vegetation cover (land cover) were calculated through Normalized Differential Vegetation Index (NDVI) from 1995 to 2015. In the year 1995, NDVI ranges from -0.4 to 0.75, 67 % of the areas fall under the vegetation and 33% of the area in non-vegetation (Figure 5).

Followed by the year 2005, NDVI value from -0.95 to 0.57; it occupies 55.6% of vegetation covered areas and 44.4% non-vegetation areas (Figure 6), particularly 2004-05 is the driest (Drought) year in the southeastern part of the study area, based on the meteorological record; Periyayanakanpalaym receives a 00 mm of rainfall from June 2004 to 2005.

Year	Vegetation Area (in Ha)	Vegetation Area (in %)	Non-Vegetation Area (in Ha)	Non-Vegetation Area (in %)
1995	8599.91	67.0	4231.61	33.0
2005	7133.74	55.6	5698.02	44.4
2015	8077.60	62.9	4754.09	37.1

Table 2. Temporal Land Cover changes from 1995 to 2015

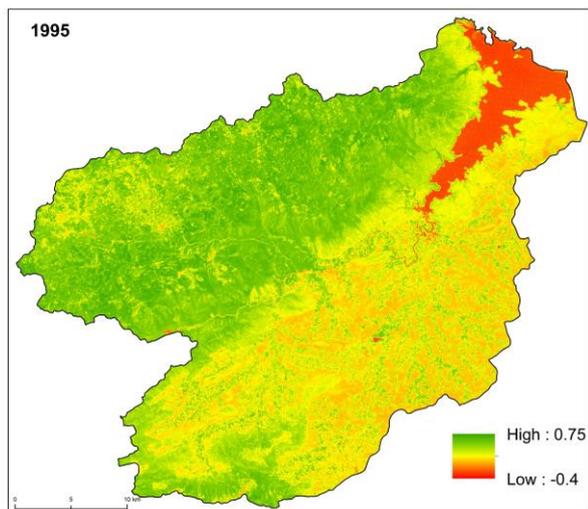


Figure 5: Land cover 1995

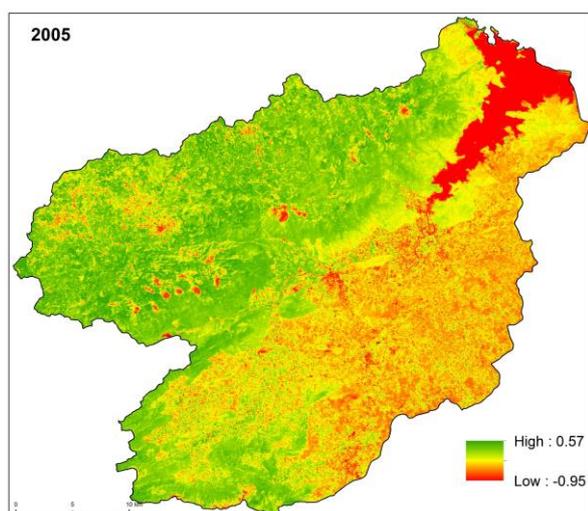


Figure 6: Land cover 2005

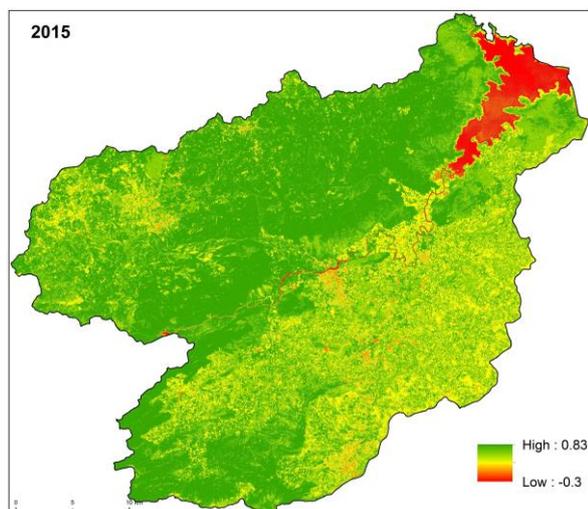


Figure 7: Land cover 2015

In the year 2015, NDVI range from -0.3 to 0.83, the vegetation area covers in 62.9% and non-vegetation covered in 37.1% (Figure 7). NDVI values (Table 2) Indicates that there is a sudden change in the year 2005 and a gradual increase in the

land cover non-vegetation area in the year 2015, compared to 1995.

4.2 Land use analysis

Land use analysis for the period 1995 to 2015 was carried out using supervised classification method based on Gaussian maximum likelihood algorithm. The satellite images were classified into five major types of land use classes; it includes Build up (urban, rural area, industrial area, and road), Forest (evergreen, deciduous), Vegetation (plantation, cropland), Water body (river, lake, and reservoir) and Others (fallow land, barren rock, quarry, and mining).

The temporal land use dynamics are given in Table 3. The build-up area has been increased from 3.2% in 1995 to 5.4% in 2015. Slight changes are seen in the forest cover area, 32.5% in 1995, 31.0 % in 2005 and 32.8% in 2015. The vegetation and water bodies shows a declined trend; vegetation area have decreased from 22.4 % in 1995 to 20.4 in 2015 and water bodies also have gradually decreased from 4.5% in 1995 and 3.4% in 2015. The decrease in vegetation and water bodies can be related to the increase in the wasteland (others). The others area classes have increased from 37.5% in 1995 to 38.15% in 2015. (Figure 8, 9, 10)

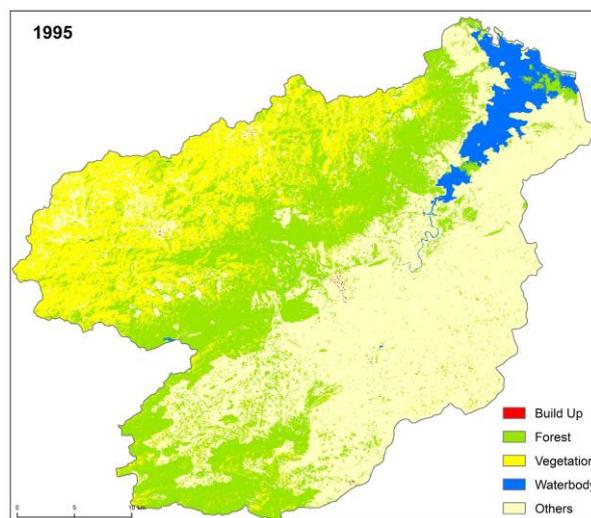


Figure 8: Land use 1995

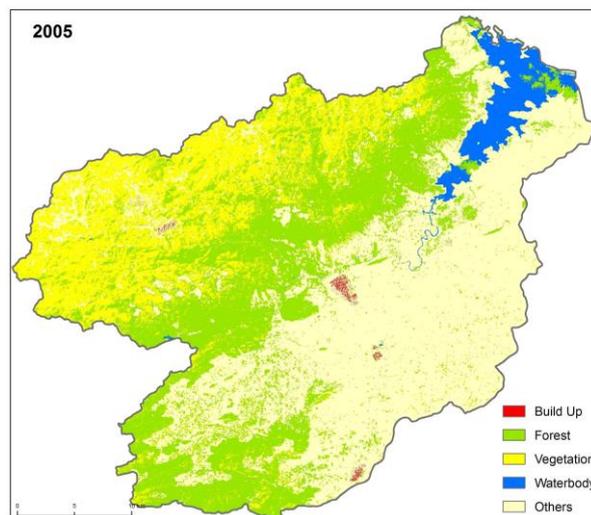


Figure 9: Land use 2005

Year	1995		2005		2015	
	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Area (%)
Build up	4120.5	3.2	5399.8	4.2	6906.9	5.4
Forest	41656.2	32.5	39808.1	31.0	42056.6	32.8
Vegetation	28748.7	22.4	27223.4	21.2	26147.7	20.4
Water Body	5714.6	4.5	4717.3	3.7	4323.9	3.4
Others	48077.7	37.5	51168.6	39.9	48882.5	38.1

Table 3. Temporal Land use changes from 1995 to 2015

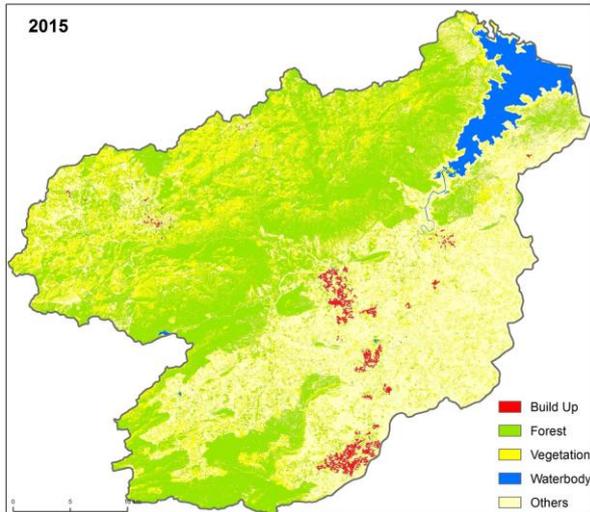


Figure 10: Land use 2015

The accuracy assessment of the classified information was performed using Kappa statistics and error matrix. The overall accuracy obtained for the classified images were 96.41%, 92.97%, and 91.41% in the year 1995, 2005, and 2015 respectively. Table 4 provides the overall accuracy and Kappa statistics of the classified data.

Year	Kappa Coefficient	Overall Accuracy
1995	0.93	96.41
2005	0.90	92.97
2015	0.87	91.41

Table 4. Kappa values and overall accuracy

Further, 2015 image was classified through hybrid method to know the detailed land use type in the study area (Table 4, Figure 11).

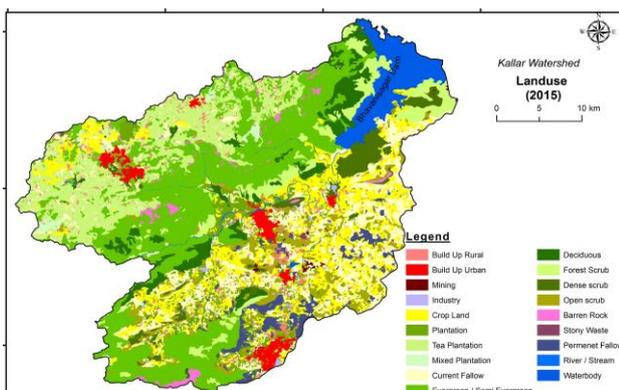


Figure 11: Land use (Hybrid) 2015

Land use Class	Area (Ha)	Area (%)
Barren Rock	1414.3	1.1
Build up Rural	2626.4	2.0
Build up Urban	2726.0	2.1
Crop Land	15580.4	12.1
Current Fallow	15630.5	12.2
Deciduous Forest	6170.3	4.8
Dense Scrub	3984.2	3.1
Evergreen / Sem. Forest	33117.9	25.8
Forest Scrub	7001.0	5.5
Industries	383.4	0.3
Mining	199.3	0.2
Mixed Plantations	807.5	0.6
Open scrub	7254.5	5.7
Permanent Fallow	3136.9	2.4
Plantation	5721.6	4.5
River / Stream	422.5	0.3
Stony Waste	50.3	0.0
Tea Plantation	15655.5	12.2
Water body	6434.9	5.0
	128317.3	100.0

Table 5. Land use 2015

4.3 Land use modeling through CA-Markov

The CA-Markov modelling was performed using IDRISI Selva software. Markov chains were used to develop transition probability. The transition probability matrices indicate the probable change in area between the land use classes provides the transformation area maps for each land use classes. This transition probability for the future state is based on the previous state and current state of the cell. Equal intervals are used in order to calibrate and simulate the model. The calibrated model is further used for predicting future land use state.

4.3.1 Modelling and Simulation: Land use data for the year 2015 and 2025 were used to develop transition probability area/matrix, the transition areas were calibrated based on the allowable error and iterations. Allowable errors such as 0.15, 0.1, 0.05, and 0.01 were used to calibrate the model. Error of 1% (0.01) during calibration simulated land use closer to the actual. Rules and neighbourhood were defined to calibrate cellular automation. Various land use change rules are described in Table 6 and the circular neighbourhood of 2 pixels radii that was considered for the analysis is depicted in Figure 3.

LAND USE CLASS CHANGES	
From	To
Build up	Build up
Forest	Forest, Vegetation
Vegetation	Build up, Others
Water body	Water body
Others	Build up, Vegetation

Table 6. Land use change rules

Land use	Build up	Forest	Vegetation	Water	Others
Build up	0.9732	0.0000	0.0130	0.0000	0.0138
Forest	0.0042	0.9761	0.0068	0.0024	0.0105
Vegetation	0.0120	0.0066	0.8747	0.0000	0.1067
Water	0.0000	0.0000	0.0070	0.9781	0.0149
Others	0.0115	0.0000	0.0066	0.0000	0.9819

Table 7. Markov transition probability matrix (2015-2025)

The resultant map of CA-Markov model predictions (Table 7, Figure 11) shows that build up area would be increased from 3.2% in 1995 to 10.8% in 2025. There is a slight changes in

the forest cover, vegetation areas are decreased 22.4% (1995) to 21.9% (2025). Further, no changes in the water body and other class areas are increased by 2.3%. The result of simulated land use for the year 2025 has been given in the Figure 12.

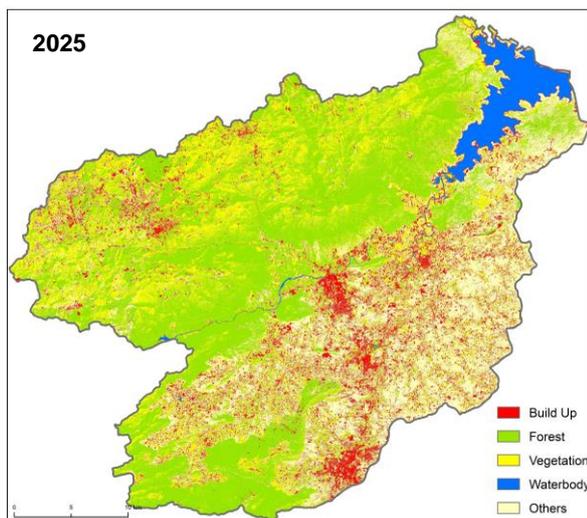


Figure 12: Predicted Land Use 2025

4.4 Validation and Comparisons

The results were validated through hybrid classification (2015), Google earth and field checks.

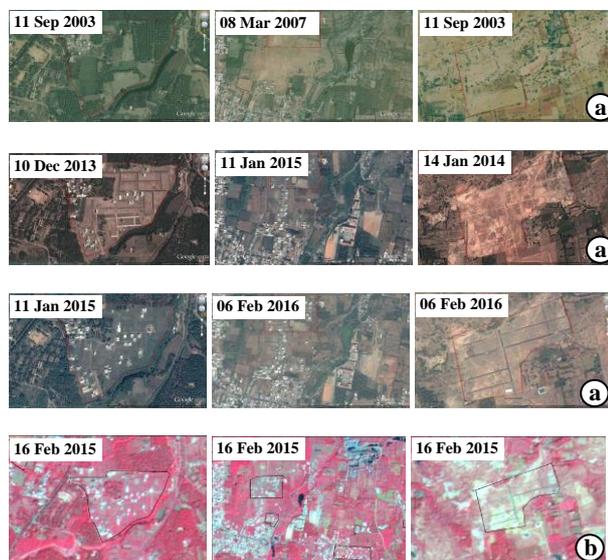


Figure 13: Settlement Plots in (a) Google Earth, (b) IRS P6 LISS – IV (2015)

The classified results, mostly matches with the Google earth images and field. Build up (urban area) are rapidly increasing and most of the agricultural (cultivable) lands were converted to settlement plots. In entire watershed, 92 settlement plots were identified (Figure 13) and these plot areas falls under the build-up area in the predicted 2025 map.

5. CONCLUSION

This paper describes an integrated approach of remote sensing and stochastic modelling techniques in explaining the land use and land cover changes in Kallar watershed of Tamil Nadu. The CA-Markov based approach was used to predict the land

use/land cover changes 1995 to 2025. Build-up and other areas are increased, forest and vegetation cover are decreased due to continuous deforestation and population explosion were the main driving forces. This study helps us to find the land use changes in the particular and which land use will be affected by changes in future by prediction. Also, biodiversity loss and ecological problems can be identified. The outcome of the results helps the farmer and policy makers to draw optimal lands use planning and better management strategies for sustainable development of natural resources.

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