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VISUALIZATION OF FOREST TRANSITIONS IN UTTARA KANNADA

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ABSTRACT:

Land use land cover changes influences on land productivity, ecosystem stability and biodiversity. Modelling and visualisation of LULC dynamics helps in understanding the causes and consequences and aid in planning to mitigate adverse impacts on ecosystems. Spatially explicit model such as Markov-cellular automata (CA–Markov) with temporal remote sensing data help in analysing the extent of future land use changes for sustainable land use planning. Uttara Kannada district of Karnataka state, India has been experiencing rapid forest transitions due to ad-hoc planning process. The trends of land use changes across three agro-climatic zones from 2004-2007, 2007–2010, 2010–2013 are derived from Remote sensing data and with application of CA–Markov analysis helped in characterizing patterns and to develop the predictive scenarios through 2010-2022. Simulation of changes in land use in 2010 to 2022 indicated significant decline in forest cover across all the zones. The demand for land, unplanned developments, neighboring effects of land use activities provide insights to the agents of and impacts on the primeval forests and natural resources. The spatio-temporal modelling results highlighted prospective effects of landscape and provides an approach to understand, project the complex and ongoing influences associated with changing forest land use due course of management activities.

KEY WORDS: Deforestation, CA-Markov, Agro-climatic zones, Central Western Ghats, Simulation.

1.0. INTRODUCTION

Land use land cover (LULC) change analysis has become the central theme of global change research due to accelerating anthropogenic changes affecting landscape structure, atmospheric environment, biodiversity, etc. (Deng, 2011). The total global forest area lost from 2000 to 2012 is accounted as 2.3 million km^2 whereas, the gain is only 0.8 million km^2 (Hansen et al., 2013). It is estimated that about 200 km^2 forest area is cleared each day for other land uses (FAO, 2006). LULC changes are influenced by the socio-economic, cultural, political activities in a short period of time, affecting the composition and structural features of landscape. Land degradation caused by LULC changes leads to substantial decrease in the biological productivity of the land system, resulting from human activities rather than natural events (Kanowski et al., 2005). Forest land use will gradually change, with industry, growth in population, agricultural activities, housing and new town areas by replacing significant cover resulting in scarcity of natural resources. The increase in such activities will create demand for residential places and amenities especially within region and spread towards the fringe areas of existing towns. Forest degradation through logging also has been an important cause of forest loss (Armesto et al., 2009). Disturbance in forested landscapes is referred as fragmentation where forested habitat is reduced into an increasing number of smaller and more isolated, patches (Bharath and Ramachandra, 2012). The sustainable land development, food and environmental security have a strong correlation with the natural ecosystem and its processes (Houet and Hubert-Moy, 2006), the mismanagement by LULC changes in the region will result in irreversible state (Kamusoko, et al., 2009). The sustainable use of resources and accounting its availability has become central point in land management. Achieving this objective requires adopting holistic and sustainable development strategies, future projections using spatial decision support tools and models.

Geo-visualisation of LULC changes will help in the assessment of unplanned development impacts, the preparation of land use plans and the search for optimal land use patterns to provide necessary facilities and services to sustain development of local people (Macedo et al., 2013). The modelling and visualisation of LULC patterns also help in analysing the biophysical, socio-economic context at multiple scales and quantifying the potential effects of land use changes support policy makers in their decision making process. Modeling and visualisation helps to adequately explore complex systems of highly nonlinear behaviours using a closely coupled combination of driving factors and neighbourhood that are described by a general law or analytic descriptive formulas to link theoretical ideas with experimental observations. The numerous models have been proposed to estimate and forecast changes of LULC at regional scale (Bell, 2001; Batty et al., 2003; Pontius and Malanson, 2005; Wu et al., 2011; Tian et al., 2011; Riccioli et al., 2013) with special scenarios, driving forces (Wimberly and Ohmann, 2004; Haase and Schwarz, 2009; Yang et al., 2012; Nole et al., 2013) to address environmental issues at global as well as local scales. Visualising and forecasting future land use changes involves a complicated set of tasks, evaluating huge datasets of various time periods using better scientific knowledge of the physical extent, character and consequences of land transformation (Turner II, 2009). The temporal remote sensing data available from 1970's provide opportunities for sustainable landscape management by using multi data approach and modelling (Ramachandra et al., 2014).

CA-Markov (Cellular automata and Markov process) models have been used extensively for modelling LULC changes across globe. CA-Markov models have incorporates a better theoretical understanding of the complex, nonlinear relationships of LULC processes and help in further forecasting changes effectively (Walsh et al., 2008). Markovian process is a novel approach in spatio temporal dynamic modeling aids in incorporating a stochastic progression that depicts the probability of one state being altered to another state. The Markov produces transition probability matrix that determines the probability of change from one land use category (ex. agricultural lands) to another (ex. built-up) over time CA is used to add spatial character to the model by a cellular entity that independently varies its state based on its previous state and that of its immediate neighbors according to series of rules. The CA–Markov model is a multi-criteria evaluation function, aids in measuring the quantity of change that is expected to achieve through Markov Chain analysis, particularly the transition area, probability matrices. This approach applies a contiguity kernel to 'produce' a land use map to a later time period through a CA function that converts the results of the Markov chain to spatially explicit outcomes (Pontius et al., 2004; Moreo et al., 2009). In the CA–Markov model, the Markov Chain manages temporal dynamics among the land use categories, based on transition probabilities, while the spatial dynamics are controlled by local rules determined either by the CA spatial filter or transition potential maps (Maguire et al., 2005). The objective of the analysis is to (1) understand the spatio-temporal changes of land use during 2004-2013, (2) identifying the drivers of land use change and how their net intensity influenced forested landscape transition, (3) visualisation and future prediction of forest status for 2022 by incorporation of previous land use extents.

2.0. STUDY AREA

The Uttara Kannada (North Canara / Karwar) district extends over an area of 10,291 km^2 with 11 taluks and have 80% under forests (Figure 1). Based on forest categories and topography, the district can be divided into 3 distinct agro-climatic zones namely narrow and flat coastal zone (Karwar, Ankola, Kumta, Honnavar and Bhatkal taluks), abruptly rising Sahyadri interior zone (Supa, Yellapura, Sirsi and Siddapur taluks), the flat eastern plains zone (Haliyal and Mundgod taluks), which joins the Deccan plateau. The average rainfall in the region varies from 4000-5000 mm. The major vegetation types of Uttara Kannada have been broadly grouped as 'natural vegetation' which includes evergreen, moist deciduous and dry deciduous forests, 'plantations or monocultures' which includes plantations of *Tectona grandis* (Teak), *Eucalyptus sp.* (Blue gum) *Casuarina equisetifolia*, *Acacia auriculiformis*, *Acacia nilotica*, and other exotics. From early 80's the region is started experiencing changes in its forest cover through various unplanned developmental activities. This conversion has occurred largely at the expense of forests and grassland (Ramachandra and Shruthi, 2007). The total population of the district is 14,37,169 with population density of 140 persons/km^2. The population growth rate is 6.17% as compared to 2001 census (per decade). The coastal zone is thickly populated with major economic activities. The major economic activity of district is fishing, agriculture and horticulture. This region is well known for the production of coconut, pepper, cardamom, cashew and areca nuts. Karwar is the district headquarter with major Industrial Infrastructure constitutes 8 Industrial Estates & 1 Industrial Area.

3.0. METHOD

Method followed in the analysis is outlined in the Figure 2. The analysis is explained in the three steps as (i) Data collection, preprocessing and land use analysis (ii) Framing Markov transitions, (iii) Modeling and prediction.

3.1. Data preprocessing and temporal land use analysis: The data used in the analysis is shown in Table 1. The field data is collected using GPS (Global Positioning System – Garmin GPS) across various land uses and forest types. The raw satellite images are geo-corrected, followed by radiometric correction and resampled to 30m resolution to maintain common resolution for multi temporal data comparisons and visualisation. The land use analysis was done using supervised classification scheme of GMLC with the collected field data based on the spectral properties of features. GRASS GIS (Geographical Analysis Support System); a free and open source geospatial software with the robust functionalities for processing vector and raster data available at (http://wgbis.ces.iisc.ernet.in/grass/). The temporal land use analysis was carried out by using supervised classification scheme of Gaussian maximum likelihood classifier under 7 different land use categories as shown in Table 2. Land use analyses involved i) generation of False Colour Composite (FCC) of remote sensing data (bands–green, red and NIR). This helped in locating heterogeneous patches in the landscape ii) selection of training polygons (these correspond to heterogeneous patches in FCC) covering 15% of the study area and uniformly distributed over the entire study area, iii) loading these training polygons co-ordinates into pre-calibrated GPS, iv) collection of the corresponding attribute data (land use types) for these polygons from the field, supplementing this information with Google Earth v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment. To classify earlier time data, training polygon along with attribute details were compiled from the historical published topographic maps, French institute vegetation maps, revenue maps, land records available from local regulatory authorities, etc. Accuracy assessments is performed to validate the classification, which is a statistical assessment decides the quality of the information derived from remotely sensed data considering reference pixels. These test samples are then used to create error matrix (also referred as confusion matrix) kappa (κ) statistics and overall (producer's and user's) accuracies to assess the classification accuracies (Lillesand et al., 1987).

Data	Usage	Source
Raster data		
Landsat ETM+ (2004, 2007, 2013) & IRS LISS-IV MX 2010	LULC dynamics, modeling	Landsat- GLCF, USGS (http://glcfapp.glcf.umd.edu:8080/esdi/index.jsp; http://glovis.usgs.gov/) IRS- purchased from NRSC, Hyderabad, India
Survey of India toposheets of 1:50000 and 1:250000	To generate base layers, to rectify remotely sensed images and scanned historical paper maps.	Survey of India
Google earth	Virtual earth database for visualisation of features	https://earth.google.com/
Vector data		
GPS data- collected by field analysis	For geo-correcting and classification, validation	Garmin
Census data (2001, 2011)	Population growth estimation	Directorate of census operation
Administrative reports	**Analysing socioeconomic, bio geophysical characteristics of region.**	**District administration, online sources**

Table 1. Data used and their significance.

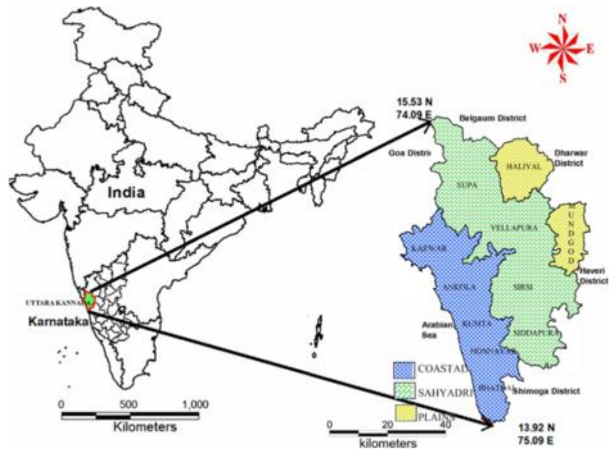

Figure 1: Study area.

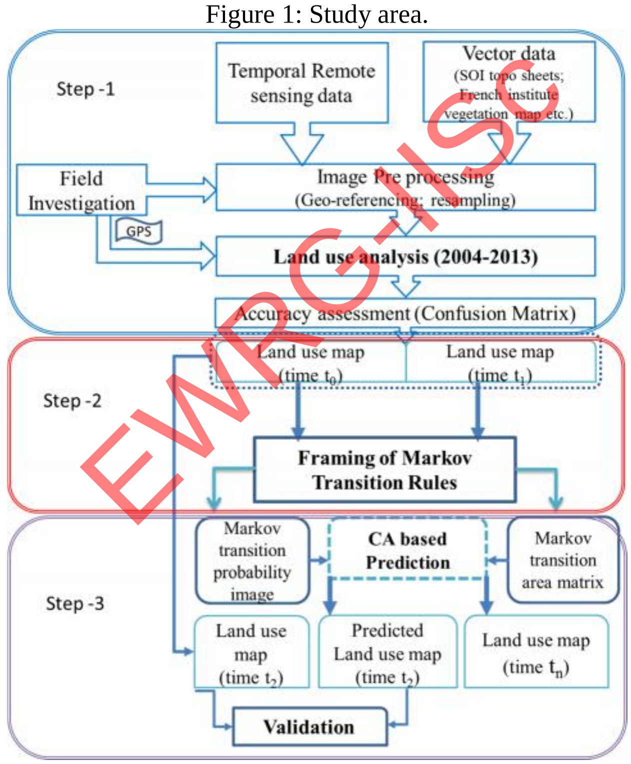

Figure 2. Method used in the analysis.

S.NO.	Land use categories	Description
1.	**Forest**	Evergreen to semi evergreen, Moist deciduous forest, Dry deciduous forest, Scrub/grass lands
2.	**Plantations**	Acacia/ Eucalyptus/ hardwood plantations, Teak/ Bamboo/ softwood plantations
3.	**Horticulture**	Coconut/ Areca nut / Cashew nut plantations
4.	**Crop land**	Agriculture fields, permanent sown areas
5.	**Built-up**	Residential Area, Industrial Area, Paved surfaces
6.	**Open fields**	Rocks, Quarry pits, Barren land
7.	**Water**	Rivers, Tanks, Lakes, Reservoirs, Drainages

Table 2. Land use categories considered.

3.2. Markov transitions: The temporal land use analysis has provided spatial pattern satisfying Markovian properties. Markovian process is a random process, defines suitability of state as a weighted linear sum of a series affecting factors, normalized to values in the range of 0–1. The neighbourhood influence area is thus calculated as summed effect of each transitional potential and its interaction with its neighbors and the transition rules: were determined by various demands of the land use categories, population growth etc. The two temporal land use analysis maps were used to account the stable and transformed land use categories which satisfy non-transition properties such as urban category to water or vice versa. The transition probability map and area matrix are obtained based on probability distribution over next state of the current cell that is assumed to only depend on current state (Equations 1 & 2). A transition probabilities matrix determines the likelihood of a pixel that will change from a land use category other category from time 1 to time 2. This matrix is the result of cross tabulation of the two images adjusted by the proportional error and is translated in a set of probability images, one for each land use category, which records the number of cells or pixels that are expected to change over the next time period. The original transition probability matrix (denoted by P) of land use type should be obtained from two former land use maps.

$$P \; N \; = P \; N - 1 \; * P \qquad (1)$$

where, $P_{(N)}$ is state probability of any times, and $P_{(N-1)}$ is preliminary state probability.

Transition area matrix can be obtained by,

$$A = \begin{matrix} A_{11} & A_{12} & A_{13} \\ \vdots & \vdots & \vdots \\ A_{N1} & A_{N2} & A_{NN} \end{matrix} \qquad (2)$$

where, A is the transition area matrix; A_{ij} is the sum of areas from the i^{th} land use category to the j^{th} category during the years from start point to target simulation periods; and n is the number of land use types. The transition area matrix must meet the following conditions

i. $0 \leq P_{ij} \leq 1$

ii. $\sum_{i,j=0}^{n} P_{ij} = 1$

3.3. Modeling and prediction: CA has a potential for modelling complex spatio-temporal processes that made up of elements represented by an array of cells, each residing in a state at any one time, discrete number of category (states), the neighbourhood effect and the transition functions, which define what the state of any given cell is going to be in the future time period. The CA conditional transition rules are an automated method that produces a set of descriptive rules or a decision tree ready to be used, defines thresholds in the composition of the neighborhood and for the driving factors, which are additional values about each cell such as the land value, the distance to a main road etc., to maximize the likelihood that a given cell configuration leads to the correct type of land use change. The CA-Markov model defines the neighboring territory using a CA filter. The CA filter creates spatial weights according to the distance of the neighboring territory from the cell to determine changes in the cellular status. A 5×5 contiguity filter shown in Figure 3 was used, which assumes that a rectangular space consisting of a 5×5 cell surrounding a given one has significant impact on change of status.

The CA coupled with Markov chain land use predictions of 2010 and 2013 were made by using the transitional probability area matrix generated from 2004-2007; 2007-2010 maps respectively. The validity of the predictions was made with the reference land use maps of 2007 and 2010. The model was analyzed for allowable error by validating the predicted versus the actual for the years 2010 and 2013 land use maps. Analysis and comparison of the simulated and actual land-use maps of 2010 &13 reveal that the CA–Markov model generally is a reliable estimator in terms of change quantification and continuous space change modelling. The accuracy of simulation is done through the calculation of Kappa index for location and quantity. The validity of the model results have been evaluated by comparing the KAPPA index of agreement for each category, spatial patterns of land use type. Based on these validations then visualisation was made for 2022 by considering equal time interval.

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Figure 3: A 5X5 mean contiguity filter created.

4.0. RESULTS

4.1. Land use analysis: The Uttara Kannada forests are rich in biological diversity and people depend on the forests for a variety of products. The pressure for forest based resources from the people like palms, bamboo grains and shoots, fruits like *Mangifera, Artocarpus, Garcinia, Phyllanthus emblica, Syzygium cumini*, pepper, cinnamon, honey, and mushroom. Apart from edible resources they are also extracting thatching, basket- and mat-weaving materials, fibers, medicinal plants, etc. These non-timber products will be exported all over the world, the recent time huge trade business is observed which is creating more disturbances due to large exploitation rather than controlled collection. The temporal land use analysis was carried out for the year 2004, 2007, 2010, and 2013 across the three agro climatic zones are depicted in Figure 4 (a, b, c) and category wise changes are listed in Table 3. The coastal zone shows the loss of forest cover from 66.55 to 59.06% by 2013 due to greater increase in population and land conversion. The area under horticulture has increased from 6.01 to 8.79 % by intensive plantation of *Cocos nucifera, Areca Catechu.* The built-up area has increased from 3.85% (2004) to 4.49% (2013). These abrupt changes are mainly due to anthropogenic activities than natural processes. The forests have undergone tremendous transformation due to increase in developmental activities (Nuclear power project, Project Seabird, major industries, etc.) and inappropriate management has led to imbalances in the ecosystem, evident from series of landslides in the coastal taluks.

The land use analysis of Sahyadri region (Figure 4 (b)) highlights the agriculture and deforestation took place at the expense of the irreversible losses of forest cover have led to the losses of vital ecosystem goods and services ranging from biodiversity to regulation of hydrological cycle used to be provided for the region. Among the three zones Sahyadri Interior region has more intact forests due to elevation. The forest cover has reduced from 65.98 to 60.61% by 2013 due to increase in plantation activities and horticulture. The Supa taluk shows least changes in its land use due to less population and major area is under Anshi-Dandeli tiger reserve (ADTR). The Sirsi, Siddapur taluks has major contribution due to intensification of horticulture, Yellapura region has major monoculture plantaions. It is also evident that the increase in plantation of exotic species such as *Acacia auriculiformis, Casuarina equisetifolia, Eucalyptus spp.*, and *Tectona grandis* are led to removal of primeval forest cover. The other driving forces are observed as market based agriculture and fuel wood requirement which pressurising the forests of nearby villages. To compensate the pressure there is intensified plantation activities took place. This is also one of the causal factors for loosing natural forest cover. The land use analysis of Plains (Figure 4 (c)) articulates the temporal changes in the region due to human induced pressure. The region has left with only 15.17% forest cover by 2013 due to intensive plantation activities to meet raw material requirements for West coast paper mill, Dandeli within Haliyal taluk, even though this region is rich in faunal diversity. The plantations constitute 39.82% is considered more important source of revenue having higher pressure in terms of wood and agriculture intensification. The region has become more and more dynamic and leading to intensified land use changes and becoming rain shadow area. The built-up area has increased from 2.92 to 6.26% due to population growth. The field data and Google earth data sets are used for analysing accuracy of classification and the accuracy assessment was included in Table 4. This approach has provided us more consistent results. The areas of each category are also verified with available administrative reports, statistical department data and forest division annual reports.

Zone	Coastal region				Sahyadri Interior				Plains			
Category (%)	2004	2007	2010	2013	2004	2007	2010	2013	2004	2007	2010	2013
Forest	66.55	63.95	63.08	59.06	65.98	63.84	62.86	60.61	27.35	23.82	20.08	15.17
Plantations	5.67	5.80	6.35	9.04	15.00	15.87	16.01	17.29	34.28	35.46	38.51	39.82
Horticulture	6.01	7.29	7.73	8.79	3.80	3.90	4.42	4.10	1.33	1.37	1.64	1.34
Crop land	10.94	10.70	10.43	10.84	10.18	10.69	10.69	10.99	29.23	30.56	30.38	28.50
Built-up	3.85	4.36	4.35	4.49	1.13	1.25	1.44	2.12	2.92	3.11	4.00	6.26
Open fields	3.02	4.29	4.34	4.23	1.29	1.73	1.82	2.40	3.06	3.94	3.55	7.16
Water	3.95	3.61	3.72	3.55	2.61	2.71	2.76	2.49	1.83	1.73	1.84	1.75
Total area (Ha)	335561.32				541195.99				152505.69			

Table 3: Land use analysis from 2004-2013.

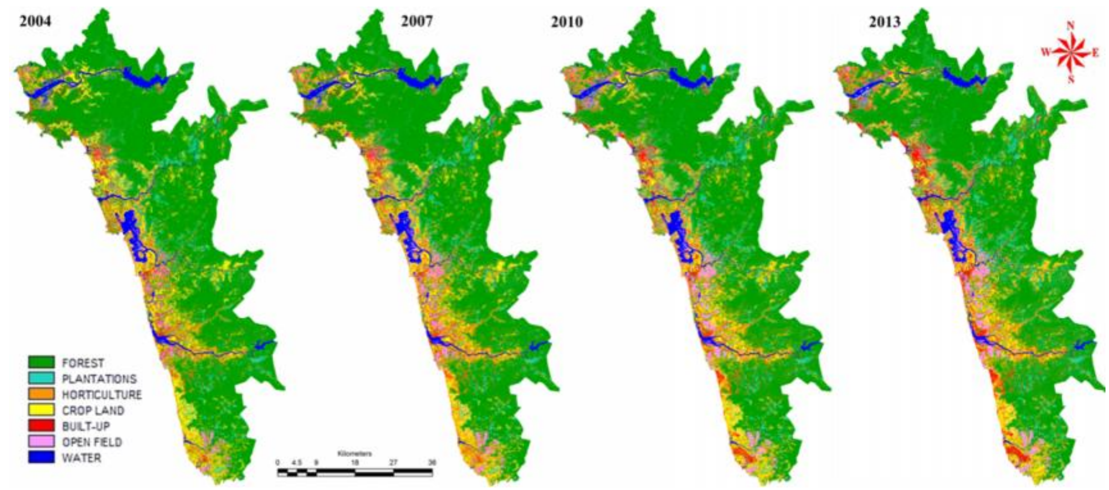

Figure 4 (a). Land use analysis of Coastal region from 2004-2013

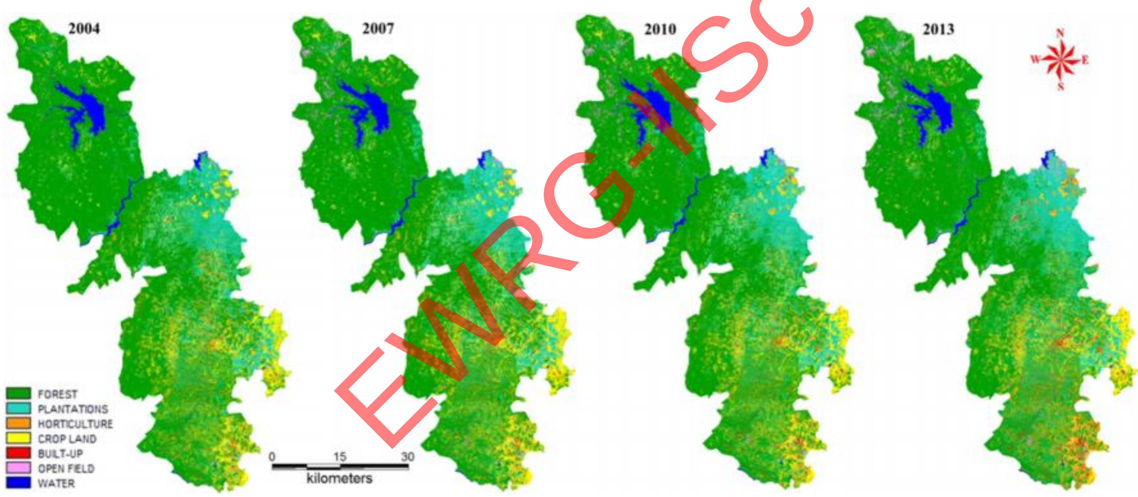

Figure 4 (b). Land use analysis of Sahyadri Interior from 2004-2013

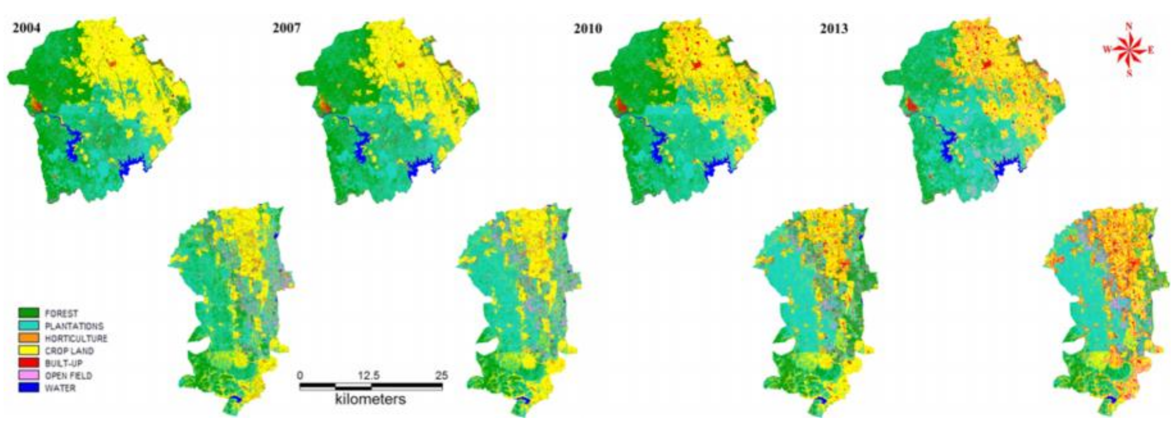

Figure 4 (c). Land use analysis of Easter Palins from 2004-2013

Year	2004		2007		2010		2013	
Categories	PA	UA	PA	UA	PA	UA	PA	UA
Forest	87.44	95.73	97.85	97.83	99.69	96.02	98.56	93.31
Plantations	92.60	76.51	84.69	84.71	60.09	95.37	98.27	91.32
Horticulture	98.01	76.49	79.30	79.26	57.91	75.69	86.13	37.46
Crop	92.50	85.96	86.67	86.69	71.46	95.02	79.66	81.85
Built-up	48.68	73.79	65.91	66.09	93.17	65.61	60.04	96.50
Open fields	68.22	68.30	62.75	62.91	89.40	83.13	93.97	89.74
Water	80.29	89.49	92.71	93.06	78.85	94.57	96.94	97.19
Kappa	0.82		0.85		0.85		0.86	
Overall Accuracy	88.67		91.67		92.6		91.02	

Table 4: Accuracy assement of the land use analysis.

4.2. Visualisation and prediction: The landscape visualisation and future land use transitions with respect to each land use category were calculated to predict land use for 2010, using Markov chain process based on 2004 and 2007 land use and CA loop time of 3 years, and was continued for 2013 by using 2007, 2010 land use maps. With the knowledge of 2004-2007, 2007-2010 and 2010-2013 for the year 2016, 2019 and 2022 were predicted under different conditions (i.e. transition rules, iteration numbers). This prediction has been done considering water bodies as a constraint and assumed to remain constant over all time frames. The validation results showed in Table 3& 7 across the zones provides a very good agreement between the actual and predicted maps of 2010, 2013. The accuracy of agreement between actual land use and predicted land use were shown in Table 5 with kappa values. The Kappa-standard index of optimum point as well as Kappa-location index was computed shows a significant correlation between the simulated and the actual maps.

The simulated land use (Table 6, Figure 5 (a, b, c)) shows likely increase in built-up area and loss in forest cover across three regions at three year time interval. The process of urbanization is observed to be high in the areas near project Sea bird, Kaiga power house and the national/state highways in the coastal zone. The analysis highlighted the decline of forest cover from 62.24 (2010) to 48.90% (2022) with increase in monoculture plantations from 6.59% to 10.29%. The natural vegetation is being replaced by the plantation activities in recent time also indicates their further growth in future years. The coasta taluks has witnessed changes within and in the neighbourhood due to the introduction of major developmental projects that has led to rapid land conversion. The built-up area shows an greater increase from 4.81 to 9.30 % and area under horticulture will reach to 8.24 to 13.13 % by 2022. The adverse effects of ad-hoc approaches in the developmental activities have led to landslides, higher erosion of top soil, etc.. The Sahyri Interior region also expressing same trend in Sirsi, Siddapur, Yellapura taluks except Supa. The area under built-up cover will reach 2.00 to 6.47% and horticultre will be 5.59% by 2022. The natural forest cover will be lost from 62.6 (2010) to 52.28 % (2022) and monoculture plantations will increase from16.16 (2010) to 19.31% (2022). The Sirsi town, Siddapur, Yellapura town and its suburban regions will expereience land coversion for built-up area. The predicted maps of Plain region stating higher growth in the built-up cover from 5.67 to 18.36% due to existing cover and increase in population. The cropland intensification also witnessed near by major reservoirs and huge lakes of Plainer regions. This necessitates comprehensive land use management focusing on restoration of ecosystems to mitigate the impacts further. Analysis and comparison of the simulated and actual land-use maps of 2022 reveal that the CA–Markov model has provided insights in terms of change quantification and continuous-space change modelling. The CA-MARKOV model is mainly constructed as a linear presumption of the Markov model. The entire ecological and economic system is not a simple linear model and is instead complex and large, this model does not consider any environmental and socio-economic variables and acts on the probable amount and location of change that are obtained through a Markov Chain execution. Recently, multi-agent models have been developed to simulate land conversions through considering the behaviours of the existing individuals, as well as other actors. So, accounting human's perception, other biophysical drivers will definitely increases the precision of prediction.

Zone	**Coastal zone**		**Sahyadri Interior**		**Plains**	
Index	**Projected 2010**	**Projected 2013**	**Projected 2010**	**Projected 2013**	**Projected 2010**	**Projected 2013**
Kno	0.86	0.92	0.89	0.9	0.88	0.92
Klocation	0.84	0.91	0.87	0.86	0.86	0.93
Kstandard	0.82	0.88	0.83	0.84	0.83	0.89

Table 5: Validation of actual and predicted with Kappa

Zone	**Coastal region**					**Sahyadri Interior**				
Category (Ha)	**P 2010**	**P 2013**	**P 2016**	**P 2019**	**P 2022**	**P 2010**	**P 2013**	**P 2016**	**P 2019**	**P 2022**
Forest	**62.24**	57.24	55.03	51.76	48.90	62.60	60.86	57.32	54.33	**52.28**
Plantations	6.59	9.25	9.68	9.96	10.29	16.16	17.45	18.89	18.96	19.31
Horticulture	8.24	8.98	11.62	12.63	13.13	4.44	4.80	4.70	5.38	5.59
Crop land	10.22	11.14	10.23	10.23	10.14	10.55	10.64	10.40	11.25	11.46
Built-up	4.81	5.02	5.48	7.55	9.30	2.00	1.78	3.81	5.19	6.47
Open land	4.29	4.65	4.53	4.69	4.94	1.73	1.86	2.40	2.40	2.40
Water	3.61	3.72	3.44	3.17	3.30	2.53	2.62	2.49	2.49	2.49

Zone	**Plains**				
Category	**P 2010**	**P 2013**	**P 2016**	**P 2019**	**P 2022**
Forest	**20.33**	14.58	11.81	10.72	**9.48**
Plantations	39.16	40.25	38.64	34.14	30.17
Horticulture	2.02	2.55	1.40	1.95	2.09
Crop land	27.11	30.00	30.94	30.55	30.94
Built-up	**5.67**	7.19	10.87	16.32	**18.36**
Open fields	3.97	3.57	4.57	4.57	7.21
Water	1.75	1.86	1.76	1.76	1.76

Table 6: Land use analysis for predicted 2010-2022. (*P - Projected)

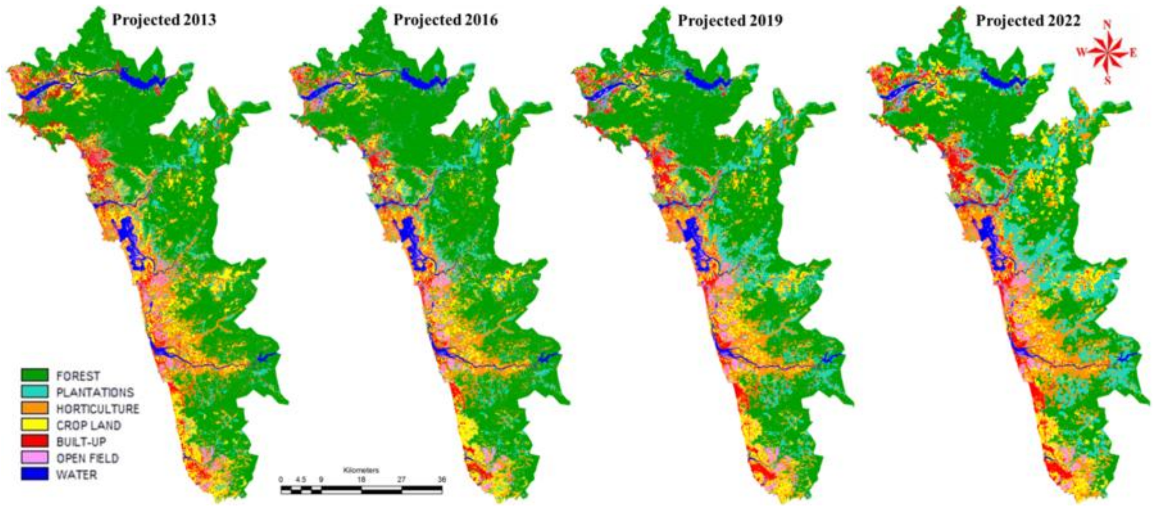

Figure 5 (a): Projected Land use of Coastal region from 2013-2022.

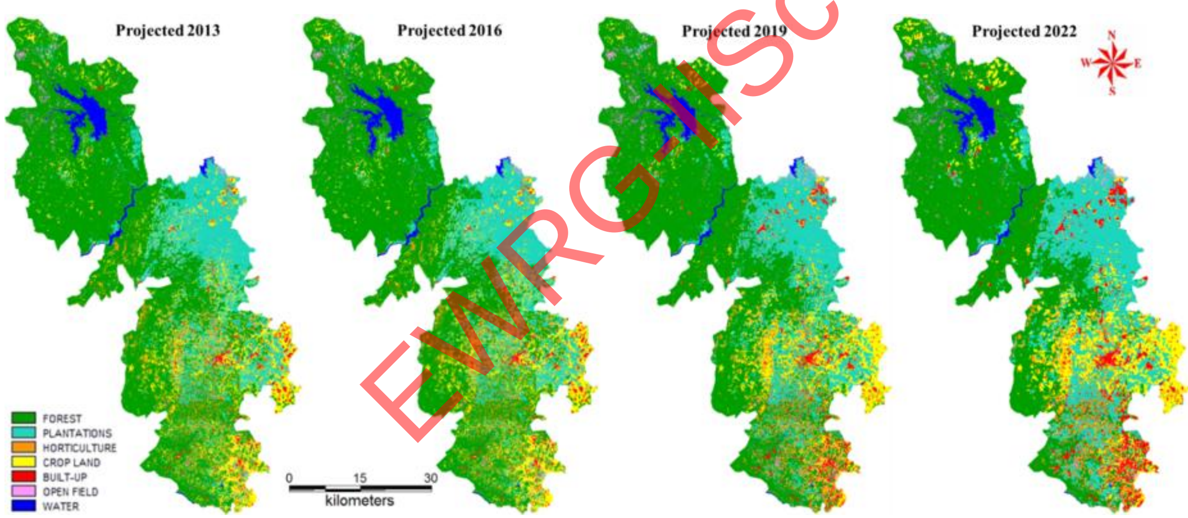

Figure 5 (b): Projected Land use of Sahyadri Interior from 2013-2022.

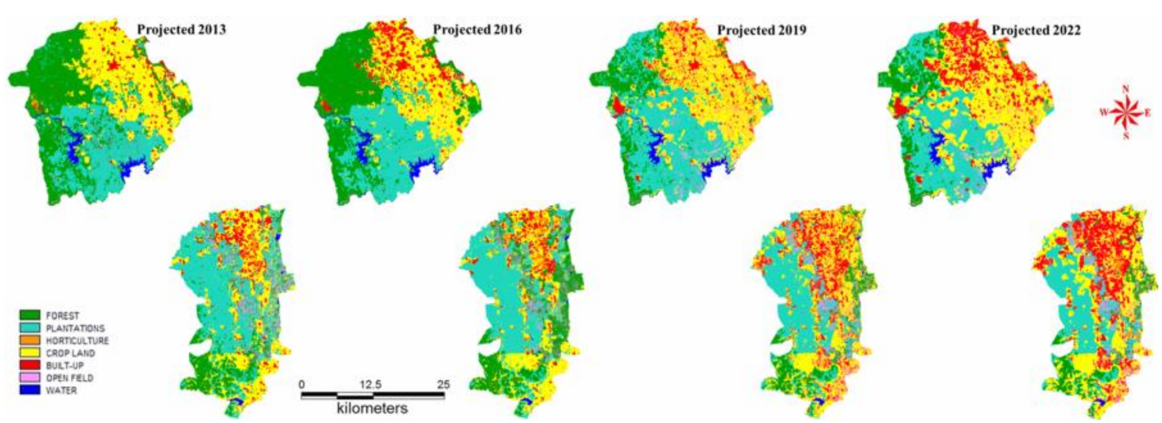

Figure 5 (c): Projected Land use of Plains region from 2013-2022.

CONCLUSION:

LULC analysis indicates the human and biophysical forces are responsible for landscape composition and configuration. The integrated modelling framework presented has potential in natural resource planning and management and in assessing of the effects of policies on land development, land cover. The analysis highlighted the decline of forest cover in coastal zone from 62.24 (2010) to 48.90% (2022) with increase in monoculture plantations from 6.59% to 10.29% and built-up area from 4.81 to 9.30%. The natural forest cover decreases in Sahyadri region from 62.6 (2010) to 52.28 % (2022) and percentage of monoculture plantations increase from 16.16 (2010) to 19.31% (2022). The Sirsi town, Siddapur, Yellapura town and its suburban regions will experience land conversion for built-up area. The Plain region is stating higher growth in the built-up cover from 5.67 to 18.36% due to existing cover and increase in population. The land use changes across zones are varying over spatio temporal scale, the coastal region, plains have higher transition as compared to Sahyadri region. The present work helps planning authorities and decision makers to articulate policies and programmes to maintain a sustainable balanced ecosystem or to mitigate the devastating consequences of severe land use changes.

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REFERENCES

1. Armesto, J., Smith-Ramírez, C., Carmona, M., Celis-Diez, J., Díaz, I., Gaxiola, A., Gutierrez, A., Nú˜nez-Avila, M., Pérez, C., Rozzi, R., 2009. Old-growth temperate rain forests of South America: conservation, plant-animal interactions, and baseline biogeochemical processes. Old-growth forests: function, fate and value. In: Wirth, C., Gleixner, G., Heimann, M. (Eds.), Ecological Studies, vol. 207. Springer, New York, Berlin, Heidelberg, 367–390.
2. Arsanjani, J.J., Helbich, M., Kainz, W., and Darvishi, A., 2013. Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion - the case of Tehran. International Journal of Applied Earth Observation and.Geoinformation, 21, 265-275.
3. Batty, Michael, Jake DeSyllas, and Elspeth Duxbury. 2003. The discrete dynamics of small-scale spatial events: agent-based models of mobility in carnivals and street parades. International Journal of Geographical Information Science, 17 (7), 673-697.
4. Bell, S., 2001. Landscape pattern, perception and visualisation in the visual management of forests. Landscape and Urban planning, 54(1), 201-211.
5. Bharath Setturu and Ramachandra. T.V., 2012. Landscape dynamics of Uttara Kannada district, Proceedings of the LAKE 2012: National Conference on Conservation and Management of Wetland Ecosystems, 06th - 09th November 2012, School of Environmental Sciences, Mahatma Gandhi University, Kottayam, Kerala, pp. 1-13.
6. Cheong, So-Min., Brown, D., Kok, K., and López-Carr, D., 2012. Mixed Methods in Land Change Research: Towards Integration. Trans.Inst. Br. Geogr. 37, 8–12.
7. Deng, X.Z., 2011. Modeling the dynamics and consequences of land system change. Beijing: Higher Education Press.
8. FAO, 2006. Global planted forests thematic study: results and analysis, by A. Del Lungo, J. Ball and J. Carle. Planted Forests and Trees Working Paper 38.
9. Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice C.O., and Townshend, J.R.G., 2013. High-Resolution Global Maps of 21st Century Forest Cover Change Science, 342 (6160), 850-853.
10. Haase, D., and Schwarz, N., 2009. Simulation models on human-nature interactions in urban landscapes – a review including system dynamics, cellular automata and agent-based approaches. Living Reviews in Landscape Research, 3, 2.
11. Houet T., and Hubert-Moy L., 2006. Modelling and Projecting Land-Use and Land-Cover Changes with a Cellular Automaton in Considering Landscape Trajectories: An Improvement for Simulation of Plausible Future States, EARSeL eProceedings, 5, 63–76.

12. Kamusoko C., Aniya M., Adi B., and Manjoro M., 2009. Rural sustainability under threat in Zimbabwe – Simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model, Applied Geography, 1.
13. Kanowski, J., Catteral, C.P., and Wardell-Johnson, G.W., 2005. Consequence of broad scale timber plantations for biodiversity in cleared rainforest landscape of tropical and subtropical Australia, Forest Ecology and Management, 208, 359–372.
14. Lillesand, T.M., and Keifer, R.W., 1987. Remote sensing and Image interpretation, John Willey and Sons, New York.
15. Macedo, R.D., de Almeida, C.M., dos Santos, J.R., and Rudorff, B.F.T., 2013. Spatial dynamic modeling of land cover and land use change associated with the sugarcane expansion. Bol. Cienc. Geod. 19, 313–337.
16. Maguire, D., Batty, M., and Goodchild, M., 2005.GIS, spatial analysis, and modelling. Redlands, CA: Esri Press.
17. Moreno, N., Wang, F., and Marceau, D.J., 2009. Implementation of a dynamic neighbourhood in a land-use vector-based cellular automata model. Computers, Environment and Urban Systems, 33 (1), 44–54.
18. Nole, G., Rosa L., and Beniamino M., 2013. Applying spatial autocorrelation techniques to multi-temporal satellite data for measuring urban sprawl. Int. J. Environ. Protect 3 (7), 11-21.
19. Pontius Jr, R.G., Shusas, E., and McEachern, M., 2004. Detecting important categorical land changes while accounting for persistence. Agriculture, Ecosystems and Environment, 101 (2–3), 251–268.
20. Pontius, R.G.J., and Malanson, J., 2005. Comparison of the structure and accuracy of two land change models. Int. J. Geogr. Inf. Sci. 19, 243-265.
21. Ramachandra T.V., and Shruthi, B.V., 2007. Spatial mapping of renewable energy potential, Renewable and Sustainable Energy Reviews, 11(7), 1460-1480.
22. Ramachandra, T.V., Setturu Bharath and Aithal Bharath., 2014. Spatio-temporal dynamics along the terrain gradient of diverse landscape, Journal of Environmental Engineering and Landscape Management, 22:1, pp. 50-63., doi:http://dx.doi.org/10.3846/16486897.2013.808639.
23. Riccioli, F., EI Asmar, T., EI Asmar, J.P., and Fratini, R., 2013. Use of cellular automata in the study of variables involved in land use changes. Environ. Monit. Assess. 185, 5361–5374.
24. Tattoni, C., Ciolli, M., and Ferretti, F., 2011. The fate of priority areas for conservation in protected areas: A fine-scale Markov chain approach. Environ. Manage. 47, 263–278.
25. Tian, G.J., Ouyang, Y., Quan, Q.A., and Wu, J.G., 2011. Simulating spatiotemporal dynamics of urbanization with multi-agent systems – A case study of the Phoenix metropolitan region, USA. Ecol. Model. 222, 1129–1138.
26. Turner II, B., 2009. Land change science. In: R. Kitchen, and N. Thrift, eds. International Encyclopedia of Human Geography. Oxford: Elsevier, 107–111.
27. Walsh, S.J., Messina, J.P., Mena, C.F., Malanson, G.P., and Page, P.H., 2008. Complexity theory, spatial simulation models, and land use dynamics in the Northern Ecuadorian Amazon. *GeoForum* 39(2), 867-878.
28. Wimberly, M.C., and Ohmann, J.L., 2004. A multi-scale assessment of human and environmental constraints on forest land cover change on the Oregon (USA) coast range. Landscape Ecology 19(6), 631-646.
29. Wu, Y.Z., Zhang, X.L., and Shen, L.Y., 2011. The impact of urbanization policy on land use change: a scenario analysis. Cities 28, 147–159.
30. Yang, X., Zheng, X.Q., and Lv, L.N., 2012. A spatiotemporal model of land use change based on ant colony optimization, Markov chain and cellular automata. Ecol. Model. 233, 11–19.