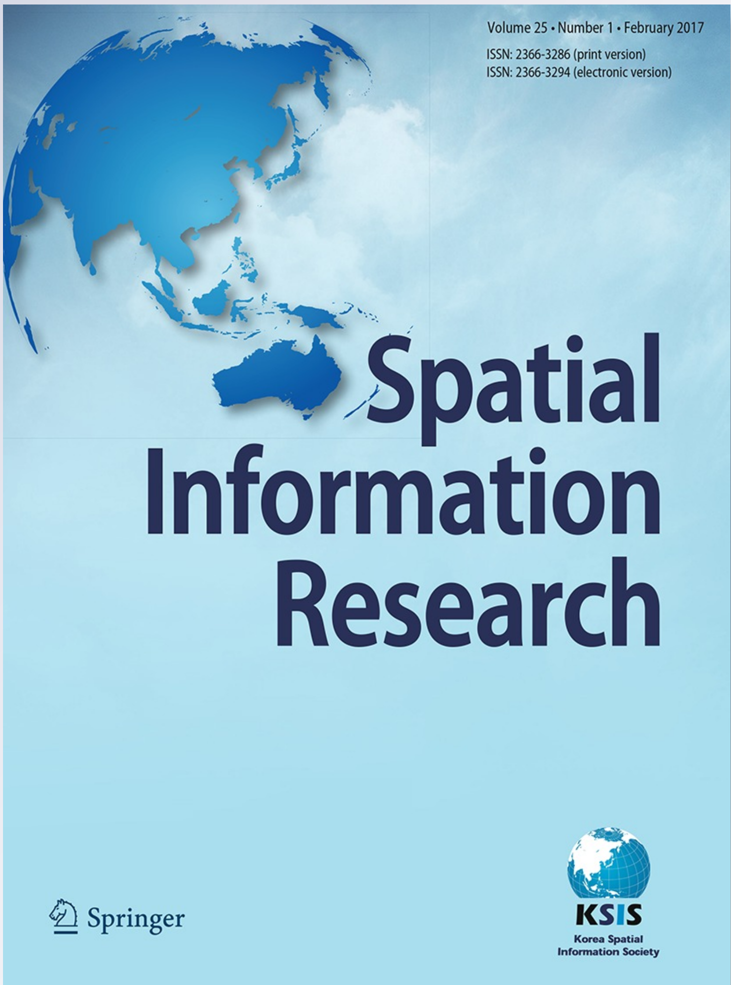
Modelling the forest transition in Central Western Ghats, India

T. V. Ramachandra, Bharath Setturu, K. S. Rajan & M. D. Subash Chandran

Spatial Information Research

ISSN 2366-3286
Volume 25
Number 1

Spat. Inf. Res. (2017) 25:117-130
DOI 10.1007/s41324-017-0084-8



Springer

Spat. Inf. Res. (2017) 25:117–130
DOI 10.1007/s41324-017-0084-8

Modelling the forest transition in Central Western Ghats, India

T. V. Ramachandra[1,2,3] · Bharath Setturu[1,4] · K. S. Rajan[4] · M. D. Subash Chandran[1]

Received: 16 October 2016 / Accepted: 1 February 2017 / Published online: 9 February 2017

Abstract The Western Ghats forms an important watershed for the entire peninsular India, being the source of 37 west flowing rivers and three major east flowing rivers and their numerous tributaries. However, deforestation due to large scale land cover changes has affected the water sustenance in the region evident from the quantity and duration of water availability during post monsoon period. Land use Land cover changes accelerated by unplanned anthropogenic activities have been the prime mover of global warming and consequent changes in the climate. This necessitates appropriate resource management with an understanding of drivers. Geo-visualization of landscape transitions considering the influential agents will aid in formulating strategies to mitigate global warming. Uttara Kannada district in the Central Western Ghats has the distinction of having highest forest cover in the country and this region is now experiencing rapid forest cover changes. Factors inducing changes in the land cover are normalized through fuzzyfication, considered for Multi criteria Evaluation using Analytical Hierarchy Process (AHP) under high protection and low protection scenarios. Likely land use transitions by 2022 across zones based on transitions during 2004–2007, 2007–2010, 2010–2013 was done through cellular automata and Markov chain process (MC). The analyses highlight the loss of forest cover by 66.55–56.76% by 2022 in the coastal zone with escalating population density. Similar situation of 65.98–55.62% decline in Sahyadri region is noticed with execution of dams, hydroelectric projects and monoculture plantations. Lower transitions as compared with the second scenario highlights regulatory framework's role in protection. However, forests in plain region show loss of 27.38–11.09% in both scenarios due to population pressure and market induced land cover changes. This necessitates policy interventions by the federal government to mitigate forest loss towards sustainable development.

Keywords Fuzzy-AHP-CA · Geo-visualization · LULC · Central Western Ghats · CA-Markov

1 Introduction

The global forest loss of 2.3 million sq.km (2000–2012) was reported to cater the growing demands of burgeoning population coupled with the unplanned developmental activities, while the afforestation due to global forest protection initiatives is only 0.8 million sq.km [1]. Forests transitions leading to deforestation in the landscape due to widespread land use land cover (LULC) changes have been acknowledged as prime agents towards contributing global warming with the enhanced emissions as well as loss of carbon sequestration potential. LULC changes information provide vital details on natural resources availability, its utilization, etc. for evolving appropriate management strategies to ensure sustainability of natural resources.

✉ T. V. Ramachandra
cestvr@ces.iisc.ernet.in; energy@ces.iisc.ernet.in;
http://ces.iisc.ernet.in/energy

1 Energy and Wetlands Research Group, CES TE 15 Center for Ecological Sciences [CES], Indian Institute of Science, New Bioscience Building, Third Floor, E-Wing [Near D-Gate], Bangalore 560012, India

2 Centre for Sustainable Technologies (astra), Indian Institute of Science, Bangalore 560012, India

3 Centre for infrastructure, Sustainable Transportation and Urban Planning [CiSTUP], Indian Institute of Science, Bangalore, Karnataka 560012, India

4 Lab of Spatial Informatics, IIIT-H, Hyderabad, India

Thus, LULC changes in a region are the outcome of the complex interaction of policy, economics, management, culture, and environmental factors. Drastic changes in LULC will have significant impact on biodiversity [2], climate [3, 4], hydrological cycles [5, 6], biogeochemical dynamics [7, 8], sustainability of natural resources [9]. This will have intensive effects on land surface climate by altering the exchange of heat, moisture and albedo at regional and global scales [4, 10–12]. Clearing of large scale forests will contribute to releasing the carbon stored in vegetation and soils by altering their physical as well as chemical properties, which affects the global climate by increasing levels of greenhouse gases in the atmosphere, decreasing evapotranspiration and hydrological cycle [13]. Land use changes in forested landscapes has gained momentum in the middle of the last century [14] due to industrialization, urbanization and globalization. Mitigation of these impacts entails actions at local/micro scale by preservation of ecosystems [15]. Knowledge of agents in LULC transition with the quantification of landscape dynamics would help in framing conservation strategies towards sustainable land uses.

LULC changes due to unplanned developmental activities have been posing serious challenges on the carrying capacity of landscape. Integrating environmental dimensions into land use planning and management process can greatly contribute to the sustenance of natural resources. Sustainable landscape management requires the advance information of likely land use changes, which would help in evolving mitigation strategies to sustain the livelihood of dependent communities. This entails modeling and visualization of landscape transitions with temporal spatial data. The change detection analyses have gained prominence with the availability of spatial data since 1970's. Multi resolution spatial data with advances in modeling techniques would aid in the sustainable resources management [16]. This would help to examine and statistically define the spatial patterns of LULC changes at a precise interval. Modeling helps in identifying the most appropriate spatial pattern of future land uses and this information helps in assessing resource availability and serves as a decision support system (DSS) for managers, planner and decisions makers [17, 18]. Modeling and visualization will satisfy numerous conditions for sustainable development path such as conservation of biological and cultural diversities through ecosystem protection [19]. Apart from inventorying, mapping, monitoring and change analyses, modeling and visualization would aid in empirically interpreting the consequences of spatial changes. Predictive statistical and geospatial models used for modelling landscape dynamics are logistic regression models [20], spatial dynamic model [21, 22], spatial Markov chains (MC) [23, 24], Cellular automata (CA) [25] and multi criteria decision making (MCDM) techniques [26]. CA model the local interaction of non-linear spatial process reflecting the dynamic system evolution [27–29] with consideration of discrete grid (lattice) units and its patterns.

MC-CA based simulation has advantages than other traditional procedures, but fails to link additional drivers of land use transitions [30]. While, techniques integrating agents and distance based relationship of driving forces include Multi criteria evaluation (MCE), Analytical Hierarchical Process (AHP) [31], Fuzzy based estimations. Fuzzy based modeling with geographic information system (GIS) helps in integrating the expert knowledge on spatial data (to determine the weight of each factor), which influences land suitability criteria [32]. However, standalone fuzzy system is insufficient for modeling complex natural resource systems, where relations between indicator variables are difficult to model [33, 34]. Integrated approach of fuzzy system with AHP has a potential to enhance the effectiveness of factor evaluation and accuracy by ranking alternatives for land suitability assessment [35, 36]. Analytical Hierarchy Process (AHP) is a well-known weight evaluation method has steps as specifying the hierarchical structure, determining relative important weights of the criteria and sub criteria, assigning preferred weights of each alternative and determining the final score [37]. AHP decision hierarchy helps in identifying 'n' criteria and 'm' alternatives in interactive decision making by comparing the relative importance of two elements (criteria or alternatives) 'i' and 'j' for a given pairwise comparison matrix of the likelihood of events for all possible alternative ranking outcomes [38, 39]. Fuzzy-AHP suitability maps are created by systematic, multi factor analysis for evaluating influence of land suitability [40, 41]. Model inputs include a variety of physical, cultural, economic and environmental factors [42]. CA-Markov models combined with MCE and AHP provides spatial land use transitions for distinct time steps [30, 43]. Fuzzy based estimations accounts for the influence of factors on land use based on distance relationship which aid in spatial allocation process of the simulation and model future changes. Hybrid approach of Markov Chain cellular automata coupling with fuzzy logic algorithms [44] helps to overcome the limitations of standalone CA model's neighborhood effect and thereby improves relative probability [45]. The objectives of this communication are:

1. Quantification of land use changes during 2007-2013 across three agro climatic regions,
2. visualizing the changes in forest cover during 2013–2022 by Fuzzy-AHP-CA analysis considering the growth agents and constraints,

3. evaluating the influence of protection measures in reserve forests towards sustainable management of forest resources.

2 Study area

The Western Ghats is one among the 35 global hotspots of biodiversity and it lies in the western part of peninsular India in a series of hills stretching over a distance of 1600 km from north to south and covering an area of about 1,60,000 sq.km. It harbours very rich flora and fauna and there are records of over 4000 species of flowering plants with 38% endemics, 330 butterflies with 11% endemics, 156 reptiles with 62% endemics, 508 birds with 4% endemics, 120 mammals with 12% endemics, 289 fishes with 41% endemics and 135 amphibians with 75% endemics. The rich biodiversity coupled with higher endemism is due to the humid tropical climate, topographical and geological characteristics, and geographical isolation (Arabian Sea to the west and the semiarid Deccan Plateau to the east) [6, 9].

Uttara Kannada district is located in the central Western Ghats at 13°55′–15°31′N and 74°9′–75°10′E (Fig. 1) and spread over an area of 10,293 km^2 in the mid-western part of Karnataka state, India has the unique a distinction of having highest forest cover in India with abundant natural resources. The total population in the district is 14, 37,169 (2011) and 29.15% lives in urban regions. The district has 11 taluks (for administrative purposes), which falls in three agro climatic zones i.e. coastal lands (Karwar, Ankola, Kumta, Honnavar and Bhatkal taluks), Sahyadrian interior (Supa, Yellapur, Sirsi and Siddapur taluks) and the eastern margin plains (Haliyal and Mundgod taluks). The region has luxuriant tropical climate coupled with heavy rainfall, harbors large number of endemic flora and faunal species of varied species composition, diversity, richness across different habitats, families etc. Unplanned developmental activities during the past three decades in the forested landscape has resulted in fragmentation of forests, evident from barren hill tops, reduction in the quantity and duration of water flow in streams apart from affecting ecologically sensitive habitats of diverse flora and fauna. The forest cover has undergone major changes, with the drastic reductions in primary forests. Intense agricultural activities coupled with developmental projects and monoculture plantations of exotic systems have depleted the native forest cover. The increase in exotic species plantation has led to removal of primeval forest cover and caused local extinctions of keystone species. Fragments of primary forests are existing now in the form of sacred groves, protected areas, etc.

3 Materials and method

Figure 2 outlines the procedure followed in the quantification and visualization of land use changes. This involved analysis of temporal land uses and visualization of likely changes through consideration of influencing agents.

3.1 Landscape dynamics

The temporal remote sensing data of Lands at ETM + series (2004, 2007, 2013) were downloaded from GCLF (http://glcfapp.glcf.umd.edu:8080/esdi/) and IRS P6 (2010) data was procured from National Remote Sensing

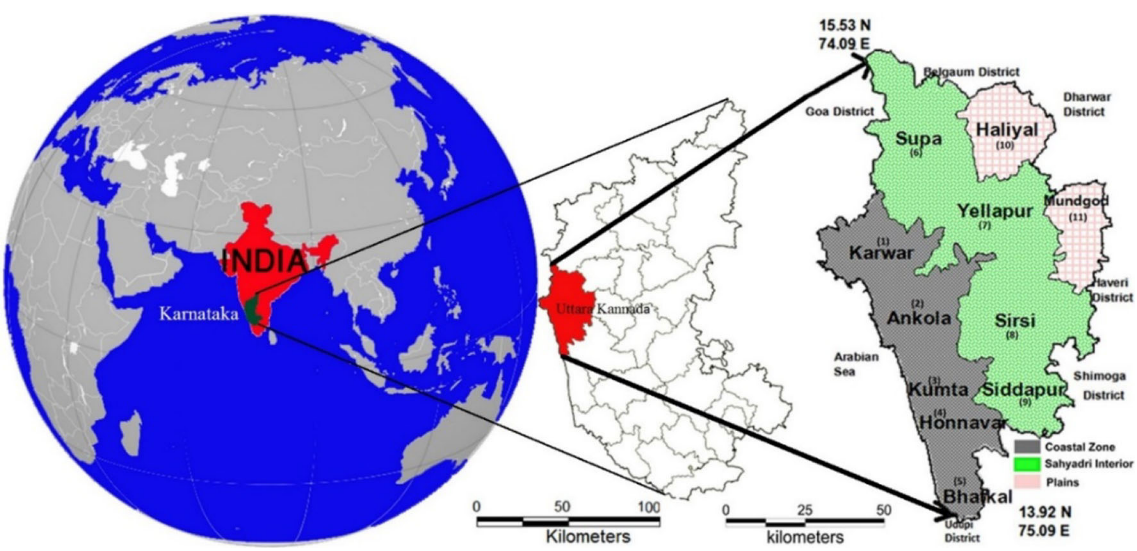


Fig. 1 Study area—Uttara Kannada district

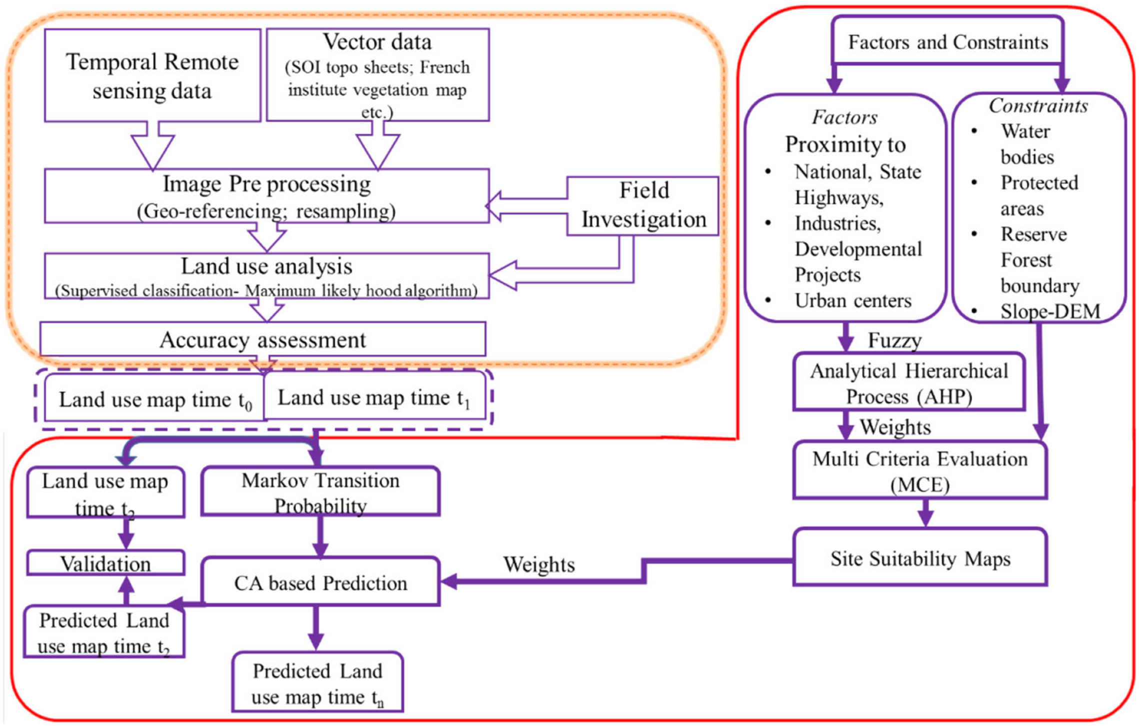


Fig. 2 Method adopted in the study

Center (http://nrsc.gov.in), India. ASTER DEM (30 m) was used to derive slope details of the region. The Survey of India topographic maps of 1:50,000 and 1:250,000 scale and online spatial data (http://bhuvan.nrsc.gov.in; https://www.google.com/earth/) were used to generate base layers of administrative boundaries, drainage network, road network, etc. GCPs (Ground control points) and training data is collected using pre calibrated GPS (Global Positioning System) from field. Land use analyses involved (i) generation of False Color Composite (FCC) of remote sensing data (bands–green, red and NIR), (ii) selection of training polygons (training data) covering 15% of the study area (polygons are uniformly distributed over the entire study area) (iii) loading these training polygons co-ordinates into pre-calibrated GPS, collection of the corresponding attribute data (land use types) for these polygons from the field, (iv) supplementing this information with Google Earth and (v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment. Error matrix (also referred as confusion matrix) kappa (κ) statistics and overall (producer's and user's) accuracies were assessed. The land use analysis was done using supervised classification technique based on Gaussian maximum likelihood algorithm using remote sensing data and training data collected from field. GRASS GIS (Geographical Resources Analysis Support System, http://ces.iisc.ernet.in/grass), a free and open source software with the robust support for processing both vector and raster data has been used for analyzing RS data.

3.2 Visualisation of forest transitions: simulation and prediction

Raster maps of the constraining factors and transition factors were generated at common resolution of 30 m for effective processing time. Likely land uses in 2022 is generated by (i) Markov Chain transition of base land uses, (ii) evaluating the driving factors and constraints, (iii) weightage metric score by fuzzy AHP based estimation and site suitability maps generation by MCE, and (iv) simulation and future prediction of land use by MC-CA algorithms. The transition probability is computed through MC analysis using land use maps of 2004, 2007 and 2010. The driving forces of land use changes and constraints (Tables 1 and 2) were identified based on the land use history, review of published literatures and policy reports. Major drivers of landscape transitions are slopes, major highways, industries, core residential areas, etc. Entities such as water bodies, river coarse, protected areas and reserve forest are considered as constraints as they are likely to change. The contributing factors for different land uses were normalized between 0 and 255 through fuzzification, 255 indicates maximum probability of change,

Table 1 Driving forces of landscape transition and constraints

S.no.	Factors	Description
1	Slope	Related to erosion, especially in the high forested areas such as Sahyadri region of study area. Priority was given to lower slope inclination for land use transformation [51–53]
2	National highways, major roads	The major transit ways have influence of land transformation in forested areas and also responsible for fragmentation, edge formation [9, 54], increases housing density and agriculture
3	Industrial activity	Industries and associated development in any region will have influence on landscape transition [55, 56]
4	Core built-up areas	Core built-up areas have greater probability of expansion in nearby areas next to it and act as a major transition of land use [57]

Table 2 Constraints of land use change

S.no.	Constraints	Description
1	Protected areas	Protected areas are prime regions of land scape which protect biological diversity, maintains ecological integrity and provides livelihoods to local communities [58–63]. Anshi Dandeli Tiger reserve (ADTR); Aghanashini lion tailed macaque (LTM) Conservation Reserve; Bedthi Conservation Reserve were created for conservation of tigers & hornbills, LTM, Myristica swamps and diverse flora, fauna. These regions are acting as an important corridor for wild life and endemic flora in Western Ghats of Karnataka, protected by Union government of India
2	Reserve forests	These regions are protected under Indian Forest Act, 1927 (an area duly notified under the provisions of India Forest Act or the State Forest Acts having full degree of protection) by state government for conserving endemic flora and fauna
3	Water bodies	Considered as a major source for food production and further expansions cannot be allowed in these regions. The land use changes in watershed will result in irreversible loss [6, 64, 65]
4	Slope	Land use changes in greater slopes (>30% is considered) will result in landslides and higher erosion [66, 67]

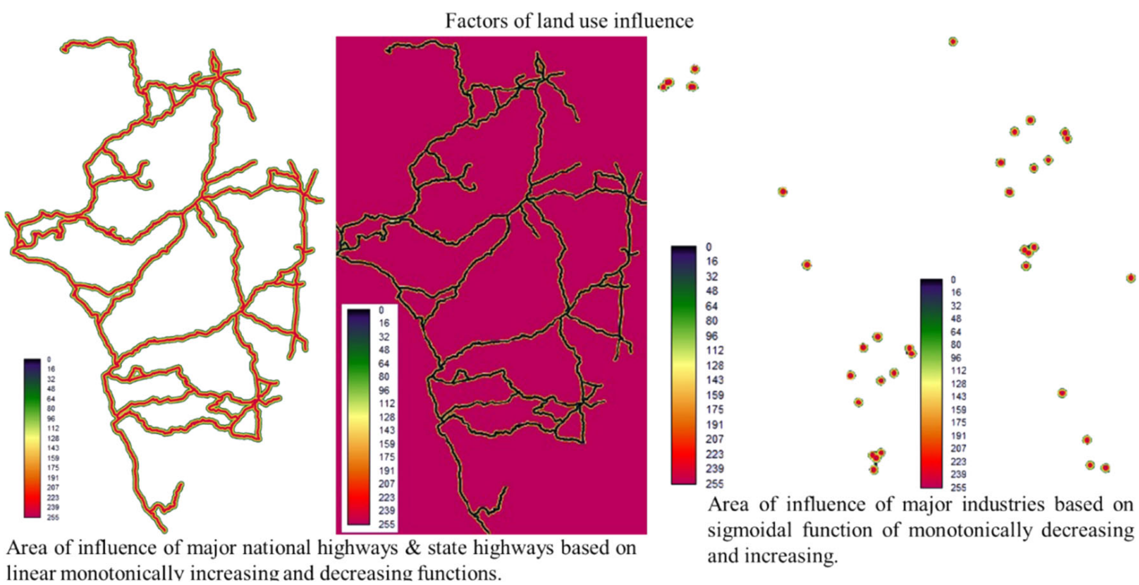


Fig. 3 Factors of land use influence by fuzzy distance tool measurement

while 0 indicates of no changes (Fig. 3), which allows to translate qualitative assessment into quantitative data by providing more logical and precise results. Constraints of land use transition is given in Fig. 4. The pair wise comparison matrices were generated across three agro climatic regions and their relative weights as Eigen vectors were estimated using AHP [46] to measure the degree of importance between criteria or factors i and j. A response matrix $A = [a_{ij}]$ is generated to measure the relative dominance of item i over item j with the decision maker's assessments a_{ij}, as pairwise comparisons that follow a uniform probability distribution (Eq 1).

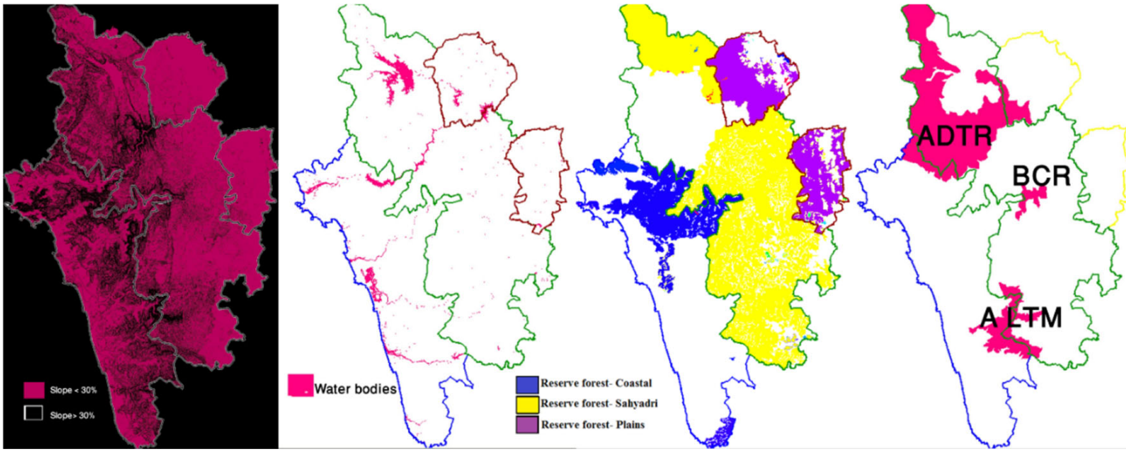


Fig. 4 Constraints of land use transition

$$a_{ij} = \frac{W_i}{W_j} * e_{ij} \tag{1}$$

where W_i and W_j are the priority weights belongs to vector W and $\sum W_j = 1$, e_{ij} is inconsistency observed in the analysis.

The comparison matrix elements were compared pair wise to relate single element at the level directly and ranked by eigenvector of the matrix [47] and eigenvalue of λ_{max} is computed [48]. The consistency index CI is computed to evaluate consistency of the judgment matrix (Eq. 2). Consistency ratio (CR) were evaluated for three regions and acceptable CR from 0.04 to 0.09 is obtained for each land use (Table 3) based on (Eq. 3). CR value below 0.1 indicates the model is consistent, obtained by the probability of the random weights from the landscape factors [49] and applied for subsequent processes. CA process is implemented based on the site suitability (the probability of that cell's changing to a given class in the future) and the transition matrix (contains the number of cells that change in the time step derived from the number of cells of each class by multiplying the probability matrix) generated from Fuzzy-AHP. The simulation and prediction of land use changes at every single time step is computed based on current land use and the state of neighboring pixels. Diamond filter of 5 × 5 kernel size was applied to the cellular automata to considered neighborhood land use effects. Two scenarios were designed to emphasize the environmental protection and violation in the region to visualize future state of forests (i) high protection scenario considering the protection of reserve forest with appropriate regulatory mechanism and (ii) least protection scenario (WRF-without reserve forest protection) with increase in population and erosion of forest resources. The Kappa statistic is an excellent measure for comparing a map of "reality" versus some "alternative "map of higher accuracy [50]. The accuracy of prediction is assessed through Kappa statistics by measuring agreement between predicted and actual land uses.

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{2}$$

where CI is the consistency index, λ_{max} is the largest or principal eigenvalue; n is the order of the matrix. If CI = 0, the matrix had a complete consistency. The worse consistency will represent greater value of CI.

The consistency ratio (CR) is calculated (Eq. 3) by

$$CR = \frac{CI}{RI} \tag{3}$$

where RI is the average of the resulting consistency index depending on order of the matrix. If CR value is less than

Table 3 Weightage Eigen vector and consistency ratio of each land use

Land use Factors	Eigen vector of weight for each land use						
	Forest	Plantations	Horticulture	Crop land	Built-up	Open land	Water
Slope	0.10	0.14	0.23	0.17	0.08	0.10	0.10
Industries	0.10	0.18	0.13	0.10	0.11	0.21	0.18
Major motor ways	0.20	0.10	0.25	0.19	0.21	0.06	0.13
Core built-up areas	0.59	0.58	0.38	0.54	0.61	0.63	0.60
Consistency ratio	0.04	0.05	0.09	0.09	0.08	0.07	0.05

0.10, the matrix had a reasonable consistency, otherwise the matrix should be altered for better CR.

4 Results and discussion

The spatial pattern analyses using temporal remote sensing data, highlights the extent of forest transition, which are given in Figs. 5, 6, 7, 8. The forest cover in coastal region has decreased from 66.5 (2004) to 59.06% (2013) due to implementation of unplanned projects such as project Sea Bird, Kaiga nuclear power house, Kadra dam, etc., increase in human populations at certain pockets of Karwar, Bhatkal, Honnavara taluks in coastal regions. The increase in population density has cleared major forest cover as built-up area has increased from 3.98 to 4.5% and plantations have increased from 5.69 to 9.04%. Sahyadri region is the core part of central Western Ghats with lush greenery, mountains, network of perennial streams and Arecanut gardens in the valleys. The evergreen to semi evergreen forested area has been transformed into moist deciduous forests due to disturbances and some have been converted into plantations such as *Acacia auriculiformis, Casuarina equisetifolia, Eucalyptus spp.,* and *Tectona grandis* etc. The commercial plantation is practiced prominently in Bedthi/Gangavali river valley and Sharavathi river estuary of Honnavar. The forest cover has lost from 65.98% to 60.6% by 2013 due to increase in built-up area (2.12%) and plantations (17.29%). Haliyal and Mundgod taluks form transitional zone, which are prone to economic activities. The market based cropping pattern and forest department based initiatives for plantation of exotic species shown

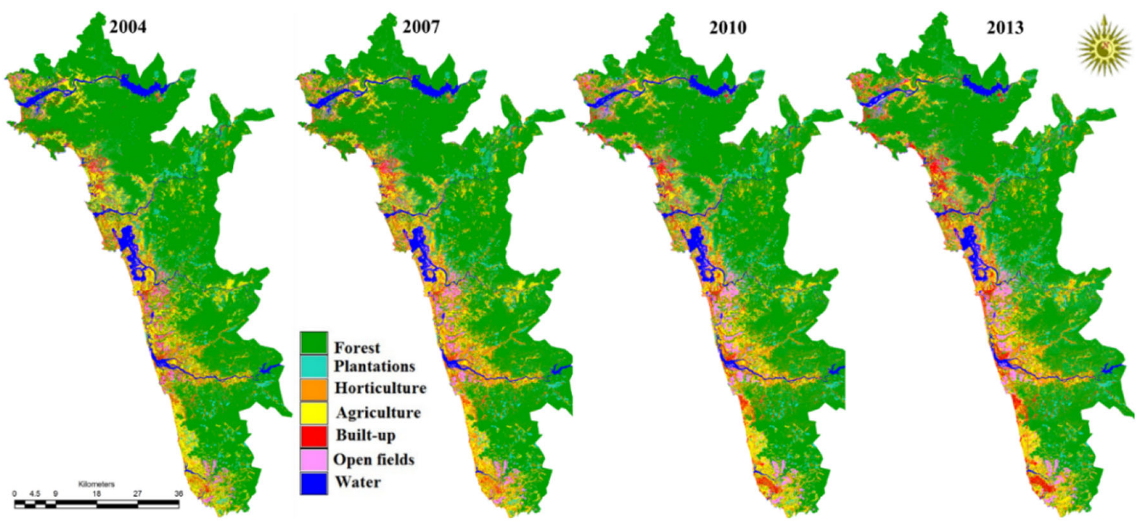


Fig. 5 Land use change across coastal region from 2004 to 2013

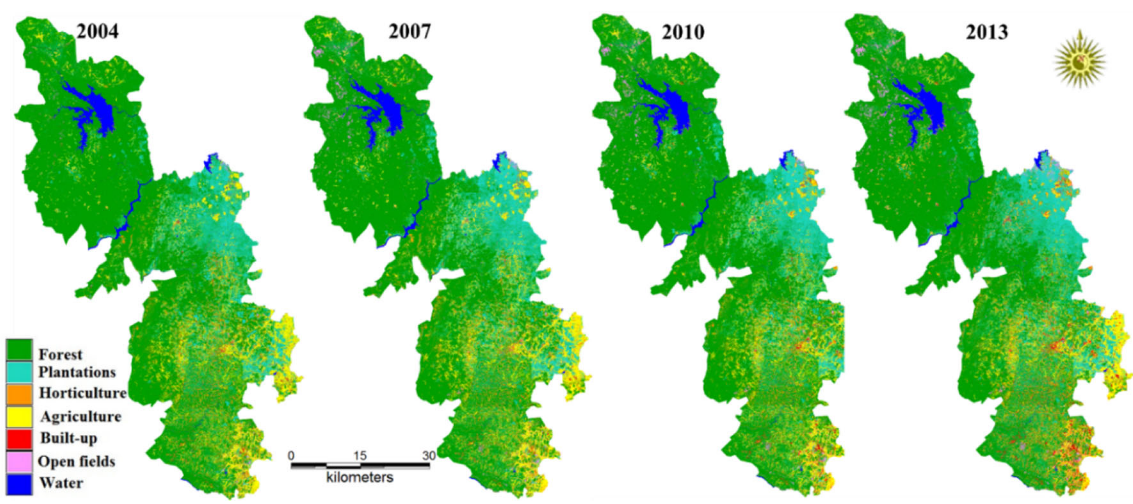


Fig. 6 Land use change across Sahyadri interior region from 2004 to 2013

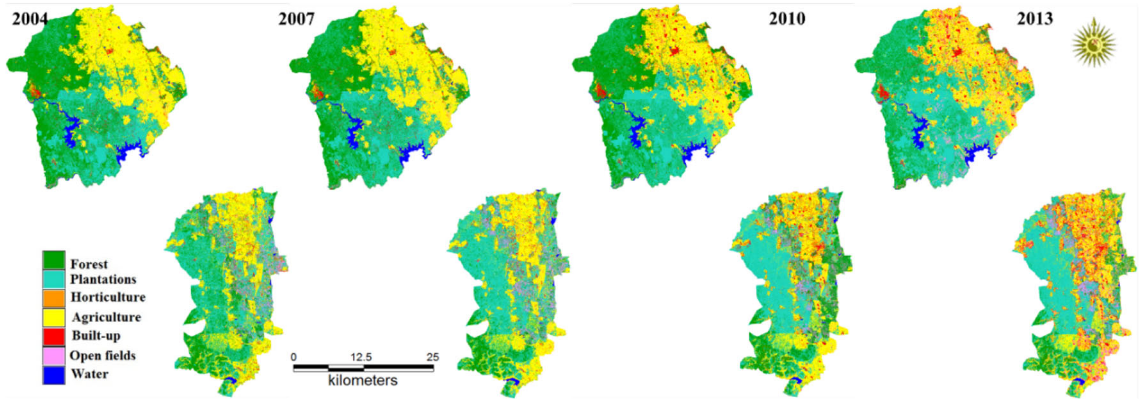


Fig. 7 Land use change across plains from 2004 to 2013

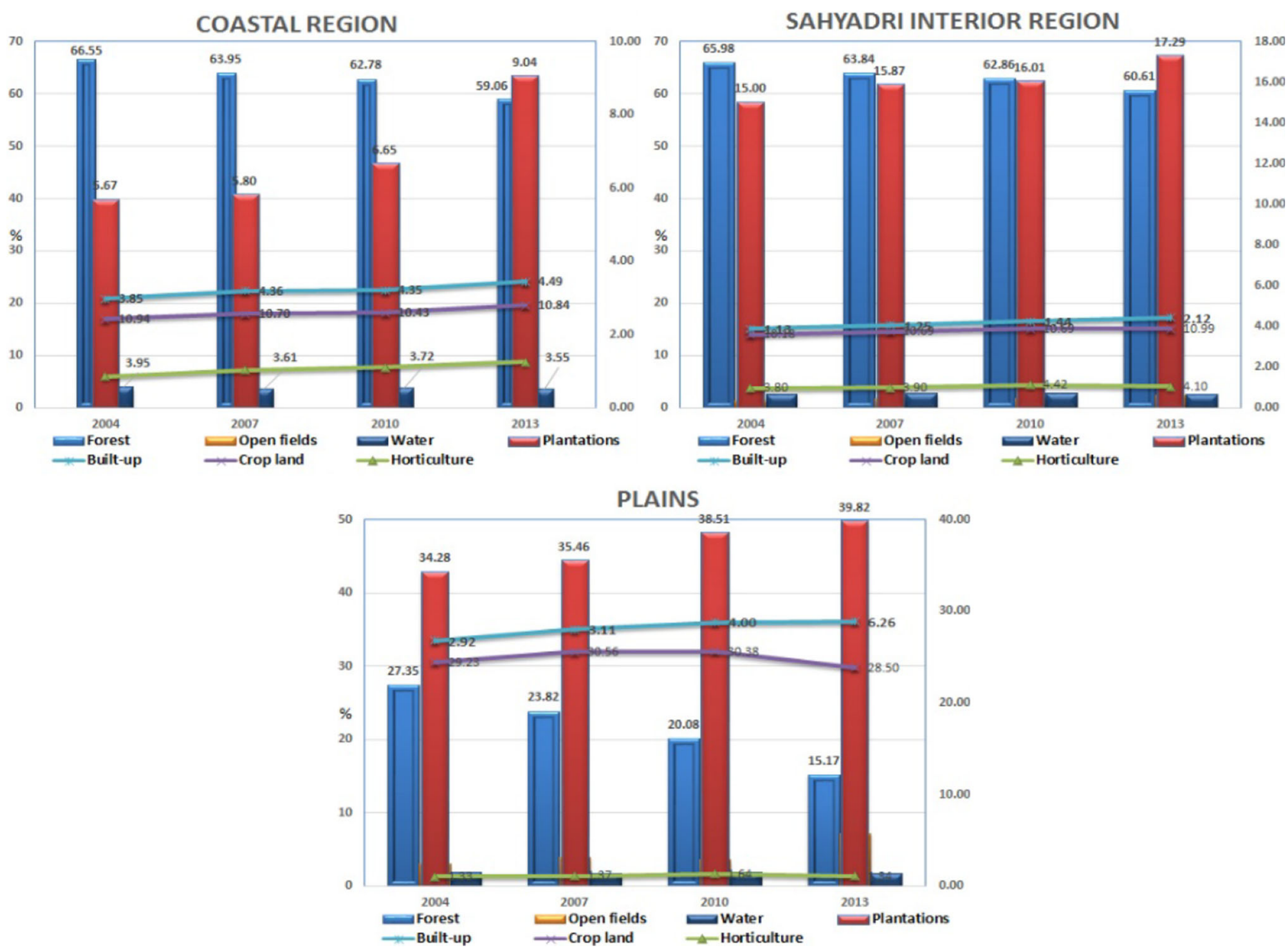


Fig. 8 Land use dynamics across three agro climatic zones

equally adverse effects on forests. The forest cover has lost from 27.35 to 15.17% (2013) by increase in plantations 34.28–39.82%. The area under paved surface has reached to 6.3 from 2.9% (2004), due to population increase and associated economic activities. Classification accuracy is assessed by considering the reference data collected from field. Table 4 with higher kappa and overall accuracy values highlights that the classification is satisfactory.

Simulation and modelling of transition at temporal scale is done using Fuzzy-AHP-CA-MC technique. Markov chain is used to determine the zone wise transition probability during 2004 and 2007 with loop time of 3 years. CA with the site suitability and the transition matrix (generated by MC and FUZZY-AHP-MCE) predicted spatially the changes under two scenarios based on the neighboring pixels for 2022 (with the knowledge of transitions during 2004–2007, 2007–2010 and 2010–2013). The accuracy of prediction is evaluated through Kappa statistics by comparing the simulated data with the actual land uses of 2010, 2013 (Table 5 for both scenarios: *P** (predicted considering the implementation of protection measures) and P_WRF: Prediction without the protection of reserve forests), which indicates that CA MC is a reliable estimator. The Fuzzy distance measurement has provided the potential transition of each land use based on factors that promote transition. AHP showed good consistency and found suitable for predicting land uses. The projected land use of 2022 for coastal region (Fig. 9, Table 6) shows forest cover will reach to 56.76% with the implementation of protection measures by regulatory framework. The urban expansion from 4.49 to 8.51% with the industrial growth and economic activities. The increase in plantation area is due to the conversion of forests and also planting in degraded forest patches. Scenario 2 reflecting the lack of protection in the coastal region will result in rampant forest changes. The forest area will reduce to 54.07% with the

Table 4 Accuracy assessment of land use analysis

Year	2004		2007		2010		2013	
Categories	PA	UA	PA	UA	PA	UA	PA	UA
Forest	92.29	98.62	86.13	37.46	89.18	91.10	96.28	76.45
Plantations	88.53	96.13	98.27	91.32	91.42	92.44	99.31	79.49
Horticulture	98.09	80.05	60.04	96.5	97.58	98.46	86.50	93.84
Crop	88.25	96.33	93.97	89.74	86.05	84.64	55.04	93.02
Built-up	88.26	80.05	79.66	81.85	99.93	96.96	93.39	62.50
Open fields	86.50	93.84	98.56	93.31	86.49	95.26	95.59	94.63
Water	98.82	90.67	96.94	97.19	97.86	81.39	99.71	99.17
Kappa	0.82		0.86		0.9		0.88	
Overall Accuracy	88.26		91.02		91.24		92.47	

Table 5 Validation of actual land use with predicted and Kappa value (P* represents Projected)

Zone	Coastal zone		Sahyadri interior		Plains	
Index	P^*_2013	P_ WRF 2013	P_2013	P_ WRF 2013	P_2013	P_ WRF 2013
Kno	0.89	0.91	0.92	0.91	0.94	0.92
Klocation	0.87	0.9	0.95	0.95	0.95	0.93
Kstandard	0.83	0.87	0.9	0.9	0.92	0.89

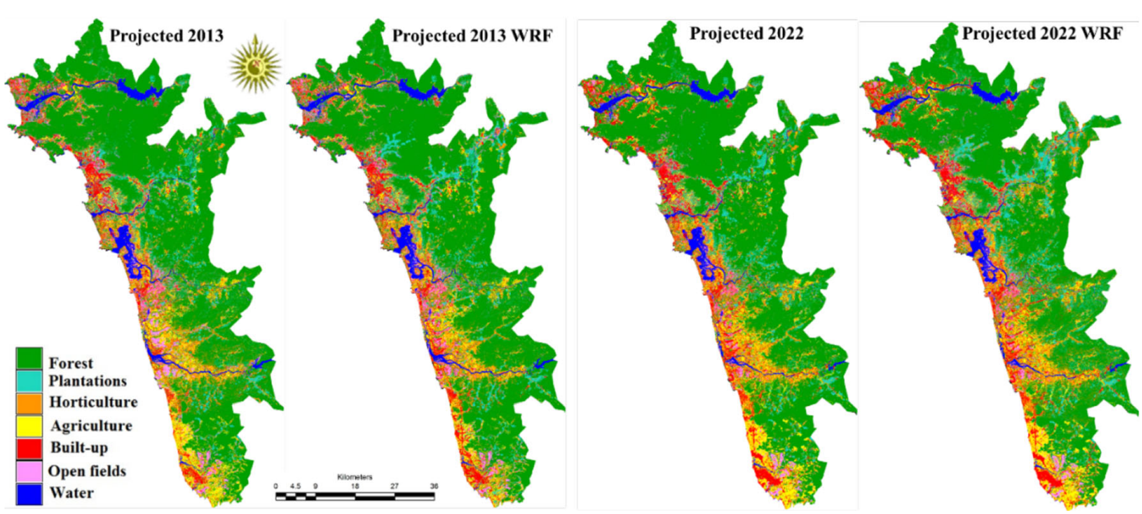


Fig. 9 Predicted and future land use of Coastal region (2013–2022 under two scenrios)

Table 6 Projected land use for 2013 to 2022 across three zones

Zone	Coastal region								Sahyadri interior							
Category	P 2013		P 2013 WRF		P 2022		P 2022 WRF		P 2013		P 2013 WRF		P 2022		P 2022 WRF	
	HA	%	HA	%	HA	%	HA	%	HA	%	HA	%	HA	%	HA	%
Forest	204,522.3	60.9	203,066.3	60.52	190,459.3	56.76	181,431.57	54.07	329,984.27	60.97	322,022	59.50	301,021.8	55.6	271,210.8	50.1
Plantations	24,520.8	7.31	25,227	7.52	27,385.9	8.16	32,822.52	9.78	101,981.9	18.84	107,255	19.82	111,460.9	20.60	110,030.6	20.33
Horticulture	24,975.7	7.44	24,560.22	7.32	29,268.7	8.72	30,803.38	9.18	23,663.7	4.37	26,643	4.92	26,449.6	4.89	25,997.1	4.80
Crop land	30,449.9	9.07	29,356.97	8.75	36,547.7	10.89	34,147.98	10.18	43,794.86	8.09	41,926	7.75	45,804.4	8.46	64,012.2	11.83
Built-up	21,464.9	6.39	24,251.33	7.23	28,567.5	8.51	32,907.01	9.81	16,338.57	3.02	17,346	3.21	28,121.06	5.20	39,104.8	7.23
Open land	17,018.6	5.07	16,401.43	4.89	11,361.6	3.39	11,489.6	3.42	11,739.47	2.17	12,309	2.27	14,717.67	2.72	17,258.3	3.19
Water	12,709.1	3.79	12,698.1	3.78	11,970.7	3.57	11,959.2	3.56	13,693.3	2.53	13,694	2.53	13,620.5	2.52	13,582.2	2.51

Eastern Plains									
Year	P 2013		P 2013 WRF		P 2022		P 2022 WRF		Total area
Category	HA	%	HA	%	HA	%	HA	%	
Forest	22,961.03	15.06	21,904.14	14.36	18,285.47	11.99	16,902.38	11.08	Coastal region
Plantations	55,025.39	36.08	56,456.78	37.02	64,054.89	42.00	59,461.46	38.99	335,561.32
Horticulture	1411.32	0.93	1575.54	1.03	3148.29	2.06	2853.44	1.87	
Crop land	44,830.87	29.40	45,389.04	29.76	45,651.73	29.93	48,331.07	31.69	Sahyadri Interior
Built-up	11,472.99	7.52	12,276.44	8.05	11,910.87	7.81	12,442.5	8.16	541,195.99
Open fields	14,126.75	9.26	12,226.4	8.02	6747.78	4.42	9875.01	6.48	
Water	2677.36	1.76	2677.36	1.76	2706.67	1.77	2639.84	1.73	Plains
									151,505.69

HA hectares

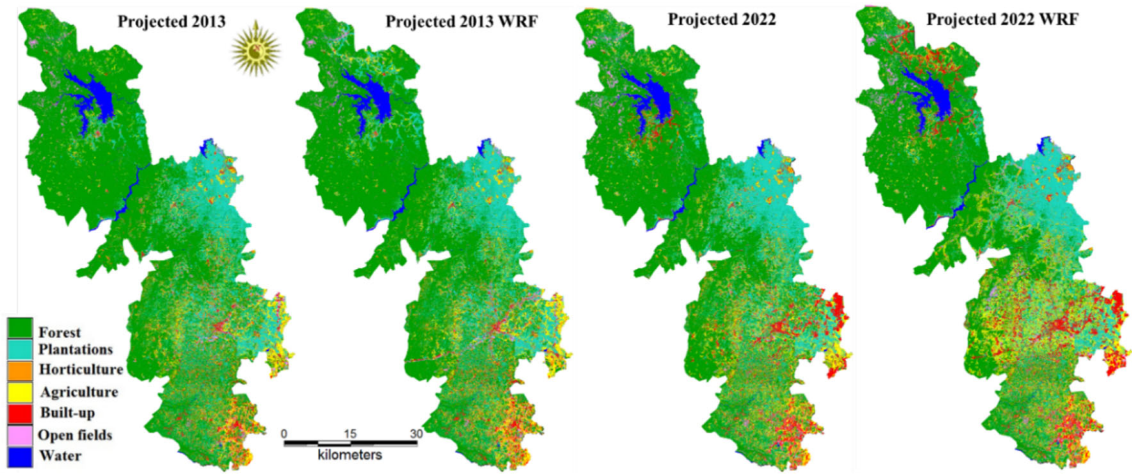


Fig. 10 Predicted and future land use of Sahyadri Interior (2013–2022 under two scenrios)

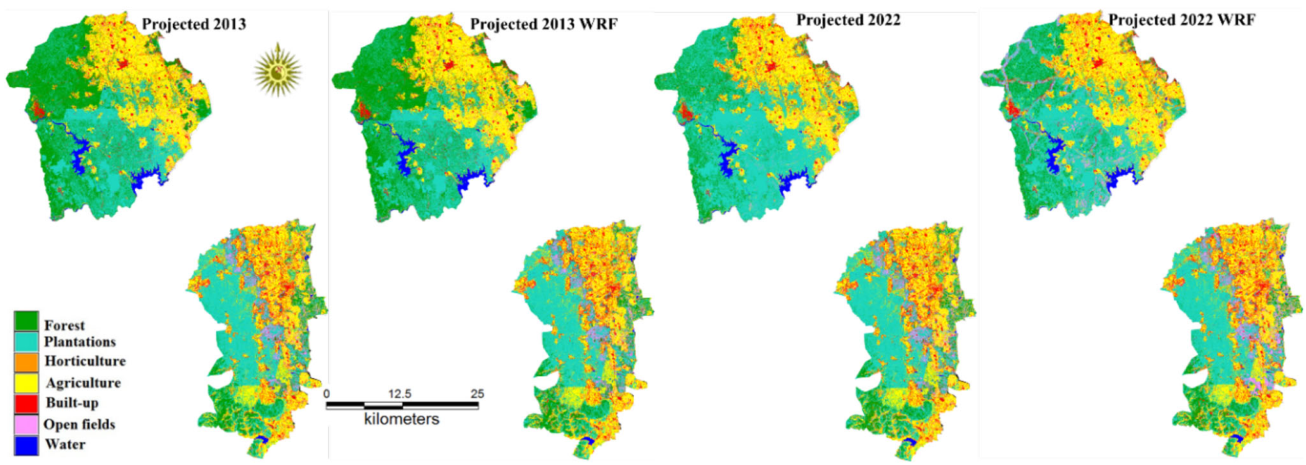


Fig. 11 Predicted and future land use of Eastern Plains (2013–2022 under two scenrios)

increase in area under plantations, horticulture and built-up in the costal taluks—Karwar, Bhatkal, and Honnavar.

Sahyadari Interior region (Fig. 10) shows moderate disturbances (60.61 (2013) to 55.62% (2022)) under high protection scenario with changes in plantations and built-up land use classes. The ADTR, ALTM, Bedthi conservation reserve areas are under protection and will remain so with the minimal disturbances. Scenario 2 highlights the decline of natural forest cover from 60.61 (2012) to 50.11% (2022) with increase in monoculture plantations from 17.29 to 20.33%. The same trend is noticed in Sirsi, Siddapur, Yellapura taluks except Supa. The area under built-up cover will reach 2.12 to 7.23% and horticulture will be 11.83% (in 2022). As per the scenario 2, forest patches in this region would be only in protected areas and *Kans*—scared forests by 2022. *Kans* are relic forest patches, protected since historical times and are expected to remain under conservation. The predicted land uses under two scenarios in the eastern plains (Fig. 11) show spurt in built-up from 6.26 to 7.81 and 8.16%. The existing towns and villages will be more urbanized due to neighbor effect of urban agglomerations—Hubli, Dharwad and Belgaum. The forest cover will be 11% and there would be an increase in plantations from 39.42 to 42% (2022). The unauthorized land conversion in plains would lead to an increase in agriculture and horticulture (31.69%).

The series of hydroelectric projects in the coastal region have adversely affected the ecology and biodiversity. The fisheries sector in the Sharavathi river is now facing serious impediment, due to the loss of spawning and breeding grounds of fishes (now only 43 taxa) and 50% reduction in the total fish taxa with the implementation of power projects at Linganmakki and Gersoppa [68]. This region is undergoing large scale forest transitions after 2005 with the implementation of large scale developmental projects (Project Sea Bird at Karwar, etc.), medium scale industry, small scale Industrial estate (comprises of 357 industries) and other developmental activities. Konkan railways, National Highway 17 (NH-17, now NH-66) from Goa to Udupi, National Highway 63 (NH-63) from Hubli to Ankola have also contributed significantly to forest degradation. Konkan Railway is the longest railway line in the region has given push to urbanization with emergence of new towns, creation of major ports. These activities have impacted the environment as well as socio-economic aspects of the west coast [69]. The forests in Sahyadri region are in different stages of secondary succession by transformation of evergreen forests into moist deciduous forests due to numerous anthropogenic factors such as heavy exploitation, large scale unplanned forest plantations, encroachment of forests [70]. Undulating terrains with the community protected reserves have several primary forest patches with greater than 80% evergreenness and endemism [71]. However, market induced commercial plantations such as *Areca catechu, Cocos nucifera* has transformed major croplands and swampy areas as horticulture plantations (10.99%) by 2013. The tourism activities are higher than all the taluks in plains because of Anshi-Dandeli tiger reserve, Anshi hornbill's national park, Kali river rafting and many more jungle resorts.

The agent based modeling has facilitated to visualize landscape development and transition under higher protection and without any control regulations. Area under built-up has increased over time with the loss of forest lands, agriculture and natural open spaces. This change has allowed recolonization of forest cover by shrub and exotic tree species across three agro climatic zones. Land use change modeling with rich spatial data provided a proper environment analyze and display spatial data to predict land use changes based on several independent spatial variables. Agent based prediction of land uses has helped in visualizing likely changes, which is essential to formulate a comprehensive land use management policies focusing on restoration of degraded forest patches and mitigation of further impacts on the pristine ecosystem. Further, prediction through logistic regression, frequency ratio, and weights of evidence techniques could be reinforced by considering the local expert knowledge [72, 73] to analyze the probability of occurrence of a dependent variable with each class of independent variables [74, 75]. The inclusion of variability in land use drivers, socio-economic variables, the processes inducing changes and their influences on modeling and prediction would augment the prediction accuracy.

5 Conclusion

The high conversion rates of natural vegetation by anthropogenic activities will have vulnerability on ecosystem and their support for livelihood. The temporal remote sensing data in conjunction with other supporting attribute data, influential factors used for visualization of land use transition at temporal scale using Fuzzy-AHP-CA-MC method predicted two different future scenarios of land use (2022) based on with appropriate regulatory mechanism. Coastal region shows loss of forest cover from 66.55 (2004) to 56.76%, by increase in built-up area from 3.85 to 8.51% (2022). Sahyadri Interior region shows moderate forest cover loss due to higher protection, seen progression in plantation from 15 (2004) to 20.60% (2022) and horticulture uses from 3.8 to 4.89%. The land use of scenario1 (2022) indicates that environmental restriction fulfilled the goals of reducing forest land transition as established for the restricted areas. If land use changes occur according scenario 2 (2022), plantations will dominate making the legal borders indistinct and maintaining the biological conservation will be a challenging task in this rich biodiversity hotspot. The implementation of a restrictive legal framework for environment protection has resulted as an efficient barrier to human pressure within high forested area. The prediction results in open fields and forest classes were registered net loss in area while built-up, agriculture and horticulture land use classes were registered as net gain in both land use scenarios. The present communication has integrated restrictive legal environmental protection scenarios demonstrates a powerful and persuasive tool to support planning and policy for sustainable landscape development.

Acknowledgements We are grateful to (i) the Ministry of Environment, Forests and Climate Change, Government of India, (ii) NRDMS Division, the Ministry of Science and Technology (DST), Government of India, (iii) Karnataka Biodiversity Board, Western Ghats Task Force, Government of Karnataka and (iv) Indian Institute of Science for the financial and infrastructure support. We acknowledge the support of Karnataka Forest Department for giving necessary permissions to undertake ecological research in Central Western Ghats. We thank Vishnu Mukri and Srikanth Naik for the assistance during field data collection (Grant Nos. R1011 and CES/TVR/DST/1045).

References

1. Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., et al. (2013). High-resolution global maps of 21st-century forest cover change. *Science, 342*(6160), 850–853.
2. Chase, T. N., Pielke, R. A., Sr., Kittel, T. G. F., Nemani, R. R., & Running, S. W. (2000). Simulated impacts of historical land cover changes on global climate in northern winter. *Climate Dynamics, 16*(2–3), 93–105.
3. Dupont, L., & Van Eetvelde, V. (2013). Assessing the potential impacts of climate change on traditional landscapes and their heritage values on the local level: Case studies in the Dender basin in Flanders, Belgium. *Land use policy, 35,* 179–191.
4. Bharath, S., Rajan, K. S., & Ramachandra, T. V. (2013). Land surface temperature responses to land use land cover dynamics. *Geoinformatics Geostatistics: An Overview, 1,* 4.

5. Ball, J. B. (2001). Global forest resources: history and dynamics. In *The Forests Handbook, Volume 1: An Overview of Forest Science*, 3–22.
6. Vinay, S., Bharath, S., Bharath, H. A., & Ramachandra, T. V. (2013). Hydrologic model with landscape dynamics for drought monitoring. In *proceeding of: Joint International Workshop of ISPRS WG VIII/1 and WG IV/4 on Geospatial Data for Disaster and Risk Reduction, Hyderabad, November* (pp. 21–22).
7. Pongratz, J., Reick, C. H., Raddatz, T., & Claussen, M. (2010). Biogeophysical versus biogeochemical climate response to historical anthropogenic land cover change. *Geophysical Research Letters, 37*(8), 438–458.
8. Bright, R. M. (2015). Metrics for biogeophysical climate forcings from land use and land cover changes and their inclusion in life cycle assessment: A critical review. *Environmental Science and Technology, 49*(6), 3291–3303.
9. Ramachandra, T. V., Bharath, S., & Bharath, A. (2014). Spatio-temporal dynamics along the terrain gradient of diverse landscape. *Journal of Environmental Engineering and Landscape Management, 22*(1), 50–63.
10. Bonan, G. B. (2008). Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. *Science, 320*(5882), 1444–1449.
11. Hidalgo, J., Masson, V., & Gimeno, L. (2010). Scaling the daytime urban heat island and urban-breeze circulation. *Journal of Applied Meteorology and Climatology, 49*(5), 889–901.
12. Lawrence, P. J., Feddema, J. J., Bonan, G. B., Meehl, G. A., O'Neill, B. C., Oleson, K. W., et al. (2012). Simulating the biogeochemical and biogeophysical impacts of transient land cover change and wood harvest in the Community Climate System Model (CCSM4) from 1850 to 2100. *Journal of Climate, 25*(9), 3071–3095.
13. Bala, G., Caldeira, K., Wickett, M., Phillips, T. J., Lobell, D. B., Delire, C., et al. (2007). Combined climate and carbon-cycle effects of large-scale deforestation. *Proceedings of the National Academy of Sciences, 104*(16), 6550–6555.
14. Antrop, M. (2005). Why landscapes of the past are important for the future. *Landscape and urban planning, 70*(1), 21–34.
15. Calvo-Iglesias, M. S., Fra-Paleo, U., & Diaz-Varela, R. A. (2009). Changes in farming system and population as drivers of land cover and landscape dynamics: the case of enclosed and semi-openfield systems in Northern Galicia (Spain). *Landscape and Urban Planning, 90*(3), 168–177.
16. Taubenböck, H., Esch, T., Felbier, A., Wiesner, M., Roth, A., & Dech, S. (2012). Monitoring urbanization in mega cities from space. *Remote Sensing of Environment, 117,* 162–176.
17. Collins, M. G., Steiner, F. R., & Rushman, M. J. (2001). Land-use suitability analysis in the United States: historical development and promising technological achievements. *Environmental Management, 28*(5), 611–621.
18. Malczewski, J., & Rinner, C. (2015). Multiattribute Decision Analysis Methods, In *Multicriteria Decision Analysis in Geographic Information Science* (pp. 81–121). Heidelberg: Springer Berlin.
19. Ryngnga, P. K. (2008). Ecotourism prioritization: a geographic information system approach. *South Asian Journal of Tourism and Heritage, 1*(1), 49–56.
20. Millington, J. D., Perry, G. L., & Romero-Calcerrada, R. (2007). Regression techniques for examining land use/cover change: a case study of a Mediterranean landscape. *Ecosystems, 10*(4), 562–578.
21. Gilruth, P. T., Marsh, S. E., & Itami, R. (1995). A dynamic spatial model of shifting cultivation in the highlands of Guinea. *West Africa. Ecological modelling, 79*(1), 179–197.
22. Pontius, R. G., Huffaker, D., & Denman, K. (2004). Useful techniques of validation for spatially explicit land-change models. *Ecological Modelling, 179*(4), 445–461.
23. Wood, E. C., Lewis, J. E., Tappan, G. G., & Lietzow, R. W. (1997, June). The development of a land cover change model for southern Senegal, In *Land Use Modeling Workshop*, June.
24. Kamusoko, C., Aniya, M., Adi, B., & 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, 29*(3), 435–447.
25. Arsanjani, J. J., Helbich, M., Kainz, W., & Boloorani, A. D. (2013). Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. *International Journal of Applied Earth Observation and Geoinformation, 21,* 265–275.
26. Zopounidis, C., & Pardalos, P. M. (Eds.). (2010). *Handbook of multicriteria analysis* (Vol. 103, pp. 450). Springer Science & Business Media.
27. Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., & Hokao, K. (2011). Modeling urban land use change by the integration of cellular automaton and Markov model. *Ecological Modelling, 222*(20), 3761–3772.
28. Wang, L., Jin, X., Du, X., & Zhou, Y. (2012). Land use scenarios simulation of Foshan city based on gray model and cellular automata model. *Transactions of the Chinese Society of Agricultural Engineering, 28*(3), 237–242.
29. Yuan, F. (2010). Urban growth monitoring and projection using remote sensing and geographic information systems: A case study in the twin cities metropolitan area. *Minnesota. Geocarto International, 25*(3), 213–230.
30. He, J., Liu, Y., Yu, Y., Tang, W., Xiang, W., & Liu, D. (2013). A counterfactual scenario simulation approach for assessing the impact of farmland preservation policies on urban sprawl and food security in a major grain-producing area of China. *Applied Geography, 37,* 127–138.
31. Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology, 15*(3), 234–281.
32. Keshavarzi, A., Sarmadian, F., Heidari, A., & Omid, M. (2010). Land suitability evaluation using fuzzy continuous classification (a case study: Ziaran region). *Modern Applied Science, 4*(7), 72.
33. Beek, M. (2000). Fuzzy logical analysis for modelling of natural resource processes. *International Archives of Photogrammetry and Remote Sensing, 33*(B4/1; PART 4), 119–125.
34. Zhang, J., Su, Y., Wu, J., & Liang, H. (2015). GIS based land suitability assessment for tobacco production using AHP and fuzzy set in Shandong province of China. *Computers and Electronics in Agriculture, 114,* 202–211.
35. Moeinaddini, M., Khorasani, N., Danehkar, A., & Darvishsefat, A. A. (2010). Siting MSW landfill using weighted linear combination and analytical hierarchy process (AHP) methodology in GIS environment (case study: Karaj). *Waste Management, 30*(5), 912–920.
36. Kordi, M., & Brandt, S. A. (2012). Effects of increasing fuzziness on analytic hierarchy process for spatial multicriteria decision analysis. *Computers, Environment and Urban Systems, 36*(1), 43–53.
37. Moeinaddini, M., Khorasani, N., Danehkar, A., & Darvishsefat, A. A. (2010). Siting MSW landfill using weighted linear combination and analytical hierarchy process (AHP) methodology in GIS environment (case study: Karaj). *Waste Management, 30*(5), 912–920.
38. Torfi, F., Farahani, R. Z., & Rezapour, S. (2010). Fuzzy AHP to determine the relative weights of evaluation criteria and Fuzzy TOPSIS to rank the alternatives. *Applied Soft Computing, 10*(2), 520–528.
39. Vettorazzi, C. A., & Valente, R. A. (2016). Priority areas for forest restoration aiming at the conservation of water resources. *Ecological Engineering, 94,* 255–267.

40. Dağdeviren, M., & Yüksel, İ. (2008). Developing a fuzzy analytic hierarchy process (AHP) model for behavior-based safety management. *Information Sciences, 178*(6), 1717–1733.
41. Lee, A. H., Kang, H. Y., & Chang, C. T. (2009). Fuzzy multiple goal programming applied to TFT-LCD supplier selection by downstream manufacturers. *Expert Systems with Applications, 36*(3), 6318–6325.
42. Malczewski, J. (2004). GIS-based land-use suitability analysis: a critical overview. *Progress in planning, 62*(1), 3–65.
43. de Noronha Vaz, E., Nijkamp, P., Painho, M., & Caetano, M. (2012). A multi-scenario forecast of urban change: A study on urban growth in the Algarve. *Landscape and Urban Planning, 104*(2), 201–211.
44. Liu, Y. (2012). Modelling sustainable urban growth in a rapidly urbanising region using a fuzzy-constrained cellular automata approach. *International Journal of Geographical Information Science, 26*(1), 151–167.
45. Poelmans, L., & Van Rompaey, A. (2010). Complexity and performance of urban expansion models. *Computers, Environment and Urban Systems, 34*(1), 17–27.
46. Bernasconi, M., Choirat, C., & Seri, R. (2010). The analytic hierarchy process and the theory of measurement. *Management Science, 56*(4), 699–711.
47. Zhang, X., Dong, S., Yin, W., Li, S., & Gao, Z. (2005, August). GIS grid calculation method application in urban eco-environment assessment: a case study of Longxi County in Gansu Province, China. In *Optics & Photonics 2005* (pp. 588410–588410). International Society for Optics and Photonics.
48. Ying, X., Zeng, G. M., Chen, G. Q., Tang, L., Wang, K. L., & Huang, D. Y. (2007). Combining AHP with GIS in synthetic evaluation of eco-environment quality—A case study of Hunan Province, China. *Ecological modelling, 209*(2), 97–109.
49. Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International journal of services sciences, 1*(1), 83–98.
50. Pontius, R. G., Jr., & Millones, M. (2011). Death to Kappa: Birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing, 32*(15), 4407–4429.
51. Tang, K., Zhang, K., & Lei, A. (1998). Critical slope gradient for compulsory abandonment of farmland on the hilly Loess Plateau. *Chinese Science Bulletin, 43*(5), 409–412.
52. Fu, B. J., Zhang, Q. J., Chen, L. D., Zhao, W. W., Gulinck, H., Liu, G. B., et al. (2006). Temporal change in land use and its relationship to slope degree and soil type in a small catchment on the Loess Plateau of China. *Catena, 65*(1), 41–48.
53. Li, Z., Liu, W., & Zheng, F. (2013). The land use changes and its relationship with topographic factors in the Jing river catchment on the Loess Plateau of China. *SpringerPlus, 2*(1), 1.
54. Terra, T. N., & dos Santos, R. F. (2012). Measuring cumulative effects in a fragmented landscape. *Ecological Modelling, 228,* 89–95.
55. Briassoulis, H. (2009). Factors influencing land-use and land-cover change. In *Land cover, land use and the global change, encyclopaedia of life support systems (EOLSS)*, (Vol. I, pp. 126–146).
56. Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., et al. (2005). Global consequences of land use. *Science, 309*(5734), 570–574.
57. Ramachandra, T. V., Setturu, B., & Aithal, B. H. (2012). Peri-urban to urban landscape patterns elucidation through spatial metrics. *International Journal of Engineering Research and Development, 2*(12), 58–81.
58. Ervin, J. (2003). Protected area assessments in perspective. *BioScience, 53*(9), 819–822.
59. Das, A., Krishnaswamy, J., Bawa, K. S., Kiran, M. C., Srinivas, V., Kumar, N. S., et al. (2006). Prioritisation of conservation areas in the Western Ghats, India. *Biological Conservation, 133*(1), 16–31.
60. Figueroa, F., & Sánchez-Cordero, V. (2008). Effectiveness of natural protected areas to prevent land use and land cover change in Mexico. *Biodiversity and Conservation, 17*(13), 3223–3240.
61. Payés, A. C. L. M., Pavão, T., & dos Santos, R. F. (2013). The conservation success over time: Evaluating the land use and cover change in a protected area under a long re-categorization process. *Land Use Policy, 30*(1), 177–185.
62. Terra, T. N., dos Santos, R. F., & Costa, D. C. (2014). Land use changes in protected areas and their future: The legal effectiveness of landscape protection. *Land Use Policy, 38,* 378–387.
63. Martinuzzi, S., Radeloff, V. C., Joppa, L. N., Hamilton, C. M., Helmers, D. P., Plantinga, A. J., et al. (2015). Scenarios of future land use change around United States' protected areas. *Biological Conservation, 184,* 446–455.
64. Steiner, F., Blair, J., McSherry, L., Guhathakurta, S., Marruffo, J., & Holm, M. (2000). A watershed at a watershed: the potential for environmentally sensitive area protection in the upper San Pedro Drainage Basin (Mexico and USA). *Landscape and urban planning, 49*(3), 129–148.
65. Mesta, P. N., Setturu, B., Chandran, S., Rajan, K. S., & Ramachandra, T. V. (2014). Inventorying, Mapping and Monitoring of Mangroves towards Sustainable Management of West Coast, India. *Journal of Geophysics & Remote Sensing, 3,* 130. doi:10.4172/2169-0049.1000130.
66. Ramachandra, T. V., Subash Chandran, M. D., Joshi, N. V., Pallav Julka, Uttam Kumar, Bharath, H. A., Prakash Mesta, Rao, & G. R., Vishnu Mukri. (2012b). Landslide Susceptible Zone Mapping in Uttara Kannada, Central Western Ghats., *ENVIS Technical Report: 28*, Energy & Wetlands Research Group, Centre for Ecological Sciences, Indian Institute of Science, Bangalore 560012.
67. Muddle, D., Briggs, K., Dashwood, C., & Dijkstra, T. (2015). The influence of slope geology on landslide occurrence during extreme rainfall.
68. Bhat, M., Nayak, V. N., Chandran, M. S., & Ramachandra, T. V. (2014). Impact of hydroelectric projects on finfish diversity in the Sharavathi River estuary of Uttara Kannada District, central west coast of India. *International Journal of Environmental Sciences, 5*(1), 58.
69. Prabha, S. R. (2009). Infrastructure Development and Its Environmental Impact: Study of Konkan Railways (p. 270), New Delhi: Concept Publishing Company.
70. Rao, G. R., Krishnakumar, G., Dudani, S. N., Chandran, M. S., & Ramachandra, T. V. (2013). Vegetation changes along altitudinal gradients in human disturbed forests of Uttara Kannada, Central Western Ghats. *Journal of Biodiversity, 4,* 61–68.
71. Chandran, M. D. S. (1998) Shifting Cultivation, Sacred Groves and Conflicts in Colonial Forest Policy in the Western Ghats. In R. H. Grove, V. Damodaran, & S. Sangwan (Eds.), *Nature and the Orient: The environmental history of South and Southeast Asia* (pp. 674–707). New Delhi: Oxford University Press.
72. van Schrojenstein Lantman, J., Verburg, P. H., Bregt, A., & Geertman, S. (2011). Core principles and concepts in land-use modelling: A literature review. *Land-Use Modelling in Planning Practice, 101,* 35.
73. Voinov, A., Kolagani, N., McCall, M. K., Glynn, P. D., Kragt, M. E., Ostermann, F. O., et al. (2016). Modelling with stakeholders–next generation. *Environmental Modelling and Software, 77,* 196–220.
74. Verburg, P. H., Schot, P. P., Dijst, M. J., & Veldkamp, A. (2004). Land use change modelling: current practice and research priorities. *GeoJournal, 61*(4), 309–324.
75. Abdullahi, S., & Pradhan, B. (2016). Sustainable brownfields land use change modeling using GIS-Based weights-of-evidence approach. *Applied Spatial Analysis and Policy, 9*(1), 21–38.