Forest cover change detection of Western Ghats of Maharashtra using satellite remote sensing based visual interpretation technique

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In this article, we attempt to quantify change in forest area of the Western Ghats of Maharashtra over a 20-year time period (1985–87 to 2005) using visual interpretation technique at 1 : 250 K scale. The study was conducted using the Forest Survey of India vegetation maps for 1985–87, prepared using Landsat TM data and IRS LISS III imagery for 2005. The results reveal loss of dense forest at an annual rate of 0.72% and that of open forest at 0.49%. It also reports an increase in mangrove vegetation and water bodies in the study area. In addition, it also reports districtwise pattern of change in forest cover.

Keywords: Change detection, forest, remote sensing, visual interpretation, Western Ghats.

FOREST cover is an important natural resource which should be conserved on priority basis for sustainable environmental management. However, escalating levels of anthropogenic disturbances have exhorted tremendous pressure on the forests. Due to the increase in human and cattle population and widespread rural poverty, forests all over the globe are subject to enormous pressure resulting in deforestation and degradation. As a result, there is significant loss of forest cover at an alarming rate. Depletion of forest affects many ecological, social and economic consequences including extinction of biotic communities leading to loss of biodiversity, soil erosion, global warming and loss in income to forest dwellers. The impacts of deforestation in tropical biodiversity hotspots like Western Ghats (WG) are of particular concern because these regions house rich biodiversity and a high concentration of globally endemic species[1]. Though it is widely believed that the natural vegetation in the tropical regions is experiencing loss of biodiversity at unprecedented rates, we lack definite information about the rate of habitat loss[2]. This calls for immediate management and conservation of this region.

An accurate and continuously updated resource data is a prerequisite for the present-day forest ecosystem management. Because of the synoptic and repetitive data acquisition capabilities, satellite-based sensors have the potential to detect, identify and map canopy changes that are important to the forest ecosystem managers[3]. Variation in the remotely sensed electromagnetic radiation values for a particular forest ecosystem can be associated with an alteration in its reflective/emissive characteristics, which are a manifestation of biophysical properties of the surface[4]. The practice of remote sensing started in 1930 using aerial photos, prior to which the forest managers were totally dependent upon resource information obtained on the ground[3]. However, with the launch of the first Earth Resources Technology Satellite (ERTS-1) in 1972 (later renamed as Landsat 1), monitoring environmental resources and study of ecosystem processes from space was initiated. Since then, the utility of space-borne remote sensing platforms in resource monitoring and allocation had been demonstrated successfully in different parts of the world. Large scale changes in land cover and repeated monitoring of forests have popularized remote sensing technology as an essential tool. Initiatives to monitor land-cover and land-use change are increasingly reliant on information derived from remotely sensed data. Such information provides inputs to other techniques designed to understand the human processes behind deforestation[5,6].

Timely and accurate change detection of earth's surface features provides the foundation for better understanding of the relationships and interactions between human and natural phenomena to better manage and use natural resources[7]. The goal of change detection in remote sensing is to discern those areas on digital images (two or more dates) that depict change in the features of interest (e.g. forest clearing or land-use/cover change)[8]. The change maps can be used to support ecological research and socio-economic studies of the driving forces and environmental consequences of land-cover and land-use change in the region. Kristensen *et al.*[9] have claimed that the forest change detection mapping from satellite imagery is the 'most powerful monitoring tool' for con-

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servation agencies, local administration and the non-government organizations (NGO). The change is usually detected by comparison between two or multiple-dates satellite images, or sometimes between old maps and a recent remote sensing images. Most of the change detection techniques are based on a pixel-to-pixel analysis and essentially comprise quantification of temporal phenomena through multispectral sensors. The effective use of remote sensing as a tool for generating land cover information is highly dependent on the measurable quality of this information[10].

During the last few decades, visual interpretation became less popular compared to automatic processing. But recent advances in software and hardware are capable of managing images and vector information, permitting interactive map editing and more possibilities for visual interpretation. Earlier literature on remote sensing change detection however, reveals that digital change detection is an easier said than done task[3], especially in case of tropical environments with prevalent landscape heterogeneity[11]. Digital classification-based change detection methods are further complicated, because one has to consider the information about accurate sun sensor geometry and environment conditions at the time of acquisition of images to nullify the atmospheric effects. In contrast to this, an interpreter having sound ground knowledge, analysing large-scale aerial photographs or satellite imagery with visual interpretation technique is likely to produce more accurate results with a higher degree of precision[11–13]. In addition, visual interpretation is the preferred method for interpreting land use and land cover in case of low and medium resolution satellite images[11]. It has been an efficient technique to overcome the risk factors in digital interpretation techniques because it provides a better control to detect change based on sound-ground knowledge[7]. Though it is a time-consuming approach and requires human expertise, which is not objective and repeatable, visual interpretation can provide better accuracy in classifying the satellite image.

Study area

The area for the present study is the region covering WG of Maharashtra extending from 72°30′–75°00′E long. to 15°30′–29°30′N lat. The WG stretch nearly 1450 km along south-west peninsular India and stands testimony to several million years of geological history. The WG are the mountain ranges separated from the Arabian Sea by a narrow strip of the west coast of India. The WG are an island of tropical humid forests at a considerable distance from the large humid forest tracts of southeast Asia, and harbour a large number of endemic species, i.e. species occurring nowhere else in the world[14]. The hill chain of WG has been recognized as one of the world's 18 (34 by now) biodiversity hotspots, i.e. a region of rich biodiversity threatened with destruction[15–17]. Climate in the WG varies with altitudinal gradation and distance from the equator. Mean temperature range from 20°C (68°F) in the south to 24°C (75°F) in the north. Rainfall in this region averages 3000–4000 mm (120–160 inches). The western slopes of the mountains experience heavy annual rainfall (with 80% during the southwest monsoon from June to September), while the eastern slopes are drier; rainfall also decreases from south to north. As the WG mediates the rainfall regime of peninsular India by intercepting the southwestern monsoon winds, the eastern region of the WG which lies in the rain shadow, receives far less rainfall averaging about 1000 mm (40 inches) bringing the average rainfall figure to 2500 mm (100 inches).

Methodology

The spatial data of 1985–87 and 2005 were selected for the change detection study. The 1985–87 (T1) vector database was generated from the forest vegetation maps prepared by Forest Survey of India (FSI) at 1 : 250,000 scale. These maps were based on visual interpretation of Landsat imagery with standard False Colour Composite (FCC) acquired during the period 1985–87. The forest classes addressed in the map are dense forest (having crown density >40%), open forest (having crown density <40%), highly dense tree farm land (crown density >40%), less dense tree farm land (crown density between 10% and 40%), mangrove, scrub-land, water bodies, 'forest blanks/grassy lands/permanent cultivation' and 'un-interpreted area/gaps/clouds/hill shadows'. Tree farm land classes are not present in the recent classification scheme, however for the present study they were considered (for the year 2005 map as well) because T1 is the base map for the change analysis. The vegetation type boundaries from the FSI maps were digitized and the T1 vector layer was re-projected to the Lambert conformal conic (LCC) projection with Clarke 1866 earth model and Maharashtra Grid specified projection parameters. The year 2005 (T2) map was generated from post-monsoon (November–December) cloud free IRS LISS III data of 2005 (of path/row: 94/59, 95/59, 95/60, 95/61, 96/61, 96/62) acquired from National Remote Sensing Centre (NRSC), Hyderabad. The radiometric correction step was skipped, as the imageries were used for visual interpretation studies using ground knowledge. All the T2 images were registered with the T1 vector layer. Locating ground control points (GCP) was a difficult task to co-register the images with the T1 vectors; hence registration was performed in an iterative manner until the T1 vector layer got overlaid perfectly on T2 images at 1 : 200 K scale (considering 1 : 250 K scale for interpretation). A total 40–50 well-scattered GCPs were collected for each LISS III imagery with <1 root mean square error (RMSE).

Registration accuracy was thoroughly assessed, as high registration accuracy is a requirement to avoid largely spurious results of change between two time databases in a change detection study[18–20]. The 1985–87 vector map was overlaid with the 2005 image database to study the forest vegetation change from T1 to T2. The same standard FCC of LISS III data with band combination of 4, 3, 2 (near infra-red, red, green) was used for interpretation (to maintain harmony with the T1 vegetation maps). An interpretation key, prepared from ground survey and image analysis for different classes (Figure 1) was used for discriminating different vegetation types. All the data generation and analysis were performed using the PCI Geomatica V10.0.3 software environment.

The vector layers of T1 and T2 were converted into raster format for change detection analysis. The change detection analysis was done using the 'MAT' module on PCI Geomatica V10.0.3 image processing software and was also confirmed with an 'EASI' script based self-developed model. The 'MAT' algorithm creates a 2×2 coincidence matrix for the two raster layers (T1 and T2), This 2×2 coincidence matrix describes the change/no change transition between different classes[21]. A cell in the ith column and jth row in the matrix represents the overlap of class i from T1 and class j from T2. The statistics were analysed for each unique combination.

The mapping accuracy of T2 (2005) map was assessed by estimating commission and omission errors in the error matrix[22]. The stratified random sampling approach was followed in allocating the sample points in different strata of forest cover classes. Two hundred and twenty-one randomly distributed points were selected based on the proportional contribution in terms of aerial extent for the different forest class strata. The overall accuracy is the proportion of correctly classified and wrongly classified pixels that are correctly interpreted by the method. Kappa (κ) analysis statistic, which is a measure of accuracy or agreement based on the difference between the error matrix and chance agreement[23] was also generated.

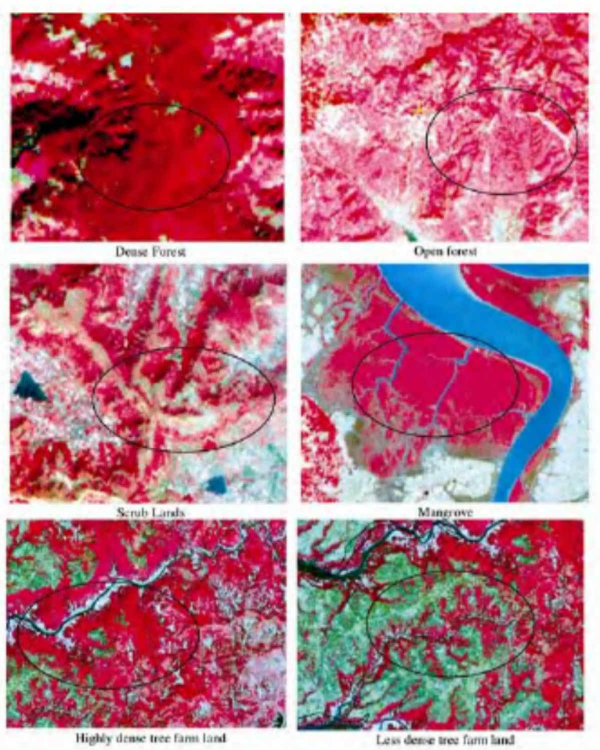

Figure 1. Interpretation key for different forest classes.

Results and discussion

An overview of 1985–87 and 2005 map of the study area is given in Figures 2 and 3. Forest vegetation classes over the northern stretch of WG in Maharashtra have changed significantly in the 20-year period from 1985–87 to 2005.

There are prominent change/no change areas under different vegetation classes from T1 to T2 (Table 1 and Figure 4). The results indicate a decrease in the dense forest class by 610.2 sq. km contributing to 10.57% of the total dense forest cover in 1985–87; out of which,

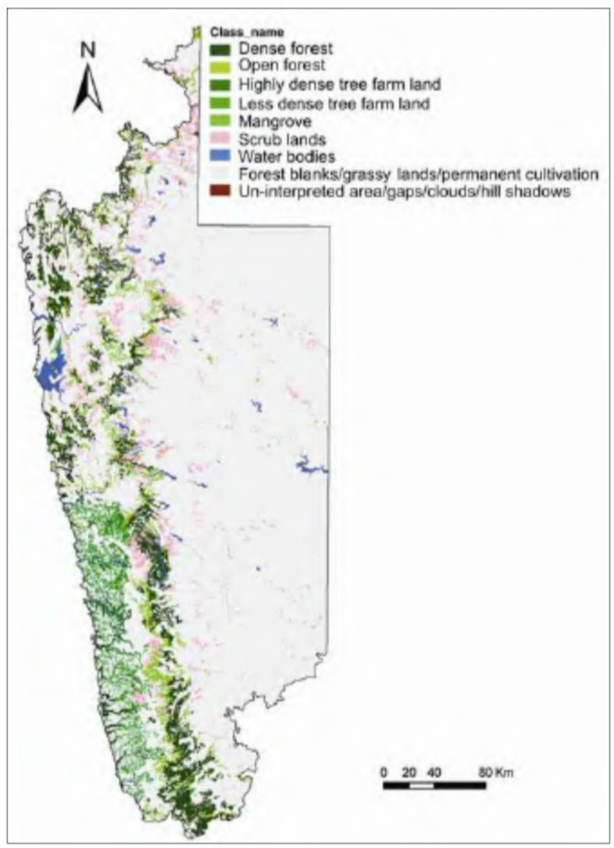

Figure 2. Forest cover interpretation map of 1985–87 (source: FSI vegetation maps).

599.45 sq. km has been changed to open forest, and the rest to classes like scrublands (90.78 sq. km) and forest blanks/grassy lands/permanent cultivation (130.26 sq. km). A small fraction (18.28 sq. km) of dense forest has also been converted to water bodies. On the other hand, 119.81 sq. km of open forest in T1 has been transformed to dense forest in T2. Though there is an increase in total open forest cover because of thinning of dense forest adding to open forest statistics, an area of 275.58 sq. km has been changed to scrub lands, followed by the 'forest blanks/grassy lands/permanent cultivation' (100.99 sq. km), and water bodies (8.58 sq. km). A total of 163.27 sq. km of highly dense tree farm land has been degraded to less dense tree farm land. But simultaneously 123.99 sq. km area of less dense tree farm land has been found to be transformed into highly dense tree farm land. In addition, around 24 sq. km area of forest blanks/grassy lands/permanent cultivation has also been transformed to highly dense tree farm land. The mangroves area statistics shows increase in T2. However, this change may not be totally attributed to change over the time. Mangroves are represented in smaller patches from the remote sensing point of view. There may be some small mangrove patches that might have missed out in the T1 interpretation but picked in the T2 interpretation, which may be due to the improved resolutions of LISS III data and improved visual interpretation tools in digital environment. The scrubland class area has increased by 193.1 sq. km in 20 years. There is an increase in water bodies from 1199.44 sq. km in T1 to 1681.33 sq. km in T2, leading to 40.17% change, which is mostly contributed by the new river valley projects developed in the past two decades. The forest blanks/grassy lands/permanent cultivation area has been slightly decreased by 0.54%, which is negligible. Though there has been a large-scale degradation of forest classes, the decrease in forest blanks/grassy lands/permanent cultivation area is because of the increase in area of other classes like water bodies, mangroves and plantations.

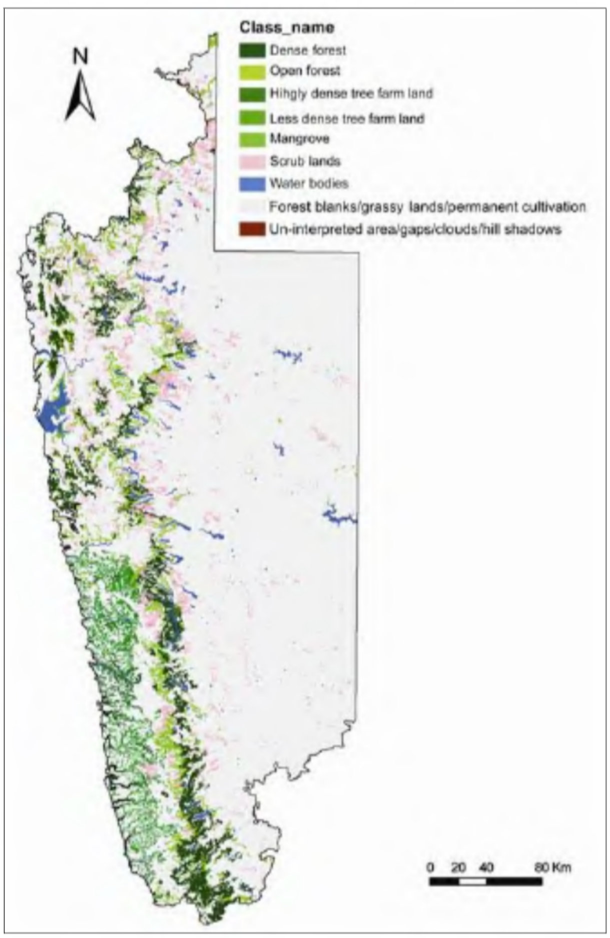

Figure 3. Forest cover interpretation map of 2005 (source: IRS LISS III imagery).

There were un-interpreted area/gaps/clouds/hill shadows areas in the T1 FSI map (69.97 sq. km), but it has been reduced in the T2 map (15.66 sq. km) by 77.62%. The unidentified areas in the T1 FSI vector data were mostly due to the steep sloped hill shadows in the satellite imagery, which was reduced in T2 due to different sun-sensor object geometry and were clearly interpreted into suitable classes. The unidentified areas in T1 were mostly identified as dense forest in T2, because dense forests were present in the deep valley areas and on the slopes and could not be identified in T1 due to shadow effect.

The present study finds loss of dense forest at an annual rate of 0.53% (Figure 5) in the WG region of Maharashtra. However, the rate of degradation may not be uniform. The change in forest cover exhibits a great deal of variation in both spatial and temporal context, maybe a result of different strategies and efforts by the forest department and due to the change in climatic conditions and other socio-economic factors. Previous studies in WG have also reported deforestation for different regions over different time periods. Jha *et al.*[2] had reported an annual rate of degradation of 0.8% and 1.5% for dense forest and open forest respectively, in their study covering southern extents of WG spread in three southern states, Karnataka, Kerala and Tamil Nadu from 1973 to 1995. Menon and Bawa[24] had reported the annual rate of deforestation in the WG to be 0.57% for a period of approximately 70 years from 1920s to 90s. Prasad[25] had reported a 0.28% loss in forest cover per annum in the WG of Kerala during the period of 30 years beginning in the late 1950s.

The T1 (1985–87) map was taken directly from the thematic vegetation map by FSI, hence importance of accuracy assessment was not considered. The T2 (2005) map has achieved an overall accuracy of 87.7% and an overall kappa of 0.84. The user's accuracy obtained for different classes were 88.89% (dense forest), 80.0%

Table 1. Change matrix between years 1985–87 and 2005 vegetation map area

	Class		1985–87									
			Dense forest	Open forest	Highly dense tree farm land	Less dense tree farm land	Mangrove	Scrub-lands	Water bodies	Forest blanks/ grossy lands/ permanent cultivation	Un-interpreted area/gaps/ clouds/hill shadows	Time 2 total
		Class code	1	2	3a	3b	4	6	8	9	10	
2005	Dense forest	1	4931.61	119.81	0.04	1.46	0.00	14.38	1.21	68.77	23.75	5161.01
	Open forest	2	599.45	3379.02	0.03	0.24	0.02	134.51	1.26	116.17	8.55	4239.24
	Highly dense tree farm land	3a	0.05	0.05	714.66	123.99	0.01	0.03	0.42	23.73	0.00	862.93
	Less dense tree farm land	3b	0.16	7.96	163.27	2435.08	0.02	0.17	1.04	57.42	0.00	2665.11
	Mangrove	4	0.55	0.06	0.01	0.35	84.03	0.00	29.49	58.46	0.00	172.95
	Scrub-lands	6	90.78	275.58	3.21	14.70	0.00	3590.02	1.73	115.29	12.88	4104.19
	Water bodies	8	18.28	8.58	0.61	4.10	1.08	25.69	1124.87	498.11	0.00	1681.33
	Forest blanks/grassy lands/permanent cultivation	9	130.26	100.99	31.04	56.40	8.25	146.27	39.44	75798.83	10.01	76321.50
	Un-interpreted area/ gaps/clouds/hill shadows	10	0.11	0.26	0.00	0.00	0.00	0.03	0.00	0.47	14.78	15.66
	Time 1 total		5771.24	3892.30	912.87	2636.32	93.41	3911.10	1199.447	6737.25	69.97	95223.90

Area values in square kilometre unit.

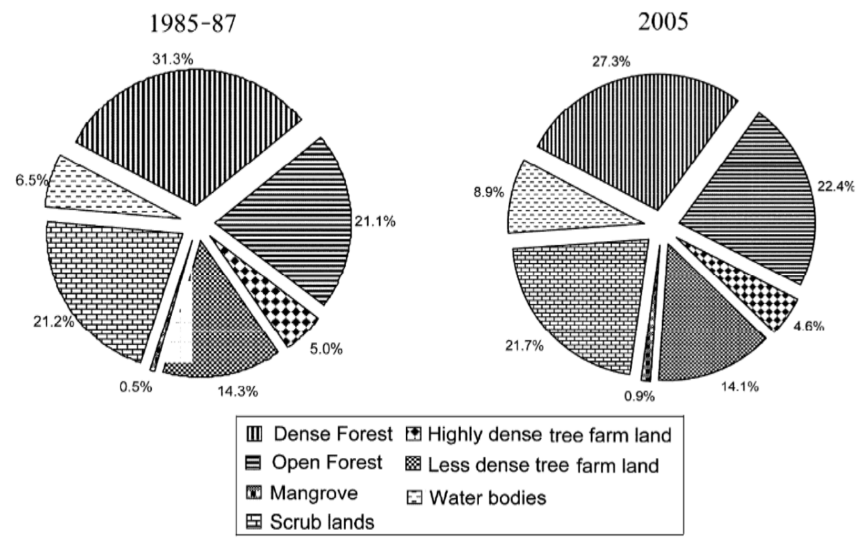

Figure 4. Forest class (except forest blanks/grossy lands/permanent cultivation) area statistics for 1985–87 and 2005.

(open forest), 91.43% (highly dense tree farm land), 83.33% (less dense tree farm land), 79.41% (mangrove), and 84.44 (scrub-lands).

The forest cover change statistics pertains to the entire WG region of Maharashtra, irrespective of the administrative boundaries. The following statistics presents the districtwise break-up of the classwise forest cover change (it is to be noted that the analysis was carried out within the study area covering WG of Maharashtra and hence the administrative extents of the districts were restricted by the extents of the present study area).

Thane district shows the highest (29.29%) decrease in dense forest followed by Nashik (22.5%) and Ratnagiri (16.45%) (Figure 6 *a*). Only Raigad district shows marginal increase (2.79%) in dense forest. All other districts follow a decreasing trend. The major chunk of

Table 2. Change in forest class area (statistics from 1985–87 to 2005)

	1985–87	2005	Change (%)	Difference (sq. km)
Dense forest	5,771.24	5,161.01	–10.57	–610.2
Open forest	3,892.30	4,239.24	8.91	346.9
Highly dense tree farm land	912.87	862.93	–5.47	–49.9
Less dense tree farm land	2,636.32	2,665.11	1.09	28.8
Mangrove	93.41	172.95	85.15	79.5
Scrub-lands	3,911.10	4,104.19	4.94	193.1
Water bodies	1,199.44	1,681.33	40.17	481.9
Forest blanks/grassy lands/permanent cultivation	76,737.25	76,321.50	–0.54	–415.7
Un-interpreted area/gaps/clouds/hill shadows	69.97	15.66	–77.62	–54.3
Forest	17,217.24	17,207.042	–0.06	–10.2
Non-forest	77,936.69	78,002.83	0.085	66.1
Total	95,223.90	95,223.90		

Area values in square kilometer unit.

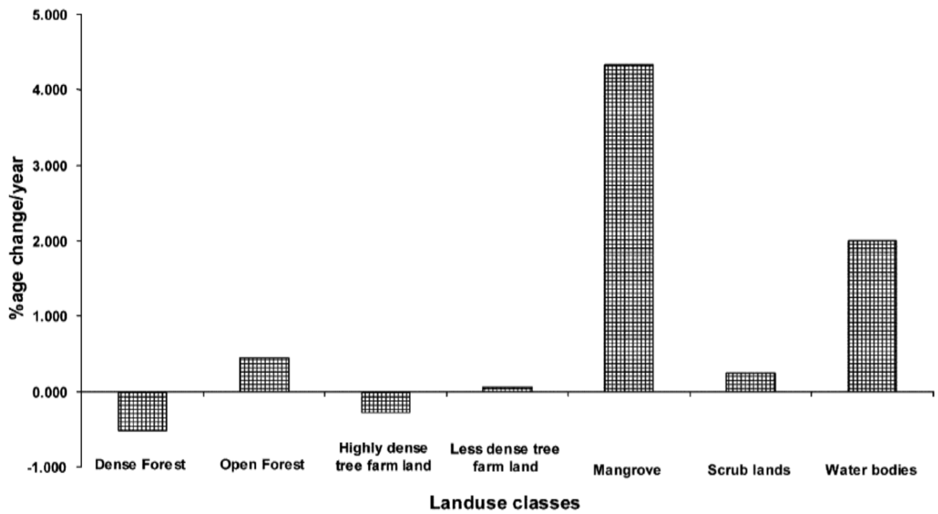

Figure 5. Annual rate of change in different vegetation classes.

dense forest is transformed to open forest and scrublands. Thane district shows large increase (30.67%) in open forest (Figure 6 *b*), which is mostly contributed by the degradation of dense forest. The increasing trend is also followed by Nashik district (>27.25%). Except Mumbai and Kolhapur, all other districts follow increasing trend. Mangrove forests were interpreted only in the four coastal districts of Maharashtra, i.e. Thane, Mumbai, Raigad and Ratnagiri. Raigad district shows highest positive change in mangroves (Figure 6 *g*) followed by Thane and Mumbai, whereas Ratnagiri district shows slight decrease. Highly dense tree farm land is mapped only in the four districts, i.e. Raigad, Ratnagiri, Satara and Sindhudurg (as per the T1 base map). The area statistics follows an increasing trend in Raigad (Figure 6 *e*), whereas a decreasing trend in Sindhudurg and more or less no change in Satara and Ratnagiri districts. Less dense tree farm land is also mapped in only four districts, i.e. Raigad, Ratnagiri, Satara and Sindhudurg. Only Sindhudurg district follows increasing trend in statistics (Figure 6 *f*), whereas Raigad and Ratnagiri follow decreasing trend. Scrubland area is decreased in Satara district (Figure 6 *c*), whereas it is increased in all other districts. Sindhudurg district (26.28%), Thane (21.72%) and Kolhapur (19.01%) exhibit the highest change in scrublands. The water body area has increased more or less in all the districts (Figure 6 *d*), out of which Kolhapur (by 10 times) and Sangli (by 6 times) show the highest change.

The degradation of forest cover is due to the increase in population pressure for food and other forest resources, natural disasters like forest fire, etc. In the recent past, many large development projects including highways, railway lines, mega dams, canals/power plants and mines have intruded into this biodiversity treasure trove. In addition, development activities lead to fragmentation of the Ghats, disturbing the habitats of wild flora and fauna, thus affecting the biodiversity in the region. It is clear that the fragile ecosystem of WG has come under severe

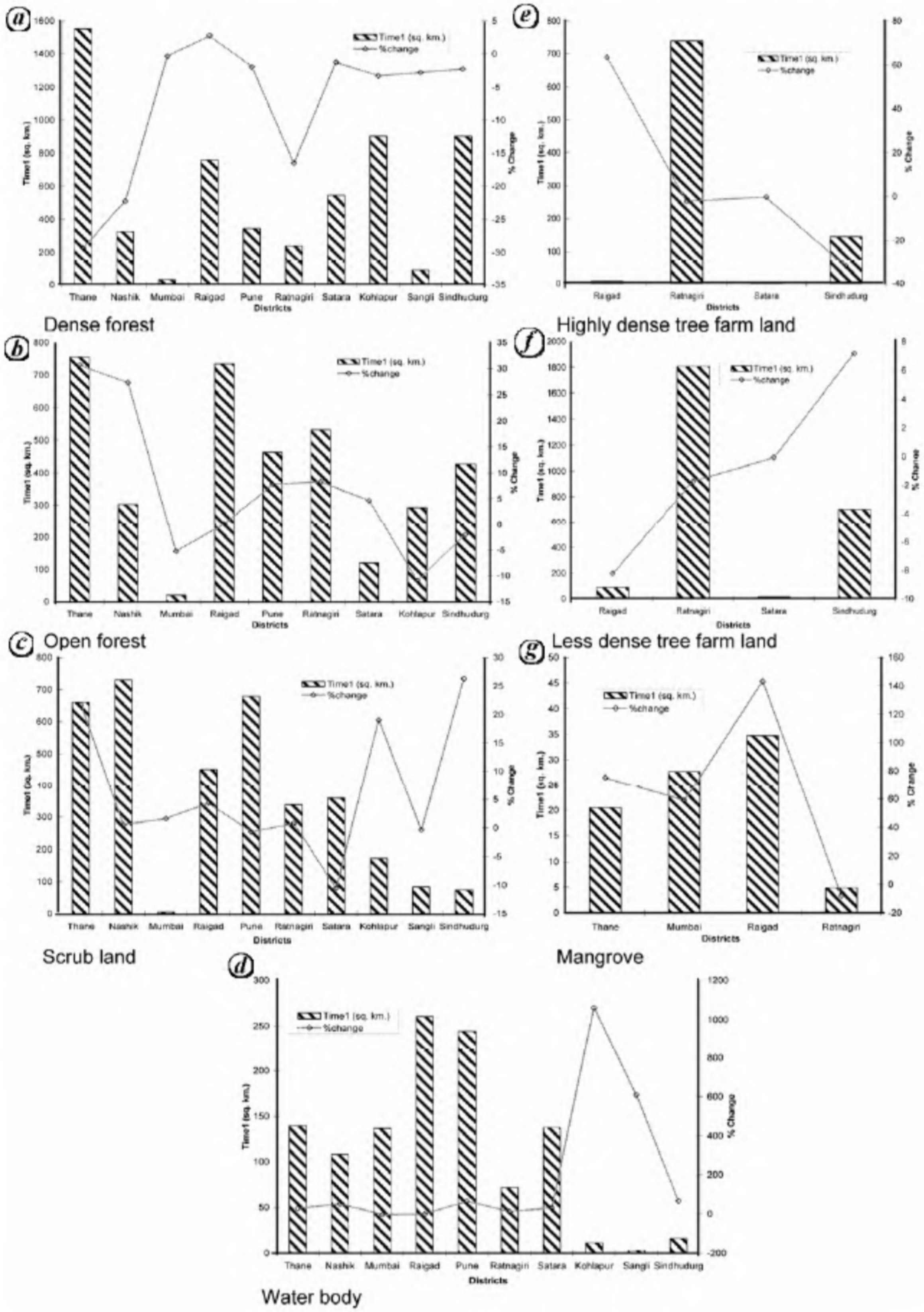

Figure 6. District wise change (%) in vegetation classes from time 1 to time 2.

pressure because of submersion of large areas under river valley projects, damage to areas due to mining[26], denudation of forest, clear felling of natural forests for raising commercial plantation, soil erosion leading to silting of reservoirs and reduction in their life span and the adverse effects of floods and landslides encroachment of forest land and poaching of wild life, etc.[27]

Conclusion

The results show loss of forest cover in the WG region over a 20-year period. The decrease in the area of dense forest and increase in open forest and scrublands are indicators of pressure on the core forest. A study of fragmentation trends may further reveal the loss of corridors.

The increase in water bodies (including dams) probably to cater the needs of the growing population has altered the ecosystem and there is need to investigate the socio-economic impacts of the same. The present study has been carried out at 1 : 250,000 scale which is suitable for regional level interpretation, therefore it is recommended to carry out detailed targeted studies at finer resolutions to fine-tune the present findings and prioritize conservation of forest cover at the local level.

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