Chapter 13
An Assessment of the Temporal Changes in Land Cover and Forest Fragmentation Using Geospatial Techniques: A Case Study from the Central Indian Highlands

Seema Yadav, Prodyut Bhattachrya, Deepakshi Babbar, and Mayuri R. Wijesinghe

Abstract The present study was carried out in the districts of Mandla and Hoshangabad, in Madhya Pradesh, India. These two districts have sizeable areas under deciduous forests. Given the high dependence of tribal communities on these forests, it is essential to characterize the land use and the status of vegetation in these districts. Land use and land cover (LULC) maps were prepared for landscape characterization for two different time periods (2000 and 2017). The area was classified into eight classes, i.e. dense forests, scrub forests, open forests, agricultural lands, water bodies, fallow lands, built-up areas, and open/sandy areas. The assessments show that dense forest areas have increased in both districts. However, this was not reflective of increases in true forests. For instance, forests in Mandla have been converted to monoculture stand of *T. grandis* (~83%). Since 2000 Mandla and Hoshangabad have lost 8.73% and 6.43% of their open forest areas, respectively. Expansion of agriculture and built-up areas is common at both sites, occurring at the cost of ecologically important land cover types such as scrub forests and open areas/ sandy areas primarily as riverbeds. Results from change detection in forest cover and other land use classes show that compactness of open and scrub forests has reduced whereas patchiness has increased. Patches in close proximity to the forest edges will be vulnerable to edge effects and encroachments. The areas under dense forests have increased, while the number of patches and edge density has decreased. However, this has occurred owing to the existing gaps inside the dense canopies deep inside the forests being replaced by plantations resulting in an increase in contiguity. Although some dense canopy areas were seen to be rich in moisture content based on high

S. Yadav (✉) · P. Bhattachrya
Guru Gobind Singh Indraprastha University, Delhi, India

D. Babbar
Botanic Garden of Indian Republic, Botanical Survey of India, Noida, Uttar Pradesh, India

M. R. Wijesinghe
Department of Zoology and Environment Sciences, University of Colombo, Colombo, Sri Lanka

NDMI values, large forest areas were under moisture stress. Emphasis has to be given to maintaining heterogeneity in species composition within the forests as well as to avoid fragmentation.

Keywords Deciduous forests · Landscape characterisation · Forest fragmentation · Central India

13.1 Introduction

The rise in human population, the expansion of settlements, and the resulting increase in the demand for food and animal fodder have led to an increase in the demand for land. One of the frequently preferred options is to compromise forest lands. In recent times, accounting of natural resources and the ecosystem services provided by natural ecosystems are gaining popularity (Acharya et al. 2021; Yang et al. 2021; Zhang et al. 2021; Hussain et al. 2020). The idea also gains currency from the fact that during the pandemic (2020–2021), of the three major sectors of economic activity in India, namely, agriculture, industry, and services, only agriculture clocked a positive growth rate of 3.4%, whereas the other two contracted 9.6% and 8.8%, respectively (Economic Survey, 2020– 2021). In India, the activities allied to agriculture include three subcomponents: (i) livestock, (ii) forestry and logging, and (iii) fishing and aquaculture. The average contribution of the second subcomponent forestry and logging to the GVA (gross value addition) during 2014–2019 was 1.44%. Recent times have seen a rise in the interest in valuing natural capital and ecosystem services (Acharya et al. 2021; Yang et al. 2021; Zhang et al. 2021; Hussain et al. 2020). Many studies have also been carried out at global, national, and regional levels emphasizing the contribution of forests to livelihood generation (Miller and Hajjar 2020; Adam et al. 2013; Singh et al. 2010; Bhattacharya and Prasad 2009; Shah and Sajitha 2009; Quang and Nam Anh 2006; Paumgarten 2005; Shackleton and Shackleton 2004). Nonetheless, forest clearance has been rampant and isolated patches of forest are often cleared to make way for settlements and agriculture. This highlights the need to monitor forest cover and other land uses at regular intervals to maintain a balance between development and rejuvenation of natural resources.

Over time, different techniques have been developed to assess land cover. Prior to the use of satellite imagery, ground studies such as enumeration of vegetation were used to assess the nature and extent of forest cover, whereas land surveys were used for studying the different land use types. These activities were laborious and time-consuming. With the advent of remote sensing, such land cover studies could be conducted relatively rapidly and easily and with a high degree of accuracy (Choudhary et al. 2021; Solanki et al. 2019). Mengistu and Salami (2007) from south-western Nigeria; Dewan and Yamaguchi (2009) from Greater Dhaka, Bangladesh; Areendran et al. (2013) in Madhya Pradesh, India; Sharma et al. (2016) from Sikkim, India; and Solanki et al. (2019) in Kerala, India, have used geospatial analytical techniques to assess spatio-temporal changes in land use in

their respective study areas. These studies document that non-forested land use types are expanding at the cost of forests, water bodies, and wetlands. Population growth, unplanned economic expansion, and increased demand for infrastructure were some of the reported factors responsible for such land conversions. The dynamic socio-economic conditions of developing countries have led to far greater changes in land use and land cover (LULC) than in developed countries (World Bank 2007).

Large tracts of natural forests worldwide are undergoing fragmentation, resulting in the formation of smaller and isolated patches. Multiple studies have shown that forest fragmentation has increased with time (Padalia et al. 2019; Sharma et al. 2016; Armenteras et al. 2003; Noss 2001; Gibson et al. 1988). In India, nearly all major biogeographic regions face similar threats of fragmentation. These include the Himalayas (Chakraborty et al. 2016; Mishra et al. 2020), Central India (Nayak et al. 2020), Northeast India (Talukdar et al. 2020), Rajasthan, India (Babbar et al. 2021), and the Western Ghats, India (Giriraj et al. 2010). Many envisage a multitude of adverse impacts from the loss of biodiversity to alterations in the regional climate, hydrological cycles, and the biophysical environment, ultimately affecting ecosystem services (Singh et al. 2015; Xu et al. 2009) and forest associations. Forest fragmentation results in the formation of small forest refugia or island landscapes that harbour stocks of native vegetation (Chakraborty et al. 2016). Many of these forest isolates are often surrounded by contrasting land uses such as agricultural fields or human settlements, which are also frequently bisected by linear infrastructural facilities such as roads, canals, railways, and powerlines (Marques et al. 2021; Nayak et al. 2020; Borda-de-Água et al. 2017; Desai and Bhargav 2010). As a consequence of these physical changes, the flow of wind, water, and nutrients across the landscapes, particularly in areas with topographical differences, is altered significantly (Watkins et al. 2003). The impact of these changes on energy fluxes will depend upon the duration of isolation and the degree of connectivity between the forest patches (Saunders et al. 1991). Although there appears to be no universally applicable minimum 'threshold' value of loss of native vegetation to assess the degree of threat (Fischer and Lindenmayer 2007), fragmentation in any magnitude exposes forests to further degradation. It is certain that fractionation increases the vulnerability of these patches to external disturbances.

Landscape metrics have been used to examine the extent of forest fragmentation and degradation (Reddy et al. 2013; Saikia et al. 2013). In recent years, open-source software tools such as FRAGSTATS are widely used to assess changes in forest structure as they are scientifically reliable, easy to use, and repeatable (Sharma et al. 2016; Midha and Mathur 2010). The present study aimed to (i) monitor the spatial and temporal changes in land use and land cover patterns in Mandla and Hoshangabad districts of Madhya Pradesh using LULC maps and (ii) characterize vegetation changes using landscape fragmentation matrices and the normalized deferential index, for the periods 2000 and 2017. The districts of Mandla and Hoshangabad were selected for the study as there is a dearth of information on these two districts where the land resources have been shaped by tribal communities. Although there are studies from other parts of India which have focused on aspects

of deforestation and fragmentation (e.g. Singh et al. 2017b for Assam; Chavan et al. 2018 for Telangana), the focus in Central India has been on areas affected by mining (Areendran et al. 2013 for Singrauli).

13.2 Materials and Methods

13.2.1 Study Areas

Madhya Pradesh (M.P) is the second largest state in India (308,245 km^2) and also has the highest forest cover which is around 25.14% of its geographical area (Forest Survey of India 2019). The dominant vegetation type here is the tropical dry deciduous forest. Some of the economically important species in these forests which have a relatively ubiquitous distribution within the state are teak (*Tectona grandis*), saaj (*Terminalia elliptica*), tendu (*Diospyros melanoxylon*), dhawra (*Anogeissus latifolia*), mahua (*Madhuca longifolia*), amaltas (*Cassia fistul*a), bael (*Aegle marmelos*), and amla (*Emblica officinalis*). The study was carried out in the districts of Hoshangabad and Mandla.

Mandla lies between latitudes 22° 12′N and 23° 22″N and longitude 79° 59′23″ E and 81° 44′ 22″ E. It has a hilly terrain which is mostly under forest cover. The district is well known for Kanha National Park. About 57.23% of the population comprises tribal communities. The climate is tropical with moderate winters and severe summers. During the field visit, it was found that nearly all the rural households were dependent on forests to fulfil their everyday needs such as fuelwood, fodder, and food. The majority of the farmers were small and marginal farmers with small landholdings (avg. landholding – 2.59 acres). Major forest products that were collected for self-consumption and sale were tendu (*D. melanoxylon*) leaves, mahua (*M. longifolia*) flowers and fruit, aonla (*E. officinalis*) fruit, achar (*B. lanzan*) kernels, and fuelwood. Many villagers were engaged in open livestock grazing in and around the forest. Hoshangabad lies between 22° 15′ N and 23° 00'N latitude and 77° 15′ E and 78° 42′E longitude and is situated at the southern bank of river Narmada. Although generally famous for its tourist attractions such as the Bhimbetka caves and Pachmarhi, it also supports the Satpura Tiger Reserve.

Characterized by a hot summer and dryness, the Hoshangabad district receives rainfall from the southwest monsoon. The map showing the geographic locations of the study districts is given in Fig. 13.1

District boundaries were extracted from planning maps obtained from the Survey of India office, Jabalpur, and National Atlas and Thematic Mapping Organisation (NATMO) office in Delhi. ESRI's ArcGIS (10.2.1), ERDAS Imagine software version 2014, FRAGSTATS 4.2, and Landscape fragmentation tool 2.0 were used for achieving the desired objectives. For LULC change detection satellite images of two time periods (2000 and 2017) were used. Details of the satellite images used are given in Table 13.1. All the images were downloaded from the United States
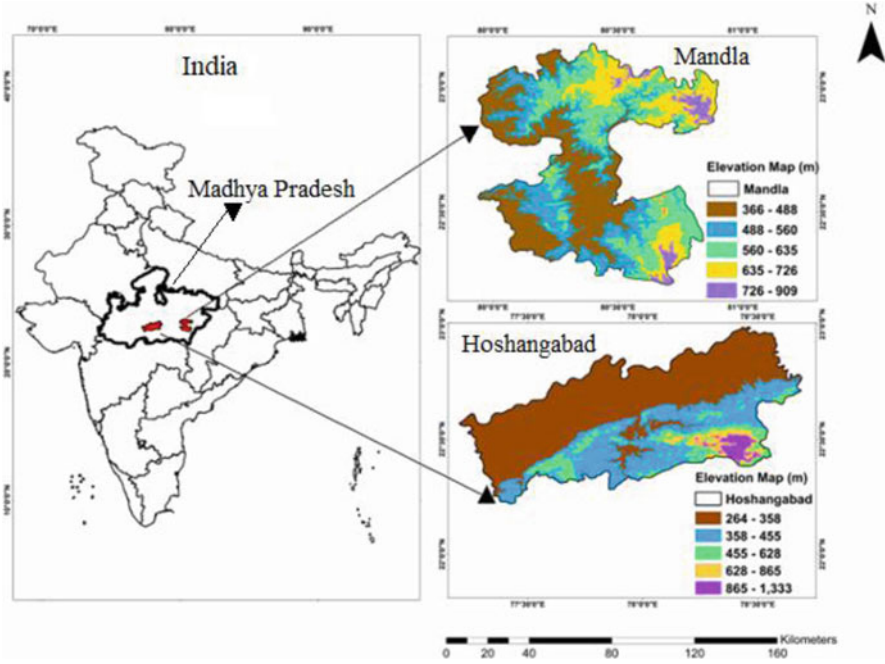
Fig. 13.1 Study area map. The locations of the two study districts within Madhya Pradesh (outlined). *Source:* (Prepared by the author)

Table 13.1 Details of the satellite data used

Satellite/time period	Sensor	Spatial resolution (m)	Bands used	Path/row	
				Mandla	Hoshangabad
Landsat 8 (Feb, March 2017)	Thermal infrared sensor	30	B1, B2, B3, B4, B5, B6, B7, B9	143/44 144/44 143/45	145/45 145/44
Landsat 7 ETM+ (Feb, March 2000)	Thematic Mapper	30	B1, B2, B3, B4, B5		

Geological Survey (USGS) earth explorer website. As given in Fig. 13.2 images were classified using unsupervised classification which was followed by recoding and cleaning. LULC maps were prepared to visualize the change using satellite imageries of the two time periods. Figure 13.2 gives the framework of the methodology followed for preparing the LULC maps. Different band layers from satellite data were stacked, mosaics were created, and the areas of interest were extracted from these images. Landsat satellites are a series of evolutionary satellites. Landsat 1–5 collects data in four different ranges or bands. Next in the series is Landsat 7, Landsat 6 being non-functional. Landsat 7 consists of eight bands. Landsat 8 has 11 bands but only bands 1–7 and band 9 were used in the present analysis. Band 8 is
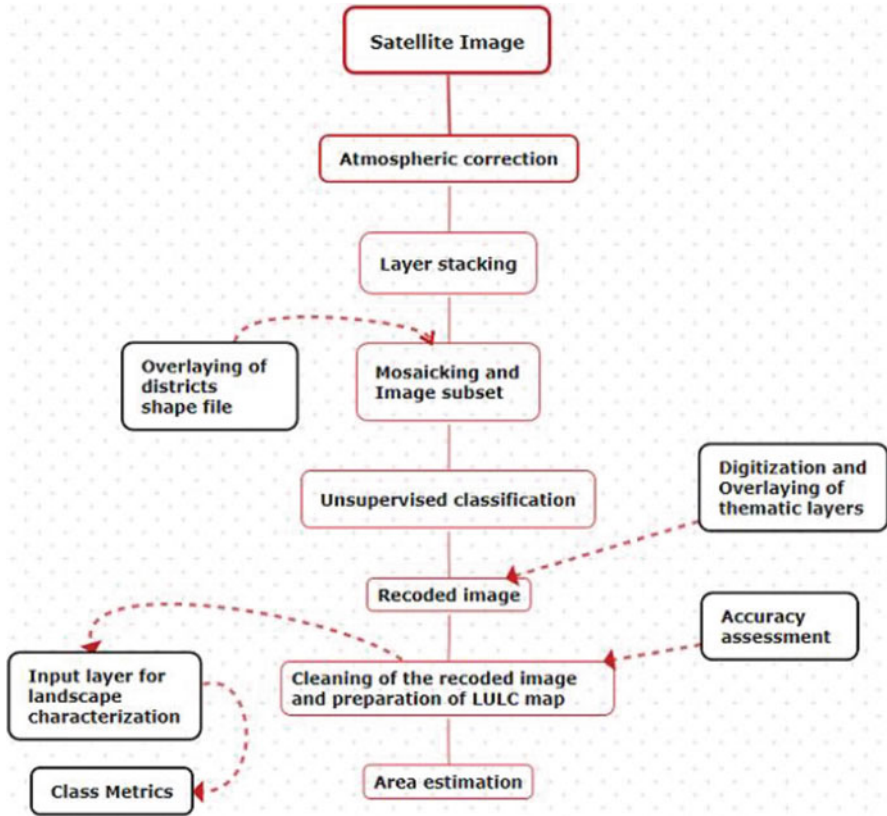
Fig. 13.2 Methodology followed for the LULC analysis

a panchromatic band and has a resolution of 15 m, while bands 10 and 11 have a resolution of 100 m. Since we need the same resolution bands for classification, we deliberately excluded bands 8, 10, and 11. Landsat 7 Enhanced Thematic Mapper has eight bands. From Landsat 7 bands 1, 2, 3, 4, and 5 were used for layer stacking. Mandla and Hoshangabad districts were masked from 2000 and 2017 satellite images. The study area was classified into eight classes following a series of steps that involved a hybrid approach for classifying the satellite data using digital image processing and visual analysis. The eight classes into which the areas of the two districts were categorized were dense forest, scrub forest, open forest, agricultural land, water bodies, fallow land, built-up areas, and open/sandy areas. Differentiation between dense and open forests was based on ground-truthing. Fallow land refers to the land that has been either abandoned after cultivation or is not under cultivation at the time of image capture. Open land refers to land that is not under any described land use, while sandy areas were primarily along the riverbeds that are not submerged. Water bodies include rivers, ponds, reservoirs, lakes, etc.

13.2.2 Accuracy Assessment

Post-classification accuracy assessment is an important step in LULC mapping. It compares the classified image with the actual features/relief on the ground. Ground truth points were collected from the forest ranges of Barella in Mandla and Sohagpur in Hoshangabad. In total, 297 points were used for accuracy assessment with a minimum of 30 points for each class. Results from accuracy assessment were reported as overall accuracy, producer's accuracy (omission errors), user's accuracy (commission errors), and the kappa statistic. Kappa statistics signify the classification precision, which expresses the level of agreement in a single value between pairwise comparisons of maps (Carletta 1996). It was Cohen (1960) who developed the kappa index for categorical data and it was initially used for psychology and psychiatric analysis. Later it was adopted for measuring the classification accuracy of remotely sensed data (Sousa et al. 2002). The strength of agreement varies from no agreement (−ve) to near perfect (0.81–1.00).

13.2.3 Landscape Characterization, Forest Fragmentation Indices, and NDMI

FRAGSTATS is a spatial pattern analysis program for categorical maps (McGarigal et al. 2012). Many scholars have used this tool to analyse the changes occurring to the landscape over time (Narmada et al. 2021; McGarigal et al. 2012; Mondal and Southworth 2010; Atesoglu and Tunay 2010; Giriraj et al. 2008). The landscape subject to analysis is user-defined and can represent any spatial phenomenon. FRAGSTATS assesses the areal extent and spatial ordering of patches throughout a landscape. Usually, three different types of metrics are calculated in FRAGSTATS: (a) Patch level – Patch metrics are defined for individual patches and characterize the spatial characteristic and context of patches and nature of patches, i.e. average patch size, number of patches, patch core area, etc. (b) Class level – Class metrics unify all the patches of a given type (class). Class indices individually quantify the configuration of each patch type in a particular class and give metrics as per the components of each class in the landscape. (c) Landscape level – Landscape configuration refers to the spatial characteristic and arrangement, position, or orientation of patches within the landscape or class (sum of all classes).

As our objective was to estimate the spatial characteristics of different classes, we derived six indices to quantify the class metrics. The six indices selected for analysis were total class area, number of patches, largest patch index, edge density, shape index, and total core area, details of which are given in Table 13.2. Figure 13.3 gives the interconnections between the total core area, largest patch index, edge density, and shape index. Shape complexity points to the geometry of patches, whether they are simple and closely packed or irregular and complex. Shape metrics reflect the overall shape complexity. The most common method to examine the complexity of

Table 13.2 Details of metrics used in landscape fragmentation analysis

Metrics	Unit	Formula	Description
Total class area	Hectare	The sum of the areas of all patches of the corresponding class type	It defines the extent of the landscape
Number of patches	None	Patch number in the class	Absolute numbers
Largest patch index	%	$a/A*100$ a = area of patch(m^2) A = total landscape area (m^2)	LPI approaches 0 when the largest patch in the landscape is increasingly small. LPI = 100 when the entire landscape consists of a single patch
Edge density	Meters/ hectare	$(E/A)*10{,}000$ E = total length (m) of edge in landscape A = total landscape area (m^2)	It facilitates comparison among landscapes of varying sizes
Shape index	None	$(0.25* P)/\sqrt{a}$ p = perimeter of patch (m) a = area of patch(m^2) 0.25 = constant	SHAPE ≥ 1, without limit SHAPE = 1 when the patch is square and increases without limit as patch shape becomes more irregular
TCA	Hectare	Sum of the core areas of each patch of the corresponding class type	TCA approaches the total class area (CA) as the specified depth-of-edge distance(s) decreases and as patch shapes are simplified

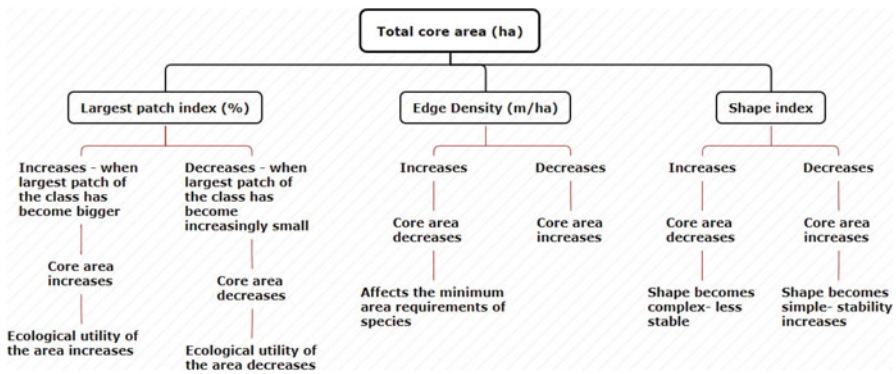Adopted from: Landscape Metrics for Categorical Map Patterns Tutorial by K. McGarigal

Fig. 13.3 Total core area as a function of the largest patch index, edge density, and shape index

the shape is to read the relative ratio of the perimeter (P) to the area (A). The interpretation varies among the various shape metrics, but in general, higher P/A values represent greater shape complexity or greater departure from simple Euclidean geometry (circular). The core area refers to the area of innermost patches when the buffer of the specified edge is eliminated, whereas the total core area is the sum of the core areas of each patch (m^2) of the corresponding class. The LULC classes were categorized based on a specified edge width of 100 m.

Simultaneously, vegetation health was assessed by examining the moisture content of vegetation using the Normalized Difference Moisture Index (NDMI). Though the normalized differential vegetation index (NDVI) is the most commonly used index for studies on vegetation cover, some have reported that NDMI is more useful for assessing forest health (Dutta et al. 2021; Zhang et al. 2016; Wang et al. 2010; Goodwin et al. 2008). NDMI has a strongly negative but linear correlation with Land Surface Temperature (LST), while the same is not true for LST and NDVI (weak correlation) (Li et al. 2017). As a result, NMDI helps in assessing moisture stress on vegetation better, a natural precursor to forest health, than does the NDVI. The calculation of the NDVI values was based on the following formula:

$$\text{NDMI} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}}$$

where NIR is near infrared and SWIR is shortwave infrared.

The selection of bands varies with the choice of Landsat image. For Landsat 8 bands 5 and 6 were used, while for Landsat 7 bands 4 and 5 were used. NDMI values range between −1 and + 1. Though the NDMI values can also vary according to the phenological stages of the stand, positive values are interpreted as the presence of healthy biomass with high moisture content, whereas areas where NDMI values are low indicate that vegetation is under water stress (Dutta et al. 2021).

13.3 Results

13.3.1 Classification Accuracy

The classification accuracy was evaluated through cross-referencing the features with the imagery available on Google Earth (https://earth.google.com/) (Sharma et al. 2016). During the field survey, it was found that at some place's barren/ uncultivated rocky lands situated between the boundary of forest and agricultural fields around forest villages were misclassified as agricultural lands. Within the forest, at a few places, water bodies and vegetation spectral signatures were found to be confusing. The lower accuracy values observed in the classes agricultural land, fallow/barren land, and water bodies at a few locations are due to their similar reflectance values. It was found that at some places under dense canopies, the signature of broad leaves and their shadows mimicked water and so were misinterpreted. Acharya et al. (2018) also attributed lower accuracy of water bodies because of the noise from shadows, clouds, and overhead canopies within forests. However, the overall accuracy reported here is within acceptable limits (80–99%) (Babbar et al. 2021; Mishra et al. 2020; Singh et al. 2017a; Chakraborty et al. 2016; Jain et al. 2016; Ellis et al. 2010; Anderson et al. 1976). The overall accuracies for Mandla for 2000 and 2017 were 84.18% (kappa 0.82) and 87.21% (kappa 0.85), respectively. At Hoshangabad, the observed overall accuracy was 83.39% (kappa

Table 13.3 Producer's and user's accuracy assessment for Mandla and Hoshangabad (2000 and 2017)

LULC class	Mandla				Hoshangabad			
	2000		2017		2000		2017	
	PA	UA	PA	UA	PA	UA	PA	UA
Dense forest	90.24	80.43	85.71	92.31	83.78	81.58	86.84	80.49
Open forest	90.32	80.00	84.21	94.12	83.33	81.08	81.58	88.57
Agricultural land	82.22	88.10	84.44	82.61	82.93	79.07	86.36	82.61
Water body	86.67	81.25	86.21	86.21	86.11	77.50	78.38	80.56
Fallow/barren land	71.11	94.12	83.33	93.75	76.32	93.55	76.47	89.66
Built-up	90.32	87.50	100.00	89.47	83.78	91.18	94.12	94.12
Scrub forest	87.18	87.18	90.24	82.22	84.62	86.84	84.62	82.50
Open land/sand	80.00	75.68	84.38	79.41	87.10	79.41	87.88	80.56
Overall accuracy (%)	84.18		87.21		83.39		84.51	
Kappa coefficient	0.82		0.85		0.81		0.82	

PA-Producers accuracy, UA- User's accuracy

0.81) for 2000 and 84.51% (kappa 0.82) for 2017. Table 13.3 gives the class-wise producer's and user's accuracy for Mandla and Hoshangabad for the two considered time periods (2000 and 2017).

13.3.2 Temporal Changes in LULC

The analysis shows that the dense forest cover increased in both districts. An increase in the core area of forests in Kanha National Park in the Mandla district has also been reported by Devi et al. (2017). But the same is not true for open forests, as during the study period Mandla and Hoshangabad have lost 8.73% and 6.43% of these forests, respectively. Overall, there has been a cumulative loss of forest cover in both districts. In Mandla, the total forest cover (dense + open) has decreased from 2432 to 2155 km^2 (net loss of 4.66%), while at Hoshangabad the total forest cover has decreased from 2254 to 1976 km^2 (net loss of 4.13%) between 2000 and 2017. We also found that Mandla has lost over 18% of its scrub forest, while its net area under agriculture has increased by 11%. Forests form the major land cover at Mandla, while agriculture is the second major land use class. In Hoshangabad the areas under agriculture and scrub forests have increased by 3.57% and 1.18%. Since agriculture is the major land use in Hoshangabad (44.69% in 2000), the change observed is less evident here (48.26%). At Hoshangabad open lands have decreased by 2.52%. There is also a marginal increase in the water bodies in both districts (0.99% in Mandla and 0.56% in Hoshangabad). Figure 13.4 gives the net change in LULC (%), while Fig. 13.5 gives the maps for 2000 and 2017 in both the study districts. Table 13.4 gives the class-wise land distribution (in km^2) in the Mandla and Hoshangabad districts.
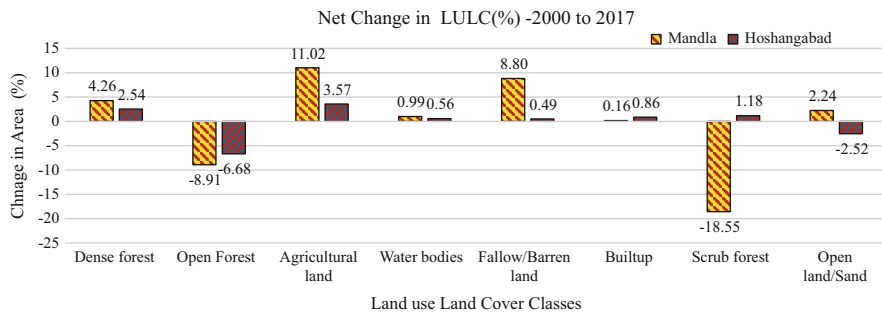
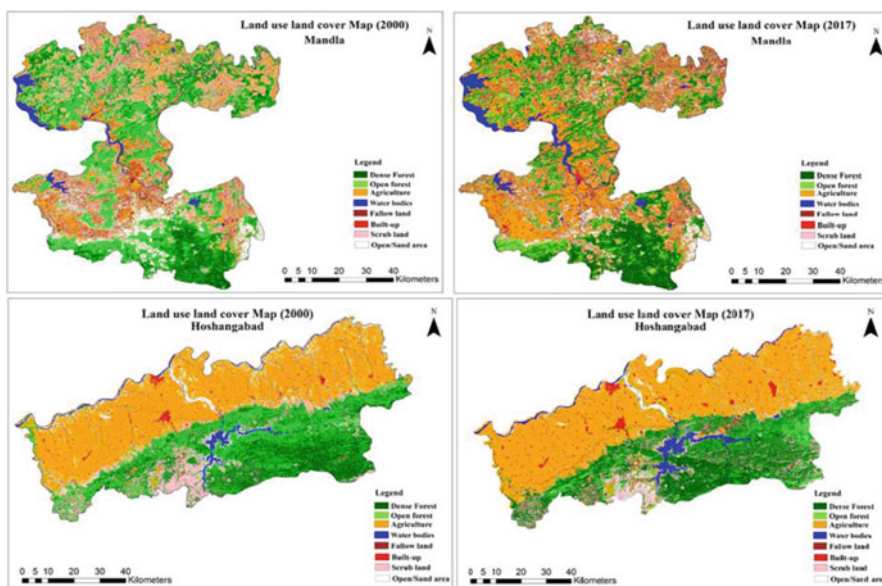Fig. 13.4   Net changes (%) in LULC types observed between 2000 and 2017

Fig. 13.5   LULC changes in the districts of Mandla and Hoshangabad

13.3.3   Landscape Characterization and Forest Fragmentation

13.3.3.1   Mandla

LULC maps have conveyed that the area falling within the class 'dense forest' increased in 2017 at Mandla but the number of patches (NP) decreased. It was, however, noted that the reduction in the number of patches is primarily due to the consolidation of patches and not owing to conversion to other land uses. This was evident from the largest patch index (LPI) value for 'dense forests' which increased

Table 13.4 Class-wise land distribution in Mandla and Hoshangabad districts

LULC classes	Mandla					Hoshangabad				
	2000		2017			2000		2017		
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Net change	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Net change
Dense forest	1022.66	17.17	1276.28	21.43	4.26	1255.48	18.66	1426.4	21.20	2.54
Open forest	1409.8	23.67	878.89	14.76	−8.91	999.11	14.85	549.8	8.17	−6.68
Agricultural land	1093.66	18.36	1750.05	29.39	11.02	3006.32	44.69	3246.16	48.26	3.57
Water bodies	168.71	2.83	227.67	3.82	0.99	181.72	2.70	219.44	3.26	0.56
Fallow/barren land	383.21	6.43	907.1	15.23	8.80	38.2	0.57	71.38	1.06	0.49
Built-up	43.9	0.74	53.661	0.90	0.16	103.88	1.54	161.61	2.40	0.86
Scrub forest	1454.62	24.42	349.61	5.87	−18.55	585.97	8.71	665.47	9.89	1.18
Open land/sand	379.04	6.36	512.32	8.60	2.24	556.18	8.27	386.59	5.75	−2.52
Total	5955.60	100	5955.58	100		6726.86	100	6726.85	100	

from 2.74% to 4.23%. The core area of dense forest patches increased over 17 years (2000 to 2017) by 27524.24 ha in Mandla, which is consistent with the observations documented in the State of Forest Report (2017) for Madhya Pradesh. As edge density is a measure of spatial heterogeneity and class compactness, it should be read in relation to the total area and number of forest patches under the class. For the class 'dense forests' the edge density decreased from 39.58 m/ha in 2000 to 33.99 m/ha in 2017. This could be due to the amalgamation of the number of differently sized patches. If the edge density values increased along with an increase in the total forest area, this could be interpreted as an increase in forest edges, hence more fragmented patches. The shape index (SI) is the measure of the shape complexity based on the perimeter of the patches. The higher the SI, the greater the shape complexity and thus the more the vulnerability to edge effects. The 'dense forests' has not shown much change with respect to the shape index values (1.30 in 2000 to 1.34 in 2017). The areas under the classes 'open forest' and 'scrub forest' have decreased from 140980.14 ha (2000) to 890262.05 ha (2017) and from 145462.05 ha (2000) to 22767.39 ha (2017), respectively. The edge density of scrub forests has reduced to about 6% (3.96 m/ha) from what it was in 2000 (65.96 m/ha). Though a lower edge density is an indication of the expansion of core areas, it is not the case here. In the present case, the reduction in the edge density is due to the removal of scrub forest patches, which is suggested from the reduction in the total core area and the reduced size of the largest patch of scrub forests. In the 'open forest' class the area of the largest patch also declined by 0.53%. The scrub forests have not shown a major change in the shape index values (1.40 in 2000 to 1.39 in 2017), whereas for open forests it increased from 1.35 to 1.42, which suggests that patches have become more irregular and discontinuous and hence would be more vulnerable to edge effects. The total core area for both the scrub and open forests has decreased by 22,639.32 ha and 1787.71 ha between 2000 and 2017, respectively.

The area under agriculture increased by 50,707.35 ha. As in the case of dense forests, the number of patches under the class 'agriculture' decreased but the largest patch size increased from 0.38% to 2.51%. Similarly, the total core area under agriculture also increased from 16827.30 ha to 46866.78 ha. The change in the shape index was not significant (1.30 to 1.34). An increase in edge density and area together with a non-significant change in the shape index suggests an expansion of the agricultural fields into new areas.

Built-up areas have increased by 48,194.82 ha, while the number of patches also increased from 1985 in 2000 to 38,968 patches in 2017. With respect to the largest forest patch size and the total core area for built-up areas, these are similar to trends observed in agricultural lands. An increased area and a greater number of patches have contributed to an increased edge density (20.15 m/ha) of built-up areas in 2017. The change in the shape index values (1.38 to 1.24) indicates that the patches that were previously small (in 2000) and widely spread have become more continuous and consolidated, owing to the expansion of built-up areas. The largest loss occurred with respect to open lands/sandy areas (dry river beds) – the extent decreased by

32,539.32 ha, while the core area decreased significantly from 10488.51 ha in 2000 to 1454.67 ha in 2017. There was a significant decrease in the area of the largest patch size (0.25 to 0.04), whereas the number of patches also decreased from 34,313 in 2000 to a mere 1559 in 2017. With the decline in area, the edge density also reduced to 1.52 m/ha, a meagre 9% of what it was in 2000 (15.62 m/ha). Open forest patches and dry river beds are under constant threat from encroachment and conversion to other preferred land uses. Table 13.5 gives the details of landscape characterization at Mandla.

13.3.3.2   Hoshangabad

At Hoshangabad the area under the class 'dense forest' increased by 17091.81 ha between 2000 and 2017. The largest patch size values of dense forests have undergone a sharp decline – from 10.11 ha in 2000 to 6.62 ha in 2017. An increase in the number of forest patches along with an increase in the total core area indicates the creation of new forest patches. For open forests, the total area decreased by 44931.43 ha, whereas scrub forests increased by 7950.53 ha between 2000 and 2017. Similar declines were noted for scrub and open forests from 2000 to 2017 [largest patch size – open forest, 1.38 (2000) to 0.36 (2017); scrub forests, 1.77 (2000) to 0.88 (2017)]. Open forests have become severely fragmented leading to a large number of small patches evident from lower edge density (26.64) and shape complexity index (1.25) values. The total core area under open forests was also reduced by 6275.88 ha between 2000 and 2017. However, scrub forests increased by 7950.51 ha in the same period although they appear to be disintegrated (as the number of patches increased by 24,029). This change is detrimental as the total core area has drastically reduced the area of the largest patch of scrub forests in 2017 which was half that observed in 2000. This indicates that, though the total area under this class has increased along with the number of patches, they are isolated in nature and are of a smaller size. The whole area is within the specified edge depth of 100 m from the perimeter of the patch and fails to contribute to the core area. Smaller-sized patches are less complex and would be vulnerable to greater edge effects and encroachments. The area under agriculture has increased, although the number of patches has reduced. The total core area under agriculture increased by 13691.25 ha between 2000 and 2017. The largest patch area too increased, indicating an expansion of cultivated areas. The built-up areas have increased, the number of patches reduced, and the total core area increased during the period of observation. The area of the largest patch also increased, indicating an expansion of settlements and other establishments. The area of open lands and sandy areas (dry river beds) decreased, whereas the number of patches increased. Table 13.6 gives the landscape characterization at Hoshangabad.

Table 13.5 Landscape characterization in the Mandla district (2000 and 2017)

Fragmentation indices	Dense forest		Open forest		Scrub land		Agricultural land		Built-up		Open land	
	2000	2017	2000	2017	2000	2017	2000	2017	2000	2017	2000	2017
Class area (ha)	102262.6	127919.2	140980.1	89026.3	145462.1	22767.4	109365.6	160072.9	4390.38	52585.2	37,905	5365.71
Number of patches	58,306	30,113	67,887	48,964	66,117	1952	90,929	65,181	1985	38,968	34,313	1559
LPI (%)	2.74	4.23	1.18	0.65	0.5	0.35	0.38	2.51	0.02	0.19	0.25	0.04
Edge density (m/ha)	39.58	33.99	45.09	58.29	65.96	3.96	58.68	53.46	1.5	20.15	15.62	1.52
Shape index	1.3	1.34	1.35	1.42	1.4	1.39	1.3	1.34	1.38	1.24	1.23	1.4
Total core area (ha)	26172.9	53797.14	31771.08	9131.76	16748.01	14960.3	16827.3	46866.78	952.65	12198.1	10488.5	1454.67

Table 13.6 Landscape characterization in the Hoshangabad district (2000 and 2017)

| Fragmentation indices	Dense forest		Open forest		Scrub land		Agricultural land		Built-up		Open land	
	2000	2017	2000	2017	2000	2017	2000	2017	2000	2017	2000	2017
Class area (ha)	125547.8	142639.6	99911.43	54,980	58596.57	66547.1	300,632	324616.4	10387.7	16160.9	55568.8	38659.2
Number of patches	26,316	47,298	49,618	79,490	46,646	70,675	11,594	6881	6444	3798	69,036	86,765
Largest patch index (%)	10.11	6.62	1.38	0.36	1.77	0.88	12.11	12.18	0.17	0.32	0.62	0.25
Edge density (m/ha)	71.87	33.41	73.94	26.64	38.74	27.34	23.26	44.59	5.81	4.66	45.58	19.53
Shape index	1.31	1.25	1.36	1.25	1.27	1.24	1.21	1.27	1.27	1.33	1.25	1.18
Total core area (ha)	33799.77	46372.77	10385.28	4109.4	15525.54	7446.06	221,872	235563.2	2840	8071.56	10593.5	6603.39
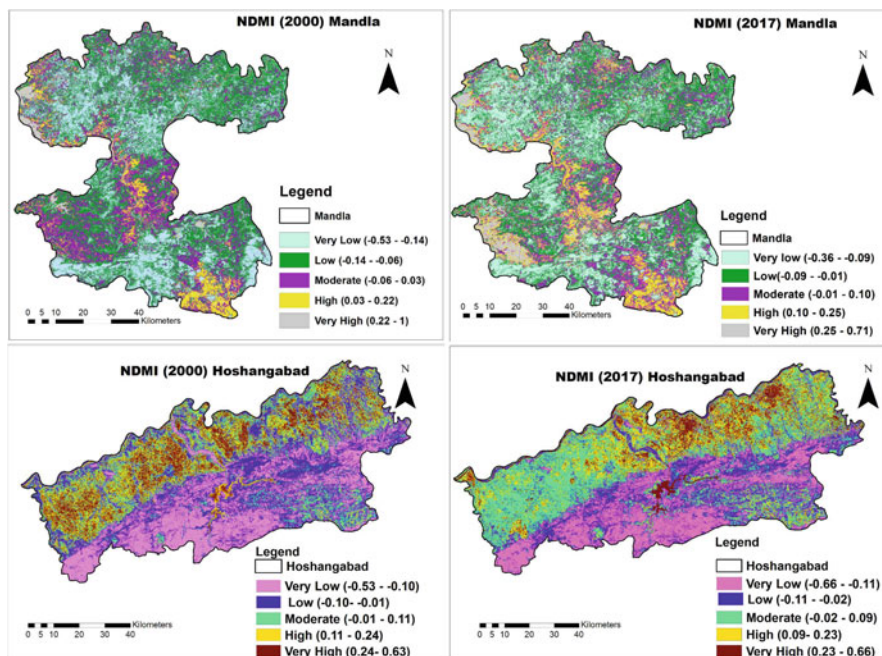
Fig. 13.6 Normalized Difference Moisture Index (NDMI) for Mandla and Hoshangabad for the years 2000 and 2107

13.3.4 Normalised Differential Moisture Index

To assess the health status of vegetation based on the level of moisture, the NDMI values were divided into five categories – very low, low, moderate, high, and very high (Fig. 13.6). The range of values under each category varied year-wise and district-wise. At Mandla these values were very low (−0.53–0.14 in 2000 and −0.36–0.09 in 2017), low (−0.14–0.06 in 2000 and −0.09–-0.01 in 2017), moderate (−0.06–0.03 in 2000 and − 0.01–0.10 in 2017), high (0.03–0.22 in 2000 and 0.10–0.25 in 2017), and very high (0.22–1 in 2000 and 0.25–0.71 in 2017), whereas in Hoshangabad the values were very low (−0.53–0.10 in 2000 and −0.66–0.11 in 2017), low (− 0.10–0.01 in 2000 and − 0.11–0.02 in 2017), moderate (−0.01–0.11 in 2000 and − 0.02–0.09 in 2017), high (0.11–0.24 in 2000 and 0.09–0.23 in 2017), and very high (0.24–0.63 in 2000 and 0.23–0.66 in 2019). It is evident from the NDMI values that the biomass and moisture content is higher in forests of Mandla (1 and 0.71 in 2000 and 2017, respectively) than in Hoshangabad. In Mandla, the areas with low moisture and biomass content have transitioned to very low moisture levels in 2017 in the central part (poor quality forests), although in the southern part of the district the moisture content has increased (healthy forests) At Hoshangabad, high NDMI values were observed across the northern part of the district which is

under cultivation, although a major part of forest vegetation was seen to be under moisture stress. In comparison, the forests in the south-western part show a relatively better moisture index.

13.4   Discussion

The increase in the overall forest cover of Madhya Pradesh is credited to an increase in the area under forest plantations (ISFR, 2019) and better management practices. The present study focused on two districts in Madhya Pradesh, Mandla and Hoshangabad. The Mandla district supports a large tribal community, around 57% of the inhabitants (www.censusindia.com); hence, forest-related employment and agriculture (farming) are the main livelihood practices here and no major industrial developments have occurred in this district. In Hoshangabad, the prevalence of a good irrigation network and the availability of large extents of fertile alluvial plains have resulted in agriculture being the most practiced occupation in the district, which was evident from the higher NDMI values in the upper areas.

The present study revealed that in both districts, the loss of forest areas due to the expansion in agriculture or in the built-up areas has been marginal (less than 1%), although there was a considerable loss in open forest areas. Our results are in line with Sharma et al. (2016) who report an increase in dense forest cover but a decrease in open forest cover. On the contrary, Ramachandra et al. (2016) studied forest fragmentation in Central Western Ghats, India, and found that forest cover declined, and this was attributed to unplanned developmental projects or conversion to other non-forest categories such as croplands and plantations. They also noted that changes in landscape structure occurred due to locally relevant socio-economic variables. Similarly, Keles et al. (2008) reported a decrease in the average forest patch sizes due to human interventions, resulting in irregular land cover types. Expansion of agriculture and settlements is occurring at the cost of ecologically important land cover types such as scrub forests, open areas, and dry river beds (Brander 1994). Our study also reports decreases in the extent of open forests, scrub forests, and open lands, whereas the area under the classis's 'agriculture' and 'built up' increased. With the expansion of human population, there is an invariable increase in forest-based industries and illegal encroachments for agriculture, which exerts pressure on forest resources (FAO 2016). Anthropogenic activities (e.g. development, timber harvesting) can disrupt the structural integrity of landscapes and most often impede ecological processes (e.g. movement of organisms) (Gardner et al. 1993).

The increase in the dense forest cover is the result of consistent efforts by the management and concerned authorities in the past, which is also reflected by a relatively higher moisture/vegetation index in some parts of the districts. The Forest Survey of India (2015) attributed the increase in forest cover in the state of Madhya Pradesh to increased plantation activities within the forest, this being a cause for concern as it creates patchiness of the forest (Estreguil et al. 2013; Almoussawi et al.

2019). It must be noted that (i) the increase in dense forest cover is not uniform and is limited to sections of the forest as evident from NDMI values and (ii) the establishment of plantations of timber species on a large scale in the Mandla district in the past has significantly altered the present-day species composition in the forest. For instance, in 1930 *Tectona grandis* (teak) occupied only 39% of the forest in West Mandla but the increase in market demand for timber induced forest departments to reorient their management policies, which resulted in a larger amount of forest land being compromised for plantations. *T. grandis* in recent years covers around 82.5% of the forest area (as per forest working plan, West Mandla 2006–2007 to 2015–2016). This also results in the loss of vegetation heterogeneity in the forest. Monoculture plantations, although they can result in an increase in tree cover, will not be beneficial in the long run. For example, the remaining forests (17.5%) which comprise mixed species are expected to support the needs of the local communities for forest products and the requirements of livestock and wildlife. The interspersed monoculture stands disrupt connectivity between synchronized stages of succession in natural forests and create contrasts along the edges of the patches. While studying the impact of tree diversity on productivity, Mahaut et al. (2019) observed strong and positive effects from increased diversity of vegetation on both above-ground and below-ground biomass production (Richards et al. 2010). They also observed that each species under investigation did not contribute equally to the functions of the ecosystem, and hence, through the conversion of a heterogeneous forest to a homogenous monoculture plantation, we forego the benefits of some species. A forest with a high diversity of tree species provides suitable conditions for ecological niches to develop and strengthens the existing species interactions while simultaneously facilitating the evolution of new species associations (Liu et al. 2018).

It has become clear from numerous studies that the many impacts of forest fragmentation are interconnected (Saiter et al. 2011; Paula et al. 2015; Arruda and Eisenlohr 2016; Duarte et al. 2019; Pereira et al. 2021; Santos et al. 2021). Forest fragmentation, driven by multiple factors, is recognized as one of the major causes of biodiversity loss (Tilman 2004) and altered ecosystem functioning across biomes. Pereira et al. (2021) studied the footprints of forest fragmentation by examining the impacts of edge effects on successional dynamics in Brazilian forests and report high mortality of trees in forest fragments surrounded by pasturelands. Here high seedling recruitment and equally high mortality were attributed to adverse consequences of fragmentation. Increased light intensity along edges combined with low humidity conditions favours the rapid growth of pioneer species. Almoussawi et al. (2019) explored how forest species (specialist vs generalist) responded to fragmentation and reported on their negative impacts on the interior-sensitive specialists, while the generalist's benefit. Herbaceous vegetation may cause competitive exclusion of forest specialists who are poor in resource exploitation and are not adapted to unstable microclimatic conditions of forest edges. On the other hand, it has been found that agricultural practices along the forest boundaries create favourable conditions for generalists (Fischer and Lindenmayer 2007). Thus, fragmentation leads to structural and floristic changes in characteristics of the plant communities of the forest edges and interior.

Forest edges also act as tangible barriers to the dispersal of forest specialists between neighbouring forests. This increases the tendency of specialist species, the slow colonizers, to concentrate in small areas, whereas the fast colonizers, the generalist species, increase their area of coverage. The abundance of forest generalists tends to decline from the edges to the forest interior, and specialists vice versa. These reverse patterns of abundance shown by specialists and generalists are a result of niche partitioning along the gradients of light, moisture, and soil conditions across edges and core areas of the forest. The depths up to which edge effects can have their influence are not uniform across ecosystems. It has been shown to be between 20 and 50 m (Hérault and Honnay 2005) and between 100 and 200 m for the forest interior (Hardiman et al. 2013). Edge effects are more deleterious for smaller and isolated habitat patches. Animals are similarly affected by fragmentation. Shahabuddin et al. (2021) assessed the effects of land use change on forest bird species in the Himalayas and reported that it negatively affected species richness and species composition. Here too it has been noted that birds that are forest specialists are highly vulnerable to land use change. Forest specialists often use mosaics of tree species found in natural forests. Therefore, the conversion of natural forests to other land use types forces these species to alter their feeding and nesting behaviour, which may lead to the local extinction of some species. Santos et al. (2021) assessing bird communities in Brazilian forests show that the abundance of birds was greater at the centre of the forest than at the edges. They further state that species occupying the forest edges demonstrated a behavioural shift which was required for communicating at the noisy forest edges. They observed that species were deploying compensatory mechanisms to adjust their acoustic conduct which is identified as the Lombard effect (Garnier and Henrich 2014). Species were investing more energy to increase their amplitude, call frequency, and call duration (Pieretti et al. 2015; Duarte et al. 2019). Pollinators are also negatively affected by land use conversions (Shahabuddin et al. 2021). As the natural areas become increasingly isolated, the links between the individual segments reduce. As forests become smaller and more distant from one another, their carrying capacity and the potential to provide ecological services also decline (Brander 1994). This alters the relationship between alpha and beta diversity with respect to both flora and fauna (Khurana and Singh 2001; Starzomski et al. 2008; Belote et al. 2009; Almoussawi et al. 2019). It must therefore be highlighted that maintaining original forest habitats should be considered a top priority.

13.5   Conclusion

This study assessed the changes in LULC patterns in two districts of Madhya Pradesh using Landsat data for two time periods – 2000 and 2017. The results reveal that forest cover is the major land cover type in Mandla, while agriculture is the major land use type in Hoshangabad. As a result of an afforestation drive by the Forest Department, the dense forest area has increased at both the study sites, which is reflected by the higher moisture index values. However, it was found that there is a

net loss of forest area in both districts, as the loss of area under open forests is greater than the area gained with respect to the dense forests. Replacement of mixed species forests at Mandla with homogenous *T. grandis* stands is a matter of concern, as such monocultures do not contribute to the resilience of the forest. To reap the benefits of multispecies ecosystems and to reduce pressures on existing forest resources, conscious efforts are needed to reverse this change. The trends in the number of patches and the extent of the largest patch suggest that forest fringes that are adjacent to agricultural lands are more likely to undergo land diversion in both districts. The expansion of built-up areas is not significant in the two studied districts. However, the shape index values indicate that built-up areas are on the rise and have become more consolidated due to expansion. Results also show an increase in the total core areas with respect to agriculture. This may suggest the lack of other employment opportunities, a matter that has to be resolved particularly as it relates to tribal communities in the two districts under consideration. New employment opportunities must be in line with their way of living and must have a minimal impact on the forests on which they depend.

This study also accentuates the ability of geospatial techniques in documenting the changing dynamics in landscapes in terms of LULC. As Peter Drucker said, 'you can't manage what you can't measure', this study while addressing an information gap in the two districts Mandla and Hoshangabad provides an information base upon which policy decisions could be made to ensure sustainability in land use planning in the tiger capital of India.

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