Land Use Land Cover in the Western Ghats, India

Effects of Human Modification and Use on Protected Areas

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ABSTRACT

In India's Western Ghats mountain range, a UNESCO World Heritage Site and Conservation International biodiversity hotspot, human-caused habitat loss threatens many native species. A number of protected areas have been created to provide a refuge for these species and prevent further habitat loss. However, encroaching development continues to threaten these delicate ecosystems. Despite the area's environmental value, there is no reliable, high-resolution land use land cover (LULC) map that would allow managers to estimate the extent and distribution of development as well as habitat condition and connectivity across the region. Using ASTER imagery, we conducted LULC classifications of 6 protected areas and their surroundings (20 km buffers). Separate classifications were conducted on Anshi-Dandeli National Park, Nagarahole and Bandipur National Parks, BRT Wildlife Sanctuary, and Kudremukh and Bhadra Wildlife Sanctuaries, for a total of four classification regions. We conducted both supervised maximum likelihood and unsupervised ISODATA classifications. Accuracy of the supervised classifications was higher than accuracy of the unsupervised classifications, with values ranging from 75.6-84.4%. Forest class accuracy ranged from 74% - 91%. We used the LULC classifications to assess the amount of forest cover within the protected areas and in the 20 km surrounding buffer. Within the classifications, 45-67% of the land is forested, while 17-35% of the land has been cleared for human use. We also conducted pilot analyses of forest fragmentation, patch connectivity, and human-affected areas in different parks. The LULC maps will be used to help managers set conservation goals and establish land use baselines for the region.

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INTRODUCTION

The Western Ghats

The Western Ghats are a mountain range running along India's western coast. Spanning 1600 km, this series of hills and mountains are on average about 40 km away from the coastline, with elevations ranging from sea level to an excess of 2000 m (Tewari, 1995). In 2012, the Western Ghats were designated as a UNESCO World Heritage Site (PTI, 2012). They are also a Conservation International biodiversity hotspot (Conservation International, 2013) (fig. 1.1). Forests in this range provide habitat for the largest Indian population of Asian elephants, as well as populations of tigers, leopards, wild dogs, and endemics such as the lion-tailed macaques (Myers *et al.*, 2000; "Western Ghats, India," 2012). In addition, more than three quarters of India's known amphibian species, half of its reptile species, and around a third of its plant species are found in the Western Ghats (Das *et al.*, 2006; "Western Ghats, India," 2012).

The region experiences two annual monsoons: a southwestern monsoon from June to September and a northeastern monsoon from December to March (Tewari, 1995). Precipitation from the southwestern monsoon greatly exceeds that of the northeastern monsoon and yearly rainfall occurs primarily during this time (Tewari, 1995). Most of the precipitation falls on the western side of the mountains, creating a rain shadow effect where the Western Ghats are significantly drier on the eastern side (Venkatesh & Jose, 2007).

Due to a variety of elevation and temperature regimes, the Western Ghats contain many diverse soil types, which allows for a wide range of agriculture and silviculture crops (Tewari, 1995). Crops grown in the Karnataka region of the Western Ghats include areca, banana, cardamom, chili pepper, coconut, coffee, cotton, eucalyptus, ginger, guava, jackfruit, mango, maize, marigold, millet, okra, orange, pepper, rice, rubber, silver oak, sugar cane, sweet potato, tamarind, teak, tobacco, and turmeric (Tewari, 1995). Mixed cropping is a common practice in the area (Tewari, 1995). A common example is that of coffee plantations where coffee plants are shade grown together with coconut, silver oak, and areca (Tewari, 1995).

Unfortunately, agricultural development and deforestation have fragmented the overall landscape (Menon & Bawa, 1997).

Human encroachment into parks is the final and arguably the biggest problem facing protected areas in India (K. K. Karanth, 2007). Villagers living on the periphery of parks use the easily available forest resources. These include firewood, wild plants, and wild animals (K. K. Karanth *et al.*, 2006). Karanth *et al.* (2006) found that the areas within one kilometer of homes were heavily utilized for firewood collection. While this may seem like a fairly low-impact practice, the collection of firewood by many people over the span of decades does take its toll. Villagers also illegally hunt wild animals within the boundaries of the protected areas (Madhusudan & Karanth, 2002).

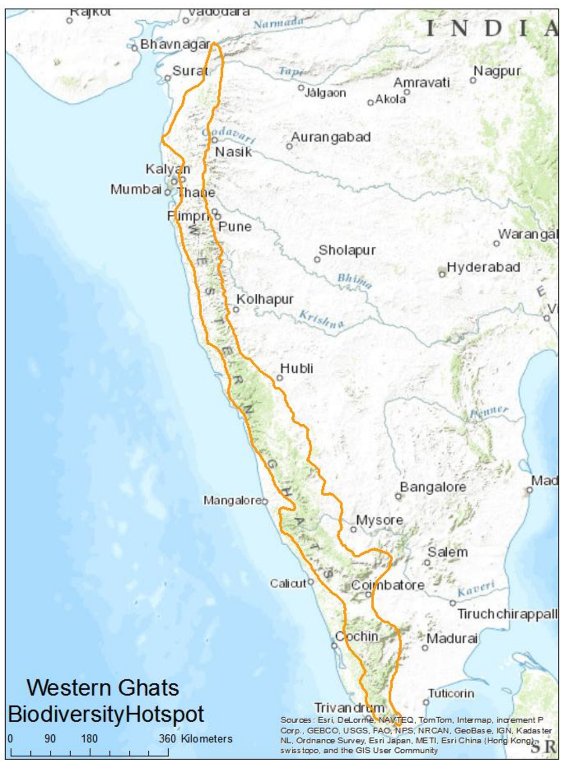

Fig. 1.1 Extent of Western Ghats mountain range, a biodiversity hotspot

Mobile Species of Concern

The tiger, *Panthera tigris*, is a large carnivore of the family Felidae with distinctive orange or white fur and vertical black stripping (Nyhus & Tilson, 2010). Tigers hold a prominent role in the history and mythology of the people of India and depictions of this majestic animal have been created by humans for at least 5,000 years (K. U. Karanth, 2001). Despite human captivation with tigers, this species is under great threat. Tiger poaching is a worldwide problem, and it is estimated that tiger populations have decreased by at least 50% since 1990 ("IUCN Red List," 2012). India contains the world's largest population of wild tigers, yet these animals are disappearing at an alarming rate (K. K. Karanth *et al.*, 2010; "WWF," 2012). Most tigers poached in India are exported as part of an illegal billion dollar industry ("WPSI," 2012). Tiger numbers are also decreasing due to human encroachment upon their territory, which causes a loss in viable habitat and a reduction in prey abundance (Christie *et al.*, 1999). Population models by K. Ullas Karanth and Bradley M. Smith (1999) show a rapid decline in tiger populations due to a reduction in prey animals. This means that it is important not only to preserve habitat for large carnivores but to conserve prey populations as well.

Human wildlife interactions

Negative human-wildlife interactions have many consequences and sometimes result in death or harm to animals (Karanth *et al.*, 2006). Elephant raids on agricultural fields can leave farmers without crops and destroy the livelihood of local villagers who depend on these crops both economically and for food (Sukumar, 1990). People in these situations go to great lengths to protect their crops, including erecting large electric fences and elephant ditches. Negative interactions often leave villagers with animosity towards wild animals, and in many cases people will kill them on sight (Kruuk, 2002). A survey conducted by Karanth and Nepal (2012) found that 78% of respondents around Nagarahole National Park identified damage caused by wild animals as a major problem.

Despite the occurrence of human-wildlife conflict, Karanth and Nepal (2012) found that the majority (60.1%) of residents living around Nagarahole National Park approve of the existence of the protected area. Residents cited protection of water resources (83.1%), animals (83.2%), and plants (82.6%) as reasons for protected area establishment, but also thought they should be allowed to collect plants and firewood within the park (67.9%). This suggests that although residents generally approve of protected areas, they aren't enamored with some of the restrictions imposed by protected areas.

Overview

The Centre for Wildlife Studies (CWS), an NGO established in 1984 in Bangalore, India, focuses on habitat and species conservation in India. It conducts ecological field studies, training programs, and monitoring programs across India. The main goals of CWS include improving the management of protected areas, developing better methods of tracking and monitoring wildlife, and increasing public involvement in conservation programs. CWS has conducted long-term research projects on many of the large, charismatic species that inhabit India's wild areas, including leopards, Asian elephants, and Bengal tigers.

CWS has asked us to create land cover maps of the areas surrounding 6 protected areas in the Western Ghats, a biodiversity hotspot located along India's west coast. This area is important due to its high biodiversity and the presence of endangered species like the tiger. Despite its significance, however, there is currently no reliable, high-resolution land cover data for the area. Land cover data would allow CWS to determine the extent and location of development, which would help determine where conservation activities should be focused.

Our study area consists of six protected areas and the regions surrounding them in the state of Karnataka. These protected areas are Anshi-Dandeli National Park, Bandipur National Park, Bhadra Wildlife Sanctuary, Biligiri Rangaswamy Temple (BRT) Wildlife Sanctuary, Kudremukh Wildlife Sanctuary, and Nagarahole National Park (fig. 1.2). These protected areas are vital habitat for preserving native plants and animals. The wildlife found in these parks is often a small subset of the biodiversity that once abounded in India before human encroachment. These parks represent the most significant relatively untouched land left in this part of the Western Ghats. The protected areas are surrounded by a mix of agriculture and plantations ("Western Ghats, India," 2012). Karanth *et al.* (2010) found that 18 of the 25 large mammal species in India had lower extinction risk within protected areas, and 13 species had lower extinction probabilities in forested areas. Therefore, change in land cover and reductions in forest cover within and around protected areas could increase the extinction probabilities of some large mammal species within our study areas (K. K. Karanth *et al.*, 2010). Estimation of the extent of cleared land within and around protected areas could therefore help managers determine where conservation efforts should be focused.

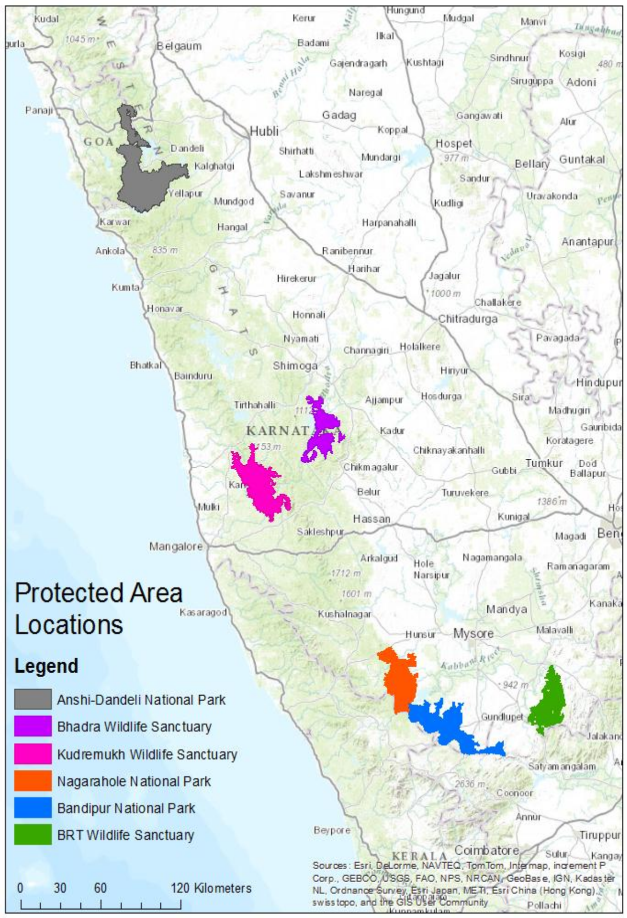

Fig. 1.2 Locations of our 6 targeted protected areas

METHODS

Overview

In this study, we created land use land cover maps within and surrounding six protected areas in western India. Using remotely-sensed ASTER imagery and ground truth data collected in the summer of 2012, we ran two different classification methods, classifying land in our study area into 6 different classes. Once the classifications had been run, we conducted accuracy assessment on each study area. We also conducted pilot landscape analyses on selected areas, including fragmentation, connectivity, and human encroachment analyses.

Study Area

This study focuses on land within and immediately surrounding seven different protected areas in the Western Ghats. These protected areas comprise three national parks, Anshi-Dandeli National Park, Bandipur National Park, and Nagarahole National Park, as well as three wildlife sanctuaries, Bhadra Wildlife Sanctuary, Biligiri Rangaswamy Temple Wildlife Sanctuary, and Kudremukh Wildlife Sanctuary. The land cover maps include the land within the protected areas as well as within a 20 km buffer surrounding the protected areas.

The protected areas contain mostly deciduous forest, semi-deciduous forest, evergreen forest, scrub forest, and shola as well as other grasslands (Tewari, 1995). The land outside of the parks consists mostly of plantations and agriculture. There is a lot of mixed cropping as well where herbaceous crops are planted beneath plantation trees (Tewari, 1995). A common example of this is shade grown coffee planted beneath silver oak trees with pepper vines growing up the trees.

The protected areas we are mapping are very significant because they represent some of the only protected forest in the Western Ghats. With agriculture and plantations making up the majority of the land between these parks, it is important to maintain and protect these habitat reserves.

Remotely-sensed image processing

Overview of remote sensing

Remote sensing is the use of remotely-collected data to assess ground attributes. In this study, we use data collected by satellite via passive remote sensing. In passive remote sensing, a sensor detects energy originating from the sun. In this process, the sun releases radiation, which reflects off the earth’s surface and is detected by a satellite. The behavior of the radiation that reflects off of the earth’s surface varies depending on what is on the ground. For example, the proportion of different wavelengths of radiation reflecting off of dense forest will look different than the proportions of radiation reflecting off of grasslands (Schowengerdt, 2007).

Remote sensing is useful for mapping our study area because our goal is to map an area covering almost 30,000 km^2 with widely-varying cover types. Mapping an area this large from the ground would be nearly impossible, and would require manpower and money we didn't have access to. The Ghats' dense vegetation cover and areas of political upheaval also contribute to the difficulty of ground mapping.

About ASTER Imagery

ASTER imagery was selected over the alternatives because it offered complete, relatively recent imagery for our study area. Landsat 7 was available over the study area, but the failure of the scan line corrector means that approximately 22% of data from each Landsat 7 image after 2003 is missing. Landsat 5 collected data until 2012 (USGS, 2013), but recent data for our study area was unavailable.

ASTER imagery is collected by NASA's Terra satellite, which is run through collaboration between NASA; Japan's Ministry of Economy, Trade, and Industry; and Japan Space Systems. The visible and near infrared (NIR) ASTER bands have 15 m resolution, short wave infrared (SWIR) bands have 30 m resolution, and thermal bands have 90 m resolution. SWIR readings from ASTER have been unusable since 2003, and since all of our images were collected between 2004 and 2012, we did not have access to these data. Each ASTER scene is 150 km x 120 km, and the satellite has a potential revisit time of 16 days (Abrams *et al.,* 2002).

Image Acquisition

ASTER imagery was acquired remotely via NASA's Reverb ECHO. Permission to access ASTER was granted to our advisor, Dr. Jennifer Swenson, by NASA, which only permits approved researchers to access ASTER data. Nine scenes from three different days were acquired and combined into three mosaics for a 20 km buffer around Anshi-Dandeli tiger preserve (fig. 2.1), 11 scenes from four days combined into four mosaics for a 20 km buffer around Bhadra Wildlife Sanctuary and Kudremukh (fig. 2.2), 8 scenes from three different days were combined into three mosaics for a 20 km buffer around Nagarahole National Park and Bandipur National Park and Tiger Preserve (fig. 2.3), and 5 scenes collected on 3 days combined into 3 mosaics for a 20 km buffer around Biligiri Rangaswamy Temple Wildlife Sanctuary (fig. 2.4). In total, we downloaded 39 scenes (table 2.1).

Cloud cover was a concern in image acquisition, as the Western Ghats are often cloudy, and are subject to seasonal monsoons that bring nearly constant cloud cover (Ray, Manoharan, and Welch, 2011). If a recent image exhibited extensive cloud cover over the study area, an older image with less cloud cover was chosen.

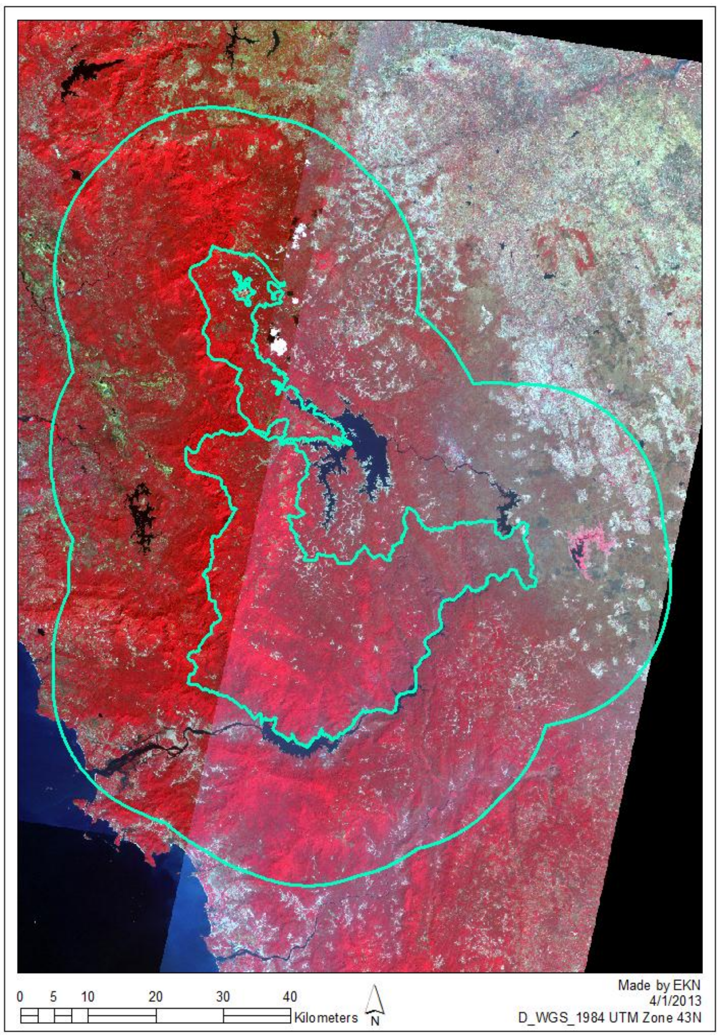

Fig. 2.1 Images used in Anshi-Dandeli Classification

ASTER Color infrared (3,2,1)

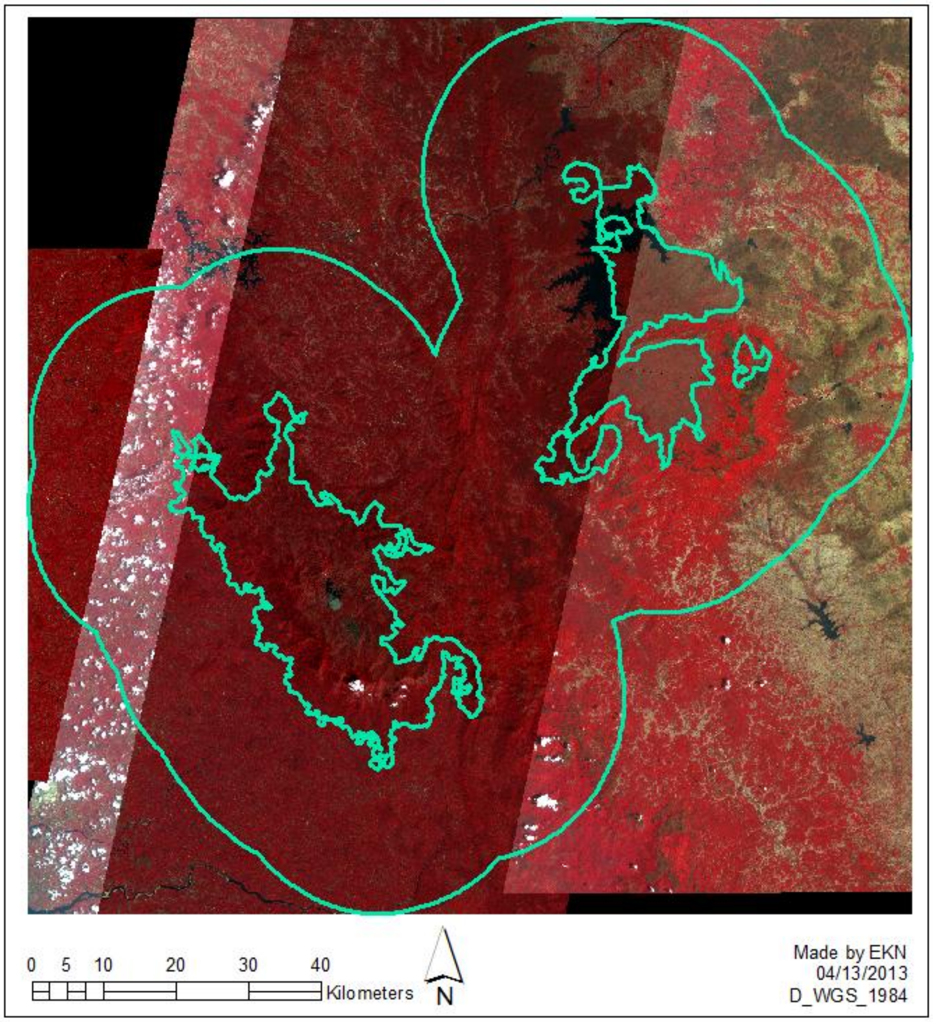

Fig. 2.2 Images used in Bhadra (northern park) and Kudremukh (southern park) Classification ASTER Color infrared (3,2,1)

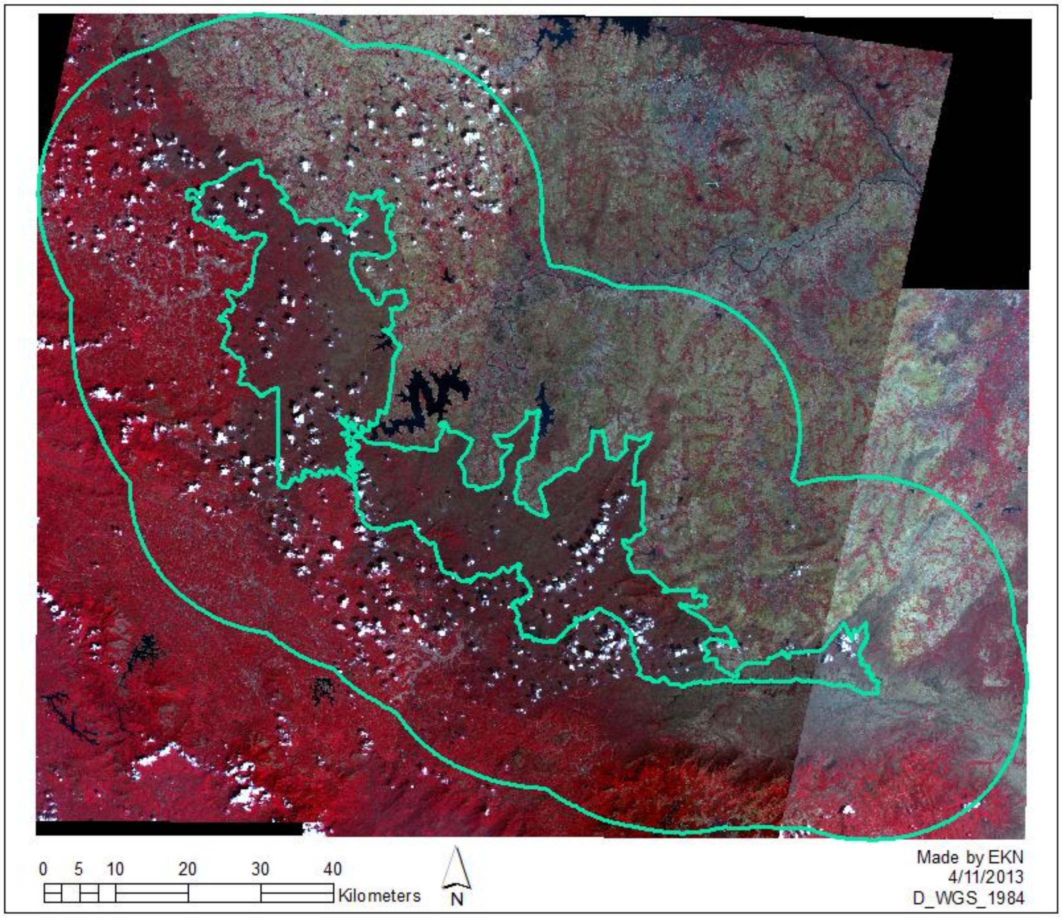

Fig. 2.3 Images used in Nagarahole (northern park) and Bandipur (southern park) Classification ASTER Color infrared (3,2,1)

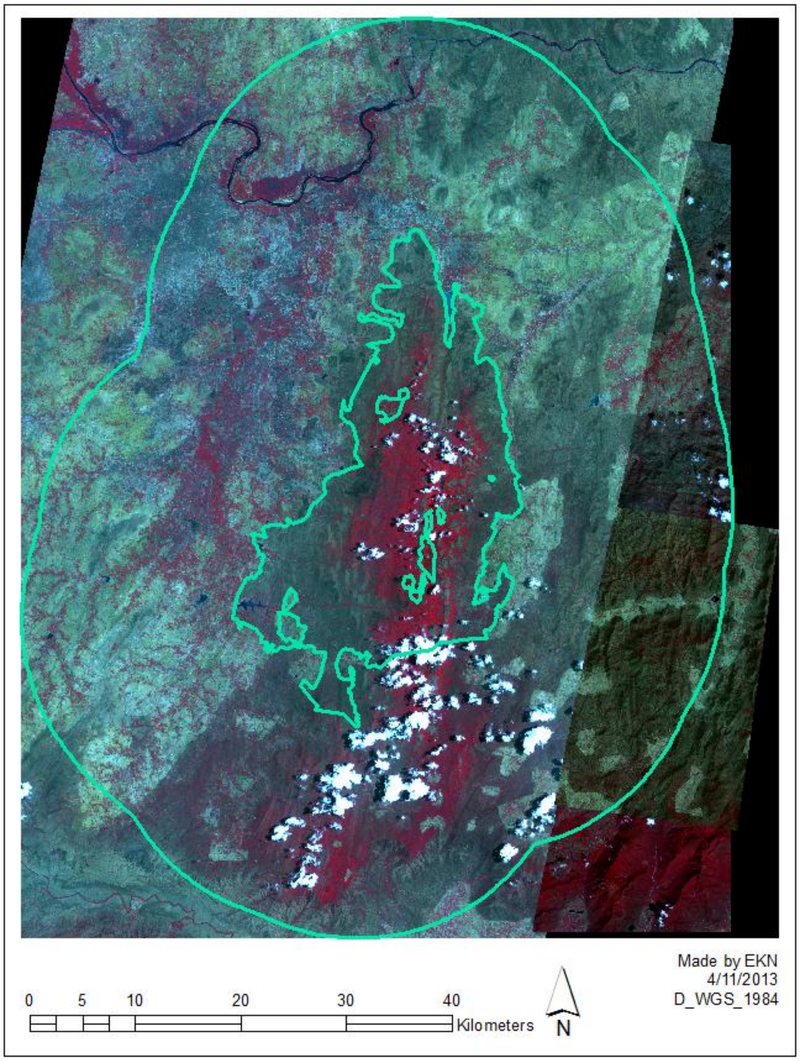

Fig. 2.4 Images used in Biligiri Rangaswamy Temple (BRT) Classification

ASTER Color infrared (3,2,1)

Table 2.1 All images obtained from NASA Reverb

Park	Date	Percent Cloud Cover
Anshi-Dandeli	11/20/2004	0%
Anshi-Dandeli	2/17/2008	0%
Anshi-Dandeli	2/17/2008	1%
Anshi-Dandeli	2/17/2008	1%
Anshi-Dandeli	2/12/2012	0%
Anshi-Dandeli	2/12/2012	1%
Anshi-Dandeli	2/12/2012	5%
Anshi-Dandeli	2/28/2012	0%
Anshi-Dandeli	2/28/2012	0%
Anshi-Dandeli	2/28/2012	1%
Anshi-Dandeli	5/25/2012	23%
Anshi-Dandeli	5/25/2012	52%
Anshi-Dandeli	5/25/2012	74%
BRT	2/24/2004	0%
BRT	1/31/2007	1%
BRT	1/21/2010	0%
BRT	1/21/2010	0%
BRT	1/21/2010	1%
Kudremukh and Bhadra	3/8/2012	6%
Kudremukh and Bhadra	3/8/2012	19%
Kudremukh and Bhadra	3/24/2012	0%
Kudremukh and Bhadra	3/24/2012	0%
Kudremukh and Bhadra	3/24/2012	1%
Kudremukh and Bhadra	4/9/2012	11%
Kudremukh and Bhadra	4/9/2012	17%
Kudremukh and Bhadra	4/9/2012	30%
Kudremukh and Bhadra	11/26/2012	1%
Kudremukh and Bhadra	11/26/2012	2%
Nagarahole and Bandipur	1/16/2010	1%
Nagarahole and Bandipur	1/16/2010	1%
Nagarahole and Bandipur	2/5/2012	1%
Nagarahole and Bandipur	2/5/2012	1%
Nagarahole and Bandipur	2/14/2012	1%
Nagarahole and Bandipur	2/14/2012	1%
Nagarahole and Bandipur	2/14/2012	3%
Nagarahole, Bandipur, and BRT	4/18/2012	7%
Nagarahole, Bandipur, and BRT	4/18/2012	37%
Nagarahole, Bandipur, and BRT	4/18/2012	64%

Pre-classification processing

HDF data downloaded from Reverb were converted into ENVI image format in ENVI 5.0. Images collected on the same day were mosaicked together under the assumption that atmospheric conditions and plant phenology would be consistent between images collected at approximately the same time.

Spectral Enhancements

We conducted principal component analysis and calculated Normalized Difference Vegetation Index (NDVI) on all images.

Vegetation reflects a high proportion of radiation in the near infrared band, and absorbs a high proportion of radiation in the red band (Sellers, 1985), so the difference of the reflectance in one band from the reflectance in the other presents a useful proxy for the amount of green vegetation in an area. NDVI ranges from -1 to 1, with high values suggesting dense vegetation, and values near or slightly less than 0 suggesting highly reflective surfaces such as cloud and free standing water.

Principal components analysis (PCA) transforms a dataset to new axes that best represent the variability within the dataset. Significant amounts of variation tend to be repeated across the bands of an image, and PCA reduces the amount of duplicate information contained in image bands by redefining the axes to minimize redundant information (Byrne, Crapper, and Mayo, 1980). Each set of axes is known as a principal component. The first component represents most of the variance within the dataset. Successive components each represent less variance than the previous components. In most software, including ENVI, the number of components is equal the number of input bands.

This processing left us with 7 layers for each mosaic: two visual, near infrared (NIR), NDVI, and three principal components. Layers for the same area were combined into one multi-band file in ENVI 5.0.

About classification methods

By trial and error, we found that using NDVI and the three PCA bands worked best in both classification methods. Additionally, because of the coarser spatial resolution of the thermal bands, using them would have reduced the overall resolution of our analysis in an area with significant spatial variation. Thermal data has also been shown to have limited correlation with land cover. Therefore, we used only the visible and NIR bands in our analysis.

Unsupervised Classification

ISODATA (Iterative Self Organizing Data Analysis Technique) is a clustering algorithm that sorts an image's pixels into a user-specified number of clusters based on spectral values. Though unsupervised classification negates the need for preprocessing class definitions, the user must define classes post-classification, which requires some knowledge of ground conditions. Unsupervised classification can serve as a prelude to supervised classification; it can give the user some information on where the spectral differences are in the image, and can help the user decide where training samples belong.

ISODATA classifications were conducted in ENVI 4.8 Classic. Separate ISODATA classifications were run for each mosaic of images. Classifications were run for 10 iterations to create 30 - 40 classes per mosaic, with a minimum of 300 pixels per class. Post-classification, cover was assessed in Google Earth, and cover types were assigned each to class created by the ISODATA algorithm. Classes with the same cover type were combined. Classes were combined into forest/plantation, agriculture, cloud, shadow, water, and scrub/sparse trees. When classifications had been run and classes combined, classification mosaics in each study area were mosaicked together in ArcGIS 10.1.

Supervised Classification

In a supervised classification, the user defines polygon training samples representing the variability in the image. These regions are input into the classification algorithm and serve to determine which class each pixel belongs to. In a maximum likelihood classification, the supervised classification algorithm we applied to our imagery, the likelihood of a pixel belonging to each class in the ROIs is calculated, and the pixel is assigned to the class to which it is most likely to belong.

We selected maximum likelihood classification because it has been demonstrated to perform well, has a long history of use, and takes into account the variability within a class as well as the variation between classes (ERDAS, 1999).

Supervised classification was conducted in ENVI 4.8 Classic. Google Earth imagery of the study areas had high enough resolution to serve as ancillary data and aid in the selection of clusters for the classification. Clusters were defined for the following classes: scrub and sparse trees, agriculture, forest, water, cloud, and shadow.

Once ROIs were defined, separability between classes was calculated. For separability values below 1.8, we edited the training samples to attempt to increase separability. For separability values below 1, we either combined the training samples into one class or deleted one of the classes.

When classification had been completed, classes were visually assessed for accuracy. If accuracy appeared inadequate, training samples were examined and edited, and the classification was rerun. This process was repeated until visual assessment of the classification suggested it was relatively accurate.

Final classifications of each mosaic were mosaicked together across each study area in ArcGIS 10.1.

Ground Data Collection

Ground data were collected over a period of five weeks during July and August 2012. Data were collected around Anshi-Dandeli National Park, Bandipur National Park, Bhadra Wildlife Sanctuary, Biligiri Rangaswamy Temple Wildlife Sanctuary, and Nagarahole National Park. We drove on paved and unpaved roads outside of each park and within a 20 km buffer, stopping every 3 km to gather data. At each stop, a team of 3-5 individuals walked out to points 100 m from the road and 50 m from each other. Each person took a point with a Garmin GPS and recorded the land cover classification of the location. For each point, we filled out a field data sheet with observational data (fig. 2.5). In total, 993 ground points were collected (table 2.2) around all of the protected areas in this study except Kudremukh (fig. 2.6). Ground points were not collected around Kudremukh because social unrest made data collection unsafe.

Point ID: ________________ Date: ________________

Long:________________ Lat:________________

Elevation: ________________ Datum: WGS 1984

Photo ID: ________________

	Park
	Anshi-Dandeli
	Bhadra
	Kudremukh
	Nagarahole
	Bandipur
	BRT

Cover Extent: ________________ % Cover: __________

Disturbance: ____

____

Comments: ____

____

Classification					
	A1	Coffee		P1	Silver Oak
	A2	Banana		P2	Teak
	A3	Tobacco		P3	Rubber
	A4	Rice		P4	Areca
	A5	Ragi		P5	
	A6	Pepper		F1	Deciduous Forest
	A7	Cardamom		F2	Evergreen Forest
	A8	Ginger		F3	Shola Forest
	A9	Sweet Potato		F4	Bamboo
	A10	Cotton		F5	
	A11	Maize		G1	Shola Grassland
	A12	Tumeric		G2	Other Grassland
	A13	Ground Nut		S	Scrubland
	A14	Sugar Cane		W	Water
	A15			O	

Fig. 2.5 Field data sheet used for collection of ground data

Table 2.2 Total Collected Points Organized by Ground Cover

Cover Type	Point Count
Forest	216
Plantation	152
Scrub	44
Agriculture	368
Rice	70
Coffee	124
Barren	10
Water	9
Total	**993**

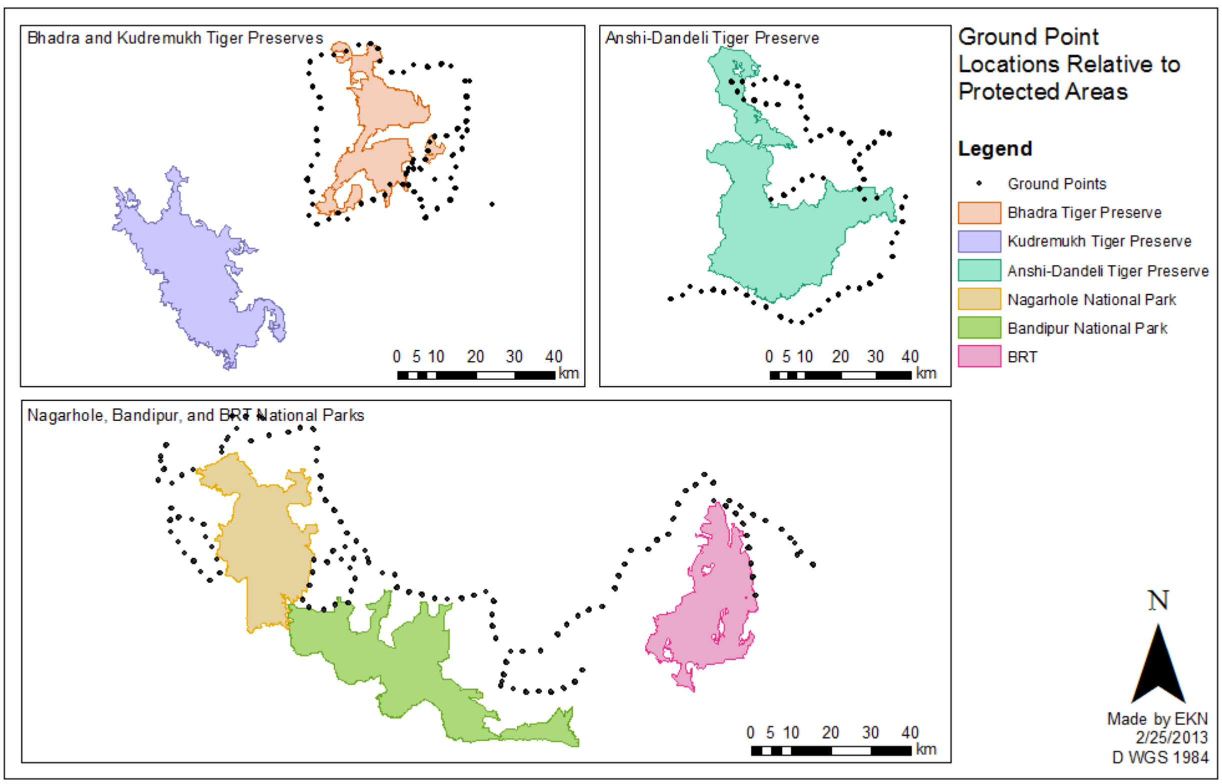

Fig. 2.6 Locations of all ground points collected

Accuracy Assessment

After classification, we conducted accuracy assessments on each classified raster using the ground points collected in the field in summer 2012 as well as points randomly generated in ArcGIS. Field-collected points were first sorted into the final classification map classes of water, cleared/agricultural land, forest, and scrub/sparse trees. We aimed to assess 50 points for each class in each classification, after Congalton (1991). If there were insufficient ground points in a class, the minimum of 50 points was reached by generating random points in ArcGIS 10.1 and assessing cover in Google Earth.

The classified category was then compared with the class identified in the field or Google Earth and input into an accuracy matrix. Errors of omission and commission, percent accuracy, and area-weighted accuracy were calculated for each supervised classification raster.

Pilot Landscape Analysis

Fragmentation

We conducted a pilot landscape fragmentation analysis in ArcMap 10.1. The Biligiri Rangaswamy Temple land use land cover map was reclassified into a forest raster with a NoData background, and was then divided into patches using the Spatial Analyst Region Group tool. Resultant raster patches were converted into polygons, and geometry was calculated using the zonal geometry as table tool. Patches of area less than 1 ha were excluded to avoid excessive noise in the calculation.

Connectivity

We also carried out a pilot connectivity analysis of the supervised land use land cover map of Nagarahole and Bandipur national parks. The goal of this analysis was to identify the least-cost corridor between two forest patches. The area classified as forest was first isolated from the rest of the map under the assumption that this would be the land cover type most suitable as habitat for large animals such as tigers. We picked two large forest patches on opposite ends of the mapped area. Cost values were assigned to each of the land cover types: low suitability classes such as cleared land were given high cost values, while highly suitable habitat like forest was given low cost values. Cost distance rasters were created for each forest patch and then combined using the Corridor tool in ArcMap 10.1, producing the least-cost corridor.

Human-affected areas

Using ArcMap 10.1 we assessed areas experiencing human influence. Human influence includes collection of firewood, grazing of cattle within the parks, clearing of land, and poaching. In our analysis, each pixel in our classified map of Anshi-Dandeli National Park was designated as being influenced by humans or not. All cleared land was considered to have been influenced by humans. Maps of roads within our study area were buffered to 1 km, which represents the distance humans commonly travel within a forest to use forest resources (K. K. Karanth *et al.*, 2006). The buffered roads were overlaid on our land use land cover map to determine which spaces are under human influence. This analysis was only conducted for the portion of the Anshi-Dandeli buffer located within the Indian state of Karnataka, since we only had road data for Karnataka.

Results

In total, 29,564 km^2 were classified, including 4,715 km^2 (16%) within the 6 protected areas and 24,849 km^2 (84%) outside of the parks (20 km buffer zone). We present supervised classification land use land cover data summaries for the entire area (table 3.1 and 3.2) and for each classification area (tables 3.3 and 3.4; figs. 3.1-3.4) along with maps (figs. 3.8-3.11), as well as summaries for forested areas only (fig. 3.5). We also present data from our less successful unsupervised ISODATA classifications (table 3.5; figs. 3.6-3.7) along with maps (figs. 3.12-3.13).

Table 3.1 Total Class area in km^2 for supervised maximum likelihood classifications

	Water	Forest	Scrub	Shadow	Cleared	Wetlands	Total
Park	67	3,770	477	30	370	1	4,715
Buffer	442	12,642	4,551	91	7,109	14	24,849
Total	509	16,413	5,028	121	7,479	15	29,564

Table 3.2 Overall class percentages for supervised maximum likelihood classifications

	Water	Forest	Scrub	Shadow	Cleared	Wetlands
Park	1%	80%	10%	1%	8%	0%
Buffer	2%	51%	18%	0%	29%	0%
Total	2%	56%	17%	0%	25%	0%

Table 3.3 Class area in km^2 for each supervised maximum likelihood classification

		Water	Forest	Scrub	Shadow	Cleared	Wetlands	Total
Anshi Dandeli								
	Park	14	1,205	21	0	129	1	1,370
	Buffer	199	3,657	442	0	1,571	13	5,882
	Total	213	4,861	463	0	1,701	14	7,252
BRT								
	Park	9	482	48	7	30	0	577
	Buffer	48	1,942	577	31	1,080	0	3,677
	Total	56	2,424	625	38	1,110	0	4,254
Bhadra and Kudremukh								
	Park	37	931	219	0	60	0	1,247
	Buffer	114	4,142	2,153	5	1,448	0	7,861
	Total	150	5,073	2,372	5	1,508	0	9,108
Nagarahole								
	Park	8	1,152	188	23	151	0	1,521
	Buffer	81	2,902	1,380	55	3,009	1	7,429
	Total	89	4,054	1,568	78	3,160	1	8,950

Table 3.4 Class percentages for each supervised maximum likelihood classification

		Water	Forest	Scrub	Shadow	Cleared	Wetlands
Anshi Dandeli							
	Park	1%	88%	2%	0%	9%	0%
	Buffer	3%	62%	8%	0%	27%	0%
	Total	3%	67%	6%	0%	23%	0%
BRT							
	Park	2%	84%	8%	1%	5%	0%
	Buffer	1%	53%	16%	1%	29%	0%
	Total	1%	57%	15%	1%	26%	0%
Bhadra and Kudremukh							
	Park	3%	75%	18%	0%	5%	0%
	Buffer	1%	53%	27%	0%	18%	0%
	Total	2%	56%	26%	0%	17%	0%
Nagarahole							
	Park	1%	76%	12%	1%	10%	0%
	Buffer	1%	39%	19%	1%	41%	0%
	Total	1%	45%	18%	1%	35%	0%

Table 3.5 Class area in km^2 for each unsupervised ISODATA classification

		Water	Forest	Scrub	Shadow	Cleared	Wetlands	Total
Anshi Dandeli								
	Park	131	10,846	2,219	28	473	0	13,696
	Buffer	1,861	30,945	16,019	487	9,557	0	58,868
	Total	1,992	41,791	18,238	514	10,030	0	72,564
Nagarahole and Bandipur								
	Park	66	5,538	7,019	309	1,966	0	14,898
	Buffer	948	25,550	16,571	1,113	29,227	0	73,408
	Total	1,015	31,087	23,590	1,422	31,192	0	88,306

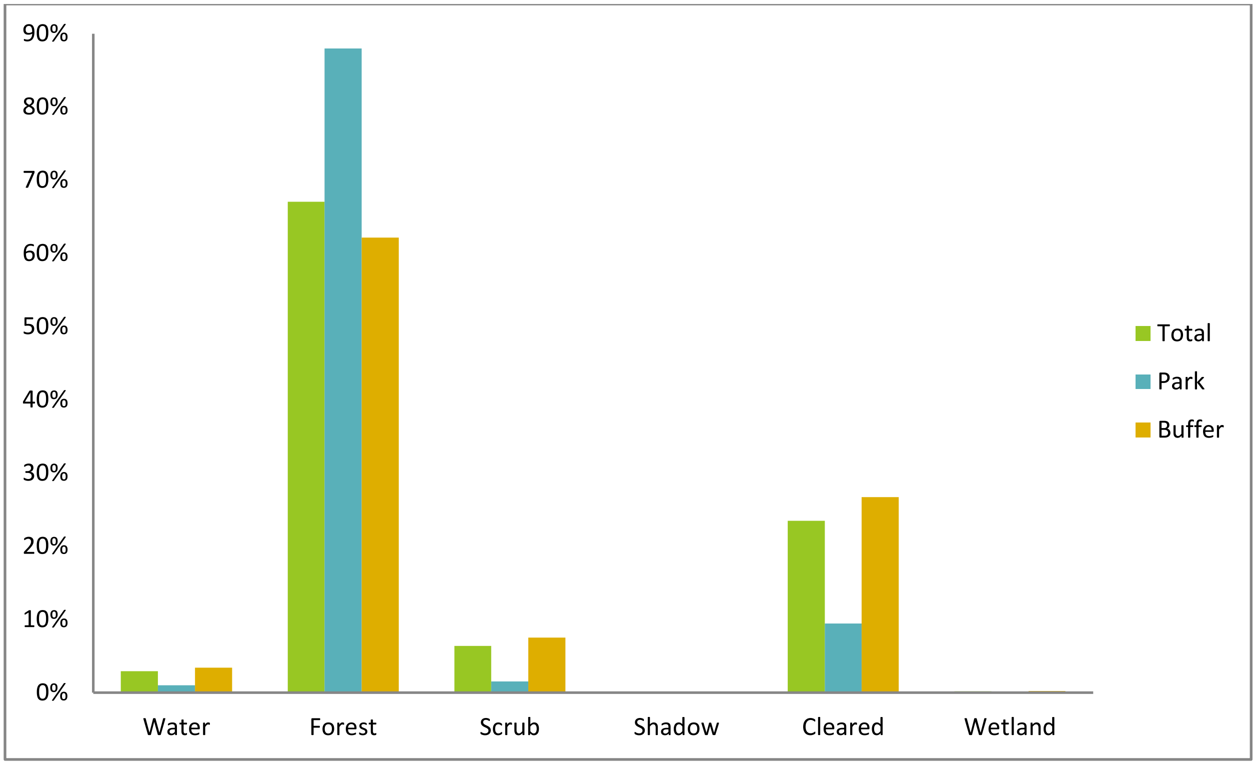

Fig. 3.1 Anshi-Dandeli supervised maximum likelihood class percentages

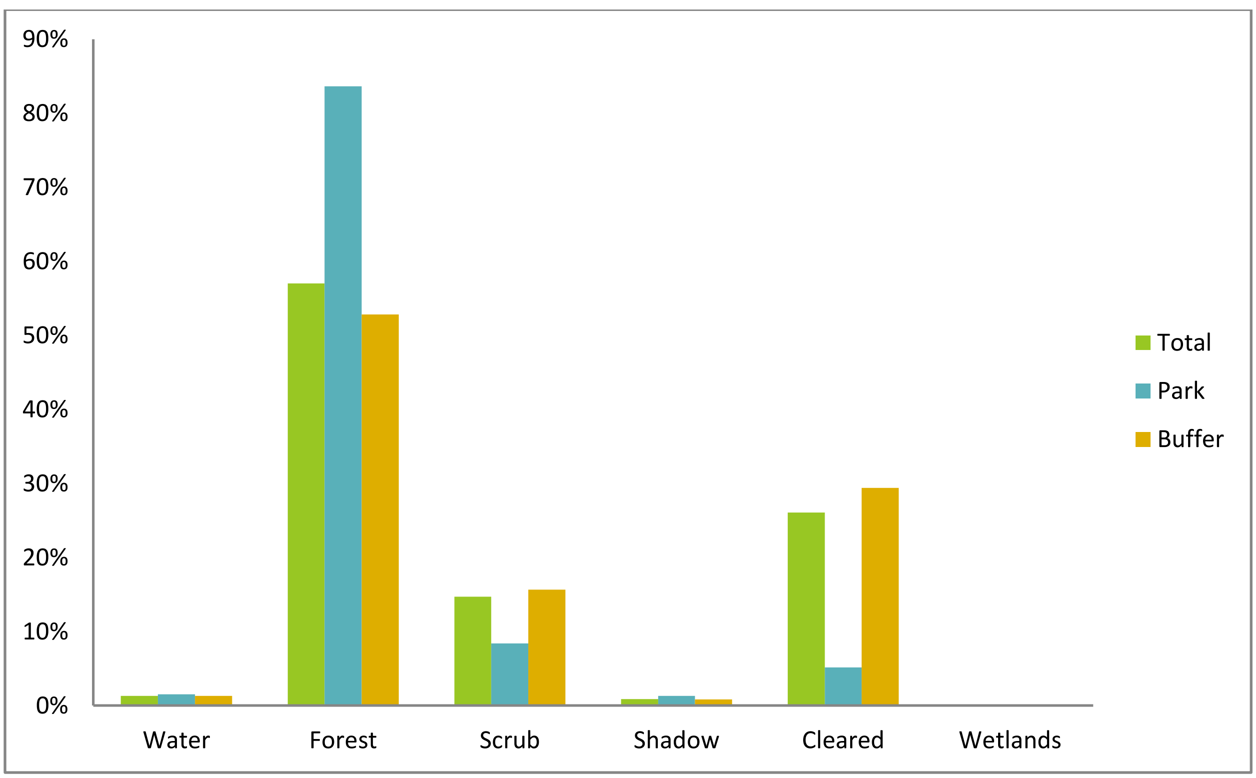

Fig. 3.2 BRT supervised maximum likelihood class percentages

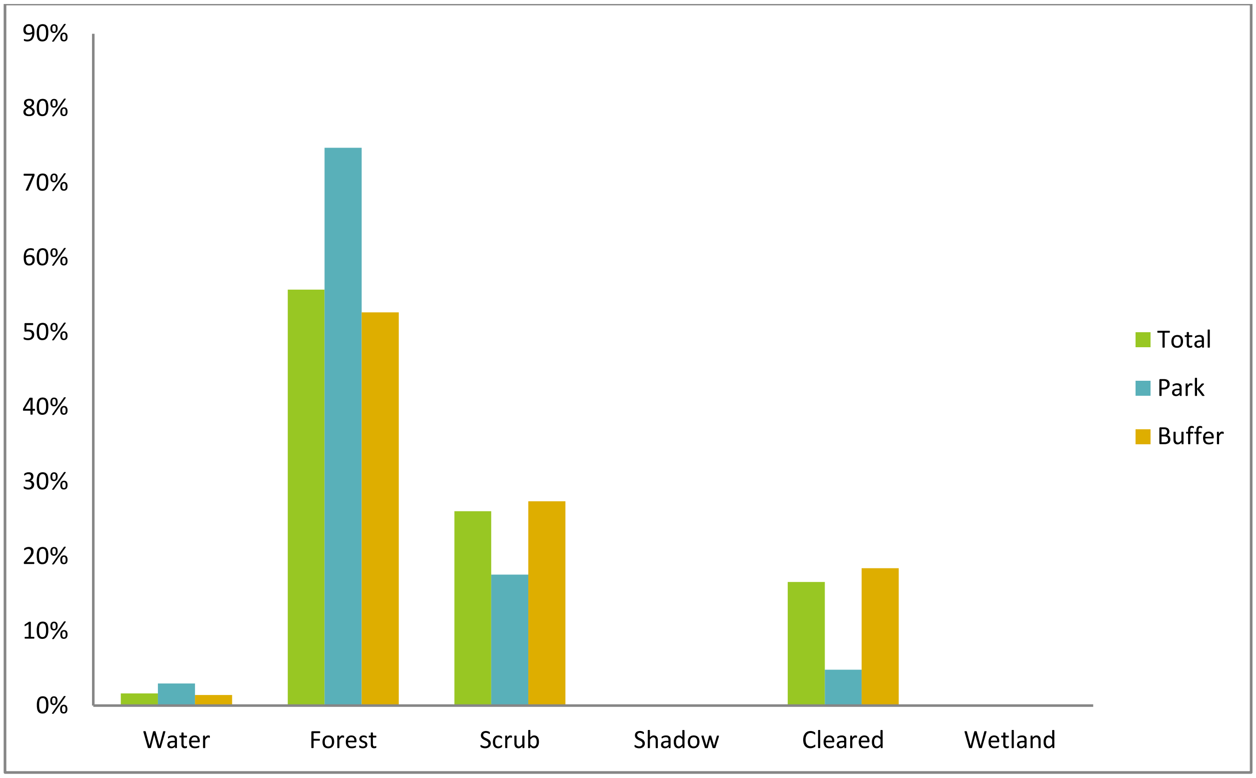

Fig. 3.3 Bhadra and Kudremukh supervised maximum likelihood class percentages

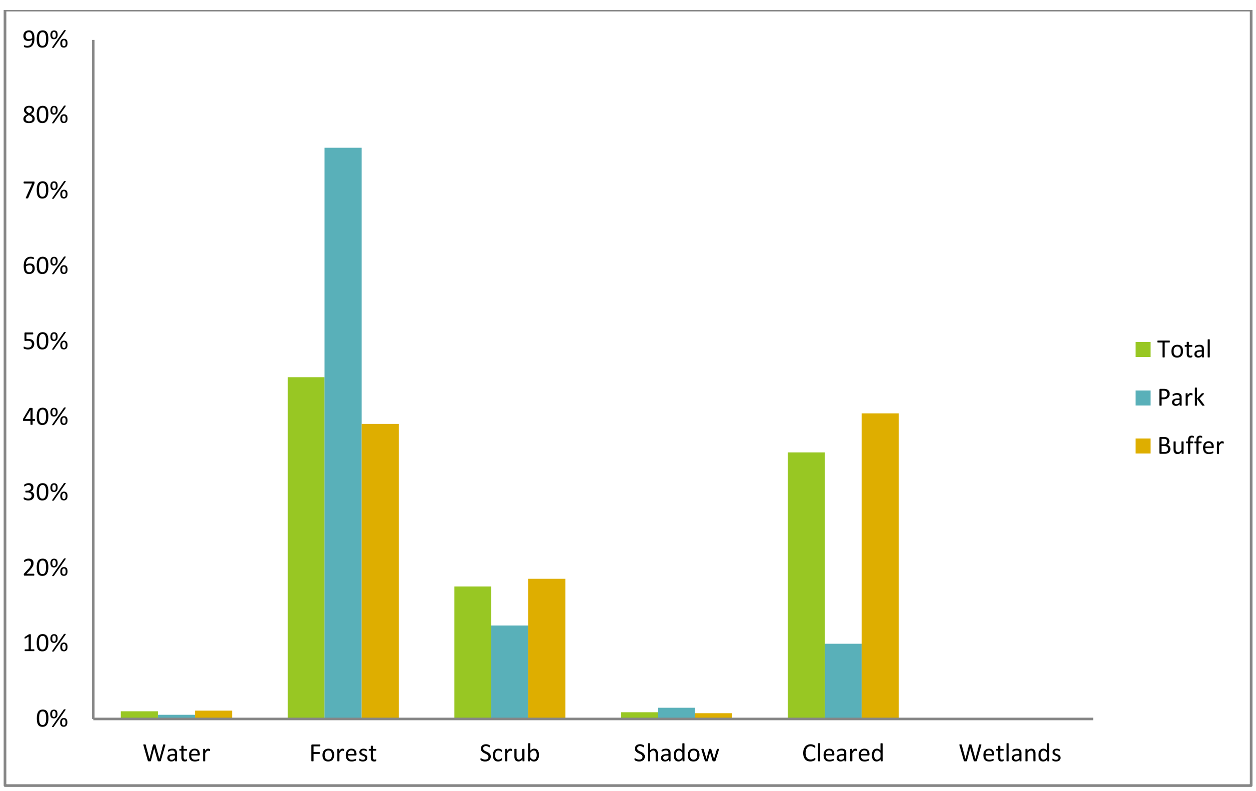

Fig. 3.4 Nagarahole and Bandipur supervised maximum likelihood class percentages

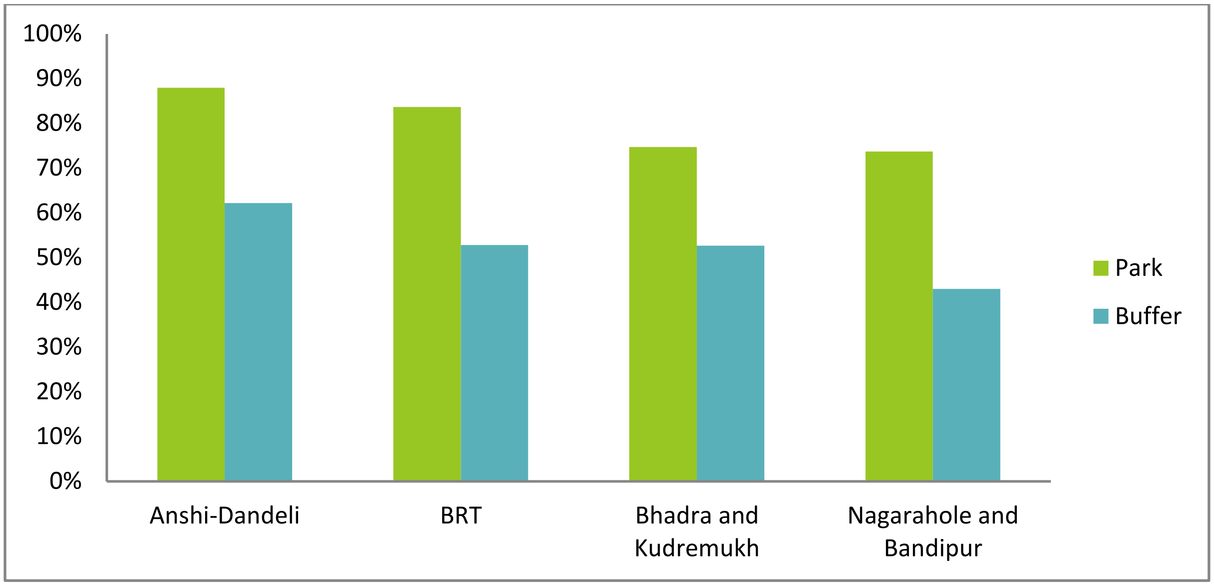

Fig. 3.5 Percent forested land in each supervised classification

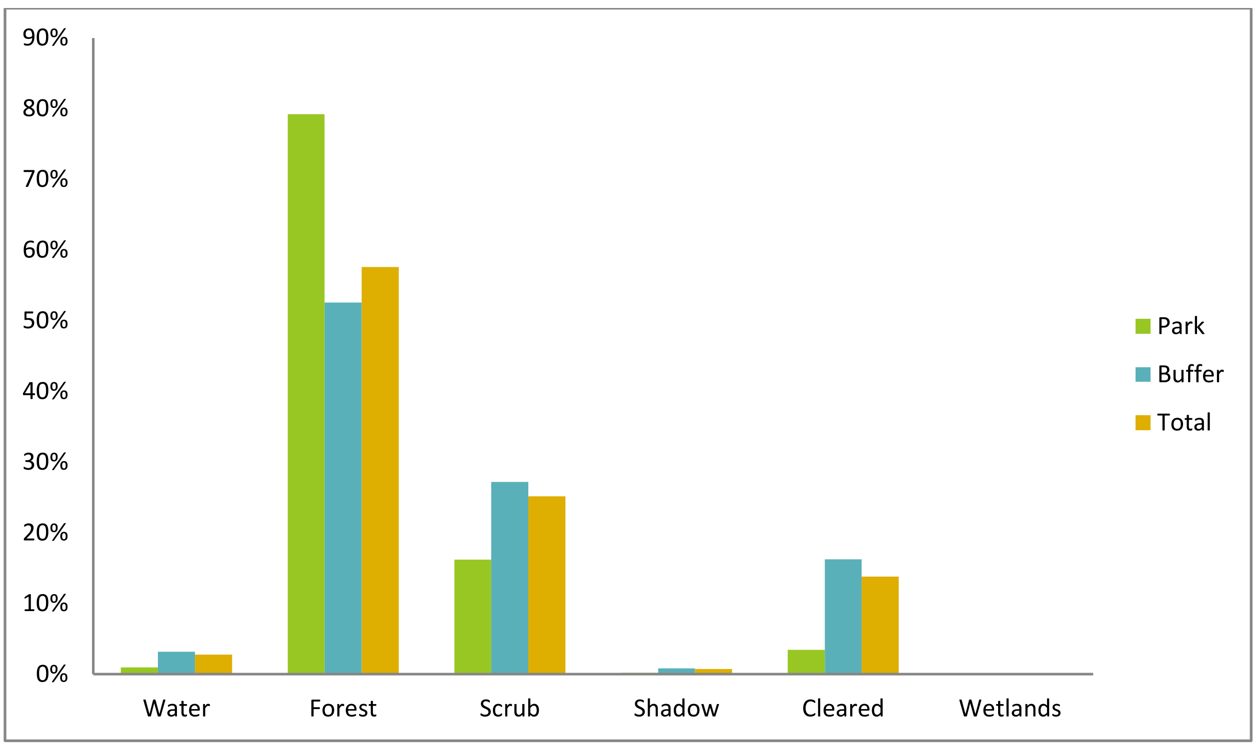

Fig. 3.6 Anshi-Dandeli ISODATA class percentages

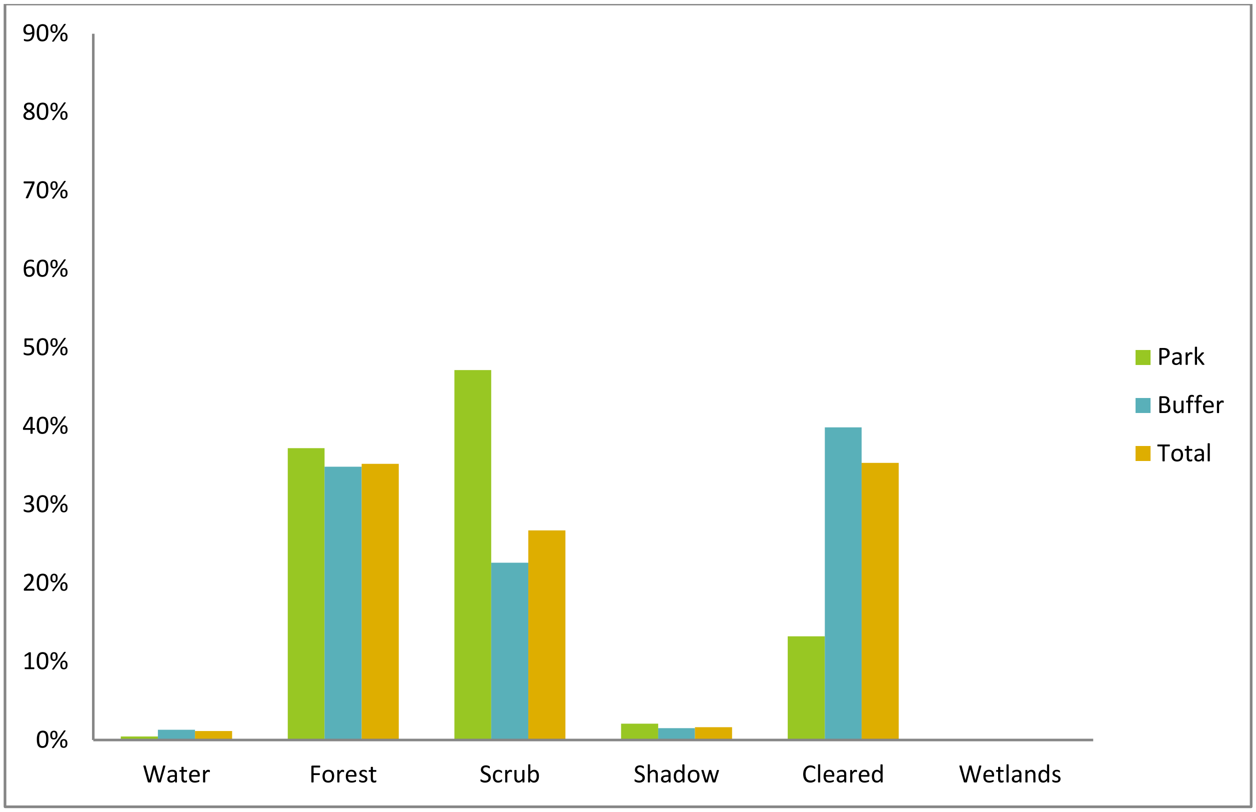

Fig. 3.7 Nagarahole and Bandipur ISODATA class percentages

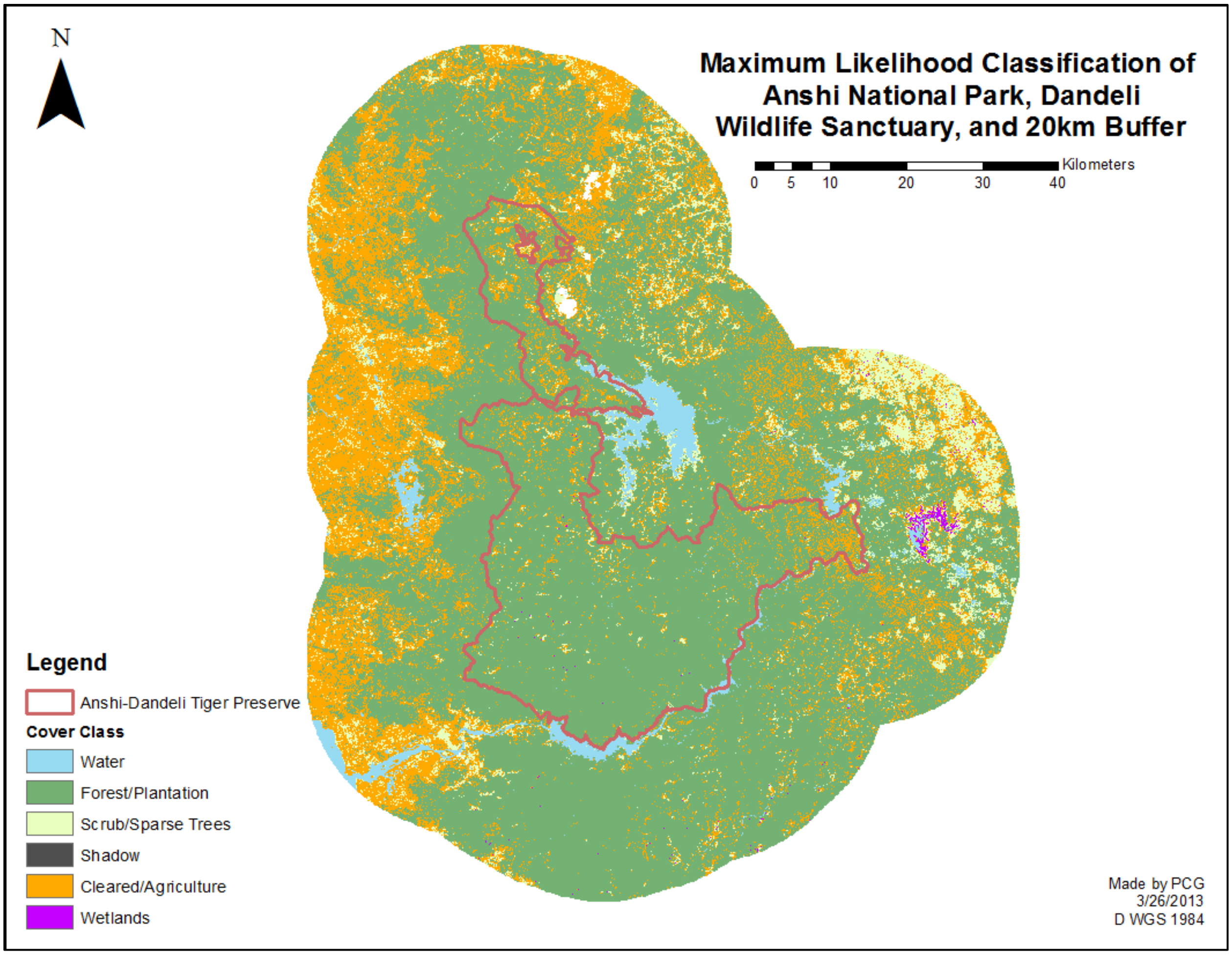

Fig. 3.8 Supervised maximum likelihood classification of Anshi-Dandeli Tiger Preserve

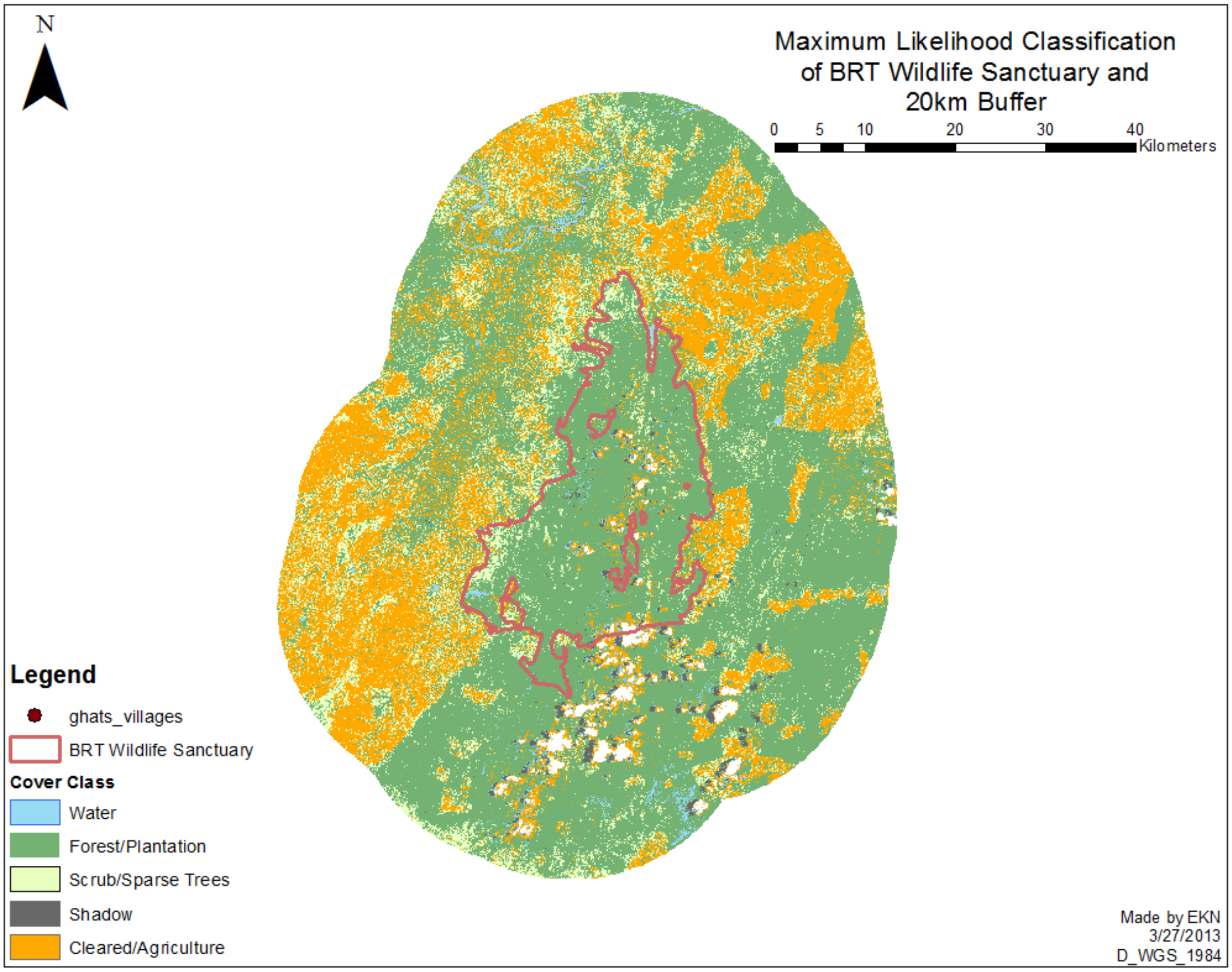

Fig. 3.9 Supervised maximum likelihood classification of BRT Wildlife Sanctuary

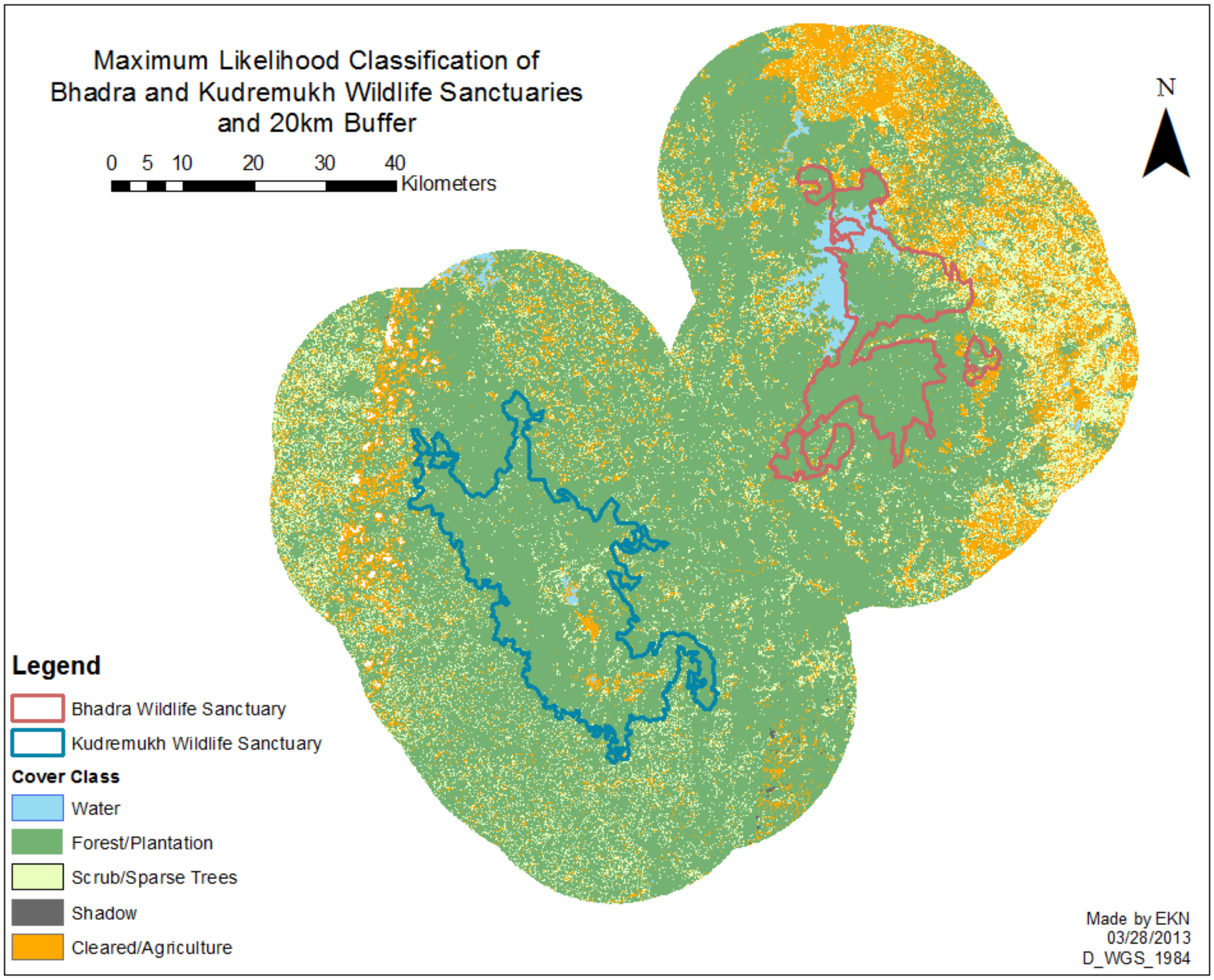

Fig. 3.10 Supervised maximum likelihood classification of Bhadra and Kudremukh Wildlife Sanctuaries

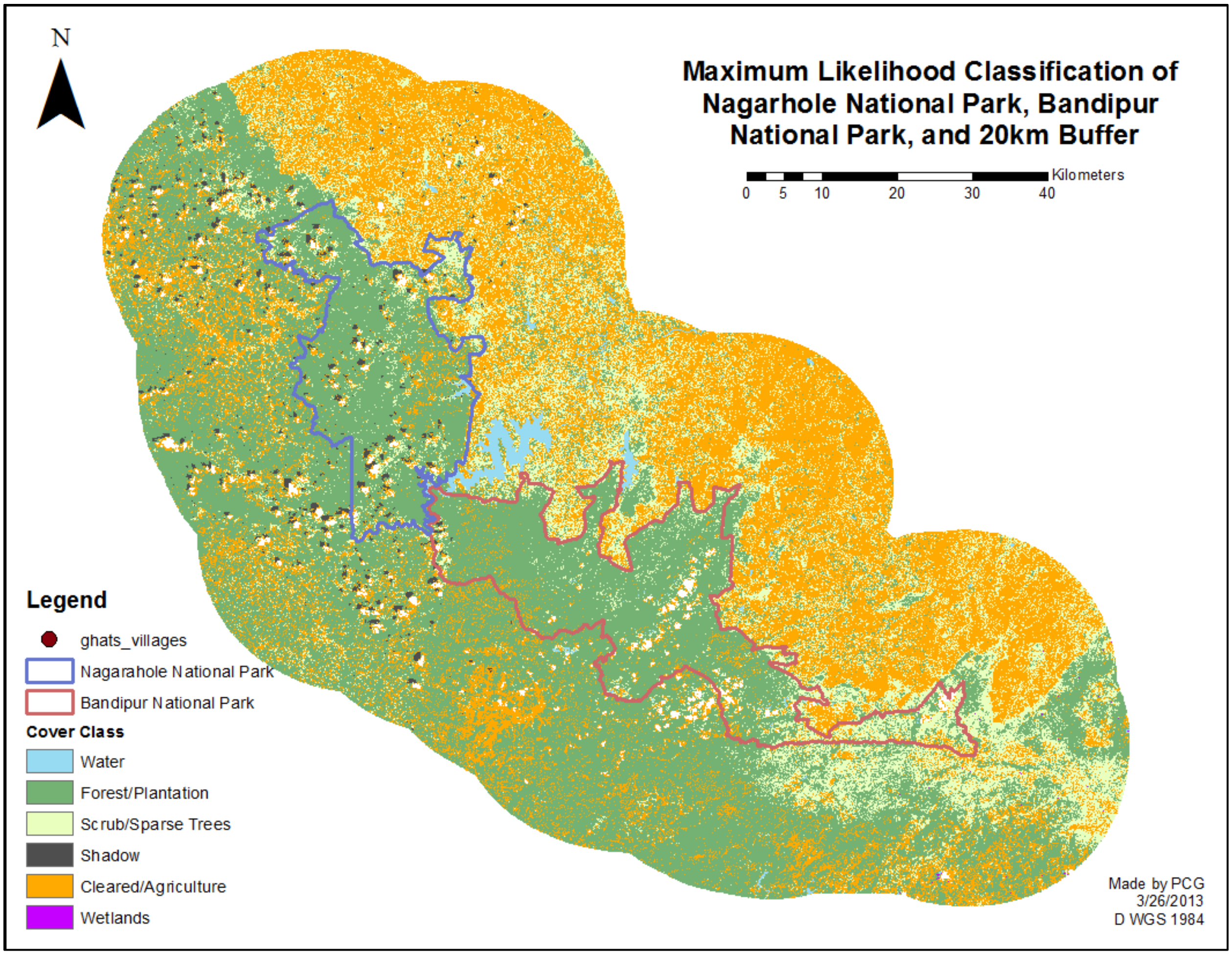

Fig. 3.11 Supervised maximum likelihood Classification of Nagarahole and Bandipur National Parks

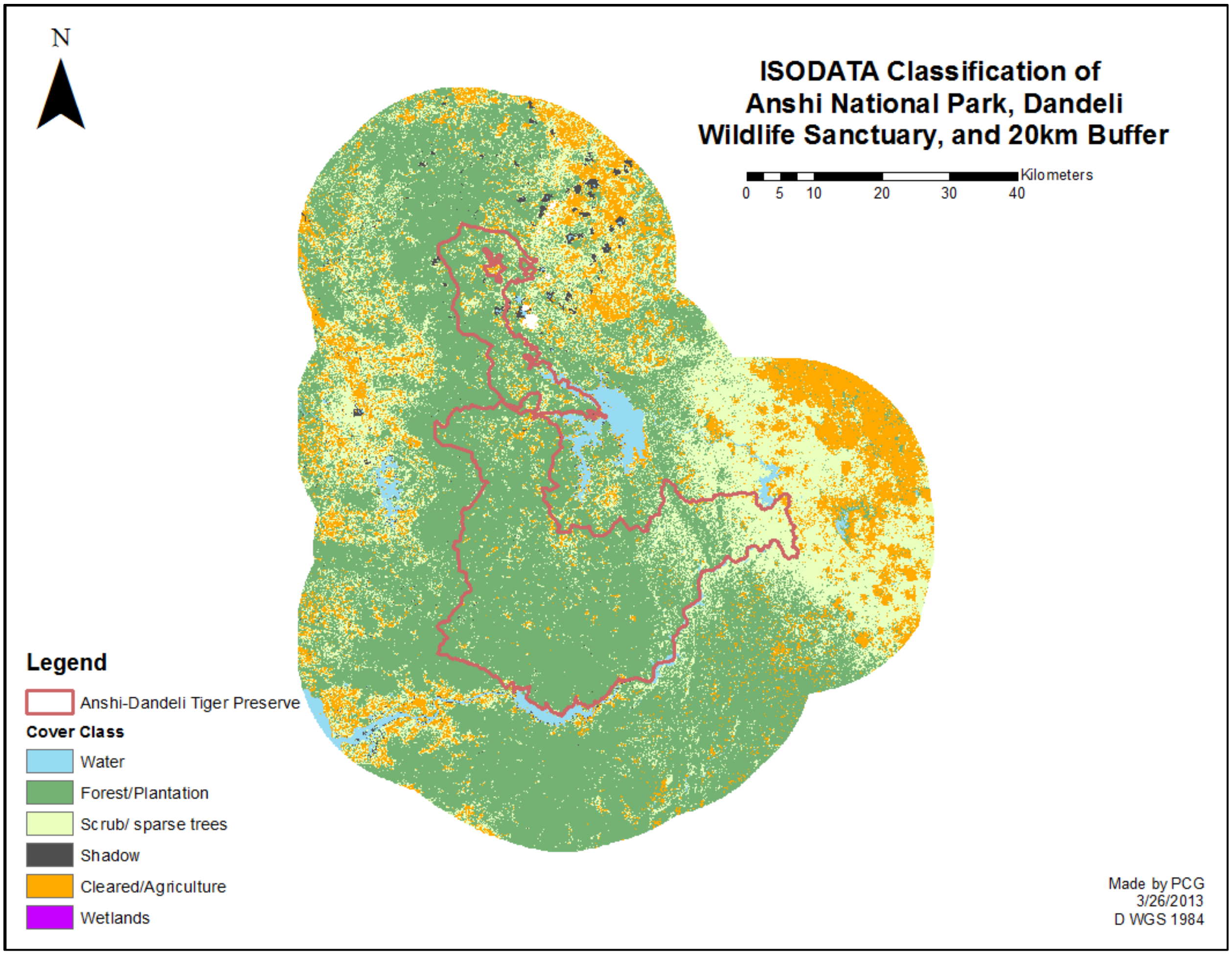

Fig. 3.12 Unsupervised ISODATA classification of Anshi-Dandeli Tiger Preserve

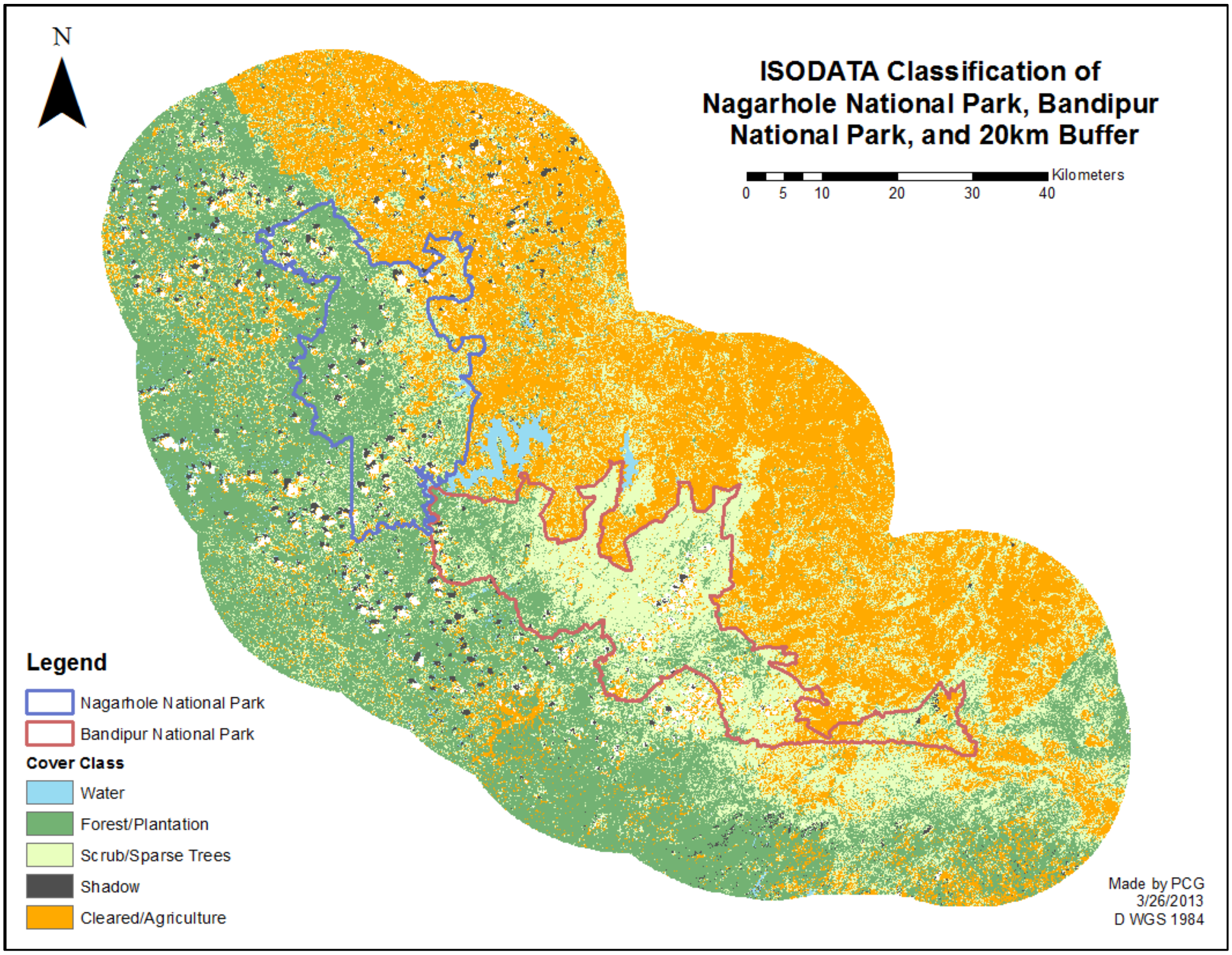

Fig. 3.13 Unsupervised ISODATA classification of Nagarahole and Bandipur National Parks

Accuracy Assessments

The accuracy assessments of our supervised classifications indicated overall accuracies of 79.2, 76.9, 84.4, and 75.6% for Anshi-Dandeli, Bhadra and Kudremukh, Nagarahole and Bandipur, and BRT respectively (fig. 3.14-3.17). The accuracies of our unsupervised classifications were 52.1% for Anshi-Dandeli and 63.7% for Nagarahole and Bandipur (fig. 3.18 and 3.19). Figure 3.20 shows the percent correctly classified (PCC) of the supervised classifications of all protected areas. Our assessments showed that our supervised classifications were more accurate than our unsupervised classifications (fig. 3.21 and 3.22).

The accuracy of the forest class was generally very good, with user accuracy values of the forest class in the supervised classifications of 90.96%, 89.99%, 81.67%, and 74.53% for Anshi-Dandeli, Bhadra and Kudremukh, Nagarahole and Bandipur, and BRT respectively (fig. 3.14-3.17). In the unsupervised classifications, forest accuracy was 90.43% for Anshi-Dandeli and 85.56% for Nagarahole and Bandipur (fig. 3.18 and 3.19).

Area-weighted overall accuracy of the supervised classifications was lower than PCC, with values of 70.86%, 59.08%, 63.72%, and 70.16% for Anshi-Dandeli, Bhadra and Kudremukh, Nagarahole and Bandipur, and BRT respectively.

Supervised Classification of Anshi-Dandeli		LULC: Water	Forest	Scrub/ Sparse Trees	Cleared/ Agricultural	Wetland	Row Total	Producer Accuracy (%)	Error of Omission
Google Earth	Water	56	0	0	1	0	57	98.25	1.75
	Forest	0	151	1	16	0	168	89.88	10.12
	Scrub/Sparse Trees	0	8	37	25	0	70	52.86	47.14
	Cleared/Agricultural	1	7	19	53	0	80	66.25	33.75
	Wetland	0	0	0	0	0	0	0.00	100.00
	Column Total	57	166	57	95	0	375		
	User Accuracy (%)	98.25	90.96	64.91	55.79	0.00			
	Error of Commission	1.75	9.04	35.09	44.21	100.00			
		PCC = 79.2%	0.792						

Fig. 3.14 Error matrix of the supervised classification of Anshi-Dandeli National Park

Supervised Classification of Bhadra and Kudremukh		Water	Forest	Scrub/ Sparse Trees	Cleared/ Agricultural Land	Wetland	Row Total	Producer Accuracy (%)	Error of Omission
		LULC							
Google Earth	Water	52	0	0	0	0	52	100.00	0.00
	Forest	2	125	23	10	0	160	78.13	21.88
	Scrub/Sparse Trees	0	6	59	12	0	77	76.62	23.38
	Cleared/Agricultural	0	8	24	47	0	79	59.49	40.51
	Wetland	0	0	0	0	0	0	0.00	100.00
	Column Total	54	139	106	69	0	368		
	User Accuracy (%)	96.30	89.93	55.66	68.12	0.00			
	Error of Commission	3.70	10.07	44.34	31.88	100.00			
		PCC = 76.9%	0.76902						

Fig. 3.15 Error matrix of the supervised classification of Bhadra Wildlife Sanctuary and Kudremukh Wildlife Sanctuary

Supervised Classification of Nagarrahole and Bandipur		Water	Forest	Scrub/ Sparse Trees	Cleared/ Agricultural Land	Wetland	Row Total	Producer Accuracy (%)	Error of Omission
		LULC							
Google Earth	Water	51	0	0	0	0	51	100.00	0.00
	Forest	0	98	11	2	0	111	88.29	11.71
	Scrub/Sparse Trees	0	4	57	4	0	65	87.69	12.31
	Cleared/Agricultural	0	18	17	102	0	137	74.45	25.55
	Wetland	0	0	0	0	1	1	100.00	0.00
	Column Total	51	120	85	108	1	365		
	User Accuracy (%)	100.00	81.67	67.06	94.44	100.00			
	Error of Commission	0.00	18.33	32.94	5.56	0.00			
		PCC = 84.4%	0.84384						

Fig. 3.16 Error matrix of the supervised classification of Nagarahole National Park and Bandipur National Park

Supervised Classification of Biligiri Rangaswamy Temple		Water	Forest	Scrub/ Sparse Trees	Cleared/ Agricultural Land	Wetland	Row Total	Producer Accuracy (%)	Error of Omission
		LULC							
Google Earth	Water	54	1	0	0	0	55	98.18	1.82
	Forest	11	79	12	8	0	110	71.82	28.18
	Scrub/Sparse Trees	0	6	47	12	0	65	72.31	27.69
	Cleared/Agricultural	0	20	15	83	0	118	70.34	29.66
	Wetland	0	0	0	0	0	0	0.00	100.00
	Column Total	65	106	74	103	0	348		
	User Accuracy (%)	83.08	74.53	63.51	80.58	0.00			
	Error of Commission	16.92	25.47	36.49	19.42	100.00			
		PCC = 75.6%	0.75575						

Fig. 3.17 Error matrix of the supervised classification of Biligiri Rangaswamy Temple Wildlife Sanctuary

Unsupervized Classification of Anshi-Dandeli		Water	Forest	Scrub/ Sparse Trees	Cleared/ Agricultural	Wetland	Row Total	Producer Accuracy (%)	Error of Omission
		LULC							
Google Earth	Water	56	0	1	0	0	57	98.25	1.75
	Forest	0	85	80	3	0	168	50.60	49.40
	Scrub/Sparse Trees	0	6	34	30	0	70	48.57	51.43
	Cleared/Agricultural	1	3	12	64	0	80	80.00	20.00
	Wetland	0	0	0	0	0	0	0.00	100.00
	Column Total	57	94	127	97	0	375		
	User Accuracy (%)	98.25	90.43	26.77	65.98	0.00			
	Error of Commission	1.75	9.57	73.23	34.02	100.00			
		PCC = 63.7%	0.63733						

Fig. 3.18 Error matrix of the unsupervised classification of Anshi-Dandeli National Park

Unsupervised Classification of Nagarahole and Bandipur		LULC Water	Forest	Scrub/ Sparse Trees	Cleared/ Agricultural Land	Wetland	Row Total	Producer Accuracy (%)	Error of Omission
Google Earth	Water	51	0	0	0	0	51	100.00	0.00
	Forest	0	77	18	16	0	111	69.37	30.63
	Scrub/Sparse Trees	0	4	35	26	0	65	53.85	46.15
	Cleared/Agricultural	0	9	101	27	0	137	19.71	80.29
	Wetland	0	0	0	0	1	1	100.00	0.00
	Column Total	51	90	154	69	1	365		
	User Accuracy (%)	100.00	85.56	22.73	39.13	100.00			
	Error of Commission	0.00	14.44	77.27	60.87	0.00			
		PCC = 52.1%	0.52055						

Fig. 3.19 Error matrix of the unsupervised classification of Nagarahole National Park and Bandipur National Park

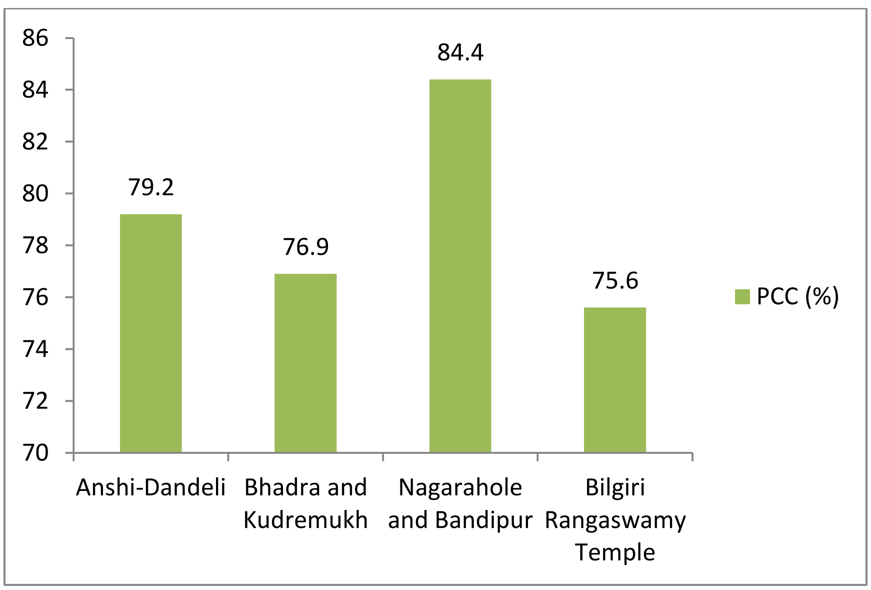

Fig. 3.20 Percent correctly classified of all maximum likelihood classifications

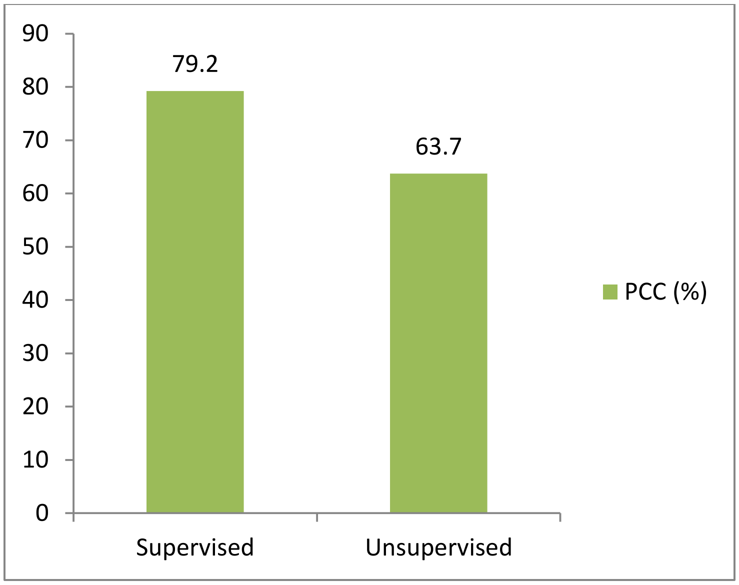

Fig. 3.21 Percent correctly classified of the supervised and unsupervised classifications of Anshi-Dandeli National Park

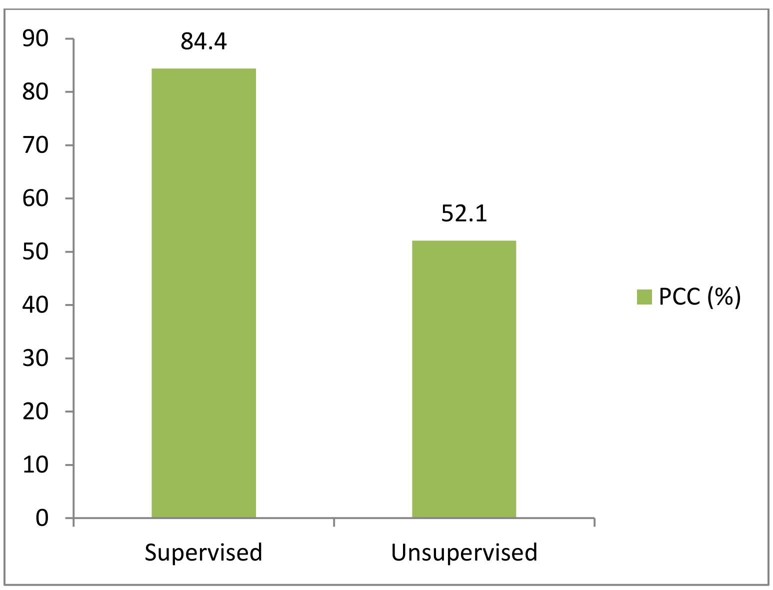

Fig. 3.22 Percent correctly classified of the supervised and unsupervised classifications of Nagarahole National Park and Bandipur National Park

Pilot analyses Results

Fragmentation

The results of the fragmentation analysis suggest that BRT Wildlife Sanctuary is dominated by one large patch of forest, which is centered on the park and extends beyond it, especially to the northwest of the park (fig. 3.23). Outside of this patch, the vast majority of forest patches are much smaller, with 3,268 of the more than 3,507 patches between 1 and 10 ha of area (fig. 3.24).

Connectivity

The least-cost corridor map produced in this analysis is shown in (fig. 3.25). The two forest patches that were used as the opposite ends of the least-cost corridor analysis are shown in blue. The least-cost corridor is the area shown in dark green. It can be seen that much of this corridor is composed of area within the park boundaries.

Human-affected Areas

Our pilot analysis shows that human influence is far more prevalent outside of the park than inside. Even with the preserve in place, a large portion of the area inside the park is also under the influence of humans (fig. 3.26). In total, 44.5% of the area within the park is potentially under the influence of humans, while 77.4% of the area outside of the park is potentially under the influence of humans.

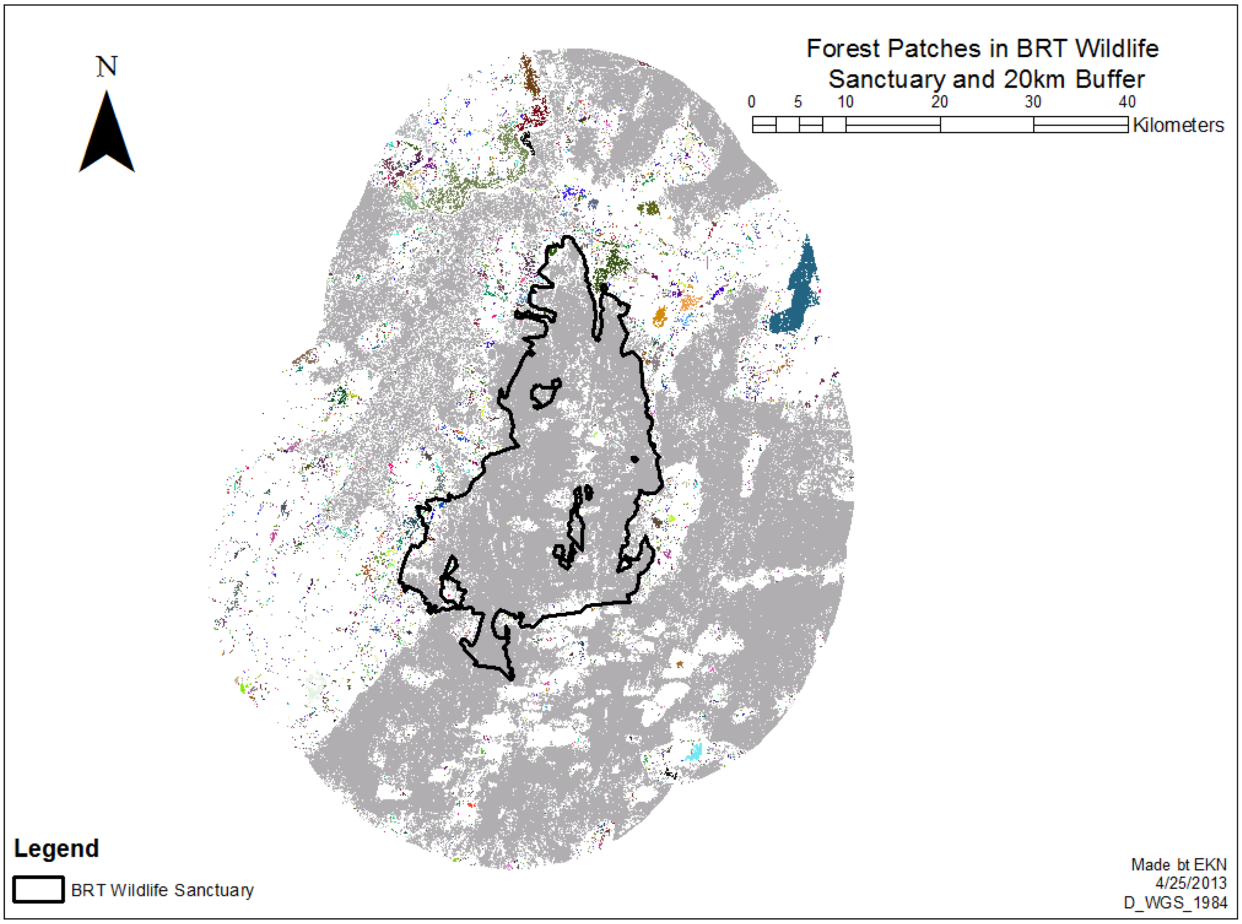

Fig. 3.23 Forest patches in BRT Wildlife Sanctuary and 20 km buffer

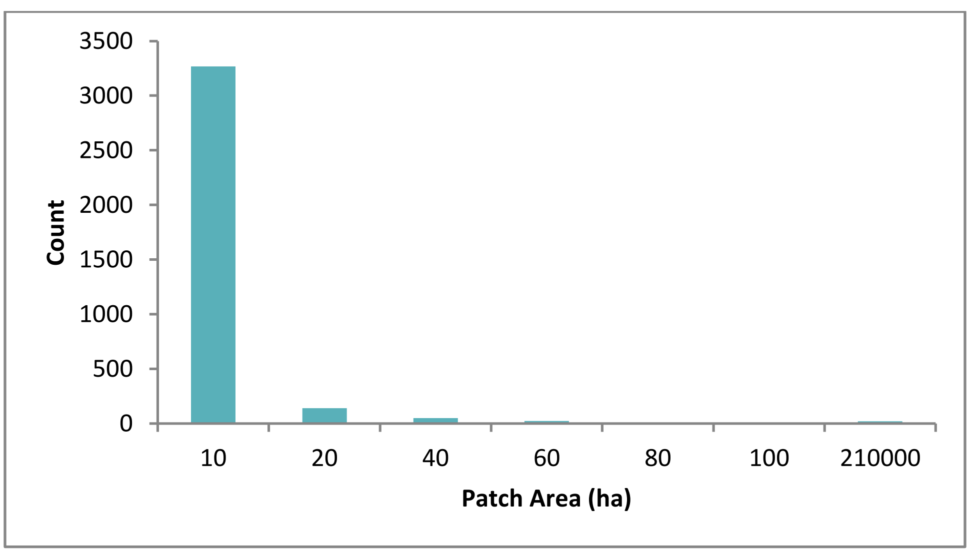

Fig. 3.24 Histogram of forest patch size in BRT Wildlife Sanctuary and 20 km Buffer

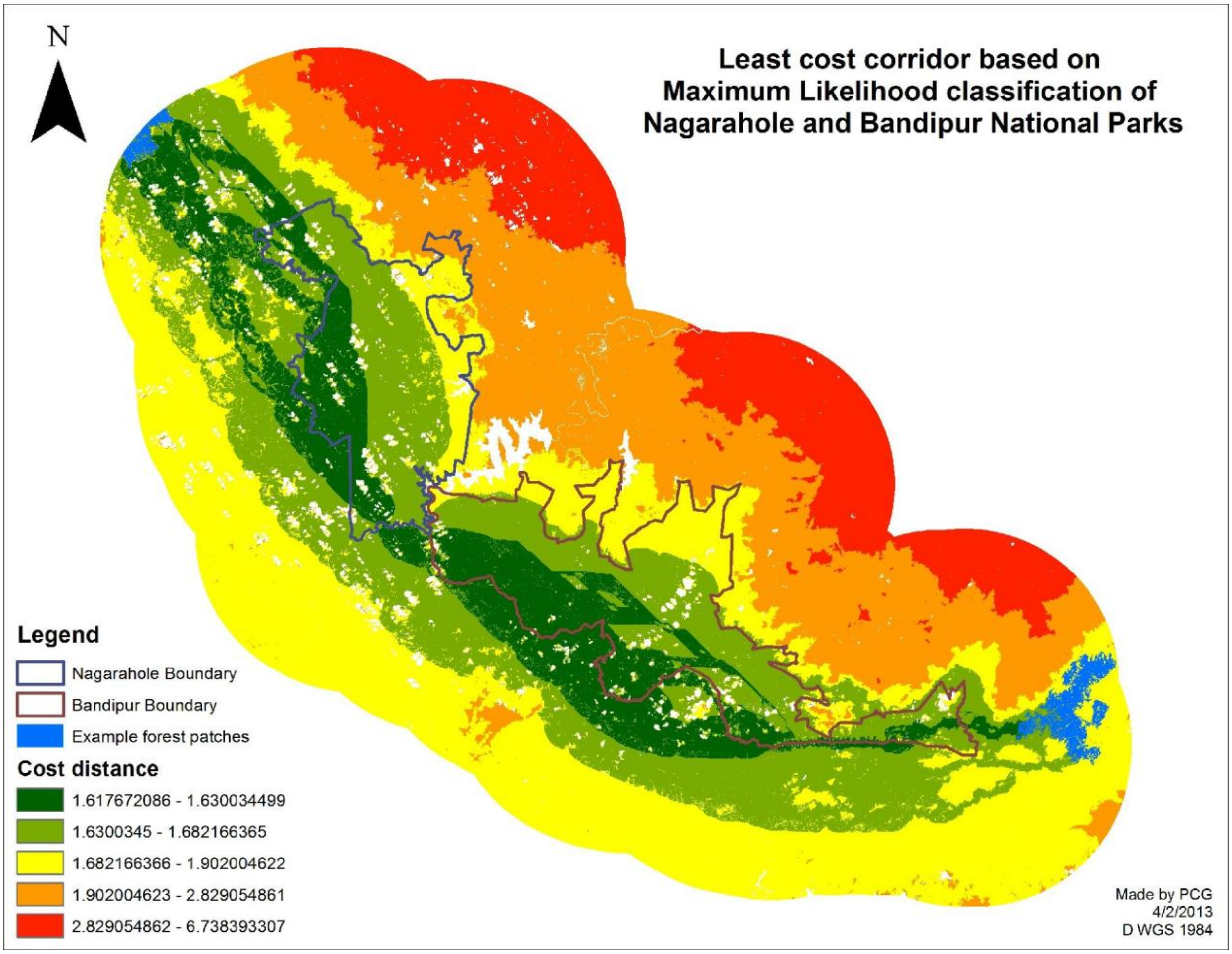

Fig. 3.25 Least Cost Corridor of Nagarahole and Bandipur National Parks

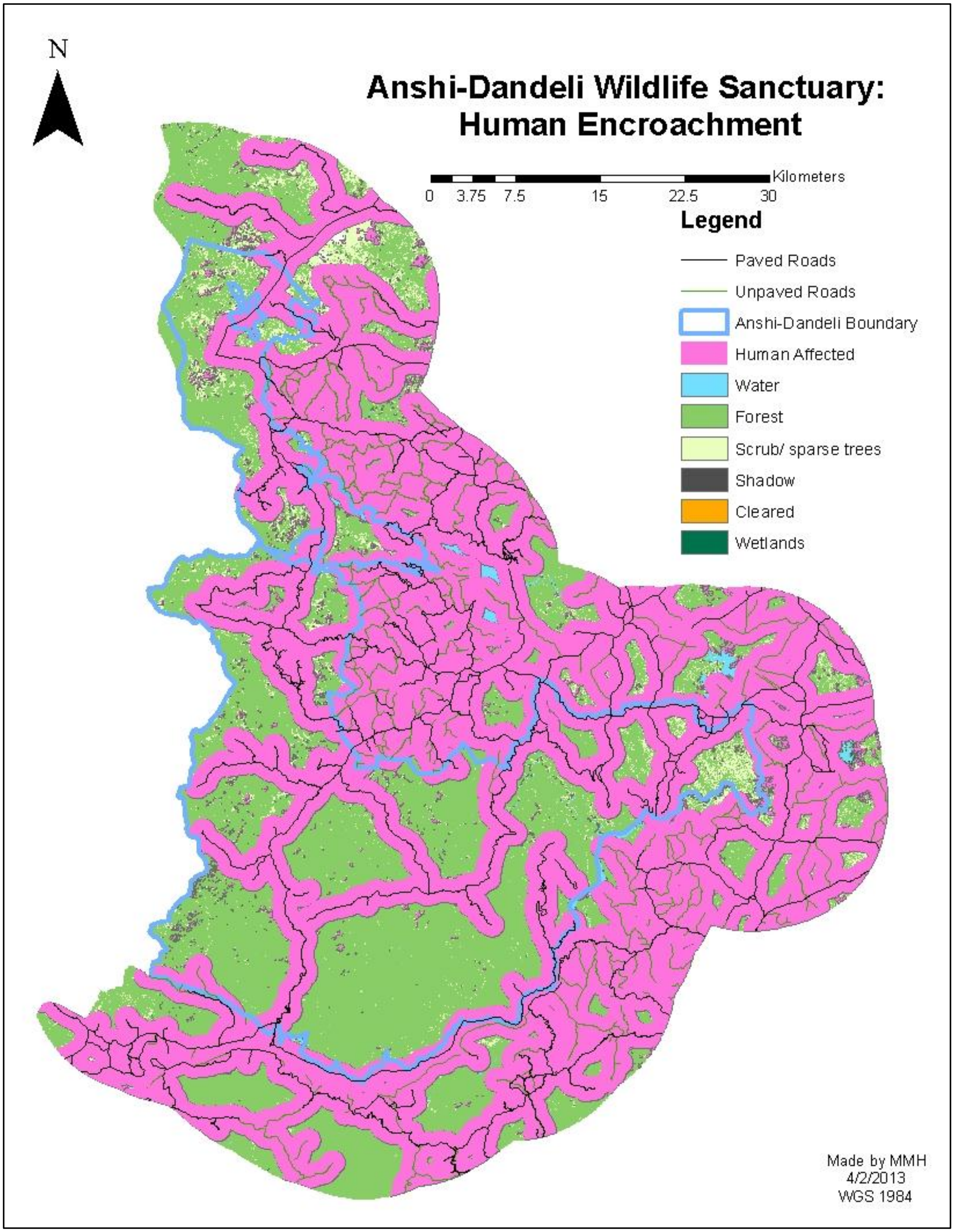

Fig. 3.26 Areas of Anshi-Dandeli Wildlife Sanctuary potentially under human influence

DISCUSSION

Mapping areas both inside and outside of the parks showed stark differences along some park borders. On the northern boundaries of the Nagarahole and Bandipur National Parks (fig. 3.11), for example, there is a very clear line between cleared area outside of the parks and forested area within the parks. The overall percentage of forested land is also greater within the parks than outside of the parks across all of the maximum likelihood classifications (fig. 3.5). Based on these factors, it seems like the protected areas are effectively limiting development activities within the park.

A number of difficulties arose in the creation of these land cover maps. At the outset, it proved challenging to find suitable imagery for the study area because of the very limited availability of Landsat imagery. Therefore we decided that the ASTER sensor on board the Terra satellite would be a viable alternative to the Landsat system. We had relatively recent Aster images that covered our study areas, but they were not 100% cloud-free. This part of the world experiences heavy rainfall during certain times of the year, and clouds are invariably present in images collected during these times. This presents a major problem in any land cover classification based on optical imagery, since clouds do not allow visible light to pass through. For this reason, areas of a landscape in an image that are occluded by clouds are impossible to classify.

Even when the imagery was high-quality and cloud free, there were still difficulties in the classification process. Some of these difficulties arose from the fact that the classification was being run over a large geographical extent. Rainfall is highly variable in the Ghats, with rainfall amounts generally decreasing from west to east. Furthermore, rainfall is highly variable throughout the year. The Ghats generally experience one prominent wet season from June to September and a second smaller one from December to March (Tewari 1995). For this reason, images collected at different times of the year could show vegetation in drastically different states of phenology. This poses a challenge in a land cover classification, since a forest in the dry season, when many trees have dropped their leaves, will have a very different spectral signature from a forest in the wet season in full leaf. This problem is reduced somewhat by running each classification only on images from the same date, as was the case for the classifications in this study.

Additional problems arose in differentiating between forest cover and agricultural areas like coffee and teak plantations (fig. 4.1). Spectrally, these areas are very similar and were difficult to separate with confidence, given the spectral and spatial characteristics of our imagery. In Google Earth imagery (0.5 – 1 m resolution), it is possible to distinguish natural forest (fig. 4.1a) from plantations (fig. 4.1c) by spatial patterns. However, the 15 m ASTER imagery lacked the spatial detail for this separation (fig. 4.1b vs. c). This also meant that the classification algorithms were unable to discern the difference between plantations and interspersed patches of remnant forest. This problem could have potentially been remedied by using higher resolution imagery. However, this imagery would have been prohibitively expensive to acquire, and running a land cover classification with high resolution imagery would have required much more extensive processing, including object oriented analysis and additional ground truth data.

Conversations with Dr. Krithi Karanth, who has done extensive research in the area, suggested that outside of the protected areas, the vast majority of areas classified as forest were actually plantations, likely with remnant forest patches distributed among them. We investigated the effect this would have on our classifications by reclassifying the areas outside of Anshi-Dandeli and Nagarahole and Bandipur as Plantation/Remnant Forest (fig. 4.2, fig. 4.4). When we assumed that forest areas outside of the park were plantations, total area within each class shifted for Anshi-Dandeli, with much less land in undisturbed forest cover (fig. 4.3). In fact, over 50% of the landscape consisted of plantation cover and remnant forest. This reclassification was complicated by the existence of other protected areas. South of Nagarahole and Bandipur national parks, for example, there exists another protected area. However, this area is located in another state, and we were unable to determine its location. It is therefore likely that some of the land to the south of Nagarahole and Bandipur (fig. 4.4) is undisturbed forest.

Despite these difficulties, we produced quality classifications over a large area. Our overall accuracies for our supervised classifications were all higher than 70%, and the accuracy of our forest class was generally high. This is important for conservation, considering that forest is the land cover type most important as habitat for the large animals that the CWS concerns itself with.

With no reliable pre-existing land cover data for this area, the classifications that we created will be useful to conservation managers working within the Western Ghats. Numerous analyses of the areas, which until now were impossible to perform, can now be conducted. Some of these possible analyses have been explored in our pilot analyses. The knowledge gained from these analyses will allow future conservationists and park planners to better manage the protected areas.

An accurate understanding of the composition of the landscape will also prove useful in assessing human-wildlife interactions on the ground. Our classified maps can help identify areas where human-wildlife interactions are more likely to occur. For example, tigers and other megafauna will be more likely to move through forested areas than cleared land, and elephants are found to raid certain crops with preference (K. K. Karanth *et al.*, 2012).

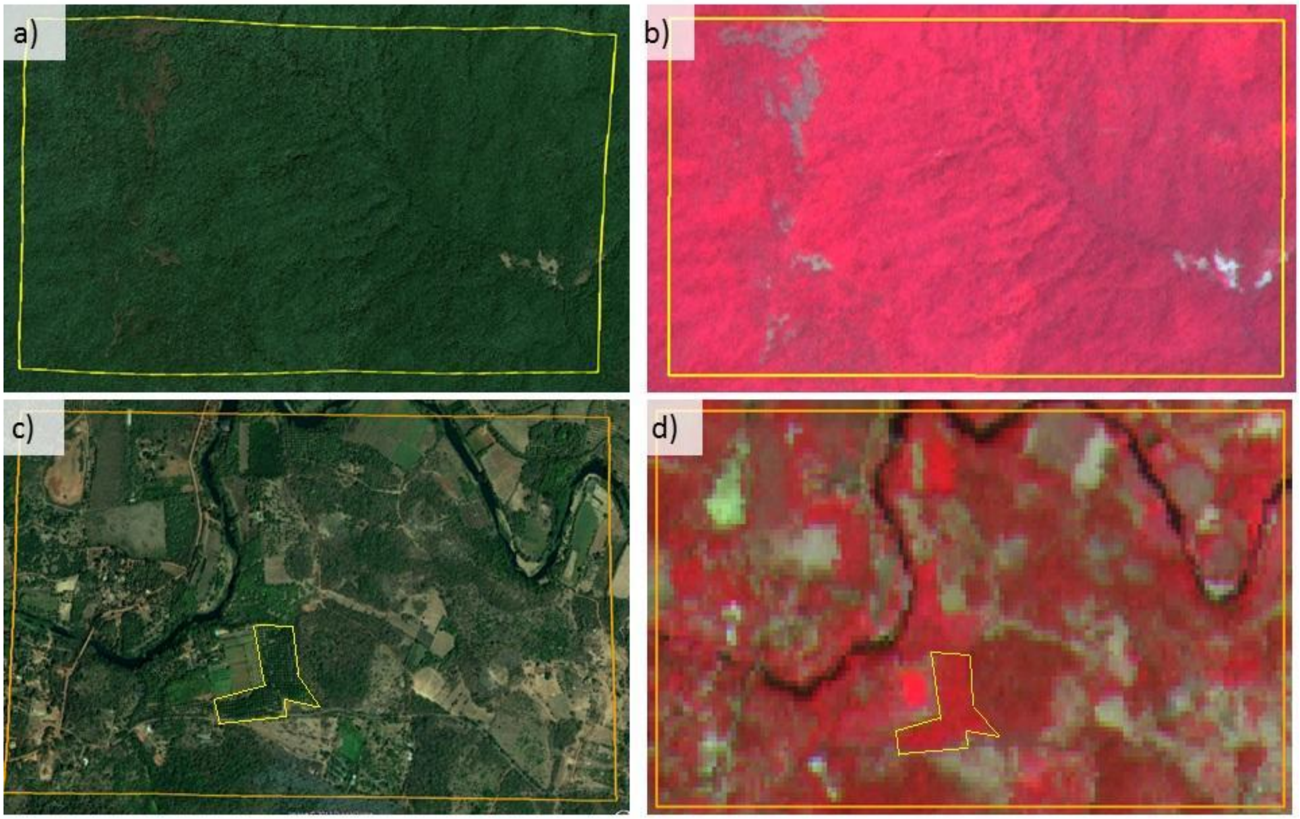

Fig. 4.1 Comparison of higher-resolution Google Earth imagery on left (a & c) with 15 m ASTER imagery on right (b & d). Example plantation shown outlined in yellow.

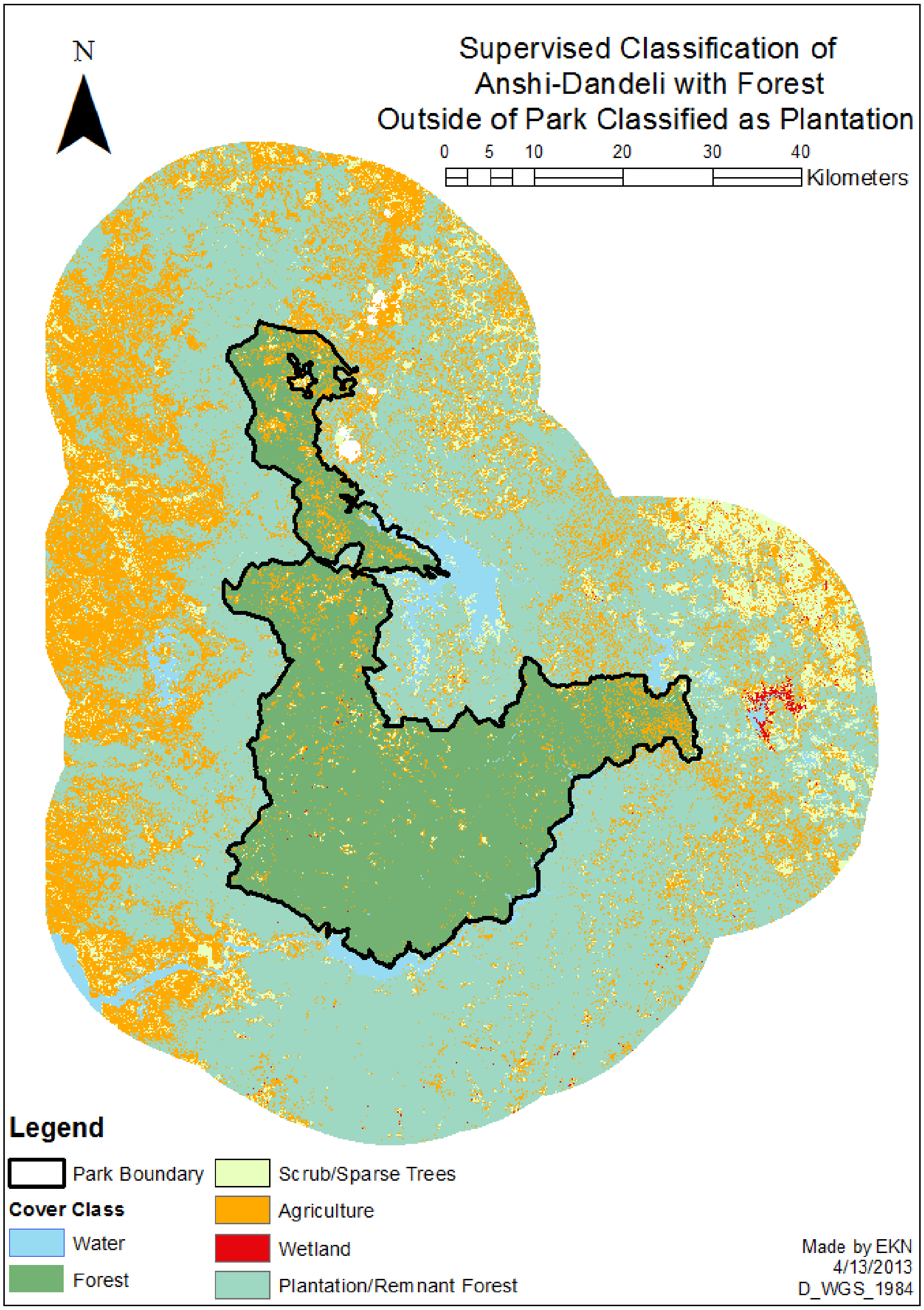

Fig. 4.2 Supervised classification of Anshi-Dandeli with areas outside of park classified as plantation

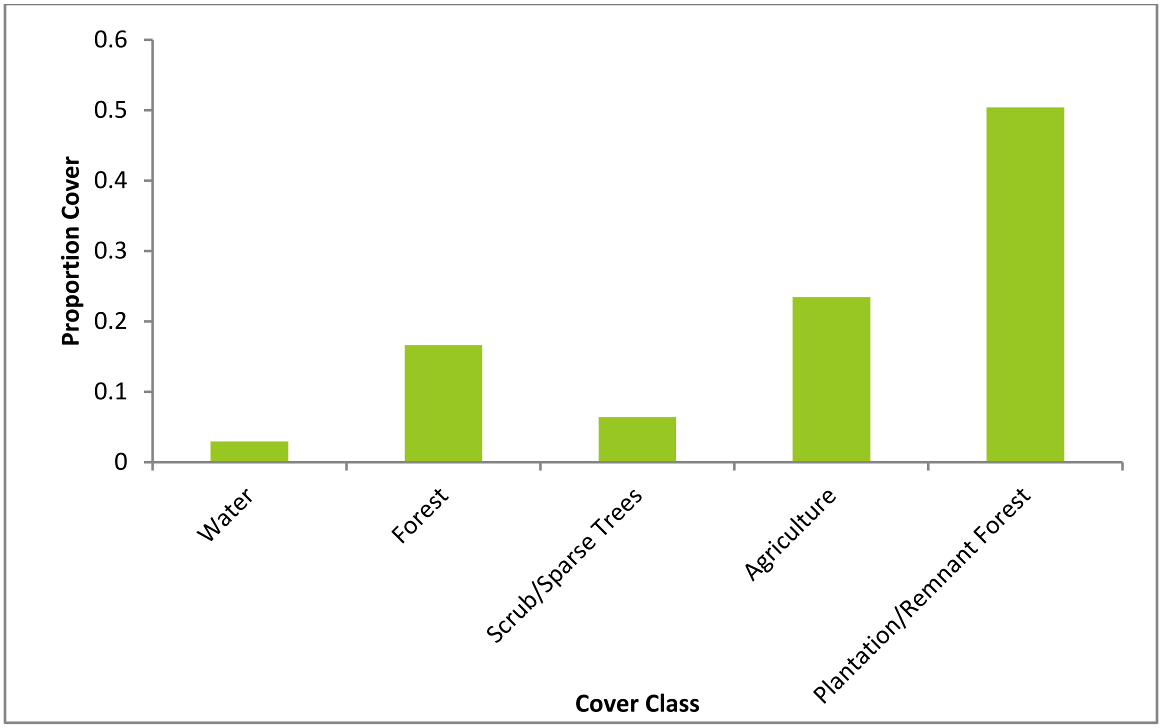

Fig. 4.3 Class proportions of Anshi-Dandeli Wildlife Sanctuary and 20 km buffer when forest cover outside of park is reclassified to plantation/remnant forests

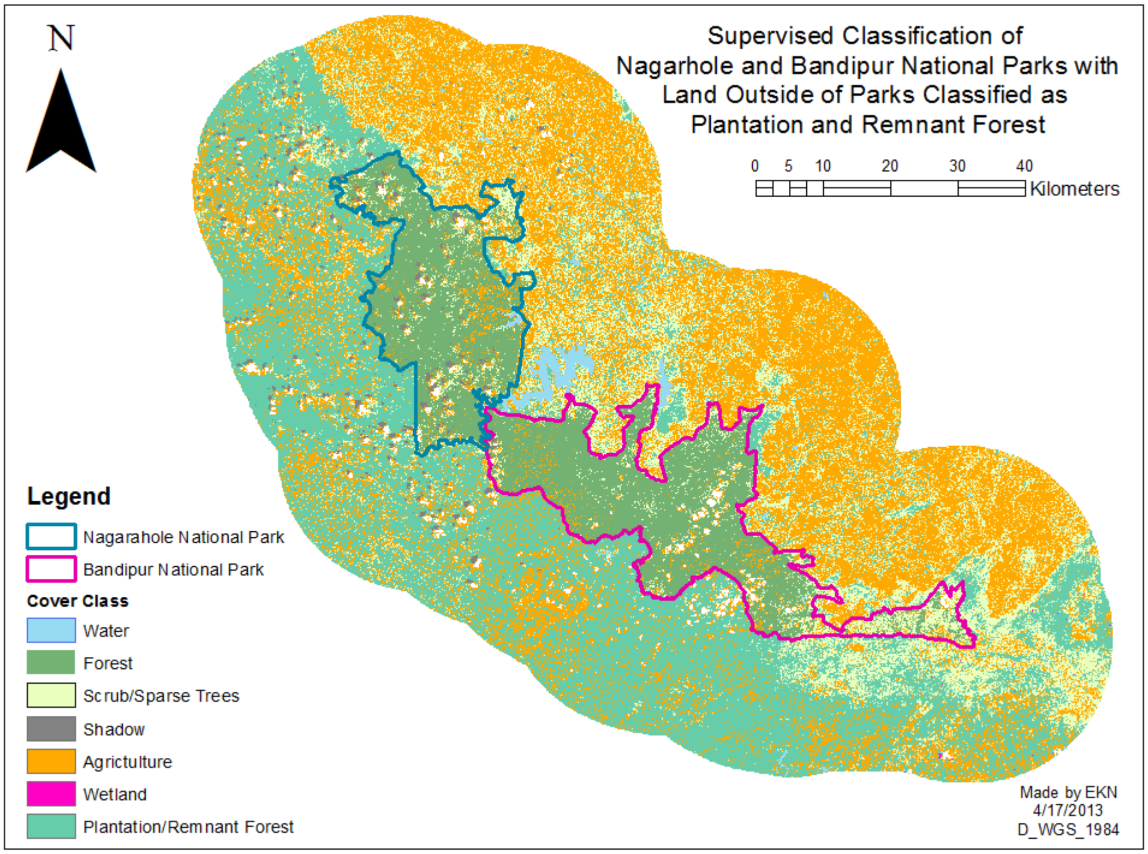

Fig. 4.4 Supervised maximum likelihood classification with land outside of the parks classified as Plantation and Remnant Forest

Pilot analyses discussion

Fragmentation

We see from the fragmentation analysis that the vast majority of forest within the park is unfragmented. Additionally, significant amounts of unprotected forest areas extend beyond the park's boundaries. Under the assumption that forest land outside of the park is largely plantation cover, the size of the largest patch is significantly reduced, and it no longer extends beyond the park's borders. When we assume most of the land outside the park is plantation, the large forest patch covers only 47,452 ha, compared with over 200,000 ha in the initial classification. It is also likely there are some remnant non-plantation forest patches outside the park; however, the spectral similarity of forest and plantation land makes determining forest patches difficult.

Even if forested land is not as widespread as it appeared in our initial classification, it is likely that large mammals will still be able to cross tree plantations, and may be able to make limited use of plantation lands in other ways. Many of these parks are specifically designated tiger preserves, and there is limited research on the extent to which Bengal tigers use plantation lands. However, Sumatran tigers have been shown to make limited use of plantations, but have a much higher preference for forest habitat (Sunarto *et al.,* 2012).

Analyses of fragmentation are useful because they can tell managers where it would be necessary to restore forest cover to facilitate large, connected areas of forest habitat. If Bengal tigers have the same habitat preferences as Sumatran tigers, for example, the ability of individuals to travel between parks would be limited by a lack of unfragmented forest cover. However, there have been reports of tigers crossing wide swaths of human-dominated landscapes. Therefore, despite the probable lack of forest cover outside of the parks, tigers may be able to move between them.

CONNECTIVITY

Our pilot connectivity analysis shows that the Nagarahole and Bandipur protected areas are important in maintaining connectivity in the landscape and ensuring that large animals are able to move between forest patches separated by large distances. The shortest distance between the two forest patches used in this analysis is a path that runs through area that was classified as cleared land. However, despite the shorter distance, the cost for these animals of using this path would be much higher, due to human-wildlife conflict and low prey densities. The forest that these parks protect is essential for providing a path for these animals to traverse the landscape.

Though cover types such as plantations might not be optimum tiger habitat, we were unable to distinguish between undisturbed forest and disturbed forest or plantation cover. Tigers in Sumatra (Sunarto, 2011) were found to cross plantation cover, so we assumed that tigers in the Western Ghats would be at least willing to occasionally use plantation and disturbed forest covers. If our assumption is incorrect, the conclusions we would be able to make from our classification would be different.

HUMAN-AFFECTED AREAS

The results of our human-affected areas pilot study show that the park is beneficial in reducing the influence humans have on the landscape. In the case of Anshi-Dandeli National Park, influence is reduced by 32.9% and areas within the park boundaries are subject to fewer human-induced pressures. This supports the notion that protected areas without human settlements are beneficial to wildlife. However, 44.5% of the areas within the park boundary continue to be affected by humans. Paved roads run through the park, and in some areas, there continue to be human settlements within the park boundaries. This implies that even within reserves, wildlife may not be fully protected from humans.

Future Steps

Classifications of larger areas will make it possible to investigate how parks might be connected. Tigers have been observed traveling between parks (Krithi Karanth, personal communication 2013) and are therefore presumably able to travel unseen through the human-dominated landscape around the parks. Expanding the mapping to a wider area would enable managers to investigate which areas tigers might be moving through at a more regional scale and could possibly help in determining which areas would be best suited for creation of new protected areas or of a forested corridor between protected areas.

More knowledge of the study area could improve the land use land cover map. Even though one of our group members spent several weeks collecting ground data in India, none of us were very familiar with the area. There were times we could see spectral differences (for example, in forest type), but were unsure what they represented. Had we been more familiar with the study area, we may have been able to define classes more finely than we were able to in this classification. However, this area is large and variable, and defining more detailed classes might prove to be a significant challenge. We also may be able to separate additional forest types if we had a wider selection of remotely sensed bands across the electromagnetic spectrum than what ASTER provides.

Though the single time period represented in this classification is able to show where forest and agricultural areas are located, a time-series of classifications would help managers determine how quickly change is occurring, as well as the spatial distribution of that change. This knowledge would help determine where conservation activities should be focused.

These LULC classifications could also be used as one if the inputs into species distribution models. Modeling species distributions across these study areas would help managers determine where species of interest are likely to occur and possibly where they could be successfully reintroduced.

Additional connectivity analyses could also be conducted using our classifications. With more imagery and more time, classification maps could be created for all of the areas between the parks. Connectivity analyses could then be run on the entire landscape in order to see how well all of the parks are connected. This would be especially important, since many large animals need a very large range in order to survive, and connectivity between the various protected areas would ensure a healthy level of gene flow in the population. Other landscape connectivity analyses could include software such as Circuitscape or the use of graph theory to investigate landscape connectivity, as in Minor and Urban (2008).

The launch of Landsat 8 in February 2013 should increase data availability in this area. We were required to get permission to access and download ASTER data, but Landsat will likely be available freely on the internet. There has also been much prior work with Landsat data; indices such as a the tasseled cap, which provides a proxy for greenness, wetness, and brightness, may have been helpful in our analysis, but were not calculable with ASTER. Additionally, and perhaps even more importantly, Landsat data includes more spectral bands than ASTER data, which may prove useful in discriminating vegetation.

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