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Conservation-induced resettlement as a driver of land cover change in India: An object-based trend analysis

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ABSTRACT

Located in the foothills of the Indian Himalaya, Rajaji National Park was established to protect and enhance the habitat of the Asian elephant (*Elephas maximus*) and tiger (*Panthera tigris*). In 2002 the Van Gujjars, indigenous forest pastoralists, were voluntarily resettled from the Chilla Range (an administrative unit of Rajaji National Park) to Gaindikhata, a nearby area where they were granted land for agriculture. In this study we used a variety of remote sensing approaches to identify changes in land cover associated with the resettlement. The methods comprise two main approaches. First, we used object-based image analysis (OBIA) to identify the pre-resettlement land cover classes of use areas (representing agricultural expansion and adjacent areas of grazing, and collection of fuelwood and fodder) and recovery areas (representing areas where settlements were removed, and the adjacent areas of resource use). Secondly, we used trend analysis to assess the gradual and abrupt changes in vegetation that took place in use and recovery areas. To conduct the trend analysis we used BFAST (Breaks For Additive Season and Trend), which separates seasonal variation from long-term trends, and identifies breaks that can be linked back to disturbances or land cover changes. We found that the OBIA classification yielded high average class accuracies, and we were able to make class distinctions that would have been difficult to make using a traditional pixel-based approach. Pre-resettlement, the recovery areas were classified as mixed forest and riparian vegetation. In contrast, the use areas were classified primarily as grass dominated, brush dominated, and plantation forest, and were located relatively far away from riparian areas. Following the resettlement, the trend analysis showed a sudden change in the seasonal variation of NDVI in areas converted to agriculture. Areas neighboring the new agricultural land experienced sudden decreases in NDVI, suggestive of disturbances, at a higher rate than the same land cover types elsewhere. At the same time, these neighboring areas experienced a gradual overall increase in NDVI which could be caused by an expansion of leafy invasive shrubs such as *Lantana camara* in areas heavily used for biomass collection. The recovery areas also experienced a gradual increase in NDVI as well as sudden breaks to this trend, but we lacked evidence to connect these changes to the resettlement. Our findings support the claim that the resettlement has shifted pressure from more ecologically valuable to less ecologically valuable land cover types, and suggest that to some degree resource use pressure has increased outside the park. The study employs a novel synthesis of OBIA and trend analysis that could be applied to land change studies more broadly.

1. Introduction

1.1. Conservation-induced resettlement

India has a wide network of protected areas (PAs) that includes national parks, wildlife sanctuaries, conservation reserves and community reserves and covers close to 5% of its land area (Lasgorceix & Kothari, 2009). As many as 5 million people live

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within India's PAs, while up to 147 million people live nearby and are dependent on resources extracted from PAs (Karanth, 2007; Lasgorceix & Kothari, 2009). People in and around PAs engage in many activities that directly influence forest ecosystems, such as wood collection, livestock grazing, and harvesting of non-timber forest products (Shahabuddin & Prasad, 2004). Pressure on PA forests also comes from demand from urban centers, commercial forestry operations, mines, and commercial tourist operations (Rangarajan & Shahabuddin, 2006).

To reduce the impacts from human habitation and forest resource extraction, many PAs have relocated communities from inside to outside the PA, a politically contentious process known as conservation-induced resettlement. Conservation-induced resettlement is a globally uneven phenomenon, with reported cases drawn most intensively from Africa, South and South East Asia and North America (Brockington & Igoe, 2006). In the western United States and East Africa, colonial land and wildlife management practices included the forceful removal of native populations to create national parks (West, Igoe, & Brockington, 2006; see also Merchant, 2005; Neumann, 1998; Spence, 1999). In South Asia, displacement was also employed for protection of timber reserves under the forestry laws and practices of the British Raj (Rangarajan & Shahabuddin, 2006).

In India, conservation-induced resettlement is authorized under the Wildlife Protection Act of 1972, which allows the Forest Department to designate areas where human settlements were forbidden in order to protect specified flora and fauna (Quereshi & Moosvi, 2008, chap.9). A 2005 review by the government-appointed Tiger Task Force reported that 4594 families have been resettled in India since 1973 (Government of India, 2005); others estimate that the number is 15,000–20,000 families (Lasgorceix & Kothari, 2009). Resettlement from PAs has often been problematic, resulting in impoverishment, political disempowerment, and social dislocation (Agrawal & Redford, 2009; see also Brockington & Igoe, 2006; West et al., 2006 and special issues of the journal *Conservation and Society* in 2006 and 2009). In response to such negative outcomes, and following the poaching of the last tigers from Sariska National Park, several recent pieces of legislation attempt to improve the success of resettlement by making it voluntary in most instances.[1]

The relationship between population and land degradation is often assumed to be a simple one, with population directly correlated to pressure on natural resources (Ives & Messerli, 1989). However, the reality is more complex and the effects of population on land degradation can be severe or mild depending on land management practices (Paudel & Thapa, 2001). While many studies have evaluated how population growth relates to land degradation (Warren, 2002), fewer have focused on effects of population decline. A study in Nepal found that outmigration from a watershed was associated with increases in vegetation cover and invasive species (Jaquet et al., 2015). It is important to assess the land impacts of conservation-induced resettlement as it has elements of both population decline and growth.

1.2. Resettlement of the Van Gujjars from Rajaji National Park

The western Terai Arc Landscape (TAL) is the forested lowland foothills of the Himalayas and has been designated as global priority tiger conservation landscape by the World Wildlife Fund and Wildlife Conservation Society (Dinerstein et al., 2006). Historically dominated by tropical dry deciduous species such as *Shorea robusta,* the forests of the TAL in northern India have come under tremendous pressure from local communities. A case in point is the Van Gujjar communities (forest Gujjars), traditionally indigenous pastoralists who live throughout the TAL. The Gujjars have a long history of marginalization, weak legal standing, and unequal treatment (Gooch, 2009). Gujjars formerly migrated between the foothill forests and alpine meadows of the Himalayas. However, due to legal conflicts over land use, the Gujjars now live year-long in the foothill forests, increasing the pressure on those forests and riparian areas (Harihar & Pandav, 2012). In many places the Gujjars are given permits to cut grass and lop trees for fodder, activities that create forest openings which are then colonized by invasive weeds such as *Parthenium histerophorous* (Gajar grass) and *Lantana camara* (Lantana) (Joshi, 2009). Grazing buffalo also foul water holes and degrades the native tall grasslands adjacent to the dry washes (*raus*) (Joshi & Singh, 2009).

While conservation-induced resettlement is not yet widespread in the TAL, more than 1000 families have been voluntarily relocated away from one ecologically valuable area: Rajaji National Park (Harihar, Ghosh-Harihar, & MacMillan, 2014). Located within the Indian state of Uttarakhand, Rajaji National Park was established in 1984 to protect and enhance the habitat of the Asian elephant (*Elephas maximus*) and tiger (*Panthera tigris*). In April 2015, the PA core zone and parts of the buffer zone were additionally declared as the Rajaji Tiger Reserve and listed as the 48th reserve under Project Tiger (Rawat, 2015). The park also holds extensive habitat for native megafauna such as Goral (*Nemorhaedus goral*), golden mahseer (*Tor putitora*), chital (*Axis axis*), and leopards (*Panthera pardus*). Extensive forest has been lost to development projects surrounding the park, such as road and rail expansion, hydropower, the resettlement of people displaced by the Tehri dam, and the creation of an army cantonment (Nandy, Kushwaha, & Mukhopadhyay, 2007). When the park was first created, 512 Gujjar families lived within the park. By 1998 that number had grown to 1390 families, each owning an average of 15–17 buffalos and dependent on selling milk for 89% of their total income (Harihar et al., 2014; Sinha, 2006).

By 2004, a total of 688 families were resettled to Gaindikhata, including all193 families from the Chilla Range (Mishra, Badola, & Bhardwaj, 2007; Rasaily, Rawat, Chandola, & Sharma, 2012). At Gaindikhata, families were moved to the *basti,* an area peripheral to the *Gaon* (village proper) (Fig. 1). Each family was given two acres for agriculture and 200 sq. meters for construction of *dehras* (traditional thatched buildings). Medical and veterinary services, irrigation facilities, and schools were provided as part of the resettlement package. Families were compensated approximately $4000 per family. It was a difficult process for the resettled Van Gujjars to acquire services that have been afforded to other settled tribal peoples, such as voting rights and ration cards (Gooch, 2009; Singh, 2012). Nevertheless, perhaps due to the perceived success of the Rajaji relocation, a survey of 158 Gujjar households across the TAL showed widespread support for resettlement out of forested areas and into agricultural settlements (Harihar et al., 2014).

The resettlement appears to have yielded ecological benefits to the park. Field surveys following the resettlement have shown that wildlife in Rajaji National Park, including elephants, has expanded its range and that vegetation fodder has increased (Joshi & Singh, 2009). Elephants have been observed utilizing the whole of the forest area and water holes for routine activities throughout the day (Joshi & Singh, 2009). Tigers have also steadily increased in number in the region since the resettlement (Harihar et al., 2014). Ecological benefits to vegetation are less clear. A study of vegetation near the evacuated areas suggested that weed cover decreased and herb

[1] The 2006 Scheduled Tribes and Other Traditional Forest-Dwellers Act provided a mechanism for voluntary relocation white asserting a need to respect the rights of local people (Harihar et al., 2014; Sekhsaria, 2007). Similarly, modifications enacted in 2008 to the National Rehabilitation and Resettlement Policy stated that resettlement out of PAs should be voluntary (Lasgorceix & Kothari, 2009).

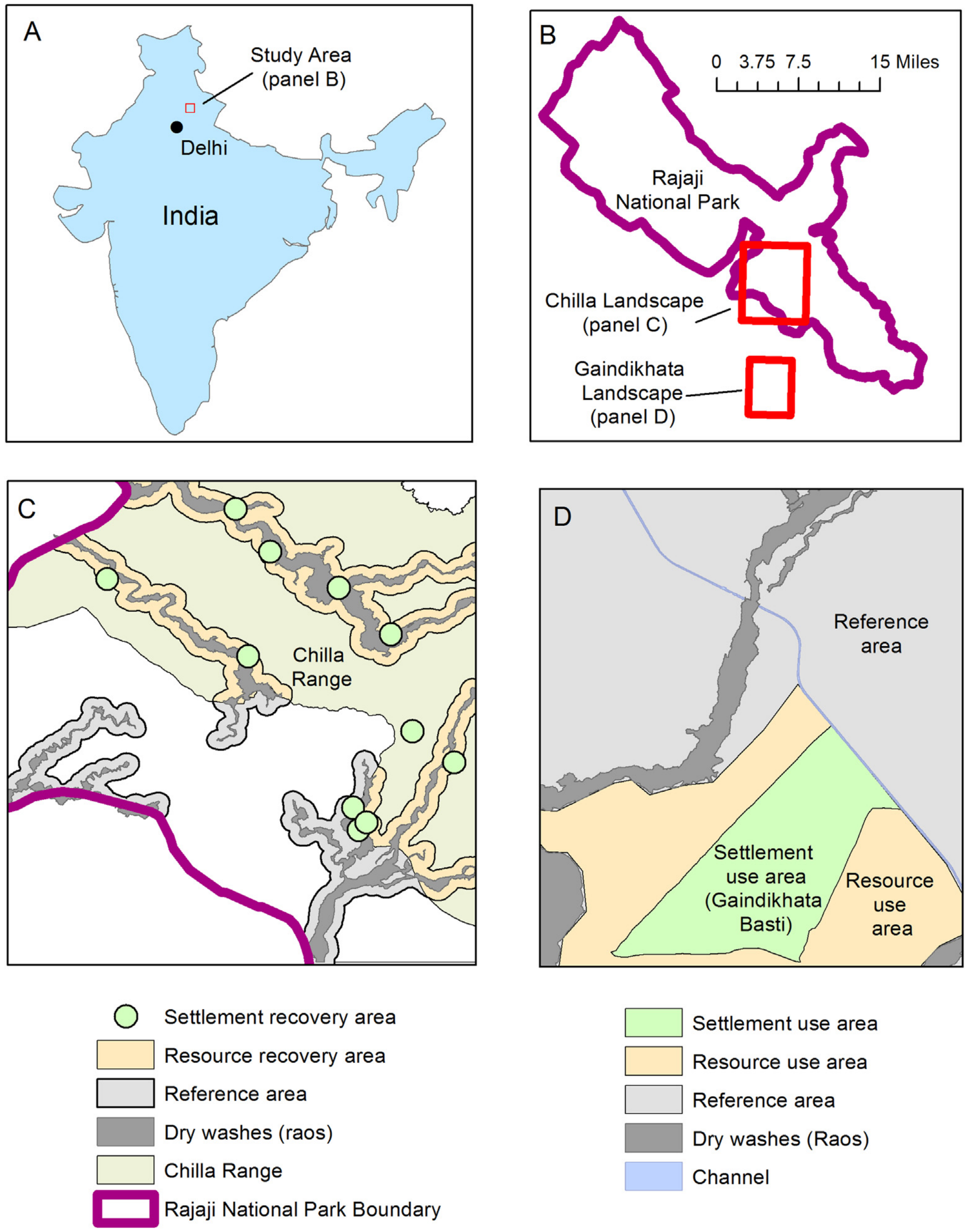

Fig. 1. Study Areas of the Chilla landscape (C) and Gaindikhata landscape (D) and how they are situated within India (A) and the region (B).

cover increased 2–3 years after resettlement, but found no clear trend in grass (Adhikari, 2009, chap.5). Another study found a downward trend in lantana from 2004 to 2008 but no significant change in canopy cover (Pandav et al. 2009, chap. 2). A limitation to these studies is that they lack comparison data from prior to resettlement, and were short in duration (though long term monitoring sites were established).

To date there has been no study of the ecological consequences of the resettlement in the Gaindikhata landscape. Around 90% of the fuelwood and fodder used by the resettlement communities of Gaindikhatta comes from the surrounding areas (Sharma, Gairola, Gaur, & Painuli, 2012). Thus, it is likely that pressure on forest and grass resources has increased in the areas surrounding the new settlement. However, as agriculturalists their forest use may be less than when they lived in the park. A study from the Western and Eastern Ghats of India suggest that households who engage in agriculture have lower levels of forest extraction pressure (Davidar et al., 2010).

1.3. Research goals

While many studies have evaluated the social impacts of resettlement (e.g. Mishra et al. 2007), few explicitly assess the environmental impacts. In the words of Lasgorceix and Kothari (2009): "We could not find a single study of the ecological costs and benefits of relocation, comparing what happens at the old site to what happens at the rehabilitation site. This is a shocking gap, given that relocation is always justified from the point of view of reducing pressures and securing wildlife habitats." Addressing this deficit, the goal of this research is to combine emerging remote sensing methods (object-based image analysis and trend analysis) to assess land cover changes associated with resettlement. The study area comprises two areas: the Chilla Landscape (comprising the Chilla Range of Rajaji National Park and a neighboring reference area) and the Gaindikhata landscape located south of the park.

We evaluated land cover changes related both to the land cover 'costs' of the resettlement (clearing for agriculture and other land cover changes in the Gaindikhata landscape) and the 'benefits' (removal of structures, regeneration of vegetation in and around the *raus* of the Chilla landscape). To do so we used object-based image analysis (OBIA) to develop accurate land cover classifications pre-resettlement. Based on the OBIA, we identified the pre-resettlement land cover classes of within the Gaindikhata and Chilla landscapes (Fig. 1). Finally, we used trend analysis to assess the gradual and abrupt changes in vegetation that took place in these landscapes following resettlement. The goal was to provide additional evidence regarding the claim that the resettlement is a conservation 'win–win' from a land systems science perspective.

2. Methods

The analysis comprised two main components: Object-Based Image Analysis (OBIA) and trend analysis of land use (described below and summarized in Fig. 2).

2.1. Object-based image analysis (OBIA)

2.1.1. OBIA segmentation and classification

OBIA uses both spectral and contextual data extracted from imagery to create meaningful objects at multiple scales (Blaschke, 2010). In OBIA, imagery is first segmented into homogeneous objects and then classified based on spectral response, texture, geometry and context. Many studies have found that OBIA yields higher classification accuracy than pixel-based methods for land cover classification and change detection (Blaschke, 2010; Platt & Rapoza, 2008). We used Trimble's eCognition Developer 9.0 software to conduct the OBIA.

Segmentation was the first step in the process. eCognition's multiresolution segmentation algorithm was applied to a VHR image from 2002, which represented conditions prior to resettlement (Table 1). We selected segmentation parameters iteratively, attempting to create objects that delineated features such as fields and woodlots. The size of the objects is set by a scale parameter, a unitless number which sets the maximum allowed heterogeneity within an object (in this study: scale parameter = 100). Heterogeneity has two components, shape and color, the proportion of which is set by the shape parameter (in this study: shape = 0.1, meaning 10% of heterogeneity is defined by shape and the remaining 90% by color). The shape parameter also has two components, compactness and smoothness, the proportion of which is set by the compactness parameter (in this study: compactness = 0.7, meaning 70% of the heterogeneity is defined by compactness and the remaining 30% by smoothness).

Once an initial set of objects were created through segmentation, they were refined and classified. We first classified all objects into three super classes (water, vegetated, and bare) using simple band thresholding (Table 2). Next, we derived sub-classes using classification rules related to spectral, textural, or contextual attributes. We based many of the rules on our own expert knowledge as image interpreters. For example, active agriculture was defined as an object that had a high NDVI in March (the heart of the winter growing season) and large decline in NDVI in May (after the harvest had concluded). Another example: a river object was defined as a water object that, when merged with adjacent water objects, shared a significant border with riparian vegetation, dry river bed, or other river object. All classification rules were created this way with the following exception: four of the vegetation sub-classes, (mixed forest, plantation forest, brush dominated, and grass dominated) were distinguished using nearest neighbor (NN) classification, a supervised classification strategy that assigns objects to the class to which it is most similar in band space based on a training sample.

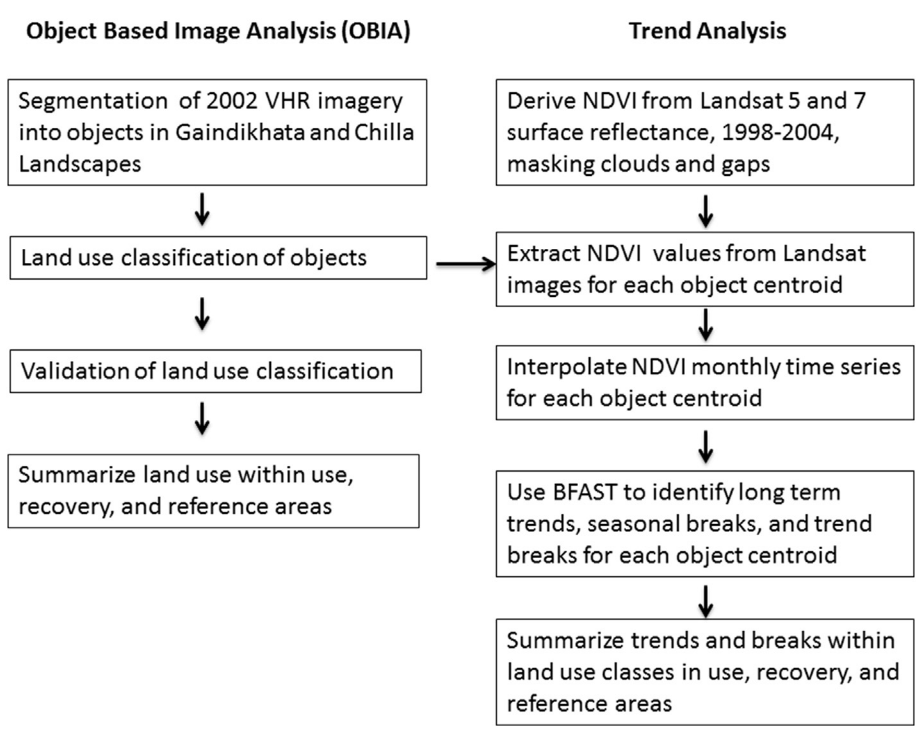

Fig. 2. Workflow of Object-Based Image Analysis (OBIA) and Trend Analysis.

Table 1
Remote sensing data sources.

Satellite	Acquisition date	Geometric correction	Radiometric correction	Spatial resolution	Number of bands	Use
Ikonos	Oct 28th, 2002	Geoprofessional	ATMOSC	4m	4	GEOBIA, visual interpretation
GeoEye-1	Feb 26th, 2012	Geoprofessional	ATMOSC	4m (resampled)	4	GEOBIA, visual interpretation
GeoEye-1	Oct 2nd, 2011	Geoprofessional	ATMOSC	4m (resampled)	4	GEOBIA, visual interpretation
Landsat 5,7	270 images 1998–2014	L1T	LEDAPS	30m	7	GEOBIA, trend analysis

Table 2
OBIA classification rules.

Super class	Sub class
Water	**River**
1 Low NDVI	1 Classified as water
2 Low NIR	2 When merged with adjacent water objects, shares significant border with river bed or river
	Channel
	1 Classified as water
	2 Large
	3 Not river
Vegetation	**Mixed Forest, Plantation Forest, Grass Dominated, Brush Dominated**
High NDVI	1 Classified as vegetation
	2 Nearest neighbor classification
	a Landsat bands used for classification: near infrared and NDVI (March, May and October 2002)
	b VHR bands used for classification: standard deviation of blue, green, red, NIR, NDVI (October 2002)
	Active agriculture
	1 Classified as vegetation
	2 High NDVI in March
	3 Steep decline in NDVI between March and May
	Riparian Vegetation
	1 River bed with high NDVI
	2 Or: grass or brush dominated sub-object > 50% surrounded by river, riparian vegetation, and river dry bed
Non-vegetation	**Bare**
1 Low NDVI	1 Classified as non-vegetation
2 Not water	2 Not dry river bed
	Dry river bed
	1 Classified as non-vegetation
	2 Bright in blue
	3 Low shape index
	4 When objects that meet the above criteria are merged, the resulting object is adjacent to water
	5 Or: non-vegetation sub-object > 50% surrounded by river, riparian vegetation, and river dry bed

2.1.2. OBIA validation

To evaluate the quality of the OBIA classification, we compared it to a manual classification of 326 objects. A simple random sample proved impractical, so we used the following strategy: approximately half of the validation objects were derived from a random sample of objects stratified by land cover class, and the remaining validation objects came from a 'windshield survey' conducted in January 2012. To conduct the windshield survey, we drove down most passable main roads in the study area, stopping approximately every kilometer, and taking geotagged pictures at each stop (note: henceforth 'pictures' refer to the geotagged pictures taken in the field, while 'imagery' refers to the satellite imagery). We used the ProCamera iPhone App, which records the cardinal direction that the picture was taken.

To manually classify the 164 objects from the 'windshield survey', we created a layer showing the location/cardinal direction of each picture overlaid with the VHR satellite imagery. We then used all information available to us to determine the 2002 class. In the example below, we determined that the geotagged picture showed plantation forest (Fig. 3). We looked at the location and direction of the picture (shown by the arrow in Fig. 3) and saw that plantation forest was visible in both the 2002 and 2011 VHR imagery. Based on these insights, we assigned the object the 'plantation forest' class for 2002. Of the 164 objects from the 'windshield survey', we determined that 77% were unchanged from the 2002 and 2011 VHR imagery. The remaining 23% had clearly changed since 2002, so while the geotagged pictures were still useful for interpretation, we had to rely more heavily on the 2002 VHR imagery itself. To manually classify the additional 162 objects from the stratified random sample, we visually interpreted the 2002 VHR imagery and assigned classes to objects, but did not have the benefit of geotagged photography. Finally, we created an error matrix to compare the OBIA classification with the manual classification for the 326 objects.

2.1.3. OBIA analysis

The most obvious changes driven by the resettlement were removal of settlements from the Chilla landscape, and creation of new agricultural land in the Gaindikhata landscape. We were particularly interested in evaluating if these changes took place in land cover classes that were likely to be ecologically valuable (mixed forest, riparian vegetation) or less valuable (plantation forest, brush dominated). The proportion of OBIA land cover classes was calculated for objects in the following areas:

1) Gaindikhata landscape (Fig. 1C)
   a. Settlement use areas: the land used for new agriculture and settlements.
   b. Resource use areas: the vegetated areas adjacent to the 'settlement use area' where grazing and fuelwood take place. The resource use area is clearly delineated by dry washes or a channel in all directions, and does not exceed 2 km from the settlement use area, the approximate distance that women in Gaindikhata report walking for fuelwood collection.

Fig. 3. VHR image overlaid with objects (left). The arrow represents location/direction of picture (right).

   c. Reference areas: the remainder of the Gaindikhata landscape.

2) Chilla landscape (Fig. 1D)
   a. Settlement recovery areas: the locations of settlements that were removed.
   b. Resource recovery areas: the vegetated areas within 200 m of the *raus* where grazing and fuelwood collection formerly took place.
   c. Reference areas: the vegetated areas within 200 m of the *raus* where grazing and fuelwood collection are ongoing (outside of the Chilla Range but still in Rajaji National Park).

2.2. Trend analysis

Using trend analysis of Landsat imagery, we assessed the gradual and abrupt changes that took place objects post-resettlement. To conduct the trend analysis we used the BFAST Package in R (Breaks For Additive Seasonal and Trend) (Verbesselt et al., 2010). BFAST takes a remote sensing time series and decomposes it into a trend component, a seasonal component, and a remainder. BFAST also identifies abrupt changes (breaks) in the time series; breaks in the seasonal component suggest a permanent change in land cover, while breaks in the trend component suggest a short-term disturbance. The BFAST model is described by the following equation:

$$Yt = Tt + St + et\,(t = 1, \ldots, n),$$

where Yt is the data at time t, Tt is the trend component, St is the seasonal component, et is the remainder component (noise), and n is the number of observed values. The trend component Tt is fitted as piecewise linear model and the seasonal component is fitted as a harmonic model. BFAST is a generic method that does not require user-defined thresholds, change trajectories, or reference periods (Verbesselt et al., 2010). It has been used to identify abrupt land and water changes in China (Chen, Michishita, & Xu, 2014); quantify abrupt and gradual changes in global vegetation (DeJong et al., 2012); and reconstructing the sequence of urbanization in Mongolia (Tsutsumida et al., 2013).

We conducted the trend analysis on the Normalized Difference Vegetation Index (NDVI), a widely used vegetation index that is strongly correlated to the amount of photosynthetic biomass. We used NDVI derived from 270 Landsat 5 and 7 scenes from 1998 to 2004 (Table 2). The scenes were from the Landsat Surface Reflectance Climate Data Records (CDR) product, which is a surface reflectance product corrected for atmospheric effects. With the R Raster Package, we stacked all 270 NDVI images and masked out clouds, cloud shadows, and image gaps using Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) mask images. We then extracted the NDVI value from the centroids of objects obtained from the 2002 VHR imagery, and then interpolated missing time series values to create a complete monthly time series from 1998 to 2014 for each object. We then calculated the following for each object:

a) NDVI Trend between October 2002 and October 2011.
b) NDVI Breaks: the dates of seasonal and trend breaks for NDVI.

To analyze the trend analysis output, we mapped the spatial distribution of NDVI trend, date of seasonal breaks, and date of trend breaks. We also used boxplots to compare the NDVI trend within land cover classes in the use and recovery areas. Finally, we calculated the proportion of each land cover type that experienced seasonal and trend breaks within the use and recovery areas. The time series runs from 1998 to 2014, but for the purposes of this study we focused on 2002–2011, the time interval for which we have VHR imagery at the endpoints. Since the objects represent the entire population, and not a sample, we did not conduct tests of statistical significance in our analysis. Furthermore, the trend analysis should be considered exploratory as it was not possible to validate in this context.

3. Results

3.1. Object-based image analysis (OBIA)

The OBIA classification shows that the Chilla landscape is dominated by mixed forest and intersected by *raus* comprising bare river bed and riparian vegetation while the Gaindikhata landscape is a more varied patchwork of human-dominated land cover types (Fig. 4). With an average producer's accuracy of 85% and average user's accuracy of 86%, the OBIA classification is of reasonably high accuracy (Table 3). Mixed forest, grass dominated, bare, dry river bed, river, and channel all displayed greater than average producer's accuracy. In contrast, active agriculture displayed the lowest producer's accuracy (53%), as many of these objects were erroneously classified as grass dominated. This lower accuracy for active agriculture may be due to the fact that some forms of agriculture do not follow the traditional harvest seasons. Mixed forest, riparian vegetation, active agriculture, river, and channel all displayed above average producer's accuracy. Plantation forest had the lowest producer's accuracy at 70%, as some mixed forest was erroneously classified as plantation forest. Overall, we found the level of accuracy of the OBIA acceptable, and we were able to discern classes that would have been impossible to identify using traditional pixel-based methods.

Based on the OBIA classification, we evaluated the pre-resettlement land cover within use and recovery areas. There were 11 objects representing the settlement recovery areas in the

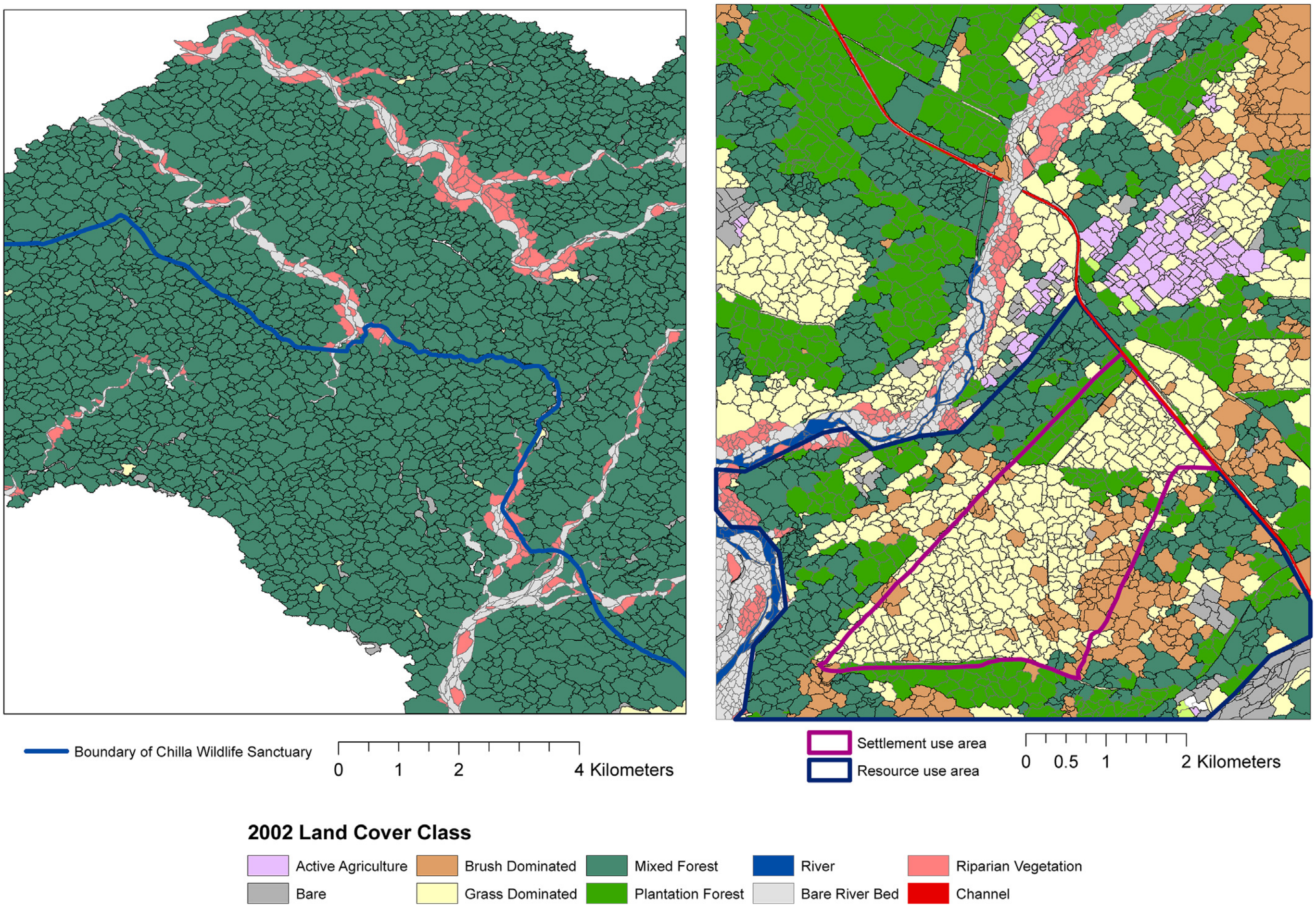

Fig. 4. OBIA Classification of the Chilla landscape (left) and Gaindikhata landscape (right).

Table 3
Confusion matrix of OBIA classification.

		OBIA classification											
		Mixed forest	Plantation forest	Grass dominated	Brush dominated	Bare	Dry river bed	Riparian vegetation	Active agriculture	River	Channel	Total	Producer's accuracy
Manual classification	Mixed forest	86	7	1	2	0	0	0	0	0	0	96	90%
	Plantation forest	2	21	0	2	0	0	0	0	0	0	25	84%
	Grass dominated	0	0	32	3	0	0	0	1	0	0	36	89%
	Brush dominated	2	0	5	22	0	0	1	0	0	0	30	73%
	Bare	0	0	0	0	18	0	0	0	0	0	18	100%
	Dry river bed	0	0	0	0	3	32	0	0	0	0	35	91%
	Riparian vegetation	5	1	0	1	0	5	33	0	0	0	45	73%
	Active agriculture	2	1	5	0	1	0	0	10	0	0	19	53%
	River	0	0	0	0	0	0	0	0	18	0	18	100%
	Channel	0	0	0	0	0	0	0	0	0	22	22	100%
	Total	97	30	43	30	22	37	34	11	18	22	344	85%
	User's accuracy	89%	70%	74%	73%	82%	86%	97%	91%	100%	100%	86%	

Chilla landscape where structures were removed. Of these, 64% were located in mixed forest and 36% were located in riparian vegetation (Table 4). The settlement recovery areas in mixed forest were an average of 67 m from the closest riparian vegetation or dry river bed object. The resource recovery areas in the Chilla landscape were dominated by riparian vegetation (25%), bare river bed (31%) and adjacent mixed forest (44%). In contrast, settlement use areas in the Gaindikhata landscape were only 3% mixed forest and were an average of 1.5 km from the closest vegetation riparian or dry river bed object. A total of 72% of settlement use areas were

Table 4
Land cover of settlement and use areas.

	Settlement use areas: Gaindikhata landscape	Resource use areas: Gaindikhata landscape	Settlement recovery areas: Chilla landscape	Resource recovery areas: Chilla landscape
Bare	1%	3%	0%	0%
Brush dominated	16%	14%	0%	0%
Grass dominated	72%	15%	0%	0%
Mixed forest	3%	38%	64%	44%
Plantation forest	8%	25%	0%	0%
Riparian vegetation	0%	7%	36%	25%
Bare river bed	0%	0%	0%	31%
Number of objects	456	778	11	655

classified as grassland (known to be cleared plantation forest) (Table 4). The neighboring resource use areas in the Gaindikhata landscape were dominated by plantation forest (25%) and mixed forest (38%). There was also a significant amount of land cover that was brush dominated (15%) and grass dominated (16%). When comparing the settlement use areas to the settlement recovery areas, it is clear that the Gujjar communities have moved from potentially ecologically valuable land covers such as mixed forest and riparian vegetation to settle in potentially less ecologically valuable land covers such as grass dominated that had formerly been plantation forest. When comparing the resource use areas in the Gaindikhata landscape to the resource recovery areas in the Chilla landscape, it is clear that Gujjar grazing and collection activities have moved from a mixed forest area with extensive riparian vegetation, to an area still with mixed forest, but also a mixture of plantation forest, brush dominated, and grass dominated.

3.2. Trend analysis

For the centroid of each object derived from 2002 VHR imagery, the BFAST algorithm created a time series plot that decomposes the seasonal (*St*), trend (*Tt*), and remainder (*et*) components (Fig. 5).

3.2.1. Trend component (Tt) of NDVI

In the Chilla landscape, NDVI trend was stable for the majority of objects from 2002 to 2011 (Fig. 6). That said, there were some interesting areas of change. In the southeast corner of the Chilla landscape, a weedy and degraded area just north of agricultural settlements, NDVI trended upwards. In addition, some mixed forest objects at higher elevations NDVI trended downwards. Finally, many riparian vegetation objects experienced an upward trend in NDVI, particularly the northernmost *rau* in the image. The overall upward trend in riparian vegetation objects is consistent with the observed increase in herbaceous vegetation post-resettlement (Adhikari, 2009, chap.5), and with the spread of lantana, which was found in 48% of Chilla Range in 2011 compared to 33% in 2001 (Rasaily et al. 2012). A boxplot revealed that the NDVI trend of the riparian vegetation and mixed forest classes in the resource recovery area in the Chilla landscape was very similar to same classes in the reference area (Fig. 7). Therefore, we found no evidence that the changes in NDVI in riparian vegetation are associated with the resettlement and exclusion of grazing.

In the Gaindikhata landscape, NDVI widely trended upward. The upward trend was particularly pronounced on either side of the border of the settlement use area (Fig. 6). The boxplot shows that vegetation in the settlement use areas experienced a higher

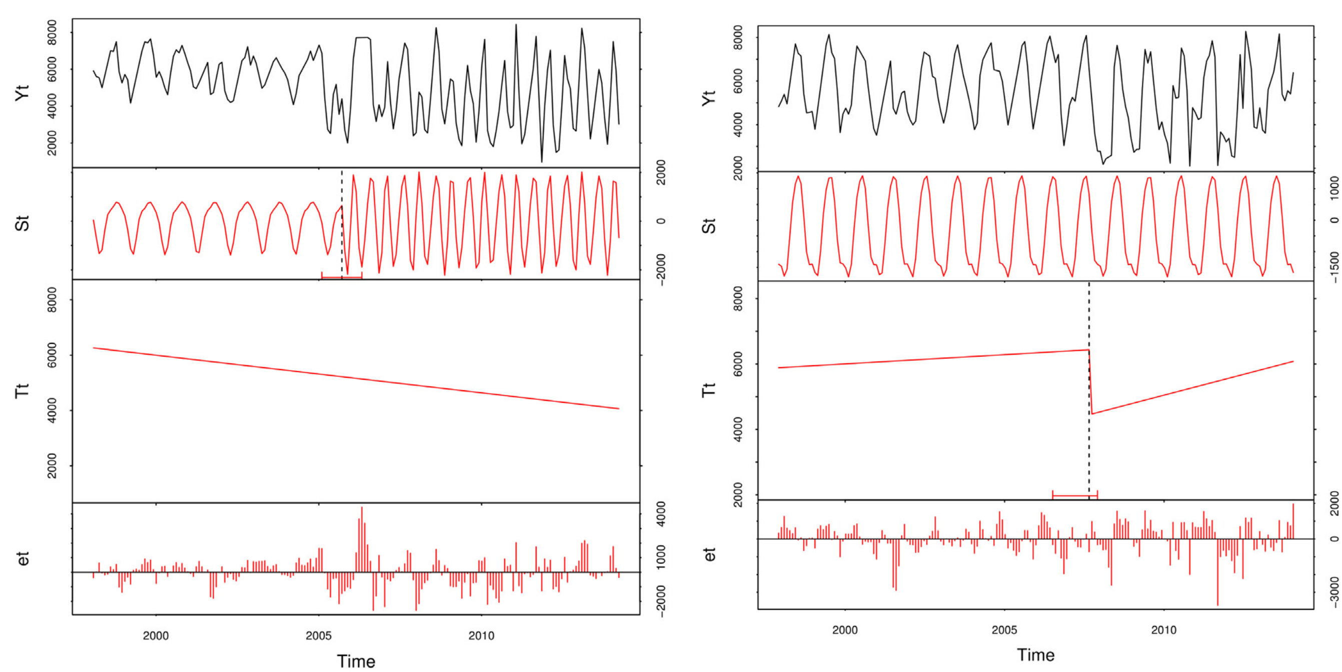

Fig. 5. Examples of BFAST output. Grass dominated object converted to agriculture in settlement use area (left), mixed forest object experiencing a trend break in resource use area (right). Units are NDVI × 10,000.

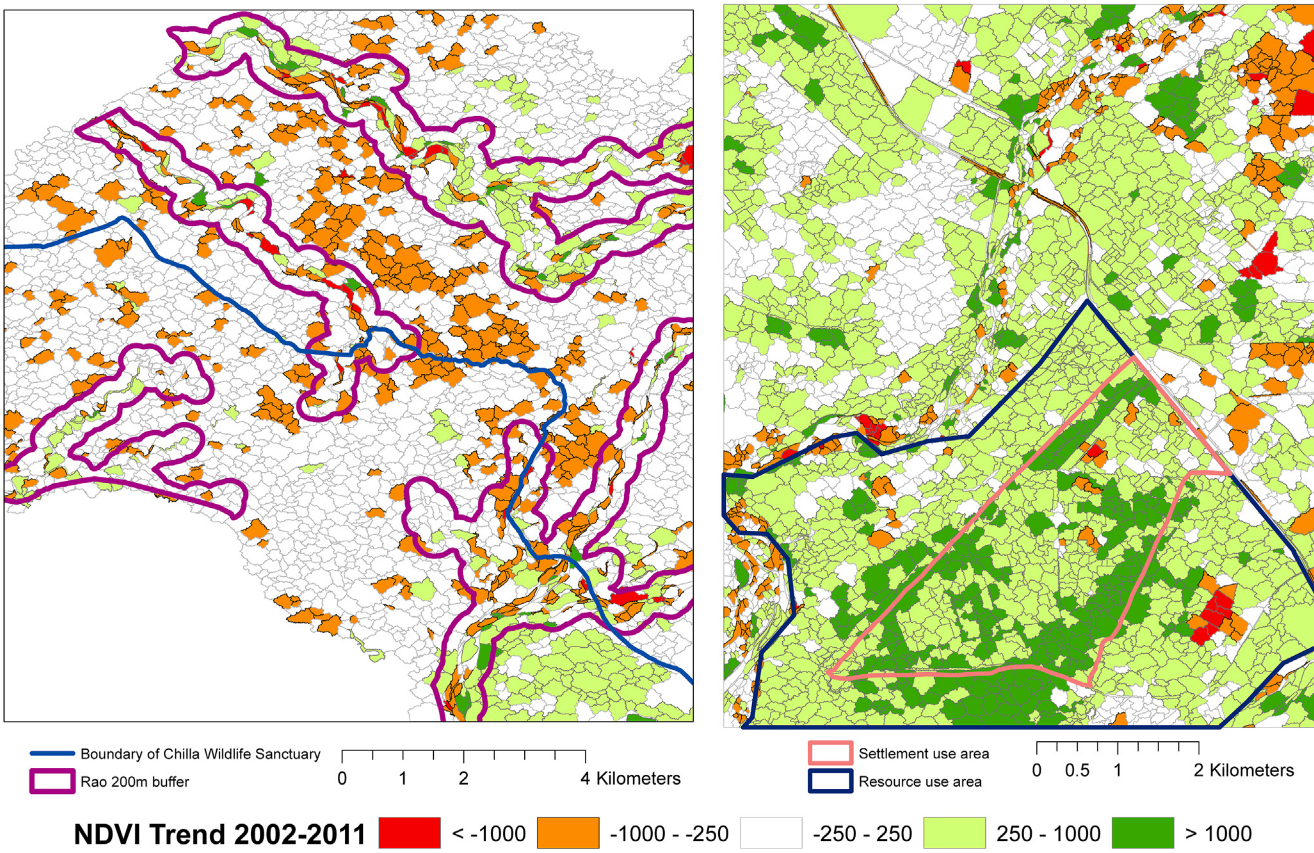

Fig. 6. NDVI Trend in the Chilla landscape (left) and Gaindikhata landscape (right).

upward trend in NDVI than in resource use or reference areas, which is not surprising since these areas were converted to agriculture (Fig. 7). In addition, the boxplot shows that brush dominated and mixed forest dominated objects in the resource use areas had a sharper upward trend in NDVI than the same classes in the reference areas (Fig. 7). The discrepancy could be explained by the expansion of leafy invasive shrubs such as lantana in areas heavily used for biomass collection. Lantana favors disturbances such as fire, grazing, and degraded soils (Bhatt, Rawat, & Singh, 1994; Duggin & Gentle, 1998).

3.2.2. Breaks in the seasonal (St) and trend component (Tt) of NDVI

In the Chilla landscape, the riparian vegetation objects experienced extensive trend and seasonal breaks (Table 5, Fig. 8). Seasonal breaks occurred in similar proportions within the resource recovery areas and the reference area, suggesting that the resettlement was not a factor in the land cover change (Table 5). It is likely that the seasonal breaks in riparian vegetation objects were caused by erosion, which occurred extensively across all *raus* in Chilla Range (Rasaily et al. 2012). Trend breaks in riparian vegetation occurred in 45% of objects in the resource recovery area versus 13% in the

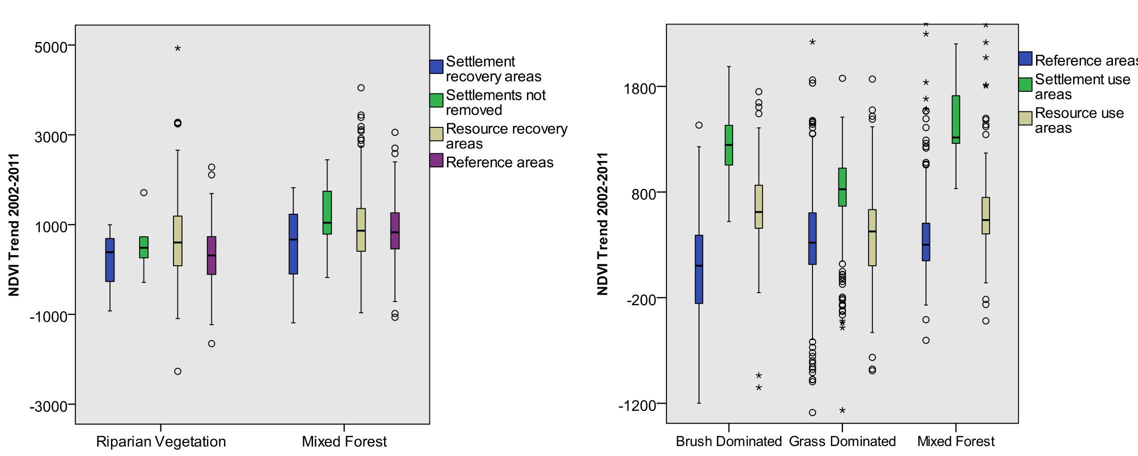

Fig. 7. Boxplot of NDVI trend from 2002 to 2011 within selected 2002 land cover classes in the Chilla landscape (left) and Gaindikhata landscape (right).

reference area (Table 5). The trend breaks occurred ca. 2006–7, coinciding with a record heat wave in Northern India, and they were most extensive in the northmost *rau* (Bindasini sot) within the Chilla landscape (Fig. 8). Bindasini sot is the largest *rau* in the Chilla landscape, is the only one entirely contained within the Chilla Range, and has the most extensive riparian grass vegetation. It also contained the largest Gujjar community in the Chilla Range prior to resettlement. In the absence of comparable *raus* in the reference area, it is unclear whether the changes in NDVI shown in the trend analysis are due to the resettlement or to other factors. Outside of riparian vegetation objects, the Chilla landscape did not undergo significant land cover change that can be detected with trend analysis of NDVI from Landsat imagery. Even the settlement recovery areas, where structures were removed, changed very little with respect to NDVI. This could be explained in part by the fact that the settlements left behind hard compacted soil that inhibited regeneration of vegetation (Rasaily et al. 2012).

In the Gaindikhata landscape, 97% of objects in the settlement use area underwent a seasonal break, indicating conversion to agriculture (Table 5). The conversion took place over several years, with the bulk of the change taking place in two primary waves ca. 2003 and 2006 (Fig. 8). The resource use area and reference area in Gaindikhata underwent only low levels of seasonal breaks for most land cover classes, though 26% of the plantation forest underwent a seasonal break in the reference area, indicating plantation harvest (Table 5). The grass dominated and mixed forest areas in the resource use areas of the underwent trend breaks at a higher rate than the same classes in the reference area (30% vs. 13% for grass dominated, 15% vs. 6% for mixed forest, 61% vs. 34% for riparian vegetation), but were otherwise broadly similar (Table 5).

4. Discussion

We found that prior to the resettlement, the settlement and resource recovery areas in the Chilla landscape were dominated by land covers with high potential ecological value (e.g. riparian vegetation, mixed forest), while the settlement use areas within the Gaindikhata landscape were dominated by land covers with lower potential ecological value (e.g. grass dominated, plantation forest, brush dominated). The settlement use areas showed extensive seasonal breaks in 2003 and 2006, showing the rapid conversion of land to agriculture during the resettlement. The resource use areas displayed frequent trend breaks, introduces the likelihood that there was an increase in resource use pressure that coincided temporally and spatially with the resettlement. In the Chilla landscape, riparian vegetation objects experienced extensive seasonal and trend breaks that are not clearly associated with the resettlement. Outside of riparian vegetation objects, the Chilla landscape did not undergo significant land cover change. These results underscore the complexity of the relationship between population change and land change (Jaquet et al. 2015; Paudel & Thapa, 2001).

This study shows the many advantages of combining an OBIA and trend analysis approach. The OBIA allows important class distinctions that would be difficult to make using pixel-based methods, for example separating grassland from riparian vegetation, and rivers from man-made channels. The objects themselves are also meaningful, representing functional units on the landscape. Unfortunately, OBIA is difficult to employ for change analysis studies with more than a small number of dates, therefore on its own it is a poor choice for high temporal resolution change studies. In contrast, trend analysis such as BFAST provides temporally detailed information on change, and helps separate gradual trends from discrete events from spurious change (Verbesselt et al., 2010). The discrete change events, in turn can be separated into short term disturbances and long term land cover shifts. A traditional change detection study based on change in discrete classes would have revealed little change in the study area aside from agricultural expansion and harvesting of plantation forest. An advantage of trend analysis is that it allows us to identify changes that do not result in a shift of land cover class, for example the increase of disturbances in the resource use areas relative to elsewhere. Trend analysis is computationally intensive, and by conducting it on objects (meaningful aggregations of pixels) rather than individual pixels, the processing time can be reduced by orders of magnitude.

One limitation to our object-based trend analysis approach is that objects are fixed in shape. In the real world, functional landscape units would split and merge over time (Hussain, Chen, Cheng, Wei, & Stanley, 2013). Consequently, over time, a single object may represent a blend of different land covers of interest (similar to the classic 'mixed pixel' problem in remote sensing). A second

Table 5
Seasonal and trend breaks of settlements and use areas.

		Gaindikhata Landscape			Chilla Landscape		
		Settlement use area	Resource use area	Reference area	Settlement recovery area	Resource recovery area	Reference area
Seasonal break	Brush dominated	71	5	4	0	0	0
		100%	5%	3%	0%	0%	0%
	Grass dominated	309	7	42	0	0	0
		97%	7%	9%	0%	0%	0%
	Mixed forest	12	4	16	0	0	2
		92%	1%	4%	0%	0%	2%
	Plantation forest	35	9	109	0	0	0
		97%	5%	26%	0%	0%	0%
	Riparian vegetation	0	1	35	1	19	6
		0%	2%	15%	20%	12%	13%
Trend break (no seasonal break)	Brush dominated	0	19	29	0	0	0
		0%	19%	22%	0%	0%	0%
	Grass dominated	1	30	52	0	0	0
		10%	30%	13%	0%	0%	0%
	Mixed forest	0	43	20	2	24	2
		0%	15%	6%	33%	9%	2%
	Plantation forest	1	50	81	0	0	0
		100%	31%	26%	0%	0%	0%
	Riparian vegetation	0	31	65	0	63	5
		0%	61%	34%	0%	45%	13%

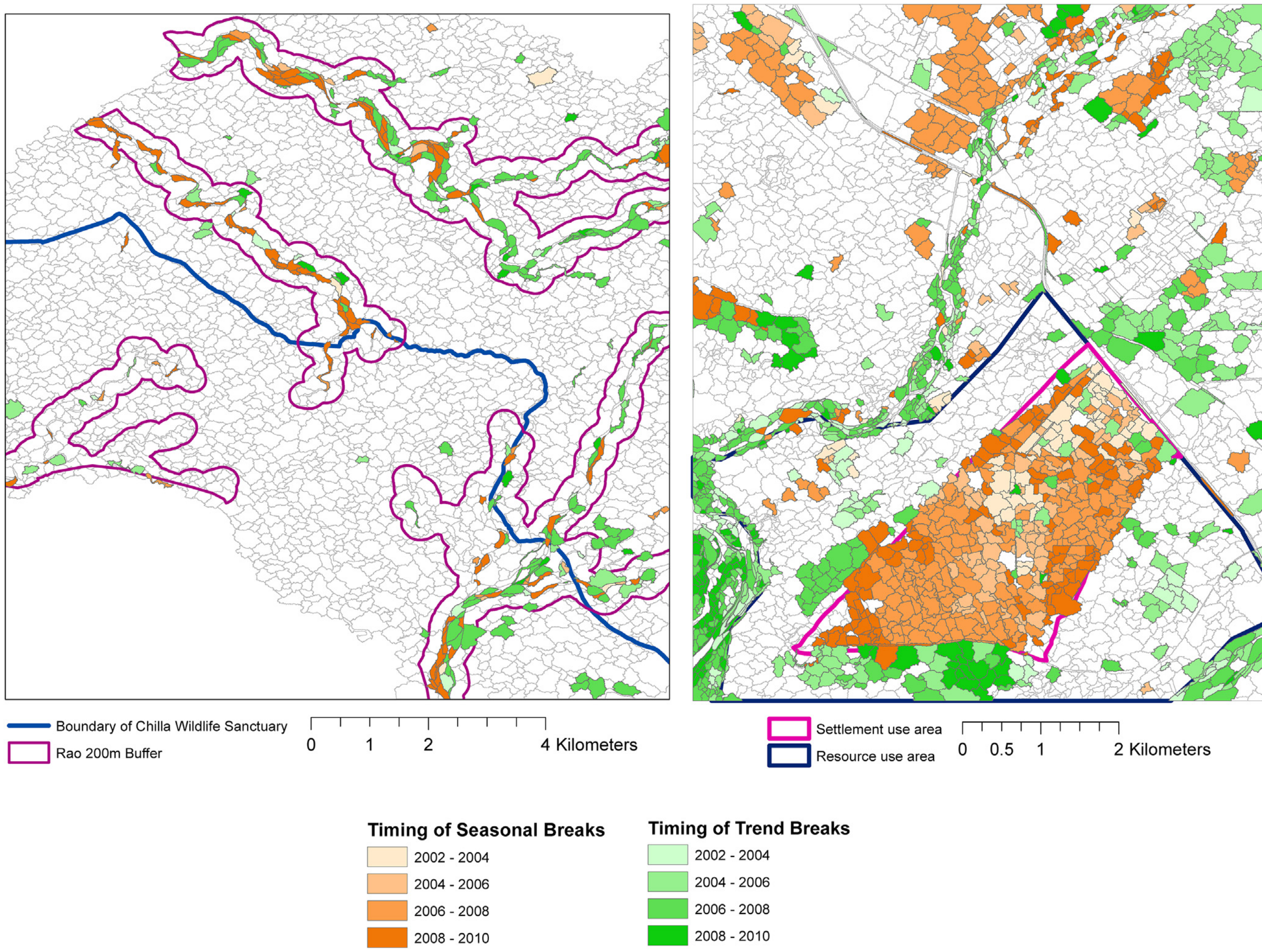

Fig. 8. Seasonal and trend breaks of settlements and use areas in the Chilla landscape (left) and Gaindikhata landscape (right). If both a seasonal and trend break have taken place, only the most recent break is shown.

limitation is that the trend analysis component of this study focuses exclusively on NDVI derived from Landsat imagery. We could not detect any change in riparian vegetation using Landsat-derived NDVI that coincides spatially and temporally with the resettlement. However, since NDVI is at best an incomplete indicator of biomass and vegetation health and is also sensitive to non-vegetation factors such as soil content, our results do not contradict studies that found improvements in vegetation health following the exclusion of grazing buffalo herds (Pandav et al. 2009, chap.2).

5. Conclusion

Conservation-induced resettlement of people from PAs can yield potential environmental benefits to evacuated areas and environmental costs in newly settled areas. In this study, we can say with high confidence that Gujjar communities left areas dominated by riparian vegetation and mixed forest to settle in primarily grassland dominated areas (previously plantation forest) that are far from major riparian zones. Thus they moved from land covers that are potentially more valuable ecologically to those that are potentially less valuable. We also found that, following resettlement, resource use areas experienced frequent trend breaks (i.e. disturbances) and a high upward trend in NDVI compared to reference areas. These changes in NDVI can be explained by the heavy use of resources, coupled with the expansion of leafy invasive shrubs such as lantana. We did not find evidence that changes in NDVI in the Chilla landscape were associated with resettlement. The results highlight the complex environmental effects of conservation induced displacement, and are specific to the social, management, and ecological context of the area. The study employs a novel synthesis of two remote sensing approaches, OBIA and trend analysis, which could be applied to land change studies more broadly.

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