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Patterns of tropical forest dynamics and human impacts: Views from above and below the canopy

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ABSTRACT

Tropical forests are influenced by regional and global bio-climatic processes as well as local anthropogenic disturbances. Most studies have ignored the synergistic influence of bio-physical processes operating at large spatial scales and local human use on forest vegetation and fauna. Assessments of forest condition change using time-series of remotely sensed data need to be supported by measurements under the canopy. The Tadoba-Andhari Tiger Reserve (TATR) in India is a protected area that has a long history of human resource extraction and settlements. Like much of South Asia, it has undergone major shifts in rainfall in the last hundred years. We examine trends in forest greenness over two and half decades and assess spatial patterns in rates of change. We also analyze ground based measurements of human impacts on flora and fauna. Trends in forest canopy greenness show two distinct phases: a period of decline from 1980s to mid-90s, followed by a recovery. These trends are a function of initial greenness and are best explained by prevailing climatic regimes, feed-backs from human use, and park management practices and protection. Negative impacts to flora and fauna on the ground were, however, wide-spread during the recovery period and are influenced by proximity to nearest settlement as well as combined distance from all settlements. Remotely sensed data cannot effectively detect these processes under the canopy. There is an urgent need to incorporate monitoring of long-term bio-climatic processes and their interaction with short and long-term effects of human-use and disturbance arising from processes at local, regional and larger spatial scales around protected areas to effectively manage these reserves.

1. Introduction

Tropical forest cover dynamics are challenging to study because they are subjected to bio-physical processes operating at various spatial and temporal scales as well as local anthropogenic disturbances arising from forest use (Lewis, 2006; Nemani et al., 2003). Characterizing forest dynamics requires understanding of synergistic interactions between both drivers: bio-physical and anthropogenic (Chazdon, 2003; Elmqvist et al., 2007). In spite of this complex interaction between human use and bio-physical processes, earlier studies in tropical and sub-tropical forests have attributed variability in net primary production and forest structure to usually single dominant drivers such as gradual global climate change effects (Nemani et al., 2003), regional climate anomalies and trends (Malhi and Wright, 2004; Mohamed et al., 2004); pulse influences such as fire (Eva and Lambin, 2000; Kodandapani et al., 2008), and biomass extraction and cattle grazing (Barbier et al., 2006; Mehta et al., 2008; Shahabuddin and Kumar, 2007). In many parts of the world, forest cover change inside and outside protected areas due to local and regional human-use is well-established (DeFries et al., 2005; Zeng et al., 2005; Hansen and DeFries, 2007), although studies of the interaction of climate with human use are rarer (Barbier et al., 2006).

In most of the forested landscape of Southern Asia, identifying key drivers of forest change becomes even more difficult due to the long history of human occupation and use of these forests. In the recent past, a number of studies in India have focused on the

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impacts of human settlements on protected areas (PAs). These studies fall into two categories, those based primarily on ground-measurements of vegetation across a human-use gradient (e.g. Barve et al., 2005; Karanth et al., 2006; Kumar and Shahabuddin, 2005; Shahabuddin and Kumar, 2006, 2007) and others that rely on some remotely sensed data from one, two or three date satellite data to assess changes over space and/or time (Barve et al., 2005; Nagendra et al., 2006; Ostrom and Nagendra, 2006; Robbins et al., 2007).

Although these two approaches elucidate influence of human settlements on PAs, both have inherent shortcomings and are constrained by use of *a priori* classification of human use into disturbed and undisturbed sites. Studies based solely on ground based measurements at one time do not fully address issues of spatial coverage. On the other hand, the use of two or three date satellite data have to deal with issues of geo-rectification, classification accuracy and more importantly, influence of bio-physical variables (e.g. rainfall). The remotely sensed based approach typically underestimates the loss in conservation values over time as it does not account for hunting, livestock-grazing, collection of Non-Timber Forest Products (NTFP), habitat degradation and other human pressures that operate under the canopy at very small patch sizes and directly contribute to species loss (Hansen and DeFries, 2007). More importantly, attributing all observed vegetation changes to either human influence or bio-physical processes leads to a simplistic view of complex patterns and dynamics in landscapes that change over time.

We address this gap by assessing the impacts of both bio-climatic and human use influences on spatial patterns and dynamics of forests over decadal time-scales in the tropical forest landscape of Tadoba-Andhari Tiger Reserve, Maharashtra, India (hereafter TATR). Our study objectives were:

1. To quantify magnitude and direction of trends in forest greenness from 1982 to 2009 and identify possible drivers of change.
2. Assess spatial variability of the observed trends in forest greenness over time and quantify the influence of internal and fringe human settlements.
3. To quantitatively assess the influences of human settlements on spatial variability of ground based measurements of disturbance to flora and fauna.

1.1. Study area

Tadoba-Andhari Tiger Reserve spread over 625 km^2 is located in Chandrapur district of Maharashtra (Fig. 1a). It was designated as a “Tiger Reserve” in 1995 and includes two PAs, the Tadoba National Park (TNP), formed in 1955 with an area of 116 km^2 and the Andhari Wildlife Sanctuary (AWS), formed in 1986 with an area of 509 km^2. The reserve is situated within one of the global priority areas for tiger conservation (Sanderson et al., 2006) and is connected with several adjoining protected areas and reserved forests forming one of the largest blocks of contiguous forests in central India.

The terrain is gently undulating and hilly, interspersed with open grasslands and tropical deciduous forests and it receives an average rainfall of 1175 mm (±200 mm) annually. These forests support an impressive large mammalian assemblage including five large sympatric carnivores, which are highly threatened (Karanth and Kumar, 2005). Within this biologically rich area, there were six interior villages and 63 villages on the periphery at the time of this study; nearly 90,000 people from these villages used the forests for their varying resource needs. The State Forest Department has initiated several management interventions to consolidate this high potential tiger habitat, including a plan to relocate the six interior villages.

The forests in and around TATR have been managed ever since the area was declared a government Reserved Forest in 1879 (Khawarey and Karnat, 1996). Over several decades, gradual restrictions were imposed on the removal of timber, fuel wood and bamboo whereas most other NTFP could be extracted virtually with out any restriction (Khawarey and Karnat, 1996; Nagendra et al., 2006). Legal collection of NTFP was stopped in 1968 in TNP and 1992 in AWS; and concessions to graze and collect firewood were withdrawn in 1990. High human dependence on the forest, and proximity of settlements to the reserve has led to intense human-wildlife conflicts including loss of livestock and human lives to tigers or leopards (Khawarey and Karnat, 1996). Further TNP and AWS were declared as a tiger reserve in 1995, increasing the management intensity and spatial coverage.

2. Materials and methods

2.1. Vegetation change

We used remotely sensed vegetation indices, a measure of greenness, at two spatial scales (8 and 1 km) to estimate changes in forest vegetation over time. A reduction in greenness indicates degradation of vegetation cover or drying effects due to climatic conditions like drought. To characterize these dynamics in vegetation we used the maximum dry-season (December–March) Advanced Very High Resolution Radiometer (AVHRR) GIMMS NDVI dataset for the period 1982–2006. We used the dry season data as aerosol load was low throughout the subcontinent during this season (Tripathi et al., 2005), thus minimizing artifacts of changing aerosols load over time.

NDVI varies between −1 and +1, values of NDVI for vegetation generally range from 0.1 to 0.7, with values greater than 0.5 indicating dense vegetation. NDVI is derived using the following algorithm:

$$\mathrm{NDVI} = (\mathrm{C2} - \mathrm{C1})/(\mathrm{C2} + \mathrm{C1});$$

where C2 and C1 are near infra red and visible red channels.

Each 8 km pixel in the GIMMS dataset has been corrected for various atmospheric, aerosols, sensor degradation effects, and other effects not related to vegetation change (Tucker et al., 2004, 2005; Pinzon et al., 2005).

To assess the influence of human settlements on the observed vegetation change we used 1 km maximum Calibrated Vegetation Index (CVI) data set for the dry-season from 1986 to 1996 (NIES, 1997). We use the derived CVI data product to overcome problems associated with higher NDVI values due to degradation and sensor drifts. Each cloud free CVI image is developed from the AVHRR LAC scenes and is calculated from albedo values rather than raw channel reflectance values (Kidwell, 1991) and is defined as:

$$\mathrm{CVI} = (\mathrm{A2} - \mathrm{A1})/(\mathrm{A2} + \mathrm{A1});$$

where A2 and A1 are albedos calculated from weekly composites of the near infra red and visible red channels.

For the dry-season from 1999 to 2009 we used the maximum NDVI values from the 10 day composites of the 1 km SPOT VGT-S10 data product (Vegetation Programme, 2002). Long-term rainfall anomalies for this region were obtained from the Indian Institute of Tropical Meteorology (Indian Institute of Tropical Meteorology, 2008). Data from 64 stations (Kulkarni and Nandargi, 1996) for the period 1900–2006 was used to calculate rainfall anomalies.

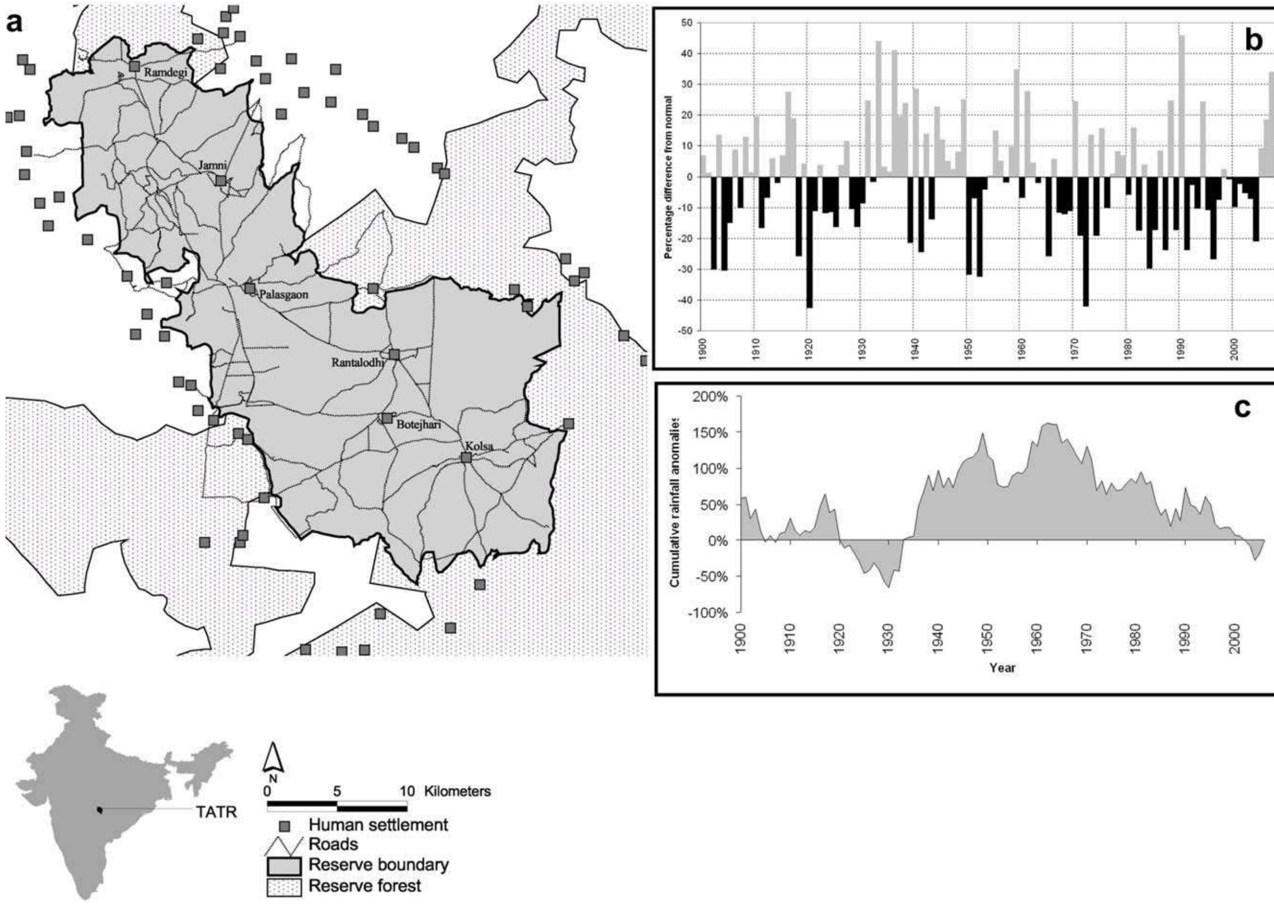

Fig. 1. (a) Location of the study site, Tadoba-Andhari Tiger Reserve (TATR) a protected area in the state of Maharastra, India. (b) Annual rainfall anomalies in the Vidharbha region, which encompasses TATR for the period 1900–2006. (c) Cumulative annual rainfall anomalies shows declining rainfall starting from the 1960s, rainfall anomalies were derived from the IITM rainfall dataset for 64 stations.

2.2. Field surveys

Field surveys were conducted between October 2002 and April 2004 to record direct observations of human impacts within TATR. We defined impacts as all illegal human activities that directly affect the integrity and functioning of the ecosystem. These were classified into six categories, wood extraction, grazing, fire, poaching, NTFP collection and human-wildlife conflicts. Human-wildlife conflicts included loss of livestock and human life to wild predators, as well as retaliatory killing of wildlife by humans. Some illegal activities, like forest fire, are difficult to distinguish from management interventions (e.g. creation of fire lines as fire protection strategy), under such circumstance the field teams consulted with the accompanying forest guard and if there was any uncertainty, data was not recorded. Entire TATR was extensively surveyed by foot or vehicle covering all the available trails within the reserve. GPS location of each illegal human activity encountered during the survey was recorded along with its forest administrative unit. A total of 534 km of road/trail network was twice surveyed jointly with forest department staff and the data was shared with the concerned forest guard.

2.3. Analytical methods

2.3.1. Trend analysis

The non-parametric Sen's slope (Sen, 1968) was used to quantify the magnitude of the trend in the time-series of CVI and NDVI data. This approach involves computing slopes for all the pairs of ordinal time points and then using the median of these slopes as an estimate of the overall slope. Unlike linear regression, it is not greatly affected by data errors, outliers, or missing data. The 1 km remotely sensed data sets were used for analyzing spatial variability of trends in each period (1986–96; 1999–2009) using all pixels within the reserve.

We used the robust non-parametric Seasonal Trend Decomposition with Loess (STL) method in R statistical software (R Development Core Team, 2009) to extract the cyclic and trend components in the time-series of NDVI and rainfall (Cleveland et al., 1990).

The STL method decomposes a time series using an iterative technique based on locally weighted least squares to progressively estimate trend, seasonal and residual components with increasing refinement:

$Y_{(t)} = TREND_{(t)} + CYCLIC_{(t)} + RESIDUAL_{(t)}$, where $Y_{(t)}$ is the response variable time-series (e.g. NDVI or rainfall). The STL method consists of a series of applications of a Loess smoother with different moving window widths chosen to extract a specified important approximate frequency corresponding to a quasi-cyclic variability within a time series. We used a 3 year cycle based on known knowledge of the most dominant quasi-cyclic (approximately cyclic) oscillations observed in rainfall in India (Vijaykumar and Kulkarni, 1995). The non-parametric nature of STL makes it suitable for dealing with non-linear trends.

2.3.2. Spatial correlation and regressions

Ecological processes, including vegetation change over time and human impacts are spatially auto-correlated and hence it is necessary to explicitly account for spatial dependence (Cressie, 1993; Legendre, 1993). In a large forested landscape, it is very likely that sites with similar (high or low) values of vegetation change would tend to be clustered and several spatially auto-correlated processes including vegetative propagation, effects of grazing, fire and human extraction of biomass are known to influence such changes at a site. Similarly, recovery in vegetation at these sites would also tend to be spatially auto-correlated.

Moran's I was used to assess spatial dependence patterns, the spatial autocorrelation dropped sharply from 0.66 ($p \sim 0$) at 1 km to 0.02 ($p \sim 0$) at 15 km for the remotely sensed trend index and from 0.70 ($p \sim 0$) to 0.02 ($p \sim 0$) for the ground based impact index. Much of the spatial autocorrelation is accounted for within 10 km for variables of interest, thus the need for a regression that explicitly incorporates spatial autocorrelation was established and we chose a 10 km neighborhood distance for defining our spatial regression models. We fit a spatially lagged regression model, given below, in which the dependant variable is the measure of vegetation change over time or measured human disturbance and the independent variable is a driver variable. The neighborhood structure was defined as all pixels within 10 km of each observation location based on Moran's I values (Kaluzny et al., 1998; Lichstein et al., 2002) and covariance model structure chosen was Conditional Auto Regression (Kaluzny et al., 1998).

$$y = \rho Wy + X\beta + \varepsilon,$$

where y is the response variable (e.g. rate of vegetation change in a pixel), Wy is a spatially lagged response variable for weights matrix W, X is the explanatory variable (e.g. distance to nearest village) and epsilon is the error term and ρ and β are parameters.

The spatial regression models were diagnosed using p-values and parameter estimates. Each model was compared with the null model of "No regression effect" using the Likelihood Ratio test (Cressie, 1993). Spatial regressions were implemented in the GEO-DA software (Anselin et al., 2006). The response variable was the vegetation change over time (Sen's-slope) and covariates included distance to nearest village, number of villages within the distance of 10 km, Human Influence Index (see below) and initial greenness as measured by NDVI/CVI.

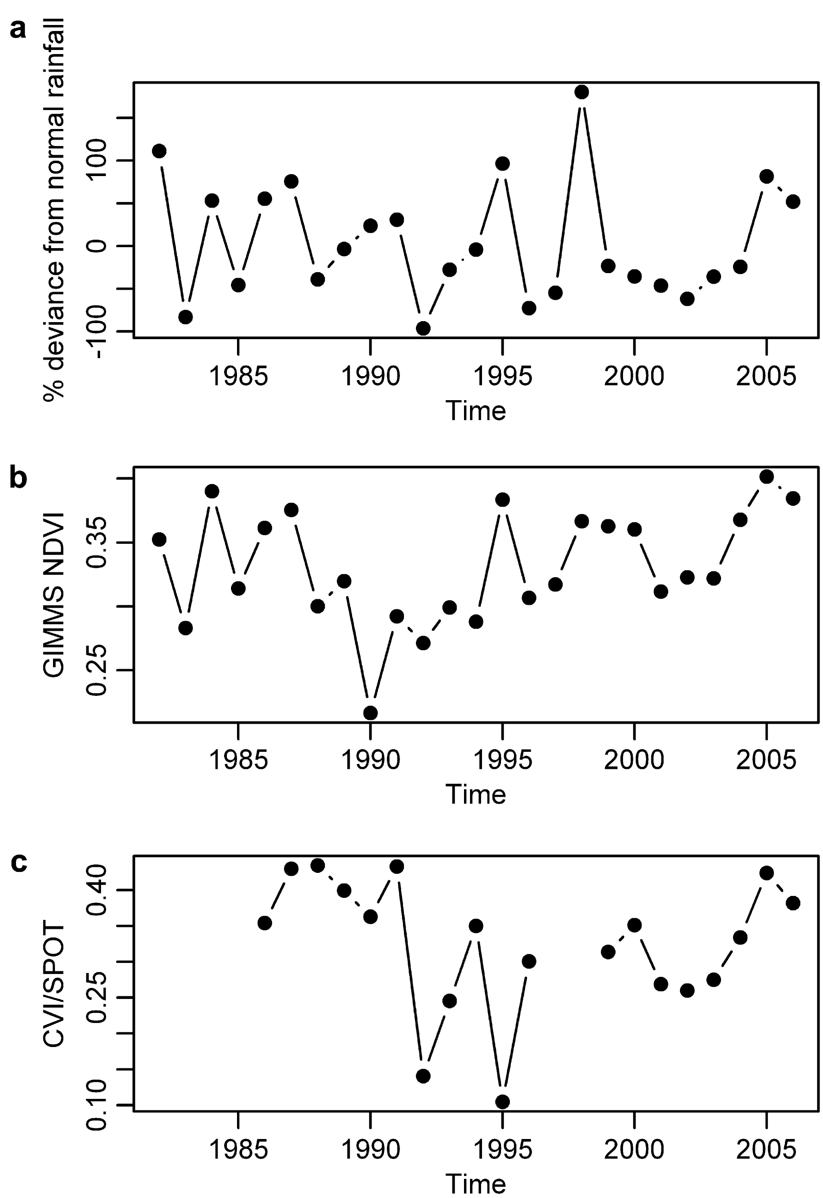

Fig. 2. Raw time series of dry-season rainfall and vegetation greenness.

2.3.3. Quantifying human impacts on biodiversity

For each disturbance type, a kernel density estimate was derived following Silverman (1986) and a Combined Impact Index (CII) was calculated by summing the individual disturbance estimates to identify zones of human impacts.

The kernel density estimate, $\hat{f}(x)$, for a set of n points is defined as:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)$$

where K is the kernel function and h window width, determined by the k nearest neighbor distance. This estimate provides a magnitude per unit area from point features using a kernel function to fit a smooth surface to the entire landscape. The density surfaces show where impacts are concentrated and also the predicted distribution of impacts throughout the landscape.

We also computed a 'Human Influence Index' for each point where a direct impact to flora or fauna was observed and, was defined as:

$$\sum_{i}^{j} n/d$$

where d is the distance to settlement within 10 km, the distance that accounted for most of the spatial autocorrelation in the data, from the point and n is the corresponding human population. This index gives higher 'influence' value to areas closer to settlements with large populations and lower 'influence' values to areas situated far away from smaller settlements.

3. Results

3.1. Vegetation change

The TATR landscape and other forests in central India have seen major trends and swings in rainfall in the last 100 years (Fig. 1b) and a reduction in rainfall starting from the 1960s (Fig. 1c). The rainfall for the period 1982–2006 indicates a high inter-annual variability of a quasi-cyclic type with high amplitude (Fig. 2a). A similar pattern is also observed in the dry season GIMMS NDVI, CVI and SPOT NDVI values (Fig. 2b and c).

Rainfall anomalies were defined over different seasonal and annual periods: over the previous year, for the months just before and during the dry-season (October–March) and correspond exactly with the dry-season (December–March) satellite data. Rainfall anomalies were analyzed in terms of their ability to explain inter-annual variability and trends in dry-season greenness. Only the dry-season rainfall anomalies emerged as a strong positive predictor of GIMMS dry-season greenness ($R^2 = 0.31$, p-value = 0.004) followed by the October–March anomalies ($R^2 = 0.21$, p-value = 0.02).

The STL trend analysis of the dry-season rainfall anomalies indicates a period of decline and recovery in rainfall (Fig. 3a). The trend analyses of vegetation greenness clearly shows similarity in the overall direction of trend in vegetation response (Fig. 3b and c), are driven by dry-season rainfall anomalies with a change point indicated in the mid-90s. However the trends in rainfall and corresponding trend in greenness differs between the loss and the recovery period (Fig. 3). In the loss period the decline in rainfall is steep, and the decline in greenness is moderate but in the recovery period, the response of vegetation is very strong (Fig. 3). The SPOT NDVI time-series (1998–2009) was very strongly and positively correlated with dry-season rainfall anomalies ($R^2 = 0.82$, $p = 0.002$), although the AVHRR CVI index (1986–96) did not show such a linkage ($p = 0.68$). These results corroborate the results from the GIMMS dataset and are supported by the graphical analyses of trends in vegetation response (Fig. 3).

3.2. Spatial variability

The spatial dependence patterns of vegetation change (Fig. 4a and b), indicate major differences in the loss and recovery periods. The loss period is characterized by spatial coherence and synchronicity in the decline over the entire landscape, whereas the spatial pattern in the recovery period is more heterogeneous (Fig. 4b). Vegetation greenness in some parts of TATR continued to show decline whereas other areas showed a recovery.

The spatial regression models indicate that the most influential covariates that explains the spatial variability in rates of vegetation greenness change during the two time periods are mainly the initial greenness, proximity to nearest village and to a much weaker extent, the number of human settlements within 10 km for a given pixel (Table 1). Other measures of human influence fared poorly, although there was some support for these covariates relative to the null model (Table 1). The most important result is that sites with *low* greenness tended to gain *more* over time and those with *higher* greenness tended to *lose* over time, and this was consistent over both time periods. However the initial values of greenness (as reflected in the intercept) were lower in the recovery period and the slope of the relationship is also steeper in the recovery period.

3.3. Impacts to flora and fauna on the ground

A total of 1089 locations with human impacts were recorded within the reserve during the study period. These included 145 instances of human-wildlife conflicts including one case of human death, 97 cases of poaching and 350 observations of NTFP collection. Fig. 4c shows the spatial distribution of the Combined Impact Index (CII), an integrated measure of observed impacts and indicates zones from low to high impacts on biodiversity. The spatial distribution of human impacts varied considerably (Fig. 5), while impacts such as human-wildlife conflicts, grazing, and wood extraction are concentrated around human settlements; others like forest fires and poaching are pervasive throughout the reserve.

The spatial regression models (Table 1) indicate that the human impacts increases with proximity to a larger number of villages, but at low magnitudes and strongly suggests that distance to nearest village is a significant driver of ground based measurements of human impacts.

4. Discussion

4.1. Vegetation change

It is increasingly evident that measurements of biodiversity or ecological attributes locally have to be linked to bio-physical and anthropogenic processes at larger spatial scales to ensure that we do not erroneously attribute changes observed locally to local drivers alone (DeFries, 2008; DeFries et al., 2009). The TATR landscape has seen major swings in rainfall over the past 106 years, and is thus expected to be dynamic over decadal and longer time-scales. In recent decades it has seen a major drying trend like other parts of India (Ramanathan et al., 2005) with implications for a range of ecological and bio-physical attributes especially degree of deciduousness, species composition, structure and sensitivity to fire. In addition to these long-term trends, there is also considerable inter-annual and seasonal variability in rainfall that could potentially drive forest vegetation response. However, there are anthropogenic feed-backs that can have major lingering effects to sustain and strengthen shorter term vegetation response to climatic variability and trends.

Rainfall and in particular, dry-season rainfall seems to be a major driver of dry-season forest greenness in TATR. Our study corroborates an earlier finding from Africa (Richard and Poccard, 1998) and Brazil (Gurgel and Ferreira, 2003) where NDVI variability is affected by the prevailing climatic conditions. Furthermore, the spatially synchronous decline in NDVI in TATR (Fig. 4a) was followed by a recovery (Fig. 4b) in the mid-90s and this was clearly driven by very similar trends in rainfall (Fig. 3a).

However, the strength of the linkage between greenness and rainfall is different between the two periods, suggesting other factors at work. Clearly the drought during 1982–85 (Fig. 1c) triggered a declining response in forest vegetation condition. This was followed by the flowering and mass death of bamboo (1981–83) and subsequent wide-spread disturbances, such as severe forest fires, extraction of dead bamboo by large deployment of workers which led to the opening up of the canopy (Choudhury, 1986). In addition greater pressure from internal and external forest dependant people may have reinforced the decline in NDVI just as better management, re-growth of bamboo, fire control, and restrictions on extraction of biomass (Nagendra et al., 2006), after the area was declared a Tiger reserve, reinforced the recovery after 1995. This interpretation is supported by the stronger relationship between rainfall and vegetation greenness in the latter period. Remarkably, studies on the rainfall-greenness dynamics in the Sahel have also reported two distinct phases similar to that observed in the TATR landscape, and have attributed the dynamics to interaction between bio-climatic processes and land-use changes (Anyamba and Tucker, 2005; Herrmann et al., 2005).

All the trends that we have detected are not likely to be due to sensor artifacts, as GIMMS NDVI has been corrected for potential

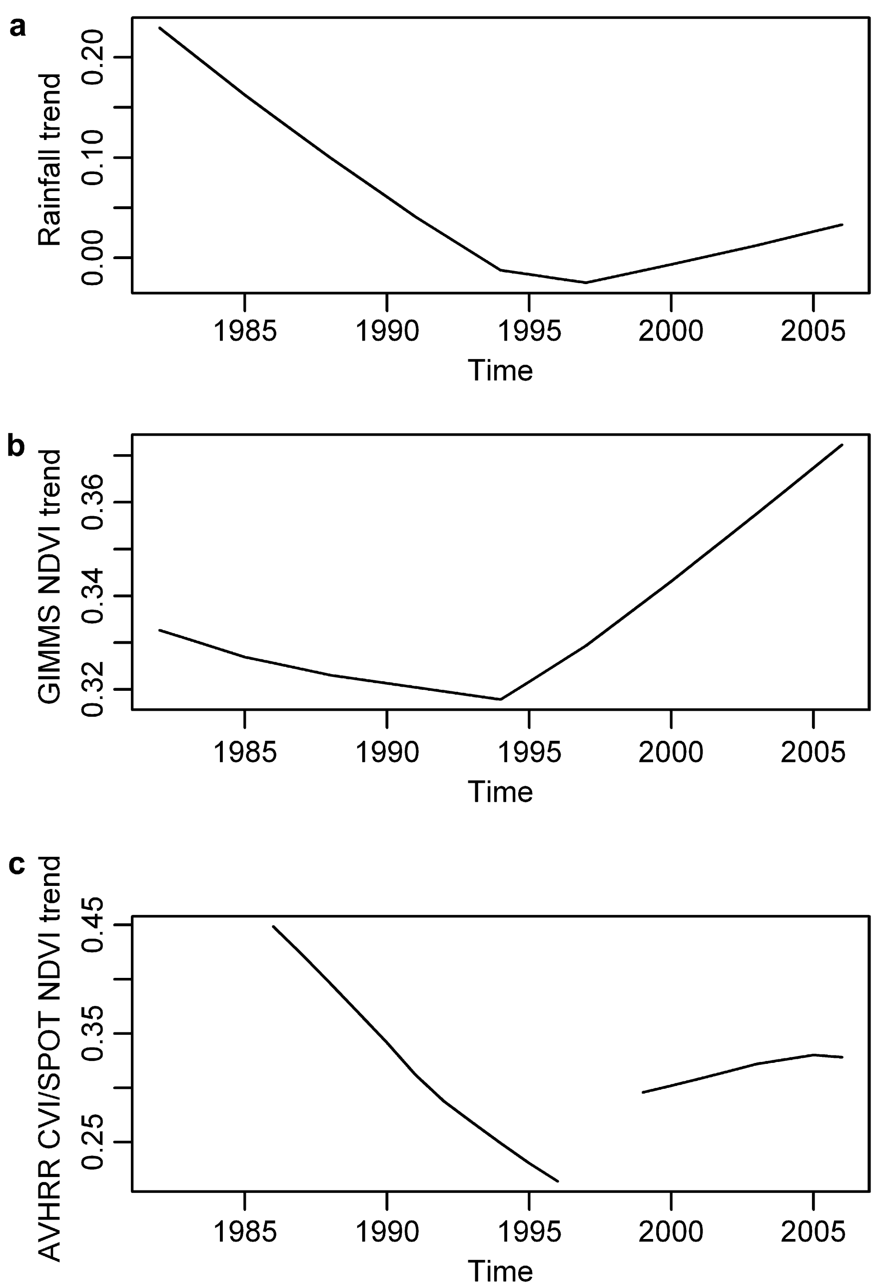

Fig. 3. STL trends in dry-season rainfall and vegetation greenness.

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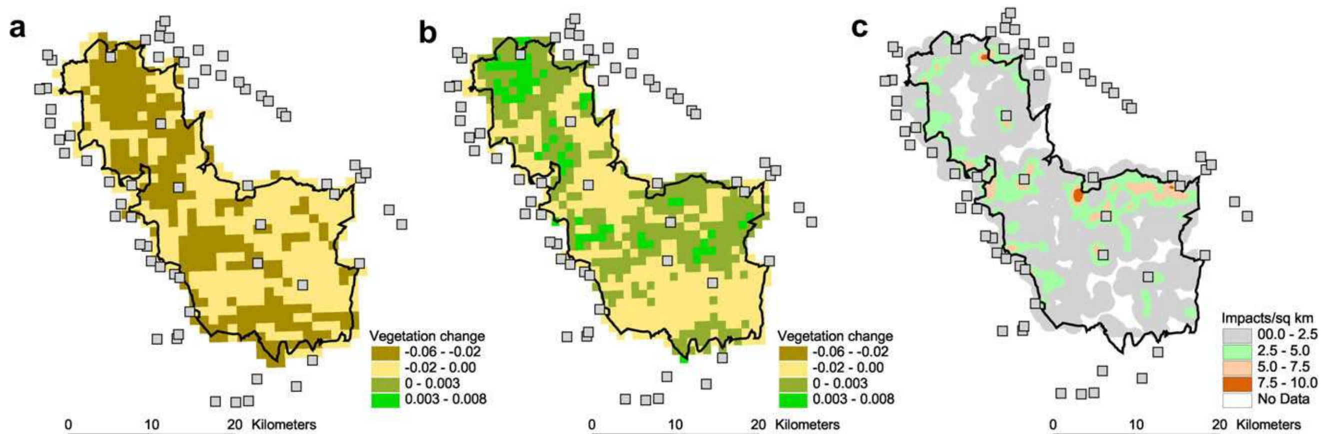

Fig. 4. A comaprison of trends from above and below the canopy. (a) Change in forest greenness in the TATR landscape for the period 1986–1996 derived from Sen's slope of the CVI datase. (b) Forest greenness change for the period 1999–2009 derived from Sen slope based on SPOT NDVI data set. (c) The derived Cumulative Impact Index of human impacts assessed from ground surveys.

Table 1
Results of spatial regression have been presented below, based on the Moran's I a spatial neighborhoods of 10 km were defined to account for spatial auto correlation. Each regression model was compared with the null model of "No regression effect" using the Likelihood Ratio test, results of this is reported in column six.

Response variable	Explanatory variable	p	β_0	β_1	LR test p value
Greenness change 1986–1996 (n = 584)	DNV	0.001	0.839	−0.001	0.000
	NoV	0.010	0.748	−0.0001	0.000
	IG	0.036	0.872	−0.0156	0.000
	HII	0.873	0.840	−5.14E−07	0.000
Initial greenness 1986–1996 (n = 584)	DNV	0.083	0.982	0.003	0.000
	NoV	0.368	0.982	0.0004	0.000
	HII	0.167	9.82	−2.8E−05	0.000
Greenness change 1999–2009 (n = 737)	DNV	0.000	0.943	0.0001	0.000
	NoV	0.000	0.663	0.0002	0.000
	IG	0.000	0.799	−0.0198	0.000
	HII	0.879	0.934	−6.3E−08	0.000
Initial greenness 1999–2009 (n = 737)	DNV	0.033	0.981	0.002	0.000
	NoV	0.006	0.979	−0.0005	0.000
	HII	0.284	0.981	5.9E−06	0.000
Combined Impact Index (n = 1085)	DNV	0.000	0.852	−0.466	0.000
	NoV	0.071	0.920	−0.026	0.000

Note: explanatory variable DNV = distance to nearest village in kilometers; NoV = number of villages within 10 km; IG = initial greenness; HII = Human Influence Index.

sources of erroneous trends (Brown et al., 2006). The trends observed using two different satellites and sensor based measures (GIMMS and SPOT NDVI) corroborate each other and furthermore, time-series of GIMMS NDVI are known to be the most conservative in trends compared to other measures and has been noted to give no spurious trends even for control sites such as deserts (Baldi et al., 2008). Thus NDVI trends in our study are more likely responses to climate and other drivers at local and regional scales rather than the artifacts of satellite measurement and/or data processing.

4.2. Spatial patterns and variability

In an earlier study carried out between 1989 and 2001, Nagendra et al. (2006) conclude that fringe villages in TATR are associated with greater deforestation rates and higher forest fragmentation compared to the settlements within the park. However, our study does not support this view and suggests a far more complex spatial pattern and dynamics showing higher rates of vegetation loss even in the interiors of TATR during the periods 1986–1996 and 1999–2009. During the first time period, the entire landscape shows a systematic decline and in the later half of the study, areas around exterior and interior human settlement continue to decline while others show recovery in vegetation greenness (Fig. 3a and b). Our results for both the time period (Table 1) indicate that the rate of greenness change is *negatively* associated with initial greenness: suggesting that sites with *higher* greenness tended to *lose more* and sites with *lower* initial greenness *gained more* over time. This suggests a spatially dynamic agent or process that selectively targets and consumes vegetation or greenness *only* if it is of sufficient quantity and quality, allowing depleted sites to recover slowly. In the TATR context, such agents include biomass extraction by people, cattle, wild herbivores and fire (as a function of fuel load). Moreover initial greenness is positively correlated with distance to nearest village and number of villages within 10 km, suggesting that historical patterns of landuse, disturbance and biomass extraction influence initial conditions of greenness. Additionally, bio-climatic processes interact with these initial conditions and local agents to generate a spatially dynamic landscape.

Furthermore, our interpretation of an interaction between landscape scale and local landuse is strengthened by the observed spatial pattern of vegetation greenness as a response to human activities, varies between the two periods: in the first period, the closer a site was to a village or to all villages, the more negative was the decline in greenness over time, whereas in the recovery period, this was reversed, highlighting the role of bio-climatic

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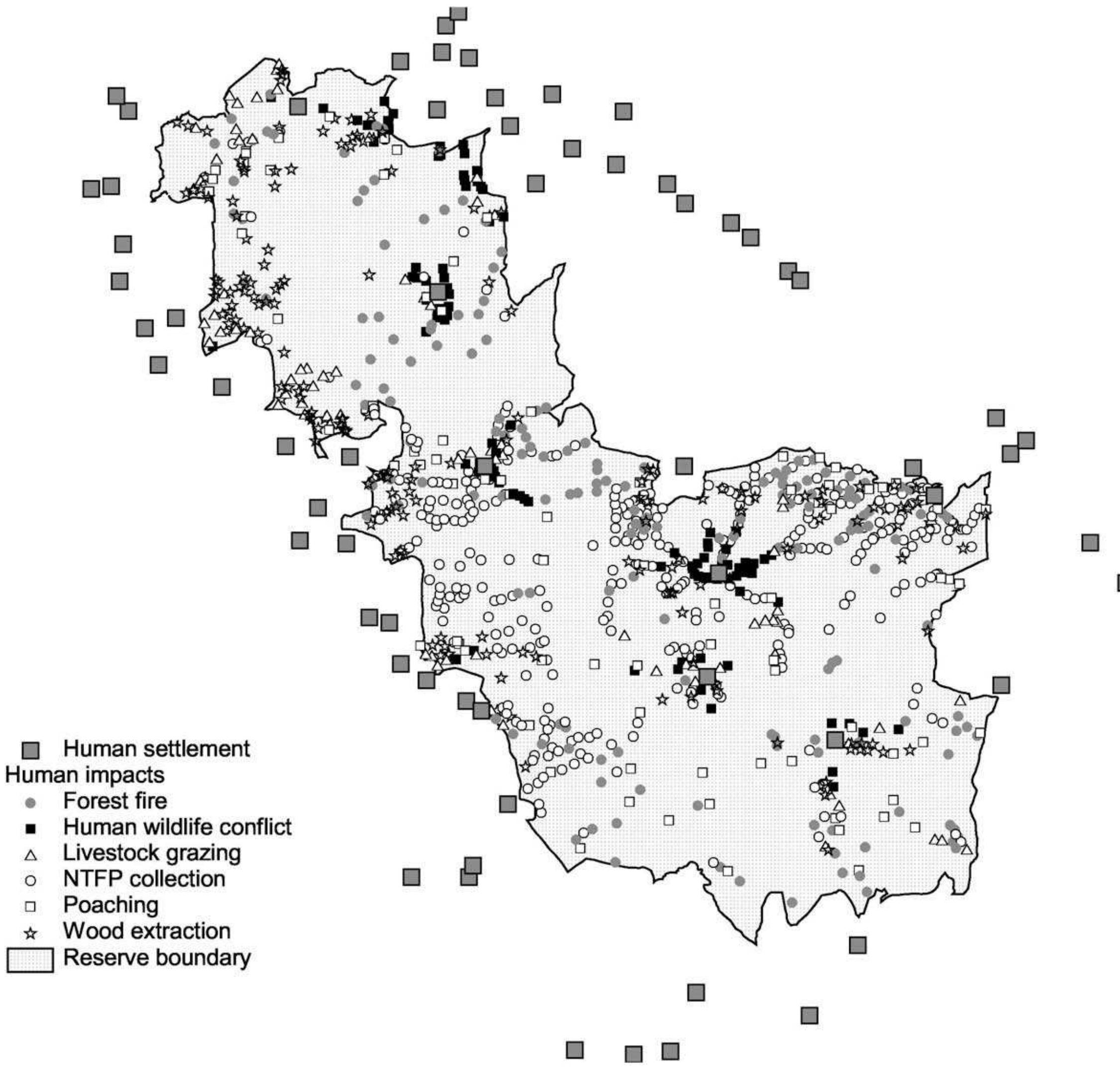

Fig. 5. Spatial representation of human disturbances collected during field surveys conducted in TATR.

change reinforced by either negative or positive feed-back from local human use of the landscape and reserve management.

4.3. Impacts to flora and fauna on the ground

Ground impacts on flora and fauna were widespread in 2002–2004 in spite of improved management effectiveness. Some impacts such as NTFP collection (which includes bamboo) was clustered, often further away from settlements, possibly reflecting the clustered nature of many NTFP species such as bamboo (Taylor and Qin, 1992). In contrast, wildlife poaching and forest fires were widespread throughout the TATR landscape. Cattle grazing, wood collection and human-wildlife conflicts were more localized around villages. The former category of impacts located away from villages are all related to products which are collected on a commercial scale in response to market demands outside the reserve, whereas the latter are largely local and subsistence driven. Fire is generally known to be associated with NTFP collection, poaching and cattle grazing, and is a collateral activity (Saha, 2002). Overall the Combined Impact Index that integrates across all ground measured impacts to flora and fauna was unambiguously positively associated with proximity to human settlements (Table 1). Even though such activities under the canopy were widespread, they would usually not affect remotely sensed measures of forest condition unless forest fires and biomass extraction are of sufficiently large spatial scale. In the current study, the remotely sensed data are of 1 km resolution, and are thus incapable of detecting smaller scale ground processes. It is possible that with use of finer scale, active satellite imagery, localized disturbances and changes would be detected with the exception of poaching, which can be widespread under a forest canopy that appears thriving and healthy from satellites.

4.4. A view from above and below the canopy

This study highlights the advantage of using a time series of satellite images over two-date post-classified change detection, which has severe limitations. In the latter approach, it is difficult to achieve consistency in the classification scheme for two different time-periods, and very high accuracies should be achieved for both image classifications in order to have some degree of confidence in the estimation of change categories, especially if the percentage of pixels undergoing change are comparable to the compounded misclassification of pixels in the two time-periods. Methods that use time-series of remotely sensed variables such as NDVI are likely to be more effective in capturing gradual changes in forest vegetation (e.g. forest degradation or improvement) over time. Limited date, change detection on classified images (e.g. Nagendra et al., 2006; Ostrom and Nagendra, 2006; Robbins et al., 2007) are likely to either overestimate deforestation, or detect it when its really forest degradation or even underestimate positive changes in forest vegetation in landscapes such as TATR. A continuous gradual change in forest condition over time could lurk within a classified category and not get detected. Therefore the use of a time-series of 1-km CVI or NDVI data that are continuous and capture dynamics of landscape change is recommended over comparisons of two or three-dates of classified land-cover maps which cannot capture these complex dynamics. Although we lose out on spatial resolution, we gain immensely in terms of accuracy and ability to capture complex dynamics. This advantage further emphasizes the need to develop and standardize methods to analyze such spatio-temporal datasets thus providing a frame work to evaluate significance of such studies in light of natural variability.

In the present study, changes in forest greenness at the landscape scale over time and its spatial distribution are influenced by climatic regimes, anthropogenic disturbances, management practices, and their interactions. In contrast, spatial variability in ground based measurements of human impacts was better explained by proximity to human settlements. Our results bring out the complex interaction of bio-physical and anthropogenic processes at the landscape level across space and time, emphasizing the need to incorporate both ground based and remotely sensed assessments to monitor ecologically critical areas. It is also essential that ground-measurements of anthropogenic impacts be periodically undertaken because these are generally not captured by trends in remotely sensed surrogates of forest condition over time. A forest may look flourishing from above the canopy, but may be severely degraded underneath. Improvements in sensors and spatial resolution may reduce the gap between information from satellite data and from ground-measurements but is unlikely to be an effective substitute for field data on abundance of vulnerable species of flora and fauna, spread of invasive species and impaired soil functions.

The ecological footprint of distant towns, cities and external pressures emanating from enhanced consumer demand for protected area goods and services (e.g. tourism, water resources, timber, NTFP, etc.) also need to be considered along with effects of local use (DeFries, this issue). A better understanding of long-term bio-climatic processes and their interactions with human activities on the ground at various spatial and temporal scales will better inform management decisions in order to maximize gains to biodiversity conservation, promote landscape connectivity and enhance people’s welfare.

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