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Parks protect forest cover in a tropical biodiversity hotspot, but high human population densities can limit success

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ABSTRACT

Maintaining forest cover is important for Biodiversity Hotspots that support many endangered and endemic species but have lost much of their original forest extent. In developing countries, ongoing economic and demographic growth within Hotspots can alter rates and patterns of deforestation, making it a concern to quantify rates of forest loss and assess landscape-scale correlates of deforestation within Hotspots. Such analyses can help set baselines for future monitoring and provide landscape-scale perspectives to design conservation policy. For the Western Ghats Biodiversity Hotspot in India, we examined correlates of forest loss following rapid economic expansion (post-2000 CE). First, we used open-source remote-sensing data to estimate annual trends in recent forest loss (from 2000 to 2016) for the entire Hotspot. Across the entire Western Ghats, we assessed the relative importance of and interactions among demographic, administrative, and biophysical factors that predicted rates of forest loss—measured as the number of 30 × 30-m pixels of forest lost within randomly selected 1 km^2 cells. Protected areas reduced forest loss by 30%, especially when forests were closer to roads (33%) and towns (36%). However, the advantage of protection declined by 32% when local population densities increased, implying that the difference in forest loss between protected and non-protected areas disappears at high local population densities. To check scale-dependency of spatial extent, we repeated the modelling process for two landscape subsets within Western Ghats. In contrast with results for the entire Western Ghats, both focal landscapes showed no difference in deforestation with protection status alone or its interactions with village population density and distance to towns. However, deforestation was 88% lower when forests were protected and farther from roads. Overall, our results indicate that protected areas help retain forest cover within a global Biodiversity Hotspot even with rapid development, but high human population densities and road development can reduce the benefits of protection.

1. Introduction

Tropical forests hold nearly half of Earth's biodiversity and provide ecosystem services to millions of humans. Despite a slowing of the tropical deforestation trends from 1990 to 2000 (Butler and Laurance, 2008; Wright and Muller-Landau, 2006), recent global analyses of forest-cover change indicate that forests continue to be lost at nearly 3% annually (Asner et al., 2009; Hansen et al., 2013; Margono et al., 2014). Meanwhile, global agreements to stem climate change and biodiversity losses mandate that 17% forest cover be maintained as biodiversity habitats (CBD; Aichi Biodiversity Targets, Strategic Goals C, Target 11). Such biodiversity goals established by global agreements are eventually met through national policies for forest protection and local drivers of deforestation (Abood et al., 2015; Kremen et al., 2000; Margono et al., 2014). Hence, underscoring the need for multiscale assessments of deforestation, the UNFCCC negotiations have encouraged countries to identify local factors linked to forest loss, and use that information to design conservation policy (UNFCCC, 2009).

Understanding contemporary patterns and identifying associated factors of forest loss is especially important for Biodiversity Hotspots—1.5% of Earth's area that hold nearly 44% of global plant richness and 35% of vertebrate richness (Myers et al., 2000). Most Hotspots encompass areas with differing intensities of human use, where protected areas are distributed in a matrix of human-dominated

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landscapes such as agriculture and multiple-use forests that are subject to greater pressures for land-use change than strictly protected forests (Barber et al., 2014; Berkes, 2009; Shahabuddin and Rao, 2010). Patterns of forest loss due to land-use change are often correlated with biophysical variables such as local climate, topography, and proximity to water sources, which determine suitability of land for conversion to agriculture or settlements. For example, forest loss tends be greater at lower elevations, shallower slopes, and closer to rivers and lakes (Green et al., 2013). However, the biophysical correlates of forest loss are mediated by land-use decisions in relation to demographic pressures of local population size and socio-economic conditions (Gardner et al., 2007; Laurance and Wright, 2009; Roy and Srivastava, 2012; Sirén, 2007; Wright and Muller-Landau, 2006).

Specifically, higher rural populations in the proximity of forests could cause greater forest loss, either through conversion of land for agriculture or through increased resource extraction from forests (Davidar et al., 2008; Laurance et al., 2002). Moreover, rural patterns of forest use and forest-based livelihoods can be directly or indirectly shaped by consumer demands in urban centres in a growing economy with increasing connections to larger markets (Rudel et al., 2009; Shackleton et al., 2011). Thus, in many developing nations, proximity to urban centres can influence forest loss by regulating market demand for forest goods or via changes in patterns of land- and forest-use (DeFries et al., 2010; Madhusudan, 2005). Besides altering patterns of forest-based livelihoods, economic development is accompanied by increased construction of infrastructures such as roads, canals, and powerlines, which often lead to forest loss and negatively impact biodiversity (Laurance et al., 2014, 2009).

In addition, administrative factors such as local governance and legal protection status (henceforth, protected areas) regulate forest-cover change (Andam et al., 2008). Local resource use and infrastructure development are often subject to greater oversight within protected areas (Barber et al., 2014; Bruner et al., 2001). However, national and local motivation to protect, which affects whether protected areas successfully retain forest cover, can change with developmental trajectories influenced by international markets, national resource base, and changing economic opportunities (Bradshaw et al., 2015; Rudel, 2007). Thus, evaluating the efficacy of protected areas in retaining forest cover in a Biodiversity Hotspot in relation to demographic and development factors could provide one benchmark of whether legal protection is meeting its objectives (Roy and Srivastava, 2012). Moreover, establishing baseline forest cover and assessing ongoing correlates of forest loss can aid long-term monitoring of changes in forest cover across large spatial scales.

Across large landscapes, baseline forest cover can be established and trends in forest cover change monitored using readily available satellite imagery of high quality and resolution (Margono et al., 2014; Rudel et al., 2005). Remotely sensed data offer a powerful tool to link patterns of forest loss to its potential drivers across large landscapes that are often impossible to survey physically in entirety (Hansen et al., 2013, 2010; Kurz, 2010; Margono et al., 2014). Furthermore, demographic and administrative factors linked to forest loss can vary with spatial scale and region across large landscapes (Margono et al., 2014). For example, development trajectories and implementation of conservation laws can differ between local governance units such as states and provinces, leading to scale-dependence in drivers of forest cover change (Nolte et al., 2013). In this regard as well, remotely sensed data can be analyzed at multiple spatial extents to link landscape assessments better with necessary policy interventions.

In this study, we analyzed landscape-scale correlates of forest loss in the Western Ghats of India—among the most threatened of global Biodiversity Hotspots (Myers et al., 2000) (Fig. 1). Recently designated a UNESCO World Heritage Site, it holds viable populations of endangered wild mammals such as tiger (*Panthera tigris*), Asian elephant (*Elephas maximus*), Asiatic wild dog (*Cuon alpinus*) and gaur (*Bos gaurus*). The Western Ghats also contains unique habitats such as the montane Shola-grassland ecosystems (Jose et al., 1994) and wet evergreen forests with high endemism for plants (56%), amphibians (78%), and reptiles (62%) (Gunawardene et al., 2007; Myers et al., 2000). Simultaneously, the region has high human population densities averaging 350 people/km^2 (Cincotta et al., 2000), good development indices, historically intensive agriculture, and a relatively small extent of area under strict protection compared to global targets (Cincotta et al., 2000; Sloan et al., 2014).

Large dams and agriculture were major causes of forest loss in the Western Ghats from 1950 to 1990 (Jha et al., 1995), but the rate of forest loss has slowed since 1990 (Reddy et al., 2016). Reduced forest loss could be driven by changing economic paradigms since 1990, which slowed agricultural expansion and increased migration of rural populations to cities, potentially lowering population pressures on forest. However, India's economic liberalization since 1994 fueled the development of roads and highways in rural and forested areas, which often required clearing forests (Bawa et al., 2007). Changing developmental paradigms and accompanying demographics could increase or decrease net forest loss and influence spatial patterns in drivers of forest loss (Rudel et al., 2009), but remain unexamined for the Western Ghats. Hence, we examined the following questions:

1. What are the recent trends in forest loss (from 2000 CE) in the Western Ghats, a populous Biodiversity Hotspot experiencing economic development and infrastructure expansion?
2. How does forest loss correlate with demographic, biophysical and administrative factors across a Biodiversity Hotspot? Specifically, does protection status, greater distance from roads and towns, and lower human population densities decrease forest loss?
3. Do correlates of forest loss vary with spatial extent of analysis?

We expected decadal forest loss to be higher in more populous areas and that shorter distances to roads and towns would be associated with greater forest loss. Importantly, we expected that the effect of population and distances to road and town would be modified by protection status—protected (wildlife sanctuaries and national parks) versus non-protected areas.

2. Materials and methods

2.1. Data collection

We quantified annual rates of deforestation using the Global Forest Change (GFC, version 1.6) forest loss dataset—a high-resolution global map compiled from Landsat ETM+ images, in which forest loss is defined as stand-replacement disturbance, or a change from forest to non-forest (Hansen et al., 2013). Using this dataset, we calculated the number of 30×30 m pixels deforested per km^2 for each year from 2000 to 2016 (89,681 total pixels).

To assess factors associated with forest loss, we compiled biophysical, demographic, administrative, socio-economic and landscape data from multiple sources (Table S1). We used slope, elevation, and distances to rivers and lake as biophysical predictors because forest loss can decrease on steeper slopes, higher elevations, and farther from water sources, all of which influence human settlements and agriculture and thus mediate forest loss (Green et al., 2013). In addition, we used mean annual rainfall—obtained from the BIOCLIM dataset (Hijmans et al., 2005)—which explains the most variation in species composition of Western Ghats forests (Krishnadas et al., 2016). We calculated elevation and slope from ASTER GDEM satellite data (Table S1) and created rasters of landscape variables for distance to the nearest lakes and rivers. As demographic indicators, we used local human populations and distances to roads and towns—proxies for market linkage and economic development (Green et al., 2013)—expecting higher forest loss in more populous areas and closer to roads and towns. We used decadal census data collected in 2001 and 2011 (Table 1) to generate

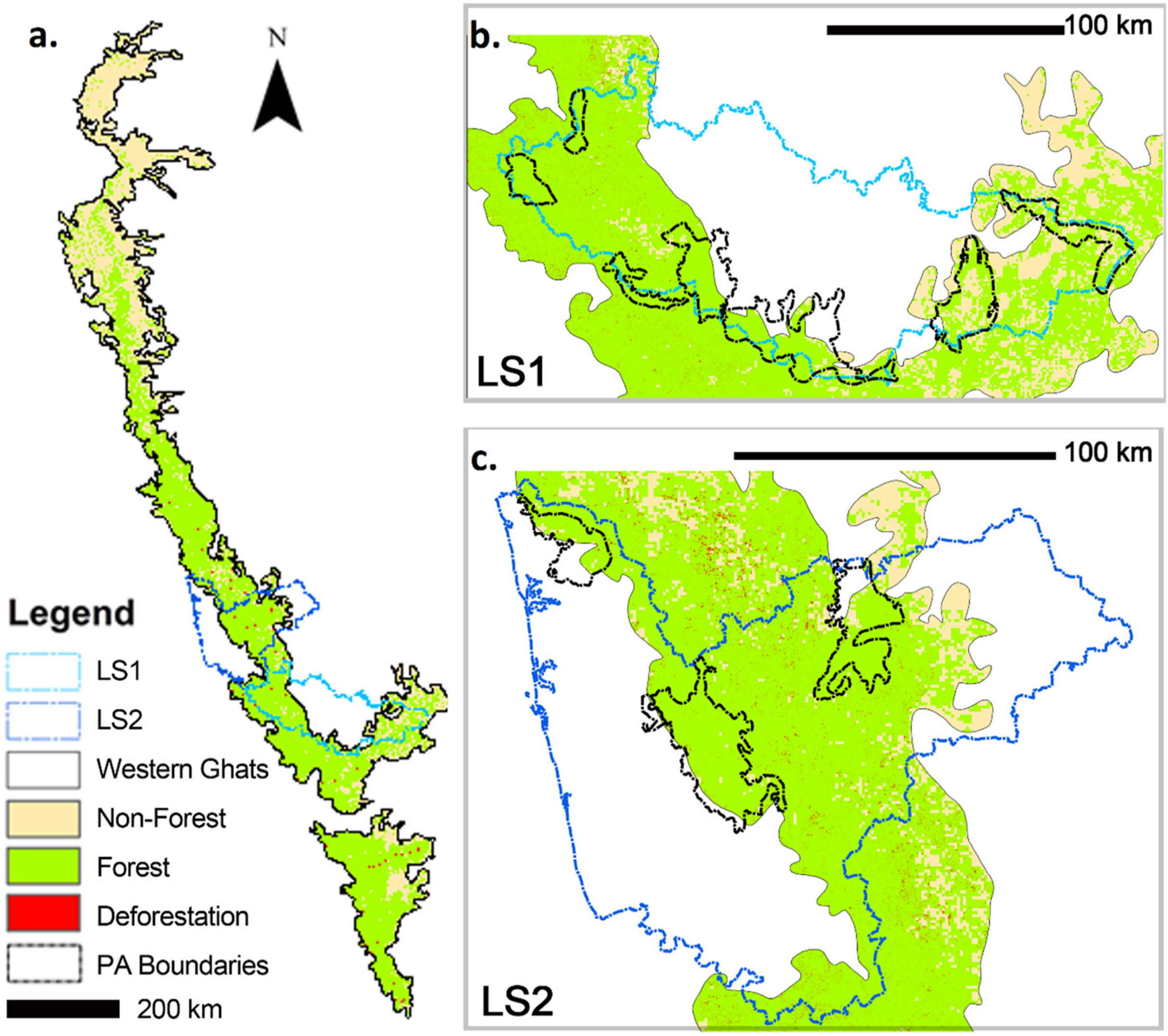

Fig. 1. Map of study area displaying pixels deforested from 2000 to 2016 in a) the entire extent of the Western Ghats and in b) and c) two landscape subsets of three districts each in the state of Karnataka (Color figure. Can provide greyscale figure for print if required).

raster layers for local population density and district-level change in population from 2000 to 2011. People in villages up to 4 km from forests have been documented to access forest resources directly (Agarwala et al., 2016; Davidar et al., 2008). Therefore, for each 1 km^2 pixel, we used village-level census data to compute local population density as a sum of the populations of all villages within 5 km of the pixel edge. Additionally, since proximity to non-forest areas can affect human impacts on forests (increased access, fragmentation etc.), we calculated 'distance to edge' per 1-km^2 as the median of distances to the nearest non-forest sub-pixel for all 30 × 30-m forested sub-pixels. For land cover, we used the dataset compiled by the Global Land Cover National Mapping Organizations (GLCNMO, version 1, 2003) from MODIS images, which classifies land cover into 20 categories, including cropland, urban areas, and various forest types (Tateishi et al., 2014). Because we were only interested in forest loss and not land-cover change in toto, we masked out non-forest pixels, resulting in a raster layer of six forest types. Finally, we created rasters assigning administrative categories of state, district and protection status per 1-km^2. We assigned a grid cell as "Protected" if > 50% of constituent forested pixels fell within a protected area.

2.2. Sampling design

We clipped all datasets to a Western Ghats boundary shapefile (with 5-km buffer) and used forest loss data from Global Forest Change dataset available at 30 × 30-m pixel resolution to quantify rates of deforestation. To match the spatial resolution at which data for predictor variables were available, we quantified number of 30 × 30-m pixels deforested per 1-km^2, obtaining 89,681 1-km^2 pixels. First, we checked for the signature of spatial autocorrelation for the entire data using semivariograms. Because we found that distances within 8 km were spatially autocorrelated, we tried models by dividing the entire landscape into grids of 5 × 5 km, 8 × 8 km, 10 × 10 km, 15 × 15 km and 20 × 20 km. At smaller grid sizes, models either ran into computational errors or residuals were spatially autocorrelated (see procedural details below). Larger grid sizes did not provide enough samples to model random effects for districts. Therefore, we used 10 × 10 km grids in our final models. The average size of protected areas in the Western Ghats is 243 km^2, and reserved forests average 69 km^2; hence, this grid size provided representative samples within the size of areas relevant to management (Das et al., 2006). Within each 10 × 10 km grid, we randomly sampled 10 1-km^2 forest pixels. We sampled 10 pixels per grid instead of a percentage of points to ensure a balanced design across grids and to sample the entire spatial extent of the Western Ghats systematically. Furthermore, our technique eliminated spatial autocorrelation that remained even with subsampling pixels across the landscape or within each grid. To ensure that all grids had sufficient data for analysis, we only used grids with > 10% pixels classified as forest in 2000.

2.3. Statistical analyses

We first used the 30 × 30-m resolution forest loss data to quantify annual rates of forest loss for each land cover. Next, we used generalized linear models in a hierarchical Bayesian framework to evaluate the relative effects of biophysical, demographic, and administrative correlates of forest loss (30 × 30-m pixels lost per km^2). The Bayesian approach allows for fitting hierarchical models that incorporate natural variability and data uncertainty, for example, when explanatory variables or the direction of their effects are incompletely known. Additionally, 95% credible intervals for parameters from their posterior distributions capture the potential variation in effect sizes of independent variables (Gelman et al., 2013). Additionally, we did a bootstrapping procedure where we ran the models 100 times randomly subsampling 10 pixels per grid per iteration and obtained a distribution of effect sizes per predictor (Fig. S2). These distributions closely match the posterior estimates obtained from the Bayesian analysis (Fig. 4), showing that subsampling did not bias parameter estimates (Fig. S3).

As biophysical predictors, we used total annual precipitation, slope, elevation, distance to nearest river, and distance to lake in the model. We scaled all continuous variables (Table S1) by subtracting the mean and dividing by two standard deviations to make effect sizes directly comparable among variables. On exploratory analysis, we found the response data was zero-skewed. So, we compared models with errors distributions defined by zero-inflated Poisson, negative binomial, and zero-inflated negative binomial (ZINB) using the widely applicable information criterion (WAIC; Gelman et al., 2013). Zero-inflated negative binomial models consistently had the lowest WAIC, so we used these as our final model. We used diffuse non-informative priors for all population- and group-level parameters.

2.4. Accounting for spatial autocorrelation

To account for potential dependence in forest loss with spatial proximity or local administrative differences, we included district and grid ID as group-level errors (random intercepts). Further, we explicitly modelled spatial correlation through stochastic partial differential equations (SPDE) by assuming a Matern spatial correlation. In other words, we overlaid a mesh of triangular areas over the entire study region and used this spatially indexed mesh to estimate a random effect to model forest loss (Lindgren et al., 2011). The Matern Gaussian field is estimated using integrated nested Laplace approximation (INLA). We refer the reader to Lindgren et al. (2011) and Blangiardo et al. (2013) for further information on INLA and its application to model spatial correlation. Additionally, we modelled zero-inflation as a function of administrative district, i.e., to account for the possibility that forest losses might depend on local administrative differences. Finally, to confirm if our modelling procedure accounted for spatial autocorrelation, we conducted a Moran's I test on the model residuals and found no evidence for spatial autocorrelation (Supplementary Information, Table S2).

2.5. Model validation

We assessed model validity in three steps. First, we performed posterior predictive checks by comparing fitted values against observed data. Next, we visually examined the cross-validated predictive ordinate values generated using model fit. Finally, we examined the rate of failure in fitting the model, expressed as the sum of probability integral transform. These model validation techniques were adopted from Rue et al. (2009), Lindgren et al. (2011), Blangiardo et al. (2013) and are standard when using INLA to make Bayesian inferences.

2.6. Scale-dependent variation in correlates of forest loss

To evaluate whether correlates of forest loss varied with spatial extent of analysis, we repeated the analysis for two landscape subsets within the Western Ghats. To control for broad administrative differences attributable to state, we chose our landscape subsets within one state. To minimize subjectivity, we subset the data district-wise and not by specific protected areas or forest corridors. The two smaller landscapes (henceforth LS-1 and LS-2) comprised three districts each and contained a mix of protected and non-protected areas with intervening human land-use. The two landscapes contained similar extents of protected areas but are important conservation landscapes for different reasons. The first landscape (LS-1; Dakshin Kannada, Udupi, and Hassan districts) primarily contains evergreen to semi-evergreen forest with endemic mammals such as the Lion-tailed macaque, Brown Palm civet, and Nilgiri marten. These high-biodiversity forests also support high endemism in plants (56%), amphibians (78%), and reptiles (62%) (Das et al., 2006; Gunawardene et al., 2007). In comparison, LS-2 (Chamrajnagar, Kodagu, and Mysore districts) is part of the Nilgiri biosphere dominated by dry- and moist-deciduous forests, with evergreen forests in the west. LS-2 harbors a Tiger Conservation Unit and is a crucial landscape for the endangered Asian elephant. Moreover, both landscape subsets are production landscapes facing similar developmental changes (mineral mining, agriculture, and linear intrusions). We followed the same modelling protocol as for the entire Western Ghats data.

3. Results

3.1. Patterns of deforestation

Across 89,681 km^2 of forest in the Western Ghats, we found that forest loss was confined to small patches (Fig. 1a) with no obvious patterns in annual deforestation from 2000 to 2016 (Fig. 2a). Greatest forest loss occurred in 2007–2008 (67.9 km^2) and 2015–16 (79.2 km^2). Deforestation was lowest in 2009–2010 (10.2 km^2). Post-2010, annual forest losses averaged 49 km^2/year. The total deforestation from 2000 to 2016 was ~ 749 km^2 (0.84%). Gross forest loss was primarily concentrated in evergreen forests (Fig. 2b), although percentage of forest loss (relative to forest area) was highest for the “sparse vegetation” category (Fig. 2c).

3.2. Demographic, administrative, and biophysical correlates of forest loss

Across the entire Western Ghats, protected areas were 30% less likely to lose forest than non-protected forest (all correlations are shown in Fig. 4). Forest loss per km^2 decreased by 21% with every 4 km increase in pixel distance from roads, and by 33% for pixels within protected areas (Fig. 3). With every 22 km increase in mean distance to town, forest loss decreased by 16%, but protected areas were 36% less likely to lose forest than non-protected forests when closer to towns. Notably, while increase in local village populations per se was not associated with greater forest loss, pixels in protected areas were 32% more likely to lose forest than non-protected areas with every increase of 24,000 people from mean local population densities (Fig. 3). We found evidence of greater forest loss at higher elevations and wetter areas. Forest loss was higher closer to rivers and lakes (Fig. 4). Counterintuitively, forest loss increased in pixels located farther from the nearest non-forest pixel, i.e., more remote areas.

Moran's I test for model residuals showed that there was no remaining spatial autocorrelation (Table S2), additionally borne out by the fairly flat line of the semivariogram of model residuals (Fig. S2). Moreover, qualitative similarity between predicted and observed values

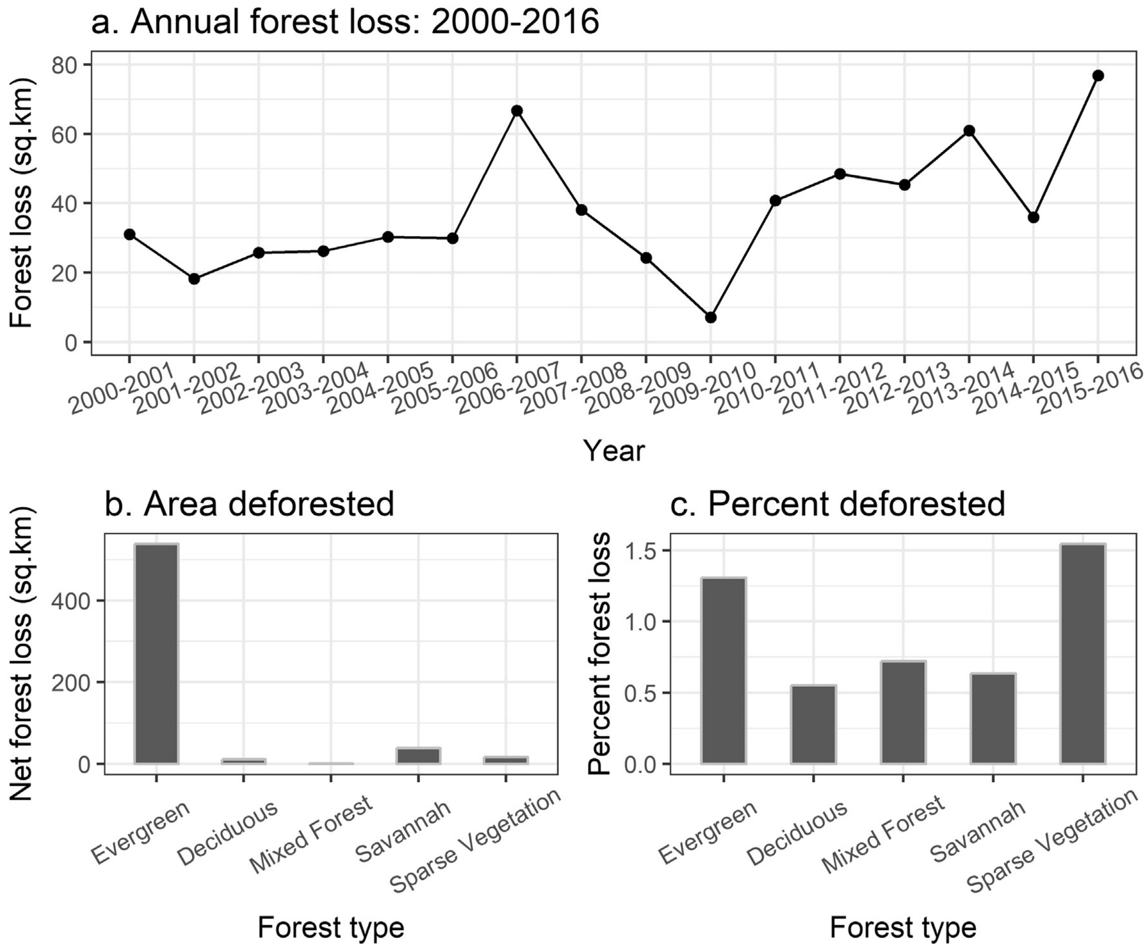

Fig. 2. (a) Annual forest losses occurring in the Western Ghats from 2000 to 2016, (b) total forest loss in different land covers, and (c) proportional forest loss in different land cover types (greyscale figure).

(Fig. S4), low failure rate of estimation for new data (70 out of 13,480 data) and approximately uniform cross-validated predictive ordinate values (Fig. S5) suggest that the model was a reasonable fit for the data.

3.3. Correlates of forest loss at smaller scales

Results from the smaller-scale analyses differed from patterns for the entire Hotspot (Fig. 4). None of the individual administrative and demographic predictors explained forest loss. For Landscape 1, forest loss doubled per 24% increase in mean elevation and per 50% increase in distance from lakes. In Landscape 2, the interaction between protection status and distance to road was the only predictor of forest loss. Forest loss decreased by 88% for pixels that were 4 km farther from roads and within protected areas.

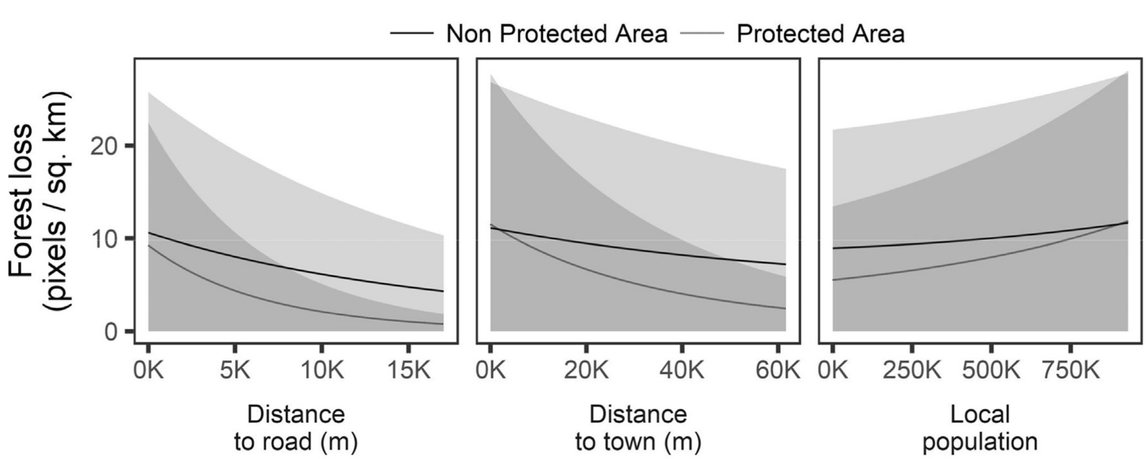

Fig. 3. Correlations of distances to road and town and local human population densities with forest loss in the Western Ghats. Forest loss was measured as number of 30 × 30 m pixels converted from forest to non-forest within a 1 km^2 grid. For comparability, all predictor variables were scaled by subtracting the observed data from its mean and dividing by two standard deviations (greyscale figure).

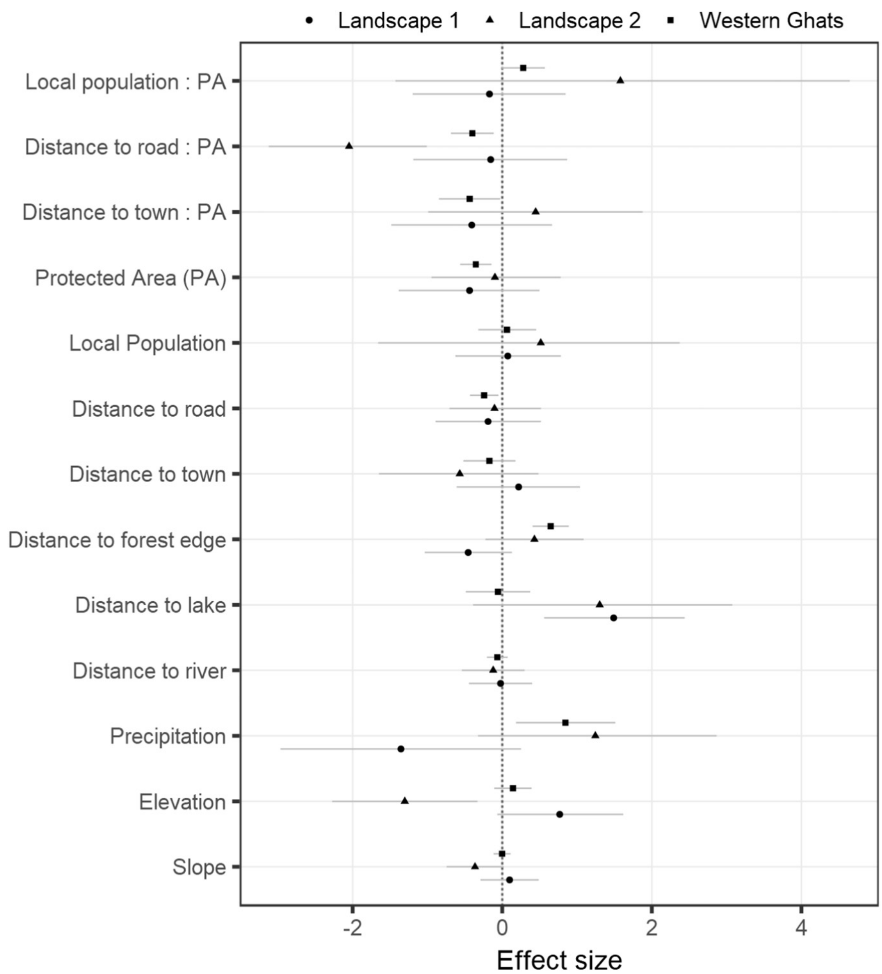

Fig. 4. Correlates of forest loss in the Western Ghats, measured as number of 30 × 30 m pixels that were converted from forest to non-forest within a 1 km^2 grid during 2000–2012. All continuous predictors were scaled by subtracting the observed data from its mean and dividing by two standard deviations to make effect sizes comparable with categorical predictors. Points represent estimated effect sizes from a hierarchical Bayesian model. Bars represent 95% Bayesian credible intervals (grayscale figure).

4. Discussion

For the entire Western Ghats Biodiversity Hotspot of India, we provide the first quantitative estimate of how recent forest loss (post-2000 CE) is associated with demographic, socioeconomic, administrative, and biophysical correlates. We found that protected areas reduced forest loss regardless of administrative boundaries and spatial scale of analysis, but not where human population densities were high. Notably, administrative and demographic determinants of forest loss Western Ghats varied with spatial extent analyzed, suggesting the importance of local factors in managing forest cover. Overall however, our results corroborate the expectation that patterns of contemporary forest loss are mediated by local population pressure and protection status of forests.

4.1. Current rates of forest loss

Approximately 750 km^2 of forest was lost within the Western Ghats between 2000 and 2016 (0.8%), slightly higher than rates estimated previously (Reddy et al., 2013). Given the mean size of protected areas in this Hotspot (280 km^2, Das et al., 2006), these results imply that the Western Ghats lost the equivalent of over 2.5 protected areas in the last 15 years. These losses are a matter of concern in a region that has already lost much of its natural habitat. While these deforestation rates are the lowest in the last 100 years (Reddy et al., 2016; Roy et al., 2015), and are substantially lower than other forested parts of India (Reddy et al., 2016), this is not unexpected in areas where much historical forest loss has occurred. Moreover, unlike in the Amazon or south-east Asia where large swaths of forests are clear felled for ranching, plantations, or timber, forest loss in the Western Ghats is occurring at smaller, more localized spatial scales.

Drivers of patchy, small-scale deforestation such as small dams and illegal mines are emergent and pervasive issues in the Western Ghats (pers. obs.), but their impacts on forest loss, degradation, biodiversity, and ecosystem function remain largely unexamined. Additionally, ongoing forest clearances to expand roads and highways would contribute to patchy losses, which is partly borne out by our findings of greater forest loss closer to roads (ibid.). Our study highlights an urgent need for field-based studies that delve into the drivers of small-scale, patch forest losses across the Western Ghats. Furthermore, the Hansen et al. (2013) dataset only captures stand replacement whereas patchy forest loss could exacerbate degradation of fragmented forests which merits further attention (Barlow et al., 2016; Newbold et al., 2014).

Due to the potential inaccuracy in distinguishing forests and plantations with the MODIS-based dataset, some of the forest loss we observed outside protected areas might have been within plantations, even though we tried to reduce this error by using pixels classified as forest in the landcover dataset. Despite this caveat, plantations with high tree cover, especially native trees, support biodiversity, provide corridors for dispersal of plants and animals, and provide ecosystem services such as carbon storage (Anand et al., 2010). Therefore, while loss of stands within plantations and agroforests can result in functional losses for wildlife movement and ecosystem services across large landscapes. Moreover, remnant forest cover in areas with higher human population densities can have higher per capita value for local ecosystem services such as watershed integrity, pollination services, and carbon storage, than in sparsely populated areas. Although, if small-scale losses are merely part of replanting cycles, they might not have any substantial effect on long-term ecological dynamics in the landscape. At the least, our results suggest a need to monitor potential causes and consequences of tree cover loss in agroforests and plantations, which has not been done in the Western Ghats.

4.2. Parks slow forest loss, but not with high population densities

The overall pattern of small-scale, localized deforestation appears to be occurring mostly outside protected areas. Forest loss within protected areas was 32% lower than non-protected areas, indicating a degree of success in conserving forest cover despite high human pressures in the Western Ghats. Higher losses in non-protected forests corroborate patterns in North-East India where community-owned lands were more likely to lose forest cover than protected areas (Reddy et al., 2017). Surprisingly however, where local human populations were higher in the Western Ghats, protected areas were 70% more likely to lose forest cover than non-protected areas. Read together with another counterintuitive result—pixels farther from the nearest non-forest pixel were more likely to lose forest—we hypothesize that villages inside protected areas might be associated with small-scale forest losses in their vicinity.

High population densities could also represent situations where non-protected forests have been lost or degraded due to intensive use or conversion of forests. As a result, such areas might experience encroachment into protected areas for agriculture or to meet their forest-based resource needs (e.g., timber, fuelwood, etc.). Our results provide a useful starting point for future analyses to examine the generality of these findings, particularly to assess local factors that drive differential use of protected and non-protected forests. Alternatively, successful community-based conservation in non-protected forests could lower deforestation rates despite these forests being in populous areas (e.g. Sirsi-Honnavar forests). Indeed, recent studies from Amazonian forests show that informal, bottom-up measures can contribute to landscape-scale conservation, sometimes better than protected areas (Schleicher et al., 2017 and references therein). We see a need to understand local governance factors better that can complement protected areas in maintaining forest cover across more human-dominated parts of the Western Ghats.

Similar to other Biodiversity Hotspots, the benefits of forest protection in the Western Ghats assumed greater importance for forests closer to roads (Barber et al., 2014; Eklund et al., 2016). Roads and linear infrastructures are among the leading global causes for forest loss and the demand for new roads or expanding existing roads is accelerating in the developing tropics (Laurance et al., 2009). Improved roads often increase local human populations and allow easier access to forests which can lead to increased forest clearance (Laurance et al., 2009). Our study reflected these global patterns—forest loss increased by 16% every 4 km closer to roads, and losses were 32% lower within protected areas. Current laws curtail unchecked road expansion within protected areas in Western Ghats, but road development is less regulated in non-protected forests. In light of the demand for development in this Hotspot, we urge decision-makers to factor in biodiversity and ecosystem services provided by non-protected areas forests and minimize fragmentation and forest loss with linear infrastructures.

Biophysical correlates of forest loss showed some deviation from expected patterns. Areas closer to water sources are usually associated with human settlements and intensive agriculture which promotes forest clearing (Green et al., 2013), but we found that distances to lakes and rivers were uncorrelated with forest loss. This paradoxical pattern could result from the long history of settled agriculture in the Western Ghats (Subash Chandran, 1997), which cleared much of the forest in low-lying areas near water sources (Reddy et al., 2016). Indeed, a global analysis of forest loss trends suggest that India is a region that has already witnessed the large-scale losses associated with clearing frontier forests (Hosonuma et al., 2012). Consequently, current losses might occur predominantly in forests farther from areas that appear to be more suitable for agriculture.

4.3. Scale-dependence of forest loss factors

Analyses of two different spatial scales highlight a few important points about drivers of forest loss. First, results varied with spatial scale indicating that local factors are important mediators of forest loss patterns. Notably, protected areas per se did not perform better than non-protected areas in retaining forest cover in the smaller-scale analyses. Moreover, only in LS-2 did protected areas have lower forest loss than non-protected areas when closer to roads. These results emphasize the need for local-scale assessment of conservation measures and protected area effectiveness to complement larger-scale policies designed for entire Hotspots. Given the increasing decentralization of decisions for infrastructure expansion and resource extraction in India, there is an urgent need to understand the synergy between local and larger-scale drivers of forest loss (Madhusudan, 2005; Meyfroidt et al., 2010; Rudel et al., 2009).

5. Conclusions

The utility of protected areas in stemming deforestation has been questioned (Ellis and Porter-Bolland, 2008; Pfeifer et al., 2012; Porter-Bolland et al., 2012), but evidence indicates that protected areas remain important bulwarks of conservation (Joppa et al., 2008; Nepstad et al., 2006). Notwithstanding the value of active forest protection, there is a need to understand patterns of land-use and development that can complement existing protected areas in preserving biodiversity at large spatial scales in populous landscapes (Lindenmayer and Cunningham, 2013). Furthermore, we only assessed overt deforestation whereas other land-use (e.g., harvesting forest products, selective logging, grazing, fire) can affect biodiversity and ecosystem services without obvious forest loss (Asner et al., 2010; Davidar et al., 2007; Nepstad et al., 2008). We thus see a need to quantify drivers of forest degradation.

In the context of development associated with rapid economic growth in India, we hope that the results of this study will convince policy-makers to a) maintain the integrity of laws governing forest protection, b) adopt best practices advocated by researchers to regulate placement of roads and other infrastructures in forested areas, c) develop site-specific interventions geared towards reducing forest pressure in populous areas, especially to reduce stresses on protected areas, and d) explore options with local stakeholders to retain forest cover outside protected areas. A better understanding of factors governing changing patterns of local land- and resource-use will help to plan biodiversity conservation in the face of population growth, economic development, and infrastructure expansion within global Biodiversity Hotspots (Joppa et al., 2008).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2018.04.034.

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