Biological Conservation
Volume 229, January 2019, Pages 152-159

https://doi.org/10.1016/j.biocon.2018.11.017

Deforestation dynamics in an endemic-rich mountain system: conservation successes and challenges in West Java 1990-2015

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Received 19 May 2018, Revised 22 October 2018, Accepted 14 November 2018, Available online 3 December 2018.

Abstract

While much has been published on recent rates of forest loss in the Sundaic lowlands, deforestation rates and patterns on Java's endemic-rich mountains have been rather neglected. We used nearly 1,000 Landsat images to examine spatio-altitudinal and temporal patterns of forest loss in montane West Java over the last 28 years, and the effectiveness of protected areas in halting deforestation over that period. Around 40% of forest has been lost since 1988, the bulk occurring pre-2000 (2.5% per annum), falling to 1% per annum post-2007. Most deforestation has occurred at lower altitudes (< 1,000 m), both as attrition of the edges of forested mountain blocks as well as the near-total clearance of lower-altitude forested areas. Deforestation within protected areas was rife pre-2000, but greatly decreased thereafter, almost ceasing post-2007 in protected areas of high International Union for Conservation of Nature (IUCN) status. While apparent recent protection against land clearance is welcome, it must be stressed that the area of remaining forest is only 5,234 km^2, that most accessible lower-altitude forest has already disappeared, and that the extant montane forest is largely fragmented and isolated. The biological value of these forests is huge and without strong intervention we anticipate imminent loss of populations of taxa such as the Javan Slow Loris *Nycticebus javanicus* and Javan Green Magpie *Cissa thalassina*.

Keywords: Java, deforestation; protected areas; Landsat, land use/land-cover change

Highlights:

- West Javan mountain forests have endemic biodiversity but a long history of deforestation
- Since 1990, roughly 40% of forest has been lost, although a decrease in the rate of deforestation has occurred
- Loss was most prevalent at low altitudes, which were almost completely cleared
- Forests at higher altitudes and within protected areas fared better
- Remaining forest is limited to higher altitudes and is vulnerable to fragmentation and clearance

1. Introduction

Deforestation is one of the main drivers of global biodiversity decline, and a major source of carbon emissions (Houghton et al., 2012; Lawrence and Vandecar, 2015). Information on the extent, severity, and causes of forest loss is therefore critical for a range of disciplines. In recent years, Earth-observation has provided a more accurate and better picture of the global rate and geographical distribution of deforestation (Skole and Tucker 1993; DeFries et al. 2002; Miettinen et al. 2011), highlighting Southeast Asia, and in particular Indonesia, as of major concern (Hansen et al. 2013). Within Indonesia, the loss of moist tropical forests on the islands of Borneo and Sumatra, primarily due to the expansion of industrial palm oil plantations, has been well documented (Broich et al., 2011, 2013; Margono et al., 2012; Shevade et al., 2017), but far less attention has been directed towards Java. Indeed, the forests of Java have not received bespoke study and are frequently omitted from published statistics, in part due to the relative sparsity of forest cover remaining since Dutch colonial rule in the eighteenth and nineteenth centuries (Smiet et al. 1990). Such neglect is unfortunate, as these forests possess high levels of biological endemism, with the montane formations on the volcanoes of West Java being particularly rich in unique species (Stattersfield et al., 1998). The West Javan mountains hold all or most of the remaining range of four 'Critically Endangered' endemic vertebrates: Javan Slow Loris *Nycticebus javanicus*, Rufous-fronted Laughingthrush *Garrulax rufifrons*, Javan Green Magpie *Cissa thalassina* and Fire Toad *Leptophryne cruentata* (IUCN, 2017), and either whole or significant portions of the ranges of many other species of conservation concern (e.g. the 'Endangered' Javan Gibbon *Hylobates moloch* and the 'Vulnerable' Javan Trogon *Apalharpactes reinwardtii* and Javan Cochoa *Cochoa azurea*). These and other endemics are known to be dependent on forest habitats (BirdLife International, 2018).

The free availability of large archives of satellite (and notably, since 2008, Landsat) imagery (Wulder et al., 2012; Kennedy et al., 2014) has greatly facilitated the monitoring of land-cover change. These datasets have enabled a shift away from single-image analysis in favour of large-area, automated data-processing chains (Roy et al., 2014), with multiple images amalgamated into target date composites or statistical metric layers (Griffiths et al., 2013). The transition towards multi-image analysis is particularly beneficial in tropical regions where cloud cover is both extensive and frequent, limiting the likelihood of obtaining a cloud-free image (Asner 2001; Hansen et al., 2013). The use of Landsat imagery is preferable for many localities. For example, the use of coarse resolution data from the Moderate-resolution Imaging Spectroradiometer (MODIS) or the Advanced Very High Resolution Radiometer (AVHRR) (e.g. Defries et al., 2002; Hansen et al., 2009) may obscure small-scale patterns which collectively accrue to a large area.

In this study, motivated by concern for West Java's endemic biodiversity, we use the Landsat archive to map the deforestation dynamics of the area's remnant upland forests. Our objectives were to: (a) characterise remaining forests; (b) uncover the spatial and temporal occurrence of forest loss events, especially in relation to changes in political order (specifically the termination of the Suharto 'New Order' regime in 1998); and (c) assess the effect of protected areas on the rate of deforestation over recent decades.

2. Study area

Our study area is ~17,000 km^2 covering the western uplands of the Indonesian island of Java (Fig 1). We defined uplands as all areas upwards of 400 m above sea level. Analysis was limited to such areas, as these are the location of a majority of remaining upland forest on the island. We focused on 19 West Javan mountains that are of known high biodiversity value (Fig 1b). These mountains include both unprotected areas and protected sites of various International Union for Conservation of Nature (IUCN) designation classes. The climate is broadly tropical, with Köppen climate classifications of Equatorial or Monsoon. Annual temperatures range from 18 to 30˚C, with a regular daily average of 28˚C. Rainfall is concentrated in the monsoon period November–March, with monthly precipitation around 270 mm. West Javan forests are not dominated by any particular tree species, but common taxa include: Moraceae (*Artocarpus elasticus*), Meliaceae (*Dysoxylum caulostachyum* and *Lansium domesticum*), and Lecythidaceae (*Planchonia valida*) (MacKinnon et al., 1993). Java contains twenty volcanoes that have been active in the historical record; accordingly, the regional geology is dominated by relatively recent volcanic rocks, interspersed with marine limestones (Whitten et al., 1996). Java's human population doubled since the 1970s to 145 million today, equating to 1,121 people per km^{-2}, the highest density in the world (World Bank, 2017). Our study area contains the major cities of Bogor and Bandung, with the Indonesian capital Jakarta just outside the perimeter. A variety of crops are grown within the study area, mainly as smallholdings, with the dominant being rice and coffee (Whitten et al., 1996).

3. Methods

3.1 Landsat data

The Landsat series is the world's longest continuously operating moderate-resolution Earth observation (EO) program. Collecting imagery at 30 m across six spectral bands (plus a thermal band), Landsat is particularly suited for monitoring land-cover change. To map such changes, we produced a series of spectral variability metrics for four epochs corresponding to relevant time periods: 1988–1992, 1998–2000, 2006–2008, and 2014–2016. Spectral metrics are pixel-level statistical summaries calculated from all co-located observations. Metric composites allow the extraction of intra-epochal information on the reflectance of a pixel, and have proved effective for mapping subtle land cover types and improving the accuracy of classifications (Müller et al., 2015). This approach copes more robustly with the problem of persistent cloud cover and atmospheric effects by using all available observations, minimising the contributions of individual pixels which may be compromised, and is therefore well suited to the wet tropics. The composites were generated in Google Earth Engine (Gorelick et al., 2017) from all available Landsat 5 TM and 7 ETM+ images. To ensure sufficient observations were present for the calculations, a three-year compositing period was used for the later three epochs, but, owing to lower image availability the 1990 composite required a five-year range.

All images were processed to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), and clouds artefacts masked according to F-mask (Masek et al., 2006; Zhu et al., 2015). For the statistical layers we calculated the mean, standard deviation and a range of percentiles (0, 20, 40, 50, 60, 80, 100%).

3.2 Forest change mapping

The Landsat spectral variability metrics were classified to produce a land-cover change map. The following classes were mapped: (i) stable forest, (ii) stable non-forest, and loss in the periods (iii) 1990–1999, (iv) 1999–2007 and (v) 2007–2015. Training data consisting of 211 polygons were derived from visual bi-temporal comparison of the Landsat composites, in conjunction with high-resolution imagery; forest loss was identified by complete removal of tree cover in the target pixels, whilst stable classes were consistent across all epochs. The classification was undertaken using a Random Forest classifier. Random Forest is a decision-tree-based technique that uses bootstrapped subsets of the training data to generate an ensemble of tree models, which are then aggregated into a final model (Breiman 2001). The internal parameters of the model, the number of trees generated and the number of variable splits, were chosen based on a 10-fold cross validation over a tuning grid of potential values (Kuhn et al., 2017). The classification was developed with the R package randomForest package (version 4.6; Liaw and Wiener, 2002; R Core Team, 2017).

To validate our classified map, we first selected a random sample of 75 points per class and calculated the Producer's accuracy. This Producer's accuracy and mapped area per class were used to determine an appropriate stratified sample for a target standard error of 0.5 (Cochran, 1977). The final stratified sample of 539 points was used to calculate Producer's, User's and Overall accuracy scores based on best practice guidelines (Congalton and Green, 2008). Finally, the mapped class areas were adjusted to account for omission errors (Olofsson et al., 2013).

3.3 Statistical analysis

The roles of altitude, period, and protection status on observed deforestation rates were analysed using a Generalised Linear Mixed Model (GLMM). To generate data for the model, the classified change map was processed as follows. First, the study area was spatially segmented into zones, approximating to mountain catchments. These zones were delineated by assigning each pixel to the most accessible mountain peak, using a cost allocation method with the Shuttle Radar Topography Mission (STRM) Digital Elevation Model (DEM) as a cost surface layer (Longley et al., 2005). This resulted in 28 zones, with an average area of 600 km^2 ranging from 254 to 1,217 km^2. Second, each zone was further subdivided according to protection status (protected or unprotected) and altitude, using successive 300 m bands. Finally, the cumulative deforestation rate within each segment for each epoch was then calculated, relative to the starting forest cover in 1990. This resulted in 668 unique sample units.

A GLMM was built with cumulative deforestation rate as the dependent variable and time period, altitude, and protection status as fixed effects. To account for spatial dependence in the data, mountain zone (catchment area) was added as a random effect. Percentage of forest loss is a proportional response, so a binomial family with logit link function was considered appropriate with the initial number of forest pixels in each segment providing the prior weighting. The R package *lme4* was used for model fitting (Bates et al., 2015), with model R^2 calculated based on the approach suggested by Nakagawa and Schielzeth (2013) and Johnson (2014). There were insufficient replicates to allow the type of protected area status, according to IUCN, to be included in the model. Therefore the deforestation rates between high protection status (IUCN Classes Ia-II: strict nature reserves and national parks) areas and other sites were compared by corresponding pixel counts.

4. Results

4.1 Land-cover change classification

Our land-cover change classification produced a map (Fig 1 and Fig 2) with an overall accuracy of 98% (Table 1). All of the mapped classes had consistently high accuracies, with the least accurate class (loss for 1999–2006) having Producer’s and User’s accuracies of 0.91 and 0.78 respectively. Adjusting the mapped area estimates using probability-based stratified sampling highlighted a moderate omission of the loss in 1999–2007, with all other classes showing minor biases between the mapped and adjusted areas (Fig 3).

4.2 Deforestation rates

Over the 1990–2015 period, 3,415 ± 290 km^2 of forest were lost, corresponding to roughly 40% of the initial coverage (Fig 3). By 2015, 5,234 ± 78 km^2 of stable forest remained. Deforestation was greatest in the 1990–1999 period, with 1,923 ± 24 km^2 lost, falling to 1,056 ± 207 km^2 in the period 1999–2007 and 436 ± 59 km^2 for 2007–2015. Deforestation rates equate to 22% (2.5% per annum), 16% (2%) and 7% (1%) for the respective periods (Fig 3).

Spatially, the greatest concentration of deforestation events was in lower-lying parts of the study area (Fig 1). In particular, forest cover in the relatively low southwestern section was almost completely lost between 1990 and 2007 (Fig 2i). Similar levels of almost total deforestation were identified for the central/southwestern areas (Fig 2ii), where loss continued into the 2007–2015 period. The remaining areas of loss were generally located on the edges of contiguous montane forests, with encroachment-style deforestation most apparent (Fig 2iii).

4.3 Correlates of deforestation rates

The fitted GLMM had good explanatory power with conditional R^2 of 0.45 (full model), with all terms significant at a $p < 0.05$ level (Table 2). The fitted model showed protection status to be a consistent buffer on deforestation, with designated sites exhibiting roughly half the cumulative deforestation of non-designated areas, an effect that was stable across all altitudes (Fig 4). Low-altitude protected sites were subject to non-trivial loss rates (estimated at 10–25% by 2015), yet this contrasts with much greater rates for non-designated areas (30–55%; Fig 4). The majority of forest loss had occurred by 1999 with abatement in deforestation post-2000 most apparent for the 2007–2015 period, which exhibited only marginal increases in forest loss, with protected sites showing insignificant changes, particularly at higher altitudes. Sites given high protection status (IUCN Classes Ia-II: strict nature reserves and national parks) enjoyed additional reductions in forest loss, particularly for the 2007–2015 period (Fig 5).

5. Discussion

West Java lost around 40% of its 8,650 km^2 montane forest in the 25 years since 1990, a figure broadly comparable to other locations in Southeast Asia, e.g. Peninsular Malaysia (Shevade et al., 2017), Kalimantan (Carlson et al., 2012), and Sumatra (Gaveau et al., 2009). What sets it apart from these areas are that (1) the annual rate of forest loss has slowed considerably over time, from a high of 2.2% pre-2000 to 0.5% post-2007, with an important brake being exerted by protected areas, especially strict nature reserves and national parks, and (2) only around 5,500 km^2 remain of this endemic-rich habitat. Optimism over the decelerating trend in deforestation must be tempered by the extensive loss of forest at altitudes of 300 to 1,800 m, which presumably hold (or held) the most accessible and biodiverse forests. Species that are restricted to or prefer such altitudes are likely to be put under increasing strain across their ranges, especially if deforestation, albeit at slower rates, continues.

The post-1999 reduction in forest loss contrasts with reports from wider Indonesia and insular Southeast Asia (Hansen et al., 2013; Kim et al., 2015; Shevade et al., 2017), which show considerable increases in deforestation in the same period. This difference may be attributable to several factors. First, owing to climatic and topographic conditions Java is not well suited to the expansion of industrial tree plantations, particularly palm and rubber, which have driven most post-millennium forest loss in Indonesia and the wider region (Kim et al., 2015). Second, the increased regional autonomy following the democratic transition may have led to a preferential shifting of logging and agriculture to other islands with more lenient planning regulations than Java (Gaveau et al., 2009). Finally, Java was already largely deforested in earlier eras, and the remaining forest is predominantly located at high altitude or on steep slopes, and is therefore less accessible and the associated land less desirable for agriculture (Fig 1, Fig 5). The contrast between Java and wider Indonesia highlights the need for tailored studies addressing localised factors.

High rates of deforestation across insular Southeast Asia during the 1990s are well documented (Hansen et al., 2009; Kim et al., 2015), and relate to both political-economic and environmental factors. The 1990s were an economic boom period for Southeast Asia, with increasing commodity prices and favourable exchange rates driving growth in both agricultural and hardwood exports (Mason, 2001). This economic situation combined with lax forest protection laws encouraged widespread logging and agricultural expansion (Hansen et al., 2009). Environmentally, the 1997 El Niño event was severe, leading to widespread forest fires across the region (Page et al., 2002).

The last two epochs of our study postdate the Asian financial crisis of July 1997 and the associated economic consequences; within six months inflation peaked at 80%, and gross domestic product dropped by 47% (World Bank 2017). The resignation of President Suharto in May 1998 ended the 42-year New Order dictatorship and initiated a shift to representative democracy. This period was also marked by a number of forestry legislation changes, such as a round wood export ban in 2001, aiming to curtail illegal logging (Resosudarmo and Yusuf, 2006). Interestingly, our results contradict those of Miettinen et al. (2011), who observed a 4.2% increase in forest cover on Java between 2000 and 2010. We attribute this to two factors: first, we did not attempt to map reforestation, so did not account for gains; and second, Miettinen et al. (2011) used 250 m MODIS data, compared to the 30 m Landsat imagery used here, so our analysis probably identified smaller clearances missed by the coarser MODIS data.

Assessing the efficacy of protected areas is critical for ensuring long-term conservation (e.g. Mallari et al. 2013, 2016). Java's officially protected areas have fared reasonably well over the study period, especially since 2000 compared to those in Sumatra and Borneo, where encroachment through small-scale logging and agriculture is rife (Curran et al., 2004; Gaveau et al., 2009). Furthermore, the high altitude of most parks and reserves has minimised the displacement of logging to unprotected areas (Gaveau et al., 2009). Since 1999, forest loss in highly protected areas (IUCN Classes Ia and II) has been minimal, with a < 0.1% rate since 2007, but further study of the efficacy of different protection levels would be valuable, as our small sample size precluded robust modelling. Moreover, this welcome trend must be set against an extremely high baseline rate in the 1990s when forests below 1,000 m suffered a decline rate of 55% overall and 20% inside protected areas. As a consequence, only 2,500 km^2 of low-altitude forest remains (around 20% coverage). This will have detrimental effects for connectivity between the better-preserved highland forests, with increasing separation of major mountain chains and individual peaks (Fig 2ii-iii). Species movement modelling to identify connectivity corridors between the remaining forest and the bottlenecks to these connections would benefit conservation planning (e.g. Bleyhl et al., 2017). Crucially, forest loss, however slow, continues in montane West Java, not only compromising the future of the island's most distinctive fauna and flora but also inevitably risking ecosystem services such as water retention and regulation. Efforts to enhance the protection status of those montane forests currently with no or low IUCN protected area designation, field surveys to assess the viability of populations of endemic and threatened taxa (many mountains have not been visited by ecologists for decades), and protection, by whatever means, of lower-altitude montane forests, are, therefore, matters of great urgency.

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Figures

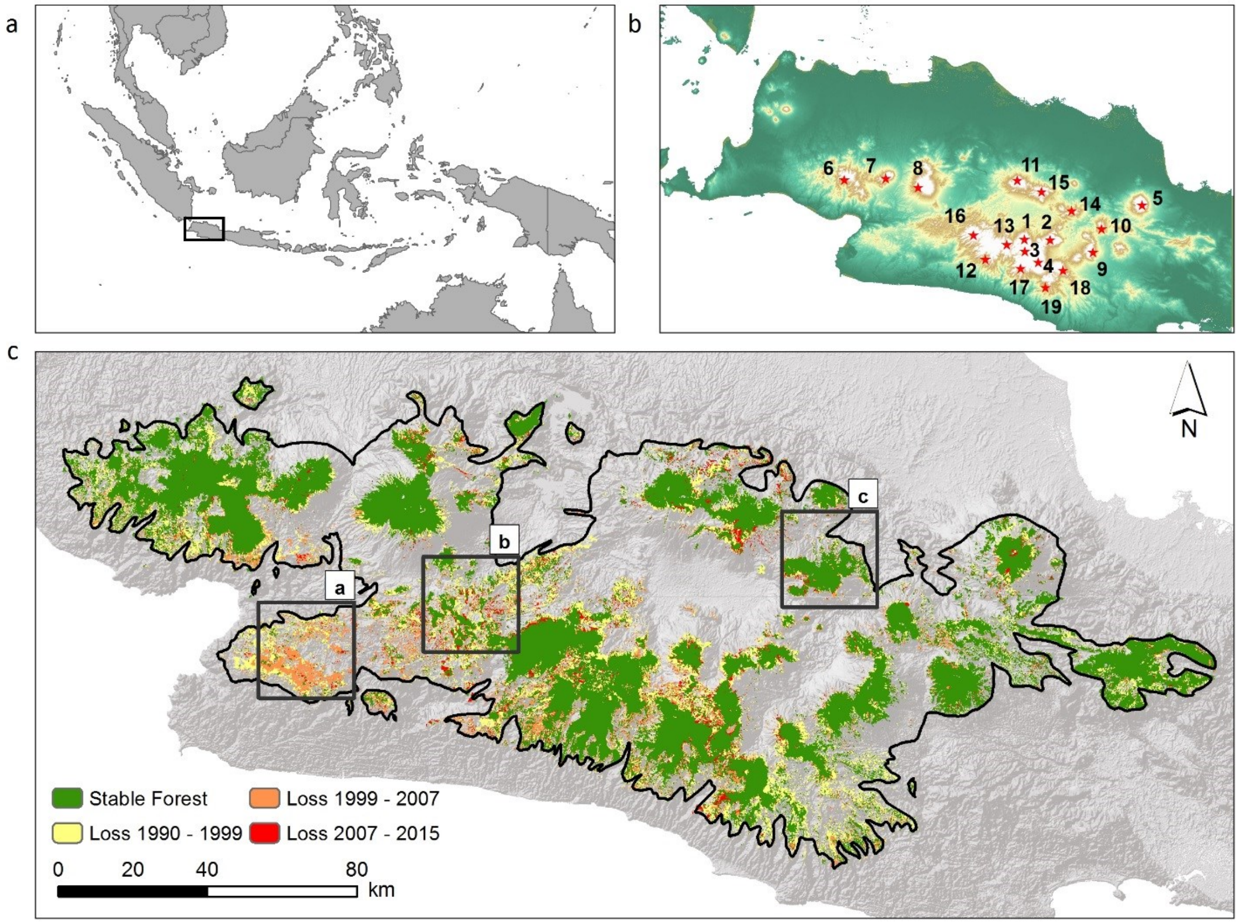

Fig 1 (a) Location of the study area within Southeast Asia; (b) Digital Elevation Model (DEM) of the study location with stars indicating the mountain sites selected for further study; (c) land-cover change map with the 400 m contour highlighted in black (grey boxes refer to the subset images in Fig 2)

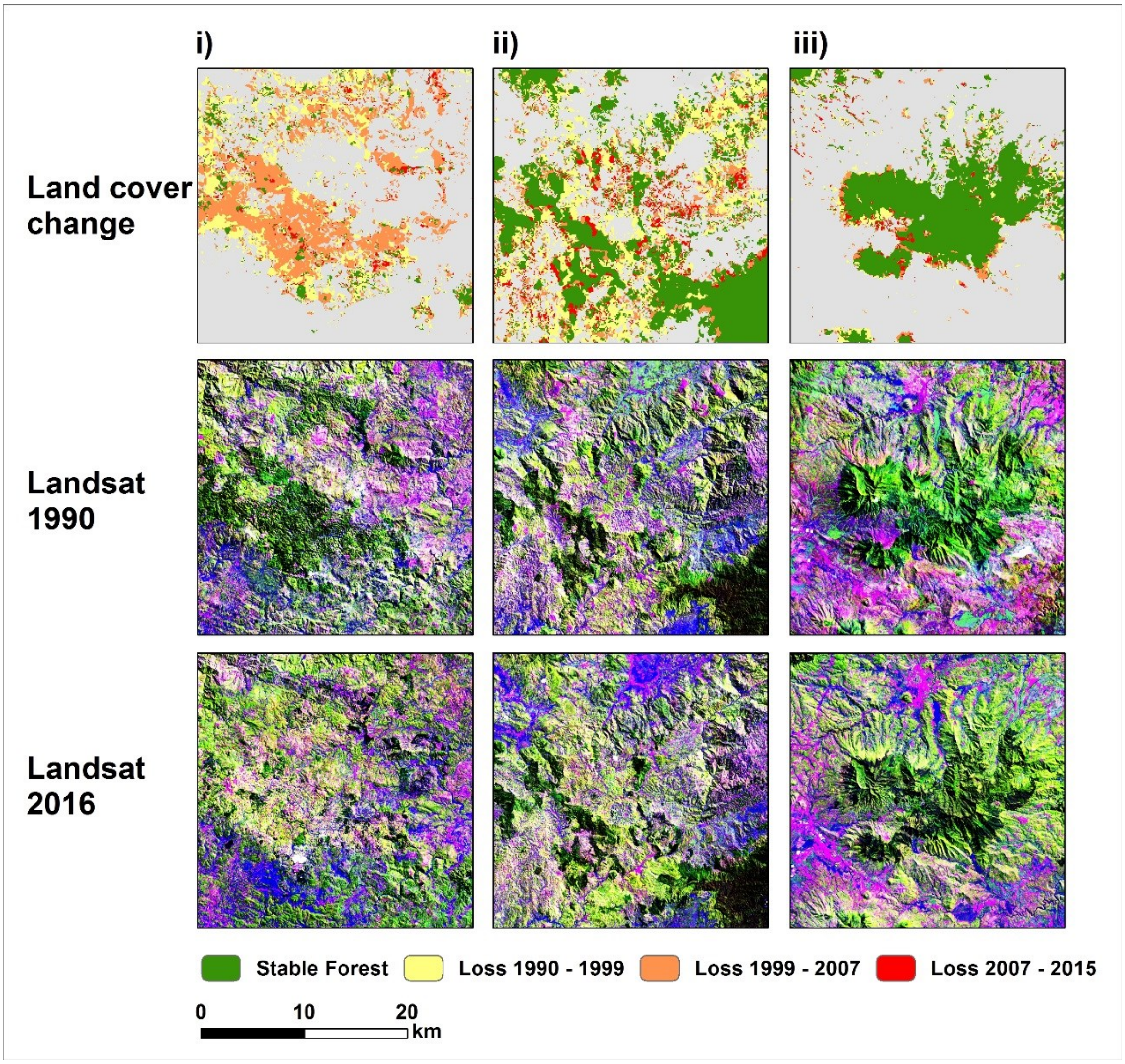

Fig 2 Results of the land-cover change classification (top row), 1990 Landsat 5 median composite (middle row), and 2016 Landsat 8 median composite (bottom row), for the three areas shown in Fig 1. Band association in the Landsat RGB false colour composites: R = shortwave infrared; G = near infrared; B = red

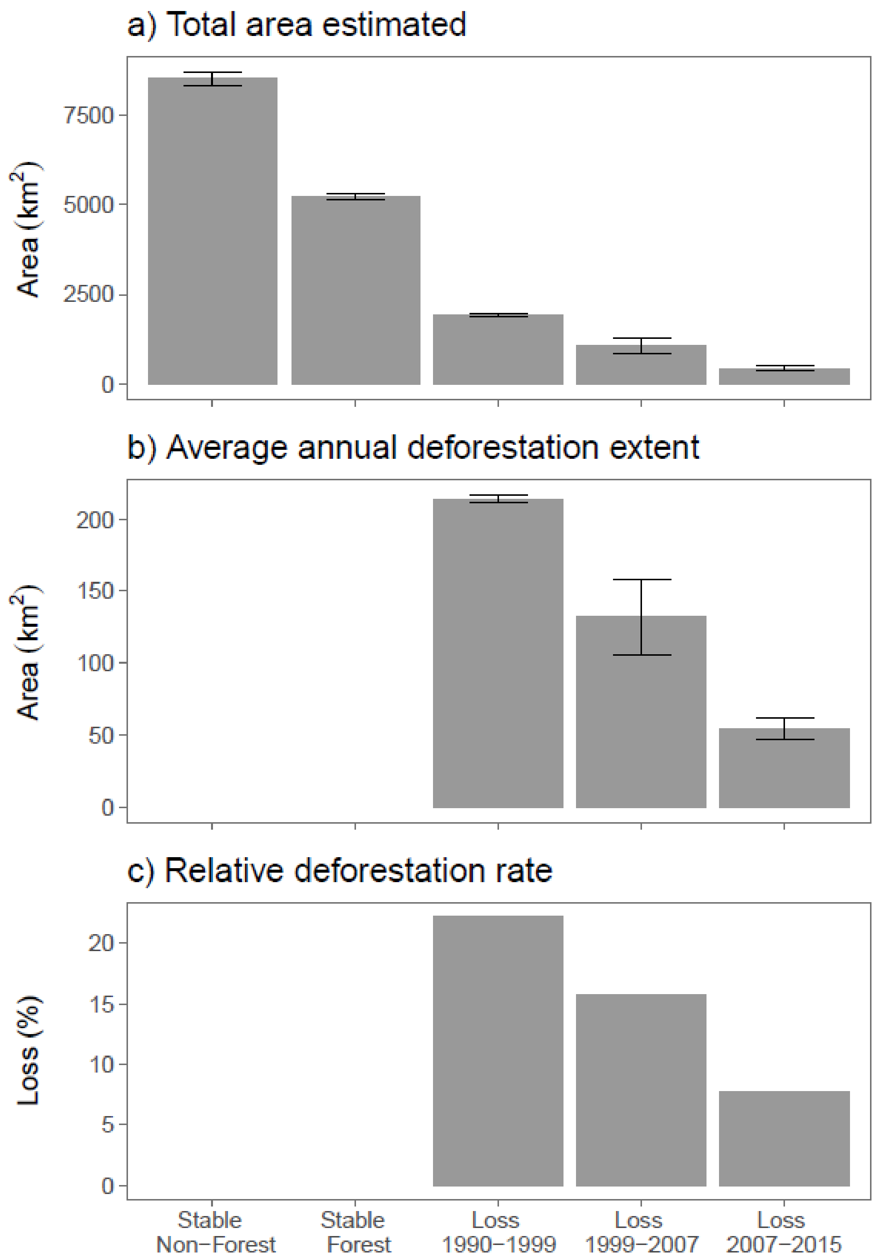

Fig 3 Area-adjusted estimated, with 95% confidence intervals, for the land-cover change classes covering the whole study area

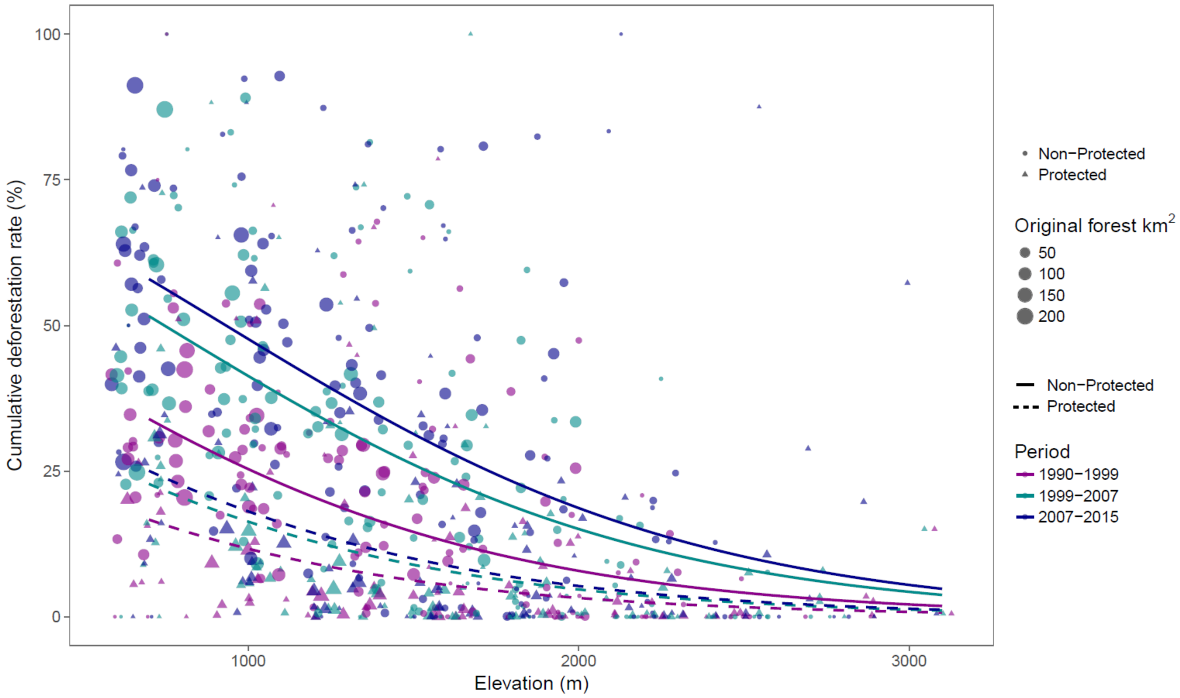

Fig 4 Role of altitude, protection, and period on cumulative deforestation rate. Curves are derived from a binomial Generalised Linear Mixed Model (GLMM).

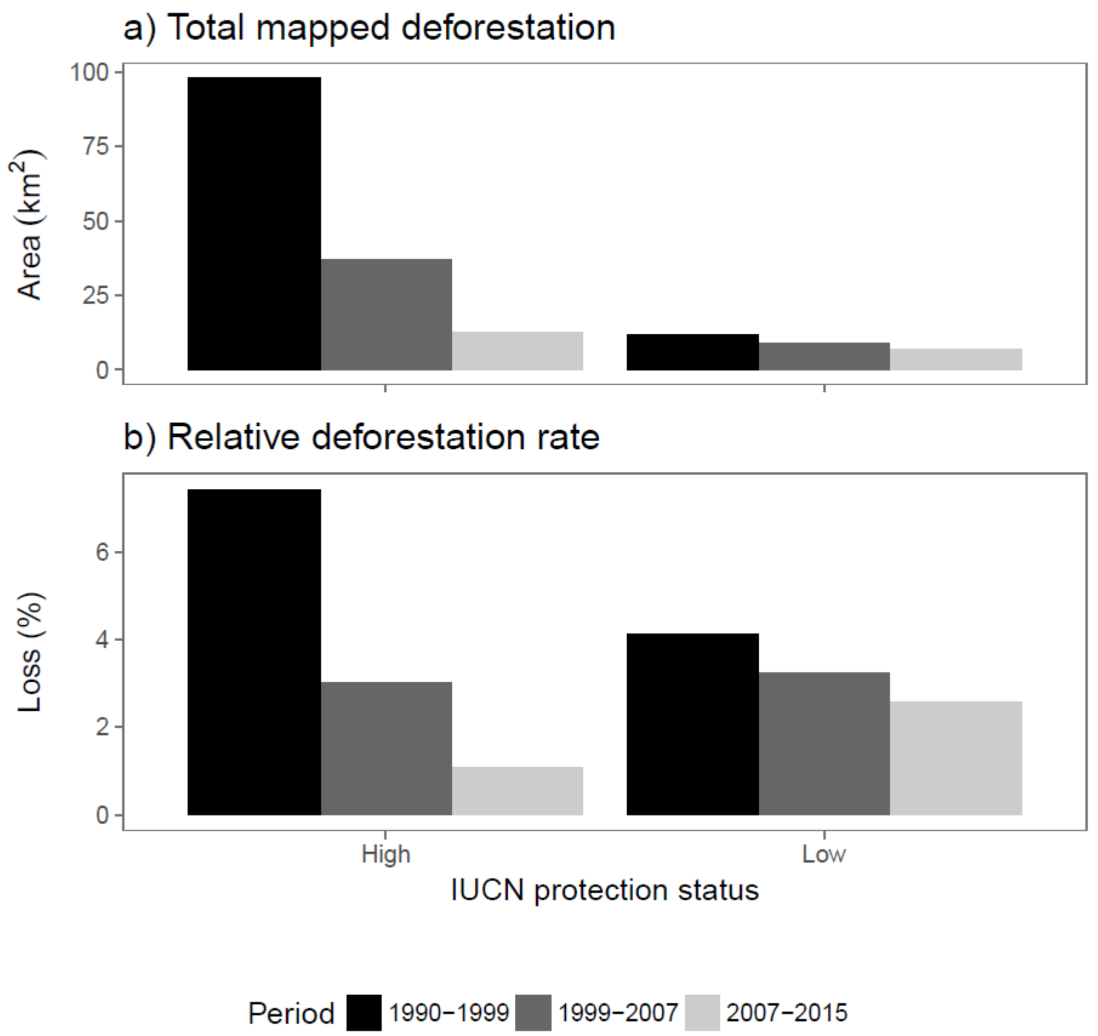

Fig 5 Total mapped deforestation per International Union for Conservation of Nature (IUCN) protected area status

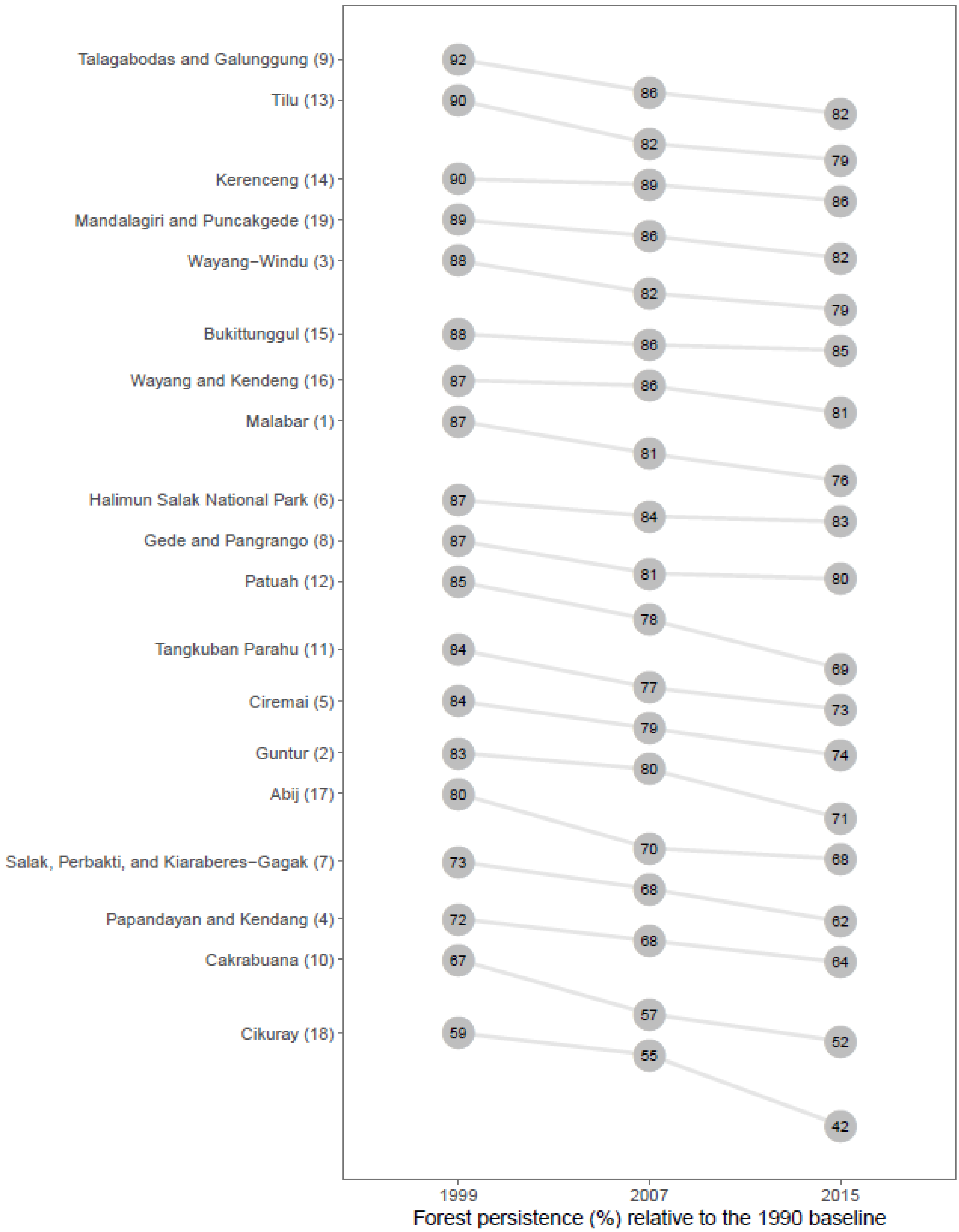

Fig 6 Forest persistence, as a percent of the 1990 baseline across the three epochs for each mountain site. Numbers next to names relate to the mountains in Figure 1

Tables

Table 1 Error matrix and derived accuracy for the land-cover change map

		REFERENCE					
		Stable forest	*Stable non-forest*	*Loss 1990–1999*	*Loss 1999–2007*	*Loss 2007–2015*	Total
MAPPED	*Stable forest*	131	0	0	1	0	132
	Stable non-forest	0	183	0	4	0	187
	Loss 1990–1999	0	0	74	0	0	74
	Loss 1999–2007	0	0	1	69	6	76
	Loss 2007–2015	0	0	0	1	69	70
	Total	131	183	75	75	75	539
	User's	0.99	0.98	1	0.91	0.99	
	Producer's	1	1	0.99	0.78	0.84	
	Overall	0.98					

Table 2 Odds ratio effects and 95% confidence intervals (CI) for the fixed and random components of the Generalised Linear Mixed Model (GLMM). The model resulted in a marginal R^2 of 0.3 (only fixed effects) and conditional R^2 of 0.45 (full model).

	Response		
	Odds ratio	*CI*	*p*
Intercept	0.17	0.13–0.24	<0.001
Altitude	0.45	0.45–0.45	<0.001
Period 1999–2007	2.07	2.06–2.08	<0.001
Period 2007–2015	2.68	2.67–2.70	<0.001
Status *Protected	0.39	0.38–0.40	<0.001
Period 1999–2007: Status Protected	0.71	0.70–0.73	<0.001
Period 2007–2015: Status Protected	0.62	0.61–0.64	<0.001
$\tau_{00, Zone}$		0.624	
N_{Zone}		27	
ICC_{Zone}		0.159	
Observations		668	