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

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20  
21 **Abstract**

22 While much has been published on recent rates of forest loss in the Sundaic lowlands, deforestation  
23 rates and patterns on Java's endemic-rich mountains have been rather neglected. We used nearly  
24 1,000 Landsat images to examine spatio-altitudinal and temporal patterns of forest loss in montane  
25 West Java over the last 28 years, and the effectiveness of protected areas in halting deforestation  
26 over that period. Around 40% of forest has been lost since 1988, the bulk occurring pre-2000 (2.5%  
27 per annum), falling to 1% per annum post-2007. Most deforestation has occurred at lower altitudes  
28 (< 1,000 m), both as attrition of the edges of forested mountain blocks as well as the near-total  
29 clearance of lower-altitude forested areas. Deforestation within protected areas was rife pre-2000,  
30 but greatly decreased thereafter, almost ceasing post-2007 in protected areas of high International  
31 Union for Conservation of Nature (IUCN) status. While apparent recent protection against land  
32 clearance is welcome, it must be stressed that the area of remaining forest is only 5,234 km<sup>2</sup>, that  
33 most accessible lower-altitude forest has already disappeared, and that the extant montane forest is  
34 largely fragmented and isolated. The biological value of these forests is huge and without strong

35 intervention we anticipate imminent loss of populations of taxa such as the Javan Slow Loris  
36 *Nycticebus javanicus* and Javan Green Magpie *Cissa thalassina*.

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

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#### 44 Highlights:

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

## 52 1. Introduction

53 Deforestation is one of the main drivers of global biodiversity decline, and a major source of carbon  
54 emissions (Houghton et al., 2012; Lawrence and Vandecar, 2015). Information on the extent,  
55 severity, and causes of forest loss is therefore critical for a range of disciplines. In recent years,  
56 Earth-observation has provided a more accurate and better picture of the global rate and  
57 geographical distribution of deforestation (Skole and Tucker 1993; DeFries et al. 2002; Miettinen et  
58 al. 2011), highlighting Southeast Asia, and in particular Indonesia, as of major concern (Hansen et al.  
59 2013). Within Indonesia, the loss of moist tropical forests on the islands of Borneo and Sumatra,  
60 primarily due to the expansion of industrial palm oil plantations, has been well documented (Broich  
61 et al., 2011, 2013; Margono et al., 2012; Shevade et al., 2017), but far less attention has been  
62 directed towards Java. Indeed, the forests of Java have not received bespoke study and are  
63 frequently omitted from published statistics, in part due to the relative sparsity of forest cover  
64 remaining since Dutch colonial rule in the eighteenth and nineteenth centuries (Smiet et al. 1990).  
65 Such neglect is unfortunate, as these forests possess high levels of biological endemism, with the  
66 montane formations on the volcanoes of West Java being particularly rich in unique species  
67 (Stattersfield et al., 1998). The West Javan mountains hold all or most of the remaining range of four  
68 ‘Critically Endangered’ endemic vertebrates: Javan Slow Loris *Nycticebus javanicus*, Rufous-fronted  
69 Laughingthrush *Garrulax rufifrons*, Javan Green Magpie *Cissa thalassina* and Fire Toad *Leptophryne*  
70 *cruentata* (IUCN, 2017), and either whole or significant portions of the ranges of many other species  
71 of conservation concern (e.g. the ‘Endangered’ Javan Gibbon *Hylobates moloch* and the ‘Vulnerable’  
72 Javan Trogon *Apalharpactes reinwardtii* and Javan Cochoa *Cochoa azurea*). These and other  
73 endemics are known to be dependent on forest habitats (BirdLife International, 2018).

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

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

## 91 2. Study area

92 Our study area is ~17,000 km<sup>2</sup> covering the western uplands of the Indonesian island of Java (Fig 1).  
93 We defined uplands as all areas upwards of 400 m above sea level. Analysis was limited to such  
94 areas, as these are the location of a majority of remaining upland forest on the island. We focused  
95 on 19 West Javan mountains that are of known high biodiversity value (Fig 1b). These mountains  
96 include both unprotected areas and protected sites of various International Union for Conservation  
97 of Nature (IUCN) designation classes. The climate is broadly tropical, with Köppen climate  
98 classifications of Equatorial or Monsoon. Annual temperatures range from 18 to 30°C, with a regular  
99 daily average of 28°C. Rainfall is concentrated in the monsoon period November–March, with  
100 monthly precipitation around 270 mm. West Javan forests are not dominated by any particular tree  
101 species, but common taxa include: Moraceae (*Artocarpus elasticus*), Meliaceae (*Dysoxylum*  
102 *caulostachyum* and *Lansium domesticum*), and Lecythidaceae (*Planchonia valida*) (MacKinnon et al.,  
103 1993). Java contains twenty volcanoes that have been active in the historical record; accordingly, the  
104 regional geology is dominated by relatively recent volcanic rocks, interspersed with marine  
105 limestones (Whitten et al., 1996). Java's human population doubled since the 1970s to 145 million  
106 today, equating to 1,121 people per km<sup>-2</sup>, the highest density in the world (World Bank, 2017). Our  
107 study area contains the major cities of Bogor and Bandung, with the Indonesian capital Jakarta just  
108 outside the perimeter. A variety of crops are grown within the study area, mainly as smallholdings,  
109 with the dominant being rice and coffee (Whitten et al., 1996).

## 110 3. Methods

### 111 3.1 Landsat data

112 The Landsat series is the world's longest continuously operating moderate-resolution Earth  
113 observation (EO) program. Collecting imagery at 30 m across six spectral bands (plus a thermal  
114 band), Landsat is particularly suited for monitoring land-cover change. To map such changes, we  
115 produced a series of spectral variability metrics for four epochs corresponding to relevant time

116 periods: 1988–1992, 1998–2000, 2006–2008, and 2014–2016. Spectral metrics are pixel-level  
117 statistical summaries calculated from all co-located observations. Metric composites allow the  
118 extraction of intra-epochal information on the reflectance of a pixel, and have proved effective for  
119 mapping subtle land cover types and improving the accuracy of classifications (Müller et al., 2015).  
120 This approach copes more robustly with the problem of persistent cloud cover and atmospheric  
121 effects by using all available observations, minimising the contributions of individual pixels which  
122 may be compromised, and is therefore well suited to the wet tropics. The composites were  
123 generated in Google Earth Engine (Gorelick et al., 2017) from all available Landsat 5 TM and 7 ETM+  
124 images. To ensure sufficient observations were present for the calculations, a three-year  
125 compositing period was used for the later three epochs, but, owing to lower image availability the  
126 1990 composite required a five-year range.

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

### 131 3.2 Forest change mapping

132 The Landsat spectral variability metrics were classified to produce a land-cover change map. The  
133 following classes were mapped: (i) stable forest, (ii) stable non-forest, and loss in the periods (iii)  
134 1990–1999, (iv) 1999–2007 and (v) 2007–2015. Training data consisting of 211 polygons were  
135 derived from visual bi-temporal comparison of the Landsat composites, in conjunction with high-  
136 resolution imagery; forest loss was identified by complete removal of tree cover in the target pixels,  
137 whilst stable classes were consistent across all epochs. The classification was undertaken using a  
138 Random Forest classifier. Random Forest is a decision-tree-based technique that uses bootstrapped  
139 subsets of the training data to generate an ensemble of tree models, which are then aggregated into  
140 a final model (Breiman 2001). The internal parameters of the model, the number of trees generated  
141 and the number of variable splits, were chosen based on a 10-fold cross validation over a tuning grid  
142 of potential values (Kuhn et al., 2017). The classification was developed with the R package  
143 randomForest package (version 4.6; Liaw and Wiener, 2002; R Core Team, 2017).

144 To validate our classified map, we first selected a random sample of 75 points per class and  
145 calculated the Producer's accuracy. This Producer's accuracy and mapped area per class were used  
146 to determine an appropriate stratified sample for a target standard error of 0.5 (Cochran, 1977). The  
147 final stratified sample of 539 points was used to calculate Producer's, User's and Overall accuracy

148 scores based on best practice guidelines (Congalton and Green, 2008). Finally, the mapped class  
149 areas were adjusted to account for omission errors (Olofsson et al., 2013).

### 150 3.3 Statistical analysis

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

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

## 172 4. Results

### 173 4.1 Land-cover change classification

174 Our land-cover change classification produced a map (Fig 1 and Fig 2) with an overall accuracy of  
175 98% (Table 1). All of the mapped classes had consistently high accuracies, with the least accurate  
176 class (loss for 1999–2006) having Producer's and User's accuracies of 0.91 and 0.78 respectively.  
177 Adjusting the mapped area estimates using probability-based stratified sampling highlighted a

178 moderate omission of the loss in 1999–2007, with all other classes showing minor biases between  
179 the mapped and adjusted areas (Fig 3).

## 180 4.2 Deforestation rates

181 Over the 1990–2015 period,  $3,415 \pm 290 \text{ km}^2$  of forest were lost, corresponding to roughly 40% of  
182 the initial coverage (Fig 3). By 2015,  $5,234 \pm 78 \text{ km}^2$  of stable forest remained. Deforestation was  
183 greatest in the 1990–1999 period, with  $1,923 \pm 24 \text{ km}^2$  lost, falling to  $1,056 \pm 207 \text{ km}^2$  in the period  
184 1999–2007 and  $436 \pm 59 \text{ km}^2$  for 2007–2015. Deforestation rates equate to 22% (2.5% per annum),  
185 16% (2%) and 7% (1%) for the respective periods (Fig 3).

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

## 192 4.3 Correlates of deforestation rates

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

204

## 205 5. Discussion

206 West Java lost around 40% of its  $8,650 \text{ km}^2$  montane forest in the 25 years since 1990, a figure  
207 broadly comparable to other locations in Southeast Asia, e.g. Peninsular Malaysia (Shevade et al.,

208 2017), Kalimantan (Carlson et al., 2012), and Sumatra (Gaveau et al., 2009). What sets it apart from  
209 these areas are that (1) the annual rate of forest loss has slowed considerably over time, from a high  
210 of 2.2% pre-2000 to 0.5% post-2007, with an important brake being exerted by protected areas,  
211 especially strict nature reserves and national parks, and (2) only around 5,500 km<sup>2</sup> remain of this  
212 endemic-rich habitat. Optimism over the decelerating trend in deforestation must be tempered by  
213 the extensive loss of forest at altitudes of 300 to 1,800 m, which presumably hold (or held) the most  
214 accessible and biodiverse forests. Species that are restricted to or prefer such altitudes are likely to  
215 be put under increasing strain across their ranges, especially if deforestation, albeit at slower rates,  
216 continues.

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

229         High rates of deforestation across insular Southeast Asia during the 1990s are well  
230 documented (Hansen et al., 2009; Kim et al., 2015), and relate to both political-economic and  
231 environmental factors. The 1990s were an economic boom period for Southeast Asia, with  
232 increasing commodity prices and favourable exchange rates driving growth in both agricultural and  
233 hardwood exports (Mason, 2001). This economic situation combined with lax forest protection laws  
234 encouraged widespread logging and agricultural expansion (Hansen et al., 2009). Environmentally,  
235 the 1997 El Niño event was severe, leading to widespread forest fires across the region (Page et al.,  
236 2002).

237         The last two epochs of our study postdate the Asian financial crisis of July 1997 and the  
238 associated economic consequences; within six months inflation peaked at 80%, and gross domestic  
239 product dropped by 47% (World Bank 2017). The resignation of President Suharto in May 1998  
240 ended the 42-year New Order dictatorship and initiated a shift to representative democracy. This

241 period was also marked by a number of forestry legislation changes, such as a round wood export  
242 ban in 2001, aiming to curtail illegal logging (Resosudarmo and Yusuf, 2006). Interestingly, our  
243 results contradict those of Miettinen et al. (2011), who observed a 4.2% increase in forest cover on  
244 Java between 2000 and 2010. We attribute this to two factors: first, we did not attempt to map  
245 reforestation, so did not account for gains; and second, Miettinen et al. (2011) used 250 m MODIS  
246 data, compared to the 30 m Landsat imagery used here, so our analysis probably identified smaller  
247 clearances missed by the coarser MODIS data.

248         Assessing the efficacy of protected areas is critical for ensuring long-term conservation (e.g.  
249 Mallari et al. 2013, 2016). Java's officially protected areas have fared reasonably well over the study  
250 period, especially since 2000 compared to those in Sumatra and Borneo, where encroachment  
251 through small-scale logging and agriculture is rife (Curran et al., 2004; Gaveau et al., 2009).  
252 Furthermore, the high altitude of most parks and reserves has minimised the displacement of  
253 logging to unprotected areas (Gaveau et al., 2009). Since 1999, forest loss in highly protected areas  
254 (IUCN Classes Ia and II) has been minimal, with a < 0.1% rate since 2007, but further study of the  
255 efficacy of different protection levels would be valuable, as our small sample size precluded robust  
256 modelling. Moreover, this welcome trend must be set against an extremely high baseline rate in the  
257 1990s when forests below 1,000 m suffered a decline rate of 55% overall and 20% inside protected  
258 areas. As a consequence, only 2,500 km<sup>2</sup> of low-altitude forest remains (around 20% coverage). This  
259 will have detrimental effects for connectivity between the better-preserved highland forests, with  
260 increasing separation of major mountain chains and individual peaks (Fig 2ii-iii). Species movement  
261 modelling to identify connectivity corridors between the remaining forest and the bottlenecks to  
262 these connections would benefit conservation planning (e.g. Bleyhl et al., 2017). Crucially, forest  
263 loss, however slow, continues in montane West Java, not only compromising the future of the  
264 island's most distinctive fauna and flora but also inevitably risking ecosystem services such as water  
265 retention and regulation. Efforts to enhance the protection status of those montane forests  
266 currently with no or low IUCN protected area designation, field surveys to assess the viability of  
267 populations of endemic and threatened taxa (many mountains have not been visited by ecologists  
268 for decades), and protection, by whatever means, of lower-altitude montane forests, are, therefore,  
269 matters of great urgency.

270

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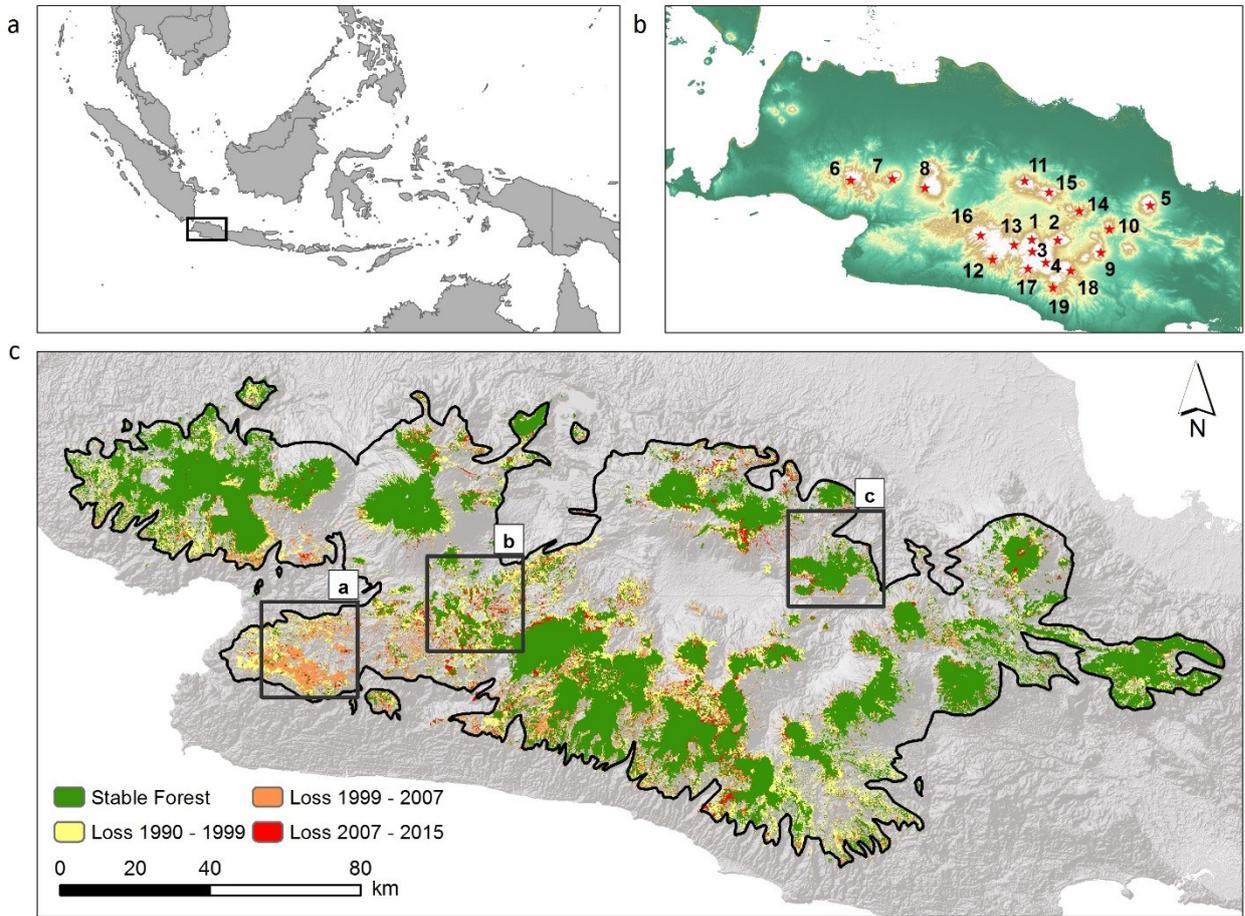
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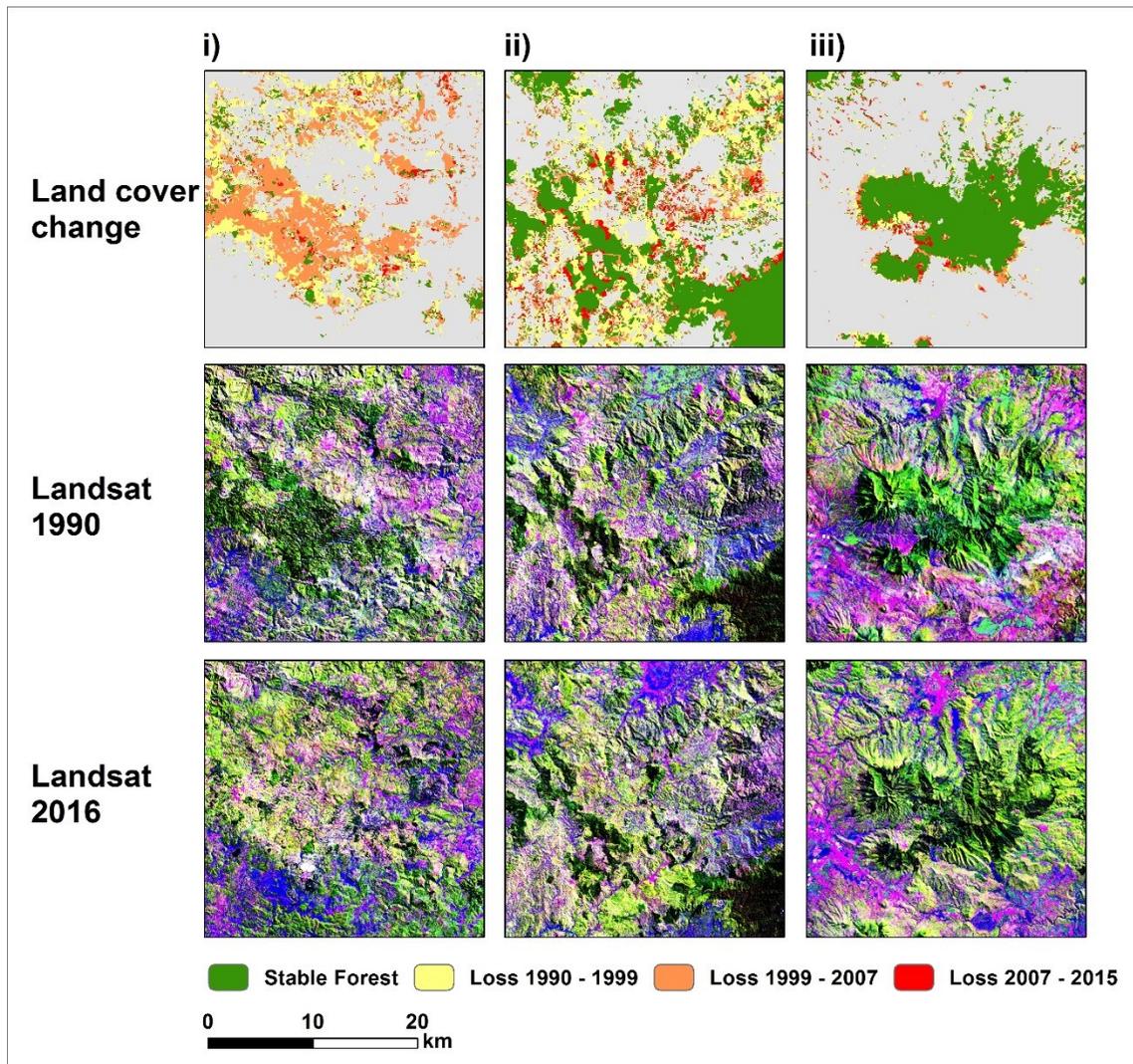
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398 **Fig 1** (a) Location of the study area within Southeast Asia; (b) Digital Elevation Model (DEM) of the  
 399 study location with stars indicating the mountain sites selected for further study; (c) land-cover  
 400 change map with the 400 m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

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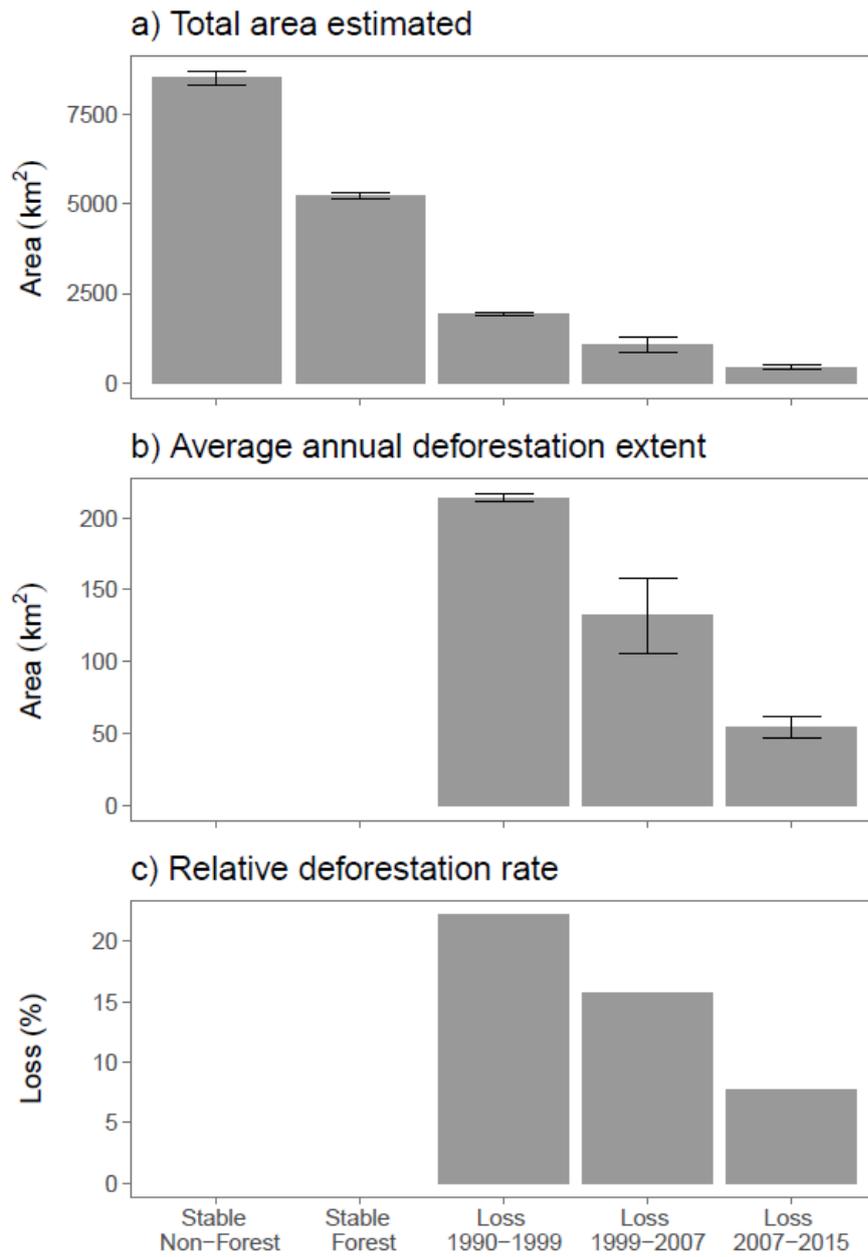


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404 **Fig 2** Results of the land-cover change classification (top row), 1990 Landsat 5 median composite  
 405 (middle row), and 2016 Landsat 8 median composite (bottom row), for the three areas shown in Fig  
 406 1. Band association in the Landsat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

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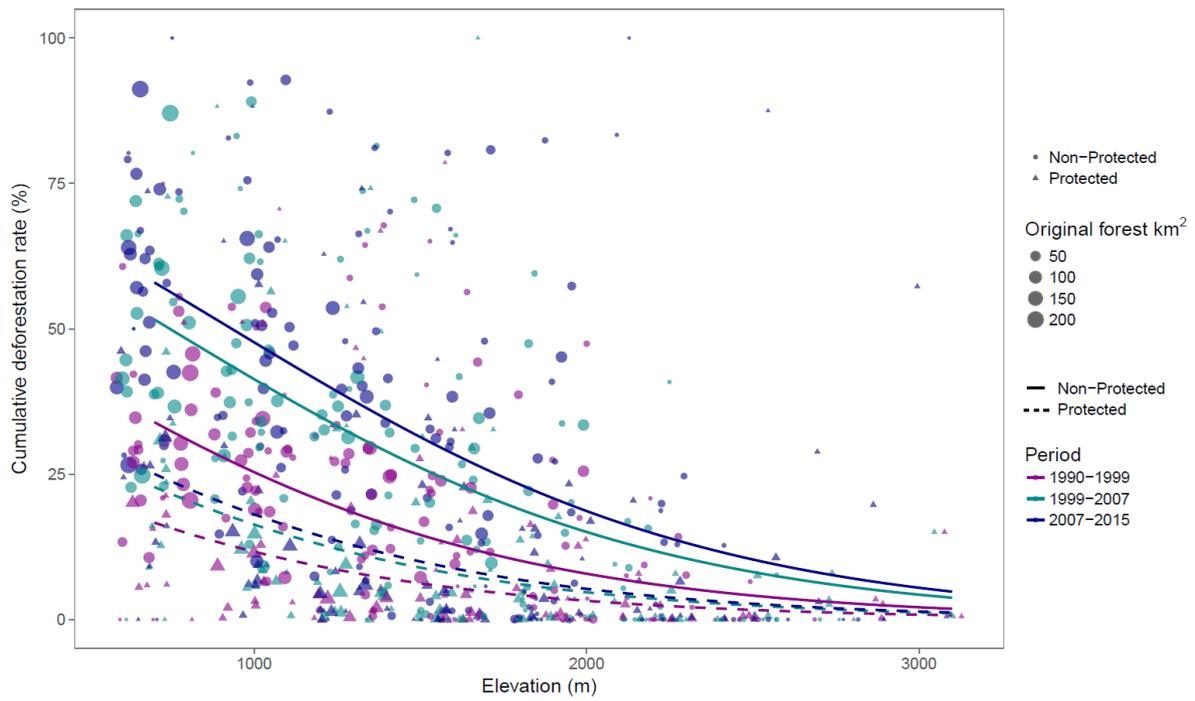
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411 **Fig 3** Area-adjusted estimated, with 95% confidence intervals, for the land-cover change classes  
 412 covering the whole study area

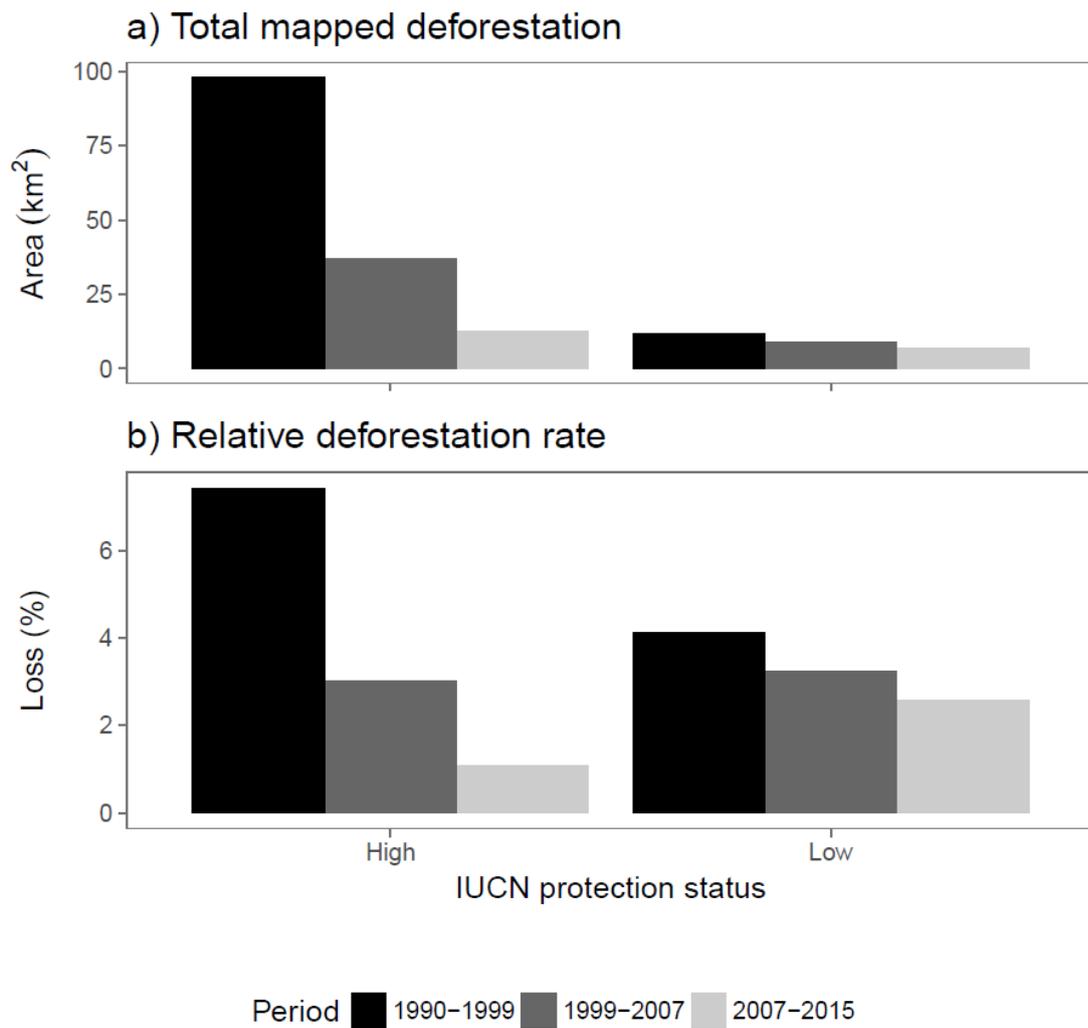
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415 **Fig 4** Role of altitude, protection, and period on cumulative deforestation rate. Curves are derived

416 from a binomial Generalised Linear Mixed Model (GLMM).



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

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

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## 430 Tables

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

		REFERENCE					Total
		<i>Stable forest</i>	<i>Stable non-forest</i>	<i>Loss 1990–1999</i>	<i>Loss 1999–2007</i>	<i>Loss 2007–2015</i>	
MAPPED	<i>Stable forest</i>	131	0	0	1	0	132
	<i>Stable non-forest</i>	0	183	0	4	0	187
	<i>Loss 1990–1999</i>	0	0	74	0	0	74
	<i>Loss 1999–2007</i>	0	0	1	69	6	76
	<i>Loss 2007–2015</i>	0	0	0	1	69	70
	<i>Total</i>	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	
	<i>Overall</i>	0.98					

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

	Response		
	<i>Odds ratio</i>	<i>CI</i>	<i>p</i>
Intercept	0.17	0.13–0.24	<0.001
Altitude	0.45	0.45–0.45	<0.001
<i>Period 1999–2007</i>	2.07	2.06–2.08	<0.001
<i>Period 2007–2015</i>	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
τ <sub>00, Zone</sub>		0.624	
N <sub>zone</sub>		27	
ICC <sub>zone</sub>		0.159	
Observations		668	

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