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Upward expansion and acceleration of forest clearance in the mountains of Southeast Asia 1 2 Yu Feng^{1,2}, Alan D. Ziegler³, Paul R. Elsen⁴, Yang Liu¹, Xinyue He^{1,5}, Dominick V. Spracklen⁵, 3 Joseph Holden⁶, Xin Jiang¹, Chunmiao Zheng¹, Zhenzhong Zeng^{1*} 4 ¹ State Environmental Protection Key Laboratory of Integrated Surface Water-Groundwater 5 Pollution Control, School of Environmental Science and Engineering, Southern University of 6 7 Science and Technology, Shenzhen, China ² Department of Civil Engineering, The University of Hong Kong, Hong Kong, China 8 ³ Faculty of Fisheries Technology and Aquatic Resources, Mae Jo University, Chiang Mai, Thailand 9 ⁴ Wildlife Conservation Society, Global Conservation Program, Bronx, NY, USA 10 ⁵ School of Earth and Environment, University of Leeds, Leeds, UK 11 ⁶ School of Geography, University of Leeds, Leeds, UK 12 *Correspondence to: zengzz@sustech.edu.cn (Z. Zeng) 13 14 15 Manuscript for *Nature Sustainability* 16 May 21, 2021 17

18 Southeast Asia contains about half of all tropical mountain forests, which are rich in 19 biodiversity and carbon stocks, yet there is debate as to whether regional mountain forest 20 cover has increased or decreased in recent decades. Here, our analysis of high-resolution 21 satellite datasets reveals increasing mountain forest loss across Southeast Asia. Total mean annual forest loss was 3.22 Mha yr⁻¹ during 2001–2019, with 31% occurring on mountains. 22 23 In the 2010s, the frontier of forest loss moved to higher elevations (15.1 \pm 3.8 m vr⁻¹ during 2011–2019, p < 0.01) and steeper slopes (0.22 ±0.05° yr⁻¹ during 2009–2019, p < 0.01) that have 24 25 high forest carbon density relative to lowlands. These shifts led to unprecedented annual forest carbon loss of 424 Tg C yr⁻¹, accelerating at a rate of 18 ±4 Tg C yr⁻² (p < 0.01) from 26 27 2001-2019. Our results underscore the immediate threat of carbon stock losses associated with accelerating forest clearance in Southeast Asian mountains, which jeopardizes 28 29 international climate agreements and biodiversity conservation.

Tropical forests are the largest terrestrial component of the global carbon cycle¹, storing 247 Pg C in above and belowground biomass². However, recent anthropogenic-influenced forest loss has reshaped tropical forests profoundly³, weakening their ability to store carbon and regulate climate⁴. Currently, across the tropics, the amount of carbon sequestered by intact forests and forest regrowth is approximately similar to that released from forest loss, suggesting that tropical forests likely act as a neutral contributor to the global carbon cycle⁵. Forest loss in the tropics, which dominates the total loss worldwide in the 21st century^{6–10}, has been driven largely by agricultural intensification

and/or extensification to support demands for human/animal food trade, profit-driven (illegal) logging, and other activities that are inherently linked to population growth^{11–13}. Of concern is that acceleration of forest clearance in the future will intensify carbon stock loss, potentially transforming tropical forests into significant net carbon sources^{5,14,15}, as well as disrupting biodiversity patterns, human livelihoods, hydro-geomorphological processes, and ecosystem functions.

44

45 The general notion is that most tropical deforestation worldwide occurs primarily in lowland areas. This sentiment aligns with prior work showing substantial forest losses at low elevations, but only 46 negligible losses, and even some forest gains, in the mountains^{6,16,17}. However, in Southeast Asia 47 (hereafter SEA), where approximately half of the world's tropical mountain forests are located^{8,18} 48 and extensive forest losses in the lowlands of Indonesia have occured^{6,9}, recent studies have 49 50 reported new croplands and plantations replacing mountain forests in Laos and Thailand of montane mainland SEA^{19,20}. Yet the applicability of these results^{19,20} as an indicator of a regional 51 trend is debatable, as some global analyses^{7,17} indicate an increase in forest cover in this region. 52 New spatiotemporal analyses conducted at high resolution and with common vegetation definitions 53 54 are needed to address these inconsistencies related to topography of forest loss in the mountains and lowlands of SEA. 55

56

57 Here, we analyze multiple high-resolution satellite datasets to provide a comprehensive assessment

58	of changes in topographical patterns of forest clearance and related carbon loss across SEA during
59	the first two decades of the 21 st century. The analyses incorporate global mountain extent map ¹⁸
60	with two 30-m resolution products reporting the global forest cover change ⁸ and aboveground live
61	woody biomass density ²¹ (for details refer to <i>Methods</i>). Owing to limitations of distinguishing tree
62	types in the satellite products used ⁸ , unless specifically stated, "forest losses" incorporate those
63	from primary forest, secondary forest disturbance, as well as tree-dominated plantations, including
64	oil palm and rubber. As the mountains of SEA hold more forest biomass carbon than lowlands ²²
65	(Fig. S1), a better understanding of forest and related biomass carbon dynamics is crucial for
66	reducing uncertainties in the global carbon cycle, as well as guiding land management in the region.
67	

68 **Results**

69 This section presents our findings of forest loss in SEA, including the patterns of forest loss and70 related topograpgy and carbon loss.

71

Accelerating forest loss and related topography. We find a total forest loss of 61 Mha in SEA during the period 2001 to 2019, which is equivalent to an annual rate of 3.22 Mha yr⁻¹ (Table 1; Figs. 1a, S2c). Annual forest loss of the 2010s (4.02 Mha yr⁻¹) was nearly twice that of the 2000s (2.33 Mha yr⁻¹), with the greatest loss occurring in 2016 (5.79 Mha yr⁻¹). Approximately 31% of the loss during the 19-year period (19 Mha; 1.00 Mha yr⁻¹) occurred within the 61 mountainous areas that occupy 1.7 million km² of the region (38% of SEA's land surface; Fig. S2a, c). We also find a significant increase in annual forest loss area across SEA since 2001, with an acceleration rate of 0.17 ± 0.03 Mha yr⁻² (p < 0.01). The annual rate of mountain forest loss increased 2.4-fold from 0.58 Mha yr⁻¹ in the first decade to 1.38 Mha yr⁻¹ in the second decade (Fig. 1a).

81

82 Forest loss occurring in the lowlands of SEA significantly accelerated only during the 2000s (0.20 ± 0.04 Mha yr⁻², p < 0.01), with a non-significantly decreasing trend in the following decade (-0.01) 83 ± 0.07 Mha yr⁻², p = 0.92). This pattern mirrors the fact that there were limited lowland forests that 84 85 can be converted to croplands in some regions over SEA during the 2010s, as lowland forests had continued to be cleared since the 1980s (ref. 6). Regarding mountain forest loss, the near doubling 86 of acceleration rates from the first (0.06 \pm 0.01 Mha yr⁻², p < 0.01) to the second (0.11 \pm 0.03 Mha 87 yr⁻², p < 0.01) decade resulted from accelerated conversion of forests for crop plantation in 88 89 mountains¹⁹. Further, the trend in lowland forest loss was significantly different from that in 90 mountains during the 2000s (p < 0.05), but this difference was no longer statistically significant 91 during the 2010s (Fig. 1a). Taken together, these patterns reveal that forest loss in the mountains 92 increasingly comprised a significant portion of total forest loss in SEA from 2001 (24%) to 2019 93 (42%), which is a finding that has not been reported by prior studies 6,9,23 .

94

Incorporating data on primary forest extent in 2001 (ref. 10), we further estimate that annual loss
of primary forest from 2001 to 2019 was 0.93 Mha yr⁻¹ (Table 1; Fig. S3), with 0.26 Mha yr⁻¹ (28%)
occurring in the mountains and 0.67 Mha yr⁻¹ (72%) in the lowlands. These equate to 2.9% and

7.3% losses of the primary forest extent in 2001. Throughout the 19-year period, secondary forest 98 99 loss always exceeded primary forest loss in both lowlands and the mountains. Whereas secondary forest loss accelerated significantly throughout the whole period (0.14 ± 0.02 Mha yr⁻², p < 0.01), 100 the significant acceleration in primary forest loss in the first decade (0.11 ± 0.02 Mha yr⁻², p < 0.01) 101 102 gave way to a non-significant decline in primary forest loss in the second decade (-0.05 ± 0.03 Mha yr^{-2} , p = 0.19). Two trends emerged during the 2010s: (1) secondary forest loss in the mountains 103 greatly increased (0.10 \pm 0.02 Mha yr⁻², p < 0.05) and (2) primary forest loss in the lowlands non-104 105 significantly decreased (-0.05 ± 0.02 Mha yr⁻², p = 0.06). As the trend in secondary forest loss is 106 much larger than that of primary forest loss over the 19-year period, the ratio of primary-to-total 107 forest loss decreased from >30% to 20%. Collectively, the increase in mountain forest loss in the 108 2010s primarily originated from secondary forest loss, while the overall reduction in primary forest 109 loss resulted from reductions in the lowlands.

110

An elevational shift in the frontier of forest loss in the region is further supported by changes in the elevation and slope of mean forest loss midway through the 19-year study period (Fig.1b). Piecewise regression reveals an inflection point (hereafter IP) for mean elevation of forest loss that occurred in 2011 and an IP for mean slope of forest loss that occurred in 2009 (Fig.1b). Within the period after the IPs, the mean elevation and slope increased significantly at rates of 15.1 \pm 3.8 m yr⁻¹ (p < 0.01) and 0.22 \pm 0.05° yr⁻¹ (p < 0.01), respectively. Importantly, forest loss in the mountains accounted for most of both the observed increases in mean elevation (64%; 9.6 \pm 2.7 m yr⁻¹, p < 118 0.01) and slope (64%; 0.14 \pm 0.04° yr⁻¹, p < 0.01) after the IPs (Fig. 2a, b).

119

120 Regional patterns of trends in the mean elevation and slope where forest loss occurred (hereafter 121 termed as forest loss topography) show that east Sumatra and Kalimantan (Indonesia), north Laos, 122 and northeast Myanmar contribute to most of the increases in forest loss topography after IPs (Figs. 123 2). In some regions, a decreasing trend in forest loss topography occurred, such as on the Malay 124 peninsula (including south Thailand and Malaysia) and in Vietnam (Fig. S5). In Indonesia, which 125 experienced the largest magnitude of forest loss (Fig. S4), a sharp increase in forest loss topography 126 occurred during the second decade (Fig. S5). These losses in Indonesia contribute to most of the increase in mean elevation (44% or 6.6 \pm 1.6 m yr⁻¹, p < 0.01) and slope (41% or 0.09 \pm 0.03° yr⁻¹, 127 p < 0.01) in SEA after the IPs (Fig. 2a, b). Also of regional importance were the increases in forest 128 129 loss topography in Laos (28% for SEA's elevation and 23% for SEA's slope) and Myanmar (26% 130 for SEA's elevation and 23% for SEA's slope). In other countries, such as Thailand and the 131 Philippines, trends in forest loss topography were comparatively small (Fig. S5).

132

133 **Carbon loss resulting from forest clearance.** The observed shift in forest loss to higher elevations 134 and steeper slopes is of concern because mountain forests in the region tend to have higher carbon 135 stocks than lowland forests²²: 141 ±49 Mg C ha⁻¹ in mountains versus 101 ±69 Mg C ha⁻¹ in 136 lowlands (Fig. S1). By incorporating the forest change calculations in the previous section with 137 forest carbon stock map²¹ (see *Methods*), we estimate the total forest carbon loss in SEA during

2001–2019 was 8,050 Tg, equivalent to a rate of 424 Tg C yr⁻¹ (Fig. 3a; Table 1). As with annual 138 139 forest loss, forest carbon stock loss increased continuously throughout the entire period, accelerating significantly at a rate of 18 ±4 Tg C yr⁻² (p < 0.01; Fig 3a, Table 1). Nearly a third of 140 the loss in forest carbon stocks (2,584 Tg C; 136 Tg C yr⁻¹) occurred in the mountains; lowland 141 forest carbon stock losses totaled 5,466 Tg (68%; 288 Tg C yr⁻¹). Mountain forest carbon loss 142 accelerated significantly both in the first (8 ± 2 Tg C yr⁻², p < 0.01) and second decade (10 ± 4 Tg C 143 yr⁻², p < 0.05), whereas the significant acceleration of lowland forest carbon stock loss (27 ±5 Tg 144 C yr⁻², p < 0.01) in the first decade was followed by a non-significant decrease in the 2010s (-9 ±8 145 Tg C yr⁻², p = 0.30). These trends result in the increasing contribution of mountain forest carbon 146 loss to total forest carbon loss in the second decade of the 21st century. Moreover, increasing 147 148 clearance of mountain forests with dense carbon stocks results in a disproportionate loss of carbon 149 stocks relative to past times when forest loss was more prevalent at lower elevations. For example, in 2019, the last year of the analysis, mountain forest carbon loss was 119 Mg C ha⁻¹ yr⁻¹, which 150 151 was 7% higher than that of the lowlands. If these carbon loss rate trajectories continue, annual 152 forest carbon loss in mountains will exceed that of lowlands by 2022.

153

In agreement with the forest loss trends, the frontier of forest carbon loss also climbed to higher elevations and steeper slopes during 2001–2019 (Fig. 3b). However, there are stark regional differences in forest carbon loss patterns with respect to topography (Fig. 4). In maritime SEA during the 2000s, most forest carbon losses took place in the lowlands (Fig. 4a), particularly on

158	some Indonesian islands (e.g., Sumatra, Kalimantan) and the Malay peninsula (Fig. 4c). Forest
159	carbon loss in the lowlands of maritime SEA accounted for 65% of SEA's total carbon loss in the
160	2000s. In the 2010s, lowland forest carbon loss decreased, particularly in Sumatra and Kalimantan
161	(Fig. 4d). However, positive trends in annual forest carbon loss occurred throughout many
162	mountainous areas of mainland SEA, pushing upwards and accelerating in the mountains of Laos,
163	and Myanmar. Although forest and related carbon loss in Vietnam and the Malay peninsula
164	increased (Figs. 4b, S4), the topography of forest loss in those regions decreased (Figs. 2, S5),
165	indicating that forest (carbon) loss accelerated in regions with lower elevations, a pattern that is
166	opposite to those observed in Myanmar and Laos. Overall, we conclude that the hotspots of forest
167	carbon loss, while mirroring those of forest loss in general, were found predominantly in lowland
168	maritime SEA in the 2000s. They were then located disproportionately in the mountains of
169	mainland SEA in the 2010s, particularly in northern Laos and northeast Myanmar, locations
170	strongly associated with increased forest loss at higher elevations and on steeper slopes (Fig. 2c,
171	d).

Discussion

In this section, we discuss the net changes in forest loss, implications, and potential limitations thatneed to further address in future studies. Finally, we summarize our findings.

177 Net changes. In the dynamic environments of SEA, forest losses were also counteracted to some

178 degree by forest gains during the study in both lowland and mountain areas. Using the data developed by Hansen et al.⁸, we determine that forest gains during the period of 2001–2012 were 179 10.3 Mha (0.86 Mha yr⁻¹) in the lowlands and 2.7 Mha (0.23 Mha yr⁻¹) in the mountains (Fig. S6). 180 181 These gains result in the net-to-gross loss proportion of 56% and 66% in lowlands and mountains, 182 respectively, during this abbreviated period. The lower net-to-gross loss rate in lowlands may be 183 related to extensive oil palm and timber plantation establishment following the removal of forest or older plantations²⁴, as maturing plantations would be counted as forest gain once plants exceed 184 the threshold 5-m tree height definition of Hansen et al.^{8,25}. By assuming that the net-to-gross loss 185 186 ratios during 2013–2019 are the same as that in the earlier period, we estimate a 23.6 Mha (1.24 Mha yr⁻¹) net forest loss in the lowlands and 12.5 Mha (0.66 Mha yr⁻¹) net forest loss in the 187 188 highlands during 2001–2019 (Fig. S6). These estimates of net loss are likely conservative, given that forest loss accelerated at a rate of 0.17 \pm 0.03 Mha yr⁻² (p < 0.01) throughout the entire period 189 190 (Table 1).

191

Overall, our net estimates also reveal a clear fingerprint of mountain forest loss that is accelerating in some countries of SEA (e.g., Indonesia, Myanmar, and Laos) during the early 21st century, primarily owing to expansion of agriculture for crop plantation^{19,20}. The accelerating mountain forest loss in the 2010s originated from secondary forest loss also mirrors the replacement of swidden fields with other agriculture systems. For example, a notable shift from swidden fields, where secondary forests regenerate during fallow period, to permanent agriculture systems is reported in mountains of Laos²⁶, indicating that these forest losses in the mountains of SEA are partly a result of agriculture intensification. This pattern, however, is different from agricultural expansion in the Midwestern United States, which made the farms in the northeastern United States not profitable and hence resulted in forest regeneration in that region²⁷.

202

203 Implications. Our results demonstrate not only a continuation of forest loss in SEA as reported in sub-regions during prior periods^{6,9}, but an acceleration in loss that includes encroachment into 204 205 forests at higher elevations with higher carbon density. These trends influence the roles tropical 206 forests play within the context of global climate mitigation, biodiversity conservation, and global 207 carbon cycling. For example, the observed acceleration in forest carbon loss counters efforts to limit global warming to below 2 °C by the end of this century²⁸. The climb in the forest loss frontier 208 209 also represents a challenge for climate change assessments, as current earth system models do not differentiate mountain from lowland forest loss because of their coarse spatial resolutions¹⁹, 210 211 potentially resulting in the misrepresentation of climate feedbacks. In addition to the warming 212 triggered by forest carbon loss to the atmosphere through biochemical feedbacks, tree replacement 213 also increases surface temperature at a variety of scales through biophysical feedbacks^{28,29}. In the 214 mountains of SEA, where most deforested lands are converted to croplands¹⁹, warming effects 215 related to forest loss tend to be amplified due to suppressed evapotranspiration, raising local temperatures by up to $2 \circ C^{29-31}$. The acceleration of mountain forest loss in the region has likely 216 217 already enhanced these warming effects and influenced the carbon budget.

219 The acceleration in forest loss also affects biodiversity conservation in the region because a great number of endemic species are found in the mountains of SEA³². While widespread conversion of 220 221 forests to croplands significantly reduces species richness and alters community composition in general, loss of mountain forest habitat is particularly detrimental^{33,34}. Tropical montane species 222 223 typically live within specific hydro-thermal environments, which are dramatically altered during forest conversion, increasing extinction risk^{35,36}. Deforestation also interacts with climate changes, 224 225 forcing species to redistribute³⁷, often to higher and cooler locations. Mountain forest loss threatens to reduce the area of suitable habitat to accommodate these types of relocations³⁸. 226

227

Beyond the direct loss of carbon associated with vegetation biomass removal and habitat loss, forest 228 229 loss also affects the carbon cycle through diminishing photosynthesis and altering soil carbon 230 stocks. For example, forest loss directly lowers landscape-wide photosynthesis due to decreases in 231 leaf area and alteration of vegetation functioning. Forest conversion also alters basic water balance processes including evapotranspiration, infiltration, and water storage³⁹⁻⁴¹, thereby modulating 232 233 vegetation growth and associated carbon assimilation. Soil erosion accelerated by forest conversion, 234 particularly on sloping lands, exhumes soil carbon that may be quickly released to the atmosphere, 235 or transported into downslope flood plain locations, water bodies, or the ocean, where it is stored/lost at variable time scales^{42,43}. Unfortunately, because of the absence of regional data on 236 soil carbon stocks, we were not able to account for losses of this component, which for some forest 237

238 conversion outcomes are substantial^{3,44}.

239

240 Uncertainties and caveats. With regard to uncertainties in our analysis, fragmentation and edge effects of forest losses can alter microclimates, and thus regulats the growth and structure of nearby 241 trees, causing additional long-term carbon losses on the landscape that we could not quantify⁴⁵. 242 243 Additional uncertainty relates to our inability to detect forest conversions at scales smaller than a 244 Landsat pixel, for example, those related to small-scale, fallow-based swidden agriculture, which is still practiced in some areas of SEA^{20,46}. Again, our estimates also represent absolute forest 245 carbon losses, not net losses that incorporate biomass carbon gains which could not be calculated 246 from available data with confidence. Even with these uncertainties in mind, the acceleration of loss 247 in mountain forests with high carbon density that we find based on immediate vegetative biomass 248 249 changes alone portends additional redistributions and losses of carbon in the near future, potentially nudging SEA's forests to be a net carbon source in the global carbon budget^{15,47}, rather than a 250 251 neutral actor⁵. To reduce the above uncertainties, future studies could integrate higher resolution 252 satellite and lidar datasets to map primary and secondary forests and related biomass carbon loss more accurately. More studies on above and belowground carbon recovery associated with forest 253 254 regrowth are also needed.

255

In summary, our results reveal changing topographical patterns associated with forest loss in
 Southeast Asia during the first two decades of the 21st century. The shift is characterized by an

258 upward expansion in the frontier of forest exploitation, from predominantly occurring in the lowlands to increasingly encroaching forests at higher elevations with comparatively higher carbon 259 260 stocks and more sensitive species. The acceleration of this trend throughout the two decades 261 provides new insight regarding forest and carbon dynamics in the region that has not been recognized in prior climate change assessments, nor parameterized in current model configurations 262 263 simulating impacts. Such exclusion misrepresents regional biophysical and biochemical feedbacks of deforestation. Collectively, knowledge of the ascent of the frontier of forest loss across Southeast 264 265 Asia is needed to develop effective policies to manage concomitant negative impacts on 266 biodiversity, water resources, land degradation, and the carbon cycle. This knowledge is valuable 267 for developing strategies to reduce future losses of remaining forests that still have great ability to 268 preserve valuable ecosystem services, including atmospheric carbon dioxide capture and biodiversity conservation. 269

270 Methods

This section provides details on the datasets and methods used for quantifying changes intopographical patterns of forest clearance and related carbon loss across SEA.

273

274 High-resolution forest cover change and primary forest extent products. To quantify forest 275 cover change over SEA from 2001 to 2019, we used a high-resolution remote sensing product that 276 maps tree cover change at a spatial resolution of 30 m (version 1.7; ref. 8). The dataset has user's 277 and producer's accuracies of > 83% over the tropics⁸. A previous independent assessment indicated that, in SEA, the data have user's and producer's accuracies of 93.2% and 81.2%, respectively¹⁹. 278 279 This dataset defines trees as "all vegetation taller than 5 m in height", and forest loss (including via 280 deforestation and forest degradation) as "the mortality or removal of all tree cover within a 30 m 281 pixel^{38,25}. This operational definition results in the case that planted vegetation, such as rubber and 282 oil palm plantations, is mapped as trees when taller than 5 m. Removal of such vegetation is counted 283 as tree cover loss. Following these definitions, the data provide maps of forest cover loss and the 284 year of loss during 2001-2019 and forest cover gain during 2001-2012. Forest loss across SEA 285 exhibits a continuous increase trend from 2001-2019, confirming that changes in loss detection 286 method do not dominate the long-term trend. To separate forest loss type, we further used a dataset 287 on the extent of primary forests at 30 m spatial resolution for the year 2001 in SEA¹⁰.

288

289 Topography data. We used both mountain extent maps and a digital elevation model to quantify

290 the topographic pattern of forest loss. Mountain extent in SEA was mapped by a series of mountain 291 polygons developed by the Global Mountain Biodiversity Assessment (GMBA) inventory (version 292 1.2; ref. 18). The GMBA inventory defines a 2.5' pixel as mountainous if the geometrical amplitude 293 between the highest and lowest elevation exceeds 200 m. Following this definition, there are 61 294 mountain regions in SEA (Fig. S2a), occupying 1.7 million km² (38%) of SEA's land surface. The 295 remaining 62% of SEA's land surface is all treated as lowland. The associated elevation 296 information in lowlands and mountains, at a spatial resolution of 30 m, is collected from the 297 Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation 298 Model (version 3; ref. 48). Slope information is estimated from elevation data using the average maximum method⁴⁹. 299

300

301 Forest carbon stocks. We calculated forest carbon losses by incorporating high-resolution aboveground live woody biomass (AGB) density map of Zarin et al.²¹ into our analyses of forest 302 303 loss. The map represents AGB density (in a unit of Mg biomass per hectare) at a spatial resolution 304 of 30 m circa 2000. The AGB map was generated using a random forest model and a statistical 305 model from measured forest biomass, GLAS lidar data, and gridded variables such as Landsat 7 306 ETM+ reflectance and biophysical variables, such as precipitation²¹. Owing to lack of data, we 307 estimate belowground biomass (BGB) at the pixel level with the empirical allometric model of Mokany et al.⁵⁰ that has been widely used for BGB estimations^{2,51}: BGB = $0.489 \times AGB^{0.89}$. Total 308 309 forest vegetation biomass, calculated as the sum of AGB and BGB, was converted to total forest 310 biomass carbon stocks using a conversion factor of 0.5 (refs. 2, 21).

311

312 Forest and carbon loss calculations and analysis. We estimated forest loss area by summing the area of forest loss pixels that is dependent on its geographical location⁴⁴. The area of forest carbon 313 loss was calculated by overlapping the forest loss data with forest carbon stock density map 314 315 (including aboveground and belowground). We used committed emissions of carbon from forests 316 to the atmosphere upon forest loss, even though some of the carbon associated with tree removal 317 degrades on site or over time or is embedded within wood products¹⁵. 318 319 As both forest loss area and forest carbon loss showed near-uniform increases over time, we applied 320 a simple least-squares linear regression model to quantify the rate of change (Figs. 1a, 3a, S4, S5). 321 In contrast, because trends in mean elevation and slope of lands incurring forest loss in the 2000s and 2010s were nonlinear (Fig. 1b), we used a piecewise linear regression model⁵²⁻⁵⁴ to (1) 322 323 determine where the trends in the time-series of mean elevation and slope change (i.e., inflection 324 points), and (2) quantify the trends before and after the inflection points. We also used a statistical 325 model in Real Statistics Resource Pack to test if the difference in trends between mountain forest 326 (carbon) loss and lowland forest (carbon) loss was statistically significant⁵⁵. 327

To demonstrate the spatial pattern of increases following inflection points, we separated them into
each 0.25° cell and used the equations:

330
$$H_{t,k} = \frac{\sum \overline{h} s_t + h_{t,k} s_{t,k}}{\sum s_t + s_{t,k}}$$
(1)

331
$$I_{t,k} = \frac{\sum \bar{i}s_t + i_{t,k}s_{t,k}}{\sum s_t + s_{t,k}}$$
(2)

where $H_{t,k}$ and $I_{t,k}$ are the mean elevation and slope in year t for the kth 0.25° cell. \bar{h} (245.5 m) and 332 i (9.3°) are the mean elevation and slope of forest loss across SEA after inflection points, 333 respectively. $s_{t,k}$ and s_t are forest loss area in year t for the kth 0.25° cell and other cells, respectively. 334 While the elevation and slope data for other cells are assumed to be the means of SEA (\bar{h} and \bar{i}). 335 the elevation and slope data for the kth 0.25° cell are realistic. Thus, trends in the time-series after 336 inflection points are caused by the changes only in the kth 0.25° cell. We then used a piecewise 337 338 linear regression model to calculate trends in mean elevation and slope before and after identified 339 inflection points. Following this method, we calculated the trends caused by each cell for countries (by summing all cells in each country), mountains (by summing all cells in mountains) and 340 341 lowlands (by summing all cells in lowlands).

342

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351	inventory; Zarin/WHRC for providing the aboveground biomass density maps.
352	
353	Author contributions
354	Z.Z. designed the research; Y.F. performed the analysis; Y.F. and A.D.Z. wrote the draft. All authors
355	contributed to the interpretation of the results and the writing of the paper.
356	
357	Competing interests
358	The authors declare that they have no competing interests.
359	
360	Data availability
361	The global map of forest cover loss and gain are available at
362	https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.7.html. The
363	ASTER elevation data are available at https://earthdata.nasa.gov/. The GMBA inventory is

364	available at https://ilias.unibe.ch/goto_ilias3_unibe_cat_1000515.html. The aboveground biomass
365	maps are available at <u>https://www.globalforestwatch.org/map/global/</u> . The primary extent data are
366	available at https://glad.umd.edu/dataset/primary-forest-humid-tropics. All datasets are also
367	available upon request from Z. Zeng.
368	
369	Code availability
370	The scripts used to generate all the results are MATLAB (R2020a). Analysis scripts are available
371	at https://doi.org/10.6084/m9.figshare.14586528.
372	
373	Additional information
374	Correspondence and requests for materials should be addressed to Z. Zeng.

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Table legend

498 Table 1. Forest and related carbon loss in the mountains and lowlands of Southeast Asia

499 (SEA). One asterisk (*) indicate statistically significant trends at level of p < 0.05.

502 Table 1. Forest and related carbon loss in the mountains and lowlands of Southeast Asia (SEA). One asterisk (*) indicate statistically

Wardshine.	Year range	All forests			Primary forests			Secondary forests		
variables		SEA	Mountains	Lowlands	SEA	Mountains	Lowlands	SEA	Mountains	Lowlands
Career formert land	2001–2019	3.22	1.00	2.22	0.93	0.26	0.67	2.29	0.74	1.55
Gross forest loss	2001-2009	2.33	0.58	1.76	0.72	0.18	0.54	1.61	0.40	1.21
(Mina yr ¹)	2010-2019	4.02	1.38	2.64	1.11	0.33	0.78	2.91	1.05	1.86
Gross forest gain (Mha yr ⁻¹)	2001–2019	1.32	0.34	0.98	N.A.	N.A.	N.A.	1.32	0.34	0.98
Gross forest carbon loss	2001-2019	424	136	288	167	48	119	257	88	169
(Tg C yr ⁻¹)	2001-2009	330	88	242	128	33	95	202	55	147
	2010-2019	508	179	329	202	62	140	306	117	189
Forest loss acceleration	2001-2019	$17 \pm 3^{*}$	8±1*	9±2*	$4 \pm 1^{*}$	$2\pm0^*$	2±1	$14 \pm 2^{*}$	7±1*	$7\pm1^*$
(10 ⁻² Mha yr ⁻²)	2001-2009	$26 \pm 5^{*}$	6±1*	20±4*	$11 \pm 2^*$	$2\pm0^*$	9±1*	$15 \pm 4^{*}$	3±1*	12±3*
	2010-2019	10±9	$11\pm3^*$	-1 ± 7	-5±3	1±1	-5 ± 2	$15\pm6^*$	$10\pm 2^{*}$	5±4
Forest carbon loss	2001-2019	$18\pm4^*$	$10\pm1^*$	8±3*	$7\pm2^*$	$3\pm0^*$	4±2	$11\pm2^{*}$	7±1*	$5\pm 2^*$
acceleration (Tg C yr ⁻²)	2001-2009	$35 \pm 7^*$	8±2*	27±5*	19±3*	$4\pm1^*$	15 ± 2*	$16\pm5^{*}$	$4\pm1^*$	12±4*
	2010-2019	1±12	$10\pm4^*$	-9±8	-7±6	1 ± 2	-9±4	8±6	9±2*	0±4
Trend in mean elevation	2001-2019	64±13*	$46 \pm 15^{*}$	16±3*	$50 \pm 17^{*}$	16±16	27±7*	52±11*	38±11*	$7\pm2^*$
$(10^{-1} \text{ m yr}^{-1})$	2001-2011	1±19	11±28	0±5	$-56 \pm 15^*$	$-66\pm23^{*}$	-16±9	8±18	20±23	-3±4
	2011-2019	$151 \pm 38^{*}$	95±57*	$37 \pm 10^{*}$	$195 \pm 30^{*}$	$127 \pm 46^{*}$	85±16 [*]	113±37*	$62 \pm 46^*$	$21\pm7^*$
Trend in mean slope	2001-2019	$11\pm 2^{*}$	$12\pm 2^{*}$	3±1*	11±3*	6±3*	$8\pm2^*$	9±2*	$11 \pm 2^*$	0±0
$(10^{-2} \circ yr^{-1})$	2001-2009	-4±3	1±5	-2±0	$-17\pm0^{*}$	$-14\pm0^{*}$	$-9\pm0^{*}$	-4±0	2 ± 4	-4±1*
	2009–2019	$22\pm5^{*}$	$20\pm8^*$	7±2	31±7*	$21\pm8^*$	19±6*	19±5*	$17 \pm 7^{*}$	$4\pm 2^{*}$

503 significant trends at level of p < 0.05.

505 Figure legends

506 Figure 1. Time-series of forest loss area and associated topography across Southeast Asia 507 during the period 2001–2019. a, Annual forest loss area in lowlands (light pink bars) and 508 mountains (light blue bars) and the ratio of mountain forest loss area to total forest loss area (orange 509 line). Inset bars show trends in lowland and mountain forest loss area in the 2000s and 2010s. 510 Different letters above the bars indicate statistically significant differences (p < 0.05) between 511 trends for lowlands and mountains during the 2000s (black letters) and 2010s (red letters). b, Mean 512 elevation (solid black lines) and slope (solid red lines) of lands incurring forest loss. Dashed lines 513 are trend lines for mean elevation (black) and slope (red) before and after inflection points, which 514 were estimated by piecewise regression. Inset bars show trends in mean elevation (black) and slope 515 (red) before and after inflection points. Error bars indicate the standard error of linear trends. One 516 and two asterisks (*, **) indicate statistically significant trends at levels of p < 0.05 and p < 0.01, 517 respectively.

518

Figure 2. Trends in mean elevation and slope of lands incurring forest loss following the inflection points (IPs). a–b, Trend in mean elevation (a) and slope (b) following the IPs in eight countries of Southeast Asia (SEA), for all of SEA, lowlands, and mountains. Three countries in SEA (Brunei, East Timor, and Singapore) are not presented here because their combined forest loss is only 0.2% of the SEA total. The error bars indicate the standard error of the linear trend. One and two asterisks (*, **) indicate statistically significant trends at levels of p < 0.05 and p < 0.01,

525	respectively. c-d, Spatial patterns of trends in mean elevation (c) and slope (d) of lands incurring
526	forest loss in 0.25° cells across SEA. Black dots indicate mountain regions. The IPs for mean
527	elevation and slope are around 2011 and 2009, respectively (see Fig. 1b). Trends in mean elevation
528	and slope of lands incurring forest loss in each 0.25° cell or each country (or in lowlands and
529	mountains) were calculated considering the weight of forest loss using Eqs. (1) and (2), respectively
530	(See Methods).

532 Figure 3. Time-series of forest carbon loss and associated topography across Southeast Asia during the period 2001-2019. a, Annual forest carbon loss in lowlands (light pink bars) and 533 534 mountains (light blue bars) and the ratio of mountain forest carbon loss to total forest carbon loss 535 (orange line). Inset bars show the trends in lowland and mountain forest carbon loss in the 2000s and 2010s. Error bars show the standard error of the linear trends. One and two asterisks (*, **) 536 537 indicate statistically significant trends at levels of p < 0.05 and p < 0.01, respectively. Different 538 letters above the bars indicate statistically significant differences (p < 0.05) between trends for 539 lowlands and mountains during the 2000s (black letters) and 2010s (red letters). b, Carbon loss in 540 elevation-year space.

541

Figure 4. Spatial patterns of forest carbon loss across Southeast Asia during the period 2001–
2019. a, Mean annual forest carbon loss in the 2000s. b, Change in mean annual forest carbon loss
in 2010s relative to 2000s. c–d, Trend in mean annual forest carbon loss in the 2000s (c) and 2010s

- 545 (d). Black dashed lines show mainland SEA (inside the box) and maritime SEA (outside the box).
- 546 Black dots indicate mountain regions.

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