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Forest gains and losses in Southeast Asia over 27 years: the slow convergence towards reforestation

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ABSTRACT

2 Forest cover has decreased dramatically in Southeast Asia over the last decades. Understanding the drivers behind these changes is critical to predict changes
4 and minimise their adverse effects. The objectives of the present study were to provide accurate estimates of forest gains and losses in each country of
6 Southeast Asia, and to test the hypothesis that changes in forest cover is linked to national socioeconomic changes. Temporal changes in forest cover were
8 quantified in eleven countries using mid-resolution land cover data. Synchrony among countries was quantified as well as relationships between changes in
10 forest cover and changes in GDPseveral socioeconomic variables. Decline in forest cover between 1992 and 2018 varied considerably among countries with
12 evidence of reforestation in some countries during the last few years. Some countries showed a positive relationship between GDP and forest cover changes
14 while others showed a negative relationship. Some countries were synchronised, particularly Indonesia and Malaysia where forest conversion
16 predominantly involved agricultural lands. A regression modelling showed evidence that changes in forest cover among countries are not independent and
18 interact in a complex way. A contrast among these countries was also shown by examining the lands converted from and to forests. The present study supports
20 the hypothesis that changes in forest cover is, at least in part, driven by socioeconomic changes and suggests that future changes in forest cover in

²² Southeast Asia will be determined by countries with important agroforestry sectors.

²⁴ **Keywords:** forest transition; **GDP**GLS; land cover; socioeconomic variables;
Southeast Asia

26 **1. Introduction**

Forests in Southeast Asia (SEA) are rich ecosystems with historical and societal
28 importance to many peoples and communities (Ashton, 2014). With a land area
of approximately 4.5 million km² (around 3% of emerged lands), this region has
30 experienced dramatic forest loss during the last three decades (Hansen et al.,
2013; Imai et al., 2018; Estoque et al., 2019). According to the Food and
32 Agriculture Organization (FAO, 2011), forest cover in SEA declined by around
0.6% every year between 1990 and 2010 (~~FAO, 2011~~). Although SEA is the most
34 populated major region in the world out of the eight ones defined by the United
Nations, recent projections predict that its population will peak in 2038, being
36 the first one to reach a zero-growth (United Nations, 2019). A more recent study
predicts that the combined population of SEA, East Asia, and Oceania will peak
38 in 2032 with 2.25 billion persons, whereas the population of SEA is predicted to
peak in 2052 with 787 million persons (Vollset et al., 2020). This evolving human
40 landscape will have a profound impact on the future dynamics of forests and
forest cover in SEA (FAO, 2015).

42 The importance of tropical forests for biodiversity has long been
acknowledged since Wallace (1890). With the increasing intensity in global trade
44 during the past decades, tropical regions are targets of deforestation pressure
driven by socio-economic demands from developed countries
46 (Lenzen et al., 2012). A recent study showed that global agriculture land use,
pasture, and forestry are expected to account for the vast majority of projected
48 extinction risks in tropical countries driven by international trade
(Chaudhary and Brooks, 2019). These prospects can be paralleled with Curtis et
50 al.'s (2018) results showing that forestry, shifting agriculture, and wildfire are
the main causes of forest loss around the world. These studies point to the

52 importance of forests in tropical countries and the current and future challenges
they face for their conservation (Coleman et al., 2019).

54 Forests provide a range of ecosystem services that are beneficial to human
societies, and a recent assessment found that these services have generally
56 increased during the past few decades (Miura et al., 2015). The 2015 report from
the FAO concluded that the world forest area declined from 42 million km² in
58 1990 to 40 million km² in 2015 (Keenan et al., 2015). However, Song et al. (2018)
found that tree cover has globally increased by more than 2 million km² between
60 1982 and 2016. Giving the importance of forests, it is crucial to have a better
understanding of the dynamics of forest cover and its drivers.

62 **2. Forest transition in the world and in Southeast Asia**

The phenomenon for a country, region, or area of moving from loss to gain in
64 forest cover, a process called forest transition (FT), has attracted a lot of attention
(Rudel, 1998). This has been compared to Kuznets curves which describe how
66 economic development, for instance measured by national wealth, has a
negative effect on social development (e.g., poverty is increased) in the early
68 stage whereas this effect becomes positive (e.g., poverty is reduced) when
national wealth continues to increase (Bhattarai and Hammig, 2001). This
70 conception appeared to be too simple to account for the more complex reality of
FT (Culas, 2007; Choumert et al., 2013). Kozak and Szwagrzyk (2016) suggested
72 that FT may be a consequence of distance-dependent interactions among land
units, so that FT may be apparent at different spatial scales. Clearly, FT is likely
74 to be heterogeneous in large countries such as Brazil or China where there are
large scale evidence of reforestation
76 (Walker et al., 2012; Lapola et al., 2014; Shi et al., 2016, 2017; Aragão et al., 2018).

Basically, forests are lost by cutting or burning trees. Conversely, forests are
78 gained by planting trees or by letting forests grow naturally. Although forest
loss and gain appear as simple phenomena at first glance, they are actually the
80 end-patterns of complex processes with many potential drivers (Table 1). It is
therefore difficult to derive a simple mechanistic models of deforestation and
82 reforestation because the potential drivers are themselves interacting and are
likely to change with time (Shi, 2015; Pendrill et al., 2019).

84 Several countries in the world have moved from loss to gain in forest cover
(Rudel, 1998; Song et al., 2018; Dang et al., 2019; Pendrill et al., 2019). It is
86 generally admitted that countries that have initiated FT have a more efficient
agriculture than other countries, and/or import food products from these latter
88 countries (Meyfroidt et al., 2010; Imai et al., 2018). Furthermore, FT is generally
related to an increase in gross domestic product (GDP) (Meyfroidt et al., 2010).
90 Recent studies have attempted to find the local and global drivers of forest
change in SEA (Li et al., 2017; Imai et al., 2018; Paradis, 2020). The
92 socio-economic structure of the region is rapidly changing mainly driven by
urbanization and migration from rural to urban areas, although this varies
94 substantially and can even be reversed from urban to agricultural areas as
during the 2008 economic crisis (FAO, 2011). ~~These interacting processes make
96 predictions of future cover in SEA a difficult task.~~

Several mechanisms of land change may explain the different deforestation
98 patterns among countries or regions: land-use displacement (the geographical
separation between places of production and places of consumption) may
100 explain why deforestation and wood product exports continue in some
countries while other countries experience forest gains and import wood
102 products (Meyfroidt et al., 2018). Land-use spillovers is another mechanism

where land use changes in some places have consequences on land use in other
104 places. At a time of unpredictable global and local changes, it is critical to have a
better understanding of the drivers of forest cover changes. This problem is
106 particularly acute in SEA where countries display important disparities in their
socioeconomic activities, therefore we may expect significant differences in forest
108 losses and gains.

In this study, we used long-term mid-resolution land cover data to assess the
110 dynamics of forest cover changes among eleven countries in SEA. Specifically,
we tested the following predictions: (1) For each country, annual change in
112 forest cover area evolved from negative to positive values possibly with a
transitory phase with (nearly) zero change; (2) Annual forest changes are
114 synchronised among countries in relation to changes in their GDP; (3) Forests
are converted into agricultural lands in countries where GDP decreases, whereas
116 they are converted into urban areas in countries where GDP increases; and (4)
Forest gains are from agricultural lands in high-GDP countries.

118 **3. Methods**

3.1. *Data Land cover data*

120 The present study considered eleven countries ([Fig. 1](#)): Brunei (BRN), Cambodia
(KHM), Indonesia (IDN), Laos (LAO), Malaysia (MYS), Myanmar (MMR),
122 Philippines (PHL), Singapore (SGP), Thailand (THA), Timor Leste (TLS), and
Vietnam (VNM). Timor Leste (or East Timor) was part of Indonesia until 1999.
124 The consideration of the present-day borders of Timor Leste for the whole
present study period (1992–2018) was done only for practical reasons. The
126 country borders were taken from the Global Administrative Areas database

(GADM version 3.6, <https://www.gadm.org/>; accessed 2020-03-07). Data on
128 land cover were obtained from the European Spatial Agency Climate Change
Initiative (ESACCI;
130 <http://maps.elie.ucl.ac.be/CCI/viewer/download.php>; accessed
2019-11-18) for the period 1992–2018. ~~Data on GDP were obtained from the
132 World Bank (; accessed 2020-03-02). Data on exports and imports of wood
products were obtained from UN Food and Agriculture Organization website (;
134 accessed 2020-04-08). These two last data sets give annual statistics for all
countries and cover the period 1961 until 2018.~~

136 3.2. *Statistical analyses*

The land cover data were extracted separately for each country and reclassified
138 using a scheme developed in a previous study ~~Paradis (2020)~~ and which proved
to be effective for SEA (Paradis, 2020). Specifically, the original 38 land cover
140 classes were reclassified into 11 classes (see Table S1 in Paradis, 2020). This
scheme considers all ‘Tree cover’ classes (deciduous, evergreen, needleleaved,
142 flooded or not, with at least 15% of tree cover) as a single class labelled ‘Forest’.
Mosaic natural vegetation (including trees) and croplands were classified as
144 ‘Crop’ whatever the proportions of these two. All types of cultivated lands were
classified as ‘Crop’, and ‘Tree or shrub cover’ was a separate class. The areas
146 covered by forest were calculated by finding all cells (with a 10 arc-seconds
resolution, approximately 300 m) and calculating their areas (see below).

148 Changes in land use were assessed by examining the lands occupied by forest in
successive years and finding the cells converted from or into forest.

150 3.2. Socio-economic data

152 The socio-economic data from the World Bank repository were screened for
candidate drivers of forest cover change
(<https://data.worldbank.org/indicator?tab=all>; accessed
154 2020-09-04). The selected variables had to be potential drivers as well as being
relatively complete for the countries and time periods considered in this study.
156 For instance, the number of machines (e.g., tractors) is a measure of
modernization of agriculture in a country but could not be used here because
158 this indicator was not available for most countries in SEA. Four variables were
finally selected: percentage of agricultural lands (AGRI), gross domestic product
160 (GDP), quantity of exported goods and services (EXP), and population size
(POP). In addition to these data from the World Bank, data on exports and
162 imports of wood products were obtained from the FAO website
(<http://www.fao.org/faostat/>; accessed 2020-04-08). These two last data
164 sets give annual statistics for all countries and cover the period 1961 until 2018.

Data on land concessions were taken from the LandMatrix database
166 (<https://landmatrix.org/>; accessed 2020-08-28). This is a recently
developed database aimed at assessing direct and indirect land use change
168 under land transactions (Magliocca et al., 2020). Each entry in the database
represents a deal with its size (land area), date, country of operation, negotiation
170 status ('Intended', 'Concluded', 'Failed'), implementation status ('In operation',
'Abandoned', 'Not started', 'Startup'), and several other information.
172 Considering the recent state of creation and development of this database and
possible concern about its geographical coverage (Magliocca et al., 2020), we
174 limited ourselves to simple descriptive statistical analyses of these data.

3.3. Exploratory analyses

176 Because the eleven countries considered here have very different areas, changes
in forest cover were calculated as both total areas and percentages. Synchrony
178 among countries were quantified using ~~Pearson correlation coefficients~~
Spearman correlation coefficients which were preferred to Pearson coefficients
180 because the former is more sensitive to nonlinearities than the latter. In order to
take autocorrelation of the temporal data into account, a randomization
182 procedure was used to test the significance of the correlations. First, the
autocorrelation function of each temporal series was calculated. Second, two
184 independent series of the same size as the analysed ones were simulated using a
covariance matrix built from the previously calculated autocorrelations. The
186 simulation was repeated 10,000 times to infer the distribution of correlation
coefficients under the null hypothesis of no (cross)correlation between the two
188 series. The P -value was calculated as the proportion of null coefficients which
were larger (in absolute value since the test was two-sided) ~~to~~ than the observed
190 one. Since the autocorrelation differed for each time-series, the whole procedure
was repeated for each calculated correlation coefficient. ~~These~~ The pairwise
192 correlations (r) were then transformed into similarity measures with $1 - r$ in
order to build a hierarchical clustering to display the overall similarity among
194 countries. The correlation between changes in forest cover and changes in GDP
(both as percentages) were compared in the same way.

196 3.4. Regression modelling

In order to model the effect of potential drivers (the predictors) on forest cover
198 (the response), we used an approach based on generalized linear least squares
(GLS) which takes the non-independence of the observations into account. Let

200 us write the predictors as x_1, x_2, \dots , and the response as y . Then the forest cover
at year t is modelled with:

$$202 \quad \underline{y_t = \beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \epsilon_t}, \quad (1)$$

where β_1, β_2, \dots are the regression coefficients and the ϵ_t 's are correlated errors
204 which follow a multivariate normal distribution:

$$\underline{\epsilon_t \sim \mathcal{N}(0, V)},$$

206 where V is a variance-covariance matrix where the diagonal elements are the
variances (denoted as σ^2) and the off-diagonal elements are the covariances
208 specifying the correlation in the data. If these covariances are equal to zero, then
GLS is identical to ordinary least squares (OLS). The selected correlation
210 structure was an order-1 autoregressive with continuous time. In this model, the
parameter ϕ controls the temporal auto-correlation in the data ($0 \leq \phi \leq 1$), so
212 that equation (1) can be rewritten in vector-form with:

$$\underline{y_t = x_t^T \beta + \phi y_{t-1} + \tilde{\epsilon}_t},$$

214 where $\beta = \{\beta_1, \beta_2, \dots\}$, $x_t = \{x_{1t}, x_{2t}, \dots\}$, and $\tilde{\epsilon}_t$ are now independent errors
following a normal distribution:

$$216 \quad \underline{\tilde{\epsilon}_t \sim \mathcal{N}(0, \sigma^2)}.$$

Forest cover was modelled separately for the eleven countries. The candidate
218 predictors (x) were the four socio-economic variables (AGRI, EXP, GDP, POP)
for each country. Four of these variables (EXP and GDP for Myanmar and Timor
220 Leste) were excluded because they contained too many missing data. The values
of EXP and GDP for Cambodia were also missing for 1992: they were replaced

222 by extrapolated values calculated assuming that the percentage changes were
the same for the pairs of years 1992–1993 and 1993–1994. There were therefore
224 40 potential predictors. A stepwise procedure was used to find the statistically
significant predictors. First, each predictor was included in the model alone, and
226 the predictor with the most significant effect (i.e., with the smallest P -value) was
selected. Second, if this P -value was less than 0.05, each of the other predictors
228 was included in the model in turn and the one with the most significant effect
was selected (again with the condition $P < 0.05$). This second step was repeated
230 until no candidate predictor was significant (i.e., all $P > 0.05$ for the remaining
variables).

232 All analyses were done with R version 3.6.3 (R Core Team, 2019) using the
packages ncd4 (Pierce, 2019), rgdal (Bivand et al., 2018), and raster (Hijmans,
234 2018) to handle the land cover data and basic R statistical functions. The GLS
regression models were fitted with the package nlme (Pinheiro et al., 2020). All
236 geographical data used longitudes and latitudes and the WGS84 coordinate
reference system. Cell areas were calculated with trigonometric relationships to
238 take the effect of latitude into account (Paradis, 2020). The R code used is
provided in the Supplementary Information.

240 **4. Results**

4.1. Changes in land cover

242 Forest cover over the eleven countries decreased from 2,168,275 km² in 1992 to
2,062,785 km² in 2018 (Fig. 2A). The net loss of forest cover ~~in SEA~~ was therefore
244 105,490 km² over 26 years, or a net loss of 4.87% of the 1992 forest cover. The
annual rate of change varied between -0.64% and $+0.19\%$ (mean = -0.19% ;

246 ~~median = -0.16%~~). The most dramatic annual net loss of forest happened
between 1994 and 1995 when 14,871 km² were lost, equivalent to approximately
248 440 m² every second or 2.6 ha every minute. ~~This exceptional net loss was
followed by a net increase in forest cover of 4040 km² between 1995 and 1996
250 which was the most important gain during the study period. Forest cover
increased in only two cases: 1995–1996 and 1999–2000 (1911 km²). When
252 ~~distinguishing forest~~ When distinguishing gains and losses ~~in each pair of
successive years, the area of forest lost annually, the annual lost area~~ varied
254 between 12.9 and 25,684 km² (Fig. 2C) which represent loss rates between
0.0006% and 1.18% (mean = ~~median = 0.47%~~). ~~The observed maximum is, this
256 maximum being~~ equivalent to a loss of 814 m² every second or 4.9 ha every
minute. The annual gains varied between 0 and 16,795 km², equivalent to rates
258 between 0% and 0.78% (mean = 0.27%, ~~median = 0.21%~~). The annual rates of loss
and gain were strongly correlated ($r = 0.71$).~~

260 Changes in forest cover in each country varied greatly (Figs. 3, S1, S2). While
nine countries seemed to show a convergence towards zero net change in forest
262 cover, Indonesia and Malaysia showed an overall trend to increasing forest loss
although this was very fluctuating for Indonesia. ~~There is~~

264 4.2. Exploratory analyses

There was some evidence for across-country synchrony (~~Table 2): 33: 36~~
266 cross-correlations were positive (maximum: ~~0.86~~) ~~whereas 22~~ 0.83 ~~whereas 19~~
were negative (minimum: ~~-0.56~~). ~~The two most synchronised countries were~~
268 ~~Cambodia and Vietnam, whereas the two most out of phase were Malaysia and~~
~~Thailand~~ (0.47; Table 2). ~~Fourteen~~ Twelve correlation coefficients were
270 statistically significant ~~after taking temporal autocorrelation into account~~

($P < 0.05$); among ~~these fourteen, thirteen~~ them, ten were positive and ~~only one~~
272 ~~was negative (between Thailand and Malaysia: $r = -0.56$, $P = 0.005$)~~ two were
negative. The clustering derived from these measures of synchrony ~~did not~~
274 ~~reveal a clear contrast among countries~~ showed a contrast between the
continental countries on one side and the others on the other side (Fig. 4).

276 The correlation between changes in forest cover and changes in GDP (both as
percentages) for each country revealed a contrast between some countries where
278 this correlation was positive (Cambodia, ~~Singapore, Thailand,~~ and Vietnam)
and those where it was negative (Indonesia, ~~Laos, Malaysia, Philippines,~~
280 Malaysia, and Timor Leste; Table 3). ~~A clustering of the countries based on a~~
~~distance measure derived from these correlations showed a~~ However, the
282 clustering analysis based on these correlations did not show a clear contrast
between these two groups (Fig. 5).

284 For most countries the value (in constant US\$) of wood product imports and
exports increased over time (Fig. S3). Indonesia and Malaysia ~~stand~~ stood
286 apart of the other countries in the fact that the export values were constantly
larger than the import values. Cambodia showed an interesting pattern: export
288 values were much larger than import values between 1990 and 2000.

The land conversions implied by forest losses and gains revealed a contrast
290 between countries where conversions from or into forest involved mainly
croplands (Brunei, Malaysia, Indonesia, Phylippines, Timor Leste) and the other
292 countries. Singapore ~~stand~~ stood apart since urban areas were mainly involved
in forest conversion. Cambodia displayed a trend over time with a shift to lesser
294 conversion from forests into croplands. ~~Because the category 'Others' is~~
~~heterogeneous, we examined its compositions for the five countries where it was~~
296 ~~most prominent (Cambodia, Laos, Myanmar, Thailand, Vietnam).~~ Specifically,

we looked at which land cover class was mainly involved in forest losses and gains: shrubland was the main class in eight cases out of ten. The two exceptions involved mosaic land uses in the case of forest loss in Thailand and forest gain in Cambodia

The LandMatrix database contained 5130 entries of deals of land concessions in 102 countries. Among these deals, 1202 (23.4%) concerned nine of the eleven countries included in the present study (no deals were made in Brunei and in Singapore). Three of these SEA countries were among the top-ten of the 102 countries in terms of number of deals: Indonesia (#1 with 315 deals), Cambodia (#2 with 293 deals), and Philippines (#6 with 174 deals). The total area of the deals made in these nine countries covered 270,472 km² (Table 4).

4.3. *Regression modelling*

Over the 11 regression models, 39 statistically significant predictors were found (Table 5): fifteen were agricultural lands (AGRI), nine exported goods and services (EXP), five gross domestic products (GDP), and ten population sizes (POP). The signs of the estimated coefficients ($\hat{\beta}$) were not in a consistent direction, except for POP where seven of the ten coefficients were negative which was as expected. A surprising result was that only two out of the 39 significant predictors concerned a country towards its own forest cover: AGRI for Malaysia and POP for Thailand.

5. Discussion

The present study had two main objectives: to give a global picture of forest cover dynamics in SEA, and to assess socio-economics as the main driver of this dynamics. The approach used in this study has several limitations. First, it is

based on country-level summaries which mask heterogeneity within countries.
322 Second, detailed socio-economic data are still lacking for these countries. And
third, global trade was not considered as a driver (e.g. Lenzen et al., 2012). In
324 spite of these limitations, the new estimates of annual forest cover change over
27 years provide a new perspective on the issue of FT in SEA. The results
326 showed an overall decline in forest cover was marked by periods of more or less
intense forest losses. Another visible trend was towards a decrease of net forest
328 loss rates, and therefore a convergence towards FT. Although almost all
countries showed a trend towards zero change in forest cover, substantial
330 variation around this trend was observed. ~~For instance, Malaysia showed a~~
~~trend towards increasing forest loss~~ These patterns combined with the regression
332 modelling strongly suggest that forest dynamics in SEA can be seen as an
integrated process, although it is still difficult to establish the cause-effect
334 relationships precisely.

A surprising result is the apparent lack of any land use change between 2014
336 and 2015. However, land use changes were clear for the preceding (2013–2014)
and following (2015–2016) pairs of years. The most likely explanation is that the
338 changes that happened between 2014 and 2015 have been accounted, for some
unknown reasons, in the preceding (2013) and following years (2016) so this
340 specific year-to-year estimate is actually biased while the overall 2013–2016
change seems correct.

342 Some significant contrasts and similarities among countries were observed.
The most synchronised countries also showed similarities in the types of land
344 conversion involved in forest losses or gains. Vietnam and Cambodia, the two
most synchronised countries, displayed similar trends from cutting forests
346 mainly for agricultural lands until approximately 2000, and afterwards mostly

for other land types (mosaic and shrubland) and at the same time decreasing the
348 forest cover area lost every year. ~~Additionally, these two countries showed a~~
~~significantly positive correlation between changes in forest cover and GDP,~~
350 ~~meaning that the observed convergence towards FT was associated with~~
~~increase in their respective GDP. Although cause-effect relationships were not~~
352 ~~directly tested in the present study, these~~ These results agree with the
predictions from land-use displacement mechanisms (Meyfroidt et al., 2018).
354 Furthermore, the pattern showed by Cambodia, where exports were far greater
than imports during the 1990s while deforestation was intense, also agrees with
356 this hypothesis. In this country, 22,779 km² of leased lands resulted in the loss of
2600 km² of forest between 2000 and 2012 (Magliocca et al., 2020).

358 ~~Lenzen et al. (2012) showed a link between global trade and extinction risks~~
~~in tropical countries since demands from developed countries drive~~
360 ~~deforestation in the former. In their study, Indonesia and Malaysia (together~~
~~with Madagascar and Papua New Guinea) were found to host large numbers of~~
362 ~~species threatened by international trade. Recent assessments found that threats~~
~~on species extinction from global trade have increased in recent years, although~~
364 ~~spatial resolution of these studies was coarse (Chaudhary and Brooks, 2019).~~

Weinzettel et al. (2018) quantified the percentage of net primary production
366 (NPP) used by human agriculture and found a contrast between the
Indo-Burmese Region (roughly the continental part of SEA) where 22% of NPP
368 are used by croplands and Sundaland where 36% are used; Philippines with 33%
was intermediate. These numbers are in agreement with the present results
370 where forest cover changes were associated with changes in agricultural lands in
Indonesia and Malaysia (both in Sundaland). In Myanmar, which reportedly
372 loses 5460 km² of forest cover every year, local population density was shown to

have a significant impact on local deforestation (Sharma et al., 2020).

374 Van Khuc et al. (2020) found that Vietnam forest cover increased from
95,000 km² in 1990 to 140,000 km² in 2015. The area gains in planted and natural
376 forests were almost identical (1580 km² and 1690 km², respectively) although the
percentage changes were very different (+500% and +48%, respectively).
378 However, forest loss or degradation still occurs in some places mainly driven by
poverty and initial forest stock (Van Khuc et al., 2018). The changes in cultivated
380 lands have been shown to be the main driver of forest losses in several countries
(Geist and Lambin, 2002; Hosonuma et al., 2012; Shi et al., 2017). Similarly to the
382 results from Van Khuc et al. (2020) for Vietnam
(see also Meyfroidt and Lambin, 2008; Sikor and Baggio, 2014), forest expansion
384 is mainly due to planted trees in Chile (Heilmayr et al., 2016) and in other
countries (Payn et al., 2015).

386 Policy and reforms are likely crucial factors in permitting reforestation, and
ultimately FT. Hyde and Yin (2019) conclude that successive reforms have been
388 generally beneficial to forests in China (Shi et al., 2016). In countries, such as
Cambodia, issues in governance at multiple levels were found to inhibit FT
390 (Riggs et al., 2018). Governance was also found to be an important factor in
Vietnam (Van Khuc et al., 2018).

392 The results presented in this paper, together with previous results from the
literature, suggest that national economic policies are an important driver of
394 forest cover dynamics. Indonesia and Malaysia have a marked negative
relationship between changes in forest cover and changes in GDP. These two
396 countries have a forestry mainly oriented towards exportations. While most
other countries in SEA seem to converge towards FT, Indonesia and Malaysia
398 lost forest cover in recent years. **Interestingly, the trend towards FT does not**

seem to be related to GDP itself since Malaysia's GDP (US\$ 359 billion in
400 Currently, Indonesia and Malaysia contribute a lot to forest loss in SEA: they
respectively lost 3548 km² and 216 km² of forest between 2017 and 2018for 33
402 million inhabitants) is much higher than Laos's (18 billion for 7 million) or
Cambodia's (25 billion for 15 million), representing 77% of the overall net forest
404 loss in SEA (both countries represent 50% of the area of SEA). Therefore, the
future policies of these two countries will have a crucial impact on the evolution
406 of forest cover in the region. These are clearly difficult issues as both countries
rely crucially on forestry for their economies as shown by the fact that their
408 export values of wood products have been larger than their import values for
several decades.

410 Estoque et al. (2019) predicted changes in forest cover in SEA that ranged
from a loss of 52,000 km² of forest to a gain of 196,000 km² by year 2050
412 depending on the scenario. ~~Clearly, prediction is a difficult exercise in a context~~
~~of rapidly changing socio-economic conditions.~~ The present study showed that
414 SEA lost 105,490 km² during 26 years and the rate of forest cover change,
although still being negative, has globally decelerated. Thus, a loss of 52,000 km²
416 of forest over the next 30 years seems plausible as a pessimistic scenario. On the
other hand, a gain of 196,000 km² would bring back SEA at a level of forest cover
418 higher than it was in 1992. If forest loss halts now and forest gain continues at
the same average rate than found in the present study (0.2%) over a forest area
420 of approximately 2,000,000 km², then we can expect forest cover to grow by
4000 km² every year resulting in the addition of 120,000 km² during 30 years.

422 ~~Currently, Indonesia and Malaysia contribute a lot to forest loss in SEA: they~~
~~respectively lost 3548 km² and 216 km² of forest (net loss) between 2017 and~~
424 ~~2018, representing 77% of the overall net forest loss in SEA (both countries~~

represent 50% of the area of SEA). Therefore, the future policies of these two
426 countries will have a crucial impact on the evolution of forest cover in the
region. These are clearly difficult issues as both countries rely crucially on
428 forestry for their economies as shown by the fact that their export values of
wood products have been larger than their import values for several decades.
430 With respect to these data, Philippines showed an interesting pattern: the import
and export values inverted their curves in 1989 and import values have
432 exceeded export values after this year. It is not possible to test a relationship
with changes in forest cover since the ESACCI data temporal coverage starts in
434 1992, but overall Philippines showed an increase in forest cover or a small
decrease in some years (with the exception of the dramatic loss between 1994
436 and 1995 observed in all countries). Additionally, d'Annunzio et al. (2015)
predicted convergence towards a stable world forest area by 2050.

438 Another important issue is where future forest growth will occur. ~~Not~~ This is
an important question since not all forest areas are equal for biodiversity and
440 ecosystem services. In a previous study, a relatively large region shared between
Myanmar, Thailand, Laos, Vietnam, and South China was found to host a high
442 level of terrestrial vertebrate species diversity Paradis (2018). However, forest
cover provides other ecosystem services such as slowing down soil erosion,
444 storing carbon, or preventing evaporation (Bastin et al., 2019). Therefore increase
in forest cover is likely to be globally beneficial not only in high biodiversity
446 areas.

6. Conclusions

448 In spite of the clear interest from the public towards deforestation in the tropics,
its causes have remained poorly understood

450 [\(Pfaff, 1999; Geist and Lambin, 2002\)](#). The present study suggest that forest cover
452 [dynamics in countries of SEA are interacting in a complex way. Deforestation](#)
[has operated with fluctuations, has overall decreased over the years, and has](#)
454 [varied considerably among countries. These results have several implications](#)
[for future research and policy implementations. In future studies of land use in](#)
456 [SEA, land use displacement deserves more attention and attempts to quantify](#)
[this process more precisely will be likely important contributions. This is clearly](#)
458 [a difficult question as illustrated by the issue of obtaining reliable socioeconomic](#)
[data. Forest dynamics in Indonesia will have a predominant effect in the future](#)
460 [decades: considering the size and heterogeneity of this country, some attention](#)
[will need to be on patterns of forest cover changes using remote sensing data](#)
462 [will be valuable. Overall, the present results and comparison with the literature](#)
[on forest transition suggest that national policy and reforms are the most](#)
[important factors in promoting reforestation in general and particularly in SEA.](#)

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Table 1: Potential drivers of forest loss and gain.

<u>Pattern</u>	<u>Processes</u>	<u>Direct drivers</u>	<u>Indirect drivers</u>
<u>Forest loss</u>	<u>logging</u>	<u>forestry</u>	<u>many</u>
		<u>agriculture</u>	<u>many</u>
	<u>fire</u>	<u>urbanization</u>	<u>socio-economic development</u>
<u>Forest gain</u>	<u>natural regrowth</u>	<u>climate change</u>	<u>CO₂ emissions</u>
		<u>illegal land clearing</u>	
	<u>land abandonment</u>	<u>socio-economic development</u>	
	<u>local climate change</u>	<u>local rainfall regime</u>	
	<u>plantations</u>	<u>agriculture</u>	<u>many</u>
		<u>incentives</u>	<u>public opinion</u>

Table 2: Pairwise correlations (upper triangle) of annual percent change in forest cover for each pair of countries and associated *P*-values (lower triangle).

	BRN	KHM	IDN	LAO	MMR	MYS	PHL
BRN		<u>-0.18-0.17</u>	<u>0.37-0.27</u>	<u>-0.35-0.47</u>	<u>-0.29-0.31</u>	<u>0.25-0.10</u>	<u>0.22-0.36</u>
KHM	<u>0.433-0.451</u>		<u>-0.18-0.08</u>	<u>0.02-0.08</u>	<u>-0.20-0.12</u>	<u>-0.34-0.23</u>	<u>0.03-0.27</u>
IDN	<u>0.074-0.203</u>	<u>0.417-0.709</u>		<u>0.16-0.15</u>	<u>-0.03-0.11</u>	<u>0.58-0.51</u>	<u>0.20-0.23</u>
LAO	<u>0.113-0.030</u>	<u>0.933-0.746</u>	<u>0.457-0.490</u>		<u>0.53-0.78</u>	<u>0.33-0.19</u>	<u>0.15-0.09</u>
MMR	<u>0.177-0.141</u>	<u>0.379-0.593</u>	<u>0.888-0.608</u>	<u>0.011-0.000</u>		<u>-0.06-0.02</u>	<u>0.21-0.14</u>
MYS	<u>0.263-0.652</u>	<u>0.137-0.317</u>	<u>0.004-0.013</u>	<u>0.143-0.406</u>	<u>0.783-0.932</u>		<u>-0.13-0.04</u>
PHL	<u>0.303-0.080</u>	<u>0.896-0.208</u>	<u>0.334-0.266</u>	<u>0.485-0.677</u>	<u>0.323-0.506</u>	<u>0.544-0.853</u>	
SGP	<u>0.340-0.742</u>	<u>0.004-0.030</u>	<u>0.390-0.600</u>	<u>0.178-0.393</u>	<u>0.014-0.011</u>	<u>0.079-0.294</u>	<u>0.009-0.404</u>
THA	<u>0.514-0.736</u>	<u>0.000-0.002</u>	<u>0.153-0.048</u>	<u>0.389-0.830</u>	<u>0.105-0.186</u>	<u>0.005-0.029</u>	<u>0.163-0.770</u>
TLS	<u>0.029-0.353</u>	<u>0.249-0.522</u>	<u>0.029-0.040</u>	<u>0.856-1.000</u>	<u>0.158-0.228</u>	<u>0.727-0.962</u>	<u>0.024-0.027</u>
VNM	<u>0.691-0.812</u>	0.000	<u>0.171-0.284</u>	<u>0.826-0.661</u>	<u>0.792-0.408</u>	<u>0.084-0.363</u>	<u>0.152-0.347</u>

Table 3: Correlation between annual percent change in forest cover and percent change in GDP from 1992 to 2018 for eleven countries in Southeast Asia.

Country	Correlation	<i>P</i> -value
Brunei	0.06-0.21	0.7940.332
Cambodia	0.57-0.53	0.0140.018
Indonesia	-0.34-0.48	0.1050.019
Laos	-0.20-0.10	0.4180.689
Myanmar	0.11-0.10	0.6260.660
Malaysia	-0.40-0.51	0.0370.011
Philippines	-0.13-0.22	0.5230.311
Singapore	0.14-0.06	0.4830.776
Thailand	0.16-0.27	0.4330.201
Timor Leste	-0.21-0.39	0.3600.074
Vietnam	0.46-0.48	0.0360.029

Table 4: Summary statistics of land concession deals in eleven countries in Southeast Asia.

Country	Number of deals	Total area (km ²)	% of country
Brunei	0	0	0
Cambodia	293	24,436	13.5
Indonesia	315	85,467	4.5
Laos	134	13,244	5.6
Malaysia	43	65,773	19.9
Myanmar	86	17,418	2.6
Philippines	174	51,609	17.0
Singapore	0	0	0
Thailand	15	2178	0.4
Timor Leste	6	4530	30.2
Vietnam	136	5817	1.8

Table 5: Results of generalized least square modelling of forest cover changes in eleven countries.

Country	Predictor	$\hat{\beta}$	SE($\hat{\beta}$)
Brunei	AGRI-KHM	1.27×10^{-2}	1.57×10^{-3}
	AGRI-SGP	-5.51	1.83
	EXP-THA	-1.34	0.26
Cambodia	AGRI-SGP	-152.54	67.86
	EXP-BRN	-52.42	13.30
	POP-MMR	-5.12×10^{-3}	8.66×10^{-4}
	POP-THA	-9.88×10^{-4}	4.50×10^{-4}
Indonesia	POP-VNM	1.90×10^{-3}	2.31×10^{-4}
	AGRI-KHM	-1.34	0.31
	AGRI-PHL	-0.98	0.23
	AGRI-TLS	18.35	4.45
	EXP-LAO	-155.04	72.69
	EXP-MYS	-90.19	36.88
	GDP-KHM	-1.81×10^{-6}	2.49×10^{-7}
Laos	POP-SGP	-4.02×10^{-3}	2.21×10^{-3}
	EXP-IDN	41.27	18.28
	EXP-PHL	174.16	36.88
Myanmar	EXP-KHM	146.20	50.80
Malaysia	AGRI-BRN	-35.87	12.67
	AGRI-MYS	0.19	7.13×10^{-2}
	GDP-LAO	-9.12×10^{-7}	9.78×10^{-8}
Philippines	AGRI-BRN	26.65	7.99
	AGRI-MMR	0.14	2.43×10^{-2}
	AGRI-VNM	4.96×10^{-2}	1.84×10^{-2}
	POP-MMR	7.81×10^{-4}	2.97×10^{-4}
Singapore	POP-VNM	-5.24×10^{-4}	1.32×10^{-4}
	GDP-LAO	8.62×10^{-10}	3.09×10^{-10}
	POP-THA	-4.57×10^{-6}	4.20×10^{-7}
Thailand	AGRI-KHM	-0.17	0.10
	GDP-LAO	3.29×10^{-7}	3.87×10^{-8}
	POP-THA	-5.58×10^{-4}	1.21×10^{-4}
Timor Leste	AGRI-KHM	1.12×10^{-2}	3.86×10^{-3}
	AGRI-VNM	1.87×10^{-3}	6.97×10^{-4}
	EXP-LAO	-1.41	0.51
Vietnam	AGRI-THA	-0.13	4.74×10^{-2}
	EXP-MYS	57.22	20.27
	POP-MYS	7.48×10^{-3}	9.97×10^{-4}
	POP-THA	-9.15×10^{-3}	9.97×10^{-4}

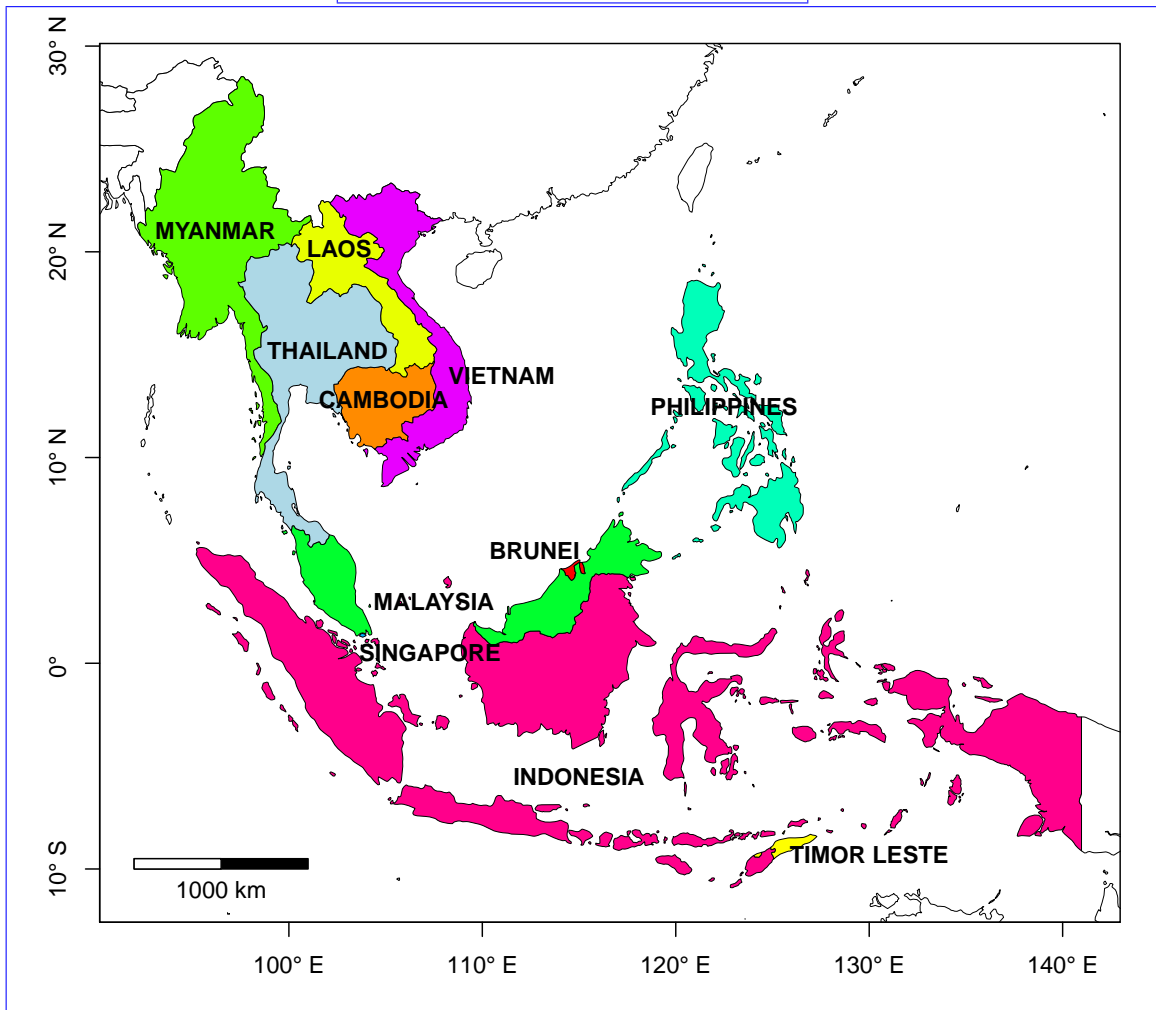
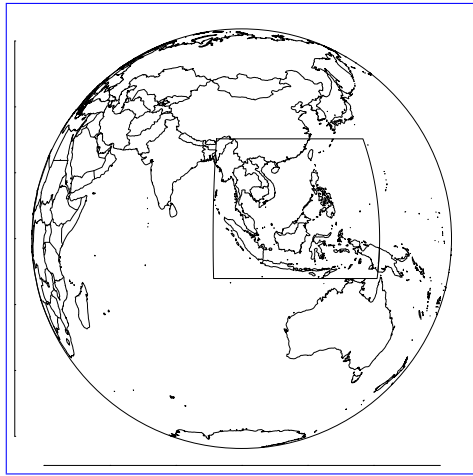


Figure 1: Geographical limits of the study area.

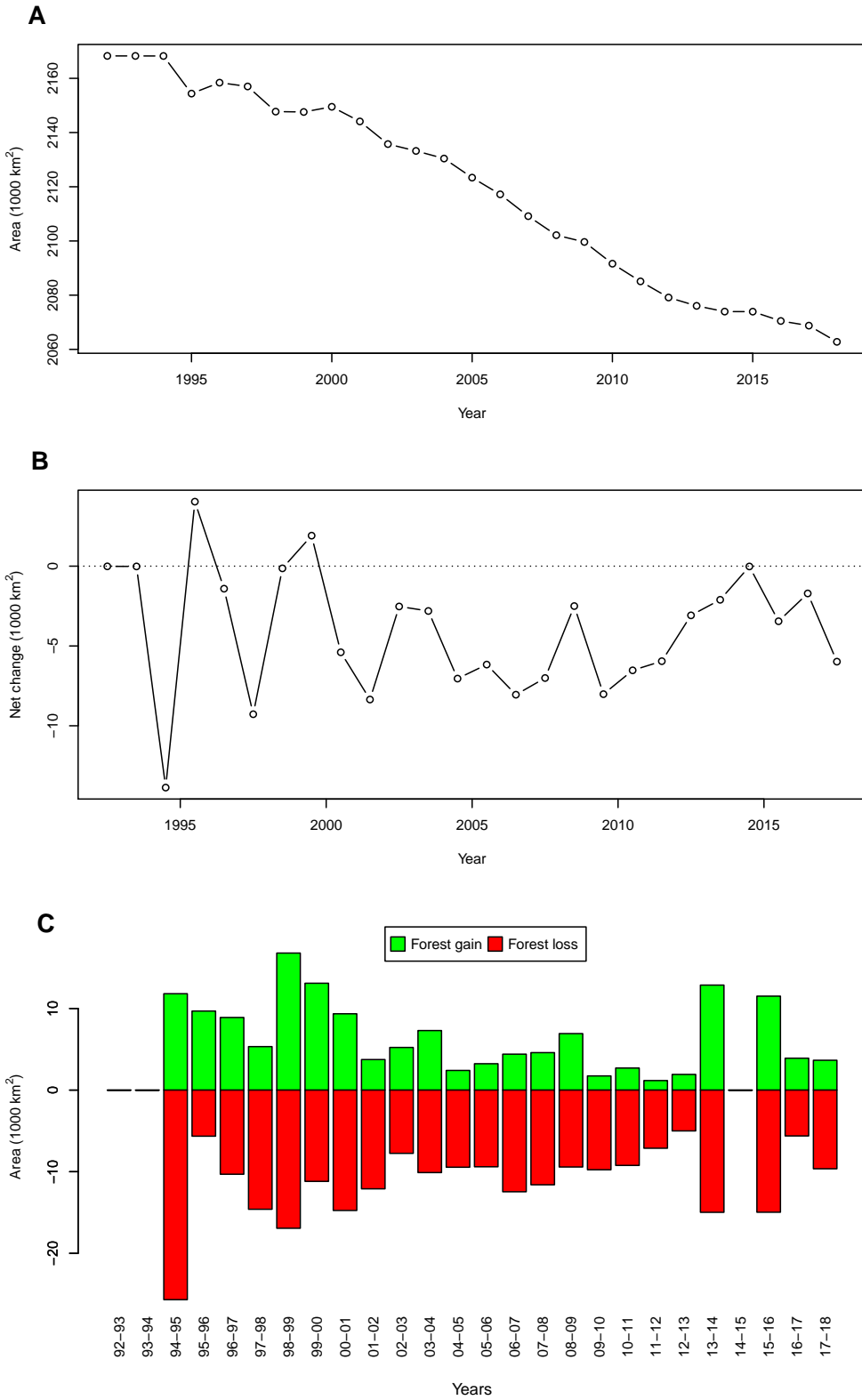


Figure 2: (A) Total forest cover area in Southeast Asia from 1992 to 2018. (B) Net changes in forest cover area (in km²) between successive years. (C) Gains and losses in each pair of successive years.

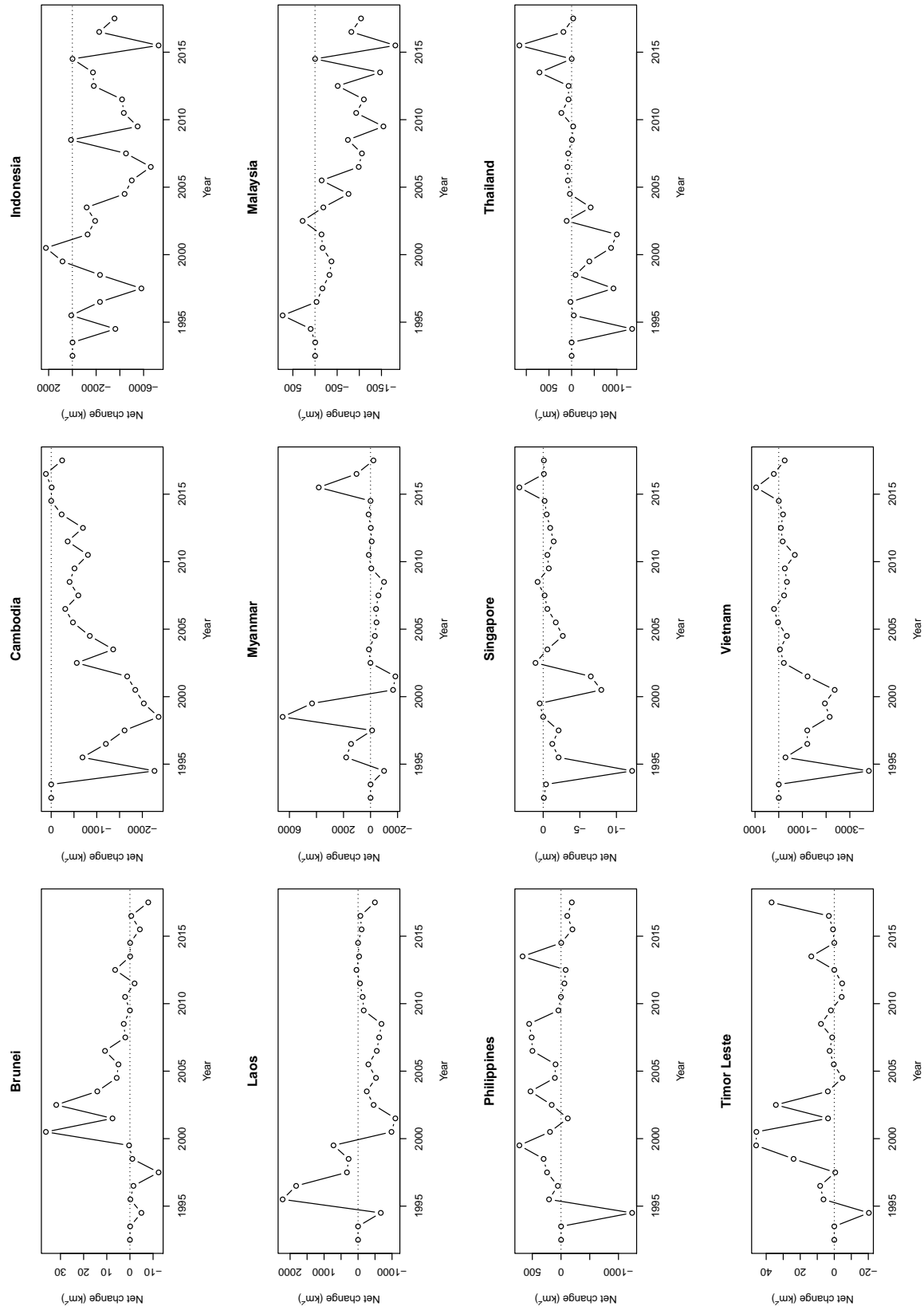


Figure 3: Net changes in forest cover area (in km²) between successive years for eleven countries in Southeast Asia.

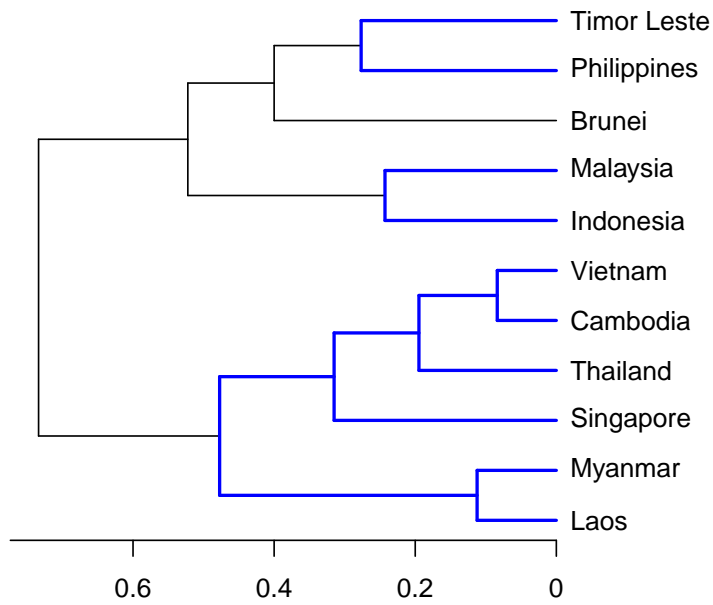


Figure 4: Hierarchical clustering of countries based on similarities derived from Table 2. Clusters in blue were significantly synchronised.

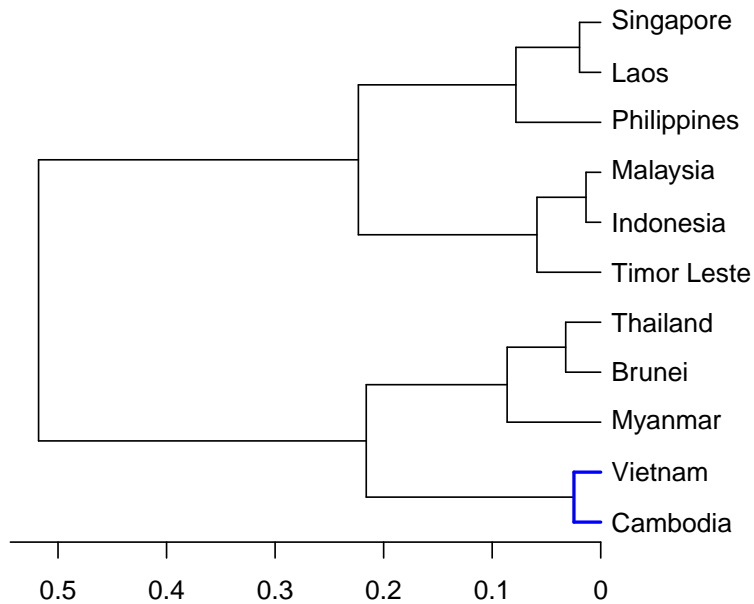


Figure 5: Hierarchical clustering of countries based on similarities derived from Table 3. The cluster in blue was significantly synchronised.

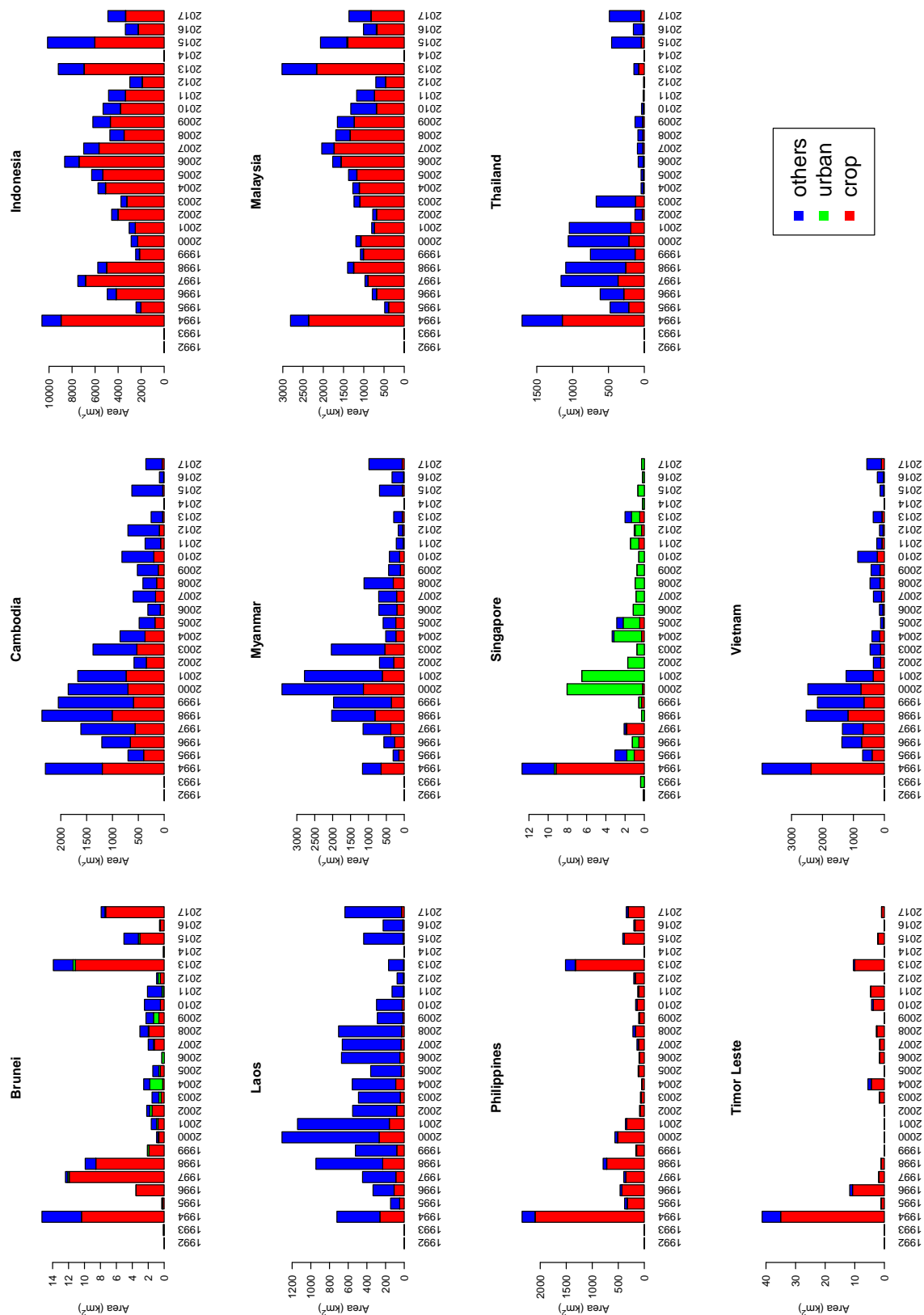


Figure 6: Conversion (in km²) from forest to one of the three land uses indicated in the legend.

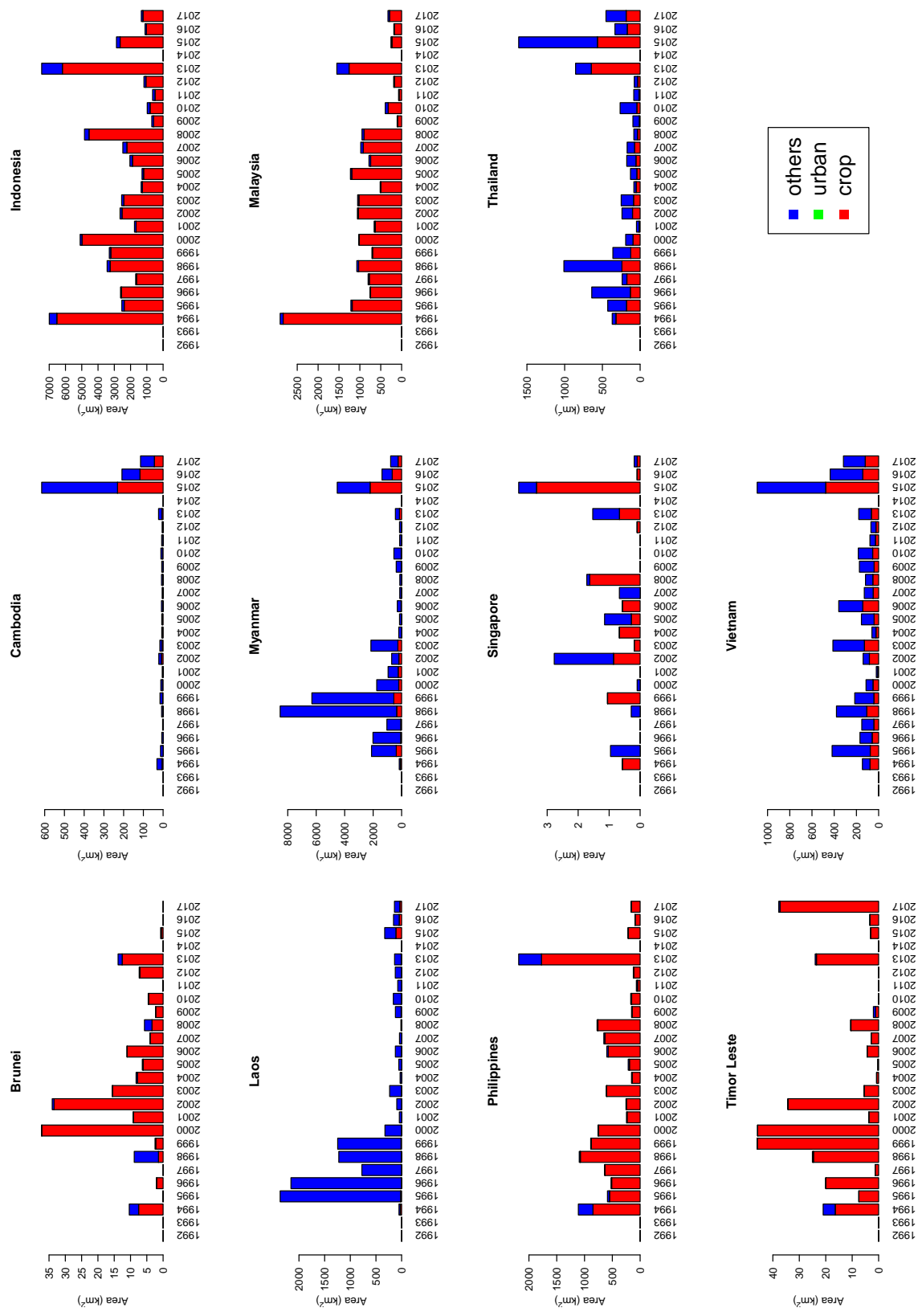


Figure 7: Conversion (in km²) from one of the tree land uses indicated in the legend into forest.