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Remotely sensed tree canopy cover-based indicators for monitoring global sustainability and environmental initiatives

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Abstract

With the intensifying challenges of global environmental change, sustainability, and biodiversity conservation, the monitoring of the world's remaining forests has become more important than ever. Today, Earth observation technologies, particularly remote sensing, are at the forefront of forest cover monitoring worldwide. Given the current conceptual understanding of what a forest is, canopy cover threshold values are used to map forest cover from remote sensing imagery and produce categorical data products such as forest/non-forest (F/NF) maps. However, multi-temporal categorical map products have important limitations because they inadequately represent the actual status of forest landscapes and the trajectories of forest cover changes as a result of the thresholding effect. Here, we examined the potential of using remotely sensed tree canopy cover (TCC) datasets, which are continuous data products, to complement F/NF maps for forest cover monitoring. We developed a conceptual analytical framework for forest cover monitoring using both types of data products and applied it to the forests of Southeast Asia. We conclude that TCC datasets and the statistics derived from them can be used to complement the information provided by categorical F/NF maps. TCC-based indicators (i.e. losses, gains, and net changes) can help in monitoring not only deforestation but also forest degradation and forest cover enhancement, all of which are highly relevant to the 2030 Agenda for Sustainable Development and other global forest cover monitoring-related initiatives. We recommend that future research should focus on the production, application, and evaluation of TCC datasets to advance the current understanding of how accurately these products can capture changes in forest landscapes across space and time.

1. Introduction

Forest ecosystems provide valuable goods and services, which are essential for human survival and development [1–4]. Forests are also critical habitats for terrestrial biodiversity [2–5], which in turn supports ecosystem functioning and productivity [1, 6, 7]. During the last 8000 years, however, over half of the world's forests have been lost due primarily to human activities [8, 9]. The continuous loss and degradation of forests threatens the survival of many species, reduces the ability of forest ecosystems to generate and provide essential services, and impacts the lives of at least 1.6 billion people worldwide whose livelihoods depend on forests [10, 11].

Today, the monitoring of the world's remaining forests is an important part of various global initiatives related to sustainability, the environment, and climate change. For example, sustainable development goal (SDG) 15 (Life on Land) of the United

Nations' (UN) SDGs under the 2030 Agenda aims to 'protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss' [12]. This goal is supported by 12 targets, at least seven of which could benefit from forest cover monitoring, directly or indirectly (table 1). Other global environmental and climate change-related initiatives that are associated with, and could benefit from, forest cover monitoring include reducing emissions from deforestation and forest degradation in developing countries, and the role of conservation, sustainable management of forests, and enhancement of forest carbon stocks (REDD+) [13], the Aichi Biodiversity Targets [14], the Bonn Challenge [15], the New York Declaration on Forests [16], the Paris Agreement [17], the Trillion Trees Vision [18], and the Manila Declaration on Forest and Landscape Restoration [11].

Earth observation (EO) technologies, particularly remote sensing (RS), are currently at the forefront of forest cover monitoring worldwide [9, 21–24]. For example, for the SDGs, the Group on Earth Observations has identified 71 (42%) targets and 30 (13%) indicators that can be supported, directly or indirectly, by EO technologies [21, 24]. RS data are particularly useful because they can be used for both spatial and temporal monitoring [24, 25]. They are useful in the mapping of forest or tree canopy cover (TCC) [22, 23, 26] and the monitoring of forest loss (including deforestation) [22, 27–30], forest degradation [25, 30–34], and forest and vegetation cover gain and improvement [22, 35, 36].

The UN's Food and Agriculture Organization (FAO) has been monitoring and assessing global forests since 1948 [37]. The FAO is also the custodian agency for a number of SDG indicators, including forest-related ones [19] (table 1). Data from the FAO's forest resources assessment (FRA) reports, however, are often criticized because they are only based on statistics consolidated from country reports [38, 39], which are not backed up with publicly available processed spatial data [24]. Nevertheless, for the 2020 FRA report [40], the FAO mentioned that it had been 'conducting a participatory global remote sensing survey (FRA 2020 RSS) with the scope of improving estimates of forest area change at global and regional scales' [41].

The FAO defines forest as 'land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10%, or trees able to reach these thresholds *in situ*. It does not include land that is predominantly under agricultural or urban land use' (p 4) [42]. It also defines deforestation as 'the conversion of forest to other land use independently whether human-induced or not' (p 6) [42]. Forest degradation refers to the reduction of the canopy and the capacity of forest ecosystems to conserve biodiversity and produce goods and services such as wood products and carbon storage [10, 43, 44]. We define forest cover enhancement as the improvement of forest cover through afforestation, reforestation, forest restoration and rehabilitation, and natural regeneration.

The FAO's definition of forest combines tree cover and land use, but this definition has been criticized because some lands that are no longer covered with trees are still classified as forest as long as their land-use type has not changed [40, 45–47]. RS-derived forest-related datasets, including forest area estimates, are also often in contradiction with FRA reports [35, 39, 48]. The primary reason for such discrepancies is differences in the definition of forest and the methods used to map forest cover. Whereas the FAO defines forest based on tree cover and land use, most RS-based studies and forest cover monitoring initiatives define forest based on tree cover alone [2, 22, 38, 40, 46, 49–51], primarily because RS alone cannot determine land use [38, 40, 46]. There are also numerous other definitions of forest [47, 50, 52, 53], but the FAO's definition is highlighted here because of its connection with the 2030 Agenda, and data for some of the forest-related SDG indicators come from the FRA reports [20] (table 1).

Essentially, if applied to RS imagery, the FAO's definition of forest results in discrete or categorical data products, such as land use/land cover or forest/non-forest (F/NF) maps, in which a pixel is classified as a particular class (e.g. forest). An area that had been classified as forest at time t_1 because it had a 50% canopy cover (aside from meeting the other FAO criteria [42]) would still be forest at time t_2 even if its canopy cover had decreased to 11% as a result of forest management practices, natural disasters, harvesting, or logging [42]. It should be noted, however, that canopy cover thresholds for defining a forest vary from 10% to 70% [22, 29, 31, 45, 47, 50, 51, 54–56] or even higher [57–60]. The United Nations Framework Convention on Climate Change (UNFCCC) defines forest as having a canopy cover of more than 10%–30% [61].

Furthermore, the land that corresponds to the 39% canopy cover loss noted in the example above (i.e. from 50% cover to 11%) would still be classified as forest if the loss were not caused by deforestation (i.e. a change in land use from forest to non-forest) or if it were expected to be regenerated within 5 years, either naturally or with the aid of silvicultural measures [42]. Similarly, an area that had been classified as non-forest at time t_1 because it only had 4% canopy cover would still be non-forest at time t_2 even if its canopy cover had increased to 9%, or even above the FAO's 10% threshold if the land is not classified as forest in terms of use [42]. Consequently, such forest cover enhancement is not considered.

Notably, categorical data products such as F/NF maps have important limitations in capturing the actual status of forest landscapes and the trajectories of forest cover change, forest degradation, and

Table 1. Some of the SDG 15 targets and indicators that could benefit from forest cover monitoring, directly or indirectly.

Target	Indicator[a]	Custodian	EO[b]
15.1 By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements	15.1.1 Forest area as a proportion of total land area	FAO	Yes
	15.1.2 Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type	UNEP-WCMC, UNEP, IUCN	No
15.2 By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally	15.2.1 Progress towards sustainable forest management	FAO[c]	Yes
15.3 By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world	15.3.1 Proportion of land that is degraded over total land area	UNCCD[d]	Yes
15.4 By 2030, ensure the conservation of mountain ecosystems, including their biodiversity, in order to enhance their capacity to provide benefits that are essential for sustainable development	15.4.1 Coverage by protected areas of important sites for mountain biodiversity	UNEP-WCMC, UNEP, IUCN	Yes
	15.4.2 Mountain Green Cover Index	FAO	Yes
15.5 Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species	15.5.1 Red List Index	IUCN	No
15.a Mobilize and significantly increase financial resources from all sources to conserve and sustainably use biodiversity and ecosystems	15.a.1/15.b.1 (a) Official development assistance on conservation and sustainable use of biodiversity; and	(none)	No
15.b Mobilize significant resources from all sources and at all levels to finance sustainable forest management and provide adequate incentives to developing countries to advance such management, including for conservation and reforestation	(b) revenue generated and finance mobilized from biodiversity- relevant economic instruments	(none)	No

[a] This list of indicators is based on the 17 July 2020 version of the Tier Classification for Global SDG Indicators document [19]. As of 25 August 2020, these indicators had some preliminary data available in the Global SDG Indicators Database [20].

[b] This indicates whether the indicator is EO-supported as identified by the Group on Earth Observations [21].

[c] The FAO has identified five sub-indicators: forest area annual net change rate, above-ground biomass stock in forest, proportion of forest area located within legally established protected areas, proportion of forest area under a long-term forest management plan, and forest area under an independently verified forest management certification scheme.

[d] The UNCCD has identified three sub-indicators: trends in land cover, land productivity, and carbon stocks.

forest cover enhancement, all of which are important in the context of the 2030 Agenda (e.g. SDG 15) and the other global environmental and climate change-related initiatives mentioned above. This article discusses RS-derived TCC maps, which are continuous data products, and posits that the statistics derived from them can be used to complement the information provided by categorical F/NF maps.

To support this proposition, we developed a conceptual analytical framework for forest cover monitoring and applied it in Southeast Asia. This region is home to nearly 15% of the world's tropical forests and at least four of the original 25 globally important biodiversity hotpots [4]. At the same time, however, the region is also among the world's hotspots for tropical deforestation and forest degradation. By using Southeast Asia as a test case, we aimed to (a) demonstrate that the use of different canopy cover thresholds in producing categorical forest map products could result in forest area and forest cover change estimates that are substantially different, (b) assess the advantages of TCC continuous data products and how they can complement F/NF categorical data products in forest cover monitoring, and (c) discuss some important current challenges, as well as some ways forward, regarding the production and use of TCC continuous data products.

2. Methods

2.1. Forest cover monitoring with remotely sensed continuous and categorical data products

TCC can be defined as the area of leaves, branches, and stems of trees covering the ground when viewed from above [62]. A remotely sensed TCC indicates the estimated percentage (0%–100%) of tree cover in a given pixel [22, 23]. Initial attempts to map percent tree cover as a continuous variable using RS data can be traced back to the late 1980s and early 1990s [63]. A related concept, called forest canopy density, was also developed in the 1990s [26].

Essentially, this approach (i.e. mapping of percent tree cover as a continuous variable) was developed on the premise that accurate information about the status of forests is needed for the development of forest rehabilitation programs (e.g. information that could help determine the intensity of rehabilitation treatment that may be required) and that RS data can be useful for such a purpose [26]. This approach can also be used to monitor transformation of forest conditions over time, including degradation, and assess the progress of reforestation activities [26]. Today, with the advances in RS technology and processing methods, global scale TCC datasets are now available [22, 23, 64–67].

RS data, such as those from MODIS, Landsat, ALOS-PALSAR, PROBA-V, and TanDEM-X interferometric SAR have been used to map global TCC and/or forest cover [9, 22, 23, 29, 64–69]. Using RS data, TCC can be mapped by employing regression tree algorithms [22, 23, 70], machine learning approaches (e.g. an artificial neural network), and spectral-based indices [26, 69, 71–74]. Categorical data products such as F/NF maps can be produced using supervised and unsupervised classification algorithms [69, 74–76], via thresholding of input TCC datasets [22, 23, 59] and backscatter coefficients [9, 77], or by employing other methods [68].

For illustrative purposes, consider the two images in figure 1(a) to be multispectral RS images at time t_1 and t_2 displayed in a false color composite, with their respective pixels or cells having been numbered from C1 to C9. Landsat Thematic Mapper is a typical example of a multispectral sensor that captures images in seven bands. Whereas continuous and categorical data products can be produced independently of each other using different mapping techniques, continuous data products such as TCC maps can also be used to generate categorical data products such as F/NF maps via thresholding [55, 56, 58–60].

For instance, by applying a >30% TCC threshold to the two hypothetical TCC maps (figure 1(b), continuous data products), two categorical F/NF maps can be produced, each containing two forest cells (cells C5 and C6 for t_1, and cells C4 and C5 for t_2) (figure 1(b), categorical data products). The results of this two-step forest cover mapping approach (from an image to a continuous data product, then to a categorial data product) may or may not be consistent with the results of a one-step mapping technique (from an image to a categorical data product). In the example presented, the hypothetical results of these one-step and two-step mapping techniques for producing categorical maps are assumed to be consistent (see figure 1(b), categorical data products).

If the categorical data products are used as inputs to a spatiotemporal analysis, a change map would reveal that only two cells experienced change between t_1 and t_2: C4 as forest gain and C6 as forest loss (figure 1(c), categorical). However, using the continuous data products as inputs, the change map would reveal that five cells experienced change between t_1 and t_2, with two cells showing TCC loss (C5 and C6) and three cells showing TCC gain (C2, C4, and C7) (figure 1(c), continuous).

In this case, the TCC loss in cell C5 of the continuous change map was not captured in the categorical change map, whereas the classification of cell C6 as forest loss in the categorical change map might be contestable because the cell showed only TCC loss in the continuous map. Similarly, the TCC gains in cells C2 and C7 were also not captured in the categorical change map. The classification of cell C4 as forest gain in the categorical change map might also be contestable because it is TCC threshold-dependent.

In sum, while the two types of data products were consistent in terms of the direction of change for cells C4 and C6, they were not consistent for cells C2, C5,

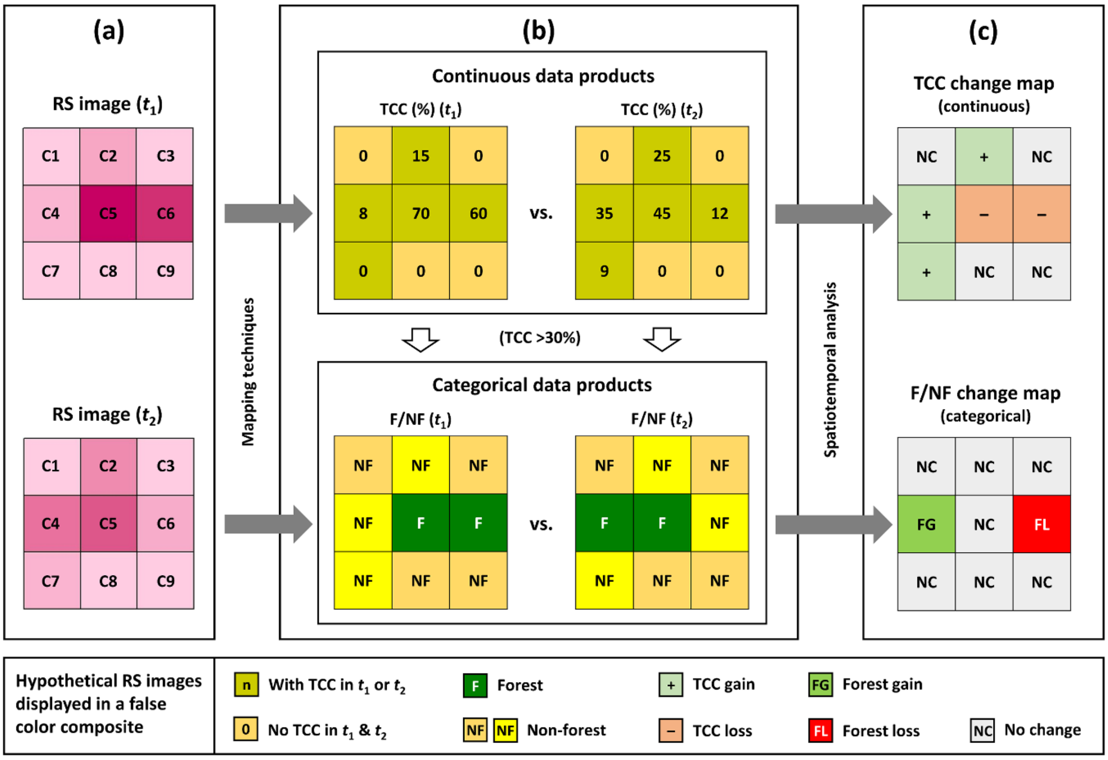

Figure 1. A conceptual analytical framework for forest cover monitoring using continuous data products (TCC maps) and discrete or categorical data products (F/NF maps). (a) Two hypothetical multispectral remote sensing (RS) images, (b) continuous and categorical data products, and (c) tree canopy cover (TCC) and forest cover change maps. The illustration shows that continuous data products such as TCC maps provide more comprehensive information regarding the extent (quantity), spatial pattern (location), and trajectory of landscape changes.

and C7. This inconsistency shows one of the important differences between continuous data products such as TCC maps and categorical data products such as F/NF maps when they are used as inputs to forest cover monitoring. Apparently, this inconsistency is due to thresholding effect.

2.2. Data used

To apply and illustrate the conceptual analytical framework presented in section 2.1, TCC maps of Southeast Asia for the years 2015 (t_1) and 2019 (t_2) were used (figure 2). These were sourced from the Copernicus Global Land Service—Land Cover map at 100 m spatial resolution (CGLS-LC100) database, Version 3 (Collection 3), created with the use of PROBA-V EO satellite data [67, 74, 78–80]. The CGLS-LC100 data products include global annual discrete or categorical land cover products at three levels over the 2015–2019 period (level 1: 10 classes with one class of forest; level 2: 11 classes with two classes of forest; level 3: 23 classes with 12 classes of forest) [78, 80].

Included in the database is a dataset of versatile cover fractions (%) for the 10 base land cover classes at level 1; the cover fraction layers can be combined to build custom classes for specific needs, such as forest cover monitoring for REDD+ (https://lcviewer.vito.be/about). The TCC datasets that we used came from the 'Tree-CoverFraction-layer', which refers to the fractional cover (0%–100%) for the forest class at level 1 [67, 78]. At the global level, the fractional cover layer for the forest class had a mean absolute error (MAE) of 8.9% and a root mean square error (RMSE) of 16.8% for 2015, and 9.6% and 17.6%, respectively, for 2019 [80]. At the regional level (Asia), it had an MAE of 7.9% and a RMSE of 16.3% for 2015 [80]. Error assessment at the regional level was not available for 2019, but we expect a similar range of error as in 2015.

A potential advantage of this dataset is that interannual errors in the mapped fractional tree cover values (e.g. due to climate variations) are reduced through a four-step process: (a) applying a weighted linear regression to the initial time-series data; (b) labeling the temporal stability of each pixel based on the deviation from the median tree cover fraction calculated for the pixel ('stable threshold' is defined as having a deviation of $\leqslant$3, and 'reliable threshold' is defined as having a deviation of $\leqslant$15); (c) applying temporal post-regression rules to the pixels, with different sets of rules applied to stable, reliable, and other pixels; and (d) normalizing the fractional cover estimates over the time series to ensure values between 0 and 100 [74].

In general, the CGLS-LC100 data products, including the fractional cover layers, were produced by using sophisticated, state-of-the-art

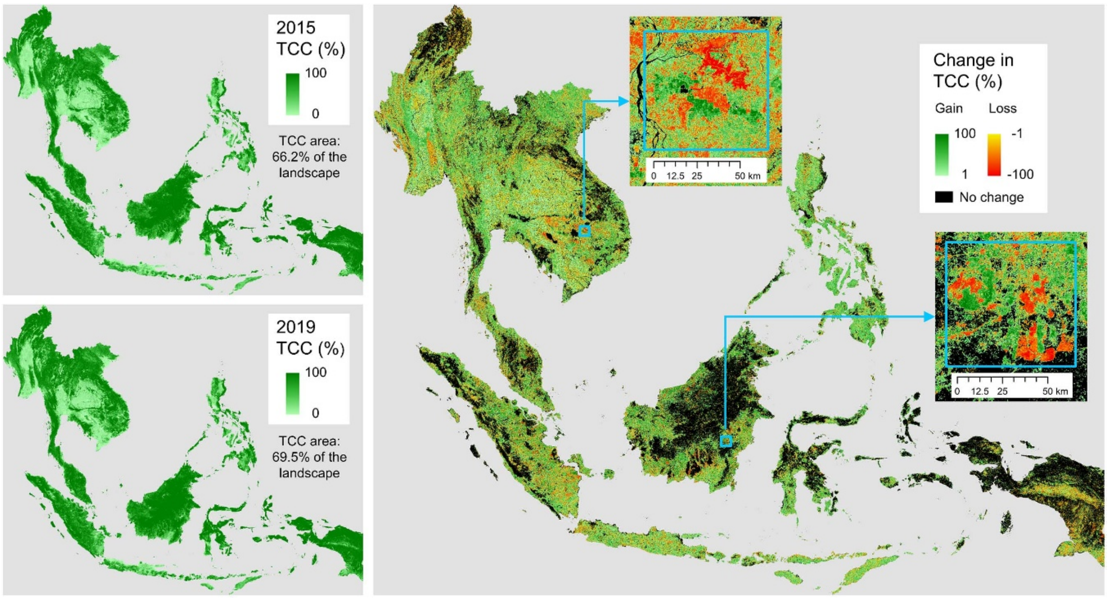

Figure 2. TCC of Southeast Asia in 2015 and 2019. The map on the right was derived by subtracting the 2015 TCC map from the 2019 TCC map. The upper inset is within Cambodia; the lower inset is within Indonesia.

methodologies, including uncertainty analysis and validation procedures, and they come with extensive documentation [69, 74, 78, 80]. The spatial data can be downloaded from https://lcviewer.vito.be/download, and the documentation can be accessed at https://land.copernicus.eu/global/products/lc.

The study area, Southeast Asia, included the spatial extent of 11 countries [4] and was based on the version 3.6 administrative boundary layer sourced from https://gadm.org/. The study area measures 446.1 million ha (Mha).

2.3. TCC and forest area estimation

We estimated the total areal extent of TCC in Southeast Asia in 2015 and 2019 by summing the areal equivalent of TCC in each pixel across the landscape (equation (1))

$$\mathrm{TTCC} = \sum_{i=1}^{n} A_i \times \frac{\mathrm{TCC}_i}{100}. \tag{1}$$

where TTCC refers to the total area of tree canopy cover, TCC_i refers to the tree canopy cover of pixel i (with values ranging from 0 to 100), A_i refers to the area of pixel i, and n refers to the number of pixels in the landscape.

To produce categorical F/NF maps, we used nine TCC thresholds to define a forest (i.e. from >10% to >90% at 10% intervals). To do this, for each map, we classified the pixels as forest (F) if their TCC was greater than the threshold or as non-forest (NF) if their TCC was equal to or less than the threshold. Subsequently, we determined the total areal extent of forest at both time points for each of the thresholds used by summing the area of pixels that belonged to the F class (equation (2)):

$$\mathrm{TF} = \sum_{i=1}^{n} A_{i\mathrm{F}}, \tag{2}$$

where TF refers to the total area of forest, A_{iF} refers to the area of pixel i of the forest (F) class, and n refers to the number of pixels that belonged to the forest class.

2.4. TCC and forest cover change detection

We overlaid (subtracted) the two TCC maps to identify the pixels that experienced change between 2015 and 2019 and those that did not. We determined the total areal extent of loss and gain in TCC by summing the areal equivalent of the TCC loss or gain in each pixel across the landscape, following the logic of equation (1).

For each TCC threshold, we also overlaid (cross-tabulated) the two F/NF maps (2015 and 2019) to identify the pixels whose cover changed over the period and those that did not. Pixels whose cover changed from F to NF are called forest loss pixels and those that changed from NF to F are called forest gain pixels. We determined the total area of forest loss and forest gain by summing the area of all forest loss and forest gain pixels across the landscape, following the logic of equation (2).

The net change in TCC and forest cover over the period was determined by subtracting the 2015 data from the 2019 data. This was counter-checked by adding up the loss (negative) and the gain (positive) in TCC and forest cover. Similar to the total area of TCC and forest cover, the loss, gain, and net change

statistics were also expressed as a percentage of the landscape.

The net annual change was expressed in terms of area per year and percentage (%) per year, derived following the FAO's procedure [40, 81]. The former was derived simply by dividing the area of net change by the number of years between the two data points, in this case, 4 years. The latter was calculated as the compound annual change rate (equation (3)):

$$\mathrm{ACR} = \left[\left(\frac{\mathrm{TA}_2}{\mathrm{TA}_1}\right)^{1/(t_2-t_1)} - 1\right] \times 100, \qquad (3)$$

where ACR refers to the annual change rate (% per year), and TA_1 and TA_2 are the total area of TCC or forest cover at time t_1 and t_2, respectively.

2.5. Forest degradation and enhancement analysis based on TCC changes

To gain further insights into the spatial pattern of forest cover changes in Southeast Asia as indicated by the changes in TCC, we performed a gradient analysis. We used the concept of gradient as commonly applied in landscape ecology [82, 83], that is, the variation in the values of the given environmental variables across their ranges of values (e.g. elevation, slope, and temperature; in our case, the TCC). We first reclassified the 2015 and 2019 TCC maps into ten TCC gradient classes at 10% intervals to gain insights into the size of each gradient class relative to the whole landscape at each time point. Subsequently, we determined the areal extent of the gross changes (loss and gain) and net changes in TCC across the 2015 TCC gradient classes.

3. Results

3.1. Extents of TCC and forest cover

The areal extent of TCC in Southeast Asia was 66.2% of the landscape (295.5 Mha) in 2015 and 69.5% (309.9 Mha) in 2019 (figure 2). Of the TCC thresholds used to map forest cover, the 10% threshold produced the largest forest area for both time points (88.8% in 2015 and 90.6% in 2019), whereas the 90% threshold produced the smallest (40.2% in 2015 and 55.1% in 2019) (figure 3). At both time points, forest area decreased as the TCC threshold increased, a trend that is expected because the definition of forest becomes more restrictive as the threshold increases. As with the TCC, forest cover in each threshold also increased over the study period. Figure 4 shows the enlarge version of the F/NF and change maps derived using the 50% threshold.

3.2. Losses and gains in TCC and forest cover

Over the study period, the region had a gross TCC loss and gain equivalent to 1.6% (7.2 Mha) and 4.8% (21.6 Mha) of the landscape, respectively (figure 5(a)). The 20% TCC threshold had the smallest gross forest loss with −0.9% (−3.8 Mha), whereas the 10% TCC threshold had the smallest gross gain with 2.8% (12.6 Mha). The 90% threshold had the largest gross change, with a gross forest loss of −3.1% (−14.0 Mha) and a gross forest gain of 7.8% (34.8 Mha) (figure 5(b)).

3.3. Net changes in TCC and forest cover

The region's gross loss and gain in TCC resulted in a net TCC gain of 3.2% of the landscape (14.5 Mha) (figure 5(a)). Forest cover also showed a net gain. The 10% TCC threshold had the lowest net gain (1.8%, 8.1 Mha), and the 80% threshold had the highest (4.8%, 21.3 Mha) (figure 5(b)).

In terms of net annual change, the region's TCC increased at the rate of 3.6 Mha yr^{-1}, equivalent to a compound annual change rate of 1.2% per year (figure 5(c)). Of the TCC thresholds used to map forest cover, the 10% threshold had the lowest net annual forest gain (2.0 Mha yr^{-1}), and the 80% threshold had the highest (5.3 Mha yr^{-1}) (figure 5(d)). These values correspond to a compound annual change rate of 0.5% and 2.4% per year, respectively. The 90% threshold had the second highest net annual forest gain in terms of area (5.2 Mha yr^{-1}), but it had the highest compound annual change rate (2.8% per year).

3.4. Forest degradation and enhancement

Figure 6(a) shows the size of the TCC gradient classes at each time point relative to the whole landscape. In 2015, the 91%–100% gradient class accounted for 40% of the region, increasing to 45% in 2019. Figure 6(b) shows the loss and gain in TCC over the study period across the 2015 TCC gradient classes, also expressed as percentage of the landscape. This information breaks down the TCC loss and gain presented in figure 5(a) for the entire region. In terms of loss, the 91%–100% TCC gradient class had the highest with −0.54% (−2.4 Mha). In terms of gain, the 61%–70% TCC gradient class had the highest with 0.69% (3.1 Mha), closely followed by the 71%–80% TCC gradient class with 0.67% (3.0 Mha). Across the TCC gradient classes, only the 91%–100% gradient class had a negative net change (−0.29%, −1.3 Mha).

The 61%–70% TCC gradient class had the highest net annual change in terms of area per year with an annual net gain of 0.6 Mha yr^{-1} (figure 6(c)). However, in terms of the compound annual change rate, the 0%–10% gradient class had the highest with 13.5% per year. The TCC gradient class with a negative net change (91%–100%) had a net annual change of −0.3 Mha yr^{-1} and a compound annual change rate of −0.2% per year.

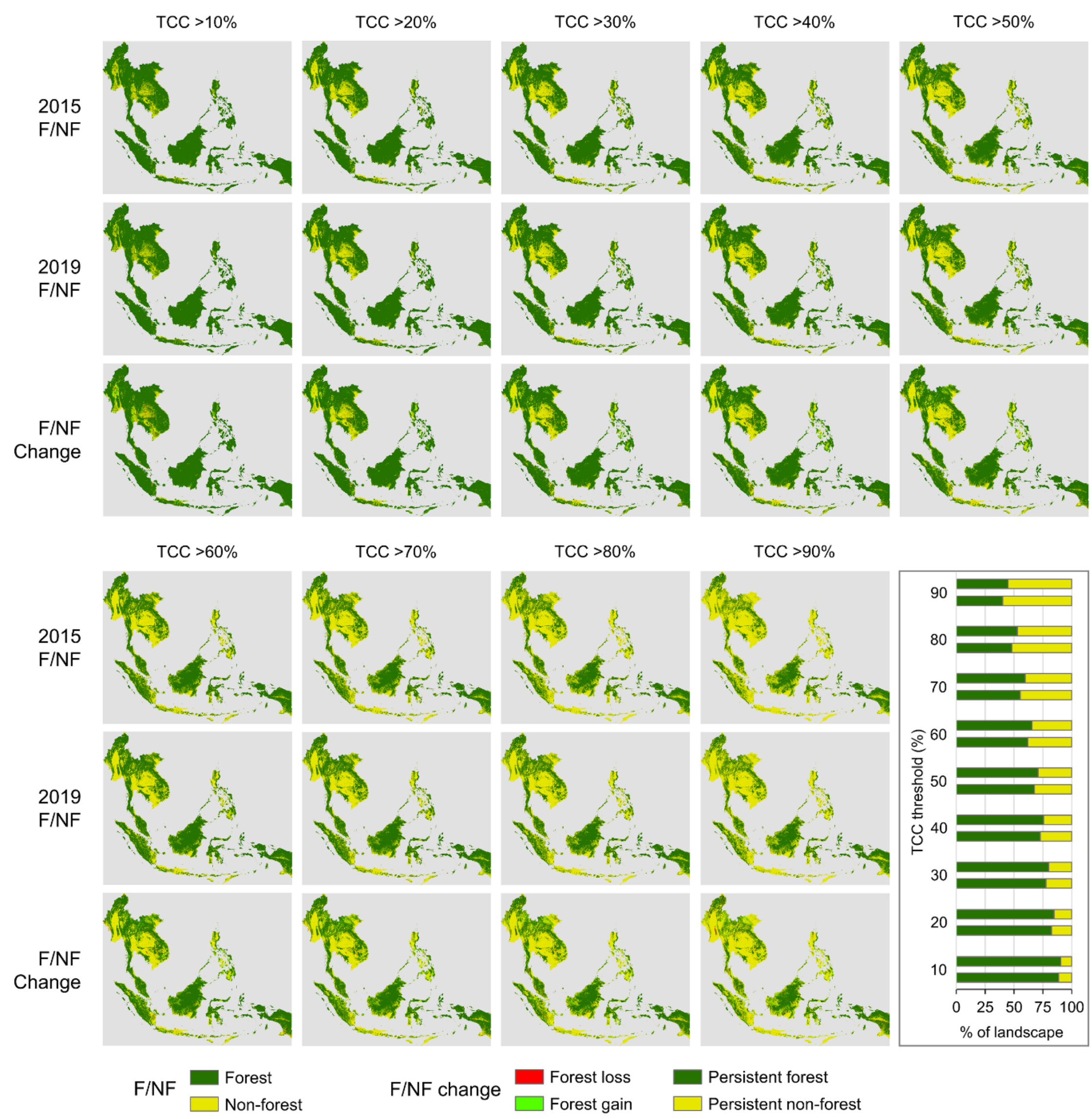

Figure 3. F/NF maps of Southeast Asia in 2015 and 2019 based on various TCC thresholds. The figure also shows the detected forest cover changes over the period (the third row of each map set). An enlarged version of 'TCC >50%' is shown in figure 4. The bar graph shows the areal extent of forest cover across TCC thresholds, in which the upper bar in each threshold refers to 2019 and the lower bar refers to 2015. The areal extent of forest loss and gain across TCC thresholds is given in figure 5.

4. Discussion

4.1. Learning and insights

Empirically, our results show that Southeast Asia's TCC has improved in recent years (figure 2). We hypothesize that much of this improvement could be the result of increased forest plantations. A recent study also found that the world has more tree cover today than it had three and a half decades ago [35], and a separate study detected a net increase of global leaf area of vegetation over the past two decades [36]. These findings indicate that the world is greening. Researchers have acknowledged that, while indirect factors such as climate change, CO_2 fertilization, and nitrogen deposition could have influenced such a greening trend, much of the increase in global tree cover and leaf area of vegetation can be attributed to forest plantations [35, 36]. More discussions on forest plantations are given in section 4.2.

In terms of gross forest loss, the estimate based on the 90% TCC threshold between 2015 and 2019 (14 Mha, 3.1% of the landscape) in our study (figure 5(b)) was closest to the sum of the estimates reported in the Global Forest Watch (GFW) for 2016, 2017, 2018, and 2019 (13.35 Mha, 3.0% of the landscape) [22, 84]. We were not able to compare our estimates of gross forest gain with the GFW because the forest gain data in the GFW is limited to the 2000–2012 period only [22]. Furthermore, it should be noted that the methodology and RS data used in the GFW [22] are different from those in our study, so the forest cover change estimates are not directly comparable.

Both categorical (e.g. F/NF maps) and continuous (e.g. TCC maps) data depict land cover

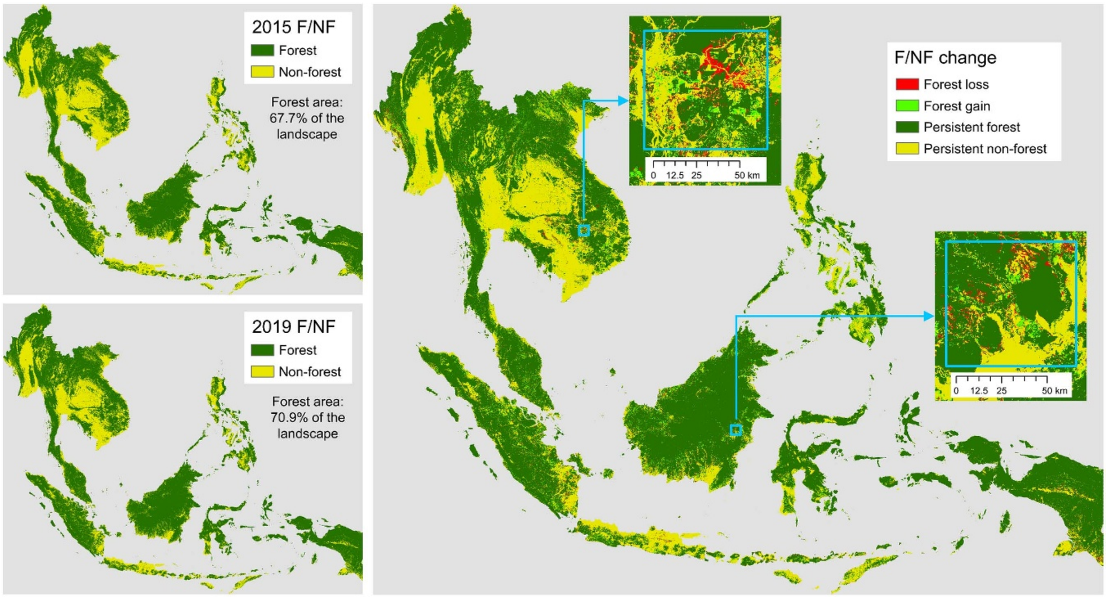

Figure 4. F/NF map of Southeast Asia in 2015 and 2019 based on the TCC >50% threshold. The map on the right shows the detected forest cover changes (loss and gain) as well as the unchanged ('persistent') areas over the period. The upper inset is within Cambodia, and the lower inset is within Indonesia.

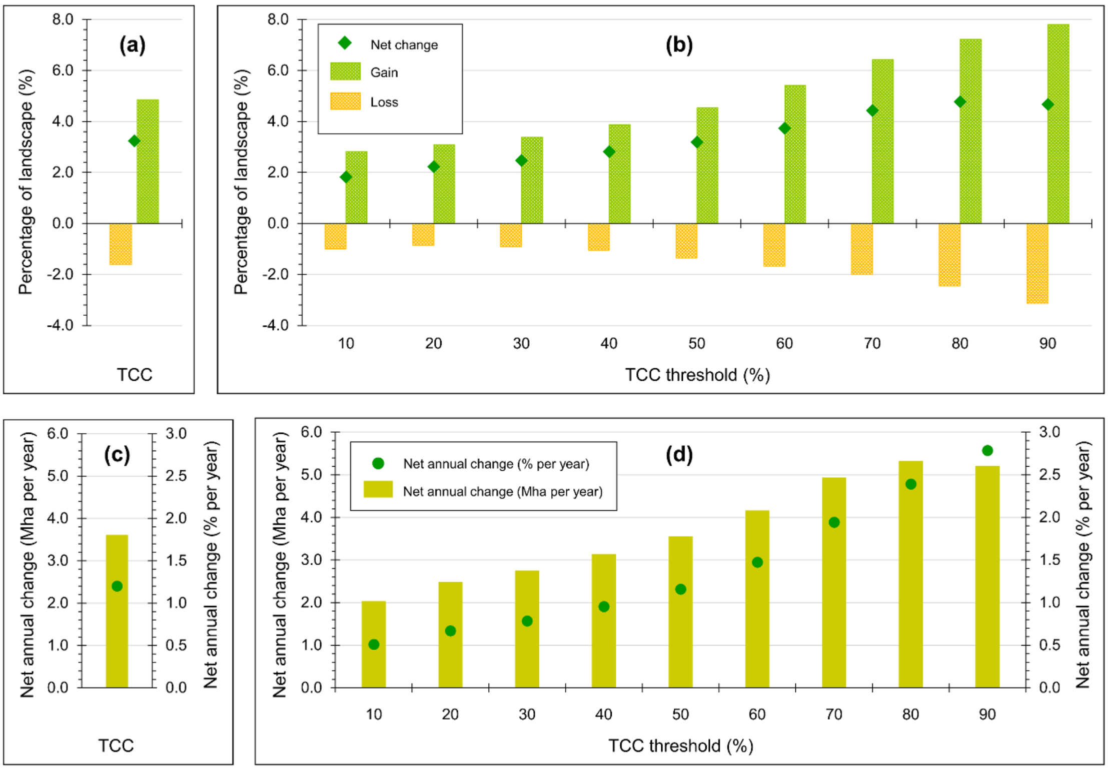

Figure 5. Changes in TCC and forest cover in Southeast Asia between 2015 and 2019. (a) Loss, gain, and net change in TCC. (b) Losses, gains, and net changes in forest cover across various TCC thresholds. (c), (d) Net annual changes in TCC and forest cover, respectively, expressed as area and percentage per year. The net annual percentage change was calculated as the compound annual change rate (equation (3)).

and are important for various purposes, including forest cover monitoring, biological conservation, land use planning, climate and carbon cycle modeling, and greenhouse gas emission estimation [9, 22, 23, 26, 69, 85]. Here, we first reflect on the use of different TCC thresholds and their respective outputs for forest cover mapping and change monitoring. We then discuss some of the important advantages of TCC datasets and how they can complement the information provided by categorical F/NF datasets.

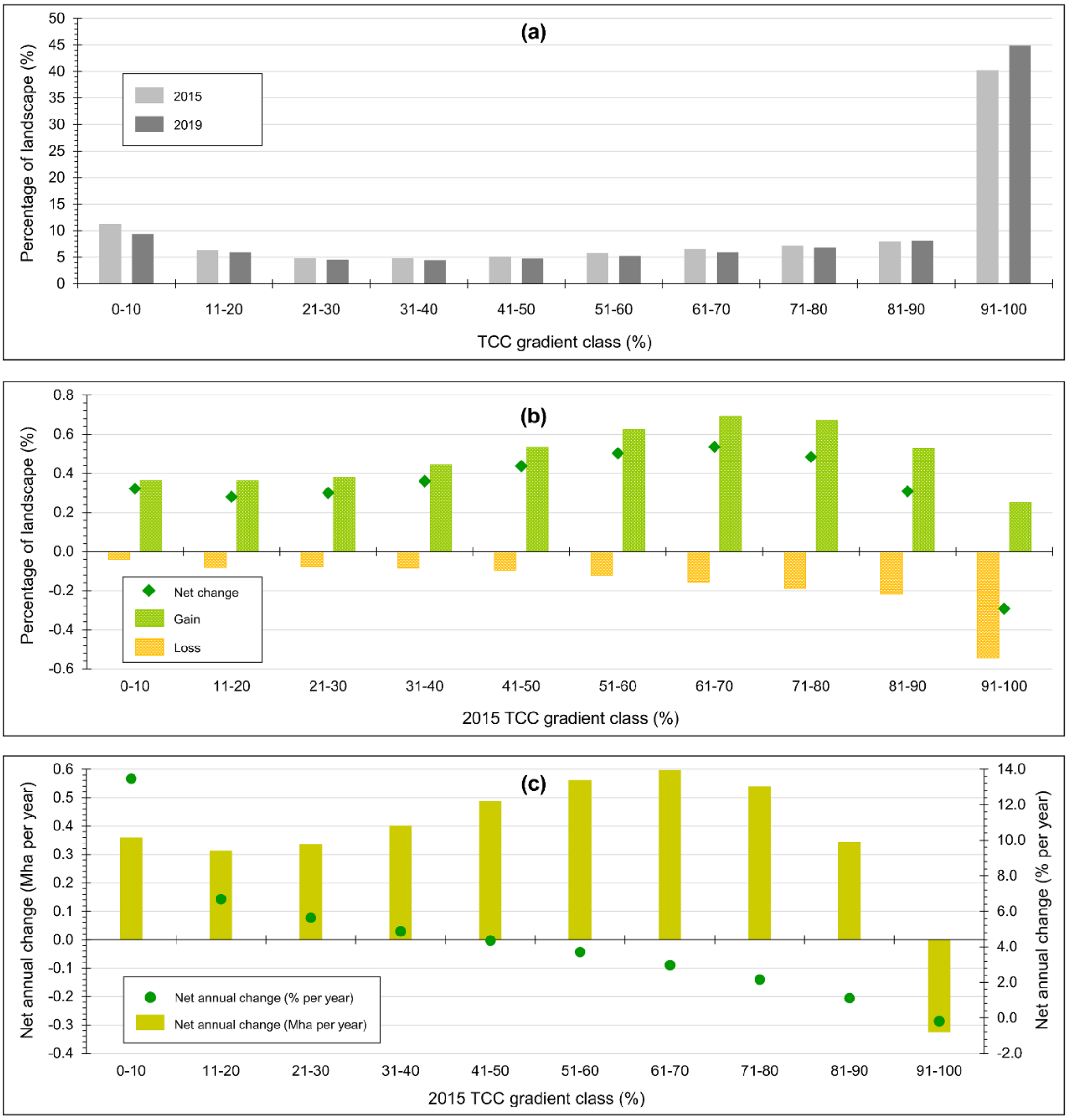

Figure 6. Changes in canopy cover in Southeast Asia between 2015 and 2019 across the TCC gradient. (a) Extents of the TCC gradient classes in 2015 and 2019. (b) Losses, gains, and net changes in TCC across the 2015 TCC gradient classes. (c) TCC net annual changes across the 2015 TCC gradient classes, expressed as area and percentage per year. The net annual percentage change was calculated as the compound annual change rate (equation (3)).

A TCC threshold for forest cover mapping can vary from one assessment to another, depending on the purpose of the assessment and the type and status of the forest landscape being assessed. In our analysis, the forest area estimate based on the 10% TCC threshold (figure 3) could have huge implications in forest cover monitoring because the forest area might be overestimated (i.e. 89%–91% of the landscape). The 10% TCC threshold is consistent with the FAO's definition of forest [42], and to a certain extent, with the UNFCCC's [61]. Other scholars have argued that the 10%–30% threshold range is too low because a forestland could be severely degraded but still be classified as a forest. Thus, a much higher threshold (>40%) has been recommended [31].

In other studies, 80% [59] and 94% [60] TCC thresholds have been recommended for use when delimiting forest cover in the Amazonian basin. One might argue that the Amazonian forests were substantially denser and less disturbed than Southeast Asian forests; hence, the recommended higher TCC threshold would be appropriate. If the purpose, however, is to produce forest area and forest cover change estimates for a particular forest biome (e.g. tropical rainforest) that can be compared globally, then the TCC threshold to be used in forest cover mapping needs to be consistent across forest landscapes inside that biome regardless of their status.

Indeed, as shown by our results, the area and spatial pattern of both forest and forest cover change were sensitive to the TCC thresholds used, and different TCC thresholds resulted in forest area and forest cover change estimates that were substantially different (figures 3 and 5(b), (d)). In our analysis, the forest

loss estimate based on the 60% TCC threshold was closest to the estimated TCC loss, but the forest gain, net change, and net annual change estimates by the 50% TCC threshold were the most consistent with the estimated TCC gain, net change, and net annual change (figures 2–5). In a previous study on global forest cover change, a 50% TCC threshold was used as the basis to estimate global forest losses and gains between 2000 and 2012 [22]. In Southeast Asia, a 50% TCC threshold had also been used to map the Philippine forests using the MODIS VCF, Sexton *et al*, and Hansen *et al* TCC datasets [56].

Although we are not suggesting which TCC threshold should be used for tropical rainforests, if the strategy for forest cover monitoring is to use multi-temporal categorical data products such as F/NF maps, then a consistent threshold or forest definition in forest cover mapping across time points should be used. The use of a harmonized or standardized forest definition will also help achieve a reliable comparison across different global and national-scale forest cover mapping efforts [49]. That said, there is a need to pay careful attention to the selection of an appropriate TCC threshold to avoid overestimation or underestimation of forest area and changes. Forest definition not only affects the estimates of the extent and spatial pattern of forest and forest cover changes (loss and gain) (figures 3–5), but also those of deforestation and forest degradation, as well as the assessment of drivers of deforestation and the development of a reference emission level [31, 86]. Because F/NF maps alone cannot capture the subtle changes in the landscape (e.g. forest degradation and forest cover enhancement), TCC-based metrics (losses, gains, and net changes) can be used as complementary indicators for forest cover monitoring. As shown in figures 3 and 4, the persistent forest category included areas that experienced forest degradation (with a decreasing TCC in figure 2), whereas the persistent non-forest category included areas that underwent forest cover enhancement (with an increasing TCC in figure 2).

F/NF maps produced using TCC thresholds cannot capture the loss of canopy cover as long as the remaining TCC is above the threshold used to define a forest. Similarly, they cannot capture an increase of canopy cover in areas where the baseline TCC is already above the threshold. In other words, the F/NF maps generated by using TCC thresholds are limited when it comes to monitoring forest degradation and forest cover enhancement. This is true even to a greater extent if the full FAO concept of forest and deforestation were to be used to map forest cover because (a) some lands without trees are classified as forest and (b) non-forest lands planted with trees are not automatically considered to be forest in terms of use [42] (the question of who classifies land use types remains).

As demonstrated by our results, the canopy cover approach also enables one to examine whether detected recent forest degradation or forest cover enhancement has occurred in less degraded (i.e. with a higher TCC) or more degraded (i.e. with a lower TCC) parts of the landscape through, for example, a TCC gradient analysis (figure 6). This is also another important advantage of TCC, and depending on the focus of conservation policies, either or both parts of the landscape can be prioritized for monitoring and conservation. In our case, the much larger loss of TCC and the negative net change in TCC in the 91%–100% TCC gradient class are indicative of forest degradation (figures 6(b) and (c)). The current practice of selective harvesting or selective logging (e.g. in Sarawak, Malaysia) [87, 88] could have contributed to this trend.

Furthermore, continuous data products such as TCC maps may depict areas of heterogeneous land cover better than standard categorical data products such as F/NF maps and, as such, can be tailored for specific applications (e.g. forest cover monitoring, including degradation and enhancement) [78]. Spatiotemporal estimates of TCC provide a biophysically relevant, sensible, and consistent basis for monitoring forest cover and change [50]. Hence, TCC datasets can also be used as a complementary tool in the assessment of forest landscape restoration potential, which is also an important current issue [89, 90]. Another important advantage of TCC datasets is they do not rely on a particular definition of forest, which makes them more standardized than categorical map products.

Additionally, TCC datasets can also help in the monitoring of forest disturbance. Forest disturbance is 'mostly used for natural causes of crown cover or biomass loss, such as from storm damage, forest fires, drought stress, insect infestations and disease outbreaks but may also include harvesting operations with a potential negative impact' (p 33) [91]. Forest disturbances have the potential to undermine ecosystem functioning, thus, the monitoring of the intensity of forest disturbance, including its size, frequency and severity are imperative for sustainable forest management [92, 93]. While basal area removal can be used to indicate the intensity of forest disturbance, the removal or change in canopy cover can also be used [92–94].

Given these findings and observations, we argue that TCC-based indicators (losses, gains, and net changes) can be used as complementary indicators for forest cover monitoring in the context of the 2030 Agenda and other global environmental and climate change-related initiatives such as those mentioned in section 1. For SDG 15, TCC-based indicators are highly relevant for targets 15.1–15.5. They are also relevant for some forest-related targets that are currently not identified as directly or indirectly

supported by EO technologies, such as 15.a and 15.b [21] (table 1). For example, when the TCC-based indicators are monitored over time, they can provide supporting evidence for the impacts or outcomes (positive or negative) of increased financial investments to conserve and sustainably use biodiversity and ecosystems (target 15.a) and advance sustainable forest management, including conservation and reforestation (target 15.b).

In our analysis, we not only reported the extents of TCC and forest cover and calculated the rates of net annual change using a methodology consistent with the FRA reports [40, 81], we also reported the gross changes (losses and gains) (figures 5 and 6). The suggested inclusion of loss and gain in our set of TCC-based indicators highlights the need to consider the gross changes in TCC between points in time, relevant information that is currently not available in FRA reports in the case of forest cover [40]. Although the net change metrics are useful, the loss and gain metrics provide more details that simultaneously capture the negative and positive trends in forest landscape changes. They thus could be more relevant in the context of forest cover monitoring in general. For example, in the context of climate change mitigation, the knowledge of loss and gain in TCC can be especially relevant in the monitoring of carbon emission (sources) and sequestration (sinks), respectively. For the 2030 Agenda (e.g. SDG 15) and other global forest cover monitoring-related initiatives, these loss and gain metrics are needed to properly monitor the impacts and feedback of global efforts to protect, conserve, and enhance the world's remaining forests.

4.2. Challenges and ways forward

The current status of forest cover monitoring with RS technology is that forest degradation, occurring within forests, is more difficult to capture than deforestation because the changes in the forest canopy and structure caused by forest degradation are often subtle and smaller [32–34]. Therefore, they are more difficult to detect, unlike in the case of deforestation where the reductions in canopy cover are often significant [32–34]. In fact, as per the FAO definition, deforestation is the conversion of forest to other land use [42]. By contrast, forest degradation leaves some canopy cover, making detection difficult [30]. Similarly, subtle improvements in forest cover are also difficult to capture. As shown by our analysis, remotely sensed TCC maps (continuous data products) (e.g. figure 2) are better at detecting and capturing subtle changes than F/NF maps (categorical data products) (e.g. figure 4). To further improve forest cover monitoring results, RS data of higher spatial resolution, including LiDAR data, can be used to complement medium spatial resolution TCC map products such as those used in this study. This is especially true for small-scale assessments (e.g. at the sub-national level).

Currently, at least four publicly available databases exist for global remotely sensed TCC. One is associated with Hansen *et al* [22], with datasets for 2000 and 2010. Both of these TCC datasets have a spatial resolution of 30 m and are currently used in the GFW (www.globalforestwatch.org). Another database is associated with Sexton *et al* [23], with datasets for 2000, 2005, 2010, and 2015. These datasets also have a spatial resolution of 30 m. The third is the MOD44B Version 6 Vegetation Continuous Fields (MODIS VCF); it has annual percent tree cover datasets starting in 2000 [64]. These datasets have a spatial resolution of 250 m. The fourth is the CGLS-LC100 dataset [67, 78] used in this study.

The current challenge for the Hansen *et al* datasets is that they are not harmonized in terms of the way they were produced (Peter Potapov, personal communication), deterring spatiotemporal analysis. Hence, one possible way forward is to harmonize these datasets. Even though the Sexton *et al* and the MODIS VCF percent tree cover datasets are harmonized, the current challenge with those is cloud coverage and line strips, which also affect change detection and analysis. It would be helpful for the Sexton *et al* and Hansen *et al* datasets to be harmonized to support data supplementation and complementation, considering that both datasets are based on Landsat data. Finally, it would be helpful to continue producing the CGLS-LC100 fractional cover data to enable long-term monitoring.

One major disadvantage with regard to TCC, in general, is that compared to categorical data products, TCC datasets are less commonly used in forest cover monitoring. Consequently, the literature about the production of TCC datasets with the use of RS data is still limited. Nevertheless, while we currently consider this to be a disadvantage, it also represents an opportunity to help advance the field of forest cover monitoring by providing a complementary source of information to categorical data products.

Another important challenge regarding TCC is reliability. For example, variations in the spectral properties of trees and soil/non-tree background as well as variation in climatic factors (e.g. different levels of rainfall in different years) across biomes may lead to errors in the estimated TCC values. The validation of TCC datasets can also be more challenging in terms of resources (e.g. validation data such as LiDAR measurements) as compared with categorical datasets. Comparatively, much more research has focused on the production, application, and accuracy assessment of categorical data products such as F/NF and land use/land cover maps. Hence, we recommend that greater attention should be given to the production, application, and accuracy assessment of TCC datasets to advance the current understanding of how well these products can capture actual changes in forest landscapes across space and time. In addition, all of the previously mentioned datasets need to include an

accuracy/error assessment in the validation process for estimated TCC changes between time points.

Furthermore, TCC datasets also do not distinguish natural forests from artificial forests (hereafter, forest plantations). As mentioned earlier, much of the detected gain in TCC in the region (figures 2 and 5(a), (c)) could have been due to forest plantations. The share of forest plantations in the world's forests is also expected to increase from the current 7% to 20% by the end of this century [95]. However, while some forest plantations are socially and ecologically beneficial (e.g. those that use native or endemic tree species and mixed species, are established in degraded lands, and are properly managed) [95–98], forest plantations generally fail to replicate all the ecosystem services that natural forests provide. Monoculture commercial and industrial plantations have also been dubbed as green deserts [99, 100] or biological deserts [101] because of their negative impacts on biodiversity, ecosystems, and society (human displacement) [99–101].

Fueled by the absence of robust institutions, commercial agriculture, through monoculture plantation of oil palm, rubber, Jatropha, and other commercially desirable species, has dominated the industrial-scale deforestation of natural forests in Asia, Africa, South America, and many other parts of the world [102, 103]. For example, rubber production in Southeast Asia has increased by 1500% since 1961, replacing traditional agroforestry systems [103]. The area under oil palm has increased by 400% since the 1980s, primarily in Indonesia and Malaysia, and accounted for 16% and 47% of total deforestation in these two countries, respectively [104]. Such expansion of forest plantations, nonetheless, has arguably driven some areas out of poverty [103–105]. As a result, expansion of forest plantations has been put forward as a core strategy of socioeconomic development of rural areas in South and Southeast Asian countries [104].

On the other hand, even though evidence is scattered, conflicting, and context-specific, researchers claim that plantation forestry has done more harm than good, aggravating resource needs, such as for water and land, while pushing farmers to further deprivation [106, 107]. As much as 57% of the area under rubber plantation in Asia is considered environmentally unsustainable [103]. Therefore, if not carefully planned and properly managed, forest plantations could also result in various ecosystem disservices (the 'disbenefits' that ecosystems provide [108]), including negative effects on hydrology, weed infestation, water pollution, soil erosion, and unfavorable impacts on communities, social values, and food production [97].

Nonetheless, forest plantations need to be considered in forest cover monitoring, which means that TCC datasets also need to be complemented by other datasets (e.g. datasets on forest types [78, 86], including forest plantations and their types and status [109]). We recognize that an overall increase in canopy cover, though indicative of a positive trend, does not necessarily and automatically indicate successful forest restoration and rehabilitation.

5. Conclusions

Drawing upon the conceptual analytical framework (figure 1, section 2) and the results of its illustrative application presented in this paper, we conclude that continuous data products such as TCC maps can be used to complement the information provided by categorical data products such as F/NF maps. TCC-based indicators (e.g. losses, gains, and net changes) can help in monitoring not only deforestation but also forest degradation and forest cover enhancement, all of which are highly relevant to the 2030 Agenda (e.g. SDG 15) and other global forest cover monitoring–related initiatives. An important advantage of TCC datasets is their non-reliance on the definition of forest. This makes them more standardized than categorical map products such as F/NF maps, which are dependent on the definition, which has remained a major issue in this field.

Data availability

All data that support the findings of this study are included within the article.

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References

[1] Gamfeldt L *et al* 2013 Higher levels of multiple ecosystem services are found in forests with more tree species *Nat. Clim. Change* **4** 1340

[2] Pan Y, Birdsey R A, Phillips O L and Jackson R B 2013 The structure, distribution, and biomass of the World's forests *Annu. Rev. Ecol. Evol. Syst.* **44** 593–622

[3] Jenkins M and Schaap B 2018 Forest Ecosystem Services: Background Analytical Study 1 - Background study prepared for the thirteenth session of the United Nations Forum on Forests (available at: https://www.un.org/esa/forests/wp-content/uploads/2018/05/UNFF13_BkgdStudy_ForestsEcoServices.pdf) (Accessed 11 September 2020)
[4] Estoque R C, Ooba M, Avitabile V, Hijioka Y, DasGupta R, Togawa T and Murayama Y 2019 The future of Southeast Asia's forests *Nat. Commun.* **10** 1829
[5] Brockerhoff E G *et al* 2017 Forest biodiversity, ecosystem functioning and the provision of ecosystem services *Biodivers. Conserv.* **26** 3005–35
[6] Hooper D U *et al* 2005 Effects of biodiversity on ecosystem functioning: a consensus of current knowledge *Ecol. Monogr.* **75** 3–35
[7] Balvanera P, Pfisterer A B, Buchmann N, He J-S, Nakashizuka T, Raffaelli D and Schmid B 2006 Quantifying the evidence for biodiversity effects on ecosystem functioning and services *Ecol. Lett.* **9** 1146–56
[8] Bryant D, Nielsen D and Tangley L 1997 *The Last Frontier Forests: Ecosystems and Economies on the Edge* (Washington, DC: World Resources Institute)
[9] Shimada M, Itoh T, Motooka T, Watanabe M, Shiraishi T, Thapa R and Lucas R 2014 New global forest/non-forest maps from ALOS PALSAR data (2007–2010) *Remote Sens. Environ.* **155** 13–31
[10] IUCN 2017 Deforestation and forest degradation (Gland: Issues Brief. International Union for Conservation of Nature)
[11] Chazdon R L *et al* 2020 Manila declaration on forest and landscape restoration: making it happen *Forests* **11** 685
[12] UN 2015 *Resolution Adopted by the General Assembly on 25 September 2015. Transforming Our World: The 2030 Agenda for Sustainable Development* (New York: United Nations)
[13] UNFCCC 2020 Reducing emissions from deforestation and forest degradation (REDD+) (available at: www.unredd.net/about/what-is-redd-plus.html) (Accessed 11 September 2020)
[14] CBD Aichi Biodiversity Targets *Aichi Biodiversity Targets* (available at: www.cbd.int/sp/targets/) (Accessed 11 September 2020)
[15] IUCN The Bonn Challenge (available at: www.bonnchallenge.org/) (Accessed 11 September 2020)
[16] BMU New York Declaration on Forests (available at: https://forestdeclaration.org/) (Accessed 11 September 2020)
[17] UNFCCC The Paris Agreement (available at: https://unfccc.int/sites/default/files/english_paris_agreement.pdf) (Accessed 11 September 2020)
[18] BLI, WCS and WWF The Trillion Trees Vision (available at: www.trilliontrees.org/) (Accessed 11 September 2020)
[19] IAEG-SDGs 2020 *Tier Classification for Global SDG Indicators (as of 17 July 2020)* (New York: United Nations Interagency and Expert Group on SDG Indicators, United Nations)
[20] UN 2020 *Global SDG Indicators Database* (available at: https://unstats.un.org/sdgs/indicators/database)
[21] GEO 2019 *EO4SDG: Earth Observations in Service of the 2030 Agenda for Sustainable Development. Strategic Implementation Plan 2020–2024* (Group on Earth Observations)
[22] Hansen M C *et al* 2013 High-resolution global maps of 21st-century forest cover change *Science* **342** 850–3
[23] Sexton J O *et al* 2013 Global, 30-m resolution continuous fields of tree cover: landsat-based rescaling of MODIS vegetation continuous fields with lidar-based estimates of error *Int. J. Digit. Earth* **6** 427–48
[24] Estoque R C 2020 A review of the sustainability concept and the state of SDG monitoring using remote sensing *Remote Sens.* **12** 1770
[25] Giuliani G, Mazzetti P, Santoro M, Nativi S, Van Bemmelen J, Colangeli G and Lehmann A 2020 Knowledge generation using satellite earth observations to support sustainable development goals (SDG): a use case on Land degradation *Int. J. Appl. Earth Obs. Geoinf.* **88** 102068
[26] Rikimaru A, Roy P S and Miyatake S 2002 Tropical forest cover density mapping *Trop. Ecol.* **43** 39–47
[27] Achard F *et al* 2002 Determination of deforestation rates of the World's humid tropical forests *Science* **297** 999–1002
[28] Achard F, Stibig H-J, Eva H D, Lindquist E J, Bouvet A, Arino O and Mayaux P 2010 Estimating tropical deforestation from Earth observation data *Carbon Manage.* **1** 271–87
[29] Hansen M C, Stehman S V and Potapov P V 2010 Quantification of global gross forest cover loss *Proc. Natl Acad. Sci. USA* **107** 8650–5
[30] Matricardi E A T, Skole D L, Costa O B, Pedlowski M A, Samek J H and Miguel E P 2020 Long-term forest degradation surpasses deforestation in the Brazilian Amazon *Science* **369** 1378–82
[31] Sasaki N and Putz F E 2009 Critical need for new definitions of 'forest' and 'forest degradation' in global climate change agreements *Conserv. Lett.* **2** 226–32
[32] Miettinen J, Stibig H and Achard F 2014 Remote sensing of forest degradation in Southeast Asia—aiming for a regional view through 5–30 m satellite data *Glob. Ecol. Conserv.* **2** 24–36
[33] Mitchell A L, Rosenqvist A and Mora B 2017 Current remote sensing approaches to monitoring forest degradation in support of countries measurement, reporting and verification (MRV) systems for REDD+ *Carbon Balance Manage.* **12** 9
[34] Gao Y, Skutsch M, Paneque-Gálvez J and Ghilardi A 2020 Remote sensing of forest degradation: a review *Environ. Res. Lett.* **1515** 103001
[35] Song X P, Hansen M C, Stehman S V, Potapov P V, Tyukavina A, Vermote E F and Townshend J R 2018 Global land change from 1982 to 2016 *Nature* **560** 639–43
[36] Chen C *et al* 2019 China and India lead in greening of the world through land-use management *Nat. Sustain.* **2** 122–9
[37] FAO 2018 *1948–2018: Seventy Years of FAO's Global Forest Resources Assessment* (Rome: Food and Agriculture Organization of the United Nations)
[38] Keenan R J, Reams G A, Achard F, De Freitas J V, Grainger A and Lindquist E 2015 Dynamics of global forest area: results from the FAO Global Forest Resources Assessment 2015 *For. Ecol. Manage.* **352** 9–20
[39] Tollefson J 2015 Tropical forest losses outpace UN estimates *Nature* (https://doi.org/10.1038/nature.2015.17009)
[40] FAO 2020 *Global Forest Resources Assessment 2020: Main Report* (Rome: Food and Agriculture Organization of the United Nations)
[41] FAO 2020 *FRA 2020 Remote Sensing Survey* (Food and Agriculture Organization of the United Nations)
[42] FAO 2018 Global forest resources assessment 2020: terms and definition *Forest Resources Assessment Working Paper 188* (Rome: Food and Agriculture Organization of the United Nations)
[43] Kissinger G, Herold M and Sy V D 2012 *Drivers of Deforestation and Forest Degradation: A Synthesis Report for REDD+ Policymakers* (Vancouver: Lexeme Consulting)
[44] Thompson I D, Guariguata M R, Okabe K, Bahamondez C, Nasi R, Heymell V and Sabogal C 2013 An operational framework for defining and monitoring forest degradation *Ecol. Soc.* **18** 20
[45] Wunder S 2003 Forests without trees? A note on problematic forest definitions and change assessment *Proc. 12th World Forestry Congress, Quebec City, Canada, September 21–28, 2003, Volume B-Forests for the Planet (Quebec, Canada)*
[46] FAO 2015 *Global Forest Resources Assessment 2015: How are the World's Forests Changing? Desk Reference* 2nd edn (Rome: UN Food and Agriculture Organization)

[47] Chazdon R L, Brancalion P H S, Laestadius L, Bennett-Curry A, Buckingham K, Kumar C, Moll-Rocek J, Vieira I C G and Wilson S J 2016 When is a forest a forest? Forest concepts and definitions in the era of forest and landscape restoration *Ambio* **45** 538–50

[48] Kim D, Sexton J O and Townshend J R 2015 Accelerated deforestation in the humid tropics from the 1990s to the 2000s *Geophys. Res. Lett.* **42** 3495–501

[49] Magdon P, Fischer C, Fuchs H and Kleinn C 2014 Translating criteria of international forest definitions into remote sensing image analysis *Remote Sens. Environ.* **149** 252–62

[50] Sexton J O *et al* 2016 Conservation policy and the measurement of forests *Nat. Clim. Change* **6** 192–6

[51] Hansen M C, Wang L, Song X-P, Tyukavina A, Turubanova S, Potapov P V and Stehman S V 2020 The fate of tropical forest fragments *Sci. Adv.* **6** eaax8574

[52] FAO 2002 *Expert Meeting on Harmonizing Forest-Related Definitions for Use by Various Stakeholders* (Rome: Food and Agriculture Organization of the United Nations)

[53] Lund G H 2018 *Definitions of Forest, Deforestation, Afforestation, and Reforestation* (Gainesville, VA: Forest Information Services)

[54] Sannier C, McRoberts R E and Fichet L 2016 Suitability of global forest change data to report forest cover estimates at national level in Gabon *Remote Sens. Environ.* **173** 326–38

[55] Yang Z, Dong J, Liu J, Zhai J, Kuang W, Zhao G, Shen W, Zhou Y, Qin Y and Xiao A X 2017 Accuracy assessment and inter-comparison of eight medium resolution forest products on the loess plateau, China *ISPRS Int. J. Geoinf.* **6** 152

[56] Estoque R C, Pontius R G, Murayama Y, Hou H, Thapa R B, Lasco R D and Villar M A 2018 Simultaneous comparison and assessment of eight remotely sensed maps of Philippine forests *Int. J. Appl. Earth Obs. Geoinf.* **67** 123–34

[57] Vieilledent G, Grinand C, Rakotomalala F A, Ranaivosoa R, Rakotoarijaona J-R, Allnutt T F and Achard F 2018 Combining global tree cover loss data with historical national forest cover maps to look at six decades of deforestation and forest fragmentation in Madagascar *Biol. Conserv.* **222** 189–97

[58] Cunningham D, Cunningham P and Fagan M E 2019 Identifying biases in global tree cover products: a case study in Costa Rica *Forests* **10** 853

[59] Gasparini K A C, Silva Junior C H L, Shimabukuro Y E, Arai E, Aragão L E O C E, Silva C A and Marshall P L 2019 Determining a threshold to delimit the Amazonian forests from the tree canopy cover 2000 GFC data *Sensors* **19** 5020

[60] Galiatsatos N, Donoghue D N M, Watt P, Bholanath P, Pickering J, Hansen M C and Mahmood A R J 2020 An assessment of global forest change datasets for national forest monitoring and reporting *Remote Sens.* **12** 1790

[61] UNFCCC 2002 *Report of the Conference of the Parties on its Seventh Session, Held at Marrakesh from 29 October to 10 November 2001* (Bonn: United Nations Framework Convention on Climate Change)

[62] Rogers K and Handley P 2017 *Plymouth Policy Area: Tree Canopy Cover Assessment* (Plymouth: Plymouth City Council)

[63] Berberoglu S, Satir O and Atkinson P M 2009 Mapping percentage tree cover from Envisat MERIS data using linear and nonlinear techniques *Int. J. Remote Sens.* **30** 4747–66

[64] Dimiceli C *et al* 2015 MOD44B MODIS/terra vegetation continuous fields yearly L3 global 250m SIN grid V006 (Sioux Falls, SD: NASA EOSDIS Land Processes DAAC)

[65] Sexton J O *et al* 2016 Earth science data records of global forest cover and change: user guide (College Park, MD: Global Land Cover Facility, University of Maryland)

[66] Townshend J R G 2016 *Global Forest Cover Change (GFCC) Tree Cover Multi-Year Global 30 m V003 [Data set]* NASA EOSDIS Land Processes DAAC (available at: https://doi.org/10.5067/MEaSUREs/GFCC/GFCC30TC.003) (Accessed 11 September 2020)

[67] Buchhorn M *et al* 2020 Copernicus global land service: land cover 100 m: collection 3: epoch 2015 and 2019: globe (Version V3.0.1) [Data set] (Geneva: Zenodo)

[68] Martone M, Rizzoli P, Wecklich C, González C, Bueso-Bello J-L, Valdo P, Schulze D, Zink M, Krieger G and Moreira A 2018 The global forest/non-forest map from TanDEM-X interferometric SAR data *Remote Sens. Environ.* **205** 352–73

[69] Buchhorn M, Lesiv M, Tsendbazar N-E, Herold M, Bertels L and Smets B 2020 Copernicus global land cover layers—collection 2 *Remote Sens.* **12** 1044

[70] Xu M, Watanachaturaporn P, Varshney P K and Arora M K 2005 Decision tree regression for soft classification of remote sensing data *Remote Sens. Environ.* **97** 322–36

[71] Joshi C, De Leeuw J, Skidmore A K, Van Duren I C and Van Oosten H 2006 Remotely sensed estimation of forest canopy density: a comparison of the performance of four methods *Int. J. Appl. Earth Obs. Geoinf.* **8** 84–95

[72] Mon M S, Mizoue N, Htun N Z, Kajisa T and Yoshida S 2012 Estimating forest canopy density of tropical mixed deciduous vegetation using Landsat data: a comparison of three classification approaches *Int. J. Remote Sens.* **33** 1042–57

[73] Sahana M, Sajjad H and Ahmed R 2015 Assessing spatio-temporal health of forest cover using forest canopy density model and forest fragmentation approach in Sundarban reserve forest, India *Model. Earth Syst. Environ.* **1** 49

[74] Buchhorn M *et al* 2020 *Copernicus Global Land Service: Land Cover 100 m: Version 3 Globe 2015–2019: Algorithm Theoretical Basis Document* (Geneva: Zenodo)

[75] Lu D and Weng Q 2007 A survey of image classification methods and techniques for improving classification performance *Int. J. Remote Sens.* **28** 823–70

[76] Li M, Zang S, Zhang B, Li S and Wu C 2014 A review of remote sensing image classification techniques: the role of spatio-contextual information *Eur. J. Remote Sens.* **47** 389–411

[77] Qin Y *et al* 2016 Mapping forests in monsoon Asia with ALOS PALSAR 50-m mosaic images and MODIS imagery in 2010 *Sci. Rep.* **6** 20880

[78] Buchhorn M *et al* 2020 *Copernicus Global Land Service: Land Cover 100 m: Version 3 Globe 2015–2019: Product User Manual* (Geneva: Zenodo)

[79] Corbane C, Pesaresi M, Kemper T, Politis P, Florczyk A J, Syrris V, Melchiorri M, Sabo F and Soille P 2019 Automated global delineation of human settlements from 40 years of Landsat satellite data archives *Big Earth Data* **3** 140–69

[80] Tsendbazar N-E *et al* 2020 *Copernicus Global Land Service: Land Cover 100 m: Version 3 Globe 2015–2019: Validation Report* (Geneva: Zenodo)

[81] Puyravaud J 2003 Standardizing the calculation of the annual rate of deforestation *For. Ecol. Manage.* **177** 593–6

[82] Luck M and Wu J 2002 A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan region, Arizona, USA *Landscape Ecol.* **17** 327–39

[83] McDonnell M J and Hahs A K 2008 The use of gradient analysis studies in advancing our understanding of the ecology of urbanizing landscapes: current status and future directions *Landscape Ecol.* **23** 1143–55

[84] Watch G F 2021 *Tree Cover Loss in [Southeast Asia]* (available at: www.globalforestwatch.org) (Accessed 08 February 2021)

[85] Gao Y, Ghilardi A, Mas J-F, Quevedo A, Paneque-Gálvez J and Skutsch M 2018 Assessing forest cover change in Mexico from annual MODIS VCF data (2000–2010) *Int. J. Remote Sens.* **39** 7901–18

[86] Romijn E, Ainembabazi J H, Wijaya A, Herold M, Angelsen A, Verchot L and Murdiyarso D 2013 Exploring different forest definitions and their impact on developing REDD+ reference emission levels: a case study for Indonesia *Environ. Sci. Policy* **33** 246–59

[87] Bryan J E, Shearman P L, Asner G P, Knapp D E, Aoro G and Lokes B 2013 Extreme differences in forest degradation in Borneo: comparing practices in Sarawak, Sabah, and Brunei *PLoS One* **8** e69679
[88] Gaveau D L A *et al* 2014 Four decades of forest persistence, clearance and logging on Borneo *PLoS One* **9** e101654
[89] Bastin J, Finegold Y, Garcia C, Mollicone D, Rezende M, Routh D, Zohner C M and Crowther T W 2019 The global tree restoration potential *Science* **365** 76–79
[90] Erbaugh J T, Pradhan N, Adams J, Oldekop J A, Agrawal A, Brockington D, Pritchard R and Chhatre A 2020 Global forest restoration and the importance of prioritizing local communities *Nat. Ecol. Evol.* **4** 1472–6
[91] Hirschmugl M *et al* 2017 Methods for mapping forest disturbance and degradation from optical Earth observation data: a review *Curr. For. Rep.* **3** 32–45
[92] Tao X, Huang C, Zhao F, Schleeweis K, Masek J and Liang S 2019 Mapping forest disturbance intensity in North and South Carolina using annual Landsat observations and field inventory data *Remote Sens. Environ.* **221** 351–62
[93] Senf C and Seidl R 2021 Mapping the forest disturbance regimes of Europe *Nat. Sustain.* **4** 63–70
[94] Healey S P, Yang Z, Cohen W B and Pierce D J 2006 Application of two regression-based methods to estimate the effects of partial harvest on forest structure using Landsat data *Remote Sens. Environ.* **101** 115–26
[95] Horák J, Brestovanská T, Mladenović S, Kout J, Bogusch P, Halda J P and Zasadil P 2019 Green desert?: biodiversity patterns in forest plantations *For. Ecol. Manage.* **433** 343–8
[96] Bremer L L and Farley K A 2010 Does plantation forestry restore biodiversity or create green deserts? A synthesis of the effects of land-use transitions on plant species richness *Biodivers. Conserv.* **19** 3893–915
[97] Baral H, Guariguata M R and Keenan R J 2016 A proposed framework for assessing ecosystem goods and services from planted forests *Ecosyst. Serv.* **22** 260–8
[98] Liu C L C, Kuchma O and Krutovsky K V 2018 Mixed-species versus monocultures in plantation forestry: development, benefits, ecosystem services and perspectives for the future *Glob. Ecol. Conserv.* **15** e00419
[99] Acosta I 2011 Green desert' monoculture forests spreading in Africa and South America (available at: www.theguardian.com/environment/2011/sep/26/monoculture-forests-africa-south-america) (Accessed 11 September 2020)
[100] Góes P 2011 *Brazil: The Chilling Beauty of the Green Desert* (available at: https://globalvoices.org/2011/06/15/brazil-the-chilling-beauty-of-the-green-desert/) (Accessed 11 September 2020)
[101] Terborgh J 1989 *Where Have All the Birds Gone?* (Princeton, NJ: Princeton University Press)
[102] Zhai D L, Cannon C H, Dai Z C, Zhang C P and Xu J C 2015 Deforestation and fragmentation of natural forests in the upper Changhua watershed, Hainan, China: implications for biodiversity conservation *Environ. Monit. Assess.* **187** 4137
[103] Ahrends A, Hollingsworth P M, Ziegler A D, Fox J M, Chen H, Su Y and Xu J 2015 Current trends of rubber plantation expansion may threaten biodiversity and livelihoods *Glob. Environ. Change* **34** 48–58
[104] Qaim M, Sibhatu K T, Siregar H and Grass I 2020 Environmental, economic, and social consequences of the oil palm boom *Annu. Rev. Resour. Econ.* **12** 321–44
[105] Qiu J 2009 Where the rubber meets the garden *Nature* **457** 246–7
[106] D'Amato D, Rekola M, Wan M, Cai D and Toppinen A 2017 Effects of industrial plantations on ecosystem services and livelihoods: perspectives of rural communities in China *Land Use Policy* **63** 266–78
[107] Ariza-Montobbio P and Lele S 2010 Jatropha plantations for biodiesel in Tamil Nadu, India: viability, livelihood trade-offs, and latent conflict *Ecol. Econ.* **70** 189–95
[108] Dunn R R 2010 Global mapping of ecosystem disservices: the unspoken reality that nature sometimes kills us *Biotropica* **42** 555–7
[109] Harris N, Goldman E D and Gibbes S 2019 *Spatial Database of Planted Tress (SDPT Version 1.0)* (Washington, DC: World Resources Institute)