Uncertainties in tree cover maps of Sub-Saharan Africa and their implications for measuring progress towards CBD Aichi Targets

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Abstract
The growing access to Earth Observations and processing capabilities have stimulated the production of global and regional products that are commonly used to assess tree-covered habitats and their changes. The popularity of these products has led to their use for defining baselines and to assess progress in conserving natural habitats, in particular, in the context of the conservation targets to 2020 set by the UN Convention on Biological Diversity. In this paper, we reviewed three tree cover products commonly used over Sub-Saharan Africa: (1) MODIS Vegetation Continuous Field percent tree cover map, (2) Global Forest Change map and (3) TREES product. Over a systematic sample of 2045 map subsets, each having a size of \(10 \times 10 \text{ km}^2\), we calculated the extent and change of tree cover from each product for the period between 2000 and 2010. Our statistical and spatial comparison shows noticeable discrepancies between the three products, which lead to uncertainties when assessing tree cover across varying ecosystems. These differences are highest in habitats where tree cover is fragmented or reaches medium density levels and overlap with areas of high economic development potential, where habitat changes are likely to occur in the near future. We discuss these findings in the context of using these remotely sensed tree cover products to support current global biodiversity conservation policies.

Introduction
The continuous conversion of natural habitats into croplands and other land-uses causes biodiversity loss at about 1000 times faster rates as they would occur without human interference (Pimm et al. 2014; Hudson et al. 2017). Sub-Saharan Africa supports a rich and unique biodiversity, but wildlife has largely been pushed back to protected or remote areas (Blake et al. 2007; Gray et al. 2016). Human pressures on the region will likely increase in the near future. Africa’s population is projected to quadruple by the end of the century (UN-DESA, 2015) and the continent holds enormous, but largely underexploited, mining (Edwards et al. 2014) and farming (Morris et al. 2009; Weng et al. 2013) potentials. Ongoing road development aims to facilitate the economic exploitation (Laporte et al. 2007; Laurance and Balmford 2013; Weng et al. 2013), but will also give easier access to some of the remaining wilderness areas. The negative impacts of road development, agriculture and mining on tropical ecosystems and biodiversity are well documented (e.g. Blom et al. 2004, 2005; Laporte et al. 2007; Laurance et al. 2009, 2014b; Durán et al. 2013; Ibisch et al. 2016). These developments may not halt at protected area (PA) boundaries, which risk to be degraded, downsized or de-gazetted to allow the exploitation of natural resources (Mascia et al. 2014).

While Sub-Saharan Africa’s rich resources promise economic prosperity to some of the poorest countries, they also hold high conflict potentials with international conservation goals. In 2010, the Parties to the UN Convention on Biological Conservation (CBD) have agreed on 20
targets to halt biodiversity loss by 2020 (Aichi Biodiversity Targets). Regular, timely and accurate monitoring is needed to inform scientists and policymakers about the accomplished progress towards achieving these targets or to alert harmful processes (Pereira et al. 2013). The Group on Earth Observation Biodiversity Observation Network (GEO BON) leads the international efforts to harmonize biodiversity monitoring programmes worldwide (GEO BON, 2015). After the proposal of an initial set of Essential Biodiversity Variables (EBVs, Pereira et al., 2013) to focus on, discussions between the remote sensing and biodiversity community are ongoing to identify a subset of EBVs that can be mapped from satellite remote sensing (SRS-EBVs) to support resource intensive field data collection (Skidmore et al. 2015; Petorelli et al. 2016). Although, remote sensing is considered crucial in global biodiversity assessments (Secades et al. 2014), the translation of satellite observations into meaningful biodiversity information is challenging (Skidmore et al. 2015) and prone to errors (Paganini et al. 2016).

Tree cover has been proposed as one of the SRS-EBVs to study the status and change in ecosystem structure supporting biodiversity (Petorelli et al. 2016). Currently, three remotely sensed products are readily available over Sub-Saharan Africa and have provided regular and consistent updates on tree cover since 1990 and more frequently since 2000. The TREES product (Achard et al. 2014) has monitored tropical forests from a regular sample of Landsat imagery since 1990 every 10 years at a minimum mapping unit (MMU) of 5 ha. Primarily developed to improve accuracies in carbon estimations (Achard et al. 2014), the product was equally used to discuss drivers of tree cover changes (Bodart et al. 2013; Mayaux et al. 2013; Brink et al. 2014; de Sy et al. 2015). Since 2000, the MODIS Vegetation Continuous Field percent tree cover product (MODIS-VCF, Hansen et al. 2003; Townshend et al. 2011) has provided global and annual maps of percent tree cover at 250 m spatial resolution. The wide use of MODIS-VCF has provided valuable insights not only into ecosystem structure and functioning (e.g. Ito et al. 2007; Archibald et al. 2009; van der Werf et al. 2010; Hirota et al. 2011; Staver et al. 2011; Chuvieco et al. 2014) but also into wildlife migration (e.g. Gschweng et al. 2012; Herkt et al. 2016; Naidoo et al. 2016) and the isolation of tropical protected areas (DeFries et al. 2005). MODIS-VCF was rarely used in forest change assessments (Song et al. 2014; Viña et al. 2016) as it requires advanced change detection methods. The Global Forest Change product (GFC, Hansen et al. 2013) builds on the MODIS-VCF experience and improves through finer spatial resolution (30 m) and the explicit mapping of changes (2000–2012, first release). Particularly, the product’s forest loss information has been used to assess the effectiveness of international conservation aid (Bare et al. 2015), protected areas (Heino et al. 2015; Spracklen et al. 2015; Bowker et al. 2017) and sustainable forest management (Brandt et al. 2016) on reducing deforestation rates. Classification errors and particularly the undifferentiated definition of commercial forests and oil palm plantations as tree cover entail, however, the risk of misinforming conservation success (Tropek et al. 2014). Despite criticism, GEO BON lists the GFC product as one of the SRS-EBV datasets (http://data.geobon.org), highlighting the importance of this product for monitoring biodiversity indicators.

The three products have been cross-compared to reference data to validate their accuracies (Townshend et al. 2011; Hansen et al. 2013; Sexton et al. 2013; Achard et al. 2014), but these assessments are limited in space and do not provide a spatially comprehensive picture of the associated uncertainties. However, a precise understanding of these uncertainties is critical to assess their impact on the accuracy of biodiversity assessments (Paganini et al. 2016). While global land cover reference datasets are becoming increasingly available, each of them is developed for a specific purpose with its own resolution, timing and legend, which hinders their use for validating other maps (TsEBnazar et al. 2016). In this study, we do not aim for a product validation, but provide a cross-comparison of the tree cover extent and change suggested by the three remotely sensed products between 2000 and 2010 over Sub-Saharan Africa, an area that is critical for biodiversity conservation. Additionally, we compare the GFC and TREES classification with reference maps derived from the Spatial Observation of Tropical Forest (SOTF) project over Cameroon and Central African Republic (Poilvè 2013) to gain more insight into observed differences. In the following, we discuss and harmonize methodological discrepancies between products to enable their comparison. Our results identified overall differences between the three products in monitoring tree-covered habitats at sub-continental level and across broad habitat types. Our observations should further provide useful insights into current uncertainties in monitoring the effectiveness of international strategies aiming at the conservation of tree-covered habitats.

Materials and Methods

Data

In this study, we compared the products of MODIS-VCF, GFC and TREES (Table 1) over Sub-Saharan Africa to identify uncertainties in the current assessments of tree cover. We acquired from the MODIS-VCF product, the raster layers of percent tree cover for year 2000 and 2010. For the GFC product, we compiled the raster layers of 2000 percent tree cover, loss year and forest gain showing tree cover extent and change between 2000 and 2012.
### Table 1. Characteristics of the tree and forest cover products acquired for this study.

| MODIS-VCF | GFC | TREES |
|-----------|-----|-------|
| **Sensor** | Terra MODIS | Landsat ETM+ | Landsat TM and ETM+, Landsat-like |
| **Temporal coverage** | Annual time series since 2000 | 2000 to 2012 with: annual disaggregation of loss, 12-year total of gain | Two time periods: 1990–2000 and 2000–2010 |
| **Spatial coverage** | Continuous, globally | Continuous, globally | Systematic sample of 10 x 10 km² size units at every 1° Lat-Lon confluence point covering the tropical and subtropical region |
| **Resolution/MMU** | Grid of 250 x 250 m² pixel size (6.25 ha) | Grid of 30 x 30 m² pixel size (0.09 ha) | Polygons with MMU of 5 ha (3 ha for up to 5% of the polygons) |
| **Projection** | Sinusoidal | Plate Carrée | Universal Transverse Mercator |
| **Thematic layers/legends** | | | Legend: |
| - Percent tree cover (0–100%) | - 2000 percent tree cover (0–100%) | - Tree Cover (TC) |
| - Forest loss (1 = loss) | - Forest gain (1 = gain) | - Tree Cover Mosaic (TCM) |
| - Loss year (1...12 = year of loss) | | - Other Wooded Land (OWL) |
| **Definitions** | Tree cover: canopy cover of woody vegetation > 5 m in height | Forest loss: complete removal of tree canopy at the Landsat pixel scale | Other Land Cover (OLC) |
| | (crown cover ~ canopy cover/0.8) | Forest gain: establishment of tree canopy from a non-forest to a forest state (> 50% TC) | - Water (W) |
| **Classification input data** | Phenological metrics derived for 10 MODIS bands covering the reference year | Time-series of spectral metrics derived from Landsat ETM+ scenes covering the growing seasons between 2000 and 2012 | Landsat and Landsat-like scenes taken as close as possible to the reference years 1990, 2000 and 2010 |
| **Classification algorithm** | Bagged regression tree model (i.e. averaging 30 independent models) | Bagged decision tree model to classify percent tree cover, forest loss, forest gain and heuristic method to disaggregate loss year | Object-based change detection and classification of the multi-temporal Landsat scenes |
| **Quality control** | 1. Quality assurance layer | 1. Cross-comparison with reference data derived from Landsat, MODIS and high resolution imagery (forest loss and gain) and MODIS NDVI time series (loss year) | 1. Visual inspection of all sample units and correction of automatic labelling by forestry experts |
| | 2. Validation with field data over 5 sites in the US and Brazil | 2. Temporal LiDAR measurements of tree height | 2. Cross-comparison with reference data derived from the interpretation of objects by independent experts using available Landsat and finer resolution imagery |
| | 3. Validation with LiDAR measurements over 4 sites in the US and Costa Rica | | |
| **RMSE percent tree cover:** | | | |
| 9–23% | | | |
| **Loss** | UA² | PA² | Agreement between TREES and cross-reference: |
| - Tropical: | 87.0% | 83.1% | - Forest labels: 94.0% |
| - Subtropical: | 79.3% | 79.4% | - Forest change labels: 90.2% |
| **Gain** | UA² | PA² | |
| - Tropical: | 81.9% | 48.0% | |
| - Subtropical: | 85.5% | 82.4% | |
| **Year of loss event matched:** | 75.2% (96.7% ± 1 year) | |
Contrary to MODIS-VCF and GFC, which provide continuous spatial coverage, the TREES product is based on a systematic sample of 10 × 10 km² forest cover subsets derived from Landsat or Landsat-like satellite imagery. We downloaded shapefiles of the TREES sample polygons as well as a table summarizing for five land cover classes, the area of extent and change detected from the sample between 2000 and 2010.

Systematic sampling

We used TREES’s systematic sampling scheme, consisting of 2045 sample units aligned along a regular grid of 1-degree latitudinal and longitudinal confluence points and covering all ecoregions of Sub-Saharan Africa between 26° North and 34° South (Fig. 1). Each sample unit covers an area of 10 × 10 km², for which we calculated the extent and change of tree cover per sample unit from each product. Our approach aggregates spatially the original observations at the sample unit level filtering out local variation. It, however, better depicts the general pattern of agreement between the products facilitating the comparison at sub-continental scale (Boschetti et al. 2004).

We classified each 100 km² size sample unit into a single dominant vegetation cover to be able to summarize tree cover extents and changes by broad habitat types (Fig. 1). We determined the dominant vegetation cover from the Global Land Cover 2000 map (GLC2000, Bartholomé and Belward 2005) by reclassifying the map into five classes of closed forest, open forest, non-woody forest vegetation, non-woody vegetation and unvegetated land (Mayaux et al. 2006). We further subdivided the two forest classes into their humid and dry realm, as considered and thematically assessed in two previous studies (Bodart et al. 2013; Mayaux et al. 2013). We assigned each sample unit to the vegetation class covering the largest portion of the sample unit.

Data pre-processing

We brought all spatial layers into a spatially consistent reference grid in Plate-Carrée projection (datum WGS-1984, 30 m resolution at the equator) and clipped them to the outlines of the sample units. The processing steps included: (1) re-projection of MODIS-VCF layers and sample unit polygons into Plate-Carrée projection, (2) spatial co-registration between products, (3) rasterization and alignment of sample unit polygons to the reference grid, and (4) sub-setting MODIS-VCF and GFC layers to the rasterized sample units. During this final step, the MODIS-VCF layers were also resampled and aligned to the finer resolution of the reference grid using the nearest neighbour method.

Calculating tree cover for 2000

While the three products provide tree cover classifications for the year 2000 (Table 1), the use of different legends and tree cover definitions hinder their direct comparison. The GFC and MODIS-VCF algorithms classify all woody vegetation taller than 5 m as trees and estimate the pixel fraction covered by trees between 0 and 100%. However, GFC’s tree cover definition is based on crown cover densities (Hansen et al. 2013), which differs from the canopy densities classified by MODIS-VCF (Hansen et al. 2003). The relationship between both depends on species, but Hansen et al. (2003) found that 80% canopy cover approximates 100% crown cover. The TREES algorithm instead classifies multi-date object-based segments (≥5 ha polygon size) into five land cover categories (Table 1), relating to three classes of tree cover density depending on the polygon fraction covered by trees (TC: 100–70%, TCM: 70–30% and OWL, OLC, W: 30–0%). Natural forests, mature forest plantations and tree cover outside forest land are considered in the trees classes (TC, TCM), whereas shrubs, regrowth, forest plantations in initial growth stages and oil plantations are classified as OWL (Stibig et al. 2014). TREES tree cover definition aims to be compatible to FAO’s forest definition (≥20% tree canopy density), meaning that theoretically, only pixels with at least 10% tree cover are considered when determining a polygon’s tree-covered portion. Although TREES defines classes by tree canopy cover, its concept of

Table 1. Continued.

| Data accessibility | MODIS-VCF | GFC | TREES |
|--------------------|-----------|-----|-------|
| Reference          | Hansen et al. (2003) and Townsend et al. (2011) | Hansen et al. (2013) | Achard et al. (2014) |

1The concept of canopy cover used by TREES corresponds to the concept of crown cover used by GFC.
2UA, user accuracy; PA, producer accuracy.
identifying tree cover densities within polygons (Eva et al., 2012) corresponds to GFC’s concept of tree crown cover within Landsat pixels (Tyukavina et al. 2015).

To harmonize thematic differences, we computed the area covered by at least 10% tree crown cover in year 2000 for each sample unit and product (Fig. 2). We first divided the MODIS-VCF 2000 percent tree cover layer by 0.8 to convert tree canopy to tree crown densities. We then summed for the modified MODIS layer and the GFC 2000 percent tree cover layer, the fraction of the pixel areas that are covered by at least 10% trees to calculate for both products, the tree cover extent in each sample unit. To compute the tree-covered area from the TREES product, we considered 100% of the sample area classified as TC and 50% of its area classified as TCM, as considered in the original product (Bodart et al. 2013; Mayaux et al. 2013; Achard et al. 2014).

Calculating tree cover change between 2000 and 2010

The products show tree cover changes in substantially different ways (Table 1). MODIS-VCF provides annual updates of the percent tree cover layers, where the comparison of subsequent years identifies change. The GFC and TREES products incorporate dedicated change detection algorithms. The GFC forest loss layer shows areas, where tree cover was completely removed, while the forest gain layer depicts areas, where new tree cover has been established from a non-forest to a forest status with at least 50% tree cover. The timing of loss events can be obtained from the loss year layer, but there is no layer to determine the year of gain. The TREES algorithm detects changes occurring between its five land cover classes by multi-date image segmentation (Table 1). Besides the thematic discrepancies, GFC covers a longer time period (2000–2012) than the other two products (2000–2010). We calculated the area of tree cover loss and gain for each sample unit and product between 2000 and 2010 for comparison purposes. The methods applied to each product for such calculations are detailed hereafter.

We used univariate image differencing (Coppin et al. 2004) to compute tree cover changes between MODIS-VCF year 2000 and 2010 percent tree cover layers (Fig. 2). After dividing both layers by 0.8 to convert pixel values into tree crown densities and removing pixels with less than 10% tree cover, we derived per-pixel change by subtracting the year 2010 from the year 2000 layer. We obtained the area of tree cover loss for each sample by adding the areas of all pixels with negative values, taking into account the indicated percentage point loss. We...
Figure 2. Flowchart for calculating areas of tree cover (T), tree cover loss (L) and tree cover gain (G) from the three products (MODIS-VCF, GFC and TREES) for each sample unit (k).

**MODIS-VCF**
- Image subsets for each sample unit
- Tree cover 2000, Tree cover 2010
- Calculate tree crown densities
  - Divide tree cover by 0.8
- Harmonise to TREES tree cover definition
  - Set to 0, where tree cover < 10%

**GFC**
- Image subsets for each sample unit
- Tree cover 2000, Loss year 2000-12, Forest gain 2000-12
- Remove regrowth
  - Set to 0, where loss year > 0 and gain = 1

**TREES**
- Table with summary statistics for each sample unit
- Land cover / change 2000-10
  - Converting land cover classes into tree cover
    - TC = 100%
    - TCM = 50%
    - OWL, OLC, W = 0%

**Tree cover** (km²)

\[ T_k = \sum_{i=1}^{n} A_i \cdot \frac{T_{00,i}}{100} \]

where:
- \( T_{00,i} \): % tree cover (2000) after transformation
- \( A_i \): pixel size
  
  at pixel i within sample unit k, with a size of 100 km²

**Tree cover loss** (km²)

\[ L_k = \sum_{i=1}^{n} A_i \cdot \frac{L_{0010,i}}{100} \]

where:
- \( L_{0010,i} \): % tree cover loss (2000-2010) after transformation

**Tree cover gain** (km²)

\[ G_k = \sum_{i=1}^{n} A_i \cdot \frac{G_{0010,i}}{100} \]

where:
- \( G_{0010,i} \): % tree cover gain (2000-2010) after transformation

\[ n \]: number of pixel in sample unit k

\[ \frac{100 \text{ km}^2}{n} \]

\[ \frac{100 \text{ km}^2}{n} \]

\[ \frac{100 \text{ km}^2}{n} \]

\[ \frac{100 \text{ km}^2}{n} \]
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proceeded likewise with positive pixel values to compute the area of tree-cover gain.

For calculating tree cover changes from GFC (Fig. 2), we first removed pixels from the year loss and forest gain layers that are classified in both. This may happen if, an area lost its 2000 tree cover, but could re-establish at least 50% tree cover by the end of 2012. These short-term dynamics occurring within the observation years are not captured by the other two datasets and were therefore excluded. To calculate tree cover losses between 2000 and 2010, we selected from the modified year loss layer all pixels classified as loss by 2010. For all identified pixels, we summed the tree-covered pixel area as given by the 2000 percent tree cover layer. We ignored pixels with <10% tree cover. Contrary to tree cover loss, the GFC product misses dedicated layers to determine magnitude and year of tree-cover gain events. Thus, we considered two assumptions to approximate gains by 2010. We first assumed a constant 50% tree cover gain for all pixels flagged in the modified forest gain layer, which covers the period 2000–2012. Based on the product’s gain definition (Hansen et al. 2013) this value accommodates the minimum increase needed for pixels with 0% tree cover in 2000 to pass the 50% threshold by 2012 and the maximum possible increase for pixels with just below 50% tree cover in 2000 to not overpass 100% tree cover by 2012. We secondly assumed that tree cover growth is a gradual process and linearly adjusted the value to 41.7% to approximate gains by 2010. The area of tree cover gain in each sample is thus 41.7% of the total pixel area identified as gain in the modified forest gain layer.

To compute the area of tree cover loss for each sample unit from TREES, we added 100% of the sample area classified as change from TC to OWL, OLC or W, 50% of its area classified as change from TC to TCM and 50% of its area classified as change from TCM to OWL, OLC or W (Fig. 2). Tree cover gain is defined as the reverse process and was calculated consequently.

Cross-reference over Cameroon and Central African Republic

We used forest change maps from the Spatial Observatory of Tropical Forests (SOTF, Poilvé 2013) project as independent reference over a limited area in Cameroon and Central African Republic. The SOTF maps show forest changes between 2000 and 2010 at 20 m resolution with a MMU of 0.5 ha. Forest is defined as the Tropical Rainforest including dense forests and networks of gallery forests. It also comprises lighter and partly forest conditions, but excludes tree savannas. Reported accuracies are above 90% for forest and above 80% for forest change labels.

We calculated areas of tree cover, loss and gain from the SOTF maps for 40 sample units, entirely covered by the dataset and compared them to the GFC and TREES values. We further selected four sample units for visual inspection, representing different ecoregions and levels of agreement between TREES and GFC. For visual presentation, we remapped the continuous GFC tree cover classification into three classes of tree cover densities (0–30%, 30–70% and 70–100%), which comply with TREES’ tree cover classes. We excluded MODIS-VCF from this comparison after initial results had shown that it indicates change magnitudes way beyond those of the other two products.

Results

Spatial distributions and differences

Distribution maps (Fig. 3) illustrate for each product, the spatial pattern of tree cover extent in the year 2000 and change between 2000 and 2010 as computed from the samples. Successively, difference maps computed for each product pair and variable (Fig. 4) highlight areas, where products suggest noticeably different magnitudes of tree cover extent and change.

Differences in tree cover estimates for the year 2000

Over the full sample, GFC shows the largest tree cover extent at 38.8 × 10^3 km² (Table 2), an area 13% to 26% larger than those indicated by TREES (34.2 × 10^3 km²) and MODIS-VCF (30.8 × 10^3 km²) respectively. Generally, GFC tends to suggest the highest and MODIS-VCF the lowest tree cover extents across all vegetation types.

Mean and median tree cover extents calculated from the three products diverge most in sample units dominated by humid open forests, but also by humid dense, dry dense and dry open forests (Fig. 5A). These
differences are spatially not equally distributed and vary between product pairs (Fig. 4). Notably is the clear pattern of differences around the Congo Basin. Not only GFC but also MODIS-VCF shows larger tree cover areas in the transition zone around the basin, while TREES depicts distinctively more tree cover in the Miombo woodlands further south. There are also substantial differences along the Central and West African coast and in mountainous terrain, like the eastern slopes of Madagascar, the Ethiopian Highlands and the Albertine Rift. GFC and TREES indicate comparable tree cover extents in samples of humid dense forests located in the Congo Basin and also MODIS-VCF agrees well in its central parts. Although products show similar tree cover extents in woody, non-woody and unvegetated sample units (Table 2), their relative disagreement might be as high as in forested sample units.

Tree cover extents derived from the three products are significantly correlated across all vegetation types (Table 3, Fig. 6). GFC and MODIS-VCF tree cover values correlate strongest, followed by TREES/GFC and TREES/MODIS-VCF. In general, associations between products are strongest over sample units dominated by humid dense forests and bare ground, while they decline over
humid open, dry dense and dry open forests as well as woody vegetation.

**Differences in tree cover change estimates for the period 2000 to 2010**

Tree cover changes calculated from MODIS-VCF for the period 2000–2010 are much larger than GFC and TREES estimates. Over the full sample, MODIS-VCF shows $4.9 \times 10^3$ km$^2$ tree cover loss (16% of year 2000 tree cover), compensated by $5.5 \times 10^3$ km$^2$ tree cover gains (18%) (Table 2). MODIS-VCF loss estimate is 4–6 times larger than those made from the other two products, while its gain estimate is about 55 times larger. These substantial differences occur independently from the broad vegetation types identified from the GLC2000 map (Fig. 5B, C) and from the individual location of the sample units (Fig. 4). MODIS-VCF depicts an overall tree cover gain over Sub-Saharan Africa, mainly due to net gains in sample units dominated by dry forests (dense, open) and non-wooded vegetation (Table 2).
TREES and GFC show substantially lower and more similar magnitudes of tree cover change than MODIS-VCF as well as an overall net tree-cover loss across all vegetation types (Table 2). Over the full sample, TREES reports about 1.6 times larger gross losses than GFC (1.3 and 0.8 x 10^3 km^2 respectively) when gross gains are nearly the same (about 0.1 x 10^3 km^2, both). However, the agreement between products, as computed from the 2045 sample units, varies with vegetation type. In particular, GFC indicates in comparison to TREES, higher gross loss and gain of tree cover in humid forests (dense and open), whereas they are below those of TREES otherwise. In humid forests, the largest differences between GFC and TREES occur across sample units dominated by humid open forests, where GFC indicates on average 1.7 times higher losses than TREES (Table 2). These discrepancies relate mostly to the forests along the West African coast (Fig. 4), where losses shown by GFC are largely absent on TREES (Fig. 3). Instead, TREES indicates on average 1.7–3.7 times higher losses throughout the dry domain (Table 2, Fig. 4), with the highest relative differences occurring in predominantly woody, non-woody and unvegetated sample units.

TREES and GFC show strong to moderate correlations between their tree cover loss estimates across all broad vegetation types, except humid open forests (Table 3, Fig. S1). Gain estimates derived from both products show equally strong to moderate correlations over sample units dominated by non-woody, dry dense and dry open forests (Table 3, Fig. S2). Instead, significant correlations between these two products and MODIS-VCF’s tree cover loss and gain estimates are mostly weak.

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**Table 2.** Areas of tree cover extent (year 2000) and changes (period 2000–2010) calculated by sampling from the TREES, GFC and MODIS-VCF products across different vegetation types.

| Product | Vegetation type          | Sample | Tree cover (TC) | Gross loss | Gross gain | Net change |
|---------|--------------------------|--------|-----------------|------------|------------|------------|
|         |                          |        | Total area (km²) | Mean area (km²) | Relative to TC (%) | Total area (km²) | Mean area (km²) | Relative to TC (%) | Total area (km²) | Mean area (km²) | Relative to TC (%) |
| TREES   | Humid dense forest       | 196    | 14832           | 75.7       | 236        | 1.6        | 12            | 0.06       | 0.1         | −224          | −1.14          | −1.5          |
|         | Humid open forest        | 69     | 1911            | 27.7       | 75         | 3.9        | 9             | 0.13       | 0.5         | −66           | −0.96          | −3.5          |
|         | Dry dense forest         | 126    | 6198            | 49.2       | 230        | 3.7        | 24            | 0.19       | 0.4         | −205          | −1.63          | −3.3          |
|         | Dry open forest          | 262    | 5997            | 22.9       | 391        | 6.5        | 29            | 0.11       | 0.5         | −362          | −1.38          | −6.0          |
|         | Woody veg.               | 358    | 2967            | 8.3        | 262        | 8.8        | 10            | 0.03       | 0.3         | −252          | −0.70          | −8.5          |
|         | Non-woody veg.           | 596    | 2273            | 3.8        | 137        | 6.0        | 17            | 0.03       | 0.8         | −120          | −0.20          | −5.3          |
|         | Unvegetated              | 438    | 62              | 0.1        | 15         | 24.3       | 0             | 0.00       | 0.0         | −15           | −0.03          | −24.3         |
| Sub-Saharan Africa | 2045 | 34238           | 16.7       | 1346       | 6.6       | 3.9        | 102           | 0.05       | 0.3         | −1245         | −0.61          | −3.6          |
| GFC     | Humid dense forest       | 196    | 16340           | 83.4       | 310        | 1.9        | 33            | 0.17       | 0.2         | −278          | −1.42          | −1.7          |
|         | Humid open forest        | 69     | 3121            | 45.2       | 131        | 4.2        | 19            | 0.27       | 0.6         | −112          | −1.63          | −3.6          |
|         | Dry dense forest         | 126    | 5561            | 44.1       | 139        | 2.5        | 20            | 0.16       | 0.4         | −119          | −0.94          | −2.1          |
|         | Dry open forest          | 262    | 8363            | 31.9       | 152        | 1.8        | 9             | 0.04       | 0.1         | −142          | −0.54          | −1.7          |
|         | Woody veg.               | 358    | 3365            | 9.4        | 72         | 2.1        | 4             | 0.01       | 0.1         | −68           | −0.19          | −2.0          |
|         | Non-woody veg.           | 596    | 1937            | 3.3        | 41         | 2.1        | 7             | 0.01       | 0.4         | −34           | −0.06          | −1.7          |
|         | Unvegetated              | 438    | 108             | 0.2        | 4          | 3.8        | 0             | 0.00       | 0.3         | −4            | −0.01          | −3.5          |
| Sub-Saharan Africa | 2045 | 38795           | 19.0       | 849        | 0.42       | 2.2        | 93            | 0.05       | 0.2         | −757          | −0.37          | −2.0          |
| MODIS-VCF | Humid dense forest   | 196    | 14122           | 72.1       | 1275       | 9.0        | 1115          | 5.69       | 7.9         | −161          | −0.82          | −1.1          |
|         | Humid open forest        | 69     | 2218            | 32.1       | 511        | 23.0       | 485           | 7.03       | 21.9        | −26           | −0.38          | −1.2          |
|         | Dry dense forest         | 126    | 4681            | 37.2       | 494        | 10.6       | 1013          | 8.04       | 21.6        | 519           | 4.12           | 11.1          |
|         | Dry open forest          | 262    | 5537            | 21.1       | 1134       | 20.5       | 1518          | 5.79       | 27.4        | 384           | 1.47           | 6.9           |
|         | Woody veg.               | 358    | 2465            | 6.9        | 936        | 38.0       | 792           | 2.21       | 32.1        | −143          | −0.40          | −5.8          |
|         | Non-woody veg.           | 596    | 1639            | 2.8        | 545        | 33.3       | 590           | 0.99       | 36.0        | 45            | 0.07           | 2.7           |
|         | Unvegetated              | 438    | 97              | 0.2        | 31         | 31.5       | 22            | 0.05       | 22.7        | −9            | −0.02          | −8.8          |
| Sub-Saharan Africa | 2045 | 30761           | 15.0       | 4926       | 2.41       | 16.0        | 5535          | 2.71       | 18.0        | 609           | 0.30           | 2.0           |

Relative changes (%) are also given, which were computed by dividing for each product and vegetation type the area of change by the area of tree cover.

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Discussion

Uncertainties in monitoring tree cover status and change

MODIS-VCF, GFC and TREES show a clear spatial pattern of disagreement in tree cover extent at sample unit level, which was highest in the transition zone around the Congo Basin, in the Miombo woodlands ranging between Angola and Tanzania, along the West and Central African coast and in mountainous terrain. MODIS-VCF shows vast gross changes and a net increase in tree cover over Sub-Saharan Africa, which are neither endorsed by results derived from TREES and GFC nor reported by other studies (Keenan et al. 2015; Kim et al. 2015). GFC and TREES show instead more similar change magnitudes, although substantial local variations persist. The observed differences may be related to misclassifications, spatial resolution, MMU and thematic differences. It has to further be noted that results by broad vegetation types can include uncertainties due to uncertainty in the GLC2000 product.

The accurate mapping of tree cover densities from a 250 m MODIS pixel is generally more challenging than from a 30 m Landsat pixel, because larger pixels contain more likely mixed vegetation cover resulting in a spectral signal more difficult to classify (Jung et al., 2006). The MODIS-VCF product has reported root mean square errors (RMSE) ranging between 9 and 23% (Table 1), with the largest RMSE found in a mixed forest/agriculture landscape (Townshend et al. 2011; Sexton et al. 2013). Cross-comparisons have further shown that the product exhibits high uncertainties at tree cover density values below 30% (Hansen et al. 2005) and the observation of changes below 10 percentage points is discouraged (Staver and Hansen 2015). Indeed, the vast changes shown by MODIS-VCF in our analysis might be the result of adding small variations during the study period over a 100 km² area. The reported 80% saturation of MODIS-VCF (Sexton et al. 2013) was mitigated in our study by converting canopy into crown cover. As a result MODIS-VCF shows good agreement in estimated tree cover areas with the two Landsat-derived products over the Congo rainforest. Nonetheless, MODIS-VCF tree cover values remain significantly lower in the coastal rainforests of Central and West Africa, a region known for its frequent cloud coverage which can have more perturbation effects on large pixels.

The GFC (30 m spatial resolution) forest loss and forest gain layers show balanced user’s and producer’s accuracies over the tropics and subtropics (≥80%, Table 1, Hansen et al. 2013). However, a much lower producer accuracy of the tree cover gains in the tropics (48%) suggests that GFC largely underestimates gain in tropical regions. The GFC 2000 percent tree cover layer was not systematically validated, but different studies suggest that GFC may misclassify complex agricultural land as tree cover (Tropek et al. 2014) and overestimate densities in sparsely tree-covered landscapes (Hojas-Gascon et al. 2015; Sannier et al. 2016).
Table 3. Pearson correlations $\rho$ between product pairs (T: TREES, G: GFC, M: MODIS-VCF) for calculated areas of tree cover extent and change at sample unit level across dominant vegetation types.

| Vegetation type          | Tree cover | Tree cover loss | Tree cover gain |
|--------------------------|------------|-----------------|-----------------|
|                          | T-G        | T-M            | G-M             | T-G        | T-M            | G-M             | T-G        | T-M            | G-M             |
| Humid dense forest       | 0.770$^1$  | 0.640$^1$      | 0.848$^1$      | 0.785$^1$  | 0.037          | 0.025          | 0.029      | -0.021         | 0.020          |
| Humid open forest        | 0.515$^1$  | 0.415$^1$      | 0.818$^1$      | 0.112      | -0.016         | 0.250$^1$      | 0.182      | -0.171         | 0.054          |
| Dry dense forest         | 0.394$^1$  | 0.537$^1$      | 0.743$^1$      | 0.411$^1$  | 0.115          | 0.272$^1$      | 0.481$^1$  | 0.111          | 0.130          |
| Dry open forest          | 0.253$^1$  | 0.498$^1$      | 0.538$^1$      | 0.726$^1$  | 0.229$^1$      | 0.300$^1$      | 0.368$^1$  | -0.004         | -0.047         |
| Woody veg.               | 0.446$^1$  | 0.413$^1$      | 0.770$^1$      | 0.588$^1$  | 0.158$^1$      | 0.260$^1$      | 0.104$^1$  | 0.204$^1$      | 0.201$^1$      |
| Non-woody veg.           | 0.514$^1$  | 0.416$^1$      | 0.863$^1$      | 0.387$^1$  | 0.170$^1$      | 0.293$^1$      | 0.830$^1$  | 0.136$^1$      | 0.219$^1$      |
| Unvegetated              | 0.514$^1$  | 0.565$^1$      | 0.834$^1$      | 0.540$^1$  | 0.480$^1$      | 0.788$^1$      | —         | —              | —              |

$^1$Significant correlation for $P < 0.05$.

Figure 6. Scatterplots showing the degree of correlation between product pairs in calculated tree cover extent (km² per sample unit). Regression lines (red) and 1:1 (grey) are shown for each plot.

The TREES classification underwent a robust control chain (Achard et al. 2014). After the automatic segmentation and labelling process, each sample unit is visually checked by a forestry expert who manually corrects any mislabelled polygon. This approach leads to 94% (forest labels) and 90% (forest change labels) agreement between TREES sample unit results and a systematic reinterpretation by independent experts of a sample of polygons.

Thematic differences may further impair the agreement between products. Our comparison has shown particularly low agreements between TREES tree cover estimates and those of GFC and MODIS-VCF for sample units with medium tree cover densities, relating largely to the systematic differences found in the transition zone around the Congo Basin and the Miombo woodlands. This clear pattern might result from different class boundaries in the original products, which are difficult to harmonize.
Indeed, the three values of percent tree cover (0, 50 and 100%) applied to the TREES’ classes can only partially replicate the continuous legend (from 0 to 100%) used in GFC and MODIS-VCF. Moreover, different definition of trees might introduce further bias. The GFC and MODIS-VCF products are purely based on a land cover definition and identify any vegetation taller than 5 m as trees, including forest or oil palm plantations (Hansen et al. 2014; Tropek et al. 2014). As a result, both products identify regrowth in these areas as tree cover gain. Instead, TREES classifies young regrowth, forest plantations in initial growth stage and oil palm plantations as Other Wooded Land (Stibig et al. 2014). Only mature forests or forest plantations with tree heights above 5 m are classified as tree cover.

To gain more insight into observed differences, we compared tree cover extents and changes suggested by TREES and GFC with reference data obtained from the SOTF project over the southern parts of Cameroon and the Central African Republic, an area where GFC shows systematically higher tree coverages than TREES. The comparison shows that GFC indicates much higher tree cover than TREES and SOTF in dry open forests (Table 4), mostly related to higher GFC tree cover in landscapes covered by shrubs and grassland (Fig. 7: samples A, B) and misclassification of croplands (samples C, D). It confirms observations also made by other studies (Tropek et al. 2014; Hojas-Gascon et al. 2015; Sannier et al. 2016). At the same time, GFC shows relatively low tree cover in swamp (sample C) and gallery forests (samples A, B). TREES misses many small forest patches depicted on the SOTF product (samples C, B), which is at least partially a result of TREES’ MMU. In comparison to SOTF, TREES and GFC underestimate change (Table 4), whereas the best agreement is achieved when changes affect a large area. Such results are in line with the conclusions of Verhegghen et al. (2016), which show over Cameroon that Landsat data used in GFC and TREES products allow to capture change caused by agro-industrial exploitation as well as shifting cultivation, infrastructure and selective logging when the area affected is large enough. But it fails to monitor forest degradation and small-scale deforestation events.

Implications for assessing progress towards Aichi Biodiversity Targets

The 10th meeting of the Conference of the Parties of the CBD adopted in 2010, a revised Strategic Plan for Biodiversity articulated around 20 Aichi Biodiversity Targets defining conservation priorities for 2020 as well as a few key indicators to assess progress towards these targets. Over the last few year, there has been a continuous effort to identify essential biodiversity variables (EBVs) that can be mapped from satellite remote sensing to harmonize and support the timely and globally consistent assessment of these key indicators (Pereira et al. 2013; Skidmore et al. 2015; Paganini et al. 2016; Pettorelli et al. 2016). By addressing uncertainties in the evaluation of coverage and changes in tree cover over an area that is critical for biodiversity conservation, this study is expected to improve assessments underpinning Targets 5, 11 and 15 (CBD, 2011). Target 5 focuses on the loss of natural habitats, including forests, which needs to be halved or even brought to zero; Target 11 covers the effective conservation of land and marine environment by protected areas; while Target 15 addresses issues of carbon stocks, which need to be enhanced through conservation and restoration. For these targets, a clear definition of baselines and consistent methods to quantify changes in forest cover across all biomes are critical to assess progress towards the objectives set by the Parties.

Target 5

The Biodiversity Indicator Partnership (BIP) lists the Forest Resource Assessment (FRA) of the UN Food and Agriculture Organisation (FAO) as a primary indicator to

Table 4. Comparison of TREES and GFC products to the SOTF reference dataset over 40 sample units located in Cameroon and Central African Republic.

| Vegetation type       | SU | TREES | GFC | SOTF | TREES | GFC | SOTF | TREES | GFC | SOTF |
|-----------------------|----|-------|-----|------|-------|-----|------|-------|-----|------|
| Humid dense forest    | 14 | 986.1 (91) | 1112.8 (102) | 1087.3 | 11.9 (57) | 14.2 (68) | 20.9 | 1.2 (59) | 2.8 (145) | 1.9 |
| Humid open forest     | 3  | 166.4 (93) | 182.4 (102) | 178.6 | 1.5 (85) | 2.0 (115) | 1.7 | 0.2 (4) | 0.1 (2) | 4.4 |
| Dry open forest       | 22 | 383.5 (109) | 1067.4 (303) | 352.5 | 10.7 (81) | 5.6 (43) | 13.2 | 0.2 (11) | 0.3 (15) | 2.1 |
| Woody vegetation      | 1  | 7.4 (43) | 28.6 (168) | 17.1 | 0.0 (4) | 0.1 (25) | 0.2 | 0.0 (0) | 0.0 (1) | 0.4 |
| Total                 | 40 | 1543.4 (94) | 2391.3 (146) | 1635.5 | 24.1 (67) | 21.8 (61) | 36.0 | 1.6 (18) | 3.2 (37) | 8.8 |

The areas calculated from TREES and GFC relative to the areas calculated from SOTF are given in brackets.
Figure 7. Visual comparison of the SOTF, TREES and GFC products for four selected sample units.

Legend

| SOTF | TREES | GFC |
|------|-------|-----|
| Forest | Tree cover (TC) | 70–100% TC |
| | Tree cover mosaic (TCM) | 30–70% TC |
| Non-forest | Other wooded land (OWL), Other land cover (OLC), water (W) | 0–30% TC |
| Loss | TC → OWL, OLC, W | Loss |
| Gain | OWL, OLC, W > TC | Gain |

Location of selected sample units
regularly assess the progress towards Aichi Target 5 (https://www.bipindicators.net). The most recent report, FRA 2015, showed that global deforestation has steadily slowed down during the last two decades, from an annual net loss of 0.18% in the 1990s to 0.08% by 2015 (Keenan et al. 2015). Deforestation rates have also declined in Sub-Saharan Africa, but remain with 0.45% annual forest loss comparatively high. Data reported in FRA 2015 come mostly from country reports prepared by national authorities (FAO, 2016). While the reporting has improved over time, globally 60% of subtropical and nearly 80% of tropical forests are documented by outdated data (>10 years old). About 57% of primary forests are even less documented. The situation is worse for Sub-Saharan Africa, where only 10% of the countries have high quality data.

The lack of reliable data in the region is likely to fade away with the increased availability of high resolution imagery and ever improving remote sensing technologies. By comparing three remotely sensed products commonly used over Sub-Saharan Africa, we highlight areas where improvements are most urgently needed. Products showed important differences, particularly in areas of medium tree cover levels and in mountainous terrain, which inherently lead to uncertainties in mapping rates of loss, fragmentation and degradation in forests and tree-covered habitats.

**Target 11**

Our results have direct implications for monitoring terrestrial protected areas (PAs) as remote sensing products are increasingly used in the region to assess PA’s effectiveness in maintaining tree-covered habitats (e.g. Pelkey et al. 2000; Pfeifer et al. 2012; Beresford et al. 2013; Bowker et al. 2017) and to estimate associated species extinction risks (Tracewski et al. 2016). To get an indication on the share of the seven broad vegetation types on the existing PA network, we overlaid the PA polygons of the World Database on Protected Areas (WDPA, version September 2016) on the reclassified GLC2000 map (Table 5).

Humid dense forests cover 9% of Sub-Saharan PAs. Most of these PAs are found in the Congo rainforest, for which tree cover can be mapped with fairly high certainty from all three products (except for MODIS-VCF in the coastal region). Tree cover losses, instead, are estimated with higher accuracies from the Landsat-derived GFC and TREES products, whose finer spatial resolution is more adapted to capture the mostly small-scale logging events in the region (Laporte et al. 2007; Verhegghen et al. 2016).

The monitoring of open, fragmented humid forests and dry forests still leads to high uncertainties. More than a quarter (27%) of PAs would ideally require a specific monitoring strategy to map human encroachments and their integrity into the wider landscape. The high rates of tree cover loss suggested by GFC but not detected by TREES in Sierra Leone and Liberia requires further investigation. Additionally, mountainous regions, like the Ethiopian Highlands, Albertine Rift and Madagascar’s eastern slopes, need special attention. They are particularly home to small-ranged and threatened species (Pimm et al. 2014), making them exceptionally sensitive to human intrusion. The need for monitoring dry forests becomes exigent in view of the region’s high potential for commercial farming (Morris et al. 2009). In concert with growing national and international demands for food and biofuel feedstocks, large-scale land conversions might be expected throughout the region.

The largest portion of Sub-Saharan African PAs (51%) is dominated by shrub and grassland cover, where tree cover plays a smaller, but still important role within the ecosystems. Single trees improve, for example, soil nutrition content and the distribution of water resources to understory grasses (Rhoades 1996; Ludwig et al. 2003; Priyadarshini et al. 2016). Thus, small tree cover changes may have large impacts on the functioning of these ecosystems. Although products tend to suggest similar estimates in absolute terms, relative differences might be as high as elsewhere. Recent research found that previous forest assessments have largely underestimated forests in dryland biomes by 40–47% (Bastin et al. 2017).

**Target 15**

Our results show high uncertainties over the whole region in estimating tree cover gains and thus assess the effectiveness of ecological restoration programmes focusing on reforestation. The intensification of tree plantations, mostly monocultures of non-native eucalyptus, pine or

### Table 5. Portion of Sub-Saharan Africa’s protected areas (PA) covered by broad vegetation types.

| Vegetation type          | % of PA |
|--------------------------|---------|
| Humid dense forest       | 9.1     |
| Humid open forest        | 2.1     |
| Dry dense forest         | 7.8     |
| Dry open forest          | 16.7    |
| Woody vegetation         | 23.0    |
| Non-woody vegetation     | 27.6    |
| Bare                     | 13.8    |
| Total                    | 100.0   |

The portions were calculated by overlapping the World Database on Protected Areas (WDPA, version September 2016) on the GLC2000 map, reclassified to seven broad vegetation types.
acacia species (WRM and TW, 2016), introduce further an important bias. The GFC and MODIS-VCF classifications do not differentiate between natural forest recovery and the plantation of oil palm or industrial forest holding the risk to misinform conservation success (Tropek et al. 2014). To date, it remains difficult to discriminate tree growth in monocultures from tree growth in areas where ecological restoration programmes aim to recover degraded habitats. Putting in place an automatic monitoring programme derived from Earth Observations in support to Target 15 remains, thus, extremely challenging.

Conclusions
By comparing three remote sensing-based tree cover products, we highlighted substantial differences between products, leading to uncertainties in assessing tree cover extents and changes. Differences were related to misclassifications, spatial resolution and MMU, but also thematic differences, which we were not able to fully remove in our comparison.

MODIS-VCF showed much larger changes than TREES and GFC (about five times for gross loss and 55 times for gross gains) by applying map differencing, making the product unsuitable for assessing tree cover change trends from a simple change detection method over Sub-Saharan Africa. Better results might be derived from MODIS-VCF by removing fine tree cover changes below 10 percentage points (Staver and Hansen 2015) or using more sophisticated methods, like the vegetation continuous fields-based change analysis (Song et al. 2014). Moreover, regionally tailored percent tree cover products based on MODIS data have shown the potential to improve accuracies in landscapes of low tree coverage (Gaughan et al. 2013; Gessner et al. 2013) and to approach change detection accuracies comparable to Landsat-derived results, if the disturbance happens at MODIS pixel level or beyond (Leinenkugel et al. 2015). However, small-scale forest changes are common over Sub-Saharan Africa (Mayaux et al. 2013) and are more accurately assessed by the LandSat-based GFC and TREES products. GFC and TREES showed in our comparison more similar tree cover extents and changes, but there are important differences. These differences were highest in areas with medium tree-cover densities as well as in mountainous terrain, overlapping with areas of high economic potential and areas hosting biodiversity particularly sensitive to environmental changes (Phalan et al. 2013; Laurance et al. 2014a; Pimm et al. 2014). Frequent and reliable monitoring over these regions is thus critically needed to alert harmful processes.

Considering the global biodiversity strategy to 2020, at a time where more global Earth Observations services such as Copernicus are becoming freely available, the observations presented in this paper underline the urgent need to review existing baselines by the end of the decade as well as the need to pay more attention to the regional ecological specificities, as these tend to be increasingly dissolved in global products and services.

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Reference
Achard, F., R. Beuchle, P. Mayaux, H.-J. Stibig, C. Bodart, A. Brink, et al. 2014. Determination of tropical deforestation rates and related carbon losses from 1990 to 2010. Glob. Change Biol. 20, 2540–2554.
Archibald, S., D. P. Roy, B. W. van Wilgen, and R. J. Scholes. 2009. What limits fire? An examination of drivers of burnt area in Southern Africa. Glob. Change Biol. 15, 613–630.
Bare, M., C. Kauffman, and D. C. Miller. 2015. Assessing the impact of international conservation aid on deforestation in sub-Saharan Africa. Environ. Res. Lett. 10, 125010.
Bartholomé, E., and A. S. Belward. 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. Int. J. Remote Sens. 26, 1959–1977.
Bastin, J.-F., N. Berrahmouni, A. Grainger, D. Maniatis, D. Mollicone, R. Moore, et al. 2017. The extent of forest in dryland biomes. Science 356, 635–638.
Beresford, A. E., G. W. Eshiamwata, P. F. Donald, A. Balmford, B. Bertzky, A. B. Brink, et al. 2013. Protection reduces loss of natural land-cover at sites of conservation importance across Africa. PloS ONE 8, e65370.
Blake, S., S. Strindberg, P. Boudjan, C. Makombo, I. Bila-Isia, O. Ilambu, et al. 2007. Forest elephant crisis in the Congo Basin. PLoS Biol. 5, e111.
Blom, A., J. Yamindou, and H. H. Prins. 2004. Status of the protected areas of the Central African Republic. Biol. Cons. 118, 479–487.
Blom, A., R. van Zalinge, I. M. A. Heitkönig, and H. H. T. Prins. 2005. Factors influencing the distribution of large mammals within a protected central African forest. Oryx 39, 381.
Bodart, C., A. B. Brink, F. Donnay, A. Lupi, P. Mayaux, and F. Achard. 2013. Continental estimates of forest cover and forest cover changes in the dry ecosystems of Africa between 1990 and 2000. J. Biogeogr. 40, 1036–1047.
Boschetti, L., H. D. Eva, P. A. Brivio, and J. M. Grégoire. 2004. Lessons to be learned from the comparison of three satellite-derived biomass burning products. Geophys. Res. Lett. 31, L21501.
Bowker, J. N., A. De Vos, J. M. Ament, and G. S. Cumming. 2017. Effectiveness of Africa’s tropical...
protected areas for maintaining forest cover. Conserv. Biol. 31, 559–569.
Brandt, J. S., C. Nolte, and A. Agrawal. 2016. Deforestation and timber production in Congo after implementation of sustainable forest management policy. Land Use Policy 52, 15–22.
Brink, A. B., C. Bodart, L. Brodsky, P. Defourny, C. Ernst, F. Donney, et al. 2014. Anthropogenic pressure in East Africa—Monitoring 20 years of land cover changes by means of medium resolution satellite data. Int. J. Appl. Earth Obs. Geoinf. 28, 60–69.
Chuvieco, E., S. Martínez, M. V. Román, S. Hantson, and M. L. Pettinari. 2014. Integration of ecological and socio-economic factors to assess global vulnerability to wildfire. Glob. Ecol. Biogeogr. 23, 245–258.
Coppin, P., I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin. 2004. Digital change detection methods in ecosystem monitoring: a review. Int. J. Remote Sens. 25, 1565–1596.
DeFries, R., A. Hansen, A. C. Newton, and M. C. Hansen. 2005. Increasing isolation of protected areas in tropical forests over the past twenty years. Ecol. Appl. 15, 19–26.
Durán, A. P., J. Rauch, and K. J. Gaston. 2013. Global spatial coincidence between protected areas and metal mining activities. Biol. Cons. 160, 272–278.
Edwards, D. P., S. Sloan, L. Weng, P. Dirks, J. Sayer, and W. F. Laurance. 2014. Mining and the African Environment. Conserv. Lett. 7, 302–311.
Eva, H. D., F. Achard, R. Beuchle, E. de Miranda, S. Carboni, R. Seliger, et al. 2012. Forest cover changes in tropical South and Central America from 1990 to 2005 and related carbon emissions and removals. Remote Sens. 4, 1369–1391.
FAO. 2016. Global Forest Resources Assessment 2015. UN Food and Agriculture Organization, Rome.
Gaughan, A. E., R. M. Holdo, and T. M. Anderson. 2013. Using short-term MODIS time-series to quantify tree cover in a highly heterogeneous African savanna. Int. J. Remote Sens. 34, 6865–6882.
GEO BON. 2015. GEO BON Bi-Annual Progress Report 2014 - 2015 (Group on Earth Observations Biodiversity Observation Network Secretariat, Leipzig). Available at: https://issuu.com/geobon/docs/biannual_progress_report_201415_hig (Accessed: 10 April 2017).
Gessner, U., M. Machwitz, C. Conrad, and S. Dech. 2013. Estimating the fractional cover of growth forms and bare surface in savannas. A multi-resolution approach based on regression tree ensembles. Remote Sens. Environ. 129, 90–102.
Gray, C. L., S. L. L. Hill, T. Newbold, L. N. Hudson, L. Börger, S. Contu, et al. 2016. Local biodiversity is higher inside than outside terrestrial protected areas worldwide. Nat. Commun. 7, 12306.
Gschweng, M., E. K. V. Kalko, P. Berthold, W. Fiedler, and J. Fahr. 2012. Multi-temporal distribution modelling with satellite tracking data: predicting responses of a long-distance migrant to changing environmental conditions. J. Appl. Ecol. 49, 803–813.
Hansen, M. C., R. S. DeFries, J. R. G. Townsendshend, M. Carroll, C. Dimiceli, and R. A. Sohlberg. 2003. Global percent tree cover at a spatial resolution of 500 meters: first results of the MODIS vegetation continuous fields algorithm. Earth Interact. 7, 1–15.
Hansen, M. C., J. R. G. Townshend, R. S. DeFries, and M. Carroll. 2005. Estimation of tree cover using MODIS data at global, continental and regional/local scales. Int. J. Remote Sens. 26, 4359–4380.
Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, et al. 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853.
Hansen, M., P. Potapov, B. Margono, S. Stehman, S. Turubanova, and A. Tyukavina. 2014. Response to comment on ‘high-resolution global maps of 21st-century forest cover change. Science 344, 981.
Heino, M., M. Kummu, M. Makkonen, M. Mulligan, P. H. Verburg, M. Jalava, et al. 2015. Forest loss in protected areas and intact forest landscapes: a global analysis. PLoS ONE 10, e0138918.
Herkt, K. M. B., G. Barnikel, A. K. Skidmore, and J. Fahr. 2016. A high-resolution model of bat diversity and endemism for continental Africa. Ecol. Model. 320, 9–28.
Hirota, M., M. Holmgren, E. H. van Nes, and M. Scheffer. 2011. Global resilience of tropical forest and savanna to critical Transitions. Science 334, 232–235.
Hojas-Gascon, L., P. O. Cerutti, H. Eva, R. Nasi, and C. Martius. 2015. Monitoring deforestation and forest degradation in the context of REDD+: Lessons from Tanzania, Center for International Forestry Research (CIFOR). Available at: http://www.cifor.org/library/5642/monitoring-deforestation-and-forest-degradation-in-the-context-of-redd-lessons-from-tanzania/ (Accessed: 6 October 2016).
Hudson, L. N., T. Newbold, S. Contu, S. L. L. Hill, L. Lysenko, A. De Palma, et al. 2017. The database of the PREDICTS (Projecting responses of ecological diversity in changing terrestrial systems) project. Ecol. Evol. 7, 145–188.
Ibisch, P. L., M. T. Hoffmann, S. Krefb, G. Pe'er, V. Kati, L. Biber-Freudenberger, et al. 2016. A global map of roadless areas and their conservation status. Science 354, 1423–1427.
Ito, A., A. Ito, and H. Akimoto. 2007. Seasonal and interannual variations in CO and BC emissions from open biomass burning in Southern Africa during 1998–2005. Global Biogeochem. Cycles 21, GB2011.
Jung, M., K. Henkel, M. Herold, and G. Churkina. 2006. Exploiting synergies of global land cover products for carbon cycle modeling. Remote Sens. Environ. 101, 534–553.
Keenan, R. J., G. A. Reams, F. Achard, J. V. de Freitas, A. Grainger, and E. Lindquist. 2015. Dynamics of global forest area: results from the FAO global forest resources assessment 2015. *For. Ecol. Manage.* 352, 9–20.

Kim, D.-H., J. O. Sexton, and J. R. Townshend. 2015. Accelerated deforestation in the humid tropics from the 1990s to the 2000s: accelerated pan-tropical deforestation. *Geophys. Res. Lett.* 42, 3495–3501.

Laporte, N. T., J. A. Stabach, R. Grosch, T. S. Lin, and S. J. Goetz. 2007. Expansion of industrial logging in Central Africa. *Science* 316, 1451.

Laurance, W. F., and A. Balmford. 2013. A global map for road building. *Nature* 495, 308–309.

Laurance, W. F., M. Goosem, and S. G. W. Laurance. 2009. Impacts of roads and linear clearings on tropical forests. *Trends Ecol. Evol.* 24, 659–669.

Laurance, W. F., G. R. Clements, S. Sloan, C. S. O’Connell, N. D. Mueller, M. Goosem, et al. 2014a. A global strategy for road building. *Nature* 513, 229–232.

Laurance, W. F., J. Sayer, and K. G. Cassman. 2014b. Agricultural expansion and its impacts on tropical nature. *Trends Ecol. Evol.* 29, 107–116.

Leinenkugel, P., M. L. Wolters, N. Oppelt, and C. Kuenzer. 2015. Tree cover and forest cover dynamics in the Mekong Basin from 2001 to 2011. *Remote Sens. Environ.* 158, 376–392.

Ludwig, F., T. E. Dawson, H. de Kroon, F. Berendse, and H. H. T. Prins. 2003. Hydraulic lift in Acacia tortilis trees on an East African savanna. *Oecologia* 134, 293–300.

Mascia, M. B., S. Pailler, R. Krithivasan, V. Roshchanka, D. Burns, M. J. Mlotha, et al. 2014. Protected area downgrading, downsizing, and degazette ment (PADDD) in Africa, Asia, and Latin America and the Caribbean, 1900–2010. *Biol. Cons.* 169, 355–361.

Mayaux, P., H. Ewa, J. Gallego, A. H. Strahler, M. Herold, S. Agrawal, et al. 2006. Validation of the global land cover 2000 map. *IEEE Trans. Geosci. Remote Sens.* 44, 1728–1739.

Mayaux, P., J.-F. Pekel, B. Desclée, F. Donnay, A. Lupi, F. Achard, et al. 2013. State and evolution of the African rainforests between 1990 and 2010. *Philos. Trans. R Soc. B: Biol. Sci.* 368, 20120300.

Morris, M., H. P. Binswanger-Mkhize, and D. Byerlee. 2009. Awakening Africa’s Sleeping Giant: Prospects for Commercial Agriculture in the Guinea Savannah Zone and Beyond (The World Bank), Available at: https://doi.org/elibrary.worldbank.org/doi/book/10.1596/978-0-8213-7941-7 (Accessed: 1 December 2016).

Naidoo, R., M. J. Chase, P. Beytell, P. D. Preece, K. Landen, G. Stuart-Hill, et al. 2016. A newly discovered wildlife migration in Namibia and Botswana is the longest in Africa. *Oryx* 50, 138–146.

Paganini, M., A. K. Leidner, G. Geller, W. Turner, and M. Wegmann. 2016. The role of space agencies in remotely sensed essential biodiversity variables. *Remote Sens. Ecol. Conserv.* 2, 132–140.

Pelkey, N. W., C. J. Stoner, and T. M. Caro. 2000. Vegetation in Tanzania: assessing long term trends and effects of protection using satellite imagery. *Biol. Cons.* 94, 297–309.

Pereira, H. M., S. Ferrier, M. Walters, G. N. Geller, R. H. G. Jongman, R. J. Scholes, et al. 2013. Essential biodiversity variables. *Science* 339, 277–278.

Pettorelli, N., M. Wegmann, A. Skidmore, S. Műcher, T. P. Dawson, M. Fernandez, et al. 2016. Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. *Remote Sens. Ecol. Conserv.* 2, 122–131.

Pfeifer, M., N. D. Burgess, R. D. Swetnam, P. J. Platts, S. Willcock, and R. Marchant. 2012. Protected areas: mixed success in conserving East Africa’s evergreen forests. *PLoS ONE* 7, e39337.

Phalan, B., M. Bertzky, S. H. M. Butchart, P. F. Donald, J. P. W. Scharlemann, A. J. Stattersfield, et al. 2013. Crop expansion and conservation priorities in tropical countries. *PLoS ONE* 8, e51759.

Pimm, S. L., C. N. Jenkins, R. Abell, T. M. Brooks, J. L. Gittleman, L. N. Joppa, et al. 2014. The biodiversity of species and their rates of extinction, distribution, and protection. *Science* 344, 1246752.

Poilvé, H. 2013. Spatial Observatory of Tropical Forests: Product User Manual of Historical Forest Maps, Airbus Defence & Space - Geo Intelligence

Priyadarshini, K. V. R., H. H. T. Prins, S. de Bie, I. M. A. Heitkönig, S. Woodborne, G. Gort, et al. 2016. Seasonality of hydraulic redistribution by trees to grasses and changes in their water-source use that change tree–grass interactions. *Ecohydrology* 9, 218–228.

Rhoades, C. C. 1996. Single-tree influences on soil properties in agroforestry: lessons from natural forest and savanna ecosystems. *Agrofor. Syst.* 35, 71–94.

Sarnier, C., R. E. McBride, and L.-V. Fichet. 2016. Suitability of global forest change data to report forest cover estimates at national level in gabon. *Remote Sens. Environ.* 173, 326–338.

Secades, C., B. O’Connor, C. Brown, and M. J. Walpole. 2014. Earth observation for biodiversity monitoring: a review of current approaches and future opportunities for tracking progress towards the Aichi Biodiversity Targets. Secretariat of the Convention on Biological Diversity, Montréal, Canada.

Sexton, J. O., X.-P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, 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. Digital Earth* 6, 427–448.

Skidmore, A. K., N. Pettorelli, N. C. Coops, G. N. Geller, M. Hansen, R. Lucas, et al. 2015. Agree on biodiversity metrics to track from space. *Nature News* 523, 403.
Song, X.-P., C. Huang, J. Sexton, S. Channan, and J. Townshend. 2014. Annual detection of forest cover loss using time series satellite measurements of percent tree cover. Remote Sens. 6, 8878–8903.

Spracklen, D. B., M. Kalamandeen, D. Galbraith, E. Gloor, and D. V. Spracklen. 2015. A global analysis of deforestation in moist tropical forest protected areas. PLoS ONE 10, e0143886.

Staver, A. C., and M. C. Hansen. 2015. Analysis of stable states in global savannas: is the CART pulling the horse? – a comment. Glob. Ecol. Biogeogr. 24, 985–987.

Staver, A. C., S. Archibald, and S. Levin. 2011. Tree cover in sub-Saharan Africa: rainfall and fire constrain forest and savanna as alternative stable states. Ecology 92, 1063–1072.

Stibig, H.-J., F. Achard, S. Carboni, R. Rasã, and J. Miettinen. 2014. Change in tropical forest cover of Southeast Asia from 1990 to 2010. Biogeosciences 11, 247–258.

de Sy, V., M. Herold, F. Achard, R. Beuchle, J. G. P. W. Clevers, E. Lindquist, et al. 2015. Land use patterns and related carbon losses following deforestation in South America. Environ. Res. Lett. 10, 124004.

Townshend, J. M., Hansen, M. Carroll, C. DiMiceli, R. Sohlberg, and C. Huang. 2011. User Guide for the MODIS Vegetation Continuous Fields product Collection 5 version 1, University of Maryland

Tracewski, L., S. H. M. Butchart, M. Di Marco, G. F. Ficetola, C. Rondinini, A. Symes, et al. 2016. Toward quantification of the impact of 21st-century deforestation on the extinction risk of terrestrial vertebrates. Conserv. Biol. 30, 1070–1079.

Tropek, R., O. Sedláček, J. Beck, P. Keil, Z. Musilová, I. Šimová, et al. 2014. Comment on ‘High-resolution global maps of 21st-century forest cover change’. Science 344, 981.

Tsendarbazar, N. E., S. de Bruin, B. Mora, L. Schouten, and M. Herold. 2016. Comparative assessment of thematic accuracy of GLC maps for specific applications using existing reference data. Int. J. Appl. Earth Obs. Geoinf. 44, 124–135.

Tyukavina, A., A. Baccini, M. C. Hansen, P. V. Potapov, S. V. Stehman, R. A. Houghton, et al. 2015. Aboveground carbon loss in natural and managed tropical forests from 2000 to 2012. Environ. Res. Lett. 10, 074002.

UN-DESA. 2015. World Population Prospects: The 2015 Revision, Key Findings and Advance Tables, United Nations, Department of Economic and Social Affairs, Population Division, New York, Available at: https://esa.un.org/unpd/wpp/publications/files/key_findings_wpp_2015.pdf (Accessed: 12 December 2016).

Verhegghen, A., H. Eva, B. Desclèe, and F. Achard. 2016. Review and combination of recent remote sensing based products for forest cover change assessments in Cameroon. Int. Forest Rev. 18, 14–25.

Viña, A., W. J. McConnell, H. Yang, Z. Xu, and J. Liu. 2016. Effects of conservation policy on China’s forest recovery. Sci. Adv. 2, e150965.

Weng, L., A. K. Boedihartono, P. H. G. M. Dirks, J. Dixon, M. I. Lubis, and J. A. Sayer. 2013. Mineral industries, growth corridors and agricultural development in Africa. Global Food Security 2, 195–202.

van der Werf, G. R., J. T. Randerson, L. Giglio, G. J. Collatz, M. Mu, P. S. Kasibhatla, et al. 2010. Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009). Atmos. Chem. Phys. 10, 11707–11735.

WRM and TW. 2016. Industrial tree plantations invading eastern & southern Africa”, World Rainforest Movement and Timberwatch Coalition. Available at: http://wrm.org.uy/wp-content/uploads/2016/10/2016-10-Plantations-in-ES-Africa-TW-WRM-med-screen.pdf (Accessed: 22 December 2016).

Supporting Information

Additional supporting information may be found online in the supporting information tab for this article.

Figure S1. Scatterplots visualizing the degree of correlation between product pairs in calculated areas of tree-cover loss (km²/sample unit). Regression lines (red) and 1:1 lines (gray) are shown for each plot.

Figure S2. Scatterplots visualizing the degree of correlation between product pairs in calculated areas of tree-cover gain (km²/sample unit). Regression lines (red) and 1:1 lines (gray) are shown for each plot.

Figure S3. Visual comparison of the SOTF, TREES and GFC products for four selected sample units

Table S1. Comparison of TREES and GFC products to the SOTF reference datasets over 40 sample units (SU) located in Cameroon and Central African Republic. Numbers in italic show the areas calculated from TREES and GFC as per cent of the areas calculated from SOTF.

Data S1. Cross-reference over Cameroon and Central African Republic.