

Assessing MODIS Vegetation Continuous Fields tree cover product (collection 6): performance and applicability in tropical forests and savannas.

5 Rahayu Adzhar^{1,2*}, Douglas I Kelley^{1*}, Ning Dong^{2,3}, Mireia Torello Raventos⁴, Elmar Veenendaal⁵, Ted R Feldpausch⁶, Oliver L Phillips⁷, Simon L Lewis^{7,8}, Bonaventure Sonké⁹, Herman Taedoum¹⁰, Beatriz Schwantes Marimon¹¹, Tomas Domingues¹², Luzmila Arroyo¹³, Gloria Djagbletey¹⁴, Gustavo Saiz¹⁵, France Gerard¹

- 10 ¹ U.K. Centre for Ecology & Hydrology, Wallingford, Oxfordshire, U.K.
² Department of Life Sciences, Imperial College London, Berkshire, U.K.
³ Department of Biological Sciences, Macquarie University, North Ryde, Australia
⁴ School of Earth and Environmental Science, James Cook University, Cairns, Australia
⁵ Plant Ecology and Nature Conservation, Wageningen University, Wageningen, The Netherlands
15 ⁶ College of Life and Environmental Sciences, University of Exeter, Exeter, U.K.
⁷ School of Geography, University of Leeds, U.K.
⁸ Department of Geography, University College London, London, U.K.
⁹ Plant Systematics and Ecology Laboratory, Department of Biology, Higher Teachers' Training College, University of Yaoundé, Yaoundé, Cameroon
20 ¹⁰ Consultative Group on International Agricultural Research | CGIAR · Bioversity International, Yaoundé, Cameroon
¹¹ State University of Mato Grosso, Mato Grosso, Brazil
¹² Departamento de Biología (Ribeirão Preto), University of São Paulo, São Paulo, Brazil
¹³ Universidad Autónoma Gabriel René Moreno, Santa Cruz, Bolivia
25 ¹⁴ Forest and Climate Change Division, Forestry Research Institute of Ghana, Ghana
¹⁵ Facultad de Ciencias, Universidad Católica de la Santísima Concepción, Concepción, Chile

Correspondence to: rahayu.adzhar@gmail.com; doukel@ceh.ac.uk

30 **Abstract.** The Moderate Resolution Imaging Spectroradiometer vegetation continuous fields (MODIS VCF) Earth observation product is widely used to estimate forest cover changes, parameterise vegetation and Earth System models, and as a reference for validation or calibration where field data are limited. However, while limited independent validations of MODIS VCF have shown that MODIS VCF's accuracy decreases when estimating tree cover in sparsely-vegetated areas such as tropical
35 savannas, no study has yet assessed the impact this may have on the VCF-based tree cover data used by many in their research. Using tropical forest and savanna inventory data collected by the TROPical Biomes in Transition (TROBIT) project, we produce a series of corrections that take into account (i) the spatial disparity between the in-situ plot size and the MODIS VCF pixel, and (ii) the trees' spatial distribution within in-situ plots. We then applied our corrections to areas identified as
40 forest or savanna in the International Geosphere-Biosphere Programme (IGBP) land cover mapping product. All IGBP classes identified as 'savanna' show substantial increases in cover after correction, indicating that the most recent version of MODIS VCF consistently underestimates woody cover in tropical savannas. We estimate that MODIS VCF could be underestimating tropical tree cover by as much as 29 %. Models that use MODIS VCF as their benchmark could therefore be underestimating
45 the carbon uptake in forest-savanna areas and misrepresenting forest-savanna dynamics. Because of the limited in-situ plot number, our results are designed to be used as an indicator of where the product is potentially more or less reliable. Until more in-situ data are available to produce more accurate corrections, we recommend caution when using uncalibrated MODIS VCF in tropical savannas.

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1 Introduction

55 Tree cover values derived from Earth observation (EO) data form a fundamental part of ecological
research. They are used to estimate forest cover change, biomass, and carbon stocks (Bastin et al.,
2019; Giriraj et al., 2017; Saatchi et al., 2011; Song et al., 2014); help identify key areas for
conservation efforts (Miles et al., 2006); and are used as a basis for climatic and vegetation modelling
and model evaluation (Brovkin et al., 2013; Burton et al., 2019; Kelley et al., 2013). All this research,
60 in turn, plays a vital role in informing local, regional, and global environmental policies (Harris et al.,
2012). As such, an EO product's accuracy is important to consider, as any errors in the initial tree
cover estimate can be further compounded in downstream work.

Only a handful of EO products provide global maps of percentage tree cover or forest and shrub cover
distributions (Bartholomé and Belward, 2005; Bicheron et al., 2008), and fewer still provide
65 information stretching over at least a decade (Friedl et al., 2002; Hansen et al., 2003). Of these, one
of the products most widely used in ecological modelling is the Moderate Resolution Imaging
Spectroradiometer Vegetation Continuous Fields (MODIS VCF) product (DiMiceli, 2017). MODIS VCF
is a yearly product that provides percent tree cover globally at a spatial resolution of 250 m and is
available for the years 2000 through to 2020. Its quantitative measure of woody cover is recorded
70 annually and is described as a percentage of ground cover, making it particularly suited for use in
evaluating dynamic global models (Lasslop et al., 2018; Rabin et al., 2017), as a proxy for in-situ data
that are harder to collect (Kelley et al., 2019), and to help define parameters for calculating global tree
restoration potential (Bastin et al., 2019). Collection 6 is the most recent iteration of the product.

75 As the VCF product has progressed from Collection 1 to its current Collection 6, several validations
using in-situ field data or higher-resolution remotely sensed data as a reference measurement have
been carried out. These have been few and limited to sites within a biome (Montesano et al., 2009a),
a region (Hansen et al., 2005; White et al., 2005), or within a country (Gao et al., 2014; Sexton et al.,
2013). The MODIS VCF product evaluated was the most recent collection available at the time (i.e.,
80 Hansen et al., 2005 and White et al., 2005 for Collection 3; Montesano et al., 2009a for Collection 4;
and Gao et al., 2015 and Sexton et al., 2013 for Collection 5). To our knowledge, no such
independent validation experiment has yet been conducted on Collection 6, which produces tree
cover estimates in the same manner as Collection 5 but with improvements made to the upstream
inputs to enhance its accuracy (DiMiceli, 2017).

85 The validations found that MODIS VCF may be less suitable for estimating tree cover in sparsely
vegetated areas. Huang & Siegert (2006) noted that MODIS VCF classified large areas of land as
'bare' where their land cover classification system identified it as sparsely-vegetated. Montesano et al.
(2009) found that MODIS VCF data (Collection 4) overestimated cover in areas of low tree cover in
90 taiga-tundra transition zones. Sexton et al. (2013) found that the Collection 5 product overestimated
cover in areas of low cover (below 20 %) and underestimated in areas of higher tree cover, while Gao
et al. (2015) found that MODIS VCF can only partially discriminate between tropical forest and non-
forest, struggling in areas that have greater heterogeneity. What is clear from the history of these
validation and comparison experiments is that MODIS VCF has accuracy issues in areas with low
95 woody vegetation cover, which has implications when its tree cover estimates are treated as
accurately representative of real-world conditions. Failure to accurately account for the product's
difficulty in estimating low woody covers can, therefore, lead to miscalibrated models and estimations
that do not reflect real-world conditions. This, in turn, has knock-on effects on environmental policy-
making, conservation efforts, and future ecological research, especially in areas with vegetation cover
100 types that are most prone to error.

Tropical savannas have woody covers that fall within the range particularly affected by the reported
MODIS VCF errors. A large proportion of these savannas can be found in tropical developing

105 countries (Boval and Dixon, 2012) and are predicted to be home to half of the world's population by
2050 (State of the Tropics, 2020). Tropical savannas are therefore highly vulnerable to anthropogenic
change. In the face of a growing population, land fragmentation, and changing climate, a savanna's
ability to maintain robust ecosystem functions is directly linked to the amount of woody cover present
(Sankaran et al., 2006). As a result, the ability to accurately monitor the state, dynamics, and woody
110 cover trends of tropical savannas is a vital part of understanding how and why savannas are changing
in the tropics (Harris et al., 2012; Miles et al., 2006), while also improving modelled climate projections
and vegetation dynamics for this complex biome.

In this study, we validate the accuracy of MODIS VCF Collection 6 in tropical savannas and forests by
115 comparing the tree cover percentage of the product to corresponding field data. We then characterise
the observed bias in woody covers across both savanna and forest ecosystems and apply our
corrections across the tropics to highlight the regions most likely to be affected by these inaccuracies
in the MODIS VCF product.

120 **2 Methods**

We used the MODIS VCF Collection 6 product (spatial resolution of 250 m, DiMiceli, 2017) with tree
cover values averaged across the years 2006 through to 2009 to reflect the range of the field data
collection period. The in-situ field data were sourced from the 'TROpical Biomes In Transition' project
(TROBIT) (www.geog.leeds.ac.uk/TROBIT, Torello-Raventos et al., 2013) and accessed via the
125 Forestplots.net database (Lopez-Gonzalez et al., 2011; Lopez-Gonzalez et al., 2009). The data we
used include the corner locations and the Canopy Area Index (CAI) values for 17 forest and 31
savanna sites distributed across Australia, Brazil, Bolivia, Cameroon, and Ghana (Fig. A1 and Table
A1, Fig. 2 in Torello-Raventos et al., 2013). The TROBIT field campaigns were carried out over a 3-
year period, from 2006 to 2009, and the field plots used in this study are 1 hectare in size except for
130 BFI-01 (0.5 ha), BFI-02 (0.5 ha), BFI-03 (0.5 ha), CTC-01 (0.93 ha), and VCR-01 (0.6 ha).

All the sites fall within the tropics, that is, within 23.5 degrees north and south of the equator, and
were selected in regions where savannas and forests were in close proximity and exist within
ecotones or 'zones of tension.' As such, the sites sampled show a large variation in physiognomy and
135 edaphic and climatic conditions (Table S1, Veenendaal et al., 2015).

The classification of the TROBIT plots as either 'forest' or 'savanna' is based on the parameters
described in Torello-Raventos et al. (2013) and Veenendaal et al. (2015). A 'savanna' is a natural land
cover that is not a forest, bare ground, or a body of water. 'Forest' is defined as woody vegetation
140 with an average tree height of or exceeding 6 m and a canopy area index (CAI) value of at least 0.3
for 'open forests' and 0.7 for 'forests.' In addition, floristic differences (i.e., dominance of 'savanna'
species) are used to differentiate forests from taller-growing savannas that have similar CAIs and tree
heights (see Fig. 9, Torello-Raventos et al., 2013).

145 There is some ambiguity in how 'savannas' and 'grasslands' are defined. Some modelling-based
research treat the two biomes as different (Whitley et al., 2017), while studies based on plant
functional traits group them together (Solofondranohatra et al., 2018; White et al., 2000). As there is
some concern that MODIS VCF will struggle to pick up woody cover in areas with really sparse
vegetation, in this paper we decided to treat 'grasslands' as part of the savanna domain.

150 CAI is defined as the sum of the projected areas of individual tree crowns divided by the ground area.
In the TROBIT project (Torello-Raventos et al. (2013) and Veenendaal et al. (2015)), plot-wide CAI is
made up of the sum of the upper-stratum, mid-stratum, and subordinate-stratum crown areas.
Membership to a stratum is determined by the tree's dbh (upper-stratum: dbh > 10 cm, mid-stratum:
155 2.5 cm < dbh < 10 cm, and subordinate-stratum: dbh < 2.5 cm, height > 1.5 m). About 50 trees per

stratum per plot were measured to derive plot-specific allometric relations between stem diameter and crown area (supplement B of Torello Raventos et al. (2013)). These were then applied to the whole plot to establish plot-level CAI. For the allometric relationships, tree crowns were treated as circles, and the individual tree projected crown area was determined using the average of crown radii measured along the four cardinal points (i.e., from the centre of the stem to the distance furthest from the stem).

CAI values do not account for within-site tree canopy distribution patterns and the overlap between individual tree canopies. We account for this by converting each CAI value into a probability distribution function incorporating the following two extreme scenarios: 'enforced overlap,' where the location probability of individual canopies increases linearly from 0 to 1 across a site; and 'unenforced overlap,' where individual canopies follow a uniform random distribution pattern and canopy overlap is not purposefully introduced (Fig. A2). We repeated this 1000 times per CAI measurement to determine the probability distribution of expected CAI for each field plot.

Unlike CAI, which is the fraction of ground covered by tree crowns, the percent tree cover value from MODIS VCF is defined as "the portion of the skylight orthogonal to the surface which is intercepted by trees" (Hansen et al. 2002). To make MODIS VCF tree cover comparable to tree cover derived from TROBIT plot CAIs, we divided the MODIS VCF values by 0.8 as suggested by Hansen et al. (2002). This is the standard approach in most modelling studies that use MODIS VCF (e.g., Lasslop et al., 2020; Kelley et al., 2013; Burton et al., 2019). The 0.8 value can be thought of as a gap correction factor (GCF) that accounts for within-canopy gaps. Although the GCF has been shown to vary with vegetation type (Lloyd et al., 2008; 0.34 - 0.60) and crown cover (Tang et al., 2019: 0.96 - 0.7), we opted to use 0.8 as we found that it yielded more conservative results compared to a variable GCF. It also avoided introducing additional parameters into our analysis.

Next, to account for the difference in size between the MODIS VCF pixel (250 m x 250 m) and the smaller field plot size (100 m x 100 m), we calculated the possible percent tree cover an area the size of a TROBIT field plot could have, given the MODIS VCF percent tree cover for a MODIS-sized pixel. This was done for two extreme scenarios: "enforced clumping," where all the tree cover for the given MODIS VCF value is forcibly 'clumped' on one side of the pixel, or "unenforced clumping," where 'clumping' is not enforced, and tree cover is distributed randomly within the pixel (Fig. A3). The clumping scenarios introduce possible variations in percent cover due to the area and location mismatch between a TROBIT field plot and a MODIS pixel. A probability distribution was generated for each MODIS VCF pixel by calculating percent tree cover values for 1000 samples (100 m x 100 m) randomly placed within the 250 m x 250 m MODIS VCF pixel.

We thereby compared MODIS VCF and TROBIT under four different scenarios: 1) unenforced overlap and clumping; 2) enforce overlap and unenforced clumping; 3) unenforced overlap and enforced clumping; 4) enforced overlap and clumping. Comparisons were conducted by fitting the following logit function:

$$\text{logit}(VCF) = C_0 + \Delta \times \log(C^{\tau_1}/(1 - C^{\tau_2})) \quad (\text{Equation 1})$$

Where $C_0, \Delta, \tau_1, \tau_2$ are optimised parameters and VCF and C are the MODIS VCF pixel and TROBIT site probability distributions, respectively. This is similar to a standard linear regression of logit transformed data, accounting for maximum and minimum bounds of 0 - 100 % tree cover, with τ_1, τ_2 allowing for a non-symmetric transformation of tree cover. To account for the probability density of each point, we inferred the parameters in Equation 1 using a Total Least Squares Bayesian Inference technique using a Metropolis-Hastings Markov Chain Monte Carlo step. Priors were uninformed but physically bounded (i.e., $\Delta, \tau_1, \tau_2 > 0$) to assume an increasing relationship between MODIS VCF and C . Equation 1 allowed us to assume normally distributed model errors, thus describing our conditional

probability of observations for a given parameter combination by a normal distribution (Gelman et al., 2013). Each combination was run over 10 chains, with 1000 warm-up iterations and 10,000 sampling iterations. Optimisation was performed using the rstan2.19.2 (Stan Development Team, 2019) package in R3.5.2 (R Core Team, 2018). Our optimization accounts for potential errors in TROBIT cover, which includes those caused by the allometric construction of the CAI, provided that the errors are unbiased and remain roughly consistent across sites (Gelman et al., 2013). As the TROBIT plots have relatively small total errors associated with the allometric relationships (Table B1, Torello-Raventos et al., 2013), systematic errors are unlikely to affect our results.

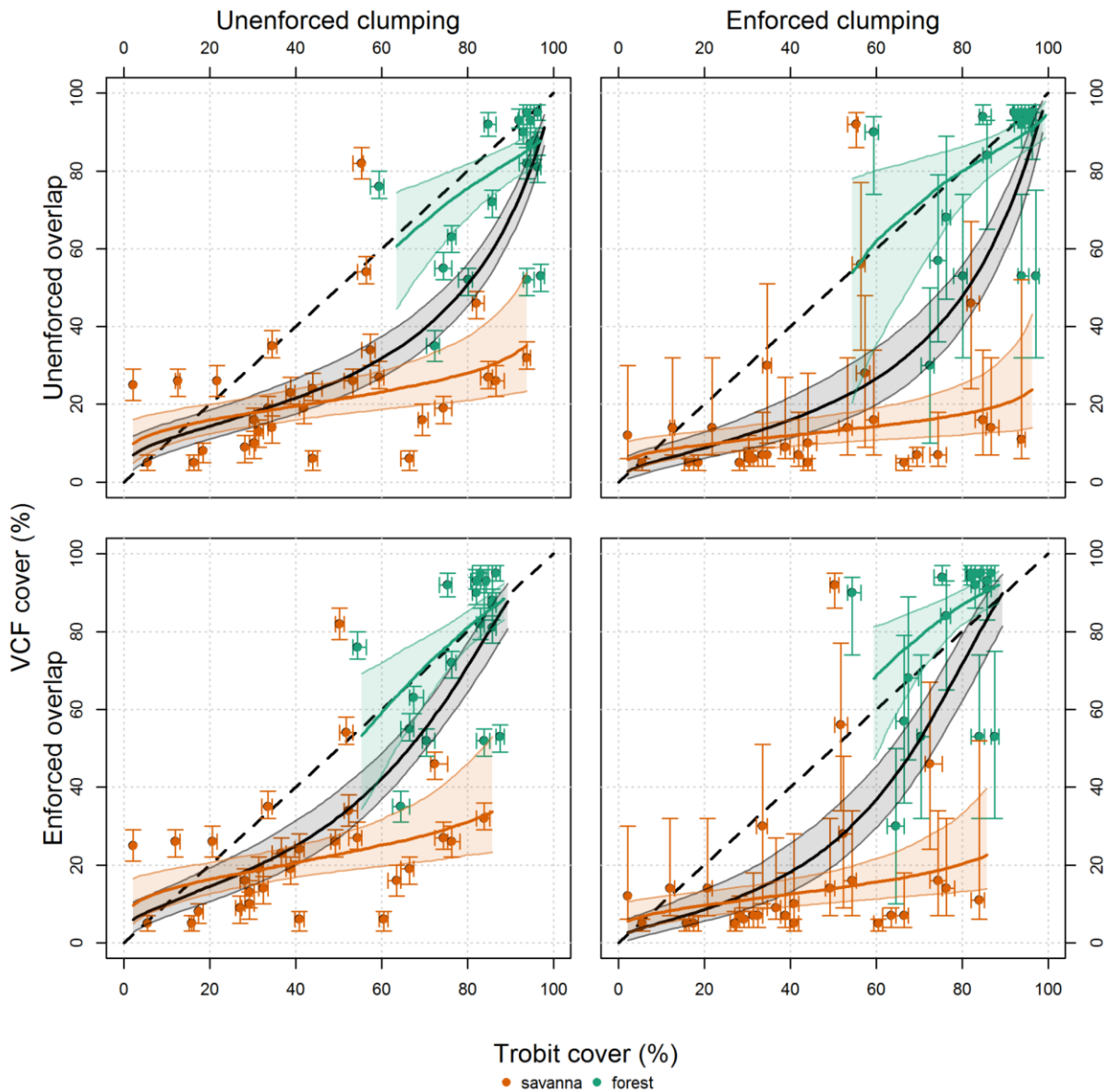
We evaluated the impact of the MODIS VCF biases inferred from this correction across the tropics by inverting our calculation of MODIS VCF bias (Fig. A4) as follows: first, the inverse (i.e., solving for C) of Equation 1 was applied to MODIS VCF values after conversion to a 100 m x 100 m pixel size grid (matching the field site area); then this corrected value was translated back to the original 250 m x 250 m VCF pixel size. As the inverse of Equation 1 has no analytical solution, we found the rounded percent value of C that minimises the absolute difference between the left- and right-hand side of the equation. For computational feasibility, we constructed maps of the tropics with corrected MODIS VCF values (Fig. 2) by sampling 5 iterations that were randomly sampled from each of our 10 optimisation chains (50 in total) and masking out pixels with cover types not considered as 'forest' or 'savanna'.

We used the 500 m MODIS Land Cover Type (MCD12Q1 - collection 6) product to identify the areas of 'forest' and 'savanna' across the tropics in the MODIS VCF product. MCD12Q1 is widely used by the global land surface modelling community (e.g., Sellar et al., 2019; Wiltshire et al., 2020) and describes land cover in terms of 17 global land cover classes as per the International Geosphere-Biosphere Programme (IGBP, Table 3 in Sulla-Menashe and Friedl, 2018). The product is based on the same spectroradiometer (MODIS) and temporal resolution as the VCF product. Referring to the definition of 'savanna' of Veenendaal et al. (2015), the following land cover classes were chosen to represent 'savanna': Closed Shrubland, Open Shrubland, Woody Savanna, Savanna, and Grassland, while 'forest' encompasses: Evergreen Needleleaf Forests, Evergreen Broadleaf Forests, Deciduous Needleleaf Forests, Deciduous Broadleaf Forests, and Mixed Forests. We subset MCD12Q1 to the tropical zone between +/- 30° North and took the median class for the 2006 to 2009 period, matching the field data collection period.

For a more detailed land-cover-specific evaluation, we resampled the corrected 250 m MODIS VCF pixels to a 500 m grid and combined it with the MCD12Q1 product to construct land-cover-specific MODIS VCF tree cover frequency distributions (Fig. A5). Our tree cover correction by cover type (Fig. 3) for the four clumping/overlap regression combinations was then calculated by multiplying each cover type MODIS VCF frequency distribution (Fig. A5) with curves representing the median, 5 %, and 95 % confidence lines of the correction equation ensembles.

3 Results

3.1 Comparing MODIS VCF to tree cover from TROBIT field sites



255 **Figure 1.** MODIS VCF percent tree cover versus percent tree cover from TROBIT field data, taking into account
 260 uncertainties associated with tree cover spatial distributions within a MODIS pixel and field plot. The 4
 combinations are: (1) no overlap and no clumping, where tree canopies are randomly distributed within both pixel
 and site; (2) no overlap and maximum clumping, where tree canopies are clustered in one area of the pixel, and
 randomly distributed throughout the field site; (3) with overlap and no clumping, where tree canopies are
 randomly distributed within the pixel, but overlap substantially within the field site; and (4) with overlap and
 maximum clumping, where tree canopies are clustered to one side within a pixel, and overlap substantially within
 the site. The bolded dashed line in black shows the 1:1 relationship. The solid lines represent the median of the
 respective regressions (green for forest; orange for savanna; black for forest and savanna combined). The thin
 lines represent the 5 and 95 % confidence interval of their respective regression lines. The vertical error bars
 represent uncertainty introduced by clumping; the horizontal error bars represent the uncertainty introduced by
 overlap.

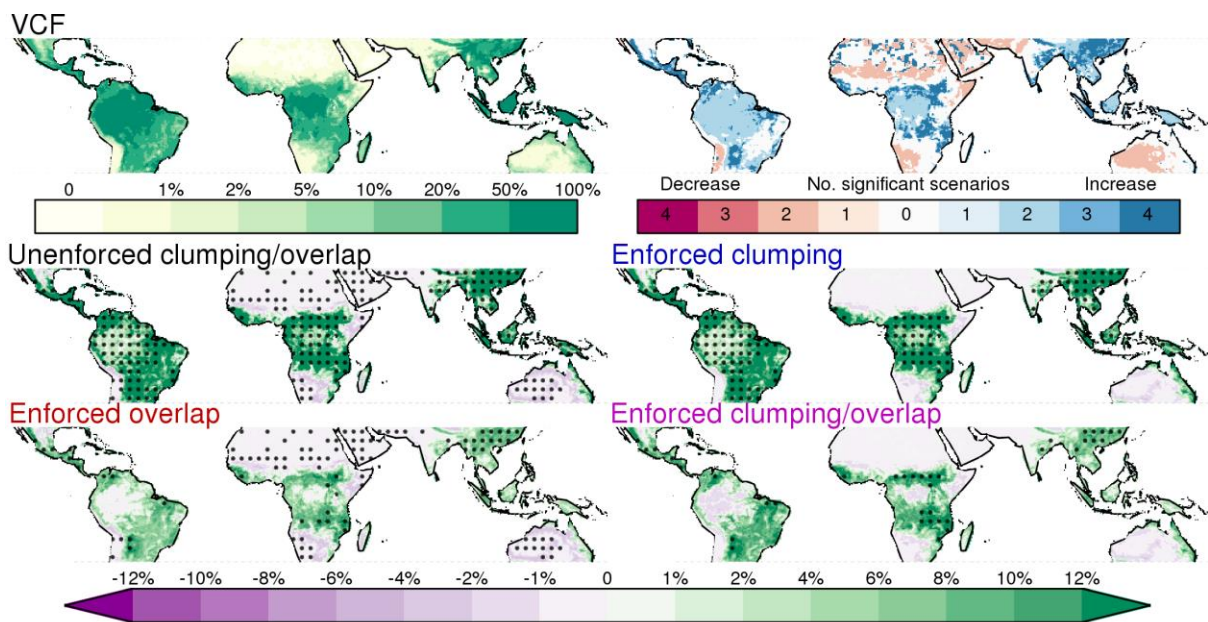
265 MODIS VCF underestimates tree cover within the 19 % to 81 % range across all four combinations of
 enforced-unenforced overlap and clumping (black line, Fig. 1). Below 12 %, MODIS VCF tree cover
 values do not significantly disagree with TROBIT field data, and may instead be overestimating tree
 cover (50 % confidence, dashed line, Fig. 1). A similar pattern is seen when tree cover exceeds 84 %:
 MODIS VCF does not differ significantly from TROBIT when there is no enforced overlap (i.e., when
 270 tree canopies are spaced randomly within the site - Fig. A2 left), but may overestimate tree cover
 when overlap is enforced (i.e., trees are clustering towards one side increasing the degree of canopy
 overlap - Fig. A2 right).

275 There is a clear difference in how accurately MODIS VCF estimates tree cover in forested areas (in green, Figure 1) as opposed to areas identified as savannas (in orange, Fig. 1). In savanna sites, MODIS VCF significantly and consistently underestimates tree cover regardless of the amount of overlap and clumping. Significant underestimation (at 95 % confidence) occurs when *in-situ* tree cover exceeds 18 – 19 % (without enforced clumping) or 9 - 10 % (with enforced clumping). In forest sites, MODIS VCF does not show the same pattern of systematic underestimation. Divergence does occur at high covers, depending on the enforcement of overlap or clumping. MODIS VCF overestimates tree cover where tree cover exceeds 78 % (at the 95 % confidence interval) when neither overlap nor clumping is enforced, and overestimates where tree cover exceeds 90 % (at 5 % confidence interval) when both overlap and clumping are enforced.

3.2 Global estimates of change in tropical tree cover

285 We assessed the impact of MODIS VCF’s underestimation of tree covers across the tropics restricted to the IGBP classes we identified as being either ‘forest’ or ‘savanna,’ using a ‘correction’ based on the combined forest and savanna sites (black curve, Fig. 1). We did not use the savanna-only sites for a savanna-specific correction (orange curve, Fig. 1) because there were few TROBIT sites representing savanna with MODIS VCF tree cover values exceeding 40 %, and global land cover maps disagree on the distribution of savannas within the forest-savanna ecotone (Herold et al., 2008).

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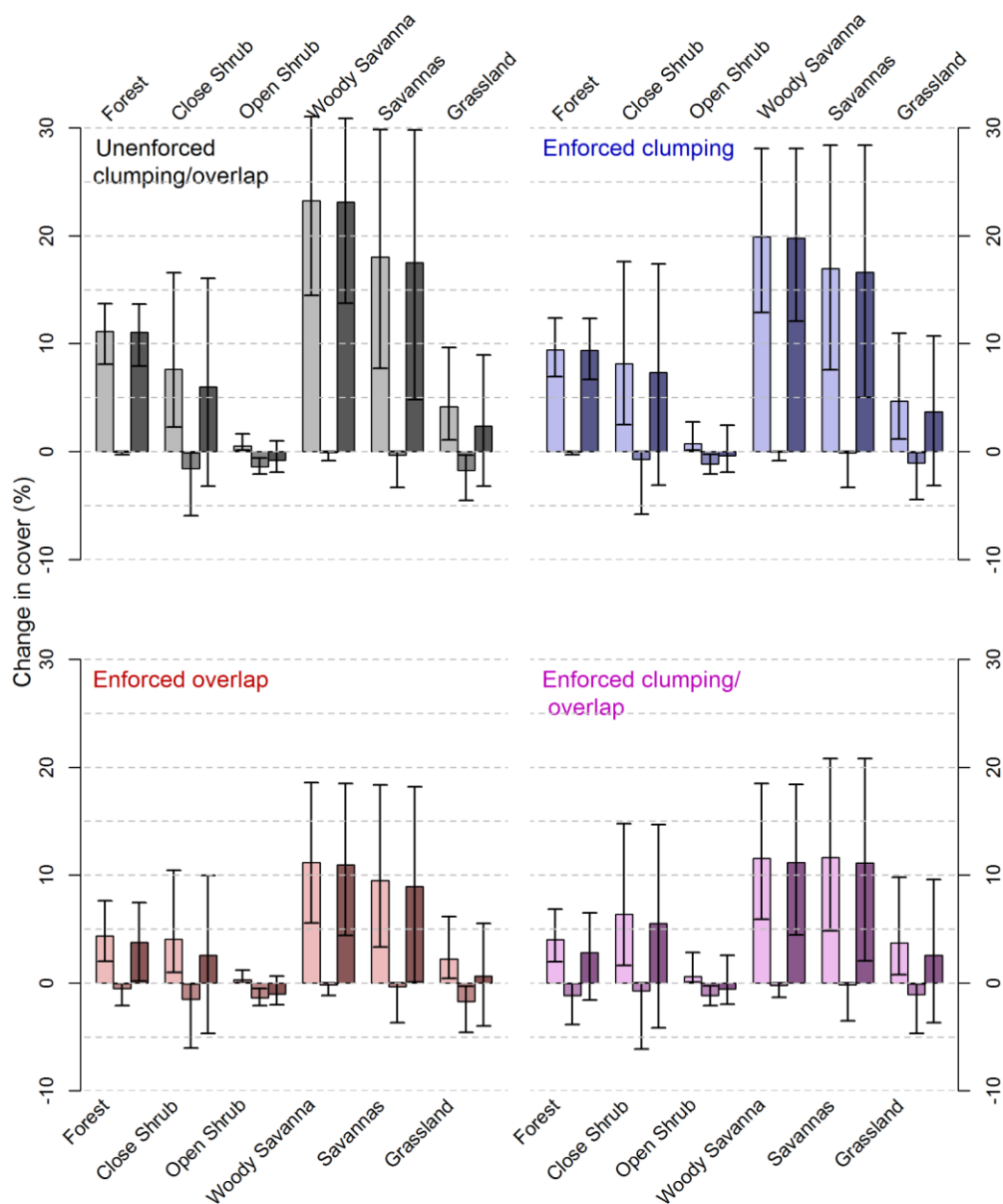
295 **Figure 2:** Distribution of tree cover across the tropics according to original MODIS VCF values (top left), the change in tree cover post-correction for all four scenarios (bottom four maps), and the change in tree cover that was statistically significant (95 % interval) in the same direction (positive or negative correction) across all four scenarios (top right). Black dots on the scenario maps indicate areas where the post-correction values have a 95 % certainty of being positive or negative corrections. These uncertainty maps are indicators of areas where MODIS VCF estimates may be more or less reliable, and cannot be used as definitive corrections due to the limited number of field sites used as reference.

300 The distribution of tree cover change after calibrating against field data are similar across the four scenarios (Fig. 2), and the regions where all four scenarios agree on the direction of change (positive and negative) are substantial. However, there are some differences caused by the uncertainty introduced by different extents of overlap and clumping. While we see a significant increase in tree cover across all clumping-overlap combinations in many regions of tropical savannas and grasslands (Pennington et al., 2018), such as in the forest-savanna mosaics that surround Congolian rainforests, 305 we do not see the same pattern in the Cerrado of Brazil. This is likely because the African forest-

savanna regions fall within the range of MODIS VCF values that consistently undergo a positive correction (~ 30 - 50 %, see Fig. A4), while the Cerrado of Brazil does not.

310 We also see a significant tree cover decrease in the Sahel post-correction in most or all of the scenarios, which runs counter to the results of Brandt et al. (2020) that found that tree cover was underestimated in the region. This disparity may be explained by our lack of field sites in more arid regions. As these corrections were based on a limited number of sites in a limited number of regions, it is important to note that the maps shown in Figure 2 are not definitive. Instead, it should be used to identify areas where MODIS VCF estimates may be more or less reliable.

315 **3.3 Change in tree cover within different vegetation classes in tropical ecosystems**



320 **Figure 3.** Percent change in tree cover after the application of the appropriate correction (clockwise: no enforced clumping or overlap (black); enforced clumping and no enforced overlap (blue); no enforced clumping and enforced overlap (red); enforced clumping and overlap (pink) in the 'forest' supercategory and the 5 savanna classes. Palest tone indicates positive change, mid-tone indicates negative change, and the darkest tone indicates net change. Error bars denote the 5-95% confidence interval; if the error bar extends past the x-axis, the post-correction change is not considered significant.

When looking at our correction in more detail, we see that MODIS VCF significantly underestimates tree cover in all the IGBP land cover classes that we considered, regardless of overlap or clumping (95 % confidence interval) (Fig. 3). The most substantial and significant underestimation is in the classes 'woody savannas' and 'savannas.' The underestimation is the largest in woody savannas, except when clumping and overlap are enforced (in purple, Fig. 3). This is because the peak in the tree cover frequency distribution for savannas aligns with where the correction for maximum overlap and clumping is the largest (i.e., at about 20 % tree cover, see Fig. A5), while the peak in cover distribution for woody savannas (26 - 67 %, Fig. A5) aligns with the cover range that undergoes the greatest correction (Fig. 4, Fig. A5) in the other clumping and overlap scenarios.

'Open shrublands' only show a small underestimation of tree cover, despite its woody cover definition (10 - 60 %) matching the range where MODIS VCF most underestimates tree cover (26 - 67 % cover). The discrepancy may be because the majority of the 'open shrublands' class commission error is with the 'grasslands' class (see Table S6 in Sulla-Menashe et al., 2019). The MODIS VCF tree cover in areas classified as 'open shrublands' is therefore likely to be lower than the IGBP definition would suggest (see Fig. A5), resulting in corrections that are more conservative.

We found significant increases in tree cover for 'forests' in every correction scenario, though net change is only significant (95 % confidence) when overlap is unenforced. This can be explained by the presence of both negative and positive corrections in the higher ranges of tree cover when overlap is enforced. Similarly, the net change is insignificant across all clumping and overlap scenarios for the IGBP classes matching the lower ranges of tree cover (grassland, close shrubland and open shrubland).

4 Discussion

While MODIS VCF is a powerful and accessible tool to map tree cover, our field data-based corrections indicate that the latest MODIS VCF collection 6 is missing a lot of woody cover even when uncertainty introduced by site canopy overlap and clumping within the MODIS VCF pixel are accounted for. Our maps (Fig. 2) highlight that this potential underestimation of woody cover is mainly occurring in tropical savannas. Moreover, the highest underestimation in the savanna classes occurs when there is no enforced overlap (i.e., when there is a uniform random distribution of trees) which is the most likely scenario for the TROBIT savanna plots as evidenced by work done by Veenendaal et al. (2015), where plots were tested for complete spatial randomness and only minor indications of overlap were found. Woody savannas, as an example, may have their tree cover underestimated by up to 32 % (95 % confidence) when neither clumping nor overlap is enforced (in black, Fig. 3). If our results are representative of the tropics, then overall, MODIS VCF may be underestimating tropical tree cover by between 7 - 29 % for unenforced clumping and overlap or 0 - 21 % for when either clumping or overlap are enforced (5 - 95 % confidence).

An overestimation at the lower end of the cover (< 20 %) (Hansen et al., 2002; Sexton et al., 2013) and underestimation in the lower to middle range of cover (20 % - 60 %) have been identified in validations of previous MODIS VCF collections (Gross et al., 2018; Yang and Crews, 2019). According to its definition, MODIS VCF only maps trees that are 5 m or taller (Hansen et al. 2003), while the TROBIT CAI includes all trees with a minimum dbh of 2.5 cm, as well as trees with a height exceeding 1.5 m when dbh < 2.5 cm. This could explain the observed underestimation in the lower tree cover ranges. However, because of how our field reference CAI is derived, we were not able to conclusively link the 5 m threshold to our observed underestimation.

On the other hand, when looking at the relationship between TROBIT's upper stratum canopy height and the difference between TROBIT and MODIS VCF we would have expected an increasing underestimation in the lower height ranges. Instead, we found a low R^2 and a mixture of under and overestimations in heights between 0 and 10 m (Fig. A6). This suggests that the inclusion of trees below 5 m height in the TROBIT inventory does not fully explain the observed underestimation. However, as the relationship between upper canopy heights and the subordinate strata composition (and canopy cover thereof) varies widely depending on factors including ecosystem type and altitude (Rutten et al., 2015), more research needs to be done with more in-situ height data.

We also found discrepancies between the tree cover values derived from MODIS VCF and the corresponding class definition of the MCD12Q1 product (Fig. A5), which again suggests that the 5 m

height threshold may not always apply in MODIS VCF. For example, MODIS VCF recorded tree cover in the 'open shrublands' and 'closed shrublands' classes of the MCD12Q1 product (Fig. A5), even though the height range for these classes is 1 - 2 m. For the 'savannas' class, MODIS VCF yields a percent tree cover range that matches closely with the 'savannas' class definition (between 10 % and 30 %), despite the differing tree thresholds for MODIS VCF and IGBP (5 m minimum for MODIS VCF, and 2 m minimum for IGBP). These discrepancies suggest one of the following three things: 'open/closed shrublands' and 'savannas' contain trees taller than 5 m; MODIS VCF is distinguishing trees below the 5 m threshold; or some combination of both.

Another explanation for the discrepancy between the IGBP class definitions and those estimated through MODIS VCF could be the between-class omission and commission errors (Fig. 4, and Table S6 in Sulla-Menashe et al., 2019). For example, the accuracy for 'closed shrublands' is particularly low. It is mainly confused with 'open shrublands,' 'woody savannas,' and 'savannas.' The majority of the 'open shrublands' class commission error is with the 'grasslands' class, and there is confusion to a lesser extent between 'open shrubland,' 'woody savannas' and 'savannas.' Also, the 'cropland/natural vegetation mosaics' class is often mapped as 'closed shrubland,' 'woody savannas,' 'savannas' or 'grasslands.'

More work needs to be done to evaluate how effective both MODIS VCF and MCD12Q1 are at implementing the height thresholds in their respective 'tree' definitions, as this may have implications when MODIS VCF and MCD12Q1 are used for global model calibration or validation.

Overall, our results suggest that the biases found in the previous collections may have persisted in collection 6, despite reported improvement in accuracy (DiMiceli et al., 2017). This indicates that the biases introduced by binning the training data (Gerard et al. 2017) and using a CART (Classification and Regression Tree) model (Hanan et al., 2013) are inherent and still present within this version of MODIS VCF. Models calibrated using MODIS VCF (Brandt et al., 2017; Lasslop et al., 2020; Burton et al., 2019; Kelley et al., 2019, 2020) risk inheriting these biases and should therefore be validated using other sources of data. We suggest that while MODIS VCF gives a good overview of tree cover on a global scale, it should be re-calibrated before it is used as a reference or training data. Special care should be taken in savannas, a biome that has long been noted as being challenging for EO products to characterise, as solitary trees in the landscape tend to be missed by global tree cover products (Jung et al., 2006, Brandt et al., 2020). The poor performance of MODIS VCF in savannas in particular (Gaughan et al., 2013; Gross et al., 2018; Kumar et al., 2019) emphasises the importance of continuous independent validation and re-calibration of the product. The ecosystem functions of savannas can vary drastically with just a slight difference in tree cover (Gaughan et al., 2013) and even slight errors may create issues in how we interpret the state and dynamics of the biome, which in turn affects how the land is managed.

Work on forest restoration potential would also be impacted. Bastin et al. (2019), for example, used MODIS VCF to estimate tree cover in agricultural land. As this tree cover is likely to have been underestimated substantially, the derived available land space for replanting may be less than projected, with the restoration potential overestimated. However, our results also indicate an underestimated tree cover in woodier savannas and forests. Accounting for this, the restoration potential could actually be greater than anticipated, as the carrying capacity of a unit of land may be greater than previously thought. The MODIS VCF correction could also result in a more uniform cover distribution across regions, producing a more gradual transition between low-cover savannas and high-cover forests. This could have implications for work that, for example, uses MODIS VCF to study forest-savanna dynamics and bi-stability (Lasslop et al., 2018; Wuyts et al., 2017; Xu et al., 2016).

To ensure the appropriate use of the product, we suggest that where field data are available, the MODIS VCF product should be calibrated for use in the target region. However, calibrating MODIS VCF on a large scale using field data as a reference do present several challenges. Firstly, different in-situ measurement techniques tend to measure different types of tree cover (e.g., Fiala et al., 2006; Korhonen et al., 2006; Rautiainen et al., 2005) and each will require a conversion to enable direct comparison with MODIS VCF. In our case, to account for gaps between tree crowns, we applied the 0.8 'gap correction factor' to the CAI. However, the GCF and resulting tree cover could vary widely on a plot-by-plot basis (Lloyd et al., 2008). With further in-situ data that describe tropical vegetation type-specific GCF variation, we may be able to incorporate site-specific GCFs into our analysis.

There is also the uncertainty associated with the field data collection. In our case, the site-specific CAI standard errors (supplement B in Torello-Raventos et al., 2013) are small and show no systematic bias and are therefore not expected to significantly change our results. Using field plots over a limited geographic extent creates additional uncertainty that may still be unaccounted for in our analysis
435 when calibration is applied across the highly variable tropical forest-savanna ecotone. The bottom map in Fig. A7 combines our uncertainty maps (Fig. 2) with a map plotting the distance of a point from the sampled TROBIT plots, and highlights Southeast Asia, Central America, and Mexico as areas where additional in-situ observations would greatly help improve confidence. Field data from the north-western region of South America, the southeast of the African continent, and Madagascar would also help.
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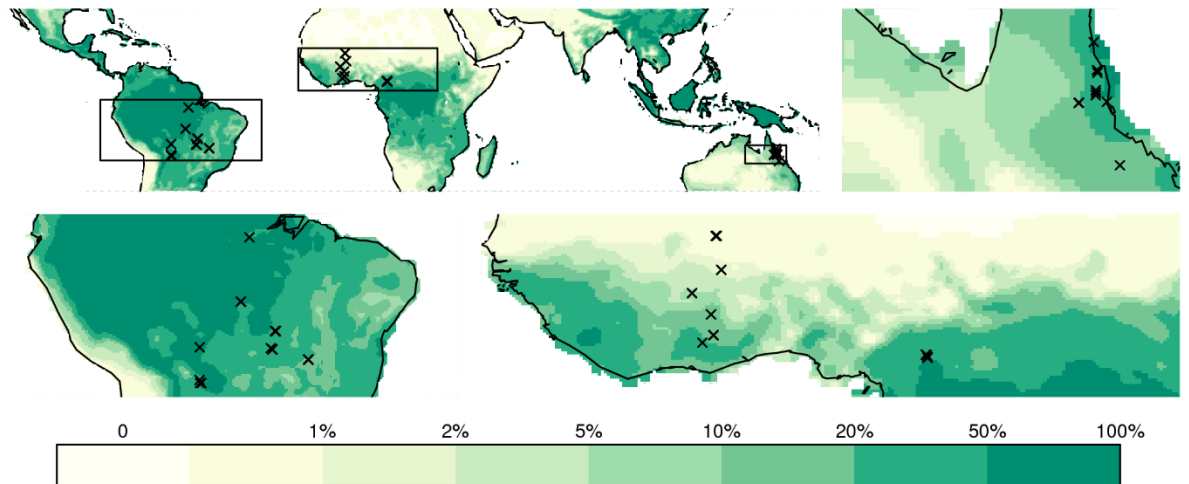
Finally, factors such as cloud cover, landscape heterogeneity, phenology, vegetation type, and soil type affect the accuracy of remotely-sensed products like MODIS VCF (Hansen et al., 2003; Huete et al., 1997; Smith et al., 2002). Data characterising these at the plot level would help identify potential confounding factors affecting MODIS VCF performance, and so help further constrain uncertainties.

445 Alternatively, comparing MODIS VCF to other land cover maps or higher-resolution remotely sensed data are recommended (Gross et al., 2018; Lary and Lait, 2006), though without a large-scale effort to re-calibrate MODIS VCF, the question of how appropriate MODIS VCF is for use in both forests and savannas in the tropics will remain. By highlighting the extent to which MODIS VCF struggles to estimate tree cover in tropical forests and savannas, we hope to inform the future use of this product
450 to improve its useability.

5 Conclusion

We found that MODIS VCF significantly underestimates tree cover in tropical forests and savannas, even when within-field site and field site-pixel variation are accounted for during validation. As MODIS VCF is a product that is commonly used in a wide variety of ecological research including vegetation
455 modelling, estimating restoration potential, and identifying forest-savanna bimodality, we stress that more independent work on validating and re-calibrating is required before its tree cover estimates can be relied upon in the tropics.

Appendix



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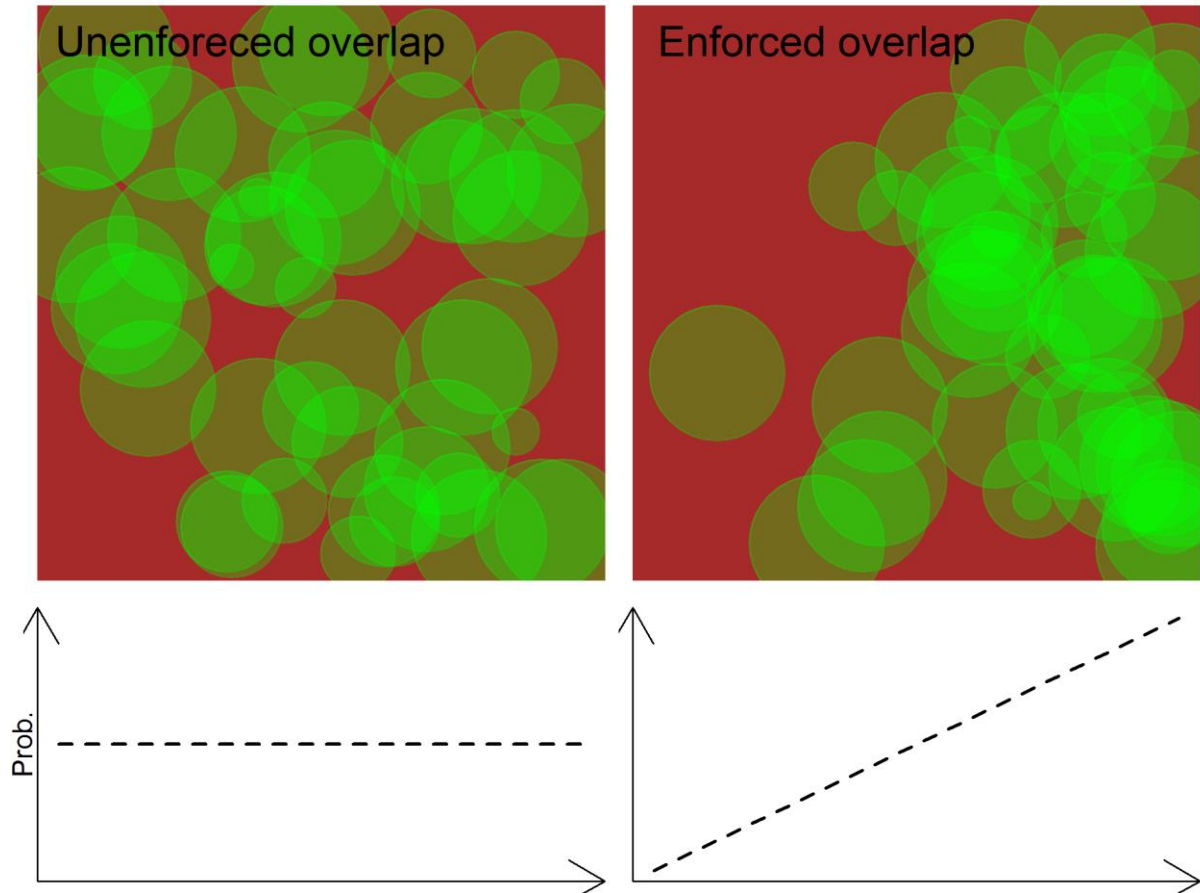
Figure A1. Location of sampling sites in Africa, Australia, and South America from the TROBIT Project (based on Fig. 2, Torello-Raventos et al., 2013) shown on MODIS VCF (DiMiceli, 2017). Of the 63 field sites, only the 48 sites with available GPS coordinates were selected.

Site Name	Country	Latitude	Longitude	MODIS VCF Tree Cover (%)	Canopy Area Index	Average Upper Stratum Height (m)	Cover Type	TROBIT Site Description
ALC-01	Brazil	-2.53	-54.91	12.5	0.32	6.56	Savanna	Savanna woodland
ALF-01	Brazil	-9.6	-55.94	77	2.31	37.02	Forest	Tall forest
ALF-02	Brazil	-9.58	-55.92	76	2.65	41.32	Forest	Tall forest
ASU-01	Ghana	7.14	-2.45	41.33	2.54	45.27	Forest	Tall forest
BBI-01	Burkina Faso	12.73	-1.17	1.33	0.52	12.53	Savanna	Savanna woodland
BBI-02	Burkina Faso	12.73	-1.16	1.5	0.99	13.6	Savanna	Savanna woodland
BDA-01	Burkina Faso	10.94	-3.15	6.17	0.3	14.53	Savanna	Shrub-rich savanna woodland
BDA-02	Burkina Faso	10.94	-3.15	4.5	0.18	14.47	Savanna	Shrub-rich savanna woodland
BFI-01	Ghana	7.71	-1.69	15	1.22	29.67	Savanna	Tall closed woodland
BFI-02	Ghana	7.71	-1.69	12.83	1.08	28.2	Savanna	Tall savanna woodland
BFI-03	Ghana	7.71	-1.7	25.83	2.54	45.07	Savanna	Tall savanna woodland
CTC-01	Australia	-16.1	145.45	72.67	2.35	40.37	Forest	Tall forest
DCR-01	Australia	-17.02	145.58	21.67	1.67	27.19	Savanna	Tall savanna woodland
DCR-02	Australia	-17.03	145.6	65.67	0.71	22.51	Savanna	Tall savanna woodland
EKP-01	Australia	-18.07	145.99	43.5	0.74	28.13	Savanna	Tall savanna woodland

FLO-01	Brazil	-12.81	-51.85	65.67	2.4	28.21	Forest	Forest
FMS-01	Australia	-18.09	144.84	7.67	0.32	20.03	Savanna	Shrub-rich savanna woodland
FMS-02	Australia	-18.11	144.82	44.17	1.21	16.69	Forest	Stunted shrub-rich forest
HOM-01	Mali	15.34	-1.47	0.5	0.05	3.87	Savanna	Savanna grassland
HOM-02	Mali	15.33	-1.55	0.83	0.16	6.13	Savanna	Savanna grassland
IBG-01	Brazil	-15.95	-47.87	20.83	0.22	7.48	Savanna	Scrub savanna
IBG-02	Brazil	-15.95	-47.87	20	0.02	6.29	Savanna	Scrub savanna
IBG-03	Brazil	-15.93	-47.87	20.5	0.12	8.01	Savanna	Scrub savanna
IBG-04	Brazil	-15.94	-47.86	27.17	0.77	12.65	Savanna	Savanna woodland
KBL-01	Australia	-17.77	145.54	75	1.69	39.5	Forest	Tall forest
KBL-02	Australia	-17.85	145.53	61.17	0.81	29.2	Savanna	Tall savanna woodland
KBL-03	Australia	-17.69	145.53	79.5	3	36.62	Forest	Tall forest
KCR-01	Australia	-17.11	145.6	78.83	2.44	42.37	Forest	Tall forest
LFB-03	Bolivia	-14.6	-60.85	28.17	0.39	9.93	Savanna	Shrub-rich savanna woodland
MDJ-01	Cameroon	6.17	12.83	42	3.24	45	Forest	Tall forest
MDJ-02	Cameroon	6.16	12.82	18.67	0.44	16.13	Savanna	Long-grass savanna
MDJ-03	Cameroon	5.98	12.87	64.67	2.97	36.53	Forest	Stunted shrub-rich forest
MDJ-04	Cameroon	6	12.87	15	0.37	18.93	Savanna	Long-grass savanna
MDJ-05	Cameroon	5.98	12.87	70.33	2.85	21.27	Forest	Stunted shrub-rich forest
MDJ-06	Cameroon	6	12.89	20.5	0.68	15.27	Savanna	Long-grass savanna
MDJ-07	Cameroon	6.01	12.89	57.33	1.75	42.67	Forest	Tall forest
MDJ-08	Cameroon	6.21	12.75	15	0.48	18	Savanna	Long-grass savanna
MLE-01	Ghana	9.3	-1.86	10	0.34	14.67	Savanna	Savanna woodland
NXV-02	Brazil	-14.7	-52.35	20.83	1.82	15.76	Savanna	Tall closed woodland
RSC-01	Australia	-20.16	146.54	28	1.15	13.14	Forest	Stunted forest
SMT-01	Brazil	-12.82	-51.77	36.67	1.55	14.37	Savanna	Savanna woodland
SMT-02	Brazil	-12.82	-51.77	41.5	1.44	14.64	Savanna	Savanna woodland
SMT-03	Brazil	-12.83	-51.77	19.33	0.53	11.19	Savanna	Savanna woodland
TUC-01	Bolivia	-18.52	-60.81	50.33	1.29	14.9	Forest	Stunted forest
TUC-02	Bolivia	-18.53	-60.63	21.67	0.81	12.05	Savanna	Shrub-rich woodland
TUC-03	Bolivia	-18.19	-60.86	10.83	0.37	14.11	Savanna	Savanna woodland
VCR-01	Brazil	-14.83	-52.16	69.5	2.81	28.94	Forest	Tall forest
VCR-02	Brazil	-14.83	-52.17	69.67	2.74	30.93	Forest	Forest

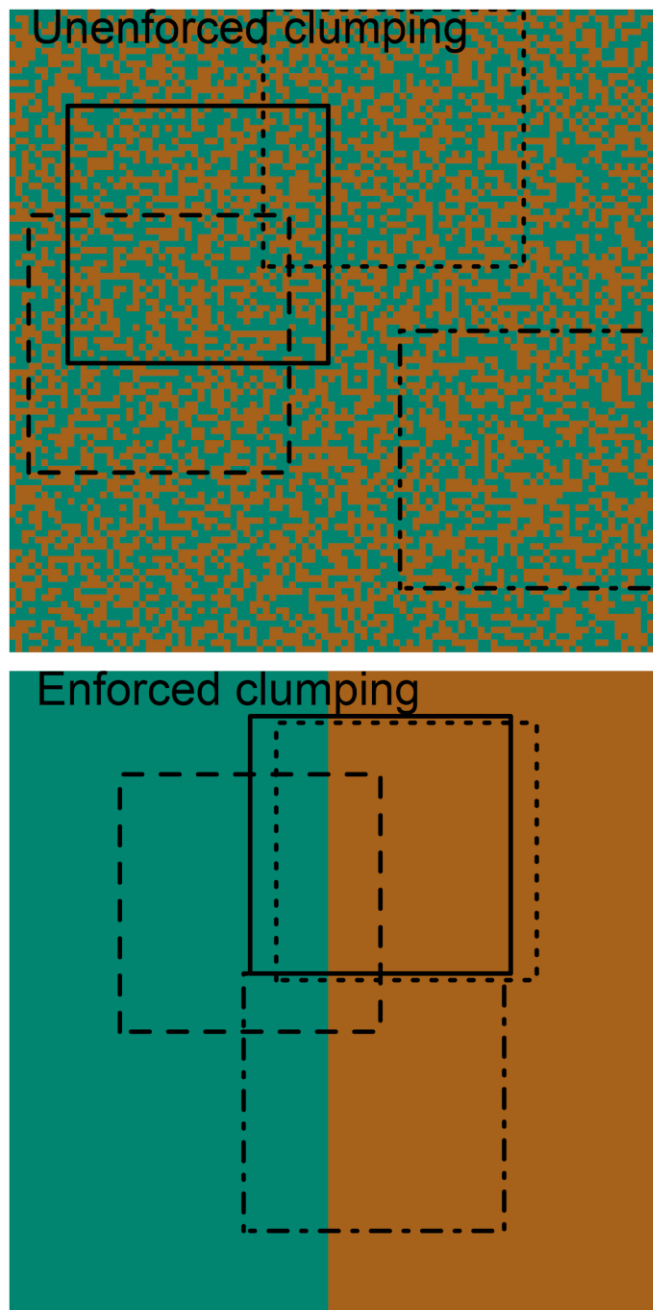
Table A1. Site names, locations, Canopy Area Index values, MODIS VCF percent tree cover values, cover type, and TROBIT site descriptions of the 48 TROBIT Project plots used in this study. TROBIT site descriptions are based on Table S1 of Veenendaal et al., 2015.

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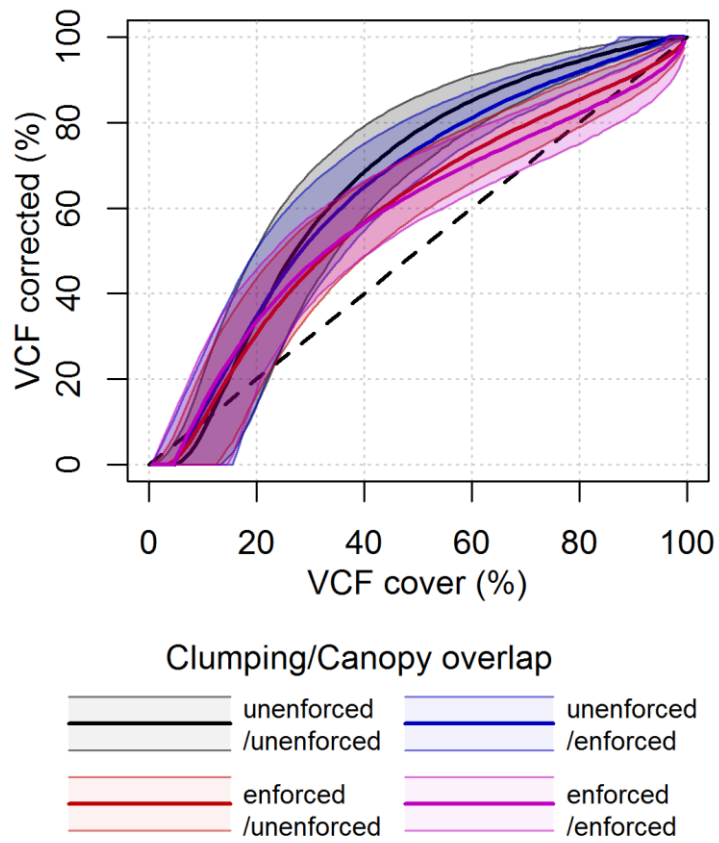


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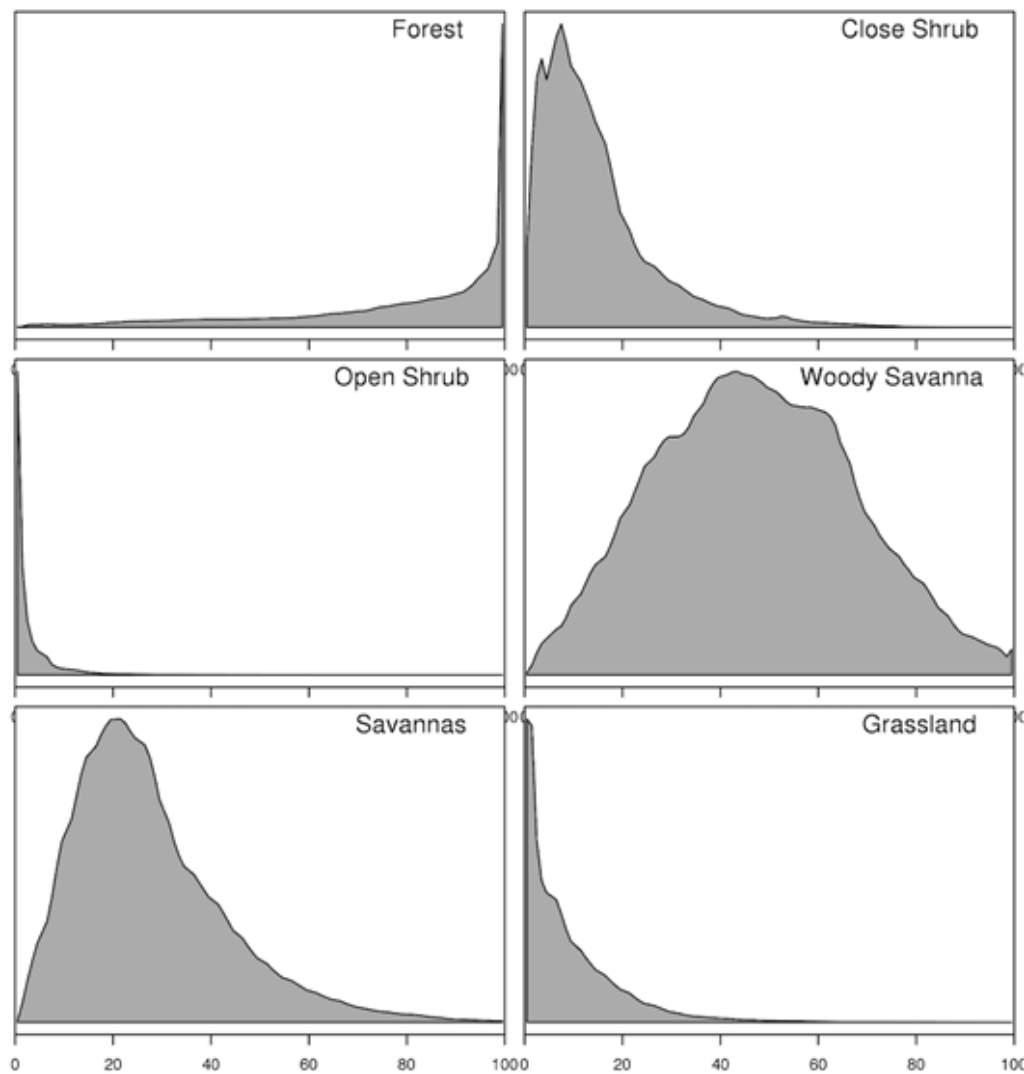
Figure A2. Visual representation of the effects of enforcing overlap within a (100 m x 100 m) TROBIT site with a given Canopy Area Index (CAI). Left: Overlap is not enforced, and individual crowns follow a uniform random distribution. Right: Overlap is enforced by linearly increasing the probability of a canopy being located more on one side of the site (i.e., illustrated here as the right side of the site) than the other. This results in tree canopies 'overlapping' to a greater extent, which affects how accurately CAI represents actual canopy cover.



480 **Figure A3.** Visual representation of the effects of unenforced and enforced clumping in a 250 m x 250 m MODIS VCF pixel with 50 % tree cover. Clumping all the cover to one side of the pixel (bottom) affects the average canopy cover value of a 100 m x 100 m-sized average TROBIT site, illustrated here as the black boxes.

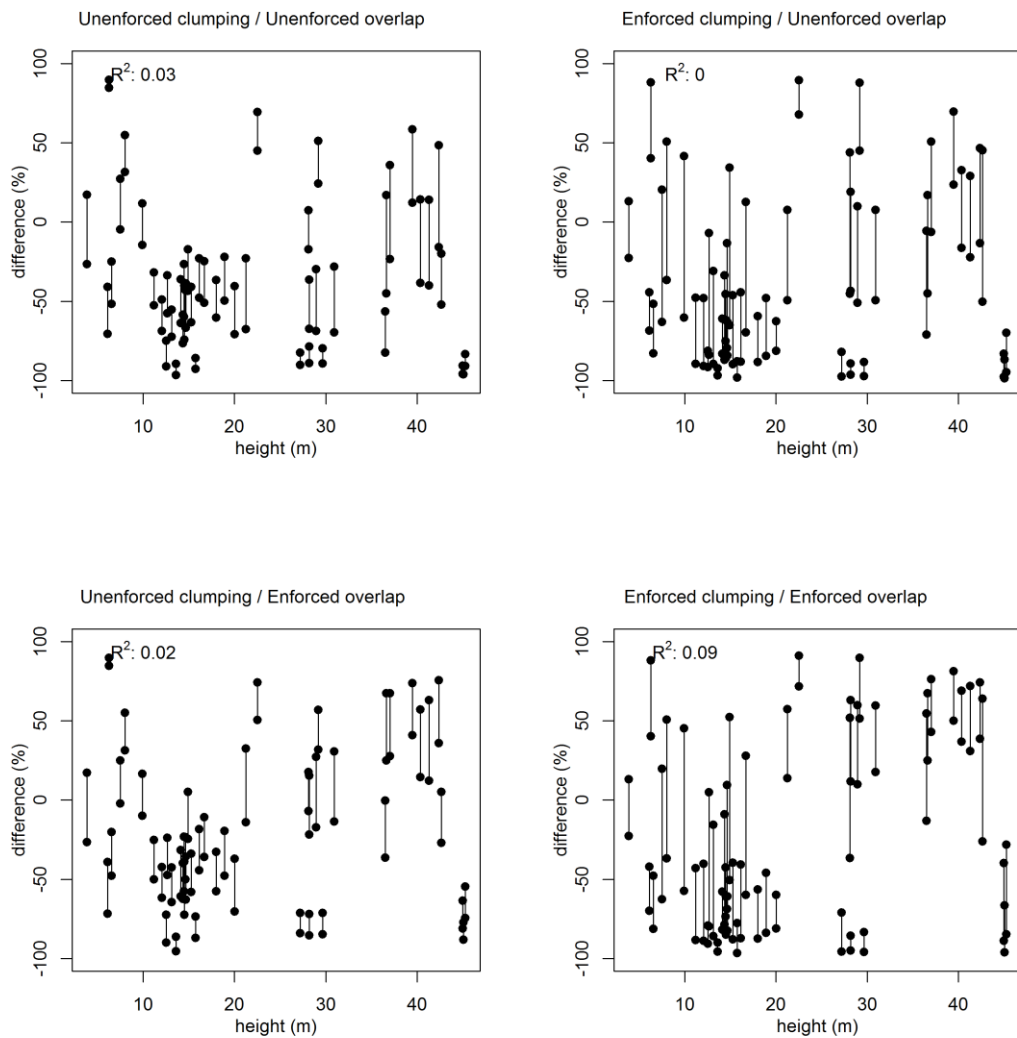


485 **Figure A4.** The correction curves developed for MODIS VCF based on the 4 pixel-site mismatch scenarios (no clumping and no overlap; enforced clumping no overlap; no clumping enforced overlap; and enforced clumping and enforced overlap). The dashed line signifies the 'ideal' 1:1 relationship wherein corrected MODIS VCF is unchanged from the original MODIS VCF values. The shaded regions represent 5 to 95 % confidence intervals for the respective corrected MODIS VCF values.



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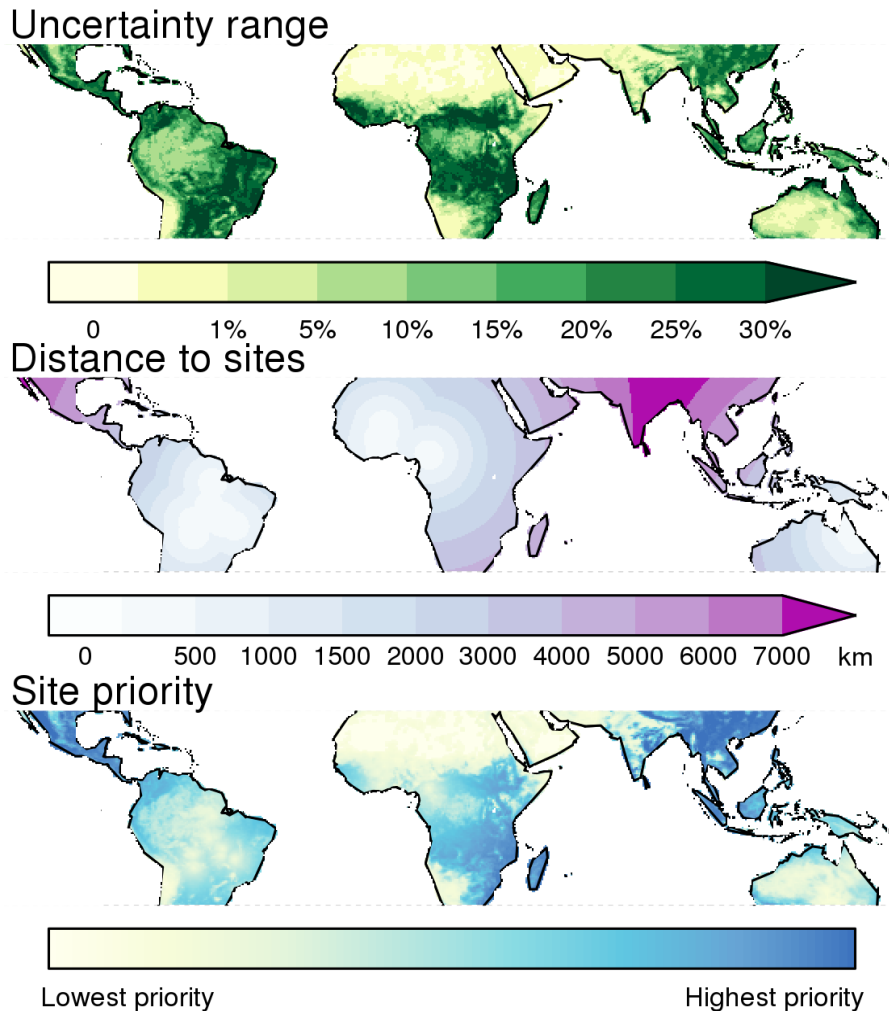
Figure A5. Frequency distributions of percent tree cover value as estimated by MODIS VCF across the ‘forest’ supercategory and the following IGBP classes that by our definition count as part of the ‘savanna’ domain: Closed Shrublands, Open Shrublands, Woody Savannas, Savannas, and Grasslands. Specific class definitions as per the User Guide for the MODIS Land Cover Product (Sulla-Menashe and Friedl, 2018).



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Figure A6: TROBIT plot upper stratum height versus the difference between MODIS VCF and TROBIT percent tree cover in the four clumping-overlap scenarios. Upper and lower bars represent the uncertainty range's 10th and 90th percentile, respectively, based on the convolution of MODIS VCF and TROBIT cover uncertainties from Fig. 1.



505 **Figure A7.** (Top) Uncertainty range of potential MODIS VCF mismatch, calculated as the 90th percentile (the highest value out of the four scenarios in Fig. 2) minus 10th percentile (the lowest value out of the four scenarios in Fig. 2). (Middle) Geographic distance to the closest TROBIT site sampled. (Bottom). Regions coloured to denote priority for field surveying to constrain map uncertainty, based on multiplying the (Top) and (Middle) maps.

Code/Data Availability.

The code and data used to support the findings of this study are archived at https://github.com/douglask3/VCF_vs_sites revision number [fdda3ff](#)

510 **Author Contribution.**

515 RA, DK, FG designed the TROBIT, MODIS VCF pixel-site comparison technique. RA, FG collated TROBIT and corresponding MODIS VCF values. DK and ND performed regression analysis and constructed global maps. RA wrote the first draft of the paper with input from DK and FG DK plotted the figures. MTR, EV, TRF, OLP, SL, BS, HT..., BSM, TD, LA, GD, and JK carried out the extensive TROBIT field campaigns. M.T.R. was the main person responsible for field data quality checking and digitising. RA, DK, FG and ND contributed to the final manuscript.

Competing Interests.

The authors declare that they have no conflict of interest.

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525 Maps in Fig. 2 and A1 were constructed using raster2.6-7 (Hijmans, 2017) and mapproj1.2-5
(Brownrigg et al., 2017) in R 3.2.0 (R Core Team, 2015). Coastlines were obtained from mapsv3.1.0
(Becker et al., 2016).

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