

Responses to the Comments and Suggestions of Referee #1

We appreciate the time and effort by the referee #1 to review this manuscript. Your constructive and insightful comments and suggestions will help us to improve the manuscript. To help you to see the revision in the manuscript, we included all your comments and suggestions at the corresponding locations in the revised manuscript and labeled all the changes using the tracking change mode. Our point-to-point response to your comments and suggestions are listed below.

Referee #1' Comments to Author:

This manuscript presents annual 30 m forest cover maps of Africa from 2015 to 2023 derived from PALSAR-2 backscatter and Landsat NDVI, and evaluates four satellite forest products against GEDI canopy height and cover under the FAO forest definition. The topic is well suited to ESSD, the continental coverage and nine year time series are valuable, the data and code are openly archived, and the use of a very large GEDI sample to build complete confusion matrices is a meaningful improvement over previous one sided assessments. However, several issues concerning the independence of the reference data, the internal consistency of the accuracy table, the validity of the time series, and the fairness of the product comparison need to be resolved before the accuracy claims can be regarded as robust. Overall, I have to recommend a reject.

Response: We appreciate your positive comments on the datasets and the use of a large number of GEDI samples for accuracy assessment. We will address your concerns in the text below.

1. Lines 227 to 230, 380 to 387: JRC GFC2020 v2 incorporates the GEDI and Landsat derived global canopy height layer among its inputs. Evaluating it against GEDI canopy height therefore does not constitute an independent assessment, and its leading overall

accuracy may partly reflect shared input data. This dependency should be stated and its effect on the ranking of products discussed.

Response: We appreciate the reviewer's comment on the JRC GFC dataset. We agree that the assessment of JRC GFC using GEDI-derived canopy height cannot be considered fully independent because a GEDI and Landsat-derived global canopy height layer was used as one of the inputs to JRC GFC. We further examined the nature and potential extent of this dependency from four perspectives.

First, according to the JRC GFC methodology (Bourgoin et al., 2025a), the global canopy height layer was not used in the initial integration of tree cover datasets that defines the maximum potential forest extent. Instead, the global canopy height layer was subsequently applied in Step 2 as one of several exclusion masks to remove tree areas with top canopy heights below 5 m. Importantly, this height-based exclusion was not applied to tropical moist forests identified by JRC-TMF, including undisturbed, degraded, regrowth, and mangrove areas. We therefore quantified the spatial overlap between JRC GFC forest (Fig. 1a) and the JRC-TMF extent (Fig. 1b) within Africa to evaluate the proportion of mapped forest for which the canopy-height exclusion was not applied. We aggregated the 10 m JRC GFC into 30 m to match JRC TMF data and found that approximately 31 % (the pink areas in Fig. 1c) of JRC GFC coverage overlaps with the JRC TMF data. The 31 % was not affected by the global canopy height layer and was independently evaluated using GEDI data.

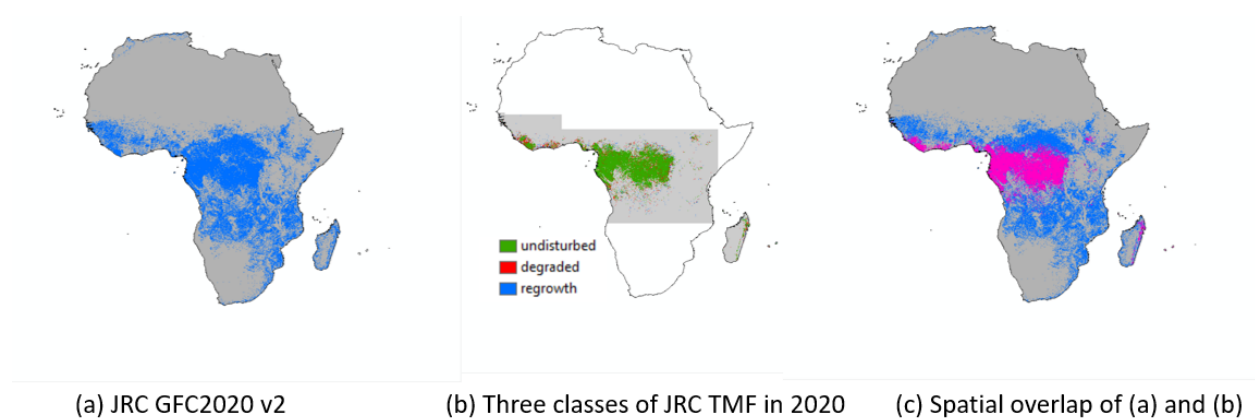


Fig. 1. Spatial overlap analysis of JRC GFC and JRC TMF.

Second, the original use of the 2019 global canopy height layer also had limitations in Africa (Potapov et al., 2021). The airborne LiDAR observations used by Potapov et al. (2021) were primarily collected over forests, while heterogeneous and treeless landscapes, including savannas and agroforestry systems, were not represented by airborne observations in Africa. Therefore, the performance of the canopy-height layer itself is less well constrained in these extent and heterogeneous African landscapes.

Third, the GEDI and Landsat datasets used to produce the global canopy height layer differ from those used in our study in both version and acquisition period. The global canopy height layer was developed using GEDI Version 1 observations acquired from April to October 2019 and Landsat Collection 1 Tier 1 data, whereas our accuracy assessment used GEDI Version 2 observations from 2020 and our OU GFC map used Landsat Collection 2 Level 2 Tier 1 data for 2020. Both GEDI Version 2 and Landsat Collection 2 include substantial processing improvements relative to the earlier versions. These differences reduce direct overlap between the observations used for the global canopy height layer development and those used in our assessment, although they do not eliminate the underlying data dependency.

Finally, there is also a temporal difference: the global canopy height layer represents 2019, whereas both JRC GFC and the GEDI-based accuracy assessment in this study represent 2020.

Taken together, these analyses indicate that shared data dependency does exist and may have contributed partly to the comparatively high agreement of JRC GFC with GEDI. We have therefore explicitly acknowledged this limitation and revised the section 4.1 of Discussion in the revised clean manuscript (Page 19, Lines 427–434).

“Among them, a GEDI- and Landsat-derived global canopy height layer was used as an exclusion mask to remove tree areas with canopy heights below 5 m in JRC GFC (Bourgoin et al., 2025b). This exclusion was not applied within JRC tropical moist forests (Vancutsem et al., 2021), which account for approximately 31 % of the JRC GFC forest extent in Africa based on our analysis . In addition, the canopy height layer was derived from GEDI version 1 measurements acquired in 2019, whereas our assessment used GEDI version 2 observations from 2020. Thus, although some shared-data

dependency exists and may partly contribute to the high agreement between JRC GFC and GEDI, differences in data version, image acquisition period, and processing limit the extent of this dependency.”

2. Lines 249 to 252, 293 to 296, Table 1: The number of footprints meeting the FAO definition and the number of footprints falling within the mapped forest class of PALSAR-2/Landsat are reported as identical, and the two figures are used interchangeably in the text describing Figure 2b. As presented, the row totals of the confusion matrix and the reference class totals cannot both be correct. Please verify the counts and clarify which quantity each column and row represents.

Response: We appreciate your comment and for pointing out the inconsistency. We carefully double-checked all sample counts and accuracy metrics and confirmed that the row totals, column totals, UA, PA, and OA values reported in the revised manuscript are correct. The inconsistency arose from two incorrect numbers reported in the 2.3.2 Accuracy assessment using GEDI footprints section.

Specifically, the correct number of GEDI footprints meeting the FAO forest biophysical (structural) metrics (tree height and canopy coverage) is 35,899,030, whereas 139,321,381 footprints do not meet these criteria. These values correspond to the column totals for the GEDI-Forest and GEDI-Non-Forest classes, respectively, in each confusion matrix in Table 2 (highlighted by the green and red boxes below). In contrast, the number of GEDI footprints falling within the forest class mapped by OU GFC is 35,280,105 (highlighted by the blue box below), which is the sum of GEDI-Forest and GEDI-Non-forest sample in the Forest class row in the OU GFC confusion matrix. Therefore, the GEDI-Forest class total (35,899,030) and the OU GFC mapped-forest total (35,280,105) represent two different quantities and should not have been used interchangeably.

We have revised the headings and notes of Table 2 to clarify the orientation and meaning of the confusion matrices. Specifically, the rows represent the forest and non-forest classes mapped by each product, whereas the columns represent the GEDI-

110 derived forest and non-forest classes based on the FAO forest definition. The row totals
111 indicate the numbers of GEDI footprints falling within each mapped class, whereas the
112 column totals indicate the numbers of GEDI footprints assigned to each GEDI reference
113 class. UA: Users' Accuracy; PA: Producers' Accuracy; OA: Overall Accuracy. UA is
114 calculated by mapped class (rows), PA by reference class (columns), and OA from the
115 correctly classified samples along the diagonal. The same set of 175,220,411 GEDI
116 footprints was used to evaluate all four satellite products.

Table 2: Accuracy assessment of multiple forest cover maps for 2020 using GEDI sample.

Forest cover data product	Mapped class	GEDI-Forest	GEDI-Non-forest	Row total	UA (%)
OU GFC	Forest	26,999,482	8,280,623	35,280,105	76.5
	Non-F	8,899,548	131,040,758	139,940,306	93.6
	Column total	35,899,030	139,321,381	175,220,411	–
	PA (%)	75.2	94.1	–	OA = 90.2
JAXA GFC	Forest	27,684,125	9,818,588	37,502,713	73.8
	Non-F	8,214,905	129,502,793	137,717,698	94.0
	Column total	35,899,030	139,321,381	175,220,411	–
	PA (%)	77.1	93.0	–	OA = 89.7
JRC GFC	Forest	25,986,789	6,031,512	32,018,301	81.2
	Non-F	9,912,241	133,289,869	143,202,110	93.1
	Column total	35,899,030	139,321,381	175,220,411	–
	PA (%)	72.4	95.7	–	OA = 90.9
UMD GFC(tree cover > 10 %)	Forest	26,691,125	12,105,633	38,796,758	68.8
	Non-F	9,207,905	127,215,748	136,423,653	93.3
	Column total	35,899,030	139,321,381	175,220,411	–
	PA (%)	74.4	91.3	–	OA = 87.8
UMD GFC (tree cover > 30 %)	Forest	17,397,232	2,827,885	20,225,117	86.0
	Non-F	18,501,798	136,493,496	154,995,294	88.0
	Column total	35,899,030	139,321,381	175,220,411	–
	PA (%)	48.5	98.0	–	OA = 87.8

Notes: Rows represent the mapped forest and non-forest classes of each forest cover data product, whereas columns represent the GEDI-derived forest and non-forest classes according to the FAO forest definition. Row totals indicate the number of GEDI footprints within each mapped class, and column totals indicate the number of GEDI footprints within each reference class. The same 175,220,411 GEDI footprints were used for all five forest cover datasets. UA: Users' Accuracy; PA: Producers' Accuracy; OA: Overall Accuracy. UA is calculated by mapped class (rows), PA by reference class (columns), and OA from the correctly classified samples along the diagonal.

3. Lines 253 to 261, 356 to 363: The dataset spans nine years, but the assessment uses GEDI data from 2020 alone. No evidence is provided that the earlier and later maps achieve comparable accuracy, yet interannual forest area values and pixel frequency statistics are reported and interpreted. Either extend the assessment to

additional years using available GEDI acquisitions, or state explicitly that the time series itself remains unvalidated.

Response: We appreciate your comments. We have added the analysis that uses GEDI footprint data from 2019,2021,2022, and 2023 to assess the accuracy for those respective years. That is, the OU GFC maps for 2019–2023 were assessed whereas the OU GFC maps for 2015–2018 were not assessed because no GEDI observations were available for those years. Table S1 lists the confusion matrices of OU GFC maps from 2019 to 2023 in the revised supplementary material.

Specifically, we made the following revisions in the revised clean manuscript:

(1) We revised the description of the GEDI data from 2019 to 2023 in Section 2.2.3 (Page 9, Lines 216–224):

“We used GEDI-derived canopy height and canopy cover as data sources for accuracy assessment. Specifically, we extracted rh98 (relative height metric at 98 %) from the version 2 of GEDI02_A product (Dubayah et al., 2021a) and total canopy cover from the version 2 of GEDI02_B product (Dubayah et al., 2021b) from 2019 to 2023 over Africa on GEE.”

“After quality control, the total number of high-quality GEDI footprints from 2019 to 2023 over Africa was 121×10^6 , 175×10^6 , 142×10^6 , 129×10^6 , and 39×10^6 , respectively”

(2) We revised the description of the method on accuracy assessment using GEDI footprints in Section of 2.3.2 (Page 12–13, Lines 285–293):

“Using the forest biophysical (structural) metrics in FAO forest definition, we first divided all high-quality GEDI footprints for each year into two subsets. The first subset satisfied both the canopy height (> 5 m) and canopy cover (> 10 %) thresholds, whereas the remaining footprints did not meet at least one of the two thresholds. We then overlaid the two annual GEDI-based datasets with the corresponding OU GFC maps for each year from 2019 to 2023 to generate annual confusion matrices and calculated overall accuracy (OA), user’s accuracy (UA), producer’s accuracy (PA), and Kappa coefficient. Taking 2020 as a representative year, we further overlaid the two GEDI-based datasets for 2020 with five satellite-based forest cover datasets over Africa for the same year

(binary forest/non-forest map; see Sect. 2.2.4). Confusion matrices were generated for each dataset, from which OA, UA, PA, and the Kappa coefficient were calculated.”

(3) We revised the description of the result of accuracy assessment in Section 3.2 (Page 14, Lines 317–319):

“We assessed the accuracy of OU GFC for 2019–2023 and other satellite-based forest cover datasets for 2020 using GEDI-derived canopy height and canopy coverage and the FAO forest stand definition. OU GFC showed consistently high and stable annual accuracy from 2019 to 2023, with OA of 89.8–91.0 % and Kappa coefficients of 0.66–0.70 (Table S1).”

(4) We revised the statement in Discussion 4.1 (Page 21, Lines 476–478):

“A limitation of this study is that the annual accuracy assessment of OU GFC data product was limited to 2019–2023. The OU GFC maps from 2015 to 2018 could not be evaluated because no GEDI observations were available for those years.”

(5) We added the statement in Section of Data availability (Page 25, Lines 563–565):

“The OU GFC datasets for Africa from 2019 to 2023 were assessed by using GEDI LiDAR footprints and FAO forest definition (forest stand metrics) and OU GFC datasets for 2015–2018 were not assessed due to GEDI data availability limitation.”

4. Lines 165 to 178, 356 to 358: The manuscript documents substantial year to year shifts in PALSAR-2 acquisition months and in Landsat good observation counts across regions. Because the decision rules use fixed backscatter and NDVI thresholds, these shifts can produce apparent forest gain or loss, particularly in seasonally dry savanna. The reported annual area range should be evaluated against this source of variability before it is presented as a change signal.

Response: We appreciate your comments on image acquisition dates and vegetation conditions. We agree that interannual differences in PALSAR-2 acquisition month and number of Landsat Gobs availability may introduce uncertainty into annual forest mapping. We have therefore further evaluated these potential sources of variability.

For PALSAR-2, acquisition months vary among years and regions. As described in the methodology, L-band PALSAR-2 backscatter signal is primarily sensitive to forest wood components (trunk and branches). These structural components generally exhibit much smaller seasonal variation than canopy greenness or leaf area index in the absence of substantial disturbance. Therefore, differences in acquisition months of PALSAR-2 images are expected to have a smaller influence on forest/non-forest classification than seasonal variations in optical vegetation indices.

For Landsat, the number of good-quality observations (G_{ob}) shows substantial spatial variation across Africa, largely because of persistent cloud contamination in some regions. However, the interannual variation in G_{ob} within the same regions is relatively limited, as shown by the spatial patterns in Fig. S4 and the annual G_{ob} statistics in Fig. 2. Nevertheless, limited G_{ob} can affect the annual $NDVI_{max}$ metric used in our study. $NDVI_{max}$ is intended to capture the maximum canopy greenness and leaf area index during the growing season each year. When sufficient observations are available, it is more likely to represent conditions close to peak greenness; when observations are sparse, however, the observed annual maximum may occur outside the actual seasonal peak, potentially causing some pixels to fall below the $NDVI_{max}$ threshold (0.7) and thereby introducing apparent interannual forest/non-forest transitions.

To further quantify this potential source of variability, we added and analyzed the spatial distribution and monthly occurrence frequency of Landsat-derived annual $NDVI_{max}$ in Africa from 2015 to 2023 (Fig. S7). The spatial patterns show clear regional seasonality, as expected from the diverse climatic regimes across Africa, but these broad spatial patterns remain generally consistent among years. At the continental scale, the monthly proportions of $NDVI_{max}$ occurrence also show relatively limited interannual variation. For example, $NDVI_{max}$ occurred in September for approximately 11–15 % of pixels and in August for approximately 10–13 % of pixels across individual years. Across all calendar months, the interannual standard deviation of the monthly occurrence proportions was only about 0.9–2.1 percentage points. These results indicate that, although the timing of maximum greenness varies substantially across space, its continent-scale interannual distribution is comparatively stable.

In addition, the temporal consistency checks in our methodology were specifically designed to reduce isolated year-to-year classification errors and noise associated with such observational limitations. Importantly, this post-processing modified only a relatively small fraction of the annual maps. The proportions of pixels corrected from NFN to NNN and from FNF to FFF in individual years ranged from 1.1–1.8 % and 1.9–2.4 %, respectively (please see the response for comment # 5 and table 1 in the manuscript). These results show that the consistency check does not broadly enforce temporal persistence across the maps but instead targets a limited subset of temporally inconsistent pixels. We agree that this check does not completely resolve all uncertainties associated with acquisition month and limited Landsat Gob, but it largely eliminates these classification errors and noise and provides additional evidence that the reported annual variations are not simply artifacts of widespread temporal smoothing or observation-date variability.

For the revisions, (1) we added the spatial distribution of the month in which annual maximum NDVI occurred in Africa from 2015 to 2023 (Fig. S7, Fig. 1) and corresponding interpretation in the manuscript (Page 7, Lines 194–199):

“We extracted the maximum NDVI value and derived the corresponding occurrence month of maximum NDVI for each pixel for each year from 2015 to 2023. The spatial patterns show pronounced regional seasonality, consistent with the diverse climatic regimes across Africa, yet remain broadly stable across years (Fig. S7). At the continental scale, the monthly distribution of maximum NDVI occurrence was relatively stable across years (Fig. 1f). For example, approximately 11–15 % of pixels reached NDVImax in September and 10–13 % in August in individual years. Across all calendar months, the interannual standard deviation of these monthly proportions was only approximately 0.9–2.1 %.”

(2) We revised the main text in Section 3.4 (Page 18, Lines 396–401):

“PALSAR-2 image acquisition months varied among years and regions, but the L-band backscatter signal is primarily sensitive to tree trunk and branches that have relatively small seasonal variation. Landsat Gob availability showed substantial spatial variation (Fig. S4), whereas its interannual variation within the same regions was relatively

limited, and the patterns of annual $NDVI_{max}$ occurrence remained generally consistent across years (Fig. S7, Fig. 2c). In addition, the temporal consistency checks were designed to reduce isolated year-to-year classification errors and noise associated with variations in acquisition timing and Gob availability.”

5. Lines 238 to 247: The three year window rule that rewrites improbable sequences alters the maps for 2016 to 2022 but is applied without justification of the assumption that single year transitions are implausible, and without any comparison of accuracy before and after correction. In regions with fire, shifting cultivation, or rapid regrowth, genuine single year changes will be removed. Please quantify how many pixels were altered and demonstrate that the procedure improves rather than degrades accuracy. The period given on line 244 also appears to be a typo?

Response: We agree that the rationale and purpose of the three-year temporal consistency check were not sufficiently explained in the original manuscript. We have therefore clarified the underlying assumption, quantified the changed pixels, and further evaluated the effect of this procedure.

First, we would like to clarify that the three-year moving window procedure does not assume that all single-year forest/non-forest transitions are implausible. Among the eight possible three-year F/NF sequences, the persistent states (NNN and FFF) and directional transitions (NNF, NFF, FFN, and FNN) remain unchanged. Thus, true forest gain or loss occurring between two consecutive years is retained in our annual maps. The procedure only modifies the two isolated temporal reversals, NFN→NNN and FNF→FFF, in which the class in the middle year differs from both the preceding and following years and immediately reverses one year later.

The rationale for treating these two sequences differently is based on both the biological characteristics of forest dynamics and the purpose of the temporal consistency check. In this study, forest cover maps are evaluated using forest biophysical (structural) metrics associated with the FAO forest definition (a tree height of > 5 m and canopy cover of > 10 %). Although vegetation canopy greenness can recover rapidly after

disturbance, one cannot assume that rapid vegetation canopy greenness regrowth is equivalent to the rapid recovery of forest structure (branches, trunks, height). In general, newly regenerating woody vegetation would not grow from a non-forest condition to trees > 5 m tall with sufficient green canopy within only one year and then disappear again in the following year (NFN). Similarly, following a disturbance that genuinely converts a forest pixel to non-forest, it is highly unlikely for the forest structure to be completely re-established within the following year (FNF). Therefore, complete F/NF reversals over 3-year period are biologically highly improbable at the annual and 30-m mapping scale.

This distinction is also important for the examples mentioned by the reviewer. Fire can cause a rapid change in canopy greenness, leaf area, or spectral characteristics without necessarily changing the underlying forest status. In such cases, a temporarily detected non-forest state between two forest years is more likely to represent disturbance-related spectral variability or classification noise rather than a true forest→non-forest→forest land-cover transition. For severe fires that genuinely cause forest loss, recovery of vegetation may begin rapidly, but recovery to a forest structure represented by trees >5 m tall and sufficient canopy cover generally requires more than one year. Likewise, shifting cultivation can cause true forest loss followed by forest regeneration, but such regeneration is normally a multi-year process rather than a complete F→N→F transition within two consecutive annual intervals. Importantly, these genuine directional changes are not removed by our procedure: sequences such as FFN, FNN, NNF, and NFF remain unchanged.

We therefore emphasize that the three-year temporal consistency check is not intended to suppress true forest disturbances or to serve as a forest-change detection algorithm. Rather, it is a post-classification quality-control procedure designed specifically to reduce isolated annual classification errors and image noise in independently generated annual F/NF maps. Similar temporal-context approaches have been widely used in annual land-cover and forest mapping (Li et al., 2015; Yuan et al., 2005). Previous forest mapping studies have specifically applied the same or similar temporal

consistency rules to isolated F/NF states to reduce noise and misclassification (Chen et al., 2016; Qin et al., 2024, 2017, 2016; Wang et al., 2024).

Second, following the referee's suggestion, we quantified the altered pixels of the temporal consistency check procedure. We added a new table below summarized the pixel counts of corrections for OU GFC maps in 2015–2023. The total number of 30-m pixel of Africa in the WGS84 coordinate system: 35.2×10^9 . The proportion of modified pixels for NFN-to-NNN and FNF-to-FFF in individual years ranged from 1.1 % to 1.8 % and 1.9 % to 2.4 %, respectively. These results demonstrate that the consistency filter affects only a small fraction of the annual maps rather than broadly enforcing temporal persistence.

Third, we agree that the effectiveness of the procedure should be demonstrated rather than assumed. We use the GEDI canopy height and cover sample within the pixels modified by the temporal consistency correction to evaluate the corrected and original 2020 OU GFC map (please see the table below). In the regions of NFN→NNN, GEDI-Non-forest sample account for 72.4 % of the total, whereas GEDI-Forest sample account for 27.6 %. In the regions of FNF→FFF, the GEDI-Forest sample account for 68.2 % of the total, whereas GEDI-Non-forest sample account for 31.8. This comparison demonstrate that the temporal correction procedure improves the classification accuracy.

Table. Number of GEDI-based sample within pixels modified by the temporal consistency correction in 2020

Temporal correction	GEDI-based class	GEDI sample number	Percentage (%)	Interpretation
NFN → NNN	GEDI-Forest	510,696	27.6	Degraded
	GEDI-Non-forest	1,342,319	72.4	Improved
	total	1,853,015	100.0	
FNF → FFF	GEDI-Forest	1,670,917	68.2	Improved
	GEDI-Non-forest	780,843	31.8	Degraded
	total	2,451,760	100.0	

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320 For the revisions in the revised manuscript,

321 (1) We revised Section 2.3.2 to strengthen description temporal and consistency check
322 (Pages 11–12, Lines 263–279).

323 (2) We added table 1 to list the Pixel counts of N-F-N-to-N-N-N and F-N-F-to-F-F-F
324 corrections for OU GFC maps in 2015–2023.

325 (3) We revised the period typo.

326

327 6. Lines 222 to 226, 288 to 292, 477 to 480: Tree canopy cover exceeding ten percent is
328 not a forest map under the FAO definition, since it excludes no height criterion, no
329 minimum mapping unit, and no land use requirement. Reporting its low accuracy
330 alongside the other products invites the reader to interpret a definitional mismatch as a
331 mapping error. The alternative threshold tested in the Discussion should be integrated
332 into the main comparison, and the framing of this product adjusted accordingly.

333 **Response:** We appreciate your comment. We agree that the UMD GFC tree cover
334 product should not be interpreted as a forest map strictly conforming to the FAO forest
335 definition because it is based primarily on tree canopy cover and does not explicitly
336 incorporate all FAO criteria, such as minimum mapping unit and land use requirements.
337 To avoid conflating definitional differences with mapping errors, we have revised the
338 framing of this product throughout the manuscript.

339 The 10 % threshold is consistent with the minimum canopy-cover threshold used in FAO
340 forest definition, and the 30 % threshold provides a more conservative representation of
341 relatively dense tree cover. We have incorporated both tree cover thresholds (> 10 %
342 and > 30 %) into the main comparison and accuracy assessment. Specifically, we
343 added the new figure 3 to show the spatial distribution of all satellite-based forest cover
344 datasets and revised Figure 5, 7, and 8. We also revised the description of UMD GFC
345 (tree cover > 10 %) and UMD (tree cover > 30 %) in the main text of Section 2.2.4 Other

forest products, 2.3.3 Comparison among multiple forest data products, 3 Result, 4 Discussion, and 5 Conclusion.

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