

Response to Editor and Referee Comments

Dear Editor and Referees,

We sincerely thank the Editor and the Referees for their careful evaluation of our manuscript and for their constructive and insightful comments. Below, we provide a point-by-point response to the Editor's and Referees' comments.

In the following responses, the *black italic text* represents the Editor's and Referees' comments, the *blue text* represents our replies, and the *red text* represents the corresponding revised content in the main text.

Response to the Editor's Comments

I thank both referees for their careful evaluations. The manuscript presents a pan-tropical monthly L-band vegetation optical depth product generated by downscaling SMOS L-VOD to a 5-km grid using ESA CCI aboveground biomass information. The dataset could be useful for vegetation monitoring and Earth-system research if its information content, uncertainty, validation, and intended interpretation are more rigorously established.

Referee 1 recommends major revision, while Referee 2 raises more fundamental concerns about the effective spatial information and independence of the validation. Despite their different recommendations, both reports identify important issues concerning methodological reproducibility, validation, interpretation of the 5-km product, and the strength of the conclusions.

*After considering both reports, my decision is **major revision**. I invite the authors to submit a substantially revised manuscript and a point-by-point response addressing both referee reports and the requirements below. For an ESSD data paper, the central question is not whether every component of the method is entirely new, but whether the dataset is useful, accessible, reproducible, scientifically reliable, and adequately characterized. The present dataset has potential value, but the manuscript does not yet sufficiently support several accuracy and spatial-resolution claims.*

We are immensely grateful for the Editor's encouragement and insightful suggestions, which proved invaluable in enhancing the quality of our manuscript. Detailed responses are provided below.

Comment 1. Clarify and document the downscaling algorithm

The gain calculation and iterative optimization must be described sufficiently for independent reproduction. The authors should:

- *explain how zero or near-zero low-pass AGB values are handled;*
- *define masking, denominator thresholds, clipping limits, and invalid-value procedures;*
- *clarify whether the optimized quantity is the pixel-level gain, a gain limit, or another parameter;*
- *correct and explain Equation 3;*
- *provide the initialization, update rule, objective function, stopping criterion, and final gain selection;*
- *justify the 0.01 step and ($\Delta R < 0.01$) stopping threshold; and*
- *include pseudocode, a revised workflow figure, and sensitivity tests.*

Response: We sincerely thank the Editor for the rigorous evaluation of our methodology. Our responses are provided below.

(1) We had already anticipated this issue and explicitly added a stabilization term c to the denominator to mathematically prevent any divide-by-zero errors. Specifically, we used the machine epsilon for double-precision floating-point format ($c=2.22\times 10^{-16}$, implemented via `torch.finfo(torch.float64).eps` in PyTorch). However, this term was inadvertently omitted from Eq. (2) in the original manuscript. It is also worth noting that, in regions where $AGB_{5km_Low_Pass}$ approaches zero, the L-band VOD (and consequently the numerator $L-VOD_{5km_NNR}$) is also very small, as both quantities are physically linked to the absence of vegetation. Since the two variables scale together, their ratio remains naturally bounded in practice. We have corrected Eq. (2) and added the corresponding explanation in the revised manuscript. (Lines 221–222)

(2) We have expanded Section 3.1 (Lines 198-199, Lines 202-204) to detail the masking and invalid-value handling procedures. Specifically, we initially exclude L-VOD data affected by Radio Frequency Interference (RFI) utilizing the methodology described by Wigneron et al. (2021), applying an 8 K threshold to the root mean square error (RMSE) between measured and simulated brightness temperatures. Following this RFI filtering, non-vegetated areas and water bodies are strictly masked out, and NoData or NaN pixels are entirely excluded from all calculations to prevent error propagation.

Furthermore, we have elaborated on the denominator threshold processing (as detailed in our response to (1)) to ensure computational stability.

We also explicitly defined the clipping limits within Algorithm 1 (Line 229). the algorithm initializes a global threshold limit ($g_{limit}^{(0)}$) based on the maximum value of the initial gain map. During each iteration k , this limit ($g_{limit}^{(k)}$) is incrementally reduced by a step size α and used to clip the pixel-level initial gain map ($g_{initial}$).

(3) The optimized quantity output by our algorithm is the pixel-level gain (g_{opt}), achieves this optimization by iteratively tuning a global gain limit (g_{limit}) (Algorithm 1; Line 229).

(4) We revised the text to explain that we employed an iterative threshold-search algorithm to maximize the Pearson correlation coefficient (R) between the downscaled L-VOD_{5km} and the reference AGB_{5km}. This is achieved by systematically iterating through a set of candidate injection gains (g) (Lines 223-231). The corrected Eq. 3 now represents as follow:

$$g_{opt} = \arg \max_g R(\text{L-VOD}_{5\text{km}}, \text{AGB}_{5\text{km}}) \quad (3)$$

(5) The initialization, update rule, objective function, stopping criterion, and final gain selection are detailed in Algorithm 1 (Line 229).

The process begins with the **initialization** (Steps 1), where the iteration counter ($k=0$), establish the starting global limit $g_{limit}^{(0)}$, and define baseline optimal values. During the iterative loop, the **objective function** (Steps 5–6) evaluates each clipped gain map by calculating the Pearson (R) between the downscaled L-VOD_{5km} and the reference AGB_{5km}. This loop is governed by a **stopping criterion** (Steps 12–13), automatically terminating when the improvement in the correlation (ΔR) falls below our convergence threshold ($\tau = 0.01$). If the criterion is not met, the **update rule** (Step 15) applies, incrementally reducing the global threshold limit by a predefined step size α for the next iteration. Finally, upon convergence, the **final gain** (Step 18) cleanly returns the optimal pixel-level gain map (g_{opt}) that achieved the highest overall spatial correlation.

(6) We conducted a new parameter sensitivity test and included Figure A1. The results justify that the chosen step size ($\alpha = 0.01$) and stopping threshold ($\tau = 0.01$) optimally balance spatial-detail injection (where correlation R plateaus) and computational efficiency.

(7) We have incorporated all three requested additions into the revised manuscript: the pseudocode is explicitly detailed in Algorithm 1 (Line 229), the revised workflow is illustrated in the updated Fig. 2 (Line 190), and the sensitivity tests are provided in Fig. A1 (Line 604) of the Appendix.

Modifications in the manuscript:

Lines 221–222:

$$g_{initial} = \frac{L-VOD_{5km_NNR}}{AGB_{5km_Low_Pass} + c} \quad (2)$$

where a small positive constant c (approximately 2.22×10^{-16}) is added to the denominator to avoid division by zero.

Lines 198–199: The monthly L-VOD_{25km} data from 2015 to 2021, which had been rigorously quality-filtered for RFI as detailed in Section 2.2

Lines 202–204: Prior to the subsequent downscaling procedure, non-vegetated areas and water bodies were masked out, and any pixels containing missing data (NoData/NaN) in either the L-VOD or AGB datasets were strictly excluded from all computations to prevent the propagation of invalid values.

Lines 224–232: To reduce the uncertainties of $g_{initial}$ and enhance the accuracy and robustness of L-VOD_{5km}, the raw gains were iteratively optimized. We employed an iterative threshold-search algorithm to maximize the Pearson correlation coefficient (R) between the L-VOD_{5km} and the CCI-AGB_{5km} by iterating through a set of candidate injection gains (g), as described in Eq. (3). The detailed procedure is explicitly presented in Algorithm 1.

$$g_{opt} = \arg \max_g R(L-VOD_{5km}, CCI-AGB_{5km}) \quad (3)$$

The detailed procedure for determining g_{opt} is explicitly presented in Algorithm 1.

Algorithm 1 Iterative Optimization of the Injection Gain (g_{opt}).

- 1: **Input:** Initial injection gain map $g_{initial}$, annual CCI-AGB_{5km}, step size $\alpha = 0.01$, convergence threshold $\tau = 0.01$
 - 2: **Initialization:** $g_{limit}^{(0)} \leftarrow \max(g_{initial})$, $k \leftarrow 0$, $R_{max} \leftarrow -1$, $g_{opt} \leftarrow g_{initial}$, $R^{(-1)} \leftarrow 0$
 - 3: **while true do**
 - 4: $g^{(k)} \leftarrow \min(g_{initial}, g_{limit}^{(k)})$
 - 5: Calculate L-VOD_{5km}^(k) $\leftarrow$ L-VOD_{5km_NNR} + $g^{(k)} \times (CCI-AGB_{5km} - CCI-AGB_{5km_Low_Pass})$
 - 6: Calculate the Pearson correlation coefficient $R^{(k)}$ between L-VOD_{5km}^(k) and CCI-AGB_{5km}
 - 7: **if** $R^{(k)} > R_{max}$ **then**
 - 8: $R_{max} \leftarrow R^{(k)}$
 - 9: $g_{opt} \leftarrow g^{(k)}$
 - 10: **end if**
 - 11: $\Delta R \leftarrow |R^{(k)} - R^{(k-1)}|$
-

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12: if  $k > 0$  and  $\Delta R < \tau$  then
13:     break;
14: end if
15:      $\mathcal{g}_{limit}^{(k+1)} \leftarrow \mathcal{g}_{limit}^{(k)} - \alpha$ 
16:      $k \leftarrow k + 1$ ;
17: end while
18: Output: Optimized injection gain map  $\mathcal{g}_{opt}$ 

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To ensure the robustness of the optimization process, the step size α and convergence threshold τ in Algorithm 1 were both conservatively set to 0.01. This configuration was selected based on systematic parameter-sensitivity tests, which yield a reasonable balance between computational cost and spatial-detail injection (Fig. A1).

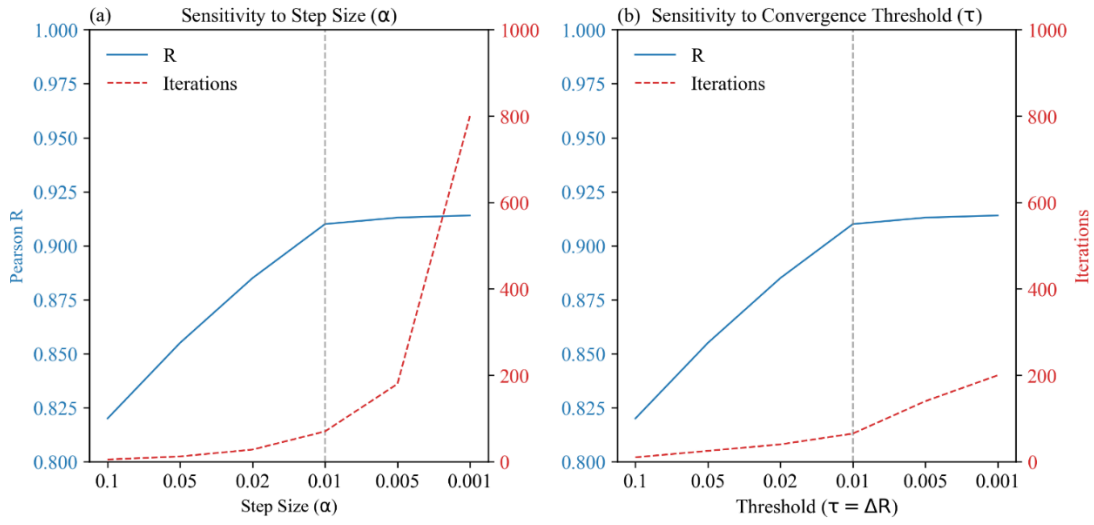


Figure R1 (Copied from Fig. A1 from the revised manuscript). Sensitivity analysis of hyperparameters in the iterative gain optimization process. (a) Impact of varying step sizes (α) on the optimized spatial correlation (Pearson R , solid blue line) and computational cost (number of iterations, dashed red line) under a fixed convergence threshold ($\tau = 0.01$). (b) Impact of varying convergence thresholds (τ) on the correlation and iteration counts under a fixed step size ($\alpha = 0.01$). The vertical gray dashed lines indicate the adopted optimal configuration ($\alpha = 0.01$, $\tau = 0.01$).

Lines 180-194:

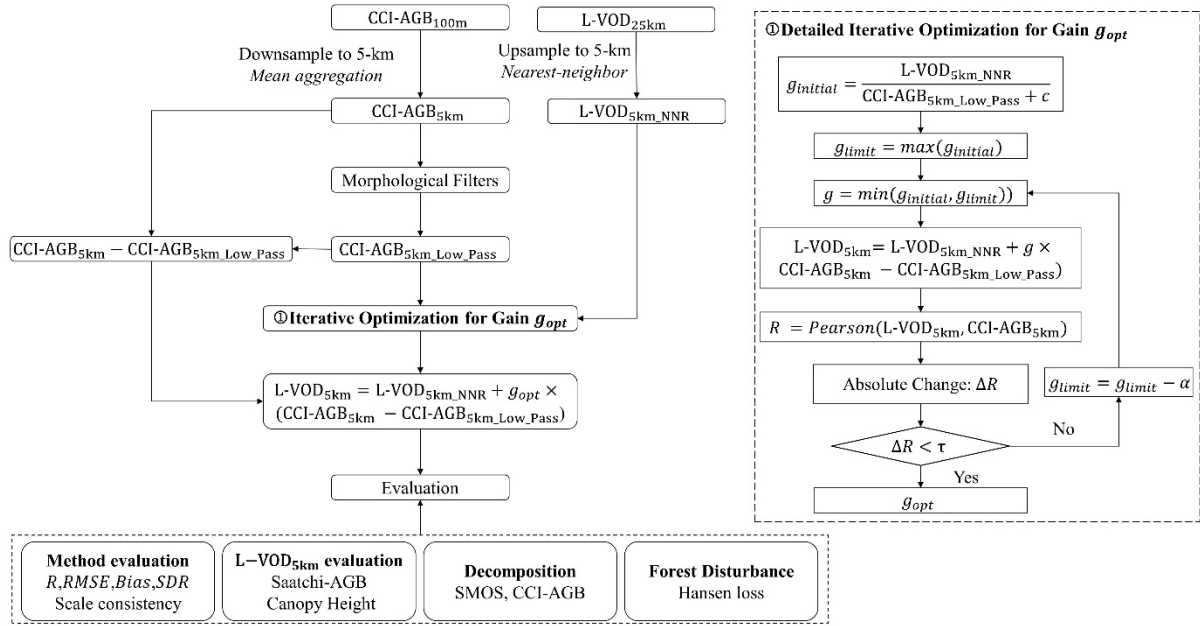


Figure R2 (Copied from Fig. 2 from the revised manuscript). Flowchart illustrating the workflow for generating and validating downscaled L-VOD products. The dashed panel on the right provides a detailed view of the iterative optimization subroutine corresponding to step ① in the main flowchart for calculating the optimal gain g_{opt} . NNR stands for Nearest-Neighbor Resampling. ΔR represents the absolute change in the Pearson correlation coefficient (R), and τ is the convergence threshold.

Comment 2. Define what the 5-km product represents

The manuscript must distinguish between a product reported on a 5-km grid and an independently observed L-band measurement with a 5-km footprint. The method spatially disaggregates the coarse SMOS signal using AGB-derived information; it does not create new microwave observations at 5-km scale.

Precise terminology such as “5-km downscaled product,” “5-km grid spacing,” or “5-km nominal spatial resolution” should be used. The manuscript and metadata must clearly state that the fine-scale structure is model-derived and partly inherited from AGB.

Response: We sincerely thank the Editor for highlighting this critical conceptual distinction. We completely agree with you. In the revised manuscript, we have conducted a comprehensive global review to replace ambiguous expressions, specifically adopting the precise terminology “**5-km downscaled product**” throughout the text to accurately reflect the nature of the dataset.

Furthermore, we have added an explicit clarifying statement in the methodology section, clearly articulating that the fine-scale spatial structures are fundamentally model-derived and inherited from the CCI-AGB dataset. (Lines 214–217)

Modifications in the manuscript:

Lines 214–217: Through this spatial disaggregation process, the coarse SMOS signal is refined using CCI-AGB-derived information. Consequently, the fine-scale structure in the resulting 5-km downscaled product is inherently model-derived and partly inherited from the CCI-AGB data, rather than representing an independent L-band measurement with a 5-km physical footprint.

Comment 3. Separate internal consistency from independent validation

ESA CCI AGB provides the injected spatial detail, contributes to the gain calculation and optimization, and is then used to assess the output. The resulting AGB correlation therefore demonstrates successful structural transfer, but it is not independent validation of 5-km L-VOD accuracy.

The authors must:

- *reclassify the AGB comparison as an internal consistency assessment;*
- *revise claims based on the reported AGB correlations throughout the manuscript; and*
- *add evaluation using information not employed in product construction or optimization.*

Independent evidence might include alternative biomass or canopy-structure products, GEDI-derived information, field observations, withheld regions, or independent disturbance records. LAI and NDVI may remain as temporal plausibility assessments but should not be presented as validation of L-VOD magnitude.

Response: Thank you for your comment. Following your comment, we have made revisions to the manuscript.

(1) We wish to clarify that in our downscaling framework, the CCI-AGB dataset is introduced strictly to provide relative spatial structural information to guide the disaggregation process, rather than being utilized as absolute numerical inputs in the calculations. That being said, we greatly appreciate and respect the editor's perspective on this matter. Following your recommendation, we have redefined the

evaluation of the correlation between the downscaled L-VOD and CCI-AGB as an 'internal consistency evaluation', and we have updated the text in Section 4.3.1 accordingly (Lines 416-430).

(2) We evaluated the 5-km downscaled L-VOD against independent Saatchi AGB and canopy height data (Lines 167-173). The results (Lines 432-445) demonstrate that the 5-km product maintains strong spatial consistency with both reference datasets ($R \approx 0.9$). Furthermore, the downscaling process effectively reduces systematic errors. Specifically, the *Bias* relative to the Saatchi dataset decreased from 0.62 (at 25-km) to -0.01 (at 5-km).

(3) We have removed the LAI and NDVI analysis entirely from the manuscript. L-VOD primarily represents vegetation water content (VWC), which conveys distinct information from optical vegetation indices (VIs); specifically, NDVI shows greater sensitivity to leaf chlorophyll content, while LAI characterizes the overall structural density of vegetation.

Modifications in the manuscript:

Lines 416-430: An analysis was conducted to assess the spatial consistency between CCI-AGB and the downscaled L-VOD_{5km} and to examine whether the fine-scale spatial gradients represented by CCI-AGB were preserved in the downscaled product. It should be emphasized that this comparison is designed as an internal consistency assessment rather than as an independent validation. Statistics show increased spatial correlation, as evidenced by an enhanced spatial correlation with an R of 0.92 and an $RMSE$ of 40.02 in 2019, compared with L-VOD_{25km}, which yields $R = 0.87$ and $RMSE = 46.31$ (Fig. 11a, b). This stronger correspondence in fine-scale spatial patterns is consistently observed across all study years (Fig. A2). Meanwhile, the median of the pixel-wise temporal correlation between L-VOD_{5km} and CCI-AGB_{5km} reached an R of 0.9 (Fig. A3), indicating strong temporal correspondence between the two variables at the pixel level. Moreover, stronger structural alignment was observed across all evaluated vegetation types in the downscaled product. For instance, the spatial R improved notably in major categories, increasing from 0.65 to 0.70 in EBF, from 0.40 to 0.70 in G, and from 0.65 to 0.81 in CSH (Fig. 11c), with CNVM showing the largest gain and EBF the smallest.

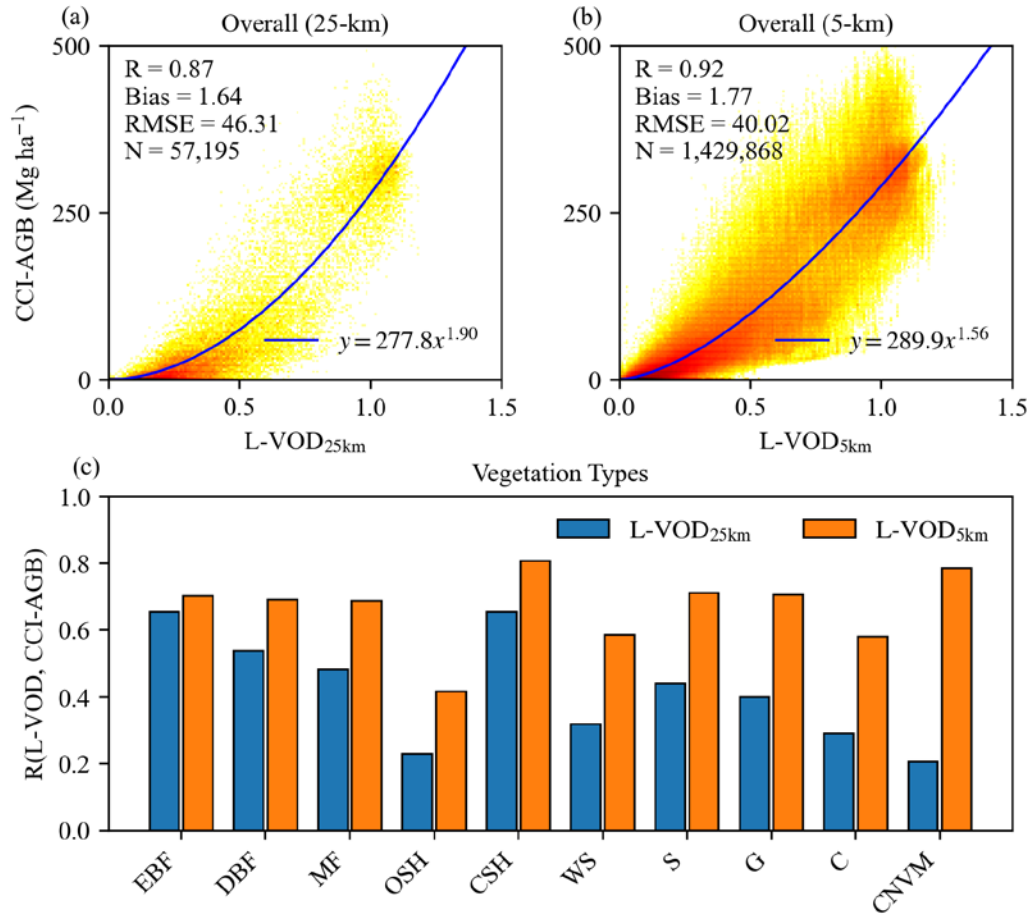


Figure R3 (Copied from Fig. 11 from the revised manuscript). Spatial relationships between annual average L-VOD and AGB at 25-km and 5-km in 2019. (a) Density scatterplot between L-VOD_{25km} and CCI-AGB_{25km}; (b) Density scatterplot between L-VOD_{5km} and CCI-AGB_{5km}; (c) Comparison median value of R of L-VOD and CCI-AGB for each vegetation type.

Lines 169-173: The Saatchi map (Saatchi et al., 2011) contains the AGB estimates at a 1-km spatial resolution circa 2015. It utilized GLAS LiDAR measurements to drive the comprehensive estimation of AGB, combining MODIS and QuickSCAT data. The Saatchi AGB map used here is an updated version derived from the Landsat, MODIS, Shuttle Radar Topography Mission, and Advanced Land Observing Satellite data.

Lines 432-445: We compared the original 25-km SMOS L-VOD and our 5-km downscaled L-VOD against two independent datasets, i.e., Saatchi-AGB and canopy height product (Fig. 12). Strong power-law correlations are observed between L-VOD and both forest variables at both resolutions. For the Saatchi AGB dataset (Fig. 12 a, b), the 5-km downscaled L-VOD maintains a high correlation coefficient ($R = 0.9$) that is nearly identical to the original 25-km observation ($R = 0.91$). The 5-km product achieves a near-zero *Bias* of -0.01, substantially lower than the 0.62 *Bias* observed at 25 km;

RMSE increases slightly from 34.04 at 25-km to 39.79 at 5-km, which is expected given the stronger fine-scale spatial heterogeneity at finer resolution. Similar pattern is observed with the canopy height data (Fig. 12c, d), the 5-km product again shows near-identical correlation ($R = 0.89$ vs. 0.90 at 25-km) and near-zero *Bias* at both resolutions, with *RMSE* increasing marginally from 3.47 at 25-km to 3.85 at 5-km, also consistent with this expectation.

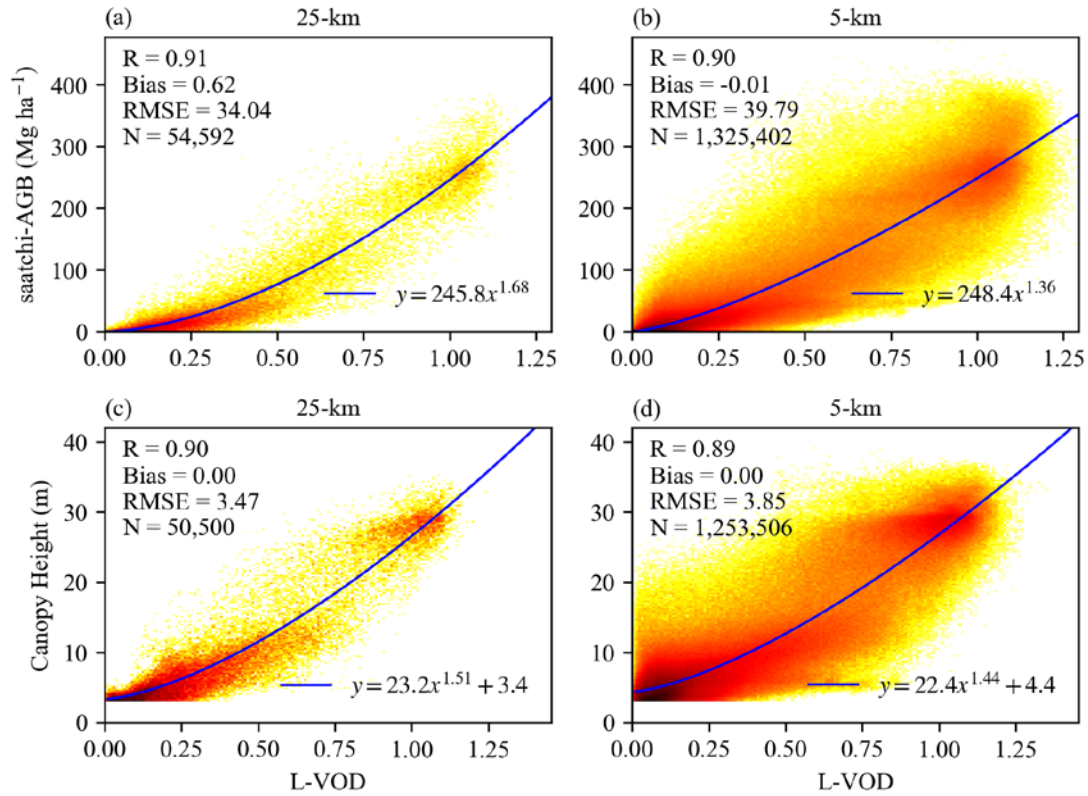


Figure R4 (Copied from Fig. 12 from the revised manuscript). Relationships between L-VOD and forest-structure variables at original 25-km and downscaled 5-km. Density scatter plots illustrate the correspondence between L-VOD and (a, b) Saatchi-AGB, as well as (c, d) canopy height. Panels (a, c) use the native 25-km L-VOD product; panels (b, d) adopt the 5-km L-VOD dataset generated in this study. Solid blue lines represent power-law regression fits. Colour indicates pixel-pair count density on a logarithmic scale.

Comment 4. Quantify the influence of annual AGB on monthly dynamics

Because AGB is held constant within each year while L-VOD is monthly, the authors must determine how much monthly variation originates from SMOS and how much is imposed by AGB and the gain procedure. They should assess repeated within-year spatial patterns, discontinuities between annual AGB maps, and differences among vegetation classes.

A useful experiment would compare products generated using a fixed reference-year AGB map and annually varying AGB maps. This would help separate temporal information inherited from SMOS from changes introduced through AGB.

Response: We greatly appreciate this highly constructive and insightful suggestion. Following your suggestion, we decomposed the temporal changes in the downscaled L-VOD ($\Delta\text{L-VOD}_{5\text{km}}$), calculated relative to the corresponding month in 2015, into three components: (1) a SMOS-driven component, (2) a CCI-AGB-driven component, and (3) an interaction term arising from the gain calculation (Lines 283-295). Specifically, we express the downscaling procedure as a generic function $f(\text{L-VOD}, \text{CCI-AGB})$, where L-VOD and CCI-AGB denote the inputs to the downscaling model. The total monthly change in the proposed downscaled product relative to the 2015 baseline, $\Delta\text{L-VOD}_{5\text{km},y,m}$ is then defined as:

$$\Delta\text{L-VOD}_{5\text{km},y,m} = f(\text{L-VOD}_{y,m}, \text{CCI-AGB}_y) - f(\text{L-VOD}_{2015,m}, \text{CCI-AGB}_{2015}) \quad (10)$$

where y denotes the year and m denotes the month.

The $\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{smos}}$ represents anomaly component driven solely by the native SMOS L-VOD, which is calculated as:

$$\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{smos}} = f(\text{L-VOD}_{y,m}, \text{CCI-AGB}_{2015}) - f(\text{L-VOD}_{2015,m}, \text{CCI-AGB}_{2015}) \quad (11)$$

Similarly, $\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{CCI-AGB}}$ denotes the anomaly component induced by the interannual variations in CCI-AGB, calculated as:

$$\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{CCI-AGB}} = f(\text{L-VOD}_{2015,m}, \text{CCI-AGB}_y) - f(\text{L-VOD}_{2015,m}, \text{CCI-AGB}_{2015}) \quad (12)$$

Finally, because the gain calculation introduces an interaction between SMOS L-VOD and CCI-AGB, the total anomaly is not necessarily equal to the simple sum of the two individual components. We therefore defined an interaction term $\varepsilon_{y,m}$ as:

$$\varepsilon_{y,m} = \Delta\text{L-VOD}_{5\text{km},y,m} - (\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{smos}} + \Delta\text{L-VOD}_{5\text{km},y,m}^{\text{CCI-AGB}}) \quad (13)$$

All metrics were computed pixel-by-pixel and then spatially averaged for each month over the pan-tropical domain. To further quantify the relative importance of the three components, their relative proportions were calculated by normalizing the mean absolute magnitude of each monthly component by the sum of the mean absolute magnitudes of all three components.

The results (Lines 447-467, Fig. 13) show that the monthly temporal evolution of the downscaled L-VOD anomalies is predominantly governed by the SMOS-driven component. At the pan-tropical scale, the relative proportions of the $\Delta\text{L-VOD}_{5\text{km}}^{\text{SMOS}}$, $\Delta\text{L-VOD}_{5\text{km}}^{\text{CCI-AGB}}$, and ε are 83.4%, 8.4%, and 8.3%, respectively. The dominance of the SMOS-driven component is consistent across vegetation classes, accounting for 76.3–86.2% of the total relative proportion, while interannual CCI-AGB variations and their interaction with SMOS make comparatively smaller contributions.

Modifications in the manuscript:

Lines 283-295: (iii) Decomposition of downscaled L-VOD changes. To decompose the monthly downscaled L-VOD changes into components associated with the native SMOS L-VOD and annual CCI-AGB inputs, we express the downscaling procedure as a generic function $f(\text{L-VOD}, \text{CCI-AGB})$, where L-VOD and CCI-AGB denote the inputs to the downscaling model. The total monthly change in the proposed downscaled product relative to the 2015 baseline, $\Delta\text{L-VOD}_{5\text{km},y,m}$ is then defined as:

$$\Delta\text{L-VOD}_{5\text{km},y,m} = f(\text{L-VOD}_{y,m}, \text{CCI-AGB}_y) - f(\text{L-VOD}_{2015,m}, \text{CCI-AGB}_{2015}) \quad (10)$$

where y denotes the year and m denotes the month.

The $\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{smos}}$ represents anomaly component driven solely by the native 25-km SMOS L-VOD, which is calculated as:

$$\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{smos}} = f(\text{L-VOD}_{y,m}, \text{CCI-AGB}_{2015}) - f(\text{L-VOD}_{2015,m}, \text{CCI-AGB}_{2015}) \quad (11)$$

Similarly, $\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{CCI-AGB}}$ denotes the component induced by the interannual variations in CCI-AGB, calculated as:

$$\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{CCI-AGB}} = f(\text{L-VOD}_{2015,m}, \text{CCI-AGB}_y) - f(\text{L-VOD}_{2015,m}, \text{CCI-AGB}_{2015}) \quad (12)$$

Finally, because the gain calculation introduces an interaction between SMOS L-VOD and CCI-AGB, the total anomaly is not necessarily equal to the simple sum of the two individual components. We therefore defined an interaction term $\varepsilon_{y,m}$, arising from the gain calculation as:

$$\varepsilon_{y,m} = \Delta\text{L-VOD}_{5\text{km},y,m} - (\Delta\text{L-VOD}_{5\text{km},y,m}^{\text{smos}} + \Delta\text{L-VOD}_{5\text{km},y,m}^{\text{CCI-AGB}}) \quad (13)$$

All metrics were computed pixel-by-pixel and then spatially averaged for each month over the pan-tropical domain. To further quantify the relative importance of the three components, their relative

proportions were calculated by normalizing the mean absolute magnitude of each monthly component by the sum of the mean absolute magnitudes of all three components.

Lines 447-467: The decomposition analysis shows that the temporal variability in the downscaled L-VOD changes is dominated by the SMOS-driven component ($\Delta L-VOD_{5km}^{SMOS}$) at the pan-tropical scale (Fig. 13a). This component closely follows the temporal evolution of the total anomaly, whereas the CCI-AGB-driven component ($\Delta L-VOD_{5km}^{CCI-AGB}$) and the interaction term (ε) generally exhibit smaller amplitudes. Negative anomalies occur more frequently in 2016 and during several periods between 2017 and 2019, while positive anomalies become more persistent after 2019, with the largest departures occurring around 2020–2021. Quantitatively, the relative proportions of the SMOS-driven, CCI-AGB-driven, and interaction components at the pan-tropical scale are 83.4%, 8.4%, and 8.3%, respectively (Fig. 13f).

This dominance of the SMOS-driven component is also evident across vegetation classes (Fig. 13b–e), accounting for 83.6% in Forest, 86.2% in Shrubland, 85.2% in Grassland, and 76.3% in Cropland (Fig. 13f). The CCI-AGB-driven component contributes 15.1%, 9.1%, 8.7%, and 12.2%, respectively, indicating a comparatively larger influence in Forest and Cropland. The interaction term remains small in Forest (1.3%) and Shrubland (4.7%), but becomes more pronounced in Grassland (6.0%) and particularly Cropland (11.4%). Overall, these results indicate that the temporal variability of the downscaled L-VOD is predominantly inherited from native SMOS observations, while interannual CCI-AGB variations and their interaction with SMOS provide smaller, vegetation-dependent contributions.

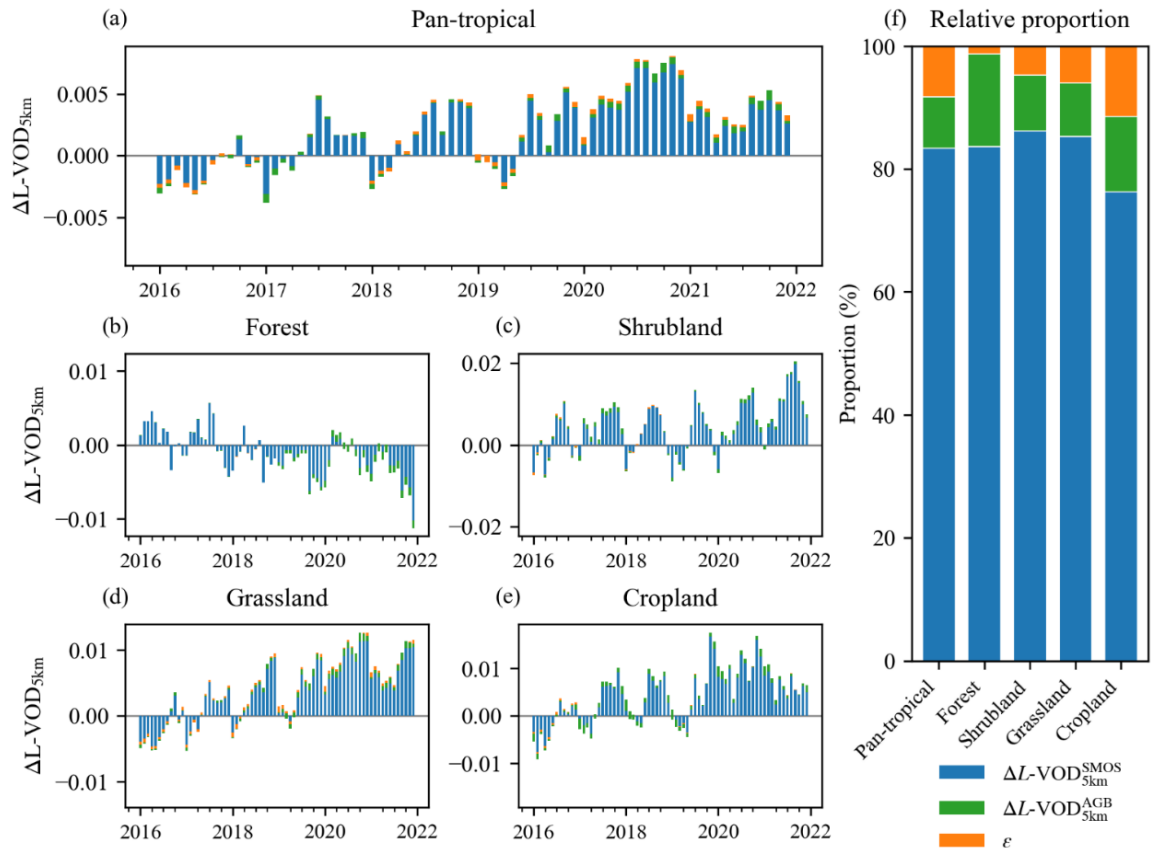


Figure R5 (Copied from Fig. 13 from the revised manuscript). Temporal decomposition of monthly $\Delta L-VOD_{5km}$ during 2016–2021 relative to the corresponding months in 2015. Panels (a–e) show the decomposition of the spatially averaged L-VOD changes over (a) the pan-tropical domain, (b) forest, (c) shrubland, (d) grassland, and (e) cropland. The total change ($\Delta L-VOD_{5km}$) is decomposed into the SMOS-driven component ($\Delta L-VOD_{5km}^{SMOS}$), the CCI-AGB-driven component ($\Delta L-VOD_{5km}^{CCI-AGB}$), and the non-additive interaction term (ϵ). Panel (f) shows the relative proportions of the three components, calculated from their temporal mean absolute magnitudes. Forest includes ENF, EBF, DBF, and MF; shrubland includes CS and OS; grassland includes G, S, and WS; and cropland includes C.

Comment 5. Strengthen the forest-disturbance assessment

The current single-grid-cell example is illustrative but insufficient for a pan-tropical dataset. The revised analysis should cover multiple events, years, disturbance intensities, and tropical regions and determine whether the 5-km product performs better than the original 25-km product.

The authors must also examine whether apparent forest-loss signals are introduced through changes in the annual AGB inputs. Limitations of the Hansen dataset—including the distinction between tree-cover loss, deforestation, degradation, fire, harvesting, and temporary loss—must be discussed. Interpretations

of subsequent land-cover transitions should be supported by independent evidence or presented as hypotheses.

Response: Thank you for your comment. Following your comment, we have made substantial revisions to the manuscript.

First, at the pan-tropical scale, we grouped forest-loss areas into two disturbance-intensity classes (20–50% and $\geq 50\%$ forest loss) and evaluated their responses across multiple years. For each class, we compared $\Delta L-VOD_{5km}$ (Eq.10) with the $\Delta L-VOD_{5km}^{SMOS}$ (Eq.11). It should be noted that while $\Delta L-VOD_{5km}^{SMOS}$ is spatially disaggregated to the 5-km grid based on the fixed 2015 AGB structure, its temporal dynamics reflect the native 25-km SMOS observations. The results (Fig. 14; Lines 467-486) show that larger forest-loss fractions are generally associated with stronger $\Delta L-VOD_{5km}$ decreases, with this response consistently observed across years. The stronger responses relative to the SMOS-driven component indicate that interannual CCI-AGB variations and the gain-related interaction modulate the magnitude of forest loss responses, which are otherwise spatially averaged at the native 25-km scale.

Second, we conducted a regional-scale forest-loss analysis for Brazil and the DRC over the full 2015–2021 study period. Specifically, we added a comparison between annual mean $L-VOD_{5km}$ with annual forest-loss percentage (Fig. 15; Lines 487-498). The results show that regional $L-VOD_{5km}$ dynamics broadly correspond to variations in forest-loss activity in both regions, with declines during periods of relatively elevated forest loss and partial recovery in subsequent years.

Third, we conducted an in-depth case analysis within a representative 25-km grid cell in Brazil (Lines 499-519; Fig. 16). Compared with $\Delta L-VOD_{5km}^{SMOS}$, $\Delta L-VOD_{5km}$ showed clearer intra-grid spatial gradients that corresponded to the observed forest-loss pattern, indicating that interannual CCI-AGB variations enhance the representation of fine-scale disturbance heterogeneity. At the individual 5-km pixel scale, the product also captured repeated $L-VOD$ decreases associated with forest loss events in 2016 and 2019.

Finally, we have added a concise discussion in Section 5.2, Limitations and Perspectives (Lines 555-573), addressing two main aspects: (i) the height-based forest definition (>5 m) can misclassify plantations and low-stature crops as forest, biasing estimates of forest cover change (Tropek et al., 2014); and (ii) the stand-replacement loss definition cannot capture non-stand-replacing processes such as partial canopy damage, drought-induced degradation, and post-drought regrowth, and the dataset does

not distinguish loss drivers such as management, harvest, or natural disturbance (Baccini et al., 2019; Liu et al., 2025).

Modifications in the manuscript:

Lines 467-486: Fig. 14 illustrates the interannual sensitivity of $\Delta L-VOD_{5km}$ to varying degrees of forest loss from 2016 to 2021. Negative $\Delta L-VOD_{5km}$ are consistently observed in pixels affected by forest loss, and their magnitude generally increases with disturbance intensity. In every year, pixels with severe forest loss (>50%) exhibit larger negative changes than those with moderate loss (20–50%). For example, in 2019 and 2021, $\Delta L-VOD_{5km}$ reaches approximately -0.085 and -0.12 under severe forest loss, compared with approximately -0.07 and -0.08 , respectively, under moderate forest loss. These results indicate a consistent sensitivity of $\Delta L-VOD_{5km}$ to forest-loss intensity across years.

Compared with the SMOS-driven component ($\Delta L-VOD_{5km}^{SMOS}$), the $\Delta L-VOD_{5km}$ generally exhibits larger negative anomalies in forest-loss areas, particularly under severe disturbance. Because the $\Delta L-VOD_{5km}^{SMOS}$ retains the temporal variability of the native SMOS observations while CCI-AGB is fixed at its 2015 state, the larger negative $\Delta L-VOD_{5km}$ indicates that interannual CCI-AGB variations modulate the magnitude of the disturbance response, which are otherwise spatially averaged at the native 25-km scale.

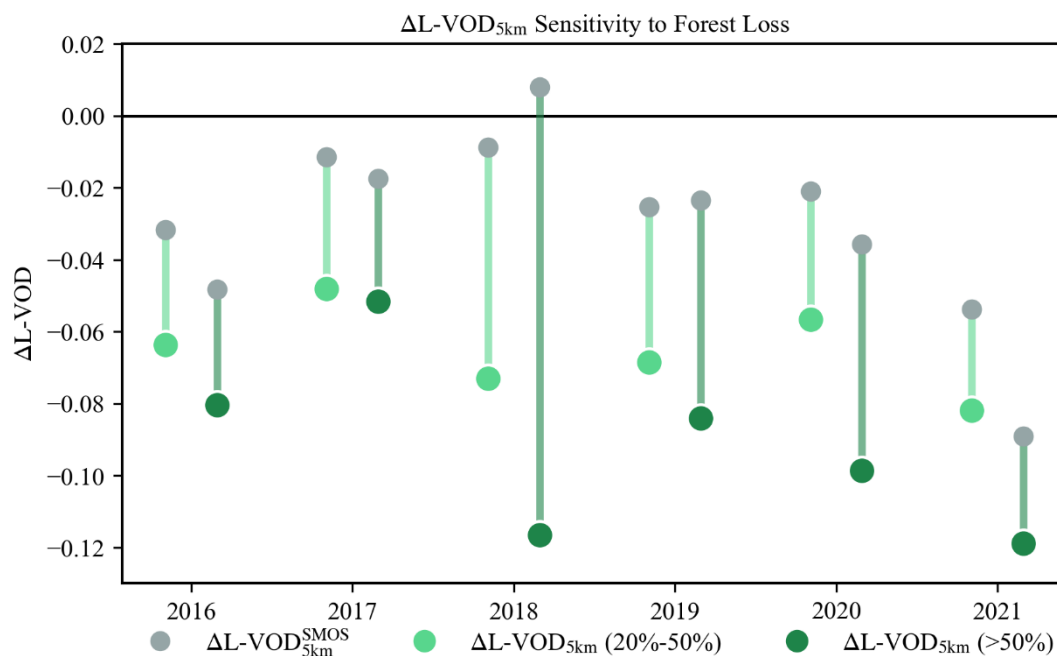


Figure R6 (Copied from Fig. 14 from the revised manuscript). Interannual sensitivity of $\Delta L-VOD_{5km}$ to forest loss from 2016 to 2021. Grey markers represent the temporal dynamics of the native 25-km SMOS L-VOD ($\Delta L-VOD_{5km}^{SMOS}$, Eq.11). Light-green markers indicate the mean values of the proposed

downscaled product ($\Delta L\text{-VOD}_{5\text{km}}$, Eq.10) for pixels with 20%–50% forest loss, while dark-green markers denote pixels experiencing >50% forest loss. Vertical lines connect the baseline signal and dynamic-VOD signal for each year, illustrating the additional VOD reduction captured when inter-annual AGB changes are incorporated. The y-axis ($\Delta L\text{-VOD}$) denotes these annual anomalies relative to the 2015 baseline.

Lines 487-498: As illustrated by the spatial pattern of forest loss extent, both Brazil and the DRC feature regions of high loss intensity with distinct spatial clustering (Fig. A4). We compared the temporal dynamics of $L\text{-VOD}_{5\text{km}}$ and forest loss in Brazil and the DRC from 2015 to 2021. $L\text{-VOD}_{5\text{km}}$ showed temporal variations broadly corresponding to forest loss dynamics in both Brazil and the DRC (Fig. 13). In Brazil, $L\text{-VOD}_{5\text{km}}$ decreased from approximately 0.485 in 2015 to 0.479 in 2017, coinciding with relatively high forest loss during 2016–2017. $L\text{-VOD}_{5\text{km}}$ subsequently increased and reached its highest value of approximately 0.490 in 2020, before declining again in 2021. In the DRC, $L\text{-VOD}_{5\text{km}}$ declined more steadily from approximately 0.616 in 2015 to 0.603 in 2018, during a period of relatively elevated forest loss, followed by a partial recovery in 2019–2020 and a modest decrease in 2021.

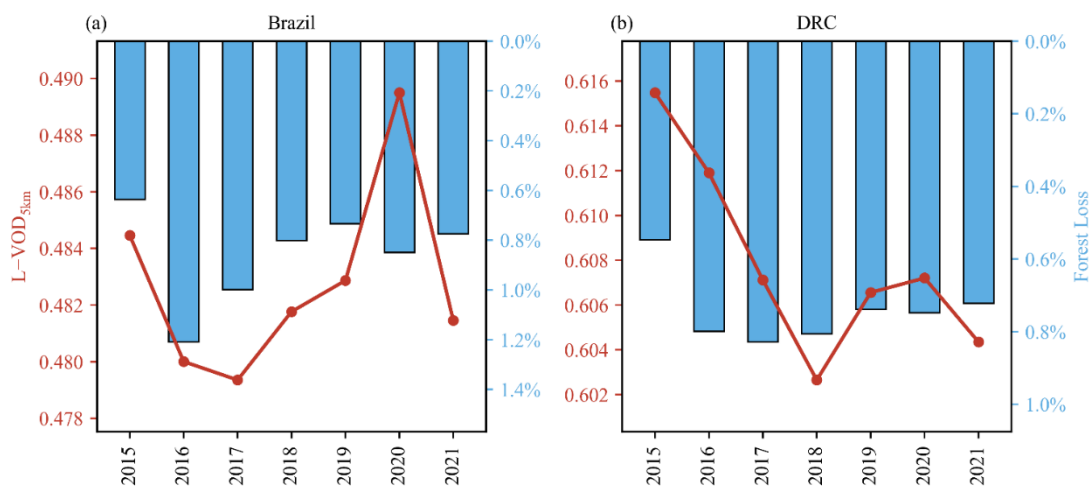


Figure R7 (Copied from Fig. 15 from the revised manuscript). Annual variations in $L\text{-VOD}_{5\text{km}}$ and forest loss in (a) Brazil and (b) the DRC during 2015–2021. $L\text{-VOD}_{5\text{km}}$ represents the annual mean value across all valid vegetation pixels within each regional study domain, while forest loss represents the annual forest-loss percentage defined in Section 2.6. For Brazil, only the area within the pan-tropical domain (25°N–25°S) was included.

Lines 499-519: We selected a single 25-km grid cell in Brazil for a case-based in-depth analysis. This site, denoted as P2, experienced severe forest disturbances in 2016 and 2019. Fig.14a–c display the fine-scale spatial patterns of inter-annual $L\text{-VOD}$ anomalies both $\Delta L\text{-VOD}_{5\text{km}}$ and the $\Delta L\text{-VOD}_{5\text{km}}^{\text{SMOS}}$ alongside forest loss at a 5-km spatial resolution within this parent 25-km grid cell. As shown in Fig. 14c, forest loss is heavily concentrated in the eastern section, exhibiting a distinct spatial gradient that

reaches local fractional loss values of up to 30%. The proposed $L-VOD_{5km}$ (Fig. 14a) captures this intra-pixel heterogeneity, exhibiting gradient-like changes. In contrast, the $\Delta L-VOD_{5km}^{SMOS}$ (Fig. 14b) shows much weaker intra-grid spatial differentiation (Fig. 14b). This comparison indicates that incorporating interannual CCI-AGB variations improves the representation of fine-scale spatial heterogeneity in disturbance-affected areas, enabling the 5-km product to resolve localized disturbance gradients that are not apparent in the coarse-scale SMOS product.

At the finer pixel scale, the temporal behavior of these disturbances is illustrated by focusing on one specific 5-km sample pixel, labeled P2_1, which is marked in Fig. 14a–c. This target pixel underwent two separate forest loss events, experiencing approximately 10% area loss in 2016 and roughly 18% area loss in 2019. The $L-VOD_{5km}$ time series exhibits detectable physical responses to both disturbance episodes (Fig. 14d). Specifically, $L-VOD_{5km}$ decreases from 0.96 to 0.90 in 2016, recovers to a stable 0.96 throughout 2017–2018, and subsequently shows a secondary drop to 0.93 coinciding with the 2019 forest-loss disturbance.

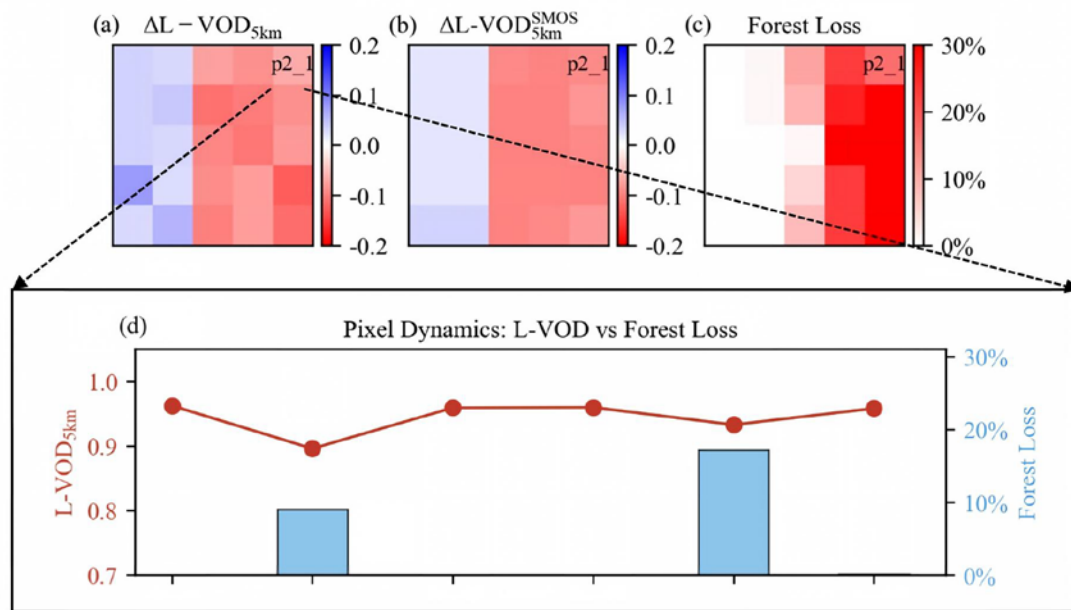


Figure R8 (Copied from Fig. 16 from the revised manuscript). Spatiotemporal responses of $L-VOD_{5km}$ to forest disturbances within a selected 25-km grid cell (P2) in Brazil. The top row presents the fine-scale spatial distribution of (a) the $L-VOD_{5km}$ change generated by the proposed downscaling method ($\Delta L-VOD_{5km}$), (b) the SMOS-driven $L-VOD$ change ($\Delta L-VOD_{5km}^{SMOS}$), and (c) the fractional forest loss. A specific 5-km sub-pixel experiencing severe deforestation is marked as p2_1. The bottom panels illustrate the pixel-scale interannual temporal dynamics (2015–2020) for this targeted sub-pixel (p2_1), detailing the trajectories of (d) $L-VOD_{5km}$ compared against annual forest loss events.

Lines 555-573: Evaluating the downscaled product against optical-based forest loss datasets introduces uncertainties. Hansen loss is defined as stand-replacement disturbance or complete canopy removal at the Landsat pixel scale, based on canopy closure of all vegetation taller than 5-m (Hansen et al., 2013). This height-based definition of forest includes plantation types that have already replaced substantial parts of tropical forests. As a result, monocultures of oil palm, rubber, or Eucalyptus are technically classified as forests, leading to an underestimation of real forest loss. Furthermore, contrary to this definition, vegetation lower than 5 m, such as pineapple, soybean, or tea plantations, is often classified as forest, which further biases estimates of forest cover gain and loss (Tropek et al., 2014).

This stand-replacement definition also means that Hansen’s binary loss records cannot capture non-stand-replacing processes such as partial canopy damage, drought-induced degradation, and post-drought regrowth, nor do they attribute detected forest loss to specific drivers such as management, harvest, or natural disturbances (Baccini et al., 2019; Liu et al., 2025). Because these non-stand-replacing processes exert opposing effects on L-VOD, they may jointly offset L-VOD declines or even generate positive anomalies. For example, in 2016 (Fig. 16d), Hansen recorded lower forest loss than in 2019, yet $L - VOD_{5km}$ declined much more strongly, consistent with the 2015–2016 El Niño drought (Dou et al., 2024). Similarly, in Brazil in 2020 (Fig. 16a), relatively elevated forest loss coincided with an increase in $L - VOD_{5km}$, which may reflect post-El Niño woody biomass recovery that partly offset localized deforestation signals (Fan et al., 2024). These discrepancies underscore the limitation of Hansen in detecting non-stand-replacing disturbances and support the added value of L-VOD for monitoring drought-induced biomass loss (Li et al., 2022b; Qin et al., 2021). Despite these observational discrepancies, the Hansen dataset remains the most globally consistent, high-resolution benchmark available, providing an indispensable reference for our evaluations.

Comment 6. Expand the methodological comparison and coarse-scale consistency tests

The existing comparison with the Gram–Schmidt Adaptive method should be moved into the main evaluation and expanded across 2015–2021, major vegetation classes, and representative regions. If feasible, an additional representative downscaling method should be included. Evaluation should report bias, slope, RMSE or normalized RMSE, correlation, and spatial variability.

The authors should also test whether aggregating the 5-km product back to the native SMOS grid reproduces the original L-VOD for individual pixels and months. The 125-to-25-km experiment is useful but should not be treated as direct validation of actual 5-km accuracy.

Response: We sincerely thank the Editor for these highly constructive recommendations. We completely agree with you. To address your detailed requirements, we have substantially expanded this section:

(1) We moved the Gram–Schmidt Adaptive (GSA) evaluation to the main text and introduced a Random Forest (RF) model as an additional benchmark, thereby expanding the methodological comparison to include the proposed Morphological Filtering–based Multi-Resolution Analysis (MF-MRA) method, GSA, and RF. The comparison was conducted over the entire 2015–2021 period (Fig. 7), across major vegetation classes (Fig. 8), and in representative tropical regions, including Brazil and the DRC (Fig. 9). We reported comprehensive quantitative metrics, including R , $Bias$, $RMSE$, and Standard Deviation Ratio (SDR , representing spatial variability) (Lines 253–263).

Our newly added results (Lines 353–400) demonstrate that while the RF model achieves low $RMSE$, it introduces a substantial smoothing effect that underestimates spatial variance, particularly in dense forests. Conversely, the GSA method excessively amplifies spatial variance and exhibits extreme instability. Our proposed framework achieves strong agreement with the reference data (high R , low $RMSE$ and low $Bias$) while maintaining SDR values closer to 1, indicating better preservation of the reference spatial variability. Overall, MF-MRA provides a more balanced performance across the evaluated metrics.

(2) We assessed scale consistency by spatially aggregating the 5-km outputs back to the native 25-km SMOS grid and comparing them with the original coarse-resolution observations at the pixel-month level (Fig. 10; Lines 402–413). The aggregated results from the proposed method exhibit close agreement with the original coarse-resolution observations ($R = 0.980$, $RMSE = 0.083$, $SDR = 0.998$).

Modifications in the manuscript:

Lines 263–268: To comprehensively evaluate the proposed approach we compared it with the Gram–Schmidt adaptive (GSA) (Aiazzi et al., 2007), which similarly utilizes CCI-AGB for spatial disaggregation but is based on a linear transformation (Method B1), and the RF. For the RF model, the vegetation and environmental covariates including NDVI, LAI, precipitation, LST and DEM follow the

variable scheme described in Yan et al. (2025). To ensure fair comparison and consistent core vegetation-related predictors across modelling frameworks, CCI-AGB was additionally included among the RF input features.

Method performance was evaluated using a comprehensive set of statistical metrics. These include the correlation coefficient (R), $RMSE$, $Bias$, Standard Deviation Ratio (SDR) and the slope of the linear regression ($Slope$). The equations corresponding to these metrics are listed as follows:

$$R = \frac{Cov(L-VOD_{25km}^{sim}, L-VOD_{25km})}{\sigma(L-VOD_{25km}^{sim})\sigma(L-VOD_{25km})} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum(L-VOD_{25km}^{sim} - L-VOD_{25km})^2}{N}} \quad (7)$$

$$Bias = \frac{\sum(L-VOD_{25km}^{sim} - L-VOD_{25km})}{N} \quad (8)$$

$$SDR = \frac{STD_{pred}}{STD_{obs}} \quad (9)$$

where Cov is the covariance and σ is the standard deviation. N is the sample size. STD_{pred} and STD_{obs} represent the standard deviations of the simulated $L-VOD_{25km}^{sim}$ and reference $L-VOD_{25km}$, respectively. The $Slope$ metric is derived from the ordinary least squares (OLS) linear regression between the simulated outputs and reference data.

Lines 353-400: The performance of the downscaling approaches was evaluated by comparing the simulated 25-km outputs from each method against the original reference observations. Overall, the proposed framework demonstrates a balance between signal agreement and the preservation of spatial variance. While the RF method yields the lowest $RMSE$ of 0.139 and nearly unbiased estimates with $Bias = 0.004$ (Fig.7c), its SDR of 0.817 (Fig. 7c) indicates a substantial smoothing effect that underestimates the true spatial variance of the L-VOD data. In contrast, the proposed framework presented in Fig. 7a achieves the highest spatial correlation with the reference dataset at an R of 0.913. This marginally outperforms the RF method with an R of 0.908 (Fig. 7c), as well as the GSA method, which yields an R of 0.868 (Fig. 7b). Furthermore, the proposed framework effectively maintains the spatial variability of the original observations by achieving an SDR of 1.082 (Fig 7a), placing it closest to the ideal value of 1.0. Conversely, the GSA approach shown in Fig. 7b exhibits the largest deviations

by producing the highest *RMSE* of 0.291 alongside an *SDR* of 1.608 (Fig.7b), signifying an excessive amplification of spatial variance.

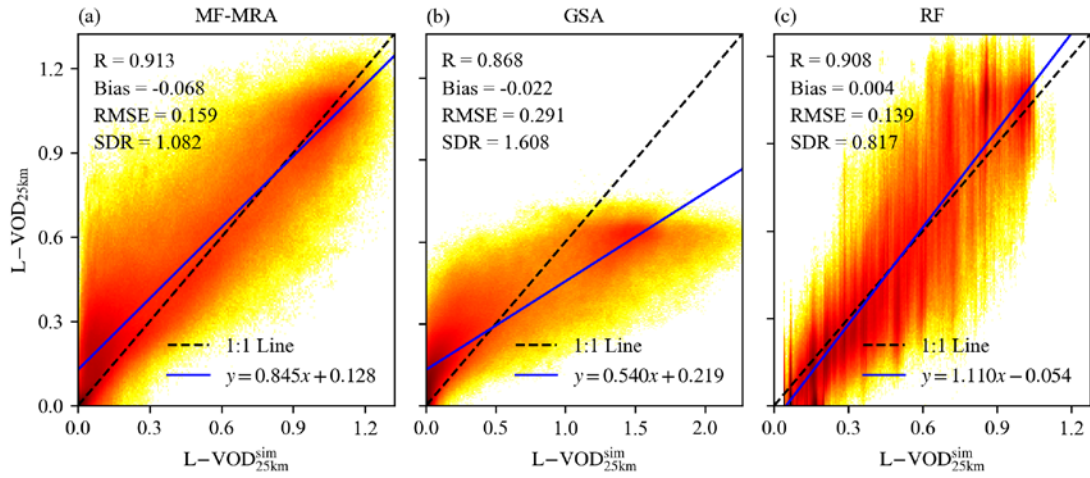


Figure R9 (Copied from Fig. 7 from the revised manuscript). Evaluation of the downscaling algorithm performance. Density scatter plots comparing the simulated 25-km outputs ($L-VOD_{25km}^{sim}$) from (a) the MF-MRA method, (b) the GSA method, and (c) the RF model against the original 25-km L-VOD reference observations ($L-VOD_{25km}$) across the pan-tropical region during the period of 2015-2021. The dashed black line represents the 1:1 reference line, and the blue line indicates the linear regression fit. Colour shading indicates the number density of pixels (log-scaled).

Fig.8 presents a detailed quantitative assessment of the three downscaling methods across various vegetation types. Overall, the analysis reveals distinct performance variations between forested and non-forested regions depending on the applied algorithm. Our framework demonstrates robust signal agreement in dense forest ecosystems. It achieves its highest *R* of 0.78 in ENF and 0.74 in EBF (Fig. 8a), along with a low *RMSE* of 0.17 in EBF (Fig. 8c), and maintains small *Bias* of -0.03 in EBF and ENF (Fig. 8b). Furthermore, in these forest categories, the proposed method yields *SDR* values > 1.0 (Fig. 8d), whereas its *SDR* drops below 1.0 in sparse vegetation like G and C. In contrast, the RF model exhibits the exact opposite regional preference, performing more effectively in non-forest or sparse vegetation categories. It reaches peak *R* of 0.81 in CS and 0.75 in G (Fig. 8a). Conversely, the RF model produces stable, near-zero biases in these sparse areas, such as 0.01 in CS, but experiences larger deviations in dense forests, dropping to -0.09 in EBF (Fig. 8b). Consequently, in forest categories like EBF and ENF, the RF model yields higher *RMSE* values of 0.18 and 0.14, respectively (Fig. 8c). Regarding the *SDR* metric (Fig. 8d), the RF model consistently produces values < 1.0 in forested areas, whereas it exceeds 1.0 in sparse vegetation like G and C. Finally, the GSA approach exhibits the largest deviations across the evaluated vegetation types. It generates the highest *RMSE*, reaching 0.44 in EBF

(Fig. 8c) and prominent bias fluctuations, including a large *Bias* of 0.27 in EBF (Fig. 8b). In terms of spatial variance, the GSA method follows a similar trend to the proposed method but exhibits extreme instability, peaking at an *SDR* of 2.19 in EBF and dropping to 0.37 in OS (Fig. 8d).

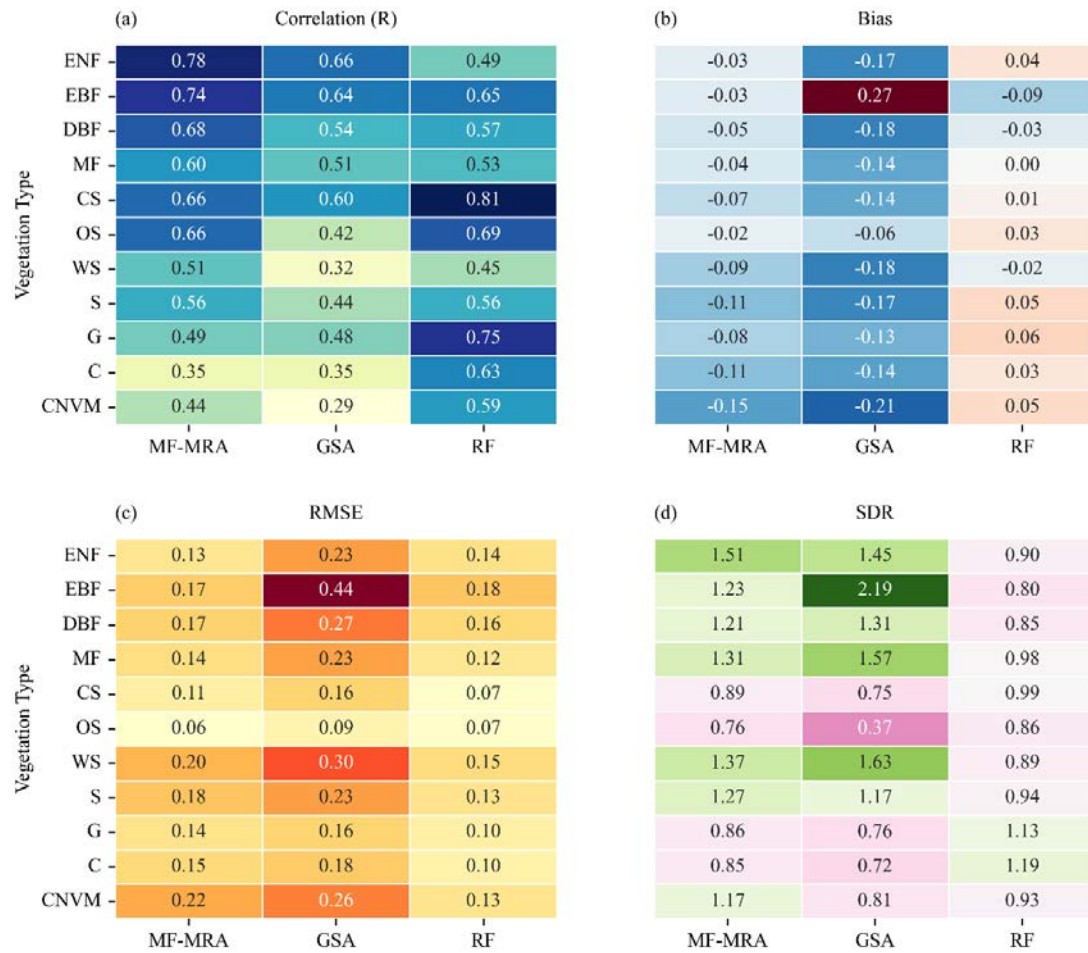


Figure R10 (Copied from Fig. 8 from the revised manuscript). Quantitative performance of the downscaling algorithms across various vegetation types. Heatmaps illustrating the (a) *R*, (b) *Bias*, (c) *RMSE*, (d) *SDR* for the 25-km simulated outputs from the MF-MRA, GSA, and RF methods compared against the original 25-km L-VOD reference data. The evaluation is conducted across IGBP vegetation categories within the pan-tropical region. Colour scales correspond to the specific magnitude of each statistical metric.

Regional downscaling performance was further evaluated across two major tropical forest regions, Brazil and the DRC. While all evaluated methods maintain robust *R* as shown in Fig. 9a, they display distinct differences in error and spatial variance. The RF model yields the lowest *RMSE* (Fig. 9c) alongside near-zero biases (Fig. 9b). However, it consistently underestimates spatial variance by yielding *SDR* below 1.0 (Fig. 9d), indicating an underestimation of spatial variability and a tendency toward spatial smoothing. Conversely, the GSA approach exhibits the largest regional deviations by

producing the highest error metrics and an excessive amplification of spatial variance, with *SDR* values substantially exceeding 1.0 (Fig. 9d). The proposed framework achieved a more balanced performance, maintaining strong pixel-wise agreement while yielding *SDR* values closest to the ideal 1.0 baseline in both regions (Fig. 9d), thereby better preserving spatial variability and vegetation heterogeneity.

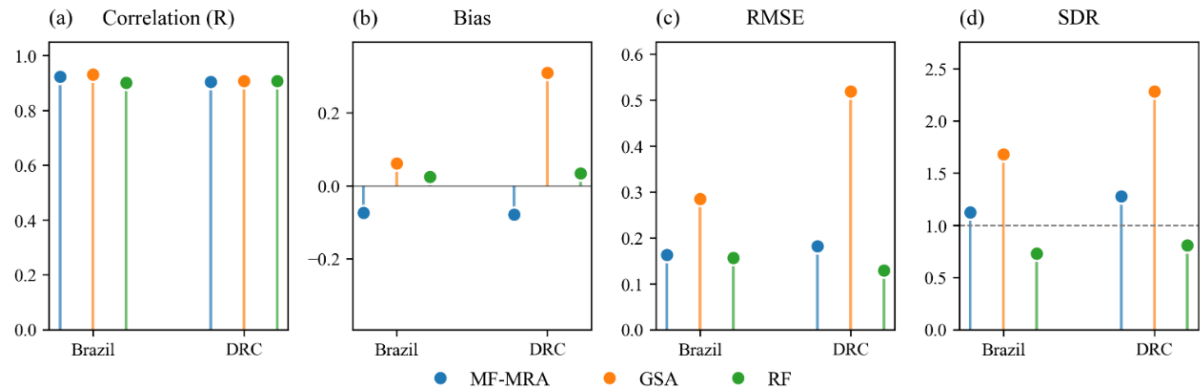


Figure R11(Copied from Fig. 9 from the revised manuscript). Quantitative performance of the downscaling algorithms across two major tropical forest domains (Brazil and the DRC). Lollipop plots illustrating the (a) *R*, (b) Bias, (c) *RMSE*, (d) *SDR* for the 25-km simulated outputs from the MF-MRA, GSA, and RF methods compared against the native 25-km SMOS L-VOD reference data.

Lines 402-413: Scale consistency was assessed by spatially aggregating the $L\text{-VOD}_{5\text{km}}$ outputs and then comparing them against the $L\text{-VOD}_{25\text{km}}$ observations. The aggregated results from the proposed method exhibit close agreement with the original coarse-resolution data, yielding the highest *R* of 0.980 and the lowest *RMSE* of 0.083 among the evaluated approaches (Fig. 10a). Furthermore, an *SDR* of 0.998 indicates that the original spatial variance is effectively preserved in the final 5-km downscaled product. By comparison, the RF model tends to underestimate spatial variability, as reflected by *SDR* of 0.874 (Fig. 10c). The GSA method displays the largest deviation from the original observations, characterized by a high *RMSE* of 0.314 and *SDR* of 1.365 (Fig. 10b).

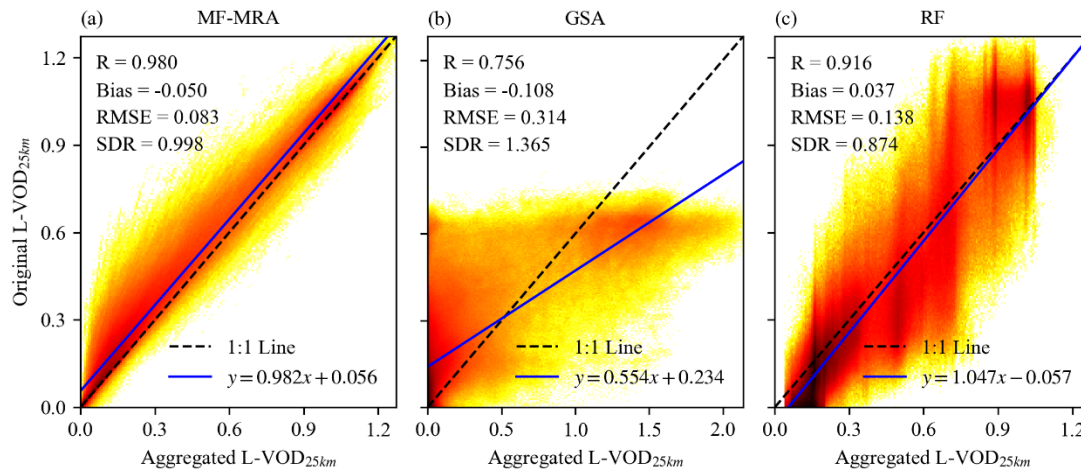


Figure R12 (Copied from Fig. 10 from the revised manuscript). Scale-consistency evaluation of the downscaled outputs. Density scatter plots comparing the spatially aggregated 25-km outputs from (a) this study (using the MF-MRA method), (b) the GSA method, and (c) the RF model against the original 25-km L-VOD observations across the pan-tropical region for 2015-2021. The dashed black line represents the 1:1 reference line, and the blue line indicates the linear regression fit. Colour shading indicates the number density of pixels (log-scaled).

Comment 7. Quantify uncertainty and define the valid application domain

The revised dataset should include quantitative uncertainty information or scientifically justified quality indicators. Particular attention should be given to low-AGB pixels, non-forest vegetation, heterogeneous landscapes, missing or RFI-affected SMOS observations, extreme gain values, and transitions between annual AGB maps.

The authors should determine whether the valid product domain needs to be restricted or whether vegetation-specific quality flags and clear usage warnings can adequately represent these limitations.

Response: We sincerely thank the Editor for highlighting the need for robust, quantitative quality indicators. Since the original 25-km L-VOD inputs have already undergone rigorous RFI filtering and frozen-soil masking during the preprocessing stage (Section 3.1 and 2.2), the product-level QA directly generates pixel-level uncertainty (*SD*) and quality flag (*QA*) layers, without repeating the RFI detection—which is technically infeasible at the 5-km downscaling level as it requires raw multi-band brightness temperature data that are not accessible during the spatial resolution enhancement process.

The implementation consists of the following three components:

1. Quantitative uncertainty analysis

We quantified the uncertainty using 1,000 bootstrap realizations. In each realization, valid 5-km pixel pairs of L-VOD and CCI AGB used in the gain-optimization criterion were resampled with replacement, and the optimal gain threshold was re-estimated. The pixel-wise standard deviation (SD) of the resulting ensemble of downscaled 5-km L-VOD estimates was then used as an uncertainty indicator and included as an accompanying quality layer in the final dataset.

2. Multi-level quality assurance (QA) flag

Using the absolute uncertainty and the spatial high-frequency injection gain (g_{opt}), we developed a discrete 8-bit categorical QA mask (Quality_Flag) to strictly regulate data usage. The classification thresholds are defined as follows:

(1) QA = 0: Pixels with acceptable uncertainty and gain values, recommended for general quantitative analysis.

(2) QA = 1: Pixels exhibiting a relative uncertainty (Coefficient of Variation, CV) > 15% (Ren and Liu, 2024; Zhang et al., 2023), indicating elevated relative uncertainty. These pixels commonly occur in heterogeneous landscapes and low-biomass transitional areas and should therefore be interpreted with caution.

(3) QA = 2: Pixels where the injection coefficient is either negative or exceeds 5.21, which is the 97th percentile of its global distribution. Such extreme values typically occur in regions with very low AGB, where the vegetation signal is too weak to support reliable spatial detail injection, and the downscaled results at these pixels are therefore considered unreliable.

(4) QA = 255: Water bodies and pixels with missing, RFI-screened, or otherwise invalid native SMOS observations.

3. Data packaging and standardization

To facilitate use of the dataset, the SD, Injection_Coefficient, and Quality_Flag layers are provided together with the primary 5-km L-VOD data in annual NetCDF files, each containing a 12-month time series.

For inter-annual transitions, the pixel-wise SD layer enables users to assess whether observed year-to-year changes exceed the local uncertainty, providing quantitative guidance for evaluating temporal dynamics without imposing an additional fixed threshold.

Comment 8. Improve reproducibility, documentation, and presentation

The processing code should be deposited in a persistent repository. Documentation should include software versions, parameter values, filtering settings, grid and projection definitions, masks, flags, missing-value conventions, file structures, variables, units, quality layers, and basic usage examples. The revised dataset must correspond exactly to the revised methodology.

Claims of “high accuracy,” independent 5-km resolving capability, successful validation, and demonstrated forest-disturbance detection should be moderated unless supported by independent evidence. The authors should distinguish among preservation of the native SMOS signal, injection of AGB-derived structure, temporal plausibility, disturbance sensitivity, and independently demonstrated accuracy. The manuscript should also undergo careful English and technical editing.

The manuscript has sufficient potential to justify major revision. However, revisions limited to language, figures, or additional explanation will not be sufficient. The central concerns regarding validation dependence, interpretation of the 5-km information, influence of annual AGB, uncertainty, and reproducibility require substantive analysis and, where necessary, revision of the dataset.

The authors should provide a detailed response identifying all changes to the manuscript, dataset, metadata, and code. Any revised submission will be evaluated on whether these scientific and data-quality concerns have been resolved and may be returned to the referees. The invitation to revise does not imply eventual acceptance.

Response: We sincerely thank the Editor for this rigorous and comprehensive evaluation, and agree with you. We have strictly followed your guidance to overhaul our data repository, temper our claims, and clarify the physical interpretation of the downscaled product. Below is a detailed summary of the substantive changes made to the manuscript, dataset, metadata, and code:

(1) We have updated the data and code repository from the previous temporary location to a permanent Zenodo archive. Accordingly, we have revised the Data Availability section in the main manuscript (Line 630) with the new persistent DOI: <https://doi.org/10.5281/zenodo.22142976> . A detailed Readme document (in PDF format) is now included in the repository. As explicitly requested, it thoroughly documents the software environment (Python 3.9+, PyTorch 2.3.1), parameter values, grid definitions (WGS 1984 EASE-Grid 2.0 Global, 5-km), missing-value conventions (e.g., -3.4028e+38 for NoData),

and basic usage examples. Furthermore, the repository fully integrates and documents the new uncertainty (SD) and quality mask (QA_Flag) layers detailed in our response to Comment 7, ensuring the final published dataset corresponds exactly to our revised methodology.

(2) We systematically revised statements such as “high accuracy,” “independent 5-km resolving capability,” and “successful validation” throughout the manuscript. The revised text now explicitly distinguishes among preservation of the native SMOS temporal signal, injection of CCI-AGB-derived spatial structure, temporal plausibility, disturbance sensitivity, and evaluation against reference datasets. In particular, we clarify that the temporal dynamics of the downscaled product are primarily inherited from native SMOS observations, whereas its fine-scale spatial heterogeneity is introduced through the CCI-AGB structural information.

(3) English and technical editing

The entire manuscript has undergone careful English and technical editing to improve clarity, consistency of terminology, logical flow, and correspondence among the manuscript, dataset, metadata, and code.

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Response to Referee #1

General Comments

This manuscript proposes a new 5-km L-band Vegetation Optical Depth (L-VOD) dataset by downscaling the 25-km L-VOD product using a 5-km Aboveground Biomass (AGB) dataset through a pan-sharpening-based framework. The resulting product is comprehensively evaluated against higher-resolution auxiliary datasets, including AGB and vegetation indices, and further demonstrated through a spatiotemporal analysis of forest loss. Overall, I appreciate the authors' effort in developing this dataset and conducting extensive experiments and comparisons. The topic is relevant and the generated product has potential value for the remote sensing community. However, I believe the manuscript would benefit from improvements in the presentation, particularly in the description of the methodology and the interpretation of the results. Therefore, I recommend major revision.

We are immensely grateful for the reviewer's encouragement and insightful suggestions, which proved invaluable in enhancing the quality of our manuscript. Detailed responses are provided below.

Major Comments

Comment 1. Study area description (Section 2). *The study area section would benefit from additional background information on the ecosystems of the two selected regions to better motivate their selection and provide readers with more context. In addition, please explicitly explain what P1 and P2 represent in Figure 1.*

Response: We sincerely thank the reviewer for this constructive suggestion. We have expanded Section 2 (Lines 127–138) to provide the requested ecological background for both regions, and explicitly defined P1 and P2 in both the main text and the caption of Fig.1.

Modifications in the manuscript:

Lines 127–138: Within this pan-tropical domain, Brazil and the Democratic Republic of the Congo (DRC) each have complete continuous tropical vegetation gradients and diverse internal ecosystem

compositions. Brazil's climate ranges from tropical to semi-arid and subtropical (Alvares et al., 2013). It contains six major biomes ranging from the dense evergreen canopy of the Amazon (Myer, 2016) to the Neotropical savanna of the Cerrado (Dos Reis et al., 2022) and the semi-arid Caatinga (Moro et al., 2016), which have been increasingly impacted by extreme drought events and rapid deforestation in recent decades (Smith et al., 2023). Within these vast Brazilian biomes exist areas with contrasting canopy structures: fragmented, spatially heterogeneous forest-edge zones with discontinuous tree canopies (P1, Fig. 1), and intact dense evergreen rainforests with closed continuous canopies (P2, Fig. 1). The DRC can be divided into three major natural regions according to vegetation types: the dense rainforest in the central basin and to the west; dry forests and savannahs in the southern part and on the northern fringe; and mountain ecosystems along the eastern border (Achille et al., 2021). These diverse ecosystems are similarly experiencing escalating pressures from widespread small-scale forest disturbances (Tyukavina et al., 2018) and shifting climatic patterns (Zhou et al., 2014).

Lines 150-152: P1 and P2 highlight areas with contrasting canopy structures, representing fragmented forest-edge zones and intact dense evergreen rainforests, respectively.

Comment 2. Potential numerical instability (Section 3.2, Eq. (2)). Since the injection gain is computed as $(g = \frac{L-VOD_{5km_NNR}}{AGB_{5km_Low_Pass}})$, what happens when $(AGB_{5km_Low_Pass})$ approaches zero? Would this lead to numerical instability or extremely large gain values? Please explain how such cases are handled.

Response: We would like to thank the reviewer for highlighting this critical issue. We apologize for the confusion. In our actual code implementation, we had already anticipated this issue and explicitly added a stabilization term c to the denominator to mathematically prevent any divide-by-zero errors. Specifically, we used the machine epsilon for double-precision floating-point format ($c=2.22 \times 10^{-16}$, implemented via `torch.finfo(torch.float64).eps` in PyTorch). However, this term was inadvertently omitted from Eq. (2) in the original manuscript. It is also worth noting that, in regions where $AGB_{5km_Low_Pass}$ approaches zero, the L-band VOD (and consequently the numerator $L-VOD_{5km_NNR}$) is also very small, as both quantities are physically linked to the absence of vegetation. Since the two variables scale together, their ratio remains naturally bounded in practice. We have corrected Eq. (2) and added the corresponding explanation in the revised manuscript (Lines 221–222).

Modifications in the manuscript:

Lines 221–222:

$$g_{initial} = \frac{L-VOD_{5km_NNR}}{AGB_{5km_Low_Pass} + c} \quad (2)$$

where a small positive constant c (approximately 2.22×10^{-16}) is added to the denominator to avoid division by zero.

Comment 3. Description of the iterative optimization of the injection gain (around Lines 190–205).

The description of the iterative optimization of the injection gain (g) (Eqs. (2)–(4)) is difficult to follow. Since this section describes an algorithm rather than a mathematical derivation, I strongly recommend presenting it as pseudocode or an algorithm box.

At present, it is unclear what variable is actually being optimized and how the optimization is performed. Specifically, Eq. (3) states that g is optimized by maximizing the Pearson correlation between the downscaled L-VOD and AGB, whereas the subsequent text only describes progressively reducing the upper bound (g_{limit}) and clipping g . It is therefore unclear whether g is recomputed following some math optimization rule for equation (3), or whether only the clipped version of the initial gain map is updated.

A pseudocode description would clearly specify the initialization, the variables updated in each iteration, how Eq. (1) is repeatedly evaluated, how the correlation is used during optimization, and what constitutes the final optimized gain map. This would greatly improve both the clarity and reproducibility of the proposed method.

Response: We sincerely thank the reviewer for this highly constructive recommendation. We have rewritten the description of the optimization process and introduced Algorithm 1.

To address the reviewer’s specific concerns, we clarified that the optimization utilizes an iterative threshold-search approach. The algorithm systematically reduces an upper-limit threshold (g_{limit}) to clip the initial gain map ($g_{initial}$), producing a candidate gain map (g). In each iteration, it applies this candidate g to the downscaling model (following the formulation of Eq. (1)) to recalculate L-VOD, and computes the Pearson correlation (R) between the downscaled L-VOD and AGB. The final optimized gain map (g_{opt}) is the specific clipped map that yields the global maximum correlation, as strictly defined in Eq. (3). The new pseudocode explicitly details all initializations, loop iterations, the repeated evaluation of Eq. (1), and the stopping criteria (step size α and convergence threshold τ) (Fig. A1). (Lines 218-232)

Modifications in the manuscript:

Lines 218-232: The optimal injection gains g_{opt} in Eq. (1) is a pixel-wise injection gain, representing the contribution of annual CCI-AGB to each monthly L-VOD. A total of 84 gain maps (7 years $\times$ 12months) were obtained to downscale the 5-km resolution monthly L-VOD series over the 7-year period (2015–2021), with each monthly gain map computed based on the corresponding annual AGB, as described in Eq. (2).

$$g_{initial} = \frac{L-VOD_{5km_NNR}}{CCI-AGB_{5km_Low_Pass} + c} \quad (2)$$

where a small positive constant c (approximately 2.22×10^{-16}) is added to the denominator to avoid division by zero. Note that the initial injection gains $g_{initial}$ contain uncertainties, because the $L-VOD_{5km_NNR}$ is not the true 5-km downscaled L-VOD although $L-VOD_{5km_NNR}$ could represent the spatial-temporal information of $L-VOD_{25km}$. To reduce the uncertainties of $g_{initial}$ and enhance the accuracy and robustness of $L-VOD_{5km}$, the raw gains were iteratively optimized. We employed an iterative threshold-search algorithm to maximize the Pearson correlation coefficient (R) between the $L-VOD_{5km}$ and the $CCI-AGB_{5km}$ by iterating through a set of candidate injection gains (g), as described in Eq. (3). The detailed procedure is explicitly presented in Algorithm 1.

$$g_{opt} = \arg \max_g R(L-VOD_{5km}, CCI-AGB_{5km}) \quad (3)$$

The detailed procedure for determining g_{opt} is explicitly presented in Algorithm 1.

Algorithm 1 Iterative Optimization of the Injection Gain (g_{opt}).

- 1: **Input:** Initial injection gain map $g_{initial}$, annual $CCI-AGB_{5km}$, step size $\alpha = 0.01$, convergence threshold $\tau = 0.01$
 - 2: **Initialization:** $g_{limit}^{(0)} \leftarrow \max(g_{initial})$, $k \leftarrow 0$, $R_{max} \leftarrow -1$, $g_{opt} \leftarrow g_{initial}$, $R^{(-1)} \leftarrow 0$
 - 3: **while true do**
 - 4: $g^{(k)} \leftarrow \min(g_{initial}, g_{limit}^{(k)})$
 - 5: Calculate $L-VOD_{5km}^{(k)} \leftarrow L-VOD_{5km_NNR} + g^{(k)} \times (CCI-AGB_{5km} - CCI-AGB_{5km_Low_Pass})$
 - 6: Calculate the Pearson correlation coefficient $R^{(k)}$ between $L-VOD_{5km}^{(k)}$ and $CCI-AGB_{5km}$
 - 7: **if** $R^{(k)} > R_{max}$ **then**
 - 8: $R_{max} \leftarrow R^{(k)}$
 - 9: $g_{opt} \leftarrow g^{(k)}$
 - 10: **end if**
 - 11: $\Delta R \leftarrow |R^{(k)} - R^{(k-1)}|$
 - 12: **if** $k > 0$ **and** $\Delta R < \tau$ **then**
 - 13: **break;**
 - 14: **end if**
 - 15: $g_{limit}^{(k+1)} \leftarrow g_{limit}^{(k)} - \alpha$
 - 16: $k \leftarrow k + 1$;
 - 17: **end while**
-

To ensure the robustness of the optimization process, the step size α and convergence threshold τ in Algorithm 1 were both conservatively set to 0.01. This configuration was selected based on systematic parameter-sensitivity tests, which yield a reasonable balance between computational cost and spatial-detail injection (Fig. A1).

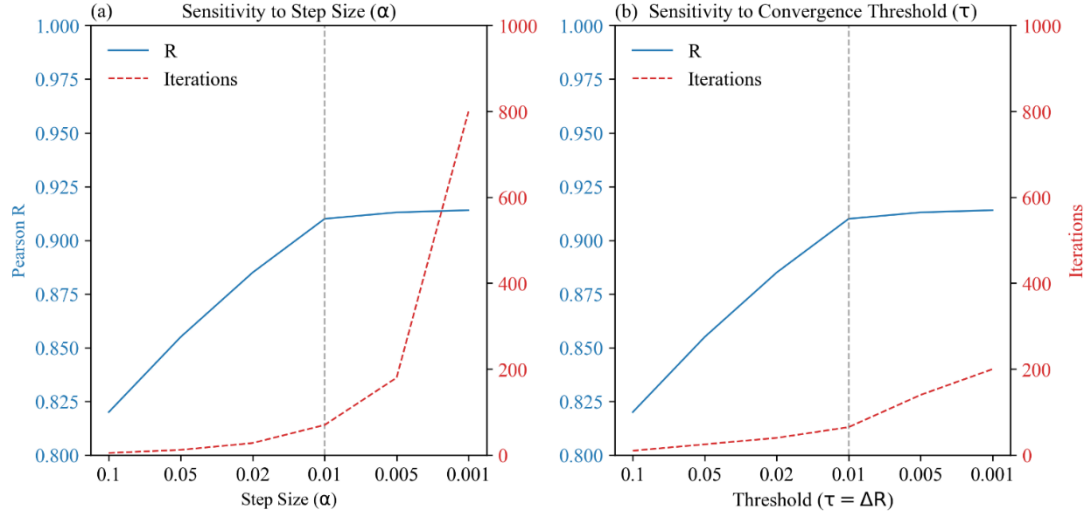


Figure R1 (Copied from Fig. A1 from the revised manuscript). Sensitivity analysis of parameters in the iterative gain optimization process. (a) Impact of varying step sizes (α) on the optimized spatial correlation (Pearson R , solid blue line) and computational cost (number of iterations, dashed red line) under a fixed convergence threshold ($\tau = 0.01$). (b) Impact of varying convergence thresholds (τ) on the correlation and iteration counts under a fixed step size ($\alpha = 0.01$). The vertical gray dashed lines indicate the adopted optimal configuration ($\alpha = 0.01$, $\tau = 0.01$).

Comment 4. Figure 2 (algorithm flowchart). The flowchart does not sufficiently clarify the iterative optimization process. In particular, the step " $g = \text{adjusted } g$ " is ambiguous, as it is unclear how the adjusted gain is obtained. Similarly, the role of (ΔR) in the optimization is not well illustrated. Revising the flowchart to explicitly show the update rule for g (or (g_{limit})) would substantially improve readability.

Response: We sincerely thank the reviewer for pointing out this ambiguity. We have completely updated Fig. 2 to explicitly illustrate the update rule for the injection gain (Lines 190-194). Specifically, we added a dedicated dashed panel (labeled "① Detailed Iterative Optimization for Gain g_{opt} ") to map out the entire subroutine. This new panel replaces the ambiguous " $g = \text{adjusted } g$ " step with the precise mathematical update operations (i.e., clipping the gain via $g = \min(g_{initial}, g_{limit})$ and progressively reducing the threshold via $g_{limit} = g_{limit} - \alpha$). Furthermore, the roles of the Pearson correlation (R), its absolute change (ΔR), and the convergence threshold (τ) are now visually integrated into the decision loop.

Modifications in the manuscript:

Lines 190-194:

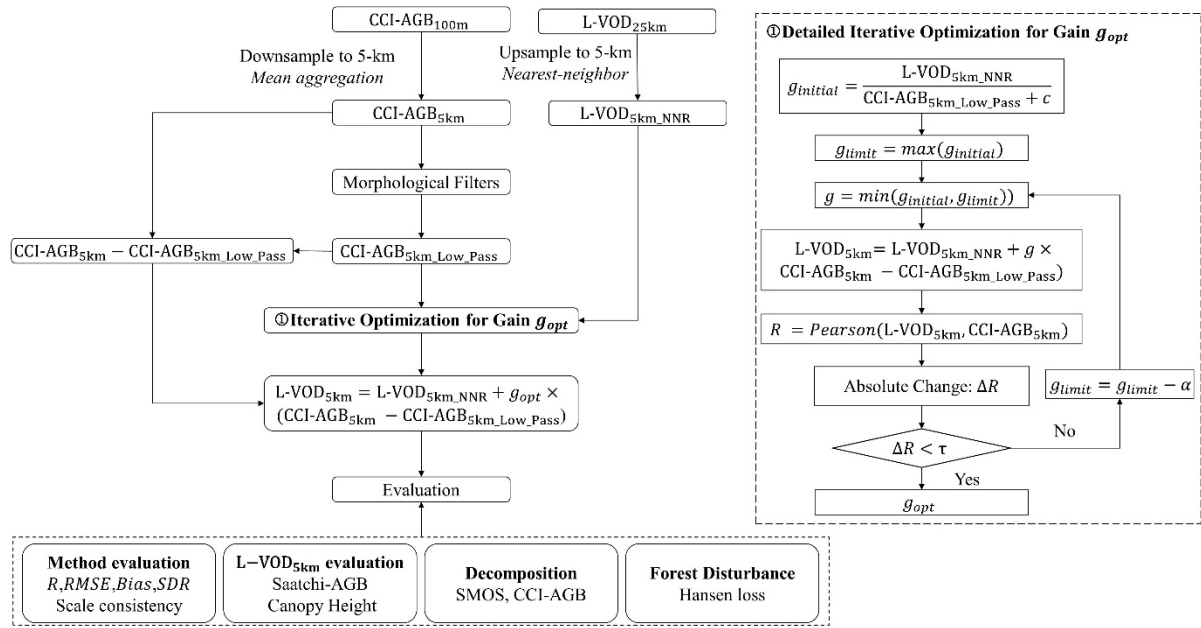


Figure R2 (Copied from Fig. 2 from the revised manuscript). Flowchart illustrating the workflow for generating and validating downscaled L-VOD products. The dashed panel illustrates the complete iterative optimization subroutine for calculating optimal gain g_{opt} . NNR stands for Nearest-Neighbor Resampling. ΔR represents the absolute change in the Pearson correlation coefficient (R), and τ is the convergence threshold.

Comment 5. Comparison with existing downscaling methods. The manuscript evaluates the proposed product against auxiliary datasets but does not compare the proposed downscaling approach with existing methods. Since the Introduction discusses alternative approaches (e.g., SAR-based methods, statistical downscaling, MF-MRA), it would strengthen the manuscript to compare the proposed method with one or more representative baselines and demonstrate its advantages.

Response: We sincerely thank the reviewer for this highly constructive recommendation. In response, we added two methods: the Gram–Schmidt adaptive (GSA) method and the Random Forest (RF) model. These were compared with the proposed Morphological Filter–based Multiresolution Analysis (MF-MRA) downscaling method using the correlation coefficient (R), $RMSE$, $Bias$, and Standard Deviation Ratio (SDR) (Lines 253-263). Furthermore, the performances of the three methods were compared across various vegetation types as well as within two representative regions, Brazil and the DRC.

Our newly added results (Lines 353-400) demonstrate that while the RF model achieves low *RMSE*, it introduces a substantial smoothing effect that underestimates spatial variance, particularly in dense forests. Conversely, the GSA method excessively amplifies spatial variance and exhibits extreme instability. Our proposed framework achieves strong agreement with the reference data (high *R*, low *RMSE* and low *Bias*) while preserving natural spatial variability. It avoids the severe smoothing of RF and the extreme variance amplification of GSA (maintaining a more stable *SDR*), including in critical forest biomes (e.g., evergreen broadleaf forest, EBF, and evergreen needleleaf forest, ENF).

Modifications in the manuscript:

Lines 253–263: To comprehensively evaluate the proposed approach we compared it with the Gram–Schmidt adaptive (GSA) (Aiazzi et al., 2007), which similarly utilizes CCI-AGB for spatial disaggregation but is based on a linear transformation (Method B1), and the RF. For the RF model, the vegetation and environmental covariates including NDVI, LAI, precipitation, LST and DEM follow the variable scheme described in Yan et al. (2025). To ensure fair comparison and consistent core vegetation-related predictors across modelling frameworks, CCI-AGB was additionally included among the RF input features.

Method performance was evaluated using a comprehensive set of statistical metrics. These include the correlation coefficient (*R*), *RMSE*, *Bias*, Standard Deviation Ratio (*SDR*) and the slope of the linear regression (*Slope*). The equations corresponding to these metrics are listed as follows:

$$R = \frac{Cov(L-VOD_{25km}^{sim}, L-VOD_{25km})}{\sigma(L-VOD_{25km}^{sim})\sigma(L-VOD_{25km})} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum (L-VOD_{25km}^{sim} - L-VOD_{25km})^2}{N}} \quad (7)$$

$$Bias = \frac{\sum (L-VOD_{25km}^{sim} - L-VOD_{25km})}{N} \quad (8)$$

$$SDR = \frac{STD_{pred}}{STD_{obs}} \quad (9)$$

where *Cov* is the covariance and σ is the standard deviation. *N* is the sample size. STD_{pred} and STD_{obs} represent the standard deviations of the simulated $L-VOD_{25km}^{sim}$ and reference $L-VOD_{25km}$, respectively. The *Slope* metric is derived from the ordinary least squares (OLS) linear regression between the simulated outputs and reference data.

Lines 353-400: The performance of the downscaling approaches was evaluated by comparing the simulated 25-km outputs from each method against the original reference observations. Overall, the proposed framework demonstrates a balance between signal agreement and the preservation of spatial variance. While the RF method yields the lowest *RMSE* of 0.139 and nearly unbiased estimates with *Bias* = 0.004 (Fig.7c), its *SDR* of 0.817 (Fig. 7c) indicates a substantial smoothing effect that underestimates the true spatial variance of the L-VOD data. In contrast, the proposed framework presented in Fig. 7a achieves the highest spatial correlation with the reference dataset at an *R* of 0.913. This marginally outperforms the RF method with an *R* of 0.908 (Fig. 7c), as well as the GSA method, which yields an *R* of 0.868 (Fig. 7b). Furthermore, the proposed framework effectively maintains the spatial variability of the original observations by achieving an *SDR* of 1.082 (Fig 7a), placing it closest to the ideal value of 1.0. Conversely, the GSA approach shown in Fig. 7b exhibits the largest deviations by producing the highest *RMSE* of 0.291 alongside an *SDR* of 1.608 (Fig.7b), signifying an excessive amplification of spatial variance.

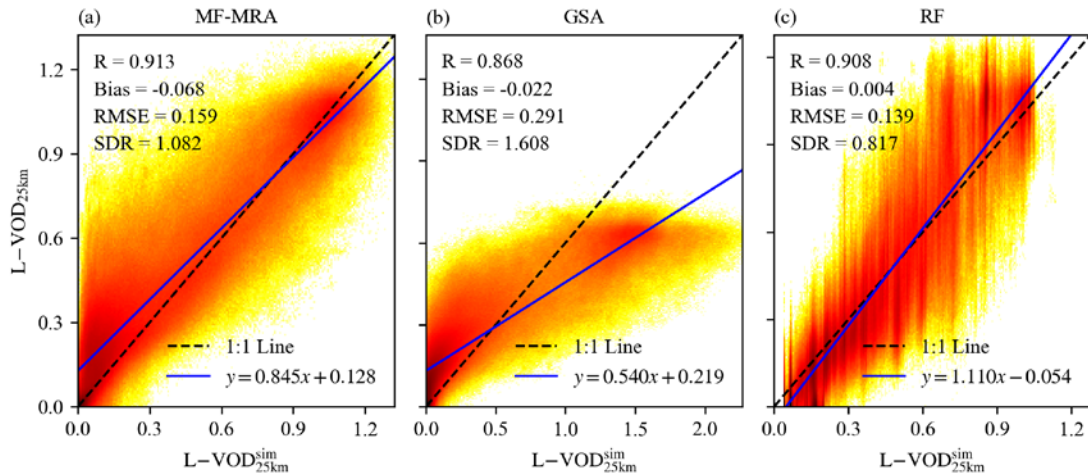


Figure R3 (Copied from Fig. 7 from the revised manuscript). Evaluation of the downscaling algorithm performance. Density scatter plots comparing the simulated 25-km outputs ($L-VOD_{25km}^{sim}$) from (a) the MF-MRA method, (b) the GSA method, and (c) the RF model against the original 25-km L-VOD reference observations ($L-VOD_{25km}$) across the pan-tropical region during the period of 2015-2021. The dashed black line represents the 1:1 reference line, and the blue line indicates the linear regression fit. Colour shading indicates the number density of pixels (log-scaled).

Fig.8 presents a detailed quantitative assessment of the three downscaling methods across various vegetation types. Overall, the analysis reveals distinct performance variations between forested and non-forested regions depending on the applied algorithm. Our framework demonstrates robust signal agreement in dense forest ecosystems. It achieves its highest *R* of 0.78 in ENF and 0.74 in EBF (Fig.

8a), along with a low *RMSE* of 0.17 in EBF (Fig. 8c), and maintains small *Bias* of -0.03 in EBF and ENF (Fig. 8b). Furthermore, in these forest categories, the proposed method yields *SDR* values > 1.0 (Fig. 8d), whereas its *SDR* drops below 1.0 in sparse vegetation like G and C. In contrast, the RF model exhibits the exact opposite regional preference, performing more effectively in non-forest or sparse vegetation categories. It reaches peak *R* of 0.81 in CS and 0.75 in G (Fig. 8a). Conversely, the RF model produces stable, near-zero biases in these sparse areas, such as 0.01 in CS, but experiences larger deviations in dense forests, dropping to -0.09 in EBF (Fig. 8b). Consequently, in forest categories like EBF and ENF, the RF model yields higher *RMSE* values of 0.18 and 0.14, respectively (Fig. 8c). Regarding the *SDR* metric (Fig. 8d), the RF model consistently produces values < 1.0 in forested areas, whereas it exceeds 1.0 in sparse vegetation like G and C. Finally, the GSA approach exhibits the largest deviations across the evaluated vegetation types. It generates the highest *RMSE*, reaching 0.44 in EBF (Fig. 8c) and prominent bias fluctuations, including a large *Bias* of 0.27 in EBF (Fig. 8b). In terms of spatial variance, the GSA method follows a similar trend to the proposed method but exhibits extreme instability, peaking at an *SDR* of 2.19 in EBF and dropping to 0.37 in OS (Fig. 8d).

(a) Correlation (R)			
Vegetation Type	MF-MRA	GSA	RF
ENF	0.78	0.66	0.49
EBF	0.74	0.64	0.65
DBF	0.68	0.54	0.57
MF	0.60	0.51	0.53
CS	0.66	0.60	0.81
OS	0.66	0.42	0.69
WS	0.51	0.32	0.45
S	0.56	0.44	0.56
G	0.49	0.48	0.75
C	0.35	0.35	0.63
CNVM	0.44	0.29	0.59

(b) Bias			
Vegetation Type	MF-MRA	GSA	RF
ENF	-0.03	-0.17	0.04
EBF	-0.03	0.27	-0.09
DBF	-0.05	-0.18	-0.03
MF	-0.04	-0.14	0.00
CS	-0.07	-0.14	0.01
OS	-0.02	-0.06	0.03
WS	-0.09	-0.18	-0.02
S	-0.11	-0.17	0.05
G	-0.08	-0.13	0.06
C	-0.11	-0.14	0.03
CNVM	-0.15	-0.21	0.05

(c) RMSE			
Vegetation Type	MF-MRA	GSA	RF
ENF	0.13	0.23	0.14
EBF	0.17	0.44	0.18
DBF	0.17	0.27	0.16
MF	0.14	0.23	0.12
CS	0.11	0.16	0.07
OS	0.06	0.09	0.07
WS	0.20	0.30	0.15
S	0.18	0.23	0.13
G	0.14	0.16	0.10
C	0.15	0.18	0.10
CNVM	0.22	0.26	0.13

(d) SDR			
Vegetation Type	MF-MRA	GSA	RF
ENF	1.51	1.45	0.90
EBF	1.23	2.19	0.80
DBF	1.21	1.31	0.85
MF	1.31	1.57	0.98
CS	0.89	0.75	0.99
OS	0.76	0.37	0.86
WS	1.37	1.63	0.89
S	1.27	1.17	0.94
G	0.86	0.76	1.13
C	0.85	0.72	1.19
CNVM	1.17	0.81	0.93

Figure R4 (Copied from Fig. 8 from the revised manuscript). Quantitative performance of the downscaling algorithms across various vegetation types. Heatmaps illustrating the (a) R , (b) Bias, (c) $RMSE$, (d) SDR for the 25-km simulated outputs from the MF-MRA, GSA, and RF methods compared against the original 25-km L-VOD reference data. The evaluation is conducted across IGBP vegetation categories within the pan-tropical region. Colour scales correspond to the specific magnitude of each statistical metric.

Regional downscaling performance was further evaluated across two major tropical forest regions, Brazil and the DRC. While all evaluated methods maintain robust R as shown in Fig. 9a, they display distinct differences in error and spatial variance. The RF model yields the lowest $RMSE$ (Fig. 9c) alongside near-zero biases (Fig. 9b). However, it consistently underestimates spatial variance by yielding SDR below 1.0 (Fig. 9d), indicating an underestimation of spatial variability and a tendency toward spatial smoothing. Conversely, the GSA approach exhibits the largest regional deviations by producing the highest error metrics and an excessive amplification of spatial variance, with SDR values substantially exceeding 1.0 (Fig. 9d). The proposed framework achieved a more balanced performance, maintaining strong pixel-wise agreement while yielding SDR values closest to the ideal 1.0 baseline in both regions (Fig. 9d), thereby better preserving spatial variability and vegetation heterogeneity.

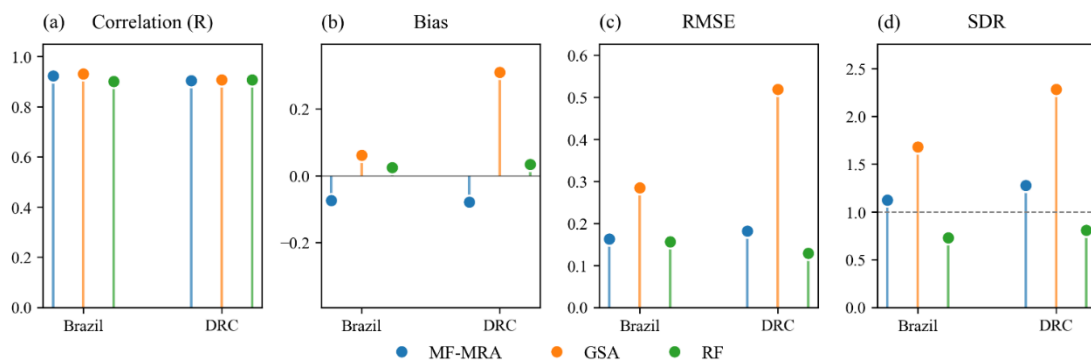


Figure R5 (Copied from Fig. 9 from the revised manuscript). Quantitative performance of the downscaling algorithms across two major tropical forest domains (Brazil and the DRC). Lollipop plots illustrating the (a) R , (b) Bias, (c) $RMSE$, (d) SDR for the 25-km simulated outputs from the MF-MRA, GSA, and RF methods compared against the native 25-km SMOS L-VOD reference data.

Comment 6. Forest loss analysis. The forest-loss analysis could be further strengthened. Since the Hansen Global Forest Change product has well-known limitations (e.g., it represents tree-cover loss rather than a broader definition of forest loss, with trees defined as taller than 5 m), these limitations should be briefly discussed in either the Results or Discussion section.

In addition, I suggest performing the analysis at the regional level rather than emphasizing pixel-level dynamics (Figure 10c, d), which may be sensitive to uncertainties in the Hansen product. Furthermore, Figure 10 only shows a single blue bar for forest loss in 2015. It would be more informative to visualize annual forest loss throughout the entire study period (2015–2021).

Response: We sincerely thank the reviewer for these highly insightful suggestions. We fully agree with you. Our point-by-point responses are provided below.

(1) We have added a concise discussion in Section 5.2, Limitations and Perspectives (Lines 555–573). Specifically, we address two aspects: (i) the height-based forest definition (>5 m) can misclassify plantations and low-stature crops as forest, biasing estimates of forest cover change (Tropek et al., 2014); and (ii) the stand-replacement loss definition cannot capture non-stand-replacing processes such as partial canopy damage, drought-induced degradation, and post-drought regrowth, and the dataset does not distinguish loss drivers such as management, harvest, or natural disturbance (Baccini et al., 2019; Liu et al., 2025).

(2) Following your suggestion, we conducted a regional scale forest-loss analysis for Brazil and the DRC over the full 2015–2021 study period. Specifically, we added a comparison between annual mean L-VOD_{5km} with annual forest-loss percentage (Fig. 15; Lines 487–498). The results show that regional L-VOD_{5km} dynamics broadly correspond to variations in forest-loss activity in both regions, with declines during periods of relatively elevated forest loss and partial recovery in subsequent years.

(3) The original pixel-scale analysis (formerly Fig. 10, now Fig. 16) has been revised (Lines 499–519). We now present a multi-year case study covering 2016 and 2019. The results show that in years when forest loss occurred, L-VOD at the same pixel declined concurrently.

Modifications in the manuscript:

Lines 555–573: Evaluating the downscaled product against optical-based forest loss datasets introduces uncertainties. Hansen loss is defined as stand-replacement disturbance or complete canopy removal at the Landsat pixel scale, based on canopy closure of all vegetation taller than 5-m (Hansen et al., 2013). This height-based definition of forest includes plantation types that have already replaced substantial parts of tropical forests. As a result, monocultures of oil palm, rubber, or Eucalyptus are technically classified as forests, leading to an underestimation of real forest loss. Furthermore, contrary to this

definition, vegetation lower than 5 m, such as pineapple, soybean, or tea plantations, is often classified as forest, which further biases estimates of forest cover gain and loss (Tropek et al., 2014).

This stand-replacement definition also means that Hansen's binary loss records cannot capture non-stand-replacing processes such as partial canopy damage, drought-induced degradation, and post-drought regrowth, nor do they attribute detected forest loss to specific drivers such as management, harvest, or natural disturbances (Baccini et al., 2019; Liu et al., 2025). Because these non-stand-replacing processes exert opposing effects on L-VOD, they may jointly offset L-VOD declines or even generate positive anomalies. For example, in 2016 (Fig. 16d), Hansen recorded lower forest loss than in 2019, yet $L - VOD_{5km}$ declined much more strongly, consistent with the 2015–2016 El Niño drought (Dou et al., 2024). Similarly, in Brazil in 2020 (Fig. 16a), relatively elevated forest loss coincided with an increase in $L - VOD_{5km}$, which may reflect post-El Niño woody biomass recovery that partly offset localized deforestation signals (Fan et al., 2024). These discrepancies underscore the limitation of Hansen in detecting non-stand-replacing disturbances and support the added value of L-VOD for monitoring drought-induced biomass loss (Li et al., 2022b; Qin et al., 2021). Despite these observational discrepancies, the Hansen dataset remains the most globally consistent, high-resolution benchmark available, providing an indispensable reference for our evaluations.

Lines 487-498: As illustrated by the spatial pattern of forest loss extent, both Brazil and the DRC feature regions of high loss intensity with distinct spatial clustering (Fig. A4). We compared the temporal dynamics of $L - VOD_{5km}$ and forest loss in Brazil and the DRC from 2015 to 2021. $L - VOD_{5km}$ showed temporal variations broadly corresponding to forest loss dynamics in both Brazil and the DRC (Fig. 13). In Brazil, $L - VOD_{5km}$ decreased from approximately 0.485 in 2015 to 0.479 in 2017, coinciding with relatively high forest loss during 2016–2017. $L - VOD_{5km}$ subsequently increased and reached its highest value of approximately 0.490 in 2020, before declining again in 2021. In the DRC, $L - VOD_{5km}$ declined more steadily from approximately 0.616 in 2015 to 0.603 in 2018, during a period of relatively elevated forest loss, followed by a partial recovery in 2019–2020 and a modest decrease in 2021.

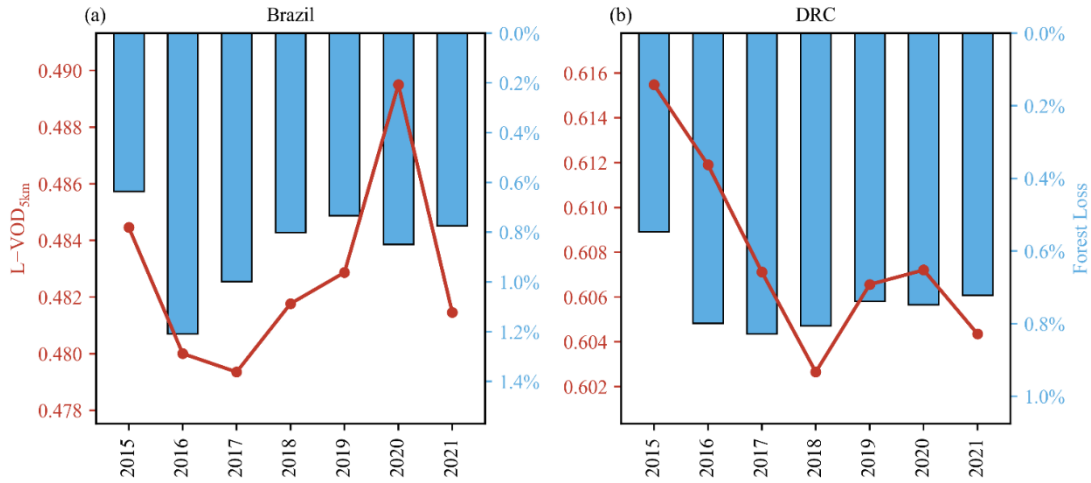


Figure R6 (Copied from Fig. 15 from the revised manuscript). Annual variations in $L\text{-VOD}_{5km}$ and forest loss in (a) Brazil and (b) the DRC during 2015–2021. $L\text{-VOD}_{5km}$ represents the annual mean value across all valid vegetation pixels within each regional study domain, while forest loss represents the annual forest-loss percentage defined in Section 2.6. For Brazil, only the area within the pan-tropical domain (25°N – 25°S) was included.

Lines 499-519: We selected a single 25-km grid cell in Brazil for a case-based in-depth analysis. This site, denoted as P2, experienced severe forest disturbances in 2016 and 2019. Fig.14a–c display the fine-scale spatial patterns of inter-annual L-VOD anomalies both $\Delta L\text{-VOD}_{5km}$ and the $\Delta L\text{-VOD}_{5km}^{\text{SMOS}}$ alongside forest loss at a 5-km spatial resolution within this parent 25-km grid cell. As shown in Fig. 14c, forest loss is heavily concentrated in the eastern section, exhibiting a distinct spatial gradient that reaches local fractional loss values of up to 30%. The proposed $L\text{-VOD}_{5km}$ (Fig. 14a) captures this intra-pixel heterogeneity, exhibiting gradient-like changes. In contrast, the $\Delta L\text{-VOD}_{5km}^{\text{SMOS}}$ (Fig. 14b) shows much weaker intra-grid spatial differentiation (Fig. 14b). This comparison indicates that incorporating interannual CCI-AGB variations improves the representation of fine-scale spatial heterogeneity in disturbance-affected areas, enabling the 5-km product to resolve localized disturbance gradients that are not apparent in the coarse-scale SMOS product.

At the finer pixel scale, the temporal behavior of these disturbances is illustrated by focusing on one specific 5-km sample pixel, labeled P2_1, which is marked in Fig. 14a–c. This target pixel underwent two separate forest loss events, experiencing approximately 10% area loss in 2016 and roughly 18% area loss in 2019. The $L\text{-VOD}_{5km}$ time series exhibits detectable physical responses to both disturbance episodes (Fig. 14d). Specifically, $L\text{-VOD}_{5km}$ decreases from 0.96 to 0.90 in 2016, recovers to a stable 0.96 throughout 2017–2018, and subsequently shows a secondary drop to 0.93 coinciding with the 2019 forest-loss disturbance.

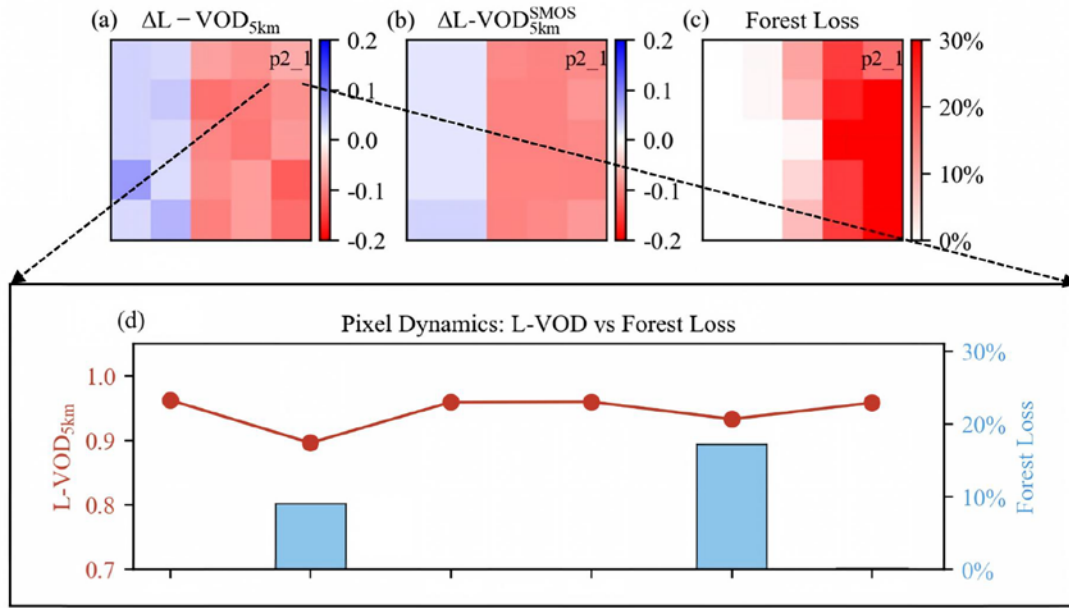


Figure R7 (Copied from Fig. 16 from the revised manuscript). Spatiotemporal responses of $L-VOD_{5km}$ to forest disturbances within a selected 25-km grid cell (P2) in Brazil. The top row presents the fine-scale spatial distribution of (a) the $L-VOD_{5km}$ change generated by the proposed downscaling method ($\Delta L-VOD_{5km}$), (b) the SMOS-driven $L-VOD_{5km}$ change ($\Delta L-VOD_{5km}^{SMOS}$), and (c) the fractional forest loss. A specific 5-km sub-pixel experiencing severe deforestation is marked as p2_1. The bottom panels illustrate the pixel-scale interannual temporal dynamics (2015–2020) for this targeted sub-pixel (p2_1), detailing the trajectories of (d) $L-VOD_{5km}$ compared against annual forest loss events.

Minor Comments

Comment 1. Section 3.3 (Accuracy assessment). Consider formatting the subsection headings such as "(i) **Evaluation of the downscaling method**" in bold to improve readability.

Response: We thank the reviewer for this helpful suggestion. We have updated the formatting for all relevant subsection headings in Section 3.3 accordingly.

Comment 2. Figure 4 (d, f). Why is the standard deviation (error bars) of the downscaled $L-VOD_{5km}$ consistently smaller than that of the original $L-VOD_{25km}$? Since the downscaled product is expected to capture more spatial details, one might expect increased variability. Please provide an explanation.

Response: We sincerely thank the reviewer for pointing out this highly insightful observation. We deeply apologize for a typo in the original figure caption. The error bars in Fig. 4 do not denote the standard deviation of spatial variations; rather, they represent the 95% bootstrap confidence intervals (CI) of the median. We have corrected this typo in the caption of Fig.4. at Lines 322-323.

Modifications in the manuscript:

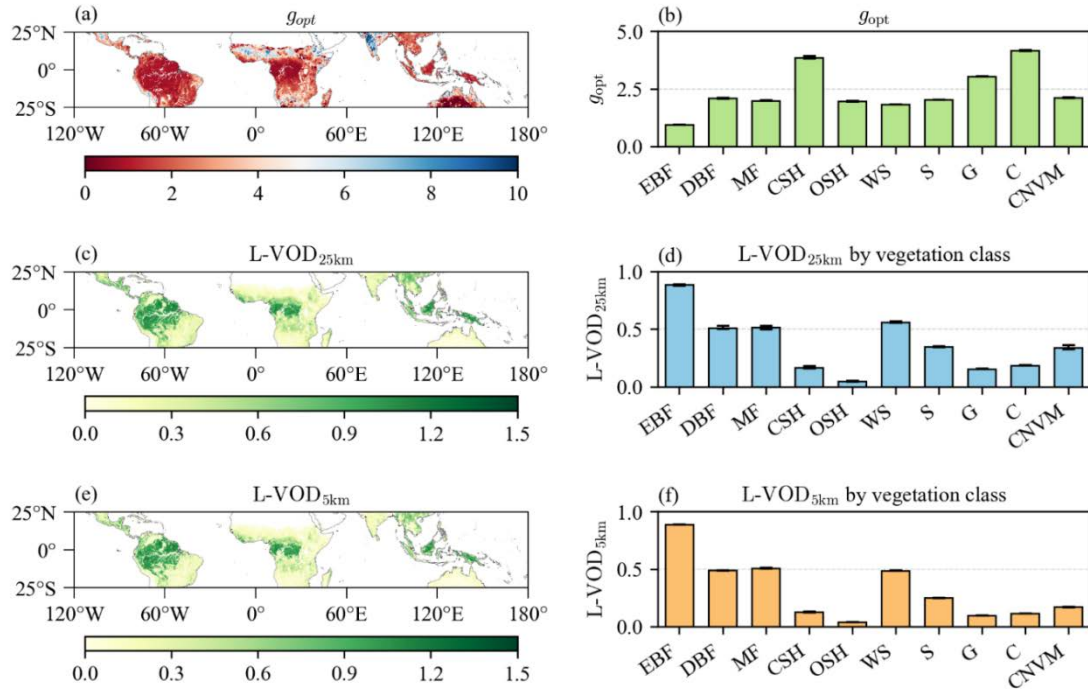


Figure R8 (Copied from Fig. 4 from the revised manuscript). Spatial patterns and vegetation-class medians of the optimal injection gains and L-VOD at 25-km and 5-km in August 2021. (a) Map of injection gains; (b) Median injection gains by vegetation class; (c) Map of L-VOD_{25km}; (d) Median L-VOD_{25km} by vegetation class; (e) Map of L-VOD_{5km}; (f) Median L-VOD_{5km} by vegetation class. Error bars show 95% bootstrap confidence intervals for median L-VOD values per vegetation class.

Comment 3. Figure 5. Consider including the corresponding AGB image and an optical Sentinel-2 image alongside the L-VOD visualization to facilitate interpretation.

Response: We thank the reviewer for this helpful suggestion. Accordingly, we have added the corresponding CCI-AGB and Sentinel-2 imagery alongside the L-VOD visualization in Fig. 5 (Lines 328-337). The results show that the spatial distribution patterns of CCI-AGB and Sentinel-2 are consistent with the downscaled L-VOD product.

Modifications in the manuscript:

Lines 327-336: A comparison with the auxiliary 5-km CCI-AGB maps (Fig. 5c, g) indicates similarities in spatial distribution. Panels (d) and (h) show corresponding Sentinel-2 true-colour imagery as a visual reference for real-world landscape conditions. Forest edges and land-cover patterns visible in the optical imagery correspond well to the spatial variations observed in the L-VOD_{5km}.

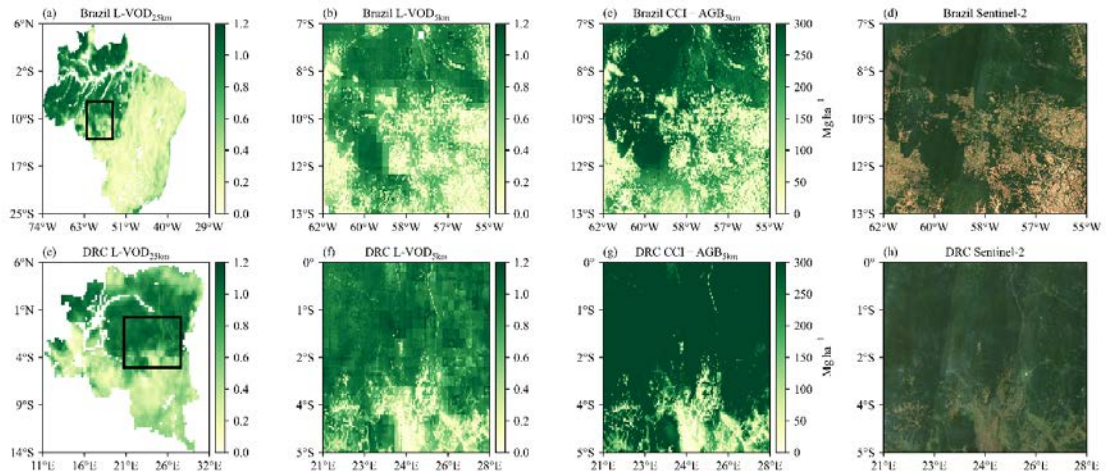


Figure R9 (Copied from Fig. 5 from the revised manuscript). Detailed spatial information of the downscaled L-VOD in August 2021. (a) 25-km L-VOD of Brazil. (b) 5-km L-VOD of the Brazil detail area (the black rectangular area in (a)). (c) 5-km CCI-AGB and (d) 300-m Sentinel-2 optical image for the Brazil detail area. (e) 25-km L-VOD of the DRC. (f) 5-km L-VOD of the DRC detail area (the black rectangular area in (e)). (g) 5-km CCI-AGB and (h) 300-m Sentinel-2 optical image for the DRC detail area. Sentinel-2 images were sourced from Google Earth Engine and upscaled (aggregated) to 300-m.

Comment 4. Figure 6 (j–l). Since all three panels show relationships involving $L - VOD_{5km}$, I suggest using a consistent x-axis label across all three plots.

Response: We thank the reviewer for pointing this out. In the revised Fig. 6, the NDVI-related panel has been removed, and the x-axis labels of the remaining panels have been consistently labeled as $L - VOD_{5km}$.

Modifications in the manuscript:

Line 346:

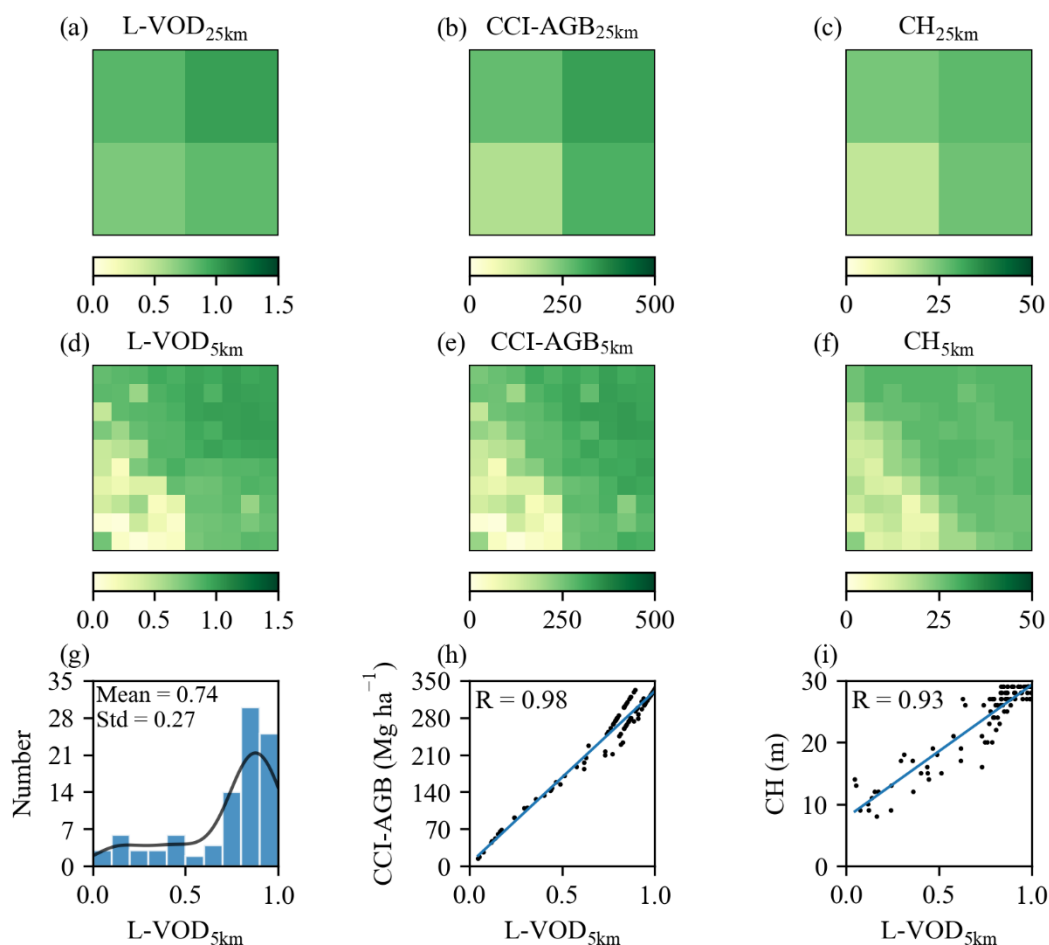


Figure R10 (Copied from Fig. 6 from the revised manuscript). Detailed spatial information and relationships of L-VOD with CCI-AGB and CH at 25-km and 5-km within four SMOS grid cells (corresponding to the locations of P1 in Fig. 1) in 2021. (a)L-VOD_{25km}; (b)CCI-AGB_{25km}; (c)CH_{25km}; (d)L-VOD_{5km}; (e)CCI-AGB_{5km}; (f)CH_{5km}; (g) Distribution of L-VOD_{5km}; (h) Scatter of L-VOD_{5km} and CCI-AGB_{5km}; (i) Scatter of L-VOD_{5km} and CH_{5km}.

Comment 5. Section 4.2 (Accuracy assessment). The manuscript states that the performance was evaluated using data from 2019. Why was only a single year selected instead of evaluating the entire study period (2015–2021)?

Response: We sincerely thank the reviewer for raising this critical point. We completely agree with you. Concurrent with the inclusion of the baseline methods (GSA and RF) as detailed in our response to Major Comment #5, we have expanded the assessment to encompass the entire study period from 2015 to 2021. All statistical metrics and spatial evaluations now reflect the full multi-year dataset. The revised results are detailed in our response to Major Comment #5.

Comment 6. Figure 8. Consider adding labels such as "DRC" and "Brazil" directly to the figure to improve readability.

Response: We thank the reviewer for this helpful suggestion. We fully agree with you. As described in our response to Major Comment #5, we have restructured the assessment figures to accommodate the newly added baseline methods (GSA and RF). Accordingly, the original panels (c) and (d) in Fig. 8 have been removed, and the regional analysis for Brazil and the DRC is now presented in a dedicated new figure (Fig. 9). Following the reviewer's suggestion, we have added clear "Brazil" and "DRC" labels directly in Fig. 9. Please refer to our response to Major Comment #5 for further details.

Comment 7. Consistency between Figures 5 and 8. Figures 5 and 8 appear to use the same study regions. To improve consistency, I recommend using the same naming convention throughout the manuscript. For example, instead of using Region 1/Region 2 in Figure 5 and Rondônia/DRC in Figure 8, consistently use **Brazil** and **DRC**.

Response: We thank the reviewer for pointing out this inconsistency. We have rigorously unified the regional naming convention to consistently use "Brazil" and "the DRC" across all text descriptions and figure labels. Specifically, we have replaced all instances of "Region 1" and "Region 2" with "Brazil" and "DRC" in the updated Fig. 5 and its accompanying main text. The regional analysis originally focused on Rondônia in Fig. 8 has been expanded to cover the entire Brazil region. As described in our response to Comment 6 (and Major Comment #5), this analysis is now presented in the new Fig. 9, where the same "Brazil" and "DRC" labels are applied.

Comment 8. Terminology consistency (around Line 365). The manuscript inconsistently uses AGB_{100} , AGB_{100m} . besides, based on the methodology, it seems more appropriate to refer to AGB_{5km} , since the downscaling uses the aggregated 5-km AGB product rather than the original 100-m spatial details.

Response: We sincerely thank the reviewer for their careful reading and for catching this inconsistency.

We have standardized the terminology throughout the manuscript. References to the original 100-m AGB product are now written as CCI- AGB_{100m} , whereas the aggregated AGB data used for downscaling are referred to as CCI- AGB_{5km} (Lines 523 and 527).

Comment 9. Section title (Section 5.2). The current title "**Uncertainties and Perspectives**" would be more appropriately renamed "**Limitations and Perspectives**", as the section primarily discusses methodological limitations and future research directions.

Response: We thank the reviewer for this constructive suggestion. We fully agree with the reviewer. The title of Section 5.2 has been changed from “Uncertainties and Perspectives” to “Limitations and Perspectives” (Line 538).

Aiazzi, B., Baronti, S., and Selva, M.: Improving component substitution pansharpening through multivariate regression of MS $\pm$ $\pm$ Pan data, *IEEE Transactions on Geoscience and Remote Sensing*, 45, 3230-3239, 2007.

Bousquet, E., Mialon, A., Rodriguez-Fernandez, N., Mermoz, S., and Kerr, Y.: Monitoring post-fire recovery of various vegetation biomes using multi-wavelength satellite remote sensing, *Biogeosciences*, 19, 3317-3336, 10.5194/bg-19-3317-2022, 2022.

Dou, Y., Tian, F., Wigneron, J.-P., Li, X., Zhang, W., Chen, Y., Feng, L., Xie, Q., and Fensholt, R.: Satellite observations indicate slower recovery of woody components compared to upper-canopy and leaves in tropical rainforests after drought, *Communications Earth & Environment*, 5, 10.1038/s43247-024-01892-9, 2024.

Fan, L., Cui, T., Wigneron, J. P., Ciais, P., Sitch, S., Brandt, M., Li, X., Niu, S., Xiao, X., Chave, J., Wu, C., Li, W., Yuan, W., Xing, Z., Li, X., Wang, M., Liu, X., Chen, X., Qin, Y., Yang, H., Tang, Q., Li, Y., Ma, M., and Fensholt, R.: Dominant role of the non-forest woody vegetation in the post 2015/16 El Niño tropical carbon recovery, *Global Change Biology*, 30, 10.1111/gcb.17423, 2024.

Fawcett, D., Sitch, S., Ciais, P., Wigneron, J. P., Silva-Junior, C. H. L., Heinrich, V., Vancutsem, C., Achard, F., Bastos, A., Yang, H., Li, X., Albergel, C., Friedlingstein, P., and Aragão, L. E. O. C.: Declining Amazon biomass due to deforestation and subsequent degradation losses exceeding gains, *Global Change Biology*, 29, 1106-1118, 10.1111/gcb.16513, 2022.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., and Loveland, T. R.: High-resolution global maps of 21st-century forest cover change, *science*, 342, 850-853, 2013.

Li, X., Wigneron, J.-P., Frappart, F., De Lannoy, G., Fan, L., Zhao, T., Gao, L., Tao, S., Ma, H., and Peng, Z.: The first global soil moisture and vegetation optical depth product retrieved from fused SMOS and SMAP L-band observations, *Remote Sensing of Environment*, 282, 113272, 2022.

Qin, Y., Xiao, X., Wigneron, J.-P., Ciais, P., Brandt, M., Fan, L., Li, X., Crowell, S., Wu, X., and Doughty, R.: Carbon loss from forest degradation exceeds that from deforestation in the Brazilian Amazon, *Nature Climate Change*, 11, 442-448, 2021.

Yan, H., Wang, C., and Lu, X.: Downscaling of vegetation optical depth based on random forest using vegetation optical depth memory, *Remote Sensing Letters*, 16, 717-727, 2025.

Zotta, R.-M., de Jeu, R., Bader, N. F., Frederikse, T., and Dorigo, W.: Improving AMSR2 vegetation optical depth retrievals via land parameter retrieval model parameter optimisation, *Remote Sensing of Environment*, 335, 10.1016/j.rse.2026.115286, 2026.

Response to Referee #2

The paper is correctly written while the English could probably be improved as some sentences are not crystal clear. The content seems sound to me and the questions raised on this type of publication are probably more generic and not always specific to the manuscript itself.

We are immensely grateful for the reviewer's encouragement and insightful suggestions, which proved invaluable in enhancing the quality of our manuscript. Detailed responses are provided below.

General comments

Comment 1. It's more semantic than anything else but I feel that it is not correct to speak about spatial resolution as done in this document. Spatial resolution is linked to the sensor characteristics and thus the area from which the measured energy comes from. It is not to be mistaken with the sampling. In terms of information content etc this is important. I would thus recommend to replace all the "spatial resolution" by "spatial sampling" in this manuscript.

Response: We sincerely thank you for your comments. However, after reviewing previous studies in the field of remote sensing data downscaling and gridded product generation, we found that the professional terminology "spatial resolution" is consistently utilized across the literature to describe the final downscaled data (Yang et al., 2026; Hu et al., 2024; Das et al., 2019; Bousquet E, 2019; Gevaert et al., 2016; Hashemi et al., 2026; Merlin et al., 2008; Merlin et al., 2013). We prefer to retain "spatial resolution" in the manuscript.

Comment 2. The second general comment is more on the approach itself. If it is a good this to try to have higher resolution L-VOD maps one may question (as the authors do incidentally) to what the product will be compared the outcome. The authors go to some details on the four-pronged approach, but unfortunately it does not really address the issue. The history is full of approaches/ models being validated against dubious (but only available for sure) data sets to be proven wrong (resp. true) while validated (resp. said wrong).

Response: We sincerely thank you for your comments. We believe our evaluation framework is methodologically sound and appropriate for this dataset. First, our evaluation approach is directly built upon established evaluation methodologies that represent the standard practice in the field of satellite product downscaling (Mohite et al., 2022; Gevaert et al., 2016; Yang et al., 2026; Li et al., 2022; Yan et

al., 2025). In the absence of direct in situ L-VOD measurements, these widely accepted frameworks serve as a rigorous baseline for proving spatial and temporal consistency.

Second, to assess whether our product captures vegetation dynamics beyond statistical agreement with auxiliary datasets, we included forest loss data in the evaluation. The downscaled L-VOD product responds to documented forest loss events with concurrent declines.

Comment 3. The first deals with usual metrics. Comparing the two LVOD -25km is straightforward but only proves that the method does not go completely awry, it is simply a sanity check and does not prove much. The fact that it works well over dense forest does not prove anything as it is where you would expect the least variability.

Response: We sincerely thank the reviewer for this constructive comment. Our detailed responses are as follows.

(1) We have added additional metrics, including *Bias* and the Standard Deviation Ratio (*SDR*) to provide a more comprehensive assessment beyond simple correlation, as detailed in Section 3.3 (Lines 258–263).

(2) We added two methods: the Gram–Schmidt adaptive (GSA) method and the Random Forest (RF) model (Lines 253–257). These were compared with the proposed Morphological Filter–based Multiresolution Analysis (MF-MRA) downscaling method using the correlation coefficient (*R*), *RMSE*, *Bias*, and *SDR*. Furthermore, the performances of the three methods were compared across various vegetation types as well as within two major countries characterized by extensive tropical forests (Brazil and the DRC).

The newly added results (Lines 353–400) demonstrate that while the RF model achieves low *RMSE*, it introduces a substantial smoothing effect that underestimates spatial variance, particularly in dense forests. Conversely, the GSA method excessively amplifies spatial variance and exhibits extreme instability. Our proposed framework achieves strong agreement with the reference data (high *R*, low *RMSE* and low *Bias*) while preserving natural spatial variability. It avoids the severe smoothing of RF and the extreme variance amplification of GSA (maintaining a more stable *SDR*), including in critical forest biomes (e.g., evergreen broadleaf forest (EBF) and evergreen needleleaf forest (ENF)). This evaluation extends beyond dense forests and covers multiple vegetation types, demonstrating that the method preserves spatial variance rather than merely matching the coarse-resolution L-VOD.

(3) We evaluated the 5-km downscaled L-VOD against independent Saatchi AGB and canopy height data (Lines 432-445). The results demonstrate that the 5-km product maintains strong spatial consistency with both reference datasets ($R \approx 0.9$). Furthermore, the downscaling process effectively reduces systematic errors. Specifically, the *Bias* relative to the Saatchi dataset decreased from 0.62 (at 25-km) to -0.01 (at 5-km).

Modifications in the manuscript:

Lines 258–263: Method performance was evaluated using a comprehensive set of statistical metrics. These include the correlation coefficient (R), $RMSE$, $Bias$, Standard Deviation Ratio (SDR) and the slope of the linear regression ($Slope$). The equations corresponding to these metrics are listed as follows:

$$R = \frac{Cov(L-VOD_{25km}^{sim}, L-VOD_{25km})}{\sigma(L-VOD_{25km}^{sim})\sigma(L-VOD_{25km})} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum (L-VOD_{25km}^{sim} - L-VOD_{25km})^2}{N}} \quad (7)$$

$$Bias = \frac{\sum (L-VOD_{25km}^{sim} - L-VOD_{25km})}{N} \quad (8)$$

$$SDR = \frac{STD_{pred}}{STD_{obs}} \quad (9)$$

where Cov is the covariance and σ is the standard deviation. N is the sample size. STD_{pred} and STD_{obs} represent the standard deviations of the simulated $L-VOD_{25km}^{sim}$ and reference $L-VOD_{25km}$, respectively. The $Slope$ metric is derived from the ordinary least squares (OLS) linear regression between the simulated outputs and reference data.

Lines 253–257: To comprehensively evaluate the proposed approach we compared it with the Gram–Schmidt adaptive (GSA) (Aiazzi et al., 2007), which similarly utilizes CCI-AGB for spatial disaggregation but is based on a linear transformation (Method B1), and the RF. For the RF model, the vegetation and environmental covariates including NDVI, LAI, precipitation, LST and DEM follow the variable scheme described in Yan et al. (2025). To ensure fair comparison and consistent core vegetation-related predictors across modelling frameworks, CCI-AGB was additionally included among the RF input features.

Lines 353-400: The performance of the downscaling approaches was evaluated by comparing the simulated 25-km outputs from each method against the original reference observations. Overall, the proposed framework demonstrates a balance between signal agreement and the preservation of spatial

variance. While the RF method yields the lowest $RMSE$ of 0.139 and nearly unbiased estimates with $Bias = 0.004$ (Fig.7c), its SDR of 0.817 (Fig. 7c) indicates a substantial smoothing effect that underestimates the true spatial variance of the L-VOD data. In contrast, the proposed framework presented in Fig. 7a achieves the highest spatial correlation with the reference dataset at an R of 0.913. This marginally outperforms the RF method with an R of 0.908 (Fig. 7c), as well as the GSA method, which yields an R of 0.868 (Fig. 7b). Furthermore, the proposed framework effectively maintains the spatial variability of the original observations by achieving an SDR of 1.082 (Fig 7a), placing it closest to the ideal value of 1.0. Conversely, the GSA approach shown in Fig. 7b exhibits the largest deviations by producing the highest $RMSE$ of 0.291 alongside an SDR of 1.608 (Fig.7b), signifying an excessive amplification of spatial variance.

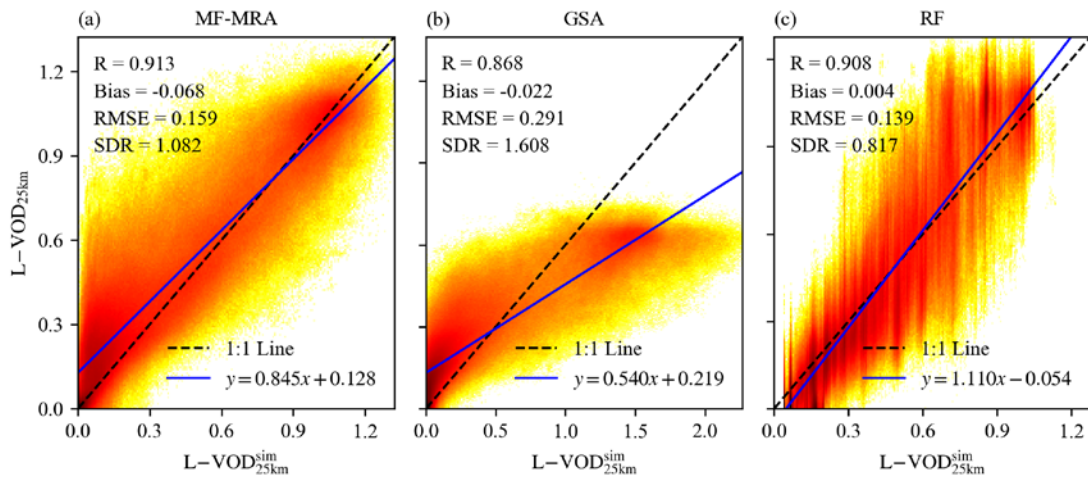


Figure R1 (Copied from Fig. 7 from the revised manuscript). Evaluation of the downscaling algorithm performance. Density scatter plots comparing the simulated 25-km outputs ($L-VOD_{25km}^{sim}$) from (a) the MF-MRA method, (b) the GSA method, and (c) the RF model against the original 25-km L-VOD reference observations ($L-VOD_{25km}$) across the pan-tropical region during the period of 2015-2021. The dashed black line represents the 1:1 reference line, and the blue line indicates the linear regression fit. Colour shading indicates the number density of pixels (log-scaled).

Fig.8 presents a detailed quantitative assessment of the three downscaling methods across various vegetation types. Overall, the analysis reveals distinct performance variations between forested and non-forested regions depending on the applied algorithm. Our framework demonstrates robust signal agreement in dense forest ecosystems. It achieves its highest R of 0.78 in ENF and 0.74 in EBF (Fig. 8a), along with a low $RMSE$ of 0.17 in EBF (Fig. 8c), and maintains small $Bias$ of -0.03 in EBF and ENF (Fig. 8b). Furthermore, in these forest categories, the proposed method yields SDR values > 1.0 (Fig. 8d), whereas its SDR drops below 1.0 in sparse vegetation like G and C. In contrast, the RF

model exhibits the exact opposite regional preference, performing more effectively in non-forest or sparse vegetation categories. It reaches peak R of 0.81 in CS and 0.75 in G (Fig. 8a). Conversely, the RF model produces stable, near-zero biases in these sparse areas, such as 0.01 in CS, but experiences larger deviations in dense forests, dropping to -0.09 in EBF (Fig. 8b). Consequently, in forest categories like EBF and ENF, the RF model yields higher $RMSE$ values of 0.18 and 0.14, respectively (Fig. 8c). Regarding the SDR metric (Fig. 8d), the RF model consistently produces values < 1.0 in forested areas, whereas it exceeds 1.0 in sparse vegetation like G and C. Finally, the GSA approach exhibits the largest deviations across the evaluated vegetation types. It generates the highest $RMSE$, reaching 0.44 in EBF (Fig. 8c) and prominent bias fluctuations, including a large $Bias$ of 0.27 in EBF (Fig. 8b). In terms of spatial variance, the GSA method follows a similar trend to the proposed method but exhibits extreme instability, peaking at an SDR of 2.19 in EBF and dropping to 0.37 in OS (Fig. 8d).

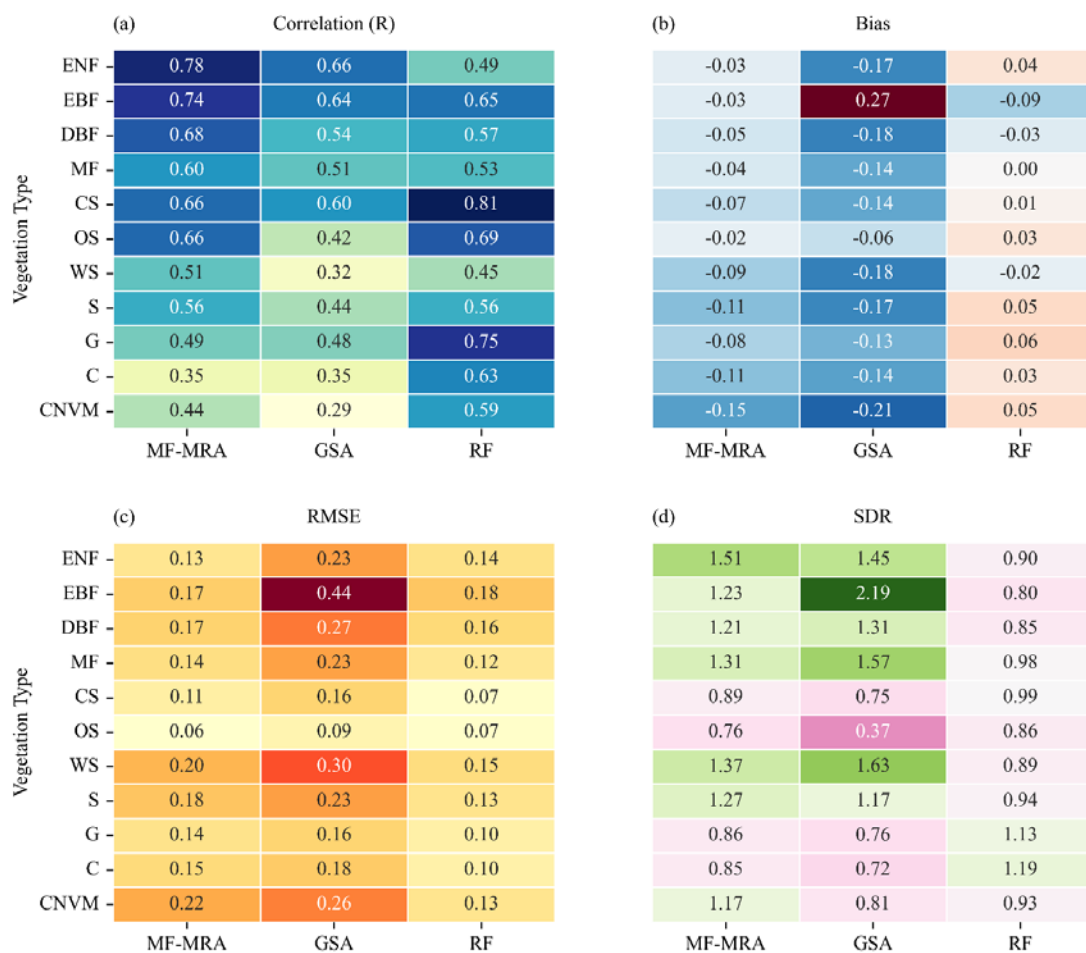


Figure R2 (Copied from Fig. 8 from the revised manuscript). Quantitative performance of the downscaling algorithms across various vegetation types. Heatmaps illustrating the (a) R , (b) Bias, (c) $RMSE$, (d) SDR for the 25-km simulated outputs from the MF-MRA, GSA, and RF methods compared against the original 25-km L-VOD reference data. The evaluation is conducted across IGBP vegetation

categories within the pan-tropical region. Colour scales correspond to the specific magnitude of each statistical metric.

Regional downscaling performance was further evaluated across two major tropical forest regions, Brazil and the DRC. While all evaluated methods maintain robust R as shown in Fig. 9a, they display distinct differences in error and spatial variance. The RF model yields the lowest $RMSE$ (Fig. 9c) alongside near-zero biases (Fig. 9b). However, it consistently underestimates spatial variance by yielding SDR below 1.0 (Fig. 9d), indicating an underestimation of spatial variability and a tendency toward spatial smoothing. Conversely, the GSA approach exhibits the largest regional deviations by producing the highest error metrics and an excessive amplification of spatial variance, with SDR values substantially exceeding 1.0 (Fig. 9d). The proposed framework achieved a more balanced performance, maintaining strong pixel-wise agreement while yielding SDR values closest to the ideal 1.0 baseline in both regions (Fig. 9d), thereby better preserving spatial variability and vegetation heterogeneity.

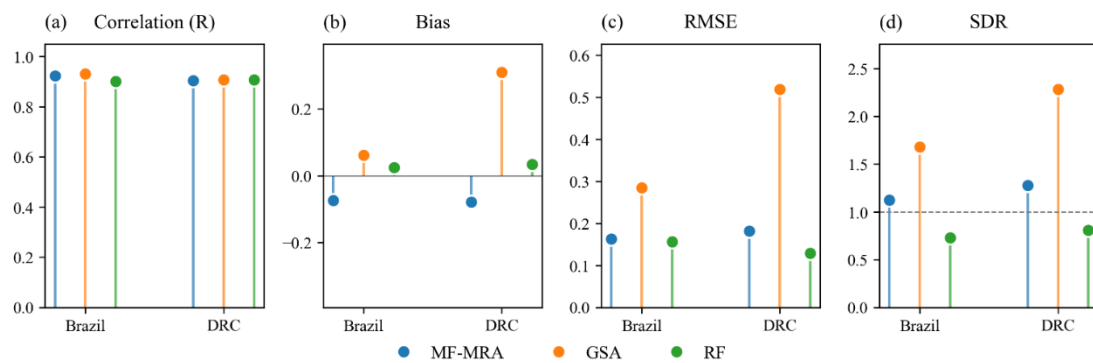


Figure R3 (Copied from Fig. 9 from the revised manuscript). Quantitative performance of the downscaling algorithms across two major tropical forest domains (Brazil and the DRC). Lollipop plots illustrating the (a) R , (b) Bias, (c) $RMSE$, (d) SDR for the 25-km simulated outputs from the MF-MRA, GSA, and RF methods compared against the native 25-km SMOS L-VOD reference data.

Lines 432-445: We compared the original 25-km SMOS L-VOD and our 5-km downscaled L-VOD against two independent datasets, i.e., Saatchi-AGB and canopy height product (Fig. 12). Strong power-law correlations are observed between L-VOD and both forest variables at both resolutions. For the Saatchi AGB dataset (Fig. 12 a, b), the 5-km downscaled L-VOD maintains a high correlation coefficient ($R = 0.9$) that is nearly identical to the original 25-km observation ($R = 0.91$). The 5-km product achieves a near-zero $Bias$ of -0.01, substantially lower than the 0.62 $Bias$ observed at 25 km; $RMSE$ increases slightly from 34.04 at 25-km to 39.79 at 5-km, which is expected given the stronger fine-scale spatial heterogeneity at finer resolution. Similar pattern is observed with the canopy height

data (Fig. 12c, d), the 5-km product again shows near-identical correlation ($R = 0.89$ vs. 0.90 at 25-km) and near-zero *Bias* at both resolutions, with *RMSE* increasing marginally from 3.47 at 25-km to 3.85 at 5-km, also consistent with this expectation.

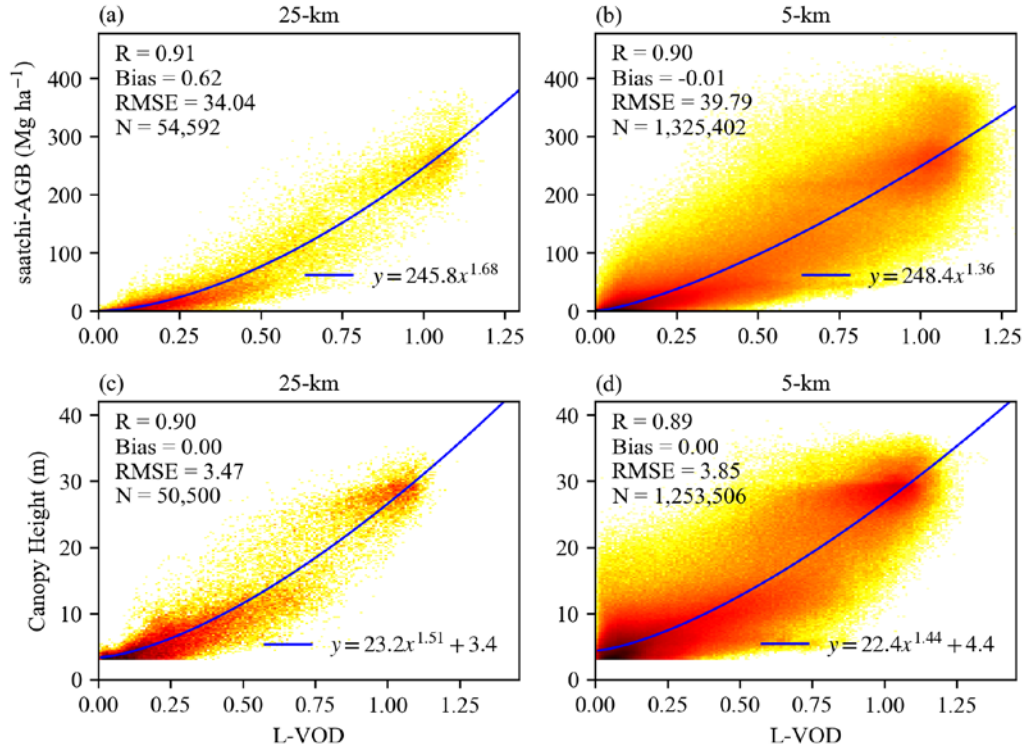


Figure R4 (Copied from Fig. 12 from the revised manuscript). Relationships between L-VOD and forest-structure variables at original 25-km and downscaled 5-km. Density scatter plots illustrate the correspondence between L-VOD and (a, b) Saatchi-AGB, as well as (c, d) canopy height. Panels (a, c) use the native 25-km L-VOD product; panels (b, d) adopt the 5-km L-VOD dataset generated in this study. Solid blue lines represent power-law regression fits. Colour indicates pixel-pair count density on a logarithmic scale.

Comment 4. For the temporal and spatial assessment, I must have missed a step as, to my understanding, the output is compared to the AGB map which was used to elaborate the dis-aggregated product. Maybe the authors could detail this a bit further.

Response: Thank you for your comment. We wish to clarify that in our downscaling framework, the CCI-AGB dataset is introduced strictly to provide relative spatial structural information to guide the disaggregation process, rather than being utilized as absolute numerical inputs in the calculations. Additionally, we have added a comparison against independent Saatchi-AGB and canopy height data, as detailed in our response to Comment 3 (3).

Comment 5. The comparison with LAI also does not bring much. First LAI and VOD are two different things. They do not look at the same characteristics of the vegetation (chlorophyll vs. water content) not the same media (top surface for LAI vs. more volume for L band). So no wonder the R are so low (and sometimes negative) except for dense forests where both tend to saturate.

Response: We sincerely thank the reviewer for this comment. We agree with the reviewer and have removed the LAI comparison entirely from the revised manuscript, including all related figures, tables, and discussions.

Comment 6. The forest loss is probably the most interesting “validation attempt but again it is not very satisfactory. Comparing a curve to a point (fig 10) is interesting but does not drive any nail in unfortunately. The explanation for the difference in NDVI vs L-VOD recovery is not very convincing. For me first again we are not comparing the same things so it does not prove much other than that L-VOD (Water and thus BIOMASS in these regions) do recover slowly (what we expect) but also if the area is deforested, it is to plant crop which have been selected to produce and thus tend to have higher LAI (NDVI) than natural vegetation. So for me this means that the area sees forest replace by crops.

Response: We would like to express our gratitude to the reviewer for raising this issue. The revisions are as follows:

- (1) We have completely removed the pixel-scale NDVI comparison from the revised manuscript.
- (2) In the revised version, we conducted a regional-scale forest loss analysis for Brazil and the DRC over the full 2015–2021 study period. Specifically, we added a comparison between annual mean L-VOD_{5km} with annual forest loss percentage (Fig. 15; Lines 487-498). The results show that regional L-VOD_{5km} dynamics broadly correspond to variations in forest-loss activity in both regions, with declines during periods of relatively elevated forest loss and partial recovery in subsequent years.

Modifications in the manuscript:

Lines 487-498: As illustrated by the spatial pattern of forest loss extent, both Brazil and the DRC feature regions of high loss intensity with distinct spatial clustering (Fig. A4). We compared the temporal dynamics of L-VOD_{5km} and forest loss in Brazil and the DRC from 2015 to 2021. L-VOD_{5km} showed temporal variations broadly corresponding to forest loss dynamics in both Brazil and the DRC (Fig. 13). In Brazil, L-VOD_{5km} decreased from approximately 0.485 in 2015 to 0.479 in 2017, coinciding with relatively high forest loss during 2016–2017. L-VOD_{5km} subsequently increased and reached its

highest value of approximately 0.490 in 2020, before declining again in 2021. In the DRC, $L\text{-}VOD_{5km}$ declined more steadily from approximately 0.616 in 2015 to 0.603 in 2018, during a period of relatively elevated forest loss, followed by a partial recovery in 2019–2020 and a modest decrease in 2021.

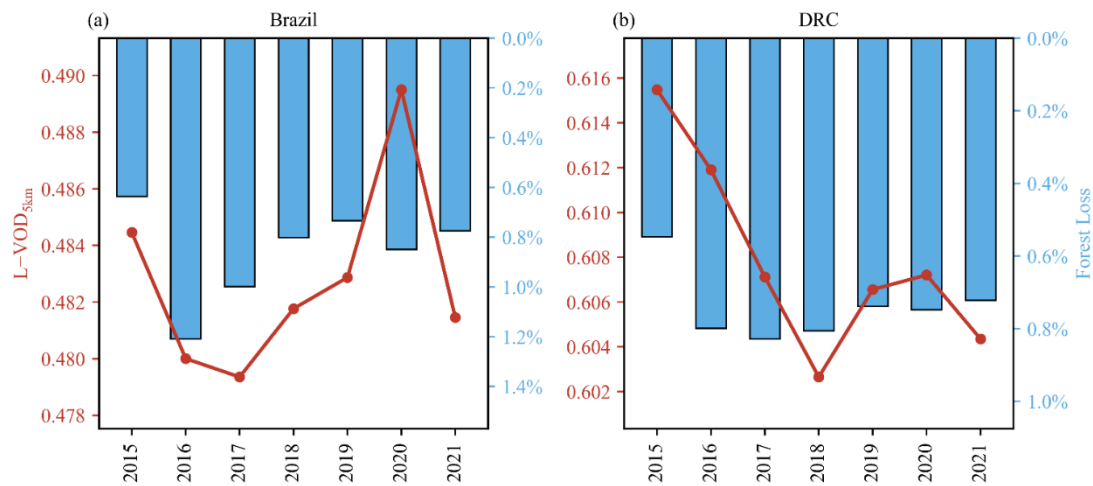


Figure R5 (Copied from Fig. 15 from the revised manuscript). Annual variations in $L\text{-}VOD_{5km}$ and forest loss in (a) Brazil and (b) the DRC during 2015–2021. $L\text{-}VOD_{5km}$ represents the annual mean value across all valid vegetation pixels within each regional study domain, while forest loss represents the annual forest-loss percentage defined in Section 2.6. For Brazil, only the area within the pan-tropical domain (25°N–25°S) was included.

Comment 7. One final general comments. The references are nice but seem to be a bit partial towards the authors. Common, practice for sure but it is always strange to see that studies by some authors seem to be under represented.

Response: We sincerely thank the reviewer for pointing this out. Following your suggestion, we have conducted a comprehensive review of previous research in this field and added relevant references.

Modifications in the manuscript:

The references have been expanded to include additional studies from a broader range of research groups, including:

Line 129: Alvares et al. (2013);

Line 130: Myster (2016), Dos Reis et al. (2022), Moro et al. (2016);

Line 131: Smith et al. (2023);

Line 136: Achille et al. (2021);

Line 137: Tyukavina et al. (2018);

Line 138: Zhou et al. (2014);

Line 268 :Yang et al. (2026);

Line 564: Baccini et al. (2019), Liu et al. (2025);

Line 567: Dou et al. (2024);

Reference

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