Responses to Reviewers' Comments for Manuscript essd-2025-96

Dynamics of China's Forest Carbon Storage: The First 30 m Annual Aboveground Biomass Mapping from 1985 to 2023

Addressed Comments for Publication to

Earth System Science Data

by

Yaotong Cai, Peng Zhu, Xing Li, Xiaoping Liu, Yuhe Chen, Qianhui Shen, Xiaocong Xu, Honghui Zhang, Sheng Nie, Cheng Wang, Jia Wang, Bingjie Li, Changjiang Wu, and Haoming Zhuang

Response Letter

Dear Editors,

Please find enclosed the revised version of our manuscript entitled *"Dynamics of China's Forest Carbon Storage: The First 30 m Annual Aboveground Biomass Mapping from 1985 to 2023"* (Manuscript ID: essd-2025-96). We sincerely thank the editor and reviewers for their continued time and constructive feedback. We appreciate the positive assessment and the helpful minor comments provided in this round, which have further improved the quality of the manuscript. All comments have been carefully addressed, and corresponding revisions have been made in the manuscript. A concise summary of the main modifications and a detailed point-by-point response to the reviewers' comments are provided below, following the order of the decision letter.

Sincerely,

Yaotong Cai, Peng Zhu, Xing Li, Xiaoping Liu, Yuhe Chen, Qianhui Shen, Xiaocong Xu, Honghui Zhang, Sheng Nie, Cheng Wang, Jia Wang, Bingjie Li, Changjiang Wu, and Haoming Zhuang

Note: To enhance the legibility of this response letter, all the editor's and reviewers' comments are typeset in boxes. Rephrased or added sentences are typeset in color. The respective parts in the manuscript are highlighted to indicate changes.

Authors' Response to the Editor

General Comments. There are a few minor suggestions from the reviewers. Please consider addressing them accordingly.

Response: We thank the editor for the guidance. All minor suggestions from the reviewers have been carefully addressed, and corresponding revisions have been made in the manuscript.

Authors' Response to Reviewer 1

Comment 1

Thanks for these revisions. Most of my concerns have been revised. I have only one minor suggestions. As the authors also concur, the underestimation of your map is greater in high-biomass plots, and your map has a large difference with existing maps (CCI and others). I suggest the authors add some caveats in the discussion to highlight these issues, since the readers may use your data with these cautions.

Response: We thank the reviewer for this valuable suggestion. We have added a statement in the Discussion section to acknowledge the underestimation in high-biomass regions and the differences from existing datasets. This addition highlights the potential sources of bias and advises users to interpret the data with these considerations in mind. The revision has been made and is marked in the manuscript.

Discussion — Page 30, Lines 620–625 (added caveats):
To guide proper use of these maps, we note several best-use recommendations: the products are most reliable at regional to national scales rather than for individual plots; caution is warranted when interpreting high-biomass tropical or subtropical forests due to potential saturation, and users are encouraged to cross-validate with other datasets when conducting local analyses; and users should consider forest definition thresholds and local biomass-to-carbon conversion factors when estimating carbon stocks. Where possible, independent validation with local field data is recommended before applying these maps for management or policy decisions. Finally, continued development of deep learning models and integration of multi-source data are likely to further enhance both the accuracy and applicability of future AGB products.

Authors' Response to Reviewer 2

General Comments. This a really good paper and the authors did a good revision. However, before publishing, some minor issues also need to be addressed.

Response: We thank the reviewer for the positive evaluation of our work and for pointing out the remaining minor issues. All comments have been carefully addressed, and corresponding revisions have been made in the manuscript.

Comment 1

Geographic location is a man-made variable and does not have physical link to AGB. Is it reasonable to include it as a predictor; I think it will not affect too much using some other predictors instead.

Response: We thank the reviewer for this insightful comment. We agree that geographic coordinates are not direct physical drivers of AGB. However, spatial autocorrelation is a well-established property of most environmental variables, and including coordinates helps the model capture large-scale spatial patterns and residual spatial dependence not fully explained by other predictors. In our feature selection process using the Recursive Feature Elimination (RFE) method, geographic coordinates were consistently identified as important variables, and removing them reduced predictive accuracy (Figure 2). This finding is consistent with previous studies, which have shown that incorporating spatial coordinates can improve both model stability and precision (Yang and Huang., 2021). We have clarified this rationale in the revised Methods section.

Methods — Page 6, Lines 170–175.
To capture large-scale spatial patterns and residual spatial autocorrelation beyond environmental predictors, we also included latitude and longitude as auxiliary spatial variables, following Tobler's First Law of Geography. This practice has proven effective in improving model generalization and reducing spatial bias in regions with sparse training data (Yang and Huang, 2021).

Comment 2

L120 and 181, the number should be consistent.

Response: Thank you for pointing this out. We have checked and corrected the inconsistency between the two numbers to ensure they are now consistent in the revised manuscript.

Where modified in manuscript:
Introduction — Page 4, Lines 119–120.

Comment 3

As a data paper, the field survey data should be given and it is important; More details should also be given how the field survey data were used for validation; because the study has a weakness for temporal validation, could you make a temporal validation using survey data for given years? See Laffitte et al., Global Change Biology, 2025

Response: We thank the reviewer for emphasizing the importance of data transparency. The field survey data used in this study were compiled from published sources (Avitabile et al., 2016; Luo et al., 2014; Usoltsev and , 2020; Zhang et al., 2019). These datasets were collected and curated by the respective authors and are publicly available through the cited publications. To respect data ownership and licensing agreements, we did not redistribute these field data directly but provided complete citations to their sources. Although we cannot share the data ourselves, all datasets are publicly accessible through the referenced studies, where detailed access information is provided.

Following the reviewer's suggestion, we have added more details in the Methods section (Section 2.2.2) to clarify how the field survey data were used for validation. Specifically, we used 2,109 ground plots as an independent validation dataset, separate from the GEDI AGBD samples used for model training (2019–2021). Model-predicted AGBD values were compared against field-based estimates to compute validation metrics including the coefficient of determination (R^2), root-mean-square error (RMSE), and mean bias. The results are presented in Figure 3 to assess the overall accuracy and potential bias of the predicted AGBD.

We appreciate the reviewer's suggestion regarding temporal validation. The Leave-One-Year-Out (LOYO) approach used in Laffitte et al. (2025) is an effective method to assess model generalization over time. However, this method requires multi-year and temporally consistent training data. In our case, the field survey data (1978–2008) were compiled from heterogeneous studies conducted in different years, regions, and sampling protocols, which makes them unsuitable for LOYO validation.

Therefore, we implemented the LOYO validation using the GEDI AGBD dataset (2019–2021), which provides consistent multi-temporal observations. Three annual models were trained, each time leaving one year out for validation. This procedure follows the same rationale as LOYO validation but is based on the most temporally consistent data available.

Where modified in manuscript:
Methods: Page 9, Lines 255–260.
To assess temporal robustness, we implemented a Leave-One-Year-Out (LOYO) validation using the multi-year GEDI AGBD record (2019–2021). In each LOYO iteration (i.e., leaving one year out for validation), the model was trained on the remaining two years, and the process was repeated three times to evaluate temporal generalization. In addition, a 5-fold cross-validation was performed within the full dataset to further assess model stability and ensure consistent predictive performance. Reported accuracy metrics represent the mean performance across LOYO and 5-fold evaluations. For assessing the accuracy of the AGBD estimation model, we utilized validation metrics such as the coefficient of determination (R2, Eq. (2)), root mean square error (RMSE, Eq. (3)), and bias (Eq. (4)). These metrics quantified the agreement between predicted AGBD values and reference values, providing insights into prediction accuracy and systematic errors.
Results: Page 11, Lines 305–315.
The ResNet model exhibited strong predictive performance for AGBD. In 5-fold cross-validation, the model achieved R2=0.91, RMSE = 16.49 Mg ha1, and a minimal bias of 0.50 Mg ha1, demonstrating its overall accuracy. Temporal validation using the LOYO approach yielded slightly lower but still robust performance (R2=0.85, RMSE = 21.20 Mg ha1, Bias = 0.66 Mg ha1; Fig. 3), highlighting the model's ability to generalize across years. The somewhat lower LOYO performance, particularly for 2021, reflects the limited training data from 2019–2020 relative to the 2021 prediction set, which reduced the model's exposure to the high-biomass conditions in 2021. Nevertheless, the model still delivered satisfactory predictions across all years. Moreover, the ResNet model outperformed other machine learning ensemble models (e.g., Random Forest, XGBoost, and LightGBM), particularly in mitigating the effects of spectral saturation in high-biomass forests (see Text S3 for details).

Comment 4

The logic of using GPP and VOD should be further clarified.

Response: We thank the reviewer for the comment. We clarified in the manuscript that GPP and VOD were used to evaluate the temporal trends of predicted AGB because they provide independent, complementary signals of vegetation dynamics: GPP reflects carbon uptake, while VOD reflects canopy structure and water content, both of which are strongly linearly related to AGB. Consistent trends between predicted AGB and these variables increase confidence that the observed temporal patterns are reliable. This rationale and the analysis procedure have been added to the Methods section.

Where modified in manuscript:
Materials and methods: Section 2.3, Page 7, Lines 200–201 (Expanded).
To cross-check the temporal dynamics of AGBD, we employed two independent datasets: vegetation optical depth (VOD) and gross primary production (GPP). VOD primarily reflects canopy structural and water characteristics, whereas GPP quantifies ecosystem carbon uptake; both are strongly and positively correlated with aboveground biomass dynamics. VOD was derived from the VOD Climate Archive (VODCA v2, CXKu band), which provides harmonized microwave retrievals from 1987 to 2021 at 0.25° resolution (Zotta et al., 2024). To better capture biomass-related signals, we filtered daily VOD by the main growing season (day of year 150–300) and composited annual medians. For ecosystem productivity, we used the Global Sunlit and Shaded GPP dataset (1992–2020, 0.05° resolution), which estimates photosynthesis with a two-leaf light use efficiency model. Annual GPP was adopted to evaluate AGBD variations at interannual to decadal scales (Bi et al., 2022). Together, VOD and GPP provide complementary perspectives on canopy structure, water content, and carbon uptake, supporting the validation of long-term AGBD trends.

Comment 5

L228: do you make a bootstrap for how many times? If you just make one random selection, the model may be unrealiable.

Response: We thank the reviewer for this insightful comment. To ensure model robustness, we included a 5-fold cross-validation scheme, in which 80% of the samples were used for training and 20% for validation in each iteration. The process was repeated five times with different random partitions, and the mean and standard deviation of model performance metrics across folds were used to assess model stability. This revision has been added to the Methods and Results section.

Where modified in manuscript:
Materials and methods: Section 2.5, Page 6, Lines 259–260; Results: Section 3.2.1, Page 11, Lines 305–320 (Revised).

Comment 6

Section 2.8, please give a definition used in this study.

Response: Thanks for the suggestion. We have added explicit definitions of the four forest change modes (forest growth, expansion, loss, and tree cover loss) in Section 2.8 to clarify how they are defined and applied in this study.

Where modified in manuscript:
Methods: Page 10, Lines 280–295.
To consistently quantify how forest dynamics influence AGC stocks, we established clear operational definitions of forest change modes based on tree cover transitions. Annual forest cover data from the CATCD were used to determine forest status, with pixels having tree cover $\geq$ 20% classified as forest. In this study, four distinct forest change modes were defined as follows:

1. *Forest growth: pixels that were forested in both 1985 and 2023 and exhibited an increase in tree cover.*
2. *Tree cover loss: pixels that were forested in both 1985 and 2023 but showed a decrease in tree cover.*
3. *Forest expansion: pixels that transitioned from non-forest in 1985 to forest in 2023.*
4. *Forest loss: pixels that changed from forest in 1985 to non-forest in 2023.*

For each pixel i, the change in aboveground carbon was calculated as:
$\Delta AGC_i = AGC_{2023,i} - AGC_{1985,i}$ (5)
Positive ΔAGC values indicate carbon gain, while negative values denote carbon loss. To facilitate interpretation, the four modes were further grouped into two broader categories: 1) Tree cover change (TCC)–induced changes, including forest growth and tree cover loss, which occur without a change in land-cover class; and 2) Land-use and land-cover change (LULCC)–induced changes, including forest expansion and forest loss, which involve transitions between forest and non-forest classes. Finally, we aggregated pixel-level ΔAGC to quantify the relative contributions of each change mode and category to the national AGC balance between 1985 and 2023.

Comment 7

Figure 3, is it make a temporal validation, see comment above

Response: We thank the reviewer for this valuable comment. As noted above, following the reviewer's suggestion, we implemented a Leave-One-Year-Out (LOYO) temporal validation following the approach of Laffitte et al. (2025), using the multi-year GEDI AGBD data (2019–2021). Three annual models were trained, each time leaving one year out for validation and repeating the process five times with different random seeds to ensure robustness.