Response to the reviewers (#essd-2025-695)

Dear Reviewer,

We sincerely appreciate the valuable and constructive comments you have provided. In response, we have conducted a comprehensive and thorough revision of the manuscript to address all the comments and suggestions. We have responded to each point in detail to ensure that all concerns have been fully addressed. Your insightful feedback has significantly improved the overall quality of this manuscript. For ease of review, the original comments are presented in *italics*, our responses are provided in regular font, and the corresponding revisions in the manuscript are highlighted in red:

Reviewer #2 (Remarks to the Author):

Reviewer #2 Overall comments *This paper is well written and presents solid data and methodological rigor. I have several suggestions that may further strengthen the manuscript:*

[Response] We sincerely thank you for this positive overall assessment of our manuscript. We greatly appreciate your recognition of the manuscript's writing quality, data basis, and methodological rigor. We have carefully considered all your suggestions and revised the manuscript accordingly to further improve its clarity, transparency, and overall contribution. Below, we provide a point-by-point response to the specific comments.

***Reviewer #2* Major comments**

***Reviewer #2* Specific comment 1** *Clarification of Water Mask (Line 176). In Line 176, please clearly specify which waterbody dataset was used as the water mask. If multiple datasets were integrated, describe their respective roles and how they were harmonized.*

[Response] Thank you for this helpful comment. We agree that the construction of the water mask should be described more clearly. In the revised manuscript, we clarified that the water mask was not derived from a single dataset, but was constructed by integrating four waterbody-related datasets: HydroLAKES, GRanD, GOODD, and GeoDar. Specifically, HydroLAKES was used to provide lake boundaries and associated attributes, while GRanD supplied reservoir polygons and reservoir-related information. GOODD and GeoDar were used as complementary dam datasets to support the identification of reservoir systems and to improve the consistency of reservoir records where polygon or attribute information was incomplete or uncertain. These datasets were harmonized into a unified maximum historical water-extent layer for the study area, which served as a stable water mask to constrain the analysis to long-term potential water bodies.

We further clarified in the revised manuscript (Section 2.2.2 "Water Body Datasets") that this integrated water mask was used as a spatial constraint for WPV candidate areas, rather than as a year-specific annual water mask. "To construct the water mask for WPV mapping, we integrated four waterbody-related datasets: HydroLAKES, GRanD, GOODD, and GeoDar (Lehner *et al.*, 2011; Messager *et al.*, 2016; Mulligan *et al.*, 2020; Wang *et al.*, 2022). HydroLAKES provided lake boundaries and associated attributes, while GRanD supplied reservoir polygons and reservoir-related information. GOODD and GeoDar, which contain georeferenced dam records, were used as complementary datasets to support reservoir identification where reservoir boundary or attribute information was incomplete or uncertain. These datasets were harmonized into a unified maximum historical water-extent layer for the study area. This integrated layer was used as a stable spatial mask to constrain the analysis to long-term potential water bodies, rather than as a year-specific annual water mask." (Pages 6–7, Lines 147–156 in the clean version of the manuscript)

Reviewer #2 **Specific comment 2** *Multicollinearity Discussion. Since the model integrates original optical bands together with derived spectral indices, it would be helpful to briefly discuss the potential multicollinearity between these variables. Although Random Forest is generally robust to correlated predictors, explicitly stating that multicollinearity does not adversely affect classification performance under tree-based models would improve methodological transparency.*

[Response] Thank you for this helpful suggestion. We agree that the potential multicollinearity between the original optical bands and the derived spectral indices should be briefly addressed. In the revised manuscript, we clarified that several spectral indices are mathematically derived from the original Sentinel-2 bands and are therefore not fully independent of them.

We also noted that such multicollinearity is unlikely to substantially affect classification performance in this study, because Random Forest is a tree-based ensemble model that is generally robust to correlated predictors. The inclusion of both original bands and derived indices was intended to retain complementary spectral information for WPV discrimination. At the same time, predictor correlation may influence the interpretation of variable importance, even though it does not materially compromise classification accuracy. The relevant text has been added to Section 2.3.1 (WPV Feature Engineering): "Although some spectral indices are derived from the original optical bands and are therefore correlated with them, Random Forest is generally robust to multicollinearity among predictors in classification tasks. As a result, the inclusion of both original bands and derived indices is unlikely to adversely affect model performance, although it may influence the interpretation of variable importance." (Page 8, Lines 202–206 in the clean version of the manuscript)

Reviewer #2 **Specific comment 3** *Random Forest Model Specification. Please provide more details about the Random Forest implementation, including key hyperparameters (e.g., number of trees, maximum tree depth, minimum samples per leaf) and whether cross-validation was used.*

[Response] Thanks for this helpful suggestion. We agree that providing more detailed information on the Random Forest implementation is important for methodological transparency and reproducibility. In the revised manuscript, we have expanded the description of the classifier settings and validation strategy.

Specifically, the Random Forest classifier was implemented in Google Earth Engine using the smileRandomForest algorithm. We used 80 trees and randomly selected 7 variables at each split. The remaining hyperparameters were left at their default values in the GEE implementation, including minimum leaf population = 1, bag fraction = 0.5, maximum nodes = null, and seed = 0. The detailed Random Forest settings are summarized in Table R4.

Table R4. Random Forest implementation settings used in this study.

Parameter	Setting
Platform	Google Earth Engine
Algorithm	smileRandomForest
Number of trees	80

Variables per split	7
Minimum leaf population	1 (default)
Bag fraction	0.5 (default)
Maximum nodes	Null (default)
Seed	0 (default)
Cross-validation	Used

To further evaluate model robustness, we performed 10-fold stratified cross-validation on the training dataset. The model achieved an average accuracy of 0.9729 ± 0.0030 across the ten folds, indicating stable classification performance. These details have now been added to Section 2.3.2, Annual WPV Classification: "The Random Forest classifier was implemented in Google Earth Engine using the smileRandomForest algorithm. We used 80 trees and randomly selected 7 variables at each split. The remaining hyperparameters were left at their default values in the GEE implementation, including minimum leaf population = 1, bag fraction = 0.5, maximum nodes = null, and seed = 0." (Page 9, Lines 223–227 in the clean version of the manuscript)

***Reviewer #2* Specific comment 4** *Comparison with Existing Global Inventories. The manuscript would benefit from a clearer introduction and discussion of existing datasets such as A Global Inventory of PV and Global Renewables Watch. Please briefly describe their data sources, spatial resolution, update frequency, and methodological framework. Additionally, discuss how your approach improves upon these traditional inventories (e.g., spatial resolution, temporal consistency, detection accuracy, validation strategy).*

[Response] Thank you for this valuable suggestion. We have revised the Introduction and Discussion to provide a clearer comparison with representative global PV inventories, including *A Global Inventory of Photovoltaic Installations* and *Global Renewables Watch*. In the revised manuscript, we now briefly summarize their data sources, spatial resolution, temporal coverage and update frequency, methodological framework, and validation characteristics, and we added Table R5 to present this comparison more clearly.

We also clarified how the present study differs from these existing products. In particular, our study focuses specifically on WPV rather than general solar infrastructure; provides annual 10-m maps for 2015–2024; uses Sentinel-1/2 SAR–optical fusion to improve detection over water surfaces; and incorporates temporal consistency control together with Google Earth time-series verification. These revisions have been added to Section 1 (Introduction): "Building on these advances, several global photovoltaic inventories have been developed to provide large-scale datasets of PV installations. For example, A Global Inventory of Photovoltaic Installations maps commercial-, industrial-, and utility-scale PV facilities worldwide using multi-source satellite imagery, including Sentinel-2 (10 m) and high-resolution SPOT-6/7 imagery, and was produced using deep learning with manual verification for installations identified primarily from 2016 to 2018 (Kruitwagen et al., 2021). Similarly, *Global Renewables Watch* integrates quarterly PlanetScope imagery at 4.7 m spatial resolution with deep learning–based semantic segmentation to map global solar and wind infrastructure from 2017 Q4 to 2024 Q2, enabling regular updates and temporal tracking of infrastructure development (Robinson et al., 2025). Compared with these products, our study is specifically designed for WPV mapping and combines SAR and optical observations to better distinguish floating PV from surrounding water backgrounds, while also providing annual, temporally consistent WPV inventories for 2015–2024." (Pages 3–4, Lines 66–79 in the clean version of the manuscript).

Table R5. Comparison of representative global PV inventories and the WPV dataset developed in this study.

Dataset	Source	Resolution	Time	Validation	WPV relevance
Global Inventory of PV	Sentinel-2, SPOT 6/7	10 m to sub-5 m	Up to 2018	Cross-validation	Not WPV-specific
Global Renewables Watch	PlanetScope	4.7 m	2017 Q4–2024 Q2	Comparison with IRENA statistics	Not optimized for WPV
This study	Sentinel-1/2	10 m	2015–2024 annual	Sample-based assessment + time-series Google Earth verification	WPV-focused regional inventory

***Reviewer #2* Specific comment 5** *Provincial-Level Proportional Analysis (Section 3.2). In Section 3.2, in addition to reporting cumulative WPV area, I recommend presenting the ratio of cumulative WPV area to total water area for each province. This proportional metric would provide more meaningful insight into deployment intensity and facilitate comparison across provinces.*

[Response] We thank the reviewer for this valuable suggestion. We agree that the ratio of WPV area to total water area is a more informative measure of deployment intensity than cumulative area alone. In the revised manuscript, we added a new inset bar chart to Fig. 9b (upper-left inset) and explicitly reported this proportional metric in Section 3.2. The revised text states: "The inset bar chart further illustrates the proportion of WPV area relative to the total water area in each province in 2024, showing that Anhui had the highest deployment intensity (1.01%), followed by Jiangsu (0.67%) and Zhejiang (0.48%)." (Page 13, Lines 330–332 in the clean version of the manuscript)

***Reviewer #2* Specific comment 6** *Overall, this study makes an important contribution. Subject to addressing the points raised above, I support publication of this manuscript.*

[Response] We sincerely thank the reviewer for the positive and encouraging assessment of our manuscript. We greatly appreciate the reviewer's recognition of the importance and contribution of this study. In response to the comments provided above, we have carefully revised the manuscript and addressed all concerns to the best of our ability.

References

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