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 #1 (Remarks to the Author):

***Reviewer #1* Overall comments** *The manuscript presents an important and timely contribution by producing the first decade-long, high-resolution (10 m) water surface PV (WPV) inventory for the Yangtze River Delta using a SAR–optical fusion approach. The topic is highly relevant, and the dataset could be valuable for future studies. However, several methodological aspects require clarification, and certain results need deeper interpretation before the manuscript can be considered for publication.*

[Response] We sincerely thank the reviewer for recognizing the importance and timeliness of our study, as well as the potential value of the decade-long, 10 m resolution WPV inventory for the Yangtze River Delta. We are encouraged that the reviewer considers the dataset to be a useful resource for future research. At the same time, we appreciate the reviewer's constructive comments regarding the need for clearer methodological descriptions and deeper interpretation of several results. These suggestions have helped us identify aspects of the manuscript that require further clarification and strengthening.

***Reviewer #1* Major Comments**

***Reviewer #1* Specific comment 1** *Use of spectral indices – lack of quantitative thresholds. The methodology states that several Sentinel 2–derived spectral indices (e.g., NDVI, MNDWI, NDBI, NDPI, SAVI) were used in the Random Forest classifier. However, the manuscript does not provide any quantitative values, ranges, or thresholds that explain how these indices contribute* *to distinguishing: water surfaces, non-vegetated land, rocky or bare surfaces. Given the importance of spectral indices in the fusion approach, the authors should provide, at minimum: typical value ranges for water vs. land features, variable importance scores from the Random Forest model, and examples of how specific indices helped resolve misclassification challenges. This transparency is essential for reproducibility.*

[Response] Thank you for this important suggestion. We agree that clearer quantitative information on the spectral indices is necessary to improve methodological transparency and reproducibility. We would like to clarify that the final WPV mapping was not based on fixed thresholds of individual indices. Instead, the Sentinel-2-derived indices were jointly used as predictor variables in the Random Forest classifier. In addition, the classification was constrained within a pre-constructed maximum historical water-extent mask, so the practical discrimination task mainly involved separating WPV from open water and other non-WPV features within water bodies.

Table R1. Typical value distributions of spectral indices for WPV and non-WPV samples.

Index	WPV median (IQR)	Non-WPV median (IQR)	*p-value*	Interpretation
NDVI	0.01 (-0.04–0.07)	0.16 (-0.07–0.41)	< 0.01	WPV concentrated near zero; non-WPV broader due to vegetation
MNDWI	-0.29 (-0.35–-0.22)	-0.10 (-0.33–0.26)	< 0.01	WPV lower than open water due to panel coverage
NDBI	0.29 (0.28–0.36)	-0.10 (-0.23–0.03)	< 0.01	WPV higher because of artificial panel surface
SAVI	0.004 (-0.01–0.03)	0.07 (-0.02–0.22)	< 0.01	WPV near zero; non-WPV elevated where vegetation exists
NDPI	-3.15 (-5.22–-0.23)	-0.58 (-0.76–-0.23)	< 0.01	WPV higher than bare/open water

Note: P-values are from a two-sided Mann–Whitney U test. Smaller values indicate more significant differences between WPV and non-WPV samples.

To address this comment, we added quantitative summaries of the major spectral indices for WPV and non-WPV training samples in the revised manuscript (Table R1). These results show that WPV pixels generally have NDVI and SAVI values concentrated near zero, whereas non-WPV samples display broader distributions because they include open water, vegetated margins, and other non-WPV surfaces within the water mask. WPV pixels also tend to have lower MNDWI values than open water because panel structures partially obscure the water surface, while NDBI and NDPI show distinct distributions between WPV and non-WPV samples, reflecting the artificial surface characteristics of photovoltaic panels. We emphasize that these values represent typical sample distributions rather than hard classification thresholds.

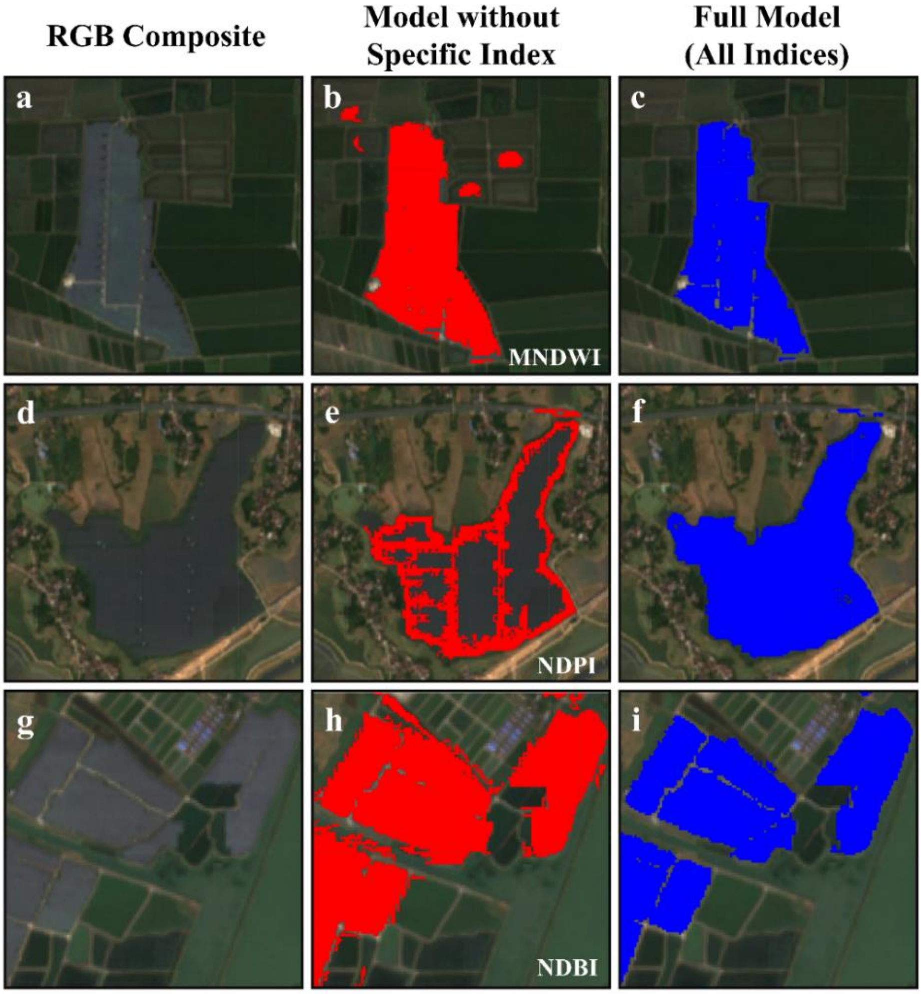

Figure R1. Examples of spectral indices helping resolve local confusion between WPV and non-WPV surfaces. Panels a–c, d–f, and g–i show three representative areas. a, d, g: displays the 2024 Sentinel-2 median RGB composites for each area; b, e, h: the classification results when a specific spectral index is omitted: b: MNDWI, e: NDPI, and h: NDBI; c, f, i: the classification results from the full random forest model using all indices. The three areas are located at a–c: 32°58′37.24″N, 119°37′23.43″E; d–f: 30°52′31.64″N, 117°35′35.81″E; and g–i: 31°29′44.93″N, 119°39′12.34″E (source: Copernicus Sentinel-2 imagery © ESA).

Table R2. Relative importance (%) of input variables in the Random Forest model.

Variable	Importance percent (%)
NDBI	33.04
NDPI	15.31
B11	8.49
MNDWI	6.29
B2	5.99
SAVI	5.91
B12	5.12
B8	5.06

Table R3. Effect of removing spectral indices on overall accuracy (OA, %).

Variable	Overall Accuracy (%)
Full (all features)	97.5
NDBI	97.3
NDPI	97.3
B11	97.3
MNDWI	97.4
B2	96.8
SAVI	97.5
B12	97.4
B8	97.4

We also quantified the contribution of individual predictors using Random Forest feature-importance scores (Table R2) and evaluated the effect of removing individual spectral variables on overall accuracy (Table R3). The results indicate that NDBI and NDPI are among the most important spectral indices, followed by MNDWI and SAVI. Although removing any single index caused only a small reduction in overall accuracy, this does not imply that the indices were uninformative; rather, it reflects the complementary and partly correlated nature of the predictor set in a high-performing ensemble classifier. To further clarify how the indices helped resolve classification challenges, we added explanatory text in Section 2.3.1 and provided representative examples in Fig. R1. The added text states: "Specifically, NDVI and SAVI helped reduce confusion between WPV and vegetated surfaces such as emergent or floating vegetation near shorelines, MNDWI improved the separation of panel-covered water from open water, and NDBI/NDPI enhanced the identification of artificial panel surfaces that might otherwise resemble dark water in optical imagery." (Page 8, Lines 198–201 in the clean version of the manuscript)

Reviewer #1 **Specific comment 2** *Interannual variability of water bodies. The surface area of lakes and reservoirs in the YRD can fluctuate significantly due to seasonal or multi year droughts. The manuscript does not explain how these hydrological variations were handled. Please clarify: Were annual water masks independently derived for each year? Did the classifiers incorporate hydrological seasonality? How were changes in water extent prevented from being misinterpreted as WPV presence or absence? This point is critical, especially when estimating decadal trends.*

[Response] Thank you for raising this important point. We agree that interannual and seasonal hydrological variability must be carefully considered when estimating decadal WPV trends. In the revised manuscript, we have clarified both the water-mask strategy and the temporal-consistency control, and we added a workflow figure (Fig. R2) to illustrate the full procedure.

First, annual water masks were not independently derived for each year. Instead, all yearly analyses were constrained using a unified maximum historical water-extent mask, representing the long-term potential water domain. This design reduces the influence of temporary shoreline expansion or contraction caused by hydrological fluctuations and helps avoid interpreting short-term water-extent changes as WPV gain or loss.

Second, the classifier did not explicitly incorporate hydrological seasonality through year-specific hydrological modeling. Rather, we mitigated its influence by generating annual Sentinel-1/2 composites for each year. The use of Sentinel-1 SAR is particularly helpful because it is less sensitive to cloud cover and illumination conditions and provides complementary structural information for WPV detection over water surfaces.

Third, to prevent temporary hydrological variation or image-quality differences from being misinterpreted as WPV disappearance, we did not treat the yearly classification outputs as fully independent final maps. Because WPV installations are generally persistent once deployed, we applied a temporal consistency rule in which previously confirmed WPV areas were retained in subsequent years and only newly detected areas were added. Thus, the final annual WPV series follows a cumulative, non-decreasing pattern. This strategy was intended to reduce spurious year-to-year disappearance caused by classification noise, short-term hydrological variability, or inconsistent image conditions. Finally, installation timing and project boundaries were further checked using Google Earth time-series imagery, which provided an additional safeguard against false temporal changes introduced by remote-sensing classification alone.

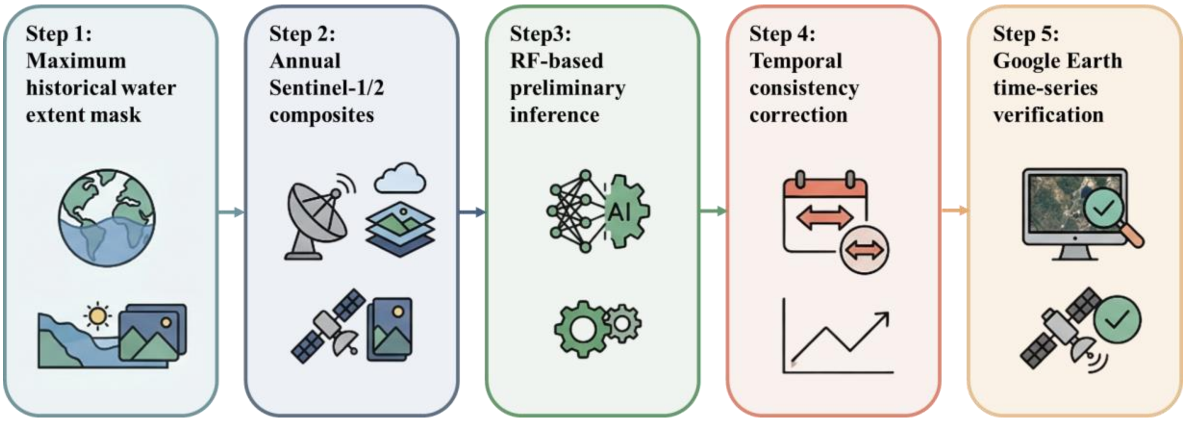

Figure R2. Workflow for annual WPV mapping and temporal consistency control. A maximum historical water extent mask was first used to constrain the analysis to long-term potential water bodies. Annual Sentinel-1/2 composites were then generated for each year and used for Random Forest-based WPV inference. To improve long-term temporal consistency, the preliminary annual maps were further updated using a cumulative temporal-consistency rule, in which previously confirmed WPV areas were retained in subsequent years and only newly detected areas were added. Finally, Google Earth time-series imagery was used to verify installation timing and project boundaries.

In response to reviewer comments, we have added a clarification in Section 2.3.1 (WPV Feature Engineering): "To reduce interference from temporary shoreline fluctuations and to focus the analysis on long-term potential aquatic areas, we filtered Sentinel-2 MSI imagery using a unified maximum historical water-extent mask, rather than deriving an independent water mask for each year." (Page 8, Lines 185–187 in the clean version of the manuscript)

We have added a detailed clarification in Section 2.4.2 (Manual Refinement and Final Dataset Creation) regarding the temporal consistency of WPV mapping: "Each potential region was then interpreted and corrected using high-resolution satellite imagery from Google Earth (Fig. 3c) to accurately identify and remove misclassified non-WPV areas, thereby substantially improving the reliability of the final dataset. Specifically, each potential WPV region was checked for (1) its location within the water body, (2) the presence of regular and repetitive photovoltaic array patterns, and (3) separation from non-WPV objects such as shoreline buildings, roads, embankments, or floating vegetation. Since WPV installations are typically long-lasting, their installation year was determined by identifying the first year each site visibly appeared in high-resolution Google Earth imagery sequences. To maintain temporal consistency across the annual series, previously confirmed WPV areas were retained in subsequent years, and only newly detected regions were added. Through this temporal consistency rule, the annual WPV series followed a cumulative, non-decreasing pattern, effectively reducing spurious year-to-year disappearance caused by classification noise, short-term hydrological variations, or image-quality differences, thereby enhancing the reliability of decadal trend estimation." (Pages 10–11, Lines 252–265 in the clean version of the manuscript)

Reviewer #1 **Specific comment 3** *Floating PV movement and texture features. The authors mention the use of texture metrics and SAR backscatter features. However, floating PV (FPV) systems—unlike fixed structures—can move due to wind, currents, or water level fluctuations. Please discuss: whether FPV motion affects texture features, whether SAR temporal variability could introduce classification noise, and whether the method is equally robust for fixed installations and mobile floating platforms. This clarification is important since China hosts many FPV plants.*

[Response] Thank you for this insightful comment. We agree that the potential movement of floating photovoltaic (FPV) systems should be considered when interpreting texture metrics and SAR backscatter features. In practice, however, most utility-scale FPV installations in China are anchored to the shoreline or lakebed. Although anchoring does not completely eliminate short-term movement caused by wind, currents, or water-level fluctuations, it generally constrains displacement to a limited range relative to the 10-m mapping scale used in this study.

To further evaluate the potential influence of FPV motion, we added a time-series analysis for three representative PV sites (Fig. R3), including two FPV plants and one stationary PV (SPV) installation. The results show that the optical texture features remain sufficiently stable for annual-scale classification after installation, although some local interannual variation is present. This suggests that limited FPV motion may affect local texture values, especially near patch boundaries, but does not systematically disrupt the patch-level spatial patterns used in our annual classification.

For SAR features, we acknowledge that Sentinel-1 observations may show temporal variability due to acquisition geometry, speckle, and short-term water-surface dynamics, which can introduce noise at the single-scene level. However, Fig. R3 shows that the annual median VV and VH backscatter values exhibit a persistent shift relative to the pre-installation period and remain distinguishable thereafter, while the scatter of individual observations mainly reflects short-term variability. This indicates that annual temporal aggregation can effectively suppress SAR-related noise while preserving the installation-related signal.

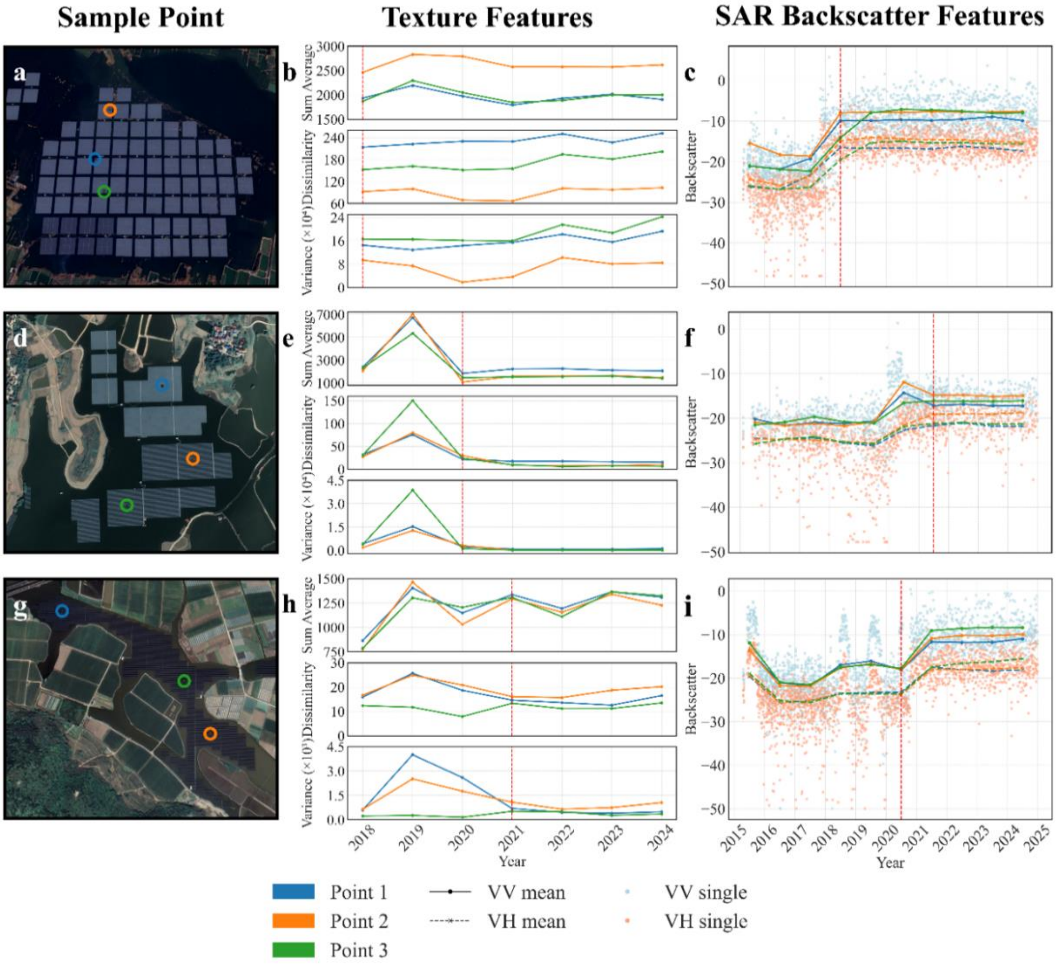

Figure R3. Time-series analysis of optical texture and SAR backscatter characteristics for representative PV sites. a, d, g: High-resolution imagery showing the locations of three representative sites and the selected sample points, where a and d are floating photovoltaic (FPV) plants, and g is a stationary photovoltaic (SPV) installation. b, e, h: Interannual variations in optical texture features derived from the gray-level co-occurrence matrix (GLCM), including B8 variance, B8 sum average, and B8 dissimilarity, for the selected points. c, f, i: Time series of Sentinel-1 SAR backscatter coefficients (VV and VH), where solid lines represent annual median values and dots represent individual observations. The comparison between annual median values and single-scene observations illustrates that, although short-term variability exists, the installation-related SAR signal remains persistent after deployment. Overall, the figure shows that both texture features and annual SAR backscatter remain sufficiently stable after installation for annual WPV classification, despite limited FPV motion. The three sites are located at a: 32°49′09.88″N, 116°17′42.57″E; d: 30°45′41.47″N, 116°59′35.97″E; and g: 29°15′38.65″N, 121°43′38.65″E (source: Google Earth Pro, © 2025 Airbus, © 2025 Airbus / CNES, © 2025 Maxar Technologies).

We also clarify that the method is not equally robust for all platform types. The current framework is expected to be most reliable for stationary PV installations and for anchored, medium- to large-scale FPV systems, which represent the dominant commercial deployment type in the study region. In contrast, uncertainty may increase for small, loosely arranged, or highly mobile floating platforms, especially where platform displacement changes patch boundaries or weakens texture regularity. We have added this discussion to Section 4.3 (Limitations and Future Research) in the revised manuscript: "The current framework is expected to be reliable for stationary PV installations and for anchored, medium- to large-scale FPV systems, which represent the dominant commercial deployment type in the study region. However, uncertainty may increase for small, loosely arranged, or highly mobile floating platforms, especially where local displacement alters patch boundaries or weakens texture regularity." (Page 18, Lines 467–471 in the clean version of the manuscript).

***Reviewer #1* Specific comment 4** *Potential use of the methodology for environmental impact studies. The developed dataset could potentially support research on the environmental effects of FPV installations. Please comment on the feasibility of using this method to investigate: water surface temperature variations due to partial shading; changes in water colour or turbidity, especially related to algae bloom development or suppression; whether SAR–optical fusion offers the sensitivity needed for such environmental applications. These points would strengthen the broader applicability of the work.*

[Response] We sincerely thank the reviewer for this insightful suggestion regarding the broader environmental applicability of the dataset. We agree that the dataset can provide valuable support for future studies on the environmental effects of FPV deployment, but its role is primarily to deliver accurate spatial boundaries and installation timing of WPV systems rather than to directly retrieve environmental variables.

In the revised manuscript, we have clarified in Section 4.2 that the dataset can support environmental impact studies when integrated with other observations: “Its high-resolution delineation of WPV-covered and uncovered areas within the same water body enables spatially explicit comparisons between shaded and unshaded zones, as well as before-and-after analyses based on installation timing. When combined with other observations, these maps may support assessment of possible water-surface temperature differences associated with partial shading using thermal infrared products, as well as potential changes in water optical properties and algal dynamics using water-color or water-quality indicators such as chlorophyll-a, turbidity, or algal bloom proxies (Chen *et al.*, 2025; Chu and He, 2023).” (Page 17, Lines 443–449 in the clean version of the manuscript)

At the same time, we have revised Section 4.2 accordingly to clarify the methodological boundary of the present approach: “It should be noted, however, that the SAR–optical fusion framework is primarily designed to detect WPV extent, boundaries, and deployment timing. Although these attributes are relevant for environmental exposure assessment, the framework does not directly quantify thermal or biogeochemical responses, which require dedicated thermal infrared, water-quality remote sensing, or field observations.” (Page 18, Lines 454–459 in the clean version of the manuscript)

***Reviewer #1* Specific comment 5** *Interpretation of high WPV coverage percentages (Fig. 11). Figure 11 shows that several basins have extremely high WPV coverage (85–95%). The manuscript should clarify: Which area was used as the denominator when computing the WPV percentage (e.g., maximum historical water extent, annual water extent, permanent water core). Whether such high coverage is physically accurate, or if classification steps may have overestimated WPV area in small or seasonally shrinking basins. The implications of these very high coverage levels for hydrological, ecological, or energy planning impacts. A deeper interpretation is needed.*

[Response] We appreciate this helpful comment. In the revised manuscript, we have clarified that WPV coverage was calculated using the maximum historical water extent of each water body as the denominator, rather than the annual water extent or a permanent-water core. We selected this reference area to provide a temporally stable basis for interannual comparison and to avoid artificial inflation of coverage values caused by seasonal or drought-induced contraction of annual water extent.

We also agree that extremely high WPV coverage values (e.g., 85-95%) require careful interpretation. To assess whether such values are physically plausible, we further examined representative high-coverage cases using high-resolution satellite imagery (Fig. R4). These examples show that some small, managed, and highly enclosed water bodies in the study area, particularly aquaculture ponds and other compact artificial basins, can indeed be almost fully occupied by WPV installations, leaving only narrow margins of open water. Therefore, such high values are physically plausible in specific local settings.

At the same time, we acknowledge that coverage estimates for small or seasonally dynamic water bodies are more sensitive to boundary delineation uncertainty than those for large lakes and reservoirs. For this reason, very high coverage values should be interpreted with caution at the individual-basin level. Nevertheless, because the denominator was defined as the maximum historical water extent rather than the annual water extent, our approach reduces the risk of overestimating coverage when water extent temporarily contracts.

Finally, we have expanded Section 4.2, Implications and Potential Applications, to further interpret the significance of these high-coverage cases: "The high-precision, decade-long WPV dataset developed in this study has both practical and scientific relevance. By quantifying the coverage, spatial distribution, and waterbody-specific deployment characteristics of WPV installations, the dataset provides a spatial basis for WPV planning, site selection, and comparative analysis across waterbody types and coverage levels. High-coverage configurations, including those associated with "fishing-solar complementarity" systems, may indicate both high energy-generation intensity and stronger local hydrological or ecological influence (Pringle *et al.*, 2017). Such settings may be associated with greater modification of light availability, air-water exchange, evaporation, and aquatic habitat conditions. From an energy-planning perspective, they also represent an intensive deployment mode, although future expansion should account for environmental carrying capacity and site-specific management constraints (Bai *et al.*, 2024; Château *et al.*, 2019)." (Pages 16–17, Lines 424–434 in the clean version of the manuscript)

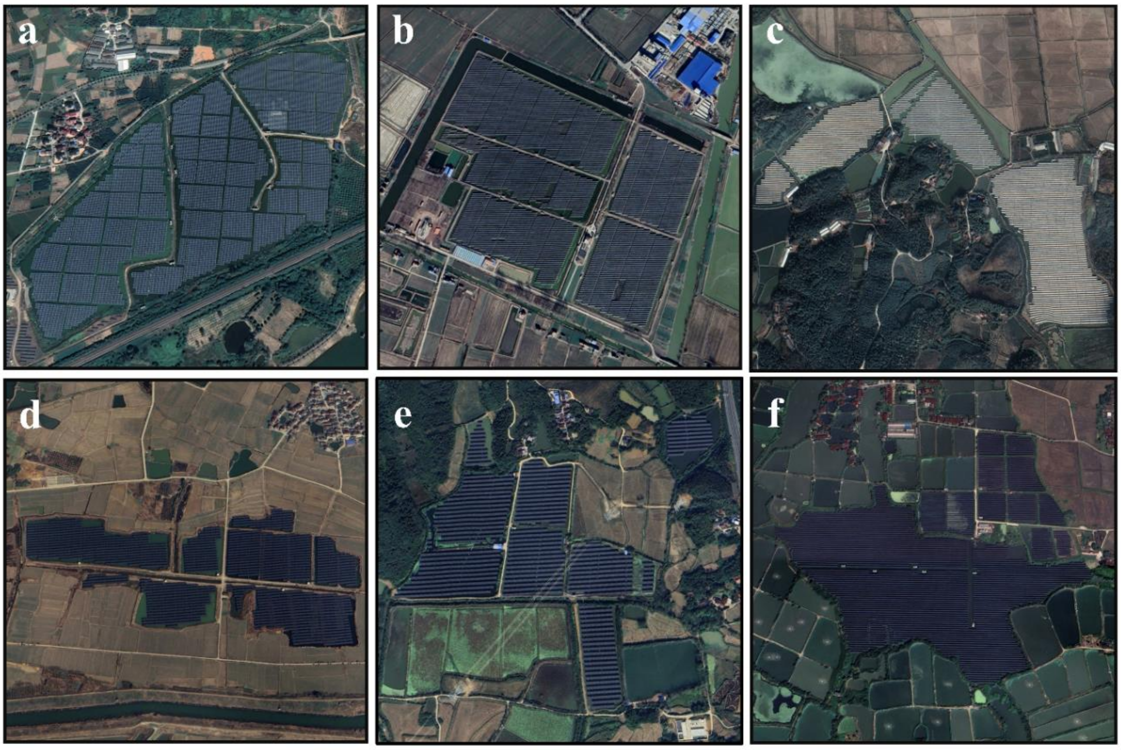

Figure R4. Examples of WPV installations with very high coverage. The six areas are located at a: 28°49′18.32″N, 118°42′34.22″E; b: 33°48′20.33″N, 119°38′24.37″E; c: 30°44′18.35″N, 117°53′33.14″E; d: 31°55′07.12″N, 119°22′59.66″E; e: 30°31′24.49″N, 117°21′25.91″E; f: 30°46′25.86″N, 120°07′53.47″E (source: Google Earth Pro, © 2025 Airbus, © 2025 Airbus / CNES, © 2025 Maxar Technologies).

***Reviewer #1* Specific comment 6** *Distinguishing lakes vs. reservoirs. Please provide a clear definition of lake versus reservoir, since the distinction is relevant for WPV siting policies, water level stability, and ownership/management regimes. A short paragraph is needed in the Methods or Study Area section.*

[Response] Thank you for this helpful comment. We agree that a clear distinction between lakes and reservoirs is important for interpreting WPV siting patterns, water-level dynamics, and waterbody management characteristics. In the revised manuscript, we added a short clarification in Section 2.2.2 (Water Body Datasets): "In this study, reservoirs were defined as water bodies formed by dams or other engineered hydraulic infrastructure and subject to artificial water-level regulation. In contrast, lakes were defined as inland water bodies without reservoir functions, including natural lakes as well as artificial water bodies such as aquaculture ponds and irrigation ponds. This distinction is relevant for WPV analysis because reservoirs generally exhibit more stable water levels and are associated with different ownership and management regimes than lakes." (Page 7, Lines 157–162 in the clean version of the manuscript)

***Reviewer #1* Minor Comments** *Figure 2 labeling error. There is an inconsistency between the letters shown in the images and those referenced in the caption. Please correct the figure annotations to ensure correspondence*

[Response] Thank you for noting this inconsistency. We have corrected the panel annotations in Figure 2 and revised the caption accordingly to ensure consistency between the figure labels and the caption text. The revised caption now reads: "a–c: Examples of typical sample regions, where red points indicate WPV samples and blue points indicate non-WPV samples; d: Spatial distribution of WPV and non-WPV samples across the study area; e: Proportions of different sample categories." (Page 28, Lines 691–694 in the clean version of the manuscript)

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