

Article

Sentinel-2-Derived Water Surface Mapping and Bathymetric Analysis of Reservoirs for Floating PV Deployment: A Case Study of the Basilicata Region, Southern Italy

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Abstract

Floating photovoltaics (FPV) offer a sustainable approach to renewable energy production while enhancing water resource management by reducing land use, improving module efficiency through natural cooling, and limiting water evaporation. However, large-scale deployment requires careful site selection, operational feasibility assessment, and integration with existing water management practices. This study presents a fully cloud-native Sentinel-2-based framework to map recent water surface extents of reservoirs and reconstruct their bathymetric profiles. Developed within the Google Earth Engine (GEE) environment, the approach employs harmonized time series, automated cloud filtering, and median composites combined with adaptive NDWI/MNDWI thresholds to generate high-resolution (10 m) water masks. These dynamic surface extents are integrated with monitored water levels to estimate bathymetry through an annual multitemporal log-ratio band-switching configuration. The method has been tested across the nine main strategic reservoirs of the Basilicata region (Southern Italy). The water-surface extraction approach achieved an Overall Accuracy of 95.33% and a Kappa coefficient of 0.907 in the internal thematic assessment. The bathymetric reconstruction results led to relative volume errors for medium-to-large water bodies ranging between 13.8% and 35.1%, while larger percentage discrepancies in smaller impoundments were driven by scale-dependent normalization effects on low storage volumes. Overall, the proposed method offers a scalable, cost-effective, and Earth Observation (EO)-driven screening tool for the initial site selection, capacity assessment, and planning of FPV systems, particularly in data-scarce regions lacking updated bathymetric surveys.

Keywords: floating photovoltaics; Sentinel-2; Google Earth Engine; water surface extraction; satellite-derived bathymetry (SDB); earth observation



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1. Introduction

Floating photovoltaics (FPV) have emerged as a promising solution to expand renewable energy generation while mitigating land-use conflicts and simultaneously enhancing water resource management [1]. Deploying photovoltaic systems on lakes and artificial reservoirs enhances FPV module efficiency through natural cooling, boosting energy

production by 4–7%. Additionally, covering just 30% of the water surface can reduce evaporation by up to 49% [2,3]. Furthermore, FPV installations can create synergies with existing water infrastructure, particularly hydropower systems, enabling shared grid connections and complementary energy production profiles [4]. Nevertheless, recent studies have demonstrated how localized climatic variables, such as elevated temperature, heavily influence the degradation rates of different silicon-based PV technologies [5].

The large-scale deployment of FPV systems is still constrained by several technical, environmental, and planning challenges. One of the most critical issues is the accurate estimation of the water body's hydro-morphometric characteristics, including the current water surface extent, depth distribution (i.e., bathymetry), bottom slope, shape, and water level variability, among others. These parameters play a fundamental role in several stages of FPV development, ranging from preliminary feasibility analysis, water body eligibility, and energy potential evaluation to environmental impact assessment and engineering design. Importantly, their reliability depends on accurately delineating the most recent water surface extent and bathymetric configuration, which serve as the primary spatial references for computing all other parameters. Reservoirs are dynamic systems whose water surface extent and storage volume are subject to significant temporal variability, driven by seasonal hydrological cycles, drought periods, and operational water management practices. This variability is further modulated by reservoir morphology: steeply banked reservoirs may experience substantial vertical level fluctuations with limited surface area changes, whereas shallow or gently sloping reservoirs can exhibit dramatic planimetric variations even under moderate water level oscillations.

From an FPV deployment perspective, water level variability represents one of the most critical site-selection constraints. Generally, eligible reservoirs should be characterized by moderate fluctuations, typically within approximately 10 m between maximum and minimum operating levels, beyond which structural stress on floating components increases significantly [6]. Excessive drawdown conditions may cause grounding or stranding of floating structures, while large amplitude fluctuations demand more sophisticated mooring and anchoring systems, thereby increasing both the costs and engineering complexity. Furthermore, water level dynamics can directly influence the energy performance of FPV systems: in reservoirs with complex surrounding topography, fluctuations alter the relative position between floating arrays and adjacent terrain, generating dynamic shading patterns throughout the day. As demonstrated by Choi et al. [7], lower water levels generally amplify topographic shading effects and reduce the energy yield, whereas higher levels minimize shading and improve the overall system performance.

Accurate and up-to-date knowledge of the actual water surface extent, its temporal dynamics, and bathymetry is therefore not merely a data requirement, but the foundation for any robust and site-specific FPV deployment analysis. However, commonly adopted approaches for reservoir geometry characterization rely on institutional or global hydrographic datasets that provide static representations of water bodies, neglecting the dynamic variations in the water surface. This simplification can introduce significant uncertainties, particularly in reservoirs subject to marked seasonal or inter-annual water level oscillations. A comprehensive investigation of the drivers behind such variability (including irrigation demand, hydropower production, and climatic changes) requires detailed hydrological and operational datasets on water withdrawals and releases, which are often difficult to access, fragmented, or unavailable for systematic analysis. Moreover, such investigations would involve complex modeling approaches that go beyond the scope of early-stage FPV planning processes.

To overcome these limitations, in this paper, we investigate a multi-temporal Earth Observation (EO)-based approach which enables analyzing the reservoir surface dynamics,

capturing actual water fluctuations and bathymetry, independently of their underlying drivers and without relying on ancillary operational records. The proposed method offers a scalable, economically sustainable, and EO-driven preliminary screening tool for the planning, site selection, and sustainable management of FPV systems, particularly in data-scarce regions where conventional bathymetric surveys are unavailable. In such data-limited contexts, this operational framework provides actionable insights to support early-stage technical decision-making and preliminary engineering assessments.

Specifically, this work presents a cloud-native digital framework that automatically extracts the near-real-time water surface extent and provides a comprehensive bathymetric characterization of reservoirs, assessing their potential for FPV deployment. The extracted surface area is adopted as the geometric reference for computing the hydro-morphometric parameters required for FPV planning, engineering design, and environmental assessment, ensuring a representation that closely reflects actual field conditions. The main contribution lies in a localized percentile inversion technique that automatically scales dimensionless relative SDB ratios to physical dimensions using only top-of-basin gauge metadata and maximum basin design capacity, eliminating the strict requirement for in situ sensor data during the tuning phase. Furthermore, we combine focal median sun-glint attenuation, strict physical vegetation masking via the Maximum Chlorophyll Index (MCI), and an advanced dual-band linear/non-linear switching mechanism to mitigate the dynamic turbidity constraints of inland water bodies within a centralized cloud platform.

The multi-temporal capabilities of the proposed EO framework allow the quantification of surface area variability over time, providing additional insights into the stability and long-term availability of potential FPV installation areas. Nevertheless, despite the extensive use of EO data in water body mapping, its systematic integration into FPV planning frameworks still represents a significant challenge.

The methodology is applied to nine multi-purpose artificial reservoirs in the Basilicata Region (Southern Italy), which exhibit significant seasonal and interannual water level variability, providing an ideal case study for FPV planning analysis. Accordingly, the primary objective of the present work is to provide a replicable methodological framework to support regulatory processes and permitting activities for the localization of FPV plants, particularly for regional public authorities that are responsible for identifying suitable sites for renewable energy systems.

2. Scientific and Technical Overview

2.1. Available Surface Water Datasets

Several water datasets (global, European, and national) are currently available that could theoretically support FPV development activities, including DBPrior10K [8], Hydro-LAKES [9], EU-Hydro [10], the Global Surface Water (GSW) dataset [11], WB100m, and CLCplus Backbone [12], among others. However, their suitability for detailed, local-scale FPV planning remains limited due to a number of intrinsic constraints, such as coarse spatial resolution, low temporal frequency, or static representations of dynamic water bodies.

To highlight these operational gaps, an overview of the existing datasets evaluated in this study is summarized in Table 1. This critical comparison underscores the necessity of moving beyond pre-existing databases and justifies the development of our dedicated EO methodology.

Table 1. Overview of open-access water datasets relevant to FPV development, including their spatial and temporal characteristics (access links are specified in the References).

Water Dataset	Spatial Resolution/Scale	Temporal Extents	Coverage
JRC Global Surface Water (GSW)	30 m	1984–2021	Global
HydroLAKES	1:100,000– 1:250,000	1980–2010	Global
EU-Hydro (Copernicus Land Monitoring Service)	1:30,000– 1:50,000	2006–2012	Europe
CLCplus Backbone 2023	10 m	2022–2024 (with biannual update)	Europe
Copernicus Global Land Service–Water Bodies (WB100m)	100 m	2020–present	Global
DBPrior10K	1:10,000	2003–2007	Italy

Most of these datasets offer static snapshots or long-term statistical representations that fail to capture the seasonal and interannual dynamics of multi-purpose reservoirs. Key resources suffer from outdated coverage, such as EU-Hydro (up to 2012) and GSW (up to 2021), thereby overlooking recent hydrological shifts. Furthermore, spatial resolutions like those of GSW (30 m) or WB100m (100 m) are too coarse to accurately delineate small reservoirs for permitting requirements, while high-resolution products like CLCplus Backbone are tailored for land-cover mapping rather than water-surface monitoring. Consequently, existing databases cannot reliably support time-specific FPV feasibility assessments.

2.2. Surface Water Identification Techniques

Recent advances in EO technologies, combined with open-access satellite imagery and cloud-processing platforms, enable the generation of up-to-date, spatially consistent water masks at regional and global scales. Currently, satellite-derived water extraction is widely applied in hydrological modeling, flood risk management, agricultural monitoring, and energy applications such as hydropower [13]. However, its integration into FPV development frameworks remains surprisingly limited, despite the critical need for timely information on effective water-surface availability.

Satellite-based water-surface mapping typically relies on three main methodological approaches: (i) optical multispectral data processing; (ii) Synthetic Aperture Radar (SAR) imagery; and (iii) machine learning algorithms applied to mono- or multi-sensor datasets [14–16].

Among optical sensors, multispectral data provided by the Sentinel-2 mission represent one of the most widely used resources for mapping continental water surfaces. Equipped with the Multispectral Instrument (MSI), Sentinel-2 acquires images across 13 spectral bands (including Visible and Near-Infrared (NIR) at a 10 m spatial resolution, and Shortwave Infrared (SWIR) at 20 m) with a 5 day revisit frequency at mid-latitudes [17]. The combination of NIR and SWIR bands, along with the atmospheric corrections provided in Level-2A (Surface Reflectance) products, makes these data particularly effective for calculating spectral indices for water discrimination and monitoring multi-temporal reservoir dynamics [13].

Complementary to optical data, Sentinel-1 Synthetic Aperture Radar (SAR) imagery enables water extraction independently of cloud cover and solar illumination, leveraging the low radar backscatter of calm water surfaces [18].

For artificial lakes characterized by defined morphologies and low cloud cover, high-resolution optical data are generally sufficient. To handle complex environments, advanced approaches increasingly employ machine learning algorithms (e.g., Random Forest) on

Sentinel-2 datasets [19,20]. However, these methods introduce operational complexity due to their reliance on extensive training datasets and rigorous calibration.

In this work, an index-based water-extraction approach was implemented on Sentinel-2 imagery. Sentinel-2 was selected due to its optimal balance of spatial resolution, temporal frequency, and spectral capabilities for water body discrimination. The overall framework was implemented within Google Earth Engine (GEE), leveraging cloud computing to ensure a reproducible, scalable workflow that was adaptable across different geographic regions and timeframes: a key requirement for public planning bodies.

2.3. Satellite-Derived Bathymetry Techniques

Over the past two decades, modern altimetry platforms like CryoSat, Jason, and SWOT have been extensively deployed for the global monitoring of ocean topography and gravitational anomalies [21,22]. Concurrently, the domain of Satellite-Derived Bathymetry (SDB) strictly emerged through multispectral sensors; today, Landsat-8 and Sentinel-2 have become the most widely adopted optical satellites for shallow-water SDB due to their open-access availability, global coverage, and consistent temporal resolution.

The typical workflow used to estimate underwater depth using satellite imagery follows these steps [23]: (i) satellite imagery acquisition (e.g., Sentinel-2, Landsat-8); (ii) data pre-processing (e.g., atmospheric correction, water masking, glint removal); (iii) depth estimation modeling (e.g., band ratios, semi-analytical models, or machine learning); (iv) calibration and validation; and (v) bathymetric mapping. This SDB workflow combines image processing, mathematical modeling, and rigorous validation.

Despite enabling rapid analysis over extensive spatial scales, SDB presents several limitations. Specifically, it is constrained by satellite spatial resolution and the critical scarcity of ground truth data, which is frequently limited in both spatial and temporal distribution. Among other challenges, water turbidity represents a primary confounding factor, leading to significant inaccuracies in depth estimation.

Empirical studies indicate that optical SDB yields optimal performance predominantly in waters characterized by low-to-moderate turbidity. Consequently, several authors have introduced specific empirical corrections designed to compensate for the influence of suspended particulate matter [24].

Currently, state-of-the-art techniques to retrieve SDB can be categorized into three main paradigms [25,26]: (i) empirical and machine learning approaches, which represent the most recent advancements, leveraging artificial neural networks or advanced regression algorithms to map non-linear relationships [27]; (ii) empirically tuned semi-analytical approaches, which model the exponential decay of light within the water column by calibrating radiative parameters with in situ data [28]; and (iii) optimization-tuned physics inversion approaches (often referred to as purely “physics-based” models), which mathematically invert the radiative transfer equation by bounding the range of inherent optical properties (IOPs) that are characteristic of the specific study sites.

In this context, the present work proposes an alternative semi-analytical approach designed for operational reservoir monitoring. Using multitemporal Sentinel-2 satellite imagery, pre-processed removing clouds, surface reflections, and aquatic vegetation, we estimate water depth through a dual-band log-ratio model. The algorithm automatically switches between two band combinations to optimize performance in both shallow and deep waters. Notably, the model is calibrated directly from the statistical properties of the satellite signal itself, completely bypassing the need for external bathymetric reference datasets (e.g., GLOBathy [29]). The resulting high-resolution bathymetric maps enable the direct and continuous monitoring of reservoir volume and surface area dynamics.

3. Methodology

The proposed methodological framework consists of three main steps: (i) Sentinel-2-based water surface extraction and masking; (ii) satellite-derived depth estimation modeling; and (iii) empirical calibration and final bathymetric mapping. Unlike many existing approaches in the literature, which use cloud platforms like GEE only as a data source and rely on traditional desktop GIS software for key processing steps, our pipeline is entirely cloud native. Conventional workflows often require manual operations such as radiometric normalization and spatial filtering to be completed outside the cloud environment, introducing reproducibility issues and operational bottlenecks. The proposed architecture eliminates these limitations by executing the entire processing chain directly within GEE. This guarantees full reproducibility, high computational scalability, and the ability to monitor reservoir bathymetry in near-real time, without any dependency on local hardware or manual intervention.

However, it must be emphasized that this remote sensing framework serves as a macro-scale reconnaissance tool rather than a replacement for high-resolution surveys for FPV planning purposes. Consequently, in situ investigations (typically performed via single or multi-beam echo sounders, side-scan sonar systems, shoreline LiDAR topographic surveys, and geotechnical bottom sampling) remain the primary and most reliable methods for acquiring definitive data.

3.1. The Study Area

The case study is represented by nine artificial reservoirs of the Basilicata Region (Southern Italy) (Figure 1). The region's Mediterranean climate and mountainous topography result in high variability of water availability across its five main river basins (Bradano, Basento, Cavone, Agri, and Sinni). This hydrographic network is managed through a system of large artificial reservoirs built since the 1950s. These infrastructures play a strategic interregional role, supporting drinking water supply, irrigation, and hydropower for both Basilicata and neighboring Apulia.

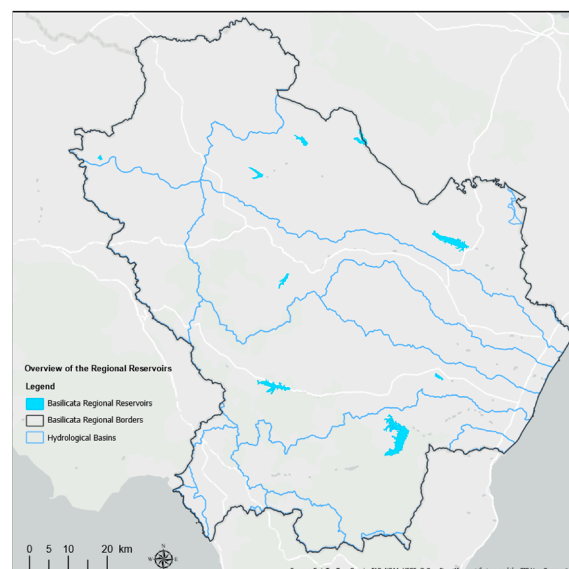


Figure 1. Map of the study area. The nine selected artificial water reservoirs located in Basilicata (South Italy).

The geographic and main hydro-morphometric characteristics of the nine selected water reservoir are listed in Table 2.

Table 2. Table of the selected water reservoirs and their geographic and hydro-morphometric characteristics. The hydro-morphometric attributes refer to maximum reservoir levels (source data: Regional Cartographic Office of the Region Basilicata). Main use: (1) hydropower; (2) drinking water; (3) irrigation; (4) industrial.

Name	River Basin	Latitude (°N) [WGS 84]	Longitude (°E) [WGS 84]	Area [ha]	Perimeter [km]	Volume [Mm ³]	Main Use
Pertusillo	Agri	40.242	15.893	698.36	46.00	159.17	(1), (2), (3)
Camastra	Basento	40.479	15.926	198.88	16.04	28.90	(2), (3), (4)
Monte Cotugno	Sinni	40.023	15.155	2168.96	96.56	530.00	(2), (3), (4)
San Giuliano	Bradano	40.533	16.410	1135.26	51.82	107.00	(3)
Gannano	Agri	40.268	16.424	103.49	8.71	2.60	(3)
Acerenza	Bradano	40.741	15.858	222.20	16.17	47.00	(2), (3)
Genzano	Bradano	40.802	16.000	257.22	13.72	57.00	(3)
Serra del Corvo	Bradano	40.793	16.162	389.35	19.93	42.65	(1), (3)
Saetta	Ofanto	40.795	15.412	57.23	4.69	3.50	(3)

3.2. Sentinel-2-Based Water Surface Extraction

The water extraction workflow automatically derives up-to-date water masks representing the effective hydrological status of the target reservoirs. Executed in GEE, the procedure involves four sequential steps: (i) query and filtering of the Sentinel-2 archive; (ii) temporal compositing and cloud/shadow masking; (iii) calculation of water-sensitive spectral indices; and (iv) rule-based classification to discriminate water bodies from surrounding land surfaces.

A schematic representation of the workflow is provided in Figure 2, while the individual processing steps are described in detail in the following sections.

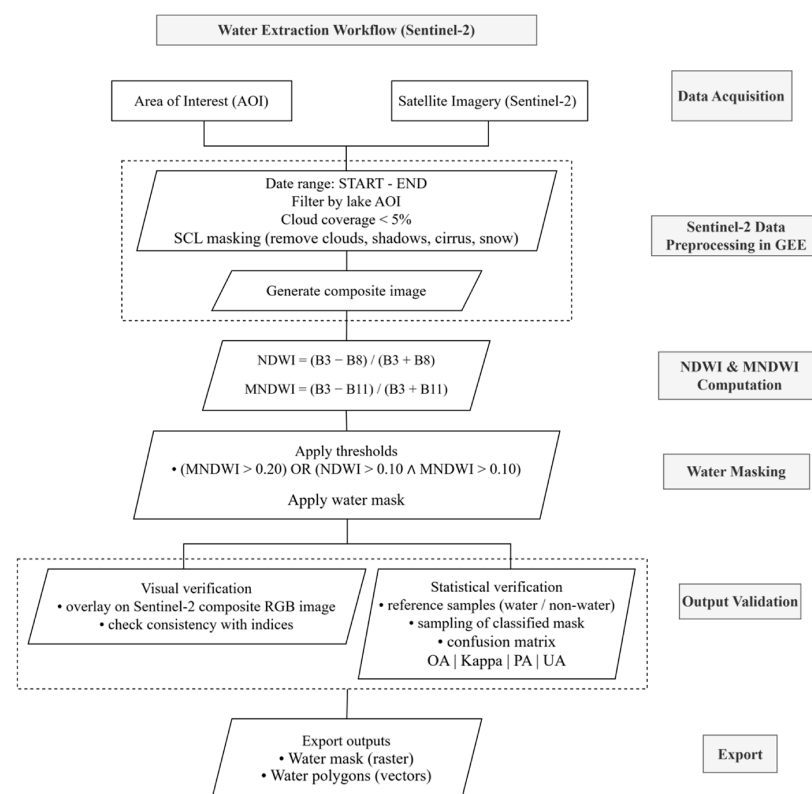


Figure 2. Methodological workflow for the automated extraction of the reservoir water surface available for FPV deployment from Sentinel-2 imagery.

3.2.1. Satellite Image Acquisition and Pre-Processing

Sentinel-2 MSI Level-2A products were selected to extract the reservoir water surfaces, providing the ideal spatial and temporal resolution required for multi-temporal monitoring. Within the GEE environment, the image acquisition and pre-processing phase involve the following steps:

- Temporal and spatial filtering: A one-year period is selected, spanning from 1 June 2024 to 31 May 2025, aimed at assessing the average surface of the reservoirs over the year, so as not to work on single occasional images that could lead to results that are not representative of the real availability of the water resource. Then, the images are filtered according to estimated global cloud coverage, setting a threshold of <5% referring to the entire tile acquired by the satellite (100 km × 100 km). This operation allows excluding images with high cloud presence, which may compromise the correct identification of surface water. Finally, a spatial filter is applied to ensure that the analysis was carried out only for surfaces corresponding to lakes included in the reference dataset provided by the regional cartographic office.
- Pixel-wise masking through SCL: Despite the image-level cloud filtering, an additional pixel-level mask is applied based on the SCL provided in Level-2A products. The SCL classifies each pixel into different categories (e.g., clouds, cloud shadows, vegetation, soil, water) and allows for excluding pixels contaminated by cloud shadows, clouds, cirrus or snow, which could otherwise introduce errors in spectral index calculations.
- Median composite computation: After filtering and masking, the selected Sentinel-2 images are aggregated using the median function, which computes, for each pixel, a median value over the period of interest. The median composite reduces the influence of residual noise and outliers present in the time series (e.g., remaining clouds, specular reflections, atmospheric phenomena not completely corrected and short-term surface variations).

The combination of these steps ensures that the data used for subsequent calculation of spectral indices and water/non-water classification are as free as possible from systematic disturbances.

3.2.2. Spectral Indices Calculation and Water Masking

In the present work, the Normalized Difference Water Index (NDWI) and the Modified Normalized Difference Water Index (MNDWI) are used for water bodies' identification. The NDWI is computed according to the following [30]:

$$NDWI = \frac{\rho_{Green} - \rho_{NIR}}{\rho_{Green} + \rho_{NIR}} \quad (1)$$

where ρ_{Green} represents reflectance in the green band and ρ_{NIR} represents reflectance in the near-infrared band.

For Sentinel-2 images, the equation becomes the following:

$$NDWI = \frac{B3 - B8}{B3 + B8} \quad (2)$$

where B3 is the green band (560 nm, 10 m), which provides excellent contrast between clean and turbid water, while band B8 corresponds to NIR (842 nm, 10 m).

According to Xu [31], the MNDWI is calculated by replacing the NIR with the short-wave infrared (SWIR) band, in order to improve separation between water, bare soil and built-up surfaces. The index is defined as follows:

$$MNDWI = \frac{\rho_{Green} - \rho_{SWIR}}{\rho_{Green} + \rho_{SWIR}} \quad (3)$$

where ρ_{SWIR} represents reflectance in the SWIR band.

For Sentinel-2 images, the expression becomes the following:

$$MNDWI = \frac{B3 - B11}{B3 + B11} \quad (4)$$

where B3 is the green band (560 nm, 10 m resolution) and B11 is the SWIR band (1610 nm, 20 m resolution).

Spectral water indices are calculated from the median composite to differentiate water from non-water surfaces. We suggest employing both the NDWI and the MNDWI. The latter replaces the NIR band with the SWIR band to reduce reflectance noise from built-up areas and dry soils, improving robustness in heterogeneous landscapes [18,19].

Since universal thresholds do not exist, we calibrated the values based on the literature ranges and a dedicated sensitivity analysis, detailed in the following section. To maximize sensitivity in shallow or turbid shoreline areas while minimizing commission errors, the following combined classification rule was applied:

$$(MNDWI > 0.20) \text{ OR } (NDWI > 0.10 \text{ AND } MNDWI > 0.10) \quad (5)$$

The decision logic prioritizes the MNDWI for its superior noise suppression while leveraging the NDWI as a supportive criterion to capture marginal pixels exhibiting high index consistency. It is worth noting that the 10 m spatial resolution MNDWI is derived from Sentinel-2 images by downscaling the 20 m SWIR band to 10 m.

3.2.3. Sensitivity Analysis

Since fixed thresholds depend on site-specific optical and shoreline conditions, a sensitivity analysis was conducted to evaluate the robustness of the classification rule. The baseline configuration was set with a main MNDWI threshold of 0.20, an NDWI threshold of 0.10, and a supporting MNDWI threshold of 0.10.

The supporting MNDWI threshold was kept fixed at 0.10 as a minimal condition to ensure that NDWI-recovered marginal pixels still exhibit a positive water response, avoiding false positives along the shoreline.

To perform the sensitivity analysis, T_{NDWI} and the main MNDWI threshold T_{MNDWI} were independently varied from -0.10 to 0.50 at intervals of 0.10 , yielding a complete factorial grid of 49 threshold combinations per reservoir. All configurations were applied to the same annual Sentinel-2 median composite within the official maximum-reservoir boundaries, keeping cloud filtering, spatial resolution, pre-processing, and the supporting MNDWI threshold constant (0.10).

For each threshold combination, the extracted water area was calculated separately (A_i) for the nine reservoirs and subsequently aggregated over the complete study area. Sensitivity was quantified through the absolute and percentage differences relative to the reference configuration (A_{ref}):

$$\Delta A_i = A_i - A_{ref} \quad (6)$$

$$\Delta A_{i,\%} = \frac{A_i - A_{ref}}{A_{ref}} \times 100 \quad (7)$$

3.3. Sentinel-2-Derived Bathymetry

Satellite-derived bathymetry (SDB) provides key depth information required for FPV mooring and anchorage design. Here, an empirically calibrated analytical SDB workflow was implemented directly within GEE (Figure 3).

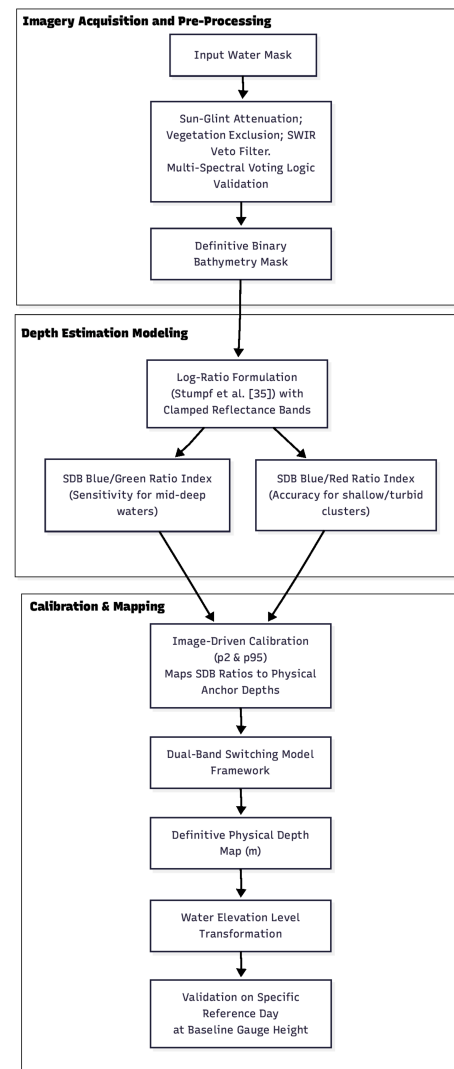


Figure 3. Methodological workflow for the SDB from Sentinel-2 imagery.

3.3.1. Satellite Imagery Acquisition and Data Pre-Processing

The temporal configuration of the Sentinel-2 input was adapted according to the specific analysis. For the representative annual bathymetric reconstruction, the framework leverages a multi-temporal median composite derived from the COPENHAGEN/S2_SR_HARMONIZED collection, thereby reducing the subjectivity and temporal bias associated with the selection of a single scene. As demonstrated in the literature [32], multi-scene median reduction can mitigate transient localized turbidity, sun-glint anomalies, and false shoaling effects, providing a more stable spectral baseline for depth reconstruction. Conversely, for the single-date assessment, individual Sentinel-2 acquisitions were processed using the same SDB workflow in order to evaluate the behavior of the methodology under temporally matched satellite and hydraulic conditions.

Following the initial water surface extraction, the framework integrates a set of optional, incremental filtering modules that can be dynamically toggled within GEE to refine

the bathymetric processing area. Radiometric pre-processing and masking are executed at the pixel level through three sequential steps:

- Sun-glint attenuation: A 10 m circular focal median filter is applied as a localized spatial moving window to smooth out high-frequency surface wave reflectance variations.
- Vegetation exclusion via MCI: Submerged or floating macrophyte infestations and algal blooms are identified and masked out by computing the Maximum Chlorophyll Index (MCI). To establish a rigorous physical baseline, the interpolation framework is parameterized using the central wavelengths (λ) and active top-of-water reflectance (ρ) of the Red (B4), Red-Edge (B5), and NIR (B6) channels as follows [33]:

$$\text{MCI} = \rho_{B5} - \rho_{B4} - \left[(\rho_{B6} - \rho_{B4}) \cdot \frac{\lambda_{B5} - \lambda_{B4}}{\lambda_{B6} - \lambda_{B4}} \right] \quad (8)$$

Substituting the nominal central wavelengths of the Sentinel-2 MSI sensor ($\lambda_{B4} = 665$ nm, $\lambda_{B5} = 705$ nm, $\lambda_{B6} = 740$ nm), the baseline slopes constant resolves to $40/75 \cong 0.5333$, yielding the following operational equation:

$$\text{MCI} \cong \rho_{B5} - \rho_{B4} - [0.5333 (\rho_{B6} - \rho_{B4})] \quad (9)$$

A rigid restrictive threshold ($\text{MCI} < 0.007$) is implemented based on the established literature guidelines for inland waters. This numerical constraint guarantees that pixels exhibiting even initial optical traits of chlorophyll-a red-edge elevation are strictly discarded, ensuring that the subsequent SDB calibration is exclusively driven by pristine bottom-reflectance attenuation features and remains uncontaminated by submerged macrophyte or phytoplankton biophysical signals.

- Water mask refinement: To isolate the most optically stable water pixels, a multi-spectral constraint combines the NDWI and MNDWI masks with an auxiliary SWIR rejection rule ($\rho_{B11} < \rho_{B3}$ AND $\rho_{B11} < 0.15$), yielding a highly conservative water mask. Additionally, to eliminate residual wet soil artifacts and mixed pixels along dynamic shorelines, an automated 6 m circular focal minimum filter can be applied to further sanitize the mask boundaries before depth estimation.

3.3.2. Depth Estimation Modeling

The core architecture builds upon the milestone log-ratio formulation introduced by Stumpf et al. [34]:

$$Z = m_1 \cdot \text{SDB} + m_0 \quad (10)$$

To overcome the physical limitations of single-band pairs in highly dynamic environments, our workflow integrates a dual-band “Switching Model” framework inspired by Caballero and Stumpf [35]. The relative optical metrics are defined as follows:

$$\text{SDB}_{\text{green}} = \frac{\ln(\rho_{B2})}{\ln(\rho_{B3})} \quad (11)$$

$$\text{SDB}_{\text{red}} = \frac{\ln(\rho_{B2})}{\ln(\rho_{B4})} \quad (12)$$

where the Blue/Green ratio ($\text{SDB}_{\text{green}}$) provides optimal penetration and sensitivity in mid-to-deep waters, while the Blue/Red ratio (SDB_{red}) demonstrates superior accuracy in shallow zones or localized turbid clusters (depths lower than 7 m [36]), where bottom reflectance from the green spectrum typically suffers from saturation or severe signal attenuation. To safeguard logarithmic stability under low-reflectance conditions, band

values are numerically clamped to a strict lower bound ($\rho_\lambda \geq 0.0001$), ensuring that the estimators remain positive under all optical scenarios.

3.3.3. Water Bodies' Geometric Input Parameters

Unlike conventional SDB approaches that require external bathymetric calibration datasets, the proposed methodology constrains the bathymetric reconstruction using reservoir morphometric parameters derived from official technical documentation together with monitored water-level data. Specifically, the model requires: (i) the theoretical maximum reservoir depth, D_{max} [m], associated with the design maximum storage condition, (ii) the maximum reservoir water elevation, Z_{max} [m a.s.l.], and (iii) the median monitored water elevation over the period corresponding to the Sentinel-2 annual median composite, Z_{med} [m a.s.l.]. Starting from these parameters, the theoretical minimum bottom elevation of each reservoir (Z_{bottom}) was estimated as follows:

$$Z_{bottom} = Z_{max} - D_{max} \quad (13)$$

The maximum water-column depth compatible with the representative monitored water level, $D_{max, ref}$ [m], was then computed as follows:

$$D_{max, ref} = Z_{med} - Z_{bottom} \quad (14)$$

This value was subsequently used as the upper physical depth constraint in the calibration of the empirical SDB model, whose coefficients were derived from the statistical distribution of the satellite-derived spectral ratios.

3.3.4. Empirical Calibration and Validation

Switching model converts relative dimensionless log-transformed indices into absolute physical depths (meters) using independent calibration frameworks.

The architecture dynamically routes pixel processing based on a localized depth threshold ($Z_{switch} = 7$ m). Calibration parameters (m_1, m_0) for the linear equations are computed via an image-driven approach. This technique maps the statistical boundaries of the water body's radiometric distribution directly to known physical depths. Specifically, the 95th percentile (p95) of the SDB signal is targeted as the shoreline anchor ($Z = m_0$), while the 2nd percentile (p2) is mapped to the deepest observable limit (Z_{target}):

$$m_1 = \frac{Z_{target}}{p_2 - p_{95}} \quad (15)$$

$$m_0 = -1 \cdot (m_1 \cdot p_{95}) \quad (16)$$

The system of equations is solved independently: for the Green Band ratio by imposing $Z_{target} = D_{max, ref}$ (maximum basin depth), and for the Red Band ratio by enforcing $Z_{target} = Z_{switch}$ (7 m). High-frequency spatial noise across the raw switching grid is subsequently suppressed by applying a robust 20 m circular spatial moving window (focal median).

It is worth noting that while the initial tests attempted to ingest the GLOBathy global dataset as a direct reference layer for the primary linear calibration, severe localized constraints and structural mismatches proved that GLOBathy was an unreliable source for direct scene-level tuning in this specific environment.

4. Results and Discussion

4.1. Water Surface Mapping

Applying the proposed water-surface extraction methodology (Figure 2), the nine selected reservoirs were mapped by using the Sentinel-2 data collection referring to June 2024–May 2025. This operation allowed us to map the effective water surface of the nine analyzed artificial reservoirs, identifying the potentially usable water extent for FPV installations during the specified reference period. Figure 4 shows the resulting maps for three representative reservoirs; similar maps were generated for all nine reservoirs considered in this study.

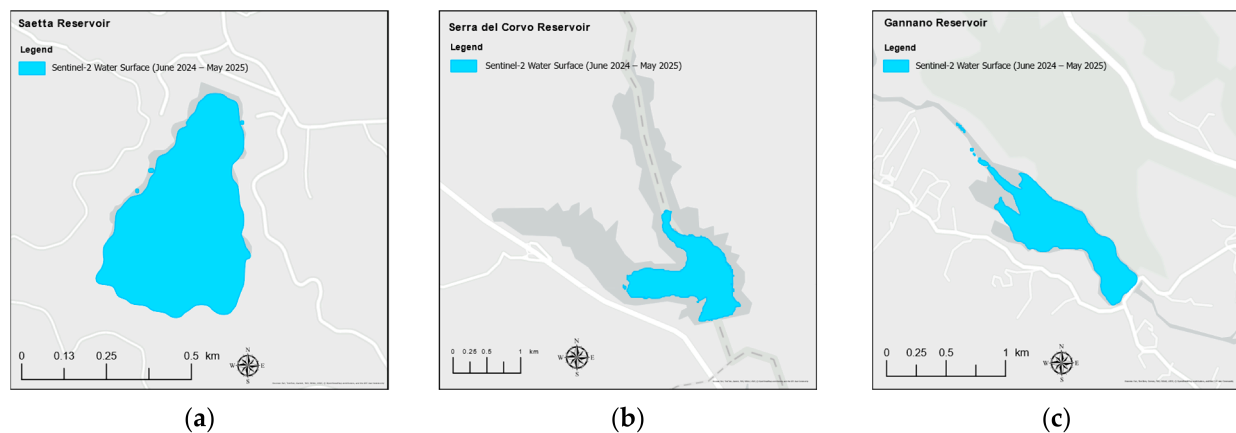


Figure 4. Maps of extracted reservoir water surfaces of three representative reservoirs of the analyzed dataset over June 2024–May 2025: (a) Saetta; (b) Serra del Corvo and (c) Gannano.

In addition to the annual median composite used as the representative surface for the main water-mask assessment, monthly median Sentinel-2 composites were generated over the June 2024–May 2025 period to characterize intra-annual reservoir surface dynamics. For each reservoir, the water-surface area was independently extracted from each monthly median composite using the same NDWI–MNDWI classification rule adopted for the annual analysis. The minimum and maximum monthly median water-surface areas, together with their corresponding months and annual surface-area range, were subsequently derived for each reservoir.

4.1.1. Extracted Water Surface Validation

To evaluate the accuracy of the extracted water masks across the nine reservoirs, a two-step validation procedure was implemented. First, a visual consistency check benchmarked the extracted water surfaces against the Sentinel-2 RGB median composite, NDWI/MNDWI maps, and official maximum extent polygons provided by the Basilicata Region. These official boundaries defined the spatial processing and validation domain, naturally excluding surrounding urban, agricultural, and impervious surfaces, while inspection focused on critical shoreline transition zones, exposed banks, islands, and shallow waters susceptible to spectral confusion. Second, this visual assessment was complemented by a quantitative sensitivity analysis (Section 4.1.2) to evaluate mask robustness under varying NDWI and MNDWI thresholds.

To quantitatively assess thematic accuracy, a validation sample of 900 reference points was generated across the nine reservoirs (100 points per reservoir, split evenly into 50 water and 50 non-water samples). Reference points were assigned via expert visual interpretation of the same Sentinel-2 annual median RGB composite and spatial context, ensuring strict temporal consistency between the classified products and reference labels. Each assessment

unit was assigned exclusively to the predominant land-cover class observed within the corresponding pixel.

Since the reference interpretation was derived from the same Sentinel-2 composite rather than from an independent higher-resolution dataset, the resulting accuracy assessment quantifies the thematic agreement between expert interpretation and the automated NDWI/MNDWI-based classification. It should therefore be interpreted as an internal thematic validation of the water/non-water discrimination procedure, rather than as an independent assessment of the absolute positional accuracy of the shoreline. This approach is consistent with established accuracy-assessment principles, according to which reference labels may be derived from the same source imagery when the interpretation procedure is more detailed than the automatic classification being evaluated, provided that the sampling and labeling criteria are explicitly documented [37–39] throughout the official maximum-impoundment polygons in order to represent both homogeneous and potentially challenging classification conditions. For the water class, samples were selected in open-water areas, shallow or turbid sectors, and near-shore zones. For the non-water class, samples included exposed dry or wet banks, vegetation, islands, infrastructures, and other emerged surfaces located within the maximum reservoir extent. Approximately half of the samples for each class were located near shoreline transition zones, while the remaining samples were distributed across more homogeneous internal areas. Adjacent pixels were avoided as far as possible in order to reduce spatial redundancy and limit the influence of spatial autocorrelation. The reference labels were then compared with the corresponding values extracted from the binary water mask, and a confusion matrix was computed (Table 3).

Table 3. Classification results and confusion matrix based on 900 reference samples. Global accuracy metrics: OA = 95.33% and KC = 0.907.

Class/Metric	Predicted Water	Predicted Non-Water	Total (Reference)	PA	UA
Water (Reference)	412	38	450	91.56%	99.04%
Non-water (Reference)	4	446	450	99.11%	92.15%

According to the relevant literature, standard classification accuracy metrics were derived, including the Kappa coefficient (KC), Overall Accuracy (OA), Producer's Accuracy (PA) and User's Accuracy (UA). The Kappa coefficient evaluates the agreement between the classified map and the reference data after accounting for chance agreement, while Overall Accuracy provides a global measure of correctly classified validation sample units. Producer's and User's Accuracy were used to assess omission and commission errors for the water and non-water classes [19,40–43].

The confusion matrix yielded an Overall Accuracy of 95.33% and a Kappa coefficient of 0.907, indicating a very high level of agreement between the expert-interpreted reference labels and the automated classification. The water class achieved a Producer's Accuracy of 91.56%, with 38 of the 450 reference-water samples incorrectly classified as non-water. Its User's Accuracy was 99.04%, indicating that nearly all pixels classified as water corresponded to actual water surfaces, with only four non-water samples incorrectly assigned to the water class.

The non-water class achieved a Producer's Accuracy of 99.11% and a User's Accuracy of 92.15%. This asymmetry indicates that the classification produced very few false water detections but was comparatively more likely to omit actual water pixels by assigning them

to the non-water class. These omission errors may be associated with spectrally ambiguous conditions within the reservoir polygons, particularly shallow or turbid waters, aquatic vegetation, shoreline transition zones, and mixed pixels.

Overall, the high global accuracy and class-specific accuracy values support the reliability of the adopted spectral-index approach for reservoir water-surface delineation. Nevertheless, since the reference labels were derived through expert interpretation of the same Sentinel-2 median composite, these results should be interpreted as an internal thematic validation of the water/non-water classification rather than as an independent assessment of the absolute shoreline positional accuracy.

4.1.2. Sensitivity Analysis Outputs

The reference threshold configuration, defined by $T_{NDWI} = 0.1$, $T_{MNDWI} = 0.2$ and a fixed supporting MNDWI threshold of 0.10, produced an aggregate extracted surface of 2036.52 ha across the nine reservoirs.

Considering the complete 7×7 factorial grid, the extracted surface ranged from 1911.49 to 2181.74 ha, corresponding to variations between -6.14% and $+7.13\%$, relative to the reference result. The mean surface obtained across the 49 configurations was 2054.03 ha, with a standard deviation of 67.48 ha and a coefficient of variation of 3.29% . These results indicate moderate overall variability across the intentionally broad range of thresholds tested (Table 4).

Table 4. Sensitivity of the aggregate extracted reservoir area to the NDWI and main MNDWI thresholds. The supporting MNDWI threshold was maintained at 0.10. Variations were calculated relative to the reference configuration $T_{NDWI} = 0.10$ and $T_{MNDWI} = 0.20$.

Component	Analysis Configuration	Area Range [ha]	$\Delta A_{i,\%}$ [%]	Maximum Absolute Deviation [%]
NDWI threshold	NDWI varied; main MNDWI fixed at 0.20	2017.12–2048.26	1.53	0.95
Main MNDWI threshold	Main MNDWI varied; NDWI fixed at 0.10	2024.31–2181.74	7.73	7.13
Complete factorial grid	49 NDWI–MNDWI combinations	1911.49–2181.74	13.27	7.13

The classification showed considerably lower sensitivity to changes in the NDWI threshold than to changes in the main MNDWI threshold. When NDWI was varied from -0.10 to 0.50 while maintaining the main MNDWI threshold at 0.20 , the aggregate surface changed by only 31.14 ha, corresponding to 1.53% of the reference surface, and the maximum absolute deviation remained below 1% . Conversely, varying the main MNDWI threshold over the same interval while maintaining NDWI at 0.10 produced a surface range of 157.43 ha, equivalent to 7.73% of the reference area.

This difference is consistent with the logical structure of the classification rule. The main MNDWI condition can independently assign a pixel to the water class, whereas the NDWI condition contributes only through the conjunctive branch and only when $MNDWI > 0.10$ is simultaneously satisfied. Therefore, variations in the main MNDWI threshold directly influence the core extent of the classified water surface, while variations in NDWI mainly affect marginal pixels.

The largest increase in extracted surface occurred when the main MNDWI threshold was reduced to -0.10 , resulting in an aggregate area of 2181.74 ha, corresponding to a 7.13% increase relative to the reference configuration. For this threshold, the extracted area remained unchanged across all tested NDWI values, demonstrating that the direct

MNDWI branch dominated the classification and made the supporting NDWI condition operationally irrelevant (Figure 5).

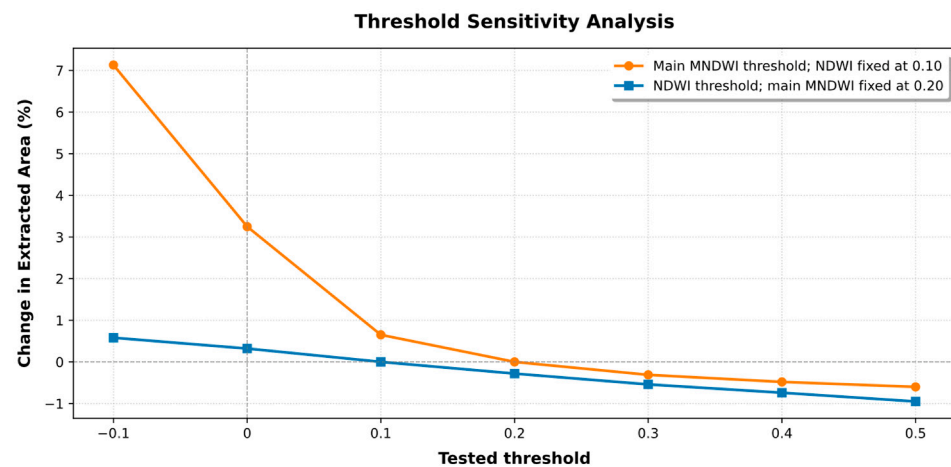


Figure 5. One-at-a-time sensitivity profiles obtained by varying NDWI while maintaining the main MNDWI threshold at 0.20 and by varying the main MNDWI threshold while maintaining NDWI at 0.10. The supporting MNDWI threshold was fixed at 0.10 in all configurations.

This behavior should not be interpreted as an intrinsic failure of MNDWI at negative values. Negative thresholds may be useful in specific environments for detecting spectrally weak water features, including narrow channels, mixed shoreline pixels, shallow or turbid water, and inundated vegetation. Nevertheless, lowering the threshold below zero reduces the selectivity of the index and may also include spectrally dark non-water surfaces. Within the official maximum-reservoir polygons used in this study, these potentially ambiguous surfaces may comprise wet or exposed sediments, shoreline vegetation, shaded areas, and mixed land–water pixels.

Therefore, the marked surface increase observed at -0.10 indicates that this threshold was excessively permissive for the investigated reservoir environments. Pixel-level visual inspection showed that the additional areas detected under negative-threshold configurations predominantly corresponded to spectrally ambiguous shoreline features and non-water surfaces within the maximum reservoir polygons, rather than to a consistent expansion of the actual water extent. These pixels were therefore excluded from the final classification. Furthermore, the loss of sensitivity to the NDWI threshold indicates that, under this configuration, the direct MNDWI branch dominated the classification and reduced its discriminatory power.

Around the adopted reference thresholds, the response remained comparatively stable. Changing the NDWI threshold from 0.10 to 0.00 or 0.20 resulted in area variations of $+0.32\%$ and -0.28% , respectively. Similarly, changing the main MNDWI threshold from 0.20 to 0.10 or 0.30 produced variations of $+0.65\%$ and -0.31% . Together with the visual agreement observed for the Sentinel-2 median composite, these limited differences indicate that the selected configuration lies within a stable portion of the response surface rather than near an abrupt classification transition. The results therefore support the choice adopted in Section 3.2.2.

4.1.3. Comparison with the GSW Dataset

A geometric and quantitative comparison has been conducted between the water surfaces extracted for the nine selected reservoirs over the year 2021 and the reference permanent-water layer derived from the JRC-GSW dataset. Specifically, we used the JRC-GSW Yearly History product (available in GEE) [11] referred to in 2021, selecting

the permanent water class (waterClass = 3). This class represents the areas classified as permanent water throughout the selected year. By overlaying the vector layers derived from the proposed water extraction procedure and the corresponding JRC-GSW reference layers, the following synthetic metrics can be calculated:

$$Retention = \frac{area(JRC \cap S2)}{area JRC} \quad (17)$$

which indicates the fraction of permanent water still present. The metric ranges between 0 and 1, where values close to 1 indicate high preservation of the permanent water surface.

$$Jaccard = \frac{area(JRC \cap S2)}{area JRC + area S2} \quad (18)$$

which measures the geometric similarity between the two datasets: 1 = perfect correspondence and 0 = no overlap [44].

$$\Delta S = \frac{S_{S2} - S_{JRC}}{S_{JRC}} \times 100 \quad (19)$$

ΔS (%) is the percentage variation in the recently observed surface compared to the historically permanent one from JRC, where negative values indicate a contraction of the observed water surface relative to the permanent extent, while positive values indicate an expansion.

The results of the comparison are summarized in Table 5. Overall, the comparison shows a high degree of correspondence between the two datasets and confirms that the estimated water surface areas are closely aligned with the reference values. In particular, we observed that the Jaccard Index values were consistently high for all analyzed reservoirs (0.91–0.98), while the Retention values exceeded 0.92 in all cases, confirming the capability of the proposed extraction framework to accurately preserve the geometry of the historically permanent water bodies. The percentage surface differences were generally limited, with slightly larger negative deviations observed for smaller reservoirs and shoreline-constrained basins.

Table 5. Results of the quantitative comparison between the extracted effective water surfaces of the nine pilot reservoirs and the corresponding JRC-GSW reference layers for the year 2021.

Reservoir	JRC Permanent Water Area [km ²]	Sentinel-2 Extracted Area [km ²]	Intersection Area [km ²]	Retention	Jaccard Index	ΔS [%] vs. JRC
Acerenza	0.651	0.615	0.611	0.938	0.933	−5.620
Pertusillo	4.283	4.255	4.229	0.988	0.982	−0.640
Camastra	0.951	0.902	0.898	0.944	0.941	−5.160
Monte Cotugno	11.529	11.348	11.326	0.982	0.980	−1.570
Gannano	0.29	0.273	0.268	0.924	0.908	−5.90
San Giuliano	6.354	6.285	6.269	0.987	0.984	−1.080
Genzano	0.262	0.248	0.25	0.956	0.965	−5.250
Saetta	0.393	0.374	0.372	0.947	0.942	−4.710
Serra del Corvo	2.543	2.373	2.369	0.932	0.930	−6.660

In the following maps (Figure 6) the spatial overlay between the extracted effective water-surface layers and the corresponding JRC-GSW reference layers is shown for three representative reservoirs of the analyzed dataset. Similar comparisons were performed for all nine reservoirs considered in the study.

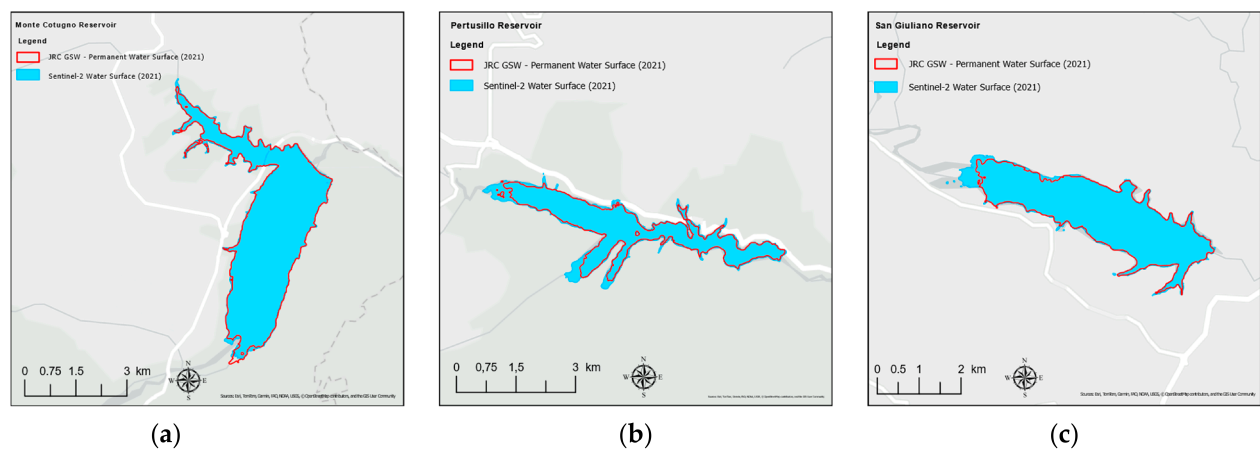


Figure 6. Maps of extracted effective water surface layers and the corresponding JRC-GSW reference layers (year 2021) of: (a) Monte Cotugno reservoir; (b) Pertusillo reservoir and (c) San Giuliano Reservoir.

4.1.4. Intra-Annual Water Surface Dynamics

To complement the representative annual water-surface mapping, the intra-annual variability of the nine reservoirs was investigated using monthly median Sentinel-2 composites covering the June 2024–May 2025 period. For each reservoir, the minimum and maximum monthly median water-surface extents were identified, and the corresponding annual surface-area range was calculated as the difference between the maximum and minimum values (Table 6).

Table 6. Minimum and maximum monthly median water-surface areas and corresponding annual surface-area ranges for the nine analyzed reservoirs over the June 2024–May 2025 period.

Reservoir	Month of Minimum	Minimum Monthly Median Area [ha]	Month of Maximum	Maximum Monthly Median Area [ha]	Annual Surface-Area Range [ha]
Camastra	January 2025	0.00	April 2025	110.25	110.25
Pertusillo	January 2025	0.00	July 2024	476.12	476.12
Acerenza	October 2024	40.46	April 2025	68.19	27.74
Gannano	June 2024	9.28	December 2024	53.69	44.41
Genzano	September 2024	5.22	May 2025	34.06	28.84
Monte Cotugno	November 2024	427.74	June 2024	998.41	570.67
Saetta	March 2025	0.00	April 2025	42.20	42.20
San Giuliano	November 2024	393.83	May 2025	598.07	204.23
Serra del Corvo	September 2024	84.70	June 2024	148.12	63.42

The analysis revealed marked differences in intra-annual surface variability among the reservoirs. Monte Cotugno exhibited the largest absolute surface-area range, varying from 427.74 ha in November 2024 to 998.41 ha in June 2024, corresponding to an annual range of 570.67 ha. San Giuliano also showed substantial variability, with monthly median surfaces ranging from 393.83 ha in November 2024 to 598.07 ha in May 2025 (204.23 ha range). Serra del Corvo showed an intermediate variation of 63.42 ha, from 84.70 ha in September 2024 to 148.12 ha in June 2024.

Smaller reservoirs exhibited lower absolute variations but, in several cases, pronounced changes relative to their typical surface extent. Gannano ranged from 9.28 ha in June 2024 to 53.69 ha in December 2024, while Genzano varied from 5.22 ha in September 2024 to 34.06 ha in May 2025. Acerenza showed comparatively more limited fluctuations, ranging from 40.46 ha in October 2024 to 68.19 ha in April 2025.

These results highlight the strongly reservoir-dependent nature of water-surface dynamics. From an FPV planning perspective, the annual median extent alone may therefore provide an incomplete representation of the effectively available surface, particularly for reservoirs characterized by pronounced seasonal contractions. The monthly analysis provides complementary information on the persistence and variability of the potentially usable water surface and may support the identification of reservoirs where large seasonal fluctuations could affect the FPV layout, mooring requirements, and operational feasibility.

To provide a more complete representation of the intra-annual dynamics, Table 7 reports the monthly median water-surface area derived for each reservoir throughout the entire observation period. The monthly values allow for the temporal evolution of the water bodies to be examined in greater detail, highlighting periods of progressive contraction, recovery, or relative stability.

Table 7. Monthly median water-surface areas [ha] derived from Sentinel-2 for the nine analyzed reservoirs over the June 2024–May 2025 observation period.

Month/Reservoir	Camastra	Pertusillo	Aacerenza	Gannano	Genzano	Monte Cotugno	Saetta	San Giuliano	Serra del Corvo
June 2024	92.36	111.35	45.62	9.28	22.41	998.41	4.83	455.08	148.12
July 2024	85.86	476.12	44.47	43.18	27.67	907.29	19.20	443.73	126.58
August 2024	82.30	445.58	44.21	43.25	28.43	796.60	18.27	428.22	111.00
September 2024	62.67	316.04	40.83	36.84	5.22	578.39	16.00	404.66	84.70
October 2024	51.57	9.91	40.46	30.34	22.45	520.74	17.46	397.30	91.88
November 2024	40.66	327.13	41.59	42.61	27.84	427.74	17.34	393.83	97.53
December 2024	42.46	355.94	45.41	53.69	17.25	494.99	22.76	396.63	103.37
January 2025	0.00	0.00	58.79	52.07	24.50	585.52	31.13	394.78	106.38
February 2025	99.48	422.89	65.55	12.96	31.75	857.15	39.03	519.24	114.21
March 2025	101.31	412.17	57.72	24.07	31.51	884.27	0.00	531.26	114.49
April 2025	110.25	453.37	68.19	52.62	33.04	959.88	42.20	586.80	127.42
May 2025	105.98	458.33	59.75	49.87	34.06	984.09	42.05	598.07	128.92

The complete monthly series further confirms that the observed variability does not follow a uniform temporal pattern across the nine reservoirs, reflecting the combined influence of reservoir morphology, seasonal hydrological conditions, and operational water management.

4.2. Bathymetry Reconstruction

To evaluate the volumetric consistency of the methodology across all nine reservoirs, the switching log-ratio model (Caballero and Stumpf [35]) was applied within GEE, using annual median Sentinel-2 composites (June 2024–May 2025; cloud cover < 5%). Water surface extents were derived from these composites, while the reference hydraulic conditions were established using the median monitored water elevation (Z_{med}) over the same period (for our case study, water-level observations were retrieved from the official monitoring service Acque del Sud: <https://acquedelsudspa.it/>, accessed on 15 December 2025).

Using multitemporal compositing reduced short-term optical variability, cloud contamination, and transient hydrological fluctuations. The resulting bathymetric grids were post-processed via median focal filtering and numerical depth clamping to derive the mean depths, surface areas, and total storage volume estimations for each reservoir.

For the Serra del Corvo, San Giuliano, and Saetta reservoirs, the MCI-based filtering step was disabled because the fixed threshold removed an excessive fraction of the water surface, making the subsequent bathymetric reconstruction spatially unrepresentative.

This behavior was associated with optically complex water conditions, characterized by a marked greenish spectral response and relatively low water levels, which may be consistent with enhanced algal or chlorophyll-related signals and increased influence of shallow water and bottom reflectance. In these cases, the MCI filter was therefore excluded from the final bathymetric mask, while the remaining spectral and spatial filtering steps were retained.

Table 8 summarizes the main morphometric and hydraulic parameters used as input for the reconstruction procedure, represented by the theoretical maximum reservoir depth and the maximum impoundment elevation.

Table 8. Input morphometric parameters of the analyzed nine reservoirs.

Reservoir	Maximum Depth [m]	Maximum Impoundment Elevation [m a.s.l.]
Monte Cotugno	63.3	255.8
Pertusillo	84.0	532.0
Camastra	54.1	534.6
Serra del Corvo	29.4	271.4
Saetta	16.0	952.7
San Giuliano	34.6	101.6
Gannano	11.0	99.0
Acerenza	52.4	457.0
Genzano	58.3	443.0

Figure 7 shows bathymetric maps of three representative reservoirs, obtained through the pro-posed Satellite-Derived Bathymetry (SDB) framework using the actual water surfaces extracted from Sentinel-2 imagery during the year June 2024–May 2025. Visual inspection confirmed that the spectral and spatial filtering effectively suppressed localized artifacts from artificial structures and spectrally complex surfaces, yielding spatially plausible depth patterns. Across all reservoirs, the deepest sectors were consistently reconstructed along the main impounded valley and near the dam axis, in line with expected reservoir morphology. For example, in the Monte Cotugno and Pertusillo reservoirs, the filtering successfully excluded the road bridge spanning the water body, preventing severe depth overestimation. However, this conservative masking strategy introduces a systematic volume underestimation: pixels excluded due to spectral ambiguity or structural coverage (e.g., the water column beneath the bridge) do not contribute to the volumetric integration. While this approach prioritizes spatial consistency over noisy inputs, these morphological patterns should be interpreted as a qualitative check of physical plausibility rather than a direct validation against ground-truth bathymetry.

The comparison with the monitored reservoir volumes revealed heterogeneous performance across the analyzed reservoirs, with both overestimation and underestimation and therefore no systematic volumetric bias in a single direction (Table 9). Relative volume differences were comparatively limited for Acerenza (−13.83%), Camastra (+20.45%), Monte Cotugno (+23.87%), Pertusillo (+30.13%), and San Giuliano (+35.10%). Larger discrepancies were observed for Serra del Corvo (+236.15%), Saetta (−62.14%), Gannano (−93.32%), and Genzano (−92.92%). These relative errors should be interpreted in relation to the different storage volumes of the analyzed reservoirs. In reservoirs characterized by low monitored storage, small absolute discrepancies can translate into very large percentage errors when normalized by the reference volume. For this reason, absolute and relative volume errors were considered jointly. Conversely, for larger reservoirs such as Monte Cotugno and Pertusillo, moderate relative errors correspond to comparatively large absolute volume dif-

ferences, since depth-estimation uncertainties are integrated over substantially larger water surfaces. More generally, volumetric discrepancies may also reflect differences in water transparency, suspended sediments, bottom and surface reflectance, shoreline mixed pixels, vegetation, and other optical conditions known to influence empirical SDB reconstructions.

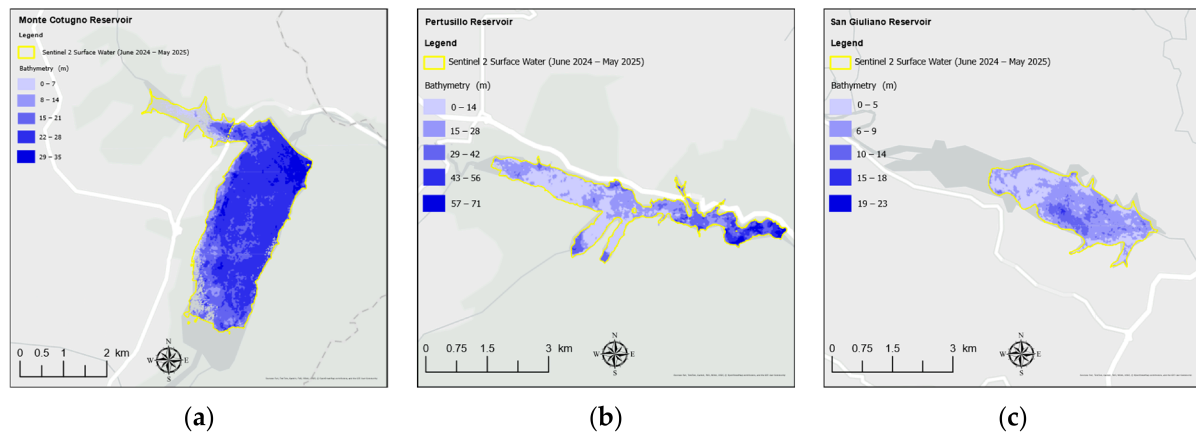


Figure 7. Sentinel-2-derived bathymetric maps obtained for three representative reservoirs over the year June 2024–May 2025: (a) Monte Cotugno; (b) Pertusillo; and (c) San Giuliano reservoir.

Table 9. Results of the annual median-based bathymetric reconstruction for the nine analyzed reservoirs. The table reports the SDB-estimated storage volume, mean and maximum estimated depths, and the absolute and relative differences between the SDB-estimated volume and the corresponding median monitored storage volume over the June 2024–May 2025 period. Positive relative differences indicate volume overestimation, whereas negative values indicate underestimation.

Name	Estimated Median Volumes [Mm ³]	Median Monitored Volumes [Mm ³]	Average Estimated Depth [m]	Maximum Estimated Depth [m]	Absolute Volume Error [Mm ³]	Relative Volume Error [%]
Monte Cotugno	157.86	127.44	21.16	34.70	30.42	23.9%
Pertusillo	92.02	70.714	20.37	71.72	21.31	30.1%
Camastra	10.82	8.98	13.13	42.44	1.84	20.4%
Serra del Corvo)	5.96	1.773	5.44	16.02	4.19	236.2%
Saetta	0.61	1.611	3.21	8.00	1.00	−62.1%
S. Giuliano	25.11	18.59	5.77	26.16	6.52	35.1%
Gannano	0.13	1.95	3.71	11.00	1.82	−93.3%
Acerenza	3.84	4.46	9.73	19.79	0.62	−13.8%
Genzano	0.09	1.27	5.91	16.07	1.18	−92.9%

A further source of uncertainty may arise from the use of temporally aggregated information to represent the annual reservoir condition. Both the Sentinel-2 median composite and the median monitored water level provide synthetic representations of conditions observed over the June 2024–May 2025 period and do not necessarily correspond to the same physical reservoir configuration occurring on a specific date. Therefore, even assuming the monitored water-level and storage-volume data provided by the managing authority to be reliable, some discrepancies between the SDB-derived and monitored volumes may result from combining temporally aggregated satellite and hydrological information. The annual comparison should consequently be interpreted as an assessment of the representative

volumetric consistency of the reconstruction over the analyzed period rather than as a direct comparison under strictly coincident hydraulic conditions.

Overall, these results indicate that the proposed framework can reproduce spatially plausible bathymetric reservoir patterns, while its volumetric performance remains reservoir-dependent and is influenced by reservoir size, storage conditions, optical complexity, and the spatial extent of filtered areas. To further investigate the behavior of the method under temporally matched satellite and hydraulic conditions, an additional single-date assessment was therefore carried out for the Monte Cotugno reservoir.

Single-Date Volumetric Consistency Assessment

To further investigate the behavior of the method under temporally matched hydraulic and satellite-observation conditions, an additional single-date assessment was therefore conducted for the Monte Cotugno reservoir.

Monte Cotugno was selected as a representative case study because of its large spatial extent, hydrological relevance, and the availability of corresponding daily water-level and storage-volume observations. One Sentinel-2 acquisition per month was selected over the June 2024–May 2025 period, based on the simultaneous availability of: (i) imagery suitable for SDB processing and characterized by minimal cloud contamination over the reservoir, and (ii) corresponding daily monitored water-level and storage-volume data provided by the managing authority.

Scene selection preferentially targeted acquisitions with a reported cloud coverage below 1%. When such conditions were not available, the acquisition with the lowest cloud coverage was selected, including scenes with approximately 3% cloud coverage for January, February, and October. Image availability and cloud conditions were preliminarily inspected through the Copernicus Browser platform [45].

For each selected date, the automatic water extraction procedure was first applied to derive the instantaneous reservoir surface geometry. Subsequently, the SDB framework was executed using the monitored water level corresponding to the selected day as hydraulic reference condition. The resulting bathymetric reconstruction was then used to estimate the mean depth and total stored volume.

During the analysis, the MCI-based filtering step was disabled for the November, December, and January Sentinel-2 images. During these dates, the fixed MCI threshold removed a substantial portion of the detected water surface, likely because of season-specific optical conditions affecting the spectral response of the reservoir. To avoid excessive loss of valid water pixels and preserve the spatial representativeness of the bathymetric reconstruction, the MCI filter was therefore excluded for these acquisitions, while the remaining processing workflow was kept unchanged.

The comparison between SDB-derived and monitored daily volumes allowed an independent evaluation of the temporal consistency of the proposed methodology under different hydrological and optical conditions. Since the same Sentinel-2-based SDB methodology was applied to each acquisition and the monitored water elevation was used as an input constraint, the analysis should be interpreted as a temporally matched volumetric consistency assessment rather than as a fully independent bathymetric validation. Table 10 summarizes the results obtained for the selected dates.

The single-date analysis showed that the proposed methodology was able to reproduce the seasonal evolution of the reservoir storage, capturing both the progressive draining phase observed in the summer to late autumn period and the subsequent recovery during winter and spring.

However, the magnitude of the estimated storage changes did not consistently match the monitored observations, and substantial discrepancies occurred for several individual dates.

Table 10. Single-date volumetric consistency assessment for the Monte Cotugno reservoir. Positive relative errors indicate volume overestimation, whereas negative values indicate underestimation.

Date	Daily Monitored Water Level [m a.s.l.]	Maximum Estimated Depth [m]	Mean Estimated Depth [m]	SDB-Estimated Volume	Monitored Daily Volume	Absolute Volume Error [Mm ³]	Relative Volume Error [%]
17 June 2024	231.7	39.2	20.88	177.56	167.1	10.46	6.3%
15 July 2024	228.9	36.4	25.71	190.47	137.5	52.97	38.5%
16 August 2024	225.3	32.8	19.1	127.9	103.6	24.3	23.5%
28 September 2024	220.3	27.8	19.18	32.82	65.9	33.08	−50.2%
13 October 2024	218.7	26.2	11.33	46.87	55.3	8.43	−15.2%
24 November 2024	215.8	23.3	5.62	24.28	38.3	14.02	−36.6%
17 December 2024	217.6	25.1	4.71	22.98	48.5	25.52	−52.6%
1 January 2025	220.3	27.8	1.82	10.7	65.8	55.1	−83.7%
22 February 2025	227.7	35.2	7.87	66.12	125.5	59.38	−47.3%
9 March 2025	227.9	35.4	13.03	108.43	127.8	19.37	−15.2%
11 April 2025	230.1	37.6	13.14	117.39	149.6	32.21	−21.5%
1 May 2025	230.5	38	17.52	163.24	153.6	9.64	6.3%

No systematic bias in a single direction was observed. SDB-derived volumes were higher than the monitored values in June, July, and August 2024 and again in May and June 2025, whereas underestimation prevailed from September 2024 to April 2025. The smallest relative discrepancies were observed on 17 June 2024 and 1 May 2025, both approximately +6.3%, while the largest relative error occurred on 1 January 2025, when the estimated volume underestimated the monitored storage by approximately 83.7%. Pronounced underestimations were also observed in September 2024 (−50.2%), December 2024 (−52.6%), and February 2025 (−47.3%).

The temporal behavior therefore suggests that the framework captures the broad reservoir filling and drawdown cycle more reliably than the absolute magnitude of storage at every individual date. In particular, the largest underestimations occurred during the low-storage and early recovery phases, when the reconstructed mean depths were also comparatively low. These discrepancies may reflect the combined influence of the instantaneous water-surface delineation, scene-specific optical conditions, the spatial extent of valid bathymetric pixels, and the sensitivity of the spectral-ratio model to changing water and bottom conditions.

The observed date-dependent errors can be attributed to several sources of uncertainty inherent in optical SDB reconstruction. The proposed methodology constrains the depth model using reservoir design information and the monitored water elevation rather than in situ bathymetric control points. Consequently, while the maximum physically admissible depth is constrained for each date, the spatial distribution of intermediate depths remains dependent on the satellite-derived spectral ratios. Consequently, variations in water transparency, suspended material, bottom reflectance, shoreline conditions, and the number and spatial distribution of valid pixels may therefore influence the resulting bathymetric surface and the integrated storage volume.

Nevertheless, the temporal sequence demonstrates that the reconstruction responds to changing reservoir conditions rather than producing a constant volumetric offset. The single-date assessment therefore provides evidence of the temporal responsiveness of

the proposed framework, while also highlighting that absolute volume accuracy remains dependent on the optical and hydrological conditions associated with each acquisition.

Figure 8 illustrates the temporal evolution of the SDB-estimated and monitored storage volumes, showing that the proposed framework captures the main hydrological fluctuations of the reservoir throughout the observation period.

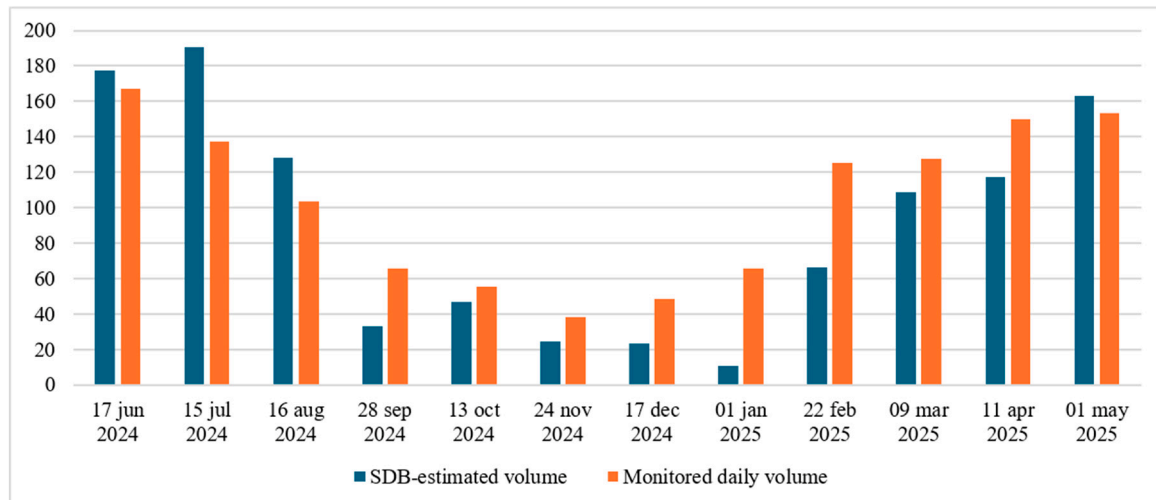


Figure 8. Monthly comparison between SDB-estimated and monitored daily storage volumes for the Monte Cotugno reservoir from June 2024 to May 2025.

5. Conclusions

Hydro-morphometric characterization of the target water body represents an essential component of early-stage Floating Photovoltaic (FPV) planning. To this end, this work presents a preliminary satellite-based methodology relying on Sentinel-2 imagery. The proposed framework, developed within a cloud-computing environment, is intended as a baseline tool to support engineers and public stakeholders during initial feasibility assessments by providing spatially and temporally updated information on the water-surface extent, surface variability, and approximate depth distribution while reducing the dependence on static hydrographic datasets and dedicated field surveys during the initial planning stages. However, it is not intended to replace detailed in situ investigations. Such direct integration remains essential to capture the morphology of water bodies and to detect structural irregularities, submerged obstacles, or sediment discontinuities that could influence anchoring and engineering choices.

The NDWI-MNDWI classification achieved an Overall Accuracy of 95.33% and a Kappa coefficient of 0.907 in the internal thematic assessment, with particularly low commission errors for the water class. The sensitivity analysis further showed that the adopted threshold configuration lies within a comparatively stable portion of the classification response, while the comparison with the JRC Global Surface Water dataset for 2021 confirmed the geometric correspondence between the independently derived water extents.

The monthly analysis additionally demonstrated that reservoir surface availability cannot always be adequately represented by a single annual geometry. Pronounced intra-annual variations were observed for several reservoirs. From an FPV perspective, this temporal information is relevant because seasonal surface contractions may affect the persistence of potentially usable installation areas and may influence the preliminary layout, mooring, and operational considerations. The integration of annual and monthly surface products therefore provides a more informative basis for FPV screening than static reservoir boundaries alone.

The annual bathymetric assessment showed spatially plausible depth patterns across most of the analyzed reservoirs. However, volumetric performance was reservoir-dependent, with both overestimation and underestimation observed across the dataset. These discrepancies reflect the combined effects of reservoir morphology, optical water conditions, spatial filtering, and the use of temporally aggregated satellite and hydrological information. In addition, masking spectrally unreliable pixels improves the spatial consistency of the reconstructed bathymetry but may exclude portions of the water column from the final volume integration.

The complementary single-date analysis performed for the Monte Cotugno reservoir further showed that the framework is responsive to changing hydrological conditions and can reproduce the main seasonal filling and drawdown dynamics. Nevertheless, the magnitude of the estimated storage volumes did not consistently match the monitored values for all acquisitions, confirming that absolute volumetric accuracy remains sensitive to scene-specific optical and hydraulic conditions.

From a broader perspective, the methodology provides public authorities, reservoir managers, and stakeholders involved in renewable-energy planning with an updatable and transferable framework for screening and monitoring water bodies that are potentially suitable for FPV deployment over large spatial datasets. Its main advantage lies in reducing dependence on dedicated bathymetric surveys during preliminary assessment stages, provided that basic reservoir design parameters and representative monitored water-level information are available.

Future developments should focus on integrating independent high-resolution bathymetric reference data, multi-sensor EO observations, improved treatment of optically complex waters, and more physically based or locally calibrated depth-retrieval approaches. Such developments would allow a more rigorous assessment of absolute depth accuracy and improve the volumetric reliability of the reconstructed reservoir geometries.

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Data Availability Statement: The data supporting the findings of this study are openly available and can be accessed through public repositories. Satellite imagery and geospatial analyses were processed using Google Earth Engine (GEE), with data catalogs available at <https://earthengine.google.com/> (Accessed on 2 June 2026) and specific datasets referenced within the text. Reservoir water-level monitoring data were retrieved from the official services of Acque del Sud at <https://acquedelsudspa.it/> (Accessed on 15 December 2025).

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Abbreviations

The following abbreviations are used in this manuscript:

EO	Earth Observation
FPV	Floating Photovoltaics
GEE	Google Earth Engine
MCI	Maximum Chlorophyll Index
MNDWI	Modified Normalized Difference Water Index
MSI	Multispectral Instrument
NDWI	Normalized Difference Water Index
NIR	Near-Infrared
SAR	Synthetic Aperture Radar
SDB	Satellite-Derived Bathymetry
SWIR	Shortwave Infrared

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