Issues and potentials of multi-sensor water level monitoring: lesson learned at Recentino Lake, Italy

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Keywords: Water surface levels monitoring, Small reservoirs, SWOT, UAV photogrammetry, Height reference frame transformations

Abstract

Monitoring surface water levels in reservoirs is often hindered by the sparse distribution of in situ gauges and inconsistencies among height reference frames. This study compares water levels obtained from the Surface Water and Ocean Topography (SWOT) satellite altimeter, an in situ gauge station, and a Unmanned Aerial Vehicle (UAV) photogrammetric survey, at Recentino Lake, a small artificial reservoir in central Italy, to quantify discrepancies arising from unknown or inconsistent height reference frames. SWOT data were processed using a two-step outlier removal procedure to derive a reliable water level time series, while the UAV survey provided a high-resolution Digital Elevation Model (DEM) (GSD 1.6 cm/pixel) in a certain epoch from which water level was extracted at the water-dam interface. All datasets were transformed to a common height reference frame for direct comparison. Assuming the gauge time series as reference, at the epoch of UAV survey, the UAV-derived water level differs from the gauge one by -0.17 m, while the SWOT and gauge time series show moderate agreement (Pearson correlation of 0.69) and a mean/median difference of - 0.08 m. Also, differences between ascending and descending SWOT passes (Pearson correlation of 0.65 and 0.76, respectively) indicate orbit-dependent effects on SWOT water level measurements. These findings emphasise the relevant contribution of multi-source datasets for water reservoir level monitoring, mainly for the detection and correction of height reference frame inconsistencies, including the bias between SWOT and the national height reference frame.

1. Introduction

Inland surface water level monitoring has become increasingly critical in the context of climate change and increasing global water demand. Traditionally, water levels are measured using in situ gauge stations that can achieve an accuracy of a few centimeters. However, these measurements are inherently local and point-based and require significant installation and maintenance costs. Consequently, these systems are typically limited to large reservoirs and are deployed mainly in developed countries (Ravanelli et al., 2023, Bocchino et al., 2023, Sergi et al., 2025). Furthermore, although gauge measurements are generally referenced to local height reference frames, the specific reference frame associated with each gauge is not always reported. This lack of clarity complicates the derivation of consistent absolute water levels and the comparison and integration of datasets from different sources.

Remote sensing techniques, including satellite altimetry and Unmanned Aerial Vehicle (UAV)-based Digital Elevation Model (DEM) generation, are well-established in geospatial disciplines, even if their operational application for lake monitoring remains somewhat limited. These techniques can effectively overcome limitations of traditional gauge measurements, including limited spatial coverage and inconsistencies in the height reference frames. In particular, satellite remote sensing enables cost-efficient large-scale surface water monitoring, provided that data processing is performed rigorously and height reference frames are consistently handled. Among recent satellite altimetry missions, the Surface Water and Ocean Topography (SWOT) mission represents a major advancement. It uses the Ka-band RADAR Interferometer (KaRIn) to provide high-quality mapping of ocean and inland water surfaces, measuring both their spatial extent and Water Surface Elevation (WSE) (Hamoudzadeh et al., 2024). Recent studies have begun to demonstrate the potential of SWOT products to improve surface water level monitoring and to support a wide range of hydrological applications. In this context, comparisons with in situ and multi-mission datasets such as DAHITI (Schwatke et al., 2015) and Hydroweb (CNES and THEIA, 2026, Crétaux et al., 2011) indicate that errors in SWOT WSE measurements are typically within the decimeter range, with Root Mean Square Error (RMSE) values generally below 0.40 m for small lakes in Australia and reaching $\sim$0.10 m for lakes under optimal conditions, such as non-mountainous lakes with minimal cloud cover and near-nadir viewing angles (Hamoudzadeh et al., 2024, Maubant et al., 2025, Jing et al., 2026). Over the Tibetan Plateau and China, SWOT demonstrated a strong capability to monitor small and remote lakes (Wu et al., 2025). In particular, water levels were successfully retrieved for 1919 lakes (covering about 99% of lakes larger than 0.2 km^2), extending monitoring capabilities to small and remote lakes that could not be observed with previous RADAR satellite altimeter missions such as Jason, Sentinel-3 and Sentinel-6. Accuracy assessment against the well-established space-borne LiDAR altimeter Ice, Cloud and land Elevation Satellite-2 (ICESat-2) showed strong agreement, with an average bias of -0.01 ± 0.13 m, RMSE of 0.14 m, and Mean Absolute Error (MAE) below 0.1 m. This high level of performance is maintained even for small lakes (down to $\sim$1 km^2), confirming the SWOT's ability to capture water level dynamics across a wide range of lake sizes in high-altitude regions (Wu et al., 2025).

In parallel, UAVs have emerged as a valuable tool for capturing high-resolution hydrometric observations over the past decade (Vélez-Nicolás et al., 2021, Mawodzeke et al., 2026). UAV-based Structure-from-Motion (Westoby et al., 2012) photogrammetry enables the generation of detailed DEMs and orthomosaics, from which the water surface level can be derived (Ridolfi and Manciola, 2018, Szostak et al., 2024). However, photogrammetry is intrinsically limited in reconstructing water surfaces because their uniform texture and specular reflections reduce the reliability of feature correspondence identification during the matching process, while refraction effects distort the apparent geometry. Consequently, the estimation of the water level typically relies on the identification of the interface between water and adjacent solid features (Bandini et al., 2020). In artificial reservoirs, engineered structures, such as dam faces, provide stable and well-defined geometric references that facilitate accurate measurement of the water level.

Based on this context, the objective of this study is to assess the consistency of water level measurements obtained from SWOT, an in situ gauge station, and a UAV-based DEM, and to quantify potential discrepancies arising from unknown or inconsistent height reference frames, in a small artificial reservoir in central Italy (Recentino Lake, Section 2). To this end, we compared two water level time series, measured by SWOT and the reservoir gauge station, together with a single-epoch water level measurement derived from UAV-based DEM cross-sections. Because the datasets considered in the study originate from different observation platforms and sensors, differences in height reference frames between satellite, aerial, and ground-based observations can introduce systematic biases when the datasets are compared. More generally, such inconsistencies represent a key issue for integrating multi-source hydrometric data and may propagate into hydrological analyses and modelling efforts, ultimately affecting the reliability of derived products. This issue underscores the broader need for international unification of height reference frames in hydrometric measurements, providing the primary motivation to evaluate the consistency of water level determinations in the present study and to highlight and remove the possible biases among the height reference frames associated with the three techniques compared.

2. Study area and data

The study focuses on Recentino Lake, an artificial reservoir located near the town of Narni (Umbria, Italy). The reservoir is formed by an embankment dam and covers an area of approximately 0.7 km^2 at an elevation of approximately 110 m above sea level (Figure 1). Three hydrometric datasets were analysed from different observation platforms and sensors: SWOT satellite altimetry, a UAV-based photogrammetric survey, and in situ gauge measurements.

The first dataset consists of SWOT measurements. SWOT operates in a near-polar orbit between 78°S and 78°N, providing coverage of approximately 86% of the Earth's surface with a revisit time of 21 days. Each orbit includes ascending (northward)

Figure 1. Study area: Recentino Lake (Google Satellite basemap, EPSG:4326) and gauge station position (in red).

and descending (southward) passes. The KaRIn instrument onboard SWOT delivers measurements across a swath approximately 120 km wide (Yao et al., 2025, Hamoudzadeh et al., 2024). SWOT water surface elevation (WSE) measurements are referenced to the Earth Gravitational Model 2008 (EGM2008) (Pavlis et al., 2012) and corrected for atmospheric propagation delays (including wet and dry tropospheric contributions and ionospheric effects) as well as for solid Earth, load, and pole tides (CNES – JPL/NASA, 2023). In this work, we used the SWOT `L2_HR_Raster_100m_2.0` (Version C) product (Surface Water Ocean Topography (SWOT), 2024), the latest version available at the time of the study (now superseded by the `L2_HR_Raster_100m_D` version), which provides 100 m resolution scenes in which the lakes consistently occupy the same position within the raster grid in the Universal Transverse Mercator (UTM) projection (Figure 2). Scene data include WSE, water surface area, water fraction, backscatter, and associated geophysical parameters. In this study, we analysed WSE data. A water mask (Figure 2) was derived from high-resolution Cosmo-SkyMed Second Generation imagery (resolution of 2.5 m/pixel acquired in October 2024) using a standard segmentation workflow (histogram equalization, bilateral filtering, and K-means clustering). The mask was used to select SWOT scenes covering Recentino Lake and spanning from the beginning of SWOT operations on 30 July 2023 to 11 December 2024, yielding 48 scene epochs from ascending and descending passes.

The second dataset comprises data collected during a UAV photogrammetric survey conducted on 12 December 2024 at Recentino Lake. Specifically, we collected high-resolution images using a DJI MAVIC 3 Enterprise UAV (Figure 3) operating in Real Time Kinematics (RTK) mode via the ITALPOS network (Leica Geosystems AG, 2026). This ensured positioning within the official Italian RDN2008 (ETRF2000 epoch 2008.0) reference frame with orthometric heights referred to the national ITALGEO2005 geoid (Barzaghi et al., 2007). The survey included the acquisition of nadir and oblique images (with a camera angle of 45°), resulting in a total of 1,930 images. In addition, we measured the positions of five Ground Control Points (GCPs) using Global Navigation Satellite System (GNSS) E-Survey E300 PRO receivers (Figure 3). During the survey, a receiver was deployed in a static configuration to record several hours of observations, applying a 15° satellite elevation cutoff to mitigate multipath effects and low-elevation signal noise. A second receiver collected additional static GNSS observations

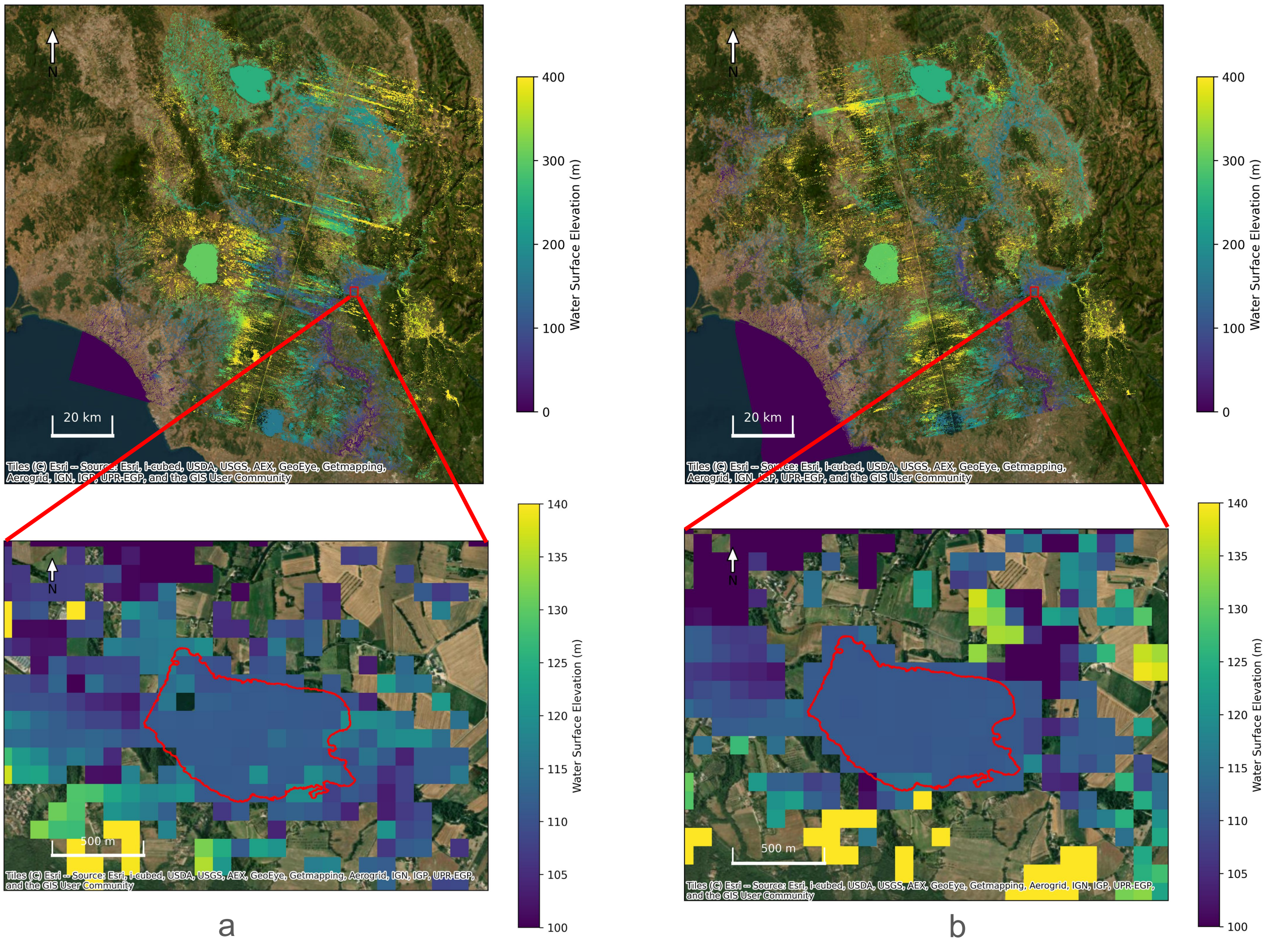


Figure 2. SWOT `L2_HR_Raster_100m_2.0` pixels after flag-based outlier removal and the Recentino Lake outline derived from Cosmo-SkyMed imagery shown in red: (a) cycle 22, pass 251 (ascending), 10 October 2024; (b) cycle 22, pass 194 (descending), 8 October 2024.

of approximately 15 minutes at each GCP location with the same cutoff angle.

The third dataset consists of hourly water level measurements recorded during the same period as the SWOT data. These were collected from a gauge station located near the operational control station of the dam (Figure 1) and provided by Ente Nazionale per l'Energia Elettrica (ENEL), operator of the Terni hydroelectric complex.

3. Methodology

This section provides a detailed description of the data processing for all sensor streams considered in the study.

3.1 SWOT data processing

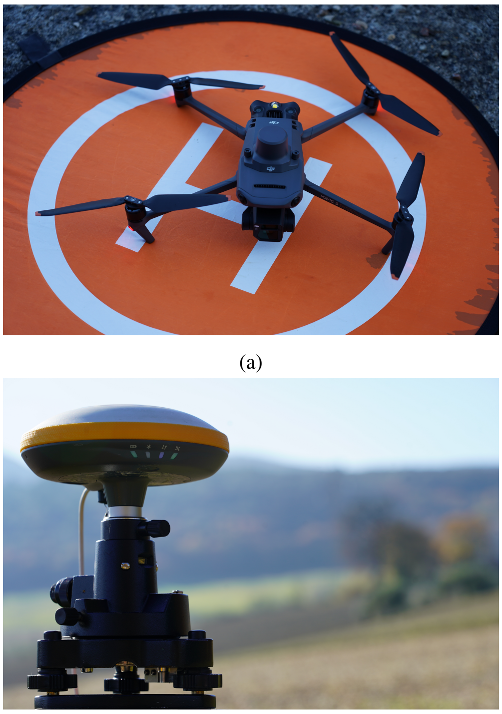
We used the Recentino lake mask (Figure 2) to exclude SWOT pixels outside the reservoir extent from subsequent analyses. Specifically, we excluded SWOT pixels with centroids outside the lake mask — given its higher resolution compared to SWOT — to avoid mixed land–water effects (Figure 2). Notably, with a maximum diameter of approximately 1 km, Recentino Lake is large enough to retain approximately 60 SWOT pixels within the masked area, providing a sufficient sample for reliable analysis.

Even within the masked area, the quality of SWOT data can be affected by several factors, including atmospheric perturbations, weak return signals (low backscatter), and near-nadir interference (Bazzi et al., 2025). To improve WSE reliability, we applied a two-step outlier removal procedure consisting of (i) a quality check for pixel validity and (ii) a temporal outlier detection procedure.

Firstly, for each epoch i, a quality check retained only SWOT pixels flagged with `wse_qual = 0`, corresponding to the highest quality level defined by the mission. The remaining pixels were then spatially aggregated by computing their median value $Me(h_S)_i$ to derive a single WSE value per epoch.

Although this step largely removes spatial anomalies within individual epochs, some epochs may still exhibit median water levels that deviate noticeably from the medians of temporally adjacent epochs. To address such residual inconsistencies, we implemented an iterative temporal filtering procedure (Hamoudzadeh et al., 2025) to remove unrealistic water level fluctuations between consecutive epochs. Firstly, we computed the per-day elevation change $\Phi_{i-1,i}$ from the SWOT median WSE time series for each pair of consecutive epochs as:

$$\Phi(i-1,i) = \frac{Me(H_S)_i - Me(H_S)_{i-1}}{\Delta D_{i-1,i}}$$



(a)

(b)

Figure 3. DJI MAVIC 3 Enterprise UAV (a) and GNSS receiver (b) used for the photogrammetric survey over Recentino Lake on December 12, 2024.

where $Me(H_S)_i$ denotes the median WSE value calculated from all filtered SWOT observations within epoch i, $Me(H_S)_{i-1}$ is the corresponding median for epoch $i-1$, and $\Delta D_{i-1,i}$ represents the time interval in days between epochs $i-1$ and i.

We then applied a temporal outlier detection procedure, based on an iterative 3NMAD (Normalised Median Absolute Deviation) filter, to the resulting time-series of per-day elevation changes (Φ). In each iteration, we computed the median and NMAD of the per-day elevation change time series across all epochs. Then, acceptance thresholds were defined as follows:

$$Thresholds_{\Phi(i-1,i)} = Me_{\Phi(i-1,i)} \pm 3\,NMAD_{\Phi(i-1,i)}$$

where $Me_{\Phi(i-1,i)}$ and $NMAD_{\Phi(i-1,i)}$ are the median and NMAD of the per-day elevation changes in all epochs.

Any value falling outside these bounds was treated as an outlier and removed. The median and NMAD were then recalculated, and the thresholds were updated. This process was repeated until all remaining per-day changes fell within the statistically defined bounds, ensuring that the time series no longer contained anomalous fluctuations relative to its overall temporal variability. Following the two-step outlier removal procedure, 38 median WSE values, corresponding to 38 inlier epochs, were retained for analysis.

3.2 UAV photogrammetric data processing

GNSS data were processed to support the photogrammetric workflow by providing accurate coordinates for the GCPs. The raw GNSS observations were first converted into Receiver Independent Exchange Format (RINEX). The RINEX files were then processed using the RTKPOST module of the RTKLIB software package (Takasu and Yasuda, 2009) to obtain epoch-by-epoch coordinate estimates, with the mean values serving as the final coordinates. All RTKPOST solutions were computed using the ionosphere-free linear combination while estimating tropospheric delay and horizontal gradients as unknown parameters. Integer ambiguities were resolved in fixed mode to achieve high-accuracy positioning. Processing was carried out in differential mode using the RIETI station from the IT-ALPOS network (Leica Geosystems AG, 2026), a commercial GNSS continuously operating reference station network providing real-time and post-processing correction services, ensuring consistency with the UAV survey, as drone data were also referenced to the same network. Finally, the coordinates of the GCPs (latitude (φ), longitude (λ), ellipsoidal height (h)) were determined by post-processing in RTKPOST using the previously estimated position of the base receiver as reference. The resulting GCP positions in the RDN2008 reference frame show centimeter-level precision, with propagated standard deviations relative to the base station below 2 cm in horizontal coordinates and height, as shown in Table 1.

	φ (°)	λ (°)	h (m)	**SD φ (m)**	**SD λ (m)**	**SD h (m)**
Base Station	42.5181242	12.5435811	167.75	0.01	0.02	0.01
GCP_01	42.5181414	12.5435870	167.73	0.01	0.02	0.01
GCP_02	42.5185637	12.5429070	163.60	0.01	0.02	0.01
GCP_03	42.5192567	12.5432742	163.53	0.01	0.02	0.02
GCP_05	42.5224871	12.5455671	162.68	0.01	0.02	0.02
GCP_06	42.5227512	12.5446346	163.91	0.01	0.02	0.01

Table 1. GCPs coordinates (latitude (φ), longitude (λ), and ellipsoidal height (h)) in the RDN2008 reference frame with their standard deviations (SD).

To process the UAV images, we used the Agisoft Metashape photogrammetric software (version 2.2.0, Professional Edition) (Agisoft LLC, 2024). First, we excluded 380 images that only captured the water surface. We then aligned the remaining images using the highest-quality setting and the generic preselection option, generating a sparse point cloud with 896,723 tie points. After importing the GCP coordinates computed using the GNSS processing with centimetre precision in the RDN2008 reference frame, we performed camera optimization. We assessed the global accuracy of our photogrammetric block in this height reference frame to be within 3 cm horizontally and 4 cm vertically, based on the final RMSE values obtained from the camera position residuals with respect to the GNSS estimated camera positions (Table 2). We then generated the final DEM with a Ground Sample Distance (GSD) of 1.6 cm/pixel, using the five available ground points as GCPs. The processing area was confined to the dam, excluding the adjacent vegetated zones. Finally, the model was georeferenced and exported in the RDN2008 + EGM2008 height reference frame.

	φ (m)	**λ (m)**	**h (m)**
RMSE	0.03	0.03	0.04

Table 2. RMSE of the camera coordinate residuals for latitude (φ), longitude (λ), and ellipsoidal height (h).

Finally, we estimated the average water level at the time of the survey using the generated DEM (Figure 4). To ensure data reliability, we selected four transverse and one longitudinal sections along the dam (Figure 4), where the interface between the water and the dam showed the highest density and the lowest noise. We computed the median orthometric height with respect to EGM2008 geoid of each profile and then calculated the final water level as the median value of all sections, precise to within 1 cm, so that the overall accuracy of the UAV-DEM derived level within the official Italian height reference frame is approximately 4 cm.

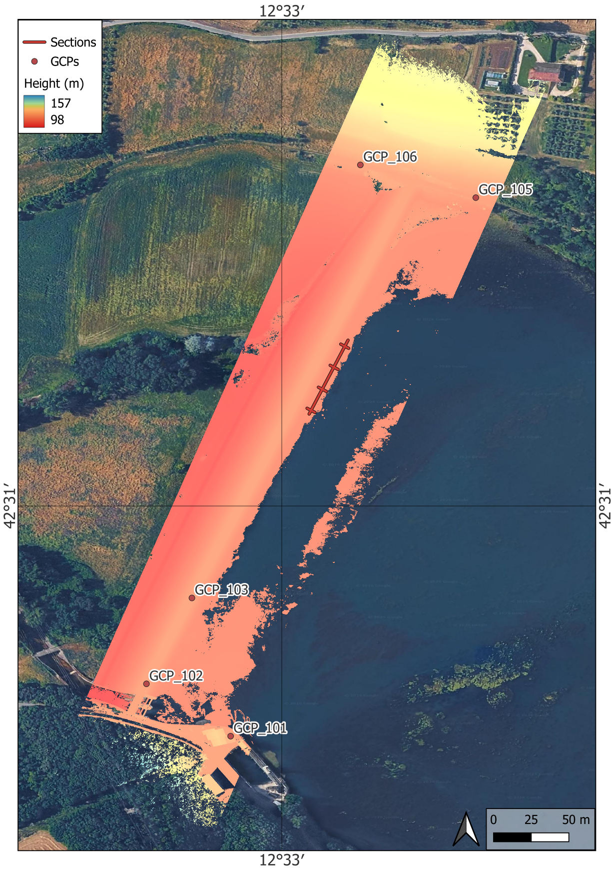


Figure 4. Generated DEM over the area of interest, Ground Control Point (GCP) distribution and sections (in red) selected for water level computation (Google Satellite basemap, EPSG:4326).

4. Results and discussion

In this section, we present the results of the comparisons between the time series of the water levels measured by the gauge station and: (i) the single-epoch water level derived from the UAV-based DEM; (ii) the time series of the water level measured by SWOT.

Firstly, although information on the height reference frame of the gauge station was not available, it was assumed that its water level measurements were referenced to the RDN2008 + ITALGEO05 official Italian height reference frame. Therefore, to ensure consistency among the three water level datasets in terms of the reference frame, we converted the gauge station measurements to the RDN2008 + EGM2008 height reference, considering the difference between the Italian geoid ITALGEO05 and the global model EGM2008.

As regards the first comparison, the gauge time series indicates stable water levels (daily standard deviation < 1 cm) during the UAV survey; therefore, the median of the hourly gauge measurements recorded on the day of the survey was used for comparison, resulting in a difference (UAV-DEM - gauge daily median level) of -0.17 m. Such a difference is significant considering the accuracies of both gauge measurements (1-2 cm) and UAV-DEM derived level (4 cm), and highlights a bias between the gauge height reference frame and the UAV-DEM RDN2008 + EGM2008 height reference frame. A possible explanation of this difference (to be checked) is the difference (-0.18 m) between the present and the old Italian height reference frame, to which the height of the fundamental leveling benchmark of the dam could still be referred. In general, this discrepancy highlights the need for reliable information when analyzing gauge station data to successfully integrate within a unique height reference frame different water level monitoring systems.

As regards the second comparison, over the entire observation period, the gauge station measurements exhibit sub-daily water level fluctuations of several centimeters. To enable direct comparison with SWOT measurements, the gauge time series was temporally aligned to the SWOT acquisition times using linear interpolation between consecutive hourly measurements, accounting for time zone differences (UTC vs. local time) and seasonal time shifts. This was possible for 36 out of 38 SWOT inlier epochs (Figure 5), as gauge data were missing during two SWOT passes. Furthermore, no SWOT measurements were available on the day of the UAV survey. For each common epoch, we computed the differences between SWOT derived water levels and the corresponding gauge measurements, as well as the Pearson correlation coefficient between the two time series. Moreover, the distribution of the differences across all the common epochs was characterized through robust (median, NMAD and MAE) and non-robust (mean difference, standard deviation and RMSE) statistics (Table 3). Despite the limited number of common epochs (36), the gauge and SWOT time series exhibited good agreement, with a Pearson correlation coefficient of 0.69 for the combined ascending and descending SWOT passes. On the other hand, when separating the SWOT-derived water levels by orbital passes, a clear difference emerges. Considering Table 3, the descending orbit shows better agreement with gauge measurements, with a lower RMSE of 0.15 m and higher correlation coefficients (Pearson coefficient of 0.76), compared to the ascending orbit (RMSE of 0.19 m and Pearson correlation of 0.65). This suggests that orbit-dependent factors, such as viewing geometry, radar backscatter conditions, or temporal sampling, might potentially influence the accuracy of SWOT-derived water levels in smaller lakes such as Recentino. The mean difference between SWOT (combined ascending and descending passes) and gauge measurements is –0.08 m, with an RMSE of 0.17 m (Table 3), consistent with Wu et al. (Wu et al., 2025), who reported an RMSE of 0.14 m when comparing SWOT with ICESat-2. Our results are also in line with other assessments of SWOT accuracy (Maubant et al., 2025, Jing et al., 2026), which indicate that under optimal conditions, WSE errors can be as low as 0.1 m and generally remain below 0.4 m. Nevertheless, it is important to note once more that unreliable information and possible differences in height reference frames among measurement techniques directly contribute to these discrepancies.

While SWOT and ICESat-2 share a common height reference frame, gauge measurements (as highlighted in the first comparison) are likely affected by height reference frame uncertainty, which can partially explain the observed differences. Moreover, the gauge data, recorded at an hourly temporal resolution, may not fully capture short-term fluctuations in water level. This limitation is particularly relevant for Recentino Lake, which

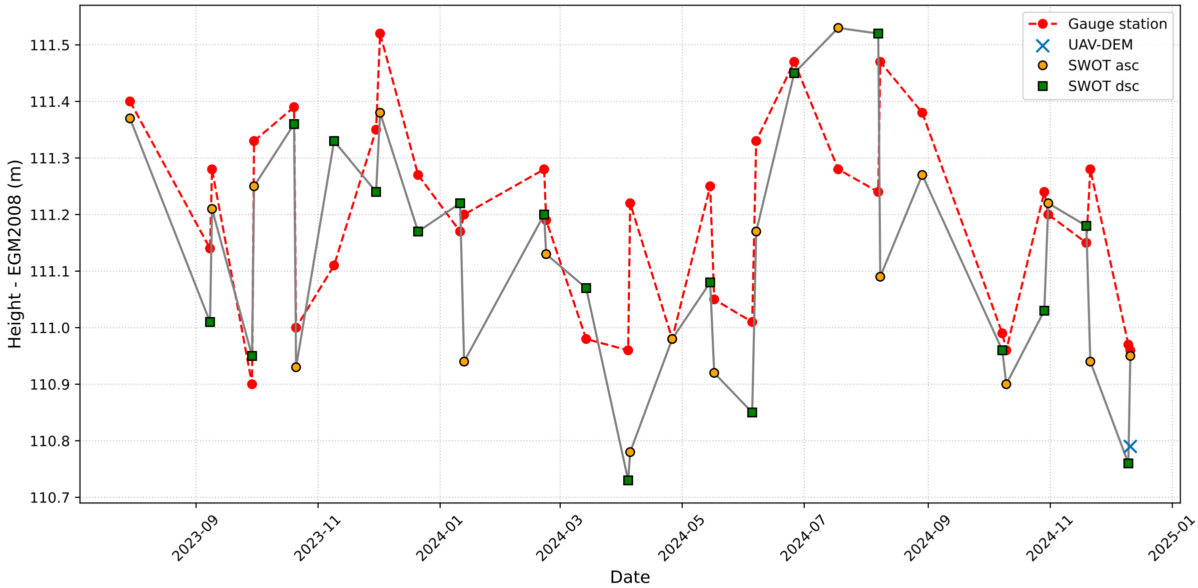


Figure 5. Comparison between water levels derived from SWOT, UAV DEM and gauge station.

	Combined Orbits	Ascending Orbit	Descending Orbit
Pearson	0.69	0.65	0.76
Mean (m)	-0.08	-0.12	-0.04
Median (m)	-0.08	-0.08	-0.06
SD (m)	0.15	0.16	0.14
NMAD (m)	0.12	0.10	0.16
RMSE (m)	0.17	0.19	0.15
MAE (m)	0.13	0.15	0.12

Table 3. Pearson correlation coefficient and statistics of the differences between SWOT and gauge station surface water level time series: mean and median difference, along with Standard Deviation (SD), Normalized Median Absolute Deviation (NMAD), Root Mean Square Error (RMSE), and Median Absolute Error (MAE).

is a regulated dam where water levels can change rapidly due to controlled charging and discharging operations. As a result, sudden variations in water levels may occur between consecutive measurement epochs, leading to temporal mismatches with the satellite observations. This dynamic behaviour introduces an additional source of uncertainty in the comparison with SWOT-derived water levels.

5. Conclusions and prospects

This study compared water level determinations obtained from SWOT, an in situ gauge station, and a UAV-based DEM, at Recentino Lake, a small artificial reservoir in central Italy, with a focus on quantifying potential discrepancies arising from unknown or inconsistent height reference frames. A UAV photogrammetric survey conducted on December 12, 2024, produced a high-resolution DEM (GSD 1.6 cm/pixel) from which the water level was extracted for the survey epoch at the water-dam interface. SWOT data were processed using a two-step outlier removal procedure to obtain a reliable water level time series, while gauge measurements were processed to temporally align as much as possible with SWOT overpass epochs. All three datasets were referred to the RDN2008 + EGM2008 height reference frame.

The first comparison between the UAV-derived DEM and gauge measurements revealed a difference (UAV-DEM - gauge) of -0.17 m, highlighting that the gauge height reference frame is significantly different from the present official Italian height reference frame. This difference, which requires additional future checks, can be explained considering the difference between the present and the old Italian height reference frame, equal to -0.18 m. The second comparison between the SWOT and gauge time series showed a good correlation (Pearson correlation coefficient equal to 0.69) and a mean difference (SWOT - gauge levels) of –0.08 m. Differences between ascending and descending SWOT passes were also observed, with ascending passes showing lower agreement than descending ones (Pearson of 0.65 vs 0.76), suggesting that orbit-dependent effects can influence water level; these effects deserve attention in future investigations. In case future checks on gauge height reference frame will confirm its present misalignment with respect to the present official Italian height reference frame, the second comparison on hopefully longer SWOT and gauge time series will be repeated after the alignment of the gauge height reference frame to the present official Italian one.

The lesson learned in this investigation is that the integration of multi-source datasets for surface water level monitoring requires careful detection and estimation of possible biases among the height reference frames of the different involved techniques. Further, considering that biases between terrestrial (e.g. gauge stations and GNSS surveys) and remote sensing (e.g. SWOT, ICESat-2, GEDI) techniques are possibly orbit dependent and characterized by long wavelength (hundreds to thousands kilometers?), their estimation where possible will enable to link new time series of remotely sensed levels to already established local/national or global height reference frames also for presently ungauged/not monitored reservoirs. This hypothesis certainly deserves to be investigated in the future.

Acknowledgements

This work was mainly (90%) funded by Italian National Recovery and Resilience Plan (NRRP) (PhD scholarship granted to Lorenza Ranaldi) and Italian Ministry for University and

Research (PhD scholarship granted to Alessandra De Pace), and partially (10%) by the project *Geomatics for Resilience Against Water Scarcity (GRAW)* (Agreement n. 2023-1-HB.0), co-funded by the Italian Space Agency (ASI) in the framework of the Innovation for Downstream Preparation for Science (I4DP_SCIENCE) program.

The authors express their sincere gratitude to ENEL, the operator of the Terni hydroelectric complex, for contributing to the collection and verification of gauge station data within its area of responsibility. The authors also thank Eng. Luca Bartoletti and Eng. Francesco Cristarella Orestano from the Water Resources Development and Protection Unit - Regional Department for Land Management, Environment and Civil Protection, Umbria Region for supporting the UAV survey and gauge data analyses.

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