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Multi-Satellite Tracking of Surface Water Storage Change in the Era of Surface Water and Ocean Topography (SWOT) Satellite Mission

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Key Points:

- Surface Water and Ocean Topography (SWOT) is very skillful in measuring water surface elevation of reservoirs as validated by in situ observations from over 100 reservoirs around the world
- The accuracy of storage estimates by SWOT elevation data is highly dependent on the accuracy of the Area-Elevation-Volume curve of reservoir
- Integrating SWOT with other satellite data to improve frequency of reservoir storage estimation currently presents challenges and requires further development

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract The Surface Water and Ocean Topography (SWOT) satellite, launched in December 2022, represents a significant advancement in the remote sensing of global water bodies, providing simultaneous measurements of Water Surface Elevation (WSE) and extent in all-weather conditions. This study evaluates SWOT's capability to estimate reservoir storage dynamics in comparison to pre-SWOT methods. SWOT demonstrates high accuracy in measuring WSE, achieving a median R^2 close to 1 and root mean square errors nearly an order of magnitude lower compared to earlier non-SWOT approaches. SWOT offers substantial improvement over single-sensor and multi-sensor methods, due to spatial averaging of distributed elevation measurements, which was further validated by similar measurements of the ICESat-2 satellite. The key limiting factor in estimating storage from elevation measuring sensors was found to be the accuracy of Area-Elevation-Volume curve. Furthermore, preliminary applications of machine learning to integrate SWOT with non-SWOT data sets show promise, although constrained by limited data availability of SWOT as of late 2024.

Plain Language Summary The Surface Water and Ocean Topography (SWOT) satellite represents a major advancement in measuring global water bodies. This study tested how well SWOT estimates reservoir storage compared to methods available before the SWOT era. SWOT's water level and storage estimates were found to be very accurate, with errors much lower than non-SWOT techniques. Results show SWOT is significantly better than single or multiple sensor methods because it measures elevation over the entire water surface. Another satellite, ICESat-2 was used to validate this, which also takes multiple measurements of the water surface. The main limitation for calculating storage from water level elevation measurements was found to be the accuracy of the reservoir's area-elevation-volume relationship. Early tests of combining SWOT and other non-SWOT data in machine learning were promising but not ready for use due to limited SWOT data. Overall, SWOT is able to improve the estimation of reservoir storage significantly and is found to live up to the gamechanger tag during mission planning.

1. Introduction

Freshwater lakes and reservoirs are an important store of water for human use. These water bodies store nearly 9% of all the freshwater on the surface of the planet (Abbott et al., 2019). There are over a million natural lakes, and over 62,000 reservoirs globally (ICOLD CIGB, 2023). Even though human-managed reservoirs account for only a tenth of the total water stored within lakes and reservoirs, they contribute to a staggering 57% of the seasonal storage variability (Cooley et al., 2021). These fully human-operated reservoirs play a very important role in the overall hydrological system of a basin, including downstream water availability, water quality, and flood safety (Darkwah et al., 2024; Suresh et al., 2024). It is hence crucial to monitor how these surface water bodies, both artificial and natural lakes, evolve over time. However, in practice, the sheer number of these water bodies spread across the world makes this task very challenging. Nearly 5.9 million lakes (>1 ha) are estimated to be present globally, covering 2% of the Earth's continents except Antarctica (Wang et al., 2025).

Due to the sheer number of lakes and reservoirs around the world, remote sensing-based Earth Observation (EO) from space has been the only viable way to study these inland surface water bodies extensively. For instance, Pekel et al. (2016) used multi-decadal Landsat observations to identify inland water bodies at a global scale from 1980s to 2015. The resulting data set has seen many uses across and has been instrumental in improving our understanding of inland surface water, such as an increase in flood risk and rapid changes in river morphology (Tellman et al., 2021; Wu et al., 2011). Yao et al. (2023a, 2023b) have reported a significant decline in the storage of more than half of all the natural lakes observed using satellites, over a period of three decades.

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In contrast to natural lakes, reservoirs are formed by man-made inundation of previously dry land when a dam is constructed on a river. Reservoirs are of special importance because their storage is completely regulated by humans. Because of the ubiquity of reservoirs and their collective regulation of rivers globally, their contribution to the hydrological cycle cannot be ignored when accounting for the hydrological budget of a basin (Abbott et al., 2019; Das et al., 2024). Hence, their impact on the environment warrants more scrutiny so that we can manage them more sustainably and equitably, especially in a changing climate. Specifically, the amount of water stored and its change over time is critical for understanding the key role played by reservoirs in the global water budget, ecosystem, and regional water management.

For storage change estimation of reservoirs using remote sensing-based EO, either the change in water surface area or the elevation of the reservoir needs to be estimated. Altimetry satellites are equipped with a radar or LiDAR sensor that can measure the elevation change of the reservoir water surface down to a few centimeters (Abdalla et al., 2021). On the other hand, Optical and Synthetic Aperture Radar (SAR) sensor based satellites can measure the area of the reservoir by mapping the lake extent, usually up to a typical pixel size of 30 × 30 m for Landsat (optical) or 10 × 10 m for Sentinel-1 (SAR) missions (Torres et al., 2012). Due to the higher measurement precision of the altimeter sensors, even small changes in WSE can be detected at centimeter-scale, while for area measuring sensors, the change in surface area needs to be relatively larger in magnitude in order to be detected with sufficient skill. Especially for mountainous reservoirs with steep bathymetry, where the area of the reservoir does not change as significantly with storage change, it is more challenging to accurately estimate the storage change using area-measuring sensors. Hence, estimates of reservoir storage change by altimetry satellites are usually more accurate as compared to the area measuring satellites (Biswas et al., 2019; Okeowo et al., 2017).

However, the higher vertical resolution comes at the cost of lower spatial coverage and temporal frequency for satellite radar altimeters. Most reservoirs are not observed by these elevation measuring sensors. Satellites with optical sensors on the other hand have more spatial coverage of the world's water bodies. For these sensors, the presence of clouds can severely limit their ability to make a valid observation of the water surface. Moreover, the ability to resolve storage change of reservoirs is limited by how much the area or elevation changes as a result. Mountainous terrain present an additional challenge for optical sensors in the form of terrain shadows, which appears dark similar to water, making it difficult to distinguish between the two. Thus, it is challenging for optical sensors to resolve small amounts of storage change accurately in mountainous terrain and in presence of clouds. Even with these limitations, the value of optically sensed reservoir observations lies in global spatial coverage afforded by multiple satellite missions. These satellite missions also have a long history such as the Landsat mission with an observational record since the 1980s. MODIS and VIIRS take daily observations, and have been utilized for tracking reservoir storage change of large reservoirs at a weekly frequency (Li et al., 2021; Shah et al., 2024).

Similarly, SAR satellite sensors can also be used to track the change in the area of the reservoir. In contrast to optical satellites that depend on the visible and near infrared part of the electromagnetic spectrum, SAR relies on microwave energy. This property lends SAR sensors their greatest strength to make observations in all-weather conditions, unlike optical sensors where clouds can present significant hindrance to the observability of reservoirs. SAR sensors depend on the surface roughness of the scene to distinguish between the target (water) and the background (surrounding landcover). Wind driven surface waves can increase surface roughness of water bodies leading to misclassification. Moreover, radar topographic shadows can significantly reduce the visibility of the reservoir in mountainous regions which can lead to missing data. SAR sensors also suffer from speckle noise that can reduce classification accuracy (Tottrup et al., 2022). Even with these above-mentioned limitations of estimating reservoir storage change using satellite observations, they have been successfully utilized, especially since SAR estimates the fluctuations in storage change of reservoirs more accurately owing to their cloud-penetrating ability (Chang et al., 2023; Das et al., 2022).

It is widely recognized that the utility of remote sensing observations increases many folds when multiple independent sources are combined (Huffman et al., 2007, 2020; Jones & Shiroma, 2023; Jung, 2023). The cloud-penetrating nature of SAR sensors and the long heritage of optical imagery naturally complement each other. By combining both these sources of data using a tiered set of logical operations, the Tiered Multi-Sensor-Optical/SAR (TMS-OS) algorithm was first introduced by Das et al. (2022). Using this TMS-OS in the backend of the open-source Reservoir Assessment Tool framework (Biswas et al., 2019; Das et al., 2022; Minocha et al., 2023), a more robust and frequent record of reservoir storage change has been obtained for river basins across the world, such as the Columbia, Nile, Tigris-Euphrates, Mekong, Indus, and Kerala (Darkwah et al., 2024; Das et al., 2022; Eldardiry & Hossain, 2019; Hossain et al., 2023; Suresh et al., 2024).

Prior to 2022, the available record of satellite remote sensing observations for reservoir storage change tracking were from satellites that either measure the surface area, or the elevation of the reservoir, and at disparate times of sampling. Optical or SAR sensor based satellites measure only the area, while altimetry satellites measure elevation, but the observations rarely coincide in time. However, the recently launched Surface Water and Ocean Topography Mission (SWOT) satellite mission can measure both the area and WSE of the reservoir simultaneously (Alsdorf et al., 2007; Biancamaria et al., 2016). Similar to SAR sensors, SWOT is able to take measurements in all-weather conditions. Due to its simultaneous ability to measure water surface extent and elevation, and its near global coverage, SWOT is expected to significantly improve the state-of-the-art of tracking storage change of inland water bodies in this new era. Prior to the launch of the SWOT mission, the scientific community has had to work around the lack of simultaneous measurements of water extent and elevation by combining various non-SWOT sensors that can estimate water extent (e.g., Landsat, MODIS and Sentinel 2, SAR Sentinel-1) with sensors that can estimate water elevation (e.g., altimeters of the Jason series) or apply remotely sensed bathymetry of reservoirs (e.g., using digital elevation data from Shuttle Radar Topography Mission [SRTM]) to derive storage changes (Bonnema et al., 2016). Naturally the results that have been reported on storage change in this "jury-rigged" fashion during the pre-SWOT era is subject to high uncertainty and the representativeness in capturing the human regulation of our Earth's surface water has remained questionable. Now that SWOT has been acquiring observations for almost 2 years, we ask the following overarching research question: *How well is the SWOT satellite able to estimate reservoir storage*, *compared to the pre-existing methods of satellite based storage change estimation*?

The specific research questions we aimed to answer are as follows: (a) How accurate are SWOT based estimates of reservoir storage dynamics? (b) How does SWOT compare to existing established methods that use non-SWOT satellites? (c) What are the factors that affect the ability of SWOT to accurately capture reservoir storage dynamics? And finally, (d) can non-SWOT satellites be calibrated to SWOT to develop a SWOT-charged multi-sensor technique for estimating reservoir storage? To answer these questions, we developed methods for combining observations from SWOT with non-SWOT satellites (Landsat 8/9, Sentinel 1, and Sentinel 2). First, we establish the baseline skill of SWOT in capturing reservoir volume dynamics and compare it to existing established techniques. We then contrast the skill against the ICESat-2's laser altimeter, which has a similar capability of acquiring multi-point elevation observations over a surface like the KaRIn sensor onboard SWOT. Finally, we provide our lessons learned while combining SWOT and non-SWOT satellite data.

2. Study Area and Data

2.1. Study Area and In Situ Data

Given the wide variability in reservoir characteristics, dynamics, and management practices, it is important to have a data set of in situ observations that is widely representative for validation of any Global Reservoir Storage (GRS) change algorithm or remote sensing sensor. In this study, we therefore built a quality controlled data set of in situ reservoir dynamics and static characteristics of 245 reservoirs (Figure 1). The reservoir water level and storage were obtained from the Royal Irrigation Department, Thailand (RID, 2024), the US Bureau of Reclamation (Bureau of Reclamation, n.d.), Steyaert et al. (2022), and Donchyts et al. (2022). Observations were obtained during the period of observation of the SWOT satellite—post July 2023 to October 2024. The static characteristics, including the reservoir capacity, geometry, location, and primary use, were obtained from the Global Reservoir and Dam Database (GRanD) (Lehner et al., 2011).

The 245 reservoirs were sampled across five distinct regions with varying ecological, climatological, and physical characteristics (Figure 1b). The capacities of the selected reservoirs vary from 11 to above 30,000 million m^3 (or 30 km^3). The selected reservoirs also capture a variety of different climatic conditions. Reservoirs in the United Sates are situated primarily in either arid, cold or temperate climatic conditions, stretching across the central and northern parts of the country. Reservoirs in Spain and South Africa experience primarily a temperate climate where temperature changes widely with the season. Reservoirs in Thailand and India experience a tropical climate, with hot temperatures and high humidity all year round. The reservoirs are also situated at varied elevations, with most reservoirs clustered around 200 and 1,800 m above mean sea level. Reservoirs at higher

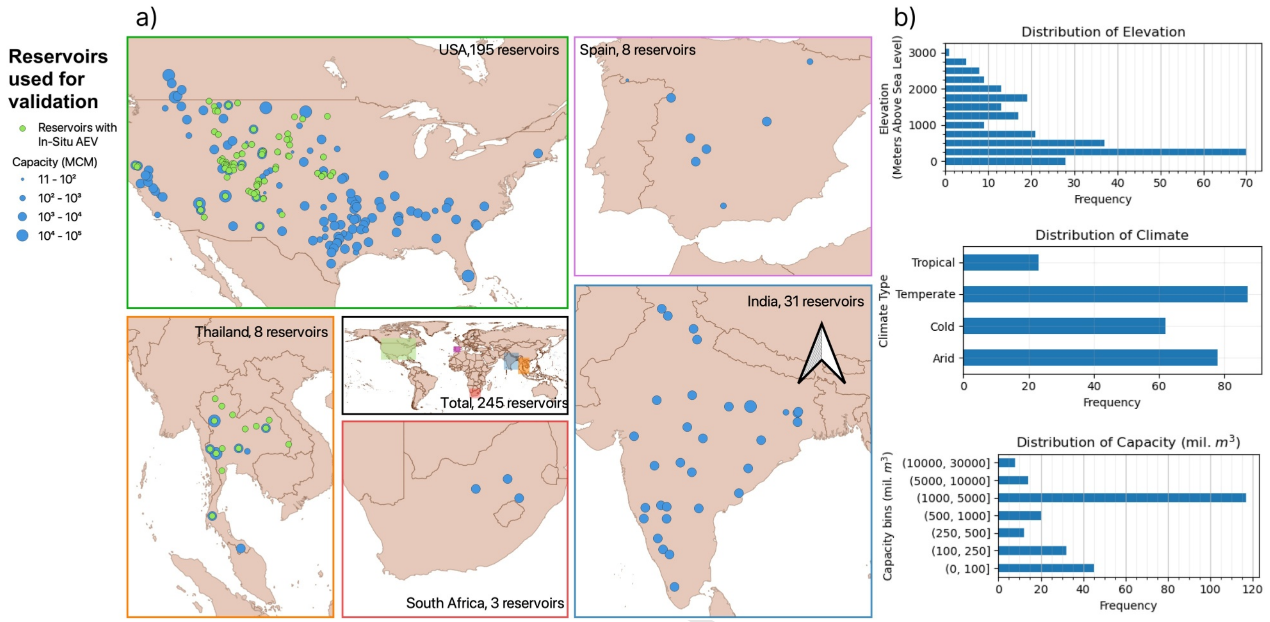

Figure 1. (a) Map of reservoirs with in situ data used for validating the satellite based storage estimates. In situ data from 5 different regions across the world were obtained—United States, Spain, India, South Africa, and Thailand. (b) Distribution of capacity, major climate, and bottom elevation of reservoirs used for validation.

elevations would likely also be surrounded by steep mountains and hence are more challenging for area estimating satellites to consistently measure surface area changes.

2.2. Establishing the Baseline of Non-SWOT Reservoir Storage Estimation

The idea of a baseline is to reference the performance of SWOT based methods relative to the pre-existing methods (see research questions (a) and (b) of Section 1) and quantify the benefit SWOT brings to the table. To define an acceptable baseline a non-SWOT (or pre-SWOT) method, the following three non-SWOT methods were first compared to each other—TMS-OS (Das et al., 2022), GRS (Li et al., 2023), and Global Lake Water Storage (GLWS, Yao et al., 2023a). The GLWS data set consists of lake surface area, storage, and water level time-series for large lakes and reservoirs from 1992 to 2020 at a monthly frequency. Similarly, the GRS data set also estimates reservoir storage globally from 1999 to 2018 at a monthly frequency. Globally, these data sets map 1972 and 7,245 reservoirs, respectively. The TMS-OS method is a globally scalable and open-source algorithm to obtain reservoir area and storage using a constellation of satellites as opposed to relying on a single sensor. It leverages SAR sensor's better ability to estimate fluctuations in change of water surface area over time, and the higher accuracy of optical sensors during clear conditions to obtain a combined time-series that is more accurate than its parts. Using four satellites at once, TMS-OS is able to estimate reservoir storage dynamics at a frequency of 1–5 days.

The estimated area by the three satellite based reservoir storage methods were used to estimate the storage of reservoirs, and compared against in situ observations at a monthly frequency. The estimates by TMS-OS were also resampled to a monthly frequency for comparison with GLWS and GRS storage estimates. The availability of range of time for which data is available in these data sets is shown in Figure 2. While GLWS and GRS timeseries have a longer period of data availability, they end by 2020 and 2018, respectively. The SWOT satellite started taking observations in its "science orbit" phase in July of 2023. Since neither GLWS, nor GRS had any corresponding data, they could not be directly compared with SWOT. TMS-OS had estimates since 2019—a 6 years long record of reservoir storage dynamics, which is sufficiently long for establishing a performance benchmark for the pre-SWOT era. We compared SWOT with TMS-OS with overlapping samples during the period of operation of SWOT since July 2023. The results of this comparison are provided in Section 4.2.

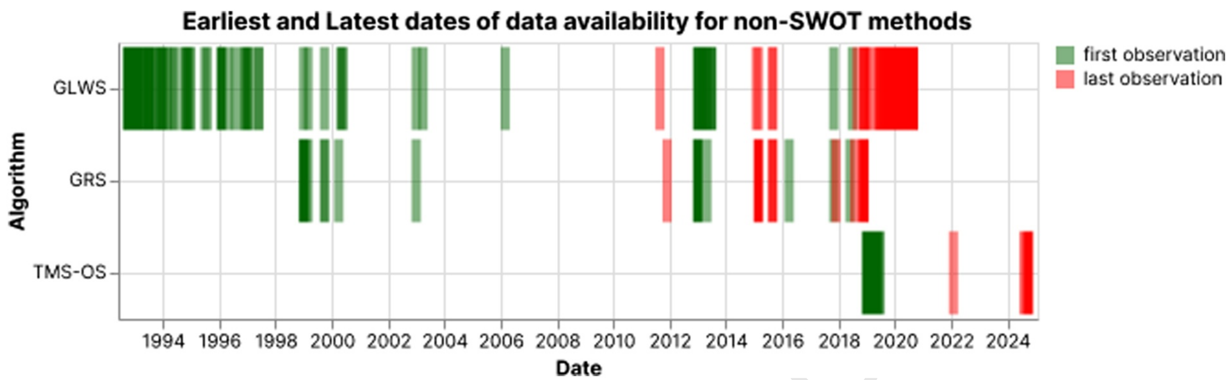

Figure 2. Range of dates for which data is available for various non-Surface Water and Ocean Topography based methods. Global Reservoir Storage ends in December 2018, while Global Lake Water Storage usually contains records until December 2020. The start date of Tiered Multi-Sensor-Optical/SAR record corresponds to the beginning of Sentinel-2's observational record, from 2019.

2.3. TMS-OS—Multi-Sensor Water Area Estimating Method

We used the ortho-rectified and ground range detected C-band SAR observations from Sentinel-1, which provides radar returns at a 12-day frequency. Additionally, we use surface reflectance observations by the Landsat 8, Landsat 9, and Sentinel-2 A/B satellites. Combined, these four satellites with optical sensors can take repeat observations every 5 days or less, providing temporally dense observations at a relevant time-scale of reservoir operations (within a week). Optical sensors are mostly limited by the presence of clouds, which can add significant noise in the time-series of estimated water surface area. Das et al. (2022) introduced the Tiered Multi-Sensor-Optical and SAR (TMS-OS) algorithm, employing a set of tiered correction steps using cloud-penetrating SAR observations to correct the noisy optical data points (Figure 3). First, uncorrected water

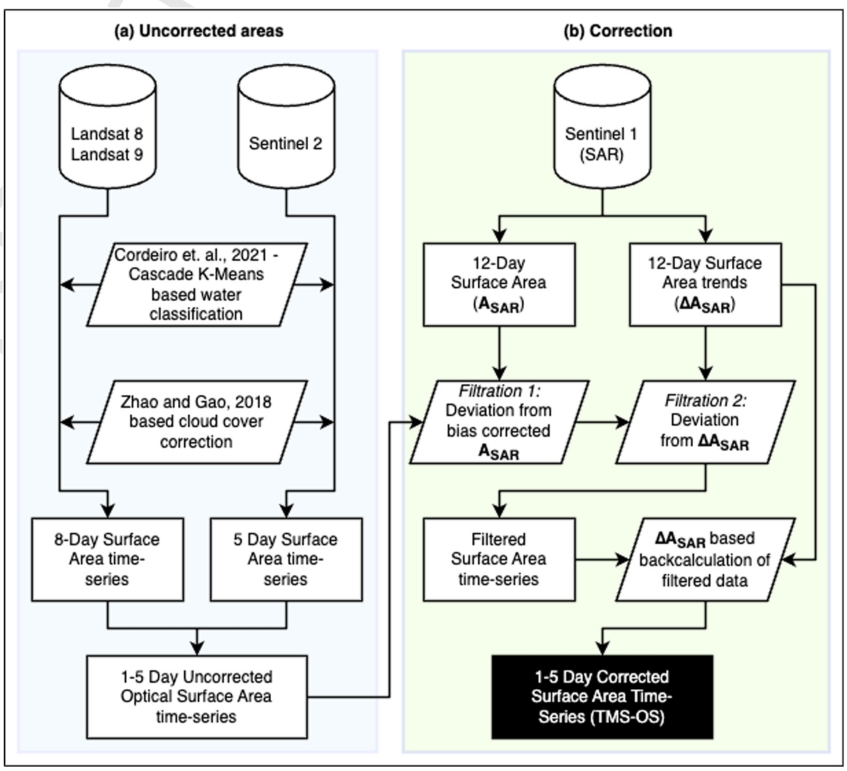

Figure 3. Methodology of the Tiered-Multi Sensor-Optical and Synthetic Aperture Radar (SAR) (Tiered Multi-Sensor-Optical/SAR) algorithm. (a) Surface areas from multi-source optical satellites are generated at a frequency of 1–5 days. (b) Tiered correction steps are applied using observations from cloud-penetrating SAR satellite.

Table 1
Summary of Satellite Data Products Used in the Study

Satellite data product	Temporal and spatial resolution	Sensor type
SWOT L2 Water Mask Raster Image (v2.0)	21 days, 100 m	SAR Interferometry (KaRIn)
SWOT L2 Nadir Altimeter GDR	21 days, minimum 300 m intersection with water body	Radar altimetry (Poseidon-3C nadir Altimeter)
Sentinel-1 C-band SAR GRD	12 days, 10 m	Synthetic Aperture Radar (SAR)
Landsat 8 Surface Reflectance	16 days, 30 m	Optical (Operational Land Imager, OLI)
Landsat 9 Surface Reflectance	16 days, 30 m	Optical (Operational Land Imager-2, OLI-2)
Sentinel 2 A/B Surface Reflectance	5 days, 20 m	Optical (Multispectral Instrument, MSI)

surface areas are obtained from optical sensors. Then, using water surface area estimates by a SAR sensor (Sentinel-1), noisy data points are filtered out and backfilled. The premise of the algorithm is that due to SAR sensors' ability to penetrate cloud cover, they are able to more accurately estimate the variation in water surface area. Theoretically, any sensor that is able to estimate the change in surface area accurately can be used for the correction step. A more detailed discussion on the algorithm can be found in Section S1 in the accompanying Supporting Information S1. The strengths and weaknesses of each sensor type are discussed in detail in the introduction section. The data sets and satellite sensors used in this study are summarized in Table 1.

2.4. Estimating Water Surface Elevation and Storage From SWOT

We used the SWOT Level 2 Water Mask Raster (SWOT, 2024b) image product at a 100 m spatial resolution which measures both the elevation and extent of a water body. It is generated by the Ka-band Radar Interferometer (KaRIn) sensor. The KaRIn sensor works on the principle of SAR interferometry, and hence is unaffected by cloud cover. It operates in a region of 10–60 km on either side of nadir, with a combined swath of 100 km. The repeat period of the satellite is 21 days near the equator and reduces pole-wards. The KaRIn sensor's wide-swath allows it to measure WSE over a surface, instead of point measurements taken by previous altimeters. This drastically increases the number of Earth's water bodies whose water elevation can be observed from space, unlike previous altimeters which had to pass directly over a water body to make a valid observation (Biancamaria et al., 2016).

We also use the SWOT Level 2 Nadir Altimeter (SWOT, 2024a) Geophysical Data Record processed from SWOT's Poseidon-3 Nadir altimeter. This Jason-class altimeter is similar to the nadir altimeters aboard the Jason-3 and Sentinel-6 satellites, which have a long history of measuring WSE at cm-scale accuracy (Abdalla et al., 2021). While all of these sensors can only measure the elevation of the water surface directly under the satellite, they have a proven record of measuring WSE reliably for inland water bodies (Okeowo et al., 2017). The data processing methodology is discussed in-depth in Section 3.2.

3. Methods

3.1. Area Elevation Volume Curve and Reservoir Storage

The storage, or the volume of the water in a reservoir was estimated using the Area-Elevation-Volume (AEV) curve. The AEV curves were generated by extending the Area-Elevation Curve (AEC) generation method by Das et al. (2022). The methodology for calculating the AEV is illustrated as a flowchart in Figure 4. The AEC was derived from the SRTM DEM by calculating the area corresponding to elevations at each 1 m interval within a small region surrounding the reservoir. The resulting curve represents the relationship between area and elevation of the portion of the reservoir bathymetry that was exposed during February 2001, when the SRTM observations were taken. For reservoirs built after February 2001, SRTM can capture the full bathymetry from the reservoir bottom to yield a complete AEV. For reservoirs built prior to 2001, the AEC generation method was extended by adding the lower limit of the AEC, corresponding to zero storage.

The lower limit of the AEC corresponds to the lowest elevation in the reservoir which was estimated as the elevation of the riverbank immediately downstream of the reservoir. The Global River Width from Landsat (GRWL) (Allen & Pavelsky, 2018) river centerlines and the Merit DEM (Yamazaki et al., 2017) were used to obtain the elevation along the river at the downstream river. For some smaller reservoirs in the upper reaches of

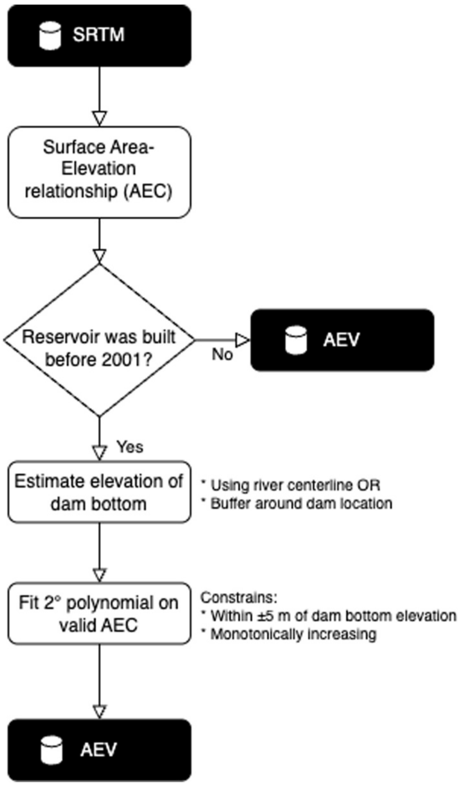

Figure 4. Flowchart showing methodology for generating the Area-Elevation-Volume from Shuttle Radar Topography Mission DEM.

their basins where GRWL river centerlines may be missing, the 1st percentile value within a 500 m region around the dam location was considered as the elevation of the riverbank immediate downstream of the reservoir.

A second-degree polynomial, constrained to an intercept near the estimated bottom elevation, was then fitted to the SRTM-derived AEC. To refine the fit, the AEC was truncated above the observed SRTM water level and below the maximum possible water level, calculated as the dam height plus the estimated bottom elevation. The rest of the AEV was generated by integrating the AEC at 1 m intervals. Using the AEV curve, the storage was obtained using the area and elevation estimates from the methods tested in the study. The accuracy of the AEV was assessed using available in situ observations which are presented in Section 4.1.

3.2. Reservoir Storage Estimation Using SWOT

First, the WSE is estimated from SWOT observations as illustrated in Figure 5. The Ka-band Radar Interferometer (KaRIn) estimates the elevation over a surface as a point-cloud. The level 2 (version 2.0) water raster elevation product is generated by aggregating these point-cloud measurements to estimate the elevation at a resolution of 100 by 100 m. However, currently, the water classification algorithm of the new KaRIN sensor misclassifies water pixels often, resulting in high uncertainty estimates of water elevation. Hence, further processing was required to obtain reliable elevations. The water elevations with high uncertainty (>100 cm) are masked out, based on the nominal accuracy of altimeters. Furthermore, if the interquartile range (IQR) of the elevation values of the remaining pixels is high (>50 cm), the observation is discarded. The rationale being that a high IQR suggests that the particular overpass had high uncertainty. Such a condition may occur due to bad viewing geometry over a reservoir such as at the edge of a reservoir and partial coverage of the reservoir. In such cases the observation may not be useful and has to be discarded. The WSE was estimated as the median value of the pixels remaining after the filtering steps.

Observations from the Jason-class Poseidon sensor—the other altimeter aboard SWOT—were processed using the Okeowo et al. (2017) method which uses unsupervised learning to estimate WSE very accurately. However, this sensor may have sparse samples over in-land reservoirs, as it is designed primarily for applications over oceans. Hence, whenever available, the WSE estimated using the Poseidon sensor was also used in tandem.

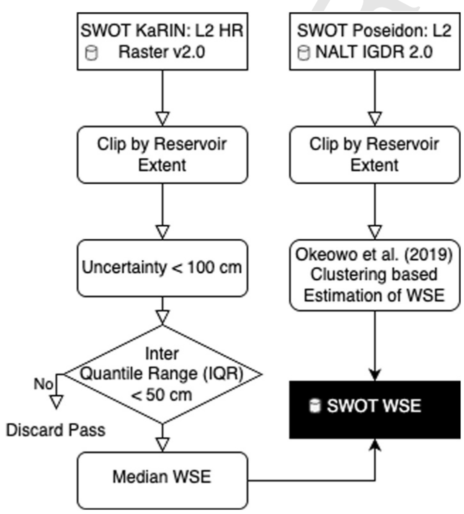

Figure 5. Flowchart for obtaining Water Surface Elevation from Surface Water and Ocean Topography.

3.3. Integration of SWOT in a Multi-Satellite Sensor Framework for Estimating Storage

To fully leverage the ability of SWOT to better estimate the WSE, we explored integration of observations from other satellites. An integrated fleet of satellites for reservoir storage tracking can have many benefits. The higher fidelity of the SWOT satellite can guide the lower-fidelity higher frequency observations by non-SWOT optical satellites just as we have experienced in the case of multi-sensor precipitation estimation, such as the IMERG data product (Huffman et al., 2020). If one satellite fails to take a valid observation, say due to cloud cover, it could be corrected using other temporally proximate observations. Overall, by using a teamwork of satellites, the combined ability of the sensors to resolve reservoir operation dynamics can become more accurate and frequent.

To integrate SWOT with non-SWOT satellites, we employed two methods. First, using Machine Learning (ML) techniques to transfer the skill of the SWOT satellite to non-SWOT area estimating satellites—Sentinel-2,

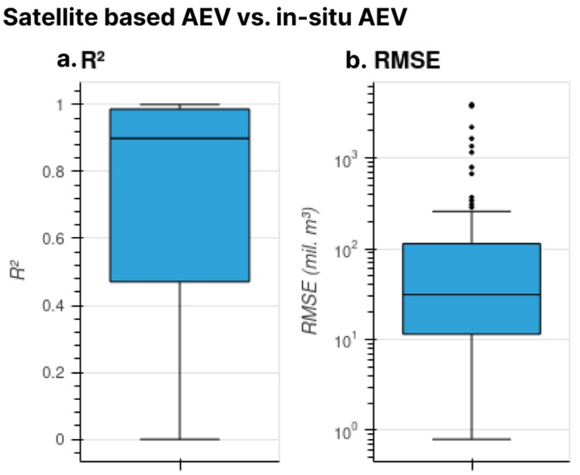

Figure 6. Performance of satellite based Area-Elevation-Volume (AEV) curve compared to in situ AEV.

Landsat-8, Landast-9, and Sentinel-1. ML methods have been used skillfully to improve the signal-to-noise ratio in time-series data (Basu & Meckesheimer, 2007). We employed a Random Forest (RF) model to calibrate non-SWOT observations to SWOT-based storages. We used area estimates from optical satellites (Sentinel-2, Landsat 8 and 9) as the primary non-SWOT satellite input. The Koppen-Geiger climate classification (Beck et al., 2018), reservoir shape irregularity index (defined as ratio of Area to Perimeter), the slope and elevation of surrounding topography (within 1 km of reservoir), cloud cover percentage, and the season (summer, autumn, winter, and spring) were used as additionally predictor variables. The model was trained using SWOT based reservoir storage estimates as the target variable. First, the training data set was split into training/validation and test sets (75% and 25%), followed by splitting the training/validation set further by a 9:1 ratio as training and validation sets. The RMSE between the validation and training sets were minimized for tuning the hyperparameters of the RF model. The tuned hyperparameters of the RandomForest model (from the scikit-learn python package) are as follows: n_estimators = 200, max_depth = 10, max_leaf_nodes = 512, and min_samples_leaf = 5. Using this model, non-SWOT data could be calibrated to SWOT-like storage estimates.

Second, we used a TMS approach (from TMS-OS) with SWOT as the calibration sensor for the correction step (Figure 3b). We used observations by the SWOT satellite to filter and correct the short-term trends (fluctuations) of non-SWOT satellite observations. Similar to the filtering and short-term trend correction done by the SAR sensor in the TMS-OS algorithm. The lessons learned from attempts at integrating non-SWOT observations with SWOT observations are presented in Section 4.5.

4. Results and Discussion

4.1. Reliability of Satellite-Based Area-Elevation Volume (AEV) Curve

The performance of satellite-derived AEV using the method described in Section 3.1 was compared with in situ derived AEV to establish reliability of the AEV generation method in terms of global scalability to the 245 reservoirs. Based on the availability of in situ elevation and storage values of 98 reservoirs, the in situ AEV was generated and compared in Figure 6. The location of these reservoirs is shown as green circles in the map of validation sites in Figure 1.

The derived Elevation-Storage relationship of these reservoirs yielded a median R^2 value of 0.9 and RMSE of 31.18 million m^3. This suggests that the satellite based method to obtain the AEV, using method to estimate reservoir bottom and complete the AEC, captures the variablity of the Elevation-Storage relationship well. While the RMSE can occasionally rise above 500 million m^3, seen as outliers in Figure 6, for the vast majority of cases, about 75%, the estimated storage is accurate to within 100 million m^3. Hence, these AEV curves were used throughout this study to estimate and compare storage of reservoirs, where previously only storage change could be compared due to a lack of information on the lower limit of the AEV.

4.2. Baseline Performance of Non-SWOT Satellite Based Reservoir Storage Tracking

The performance of estimation of monthly reservoir storage in the pre-SWOT era are represented by the R^2 and RMSE in Figure 7. R^2 is a measure of how well the method is able to explain the variance in the observed storage, while the RMSE represents the overall error in the estimated and observed values. Although GLWS is able to explain the variability in storage, the actual estimated storage has the highest median error among all the three potential baseline methods, at 600 million m^3. On the other hand, TMS-OS and GRS have a median RMSE of around 40 and 50 million m^3, respectively.

GLWS shows high precision with a strong R^2 and tight RMSE spread, however it consistently overestimates, as reflected in its higher median RMSE. GRS performs well in consistency but faces challenges due to limited historical data and low temporal resolution. TMS-OS performs similarly or better than the other two methods, with a lower RMSE and more frequent data. Additionally, TMS-OS is an open-source methodology applicable to

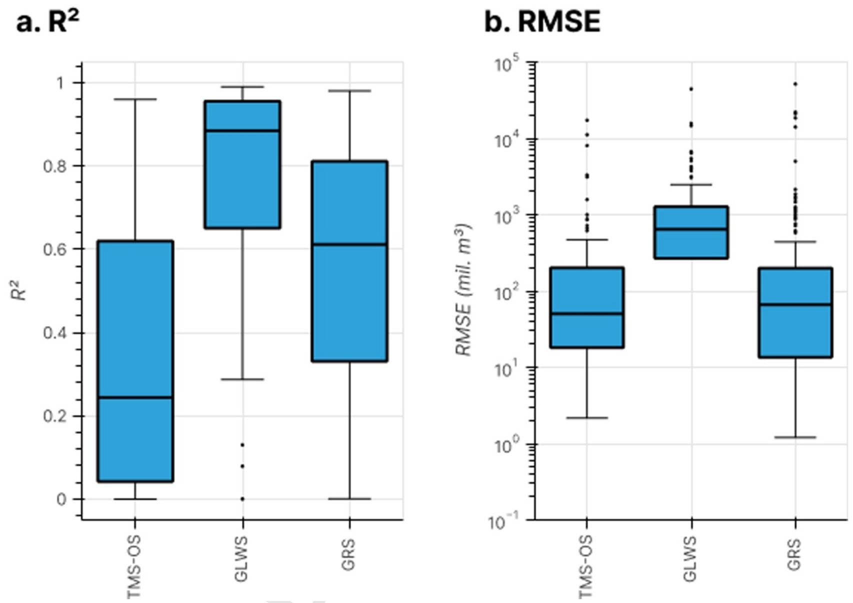

Figure 7. Baseline performance of three non-Surface Water and Ocean Topography (SWOT) (pre-SWOT) techniques for estimating reservoir storage. The edges of the box show the 25th and 75th percentiles of the distribution. The horizontal line inside the box represents the median and the vertical line capped by horizontal lines represents the 1.5X the interquartile range. Outliers are represented as individual circles. Panels (a, b) plot the performance metrics—coefficient of determination and the root mean squared error.

any reservoir in the world to obtain reservoir storage estimates using latest satellite observations, unlike the static number of reservoirs mapped in GRS and GLWS which are also limited to a set date in the past (Figure). Another distinct feature of TMS-OS is the ease with which sensors can be added or removed as well as sensor calibration methods altered. Hence, because of TMS-OS's versatility, comparable accuracy, and observations available during SWOT's observational period, it is used hereafter as an acceptable baseline of non-SWOT methods to compare against SWOT estimates.

4.3. Impact of SWOT Relative to Non-SWOT Baseline

Reservoir storage estimates from SWOT observations were compared against non-SWOT baseline (TMS-OS). SWOT has a median R^2 value exceeding 0.8 and relatively compact interquartile ranges, indicating consistently good performance, irrespective of the AEV used (Figure 8a). The in situ E-S variants of SWOT perform only marginally better than its counterpart, with the same median R^2 and a slightly tighter inter-quartile range (IQR). Comparatively, TMS-OS has a poorer R^2, suggesting that SWOT is able to capture the variability of storage dynamics far better, irrespective of the AEV used.

Counterintuitively, the performance in estimating the absolute values of storage, as indicated by the RMSE, was similar for SWOT and TMS-OS using satellite derived AEV (Figure 8b). Common sense would dictate that with more accurate WSE would result in more accurate estimated storage. This discrepancy in high skill in estimating variability, but lower skill in estimating absolute values, can be explained by a poor Elevation-Storage relationship. The performance of storage estimated using these in situ AEV curves are also shown in Figure 8. The RMSE improved by nearly an order for SWOT (see Figure 8b), without an alteration in the R^2. This means that with an improved AEV relationship, the absolute values of estimated storage improved significantly as well, while the performance of estimating the variability in storage remained nearly the same. The uncertainty in estimated storage values was largely due to the uncertainty in the AEV curve. Similarly, the uncertainty in the storage estimated using TMS-OS is largely due to the uncertainty in the water surface area time-series by the teamwork of non-SWOT satellite sensors, as indicated by poorer R^2 values.

Figure 9 illustrates the spatial distribution of the performance. This disparity highlights the considerable advantage offered by SWOT. Nearly all reservoirs demonstrate an order of magnitude improvement in performance when using SWOT compared to the non-SWOT baseline, showcasing SWOT's ability to enhance accuracy

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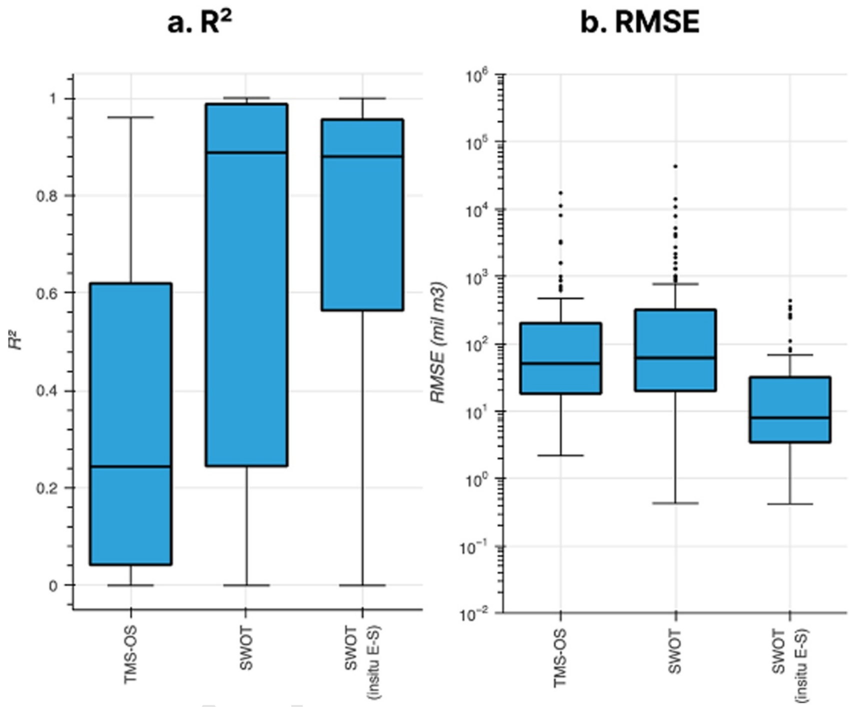

Figure 8. Comparison of performance of Surface Water and Ocean Topography (SWOT) and Tiered Multi-Sensor-Optical/SAR in estimating the storage dynamics of reservoirs between July 2023 and October 2024. Storage from SWOT is first obtained using satellite derived Area-Elevation Volume (AEV), referred to as satellite E-S in the figure, and in situ observations derived AEV (in situ E-S).

across diverse locations. In monsoon-prone regions like Thailand, a higher proportion of reservoirs perform poorly with TMS-OS due to structural limitations; however, these same reservoirs show marked improvement with SWOT, benefiting from its all-weather capabilities and superior fidelity in WSE estimation.

Comparison of storage time-series of six selected reservoirs in Figure 10 highlight the difference in storage estimation ability of SWOT relative to TMS-OS, the non-SWOT baseline. The results clearly show that SWOT is significantly more accurate than TMS-OS, effectively capturing not only the variability but also the absolute storage as a time-series. In contrast, TMS-OS provides relatively less accurate estimates, which, while in the general ballpark, can deviate considerably from in situ observations. Occasionally SWOT may produce outliers, as seen in the Lam Pao Dam (top-left panel of Figure 10), such instances are rare based on our manual inspection of performance over remaining reservoirs. For most reservoirs, SWOT's storage estimates align closely with in situ observations. Overall, SWOT represents a substantial improvement in the ability to estimate reservoir storage compared to previous satellite based methods. Additional time-series figures are provided (Figures S1–S3) in the accompanying Supporting Information S1.

4.4. Performance of SWOT as a Function of Physical Characteristics of the Reservoirs

The performance of SWOT was assessed based on key physical characteristics of reservoirs: capacity, nominal elevation, and irregularity index (Area/Perimeter, A/P). Capacity refers to the total storage volume. Elevation indicates whether the reservoir is in mountainous or low-lying regions. The irregularity index measures shoreline complexity, with higher A/P values indicating smoother shorelines and lower values indicating jagged, irregular boundaries.

Performance metrics for both TMS-OS and SWOT were divided into four groups with equal numbers of reservoirs using a quantile-based method. Due to a few missing data points, group boundaries for TMS-OS and SWOT may differ slightly, but overall they capture how performance varies with reservoir characteristics. RMSE was also normalized by reservoir capacity to better interpret absolute errors relative to total volume.

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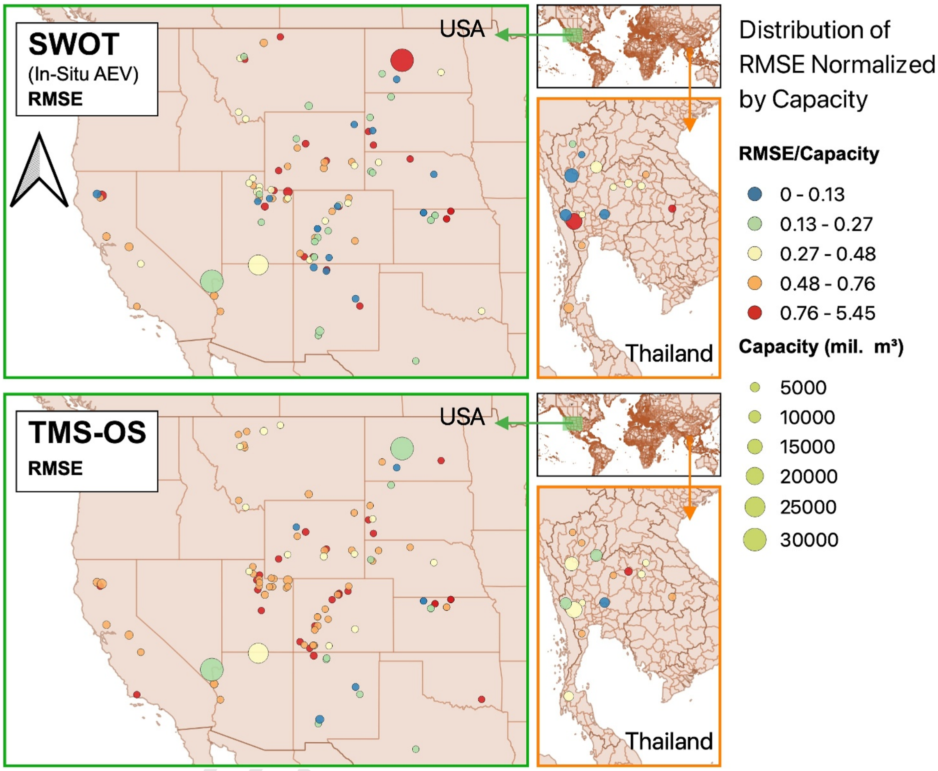

Figure 9. Spatial distribution of performance of Surface Water and Ocean Topography and Tiered Multi-Sensor-Optical/SAR compared against in situ reservoir storage observations, measured as the root mean squared error as a fraction of the reservoir capacity.

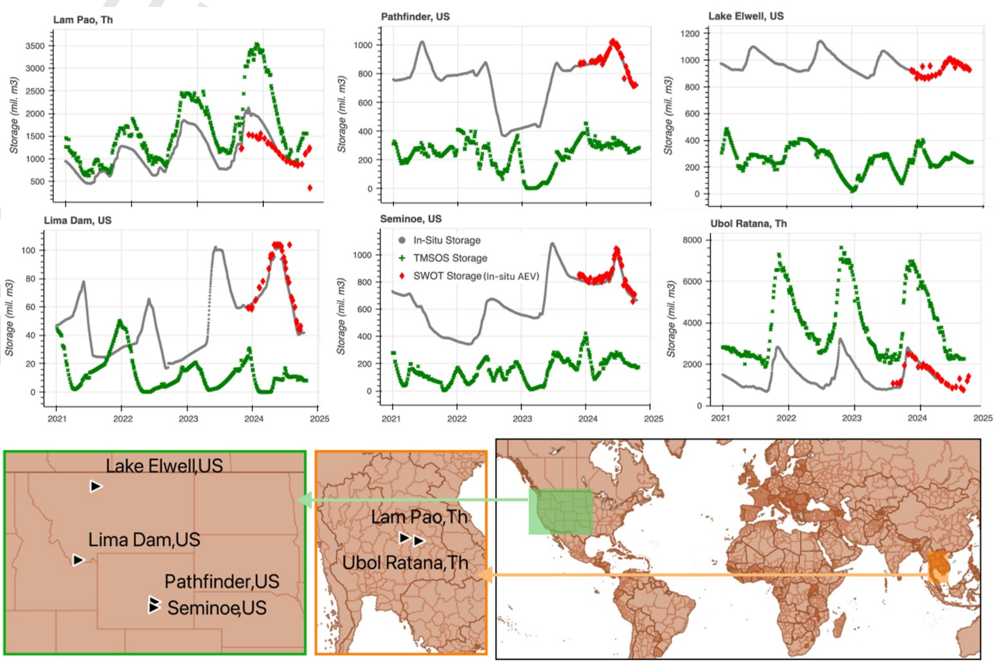

Figure 10. Selected time-series of six dams comparing Tiered Multi-Sensor-Optical/SAR and Surface Water and Ocean Topography (in situ Area-Elevation-Volume) based storage estimates against in situ observations.

Key findings show that SWOT consistently outperforms TMS-OS based on irregularity index. For irregular reservoirs, SWOT performs substantially better, while the improvement is less for regular reservoirs (Figure 11a). This can be attributed to SWOT measuring elevation versus TMS-OS measuring area. Irregular reservoirs are often located in mountainous regions, forming jagged boundaries, while lower-elevation reservoirs tend to be wider and smoother.

SWOT also outperforms TMS-OS across all elevation categories and performs especially well at higher elevations (Figure 11b). This supports the idea that elevation-based sensors more effectively capture reservoir dynamics than area-based sensors.

The performance across different climatic classifications suggests a clear improvement in performance due to SWOT's SAR interferometry based water classification/elevation measurement (Figure 11d). While TMS-OS struggles in continental/cold and dry conditions, SWOT can perform well consistently across all climate classifications. The poor performance of TMS-OS in these climates can be explained by the reliance on SAR backscatter for classifying water. In dry conditions, sand and bare soil would typically be the dominant land cover, which can be misclassified as water pixels due to low backscatter values (Martinis et al., 2018). Moreover, continental/cold climate conditions can cause ice formation on reservoir surface for a significant portion of the year and increase the surface roughness of the water surface due to high wind speeds. Both conditions can reduce the performance of optical and SAR sensors. It is most evident in the low performance of TMS-OS, but it is also evident in SWOT's performance.

In contrast, performance differences across reservoir capacities show no clear pattern (Figure 11c), though SWOT consistently outperforms TMS-OS.

4.5. Multi-Point Sampling of Water Surface Elevation Results in Improved Reservoir Storage Dynamics

While the previous section demonstrates the higher accuracy of SWOT, this section focuses on exploring the key factor yielding better performance from SWOT. We hypothesize here that the multiple elevations over a reservoir, resulting in a spatially distributed "water terrain" leads to a more robust mean elevation for the reservoir than sensors that produce single or limited elevations such as the non-SWOT sensors of TMS-OS. To test this hypothesis, WSE of over 100 reservoirs were obtained from the ICESat-2 sensor that can also produce a "water terrain." ICESat-2 has a laser altimeter onboard that takes measurements at 10 kHz, pinging the water surface multiple times during a single overpass and producing numerous elevation returns. SWOT and ICESat-2 are similar in the sense that they estimate the WSE over multiple different points on the reservoir water surface. Hence, even if a single measurement is erroneous, we believe the central tendency of all the measurements during an overpass tends to closely represent the actual mean WSE at that time. Comparatively, area measuring sensors, such as Sentinel-1 and Landsat-8 capture just a single snapshot in time.

The effect of multi-point averaging can be clearly seen translated into performance metrics in Figures 12a and 12b. The median coefficients of determination (R^2) are 0.91 and 0.98, respectively for SWOT and ICESat-2. Similarly, the median RMSE is 0.92 and 0.98 m, respectively. While ICESat-2 altimetry satellites offer superior overall performance, their ability to repeatedly observe a reservoir is significantly lower compared to area-measuring satellites. Figure 12 proves the hypothesis that "Multi-point sampling of WSE results in improved reservoir storage dynamics."

While performing better due to multi-point averaging in absolute performance, the strength of area-measuring sensors lie in their ability to obtain storage estimates at a much higher temporal frequency. ICESat-2 managed to observe reservoirs an average of four times, while SWOT observed reservoirs an average of 30 times, and TMS-OS could obtain an impressive 140 observations during the same period. In terms of the median revisit time, a reservoir was observed once every 59 days by ICESat-2, 10 days by SWOT, and 3 days by TMS-OS, over the entire period of observation. It is clear that SWOT can offer an optimal balance between accuracy and sampling frequency. The performance and number of observations together highlight that SWOT provides high accuracy estimates of the WSE at a higher frequency than ICESat-2 and higher accuracy than TMS-OS.

4.6. Lessons Learned From Multi-Sensor Integration

SWOT's KaRIN sensor is designed to estimate both the area and elevation of the water surface. However, in the current version of processed L2 data, the L2-HR-Water Mask Raster v2.0, water pixels are often misclassified.

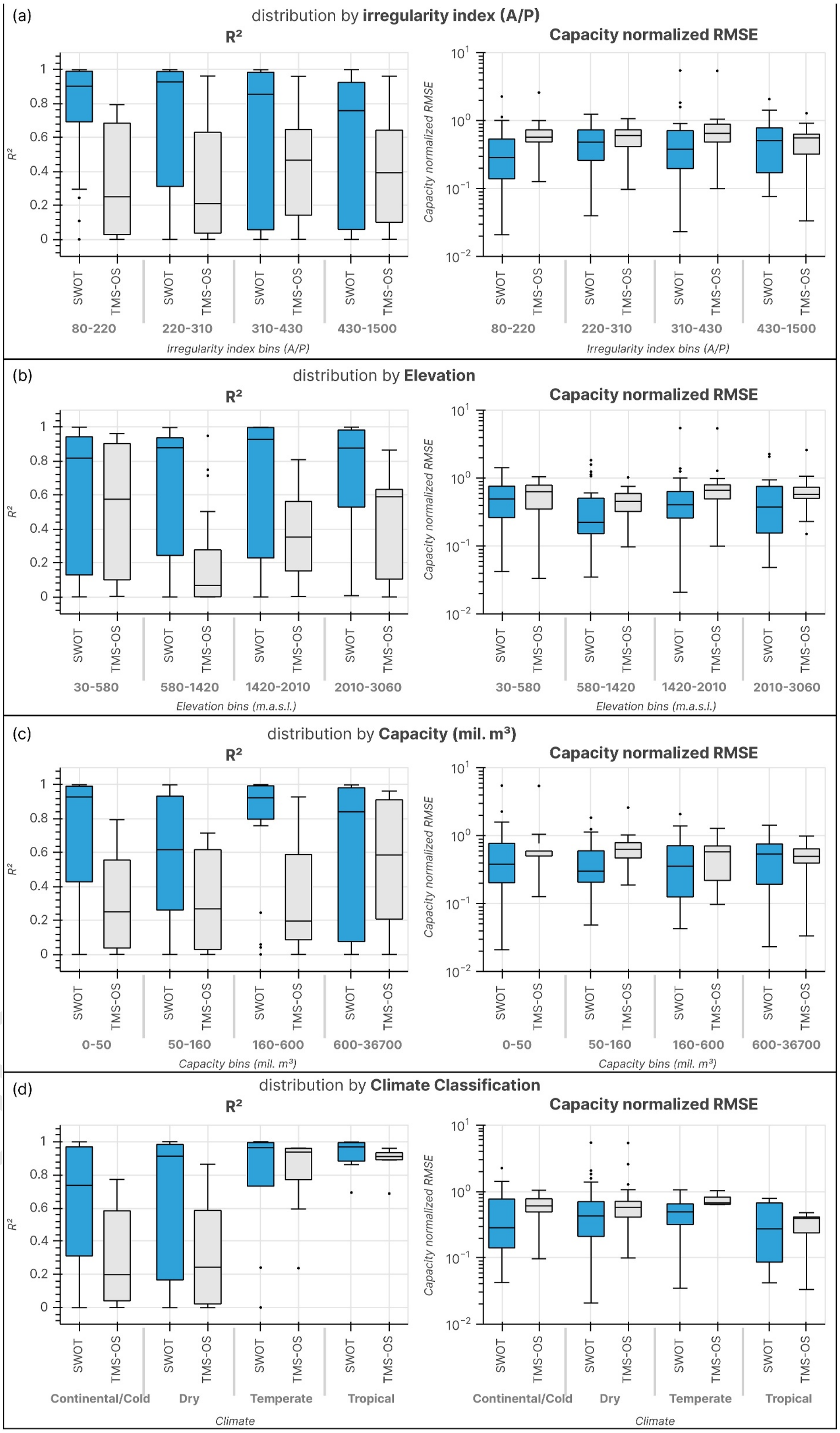

Figure 11. Performance of Surface Water and Ocean Topography and Tiered Multi-Sensor-Optical/SAR using satellite derived Area-Elevation-Volume to estimate storage varying with physical characteristics of reservoirs and climate—(a) irregularity of shoreline, defined as the ratio of nominal surface area to the perimeter of shore, (b) nominal elevation, (c) capacity, and (d) Koppen-Geiger climate classification (Beck et al., 2018).

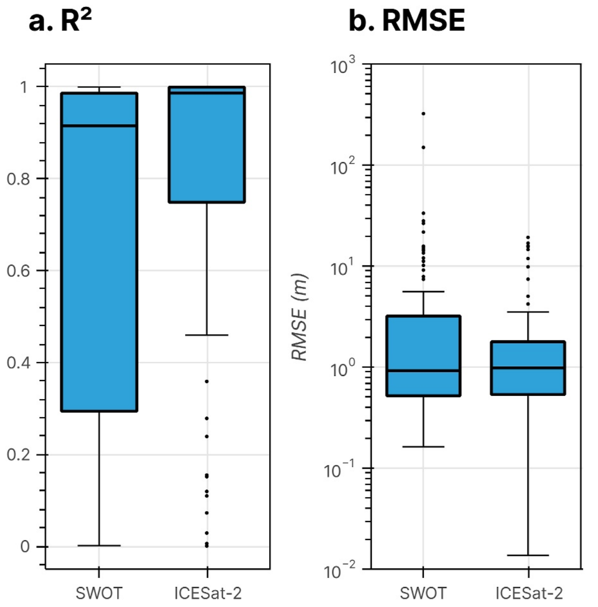

Figure 12. Inter-comparison of performance of Surface Water and Ocean Topography and ICESat-2 for estimating the water surface elevation of reservoirs against in situ data obtained between 2023 and 2024.

The area estimates, hence, can be quite noisy. While misclassification of water pixels can also result in higher uncertainties in WSE estimates if any additional processing is not conducted. The approach in Figure 5 alleviates this problem by filtering out individual pixels based on their uncertainties, and entire passes if required, so that the estimated WSE is accurate over time. Using this approach, and SWOT's observations, the WSE of nearly any water surface on Earth can be obtained. Unlike previous altimeter missions which missed vast portions of the Earth, the ability of SWOT as a global altimeter can be leveraged independent of its area estimating ability.

We trained a RF model using the area estimates by optical satellites, climate classification, reservoir shape irregularity index, slope and elevation of surrounding terrain, cloud percentage, and the season as input features. We quantified the performance of the model trained on currently available SWOT observations to gauge the adequacy of currently available SWOT data for an ML based approach to combining non-SWOT and SWOT sensor data. Figure 13a illustrates the performance of predicted storage by the RF model, compared against the target—SWOT based storages. The scatterplot visually shows a generally good agreement between model predictions and the target values, illustrating that training a ML model to estimate SWOT-like storages from observations by non-SWOT sensors are possible.

To assess the role of data availability, the model was trained on limited data. The available record of SWOT observations used for training were limited to various fractions, from 0.1 (10% values used) to 1.0 (all values used). Figure 13b quantifies the performance of the model in terms of RMSE and R^2. The resulting performance of these models shows the trend with which increasing data availability improves the predictive performance of the model. Using all the available data after removing no-data values (3,617 records across 129 reservoirs), the RMSE is 377 million m^3, which gradually increases as data available for model training reduces. The R^2 doesn't improve as drastically with more data and stays relatively stagnant. However, the trend of decrease in RMSE with increasing data availability is promising,

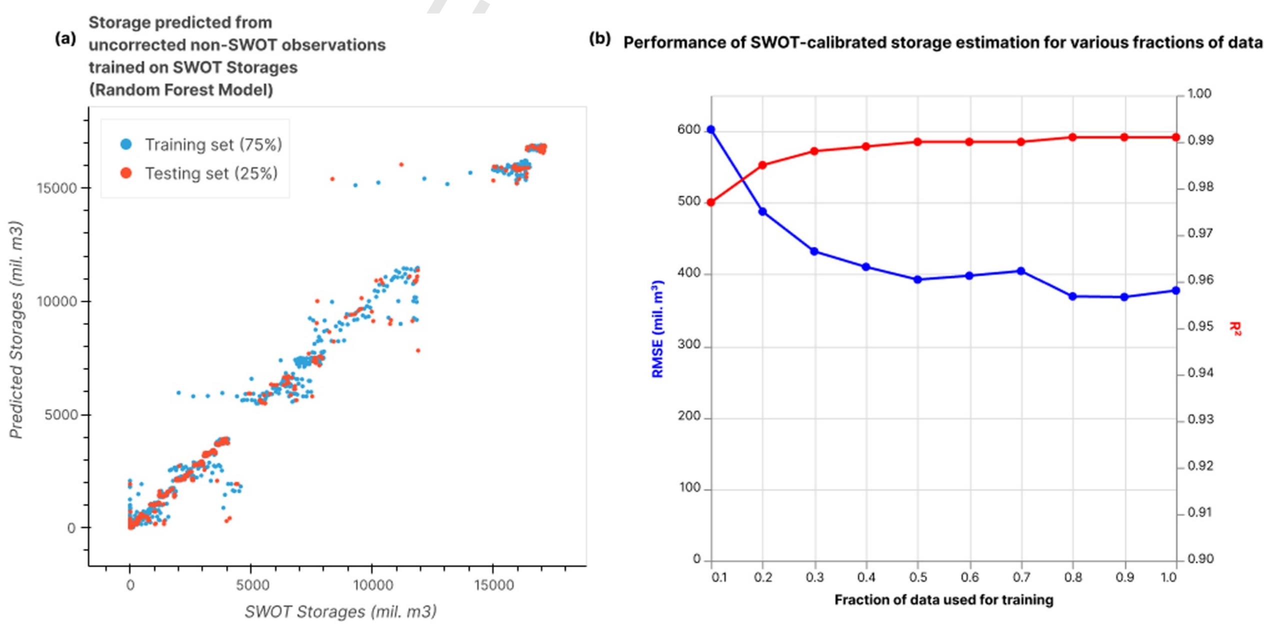

Figure 13. (a) Performance of a Random Forest Machine Learning model trained on uncorrected areas from non-Surface Water and Ocean Topography (SWOT) sensors and other relevant features, with SWOT-storages as the target. (b) To establish a relationship between data availability and model performance, different fractions of data were used for training and the root mean squared error and R^2 of predicted storages were compared against the target values (SWOT storages). For instance, at 0.1 data fraction, only 10% of the entire data set was used.

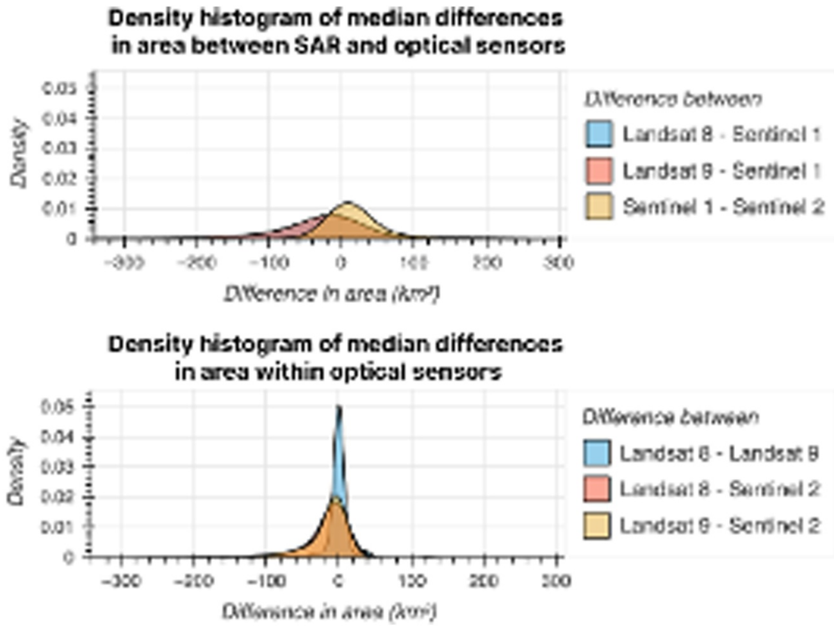

Figure 14. Distribution of the difference in median area of reservoirs estimated by optical and Synthetic Aperture Radar (SAR) sensors. The first panel shows differences between optical and SAR sensors, while the second panel shows the difference within optical sensors. Optical sensors tend to agree more amongst themselves, indicated by the higher magnitude peak centered around 0. Comparatively, the SAR sensor tends to disagree with optical sensors more, indicated by larger tails of the distribution.

indicating that the model's predictive capability increases with more data. While currently the performance of models leaves much to be desired for, the poor performance of the ML model is probably best explained by the short observation record of SWOT so far—only 1.5 years. With a more extensive record of observations in future, ML models trained for predicting reservoir storage calibrated to SWOT is expected to perform much better as seen in Figure 13b. Continuing from the trends, with about 1.5 years more data (double the current available), the RMSE may potentially reduce to under 100 million m^3.

On the second approach for integrating SWOT with non-SWOT sensors using the TMS approach, we conclude two findings. First, SWOT's elevation estimates at a global scale are usable by themselves if the observational frequency or timeliness is not a concern. The area-averaging nature of observations by SWOT (as validated with the use of ICESat-2 elevation data) allows these sensors to estimate the elevation of water surface more accurately. Second, the area estimated by Optical and SAR sensors cannot be trivially grouped together for applying the TMS algorithm. Figure 14 shows the difference in estimated area by different sensors. Sentinel-1, when compared to any other optical sensor tends to have a larger difference in estimated area (bias at reservoir-level). On the other hand, optical satellites irrespective of the mission, tend to have more agreement amongst themselves, as indicated by the larger peak centered around 0 and tighter spread. Hence, when SAR and Optical are used together as area-estimating sensors, it results in high apparent noise due to the difference in the area estimated by the two sensors (Figure 14). Furthermore, for using SWOT observations for filtering and short-term trend correction, the elevations first have to be converted to area values using the satellite derived AEC. This adds additional uncertainty, because of the relatively high vertical uncertainty of SRTM DEM which can be a few meters (Chai et al., 2022).

Due to these limitations, integration of multiple satellites observations still requires further development to improve the accuracy of estimated storage than what is afforded by SWOT alone. However, with further improvements in the algorithm for classifying water pixels in SWOT's KaRIN sensor, and a longer observational record, accurate multi-satellite estimation of reservoir storage at a higher frequency using ML techniques should be possible.

5. Conclusion

This research paper examined the ability of the recently launched SWOT mission to estimate reservoir storage around the world. It examined the performance of recently launched SWOT satellites in estimating reservoir storage dynamics, comparing it to pre-existing multi-sensor and single-sensor non-SWOT methods. SWOT's all-weather SAR Interferometry based sensor, KaRIN, was found able to estimate both water elevation with superior accuracy. The water surface elevations were estimated accurately at 245 reservoirs making SWOT a one-of-its-kind global sensor. This global coverage distinguishes SWOT from previous altimeter missions, which do not observe vast portions of the planet.

Two key findings emerged from this study—(a) SWOT is able to capture the variability and absolute values of reservoir storage well using its elevation measurements. (b) The error of storage estimates (RMSE) reduced drastically when in situ AEV was used. R^2 stayed relatively consistent for SWOT, suggesting that the limiting factor for accurately estimate reservoir storage using SWOT is the accuracy of AEV. The reason for superior performance of SWOT elevations in estimating storage to the pre-SWOT baseline was further validated using the ICESat-2 satellite. SWOT is able to estimate the storage dynamics of reservoirs situated in mountainous regions especially well. Mountainous regions are a weakness of existing methods—area measuring sensors struggle with terrain shadow, and radar altimetry satellites struggle with small intersections in irregular reservoirs. This gap in existing methods is filled in a timely manner by the SWOT satellite's ability to measure WSE over a surface.

Another no less important finding that emerged is that the integration of SWOT data in non-SWOT methods, whether it is using ML or calibration techniques, needs further development. The paucity of SWOT record (<2.0 years) is likely the reason and a longer data record from SWOT should be able to make the sensor ready to “run the show” of multi-sensor storage estimation akin to how the Global Precipitation Measurement sensor for multi-sensor precipitation product development.

Data Availability Statement

SWOT data was obtained from PODAAC at https://podaac.jpl.nasa.gov/dataset/SWOT_L2_HR_Raster_2.0 and Earthdata at https://search.earthdata.nasa.gov/search. ICESat-2 data was also obtained from Earthdata. Google Earth Engine (https://earthengine.google.com/) was used to obtain observations from Landsat 8, Landsat 9, Sentinel 2, and Sentinel 1 satellites for the multi-sensor TMS-OS approach. The code for the study is available at the following github repository: https://github.com/UW-SASWE/tmspp and the following zenodo repository: https://zenodo.org/records/14984614 (Das, 2025).

Acknowledgments
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